k-Means

Source:

[https://www.kaggle.com/lava18/google-play-store-apps (https://www.kaggle.com/lava18/google-play-store-apps)](https://www.kaggle.com/lava18/google-play-store-apps)

Defining the Problem Statement

This dataset records the attributes of Android mobile applications in the Google Play Store. From this dataset, we would like to be able to find the best clustering results/optimum number of clusters.

Collecting the Data

In [1]:

```
#importing the libraries
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
from sklearn import datasets
from sklearn.cluster import KMeans
import time
```

In [2]:

```
dataset = pd.read_csv('googleps_cleaned.csv')
```

In [3]:

```
dataset.head()
```

Out[3]:

	Category	Rating	Reviews	Size	Installs	Type	Price	Content Rating	Genres
0	0	High Rating	159.0	19.0	9	0	0.0	1	9
1	0	Average Rating	967.0	14.0	12	0	0.0	1	11
2	0	High Rating	87510.0	8.7	14	0	0.0	1	9
3	0	High Rating	215644.0	25.0	16	0	0.0	4	9
4	0	High Rating	967.0	2.8	11	0	0.0	1	10

In [4]:

```
ds1_7 = dataset.iloc[:, [0,2,3,4, 5, 6, 7, 8]]
print (ds1_7.head())
```

```
   Category   Reviews  Size  Installs  Type  Price  Content Rating  Genres
0         0     159.0  19.0         9     0    0.0               1       9
1         0     967.0  14.0        12     0    0.0               1      11
2         0   87510.0   8.7        14     0    0.0               1       9
3         0  215644.0  25.0        16     0    0.0               4       9
4         0     967.0   2.8        11     0    0.0               1      10
```

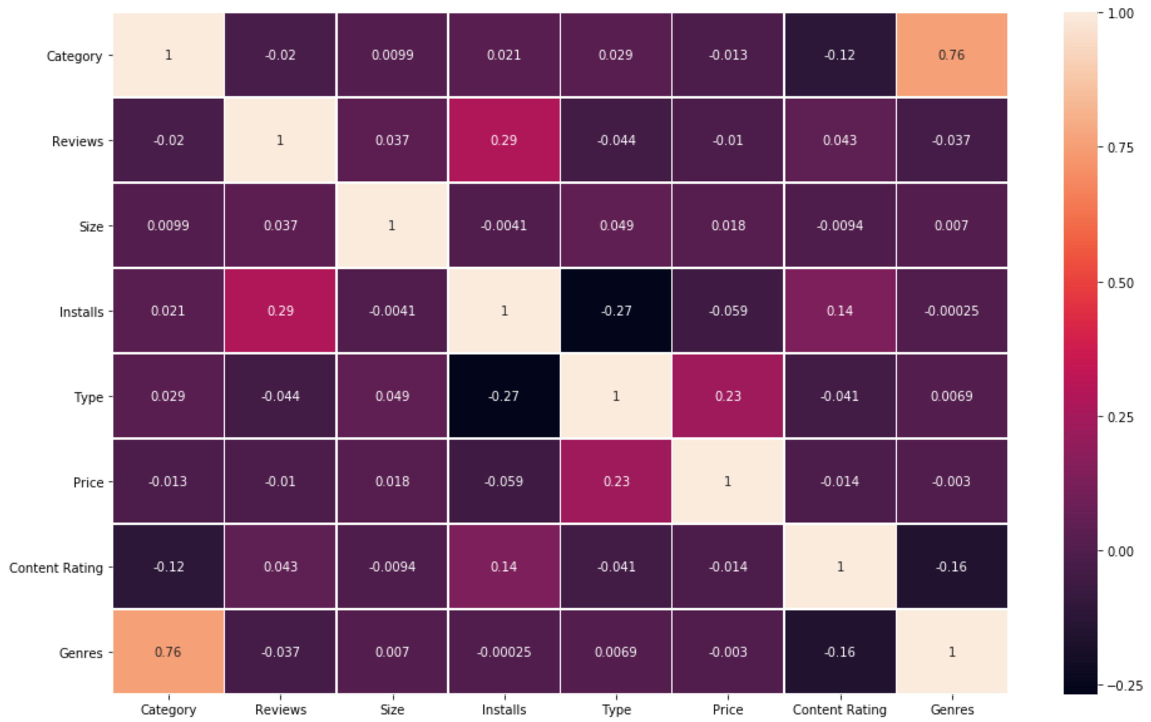
Feature Selection using Scatter Map and Correlation

In [5]:

```
import seaborn as sns
plt.figure(figsize=(16, 10))
sns.heatmap(dataset.corr(), annot=True,linewidths=.5)
```

Out[5]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x21947c4bfd0>
```



In [6]:

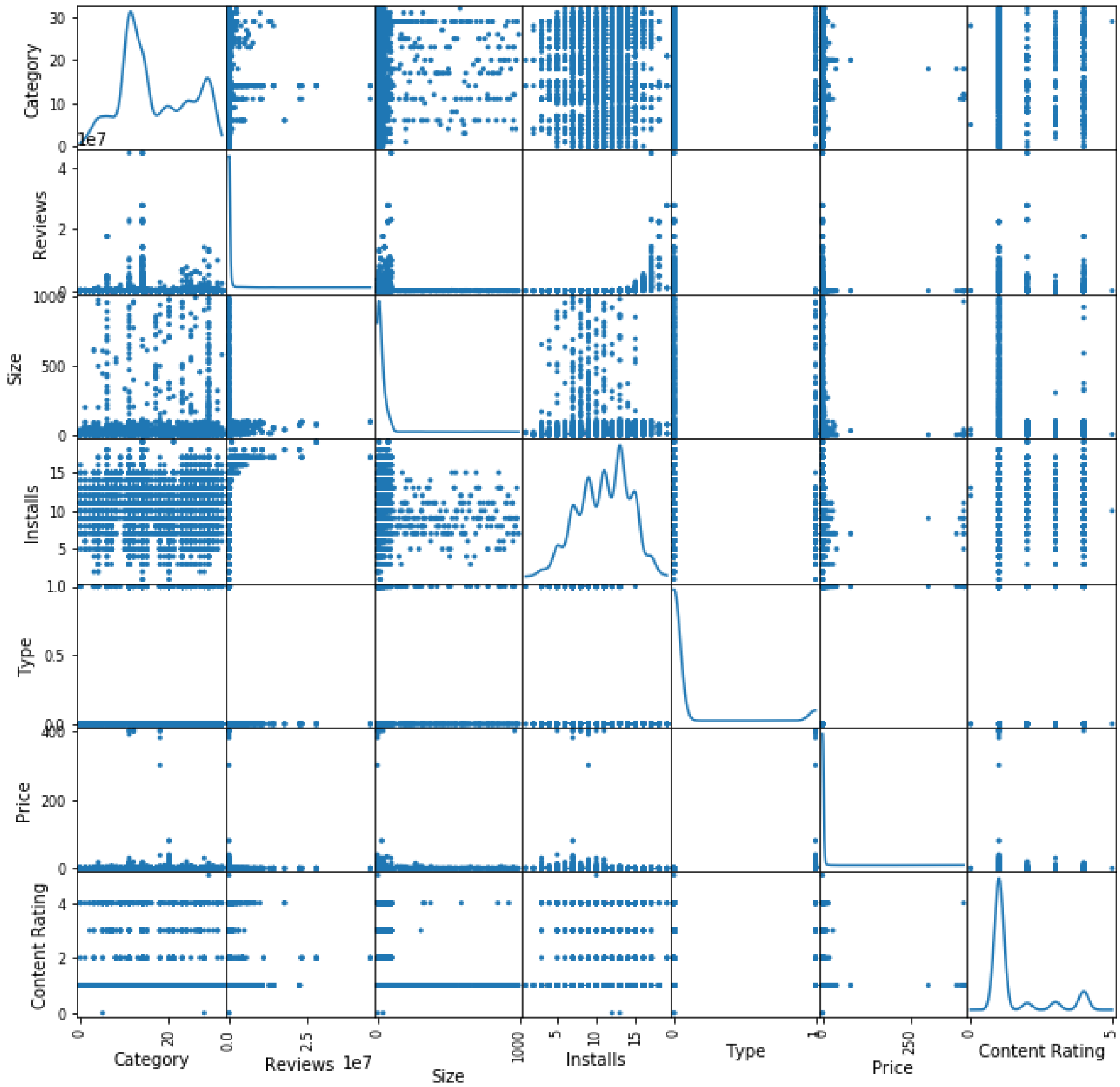
```
from pandas.plotting import scatter_matrix

scatter_matrix(dataset.iloc[:,0:8], alpha=1, figsize=(11, 11), diagonal='kde')
```

Out[6]:

```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x00000219484033C
8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000002194843255
0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x0000021948013AC
8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x00000219480540B
8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000002194808466
8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x00000219480B3C1
8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x00000219480F320
8>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x00000219481257F
0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000002194812582
8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000002194819535
8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x00000219481C590
8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x00000219481F7EB
8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x00000219482334A
8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x0000021948267A5
8>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x00000219482A604
8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x00000219482D45F
8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x0000021948308BA
8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000002194867619
8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x00000219486A674
8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x00000219486D9CF
8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x00000219487182E
8>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x000002194874889
8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000002194877AE4
8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x00000219487B843
8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x00000219487E79E
8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000002194881BF9
8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000002194885758
8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x0000021948889B3
8>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x00000219488C812
8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x00000219488F96D
```

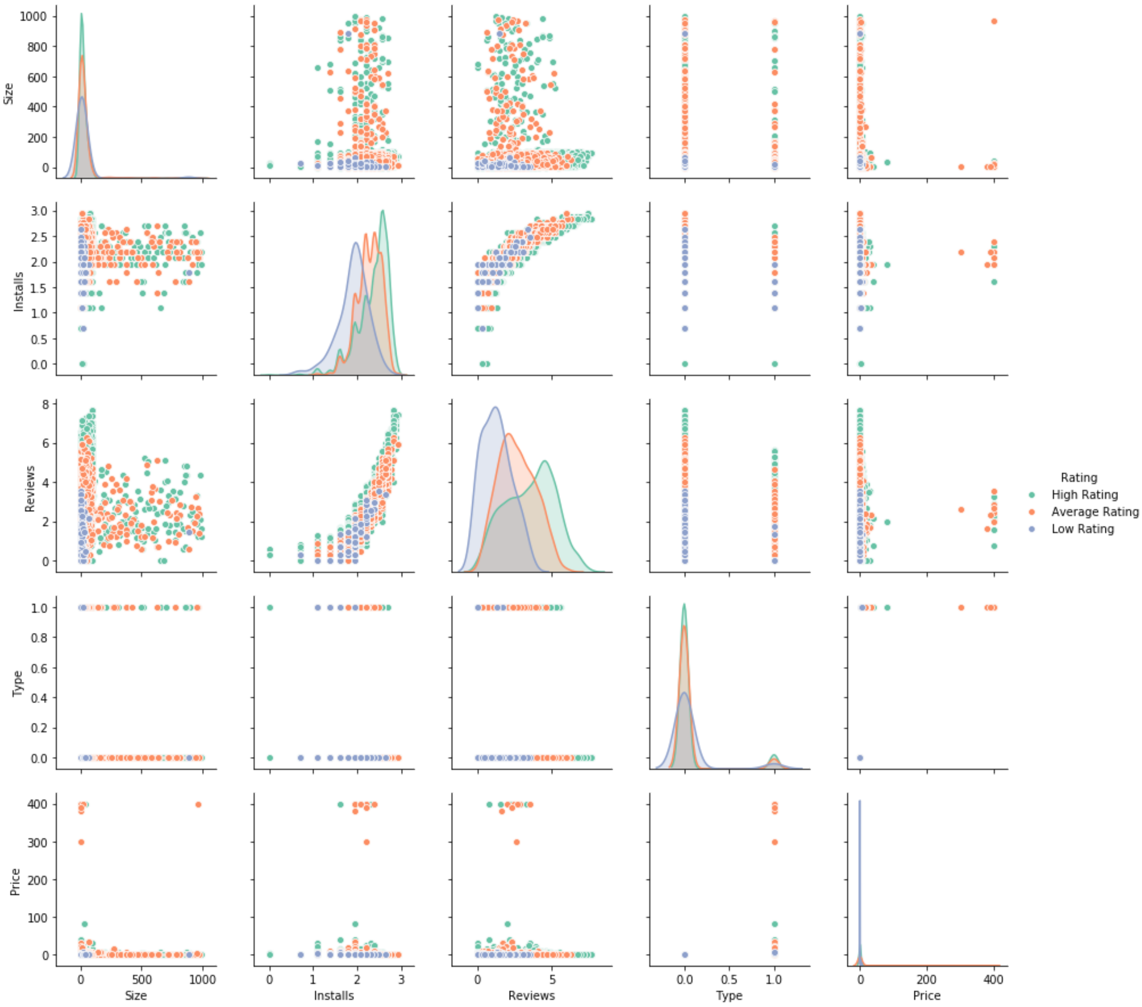
```
8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000002194892CC8
8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000002194896A27
8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000002194899A82
8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x00000219489CCDD
8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x0000021948A0A3C
8>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x0000021948A3997
8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x0000021948A6EF2
8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x00000219483D951
8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x0000021948AC1AC
8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x0000021948B020B
8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x0000021948B3166
8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x0000021948B64C1
8>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x0000021948BA320
8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x0000021948BD27B
8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x0000021948C03D6
8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x0000021948C4235
8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x0000021948C7190
8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x0000021948CA6EB
8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x0000021948CE34A
8>]],
      dtype=object)
```


Category
Reviews
Size
Installs
Type
Price
Content Rating
1e7

In [7]:

```
a = dataset['Rating'].dropna()
b = dataset['Size'].dropna()
z = dataset['Installs'][dataset.Installs!=0].dropna()
p = dataset['Reviews'][dataset.Reviews!=0].dropna()
t = dataset['Type']
price = dataset['Price']

p = sns.pairplot(pd.DataFrame(list(zip(a, b, np.log(z), np.log10(p), t,price)),
                        columns=['Rating','Size', 'Installs', 'Reviews', 'Type', 'Pric
e']), hue='Rating', palette="Set2")
```



- According to the Pearson Correlation Matrix, we can see that 'Genres' and 'Category' have high positive correlation.
- We are going to ignore some features that do not contribute much to the model.
- Selected features are Reviews and Size, Reviews and Price.

Elbow Method - Finding the Optimum Number of Clusters

In [8]:

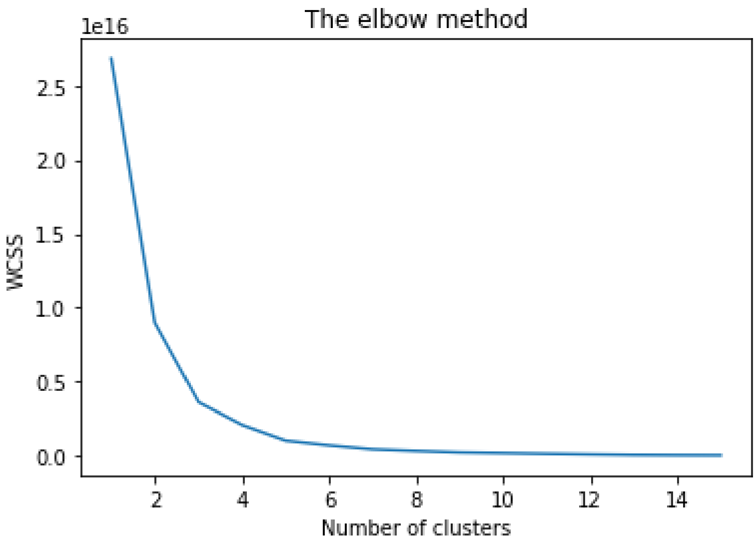
```
x = ds1_7.values
y = dataset['Rating']
```

In [9]:

```
from sklearn.cluster import KMeans
wcss = []

# Trying kmeans for k=1 to k=15
for i in range(1, 16):
    kmeans = KMeans(n_clusters = i, init = 'k-means++', max_iter = 300, n_init = 10, ra
ndom_state = 0)
    kmeans.fit(x)
    wcss.append(kmeans.inertia_)

#Plotting the results onto a line graph, allowing us to observe 'The elbow'
plt.plot(range(1, 16), wcss)
plt.title('The elbow method')
plt.xlabel('Number of clusters')
plt.ylabel('WCSS') #within cluster sum of squares
plt.show()
```



k- Means Part 1

- Using the elbow method, we decided that the optimal number of cluster is 3.
- We try running KMeans with 3 clusters first:

In [10]:

```
start=time.time()
kmeans = KMeans(n_clusters = 3, init = 'k-means++', max_iter = 300, n_init = 10, random
_state = 0)
y_kmeans = kmeans.fit_predict(x)
end=time.time()
print(end-start)
```

```
0.07878851890563965
```

In [11]:

```
ds1_7[y_kmeans==0].head()
```

Out[11]:

	Category	Reviews	Size	Installs	Type	Price	Content Rating	Genres
0	0	159.0	19.0	9	0	0.0	1	9
1	0	967.0	14.0	12	0	0.0	1	11
2	0	87510.0	8.7	14	0	0.0	1	9
3	0	215644.0	25.0	16	0	0.0	4	9
4	0	967.0	2.8	11	0	0.0	1	10

In [ ]:

```
### Select 'Reviews' and 'Size' to figure out the clustering
```

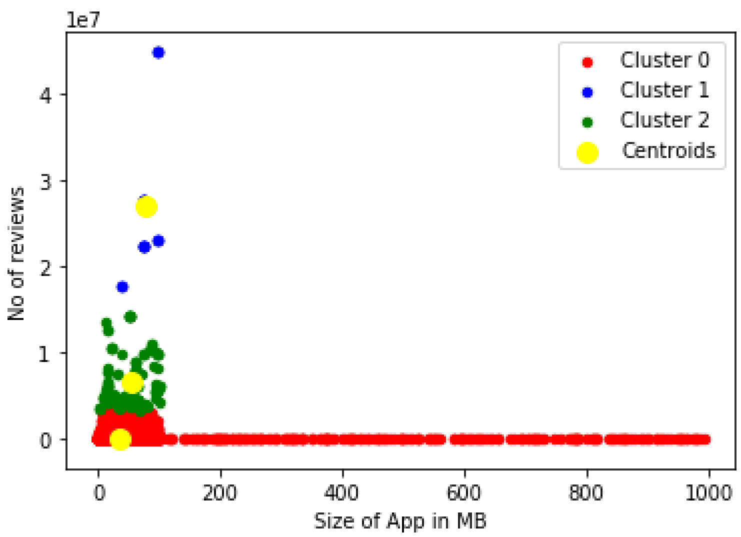
In [12]:

```
#Visualising the clusters
plt.scatter(x[y_kmeans == 0, 2], x[y_kmeans == 0, 1], s = 20, c = 'red', label = 'Clust
er 0')
plt.scatter(x[y_kmeans == 1, 2], x[y_kmeans == 1, 1], s = 20, c = 'blue', label = 'Clus
ter 1')
plt.scatter(x[y_kmeans == 2, 2], x[y_kmeans == 2, 1], s = 20, c = 'green', label = 'Clu
ster 2')

#Plotting the centroids of the clusters
plt.scatter(kmeans.cluster_centers_[:, 2], kmeans.cluster_centers_[:,1], s = 100, c =
'yellow', label = 'Centroids')
plt.xlabel("Size of App in MB")
plt.ylabel("No of reviews")
plt.legend()
```

Out[12]:

<matplotlib.legend.Legend at 0x2194ce9ebe0>



Filtering the Data - The presence of the long tail seems to disturb our visualization. We will filter the data to get a clearer picture.

In [13]:

```
dataset.shape
```

Out[13]:

```
(7723, 9)
```

In [14]:

```
df=dataset.loc[(dataset['Size'] < 100) & (dataset['Reviews'] <= 1000000)]
```

In [15]:

```
ds1 = df.iloc[:, [0,2,3,4, 5, 6, 7, 8]]
```

In [16]:

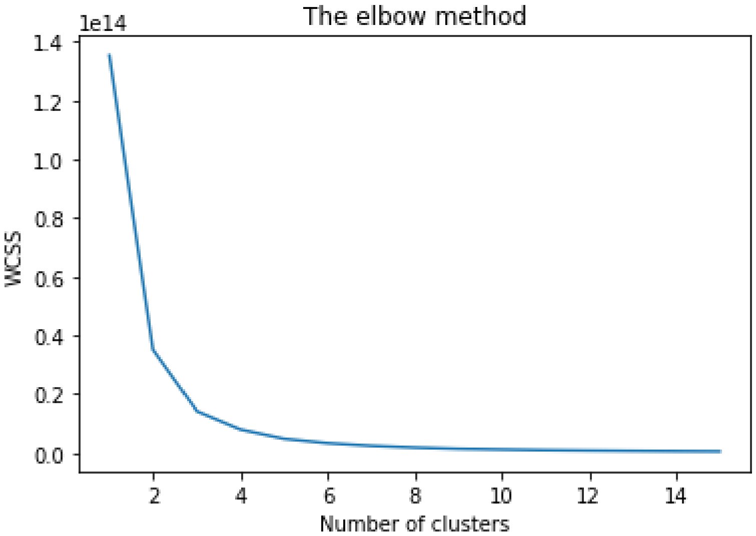
```
x = ds1.values
y = df['Rating']
```

In [17]:

```
from sklearn.cluster import KMeans
wcss = []

# Trying kmeans for k=1 to k=15
for i in range(1, 16):
    kmeans = KMeans(n_clusters = i, init = 'k-means++', max_iter = 300, n_init = 10, ra
ndom_state = 0)
    kmeans.fit(x)
    wcss.append(kmeans.inertia_)

#Plotting the results onto a line graph, allowing us to observe 'The elbow'
plt.plot(range(1, 16), wcss)
plt.title('The elbow method')
plt.xlabel('Number of clusters')
plt.ylabel('WCSS') #within cluster sum of squares
plt.show()
```



In [18]:

```
kmeans = KMeans(n_clusters = 3, init = 'k-means++', max_iter = 300, n_init = 10, random
_state = 0)
y_kmeans = kmeans.fit_predict(x)
```

In [19]:

```
ds1[y_kmeans==0].head()
```

Out[19]:

	Category	Reviews	Size	Installs	Type	Price	Content Rating	Genres
254	6	659395.0	11.0	17	0	0.0	1	33
262	6	615381.0	37.0	15	0	0.0	3	33
303	6	483565.0	20.0	15	0	0.0	1	33
304	6	552441.0	29.0	15	0	0.0	1	33
607	9	702975.0	49.0	16	0	0.0	1	49

In [20]:

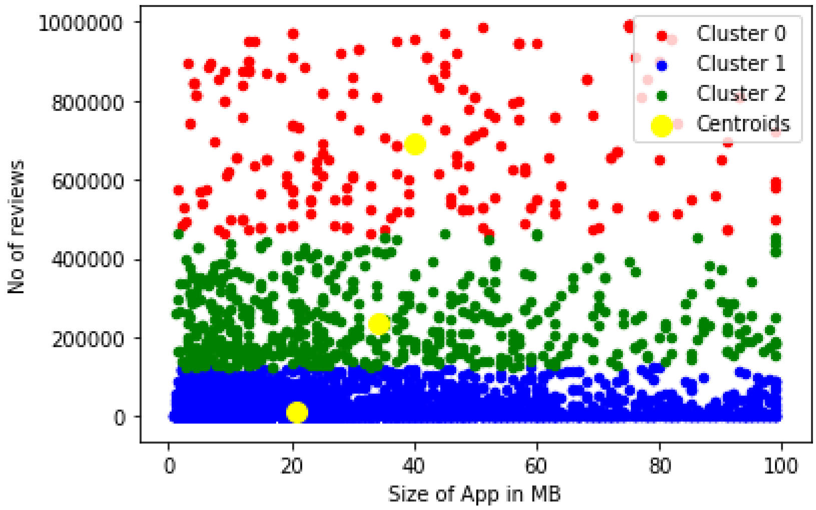
```
#Visualising the clusters
plt.scatter(x[y_kmeans == 0, 2], x[y_kmeans == 0, 1], s = 20, c = 'red', label = 'Clust
er 0')
plt.scatter(x[y_kmeans == 1, 2], x[y_kmeans == 1, 1], s = 20, c = 'blue', label = 'Clus
ter 1')
plt.scatter(x[y_kmeans == 2, 2], x[y_kmeans == 2, 1], s = 20, c = 'green', label = 'Clu
ster 2')

#Plotting the centroids of the clusters
plt.scatter(kmeans.cluster_centers_[:, 2], kmeans.cluster_centers_[:,1], s = 100, c =
'yellow', label = 'Centroids')

plt.xlabel("Size of App in MB")
plt.ylabel("No of reviews")
plt.legend()
```

Out[20]:

```
<matplotlib.legend.Legend at 0x2194ef4edd8>
```



- We can interpret the segmentation as follows:
  - Cluster 1: Small apps with very limited reviews
  - Cluster 2: Medium sized apps with some reviews
  - Cluster 0: Large apps with many reviews

- On the surface, it appears that large android apps are generally more popular with users, which explains why the larger apps get more reviews. For a company targeting to launch new apps, they should aim for bigger apps (30-40MB), which means more features and longer development time/time to market. The small apps (20MB and below) segment generally struggles to get user reviews.
- However, it could also mean that large apps and small apps have different markets altogether. For example,large apps take up alot of space in the phone and also need a longer time to download, if the network speed is low. In emerging markets, where the internet speed is slow and device storage space is limited, the smaller apps may be more popular. Thus, the issue may be that smaller apps tend to be more popular in emerging markets, where cultures are not used to providing reviews. The company launching the app will have to study their target market carefully.

Model Evaluation

In [21]:

```
from sklearn import metrics
print("Homogeneity: %0.3f" % metrics.homogeneity_score(y, y_kmeans))
print("Completeness: %0.3f" % metrics.completeness_score(y, y_kmeans))
print("V-measure: %0.3f" % metrics.v_measure_score(y, y_kmeans))
print("Adjusted Rand Index: %0.3f"
      % metrics.adjusted_rand_score(y, y_kmeans))
print("Adjusted Mutual Information: %0.3f"
      % metrics.adjusted_mutual_info_score(y, y_kmeans))
print("Silhouette Coefficient: %0.3f"
      % metrics.silhouette_score(x, y_kmeans))
```

```
Homogeneity: 0.029
Completeness: 0.040
V-measure: 0.034
Adjusted Rand Index: -0.085
Adjusted Mutual Information: 0.029

C:\Users\patch\Anaconda3\envs\hans\lib\site-packages\sklearn\metrics\clust
er\supervised.py:746: FutureWarning: The behavior of AMI will change in ve
rsion 0.22. To match the behavior of 'v_measure_score', AMI will use avera
ge_method='arithmetic' by default.
  FutureWarning)

Silhouette Coefficient: 0.852
```

- The homogenity, completement, v-measure, and ARI scores are all very low, indicating that K-Means is not suitable here. This could be due to the odd shapes of the clusters.
- Only silhouette coefficient is high here, indicating good/dense clustering.

k-Means Part 2

- Here, we select 'Reviews' and 'Price' to figure out the clustering.

In [22]:

```
df=dataset.loc[(dataset['Price'] < 20) & (dataset['Reviews'] <= 200000)&(dataset['Type'
]==1)]
df.shape
```

Out[22]:

```
(543, 9)
```

In [23]:

```
ds1 = df.iloc[:, [0,2,3,4, 5, 6, 7, 8]]
print (ds1.head())
```

```
     Category  Reviews  Size  Installs  Type  Price  Content Rating  Genre
s
174         4  11442.0   6.8        11     1   4.99               1      1
9
175         4  10295.0  39.0        11     1   4.99               1      1
9
214         4  11442.0   6.8        11     1   4.99               1      1
9
215         4  10295.0  39.0        11     1   4.99               1      1
9
320         7     57.0   6.2         7     1   6.99               1      3
5
```

In [24]:

```
x = ds1.values
y=df['Rating']
```

In [25]:

```
start=time.time()
kmeans = KMeans(n_clusters = 3, init = 'k-means++', max_iter = 300, n_init = 10, random
_state = 0)
y_kmeans = kmeans.fit_predict(x)
end=time.time()
print(end-start)
```

```
0.030916929244995117
```

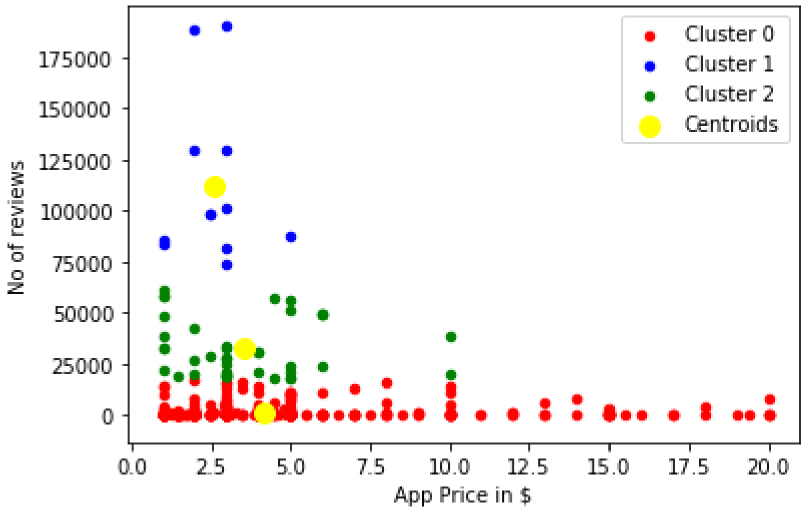
In [26]:

```
#Visualising the clusters
plt.scatter(x[y_kmeans == 0, 5], x[y_kmeans == 0, 1], s = 20, c = 'red', label = 'Clust
er 0')
plt.scatter(x[y_kmeans == 1, 5], x[y_kmeans == 1, 1], s = 20, c = 'blue', label = 'Clus
ter 1')
plt.scatter(x[y_kmeans == 2, 5], x[y_kmeans == 2, 1], s = 20, c = 'green', label = 'Clu
ster 2')

#Plotting the centroids of the clusters
plt.scatter(kmeans.cluster_centers_[:, 5], kmeans.cluster_centers_[:,1], s = 100, c =
'yellow', label = 'Centroids')
plt.xlabel("App Price in $")
plt.ylabel("No of reviews")
plt.legend()
```

Out[26]:

```
<matplotlib.legend.Legend at 0x2190000bfd0>
```



- In this price analysis section, we assume that the company is only interested in the segmentation of paid apps, so free apps were filtered out.
- In the analysis above, cluster 0 enjoys the highest number of customer reviews. The centroid of this cluster appears to be closer to $2.50.
- On the other hand, clusters 1 and 2 seems to receive significantly fewer user reviews.
- This indicates that app pricing is important for app popularity. Users would expect more functionality for a higher priced app, so if a company is going to set the app price above $3-5, the design of the app will have to be extraordinary, with stunning features and functionality.

Applying PCA

In [27]:

```
df = pd.read_csv('googleps_cleaned.csv')
```

In [28]:

```
from sklearn.preprocessing import StandardScaler
features = ['Category', 'Reviews', 'Size', 'Installs', 'Type', 'Price', 'Content Ratin
g', 'Genres']

x = df.loc[:, features].values
y = df.loc[:,['Rating']].values
x = StandardScaler().fit_transform(x)

pd.DataFrame(data=x, columns = features).head()
```

Out[28]:

	Category	Reviews	Size	Installs	Type	Price	Content Rating	Genres
0	-2.03631	-0.158138	-0.195722	-0.622513	-0.284156	-0.064812	-0.469001	-1.590283
1	-2.03631	-0.157704	-0.249177	0.311196	-0.284156	-0.064812	-0.469001	-1.528596
2	-2.03631	-0.111271	-0.305840	0.933669	-0.284156	-0.064812	-0.469001	-1.590283
3	-2.03631	-0.042523	-0.131576	1.556141	-0.284156	-0.064812	2.499928	-1.590283
4	-2.03631	-0.157704	-0.368917	-0.000040	-0.284156	-0.064812	-0.469001	-1.559440

In [29]:

```
from sklearn.decomposition import PCA
pca = PCA(n_components=2)
principalComponents = pca.fit_transform(x)
principalDf = pd.DataFrame(data = principalComponents
             , columns = ['principal component 1', 'principal component 2'])
principalDf.head()
```

Out[29]:

	principal component 1	principal component 2
0	2.289136	-0.859828
1	2.329817	-0.278366
2	2.431526	0.115043
3	3.235964	1.048576
4	2.325821	-0.468200

In [30]:

```
finalDf = pd.concat([principalDf, df[['Rating']]], axis = 1)
```

In [31]:

```
x = principalDf.values
y=finalDf['Rating'].values
```

In [32]:

```
start=time.time()
kmeans = KMeans(n_clusters = 3, init = 'k-means++', max_iter = 300, n_init = 10, random
_state = 0)
y_kmeans = kmeans.fit_predict(x)
end=time.time()
print(end-start)
```

```
0.1416158676147461
```

In [33]:

```
from sklearn import metrics
print("Homogeneity: %0.3f" % metrics.homogeneity_score(y, y_kmeans))
print("Completeness: %0.3f" % metrics.completeness_score(y, y_kmeans))
print("V-measure: %0.3f" % metrics.v_measure_score(y, y_kmeans))
print("Adjusted Rand Index: %0.3f"
      % metrics.adjusted_rand_score(y, y_kmeans))
print("Adjusted Mutual Information: %0.3f"
      % metrics.adjusted_mutual_info_score(y, y_kmeans))
print("Silhouette Coefficient: %0.3f"
      % metrics.silhouette_score(x, y_kmeans))
```

```
Homogeneity: 0.002
Completeness: 0.001
V-measure: 0.001
Adjusted Rand Index: -0.005
Adjusted Mutual Information: 0.001

C:\Users\patch\Anaconda3\envs\hans\lib\site-packages\sklearn\metrics\clust
er\supervised.py:746: FutureWarning: The behavior of AMI will change in ve
rsion 0.22. To match the behavior of 'v_measure_score', AMI will use avera
ge_method='arithmetic' by default.
  FutureWarning)

Silhouette Coefficient: 0.446
```

Conclusion

Using PCA also did not improve the model evaluation scores.