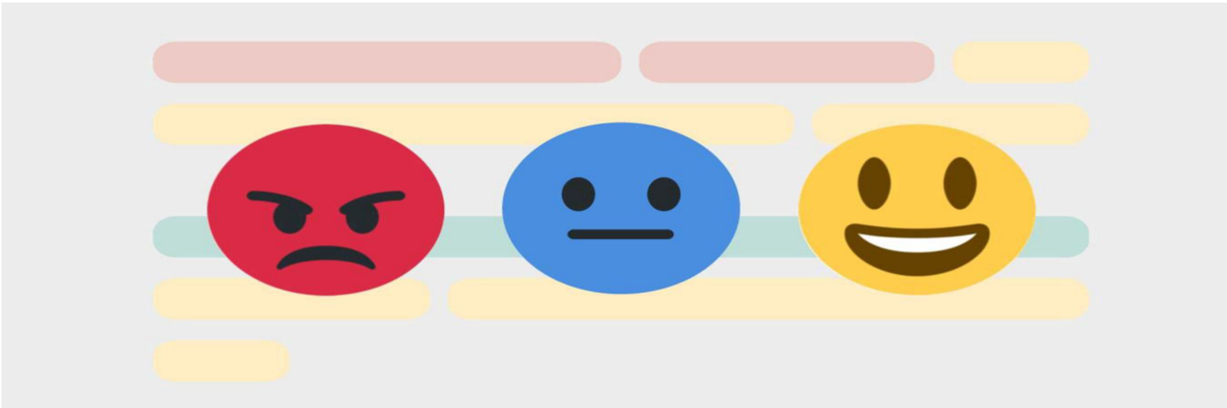
PROJECT: E-COMMERCE SENTIMENT ANALYSIS FOR CUSTOMER REVIEWS

In [1]:
```
from PIL import Image
Image.open('emotion.jpeg').resize((1200,400))
```

Out[1]:



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1. Introduction:

In today's world, we encounter a multitude of products and services, especially online. When making a choice, customer reviews play a crucial role. Ratings offer a quick overview, but understanding the sentiment in sentence reviews is equally important. With advancements in Natural Language Processing (NLP) technology, we can now easily extract insights from these reviews, helping consumers make informed decisions.

What is Sentiment Analysis

Sentiment analysis, also known as opinion mining, is a natural language processing (NLP) technique used to determine the sentiment or emotional tone expressed in a piece of text. It involves analyzing text data, such as reviews, social media posts, or customer feedback, to determine whether the sentiment expressed is positive, negative, neutral, or even more nuanced emotions like joy, anger, sadness, etc. The primary goal of sentiment analysis is to automatically classify and understand the subjective information in text data.

Project Objective:

- Collect customer review data from selected e-commerce sites - Amazon.com
- Analyze sentiment trends across different porduct categories.
- Develop sentiment analysis model to classify reviews as positive, negative, and neutral.

In [ ]:

```

```

Import of Libraries

In [2]:

```
# Data Analysis and Visualiztion Libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
sns.set()
import missingno as msno
%matplotlib inline

# NLP Libraries
from textblob import TextBlob
import re
import nltk
from nltk.corpus import stopwords
from nltk.stem.porter import PorterStemmer
from nltk.stem import WordNetLemmatizer
from nltk.util import ngrams
from nltk import word_tokenize
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.feature_extraction.text import ENGLISH_STOP_WORDS
from collections import Counter
from wordcloud import WordCloud
from nltk.sentiment.vader import SentimentIntensityAnalyzer

# Model building Libraries
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.naive_bayes import MultinomialNB
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, roc_auc_score, confusion_matrix, classific
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import GridSearchCV
from imblearn.over_sampling import SMOTE
```

```
import warnings
warnings.filterwarnings("ignore")
```

Import of dataset

Dataset was scraped from Amazon.com

In [3]:
```
df = pd.read_csv('amazon_data.csv')
df.head(3)
```

Out[3]:

	Customer_i_ID	Customer_i_Star_Rating	Customer_i_Comment	Customer_i_buying_influence	Custo
0	R2XDX5EDQSDK1F	5.0	Fantastic	0.0	
1	RRUZC22ZU7FTB	5.0	Bueno	0.0	
2	R3O181F9WBJWYS	4.0	Quality product, good price!	0.0	

Data Assessment

In [4]:
```
# Check data dimensionality
rows, columns = df.shape
print('Number of rows:', rows)
print('Number of columns:', columns)
```

```
Number of rows: 18210
Number of columns: 9
```

In [5]:
```
# Display information about the DataFrame
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 18210 entries, 0 to 18209
Data columns (total 9 columns):
 #   Column                     Non-Null Count  Dtype  
---  ------                     --------------  -----  
 0   Customer_i_ID              18210 non-null  object 
 1   Customer_i_Star_Rating     15347 non-null  float64
 2   Customer_i_Comment         18127 non-null  object 
 3   Customer_i_buying_influence 15347 non-null  float64
 4   Customer_i_Date            18210 non-null  object 
 5   product                    18210 non-null  object 
 6   category                   18210 non-null  object 
 7   price_dollars              18210 non-null  float64
 8   total_ratings              18210 non-null  int64  
dtypes: float64(3), int64(1), object(5)
memory usage: 1.3+ MB
```

In [ ]:

2. Data Preprocessing and Feature Engineering

Renaming of features

- This is done for clarity and easy readability of feature names.

In [6]:

```
df.rename(columns={"Customer_i_ID":"Cutomer_ID", "Customer_i_Star_Rating":"Rating", "C
                   "Customer_i_buying_influence":"Customer_Influence", "Customer_i_Dat
                   "price_dollars":"Price", "total_ratings":"Total_Rating"}, inplace=T

df.head(2)
```

Out[6]:

	Cutomer_ID	Rating	Review	Customer_Influence	Date	Product	Category	Price
0	R2XDX5EDQSDK1F	5.0	Fantastic	0.0	10/21/2023	Five Nights at Freddy's: The Core Collection (...	video_games	19.93
1	RRUZC22ZU7FTB	5.0	Bueno	0.0	10/25/2023	Super Smash Bros. Ultimate - US Version	video_games	50.55

Handling of duplicates

- This step is to remove all duplicated rows.

In [7]:
```python
# Check for duplicates
dup = df.duplicated().sum()
print(f"Duplicated rows: {dup}")
```

```
Duplicated rows: 3889
```

In [8]:
```python
# Dropping of duplicated rows
df.drop_duplicates(inplace=True)
```

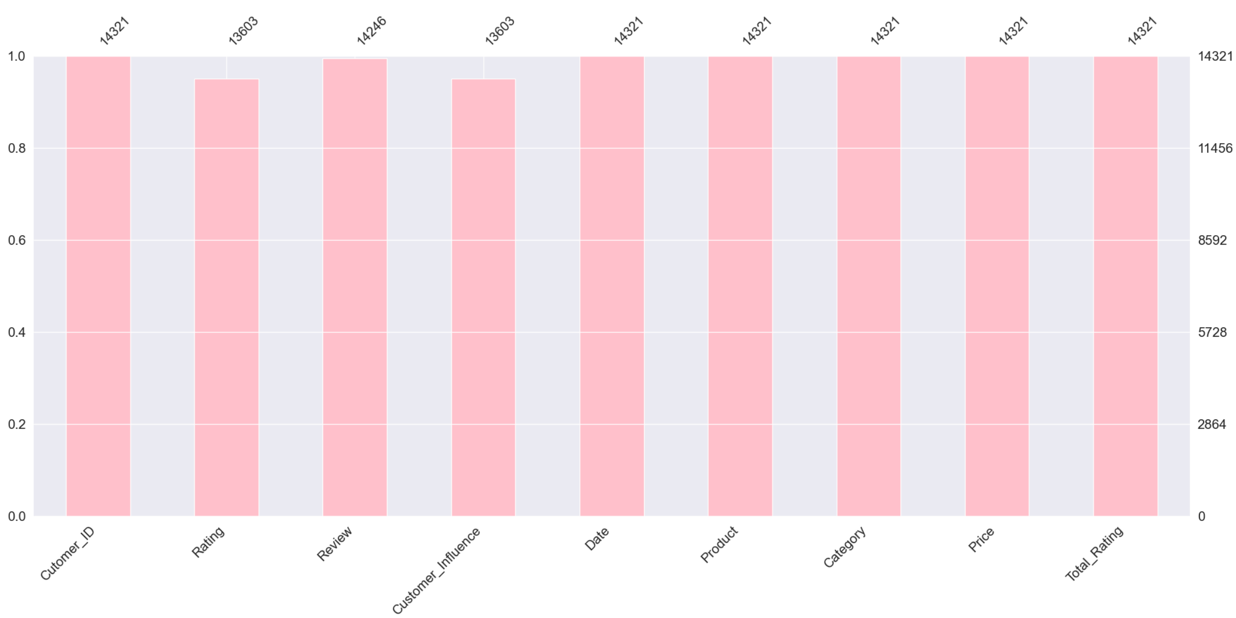
Handling of null values

- Rows with null values will be removed and not replaced, inorder to maintain data integrity and also there are enough rows even after removal of null values

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

Out[9]:
```
Cutomer_ID             0
Rating               718
Review                75
Customer_Influence   718
Date                   0
Product                0
Category               0
Price                  0
Total_Rating           0
dtype: int64
```

In [10]:
```python
# Visualization of missing values
msno.bar(df, color='pink');
```



In [11]:
```python
# Drop all null values:
df.dropna(inplace=True)
```

Handling of date column

- Target here is convert Date column into Datetime and split the column into year, month and day. Also, some dates have OutOfBoundDatetime of "1677-09-21" which will be filtered out.

In [12]:
```
# Rows with 'OutOfBoundDatetime': this rows don't have 0 rating and non-english review
df[df["Date"] == "1677-09-21"].iloc[10:13]
```

Out[12]:

	Cutomer_ID	Rating	Review	Customer_Influence	Date	Product	Category	F
1119	R2OSGO4UH8JA5T	0.0	Tres solide correspond aux attentes demandées!	0.0	1677-09-21	Blackview Rugged Smartphone Unlocked, 2023 BV6...	Smartphones	
1124	R3FFQHSWQATNU5	0.0	Posso considerarla una fregatura?	0.0	1677-09-21	Honor X8a Dual SIM 128GB ROM + 6GB RAM Factory...	Smartphones	
1321	R17T7NNUBYWXR7	0.0	Spedizione arrivata in largo anticipo	1.0	1677-09-21	Motorola Edge 30 Neo Dual-Sim 128GB ROM + 8GB ...	Smartphones	2

In [13]:
```
# Number of rows with 'OutOfBoundDatetime'
outtime = df[df["Date"] == "1677-09-21"].value_counts().sum()
print(f"Total number of rows with OutOfBoundDatetime: {outtime}")
```

```
Total number of rows with OutOfBoundDatetime: 169
```

In [14]:
```
# Filter dataframe to exclude rows with 'OutofBoundDatetime'
df = df[df["Date"] != "1677-09-21"]
```

In [15]:
```
# Convert the Date column from Object to Datetime
df["Date"] = pd.to_datetime(df["Date"])
```

In [16]:
```
# Splitting of Date column into Year, Month and Day
df["Year"] = df["Date"].dt.year
df["Month"] = df["Date"].dt.month
df["Day"] = df["Date"].dt.day

# Drop date column
df = df.drop("Date", axis=1)
```

In [17]:
```
df.head(2)
```

Out[17]:

	Cutomer_ID	Rating	Review	Customer_Influence	Product	Category	Price	Total_Rating
0	R2XDX5EDQSDK1F	5.0	Fantastic	0.0	Five Nights at Freddy's: The Core Collection (...	video_games	19.93	478
1	RRUZC22ZU7FTB	5.0	Bueno	0.0	Super Smash Bros. Ultimate - US Version	video_games	50.55	6887

Text cleaning

- Target here remove unnecessary columns and clean the Review column

In [18]:

```
# Removing unnecessary columns
df = df.drop(["Product", "Customer_Influence", "Total_Rating"], axis=1)
```

In [19]:

```
# Lowercase all text in the review column
df["Review"] = df["Review"].str.lower()
```

In [20]:

```
# Remove non-alphabets
df["Review"] = df["Review"].str.replace('[^a-zA-Z\s]', '')
```

In [21]:

```
df[400:404]
```

Out[21]:

	Cutomer_ID	Rating	Review	Category	Price	Year	Month	Day
465	R28QJP5YRNXXU2	1.0	the soundcard stopped working after three mont...	Laptops	299.0	2022	12	19
466	R1LYAQWYGRFFWH	4.0	excellent for work on the fly	Laptops	689.0	2023	10	20
467	R2GKLOQRBUGOOB	3.0	no cd drive	Laptops	339.0	2023	10	26
469	RUDHYI6DTGPF9	2.0	didnt get my moneys worth	Laptops	0.0	2023	10	24

Creating Sentiment Column

In [22]:

```
# Initialize the Sentiment Intensity Analyzer
sia = SentimentIntensityAnalyzer()

# sia function to classify sentiment_score
def get_sentiment(comment):
    return sia.polarity_scores(comment)["compound"]
```

In [23]:
```python
# Applying sentiment analyszer on Review column to Sentiment Score
df['Score'] = df['Review'].apply(get_sentiment)

df['Score'].head()
```

Out[23]:
```
0    0.5574
1    0.0000
2    0.4404
3    0.6249
4   -0.4019
Name: Score, dtype: float64
```

In [24]:
```python
# Function to classify sentiment scores
def sentiment(polarity):
    if polarity < 0:
        return "Negative"
    elif polarity > 0:
        return "Positive"
    else:
        return "Neutral"
```

In [25]:
```python
df['Sentiment'] = df['Score'].apply(sentiment)
```

In [26]:
```python
# Count of Sentiments
df['Sentiment'].value_counts()
```

Out[26]:
```
Positive    7119
Neutral     4614
Negative    1626
Name: Sentiment, dtype: int64
```

Creating more Features for Text Analysis

- Polarity: We use Textblob for for figuring out the rate of sentiment . It is between [-1,1] where -1 is negative and 1 is positive polarity
- Review length: length of the review which includes each letters and spaces
- Word length: This measures how many words are there in review

In [27]:
```python
df['Polarity'] = df['Review'].map(lambda text: TextBlob(text).sentiment.polarity)
df['Review_len'] = df['Review'].astype(str).apply(len)
df['Word_count'] = df['Review'].apply(lambda x: len(str(x).split()))
```

In [28]:
```python
df[2019:2023]
```

Out[28]:

	Cutomer_ID	Rating	Review	Category	Price	Year	Month	Day	Score	Sentiment	Pol
2509	R8YULHTM7XIYN	5.0	cute	Dresses	43.98	2023	10	23	0.4588	Positive	
2510	R1YIM89N821KDT	2.0	shrinks when washed	Dresses	37.99	2023	10	18	0.0000	Neutral	
2511	R32Y3VT8T2JCD4	2.0	midi dress	Dresses	47.99	2023	10	25	0.0000	Neutral	
2512	R3QZOCU8QJD37F	5.0	perfect fit	Dresses	28.51	2023	10	24	0.7351	Positive	

In [ ]:

3. Exploratory Data Analysis (EDA)

Customer Sentiment

In [29]:

```
plt.figure(figsize=(12,5))
custom_palette = {"Positive": "green", "Neutral": "grey", "Negative": "red"}
ax = sns.countplot(df, x='Sentiment', palette=custom_palette)
val = df['Sentiment'].value_counts().values
ax.bar_label(container=ax.containers[0], labels=val)
plt.title('Customer Sentiment');
```

Insight:
A total of 7119 customers hold a positive view towards the products, whereas 1626 customers have expressed their negative sentiment. The remaining 4614 customers have a neutral sentiment.

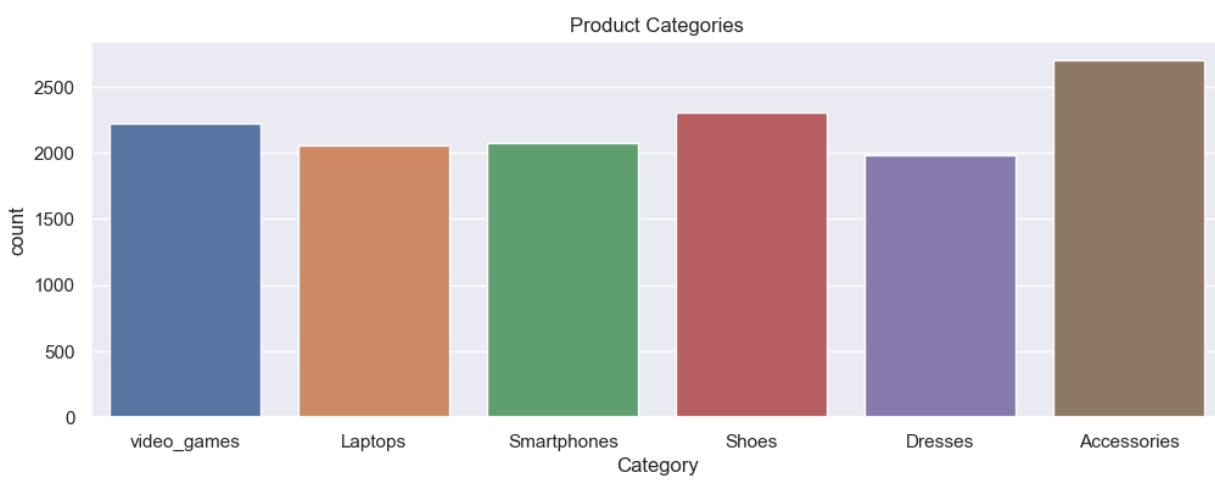
Customer Rating

In [30]:
```
# Rating distribution
plt.figure(figsize=(12,4))
sns.histplot(x=df['Rating'], edgecolor='black', bins=[1,2,3,4,5,6])
plt.title('Customer Rating Distribution');
```

Insight:
Most customers rate products highly with high rating for 5 though there are significant rating 1 which represent negative view of products.

Product Category

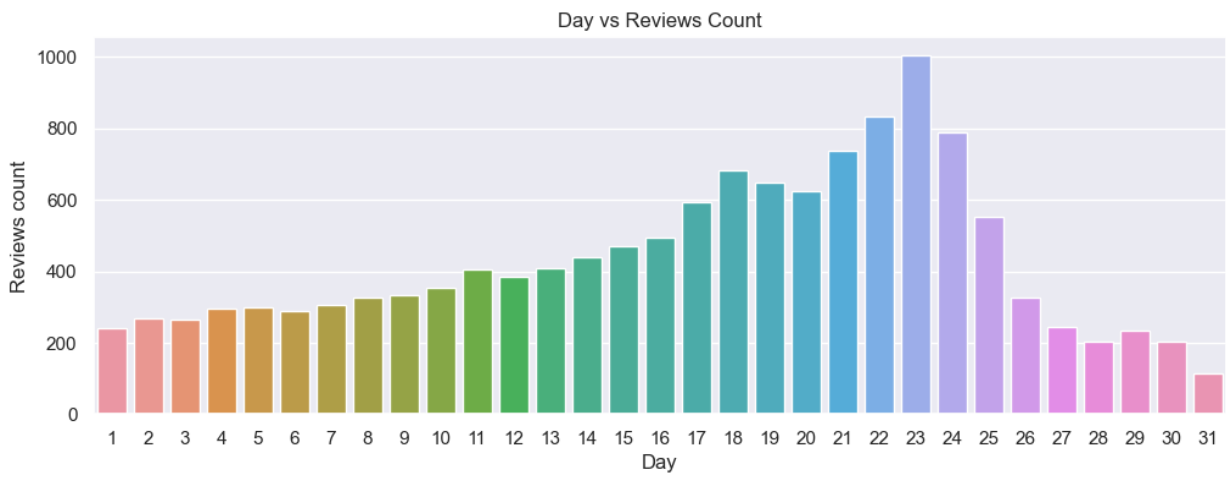
In [31]:
```
# Count of product categories
plt.figure(figsize=(12,4))
sns.countplot(data=df, x='Category')
plt.title('Product Categories');
```



Insight:
Accessories has most customer interaction, shoes and video_games, the remaining three categories of laptops, smartphones and dresses have similar customer interaction.

Day vs Review Count

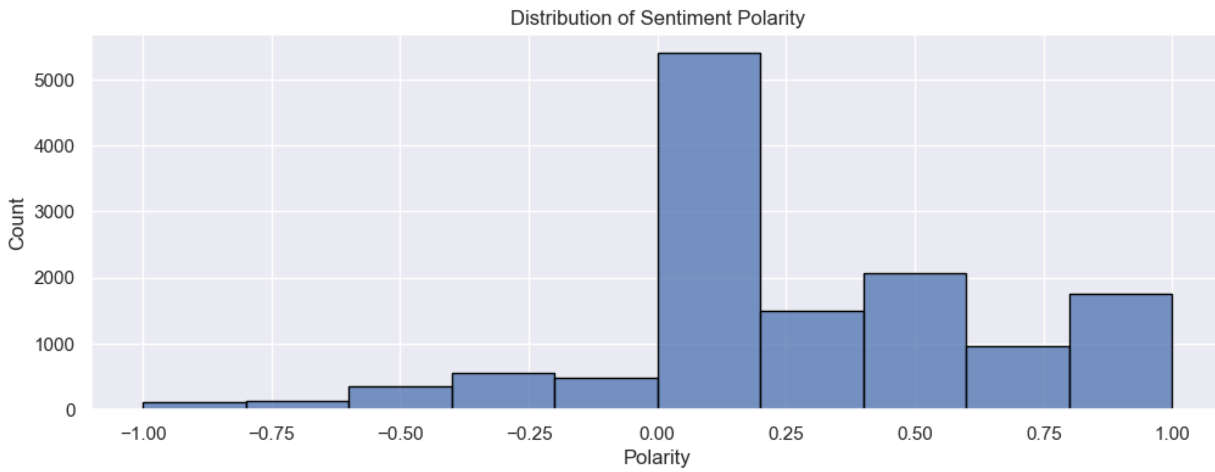
In [32]:
```
#Creating a dataframe
day=pd.DataFrame(df.groupby('Day')['Review'].count()).reset_index()
day['Day']=day['Day'].astype('int64')
day.sort_values(by=['Day'])

#Plotting the graph
plt.figure(figsize=(12,4))
sns.barplot(x="Day", y="Review", data=day)
plt.title('Day vs Reviews Count')
plt.xlabel('Day')
plt.ylabel('Reviews count');
```



Insight:
Customer reviews are high around the 17th to 24th days of the months but dwindle at the ending and beginning days of the month.

Sentiment Polarity Distribution

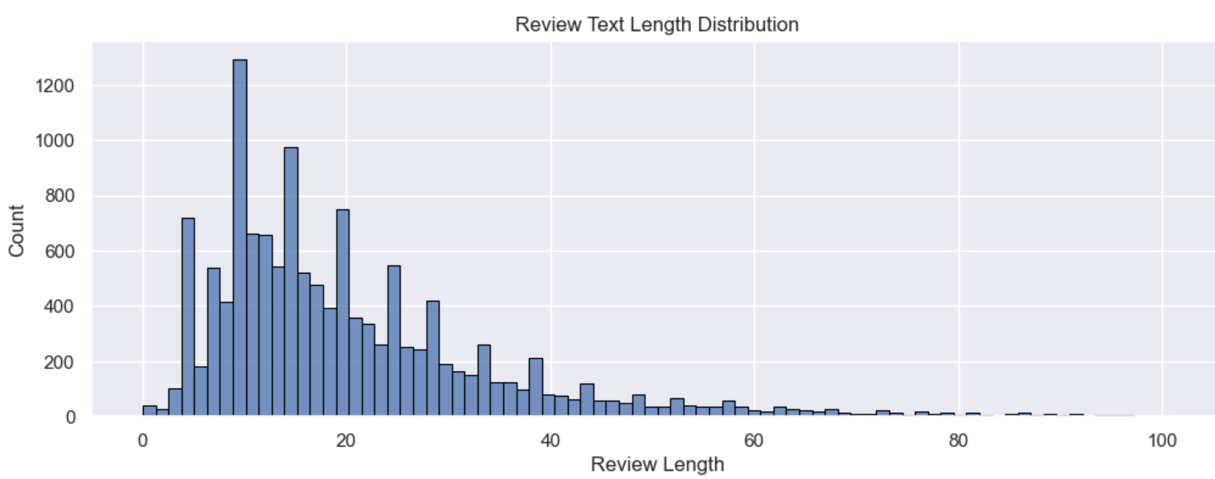
In [33]:
```
plt.figure(figsize=(12, 4))
sns.histplot(data=df, x='Polarity', bins=10, edgecolor='black')
plt.title('Distribution of Sentiment Polarity')
plt.xlabel('Polarity')
plt.ylabel('Count');
```



Insight:
The polarity represent sentiment of customers, and this chart butress the customers positive view of products with the polartiy been positively skewed.

Review Text Length

In [34]:
```
plt.figure(figsize=(12, 4))
sns.histplot(data=df, x='Review_len', edgecolor='black')
plt.title('Review Text Length Distribution')
plt.xlabel('Review Length')
plt.ylabel('Count');
```

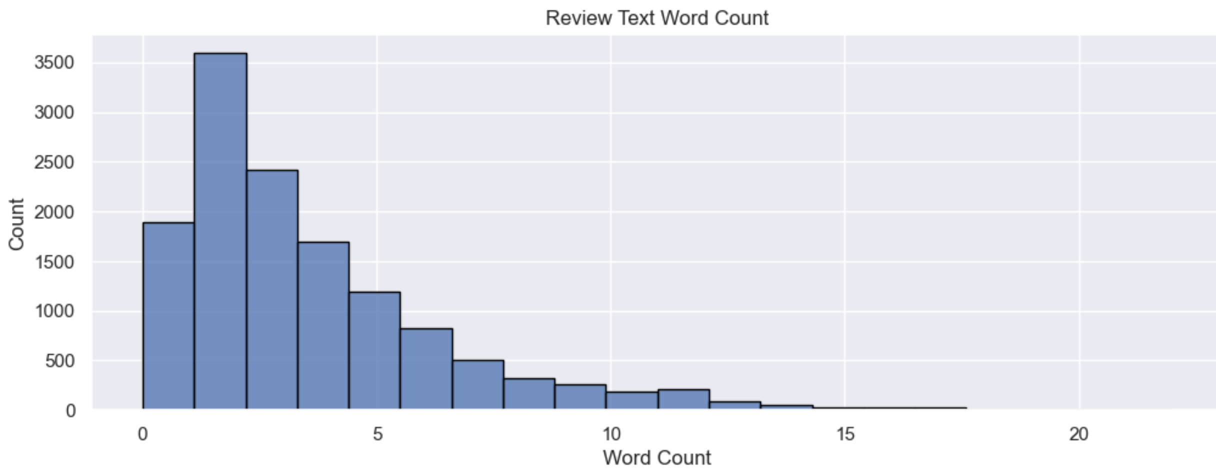


Insight:
Review text length is rightly skewed with customers usually review length usually falling between 0 and 60 letters count.

Review Text Word Count

In [35]:
```
plt.figure(figsize=(12, 4))
sns.histplot(data=df, x='Word_count', edgecolor='black', bins=20)
plt.title('Review Text Word Count')
```

```
plt.xlabel('Word Count')
plt.ylabel('Count');
```



Insight:

Review word count is rightly skewed with review words less than 20 among all customers.

N-gram Analysis

Here we analyze text in the Review column based on Sentiment

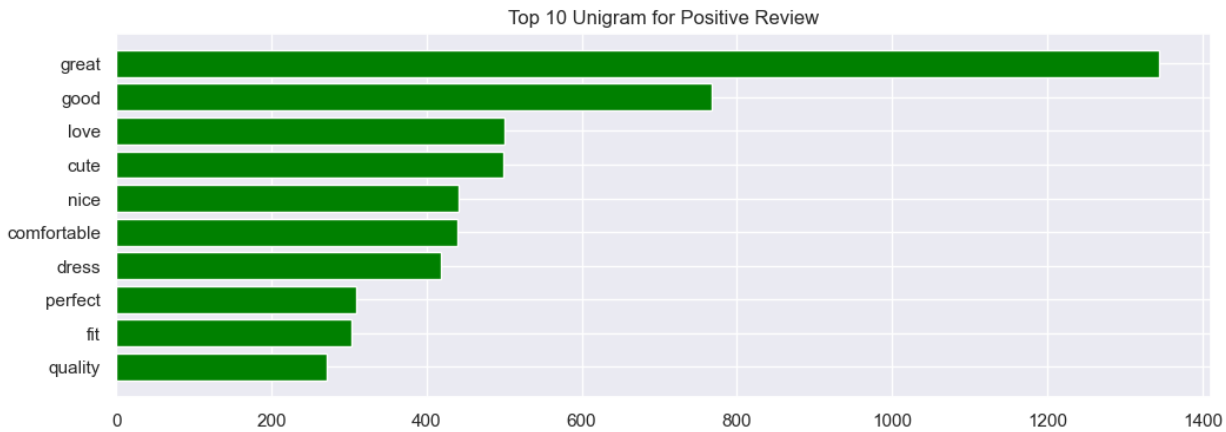
Unigram Analysis

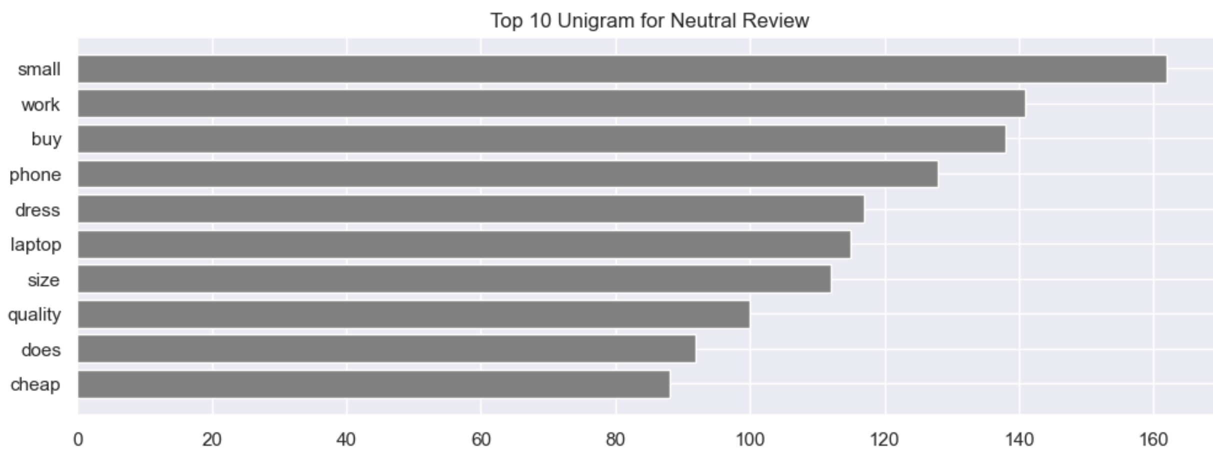
Unigrams are single words, and each word in a text is considered independently.

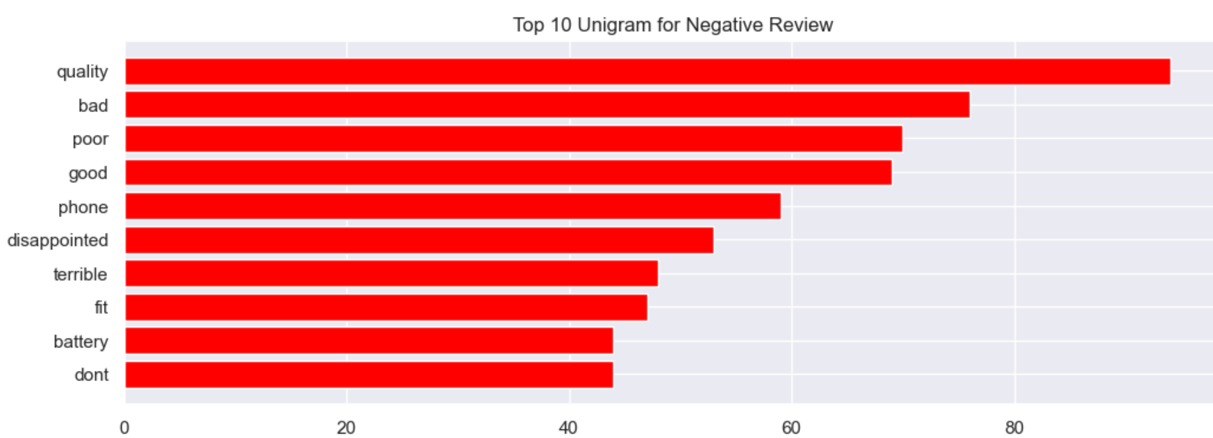
In [36]:
```
# Filter dataframe based on Sentiment labels
negative_reviews = df[df["Sentiment"] == "Negative"]
neutral_reviews = df[df["Sentiment"] == "Neutral"]
positive_reviews = df[df["Sentiment"] == "Positive"]
```

In [37]:
```
from sklearn.feature_extraction.text import CountVectorizer

def plot_ngrams(reviews, ngram_range, num_top_ngrams=10, color='blue', title='Top 10')
    ngram_vectorizer = CountVectorizer(ngram_range=ngram_range, stop_words='english')
    ngram_counts = ngram_vectorizer.fit_transform(reviews["Review"])

    ngram_names = ngram_vectorizer.get_feature_names_out()
    ngram_counts = ngram_counts.sum(axis=0).A1
    ngram_freq = dict(zip(ngram_names, ngram_counts))

    top_ngrams = Counter(ngram_freq)
    top_ngrams = top_ngrams.most_common(num_top_ngrams)

    ngram, count = zip(*top_ngrams)

    plt.figure(figsize=(12, 4))
    plt.barh(ngram[::-1], count[::-1], color=color)  # Reversed order and color custom
    plt.title(title)  # Customize the title
    plt.show()

# Customize colors and titles for each sentiment type
```

```
plot_ngrams(positive_reviews, (1, 1), num_top_ngrams=10, color='green', title='Top 10 
plot_ngrams(neutral_reviews, (1, 1), num_top_ngrams=10, color='grey', title='Top 10 Ur
plot_ngrams(negative_reviews, (1, 1), num_top_ngrams=10, color='red', title='Top 10 Ur
```







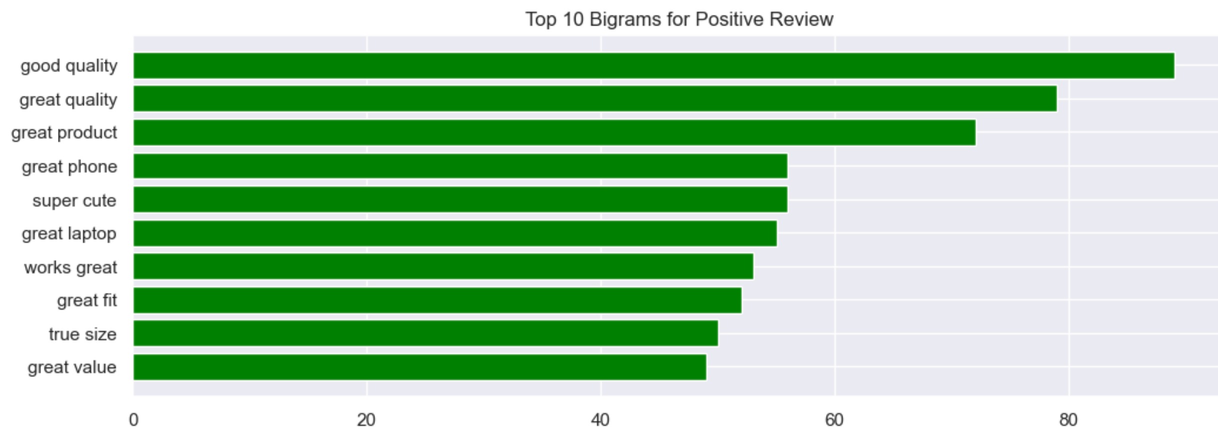
Bigram Analysis

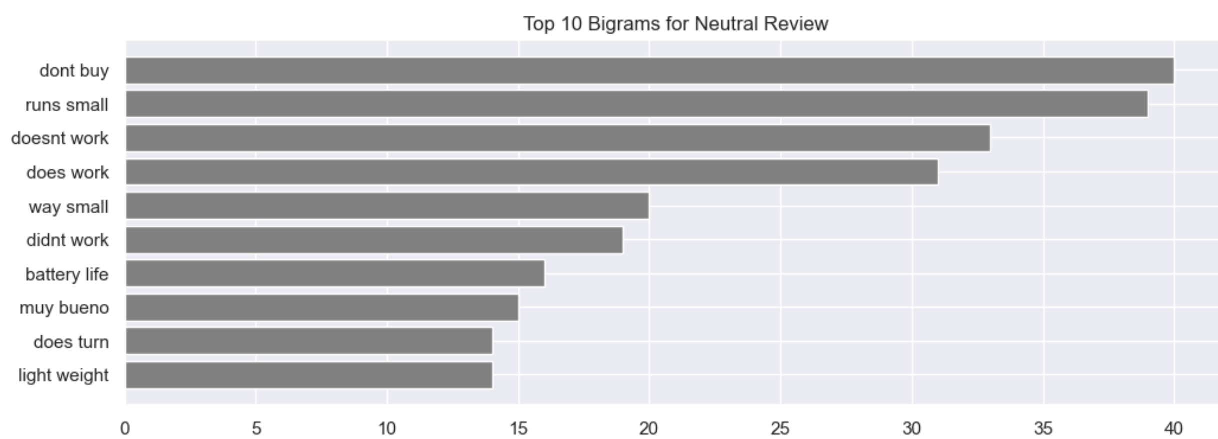
Bigrams consist of two adjacent words in the text. They capture word pairs that occur together.

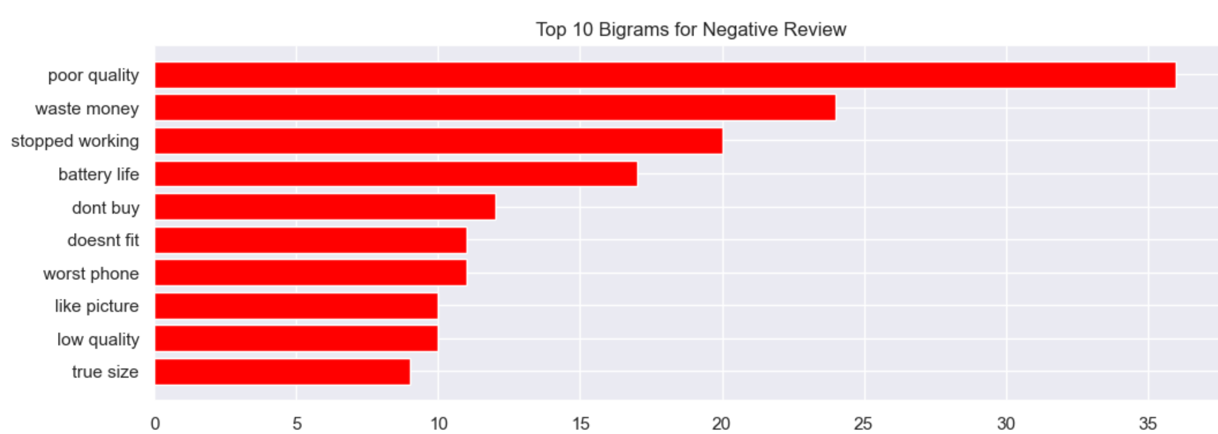
In [38]:

```
from sklearn.feature_extraction.text import CountVectorizer

def plot_ngrams(reviews, ngram_range, num_top_ngrams=10, color='blue', title='Top 10')
    ngram_vectorizer = CountVectorizer(ngram_range=ngram_range, stop_words='english')
    ngram_counts = ngram_vectorizer.fit_transform(reviews["Review"])
```

```
    ngram_names = ngram_vectorizer.get_feature_names_out()
    ngram_counts = ngram_counts.sum(axis=0).A1
    ngram_freq = dict(zip(ngram_names, ngram_counts))

    top_ngrams = Counter(ngram_freq)
    top_ngrams = top_ngrams.most_common(num_top_ngrams)

    ngram, count = zip(*top_ngrams)

    plt.figure(figsize=(12, 4))
    plt.barh(ngram[::-1], count[::-1], color=color)  # Reversed order and color custom
    plt.title(title)  # Customize the title
    plt.show()

# Customize colors and titles for each sentiment type
plot_ngrams(positive_reviews, (2, 2), num_top_ngrams=10, color='green', title='Top 10
plot_ngrams(neutral_reviews, (2, 2), num_top_ngrams=10, color='grey', title='Top 10 Bi
plot_ngrams(negative_reviews, (2, 2), num_top_ngrams=10, color='red', title='Top 10 Bi
```





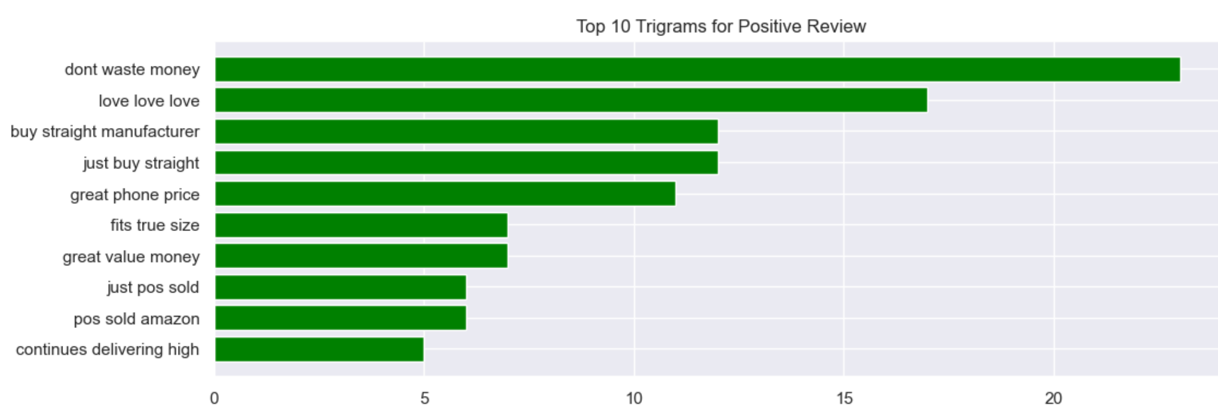


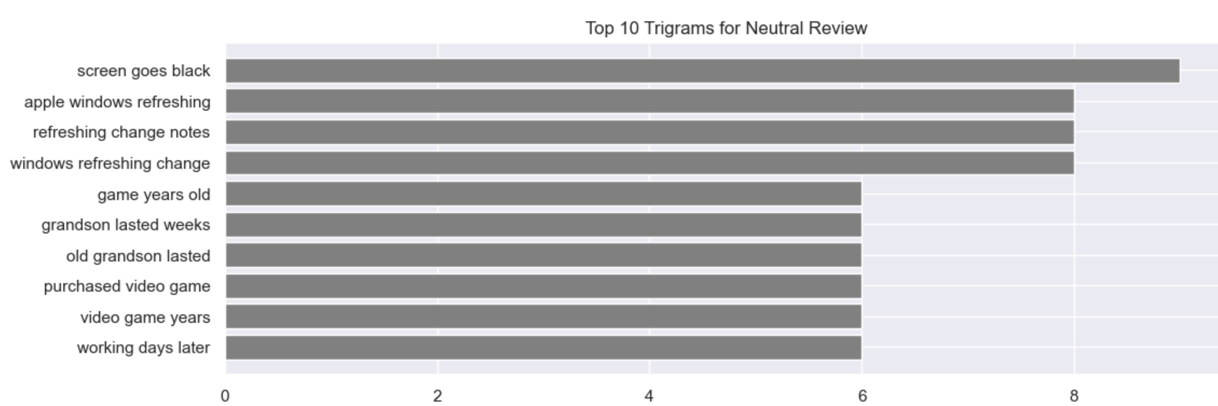
Trigram Analysis

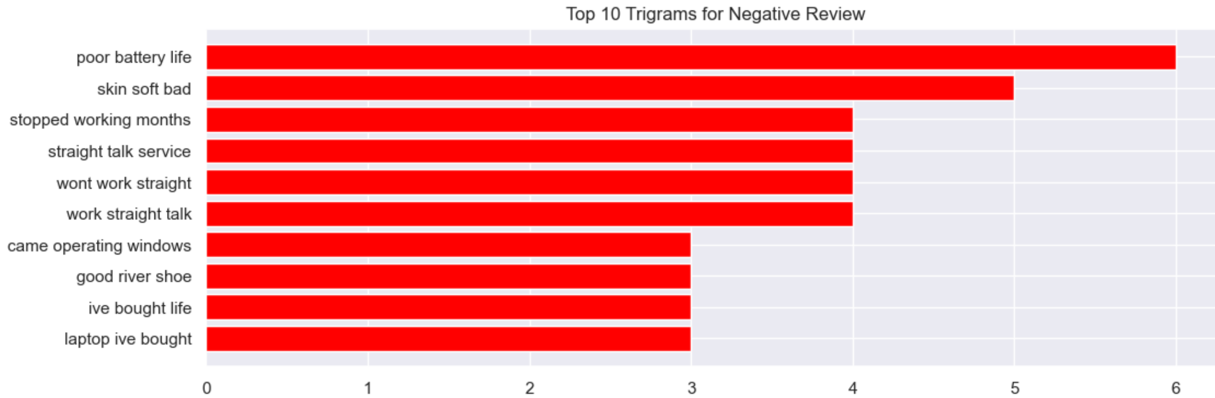
Trigrams consist of three adjacent words in the text. They capture triplets of words that often occur together.

In [39]:

```
from sklearn.feature_extraction.text import CountVectorizer

def plot_ngrams(reviews, ngram_range, num_top_ngrams=10, color='blue', title='Top 10')
    ngram_vectorizer = CountVectorizer(ngram_range=ngram_range, stop_words='english')
    ngram_counts = ngram_vectorizer.fit_transform(reviews["Review"])

    ngram_names = ngram_vectorizer.get_feature_names_out()
    ngram_counts = ngram_counts.sum(axis=0).A1
    ngram_freq = dict(zip(ngram_names, ngram_counts))

    top_ngrams = Counter(ngram_freq)
    top_ngrams = top_ngrams.most_common(num_top_ngrams)

    ngram, count = zip(*top_ngrams)

    plt.figure(figsize=(12, 4))
    plt.barh(ngram[::-1], count[::-1], color=color)  # Reversed order and color custom
    plt.title(title)  # Customize the title
    plt.show()

# Customize colors and titles for each sentiment type
plot_ngrams(positive_reviews, (3, 3), num_top_ngrams=10, color='green', title='Top 10
plot_ngrams(neutral_reviews, (3, 3), num_top_ngrams=10, color='grey', title='Top 10 Tr
plot_ngrams(negative_reviews, (3, 3), num_top_ngrams=10, color='red', title='Top 10 Tr
```







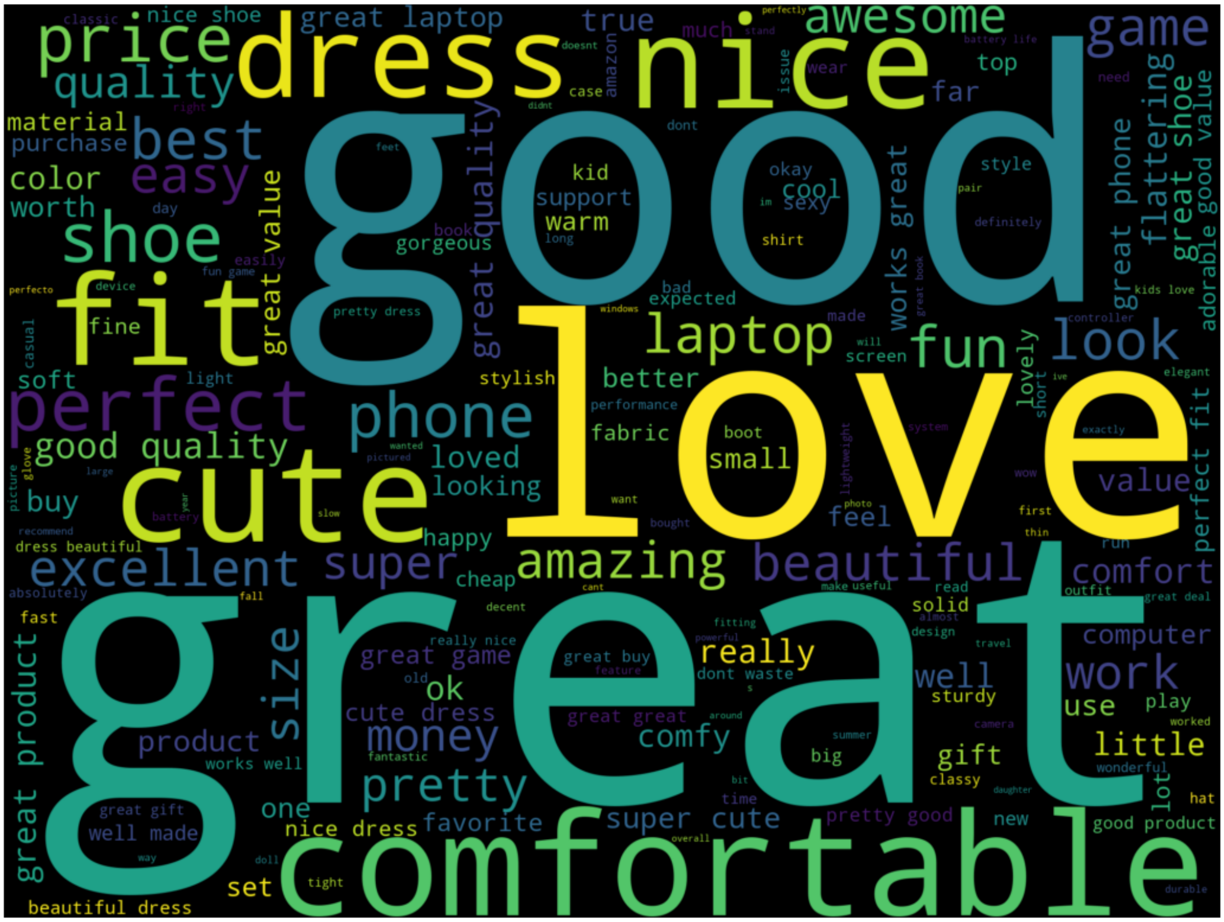
Wordcloud Analysis

Here we visualize the text in customer reviews per sentiments. Most frequent words in review are displayed, with the size of each word in the word cloud proportional to its frequency.

In [40]:
```
# Create text data for each sentiment category
positive_text = " ".join(positive_reviews["Review"])
neutral_text = " ".join(neutral_reviews["Review"])
negative_text = " ".join(negative_reviews["Review"])
```

Wordcloud - Positive Review

In [41]:
```
# Create and display word cloud for positive sentiment
wordcloud = WordCloud(width=2000, height=1500, background_color='black').generate(posi
plt.figure(figsize=(15, 10))
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis("off")
plt.show()
```



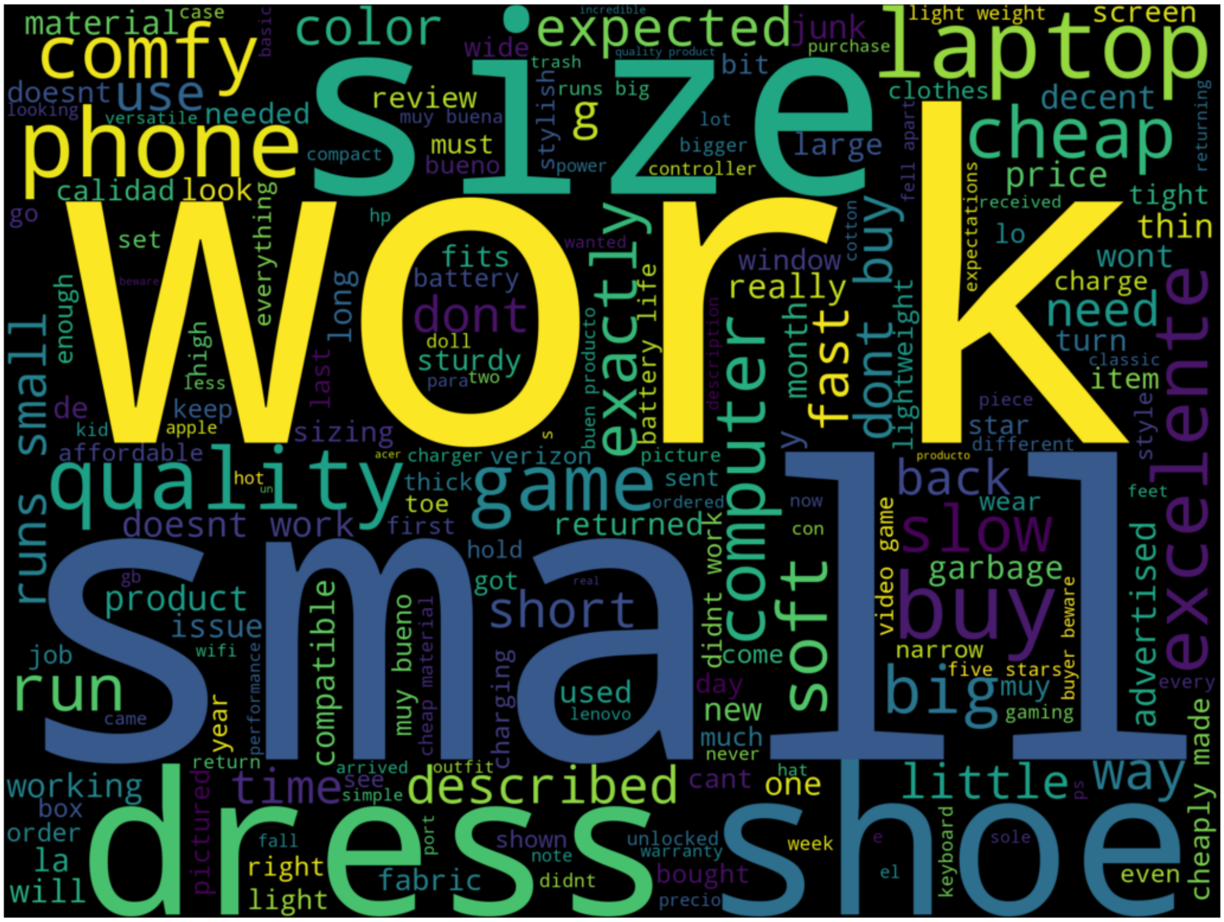
In [ ]:

```

```

Wordcloud - Neutral Review

In [42]:

```
# Create and display word cloud for neutral sentiment
wordcloud = WordCloud(width=2000, height=1500, background_color='black').generate(neut
plt.figure(figsize=(15, 10))
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis("off")
plt.show()
```

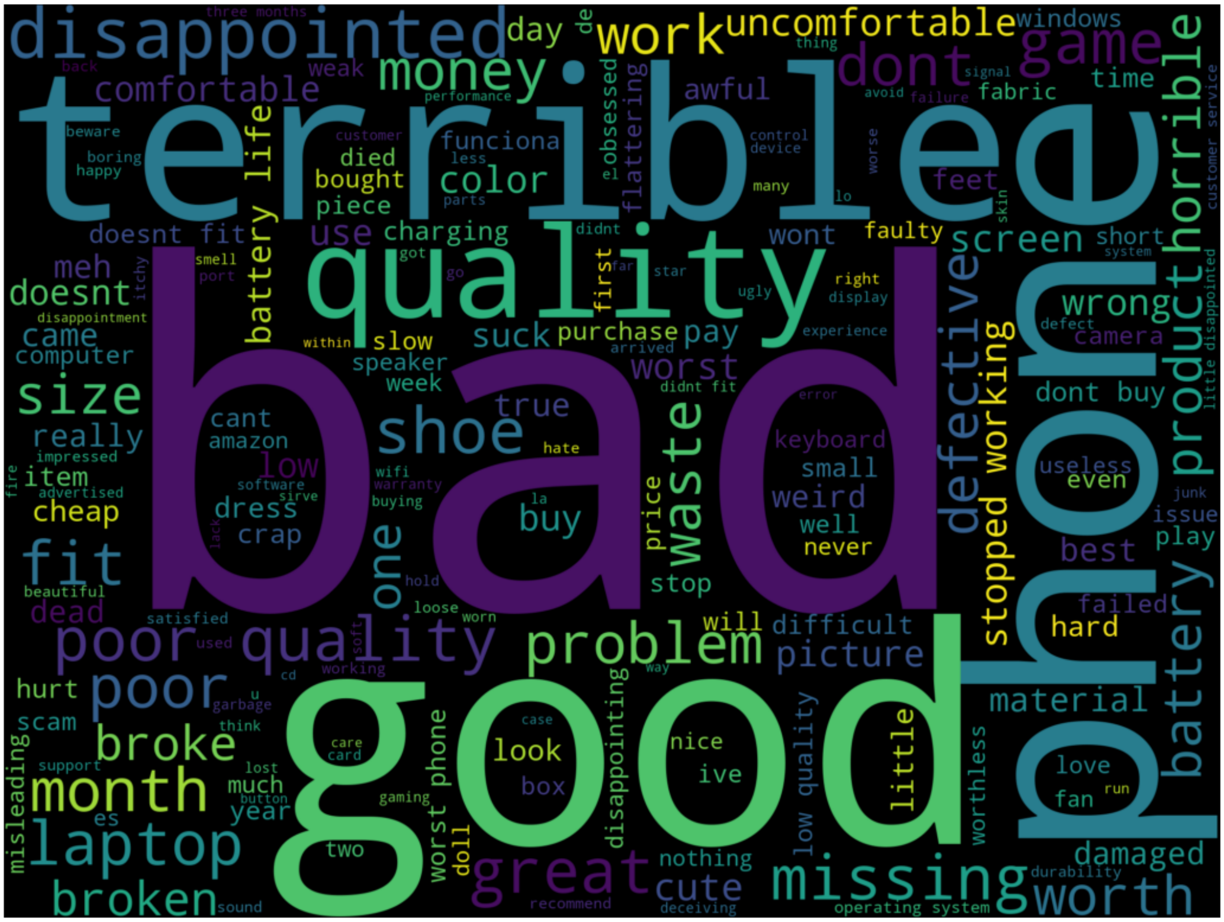


In [ ]:

Wordcloud - Negative Review

In [43]:

```python
# Create and display word cloud for neutral sentiment
wordcloud = WordCloud(width=2000, height=1500, background_color='black').generate(nega
plt.figure(figsize=(15, 10))
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis("off")
plt.show()
```



In [ ]:

4. Features Extraction for Model Building

Lemmatization Reviews

Lemmatization is the process of reducing words to their base or dictionary form (lemma). It aims to group together words with the same meaning.

Example:

- Lemmatization of the word "running" results in "run."
- Lemmatization of "better" gives "good," and "greatest" becomes "great."

In [44]:

```
# Extracting 'reviews' for preprocessing
df = df.copy()
text = df[['Review']].reset_index(drop=True)
text[100:103]
```

Out[44]:

	Review
100	a great format to get folks interested in game...
101	choice of entertainment
102	outdated

In [45]:

```
stop_words= ['yourselves', 'between', 'whom', 'itself', 'is', "she's", 'up', 'herself'
             'we', 'he', 'my', "you've", 'having', 'in', 'both', 'for', 'themselves',
             'and', 'an', 'during', 'their', 'can', 'yourself', 'she', 'until', 'so',
             'what', 'while', 'have', 're', 'more', 'only', "needn't", 'when', 'just',
             'very', 'should', 'any', 'y', 'isn', 'who',  'a', 'they', 'to', 'too', "s
             'into', 'yours', "it's", 'do', 'against', 'on',  'now', 'her', 've', 'd',
             'about', 'further', "that'll", "you'd", 'you', 'as', 'how', 'been', 'the'
             'his', 'himself', 'ourselves',  'was', 'through', 'out', 'below', 'own',
             'me', 'why', 'once',  'him', 'than', 'be', 'most', "you'll", 'same', 'som
             'at', 'after', 'its', 'which', 'there','our', 'this', 'hers', 'being', 'c
             'over','again', 'where', 'those', 'then', "you're", 'i', 'because', 'does
```

In [46]:

```
# Initialize the Lemmatizatizer
wn = WordNetLemmatizer()

corpus = []
for i in range(0, len(text)):
    review = re.sub('[^a-zA-Z]', ' ', text['Review'][i])
    review = review.split()

    review = [wn.lemmatize(word) for word in review if not word in (stop_words)]
    review = ' '.join(review)
    corpus.append(review)
```

In [47]:

```
corpus[100]
```

Out[47]:

```
'great format get folk interested game history'
```

Encoding Review text using Bag of Words (BoW)

The Bag of Words (BoW) method is a text analysis technique used to represent text data. It treats documents as an unordered collection of words and their frequencies, creating a numerical vector for each document. This approach is fundamental in Natural Language Processing and text analysis.

In BoW, text is tokenized, and a vocabulary of unique words is built. Each document's word frequency is counted and converted into a numerical format. The resulting matrix represents documents and their word frequencies. BoW simplifies text data for machine learning but lacks word order and context information.

In [48]:

```
# Creation of bag of words for Review
vectorizer = CountVectorizer()
X = vectorizer.fit_transform(corpus).toarray()
```

In [49]:

```
X.shape
```

Out[49]: (13359, 4538)

In [50]:
```
X
```

Out[50]:
```
array([[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]], dtype=int64)
```

Encoding target (sentiment) label

In [51]:
```
# Initialize label encoder
encoder = LabelEncoder()

# Use label encoder to transform sentiment
df['Target'] = encoder.fit_transform(df['Sentiment'])
df['Target'].unique()
```

Out[51]:
```
array([2, 1, 0])
```

In [52]:
```
df['Target'].value_counts()
```

Out[52]:
```
2    7119
1    4614
0    1626
Name: Target, dtype: int64
```

In [53]:
```
y = df['Target']
```

In [54]:
```
y.shape
```

Out[54]:
```
(13359,)
```

Handling Imbalance Target Feature - SMOTE

SMOTE, which stands for Synthetic Minority Over-sampling Technique, is a technique used in machine learning to address the class imbalance problem in a dataset. As in this case, where there is significant "positive" sentiment making majority class, while "neutral" and "negative" classes are the minority.

It works by doing the following: 1) SMOTE identify the minority class instances and selects k-nearest neighbors from the same class. 2) SMOTE generates synthetic examples for each instance in the minority class by creating convex combinations of the feature vectors of the instance and its k-nearest neighbors. These synthetic examples are then added to the dataset. 3) The dataset is now more balanced to train machine learning models without the bias introduced by the class imbalance.

In [55]:
```python
# Instantiate SMOTE
smote = SMOTE(sampling_strategy='auto', random_state=42)

# Resample your dataset
X_resampled, y_resampled = smote.fit_resample(X, y)
```

In [56]:
```python
# Shape of Original and Resampled Target (y) label
print(f'Original dataset shape : {Counter(y)}')
print(f'Resampled dataset shape: {Counter(y_resampled)}')
```

```
Original dataset shape : Counter({2: 7119, 1: 4614, 0: 1626})
Resampled dataset shape: Counter({2: 7119, 1: 7119, 0: 7119})
```

Splitting of dataset (75:25)

In [57]:
```python
# Splitting dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X_resampled, y_resampled, test_siz
```

In [ ]:
```python

```

5. Sentiment Model Building

Model Selection

Using cross validation, the best performing algorithm is selected for the sentiment model building.

In [58]:
```python
# Creating the objects
rf_cv = RandomForestClassifier(random_state=0)
knn_cv = KNeighborsClassifier()
logreg_cv = LogisticRegression(random_state=0)
nb_cv = MultinomialNB()
cv_dict = {0: 'Random Forest', 1:'KNN', 2:'Logistic Regression', 3:'Naive Bayes'}
cv_models = [rf_cv, knn_cv, logreg_cv, nb_cv]

for i,model in enumerate(cv_models):
    print("{} Test Accuracy: {}".format(cv_dict[i], cross_val_score(model, X, y, cv=5,
```

```
Random Forest Test Accuracy: 0.9321805004741547
KNN Test Accuracy: 0.8587467240733808
Logistic Regression Test Accuracy: 0.9244706674259119
Naive Bayes Test Accuracy: 0.8256593327758559
```

From the above result, Random Forest Classifier performed best at an accuracy 93.2% on our dataset and therefore is selected for the sentiment model building.

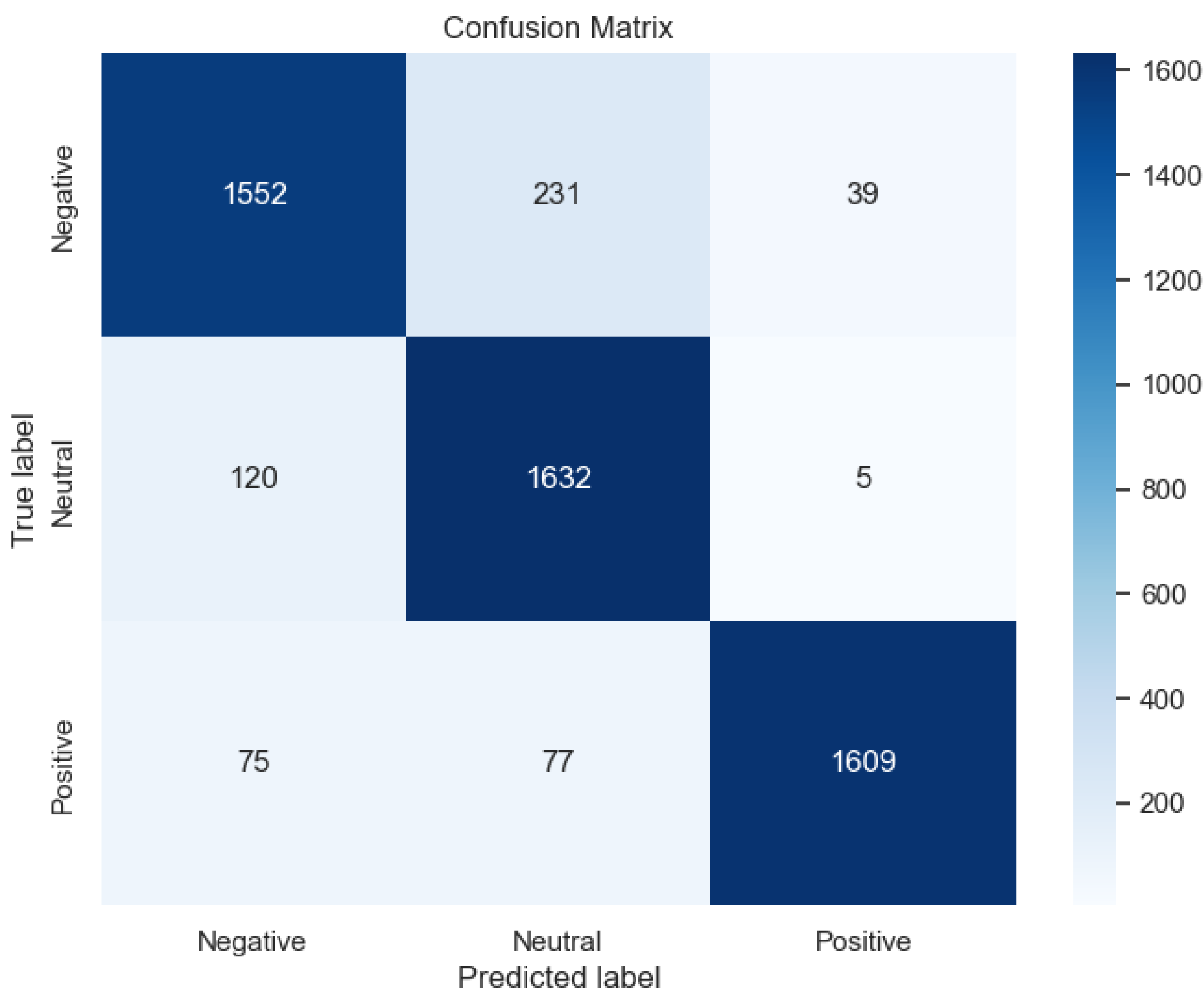
Sentiment Model Building - Random Forest Classifier

In [59]:
```
# Training model with the best parameters
model = RandomForestClassifier(random_state=0)
model.fit(X_train, y_train)
model_pred = model.predict(X_test)
print('Accuracy of random forest classifier on test set: {:.2f}'.format(model.score(X_
```

```
Accuracy of random forest classifier on test set: 0.90
```

Sentiment Model Evaluation

In [60]:
```
# Confusion matrix
cm = confusion_matrix(y_test, model_pred)

# Create a heatmap for the confusion matrix
plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=['Negative', 'Neutral',
plt.xlabel('Predicted label')
plt.ylabel('True label')
plt.title('Confusion Matrix');
```



The diagonal elements (1552 + 1632 + 1609) are the correctly predicted instances by the model and rest are incorrectly classified by the model.

In [61]:
```
print("Classification Report:\n",classification_report(y_test, model_pred))
```

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

           0       0.89      0.85      0.87      1822
           1       0.84      0.93      0.88      1757
           2       0.97      0.91      0.94      1761

    accuracy                           0.90      5340
   macro avg       0.90      0.90      0.90      5340
weighted avg       0.90      0.90      0.90      5340
```

Considering the F1-score, the model performs well in distinguishing positive sentiment (94%), moderately well in identifying neutral sentiment (88%), and negative sentiment (87%).

In [ ]:

6. Conclusion

In this project, we undertook a series of tasks, including data preprocessing and feature engineering, sentiment classification based on customer ratings, exploratory data analysis, addressing data imbalance using SMOTE, and the development of a sentiment classification model. The project yielded valuable insights, which can be summarized as follows:

Introduction:

- We conducted a project to understand customer sentiments on Amazon.com product reviews. Our goal was to uncover insights and improve customer experience.

Data Preprocessing and Feature Engineering:

- We cleaned the dataset, ensuring data quality.
- We created new features like sentiment polarity to gauge the emotional tone in reviews.

Understanding Sentiments:

- We analyzed customer reviews and identified three sentiment categories: positive, neutral, and negative.
- We explored the emotional tone of reviews, helping us understand customer feedback.

Review Characteristics:

- We looked into review length and word count, providing insights into customers' communication style.

Keywords and Phrases:

- We found that certain words and phrases strongly correlated with sentiments using n-gram analysis and word cloud visualization.

Balancing Data:

- We tackled data imbalance issues by applying a technique called SMOTE, improving the model's ability to learn from positive, neutral and negative sentiments.

Model Building and Performance:

- We developed a model to automatically classify sentiments in reviews.
- The model achieved a 90% accuracy rate, suggesting a good balance between precision and recall, which contributes to accurate predictions.

Key Takeaways:

- Our findings offer insights into customer feedback, which can be valuable for product improvements.
- Understanding customer sentiments is essential for enhancing customer satisfaction.

Conclusion:

- Our project equips businesses with tools to gain deeper insights from customer reviews, leading to better products and services.

In [ ]:

```

```