In [3]:
```
# section 2.1 Processing and Import necessary libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import missingno as msno

# Load the dataset
df = pd.read_csv("/content/The Climate Change Twitter Dataset.csv")

# Display first 5 rows
print("First 5 rows of the dataset:")
display(df.head())

# Shape of the dataset
print(f"Dataset contains {df.shape[0]} rows and {df.shape[1]} columns.")

# Data types and missing values
print("\nData info:")
df.info()

# Summary statistics for numeric and categorical features
print("\nSummary statistics (numeric):")
display(df.describe())

print("\nSummary statistics (categorical):")
display(df.describe(include='object'))

# Check missing values
print("\nMissing values count:")
display(df.isnull().sum())

# Visualize missing values
msno.matrix(df)
plt.title("Missing Value Matrix")
plt.show()
```

```
First 5 rows of the dataset:
```

	created_at	id	lng	lat	topic	sentiment	stance	gender	temperature_avg	aggressiveness
0	2006-06-06 16:06:42+00:00	6132	NaN	NaN	Weather Extremes	-0.097180	neutral	female	NaN	aggressive
1	2006-07-23 21:52:30+00:00	13275	-73.949582	40.650104	Weather Extremes	0.575777	neutral	undefined	-1.114768	aggressive
2	2006-08-29 01:52:30+00:00	23160	NaN	NaN	Weather Extremes	0.500479	neutral	male	NaN	aggressive
3	2006-11-07 02:46:52+00:00	57868	NaN	NaN	Weather Extremes	0.032816	neutral	male	NaN	aggressive
4	2006-11-27 14:27:43+00:00	304553	NaN	NaN	Importance of Human Intervantion	-0.090428	neutral	male	NaN	aggressive

```
Dataset contains 15789411 rows and 10 columns.

Data info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 15789411 entries, 0 to 15789410
Data columns (total 10 columns):
 #   Column           Dtype  
---  ------           -----  
 0   created_at       object 
 1   id               int64  
 2   lng              float64
 3   lat              float64
 4   topic            object 
 5   sentiment        float64
 6   stance           object 
 7   gender           object 
 8   temperature_avg  float64
 9   aggressiveness   object 
dtypes: float64(4), int64(1), object(5)
memory usage: 1.2+ GB

Summary statistics (numeric):
```

	id	lng	lat	sentiment	temperature_avg
count	1.578941e+07	5.307538e+06	5.307538e+06	1.578941e+07	5.307538e+06
mean	8.459853e+17	-4.639117e+01	3.408025e+01	2.536663e-03	1.245156e+00
std	3.113522e+17	7.523162e+01	2.229430e+01	4.379192e-01	3.799786e+00
min	6.132000e+03	-1.796670e+02	-9.000000e+01	-9.942049e-01	-2.328904e+01
25%	7.354169e+17	-9.536327e+01	3.315067e+01	-3.957429e-01	-1.140978e+00
50%	9.564851e+17	-7.703637e+01	3.995233e+01	-2.328273e-03	1.211522e+00
75%	1.049540e+18	-1.483154e-01	4.550884e+01	4.161248e-01	3.867153e+00
max	1.178912e+18	1.793830e+02	8.500000e+01	9.917458e-01	2.100350e+01

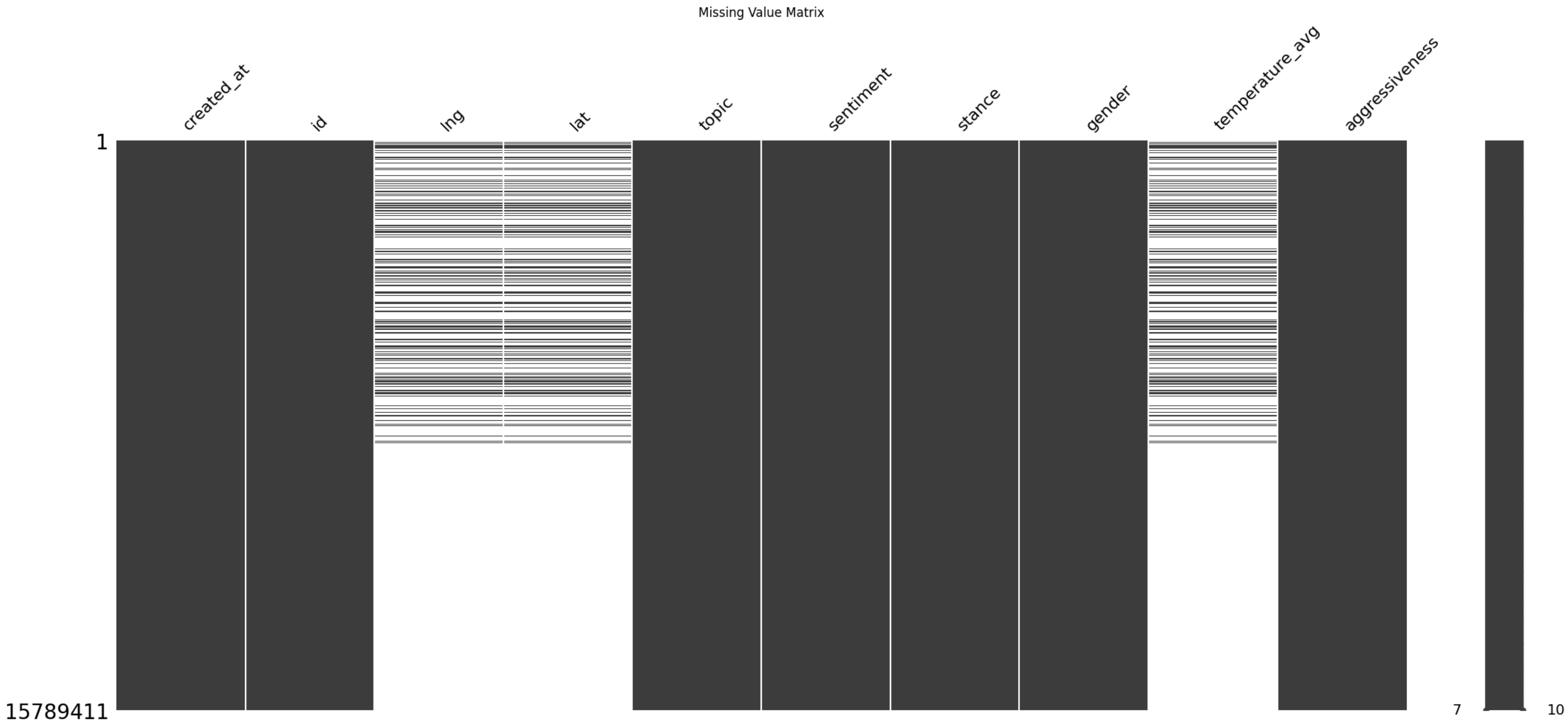
```
Summary statistics (categorical):
```

	created_at	topic	stance	gender	aggressiveness
count	15789411	15789411	15789411	15789411	15789411
unique	13390455	10	3	3	2
top	2016-09-25 19:35:06+00:00	Global stance	believer	male	not aggressive
freq	68	4135619	11292424	10307402	11262144

```
Missing values count:
```

	0
created_at	0
id	0
lng	10481873
lat	10481873
topic	0
sentiment	0
stance	0
gender	0
temperature_avg	10481873
aggressiveness	0

dtype: int64



In [4]:
```
# Drop rows with missing values for key predictive features
df_cleaned = df[['id','created_at','lng','lat','sentiment', 'temperature_avg', 'gender', 'stance', 'topic', 'aggressiveness']]
print("First 5 rows of the dataset:")
df_cleaned['created_at'] = pd.to_datetime(df_cleaned['created_at'], errors='coerce')
display(df_cleaned.head())
```

```
First 5 rows of the dataset:
```

	id	created_at	lng	lat	sentiment	temperature_avg	gender	stance	topic	aggressiveness
1	13275	2006-07-23 21:52:30+00:00	-73.949582	40.650104	0.575777	-1.114768	undefined	neutral	Weather Extremes	aggressive
7	1092823	2006-12-14 01:39:10+00:00	-122.419420	37.774930	-0.544195	4.228540	male	neutral	Ideological Positions on Global Warming	aggressive
8	1278023	2006-12-17 19:43:09+00:00	-79.791980	36.072640	-0.565028	5.478175	male	denier	Weather Extremes	aggressive
9	1455543	2006-12-21 01:39:01+00:00	-121.805790	38.004920	0.650960	-1.652156	male	neutral	Weather Extremes	not aggressive
11	1893063	2006-12-31 10:47:25+00:00	-1.902691	52.479699	0.670905	4.864521	male	neutral	Weather Extremes	aggressive

In [ ]:

```
```

In [5]:

```python
#Data Transformation- Encoding Categorical Variables
from sklearn.preprocessing import LabelEncoder

# Initialize dictionary to hold the encoders
encoders = {}

# Iterate over the categorical columns and encode them
for col in ['gender', 'stance', 'topic', 'aggressiveness']:
    le = LabelEncoder()
    original_values = df_cleaned[col].copy()  # Save original values for display
    encoded_column_name = f"{col}_encoded"  # Name for encoded column

    # Create a new column for the encoded values
    df_cleaned[encoded_column_name] = le.fit_transform(df_cleaned[col])

    # Store the encoder for possible future inverse transformation
    encoders[col] = le

    # Display actual value and encoded value side-by-side
    print(f"\nEncoding for column: {col}")
```

```python
    mapping = dict(zip(le.classes_, le.transform(le.classes_)))
    for label, val in mapping.items():
        print(f"  {label} -> {val}")

# Check the first few rows to confirm
#print("\nSample of DataFrame with original and encoded columns:")
#print(df_cleaned.head())
print("First 5 rows of the dataset:")
display(df_cleaned.head())
```

```
Encoding for column: gender
  female -> 0
  male -> 1
  undefined -> 2

Encoding for column: stance
  believer -> 0
  denier -> 1
  neutral -> 2

Encoding for column: topic
  Donald Trump versus Science -> 0
  Global stance -> 1
  Ideological Positions on Global Warming -> 2
  Impact of Resource Overconsumption -> 3
  Importance of Human Intervention -> 4
  Politics -> 5
  Seriousness of Gas Emissions -> 6
  Significance of Pollution Awareness Events -> 7
  Undefined / One Word Hashtags -> 8
  Weather Extremes -> 9

Encoding for column: aggressiveness
  aggressive -> 0
  not aggressive -> 1
First 5 rows of the dataset:
```

	id	created_at	lng	lat	sentiment	temperature_avg	gender	stance	topic	aggressiveness	gender_enc
1	13275	2006-07-23 21:52:30+00:00	-73.949582	40.650104	0.575777	-1.114768	undefined	neutral	Weather Extremes	aggressive	
7	1092823	2006-12-14 01:39:10+00:00	-122.419420	37.774930	-0.544195	4.228540	male	neutral	Ideological Positions on Global Warming	aggressive	
8	1278023	2006-12-17 19:43:09+00:00	-79.791980	36.072640	-0.565028	5.478175	male	denier	Weather Extremes	aggressive	
9	1455543	2006-12-21 01:39:01+00:00	-121.805790	38.004920	0.650960	-1.652156	male	neutral	Weather Extremes	not aggressive	
11	1893063	2006-12-31 10:47:25+00:00	-1.902691	52.479699	0.670905	4.864521	male	neutral	Weather Extremes	aggressive	

In [ ]:

In [6]:
```python
#Scaling Numerical Features
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
df_cleaned[['sentiment', 'temperature_avg']] = scaler.fit_transform(df_cleaned[['sentiment', 'temperature_avg']])
```

In [7]:
```python
#Dimensionality Reduction
from sklearn.decomposition import PCA

# Selecting numeric columns for PCA
features = df_cleaned[['sentiment', 'temperature_avg']]
pca = PCA(n_components=2)
principal_components = pca.fit_transform(features)

df_cleaned[['PC1', 'PC2']] = principal_components
```

In [8]:
```
#Data Wrangling Operations
# Clean category labels and lowercase
df_cleaned['gender'] = df_cleaned['gender'].astype(str).str.lower().str.strip()
df_cleaned['stance'] = df_cleaned['stance'].astype(str).str.lower().str.strip()
df_cleaned['topic'] = df_cleaned['topic'].astype(str).str.lower().str.strip()
```

In [ ]:
```
# Preparation for Modeling
#X = df_cleaned.drop(columns=['aggressiveness'])  # Features
#y = df_cleaned['aggressiveness']                # Target
```

In [11]:
```
#Descriptive Analytics
# Shape of the dataset
print(f"Dataset contains {df_cleaned.shape[0]} rows and {df_cleaned.shape[1]} columns.")

# Data types and missing values
print("\nData info:")
df_cleaned.info()

# Summary statistics for numeric and categorical features
print("\nSummary statistics (numeric):")
display(df_cleaned.describe())

print("\nSummary statistics (categorical):")
display(df_cleaned.describe(include='object'))

# Check missing values
print("\nMissing values count:")
display(df_cleaned.isnull().sum())
```

```
Dataset contains 5307538 rows and 16 columns.

Data info:
<class 'pandas.core.frame.DataFrame'>
Index: 5307538 entries, 1 to 15789408
Data columns (total 16 columns):
 #   Column                  Dtype
---  ------                  -----
 0   id                      int64
 1   created_at              datetime64[ns, UTC]
 2   lng                     float64
 3   lat                     float64
 4   sentiment               float64
 5   temperature_avg         float64
 6   gender                  object
 7   stance                  object
 8   topic                   object
 9   aggressiveness          object
 10  gender_encoded          int64
 11  stance_encoded          int64
 12  topic_encoded           int64
 13  aggressiveness_encoded  int64
 14  PC1                     float64
 15  PC2                     float64
dtypes: datetime64[ns, UTC](1), float64(6), int64(5), object(4)
memory usage: 688.4+ MB

Summary statistics (numeric):
```

	id	lng	lat	sentiment	temperature_avg	gender_encoded	stance_encoded	topic_encoded	aggr
count	5.307538e+06	5.307538e+06	5.307538e+06	5.307538e+06	5.307538e+06	5.307538e+06	5.307538e+06	5.307538e+06	
mean	8.620935e+17	-4.639117e+01	3.408025e+01	-3.847011e-17	-4.896585e-17	7.179193e-01	4.437091e-01	4.198164e+00	
std	2.953852e+17	7.523162e+01	2.229430e+01	1.000000e+00	1.000000e+00	5.134762e-01	7.884864e-01	3.028200e+00	
min	1.327500e+04	-1.796670e+02	-9.000000e+01	-2.291631e+00	-6.456731e+00	0.000000e+00	0.000000e+00	0.000000e+00	
25%	7.805130e+17	-9.536327e+01	3.315067e+01	-9.138123e-01	-6.279653e-01	0.000000e+00	0.000000e+00	1.000000e+00	
50%	9.596823e+17	-7.703637e+01	3.995233e+01	-1.637279e-02	-8.851528e-03	1.000000e+00	0.000000e+00	4.000000e+00	
75%	1.049333e+18	-1.483154e-01	4.550884e+01	9.384739e-01	6.900383e-01	1.000000e+00	1.000000e+00	7.000000e+00	
max	1.178911e+18	1.793830e+02	8.500000e+01	2.206074e+00	5.199858e+00	2.000000e+00	2.000000e+00	9.000000e+00	

```
Summary statistics (categorical):
```

	gender	stance	topic	aggressiveness
count	5307538	5307538	5307538	5307538
unique	3	3	10	2
top	male	believer	global stance	not aggressive
freq	3485846	3947378	1462525	3774449

```
Missing values count:
```

	0
id	0
created_at	0
lng	0
lat	0
sentiment	0
temperature_avg	0
gender	0
stance	0
topic	0
aggressiveness	0
gender_encoded	0
stance_encoded	0
topic_encoded	0
aggressiveness_encoded	0
PC1	0
PC2	0

dtype: int64

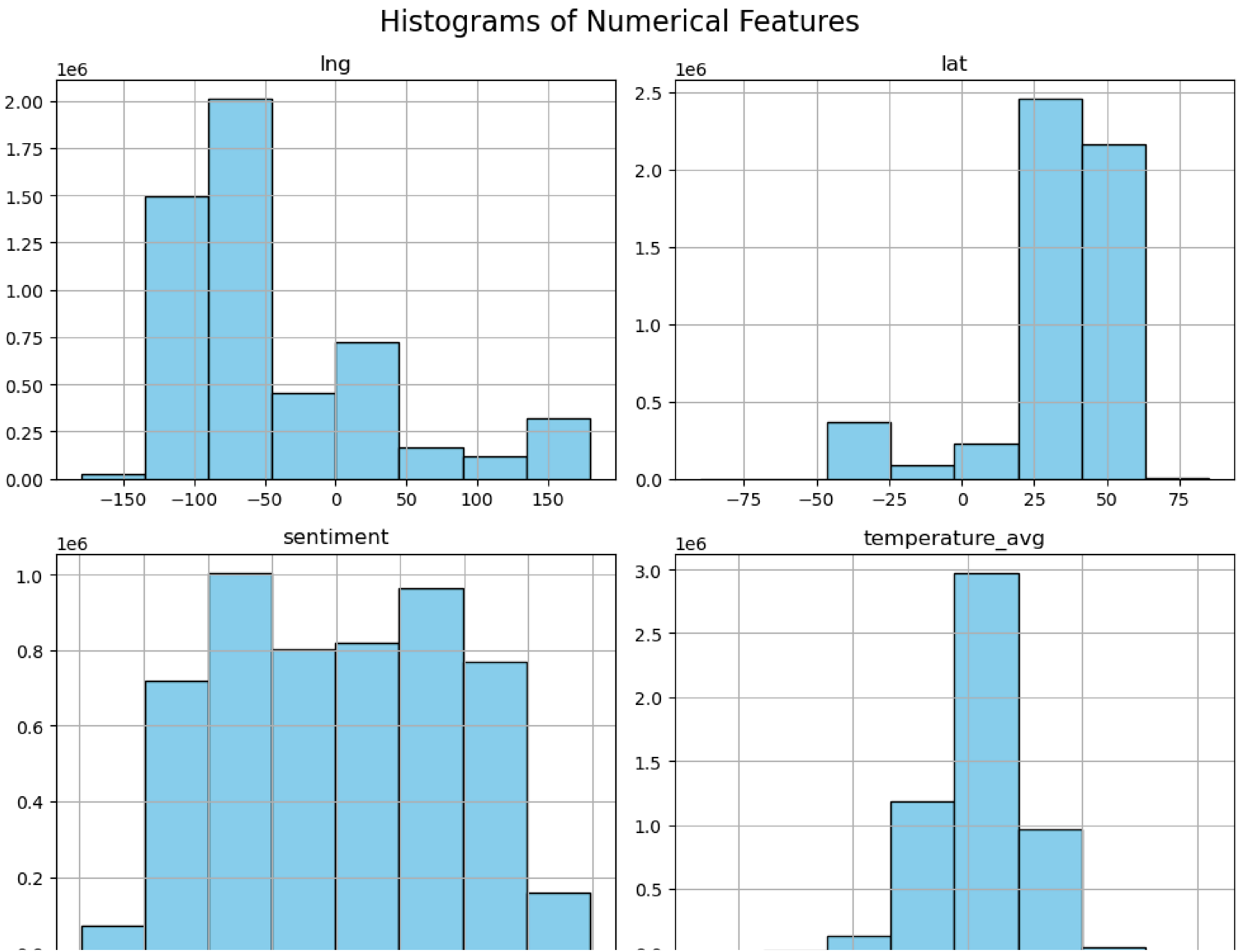
In [ ]:
```
# positive value means right
skewness = df_cleaned['sentiment'].skew()
print(f"Sentiment skewness: {skewness:.4f}")

skewness_temp = df_cleaned['temperature_avg'].skew()
print(f"Temparature skewness: {skewness_temp:.4f}")
```

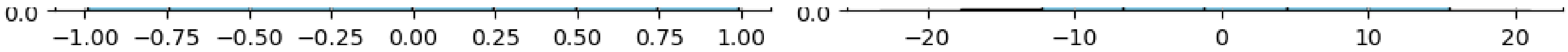
```python
skewness_lng = df_cleaned['lng'].skew()
print(f"Longitude skewness: {skewness_lng:.4f}")

skewness_lat = df_cleaned['lat'].skew()
print(f"Laitude skewness: {skewness_lat:.4f}")
```

```
Sentiment skewness: 0.0244
Temparature skewness: -0.2713
Longitude skewness: 1.2814
Laitude skewness: -2.0892
```

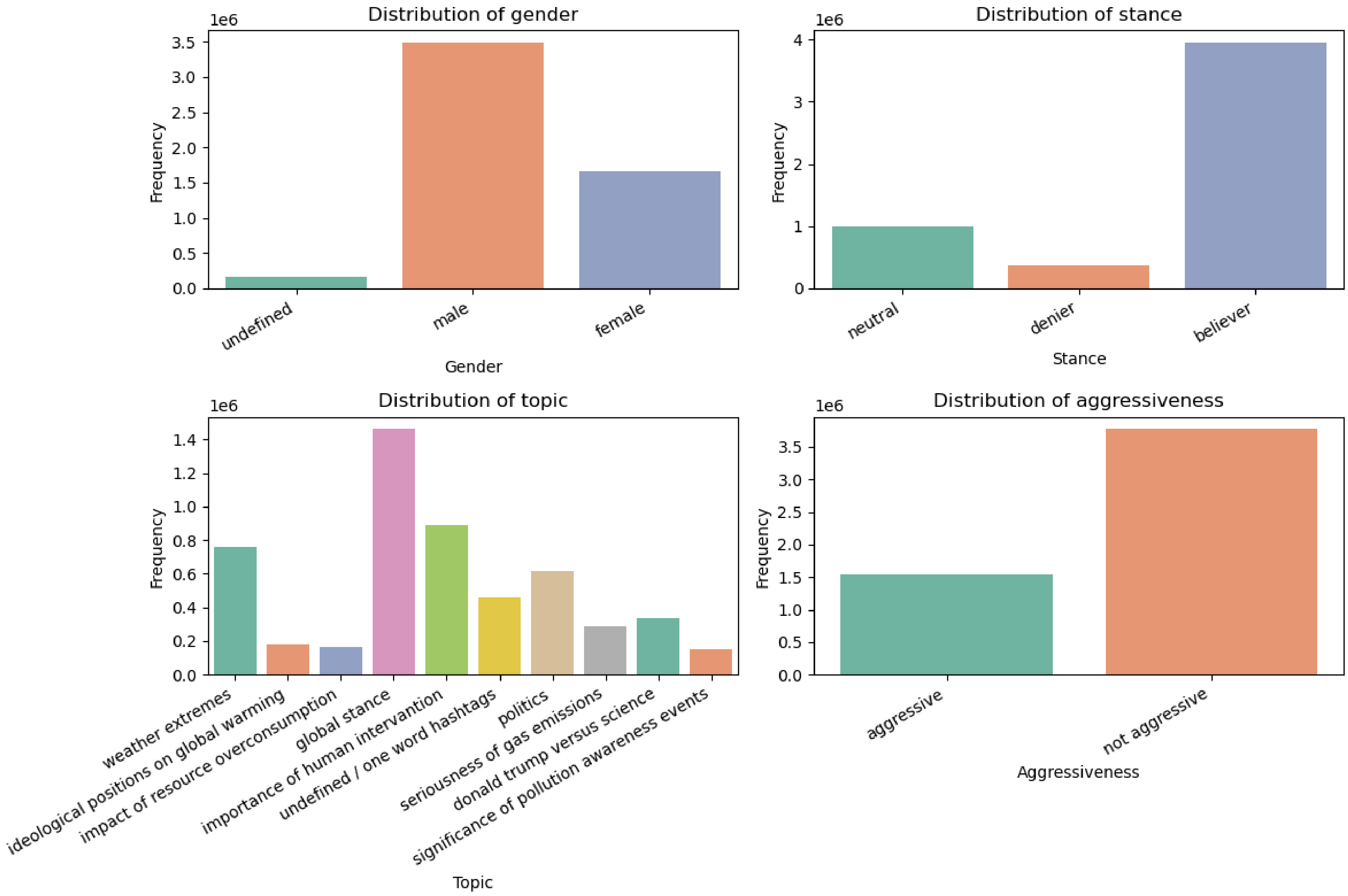
In [ ]:

```python
#Histograms (Distribution Analysis)
df_cleaned[['lng', 'lat', 'sentiment', 'temperature_avg']].hist(
    bins=8, figsize=(10, 8), color='skyblue', edgecolor='black'
)
plt.suptitle("Histograms of Numerical Features", fontsize=16)
plt.tight_layout()
plt.show()
```


Histograms of Numerical Features
lng
1e6
2.00
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00
−150 −100 −50 0 50 100 150
lat
1e6
2.5
2.0
1.5
1.0
0.5
0.0
−75 −50 −25 0 25 50 75
sentiment
1e6
1.0
0.8
0.6
0.4
0.2
temperature_avg
1e6
3.0
2.5
2.0
1.5
1.0
0.5

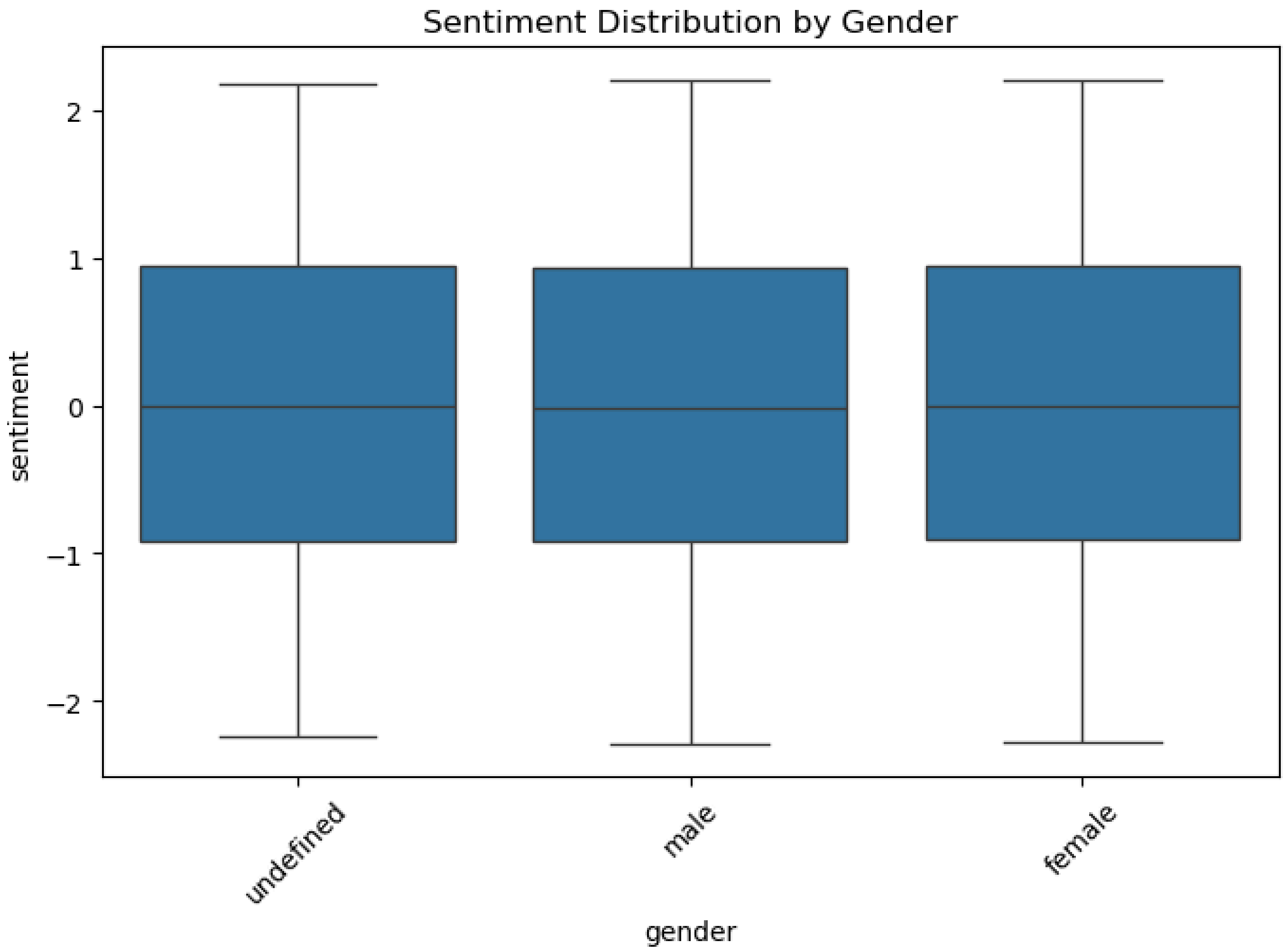


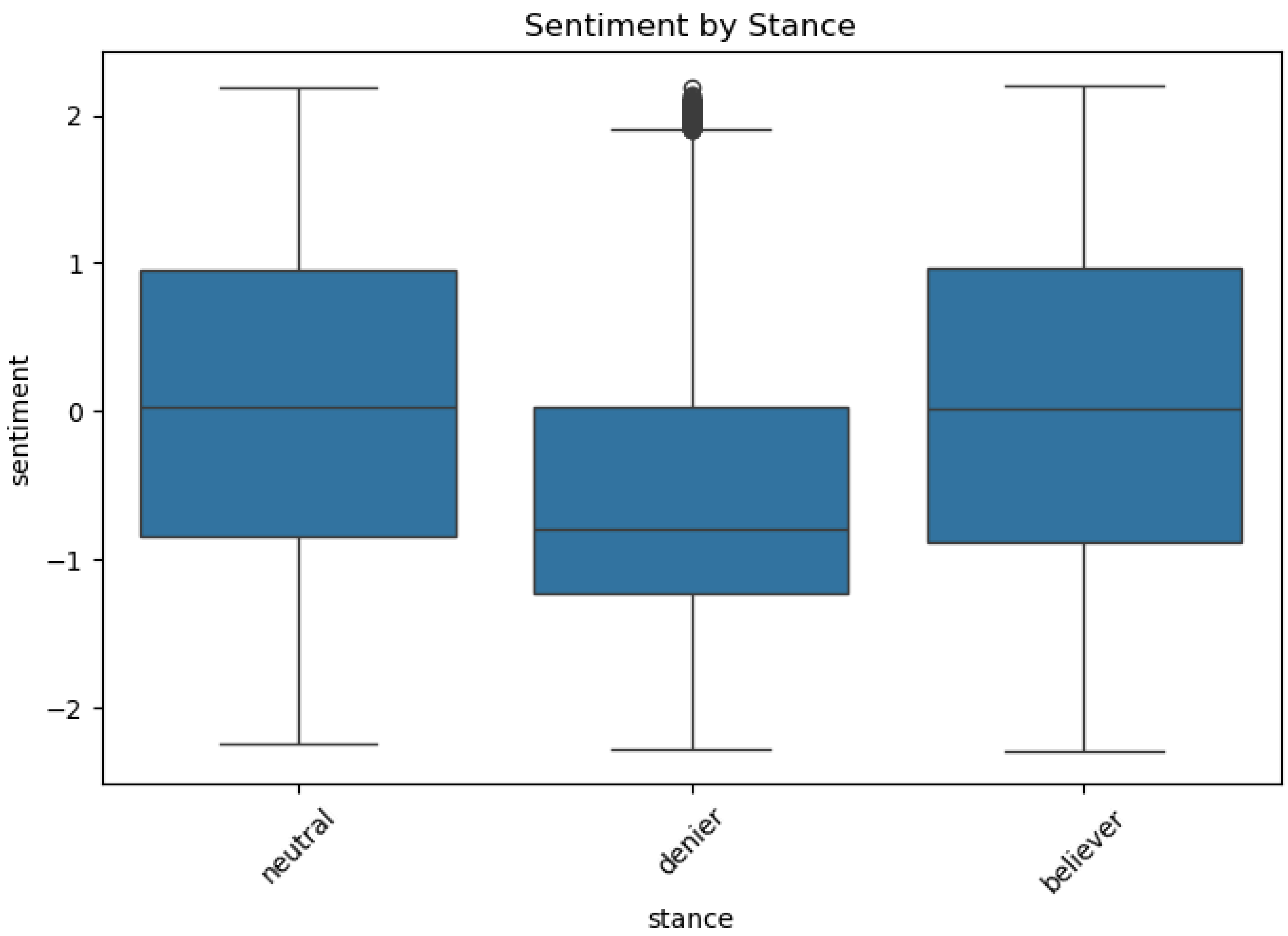
In [ ]:
```
#bar chart Count of Categorical Variables
import seaborn as sns
import matplotlib.pyplot as plt

categorical_cols = ['gender', 'stance', 'topic', 'aggressiveness']

fig, axes = plt.subplots(2, 2, figsize=(12, 8))
for ax, col in zip(axes.flatten(), categorical_cols):
    sns.countplot(data=df_cleaned, x=col, hue=col, palette="Set2", legend=False, ax=ax)
    ax.set_title(f"Distribution of {col}")
    ax.set_ylabel("Frequency")
    ax.set_xlabel(col.capitalize())
    plt.setp(ax.get_xticklabels(), rotation=30, ha="right")  # <- correct and safe way
plt.tight_layout()
plt.show()
```



In [ ]:
```
#Compare distributions across groups like gender and stance
plt.figure(figsize=(8, 5))
sns.boxplot(x='gender', y='sentiment', data=df_cleaned)
```

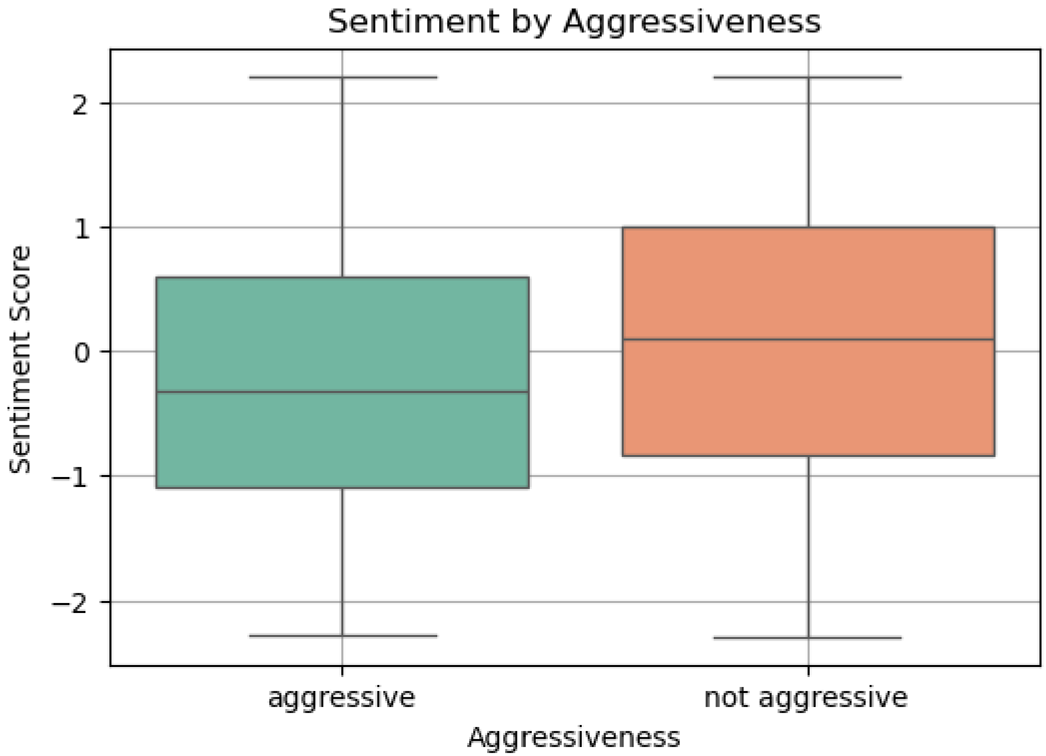
```
plt.title('Sentiment Distribution by Gender')
plt.xticks(rotation=45)
plt.show()

plt.figure(figsize=(8, 5))
sns.boxplot(x='stance', y='sentiment', data=df_cleaned)
plt.title('Sentiment by Stance')
plt.xticks(rotation=45)
plt.show()
```





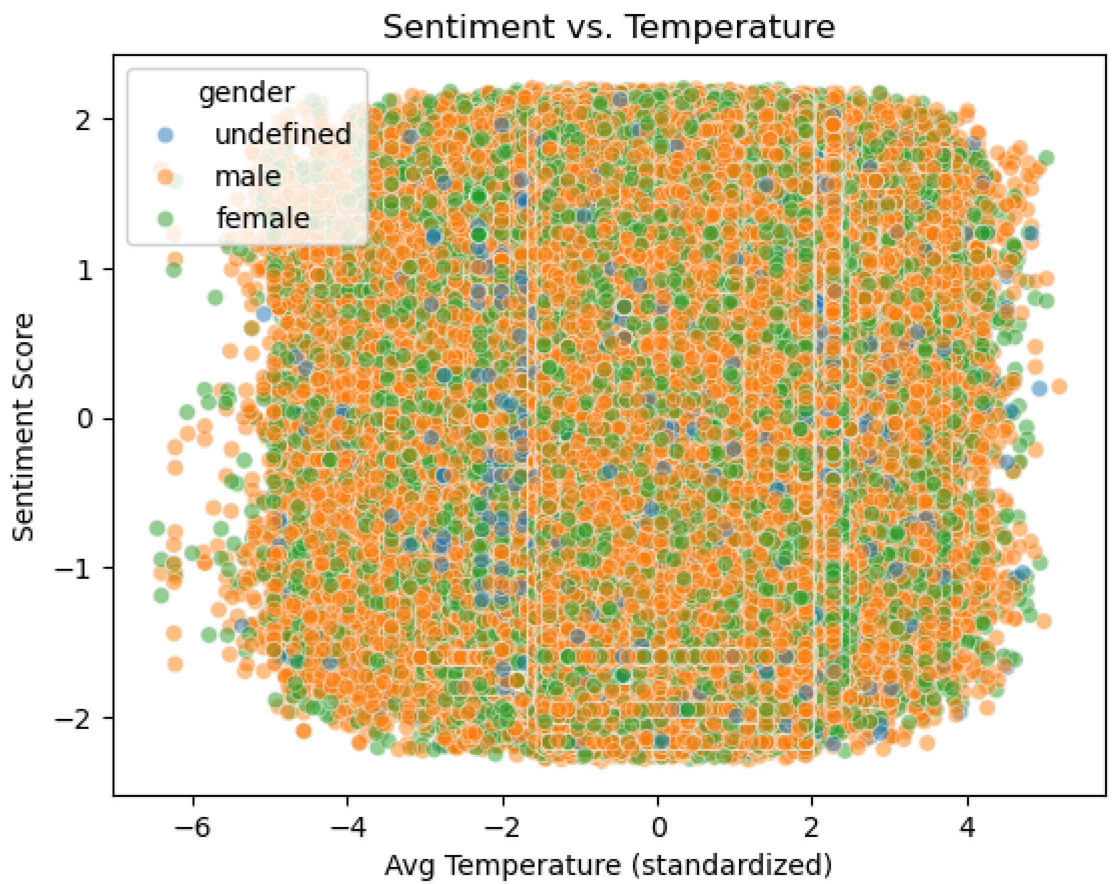
In [ ]:
```
#Boxplot: Sentiment by Aggressiveness
plt.figure(figsize=(6, 4))
sns.boxplot(data=df_cleaned, x='aggressiveness', y='sentiment', palette='Set2')
plt.title('Sentiment by Aggressiveness')
plt.ylabel('Sentiment Score')
plt.xlabel('Aggressiveness')
plt.grid(True)
plt.show()
```

```
/tmp/ipykernel_8162/2581342232.py:3: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and se
t `legend=False` for the same effect.

  sns.boxplot(data=df_cleaned, x='aggressiveness', y='sentiment', palette='Set2')
```



In [ ]:
```
# Sentimenplt.figure(figsize=(8, 5))
sns.scatterplot(data=df_cleaned, x='temperature_avg', y='sentiment', hue='gender', alpha=0.5)
plt.title('Sentiment vs. Temperature')
plt.xlabel('Avg Temperature (standardized)')
plt.ylabel('Sentiment Score')
plt.show()
```

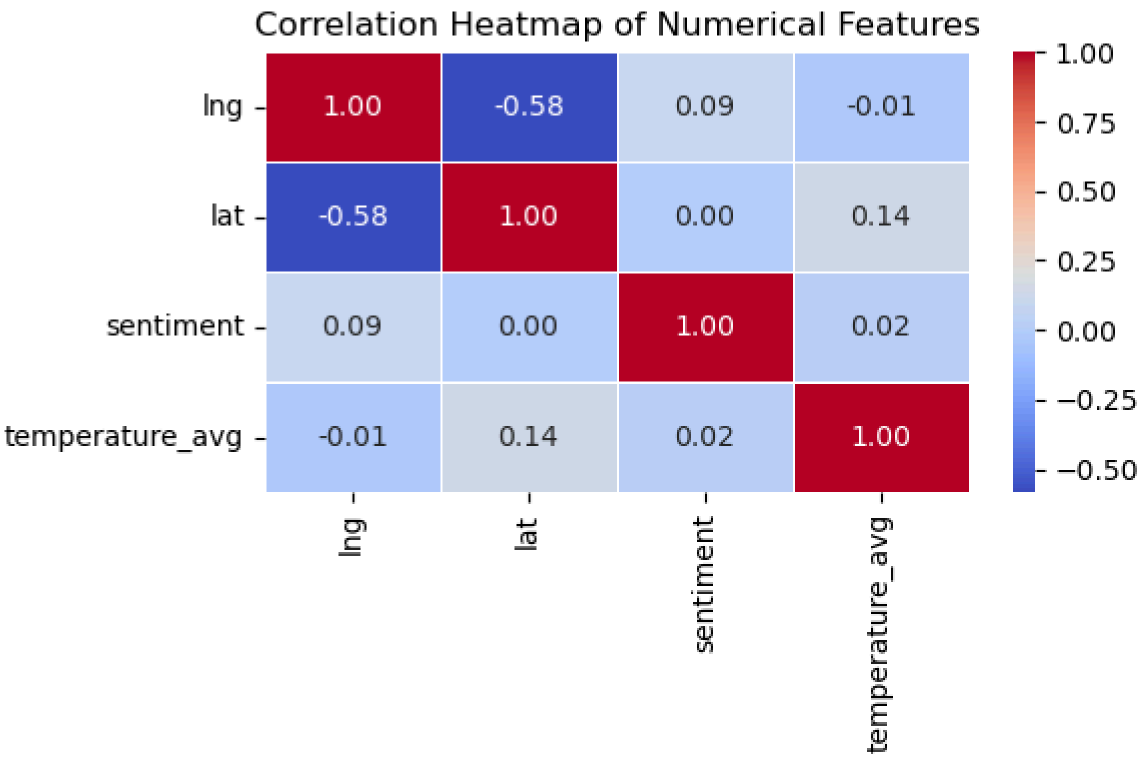
```
/home/opc/anaconda3/lib/python3.12/site-packages/IPython/core/pylabtools.py:170: UserWarning: Creating legend with loc="best" c
an be slow with large amounts of data.
  fig.canvas.print_figure(bytes_io, **kw)
```



In [ ]:

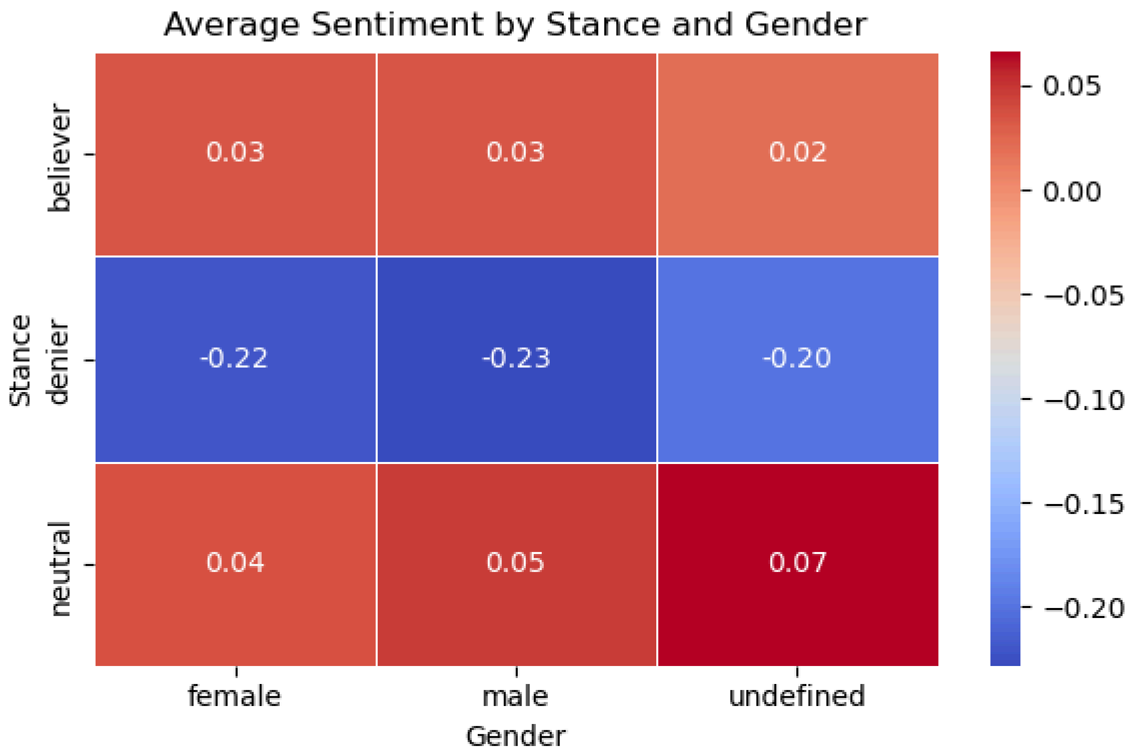
```
import seaborn as sns
import matplotlib.pyplot as plt

# Select only numerical columns
numeric_cols = ['lng', 'lat', 'sentiment', 'temperature_avg']
corr_matrix = df_cleaned[numeric_cols].corr()

# Create heatmap
plt.figure(figsize=(6, 4))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', fmt=".2f", linewidths=0.5)
plt.title('Correlation Heatmap of Numerical Features')
```

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



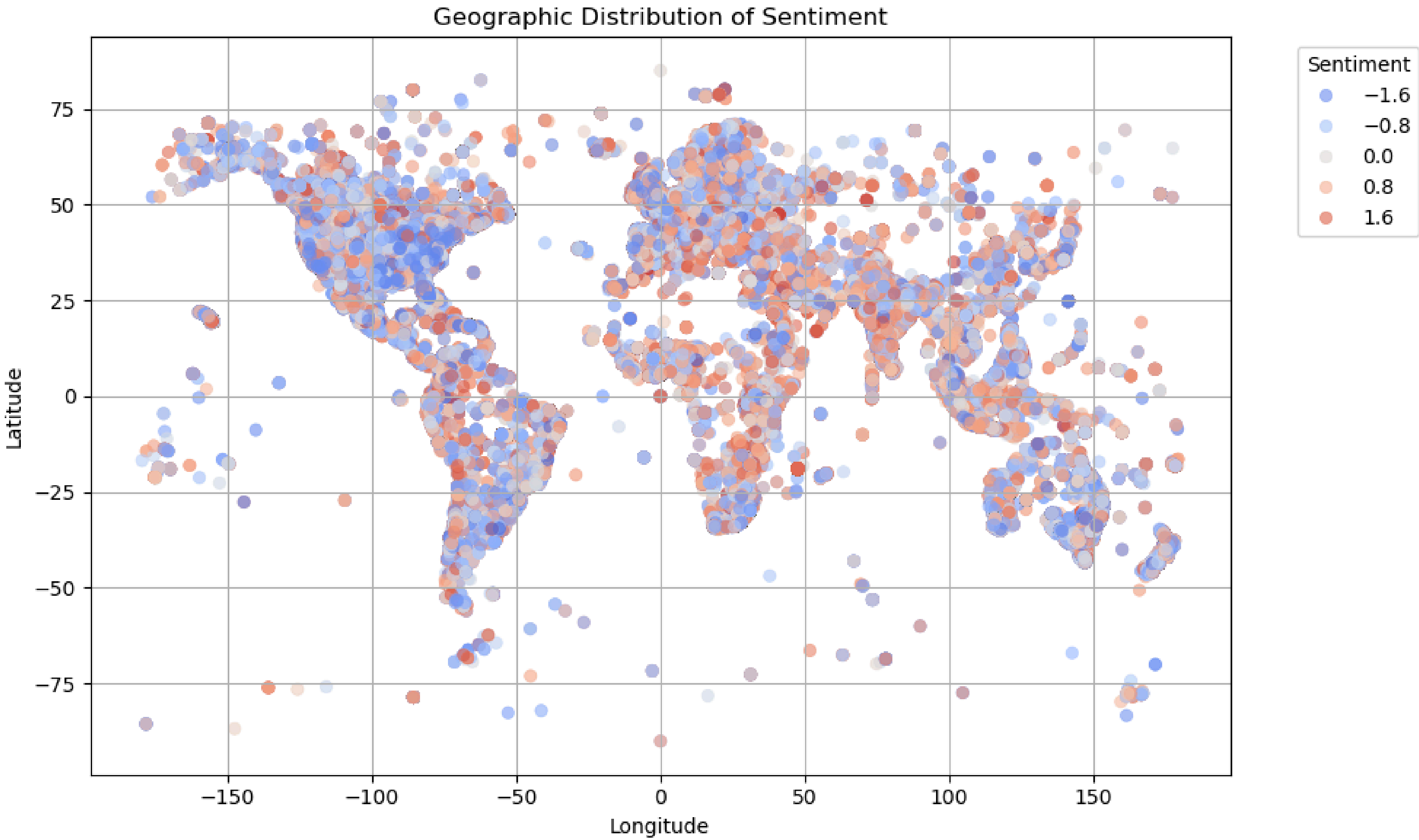
In [ ]:
```
# Create pivot table from df_cleaned
pivot_table = df_cleaned.pivot_table(
    values='sentiment',
    index='stance',
    columns='gender',
    aggfunc='mean'
)

# Plot heatmap
plt.figure(figsize=(6, 4))
sns.heatmap(pivot_table, annot=True, cmap='coolwarm', fmt=".2f", linewidths=0.5)
plt.title("Average Sentiment by Stance and Gender")
plt.xlabel("Gender")
plt.ylabel("Stance")
```

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



In [ ]:
```
plt.figure(figsize=(10, 6))
sns.scatterplot(
    data=df_cleaned,
    x='lng',         # Longitude on X-axis
    y='lat',         # Latitude on Y-axis
    hue='sentiment', # Color-coded by sentiment
    palette='coolwarm', # Blue to red color gradient
    alpha=0.6,
    edgecolor=None
)

plt.title('Geographic Distribution of Sentiment')
plt.xlabel('Longitude')
plt.ylabel('Latitude')
```

```
plt.legend(title='Sentiment', bbox_to_anchor=(1.05, 1), loc='upper left')
plt.grid(True)
plt.tight_layout()
plt.show()
```



In [ ]:
```
#descriptive for categorical feautures - Frequency Counts (Distribution)
categorical_cols = ['gender', 'stance', 'topic', 'aggressiveness']
for col in categorical_cols:
```

```
    print(f"\n{col} value counts:\n")
    display(df_cleaned[col].value_counts())
```

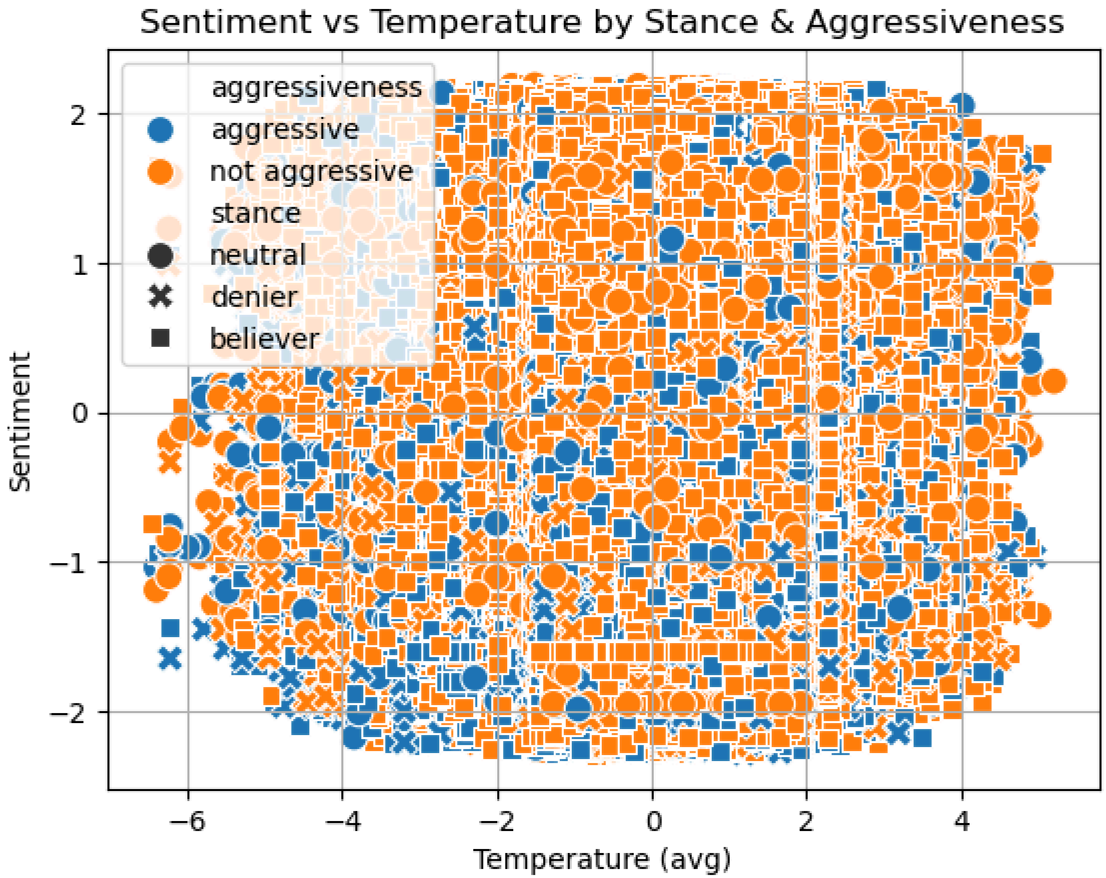
```
gender value counts:

gender
male         3485846
female       1659423
undefined     162269
Name: count, dtype: int64
stance value counts:

stance
believer    3947378
neutral      994843
denier       365317
Name: count, dtype: int64
topic value counts:

topic
global stance                                 1462525
importance of human intervention               889463
weather extremes                               761129
politics                                       618945
undefined / one word hashtags                  458904
donald trump versus science                    333777
seriousness of gas emissions                   291323
ideological positions on global warming        176568
impact of resource overconsumption             164996
significance of pollution awareness events     149908
Name: count, dtype: int64
aggressiveness value counts:

aggressiveness
not aggressive    3774449
aggressive        1533089
Name: count, dtype: int64
```

In [ ]:

```
#Sentiment vs. Temperature (with Aggressiveness)
sns.scatterplot(
    data=df_cleaned,
```

```
    x='temperature_avg',
    y='sentiment',
    hue='aggressiveness',
    style='stance',
    s=100
)
plt.title("Sentiment vs Temperature by Stance & Aggressiveness")
plt.xlabel("Temperature (avg)")
plt.ylabel("Sentiment")
plt.grid(True)
plt.show()
```

```
/home/opc/anaconda3/lib/python3.12/site-packages/IPython/core/pylabtools.py:170: UserWarning: Creating legend with loc="best" c
an be slow with large amounts of data.
  fig.canvas.print_figure(bytes_io, **kw)
```



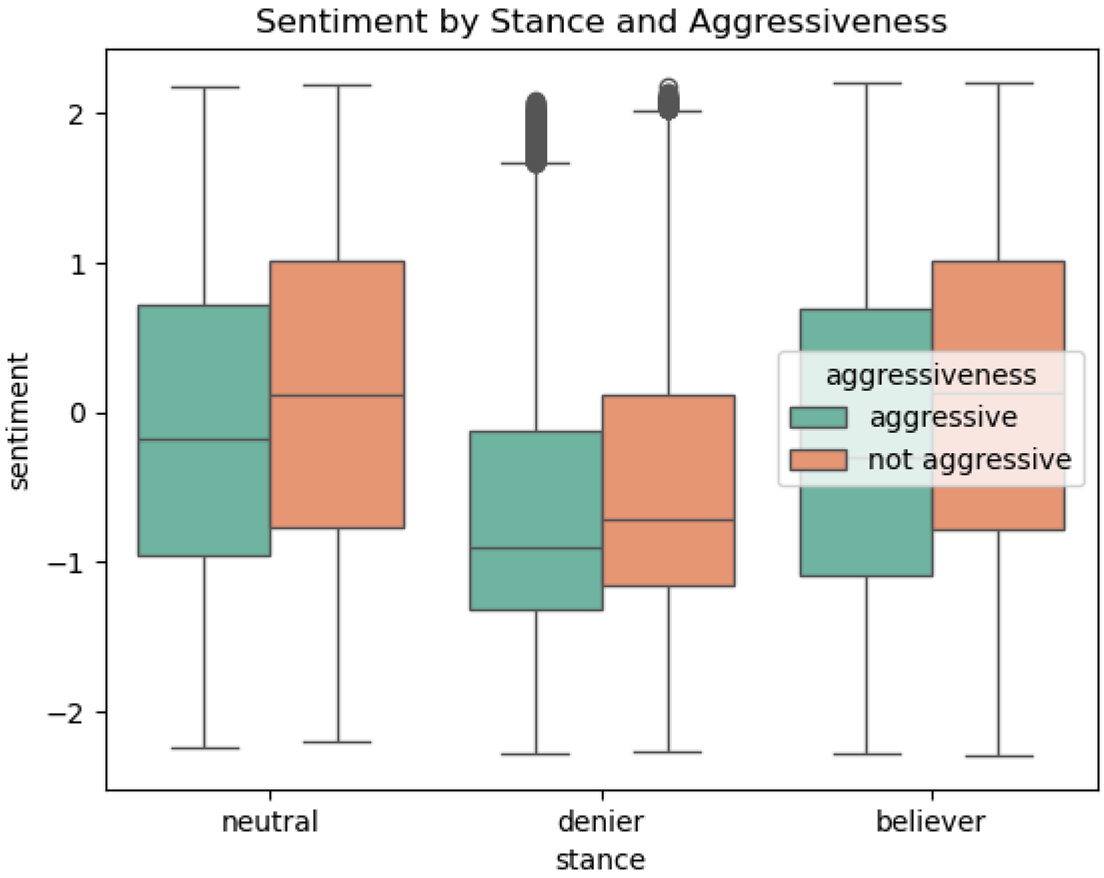
In [ ]:

```
#Cross-tabulations (e.g., stance vs aggressiveness)
pd.crosstab(df_cleaned['stance'], df_cleaned['aggressiveness'], normalize='index') * 100
```

Out[ ]:

aggressiveness	aggressive	not aggressive
stance		
believer	27.497671	72.502329
denier	42.678277	57.321723
neutral	29.325331	70.674669

In [ ]:
```
#Boxplots for Numerical Variables by Category
sns.boxplot(data=df_cleaned, x='stance', y='sentiment', hue='aggressiveness', palette='Set2')
plt.title("Sentiment by Stance and Aggressiveness")
plt.show()
```



In [ ]:
```
#Diagnostic Analytics - Hypothesis Testing - T-Test- Does gender affect sentiment?
#If p < 0.05, then gender has a significant impact on sentiment.
from scipy.stats import ttest_ind

# Extract sentiment scores by gender
male = df_cleaned[df_cleaned['gender'] == 'male']['sentiment'].dropna()
female = df_cleaned[df_cleaned['gender'] == 'female']['sentiment'].dropna()
```

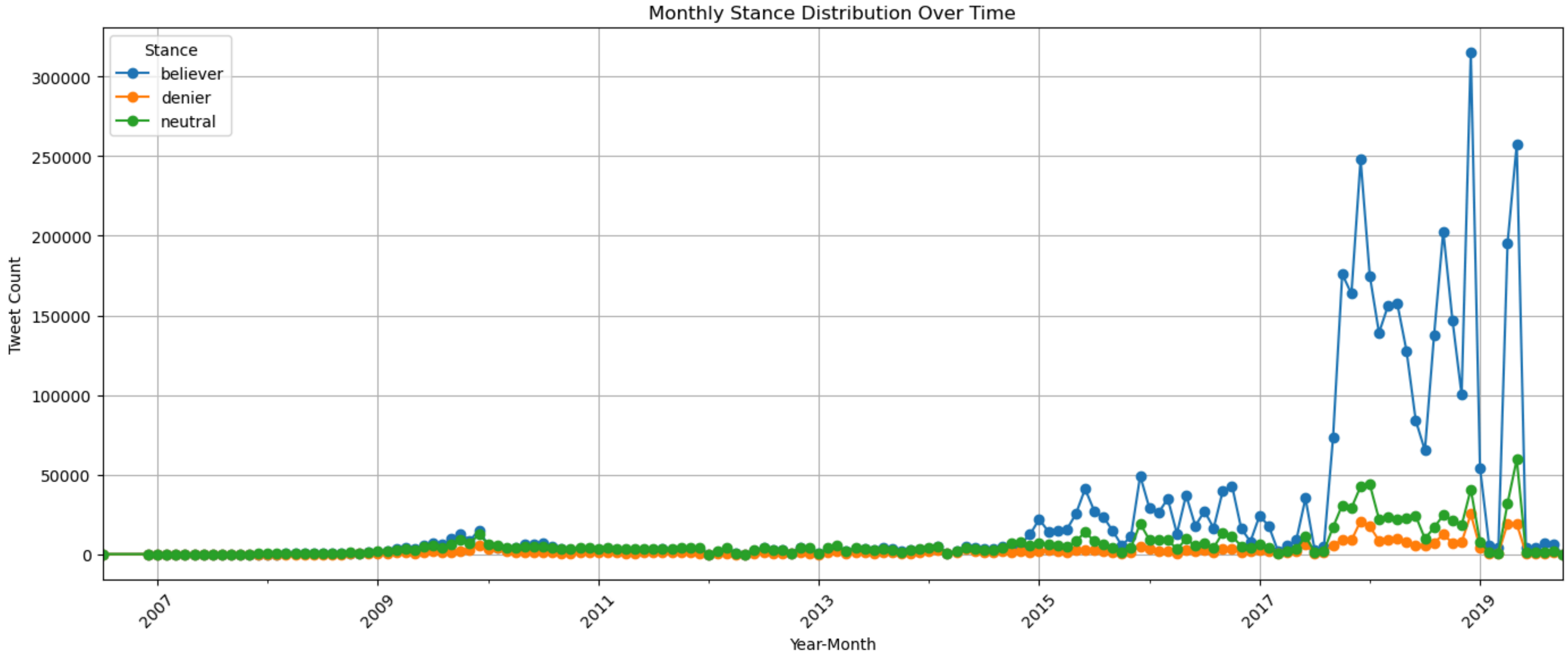
```
print("Male count:", len(male))
print("Female count:", len(female))


# Perform t-test assuming unequal variances (t-test)
t_stat, p_val = ttest_ind(male, female, equal_var=False)

print(f"T-Test: t={t_stat:.4f}, p={p_val:.4f}")
```

```
Male count: 3485846
Female count: 1659423
T-Test: t=-11.5635, p=0.0000
```

In [ ]:

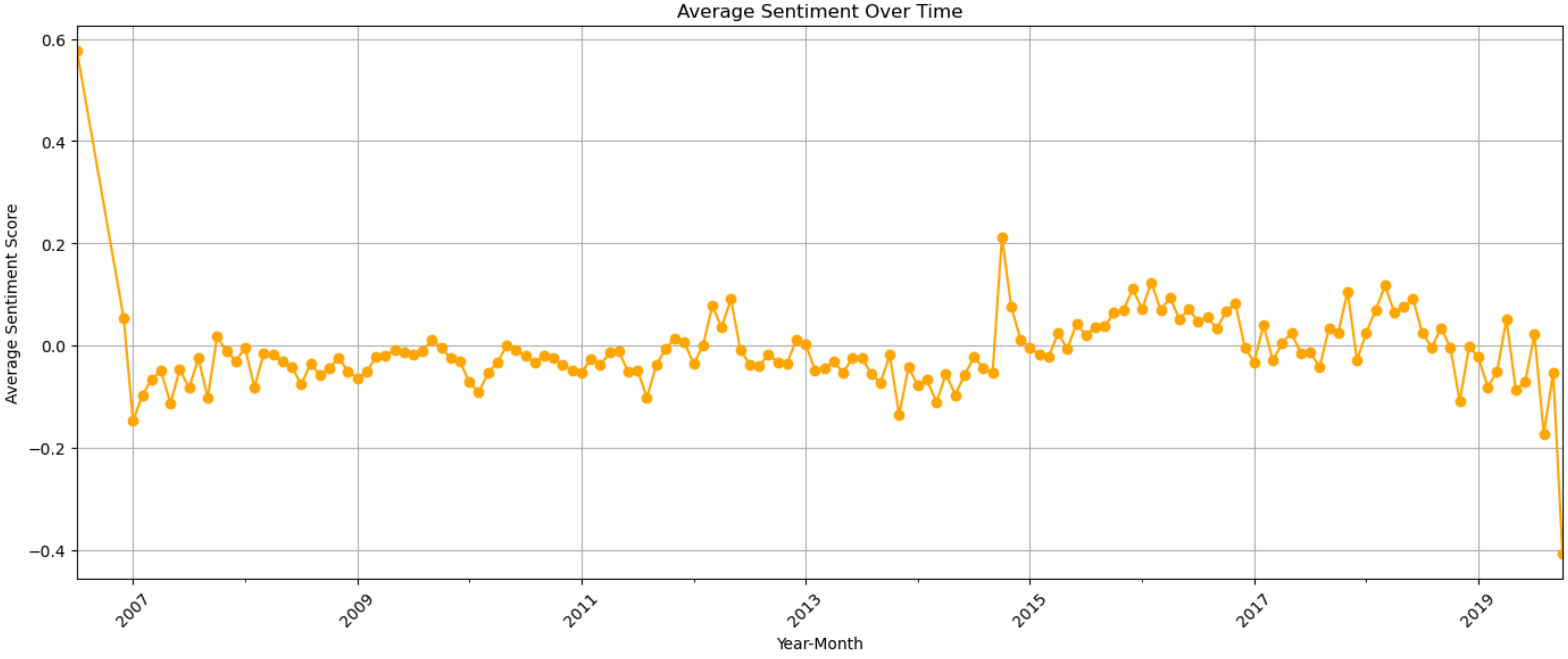
```
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd

# Convert created_at to datetime
df['created_at'] = pd.to_datetime(df_cleaned['created_at'], errors='coerce')
df = df.dropna(subset=['created_at', 'stance'])

# Create a new column for year-month
df['year_month'] = df['created_at'].dt.to_period('M')
#df['year_month'] = df['created_at'].dt.strftime('%Y-%b').str.upper()

# Group by month and stance
stance_trends = df.groupby(['year_month', 'stance']).size().unstack(fill_value=0)

# Plot stance trends over time
plt.figure(figsize=(14, 6))
stance_trends.plot(marker='o', figsize=(14, 6))
plt.title('Monthly Stance Distribution Over Time')
plt.xlabel('Year-Month')
plt.ylabel('Tweet Count')
plt.xticks(rotation=45)
plt.grid(True)
plt.tight_layout()
plt.legend(title='Stance')
plt.show()
```

```
/tmp/ipykernel_299505/1667700143.py:10: UserWarning: Converting to PeriodArray/Index representation will drop timezone informat
ion.
  df['year_month'] = df['created_at'].dt.to_period('M')
<Figure size 1400x600 with 0 Axes>
```



In [ ]:
```python
# Group by year-month and calculate average sentiment
sentiment_trends = df.groupby('year_month')['sentiment'].mean()

# Plot sentiment trends over time
plt.figure(figsize=(14, 6))
sentiment_trends.plot(marker='o', color='orange')
plt.title('Average Sentiment Over Time')
plt.xlabel('Year-Month')
plt.ylabel('Average Sentiment Score')
plt.xticks(rotation=45)
plt.grid(True)
```

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



In [ ]:

```
# NOVA - Sentiment across stances
# A significant p-value suggests sentiment varies by stance
from scipy.stats import f_oneway

groups = [group['sentiment'].dropna() for name, group in df_cleaned.groupby('stance')]
f_stat, p_val = f_oneway(*groups)
print(f"ANOVA: F={f_stat:.4f}, p={p_val:.4f}")
```

```
ANOVA: F=61007.3680, p=0.0000
```

In [ ]:

```
#Diagnostic Regression - Sentiment as Dependent Variable
#R² tells how much variance is explained by predictors.
#Feature weights can suggest direction of influence (positive/negative).
from sklearn.linear_model import LinearRegression
```

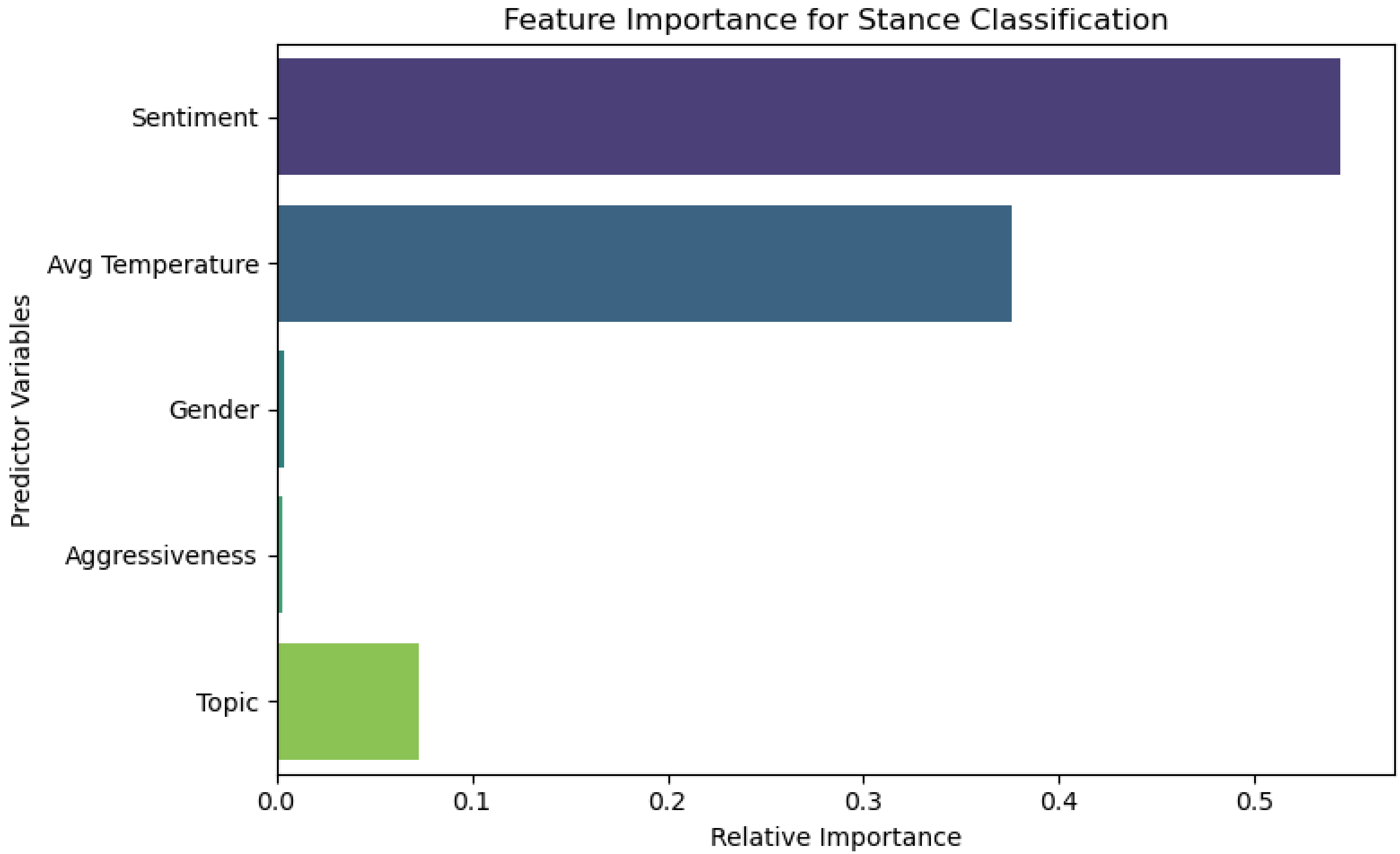
```python
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.metrics import r2_score, root_mean_squared_error
import pandas as pd

# Prepare the data
diag_df = df_cleaned[['sentiment', 'temperature_avg', 'gender_encoded', 'stance_encoded', 'topic_encoded']].dropna()

# Encode categorical features
#for col in ['gender', 'stance', 'topic']:
#    diag_df[col] = LabelEncoder().fit_transform(diag_df[col])

# Define features and target
X = diag_df.drop(columns='sentiment')
y = diag_df['sentiment']

# Standardize features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Split data into train and test sets
X_train, X_test, y_train, y_test = train_test_split(
    X_scaled, y, test_size=0.3, random_state=42
)

# Train linear regression model
model = LinearRegression()
model.fit(X_train, y_train)

# Predict on test set
y_pred = model.predict(X_test)

# Evaluate the model
r2 = r2_score(y_test, y_pred)
rmse = root_mean_squared_error(y_test, y_pred)

print(f"R²: {r2:.4f}")
print(f"RMSE: {rmse:.4f}")
```

```
R²: 0.0008
RMSE: 0.4406
```

In [ ]:
```
# Diagnostic Visualization ⍰ Feature Importance for Stance Prediction

import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler

# 1. Define features (exclude 'stance_encoded') and target = 'stance_encoded'
features = [
    'sentiment',
    'temperature_avg',
    'gender_encoded',
    'aggressiveness_encoded',  # now used as a predictor
    'topic_encoded'
]
X_diag = df_cleaned[features].dropna()
y_diag = df_cleaned.loc[X_diag.index, 'stance_encoded']

# 2. Standardize numeric features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X_diag)
X_diag = pd.DataFrame(X_scaled, columns=features)

# 3. Train/test split
X_train, X_test, y_train, y_test = train_test_split(
    X_diag, y_diag, test_size=0.3, random_state=42, stratify=y_diag
)

# 4. Train Random Forest
rf_model = RandomForestClassifier(n_estimators=100, random_state=42)
rf_model.fit(X_train, y_train)

# 5. Extract feature importances
importances = rf_model.feature_importances_
feature_names = features

# 6. Map to readable labels
labels = {
```

```
    'sentiment': 'Sentiment',
    'temperature_avg': 'Avg Temperature',
    'gender_encoded': 'Gender',
    'aggressiveness_encoded': 'Aggressiveness',
    'topic_encoded': 'Topic'
}
readable = [labels[f] for f in feature_names]

# 7. Plot
plt.figure(figsize=(8, 5))
sns.barplot(x=importances, y=readable, palette="viridis")
plt.title("Feature Importance for Stance Classification")
plt.xlabel("Relative Importance")
plt.ylabel("Predictor Variables")
plt.tight_layout()
plt.show()
```

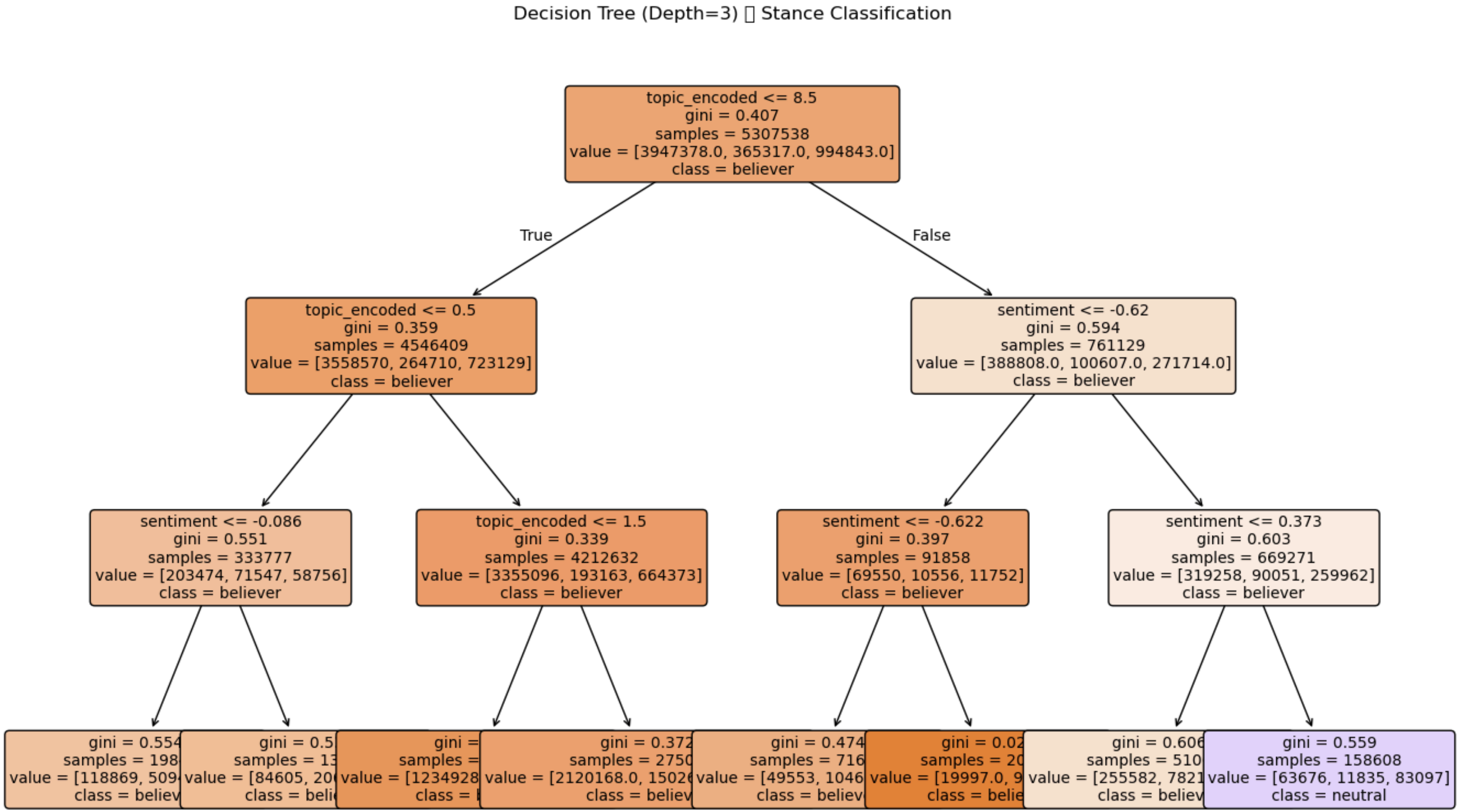
```
/tmp/ipykernel_52256/2863863304.py:51: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `y` variable to `hue` and se
t `legend=False` for the same effect.

  sns.barplot(x=importances, y=readable, palette="viridis")
```



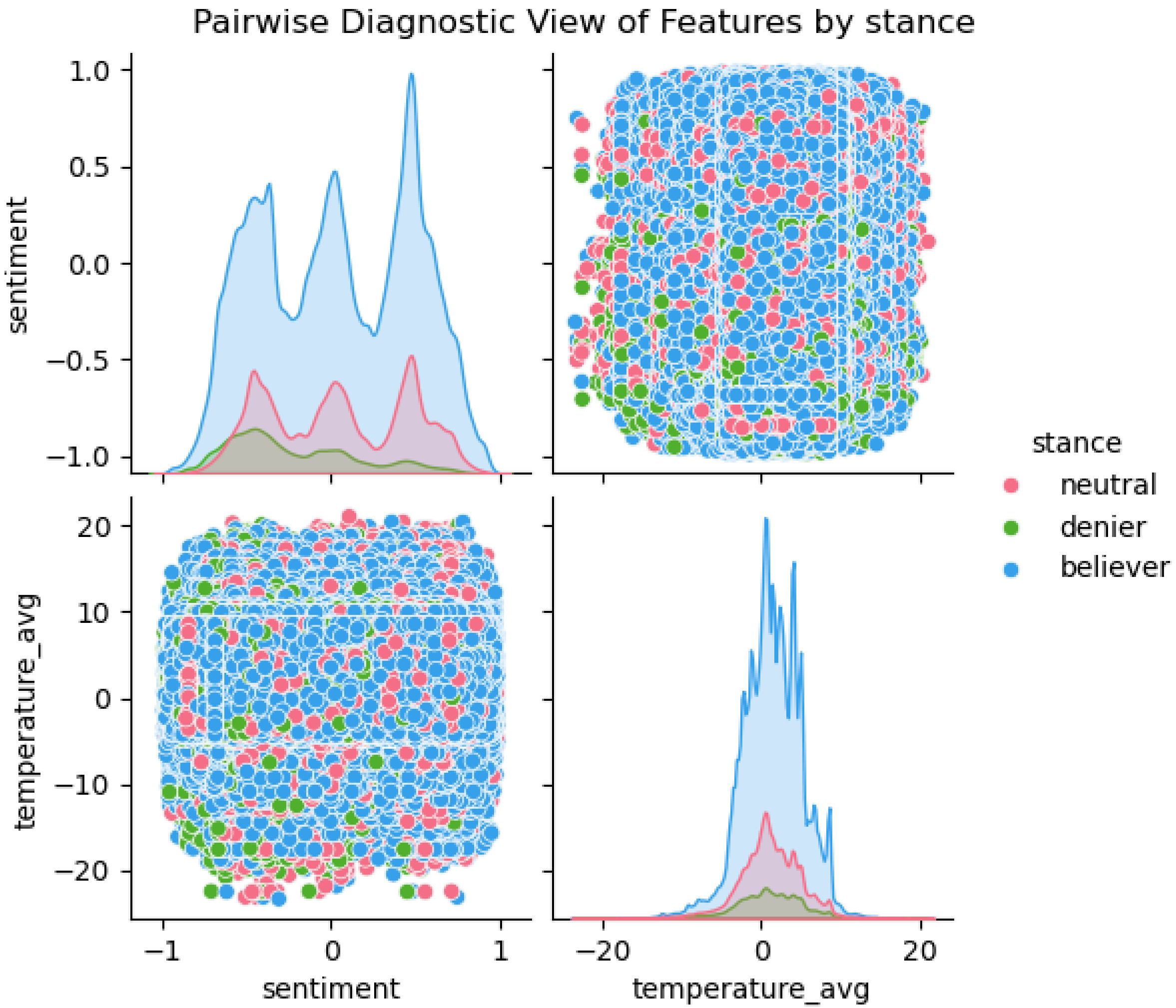
In [ ]:
```
from sklearn.tree import DecisionTreeClassifier, plot_tree
from sklearn.preprocessing import LabelEncoder
import matplotlib.pyplot as plt

# 1. Encode stance if not already encoded
#le_stance = LabelEncoder()
#df_cleaned['stance_encoded'] = le_stance.fit_transform(df_cleaned['stance'])
#tance_classes = list(le_stance.classes_)  # e.g. ['believer','denier','neutral']

# 2. Define features (exclude 'stance_encoded') and new target
features = ['sentiment', 'temperature_avg', 'gender_encoded', 'aggressiveness_encoded', 'topic_encoded']
```

```
X_cls = df_cleaned[features].dropna()
y_cls = df_cleaned.loc[X_cls.index, 'stance_encoded']

# 3. Train the Decision Tree
tree_model = DecisionTreeClassifier(max_depth=3, random_state=42)
tree_model.fit(X_cls, y_cls)

# 4. Plot the tree
plt.figure(figsize=(16, 10))
plot_tree(
    tree_model,
    feature_names=features,
    class_names=  ['believer','denier','neutral'],# stance_classes,
    filled=True,
    rounded=True,
    fontsize=10
)
plt.title("Decision Tree (Depth=3) ▯ Stance Classification")
plt.show()
```

```
/home/opc/anaconda3/lib/python3.12/site-packages/IPython/core/pylabtools.py:170: UserWarning: Glyph 150 (\x96) missing from fon
t(s) DejaVu Sans.
  fig.canvas.print_figure(bytes_io, **kw)
```




```
In [ ]: #Pairplot with Hue by stance - Visualize pairwise feature relationships, colored by target class.
sns.pairplot(df_cleaned, vars=['sentiment', 'temperature_avg'], hue='stance', palette='husl')
plt.suptitle('Pairwise Diagnostic View of Features by stance', y=1.02)
plt.show()
```



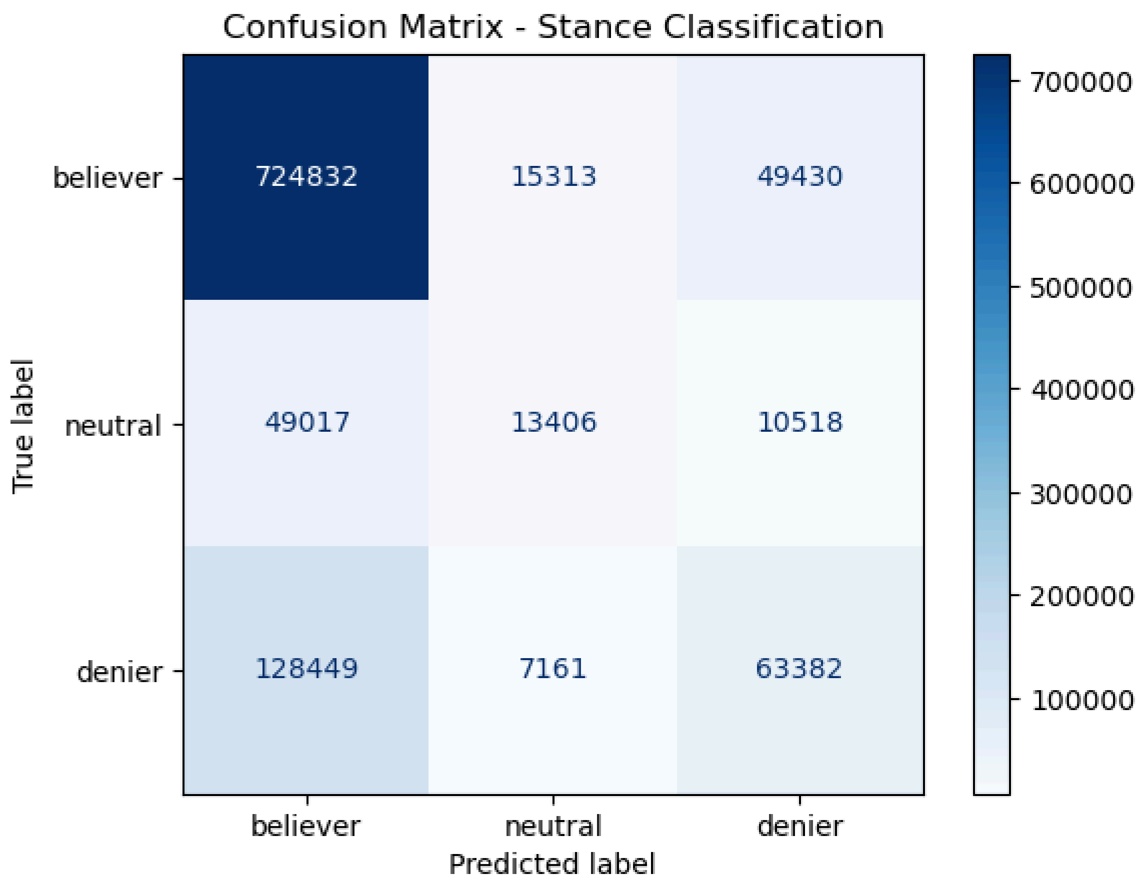
In [ ]:

```
# Predictive Analytics
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
#from sklearn.metrics import classification_report, confusion_matrix
from sklearn.preprocessing import StandardScaler

from sklearn.metrics import (
    classification_report,
    confusion_matrix,
```

```
    ConfusionMatrixDisplay,
    roc_curve,
    roc_auc_score
)
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import label_binarize
from sklearn.metrics import roc_curve, auc

# Load the full sheet
#df = xls.parse("Sheet1")

# Define features and target
features = ['sentiment', 'temperature_avg', 'gender_encoded', 'topic_encoded', 'aggressiveness_encoded', 'PC1', 'PC2']
target = 'stance_encoded'

# Drop rows with missing target or feature values
df_model = df_cleaned.dropna(subset=features + [target])

# Split into train and test sets
X = df_model[features]
y = df_model[target]
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Standardize features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Train a Random Forest Classifier
clf = RandomForestClassifier(random_state=42)
clf.fit(X_train_scaled, y_train)

# Make predictions
y_pred = clf.predict(X_test_scaled)

# Evaluate the model
#report = classification_report(y_test, y_pred, output_dict=True)
#conf_matrix = confusion_matrix(y_test, y_pred)

#report, conf_matrix
```

```python
# Classification Report
stance_labels = ['believer', 'neutral', 'denier']
print("Classification Report:\n")
print(classification_report(y_test, y_pred, target_names=stance_labels))

# Confusion Matrix
cm = confusion_matrix(y_test, y_pred)
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=stance_labels)

plt.figure(figsize=(6, 5))
disp.plot(cmap="Blues", values_format='d')
plt.title("Confusion Matrix - Stance Classification")
plt.grid(False)
plt.show()
```

```
Classification Report:

              precision    recall  f1-score   support

    believer       0.80      0.92      0.86    789575
     neutral       0.37      0.18      0.25     72941
      denier       0.51      0.32      0.39    198992

    accuracy                           0.76   1061508
   macro avg       0.56      0.47      0.50   1061508
weighted avg       0.72      0.76      0.73   1061508

<Figure size 600x500 with 0 Axes>
```



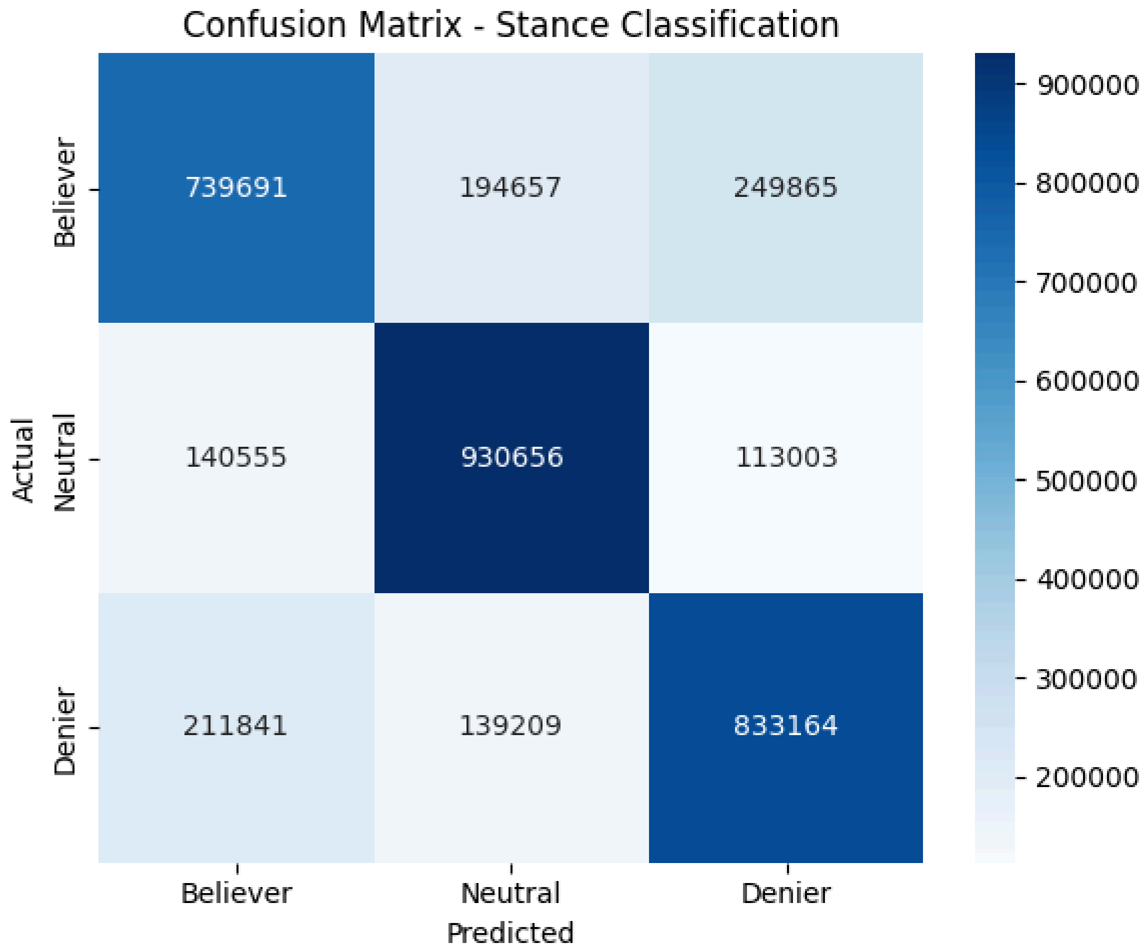
In [13]:

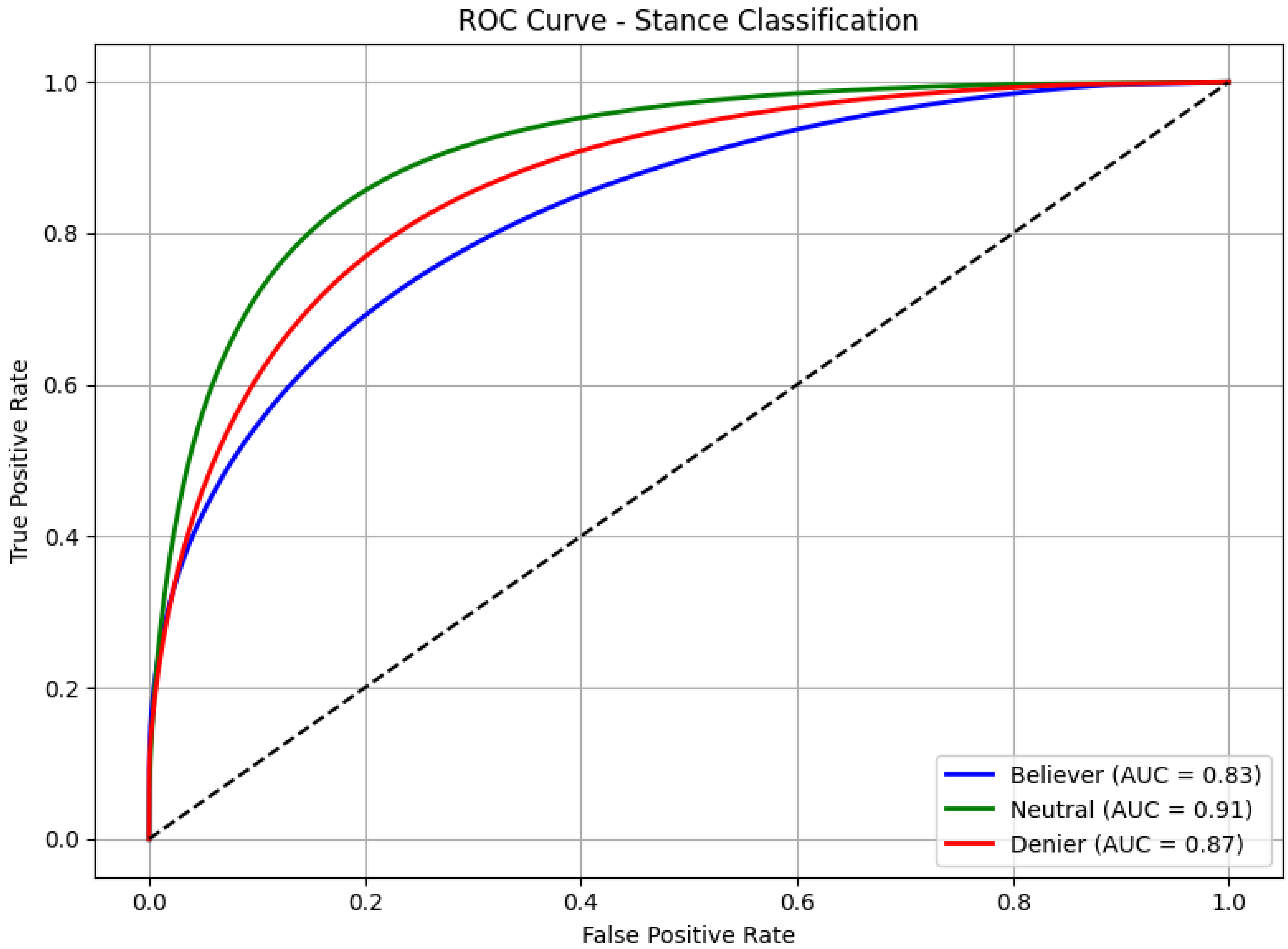
```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report, confusion_matrix, roc_curve, auc
from sklearn.preprocessing import StandardScaler, label_binarize
import matplotlib.pyplot as plt
import seaborn as sns
from imblearn.over_sampling import SMOTE

# Features and target
features = ['sentiment', 'temperature_avg', 'gender_encoded', 'aggressiveness_encoded']
target = 'stance_encoded'
```

```
X = df_cleaned[features]
y = df_cleaned[target]

# Standardize features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# SMOTE oversampling
smote = SMOTE(random_state=42)
X_resampled, y_resampled = smote.fit_resample(X_scaled, y)

# Train-test split
X_train, X_test, y_train, y_test = train_test_split(
    X_resampled, y_resampled, test_size=0.3, random_state=42, stratify=y_resampled
)

# Train classifier --estimator set to 100, fist tried with diff value due to low cpu/gpu power
clf = RandomForestClassifier(n_estimators=100, max_depth=None, n_jobs=2, class_weight='balanced', random_state=42)
clf.fit(X_train, y_train)

# Predictions
y_pred = clf.predict(X_test)
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred))
print("\nClassification Report:\n", classification_report(y_test, y_pred))

# Confusion Matrix Plot
labels = ['Believer', 'Neutral', 'Denier']
cm = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(6, 5))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=labels, yticklabels=labels)
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix - Stance Classification')
plt.tight_layout()
plt.show()

# ROC Curve and AUC
y_test_bin = label_binarize(y_test, classes=np.unique(y))
y_score = clf.predict_proba(X_test)
n_classes = y_score.shape[1]
```

```python
fpr, tpr, roc_auc = {}, {}, {}
for i in range(n_classes):
    fpr[i], tpr[i], _ = roc_curve(y_test_bin[:, i], y_score[:, i])
    roc_auc[i] = auc(fpr[i], tpr[i])

plt.figure(figsize=(8, 6))
colors = ['blue', 'green', 'red']
for i, color in zip(range(n_classes), colors):
    plt.plot(fpr[i], tpr[i], color=color, lw=2,
             label=f'{labels[i]} (AUC = {roc_auc[i]:.2f})')

plt.plot([0, 1], [0, 1], 'k--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve - Stance Classification')
plt.legend(loc="lower right")
plt.grid()
plt.tight_layout()
plt.show()
```

```
Confusion Matrix:
 [[739691 194657 249865]
 [140555 930656 113003]
 [211841 139209 833164]]

Classification Report:
              precision    recall  f1-score   support

           0       0.68      0.62      0.65   1184213
           1       0.74      0.79      0.76   1184214
           2       0.70      0.70      0.70   1184214

    accuracy                           0.70   3552641
   macro avg       0.70      0.70      0.70   3552641
weighted avg       0.70      0.70      0.70   3552641
```


Confusion Matrix - Stance Classification
Actual
Believer
Neutral
Denier
739691
194657
249865
140555
930656
113003
211841
139209
833164
Believer
Neutral
Denier
Predicted
900000
800000
700000
600000
500000
400000
300000
200000


ROC Curve - Stance Classification
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
Believer (AUC = 0.83)
Neutral (AUC = 0.91)
Denier (AUC = 0.87)