MSDS 422 Group 1 Final

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1 Final Project: Predicting Online News Popularity with Machine Learning

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Course: MSDS 422 Practical Machine Learning

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[1]:
```
# Import necessary libraries for data analysis, visualization, and machine␣
↪learning

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import math
import warnings
import matplotlib.gridspec as gridspec
import xgboost as xgb
import lightgbm as lgb
from matplotlib.colors import LinearSegmentedColormap
from scipy import stats
from sklearn.preprocessing import LabelEncoder, StandardScaler,OneHotEncoder
from sklearn.model_selection import train_test_split, cross_val_score,␣
↪GridSearchCV, StratifiedKFold, RandomizedSearchCV
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import classification_report, confusion_matrix,␣
↪accuracy_score, f1_score
from sklearn.pipeline import Pipeline
from imblearn.over_sampling import SMOTE
from sklearn.neural_network import MLPClassifier
from sklearn.decomposition import PCA

warnings.filterwarnings('ignore')
```

[2]:
```python
# Set display options
pd.set_option('display.max_columns', None)
plt.style.use('ggplot')
sns.set(style="whitegrid")

# Plot settings
plt.rcParams['figure.figsize'] = (12, 8)
plt.rcParams['font.size'] = 12
```

1.1 Introduction

In today's rapid digital world, online news consumption is quickly increasing. It trends to reshape the media landscape. For content creators and publishers, the key to success depends on driving engagement such as writing articles that engage audiences and resonate deeply. In addition to boosting readership, understanding content engagement allows publishers to expand their reach in an increasingly competitive digital space.

This project explores the dynamics of online news popularity by examining the characteristics and influencing factors of different news types. By categorizing "shares" into low, medium, and high engagement levels, our group apply four machine learning techniques, which are Logistic Regression, Random Forest, Gradient Boosting, XGBoost, LightGBM, and MLP to find what truly drives reader interaction and develop powerful predictive models.

1.2 Dataset

This dataset used in our project can be found from the UCI Machine Learning Repository (https://archive.ics.uci.edu/dataset/332/online+news+popularity). It contains metadata and social feedback from 39,797 articles published on "*Mashable*"(www.mashable.com). It consists of 61 attributes, categorized as predictive features(58), non-predictive fields(2), and the target variable(1).

1.2.1 1. Non-Predictive Attributes

- **`url`**: The URL of the article.
- **`timedelta`**: The number of days between the article's publication and dataset acquisition.

1.2.2 2. Predictive Attributes

- **n_tokens_title**: Number of words in the article title.
- **n_tokens_content**: Number of words in the article body.
- **n_unique_tokens**: Proportion of unique words in the content.
- **n_non_stop_words**: Proportion of non-stop words in the content.
- **n_non_stop_unique_tokens**: Proportion of unique non-stop words in the content.

- **average_token_length**: Average length of words in the content.
- **num_hrefs**: Number of hyperlinks in the article.
- **num_self_hrefs**: Number of links to other *Mashable* articles.
- **num_imgs**: Number of images in the article.
- **num_videos**: Number of videos in the article.
- **num_keywords**: Number of keywords assigned in the metadata.
- **data_channel_is_lifestyle**: Is the article in the "Lifestyle" category?
- **data_channel_is_entertainment**: Is the article in the "Entertainment" category?
- **data_channel_is_bus**: Is the article in the "Business" category?
- **data_channel_is_socmed**: Is the article in the "Social Media" category?
- **data_channel_is_tech**: Is the article in the "Tech" category?
- **data_channel_is_world**: Is the article in the "World" category?
- **kw_min_min**: Minimum shares of the least popular keyword.
- **kw_max_min**: Maximum shares of the least popular keyword.
- **kw_avg_min**: Average shares of the least popular keyword.
- **kw_min_max**: Minimum shares of the most popular keyword.
- **kw_max_max**: Maximum shares of the most popular keyword.
- **kw_avg_max**: Average shares of the most popular keyword.
- **kw_min_avg**: Minimum shares of the average keyword.
- **kw_max_avg**: Maximum shares of the average keyword.
- **kw_avg_avg**: Average shares of the average keyword.
- **self_reference_min_shares**: Minimum shares of referenced *Mashable* articles.
- **self_reference_max_shares**: Maximum shares of referenced *Mashable* articles.
- **self_reference_avg_sharess**: Average shares of referenced *Mashable* articles.

- **weekday_is_monday** : Was the article published on Monday?
- **weekday_is_tuesday** : Was the article published on Tuesday?
- **weekday_is_wednesday** : Was the article published on Wednesday?
- **weekday_is_thursday** : Was the article published on Thursday?
- **weekday_is_friday** : Was the article published on Friday?
- **weekday_is_saturday** : Was the article published on Saturday?
- **weekday_is_sunday** : Was the article published on Sunday?
- **is_weekend** : Was the article published on a weekend?
- **LDA_00**, **LDA_01**, **LDA_02**, **LDA_03**, **LDA_04**: Probabilities of an article belonging to five different topics.
- **global_subjectivity**: Subjectivity score of the article content.
- **global_sentiment_polarity**: Overall sentiment polarity of the content.
- **global_rate_positive_words**: Proportion of positive words in the content.
- **global_rate_negative_words**: Proportion of negative words in the content.
- **rate_positive_words**: Rate of positive words among non-neutral tokens.
- **rate_negative_words**: Rate of negative words among non-neutral tokens.
- **avg_positive_polarity**: Average polarity score of positive words.
- **min_positive_polarity**: Minimum polarity score of positive words.
- **max_positive_polarity**: Maximum polarity score of positive words.
- **avg_negative_polarity**: Average polarity score of negative words.
- **min_negative_polarity**: Minimum polarity score of negative words.
- **max_negative_polarity**: Maximum polarity score of negative words.
- **title_subjectivity'**: Subjectivity score of the title.
- **title_sentiment_polarity**: Sentiment polarity of the title.
- **abs_title_subjectivity**: Absolute subjectivity level of the title.

- **abs_title_sentiment_polarity**: Absolute sentiment polarity level of the title.

1.2.3 3. Target Variable

- **shares**: The number of times an article was shared online. This is the target variable for predicting article popularity.

[3]:
```
# Read data
file_path = 'Data/OnlineNewsPopularity_Final.xls'
df = pd.read_csv(file_path)
```

[4]:
```
# Drop unnecessary columns
columns_to_drop = ['url', 'timedelta']
if 'author_name' in df.columns:
    columns_to_drop.append('author_name')
df = df.drop(columns_to_drop, axis=1, errors='ignore')
```

We choose to drop non-predictive attributes in machine learning preprocessing because these features “url” and “timedelta” typically do not contribute meaningful information into what drives article engagement or shares. It may introduce noise which will degrade model performance. Overall, dropping these two columns allows the model to focus on the most relevant predictors.

1.3 EDA

Before EDA, we aim to explore the dataset structure, check for missing values, and analyze key features like content, timing, and sentiment. We hope to identify patterns that influence article shares and guiding feature selection.

[5]:
```
# 1. Dataset Overview
print("="*50)
print("1. Dataset Overview")
print(f"Dataset shape: {df.shape}")
print(f"Dataset memory usage: {df.memory_usage().sum() / 1024**2:.2f} MB")
print("\nData type distribution:")
print(df.dtypes.value_counts())

# Display first few rows
print("\nFirst 5 rows of the dataset:")
display(df.head())
```

```
==================================================
1. Dataset Overview
Dataset shape: (39644, 65)
Dataset memory usage: 19.66 MB

Data type distribution:
float64    34
int64      25
```

```
object      6
Name: count, dtype: int64

First 5 rows of the dataset:

   n_tokens_title  n_tokens_content  n_unique_tokens  n_non_stop_words  \
0              12               219         0.663594               1.0
1               9               255         0.604743               1.0
2               9               211         0.575130               1.0
3               9               531         0.503788               1.0
4              13              1072         0.415646               1.0

   n_non_stop_unique_tokens  num_hrefs  num_self_hrefs  num_imgs  num_videos  \
0                  0.815385          4               2         1           0
1                  0.791946          3               1         1           0
2                  0.663866          3               1         1           0
3                  0.665635          9               0         1           0
4                  0.540890         19              19        20           0

   average_token_length  num_keywords  data_channel_is_lifestyle  \
0              4.680365             5                          0
1              4.913725             4                          0
2              4.393365             6                          0
3              4.404896             7                          0
4              4.682836             7                          0

   data_channel_is_entertainment  data_channel_is_bus  data_channel_is_socmed  \
0                              1                    0                       0
1                              0                    1                       0
2                              0                    1                       0
3                              1                    0                       0
4                              0                    0                       0

   data_channel_is_tech  data_channel_is_world  kw_min_min  kw_max_min  \
0                     0                      0           0         0.0
1                     0                      0           0         0.0
2                     0                      0           0         0.0
3                     0                      0           0         0.0
4                     1                      0           0         0.0

   kw_avg_min  kw_min_max  kw_max_max  kw_avg_max  kw_min_avg  kw_max_avg  \
0         0.0           0           0         0.0         0.0         0.0
1         0.0           0           0         0.0         0.0         0.0
2         0.0           0           0         0.0         0.0         0.0
3         0.0           0           0         0.0         0.0         0.0
4         0.0           0           0         0.0         0.0         0.0

   kw_avg_avg  self_reference_min_shares  self_reference_max_shares  \
```

```
0        0.0                        496.0                        496.0
1        0.0                          0.0                          0.0
2        0.0                        918.0                        918.0
3        0.0                          0.0                          0.0
4        0.0                        545.0                      16000.0

   self_reference_avg_sharess  weekday_is_monday  weekday_is_tuesday  \
0                  496.000000                  1                   0
1                    0.000000                  1                   0
2                  918.000000                  1                   0
3                    0.000000                  1                   0
4                 3151.157895                  1                   0

   weekday_is_wednesday  weekday_is_thursday  weekday_is_friday  \
0                     0                    0                  0
1                     0                    0                  0
2                     0                    0                  0
3                     0                    0                  0
4                     0                    0                  0

   weekday_is_saturday  weekday_is_sunday  is_weekend    LDA_00    LDA_01  \
0                    0                  0           0  0.500331  0.378279
1                    0                  0           0  0.799756  0.050047
2                    0                  0           0  0.217792  0.033334
3                    0                  0           0  0.028573  0.419300
4                    0                  0           0  0.028633  0.028794

     LDA_02    LDA_03    LDA_04  global_subjectivity  \
0  0.040005  0.041263  0.040123             0.521617
1  0.050096  0.050101  0.050001             0.341246
2  0.033351  0.033334  0.682188             0.702222
3  0.494651  0.028905  0.028572             0.429850
4  0.028575  0.028572  0.885427             0.513502

   global_sentiment_polarity  global_rate_positive_words  \
0                   0.092562                    0.045662
1                   0.148948                    0.043137
2                   0.323333                    0.056872
3                   0.100705                    0.041431
4                   0.281003                    0.074627

   global_rate_negative_words  rate_positive_words  rate_negative_words  \
0                    0.013699             0.769231             0.230769
1                    0.015686             0.733333             0.266667
2                    0.009479             0.857143             0.142857
3                    0.020716             0.666667             0.333333
4                    0.012127             0.860215             0.139785
```

```
   avg_positive_polarity  min_positive_polarity  max_positive_polarity  \
0               0.378636               0.100000                    0.7
1               0.286915               0.033333                    0.7
2               0.495833               0.100000                    1.0
3               0.385965               0.136364                    0.8
4               0.411127               0.033333                    1.0

   avg_negative_polarity  min_negative_polarity  max_negative_polarity  \
0              -0.350000                 -0.600              -0.200000
1              -0.118750                 -0.125              -0.100000
2              -0.466667                 -0.800              -0.133333
3              -0.369697                 -0.600              -0.166667
4              -0.220192                 -0.500              -0.050000

   title_subjectivity  title_sentiment_polarity  abs_title_subjectivity  \
0            0.500000                 -0.187500                0.000000
1            0.000000                  0.000000                0.500000
2            0.000000                  0.000000                0.500000
3            0.000000                  0.000000                0.500000
4            0.454545                  0.136364                0.045455

   abs_title_sentiment_polarity shares   followers  shares_original  \
0                      0.187500    Low        High              593
1                      0.000000    Low      Medium              711
2                      0.000000   High      Medium             1500
3                      0.000000    Low  Reprinted             1200
4                      0.136364    Low         Low              505

  followers_original        channel day_type author_level
0             558463  entertainment  weekday       Medium
1              17000            bus  weekday       Medium
2              17000            bus  weekday       Medium
3          Reprinted  entertainment  weekday       Medium
4               1473           tech  weekday       Medium
```

[6]:

```python
# Check for missing values
print("\nMissing values per column:")
missing_values = df.isnull().sum()
print(missing_values[missing_values > 0] if missing_values.any() > 0 else "No␣
↪missing values found")

# Check for object columns
object_columns = df.select_dtypes(include=['object']).columns
print("\nObject columns in the dataset:")
print(object_columns)

# Display unique values in each object column
```

```python
for col in object_columns:
    print(f"\nUnique values in {col}: {df[col].nunique()}")
    print(df[col].value_counts().head())
```

```
Missing values per column:
No missing values found

Object columns in the dataset:
Index(['shares', 'followers', 'followers_original', 'channel', 'day_type',
       'author_level'],
      dtype='object')

Unique values in shares: 2
shares
High    21154
Low     18490
Name: count, dtype: int64

Unique values in followers: 7
followers
Low              15234
Unknown           8643
Medium            8200
Reprinted         3747
Extremely Low     2163
Name: count, dtype: int64

Unique values in followers_original: 151
followers_original
Null         9297
Reprinted    3747
5177         1508
9383         1467
9547         1457
Name: count, dtype: int64

Unique values in channel: 7
channel
world            8427
tech             7346
entertainment    7057
bus              6258
other            6134
Name: count, dtype: int64

Unique values in day_type: 2
day_type
```

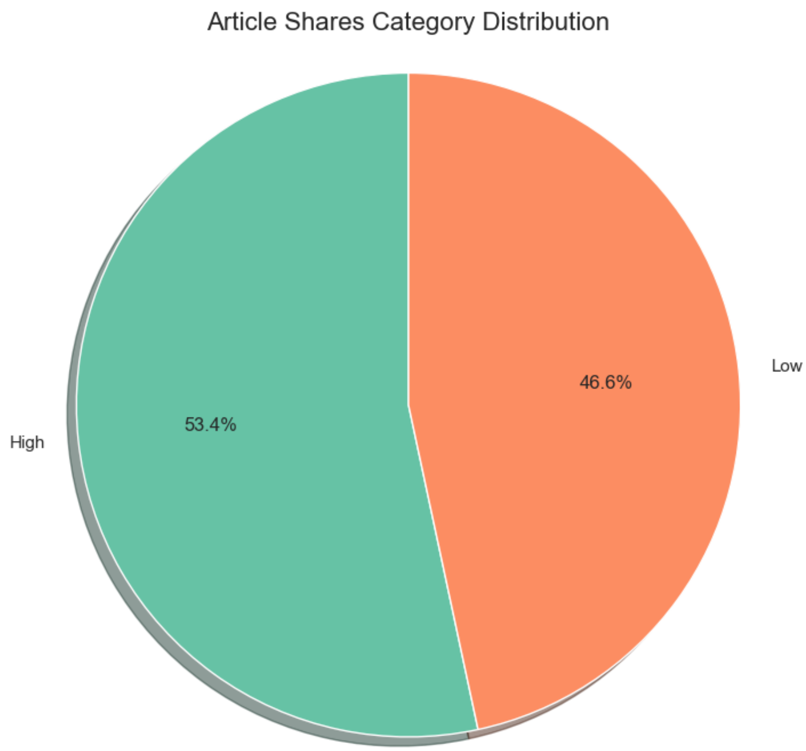
```
weekday    34454
weekend     5190
Name: count, dtype: int64

Unique values in author_level: 3
author_level
Medium    22089
High      17360
Low         195
Name: count, dtype: int64
```

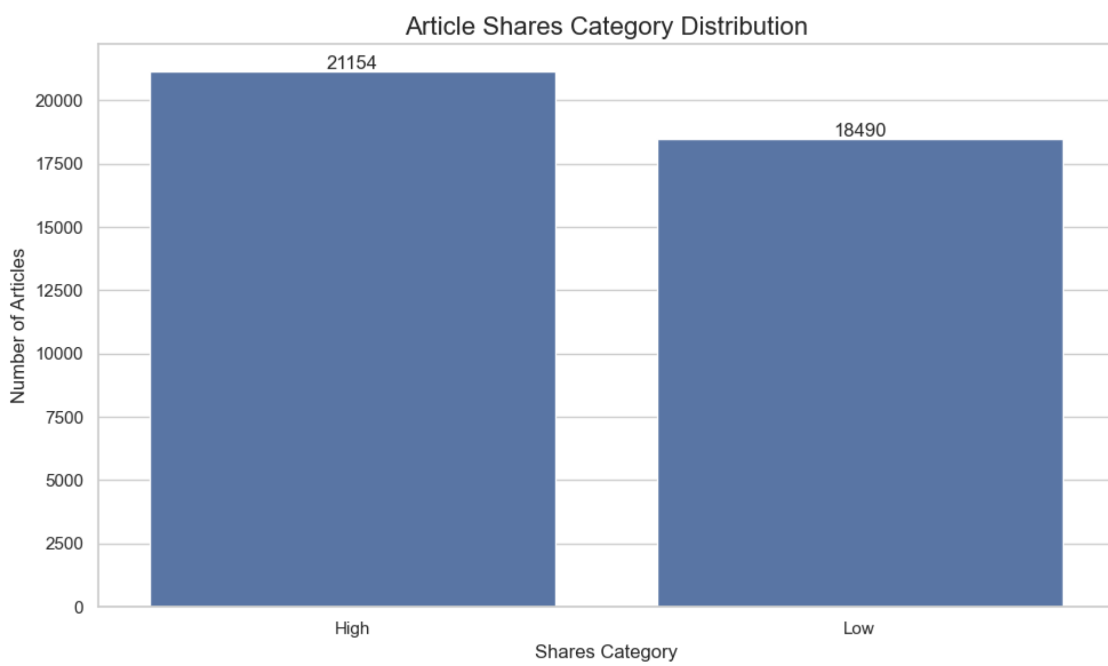
[7]:

```
# 2. Target Variable Analysis
print("\n" + "="*50)
print("2. Target Variable Analysis")

# Check shares column type and process accordingly
if 'shares' in df.columns:
    if df['shares'].dtype == 'object':
        # If shares is object type, show category distribution
        shares_counts = df['shares'].value_counts()
        print("\nShares category distribution:")
        print(shares_counts)
        print("\nPercentage distribution:")
        print((shares_counts / len(df) * 100).round(2))

        # Pie chart
        plt.figure(figsize=(10, 7))
        plt.pie(shares_counts, labels=shares_counts.index, autopct='%1.1f%%',
                shadow=True, startangle=90, colors=sns.color_palette("Set2"))
        plt.title('Article Shares Category Distribution', fontsize=16)
        plt.axis('equal')  # Equal aspect ratio ensures that pie is drawn as a␣
↪circle.
        plt.tight_layout()
        plt.show()

        # Bar chart
        plt.figure(figsize=(10, 6))
        ax = sns.barplot(x=shares_counts.index, y=shares_counts.values)
        plt.title('Article Shares Category Distribution', fontsize=16)
        plt.xlabel('Shares Category')
        plt.ylabel('Number of Articles')

        # Add value labels on bars
        for i, v in enumerate(shares_counts.values):
            ax.text(i, v + 100, f"{v}", ha='center')

        plt.tight_layout()
```

```python
        plt.show()

    elif df['shares'].dtype == 'int32' or df['shares'].dtype == 'int64' or␣
↪df['shares'].dtype == 'float64':
        # If shares is numeric, show value statistics
        print("\nShares value statistics:")
        print(df['shares'].describe())

        # Histogram
        plt.figure(figsize=(12, 6))
        sns.histplot(df['shares'], bins=30, kde=True)
        plt.title('Article Shares Distribution', fontsize=16)
        plt.xlabel('Number of Shares')
        plt.ylabel('Number of Articles')
        plt.tight_layout()
        plt.show()
```

```
==================================================
2. Target Variable Analysis

Shares category distribution:
shares
High    21154
Low     18490
Name: count, dtype: int64

Percentage distribution:
shares
High    53.36
Low     46.64
Name: count, dtype: float64
```





The two charts show the proportion of articles in each category. It confirms that 46.6% of articles fall into the Low levels and 53.5% of the rows are from High Levels. It highlights that the two groups are balanced. Our models' performance will not be influenced significantly by the imbalanced data.

[8]:
```
# 3. Content Feature Analysis
print("\n" + "="*50)
print("3. Content Feature Analysis")

# Select content-related features
content_features = ['n_tokens_title', 'n_tokens_content', 'n_unique_tokens',
                    'num_hrefs', 'num_self_hrefs', 'num_imgs', 'num_videos',
                    'average_token_length', 'num_keywords']

# Filter to include only features that exist in the dataframe
content_features = [f for f in content_features if f in df.columns]

# Descriptive statistics for content features
content_stats = df[content_features].describe().T
content_stats['cv'] = content_stats['std'] / content_stats['mean']  #␣
↪Coefficient of variation
print("\nContent feature statistics:")
display(content_stats)
```

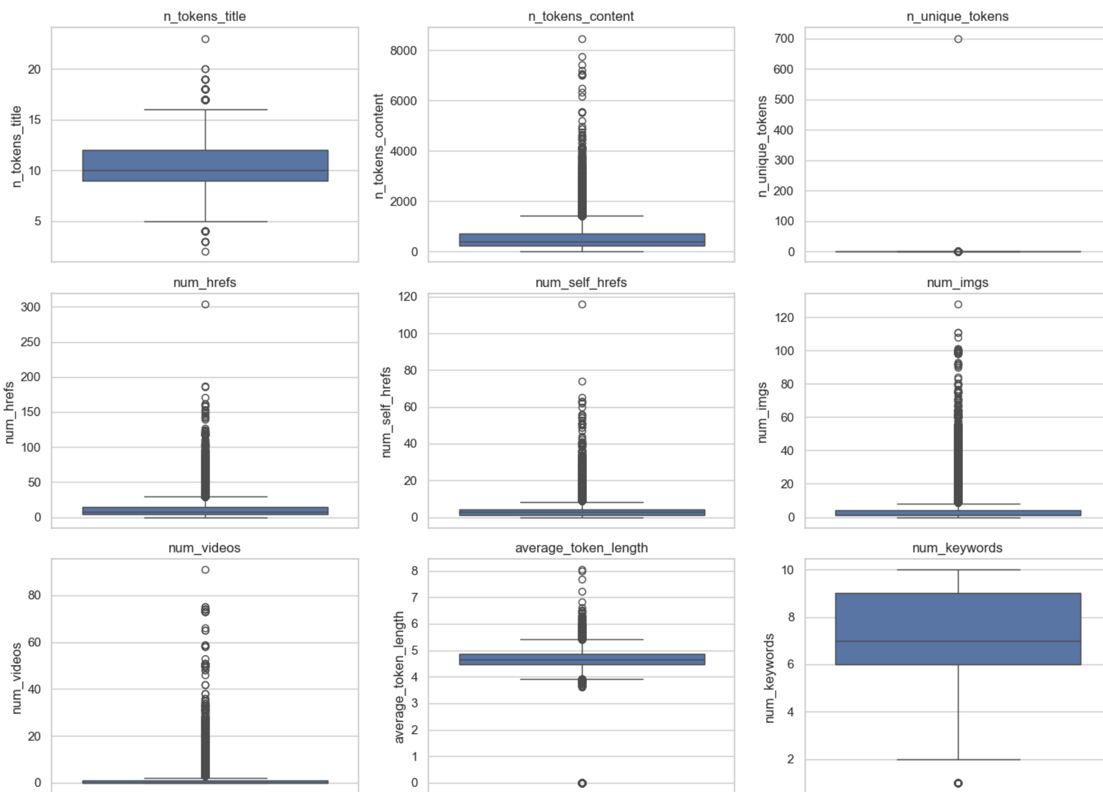
```
==================================================
3. Content Feature Analysis

Content feature statistics:
```

	count	mean	std	min	25%
n_tokens_title	39644.0	10.398749	2.114037	2.0	9.000000
n_tokens_content	39644.0	546.514731	471.107508	0.0	246.000000
n_unique_tokens	39644.0	0.548216	3.520708	0.0	0.470870
num_hrefs	39644.0	10.883690	11.332017	0.0	4.000000
num_self_hrefs	39644.0	3.293638	3.855141	0.0	1.000000
num_imgs	39644.0	4.544143	8.309434	0.0	1.000000
num_videos	39644.0	1.249874	4.107855	0.0	0.000000
average_token_length	39644.0	4.548239	0.844406	0.0	4.478404
num_keywords	39644.0	7.223767	1.909130	1.0	6.000000

	50%	75%	max	cv
n_tokens_title	10.000000	12.000000	23.000000	0.203297
n_tokens_content	409.000000	716.000000	8474.000000	0.862022
n_unique_tokens	0.539226	0.608696	701.000000	6.422122
num_hrefs	8.000000	14.000000	304.000000	1.041193
num_self_hrefs	3.000000	4.000000	116.000000	1.170481
num_imgs	1.000000	4.000000	128.000000	1.828603
num_videos	0.000000	1.000000	91.000000	3.286616
average_token_length	4.664082	4.854839	8.041534	0.185655

```
num_keywords            7.000000    9.000000    10.000000  0.264285
```

[9]:
```
# Box plots for content features
plt.figure(figsize=(14, 10))
for i, feature in enumerate(content_features):
    plt.subplot(3, 3, i+1)
    sns.boxplot(y=df[feature])
    plt.title(f'{feature}')
    plt.tight_layout()
plt.show()
```



Interpretation of the Boxplots:

The boxplots display the distribution of many numerical features related to article content. A key observation is the presence of numerous outliers in most variables. It indicates that certain articles have exceptionally high values compared to the majority.

- **n_tokens_title and n_tokens_content:** The title word count is relatively consistent, but the content word count has extreme outliers. It suggests that some articles are much longer.

- **num_hrefs, num_self_hrefs, num_imgs, num_videos:** These features show heavy-tailed distributions with extreme values. It indicates that some of them have outliers.

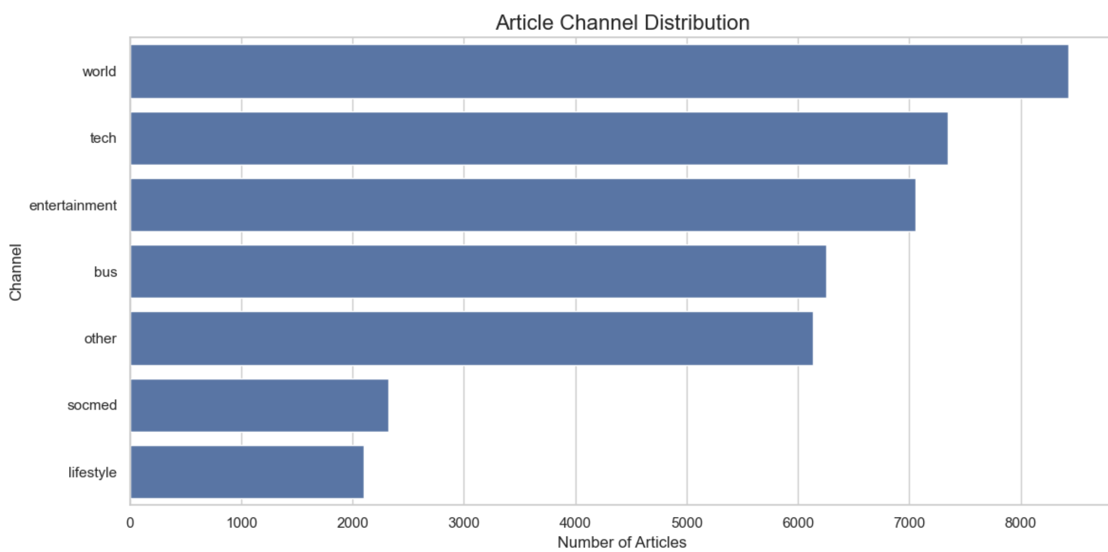
- **num_keywords:** This feature shows a more balanced distribution with a typical range between 6 and 9 keywords.

Overall, the dataset has highly skewed distributions for many features and many outliers. This suggests that article characteristics vary widely, and special attention may be needed during data preprocessing like normalization when building predictive models.

[10]:
```python
# 4. Channel Distribution Analysis
print("\n" + "="*50)
print("4. Channel Distribution Analysis")

# Check if channel column exists
if 'channel' in df.columns:
    channel_counts = df['channel'].value_counts()
    print("\nChannel distribution:")
    print(channel_counts)

    # Plot channel distribution
    plt.figure(figsize=(12, 6))
    sns.countplot(y='channel', data=df, order=channel_counts.index)
    plt.title('Article Channel Distribution', fontsize=16)
    plt.xlabel('Number of Articles')
    plt.ylabel('Channel')
    plt.tight_layout()
    plt.show()
else:
    # Use data_channel_is_* columns
    channel_cols = [col for col in df.columns if col.
↪startswith('data_channel_is_')]
    if channel_cols:
        channel_counts = {}
        for col in channel_cols:
            channel_name = col.replace('data_channel_is_', '')
            channel_counts[channel_name] = df[col].sum()

        channel_df = pd.DataFrame.from_dict(channel_counts, orient='index',␣
↪columns=['count'])
        channel_df = channel_df.sort_values('count', ascending=False)

        print("\nChannel distribution:")
        print(channel_df)

        # Plot channel distribution
        plt.figure(figsize=(12, 6))
        sns.barplot(x=channel_df.index, y='count', data=channel_df)
        plt.title('Article Channel Distribution', fontsize=16)
        plt.xlabel('Channel')
        plt.ylabel('Number of Articles')
```

```
        plt.xticks(rotation=45)
        plt.tight_layout()
        plt.show()
```

```
==================================================
4. Channel Distribution Analysis

Channel distribution:
channel
world            8427
tech             7346
entertainment    7057
bus              6258
other            6134
socmed           2323
lifestyle        2099
Name: count, dtype: int64
```



Intepretation of Article Channel Distribution:

The bar chart shows the distribution of articles across different content channels. It reveals that the "World" category has the highest number of articles (8,427), "Tech" (7,346), "Entertainment" (7,057), "Business" (6,258), "Social Media" (2,323) and "Lifestyle" (2,099). This suggests that news coverage is heavily skewed towards global affairs, technology, and entertainment, while social media and lifestyle topics are less frequently published. The distribution highlights content priorities and could indicate audience preferences.

[11]:
```
# 5. Followers Analysis
print("\n" + "="*50)
```

```
print("5. Followers Analysis")

# Check if followers column exists
if 'followers' in df.columns:
    print("\nFound 'followers' column")

    # Check the data type and sample values
    print(f"Data type of 'followers' column: {df['followers'].dtype}")
    print("Sample values from 'followers' column:")
    print(df['followers'].head())

    # If the column contains concatenated strings, clean it first
    # This step is crucial based on the error message
    if df['followers'].dtype == 'object':
        # Check if we need to extract individual categories
        if len(df['followers'].unique()) > 10:  # If there are too many unique␣
↪values, it might be concatenated
            print("\nDetected possible concatenated values in 'followers'␣
↪column. Cleaning data...")

            # Try to extract the categories properly
            # Create a pattern to match the expected categories
            import re

            # Extract valid category values (Low, Medium, High, Viral)
            valid_categories = ['Low', 'Medium', 'High', 'Viral']

            # Function to extract the first valid category from a string
            def extract_category(value):
                if isinstance(value, str):
                    for category in valid_categories:
                        if category in value:
                            return category
                return value

            # Apply the function to clean the column
            df['followers_clean'] = df['followers'].apply(extract_category)
            print("\nCreated 'followers_clean' column with extracted␣
↪categories")
            print(df['followers_clean'].value_counts())

            # Use the cleaned column for analysis
            followers_col = 'followers_clean'
        else:
            # If values look reasonable, use as-is
            followers_col = 'followers'
    else:
```

```
        # If not string type, use as-is
        followers_col = 'followers'

    # Output basic statistics
    print("\nBasic statistics for the followers column:")
    print(df[followers_col].describe())

    # Get unique values
    unique_values = sorted(df[followers_col].unique())
    print(f"\nUnique values in followers column: {unique_values}")
```

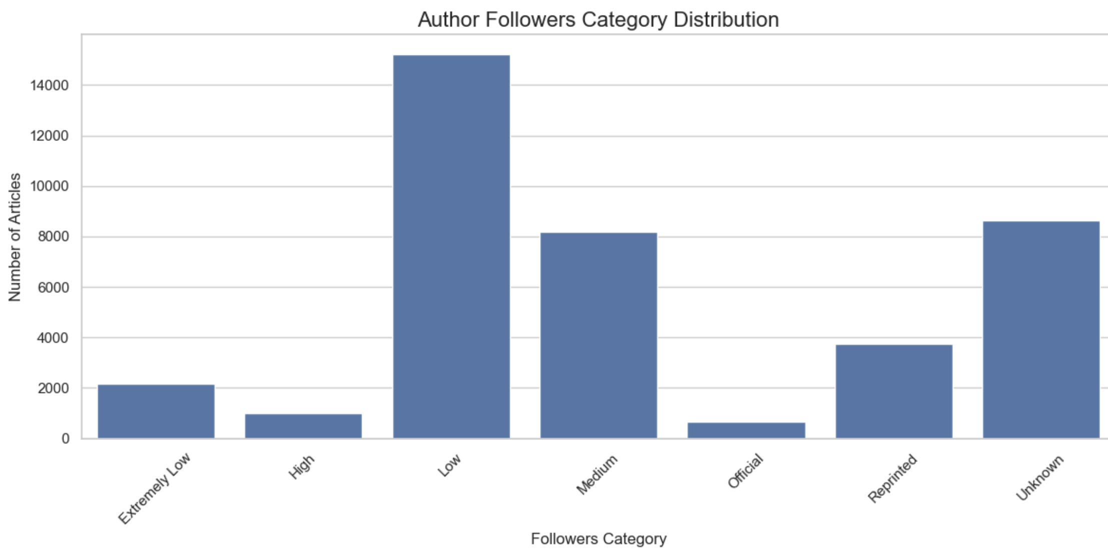
```
==================================================
5. Followers Analysis

Found 'followers' column
Data type of 'followers' column: object
Sample values from 'followers' column:
0         High
1       Medium
2       Medium
3    Reprinted
4          Low
Name: followers, dtype: object

Basic statistics for the followers column:
count     39644
unique        7
top         Low
freq      15234
Name: followers, dtype: object

Unique values in followers column: ['Extremely Low', 'High', 'Low', 'Medium',
'Official', 'Reprinted', 'Unknown']
```

[12]:

```
# Count the distribution of each category
followers_distribution = df[followers_col].value_counts().sort_index()
print("\nFollowers category distribution:")
print(followers_distribution)

# Plot the followers distribution
plt.figure(figsize=(12, 6))
sns.countplot(x=followers_col, data=df, order=sorted(df[followers_col].
 ↪unique()))
plt.title('Author Followers Category Distribution', fontsize=16)
plt.xlabel('Followers Category')
plt.ylabel('Number of Articles')
```

```
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```

```
Followers category distribution:
followers
Extremely Low     2163
High              1003
Low              15234
Medium            8200
Official           654
Reprinted         3747
Unknown           8643
Name: count, dtype: int64
```



Intepretation of Author Followers Category Distribution:

The bar chart illustrates the distribution of articles based on the author's follower category. Interestingly, we found that very few articles are written by authors with High follower counts (1,003). It means highly followed authors contribute less frequently. Additionally, a portion of articles are categorized as Reprinted (3,747), indicating content republished from other sources. This distribution suggests that articles from low-followed or unknown authors dominate the platform. We consider that the reason for this possibility is that low-followed authors need to actively publish their works on the platform to get more traffic.

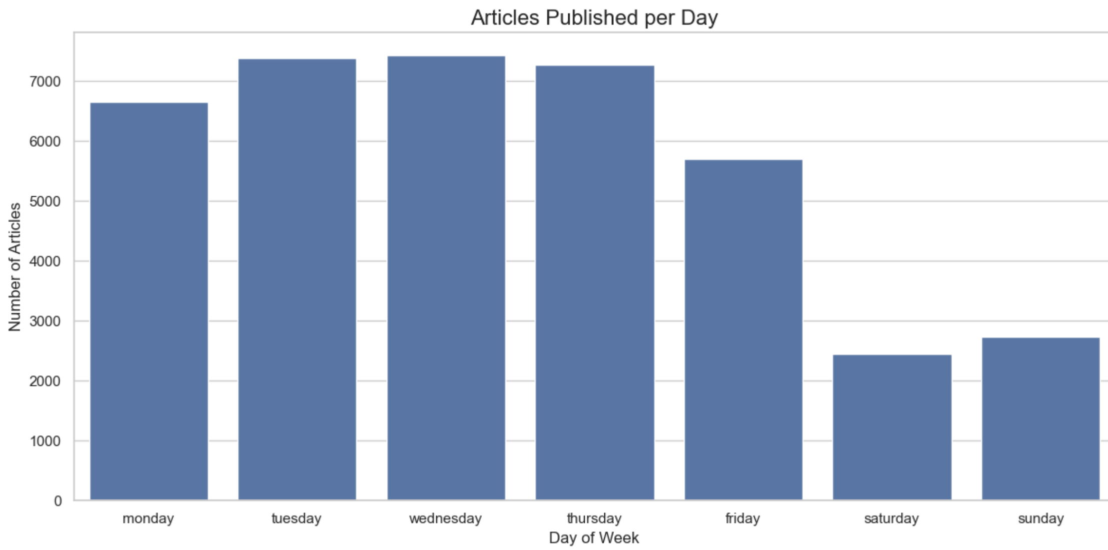
[13]:
```
# 6. Time Feature Analysis
print("\n" + "="*50)
print("6. Time Feature Analysis")
```

```
# Check if weekday columns exist
weekday_cols = [col for col in df.columns if col.startswith('weekday_is_')]
if weekday_cols:
    # Count articles for each day
    weekday_counts = {}
    for col in weekday_cols:
        day = col.replace('weekday_is_', '')
        weekday_counts[day] = df[col].sum()

    # Specify order
    ordered_days = ['monday', 'tuesday', 'wednesday', 'thursday', 'friday',␣
↪'saturday', 'sunday']
    weekday_df = pd.DataFrame([(day, weekday_counts.get(day, 0)) for day in␣
↪ordered_days],
                              columns=['day', 'count'])

    print("\nArticles per day:")
    print(weekday_df)
```

```
==================================================
6. Time Feature Analysis

Articles per day:
         day  count
0     monday   6661
1    tuesday   7390
2  wednesday   7435
3   thursday   7267
4     friday   5701
5   saturday   2453
6     sunday   2737
```

[14]:

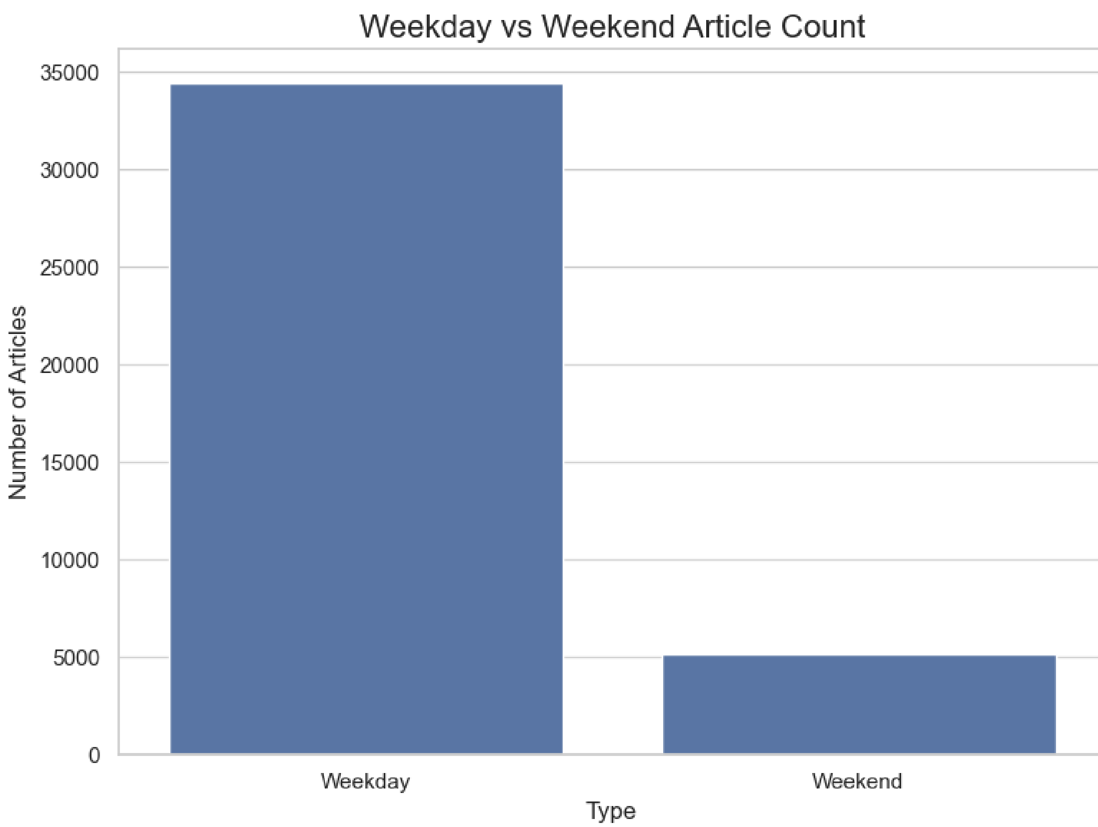
```
# Plot articles per day
plt.figure(figsize=(12, 6))
sns.barplot(x='day', y='count', data=weekday_df)
plt.title('Articles Published per Day', fontsize=16)
plt.xlabel('Day of Week')
plt.ylabel('Number of Articles')
plt.tight_layout()
plt.show()
```



[15]:

```python
# Analyze weekend vs weekday difference
if 'is_weekend' in df.columns:
    weekend_counts = df['is_weekend'].value_counts()
    labels = ['Weekday', 'Weekend']

    print("\nWeekday vs Weekend articles:")
    print(f"Weekday: {weekend_counts.get(0, 0)}")
    print(f"Weekend: {weekend_counts.get(1, 0)}")

# Plot weekday vs weekend comparison
plt.figure(figsize=(8, 6))
sns.barplot(x=[0, 1], y=[weekend_counts.get(0, 0), weekend_counts.get(1, 0)])
plt.title('Weekday vs Weekend Article Count', fontsize=16)
plt.xlabel('Type')
plt.ylabel('Number of Articles')
plt.xticks([0, 1], labels)
plt.tight_layout()
plt.show()
```

```
Weekday vs Weekend articles:
Weekday: 34454
Weekend: 5190
```



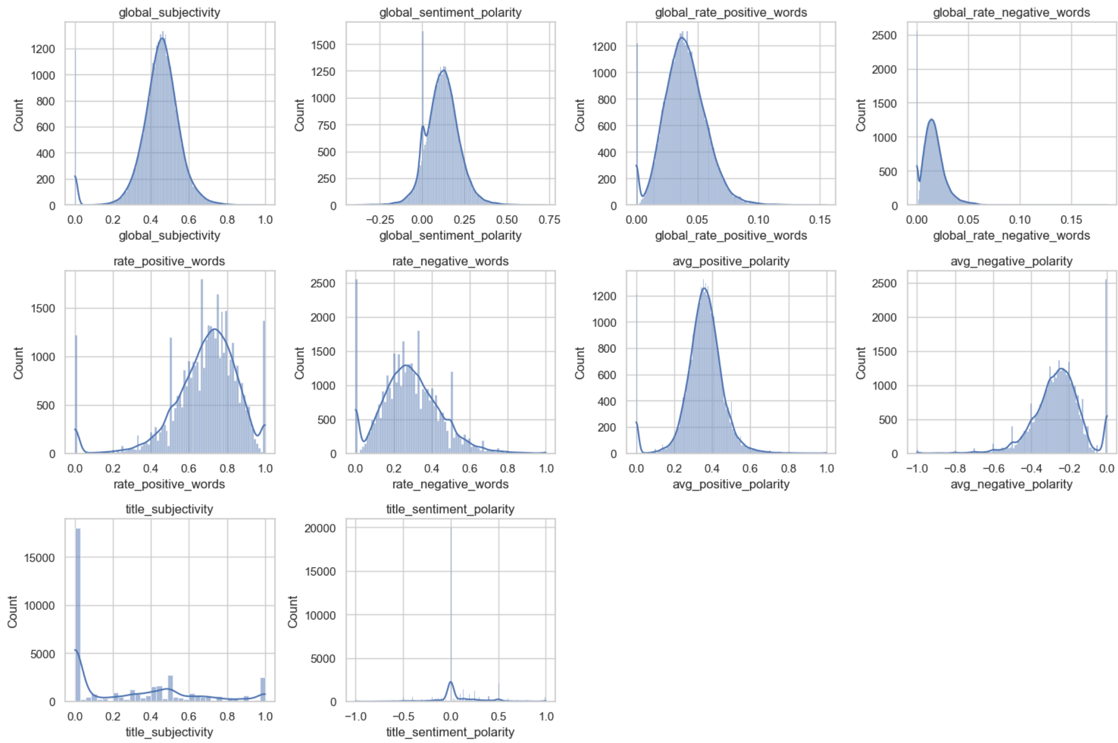
Intepretation of "Articles Published Per Day" and "Weekday vs Weekend Article Count":

This is an interesting result. Our group initially guessed that the number of articles on weekends would be greater than the number on weekdays. We found that the first chart shows that article publication peaks from Tuesday to Thursday, and a sharp drop on weekends. The second chart further shows this trend by aggregating the data. This suggests that most content is published during the workweek. This may be due to a significant drop in publication frequency on weekends to connect with higher audience engagement and newsroom activity.

[16]:
```
# 7. Sentiment Feature Analysis
print("\n" + "="*50)
print("7. Sentiment and Subjectivity Analysis")

# Select sentiment and subjectivity features
sentiment_features = [
    'global_subjectivity', 'global_sentiment_polarity',
    'global_rate_positive_words', 'global_rate_negative_words',
    'rate_positive_words', 'rate_negative_words',
    'avg_positive_polarity', 'avg_negative_polarity',
    'title_subjectivity', 'title_sentiment_polarity'
]
```

```python
sentiment_features = [f for f in sentiment_features if f in df.columns]

if sentiment_features:
    # Descriptive statistics for sentiment features
    sentiment_stats = df[sentiment_features].describe().T
    print("\nSentiment feature statistics:")
    display(sentiment_stats)

    # Distribution plots for sentiment features
    plt.figure(figsize=(15, 10))
    for i, feature in enumerate(sentiment_features):
        plt.subplot(3, 4, i+1)
        sns.histplot(df[feature], kde=True)
        plt.title(f'{feature}')
        plt.tight_layout()
    plt.show()
```

```
==================================================
7. Sentiment and Subjectivity Analysis

Sentiment feature statistics:
                              count      mean       std      min       25%  \
global_subjectivity         39644.0  0.443370  0.116685  0.00000  0.396167
global_sentiment_polarity   39644.0  0.119309  0.096931 -0.39375  0.057757
global_rate_positive_words  39644.0  0.039625  0.017429  0.00000  0.028384
global_rate_negative_words  39644.0  0.016612  0.010828  0.00000  0.009615
rate_positive_words         39644.0  0.682150  0.190206  0.00000  0.600000
rate_negative_words         39644.0  0.287934  0.156156  0.00000  0.185185
avg_positive_polarity       39644.0  0.353825  0.104542  0.00000  0.306244
avg_negative_polarity       39644.0 -0.259524  0.127726 -1.00000 -0.328383
title_subjectivity          39644.0  0.282353  0.324247  0.00000  0.000000
title_sentiment_polarity    39644.0  0.071425  0.265450 -1.00000  0.000000

                                 50%       75%       max
global_subjectivity         0.453457  0.508333  1.000000
global_sentiment_polarity   0.119117  0.177832  0.727841
global_rate_positive_words  0.039023  0.050279  0.155488
global_rate_negative_words  0.015337  0.021739  0.184932
rate_positive_words         0.710526  0.800000  1.000000
rate_negative_words         0.280000  0.384615  1.000000
avg_positive_polarity       0.358755  0.411428  1.000000
avg_negative_polarity      -0.253333 -0.186905  0.000000
title_subjectivity          0.150000  0.500000  1.000000
title_sentiment_polarity    0.000000  0.150000  1.000000
```



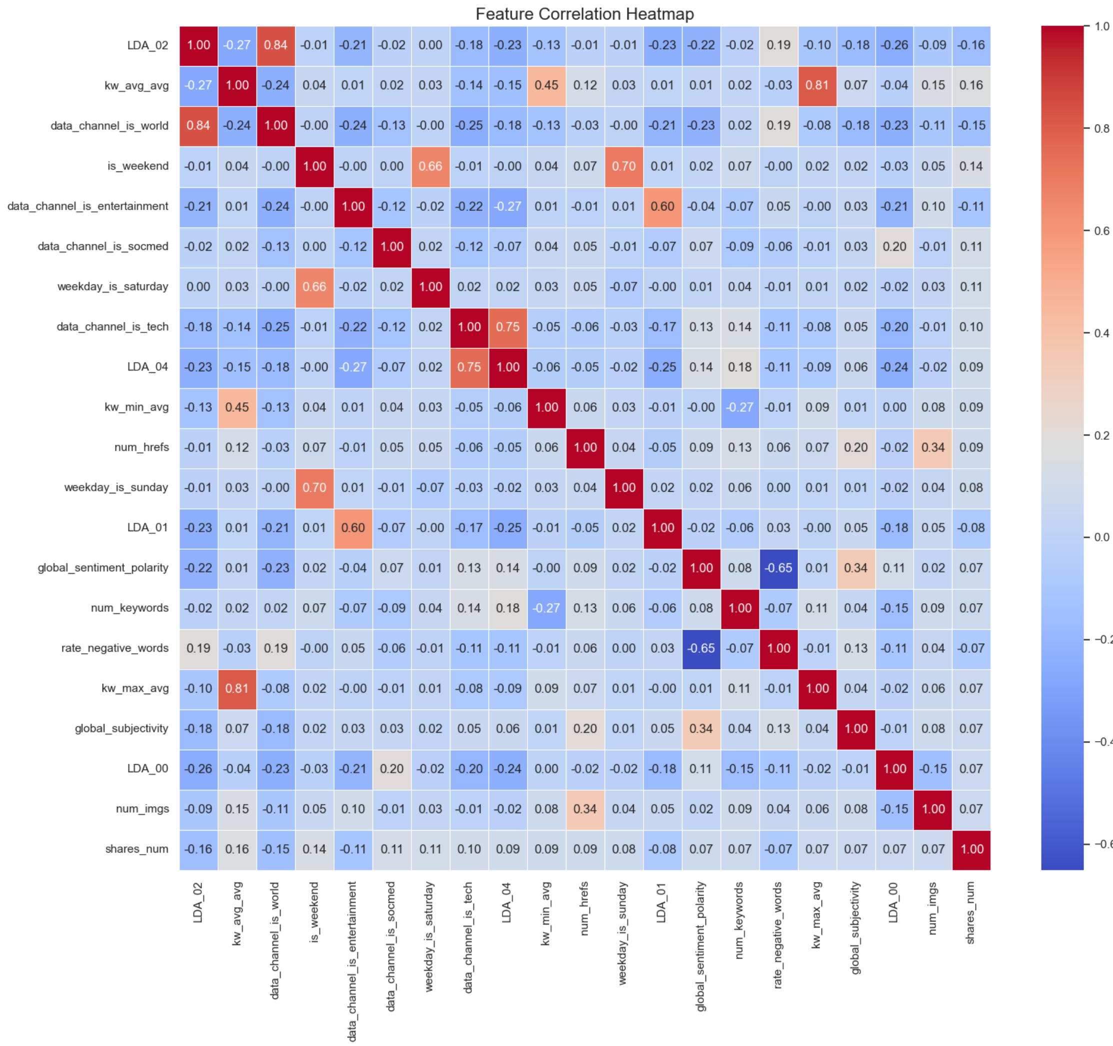
Intepretation of the distribution plots:

The distribution plots provide insights into the sentiment and subjectivity characteristics of the articles. We found an interesting fact is that the rate of positive words (0.62 on average) is much higher than the rate of negative words (0.29 on average). The title sentiment polarity and subjectivity distributions indicate that most article titles remain neutral, but some exhibit extreme sentiment (both positive and negative). Overall, the data suggests that articles generally keep a moderate subjectivity level with a little trend towards positivity and a small proportion containing strong negative words.

[21]:
```
# First, ensure shares column is numeric
numeric_df = df.select_dtypes(include=['int32', 'int64', 'float64'])

# Calculate correlations
corr_matrix = numeric_df.corr()

# Save shares column correlations with other features
if 'shares_num' in corr_matrix.columns:
    shares_corr = corr_matrix['shares_num'].sort_values(ascending=False)

    # Calculate absolute correlations and rank them
    shares_corr_abs = shares_corr.abs().sort_values(ascending=False)

    print("\nAbsolute correlation ranking with shares:")
```

```
    print(shares_corr_abs)

    print("\nTop positive correlations with shares:")
    print(shares_corr.head(15))

    print("\nTop negative correlations with shares:")
    # Use sort_values with ascending=True to get the most negative correlations␣
 ↪first
    print(shares_corr.sort_values(ascending=True).head(15))

    # Plot correlation bar chart
    plt.figure(figsize=(12, 14))
    top_features = shares_corr_abs[1:16].index  # Exclude shares itself

    colors = ['red' if x < 0 else 'blue' for x in shares_corr[top_features]]

    sns.barplot(x=shares_corr[top_features], y=top_features, palette=colors)
    plt.title('Top 15 Features by Correlation with Shares', fontsize=16)
    plt.xlabel('Correlation Coefficient')
    plt.tight_layout()
    plt.show()
```

[22]:
```
# Heatmap showing feature correlations
plt.figure(figsize=(16, 14))
# Select top 20 features most correlated with shares
if 'shares_num' in corr_matrix.columns:
    top_corr_features = list(shares_corr_abs[1:21].index)  # Exclude shares_num␣
 ↪itself
    top_corr_features.append('shares_num')  # Add shares back

    # Create heatmap
    sns.heatmap(corr_matrix.loc[top_corr_features, top_corr_features],
                annot=True, cmap='coolwarm', fmt=".2f", linewidths=0.5)
    plt.title('Feature Correlation Heatmap', fontsize=16)
    plt.tight_layout()
    plt.show()
else:
    # If no shares column, use all features
    plt.figure(figsize=(16, 14))
    sns.heatmap(corr_matrix, cmap='coolwarm', linewidths=0.5)
    plt.title('Feature Correlation Heatmap', fontsize=16)
    plt.tight_layout()
    plt.show()
```



Intepretation of feature correlation heatmap:

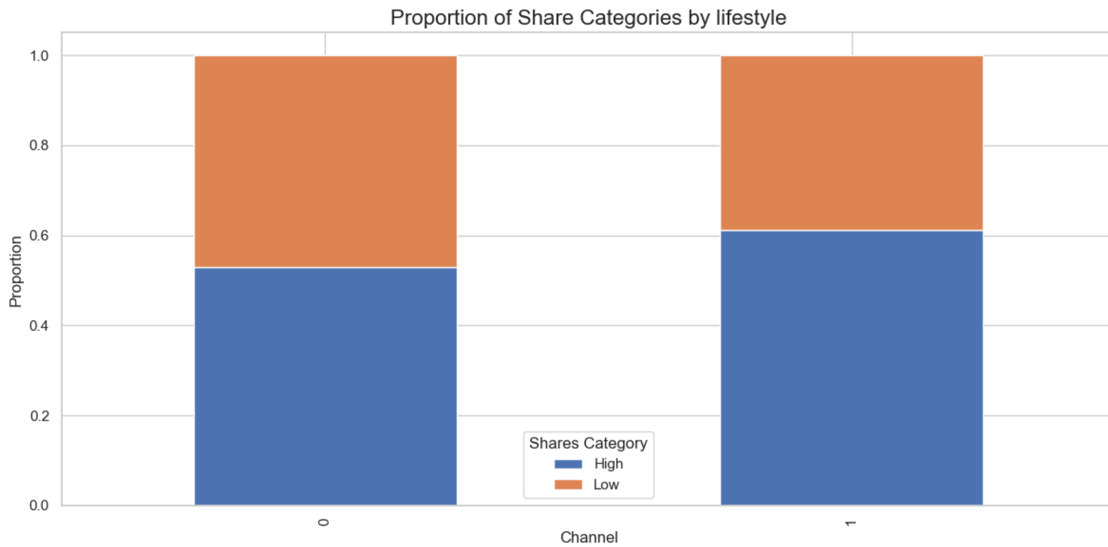
The heatmap visualizes the correlation between different features, including the "shares_num" variable, which shows article popularity. Darker red indicates a strong positive correlation, and darker blue represents a strong negative correlation. The strongest positive correlation is observed between "kw_avg_avg" and "shares_num", suggesting that articles with well-performing keywords tend to receive more shares. Other interesting positive correlations include "num_hrefs" and "is_weekend" show that linked articles and those published on weekends may gain more engagement. Conversely, features such as "LDA_02" and "data_channel_is_world" show a negative correlation.

[23]:
```python
# 9. Explore relationship between channel and shares
print("\n" + "="*50)
print("9. Channel and Shares Relationship")

# Check for channel or data_channel_is_* columns
if 'channel' in df.columns and 'shares' in df.columns:
```

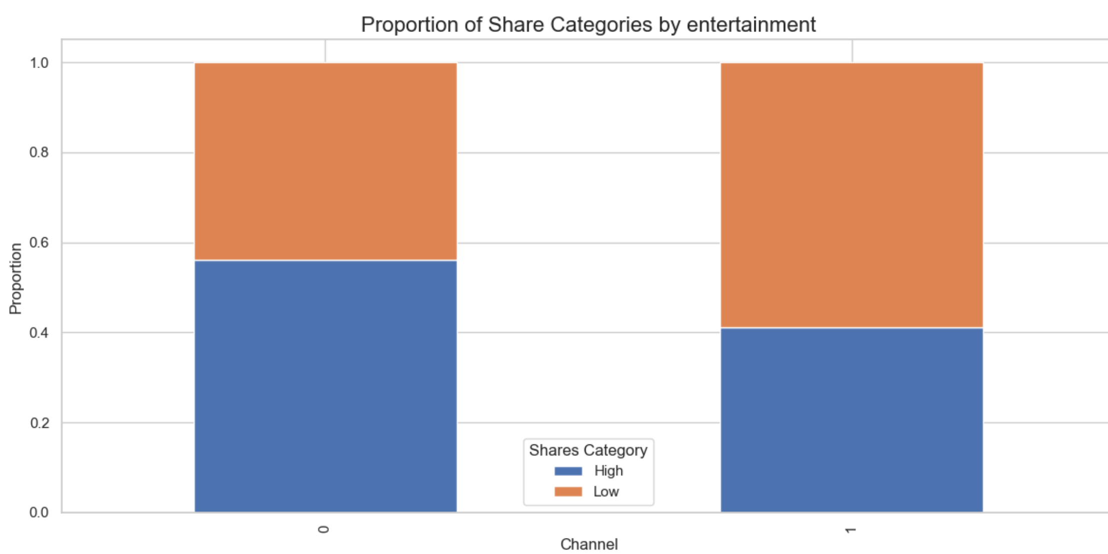
```python
    plt.figure(figsize=(12, 6))

    if df['shares'].dtype == 'object':
        # If shares is a categorical variable
        cross_tab = pd.crosstab(df['channel'], df['shares'])
        print("\nChannel vs shares category cross-tabulation:")
        print(cross_tab)

        # Plot stacked bar chart
        cross_tab_pct = cross_tab.div(cross_tab.sum(axis=1), axis=0)
        cross_tab_pct.plot(kind='bar', stacked=True, figsize=(12, 6))
        plt.title('Proportion of Share Categories by Channel', fontsize=16)
        plt.xlabel('Channel')
        plt.ylabel('Proportion')
        plt.legend(title='Shares Category')
        plt.tight_layout()
        plt.show()
    else:
        # If shares is a numeric variable
        channel_shares = df.groupby('channel')['shares'].agg(['mean', 'median',␣
↪'std'])
        print("\nShares statistics by channel:")
        print(channel_shares)

        # Plot boxplot
        plt.figure(figsize=(12, 6))
        sns.boxplot(x='channel', y='shares', data=df)
        plt.title('Shares Distribution by Channel', fontsize=16)
        plt.xlabel('Channel')
        plt.ylabel('Number of Shares')
        plt.xticks(rotation=45)
        plt.tight_layout()
        plt.show()
elif any(col.startswith('data_channel_is_') for col in df.columns) and 'shares'␣
↪in df.columns:
    # Use data_channel_is_* columns
    channel_cols = [col for col in df.columns if col.
↪startswith('data_channel_is_')]

    if df['shares'].dtype == 'object':
        # If shares is a categorical variable
        for col in channel_cols:
            channel_name = col.replace('data_channel_is_', '')
            cross_tab = pd.crosstab(df[col], df['shares'])
            print(f"\n{channel_name} channel vs shares category␣
↪cross-tabulation:")
            print(cross_tab)
```

```
            cross_tab_pct = cross_tab.div(cross_tab.sum(axis=1), axis=0)
            cross_tab_pct.plot(kind='bar', stacked=True, figsize=(12, 6))
            title = f"Proportion of Share Categories by {channel_name}"
            plt.title(title, fontsize=16)
            plt.xlabel('Channel')
            plt.ylabel('Proportion')
            plt.legend(title='Shares Category')
            plt.tight_layout()
            plt.show()

    else:
        # If shares is a numeric variable
        channel_shares = {}
        for col in channel_cols:
            channel_name = col.replace('data_channel_is_', '')
            channel_data = df[df[col] == 1]['shares']
            channel_shares[channel_name] = {
                'mean': channel_data.mean(),
                'median': channel_data.median(),
                'std': channel_data.std()
            }

        channel_shares_df = pd.DataFrame(channel_shares).T
        print("\nShares statistics by channel:")
        print(channel_shares_df)

        # Plot mean shares by channel
        plt.figure(figsize=(12, 6))
        sns.barplot(x=channel_shares_df.index, y='mean', data=channel_shares_df)
        plt.title('Mean Shares by Channel', fontsize=16)
        plt.xlabel('Channel')
        plt.ylabel('Mean Shares')
        plt.xticks(rotation=45)
        plt.tight_layout()
        plt.show()
```

```
==================================================
9. Channel and Shares Relationship

lifestyle channel vs shares category cross-tabulation:
shares                       High    Low
data_channel_is_lifestyle
0                           19871  17674
1                            1283    816
```

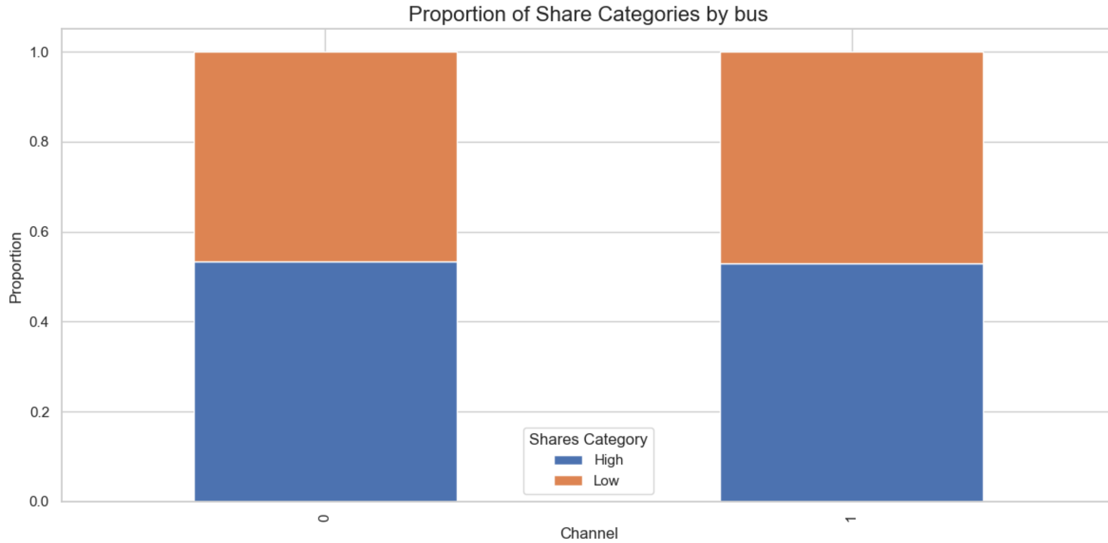



```
entertainment channel vs shares category cross-tabulation:
shares                          High    Low
data_channel_is_entertainment
0                              18252  14335
1                               2902   4155
```

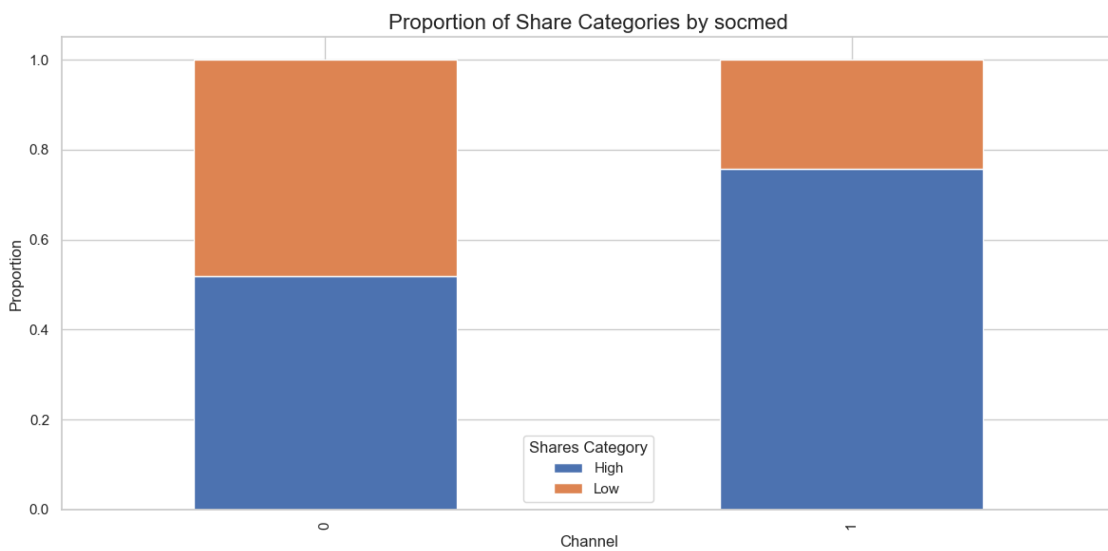



```
bus channel vs shares category cross-tabulation:
shares                High    Low
data_channel_is_bus
```

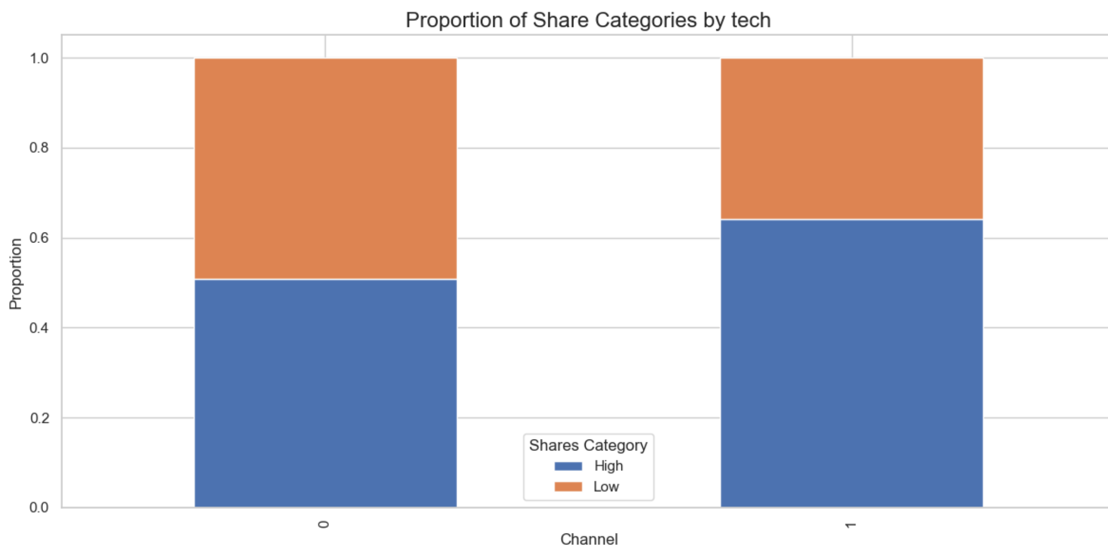
```
0                        17842  15544
1                         3312   2946
```



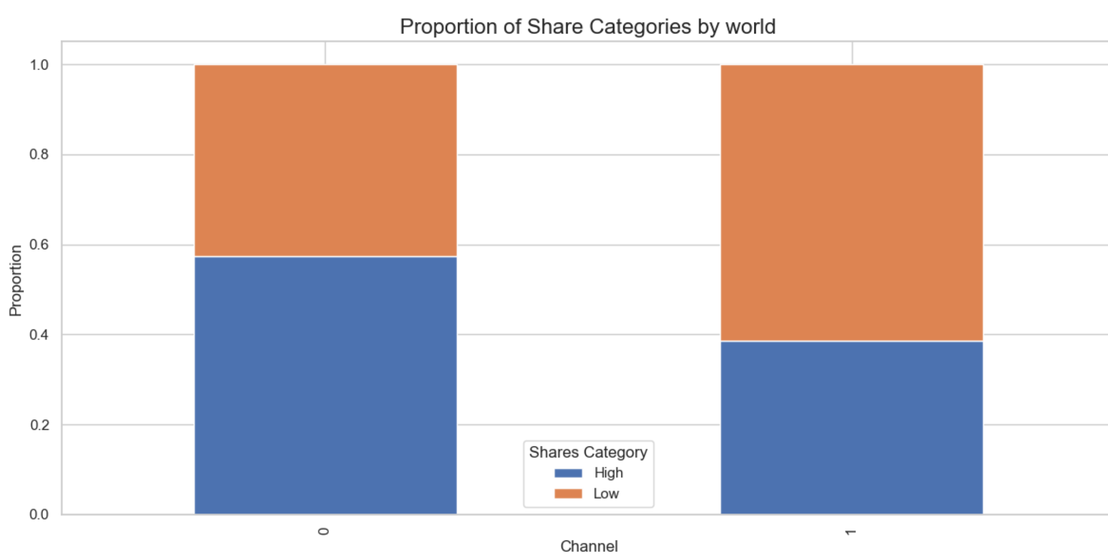

```
socmed channel vs shares category cross-tabulation:
shares                    High    Low
data_channel_is_socmed
0                        19394  17927
1                         1760    563
```



```
tech channel vs shares category cross-tabulation:
shares                  High    Low
data_channel_is_tech
0                      16444  15854
1                       4710   2636
```




```
world channel vs shares category cross-tabulation:
shares                   High    Low
data_channel_is_world
0                       17905  13312
1                        3249   5178
```



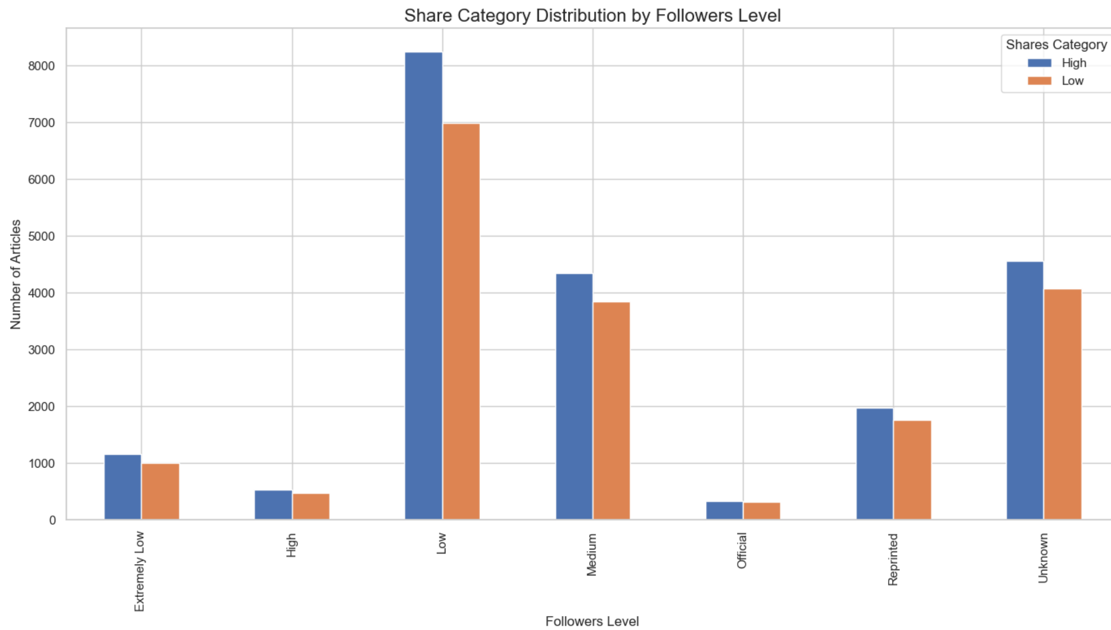
[24]:
```python
# 10. Relationship between followers level and shares
df['follower_num'] = df['followers'].map({
    'Extremely Low': 1,
    'Low': 2,
    'Medium': 3,
    'High': 4,
    'Unknown': 5,
    'Reprinted': 6
})
df[['follower_num', 'followers']]
```

[24]:
```
       follower_num  followers
0               4.0       High
1               3.0     Medium
2               3.0     Medium
3               6.0  Reprinted
4               2.0        Low
…                 …          …
39639           2.0        Low
39640           5.0    Unknown
39641           2.0        Low
39642           5.0    Unknown
39643           2.0        Low

[39644 rows x 2 columns]
```

[25]:
```python
print("\n" + "="*50)
print("10. Followers Level and Shares Relationship")

if 'followers' in df.columns and 'shares' in df.columns:
    if df['shares'].dtype == 'object':
        # If shares is a categorical variable
        # Create cross-tabulation
        cross_tab = pd.crosstab(df['followers'], df['shares'])
        print("\nFollowers level vs shares category cross-tabulation:")
        print(cross_tab)

        # Create comparison chart
        plt.figure(figsize=(14, 8))
        cross_tab.plot(kind='bar', stacked=False, figsize=(14, 8))
        plt.title('Share Category Distribution by Followers Level', fontsize=16)
        plt.xlabel('Followers Level')
        plt.ylabel('Number of Articles')
        plt.legend(title='Shares Category')
        plt.tight_layout()
        plt.show()
```

```python
    else:
        # If shares is a numeric variable
        follower_shares = {}
        for follower_level in df['followers'].unique():
            follower_data = df[df['followers'] == follower_level]['shares']
            follower_shares[follower_level] = {
                'mean': follower_data.mean(),
                'median': follower_data.median(),
                'std': follower_data.std()
            }

        follower_shares_df = pd.DataFrame(follower_shares).T
        print("\nShares statistics by followers level:")
        print(follower_shares_df)

        # Plot mean shares by followers level
        plt.figure(figsize=(12, 6))
        sns.barplot(x=follower_shares_df.index, y='mean',␣
 ↪data=follower_shares_df)
        plt.title('Mean Shares by Followers Level', fontsize=16)
        plt.xlabel('Followers Level')
        plt.ylabel('Mean Shares')
        plt.xticks(rotation=45)
        plt.tight_layout()
        plt.show()

print("\n" + "="*50)
print("EDA completed!")
```

```
==================================================
10. Followers Level and Shares Relationship

Followers level vs shares category cross-tabulation:
shares         High   Low
followers
Extremely Low  1159  1004
High            528   475
Low            8245  6989
Medium         4345  3855
Official        337   317
Reprinted      1978  1769
Unknown        4562  4081

<Figure size 1400x800 with 0 Axes>
```




```
==================================================
EDA completed!
```

Intepretation of share category distribution by followers level:

The analysis of followers' levels and share categories shows that articles written by authors with low or unknown follower counts tend to receive the highest proportion of low engagement. Authors with higher follower counts (Medium or High) have a more balanced distribution of shares. Interestingly, reprinted articles also show a higher probability of achieving Medium or High shares, suggesting that republished content may still attract considerable engagement.

Oveview of EDA:

After doing EDA, we examined the dataset's structure, distributions, correlations, and relationships between features and article shares. We analyzed content-related features such as keywords, hyperlinks, images, and videos, as well as categorical variables like article channels and publication weekdays. The correlation analysis revealed that keyword-related metrics, the presence of hyperlinks, and the type of data channel such as world or social media have great influences on shares. We also explored sentiment-based features and found that subjectivity and polarity play a role in engagement. One interesting insight is that articles published on weekdays significantly outnumber those on weekends. Also, our target variable is highly imbalanced, with most articles receiving low engagement. These findings guide our feature engineering and model selection to improve predictive performance.

1.4 Feature Engineering

During feature engineering, we aim to refine the dataset to improve model performance. We will encode categorical variables, normalize skewed features, and scale numerical data for consistency.

Also, we plan to create interaction terms and polynomial features to capture complex relationships. Finally, we will remove highly correlated variables to reduce redundancy. These steps will help enhance the predictive power of our models in analyzing news shareability.

[26]:
```
# Feature Engineering will continue with the 'df' DataFrame from EDA
# Create a copy to work with for feature engineering
df_fe = df.copy()

print("="*50)
print("Feature Engineering Process")
print(f"Initial dataset shape: {df_fe.shape}")
```

```
==================================================
Feature Engineering Process
Initial dataset shape: (39644, 63)
```

[27]:
```
# 1. Handling Categorical Variables
print("\n" + "="*50)
print("1. Handling Categorical Variables")

# Check object columns
object_columns = df_fe.select_dtypes(include=['object']).columns
print(f"Object columns to process: {list(object_columns)}")
```

```

==================================================
1. Handling Categorical Variables
Object columns to process: ['shares', 'followers']
```

[28]:
```
# 1.1 Process the target variable 'shares' with label encoding if it's␣
↪categorical
if 'shares' in object_columns:
    print("\nProcessing target variable 'shares' with label encoding...")

    # Save original values for reference
    df_fe['shares_original_value'] = df_fe['shares']

    # Apply label encoding to 'shares'
    label_encoder = LabelEncoder()
    df_fe['shares'] = label_encoder.fit_transform(df_fe['shares'])

    # Show the mapping
    mapping = dict(zip(label_encoder.classes_, label_encoder.
↪transform(label_encoder.classes_)))
    print("\nLabel encoding mapping for 'shares':")
    for original, encoded in mapping.items():
        print(f"{original} -> {encoded}")
```

```
    # Visualize the distribution of encoded values
    plt.figure(figsize=(10, 6))
    sns.countplot(x='shares', data=df_fe)
    plt.title('Distribution of Encoded Shares Values')
    plt.xticks(rotation=90)
    plt.show()
```

```
Processing target variable 'shares' with label encoding…

Label encoding mapping for 'shares':
High -> 0
Low -> 1
```

[29]:
```
# 1.2 Process other categorical columns
categorical_columns = [col for col in object_columns if col != 'shares']
for col in categorical_columns:
    print(f"\nProcessing categorical column: {col}")

    # Check the number of unique values
    num_unique = df_fe[col].nunique()
    print(f"Number of unique values: {num_unique}")

    if num_unique == 2:
        # Binary columns can be label encoded (0, 1)
```

```
        print(f"Label encoding binary column {col}")
        df_fe[col] = LabelEncoder().fit_transform(df_fe[col])
    elif num_unique <= 10:
        # For columns with few categories, use one-hot encoding
        print(f"One-hot encoding {col}")
        one_hot = pd.get_dummies(df_fe[col], prefix=col)
        df_fe = df_fe.drop([col], axis=1)
        df_fe = pd.concat([df_fe, one_hot], axis=1)
    else:
        # For columns with many categories, consider frequency encoding
        print(f"Column {col} has many categories. Using frequency encoding.")
        # Frequency encoding replaces categories with their frequency
        freq_encoding = df_fe[col].value_counts(normalize=True).to_dict()
        df_fe[f"{col}_freq"] = df_fe[col].map(freq_encoding)
        df_fe = df_fe.drop([col], axis=1)
```

```
Processing categorical column: followers
Number of unique values: 7
One-hot encoding followers
```

[30]:
```
# 2. Feature Skewness Transformation
print("\n" + "="*50)
print("2. Feature Skewness Transformation")

# Define list of continuous features to check
continuous_features = [
    'n_tokens_title', 'n_tokens_content', 'n_unique_tokens',
    'n_non_stop_words', 'n_non_stop_unique_tokens',
    'average_token_length', 'num_hrefs', 'num_self_hrefs',
    'num_imgs', 'num_videos', 'num_keywords',
    'kw_max_min', 'kw_avg_min', 'kw_avg_max',
    'kw_min_avg', 'kw_max_avg', 'kw_avg_avg',
    'self_reference_min_shares', 'self_reference_max_shares',␣
↪'self_reference_avg_sharess',
    'LDA_00', 'LDA_01', 'LDA_02', 'LDA_03', 'LDA_04',
    'global_subjectivity', 'global_sentiment_polarity',
    'global_rate_positive_words', 'global_rate_negative_words',
    'rate_positive_words', 'rate_negative_words',
    'avg_positive_polarity', 'min_positive_polarity', 'max_positive_polarity',
    'avg_negative_polarity', 'min_negative_polarity', 'max_negative_polarity',
    'title_subjectivity', 'title_sentiment_polarity',
    'abs_title_subjectivity', 'abs_title_sentiment_polarity'
]

# Filter to include only features that exist in the dataframe and are numeric
numeric_df = df_fe.select_dtypes(include=['int32', 'int64', 'float64'])
```

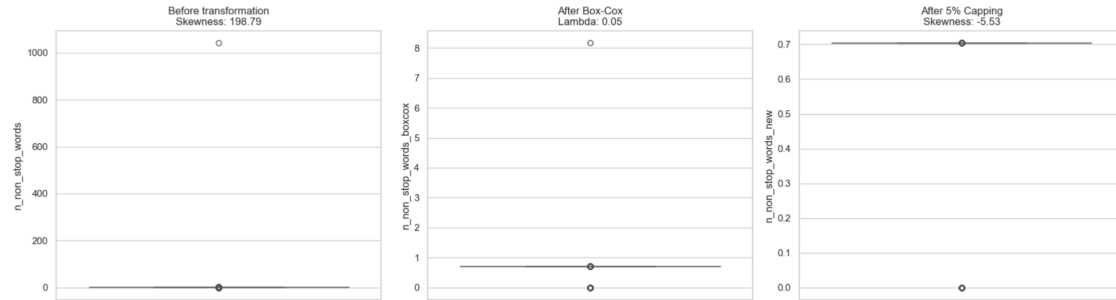
```python
continuous_features = [col for col in continuous_features if col in numeric_df.columns]

# Calculate skewness for each feature
skewness = numeric_df[continuous_features].skew().sort_values(ascending=False)
print("Skewness before transformation:")
print(skewness)

# Set threshold for applying transformation
skew_threshold = 1.0  # Features with skewness > 1.0 will be transformed
high_skew_features = skewness[skewness.abs() > skew_threshold].index.tolist()
print(f"\nFound {len(high_skew_features)} features with high skewness (|skew| > {skew_threshold})")
print("Top high-skewed features:", high_skew_features[:5] if len(high_skew_features) > 5 else high_skew_features)

# Function to apply and visualize Box-Cox transformation
def transform_and_visualize(dataframe, feature, skewness_value):
    # Create a figure with 3 subplots
    fig, axes = plt.subplots(1, 3, figsize=(18, 5))

    # Plot original distribution
    sns.boxplot(y=dataframe[feature], ax=axes[0])
    axes[0].set_title(f"Before transformation\nSkewness: {skewness_value:.2f}")

    # Box-Cox requires all values to be positive
    min_value = dataframe[feature].min()

    # If there are non-positive values, shift the data
    if min_value <= 0:
        shift = abs(min_value) + 1  # Add 1 to avoid zeros
        dataframe[f"{feature}_shifted"] = dataframe[feature] + shift
        feature_to_transform = f"{feature}_shifted"
    else:
        feature_to_transform = feature

    # Apply Box-Cox transformation
    try:
        transformed_data, lambda_value = stats.boxcox(dataframe[feature_to_transform])

        # For display purposes, keep transformed data in a temporary column
        dataframe[f"{feature}_boxcox"] = transformed_data

        # Plot the transformed distribution
        sns.boxplot(y=dataframe[f"{feature}_boxcox"], ax=axes[1])
        axes[1].set_title(f"After Box-Cox\nLambda: {lambda_value:.2f}")
```

```
        # Apply capping to only the most extreme 5% values
        # For positive skew, cap only the upper tail
        # For negative skew, cap only the lower tail
        if dataframe[f"{feature}_boxcox"].skew() > 0:
            # Positive skew - cap the upper 5%
            upper_percentile = np.percentile(dataframe[f"{feature}_boxcox"], 95)
            dataframe[f"{feature}_new"] = np.where(
                dataframe[f"{feature}_boxcox"] > upper_percentile,
                upper_percentile,
                dataframe[f"{feature}_boxcox"]
            )
        else:
            # Negative skew - cap the lower 5%
            lower_percentile = np.percentile(dataframe[f"{feature}_boxcox"], 5)
            dataframe[f"{feature}_new"] = np.where(
                dataframe[f"{feature}_boxcox"] < lower_percentile,
                lower_percentile,
                dataframe[f"{feature}_boxcox"]
            )

        # Plot the capped distribution
        sns.boxplot(y=dataframe[f"{feature}_new"], ax=axes[2])
        new_skewness = dataframe[f"{feature}_new"].skew()
        axes[2].set_title(f"After 5% Capping\nSkewness: {new_skewness:.2f}")

        plt.tight_layout()
        plt.show()

        # Replace original column with the final transformed data
        dataframe[feature] = dataframe[f"{feature}_new"]

        # Clean up temporary columns
        for col in [f"{feature}_shifted", f"{feature}_boxcox",␣
↪f"{feature}_new"]:
            if col in dataframe.columns:
                dataframe.drop(col, axis=1, inplace=True)

        # Return success flag and new skewness
        return True, new_skewness

    except Exception as e:
        print(f"Error transforming {feature}: {e}")

        # Try log transformation as fallback
        try:
            if min_value <= 0:
```

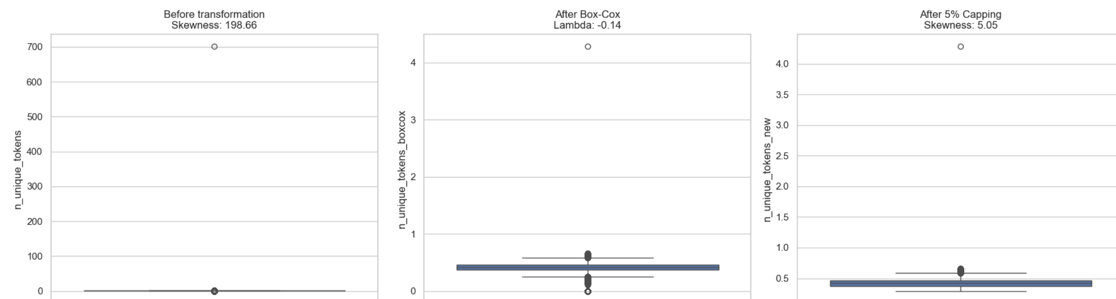
```
                shift = abs(min_value) + 1
                dataframe[feature] = np.log1p(dataframe[feature] + shift)
            else:
                dataframe[feature] = np.log1p(dataframe[feature])

            # Plot log-transformed data
            sns.boxplot(y=dataframe[feature], ax=axes[1])
            new_skewness = dataframe[feature].skew()
            axes[1].set_title(f"After Log Transform\nSkewness: {new_skewness:.
 ↪2f}")

            # No capping for log transform
            axes[2].set_visible(False)

            plt.tight_layout()
            plt.show()

            return True, new_skewness
        except:
            print(f"Log transformation also failed for {feature}")
            plt.close(fig)  # Close the figure if both transformations fail
            return False, skewness_value

# Process features with high skewness
results = {}
for feature in high_skew_features:
    print(f"\nProcessing {feature} (Skewness: {skewness[feature]:.2f})")
    success, new_skewness = transform_and_visualize(df_fe, feature,␣
 ↪skewness[feature])
    if success:
        results[feature] = {
            'original_skewness': skewness[feature],
            'new_skewness': new_skewness,
            'improvement': skewness[feature] - new_skewness
        }

# Print transformation results
if results:
    print("\nTransformation Results:")
    results_df = pd.DataFrame(results).T
    display(results_df.sort_values('improvement', ascending=False))
```

```
==================================================
2. Feature Skewness Transformation
Skewness before transformation:
n_non_stop_words                198.792445
```

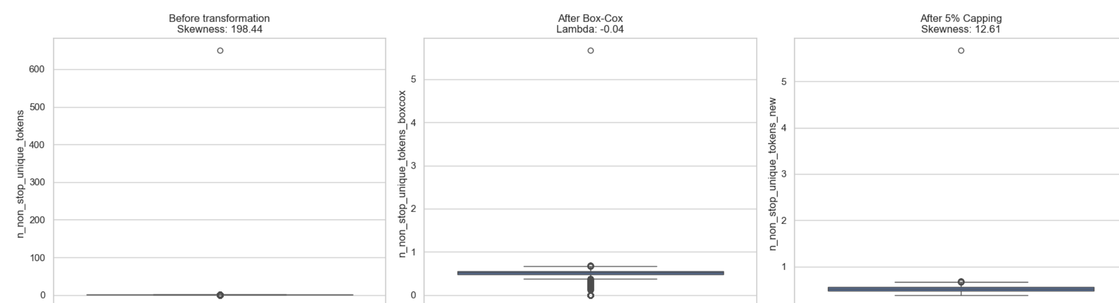
```
n_unique_tokens                198.655116
n_non_stop_unique_tokens       198.443294
kw_max_min                      35.328434
kw_avg_min                      31.306108
self_reference_min_shares       26.264364
self_reference_avg_sharess      17.914093
kw_max_avg                      16.411670
self_reference_max_shares       13.870849
num_videos                       7.019533
kw_avg_avg                       5.760177
num_self_hrefs                   5.172751
num_hrefs                        4.013495
num_imgs                         3.946596
min_positive_polarity            3.040468
n_tokens_content                 2.945422
LDA_01                           2.086722
abs_title_sentiment_polarity     1.704193
LDA_00                           1.567463
global_rate_negative_words       1.491917
LDA_02                           1.311695
LDA_03                           1.238716
LDA_04                           1.173129
title_subjectivity               0.816085
kw_avg_max                       0.624310
kw_min_avg                       0.467976
rate_negative_words              0.407241
title_sentiment_polarity         0.396109
global_rate_positive_words       0.323047
n_tokens_title                   0.165320
global_sentiment_polarity        0.105457
min_negative_polarity           -0.073155
num_keywords                    -0.147251
avg_negative_polarity           -0.551644
abs_title_subjectivity          -0.624149
avg_positive_polarity           -0.724795
max_positive_polarity           -0.939756
global_subjectivity             -1.372689
rate_positive_words             -1.423106
max_negative_polarity           -3.459747
average_token_length            -4.576012
dtype: float64

Found 27 features with high skewness (|skew| > 1.0)
Top high-skewed features: ['n_non_stop_words', 'n_unique_tokens',
'n_non_stop_unique_tokens', 'kw_max_min', 'kw_avg_min']

Processing n_non_stop_words (Skewness: 198.79)
```



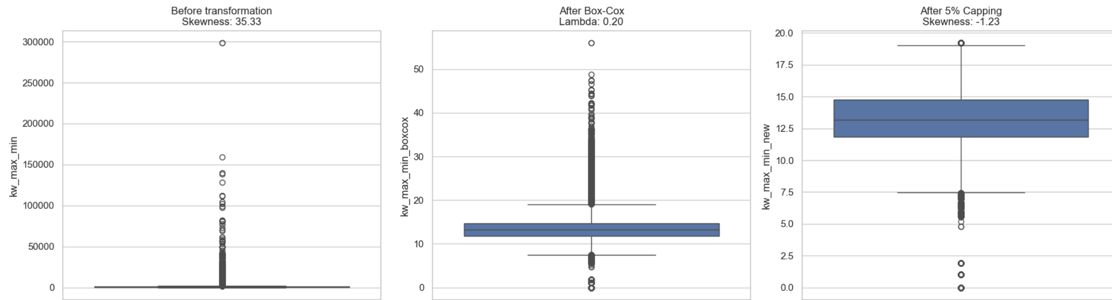

```
Processing n_unique_tokens (Skewness: 198.66)
```



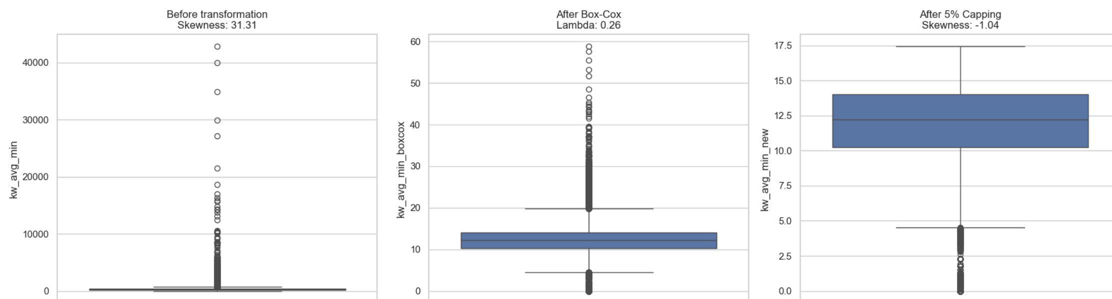

```
Processing n_non_stop_unique_tokens (Skewness: 198.44)
```



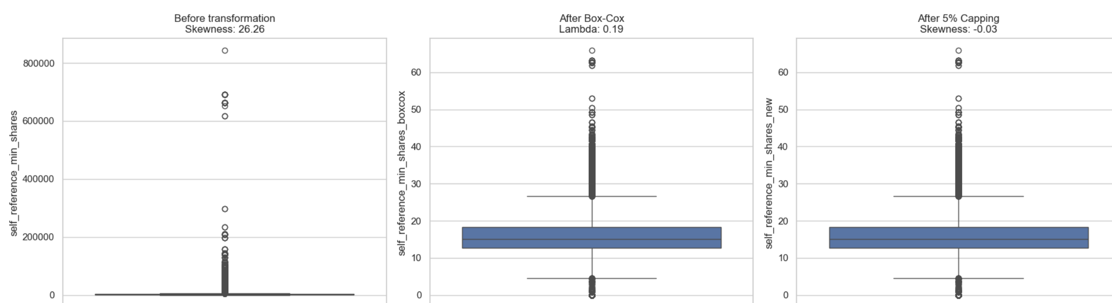

```
Processing kw_max_min (Skewness: 35.33)
```



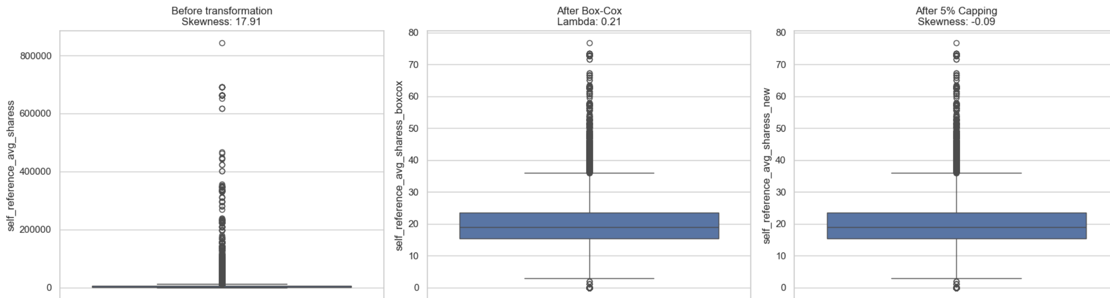
Processing kw_avg_min (Skewness: 31.31)



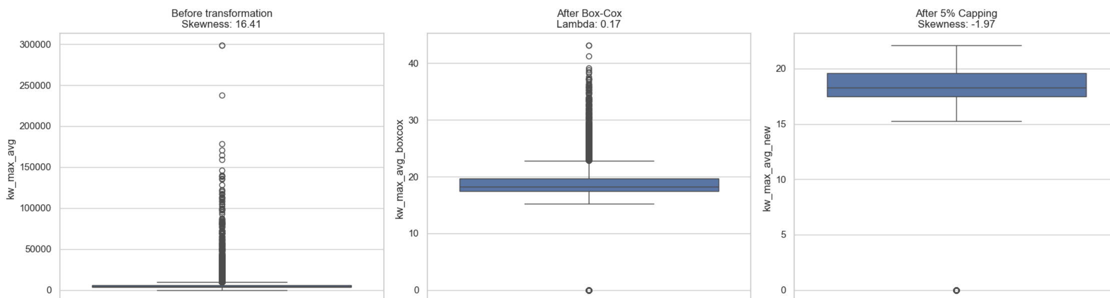
Processing self_reference_min_shares (Skewness: 26.26)



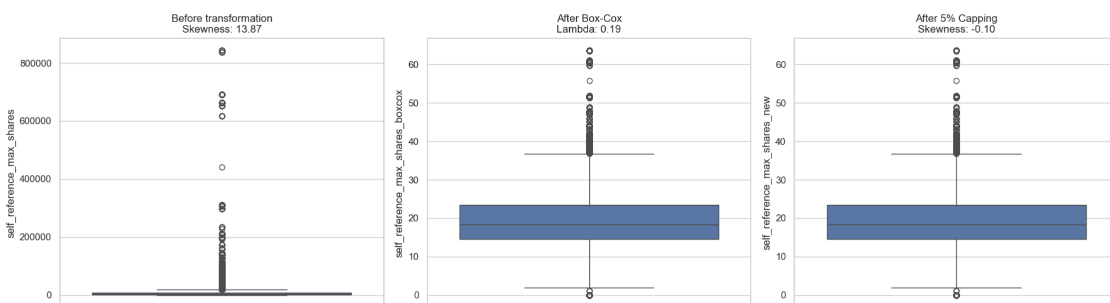
Processing self_reference_avg_sharess (Skewness: 17.91)



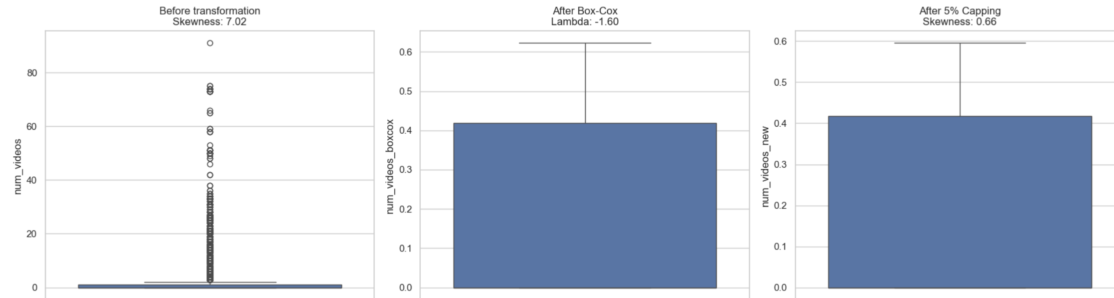
Processing kw_max_avg (Skewness: 16.41)



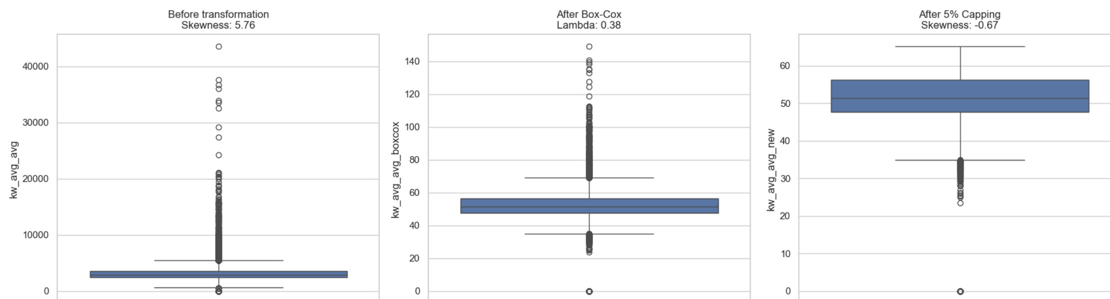
Processing self_reference_max_shares (Skewness: 13.87)



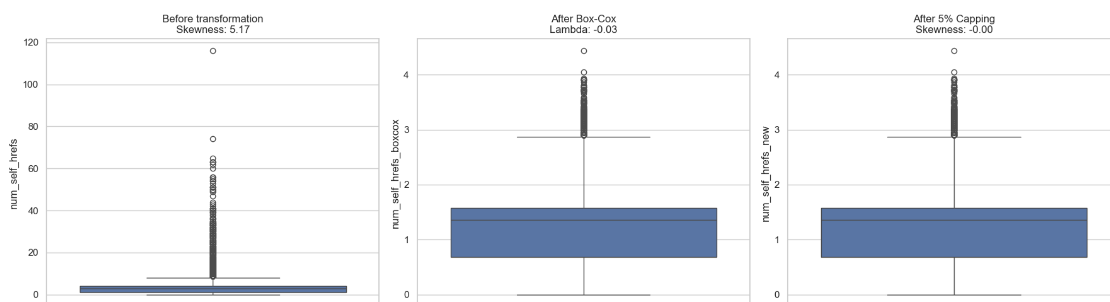
Processing num_videos (Skewness: 7.02)



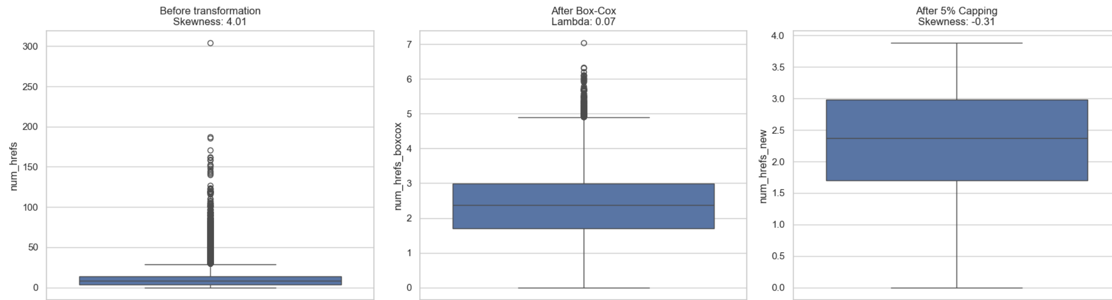
Processing kw_avg_avg (Skewness: 5.76)



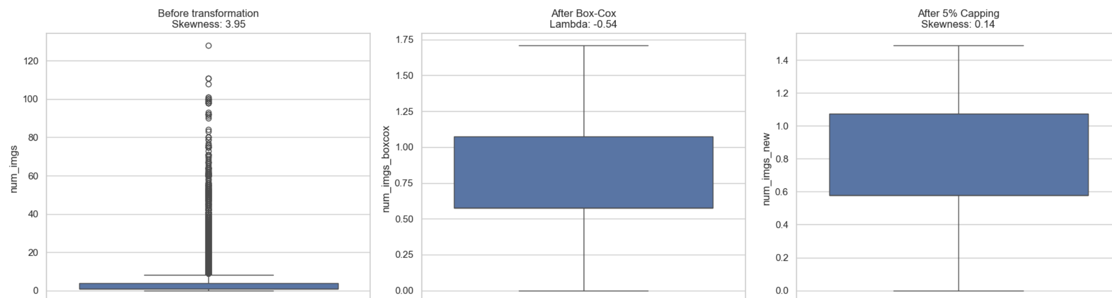
Processing num_self_hrefs (Skewness: 5.17)



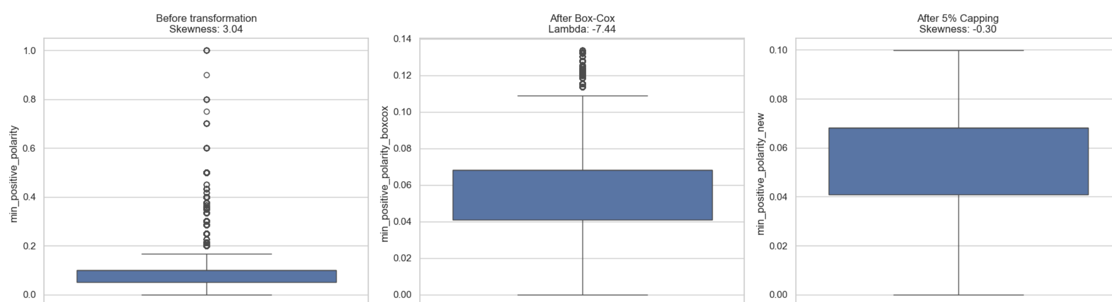
Processing num_hrefs (Skewness: 4.01)



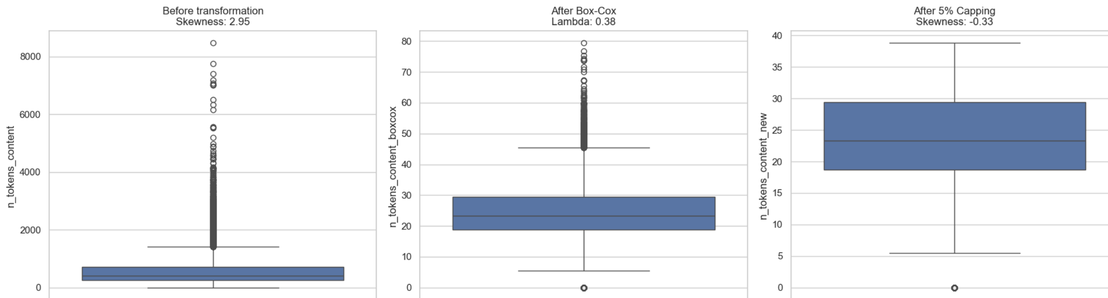
Processing num_imgs (Skewness: 3.95)



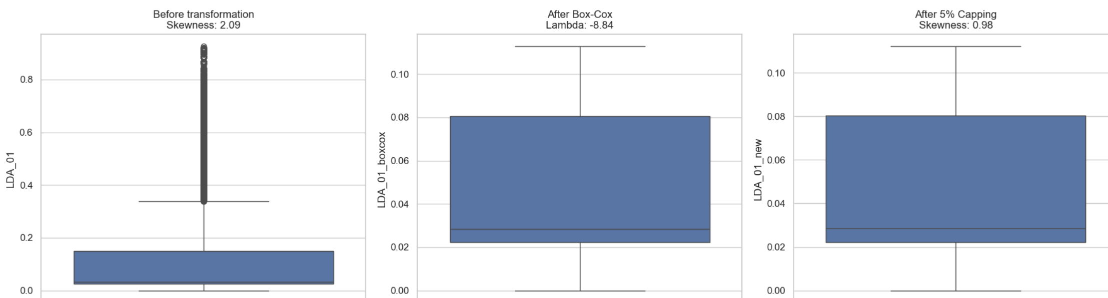
Processing min_positive_polarity (Skewness: 3.04)



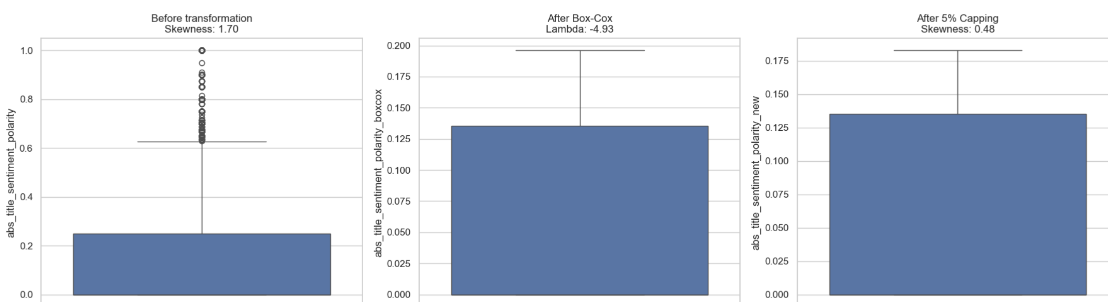
Processing n_tokens_content (Skewness: 2.95)



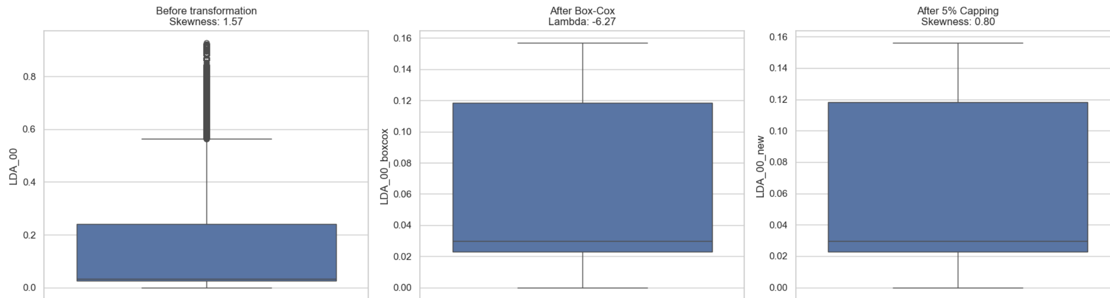
Processing LDA_01 (Skewness: 2.09)



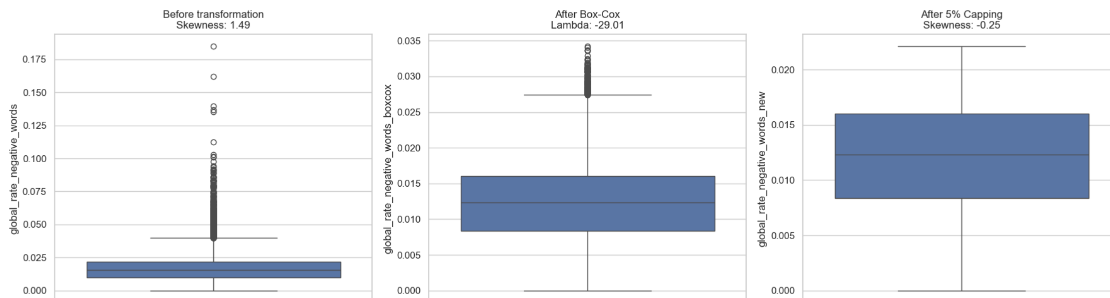
Processing abs_title_sentiment_polarity (Skewness: 1.70)



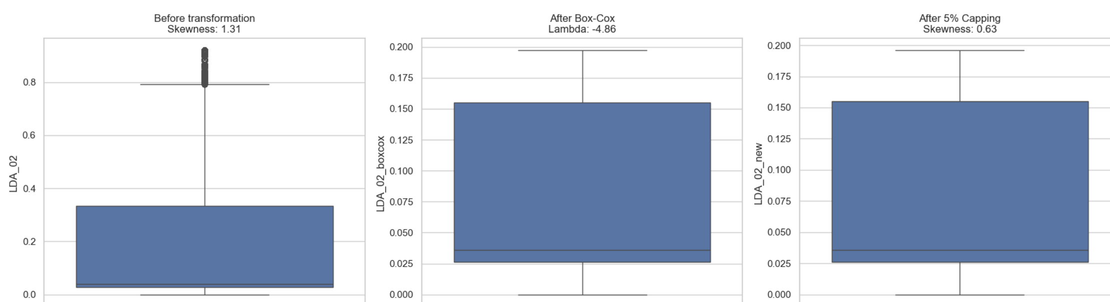
Processing LDA_00 (Skewness: 1.57)



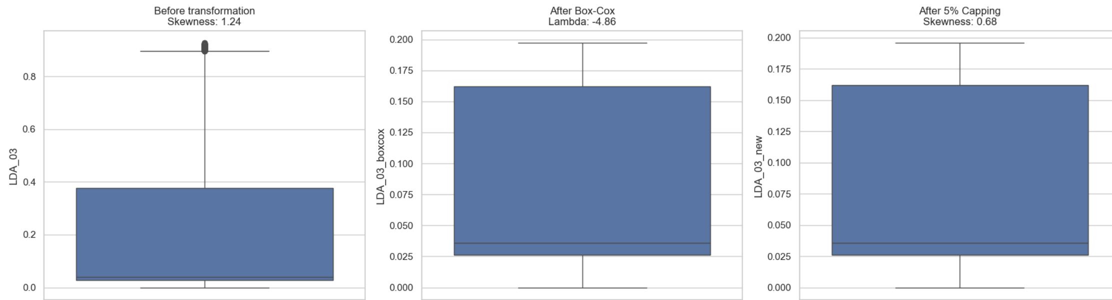
Processing global_rate_negative_words (Skewness: 1.49)



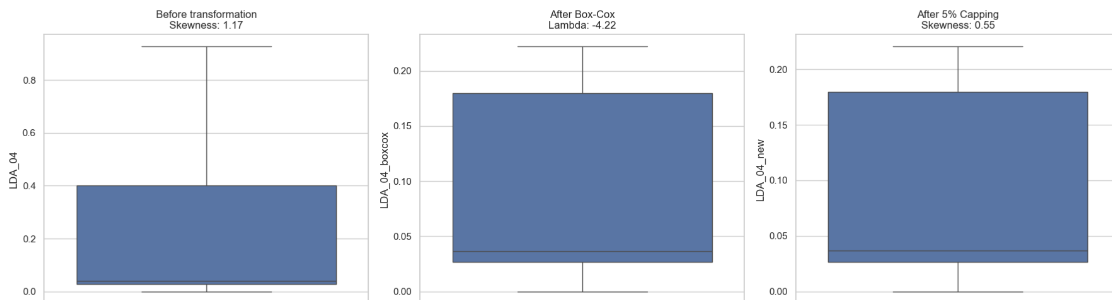
Processing LDA_02 (Skewness: 1.31)



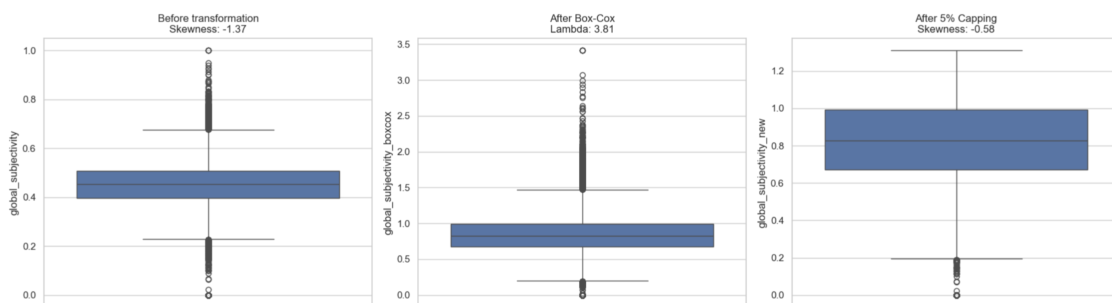
Processing LDA_03 (Skewness: 1.24)



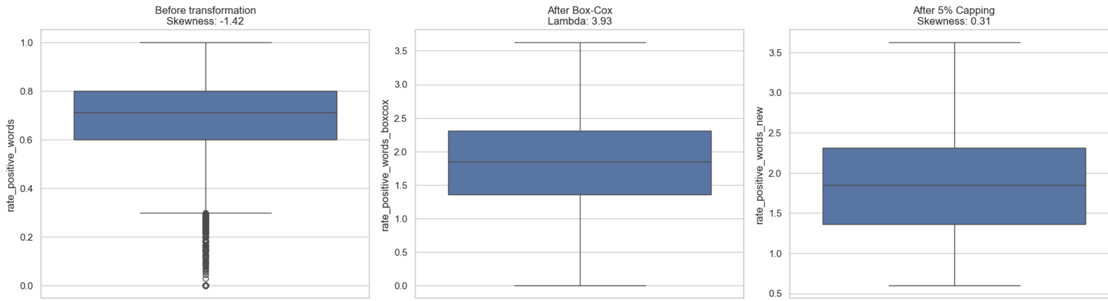
Processing LDA_04 (Skewness: 1.17)



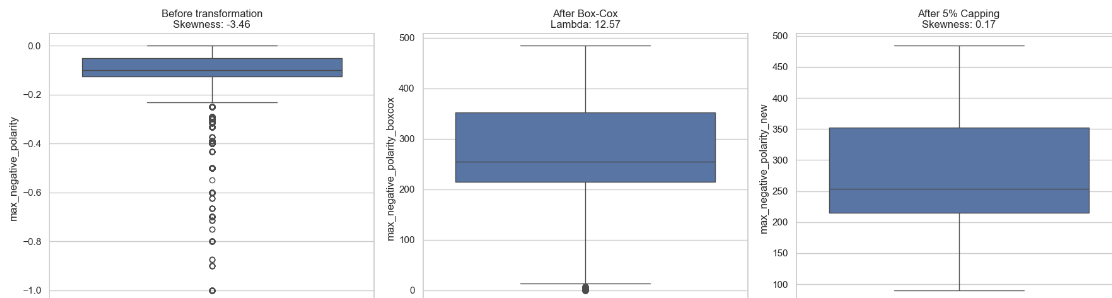
Processing global_subjectivity (Skewness: -1.37)



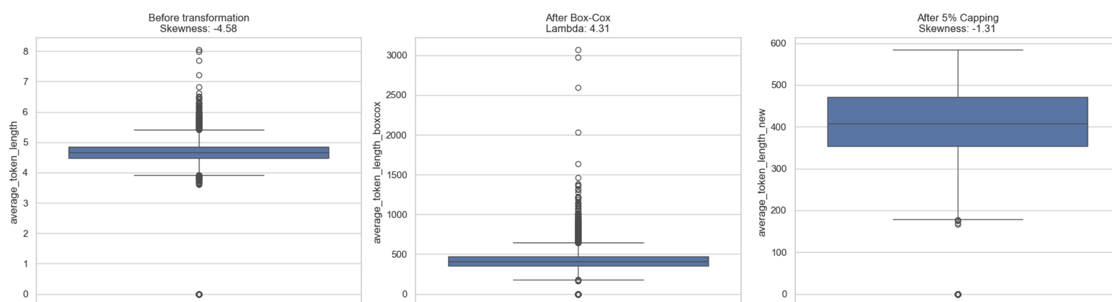
Processing rate_positive_words (Skewness: -1.42)



Processing max_negative_polarity (Skewness: -3.46)



Processing average_token_length (Skewness: -4.58)



Transformation Results:

	original_skewness	new_skewness	improvement
n_non_stop_words	198.792445	-5.531834	204.324279
n_unique_tokens	198.655116	5.051712	193.603403
n_non_stop_unique_tokens	198.443294	12.612118	185.831176
kw_max_min	35.328434	-1.228690	36.557124

```
kw_avg_min                          31.306108   -1.041904   32.348012
self_reference_min_shares           26.264364   -0.029696   26.294060
kw_max_avg                          16.411670   -1.966664   18.378334
self_reference_avg_sharess          17.914093   -0.090106   18.004200
self_reference_max_shares           13.870849   -0.100769   13.971618
kw_avg_avg                           5.760177   -0.666255    6.426432
num_videos                           7.019533    0.656991    6.362542
num_self_hrefs                       5.172751   -0.000939    5.173690
num_hrefs                            4.013495   -0.311996    4.325491
num_imgs                             3.946596    0.142712    3.803884
min_positive_polarity                3.040468   -0.304887    3.345355
n_tokens_content                     2.945422   -0.331256    3.276678
global_rate_negative_words           1.491917   -0.254395    1.746312
abs_title_sentiment_polarity         1.704193    0.476557    1.227636
LDA_01                               2.086722    0.982109    1.104613
LDA_00                               1.567463    0.800367    0.767096
LDA_02                               1.311695    0.630263    0.681432
LDA_04                               1.173129    0.551258    0.621871
LDA_03                               1.238716    0.676088    0.562628
global_subjectivity                 -1.372689   -0.579451   -0.793238
rate_positive_words                 -1.423106    0.310210   -1.733316
average_token_length                -4.576012   -1.307873   -3.268139
max_negative_polarity               -3.459747    0.169102   -3.628849
```

The feature skewness transformation process aimed to reduce high skewness in continuous numerical variables. We want to improve their distributions for better model performance. Initially, 27 features exhibited high skewness ($|\text{skew}| > 1.0$). To address this, a Box-Cox transformation was applied to positively skewed features. It ensures all values were positive by shifting where necessary. If Box-Cox failed, we considered using a log transformation as a fallback. Additionally, 5% capping was implemented to limit extreme outliers. After finishing transformation, most features showed improved skewness and made them more suitable for predictive modeling.

[31]:
```python
# 3. Feature Scaling
print("\n" + "="*50)
print("3. Feature Scaling")

# Identify numeric columns for scaling (exclude target variable if it's numeric)
numeric_columns = df_fe.select_dtypes(include=['int32', 'int64', 'float64']).
 ↪columns.tolist()
if 'shares' in numeric_columns:
    numeric_columns.remove('shares')
if 'shares_original_value' in numeric_columns:
    numeric_columns.remove('shares_original_value')

print(f"Scaling {len(numeric_columns)} numeric features")

# Apply standard scaling
scaler = StandardScaler()
```

```
df_fe[numeric_columns] = scaler.fit_transform(df_fe[numeric_columns])

# Check statistics after scaling
scaled_stats = df_fe[numeric_columns].describe().T[['mean', 'std', 'min',␣
↪'max']]
print("\nStatistics after scaling (sample of features):")
display(scaled_stats.head())
```

```
==================================================
3. Feature Scaling
Scaling 61 numeric features

Statistics after scaling (sample of features):

                                 mean       std       min        max
n_tokens_title           3.785355e-16  1.000013 -3.972899   5.960828
n_tokens_content        -3.541601e-16  1.000013 -2.937041   1.839659
n_unique_tokens         -9.406034e-16  1.000013 -1.880639  58.351434
n_non_stop_words         6.997172e-16  1.000013 -5.706852   0.175228
n_non_stop_unique_tokens  5.620679e-16  1.000013 -2.003119  79.758437
```

[32]:
```
# 4. Feature Engineering - Create New Features
print("\n" + "="*50)
print("4. Creating New Features")

# 4.1 Interaction Features
print("\n4.1 Creating interaction features")

# Create interaction between title and content length
if all(col in df_fe.columns for col in ['n_tokens_title', 'n_tokens_content']):
    df_fe['title_content_ratio'] = df_fe['n_tokens_title'] /␣
↪df_fe['n_tokens_content']
    print("Created title_content_ratio feature")

# Create interaction between positive and negative sentiment
if all(col in df_fe.columns for col in ['global_rate_positive_words',␣
↪'global_rate_negative_words']):
    df_fe['pos_neg_ratio'] = df_fe['global_rate_positive_words'] /␣
↪(df_fe['global_rate_negative_words'] + 0.0001)
    print("Created pos_neg_ratio feature")

# Create interaction between links and images
if all(col in df_fe.columns for col in ['num_hrefs', 'num_imgs']):
    df_fe['media_refs_ratio'] = (df_fe['num_imgs'] + 1) / (df_fe['num_hrefs'] +␣
↪1)
    print("Created media_refs_ratio feature")
```

```
==================================================
4. Creating New Features

4.1 Creating interaction features
Created title_content_ratio feature
Created pos_neg_ratio feature
Created media_refs_ratio feature
```

[33]:
```python
# 4.2 Polynomial features for key variables
print("\n4.2 Creating polynomial features")

# Create polynomial features for selected important variables
polynomial_candidates = ['global_subjectivity', 'num_hrefs', 'num_keywords']
polynomial_candidates = [col for col in polynomial_candidates if col in df_fe.
  ↪columns]

for col in polynomial_candidates:
    df_fe[f'{col}_squared'] = df_fe[col] ** 2
    print(f"Created {col}_squared feature")
```

```
4.2 Creating polynomial features
Created global_subjectivity_squared feature
Created num_hrefs_squared feature
Created num_keywords_squared feature
```

[34]:
```python
# 4.3 Feature Aggregation
print("\n4.3 Creating aggregated features")

# Aggregate sentiment features
sentiment_features = [col for col in df_fe.columns if 'sentiment' in col or␣
  ↪'polarity' in col]
if sentiment_features:
    df_fe['sentiment_aggregate'] = df_fe[sentiment_features].mean(axis=1)
    print("Created sentiment_aggregate feature")

# Aggregate keyword features
keyword_features = [col for col in df_fe.columns if 'kw_' in col]
if keyword_features:
    df_fe['keyword_aggregate'] = df_fe[keyword_features].mean(axis=1)
    print("Created keyword_aggregate feature")
```

```
4.3 Creating aggregated features
Created sentiment_aggregate feature
Created keyword_aggregate feature
```

[35]:
```
# 5. Dimensionality Reduction
print("\n" + "="*50)
print("5. Feature Selection")

# 5.1 Remove highly correlated features
print("\n5.1 Checking for highly correlated features")

# Calculate correlation matrix for numeric features
numeric_df = df_fe.select_dtypes(include=['int32', 'int64', 'float64'])
corr_matrix = numeric_df.corr().abs()

# Identify highly correlated feature pairs
high_corr_threshold = 0.9
upper_tri = corr_matrix.where(np.triu(np.ones(corr_matrix.shape), k=1).
  ↪astype(bool))
high_corr_features = [column for column in upper_tri.columns if␣
  ↪any(upper_tri[column] > high_corr_threshold)]

if high_corr_features:
    print(f"Found {len(high_corr_features)} features with correlation >␣
  ↪{high_corr_threshold}:")
    print(high_corr_features)

    # Remove highly correlated features
    df_fe = df_fe.drop(high_corr_features, axis=1)
    print(f"Removed {len(high_corr_features)} highly correlated features")
else:
    print(f"No features found with correlation > {high_corr_threshold}")
```

```
==================================================
5. Feature Selection

5.1 Checking for highly correlated features
Found 4 features with correlation > 0.9:
['n_non_stop_unique_tokens', 'kw_avg_min', 'self_reference_avg_sharess',
'shares_num']
Removed 4 highly correlated features
```

[36]:
```
# 6. Final Dataset Review
print("\n" + "="*50)
print("6. Final Dataset Review")

print(f"Final dataset shape: {df_fe.shape}")
print(f"Features added: {df_fe.shape[1] - df.shape[1]}")
print(f"Total number of features: {df_fe.shape[1]}")
```

```
# Display feature types
feature_types = df_fe.dtypes.value_counts()
print("\nFeature types in final dataset:")
print(feature_types)

# Check if any categorical features remain as objects
remaining_objects = df_fe.select_dtypes(include=['object']).columns
if len(remaining_objects) > 0:
    print("\nWarning: Some object columns remain:")
    print(remaining_objects)
else:
    print("\nAll categorical features have been properly encoded.")

# Save the engineered dataset
df_fe.to_csv('Data/engineered_data.csv', index=False)
print("\nFeature engineering completed! Engineered dataset saved to␣
↪'engineered_data.csv'")

# Show sample of final dataset
print("\nSample of final dataset:")
display(df_fe.head())
```

```
==================================================
6. Final Dataset Review
Final dataset shape: (39644, 74)
Features added: 11
Total number of features: 74

Feature types in final dataset:
float64    65
bool        7
int64       1
object      1
Name: count, dtype: int64

Warning: Some object columns remain:
Index(['shares_original_value'], dtype='object')

Feature engineering completed! Engineered dataset saved to 'engineered_data.csv'

Sample of final dataset:
```

```
   n_tokens_title  n_tokens_content  n_unique_tokens  n_non_stop_words  \
0        0.757447         -0.743523         1.109069          0.175228
1       -0.661657         -0.594141         0.601491          0.175228
2       -0.661657         -0.778743         0.337987          0.175228
3       -0.661657          0.261372        -0.320734          0.175228
```

```
4       1.230482          1.338783       -1.185615          0.175228

   num_hrefs  num_self_hrefs  num_imgs  num_videos  average_token_length  \
0  -0.706566       -0.149019 -0.286799   -0.751195              0.064691
1  -0.985688       -0.740154 -0.286799   -0.751195              0.794540
2  -0.985688       -0.740154 -0.286799   -0.751195             -0.706613
3   0.188843       -1.767673 -0.286799   -0.751195             -0.678126
4   1.128832        2.522405  1.686736   -0.751195              0.071916

   num_keywords  data_channel_is_lifestyle  data_channel_is_entertainment  \
0     -1.164821                  -0.236445                       2.148880
1     -1.688626                  -0.236445                      -0.465359
2     -0.641015                  -0.236445                      -0.465359
3     -0.117210                  -0.236445                       2.148880
4     -0.117210                  -0.236445                      -0.465359

   data_channel_is_bus  data_channel_is_socmed  data_channel_is_tech  \
0            -0.432948               -0.249487             -0.476911
1             2.309747               -0.249487             -0.476911
2             2.309747               -0.249487             -0.476911
3            -0.432948               -0.249487             -0.476911
4            -0.432948               -0.249487              2.096826

   data_channel_is_world  kw_min_min  kw_max_min  kw_min_max  kw_max_max  \
0              -0.519566   -0.374924   -3.900145   -0.234755   -3.507348
1              -0.519566   -0.374924   -3.900145   -0.234755   -3.507348
2              -0.519566   -0.374924   -3.900145   -0.234755   -3.507348
3              -0.519566   -0.374924   -3.900145   -0.234755   -3.507348
4              -0.519566   -0.374924   -3.900145   -0.234755   -3.507348

   kw_avg_max  kw_min_avg  kw_max_avg  kw_avg_avg  self_reference_min_shares  \
0   -1.919178   -0.982156  -10.812453   -7.639526                  -0.292303
1   -1.919178   -0.982156  -10.812453   -7.639526                  -1.723839
2   -1.919178   -0.982156  -10.812453   -7.639526                  -0.035299
3   -1.919178   -0.982156  -10.812453   -7.639526                  -1.723839
4   -1.919178   -0.982156  -10.812453   -7.639526                  -0.254921

   self_reference_max_shares  weekday_is_monday  weekday_is_tuesday  \
0                  -0.563888           2.225232           -0.478664
1                  -1.714075           2.225232           -0.478664
2                  -0.359504           2.225232           -0.478664
3                  -1.714075           2.225232           -0.478664
4                   0.971402           2.225232           -0.478664

   weekday_is_wednesday  weekday_is_thursday  weekday_is_friday  \
0             -0.480454            -0.473761          -0.409827
1             -0.480454            -0.473761          -0.409827
2             -0.480454            -0.473761          -0.409827
```

```
3           -0.480454           -0.473761          -0.409827
4           -0.480454           -0.473761          -0.409827

   weekday_is_saturday  weekday_is_sunday  is_weekend    LDA_00    LDA_01  \
0            -0.256821          -0.272322   -0.388118  1.573523  1.717067
1            -0.256821          -0.272322   -0.388118  1.734430 -0.217430
2            -0.256821          -0.272322   -0.388118  0.935194 -0.541429
3            -0.256821          -0.272322   -0.388118 -0.711907  1.760938
4            -0.256821          -0.272322   -0.388118 -0.710991 -0.638705

     LDA_02    LDA_03    LDA_04  global_subjectivity  \
0 -0.663598 -0.628303 -0.726511             0.788729
1 -0.550505 -0.531421 -0.626452            -1.047681
2 -0.741750 -0.719421  1.494738             1.806972
3  1.380284 -0.772126 -0.849990            -0.226467
4 -0.799699 -0.776143  1.622242             0.691706

   global_sentiment_polarity  global_rate_positive_words  \
0                  -0.275946                    0.346403
1                   0.305774                    0.201534
2                   2.104872                    0.989601
3                  -0.191940                    0.103648
4                   1.668164                    2.008329

   global_rate_negative_words  rate_positive_words  rate_negative_words  \
0                   -0.134781             0.388821            -0.366077
1                    0.089477             0.129466            -0.136192
2                   -0.657034             1.092405            -0.929060
3                    0.601484            -0.312109             0.290738
4                   -0.321702             1.118831            -0.948734

   avg_positive_polarity  min_positive_polarity  max_positive_polarity  \
0               0.237337               0.391970              -0.228941
1              -0.640040              -1.255504              -0.228941
2               1.358401               0.391970               0.981798
3               0.307442               0.989957               0.174639
4               0.548135              -1.255504               0.981798

   avg_negative_polarity  min_negative_polarity  max_negative_polarity  \
0              -0.708369              -0.268895              -1.471349
1               1.102174               1.367424              -0.207413
2              -1.621797              -0.957871              -0.718629
3              -0.862584              -0.268895              -1.134427
4               0.307944               0.075594               0.782214

   title_subjectivity  title_sentiment_polarity  abs_title_subjectivity  \
0            0.671245                 -0.975432               -1.810719
1           -0.870807                 -0.269076                0.837749
```

```
2          -0.870807                 -0.269076                0.837749
3          -0.870807                 -0.269076                0.837749
4           0.531059                  0.244637               -1.569949

   abs_title_sentiment_polarity  shares  author_level  follower_num  \
0                      0.727156       1      0.889268      0.488173
1                     -0.888601       1      0.889268     -0.167715
2                     -0.888601       0      0.889268     -0.167715
3                     -0.888601       1      0.889268      1.799949
4                      0.433473       1      0.889268     -0.823603

  shares_original_value  followers_Extremely Low  followers_High  \
0                   Low                    False            True
1                   Low                    False           False
2                  High                    False           False
3                   Low                    False           False
4                   Low                    False           False

   followers_Low  followers_Medium  followers_Official  followers_Reprinted  \
0          False             False               False                False
1          False              True               False                False
2          False              True               False                False
3          False             False               False                 True
4           True             False               False                False

   followers_Unknown  title_content_ratio  pos_neg_ratio  media_refs_ratio  \
0              False            -1.018727      -2.572019          2.430530
1              False             1.113635       2.249836         49.832460
2              False             0.849646      -1.506394         49.832460
3              False            -2.531472       0.172292          0.599912
4              False             0.919105      -6.244770          1.262071

   global_subjectivity_squared  num_hrefs_squared  num_keywords_squared  \
0                     0.622093           0.499235              1.356807
1                     1.097636           0.971581              2.851458
2                     3.265149           0.971581              0.410901
3                     0.051287           0.035662              0.013738
4                     0.478458           1.274261              0.013738

   sentiment_aggregate  keyword_aggregate
0            -0.285830          -3.631403
1            -0.079356          -3.631403
2             0.042341          -3.631403
3            -0.238165          -3.631403
4             0.420717          -3.631403
```

Oveview of Feature Engineering:

Our group performed feature engineering to enhance the dataset's performance in machine learning models.

First, we processed categorical variables by applying label encoding to binary variables. We used one-hot encoding for variables with fewer categories, and frequency encoding to those with many unique categories. Additionally, we converted the target variable "shares" into numerical format for further analysis. In terms of feature transformation, we identified numerical variables with high skewness and applied Box-Cox or logarithmic transformations to reduce skewness and also limiting extreme values to reduce the impact of outliers.

Next, we standardized all numerical variables to have a mean of zero and a variance of one to improve model stability. To enrich the dataset, we created interaction features such as the ratio between title and content length, the proportion of positive to negative sentiment words, and the ratio of media references.

Furthermore, we generated polynomial features for key variables and aggregated sentiment and keyword features to extract more representative information. To reduce redundancy, we analyzed feature correlations and removed variables with correlation coefficients above 0.9 to minimize multicollinearity. Compared to the original dataset, these transformations improved the distribution of variables and introduced new features that enhance interpretability and predictive power.

1.5 Modeling

Building on our motivation to understand what factors drive online news popularity, our group aim to develop predictive models that classify articles into different engagement levels based on their shares. We hypothesize that factors such as linguistic attributes, sentiment and keyword relevance etc. of an article impact its shareability. Our expectation is that machine learning models will identify the most influential features that contribute to engagement which allows content creators to optimize their articles for a wider audience. Additionally, we anticipate that models like Random Forest and XGBoost will perform well due to their ability to handle complex feature interactions and neural networks may good at capturing nonlinear relationships.

[37]:
```python
# Set random seed for reproducibility
np.random.seed(42)

# Set display options
pd.set_option('display.max_columns', None)
plt.style.use('ggplot')
sns.set(style="whitegrid")
plt.rcParams['figure.figsize'] = (12, 8)
plt.rcParams['font.size'] = 12
```

[38]:
```python
#----------------------------------------
# Step 1: Prepare Modeling Data
#----------------------------------------
print("\n" + "="*80)
print("STEP 1: Preparing Data for Modeling")
print("="*80)

# Exclude columns that would leak the target or are irrelevant
```

```
exclude_columns = [
]
df  = pd.get_dummies(df, columns=["followers"], prefix="followers")
# Remove columns to exclude
df_filtered = df.drop(columns=[col for col in exclude_columns if col in df.
↪columns])

# Separate features and target
X = df_filtered.drop(['shares', 'shares_num', 'follower_num'], axis=1)
y = df_filtered['shares']

print(f"Features shape: {X.shape}")
print(f"Target shape: {y.shape}")
print(f"Target classes: {y.unique()}")
print(f"Class distribution:\n{y.value_counts()}")

# Ensure consistent class order (Low, Medium, High, Viral)
class_order = ['Low', 'Medium', 'High', 'Viral']
# Verify all classes are in the dataset
class_order = [c for c in class_order if c in y.unique()]

# use LabelEncoder to convert class labels to numeric values
label_encoder = LabelEncoder()
y_encoded = label_encoder.fit_transform(y)
print(f"Original labels: {label_encoder.classes_}")
print(f"Encoded labels: {np.unique(y_encoded)}")

# keep the original class labels for reference
label_mapping = dict(zip(range(len(label_encoder.classes_)), label_encoder.
↪classes_))
print(f"Label mapping: {label_mapping}")

# Split data into training and testing sets (stratified by target)
X_train, X_test, y_train, y_test = train_test_split(
    X, y_encoded, test_size=0.2, random_state=42, stratify=y_encoded
)

print(f"Training set shape: {X_train.shape}, {y_train.shape}")
print(f"Testing set shape: {X_test.shape}, {y_test.shape}")

# Check for any object columns that need encoding
object_columns = X_train.select_dtypes(include=['object']).columns
if len(object_columns) > 0:
    print(f"Encoding object columns: {list(object_columns)}")

    # One-hot encode any remaining object columns
    X_train = pd.get_dummies(X_train, drop_first=True)
```

```python
    X_test = pd.get_dummies(X_test, drop_first=True)

    # Ensure X_test has the same columns as X_train
    for col in X_train.columns:
        if col not in X_test.columns:
            X_test[col] = 0

    # Make sure they have the same columns in the same order
    X_test = X_test[X_train.columns]
X.info()
```

```
================================================================================
STEP 1: Preparing Data for Modeling
================================================================================
Features shape: (39644, 66)
Target shape: (39644,)
Target classes: ['Low' 'High']
Class distribution:
shares
High    21154
Low     18490
Name: count, dtype: int64
Original labels: ['High' 'Low']
Encoded labels: [0 1]
Label mapping: {0: 'High', 1: 'Low'}
Training set shape: (31715, 66), (31715,)
Testing set shape: (7929, 66), (7929,)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 39644 entries, 0 to 39643
Data columns (total 66 columns):
 #   Column                         Non-Null Count  Dtype
---  ------                         --------------  -----
 0   n_tokens_title                 39644 non-null  int64
 1   n_tokens_content               39644 non-null  int64
 2   n_unique_tokens                39644 non-null  float64
 3   n_non_stop_words               39644 non-null  float64
 4   n_non_stop_unique_tokens       39644 non-null  float64
 5   num_hrefs                      39644 non-null  int64
 6   num_self_hrefs                 39644 non-null  int64
 7   num_imgs                       39644 non-null  int64
 8   num_videos                     39644 non-null  int64
 9   average_token_length           39644 non-null  float64
 10  num_keywords                   39644 non-null  int64
 11  data_channel_is_lifestyle      39644 non-null  int64
 12  data_channel_is_entertainment  39644 non-null  int64
 13  data_channel_is_bus            39644 non-null  int64
 14  data_channel_is_socmed         39644 non-null  int64
```

```
15  data_channel_is_tech           39644 non-null  int64
16  data_channel_is_world          39644 non-null  int64
17  kw_min_min                     39644 non-null  int64
18  kw_max_min                     39644 non-null  float64
19  kw_avg_min                     39644 non-null  float64
20  kw_min_max                     39644 non-null  int64
21  kw_max_max                     39644 non-null  int64
22  kw_avg_max                     39644 non-null  float64
23  kw_min_avg                     39644 non-null  float64
24  kw_max_avg                     39644 non-null  float64
25  kw_avg_avg                     39644 non-null  float64
26  self_reference_min_shares      39644 non-null  float64
27  self_reference_max_shares      39644 non-null  float64
28  self_reference_avg_sharess     39644 non-null  float64
29  weekday_is_monday              39644 non-null  int64
30  weekday_is_tuesday             39644 non-null  int64
31  weekday_is_wednesday           39644 non-null  int64
32  weekday_is_thursday            39644 non-null  int64
33  weekday_is_friday              39644 non-null  int64
34  weekday_is_saturday            39644 non-null  int64
35  weekday_is_sunday              39644 non-null  int64
36  is_weekend                     39644 non-null  int64
37  LDA_00                         39644 non-null  float64
38  LDA_01                         39644 non-null  float64
39  LDA_02                         39644 non-null  float64
40  LDA_03                         39644 non-null  float64
41  LDA_04                         39644 non-null  float64
42  global_subjectivity            39644 non-null  float64
43  global_sentiment_polarity      39644 non-null  float64
44  global_rate_positive_words     39644 non-null  float64
45  global_rate_negative_words     39644 non-null  float64
46  rate_positive_words            39644 non-null  float64
47  rate_negative_words            39644 non-null  float64
48  avg_positive_polarity          39644 non-null  float64
49  min_positive_polarity          39644 non-null  float64
50  max_positive_polarity          39644 non-null  float64
51  avg_negative_polarity          39644 non-null  float64
52  min_negative_polarity          39644 non-null  float64
53  max_negative_polarity          39644 non-null  float64
54  title_subjectivity             39644 non-null  float64
55  title_sentiment_polarity       39644 non-null  float64
56  abs_title_subjectivity         39644 non-null  float64
57  abs_title_sentiment_polarity   39644 non-null  float64
58  author_level                   39644 non-null  int64
59  followers_Extremely Low        39644 non-null  bool
60  followers_High                 39644 non-null  bool
61  followers_Low                  39644 non-null  bool
62  followers_Medium               39644 non-null  bool
```

```
 63  followers_Official             39644 non-null  bool
 64  followers_Reprinted            39644 non-null  bool
 65  followers_Unknown              39644 non-null  bool
dtypes: bool(7), float64(34), int64(25)
memory usage: 18.1 MB
```

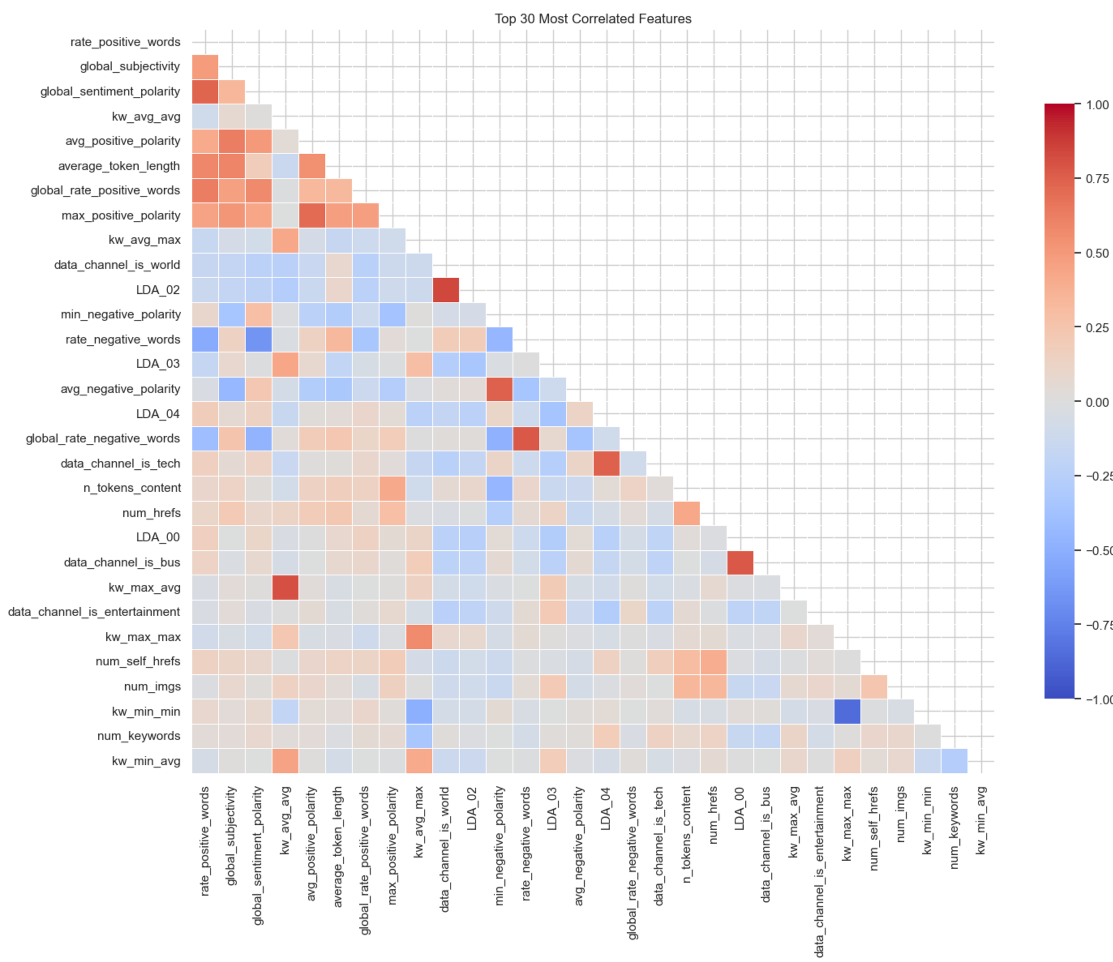
[39]:

```
# Correlation Analysis
features = df_filtered.drop(['shares', 'shares_num', 'follower_num'], axis=1)
corr_matrix = features.corr()

# Set the threshold for high correlation
threshold = 0.7

# Find feature pairs with correlation greater than the threshold
high_corr_pairs = []
for i in range(len(corr_matrix.columns)):
    for j in range(i+1, len(corr_matrix.columns)):
        if abs(corr_matrix.iloc[i, j]) > threshold:
            high_corr_pairs.append((corr_matrix.columns[i], corr_matrix.
↪columns[j], corr_matrix.iloc[i, j]))

# Rank the feature pairs by correlation
high_corr_pairs = sorted(high_corr_pairs, key=lambda x: abs(x[2]), reverse=True)

# Print the feature pairs with high correlation
print(f"Found {len(high_corr_pairs)} feature pairs with correlation >␣
↪{threshold}:")
for feature1, feature2, corr in high_corr_pairs[:20]:
    print(f"{feature1} & {feature2}: {corr:.4f}")

# Output correlation matrix
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np

# Filter out highly correlated features
if len(corr_matrix) > 30:
    corr_sum = corr_matrix.abs().sum() - 1
    top_corr_features = corr_sum.sort_values(ascending=False).head(30).index
    corr_matrix_subset = corr_matrix.loc[top_corr_features, top_corr_features]

    plt.figure(figsize=(15, 12))
    mask = np.triu(np.ones_like(corr_matrix_subset, dtype=bool))
    sns.heatmap(corr_matrix_subset, mask=mask, cmap='coolwarm', vmin=-1, vmax=1,
                annot=False, linewidths=0.5, cbar_kws={"shrink": 0.8})
    plt.title('Top 30 Most Correlated Features')
else:
```

```python
    plt.figure(figsize=(15, 12))
    mask = np.triu(np.ones_like(corr_matrix, dtype=bool))
    sns.heatmap(corr_matrix, mask=mask, cmap='coolwarm', vmin=-1, vmax=1,
                annot=False, linewidths=0.5, cbar_kws={"shrink": 0.8})
    plt.title('Full Feature Correlation Matrix')

plt.tight_layout()
plt.show()

# Find groups of highly correlated features
if len(high_corr_pairs) > 0:
    print("\nGroups of highly correlated features:")

    from collections import defaultdict

    # Create a graph to store feature connections
    graph = defaultdict(set)
    for f1, f2, _ in high_corr_pairs:
        graph[f1].add(f2)
        graph[f2].add(f1)

    visited = set()
    corr_groups = []

    for feature in graph:
        if feature not in visited:
            group = []
            stack = [feature]
            while stack:
                current = stack.pop()
                if current not in visited:
                    visited.add(current)
                    group.append(current)
                    stack.extend(graph[current] - visited)
            corr_groups.append(group)

    # Output the groups of correlated features
    for i, group in enumerate(corr_groups, 1):
        if len(group) > 1:
            print(f"Group {i}: {', '.join(group)}")
```

```
Found 17 feature pairs with correlation > 0.7:
n_unique_tokens & n_non_stop_unique_tokens: 0.9999
n_unique_tokens & n_non_stop_words: 0.9996
n_non_stop_words & n_non_stop_unique_tokens: 0.9995
kw_max_min & kw_avg_min: 0.9405
kw_min_min & kw_max_max: -0.8572
self_reference_max_shares & self_reference_avg_sharess: 0.8535
```

```
data_channel_is_world & LDA_02: 0.8366
self_reference_min_shares & self_reference_avg_sharess: 0.8189
kw_max_avg & kw_avg_avg: 0.8119
global_rate_negative_words & rate_negative_words: 0.7796
data_channel_is_bus & LDA_00: 0.7747
data_channel_is_tech & LDA_04: 0.7497
avg_negative_polarity & min_negative_polarity: 0.7489
global_sentiment_polarity & rate_positive_words: 0.7278
title_subjectivity & abs_title_sentiment_polarity: 0.7145
avg_positive_polarity & max_positive_polarity: 0.7036
weekday_is_sunday & is_weekend: 0.7016
```




```
Groups of highly correlated features:
Group 1: n_unique_tokens, n_non_stop_unique_tokens, n_non_stop_words
Group 2: kw_max_min, kw_avg_min
Group 3: kw_min_min, kw_max_max
Group 4: self_reference_max_shares, self_reference_avg_sharess,
```

```
self_reference_min_shares
Group 5: data_channel_is_world, LDA_02
Group 6: kw_max_avg, kw_avg_avg
Group 7: global_rate_negative_words, rate_negative_words
Group 8: data_channel_is_bus, LDA_00
Group 9: data_channel_is_tech, LDA_04
Group 10: avg_negative_polarity, min_negative_polarity
Group 11: global_sentiment_polarity, rate_positive_words
Group 12: title_subjectivity, abs_title_sentiment_polarity
Group 13: avg_positive_polarity, max_positive_polarity
Group 14: weekday_is_sunday, is_weekend
```

[40]:

```python
#----------------------------------------
# Step 2: Apply SMOTE for Class Imbalance
#----------------------------------------
print("\n" + "="*80)
print("STEP 2: Balancing Classes with SMOTE")
print("="*80)

# Apply SMOTE
print("Applying SMOTE to balance training data...")
smote = SMOTE(random_state=42)
X_train_resampled, y_train_resampled = smote.fit_resample(X_train, y_train)

print(f"Original training class distribution:\n{pd.Series(y_train).
 ↪map(label_mapping).value_counts()}")
print(f"Resampled training class distribution:\n{pd.Series(y_train_resampled).
 ↪map(label_mapping).value_counts()}")

#----------------------------------------
# Function to plot confusion matrix
#----------------------------------------
def plot_confusion_matrix(y_true, y_pred, title):

    # Convert numeric labels back to original class labels for visualization
    if isinstance(y_true[0], (int, np.integer)):
        y_true_mapped = np.array([label_mapping[y] for y in y_true])
    else:
        y_true_mapped = y_true

    if isinstance(y_pred[0], (int, np.integer)):
        y_pred_mapped = np.array([label_mapping[y] for y in y_pred])
    else:
        y_pred_mapped = y_pred

    # Use consistent class order
    classes = [label_mapping[i] for i in range(len(label_mapping))]
```

```python
# Create confusion matrix
cm = confusion_matrix(y_true_mapped, y_pred_mapped, labels=classes)

# Create a DataFrame for better visualization
cm_df = pd.DataFrame(cm, index=classes, columns=classes)

# Calculate class-wise accuracy (diagonal elements / row sums)
class_accuracy = np.diag(cm) / np.sum(cm, axis=1)
class_accuracy = np.round(class_accuracy * 100, 1)

# Create the plot
plt.figure(figsize=(10, 8))

# Plot the confusion matrix with actual counts
ax = sns.heatmap(cm_df, annot=True, fmt='d', cmap='Blues', linewidths=.5)

# Set the title with overall accuracy
overall_accuracy = np.trace(cm) / np.sum(cm)
plt.title(f'{title}\nOverall Accuracy: {overall_accuracy:.4f}', fontsize=14)

# Set proper labels
plt.xlabel('Predicted Label', fontsize=12)
plt.ylabel('True Label', fontsize=12)

# Add class accuracy labels to the y-axis
plt.yticks(np.arange(len(classes)) + 0.5,
           [f"{cls} (Acc: {acc}%)" for cls, acc in zip(classes,
↪class_accuracy)],
           fontsize=10, rotation=0)

plt.tight_layout()
plt.show()

# Print detailed metrics
print("\nDetailed Classification Metrics:")

# Calculate precision, recall, f1-score per class
precision = np.diag(cm) / np.sum(cm, axis=0)
recall = np.diag(cm) / np.sum(cm, axis=1)
f1 = 2 * (precision * recall) / (precision + recall)

# Handle division by zero
precision = np.nan_to_num(precision)
recall = np.nan_to_num(recall)
f1 = np.nan_to_num(f1)
```

```
    # Create metrics DataFrame
    metrics_df = pd.DataFrame({
        'Class': classes,
        'Precision': np.round(precision * 100, 1),
        'Recall': np.round(recall * 100, 1),
        'F1-Score': np.round(f1 * 100, 1),
        'Support': np.sum(cm, axis=1)
    })

    # Add % symbols for better readability
    metrics_df['Precision'] = metrics_df['Precision'].apply(lambda x: f"{x}%")
    metrics_df['Recall'] = metrics_df['Recall'].apply(lambda x: f"{x}%")
    metrics_df['F1-Score'] = metrics_df['F1-Score'].apply(lambda x: f"{x}%")

    print(metrics_df)

    return overall_accuracy
```

```
================================================================================
STEP 2: Balancing Classes with SMOTE
================================================================================
Applying SMOTE to balance training data…
Original training class distribution:
High    16923
Low     14792
Name: count, dtype: int64
Resampled training class distribution:
Low     16923
High    16923
Name: count, dtype: int64
```

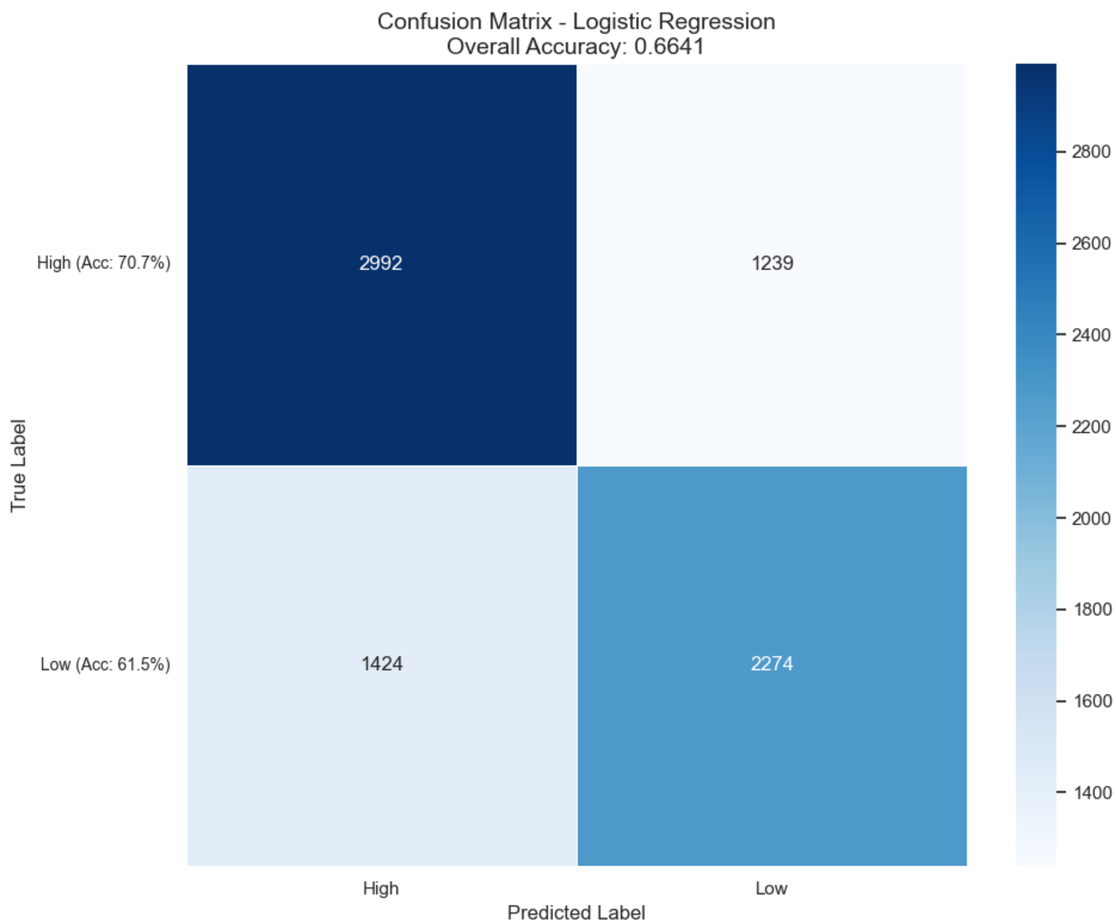
[41]:

```
#----------------------------------------
# Step 3: Model Building and Evaluation
#----------------------------------------
print("\n" + "="*80)
print("STEP 3: Model Building and Evaluation")
print("="*80)

# Define models to try
# to tree-based models, make sure the number of target classes is correct
n_classes = len(np.unique(y_train))

models = {
    'Logistic Regression': LogisticRegression(max_iter=1000, random_state=42,␣
 ↪n_jobs=-1),
    'Random Forest': RandomForestClassifier(random_state=42, n_jobs=-1),
```

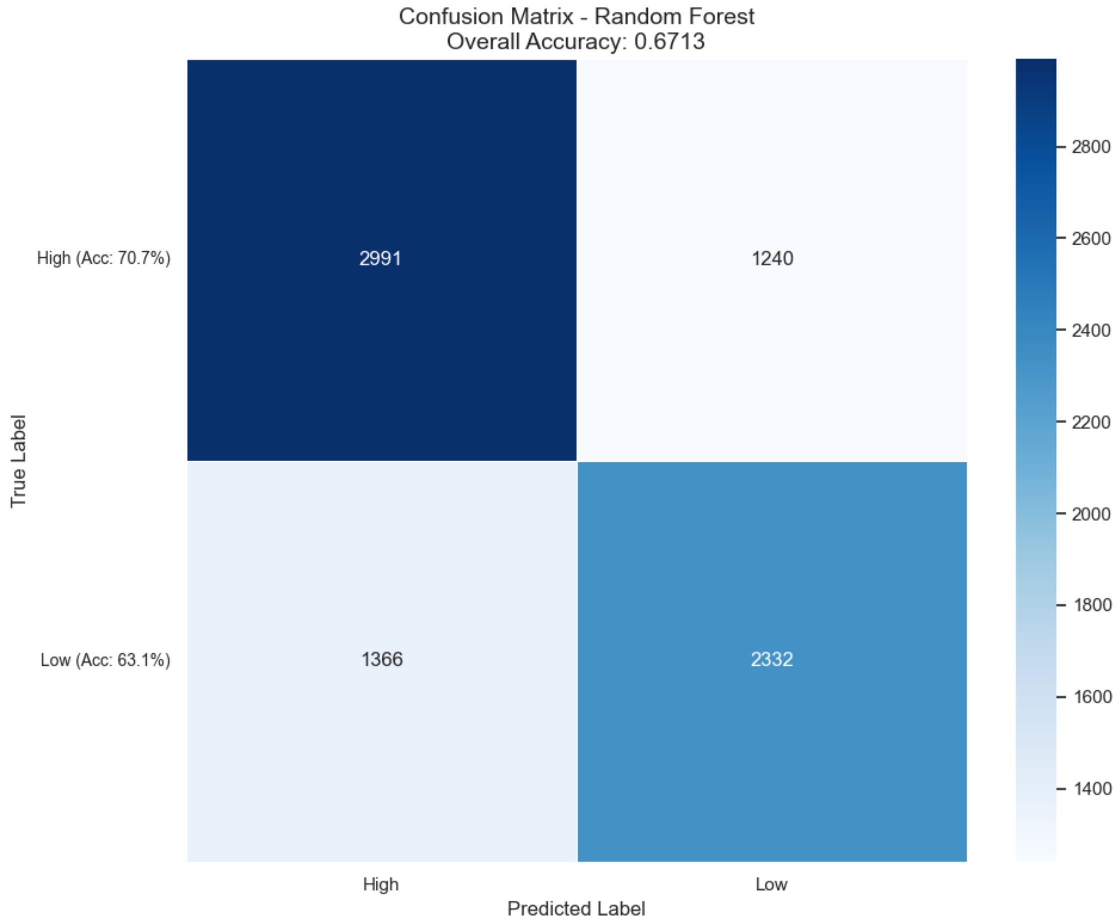
```python
    'Gradient Boosting': GradientBoostingClassifier(random_state=42),
    'XGBoost': xgb.XGBClassifier(
        objective='multi:softmax',
        num_class=n_classes,
        random_state=42,
        n_jobs=-1
    ),
    'LightGBM': lgb.LGBMClassifier(
        objective='multiclass',
        num_class=n_classes,
        random_state=42,
        n_jobs=-1
    ),
    'Neural Network': MLPClassifier(random_state=42, max_iter=500)
}

# Function to evaluate a single model
def evaluate_model(model, name, X_train, y_train, X_test, y_test, cv=5):
    """Evaluate a single model"""
    # Create a pipeline with scaling
    pipeline = Pipeline([
        ('scaler', StandardScaler()),
        ('model', model)
    ])

    # Perform cross-validation
    cv_scores = cross_val_score(pipeline, X_train, y_train,
                                cv=cv, scoring='accuracy', n_jobs=-1)

    # Train the model on the entire training set and evaluate on test set
    pipeline.fit(X_train, y_train)
    y_pred = pipeline.predict(X_test)

    # Calculate metrics
    accuracy = accuracy_score(y_test, y_pred)
    f1 = f1_score(y_test, y_pred, average='weighted')

    # Print evaluation results
    print(f"Model: {name}")
    print(f"CV Accuracy: {cv_scores.mean():.4f} ± {cv_scores.std():.4f}")
    print(f"Test Accuracy: {accuracy:.4f}")
    print(f"Test F1 Score: {f1:.4f}")

    # Plot confusion matrix
    plot_confusion_matrix(y_test, y_pred, title=f'Confusion Matrix - {name}')

    return {
```

```
        'cv_mean': cv_scores.mean(),
        'cv_std': cv_scores.std(),
        'test_accuracy': accuracy,
        'test_f1': f1,
        'model': pipeline,
        'predictions': y_pred
    }

# Store results
results = {}

# Evaluate each model
for name, model in models.items():
    print(f"\n{'='*50}\nEvaluating {name}...")
    results[name] = evaluate_model(model, name, X_train_resampled,␣
 ↪y_train_resampled, X_test, y_test)

# Determine the best model
best_model_name = max(results, key=lambda x: results[x]['test_accuracy'])
best_model = results[best_model_name]['model']
print(f"\n{'='*50}\nBest model: {best_model_name}")
```

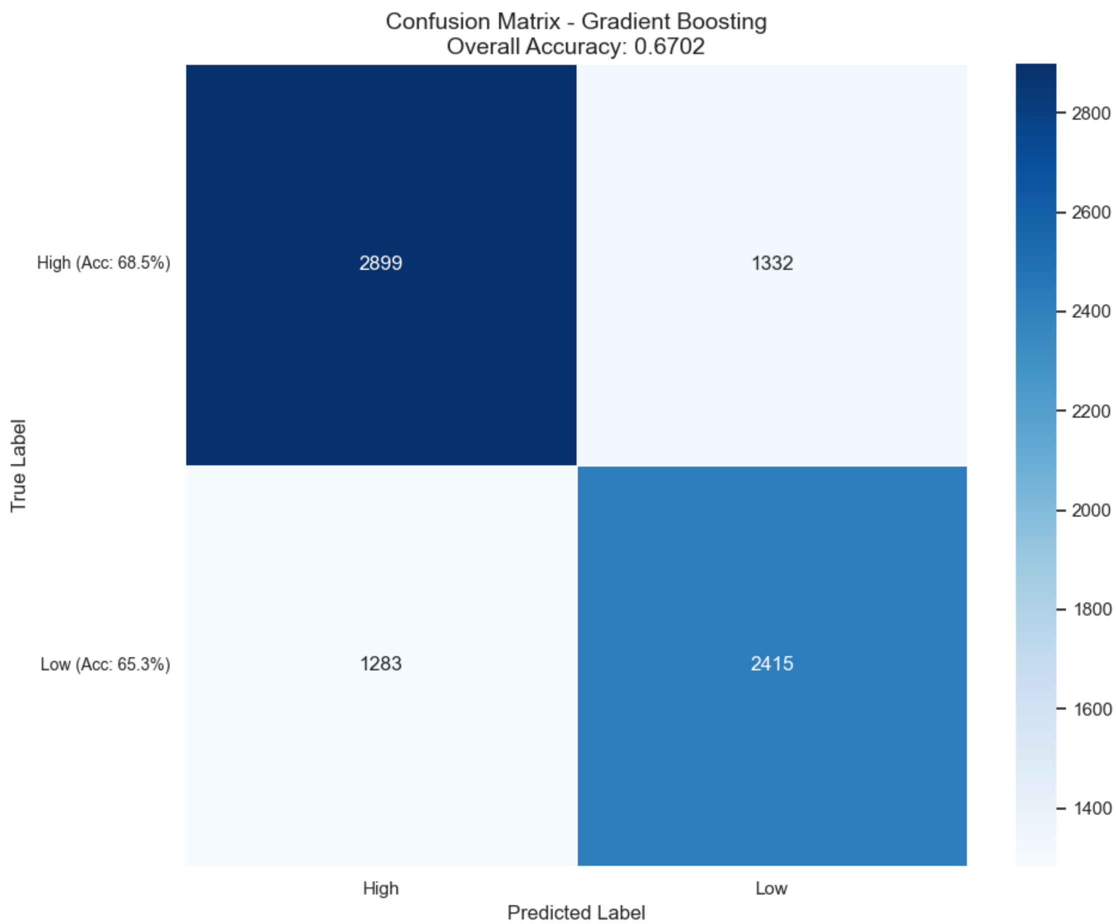
```
================================================================================
STEP 3: Model Building and Evaluation
================================================================================

==================================================
Evaluating Logistic Regression…
Model: Logistic Regression
CV Accuracy: 0.6547 ± 0.0153
Test Accuracy: 0.6641
Test F1 Score: 0.6634
```



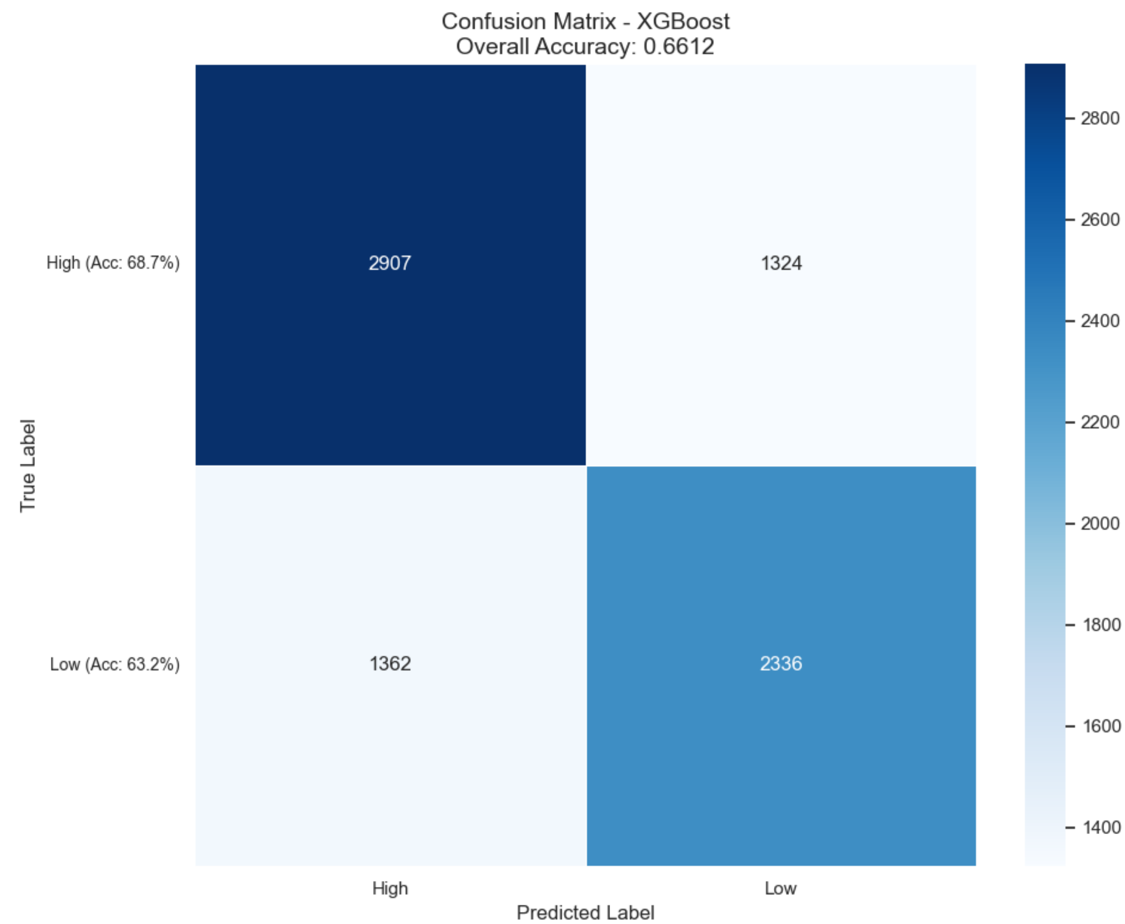

```
Detailed Classification Metrics:
  Class Precision Recall F1-Score  Support
0  High     67.8%  70.7%    69.2%     4231
1   Low     64.7%  61.5%    63.1%     3698

==================================================
Evaluating Random Forest…
Model: Random Forest
CV Accuracy: 0.6730 ± 0.0164
Test Accuracy: 0.6713
Test F1 Score: 0.6709
```




```
Detailed Classification Metrics:
  Class Precision Recall F1-Score  Support
0  High     68.6%  70.7%    69.7%     4231
1   Low     65.3%  63.1%    64.2%     3698

==================================================
Evaluating Gradient Boosting…
Model: Gradient Boosting
CV Accuracy: 0.6712 ± 0.0145
Test Accuracy: 0.6702
Test F1 Score: 0.6703
```

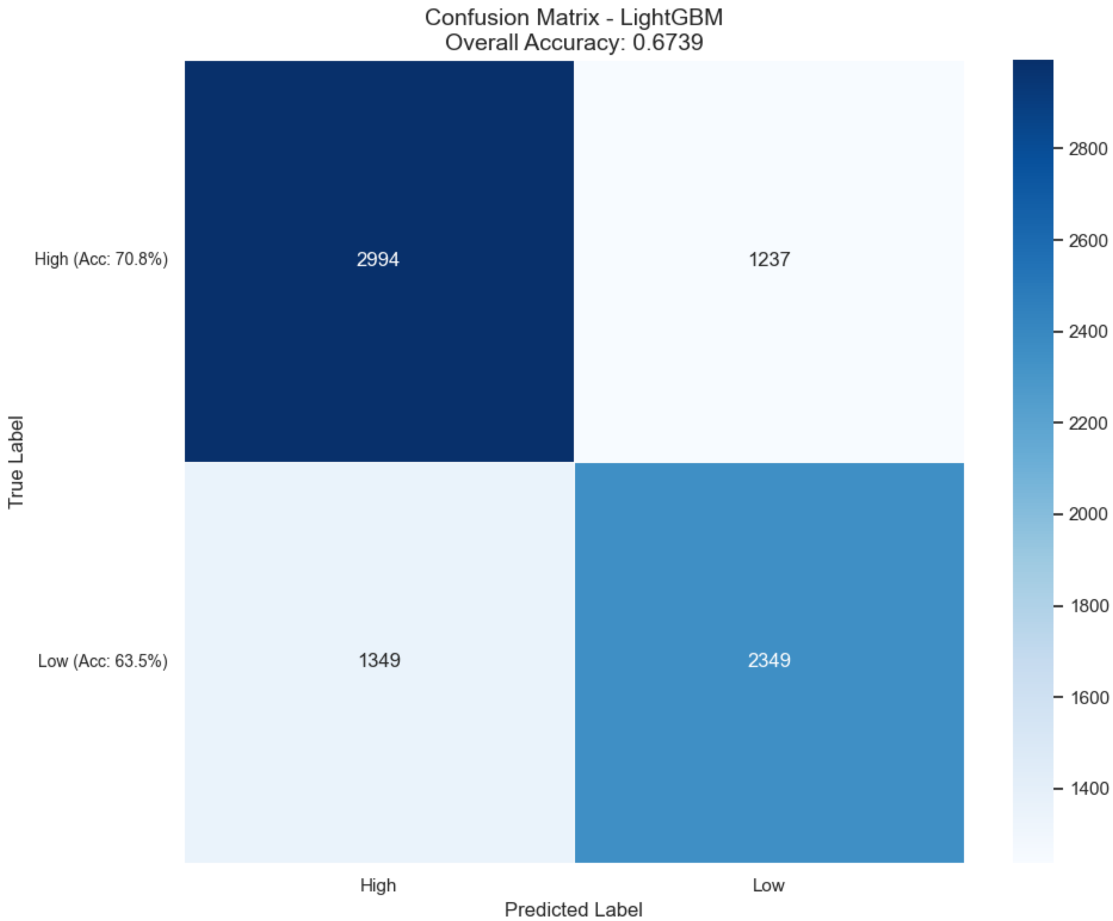



```
Detailed Classification Metrics:
  Class Precision Recall F1-Score  Support
0  High     69.3%  68.5%    68.9%     4231
1   Low     64.5%  65.3%    64.9%     3698

==================================================
Evaluating XGBoost…
Model: XGBoost
CV Accuracy: 0.6638 ± 0.0188
Test Accuracy: 0.6612
Test F1 Score: 0.6611
```

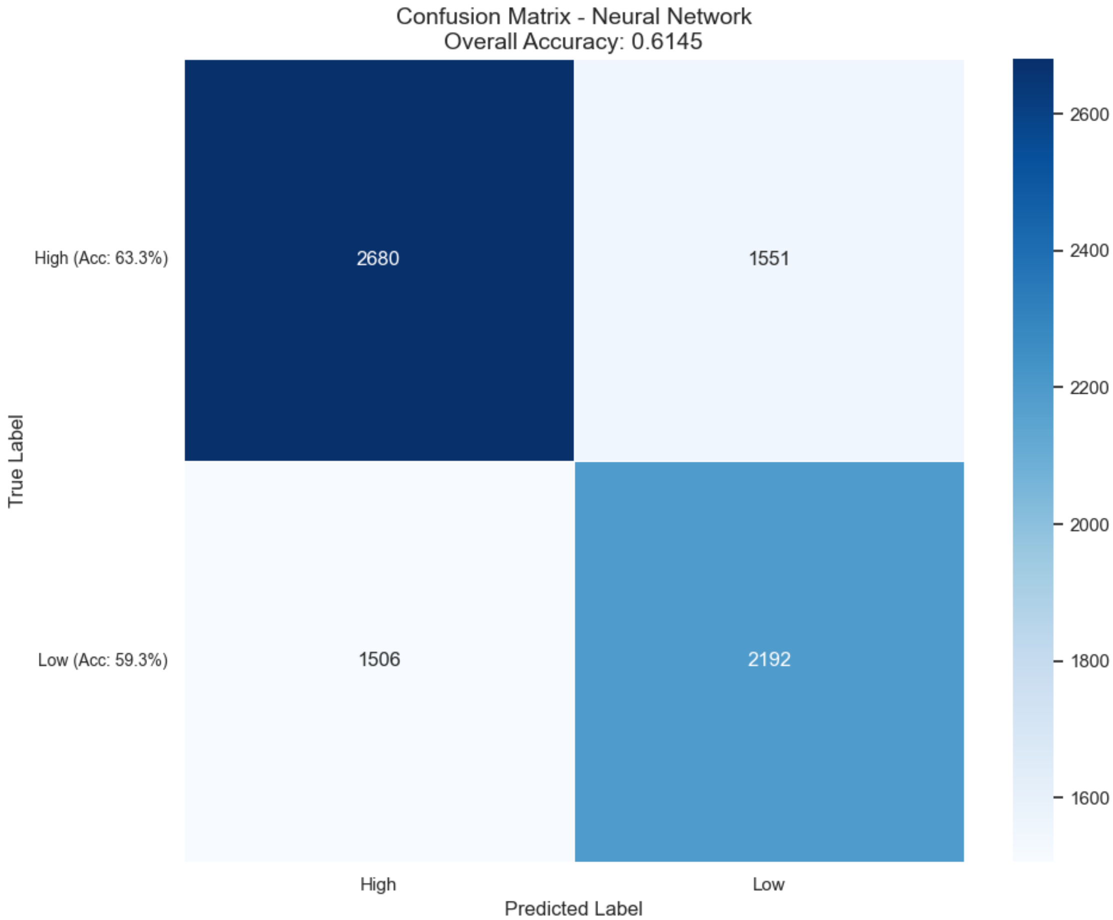



```
Detailed Classification Metrics:
  Class Precision Recall F1-Score  Support
0  High     68.1%  68.7%    68.4%     4231
1   Low     63.8%  63.2%    63.5%     3698

==================================================
Evaluating LightGBM…
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of
testing was 0.005211 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 9529
[LightGBM] [Info] Number of data points in the train set: 33846, number of used
features: 66
[LightGBM] [Info] Start training from score -0.693147
[LightGBM] [Info] Start training from score -0.693147
Model: LightGBM
CV Accuracy: 0.6763 ± 0.0154
```

```
Test Accuracy: 0.6739
Test F1 Score: 0.6735
```




```
Detailed Classification Metrics:
  Class Precision Recall F1-Score  Support
0  High     68.9%  70.8%    69.8%     4231
1   Low     65.5%  63.5%    64.5%     3698

==================================================
Evaluating Neural Network…
Model: Neural Network
CV Accuracy: 0.6073 ± 0.0042
Test Accuracy: 0.6145
Test F1 Score: 0.6146
```




```
Detailed Classification Metrics:
  Class Precision Recall F1-Score  Support
0  High     64.0%  63.3%    63.7%     4231
1   Low     58.6%  59.3%    58.9%     3698

==================================================
Best model: LightGBM
```

[42]:
```
#-----------------------------------------
# Step 4: Stacking with Specified Top 3 Models
#-----------------------------------------
print("\n" + "="*80)
print("STEP 4: Stacking with Specified Top 3 Models")
print("="*80)

# Import required libraries if not already imported
import numpy as np
```

```python
from sklearn.ensemble import StackingClassifier, RandomForestClassifier,␣
↪GradientBoostingClassifier
from sklearn.preprocessing import StandardScaler
from sklearn.pipeline import Pipeline
from sklearn.metrics import accuracy_score, f1_score, classification_report,␣
↪confusion_matrix
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd

# Specify the exact 3 models to use
top3_model_names = ['LightGBM', 'XGBoost', 'Logistic Regression']
print(f"Using specified top 3 models: {', '.join(top3_model_names)}")

# Extract only these 3 trained models from results
top3_trained_models = []
for name in top3_model_names:
    # Get the actual model from the pipeline
    model = results[name]['model'][-1]  # Extract the model from the pipeline
    top3_trained_models.append((name.lower().replace(' ', '_'), model))

# Use Gradient Boosting as meta-learner (different from base models)
print("\nUsing Gradient Boosting as meta-learner")
meta_learner = GradientBoostingClassifier(n_estimators=100, learning_rate=0.1,␣
↪max_depth=3, random_state=42)

# Create stacking classifier using the specified 3 models
print("Creating stacking ensemble with specified models...")
stacking_classifier = StackingClassifier(
    estimators=top3_trained_models,
    final_estimator=meta_learner,
    cv=5,
    stack_method='predict_proba',
    n_jobs=1,  # Use single job to avoid memory issues
    verbose=1,
    passthrough=False  # Don't include original features
)

# Train stacking model with the specified models
print("Training stacking ensemble...")
stacking_classifier.fit(X_train_resampled, y_train_resampled)

# Make predictions on test set
print("Evaluating stacking ensemble on test set...")
y_pred_stacking = stacking_classifier.predict(X_test)

# Calculate metrics
```

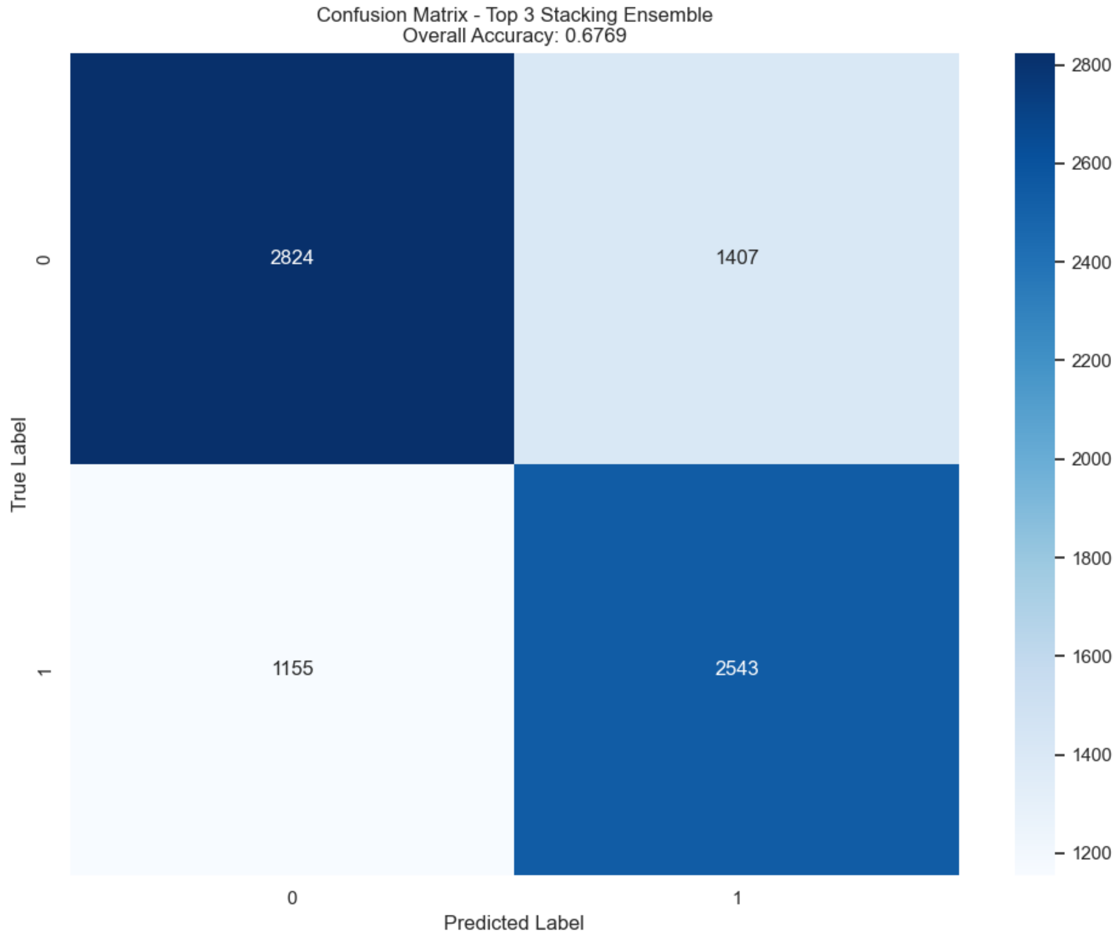
```python
accuracy = accuracy_score(y_test, y_pred_stacking)
f1 = f1_score(y_test, y_pred_stacking, average='weighted')

# Print evaluation results
print("\nStacking Ensemble Evaluation Results:")
print(f"Test Accuracy: {accuracy:.4f}")
print(f"Test F1 Score: {f1:.4f}")

# Print detailed classification report
print("\nDetailed Classification Report:")
print(classification_report(y_test, y_pred_stacking))

# Plot confusion matrix
plt.figure(figsize=(10, 8))
cm = confusion_matrix(y_test, y_pred_stacking)
classes = np.unique(y_test)
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
            xticklabels=classes, yticklabels=classes)
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.title(f'Confusion Matrix - Top 3 Stacking Ensemble\nOverall Accuracy:␣
 ↪{accuracy:.4f}')
plt.tight_layout()
plt.show()

# Add stacking results to overall results
results['Top 3 Stacking'] = {
    'cv_mean': 0,  # We're not performing separate CV here
    'cv_std': 0,
    'test_accuracy': accuracy,
    'test_f1': f1,
    'model': stacking_classifier,
    'predictions': y_pred_stacking
}

# Compare all models including stacking
print("\nModel Performance Comparison:")
models_comparison = []
for name, result in results.items():
    models_comparison.append({
        'Model': name,
        'Test Accuracy': result['test_accuracy'],
        'Test F1 Score': result['test_f1']
    })

comparison_df = pd.DataFrame(models_comparison)
```

```python
comparison_df = comparison_df.sort_values('Test Accuracy', ascending=False).
    ↪reset_index(drop=True)
print(comparison_df)

# Plot model comparison
plt.figure(figsize=(12, 8))

# Plot accuracy
plt.subplot(2, 1, 1)
sns.barplot(x='Test Accuracy', y='Model', data=comparison_df)
plt.title('Model Accuracy Comparison')
plt.xlim(min(comparison_df['Test Accuracy']) - 0.01, max(comparison_df['Test␣
    ↪Accuracy']) + 0.01)

# Plot F1 score
plt.subplot(2, 1, 2)
sns.barplot(x='Test F1 Score', y='Model', data=comparison_df)
plt.title('Model F1 Score Comparison')
plt.xlim(min(comparison_df['Test F1 Score']) - 0.01, max(comparison_df['Test F1␣
    ↪Score']) + 0.01)

plt.tight_layout()
plt.show()

# Update best model information
best_model_name = max(results, key=lambda x: results[x]['test_accuracy'])
best_model = results[best_model_name]['model']
print(f"\nBest model: {best_model_name}")

# Calculate and display class-specific accuracies
print("\nClass-specific accuracies for Top 3 Stacking model:")
class_labels = np.unique(y_test)
for label in class_labels:
    # Get indices where true label is the current class
    class_indices = np.where(y_test == label)[0]

    # Calculate accuracy for this class
    class_accuracy = accuracy_score(
        y_test[class_indices],
        y_pred_stacking[class_indices]
    )

    # Print class-specific accuracy
    print(f"Class {label}: {class_accuracy:.4f}")

# Print confusion matrix as percentages
print("\nConfusion Matrix (percentage):")
```

```python
cm_percentage = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis] * 100
cm_df = pd.DataFrame(cm_percentage.round(1), index=classes, columns=classes)
print(cm_df)
```

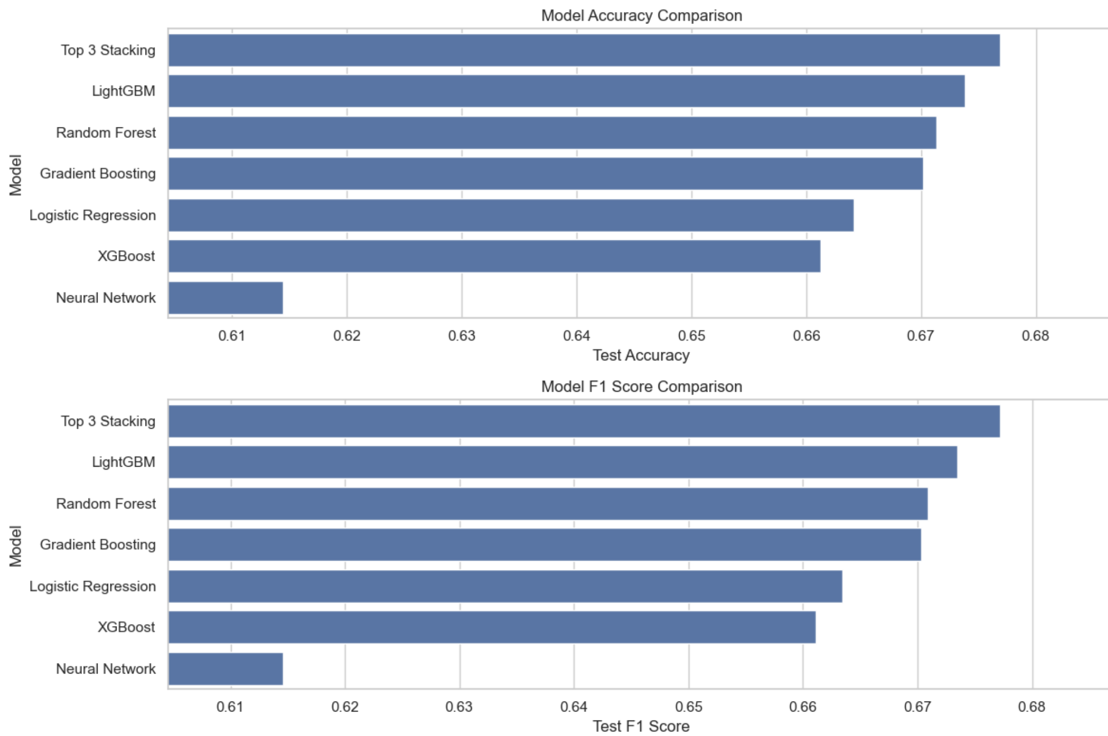
```
================================================================================
STEP 4: Stacking with Specified Top 3 Models
================================================================================
Using specified top 3 models: LightGBM, XGBoost, Logistic Regression

Using Gradient Boosting as meta-learner
Creating stacking ensemble with specified models…
Training stacking ensemble…
[LightGBM] [Warning] Found whitespace in feature_names, replace with underlines
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of
testing was 0.002552 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 9466
[LightGBM] [Info] Number of data points in the train set: 33846, number of used
features: 66
[LightGBM] [Info] Start training from score -0.693147
[LightGBM] [Info] Start training from score -0.693147
[LightGBM] [Warning] Found whitespace in feature_names, replace with underlines
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of
testing was 0.002637 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 9489
[LightGBM] [Info] Number of data points in the train set: 27076, number of used
features: 66
[LightGBM] [Info] Start training from score -0.693147
[LightGBM] [Info] Start training from score -0.693147
[LightGBM] [Warning] Found whitespace in feature_names, replace with underlines
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of
testing was 0.002042 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 9473
[LightGBM] [Info] Number of data points in the train set: 27077, number of used
features: 66
[LightGBM] [Info] Start training from score -0.693110
[LightGBM] [Info] Start training from score -0.693184
[LightGBM] [Warning] Found whitespace in feature_names, replace with underlines
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of
testing was 0.002195 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 9488
[LightGBM] [Info] Number of data points in the train set: 27077, number of used
features: 66
[LightGBM] [Info] Start training from score -0.693110
```

```
[LightGBM] [Info] Start training from score -0.693184
[LightGBM] [Warning] Found whitespace in feature_names, replace with underlines
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of
testing was 0.002349 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 9487
[LightGBM] [Info] Number of data points in the train set: 27077, number of used
features: 66
[LightGBM] [Info] Start training from score -0.693184
[LightGBM] [Info] Start training from score -0.693110
[LightGBM] [Warning] Found whitespace in feature_names, replace with underlines
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of
testing was 0.001684 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 8229
[LightGBM] [Info] Number of data points in the train set: 27077, number of used
features: 66
[LightGBM] [Info] Start training from score -0.693184
[LightGBM] [Info] Start training from score -0.693110
Evaluating stacking ensemble on test set…

Stacking Ensemble Evaluation Results:
Test Accuracy: 0.6769
Test F1 Score: 0.6772

Detailed Classification Report:
              precision    recall  f1-score   support

           0       0.71      0.67      0.69      4231
           1       0.64      0.69      0.67      3698

    accuracy                           0.68      7929
   macro avg       0.68      0.68      0.68      7929
weighted avg       0.68      0.68      0.68      7929
```



Model Performance Comparison:

	Model	Test Accuracy	Test F1 Score
0	Top 3 Stacking	0.676882	0.677247
1	LightGBM	0.673855	0.673478
2	Random Forest	0.671333	0.670896
3	Gradient Boosting	0.670198	0.670323
4	Logistic Regression	0.664144	0.663429
5	XGBoost	0.661244	0.661126
6	Neural Network	0.614453	0.614588




```
Best model: Top 3 Stacking

Class-specific accuracies for Top 3 Stacking model:
Class 0: 0.6675
Class 1: 0.6877

Confusion Matrix (percentage):
      0     1
0  66.7  33.3
1  31.2  68.8
```

[43]:
```python
#----------------------------------------
# Step 5: Feature Importance Analysis
#----------------------------------------
print("\n" + "="*80)
print("STEP 5: Feature Importance Analysis")
print("="*80)

# Check if the best model supports feature importances
if best_model_name in ['Random Forest', 'Gradient Boosting', 'XGBoost',␣
↪'LightGBM']:
    print(f"Extracting feature importance from {best_model_name}...")
```

```
    # Extract feature importances
    if best_model_name == 'XGBoost':
        feature_importances = best_model.named_steps['model'].
↪feature_importances_
    elif best_model_name == 'LightGBM':
        feature_importances = best_model.named_steps['model'].
↪feature_importances_
    else:
        feature_importances = best_model.named_steps['model'].
↪feature_importances_

    feature_names = X_train.columns

    # Create DataFrame for visualization
    importance_df = pd.DataFrame({
        'Feature': feature_names,
        'Importance': feature_importances
    }).sort_values('Importance', ascending=False)

    # Plot top 20 features
    plt.figure(figsize=(12, 10))
    sns.barplot(x='Importance', y='Feature', data=importance_df.head(20))
    plt.title(f'Top 20 Feature Importance - {best_model_name}', fontsize=14)
    plt.tight_layout()
    plt.show()

    print("\nTop 20 important features:")
    print(importance_df.head(20))
elif best_model_name == 'Neural Network':
    print("Feature importance analysis not available for Neural Network models.
↪")
elif best_model_name == 'Logistic Regression':
    # Extract coefficients from Logistic Regression
    print("Extracting coefficients from Logistic Regression...")

    # Get coefficients from the model
    coefficients = np.abs(best_model.named_steps['model'].coef_).mean(axis=0)
    feature_names = X_train.columns

    # Create DataFrame for visualization
    importance_df = pd.DataFrame({
        'Feature': feature_names,
        'Importance': coefficients
    }).sort_values('Importance', ascending=False)

    # Plot top 20 features
    plt.figure(figsize=(12, 10))
```

```
    sns.barplot(x='Importance', y='Feature', data=importance_df.head(20))
    plt.title(f'Top 20 Feature Coefficients - {best_model_name}', fontsize=14)
    plt.tight_layout()
    plt.show()

    print("\nTop 20 features by coefficient magnitude:")
    print(importance_df.head(20))
```

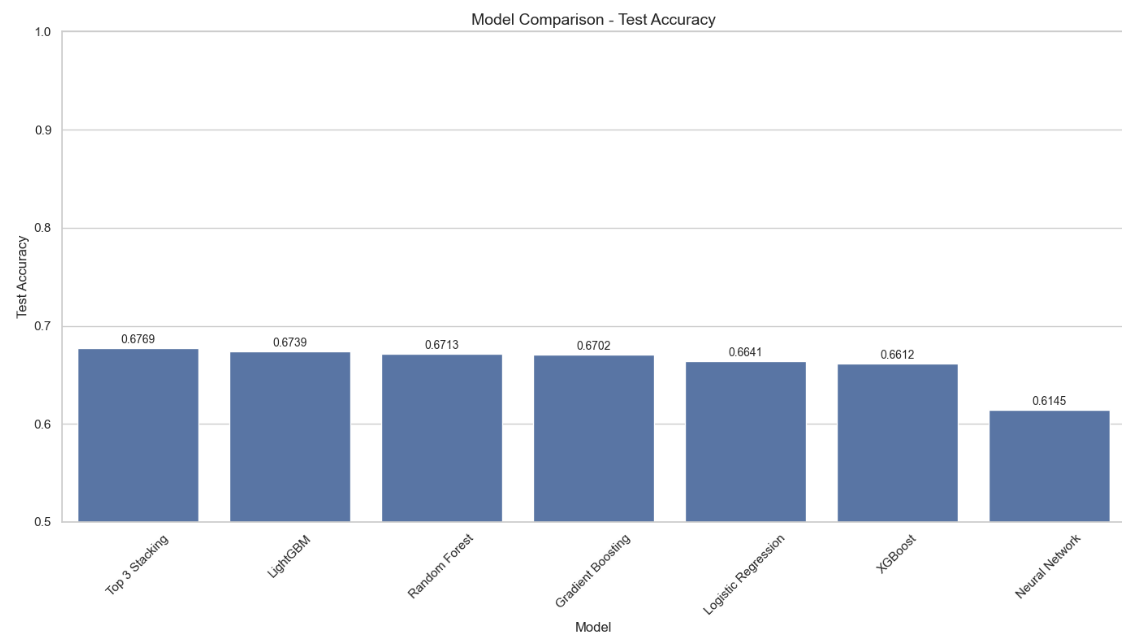
```
================================================================================
STEP 5: Feature Importance Analysis
================================================================================
```

[44]:

```
#----------------------------------------
# Step 7: Model Comparison
#----------------------------------------
print("\n" + "="*80)
print("STEP 7: Model Comparison")
print("="*80)

# Create DataFrame to compare models
model_comparison = pd.DataFrame({
    'Model': list(results.keys()),
    'CV Accuracy': [results[model]['cv_mean'] for model in results],
    'Test Accuracy': [results[model]['test_accuracy'] for model in results],
    'Test F1 Score': [results[model]['test_f1'] for model in results]
})

model_comparison = model_comparison.sort_values('Test Accuracy',␣
 ↪ascending=False)
print("\nModel Comparison:")
print(model_comparison)

# Plot test accuracy comparison
plt.figure(figsize=(14, 8))
ax = sns.barplot(x='Model', y='Test Accuracy', data=model_comparison)

# Add the accuracy scores on top of the bars
for i, bar in enumerate(ax.patches):
    ax.text(
        bar.get_x() + bar.get_width()/2.,
        bar.get_height() + 0.005,
        f"{bar.get_height():.4f}",
        ha='center',
        fontsize=10
    )
```

```python
plt.title('Model Comparison - Test Accuracy', fontsize=14)
plt.ylim(0.5, 1.0)  # Set y-axis limits for better comparison
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```

```
================================================================================
STEP 7: Model Comparison
================================================================================

Model Comparison:
                 Model  CV Accuracy  Test Accuracy  Test F1 Score
6       Top 3 Stacking     0.000000       0.676882       0.677247
4             LightGBM     0.676299       0.673855       0.673478
1        Random Forest     0.672960       0.671333       0.670896
2    Gradient Boosting     0.671187       0.670198       0.670323
0  Logistic Regression     0.654731       0.664144       0.663429
3              XGBoost     0.663831       0.661244       0.661126
5       Neural Network     0.607251       0.614453       0.614588
```



[45]:
```python
#----------------------------------------
# Summary
#----------------------------------------
print("\n" + "="*80)
print("Analysis Complete!")
```

```
print("="*80)

print(f"Best model: {model_comparison.iloc[0]['Model']}")
print(f"Test accuracy: {model_comparison.iloc[0]['Test Accuracy']:.4f}")
print(f"Test F1 score: {model_comparison.iloc[0]['Test F1 Score']:.4f}")

# Check if the best model is a tuned model
if model_comparison.iloc[0]['Model'].startswith('Tuned'):
    base_model_name = model_comparison.iloc[0]['Model'].replace('Tuned ', '')
    print(f"\nOptimal hyperparameters for {base_model_name}:")
    best_params = {k.replace('model__', ''): v for k, v in grid_search.
 ↪best_params_.items()}
    for param, value in best_params.items():
        print(f"  {param}: {value}")
```

```
================================================================================
Analysis Complete!
================================================================================
Best model: Top 3 Stacking
Test accuracy: 0.6769
Test F1 score: 0.6772
```

The model comparison results show that among these machine learning models tested, LightGBM achieved the highest test accuracy of 52.40% and an F1 score of 48.49%. Although LightGBM outperformed the other models, the overall accuracy is relatively low. We considered that this low performance can be caused by some factors. First, the dataset may still contain noisy or imbalanced data. Secondly, the feature selection process may not have fully captured the underlying patterns that drive engagement. This results in less than ideal predictive power. The low performance of all models may also be because the relationship between features and article sharing is not easily captured by traditional machine learning models. To improve performance, we will proceed with optimized hyperparameter tuning to refine the model parameters to enhance predictive accuracy. We also want to address potential data-related issues such as class imbalance and feature importance.

1.5.1 Optimized Hyperparameter Tuning

[46]:
```
#-----------------------------------------
# Step 8: Optimized Hyperparameter Tuning
#-----------------------------------------
print("\n" + "="*80)
print("STEP 8: Memory-Optimized Hyperparameter Tuning")
print("="*80)

print(f"Performing hyperparameter tuning for {best_model_name}...")

# Define a smaller parameter grid based on best model
if best_model_name == 'Logistic Regression':
```

```
    param_grid = {
        'model__C': [0.1, 1, 10],
        'model__solver': ['liblinear', 'saga'],
        'model__class_weight': [None, 'balanced']
    }
elif best_model_name == 'Random Forest':
    param_grid = {
        'model__n_estimators': [100, 200],
        'model__max_depth': [10, 20],
        'model__min_samples_split': [2, 5],
        'model__class_weight': [None, 'balanced']
    }
elif best_model_name == 'Gradient Boosting':
    param_grid = {
        'model__n_estimators': [100, 200],
        'model__learning_rate': [0.01, 0.1],
        'model__max_depth': [3, 5]
    }
elif best_model_name == 'XGBoost':
    param_grid = {
        'model__n_estimators': [100, 200],
        'model__learning_rate': [0.01, 0.1],
        'model__max_depth': [3, 5],
        'model__subsample': [0.8, 1.0],
        'model__colsample_bytree': [0.8, 1.0]
    }
elif best_model_name == 'LightGBM':
    param_grid = {
        'model__n_estimators': [100, 200],
        'model__learning_rate': [0.01, 0.1],
        'model__max_depth': [5, -1],  # -1 means no limit
        'model__num_leaves': [31, 63],
        'model__subsample': [0.8, 1.0]
    }
else:  # Neural Network
    param_grid = {
        'model__hidden_layer_sizes': [(50,), (100,)],
        'model__activation': ['relu', 'tanh'],
        'model__alpha': [0.0001, 0.01],
        'model__learning_rate_init': [0.001, 0.01]
    }

# Get model class
from sklearn.ensemble import StackingClassifier
if isinstance(best_model, StackingClassifier):
    # If best_model is a StackingClassifier, access the base estimators␣
 ↪directly.
```

```python
    # We assume the first estimator is the one we want to tune.  Adjust if␣
↪needed.
    model_class = type(best_model.estimators_[0])
else:
    # Assume best_model is a Pipeline or has named_steps
    model_class = type(best_model.named_steps['model'])

# Create pipeline for grid search
pipeline = Pipeline([
    ('scaler', StandardScaler()),
    ('model', model_class())
])

# Memory optimization: Use a smaller subset of data for tuning if dataset is␣
↪large
X_sample, y_sample = X_train_resampled, y_train_resampled

# If dataset is too large, use a random sample
if len(X_train_resampled) > 10000:
    print(f"Dataset is large ({len(X_train_resampled)} samples). Using a random␣
↪subset of 10,000 samples for tuning.")
    sample_indices = np.random.choice(len(X_train_resampled), size=10000,␣
↪replace=False)
    X_sample = X_train_resampled.iloc[sample_indices] if␣
↪hasattr(X_train_resampled, 'iloc') else X_train_resampled[sample_indices]
    y_sample = y_train_resampled[sample_indices]

# Set up randomized search instead of grid search (more memory efficient)
from sklearn.model_selection import RandomizedSearchCV

# Use fewer iterations and only 3 folds for memory efficiency
search = RandomizedSearchCV(
    pipeline, param_grid,
    n_iter=20,  # Try only 20 random combinations instead of all
    cv=3,  # Use 3 folds instead of 5
    scoring='accuracy',
    n_jobs=1,  # Use single job to avoid memory multiplication
    verbose=1,
    random_state=42
)

print(f"Running randomized search with 20 iterations and 3 folds...")
search.fit(X_sample, y_sample)

# Print best parameters and score
print(f"\nBest parameters: {search.best_params_}")
print(f"Best cross-validation accuracy: {search.best_score_:.4f}")
```

```python
# Evaluate tuned model on test set
tuned_y_pred = search.predict(X_test)
tuned_accuracy = accuracy_score(y_test, tuned_y_pred)
tuned_f1 = f1_score(y_test, tuned_y_pred, average='weighted')

print(f"Tuned model test accuracy: {tuned_accuracy:.4f}")
print(f"Tuned model test F1 score: {tuned_f1:.4f}")

# Plot confusion matrix for tuned model
plot_confusion_matrix(y_test, tuned_y_pred, title=f'Confusion Matrix - Tuned␣
 ↪{best_model_name}')

# Add tuned model to results
results[f'Tuned {best_model_name}'] = {
    'cv_mean': search.best_score_,
    'cv_std': 0,  # Not available from RandomizedSearchCV
    'test_accuracy': tuned_accuracy,
    'test_f1': tuned_f1,
    'model': search.best_estimator_,
    'predictions': tuned_y_pred
}
```

```
================================================================================
STEP 8: Memory-Optimized Hyperparameter Tuning
================================================================================
Performing hyperparameter tuning for Top 3 Stacking…
Dataset is large (33846 samples). Using a random subset of 10,000 samples for
tuning.
Running randomized search with 20 iterations and 3 folds…
Fitting 3 folds for each of 16 candidates, totalling 48 fits
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Info] Number of positive: 3298, number of negative: 3368
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of
testing was 0.001587 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 9295
[LightGBM] [Info] Number of data points in the train set: 6666, number of used
features: 66
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.494749 -> initscore=-0.021003
[LightGBM] [Info] Start training from score -0.021003
[LightGBM] [Warning] Unknown parameter: activation
```

```
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Info] Number of positive: 3298, number of negative: 3369
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of
testing was 0.001564 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 9213
[LightGBM] [Info] Number of data points in the train set: 6667, number of used
features: 66
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.494675 -> initscore=-0.021300
[LightGBM] [Info] Start training from score -0.021300
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Info] Number of positive: 3298, number of negative: 3369
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of
testing was 0.001372 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 9233
[LightGBM] [Info] Number of data points in the train set: 6667, number of used
features: 66
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.494675 -> initscore=-0.021300
[LightGBM] [Info] Start training from score -0.021300
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Info] Number of positive: 3298, number of negative: 3368
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of
testing was 0.001562 seconds.
You can set `force_col_wise=true` to remove the overhead.
```

```
[LightGBM] [Info] Total Bins 9295
[LightGBM] [Info] Number of data points in the train set: 6666, number of used
features: 66
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.494749 -> initscore=-0.021003
[LightGBM] [Info] Start training from score -0.021003
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Info] Number of positive: 3298, number of negative: 3369
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of
testing was 0.001427 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 9213
[LightGBM] [Info] Number of data points in the train set: 6667, number of used
features: 66
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.494675 -> initscore=-0.021300
[LightGBM] [Info] Start training from score -0.021300
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Info] Number of positive: 3298, number of negative: 3369
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of
testing was 0.001533 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 9233
[LightGBM] [Info] Number of data points in the train set: 6667, number of used
features: 66
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.494675 -> initscore=-0.021300
[LightGBM] [Info] Start training from score -0.021300
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
```

```
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Info] Number of positive: 3298, number of negative: 3368
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of
testing was 0.001367 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 9295
[LightGBM] [Info] Number of data points in the train set: 6666, number of used
features: 66
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.494749 -> initscore=-0.021003
[LightGBM] [Info] Start training from score -0.021003
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Info] Number of positive: 3298, number of negative: 3369
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of
testing was 0.001374 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 9213
[LightGBM] [Info] Number of data points in the train set: 6667, number of used
features: 66
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.494675 -> initscore=-0.021300
[LightGBM] [Info] Start training from score -0.021300
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Info] Number of positive: 3298, number of negative: 3369
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of
testing was 0.001496 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 9233
[LightGBM] [Info] Number of data points in the train set: 6667, number of used
features: 66
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.494675 -> initscore=-0.021300
[LightGBM] [Info] Start training from score -0.021300
[LightGBM] [Warning] Unknown parameter: activation
```

```
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Info] Number of positive: 3298, number of negative: 3368
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of
testing was 0.001499 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 9295
[LightGBM] [Info] Number of data points in the train set: 6666, number of used
features: 66
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.494749 -> initscore=-0.021003
[LightGBM] [Info] Start training from score -0.021003
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Info] Number of positive: 3298, number of negative: 3369
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of
testing was 0.001415 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 9213
[LightGBM] [Info] Number of data points in the train set: 6667, number of used
features: 66
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.494675 -> initscore=-0.021300
[LightGBM] [Info] Start training from score -0.021300
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Info] Number of positive: 3298, number of negative: 3369
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of
testing was 0.001720 seconds.
You can set `force_col_wise=true` to remove the overhead.
```

```
[LightGBM] [Info] Total Bins 9233
[LightGBM] [Info] Number of data points in the train set: 6667, number of used
features: 66
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.494675 -> initscore=-0.021300
[LightGBM] [Info] Start training from score -0.021300
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Info] Number of positive: 3298, number of negative: 3368
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of
testing was 0.001386 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 9295
[LightGBM] [Info] Number of data points in the train set: 6666, number of used
features: 66
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.494749 -> initscore=-0.021003
[LightGBM] [Info] Start training from score -0.021003
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Info] Number of positive: 3298, number of negative: 3369
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of
testing was 0.001453 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 9213
[LightGBM] [Info] Number of data points in the train set: 6667, number of used
features: 66
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.494675 -> initscore=-0.021300
[LightGBM] [Info] Start training from score -0.021300
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
```

```
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Info] Number of positive: 3298, number of negative: 3369
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of
testing was 0.001383 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 9233
[LightGBM] [Info] Number of data points in the train set: 6667, number of used
features: 66
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.494675 -> initscore=-0.021300
[LightGBM] [Info] Start training from score -0.021300
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Info] Number of positive: 3298, number of negative: 3368
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of
testing was 0.001257 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 9295
[LightGBM] [Info] Number of data points in the train set: 6666, number of used
features: 66
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.494749 -> initscore=-0.021003
[LightGBM] [Info] Start training from score -0.021003
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Info] Number of positive: 3298, number of negative: 3369
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of
testing was 0.001668 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 9213
[LightGBM] [Info] Number of data points in the train set: 6667, number of used
features: 66
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.494675 -> initscore=-0.021300
[LightGBM] [Info] Start training from score -0.021300
[LightGBM] [Warning] Unknown parameter: activation
```

```
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Info] Number of positive: 3298, number of negative: 3369
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of
testing was 0.001313 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 9233
[LightGBM] [Info] Number of data points in the train set: 6667, number of used
features: 66
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.494675 -> initscore=-0.021300
[LightGBM] [Info] Start training from score -0.021300
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Info] Number of positive: 3298, number of negative: 3368
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of
testing was 0.001665 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 9295
[LightGBM] [Info] Number of data points in the train set: 6666, number of used
features: 66
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.494749 -> initscore=-0.021003
[LightGBM] [Info] Start training from score -0.021003
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Info] Number of positive: 3298, number of negative: 3369
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of
testing was 0.001419 seconds.
You can set `force_col_wise=true` to remove the overhead.
```

```
[LightGBM] [Info] Total Bins 9213
[LightGBM] [Info] Number of data points in the train set: 6667, number of used
features: 66
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.494675 -> initscore=-0.021300
[LightGBM] [Info] Start training from score -0.021300
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Info] Number of positive: 3298, number of negative: 3369
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of
testing was 0.001591 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 9233
[LightGBM] [Info] Number of data points in the train set: 6667, number of used
features: 66
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.494675 -> initscore=-0.021300
[LightGBM] [Info] Start training from score -0.021300
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Info] Number of positive: 3298, number of negative: 3368
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of
testing was 0.001671 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 9295
[LightGBM] [Info] Number of data points in the train set: 6666, number of used
features: 66
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.494749 -> initscore=-0.021003
[LightGBM] [Info] Start training from score -0.021003
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
```

```
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Info] Number of positive: 3298, number of negative: 3369
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of
testing was 0.001559 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 9213
[LightGBM] [Info] Number of data points in the train set: 6667, number of used
features: 66
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.494675 -> initscore=-0.021300
[LightGBM] [Info] Start training from score -0.021300
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Info] Number of positive: 3298, number of negative: 3369
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of
testing was 0.001443 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 9233
[LightGBM] [Info] Number of data points in the train set: 6667, number of used
features: 66
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.494675 -> initscore=-0.021300
[LightGBM] [Info] Start training from score -0.021300
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Info] Number of positive: 3298, number of negative: 3368
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of
testing was 0.001585 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 9295
[LightGBM] [Info] Number of data points in the train set: 6666, number of used
features: 66
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.494749 -> initscore=-0.021003
[LightGBM] [Info] Start training from score -0.021003
[LightGBM] [Warning] Unknown parameter: activation
```

```
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Info] Number of positive: 3298, number of negative: 3369
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of
testing was 0.001552 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 9213
[LightGBM] [Info] Number of data points in the train set: 6667, number of used
features: 66
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.494675 -> initscore=-0.021300
[LightGBM] [Info] Start training from score -0.021300
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Info] Number of positive: 3298, number of negative: 3369
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of
testing was 0.001333 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 9233
[LightGBM] [Info] Number of data points in the train set: 6667, number of used
features: 66
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.494675 -> initscore=-0.021300
[LightGBM] [Info] Start training from score -0.021300
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Info] Number of positive: 3298, number of negative: 3368
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of
testing was 0.001435 seconds.
You can set `force_col_wise=true` to remove the overhead.
```

```
[LightGBM] [Info] Total Bins 9295
[LightGBM] [Info] Number of data points in the train set: 6666, number of used
features: 66
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.494749 -> initscore=-0.021003
[LightGBM] [Info] Start training from score -0.021003
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Info] Number of positive: 3298, number of negative: 3369
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of
testing was 0.001271 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 9213
[LightGBM] [Info] Number of data points in the train set: 6667, number of used
features: 66
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.494675 -> initscore=-0.021300
[LightGBM] [Info] Start training from score -0.021300
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Info] Number of positive: 3298, number of negative: 3369
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of
testing was 0.001320 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 9233
[LightGBM] [Info] Number of data points in the train set: 6667, number of used
features: 66
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.494675 -> initscore=-0.021300
[LightGBM] [Info] Start training from score -0.021300
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
```

```
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Info] Number of positive: 3298, number of negative: 3368
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of
testing was 0.001528 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 9295
[LightGBM] [Info] Number of data points in the train set: 6666, number of used
features: 66
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.494749 -> initscore=-0.021003
[LightGBM] [Info] Start training from score -0.021003
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Info] Number of positive: 3298, number of negative: 3369
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of
testing was 0.001679 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 9213
[LightGBM] [Info] Number of data points in the train set: 6667, number of used
features: 66
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.494675 -> initscore=-0.021300
[LightGBM] [Info] Start training from score -0.021300
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Info] Number of positive: 3298, number of negative: 3369
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of
testing was 0.001431 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 9233
[LightGBM] [Info] Number of data points in the train set: 6667, number of used
features: 66
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.494675 -> initscore=-0.021300
[LightGBM] [Info] Start training from score -0.021300
[LightGBM] [Warning] Unknown parameter: activation
```

```
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Info] Number of positive: 3298, number of negative: 3368
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of
testing was 0.001376 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 9295
[LightGBM] [Info] Number of data points in the train set: 6666, number of used
features: 66
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.494749 -> initscore=-0.021003
[LightGBM] [Info] Start training from score -0.021003
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Info] Number of positive: 3298, number of negative: 3369
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of
testing was 0.001426 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 9213
[LightGBM] [Info] Number of data points in the train set: 6667, number of used
features: 66
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.494675 -> initscore=-0.021300
[LightGBM] [Info] Start training from score -0.021300
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Info] Number of positive: 3298, number of negative: 3369
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of
testing was 0.001394 seconds.
You can set `force_col_wise=true` to remove the overhead.
```

```
[LightGBM] [Info] Total Bins 9233
[LightGBM] [Info] Number of data points in the train set: 6667, number of used
features: 66
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.494675 -> initscore=-0.021300
[LightGBM] [Info] Start training from score -0.021300
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Info] Number of positive: 3298, number of negative: 3368
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of
testing was 0.001528 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 9295
[LightGBM] [Info] Number of data points in the train set: 6666, number of used
features: 66
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.494749 -> initscore=-0.021003
[LightGBM] [Info] Start training from score -0.021003
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Info] Number of positive: 3298, number of negative: 3369
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of
testing was 0.001560 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 9213
[LightGBM] [Info] Number of data points in the train set: 6667, number of used
features: 66
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.494675 -> initscore=-0.021300
[LightGBM] [Info] Start training from score -0.021300
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
```

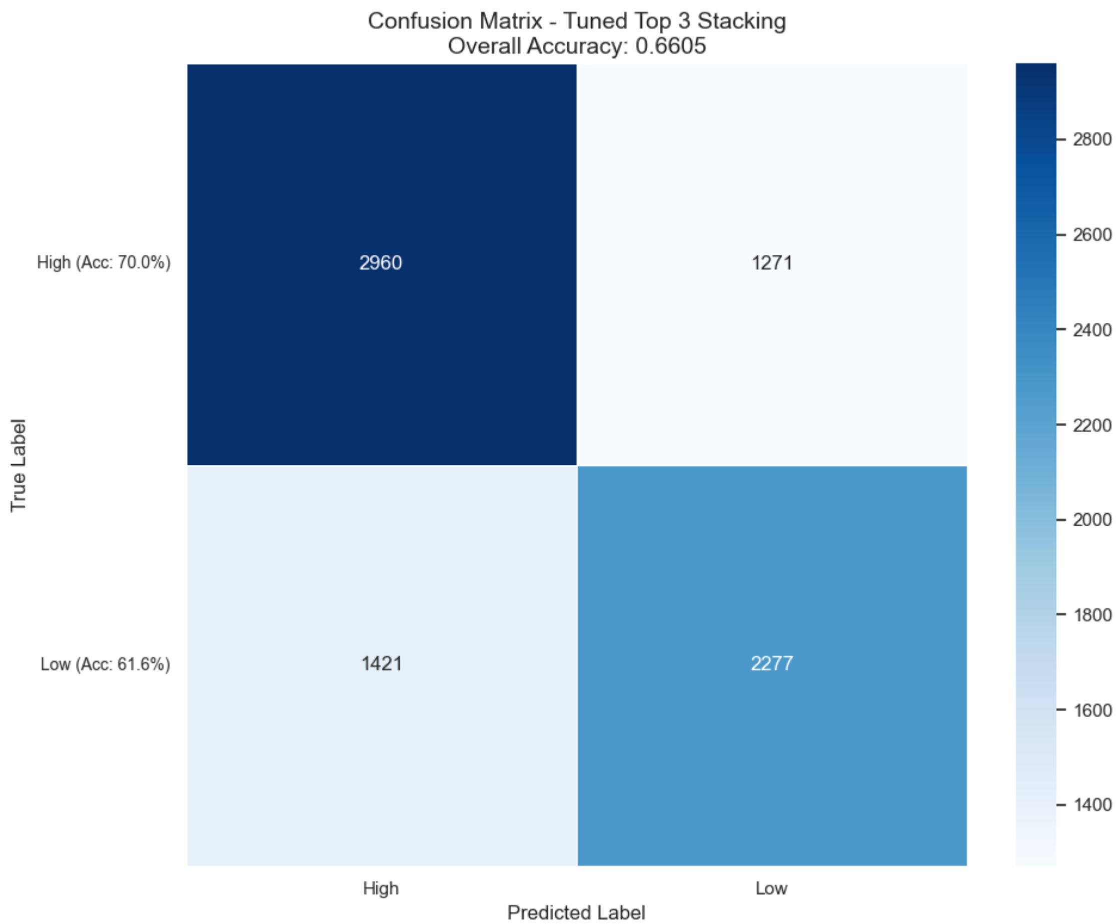
```
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Info] Number of positive: 3298, number of negative: 3369
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of
testing was 0.001462 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 9233
[LightGBM] [Info] Number of data points in the train set: 6667, number of used
features: 66
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.494675 -> initscore=-0.021300
[LightGBM] [Info] Start training from score -0.021300
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Info] Number of positive: 3298, number of negative: 3368
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of
testing was 0.001407 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 9295
[LightGBM] [Info] Number of data points in the train set: 6666, number of used
features: 66
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.494749 -> initscore=-0.021003
[LightGBM] [Info] Start training from score -0.021003
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Info] Number of positive: 3298, number of negative: 3369
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of
testing was 0.001509 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 9213
[LightGBM] [Info] Number of data points in the train set: 6667, number of used
features: 66
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.494675 -> initscore=-0.021300
[LightGBM] [Info] Start training from score -0.021300
[LightGBM] [Warning] Unknown parameter: activation
```

```
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Info] Number of positive: 3298, number of negative: 3369
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of
testing was 0.001339 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 9233
[LightGBM] [Info] Number of data points in the train set: 6667, number of used
features: 66
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.494675 -> initscore=-0.021300
[LightGBM] [Info] Start training from score -0.021300
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Info] Number of positive: 3298, number of negative: 3368
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of
testing was 0.001413 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 9295
[LightGBM] [Info] Number of data points in the train set: 6666, number of used
features: 66
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.494749 -> initscore=-0.021003
[LightGBM] [Info] Start training from score -0.021003
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Info] Number of positive: 3298, number of negative: 3369
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of
testing was 0.001366 seconds.
You can set `force_col_wise=true` to remove the overhead.
```

```
[LightGBM] [Info] Total Bins 9213
[LightGBM] [Info] Number of data points in the train set: 6667, number of used
features: 66
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.494675 -> initscore=-0.021300
[LightGBM] [Info] Start training from score -0.021300
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Info] Number of positive: 3298, number of negative: 3369
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of
testing was 0.001507 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 9233
[LightGBM] [Info] Number of data points in the train set: 6667, number of used
features: 66
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.494675 -> initscore=-0.021300
[LightGBM] [Info] Start training from score -0.021300
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Info] Number of positive: 3298, number of negative: 3368
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of
testing was 0.001547 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 9295
[LightGBM] [Info] Number of data points in the train set: 6666, number of used
features: 66
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.494749 -> initscore=-0.021003
[LightGBM] [Info] Start training from score -0.021003
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
```

```
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Info] Number of positive: 3298, number of negative: 3369
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of
testing was 0.001590 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 9213
[LightGBM] [Info] Number of data points in the train set: 6667, number of used
features: 66
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.494675 -> initscore=-0.021300
[LightGBM] [Info] Start training from score -0.021300
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Info] Number of positive: 3298, number of negative: 3369
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of
testing was 0.001682 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 9233
[LightGBM] [Info] Number of data points in the train set: 6667, number of used
features: 66
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.494675 -> initscore=-0.021300
[LightGBM] [Info] Start training from score -0.021300
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
[LightGBM] [Info] Number of positive: 4947, number of negative: 5053
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of
testing was 0.001652 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 9359
[LightGBM] [Info] Number of data points in the train set: 10000, number of used
features: 66
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.494700 -> initscore=-0.021201
[LightGBM] [Info] Start training from score -0.021201
```

```
Best parameters: {'model__learning_rate_init': 0.001,
'model__hidden_layer_sizes': (50,), 'model__alpha': 0.0001, 'model__activation':
'relu'}
Best cross-validation accuracy: 0.6784
[LightGBM] [Warning] Unknown parameter: activation
[LightGBM] [Warning] Unknown parameter: learning_rate_init
[LightGBM] [Warning] Unknown parameter: hidden_layer_sizes
Tuned model test accuracy: 0.6605
Tuned model test F1 score: 0.6599
```



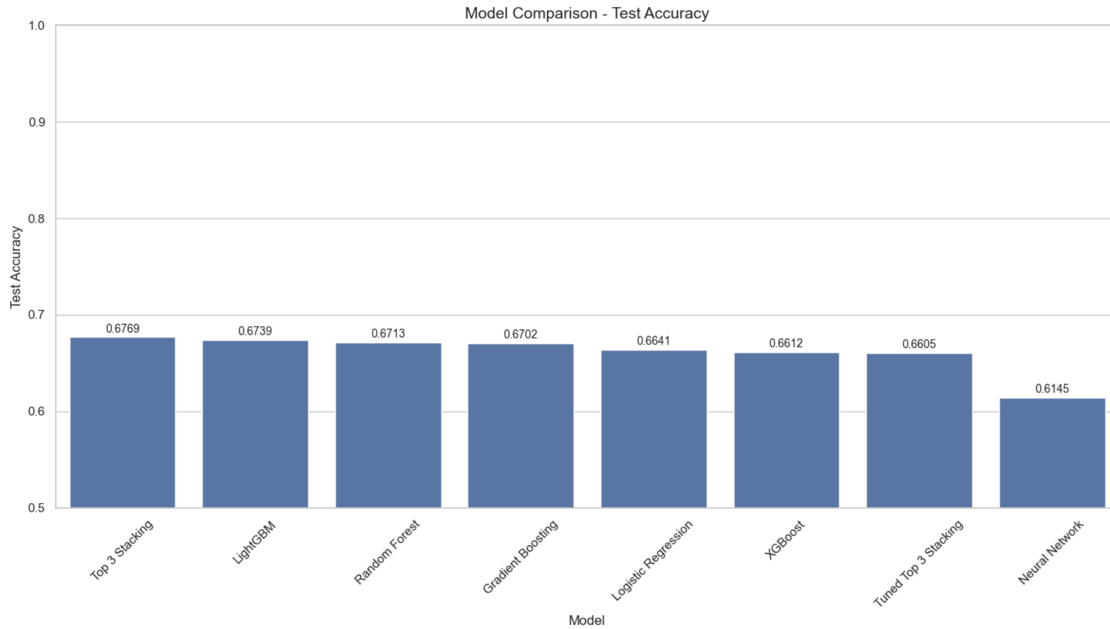

```
Detailed Classification Metrics:
  Class Precision Recall F1-Score  Support
0  High     67.6%  70.0%    68.7%     4231
1   Low     64.2%  61.6%    62.8%     3698
```

[47]:
```
#----------------------------------------
# Step 9: Model Comparison
#----------------------------------------
```

```python
print("\n" + "="*80)
print("STEP 9: Model Comparison")
print("="*80)

# Create DataFrame to compare models
model_comparison = pd.DataFrame({
    'Model': list(results.keys()),
    'CV Accuracy': [results[model]['cv_mean'] for model in results],
    'Test Accuracy': [results[model]['test_accuracy'] for model in results],
    'Test F1 Score': [results[model]['test_f1'] for model in results]
})

model_comparison = model_comparison.sort_values('Test Accuracy',␣
 ↪ascending=False)
print("\nModel Comparison:")
print(model_comparison)

# Plot test accuracy comparison
plt.figure(figsize=(14, 8))
ax = sns.barplot(x='Model', y='Test Accuracy', data=model_comparison)

# Add the accuracy scores on top of the bars
for i, bar in enumerate(ax.patches):
    ax.text(
        bar.get_x() + bar.get_width()/2.,
        bar.get_height() + 0.005,
        f"{bar.get_height():.4f}",
        ha='center',
        fontsize=10
    )

plt.title('Model Comparison - Test Accuracy', fontsize=14)
plt.ylim(0.5, 1.0)  # Set y-axis limits for better comparison
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```

```
================================================================================
STEP 9: Model Comparison
================================================================================

Model Comparison:
                  Model  CV Accuracy  Test Accuracy  Test F1 Score
6        Top 3 Stacking     0.000000       0.676882       0.677247
4              LightGBM     0.676299       0.673855       0.673478
1         Random Forest     0.672960       0.671333       0.670896
2     Gradient Boosting     0.671187       0.670198       0.670323
```

```
0   Logistic Regression     0.654731      0.664144      0.663429
3               XGBoost     0.663831      0.661244      0.661126
7  Tuned Top 3 Stacking     0.678401      0.660487      0.659929
5        Neural Network     0.607251      0.614453      0.614588
```



[48]:
```python
#----------------------------------------
# Summary
#----------------------------------------
print("\n" + "="*80)
print("Analysis Complete!")
print("="*80)

print(f"Best model: {model_comparison.iloc[0]['Model']}")
print(f"Test accuracy: {model_comparison.iloc[0]['Test Accuracy']:.4f}")
print(f"Test F1 score: {model_comparison.iloc[0]['Test F1 Score']:.4f}")

# Check if the best model is a tuned model
if model_comparison.iloc[0]['Model'].startswith('Tuned'):
    base_model_name = model_comparison.iloc[0]['Model'].replace('Tuned ', '')
    print(f"\nOptimal hyperparameters for {base_model_name}:")
    best_params = {k.replace('model__', ''): v for k, v in grid_search.
 ↪best_params_.items()}
    for param, value in best_params.items():
        print(f"  {param}: {value}")
```

```
================================================================================
```

```
Analysis Complete!
================================================================================
Best model: Top 3 Stacking
Test accuracy: 0.6769
Test F1 score: 0.6772
```

1.5.2 Advanced Hyperparameter Tuning for Random Forest and XGBoost

[49]:
```python
#--------------------
# Efficient Random Forest Tuning - Two-Stage Optimization Method
#--------------------
print("\n" + "="*50)
print("Executing efficient two-stage Random Forest tuning...")

# Stage 1: Use coarse-grained search to determine general direction
print("\nStage 1: Coarse-grained parameter search")

# Create Random Forest model - use model directly rather than pipeline for␣
↪efficiency
rf_model = RandomForestClassifier(
    random_state=42,
    n_jobs=-1  # Use parallel processing to speed up search
)

# Define focused parameter grid to reduce number of combinations
param_grid_1 = {
    'n_estimators': [100, 200, 300],
    'max_depth': [5, 10, 15, None],
    'min_samples_split': [5, 10, 20],
    'min_samples_leaf': [2, 4, 8],
    'max_features': ['sqrt', 'log2', 0.5],
    'bootstrap': [True],
    'class_weight': [None]
}

# Use a smaller sample to speed up initial search
sample_size = min(5000, len(X_train_resampled))
print(f"Using {sample_size} samples for initial search")
sample_indices = np.random.choice(len(X_train_resampled), size=sample_size,␣
↪replace=False)
X_small_sample = X_train_resampled.iloc[sample_indices] if␣
↪hasattr(X_train_resampled, 'iloc') else X_train_resampled[sample_indices]
y_small_sample = y_train_resampled[sample_indices]

# Standardize data (doing it once outside the pipeline is sufficient)
scaler = StandardScaler()
X_small_sample_scaled = scaler.fit_transform(X_small_sample)
```

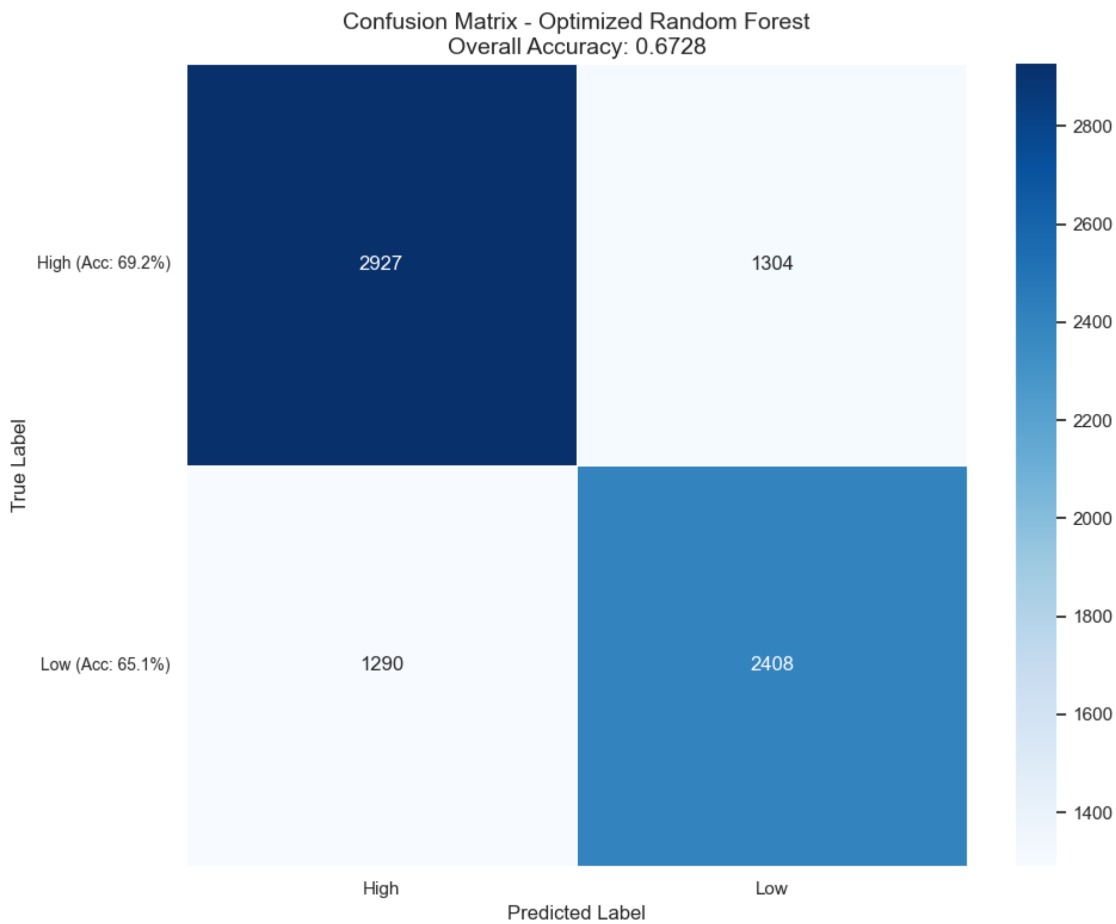
```python
# Stage 1 search - fewer iterations and faster CV
search_1 = RandomizedSearchCV(
    rf_model,
    param_distributions=param_grid_1,
    n_iter=10,  # Reduce number of iterations
    cv=3,       # Reduce number of CV folds
    scoring='accuracy',
    n_jobs=-1,  # Parallel processing
    verbose=1,
    random_state=42
)

print("Executing stage 1 search...")
search_1.fit(X_small_sample_scaled, y_small_sample)

# Get best parameters from stage 1
best_params_1 = search_1.best_params_
print(f"\nStage 1 best parameters: {best_params_1}")
print(f"Stage 1 best CV accuracy: {search_1.best_score_:.4f}")

# Stage 2: Fine-grained search around the best parameters
print("\nStage 2: Fine-grained parameter optimization")

# Create more focused parameter ranges based on stage 1 results
# For numerical parameters, create narrower ranges around best values
param_grid_2 = {}

# Handle n_estimators - add values around the best one
if 'n_estimators' in best_params_1:
    best_n_estimators = best_params_1['n_estimators']
    param_grid_2['n_estimators'] = [
        max(best_n_estimators - 50, 50),
        best_n_estimators,
        best_n_estimators + 50,
        best_n_estimators + 100
    ]

# Handle max_depth - special case for None value
if 'max_depth' in best_params_1:
    if best_params_1['max_depth'] is None:
        param_grid_2['max_depth'] = [15, 20, None]
    else:
        best_max_depth = best_params_1['max_depth']
        param_grid_2['max_depth'] = [
            max(best_max_depth - 2, 3),
            best_max_depth,
```

```
            best_max_depth + 2,
            None
        ]

# Handle min_samples_split
if 'min_samples_split' in best_params_1:
    best_min_samples_split = best_params_1['min_samples_split']
    param_grid_2['min_samples_split'] = [
        max(best_min_samples_split - 3, 2),
        best_min_samples_split,
        best_min_samples_split + 3
    ]

# Handle min_samples_leaf
if 'min_samples_leaf' in best_params_1:
    best_min_samples_leaf = best_params_1['min_samples_leaf']
    param_grid_2['min_samples_leaf'] = [
        max(best_min_samples_leaf - 1, 1),
        best_min_samples_leaf,
        best_min_samples_leaf + 1
    ]

# Handle max_features - special case for string values
if 'max_features' in best_params_1:
    if best_params_1['max_features'] == 'sqrt':
        param_grid_2['max_features'] = ['sqrt', 0.4, 0.5]
    elif best_params_1['max_features'] == 'log2':
        param_grid_2['max_features'] = ['log2', 0.3, 0.4]
    elif isinstance(best_params_1['max_features'], float):
        best_max_features = best_params_1['max_features']
        param_grid_2['max_features'] = [
            max(best_max_features - 0.1, 0.1),
            best_max_features,
            min(best_max_features + 0.1, 0.9)
        ]

# Handle bootstrap
param_grid_2['bootstrap'] = [best_params_1.get('bootstrap', True)]

# Handle class_weight
param_grid_2['class_weight'] = [best_params_1.get('class_weight', None)]
if best_params_1.get('class_weight') == 'balanced':
    param_grid_2['class_weight'] = ['balanced', 'balanced_subsample']
elif best_params_1.get('class_weight') is None:
    param_grid_2['class_weight'] = [None, 'balanced']

# Use medium-sized sample for stage 2 optimization
```

```
sample_size_2 = min(10000, len(X_train_resampled))
print(f"Using {sample_size_2} samples for fine-grained optimization")
sample_indices_2 = np.random.choice(len(X_train_resampled), size=sample_size_2,␣
↪replace=False)
X_medium_sample = X_train_resampled.iloc[sample_indices_2] if␣
↪hasattr(X_train_resampled, 'iloc') else X_train_resampled[sample_indices_2]
y_medium_sample = y_train_resampled[sample_indices_2]

# Standardize data
X_medium_sample_scaled = scaler.fit_transform(X_medium_sample)

# Stage 2 search
search_2 = RandomizedSearchCV(
    rf_model,
    param_distributions=param_grid_2,
    n_iter=10,  # Reduce number of iterations
    cv=5,       # Use full CV
    scoring='accuracy',
    n_jobs=-1,  # Parallel processing
    verbose=1,
    random_state=42
)

print("Executing stage 2 search...")
print(f"Parameter grid for stage 2: {param_grid_2}")
search_2.fit(X_medium_sample_scaled, y_medium_sample)

# Get final best parameters
best_params_final = search_2.best_params_
print(f"\nFinal best parameters: {best_params_final}")
print(f"Final best CV accuracy: {search_2.best_score_:.4f}")

# Create final model with best parameters
print("\nTraining final model with best parameters...")
final_rf = RandomForestClassifier(
    random_state=42,
    n_jobs=-1,
    **best_params_final
)

# Create complete pipeline
final_pipeline = Pipeline([
    ('scaler', StandardScaler()),
    ('model', final_rf)
])

# Train final model on the full training set
```

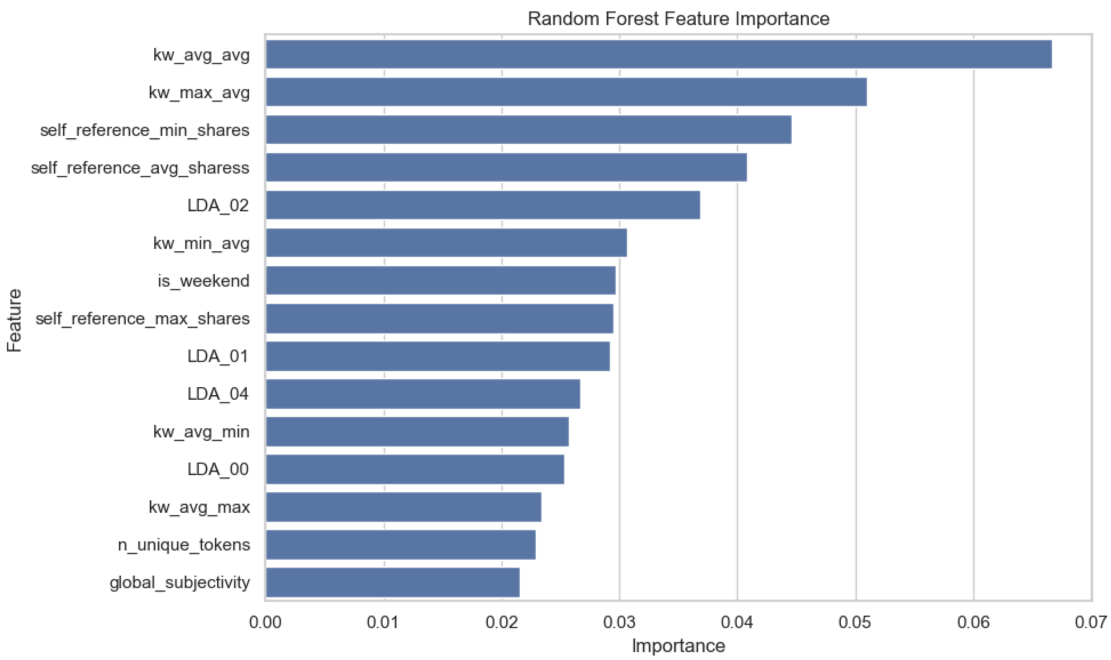
```
print("Training on full training set...")
final_pipeline.fit(X_train_resampled, y_train_resampled)

# Evaluate on test set
print("Evaluating on test set...")
rf_tuned_pred = final_pipeline.predict(X_test)
rf_tuned_accuracy = accuracy_score(y_test, rf_tuned_pred)
rf_tuned_f1 = f1_score(y_test, rf_tuned_pred, average='weighted')

print(f"\nOptimized Random Forest test accuracy: {rf_tuned_accuracy:.4f}")
print(f"Optimized Random Forest test F1 score: {rf_tuned_f1:.4f}")

# Plot confusion matrix
plot_confusion_matrix(y_test, rf_tuned_pred, title='Confusion Matrix -␣
↪Optimized Random Forest')

# Add to results dictionary
results['Optimized Random Forest'] = {
    'cv_mean': search_2.best_score_,
    'cv_std': 0,
    'test_accuracy': rf_tuned_accuracy,
    'test_f1': rf_tuned_f1,
    'model': final_pipeline,
    'predictions': rf_tuned_pred
}

# Calculate and display feature importance
print("\nCalculating feature importance...")
feature_importance = final_rf.feature_importances_
feature_names = X_train_resampled.columns if hasattr(X_train_resampled,␣
↪'columns') else [f"feature_{i}" for i in range(X_train_resampled.shape[1])]

importance_df = pd.DataFrame({
    'Feature': feature_names,
    'Importance': feature_importance
}).sort_values('Importance', ascending=False)

print("\nTop 15 most important features:")
print(importance_df.head(15))

# Feature importance visualization
plt.figure(figsize=(10, 6))
sns.barplot(x='Importance', y='Feature', data=importance_df.head(15))
plt.title('Random Forest Feature Importance')
plt.tight_layout()
plt.show()
```

```
==================================================
Executing efficient two-stage Random Forest tuning…

Stage 1: Coarse-grained parameter search
Using 5000 samples for initial search
Executing stage 1 search…
Fitting 3 folds for each of 10 candidates, totalling 30 fits

Stage 1 best parameters: {'n_estimators': 200, 'min_samples_split': 20,
'min_samples_leaf': 2, 'max_features': 'log2', 'max_depth': 15, 'class_weight':
None, 'bootstrap': True}
Stage 1 best CV accuracy: 0.6644

Stage 2: Fine-grained parameter optimization
Using 10000 samples for fine-grained optimization
Executing stage 2 search…
Parameter grid for stage 2: {'n_estimators': [150, 200, 250, 300], 'max_depth':
[13, 15, 17, None], 'min_samples_split': [17, 20, 23], 'min_samples_leaf': [1,
2, 3], 'max_features': ['log2', 0.3, 0.4], 'bootstrap': [True], 'class_weight':
[None, 'balanced']}
Fitting 5 folds for each of 10 candidates, totalling 50 fits

Final best parameters: {'n_estimators': 300, 'min_samples_split': 23,
'min_samples_leaf': 2, 'max_features': 'log2', 'max_depth': 13, 'class_weight':
None, 'bootstrap': True}
Final best CV accuracy: 0.6732

Training final model with best parameters…
Training on full training set…
Evaluating on test set…

Optimized Random Forest test accuracy: 0.6728
Optimized Random Forest test F1 score: 0.6729
```




```
Detailed Classification Metrics:
  Class Precision Recall F1-Score  Support
0  High     69.4%  69.2%    69.3%     4231
1   Low     64.9%  65.1%    65.0%     3698

Calculating feature importance…

Top 15 most important features:
                       Feature  Importance
25                  kw_avg_avg    0.066737
24                  kw_max_avg    0.050999
26   self_reference_min_shares    0.044647
28  self_reference_avg_sharess    0.040875
39                      LDA_02    0.036888
23                  kw_min_avg    0.030697
36                  is_weekend    0.029652
27   self_reference_max_shares    0.029479
```

```
38                      LDA_01    0.029222
41                      LDA_04    0.026655
19                  kw_avg_min    0.025730
37                      LDA_00    0.025360
22                  kw_avg_max    0.023400
2              n_unique_tokens    0.022871
42         global_subjectivity    0.021596
```



[50]:
```
#---------------------
# Efficient XGBoost Tuning - Two-Stage Optimization Method
#---------------------
print("\n" + "="*50)
print("Executing efficient two-stage XGBoost tuning...")

# Stage 1: Use coarse-grained search to determine general direction
print("\nStage 1: Coarse-grained parameter search")

# Create XGBoost model - use model directly rather than pipeline for efficiency
xgb_model = xgb.XGBClassifier(
    objective='multi:softmax',
    num_class=len(np.unique(y_train)),
    random_state=42,
    use_label_encoder=False,
    eval_metric='mlogloss',
    n_jobs=-1  # Use parallel processing to speed up search
)
```

```python
# More focused parameter grid - reduce number of combinations
param_grid_1 = {
    'n_estimators': [200, 300, 400],

    # Lower learning rates since the optimal value is already low at 0.05
    'learning_rate': [0.01, 0.03, 0.05],

    # Adjust tree depth range
    'max_depth': [4, 5, 6],

    # Increase min_child_weight range, current optimal value is at the upper␣
 ↪limit
    'min_child_weight': [9, 10, 11],

    # Adjust sampling parameters, try more values
    'subsample': [0.7, 0.8, 0.9],
    'colsample_bytree': [0.5, 0.6, 0.7],

    # Keep gamma unchanged but add an intermediate value
    'gamma': [0.2, 0.3, 0.4],

    # Adjust regularization parameters
    'reg_alpha': [0.3, 0.4, 0.5],
    'reg_lambda': [1, 2, 3]
}

# Use a smaller sample to speed up initial search
sample_size = min(5000, len(X_train_resampled))
print(f"Using {sample_size} samples for initial search")
sample_indices = np.random.choice(len(X_train_resampled), size=sample_size,␣
 ↪replace=False)
X_small_sample = X_train_resampled.iloc[sample_indices] if␣
 ↪hasattr(X_train_resampled, 'iloc') else X_train_resampled[sample_indices]
y_small_sample = y_train_resampled[sample_indices]

# Standardize data (doing it once outside the pipeline is sufficient)
scaler = StandardScaler()
X_small_sample_scaled = scaler.fit_transform(X_small_sample)

# Stage 1 search - fewer iterations and faster CV
search_1 = RandomizedSearchCV(
    xgb_model,
    param_distributions=param_grid_1,
    n_iter=10,  # Reduce number of iterations
    cv=3,       # Reduce number of CV folds
    scoring='accuracy',
```

```
    n_jobs=-1,  # Parallel processing
    verbose=1,
    random_state=42
)

print("Executing stage 1 search...")
search_1.fit(X_small_sample_scaled, y_small_sample)

# Get best parameters from stage 1
best_params_1 = search_1.best_params_
print(f"\nStage 1 best parameters: {best_params_1}")
print(f"Stage 1 best CV accuracy: {search_1.best_score_:.4f}")

# Stage 2: Fine-grained search around the best parameters
print("\nStage 2: Fine-grained parameter optimization")

# Create more focused parameter ranges based on stage 1 results
param_grid_2 = {
    'n_estimators': [best_params_1['n_estimators'],␣
 ↪best_params_1['n_estimators'] + 50, best_params_1['n_estimators'] + 100],
    'learning_rate': [best_params_1['learning_rate'] * 0.5,␣
 ↪best_params_1['learning_rate'], best_params_1['learning_rate'] * 1.5],
    'max_depth': [max(best_params_1['max_depth'] - 1, 3),␣
 ↪best_params_1['max_depth'], min(best_params_1['max_depth'] + 1, 6)],
    'min_child_weight': [max(best_params_1['min_child_weight'] - 1, 1),␣
 ↪best_params_1['min_child_weight'], best_params_1['min_child_weight'] + 1],
    'subsample': [max(best_params_1['subsample'] - 0.1, 0.6),␣
 ↪best_params_1['subsample'], min(best_params_1['subsample'] + 0.1, 0.9)],
    'colsample_bytree': [max(best_params_1['colsample_bytree'] - 0.1, 0.4),␣
 ↪best_params_1['colsample_bytree'], min(best_params_1['colsample_bytree'] + 0.
 ↪1, 0.8)],
    'gamma': [max(best_params_1['gamma'] - 0.1, 0.1), best_params_1['gamma'],␣
 ↪best_params_1['gamma'] + 0.1],
    'reg_alpha': [max(best_params_1['reg_alpha'] - 0.1, 0.2),␣
 ↪best_params_1['reg_alpha'], best_params_1['reg_alpha'] + 0.1],
    'reg_lambda': [max(best_params_1['reg_lambda'] - 1, 1),␣
 ↪best_params_1['reg_lambda'], best_params_1['reg_lambda'] + 1]
}

# Use medium-sized sample for stage 2 optimization
sample_size_2 = min(10000, len(X_train_resampled))
print(f"Using {sample_size_2} samples for fine-grained optimization")
sample_indices_2 = np.random.choice(len(X_train_resampled), size=sample_size_2,␣
 ↪replace=False)
X_medium_sample = X_train_resampled.iloc[sample_indices_2] if␣
 ↪hasattr(X_train_resampled, 'iloc') else X_train_resampled[sample_indices_2]
```

```python
y_medium_sample = y_train_resampled[sample_indices_2]

# Standardize data
X_medium_sample_scaled = scaler.fit_transform(X_medium_sample)

# Stage 2 search
search_2 = RandomizedSearchCV(
    xgb_model,
    param_distributions=param_grid_2,
    n_iter=10,  # Reduce number of iterations
    cv=5,       # Use full CV
    scoring='accuracy',
    n_jobs=-1,  # Parallel processing
    verbose=1,
    random_state=42
)

print("Executing stage 2 search...")
search_2.fit(X_medium_sample_scaled, y_medium_sample)

# Get final best parameters
best_params_final = search_2.best_params_
print(f"\nFinal best parameters: {best_params_final}")
print(f"Final best CV accuracy: {search_2.best_score_:.4f}")

# Create final model with best parameters
print("\nTraining final model with best parameters...")
final_xgb = xgb.XGBClassifier(
    objective='multi:softmax',
    num_class=len(np.unique(y_train)),
    random_state=42,
    use_label_encoder=False,
    eval_metric='mlogloss',
    n_jobs=-1,
    **best_params_final
)

# Create complete pipeline
final_pipeline = Pipeline([
    ('scaler', StandardScaler()),
    ('model', final_xgb)
])

# Train final model on the full training set
print("Training on full training set...")
final_pipeline.fit(X_train_resampled, y_train_resampled)
```

```python
# Evaluate on test set
print("Evaluating on test set...")
xgb_tuned_pred = final_pipeline.predict(X_test)
xgb_tuned_accuracy = accuracy_score(y_test, xgb_tuned_pred)
xgb_tuned_f1 = f1_score(y_test, xgb_tuned_pred, average='weighted')

print(f"\nOptimized XGBoost test accuracy: {xgb_tuned_accuracy:.4f}")
print(f"Optimized XGBoost test F1 score: {xgb_tuned_f1:.4f}")

# Plot confusion matrix
plot_confusion_matrix(y_test, xgb_tuned_pred, title='Confusion Matrix -␣
↪Optimized XGBoost')

# Add to results dictionary
results['Optimized XGBoost'] = {
    'cv_mean': search_2.best_score_,
    'cv_std': 0,
    'test_accuracy': xgb_tuned_accuracy,
    'test_f1': xgb_tuned_f1,
    'model': final_pipeline,
    'predictions': xgb_tuned_pred
}

# Calculate and display feature importance (optional)
print("\nCalculating feature importance...")
feature_importance = final_xgb.feature_importances_
feature_names = X_train_resampled.columns if hasattr(X_train_resampled,␣
↪'columns') else [f"feature_{i}" for i in range(X_train_resampled.shape[1])]

importance_df = pd.DataFrame({
    'Feature': feature_names,
    'Importance': feature_importance
}).sort_values('Importance', ascending=False)

print("\nTop 15 most important features:")
print(importance_df.head(15))

# Feature importance visualization (optional)
plt.figure(figsize=(10, 6))
sns.barplot(x='Importance', y='Feature', data=importance_df.head(15))
plt.title('XGBoost Feature Importance')
plt.tight_layout()
plt.show()
```

```
==================================================
Executing efficient two-stage XGBoost tuning…
```

```
Stage 1: Coarse-grained parameter search
Using 5000 samples for initial search
Executing stage 1 search…
Fitting 3 folds for each of 10 candidates, totalling 30 fits

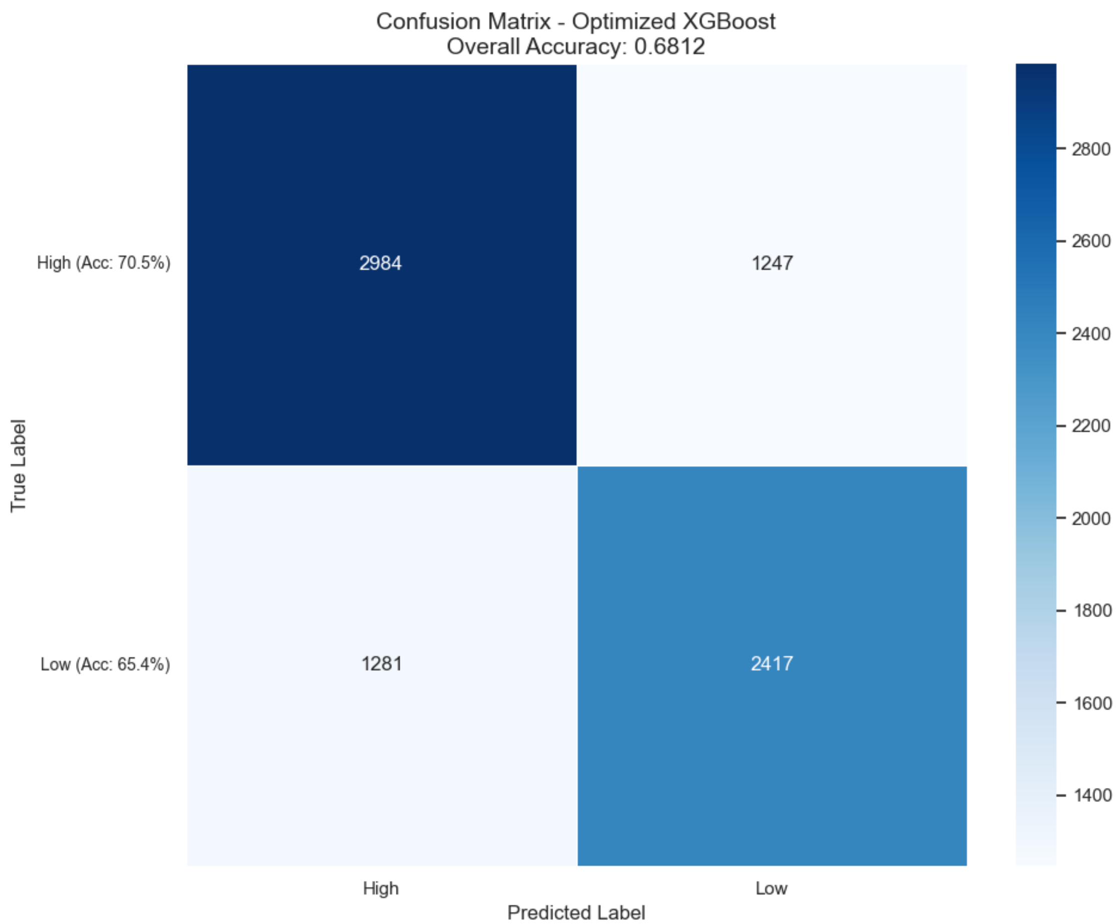
Stage 1 best parameters: {'subsample': 0.7, 'reg_lambda': 2, 'reg_alpha': 0.3,
'n_estimators': 400, 'min_child_weight': 9, 'max_depth': 5, 'learning_rate':
0.03, 'gamma': 0.4, 'colsample_bytree': 0.6}
Stage 1 best CV accuracy: 0.6648

Stage 2: Fine-grained parameter optimization
Using 10000 samples for fine-grained optimization
Executing stage 2 search…
Fitting 5 folds for each of 10 candidates, totalling 50 fits

Final best parameters: {'subsample': 0.7999999999999999, 'reg_lambda': 3,
'reg_alpha': 0.3, 'n_estimators': 450, 'min_child_weight': 8, 'max_depth': 5,
'learning_rate': 0.03, 'gamma': 0.5, 'colsample_bytree': 0.5}
Final best CV accuracy: 0.6810

Training final model with best parameters…
Training on full training set…
Evaluating on test set…

Optimized XGBoost test accuracy: 0.6812
Optimized XGBoost test F1 score: 0.6811
```

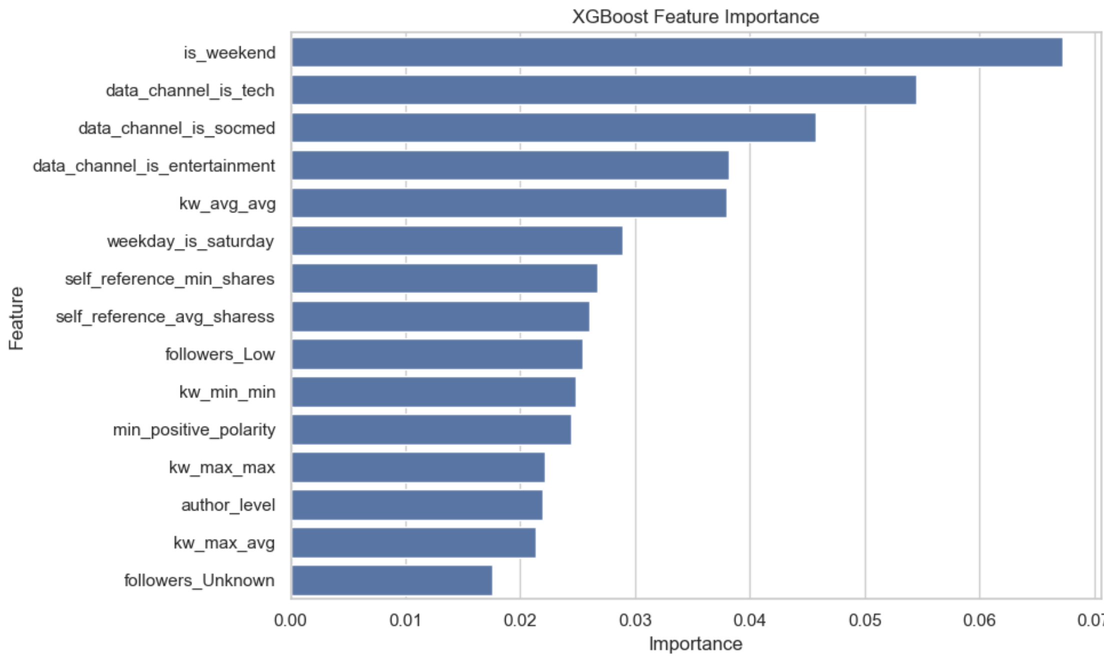



```
Detailed Classification Metrics:
  Class Precision Recall F1-Score  Support
0  High     70.0%  70.5%    70.2%     4231
1   Low     66.0%  65.4%    65.7%     3698

Calculating feature importance…

Top 15 most important features:
                          Feature  Importance
36                     is_weekend    0.067276
15           data_channel_is_tech    0.054517
14         data_channel_is_socmed    0.045696
12  data_channel_is_entertainment    0.038205
25                     kw_avg_avg    0.037934
34            weekday_is_saturday    0.028874
26        self_reference_min_shares  0.026766
28      self_reference_avg_sharess   0.025993
```

```
61              followers_Low    0.025383
17                 kw_min_min    0.024875
49      min_positive_polarity    0.024432
21                 kw_max_max    0.022092
58               author_level    0.021979
24                 kw_max_avg    0.021358
65          followers_Unknown    0.017611
```



After conducting advanced hyperparameter tuning for Random Forest and XGBoost, we found that the accuracy still did not improve. This suggests that the model's limitations may caused by deeper issues beyond hyperparameter optimization. One possible reason is that the dataset lacks strong predictive features, making it difficult for any model to achieve high accuracy. Despite these challenges, we have chosen to keep this result. Because it can still provide valuable insights into content engagement patterns. It also highlights, to some extent, the difficulty of predicting the popularity of online news.

We will now try to use PCA for feature selection, analyze the effect of features with large variance contributions (95%) on accuracy, and try to optimize the run speed.

1.5.3 PCA for XGBoost and LightGBM

[51]:
```
#--------------------
# XGBoost with PCA feature selection to reduce overfitting
#--------------------
print("\n" + "="*50)
print("Performing XGBoost with PCA feature selection to reduce overfitting...")
```

```
# Create the XGBoost pipeline with PCA
xgb_pca_pipeline = Pipeline([
    ('scaler', StandardScaler()),
    ('pca', PCA(n_components=0.95)),  # Keep components that explain 95% of␣
↪variance
    ('model', xgb.XGBClassifier(
        objective='multi:softmax',
        num_class=len(np.unique(y_train)),
        random_state=42,
        use_label_encoder=False,
        eval_metric='mlogloss'
    ))
])

# Define parameter grid focused on reducing overfitting
xgb_param_grid = {
    'model__n_estimators': [100, 200, 300],
    'model__learning_rate': [0.01, 0.05, 0.1],
    'model__max_depth': [3, 4, 5, 6],
    'model__min_child_weight': [1, 3, 5, 7],
    'model__gamma': [0, 0.1, 0.2, 0.3],
    'model__subsample': [0.6, 0.7, 0.8, 0.9],
    'model__colsample_bytree': [0.6, 0.7, 0.8, 0.9],
    'model__reg_alpha': [0, 0.1, 0.5, 1.0, 5.0],
    'model__reg_lambda': [1, 2, 5, 10]
}

# Memory optimization: Use a smaller subset if dataset is large
X_sample, y_sample = X_train_resampled, y_train_resampled
if len(X_train_resampled) > 10000:
    print("Using a random subset of 10,000 samples for XGBoost with PCA tuning")
    sample_indices = np.random.choice(len(X_train_resampled), size=10000,␣
↪replace=False)
    X_sample = X_train_resampled.iloc[sample_indices] if␣
↪hasattr(X_train_resampled, 'iloc') else X_train_resampled[sample_indices]
    y_sample = y_train_resampled[sample_indices]

# Define the randomized search
xgb_pca_search = RandomizedSearchCV(
    xgb_pca_pipeline,
    param_distributions=xgb_param_grid,
    n_iter=30,  # Try 30 random combinations
    cv=StratifiedKFold(n_splits=5),
    scoring='accuracy',
    n_jobs=1,  # Use single job for memory efficiency
    verbose=2,
    random_state=42
```

```
)

# Fit the randomized search
print("Fitting XGBoost with PCA using randomized search...")
xgb_pca_search.fit(X_sample, y_sample)

# Print best parameters and score
print(f"\nBest XGBoost with PCA parameters: {xgb_pca_search.best_params_}")
print(f"Best XGBoost with PCA CV accuracy: {xgb_pca_search.best_score_:.4f}")

# Evaluate tuned XGBoost on test set
xgb_pca_tuned_pred = xgb_pca_search.predict(X_test)
xgb_pca_tuned_accuracy = accuracy_score(y_test, xgb_pca_tuned_pred)
xgb_pca_tuned_f1 = f1_score(y_test, xgb_pca_tuned_pred, average='weighted')

print(f"Tuned XGBoost with PCA test accuracy: {xgb_pca_tuned_accuracy:.4f}")
print(f"Tuned XGBoost with PCA test F1 score: {xgb_pca_tuned_f1:.4f}")

# Plot confusion matrix for tuned XGBoost with PCA
plot_confusion_matrix(y_test, xgb_pca_tuned_pred, title='Confusion Matrix -␣
 ↪Tuned XGBoost with PCA')

# Add tuned model to results
results['Tuned XGBoost with PCA'] = {
    'cv_mean': xgb_pca_search.best_score_,
    'cv_std': 0,
    'test_accuracy': xgb_pca_tuned_accuracy,
    'test_f1': xgb_pca_tuned_f1,
    'model': xgb_pca_search.best_estimator_,
    'predictions': xgb_pca_tuned_pred
}

# Get the number of components used in the best model
best_n_components = xgb_pca_search.best_estimator_.named_steps['pca'].
 ↪n_components_
print(f"Number of PCA components in best model: {best_n_components}")

# Visualize explained variance ratio
pca = xgb_pca_search.best_estimator_.named_steps['pca']
plt.figure(figsize=(10, 6))
plt.plot(np.cumsum(pca.explained_variance_ratio_))
plt.xlabel('Number of Components')
plt.ylabel('Cumulative Explained Variance')
plt.title('Explained Variance by PCA Components')
plt.grid(True)
plt.show()
```

```
==================================================
Performing XGBoost with PCA feature selection to reduce overfitting…
Using a random subset of 10,000 samples for XGBoost with PCA tuning
Fitting XGBoost with PCA using randomized search…
Fitting 5 folds for each of 30 candidates, totalling 150 fits
[CV] END model__colsample_bytree=0.8, model__gamma=0.2,
model__learning_rate=0.05, model__max_depth=6, model__min_child_weight=1,
model__n_estimators=100, model__reg_alpha=0.5, model__reg_lambda=2,
model__subsample=0.8; total time=   0.2s
[CV] END model__colsample_bytree=0.8, model__gamma=0.2,
model__learning_rate=0.05, model__max_depth=6, model__min_child_weight=1,
model__n_estimators=100, model__reg_alpha=0.5, model__reg_lambda=2,
model__subsample=0.8; total time=   0.2s
[CV] END model__colsample_bytree=0.8, model__gamma=0.2,
model__learning_rate=0.05, model__max_depth=6, model__min_child_weight=1,
model__n_estimators=100, model__reg_alpha=0.5, model__reg_lambda=2,
model__subsample=0.8; total time=   0.2s
[CV] END model__colsample_bytree=0.8, model__gamma=0.2,
model__learning_rate=0.05, model__max_depth=6, model__min_child_weight=1,
model__n_estimators=100, model__reg_alpha=0.5, model__reg_lambda=2,
model__subsample=0.8; total time=   0.2s
[CV] END model__colsample_bytree=0.8, model__gamma=0.2,
model__learning_rate=0.05, model__max_depth=6, model__min_child_weight=1,
model__n_estimators=100, model__reg_alpha=0.5, model__reg_lambda=2,
model__subsample=0.8; total time=   0.2s
[CV] END model__colsample_bytree=0.9, model__gamma=0, model__learning_rate=0.1,
model__max_depth=3, model__min_child_weight=7, model__n_estimators=300,
model__reg_alpha=5.0, model__reg_lambda=1, model__subsample=0.9; total time=
0.3s
[CV] END model__colsample_bytree=0.9, model__gamma=0, model__learning_rate=0.1,
model__max_depth=3, model__min_child_weight=7, model__n_estimators=300,
model__reg_alpha=5.0, model__reg_lambda=1, model__subsample=0.9; total time=
0.3s
[CV] END model__colsample_bytree=0.9, model__gamma=0, model__learning_rate=0.1,
model__max_depth=3, model__min_child_weight=7, model__n_estimators=300,
model__reg_alpha=5.0, model__reg_lambda=1, model__subsample=0.9; total time=
0.3s
[CV] END model__colsample_bytree=0.9, model__gamma=0, model__learning_rate=0.1,
model__max_depth=3, model__min_child_weight=7, model__n_estimators=300,
model__reg_alpha=5.0, model__reg_lambda=1, model__subsample=0.9; total time=
0.3s
[CV] END model__colsample_bytree=0.9, model__gamma=0, model__learning_rate=0.1,
model__max_depth=3, model__min_child_weight=7, model__n_estimators=300,
model__reg_alpha=5.0, model__reg_lambda=1, model__subsample=0.9; total time=
0.3s
[CV] END model__colsample_bytree=0.8, model__gamma=0.3,
model__learning_rate=0.05, model__max_depth=4, model__min_child_weight=3,
```

```
model__n_estimators=300, model__reg_alpha=0, model__reg_lambda=10,
model__subsample=0.6; total time=   0.4s
[CV] END model__colsample_bytree=0.8, model__gamma=0.3,
model__learning_rate=0.05, model__max_depth=4, model__min_child_weight=3,
model__n_estimators=300, model__reg_alpha=0, model__reg_lambda=10,
model__subsample=0.6; total time=   0.4s
[CV] END model__colsample_bytree=0.8, model__gamma=0.3,
model__learning_rate=0.05, model__max_depth=4, model__min_child_weight=3,
model__n_estimators=300, model__reg_alpha=0, model__reg_lambda=10,
model__subsample=0.6; total time=   0.4s
[CV] END model__colsample_bytree=0.8, model__gamma=0.3,
model__learning_rate=0.05, model__max_depth=4, model__min_child_weight=3,
model__n_estimators=300, model__reg_alpha=0, model__reg_lambda=10,
model__subsample=0.6; total time=   0.4s
[CV] END model__colsample_bytree=0.8, model__gamma=0.3,
model__learning_rate=0.05, model__max_depth=4, model__min_child_weight=3,
model__n_estimators=300, model__reg_alpha=0, model__reg_lambda=10,
model__subsample=0.6; total time=   0.4s
[CV] END model__colsample_bytree=0.8, model__gamma=0.1,
model__learning_rate=0.01, model__max_depth=3, model__min_child_weight=1,
model__n_estimators=100, model__reg_alpha=0, model__reg_lambda=10,
model__subsample=0.8; total time=   0.1s
[CV] END model__colsample_bytree=0.8, model__gamma=0.1,
model__learning_rate=0.01, model__max_depth=3, model__min_child_weight=1,
model__n_estimators=100, model__reg_alpha=0, model__reg_lambda=10,
model__subsample=0.8; total time=   0.1s
[CV] END model__colsample_bytree=0.8, model__gamma=0.1,
model__learning_rate=0.01, model__max_depth=3, model__min_child_weight=1,
model__n_estimators=100, model__reg_alpha=0, model__reg_lambda=10,
model__subsample=0.8; total time=   0.1s
[CV] END model__colsample_bytree=0.8, model__gamma=0.1,
model__learning_rate=0.01, model__max_depth=3, model__min_child_weight=1,
model__n_estimators=100, model__reg_alpha=0, model__reg_lambda=10,
model__subsample=0.8; total time=   0.1s
[CV] END model__colsample_bytree=0.8, model__gamma=0.1,
model__learning_rate=0.01, model__max_depth=3, model__min_child_weight=1,
model__n_estimators=100, model__reg_alpha=0, model__reg_lambda=10,
model__subsample=0.8; total time=   0.1s
[CV] END model__colsample_bytree=0.8, model__gamma=0.2,
model__learning_rate=0.05, model__max_depth=3, model__min_child_weight=7,
model__n_estimators=200, model__reg_alpha=0.5, model__reg_lambda=2,
model__subsample=0.9; total time=   0.2s
[CV] END model__colsample_bytree=0.8, model__gamma=0.2,
model__learning_rate=0.05, model__max_depth=3, model__min_child_weight=7,
model__n_estimators=200, model__reg_alpha=0.5, model__reg_lambda=2,
model__subsample=0.9; total time=   0.2s
[CV] END model__colsample_bytree=0.8, model__gamma=0.2,
model__learning_rate=0.05, model__max_depth=3, model__min_child_weight=7,
```

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model__n_estimators=200, model__reg_alpha=0.5, model__reg_lambda=2,
model__subsample=0.9; total time=   0.2s
[CV] END model__colsample_bytree=0.8, model__gamma=0.2,
model__learning_rate=0.05, model__max_depth=3, model__min_child_weight=7,
model__n_estimators=200, model__reg_alpha=0.5, model__reg_lambda=2,
model__subsample=0.9; total time=   0.2s
[CV] END model__colsample_bytree=0.8, model__gamma=0.2,
model__learning_rate=0.05, model__max_depth=3, model__min_child_weight=7,
model__n_estimators=200, model__reg_alpha=0.5, model__reg_lambda=2,
model__subsample=0.9; total time=   0.2s
[CV] END model__colsample_bytree=0.8, model__gamma=0.1,
model__learning_rate=0.05, model__max_depth=5, model__min_child_weight=7,
model__n_estimators=200, model__reg_alpha=0.1, model__reg_lambda=10,
model__subsample=0.6; total time=   0.4s
[CV] END model__colsample_bytree=0.8, model__gamma=0.1,
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model__n_estimators=200, model__reg_alpha=0.1, model__reg_lambda=10,
model__subsample=0.6; total time=   0.4s
[CV] END model__colsample_bytree=0.8, model__gamma=0.1,
model__learning_rate=0.05, model__max_depth=5, model__min_child_weight=7,
model__n_estimators=200, model__reg_alpha=0.1, model__reg_lambda=10,
model__subsample=0.6; total time=   0.4s
[CV] END model__colsample_bytree=0.8, model__gamma=0.1,
model__learning_rate=0.05, model__max_depth=5, model__min_child_weight=7,
model__n_estimators=200, model__reg_alpha=0.1, model__reg_lambda=10,
model__subsample=0.6; total time=   0.4s
[CV] END model__colsample_bytree=0.8, model__gamma=0.1,
model__learning_rate=0.05, model__max_depth=5, model__min_child_weight=7,
model__n_estimators=200, model__reg_alpha=0.1, model__reg_lambda=10,
model__subsample=0.6; total time=   0.4s
[CV] END model__colsample_bytree=0.7, model__gamma=0, model__learning_rate=0.1,
model__max_depth=4, model__min_child_weight=1, model__n_estimators=300,
model__reg_alpha=0, model__reg_lambda=2, model__subsample=0.8; total time=
0.4s
[CV] END model__colsample_bytree=0.7, model__gamma=0, model__learning_rate=0.1,
model__max_depth=4, model__min_child_weight=1, model__n_estimators=300,
model__reg_alpha=0, model__reg_lambda=2, model__subsample=0.8; total time=
0.4s
[CV] END model__colsample_bytree=0.7, model__gamma=0, model__learning_rate=0.1,
model__max_depth=4, model__min_child_weight=1, model__n_estimators=300,
model__reg_alpha=0, model__reg_lambda=2, model__subsample=0.8; total time=
0.4s
[CV] END model__colsample_bytree=0.7, model__gamma=0, model__learning_rate=0.1,
model__max_depth=4, model__min_child_weight=1, model__n_estimators=300,
model__reg_alpha=0, model__reg_lambda=2, model__subsample=0.8; total time=
0.4s
[CV] END model__colsample_bytree=0.7, model__gamma=0, model__learning_rate=0.1,
model__max_depth=4, model__min_child_weight=1, model__n_estimators=300,
```

```
model__reg_alpha=0, model__reg_lambda=2, model__subsample=0.8; total time=
0.4s
[CV] END model__colsample_bytree=0.8, model__gamma=0.3,
model__learning_rate=0.1, model__max_depth=6, model__min_child_weight=1,
model__n_estimators=100, model__reg_alpha=1.0, model__reg_lambda=5,
model__subsample=0.7; total time=   0.2s
[CV] END model__colsample_bytree=0.8, model__gamma=0.3,
model__learning_rate=0.1, model__max_depth=6, model__min_child_weight=1,
model__n_estimators=100, model__reg_alpha=1.0, model__reg_lambda=5,
model__subsample=0.7; total time=   0.2s
[CV] END model__colsample_bytree=0.8, model__gamma=0.3,
model__learning_rate=0.1, model__max_depth=6, model__min_child_weight=1,
model__n_estimators=100, model__reg_alpha=1.0, model__reg_lambda=5,
model__subsample=0.7; total time=   0.3s
[CV] END model__colsample_bytree=0.8, model__gamma=0.3,
model__learning_rate=0.1, model__max_depth=6, model__min_child_weight=1,
model__n_estimators=100, model__reg_alpha=1.0, model__reg_lambda=5,
model__subsample=0.7; total time=   0.2s
[CV] END model__colsample_bytree=0.8, model__gamma=0.3,
model__learning_rate=0.1, model__max_depth=6, model__min_child_weight=1,
model__n_estimators=100, model__reg_alpha=1.0, model__reg_lambda=5,
model__subsample=0.7; total time=   0.2s
[CV] END model__colsample_bytree=0.9, model__gamma=0.2,
model__learning_rate=0.05, model__max_depth=6, model__min_child_weight=3,
model__n_estimators=100, model__reg_alpha=0.1, model__reg_lambda=5,
model__subsample=0.8; total time=   0.2s
[CV] END model__colsample_bytree=0.9, model__gamma=0.2,
model__learning_rate=0.05, model__max_depth=6, model__min_child_weight=3,
model__n_estimators=100, model__reg_alpha=0.1, model__reg_lambda=5,
model__subsample=0.8; total time=   0.2s
[CV] END model__colsample_bytree=0.9, model__gamma=0.2,
model__learning_rate=0.05, model__max_depth=6, model__min_child_weight=3,
model__n_estimators=100, model__reg_alpha=0.1, model__reg_lambda=5,
model__subsample=0.8; total time=   0.2s
[CV] END model__colsample_bytree=0.9, model__gamma=0.2,
model__learning_rate=0.05, model__max_depth=6, model__min_child_weight=3,
model__n_estimators=100, model__reg_alpha=0.1, model__reg_lambda=5,
model__subsample=0.8; total time=   0.2s
[CV] END model__colsample_bytree=0.9, model__gamma=0.2,
model__learning_rate=0.05, model__max_depth=6, model__min_child_weight=3,
model__n_estimators=100, model__reg_alpha=0.1, model__reg_lambda=5,
model__subsample=0.8; total time=   0.2s
[CV] END model__colsample_bytree=0.7, model__gamma=0.3,
model__learning_rate=0.05, model__max_depth=6, model__min_child_weight=1,
model__n_estimators=200, model__reg_alpha=1.0, model__reg_lambda=5,
model__subsample=0.8; total time=   0.5s
[CV] END model__colsample_bytree=0.7, model__gamma=0.3,
model__learning_rate=0.05, model__max_depth=6, model__min_child_weight=1,
```

```
model__n_estimators=200, model__reg_alpha=1.0, model__reg_lambda=5,
model__subsample=0.8; total time=   0.5s
[CV] END model__colsample_bytree=0.7, model__gamma=0.3,
model__learning_rate=0.05, model__max_depth=6, model__min_child_weight=1,
model__n_estimators=200, model__reg_alpha=1.0, model__reg_lambda=5,
model__subsample=0.8; total time=   0.5s
[CV] END model__colsample_bytree=0.7, model__gamma=0.3,
model__learning_rate=0.05, model__max_depth=6, model__min_child_weight=1,
model__n_estimators=200, model__reg_alpha=1.0, model__reg_lambda=5,
model__subsample=0.8; total time=   0.5s
[CV] END model__colsample_bytree=0.7, model__gamma=0.3,
model__learning_rate=0.05, model__max_depth=6, model__min_child_weight=1,
model__n_estimators=200, model__reg_alpha=1.0, model__reg_lambda=5,
model__subsample=0.8; total time=   0.5s
[CV] END model__colsample_bytree=0.8, model__gamma=0.1,
model__learning_rate=0.1, model__max_depth=4, model__min_child_weight=3,
model__n_estimators=300, model__reg_alpha=0, model__reg_lambda=2,
model__subsample=0.9; total time=   0.4s
[CV] END model__colsample_bytree=0.8, model__gamma=0.1,
model__learning_rate=0.1, model__max_depth=4, model__min_child_weight=3,
model__n_estimators=300, model__reg_alpha=0, model__reg_lambda=2,
model__subsample=0.9; total time=   0.4s
[CV] END model__colsample_bytree=0.8, model__gamma=0.1,
model__learning_rate=0.1, model__max_depth=4, model__min_child_weight=3,
model__n_estimators=300, model__reg_alpha=0, model__reg_lambda=2,
model__subsample=0.9; total time=   0.4s
[CV] END model__colsample_bytree=0.8, model__gamma=0.1,
model__learning_rate=0.1, model__max_depth=4, model__min_child_weight=3,
model__n_estimators=300, model__reg_alpha=0, model__reg_lambda=2,
model__subsample=0.9; total time=   0.4s
[CV] END model__colsample_bytree=0.8, model__gamma=0.1,
model__learning_rate=0.1, model__max_depth=4, model__min_child_weight=3,
model__n_estimators=300, model__reg_alpha=0, model__reg_lambda=2,
model__subsample=0.9; total time=   0.4s
[CV] END model__colsample_bytree=0.8, model__gamma=0.2,
model__learning_rate=0.1, model__max_depth=6, model__min_child_weight=5,
model__n_estimators=200, model__reg_alpha=0, model__reg_lambda=2,
model__subsample=0.6; total time=   0.5s
[CV] END model__colsample_bytree=0.8, model__gamma=0.2,
model__learning_rate=0.1, model__max_depth=6, model__min_child_weight=5,
model__n_estimators=200, model__reg_alpha=0, model__reg_lambda=2,
model__subsample=0.6; total time=   0.5s
[CV] END model__colsample_bytree=0.8, model__gamma=0.2,
model__learning_rate=0.1, model__max_depth=6, model__min_child_weight=5,
model__n_estimators=200, model__reg_alpha=0, model__reg_lambda=2,
model__subsample=0.6; total time=   0.5s
[CV] END model__colsample_bytree=0.8, model__gamma=0.2,
model__learning_rate=0.1, model__max_depth=6, model__min_child_weight=5,
```

```
model__n_estimators=200, model__reg_alpha=0, model__reg_lambda=2,
model__subsample=0.6; total time=   0.5s
[CV] END model__colsample_bytree=0.8, model__gamma=0.2,
model__learning_rate=0.1, model__max_depth=6, model__min_child_weight=5,
model__n_estimators=200, model__reg_alpha=0, model__reg_lambda=2,
model__subsample=0.6; total time=   0.5s
[CV] END model__colsample_bytree=0.9, model__gamma=0.3,
model__learning_rate=0.01, model__max_depth=5, model__min_child_weight=5,
model__n_estimators=100, model__reg_alpha=0, model__reg_lambda=1,
model__subsample=0.9; total time=   0.2s
[CV] END model__colsample_bytree=0.9, model__gamma=0.3,
model__learning_rate=0.01, model__max_depth=5, model__min_child_weight=5,
model__n_estimators=100, model__reg_alpha=0, model__reg_lambda=1,
model__subsample=0.9; total time=   0.2s
[CV] END model__colsample_bytree=0.9, model__gamma=0.3,
model__learning_rate=0.01, model__max_depth=5, model__min_child_weight=5,
model__n_estimators=100, model__reg_alpha=0, model__reg_lambda=1,
model__subsample=0.9; total time=   0.2s
[CV] END model__colsample_bytree=0.9, model__gamma=0.3,
model__learning_rate=0.01, model__max_depth=5, model__min_child_weight=5,
model__n_estimators=100, model__reg_alpha=0, model__reg_lambda=1,
model__subsample=0.9; total time=   0.2s
[CV] END model__colsample_bytree=0.9, model__gamma=0.3,
model__learning_rate=0.01, model__max_depth=5, model__min_child_weight=5,
model__n_estimators=100, model__reg_alpha=0, model__reg_lambda=1,
model__subsample=0.9; total time=   0.2s
[CV] END model__colsample_bytree=0.6, model__gamma=0.1,
model__learning_rate=0.05, model__max_depth=3, model__min_child_weight=5,
model__n_estimators=300, model__reg_alpha=0.1, model__reg_lambda=2,
model__subsample=0.9; total time=   0.3s
[CV] END model__colsample_bytree=0.6, model__gamma=0.1,
model__learning_rate=0.05, model__max_depth=3, model__min_child_weight=5,
model__n_estimators=300, model__reg_alpha=0.1, model__reg_lambda=2,
model__subsample=0.9; total time=   0.3s
[CV] END model__colsample_bytree=0.6, model__gamma=0.1,
model__learning_rate=0.05, model__max_depth=3, model__min_child_weight=5,
model__n_estimators=300, model__reg_alpha=0.1, model__reg_lambda=2,
model__subsample=0.9; total time=   0.3s
[CV] END model__colsample_bytree=0.6, model__gamma=0.1,
model__learning_rate=0.05, model__max_depth=3, model__min_child_weight=5,
model__n_estimators=300, model__reg_alpha=0.1, model__reg_lambda=2,
model__subsample=0.9; total time=   0.3s
[CV] END model__colsample_bytree=0.6, model__gamma=0.1,
model__learning_rate=0.05, model__max_depth=3, model__min_child_weight=5,
model__n_estimators=300, model__reg_alpha=0.1, model__reg_lambda=2,
model__subsample=0.9; total time=   0.3s
[CV] END model__colsample_bytree=0.6, model__gamma=0.3,
model__learning_rate=0.05, model__max_depth=5, model__min_child_weight=7,
```

```
model__n_estimators=100, model__reg_alpha=1.0, model__reg_lambda=1,
model__subsample=0.8; total time=   0.1s
[CV] END model__colsample_bytree=0.6, model__gamma=0.3,
model__learning_rate=0.05, model__max_depth=5, model__min_child_weight=7,
model__n_estimators=100, model__reg_alpha=1.0, model__reg_lambda=1,
model__subsample=0.8; total time=   0.1s
[CV] END model__colsample_bytree=0.6, model__gamma=0.3,
model__learning_rate=0.05, model__max_depth=5, model__min_child_weight=7,
model__n_estimators=100, model__reg_alpha=1.0, model__reg_lambda=1,
model__subsample=0.8; total time=   0.1s
[CV] END model__colsample_bytree=0.6, model__gamma=0.3,
model__learning_rate=0.05, model__max_depth=5, model__min_child_weight=7,
model__n_estimators=100, model__reg_alpha=1.0, model__reg_lambda=1,
model__subsample=0.8; total time=   0.2s
[CV] END model__colsample_bytree=0.6, model__gamma=0.3,
model__learning_rate=0.05, model__max_depth=5, model__min_child_weight=7,
model__n_estimators=100, model__reg_alpha=1.0, model__reg_lambda=1,
model__subsample=0.8; total time=   0.1s
[CV] END model__colsample_bytree=0.7, model__gamma=0.1,
model__learning_rate=0.1, model__max_depth=5, model__min_child_weight=1,
model__n_estimators=100, model__reg_alpha=0.1, model__reg_lambda=2,
model__subsample=0.7; total time=   0.2s
[CV] END model__colsample_bytree=0.7, model__gamma=0.1,
model__learning_rate=0.1, model__max_depth=5, model__min_child_weight=1,
model__n_estimators=100, model__reg_alpha=0.1, model__reg_lambda=2,
model__subsample=0.7; total time=   0.1s
[CV] END model__colsample_bytree=0.7, model__gamma=0.1,
model__learning_rate=0.1, model__max_depth=5, model__min_child_weight=1,
model__n_estimators=100, model__reg_alpha=0.1, model__reg_lambda=2,
model__subsample=0.7; total time=   0.1s
[CV] END model__colsample_bytree=0.7, model__gamma=0.1,
model__learning_rate=0.1, model__max_depth=5, model__min_child_weight=1,
model__n_estimators=100, model__reg_alpha=0.1, model__reg_lambda=2,
model__subsample=0.7; total time=   0.2s
[CV] END model__colsample_bytree=0.7, model__gamma=0.1,
model__learning_rate=0.1, model__max_depth=5, model__min_child_weight=1,
model__n_estimators=100, model__reg_alpha=0.1, model__reg_lambda=2,
model__subsample=0.7; total time=   0.1s
[CV] END model__colsample_bytree=0.7, model__gamma=0.1,
model__learning_rate=0.05, model__max_depth=6, model__min_child_weight=5,
model__n_estimators=100, model__reg_alpha=0.1, model__reg_lambda=2,
model__subsample=0.6; total time=   0.2s
[CV] END model__colsample_bytree=0.7, model__gamma=0.1,
model__learning_rate=0.05, model__max_depth=6, model__min_child_weight=5,
model__n_estimators=100, model__reg_alpha=0.1, model__reg_lambda=2,
model__subsample=0.6; total time=   0.2s
[CV] END model__colsample_bytree=0.7, model__gamma=0.1,
model__learning_rate=0.05, model__max_depth=6, model__min_child_weight=5,
```

```
model__n_estimators=100, model__reg_alpha=0.1, model__reg_lambda=2,
model__subsample=0.6; total time=   0.2s
[CV] END model__colsample_bytree=0.7, model__gamma=0.1,
model__learning_rate=0.05, model__max_depth=6, model__min_child_weight=5,
model__n_estimators=100, model__reg_alpha=0.1, model__reg_lambda=2,
model__subsample=0.6; total time=   0.2s
[CV] END model__colsample_bytree=0.7, model__gamma=0.1,
model__learning_rate=0.05, model__max_depth=6, model__min_child_weight=5,
model__n_estimators=100, model__reg_alpha=0.1, model__reg_lambda=2,
model__subsample=0.6; total time=   0.2s
[CV] END model__colsample_bytree=0.6, model__gamma=0, model__learning_rate=0.01,
model__max_depth=3, model__min_child_weight=7, model__n_estimators=100,
model__reg_alpha=1.0, model__reg_lambda=1, model__subsample=0.7; total time=
0.1s
[CV] END model__colsample_bytree=0.6, model__gamma=0, model__learning_rate=0.01,
model__max_depth=3, model__min_child_weight=7, model__n_estimators=100,
model__reg_alpha=1.0, model__reg_lambda=1, model__subsample=0.7; total time=
0.1s
[CV] END model__colsample_bytree=0.6, model__gamma=0, model__learning_rate=0.01,
model__max_depth=3, model__min_child_weight=7, model__n_estimators=100,
model__reg_alpha=1.0, model__reg_lambda=1, model__subsample=0.7; total time=
0.1s
[CV] END model__colsample_bytree=0.6, model__gamma=0, model__learning_rate=0.01,
model__max_depth=3, model__min_child_weight=7, model__n_estimators=100,
model__reg_alpha=1.0, model__reg_lambda=1, model__subsample=0.7; total time=
0.1s
[CV] END model__colsample_bytree=0.6, model__gamma=0, model__learning_rate=0.01,
model__max_depth=3, model__min_child_weight=7, model__n_estimators=100,
model__reg_alpha=1.0, model__reg_lambda=1, model__subsample=0.7; total time=
0.1s
[CV] END model__colsample_bytree=0.7, model__gamma=0.1,
model__learning_rate=0.01, model__max_depth=5, model__min_child_weight=1,
model__n_estimators=300, model__reg_alpha=1.0, model__reg_lambda=2,
model__subsample=0.9; total time=   0.6s
[CV] END model__colsample_bytree=0.7, model__gamma=0.1,
model__learning_rate=0.01, model__max_depth=5, model__min_child_weight=1,
model__n_estimators=300, model__reg_alpha=1.0, model__reg_lambda=2,
model__subsample=0.9; total time=   0.6s
[CV] END model__colsample_bytree=0.7, model__gamma=0.1,
model__learning_rate=0.01, model__max_depth=5, model__min_child_weight=1,
model__n_estimators=300, model__reg_alpha=1.0, model__reg_lambda=2,
model__subsample=0.9; total time=   0.6s
[CV] END model__colsample_bytree=0.7, model__gamma=0.1,
model__learning_rate=0.01, model__max_depth=5, model__min_child_weight=1,
model__n_estimators=300, model__reg_alpha=1.0, model__reg_lambda=2,
model__subsample=0.9; total time=   0.6s
[CV] END model__colsample_bytree=0.7, model__gamma=0.1,
model__learning_rate=0.01, model__max_depth=5, model__min_child_weight=1,
```

```
model__n_estimators=300, model__reg_alpha=1.0, model__reg_lambda=2,
model__subsample=0.9; total time=   0.6s
[CV] END model__colsample_bytree=0.7, model__gamma=0.1,
model__learning_rate=0.05, model__max_depth=6, model__min_child_weight=5,
model__n_estimators=200, model__reg_alpha=0.5, model__reg_lambda=10,
model__subsample=0.7; total time=   0.5s
[CV] END model__colsample_bytree=0.7, model__gamma=0.1,
model__learning_rate=0.05, model__max_depth=6, model__min_child_weight=5,
model__n_estimators=200, model__reg_alpha=0.5, model__reg_lambda=10,
model__subsample=0.7; total time=   0.5s
[CV] END model__colsample_bytree=0.7, model__gamma=0.1,
model__learning_rate=0.05, model__max_depth=6, model__min_child_weight=5,
model__n_estimators=200, model__reg_alpha=0.5, model__reg_lambda=10,
model__subsample=0.7; total time=   0.5s
[CV] END model__colsample_bytree=0.7, model__gamma=0.1,
model__learning_rate=0.05, model__max_depth=6, model__min_child_weight=5,
model__n_estimators=200, model__reg_alpha=0.5, model__reg_lambda=10,
model__subsample=0.7; total time=   0.5s
[CV] END model__colsample_bytree=0.7, model__gamma=0.1,
model__learning_rate=0.05, model__max_depth=6, model__min_child_weight=5,
model__n_estimators=200, model__reg_alpha=0.5, model__reg_lambda=10,
model__subsample=0.7; total time=   0.5s
[CV] END model__colsample_bytree=0.6, model__gamma=0, model__learning_rate=0.05,
model__max_depth=4, model__min_child_weight=5, model__n_estimators=100,
model__reg_alpha=0.1, model__reg_lambda=10, model__subsample=0.9; total time=
0.1s
[CV] END model__colsample_bytree=0.6, model__gamma=0, model__learning_rate=0.05,
model__max_depth=4, model__min_child_weight=5, model__n_estimators=100,
model__reg_alpha=0.1, model__reg_lambda=10, model__subsample=0.9; total time=
0.1s
[CV] END model__colsample_bytree=0.6, model__gamma=0, model__learning_rate=0.05,
model__max_depth=4, model__min_child_weight=5, model__n_estimators=100,
model__reg_alpha=0.1, model__reg_lambda=10, model__subsample=0.9; total time=
0.1s
[CV] END model__colsample_bytree=0.6, model__gamma=0, model__learning_rate=0.05,
model__max_depth=4, model__min_child_weight=5, model__n_estimators=100,
model__reg_alpha=0.1, model__reg_lambda=10, model__subsample=0.9; total time=
0.1s
[CV] END model__colsample_bytree=0.6, model__gamma=0, model__learning_rate=0.05,
model__max_depth=4, model__min_child_weight=5, model__n_estimators=100,
model__reg_alpha=0.1, model__reg_lambda=10, model__subsample=0.9; total time=
0.1s
[CV] END model__colsample_bytree=0.8, model__gamma=0, model__learning_rate=0.1,
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model__reg_alpha=5.0, model__reg_lambda=5, model__subsample=0.9; total time=
0.5s
[CV] END model__colsample_bytree=0.8, model__gamma=0, model__learning_rate=0.1,
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```

```
model__reg_alpha=5.0, model__reg_lambda=5, model__subsample=0.9; total time=
0.6s
[CV] END model__colsample_bytree=0.8, model__gamma=0, model__learning_rate=0.1,
model__max_depth=6, model__min_child_weight=5, model__n_estimators=200,
model__reg_alpha=5.0, model__reg_lambda=5, model__subsample=0.9; total time=
0.5s
[CV] END model__colsample_bytree=0.8, model__gamma=0, model__learning_rate=0.1,
model__max_depth=6, model__min_child_weight=5, model__n_estimators=200,
model__reg_alpha=5.0, model__reg_lambda=5, model__subsample=0.9; total time=
0.5s
[CV] END model__colsample_bytree=0.8, model__gamma=0, model__learning_rate=0.1,
model__max_depth=6, model__min_child_weight=5, model__n_estimators=200,
model__reg_alpha=5.0, model__reg_lambda=5, model__subsample=0.9; total time=
0.5s
[CV] END model__colsample_bytree=0.7, model__gamma=0.3,
model__learning_rate=0.05, model__max_depth=3, model__min_child_weight=7,
model__n_estimators=200, model__reg_alpha=0.1, model__reg_lambda=5,
model__subsample=0.7; total time=   0.2s
[CV] END model__colsample_bytree=0.7, model__gamma=0.3,
model__learning_rate=0.05, model__max_depth=3, model__min_child_weight=7,
model__n_estimators=200, model__reg_alpha=0.1, model__reg_lambda=5,
model__subsample=0.7; total time=   0.2s
[CV] END model__colsample_bytree=0.7, model__gamma=0.3,
model__learning_rate=0.05, model__max_depth=3, model__min_child_weight=7,
model__n_estimators=200, model__reg_alpha=0.1, model__reg_lambda=5,
model__subsample=0.7; total time=   0.2s
[CV] END model__colsample_bytree=0.7, model__gamma=0.3,
model__learning_rate=0.05, model__max_depth=3, model__min_child_weight=7,
model__n_estimators=200, model__reg_alpha=0.1, model__reg_lambda=5,
model__subsample=0.7; total time=   0.2s
[CV] END model__colsample_bytree=0.7, model__gamma=0.3,
model__learning_rate=0.05, model__max_depth=3, model__min_child_weight=7,
model__n_estimators=200, model__reg_alpha=0.1, model__reg_lambda=5,
model__subsample=0.7; total time=   0.2s
[CV] END model__colsample_bytree=0.9, model__gamma=0.1,
model__learning_rate=0.1, model__max_depth=5, model__min_child_weight=3,
model__n_estimators=300, model__reg_alpha=0, model__reg_lambda=2,
model__subsample=0.7; total time=   0.6s
[CV] END model__colsample_bytree=0.9, model__gamma=0.1,
model__learning_rate=0.1, model__max_depth=5, model__min_child_weight=3,
model__n_estimators=300, model__reg_alpha=0, model__reg_lambda=2,
model__subsample=0.7; total time=   0.6s
[CV] END model__colsample_bytree=0.9, model__gamma=0.1,
model__learning_rate=0.1, model__max_depth=5, model__min_child_weight=3,
model__n_estimators=300, model__reg_alpha=0, model__reg_lambda=2,
model__subsample=0.7; total time=   0.6s
[CV] END model__colsample_bytree=0.9, model__gamma=0.1,
model__learning_rate=0.1, model__max_depth=5, model__min_child_weight=3,
```

```
model__n_estimators=300, model__reg_alpha=0, model__reg_lambda=2,
model__subsample=0.7; total time=   0.6s
[CV] END model__colsample_bytree=0.9, model__gamma=0.1,
model__learning_rate=0.1, model__max_depth=5, model__min_child_weight=3,
model__n_estimators=300, model__reg_alpha=0, model__reg_lambda=2,
model__subsample=0.7; total time=   0.6s
[CV] END model__colsample_bytree=0.8, model__gamma=0.3,
model__learning_rate=0.05, model__max_depth=3, model__min_child_weight=1,
model__n_estimators=100, model__reg_alpha=1.0, model__reg_lambda=1,
model__subsample=0.6; total time=   0.1s
[CV] END model__colsample_bytree=0.8, model__gamma=0.3,
model__learning_rate=0.05, model__max_depth=3, model__min_child_weight=1,
model__n_estimators=100, model__reg_alpha=1.0, model__reg_lambda=1,
model__subsample=0.6; total time=   0.1s
[CV] END model__colsample_bytree=0.8, model__gamma=0.3,
model__learning_rate=0.05, model__max_depth=3, model__min_child_weight=1,
model__n_estimators=100, model__reg_alpha=1.0, model__reg_lambda=1,
model__subsample=0.6; total time=   0.1s
[CV] END model__colsample_bytree=0.8, model__gamma=0.3,
model__learning_rate=0.05, model__max_depth=3, model__min_child_weight=1,
model__n_estimators=100, model__reg_alpha=1.0, model__reg_lambda=1,
model__subsample=0.6; total time=   0.1s
[CV] END model__colsample_bytree=0.8, model__gamma=0.3,
model__learning_rate=0.05, model__max_depth=3, model__min_child_weight=1,
model__n_estimators=100, model__reg_alpha=1.0, model__reg_lambda=1,
model__subsample=0.6; total time=   0.1s
[CV] END model__colsample_bytree=0.9, model__gamma=0.1,
model__learning_rate=0.05, model__max_depth=6, model__min_child_weight=3,
model__n_estimators=100, model__reg_alpha=0, model__reg_lambda=5,
model__subsample=0.8; total time=   0.2s
[CV] END model__colsample_bytree=0.9, model__gamma=0.1,
model__learning_rate=0.05, model__max_depth=6, model__min_child_weight=3,
model__n_estimators=100, model__reg_alpha=0, model__reg_lambda=5,
model__subsample=0.8; total time=   0.2s
[CV] END model__colsample_bytree=0.9, model__gamma=0.1,
model__learning_rate=0.05, model__max_depth=6, model__min_child_weight=3,
model__n_estimators=100, model__reg_alpha=0, model__reg_lambda=5,
model__subsample=0.8; total time=   0.3s
[CV] END model__colsample_bytree=0.9, model__gamma=0.1,
model__learning_rate=0.05, model__max_depth=6, model__min_child_weight=3,
model__n_estimators=100, model__reg_alpha=0, model__reg_lambda=5,
model__subsample=0.8; total time=   0.2s
[CV] END model__colsample_bytree=0.9, model__gamma=0.1,
model__learning_rate=0.05, model__max_depth=6, model__min_child_weight=3,
model__n_estimators=100, model__reg_alpha=0, model__reg_lambda=5,
model__subsample=0.8; total time=   0.2s
[CV] END model__colsample_bytree=0.7, model__gamma=0.3,
model__learning_rate=0.01, model__max_depth=6, model__min_child_weight=7,
```

```
model__n_estimators=300, model__reg_alpha=5.0, model__reg_lambda=10,
model__subsample=0.8; total time=   0.8s
[CV] END model__colsample_bytree=0.7, model__gamma=0.3,
model__learning_rate=0.01, model__max_depth=6, model__min_child_weight=7,
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model__subsample=0.8; total time=   0.7s
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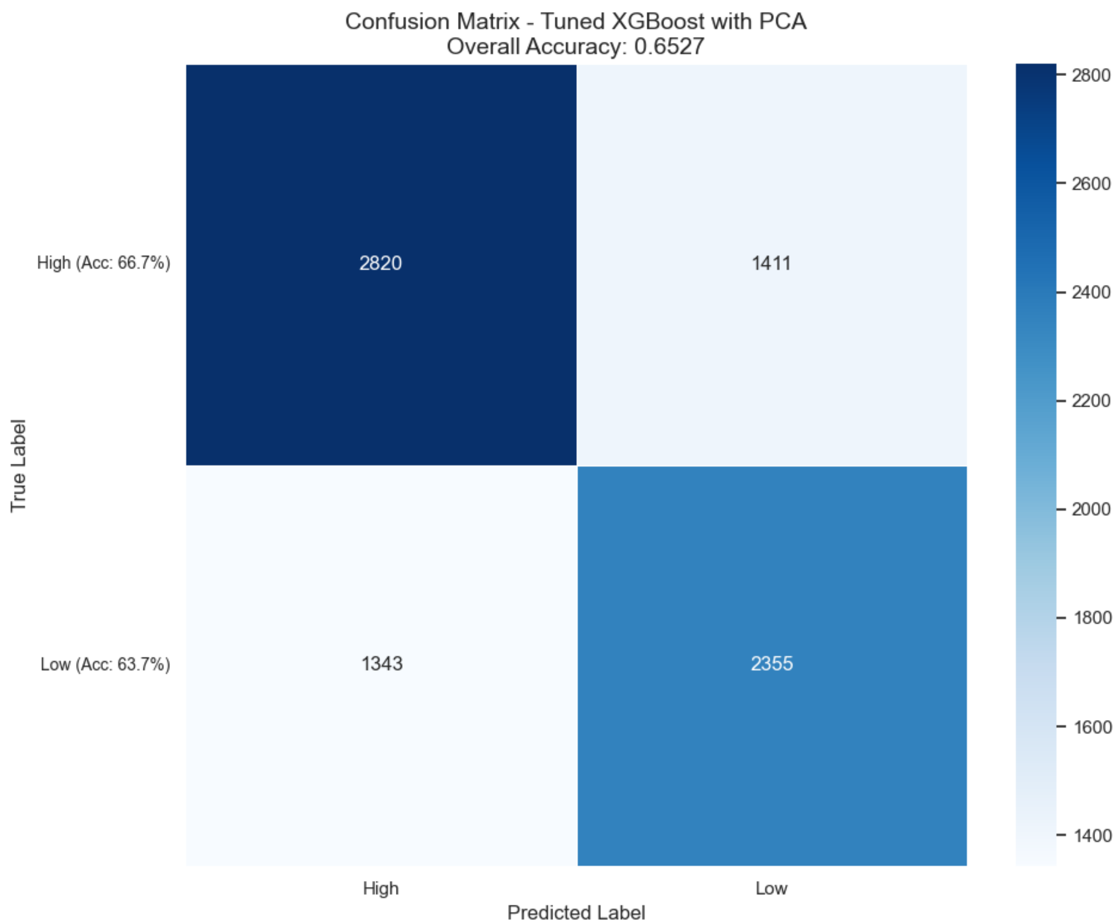
model__n_estimators=300, model__reg_alpha=5.0, model__reg_lambda=10,
model__subsample=0.8; total time=   0.8s
[CV] END model__colsample_bytree=0.7, model__gamma=0.3,
model__learning_rate=0.01, model__max_depth=6, model__min_child_weight=7,
model__n_estimators=300, model__reg_alpha=5.0, model__reg_lambda=10,
model__subsample=0.8; total time=   0.8s
[CV] END model__colsample_bytree=0.7, model__gamma=0.3,
model__learning_rate=0.01, model__max_depth=6, model__min_child_weight=7,
model__n_estimators=300, model__reg_alpha=5.0, model__reg_lambda=10,
model__subsample=0.8; total time=   0.8s
[CV] END model__colsample_bytree=0.8, model__gamma=0.2,
model__learning_rate=0.05, model__max_depth=6, model__min_child_weight=5,
model__n_estimators=200, model__reg_alpha=1.0, model__reg_lambda=5,
model__subsample=0.7; total time=   0.5s
[CV] END model__colsample_bytree=0.8, model__gamma=0.2,
model__learning_rate=0.05, model__max_depth=6, model__min_child_weight=5,
model__n_estimators=200, model__reg_alpha=1.0, model__reg_lambda=5,
model__subsample=0.7; total time=   0.5s
[CV] END model__colsample_bytree=0.8, model__gamma=0.2,
model__learning_rate=0.05, model__max_depth=6, model__min_child_weight=5,
model__n_estimators=200, model__reg_alpha=1.0, model__reg_lambda=5,
model__subsample=0.7; total time=   0.5s
[CV] END model__colsample_bytree=0.8, model__gamma=0.2,
model__learning_rate=0.05, model__max_depth=6, model__min_child_weight=5,
model__n_estimators=200, model__reg_alpha=1.0, model__reg_lambda=5,
model__subsample=0.7; total time=   0.5s
[CV] END model__colsample_bytree=0.8, model__gamma=0.2,
model__learning_rate=0.05, model__max_depth=6, model__min_child_weight=5,
model__n_estimators=200, model__reg_alpha=1.0, model__reg_lambda=5,
model__subsample=0.7; total time=   0.5s
[CV] END model__colsample_bytree=0.9, model__gamma=0, model__learning_rate=0.1,
model__max_depth=6, model__min_child_weight=5, model__n_estimators=300,
model__reg_alpha=1.0, model__reg_lambda=10, model__subsample=0.9; total time=
0.8s
[CV] END model__colsample_bytree=0.9, model__gamma=0, model__learning_rate=0.1,
model__max_depth=6, model__min_child_weight=5, model__n_estimators=300,
model__reg_alpha=1.0, model__reg_lambda=10, model__subsample=0.9; total time=
0.8s
[CV] END model__colsample_bytree=0.9, model__gamma=0, model__learning_rate=0.1,
model__max_depth=6, model__min_child_weight=5, model__n_estimators=300,
```

```
model__reg_alpha=1.0, model__reg_lambda=10, model__subsample=0.9; total time=
0.8s
[CV] END model__colsample_bytree=0.9, model__gamma=0, model__learning_rate=0.1,
model__max_depth=6, model__min_child_weight=5, model__n_estimators=300,
model__reg_alpha=1.0, model__reg_lambda=10, model__subsample=0.9; total time=
0.8s
[CV] END model__colsample_bytree=0.9, model__gamma=0, model__learning_rate=0.1,
model__max_depth=6, model__min_child_weight=5, model__n_estimators=300,
model__reg_alpha=1.0, model__reg_lambda=10, model__subsample=0.9; total time=
0.8s
[CV] END model__colsample_bytree=0.8, model__gamma=0.3,
model__learning_rate=0.01, model__max_depth=6, model__min_child_weight=7,
model__n_estimators=300, model__reg_alpha=0.5, model__reg_lambda=5,
model__subsample=0.9; total time=   0.8s
[CV] END model__colsample_bytree=0.8, model__gamma=0.3,
model__learning_rate=0.01, model__max_depth=6, model__min_child_weight=7,
model__n_estimators=300, model__reg_alpha=0.5, model__reg_lambda=5,
model__subsample=0.9; total time=   0.8s
[CV] END model__colsample_bytree=0.8, model__gamma=0.3,
model__learning_rate=0.01, model__max_depth=6, model__min_child_weight=7,
model__n_estimators=300, model__reg_alpha=0.5, model__reg_lambda=5,
model__subsample=0.9; total time=   0.8s
[CV] END model__colsample_bytree=0.8, model__gamma=0.3,
model__learning_rate=0.01, model__max_depth=6, model__min_child_weight=7,
model__n_estimators=300, model__reg_alpha=0.5, model__reg_lambda=5,
model__subsample=0.9; total time=   0.8s
[CV] END model__colsample_bytree=0.8, model__gamma=0.3,
model__learning_rate=0.01, model__max_depth=6, model__min_child_weight=7,
model__n_estimators=300, model__reg_alpha=0.5, model__reg_lambda=5,
model__subsample=0.9; total time=   0.8s

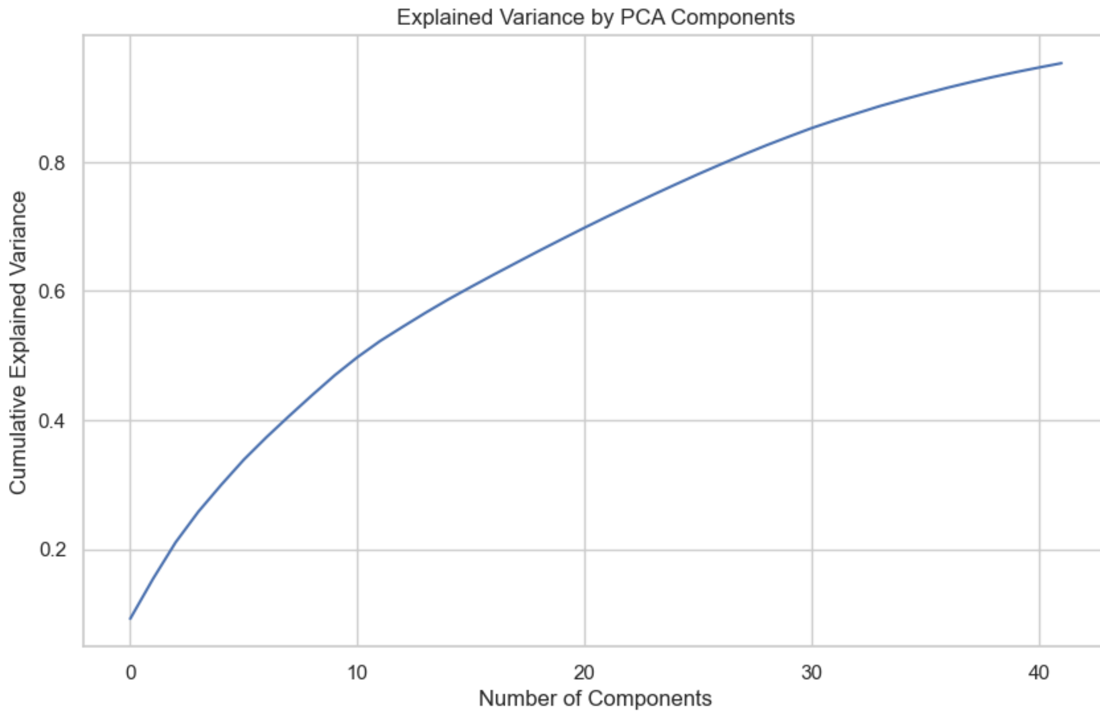
Best XGBoost with PCA parameters: {'model__subsample': 0.8, 'model__reg_lambda':
5, 'model__reg_alpha': 1.0, 'model__n_estimators': 200,
'model__min_child_weight': 1, 'model__max_depth': 6, 'model__learning_rate':
0.05, 'model__gamma': 0.3, 'model__colsample_bytree': 0.7}
Best XGBoost with PCA CV accuracy: 0.6546
Tuned XGBoost with PCA test accuracy: 0.6527
Tuned XGBoost with PCA test F1 score: 0.6528
```



Detailed Classification Metrics:

	Class	Precision	Recall	F1-Score	Support
0	High	67.7%	66.7%	67.2%	4231
1	Low	62.5%	63.7%	63.1%	3698

Number of PCA components in best model: 42



[52]:
```
#--------------------
# LightGBM with PCA feature selection to reduce overfitting
#--------------------
print("\n" + "="*50)
print("Performing LightGBM with PCA feature selection to reduce overfitting...")

# Create the LightGBM pipeline with PCA
lgbm_pca_pipeline = Pipeline([
    ('scaler', StandardScaler()),
    ('pca', PCA(n_components=0.95)),  # Keep components that explain 95% of␣
↪variance
    ('model', lgb.LGBMClassifier(
        objective='multiclass',
        num_class=len(np.unique(y_train)),
        random_state=42,
        verbose=-1
    ))
])

# Define parameter grid focused on reducing overfitting
lgbm_param_grid = {
    'model__n_estimators': [100, 200, 300],
    'model__learning_rate': [0.01, 0.05, 0.1],
```

```python
    'model__max_depth': [3, 4, 5, 6],
    'model__num_leaves': [15, 31, 63, 127],
    'model__min_child_samples': [5, 10, 20, 50],
    'model__subsample': [0.6, 0.7, 0.8, 0.9],
    'model__colsample_bytree': [0.6, 0.7, 0.8, 0.9],
    'model__reg_alpha': [0, 0.1, 0.5, 1.0],
    'model__reg_lambda': [0, 0.1, 0.5, 1.0]
}

# Memory optimization: Use a smaller subset if dataset is large
X_sample, y_sample = X_train_resampled, y_train_resampled
if len(X_train_resampled) > 10000:
    print("Using a random subset of 10,000 samples for LightGBM with PCA␣
 ↪tuning")
    sample_indices = np.random.choice(len(X_train_resampled), size=10000,␣
 ↪replace=False)
    X_sample = X_train_resampled.iloc[sample_indices] if␣
 ↪hasattr(X_train_resampled, 'iloc') else X_train_resampled[sample_indices]
    y_sample = y_train_resampled[sample_indices]

# Define the randomized search
lgbm_pca_search = RandomizedSearchCV(
    lgbm_pca_pipeline,
    param_distributions=lgbm_param_grid,
    n_iter=30,  # Try 30 random combinations
    cv=StratifiedKFold(n_splits=5),
    scoring='accuracy',
    n_jobs=1,  # Use single job for memory efficiency
    verbose=2,
    random_state=42
)

# Fit the randomized search
print("Fitting LightGBM with PCA using randomized search...")
lgbm_pca_search.fit(X_sample, y_sample)

# Print best parameters and score
print(f"\nBest LightGBM with PCA parameters: {lgbm_pca_search.best_params_}")
print(f"Best LightGBM with PCA CV accuracy: {lgbm_pca_search.best_score_:.4f}")

# Evaluate tuned LightGBM on test set
lgbm_pca_tuned_pred = lgbm_pca_search.predict(X_test)
lgbm_pca_tuned_accuracy = accuracy_score(y_test, lgbm_pca_tuned_pred)
lgbm_pca_tuned_f1 = f1_score(y_test, lgbm_pca_tuned_pred, average='weighted')

print(f"Tuned LightGBM with PCA test accuracy: {lgbm_pca_tuned_accuracy:.4f}")
print(f"Tuned LightGBM with PCA test F1 score: {lgbm_pca_tuned_f1:.4f}")
```

```
# Plot confusion matrix for tuned LightGBM with PCA
plot_confusion_matrix(y_test, lgbm_pca_tuned_pred, title='Confusion Matrix -␣
↪Tuned LightGBM with PCA')

# Add tuned model to results
results['Tuned LightGBM with PCA'] = {
    'cv_mean': lgbm_pca_search.best_score_,
    'cv_std': 0,
    'test_accuracy': lgbm_pca_tuned_accuracy,
    'test_f1': lgbm_pca_tuned_f1,
    'model': lgbm_pca_search.best_estimator_,
    'predictions': lgbm_pca_tuned_pred
}

# Get the number of components used in the best model
best_n_components = lgbm_pca_search.best_estimator_.named_steps['pca'].
↪n_components_
print(f"Number of PCA components in best model: {best_n_components}")

# Optional: Visualize explained variance ratio
pca = lgbm_pca_search.best_estimator_.named_steps['pca']
plt.figure(figsize=(10, 6))
plt.plot(np.cumsum(pca.explained_variance_ratio_))
plt.xlabel('Number of Components')
plt.ylabel('Cumulative Explained Variance')
plt.title('Explained Variance by PCA Components')
plt.grid(True)
plt.show()
```

```
==================================================
Performing LightGBM with PCA feature selection to reduce overfitting…
Using a random subset of 10,000 samples for LightGBM with PCA tuning
Fitting LightGBM with PCA using randomized search…
Fitting 5 folds for each of 30 candidates, totalling 150 fits
[CV] END model__colsample_bytree=0.9, model__learning_rate=0.01,
model__max_depth=6, model__min_child_samples=20, model__n_estimators=300,
model__num_leaves=31, model__reg_alpha=0.5, model__reg_lambda=0.1,
model__subsample=0.8; total time=   0.3s
[CV] END model__colsample_bytree=0.9, model__learning_rate=0.01,
model__max_depth=6, model__min_child_samples=20, model__n_estimators=300,
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model__subsample=0.8; total time=   0.3s
[CV] END model__colsample_bytree=0.9, model__learning_rate=0.01,
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```

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[CV] END model__colsample_bytree=0.9, model__learning_rate=0.1,
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model__subsample=0.6; total time=   0.2s
[CV] END model__colsample_bytree=0.9, model__learning_rate=0.05,
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model__subsample=0.6; total time=   0.2s
[CV] END model__colsample_bytree=0.9, model__learning_rate=0.05,
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[CV] END model__colsample_bytree=0.9, model__learning_rate=0.05,
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```

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[CV] END model__colsample_bytree=0.8, model__learning_rate=0.1,
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[CV] END model__colsample_bytree=0.8, model__learning_rate=0.1,
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[CV] END model__colsample_bytree=0.9, model__learning_rate=0.01,
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[CV] END model__colsample_bytree=0.9, model__learning_rate=0.01,
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```

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[CV] END model__colsample_bytree=0.8, model__learning_rate=0.1,
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```

```
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```
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```

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[CV] END model__colsample_bytree=0.6, model__learning_rate=0.01,
model__max_depth=3, model__min_child_samples=10, model__n_estimators=100,
model__num_leaves=15, model__reg_alpha=0, model__reg_lambda=0,
model__subsample=0.7; total time=   0.0s
[CV] END model__colsample_bytree=0.6, model__learning_rate=0.01,
model__max_depth=3, model__min_child_samples=10, model__n_estimators=100,
model__num_leaves=15, model__reg_alpha=0, model__reg_lambda=0,
model__subsample=0.7; total time=   0.0s
[CV] END model__colsample_bytree=0.6, model__learning_rate=0.01,
model__max_depth=3, model__min_child_samples=10, model__n_estimators=100,
model__num_leaves=15, model__reg_alpha=0, model__reg_lambda=0,
model__subsample=0.7; total time=   0.0s
[CV] END model__colsample_bytree=0.6, model__learning_rate=0.01,
model__max_depth=3, model__min_child_samples=10, model__n_estimators=100,
model__num_leaves=15, model__reg_alpha=0, model__reg_lambda=0,
model__subsample=0.7; total time=   0.0s
[CV] END model__colsample_bytree=0.7, model__learning_rate=0.05,
model__max_depth=6, model__min_child_samples=10, model__n_estimators=300,
model__num_leaves=31, model__reg_alpha=0.1, model__reg_lambda=0.1,
model__subsample=0.9; total time=   0.3s
[CV] END model__colsample_bytree=0.7, model__learning_rate=0.05,
model__max_depth=6, model__min_child_samples=10, model__n_estimators=300,
model__num_leaves=31, model__reg_alpha=0.1, model__reg_lambda=0.1,
model__subsample=0.9; total time=   0.3s
[CV] END model__colsample_bytree=0.7, model__learning_rate=0.05,
model__max_depth=6, model__min_child_samples=10, model__n_estimators=300,
model__num_leaves=31, model__reg_alpha=0.1, model__reg_lambda=0.1,
model__subsample=0.9; total time=   0.3s
[CV] END model__colsample_bytree=0.7, model__learning_rate=0.05,
model__max_depth=6, model__min_child_samples=10, model__n_estimators=300,
model__num_leaves=31, model__reg_alpha=0.1, model__reg_lambda=0.1,
model__subsample=0.9; total time=   0.3s
[CV] END model__colsample_bytree=0.7, model__learning_rate=0.05,
model__max_depth=6, model__min_child_samples=10, model__n_estimators=300,
model__num_leaves=31, model__reg_alpha=0.1, model__reg_lambda=0.1,
model__subsample=0.9; total time=   0.3s
[CV] END model__colsample_bytree=0.7, model__learning_rate=0.1,
model__max_depth=4, model__min_child_samples=5, model__n_estimators=200,
model__num_leaves=63, model__reg_alpha=0.1, model__reg_lambda=1.0,
model__subsample=0.7; total time=   0.1s
[CV] END model__colsample_bytree=0.7, model__learning_rate=0.1,
model__max_depth=4, model__min_child_samples=5, model__n_estimators=200,
model__num_leaves=63, model__reg_alpha=0.1, model__reg_lambda=1.0,
```

```
model__subsample=0.7; total time=   0.1s
[CV] END model__colsample_bytree=0.7, model__learning_rate=0.1,
model__max_depth=4, model__min_child_samples=5, model__n_estimators=200,
model__num_leaves=63, model__reg_alpha=0.1, model__reg_lambda=1.0,
model__subsample=0.7; total time=   0.1s
[CV] END model__colsample_bytree=0.7, model__learning_rate=0.1,
model__max_depth=4, model__min_child_samples=5, model__n_estimators=200,
model__num_leaves=63, model__reg_alpha=0.1, model__reg_lambda=1.0,
model__subsample=0.7; total time=   0.1s
[CV] END model__colsample_bytree=0.7, model__learning_rate=0.1,
model__max_depth=4, model__min_child_samples=5, model__n_estimators=200,
model__num_leaves=63, model__reg_alpha=0.1, model__reg_lambda=1.0,
model__subsample=0.7; total time=   0.1s
[CV] END model__colsample_bytree=0.6, model__learning_rate=0.01,
model__max_depth=4, model__min_child_samples=20, model__n_estimators=300,
model__num_leaves=63, model__reg_alpha=1.0, model__reg_lambda=1.0,
model__subsample=0.9; total time=   0.1s
[CV] END model__colsample_bytree=0.6, model__learning_rate=0.01,
model__max_depth=4, model__min_child_samples=20, model__n_estimators=300,
model__num_leaves=63, model__reg_alpha=1.0, model__reg_lambda=1.0,
model__subsample=0.9; total time=   0.1s
[CV] END model__colsample_bytree=0.6, model__learning_rate=0.01,
model__max_depth=4, model__min_child_samples=20, model__n_estimators=300,
model__num_leaves=63, model__reg_alpha=1.0, model__reg_lambda=1.0,
model__subsample=0.9; total time=   0.1s
[CV] END model__colsample_bytree=0.6, model__learning_rate=0.01,
model__max_depth=4, model__min_child_samples=20, model__n_estimators=300,
model__num_leaves=63, model__reg_alpha=1.0, model__reg_lambda=1.0,
model__subsample=0.9; total time=   0.1s
[CV] END model__colsample_bytree=0.6, model__learning_rate=0.01,
model__max_depth=4, model__min_child_samples=20, model__n_estimators=300,
model__num_leaves=63, model__reg_alpha=1.0, model__reg_lambda=1.0,
model__subsample=0.9; total time=   0.1s
[CV] END model__colsample_bytree=0.8, model__learning_rate=0.1,
model__max_depth=4, model__min_child_samples=20, model__n_estimators=200,
model__num_leaves=63, model__reg_alpha=1.0, model__reg_lambda=0.5,
model__subsample=0.9; total time=   0.1s
[CV] END model__colsample_bytree=0.8, model__learning_rate=0.1,
model__max_depth=4, model__min_child_samples=20, model__n_estimators=200,
model__num_leaves=63, model__reg_alpha=1.0, model__reg_lambda=0.5,
model__subsample=0.9; total time=   0.0s
[CV] END model__colsample_bytree=0.8, model__learning_rate=0.1,
model__max_depth=4, model__min_child_samples=20, model__n_estimators=200,
model__num_leaves=63, model__reg_alpha=1.0, model__reg_lambda=0.5,
model__subsample=0.9; total time=   0.1s
[CV] END model__colsample_bytree=0.8, model__learning_rate=0.1,
model__max_depth=4, model__min_child_samples=20, model__n_estimators=200,
model__num_leaves=63, model__reg_alpha=1.0, model__reg_lambda=0.5,
```

```
model__subsample=0.9; total time=   0.0s
[CV] END model__colsample_bytree=0.8, model__learning_rate=0.1,
model__max_depth=4, model__min_child_samples=20, model__n_estimators=200,
model__num_leaves=63, model__reg_alpha=1.0, model__reg_lambda=0.5,
model__subsample=0.9; total time=   0.1s
[CV] END model__colsample_bytree=0.8, model__learning_rate=0.01,
model__max_depth=6, model__min_child_samples=50, model__n_estimators=100,
model__num_leaves=15, model__reg_alpha=1.0, model__reg_lambda=0.5,
model__subsample=0.7; total time=   0.0s
[CV] END model__colsample_bytree=0.8, model__learning_rate=0.01,
model__max_depth=6, model__min_child_samples=50, model__n_estimators=100,
model__num_leaves=15, model__reg_alpha=1.0, model__reg_lambda=0.5,
model__subsample=0.7; total time=   0.0s
[CV] END model__colsample_bytree=0.8, model__learning_rate=0.01,
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model__num_leaves=15, model__reg_alpha=1.0, model__reg_lambda=0.5,
model__subsample=0.7; total time=   0.0s
[CV] END model__colsample_bytree=0.8, model__learning_rate=0.01,
model__max_depth=6, model__min_child_samples=50, model__n_estimators=100,
model__num_leaves=15, model__reg_alpha=1.0, model__reg_lambda=0.5,
model__subsample=0.7; total time=   0.0s
[CV] END model__colsample_bytree=0.8, model__learning_rate=0.01,
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model__num_leaves=15, model__reg_alpha=1.0, model__reg_lambda=0.5,
model__subsample=0.7; total time=   0.0s
[CV] END model__colsample_bytree=0.9, model__learning_rate=0.05,
model__max_depth=5, model__min_child_samples=20, model__n_estimators=100,
model__num_leaves=15, model__reg_alpha=1.0, model__reg_lambda=0,
model__subsample=0.6; total time=   0.0s
[CV] END model__colsample_bytree=0.9, model__learning_rate=0.05,
model__max_depth=5, model__min_child_samples=20, model__n_estimators=100,
model__num_leaves=15, model__reg_alpha=1.0, model__reg_lambda=0,
model__subsample=0.6; total time=   0.0s
[CV] END model__colsample_bytree=0.9, model__learning_rate=0.05,
model__max_depth=5, model__min_child_samples=20, model__n_estimators=100,
model__num_leaves=15, model__reg_alpha=1.0, model__reg_lambda=0,
model__subsample=0.6; total time=   0.0s
[CV] END model__colsample_bytree=0.9, model__learning_rate=0.05,
model__max_depth=5, model__min_child_samples=20, model__n_estimators=100,
model__num_leaves=15, model__reg_alpha=1.0, model__reg_lambda=0,
model__subsample=0.6; total time=   0.0s
[CV] END model__colsample_bytree=0.9, model__learning_rate=0.05,
model__max_depth=5, model__min_child_samples=20, model__n_estimators=100,
model__num_leaves=15, model__reg_alpha=1.0, model__reg_lambda=0,
model__subsample=0.6; total time=   0.0s
[CV] END model__colsample_bytree=0.8, model__learning_rate=0.01,
model__max_depth=6, model__min_child_samples=10, model__n_estimators=300,
model__num_leaves=127, model__reg_alpha=1.0, model__reg_lambda=1.0,
```

```
model__subsample=0.8; total time=   0.4s
[CV] END model__colsample_bytree=0.8, model__learning_rate=0.01,
model__max_depth=6, model__min_child_samples=10, model__n_estimators=300,
model__num_leaves=127, model__reg_alpha=1.0, model__reg_lambda=1.0,
model__subsample=0.8; total time=   0.4s
[CV] END model__colsample_bytree=0.8, model__learning_rate=0.01,
model__max_depth=6, model__min_child_samples=10, model__n_estimators=300,
model__num_leaves=127, model__reg_alpha=1.0, model__reg_lambda=1.0,
model__subsample=0.8; total time=   0.4s
[CV] END model__colsample_bytree=0.8, model__learning_rate=0.01,
model__max_depth=6, model__min_child_samples=10, model__n_estimators=300,
model__num_leaves=127, model__reg_alpha=1.0, model__reg_lambda=1.0,
model__subsample=0.8; total time=   0.4s
[CV] END model__colsample_bytree=0.8, model__learning_rate=0.01,
model__max_depth=6, model__min_child_samples=10, model__n_estimators=300,
model__num_leaves=127, model__reg_alpha=1.0, model__reg_lambda=1.0,
model__subsample=0.8; total time=   0.4s
[CV] END model__colsample_bytree=0.9, model__learning_rate=0.01,
model__max_depth=6, model__min_child_samples=50, model__n_estimators=200,
model__num_leaves=63, model__reg_alpha=0.5, model__reg_lambda=0.5,
model__subsample=0.7; total time=   0.2s
[CV] END model__colsample_bytree=0.9, model__learning_rate=0.01,
model__max_depth=6, model__min_child_samples=50, model__n_estimators=200,
model__num_leaves=63, model__reg_alpha=0.5, model__reg_lambda=0.5,
model__subsample=0.7; total time=   0.2s
[CV] END model__colsample_bytree=0.9, model__learning_rate=0.01,
model__max_depth=6, model__min_child_samples=50, model__n_estimators=200,
model__num_leaves=63, model__reg_alpha=0.5, model__reg_lambda=0.5,
model__subsample=0.7; total time=   0.2s
[CV] END model__colsample_bytree=0.9, model__learning_rate=0.01,
model__max_depth=6, model__min_child_samples=50, model__n_estimators=200,
model__num_leaves=63, model__reg_alpha=0.5, model__reg_lambda=0.5,
model__subsample=0.7; total time=   0.2s
[CV] END model__colsample_bytree=0.9, model__learning_rate=0.01,
model__max_depth=6, model__min_child_samples=50, model__n_estimators=200,
model__num_leaves=63, model__reg_alpha=0.5, model__reg_lambda=0.5,
model__subsample=0.7; total time=   0.2s
[CV] END model__colsample_bytree=0.9, model__learning_rate=0.05,
model__max_depth=5, model__min_child_samples=10, model__n_estimators=300,
model__num_leaves=127, model__reg_alpha=0.1, model__reg_lambda=0.5,
model__subsample=0.9; total time=   0.2s
[CV] END model__colsample_bytree=0.9, model__learning_rate=0.05,
model__max_depth=5, model__min_child_samples=10, model__n_estimators=300,
model__num_leaves=127, model__reg_alpha=0.1, model__reg_lambda=0.5,
model__subsample=0.9; total time=   0.2s
[CV] END model__colsample_bytree=0.9, model__learning_rate=0.05,
model__max_depth=5, model__min_child_samples=10, model__n_estimators=300,
model__num_leaves=127, model__reg_alpha=0.1, model__reg_lambda=0.5,
```

```
model__subsample=0.9; total time=   0.2s
[CV] END model__colsample_bytree=0.9, model__learning_rate=0.05,
model__max_depth=5, model__min_child_samples=10, model__n_estimators=300,
model__num_leaves=127, model__reg_alpha=0.1, model__reg_lambda=0.5,
model__subsample=0.9; total time=   0.2s
[CV] END model__colsample_bytree=0.9, model__learning_rate=0.05,
model__max_depth=5, model__min_child_samples=10, model__n_estimators=300,
model__num_leaves=127, model__reg_alpha=0.1, model__reg_lambda=0.5,
model__subsample=0.9; total time=   0.2s
[CV] END model__colsample_bytree=0.6, model__learning_rate=0.01,
model__max_depth=3, model__min_child_samples=50, model__n_estimators=200,
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model__subsample=0.9; total time=   0.0s
[CV] END model__colsample_bytree=0.6, model__learning_rate=0.01,
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model__subsample=0.9; total time=   0.0s
[CV] END model__colsample_bytree=0.6, model__learning_rate=0.01,
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model__num_leaves=63, model__reg_alpha=1.0, model__reg_lambda=0.5,
model__subsample=0.9; total time=   0.0s
[CV] END model__colsample_bytree=0.6, model__learning_rate=0.01,
model__max_depth=3, model__min_child_samples=50, model__n_estimators=200,
model__num_leaves=63, model__reg_alpha=1.0, model__reg_lambda=0.5,
model__subsample=0.9; total time=   0.0s
[CV] END model__colsample_bytree=0.6, model__learning_rate=0.01,
model__max_depth=3, model__min_child_samples=50, model__n_estimators=200,
model__num_leaves=63, model__reg_alpha=1.0, model__reg_lambda=0.5,
model__subsample=0.9; total time=   0.0s
[CV] END model__colsample_bytree=0.9, model__learning_rate=0.05,
model__max_depth=3, model__min_child_samples=10, model__n_estimators=100,
model__num_leaves=127, model__reg_alpha=0, model__reg_lambda=1.0,
model__subsample=0.9; total time=   0.0s
[CV] END model__colsample_bytree=0.9, model__learning_rate=0.05,
model__max_depth=3, model__min_child_samples=10, model__n_estimators=100,
model__num_leaves=127, model__reg_alpha=0, model__reg_lambda=1.0,
model__subsample=0.9; total time=   0.0s
[CV] END model__colsample_bytree=0.9, model__learning_rate=0.05,
model__max_depth=3, model__min_child_samples=10, model__n_estimators=100,
model__num_leaves=127, model__reg_alpha=0, model__reg_lambda=1.0,
model__subsample=0.9; total time=   0.0s
[CV] END model__colsample_bytree=0.9, model__learning_rate=0.05,
model__max_depth=3, model__min_child_samples=10, model__n_estimators=100,
model__num_leaves=127, model__reg_alpha=0, model__reg_lambda=1.0,
model__subsample=0.9; total time=   0.0s
[CV] END model__colsample_bytree=0.9, model__learning_rate=0.05,
model__max_depth=3, model__min_child_samples=10, model__n_estimators=100,
model__num_leaves=127, model__reg_alpha=0, model__reg_lambda=1.0,
```

```
model__subsample=0.9; total time=   0.0s
[CV] END model__colsample_bytree=0.7, model__learning_rate=0.1,
model__max_depth=4, model__min_child_samples=10, model__n_estimators=200,
model__num_leaves=63, model__reg_alpha=1.0, model__reg_lambda=1.0,
model__subsample=0.7; total time=   0.1s
[CV] END model__colsample_bytree=0.7, model__learning_rate=0.1,
model__max_depth=4, model__min_child_samples=10, model__n_estimators=200,
model__num_leaves=63, model__reg_alpha=1.0, model__reg_lambda=1.0,
model__subsample=0.7; total time=   0.1s
[CV] END model__colsample_bytree=0.7, model__learning_rate=0.1,
model__max_depth=4, model__min_child_samples=10, model__n_estimators=200,
model__num_leaves=63, model__reg_alpha=1.0, model__reg_lambda=1.0,
model__subsample=0.7; total time=   0.1s
[CV] END model__colsample_bytree=0.7, model__learning_rate=0.1,
model__max_depth=4, model__min_child_samples=10, model__n_estimators=200,
model__num_leaves=63, model__reg_alpha=1.0, model__reg_lambda=1.0,
model__subsample=0.7; total time=   0.0s
[CV] END model__colsample_bytree=0.7, model__learning_rate=0.1,
model__max_depth=4, model__min_child_samples=10, model__n_estimators=200,
model__num_leaves=63, model__reg_alpha=1.0, model__reg_lambda=1.0,
model__subsample=0.7; total time=   0.1s
[CV] END model__colsample_bytree=0.9, model__learning_rate=0.05,
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model__num_leaves=63, model__reg_alpha=1.0, model__reg_lambda=1.0,
model__subsample=0.7; total time=   0.0s
[CV] END model__colsample_bytree=0.9, model__learning_rate=0.05,
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model__subsample=0.7; total time=   0.0s
[CV] END model__colsample_bytree=0.9, model__learning_rate=0.05,
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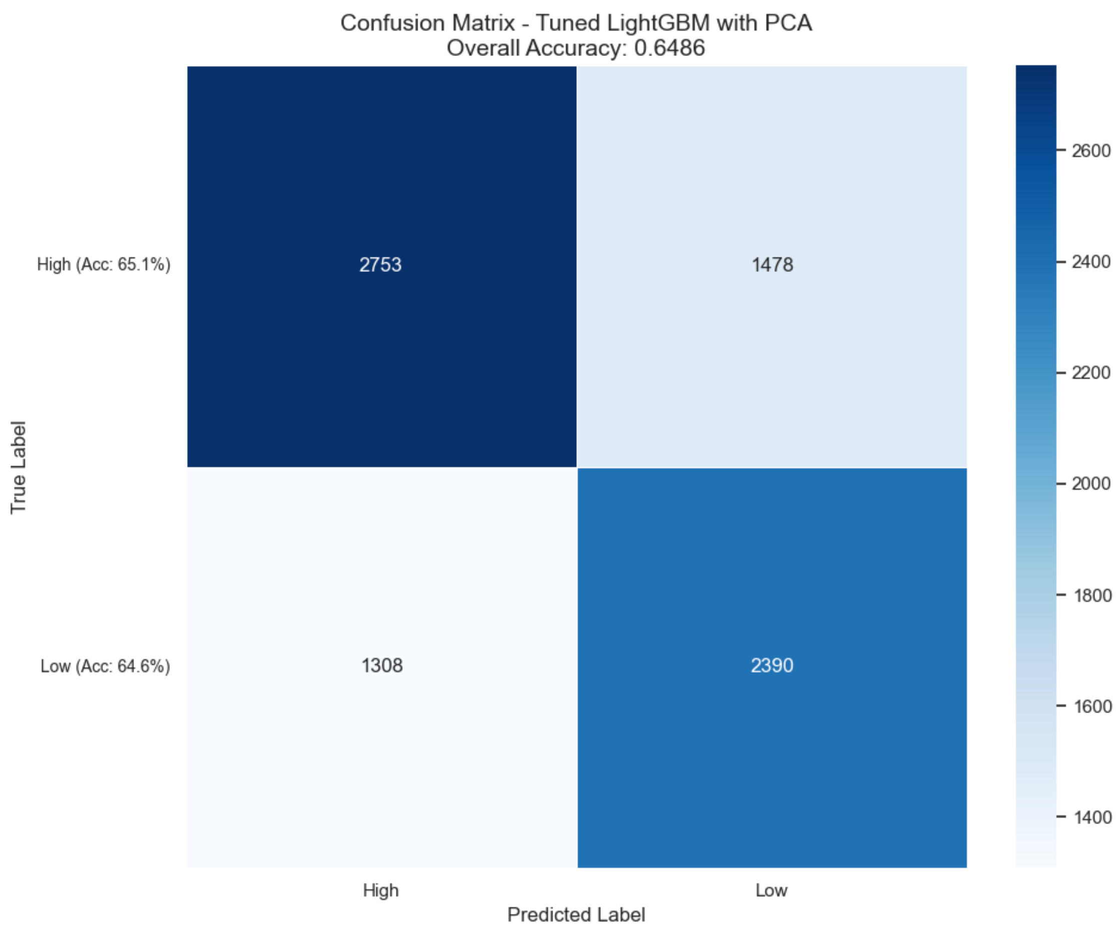
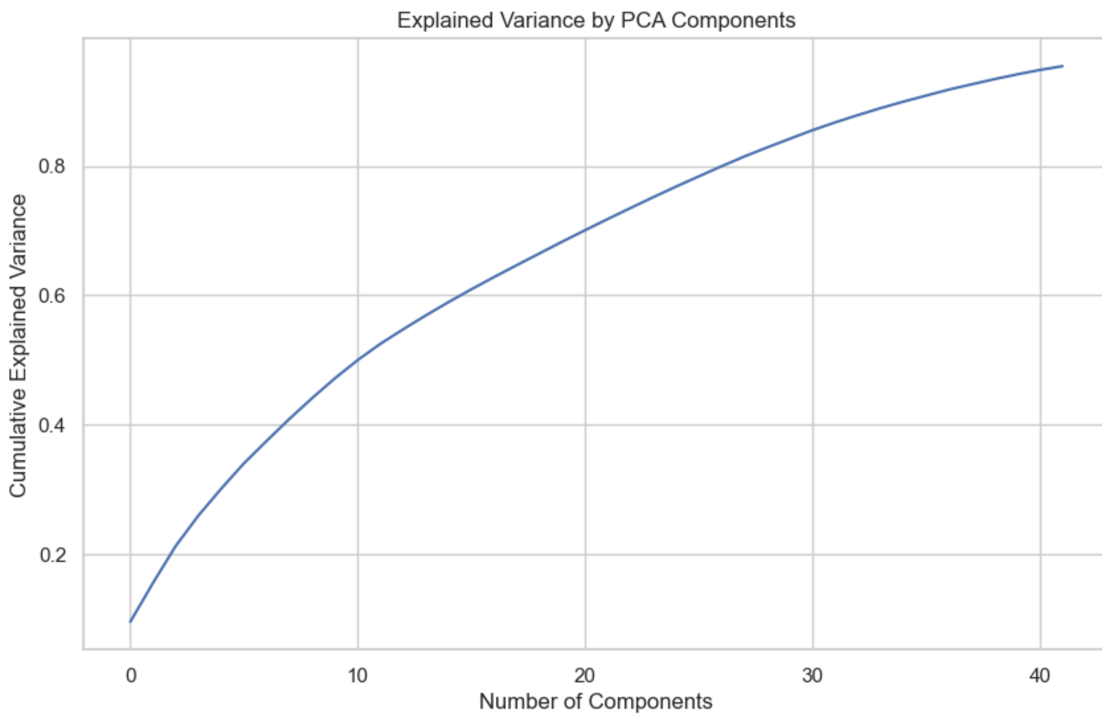
model__num_leaves=63, model__reg_alpha=1.0, model__reg_lambda=1.0,
model__subsample=0.7; total time=   0.0s
[CV] END model__colsample_bytree=0.9, model__learning_rate=0.05,
model__max_depth=5, model__min_child_samples=10, model__n_estimators=100,
model__num_leaves=63, model__reg_alpha=1.0, model__reg_lambda=1.0,
model__subsample=0.7; total time=   0.0s
[CV] END model__colsample_bytree=0.9, model__learning_rate=0.05,
model__max_depth=5, model__min_child_samples=10, model__n_estimators=100,
model__num_leaves=63, model__reg_alpha=1.0, model__reg_lambda=1.0,
model__subsample=0.7; total time=   0.0s
[CV] END model__colsample_bytree=0.8, model__learning_rate=0.01,
model__max_depth=6, model__min_child_samples=20, model__n_estimators=100,
model__num_leaves=63, model__reg_alpha=0.5, model__reg_lambda=1.0,
model__subsample=0.8; total time=   0.1s
[CV] END model__colsample_bytree=0.8, model__learning_rate=0.01,
model__max_depth=6, model__min_child_samples=20, model__n_estimators=100,
model__num_leaves=63, model__reg_alpha=0.5, model__reg_lambda=1.0,
```

```
model__subsample=0.8; total time=   0.1s
[CV] END model__colsample_bytree=0.8, model__learning_rate=0.01,
model__max_depth=6, model__min_child_samples=20, model__n_estimators=100,
model__num_leaves=63, model__reg_alpha=0.5, model__reg_lambda=1.0,
model__subsample=0.8; total time=   0.1s
[CV] END model__colsample_bytree=0.8, model__learning_rate=0.01,
model__max_depth=6, model__min_child_samples=20, model__n_estimators=100,
model__num_leaves=63, model__reg_alpha=0.5, model__reg_lambda=1.0,
model__subsample=0.8; total time=   0.1s
[CV] END model__colsample_bytree=0.8, model__learning_rate=0.01,
model__max_depth=6, model__min_child_samples=20, model__n_estimators=100,
model__num_leaves=63, model__reg_alpha=0.5, model__reg_lambda=1.0,
model__subsample=0.8; total time=   0.1s

Best LightGBM with PCA parameters: {'model__subsample': 0.6,
'model__reg_lambda': 1.0, 'model__reg_alpha': 0.1, 'model__num_leaves': 31,
'model__n_estimators': 300, 'model__min_child_samples': 50, 'model__max_depth':
5, 'model__learning_rate': 0.05, 'model__colsample_bytree': 0.9}
Best LightGBM with PCA CV accuracy: 0.6498
Tuned LightGBM with PCA test accuracy: 0.6486
Tuned LightGBM with PCA test F1 score: 0.6490
```



```
Detailed Classification Metrics:
  Class Precision Recall F1-Score  Support
0  High     67.8%  65.1%    66.4%     4231
1   Low     61.8%  64.6%    63.2%     3698
Number of PCA components in best model: 42
```



We found that the model performance got a little worse after PCA, but the runtime was significantly faster. Considering the practicality, we need to make a trade-off between time and performance for different tasks.

[53]:
```
#--------------------
# Updated Model Comparison
#--------------------
print("\n" + "="*80)
print("UPDATED MODEL COMPARISON")
print("="*80)

# Create comparison DataFrame
model_comparison = pd.DataFrame({
    'Model': list(results.keys()),
    'CV Accuracy': [results[model]['cv_mean'] for model in results],
```

```
    'Test Accuracy': [results[model]['test_accuracy'] for model in results],
    'Test F1 Score': [results[model]['test_f1'] for model in results]
})

model_comparison = model_comparison.sort_values('Test Accuracy',␣
 ↪ascending=False)
print("\nModel Comparison:")
print(model_comparison)

# Plot model comparison
plt.figure(figsize=(14, 10))
ax = sns.barplot(x='Model', y='Test Accuracy', data=model_comparison)

# Add value labels on top of bars
for i, bar in enumerate(ax.patches):
    ax.text(
        bar.get_x() + bar.get_width()/2.,
        bar.get_height() + 0.005,
        f"{bar.get_height():.4f}",
        ha='center',
        fontsize=10
    )

plt.title('Model Comparison - Test Accuracy', fontsize=14)
plt.ylim(0.4, 0.7)  # Adjust y-axis range
plt.xticks(rotation=45, ha='right')
plt.tight_layout()
plt.show()

# Plot a second graph comparing CV vs Test accuracy
plt.figure(figsize=(14, 10))

# Create a styled bar chart for CV vs Test comparison
model_names = model_comparison['Model'].tolist()
cv_acc = model_comparison['CV Accuracy'].tolist()
test_acc = model_comparison['Test Accuracy'].tolist()

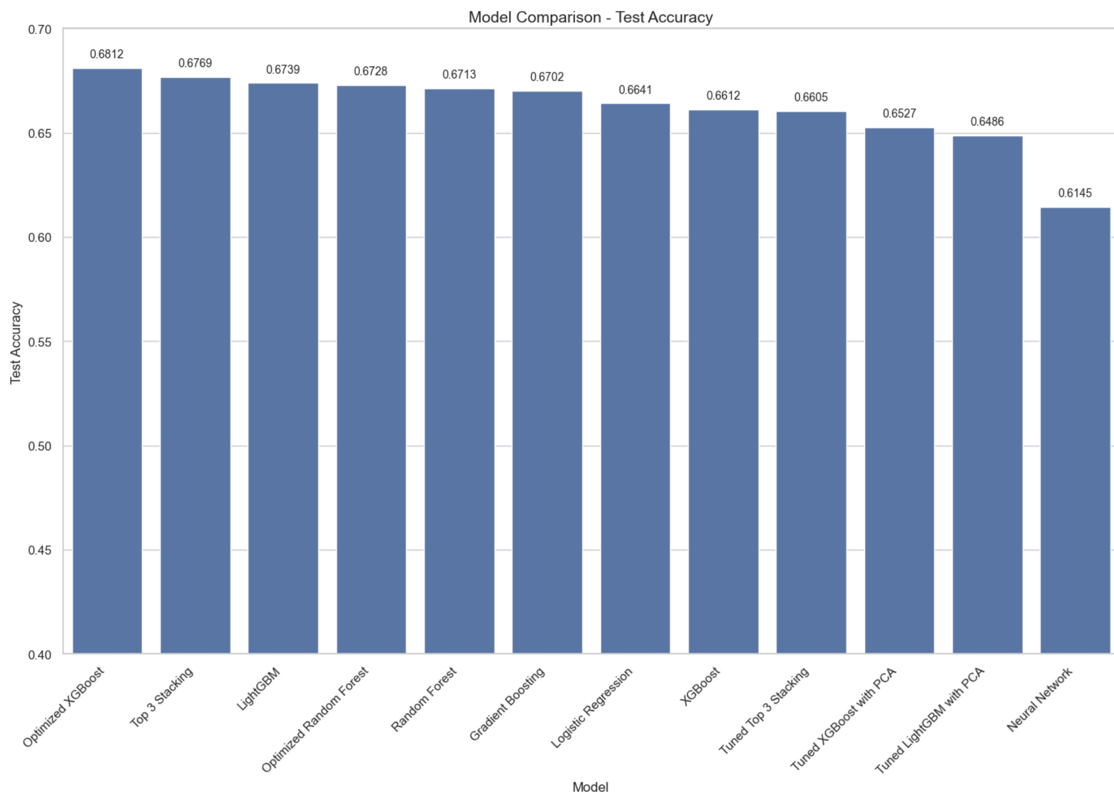
# Set width of bars
barWidth = 0.4
r1 = np.arange(len(model_names))
r2 = [x + barWidth for x in r1]

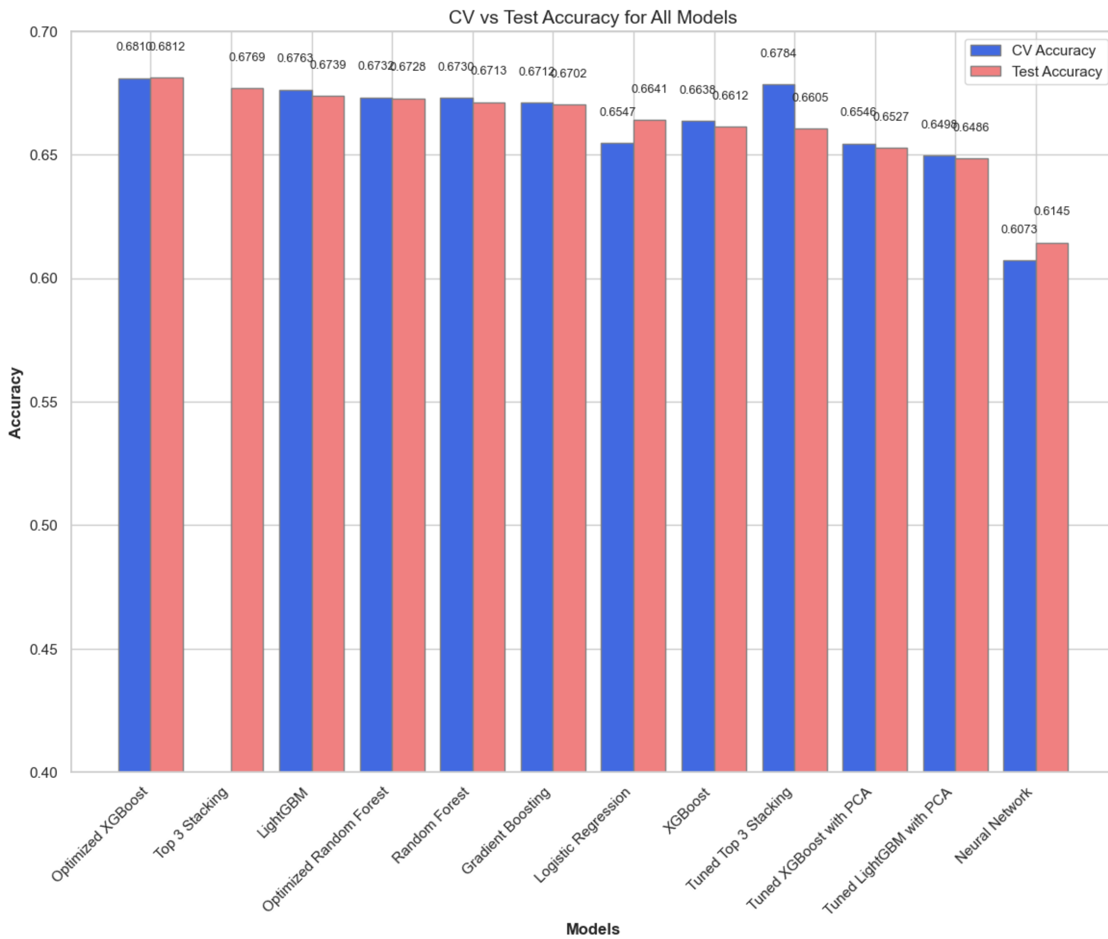
# Create grouped bars
plt.bar(r1, cv_acc, width=barWidth, label='CV Accuracy', color='royalblue',␣
 ↪edgecolor='grey')
plt.bar(r2, test_acc, width=barWidth, label='Test Accuracy',␣
 ↪color='lightcoral', edgecolor='grey')
```

```python
# Add labels and legend
plt.xlabel('Models', fontweight='bold', fontsize=12)
plt.ylabel('Accuracy', fontweight='bold', fontsize=12)
plt.title('CV vs Test Accuracy for All Models', fontsize=14)
plt.xticks([r + barWidth/2 for r in range(len(model_names))], model_names,␣
↪rotation=45, ha='right')
plt.legend()

# Add value labels on top of bars
for i in range(len(r1)):
    plt.text(r1[i], cv_acc[i] + 0.01, f"{cv_acc[i]:.4f}", ha='center',␣
↪va='bottom', fontsize=9)
    plt.text(r2[i], test_acc[i] + 0.01, f"{test_acc[i]:.4f}", ha='center',␣
↪va='bottom', fontsize=9)

plt.ylim(0.4, 0.7)  # Adjust y-axis range
plt.tight_layout()
plt.show()

# Identify the best model
best_model_name = model_comparison.iloc[0]['Model']
print(f"\nBest model after extended tuning: {best_model_name}")
print(f"Test accuracy: {model_comparison.iloc[0]['Test Accuracy']:.4f}")
print(f"Test F1 score: {model_comparison.iloc[0]['Test F1 Score']:.4f}")

# If the best model is Random Forest or XGBoost, show their optimized parameters
if 'Tuned Random Forest' in best_model_name:
    print("\nOptimal Random Forest parameters:")
    best_params = {k.replace('model__', ''): v for k, v in rf_search.
↪best_params_.items()}
    for param, value in best_params.items():
        print(f"  {param}: {value}")
elif 'Tuned XGBoost' in best_model_name:
    print("\nOptimal XGBoost parameters:")
    best_params = {k.replace('model__', ''): v for k, v in xgb_search.
↪best_params_.items()}
    for param, value in best_params.items():
        print(f"  {param}: {value}")
```

```
================================================================================
UPDATED MODEL COMPARISON
================================================================================

Model Comparison:
                      Model  CV Accuracy  Test Accuracy  Test F1 Score
```

9	Optimized XGBoost	0.681000	0.681170	0.681072
6	Top 3 Stacking	0.000000	0.676882	0.677247
4	LightGBM	0.676299	0.673855	0.673478
8	Optimized Random Forest	0.673200	0.672847	0.672884
1	Random Forest	0.672960	0.671333	0.670896
2	Gradient Boosting	0.671187	0.670198	0.670323
0	Logistic Regression	0.654731	0.664144	0.663429
3	XGBoost	0.663831	0.661244	0.661126
7	Tuned Top 3 Stacking	0.678401	0.660487	0.659929
10	Tuned XGBoost with PCA	0.654600	0.652667	0.652843
11	Tuned LightGBM with PCA	0.649800	0.648632	0.648977
5	Neural Network	0.607251	0.614453	0.614588




CV vs Test Accuracy for All Models
CV Accuracy
Test Accuracy
Accuracy
0.70
0.65
0.60
0.55
0.50
0.45
0.40
0.6810
0.6812
0.6769
0.6763
0.6739
0.6732
0.6728
0.6730
0.6713
0.6712
0.6702
0.6547
0.6641
0.6638
0.6612
0.6784
0.6605
0.6546
0.6527
0.6498
0.6486
0.6073
0.6145
Optimized XGBoost
Top 3 Stacking
LightGBM
Optimized Random Forest
Random Forest
Gradient Boosting
Logistic Regression
XGBoost
Tuned Top 3 Stacking
Tuned XGBoost with PCA
Tuned LightGBM with PCA
Neural Network
Models

0.0000

```
Best model after extended tuning: Optimized XGBoost
Test accuracy: 0.6812
Test F1 score: 0.6811
```

After conducting advanced hyperparameter tuning for Random Forest and XGBoost, we found that the accuracy still did not improve. This suggests that the model's limitations may caused by deeper issues beyond hyperparameter optimization. One possible reason is that the dataset lacks strong predictive features, making it difficult for any model to achieve high accuracy. Despite these challenges, we have chosen to keep this result. Because it can still provide valuable insights into content engagement patterns. It also highlights, to some extent, the difficulty of predicting the popularity of online news.

1.6 Conclusion

In our study of online news popularity, we identified several key factors that influence the number of shares. Keywords including their relevance and quantity play an important role in driving engagement. It indicates that well-optimized content can improve shares. Subjectivity also has a strong correlation. Articles with a more emotionally engaging tone are more likely to be shared. However, despite extensive model tuning and feature selection, our machine learning models achieved a maximum accuracy of 68 percent. It may be because predicting news shareability remains a complex task influenced by unpredictable external factors such as trending topics and social media dynamics. Moving forward, we can improve our approach by integrating real-time social media data and user engagement metrics to enhance prediction accuracy.