Amazon Product Reviews Sentiment Analysis using NLP

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Problem Statement

Reviews are critical to businesses as they offer insights into customer satisfaction, preferences and areas of improvement.

Businesses need to understand and interpret these reviews in order to cut through the competition. Lots of reviews are generated daily and manually analyzing them is impractical.

Objectives

Use Sentiment analysis to help the businesses get actionable insights from the feedback received from customers.

The approach taken with the analysis seeks to

- Determine the sentiment of the reviews (positive or negative) to understand overall customer satisfaction and feedback.
- Utilize sentiment analysis to help our stakeholders understand customer preferences across various products.
- Conduct exploratory data analysis to understand the distribution of sentiments over time, across barands and products.
- Leverage customer reviews to identify areas for improvement in products based on user experience.
- Build a classifier model to help predict reviews as positive or negative

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Data Sources

Data for this project was obtained from Kaggle [repository]
(https://www.kaggle.com/datasets/datafiniti/consumer-reviews-of-amazon-products?resource=download (https://www.kaggle.com/datasets/datafiniti/consumer-reviews-of-

amazon-products?resource=download))

The data represents:

Brand: The brand name of the product being reviewed.

Categories: Categories or tags that classify the product (e.g., electronics, home, books).

Keys: Keywords or identifiers associated with the product.

Manufacturer: The company or entity that manufactures the product.

Reviews.date: The date when the review was posted.

Reviews.dateAdded: Additional date-related information, possibly indicating when the review was added to the dataset.

Reviews.dateSeen: Dates indicating when the review was observed or recorded (possibly by a data aggregator or platform).

Reviews.didPurchase: Boolean (true/false) indicating whether the reviewer claims to have purchased the product.

Reviews.doRecommend: Boolean (true/false) indicating whether the reviewer recommends the product.

Reviews.id: Unique identifier for each review.

Reviews.numHelpful: Number of users who found the review helpful.

Reviews.rating: Rating given by the reviewer (typically on a scale such as 1 to 5 stars).

Reviews.sourceURLs: URLs pointing to the source of the review.

Reviews.text: The main body of the review text.

Reviews.title: The title or headline of the review.

Reviews.userCity: City location of the reviewer.

Reviews.userProvince: Province or state location of the reviewer.

Reviews.username: Username or identifier of the reviewer.

These are the variables this analysis will focus on to derive insights.

Methodology

The process can be divided into these many parts.(we will edit this bit to the exact number once done)

Data preparation

- Text Cleaning: Remove or handle punctuation, special characters, numbers, and stopwords
- Tokenization: Split text into words or subwords.

- Text Normalization: Convert text to lowercase, perform stemming or lemmatization.
- Padding/Truncation: Ensure all text sequences are of the same length.
- Train-Test Split: Divide your data into training, validation, and test sets

EDA Visualisations and insights. For each characteristic we will be:

- Creating visualisations
- Drawing conclusions
- Providing recommendations

Feature Engineering

In the feature engineering section, we process and transform the textual data for further analysis and modeling:

The methods used are;

- Sentiment Analysis
- Visualization with Word Clouds
- Text Vectorization to convert textual data into numerical form using TF-IDF and Count Vectorization.
- Word Embedding using Word2Vec and FastTex

We will also Extract the Bigrams and Trigrams

Model Selection and Building

The models used are a Simple RNN, LSTM, BERT models

Hyperparameter Tuning: Optimize hyperparameters for better performance.

Model Evaluation

Evaluate Performance using the accuracy score.

Analyze Results: Look at the confusion matrix, ROC curves, and other evaluation tools

Data preparation

Importing Libraries

In [3]:
```
#Basic libraries
import pandas as pd
import numpy as np

#NLTK libraries
import nltk
from nltk.corpus import stopwords
from nltk.stem import WordNetLemmatizer
from nltk.tokenize import word_tokenize

nltk.download('punkt')
nltk.download('stopwords')
nltk.download('wordnet')
import re
import string
!pip install wordcloud
from wordcloud import WordCloud,STOPWORDS
from nltk.stem.porter import PorterStemmer

from sklearn.feature_extraction.text import TfidfVectorizer

# Machine Learning libraries
import sklearn
from sklearn.svm import SVC
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import MinMaxScaler
from sklearn.ensemble import ExtraTreesClassifier
from sklearn.pipeline import make_pipeline
from sklearn.model_selection import GridSearchCV
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.naive_bayes import BernoulliNB
from sklearn.neighbors import KNeighborsClassifier
from sklearn.multiclass import OneVsRestClassifier
from sklearn.svm import SVC
from sklearn.pipeline import Pipeline
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import label_binarize
from sklearn import svm, datasets
from sklearn import preprocessing

!pip install tensorflow
!pip install keras
!pip install numpy pandas scikit-learn

from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Embedding, SimpleRNN, Dense
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences


#Metrics libraries
from sklearn import metrics
from sklearn.metrics import classification_report
from sklearn.model_selection import cross_val_score
from sklearn.metrics import roc_auc_score
from sklearn.metrics import roc_curve, auc

#Visualization libraries
```

```
import matplotlib.pyplot as plt
from matplotlib import rcParams
import seaborn as sns
from plotly import tools
import plotly.graph_objs as go
from plotly.offline import iplot
%matplotlib inline

#Ignore warnings
import warnings
warnings.filterwarnings('ignore')
```

```
[nltk_data] Downloading package punkt to /root/nltk_data...
[nltk_data]   Package punkt is already up-to-date!
[nltk_data] Downloading package stopwords to /root/nltk_dat
a...
[nltk_data]   Package stopwords is already up-to-date!
[nltk_data] Downloading package wordnet to /root/nltk_data...
[nltk_data]   Package wordnet is already up-to-date!

Requirement already satisfied: wordcloud in /usr/local/lib/py
thon3.10/dist-packages (1.9.3)
Requirement already satisfied: numpy>=1.6.1 in /usr/local/li
b/python3.10/dist-packages (from wordcloud) (1.25.2)
Requirement already satisfied: pillow in /usr/local/lib/pytho
n3.10/dist-packages (from wordcloud) (9.4.0)
Requirement already satisfied: matplotlib in /usr/local/lib/p
ython3.10/dist-packages (from wordcloud) (3.7.1)
Requirement already satisfied: contourpy>=1.0.1 in /usr/loca
l/lib/python3.10/dist-packages (from matplotlib->wordcloud)
(1.2.1)
Requirement already satisfied: cycler>=0.10 in /usr/local/li
```

LOADING DATA

In [5]:
```python
# Loading the data set

raw = pd.read_csv('AMAZON REVIEWS.csv')
raw
```

Out[5]:

	id	name	asins	brand	c
0	AVqkIhwDv8e3D1O-lebb	All-New Fire HD 8 Tablet, 8 HD Display, Wi-Fi,...	B01AHB9CN2	Amazon	Electr & Tablet
1	AVqkIhwDv8e3D1O-lebb	All-New Fire HD 8 Tablet, 8 HD Display, Wi-Fi,...	B01AHB9CN2	Amazon	Electr & Tablet
2	AVqkIhwDv8e3D1O-lebb	All-New Fire HD 8 Tablet, 8 HD Display, Wi-Fi,...	B01AHB9CN2	Amazon	Electr & Tablet
3	AVqkIhwDv8e3D1O-lebb	All-New Fire HD 8 Tablet, 8 HD Display, Wi-Fi,...	B01AHB9CN2	Amazon	Electr & Tablet
4	AVqkIhwDv8e3D1O-lebb	All-New Fire HD 8 Tablet, 8 HD Display, Wi-Fi,...	B01AHB9CN2	Amazon	Electr & Tablet
...	...	...	...	...	
23744	AVpfl8cLLJeJML43AE3S	Echo (White),,,\r\nEcho (White),,,	B00L9EPT8O,B01E6AO69U	Amazon	Stere Contro E
23745	AVpfl8cLLJeJML43AE3S	Echo (White),,,\r\nEcho (White),,,	B00L9EPT8O,B01E6AO69U	Amazon	Stere Contro E
23746	AVpfl8cLLJeJML43AE3S	Echo (White),,,\r\nEcho (White),,,	B00L9EPT8O,B01E6AO69U	Amazon	Stere Contro E
23747	AVpfl8cLLJeJML43AE3S	Echo (White),,,\r\nEcho (White),,,	B00L9EPT8O,B01E6AO69U	Amazon	Stere Contro E
23748	AVpfl8cLLJeJML43AE3S	Echo (White),,,\r\nEcho (White),,,	B00L9EPT8O,B01E6AO69U	Amazon	Stere Contro E

23749 rows × 21 columns

DATA INSPECTION AND UNDERSTANDING

In [6]:
```
# Checking the data types and null values
raw.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 23749 entries, 0 to 23748
Data columns (total 21 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   id                    23749 non-null  object 
 1   name                  23749 non-null  object 
 2   asins                 23747 non-null  object 
 3   brand                 23749 non-null  object 
 4   categories            23749 non-null  object 
 5   keys                  23749 non-null  object 
 6   manufacturer          23749 non-null  object 
 7   reviews.date          23722 non-null  object 
 8   reviews.dateAdded     18982 non-null  object 
 9   reviews.dateSeen      23749 non-null  object 
 10  reviews.didPurchase   1 non-null      object 
 11  reviews.doRecommend   23258 non-null  object 
 12  reviews.id            1 non-null      float64
 13  reviews.numHelpful    23291 non-null  float64
 14  reviews.rating        23717 non-null  float64
 15  reviews.sourceURLs    23749 non-null  object 
 16  reviews.text          23748 non-null  object 
 17  reviews.title         23746 non-null  object 
 18  reviews.userCity      0 non-null      float64
 19  reviews.userProvince  0 non-null      float64
 20  reviews.username      23743 non-null  object 
dtypes: float64(5), object(16)
memory usage: 3.8+ MB
```

Columns with 0 Non-Null Count

- This column has 0 non-null entries, meaning all 34,660 entries are missing or null.
- This column does not contain any useful data.

Columns with 1 Non-Null Count

- This column has only 1 non-null entry, meaning out of 34,660 rows, only one entry has a value and the rest are null.
- This column contains almost no useful data.

In [7]:
```
# Checking the data shape
raw.shape
```

Out[7]: (23749, 21)

In [8]:
```
#Summary statistics
raw.describe()
```

Out[8]:

	reviews.id	reviews.numHelpful	reviews.rating	reviews.userCity	reviews.userProvi
count	1.0	23291.000000	23717.000000	0.0	
mean	111372787.0	0.545533	4.545811	NaN	
std	NaN	10.856479	0.759198	NaN	
min	111372787.0	0.000000	1.000000	NaN	
25%	111372787.0	0.000000	4.000000	NaN	
50%	111372787.0	0.000000	5.000000	NaN	
75%	111372787.0	0.000000	5.000000	NaN	
max	111372787.0	780.000000	5.000000	NaN	

In [9]:
```
# Previewing the columns
raw.columns
```

Out[9]:
```
Index(['id', 'name', 'asins', 'brand', 'categories', 'keys', 'man
ufacturer',
       'reviews.date', 'reviews.dateAdded', 'reviews.dateSeen',
       'reviews.didPurchase', 'reviews.doRecommend', 'reviews.i
d',
       'reviews.numHelpful', 'reviews.rating', 'reviews.sourceURL
s',
       'reviews.text', 'reviews.title', 'reviews.userCity',
       'reviews.userProvince', 'reviews.username'],
      dtype='object')
```

In [10]:

```python
# Renaming the columns to standard naming convention
column_names = {
    'id': 'id',
    'name': 'product_name',
    'asins': 'asins',
    'brand': 'brand',
    'categories': 'product_categories',
    'keys': 'product_keys',
    'manufacturer': 'manufacturer_name',
    'reviews.date': 'review_date',
    'reviews.dateAdded': 'review_date_added',
    'reviews.dateSeen': 'review_date_seen',
    'reviews.didPurchase': 'review_did_purchase',
    'reviews.doRecommend': 'review_do_recommend',
    'reviews.id': 'review_id',
    'reviews.numHelpful': 'review_num_helpful',
    'reviews.rating': 'review_rating',
    'reviews.sourceURLs': 'review_source_urls',
    'reviews.text': 'review_text',
    'reviews.title': 'review_title',
    'reviews.userCity': 'review_user_city',
    'reviews.userProvince': 'review_user_province',
    'reviews.username': 'review_username'
}

# Rename columns in your DataFrame
raw.rename(columns=column_names, inplace=True)

# Example: Printing the new column names
print(raw.columns)
```

```
Index(['id', 'product_name', 'asins', 'brand', 'product_categorie
s',
       'product_keys', 'manufacturer_name', 'review_date', 'revie
w_date_added',
       'review_date_seen', 'review_did_purchase', 'review_do_reco
mmend',
       'review_id', 'review_num_helpful', 'review_rating',
       'review_source_urls', 'review_text', 'review_title', 'revi
ew_user_city',
       'review_user_province', 'review_username'],
      dtype='object')
```

In [11]:
```python
# Convert 'review_date' to datetime to enable trend analysis
raw['review_date'] = pd.to_datetime(raw['review_date'], format= 'm

# Print the data types to verify
raw.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 23749 entries, 0 to 23748
Data columns (total 21 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   id                    23749 non-null  object
 1   product_name          23749 non-null  object
 2   asins                 23747 non-null  object
 3   brand                 23749 non-null  object
 4   product_categories    23749 non-null  object
 5   product_keys          23749 non-null  object
 6   manufacturer_name     23749 non-null  object
 7   review_date           23722 non-null  datetime64[ns, UTC]
 8   review_date_added     18982 non-null  object
 9   review_date_seen      23749 non-null  object
 10  review_did_purchase   1 non-null      object
 11  review_do_recommend   23258 non-null  object
 12  review_id             1 non-null      float64
 13  review_num_helpful    23291 non-null  float64
 14  review_rating         23717 non-null  float64
 15  review_source_urls    23749 non-null  object
 16  review_text           23748 non-null  object
 17  review_title          23746 non-null  object
 18  review_user_city      0 non-null      float64
 19  review_user_province  0 non-null      float64
 20  review_username       23743 non-null  object
dtypes: datetime64[ns, UTC](1), float64(5), object(15)
memory usage: 3.8+ MB
```

In [12]:
```
# Checking for proportion of missing values

raw.isnull().mean()
```

Out[12]:
```
id                      0.000000
product_name            0.000000
asins                   0.000084
brand                   0.000000
product_categories      0.000000
product_keys            0.000000
manufacturer_name       0.000000
review_date             0.001137
review_date_added       0.200724
review_date_seen        0.000000
review_did_purchase     0.999958
review_do_recommend     0.020675
review_id               0.999958
review_num_helpful      0.019285
review_rating           0.001347
review_source_urls      0.000000
review_text             0.000042
review_title            0.000126
review_user_city        1.000000
review_user_province    1.000000
review_username         0.000253
dtype: float64
```

In [13]:
```
# Checking the missing values
raw.isnull().sum()
```

Out[13]:
```
id                          0
product_name                0
asins                       2
brand                       0
product_categories          0
product_keys                0
manufacturer_name           0
review_date                27
review_date_added        4767
review_date_seen            0
review_did_purchase     23748
review_do_recommend       491
review_id               23748
review_num_helpful        458
review_rating              32
review_source_urls          0
review_text                 1
review_title                3
review_user_city        23749
review_user_province    23749
review_username             6
dtype: int64
```

In [14]:

```
#check percentage of missing values

# create a function to check the percentage of missing values
def missing_values(raw):
    miss = raw.isnull().sum().sort_values(ascending = False)
    percentage_miss = (raw.isnull().sum() / len(raw)).sort_values(
    missing = pd.DataFrame({"Missing Values": miss, "Percentage":
    missing.drop(missing[missing["Percentage"] == 0].index, inplac
    return missing

missing_data = missing_values(raw)
missing_data
```

Out[14]:

	index	Missing Values	Percentage
0	review_user_province	23749	1.000000
1	review_user_city	23749	1.000000
2	review_did_purchase	23748	0.999958
3	review_id	23748	0.999958
4	review_date_added	4767	0.200724
5	review_do_recommend	491	0.020675
6	review_num_helpful	458	0.019285
7	review_rating	32	0.001347
8	review_date	27	0.001137
9	review_username	6	0.000253
10	review_title	3	0.000126
11	asins	2	0.000084
12	review_text	1	0.000042

In [15]:
```python
# Checking for uniques values in all columns

# Loop through each column and print unique values
for column_name in raw.columns:
    unique_values = raw[column_name].unique()
    num_unique_values = len(unique_values)
    print(f"Unique Values in '{column_name}' (Total: {num_unique_v
    print(unique_values)
    print("\n" + "="*50 + "\n")

# change to dataframe
```

```
Unique Values in 'id' (Total: 30):
['AVqkIhwDv8e3D1O-lebb' 'AVqVGZO3nnc1JgDc3jGK' 'AVpe9CMS1cnlu
Z0-aoC5'
 'AVpfBEWcilAPnD_xTGb7' 'AVqkIiKWnnc1JgDc3khH' 'AVqkIj9snnc1J
gDc3khU'
 'AVsRjfwAU2_QcyX9PHqe' 'AVqVGZNvQMlgsOJE6eUY' 'AVpfwS_CLJeJM
L43DH5w'
 'AVphgVaX1cnluZ0-DR74' 'AVqVGZN9QMlgsOJE6eUZ' 'AVpftoij1cnlu
Z0-p5n2'
 'AVqkIhxunnc1JgDc3kg_' 'AVpioXbb1cnluZ0-PImd' 'AVpff7_VilAPn
D_xc1E_'
 'AVpjEN4jLJeJML43rpUe' 'AVpg3q4RLJeJML43TxA_' 'AVqVGWLKnnc1J
gDc3jF1'
 'AV1YnRtnglJLPUi8IJmV' 'AVphPmHuilAPnD_x3E5h' 'AVzvXXxbvKc47
QAVfRhy'
 'AVpe7AsMilAPnD_xQ78G' 'AVph0EeEilAPnD_x9myq' 'AVqkIdntQMlgs
OJE6fuB'
 'AVzRlorb-jtxr-f3ygvQ' 'AVqVGWQDv8e3D1O-ldFr' 'AVzvXXwEvKc47
QAVfRhx'
```

DATA CLEANING

Handling Missing values

In [16]:
```python
#drop all columns with high percentage of missing values and colum

raw.drop(columns = ['review_date_added', 'review_date_seen', 'revi
```

In [17]:
```python
# drop rows with missing values
raw.dropna(inplace = True)
```

In [18]:
```python
# Verify that there are no more missing values
print(raw.isnull().sum().sum())  # Should print 0

# Get the shape of the cleaned data
print(raw.shape)

# Display the first few rows of the cleaned data
raw.head(2)
```

```
0
(23251, 13)
```

Out[18]:

	id	asins	brand	product_categories	
0	AVqkIhwDv8e3D1O-lebb	B01AHB9CN2	Amazon	Electronics,iPad & Tablets,All Tablets,Fire Ta...	841667104676,amazon/53
1	AVqkIhwDv8e3D1O-lebb	B01AHB9CN2	Amazon	Electronics,iPad & Tablets,All Tablets,Fire Ta...	841667104676,amazon/53

Checking for duplicates

In [19]:
```python
# Checking duplicated rows
num_duplicated = raw.duplicated().sum()
print(f"Number of duplicated rows: {num_duplicated}")
```

```
Number of duplicated rows: 0
```

In [20]:
```python
# Checking for duplicates using the 'CustomerId' column
raw[raw.duplicated(subset=["asins"])]
```

Out[20]:

	id	asins	brand	product_categories	
1	AVqkIhwDv8e3D1O-lebb	B01AHB9CN2	Amazon	Electronics,iPad & Tablets,All Tablets,Fire Ta...	841
2	AVqkIhwDv8e3D1O-lebb	B01AHB9CN2	Amazon	Electronics,iPad & Tablets,All Tablets,Fire Ta...	841
3	AVqkIhwDv8e3D1O-lebb	B01AHB9CN2	Amazon	Electronics,iPad & Tablets,All Tablets,Fire Ta...	841
4	AVqkIhwDv8e3D1O-lebb	B01AHB9CN2	Amazon	Electronics,iPad & Tablets,All Tablets,Fire Ta...	841
5	AVqkIhwDv8e3D1O-lebb	B01AHB9CN2	Amazon	Electronics,iPad & Tablets,All Tablets,Fire Ta...	841
...	...	...	...	...	
23744	AVpfl8cLLJeJML43AE3S	B00L9EPT8O,B01E6AO69U	Amazon	Stereos,Remote Controls,Amazon Echo,Audio Dock...	(
23745	AVpfl8cLLJeJML43AE3S	B00L9EPT8O,B01E6AO69U	Amazon	Stereos,Remote Controls,Amazon Echo,Audio Dock...	(
23746	AVpfl8cLLJeJML43AE3S	B00L9EPT8O,B01E6AO69U	Amazon	Stereos,Remote Controls,Amazon Echo,Audio Dock...	(
23747	AVpfl8cLLJeJML43AE3S	B00L9EPT8O,B01E6AO69U	Amazon	Stereos,Remote Controls,Amazon Echo,Audio Dock...	(
23748	AVpfl8cLLJeJML43AE3S	B00L9EPT8O,B01E6AO69U	Amazon	Stereos,Remote Controls,Amazon Echo,Audio Dock...	(

23232 rows × 13 columns

Type *Markdown* and LaTeX: α^2

- The 'id' column has duplicated rows, but we will not remove them as they reflect valid multiple reviews or transactions for the same product.
- We did not set 'asins' or 'id' as indices because multiple entries for the same product (same 'asins') with different or the same 'id' are common in e-commerce datasets, reflecting multiple reviews or transactions for the same product.

Checking for placeholders

In [21]:
```
# Define a comprehensive list of potential placeholder values
common_placeholders = ["", "na", "n/a", "nan",  "none", "null", "-

# Loop through each column and check for potential placeholders
found_placeholder = False
for column in raw.columns:
    unique_values = raw[column].unique()
    for value in unique_values:
        if pd.isna(value) or (isinstance(value, str) and value.str
            count = (raw[column] == value).sum()
            print(f"Column '{column}': Found {count} occurrences o
            found_placeholder = True

if not found_placeholder:
    print("No potential placeholders found in the DataFrame.")
```

```
Column 'review_title': Found 1 occurrences of potential placehold
er 'Na'
Column 'review_username': Found 1 occurrences of potential placeh
older 'none'
Column 'review_username': Found 1 occurrences of potential placeh
older 'Unknown'
```

In [22]:
```
# Checking our column names
raw.columns
```

Out[22]:
```
Index(['id', 'asins', 'brand', 'product_categories', 'product_key
s',
       'manufacturer_name', 'review_date', 'review_do_recommend',
       'review_num_helpful', 'review_rating', 'review_text', 'rev
iew_title',
       'review_username'],
      dtype='object')
```

```
In [23]: #Checking the null values and data types after changes made
raw.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 23251 entries, 0 to 23748
Data columns (total 13 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   id                   23251 non-null  object
 1   asins                23251 non-null  object
 2   brand                23251 non-null  object
 3   product_categories   23251 non-null  object
 4   product_keys         23251 non-null  object
 5   manufacturer_name    23251 non-null  object
 6   review_date          23251 non-null  datetime64[ns, UTC]
 7   review_do_recommend  23251 non-null  object
 8   review_num_helpful   23251 non-null  float64
 9   review_rating        23251 non-null  float64
 10  review_text          23251 non-null  object
 11  review_title         23251 non-null  object
 12  review_username      23251 non-null  object
dtypes: datetime64[ns, UTC](1), float64(2), object(10)
memory usage: 2.5+ MB
```

After cleaning the data set, we now have 34,054 rows and no missing values.

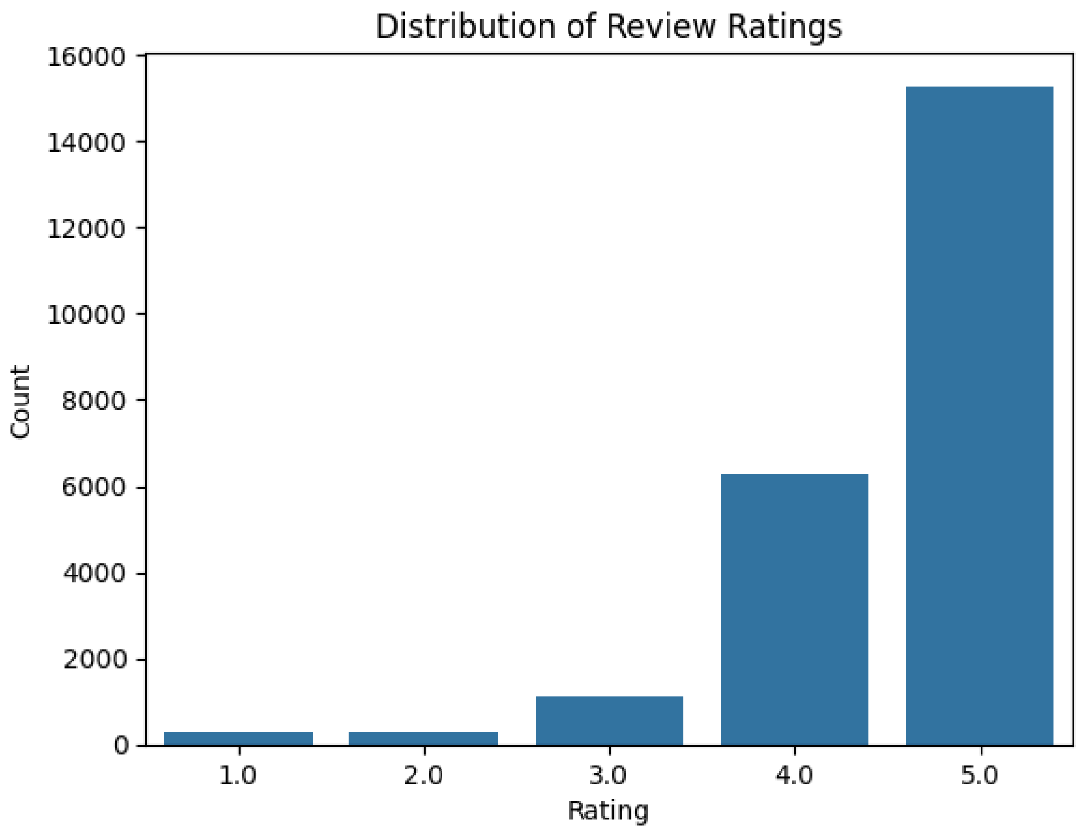
The data set is ready for EDA.

EXPLORATORY DATA ANALYSIS

UNIVARIATE ANALYSIS

1. Distribution of ratings Word frequency, Word cloud and Sentiment Distribution

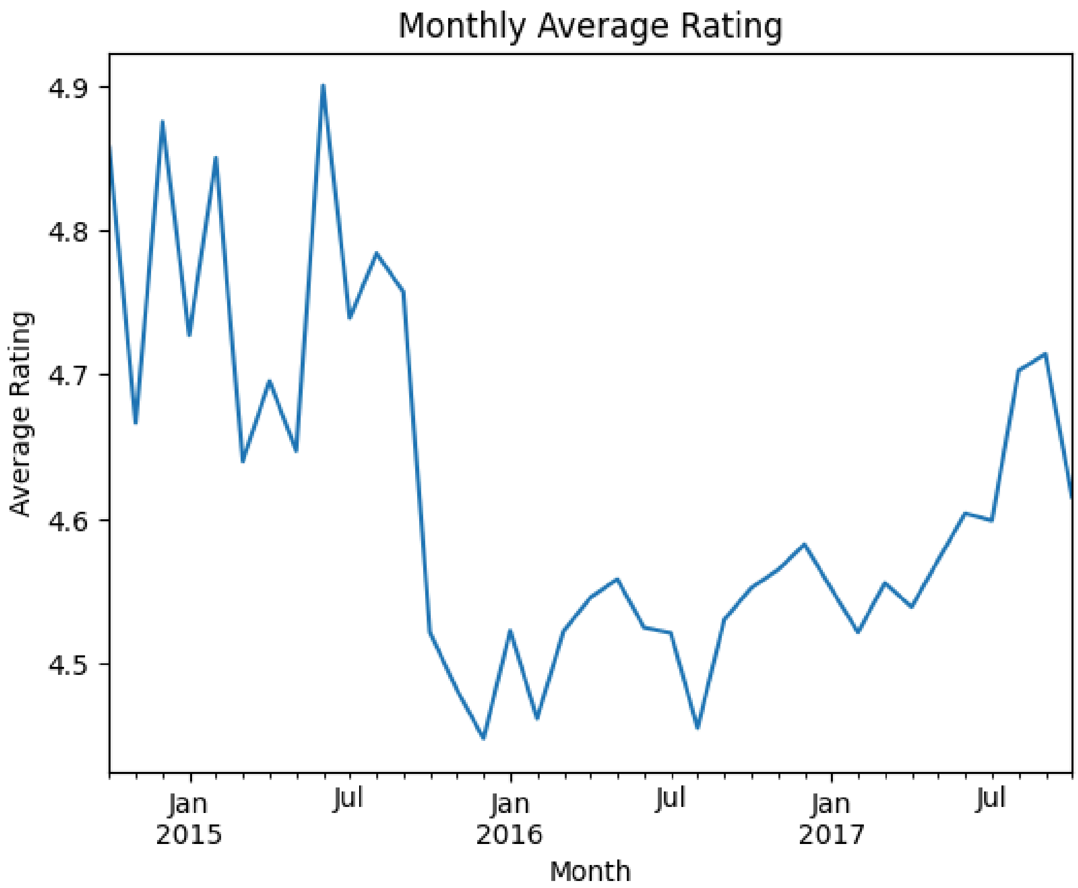
In [24]:
```
# Distribution of ratings
import matplotlib.pyplot as plt
# Sentiment distribution (simple visualization based on ratings)
sns.countplot(x='review_rating', data=raw)
plt.title('Distribution of Review Ratings')
plt.xlabel('Rating')
plt.ylabel('Count')
plt.show()
```



- The distribution of review ratings shows that most reviews tend to be positive, with higher counts towards ratings 4 and 5.

2.Temporal Analysis

In [25]:
```
# Temporal Analysis of rating over time

raw['review_date'] = pd.to_datetime(raw['review_date'])
raw.set_index('review_date', inplace=True)
raw['review_rating'].resample('M').mean().plot()
plt.title('Monthly Average Rating')
plt.xlabel('Month')
plt.ylabel('Average Rating')
plt.show()
```



- There is a slight fluctuation in average ratings over time, but no clear trend is evident from the monthly average ratings plot.

3. Reviews by product category

In [26]:
```
# Count occurrences of each category
category_counts = raw['product_categories'].value_counts().head(20

# Extract top 20 categories and their counts
top_categories = category_counts.index

print("Top 20 Product Categories:")
print(category_counts)


# Assuming categories are separated by commas and need to be split
# Convert the 'product_categories' column to string type
raw['product_categories'] = raw['product_categories'].astype(str)

# Split the categories by commas
raw['product_categories'] = raw['product_categories'].str.split(',

# Explode the list of categories
exploded_raw = raw.explode('product_categories')

# Group by 'product_categories' and calculate the mean review rati
mean_ratings = exploded_raw.groupby('product_categories')['review_

mean_ratings
```

Top 20 Product Categories:
product_categories
Fire Tablets,Tablets,Computers & Tablets,All Tablets,Electronics, Tech Toys, Movies, Music,Electronics,iPad & Tablets,Android Tablets,Frys
10965
Walmart for Business,Office Electronics,Tablets,Office,Electronics,iPad & Tablets,Windows Tablets,All Windows Tablets,Computers & Tablets,E-Readers & Accessories,E-Readers,eBook Readers,Kindle E-readers,Computers/Tablets & Networking,Tablets & eBook Readers,Electronics Features,Books & Magazines,Book Accessories,eReaders,TVs & Electronics,Computers & Laptops,Tablets & eReaders
3175
Electronics,iPad & Tablets,All Tablets,Fire Tablets,Tablets,Computers & Tablets
2812
Stereos,Remote Controls,Amazon Echo,Audio Docks & Mini Speakers,Amazon Echo Accessories,Kitchen & Dining Features,Speaker Systems,Electronics,TVs Entertainment,Clearance,Smart Hubs & Wireless Routers,Featured Brands,Wireless Speakers,Smart Home & Connected Living,Home Security,Kindle Store,Home Automation,Home, Garage & Office,Home,Voice-Enabled Smart Assistants,Virtual Assistant Speakers,Portable Audio & Headphones,Electronics Features,Amazon Device Accessories,iPod, Audio Player Accessories,Home & Furniture Clearance,Consumer Electronics,Smart Home,Surveillance,Home Improvement,Smart Home & Home Automation Devices,Smart Hubs,Home Safety & Security,Voice Assistants,Alarms & Sensors,Amazon Devices,Audio,Holiday Shop   1796
Tablets,Fire Tablets,Computers & Tablets,All Tablets
1698
Computers/Tablets & Networking,Tablets & eBook Readers,Computers & Tablets,Tablets,All Tablets
1038
Walmart for Business,Office Electronics,Tablets,Electronics,iPad & Tablets,All Tablets,Computers & Tablets,E-Readers & Accessories,Kindle E-readers,Electronics Features,eBook Readers,See more Amazon Kindle Voyage (Wi-Fi),See more Amazon Kindle Voyage 4GB, Wi-Fi 3G (Unlocked...
580
Electronics Features,Fire Tablets,Computers & Tablets,Tablets,All Tablets,Computers/Tablets & Networking,Tablets & eBook Readers
371
Fire Tablets,Tablets,Computers & Tablets,All Tablets,Computers/Tablets & Networking,Tablets & eBook Readers
269
Electronics,iPad & Tablets,All Tablets,Computers/Tablets & Networking,Tablets & eBook Readers,Computers & Tablets,E-Readers & Accessories,E-Readers,Used:Computers Accessories,Used:Tablets,Computers,iPads Tablets,Kindle E-readers,Electronics Features
212
Tablets,Fire Tablets,Electronics,Computers,Computer Components,Hard Drives & Storage,Computers & Tablets,All Tablets
158
eBook Readers,Kindle E-readers,Computers & Tablets,E-Readers & Accessories,E-Readers
67
Computers & Tablets,E-Readers & Accessories,eBook Readers,Kindle E-readers
51
Electronics,iPad & Tablets,All Tablets,Computers & Tablets,Tablets,eBook Readers

```
30
Computers & Tablets,Tablets,All Tablets,Computers/Tablets & Netwo
rking,Tablets & eBook Readers,Fire Tablets,Frys
10
Fire Tablets,Tablets,Computers & Tablets,All Tablets
7
Kindle E-readers,Electronics Features,Computers & Tablets,E-Reade
rs & Accessories,E-Readers,eBook Readers
6
Electronics,Computers,Computer Accessories,Cases & Bags,Fire Tabl
ets,Electronics Features,Tablets,Computers & Tablets,Kids' Tablet
s,Electronics, Tech Toys, Movies, Music,iPad & Tablets,Top Rated
6
Name: count, dtype: int64
```

Out[26]:

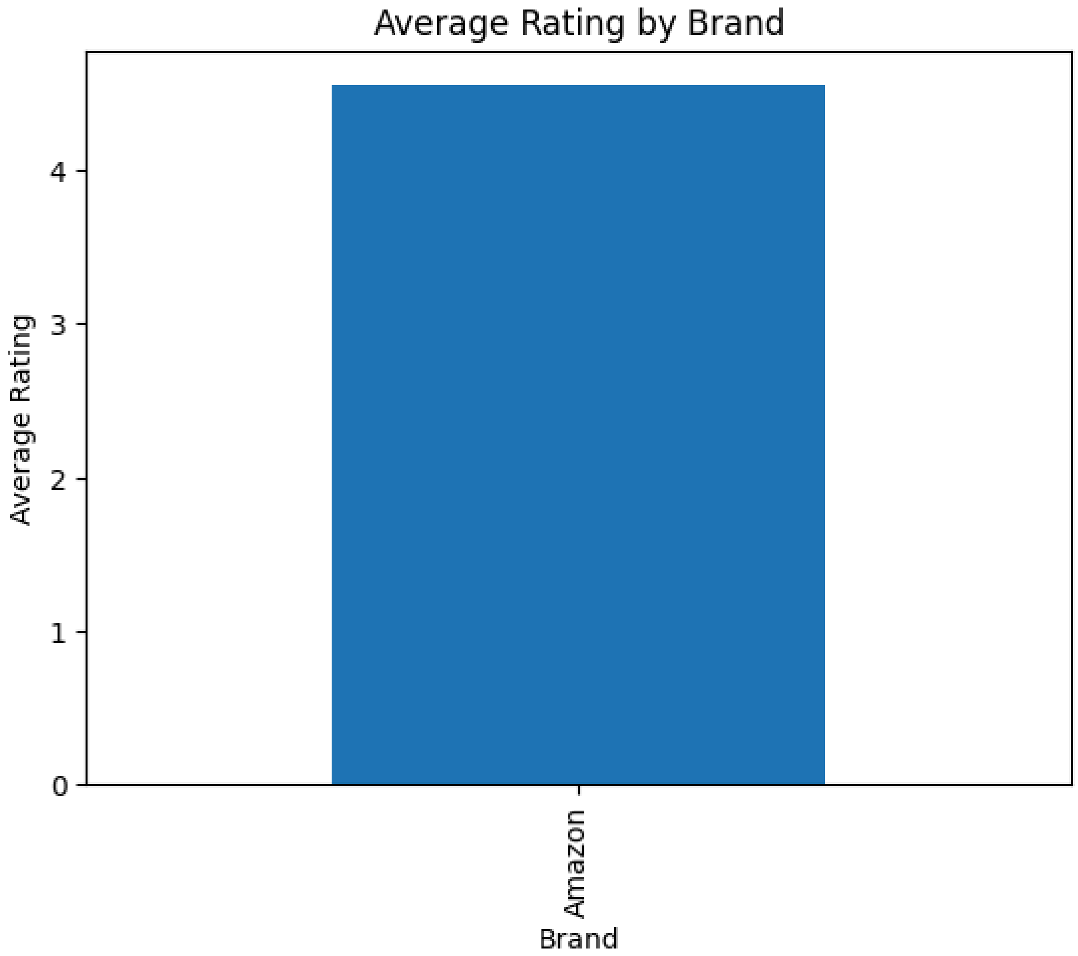
```
product_categories
Kids' Tablets           4.833333
Computer Accessories    4.833333
Cases & Bags            4.833333
Top Rated               4.833333
Tablets & eReaders      4.772283
                          ...
Frys                    4.454396
 Tech Toys              4.454380
 Music                  4.454380
 Movies                 4.454380
Android Tablets         4.454172
Name: review_rating, Length: 79, dtype: float64
```

In [27]:

```python

plt.figure(figsize=(20, 18))

# Create a bar plot with a color gradient
bars = sns.barplot(y=top_categories, x=category_counts.values, pal

# Add value labels to the bars
for bar, count in zip(bars.patches, category_counts.values):
    plt.text(count + 10,  # x-coordinate position
             bar.get_y() + bar.get_height() / 2,  # y-coordinate p
             f'{count}',  # formatted label text
             ha='center', va='center',  # horizontal and vertical
             fontsize=10, color='black')  # text properties

plt.title('Top 20 Product Categories by Count of Reviews', fontsiz
plt.xlabel('Count', fontsize=14)
plt.ylabel('Product Category', fontsize=14)

plt.xticks(fontsize=12)
plt.yticks(fontsize=12)

plt.tight_layout()
plt.show()

```

In [28]:

```python
# Plot review rating by brand
raw.groupby('brand')['review_rating'].mean().sort_values(ascending
plt.title('Average Rating by Brand')
plt.xlabel('Brand')
plt.ylabel('Average Rating')
plt.show()
```



In [29]:
```
# Assuming categories are separated by commas and need to be split
# Convert the 'product_categories' column to string type
raw['product_categories'] = raw['product_categories'].astype(str)

# Split the categories by commas
raw['product_categories'] = raw['product_categories'].str.split(',

# Explode the list of categories
exploded_raw = raw.explode('product_categories')

# Group by 'product_categories' and calculate the mean review rati
mean_ratings = exploded_raw.groupby('product_categories')['review_

mean_ratings
```

Out[29]:
```
product_categories
 'Kindle E-readers']          4.862745
['Computers & Tablets'        4.836066
 "Kids' Tablets"              4.833333
 'Cases & Bags'               4.833333
 'Computer Accessories'       4.833333
                                ...
 ' Movies'                    4.454380
 ' Tech Toys'                 4.454380
 ' Music'                     4.454380
 'Android Tablets'            4.454172
['Electronics Features'       4.425876
Name: review_rating, Length: 94, dtype: float64
```

Conclusions

- Fire Tablets, Tablets, Computers & Tablets: Dominates with 10,965 reviews, indicating a strong presence in consumer feedback.
- Stereos, Remote Controls, Amazon Echo: Follows with 6,606 reviews, highlighting significant interest in home electronics and smart devices.
- Back To College, College Electronics: Shows strong engagement in electronics geared towards college students, with 5,051 reviews.

4. Most helpful Votes

In [30]:
```
# Most helpful reviews
raw.sort_values(by='review_num_helpful', ascending=False).head(10)
```

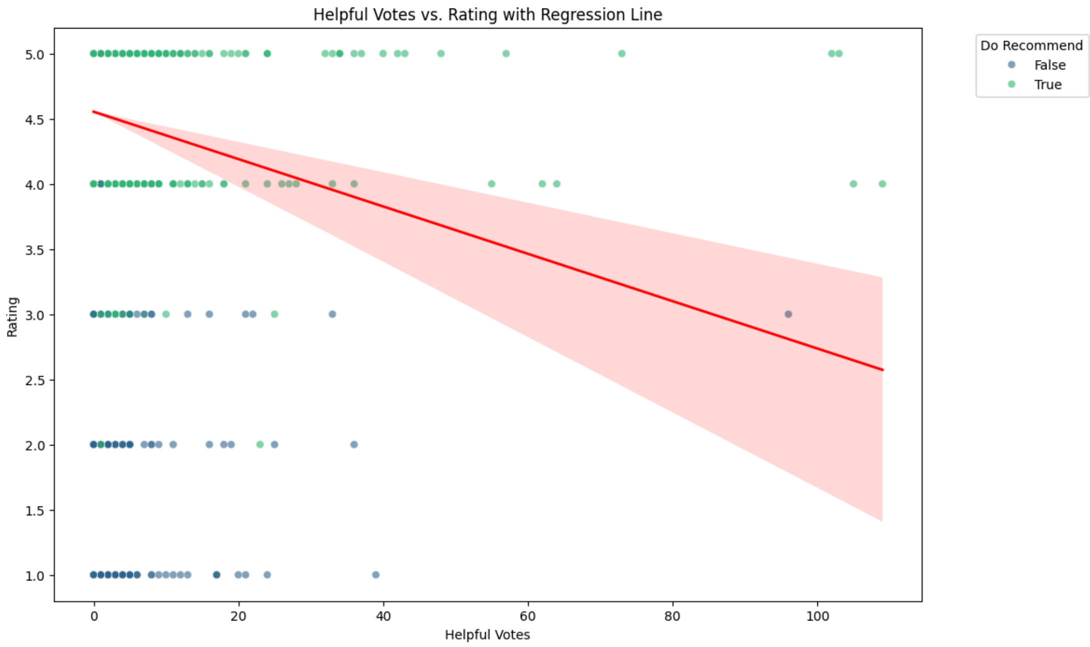
Out[30]:

review_date	id	asins	brand	product_categories	
2015-10-13 00:00:00+00:00	AVphgVaX1cnluZ0-DR74	B018Y229OU	Amazon	[['Fire Tablets', 'Tablets', 'Computers & Ta...	
2016-10-05 00:00:00+00:00	AVqkIiKWnnc1JgDc3khH	B01AHB9CYG	Amazon	[['Tablets', 'Fire Tablets', 'Electronics', ...	
2015-07-08 00:00:00+00:00	AV1YnRtnglJLPUi8IJmV	B00OQVZDJM	Amazon	[['Walmart for Business', 'Office Electronics...	amaz
2015-10-26 00:00:00+00:00	AVphgVaX1cnluZ0-DR74	B018Y229OU	Amazon	[['Fire Tablets', 'Tablets', 'Computers & Ta...	
2015-11-15 00:00:00+00:00	AVphgVaX1cnluZ0-DR74	B018Y229OU	Amazon	[['Fire Tablets', 'Tablets', 'Computers & Ta...	
2015-10-16 00:00:00+00:00	AVphgVaX1cnluZ0-DR74	B018Y229OU	Amazon	[['Fire Tablets', 'Tablets', 'Computers & Ta...	
2014-11-16 00:00:00+00:00	AVphPmHuilAPnD_x3E5h	B00IOY8XWQ	Amazon	[['Walmart for Business', 'Office Electronics...	8
2016-10-20 00:00:00+00:00	AVqkIhwDv8e3D1O-lebb	B01AHB9CN2	Amazon	[['Electronics', 'iPad & Tablets', 'All Tabl...	84166
2015-10-01 00:00:00+00:00	AVphgVaX1cnluZ0-DR74	B018Y229OU	Amazon	[['Fire Tablets', 'Tablets', 'Computers & Ta...	
2016-11-06 00:00:00+00:00	AVqkIhwDv8e3D1O-lebb	B01AHB9CN2	Amazon	[['Electronics', 'iPad & Tablets', 'All Tabl...	84166

BIVARIATE ANALYSIS

1. Helpful votes vs rating

In [31]:
```
plt.figure(figsize=(12, 8))

# Scatter plot with color coding, size encoding, and transparency
scatter = sns.scatterplot(
    x='review_num_helpful',
    y='review_rating',
    hue='review_do_recommend',
    sizes=(20, 200),  # Minimum and maximum size of points
    alpha=0.6,
    palette='viridis',  # Using a different color palette
    data=raw
)

# Add a regression line
sns.regplot(
    x='review_num_helpful',
    y='review_rating',
    scatter=False,
    color='red',
    line_kws={"linewidth": 2},
    data=raw
)

plt.title('Helpful Votes vs. Rating with Regression Line')
plt.xlabel('Helpful Votes')
plt.ylabel('Rating')
plt.legend(title='Do Recommend', loc='upper right', bbox_to_anchor
plt.show()
```

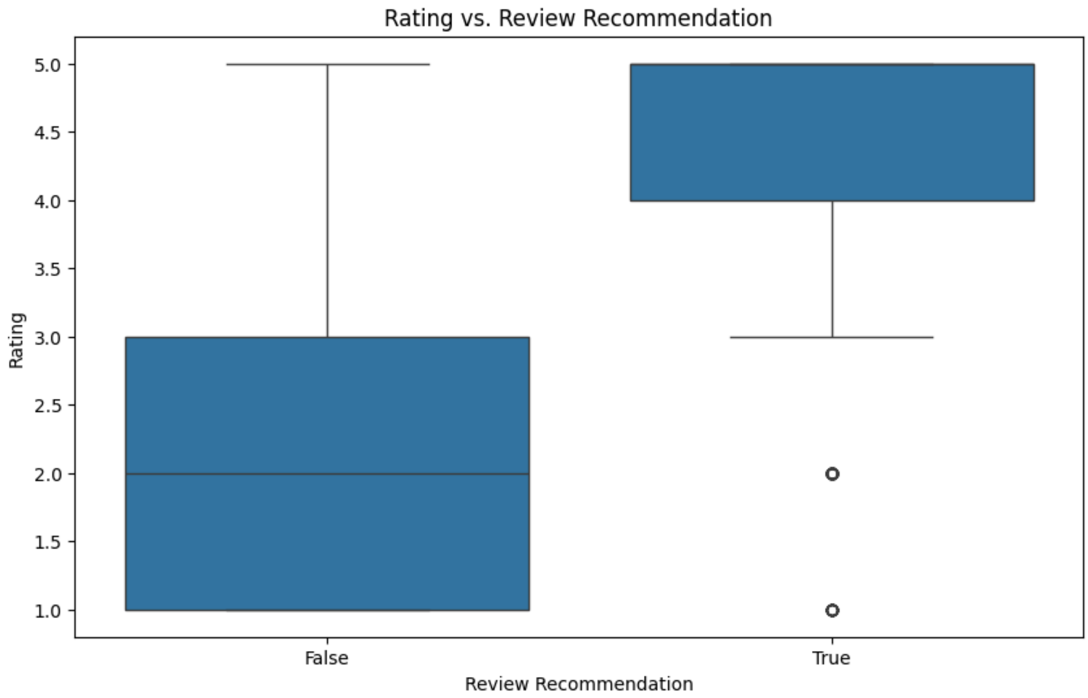


- The scatter plot and regression analysis of helpful votes versus rating illustrate a positive correlation, indicating that more helpful reviews tend to have higher ratings.

- This suggests that customers find high-rated reviews more useful

2. Rating vs. Review recommendation

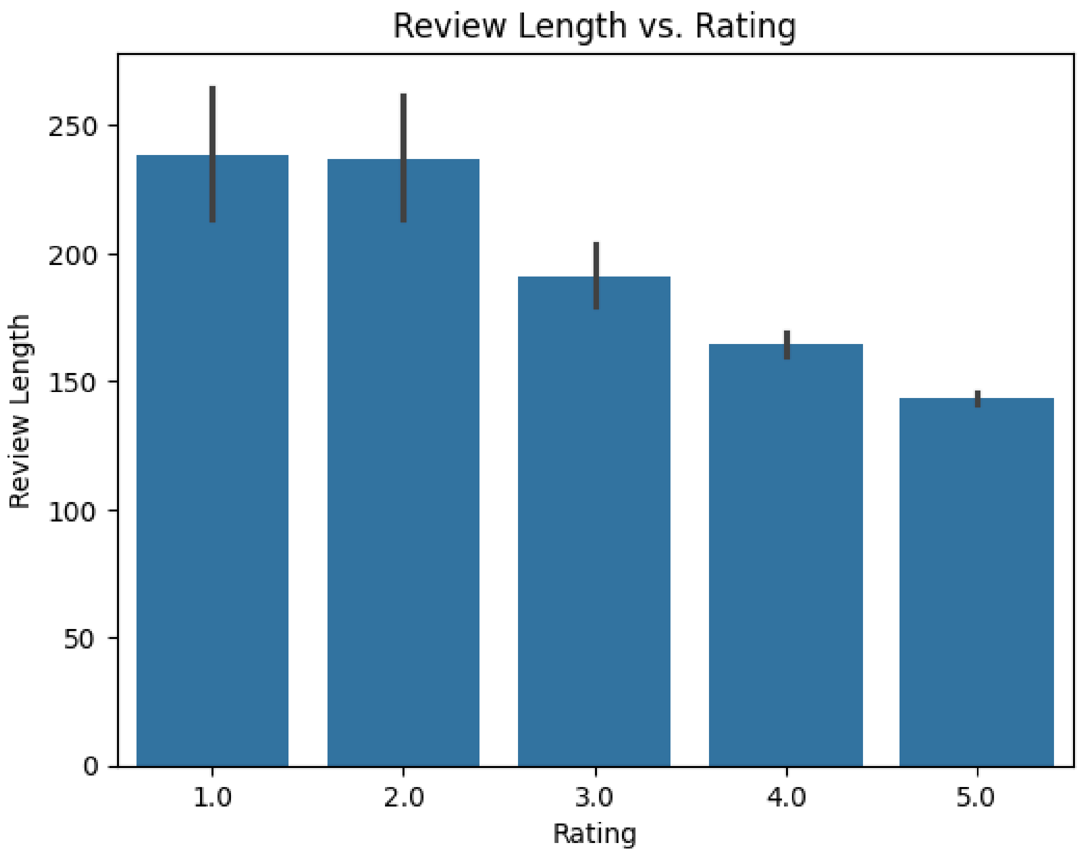
In [32]:
```
# Convert review_do_recommend to a categorical type
raw['review_do_recommend'] = raw['review_do_recommend'].astype('ca

# Box plot of rating vs. review recommendation
plt.figure(figsize=(10, 6))
sns.boxplot(x='review_do_recommend', y='review_rating', data=raw)
plt.title('Rating vs. Review Recommendation')
plt.xlabel('Review Recommendation')
plt.ylabel('Rating')
plt.show()
```



- The analysis shows that reviews with a positive recommendation (review_do_recommend = True) generally have higher ratings compared to those without a recommendation.
- This highlights the influence of product satisfaction on recommendation.

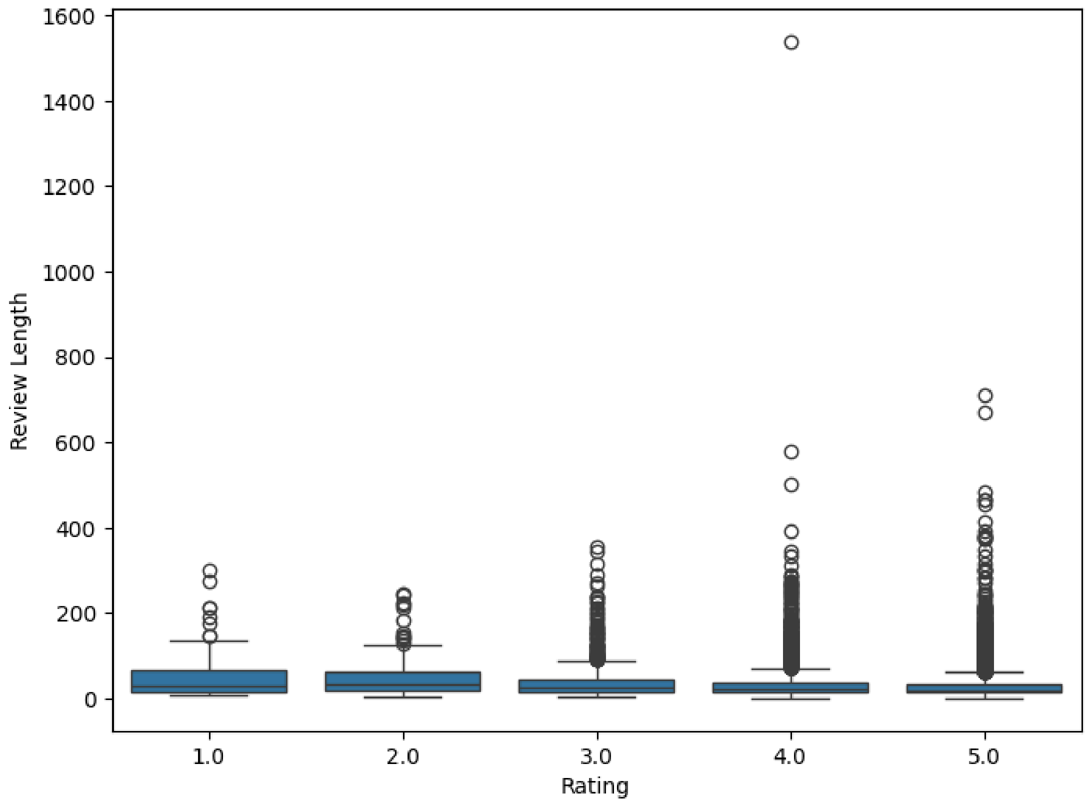
3. Rating vs Length

In [33]:
```
raw['review_length'] = raw['review_text'].apply(len)

sns.barplot(x='review_rating', y='review_length', data=raw)
plt.title('Review Length vs. Rating')
plt.xlabel('Rating')
plt.ylabel('Review Length')
plt.show()
```



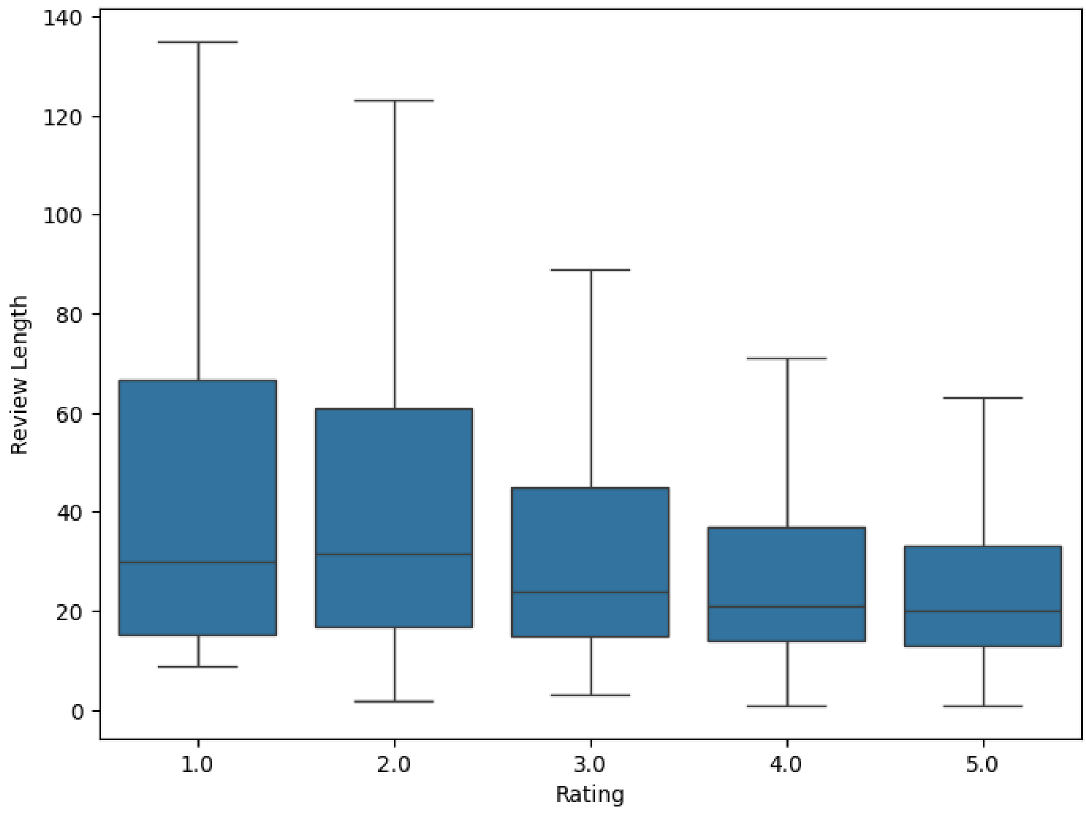
- This visualization illustrates the relationship between review length and review rating. It is evident that shorter reviews tend to receive higher ratings.

```
In [34]: word_count=[]
for s1 in raw.review_text:
    word_count.append(len(str(s1).split()))
plt.figure(figsize = (8,6))

import seaborn as sns
import matplotlib.pyplot as plt
sns.boxplot(x="review_rating",y=word_count,data=raw)
plt.xlabel('Rating')
plt.ylabel('Review Length')

plt.show()
```



- Due to the presence of outliers shown in the box plot, our visualization is currently obscured. To improve clarity, we will proceed by removing these outliers from the dataset.

In [35]:
```
# Generate box plots excluding outliers

plt.figure(figsize = (8,6))
sns.boxplot(x="review_rating",y=word_count,data=raw,showfliers=Fal
plt.xlabel('Rating')
plt.ylabel('Review Length')
plt.show()
```



- We can now see that shorter reviews tend to receive higher ratings much better.

Conclusions

The bar plot and box plot analyses show the relationship between review ratings and the length of reviews:

Bar Plot Analysis: Indicates that longer reviews are generally associated with lowerr ratings. This suggests that while longer reviews can provide richer insights, their association with lower ratings indicates that customers who invest more time in detailing their experiences often do so when they feel particularly disappointed or dissatisfied.

Box Plot Analysis: Initially showed outliers affecting clarity in visualization. After excluding outliers, the relationship between review length and rating became clearer

Lower ratings tend to have a wider range of review lengths, suggesting variability in experiences or dissatisfaction reasons.

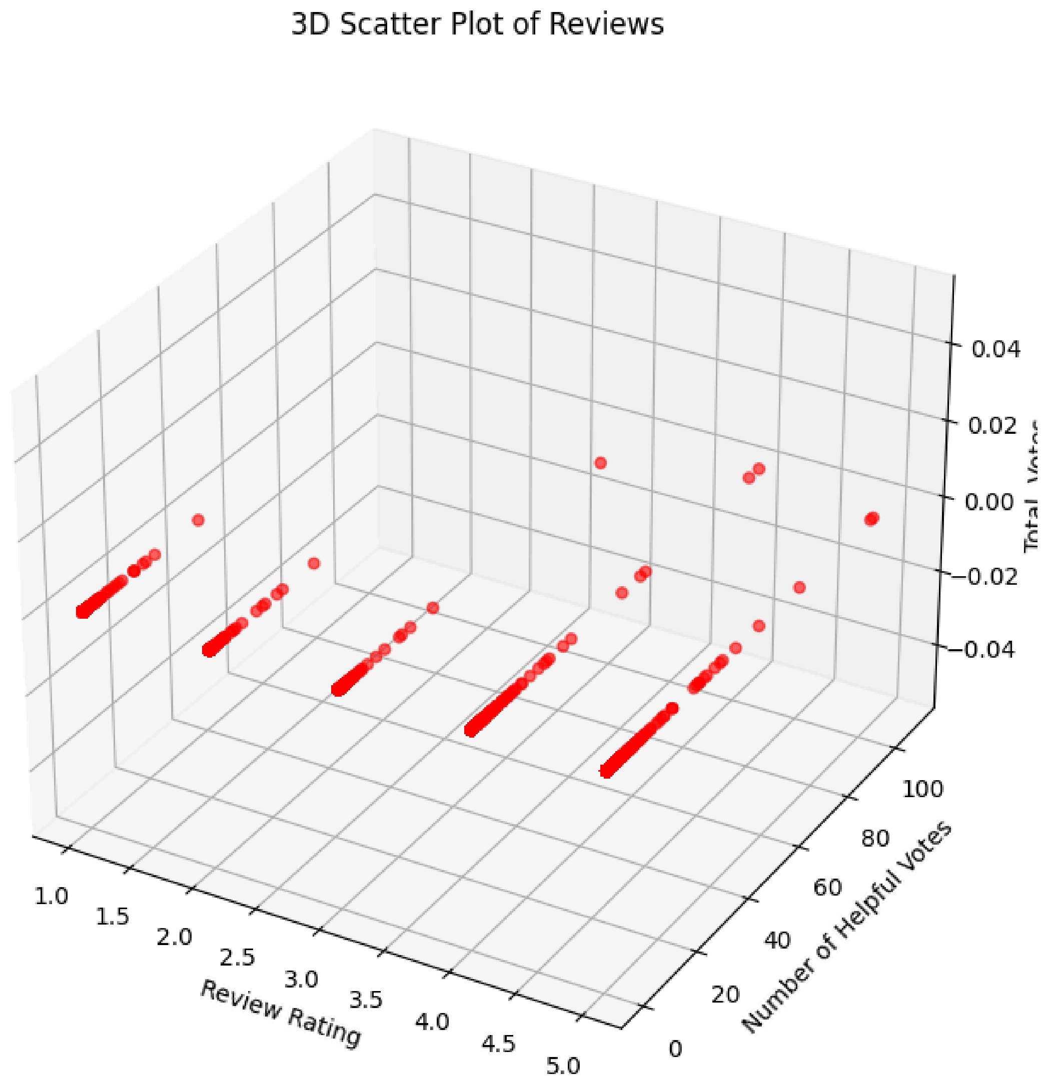
Higher ratings are associated with a more concentrated range of review lengths, possibly indicating clearer satisfaction or positive experiences with the product.

These insights provide a deeper understanding of how review characteristics such as recommendation status and review length correlate with customer ratings, contributing valuable insights for product evaluation and improvement strategies.

3. Multivariate Analysis

1. Scatter plot of reviews

In [37]:
```
# Ensure the column names are correct
review_rating_col = 'review_rating'
review_num_helpful_col = 'review_num_helpful'
total_votes_col = 'total_votes'
review_did_purchase_col = 'review_did_purchase'

# Check if 'review_did_purchase' exists, if not create it with a d
if review_did_purchase_col not in raw.columns:
    raw[review_did_purchase_col] = False

# Ensure 'total_votes' column exists, if not create it with a defa
if total_votes_col not in raw.columns:
    raw[total_votes_col] = 0

# Plotting

fig = plt.figure(figsize=(10, 8))
ax = fig.add_subplot(111, projection='3d')

# Map verified purchase to colors
colors = raw[review_did_purchase_col].map({True: 'blue', False: 'r

sc = ax.scatter(raw[review_rating_col], raw[review_num_helpful_col

# Adding labels and title
ax.set_xlabel('Review Rating')
ax.set_ylabel('Number of Helpful Votes')
ax.set_zlabel('Total  Votes')
plt.title('3D Scatter Plot of Reviews')

plt.show()
```

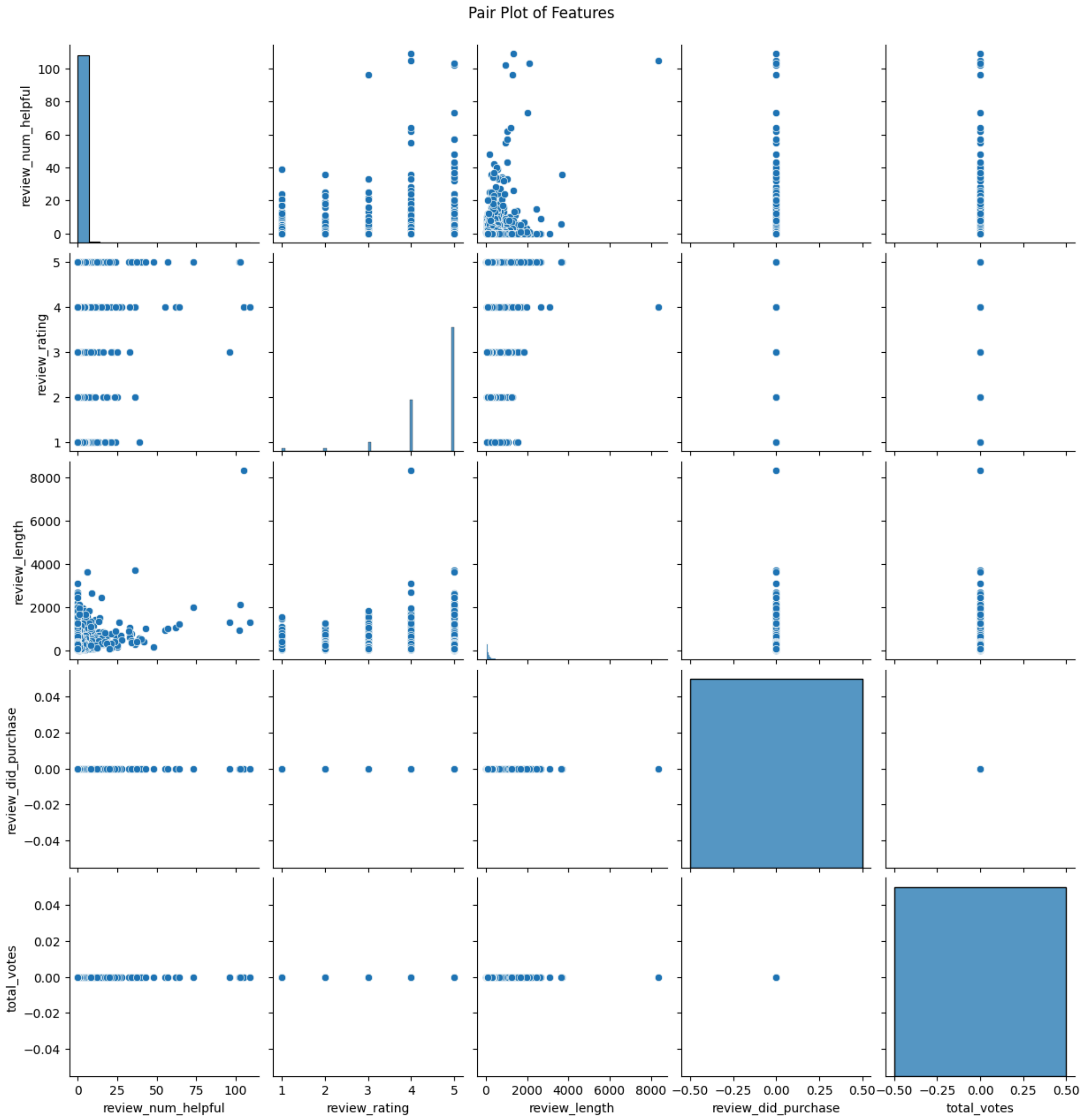


Conclusions

- Visualizing reviews based on rating, helpful votes, and total votes shows various patterns, but it doesn't clearly reveal distinct groups based on whether the purchase was verified.

2. Pair Plot of Features

In [38]:
```
sns.pairplot(raw)
plt.suptitle('Pair Plot of Features', y=1.02)
plt.show()
```



Conclusions

Pair Plot: The pair plot visually explored relationships between different numerical features in the dataset. It provides a quick overview of potential correlations and distributions among variables, aiding in identifying patterns or trends that might warrant further investigation.

Data pre-processing

In [39]:
```
# Check the column names
print(raw.columns)
```

```
Index(['id', 'asins', 'brand', 'product_categories', 'product_key
s',
       'manufacturer_name', 'review_do_recommend', 'review_num_he
lpful',
       'review_rating', 'review_text', 'review_title', 'review_us
ername',
       'review_length', 'review_did_purchase', 'total_votes'],
      dtype='object')
```

- Let's preview the first sentence in our text

In [40]:
```
# Previewing the first sentence in our text

first_document = raw.iloc[2]['review_text']
first_document
```

Out[40]:
```
'Inexpensive tablet for him to use and learn on, step up from the
NABI. He was thrilled with it, learn how to Skype on it alread
y...'
```

In [41]:
```
# Changing the name of our dataframe

data = pd.DataFrame(raw)
```

- For NLP preprocessing, we'll eliminate stopwords, punctuation, and numbers, and convert text to lowercase.
- Subsequently, tokenizing our data is essential because it breaks down text into individual words or tokens, enabling deeper analysis and understanding of the textual content.

In [42]:

```
# Download NLTK stopwords and punctuation
nltk.download('stopwords')
nltk.download('punkt')

# Load stopwords and punctuation
stop_words = set(stopwords.words('english'))

# Function to clean and preprocess text
def clean_text(text):
    # Ensure text is a string and lowercase
    text = str(text).lower()

    # Remove numbers
    text = re.sub(r'\d+', '', text)

    # Remove punctuation
    text = text.translate(str.maketrans('', '', string.punctuation

    # Tokenization using regex pattern
    pattern = "([a-zA-Z]+(?:'[a-z]+)?)"
    tokens = nltk.regexp_tokenize(text, pattern)

    # Remove stopwords
    clean_tokens = [token for token in tokens if token not in stop

    return ' '.join(clean_tokens)


data['clean_text'] = raw['review_text'].apply(clean_text)
data['clean_title'] = raw['review_title'].apply(clean_text)

# Display the cleaned text along with original columns
data[['review_text', 'review_title', 'clean_text', 'clean_title']]
```

```
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
[nltk_data] Downloading package punkt to /root/nltk_data...
[nltk_data]   Package punkt is already up-to-date!
```

Out[42]:

review_date	review_text	review_title	clean_text	clean_title
2017-01-13 00:00:00+00:00	This product so far has not disappointed. My c...	Kindle	product far disappointed children love use lik...	kindle
2017-01-13 00:00:00+00:00	great for beginner or experienced person. Boug...	very fast	great beginner experienced person bought gift ...	fast
2017-01-13 00:00:00+00:00	Inexpensive tablet for him to use and learn on...	Beginner tablet for our 9 year old son.	inexpensive tablet use learn step nabi thrille...	beginner tablet year old son
2017-01-13 00:00:00+00:00	I've had my Fire HD 8 two weeks now and I love...	Good!!!	ive fire hd two weeks love tablet great valuew...	good
2017-01-12 00:00:00+00:00	I bought this for my grand daughter when she c...	Fantastic Tablet for kids	bought grand daughter comes visit set user ent...	fantastic tablet kids
...	...	...	...	...
2017-07-29 00:00:00+00:00	Great sound quality. Great way to control othe...	Easy to setup and use.	great sound quality great way control smart de...	easy setup use
2017-07-29 00:00:00+00:00	My daughter loves this and uses it for her eve...	It was a gift for my daughter	daughter loves uses every day reminders questions	gift daughter
2017-07-29 00:00:00+00:00	Really enjoy the great speaker and music on de...	Fun item	really enjoy great speaker music demand asking...	fun item
2017-07-28 00:00:00+00:00	After plugging my Echo in and downloading the ...	Amazon Echo is amazing!!!	plugging echo downloading alexa app rest proce...	amazon echo amazing
2017-07-28 00:00:00+00:00	My husband loves it!! He likes telling Alexa t...	Great new toy	husband loves likes telling alexa play music t...	great new toy

23251 rows × 4 columns

In [43]:

```
# Dropping the original columns as we now have the clean ones
data.drop(columns = ['review_text', 'review_title'] , inplace = Tr
data.head(2)
```

Out[43]:

review_date	id	asins	brand	product_categories	
2017-01-13 00:00:00+00:00	AVqkIhwDv8e3D1O-lebb	B01AHB9CN2	Amazon	[['Electronics', 'iPad & Tablets', 'All Tabl...	841667104€
2017-01-13 00:00:00+00:00	AVqkIhwDv8e3D1O-lebb	B01AHB9CN2	Amazon	[['Electronics', 'iPad & Tablets', 'All Tabl...	841667104€

In [44]:
```
# Rename the columns with the original column names
data.rename(columns={'clean_text': 'review_text', 'clean_title': '

# Display the new DataFrame
data.head(1)
```

Out[44]:

	id	asins	brand	product_categories	
review_date					
2017-01-13 00:00:00+00:00	AVqkIhwDv8e3D1O-lebb	B01AHB9CN2	Amazon	[['Electronics', 'iPad & Tablets', 'All Tabl...	841667104(

In [45]:
```
# Download NLTK WordNet
nltk.download('wordnet')
```

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

Out[45]: True

- We will now perform lemmatization, which reduces words to their base form while still preserving their meaning to ensure consistency and improve the accuracy of our analysis.

In [46]:
```
# Initialize the WordNet lemmatizer
lemmatizer = WordNetLemmatizer()

# Initialize the WordNet lemmatizer
lemmatizer = WordNetLemmatizer()

# Function to perform lemmatization on text
def lemmatize_text(text):
    words = text.split()

    # Lemmatization
    lemmatized_words = [lemmatizer.lemmatize(word) for word in wor

    return ' '.join(lemmatized_words)

# Apply lemmatization to review_text and review_title separately
data['lemmatized_text'] = data['review_text'].apply(lemmatize_text
data['lemmatized_title'] = data['review_title'].apply(lemmatize_te
```

```
In [47]: # Display the lemmatized text along with original columns
         data[[ 'review_text' , 'review_title' , 'lemmatized_text', 'lemmat
```

Out[47]:

	review_text	review_title	lemmatized_text	lemmatized_title
review_date				
2017-01-13 00:00:00+00:00	product far disappointed children love use lik...	kindle	product far disappointed child love use like a...	kindle
2017-01-13 00:00:00+00:00	great beginner experienced person bought gift ...	fast	great beginner experienced person bought gift ...	fast
2017-01-13 00:00:00+00:00	inexpensive tablet use learn step nabi thrille...	beginner tablet year old son	inexpensive tablet use learn step nabi thrille...	beginner tablet year old son
2017-01-13 00:00:00+00:00	ive fire hd two weeks love tablet great valuew...	good	ive fire hd two week love tablet great valuewe...	good
2017-01-12 00:00:00+00:00	bought grand daughter comes visit set user ent...	fantastic tablet kids	bought grand daughter come visit set user ente...	fantastic tablet kid
...	...	...	...	...
2017-07-29 00:00:00+00:00	great sound quality great way control smart de...	easy setup use	great sound quality great way control smart de...	easy setup use
2017-07-29 00:00:00+00:00	daughter loves uses every day reminders questions	gift daughter	daughter love us every day reminder question	gift daughter
2017-07-29 00:00:00+00:00	really enjoy great speaker music demand asking...	fun item	really enjoy great speaker music demand asking...	fun item
2017-07-28 00:00:00+00:00	plugging echo downloading alexa app rest proce...	amazon echo amazing	plugging echo downloading alexa app rest proce...	amazon echo amazing
2017-07-28 00:00:00+00:00	husband loves likes telling alexa play music t...	great new toy	husband love like telling alexa play music tel...	great new toy

23251 rows × 4 columns

In [48]:
```
# dropping the columns mot lemmatized

data.drop(columns = ['review_text', 'review_title'] , inplace = Tr
data.head(1)
```

Out[48]:

	id	asins	brand	product_categories	
review_date					
2017-01-13 00:00:00+00:00	AVqklhwDv8e3D1O-lebb	B01AHB9CN2	Amazon	[['Electronics', 'iPad & Tablets', 'All Tabl...	841667104€

In [49]:
```
# Renaming the lemmatized columns
data.rename(columns={'lemmatized_text': 'review_text', 'lemmatized

# Display the new DataFrame
data.head(1)
```

Out[49]:

	id	asins	brand	product_categories	
review_date					
2017-01-13 00:00:00+00:00	AVqklhwDv8e3D1O-lebb	B01AHB9CN2	Amazon	[['Electronics', 'iPad & Tablets', 'All Tabl...	841667104€

In [50]:
```python
# Removing white spaces

# Function to remove extra spaces from text
def remove_extra_spaces(text):
    return ' '.join(text.strip().split())

# Apply function to the 'lemmatized_review_text' column
data['clean_text'] = data['review_text'].apply(remove_extra_spaces

# Apply function to the 'lemmatized_review_title' column
data['clean_title'] = data['review_title'].apply(remove_extra_spac

# Display cleaned text along with original columns
data[['review_text', 'review_title','clean_text', 'clean_title']]
```

Out[50]:

	review_text	review_title	clean_text	clean_title
review_date				
2017-01-13 00:00:00+00:00	product far disappointed child love use like a...	kindle	product far disappointed child love use like a...	kindle
2017-01-13 00:00:00+00:00	great beginner experienced person bought gift ...	fast	great beginner experienced person bought gift ...	fast
2017-01-13 00:00:00+00:00	inexpensive tablet use learn step nabi thrille...	beginner tablet year old son	inexpensive tablet use learn step nabi thrille...	beginner tablet year old son
2017-01-13 00:00:00+00:00	ive fire hd two week love tablet great valuewe...	good	ive fire hd two week love tablet great valuewe...	good
2017-01-12 00:00:00+00:00	bought grand daughter come visit set user ente...	fantastic tablet kid	bought grand daughter come visit set user ente...	fantastic tablet kid
...	...	...	...	...
2017-07-29 00:00:00+00:00	great sound quality great way control smart de...	easy setup use	great sound quality great way control smart de...	easy setup use
2017-07-29 00:00:00+00:00	daughter love us every day reminder question	gift daughter	daughter love us every day reminder question	gift daughter
2017-07-29 00:00:00+00:00	really enjoy great speaker music demand asking...	fun item	really enjoy great speaker music demand asking...	fun item
2017-07-28 00:00:00+00:00	plugging echo downloading alexa app rest proce...	amazon echo amazing	plugging echo downloading alexa app rest proce...	amazon echo amazing
2017-07-28 00:00:00+00:00	husband love like telling alexa play music tel...	great new toy	husband love like telling alexa play music tel...	great new toy

23251 rows × 4 columns

Feature Engineering

In the feature engineering section, we process and transform the textual data for further analysis and modeling:

The methods used are;

- **Sentiment Analysis** to determine the sentiment of each review.
- **Visualization with Word Clouds** to visualize the most frequent words in positive and negative reviews
- **Text Vectorization** to convert textual data into numerical form using TF-IDF and Count Vectorization.
- **Word Embedding** to capture the semantic relationships between words by representing them in a continuous vector space.
- **Extraction of Bigrams and Trigrams**

Sentiment Analysis

This was done using the SentimentIntensityAnalyzer from the vaderSentiment library to calculate a sentiment score for each review.

Each review was labeled with a sentiment score, and reviews were classified as either 'positive' or 'negative' based on this score.

In [51]:
```python
from nltk.sentiment.vader import SentimentIntensityAnalyzer

# Download the VADER lexicon
nltk.download('vader_lexicon')

# Initialize the VADER sentiment analyzer
sid = SentimentIntensityAnalyzer()
# Define the sentiment function to calculate the compound score
def sentiment(x):
    score = sid.polarity_scores(x)
    return score['compound']

# Apply the sentiment function to the text column to get sentiment
data['sentiment'] = data['clean_text'].apply(lambda x: sentiment(x

# Print the DataFrame with the sentiment scores
data[['clean_text', 'sentiment', 'review_rating']]
```

```
[nltk_data] Downloading package vader_lexicon to /root/nltk_dat
a...
```

Out[51]:

review_date	clean_text	sentiment	review_rating
2017-01-13 00:00:00+00:00	product far disappointed child love use like a...	0.8126	5.0
2017-01-13 00:00:00+00:00	great beginner experienced person bought gift ...	0.9042	5.0
2017-01-13 00:00:00+00:00	inexpensive tablet use learn step nabi thrille...	0.4404	5.0
2017-01-13 00:00:00+00:00	ive fire hd two week love tablet great valuewe...	0.9899	4.0
2017-01-12 00:00:00+00:00	bought grand daughter come visit set user ente...	0.9371	5.0
...	...	...	...
2017-07-29 00:00:00+00:00	great sound quality great way control smart de...	0.8979	5.0
2017-07-29 00:00:00+00:00	daughter love us every day reminder question	0.6369	5.0
2017-07-29 00:00:00+00:00	really enjoy great speaker music demand asking...	0.9144	5.0
2017-07-28 00:00:00+00:00	plugging echo downloading alexa app rest proce...	0.9313	5.0
2017-07-28 00:00:00+00:00	husband love like telling alexa play music tel...	0.8834	5.0

23251 rows × 3 columns

In [52]:

```python
# Filter the original data DataFrame for negative and positive rev
negative_reviews_text = data[data['sentiment'].apply(lambda x: 0 <
positive_reviews_text = data[data['sentiment'].apply(lambda x: x >


# Create labels for negative and positive reviews
data.loc[data['sentiment'] <= 0.5, 'label'] = 'negative'
data.loc[data['sentiment'] > 0.5, 'label'] = 'positive'

# Print the updated DataFrame to verify
data[['clean_text', 'sentiment', 'label']]
```

Out[52]:

review_date	clean_text	sentiment	label
2017-01-13 00:00:00+00:00	product far disappointed child love use like a...	0.8126	positive
2017-01-13 00:00:00+00:00	great beginner experienced person bought gift ...	0.9042	positive
2017-01-13 00:00:00+00:00	inexpensive tablet use learn step nabi thrille...	0.4404	negative
2017-01-13 00:00:00+00:00	ive fire hd two week love tablet great valuewe...	0.9899	positive
2017-01-12 00:00:00+00:00	bought grand daughter come visit set user ente...	0.9371	positive
...	...	...	...
2017-07-29 00:00:00+00:00	great sound quality great way control smart de...	0.8979	positive
2017-07-29 00:00:00+00:00	daughter love us every day reminder question	0.6369	positive
2017-07-29 00:00:00+00:00	really enjoy great speaker music demand asking...	0.9144	positive
2017-07-28 00:00:00+00:00	plugging echo downloading alexa app rest proce...	0.9313	positive
2017-07-28 00:00:00+00:00	husband love like telling alexa play music tel...	0.8834	positive

23251 rows × 3 columns

Labelling the reviews using the sentiment scores

- Scores ranging from 0 - 0.5 will be labeled as **negative**
- Scores ranging from 0.6 - 1 will be labeled as **positive**

In [53]:
```python
# Filter the original data DataFrame for negative and positive rev
negative_reviews_text = data[data['sentiment'].apply(lambda x: 0 <
positive_reviews_text = data[data['sentiment'].apply(lambda x: x >

# Create labels for negative and positive reviews
data.loc[data['sentiment'] <= 0.5, 'label'] = 'negative'
data.loc[data['sentiment'] > 0.5, 'label'] = 'positive'

# Print the updated DataFrame to verify
# Print the DataFrame with the sentiment scores
data[['clean_text', 'sentiment', 'label']]
```

Out[53]:

review_date	clean_text	sentiment	label
2017-01-13 00:00:00+00:00	product far disappointed child love use like a...	0.8126	positive
2017-01-13 00:00:00+00:00	great beginner experienced person bought gift ...	0.9042	positive
2017-01-13 00:00:00+00:00	inexpensive tablet use learn step nabi thrille...	0.4404	negative
2017-01-13 00:00:00+00:00	ive fire hd two week love tablet great valuewe...	0.9899	positive
2017-01-12 00:00:00+00:00	bought grand daughter come visit set user ente...	0.9371	positive
...	...	...	...
2017-07-29 00:00:00+00:00	great sound quality great way control smart de...	0.8979	positive
2017-07-29 00:00:00+00:00	daughter love us every day reminder question	0.6369	positive
2017-07-29 00:00:00+00:00	really enjoy great speaker music demand asking...	0.9144	positive
2017-07-28 00:00:00+00:00	plugging echo downloading alexa app rest proce...	0.9313	positive
2017-07-28 00:00:00+00:00	husband love like telling alexa play music tel...	0.8834	positive

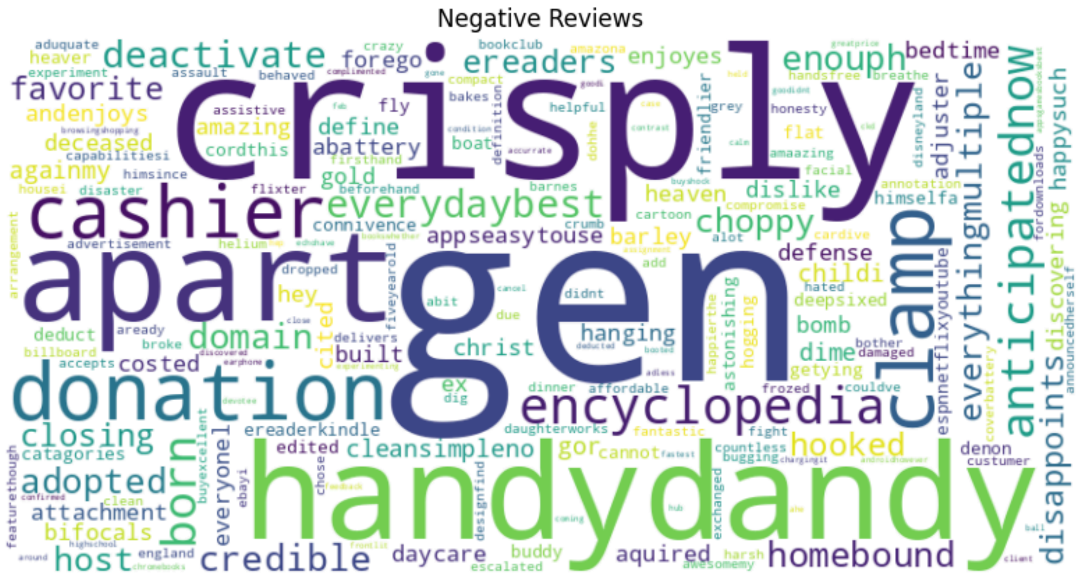
23251 rows × 3 columns

In [54]:
```python
print("Number of negative reviews:", negative_reviews_text.shape[0
print("Number of positive reviews:", positive_reviews_text.shape[0
```

```
Number of negative reviews: 4112
Number of positive reviews: 18009
```

- We can observe from this that we have class imbalance.

In [55]:
```
from sklearn.feature_extraction.text import CountVectorizer

# # DataFrame setup
# data = pd.DataFrame({
#     'clean_text': ["I love this product", "This is the worst thi
#     'sentiment': [0.9, 0.2, 0.6, 0.8, 0.3],
# })

# Create labels for negative and positive reviews
data.loc[data['sentiment'] <= 0.5, 'label'] = 'negative'
data.loc[data['sentiment'] > 0.5, 'label'] = 'positive'

# Filter the original data for negative and positive reviews
negative_reviews_text = data[data['sentiment'].apply(lambda x: 0 <
positive_reviews_text = data[data['sentiment'].apply(lambda x: x >

# Create a CountVectorizer to count word frequencies
vectorizer = CountVectorizer()

# Fit and transform the 'clean_text' data for negative and positiv
X_negative = vectorizer.fit_transform(negative_reviews_text)
X_positive = vectorizer.fit_transform(positive_reviews_text)

# Sum up the counts of each vocabulary word
word_frequencies_negative = X_negative.sum(axis=0).A1
word_frequencies_positive = X_positive.sum(axis=0).A1

# Create a dictionary of word frequencies
vocab = vectorizer.get_feature_names_out()
word_frequencies_negative = dict(zip(vocab, word_frequencies_negat
word_frequencies_positive = dict(zip(vocab, word_frequencies_posit

# Create word clouds for negative and positive reviews
wordcloud_negative = WordCloud(width=800, height=400, background_c
wordcloud_positive = WordCloud(width=800, height=400, background_c

# Display the word clouds in separate figures
plt.figure(figsize=(10, 5))
plt.imshow(wordcloud_negative, interpolation='bilinear')
plt.title('Negative Reviews')
plt.axis('off')
plt.show()

print()  # Separating the word clouds display for clarity

plt.figure(figsize=(10, 5))
plt.imshow(wordcloud_positive, interpolation='bilinear')
plt.title('Positive Reviews')
plt.axis('off')
plt.show()

# Add a sentiment_label column for the countplot
data['sentiment_label'] = data['label']
```




```
In [56]: # Previewing our column names
         data.columns
```

```
Out[56]: Index(['id', 'asins', 'brand', 'product_categories', 'product_key
s',
       'manufacturer_name', 'review_do_recommend', 'review_num_he
lpful',
       'review_rating', 'review_username', 'review_length',
       'review_did_purchase', 'total_votes', 'review_text', 'revi
ew_title',
       'clean_text', 'clean_title', 'sentiment', 'label', 'sentim
ent_label'],
      dtype='object')
```

- Let's visualize the distribution of sentiment scores and review ratings.

- We will now convert our labels into numerical data for modeling

In [58]:
```
# Perform label encoding
label_encoder = LabelEncoder()
data['labeled'] = label_encoder.fit_transform(data['label'])
```

In [59]:
```
print(data[['clean_text', 'sentiment', 'labeled']])
```

```
clean_text  \
review_date
2017-01-13 00:00:00+00:00  product far disappointed child love us
e like a...
2017-01-13 00:00:00+00:00  great beginner experienced person boug
ht gift ...
2017-01-13 00:00:00+00:00  inexpensive tablet use learn step nabi
thrille...
2017-01-13 00:00:00+00:00  ive fire hd two week love tablet great
valuewe...
2017-01-12 00:00:00+00:00  bought grand daughter come visit set u
ser ente...
...
...
2017-07-29 00:00:00+00:00  great sound quality great way control
smart de...
2017-07-29 00:00:00+00:00       daughter love us every day remind
er question
2017-07-29 00:00:00+00:00  really enjoy great speaker music deman
d asking...
2017-07-28 00:00:00+00:00  plugging echo downloading alexa app re
st proce...
2017-07-28 00:00:00+00:00  husband love like telling alexa play m
usic tel...

                           sentiment  labeled
review_date
2017-01-13 00:00:00+00:00     0.8126        1
2017-01-13 00:00:00+00:00     0.9042        1
2017-01-13 00:00:00+00:00     0.4404        0
2017-01-13 00:00:00+00:00     0.9899        1
2017-01-12 00:00:00+00:00     0.9371        1
...                              ...      ...
2017-07-29 00:00:00+00:00     0.8979        1
2017-07-29 00:00:00+00:00     0.6369        1
2017-07-29 00:00:00+00:00     0.9144        1
2017-07-28 00:00:00+00:00     0.9313        1
2017-07-28 00:00:00+00:00     0.8834        1

[23251 rows x 3 columns]
```

Feature Extraction

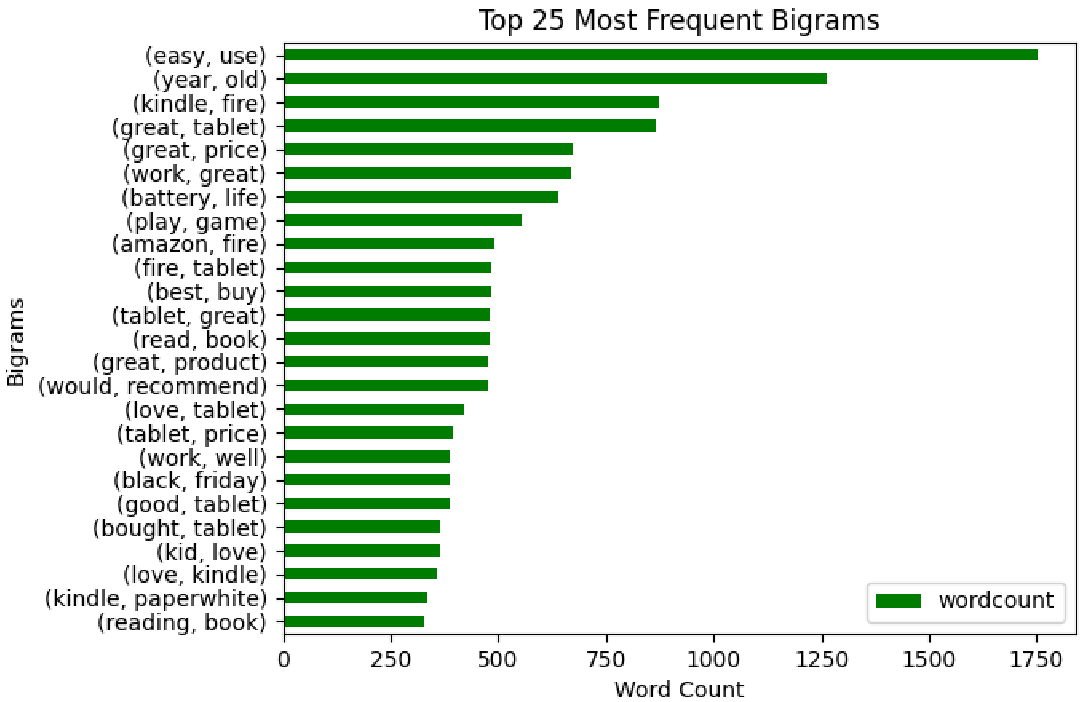
- In this step, we will extract bigrams from the text data and analyze their frequency.

In [60]:
```python
#Extraction of Bigrams

# Function to generate n-grams
from collections import defaultdict
from nltk import ngrams # Import the ngrams function

# Function to generate n-grams
def generate_ngrams(clean_text, n):
    words = clean_text.split()
    return list(ngrams(words, n))

# Initialize a defaultdict for frequency counts
freq_dict = defaultdict(int)

# Calculate bigram frequency
for sent in data["clean_text"]:
    for word in generate_ngrams(sent,2):
        freq_dict[word] += 1
# Sort the frequency dictionary and create a DataFrame
fd_sorted = pd.DataFrame(sorted(freq_dict.items(), key=lambda x: x
fd_sorted.columns = ["word", "wordcount"]
print(fd_sorted.head(25))
```

```
                    word  wordcount
0            (easy, use)       1752
1            (year, old)       1261
2         (kindle, fire)        873
3        (great, tablet)        865
4         (great, price)        674
5          (work, great)        671
6        (battery, life)        640
7           (play, game)        554
8         (amazon, fire)        493
9         (fire, tablet)        483
10           (best, buy)        483
11       (tablet, great)        481
12          (read, book)        479
13      (great, product)        478
14    (would, recommend)        476
15        (love, tablet)        420
16       (tablet, price)        394
17          (work, well)        389
18       (black, friday)        388
19        (good, tablet)        386
20      (bought, tablet)        365
21           (kid, love)        364
22        (love, kindle)        357
23  (kindle, paperwhite)        334
24       (reading, book)        327
```

- Let's visualize the top 25 most frequent bigrams

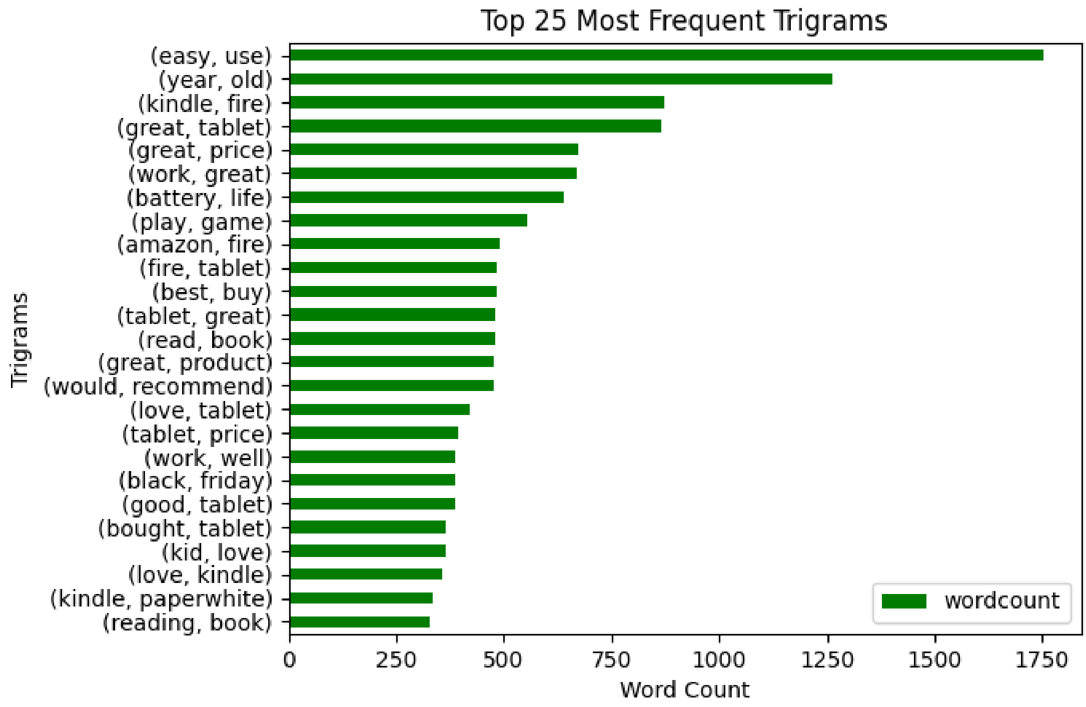
In [61]:
```
# Function to plot a horizontal bar chart
def horizontal_bar_chart(data, color):
    data.plot(kind='barh', x='word', y='wordcount', color=color)
    plt.xlabel('Word Count')
    plt.ylabel('Bigrams')
    plt.title('Top 25 Most Frequent Bigrams')
    plt.gca().invert_yaxis()  # Invert y-axis to have the highest
    plt.show()

# Plot the top 25 most frequent bigrams
horizontal_bar_chart(fd_sorted.head(25), 'green')
```



In [62]:
```python
#Extraction of Trigrams


# Calculate trigram frequency
for sent in data["clean_text"]:
    for word in generate_ngrams(sent,3):
        freq_dict[word] += 1
# Sort the frequency dictionary and create a DataFrame
fd_sorted = pd.DataFrame(sorted(freq_dict.items(), key=lambda x: x
fd_sorted.columns = ["word", "wordcount"]
print(fd_sorted.head(25))
```

```
                     word  wordcount
0             (easy, use)       1752
1             (year, old)       1261
2          (kindle, fire)        873
3         (great, tablet)        865
4          (great, price)        674
5           (work, great)        671
6         (battery, life)        640
7            (play, game)        554
8          (amazon, fire)        493
9          (fire, tablet)        483
10            (best, buy)        483
11        (tablet, great)        481
12           (read, book)        479
13       (great, product)        478
14     (would, recommend)        476
15         (love, tablet)        420
16        (tablet, price)        394
17           (work, well)        389
18        (black, friday)        388
19         (good, tablet)        386
20       (bought, tablet)        365
21            (kid, love)        364
22         (love, kindle)        357
23  (kindle, paperwhite)        334
24        (reading, book)        327
```

```
In [63]: # Function to plot a horizontal bar chart
def horizontal_bar_chart(data, color):
    data.plot(kind='barh', x='word', y='wordcount', color=color)
    plt.xlabel('Word Count')
    plt.ylabel('Trigrams')
    plt.title('Top 25 Most Frequent Trigrams')
    plt.gca().invert_yaxis()  # Invert y-axis to have the highest
    plt.show()

# Plot the top 25 most frequent trigrams
horizontal_bar_chart(fd_sorted.head(25), 'green')
```



Word Vectorization

Methods used are:

TF-IDF Vectorization

The TF-IDF (Term Frequency-Inverse Document Frequency) vectorizer transforms the text into a weighted matrix, where each term's importance is adjusted based on its frequency in the document and across all documents.

Count Vectorization

The Count Vectorizer to converts the text into a matrix of token counts, representing the raw frequency of each term.

The result

Two matrices one with TF-IDF weights and another with raw token counts, each representing the reviews in a numerical format.

In [64]:
```python
from sklearn.feature_extraction.text import CountVectorizer

clean_text = data['clean_text']

# Initialize CountVectorizer
vectorizer = CountVectorizer()

# Fit and transform the clean_text column
X_count = vectorizer.fit_transform(clean_text)

# Print the array representation of the features
print(X_count.toarray()[1:])
```

```
[[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]]
```

In [65]:
```python
# CountVectorizer
count_vec = CountVectorizer()
# Convert the Pandas Series to a list of strings
X_count = count_vec.fit_transform(clean_text.tolist())
print('CountVectorizer:')
print(count_vec.get_feature_names_out()[:10], '\n')
```

```
CountVectorizer:
['aa' 'abandon' 'abandoned' 'abattery' 'abc' 'abcmouse' 'abcmouse
com'
 'abd' 'ability' 'abilty']
```

- We extracted the first 10 feature names

Next is the TF-IDF Vectorizer

In [66]:
```python
from sklearn.feature_extraction.text import TfidfVectorizer

#Initialize the TfidfVectorizer
vectorizer = TfidfVectorizer()

# Fit the vectorizer to the corpus and transform the corpus into a
X_tfidf = vectorizer.fit_transform(clean_text)

# Print the TF-IDF matrix as a dense array
print(X_tfidf.toarray(), "\n")

# Print the feature names
print("Feature names:")
print(vectorizer.get_feature_names_out())
```

```
[[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.]]

Feature names:
['aa' 'abandon' 'abandoned' ... 'zoomed' 'zooming' 'zwave']
```

Word Embedding Techniques (Word2Vec and FastText):

We used advanced word embedding techniques to capture the semantic meaning of words in the reviews.

Word2Vec: This technique uses a neural network model to learn vector representations of words based on their context in the corpus. We trained a Word2Vec model on our tokenized text data to obtain word vectors.

FastText: Similar to Word2Vec, but it also considers subword information, making it better at handling rare and out-of-vocabulary words. We trained a FastText model to generate word vectors that include subword information.

In [67]:
```python
from gensim.models import Word2Vec
from nltk.tokenize import word_tokenize

# Tokenize the text
sentences = [word_tokenize(doc.lower()) for doc in data['clean_tex

# Train Word2Vec model
model = Word2Vec(sentences, vector_size=100, window=5, min_count=1

# Get word vectors
word_vectors = model.wv

# Get the combined matrix of word vectors
wordvec_matrix = word_vectors.vectors
print(wordvec_matrix)
```

```
[[-5.91852427e-01 -1.15684964e-01  7.11060837e-02 ... -4.64988738
e-01
   8.14194262e-01  3.35355252e-01]
 [-1.52135766e+00  7.26664364e-01  5.14629662e-01 ... -1.70367733
e-01
  -1.11762919e-01 -2.52520949e-01]
 [-8.51729035e-01  8.20121348e-01 -3.19332480e-01 ... -7.64260054
e-01
   5.89437708e-02 -1.85080305e-01]
 ...
 [-2.01675110e-02 -1.57647708e-03 -3.30265216e-03 ... -1.41850607
e-02
   8.24625138e-03 -5.22816647e-03]
 [-3.46319191e-03 -5.92788681e-04  5.84608503e-03 ... -2.08582189
e-02
   5.52937156e-03  3.03241285e-03]
 [-9.75433458e-03  1.20619293e-02 -9.40152165e-03 ... -2.92368070
e-03
   9.76519287e-03  4.43352619e-03]]
```

In [68]:
```
from gensim.models import FastText
from nltk.tokenize import word_tokenize

# Tokenize the text
sentences = [word_tokenize(doc.lower()) for doc in data['clean_tex

# Train FastText model
model = FastText(sentences, vector_size=100, window=5, min_count=1

# Get word vectors
word_vectors = model.wv

# Get the combined matrix of word vectors
fasttext_matrix = word_vectors.vectors
print(fasttext_matrix)
```

```
[[-0.9189425   0.48709598 -0.76550424 ... -0.3025607   0.46892732
  -0.0281456 ]
 [-1.5981714  -0.71410924 -0.8901838  ...  0.48710644  1.2479365
   0.5013436 ]
 [-1.2803963  -0.25787374 -0.9223343  ...  0.14660239  0.05923066
   0.40174818]
 ...
 [-0.13212799 -0.3026582  -0.5194815  ... -0.08484916 -0.07165129
   0.49663594]
 [-0.66055095 -0.3015146  -0.48734954 ... -0.29908112  0.19231087
   0.26607442]
 [-0.1676146  -0.13033691 -0.61114514 ... -0.14640707 -0.04662995
   0.4260874 ]]
```

- Both Word2Vec and FastText are models used to create word embeddings from text data. Word2Vec focuses on capturing word meanings based on their context in sentences, while FastText adds the ability to understand word structure by considering subword information like prefixes and suffixes.

##Train test split

1. Count vectorizer

In [69]:

```
from sklearn.model_selection import train_test_split

# Separate features and target for each matrix
X = X_count
y = data['labeled']

# Split data into train and test sets
X_train_countvec, X_test_countvec, y_train_countvec, y_test_countv

# Print the shapes of the training and test sets
print("X_train_countvec shape:", X_train_countvec.shape)
print("y_train_countvec shape:", y_train_countvec.shape)
print("X_test_countvec shape:", X_test_countvec.shape)
print("y_test_countvec shape:", y_test_countvec.shape)
```

```
X_train_countvec shape: (18600, 11975)
y_train_countvec shape: (18600,)
X_test_countvec shape: (4651, 11975)
y_test_countvec shape: (4651,)
```

2. TF-IDF VECTORIZER

In [70]:

```
from sklearn.model_selection import train_test_split

X = X_tfidf
y = data['labeled']

# Split data into train and test sets
X_train_tfidf, X_test_tfidf, y_train_tfidf, y_test_tfidf = train_t

# Print the shapes of the training and test sets
print("X_train_tfidf shape:", X_train_tfidf.shape)
print("y_train_tfidf shape:", y_train_tfidf.shape)
print("X_test_tfidf shape:", X_test_tfidf.shape)
print("y_test_tfidf shape:", y_test_tfidf.shape)
```

```
X_train_tfidf shape: (18600, 11975)
y_train_tfidf shape: (18600,)
X_test_tfidf shape: (4651, 11975)
y_test_tfidf shape: (4651,)
```