Clustering

May 22, 2022

0.1 Segmenting customers into clusters -

0.1.1 Performing Customer Segmentation on the transactional data to build an efficient marketing model.

[1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline

import warnings
warnings.filterwarnings('ignore')
```

[2]:
```
df = pd.read_excel('Segmenting_customers_into_clusters_dataset.xlsx')
```

[3]:
```
df.head()
```

[3]:
```
  InvoiceNo StockCode                          Description  Quantity  \
0    536365    85123A   WHITE HANGING HEART T-LIGHT HOLDER         6
1    536365     71053                  WHITE METAL LANTERN         6
2    536365    84406B       CREAM CUPID HEARTS COAT HANGER         8
3    536365    84029G  KNITTED UNION FLAG HOT WATER BOTTLE         6
4    536365    84029E       RED WOOLLY HOTTIE WHITE HEART.         6

          InvoiceDate  UnitPrice  CustomerID         Country
0 2010-12-01 08:26:00       2.55     17850.0  United Kingdom
1 2010-12-01 08:26:00       3.39     17850.0  United Kingdom
2 2010-12-01 08:26:00       2.75     17850.0  United Kingdom
3 2010-12-01 08:26:00       3.39     17850.0  United Kingdom
4 2010-12-01 08:26:00       3.39     17850.0  United Kingdom
```

[4]:
```
df.tail()
```

[4]:
```
       InvoiceNo StockCode                      Description  Quantity  \
541904    581587     22613      PACK OF 20 SPACEBOY NAPKINS        12
541905    581587     22899     CHILDREN'S APRON DOLLY GIRL          6
541906    581587     23254    CHILDRENS CUTLERY DOLLY GIRL          4
541907    581587     23255  CHILDRENS CUTLERY CIRCUS PARADE         4
```

```
541908    581587     22138    BAKING SET 9 PIECE RETROSPOT          3

               InvoiceDate  UnitPrice  CustomerID Country
541904 2011-12-09 12:50:00       0.85     12680.0  France
541905 2011-12-09 12:50:00       2.10     12680.0  France
541906 2011-12-09 12:50:00       4.15     12680.0  France
541907 2011-12-09 12:50:00       4.15     12680.0  France
541908 2011-12-09 12:50:00       4.95     12680.0  France
```

0.1.2 Dataset Variables are as follows:-

Invoice No: Invoice number, a 6-digit integral number uniquely assigned to each transaction. If this code starts with the letter 'c', it indicates a cancellation.

StockCode: Product / item code, a 5-digit integral number uniquely assigned to each distinct product.

Description: Product / item name.

Quantity: The quantities of each product / item per transaction.

Invoice Date: Invoice Date and time, the day and time when each transaction was generated.

UnitPrice: Unit price, Product price per unit in sterling.

CustomerID: Customer number, a 5-digit integral number uniquely assigned to each customer.

Country: Country name, the name of the country where each customer resides.

[5]:
```python
# Exploring our dataset
df.shape
```

[5]:
```
(541909, 8)
```

[6]:
```python
df.dtypes
```

[6]:
```
InvoiceNo              object
StockCode              object
Description            object
Quantity                int64
InvoiceDate    datetime64[ns]
UnitPrice             float64
CustomerID            float64
Country                object
dtype: object
```

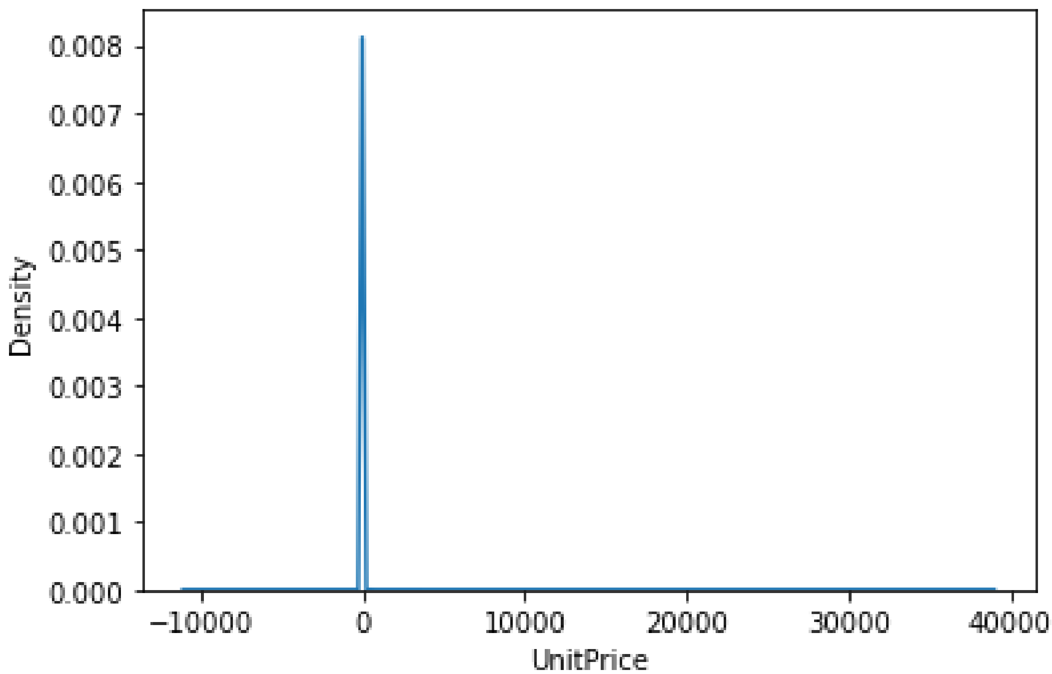
[7]:
```
df.describe()
```

[7]:

	Quantity	UnitPrice	CustomerID
count	541909.000000	541909.000000	406829.000000
mean	9.552250	4.611114	15287.690570
std	218.081158	96.759853	1713.600303
min	-80995.000000	-11062.060000	12346.000000
25%	1.000000	1.250000	13953.000000
50%	3.000000	2.080000	15152.000000
75%	10.000000	4.130000	16791.000000
max	80995.000000	38970.000000	18287.000000

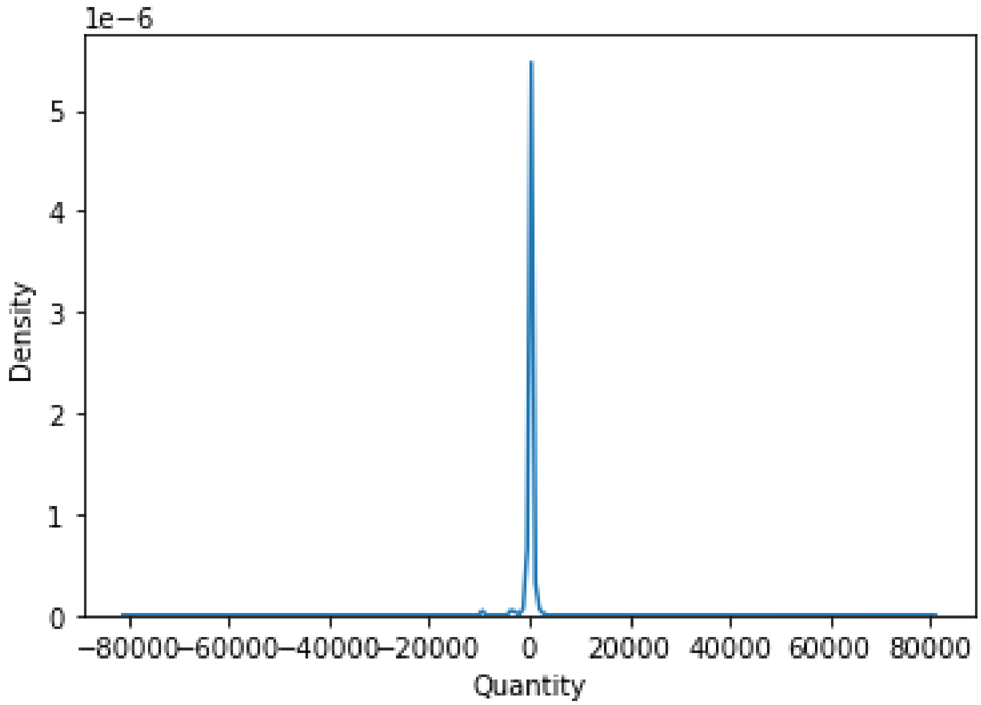
[8]:
```
sns.kdeplot(df['UnitPrice'])
```

[8]: <AxesSubplot:xlabel='UnitPrice', ylabel='Density'>



[9]:
```
sns.kdeplot(df['Quantity'])
```

[9]: <AxesSubplot:xlabel='Quantity', ylabel='Density'>



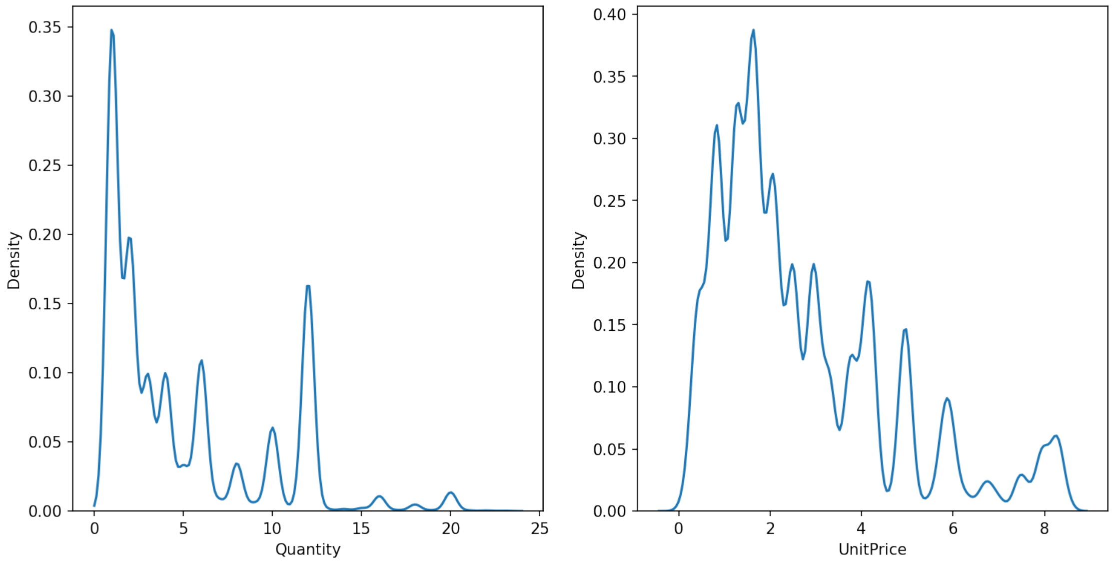
In our dataset, we have outliers present in the data as there are negative values observed from the plot.

[10]:
```
def abs_val(value, data):
    for i in value:
        quant1 = data[i].quantile(0.25)
        quant2 = data[i].quantile(0.75)
        IQR = quant2 - quant1
        val_max = quant2 + 1.5*IQR
        data = data.loc[(data[i] > 0) & (data[i] < val_max)]
    return data
```

[11]:
```
item = ['Quantity', 'UnitPrice']
frame = abs_val(item, df)
```

[12]:
```
def clean(value, data):
    plt.figure(figsize = (12,6), dpi=150)
    for j,k in enumerate(value):
        plt.subplot(1, len(value), j+1)
        sns.kdeplot(data[k])
```

[13]:
```
clean(item, frame)
```



[14]:
```
frame.describe()
```

[14]:

	Quantity	UnitPrice	CustomerID
count	437169.000000	437169.000000	321030.000000
mean	4.932159	2.712419	15352.180587
std	4.507273	1.944784	1703.612290
min	1.000000	0.001000	12347.000000
25%	1.000000	1.250000	14049.000000
50%	3.000000	2.080000	15298.000000
75%	8.000000	3.750000	16873.000000
max	23.000000	8.490000	18287.000000

[15]:
```
import datetime as dt
frame['Trans_year'] = df['InvoiceDate'].dt.year.astype('category')
frame['Trans_month'] = df['InvoiceDate'].dt.month.astype('category')
frame['Trans_day'] = df['InvoiceDate'].dt.day.astype('category')
frame['Trans_hour'] = df['InvoiceDate'].dt.hour.astype('category')
df['CustomerID'] = df['CustomerID'].astype('category')
```

[16]:
```
df = frame
```

[17]:
```
df.head()
```

[17]:

	InvoiceNo	StockCode	Description	Quantity \
0	536365	85123A	WHITE HANGING HEART T-LIGHT HOLDER	6
1	536365	71053	WHITE METAL LANTERN	6
2	536365	84406B	CREAM CUPID HEARTS COAT HANGER	8
3	536365	84029G	KNITTED UNION FLAG HOT WATER BOTTLE	6

```
4    536365    84029E       RED WOOLLY HOTTIE WHITE HEART.         6

          InvoiceDate  UnitPrice  CustomerID         Country Trans_year  \
0 2010-12-01 08:26:00       2.55     17850.0  United Kingdom       2010
1 2010-12-01 08:26:00       3.39     17850.0  United Kingdom       2010
2 2010-12-01 08:26:00       2.75     17850.0  United Kingdom       2010
3 2010-12-01 08:26:00       3.39     17850.0  United Kingdom       2010
4 2010-12-01 08:26:00       3.39     17850.0  United Kingdom       2010

  Trans_month Trans_day Trans_hour
0          12         1          8
1          12         1          8
2          12         1          8
3          12         1          8
4          12         1          8
```

[18]:
```
df.isnull().sum()
```

[18]:
```
InvoiceNo           0
StockCode           0
Description         0
Quantity            0
InvoiceDate         0
UnitPrice           0
CustomerID     116139
Country             0
Trans_year          0
Trans_month         0
Trans_day           0
Trans_hour          0
dtype: int64
```

[19]:
```
df['CustomerID'].fillna(df['CustomerID'].mode()[0], inplace = True)
```

[20]:
```
df.isnull().sum()
```

[20]:
```
InvoiceNo      0
StockCode      0
Description    0
Quantity       0
InvoiceDate    0
UnitPrice      0
CustomerID     0
Country        0
Trans_year     0
Trans_month    0
Trans_day      0
```

```
Trans_hour     0
dtype: int64
```

We have replaced the missing values of Customer ID by the mode of the feature. Now we will Encode the categorical features of the dataset.

[24]:
```python
def encode(value):
    for a in value:
        mapped = {}
        obj = list(df[a].unique())
        for m,n in enumerate(obj):
            mapped.update({n:m+1})
        df[a] = df[a].map(mapped)
        df[a] = df[a].astype('int64')
```

[25]:
```python
items = ['InvoiceNo', 'StockCode', 'Description', 'CustomerID', 'Country']
```

[26]:
```python
encode(items)
```

[27]:
```python
df.head()
```

[27]:
```
   InvoiceNo  StockCode  Description  Quantity         InvoiceDate  UnitPrice  \
0          1          1            1         6 2010-12-01 08:26:00       2.55
1          1          2            2         6 2010-12-01 08:26:00       3.39
2          1          3            3         8 2010-12-01 08:26:00       2.75
3          1          4            4         6 2010-12-01 08:26:00       3.39
4          1          5            5         6 2010-12-01 08:26:00       3.39

   CustomerID  Country Trans_year Trans_month Trans_day Trans_hour
0           1        1       2010          12         1          8
1           1        1       2010          12         1          8
2           1        1       2010          12         1          8
3           1        1       2010          12         1          8
4           1        1       2010          12         1          8
```

[28]:
```python
df = df.drop(['InvoiceDate'], axis = 1)
```

[29]:
```python
# Feature Scaling

from sklearn.preprocessing import StandardScaler
scale = StandardScaler()
```

[30]:
```python
scale_data = scale.fit_transform(df)
```

[32]:
```python
scale_data = pd.DataFrame(scale_data, columns = df.columns)
scale_data.head()
```

[32]:

	InvoiceNo	StockCode	Description	Quantity	UnitPrice	CustomerID	\
0	0.0	-1.139680	-1.152371	0.236915	-0.083515	-0.905703	
1	0.0	-1.138779	-1.151482	0.236915	0.348410	-0.905703	
2	0.0	-1.137878	-1.150593	0.680643	0.019324	-0.905703	
3	0.0	-1.136977	-1.149704	0.236915	0.348410	-0.905703	
4	0.0	-1.136076	-1.148815	0.236915	0.348410	-0.905703	

	Country	Trans_year	Trans_month	Trans_day	Trans_hour
0	-0.190424	-3.42424	1.254859	-1.616542	-2.13674
1	-0.190424	-3.42424	1.254859	-1.616542	-2.13674
2	-0.190424	-3.42424	1.254859	-1.616542	-2.13674
3	-0.190424	-3.42424	1.254859	-1.616542	-2.13674
4	-0.190424	-3.42424	1.254859	-1.616542	-2.13674

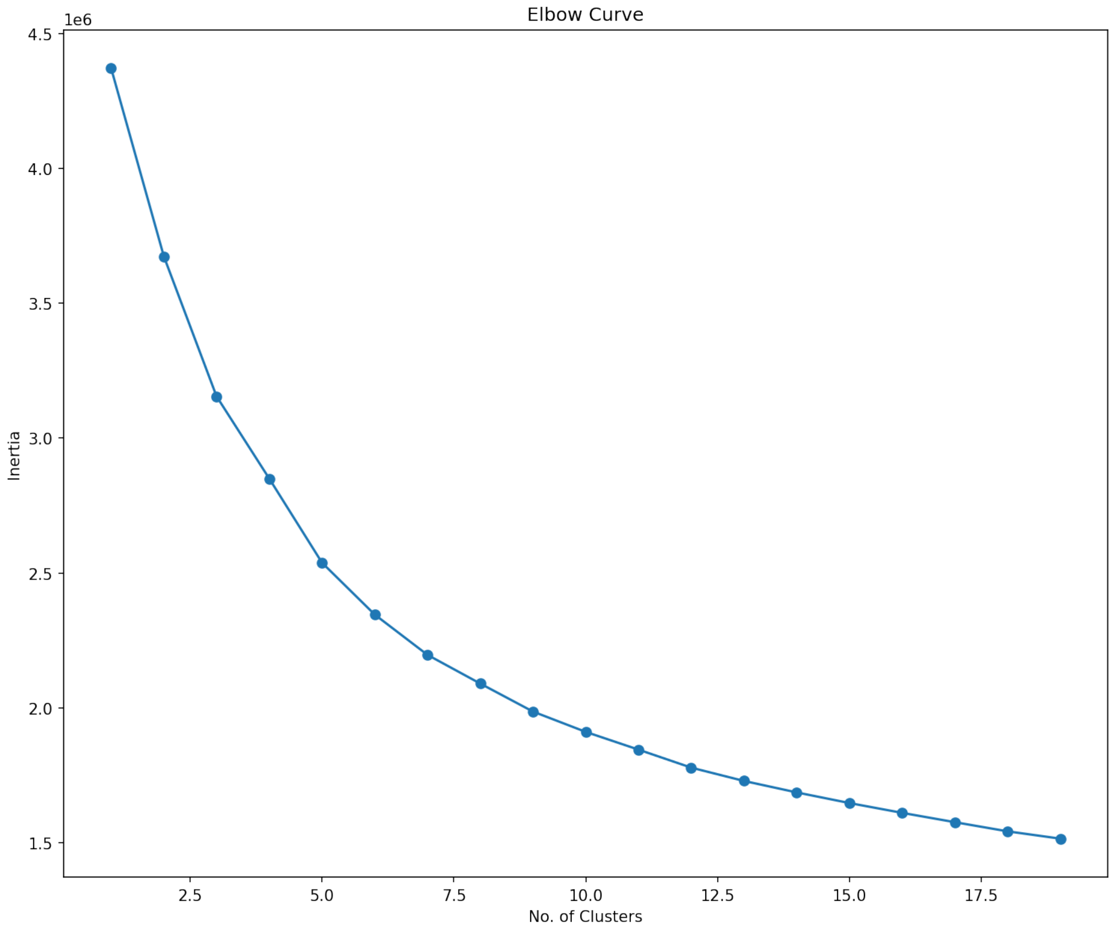
0.1.3 Segmenting the customers into Clusters with K-Means

[33]:
```
from sklearn.cluster import KMeans
```

[35]:
```
distance = []
for i in range(1,20):
    kmeans = KMeans(n_clusters = i)
    kmeans.fit(scale_data)
    distance.append(kmeans.inertia_)
```

[36]:
```
plt.figure(figsize=(12,10),dpi=150)
plt.plot(range(1,20),distance, marker='o')
plt.xlabel('No. of Clusters')
plt.ylabel('Inertia')
plt.title('Elbow Curve')
```

[36]: Text(0.5, 1.0, 'Elbow Curve')



From the Elbow Curve, it can be observed that after cluster 7 inertia of the remaining clusters is almost constant and hence the number of clusters present in the data can be choosen as 7.

[37]:
```python
kmeans = KMeans(n_clusters = 7)
kmeans.fit(scale_data)
k_pred = kmeans.predict(scale_data)
```

[38]:
```python
k_pred
```

[38]:
```
array([4, 4, 4, …, 5, 5, 5])
```

[40]:
```python
scale_data['Cluster_no'] = k_pred
```

[41]:
```python
scale_data.head()
```

[41]:
```
   InvoiceNo  StockCode  Description  Quantity  UnitPrice  CustomerID  \
0        0.0  -1.139680    -1.152371  0.236915  -0.083515   -0.905703
1        0.0  -1.138779    -1.151482  0.236915   0.348410   -0.905703
2        0.0  -1.137878    -1.150593  0.680643   0.019324   -0.905703
```

```
3        0.0  -1.136977    -1.149704  0.236915   0.348410   -0.905703
4        0.0  -1.136076    -1.148815  0.236915   0.348410   -0.905703

    Country  Trans_year  Trans_month  Trans_day  Trans_hour  Cluster_no
0 -0.190424    -3.42424     1.254859  -1.616542    -2.13674           4
1 -0.190424    -3.42424     1.254859  -1.616542    -2.13674           4
2 -0.190424    -3.42424     1.254859  -1.616542    -2.13674           4
3 -0.190424    -3.42424     1.254859  -1.616542    -2.13674           4
4 -0.190424    -3.42424     1.254859  -1.616542    -2.13674           4
```

[42]:
```
scale_data['Cluster_no'].value_counts()
```

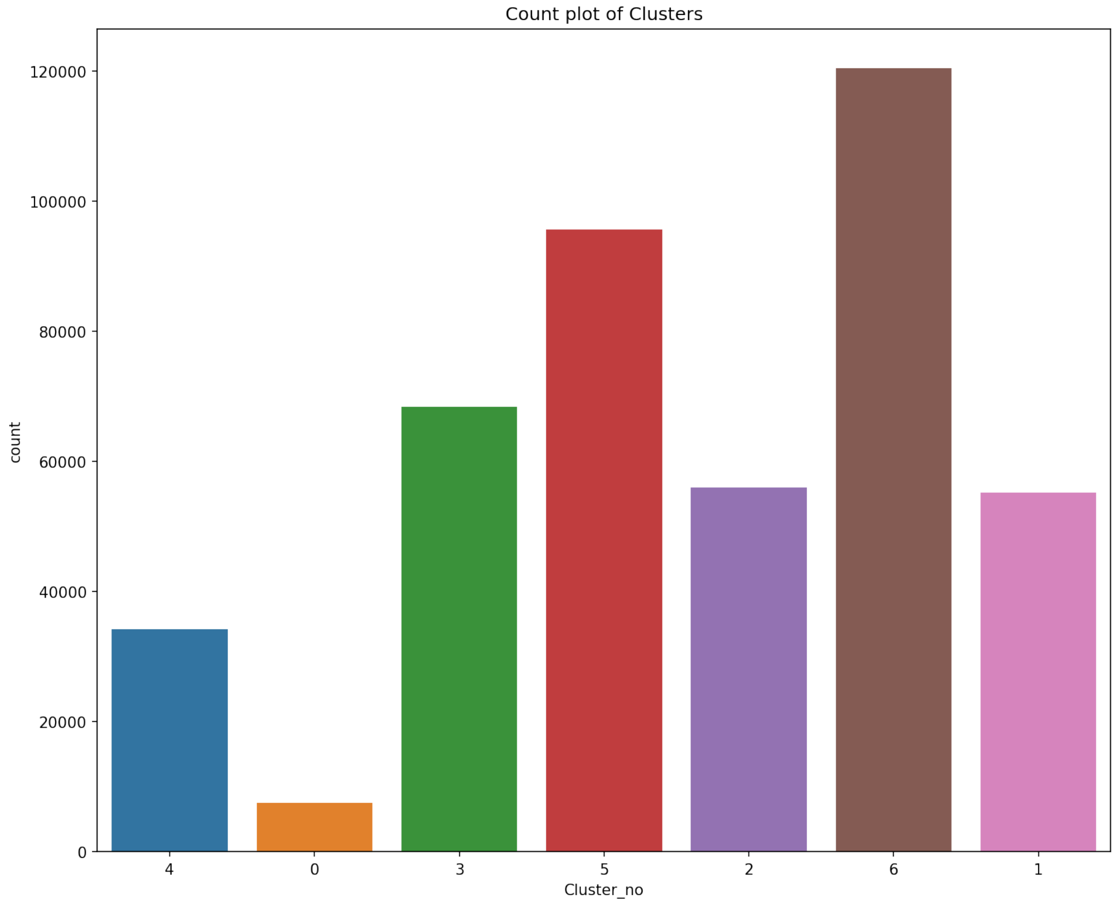
[42]:
```
6    120488
5     95618
3     68353
2     55950
1     55147
4     34146
0      7467
Name: Cluster_no, dtype: int64
```

[56]:
```
print(kmeans.cluster_centers_)
```

```
[[ 0.00000000e+00  2.65964335e-02  2.78644355e-02  6.59217475e-01
   5.54969996e-03  5.48335526e-01  6.63494875e+00  1.88501571e-01
  -1.81997186e-01  1.44936872e-02 -4.32035307e-01]
 [ 0.00000000e+00 -5.34143123e-01 -5.05233035e-01 -1.01289474e-01
  -2.65761983e-01  1.63961212e+00 -1.21526574e-01  2.92035628e-01
   5.95841672e-01  3.97701344e-02  2.98482156e-02]
 [ 0.00000000e+00 -4.14371556e-01 -4.10096508e-01 -5.38554748e-01
   1.62033421e+00 -3.86226776e-01 -1.22897475e-01  2.92035628e-01
  -4.67761206e-01  8.47083275e-02 -2.46670688e-01]
 [ 0.00000000e+00 -4.87913074e-01 -4.63925369e-01  1.44361665e+00
  -5.64948691e-01 -1.19483629e-02 -1.80348918e-02  2.92035628e-01
  -4.65199320e-01  5.33701444e-02 -4.99917614e-01]
 [ 0.00000000e+00 -4.98768369e-01 -5.25752989e-01 -1.70114484e-01
   1.67918014e-01 -7.04513983e-01 -1.33859744e-01 -3.42423973e+00
   1.25485859e+00 -5.75130670e-01  1.00602947e-02]
 [ 0.00000000e+00  1.58374204e+00  1.55190197e+00  5.24522697e-02
  -9.67132036e-03  2.19405460e-01 -9.96604905e-02  2.92035628e-01
   3.42216599e-01  5.21963823e-02 -3.13213686e-02]
 [ 0.00000000e+00 -4.03308787e-01 -3.99309048e-01 -5.57041243e-01
  -3.51688895e-01 -5.73631503e-01 -1.71234909e-01  2.92035628e-01
  -4.07799491e-01  3.28218631e-02  4.33830560e-01]]
```

[66]:
```
plt.figure(figsize = (12,10), dpi=150)
sns.countplot(scale_data['Cluster_no'])
plt.title('Count plot of Clusters')
```

[66]: Text(0.5, 1.0, 'Count plot of Clusters')



As we can see the above plot describes the number of datapoints present in each of the clusters.

[ ]: