sentiment analysis on the reviews

Objective:

The objective of this use case is to perform sentiment analysis on the reviews of the All-New Fire HD 8 Tablet to understand customer sentiments towards the product. By analyzing these reviews, we aim to identify the overall customer satisfaction and key factors influencing positive and negative sentiments. This analysis will help Amazon and potential buyers gain insights into the strengths and weaknesses of the product. The results can also guide improvements in future product development and marketing strategies.

Importing Libraries

In [14]:

```
import warnings
warnings.filterwarnings('ignore')
import pandas as pd
import re
import string
import seaborn as sns
from sklearn.feature_extraction.text import TfidfVectorizer
import matplotlib.pyplot as plt
```

Load the dataset

In [6]:
```
df = pd.read_csv(r"C:\Users\jayak\OneDrive\Desktop\flipkart_review.csv")

# Display the first few rows of the dataset
df.head()
```

Out[6]:

	id	name	asins	brand	categories	keys	manufacturer	reviews.date	revie
0	AVqkIhwDv8e3D1O-lebb	All-New Fire HD 8 Tablet, 8 HD Display, Wi-Fi,...	B01AHB9CN2	Amazon	Electronics,iPad & Tablets,All Tablets,Fire Ta...	841667104676,amazon/53004484,amazon/b01ahb9cn2...	Amazon	2017-01-13T00:00:00.000Z	
1	AVqkIhwDv8e3D1O-lebb	All-New Fire HD 8 Tablet, 8 HD Display, Wi-Fi,...	B01AHB9CN2	Amazon	Electronics,iPad & Tablets,All Tablets,Fire Ta...	841667104676,amazon/53004484,amazon/b01ahb9cn2...	Amazon	2017-01-13T00:00:00.000Z	
2	AVqkIhwDv8e3D1O-lebb	All-New Fire HD 8 Tablet, 8 HD Display,	B01AHB9CN2	Amazon	Electronics,iPad & Tablets,All Tablets,Fire Ta...	841667104676,amazon/53004484,amazon/b01ahb9cn2...	Amazon	2017-01-13T00:00:00.000Z	
3	AVqkIhwDv8e3D1O-lebb	All-New Fire HD 8 Tablet, 8 HD Display, Wi-Fi,...	B01AHB9CN2	Amazon	Electronics,iPad & Tablets,All Tablets,Fire Ta...	841667104676,amazon/53004484,amazon/b01ahb9cn2...	Amazon	2017-01-13T00:00:00.000Z	
4	AVqkIhwDv8e3D1O-lebb	All-New Fire HD 8 Tablet, 8 HD Display, Wi-Fi,...	B01AHB9CN2	Amazon	Electronics,iPad & Tablets,All Tablets,Fire Ta...	841667104676,amazon/53004484,amazon/b01ahb9cn2...	Amazon	2017-01-12T00:00:00.000Z	

5 rows × 21 columns

In [7]:
```
df.columns
```

Out[7]:
```
Index(['id', 'name', 'asins', 'brand', 'categories', 'keys', 'manufacturer',
       'reviews.date', 'reviews.dateAdded', 'reviews.dateSeen',
       'reviews.didPurchase', 'reviews.doRecommend', 'reviews.id',
       'reviews.numHelpful', 'reviews.rating', 'reviews.sourceURLs',
       'reviews.text', 'reviews.title', 'reviews.userCity',
       'reviews.userProvince', 'reviews.username'],
      dtype='object')
```

In [9]:
```
# Check for missing values
print(df.isnull().sum())
```

```
id                         0
name                    6760
asins                      2
brand                      0
categories                 0
keys                       0
manufacturer               0
reviews.date              39
reviews.dateAdded      10621
reviews.dateSeen           0
reviews.didPurchase    34659
reviews.doRecommend      594
reviews.id             34659
reviews.numHelpful       529
reviews.rating            33
reviews.sourceURLs         0
reviews.text               1
reviews.title              6
reviews.userCity       34660
reviews.userProvince   34660
reviews.username           7
dtype: int64
```

Data Cleaning and Preprocessing

Data cleaning and preprocessing involve preparing raw data for analysis by addressing inconsistencies and ensuring data quality. This process includes handling missing values, correcting errors, removing duplicates, and standardizing data formats. Preprocessing steps may also involve normalization, encoding categorical variables, and feature scaling. Effective data cleaning and preprocessing are crucial for accurate and reliable analytical results.

In [10]:
```
# Drop irrelevant columns (example: 'id', 'asins', 'keys', 'reviews.sourceURLs', 'reviews.userCity', 'reviews.userProvince')
columns_to_drop = ['id', 'asins', 'keys', 'reviews.sourceURLs', 'reviews.userCity', 'reviews.userProvince']
df = df.drop(columns=columns_to_drop)
```

In [11]:
```
# Handle missing values
# Fill missing values in 'reviews.text' with an empty string
df['reviews.text'] = df['reviews.text'].fillna('')
```

In [12]:
```
# Fill missing values in 'reviews.title' with an empty string
df['reviews.title'] = df['reviews.title'].fillna('')
```

In [15]:
```
# Normalize text data by converting to lowercase and removing punctuation
def preprocess_text(text):
    text = text.lower()  # Convert to lowercase
    text = re.sub(f"[{re.escape(string.punctuation)}]", "", text)  # Remove punctuation
    text = re.sub(r'\s+', ' ', text).strip()  # Remove extra spaces
    return text

df['reviews.text'] = df['reviews.text'].apply(preprocess_text)
df['reviews.title'] = df['reviews.title'].apply(preprocess_text)
```

In [16]:
```
# Display the cleaned DataFrame
df.head()
```

Out[16]:

	name	brand	categories	manufacturer	reviews.date	reviews.dateAdded	reviews.dateSeen	reviews.didPurchase	reviews.doRecommend	rev
0	All-New Fire HD 8 Tablet, 8 HD Display, Wi-Fi,...	Amazon	Electronics,iPad & Tablets,All Tablets,Fire Ta...	Amazon	2017-01-13T00:00:00.000Z	2017-07-03T23:33:15Z	2017-06-07T09:04:00.000Z,2017-04-30T00:45:00.000Z	NaN	True	
1	All-New Fire HD 8 Tablet, 8 HD Display,	Amazon	Electronics,iPad & Tablets,All Tablets,Fire Ta...	Amazon	2017-01-13T00:00:00.000Z	2017-07-03T23:33:15Z	2017-06-07T09:04:00.000Z,2017-04-30T00:45:00.000Z	NaN	True	

Exploratory Data Analysis (EDA):

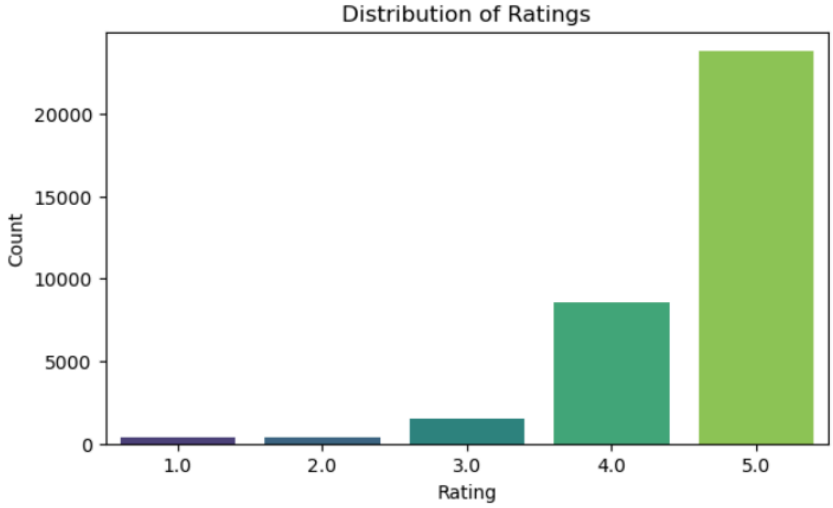
Exploratory Data Analysis (EDA) involves analyzing and visualizing data to uncover patterns, anomalies, and relationships. It includes data cleaning, calculating descriptive statistics, and creating visualizations like histograms and scatter plots. EDA helps identify trends, correlations, and outliers, providing a deeper understanding of the data. This process is essential for making informed decisions and preparing data for further analysis or modeling.

In [17]:
```
# Display basic statistics
df.describe()
```

Out[17]:

	reviews.id	reviews.numHelpful	reviews.rating
count	1.0	34131.000000	34627.000000
mean	111372787.0	0.630248	4.584573
std	NaN	13.215775	0.735653
min	111372787.0	0.000000	1.000000
25%	111372787.0	0.000000	4.000000
50%	111372787.0	0.000000	5.000000
75%	111372787.0	0.000000	5.000000
max	111372787.0	814.000000	5.000000

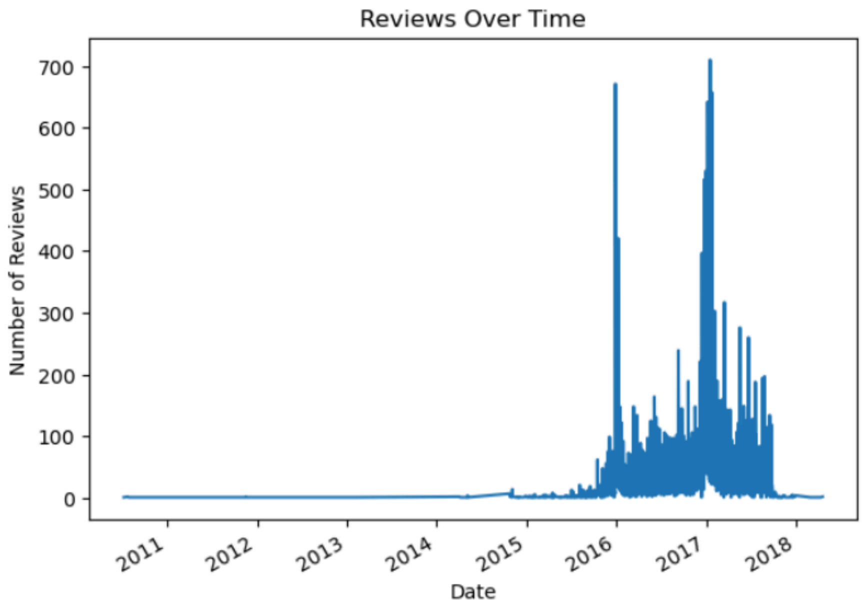
In [53]:
```
# Distribution of Ratings
plt.figure(figsize=(7, 4))
sns.countplot(x='reviews.rating', data=df, palette='viridis')
plt.title('Distribution of Ratings')
plt.xlabel('Rating')
plt.ylabel('Count')
plt.show()
```



In [21]:
```
# Convert the 'reviews.date' column to datetime
df['reviews.date'] = pd.to_datetime(df['reviews.date'], format='ISO8601', errors='coerce')

# Drop rows with invalid dates
df = df.dropna(subset=['reviews.date'])
```

In [55]:
```
# Distribution of Reviews Over Time
plt.figure(figsize=(7, 5))
df['reviews.date'].value_counts().sort_index().plot()
plt.title('Reviews Over Time')
plt.xlabel('Date')
plt.ylabel('Number of Reviews')
plt.show()
```



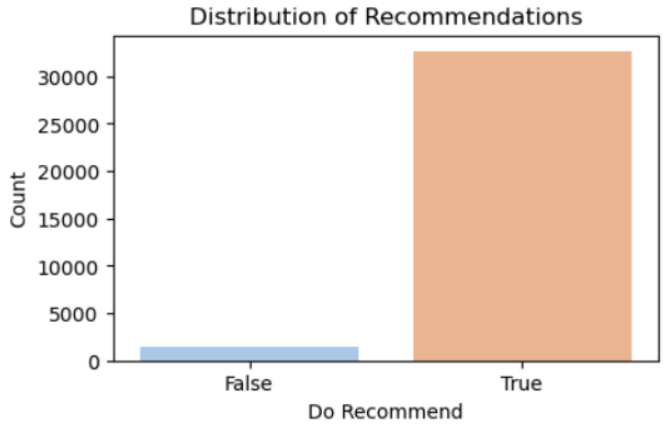
In [56]:
```python
# Most Frequent Words in Review Text
all_text = ' '.join(df['reviews.text'])
wordcloud = WordCloud(width=800, height=400, background_color='white').generate(all_text)
plt.figure(figsize=(8, 5))
plt.imshow(wordcloud, interpolation='bilinear')
plt.title('Most Frequent Words in Review Text')
plt.axis('off')
plt.show()
```

Most Frequent Words in Review Text

In [57]:
```python
# Most Frequent Words in Review Titles
all_titles = ' '.join(df['reviews.title'])
wordcloud_titles = WordCloud(width=800, height=400, background_color='white').generate(all_titles)
plt.figure(figsize=(8, 5))
plt.imshow(wordcloud_titles, interpolation='bilinear')
plt.title('Most Frequent Words in Review Titles')
plt.axis('off')
plt.show()
```

Most Frequent Words in Review Titles

In [59]:
```
# Recommendations Analysis
plt.figure(figsize=(5, 3))
sns.countplot(x='reviews.doRecommend', data= df, palette='pastel')
plt.title('Distribution of Recommendations')
plt.xlabel('Do Recommend')
plt.ylabel('Count')
plt.show()
```



In [28]:
```
# Define sentiment labels based on ratings
def label_sentiment(rating):
    if rating >= 4:
        return 'positive'
    elif rating == 3:
        return 'neutral'
    else:
        return 'negative'
```

In [29]:
```
# Apply the function to create a new column 'sentiment'
df['sentiment'] = df['reviews.rating'].apply(label_sentiment)
```

In [30]:
```
# Display the first few rows of the dataset to check the new sentiment column
df[['reviews.rating', 'sentiment']].head()
```

Out[30]:

	reviews.rating	sentiment
0	5.0	positive
1	5.0	positive
2	5.0	positive
3	4.0	positive
4	5.0	positive

Text Preprocessing

Text preprocessing is a critical step in natural language processing (NLP) that transforms raw text into a cleaner, standardized format for analysis. It involves converting text to lowercase, removing punctuation, and eliminating stop words. Additional steps include tokenization, stemming, lemmatization, and handling special characters or numbers. These processes help in reducing noise and extracting meaningful information, making the text data suitable for machine learning models and other analytical tasks

]:
```
import nltk
nltk.download('stopwords')
nltk.download('punkt')
nltk.download('wordnet')
from wordcloud import WordCloud
from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize
from nltk.stem import WordNetLemmatizer
```

]:
```
# Initialize stopwords and lemmatizer
stop_words = set(stopwords.words('english'))
lemmatizer = WordNetLemmatizer()
```

]:
```
# Define text preprocessing function
def preprocess_text(text):
    # Tokenize text
    tokens = word_tokenize(text)
    # Remove stopwords and non-alphabetic tokens, and apply lemmatization
    tokens = [lemmatizer.lemmatize(word.lower()) for word in tokens if word.isalpha() and word.lower() not in stop_words]
    # Join tokens back to a single string
    return ' '.join(tokens)
```

```
# Apply the preprocessing function to the review text
df['processed_text'] = df['reviews.text'].apply(preprocess_text)
```

```
# Display the first few rows of the dataset to check the processed text
df[['reviews.text', 'processed_text']].head()
```

	reviews.text	processed_text
0	this product so far has not disappointed my ch...	product far disappointed child love use like a...
1	great for beginner or experienced person bough...	great beginner experienced person bought gift ...
2	inexpensive tablet for him to use and learn on...	inexpensive tablet use learn step nabi thrille...
3	ive had my fire hd 8 two weeks now and i love ...	ive fire hd two week love tablet great valuewe...
4	i bought this for my grand daughter when she c...	bought grand daughter come visit set user ente...

Converting text into Vectors ¶

TF-IDF calculates that how relevant a word in a series or corpus is to a text. The meaning increases proportionally to the number of times in the text a word appears but is compensated by the word frequency in the corpus (data-set). We will be implementing this with the code below.

```
# Initialize the TF-IDF vectorizer
tfidf_vectorizer = TfidfVectorizer(max_features=5000)
```

```
# Fit and transform the processed text
tfidf_matrix = tfidf_vectorizer.fit_transform(df['processed_text'])
```

```
# Convert the TF-IDF matrix to a DataFrame
tfidf_df = pd.DataFrame(tfidf_matrix.toarray(), columns=tfidf_vectorizer.get_feature_names_out())
```

```
# Add sentiment labels to the TF-IDF DataFrame
tfidf_df['sentiment'] = df['sentiment']
```

```
# Display the first few rows of the TF-IDF DataFrame
tfidf_df.head()
```

	abc	ability	able	abroad	absolute	absolutely	absolutly	abundance	abundant	abuse	...	youtube	youve	yr	zero	zip	zippy	zone	zoom	zwa
0	0.0	0.315445	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	
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	
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	
3	0.0	0.000000	0.104977	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	

Model training, Evaluation, and Prediction

We can now explore any machine learning model to train the data

```
]: # Fit and transform the processed text
X = tfidf_vectorizer.fit_transform(df['processed_text'])

# Define the target variable
y = df['sentiment']
```

```
]: # Split the dataset into training and testing sets
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.33, random_state=42, stratify=y)
```

```
]: from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score

model = DecisionTreeClassifier(random_state=0)
model.fit(X_train,y_train)

#testing the model
pred = model.predict(X_train)
print(accuracy_score(y_train,pred))
```

```
0.9999137782376272
```

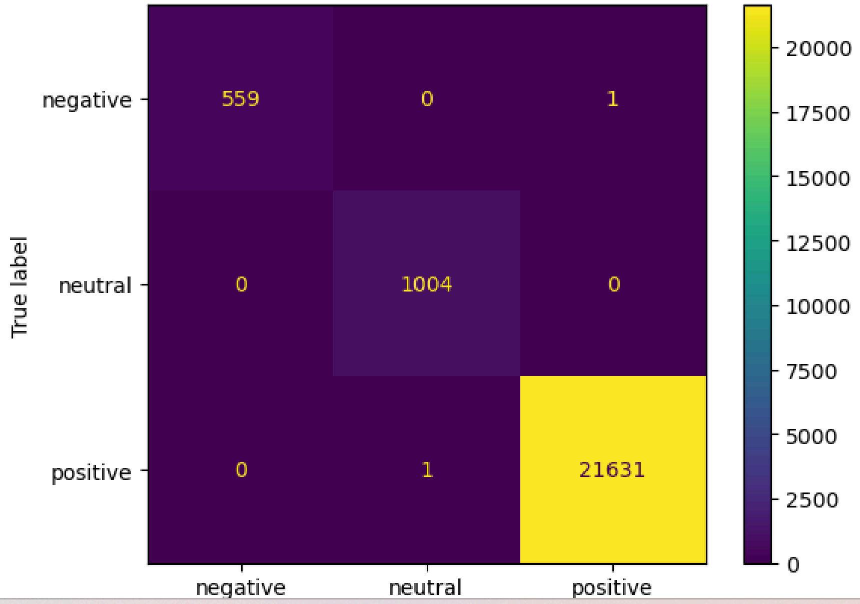
Let's see the confusion matrix for the results.

```
from sklearn import metrics
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay

# Generate confusion matrix
cm = confusion_matrix(y_train, pred)

# Get unique classes from the target variable
unique_classes = model.classes_

# Display the confusion matrix
cm_display = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=unique_classes)
cm_display.plot()
plt.show()
```



Conclusion:

The Decision Tree Classifier has demonstrated strong performance with this dataset, effectively capturing the sentiment nuances in the reviews. Its ability to handle complex decision-making processes allows it to classify sentiments accurately. The model's interpretability makes it easier to understand which features influence sentiment predictions. This promising result suggests that the Decision Tree Classifier is well-suited for sentiment analysis in this context, providing valuable insights into customer opinions on the All-New Fire HD 8 Tablet.