climate-change

October 21, 2024

0.1 Load the Dataset

[1]:
```python
import pandas as pd

# Load the dataset
df = pd.read_csv('climate_nasa.csv')

# Display the first few rows of the dataset
print(df.head())
```

```
                       date  likesCount  \
0  2022-09-07T17:12:32.000Z           2
1  2022-09-08T14:51:13.000Z           0
2  2022-09-07T17:19:41.000Z           1
3  2022-09-08T00:51:30.000Z           4
4  2022-09-07T19:06:20.000Z          16

                                         profileName  commentsCount  \
0  4dca617d86b3fdce80ba7e81fb16e048c9cd9798cdfd6d…            NaN
1  518ab97f2d115ba5b6f03b2fba2ef2b120540c9681288b…            NaN
2  d82e8e24eb633fd625b0aef9b3cb625cfb044ceb8483e1…            3.0
3  37a509fa0b5177a2233c7e2d0e2b2d6916695fa9fba3f2…            NaN
4  e54fbbd42a729af9d04d9a5cc1f9bbfe8081a31c219ecb…           26.0

                                                text
0  Neat comparison I have not heard it before.\n …
1  An excellent way to visualise the invisible! T…
2  Does the CO2/ghg in the troposphere affect the…
3  excellent post! I defo feel the difference - o…
4  Yes, and carbon dioxide does not harm the Eart…
```

0.2 Step 2: Data Cleaning

[5]:
```python
# Check for duplicates
duplicates = df.duplicated().sum()
print(f"Number of duplicate entries: {duplicates}")

# Drop duplicates if any
```

```
df.drop_duplicates(inplace=True)

# Check for missing values
missing_values = df.isnull().sum()
print("Missing values in each column:")
print(missing_values)

# Convert the 'Date' column to datetime format
df['date'] = pd.to_datetime(df['date'])

# Display the cleaned dataset info
print(df.info())
```

```
Number of duplicate entries: 0
Missing values in each column:
date              0
likesCount        0
profileName       0
commentsCount   278
text             18
dtype: int64
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 522 entries, 0 to 521
Data columns (total 5 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   date           522 non-null    datetime64[ns, UTC]
 1   likesCount     522 non-null    int64
 2   profileName    522 non-null    object
 3   commentsCount  244 non-null    float64
 4   text           504 non-null    object
dtypes: datetime64[ns, UTC](1), float64(1), int64(1), object(2)
memory usage: 20.5+ KB
None
```

0.2.1 Handle Missing Values

[6]:
```
# Handling missing values for commentsCount
# Option 1: Fill with median
df['commentsCount'].fillna(df['commentsCount'].median(), inplace=True)

# Option 2: Drop rows (Uncomment if you prefer this option)
# df.dropna(subset=['commentsCount'], inplace=True)

# Handling missing values for text
df.dropna(subset=['text'], inplace=True)
```

```
# Check the updated dataset info
print(df.info())
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 504 entries, 0 to 521
Data columns (total 5 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   date           504 non-null    datetime64[ns, UTC]
 1   likesCount     504 non-null    int64
 2   profileName    504 non-null    object
 3   commentsCount  504 non-null    float64
 4   text           504 non-null    object
dtypes: datetime64[ns, UTC](1), float64(1), int64(1), object(2)
memory usage: 23.6+ KB
None
```

0.3 Step 3: Exploratory Data Analysis (EDA)

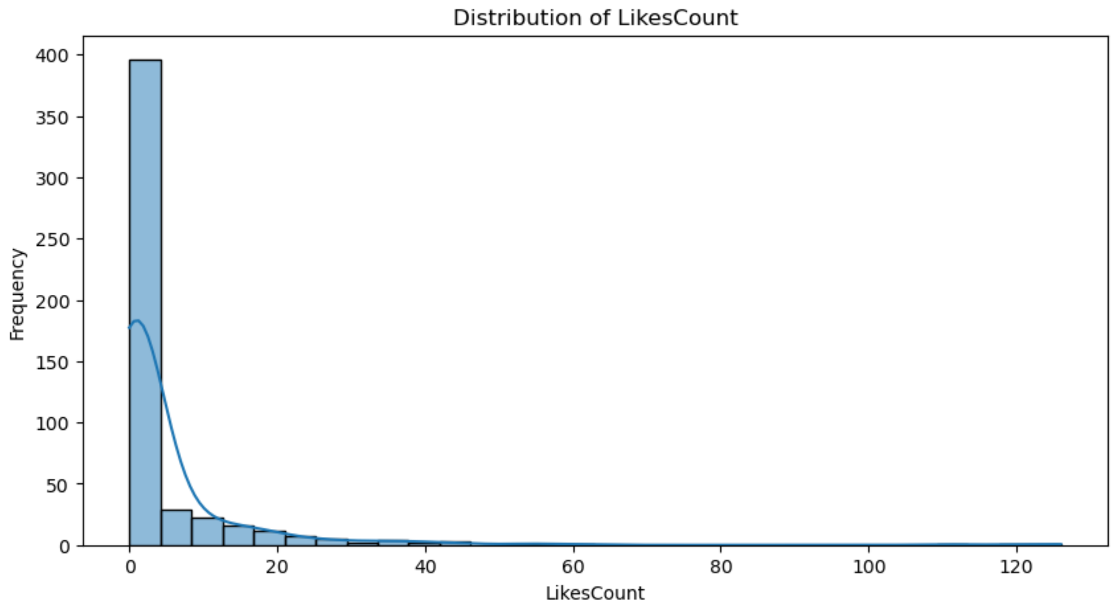
[9]:
```
# Histogram for LikesCount
plt.figure(figsize=(10, 5))
sns.histplot(df['likesCount'], bins=30, kde=True)
plt.title('Distribution of LikesCount')
plt.xlabel('LikesCount')
plt.ylabel('Frequency')
plt.show()

# Histogram for CommentsCount
plt.figure(figsize=(10, 5))
sns.histplot(df['commentsCount'], bins=30, kde=True)
plt.title('Distribution of CommentsCount')
plt.xlabel('CommentsCount')
plt.ylabel('Frequency')
plt.show()

# Time series plot for comment counts over time
plt.figure(figsize=(12, 6))
df.set_index('date').resample('M').size().plot()
plt.title('Number of Comments Over Time')
plt.xlabel('Date')
plt.ylabel('Number of Comments')
plt.xticks(rotation=45)
plt.show()
```

```
C:\Users\tikul\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119:
FutureWarning: use_inf_as_na option is deprecated and will be removed in a
future version. Convert inf values to NaN before operating instead.
```

```
  with pd.option_context('mode.use_inf_as_na', True):
```




```
C:\Users\tikul\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119:
FutureWarning: use_inf_as_na option is deprecated and will be removed in a
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```
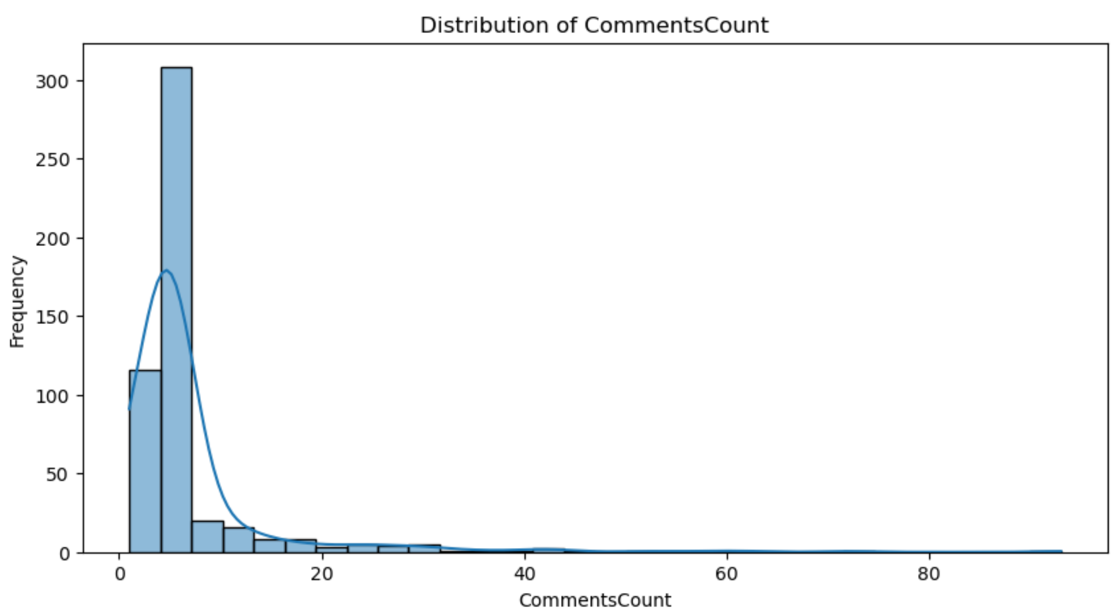
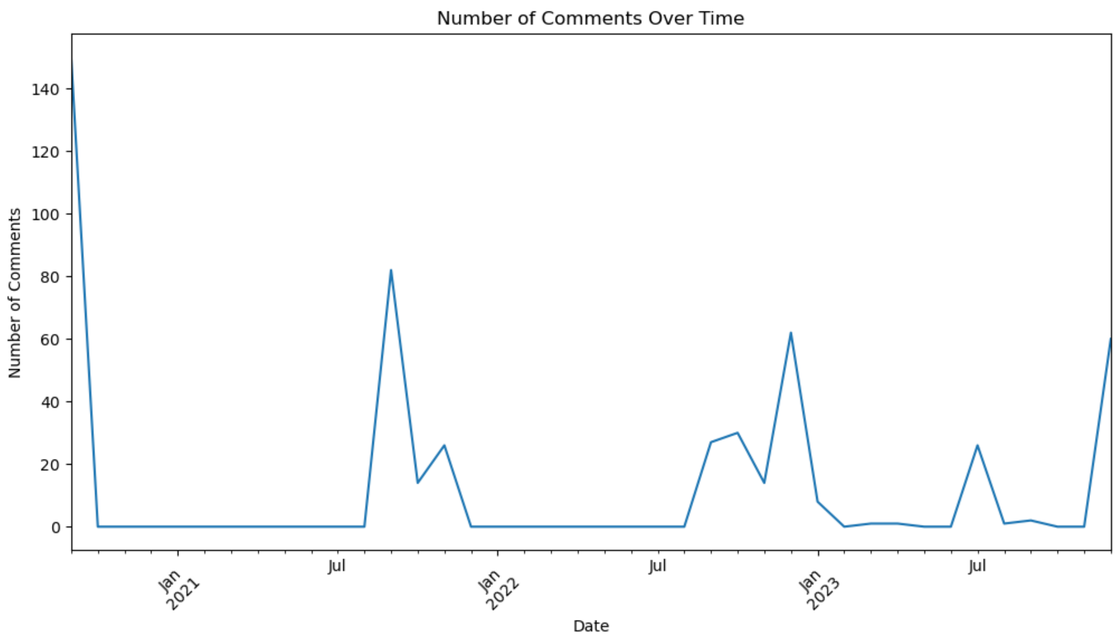





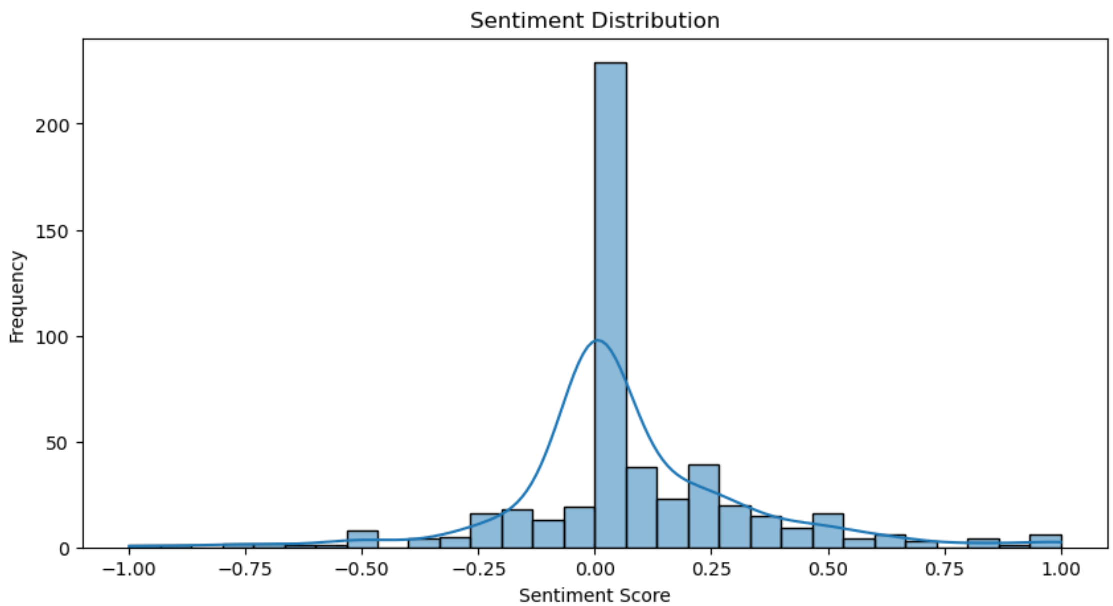
0.4 Step 4: Sentiment Analysis

[11]:
```python
from textblob import TextBlob

# Define a function to calculate sentiment
def get_sentiment(text):
    analysis = TextBlob(text)
    return analysis.sentiment.polarity

# Apply the sentiment function to the 'Text' column
df['Sentiment'] = df['text'].apply(get_sentiment)

# Display the first few rows with sentiment scores
print(df[['text', 'Sentiment']].head())

# Visualize sentiment distribution
plt.figure(figsize=(10, 5))
sns.histplot(df['Sentiment'], bins=30, kde=True)
plt.title('Sentiment Distribution')
plt.xlabel('Sentiment Score')
plt.ylabel('Frequency')
plt.show()
```

```
                                                text  Sentiment
0  Neat comparison I have not heard it before.\n …   0.000000
1  An excellent way to visualise the invisible! T…   0.600000
```

```
2  Does the CO2/ghg in the troposphere affect the…   0.000000
3  excellent post! I defo feel the difference - o…   0.053571
4  Yes, and carbon dioxide does not harm the Eart…  -0.375000
```

```
C:\Users\tikul\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119:
FutureWarning: use_inf_as_na option is deprecated and will be removed in a
future version. Convert inf values to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
```



0.5 Step 5: Save Cleaned Data

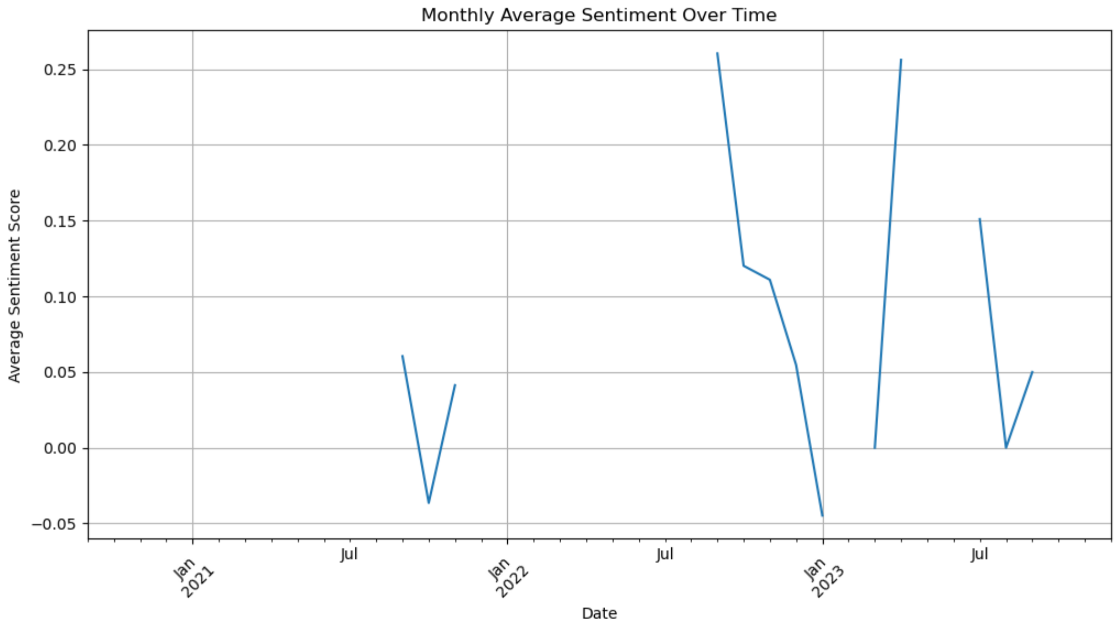
[12]:
```
df.to_csv('cleaned_comments_data.csv', index=False)
```

0.6 Step 6: Trend Analysis

0.6.1 6.1 Sentiment Trend Over Time

[14]:
```
# Resampling sentiment scores by month
monthly_sentiment = df.resample('M', on='date')['Sentiment'].mean()

# Plotting the trend of sentiment over time
plt.figure(figsize=(12, 6))
monthly_sentiment.plot()
plt.title('Monthly Average Sentiment Over Time')
plt.xlabel('Date')
plt.ylabel('Average Sentiment Score')
plt.xticks(rotation=45)
plt.grid()
```

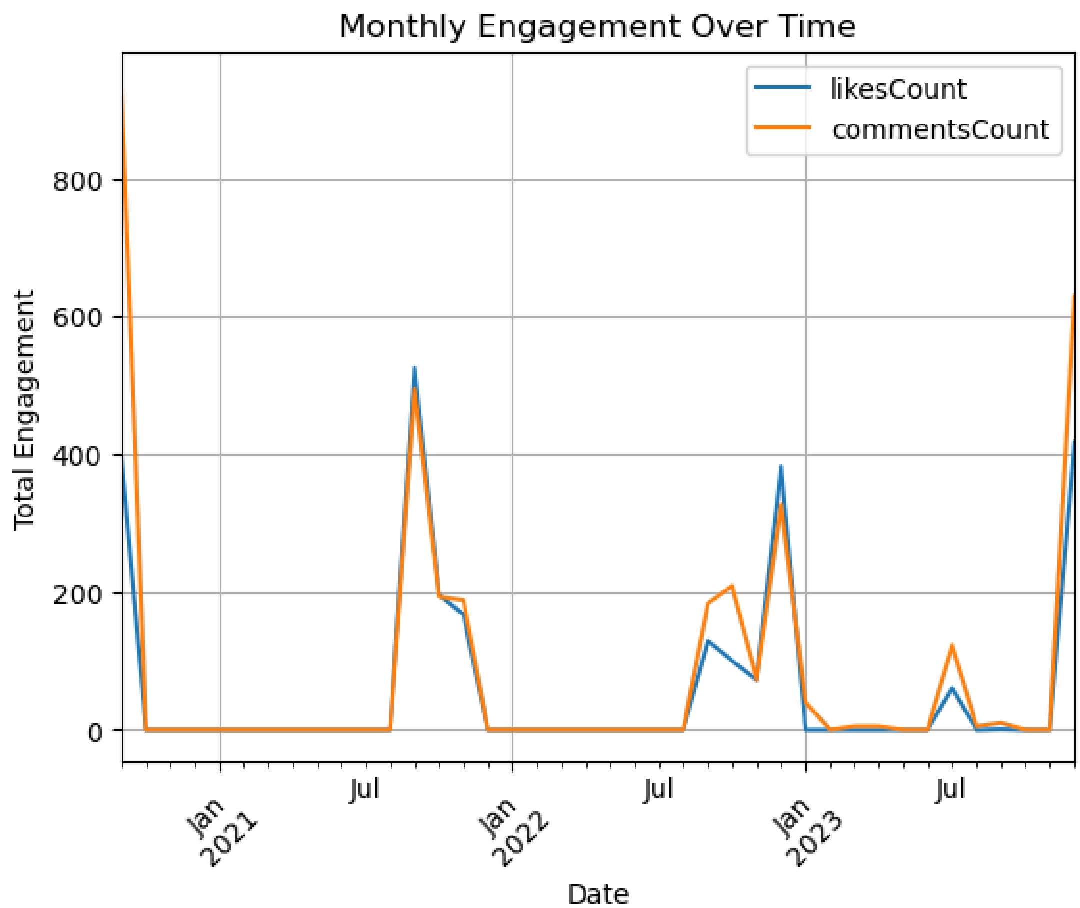
```
plt.show()
```



0.6.2 6.2 Engagement Trend Over Time

[19]:
```
# Resampling likesCount and commentsCount by month
monthly_engagement = df.resample('M', on='date').agg({'likesCount': 'sum',␣
↪'commentsCount': 'sum'})

# Plotting the trends
plt.figure(figsize=(12, 6))
monthly_engagement.plot()
plt.title('Monthly Engagement Over Time')
plt.xlabel('Date')
plt.ylabel('Total Engagement')
plt.xticks(rotation=45)
plt.grid()
plt.show()
```

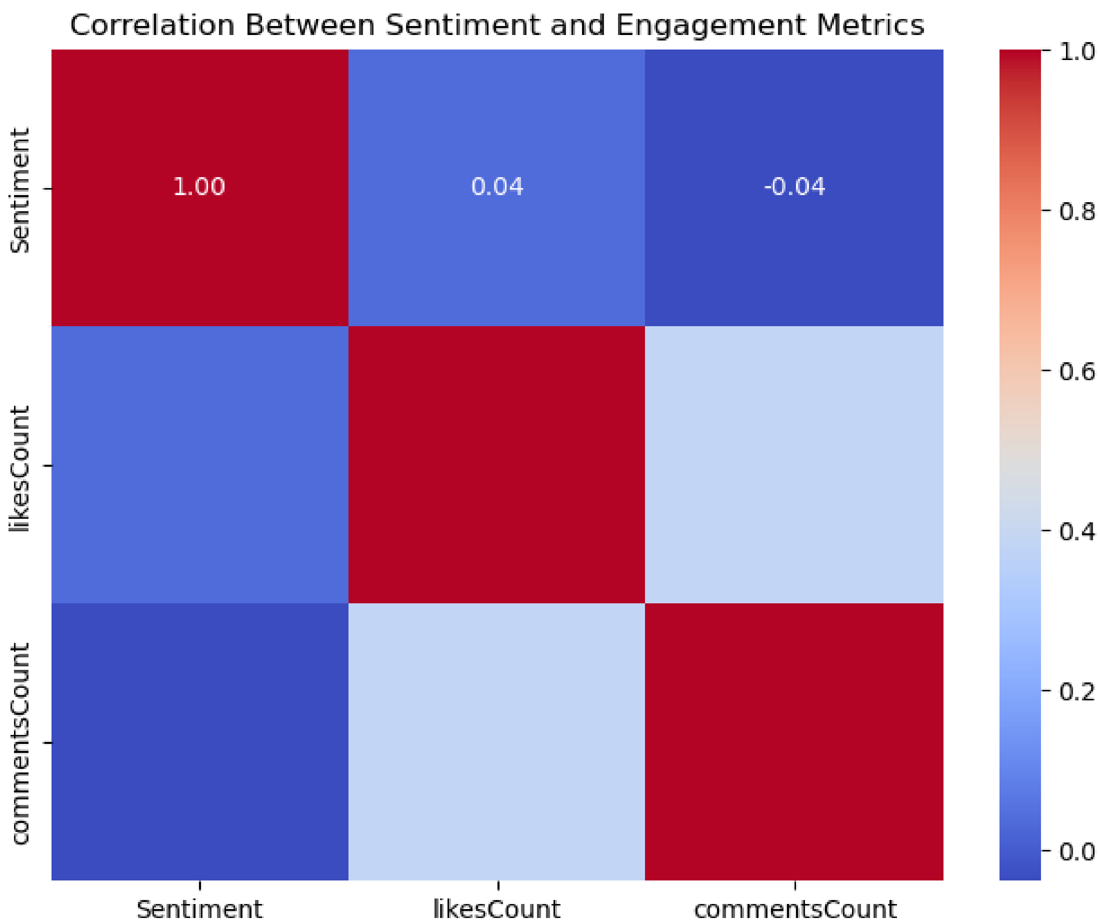
```
<Figure size 1200x600 with 0 Axes>
```



0.7 Step 7: Engagement Analysis

[21]:
```
# Calculate correlation between sentiment and engagement metrics
correlation = df[['Sentiment', 'likesCount', 'commentsCount']].corr()
print(correlation)

# Visualize the correlation matrix
plt.figure(figsize=(8, 6))
sns.heatmap(correlation, annot=True, cmap='coolwarm', fmt='.2f')
plt.title('Correlation Between Sentiment and Engagement Metrics')
plt.show()
```

```
               Sentiment  likesCount  commentsCount
Sentiment       1.000000    0.035299      -0.038887
likesCount      0.035299    1.000000       0.385142
commentsCount  -0.038887    0.385142       1.000000
```



0.8 Step 8: Topic Modeling

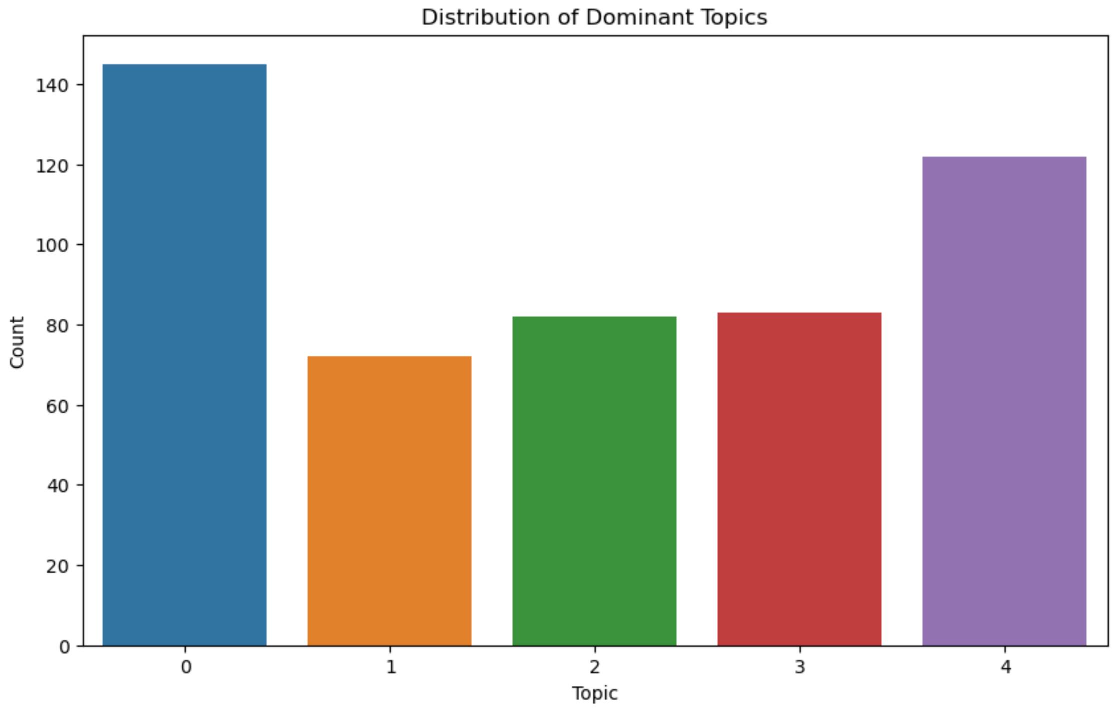
[22]:
```python
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.decomposition import LatentDirichletAllocation

# Preprocess the text data
vectorizer = CountVectorizer(stop_words='english')
text_matrix = vectorizer.fit_transform(df['text'])  # Use the original 'text'␣
↪column

# Apply LDA
lda = LatentDirichletAllocation(n_components=5, random_state=0)  # You can␣
↪adjust n_components
lda.fit(text_matrix)

# Display the topics
def display_topics(model, feature_names, no_top_words):
```

```
    for topic_idx, topic in enumerate(model.components_):
        print(f"Topic {topic_idx}:")
        print(" ".join([feature_names[i] for i in topic.argsort()[:
 ↪-no_top_words - 1:-1]]))

display_topics(lda, vectorizer.get_feature_names_out(), 5)
```

```
Topic 0:
global temperature climate warming change
Topic 1:
co2 climate heat earth change
Topic 2:
carbon sea earth atmosphere dioxide
Topic 3:
climate warming global change people
Topic 4:
climate change earth nasa planet
```

0.8.1 Topic Distribution Visualization

[26]:
```
topic_distribution = lda.transform(text_matrix)

# Add the dominant topic for each comment to the DataFrame
df['Dominant Topic'] = topic_distribution.argmax(axis=1)

# Plot the distribution of topics
plt.figure(figsize=(10, 6))
sns.countplot(x='Dominant Topic', data=df)
plt.title('Distribution of Dominant Topics')
plt.xlabel('Topic')
plt.ylabel('Count')
plt.show()
```



Distribution of Dominant Topics
0
20
40
60
80
100
120
140
Count
0
1
2
3
4
Topic


```
[ ]:
```