IMPORTING LIBRARIES & LOADING DATA

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.cluster import KMeans
```

In [2]:
```
df = pd.read_csv('OnlineRetail.csv', encoding='unicode_escape')
```

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

Out[3]:

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country
0	536365	85123A	WHITE HANGING HEART T-LIGHT HOLDER	6	12/1/2010 8:26	2.55	17850.0	United Kingdom
1	536365	71053	WHITE METAL LANTERN	6	12/1/2010 8:26	3.39	17850.0	United Kingdom
2	536365	84406B	CREAM CUPID HEARTS COAT HANGER	8	12/1/2010 8:26	2.75	17850.0	United Kingdom
3	536365	84029G	KNITTED UNION FLAG HOT WATER BOTTLE	6	12/1/2010 8:26	3.39	17850.0	United Kingdom
4	536365	84029E	RED WOOLLY HOTTIE WHITE HEART.	6	12/1/2010 8:26	3.39	17850.0	United Kingdom

EXPLORATORY DATA ANALYSIS

In [4]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 541909 entries, 0 to 541908
Data columns (total 8 columns):
 #   Column       Non-Null Count   Dtype  
---  ------       --------------   -----  
 0   InvoiceNo    541909 non-null  object 
 1   StockCode    541909 non-null  object 
 2   Description  540455 non-null  object 
 3   Quantity     541909 non-null  int64  
 4   InvoiceDate  541909 non-null  object 
 5   UnitPrice    541909 non-null  float64
 6   CustomerID   406829 non-null  float64
 7   Country      541909 non-null  object 
dtypes: float64(2), int64(1), object(5)
memory usage: 33.1+ MB
```

In [5]:
```
df.describe()
```

Out[5]:

	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

DATA ENGINEERING

In [6]:
```
df['InvoiceDate'] = pd.to_datetime(df['InvoiceDate'])
```

In [7]:
```
df_uk = df[df['Country']=='United Kingdom']
```

In [8]:
```
df_uk.shape
```

Out[8]: (495478, 8)

In [9]:
```
df_uk_user = pd.DataFrame(df_uk['CustomerID'].unique())
```

In [10]:
```
df_uk_user.columns = ['CustomerID']
```

In [11]:
```
df_uk_user
```

Out[11]:

	CustomerID
0	17850.0
1	13047.0
2	13748.0
3	15100.0
4	15291.0
...	...
3946	15471.0
3947	13436.0
3948	15520.0
3949	13298.0
3950	14569.0

3951 rows × 1 columns

I RECENCY

In [12]:
```
temp = df_uk[['CustomerID', 'InvoiceDate']].groupby(['CustomerID']).max().res
```

In [13]:
```
temp['recency'] = (temp['InvoiceDate'].max()-temp['InvoiceDate']).dt.days
```

In [14]:
```
temp
```

Out[14]:

	CustomerID	InvoiceDate	recency
0	12346.0	2011-01-18 10:17:00	325
1	12747.0	2011-12-07 14:34:00	1
2	12748.0	2011-12-09 12:20:00	0
3	12749.0	2011-12-06 09:56:00	3
4	12820.0	2011-12-06 15:12:00	2
...	...	...	...
3945	18280.0	2011-03-07 09:52:00	277
3946	18281.0	2011-06-12 10:53:00	180
3947	18282.0	2011-12-02 11:43:00	7
3948	18283.0	2011-12-06 12:02:00	3
3949	18287.0	2011-10-28 09:29:00	42

3950 rows × 3 columns

In [15]:
```
df_uk_user = df_uk_user.merge(temp, on='CustomerID')
```

In [16]:
```
df_uk_user.drop(['InvoiceDate'], axis=1, inplace=True)
```

II FREQUENCY

In [17]:
```
temp = df_uk[['CustomerID', 'InvoiceDate']].groupby(['CustomerID']).count().r
```

In [18]:
```
temp.columns = ['CustomerID', 'frequency']
```

In [19]:
```
df_uk_user = df_uk_user.merge(temp, on='CustomerID')
```

In [20]:
```
df_uk_user
```

Out[20]:

	CustomerID	recency	frequency
0	17850.0	301	312
1	13047.0	31	196
2	13748.0	95	28
3	15100.0	329	6
4	15291.0	25	109
...	...	...	...
3945	15471.0	1	77
3946	13436.0	1	12
3947	15520.0	1	18
3948	13298.0	0	2
3949	14569.0	0	12

3950 rows × 3 columns

III MONETARY

In [21]:
```
temp = df_uk
```

In [22]:
```
temp['net_order'] = temp['Quantity']*temp['UnitPrice']
```

```
C:\Users\15516\anaconda3\lib\site-packages\ipykernel_launcher.py:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy (https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy)
  """Entry point for launching an IPython kernel.
```

In [23]:
```
temp = temp[['CustomerID', 'net_order']].groupby(['CustomerID']).sum().reset_
```

In [24]:
```
temp
```

Out[24]:

	CustomerID	net_order
0	12346.0	0.00
1	12747.0	4196.01
2	12748.0	29072.10
3	12749.0	3868.20
4	12820.0	942.34
...	...	...
3945	18280.0	180.60
3946	18281.0	80.82
3947	18282.0	176.60
3948	18283.0	2094.88
3949	18287.0	1837.28

3950 rows × 2 columns

In [25]:
```
df_uk_user = df_uk_user.merge(temp, on='CustomerID')
```

In [26]:
```
df_uk_user.columns = ['CustomerID', 'recency', 'frequency', 'monetary']
```

In [27]:
```
df_uk_user
```

Out[27]:

	CustomerID	recency	frequency	monetary
0	17850.0	301	312	5288.63
1	13047.0	31	196	3079.10
2	13748.0	95	28	948.25
3	15100.0	329	6	635.10
4	15291.0	25	109	4596.51
...	...	...	...	...
3945	15471.0	1	77	469.48
3946	13436.0	1	12	196.89
3947	15520.0	1	18	343.50
3948	13298.0	0	2	360.00
3949	14569.0	0	12	227.39

3950 rows × 4 columns

In [28]:
```
df_uk_user.describe()
```

Out[28]:

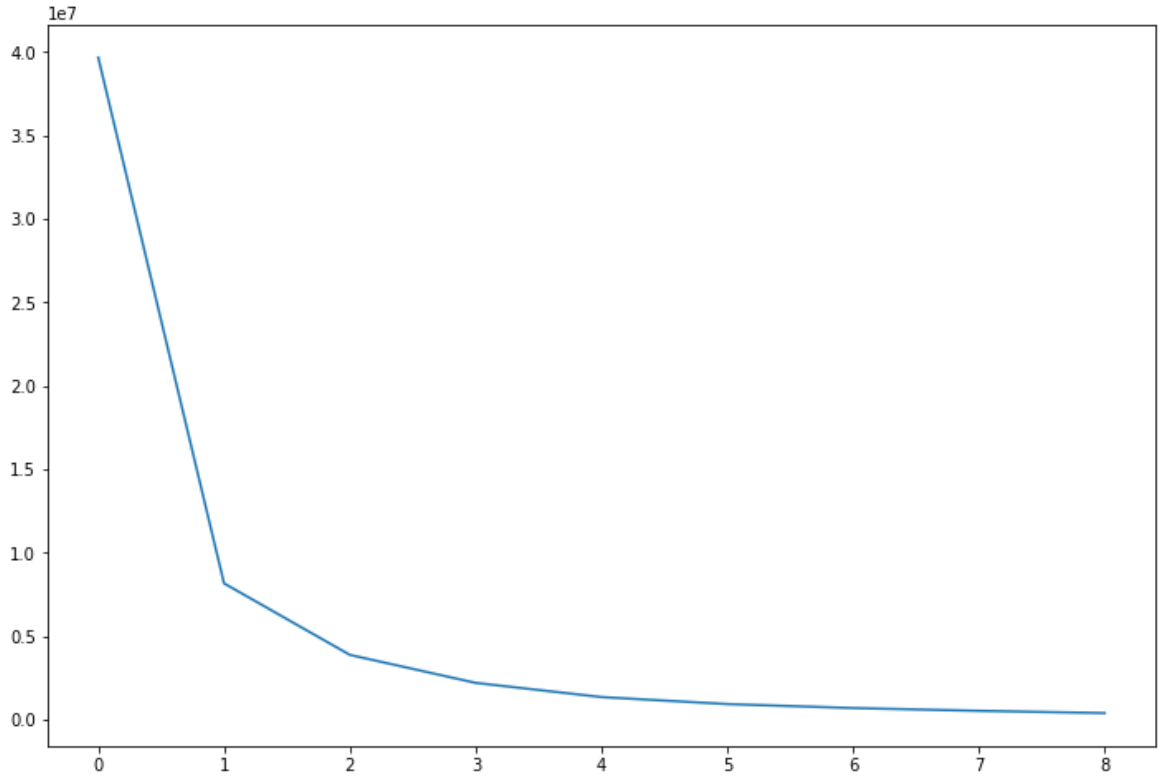
	CustomerID	recency	frequency	monetary
count	3950.000000	3950.000000	3950.000000	3950.000000
mean	15562.029367	90.778481	91.614684	1713.385669
std	1576.848325	100.230349	220.557389	6548.608224
min	12346.000000	0.000000	1.000000	-4287.630000
25%	14208.250000	16.000000	17.000000	282.255000
50%	15571.500000	49.000000	41.000000	627.060000
75%	16913.750000	142.000000	101.000000	1521.782500
max	18287.000000	373.000000	7983.000000	256438.490000

RECENCY CLUSTER

In [29]:
```
wcss = []
for i in range(1,10):
        model_r = KMeans(n_clusters=i)
        model_r.fit(pd.DataFrame(df_uk_user['recency']))
        wcss.append(model_r.inertia_)
```

In [30]:
```
plt.figure(figsize=(12,8))
plt.plot(wcss)
```

Out[30]: [<matplotlib.lines.Line2D at 0x233c7fca488>]

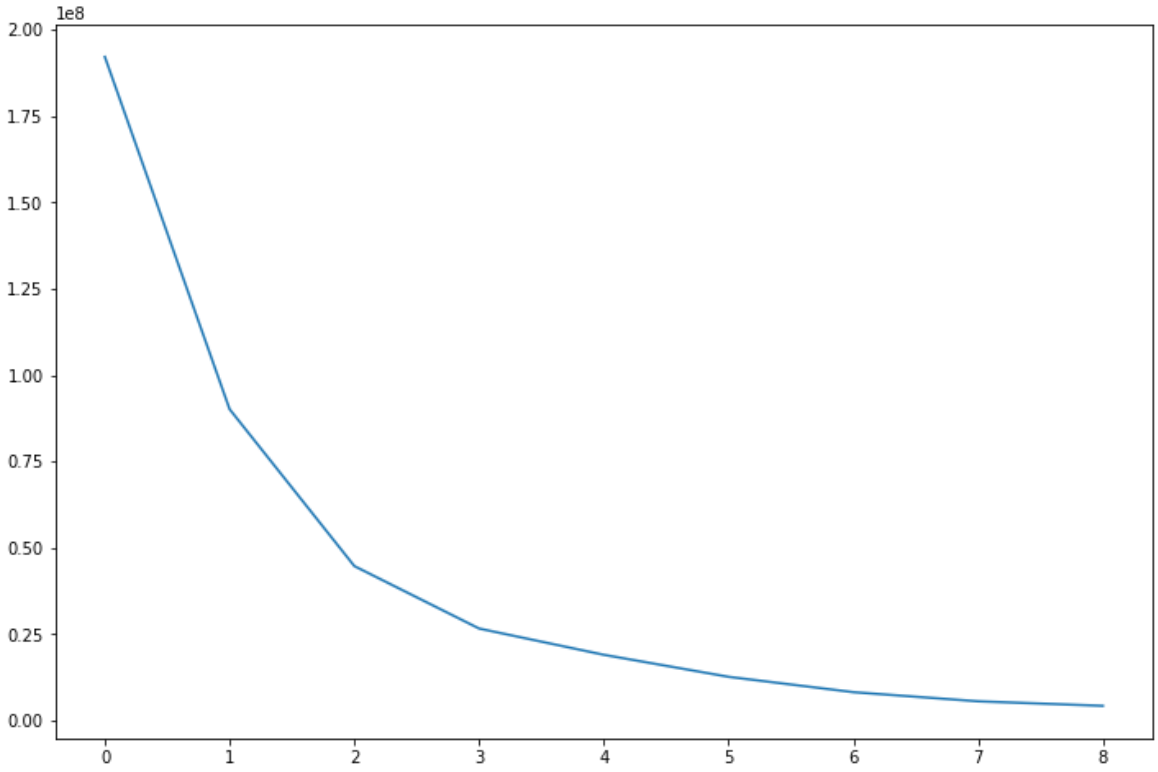


FREQUENCY CLUSTER

In [31]:
```
wcss = []
for i in range(1,10):
        model_f = KMeans(n_clusters=i)
        model_f.fit(pd.DataFrame(df_uk_user['frequency']))
        wcss.append(model_f.inertia_)
```

In [32]:
```
plt.figure(figsize=(12,8))
plt.plot(wcss)
```

Out[32]: [<matplotlib.lines.Line2D at 0x233cbbbb2c8>]

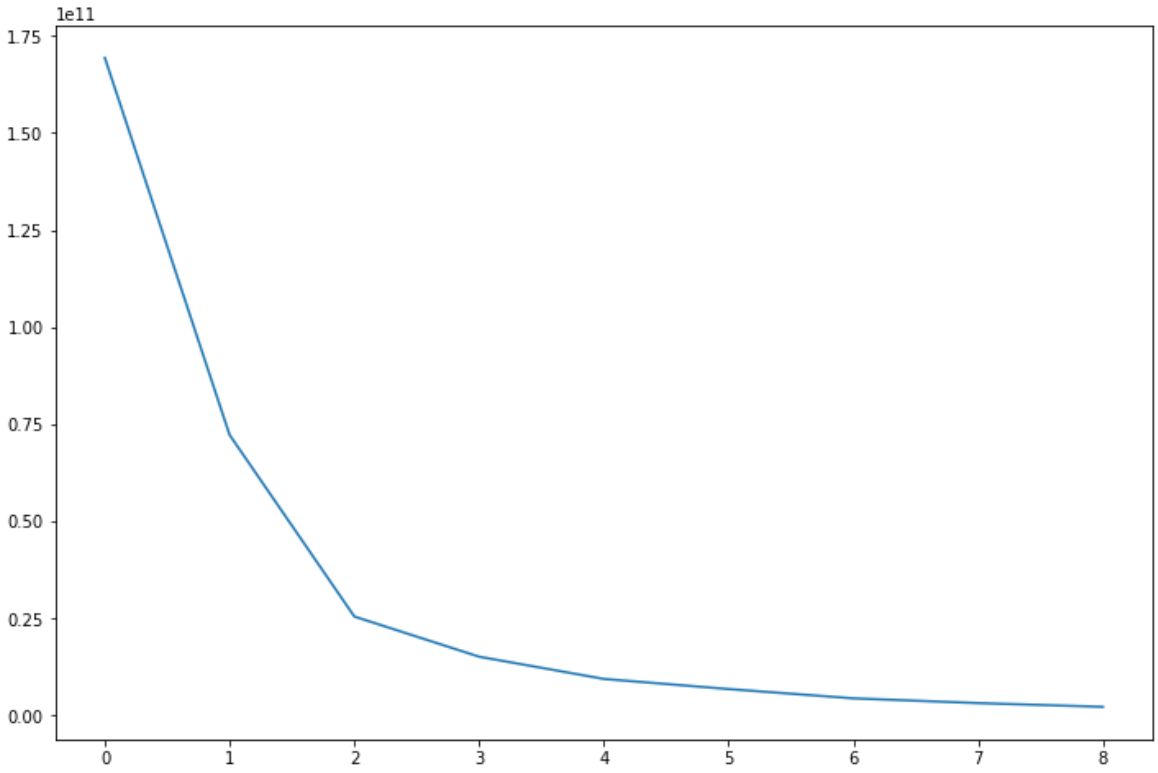


MONETARY CLUSTER

In [33]:
```
wcss = []
for i in range(1,10):
        model_m = KMeans(n_clusters=i)
        model_m.fit(pd.DataFrame(df_uk_user['monetary']))
        wcss.append(model_m.inertia_)
```

In [34]:
```
plt.figure(figsize=(12,8))
plt.plot(wcss)
```

Out[34]:
```
[<matplotlib.lines.Line2D at 0x233cbf467c8>]
```



4 Clusters seems to be an ideal number of cluster based on all WCSS

In [35]:
```
model_r = KMeans(n_clusters=4, random_state=0)
model_r.fit(pd.DataFrame(df_uk_user['recency']))
```

Out[35]:
```
KMeans(algorithm='auto', copy_x=True, init='k-means++', max_iter=300,
       n_clusters=4, n_init=10, n_jobs=None, precompute_distances='auto',
       random_state=0, tol=0.0001, verbose=0)
```

In [36]:
```
df_uk_user['recency_cluster'] = model_r.predict(pd.DataFrame(df_uk_user['rece
```

In [37]:
```
model_f = KMeans(n_clusters=4, random_state=0)
model_f.fit(pd.DataFrame(df_uk_user['frequency']))
```

Out[37]:
```
KMeans(algorithm='auto', copy_x=True, init='k-means++', max_iter=300,
       n_clusters=4, n_init=10, n_jobs=None, precompute_distances='auto',
       random_state=0, tol=0.0001, verbose=0)
```

In [38]:
```
df_uk_user['frequency_cluster'] = model_f.predict(pd.DataFrame(df_uk_user['fr
```

In [39]:
```
model_m = KMeans(n_clusters=4, random_state=0)
model_m.fit(pd.DataFrame(df_uk_user['monetary']))
```

Out[39]:
```
KMeans(algorithm='auto', copy_x=True, init='k-means++', max_iter=300,
       n_clusters=4, n_init=10, n_jobs=None, precompute_distances='auto',
       random_state=0, tol=0.0001, verbose=0)
```

In [40]:
```
df_uk_user['monetary_cluster'] = model_m.predict(pd.DataFrame(df_uk_user['mon
```

SORTING THE CLUSTER

In [41]:
```
df_uk_user
```

Out[41]:

	CustomerID	recency	frequency	monetary	recency_cluster	frequency_cluster	monetary
0	17850.0	301	312	5288.63	2	2	
1	13047.0	31	196	3079.10	1	2	
2	13748.0	95	28	948.25	3	0	
3	15100.0	329	6	635.10	2	0	
4	15291.0	25	109	4596.51	1	0	
...	...	...	...	...	...	...	
3945	15471.0	1	77	469.48	1	0	
3946	13436.0	1	12	196.89	1	0	
3947	15520.0	1	18	343.50	1	0	
3948	13298.0	0	2	360.00	1	0	
3949	14569.0	0	12	227.39	1	0	

3950 rows × 7 columns

In [42]:
```
df_uk_user.groupby(['recency_cluster']).mean()
```

Out[42]:

recency_cluster	CustomerID	recency	frequency	monetary	frequency_cluster	moneta
0	15644.091549	184.625000	34.896127	545.543347	0.021127	
1	15571.513333	17.488205	143.666667	2764.957257	0.427179	
2	15568.018828	304.393305	23.374477	345.192448	0.008368	
3	15490.784067	77.679245	53.180294	944.796784	0.073375	

In [43]:
```
clust_r = {0:1, 1:3, 2:0, 3:2}
```

In [44]:
```
df_uk_user['recency_cluster'] = df_uk_user['recency_cluster'].map(clust_r)
```

In [45]:
```
df_uk_user.groupby(['recency_cluster']).mean()
```

Out[45]:

recency_cluster	CustomerID	recency	frequency	monetary	frequency_cluster	moneta
0	15568.018828	304.393305	23.374477	345.192448	0.008368	
1	15644.091549	184.625000	34.896127	545.543347	0.021127	
2	15490.784067	77.679245	53.180294	944.796784	0.073375	
3	15571.513333	17.488205	143.666667	2764.957257	0.427179	

In [46]:
```
df_uk_user.groupby(['frequency_cluster']).mean()
```

Out[46]:

frequency_cluster	CustomerID	recency	frequency	monetary	recency_cluster	monet
0	15551.502857	99.888000	49.687429	1005.862198	2.008286	
1	14895.000000	1.333333	5917.666667	42177.930000	3.000000	
2	15671.503529	20.781176	332.541176	6374.881435	2.875294	
3	15212.818182	5.954545	1313.136364	18704.422727	3.000000	

In [47]:
```
clust_f = {0:0, 1:3, 2:1, 3:2}
```

In [48]:
```
df_uk_user['frequency_cluster'] = df_uk_user['frequency_cluster'].map(clust_f
```

In [49]:
```
df_uk_user.groupby(['frequency_cluster']).mean()
```

Out[49]:

frequency_cluster	CustomerID	recency	frequency	monetary	recency_cluster	monet
0	15551.502857	99.888000	49.687429	1005.862198	2.008286	
1	15671.503529	20.781176	332.541176	6374.881435	2.875294	
2	15212.818182	5.954545	1313.136364	18704.422727	3.000000	
3	14895.000000	1.333333	5917.666667	42177.930000	3.000000	

In [50]:
```
df_uk_user.groupby(['monetary_cluster']).mean()
```

Out[50]:

monetary_cluster	CustomerID	recency	frequency	monetary	recency_cluster	frequ
0	15569.806075	95.937347	67.382967	907.254414	2.051804	
1	17776.000000	3.500000	392.000000	221960.330000	3.000000	
2	15140.481481	5.777778	1165.703704	43070.445185	3.000000	
3	15469.213675	20.047009	346.918803	7760.699530	2.880342	

In [51]:
```
clust_m = {0:0, 1:3, 2:2, 3:1}
```

In [52]:
```
df_uk_user['monetary_cluster'] = df_uk_user['monetary_cluster'].map(clust_m)
```

In [53]:
```
df_uk_user.groupby(['monetary_cluster']).mean()
```

Out[53]:

monetary_cluster	CustomerID	recency	frequency	monetary	recency_cluster	frequ
0	15569.806075	95.937347	67.382967	907.254414	2.051804	
1	15469.213675	20.047009	346.918803	7760.699530	2.880342	
2	15140.481481	5.777778	1165.703704	43070.445185	3.000000	
3	17776.000000	3.500000	392.000000	221960.330000	3.000000	

In [54]:
```
df_uk_user['overall_score'] = df_uk_user['recency_cluster']+df_uk_user['frequ
```

In [55]:
```
df_uk_user.head()
```

Out[55]:

	CustomerID	recency	frequency	monetary	recency_cluster	frequency_cluster	monetary_cl
0	17850.0	301	312	5288.63	0	1	
1	13047.0	31	196	3079.10	3	1	
2	13748.0	95	28	948.25	2	0	
3	15100.0	329	6	635.10	0	0	
4	15291.0	25	109	4596.51	3	0	

In [56]:
```
df_uk_user.groupby(['overall_score']).sum()
```

Out[56]:

overall_score	CustomerID	recency	frequency	monetary	recency_cluster	frequency_cluste
0	7379730.0	144373	10426	143783.020	0	
1	8787517.0	104174	18319	279925.201	559	
2	14239757.0	72672	43206	798636.352	1829	
3	23605396.0	31330	104146	1657727.171	4505	3
4	4588094.0	4370	80219	1066317.970	878	23
5	2307480.0	1430	55247	1352268.010	444	14
6	408515.0	209	23653	615003.700	81	4
7	108842.0	13	8909	727678.180	21	1
8	44685.0	4	17753	126533.790	9	

In [57]:
```
df_uk_user.groupby(['overall_score']).mean()
```

Out[57]:

overall_score	CustomerID	recency	frequency	monetary	recency_cluster	frequenc
0	15569.050633	304.584388	21.995781	303.339705	0.000000	
1	15636.151246	185.362989	32.596085	498.087546	0.994662	
2	15477.996739	78.991304	46.963043	868.082991	1.988043	
3	15581.119472	20.679868	68.743234	1094.209354	2.973597	
4	15605.761905	14.863946	272.853741	3626.931871	2.986395	
5	15591.081081	9.662162	373.290541	9136.946014	3.000000	
6	15130.185185	7.740741	876.037037	22777.914815	3.000000	
7	15548.857143	1.857143	1272.714286	103954.025714	3.000000	
8	14895.000000	1.333333	5917.666667	42177.930000	3.000000	

We can clearly notice that customer that fall under 7 & 8 score are high in monetary value, recency & frequency

SEGMENTATION

In [58]:
```
df_uk_user['segment'] = 'low-value'
df_uk_user.loc[df_uk_user['overall_score']>4,'segment'] = 'mid-value'
df_uk_user.loc[df_uk_user['overall_score']>6,'segment'] = 'high-value'
```

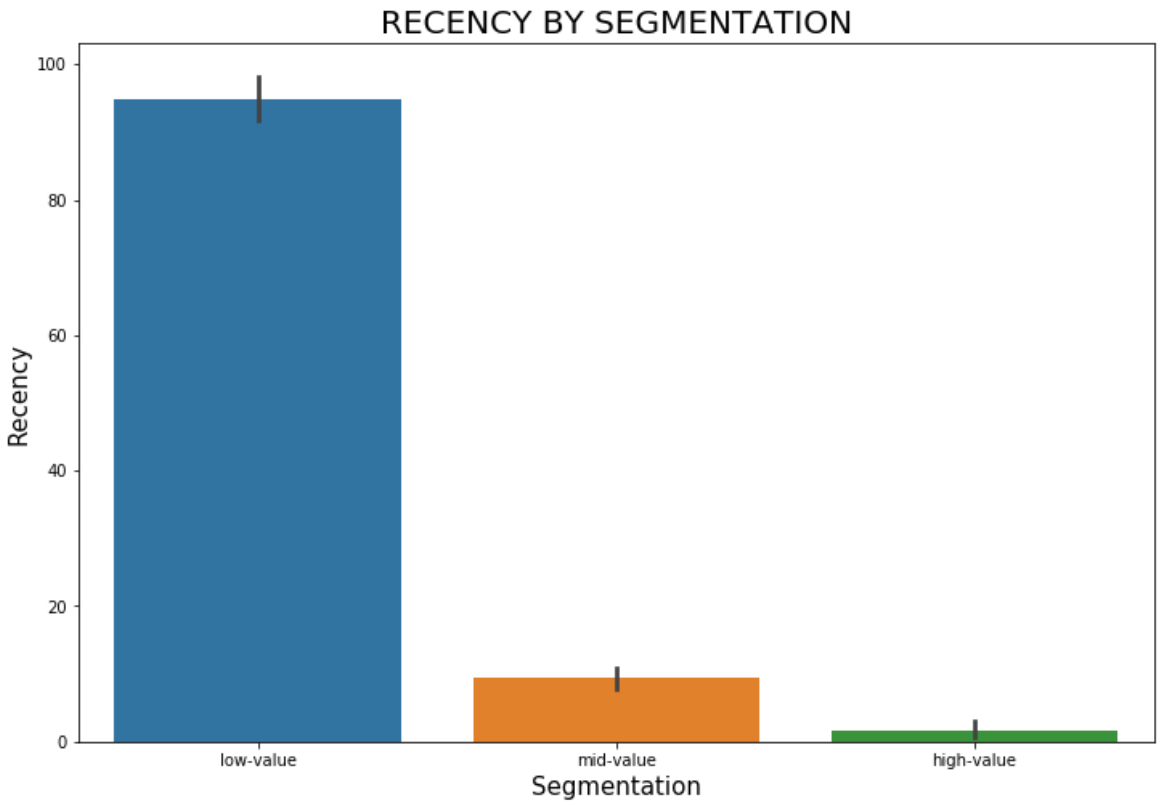
In [59]:
```
temp = df_uk_user.groupby(['segment']).mean()
```

In [60]:
```
temp
```

Out[60]:

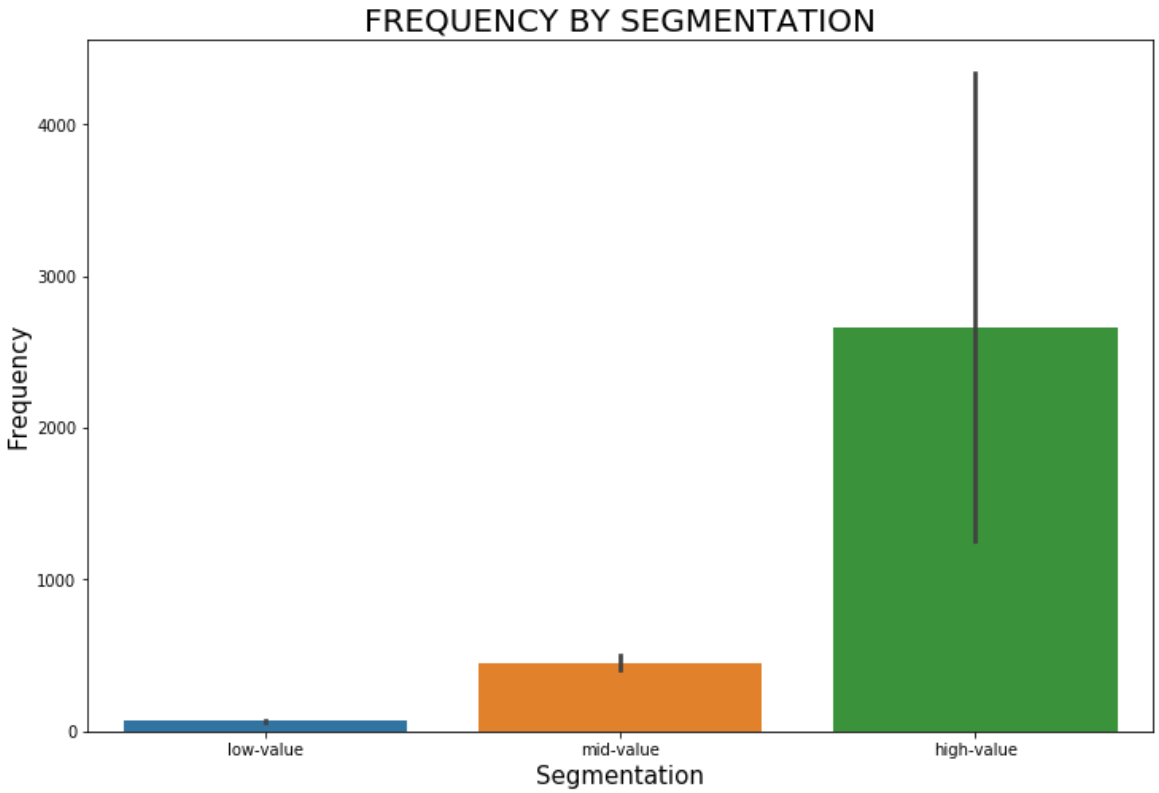
segment	CustomerID	recency	frequency	monetary	recency_cluster	frequency_clus
high-value	15352.700000	1.700000	2666.200000	85421.197000	3.000000	2.1000
low-value	15564.540239	94.799203	68.078619	1048.177879	2.064011	0.0722
mid-value	15519.971429	9.365714	450.857143	11241.552629	3.000000	1.0571

In [61]:
```
plt.figure(figsize=(12,8))
sns.barplot(df_uk_user['segment'], df_uk_user['recency'])
plt.title('RECENCY BY SEGMENTATION', fontdict={'fontsize':20})
plt.xlabel('Segmentation', fontdict={'fontsize':15})
plt.ylabel('Recency', fontdict={'fontsize':15})
plt.show()
```



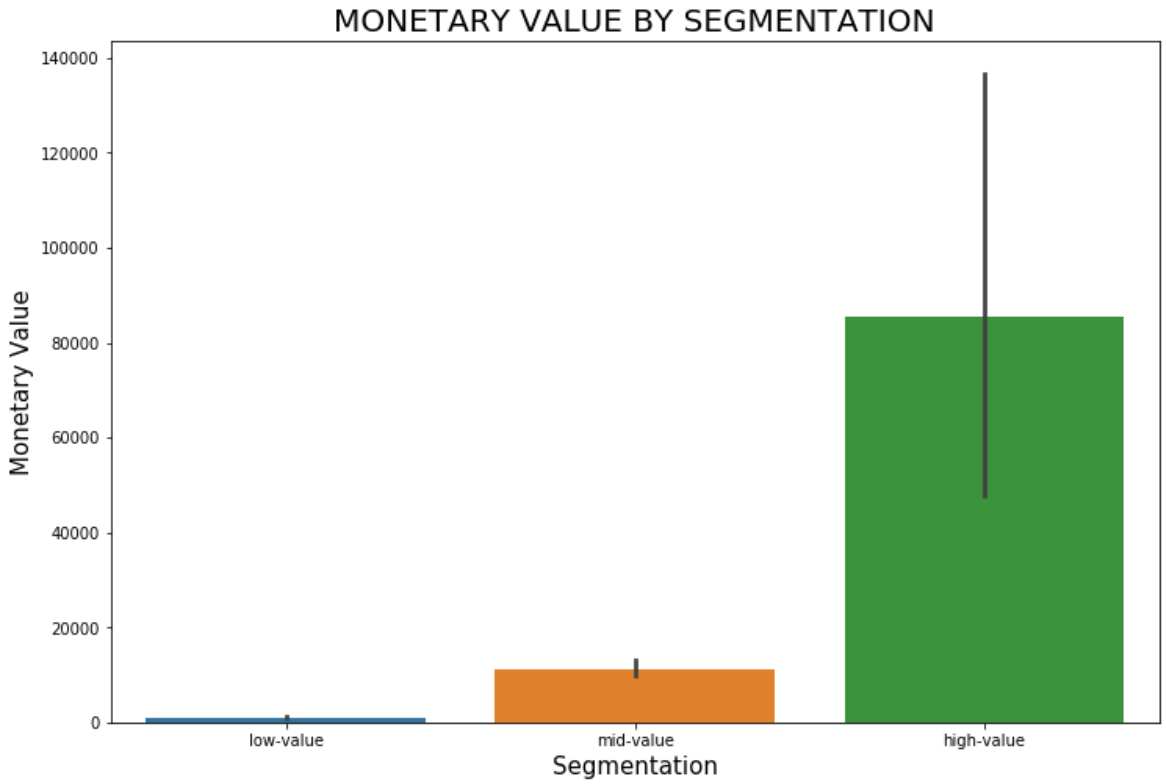
In [62]:

```
plt.figure(figsize=(12,8))
sns.barplot(df_uk_user['segment'], df_uk_user['frequency'])
plt.title('FREQUENCY BY SEGMENTATION', fontdict={'fontsize':20})
plt.xlabel('Segmentation', fontdict={'fontsize':15})
plt.ylabel('Frequency', fontdict={'fontsize':15})
plt.show()
```



In [63]:

```
plt.figure(figsize=(12,8))
sns.barplot(df_uk_user['segment'], df_uk_user['monetary'])
plt.title('MONETARY VALUE BY SEGMENTATION', fontdict={'fontsize':20})
plt.xlabel('Segmentation', fontdict={'fontsize':15})
plt.ylabel('Monetary Value', fontdict={'fontsize':15})
plt.show()
```



In [ ]: