AI_AND_DEV_PROJECT

June 18, 2025

1 LOADING THE DATASET

Here I will load my dataset and access some properties, like the shape, certain columns, duplicates, null values, redundant columns, e.t.c.

[18]:
```
import pandas as pd
```

[19]:
```
df = pd.read_csv("behaviour_simulation_train.csv")
```

[20]:
```
df.isnull().sum()
```

[20]:
```
id                   0
date                 0
likes                0
content              0
username             0
media                0
inferred company     0
dtype: int64
```

[21]:
```
df.duplicated().sum()
```

[21]:
```
np.int64(0)
```

[22]:
```
df.dtypes
```

[22]:
```
id                    int64
date                 object
likes                 int64
content              object
username             object
media                object
inferred company     object
dtype: object
```

[23]:
```
df.shape
```

[23]:
```
(17331, 7)
```

[24]:
```
df
```

[24]:
```
           id                 date  likes  \
0           1  2020-12-12 00:47:00      1
1           2  2018-06-30 10:04:20   2750
2           3  2020-09-29 19:47:28     57
3           4  2020-10-01 11:40:09    152
4           5  2018-10-19 14:30:46     41
…         …                   …    …
17326   17327  2020-12-12 03:15:00     56
17327   17328  2018-02-09 21:47:11      2
17328   17329  2018-05-03 14:26:09    181
17329   17330  2020-01-27 11:52:03      0
17330   17331  2020-03-10 02:58:14    112

                                                 content       username  \
0      Spend your weekend morning with a Ham, Egg, an…    TimHortonsPH
1      Watch rapper <mention> freestyle for over an H…       IndyMusic
2      Canadian Armenian community demands ban on mil…       CBCCanada
3      1st in Europe to be devastated by COVID-19, It…   MKWilliamsRome
4      Congratulations to Pauletha Butts of <mention>…           BGISD
…                                                    …             …
17326  After 66 years together, this couple died of #…       cbcnewsbc
17327  Where to add wireless measurements &amp;amp; a…   EMR_Automation
17328  This is what happened outside a Bromley pollin…     Independent
17329  Int'l Day Of Education: CSO Sensitises Childre…   IndependentNGR
17330  Happy Tuesday \nWelcome to #TheMorningFlava\nW…       METROFMSA

                                                   media inferred company
0      [Photo(previewUrl='https://pbs.twimg.com/media…      tim hortons
1      [Photo(previewUrl='https://pbs.twimg.com/media…      independent
2      [Photo(previewUrl='https://pbs.twimg.com/media…              cbc
3      [Photo(previewUrl='https://pbs.twimg.com/media…         williams
4      [Photo(previewUrl='https://pbs.twimg.com/media…      independent
…                                                    …              …
17326  [Video(thumbnailUrl='https://pbs.twimg.com/amp…              cbc
17327  [Photo(previewUrl='https://pbs.twimg.com/media…          emerson
17328  [Video(thumbnailUrl='https://pbs.twimg.com/ext…      independent
17329  [Photo(previewUrl='https://pbs.twimg.com/media…      independent
17330  [Photo(previewUrl='https://pbs.twimg.com/media…             sabc

[17331 rows x 7 columns]
```

[25]:
```
for column in df.columns:
  print(column)
```

```
id
```

```
date
likes
content
username
media
inferred company
```

[26]:
```
for col in df.columns:
  print(f"Column '{col}': {df[col].nunique()} unique values")
```

```
Column 'id': 17331 unique values
Column 'date': 17292 unique values
Column 'likes': 2589 unique values
Column 'content': 17126 unique values
Column 'username': 1325 unique values
Column 'media': 17307 unique values
Column 'inferred company': 194 unique values
```

[27]:
```
df.describe()
```

[27]:

	id	likes
count	17331.000000	17331.000000
mean	8666.000000	718.392130
std	5003.173093	3866.475948
min	1.000000	0.000000
25%	4333.500000	3.000000
50%	8666.000000	73.000000
75%	12998.500000	352.000000
max	17331.000000	254931.000000

2 LIGHT PREPROCESSING (FOR EDA AND DEV READINESS)

I will clean my dataset, of redundant columns, change the format of the date column to DateTime format and extract some features, and I will add some more features to the data frame which will help us in exploratory data analysis.

[28]:
```
df['has_media'] = df['media'].apply(lambda x: x != 'no_media')
df['content'] = df['content'].astype(str).str.strip().str.lower()
df['datetime'] = pd.to_datetime(df['date'], errors='coerce')
```

[29]:
```
df.drop(columns=['date', 'media'], inplace=True)
```

[30]:
```
df = df.rename(columns={'id': 'Id', 'likes': 'Likes', 'content': 'Content',␣
↪'username': 'Username', 'inferred company': 'Inferred_Company', 'datetime':␣
↪'Release Time', 'has_media': 'Has_Media'})
```

[31]:
```python
from datetime import time
df['Release_Time_Year'] = df['Release Time'].dt.year
df['Release_Time_Month'] = df['Release Time'].dt.month
df['Release_Time_Day'] = df['Release Time'].dt.day
df['Release_Time_hour'] = df['Release Time'].dt.hour
df['Release_Time_minute'] = df['Release Time'].dt.minute
df['Release_Time_second'] = df['Release Time'].dt.second
df['Release_Time_Of_Day'] = df.apply(lambda row: time(row['Release_Time_hour'], row['Release_Time_minute'], row['Release_Time_second']), axis=1)
df.drop(columns = "Release Time", inplace = True)
```

[32]:
```python
df['Has_Mention'] = df['Content'].str.contains('<mention>')
import re
def emoji_count(text):
    emoji_pattern = re.compile(
        "["
        "\U0001F600-\U0001F64F"
        "\U0001F300-\U0001F5FF"
        "\U0001F680-\U0001F6FF"
        "\U0001F700-\U0001F77F"
        "\U0001F780-\U0001F7FF"
        "\U0001F800-\U0001F8FF"
        "\U0001F900-\U0001F9FF"
        "\U0001FA00-\U0001FA6F"
        "\U0001FA70-\U0001FAFF"
        "\U00002702-\U000027B0"
        "\U000024C2-\U0001F251"
        "]+"
    )
    return len(emoji_pattern.findall(text))
df['Emoji_Count'] = df['Content'].apply(emoji_count)
df['Has_Hashtag'] = df['Content'].str.contains(r'#\w+', na=False)
df['Has_Url'] = df['Content'].str.contains(r'http[s]?://(?:[a-zA-Z]|[0-9]|[$-_@.&+]|[!*\\(\\),]|(?:%[0-9a-fA-F][0-9a-fA-F]))+', na=False)
df['Is_Weekend'] = pd.to_datetime({'year': df['Release_Time_Year'],
                                   'month': df['Release_Time_Month'],
                                   'day': df['Release_Time_Day'],
                                   'hour': df['Release_Time_hour'],
                                   'minute': df['Release_Time_minute'],
                                   'second': df['Release_Time_second']}).dt.dayofweek >= 5
```

[33]:
```python
from sklearn.preprocessing import LabelEncoder
label_encoder = LabelEncoder()
df['Inferred_Company_Encoded'] = label_encoder.fit_transform(df['Inferred_Company'])
df['Has_Media'] = label_encoder.fit_transform(df['Has_Media'])
```

```
df['Has_Mention'] = label_encoder.fit_transform(df['Has_Mention'])
df['Has_Hashtag'] = label_encoder.fit_transform(df['Has_Hashtag'])
df['Has_Url'] = label_encoder.fit_transform(df['Has_Url'])
df['Is_Weekend'] = label_encoder.fit_transform(df['Is_Weekend'])
encoded_companies = df[['Inferred_Company', 'Inferred_Company_Encoded']].
  ↪drop_duplicates()
encoded_companies.to_csv('inferred_company_encoded_values.csv', index=False)
df.drop(columns = ['Release_Time_minute', 'Release_Time_hour',␣
  ↪'Release_Time_second', 'Inferred_Company'], inplace = True)
```

[34]:
```
from textblob import TextBlob
df['Content_Length'] = df['Content'].str.len()
df['Word_Count'] = df['Content'].str.split().str.len()
user_agg_data = df.groupby('Username')['Likes'].agg(['count', 'sum']).
  ↪reset_index()
user_agg_data.columns = ['Username', 'User_Post_Count', 'Total_Likes']
user_agg_data['Average_Likes_Post'] = user_agg_data['Total_Likes'] /␣
  ↪user_agg_data['User_Post_Count']
df = df.merge(user_agg_data[['Username', 'User_Post_Count',␣
  ↪'Average_Likes_Post']], on='Username', how='left')
df['Sentiment'] = df['Content'].apply(lambda x: TextBlob(x).sentiment.polarity)
new_column_order = ['Username', 'User_Post_Count', 'Average_Likes_Post',␣
  ↪'Content',
                    'Word_Count', 'Content_Length', 'Has_Media', 'Has_Mention',␣
  ↪'Release_Time_Year',
                    'Release_Time_Month', 'Release_Time_Day',␣
  ↪'Release_Time_Of_Day',
                    'Is_Weekend', 'Inferred_Company_Encoded', 'Sentiment',␣
  ↪'Likes']
df = df[new_column_order]
```

[35]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 17331 entries, 0 to 17330
Data columns (total 16 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   Username                  17331 non-null  object
 1   User_Post_Count           17331 non-null  int64
 2   Average_Likes_Post        17331 non-null  float64
 3   Content                   17331 non-null  object
 4   Word_Count                17331 non-null  int64
 5   Content_Length            17331 non-null  int64
 6   Has_Media                 17331 non-null  int64
 7   Has_Mention               17331 non-null  int64
 8   Release_Time_Year         17331 non-null  int32
```

```
 9   Release_Time_Month        17331 non-null  int32
 10  Release_Time_Day          17331 non-null  int32
 11  Release_Time_Of_Day       17331 non-null  object
 12  Is_Weekend                17331 non-null  int64
 13  Inferred_Company_Encoded  17331 non-null  int64
 14  Sentiment                 17331 non-null  float64
 15  Likes                     17331 non-null  int64
dtypes: float64(2), int32(3), int64(8), object(3)
memory usage: 1.9+ MB
```

[36]:
```
df.describe()
```

[36]:
```
       User_Post_Count  Average_Likes_Post   Word_Count  Content_Length  \
count      17331.00000        17331.000000 17331.000000    17331.000000
mean         310.11315          718.392130    22.501356      147.868617
std          597.97351         2151.111797    11.842720       71.690684
min            1.00000            0.000000     2.000000       20.000000
25%           16.00000            3.604651    12.000000       88.000000
50%           49.00000          161.631579    21.000000      136.000000
75%          162.00000          603.562500    31.000000      202.000000
max         1927.00000        71375.500000    63.000000      323.000000

       Has_Media   Has_Mention  Release_Time_Year  Release_Time_Month  \
count    17331.0  17331.000000       17331.000000        17331.000000
mean         0.0      0.280249        2019.085108            6.522647
std          0.0      0.449134           0.816360            3.462951
min          0.0      0.000000        2018.000000            1.000000
25%          0.0      0.000000        2018.000000            3.000000
50%          0.0      0.000000        2019.000000            7.000000
75%          0.0      1.000000        2020.000000           10.000000
max          0.0      1.000000        2020.000000           12.000000

       Release_Time_Day    Is_Weekend  Inferred_Company_Encoded     Sentiment  \
count      17331.000000  17331.000000              17331.000000  17331.000000
mean          15.682534      0.221049                 83.462235      0.152969
std            8.777625      0.414965                 54.537641      0.266508
min            1.000000      0.000000                  0.000000     -1.000000
25%            8.000000      0.000000                 38.000000      0.000000
50%           16.000000      0.000000                 87.000000      0.053333
75%           23.000000      0.000000                120.000000      0.300000
max           31.000000      1.000000                193.000000      1.000000

               Likes
count   17331.000000
mean      718.392130
std      3866.475948
min         0.000000
```

```
25%           3.000000
50%          73.000000
75%         352.000000
max      254931.000000
```

[37]:
```
for col in df.columns:
  print(f"Column '{col}': {df[col].nunique()} unique values")
```

```
Column 'Username': 1325 unique values
Column 'User_Post_Count': 93 unique values
Column 'Average_Likes_Post': 1094 unique values
Column 'Content': 17124 unique values
Column 'Word_Count': 60 unique values
Column 'Content_Length': 288 unique values
Column 'Has_Media': 1 unique values
Column 'Has_Mention': 2 unique values
Column 'Release_Time_Year': 3 unique values
Column 'Release_Time_Month': 12 unique values
Column 'Release_Time_Day': 31 unique values
Column 'Release_Time_Of_Day': 13183 unique values
Column 'Is_Weekend': 2 unique values
Column 'Inferred_Company_Encoded': 194 unique values
Column 'Sentiment': 2142 unique values
Column 'Likes': 2589 unique values
```

[38]:
```
import numpy as np
df['Log_Likes'] = np.log(df['Likes'] + 1)
```

```
<ipython-input-38-442408419>:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df['Log_Likes'] = np.log(df['Likes'] + 1)
```

[39]:
```
df['Has_Media'].value_counts()
```

[39]:
```
Has_Media
0    17331
Name: count, dtype: int64
```

[40]:
```
df.drop(columns = ['Has_Media'], inplace = True)
```

```
<ipython-input-40-2532181239>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-
```

```
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df.drop(columns = ['Has_Media'], inplace = True)
```

[41]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 17331 entries, 0 to 17330
Data columns (total 16 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   Username                 17331 non-null  object
 1   User_Post_Count          17331 non-null  int64
 2   Average_Likes_Post       17331 non-null  float64
 3   Content                  17331 non-null  object
 4   Word_Count               17331 non-null  int64
 5   Content_Length           17331 non-null  int64
 6   Has_Mention              17331 non-null  int64
 7   Release_Time_Year        17331 non-null  int32
 8   Release_Time_Month       17331 non-null  int32
 9   Release_Time_Day         17331 non-null  int32
 10  Release_Time_Of_Day      17331 non-null  object
 11  Is_Weekend               17331 non-null  int64
 12  Inferred_Company_Encoded 17331 non-null  int64
 13  Sentiment                17331 non-null  float64
 14  Likes                    17331 non-null  int64
 15  Log_Likes                17331 non-null  float64
dtypes: float64(3), int32(3), int64(7), object(3)
memory usage: 1.9+ MB
```

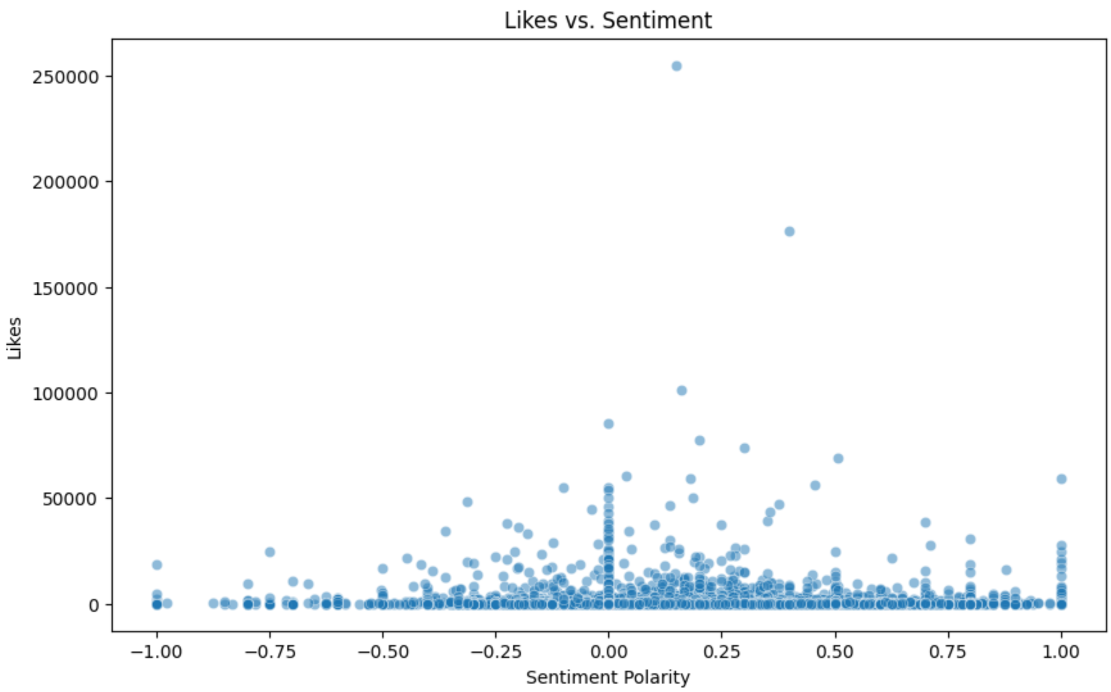
[42]:
```
df.to_excel('Cleaned_Dataset.xlsx', index=False)
```

3 EXPLORATORY DATA ANALYSIS

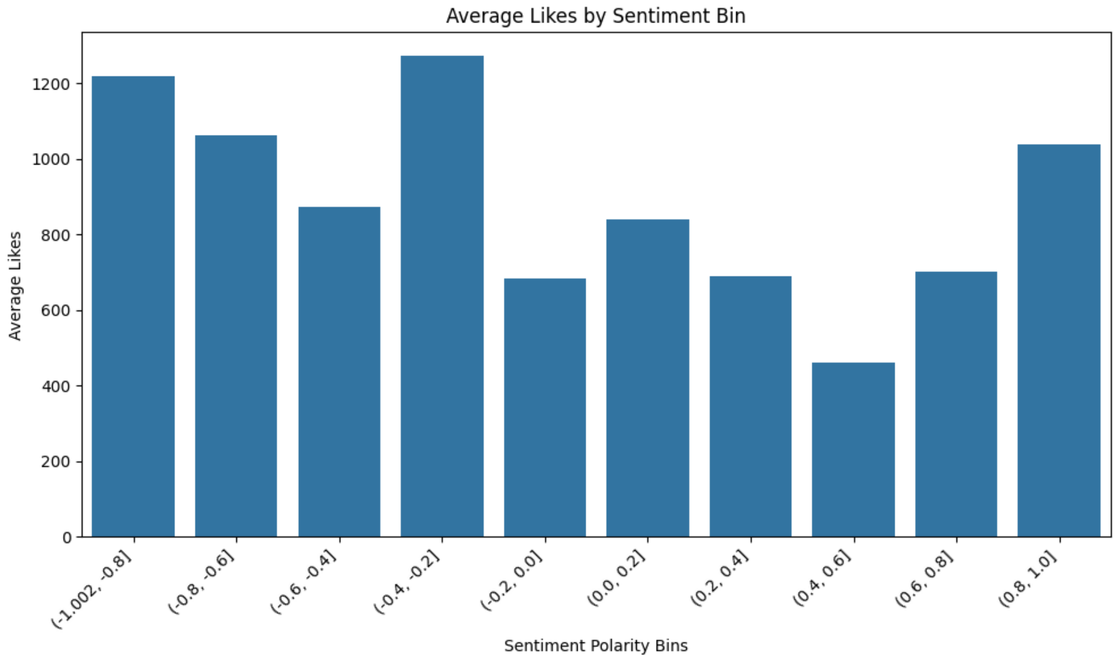
Here I will explore the dataset, by plotting some bar graphs, histograms, line charts and more, to compare the number of likes to the features in my data.

[43]:
```
import matplotlib.pyplot as plt
import seaborn as sns
plt.figure(figsize=(10, 6))
sns.scatterplot(x='Sentiment', y='Likes', data=df, alpha=0.5)
plt.title('Likes vs. Sentiment')
plt.xlabel('Sentiment Polarity')
plt.ylabel('Likes')
plt.show()
sentiment_bins = pd.cut(df['Sentiment'], bins=10)
avg_likes_by_sentiment = df.groupby(sentiment_bins)['Likes'].mean().
 ↪reset_index()
```

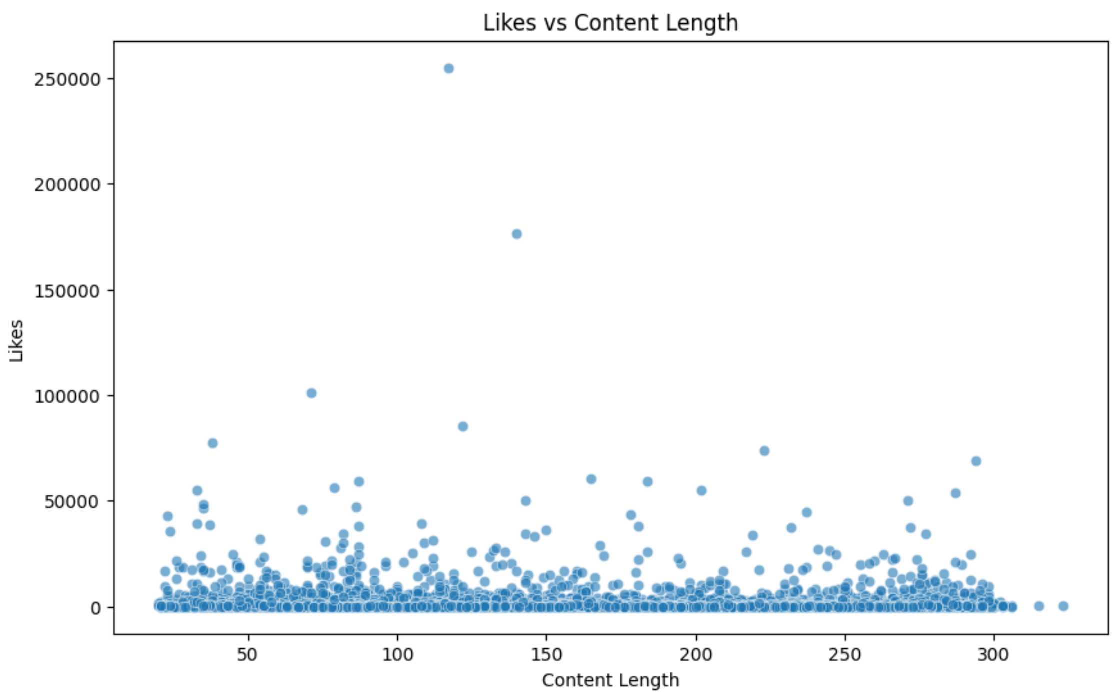
```
plt.figure(figsize=(10, 6))
sns.barplot(x='Sentiment', y='Likes', data=avg_likes_by_sentiment)
plt.title('Average Likes by Sentiment Bin')
plt.xlabel('Sentiment Polarity Bins')
plt.ylabel('Average Likes')
plt.xticks(rotation=45, ha='right')
plt.tight_layout()
plt.show()
```

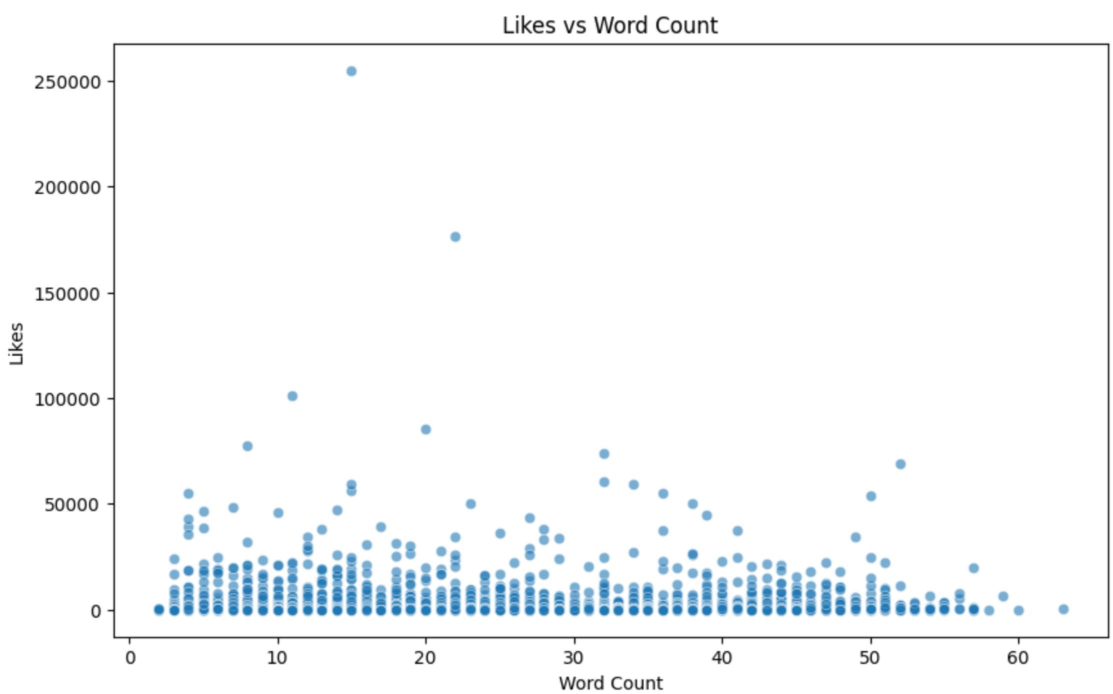



```
<ipython-input-43-2884293791>:10: FutureWarning: The default of observed=False
is deprecated and will be changed to True in a future version of pandas. Pass
observed=False to retain current behavior or observed=True to adopt the future
default and silence this warning.
  avg_likes_by_sentiment =
df.groupby(sentiment_bins)['Likes'].mean().reset_index()
```



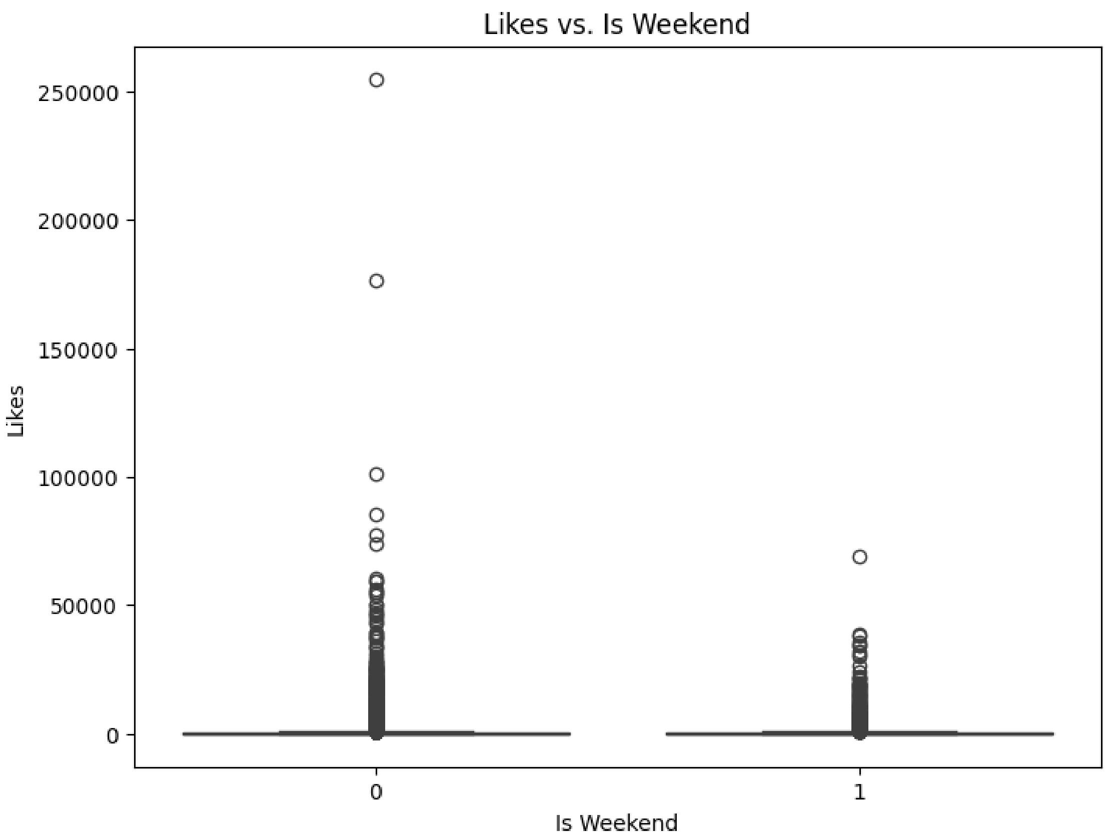
[44]:
```
plt.figure(figsize=(10, 6))
sns.scatterplot(x='Content_Length', y='Likes', data=df, alpha=0.6)
plt.title('Likes vs Content Length')
plt.xlabel('Content Length')
plt.ylabel('Likes')
plt.show()
plt.figure(figsize=(10, 6))
sns.scatterplot(x='Word_Count', y='Likes', data=df, alpha=0.6)
plt.title('Likes vs Word Count')
plt.xlabel('Word Count')
plt.ylabel('Likes')
plt.show()
```





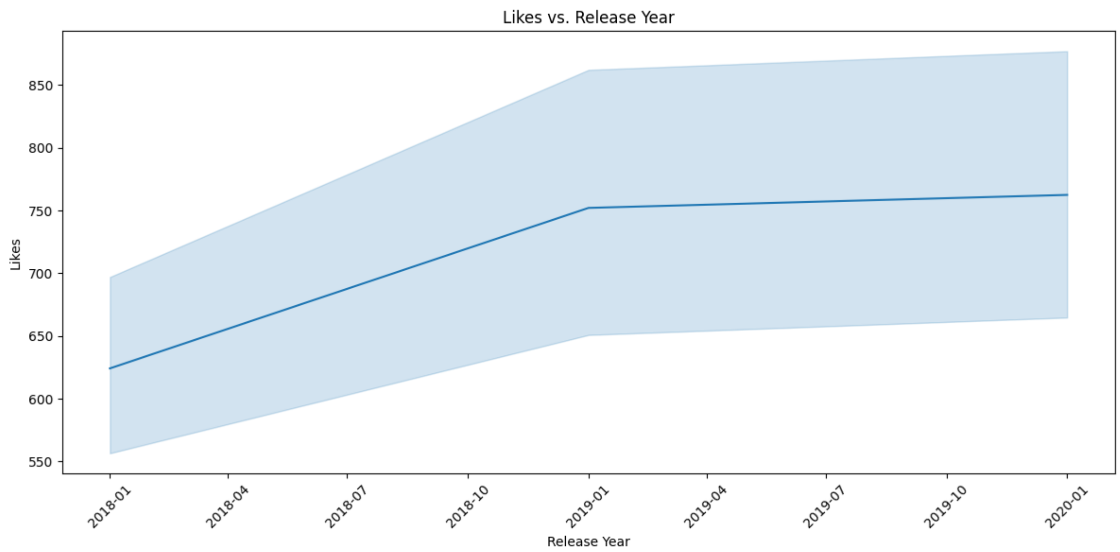
[45]:
```
plt.figure(figsize=(8, 6))
sns.boxplot(x='Is_Weekend', y='Likes', data=df)
```

```
plt.title('Likes vs. Is Weekend')
plt.xlabel('Is Weekend')
plt.ylabel('Likes')
plt.show()
```

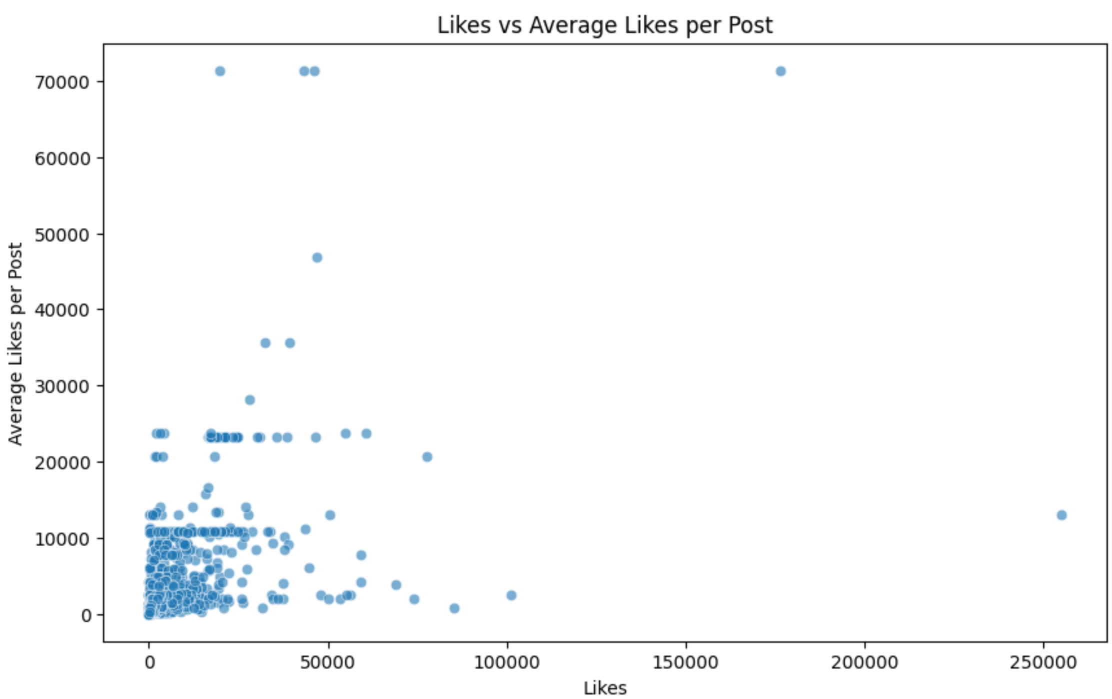


[46]:

```
df['release_year_date'] = pd.to_datetime(df['Release_Time_Year'].astype(str) +
 ↪'-01-01')
plt.figure(figsize=(12, 6))
sns.lineplot(x='release_year_date', y='Likes', data=df)
plt.title('Likes vs. Release Year')
plt.xlabel('Release Year')
plt.ylabel('Likes')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
df.drop(columns = "release_year_date",inplace = True)
```

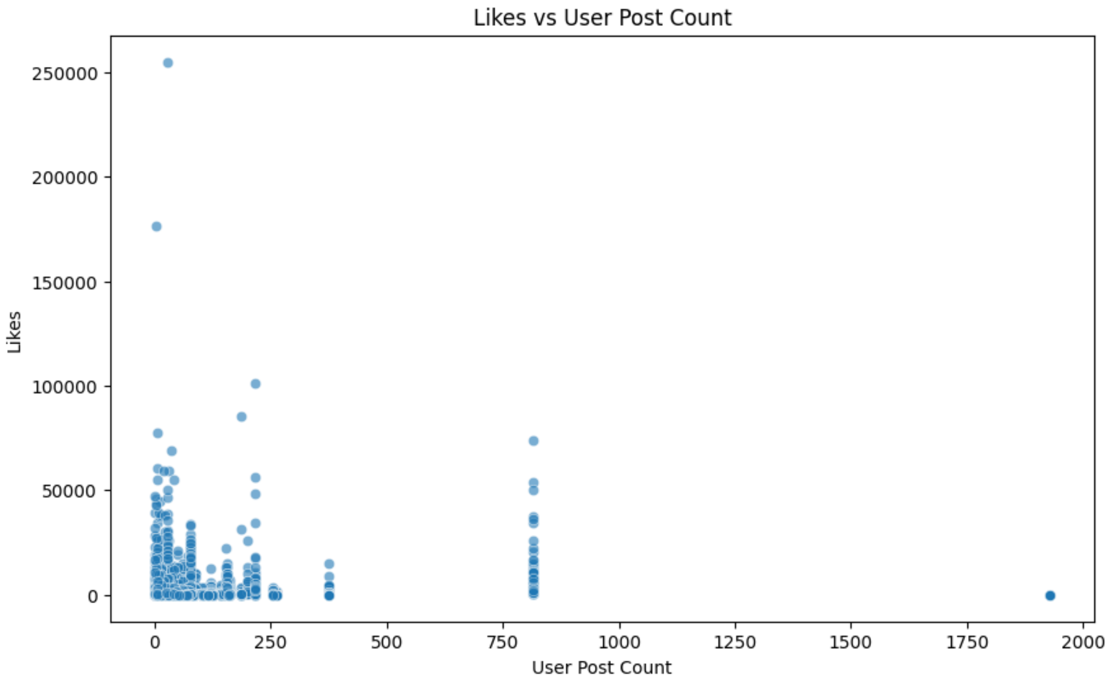


[47]:
```
plt.figure(figsize=(10, 6))
sns.scatterplot(x='Likes', y='Average_Likes_Post', data=df, alpha=0.6)
plt.title('Likes vs Average Likes per Post')
plt.xlabel('Likes')
plt.ylabel('Average Likes per Post')
plt.show()
```



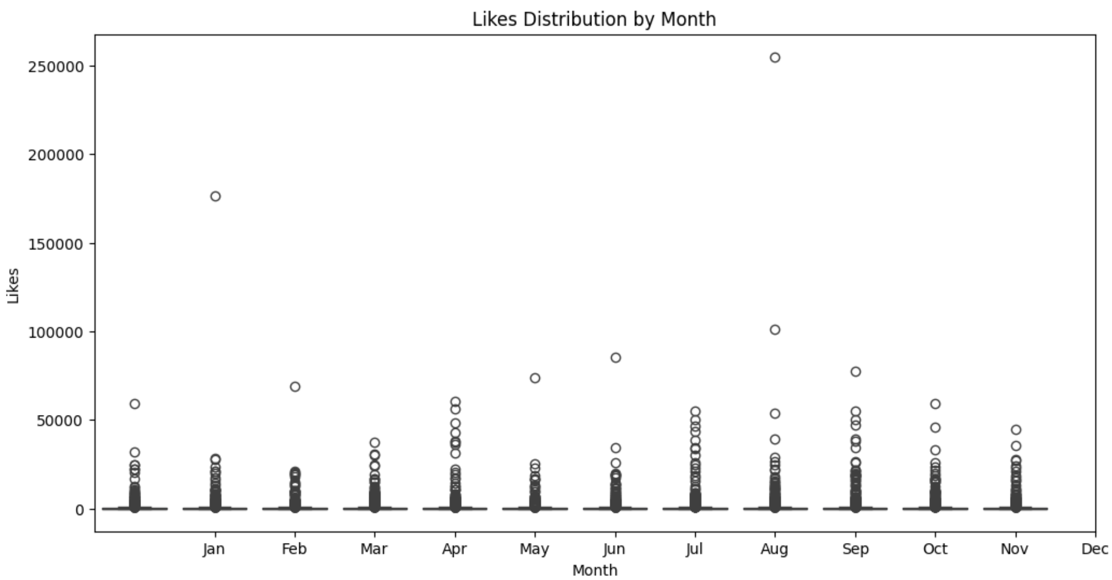
[48]:

```
plt.figure(figsize=(10, 6))
sns.scatterplot(x='User_Post_Count', y='Likes', data=df, alpha=0.6)
plt.title('Likes vs User Post Count')
plt.xlabel('User Post Count')
plt.ylabel('Likes')
plt.show()
```



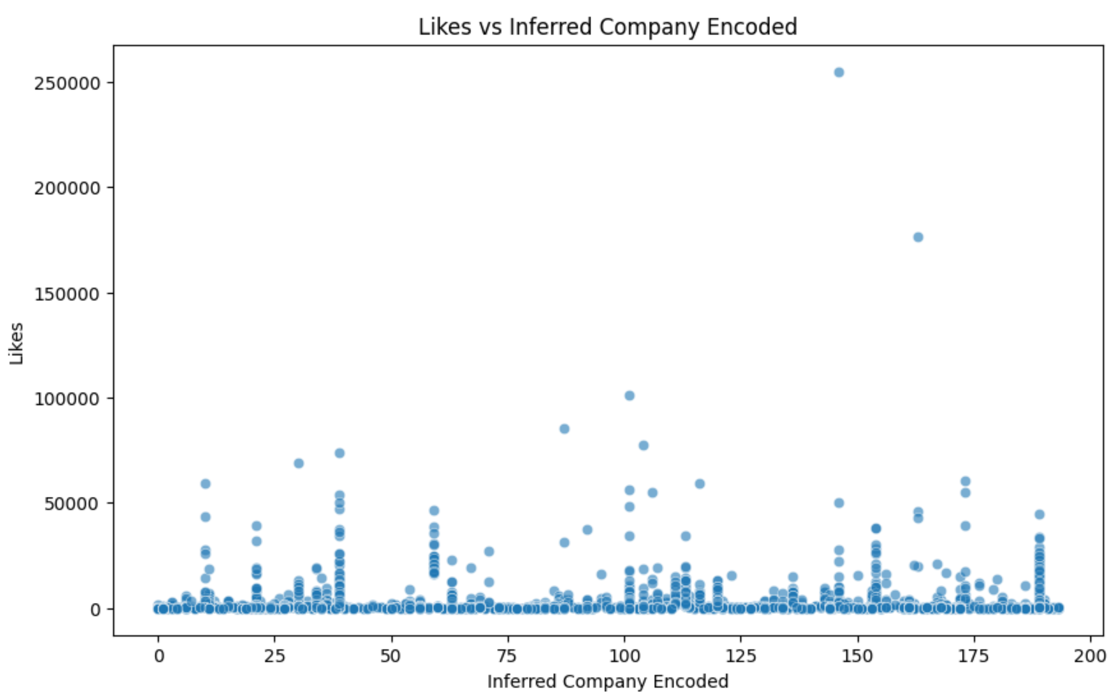
[49]:

```
plt.figure(figsize=(12, 6))
sns.boxplot(x='Release_Time_Month', y='Likes', data=df)
plt.title('Likes Distribution by Month')
plt.xlabel('Month')
plt.ylabel('Likes')
plt.xticks(range(1, 13), ['Jan', 'Feb', 'Mar', 'Apr', 'May', 'Jun', 'Jul',␣
↪'Aug', 'Sep', 'Oct', 'Nov', 'Dec'])
plt.show()
```

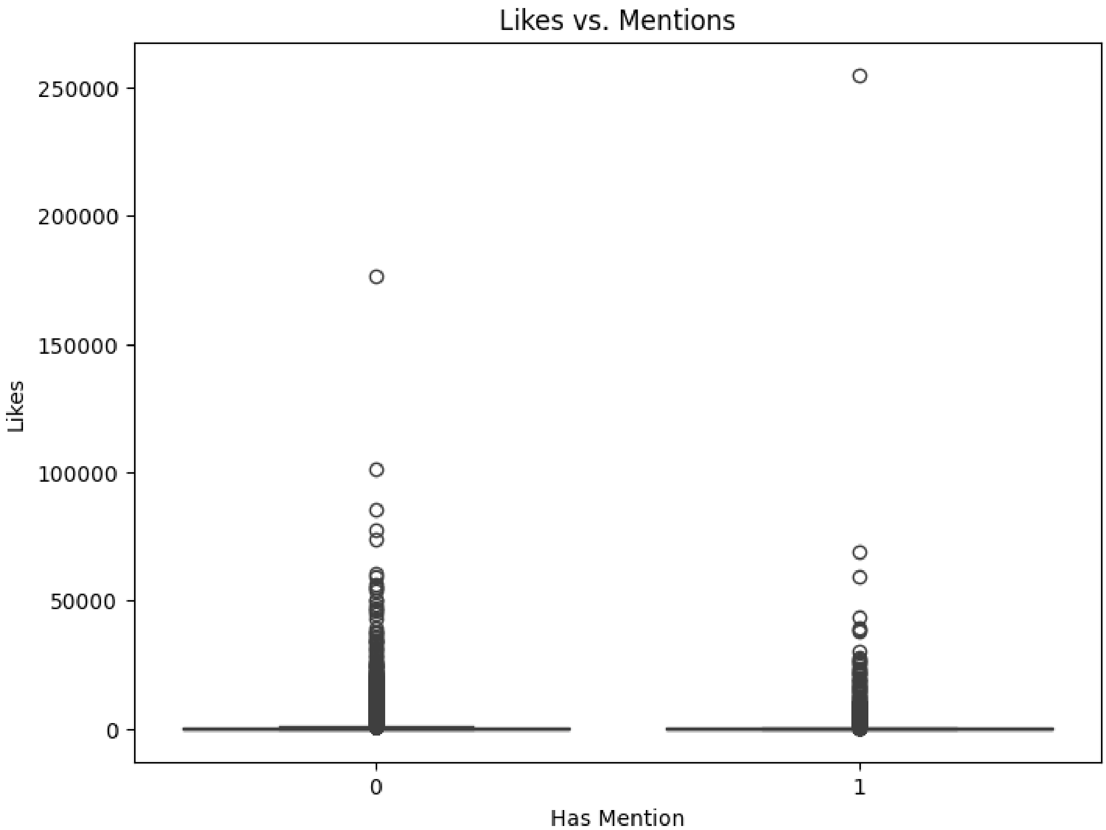


[50]:

```
plt.figure(figsize=(10, 6))
sns.scatterplot(x='Inferred_Company_Encoded', y='Likes', data=df, alpha=0.6)
plt.title('Likes vs Inferred Company Encoded')
plt.xlabel('Inferred Company Encoded')
plt.ylabel('Likes')
plt.show()
```



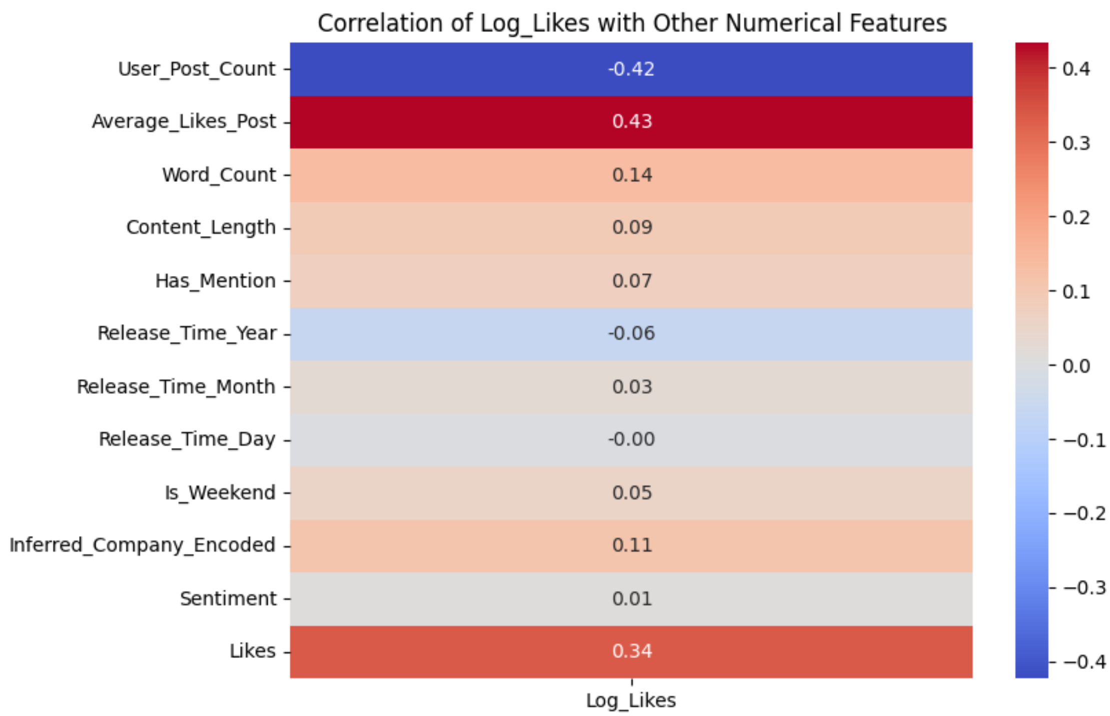
[51]:
```
plt.figure(figsize=(8, 6))
sns.boxplot(x='Has_Mention', y='Likes', data=df)
plt.title('Likes vs. Mentions')
plt.xlabel('Has Mention')
plt.ylabel('Likes')
plt.show()
```



[52]:
```
correlation_matrix = df.select_dtypes(include=np.number).corr()['Log_Likes'].
  ↪drop('Log_Likes')
print("Correlation Matrix of Log_Likes vs remaining numerical columns:")
print(correlation_matrix)
plt.figure(figsize=(8, 6))
sns.heatmap(correlation_matrix.to_frame(), annot=True, cmap='coolwarm', fmt=".
  ↪2f")
plt.title('Correlation of Log_Likes with Other Numerical Features')
plt.show()
```

```
Correlation Matrix of Log_Likes vs remaining numerical columns:
User_Post_Count             -0.423433
```

```
Average_Likes_Post          0.433754
Word_Count                  0.138015
Content_Length              0.089585
Has_Mention                 0.074083
Release_Time_Year          -0.063429
Release_Time_Month          0.028296
Release_Time_Day           -0.003694
Is_Weekend                  0.052465
Inferred_Company_Encoded    0.110186
Sentiment                   0.011674
Likes                       0.336056
Name: Log_Likes, dtype: float64
```



4 TRAINING AND STORING THE MODEL

Here I will train my model using various model types, like linear regression, gradient boosting, neural networks and many more. Then I will choose the model that yields the best results and save it.

4.1 DATA PREPARATION

I will prepare my data, first split the dataset with 75% training data and 25% testing data. Next I will split the columns with likes representing the y column (The value to be predicted) and the remaining columns representing the independent variables.

[53]:
```
y = df['Log_Likes']
x = df.drop(columns=['Log_Likes'], axis = 1)
numerical_cols = [
    'Average_Likes_Post',
    'User_Post_Count',
    'Word_Count',
    'Inferred_Company_Encoded',
    'Content_Length',
    'Has_Mention',
    'Is_Weekend',
    'Release_Time_Year'
]
```

[54]:
```
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(x , y, test_size=0.25,␣
↪random_state=42)
```

4.2 TESTING ALGORITHMS

First I will normalize my data, then I will test various algorithms, test their accuracy, and choose the best one.

4.2.1 NORMALIZED DATA

[55]:
```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
x_train_normalized = x_train.copy()
x_test_normalized = x_test.copy()
x_train_normalized[numerical_cols] = scaler.
↪fit_transform(x_train[numerical_cols])
x_test_normalized[numerical_cols] = scaler.transform(x_test[numerical_cols])
```

4.2.2 LINEAR REGRESSION

[56]:
```
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
lr_model = LinearRegression()
lr_model.fit(x_train_normalized[numerical_cols], y_train)
y_pred_lr = lr_model.predict(x_test_normalized[numerical_cols])
mse_lr = mean_squared_error(y_test, y_pred_lr)
r2_lr = r2_score(y_test, y_pred_lr)
print("Linear Regression Model Evaluation:")
print(f"Mean Squared Error (MSE): {mse_lr:.2f}")
print(f"R-squared (R2): {r2_lr:.2f}")
```

```
Linear Regression Model Evaluation:
Mean Squared Error (MSE): 4.38
```

R-squared (R2): 0.36

4.2.3 RANDOM FOREST

[57]:
```
from sklearn.ensemble import RandomForestRegressor
rf_model = RandomForestRegressor(n_estimators=1000, random_state=42)
rf_model.fit(x_train[numerical_cols], y_train)
y_pred_rf = rf_model.predict(x_test[numerical_cols])
mse_rf = mean_squared_error(y_test, y_pred_rf)
r2_rf = r2_score(y_test, y_pred_rf)
print("Random Forest Regressor Model Evaluation:")
print(f"Mean Squared Error (RMSE): {mse_rf:.2f}")
print(f"R-squared (R2): {r2_rf:.2f}")
```

```
Random Forest Regressor Model Evaluation:
Mean Squared Error (RMSE): 0.73
R-squared (R2): 0.89
```

4.2.4 GRADIENT BOOSTING

[58]:
```
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.metrics import mean_squared_error, r2_score
gbr_model = GradientBoostingRegressor(n_estimators=1000, learning_rate=0.1,␣
 ↪max_depth=3, random_state=42)
gbr_model.fit(x_train[numerical_cols], y_train)
y_pred_gbr = gbr_model.predict(x_test[numerical_cols])
mse_gbr = mean_squared_error(y_test, y_pred_gbr)
r2_gbr = r2_score(y_test, y_pred_gbr)
print("Gradient Boosting Regressor Model Evaluation:")
print(f"Mean Squared Error (RMSE): {mse_gbr:.2f}")
print(f"R-squared (R2): {r2_gbr:.2f}")
```

```
Gradient Boosting Regressor Model Evaluation:
Mean Squared Error (RMSE): 0.72
R-squared (R2): 0.90
```

4.2.5 NEURAL NETWORKS

[59]:
```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.callbacks import EarlyStopping
model = Sequential()
model.add(Dense(128, input_dim=len(numerical_cols), activation='relu'))
model.add(Dropout(0.3))
model.add(Dense(64, activation='relu'))
model.add(Dropout(0.3))
model.add(Dense(32, activation='relu'))
```

```
model.add(Dense(1, activation='linear'))
optimizer = Adam(learning_rate=0.001)
model.compile(loss='mse', optimizer=optimizer)
early_stopping = EarlyStopping(monitor='val_loss', patience=10,␣
↪restore_best_weights=True)
history = model.fit(x_train_normalized[numerical_cols], y_train,
                    validation_split=0.2,
                    epochs=200,
                    batch_size=32,
                    callbacks=[early_stopping],
                    verbose=0)
loss_nn = model.evaluate(x_test_normalized[numerical_cols], y_test, verbose=0)
y_pred_nn = model.predict(x_test_normalized[numerical_cols])
from sklearn.metrics import r2_score
r2_nn = r2_score(y_test, y_pred_nn)
print("\nNeural Network Model Evaluation:")
print(f"Mean Squared Error (MSE): {loss_nn:.2f}")
print(f"R-squared (R2): {r2_nn:.2f}")
```

```
/usr/local/lib/python3.11/dist-packages/keras/src/layers/core/dense.py:87:
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

```
136/136              0s 2ms/step
```

```
Neural Network Model Evaluation:
Mean Squared Error (MSE): 0.92
R-squared (R2): 0.87
```

4.2.6 TABULAR TRANSFORMS

[60]:
```
!pip install pytorch-tabnet -q
import torch
import numpy as np
import pandas as pd
from pytorch_tabnet.tab_model import TabNetRegressor
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import LabelEncoder
from sklearn.metrics import mean_squared_error, r2_score
categorical_features = ['Has_Mention', 'Is_Weekend', 'Release_Time_Year',
                        'Release_Time_Month', 'Release_Time_Day',␣
↪'Inferred_Company_Encoded']
numerical_features = ['Average_Likes_Post', 'User_Post_Count', 'Word_Count',
                      'Content_Length', 'Sentiment']
features = numerical_features + categorical_features
target = 'Log_Likes'
```

```
X_train_tab = x_train[features].copy()
X_test_tab = x_test[features].copy()
y_train_tab = y_train.copy()
y_test_tab = y_test.copy()
full_data = pd.concat([X_train_tab, X_test_tab], axis=0)
for col in categorical_features:
    le = LabelEncoder()
    le.fit(full_data[col])
    X_train_tab[col] = le.transform(X_train_tab[col])
    X_test_tab[col] = le.transform(X_test_tab[col])
scaler = StandardScaler()
X_train_tab[numerical_features] = scaler.
 ↪fit_transform(X_train_tab[numerical_features])
X_test_tab[numerical_features] = scaler.
 ↪transform(X_test_tab[numerical_features])
categorical_dims = [full_data[col].nunique() for col in categorical_features]
cat_idxs = [X_train_tab.columns.get_loc(col) for col in categorical_features]
cat_emb_dim = [min(50, (dim // 2) + 1) for dim in categorical_dims]
tabnet_model = TabNetRegressor(
    cat_idxs=cat_idxs,
    cat_dims=categorical_dims,
    cat_emb_dim=cat_emb_dim,
    optimizer_fn=torch.optim.Adam,
    optimizer_params=dict(lr=2e-2),
    scheduler_params={"step_size":50, "gamma":0.9},
    scheduler_fn=torch.optim.lr_scheduler.StepLR,
    mask_type='sparsemax'
)
X_train_np = X_train_tab.values
X_test_np = X_test_tab.values
y_train_np = y_train_tab.values.reshape(-1, 1)
y_test_np = y_test_tab.values.reshape(-1, 1)
tabnet_model.fit(
    X_train=X_train_np, y_train=y_train_np,
    eval_set=[(X_test_np, y_test_np)],
    eval_metric=['mse'],
    max_epochs=1000,
    patience=50,
    batch_size=1024,
    virtual_batch_size=128,
    num_workers=0,
    drop_last=False
)
y_pred = tabnet_model.predict(X_test_np)
mse = mean_squared_error(y_test_np, y_pred)
r2 = r2_score(y_test_np, y_pred)
print("\n  TabNet Evaluation Metrics:")
```

```python
print(f" Mean Squared Error (MSE): {mse:.2f}")
print(f" R-squared Score (R²): {r2:.2f}")
```

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```

```
/usr/local/lib/python3.11/dist-packages/pytorch_tabnet/abstract_model.py:82:
UserWarning: Device used : cuda
  warnings.warn(f"Device used : {self.device}")
```

```
epoch 0  | loss: 9.6407  | val_0_mse: 5.46592 |  0:00:01s
epoch 1  | loss: 4.10906 | val_0_mse: 3.6752  |  0:00:02s
epoch 2  | loss: 2.43604 | val_0_mse: 2.36761 |  0:00:03s
epoch 3  | loss: 1.66853 | val_0_mse: 2.76034 |  0:00:03s
epoch 4  | loss: 1.41725 | val_0_mse: 3.34481 |  0:00:04s
epoch 5  | loss: 1.33007 | val_0_mse: 1.54035 |  0:00:05s
epoch 6  | loss: 1.1197  | val_0_mse: 3.14923 |  0:00:05s
epoch 7  | loss: 1.06123 | val_0_mse: 2.93619 |  0:00:06s
epoch 8  | loss: 1.02114 | val_0_mse: 3.95188 |  0:00:07s
epoch 9  | loss: 0.98628 | val_0_mse: 3.1481  |  0:00:07s
epoch 10 | loss: 0.96606 | val_0_mse: 3.56295 |  0:00:08s
epoch 11 | loss: 0.95151 | val_0_mse: 3.38783 |  0:00:09s
epoch 12 | loss: 0.91869 | val_0_mse: 2.93638 |  0:00:10s
epoch 13 | loss: 0.92224 | val_0_mse: 3.37545 |  0:00:11s
epoch 14 | loss: 0.89167 | val_0_mse: 3.37287 |  0:00:12s
epoch 15 | loss: 0.9591  | val_0_mse: 4.05188 |  0:00:12s
epoch 16 | loss: 0.89315 | val_0_mse: 3.53909 |  0:00:13s
```

```
epoch 17 | loss: 0.86606 | val_0_mse: 3.85364 |  0:00:14s
epoch 18 | loss: 0.86322 | val_0_mse: 3.74323 |  0:00:14s
epoch 19 | loss: 0.86984 | val_0_mse: 4.00857 |  0:00:15s
epoch 20 | loss: 0.88552 | val_0_mse: 3.78432 |  0:00:16s
epoch 21 | loss: 0.87276 | val_0_mse: 3.40182 |  0:00:16s
epoch 22 | loss: 0.85258 | val_0_mse: 3.75787 |  0:00:17s
epoch 23 | loss: 0.85386 | val_0_mse: 3.58313 |  0:00:18s
epoch 24 | loss: 0.83297 | val_0_mse: 3.45828 |  0:00:18s
epoch 25 | loss: 0.8465  | val_0_mse: 3.4362  |  0:00:19s
epoch 26 | loss: 0.83184 | val_0_mse: 3.30189 |  0:00:20s
epoch 27 | loss: 0.85874 | val_0_mse: 3.81208 |  0:00:20s
epoch 28 | loss: 0.84129 | val_0_mse: 3.38096 |  0:00:21s
epoch 29 | loss: 0.83909 | val_0_mse: 3.82073 |  0:00:22s
epoch 30 | loss: 0.81895 | val_0_mse: 3.19629 |  0:00:23s
epoch 31 | loss: 0.82315 | val_0_mse: 3.51957 |  0:00:24s
epoch 32 | loss: 0.82129 | val_0_mse: 3.38002 |  0:00:25s
epoch 33 | loss: 0.81679 | val_0_mse: 3.67287 |  0:00:25s
epoch 34 | loss: 0.82891 | val_0_mse: 3.37586 |  0:00:26s
epoch 35 | loss: 0.80258 | val_0_mse: 3.61826 |  0:00:27s
epoch 36 | loss: 0.80706 | val_0_mse: 3.57138 |  0:00:27s
epoch 37 | loss: 0.80723 | val_0_mse: 3.7322  |  0:00:28s
epoch 38 | loss: 0.80528 | val_0_mse: 3.77227 |  0:00:29s
epoch 39 | loss: 0.83284 | val_0_mse: 3.3471  |  0:00:29s
epoch 40 | loss: 0.79295 | val_0_mse: 3.53966 |  0:00:30s
epoch 41 | loss: 0.79117 | val_0_mse: 3.94565 |  0:00:31s
epoch 42 | loss: 0.78901 | val_0_mse: 3.68475 |  0:00:31s
epoch 43 | loss: 0.77249 | val_0_mse: 3.64262 |  0:00:32s
epoch 44 | loss: 0.77542 | val_0_mse: 3.79754 |  0:00:33s
epoch 45 | loss: 0.76996 | val_0_mse: 4.00849 |  0:00:34s
epoch 46 | loss: 0.7682  | val_0_mse: 3.76433 |  0:00:35s
epoch 47 | loss: 0.74802 | val_0_mse: 3.89088 |  0:00:36s
epoch 48 | loss: 0.73948 | val_0_mse: 3.60937 |  0:00:36s
epoch 49 | loss: 0.74091 | val_0_mse: 3.62948 |  0:00:37s
epoch 50 | loss: 0.72461 | val_0_mse: 3.71516 |  0:00:38s
epoch 51 | loss: 0.72702 | val_0_mse: 3.94767 |  0:00:38s
epoch 52 | loss: 0.71827 | val_0_mse: 3.95507 |  0:00:39s
epoch 53 | loss: 0.71897 | val_0_mse: 3.97618 |  0:00:40s
epoch 54 | loss: 0.70443 | val_0_mse: 4.00229 |  0:00:40s
epoch 55 | loss: 0.71089 | val_0_mse: 3.90055 |  0:00:41s

Early stopping occurred at epoch 55 with best_epoch = 5 and best_val_0_mse =
1.54035

/usr/local/lib/python3.11/dist-packages/pytorch_tabnet/callbacks.py:172:
UserWarning: Best weights from best epoch are automatically used!
  warnings.warn(wrn_msg)


 TabNet Evaluation Metrics:
```

```
Mean Squared Error (MSE): 1.54
R-squared Score (R²): 0.78
```

4.3 STORING THE MODEL

I will store the best-performing model, Gradient Boosting Regressor, in my case, and implement it in future algorithms.

[61]:
```python
import joblib
joblib.dump(gbr_model, 'like_predictor.pkl')
```

[61]:
```
['like_predictor.pkl']
```