ALLIANCE UNIVERSITY

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PROJECT REPORT

BACHELOR OF COMPUTER APPLICATION

SEMESTER – II

INTRODUCATION TO DATASCIENCE

Political Media Messaging & Bias Detection

Dataset: Political-media.

BY

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BANGALORE-562106

APRIL – 2025

📊 Political Media Messaging & Bias Detection

Dataset: Political-media.

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GITHUB LINK : https://github.com/chaturya0229/Political-Media-Messaging-Bias-Detection

📚 Table of Contents

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📘 Project Title and Info

📊 Political Media Messaging & Bias Detection

📜 **Course:** Introduction to Data Science

Semester: 2nd Semester – BCA
Project Type: Beginner-level Data Science & Machine Learning

Tools Used: Python, Pandas, Seaborn, Scikit-learn
Dataset: Bank Churners Dataset

🔰 Project Overview

We'll perform:

- Statistical analysis of message types and political bias
- Hypothesis testing (Chi-square test)
- Classification model to predict bias based on message features

🎯 Project Goal

- Discover patterns in political content
- Test if bias and message types are statistically related
- Build a classification model to predict political bias

❗ Challenges Faced

- Imbalanced classes (more "neutral" than "partisan")
- Qualitative text data needs encoding or transformation
- Limited numeric features for regression

1.Bussiness Understanding

Goal: Analyze and model relationships between message types, political bias, and social media usage.

📦 Import Libraries & Load Dataset

Standard imports for data analysis and visualization.

```
import pandas as pd
import numpy as np Keeps only useful features like bias, message, source,
etc.
      •     Ensures no missing values remain.
import seaborn as sns
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import LabelEncoder
from scipy import stats
from scipy.stats import norm, ttest_ind, chi2_contingency
# 📌 2. Load the Dataset
df = pd.read_csv(r"C:\Users\thuki\Downloads\Political-media-DFE.csv")
df
```

```
      index   _unit_id  _golden _unit_state  _trusted_judgments  \
0         0  766192484    False   finalized                   1
1         1  766192485    False   finalized                   1
2         2  766192486    False   finalized                   1
3         3  766192487    False   finalized                   1
4         4  766192488    False   finalized                   1
...     ...        ...      ...         ...                 ...
4995   4995  766197482    False   finalized                   1
4996   4996  766197483    False   finalized                   1
4997   4997  766197484    False   finalized                   1
4998   4998  766197485    False   finalized                   1
4999   4999  766197486    False   finalized                   1

     _last_judgment_at  audience  audience:confidence      bias  \
0         8/4/15 21:17  national                  1.0  partisan
1         8/4/15 21:20  national                  1.0  partisan
2         8/4/15 21:14  national                  1.0   neutral
3         8/4/15 21:08  national                  1.0   neutral
4         8/4/15 21:26  national                  1.0  partisan
...                ...       ...                  ...       ...
4995       8/5/15 6:05  national                  1.0  partisan
4996       8/5/15 5:57  national                  1.0  partisan
4997       8/5/15 5:10  national                  1.0   neutral
4998       8/5/15 6:08  national                  1.0   neutral
4999       8/5/15 5:04  national                  1.0   neutral

      bias:confidence  ... orig__golden  audience_gold  bias_gold    bioid  \
0                 1.0  ...          NaN            NaN        NaN  R000596
1                 1.0  ...          NaN            NaN        NaN  M000355
2                 1.0  ...          NaN            NaN        NaN  S001180
3                 1.0  ...          NaN            NaN        NaN  C000880
4                 1.0  ...          NaN            NaN        NaN  U000038
...               ...  ...          ...            ...        ...      ...
4995              1.0  ...          NaN            NaN        NaN  Y000065
4996              1.0  ...          NaN            NaN        NaN  Y000065
```

```
4997             1.0  ...          NaN            NaN        NaN  Y000065
4998             1.0  ...          NaN            NaN        NaN  Y000065
4999             1.0  ...          NaN            NaN        NaN  Y000065

                                                  embed  \
0     <blockquote class="twitter-tweet" width="450">...
1     <blockquote class="twitter-tweet" width="450">...
2     <blockquote class="twitter-tweet" width="450">...
3     <blockquote class="twitter-tweet" width="450">...
4     <blockquote class="twitter-tweet" width="450">...
...                                                 ...
4995  <div id="fb-root"></div> <script>(function(d, ...
4996  <div id="fb-root"></div> <script>(function(d, ...
4997  <div id="fb-root"></div> <script>(function(d, ...
4998  <div id="fb-root"></div> <script>(function(d, ...
4999  <div id="fb-root"></div> <script>(function(d, ...

                                    id  \
0                           3.83249E+17
1                           3.11208E+17
2                           3.39069E+17
3                           2.98528E+17
4                           4.07643E+17
...                                 ...
4995    563532937006022_939071892785456
4996    563532937006022_936080056417973
4997    563532937006022_905547326137913
4998  563532937006022_10101529848812566
4999    563532937006022_730010240358290

                                                label message_gold    source
\
0       From: Trey Radel (Representative from Florida)          NaN   twitter
1        From: Mitch McConnell (Senator from Kentucky)          NaN   twitter
2     From: Kurt Schrader (Representative from Oregon)          NaN   twitter
3             From: Michael Crapo (Senator from Idaho)          NaN   twitter
4             From: Mark Udall (Senator from Colorado)          NaN   twitter
...                                                ...          ...       ...
4995      From: Ted Yoho (Representative from Florida)          NaN  facebook
4996      From: Ted Yoho (Representative from Florida)          NaN  facebook
4997      From: Ted Yoho (Representative from Florida)          NaN  facebook
4998      From: Ted Yoho (Representative from Florida)          NaN  facebook
4999      From: Ted Yoho (Representative from Florida)          NaN  facebook

                                                  text
0     RT @nowthisnews: Rep. Trey Radel (R- #FL) slam...
1     VIDEO - #Obamacare:  Full of Higher Costs and ...
2     Please join me today in remembering our fallen...
3     RT @SenatorLeahy: 1st step toward Senate debat...
```

```
4     .@amazon delivery #drones show need to update ...
...                                                 ...
4995  I applaud Governor Perry⍰Ûªs recent decision t...
4996  Today, I voted in favor of H.R. 5016 - Financi...
4997  (Taken from posted WOKV interview)   Congressm...
4998  Join me next week for a town hall in Ocala! I'...
4999  Foreign Affairs Committee Hearing on Syria. I ...

[5000 rows x 22 columns]
```

🖌️ Data Preprocessing

- Keeps only useful features like bias, message, source, etc.
- Ensures no missing values remain.

```
print(df.shape)
print(df.columns)
print(df.head())
```

```
(5000, 22)
Index(['index', '_unit_id', '_golden', '_unit_state', '_trusted_judgments',
       '_last_judgment_at', 'audience', 'audience:confidence', 'bias',
       'bias:confidence', 'message', 'message:confidence', 'orig__golden',
       'audience_gold', 'bias_gold', 'bioid', 'embed', 'id', 'label',
       'message_gold', 'source', 'text'],
      dtype='object')
   index   _unit_id  _golden _unit_state  _trusted_judgments  \
0      0  766192484    False   finalized                   1
1      1  766192485    False   finalized                   1
2      2  766192486    False   finalized                   1
3      3  766192487    False   finalized                   1
4      4  766192488    False   finalized                   1

  _last_judgment_at  audience  audience:confidence      bias  bias:confidence
\
0      8/4/15 21:17  national                  1.0  partisan              1.0
1      8/4/15 21:20  national                  1.0  partisan              1.0
2      8/4/15 21:14  national                  1.0   neutral              1.0
3      8/4/15 21:08  national                  1.0   neutral              1.0
4      8/4/15 21:26  national                  1.0  partisan              1.0

   ... orig__golden  audience_gold  bias_gold    bioid  \
0  ...          NaN            NaN        NaN  R000596
1  ...          NaN            NaN        NaN  M000355
2  ...          NaN            NaN        NaN  S001180
3  ...          NaN            NaN        NaN  C000880
4  ...          NaN            NaN        NaN  U000038
```

```
                                                 embed           id  \
0  <blockquote class="twitter-tweet" width="450">...  3.83249E+17
1  <blockquote class="twitter-tweet" width="450">...  3.11208E+17
2  <blockquote class="twitter-tweet" width="450">...  3.39069E+17
3  <blockquote class="twitter-tweet" width="450">...  2.98528E+17
4  <blockquote class="twitter-tweet" width="450">...  4.07643E+17

                                            label message_gold   source  \
0    From: Trey Radel (Representative from Florida)          NaN  twitter
1     From: Mitch McConnell (Senator from Kentucky)          NaN  twitter
2  From: Kurt Schrader (Representative from Oregon)          NaN  twitter
3          From: Michael Crapo (Senator from Idaho)          NaN  twitter
4          From: Mark Udall (Senator from Colorado)          NaN  twitter

                                                text
0  RT @nowthisnews: Rep. Trey Radel (R- #FL) slam...
1  VIDEO - #Obamacare:  Full of Higher Costs and ...
2  Please join me today in remembering our fallen...
3  RT @SenatorLeahy: 1st step toward Senate debat...
4  .@amazon delivery #drones show need to update ...

[5 rows x 22 columns]
```

```python
# Drop unnecessary columns
df_clean = df.drop(columns=[
    'index', '_unit_id', '_golden', '_unit_state', '_trusted_judgments',
    '_last_judgment_at', 'orig__golden', 'audience_gold', 'bias_gold',
    'message_gold', 'bioid', 'embed', 'id', 'label'
])

# Drop nulls if any
df_clean.dropna(inplace=True)

# Check for missing values
print(df_clean.isnull().sum())

# Drop rows with any missing values (if minimal)
df_clean = df_clean.dropna()
```

```
audience              0
audience:confidence    0
bias                  0
bias:confidence        0
message               0
message:confidence     0
source                0
text                  0
dtype: int64
```

```
# Confirm cleaned dataset
print(df_clean[['message', 'source', 'bias', 'message', 'source', 'bias']].he
ad())
```

```
   message   source      bias  message   source      bias
0   policy  twitter  partisan   policy  twitter  partisan
1   attack  twitter  partisan   attack  twitter  partisan
2  support  twitter   neutral  support  twitter   neutral
3   policy  twitter   neutral   policy  twitter   neutral
4   policy  twitter  partisan   policy  twitter  partisan
```

```
df_clean.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5000 entries, 0 to 4999
Data columns (total 8 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   audience             5000 non-null   object
 1   audience:confidence  5000 non-null   float64
 2   bias                 5000 non-null   object
 3   bias:confidence      5000 non-null   float64
 4   message              5000 non-null   object
 5   message:confidence   5000 non-null   float64
 6   source               5000 non-null   object
 7   text                 5000 non-null   object
dtypes: float64(3), object(5)
memory usage: 312.6+ KB
```

📊 Univariate and Multivariate Analysis

◇ Univariate Analysis

Univariate analysis is a statistical examination of a single variable at the time.it helps to describe the basic characteristics of the data, such as its distribution, central tendency(mean,median,mode),and description(range,variance,standard deviation).

◇ Multivariate Analysis

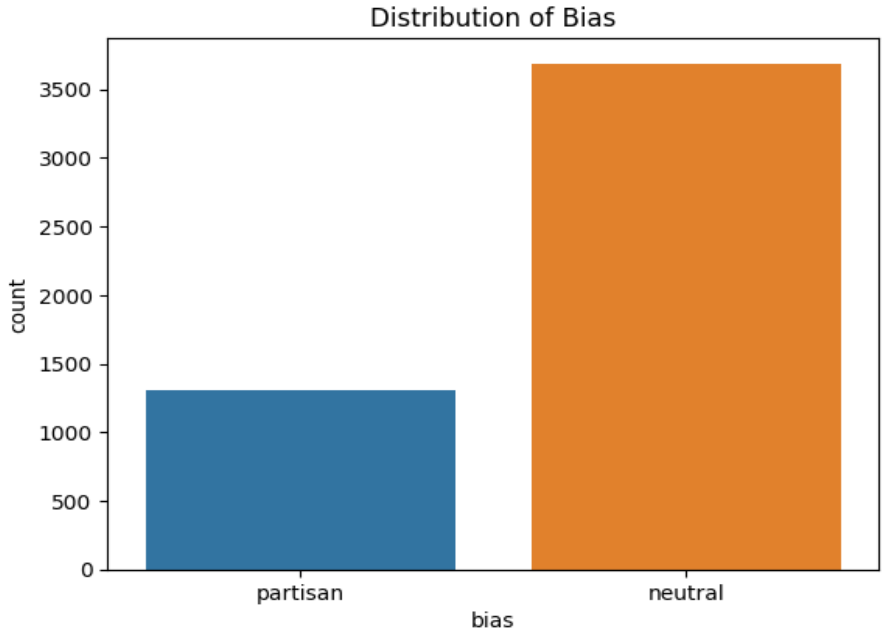
Multivariate analysis is a statistical technique used to examine the relationship between three or more variables at the same time. it helps to identify patterns, correlations and interactions among variables to understand how they influence each other.

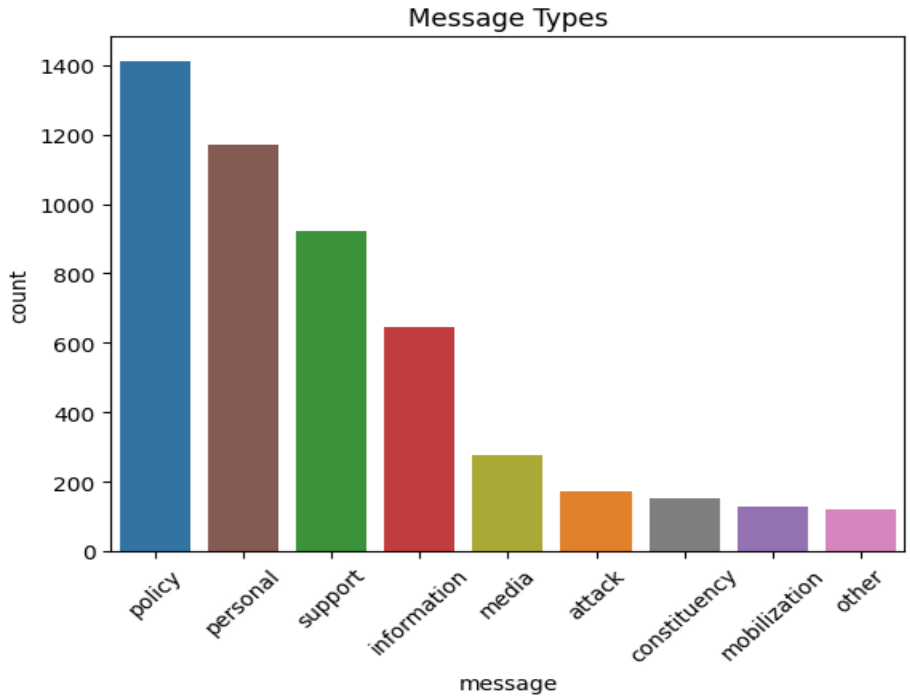
```
sns.countplot(data=df_clean, x='bias',hue="bias")
plt.title('Distribution of Bias')
plt.show()
```

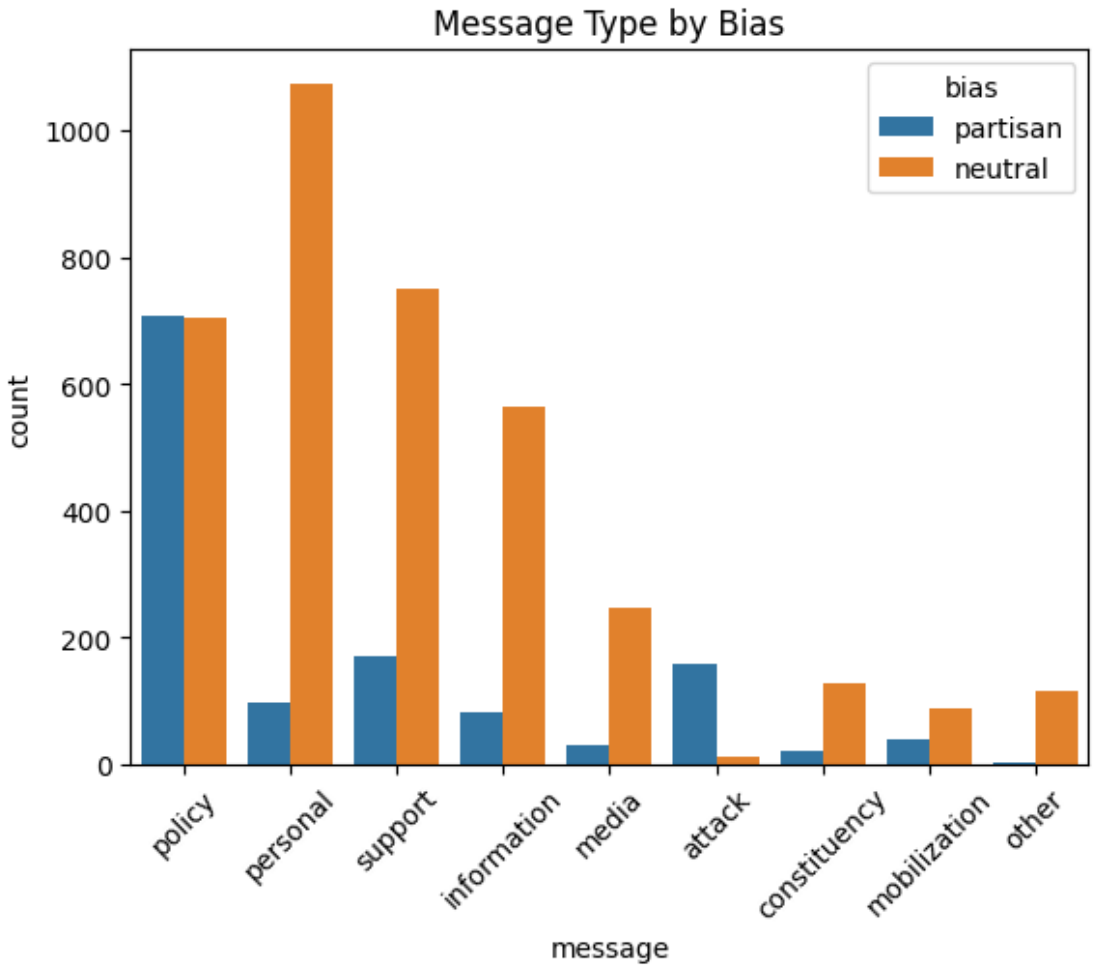
```
sns.countplot(data=df_clean, x='message',hue="message", order=df_clean['messa
ge'].value_counts().index)
```

```
plt.title('Message Types')
plt.xticks(rotation=45)
plt.show()

sns.countplot(data=df_clean, x='message', hue='bias', order=df_clean['message
'].value_counts().index)
plt.title('Message Type by Bias')
plt.xticks(rotation=45)
plt.show()
```



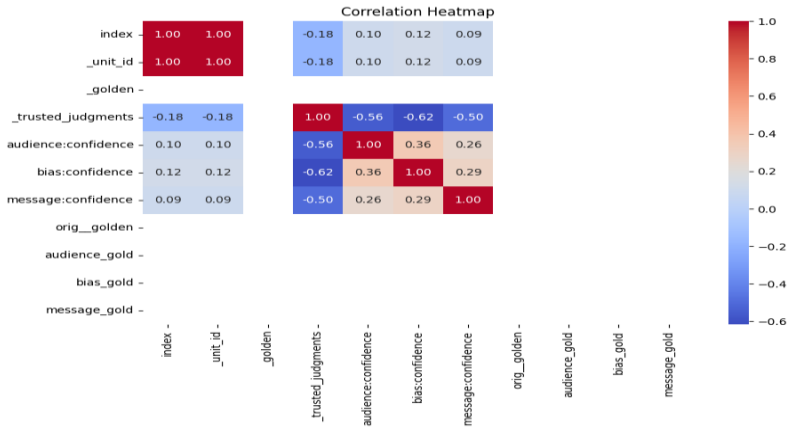

Message Types
1400
1200
1000
800
600
400
200
0
count
policy
personal
support
information
media
attack
constituency
mobilization
other
message


Message Type by Bias
bias
partisan
neutral
1000
800
600
400
200
0
count
policy
personal
support
information
media
attack
constituency
mobilization
other
message

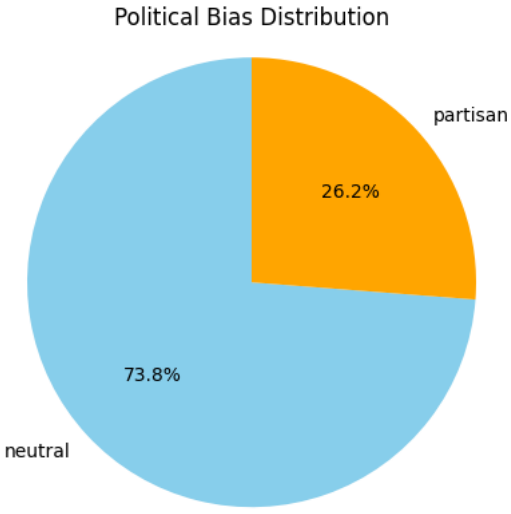
```
numeric_df = df.select_dtypes(exclude="object")
```

🔥 Heatmap - Correlation Matrix

```
# Plot heatmap to visualize correlation between numerical features
plt.figure(figsize=(10, 6))
sns.heatmap(numeric_df.corr(), annot=True, cmap="coolwarm", fmt=".2f")
plt.title("Correlation Heatmap")
plt.show()
```

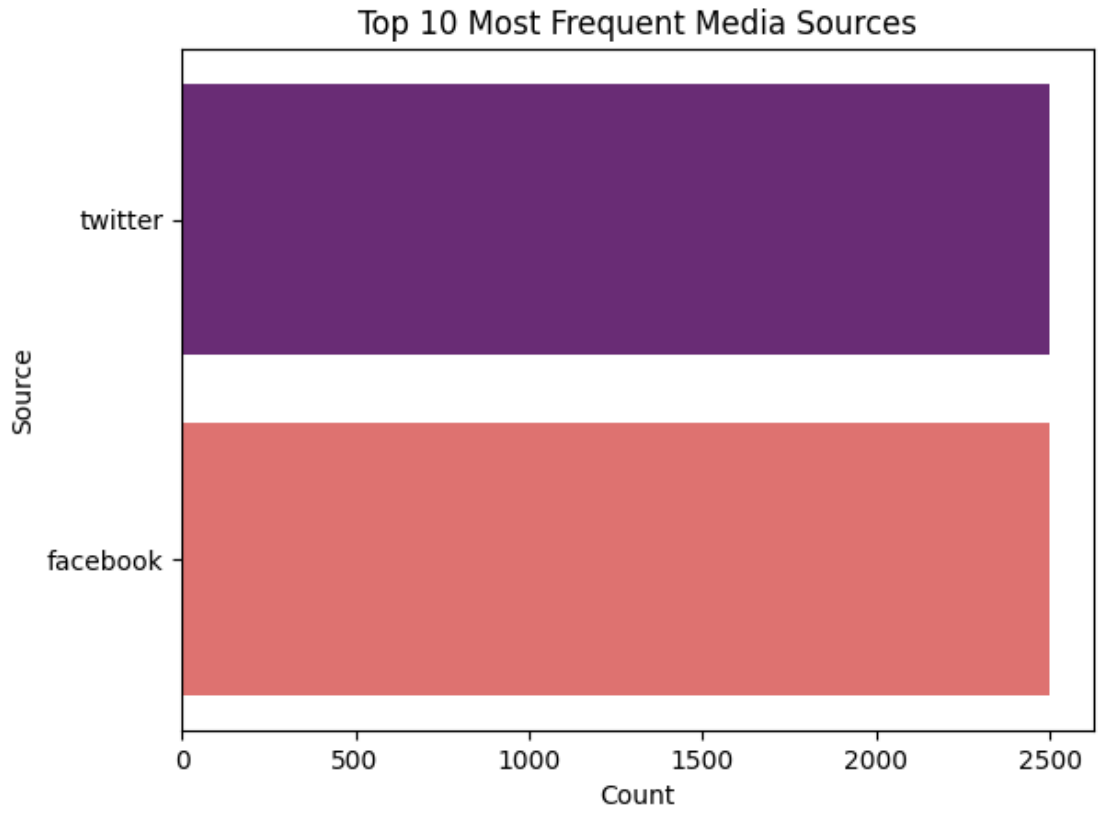



```
# Pie chart for bias
bias_counts = df_clean['bias'].value_counts()
plt.pie(bias_counts, labels=bias_counts.index, autopct='%1.1f%%', startangle=
90, colors=['skyblue', 'orange'])
plt.title("Political Bias Distribution")
plt.axis('equal')  # Equal aspect ratio ensures the pie is circular.
plt.show()
```



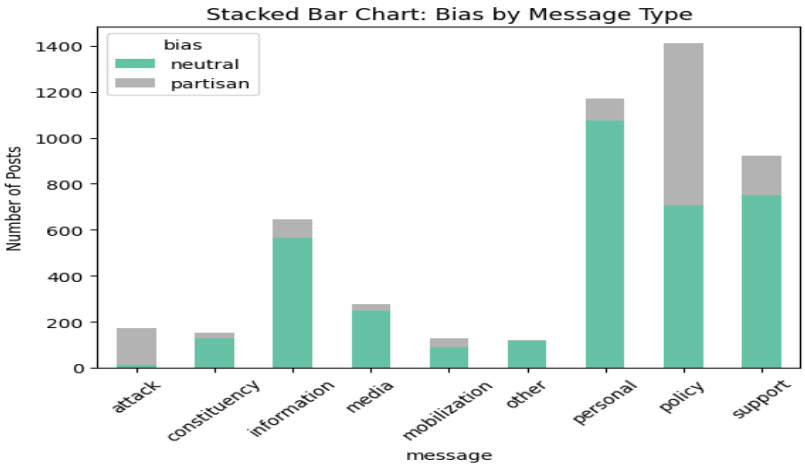
```
top_sources = df_clean['source'].value_counts().head(10)

# Bar plot of top sources
sns.barplot(x=top_sources.values, y=top_sources.index, palette='magma',hue=to
p_sources.index)
plt.title("Top 10 Most Frequent Media Sources")
plt.xlabel("Count")
plt.ylabel("Source")
plt.show()
```



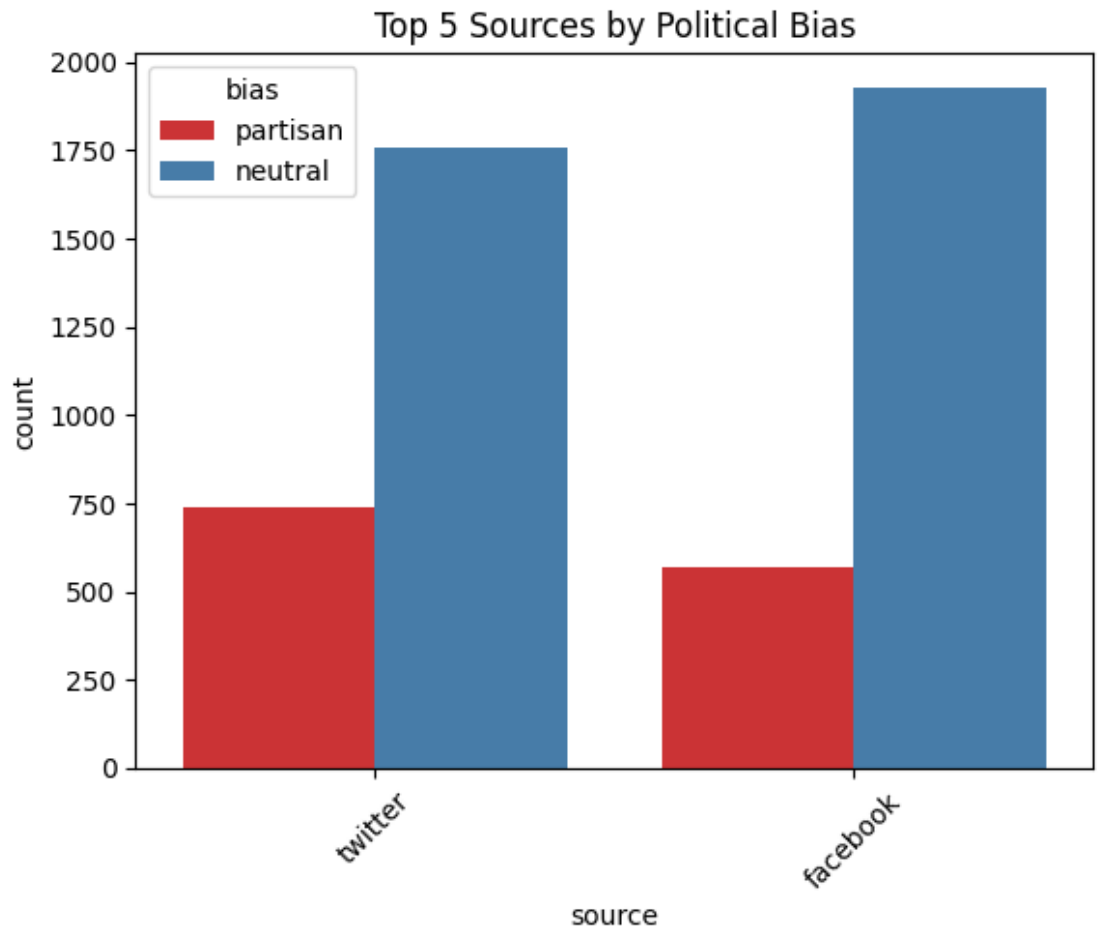

```
# Grouped bias by message
msg_bias = pd.crosstab(df_clean['message'], df_clean['bias'])

# Stacked bar chart
msg_bias.plot(kind='bar', stacked=True, colormap='Set2')
plt.title("Stacked Bar Chart: Bias by Message Type")
plt.ylabel("Number of Posts")
plt.xticks(rotation=45)
plt.show()
```




```
# Top N sources for clarity
top_n_sources = df_clean['source'].value_counts().head(5).index
df_top_sources = df_clean[df_clean['source'].isin(top_n_sources)]

sns.countplot(data=df_top_sources, x='source', hue='bias', palette='Set1')
plt.title("Top 5 Sources by Political Bias")
plt.xticks(rotation=45)
plt.show()
```



📝 Hypothesis Testing

by doing t-Test, chi-square test that helps us to make data-driven decisions by Statistically evaluating patterns assumptions and differences in data.

```
# Chi-square test between bias and message
contingency = pd.crosstab(df_clean['bias'], df_clean['message'])
chi2, p, dof, expected = chi2_contingency(contingency)

print(f"Chi-square value: {chi2}")
print(f"Degrees of Freedom: {dof}")
print(f"P-value: {p}")
```

```
Chi-square value: 1172.4348079207407
Degrees of Freedom: 8
P-value: 8.654969720482628e-248
```

```
from sklearn.preprocessing import LabelEncoder

# Encode categorical features
le_message = LabelEncoder()
```

```
le_source = LabelEncoder()

df_clean['message_encoded'] = le_message.fit_transform(df_clean['message'])
df_clean['source_encoded'] = le_source.fit_transform(df_clean['source'])

# Encode the target variable: bias (neutral = 0, partisan = 1)
df_clean['bias_encoded'] = df_clean['bias'].map({'neutral': 0, 'partisan': 1}
)

from sklearn.model_selection import train_test_split

# Define features and target
X = df_clean[['message_encoded', 'source_encoded']]
y = df_clean['bias_encoded']

# Split dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, rand
om_state=42)

from sklearn.linear_model import LogisticRegression

# Create and train the logistic regression model
log_model = LogisticRegression()
log_model.fit(X_train, y_train)

# Predict on test data
y_pred = log_model.predict(X_test)

from sklearn.metrics import classification_report, confusion_matrix
```

📊 **Evaluation Metrics Mean Squared Error (MSE)** – Measures average squared difference between actual and predicted values

Mean Absolute Error (MAE) – Measures average absolute difference

R^2 Score – Indicates how well the model explains the variance in revenue (1.0 is perfect)

```
# Print evaluation metrics
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred))
print("\nClassification Report:\n", classification_report(y_test, y_pred))
```

```
Confusion Matrix:
 [[767   0]
 [233   0]]
```

```
Classification Report:
              precision    recall  f1-score   support

           0       0.77      1.00      0.87       767
           1       0.00      0.00      0.00       233

    accuracy                           0.77      1000
   macro avg       0.38      0.50      0.43      1000
weighted avg       0.59      0.77      0.67      1000
```

```
from sklearn.metrics import confusion_matrix
# Predict using the model
y_pred = log_model.predict(X_test)
```

📨 Confusion Matrix

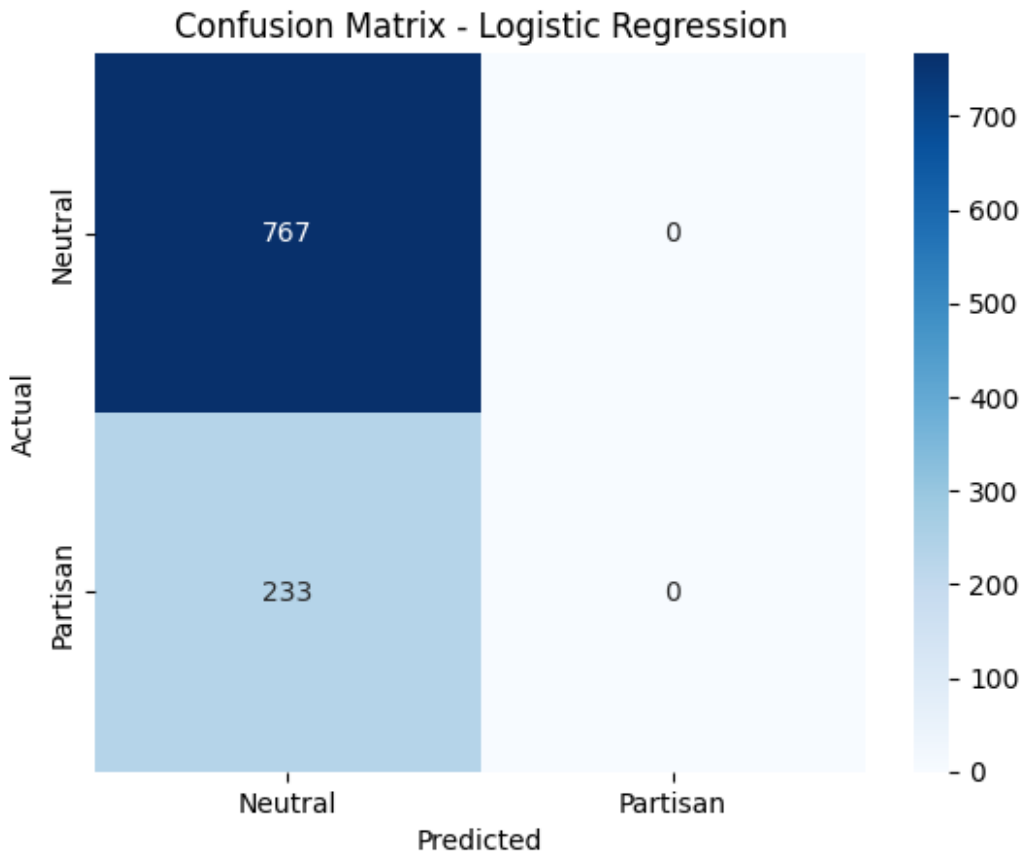
A confusion matrix is a table used to evaluate the performance of a classification model. It shows how well the model is predicting actual classes.

For a multi-class classification the Matrix compares:

- **Actual classes**(True labels) vs.
- **Predicted classes**(From your model)

```
# Get the confusion matrix
cm = confusion_matrix(y_test, y_pred)
labels = ['Neutral', 'Partisan']

# Plot confusion matrix
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=labels, yticklabels=labels)
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix - Logistic Regression')
plt.show()
```



📝 Final Conclusion

This project successfully demonstrated the application of data science techniques in politic al media analysis. Exploratory and statistical methods revealed strong relationships betwe en message content and political bias. Although the initial logistic regression model achieve d moderate accuracy, it struggled with class imbalance, indicating room for model improve ment. Overall, this project emphasized the importance of preprocessing, visualization, and model evaluation in drawing meaningful insights from text-based social media data.

🎯 Project Goals

- To analyze the political messaging and bias present in social media posts by pu blic figures.
- To understand the relationship between message content, source platform, an d the political bias (neutral or partisan).
- To build a predictive model (logistic regression and random forest) that can cl assify a message's political bias based on content and source.

- To validate the statistical significance of relationships using hypothesis testing (e.g., Chi-square test).

🔄 Workflow Followed

We applied the key steps of a typical data science project:

✅ **Collected and cleaned the data**

📊 **Explored and visualized patterns**

📐 **Applied statistical techniques**

🤖 **Built and evaluated machine learning models**

📌 Key Learnings

- Learned to preprocess a real-world, multi-feature dataset by cleaning, transfor ming, and encoding categorical data.
- Gained experience in exploratory data analysis (EDA) using visualization techn iques to detect patterns and distributions.
- Applied univariate and multivariate analysis to explore associations between v ariables such as message type and bias.
- Conducted hypothesis testing (Chi-square test) and interpreted p-values to det ermine statistical significance.
- Built and evaluated classification models (logistic regression and random fores t) to predict political bias.
- Understood model limitations such as class imbalance and the need for tuning and better feature engineering.

References:

- **Imran Ali Shah**. (2023). *Sales and Customer Insights Dataset*. Kaggle. Available at: https://www.kaggle.com/datasets/thedevastator/uncovering-political-bias-in-social-media-commun?resource=download

- Pandas Documentation – Data preprocessing, handling missing values, and exploratory data analysis. https://pandas.pydata.org/docs/

- **Virtanen, P., Gommers, R., Oliphant, T. E., et al.** (2020). *SciPy 1.0: Fundamental Algorithms for Scientific Computing in Python*. Nature Methods, 17, 261–272. (Used for hypothesis testing, probability distributions)

- **McKinney, W.** (2010). *Data Structures for Statistical Computing in Python*. In Proceedings of the 9th Python in Science Conference, 51–56. (Used for structured data handling with Pandas)

- **Waskom, M. L.** (2021). *Seaborn: Statistical Data Visualization*. Journal of Open-Source Software, 6(60), 3021. (Used for histogram and KDE plots in probability analysis)

- **Pedregosa, F., Varoquaux, G., Gramfort, A., et al.** (2011). *Scikit-learn: Machine Learning in Python*. Journal of Machine Learning Research, 12, 2825–2830. (Used for linear regression and classification algorithms)