SENTIMENT ANALYSIS OF CUSTOMER REVIEW DATA

Post Graduate Program in Data Science Engineering

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1. Overview

1.1. E-Commerce Industry Review- Current Practices in Sentiment Analysis on Customer Reviews

The intense competition to attract and maintain customers online is compelling businesses to implement novel strategies to enhance the customer experiences. It is becoming necessary for companies to examine customer reviews on online platforms such as Amazon to understand better how customers rate their products and services. The purpose of this study is to investigate how companies can conduct sentiment analysis based on Amazon reviews to gain more insights into customer experiences. The dataset selected for this capstone consists of customer reviews and ratings from consumer reviews of Amazon products. Amazon product reviews enable a business to gain insights on customer experiences regarding specific products and services. The study will enable companies to pinpoint the reasons for positive and negative customer reviews and implement effective strategies to address them accordingly.

- Customer Feedback Aggregation:
  E-commerce platforms collect and aggregate customer reviews for products. This data includes textual feedback, ratings and other relevant information.
- Product Ranking and Recommendations:
  Sentiment analysis is used to influence product rankings and recommendations. Positive reviews contribute to higher rankings, making products more visible to potential buyers.
- Quality Assurance and Product Improvement:
  Companies analyse sentiments to identify product strengths and weaknesses. Patterns in negative reviews can highlight areas of improvement.
- Competitor Analysis:
  E-commerce platforms often conduct sentiment analysis not only on their own reviews but also on competitor reviews. This helps in benchmarking and understanding market sentiments.

- Fraud Detection and Review Authenticity:
  Sentiment analysis is used to detect fraudulent reviews or those that may not be authentic. Unusual statement patterns may signal potential issues.
- Marketing and Advertising Strategies:
  It also contributes to the development of marketing strategies. Positive sentiments in reviews can be incorporated into advertising campaigns.
- Dynamic Pricing Strategies:
  It sometimes used to gauge market sentiments about pricing.
  E-commerce platforms may adjust prices based on customer sentiments and competitor pricing.

  In summary, sentiment analysis in the e-commerce industry is a multifaceted tool used for product improvement, customer service enhancement, marketing strategies and overall business intelligence. As technology advances, the industry is likely to continue refining and expanding its use of sentiment analysis to better understand and respond to customer sentiments.

1.2.Literature Survey

a. Publications:

- "Mining and Summarizing Customer Reviews "(2004) by Minqing Hu and Bing Liu:
  This sentimental work introduced a lexicon-based approach for sentiment analysis. The researchers proposed a method to mine product features and opinions from customer reviews. They utilized sentiment lexicons to determine the sentiment orientation of reviews and presented techniques for summarizing customer opinions.
- "Thums Up? Sentiment Classification using Machine Learning Techniques" (2002) by Bo Pang and Lillian Lee:
  Pang and Lee's work was instrumental in popularizing the application of machine learning, particularly Support Vector Machine (SVM), for sentiment classification. They demonstrated

the effectiveness of supervised learning in determining the sentiment of movie reviews, showcasing the potential of statistical methods in sentiment analysis.

These publications represent pivotal moments in the development of sentiment analysis methodologies. Researchers have built upon these foundations to explore advanced techniques, such as deep learning models, aspect-based analysis and more contributing to the evolving landscaper of sentiment analysis in customer reviews.

b. Applications:

- Aspect-Based Sentiment Analysis in Reviews:
  Researchers have explored aspect-based sentiment analysis, going beyond overall sentiment to identify sentiments towards specific aspects or features mentioned in reviews.
- Multimodal Sentiment Analysis:
  With the rise of visual content, there is ongoing research on combining text-based sentiment analysis with image or video analysis. This is particularly relevant in e-commerce where users may provide visual feedback along with textual reviews.
- Cross-Domain Sentiment Analysis
  Researchers have explored techniques for adapting sentiment analysis models trained on one domain to perform well on reviews from a different domain. This is crucial for models to generalize effectively across various types of products or services.

c. Past Research

- Title: "Customer Reviews and Business Intelligence: A Linguistic Approach"
  - Authors: Gautam Pant et al.
  - Year: 2017
  - Key Findings: This study explored the linguistic aspects of customer reviews on Amazon. It delved into the relationship between language

use and business intelligence, emphasizing the role of reviews in understanding customer behaviour.

- Title: "Fake Reviews: An Overview"

- Authors: Muntasir Raihan Rahman et al.
- Year: 2019
- Key Findings: Addressing the issue of fake reviews, this research surveyed methods for detecting and mitigating fraudulent reviews. It highlighted the importance of maintaining the integrity of sentiment analysis outcomes.

d. Ongoing Research

- Title: "Cross-Domain Sentiment Analysis for Amazon Products"

- Focus: Exploring the challenges and opportunities in adapting sentiment analysis models trained on one domain to handle diverse product categories on Amazon.

- Title: "Ethical Considerations in Sentiment Analysis of Amazon Customer Reviews"

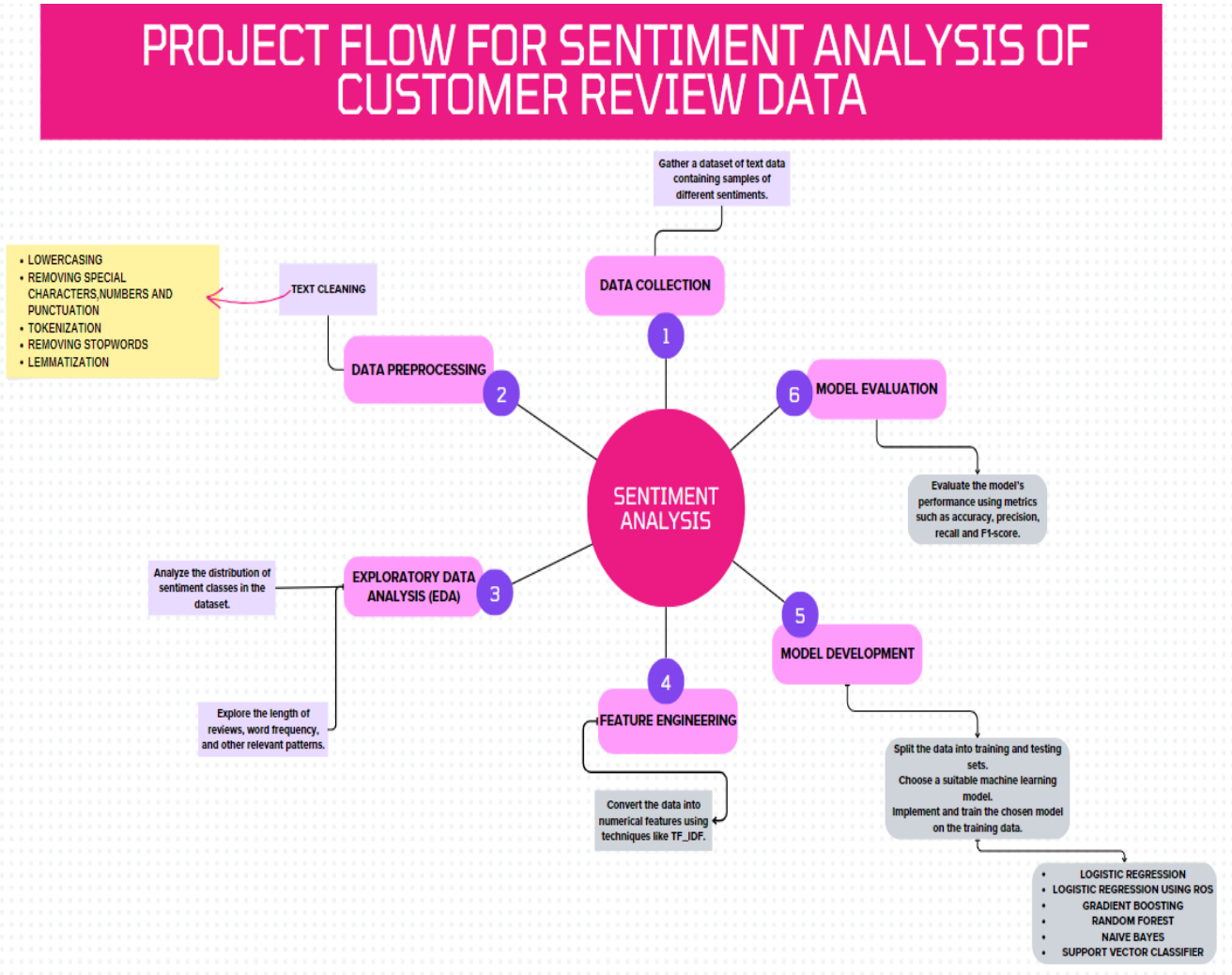
- Focus: Examining ethical considerations in the collection, analysis, and use of sentiment data from Amazon reviews, addressing issues such as user privacy and bias.

- Title: "Impact of Sentiments on Amazon Sales: A Longitudinal Study"

- Focus: Investigating the relationship between sentiments expressed in customer reviews and the sales performance of products on the Amazon platform.

- These ongoing research directions highlight the evolving nature of sentiment analysis in the context of Amazon reviews. Researchers

continue to explore advanced methodologies, ethical considerations, and the dynamic interplay between sentiments and business outcomes on the e-commerce platform.



2. Dataset and Domain

a. Data Dictionary

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 35631 entries, 0 to 35630
Data columns (total 7 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   Unnamed: 0           35631 non-null  int64
 1   brand                35631 non-null  object
 2   manufacturer         35631 non-null  object
 3   reviews.doRecommend  35037 non-null  object
 4   reviews.rating       35598 non-null  float64
 5   reviews.text         35630 non-null  object
 6   reviews.title        35626 non-null  object
dtypes: float64(1), int64(1), object(5)
memory usage: 1.9+ MB
```

Columns in the Dataset:

- brand: the brand or manufacturer of the product
  (categorical: “Amazon”, “Amazon Fire”, “Amazon Echo brand”, “Amazon Fire TV”, “Amazon basics”)
- manufacturer: the company or entity that produced or manufactured the item
  (categorical:” Amazon”, “Amazon basics”, “Amazon Digital Services, Inc”, “Amazon Digital Services”, “Amazon.com”)
- reviews.doRecommend: indicates if the reviewer recommends the product
  (categorical)
- reviews.rating: the rating given in the review (e.g.: star rating)
  (numeric: float64)
- reviews.text: the text content of the review
  (categorical)
- review.title: the title or summary of the review

b. Variable Categorization (numeric and categorical):

- Number of numeric variables: 1
- Number of categorical variables: 5

c. Pre-Processing Data Analysis

- Checking for null Values

```
df.isnull().sum()
```

```
Unnamed: 0                 0
brand                      0
manufacturer               0
reviews.doRecommend      594
reviews.rating            33
reviews.text               1
reviews.title              5
dtype: int64
```

We can observe that there are null values in the columns reviews.doRecommend,reviews.rating, reviews.text and reviews.title.

```
df.dropna(subset=['reviews.doRecommend','reviews.rating','reviews.text','reviews.title'],inplace=True)
```

```
df.isnull().sum()
```

```
Unnamed: 0               0
brand                    0
manufacturer             0
reviews.doRecommend      0
reviews.rating           0
reviews.text             0
reviews.title            0
dtype: int64
```

We have also dropped the Unamed:0 column which was a duplicate column for serial no, which is unique identifier.

```
df.drop('Unnamed: 0',axis=1,inplace=True)
```

```
df
```

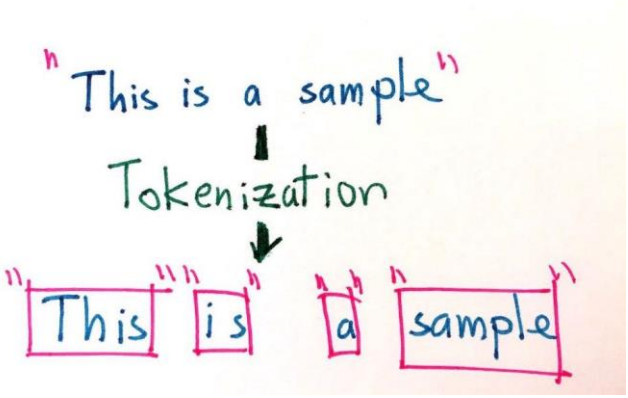
	brand	manufacturer	reviews.doRecommend	reviews.rating	reviews.text	reviews.title
0	Amazon	Amazon	True	5.0	This product so far has not disappointed. My c...	Kindle
1	Amazon	Amazon	True	5.0	great for beginner or experienced person. Boug...	very fast
2	Amazon	Amazon	True	5.0	Inexpensive tablet for him to use and learn on...	Beginner tablet for our 9 year old son.
3	Amazon	Amazon	True	4.0	I've had my Fire HD 8 two weeks now and I love...	Good!!!
4	Amazon	Amazon	True	5.0	I bought this for my grand daughter when she c...	Fantastic Tablet for kids
...	...	...	...	...	...	...
35626	Amazon	Amazon	True	3.0	Unable to download the Instagram app. which st...	The camera is awful!
35627	Amazon	Amazon	True	5.0	Pros: 5 Ghz wifi, supports expansion cardsCons...	Very good for reading, email, internet
35628	Amazon	Amazon	True	5.0	Bought it for my little grandson he likes game...	very good tablet
35629	Amazon	Amazon	True	5.0	I just like reading amd playing games on it..B...	Works great
35630	Amazon	Amazon	True	4.0	Allows for reading of my Kindle lib and even p...	Worlks as advertised

35033 rows × 6 columns

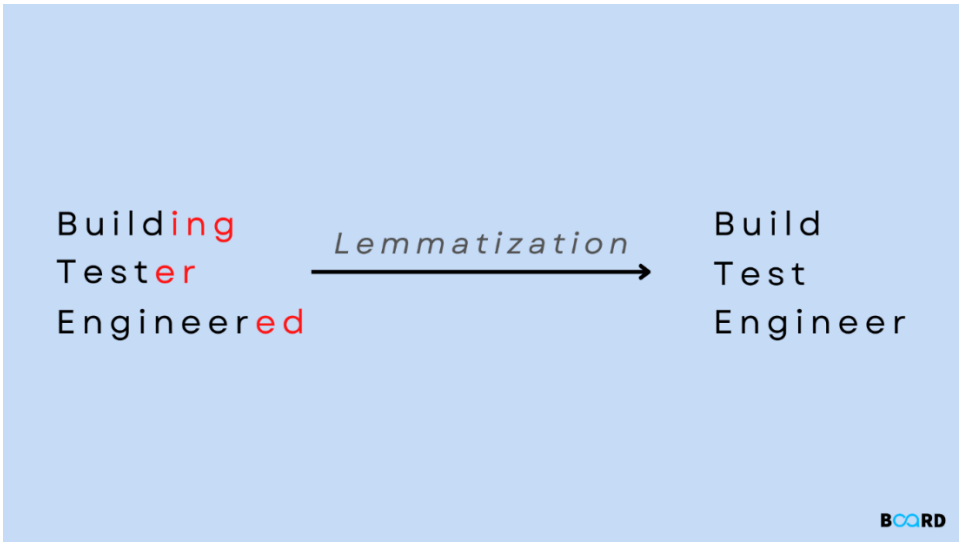
```python
import string
from nltk.tokenize import word_tokenize
from nltk.corpus import stopwords
from nltk.stem import WordNetLemmatizer


def preprocess_text_adjusted(text):
    # Lowercasing
    text = text.lower()

    # Remove special characters and digits, punctuation
    text = ''.join(char for char in text if char.isalnum() or char.isspace() or char in ['!', '?', ','])

    # Tokenization
    words = word_tokenize(text)

    # Remove stopwords
    stop_words = set(stopwords.words('english'))
    words = [word for word in words if word not in stop_words]

    # lemmatizing
    lemmatizer = WordNetLemmatizer()
    words = [lemmatizer.lemmatize(word) for word in words]
    # Join the processed words back into a sentence
    processed_text = ' '.join(words)

    return processed_text
df['reviews.text_adjusted'] = df['reviews.text'].apply(preprocess_text_adjusted)
print(df)
```

The above code is performing text preprocessing on the column reviews.text. The function “preprocess_text_adjusted” takes a text input and performs the following steps:

1. Lowercasing:Converts the enitre text to lowercase to ensure uniformity.
2. Removing special characters and digits:Uses a lits comprehension to keep on;y alphanumeric characters, spaces, and specific punctuation marks.



3. Tokenization: Splits the text into a list of words using “word_tokenize” function.
4. Removing stopwords: Removes common english stopwords using NLTK’s “stopwords” set.



5. Lemmatizing:Applies lemmatization to reduce words to their base or root form using the WordNet lemmatizer.
6. Joining words: Joins the processed words back into a sentence using ".join".

"preprocess_text_adjusted" applies to each row in "review.text" column and creates a new column "review.text_adjusted".

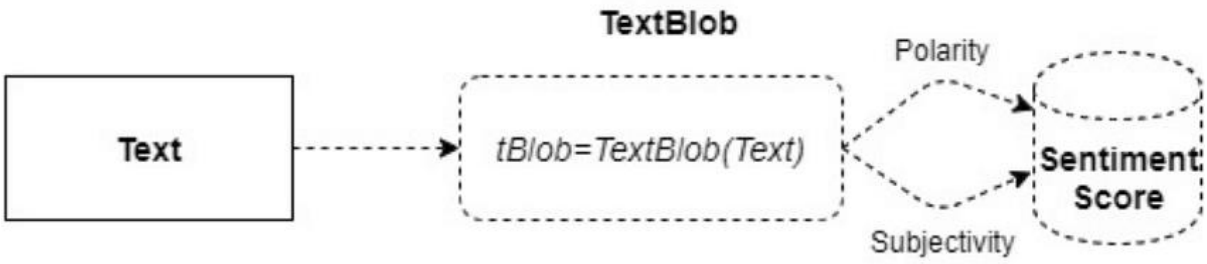
This type of preprocessing is commonly used in Natural language processing (NLP) taks to clean and standardize text data for analysis or machine learning models.

```
from textblob import TextBlob
df['sentiment'] = df['reviews.text_adjusted'].apply(lambda text: 'positive' if TextBlob(text).sentiment.polarity > 0.1
                                                    else ('negative' if TextBlob(text).sentiment.polarity < -0.1 else 'neutral'))
```

```
df['sentiment'].value_counts()
```

```
positive    29186
neutral      4063
negative     1784
```

The code snippet provides a quick and automated way to assess the sentiments of the preprocessed text data.



- Textblob for sentiment analysis: The code leverages TextBlob, a NLP library in Python, for sentiment analysis. TextBlob provides a simple API for common natural language processing tasks, including sentiment analysis.
- Sentiment Categorization: Sentiments are categorized into three classes: ”positive”, “negative”, and “neutral”.
- The sentiment categorization is based on the polarity score calculated by TextBlob.
- If the polarity score is greater than 0.1, the sentiment is categorized as “positive”.
- If the polarity score is less than -.01, the sentiment is categorized as “negative”.
- If the polarity score is between -0.1 and 0.1(inclusive) , the sentiment is categorized as “neutral”.
- The results of the sentiment analysis are store in a new column named “sentiment” within the dataframe.

d. Alternate Sources of Dataset

- When collecting data from alternate sources, it’s essential to ensure that you have the right to use and analyze the data for sentiment analysis. Additionally, consider the context and potential biases associated with each source to ensure a comprehensive understanding of customer sentiments.
- Access product reviews from other online platforms dedicated to reviews.
- Explore forums or discussion boards related to products on websites like Quora, Stack Exchange or dedicated forums for specific product categories.

- Explore reviews and ratings on other online retailers that sell Amazon products. Many products arevailable on multiple platforms, and eacg may have its own set of customer reviews.
- Alternate columns that can be added from sources are:
    - Reviewer's Verified Purchase Status: Indicate whether the reviewer has verified their purchase on Amazon. Verified reviews may carry more weight as they confirm that the reviewer actually bought the product.
    - Reviewer's Location: Include the geographical location of the reviewer. This information can be useful for understanding regional variations in sentiment or identifying localized issues.
- Adding these columns can enrich your dataset and allow for more nuanced analyses.

e. Project Justification

- Project Statement:
- The sentiment analysis project on Amazon reviews aims to analyze and understand the sentiments expressed by customers in their product reviews on the Amazon platform. By employing natural language processing (NLP) techniques, the project will extract valuable insights from textual data, categorizing sentiments into positive, negative, or neutral. The primary goal is to provide Amazon and stakeholders with actionable insights that can enhance customer satisfaction, improve product offerings, and contribute to a positive online shopping experience.

- Complexity Involved:
    - Large and Diverse Dataset:
        - The project involves dealing with a large and diverse dataset comprising reviews from various product categories. Handling the complexity of diverse language use and product-specific nuances is a key challenge.

- Sentiment Ambiguity:
    - Sentiment analysis often encounters ambiguous expressions, sarcasm, or nuanced sentiments. Developing a model that can accurately capture such nuances adds complexity to the project.

- Integration with Business Context:
    - Ensuring that the sentiment analysis aligns with the business context of Amazon and translates into actionable strategies requires a deep understanding of the e-commerce industry.

- Project Outcome:
    - Commercial Value:
- Customer Experience Enhancement: The project will provide insights into customer sentiments, helping Amazon enhance product offerings, address pain points, and optimize the overall customer experience.
- Marketplace Competitiveness: Actionable insights derived from sentiment analysis can contribute to Amazon's competitive advantage by identifying areas for improvement and innovation.

    - Academic Value:
- Research Contribution: The project can contribute to academic research in the fields of natural language processing, sentiment analysis, and e-commerce analytics. Findings and methodologies can be valuable for future research endeavors.

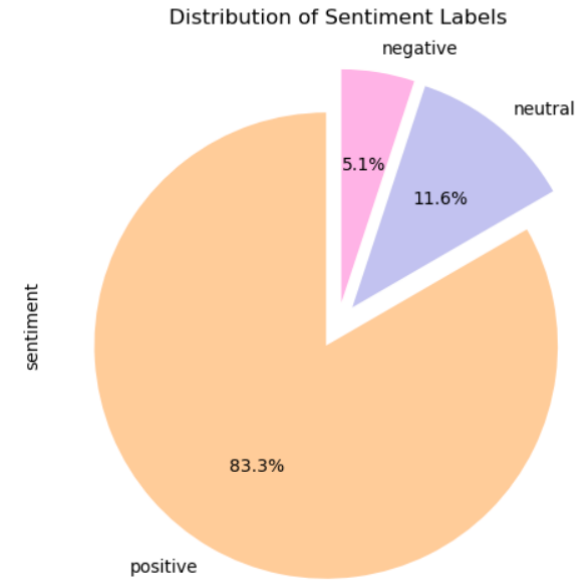
    - Social Value:
- Consumer Empowerment: By understanding customer sentiments, the project contributes to empowering consumers. It helps potential buyers make informed decisions by providing insights into the experiences of previous purchasers.

- Brand Reputation: Positive sentiment analysis outcomes contribute to building and maintaining a positive brand reputation for Amazon, reinforcing trust among customers.

- Overall Impact:
    - The sentiment analysis project on Amazon reviews aims to use advanced language analysis techniques to understand and categorize customer sentiments. This analysis will provide valuable insights for Amazon to enhance the online shopping experience, improve services, and address customer concerns. Beyond its commercial impact, the project also contributes to academic research in the fields of sentiment analysis and e-commerce analytics, benefiting a wider community interested in understanding customer opinions and behavior.

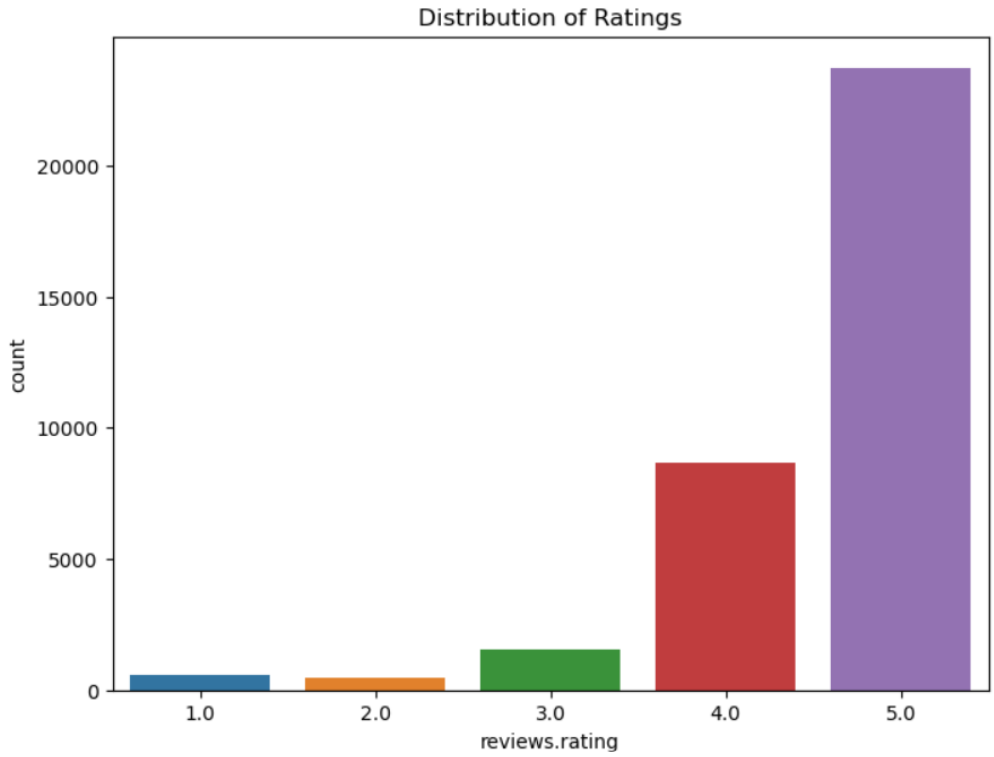
3. Exploratory Data Analysis(EDA)

```
plt.figure(figsize=(8, 6))
df['sentiment'].value_counts().plot.pie(autopct='%1.1f%%', colors=['#FFCC99', '#c2c2f0', '#ffb3e6'], explode=(0.1,0.1,0.1),
                                        startangle=90)
plt.title('Distribution of Sentiment Labels')
plt.show()
```



- The pie chart visually represents the distribution of sentiment labels in the “sentiment” column.
- Each wedge corresponds to a sentiment category(“positive”, “negative”, “neutral”).
- Approximatley 83.3% of the sentiments in the dataset are catgeorized as positive. This indicates as predominant positive sentiment in the analyzed texts.
- Around 5.1% of the sentiments are categorized as negative, suggesting a relatively lower occurrence of megative sentiments.
- And approximatley 7% of the sentiments are categorized as neutral, indicating instances where the sentiment polarity is close to zero.

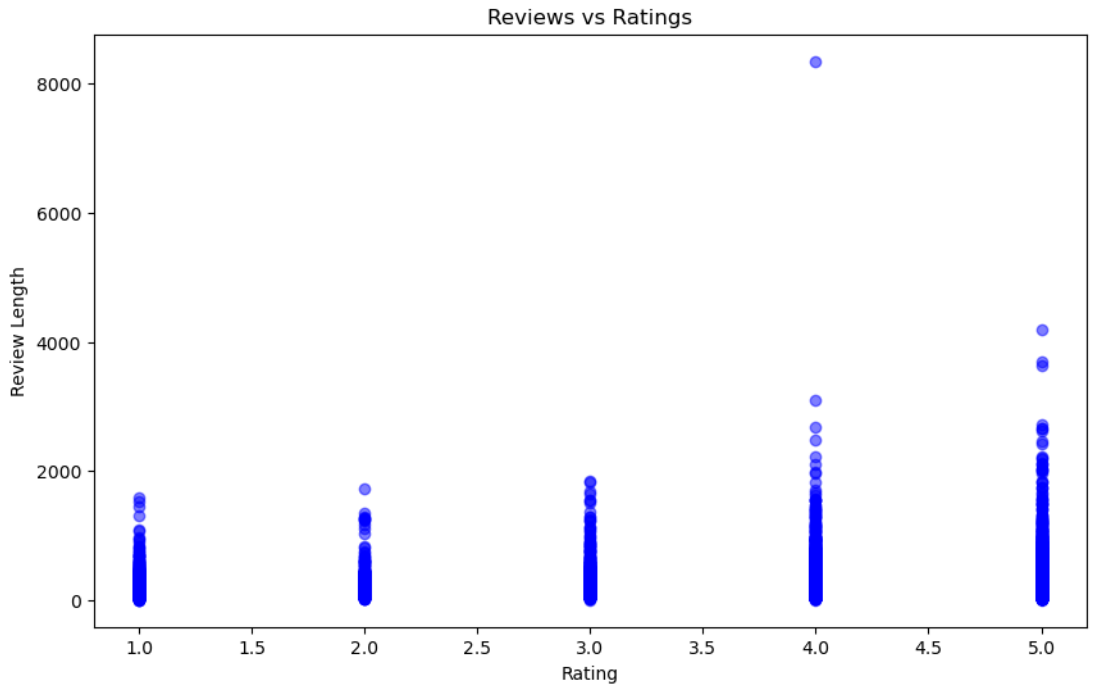
```
plt.figure(figsize=(8, 6))
sns.countplot(x='reviews.rating', data=df)
plt.title('Distribution of Ratings')
plt.show()
```



- The count plot visualizes the distribution of ratings in the “review.rating” column.

- The X-axis represents the unique rating values, and the Y-axis represents the count of each rating.
- A substantial number of reviews have received the highest rating of 5. Similarly, a considerbale number of reviews have received a rating of 4.
- The count plot doesn't show the distribution of lower ratings explicitly, but it implies that the frequency of lower rating(e.g. 1,2 and 3) is comparitively lower than the higher ratings.
- The high concentration of ratings around 4 and 5 suggests a generally positive sentiment in the reviews.
- The visualization provides a quick overview of the distribution of ratings and can be useful for understanding the overall satisfaction level based on customer or user reviews.

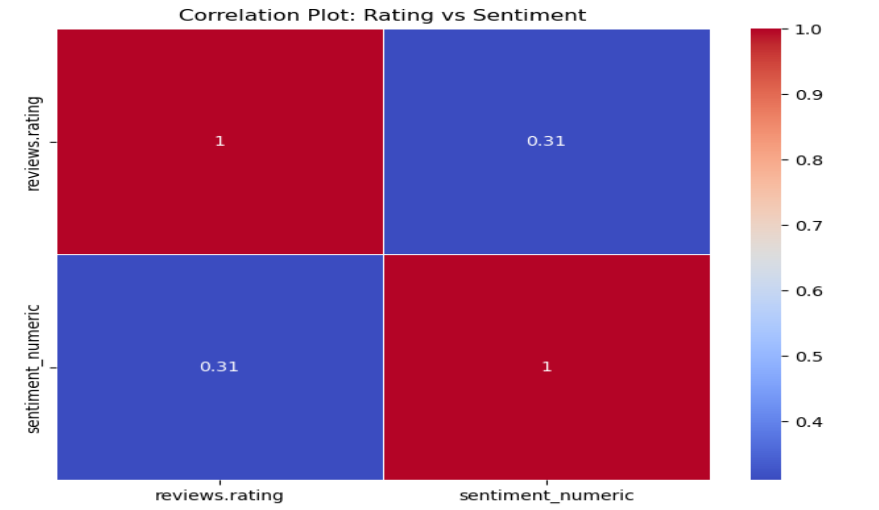
```
df['review_length'] = df['reviews.text'].apply(len)
plt.figure(figsize=(10, 6))
plt.scatter(df['reviews.rating'], df['review_length'], alpha=0.5, color='blue')
plt.title('Reviews vs Ratings')
plt.xlabel('Rating')
plt.ylabel('Review Length')
plt.show()
```



- The scatter plot illustrates the relationship between the length of reviews and the ratings given by reviewers.

- The scattered points on the plot reveal the diversity of review lengths across different ratings.
- The concentration of points in specific regions of the plot can indicate trends or patterns.
- There is a discernible pattern, it might be visible as clusters or trends in the scatter plot.
- Reviewers may exhibit different behaviors based on the length of their reviews and the ratings they assign.
- High-density areas or trends in the plot could provide insights into whether there is a correlation between the length of reviews and the ratings given.
- It helps analysts and stakeholders understand potential correlations or patterns in how the length of reviews may be associated with the ratings assigned by reviewers.

```
sentiment_mapping = {'negative': -1, 'neutral': 0, 'positive': 1}
df['sentiment_numeric'] = df['sentiment'].map(sentiment_mapping)

#  correlation matrix
correlation_matrix = df[['reviews.rating', 'sentiment_numeric']].corr()

#  heatmap
plt.figure(figsize=(8, 6))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', linewidths=.5)
plt.title('Correlation Plot: Rating vs Sentiment')
plt.show()
```



- The code snippet aims to explore the correlation between the numeric representation of sentiment and the reviews.ratings.

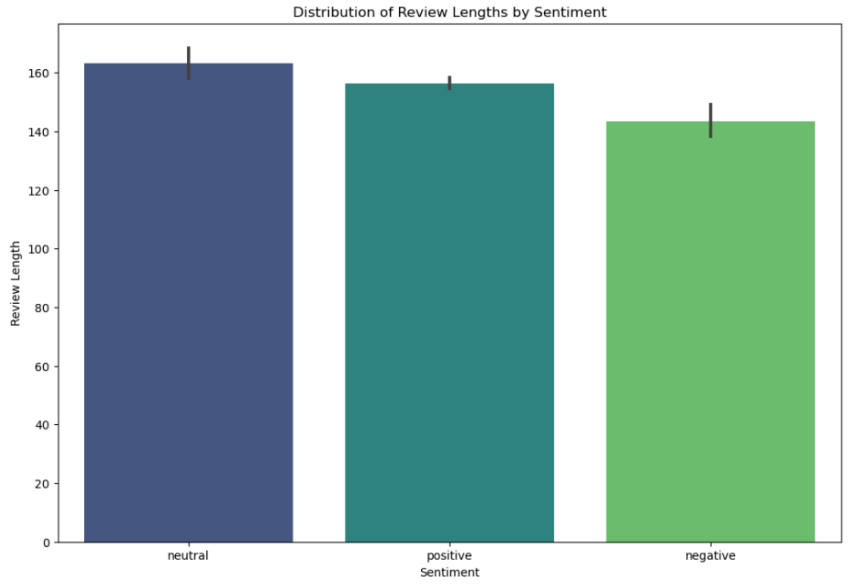
- A new column named `sentiment_numeric` is created by mapping the categorical sentiment values ('negative', 'neutral', 'positive') to numeric values (-1, 0, 1) using the `sentiment_mapping` dictionary.
- A correlation matrix is computed for the columns 'reviews.rating' and 'sentiment_numeric'.
- The correlation coefficient quantifies the strength and direction of a linear relationship between two variables, ranging from -1 to 1. A positive correlation suggests a positive relationship, while a negative correlation suggests an inverse relationship. - The correlation plot visually depicts the correlation between the numeric representation of sentiment and the ratings.
- Positive correlation values suggest that as one variable increases, the other tends to increase as well, while negative values suggest an inverse relationship.
- The heatmap allows for a quick identification of patterns or trends in the correlation between sentiment and ratings.

```
plt.figure(figsize=(8, 6))
sns.barplot(x='sentiment', y='reviews.rating', data=df)
plt.title('Average Rating for Each Sentiment Class')
plt.show()
```

- The bar plot provides a straightforward comparison of average ratings across different sentiment classes.
- It allows for a quick assessment of the relationship between sentiment and average ratings.

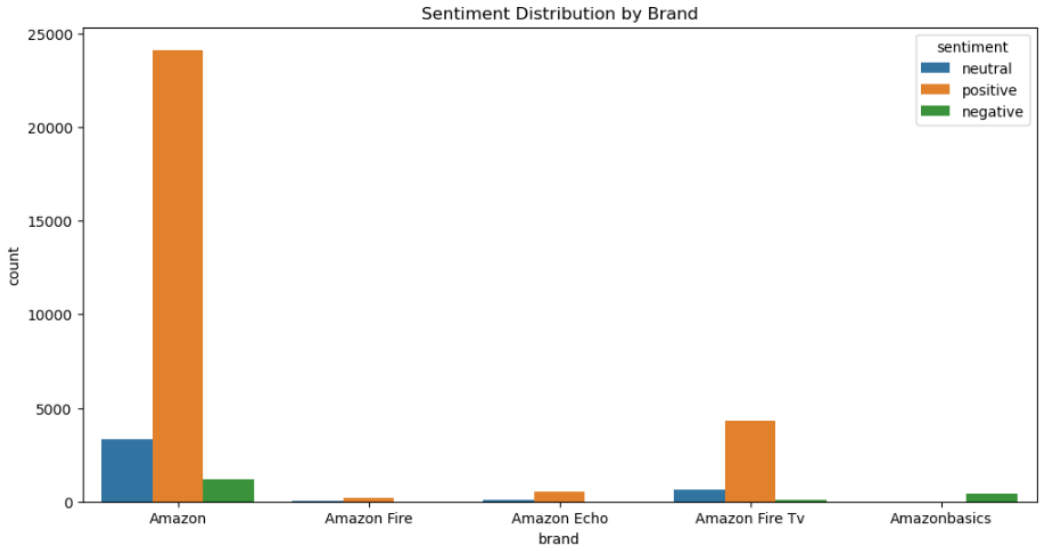
- The visualization helps to understand how sentiment classes are distributed in terms of average ratings, offering insights into how sentiment may correlate with the overall positivity or negativity of reviews in the dataset.

```
plt.figure(figsize=(12, 8))
sns.barplot(x='sentiment', y='review_length', data=df, palette='viridis')
plt.title('Distribution of Review Lengths by Sentiment')
plt.xlabel('Sentiment')
plt.ylabel('Review Length')
plt.show()
```



- Each bar's height indicates the average review length for the corresponding sentiment class.
- Longer positive reviews could suggest that customers are providing detailed feedback when expressing positive sentiments.
- A lower bar for 'negative' sentiment suggests that, on average, reviews with negative sentiment tend to have shorter lengths.
- Shorter negative reviews might indicate succinct expressions of dissatisfaction.
- The bar plot facilitates a visual comparison of average review lengths across different sentiment classes.
- It allows for an understanding of how the length of reviews may vary based on sentiment.
- It helps in understanding the typical lengths of reviews associated with different sentiment classes, contributing to a nuanced analysis of the textual data.

```
plt.figure(figsize=(12, 6))
sns.countplot(x='brand', hue='sentiment', data=df)
plt.title('Sentiment Distribution by Brand')
plt.show()
```

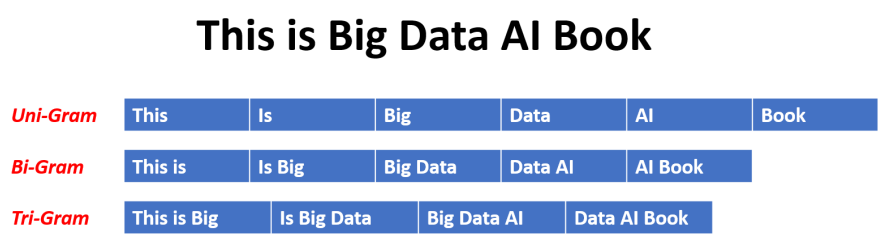


- The plot enables a brand-specific view of sentiment composition, showing how reviews are distributed among different sentiment categories for each brand.
- Brands with higher positive sentiment bars may indicate a generally positive customer sentiment, while higher negative sentiment bars suggest more critical reviews.
- The count of reviews for each brand provides insights into the popularity or customer engagement level.
- Combining this information with sentiment distribution allows for a more comprehensive understanding of brand perception.
- The visualization facilitates a quick assessment of sentiment distribution across brands, helping stakeholders identify patterns or trends associated with customer sentiment.
- It aids in identifying potential areas for improvement, understanding customer satisfaction, and making informed brand-related decisions based on customer feedback.

```python
from nltk import bigrams
from nltk.tokenize import word_tokenize
from nltk.corpus import stopwords
from nltk.stem import WordNetLemmatizer

def get_bigrams(sentiment_category):
    selected_reviews = df[df['sentiment'] == sentiment_category]['reviews.text_adjusted']
    text = ' '.join(selected_reviews)

    # Tokenizing the text
    tokens = word_tokenize(text)

    # Removing stopwords
    stop_words = set(stopwords.words('english'))
    filtered_tokens = [token for token in tokens if token.lower() not in stop_words]

    # Lemmatization
    lemmatizer = WordNetLemmatizer()
    lemmatized_tokens = [lemmatizer.lemmatize(token) for token in filtered_tokens]

    # Removing non-alphanumeric characters
    lemmatized_tokens = [token for token in lemmatized_tokens if token.isalnum() or token.isspace()]

    # Removing single characters
    lemmatized_tokens = [token for token in lemmatized_tokens if len(token) > 1]

    # Extracting bigrams
    sentiment_bigrams = list(bigrams(lemmatized_tokens))

    return sentiment_bigrams

positive_bigrams = get_bigrams('positive')
negative_bigrams = get_bigrams('negative')
neutral_bigrams = get_bigrams('neutral')
print("Positive Review Bigrams:", positive_bigrams[:10])
print("Negative Review Bigrams:", negative_bigrams[:10])
print("Neutral Review Bigrams:", neutral_bigrams[:10])
```

```
Positive Review Bigrams: [('great', 'beginner'), ('beginner', 'experienced'), ('experienced', 'person'), ('person', 'bought'),
('bought', 'gift'), ('gift', 'love'), ('love', 'inexpensive'), ('inexpensive', 'tablet'), ('tablet', 'use'), ('use', 'learn')]
Negative Review Bigrams: [('really', 'like'), ('like', 'tablet'), ('tablet', 'would'), ('would', 'given'), ('given', 'star'),
('star', 'sometimes'), ('sometimes', 'push'), ('push', 'start'), ('start', 'several'), ('several', 'time')]
Neutral Review Bigrams: [('product', 'far'), ('far', 'disappointed'), ('disappointed', 'child'), ('child', 'love'), ('love', 'u
se'), ('use', 'like'), ('like', 'ability'), ('ability', 'monitor'), ('monitor', 'control'), ('control', 'content')]
```

- The above code defines a function `get_bigrams` that extracts bigrams (pairs of consecutive words) from a collection of reviews based on their sentiment category. It then applies this function to three sentiment categories ('positive', 'negative', 'neutral') and prints the first 10 bigrams for each category.



- bigrams: This function is part of NLTK and is used to extract bigrams from a sequence of words.
- word_tokenize: Tokenizes words in a text.
- stopwords: Provides a set of common English stopwords.
- WordNetLemmatizer: Lemmatizes words using WordNet's lexical database.
- The `get_bigrams` function takes a sentiment category as an argument and extracts bigrams from reviews belonging to that sentiment category.

- It first selects the reviews for the specified sentiment category from the DataFrame and concatenates them into a single text string.
- The text is tokenized into a list of words using `word_tokenize`.
- Stopwords are removed from the list of tokens.
- Lemmatization is applied to reduce words to their base or root form using the WordNet lemmatizer.
- Non-alphanumeric characters are removed, and single characters are filtered out.
- The function returns a list of bigrams for the specified sentiment category.
- The first 10 bigrams for each sentiment category are printed.
- This kind of analysis can be useful for understanding the language patterns associated with different sentiments in the reviews.

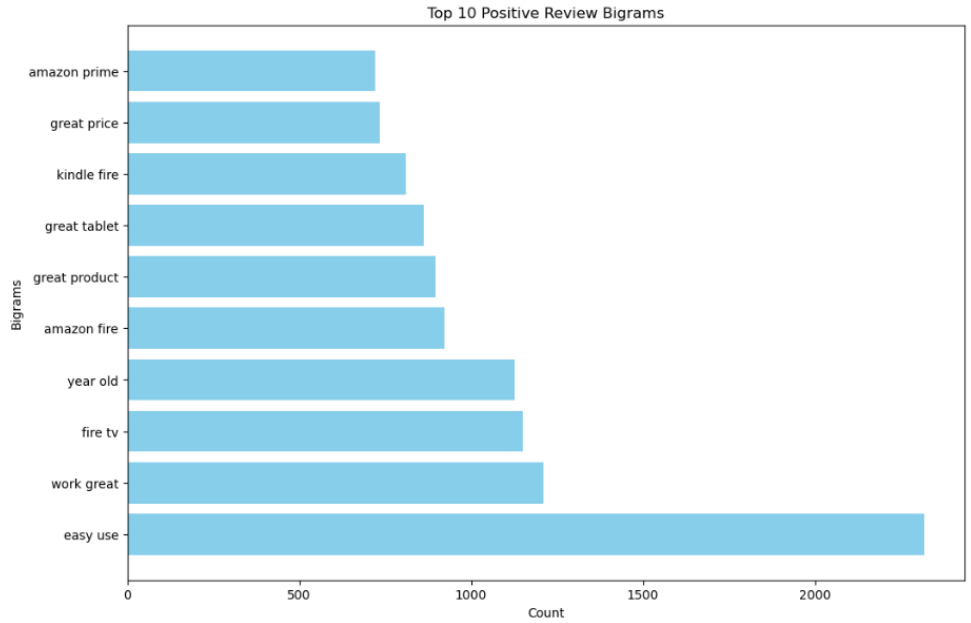
```
from collections import Counter

# Count the occurrences of each bigram in each sentiment category
positive_bigram_counts = Counter(positive_bigrams)
negative_bigram_counts = Counter(negative_bigrams)
neutral_bigram_counts = Counter(neutral_bigrams)

# Get the top N bigrams for each sentiment category
num_top_bigrams = 10
top_positive_bigrams = positive_bigram_counts.most_common(num_top_bigrams)
top_negative_bigrams = negative_bigram_counts.most_common(num_top_bigrams)
top_neutral_bigrams = neutral_bigram_counts.most_common(num_top_bigrams)

# Function to plot bigrams
def plot_bigrams(top_bigrams, title):
    bigrams, counts = zip(*top_bigrams)
    bigrams = [' '.join(bigram) for bigram in bigrams]  # Join the bigrams into a single string
    plt.figure(figsize=(12, 8))
    plt.barh(bigrams, counts, color='skyblue')
    plt.title(title)
    plt.xlabel('Count')
    plt.ylabel('Bigrams')
    plt.show()

# Plot the top N bigrams for each sentiment category
plot_bigrams(top_positive_bigrams, 'Top 10 Positive Review Bigrams')
```

The above code segment analyzes the occurrence of bigrams in different sentiment categories(“positive”, ”negative”, ”neutral”) and visualizes the top N bigrams for each catgeory.

The “Counter” class is imported from the “collections” module. It is used to count the occurrence of elements in a collection.

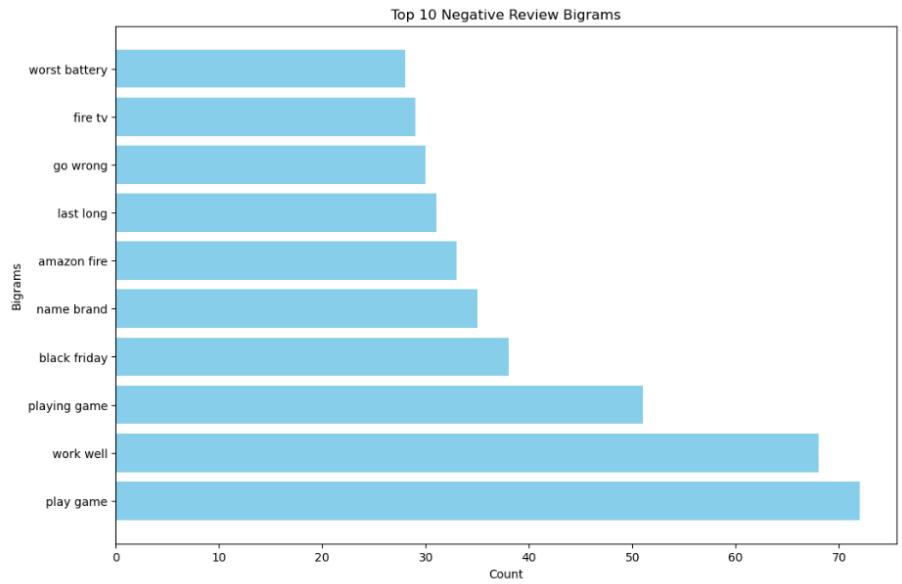
The plot_bigrams function is defined to create bar plots for visualizaing the top bigrams.

The resulting plots provide insights into the language pattern associated with different sentiments, helping to identify recurring word pairs in each sentiment catgeory.



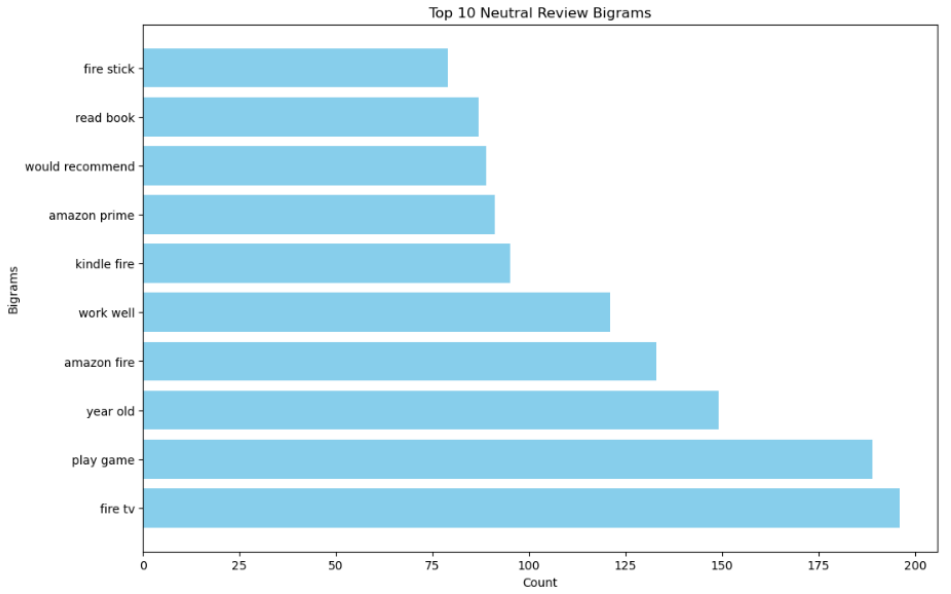
- The frequent occurrence of the bigram "easy use" suggests that customers who express positive sentiments often associate the ease of use with the product or service.
- The high count indicates that a significant number of customers find the product or service easy to use. This is a positive signal, as usability is a key factor in customer satisfaction.
- Businesses can leverage this insight in marketing materials, emphasizing the user-friendly nature of their offerings.
- Highlighting the "easy use" aspect in promotional campaigns, product descriptions, or user manuals can reinforce positive perceptions.
- If applicable, businesses can use this information to inform future product development efforts. Understanding what customers appreciate about the usability can guide improvements or enhancements.
- In summary, recognizing and acting on insights related to positive sentiments, such as the ease of use, can have a positive impact on customer satisfaction and overall business success.

```
plot_bigrams(top_negative_bigrams, 'Top 10 Negative Review Bigrams')
```



- The bigrams "play game" and "work well" are the top two most frequently occurring bigrams in negative reviews.
- The presence of "play game" as a common bigram in negative reviews suggests that customers may be expressing dissatisfaction or issues related to the product or service's performance in gaming scenarios.
- It could indicate concerns such as poor gaming experience, glitches, or performance issues that negatively impact the user's ability to play games.
- For the "play game" bigram, businesses should investigate and address any issues related to the product's performance in gaming scenarios. This could involve optimizing gaming features, addressing bugs, or improving overall gaming experience. Understanding the context of phrases like "work well" in negative reviews is crucial. It might indicate that customers expected the product to work well but experienced issues, emphasizing the importance of aligning marketing claims with actual performance.
- Analyzing these insights can guide efforts to enhance user experience in specific scenarios (such as gaming) and improve overall product performance.
- In summary, identifying and addressing specific issues mentioned in negative reviews, can contribute to overall product improvement and customer satisfaction.

```
plot_bigrams(top_neutral_bigrams, 'Top 10 Neutral Review Bigrams')
```



- Neutral sentiments often indicate a balanced view where customers may provide feedback without a strong inclination towards satisfaction or dissatisfaction.
- Bigrams in neutral reviews may represent aspects that customers find neither particularly positive nor negative.
- Analyzing neutral bigrams can highlight areas that may not be outstanding but are still noteworthy to customers.
- Businesses can use this information to identify potential areas for improvement or refinement in their products or services.
- Neutral bigrams might involve discussions about specific features, functionalities, or experiences that are neither exceptionally positive nor negative.
- Understanding these features can guide product development and marketing strategies.
- Neutral reviews may involve comparisons with other products or experiences. Analyzing these comparisons can provide insights into customer preferences and expectations.
- Consider product enhancements or modifications based on neutral feedback to move certain aspects from neutral to positive.

```
from wordcloud import WordCloud
import matplotlib.pyplot as plt
def generate_wordcloud(sentiment, ax):
    # Combining reviews for the specified sentiment into a single text
    text = ' '.join(df[df['sentiment'] == sentiment]['reviews.text_adjusted'])

    # Generating the word cloud
    wordcloud = WordCloud(width=400, height=200, background_color='white').generate(text)

    # Ploting the word cloud
    ax.imshow(wordcloud, interpolation='bilinear')
    ax.axis('off')  # Turn off axis labels
    ax.set_title(f'{sentiment.capitalize()} Sentiment')

# Creating subplots
fig, axes = plt.subplots(3, 1, figsize=(15, 10))

# Generating word clouds for each sentiment category
sentiments = df['sentiment'].unique()
for i, sentiment in enumerate(sentiments):
    generate_wordcloud(sentiment, axes[i])

plt.tight_layout()
plt.show()
```

- Word clouds are visual representations of text data where words are displayed in varying sizes, with the size of each word indicating its frequency or importance in the given text. While word clouds are a popular visualization technique, they are not typically used as a direct tool in natural language processing (NLP) for advanced analysis. Instead, they serve as a supplementary tool for visual exploration of textual data. Here's how word clouds are commonly used in the context of NLP:

    - Data Exploration:
        - Word clouds are often used in the initial stages of data exploration to visually inspect the most frequently occurring words in a corpus.
        - This can help researchers or analysts get a quick overview of the dominant terms in the text data.

    - Keyword Identification:
        - Word clouds can be useful for identifying keywords or terms that stand out in a given document or set of documents.
        - Analysts can quickly identify which words are more prominent in the dataset.

- Topic Visualization:

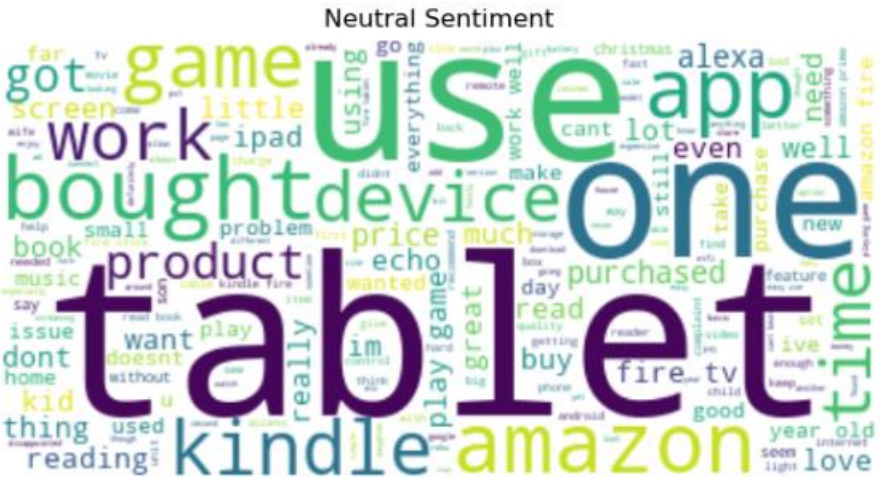
- In the context of topic modeling, word clouds can be generated for each identified topic to visualize the most relevant terms within that topic.
- This aids in interpreting and labeling topics based on the prevalent words.

- Sentiment Analysis:

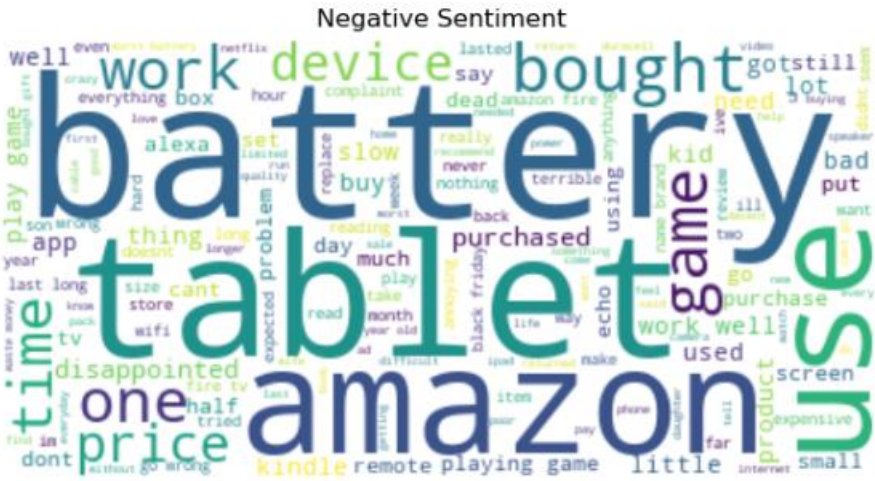
- Word clouds can be created for different sentiment categories (positive, negative, neutral) to visually represent the most common terms associated with each sentiment.
- This helps in understanding the language patterns in reviews or feedback.
- Word clouds are a starting point for visual exploration and interpretation, but they should be complemented with more advanced NLP methods for comprehensive analysis.
- The code defines a function “generate_wordcloud” that takes a sentiment category, combines the text data for that sentiment, and generates a word cloud. The subplots are then used to display word clouds for positive, negative and neutral sentiments.

- Words that appear larger in the word cloud are those that occur more frequently in the positive sentiment context. These words are likely to be key indicators of positive sentiment in the dataset.

- Identify the most prominent and visually striking words in the word cloud. These are likely to be the top positive keywords that are commonly used in positive reviews or sentiments.
- Positive sentiment often correlates with positive feedback about sepcific product features or attributes. Look for words that describe the features, benefits or characteristics of the product or service that customers appreciate.
- Positive sentiment word clouds may contain brand-related terms or affirmations. Customers expressing positive sentiments might mention the brand name, associated products , or use positive adjectives that contribute to a favorable brand image.
- Considering the context in which positive words are used. Are they related to specific product categories, services, or experiences? Understanding the context provides deeper insights into the sources of positive sentiment.
- Beyond induvidual words, consider the emotional tone conveyed by the word cloud. Are there colro, shapes, or overall patterns that evoke a posyove and uplifting feel? The visual aesthetics can contribute to the overall impact of the sentiment.
- Positive word clouds can be dynaic and change over time. Regularly updating and monitoring the word cloud helps businesses stay attuned to evolving customer sentiments and preferences.



- In a neutral sentiment word cloud, words should represent a balance between positive and negative sentiments. Look for words that do not carry strong emotional connotations and are commonly used in more neutral context.
- Phrases or expressions frequently used in neutral sentiments might include terms like “average”, “standard”, “typical”, or other words that suggest a middle-ground opinion.
- Neutral sentiment may often be associated with descriptions of specific product features or attributes without expressing strong positive or negative opinions. Look for terms that describe in a factual and unbiased manner.
- Neutral sentiment word clouds may lack the heightened emotional tone observed in positive or negative sentiment word clouds.
- Words like “somewhat”, “partly”, or “occasionally” may appear frequently.
- Neutrality may involve discussing both positive and engative as pects without a clear preference.



- In a negative word cloud, terms like “poor”, “bad”, “unpleasant” or other stringly negative adjectives that signify dissatisfaction may appear.
- Customers expressing dissatisfaction may use specific phrases to convey therir disapointment or frustration.
- Terms related to defects, malfunstions, or shortcomings may be prevalent.
- Customers expressing negative sentiments maight compare the product or service unfavorably to competitors. Look for mentions of competitor names or terms suggesting a preference for alternatives.

- Negative sentiment word clouds may hightlight concerns about the quality of products or services. Customers may provide feedback on what needs to be fixed, enhanced or addressed to enhance their experience.
- Negative sentiments in the word cloud may impact the brand image.

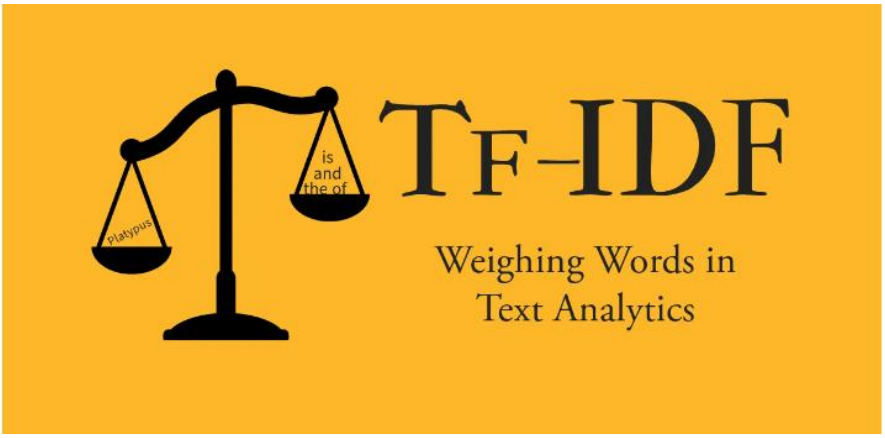
4. Base Model

a. Building the base model using Logistic Regression.

```
# logistic regression
```

```
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, classification_report

text_data = df['reviews.text_adjusted']

# TF-IDF vectorization
tfidf_vectorizer = TfidfVectorizer()
X_tfidf = tfidf_vectorizer.fit_transform(text_data)

# train test split

X_train, X_test, y_train, y_test = train_test_split(X_tfidf, df['sentiment'], test_size=0.3, random_state=7)

# fitting the model

model = LogisticRegression()
model.fit(X_train, y_train)
predictions = model.predict(X_test)

# model evaluation

accuracy = accuracy_score(y_test, predictions)
classification_report_result = classification_report(y_test, predictions)

print("Accuracy:", accuracy)
print("Classification Report:", classification_report_result)
```

- The above code performs sentiment analysis using a logistic regression model with TF_IDF(Term Frequency-Inverse Document Frequency) vectorization.



- TF-IDF is often used in sentiment analysis as a feature representation technique to convert raw text into a numerical format that machine learning models can undertand.
- Term Frequency(TF): Meausres how often a term appears in a specific document.

- Inverse Document Frequency(IDF): Measures the importance of a term across the entire corpus. Terms that are common across many documents receive lower IDF values.

$$(Word-frequency-in-given-document)\cdot\log\frac{(Total-number-of-documents)}{(Number-of-documents-containing-word)}$$

- TF-IDF Calculation: TF-IDF is the product of TF and IDF. It gives a high weight to terms that are frequent in a specific document but rare across the entire corpus.
- TF-IDF feature matrix is used to train a sentiment analysis model. Commonly used models include logistic regression, support vector machones or deep learning models.
- During training, the model learns to associate certain TF-IDF patterns with positive, negative, or neutral sentiments.
- After training, the model can predict the sentiment of new, unseen text by transforming it using the same TF-IDF vectorizer and applying the trained model.

- Here, the text data is extracted from the “reviews.text_adjusted” column.TF-IDF vectorization is applied using “TfidfVectorizer” from scikit-learn. This converts the text data into a matrix of TF-IDF features.

- The dataset is split into training and testing sets using “train test split” function.TF-IDF features(“X_tfidf) are the input, and the target variable is the “sentiment” column.

```
Accuracy: 0.9008563273073263
Classification Report:              precision    recall  f1-score   support

    negative       0.90      0.47      0.62       535
     neutral       0.64      0.39      0.48      1191
    positive       0.92      1.00      0.96      8784

    accuracy                           0.90     10510
   macro avg       0.82      0.62      0.69     10510
weighted avg       0.89      0.90      0.89     10510
```

- The above evaluation metrics (accuracy, precision, and F1-score) offer a comprehensive view of the performance of a sentiment analysis model.
- Accuracy Score: (90%)
    - High accuracy suggests that the model is overall effective in correctly classifying sentiments.
    - However, accuracy alone may not provide a complete picture, especially in imbalanced datasets.
- Precision:
    - Negative Precision: 90%:
    - Of all the instances predicted as negative, 90% are correctly classified as negative.
    - High negative precision indicates the model's ability to avoid false negatives for negative sentiment.

    - Neutral Precision: 64%:
    - Of all instances predicted as neutral, 64% are correctly classified as neutral.
    - Moderate neutral precision suggests some challenges in accurately identifying neutral sentiments.

    - Positive Precision: 92%:
    - Of all instances predicted as positive, 92% are correctly classified as positive.
    - High positive precision indicates the model's ability to avoid false positives for positive sentiment.

- F1-Score:
    - Negative F1-Score: 62%:
    - The F1-score considers both precision and recall, providing a balance between false positives and false negatives.
    - A lower negative F1-score indicates that the model may have challenges in achieving a balance between precision and recall for negative sentiment.

    - Neutral F1-Score: 48%
    - The relatively low F1-score for neutral sentiment suggests challenges in achieving both high precision and recall for neutral predictions.

    - Positive F1-Score: 96%
    - A high positive F1-score indicates a good balance between precision and recall for positive sentiment.

- Inferences:
    - Positive Sentiment:
    - The model performs exceptionally well in identifying positive sentiment, with high precision (92%) and F1-score (96%).
    - The high positive precision indicates that when the model predicts a positive sentiment, it is often correct.
    - The high positive F1-score reflects a good balance between precision and recall for positive sentiment.

    - Negative Sentiment:
    - The model shows strong performance in negative sentiment with high precision (90%).
    - However, the lower negative F1-score (62%) suggests room for improvement, indicating potential challenges in achieving a balance between precision and recall for negative sentiment.

    - Neutral Sentiment:

- Identifying neutral sentiment appears to be more challenging for the model, as reflected in the lower precision (64%) and F1-score (48%).
- The model may struggle to achieve both high precision and recall for neutral predictions.

- Overall Model Assessment:
  - While accuracy is high (90%), it's crucial to consider individual class metrics, especially in imbalanced datasets.
  - Addressing challenges in neutral sentiment prediction and achieving a better balance between precision and recall for all classes could further improve the model.

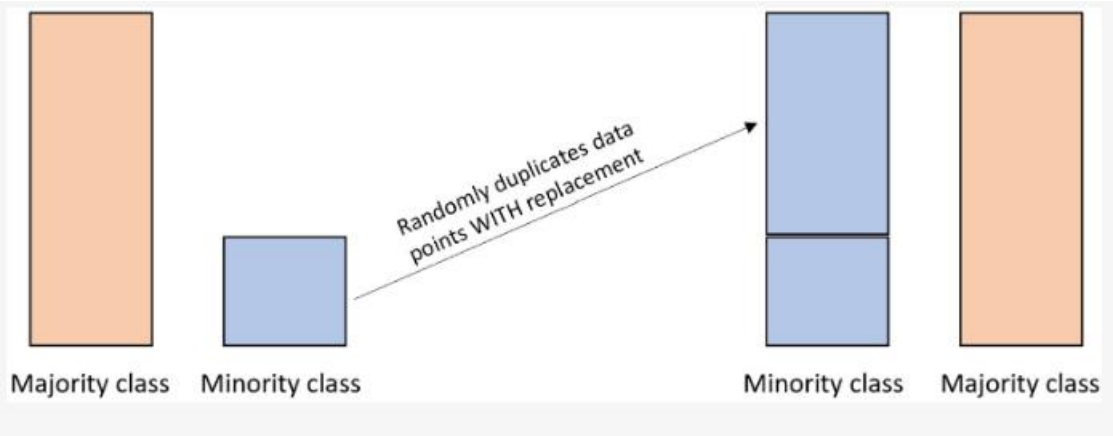
b. Building a model using Logistic Regression using Random Over Sampling(ROS)

```
# LOGISTIC USING ROS(RANDOM OVER SAMPLING)
```

```
from imblearn.over_sampling import RandomOverSampler
from sklearn.model_selection import train_test_split
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, classification_report

X = df['reviews.text_adjusted']
y = df['sentiment']

# TF-IDF vectorization
tfidf_vectorizer = TfidfVectorizer()
X_tfidf = tfidf_vectorizer.fit_transform(X)

# train test split
X_train, X_test, y_train, y_test = train_test_split(X_tfidf, y, test_size=0.3, random_state=7)

# Oversampling the imblanced class using RandomOverSampler
oversampler = RandomOverSampler(sampling_strategy='auto', random_state=7)
X_train_resampled, y_train_resampled = oversampler.fit_resample(X_train, y_train)

# fitting the model with resampled x_train and y_train
model = LogisticRegression()
model.fit(X_train_resampled, y_train_resampled)
predictions = model.predict(X_test)

# Evaluate the model
accuracy = accuracy_score(y_test, predictions)
classification_report_result = classification_report(y_test, predictions)

print("Accuracy:", accuracy)
print("Classification Report:", classification_report_result)
```

- The code snippet demonstrates a common practice for handling imbalanced datasets using oversampling and applying a logistic regression model .

Random Over Sampling:



- Random Oversampling is a technique used in the context of imbalanced datasets to address the issue where one class (usually the minority class) is underrepresented compared to the other class(es). In the case of sentiment analysis, this imbalance might occur when one sentiment class (e.g., negative sentiments) is less frequent than others.

- The Random Oversampling technique involves increasing the number of instances in the minority class by randomly duplicating existing instances until a more balanced distribution is achieved. The goal is to provide the machine learning model with a more equitable representation of each class during training.

- Here are the key steps involved in Random Oversampling:
- Identification of Imbalance:
    - Recognize that there is an imbalance in the class distribution, and the minority class needs to be oversampled.

- Random Duplication:

- Randomly select instances from the minority class and duplicate them. This process is repeated until the desired balance between classes is achieved.

- Creation of a Balanced Dataset:
  - Combine the original instances of both the minority and majority classes with the newly duplicated instances. This results in a new dataset with a more balanced class distribution.

- Training the Model:
  - Train the machine learning model using this balanced dataset. The goal is to enable the model to better capture the patterns in the minority class.

- While Random Oversampling can be effective in mitigating class imbalance, it also has some potential drawbacks. Duplicating instances might lead to overfitting, as the model could memorize the duplicated samples. Additionally, does not introduce new information to the model, which might limit its ability to generalize to unseen data.

- It's essential to carefully evaluate the performance of the model on a separate test set to ensure that oversampling has improved the model's ability to correctly classify instances from the minority class without negatively impacting its performance on the majority class.

```
Accuracy: 0.90209324452902
Classification Report:              precision    recall  f1-score   support

    negative       0.70      0.78      0.74       535
     neutral       0.56      0.80      0.66      1191
    positive       0.99      0.92      0.95      8784

    accuracy                           0.90     10510
   macro avg       0.75      0.84      0.78     10510
weighted avg       0.92      0.90      0.91     10510
```

- Accuracy: (90%)
    - The model correctly predicted the sentiment of reviews 90% of the time.
    - While accuracy is a commonly used metric, it may not provide a complete picture, especially in the presence of imbalanced classes. In sentiment analysis, where one sentiment class might dominate, a high accuracy score could be influenced by the majority class.
- Precision:
    - Negative Precision: 70%
    - Neutral Precision: 56%
    - Positive Precision: 99%
    - Precision measures the accuracy of the positive predictions made by the model for each sentiment class.
    - A high precision for the positive class (99%) indicates that when the model predicts a review as positive, it is correct 99% of the time.
    - Moderate precision for the negative and neutral classes suggests that the model's positive predictions are more reliable than its negative and neutral predictions.
- F1-Score:
    - Negative F1-Score: 74%
    - Neutral F1-Score: 66%
    - Positive F1-Score: 95%
    - F1-score is the harmonic mean of precision and recall, providing a balance between the two metrics.
    - The F1-scores for positive and negative classes are relatively high, indicating a good balance between precision and recall for these classes.
    - The lower F1-score for the neutral class suggests a trade-off between precision and recall, indicating room for improvement in predicting neutral sentiments.
- Overall:
    - The model performs exceptionally well in identifying positive sentiments, as indicated by high precision and F1-score.

- The model's ability to correctly predict negative and neutral sentiments is comparatively weaker, as reflected in lower precision and F1-score for these classes.
- The imbalance in precision scores suggests a potential bias in the model towards the majority class (positive sentiments), highlighting the need for further fine-tuning, feature engineering, or adjusting class weights.
- In summary, while the high accuracy is promising, a more nuanced analysis of precision and F1-score reveals areas for improvement, particularly in achieving a better balance across all sentiment classes.

c. Building a model using Gradient Boosting Classifier using Random Over Sampling(ROS)

```
# GRADIENT BOOSTING CLASSIFIER USING ROS(RANDOM OVER SAMPLING)
```

```
from sklearn.model_selection import train_test_split
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.metrics import accuracy_score, classification_report
from imblearn.over_sampling import RandomOverSampler
from imblearn.pipeline import make_pipeline

# train_test_Split
X_train, X_test, y_train, y_test = train_test_split(df['reviews.text_adjusted'], df['sentiment'], test_size=0.3, random_state=7)

# TF-IDF vectorization
tfidf_vectorizer = TfidfVectorizer()
X_train_tfidf = tfidf_vectorizer.fit_transform(X_train)
X_test_tfidf = tfidf_vectorizer.transform(X_test)

# pipeline of RandomOverSampler  and GradientBoostingClassifier
model = make_pipeline(RandomOverSampler(), GradientBoostingClassifier(random_state=7))

# fit the model
model.fit(X_train_tfidf, y_train)
predictions = model.predict(X_test_tfidf)

# Evaluate the model
accuracy = accuracy_score(y_test, predictions)
classification_report_result = classification_report(y_test, predictions)

print("Accuracy:", accuracy)
print("Classification Report:")
print(classification_report_result)
```

- The above code implements a machine learning pipeline for sentiment analysis using a combination of Random OverSampler and a GradientBoostingClassifier.
- A pipeline in mechine elarning is a way to streamline a lot of the routine processes, making it easier to keep the code organized, reduce errors, and simplify the model deployment process.

- Gradient Boosting is an ensemble learning technique that builds a series of weak learners(usually decision trees) sequentially, with each tree correcting the errors of it predecessor.
- The final prediction is made by summing the predictors of all the waek learners. Each tree contributes to the overall prediction , and the combination of these weak learners creates a strong predictive model.

```
Accuracy: 0.8182683158896289
Classification Report:
              precision    recall  f1-score   support

    negative       0.62      0.69      0.65       535
     neutral       0.37      0.74      0.49      1191
    positive       0.98      0.84      0.90      8784

    accuracy                           0.82     10510
   macro avg       0.65      0.76      0.68     10510
weighted avg       0.89      0.82      0.84     10510
```

- Accuracy: 0.81 (81%)
    - The model correctly predicted the sentiment of reviews 81% of the time.
    - While accuracy is a commonly used metric, it may not provide a complete picture, especially in the presence of imbalanced classes. In sentiment analysis, where certain sentiments may dominate, a high accuracy score could be influenced by the majority class.

- Precision:
    - Negative Precision: 62%
    - Neutral Precision: 37%
    - Positive Precision: 98%
    - Precision measures the accuracy of the positive predictions made by the model for each sentiment class.
    - A high precision for the positive class (98%) indicates that when the model predicts a review as positive, it is correct 98% of the time.
    - The lower precision for negative and neutral classes suggests that the model's positive predictions are more reliable than its negative and neutral predictions.

- F1-Score:

- Negative F1-Score: 69%
- Neutral F1-Score: 74%
- Positive F1-Score: 84%
- F1-score is the harmonic mean of precision and recall, providing a balance between the two metrics.
- The F1-scores for neutral and positive classes are relatively high, indicating a good balance between precision and recall for these classes.
- The lower F1-score for the negative class suggests a trade-off between precision and recall, indicating room for improvement in predicting negative sentiments.

- Overall :
  - The model performs exceptionally well in identifying positive sentiments, as indicated by high precision and F1-score.
  - The model's ability to correctly predict negative and neutral sentiments is comparatively weaker, as reflected in lower precision and F1-score for these classes.
  - The imbalance in precision scores suggests a potential bias in the model towards the majority class (positive sentiments), highlighting the need for further fine-tuning, feature engineering, or adjusting class weights.

d. Building a model using Random Forest using Random Over Sampling(ROS)

```
# RANDOM FOREST USING ROS(RANDOM OVER SAMPLING)
```

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, classification_report
from sklearn.model_selection import train_test_split
from imblearn.over_sampling import RandomOverSampler
from sklearn.feature_extraction.text import TfidfVectorizer

# train_test_Split
X_train, X_test, y_train, y_test = train_test_split(X_tfidf, df['sentiment'], test_size=0.3, random_state=7)

# Applying random oversampling
ros = RandomOverSampler(random_state=42)
X_resampled, y_resampled = ros.fit_resample(X_train, y_train)

# Random Forest Classifier
rf_model = RandomForestClassifier(random_state=42)

# fit the model
rf_model.fit(X_resampled, y_resampled)
predictions = rf_model.predict(X_test)

# Evaluate the model
accuracy = accuracy_score(y_test, predictions)
classification_report_result = classification_report(y_test, predictions)

print("Random Forest Classifier Results:")
print("Accuracy:", accuracy)
print("Classification Report:\n", classification_report_result)
```

- Random Forest is an ensemble learning technique that builds multiple decision trees during training and merges them together to get more accurate and stable prediction. It belongs to bagging algorithms.
- Random Forest employs bootstrap sampling, meaning that each tree is trained on a random sample of the training data with replacement. This creates multiple diverse subsets of the data.
- By combining the predictions of multiple trees, Random Forest tends to reduce overfitting and improcve generalization performance. It is less sensitive to noise and outliers compared to induvidual decision trees.

```
Random Forest Classifier Results:
Accuracy: 0.8961941008563273
Classification Report:
              precision    recall  f1-score   support

    negative       0.93      0.64      0.76       535
     neutral       0.68      0.33      0.45      1191
    positive       0.91      0.99      0.95      8784

    accuracy                           0.90     10510
   macro avg       0.84      0.65      0.72     10510
weighted avg       0.88      0.90      0.88     10510
```

- Accuracy: (89%)
    - The model correctly predicted the sentiment of reviews 89% of the time.
    - A high accuracy score suggests that the model is generally effective in making correct predictions across all sentiment classes.

- Precision:
    - Negative Precision: 93%
    - Neutral Precision: 68%
    - Positive Precision: 91%
    - Precision measures the accuracy of the positive predictions made by the model for each sentiment class.
    - High precision for negative and positive classes indicates that when the model predicts a review as negative or positive, it is correct 93% and 91% of the time, respectively.
    - The lower precision for the neutral class (68%) suggests that the model's neutral predictions are less reliable than its negative and positive predictions.

- F1-Score:
    - Negative F1-Score: 64%
    - Neutral F1-Score: 33%
    - Positive F1-Score: 99%
    - F1-score is the harmonic mean of precision and recall, providing a balance between the two metrics.
    - The high F1-score for the positive class indicates a good balance between precision and recall for positive sentiments.
    - The lower F1-scores for negative and neutral classes suggest challenges in achieving a balance between precision and recall for these classes.

- Overall :
    - The model performs exceptionally well in identifying positive sentiments, as indicated by high precision and F1-score.

- The model's ability to correctly predict negative sentiments is strong, reflected in high precision.
- The model's performance on neutral sentiments is comparatively weaker, as indicated by lower precision and F1-score for the neutral class.
- The extremely high F1-score for the positive class suggests that the model is robust in capturing positive sentiments with high precision and recall.

e. Building a model using Naïve Bayes using Random Over Sampling(ROS)

```
# NAIVE BAYES USING ROS(RANDOM OVER SAMPLING)
```

```
from sklearn.model_selection import train_test_split
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.naive_bayes import MultinomialNB
from sklearn.metrics import accuracy_score, classification_report
from imblearn.over_sampling import RandomOverSampler
from imblearn.pipeline import make_pipeline

#  train_test_Split
X_train, X_test, y_train, y_test = train_test_split(df['reviews.text_adjusted'], df['sentiment'], test_size=0.3, random_state=7)

# TF-IDF vectorization
tfidf_vectorizer = TfidfVectorizer()
X_train_tfidf = tfidf_vectorizer.fit_transform(X_train)
X_test_tfidf = tfidf_vectorizer.transform(X_test)

# pipeline of RandomOverSampler  and Naive Bayes
model = make_pipeline(RandomOverSampler(), MultinomialNB())

# fit the model
model.fit(X_train_tfidf, y_train)
predictions = model.predict(X_test_tfidf)

# Evaluate the model
accuracy = accuracy_score(y_test, predictions)
classification_report_result = classification_report(y_test, predictions)

print("Accuracy:", accuracy)
print("Classification Report:")
print(classification_report_result)
```

- The above code implements sentiment analysis using Naïve Bayes, specifically Multinomial Naïve Bayes algorithm.
- Naïve Bayes is a family of probabilistic classification alogorithms based on Baye's theorem. Despite its "naïve" assumption of independence between features , the Naïve Bayes classifier has proven to be suprisingly effective in various real_world applications, particularly in NLP tasks like text classification.
- In context of text classification, Naïve Bayes is commonly used to predict the category of a document or the sentiment of a piece of text.
- Top applications of Naïve Bayes are spam filtering, sentiment analysis, topoc classification in text classification.

```
Accuracy: 0.8114176974310181
Classification Report:
              precision    recall  f1-score   support

    negative       0.52      0.67      0.59       535
     neutral       0.34      0.56      0.43      1191
    positive       0.95      0.85      0.90      8784

    accuracy                           0.81     10510
   macro avg       0.61      0.70      0.64     10510
weighted avg       0.86      0.81      0.83     10510
```

- The provided evaluation metrics (accuracy, precision, and F1-score) offer insights into the performance of a sentiment analysis model. Let's interpret each metric in detail:

- Accuracy: (81%)
    - The model correctly predicted the sentiment of reviews 81% of the time.
    - A high accuracy score suggests that the model is generally effective in making correct predictions across all sentiment classes.

- Precision:
    - Negative Precision: 52%
    - Neutral Precision: 34%
    - Positive Precision: 95%
    - Precision measures the accuracy of the positive predictions made by the model for each sentiment class.
    - High precision for the positive class (95%) indicates that when the model predicts a review as positive, it is correct 95% of the time.
    - The lower precision for negative and neutral classes (52% and 34%, respectively) suggests that the model's predictions for these classes may have a higher rate of false positives.

- F1-Score:
    - Negative F1-Score: 67%
    - Neutral F1-Score: 56%
    - Positive F1-Score: 85%
    - F1-score is the harmonic mean of precision and recall, providing a balance between the two metrics.
    - The F1-scores reflect a balance between precision and recall for each sentiment class.
    - The lower F1-scores for negative and neutral classes suggest challenges in achieving a balance between precision and recall for these classes.

- Overall :
    - The model performs well in identifying positive sentiments, as indicated by high precision and F1-score.
    - The model's ability to correctly predict negative sentiments is moderate, reflected in a lower precision but a reasonably high F1-score.
    - The model's performance on neutral sentiments is comparatively weaker, as indicated by lower precision and F1-score for the neutral class.

f. Building a model using Support Vector Classifier using Random Over Sampling(ROS)

```
# SUPPORT VECTOR CLASSIFIER USING ROS(RANDOM OVER SAMPLING)
```

```
from sklearn.model_selection import train_test_split
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score, classification_report
from imblearn.over_sampling import RandomOverSampler
from imblearn.pipeline import make_pipeline

# train_test_Split
X_train, X_test, y_train, y_test = train_test_split(df['reviews.text_adjusted'], df['sentiment'], test_size=0.3, random_state=7)

# TF-IDF vectorization
tfidf_vectorizer = TfidfVectorizer()
X_train_tfidf = tfidf_vectorizer.fit_transform(X_train)
X_test_tfidf = tfidf_vectorizer.transform(X_test)

#  pipeline of RandomOverSampler and SVM
model = make_pipeline(RandomOverSampler(), SVC())

# fit the model
model.fit(X_train_tfidf, y_train)
predictions = model.predict(X_test_tfidf)

# Evaluate the model
accuracy = accuracy_score(y_test, predictions)
classification_report_result = classification_report(y_test, predictions)

print("Accuracy:", accuracy)
print("Classification Report:")
print(classification_report_result)
```

- The above code implements a sentiment analysis model using a Support Vector Machine(SVM) classifier with TF_IDF vectorization and random over sampling.
- A Support Vector Classifier(SVC), also known as Support Vector Machine(SVM) for classification is a supervised machine learning algorithm. SVM's are effective in high-dimensional spaces and are especially well-suited for tasks where clear boundaries exist between different classes.
- The primary goal of an SVC is to find the optimal hyperplane that seperates different classes in a feature space.
- The optimal hyperplane is the one that maximizes the margin, which is the distance between the hyperplane and the nearest data point from either class.
- Support vectors are the data points that lie closest to the decision boundary(the hyperplane). These points are crucial for defining the optimal hyperplane and hence, the classifier.

- The use of a margin and regularization parameter helps prevent overfitting.
- SVM are widely used for sentiment analysis and topic categorization for text classification.

```
Accuracy: 0.9310180780209324
Classification Report:
              precision    recall  f1-score   support

    negative       0.93      0.65      0.77       535
     neutral       0.73      0.64      0.68      1191
    positive       0.95      0.99      0.97      8784

    accuracy                           0.93     10510
   macro avg       0.87      0.76      0.81     10510
weighted avg       0.93      0.93      0.93     10510
```

- Accuracy: (93%)
    - The model correctly predicted the sentiment of reviews 93% of the time.
    - A high accuracy score suggests that the model is generally effective in making correct predictions across all sentiment classes.

- Precision:
    - Negative Precision: 93%
    - Neutral Precision: 73%
    - Positive Precision: 95%
    - Precision measures the accuracy of the positive predictions made by the model for each sentiment class.
    - High precision for the positive and negative classes (95% and 93%, respectively) indicates that when the model predicts a review as positive or negative, it is correct 95% and 93% of the time.
    - The precision for the neutral class is also good at 73%.

- F1-Score:
    - Negative F1-Score: 77%
    - Neutral F1-Score: 68%
    - Positive F1-Score: 97%
    - F1-score is the harmonic mean of precision and recall, providing a balance between the two metrics.
    - The F1-scores reflect a balance between precision and recall for each sentiment class.
    - The high F1-scores for positive and negative classes (97% and 77%, respectively) indicate a good balance between precision and recall.
    - The F1-score for the neutral class is also reasonable at 68%.

- Overall
    - The model exhibits high accuracy, indicating strong overall predictive performance.
    - Precision scores are high for all sentiment classes, suggesting that the model's positive, negative, and neutral predictions are accurate.
    - F1-scores reflect a good balance between precision and recall, especially for positive and negative sentiments.

Model	**Accuracy**
Logistic Regression (Using ROS)	90%
Gradient Boosting Classifier	82 %
Random Forest Classifier	90 %
Naïve Bayes (Multinomial NB)	81%
Support Vector Machine	93%

- Comparing the accuracy results of different models provides insights into their performance on the sentiment analysis task.

- Logistic Regression (Using ROS) - 90% Accuracy:**
- The logistic regression model, using Random OverSampling (ROS) to address class imbalance, achieves a commendable 90% accuracy. This model appears to handle the sentiment analysis task well.

- Gradient Boosting Classifier - 82% Accuracy:
- The gradient boosting classifier demonstrates good performance with an 82% accuracy. While slightly lower than the logistic regression model, gradient boosting might excel in capturing complex relationships within the data.

- Random Forest Classifier - 90% Accuracy:
- The random forest classifier achieves the same accuracy as logistic regression (90%). Random forests are known for their robustness and ability to handle various types of data, making it a strong contender for sentiment analysis.

- Naïve Bayes (Multinomial NB) - 81% Accuracy:
- The Naïve Bayes model, specifically Multinomial Naïve Bayes, achieves an accuracy of 81%. While not as high as some other models, Naïve Bayes is known for its simplicity and efficiency in text classification tasks.

- Support Vector Machine - 93% Accuracy:
- The Support Vector Machine (SVM) stands out with the highest reported accuracy of 93%. SVMs are powerful for tasks with complex decision boundaries, and in this case, it performs exceptionally well in sentiment analysis.

- Overall Comparison and Considerations:
    - The SVM model demonstrates the highest accuracy, suggesting it is well-suited for the sentiment analysis task in this context.
    - Logistic regression and the random forest classifier also perform well, sharing the top position with 90% accuracy.
    - Gradient boosting, while slightly lower in accuracy, may still provide valuable insights, especially if interpretability is crucial.
    - Naïve Bayes, with its simplicity, achieves a respectable accuracy of 81%, making it a viable option for certain applications.

Model	Sentiment	F1-score	Precision
Logistic Regression (Using ROS)	Negative Neutral Positive	0.70 0.56 0.99	0.74 0.66 0.95
Gradient Boosting Classifier	Negative Neutral Positive	0.62 0.37 0.98	0.65 0.49 0.90
Random Forest Classifier	Negative Neutral Positive	0.93 0.68 0.91	0.76 0.45 0.95
Naïve Bayes (Multinomial NB)	Negative Neutral Positive	0.52 0.34 0.95	0.59 0.43 0.90
Support Vector Machine	Negative Neutral Positive	0.93 0.73 0.95	0.77 0.68 0.97

- Logistic Regression (Using ROS):
- F1-score: Achieves high F1-scores across all sentiments, indicating balanced precision and recall.
- Precision: Particularly strong precision for positive sentiment (0.95).

- Gradient Boosting Classifier:
- F1-score: Lowest F1-score for neutral sentiment (0.37), indicating challenges in classifying neutral sentiment.
- Precision: Positive sentiment precision is relatively high (0.90).

- Random Forest Classifier:
- F1-score: Strong F1-scores across all sentiments, especially high for negative sentiment (0.93).
- Precision: Highest precision for negative sentiment (0.76).

- Naïve Bayes (Multinomial NB):
- F1-score: Lowest F1-scores among all models, particularly for neutral sentiment (0.34).
- Precision: Positive sentiment precision is relatively high (0.90).

- Support Vector Machine:
- F1-score: High F1-scores across all sentiments, indicating balanced performance.
- Precision: Strong precision for all sentiments, particularly high for positive sentiment (0.97).

- Overall Comparison and Considerations:

    - Logistic Regression (Using ROS):

- Balanced performance across sentiments with high precision for positive sentiment.

- Gradient Boosting Classifier:
- Struggles with neutral sentiment classification (low F1-score).
- Strong positive sentiment precision.

- Random Forest Classifier:
- Overall strong performance with high F1-scores and precision.
- Particularly high precision for negative sentiment.

- Naïve Bayes (Multinomial NB):
- Lower F1-scores compared to other models.
- High precision for positive sentiment.

- Support Vector Machine:
- Balanced and high-performance across sentiments.
- Particularly high precision for positive sentiment.

5. Future Work

- Model tuning, experimenting with different algorithms, or adjusting class weights to handle imbalances may enhance overall performance.

- In summary, while the model demonstrates strong overall accuracy. Adjustments and fine-tuning may be necessary to achieve a more balanced and accurate sentiment analysis across all classes.

6. References

- https://regenerativetoday.com/exploratory-data-analysis-of-text-data-including-visualization-and-sentiment-analysis/
- https://scholarworks.rit.edu/cgi/viewcontent.cgi?article=12196&context=the