Automated Review Rating System

1. Project Overview

The project **Automated Review Rating System** aims to develop a smart framework capable of predicting star ratings from customer reviews. Using natural language processing techniques, the system interprets textual feedback to identify sentiment and linguistic patterns. Machine learning models are trained on labeled review data to establish relationships between customer opinions and corresponding rating levels. By evaluating performance across different dataset distributions, the system demonstrates the effectiveness of AI-driven solutions in providing consistent, scalable, and efficient review analysis.

2. Environment Setup

The project was developed and executed in **Jupyter Notebook**, providing an interactive environment for code execution and analysis. The implementation was carried out using **Python 3.10**, along with several essential libraries for data preprocessing, visualization, and machine learning.

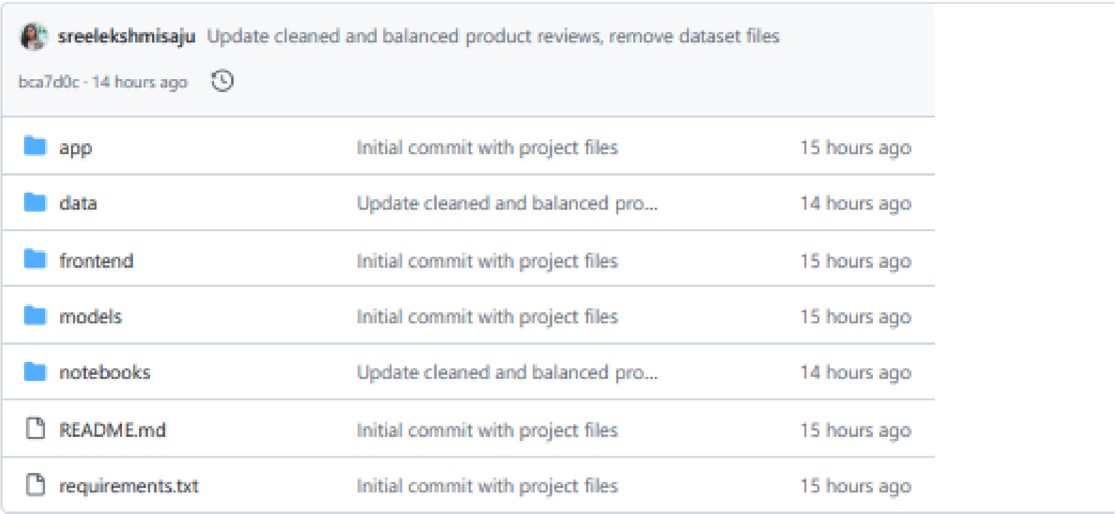
The following libraries were installed and utilized:

- **pandas** – for dataset loading, manipulation, and analysis.
- **numpy** – for numerical computations and efficient array handling.
- **matplotlib** & **seaborn** – for data visualization and graphical representation of trends.
- **scikit-learn** – for feature extraction, model training, evaluation, and performance metrics.
- **spaCy** – for natural language processing and lemmatization.
- **re** – for text pattern recognition and cleaning using regular expressions.

3. GitHub Project Setup

A GitHub repository named Automated-Review-Rating-System was created to manage the project's code, notebooks, and resources. The repository provides version control, collaboration capabilities, and a centralized location for all project files.The GitHub Repository Setup is illustrated in Figure 1.

3.1 Directory Structure



sreelekshmisaju Update cleaned and balanced product reviews, remove dataset files

bca7d0c · 14 hours ago

app	Initial commit with project files	15 hours ago
data	Update cleaned and balanced pro...	14 hours ago
frontend	Initial commit with project files	15 hours ago
models	Initial commit with project files	15 hours ago
notebooks	Update cleaned and balanced pro...	14 hours ago
README.md	Initial commit with project files	15 hours ago
requirements.txt	Initial commit with project files	15 hours ago

Figure_1: GitHub Repository Setup

4. Data Collection

The project utilizes publicly available datasets from Kaggle to train and evaluate the Automated Review Rating System. The datasets collected include:

- **Amazon kindle_reviews.csv** – contains 71221 reviews across 10 columns. Dataset Link

After preprocessing, the final cleaned dataset contains 71,217 reviews. The distribution of ratings in the merged_reviews.csv dataset is as follows:

Rating	**Count**
1	3786
2	5435
3	6000
4	19999
5	35997

Table 1: Distribution of ratings in the merged dataset

The cleaned and the new dataset is available at the following link: New Dataset Link

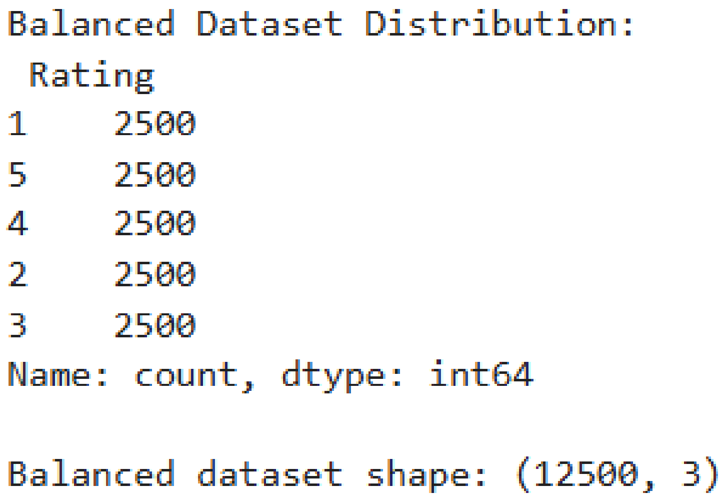
This new dataset provides a robust foundation for training machine learning models to predict review ratings.

4.1 Balanced Dataset

Balanced dataset ensures that each rating category is equally represented, preventing bias during model training. The balanced dataset used contains 12,500 reviews with 2,500 reviews for each rating level. Maintaining equal representation across ratings helps the model learn patterns from all categories fairly and improves prediction reliability.

The dataset is available at the following link: Balanced Dataset Link

Balanced Dataset Details:



```
Balanced Dataset Distribution:
 Rating
1    2500
5    2500
4    2500
2    2500
3    2500
Name: count, dtype: int64

Balanced dataset shape: (12500, 3)
```

5. Data Preprocessing

Data preprocessing is a critical step in preparing raw text data for machine learning. It involves cleaning, standardizing, and transforming the data to ensure it is consistent, meaningful, and suitable for analysis. These steps help improve model accuracy and reliability by removing noise, normalizing text, and structuring the reviews for effective feature extraction.

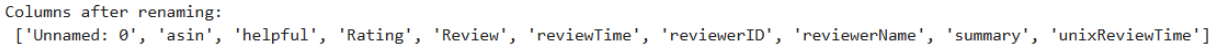
5.1 Column Renaming

Column names are standardized to improve clarity and make the dataset easier to work with. For example, columns containing review text and ratings are renamed to `Review` and `Rating`, respectively. Standardized column names help avoid confusion during analysis and make the code and documentation more readable and consistent. This step ensures uniformity across different datasets, facilitating seamless merging and preprocessing operations.

The following Python code was used to rename dataset columns for consistency:

```python
# Rename columns for better readability and consistency
df.rename(columns={'reviewText': 'Review', 'overall': 'Rating'},
    inplace=True)
print("Columns after renaming:\n", df.columns.tolist())
```

Output:



```
Columns after renaming:
 ['Unnamed: 0', 'asin', 'helpful', 'Rating', 'Review', 'reviewTime', 'reviewerID', 'reviewerName', 'summary', 'unixReviewTime']
```

5.2 Handling Missing Values

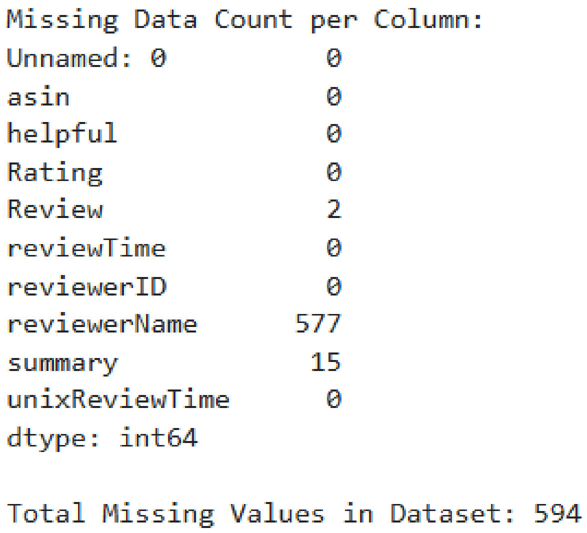
Identifying and handling missing data is a crucial step in preparing a clean dataset for machine learning. Missing values can introduce bias, reduce model performance, and cause errors during analysis. In this project, the number of missing values in each column was calculated to assess data completeness and determine the necessary preprocessing actions.

The following Python code was used to quantify missing data in the dataset:

```
# Count missing values in each column
missing_data = df.isnull().sum()
print("\nMissing Data Count per Column:")
print(missing_data)
# Total missing values in the dataset
total_missing = missing_data.sum()
print("\nTotal Missing Values in Dataset:", total_missing)
```

This step provides an overview of data quality by reporting both per-column missing values and the total missing entries in the dataset. Understanding the extent of missing data is essential for deciding whether to remove, impute, or otherwise handle incomplete entries before model training.

Output:



```
Missing Data Count per Column:
Unnamed: 0          0
asin                0
helpful             0
Rating              0
Review              2
reviewTime          0
reviewerID          0
reviewerName      577
summary            15
unixReviewTime      0
dtype: int64

Total Missing Values in Dataset: 594
```

5.3 Handling Missing Data

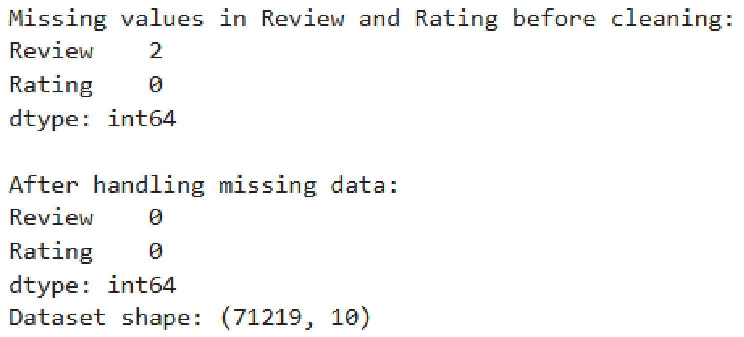
To ensure the integrity of the dataset and avoid errors during model training, rows containing missing values in critical columns were removed. Specifically, entries with missing values in the `Review` or `Rating` columns were identified and dropped. After removal, the dataset index was reset to maintain sequential ordering and prevent indexing issues during subsequent processing steps.

The following Python code was used to clean and verify the dataset:

```
# Count missing values in 'Review' and 'Rating'
print("Missing values in Review and Rating before cleaning:")
print(df[['Review', 'Rating']].isnull().sum())
# Drop rows with missing 'Review' or 'Rating'
df.dropna(subset=['Review', 'Rating'], inplace=True)
df.reset_index(drop=True, inplace=True)
print("\nAfter handling missing data:")
print(df[['Review', 'Rating']].isnull().sum())
print("Dataset shape:", df.shape)
print("\nDataset Information:")
df.info()
df.head()
```

This step ensures that the dataset contains only complete records, thereby improving the reliability of feature extraction and model training. It also provides a clear understanding of the dataset's structure and size after cleaning, which is essential for accurate performance evaluation.

Output:



```
Missing values in Review and Rating before cleaning:
Review    2
Rating    0
dtype: int64

After handling missing data:
Review    0
Rating    0
dtype: int64
Dataset shape: (71219, 10)
```

5.4 Count Number of duplicates

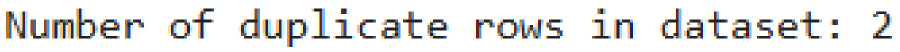
Duplicate entries in a dataset can introduce bias and inflate the importance of certain observations, potentially affecting the performance of machine learning models. In the Automated Review Rating System, duplicate reviews with identical ratings were identified to ensure data integrity and avoid redundancy in training data.

The following Python code was used to detect duplicate records based on the `Review` and `Rating` columns:

```python
# Count duplicates based on 'Review' and 'Rating'
duplicate_count = df.duplicated(subset=['Review', 'Rating']).sum()
print(f"Number of duplicate rows in dataset: {duplicate_count}")
duplicates = df[df.duplicated(subset=['Review', 'Rating'], keep=False)]
print("\nSample duplicate rows:")
duplicates.head()
```

This process provides an overview of redundancy within the dataset, allowing for informed decisions on whether to remove duplicates. Handling duplicates is critical for training a robust model that generalizes well across unique customer reviews.

Output:



```
Number of duplicate rows in dataset: 2
```

5.5 Removing Duplicate and Conflicting Records

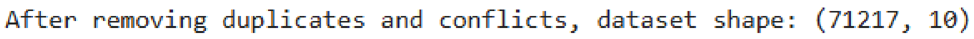
To maintain the quality and reliability of the dataset, exact duplicates and conflicting entries were removed. Exact duplicates, where both the `Review` text and `Rating` were identical, were dropped while keeping the first occurrence. Additionally, conflicting reviews, where the same review text had different ratings, were identified and removed to prevent contradictory information from affecting model training. After these removals, the dataset index was reset to ensure sequential ordering for smooth processing.

The following Python code was used to perform these operations:

```
# Remove exact duplicates (same Review + Rating)
df = df.drop_duplicates(subset=['Review', 'Rating'], keep='first')
# Remove conflicting reviews (same Review text, different Ratings)
conflict_idx = df[df.duplicated(subset=['Review'], keep=False) &
                  ~df.duplicated(subset=['Review', 'Rating'], keep=False)
                     ].index
df.drop(index=conflict_idx, inplace=True)
# Reset index after removals
df.reset_index(drop=True, inplace=True)
print("After removing duplicates and conflicts, dataset shape:", df.
    shape)
df.head()
```

By removing duplicate and conflicting records, the dataset is refined to contain only unique and consistent entries. This step ensures that the machine learning models learn meaningful patterns from authentic and reliable data, thereby improving prediction accuracy.

Output:



```
After removing duplicates and conflicts, dataset shape: (71217, 10)
```

5.6 Selecting Relevant Columns

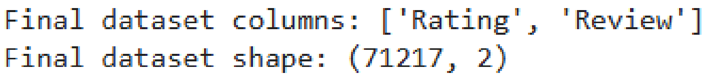
To streamline the dataset for model training, only the essential columns, `Rating` and `Review`, were retained. This step eliminates unnecessary information that does not contribute to the predictive task, thereby simplifying the dataset and reducing computational overhead during feature extraction and model training.

The following Python code was used to select the relevant columns:

```
# Keep only 'Rating' and 'Review' columns for modeling
df = df[['Rating', 'Review']]
print("Final dataset columns:", df.columns.tolist())
print("Final dataset shape:", df.shape)
df.head()
```

By focusing on only the necessary features, the preprocessing pipeline ensures that the machine learning models operate efficiently and learn patterns directly related to predicting customer review ratings. This step also lays the foundation for consistent and structured input to subsequent text processing and modeling stages.

Output:



```
Final dataset columns: ['Rating', 'Review']
Final dataset shape: (71217, 2)
```

5.7 Grouping and Aggregation

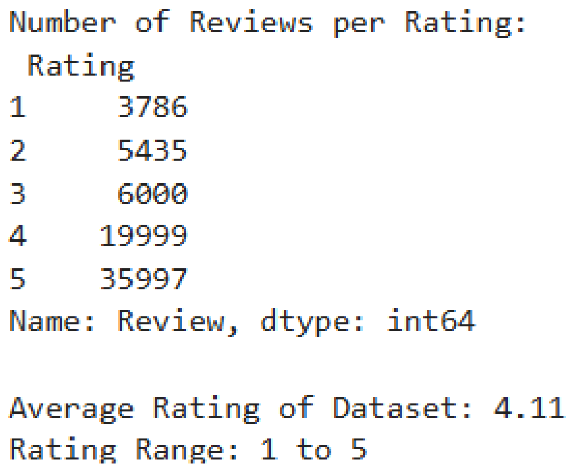
Understanding the distribution of ratings within the dataset is a crucial step in exploratory data analysis. It provides insights into class balance, potential biases, and the overall sentiment trends expressed by customers. In this project, the count of reviews per rating, the average rating, and the minimum and maximum ratings were calculated to summarize the dataset's characteristics.

The following Python code was used to analyze the rating distribution:

```
# Count of reviews per rating
review_count_per_rating = df.groupby('Rating')['Review'].count()
print("Number of Reviews per Rating:\n", review_count_per_rating)
# Average rating
average_rating = df['Rating'].mean()
print("\nAverage Rating of Dataset:", round(average_rating, 2))
# Minimum and Maximum rating
min_rating = df['Rating'].min()
max_rating = df['Rating'].max()
print("Rating Range: {} to {}".format(min_rating, max_rating))
```

This analysis revealed the number of reviews corresponding to each rating level, the overall average rating, and the rating range. Such insights are important for identifying imbalances in the dataset, which can inform subsequent steps such as creating balanced datasets and selecting appropriate machine learning strategies.

Output:



```
Number of Reviews per Rating:
 Rating
1     3786
2     5435
3     6000
4    19999
5    35997
Name: Review, dtype: int64

Average Rating of Dataset: 4.11
Rating Range: 1 to 5
```

5.8 Cleaning text - Remove emojis, Special characters and Symbols

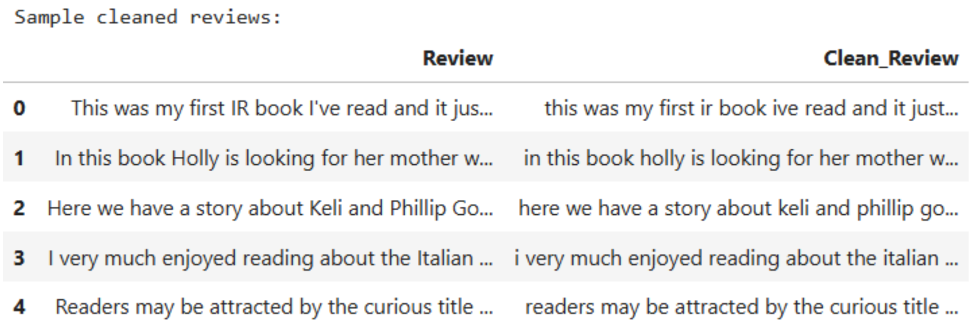
Text data often contains noise such as punctuation, special characters, emojis, and inconsistent capitalization, which can negatively impact machine learning models. To address this, a text cleaning function was implemented to standardize the review content. The cleaning process includes converting all text to lowercase, removing punctuation and symbols, eliminating emojis and non-ASCII characters, and reducing extra whitespace. These steps help in normalizing the textual data, making it suitable for feature extraction and model training.

The following Python code was used to clean and normalize the review text:

```
import string
import re
# Function to clean review text
def clean_text(text):
    # Convert to string in case of missing or non-string entries
   text = str(text)
   # Remove emojis and special unicode characters
   text = text.encode('ascii', 'ignore').decode('ascii')
   # Remove punctuation and symbols
   text = re.sub(f"[{re.escape(string.punctuation)}]", "", text)
   # Remove extra whitespace
   text = re.sub(r'\s+', ' ', text).strip()
   # Convert to lowercase
   text = text.lower()
   return text
# Apply cleaning function to 'Review' column
df['Clean_Review'] = df['Review'].apply(clean_text)
df[['Review', 'Clean_Review']].head()
```

By performing text cleaning, the reviews are transformed into a standardized and simplified format. This improves the quality of input for natural language processing techniques and ensures that the machine learning models can focus on meaningful linguistic patterns rather than noise.

Output:



Sample cleaned reviews:

	Review	Clean_Review
0	This was my first IR book I've read and it jus...	this was my first ir book ive read and it just...
1	In this book Holly is looking for her mother w...	in this book holly is looking for her mother w...
2	Here we have a story about Keli and Phillip Go...	here we have a story about keli and phillip go...
3	I very much enjoyed reading about the Italian ...	i very much enjoyed reading about the italian ...
4	Readers may be attracted by the curious title ...	readers may be attracted by the curious title ...

5.9 Detection of Consecutive Repeated Words

In textual data, consecutive repeated words can occur due to typing errors or emphasis, which may introduce noise and affect model performance. Identifying these repeated words is an important preprocessing step to clean the text and improve feature quality. In this project, a function was implemented to detect consecutive duplicate words using regular expressions. The function searches for any word that appears twice in succession, ignoring case, and returns all occurrences for further inspection.

The following Python code was used to identify repeated words in the dataset:

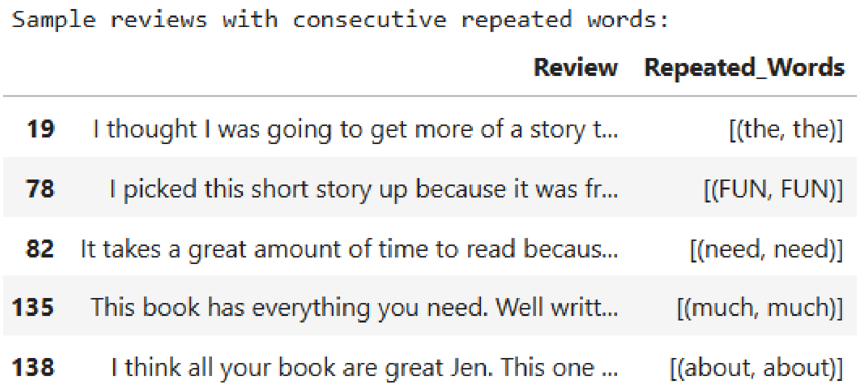
```
import re

# Function to find consecutive duplicate words
def find_repeated_words(text):
    # Regex pattern: captures consecutive duplicate words, ignoring case
    pattern = r'\b(\w+)\s+\1\b'
    # Find all matches, preserve original casing
    matches = re.findall(pattern, text, flags=re.IGNORECASE)
    # Return list of tuples like [(word, word)]
    return [(match, match) for match in matches]
# Apply function to dataset
```

```
df['Repeated_Words'] = df['Review'].apply(find_repeated_words)
print("Sample reviews with consecutive repeated words:")
df[df['Repeated_Words'].str.len() > 0][['Review', 'Repeated_Words']].
    head()
```

By detecting consecutive repeated words, the preprocessing pipeline can address potential noise in the dataset. This step ensures that the textual data fed to machine learning models is more consistent and representative of actual customer feedback, enhancing the reliability of sentiment and rating predictions.

Output:



```
Sample reviews with consecutive repeated words:
```

	Review	Repeated_Words
19	I thought I was going to get more of a story t...	[(the, the)]
78	I picked this short story up because it was fr...	[(FUN, FUN)]
82	It takes a great amount of time to read becaus...	[(need, need)]
135	This book has everything you need. Well writt...	[(much, much)]
138	I think all your book are great Jen. This one ...	[(about, about)]

5.10 Removing Consecutive Repeated Words

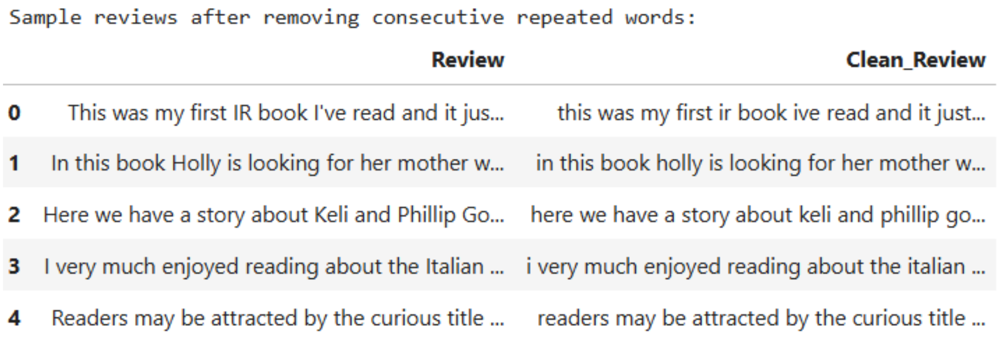
Consecutive repeated words can introduce redundancy and noise into textual data, potentially affecting the learning process of machine learning models. To enhance text quality, repeated words were removed by replacing consecutive duplicates with a single occurrence. This normalization step ensures that the review content is more concise and accurately represents the customer's sentiment.

The following Python code was used to remove consecutive repeated words:

```
# Function to remove consecutive repeated words
def remove_repeated_words(text):
    # Regex: replace consecutive duplicate words with a single
       occurrence
    pattern = r'\b(\w+)(\s+\1\b)+'
    return re.sub(pattern, r'\1', text, flags=re.IGNORECASE)
df['Clean_Review'] = df['Clean_Review'].apply(remove_repeated_words)
print("Sample reviews after removing consecutive repeated words:")
df[['Review', 'Clean_Review']].head()
```

By removing consecutive repeated words, the dataset becomes cleaner and more consistent. This preprocessing step improves the quality of input for feature extraction, helping the machine learning models focus on meaningful linguistic patterns rather than redundant information.

Output:



Sample reviews after removing consecutive repeated words:

	Review	Clean_Review
0	This was my first IR book I've read and it jus...	this was my first ir book ive read and it just...
1	In this book Holly is looking for her mother w...	in this book holly is looking for her mother w...
2	Here we have a story about Keli and Phillip Go...	here we have a story about keli and phillip go...
3	I very much enjoyed reading about the Italian ...	i very much enjoyed reading about the italian ...
4	Readers may be attracted by the curious title ...	readers may be attracted by the curious title ...

5.11 Sorting Dataset by Rating

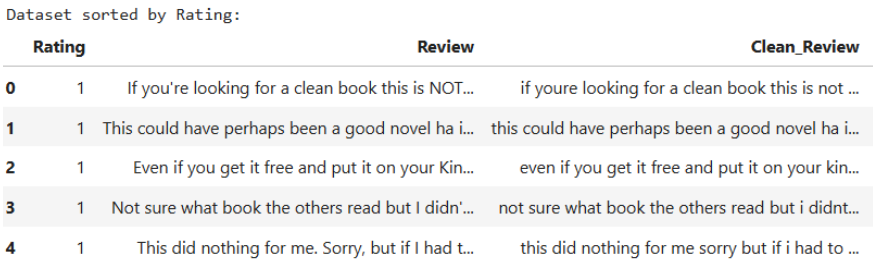
Sorting the dataset based on rating values provides a structured view of reviews from the lowest to highest ratings. This organization facilitates better understanding of rating distribution, enables easier inspection of extreme cases, and can assist in subsequent analysis or sampling strategies for balanced datasets.

The following Python code was used to sort the dataset by the `Rating` column:

```
# Sort dataset by Rating in ascending order
df_sorted = df.sort_values(by='Rating', ascending=True).reset_index(
    drop=True)
print("Dataset sorted by Rating:")
df_sorted.head()
```

By arranging reviews in ascending order of ratings, the dataset becomes more interpretable and allows for systematic examination of patterns across different rating levels. This step also aids in the preparation of balanced datasets for model training.

Output:



Dataset sorted by Rating:

	Rating	Review	Clean_Review
0	1	If you're looking for a clean book this is NOT...	if youre looking for a clean book this is not ...
1	1	This could have perhaps been a good novel ha i...	this could have perhaps been a good novel ha i...
2	1	Even if you get it free and put it on your Kin...	even if you get it free and put it on your kin...
3	1	Not sure what book the others read but I didn'...	not sure what book the others read but i didnt...
4	1	This did nothing for me. Sorry, but if I had t...	this did nothing for me sorry but if i had to ...

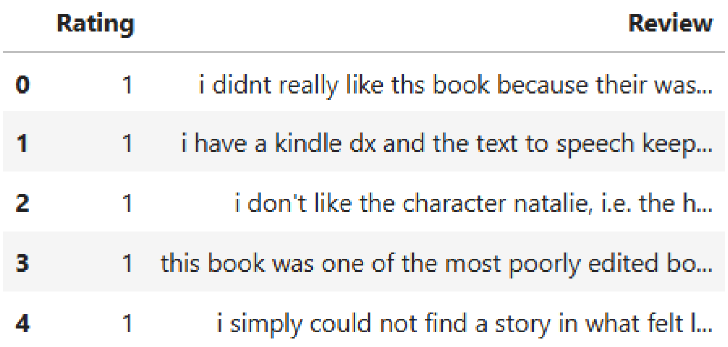
5.12 Text Normalization: Lowercasing

To ensure uniformity in textual data, all review text was converted to lowercase. This normalization step helps in reducing redundancy caused by variations in letter casing, allowing the model to treat words like “Good” and “good” as the same token. Consistent text representation is essential for accurate feature extraction and improves the performance of machine learning models on natural language data.

The following Python code was used to apply lowercasing to all reviews:

```
# Convert all review text to lowercase
df['Review'] = df['Review'].str.lower()
df.head()
```

Output:



	Rating	Review
0	1	i didnt really like ths book because their was...
1	1	i have a kindle dx and the text to speech keep...
2	1	i don't like the character natalie, i.e. the h...
3	1	this book was one of the most poorly edited bo...
4	1	i simply could not find a story in what felt l...

5.13 Removing URLs from Reviews

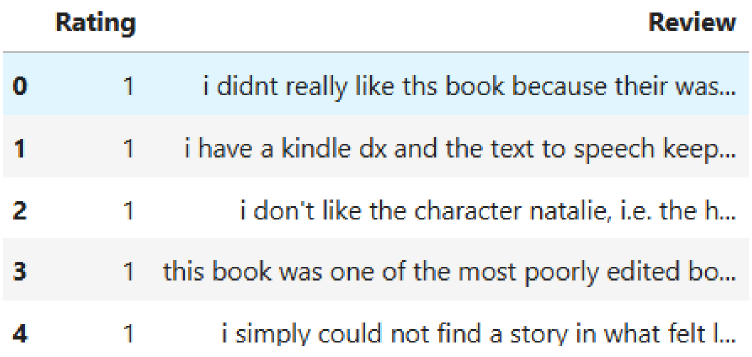
Customer reviews may contain URLs linking to external content, which are generally irrelevant for sentiment or rating prediction. To prevent noise and improve model performance, all URLs were removed from the review text using regular expressions. This step ensures that only meaningful textual content is retained for feature extraction and modeling.

The following Python code was used to remove URLs from the reviews:

```
import re
# Remove URLs from the review text
df['Review'] = df['Review'].apply(lambda x: re.sub(r'http\S+|www\S+|
    https\S+', '', x, flags=re.IGNORECASE))
df.head()
```

By eliminating URLs, the dataset becomes cleaner and more focused on the actual customer opinions, allowing machine learning models to learn patterns from relevant textual content without distraction from extraneous links.

Output:



	Rating	Review
0	1	i didnt really like ths book because their was...
1	1	i have a kindle dx and the text to speech keep...
2	1	i don't like the character natalie, i.e. the h...
3	1	this book was one of the most poorly edited bo...
4	1	i simply could not find a story in what felt l...

5.14 Removing HTML Tags

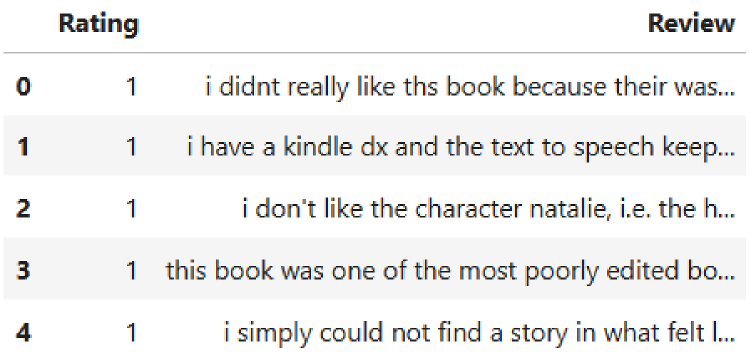
Customer reviews may occasionally contain HTML tags, which do not contribute to the semantic meaning of the text and can introduce noise in the dataset. To ensure clean and meaningful textual data, all HTML tags were removed from the reviews using regular expressions. This step improves the quality of input for natural language processing and feature extraction.

The following Python code was used to remove HTML tags from the reviews:

```
# Remove HTML tags from review text
df['Review'] = df['Review'].apply(lambda x: re.sub(r'<.*?>', '', x))
df.head()
```

By stripping HTML tags, the dataset becomes more consistent and focused solely on the textual content, which enhances the effectiveness of machine learning models in predicting review ratings accurately.

Output:



	Rating	Review
0	1	i didnt really like ths book because their was...
1	1	i have a kindle dx and the text to speech keep...
2	1	i don't like the character natalie, i.e. the h...
3	1	this book was one of the most poorly edited bo...
4	1	i simply could not find a story in what felt l...

5.15 Removing Emojis, Punctuation, and Special Characters

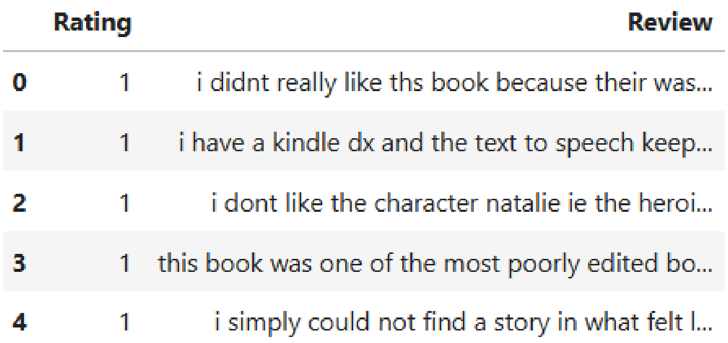
Text data often contains emojis, punctuation marks, and other special characters that do not contribute meaningfully to sentiment or rating prediction. To enhance the quality of the dataset, all non-alphanumeric characters were removed from the reviews. Additionally, extra whitespaces were eliminated to ensure uniform spacing between words. These preprocessing steps help create clean and consistent textual data for feature extraction and machine learning.

The following Python code was used to remove unwanted characters and normalize spacing:

```
import re
# Remove emojis, punctuation, and special characters
df['Review'] = df['Review'].apply(lambda x: re.sub(r'[^a-zA-Z0-9\s]', '
    ', x))
# Remove extra whitespaces
df['Review'] = df['Review'].apply(lambda x: re.sub(r'\s+', ' ', x).
    strip())
df.head()
```

By cleaning the text of unnecessary symbols and normalizing whitespace, the dataset is better prepared for downstream natural language processing tasks, improving the reliability and performance of machine learning models.

Output:



	Rating	Review
0	1	i didnt really like ths book because their was...
1	1	i have a kindle dx and the text to speech keep...
2	1	i dont like the character natalie ie the heroi...
3	1	this book was one of the most poorly edited bo...
4	1	i simply could not find a story in what felt l...

5.16 Stopword Identification and Analysis

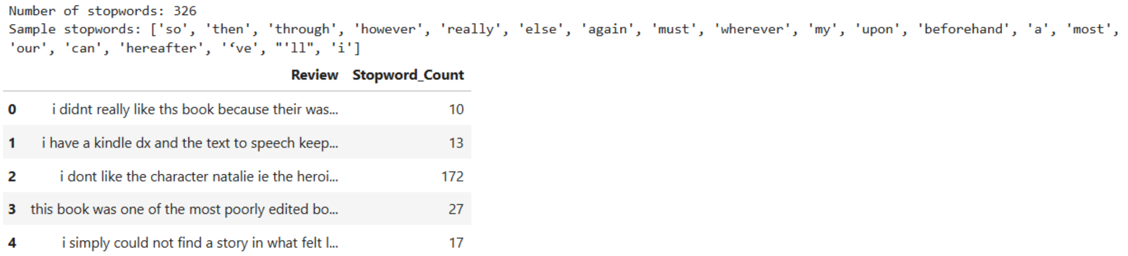
Stopwords are common words such as “the,” “is,” and “and” that carry minimal semantic meaning and can often be removed to reduce noise in text data. In this project, the English stopwords list provided by SpaCy was used to identify and analyze the presence of stopwords in customer reviews. Each review was evaluated to count the number of stopwords it contains, providing insight into the textual composition and helping guide further preprocessing steps such as stopword removal.

The following Python code was used to identify and count stopwords in the dataset:

```python
import spacy
# Load SpaCy English model
nlp = spacy.load('en_core_web_sm')
# Get stopwords list
stopwords = nlp.Defaults.stop_words
print(f"Number of stopwords: {len(stopwords)}")
print("Sample stopwords:", list(stopwords)[:20])
# Count stopwords in each review
df['Stopword_Count'] = df['Review'].apply(lambda x: sum(1 for token in
    x.split() if token in stopwords))
df[['Review', 'Stopword_Count']].head()
```

Analyzing stopwords helps in understanding the structure of the reviews and informs decisions on removing non-informative words to improve the quality of features for machine learning models. This step contributes to a more focused and semantically meaningful representation of the review text.

Output:



```
Number of stopwords: 326
Sample stopwords: ['so', 'then', 'through', 'however', 'really', 'else', 'again', 'must', 'wherever', 'my', 'upon', 'beforehand', 'a', 'most',
'our', 'can', 'hereafter', '‘ve', "'ll", 'i']
```

	Review	Stopword_Count
0	i didnt really like ths book because their was...	10
1	i have a kindle dx and the text to speech keep...	13
2	i dont like the character natalie ie the heroi...	172
3	this book was one of the most poorly edited bo...	27
4	i simply could not find a story in what felt l...	17

5.17 Total Stopwords Analysis

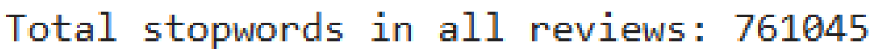
Quantifying the total number of stopwords across the dataset provides a broader understanding of how prevalent non-informative words are in the reviews. This analysis helps evaluate the potential impact of stopwords on feature extraction and model performance, and informs whether additional preprocessing, such as stopword removal, is necessary.

The following Python code was used to calculate the total number of stopwords in the dataset:

```
# Total stopwords in the entire dataset
total_stopwords = df['Stopword_Count'].sum()
print("Total stopwords in all reviews:", total_stopwords)
```

By analyzing the total stopwords, the preprocessing pipeline gains insight into the textual composition of the reviews. Removing or handling stopwords appropriately can enhance the quality of features and improve the accuracy and efficiency of machine learning models for review rating prediction.

Output:



```
Total stopwords in all reviews: 761045
```

5.18 Stopword Removal

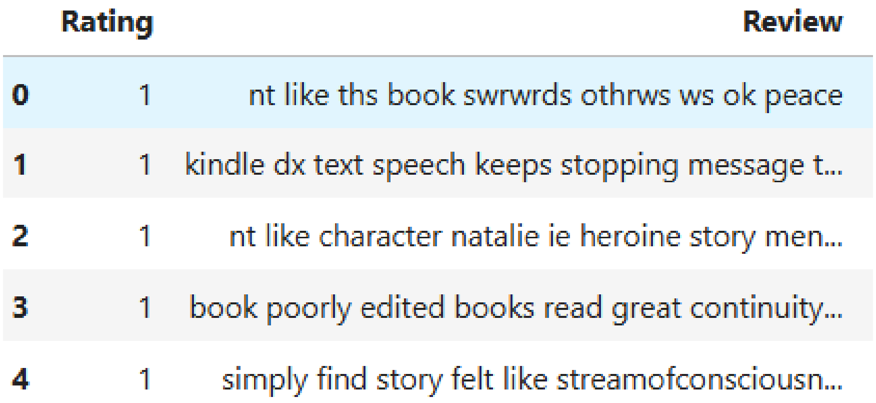
To reduce noise and focus on the meaningful content of reviews, stopwords were removed from the text. Stopwords, such as “the,” “is,” and “and,” generally do not contribute to the sentiment or rating prediction and can dilute feature significance. By eliminating these non-informative words, the dataset is transformed into a more concise and semantically rich representation suitable for machine learning.

The following Python code was used to remove stopwords from the reviews:

```
# Function to remove stopwords
def remove_stopwords(text):
   doc = nlp(text)
   return ' '.join([token.text for token in doc if token.text not in
      nlp.Defaults.stop_words])
# Apply to the Review column
df['Review'] = df['Review'].apply(remove_stopwords)
df.head()
```

Removing stopwords improves the quality of input for feature extraction techniques, such as TF-IDF or word embeddings, ensuring that the models learn from words that carry meaningful information relevant to predicting customer ratings.

Output:



	Rating	Review
0	1	nt like ths book swrwrds othrws ws ok peace
1	1	kindle dx text speech keeps stopping message t...
2	1	nt like character natalie ie heroine story men...
3	1	book poorly edited books read great continuity...
4	1	simply find story felt like streamofconsciousn...

5.19 Choice of spaCy for NLP Tasks

In this project, **spaCy** was chosen over **NLTK** for natural language processing tasks such as tokenization, stopword handling, and lemmatization. While NLTK provides a broad range of NLP tools, spaCy is optimized for industrial-scale applications, offering faster processing speeds and more efficient memory usage.

SpaCy also provides pretrained models that support part-of-speech tagging, dependency parsing, and named entity recognition with high accuracy. Additionally, spaCy's pipeline design allows seamless integration of multiple preprocessing steps, making it more suitable for handling large datasets of customer reviews.

The choice of spaCy ensures that the text preprocessing pipeline is both efficient and scalable, improving the overall performance of machine learning models.

5.20 Lemmatization

Lemmatization is the process of reducing words to their base or root form, ensuring that different inflections of the same word are treated uniformly. For example, "running" and "ran" are both reduced to "run". This normalization step reduces feature dimensionality and improves the ability of machine learning models to recognize meaningful patterns in text.

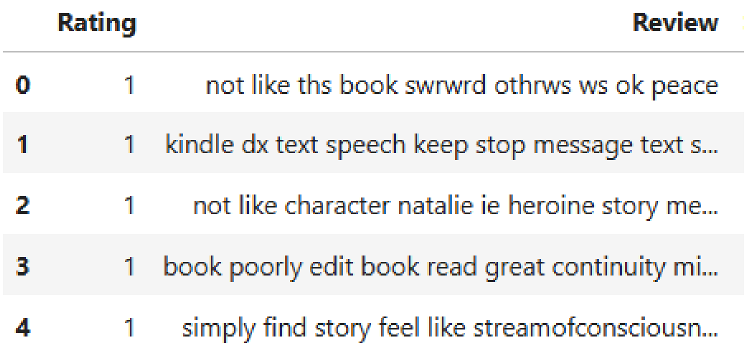
In this project, **spaCy**'s lemmatization capabilities were used to transform reviews into their base forms, enhancing the semantic consistency of the dataset.

The following Python code was used to perform lemmatization on the reviews:

```
# Function for lemmatization
def lemmatize_text(text):
    doc = nlp(text)
    return ' '.join([token.lemma_ for token in doc])
# Apply lemmatization to the Review column
df['Review'] = df['Review'].apply(lemmatize_text)
df.head()
```

By applying lemmatization, the dataset becomes more standardized, reducing redundancy caused by word variations and improving the quality of features for model training and rating prediction.

Output:



	Rating	Review
0	1	not like ths book swrwrd othrws ws ok peace
1	1	kindle dx text speech keep stop message text s...
2	1	not like character natalie ie heroine story me...
3	1	book poorly edit book read great continuity mi...
4	1	simply find story feel like streamofconsciousn...

5.21 Choice of Lemmatization Over Stemming

Lemmatization was preferred over stemming for preprocessing textual data in this project because it preserves the semantic meaning of words while reducing them to their base forms. Unlike stemming, which often truncates words arbitrarily (e.g., "running" → "run" but "better" → "bett"), lemmatization considers the context and part-of-speech of words, producing linguistically correct lemmas (e.g., "better" → "good"). This is particularly important for customer reviews, where accurate representation of sentiment and meaning is crucial for rating prediction. By using lemmatization, the project ensures that feature extraction reflects true semantic relationships in the text, leading to better performance of machine learning models.

Comparison of Lemmatization and Stemming

Feature	**Lemmatization**	**Stemming**
Definition	Reduces words to their base or dictionary form (lemma)	Reduces words to their root form by chopping off suffixes/prefixes
Preserves Meaning	Yes, context-aware and linguistically accurate	No, may produce non-words or incorrect roots
Example	"running" → "run", "better" → "good"	"running" → "run", "better" → "bett"
Accuracy	High, retains semantic meaning	Lower, may distort meaning
Computational Cost	Slightly higher due to NLP model requirements	Lower, simpler rule-based approach
Use Case	Sentiment analysis, text classification, and NLP tasks requiring semantic understanding	Quick preprocessing, search indexing, or when meaning preservation is not critical

Table 2: Comparison between Lemmatization and Stemming

5.22 Filter out reviews with: Fewer than minimum words and Excessively long text

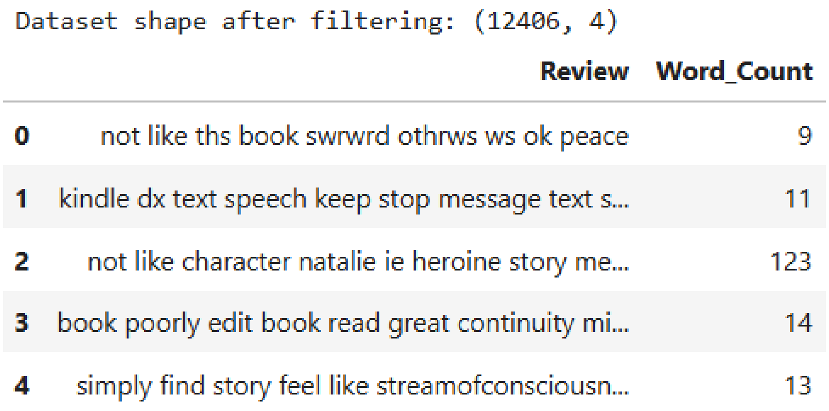
To maintain consistency and ensure meaningful input for machine learning models, reviews were filtered based on their word count. Very short reviews may lack sufficient context, while excessively long reviews can introduce noise or computational overhead. In this project, reviews with fewer than 3 words or more than 300 words were removed, ensuring that the dataset contains reviews of reasonable length for feature extraction and model training.

The following Python code was used to filter reviews by word count:

```
# Define thresholds
min_words = 3 # Minimum words per review
max_words = 300 # Maximum words per review
# Count words in each review
df['Word_Count'] = df['Review'].apply(lambda x: len(x.split()))
# Filter reviews
df = df[(df['Word_Count'] >= min_words) & (df['Word_Count'] <=
    max_words)].reset_index(drop=True)
print("Dataset shape after filtering:", df.shape)
df[['Review', 'Word_Count']].head()
```

By filtering reviews based on word count, the dataset becomes more standardized, eliminating extremely short or long reviews that could skew feature representation and adversely affect the performance of machine learning models.

Output:



```
Dataset shape after filtering: (12406, 4)
```

	Review	Word_Count
0	not like ths book swrwrd othrws ws ok peace	9
1	kindle dx text speech keep stop message text s...	11
2	not like character natalie ie heroine story me...	123
3	book poorly edit book read great continuity mi...	14
4	simply find story feel like streamofconsciousn...	13

5.23 Calculating Word Count

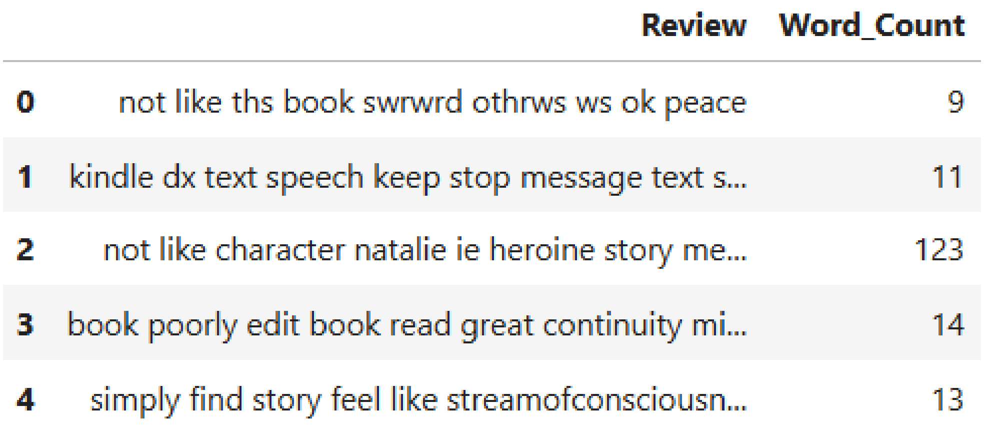
To facilitate analysis of review length and support preprocessing decisions, a Word_Count column was added to the dataset. This column records the number of words in each review, providing a quantitative measure of review length. Such information is useful for filtering extreme cases, analyzing textual complexity, and understanding the distribution of review content across the dataset.

The following Python code was used to compute and add the word count:

```
# Add a column with word count for each review
df['Word_Count'] = df['Review'].apply(lambda x: len(x.split()))
df[['Review', 'Word_Count']].head()
```

By including the word count as a feature, the preprocessing pipeline gains a simple yet informative metric that can guide further data cleaning, exploration, and feature engineering.

Output:



	Review	Word_Count
0	not like ths book swrwrd othrws ws ok peace	9
1	kindle dx text speech keep stop message text s...	11
2	not like character natalie ie heroine story me...	123
3	book poorly edit book read great continuity mi...	14
4	simply find story feel like streamofconsciousn...	13

6. Sample Reviews per Rating

To better understand the textual content and sentiment patterns associated with each rating, a random sample of reviews was extracted for each rating category. Examining sample reviews helps verify the quality of preprocessing, provides qualitative insight into the dataset, and ensures that each rating class contains representative textual examples.

The following Python code was used to sample reviews per rating:

```
# Sample reviews from each rating category
for rating, group in df.groupby('Rating'):
   print(f"\n--- Rating: {rating} ---\n")
   sample_reviews = group['Review'].sample(
      n=min(5, len(group)),
      random_state=42
   )
   for i, review in enumerate(sample_reviews, 1):
      print(f"{i}. {review}\n")
```

By inspecting representative reviews from each rating level, researchers can qualitatively confirm that preprocessing steps such as cleaning, lemmatization, and stopword removal have preserved meaningful content. This step also aids in understanding linguistic patterns that may influence rating prediction.

Sample Reviews

```
--- Rating: 1 ---

1. free read know not bother time waste reading
2. thing get end story sheer cussedness storyline flat absolutely
   character development dialog cheesy porn find increasingly disgusted
    female lead whine way find sympathetic protagonist find caring
   story explain bring main character point book suspend belief well
   not buy time
3. story alex alley taylor like cup tea threesome happy story
4. write terrible grammer terrible plot ridiculous bad stereotype thing
```

5. writer learn difference betweenthere theyreyour yourewere wereand standard grammar book find book actually painful read attempt humor funny time hard translate mush real english take away pure joy type story

--- Rating: 2 ---

1. idea story good fact vampires not feed leave mark neck confuse give book 2 star possibility need rework need lot editing begin pay attention misspelling space period part not line happen etc detract away story vampire not end book big let wellthe love story force way fast way unrealistic care family ridiculousit buy not like book overly descriptive book descriptive not happen feel character go think author vision probably see clearly head get paper draw story hard partreviewe jessica book sake
2. reviewraine misfit try fit not like kid like love goth type look vampire lonely hope find love someday walk mysterious tristan moment world turn upside downa excited read book vampire lore fanatic book leave disappoint not feel connection character like feel havewhat likei love premiselove triangle fight bad guy fight scene train visualize root good guy speak lastly fairly fast readwhat not likea mention biggy not feel emotion character feel flat want not downside fast read leave confused kept jumping story felt wrap upthat say recommend book think leave decide cup tea yoursmy ratie 2 star 5i recieve complimentary copy book exchange honest review
3. overall story pretty awesome apocalypse cause vampire postapocalypticdystopian society vampire hunter turn vampire kick ass fight scene love suspense snitch secret killer disclosure villain identity good twist storyi like postapocalypse vampire excited beginning thinking find amazing read give 5 immediatelybut turn bring hide vampire society care quickly give fight yes know fight internally somewhat strategy gain trust escape ve like fight bit long try hard escape join forgave aden way quickly love react find turn feeling ve internal struggle fact aden feel bad act thankful help apologize behavior baffle meaden turn not resort not brink death aden choice fight vampire vampire hunter decide turn like someone daughter birthmark show regret find end behavior antagonist love interest s not like nt like sloane behavior think switch team fight conflict internal dialogue believable mellow mei enjoyed fight scene rest taste dialogue clicheacute keep roll eye struggle obnoxious high school fall love scene ve uniquely write great twist story pull bit liked turn end wish depth believable idea nero end evil not accept action way portrayedim sorry want like book begin not taste mean m fan ya genre vampire dystopia bring not well execution story good
4. not feel worth pay buy not realize come part rush
5. poor character development improbable story line add waste read time big green machine work adroitly 34cia34 operative everit good book exaggerated action super human exploitsjust likely happen

--- Rating: 3 ---

1. purchase book october november year september not care
2. sorry book interested get boring middle find skim page finally decide stop read 50 go end big bang apologize slow go book loose quick need pull begin middle end not
3. like shortie sex hot character believable thing not care tyler whine moment thought read girl express emotion tyler keep go point not finish story 3starsstill m willing buy rest series hopefully tyler will not whiny chick book
4. actually pretty good book enjoy buy book 2 write fulllength good plot bit christian turn face good read
5. wow daisy go hiding man want know s baby daddy not care say baby aiden guess get to wait book read daisy aiden love story

--- Rating: 4 ---

1. little science fiction mystery imagine clone human computer interesting hope happens read want entertain book wish edit little not let stop read booknow m read necromancer
2. story woman catch group schoolfriend 20 year social networking site encourage play new game round call 25 random fact 20 year long time woman harbour devastate secretthis great story grip page not let finish secret tease slowly intrigue pile spade secret reveal story take turn huge twist tale not comingthis great novel intrigue twist turn chance will not regret iti receive complimentary copy book order review
3. wonder happen suffer country worldwide lethal pandemic we8217ve share sar mad cow bird flu virus8217 contain relatively quickly8212but high scale outbreak sector c take look government respond outbreak like sar mad cow happen high level let tell isn8217 t pretty8212though i8217 m sure it8217s realistic we8217d like admit appalled situation reaction character novel realistically call question philosophical debate greater good well let limited number suffer great good suffer sullivan look question rivet novel unfold isn8217 t pretty picture definitely reader thinkthis wellwritten novel takes look clone it8217s intense interesting8211both situation character keep glue page highly enjoy itthe novel follow different character unfolds8212donna rural vet mike cdc analyst worker triple e8212allowe reader gain omniscient insight happen spectrum rash animal people begin symptom stroke8230 ultimately lead death sound scientific nature sector c easy follow find highly interested character situation find sullivan great job explain boring reader scientific datum jargon appreciate highly suggest give novel read
4. great story love character way learn depends provide balance world trouble keep read action space great descriptive character reason character action enjoy read new race civilization make race alike greed power cause turmoil life
5. bootscootin blahniksby dd scottroxy rae vaughn tired live parent spotlight dime want clothe designer start shop little corner feed store sink dime money hop imagine dismay rear ends cowboy not money fix truck cowboy turn tomato farmer zayne mcdonald intrigue roxy

```
   think hard aroundthis book alight feel good book roxy feisty care
   individual heart gold zayne kind man want protagonist find vivid
   description take reader bootscootin good time imagine reaction roxy
   zayne truly book ll want read love good romance4 star

--- Rating: 5 ---

1. enjoy story m sucker sweet story heart ache heroines pain m try
   spoiler love honest regret book feel grief attitude beginning story
   feel genuine love story resolve bit surprised end big bonus lovemake
    craft happy deserve hea character sister character amusing d love 1
   ns
2. fascinating book private eye want education definitely read learn
   not imagine write private eye reading book
3. think love story get going shock good literally stop read love book
   soon wanted purchase sequel good recommend book easy read entertain
4. enjoy book character plot realistic story simple intense look
   forward read book series
5. not remember time read quirky cute love sooo short love little fairy
    tale like
```

7. Data Visualization

7.1 Bar Plot: Review Count per Rating

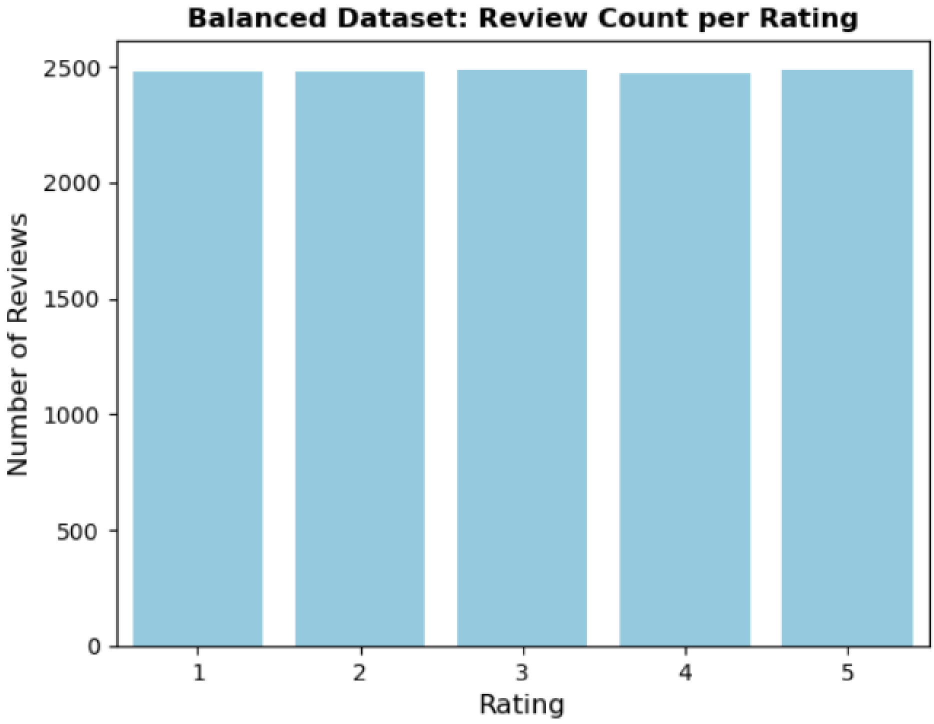
Visualizing the distribution of ratings provides a clear overview of how reviews are spread across different rating levels. This step helps identify potential class imbalances, which is critical for training unbiased machine learning models. In this project, a count plot was created to display the number of reviews corresponding to each rating in the balanced dataset.

The following Python code was used to generate the visualization:

Listing 1: Visualizing Rating Distribution

```python
import seaborn as sns
import matplotlib.pyplot as plt
# Plot count of reviews per rating
sns.countplot(x='Rating', data=df, color='skyblue')
plt.title('Balanced Dataset: Review Count per Rating', fontsize=12,
   weight='bold')
plt.xlabel('Rating', fontsize=12)
plt.ylabel('Number of Reviews', fontsize=12)
plt.xticks(fontsize=10)
plt.yticks(fontsize=10)
plt.show()
```

This visualization confirms that the dataset is balanced, with an approximately equal number of reviews for each rating level. Balanced datasets are essential for preventing model bias and ensuring accurate prediction across all rating categories.



Balanced Dataset Review Count per Rating Visualization

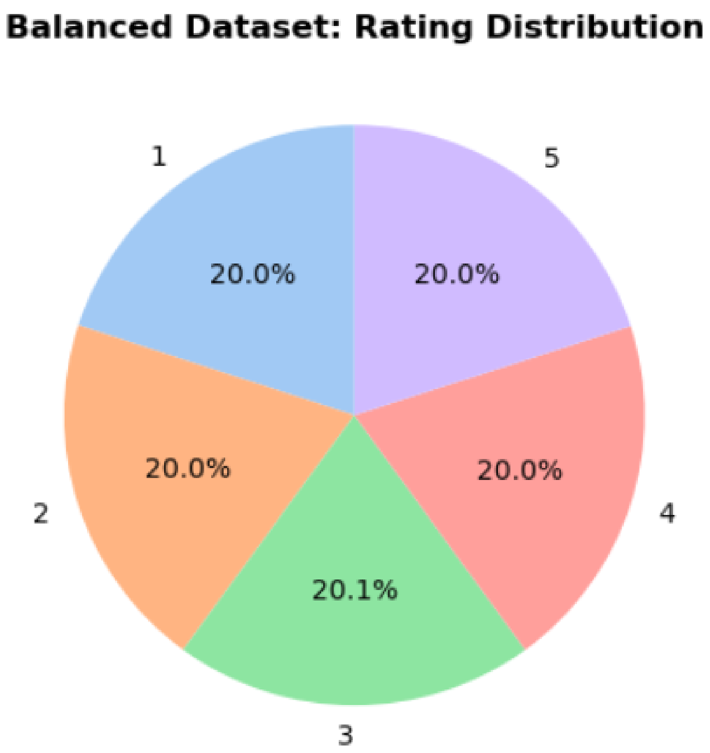
7.2 Pie Chart: Rating Distribution

To provide a more intuitive understanding of the rating distribution, a pie chart was created. This visualization illustrates the proportion of reviews corresponding to each rating level, helping to confirm dataset balance and highlighting the relative frequency of different ratings.

The following Python code was used to generate the pie chart:

```
import matplotlib.pyplot as plt
import seaborn as sns
# Count of reviews per rating
rating_counts = df['Rating'].value_counts().sort_index()
# Labels and values for pie chart
categories = rating_counts.index
values = rating_counts.values
# Plot pie chart
plt.pie(values, labels=categories, autopct='%1.1f%%', startangle=90,
       colors=sns.color_palette("pastel"))
plt.title("Balanced Dataset: Rating Distribution", fontsize=12, weight=
    'bold')
plt.show()
```

This visualization confirms that the dataset is well-balanced, with each rating category represented approximately equally. Such balanced representation is crucial for preventing model bias and ensuring reliable performance across all classes in machine learning tasks.



Balanced Dataset Rating Distribution Visualization

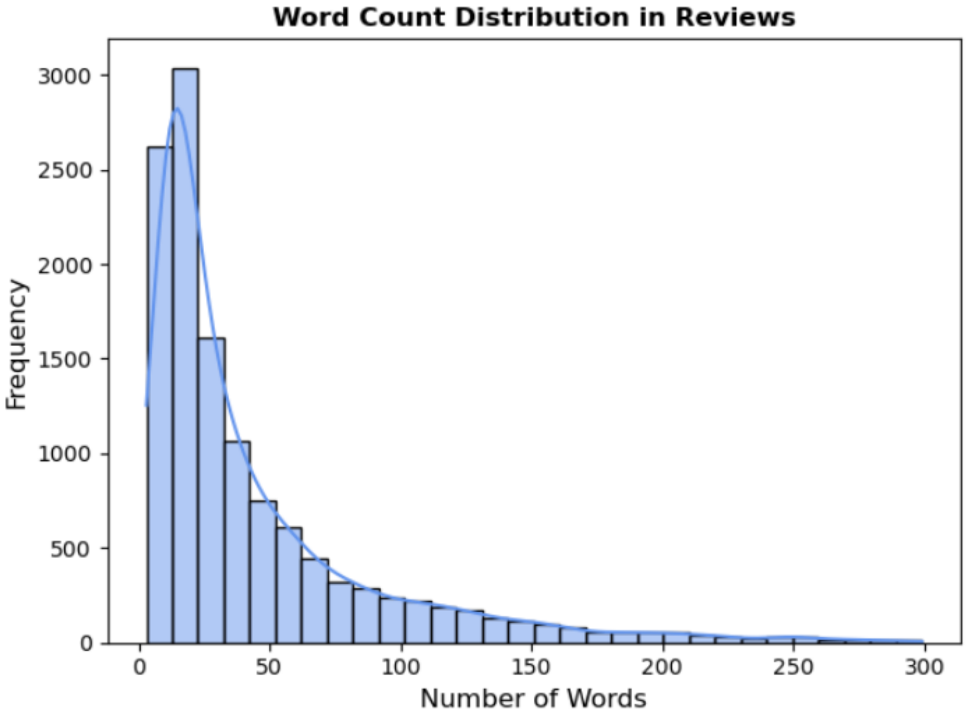
7.3 Histogram: Word Count Distribution

Analyzing the distribution of review lengths provides insights into the textual characteristics of the dataset. A histogram was created to visualize the word count across all reviews, highlighting the frequency of reviews with different lengths. This analysis helps identify extreme cases and ensures that the dataset contains reviews of reasonable length for feature extraction and model training.

The following Python code was used to generate the histogram:

```
import seaborn as sns
import matplotlib.pyplot as plt
sns.histplot(df['Word_Count'], bins=30, kde=True, color='cornflowerblue
    ')
plt.title('Word Count Distribution in Reviews', fontsize=12, weight='
    bold')
plt.xlabel('Number of Words', fontsize=12)
plt.ylabel('Frequency', fontsize=12)
plt.tight_layout()
plt.show()
```

This visualization confirms that the majority of reviews fall within a moderate word count range, validating the earlier filtering step and ensuring that the dataset is suitable for text-based machine learning models.



Balanced Dataset Word Count Distribution in Review Visualization

7.4 Box Plot: Word Count Distribution by Rating

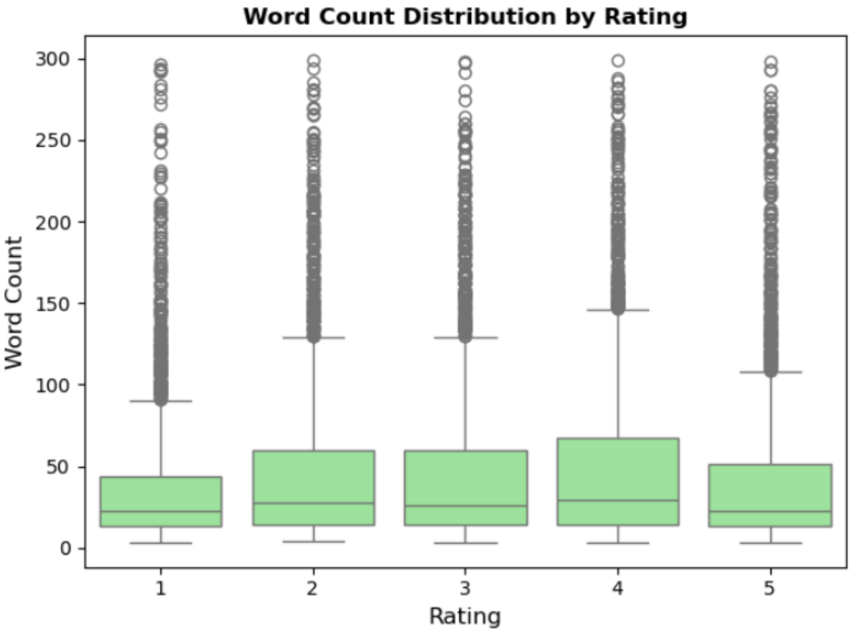
To examine how review length varies across different rating levels, a box plot was created showing the distribution of word counts for each rating category. This visualization helps identify patterns, such as whether higher or lower ratings tend to have longer or shorter reviews, and can inform feature engineering or preprocessing decisions.

The following Python code was used to generate the box plot:

Listing 2: Box Plot of Word Count by Rating

```
import seaborn as sns
import matplotlib.pyplot as plt
sns.boxplot(x='Rating', y='Word_Count', data=df, color='lightgreen')
plt.title('Word Count Distribution by Rating', fontsize=12, weight='
   bold')
plt.xlabel('Rating', fontsize=12)
plt.ylabel('Word Count', fontsize=12)
plt.xticks(fontsize=10)
plt.yticks(fontsize=10)
plt.tight_layout()
plt.show()
```

This visualization provides insights into the relationship between review length and ratings, helping ensure that text preprocessing and modeling decisions account for differences in review characteristics across rating categories.



Word Count Distribution by Rating Visualization

8. Natural Language Processing (NLP)

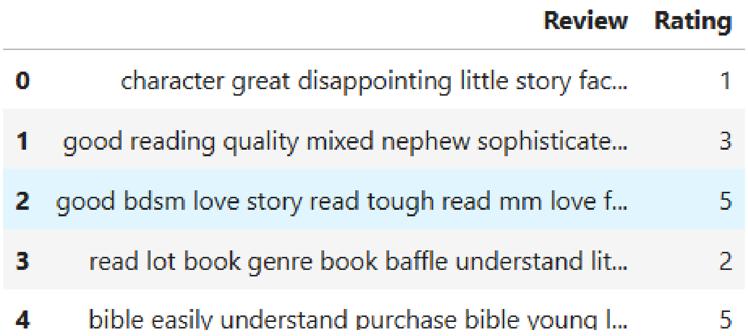
8.1 Shuffling the Dataset

Shuffling the dataset is an important preprocessing step to ensure that the order of reviews does not introduce any unintended bias during model training. Randomizing the sequence of data helps machine learning algorithms learn patterns more effectively and prevents overfitting to any particular sequence of ratings.

The following Python code was used to shuffle the dataset:

```
# Shuffle the dataset
df = df.sample(frac=1, random_state=42).reset_index(drop=True)
df.head()
```

By shuffling the dataset, the training and evaluation processes become more robust, ensuring that the model is exposed to a representative mix of all rating categories throughout the learning process.



	Review	Rating
0	character great disappointing little story fac...	1
1	good reading quality mixed nephew sophisticate...	3
2	good bdsm love story read tough read mm love f...	5
3	read lot book genre book baffle understand lit...	2
4	bible easily understand purchase bible young l...	5

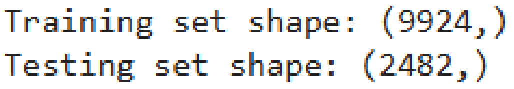
8.2 Train-Test Split

To evaluate the performance of machine learning models, the dataset was divided into training and testing sets. The training set is used to learn patterns from the data, while the testing set evaluates how well the model generalizes to unseen reviews. An 80:20 split was applied, with stratification based on ratings to ensure that all rating categories are proportionally represented in both sets.

The following Python code was used to split the dataset:

```python
from sklearn.model_selection import train_test_split
# Features and target
X = df['Review']
y = df['Rating']
# Split into train and test sets (80% train, 20% test)
X_train, X_test, y_train, y_test = train_test_split(
   X, y, test_size=0.2, random_state=42, stratify=y
)
print("Training set shape:", X_train.shape)
print("Testing set shape:", X_test.shape)
```

By stratifying the split, the distribution of ratings in the training and testing sets mirrors that of the overall dataset. This ensures balanced evaluation and reliable performance metrics across all rating classes.



```
Training set shape: (9924,)
Testing set shape: (2482,)
```

8.3 Stratified Split

A stratified split is a method of dividing a dataset into training and testing sets while preserving the proportion of each class in both sets. In classification tasks, especially with imbalanced classes, a simple random split may result in uneven representation of some categories, which can bias the model. Stratification ensures that the distribution of target labels (e.g., review ratings 1–5) in the train and test sets matches the distribution in the original dataset.

Example:

Original dataset: 50% rating 5, 20% rating 4, 30% other ratings

Stratified split (80:20) → Training set and testing set will maintain the same 50:20:30 ratio.

This technique helps improve model evaluation reliability and prevents certain classes from being underrepresented in either the training or testing set.

8.4 TF-IDF Vectorization

After preprocessing the text, the next step is converting textual data into numerical features that machine learning models can understand. TF-IDF (Term Frequency-Inverse Document Frequency) is a widely used technique for this purpose. It assigns weights to each term in the corpus based on its importance in a document relative to the entire dataset.

TF-IDF Concept

TF-IDF combines two metrics: Term Frequency (TF) and Inverse Document Frequency (IDF).

- **Term Frequency (TF):** Measures how frequently a word occurs in a document.

$$TF(t,d) = \frac{\text{Number of times term } t \text{ appears in document } d}{\text{Total number of terms in document } d}$$

- **Inverse Document Frequency (IDF):** Measures how important a term is by reducing the weight of terms that appear in many documents (common words) and increasing the weight for rarer terms.

$$IDF(t) = \log \frac{N}{1 + n_t}$$

  Where:

  - N = Total number of documents
  - n_t = Number of documents containing term t

- **TF-IDF Weight:** Combines TF and IDF to assign a weight to each term.

$$TF\text{-}IDF(t,d) = TF(t,d) \times IDF(t)$$

8.5 TF-IDF Implementation

To convert textual reviews into numerical features suitable for machine learning models, Term Frequency-Inverse Document Frequency (TF-IDF) vectorization was applied. TF-IDF assigns higher weight to words that are important in a particular document but less frequent across the corpus, allowing the model to focus on meaningful terms. In this project, word-level TF-IDF was computed using unigrams, bigrams, and trigrams to capture both individual words and short phrases.

Parameters used:

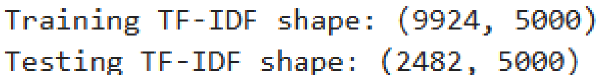
- `sublinear_tf=True`: Applies logarithmic scaling to term frequency.
- `max_features=5000`: Limits the feature space to the 5000 most informative terms.
- `ngram_range=(1,3)`: Includes unigrams, bigrams, and trigrams.
- `min_df=3` and `max_df=0.9`: Filters out extremely rare and overly common terms.

```
from sklearn.feature_extraction.text import TfidfVectorizer
# Word-level TF-IDF
vectorizer = TfidfVectorizer(
   sublinear_tf=True,
   max_features=5000,
   ngram_range=(1, 3),
   min_df=3,
   max_df=0.9
)
# Fit TF-IDF on training data and transform
X_train_tfidf = vectorizer.fit_transform(X_train)
# Transform test data
```

```
X_test_tfidf = vectorizer.transform(X_test)
print("Training TF-IDF shape:", X_train_tfidf.shape)
print("Testing TF-IDF shape:", X_test_tfidf.shape)
```

By applying TF-IDF vectorization, textual reviews are transformed into a numerical feature matrix, enabling machine learning models to learn patterns and relationships between words/phrases and review ratings efficiently.

Output:



```
Training TF-IDF shape: (9924, 5000)
Testing TF-IDF shape: (2482, 5000)
```

8.6 Choice of TF-IDF Over Bag of Words (BoW)

In this project, TF-IDF was preferred over the traditional Bag of Words (BoW) approach for feature extraction due to its ability to emphasize informative words while reducing the impact of commonly occurring, less meaningful terms. While BoW simply counts the frequency of words in a document, TF-IDF scales these counts by the inverse document frequency, assigning lower weight to words that appear across many reviews (e.g., “product”, “good”) and higher weight to distinctive words that provide meaningful sentiment cues.

This weighting mechanism allows machine learning models to focus on terms that are more predictive of review ratings, improving model performance, robustness, and interpretability. TF-IDF is particularly effective in text classification tasks like review rating prediction, where distinguishing between subtle differences in word usage can significantly influence model accuracy.

8.7 Comparison of TF-IDF and Bag of Words (BoW)

Feature	**TF-IDF**	**Bag of Words (BoW)**
Definition	Weights words by frequency & uniqueness	Counts word occurrences
Word Importance	Highlights rare/informative words	All words treated equally
Context	Considers significance in corpus	Ignores importance/context
Scaling	Inverse document frequency applied	Raw counts only
Use Case	Sentiment analysis, text classification	Basic text analysis
Performance	Often higher accuracy & interpretability	May lower model accuracy

Table 3: Comparison of TF-IDF and Bag of Words (BoW) for feature extraction

8.8 Converting TF-IDF Matrices to DataFrames

After computing TF-IDF features, the resulting matrices are sparse numeric arrays. Converting them into pandas DataFrames allows for easier inspection, analysis, and integration with machine learning pipelines. Each column in the DataFrame corresponds to a feature (word, bigram, or trigram), and each row represents a review. This structured format facilitates visualization, feature selection, and debugging during model development.

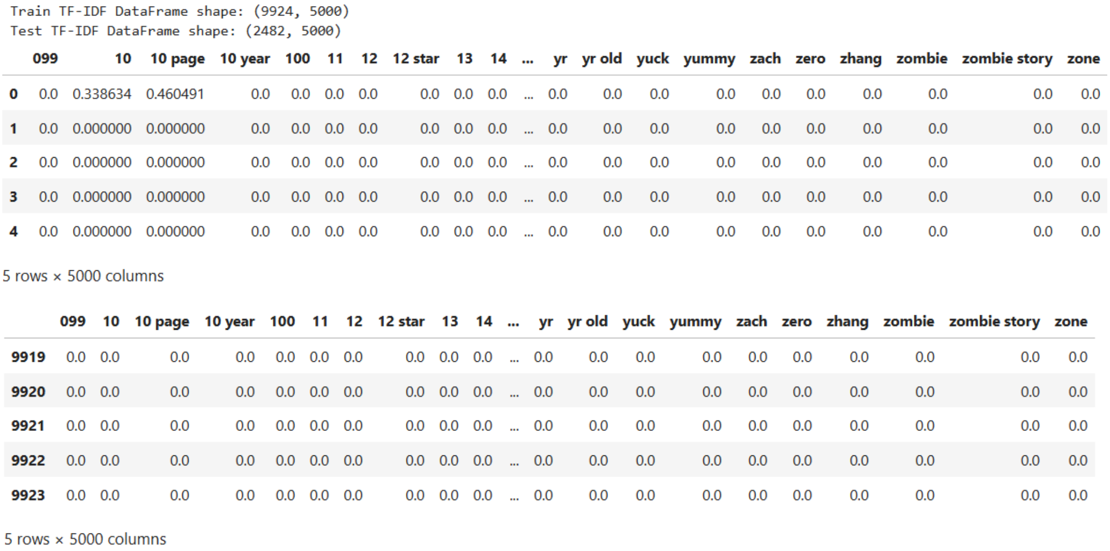
Listing 3: Convert TF-IDF Matrices to Pandas DataFrames

```
# Get feature names from the vectorizer
```

```
feature_names = vectorizer.get_feature_names_out()
# Convert TF-IDF matrices to DataFrames
X_train_df = pd.DataFrame(X_train_tfidf.toarray(), columns=
    feature_names)
X_test_df = pd.DataFrame(X_test_tfidf.toarray(), columns=feature_names)
print("\nTrain TF-IDF DataFrame shape:", X_train_df.shape)
print("Test TF-IDF DataFrame shape:", X_test_df.shape)
X_train_df.head()
X_train_df.tail()
```

By converting TF-IDF matrices to DataFrames, researchers can easily explore features, identify top-weighted terms, and ensure that the preprocessing pipeline correctly represents the textual data in numerical form for machine learning models.

Output:



```
Train TF-IDF DataFrame shape: (9924, 5000)
Test TF-IDF DataFrame shape: (2482, 5000)
```

	099	10	10 page	10 year	100	11	12	12 star	13	14	...	yr	yr old	yuck	yummy	zach	zero	zhang	zombie	zombie story	zone
0	0.0	0.338634	0.460491	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	0.0	0.0
1	0.0	0.000000	0.000000	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	0.0	0.0
2	0.0	0.000000	0.000000	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	0.0	0.0
3	0.0	0.000000	0.000000	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	0.0	0.0
4	0.0	0.000000	0.000000	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	0.0	0.0

5 rows × 5000 columns

	099	10	10 page	10 year	100	11	12	12 star	13	14	...	yr	yr old	yuck	yummy	zach	zero	zhang	zombie	zombie story	zone
9919	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	0.0	0.0	0.0	0.0	0.0
9920	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	0.0	0.0	0.0	0.0	0.0
9921	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	0.0	0.0	0.0	0.0	0.0
9922	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	0.0	0.0	0.0	0.0	0.0
9923	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	0.0	0.0	0.0	0.0	0.0

5 rows × 5000 columns

8.9 Saving the TF-IDF Vectorizer

To enable consistent feature extraction for future use and deployment, the trained TF-IDF vectorizer was saved to disk. Persisting the vectorizer ensures that the same vocabulary and feature mappings are applied to new data, maintaining consistency in model predictions. This is especially important when deploying machine learning models in production environments.

```
import os
import joblib
# Create directory to save models
model_dir = r"..\models"
os.makedirs(model_dir, exist_ok=True)
# Save word-level TF-IDF vectorizer
word_vectorizer_path = os.path.join(model_dir, "tfidf_balanced.pkl")
joblib.dump(vectorizer, word_vectorizer_path)
print(f"TF-IDF Vectorizer saved at: {word_vectorizer_path}")
```

By saving the TF-IDF vectorizer, the preprocessing pipeline becomes reproducible and allows new reviews to be transformed consistently before feeding them into trained models.

9. Machine Learning Model Training and Evaluation

9.1 Overview

Predicting review ratings from textual feedback was formulated as a multi-class classification problem. Several supervised learning algorithms were explored to determine the most effective model for this task. Textual features were extracted using TF-IDF vectorization, capturing the significance of unigrams, bigrams, and trigrams. All experiments were conducted on a balanced dataset, ensuring equal representation of each rating category to prevent bias in model predictions and promote reliable evaluation.

9.2 Models Evaluated

The following machine learning models were assessed for their suitability in review rating prediction:

- **Logistic Regression (LR):** A linear model for multi-class classification, effective for linearly separable data.
- **Support Vector Machine (LinearSVC):** Utilizes a linear kernel to separate classes with maximum margin.
- **Multinomial Naive Bayes (MultinomialNB):** A probabilistic model well-suited for text-based data and word count features.
- **Decision Tree (DT):** A tree-based classifier that captures non-linear relationships in the feature space.
- **Random Forest (RF):** An ensemble of decision trees that leverages bagging and feature randomness to improve generalization.

9.3 Model Selection – Logistic Regression

After evaluating performance across multiple algorithms, Logistic Regression was selected as the primary model due to its high accuracy, interpretability, and efficiency on TF-IDF features derived from textual reviews. Logistic Regression provided consistent predictions across all rating categories and demonstrated robust generalization on the test dataset.