Dataset loaded successfully! Shape of the dataset: (4846, 2)

	Sentiment	News_Headline
0	neutral	According to Gran , the company has no plans t
1	neutral	Technopolis plans to develop in stages an area
2	negative	The international electronic industry company
3	positive	With the new production plant the company woul
4	positive	According to the company 's updated strategy f

```
In [2]: # Check for missing values
    print("Missing values per column:")
    display(df.isnull().sum())

# Check the distribution of sentiment labels
    print("\nDistribution of Sentiment Labels:")
    display(df['Sentiment'].value_counts())

# Analyze text length of headlines
    df['Headline_Length'] = df['News_Headline'].apply(len)
    print("\nDescriptive statistics for Headline Length:")
    display(df['Headline_Length'].describe())

# You can add more exploration steps here, e.g., word frequency analysis
```

Missing values per column:

0

Sentiment 0

**News\_Headline** 0

dtype: int64

Distribution of Sentiment Labels:

#### count

### Sentiment

neutral	2879
positive	1363
negative	604

## dtype: int64

Descriptive statistics for Headline Length:

## Headline\_Length

count
mean
std
min
25%
50%
<b>75</b> %
max
ean std min 25% 50%

```
In [3]: import re
        import nltk
        from nltk.corpus import stopwords
        from nltk.stem import WordNetLemmatizer
        import pandas as pd
        # Download necessary NLTK data
        try:
            nltk.data.find('corpora/stopwords')
        except LookupError:
            nltk.download('stopwords')
        try:
            nltk.data.find('tokenizers/punkt')
        except LookupError:
            nltk.download('punkt')
            nltk.data.find('corpora/wordnet')
        except LookupError:
            nltk.download('wordnet')
        # Initialize lemmatizer and stopwords
        lemmatizer = WordNetLemmatizer()
        stop words = set(stopwords.words('english'))
```

```
def preprocess text(text):
   # Ensure the input is a string
    if not isinstance(text, str):
        return "" # Return an empty string for non-string inputs
    # Remove punctuation and special characters, but keep numbers
    text = re.sub(r'[^a-zA-Z0-9\s]', '', text)
    # Convert to lowercase
   text = text.lower()
   # Tokenize the text
   tokens = nltk.word tokenize(text)
   # Remove stop words and lemmatize the words
   tokens = [lemmatizer.lemmatize(word) for word in tokens]
    # Join tokens back into a string
    return ' '.join(tokens)
# Apply preprocessing to the News Headline column
# Add a check for non-string types in the column before applying
if not pd.api.types.is string dtype(df['News Headline']):
    print("Warning: 'News Headline' column contains non-string types. Attemp
    df['News Headline'] = df['News Headline'].astype(str)
df['Cleaned Headline'] = df['News Headline'].apply(preprocess text)
print("Original Headlines:")
display(df['News Headline'].head())
print("\nCleaned Headlines:")
display(df['Cleaned Headline'].head())
```

[nltk data] Downloading package wordnet to /root/nltk data... [nltk data] Package wordnet is already up-to-date!

Original Headlines:

#### **News Headline**

- 0 According to Gran, the company has no plans t...
- 1 Technopolis plans to develop in stages an area...
- 2 The international electronic industry company ...
- **3** With the new production plant the company woul...
- According to the company 's updated strategy f...

**dtype:** object Cleaned Headlines:

#### **Cleaned Headline**

- **0** according to gran the company ha no plan to mo...
- **1** technopolis plan to develop in stage an area o...
- **2** the international electronic industry company ...
- **3** with the new production plant the company woul...
- **4** according to the company s updated strategy fo...

## dtype: object

```
In [4]: # Check the distribution of sentiment labels again to confirm
    print("Distribution of Sentiment Labels after Preprocessing:")
    display(df['Sentiment'].value_counts())

# Based on the distribution, we can decide if we need to handle imbalance.
# If there's significant imbalance, we can use techniques like SMOTE.
# We'll address this in the next steps if necessary.
```

Distribution of Sentiment Labels after Preprocessing:

#### count

#### Sentiment

neutral 2879
positive 1363
negative 604

## dtype: int64

```
In [5]: from imblearn.over_sampling import SMOTE
    from sklearn.feature_extraction.text import TfidfVectorizer
    from sklearn.model_selection import train_test_split

# Separate features (X) and target (y)
X = df['Cleaned_Headline']
y = df['Sentiment']

# Split the data into training and testing sets before applying SMOTE
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, ran)

# Vectorize the text data using TF-IDF on the training data
tfidf_vectorizer = TfidfVectorizer(max_features=5000) # You can adjust max_f
X_train_tfidf = tfidf_vectorizer.fit_transform(X_train)

# Apply SMOTE to the training vectorized data
smote = SMOTE(random_state=42)
X_train_resampled, y_train_resampled = smote.fit_resample(X_train_tfidf, y_t
print("Shape of training data before SMOTE:", X_train_tfidf.shape)
```

```
print("Shape of training data after SMOTE:", X_train_resampled.shape)
print("\nDistribution of Sentiment Labels in training data after SMOTE:")
display(y_train_resampled.value_counts())

# Vectorize the test data using the same TF-IDF vectorizer fitted on the tra
X_test_tfidf = tfidf_vectorizer.transform(X_test)
```

Shape of training data before SMOTE: (3876, 5000) Shape of training data after SMOTE: (6909, 5000)

Distribution of Sentiment Labels in training data after SMOTE:

#### count

#### Sentiment

positive	2303
neutral	2303
negative	2303

## dtype: int64

```
In [6]: # Add custom feature: Number of words in cleaned headline
    df['Cleaned_Word_Count'] = df['Cleaned_Headline'].apply(lambda x: len(x.spli)

# Add custom feature: Average word length in cleaned headline
    df['Average_Word_Length'] = df['Cleaned_Headline'].apply(lambda x: sum(len(w)
        print("\nDescriptive statistics for Cleaned Word Count:")
        display(df['Cleaned_Word_Count'].describe())

        print("\nDescriptive statistics for Average Word Length:")
        display(df['Average_Word_Length'].describe())
```

Descriptive statistics for Cleaned Word Count:

## Cleaned\_Word\_Count

count	4846.000000
mean	20.489682
std	8.792611
min	1.000000
25%	14.000000
50%	19.000000
<b>75</b> %	26.000000
max	52.000000

## Descriptive statistics for Average Word Length:

## **Average\_Word\_Length**

count	4846.000000
mean	4.902997
std	0.782964
min	2.000000
25%	4.375000
50%	4.850000
<b>75</b> %	5.400000
max	8.600000

	Sentiment	News_Headline	${\bf Head line\_Length}$	Cleaned_Headline	Cleaned_Wo
0	neutral	According to Gran , the company has no plans t	127	according to gran the company ha no plan to mo	
1	neutral	Technopolis plans to develop in stages an area	190	technopolis plan to develop in stage an area o	
2	negative	The international electronic industry company	228	the international electronic industry company	
3	positive	With the new production plant the company woul	206	with the new production plant the company woul	
4	positive	According to the company 's updated strategy f	203	according to the company s updated strategy fo	

```
In [7]: import nltk
from nltk.sentiment import SentimentIntensityAnalyzer

# Download necessary NLTK data for SentimentIntensityAnalyzer
try:
        nltk.data.find('sentiment/vader_lexicon.zip')
except LookupError:
        nltk.download('vader_lexicon')

# Initialize SentimentIntensityAnalyzer
sid = SentimentIntensityAnalyzer()
```

```
# Add custom feature: Count of words in the cleaned headline (already done,
# df['Cleaned_Word_Count'] = df['Cleaned_Headline'].apply(lambda x: len(x.sp
# Add custom features: Count of positive, negative, and neutral words (This
# We can revisit this if needed, but VADER's polarity scores cover this sent
# Add custom features: Polarity scores from SentimentIntensityAnalyzer
df['VADER_Negative'] = df['Cleaned_Headline'].apply(lambda x: sid.polarity_scoredf['VADER_Neutral'] = df['Cleaned_Headline'].apply(lambda x: sid.polarity_scoredf['VADER_Positive'] = df['Cleaned_Headline'].apply(lambda x: sid.polarity_scoredf['VADER_Compound'] = df['Cleaned_Headline'].apply(lambda x: sid
```

Descriptive statistics for VADER Sentiment Scores:

	VADER_Negative	VADER_Neutral	VADER_Positive	VADER_Compound
count	4846.000000	4846.000000	4846.000000	4846.000000
mean	0.018802	0.879398	0.101803	0.221318
std	0.055491	0.120968	0.114028	0.311683
min	0.000000	0.000000	0.000000	-0.865800
25%	0.000000	0.802000	0.000000	0.000000
50%	0.000000	0.893000	0.083000	0.202300
75%	0.000000	1.000000	0.168750	0.440400
max	0.444000	1.000000	1.000000	0.946000

	Sentiment	News_Headline	Headline_Length	Cleaned_Headline	Cleaned_Wo	
0	neutral	According to Gran , the company has no plans t	127	according to gran the company ha no plan to mo		
1	neutral	Technopolis plans to develop in stages an area	190	technopolis plan to develop in stage an area o		
2	negative	The international electronic industry company	228	the international electronic industry company		
3	positive	With the new production plant the company woul	206	with the new production plant the company woul		
4	positive	According to the company 's updated strategy f	203	according to the company s updated strategy fo		
	: import nltk from nltk.corpus import opinion_lexicon					

```
In [8]
        # Download necessary NLTK data for Opinion Lexicon
        try:
            nltk.data.find('corpora/opinion lexicon')
        except LookupError:
            nltk.download('opinion_lexicon')
        # Get positive and negative word lists from the opinion lexicon
        positive words = set(opinion lexicon.positive())
        negative words = set(opinion lexicon.negative())
        # Add custom feature: Count of positive words in cleaned headline
        df['Positive_Word_Count'] = df['Cleaned_Headline'].apply(lambda x: sum(1 for
        # Add custom feature: Count of negative words in cleaned headline
        df['Negative Word Count'] = df['Cleaned Headline'].apply(lambda x: sum(1 for
        print("\nDescriptive statistics for Positive Word Count:")
        display(df['Positive_Word_Count'].describe())
        print("\nDescriptive statistics for Negative Word Count:")
        display(df['Negative Word Count'].describe())
        display(df.head())
```

Descriptive statistics for Positive Word Count:

## Positive\_Word\_Count

count	4846.000000
mean	0.350392
std	0.634579
min	0.000000
25%	0.000000
50%	0.000000
<b>75</b> %	1.000000
max	6.000000

dtype: float64

Descriptive statistics for Negative Word Count:

Negative\_Word\_Count

count	4846.000000
mean	0.155592
std	0.412069
min	0.000000
25%	0.000000
50%	0.000000
75%	0.000000
max	4.000000

•	Sentiment	News_Headline	Headline_Length	Cleaned_Headline	Cleaned_Wo		
0	neutral	According to Gran , the company has no plans t	127	according to gran the company ha no plan to mo			
1	neutral	Technopolis plans to develop in stages an area	190	technopolis plan to develop in stage an area o			
2	negative	The international electronic industry company	228	the international electronic industry company			
3	positive	With the new production plant the company woul	206	with the new production plant the company woul			
4	positive	According to the company 's updated strategy f	203	according to the company s updated strategy fo			
fr fr im im #	<pre>from sklearn.feature_extraction.text import TfidfVectorizer from imblearn.over_sampling import SMOTE import numpy as np import pandas as pd # Import pandas  # Separate features (X) and target (y) including all custom features X = df[['Cleaned_Headline', 'Cleaned_Word_Count', 'Average_Word_Length', 'VA</pre>						
#	<pre>from sklearn.preprocessing import LabelEncoder  # Initialize encoder label_encoder = LabelEncoder()</pre>						
	<pre># Fit and transform target labels y = label_encoder.fit_transform(df['Sentiment'])</pre>						
<pre># Split the data into training and testing sets before applying X_train, X_test, y_train, y_test = train_test_split(X, y, test_</pre>							
tf	<pre># Vectorize the text data using TF-IDF on the 'Cleaned_Headline' column of t tfidf_vectorizer = TfidfVectorizer(max_features=5000) # You can adjust max_f X_train_tfidf = tfidf_vectorizer.fit_transform(X_train['Cleaned_Headline'])</pre>						
	<pre># Get the custom features for the training set X_train_custom = X_train[['Cleaned_Word_Count', 'Average_Word_Length', 'VADE</pre>						
				for the training			

X\_train\_combined = np.hstack((X\_train\_tfidf.toarray(), X\_train\_custom))

Sentiment News Headline Headline Length Cleaned Headline Cleaned Wo

```
# Apply SMOTE to the combined training data
         smote = SMOTE(random state=42)
         X train resampled, y train resampled = smote.fit resample(X train combined,
         print("Shape of training data before SMOTE:", X train combined.shape)
         print("Shape of training data after SMOTE:", X_train_resampled.shape)
         print("\nDistribution of Sentiment Labels in training data after SMOTE:")
         display(pd.Series(y train resampled).value counts()) # Convert to pandas Ser
         # Vectorize the test data using the same TF-IDF vectorizer fitted on the tra
         X test tfidf = tfidf vectorizer.transform(X test['Cleaned Headline'])
         # Get the custom features for the test set
         X test custom = X test[['Cleaned Word Count', 'Average Word Length', 'VADER
         # Combine TF-IDF features and custom features for the test set
         X test combined = np.hstack((X test tfidf.toarray(), X test custom))
         print("\nShape of test data:", X test combined.shape)
        Shape of training data before SMOTE: (3876, 5008)
        Shape of training data after SMOTE: (6909, 5008)
       Distribution of Sentiment Labels in training data after SMOTE:
          count
       2
          2303
          2303
       1
       0 2303
       dtype: int64
        Shape of test data: (970, 5008)
In [ ]:
In [10]: from sklearn.naive bayes import MultinomialNB
         from sklearn.linear model import LogisticRegression
         from sklearn.svm import SVC
         from sklearn.metrics import classification report, accuracy score
         # Train a Logistic Regression model
         print("\nTraining Logistic Regression model...")
         lr model = LogisticRegression(max iter=1000) # Increased max iter for conver
         lr model.fit(X train resampled, y train resampled)
         # Evaluate the Logistic Regression model
         y pred lr = lr model.predict(X test combined)
         print("\nLogistic Regression Model Performance:")
         print("Accuracy:", accuracy score(y test, y pred lr))
         print(classification report(y test, y pred lr))
```

Training Logistic Regression model...

Logistic Regression Model Performance:

Accuracy: 0.7546391752577319

	precision	recall	f1-score	support
0 1 2	0.63 0.84 0.66	0.77 0.80 0.66	0.69 0.82 0.66	121 576 273
accuracy macro avg weighted avg	0.71 0.76	0.74 0.75	0.75 0.72 0.76	970 970 970

```
In [13]: import numpy as np
         import pandas as pd # Import pandas
         # Example real headlines (you can replace this list with any headlines you w
         real headlines = [
             "India's HDFC Bank reports 12.2% profit growth in Q1 due to higher inter
             "Wells Fargo exit ban revives fears about doing business in China",
             "American Express allays competition concerns after profit beat",
             "Hedge funds lure record inflows in first half of 2025",
             "Trump signs stablecoin law as crypto industry aims for mainstream adopt
             "U.S. equities edge lower after tariff headlines and mixed earnings",
             "Lofty U.S. stock market valuations bank on earnings strength",
             "Dow Jones futures: Tesla, Google Step Up With Earnings Due; AI Stock Br
             "Take Five: global markets to test industrial sector gains as earnings r
             "Why stock market fell today: Sensex settles 501 pts lower, Nifty below
         1
         print("Testing multiple real headlines:")
         for real headline in real headlines:
             print(f"\n0riginal Headline: {real headline}")
             # Preprocess the headline using the same function used for the training
             cleaned real headline = preprocess text(real headline)
             print(f"Cleaned Headline: {cleaned real headline}")
             # Calculate custom features for the real headline directly
             tokens = cleaned real headline.split()
             cleaned word count = len(tokens)
             average word length = sum(len(word) for word in tokens) / cleaned word d
             # Calculate VADER sentiment scores
             vader scores = sid.polarity scores(cleaned real headline)
             vader negative = vader scores['neg']
             vader neutral = vader scores['neu']
             vader positive = vader scores['pos']
             vader compound = vader scores['compound']
             # Calculate Opinion Lexicon word counts
             positive word count = sum(1 for word in tokens if word in positive words
             negative word count = sum(1 for word in tokens if word in negative words
```

```
# Arrange custom features in a NumPy array
real_headline_custom = np.array([[cleaned_word_count, average_word_lengt

# Vectorize the cleaned headline using the fitted TF-IDF vectorizer
real_headline_tfidf = tfidf_vectorizer.transform([cleaned_real_headline]

# Combine TF-IDF features and custom features for the real headline
real_headline_combined = np.hstack((real_headline_tfidf.toarray(), real_

# Predict the sentiment using the trained Logistic Regression model
predicted_sentiment_encoded = lr_model.predict(real_headline_combined)

# Inverse transform the predicted sentiment to get the original label
predicted_sentiment = label_encoder.inverse_transform(predicted_sentimer

print(f"Predicted Sentiment: {predicted_sentiment[0]}")

# You can manually compare the predicted sentiment with what you expect
```

Testing multiple real headlines:

Original Headline: India's HDFC Bank reports 12.2% profit growth in Q1 due t o higher interest income

Cleaned Headline: india hdfc bank report 122 profit growth in q1 due to high

er interest income

Predicted Sentiment: positive

Original Headline: Wells Fargo exit ban revives fears about doing business i n China

Cleaned Headline: well fargo exit ban revives fear about doing business in c

Predicted Sentiment: negative

Original Headline: American Express allays competition concerns after profit

beat

Cleaned Headline: american express allays competition concern after profit b

eat

Predicted Sentiment: neutral

Original Headline: Hedge funds lure record inflows in first half of 2025 Cleaned Headline: hedge fund lure record inflow in first half of 2025

Predicted Sentiment: negative

Original Headline: Trump signs stablecoin law as crypto industry aims for ma instream adoption

Cleaned Headline: trump sign stablecoin law a crypto industry aim for mainst

ream adoption

Predicted Sentiment: neutral

Original Headline: U.S. equities edge lower after tariff headlines and mixed

Cleaned Headline: u equity edge lower after tariff headline and mixed earnin

Predicted Sentiment: negative

Original Headline: Lofty U.S. stock market valuations bank on earnings stren ath

Cleaned Headline: lofty u stock market valuation bank on earnings strength Predicted Sentiment: positive

Original Headline: Dow Jones futures: Tesla, Google Step Up With Earnings Du e; AI Stock Breaks Out

Cleaned Headline: dow jones future tesla google step up with earnings due ai

stock break out

Predicted Sentiment: neutral

Original Headline: Take Five: global markets to test industrial sector gains as earnings ramp up

Cleaned Headline: take five global market to test industrial sector gain a e arnings ramp up

Predicted Sentiment: positive

Original Headline: Why stock market fell today: Sensex settles 501 pts lowe r, Nifty below 25,000; 5 reasons

Cleaned Headline: why stock market fell today sensex settle 501 pt lower nif

ty below 25000 5 reason Predicted Sentiment: negative

```
In [12]: # Train a Support Vector Machine model
    print("\nTraining Support Vector Machine model...")
    svm_model = SVC()
    svm_model.fit(X_train_resampled, y_train_resampled)

# Evaluate the Support Vector Machine model
    y_pred_svm = svm_model.predict(X_test_combined)
    print("\nSupport Vector Machine Model Performance:")
    print("Accuracy:", accuracy_score(y_test, y_pred_svm))
    print(classification_report(y_test, y_pred_svm))
```

Training Support Vector Machine model...

Support Vector Machine Model Performance:

Accuracy: 0.5639175257731959

	precision	recall	f1-score	support
0 1 2	0.37 0.74 0.43	0.48 0.58 0.56	0.42 0.65 0.49	121 576 273
accuracy macro avg weighted avg	0.51 0.61	0.54 0.56	0.56 0.52 0.58	970 970 970

```
In []:
In [11]: !pip install gensim
```

```
Collecting gensim
         Downloading gensim-4.3.3-cp311-cp311-manylinux 2 17 x86 64.manylinux2014 x
       86 64.whl.metadata (8.1 kB)
       Collecting numpy<2.0,>=1.18.5 (from gensim)
         Downloading numpy-1.26.4-cp311-cp311-manylinux 2 17 x86 64.manylinux2014 x
       86 64.whl.metadata (61 kB)
                                           61.0/61.0 kB 2.5 MB/s eta 0:0
       0:00
       Collecting scipy<1.14.0,>=1.7.0 (from gensim)
         Downloading scipy-1.13.1-cp311-cp311-manylinux 2 17 x86 64.manylinux2014 x
       86 64.whl.metadata (60 kB)
                                           60.6/60.6 kB 4.9 MB/s eta 0:0
       0:00
      Requirement already satisfied: smart-open>=1.8.1 in /usr/local/lib/python3.1
       1/dist-packages (from gensim) (7.3.0.post1)
      Requirement already satisfied: wrapt in /usr/local/lib/python3.11/dist-packa
      qes (from smart-open>=1.8.1->qensim) (1.17.2)
      Downloading gensim-4.3.3-cp311-cp311-manylinux 2 17 x86 64.manylinux2014 x86
       64.whl (26.7 MB)
                                         26.7/26.7 MB 52.9 MB/s eta 0:00:
      Downloading numpy-1.26.4-cp311-cp311-manylinux 2 17 x86 64.manylinux2014 x86
       64.whl (18.3 MB)
                                         18.3/18.3 MB 67.2 MB/s eta 0:00:
       00
       Downloading scipy-1.13.1-cp311-cp311-manylinux 2 17 x86 64.manylinux2014 x86
       64.whl (38.6 MB)
                                      38.6/38.6 MB 12.6 MB/s eta 0:00:
       Installing collected packages: numpy, scipy, gensim
        Attempting uninstall: numpy
           Found existing installation: numpy 2.0.2
           Uninstalling numpy-2.0.2:
             Successfully uninstalled numpy-2.0.2
         Attempting uninstall: scipy
           Found existing installation: scipy 1.15.3
           Uninstalling scipy-1.15.3:
             Successfully uninstalled scipy-1.15.3
       ERROR: pip's dependency resolver does not currently take into account all th
       e packages that are installed. This behaviour is the source of the following
      dependency conflicts.
       opency-python-headless 4.12.0.88 requires numpy<2.3.0,>=2; python version >=
       "3.9", but you have numpy 1.26.4 which is incompatible.
       thinc 8.3.6 requires numpy<3.0.0,>=2.0.0, but you have numpy 1.26.4 which is
       incompatible.
       tsfresh 0.21.0 requires scipy>=1.14.0; python version >= "3.10", but you hav
       e scipy 1.13.1 which is incompatible.
      Successfully installed gensim-4.3.3 numpy-1.26.4 scipy-1.13.1
In [9]: # Word2vec
        import numpy as np
        import pandas as pd
        from sklearn.model selection import train test split
        from sklearn.preprocessing import LabelEncoder
        from imblearn.over sampling import SMOTE
```

```
import gensim.downloader as api
# Step 1: Encode target labels
label encoder = LabelEncoder()
y = label encoder.fit transform(df['Sentiment'])
# Step 2: Prepare features
X = df[['Cleaned_Headline', 'Cleaned_Word_Count', 'Average_Word_Length',
        'VADER_Negative', 'VADER_Neutral', 'VADER_Positive',
        'VADER Compound', 'Positive Word Count', 'Negative Word Count']]
# Step 3: Train-test split
X train, X test, y train, y test = train test split(
   X, y, test size=0.2, random state=42, stratify=y
# Step 4: Load pre-trained Word2Vec Google News
wv = api.load('word2vec-google-news-300') # Pre-trained 300d Google News md
# Step 5: Tokenize headlines
X train tokens = X train['Cleaned Headline'].apply(str.split)
X test tokens = X test['Cleaned Headline'].apply(str.split)
# Step 6: Convert each headline to average Word2Vec vector
def document vector(tokens):
   valid = [t for t in tokens if t in wv]
    if not valid:
        return np.zeros(wv.vector size)
    return np.mean(wv[valid], axis=0)
X train w2v = np.vstack(X train tokens.apply(document vector))
X test w2v = np.vstack(X test tokens.apply(document vector))
# Step 7: Extract custom features
custom cols = ['Cleaned Word Count', 'Average Word Length',
               'VADER_Negative', 'VADER_Neutral', 'VADER Positive',
               'VADER Compound', 'Positive Word Count', 'Negative Word Count
X train custom = X train[custom cols].values
X test custom = X test[custom cols].values
# Step 8: Combine embeddings + custom features
X train combined = np.hstack((X train w2v, X train custom))
X test combined = np.hstack((X test w2v, X test custom))
# Step 9: Apply SMOTE
smote = SMOTE(random state=42)
X train resampled, y train resampled = smote.fit resample(X train combined,
# Step 10: Print shapes and label distribution
print("Before SMOTE:", X train combined.shape)
print("After SMOTE:", X train resampled.shape)
print(pd.Series(y train resampled).value counts())
print("Test data shape:", X_test_combined.shape)
```

```
Before SMOTE: (3876, 308)
After SMOTE: (6909, 308)
2 2303
1 2303
0 2303
Name: count, dtype: int64
Test data shape: (970, 308)
```

## Task

Generate a markdown summary of the financial news headline sentiment analysis project, including data preprocessing, feature engineering, handling of class imbalance, model training and evaluation (focusing on Logistic Regression), and a real headline prediction example.

# Summarize the project goal

## Subtask:

Briefly state the objective of the project (Financial News Headline Sentiment Analysis).

**Reasoning**: State the objective of the project in a markdown block.

**Reasoning**: State the objective of the project in a markdown block.

```
In [15]: # The objective of this project is to perform sentiment analysis on financia # This helps in understanding the market sentiment conveyed by news.
```

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