#Importing Libraries and Reading the Dataset

```
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd

#Reading the dataset
df = 
pd.read_csv('drive/MyDrive/FinlaticsML/Facebook_Marketplace_data.csv')
```

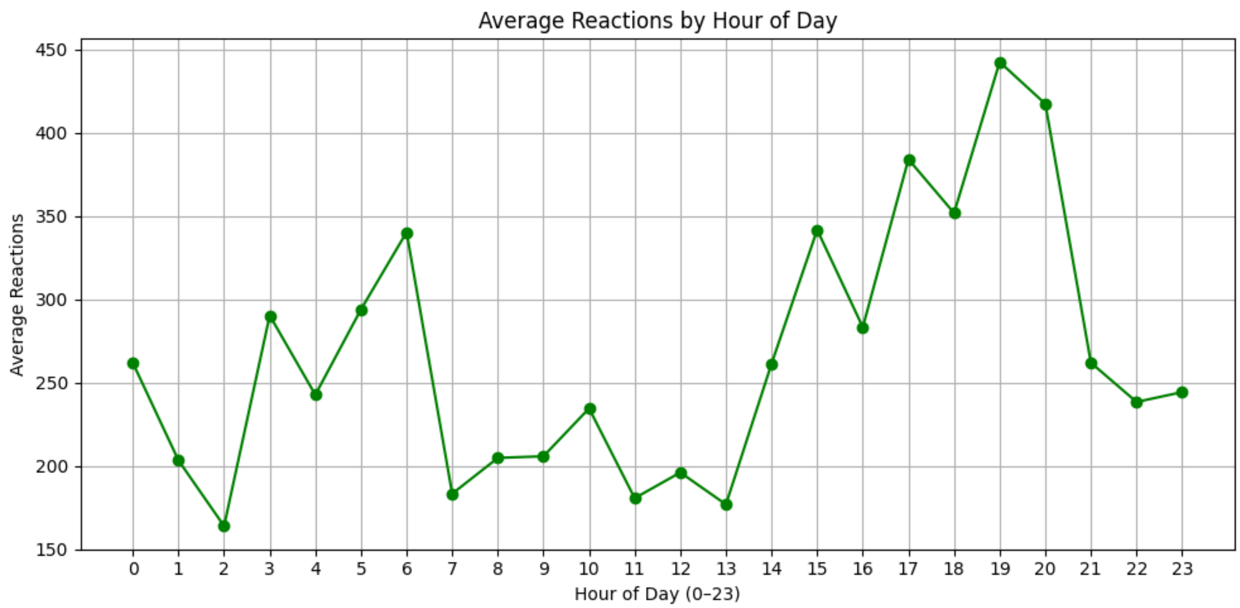
#Data Preprocessing

```
#Removing the last 4 unwanted columns in the dataset
df = df.iloc[:,:-4]

#Handling missing values

df.isnull().sum()
#As there are no NULL values, we can proceed

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
dtype: int64

#Break status_published into date and time separately
df['status_published'] = pd.to_datetime(df['status_published'])
df['publish_date'] = df['status_published'].dt.date
df['publish_time'] = df['status_published'].dt.time
```

#1. How does the time of upload (`status_published`) affects the `num_reaction`?

```
#Creating a Line plot of average reactions varying by hour of the day
df['publish_hour'] = df['status_published'].dt.hour
hourly_avg = df.groupby('publish_hour')
['num_reactions'].mean().reset_index()

fig, ax = plt.subplots(figsize=(10, 5))
```

```
ax.plot(hourly_avg['publish_hour'], hourly_avg['num_reactions'],
marker='o', color='green')
ax.set_title('Average Reactions by Hour of Day')
ax.set_xlabel('Hour of Day (0–23)')
ax.set_ylabel('Average Reactions')
ax.set_xticks(range(0, 24))
ax.grid(True)

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



Key Patterns Observed

Peak Engagement Windows

- **Morning Peak (3 AM):** ~290 reactions
  Likely catching international audiences or early risers
- **Evening Prime Time (19:00 / 7 PM):** Highest peak at ~440 reactions
  When most users are active after work
- **Secondary Evening Peak (15:00 / 3 PM):** ~340 reactions
  Afternoon browsing period

Low Engagement Periods

- **Early Morning Trough (2 AM):** Lowest point at ~165 reactions
- **Mid-day Lull (07:00–13:00):**
  Consistently lower engagement during work/school hours

- **Late Night Decline (21:00–23:00):**
  Gradual decrease as users wind down

Strategic Recommendations

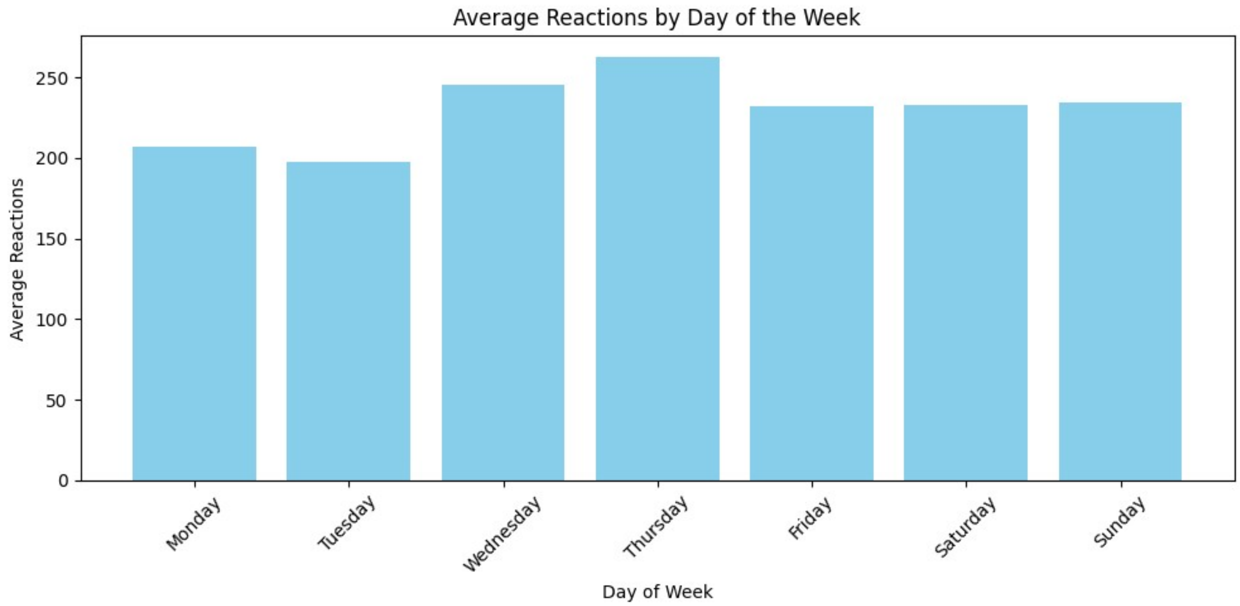
Optimal Posting Schedule

- **Primary window:** 18:00–20:00 (6–8 PM) for maximum reach
- **Secondary window:** 14:00–16:00 (2–4 PM) for afternoon engagement
- **Avoid:** 01:00–02:00 AM and 07:00–13:00 for regular content

Content Strategy

- Schedule high-priority posts (new products, promotions) during the 19:00 peak
- Use the afternoon window for customer service responses and follow-ups
- Consider the early morning peak (3 AM) for targeting international customers or time-sensitive deals

```
df['day_of_week'] = df['status_published'].dt.day_name()
weekday_order = ['Monday', 'Tuesday', 'Wednesday', 'Thursday',
'Friday', 'Saturday', 'Sunday']

weekday_avg = df.groupby('day_of_week')
['num_reactions'].mean().reindex(weekday_order).reset_index()

fig, ax = plt.subplots(figsize=(10, 5))

ax.bar(weekday_avg['day_of_week'], weekday_avg['num_reactions'],
color='skyblue')
ax.set_title('Average Reactions by Day of the Week')
ax.set_xlabel('Day of Week')
ax.set_ylabel('Average Reactions')
ax.tick_params(axis='x', rotation=45)

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



Key Patterns

Peak Engagement Days

- **Thursday** leads with ~260 reactions – highest engagement day
- **Wednesday** follows closely at ~245 reactions
- Both mid-week days show significantly higher activity than weekends

Lower Engagement Period

- **Monday–Tuesday** show the lowest engagement (~205–200 reactions)
- Classic "Monday blues" effect with users less active at week start

Weekend Performance

- **Friday–Sunday** maintain consistent moderate engagement (~230–235 reactions)
- Weekend activity remains steady but below mid-week peaks

Strategic Recommendations

Content Scheduling

- **Primary posting days:** Wednesday–Thursday for maximum organic reach
- **Product launches:** Schedule for Thursday to capitalize on peak engagement
- **Weekly promotions:** Launch Wednesday, maintain momentum through Thursday

Campaign Timing

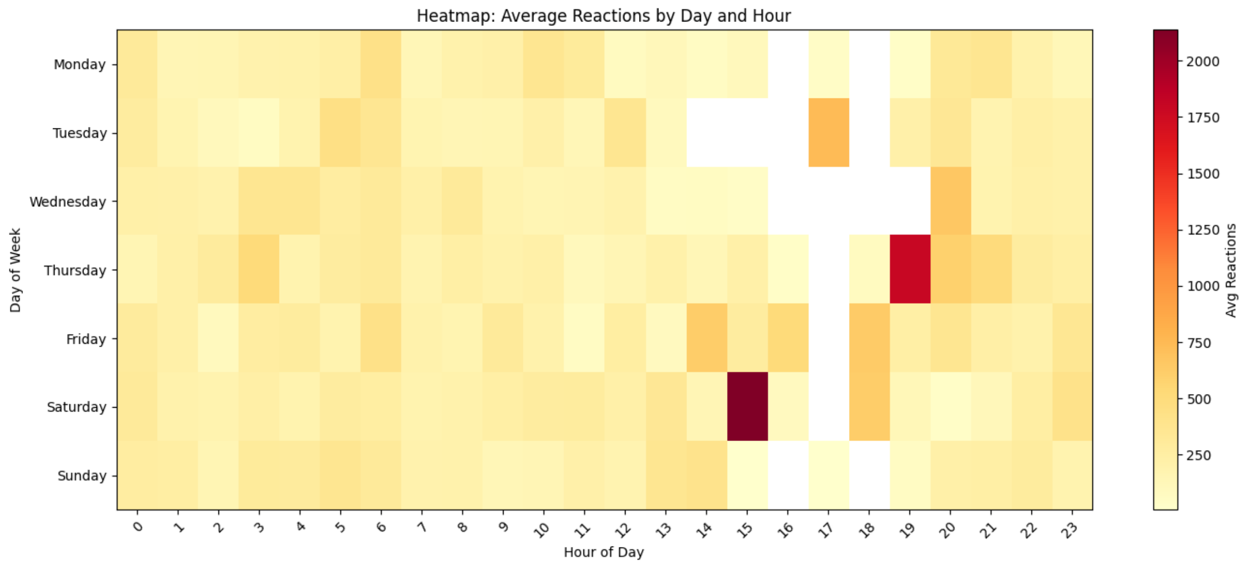
- Avoid major announcements on Monday–Tuesday when engagement is lowest
- Use weekends for community building and customer service activities
- Mid-week (Wed–Thu) is optimal for conversion-focused content

Weekly Content Strategy

- **Monday–Tuesday:** Behind-the-scenes content, preparation posts
- **Wednesday–Thursday:** High-priority posts, new arrivals, special offers
- **Friday–Sunday:** User-generated content, reviews, lifestyle posts

```
df['day_of_week'] =
pd.Categorical(df['status_published'].dt.day_name(),
                                    categories=['Monday', 'Tuesday',
'Wednesday', 'Thursday', 'Friday', 'Saturday', 'Sunday'],
                                    ordered=True)

# Pivot table: rows=day, cols=hour
heatmap_data = df.pivot_table(values='num_reactions',
                              index='day_of_week',
                              columns='publish_hour',
                              aggfunc='mean',
                              observed='False')

fig, ax = plt.subplots(figsize=(14, 6))

cax = ax.imshow(heatmap_data, aspect='auto', cmap='YlOrRd')

# Set ticks
ax.set_xticks(np.arange(len(heatmap_data.columns)))
ax.set_xticklabels(heatmap_data.columns)
ax.set_yticks(np.arange(len(heatmap_data.index)))
ax.set_yticklabels(heatmap_data.index)

# Rotate x labels
plt.setp(ax.get_xticklabels(), rotation=45, ha="right",
rotation_mode="anchor")

# Colorbar
cbar = fig.colorbar(cax, ax=ax)
cbar.set_label('Avg Reactions')

ax.set_title('Heatmap: Average Reactions by Day and Hour')
ax.set_xlabel('Hour of Day')
ax.set_ylabel('Day of Week')
```

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



Absolute Peak

- **Saturday at 15:00 (3 PM):**
  The darkest red spot on the heatmap indicates **over 2000 average reactions**, marking this as the **single highest engagement time** in the dataset.

Major High-Engagement Times

- **Wednesday at 19:00 (7 PM):**
  Very high engagement, with reactions exceeding 1750+. A strong candidate for major content drops.

- **Thursday at 18:00 (6 PM):**
  Notable deep red zone with **~1500–1750** reactions. Late afternoon is highly effective on Thursdays.

- **Tuesday at 16:00 (4 PM):**
  Bright orange zone indicating **~900–1000** reactions – a reliable afternoon window.

Day-Specific Patterns

- **Wednesday:**
  High activity in the evening, peaking at 7 PM. Strong candidate for conversion-driven content.

- **Thursday:**
  A consistent engagement stretch from afternoon (around 15:00) to early evening (18:00–19:00).

- **Saturday:**
  Peak mid-afternoon engagement at 15:00. Suggests strong user activity during leisure hours.

- **Tuesday:**
  A focused peak in the afternoon (16:00), but relatively low engagement outside that hour.

- **Monday, Sunday, Friday:**
  Display generally lower and more uniform engagement across hours. No significant peaks.

Strategic Takeaways

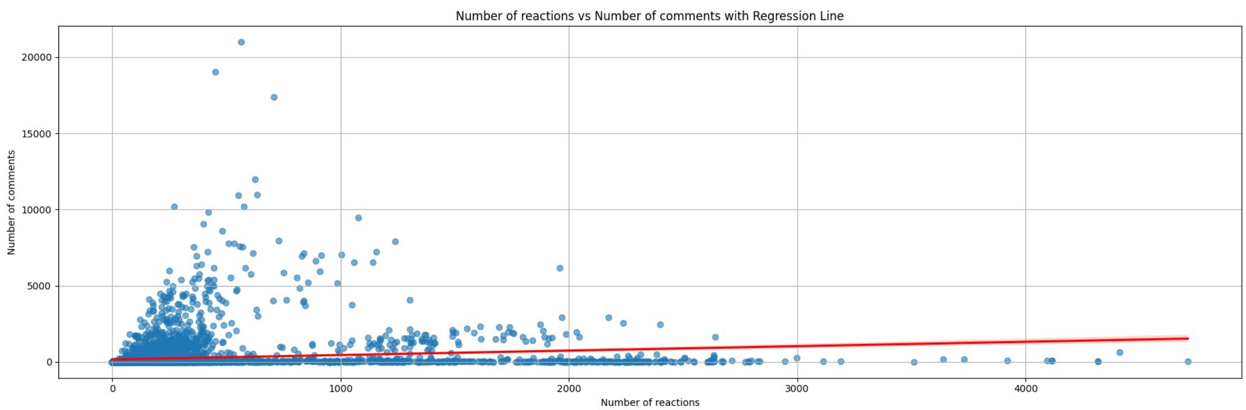
- **Best time to post:**
  - **Saturday 15:00 (3 PM)**
  - **Wednesday 19:00 (7 PM)**
  - **Thursday 18:00 (6 PM)**
- **Secondary windows:**
  - **Tuesday 16:00 (4 PM)**
  - **Thursday 17:00–19:00**
- **Avoid posting during:**
  - Early morning hours (especially 0:00–10:00)
  - Most hours on Monday and Sunday, which show very light engagement

2. Is there a correlation between the number of reactions (num_reactions) and other engagement metrics such as comments (num_comments) and shares (num_shares)? If so, what is the strength and direction of this correlation?

```
print(df[['num_reactions', 'num_comments']].describe())
```

```
       num_reactions  num_comments
count    7050.000000   7050.000000
mean      230.117163    224.356028
std       462.625309    889.636820
min         0.000000      0.000000
25%        17.000000      0.000000
50%        59.500000      4.000000
```

```
75%        219.000000     23.000000
max       4710.000000  20990.000000

#Generating a scatter plot with regression line for better
visualization
plt.figure(figsize=(18,6))
sns.regplot(x='num_reactions', y='num_comments', data=df,
scatter_kws={'alpha':0.6}, line_kws={'color':'red'})
plt.title('Number of reactions vs Number of comments with Regression
Line')
plt.xlabel('Number of reactions')
plt.ylabel('Number of comments')
plt.grid(True)
plt.tight_layout()
plt.show()
```




```
#Calculating the pearson relation coefficient between number of
comments and the number of reactions
corr_rec_comm = df['num_reactions'].corr(df['num_comments'])
print(f"Correlation between num_reactions and num_comments:
{corr_rec_comm:.2f}")

Correlation between num_reactions and num_comments: 0.15
```

Correlation Analysis: Reactions vs Comments

Correlation Findings

Yes, there is a correlation between reactions and comments, but it is **very weak**.

Strength and Direction:

- **Pearson correlation coefficient:** 0.15
- **Direction:** Positive (as reactions increase, comments tend to increase slightly)
- **Strength:** Very weak correlation

Interpretation

What the data shows:

- The scatter plot reveals a very loose positive relationship with significant scatter.
- Most data points cluster in the lower left (low reactions, low comments).
- A few outliers show high engagement in both metrics.
- The regression line (red) shows a very gentle upward slope, confirming the weak positive trend.

Practical meaning:

- Only **2.25% of the variance** in comments is explained by reactions ($0.15^2 = 0.0225$).
- **97.75%** of comment variation is due to other factors.
- Posts can have many reactions but few comments, or vice versa.

Business Implications

Key insights:

- **Different engagement types:** Reactions and comments represent different user behaviors.
- **Independent metrics:** They should be tracked and optimized separately.
- **Content strategy:** Focus on specific goals — reactions for awareness, comments for engagement depth.

Recommendations:

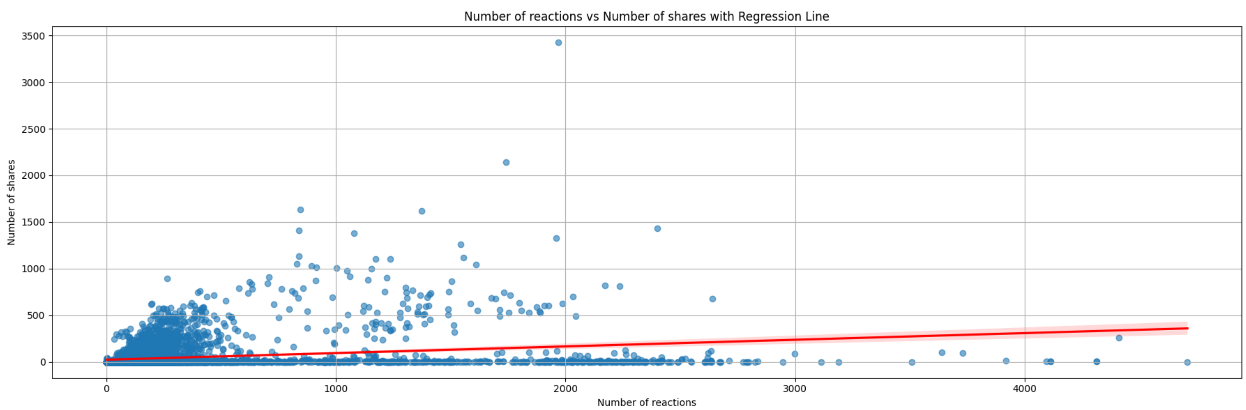
- Don't assume high reactions will automatically generate comments.
- Create **comment-specific strategies** (e.g., questions, polls, discussions).
- Track both metrics independently for a **comprehensive engagement analysis**.
- Consider that some content types naturally drive reactions while others encourage comments.

```
print(df[['num_reactions', 'num_shares']].describe())
```

```
       num_reactions   num_shares
count    7050.000000  7050.000000
mean      230.117163    40.022553
std       462.625309   131.599965
min         0.000000     0.000000
25%        17.000000     0.000000
50%        59.500000     0.000000
75%       219.000000     4.000000
max      4710.000000  3424.000000
```

```
#Generating a scatter plot with regression line for better 
visualization
plt.figure(figsize=(18,6))
sns.regplot(x='num_reactions', y='num_shares', data=df,
```

```
scatter_kws={'alpha':0.6}, line_kws={'color':'red'})
plt.title('Number of reactions vs Number of shares with Regression
Line')
plt.xlabel('Number of reactions')
plt.ylabel('Number of shares')
plt.grid(True)
plt.tight_layout()
plt.show()
```




```
#Calculating the pearson relation coefficient between number of shares
and the number of reactions
corr_rec_shr = df['num_reactions'].corr(df['num_shares'])
print(f"Correlation between num_reactions and num_shares:
{corr_rec_shr:.2f}")

Correlation between num_reactions and num_shares: 0.25
```

Correlation Analysis: Reactions vs Shares

Correlation Findings

Yes, there is a correlation between reactions and shares, but it is **weak**.

Strength and Direction:

- **Pearson correlation coefficient:** 0.25
- **Direction:** Positive (as reactions increase, shares tend to increase)
- **Strength:** Weak correlation

Interpretation

What the data shows:

- The scatter plot shows a positive relationship with considerable scatter
- Most data points cluster heavily in the lower left (low reactions, low shares)
- Several outliers demonstrate high share counts (up to 3,400+ shares)
- The regression line (red) shows a gentle upward slope, confirming the weak positive trend

Statistical meaning:

- Only **6.25%** of the variance in shares is explained by reactions ($0.25^2 = 0.0625$)
- **93.75%** of share variation is due to other factors
- This is a **stronger** relationship than reactions–comments (0.15) but still **weak overall**

Business Implications

Key insights:

- **Shares are more selective:** Users share content more deliberately than giving reactions
- **Content quality matters:** High-share content likely has inherent value or appeal
- **Viral potential:** Some posts can achieve high shares regardless of reaction count

Recommendations

- **Don't rely solely on reactions:** High reactions don't guarantee sharing behavior
- **Track sharing patterns:** Identify what content types drive shares specifically
- **Leverage viral content:** Analyze high-share posts to understand what makes content shareable

Content Strategy

- **Monitor share-to-reaction ratios** to identify truly engaging content
- **Consider that shares** have higher business value due to expanded reach

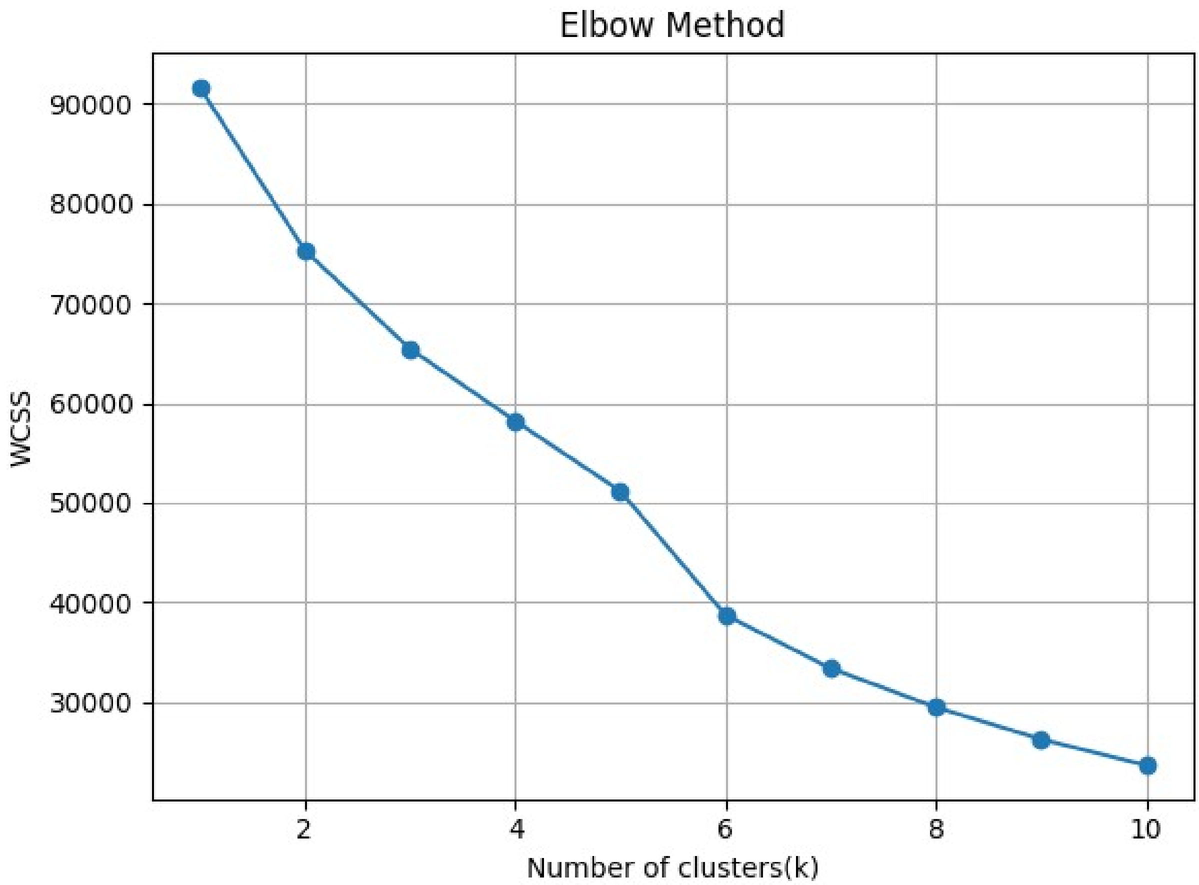
#3. Use the columns status_type, num_reactions, num_comments, num_shares, num_likes, num_loves, num_wows, num_hahas, num_sads, and num_angrys to train a K-Means clustering model on the Facebook Live Sellers dataset.

```
#Copying the required columns into another dataframe
df_kmeans = df[['status_type', 'num_reactions', 'num_comments',
'num_shares', 'num_likes', 'num_loves', 'num_wows', 'num_hahas',
'num_sads', 'num_angrys']].copy()
```

```python
#Using OneHotEncoding on Status Type column
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import OneHotEncoder
ct = ColumnTransformer(transformers=[('encoder', OneHotEncoder(),
['status_type'])], remainder='passthrough')
X = np.array(ct.fit_transform(df_kmeans))
print(X);
```

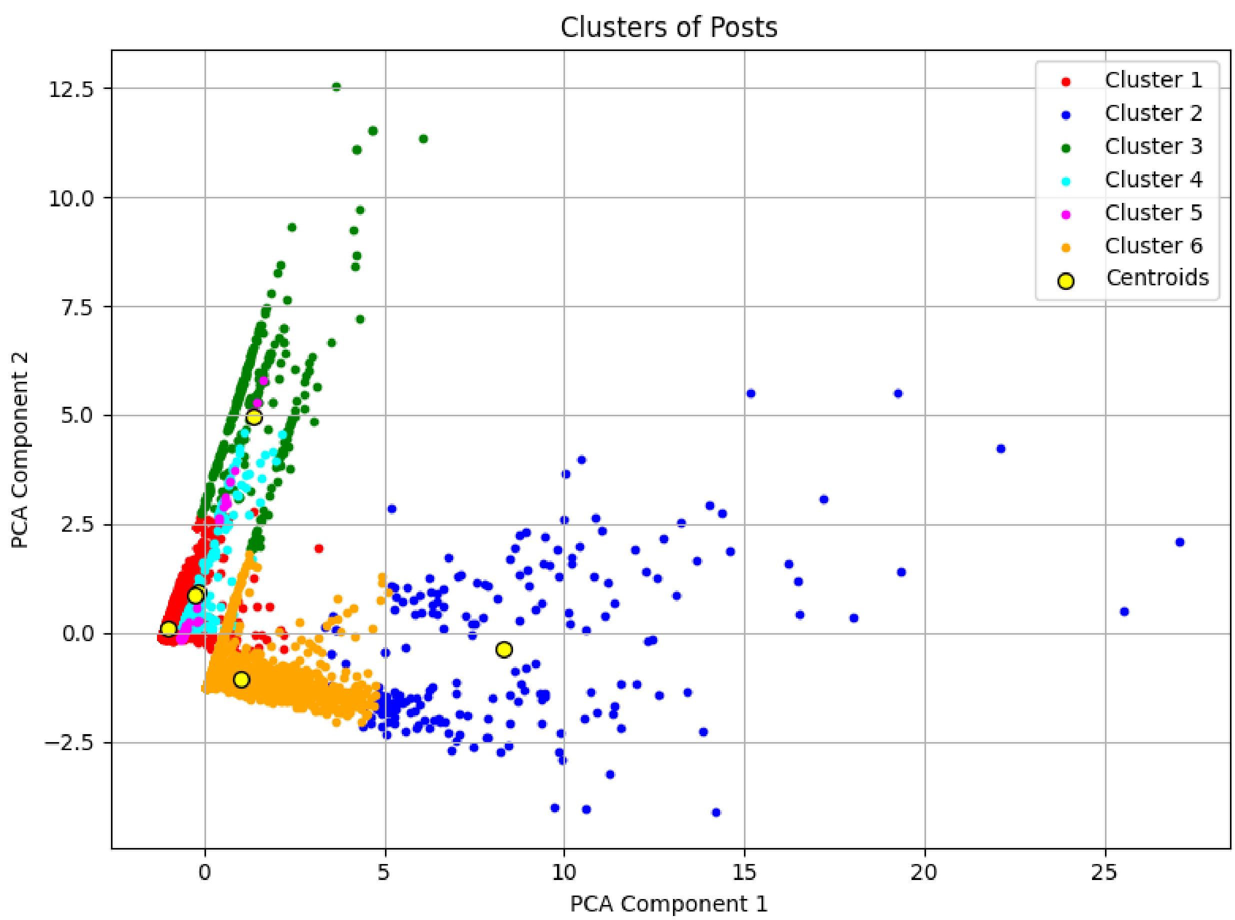
```
[[0. 0. 0. ... 1. 1. 0.]
 [0. 1. 0. ... 0. 0. 0.]
 [0. 0. 0. ... 1. 0. 0.]
 ...
 [0. 1. 0. ... 0. 0. 0.]
 [0. 1. 0. ... 0. 0. 0.]
 [0. 1. 0. ... 0. 0. 0.]]
```

```python
#Scaling the data to remove any bias
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_scaled = sc.fit_transform(X)

#Applying the elbow method
from sklearn.cluster import KMeans
wcss = []

for i in range(1,11):
  kmeans = KMeans(n_clusters=i, init='k-means++', random_state=42)
  kmeans.fit(X_scaled)
  wcss.append(kmeans.inertia_)

plt.plot(range(1,11), wcss, marker='o')
plt.title('Elbow Method')
plt.xlabel('Number of clusters(k)')
plt.ylabel('WCSS')
plt.grid(True)
plt.tight_layout()
plt.show()
```




```
#Training the KMeans model on the dataset taking the number of
clusters to be 6
kmeans = KMeans(n_clusters=6,init='k-means++',random_state=42)
y_kmeans = kmeans.fit_predict(X_scaled)

#Reducing the data and centroids to 2D for visualisation
from sklearn.decomposition import PCA
pca = PCA(n_components=2)
X_pca = pca.fit_transform(X_scaled)
reduced_centroids = pca.transform(kmeans.cluster_centers_)

# Colors for clusters
colors = ['red', 'blue', 'green', 'cyan', 'magenta', 'orange']

plt.figure(figsize=(8, 6))

for i in range(6):
    plt.scatter(
        X_pca[y_kmeans == i, 0],
        X_pca[y_kmeans == i, 1],
        s=10,
        c=colors[i],
        label=f'Cluster {i+1}'
```

```
    )

plt.scatter(
    reduced_centroids[:, 0], reduced_centroids[:, 1],
    s=50, c='yellow', edgecolors='black', label='Centroids'
)

plt.title('Clusters of Posts')
plt.xlabel('PCA Component 1')
plt.ylabel('PCA Component 2')
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()
```




```
df_kmeans['cluster'] = y_kmeans
numeric_cols = df_kmeans.select_dtypes(include='number').columns
cluster_summary = df_kmeans.groupby('cluster')[numeric_cols].mean()
print(cluster_summary)

type_distribution = df_kmeans.groupby('cluster')
```

```
['status_type'].value_counts(normalize=True)
print(type_distribution)
```

```
         num_reactions  num_comments  num_shares    num_likes
num_loves  \
cluster

0            91.784767     11.242752    1.767568    89.670762
1.287224
1           922.153465   3540.534653  564.559406   713.440594
169.465347
2          1980.359322     59.888136   11.979661  1974.508475
3.257627
3           307.581121     31.533923    2.365782   304.427729
1.587021
4           370.142857      5.698413    4.396825   369.619048
0.301587
5           168.520903    380.609322   75.113407   143.206151
23.425276

          num_wows  num_hahas  num_sads  num_angrys  cluster
cluster
0         0.552088   0.145455  0.101966    0.024079      0.0
1        22.306931  11.678218  3.321782    1.940594      1.0
2         2.345763   0.220339  0.023729    0.003390      2.0
3         1.005900   0.117994  0.415929    0.026549      3.0
4         0.190476   0.031746  0.000000    0.000000      4.0
5         0.620855   0.889957  0.232580    0.143200      5.0
cluster  status_type
0        photo          1.000000
1        video          0.935644
         photo          0.064356
2        photo          0.694915
         video          0.216949
         status         0.088136
3        status         1.000000
4        link           1.000000
5        video          1.000000
Name: proportion, dtype: float64
```

Cluster Analysis Summary

Cluster 1: Low Engagement Photo Posts

Post Type: 100% Photo
Average Reactions: 91.8
Average Comments/Shares: 11 comments, 1.8 shares
Reaction Breakdown: Predominantly likes (89.7) with very few emotional responses

Interpretation:
This cluster includes frequent but underperforming photo posts that fail to spark meaningful engagement or emotional response.

Label: Passive Photos – Low Engagement

Cluster 2: Viral Videos with Explosive Engagement

Post Type: 93.6% Video, 6.4% Photo
Average Reactions: ~922
Average Comments: ~3540
Average Shares: ~564
Reaction Breakdown: High levels across all emotional reactions including wows, hahas, sads, and angrys

Interpretation:
These posts represent highly interactive and viral video content that attracts large numbers of comments and shares, driving extensive user engagement.

Label: Viral Videos – Maximum Comments and Shares

Cluster 3: Mega-Reaction Photo Posts

Post Type: 69% Photo, 21% Video, 8.8% Status
Average Reactions: 1980
Average Comments/Shares: 60 comments, 12 shares
Reaction Breakdown: Dominated by likes (1975) with minimal emotional engagement

Interpretation:
This group features visually appealing or promotional content that garners a high volume of likes but fails to drive further interaction.

Label: High-Reach Posts – Likes Without Interaction

Cluster 4: Status Updates with Moderate Engagement

Post Type: 100% Status
Average Reactions: ~307
Average Comments/Shares: 31 comments, 2.3 shares
Reaction Breakdown: Mostly likes with a small number of wows and sads

Interpretation:
These are basic text-based updates that yield moderate engagement and limited emotional response, suitable for informational or routine communication.

Label: Basic Text Posts – Moderate Engagement

Cluster 5: Link-Based Low Engagement Posts

Post Type: 100% Link
Average Reactions: ~370
Average Comments: 5.7

Average Shares: 4.4
Reaction Breakdown: Low across all metrics

Interpretation:
These posts, although low in direct interaction, may offer value through external content and receive a modest level of shares.

Label: Link-Oriented Content – Low Engagement, Moderate Shareability

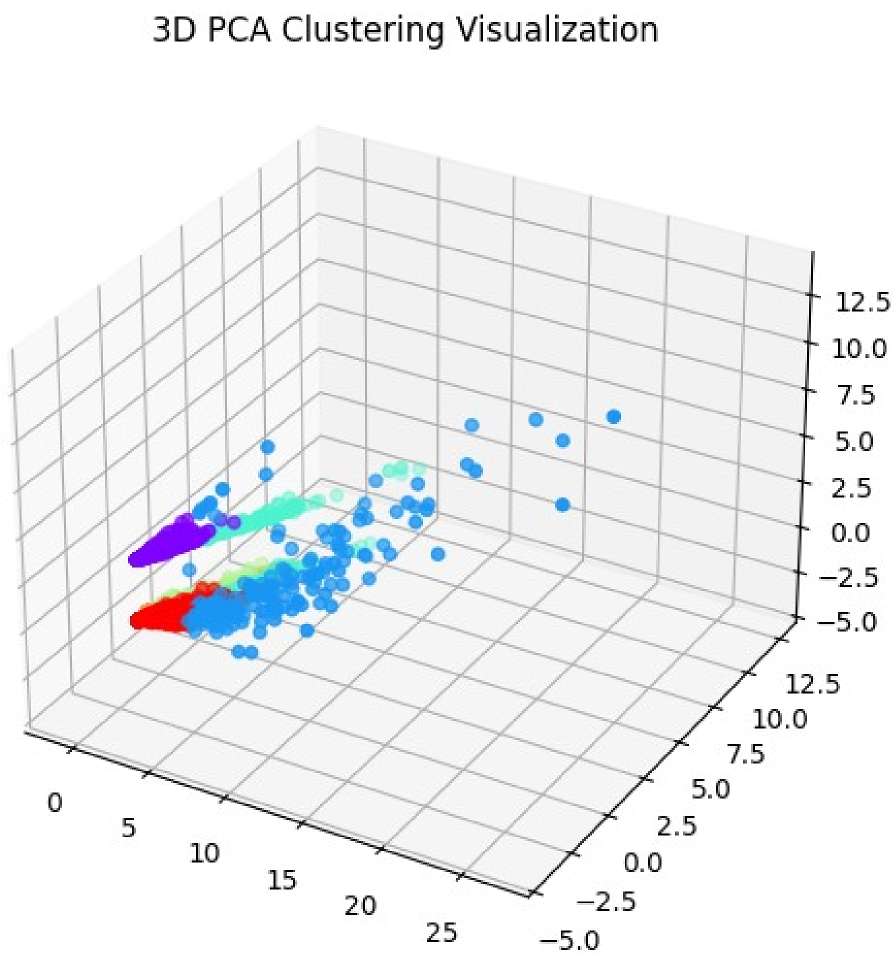
Cluster 6: Discussion-Driven Video Posts

Post Type: 100% Video
Average Reactions: ~168
Average Comments: ~381
Average Shares: ~75
Reaction Breakdown: Balanced distribution of likes, loves, and hahas

Interpretation:
This cluster is composed of video content that triggers conversations and community engagement, making it ideal for feedback and discussion.

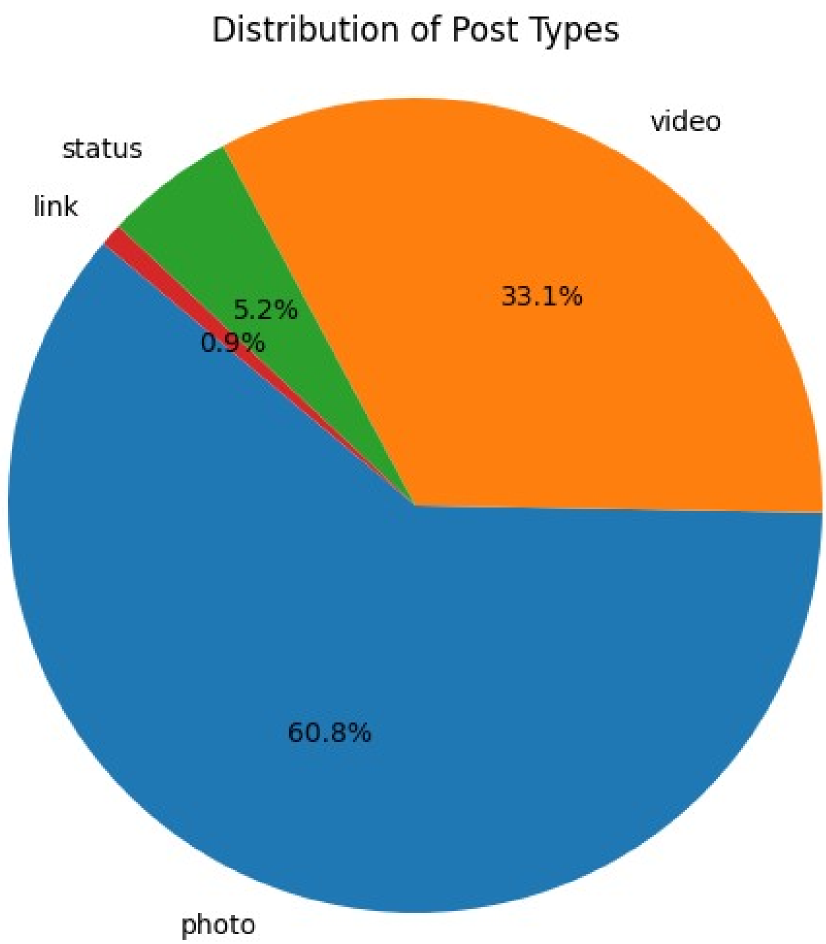
Label: Conversation-Starters – High Comments, Modest Reactions

```
#Using 3 principal components in PCA
pca = PCA(n_components=3)
X_pca = pca.fit_transform(X_scaled)
reduced_centroids = pca.transform(kmeans.cluster_centers_)

#Generating a 3D graph for PCA representation
from mpl_toolkits.mplot3d import Axes3D

fig = plt.figure(figsize=(8,6))
ax = fig.add_subplot(111, projection='3d')

# Assuming y_kmeans contains your cluster labels
ax.scatter(X_pca[:, 0], X_pca[:, 1], X_pca[:, 2], c=y_kmeans,
cmap='rainbow')
ax.set_title('3D PCA Clustering Visualization')
plt.show()
```



#5. What is the count of different types of posts in the dataset?

```
status_counts = df['status_type'].value_counts()
plt.figure(figsize=(8, 6))
plt.pie(status_counts, labels=status_counts.index, autopct='%1.1f%%',
startangle=140)
plt.title('Distribution of Post Types')
plt.axis('equal')
plt.show()
```



The dataset contains a total of **4** different types of posts:

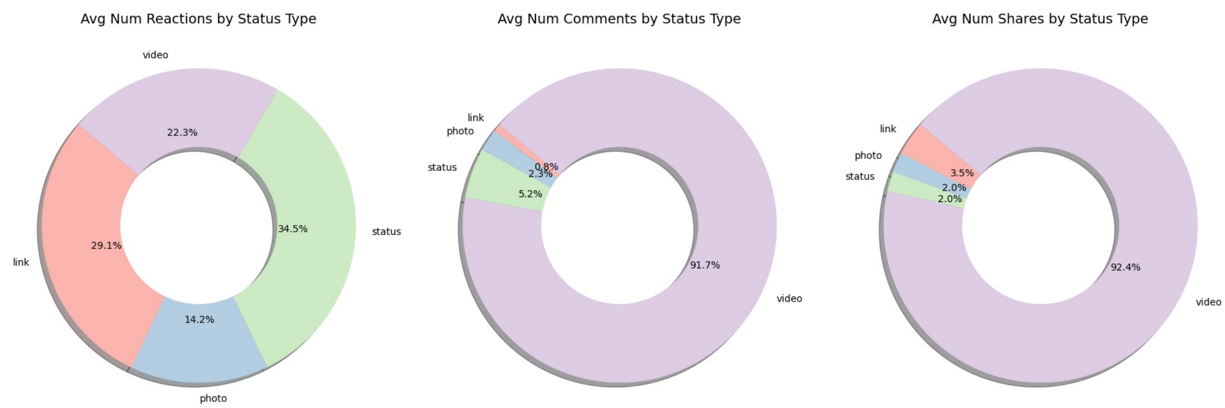
Status Type	Count
photo	4288
video	2334
status	365
link	63

- **Most common** post type: `photo` (4288 posts)
- **Least common** post type: `link` (63 posts)

#6. What is the average value of num_reaction, num_comments, num_shares for each post type?

```
grouped_avg = df.groupby('status_type')[['num_reactions',
'num_comments', 'num_shares']].mean()

fig, axes = plt.subplots(1, 3, figsize=(18, 6))

metrics = ['num_reactions', 'num_comments', 'num_shares']
```

```python
colors = plt.cm.Pastel1.colors  # Soft pastel colors

for i, metric in enumerate(metrics):
    axes[i].pie(
        grouped_avg[metric],
        labels=grouped_avg.index,
        autopct='%1.1f%%',
        startangle=140,
        colors=colors,
        wedgeprops=dict(width=0.5),  # donut style for depth
        shadow=True  # subtle 3D look
    )
    axes[i].set_title(f'Avg {metric.replace("_", " ").title()} by
Status Type', fontsize=14)

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



Post Type	Avg. Reactions	Avg. Comments	Avg. Shares
Link	370.14	5.70	4.40
Photo	181.29	15.99	2.55
Status	438.78	36.24	2.56
Video	283.41	642.48	115.68

Insights:

- **Videos dominate** in terms of **engagement**, especially:
  - **Comments:** Averaging **642**, far surpassing all other post types.
  - **Shares:** Highest with **115.68**, indicating strong shareability.
- **Status posts** receive the **highest average reactions** (**438.78**) among non-video content, but are shared relatively less.
- **Photos** are commonly posted but receive **fewer reactions and shares**, although they have decent comment engagement.

- **Links** have a moderate number of reactions and the **second-highest share count**, indicating they are still moderately engaging.

Conclusion:

- For **virality** (high shares): use **video** or **link** posts.
- For **discussions and interactions**: **video** and **status** posts perform best.
- **Photo posts**, while frequent, show lower engagement — suggesting the need for better content or targeting.