IS&Digital Innovation 2024

May 12, 2024

[41]:
```python
## Importing all required libraries ##
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
%matplotlib inline
#Other important libraries are imported later on in the notebook for ease of␣
↪understanding, usually it is a good practice to import everything at the␣
↪start of your notebook
```

[15]:
```python
df = pd.read_csv('Live.csv')
```

[ ]:
```python
# Some elementary EDA
```

[ ]:
```python
#Lets take a look at the data to determine which features to use for clustering.
↪ Let's start by loading the data and examining the first few rows and the␣
↪structure of the dataset.
```

[17]:
```python
# Display the first few rows of the dataframe and the data types
df.head(), df.dtypes
```

[17]:
```
(                          status_id status_type status_published  \
 0  246675545449582_1649696485147474       video   4/22/2018 6:00
 1  246675545449582_1649426988507757       photo  4/21/2018 22:45
 2  246675545449582_1648730588577397       video   4/21/2018 6:17
 3  246675545449582_1648576705259452       photo   4/21/2018 2:29
 4  246675545449582_1645700502213739       photo   4/18/2018 3:22

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

```
   num_hahas  num_sads  num_angrys  Column1  Column2  Column3  Column4
0          1         1           0      NaN      NaN      NaN      NaN
1          0         0           0      NaN      NaN      NaN      NaN
2          1         0           0      NaN      NaN      NaN      NaN
3          0         0           0      NaN      NaN      NaN      NaN
4          0         0           0      NaN      NaN      NaN      NaN   ,
status_id           object
status_type         object
status_published    object
num_reactions        int64
num_comments         int64
num_shares           int64
num_likes            int64
num_loves            int64
num_wows             int64
num_hahas            int64
num_sads             int64
num_angrys           int64
Column1            float64
Column2            float64
Column3            float64
Column4            float64
dtype: object)
```

[21]:
```python
#Checking for Missing values
df.isnull().sum()
```

[21]:
```
status_id              0
status_type            0
status_published       0
num_reactions          0
num_comments           0
num_shares             0
num_likes              0
num_loves              0
num_wows               0
num_hahas              0
num_sads               0
num_angrys             0
Column1             7050
Column2             7050
Column3             7050
Column4             7050
dtype: int64
```

[23]:
```python
#Col 1,2,3 and 4 are Null and redundant completely, hence we should remove␣
↪(drop) them
```

```
df.drop(['Column1', 'Column2', 'Column3', 'Column4'], axis=1, inplace=True)
```

[29]:
```
#Checking for no of unique values within our features (using len to get the␣
↪count)
len(df['status_id'].unique())
```

[29]: 6997

[39]:
```
len(df['status_type'].unique())
```

[39]: 4

[37]:
```
#further examination of this feature
df['status_type'].unique()
#can be valuable in our analysis
```

[37]: array(['video', 'photo', 'link', 'status'], dtype=object)

[33]:
```
len(df['status_published'].unique())
```

[33]: 6913

[43]:
```
''' The dataset includes various features related to social media status␣
↪updates.

Overview of Features:

The dataset includes numerical metrics that measure different types of user␣
↪interactions:

num_reactions: Total number of reactions to a post. Reactions can include␣
↪likes, loves, wows, etc. This is a broad measure of how users respond to␣
↪content.

num_comments: Counts how many comments were made on the post. High numbers␣
↪might indicate that the content is provocative (Provokes a response), asks a␣
↪question, or otherwise encourages discussions.

num_shares: Indicates how many times the post was shared. Shares can␣
↪significantly increase a post's reach and are often a sign of endorsement or␣
↪the desire to spread the information.

num_likes, num_loves, num_wows, num_hahas, num_sads, num_angrys: These are more␣
↪specific types of reactions that give insights into the emotional response␣
↪of the audience towards the content.'''
```

[43]: " The dataset includes various features related to social media status updates.\n\nOverview of Features:\n\nThe dataset includes numerical metrics that measure different types of user interactions:\n\nnum_reactions: Total number of reactions to a post. Reactions can include likes, loves, wows, etc. This is a broad measure of how users respond to content.\n\nnum_comments: Counts how many comments were made on the post. High numbers might indicate that the content is provocative (Provokes a response), asks a question, or otherwise encourages discussions.\n\nnum_shares: Indicates how many times the post was shared. Shares can significantly increase a post's reach and are often a sign of endorsement or the desire to spread the information.\n\nnum_likes, num_loves, num_wows, num_hahas, num_sads, num_angrys: These are more specific types of reactions that give insights into the emotional response of the audience towards the content."

[ ]:
```
'''Logic behind chosen features:

1. Relevance to the Domain
The selected features are all directly related to user engagement metrics on␣
 ↪social media posts, which include:

num_reactions
num_comments
num_shares
num_likes
num_loves
num_wows
num_hahas
num_sads
num_angrys

These features are quantifiable indicators of how users interact with content,␣
 ↪such as through likes, shares, comments, and various emotional reactions␣
 ↪(love, wow, haha, sad, angry). This makes them highly relevant for analysing␣
 ↪and understanding patterns in social media behavior, such as identifying␣
 ↪posts that display strong emotional responses or those that encourage␣
 ↪discussion.

3. Avoiding High Cardinality
We specifically avoided using features with a high number of unique values,␣
 ↪such as status_id and status_published. These features are essentially␣
 ↪identifiers and timestamps that are unique to individual posts, offering no␣
 ↪meaningful way to group data points since each unique identifier only␣
 ↪applies to a single post. Clustering algorithms like K-means aim to find␣
 ↪groups of similar items, and using features that are unique to each item␣
 ↪would not help in finding such groups.

4. Potential for Insight
The chosen features allow us to potentially uncover insights such as:
```

```
Similarities in engagement types across different posts.
Grouping posts by engagement patterns, which could reveal what types of content␣
↪tend to receive similar types and amounts of interactions.

5. Scalability and Standardization

By selecting features that are on a similar scale (counts of different types of␣
↪interactions), it ensures that one feature does not disproportionately␣
↪influence the cluster assignment due to its scale. Standardising these␣
↪features, which we will do via scaling, further helps in treating all␣
↪features equally in the clustering process.
This approach ensures that the clustering results are not only statistically␣
↪valid but also meaningful and interpretable within the context of social␣
↪media analytics.
```

[45]:

```
#Feature Selection : Based on the logic written above we select these features␣
↪for our K-Means Clustering
features = ['num_reactions', 'num_comments', 'num_shares', 'num_likes',
            'num_loves', 'num_wows', 'num_hahas', 'num_sads', 'num_angrys']
```

[47]:

```
from sklearn.preprocessing import StandardScaler #To standardise our values
from sklearn.cluster import KMeans # Our Model
from sklearn.decomposition import PCA # Since our dimesionality is of a higher␣
↪degree, we use PCA to create meaningful 2D visuals
from sklearn.metrics import silhouette_score
#Other necessary tools from the sklearn library

X = df[features]
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
```

[ ]:

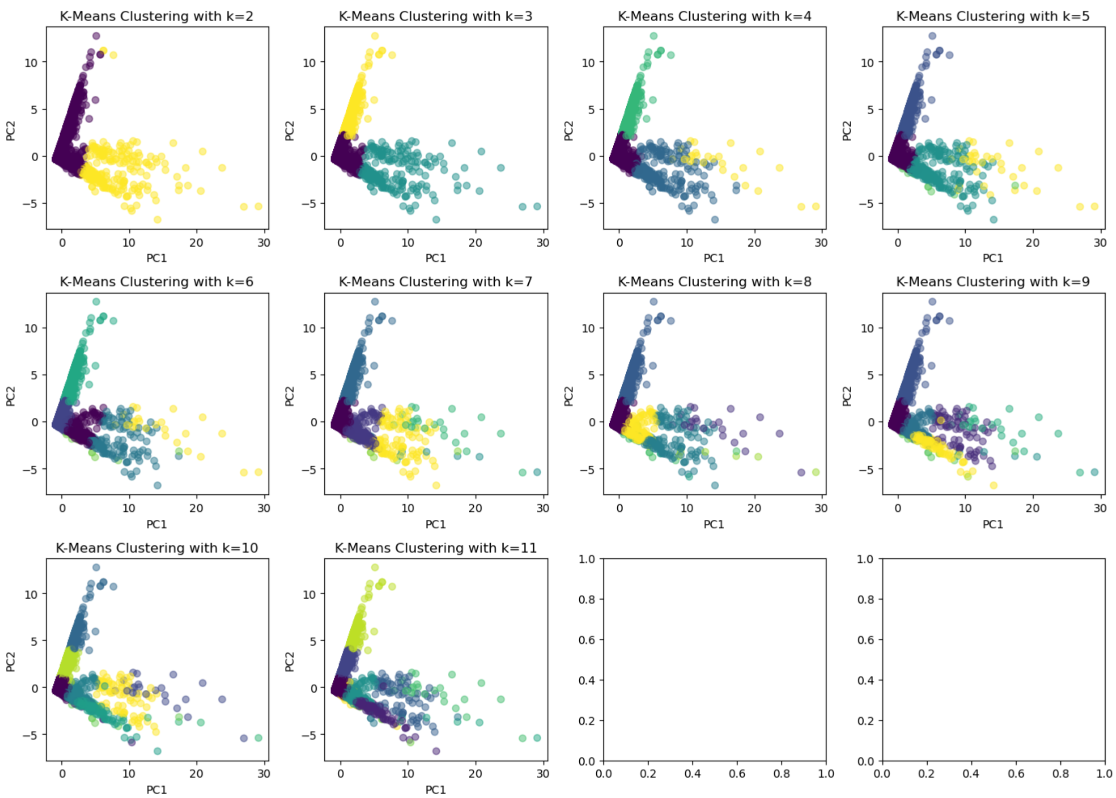
```
'''To thoroughly evaluate the clustering models for different values of k
using K-means, we can compute metrics such as the silhouette score for each
k (which provides a sense of cluster cohesion and separation)'''
```

[103]:

```
# Applying K-means
results = {}
for k in [2, 3, 4, 5,6,7,8,9,10,11]:
    kmeans = KMeans(n_clusters=k, random_state=42)
    kmeans.fit(X_scaled)
    labels = kmeans.labels_

    # PCA for dimensionality reduction to 2D for visualization
    pca = PCA(n_components=2)
    principal_components = pca.fit_transform(X_scaled)

    results[k] = {
```

```
        'labels': labels,
        'pca_components': principal_components
    }
```

[111]:
```
# Plotting the results
fig, axes = plt.subplots(3, 4, figsize=(14, 10))
axes = axes.ravel()

for i, k in enumerate([2, 3, 4, 5, 6, 7, 8, 9, 10, 11]):
    pca_components = results[k]['pca_components']
    labels = results[k]['labels']
    if i < 10:
        axes[i].scatter(pca_components[:, 0], pca_components[:, 1], c=labels,␣
 ↪cmap='viridis', alpha=0.5)
        axes[i].set_title(f'K-Means Clustering with k={k}')
        axes[i].set_xlabel('PC1')
        axes[i].set_ylabel('PC2')

plt.tight_layout()
plt.show()
```

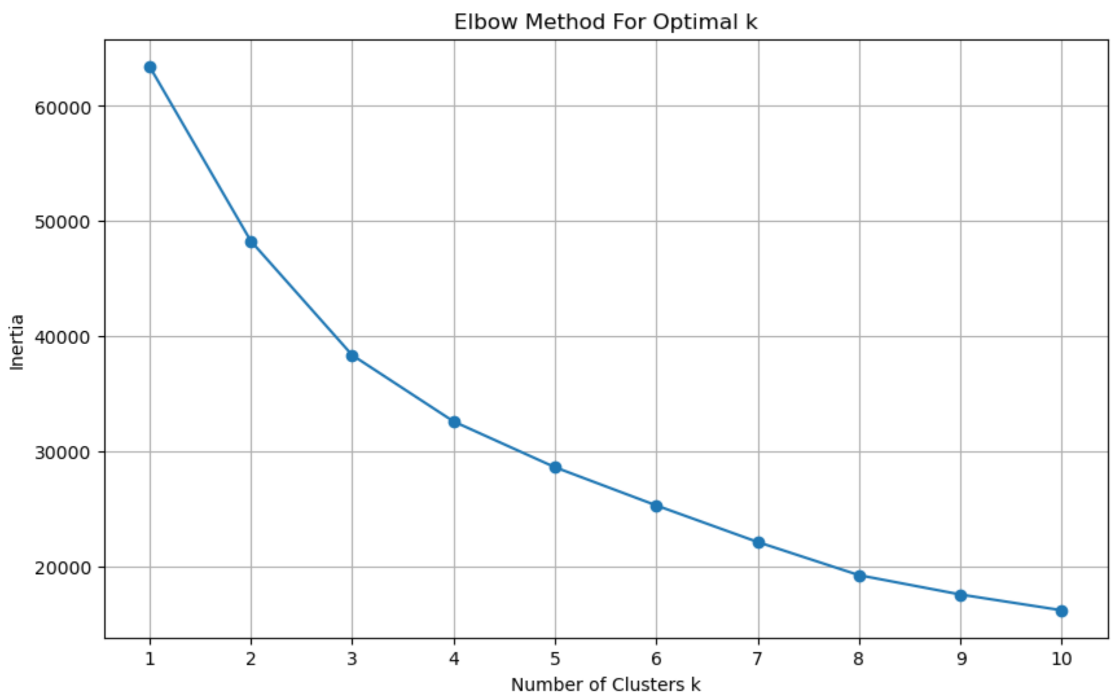


[113]:
```python
# Calculate the silhouette scores for different values of k
silhouette_scores = {}
for k in [2, 3, 4, 5,6,7,8,9,10,11]:
    labels = results[k]['labels']
    score = silhouette_score(X_scaled, labels)
    silhouette_scores[k] = score

silhouette_scores
```

[113]:
```
{2: 0.8157664963353164,
 3: 0.7499921477392748,
 4: 0.7566415831793409,
 5: 0.7609294896257128,
 6: 0.7140576613050015,
 7: 0.7181418523656731,
 8: 0.7121833991238358,
 9: 0.7104098182809936,
 10: 0.6932667670715073,
 11: 0.6966510920680359}
```

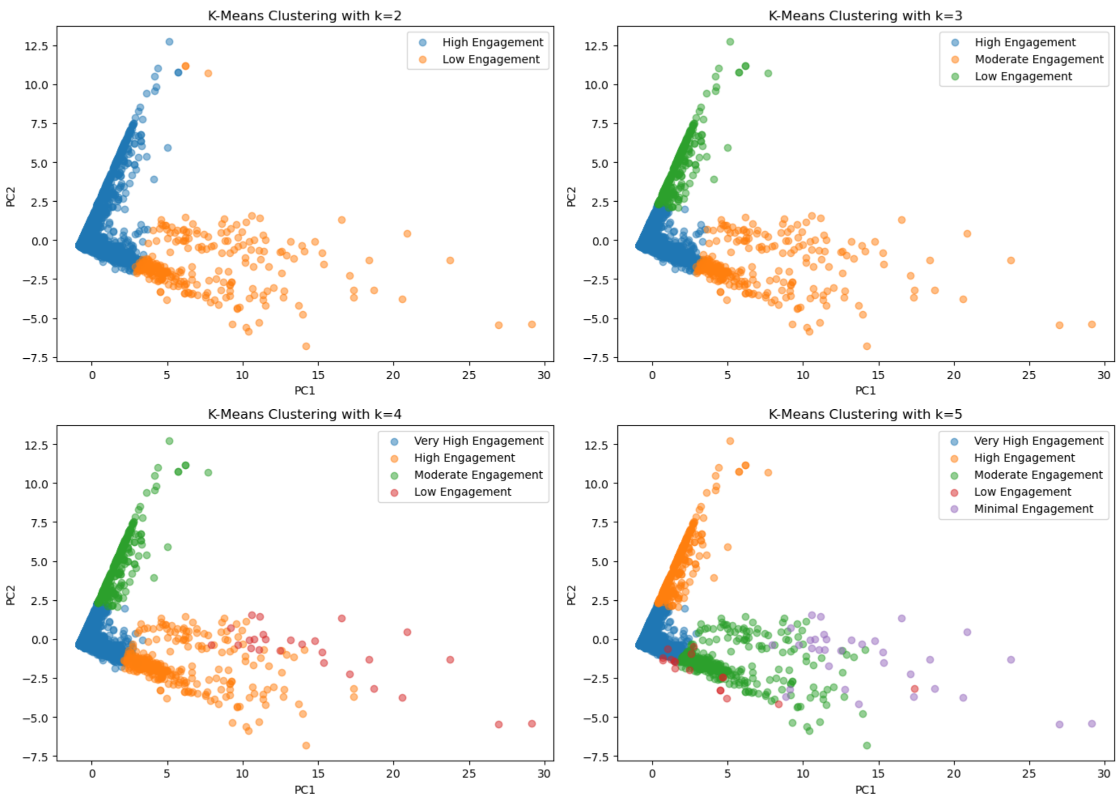
[ ]:
```python
'''The silhouette score runs from -1 to 1, with 1 indicating a perfect fit and␣
↪-1 indicating a poor match between
the data points and their corresponding cluster'''
```

[115]:
```python
# Calculate and plot the Elbow Method for k = 1 to 10
inertia = []
range_k = range(1, 11)

for k in range_k:
    kmeans = KMeans(n_clusters=k, random_state=42)
    kmeans.fit(X_scaled)
    inertia.append(kmeans.inertia_)

# Plotting the inertia
plt.figure(figsize=(10, 6))
plt.plot(range_k, inertia, marker='o')
plt.xlabel('Number of Clusters k')
plt.ylabel('Inertia')
plt.title('Elbow Method For Optimal k')
plt.xticks(range_k)
plt.grid(True)
plt.show()
```



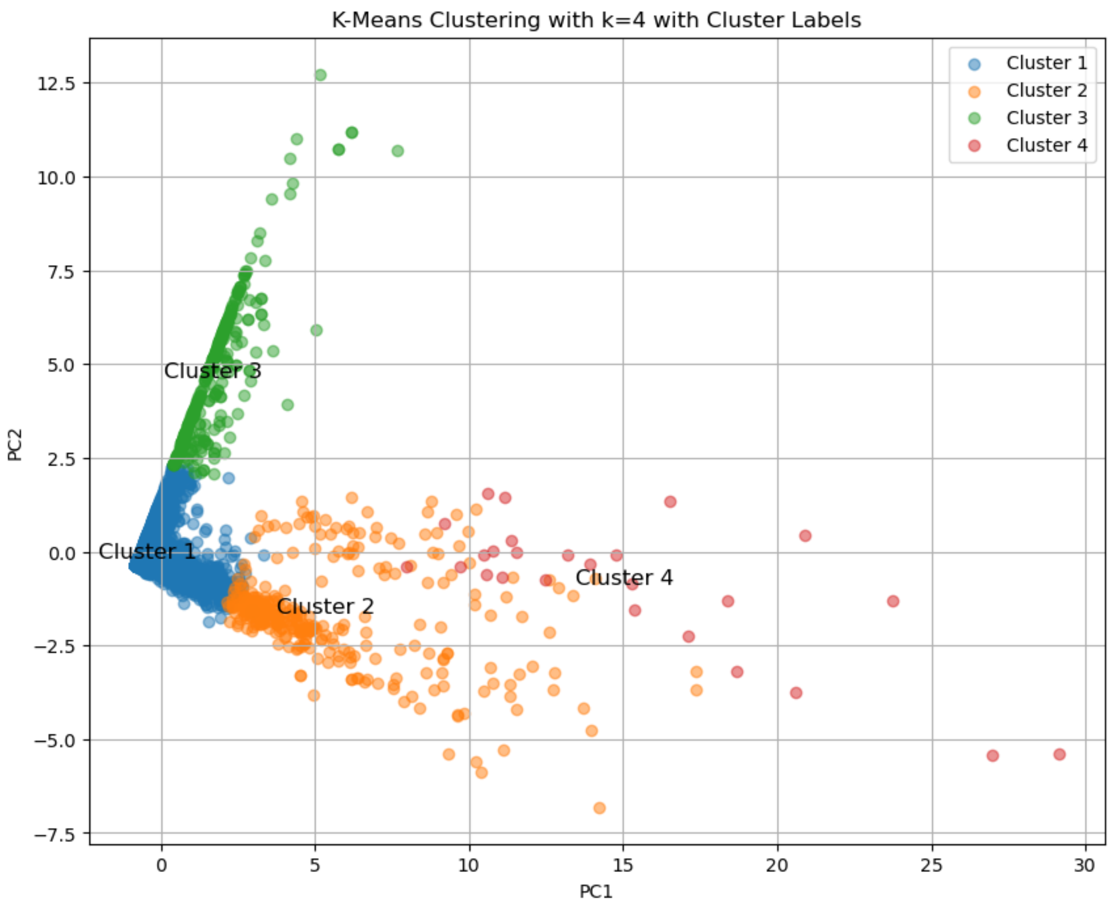
[119]:
```
# Replotting with meaningful legend labels for each k
fig, axes = plt.subplots(2, 2, figsize=(14, 10))
axes = axes.ravel()

cluster_labels = {
    2: ['High Engagement', 'Low Engagement'],
    3: ['High Engagement', 'Moderate Engagement', 'Low Engagement'],
    4: ['Very High Engagement', 'High Engagement', 'Moderate Engagement', 'Low␣
↪Engagement'],
    5: ['Very High Engagement', 'High Engagement', 'Moderate Engagement', 'Low␣
↪Engagement', 'Minimal Engagement']
}
for i, k in enumerate([2, 3, 4, 5]):
    pca_components = results[k]['pca_components']
    labels = results[k]['labels']
    unique_labels = set(labels)

    for label in unique_labels:
        # Select indices and respective components
        indices = [idx for idx, val in enumerate(labels) if val == label]
        components_x = pca_components[indices, 0]
        components_y = pca_components[indices, 1]

        # Plot each cluster
```

```
        axes[i].scatter(components_x, components_y, alpha=0.5,␣
↪label=f'{cluster_labels[k][label]}')

    axes[i].set_title(f'K-Means Clustering with k={k}')
    axes[i].set_xlabel('PC1')
    axes[i].set_ylabel('PC2')
    axes[i].legend()

plt.tight_layout()
plt.show()
```



[135]:
```
#labelling for k=4 as an example
plt.figure(figsize=(10, 8))
pca_components = results[4]['pca_components']
labels = results[4]['labels']

# Scatter plot
for label in set(labels):
    indices = labels == label
    plt.scatter(pca_components[indices, 0], pca_components[indices, 1], alpha=0.
↪5, label=f'Cluster {label+1}')
    # Annotate cluster number
```

```
    center = pca_components[indices].mean(axis=0)
    plt.text(center[0], center[1], f'Cluster {label+1}', fontsize=12,␣
 ↪ha='center')

plt.title('K-Means Clustering with k=4 with Cluster Labels')
plt.xlabel('PC1')
plt.ylabel('PC2')
plt.legend()
plt.grid(True)
plt.show()
```



[121]:
```
# Check for content type in the dataset and calculate the mean of features for␣
 ↪each cluster
content_types = df['status_type'].unique() if 'status_type' in df.columns else␣
 ↪None

# Mean of features for k=2 to k=5
```

```
cluster_means_k2 = df.assign(cluster=results[2]['labels']).
    ↪groupby('cluster')[features].mean()
cluster_means_k3 = df.assign(cluster=results[3]['labels']).
    ↪groupby('cluster')[features].mean()
cluster_means_k4 = df.assign(cluster=results[4]['labels']).
    ↪groupby('cluster')[features].mean()
cluster_means_k5 = df.assign(cluster=results[5]['labels']).
    ↪groupby('cluster')[features].mean()

content_types,cluster_means_k2,cluster_means_k3, cluster_means_k4,␣
    ↪cluster_means_k5
```

[121]:
```
(array(['video', 'photo', 'link', 'status'], dtype=object),
          num_reactions  num_comments  num_shares   num_likes   num_loves  \
 cluster
 0           206.013725    104.041913   21.208973  197.605962    7.233471
 1           826.193431   3199.715328  505.281022  646.262774  148.624088

           num_wows  num_hahas  num_sads  num_angrys
 cluster
 0         0.646104   0.331169  0.142710    0.051505
 1        17.197080   9.729927  2.740876    1.638686  ,
          num_reactions  num_comments  num_shares    num_likes   num_loves  \
 cluster
 0           113.854489    106.228571   21.711319   105.294770    7.464637
 1           786.871795   3217.948718  508.300366   606.293040  149.344322
 2          1823.311828     61.333333   11.645161  1817.534946    3.104839

           num_wows  num_hahas  num_sads  num_angrys
 cluster
 0         0.549727   0.339578  0.148790    0.054020
 1        17.080586   9.747253  2.758242    1.648352
 2         2.435484   0.198925  0.032258    0.005376  ,
          num_reactions  num_comments  num_shares    num_likes   num_loves  \
 cluster
 0           111.235527     85.856216   18.488611   103.664030    6.556628
 1           602.287879   2950.948485  423.684848   468.927273  117.396970
 2          1823.311828     61.333333   11.645161  1817.534946    3.104839
 3          1618.000000   1626.846154  812.538462  1146.961538  322.692308

            num_wows  num_hahas  num_sads  num_angrys
 cluster
 0          0.537646   0.305599  0.125751    0.043499
 1          4.687879   7.190909  2.639394    1.433333
 2          2.435484   0.198925  0.032258    0.005376
 3        124.538462  20.423077  1.538462    1.846154  ,
          num_reactions  num_comments  num_shares    num_likes   num_loves  \
```

```
cluster
0          109.824976    74.464548   16.564037   102.863302    6.005110
1         1823.311828    61.333333   11.645161  1817.534946    3.104839
2          545.732240  2808.262295  405.508197   422.497268  111.010929
3          403.294118   488.529412   51.588235   333.294118   37.058824
4         1507.151515  1711.151515  751.818182  1075.787879  294.484848

           num_wows  num_hahas   num_sads  num_angrys
cluster
0          0.523315   0.287608   0.105717    0.037847
1          2.435484   0.198925   0.032258    0.005376
2          3.830601   5.562842   1.502732    1.311475
3          4.823529   1.647059  25.294118    1.176471
4        103.727273  29.424242   1.939394    1.787879  )
```

[123]:

```python
cluster_summaries = {}
for k in results:
    cluster_summary = df.assign(cluster=results[k]['labels']).
 ↪groupby('cluster')[features].mean()
    cluster_summaries[k] = cluster_summary
```

[133]:

```python
cluster_summary
```

[133]:

```
         num_reactions  num_comments  num_shares    num_likes   num_loves  \
cluster
0            82.294128     27.574377    4.332740    79.619217    2.083808
1           401.875000   5808.579545  367.943182   315.000000   71.988636
2           974.160819     45.190058    7.593567   967.105263    4.043860
3          1235.962025   2814.240506  717.265823   991.000000  221.468354
4           750.000000    512.000000  178.250000   581.250000  108.000000
5           256.395672    942.582689  216.573416   185.077280   66.159196
6          1250.428571   1038.285714  368.142857   891.428571  228.714286
7          1551.434783   1606.782609  830.652174  1105.347826  299.478261
8           225.400000     28.800000    2.600000   200.400000    0.200000
9          2277.570048     65.531401   13.434783  2271.458937    3.497585
10          277.000000    284.821429   30.607143   246.714286   12.892857

           num_wows  num_hahas   num_sads  num_angrys
cluster
0          0.391993   0.122064   0.061388    0.013345
1          3.318182   8.056818   2.920455    0.590909
2          2.783626   0.154971   0.052632    0.020468
3         11.240506   8.240506   1.797468    2.215190
4         10.750000   4.250000  45.000000    0.750000
5          1.408037   2.752705   0.499227    0.489954
6         28.571429  97.142857   3.000000    1.571429
7        131.826087  11.478261   1.521739    1.782609
```

```
8           4.400000   1.200000   1.000000   18.200000
9           2.381643   0.212560   0.019324    0.000000
10          1.928571   0.678571  13.857143    0.928571
```

[ ]:
```
''' But what is the data telling me?

Content Engagement:
for k=4 & 5 there is a common recurrence,

We typically see high numbers across all engagement metrics,
especially loves and wows, indicating that this content is highly resonant,␣
 ↪possibly emotionally charged or highly entertaining.

The "High Engagement" clusters (e.g., Cluster 1) show high reactions and likes␣
 ↪but significantly lower comments and shares,
suggesting these might be content that is widely liked but less controversial␣
 ↪or requiring less interaction.
```

[ ]:
```
'''
Content Type Hypothesis:

Videos and statuses might be driving higher engagement in terms of comments and␣
 ↪shares,
particularly if they involve topical or controversial subjects that encourage␣
 ↪discussion or sharing.

Whereas, photos might be driving higher reactions in terms of likes and loves,
especially if they are visually appealing or emotionally touching.
'''
```

[ ]:
```
'''
Strategic Insights:

Emotionally Engaging Content: Content that stimulates higher loves and wows may␣
 ↪be particularly
effective in creating emotional connections with the audience.
This could include inspirational, humorous, or awe-inspiring content.
Identifying what specific characteristics these high-love and high-wow posts␣
 ↪share
could guide the creation of future content that aims to strike similar␣
 ↪emotional chords.

Interactive Content: Posts that generate a lot of comments and shares typically␣
 ↪encourage interaction.
These might include question-based posts, contests, or topics that are␣
 ↪currently trending or controversial.
```

```
For a social media strategy, focusing on interactive content can boost␣
 ↪community
engagement and increase visibility due to the algorithmic preferences of many␣
 ↪platforms for content that generates conversation.

Visual Content: High engagements in clusters with lots of likes but fewer␣
 ↪comments might indicate the effectiveness
of visually appealing content or straightforward posts that are easily␣
 ↪consumable and likable, such as high-quality
images or graphics. These are likely to attract quick reactions like likes and␣
 ↪loves without necessarily prompting
further interaction.'''
```

[ ]:

```
'''
Optimisation for Different Goals: Depending on the social media goals␣
 ↪(awareness, engagement, conversion), the strategy might differ.
For instance:

If the goal is to maximise reach and visibility, focus might be placed on␣
 ↪content types that are highly shared and commented on.
If the goal is to build a loyal community or emotional brand connection, the␣
 ↪focus could be on content that garners loves and wows.'''
```