Sentiment_Analysis_on_Netflix_Ratings

November 28, 2024

1 IMPORT DATA

1.1 Read Data

[1]:
```
# Import pandas library
import pandas as pd
```

[2]:
```
# Read data
data = pd.read_csv("netflix_reviews.csv")

# Show data
data
```

[2]:

	reviewId	userName	content	score
0	61a10e0d-e868-4d87-aa30-f41d30285a3f	badr mosa	Terrible app I can't watch anything because of…	1
1	1a7ce341-afc6-46da-9d08-793582e8ed3c	Ivan Berry	I love to download it,,	5
2	1bd445c3-7f36-4717-810a-63c5533207d0	Ryan Murray	Exceptional	5
3	59f306cd-852b-4459-b24f-3e4436df8465	Shannon Bonacci	Can't even make it through a full episode of a…	2
4	f21a1d8a-2b4c-4385-8aff-ca317a00e032	Katie Hutchinson	Great	5
…	…	…	…	…
113615	a760ead9-e7aa-4ed1-a651-5c37c3600dac	A Google user	i really like it! there are so many movies and…	5
113616	4957f9e7-d7f4-4a52-9764-031cebcac83f	Captain Jeoy	I love Netflix. I always enjoy my time using it.	5
113617	9acf7586-7abf-4b50-8c50-3ede3b2a42c4	Suryansh	Sound quality is very slow of movies	1
113618	32870f7f-c461-4256-b602-75244ca60248	A Google user	Rate is very expensive.. bcos we see netflix s…	1
113619	dc1352e9-10a8-41ca-ab23-05d045b08e90	suraj soni	this app is awesome for english movies ,series…	4

```
        thumbsUpCount    reviewCreatedVersion                   at  \
0                   0  8.121.2 build 22 50727  2024-07-08 15:41:17
1                   0                     NaN  2024-07-07 17:47:19
2                   1  8.121.2 build 22 50727  2024-07-07 12:31:53
3                   2  8.121.2 build 22 50727  2024-07-07 05:21:45
4                   0   8.26.0 build 11 40221  2024-07-06 19:47:34
…                 …                       …                   …
113615              0                     NaN  2019-08-03 15:06:03
113616              0    8.34.0 build 4 50250  2022-08-15 16:16:30
113617              0                     NaN  2020-08-17 07:26:58
113618              0   7.17.0 build 13 34346  2019-07-21 09:41:42
113619              0                     NaN  2020-05-24 11:04:08

                    appVersion
0       8.121.2 build 22 50727
1                          NaN
2       8.121.2 build 22 50727
3       8.121.2 build 22 50727
4        8.26.0 build 11 40221
…                        …
113615                     NaN
113616    8.34.0 build 4 50250
113617                     NaN
113618   7.17.0 build 13 34346
113619                     NaN

[113620 rows x 8 columns]
```

1.2 Data Information

[3]:
```
# Show data information
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 113620 entries, 0 to 113619
Data columns (total 8 columns):
 #   Column                Non-Null Count   Dtype
---  ------                --------------   -----
 0   reviewId              113620 non-null  object
 1   userName              113618 non-null  object
 2   content               113618 non-null  object
 3   score                 113620 non-null  int64
 4   thumbsUpCount         113620 non-null  int64
 5   reviewCreatedVersion  96981 non-null   object
 6   at                    113620 non-null  object
 7   appVersion            96981 non-null   object
dtypes: int64(2), object(6)
```

```
memory usage: 6.9+ MB
```

2 DATA PREPROCESSING

The first step after importing data is to process the data. Data processing involves two things, i.e: - Checking for missing values - Checking for duplication in the data.

2.1 Data Cleaning

2.1.1 Missing Value Check

- Model Performance: Missing values can significantly affect the performance of machine learning models. In NLP, if parts of the text are missing, it could lead to **incomplete information** for **model training** and **predictions**.
- Bias: Missing data can introduce **bias**, leading to **incorrect conclusions** or **predictions**.

[4]:
```
# Show missing value
data.isnull().sum()
```

[4]:
```
reviewId                  0
userName                  2
content                   2
score                     0
thumbsUpCount             0
reviewCreatedVersion    16639
at                        0
appVersion              16639
dtype: int64
```

[5]:
```
# Drop missing value
data = data.dropna()
data.isnull().sum()
```

[5]:
```
reviewId                0
userName                0
content                 0
score                   0
thumbsUpCount           0
reviewCreatedVersion    0
at                      0
appVersion              0
dtype: int64
```

2.1.2 Duplicate Value Check

- Redundancy: Duplicate entries can lead to redundancy, causing the model to give more importance to repeated information.
- Bias: Duplication can skew the model's understanding of the text, leading to overfitting or biased results.

[6]:
```
# Show data duplicated
data_duplicated = data.duplicated().sum()
data_duplicated
```

[6]: 226

[7]:
```
# Drop data duplicated
data = data.drop_duplicates()
data_duplicated = data.duplicated().sum()
data_duplicated
```

[7]: 0

[8]:
```
data
```

[8]:

	reviewId	userName	content	score	thumbsUpCount	reviewCreatedVersion	at
0	61a10e0d-e868-4d87-aa30-f41d30285a3f	badr mosa	Terrible app I can't watch anything because of…	1	0	8.121.2 build 22 50727	2024-07-08 15:41:17
2	1bd445c3-7f36-4717-810a-63c5533207d0	Ryan Murray	Exceptional	5	1	8.121.2 build 22 50727	2024-07-07 12:31:53
3	59f306cd-852b-4459-b24f-3e4436df8465	Shannon Bonacci	Can't even make it through a full episode of a…	2	2	8.121.2 build 22 50727	2024-07-07 05:21:45
4	f21a1d8a-2b4c-4385-8aff-ca317a00e032	Katie Hutchinson	Great	5	0	8.26.0 build 11 40221	2024-07-06 19:47:34
5	bdd267b4-4231-4a5d-b369-3ac9e5082fc5	Mirza Irfan	Your device is not part of the Netflix Househo…	1	0	8.120.0 build 10 50712	2024-07-05 17:09:39
…	…	…	…	…	…	…	…
113612	9996579a-cf67-40a6-94eb-9ccd63c7d46a	dady mon mari	How can I delete one of the users? Please. Hel…	3	0	8.121.2 build 22 50727	2024-07-08 15:41:17
113613	f2e61d1c-21eb-44d2-924c-35df26ed3bd2	Romnick Arcangel	Good app in easy to use	5	1	8.121.2 build 22 50727	2024-07-07 12:31:53
113614	cbb04dd9-1a1d-46df-80a4-8ae987fe5d85	Ciaran Worthington	Everytime I watch a show it goes so dark so I …	1	2	8.121.2 build 22 50727	2024-07-07 05:21:45
113616	4957f9e7-d7f4-4a52-9764-031cebcac83f	Captain Jeoy	I love Netflix. I always enjoy my time using it.	5	0	8.26.0 build 11 40221	2024-07-06 19:47:34
113618	32870f7f-c461-4256-b602-75244ca60248	A Google user	Rate is very expensive.. bcos we see netflix s…	1	0	8.120.0 build 10 50712	2024-07-05 17:09:39

```
…                …                        …                    …
113612             0   8.104.0 build 5 50619  2024-03-01 04:54:36
113613             0   8.96.1 build 16 50568  2023-12-22 22:08:03
113614             0   7.48.0 build 10 34747  2020-08-22 14:58:10
113616             0    8.34.0 build 4 50250  2022-08-15 16:16:30
113618             0   7.17.0 build 13 34346  2019-07-21 09:41:42

                   appVersion
0       8.121.2 build 22 50727
2       8.121.2 build 22 50727
3       8.121.2 build 22 50727
4        8.26.0 build 11 40221
5       8.120.0 build 10 50712
…                          …
113612   8.104.0 build 5 50619
113613   8.96.1 build 16 50568
113614   7.48.0 build 10 34747
113616    8.34.0 build 4 50250
113618   7.17.0 build 13 34346

[96753 rows x 8 columns]
```

[9]:
```
# Show data content
data['content']
```

[9]:
```
0         Terrible app I can't watch anything because of…
2                                                Exceptional
3         Can't even make it through a full episode of a…
4                                                      Great
5         Your device is not part of the Netflix Househo…
                                …
113612    How can I delete one of the users? Please. Hel…
113613                              Good app in easy to use
113614    Everytime I watch a show it goes so dark so I …
113616     I love Netflix. I always enjoy my time using it.
113618    Rate is very expensive.. bcos we see netflix s…
Name: content, Length: 96753, dtype: object
```

3 TEXT PREPROCESSING

In text processing, it is split into 6 steps sequentially, i.e: - **Case Folding** - **Cleaning** - **Tokenizing** - **Lemmatization** - **Stop Removal** - **Labeling**

3.1 Case Folding

The first thing to do is case folding. Case folding is changing sentences that have **capital letters** into **lowercase letters**. This will have an impact on the results of the analysis.

[10]:
```
# Define case folding function
def case_folding(text):
    # Convert to lowercase
    text_lower = text.lower()
    # Return the value
    return text_lower

# Apply case folding function
data['content'] = data['content'].apply(case_folding)
# Show data
data['content']
```

[10]:
```
0         terrible app i can't watch anything because of…
2                                                exceptional
3         can't even make it through a full episode of a…
4                                                      great
5         your device is not part of the netflix househo…
                              …
113612    how can i delete one of the users? please. hel…
113613                           good app in easy to use
113614    everytime i watch a show it goes so dark so i …
113616     i love netflix. i always enjoy my time using it.
113618    rate is very expensive.. bcos we see netflix s…
Name: content, Length: 96753, dtype: object
```

3.2 Cleansing

Then perform data cleansing by removing extra punctuation, numbers, and spaces.

[11]:
```
# Import regular expression library
import re
```

[12]:
```
# Defince cleansing function
def cleansing(text_lower):
    # Remove hashtag
    text_cleans = re.sub(r'#\w+', '', text_lower)
    # Remove URLs
    text_cleans = re.sub(r'http\S+', '', text_cleans)
    # Remove mentions
    text_cleans = re.sub(r'@\w+', '', text_cleans)
    # Keep only alphabets and whitespace
    text_cleans = re.sub(r'[^A-Za-z\s]', '', text_cleans)
    # Remove non-ASCII
    text_cleans = text_cleans.encode('ascii', 'ignore').decode('utf-8')
    # Remove extra whitespace
    text_cleans = re.sub(r'\s+', ' ', text_cleans).strip()
    # Return the value
    return text_cleans
```

```
# Apply cleansing function
data['content'] = data['content'].apply(cleansing)
# Show data
data['content']
```

[12]:
```
0         terrible app i cant watch anything because of …
2                                                exceptional
3         cant even make it through a full episode of a …
4                                                      great
5         your device is not part of the netflix househo…
                               …
113612     how can i delete one of the users please help me
113613                             good app in easy to use
113614    everytime i watch a show it goes so dark so i …
113616       i love netflix i always enjoy my time using it
113618    rate is very expensive bcos we see netflix sun…
Name: content, Length: 96753, dtype: object
```

3.3 Tokenizing

After the data have been cleaned, each sentence's words are transformed into **tokens** according to **spaces** or **punctuation signs**.

[13]:
```
# Import natural language library
import nltk
# Import tokenize library
from nltk.tokenize import word_tokenize
# Download punkt tokenizer
nltk.download('punkt_tab')
```

```
[nltk_data] Downloading package punkt_tab to /root/nltk_data…
[nltk_data]   Unzipping tokenizers/punkt_tab.zip.
```

[13]:
```
True
```

[14]:
```
# Define tokenizing function
def tokenizing(text_cleans):
    # Convert to token
    tokens = word_tokenize(text_cleans)
    # Return the value
    return tokens

# Apply tokenizing function
data['content'] = data['content'].apply(tokenizing)
# Show data
data['content']
```

[14]:
```
0         [terrible, app, i, cant, watch, anything, beca…
2                                                [exceptional]
3         [cant, even, make, it, through, a, full, episo…
4                                                      [great]
5         [your, device, is, not, part, of, the, netflix…
                                …
113612    [how, can, i, delete, one, of, the, users, ple…
113613                       [good, app, in, easy, to, use]
113614    [everytime, i, watch, a, show, it, goes, so, d…
113616    [i, love, netflix, i, always, enjoy, my, time,…
113618    [rate, is, very, expensive, bcos, we, see, net…
Name: content, Length: 96753, dtype: object
```

3.4 Stop Words Removal

The process of removing meaningless words, like **articles**, **prepositions**, **conjunctions**, and **other words** that often appear but are not meaningful. This is to reduce the dimensionality of the data and focus only on meaningful words.

[18]:
```
nltk.download('stopwords')
# Import stopword library
from nltk.corpus import stopwords
```

```
[nltk_data] Downloading package stopwords to /root/nltk_data…
[nltk_data]   Unzipping corpora/stopwords.zip.
```

[19]:
```
def stopword(tokens):
    # Remove stop words
    stop_words = set(stopwords.words('english'))
    filtered_words = [word for word in tokens if word not in stop_words]
    return filtered_words

data['content'] = data['content'].apply(stopword)
data['content'].head(10)
```

[19]:
```
0     [terrible, app, cant, watch, anything, househo…
2                                          [exceptional]
3     [cant, even, make, full, episode, show, app, c…
4                                                [great]
5     [device, part, netflix, householde, good, poli…
6     [ive, trying, pay, month, since, created, acco…
7                                       [kayla, kwadau]
8                                  [abdulrhamam, sekh]
9                                                [good]
10    [plssssss, stoppppp, giving, screen, limit, lik…
Name: content, dtype: object
```

3.5 Lemmatization

This process involved reducing words to their **original words** or dictionary forms (lemma).

[22]:
```
nltk.download('wordnet')
# Import lemmatization library
from nltk.stem import WordNetLemmatizer
```

```
[nltk_data] Downloading package wordnet to /root/nltk_data…
```

[23]:
```
def lemmatization(filtered_words):
    # Initialize Lemmatizer
    lemmatizer = WordNetLemmatizer()
    # Lemmatize
    lemmatized_words = [lemmatizer.lemmatize(normal_token) for normal_token in␣
 ↪filtered_words]
    return lemmatized_words

data['content'] = data['content'].apply(lemmatization)
data['content'].head(10)
```

[23]:
```
0     [terrible, app, cant, watch, anything, househo…
2                                          [exceptional]
3     [cant, even, make, full, episode, show, app, c…
4                                                [great]
5     [device, part, netflix, householde, good, poli…
6     [ive, trying, pay, month, since, created, acco…
7                                       [kayla, kwadau]
8                                    [abdulrhamam, sekh]
9                                                 [good]
10    [plssssss, stoppppp, giving, screen, limit, lik…
Name: content, dtype: object
```

3.6 Labeling

Automatic labeling of each word using the VADER Lexicon. Each word will be given a different sentiment score. In this case, each word will be categorized into 3 categories, i.e.: - Positive, if the **compound value >= 0.05** - Negative, if the **value -0.05 < compound < 0.05** - Neutral, if the **compound value <= -0.05**

[25]:
```
nltk.download('vader_lexicon')
# Import library
from nltk.sentiment.vader import SentimentIntensityAnalyzer
```

```
[nltk_data] Downloading package vader_lexicon to /root/nltk_data…
```

[26]:
```
# Initialize Vader Analyzer
analyzer = SentimentIntensityAnalyzer()
```

[27]:
```
# Function to get sentiment
def vader_sentiment(lemmatized_words):
    # Convert text to string if it's not already
    if isinstance(lemmatized_words, list):
        lemmatized_words = ' '.join(lemmatized_words)
    score = analyzer.polarity_scores(lemmatized_words)
    return score['compound']
```

[28]:
```
# Function to label sentiment based on compound score
def vader_sentiment_label(compound):
    # Label sentiment
    if compound >= 0.05:
        return 'Positive'
    elif compound > -0.05 and compound < 0.05:
        return 'Neutral'
    else:
        return 'Negative'
```

[29]:
```
data['vader_sentiment'] = data['content'].apply(vader_sentiment)
data['vader_sentiment_label'] = data['vader_sentiment'].
 ↪apply(vader_sentiment_label)
data[['content', 'vader_sentiment', 'vader_sentiment_label']].head(10)
```

[29]:

	content	vader_sentiment	vader_sentiment_label
0	[terrible, app, cant, watch, anything, househo…	-0.6705	Negative
2	[exceptional]	0.0000	Neutral
3	[cant, even, make, full, episode, show, app, c…	-0.1280	Negative
4	[great]	0.6249	Positive
5	[device, part, netflix, householde, good, poli…	0.1779	Positive
6	[ive, trying, pay, month, since, created, acco…	0.1531	Positive
7	[kayla, kwadau]	0.0000	Neutral
8	[abdulrhamam, sekh]	0.0000	Neutral
9	[good]	0.4404	Positive
10	[plsssss, stoppppp, giving, screen, limit, lik…	0.7269	Positive

Label encoding is a process used to **convert categorical labels** into **numeric** form so that they

can be fed into machine learning models. In the context of NLP and sentiment analysis, label encoding is often used to convert text labels (like "Positive," "Negative," and "Neutral") into numerical values.

[30]:
```
# Import library
from sklearn.preprocessing import LabelEncoder
```

[31]:
```
# Label Encoding
label_encoder = LabelEncoder()
data['vader_sentiment_label_encoded'] = label_encoder.
 ↪fit_transform(data['vader_sentiment_label'])
data.head()
```

[31]:

	reviewId	userName	content	score	thumbsUpCount	reviewCreatedVersion	at	appVersion	vader_sentiment	vader_sentiment_label	vader_sentiment_label_encoded
0	61a10e0d-e868-4d87-aa30-f41d30285a3f	badr mosa	[terrible, app, cant, watch, anything, househo…	1	0	8.121.2 build 22 50727	2024-07-08 15:41:17	8.121.2 build 22 50727	-0.6705	Negative	0
2	1bd445c3-7f36-4717-810a-63c5533207d0	Ryan Murray	[exceptional]	5	1	8.121.2 build 22 50727	2024-07-07 12:31:53	8.121.2 build 22 50727	0.0000	Neutral	1
3	59f306cd-852b-4459-b24f-3e4436df8465	Shannon Bonacci	[cant, even, make, full, episode, show, app, c…	2	2	8.121.2 build 22 50727	2024-07-07 05:21:45	8.121.2 build 22 50727	-0.1280	Negative	0
4	f21a1d8a-2b4c-4385-8aff-ca317a00e032	Katie Hutchinson	[great]	5	0	8.26.0 build 11 40221	2024-07-06 19:47:34	8.26.0 build 11 40221	0.6249	Positive	2
5	bdd267b4-4231-4a5d-b369-3ac9e5082fc5	Mirza Irfan	[device, part, netflix, householde, good, poli…	1	0	8.120.0 build 10 50712	2024-07-05 17:09:39	8.120.0 build 10 50712	0.1779	Positive	2

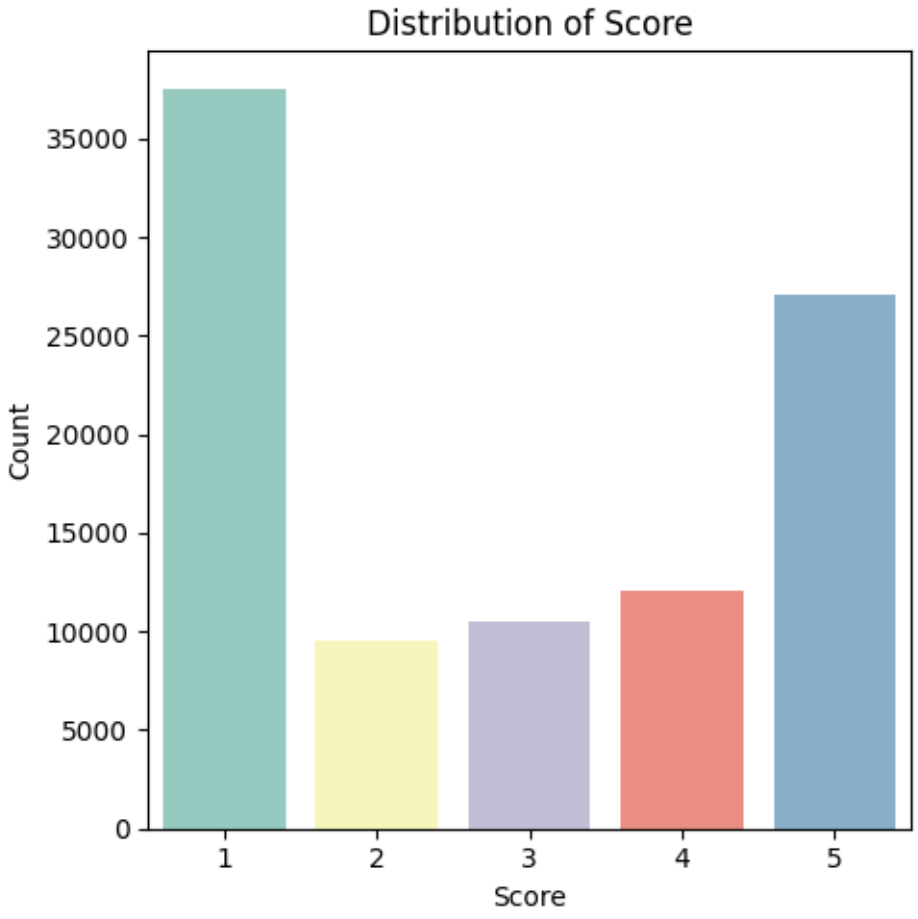
4 EXPLORATORY DATA ANALYSIS

[32]:
```
# Import library
import matplotlib.pyplot as plt
import seaborn as sns
```

4.0.1 Distribution of Score

[33]:
```
plt.figure(figsize=(5, 5))
sns.countplot(x="score", data=data, palette='Set3')
plt.title('Distribution of Score', fontsize=12)
plt.xlabel('Score')
plt.ylabel('Count')
plt.tight_layout()
plt.show()
```

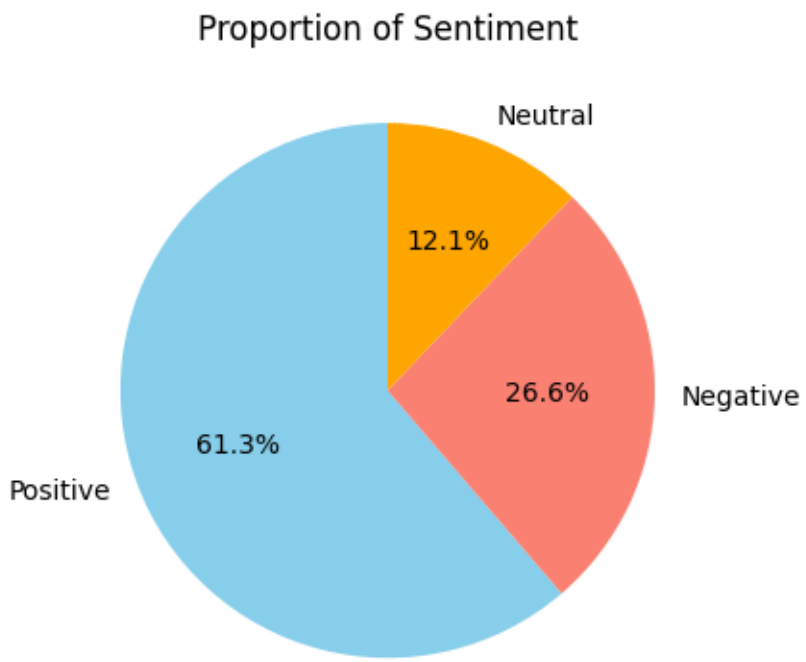
```
<ipython-input-33-7e4fb77df5fe>:2: FutureWarning:

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

  sns.countplot(x="score", data=data, palette='Set3')
```



4.1 Proportion of Sentiment

Exploring labels to find out the sentiment proportion of each category

[34]:
```
# Pie Chart
plt.figure(figsize=(8, 4))
data['vader_sentiment_label'].value_counts().plot(kind='pie', autopct='%1.
 ↪1f%%', startangle=90, colors=['skyblue', 'salmon', 'orange'])
plt.title('Proportion of Sentiment', fontsize=12)
plt.ylabel('')
plt.tight_layout()
plt.show()
```



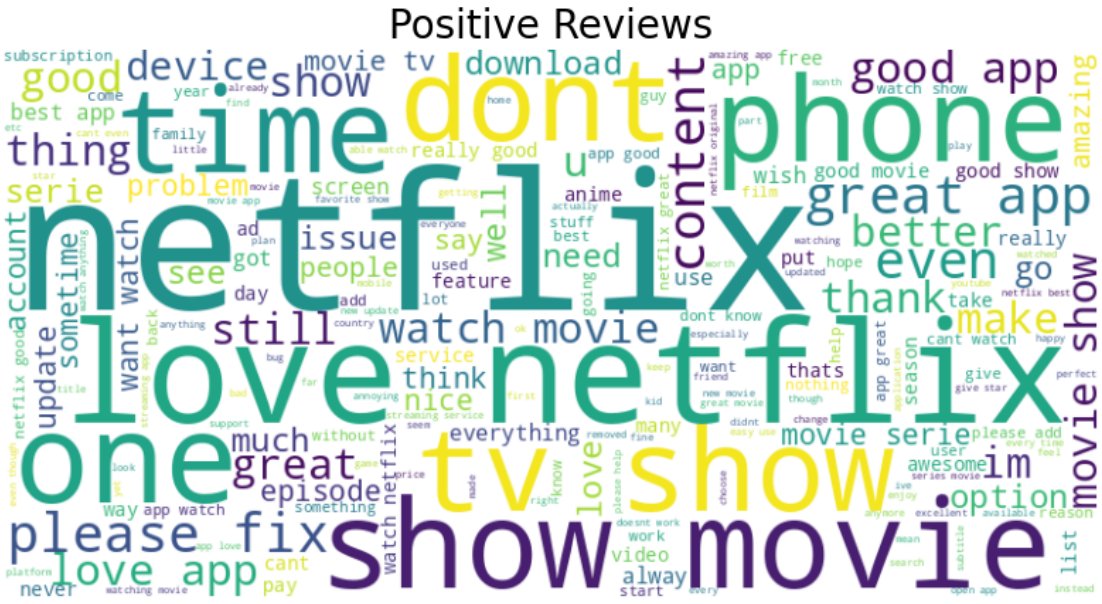
4.2 Word Cloud

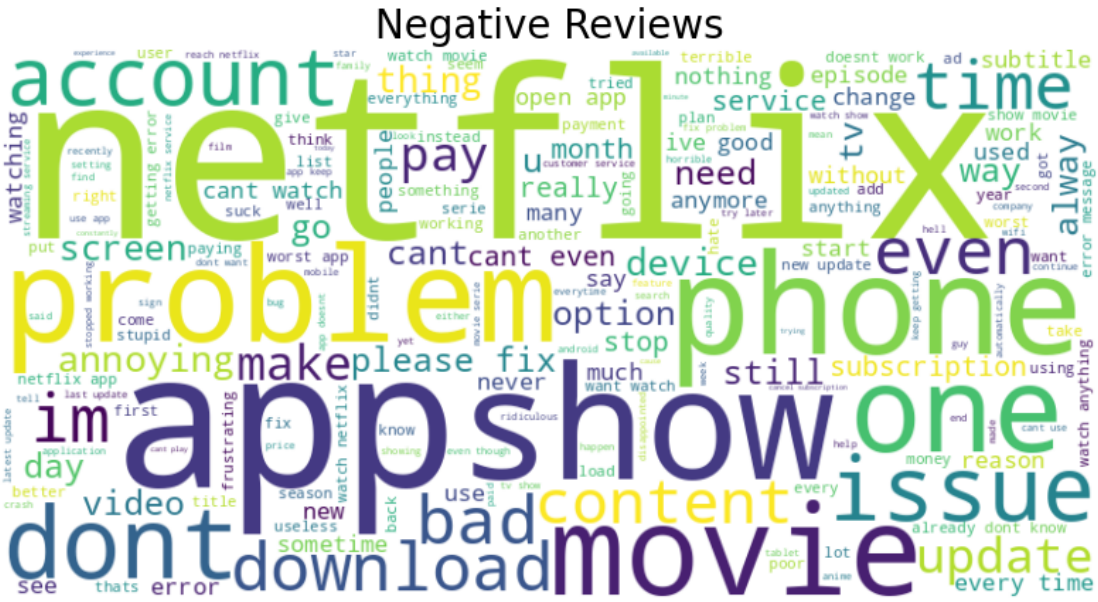
A word cloud helps in visualizing the most frequent words in the dataset. This can give an immediate sense of what the text data is about.

[35]:
```
# Import word cloud library
from wordcloud import WordCloud, STOPWORDS
```

[37]:
```
def create_wordcloud(lemmatized_words, title=None):
    # Join all text elements into a single string, handling potential lists␣
 ↪within the Series
```

```
    all_text = " ".join( " ".join(text_item) if isinstance(text_item, list)␣
 ↪else text_item for text_item in lemmatized_words)
    stop_words = set(STOPWORDS.union(set(stopwords.words('english'))))
    wordcloud = WordCloud(width=800, height=400, background_color='white',␣
 ↪stopwords=stop_words).generate(all_text)
    plt.figure(figsize=(10, 6))
    plt.imshow(wordcloud, interpolation='bilinear')
    plt.axis('off')
    if title:
        plt.title(title, fontsize=20)
    plt.show()

# Create Word Clouds for each sentiment
positive_reviews = data[data['vader_sentiment_label'] == 'Positive']['content']
negative_reviews = data[data['vader_sentiment_label'] == 'Negative']['content']
neutral_reviews = data[data['vader_sentiment_label'] == 'Neutral']['content']

create_wordcloud(positive_reviews, "Positive Reviews")
create_wordcloud(negative_reviews, "Negative Reviews")
create_wordcloud(neutral_reviews, "Neutral Reviews")
```





5 FEATURE EXTRACTION

5.1 CountVectorizer

Extraction of features that **transform text** into a **matrix of token counts.** It counts the number of occurrences of each word in the document. In other words, it **converts text data** into a **numerical representation** for modeling.

[38]:
```
# Import library
from sklearn.feature_extraction.text import CountVectorizer
```

[39]:
```
# Function Vectorizer
def vectorizer(lemmatized_words):
    # Convert text to string if it's not already
    if isinstance(lemmatized_words[0], list):
        lemmatized_words = [' '.join(doc) for doc in lemmatized_words]

    # Initialize CountVectorizer
    vectorizer = CountVectorizer()
    X = vectorizer.fit_transform(lemmatized_words)
    return X, vectorizer
```

[40]:
```
X_counts, count_vectorizer = vectorizer(data['content'])
```

5.2 Change to TF-IDF

It converts the **token count matrix** from CountVectorizer into **TF-IDF representation**. It not only considers the word frequency, but also how **unique** or **important** a word is in all documents.

[41]:
```
# Import library
from sklearn.feature_extraction.text import TfidfTransformer
```

[42]:
```
# Function to change representation to TF-IDF
def tfidf_transformer(X_counts):
    # Initialize TF-IDF Transformer
    transformer = TfidfTransformer()
    X_tfidf = transformer.fit_transform(X_counts)
    return X_tfidf

# Inisialize TF-IDF
X_tfidf = tfidf_transformer(X_counts)
print("TF-IDF Shape:", X_tfidf.shape)
```

```
TF-IDF Shape: (96753, 40814)
```

6 SPLIT DATA

Partitioned data into training data and testing data randomly. The training data is 80% of the total data, while the testing data is 20% of the overall data.

[46]:
```
# Import library
from sklearn.model_selection import train_test_split
```

[47]:
```
y = data['vader_sentiment_label_encoded']
X_train, X_test, y_train, y_test = train_test_split(X_tfidf, y, test_size=0.2,␣
 ↪random_state=42)
```

[48]:
```
print(X_train.toarray()[:5])
```

```
[[0. 0. 0. … 0. 0. 0.]
 [0. 0. 0. … 0. 0. 0.]
 [0. 0. 0. … 0. 0. 0.]
 [0. 0. 0. … 0. 0. 0.]
 [0. 0. 0. … 0. 0. 0.]]
```

[49]:
```
print(X_test.toarray()[:5])
```

```
[[0. 0. 0. … 0. 0. 0.]
 [0. 0. 0. … 0. 0. 0.]
 [0. 0. 0. … 0. 0. 0.]
 [0. 0. 0. … 0. 0. 0.]
 [0. 0. 0. … 0. 0. 0.]]
```

[50]:
```
print(y_train.head())
```

```
86258    2
97186    2
72919    1
32864    2
70266    2
Name: vader_sentiment_label_encoded, dtype: int64
```

[51]:
```
print(y_test.head())
```

```
69627    2
50960    2
43295    1
46308    2
38955    0
Name: vader_sentiment_label_encoded, dtype: int64
```

7 MODELLING

Machine learning modeling using **Multinomial Logistic Regression** and **Multinomial Naïve Bayes** algorithms

7.1 Multinomial Logistic Regression

7.1.1 Build Model

The **Stochastic Average Gradient Descent** (sag) optimization technique is used to minimize the cost function. This technique is suitable for **large data**.

The Basic Idea: - Calculates the probability of each class (positive, negative, and neutral) using a softmax activation function. This activation function ensures that the total probability is 1 - Model coefficients are optimized using a 'sag' optimization technique that iteratively updates by considering the average gradient of the training data

[52]:
```
# Import library
from sklearn.linear_model import LogisticRegression
```

[53]:
```
# Build Model
model_mlg = LogisticRegression(multi_class='multinomial',
                               solver='sag')
```

7.1.2 Train Model

[54]:
```
# Train Model
model_mlg.fit(X_train, y_train)
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/linear_model/_logistic.py:1247:
FutureWarning: 'multi_class' was deprecated in version 1.5 and will be removed
in 1.7. From then on, it will always use 'multinomial'. Leave it to its default
value to avoid this warning.
  warnings.warn(
```

[54]:
```
LogisticRegression(multi_class='multinomial', solver='sag')
```

7.2 Naive Bayes Multinomial

7.2.1 Build Model

Multinomial Naïve Bayes algorithm is a commonly used algorithm for solving text processing cases.

Basic idea: - The prediction of naive bayes requires that each conditional probability cannot be zero. To avoid this problem, an alpha parameter called Laplacian Smoothing/Correction can be set. - The model learns the prior probability distribution which provides information about the parameter distribution. By setting fit_prior to True, the model will estimate the class odds from the training data. - Similarly to alpha, force_alpha when set to True, alpha will be added when a feature does not appear in a particular class during training.

[55]:
```
# Import library
from sklearn.naive_bayes import MultinomialNB
```

[56]:
```
# Build Model
model_nbm = MultinomialNB(alpha = 1,
                          fit_prior = True,
                          force_alpha = True)
```

7.2.2 Train Model

[57]:
```
# Train Model
model_nbm.fit(X_train, y_train)
```

[57]:
```
MultinomialNB(alpha=1)
```

8 MODEL EVALUATION

The model was evaluated with several considerations, i.e: - **Classification evaluation metrics** - **AUC score** - **Classification Report**

8.1 Multinomial Logistic Regression

8.1.1 Predict

The steps in making predictions are as follows: - Calculate the linear combination between features and weights (parameters) added with bias. - Using softmax activation function to get the probability of each class (positive, negative, and neutral). - Calculating the loss function using "sag" to get the chance of class prediction. - Update using gradient descent by iteration until converged.

[58]:
```
# Predict
y_pred_mlg = model_mlg.predict(X_test)
y_pred_mlg
```

[58]:
```
array([2, 2, 1, …, 2, 2, 1])
```

8.1.2 Probability

[59]:
```
# Probability
y_prob_mlg = model_mlg.predict_proba(X_test)
print(y_prob_mlg)
```

```
[[0.00600136 0.00105659 0.99294205]
 [0.1893026  0.06791439 0.742783  ]
 [0.28309772 0.36323925 0.35366303]
 …
 [0.00178745 0.0018218  0.99639075]
 [0.05758902 0.06216167 0.88024931]
 [0.11034019 0.65579814 0.23386167]]
```

8.1.3 Evaluation Metric

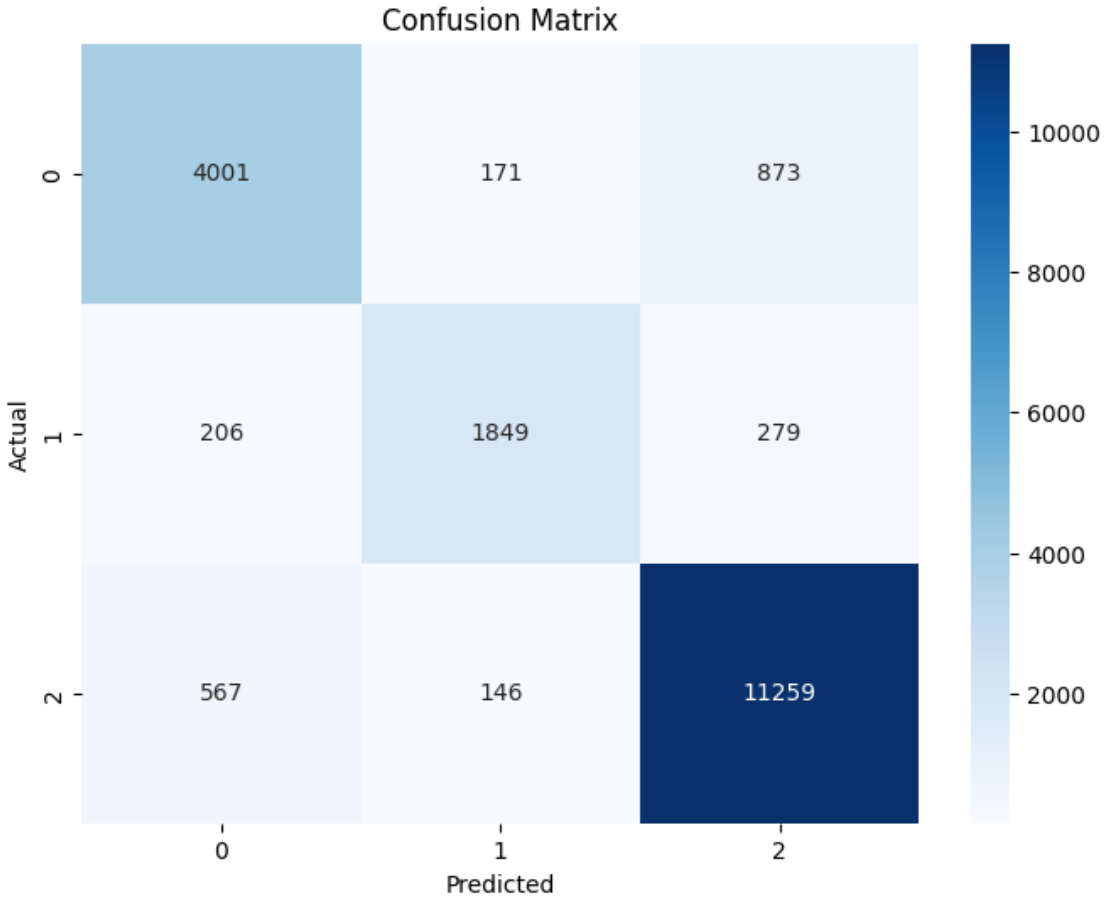
[60]:
```
# Import library
from sklearn.metrics import accuracy_score, precision_score, recall_score,␣
↪f1_score, confusion_matrix, roc_auc_score, roc_curve, classification_report
```

[61]:
```
# Evaluation Metric
print(f'Accuracy: {accuracy_score(y_test, y_pred_mlg)}')
print(f'Precision: {precision_score(y_test, y_pred_mlg, average="weighted")}')
print(f'Recall: {recall_score(y_test, y_pred_mlg, average="weighted")}')
print(f'F1-Score: {f1_score(y_test, y_pred_mlg, average="weighted")}')
```

```
Accuracy: 0.8841403545036433
Precision: 0.8827079290941716
Recall: 0.8841403545036433
F1-Score: 0.8829385661873285
```

8.1.4 Confusion Matrix

[62]:
```
# Confusion Matrix
conf_mat = confusion_matrix(y_test, y_pred_mlg)
plt.figure(figsize=(8, 6))
sns.heatmap(conf_mat, annot=True, fmt='d', cmap='Blues', xticklabels=model_mlg.
 ↪classes_, yticklabels=model_mlg.classes_)
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix')
plt.show()
```



8.1.5 ROC Score

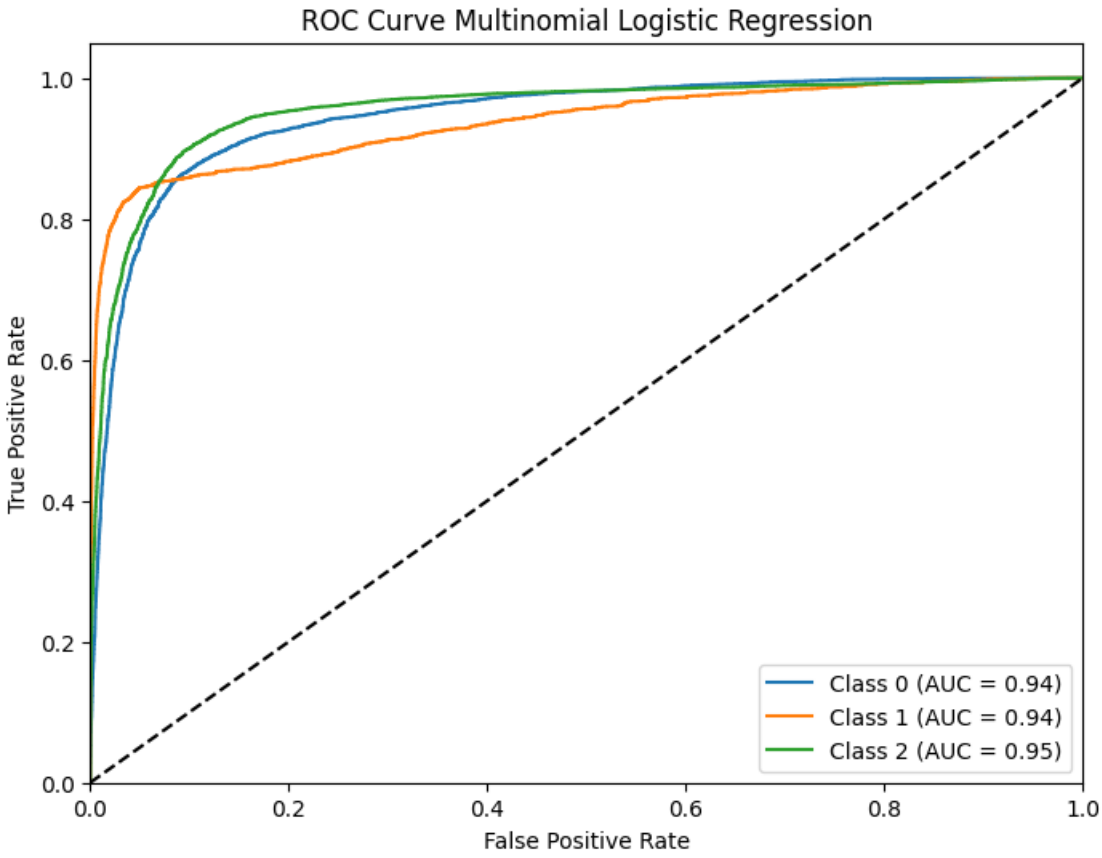
[63]:
```
# Import library
from sklearn.metrics import roc_auc_score, roc_curve, auc
```

[64]:
```
# ROC Score
mlg_roc_auc = roc_auc_score(y_test, y_prob_mlg, multi_class='ovr')
print(f'ROC AUC Score: {mlg_roc_auc}')
```

```
ROC AUC Score: 0.9452340751225373
```

8.1.6 ROC Curve

[65]:
```
# ROC Curve
fpr = dict()
tpr = dict()
roc_auc = dict()
for i in range(len(model_mlg.classes_)):
    fpr[i], tpr[i], _ = roc_curve(y_test == i, model_mlg.predict_proba(X_test)[:
 ↪, i])  # Use predict_proba for multi-class
    roc_auc[i] = auc(fpr[i], tpr[i])

# Plot ROC curve
plt.figure(figsize=(8, 6))
for i in range(len(model_mlg.classes_)):
    plt.plot(fpr[i], tpr[i], label=f'Class {i} (AUC = {roc_auc[i]:.2f})')

plt.plot([0, 1], [0, 1], 'k--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve Multinomial Logistic Regression')
plt.legend(loc="lower right")
plt.show()
```



8.1.7 Classification Report

[66]:
```
# Import library
from sklearn.metrics import classification_report
```

[67]:
```
# Classification Report
print(classification_report(y_test, y_pred_mlg))
```

```
              precision    recall  f1-score   support

           0       0.84      0.79      0.81      5045
           1       0.85      0.79      0.82      2334
           2       0.91      0.94      0.92     11972

    accuracy                           0.88     19351
   macro avg       0.87      0.84      0.85     19351
weighted avg       0.88      0.88      0.88     19351
```

8.2 Naive Bayes Multinomial

8.2.1 Predict

The steps in making predictions are as follows: - Calculate the prior probability of each class, which is the proportion of documents in that class to the total number of documents. - Calculate the likelihood of each features (words) based on the frequency of the word in the documents of that class. - Calculating predictions with the class that has the highest likelihood that will be selected as the prediction class.

[68]:
```
# Predict
y_pred_nbm = model_nbm.predict(X_test)
y_pred_nbm
```

[68]:
```
array([2, 2, 2, …, 2, 2, 2])
```

8.2.2 Probability

[69]:
```
# Probability
y_prob_nbm = model_nbm.predict_proba(X_test)
print(y_prob_nbm)
```

```
[[0.08021062 0.00582751 0.91396187]
 [0.21034246 0.03174683 0.75791072]
 [0.17440449 0.04158244 0.78401306]
 …
 [0.03366728 0.00823769 0.95809503]
 [0.04090234 0.00489655 0.95420111]
 [0.1695457  0.09220592 0.73824838]]
```

8.2.3 Evaluation Metric

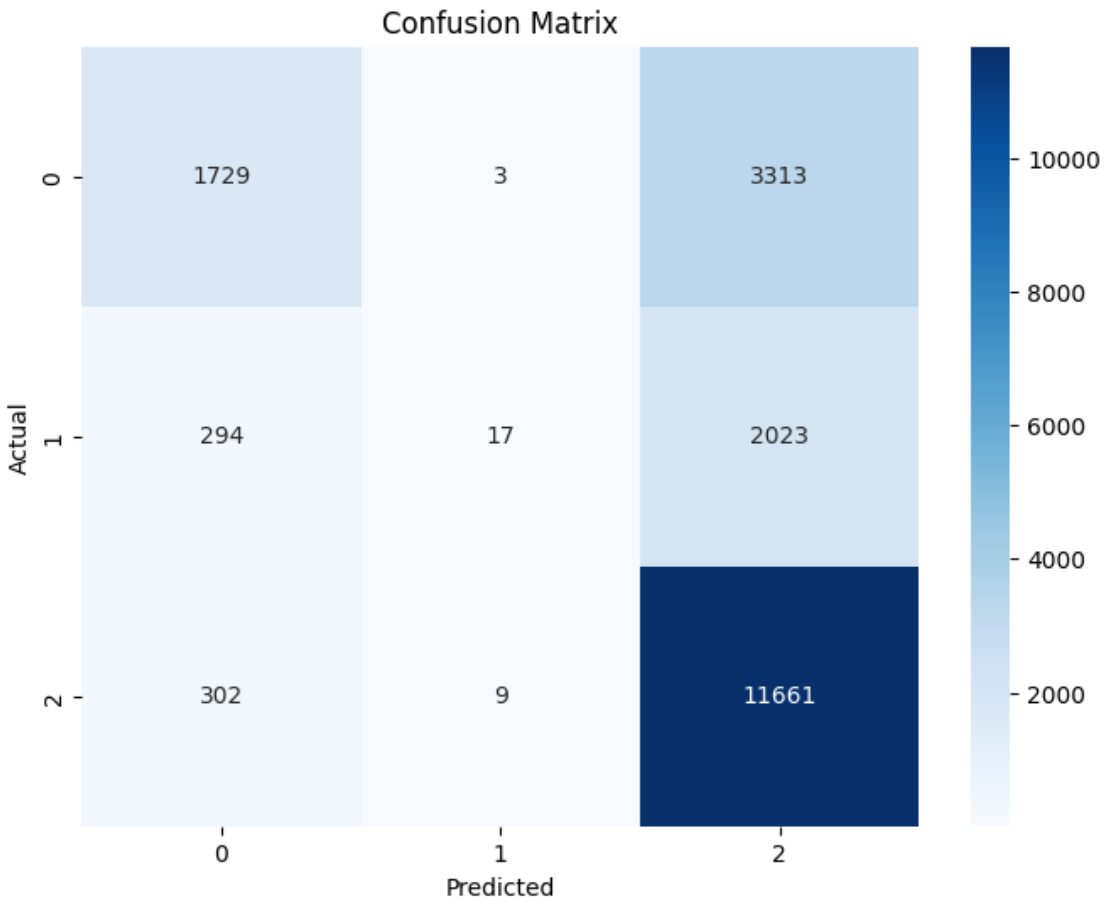
[70]:
```
# Evaluation Metric
print(f'Accuracy: {accuracy_score(y_test, y_pred_nbm)}')
print(f'Precision: {precision_score(y_test, y_pred_nbm, average="weighted")}')
print(f'Recall: {recall_score(y_test, y_pred_nbm, average="weighted")}')
print(f'F1-Score: {f1_score(y_test, y_pred_nbm, average="weighted")}')
```

```
Accuracy: 0.6928324117616661
Precision: 0.6890335483965938
Recall: 0.6928324117616661
F1-Score: 0.6221364238167609
```

8.2.4 Confusion Matrix

[71]:
```
# Confusion Matrix
con_mat = confusion_matrix(y_test, y_pred_nbm)
plt.figure(figsize=(8, 6))
sns.heatmap(con_mat, annot=True, fmt='d', cmap='Blues', xticklabels=model_nbm.
 ↪classes_, yticklabels=model_nbm.classes_)
```

```
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix')
plt.show()
```



8.2.5 ROC Score

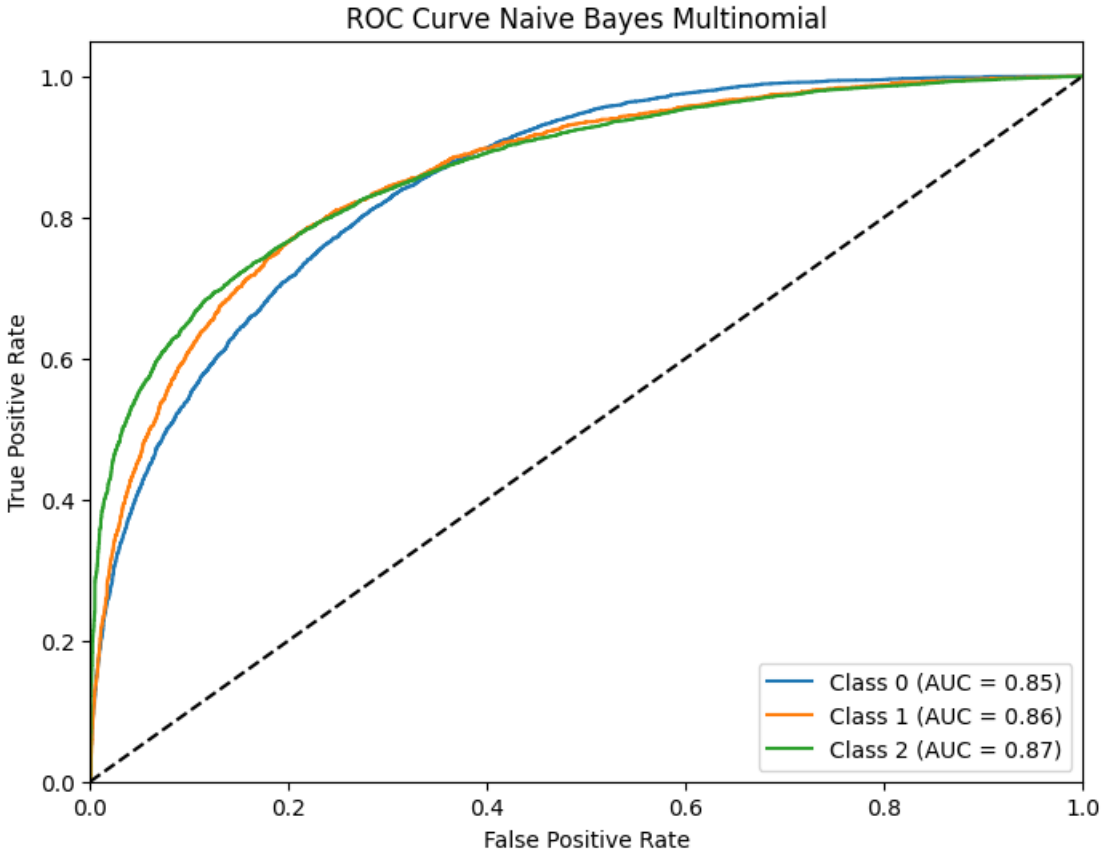
[72]:
```
# ROC Score
nbm_roc_auc = roc_auc_score(y_test, y_prob_nbm, multi_class='ovr')
print(f'ROC AUC Score: {nbm_roc_auc}')
```

```
ROC AUC Score: 0.8604770735198083
```

8.2.6 ROC Curve

[73]:
```
# ROC Curve
fpr = dict()
tpr = dict()
roc_auc = dict()
```

```
for i in range(len(model_nbm.classes_)):
    fpr[i], tpr[i], _ = roc_curve(y_test == i, model_nbm.predict_proba(X_test)[:
 ↪, i])  # Use predict_proba for multi-class
    roc_auc[i] = auc(fpr[i], tpr[i])

# Plot ROC Curve
plt.figure(figsize=(8, 6))
for i in range(len(model_nbm.classes_)):
    plt.plot(fpr[i], tpr[i], label=f'Class {i} (AUC = {roc_auc[i]:.2f})')

plt.plot([0, 1], [0, 1], 'k--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve Naive Bayes Multinomial')
plt.legend(loc="lower right")
plt.show()
```



8.2.7 Classification Report

[74]:
```
# Classification Report
print(classification_report(y_test, y_pred_nbm))
```

```
              precision    recall  f1-score   support

           0       0.74      0.34      0.47      5045
           1       0.59      0.01      0.01      2334
           2       0.69      0.97      0.81     11972

    accuracy                           0.69     19351
   macro avg       0.67      0.44      0.43     19351
weighted avg       0.69      0.69      0.62     19351
```

8.3 Score Comparison

[75]:
```
score_comparison = pd.DataFrame({'Model': ['Multinomial Logistic Regression',␣
 ↪'Naive Bayes Multinomial'],
                                 'Accuracy': [accuracy_score(y_test,␣
 ↪y_pred_mlg), accuracy_score(y_test, y_pred_nbm)],
                                 'Precision': [precision_score(y_test,␣
 ↪y_pred_mlg, average="weighted"), precision_score(y_test, y_pred_nbm,␣
 ↪average="weighted"),],
                                 'Recall': [recall_score(y_test, y_pred_mlg,␣
 ↪average="weighted"), recall_score(y_test, y_pred_nbm, average="weighted")],
                                 'F1-Score': [f1_score(y_test, y_pred_mlg,␣
 ↪average="weighted"), f1_score(y_test, y_pred_nbm, average="weighted")],
                                 'ROC AUC Score': [mlg_roc_auc, nbm_roc_auc]})
score_comparison
```

[75]:

	Model	Accuracy	Precision	Recall	F1-Score	ROC AUC Score
0	Multinomial Logistic Regression	0.884140	0.882708	0.884140	0.882939	0.945234
1	Naive Bayes Multinomial	0.692832	0.689034	0.692832	0.622136	0.860477