

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

```
dataset = pd.read_csv('Facebook_Marketplace_data.csv')
```

```
print(dataset.info())
```

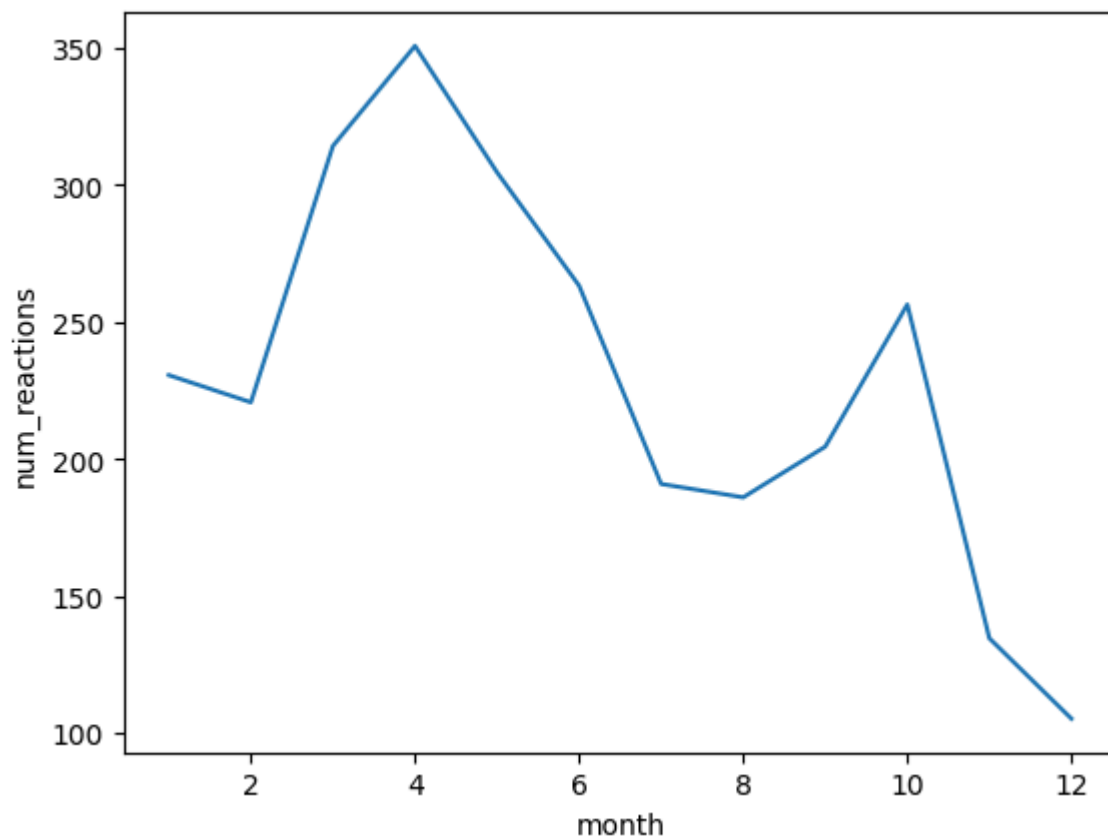
```
>>> <class 'pandas.core.frame.DataFrame'>
RangeIndex: 7050 entries, 0 to 7049
Data columns (total 16 columns):
#   Column              Non-Null Count  Dtype
---  -
0   status_id           7050 non-null   int64
1   status_type         7050 non-null   object
2   status_published    7050 non-null   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
None
```

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

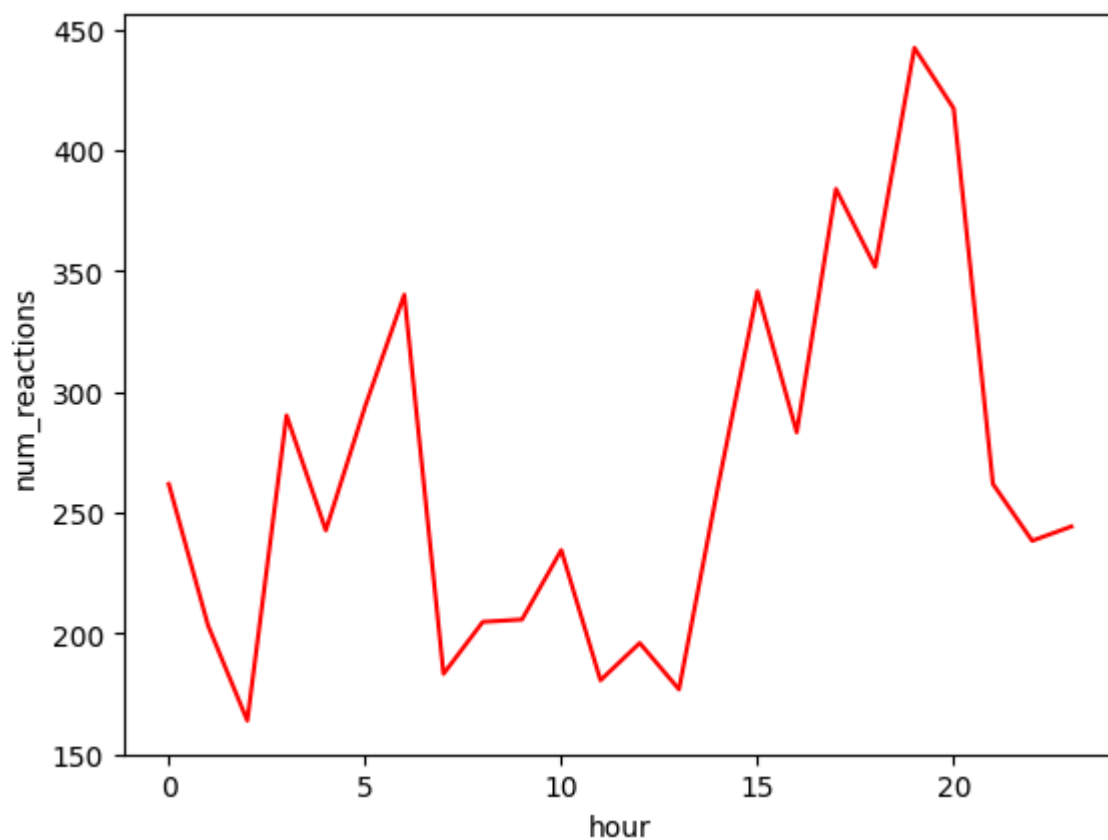
1.) How does the time of upload ( status\_published ) affects the num\_reaction ?

```
dataset['status_published'] = pd.to_datetime(dataset['status_published'])
dataset['month'] = dataset['status_published'].dt.month
dataset['hour'] = dataset['status_published'].dt.hour
```

```
df_month = dataset.groupby(['month'])['num_reactions'].mean()
plt.plot(df_month.index, df_month.values)
plt.xlabel('month')
plt.ylabel('num_reactions')
plt.show()
```



```
df_hour = dataset.groupby(['hour'])['num_reactions'].mean()
plt.plot(df_hour.index, df_hour.values, color='red')
plt.xlabel('hour')
plt.ylabel('num_reactions')
plt.show()
```



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?

```
def result(result_correlation):
    if result_correlation > 0.9:
        print("Very high positive correlation")
    elif result_correlation > 0.7:
        print("High positive correlation")
    elif result_correlation > 0.5:
        print("Moderate high positive correlation")
    elif result_correlation > 0.3:
        print("Low positive correlation")
    elif result_correlation > 0.0:
        print("negligible positive correlation")
    elif result_correlation == 0:
        print("No correlation")
    elif result_correlation > -0.3:
        print("Negligible negative correlation")
    elif result_correlation > -0.5:
        print("Low negative correlation")
    elif result_correlation > -0.7:
        print("Moderate negative correlation")
    elif result_correlation > -0.9:
        print("High negative correlation")
    else:
        print("Very high negative correlation.")

engagement_cols = ['num_reactions', 'num_comments', 'num_shares']
correlation_matrix = dataset[engagement_cols].corr()
print("Correlation Matrix:")
print(correlation_matrix)

plt.figure(figsize=(8, 6))
sns.heatmap(correlation_matrix,
            annot=True,
            cmap='coolwarm',
            center=0,
            square=True,
            fmt='.3f')
plt.show()

correlation1 = correlation_matrix.loc['num_reactions', 'num_comments']

print(f"\nCorrelation between reactions and comments: {correlation1}")
result(correlation1)

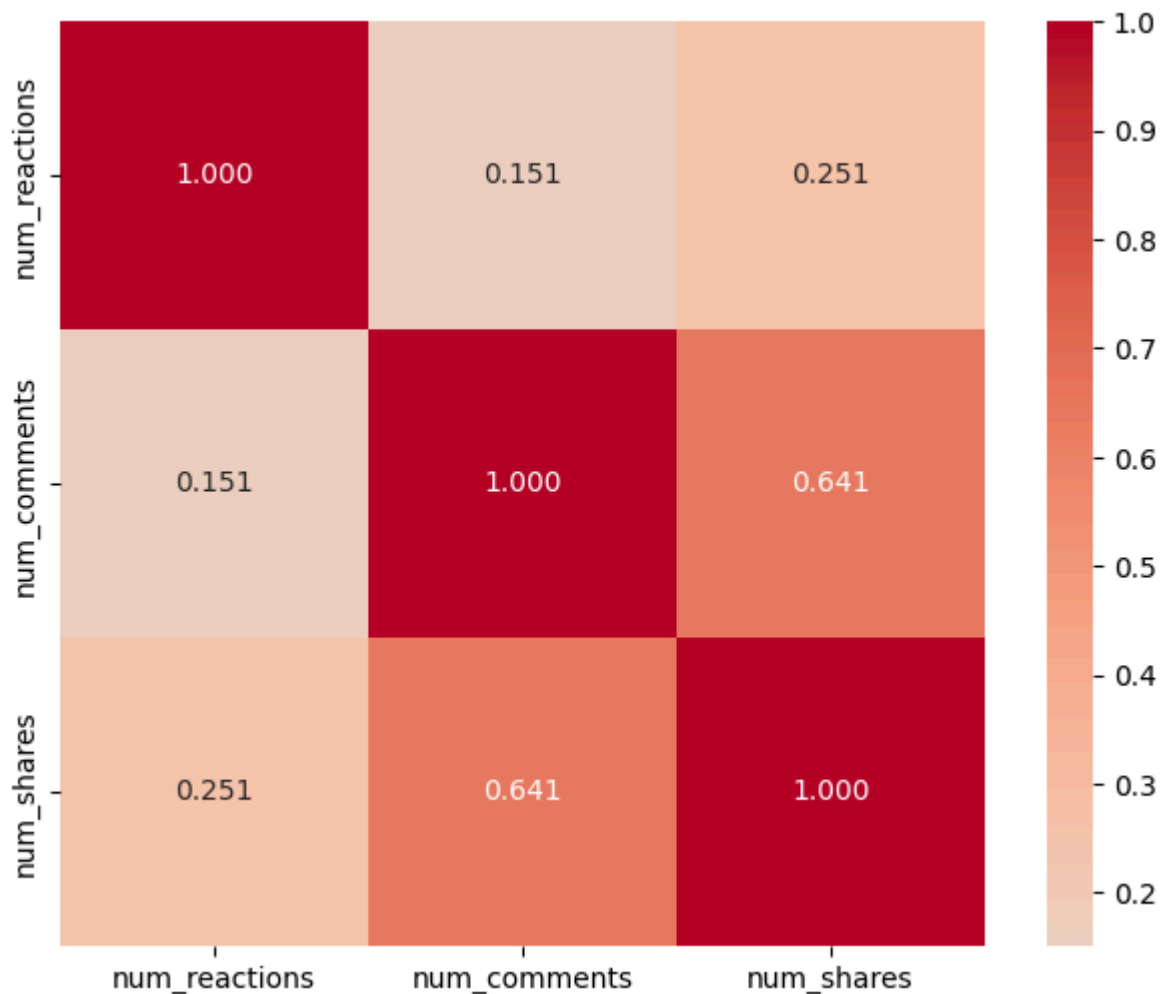
correlation2 = correlation_matrix.loc['num_reactions', 'num_shares']

print(f"\nCorrelation between reactions and shares: {correlation2}")
result(correlation2)
```



Correlation Matrix:

	num_reactions	num_comments	num_shares
num_reactions	1.000000	0.150843	0.250723
num_comments	0.150843	1.000000	0.640637
num_shares	0.250723	0.640637	1.000000



Correlation between reactions and comments: 0.15084290344217685  
negligible positive correlation

Correlation between reactions and shares: 0.25072251662831907  
negligible positive correlation

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.

```
from sklearn.cluster import KMeans
```

```
from sklearn.preprocessing import LabelEncoder
```

```
dataset['status_type'] = LabelEncoder().fit_transform(dataset['status_type'])
```

```
cols = ['status_type', 'num_reactions', 'num_comments', 'num_shares',
        'num_likes', 'num_loves', 'num_wows', 'num_hahas', 'num_sads', 'num_angry']
x = dataset[cols].values
```

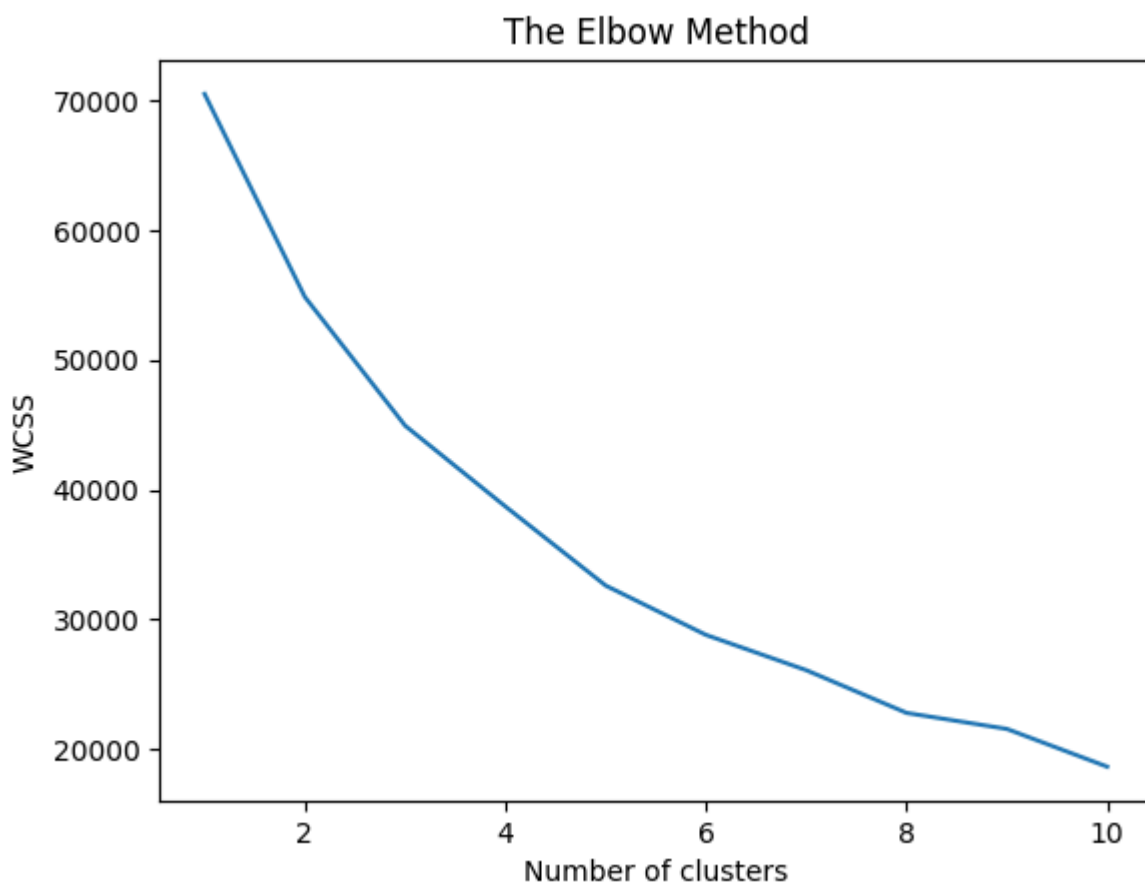
```
from sklearn.preprocessing import StandardScaler
```

```
scaler = StandardScaler()
x_scaled = scaler.fit_transform(x)
```

4.) Use the elbow method to find the optimum number of clusters.


```
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_)

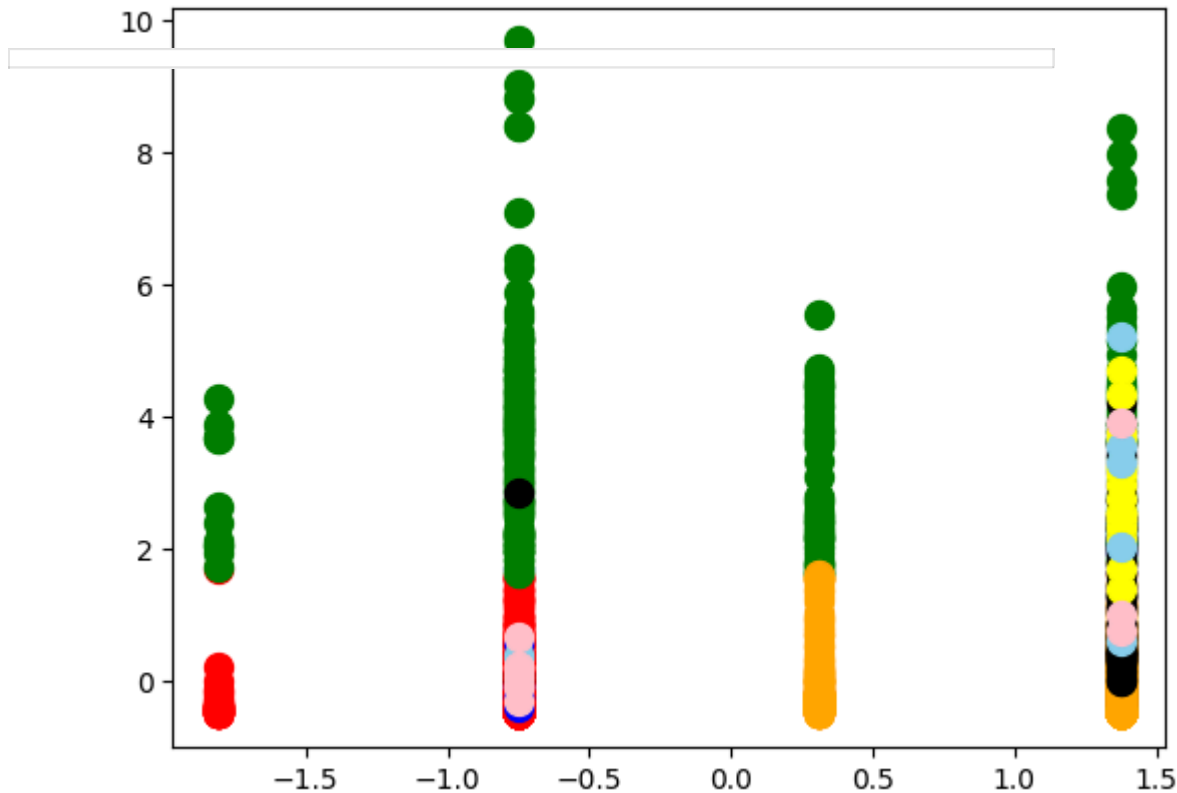
plt.plot(range(1, 11), wcss)
plt.title('The Elbow Method')
plt.xlabel('Number of clusters')
plt.ylabel('WCSS')
plt.show()
```



```
kmeans = KMeans(n_clusters=8, init='k-means++', random_state=42)
y_kmeans = kmeans.fit_predict(x_scaled)
```

```
plt.scatter(x_scaled[y_kmeans == 0,0], x_scaled[y_kmeans == 0,1], s= 100, c= 're
plt.scatter(x_scaled[y_kmeans == 1,0], x_scaled[y_kmeans == 1,1], s= 100, c= 'bl
plt.scatter(x_scaled[y_kmeans == 2,0], x_scaled[y_kmeans == 2,1], s= 100, c= 'gr
plt.scatter(x_scaled[y_kmeans == 3,0], x_scaled[y_kmeans == 3,1], s= 100, c= 'or
plt.scatter(x_scaled[y_kmeans == 4,0], x_scaled[y_kmeans == 4,1], s= 100, c= 'bl
plt.scatter(x_scaled[y_kmeans == 5,0], x_scaled[y_kmeans == 5,1], s= 100, c= 'ye
plt.scatter(x_scaled[y_kmeans == 6,0], x_scaled[y_kmeans == 6,1], s= 100, c= 'sk
plt.scatter(x_scaled[y_kmeans == 7,0], x_scaled[y_kmeans == 7,1], s= 100, c= 'pi
```

 <matplotlib.collections.PathCollection at 0x7b5dfbcb5250>



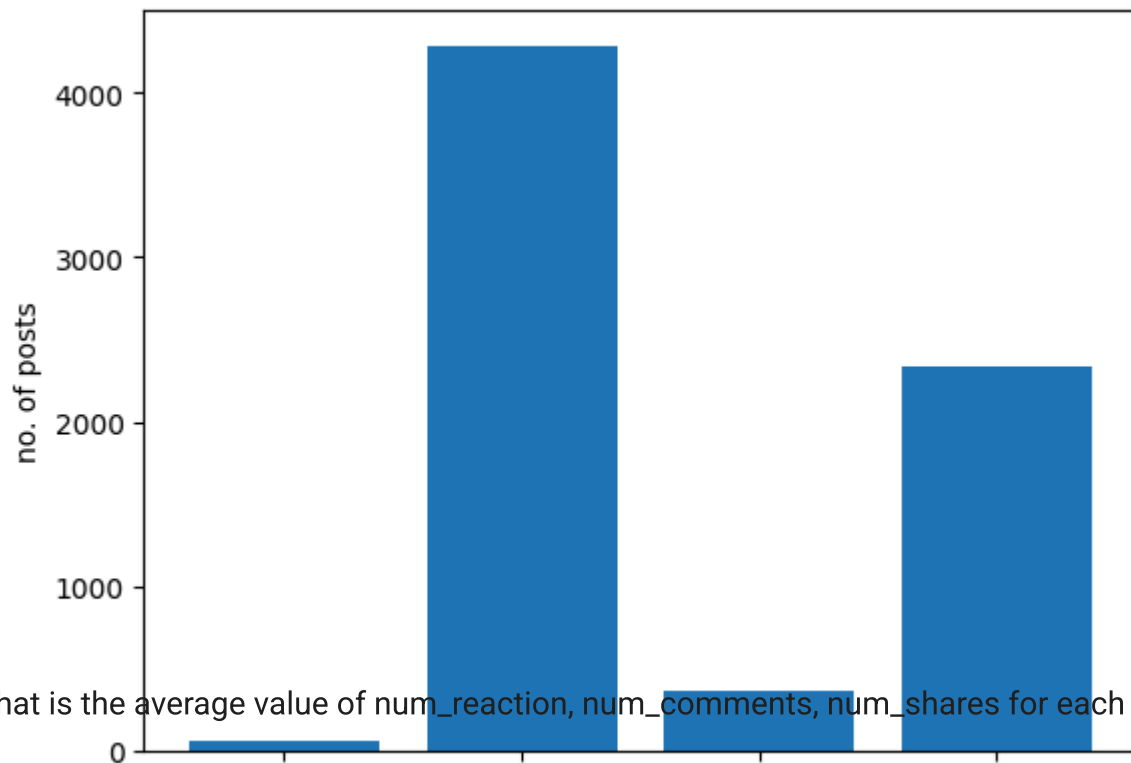
5.) What is the count of different types of posts in the dataset?

```
df_status_type = dataset.groupby(['status_type']).agg({
    'status_id' : 'count',
    'num_reactions' : 'mean',
    'num_comments' : 'mean',
    'num_shares' : 'mean'
})
print(df_status_type.index, df_status_type['status_id'])
plt.bar(df_status_type.index, df_status_type['status_id'])
plt.xlabel('post type')
plt.ylabel('no. of posts')
plt.show()
```

```

Index(['link', 'photo', 'status', 'video'], dtype='object', name='status_type')
link      63
photo    4288
status    365
video    2334
Name: status_id, dtype: int64

```



6.) What is the average value of num\_reaction, num\_comments, num\_shares for each post type?

```
print(df_status_type)
```

```

status_id  num_reactions  num_comments  num_shares
status_type
link      63      370.142857      5.698413      4.396825
photo    4288      181.290345     15.993470      2.553871
status    365      438.783562     36.238356      2.558904
video    2334      283.409597     642.478149     115.679949

```