Portfolio Examination for the Data Science Course MADS-MMS

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In [ ]:

```

```

Importing the libraries

In [9]:

```
import numpy as np
import pandas as pd
from matplotlib import pyplot as plt
import seaborn as sns
sns.set()
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score
```

Solution to Exercise 1

Data acquisition and Initial Data Analysis.

The data is about live selling feature on the Facebook platform.
The dataset was obtained from the UCI Machine Learning repository
[https://archive.ics.uci.edu/ml/datasets/Facebook+Live+Sellers+in+Thailand (https://archive.ics.uci.edu/ml/datasets/Facebook+Live+Sellers+in+Thailand)](https://archive.ics.uci.edu/ml/datasets/Facebook+Live+Sellers+in+Thailand).

Loading the Dataset

In [2]:

```
#The dataset(facebook_live_thailand) is loaded with pandas library

Dataset_A = pd.read_csv("facebook_live_thailand.csv")
```

In [3]:

```
#dataframe.head(n) to test if the object contains the right data
Dataset_A.head(4)
```

Out[3]:

	status_id	status_type	status_published	num_reactions	num_comments	num_shares	num_
0	1	video	4/22/2018 6:00	529	512	262	
1	2	photo	4/21/2018 22:45	150	0	0	
2	3	video	4/21/2018 6:17	227	236	57	
3	4	photo	4/21/2018 2:29	111	0	0	

1.1

The rows represent the information about the time live information of sale posted on Facebook and engagements in the data.
The rows contains the resulting engagement metrics comprising type(text, deferred, video, photo),shares, comments, and emoji
reactions within which to distinguish traditional “likes” from recently introduced emoji reactions, that are “love”, “wow”, “haha”, “sad” and “angry”

In [21]:

```
#To get more information about the dataset including the index dtype and columns, non-null

Dataset_A.info()
```

```
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   status_id          7050 non-null   int64
 1   status_type        7050 non-null   object
 2   status_published   7050 non-null   object
 3   num_reactions      7050 non-null   int64
 4   num_comments       7050 non-null   int64
 5   num_shares         7050 non-null   int64
 6   num_likes          7050 non-null   int64
 7   num_loves          7050 non-null   int64
 8   num_wows           7050 non-null   int64
 9   num_hahas          7050 non-null   int64
 10  num_sads           7050 non-null   int64
 11  num_angrys         7050 non-null   int64
 12  Column1            0 non-null      float64
 13  Column2            0 non-null      float64
 14  Column3            0 non-null      float64
 15  Column4            0 non-null      float64
dtypes: float64(4), int64(10), object(2)
memory usage: 881.4+ KB
```

1.2

The dataset contains 7050 rows/instances with rangeindex 0 to 7049

1.3

The dataset contains 16 columns including column1 to column4 with null values

1.4

To calculate the standard deviation of num_likes. Pandas dataframe.std() function return sample standard deviation over requested axis.

In [6]:

```
Dataset_A["num_likes"].std()
```

Out[6]:

```
449.4723570561426
```

Exercise 2

2.1

Features of the dataset that do not suggest themselves as features for clustering analysis

In [4]:

```
Dataset_A.head()
```

Out[4]:

	status_id	status_type	status_published	num_reactions	num_comments	num_shares	num_
0	1	video	4/22/2018 6:00	529	512	262	
1	2	photo	4/21/2018 22:45	150	0	0	
2	3	video	4/21/2018 6:17	227	236	57	
3	4	photo	4/21/2018 2:29	111	0	0	
4	5	photo	4/18/2018 3:22	213	0	0	

From the dataset, we can see that 7 features do not suggest themselves to be used for clustering analysis. The features include status_id, status_type, status_published, column1, column2, column3 and column4 contain null values(NaN).

status_id: This is a unique identifier for each of the instances
status_type contains 4 different categorical data and cannot be used for clustering
status_published contains the datetime datatype and cannot be used for clustering analysis
column1 to column4: are redundant features containing null values(NaN)

In [7]:

2.2

Creating Dataset_B from Dataset_A by restricting it to the following features: num_reactions,num_comments, num_shares, num_likes, num_loves, num_wows, num_hahas

In [8]:

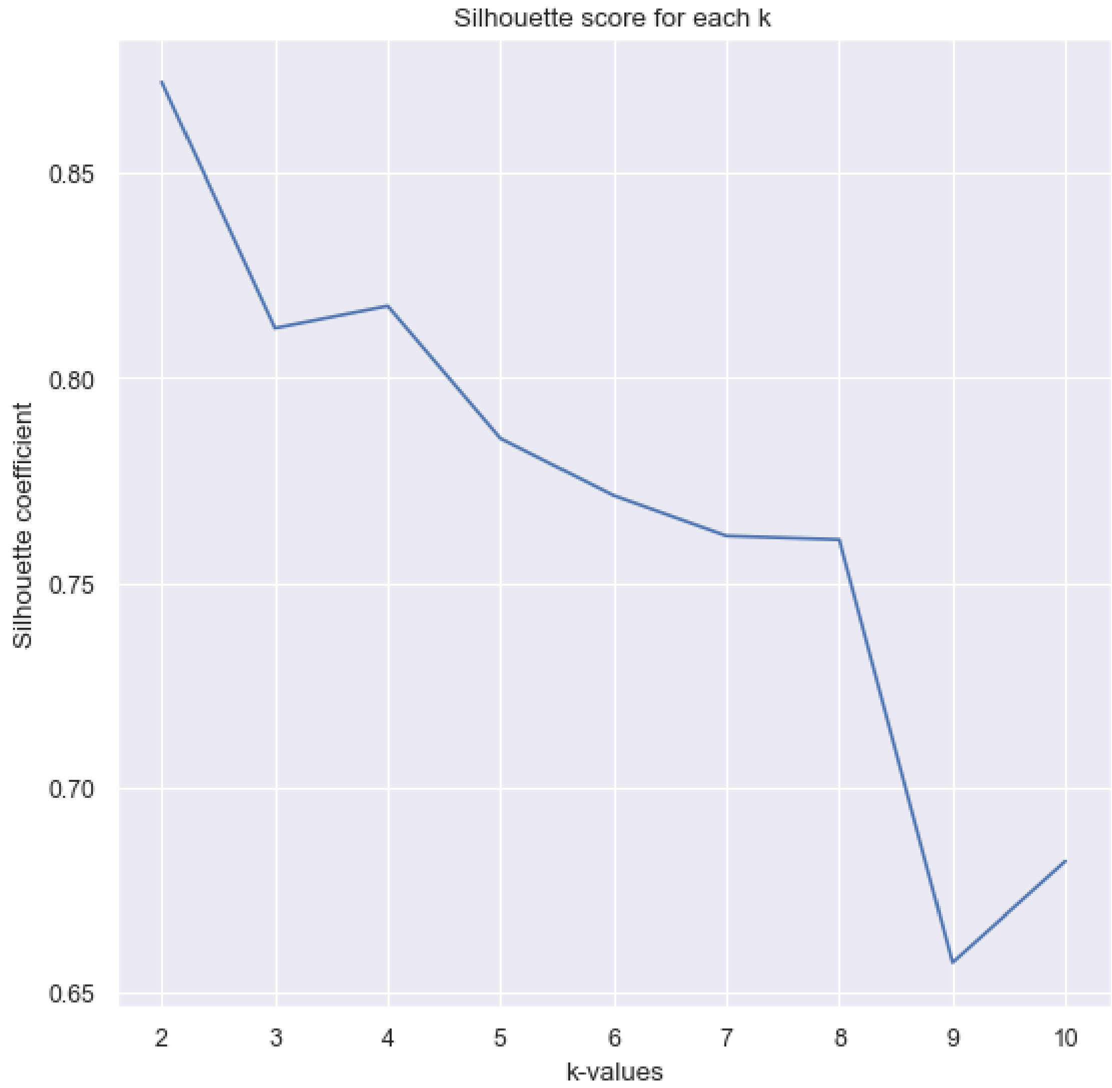
```
Dataset_B = Dataset_A.loc[:,['num_reactions','num_comments', 'num_shares', 'num_likes', 'nu
Dataset_B.head()
```

Out[8]:

	num_reactions	num_comments	num_shares	num_likes	num_loves	num_wows	num_hahas
0	529	512	262	432	92	3	1
1	150	0	0	150	0	0	0
2	227	236	57	204	21	1	1
3	111	0	0	111	0	0	0
4	213	0	0	204	9	0	0

In [13]:

```
#A function that creates a Silhouette plot with different choices of k from 2,3,...,10 usin

silhouette = []

for k in range(2,11):
    kmeans = KMeans(n_clusters = k, random_state = 1)
    cluster_assignments = kmeans.fit_predict(Dataset_B)
    silhouette_coeff = silhouette_score(Dataset_B, kmeans.labels_, metric = 'euclidean')
    silhouette.append(silhouette_coeff)


plt.figure(figsize = (8, 8), dpi = 80)
plt.title("Silhouette score for each k")
plt.xlabel("k-values")
plt.ylabel("Silhouette coefficient")
plt.savefig("images/Silhouette score for each k.pdf")
plt.plot(range(2,11), silhouette)
plt.show()
```



Interprete the above diagram

From the diagram above, k=2 yield the best results, with the highest silhouette coefficient. k = 3 and k = 4 are fairly good

2.3

Creating a silhouette plot with k = 2 having the highest silhouette coefficint in the previous experiment

In [21]:

```
#converting Dataset_B to a numpy array
df_Bval = Dataset_B.values
```

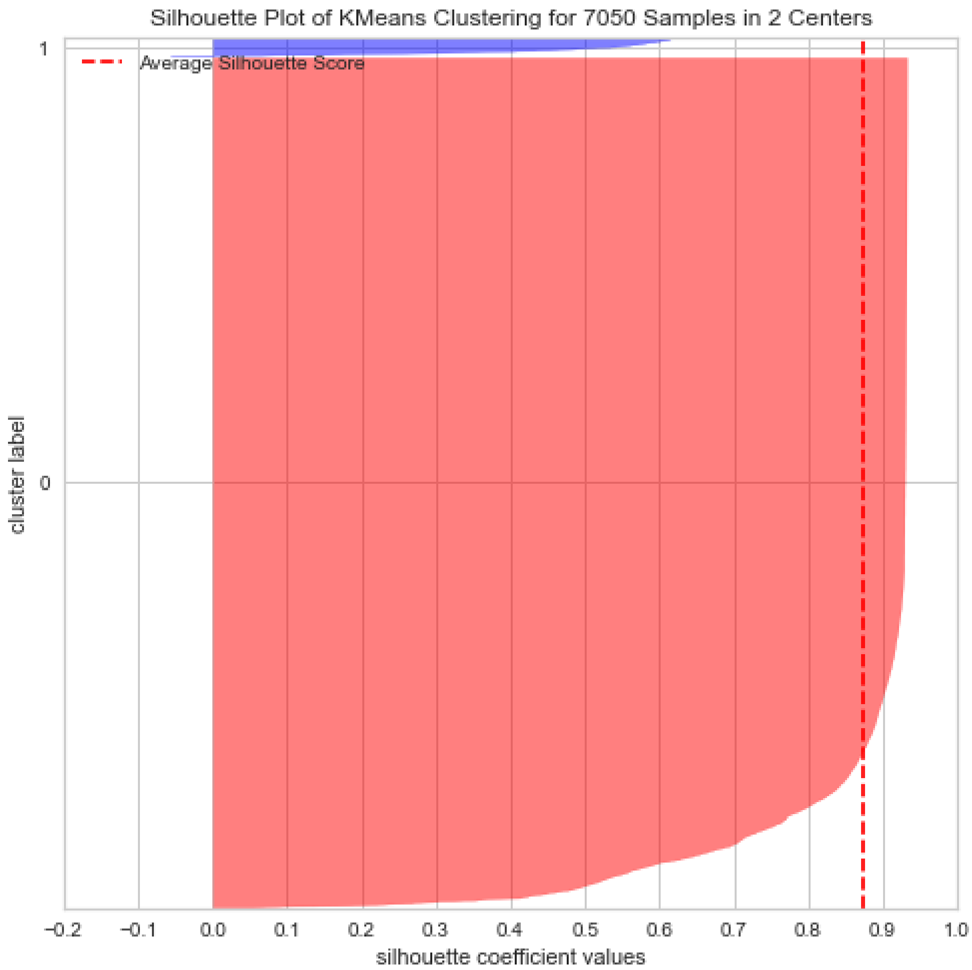
In [28]:

```
def plot_silhouette(kmeans, df_Bval, title, filename):
    colors=['red', 'blue', 'yellow']
    plt.figure(figsize=(8, 8))
    X_sub=df_Bval
    y_pred = kmeans.fit_predict(X_sub)
    visualizer = SilhouetteVisualizer(kmeans, colors=colors, is_fitted=True)
    visualizer.fit(X_sub) # Fit the data to the visualizer
    visualizer.finalize()
    plt.savefig(f'images/Silhouette score.pdf')
    print(f'Silhoutte score: {visualizer.silhouette_score_}')
    visualizer.show() # Finalize and render the figure
```

In [29]:

```
kmeans=KMeans(n_clusters=2, random_state=1)
plot_silhouette(kmeans, df_Bval, ' k=2', 'datasetB')
```

```
Silhoutte score: 0.8721940910132095
```



Intepretation of the above silhouette plot

The silhouette plot shows that the n_cluster value of 2 is a good pick for the given data due to the presence of clusters with silhouette scores close to +1

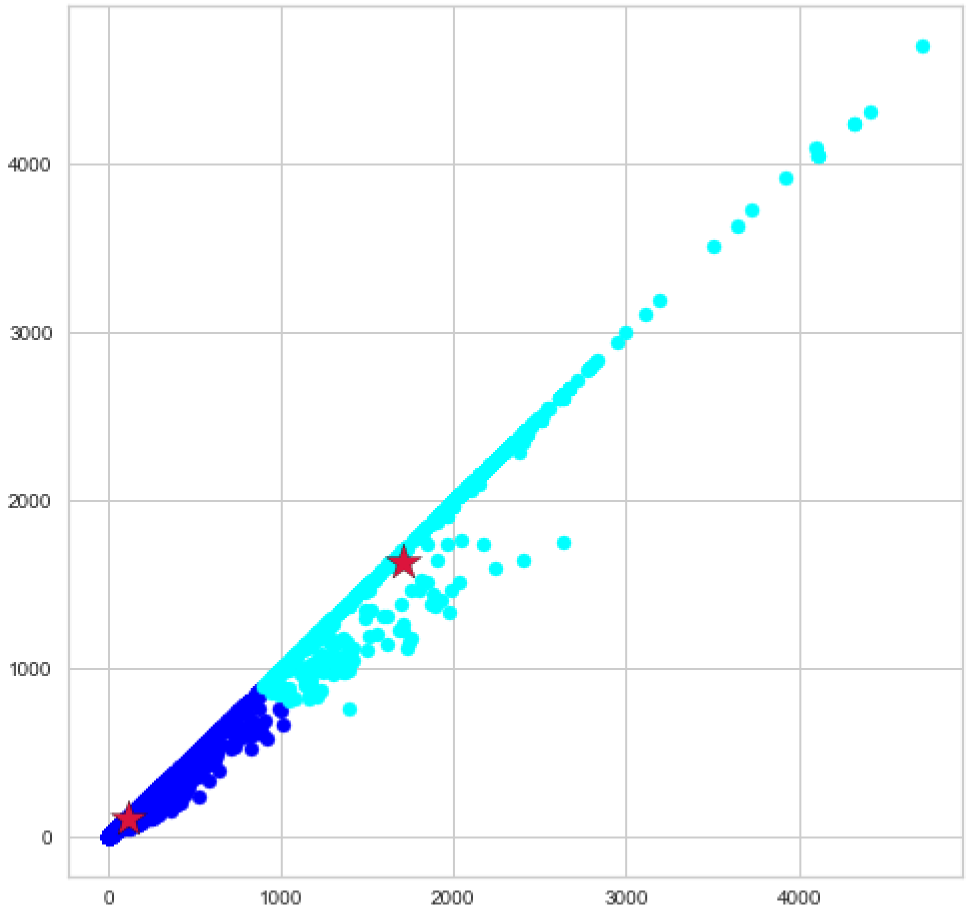
2.4

In [48]:

```
from yellowbrick.cluster import SilhouetteVisualizer

colors=['blue', 'cyan', 'dodgerblue']

def plot_clusters_with_centers(kmeans, df_B, index_x, index_y, title, filename):
    plt.figure(figsize=(8, 8))
    X_sub=df_B[:,[index_x, index_y]]
    y_pred = kmeans.fit_predict(X_sub)
    for i in range(0,len(np.unique(y_pred))):
        plt.scatter(X_sub[y_pred==i, 0], X_sub[y_pred==i, 1], c=colors[i], label=i)



    plt.scatter(
        kmeans.cluster_centers_[:, 0],
        kmeans.cluster_centers_[:, 1],
        s=350, marker='*', c='crimson', edgecolor='black'
    )
    plt.savefig("images/ plot of data(2.4).pdf")
```

In [49]:

```
kmeans=KMeans(n_clusters=2, random_state=1)
plot_clusters_with_centers(kmeans, df_B, 0,3, ' k=2', 'datasetB')
```



Interpretation: A centroid was formed but there is no clear separation between the clusters. This, the sample formed a linear cluster

Exercise 3

3.1

The variance threshold is a simple baseline approach to feature selection. It removes all features which variance doesn't meet some threshold. By default, it removes all zero-variance features, i.e., features that have the same value in all samples.

3.2

MinMax Scaler is better for variance comparison.

MinMaxScaler(feature_range = (0, 1)) will transform each value in the column proportionally within the range [0,1]. It is the first scaler choice to transform a feature, as it will preserve the shape of the dataset (no distortion). This transformation is often used as an alternative to zero mean, unit variance scaling.

3.3

X_std = (X - X.min(axis = 0)) / (X.max(axis = 0) - X.min(axis = 0))

In [51]:

```
from sklearn.preprocessing import MinMaxScaler

scaler = MinMaxScaler()
Dataset_C = scaler.fit_transform(df_B)
```

In [52]:

```
Dataset_C
```

Out[52]:

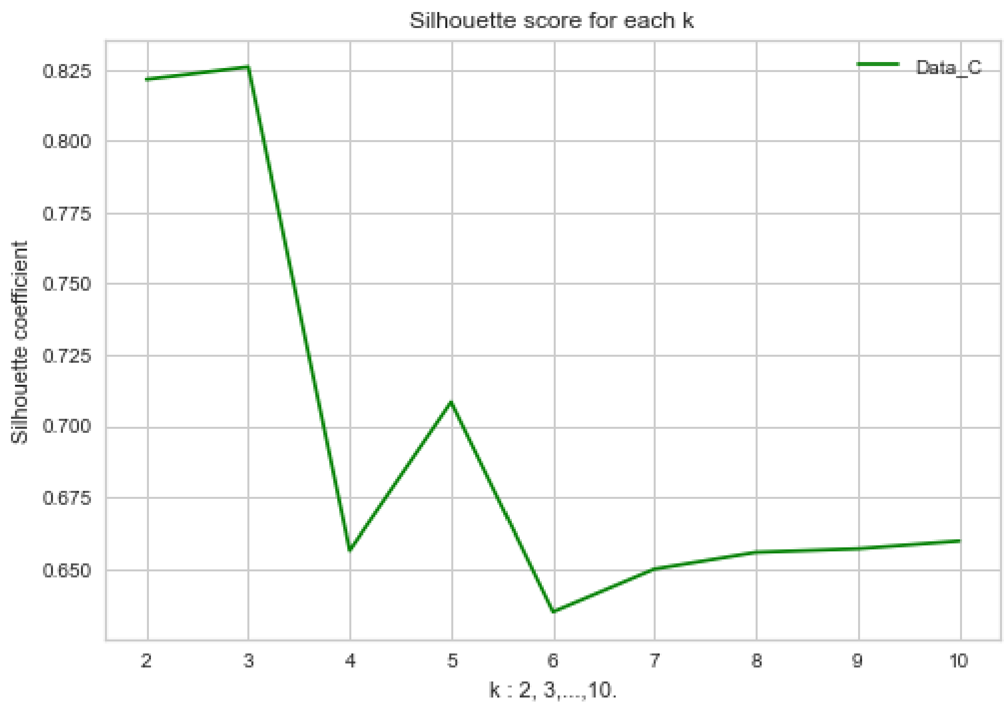
```
array([[0.11231423, 0.02439257, 0.07651869, ..., 0.14003044, 0.01079137,
        0.00636943],
       [0.03184713, 0.        , 0.        , ..., 0.        , 0.        ,
        0.        ],
       [0.04819533, 0.01124345, 0.0166472 , ..., 0.03196347, 0.00359712,
        0.00636943],
       ...,
       [0.00042463, 0.        , 0.        , ..., 0.00152207, 0.        ,
        0.        ],
       [0.07452229, 0.0005717 , 0.00642523, ..., 0.00304414, 0.        ,
        0.        ],
       [0.00360934, 0.        , 0.        , ..., 0.        , 0.        ,
        0.        ]])
```

In [ ]:

```
silhouette2 = [] # Assigning a secondary address so it does not add to the previous one in
for k in range (2,11):
kmeans = KMeans(n_clusters=k, random_state=1)
kmeans.fit_predict(Dataset_C)
silhouette_coefficient = silhouette_score(Dataset_C, kmeans.labels_,metric='euclidean')
silhouette2.append(silhouette_coefficient)
plt.figure(figsize = (8, 8), dpi = 80)
plt.plot(range(2,11), silhouette2, color="green", label="Data_C")
plt.plot(range(2,11), silhouette, color="blue", label="Data_B")
plt.title("Silhouette score for each k")
plt.legend()
plt.xlabel("k : 2, 3,...,10.")
plt.ylabel("Silhouette coefficient")
#plt.savefig('Images/Silhouette score each k 3_3.png', bbox_inches='tight')
plt.savefig('Images/Silhouette score each k 3_3.pdf')
plt.show()
```

In [60]:

```
silhouette_C = []

for k in range(2,11):
    kmeans = KMeans(n_clusters = k, random_state = 1)
    cluster_assignments = kmeans.fit_predict(Dataset_C)
    silhouette_coeff = silhouette_score(Dataset_C, kmeans.labels_, metric = 'euclidean')
    silhouette_C.append(silhouette_coeff)
    #plt.figure(figsize = (8, 8), dpi = 80)
plt.plot(range(2,11), silhouette_C, color="green", label="Data_C")
plt.title("Silhouette score for each k")
plt.legend()
plt.xlabel("k : 2, 3,...,10.")
plt.ylabel("Silhouette coefficient")
#plt.savefig('Images/Silhouette score each k 3_3.png', bbox_inches='tight')
plt.savefig('Images/Silhouette score each k 3_3.pdf')
```

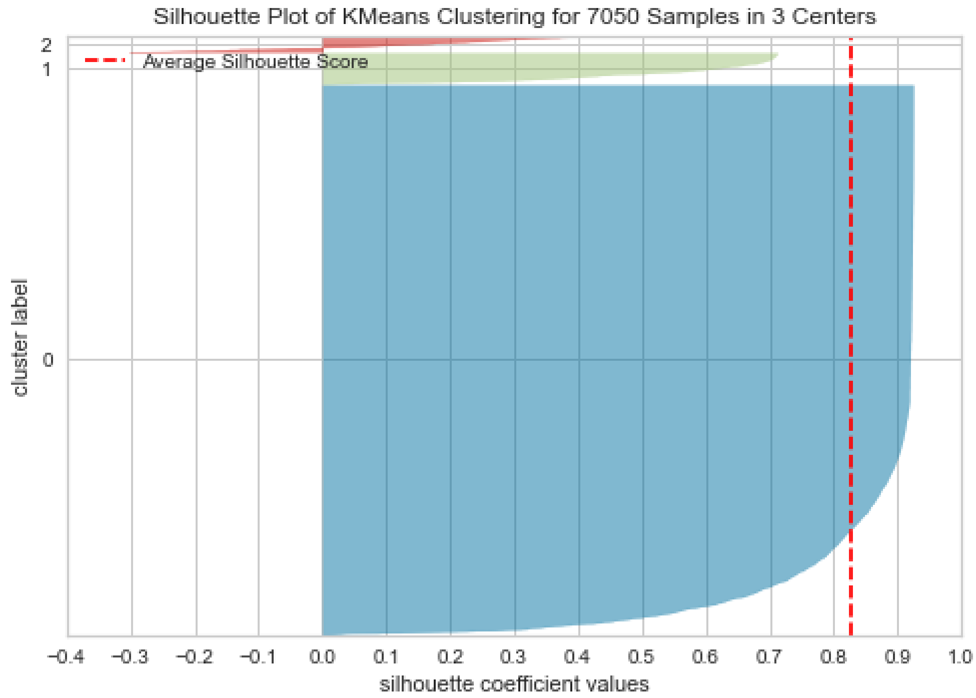


In [ ]:

```

```

In [24]:

```
from yellowbrick.cluster import SilhouetteVisualizer

# Instantiate the clustering model and visualizer
model = KMeans(3, random_state=1)
visualizer = SilhouetteVisualizer(model, colors='yellowbrick')

visualizer.fit(Dataset_C)        # Fit the data to the visualizer
visualizer.show()        # Finalize and render the figure
```



Out[24]:

```
<AxesSubplot:title={'center':'Silhouette Plot of KMeans Clustering for 7050
Samples in 3 Centers'}, xlabel='silhouette coefficient values', ylabel='clus
ter label'>
```

3.4

In [ ]:

```

```

In [62]:

```
from sklearn.feature_selection import VarianceThreshold

vt = VarianceThreshold(0.005)
Dataset_D = vt.fit_transform(Dataset_C)
```

In [63]:

```
Dataset_D
```

Out[63]:

```
array([[0.11231423, 0.09171975],
       [0.03184713, 0.03184713],
       [0.04819533, 0.0433121 ],
       ...,
       [0.00042463, 0.00021231],
       [0.07452229, 0.07409766],
       [0.00360934, 0.00360934]])
```

In [ ]:

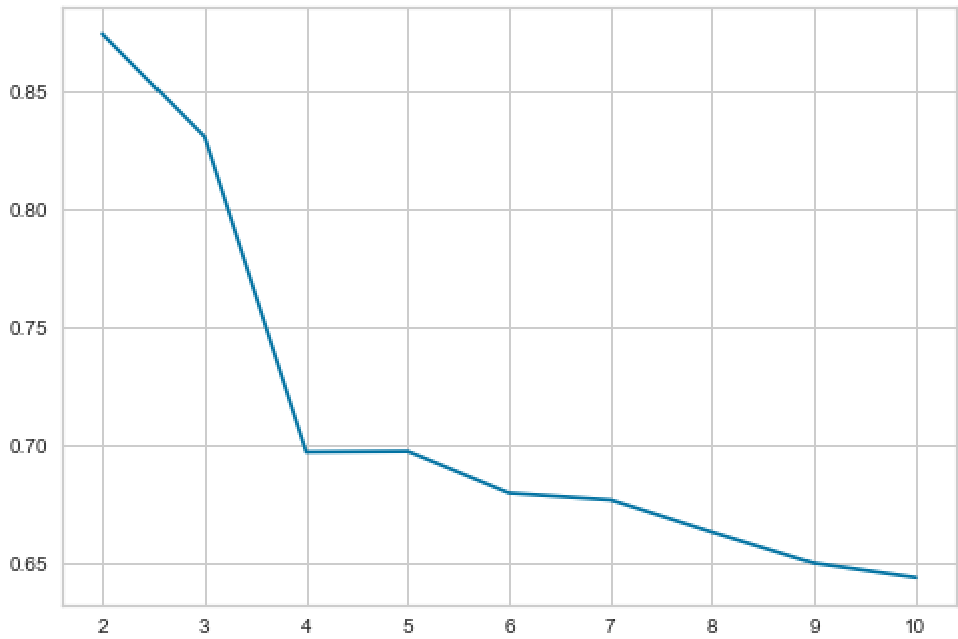
```

```

In [26]:

```
silhouette = []

for k in range(2,11):
    kmeans = KMeans(n_clusters = k, random_state = 1)
    cluster_assignments = kmeans.fit_predict(Dataset_D)
    silhouette_coeff = silhouette_score(Dataset_D, kmeans.labels_, metric = 'euclidean')
    silhouette.append(silhouette_coeff)

plt.plot(range(2,11), silhouette)
```

Out[26]:

```
[<matplotlib.lines.Line2D at 0x1c90d250400>]
```

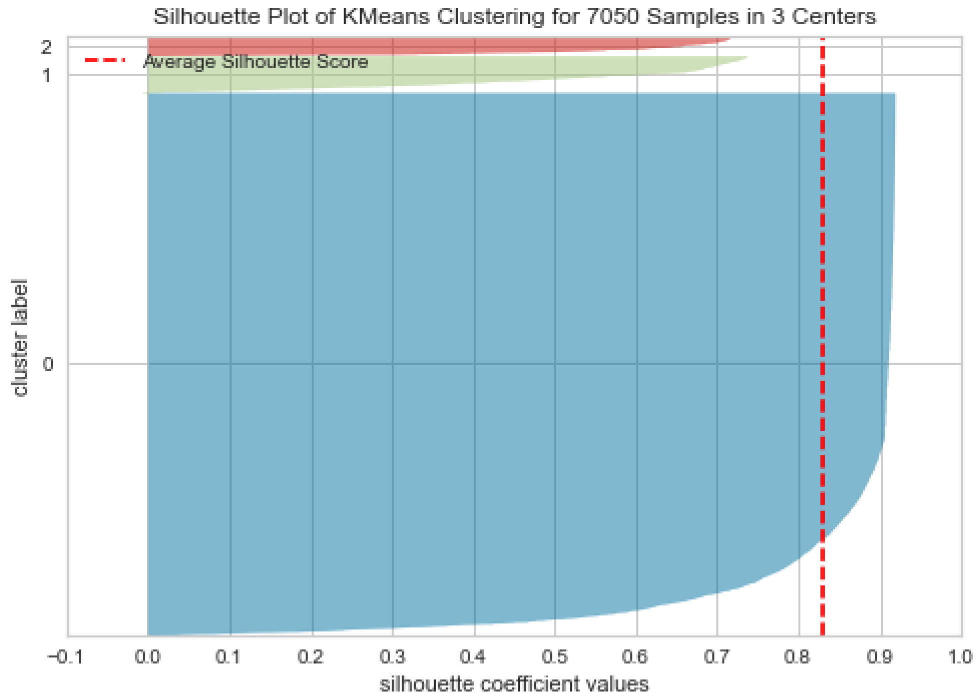


In [ ]:

```

```

In [27]:

```
from yellowbrick.cluster import SilhouetteVisualizer

# Instantiate the clustering model and visualizer
model = KMeans(3, random_state=1)
visualizer = SilhouetteVisualizer(model, colors='yellowbrick')

visualizer.fit(Dataset_D)        # Fit the data to the visualizer
visualizer.show()        # Finalize and render the figure
```



Out[27]:

```
<AxesSubplot:title={'center':'Silhouette Plot of KMeans Clustering for 7050
Samples in 3 Centers'}, xlabel='silhouette coefficient values', ylabel='clus
ter label'>
```

In [ ]:

```
#3.6
```

In [ ]:

```

```

In [64]:

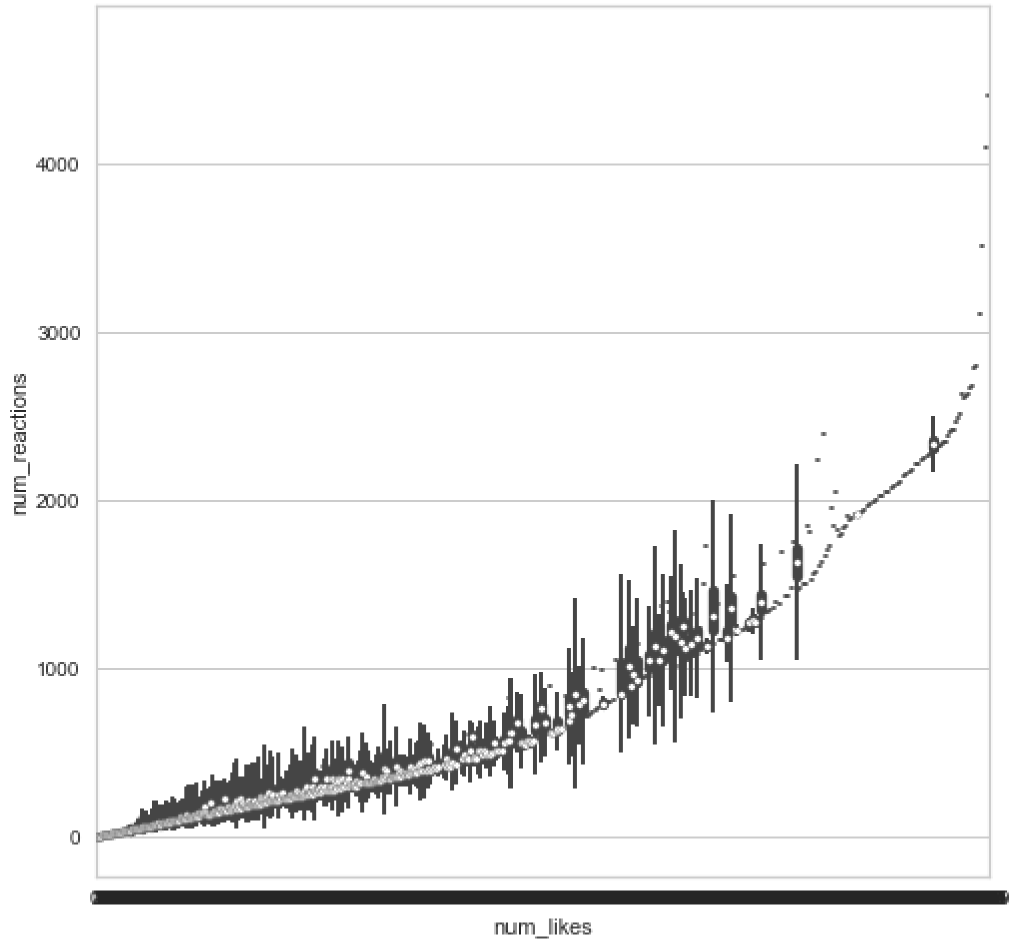
```
df_D=pd.DataFrame(Dataset_D, columns=['num_reactions', 'num_likes'])
```

In [88]:

```
# using k=2 and default values from sklearn
kmeans = KMeans(n_clusters=2, random_state=1, init='k-means++', max_iter=300, tol=0.0001)
# compute cluster centers and predict cluster index for each sample
Dataset_D_comp = kmeans.fit_predict(df_D, sample_weight=None)
Dataset_B_comp = kmeans.fit_predict(Dataset_B, sample_weight=None)
# add the distribution within the clusters of D and B to the full Dataset A
#Dataset_A['D_comp'] = Dataset_D_comp

#Dataset_B['B_comp'] = Dataset_B_comp
```

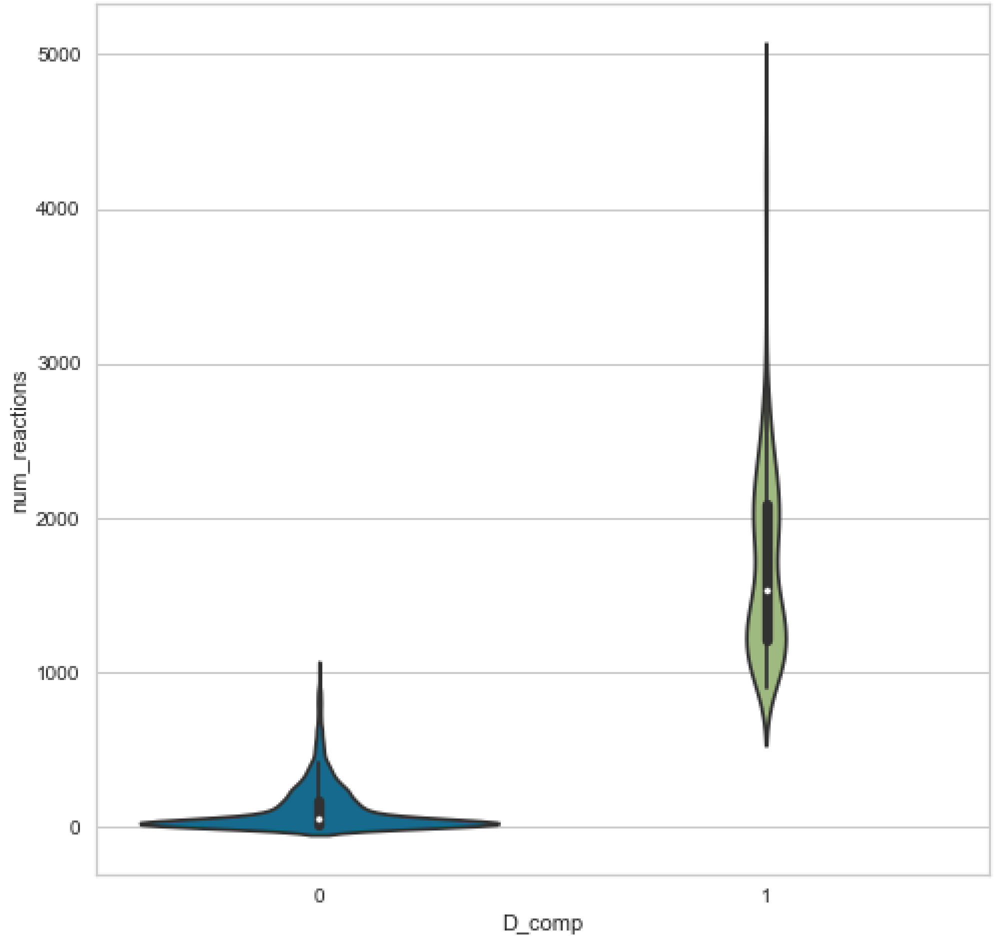
In [93]:

```
plt.figure(figsize=(8, 8))
violin_plot = sns.violinplot(x='num_likes', y='num_reactions', data=Dataset_B)
plt.savefig('images/Violinplot Dataset_D num_reactions.pdf')
plt.show()
```



In [90]:

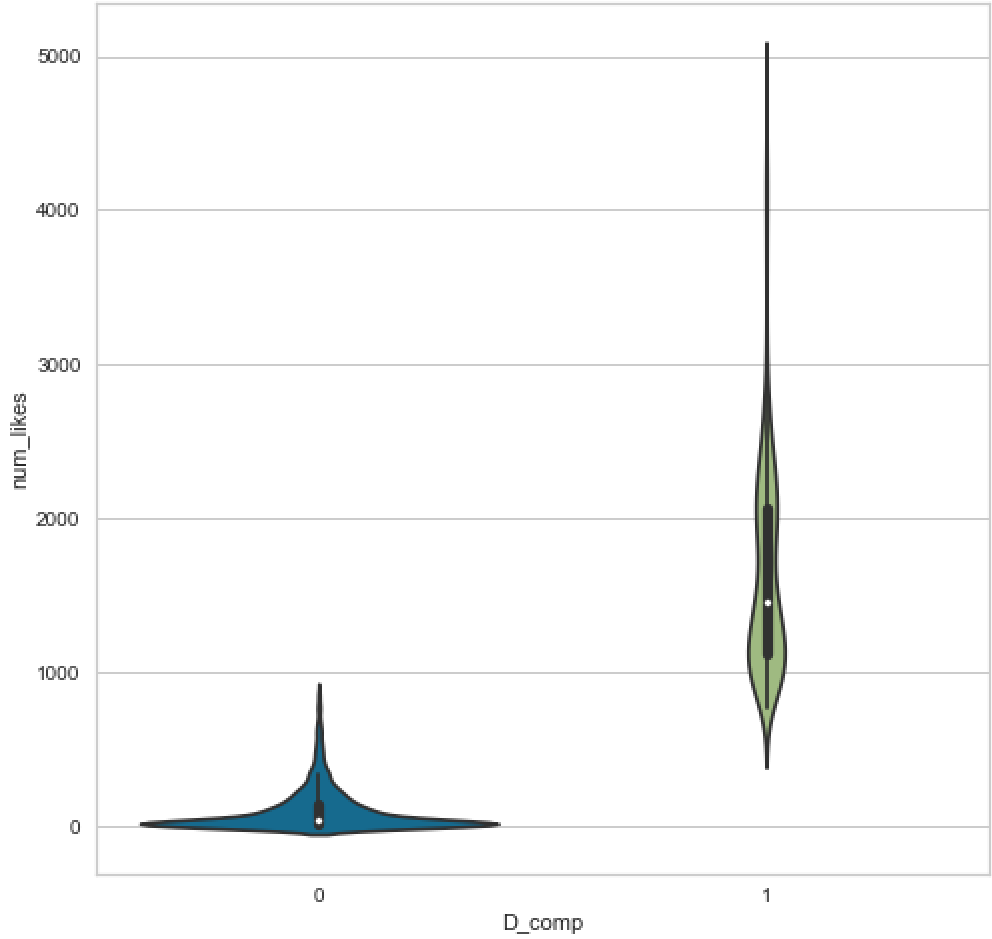
```
plt.figure(figsize=(8, 8))
violin_plot = sns.violinplot(x='D_comp', y='num_reactions', data=Dataset_A)
plt.savefig('images/Violinplot Dataset_D num_likes.pdf')
plt.show()
```



In [ ]:

In [92]:

```
plt.figure(figsize=(8, 8))
violin_plot = sns.violinplot(x='D_comp', y='num_likes', data=Dataset_A)
plt.savefig('images/Violinplot Dataset_D num_likes.pdf')
plt.show()
```



In [ ]:

In [ ]: