Modeling-Clustering

June 6, 2021

1 Modeling

1.1 Clustering

in this notebook we are going to implement the clustering algorithms for stories and posts dataset. these two datasets hosts the stories and posts which published by the campaign's account. since the clusteirng is a unsupervised learning algorithm, and in these datasets we don't have dependent variable, this approach is our go to method for extracting insightful things out of these data. the goal of this step is to cluster posts and stories so the trained model will be able to predict the performance of aforementioned form of content.

we will implement two clustering algorithms, partitioned based clustering (K-means) and density based clustering (DBSCAN). before implementing these algorithms for each dataset we have to find the optimized number of neighbors which we will check via elbow and silhouette method

---

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import matplotlib.patches as patches
import warnings
import matplotlib
warnings.filterwarnings("ignore")
pd.set_option('display.max_rows', 200)
import seaborn as sns
from openpyxl import load_workbook
np.set_printoptions(suppress=True)
pd.set_option('display.float_format', lambda x: '%.2f' % x)
from tqdm import tqdm_notebook, tqdm
from sklearn import preprocessing
```

[2]:
```
xls = pd.ExcelFile('data/Main Dataset V3.0 .xlsx')
ad_post = pd.read_excel(xls, 'Ad-Post')
ad_story = pd.read_excel(xls, 'Ad-Story')
influencer = pd.read_excel(xls, 'Influencer')
leaders_post = pd.read_excel(xls, 'Leaders-Post')
leaders_story = pd.read_excel(xls, 'Leaders-Story')
post = pd.read_excel(xls, 'Post')
```

```
story = pd.read_excel(xls, 'Story')
print('Datasets Loaded Completely.')
```

```
Datasets Loaded Completely.
```

[3]:
```
post['view'] = post['view'].fillna(0)
```

[4]:
```
labels, _ = pd.factorize(story['type'])
story_labelencoded = story
story_labelencoded['type_labelencoded'] = labels.tolist()
story.drop(columns=['type'], axis=1, inplace=True)
```

[5]:
```
post_x = np.asarray(post)
story_x = np.asarray(story)
post_x = preprocessing.StandardScaler().fit(post_x).transform(post_x)
story_x = preprocessing.StandardScaler().fit(story_x).transform(story_x)
```

1.1.1 Elbow & Silhouette Method

[6]:
```
from scipy.spatial.distance import cdist
from sklearn.metrics import silhouette_score
from sklearn.cluster import KMeans
```

[7]:
```
def calc_elbow(X, no_clusters):
    '''
    This functions is for calculating the elbow method, this code is mainly␣
 ↪inspired and refactored from:
    https://www.geeksforgeeks.org/elbow-method-for-optimal-value-of-k-in-kmeans/
 ↪    last update: 06 Jun, 2019
        Input -> X: array of Xs for calculating Kmeans
                 no_clusters: number of clusters we want to test.
        Returns -> Distortions
                   Inertias (to get more information please check the refrence.)
    '''

    distortions = []
    inertias = []
    for k in tqdm(range(1, no_clusters + 1)):
        #Building and fitting the model
        clus_kmean = KMeans(n_clusters=k).fit(X)
        clus_kmean.fit(X)
        distortions.append(sum(np.min(cdist(X, clus_kmean.cluster_centers_,
                           'euclidean'),axis=1)) / X.shape[0])
        inertias.append(clus_kmean.inertia_)
    return distortions, inertias


def calc_silhouette(X, no_clusters):
```

```
    '''
    This function is for calculating the sillhouette method, this code is␣
↪mainly inspired and refactored from:
    https://medium.com/analytics-vidhya/
↪how-to-determine-the-optimal-k-for-k-means-708505d204eb       by: Khyati␣
↪Mahendru - Jun 17, 2019
        Input -> X: array of Xs for calculating Kmeans
                 no_clusters: number of clusters we want to test.
        Returns -> sil: array of silhouette scores for each number of clusters.
    '''
    sil = []
    # dissimilarity would not be defined for a single cluster, thus, minimum␣
↪number of clusters should be 2
    for k in tqdm(range(2, no_clusters + 1)):
        clus_kmean = KMeans(n_clusters = k).fit(X)
        labels = clus_kmean.labels_
        sil.append(silhouette_score(X, labels, metric = 'euclidean'))
    return sil
```

[8]:

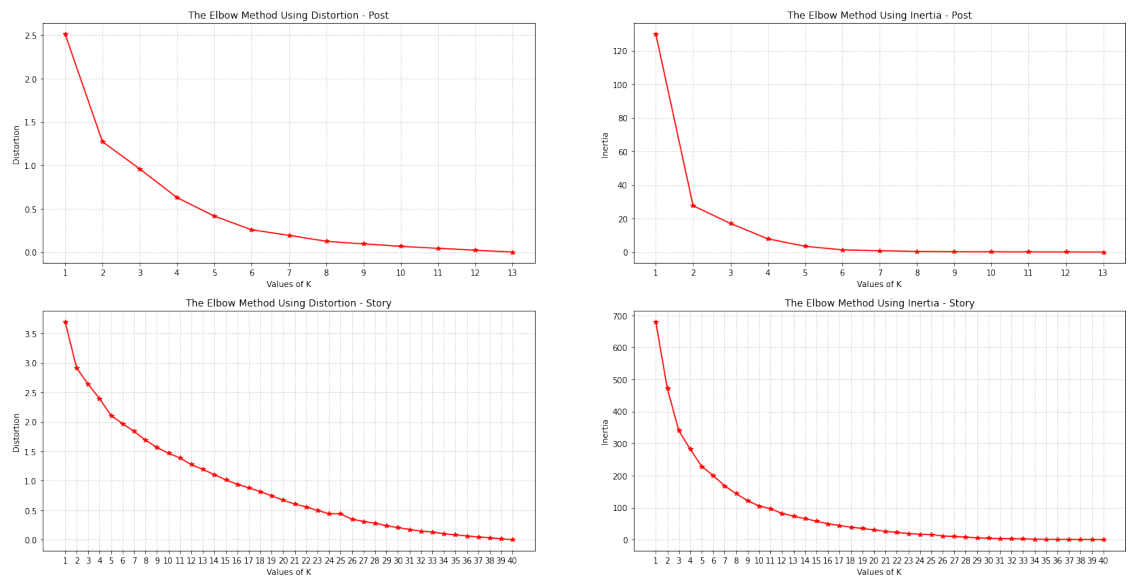
```
dist_post, inert_post = calc_elbow(post_x, post_x.shape[0])
dist_story, inert_story = calc_elbow(story_x, story_x.shape[0])
```

```
100%|      | 13/13 [00:02<00:00,  6.15it/s]
100%|      | 40/40 [00:06<00:00,  6.36it/s]
```

[9]:

```
fig = plt.figure(figsize = (24, 12))
ax1 = fig.add_subplot(2,2,1)
ax2 = fig.add_subplot(2,2,2)
ax3 = fig.add_subplot(2,2,3)
ax4 = fig.add_subplot(2,2,4)

ax1.plot(range(1, post_x.shape[0] + 1), dist_post, 'r*-')
ax1.set_ylabel('Distortion')
ax1.set_xlabel('Values of K')
ax1.set_title('The Elbow Method Using Distortion - Post')
ax1.grid(linestyle='--', alpha=0.5)
ax1.set_xticks(range(1, post_x.shape[0] + 1))
ax2.plot(range(1, post_x.shape[0] + 1), inert_post, 'r*-')
ax2.set_ylabel('Inertia')
ax2.set_xlabel('Values of K')
ax2.set_title('The Elbow Method Using Inertia - Post')
ax2.grid(linestyle='--', alpha=0.5)
ax2.set_xticks(range(1, post_x.shape[0] + 1))

ax3.plot(range(1, story_x.shape[0] + 1), dist_story, 'r*-')
ax3.set_ylabel('Distortion')
ax3.set_xlabel('Values of K')
```

```python
ax3.set_title('The Elbow Method Using Distortion - Story')
ax3.grid(linestyle='--', alpha=0.5)
ax3.set_xticks(range(1, story_x.shape[0] + 1))
ax4.plot(range(1, story_x.shape[0] + 1), inert_story, 'r*-')
ax4.set_ylabel('Inertia')
ax4.set_xlabel('Values of K')
ax4.set_title('The Elbow Method Using Inertia - Story')
ax4.grid(linestyle='--', alpha=0.5)
ax4.set_xticks(range(1, story_x.shape[0] + 1))

plt.show()
```



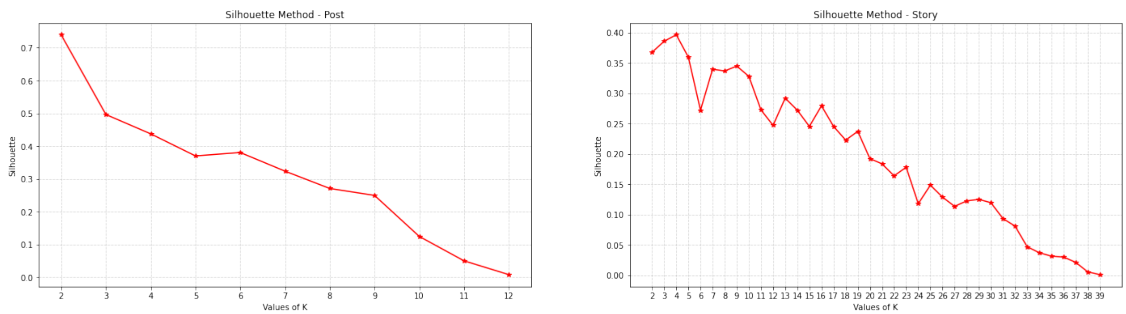
as you can see in the graph above, we have a solid elbow point in posts datasets which is **2**, but there are no solid and definite point of elbow in story dataset, the most appropriate elbow point in story dataset seems to be **3**.

[10]:
```python
sil_post = calc_silhouette(post_x, post_x.shape[0] - 1)
sil_story = calc_silhouette(story_x, story_x.shape[0] - 1)
```

```
100%|      | 11/11 [00:00<00:00, 33.83it/s]
100%|      | 38/38 [00:02<00:00, 13.19it/s]
```

[11]:
```python
fig = plt.figure(figsize = (24, 6))
ax1 = fig.add_subplot(1,2,1)
ax2 = fig.add_subplot(1,2,2)

ax1.plot(range(2, post_x.shape[0]), sil_post, 'r*-')
ax1.set_ylabel('Silhouette')
ax1.set_xlabel('Values of K')
```

```
ax1.set_title('Silhouette Method - Post')
ax1.grid(linestyle='--', alpha=0.5)
ax1.set_xticks(range(2, post_x.shape[0]))

ax2.plot(range(2, story_x.shape[0]), sil_story, 'r*-')
ax2.set_ylabel('Silhouette')
ax2.set_xlabel('Values of K')
ax2.set_title('Silhouette Method - Story')
ax2.grid(linestyle='--', alpha=0.5)
ax2.set_xticks(range(2, story_x.shape[0]))

plt.show()
```



As I anticipated, Silhouette method gives us a better definition, Although the estimated values for K with elbow method was correct, **2 clusters** for post dataset and **3 clusters** for story dataset give us the best performance. It's worth to mention that in post dataset highest score we can achieve via silhouette estimation is a little of than 0.70 and in story dataset is ~0.35.

This fact means that Partitioned based clustering is not good solution for our clustering problem. Regardless of this matter, I'm going to implement it since it just a few lines and after that we can move to the next method.

1.1.2 K-Means

[12]:
```
clus_kmeans_post = KMeans(n_clusters = 2).fit(post_x)
clus_kmeans_story = KMeans(n_clusters = 3).fit(story_x)
labels_post = clus_kmeans_post.labels_
labels_story = clus_kmeans_story.labels_

df_post_kmeans = post
df_story_kmeans = story
df_post_kmeans['clus_kmeans'] = labels_post
df_story_kmeans['clus_kmeans'] = labels_story
```

[13]:
```
df_post_kmeans.groupby('clus_kmeans').mean()
```

[13]:

```
             post_no    like  comment   share   save  profile_visit    reach  \
clus_kmeans
0               7.91  464.36    62.45   25.64  18.82          56.27  2962.00
1               2.00 1763.00 15537.00 1155.00 255.00         342.00 10958.50

             impression  ig_tv      view
clus_kmeans
0               3572.91   0.09    251.09
1              13100.00   1.00 134375.00
```

[14]:

```python
df_story_kmeans.groupby('clus_kmeans').mean()
```

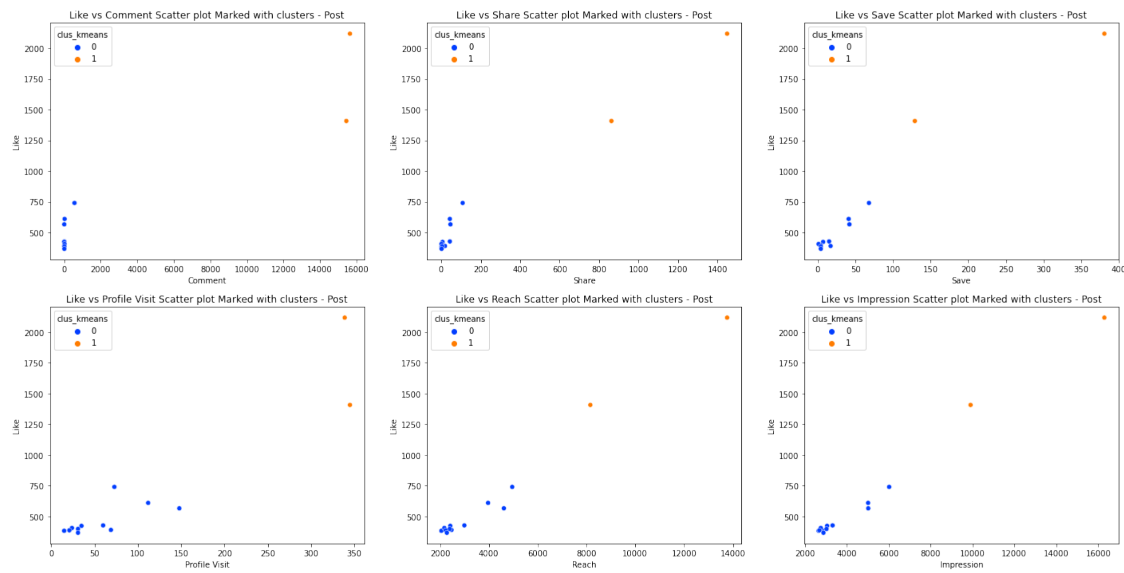
[14]:

```
             story_no    view  action  reply  profile_visit  share  \
clus_kmeans
0               13.25 1183.17   55.08   4.00          44.08   6.17
1               21.63  648.30   21.78   2.81          11.26   1.78
2               37.00  803.00  397.00   3.00          18.00  80.00

             website_click  sticker_tap  impression  follow  navigation  \
clus_kmeans
0                     0.83         0.00     1234.83    0.92     1432.42
1                     0.04         5.89      669.33    0.15      776.41
2                     0.00       296.00      836.00    3.00     1192.00

              back  forward   next   exit  vote  type_labelencoded
clus_kmeans
0            70.25   914.25 160.83 278.83 22.83               0.33
1            40.37   532.70  68.81 134.74  2.74               0.37
2           405.00   539.00 -53.00 338.00  0.00               2.00
```

[15]:

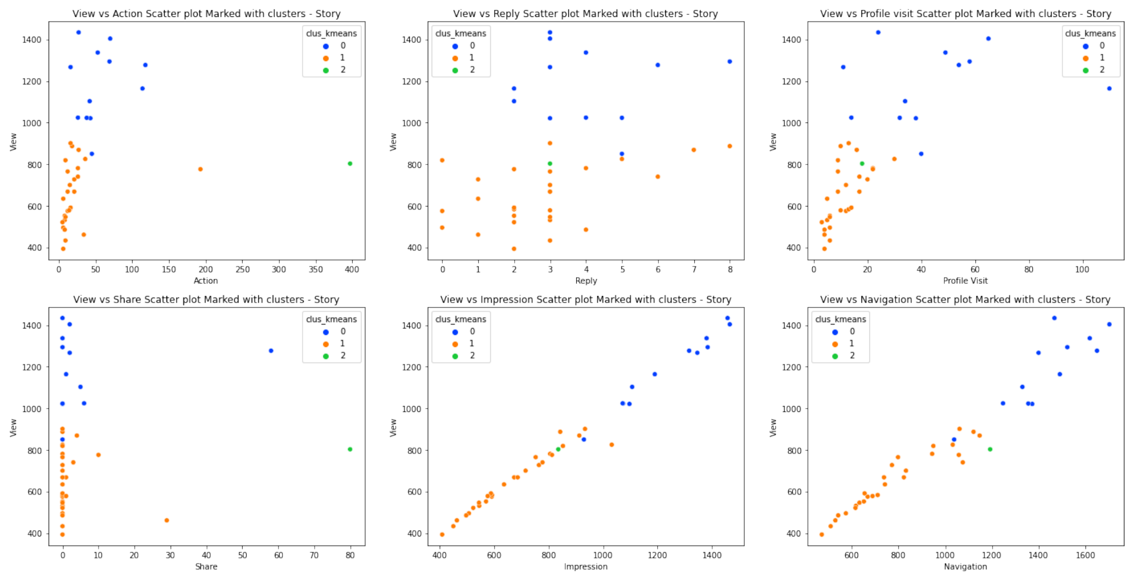
```python
post_clus_x = np.asarray(df_post_kmeans.loc[:, ['like', 'comment', 'share',␣
 ↪'save', 'profile_visit', 'reach', 'impression']])
fig = plt.figure(figsize = (24, 12))
ax1 = fig.add_subplot(2,3,1)
ax2 = fig.add_subplot(2,3,2)
ax3 = fig.add_subplot(2,3,3)
ax4 = fig.add_subplot(2,3,4)
ax5 = fig.add_subplot(2,3,5)
ax6 = fig.add_subplot(2,3,6)

sns.scatterplot(x=post_clus_x[:, 1], y=post_clus_x[:, 0],␣
 ↪hue=df_post_kmeans['clus_kmeans'], palette='bright', alpha=1.0,␣
 ↪edgecolor='white', ax=ax1)
ax1.set_ylabel('Like')
ax1.set_xlabel('Comment')
ax1.set_title('Like vs Comment Scatter plot Marked with clusters - Post')
```

```
sns.scatterplot(x=post_clus_x[:, 2], y=post_clus_x[:, 0],␣
↪hue=df_post_kmeans['clus_kmeans'], palette='bright', alpha=1.0,␣
↪edgecolor='white', ax=ax2)
ax2.set_ylabel('Like')
ax2.set_xlabel('Share')
ax2.set_title('Like vs Share Scatter plot Marked with clusters - Post')

sns.scatterplot(x=post_clus_x[:, 3], y=post_clus_x[:, 0],␣
↪hue=df_post_kmeans['clus_kmeans'], palette='bright', alpha=1.0,␣
↪edgecolor='white', ax=ax3)
ax3.set_ylabel('Like')
ax3.set_xlabel('Save')
ax3.set_title('Like vs Save Scatter plot Marked with clusters - Post')

sns.scatterplot(x=post_clus_x[:, 4], y=post_clus_x[:, 0],␣
↪hue=df_post_kmeans['clus_kmeans'], palette='bright', alpha=1.0,␣
↪edgecolor='white', ax=ax4)
ax4.set_ylabel('Like')
ax4.set_xlabel('Profile Visit')
ax4.set_title('Like vs Profile Visit Scatter plot Marked with clusters - Post')

sns.scatterplot(x=post_clus_x[:, 5], y=post_clus_x[:, 0],␣
↪hue=df_post_kmeans['clus_kmeans'], palette='bright', alpha=1.0,␣
↪edgecolor='white', ax=ax5)
ax5.set_ylabel('Like')
ax5.set_xlabel('Reach')
ax5.set_title('Like vs Reach Scatter plot Marked with clusters - Post')

sns.scatterplot(x=post_clus_x[:, 6], y=post_clus_x[:, 0],␣
↪hue=df_post_kmeans['clus_kmeans'], palette='bright', alpha=1.0,␣
↪edgecolor='white', ax=ax6)
ax6.set_ylabel('Like')
ax6.set_xlabel('Impression')
ax6.set_title('Like vs Impression Scatter plot Marked with clusters - Post')

plt.show()
```



[16]:
```python
story_clus_x = np.asarray(df_story_kmeans.loc[:, ['view', 'action', 'reply', 'profile_visit', 'share', 'impression', 'navigation']])
fig = plt.figure(figsize = (24, 12))
ax1 = fig.add_subplot(2,3,1)
ax2 = fig.add_subplot(2,3,2)
ax3 = fig.add_subplot(2,3,3)
ax4 = fig.add_subplot(2,3,4)
ax5 = fig.add_subplot(2,3,5)
ax6 = fig.add_subplot(2,3,6)

sns.scatterplot(x=story_clus_x[:, 1], y=story_clus_x[:, 0], hue=df_story_kmeans['clus_kmeans'], palette='bright', alpha=1.0, edgecolor='white', ax=ax1)
ax1.set_ylabel('View')
ax1.set_xlabel('Action')
ax1.set_title('View vs Action Scatter plot Marked with clusters - Story')

sns.scatterplot(x=story_clus_x[:, 2], y=story_clus_x[:, 0], hue=df_story_kmeans['clus_kmeans'], palette='bright', alpha=1.0, edgecolor='white', ax=ax2)
ax2.set_ylabel('View')
ax2.set_xlabel('Reply')
ax2.set_title('View vs Reply Scatter plot Marked with clusters - Story')

sns.scatterplot(x=story_clus_x[:, 3], y=story_clus_x[:, 0], hue=df_story_kmeans['clus_kmeans'], palette='bright', alpha=1.0, edgecolor='white', ax=ax3)
ax3.set_ylabel('View')
```

```
ax3.set_xlabel('Profile Visit')
ax3.set_title('View vs Profile visit Scatter plot Marked with clusters - Story')

sns.scatterplot(x=story_clus_x[:, 4], y=story_clus_x[:, 0],␣
 ↪hue=df_story_kmeans['clus_kmeans'], palette='bright', alpha=1.0,␣
 ↪edgecolor='white', ax=ax4)
ax4.set_ylabel('View')
ax4.set_xlabel('Share')
ax4.set_title('View vs Share Scatter plot Marked with clusters - Story')

sns.scatterplot(x=story_clus_x[:, 5], y=story_clus_x[:, 0],␣
 ↪hue=df_story_kmeans['clus_kmeans'], palette='bright', alpha=1.0,␣
 ↪edgecolor='white', ax=ax5)
ax5.set_ylabel('View')
ax5.set_xlabel('Impression')
ax5.set_title('View vs Impression Scatter plot Marked with clusters - Story')

sns.scatterplot(x=story_clus_x[:, 6], y=story_clus_x[:, 0],␣
 ↪hue=df_story_kmeans['clus_kmeans'], palette='bright', alpha=1.0,␣
 ↪edgecolor='white', ax=ax6)
ax6.set_ylabel('View')
ax6.set_xlabel('Navigation')
ax6.set_title('View vs Navigation Scatter plot Marked with clusters - Story')

plt.show()
```

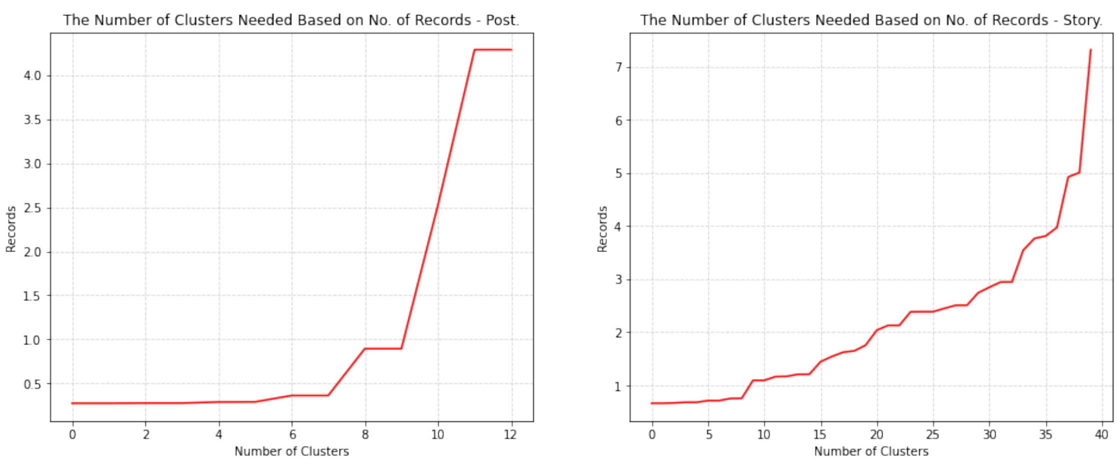


1.1.3 DBSCAN

[17]:
```
from sklearn.neighbors import NearestNeighbors
from sklearn.cluster import DBSCAN
from matplotlib.lines import Line2D
```

[18]:
```
neigh_post = NearestNeighbors(n_neighbors=2)
neigh_story = NearestNeighbors(n_neighbors=2)
nbrs_post = neigh_post.fit(post_x)
nbrs_story = neigh_story.fit(story_x)
distances_post, _ = nbrs_post.kneighbors(post_x)
distances_story, _ = nbrs_story.kneighbors(story_x)
distances_post = np.sort(distances_post, axis=0)
distances_story = np.sort(distances_story, axis=0)
distances_post = distances_post[:,1]
distances_story = distances_story[:,1]
```

[19]:
```
fig = plt.figure(figsize = (16,6))
ax1 = fig.add_subplot(1,2,1)
ax2 = fig.add_subplot(1,2,2)

ax1.plot(distances_post, 'r-')
ax1.set_ylabel('Records')
ax1.set_xlabel('Number of Clusters')
ax1.set_title('The Number of Clusters Needed Based on No. of Records - Post.')
ax1.grid(linestyle='--', alpha=0.5)
ax2.plot(distances_story, 'r-')
ax2.set_ylabel('Records')
ax2.set_xlabel('Number of Clusters')
ax2.set_title('The Number of Clusters Needed Based on No. of Records - Story.')
ax2.grid(linestyle='--', alpha=0.5)
plt.show()
```



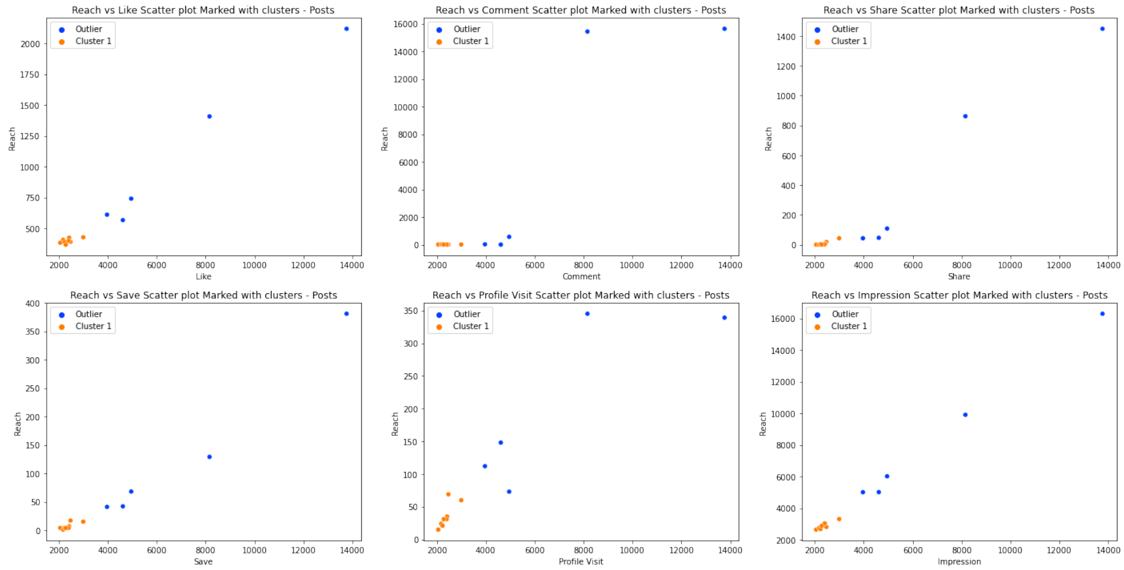
Like the Elbow Method, we pick the point that our curvature starts to rise exponentially as the epsilon, for Posts dataset it is **0.8** and for Story dataset is **3**.

[53]:
```
clus_dbscan_post = DBSCAN(eps=.8, min_samples=2)
clus_dbscan_story = DBSCAN(eps=3, min_samples=3)
clus_dbscan_post.fit(post_x)
clus_dbscan_story.fit(story_x)
clusters_post = clus_dbscan_post.labels_
clusters_story = clus_dbscan_story.labels_
```

[54]:
```
clusters_post = np.where(clusters_post == -1, 'Outlier', clusters_post)
clusters_post = np.where(clusters_post == '0', 'Cluster 1', clusters_post)

clusters_story = np.where(clusters_story == -1, 'Outlier', clusters_story)
clusters_story = np.where(clusters_story == '0', 'Cluster 1', clusters_story)

df_post_dbscan = post
df_post_dbscan['clus_dbscan'] = clusters_post
df_story_dbscan = story
df_story_dbscan['clus_dbscan'] = clusters_story
```

[71]:
```
post_clus_x = np.asarray(df_post_dbscan.loc[:, ['like', 'comment', 'share',␣
↪'save', 'profile_visit', 'reach', 'impression']])
fig = plt.figure(figsize = (24, 12))
ax1 = fig.add_subplot(2,3,1)
ax2 = fig.add_subplot(2,3,2)
ax3 = fig.add_subplot(2,3,3)
ax4 = fig.add_subplot(2,3,4)
ax5 = fig.add_subplot(2,3,5)
ax6 = fig.add_subplot(2,3,6)


g1 = sns.scatterplot(x=post_clus_x[:, 5], y=post_clus_x[:, 0],␣
↪hue=df_post_dbscan['clus_dbscan'], palette='bright', alpha=1.0,␣
↪edgecolor='white', ax=ax1)
g1.get_legend().set_title('')
ax1.set_ylabel('Reach')
ax1.legend(loc='upper left')
ax1.set_xlabel('Like')
ax1.set_title('Reach vs Like Scatter plot Marked with clusters - Posts')

g2 = sns.scatterplot(x=post_clus_x[:, 5], y=post_clus_x[:, 1],␣
↪hue=df_post_dbscan['clus_dbscan'], palette='bright', alpha=1.0,␣
↪edgecolor='white', ax=ax2)
g2.get_legend().set_title('')
ax2.set_ylabel('Reach')
ax2.legend(loc='upper left')
```

```python
ax2.set_xlabel('Comment')
ax2.set_title('Reach vs Comment Scatter plot Marked with clusters - Posts')

g3 = sns.scatterplot(x=post_clus_x[:, 5], y=post_clus_x[:, 2],␣
 ↪hue=df_post_dbscan['clus_dbscan'], palette='bright', alpha=1.0,␣
 ↪edgecolor='white', ax=ax3)
g3.get_legend().set_title('')
ax3.set_ylabel('Reach')
ax3.legend(loc='upper left')
ax3.set_xlabel('Share')
ax3.set_title('Reach vs Share Scatter plot Marked with clusters - Posts')

g4 = sns.scatterplot(x=post_clus_x[:, 5], y=post_clus_x[:, 3],␣
 ↪hue=df_post_dbscan['clus_dbscan'], palette='bright', alpha=1.0,␣
 ↪edgecolor='white', ax=ax4)
g4.get_legend().set_title('')
ax4.set_ylabel('Reach')
ax4.legend(loc='upper left')
ax4.set_xlabel('Save')
ax4.set_title('Reach vs Save Scatter plot Marked with clusters - Posts')

g5 = sns.scatterplot(x=post_clus_x[:, 5], y=post_clus_x[:, 4],␣
 ↪hue=df_post_dbscan['clus_dbscan'], palette='bright', alpha=1.0,␣
 ↪edgecolor='white', ax=ax5)
g5.get_legend().set_title('')
ax5.set_ylabel('Reach')
ax5.legend(loc='upper left')
ax5.set_xlabel('Profile Visit')
ax5.set_title('Reach vs Profile Visit Scatter plot Marked with clusters -␣
 ↪Posts')

g6 = sns.scatterplot(x=post_clus_x[:, 5], y=post_clus_x[:, 6],␣
 ↪hue=df_post_dbscan['clus_dbscan'], palette='bright', alpha=1.0,␣
 ↪edgecolor='white', ax=ax6)
g6.get_legend().set_title('')
ax6.set_ylabel('Reach')
ax6.legend(loc='upper left')
ax6.set_xlabel('Impression')
ax6.set_title('Reach vs Impression Scatter plot Marked with clusters - Posts')

plt.show()
```

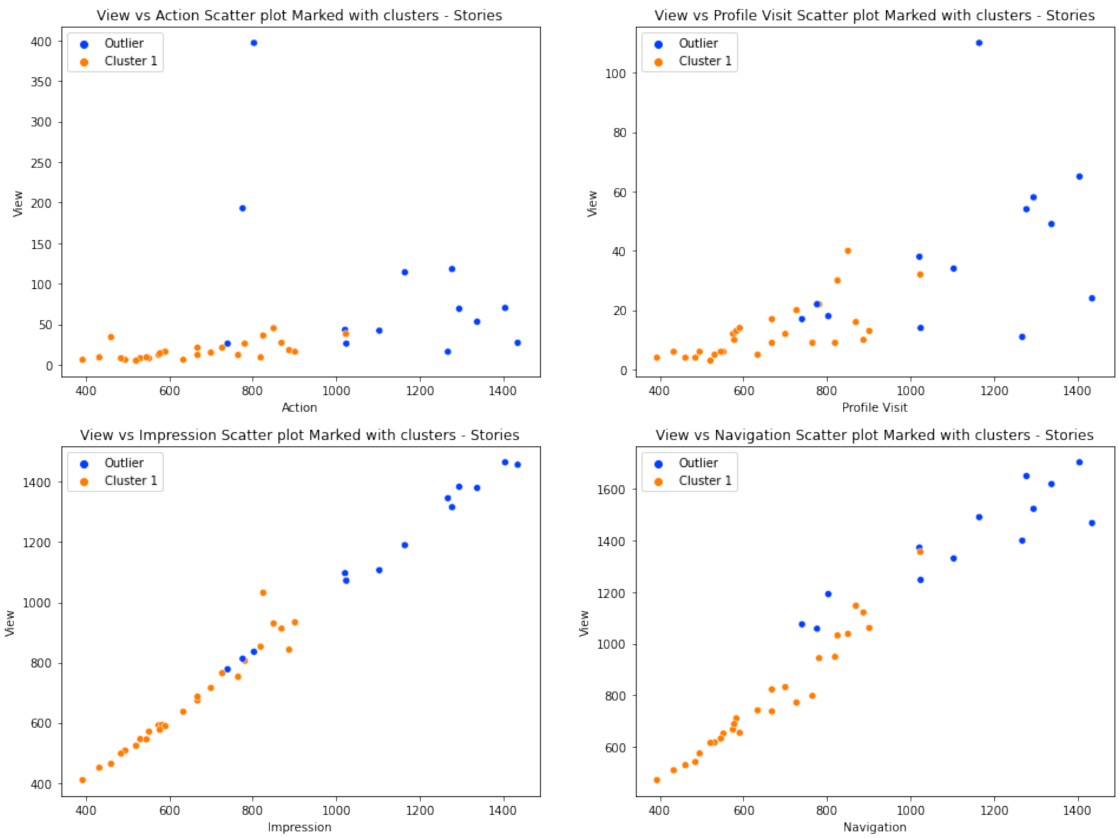


[70]:
```
df_story_dbscan[:5]
```

[70]:
```
   story_no  view  action  reply  profile_visit  share  website_click  \
0         0  1337      53      4             49      0              0
1         1  1164     114      2            110      1              1
2         2   727      21      1             20      0              0
3         3   850      45      5             40      0              0
4         4  1294      69      8             58      0              3

   sticker_tap  impression  follow  navigation  back  forward  next  exit  \
0            0        1380       0        1618    28     1048   179   363
1            0        1190       1        1490   106      919   119   350
2            0         765       0         772    38      428    92   214
3            0         930       1        1038    31      531   125   351
4            0        1384       0        1522    35      909   186   392

   vote  type_labelencoded  clus_kmeans clus_dbscan
0     0                  0            0     Outlier
1     0                  0            0     Outlier
2     0                  0            1   Cluster 1
3     0                  0            0   Cluster 1
4     0                  0            0     Outlier
```

[75]:
```
story_clus_x = np.asarray(df_story_dbscan.loc[:, ['view', 'action',␣
 ↪'profile_visit', 'impression', 'navigation']])
fig = plt.figure(figsize = (16, 12))
ax1 = fig.add_subplot(2,2,1)
ax2 = fig.add_subplot(2,2,2)
```

```
ax3 = fig.add_subplot(2,2,3)
ax4 = fig.add_subplot(2,2,4)


g1 = sns.scatterplot(x=story_clus_x[:, 0], y=story_clus_x[:, 1],␣
 ↪hue=df_story_dbscan['clus_dbscan'], palette='bright', alpha=1.0,␣
 ↪edgecolor='white', ax=ax1)
g1.get_legend().set_title('')
ax1.set_ylabel('View')
ax1.legend(loc='upper left')
ax1.set_xlabel('Action')
ax1.set_title('View vs Action Scatter plot Marked with clusters - Stories')

g2 = sns.scatterplot(x=story_clus_x[:, 0], y=story_clus_x[:, 2],␣
 ↪hue=df_story_dbscan['clus_dbscan'], palette='bright', alpha=1.0,␣
 ↪edgecolor='white', ax=ax2)
g2.get_legend().set_title('')
ax2.set_ylabel('View')
ax2.legend(loc='upper left')
ax2.set_xlabel('Profile Visit')
ax2.set_title('View vs Profile Visit Scatter plot Marked with clusters -␣
 ↪Stories')

g3 = sns.scatterplot(x=story_clus_x[:, 0], y=story_clus_x[:, 3],␣
 ↪hue=df_story_dbscan['clus_dbscan'], palette='bright', alpha=1.0,␣
 ↪edgecolor='white', ax=ax3)
g3.get_legend().set_title('')
ax3.set_ylabel('View')
ax3.legend(loc='upper left')
ax3.set_xlabel('Impression')
ax3.set_title('View vs Impression Scatter plot Marked with clusters - Stories')

g4 = sns.scatterplot(x=story_clus_x[:, 0], y=story_clus_x[:, 4],␣
 ↪hue=df_story_dbscan['clus_dbscan'], palette='bright', alpha=1.0,␣
 ↪edgecolor='white', ax=ax4)
g4.get_legend().set_title('')
ax4.set_ylabel('View')
ax4.legend(loc='upper left')
ax4.set_xlabel('Navigation')
ax4.set_title('View vs Navigation Scatter plot Marked with clusters - Stories')

plt.show()
```



[77]:
```python
df_post_dbscan.groupby('clus_dbscan').mean().drop(columns=['post_no',␣
↪'clus_kmeans'])
```

[77]:
```
                like  comment  share   save  profile_visit   reach  impression  \
clus_dbscan
Cluster 1     398.62    11.12  10.25   7.00          35.75 2380.12     2904.50
Outlier      1089.00  6334.40 502.00 132.20         203.40 7091.60     8453.20

             ig_tv     view
clus_dbscan
Cluster 1     0.00     0.00
Outlier       0.60 54302.40
```

[80]:
```python
df_story_dbscan.groupby('clus_dbscan').mean().drop(columns=['story_no',␣
↪'clus_kmeans', 'type_labelencoded'])
```

[80]:
```
                view  action  reply  profile_visit  share  website_click  \
clus_dbscan
Cluster 1     661.52   16.74   2.89          12.48   1.30           0.07
Outlier      1126.46   91.85   3.77          39.54  12.85           0.69
```

```
            sticker_tap  impression  follow  navigation   back  forward  \
clus_dbscan
Cluster 1          0.00      684.63    0.22      786.04  28.04   539.11
Outlier           35.00     1172.38    0.92     1393.92 121.62   872.08

              next   exit  vote
clus_dbscan
Cluster 1    76.26 138.78  2.74
Outlier     128.92 275.00 21.08
```

[ ]: