Library Imports for Data Processing and Machine Learning

In this code block, we import the essential libraries and modules needed for various tasks in data analysis and machine learning:

- NumPy and Pandas for efficient data manipulation and numerical operations,
- Seaborn and Matplotlib for creating data visualizations,
- Missingno for handling missing data visualizations,
- Datetime to work with date objects,
- Scikit-learn submodules for tasks such as model accuracy scoring, train-test data splitting, detecting outliers, and scaling/encoding features. These imports will help streamline our data analysis workflow.

In [1]:
```
import numpy as np
import pandas as pd
import seaborn as sns
from matplotlib import pyplot as plt
# !pip install missingno
import missingno as msno
from datetime import date
from sklearn.metrics import accuracy_score
from sklearn.model_selection import train_test_split
from sklearn.neighbors import LocalOutlierFactor
from sklearn.preprocessing import MinMaxScaler, LabelEncoder, StandardScaler, RobustScaler
```

Loading the Dataset

In [2]:
```
df=pd.read_csv("/kaggle/input/twitter-entity-sentiment-analysis/twitter_training.csv")
```

In [3]:
```
df.head()
```

Out[3]:

	2401	Borderlands	Positive	im getting on borderlands and i will murder you all ,
0	2401	Borderlands	Positive	I am coming to the borders and I will kill you...
1	2401	Borderlands	Positive	im getting on borderlands and i will kill you ...
2	2401	Borderlands	Positive	im coming on borderlands and i will murder you...
3	2401	Borderlands	Positive	im getting on borderlands 2 and i will murder ...
4	2401	Borderlands	Positive	im getting into borderlands and i can murder y...

Renaming and Selecting Relevant Columns

In this step, we rename the columns in the dataset to more meaningful names. The new columns include:

- Tweet ID: A unique identifier for each tweet.
- Entity: The entity or subject being discussed in the tweet.
- Sentiment: The sentiment associated with the tweet (e.g., Positive, Negative, Neutral).
- Tweet Content: The actual content or text of the tweet.

This renaming helps improve readability and ensures easier manipulation of the data for further analysis.

In [4]:
```
df["Tweet ID"]=df["2401"]
df["entity"]=df["Borderlands"]
df["sentiment"]=df["Positive"]
df["Tweet content"]=df["im getting on borderlands and i will murder yo
u all ,"]
```

In [5]:
```
df.drop(['2401', 'Borderlands','Positive','im getting on borderlands a
nd i will murder you all ,'], axis=1,inplace=True)
```

In [6]:
```
df.isnull().sum()
```

Out[6]:
```
Tweet ID           0
entity             0
sentiment          0
Tweet content    686
dtype: int64
```

Removing Missing Data

In [7]:
```
df.dropna(inplace=True)
```

In [8]:
```
df.isnull().sum()
```

Out[8]:
```
Tweet ID         0
entity           0
sentiment        0
Tweet content    0
dtype: int64
```

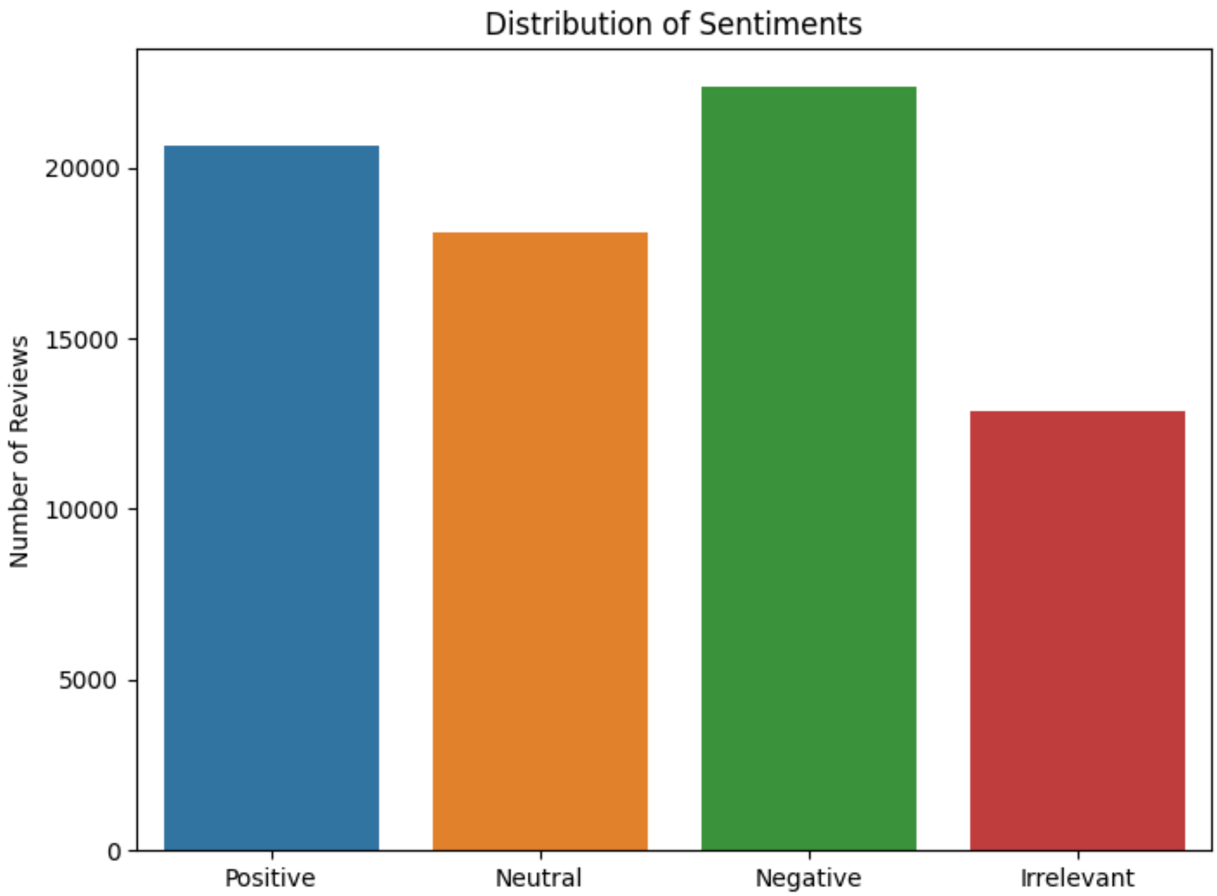
Visualizing Sentiment Distribution

In this section, we visualize the distribution of sentiments in the dataset using a count plot. The plot displays the number of reviews categorized as positive or negative.

- The x-axis represents the sentiment categories, while the y-axis shows the count of reviews for each category.

Additionally, we calculate and print the percentage distribution of sentiments in the dataset using the value_counts() function, normalized to reflect proportions. This information provides insights into the overall sentiment trends present in the data.

In [9]:
```
plt.figure(figsize=(8, 6))
sns.countplot(x='sentiment', data=df)
plt.title('Distribution of Sentiments')
plt.xlabel('')
plt.ylabel('Number of Reviews')
plt.show()

distribution = df['sentiment'].value_counts(normalize=True) * 100
print(distribution)
```




```
sentiment
Negative       30.215555
Positive       27.912697
Neutral        24.471924
Irrelevant     17.399824
Name: proportion, dtype: float64
```

In [10]:
```
df["Tweet content"][0]
```

Out[10]:
```
'I am coming to the borders and I will kill you all,'
```

Text Cleaning and Preprocessing

In [11]:
```
import gensim
from gensim.models import Word2Vec
import nltk
from nltk.corpus import stopwords
import re
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
```

```
stop_words = stop_words = set([
    'i','twitter','https', 'me', 'my', 'myself', 'we', 'our', 'ours', 'ourselves', 'you', "you're", "you've",
    "you'll", "you'd", 'your', 'yours', 'yourself', 'yourselves', 'he', 'him', 'his', 'himself',
    'she', "she's", 'her', 'hers', 'herself', 'it', "it's", 'its', 'itself', 'they', 'them',
    'their', 'theirs', 'themselves', 'what', 'which', 'who', 'whom', 'this', 'that', "that'll",
    'these', 'those', 'am', 'is', 'are', 'was', 'were', 'be', 'been', 'being', 'have', 'has',
    'had', 'having', 'do', 'does', 'did', 'doing', 'a', 'an', 'the', 'and', 'but', 'if', 'or',
    'because', 'as', 'until', 'while', 'of', 'at', 'by', 'for', 'with', 'about', 'against',
    'between', 'into', 'through', 'during', 'before', 'after', 'above', 'below', 'to', 'from',
    'up', 'down', 'in', 'out', 'on', 'off', 'over', 'under', 'again', 'further', 'then', 'once',
    'here', 'there', 'when', 'where', 'why', 'how', 'all', 'any', 'both', 'each', 'few', 'more',
    'most', 'other', 'some', 'such', 'no', 'nor', 'not', 'only', 'own', 'same', 'so', 'than',
    'too', 'very', 's', 't', 'can', 'will', 'just', 'don', "don't", 'should', "should've", 'now',
    'd', 'll', 'm', 'o', 're', 've', 'y', 'ain', 'aren', "aren't", 'couldn', "couldn't",
    'didn', "didn't", 'doesn', "doesn't", 'hadn', "hadn't", 'hasn', "hasn't", 'haven', "haven't",
    'isn', "isn't", 'ma', 'mightn', "mightn't", 'mustn', "mustn't", 'needn', "needn't",
    'shan', "shan't", 'shouldn', "shouldn't", 'wasn', "wasn't", 'weren', "weren't", 'won',
    "won't", 'wouldn', "wouldn't"
])


def clean_text(text):
    text = re.sub(r'\W', ' ', str(text))
    text = text.lower()
    text = text.split()
    text = [word for word in text if word not in stop_words]
    text = ' '.join(text)
    return text


df['cleaned_text'] = df['Tweet content'].apply(clean_text)
```

In [12]:
```
df['cleaned_text'][0]
```

Out[12]:
```
'coming borders kill'
```

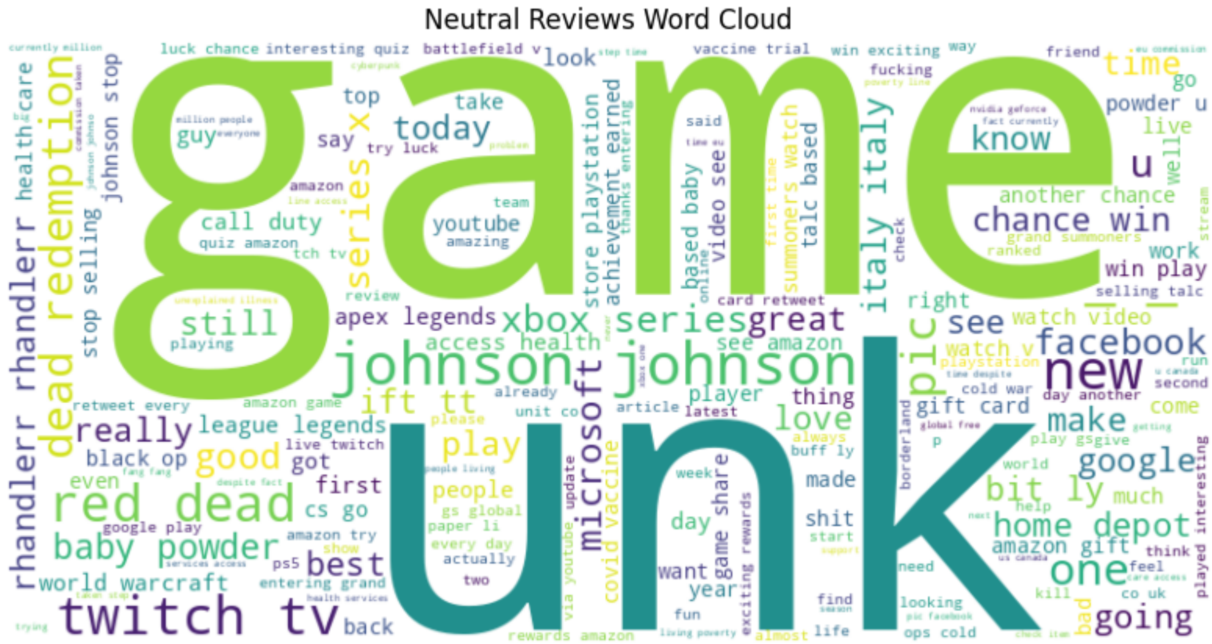
In [13]:
```
positive_reviews = df[df['sentiment'] == 'Positive']['cleaned_text']
neutral_reviews = df[df['sentiment'] == 'Neutral']['cleaned_text']
negative_reviews = df[df['sentiment'] == 'Negative']['cleaned_text']
irrelevant_reviews = df[df['sentiment'] == 'Irrelevant']['cleaned_tex
t']
```

Generating Word Clouds for Each Sentiment

In [14]:
```
from wordcloud import WordCloud
import matplotlib.pyplot as plt

def create_wordcloud(text, title):
    wordcloud = WordCloud(width=800, height=400, background_color='whi
te').generate(" ".join(text))
    plt.figure(figsize=(10, 5))
    plt.imshow(wordcloud, interpolation='bilinear')
    plt.title(title)
    plt.axis('off')
    plt.show()

create_wordcloud(positive_reviews, "Positive Reviews Word Cloud")
```

Positive Reviews Word Cloud

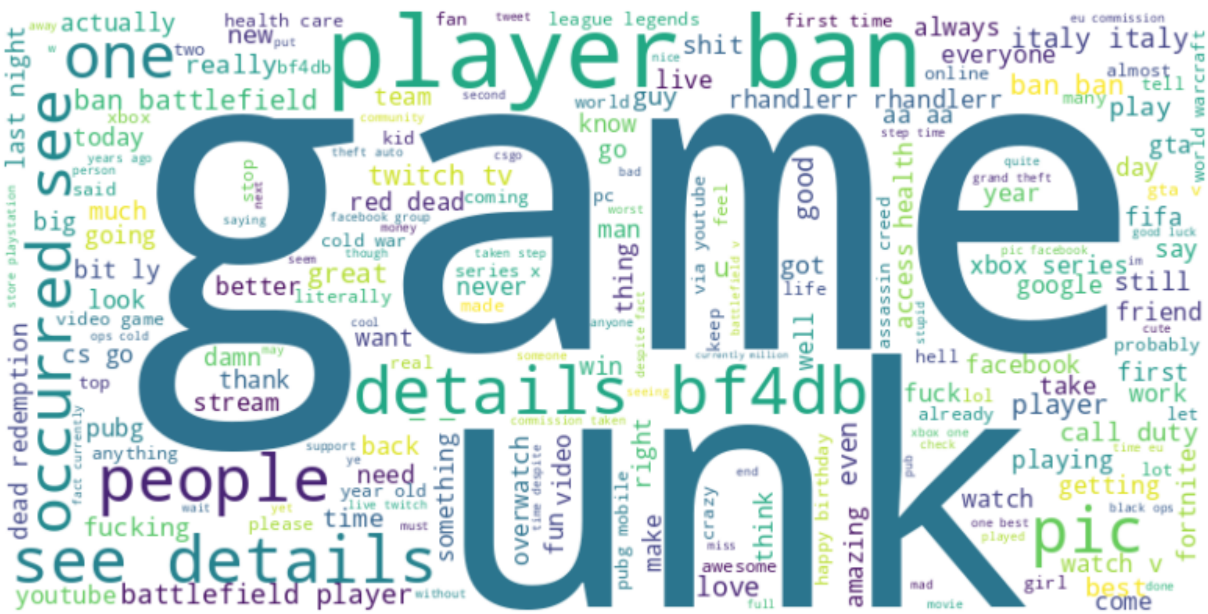
In [15]:
```
create_wordcloud(neutral_reviews, "Neutral Reviews Word Cloud")
```



In [16]:
```
create_wordcloud(negative_reviews, "Negative Reviews Word Cloud")
```

In [17]:
```
create_wordcloud(irrelevant_reviews, "Irrelevant Reviews Word Cloud")
```

Irrelevant Reviews Word Cloud



Training a Word2Vec Model

In [18]:
```
sentences = [text.split() for text in df['cleaned_text']]

word2vec_model = Word2Vec(sentences, vector_size=100, window=5, min_co
unt=1, workers=4)

word2vec_model.wv.most_similar('bad')
```

Out[18]:
```
[('sad', 0.9033304452896118),
 ('inadequate', 0.8605284690856934),
 ('terrible', 0.8416652679443359),
 ('like', 0.8387760519981384),
 ('gooft', 0.8370936512947083),
 ('miserable', 0.8260395526885986),
 ('ik', 0.823885977268219),
 ('sometimes', 0.818303108215332),
 ('actually', 0.8162209391593933),
 ('boring', 0.8110977411270142)]
```

In [19]:
```
def get_review_vector(review, model):
    words = review.split()
    word_vectors = [model.wv[word] for word in words if word in model.wv]
    if len(word_vectors) == 0:
        return np.zeros(model.vector_size)
    else:
        return np.mean(word_vectors, axis=0)

df['review_vector'] = df['cleaned_text'].apply(lambda x: get_review_vector(x, word2vec_model))
```

Preparing Data for Model Training

In this section, we prepare the data for training machine learning models by performing the following steps:

Feature and Target Variables:

- X: We create a NumPy array from the review_vector column, which contains the vector representations of the reviews.
- y: We define the target variable as the sentiment column.
- Label Encoding: We use LabelEncoder from Scikit-learn to convert the categorical sentiment labels into numerical format, facilitating their use in machine learning models.
- Train-Test Split: We split the dataset into training and testing sets using the train_test_split function, with 80% of the data allocated for training and 20% for testing. The random_state=42 ensures reproducibility of the split.

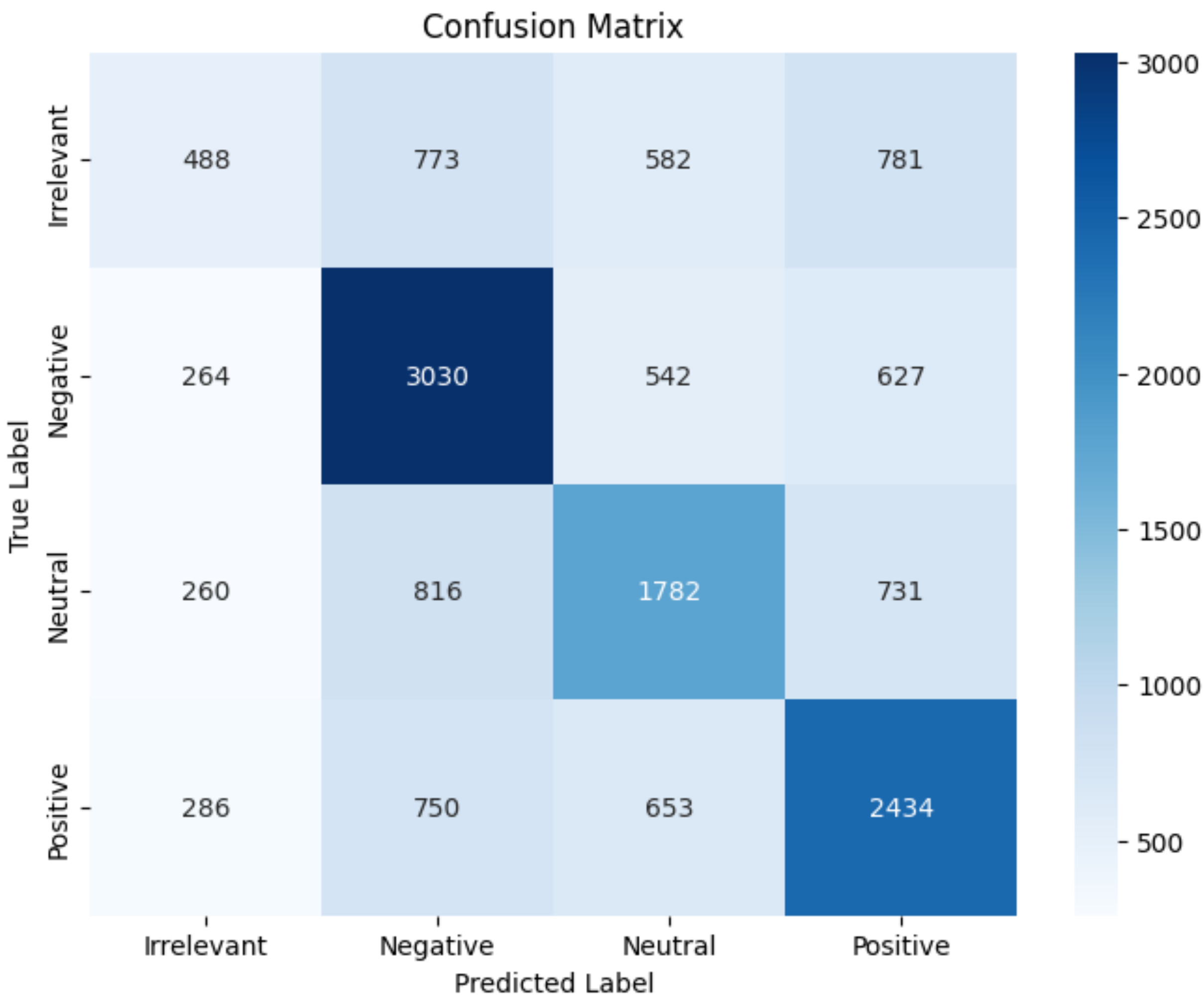
In [20]:
```
X = np.array(df['review_vector'].tolist())
y = df['sentiment']

# Label encoding
label_encoder = LabelEncoder()
y = label_encoder.fit_transform(y)

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

In [21]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, classification_report, con
fusion_matrix

model = LogisticRegression(max_iter=1000)

model.fit(X_train, y_train)

y_pred = model.predict(X_test)

accuracy = accuracy_score(y_test, y_pred)
print(f'Model Accuracy: {accuracy:.2f}')

conf_matrix = confusion_matrix(y_test, y_pred)
print("Confusion Matrix:\n", conf_matrix)
```

```
Model Accuracy: 0.52
Confusion Matrix:
 [[ 488  773  582  781]
 [ 264 3030  542  627]
 [ 260  816 1782  731]
 [ 286  750  653 2434]]
```

Visualizing the Confusion Matrix

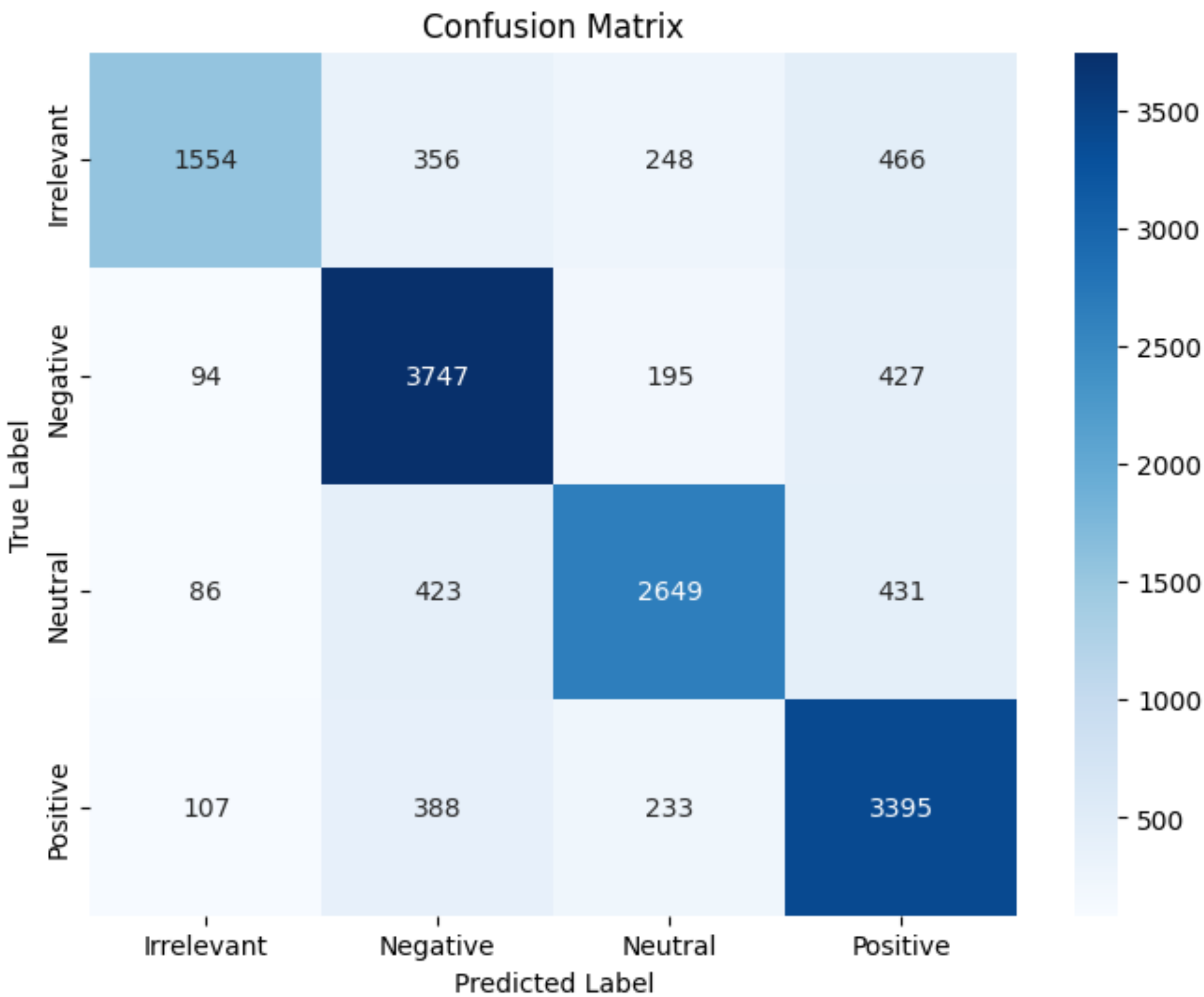
In [22]:
```
conf_matrix = confusion_matrix(y_test, y_pred)

plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues', xticklabel
s=label_encoder.classes_, yticklabels=label_encoder.classes_)
plt.title('Confusion Matrix')
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.show()
```


Confusion Matrix
True Label
Irrelevant
Negative
Neutral
Positive
488
773
582
781
264
3030
542
627
260
816
1782
731
286
750
653
2434
Irrelevant
Negative
Neutral
Positive
Predicted Label
3000
2500
2000
1500
1000
500

In [23]:
```
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier, VotingClassifier
from sklearn.model_selection import GridSearchCV, cross_validate, RandomizedSearchCV, validation_curve

model = RandomForestClassifier(random_state=20)

model.fit(X_train, y_train)

y_pred = model.predict(X_test)

accuracy = accuracy_score(y_test, y_pred)
print(f'Model Accuracy: {accuracy:.2f}')

conf_matrix = confusion_matrix(y_test, y_pred)
print("Confusion Matrix:\n", conf_matrix)
```

```
Model Accuracy: 0.77
Confusion Matrix:
 [[1554  356  248  466]
 [  94 3747  195  427]
 [  86  423 2649  431]
 [ 107  388  233 3395]]
```

In [24]:
```
conf_matrix = confusion_matrix(y_test, y_pred)

# Confusion matrix'i görselleştir
plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues', xticklabels=label_encoder.classes_, yticklabels=label_encoder.classes_)
plt.title('Confusion Matrix')
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.show()
```


Confusion Matrix
Irrelevant
Negative
Neutral
Positive
True Label
1554
356
248
466
94
3747
195
427
86
423
2649
431
107
388
233
3395
Irrelevant
Negative
Neutral
Positive
Predicted Label
3500
3000
2500
2000
1500
1000
500