Sentiment Analysis

This is a notebook containing Sentiment Analysis Mini Project on Amazon Musical Instruments Reviews. I am interested in Natural Language Processing and that is my motivation to make this project. I think that sentiment analysis has a really powerful impacts in business developments because we can gain so many insights from here.

Libraries

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

NLP Text Libraries

```
import string
import re
import nltk
import nltk.corpus
nltk.download("punkt")
nltk.download("stopwords")
nltk.download("wordnet")
from nltk.stem import WordNetLemmatizer
```

```
[nltk_data] Downloading package punkt to /root/nltk_data...
[nltk_data]   Unzipping tokenizers/punkt.zip.
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Unzipping corpora/stopwords.zip.
[nltk_data] Downloading package wordnet to /root/nltk_data...
```

EDA Analysis

```
# Text Polarity
from textblob import TextBlob

# Text Vectorizer
from sklearn.feature_extraction.text import CountVectorizer

# Word Cloud
from wordcloud import WordCloud
```

Feature Engineering

```
# Label Encoding
from sklearn.preprocessing import LabelEncoder

# TF-IDF Vectorizer
from sklearn.feature_extraction.text import TfidfVectorizer

# Resampling
from imblearn.over_sampling import SMOTE
from collections import Counter

# Splitting Dataset
from sklearn.model_selection import train_test_split
```

Model Selection and Evaluation

```
# Model Building
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.naive_bayes import BernoulliNB
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import cross_val_score

# Hyperparameter Tuning
from sklearn.model_selection import GridSearchCV

# Model Metrics
from sklearn.metrics import confusion_matrix, accuracy_score, classification_report
```

The Dataset

The dataset that we will use is taken from Kaggle website and can be downloaded here:

Amazon Musical Instruments Reviews

There are two formats available of the dataset: JSON and CSV. We will use the CSV one in this project.

Overall, the dataset talks about the feedback received after the customers purchased musical instruments from Amazon.

Read The Dataset

```
dataset = pd.read_csv("/content/Instruments_Reviews.csv")
```

Shape of The Dataset

```
dataset.shape
```

```
(10261, 9)
```

From this, we can infer that the dataset consists of 10261 rows and 9 columns.

Data Preprocessing

Checking Null Values

```
dataset.isnull().sum()
```

```
reviewerID        0
asin              0
reviewerName     27
helpful           0
reviewText        7
overall           0
summary           0
unixReviewTime    0
reviewTime        0
dtype: int64
```

From above, there are two columns in the dataset with null values: reviewText and reviewerName. While the latter one is not really important, we should focus on the first column. We cannot remove these rows because the ratings and summary given from the customers will have some effects to our model later (although the number of missing rows is small). Because of it, we can fill the empty values with an empty string.

Filling Missing Values

```
dataset.reviewText.fillna(value = "", inplace = True)
```

Concatenate reviewText and summary Columns

```
dataset["reviews"] = dataset["reviewText"] + " " + dataset["summary"]
dataset.drop(columns = ["reviewText", "summary"], axis = 1, inplace = True)
```

Statistic Description of The Dataset

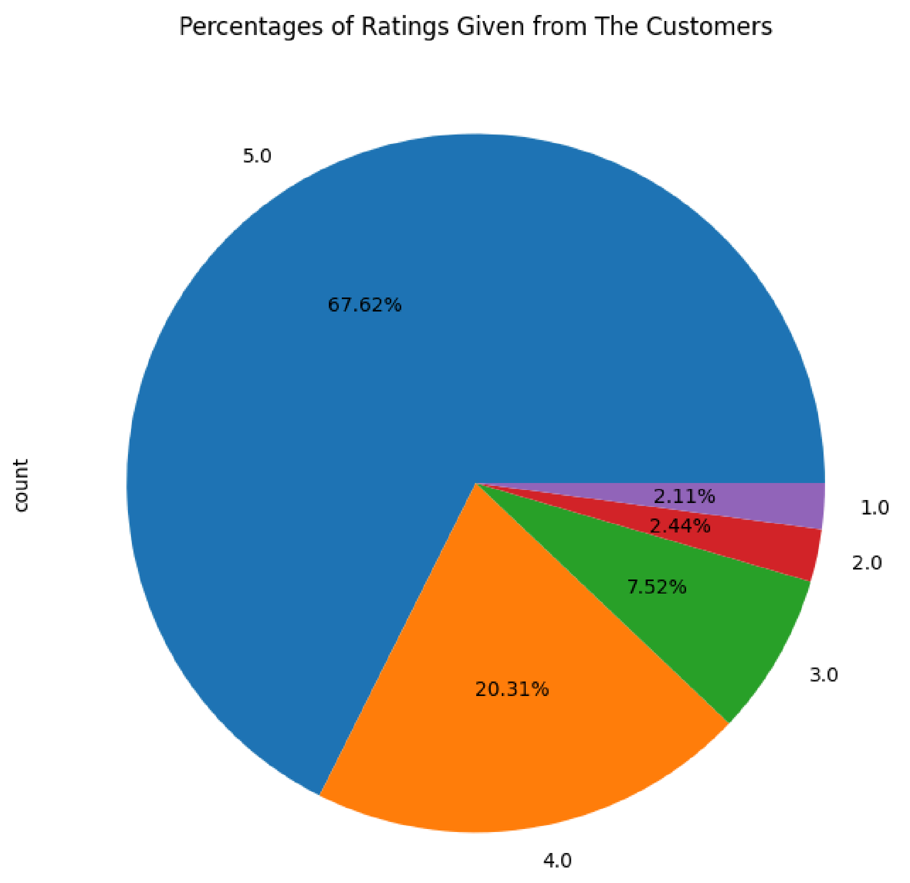
```
dataset.describe(include = "all")
```

	reviewerID	asin	reviewerName	helpful	overall	unixReviewTime	reviewTime	reviews
count	10261	10261	10234	10261	10261.000000	1.026100e+04	10261	10261
unique	1429	900	1397	269	NaN	NaN	1570	10261
top	ADH0O8UVJOT10	B003VWJ2K8	Amazon Customer	[0, 0]	NaN	NaN	01 22, 2013	Not much to write about here, but it does exac...
freq	42	163	66	6796	NaN	NaN	40	1
mean	NaN	NaN	NaN	NaN	4.488744	1.360606e+09	NaN	NaN
std	NaN	NaN	NaN	NaN	0.894642	3.779735e+07	NaN	NaN
min	NaN	NaN	NaN	NaN	1.000000	1.095466e+09	NaN	NaN
25%	NaN	NaN	NaN	NaN	4.000000	1.343434e+09	NaN	NaN
50%	NaN	NaN	NaN	NaN	5.000000	1.368490e+09	NaN	NaN
75%	NaN	NaN	NaN	NaN	5.000000	1.388966e+09	NaN	NaN
max	NaN	NaN	NaN	NaN	5.000000	1.405987e+09	NaN	NaN

From the description above, we know that the ratings given from the customers will have the range of [1, 5] as shown above. Also, the average rating given to musical instruments sold is 4.48. We can also see our new column reviews is there to concate both summary and reviewText.

Percentages of Ratings Given from The Customers

```
dataset.overall.value_counts().plot(kind = "pie", legend = False, autopct = "%1.2f%%", fontsize = 10, figsize=(8,8))
plt.title("Percentages of Ratings Given from The Customers", loc = "center")
plt.show()
```



From the chart above, the majority of musical instruments sold on Amazon have perfect ratings of 5.0, meaning the condition of the products are good. If we were to denote that ratings above 3 are positive, ratings equal to 3 are neutral, and ratings under 3 are negative, we know that the number of negative reviews given in the dataset are relatively small. This might affect our model later.

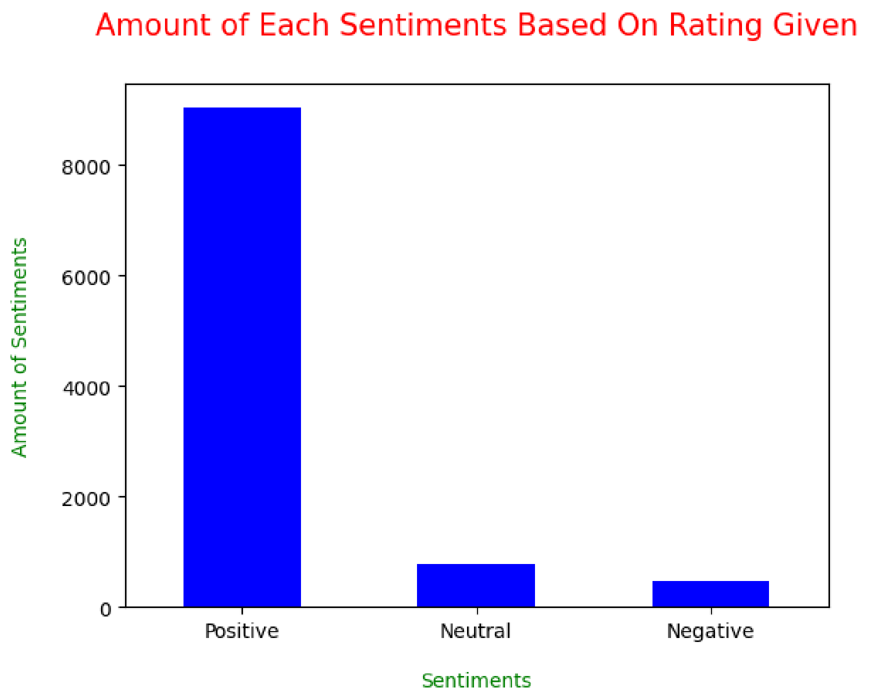
Labelling Products Based On Ratings Given

Our dataset does not have any dependent variable, or in other words we haven't had any prediction target yet. We will categorize each sentiment according to ratings given for each row based on the explanation before: Positive Label for products with rating bigger than 3.0, Neutral Label for products with rating equal to 3.0, else Negative Label.

```
def Labelling(Rows):
  if(Rows["overall"] > 3.0):
    Label = "Positive"
  elif(Rows["overall"] < 3.0):
    Label = "Negative"
  else:
    Label = "Neutral"
  return Label
```

```
dataset["sentiment"] = dataset.apply(Labelling, axis = 1)
```

```
dataset["sentiment"].value_counts().plot(kind = "bar", color = "blue")
plt.title("Amount of Each Sentiments Based On Rating Given", loc = "center", fontsize = 15, color = "red", pad = 25)
plt.xlabel("Sentiments", color = "green", fontsize = 10, labelpad = 15)
plt.xticks(rotation = 0)
plt.ylabel("Amount of Sentiments", color = "green", fontsize = 10, labelpad = 15)
plt.show()
```



In this part we can actually change the labels into numeric values but for the sake of experiments we will do it later. Also, notice that from the graph we can know that most of our data contains positive sentiments, which is true from the exploration before.

Text Preprocessing

Text Cleaning

```
def Text_Cleaning(Text):
  # Lowercase the texts
  Text = Text.lower()

  # Cleaning punctuations in the text
  punc = str.maketrans(string.punctuation, ' '*len(string.punctuation))
  Text = Text.translate(punc)

  # Removing numbers in the text
  Text = re.sub(r'\d+', '', Text)

  # Remove possible links
  Text = re.sub('https?://\S+|www\.\S+', '', Text)

  # Deleting newlines
  Text = re.sub('\n', '', Text)

  return Text
```

Text Processing

```
# Stopwords
Stopwords = set(nltk.corpus.stopwords.words("english")) - set(["not"])

def Text_Processing(Text):
  Processed_Text = list()
  Lemmatizer = WordNetLemmatizer()

  # Tokens of Words
  Tokens = nltk.word_tokenize(Text)

  # Removing Stopwords and Lemmatizing Words
  # To reduce noises in our dataset, also to keep it simple and still
  # powerful, we will only omit the word `not` from the list of stopwords

  for word in Tokens:
    if word not in Stopwords:
      Processed_Text.append(Lemmatizer.lemmatize(word))

  return(" ".join(Processed_Text))
```

Applying The Functions

```
dataset["reviews"] = dataset["reviews"].apply(lambda Text: Text_Cleaning(Text))
dataset["reviews"] = dataset["reviews"].apply(lambda Text: Text_Processing(Text))
```

Exploratory Data Analysis

Overview of The Dataset

```
dataset.head(n = 10)
```

	reviewerID	asin	reviewerName	helpful	overall	unixReviewTime	reviewTime	reviews	sentiment
0	A2IBPI20UZIR0U	1384719342	cassandra tu "Yeah, well, that's just like, u...	[0, 0]	5.0	1393545600	02 28, 2014	not much write exactly supposed filter pop sou...	Positive
1	A14VAT5EAX3D9S	1384719342	Jake	[13, 14]	5.0	1363392000	03 16, 2013	product exactly quite affordable not realized ...	Positive
2	A195EZSQDW3E21	1384719342	Rick Bennette "Rick Bennette"	[1, 1]	5.0	1377648000	08 28, 2013	primary job device block breath would otherwis...	Positive
3	A2C00NNG1ZQQG2	1384719342	RustyBill "Sunday Rocker"	[0, 0]	5.0	1392336000	02 14, 2014	nice windscreen protects mxl mic prevents pop ...	Positive
4	A94QU4C90B1AX	1384719342	SEAN MASLANKA	[0, 0]	5.0	1392940800	02 21, 2014	pop filter great look performs like studio fil...	Positive
5	A2A039TZMZHH9Y	B00004Y2UT	Bill Lewey "blewey"	[0, 0]	5.0	1356048000	12 21, 2012	good bought another one love heavy cord gold c...	Positive
6	A1UPZM995ZAH90	B00004Y2UT	Brian	[0, 0]	5.0	1390089600	01 19, 2014	used monster cable year good reason lifetime w...	Positive
7	AJNFQI3YR6XJ5	B00004Y2UT	Fender Guy "Rick"	[0, 0]	3.0	1353024000	11 16, 2012	use cable run output pedal chain input fender ...	Neutral
8	A3M1PLEYNDEYO8	B00004Y2UT	G. Thomas "Tom"	[0, 0]	5.0	1215302400	07 6, 2008	perfect epiphone sheraton ii monster cable wel...	Positive
9	AMNTZU1YQN1TH	B00004Y2UT	Kurt Robair	[0, 0]	5.0	1389139200	01 8, 2014	monster make best cable lifetime warranty does...	Positive

Next steps: Generate code with dataset | View recommended plots | New interactive sheet

With the overview above, we know that for sentiment analysis that we will do, reviews is important to our model and we should use this aspect as our feature. By using this feature, we will need to predict what our sentiment will be classified into.

About Other Features

```
dataset.describe(include = "all")
```

	reviewerID	asin	reviewerName	helpful	overall	unixReviewTime	reviewTime	reviews	sentiment
count	10261	10261	10234	10261	10261.000000	1.026100e+04	10261	10261	10261
unique	1429	900	1397	269	NaN	NaN	1570	10254	3
top	ADH0O8UVJOT10	B003VWJ2K8	Amazon Customer	[0, 0]	NaN	NaN	01 22, 2013	good string five star	Positive
freq	42	163	66	6796	NaN	NaN	40	3	9022
mean	NaN	NaN	NaN	NaN	4.488744	1.360606e+09	NaN	NaN	NaN
std	NaN	NaN	NaN	NaN	0.894642	3.779735e+07	NaN	NaN	NaN
min	NaN	NaN	NaN	NaN	1.000000	1.095466e+09	NaN	NaN	NaN
25%	NaN	NaN	NaN	NaN	4.000000	1.343434e+09	NaN	NaN	NaN
50%	NaN	NaN	NaN	NaN	5.000000	1.368490e+09	NaN	NaN	NaN
75%	NaN	NaN	NaN	NaN	5.000000	1.388966e+09	NaN	NaN	NaN
max	NaN	NaN	NaN	NaN	5.000000	1.405987e+09	NaN	NaN	NaN

Now, we will go back to statistic description of our dataset. Intuitively, the other features from our dataset does not really have any impact in determining our sentiment later. We might use the helpful part in our model, but as we can see from the description above, the top values of it is [0,0], which means that most users do not really take their votes in it. Because of it, we can also decide that we don't really need it in our model.

Polarity, Review Length, and Word Counts

To justify our analysis before, we will dive further into the dataset a bit more from the polarity of the texts, also from the words used in the reviews. We will generate some new columns in our dataset and visualize it.

Polarity

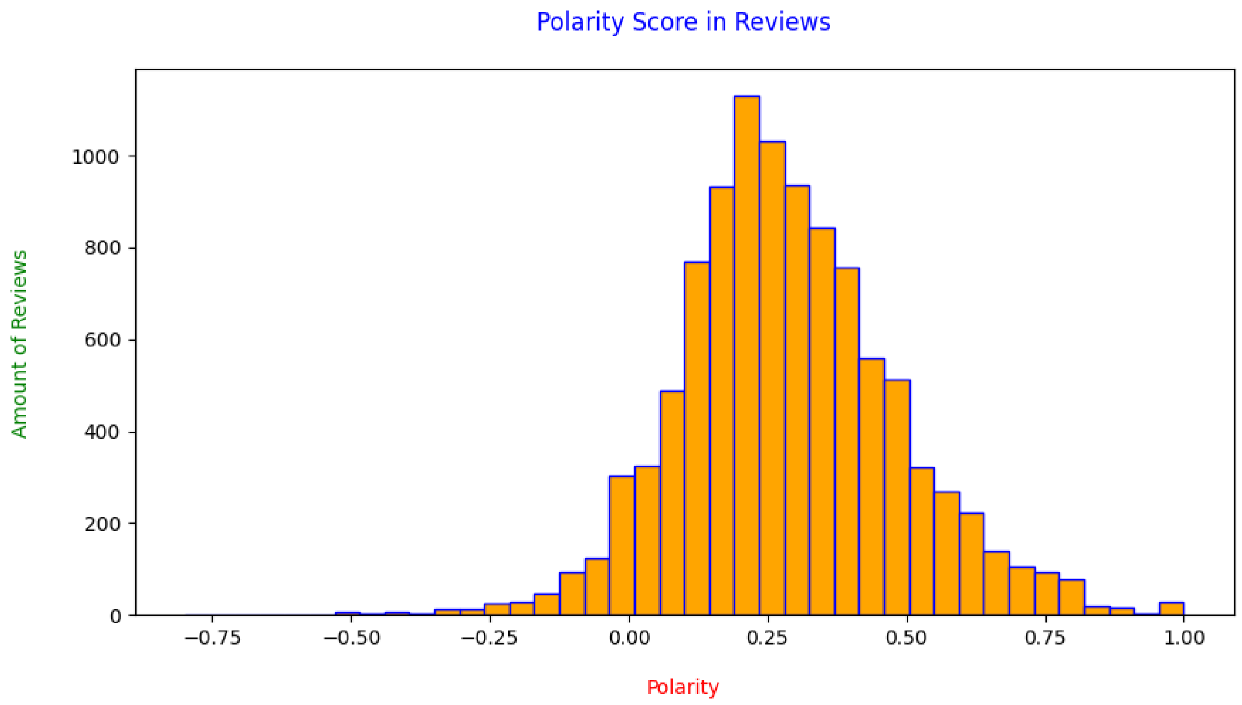
```
pip install textblob
```

```
Requirement already satisfied: textblob in /usr/local/lib/python3.10/dist-packages (0.17.1)
Requirement already satisfied: nltk>=3.1 in /usr/local/lib/python3.10/dist-packages (from textblob) (3.8.1)
Requirement already satisfied: click in /usr/local/lib/python3.10/dist-packages (from nltk>=3.1->textblob) (8.1.7)
Requirement already satisfied: joblib in /usr/local/lib/python3.10/dist-packages (from nltk>=3.1->textblob) (1.4.2)
Requirement already satisfied: regex>=2021.8.3 in /usr/local/lib/python3.10/dist-packages (from nltk>=3.1->textblob) (2024.5.15)
Requirement already satisfied: tqdm in /usr/local/lib/python3.10/dist-packages (from nltk>=3.1->textblob) (4.66.4)
```

```
from textblob import TextBlob
```

```
dataset["polarity"] = dataset["reviews"].map(lambda Text: TextBlob(Text).sentiment.polarity)
```

```
dataset["polarity"].plot(kind = "hist", bins = 40, edgecolor = "blue", linewidth = 1, color = "orange", figsize = (10,5))
plt.title("Polarity Score in Reviews", color = "blue", pad = 20)
plt.xlabel("Polarity", labelpad = 15, color = "red")
plt.ylabel("Amount of Reviews", labelpad = 20, color = "green")

plt.show()
```



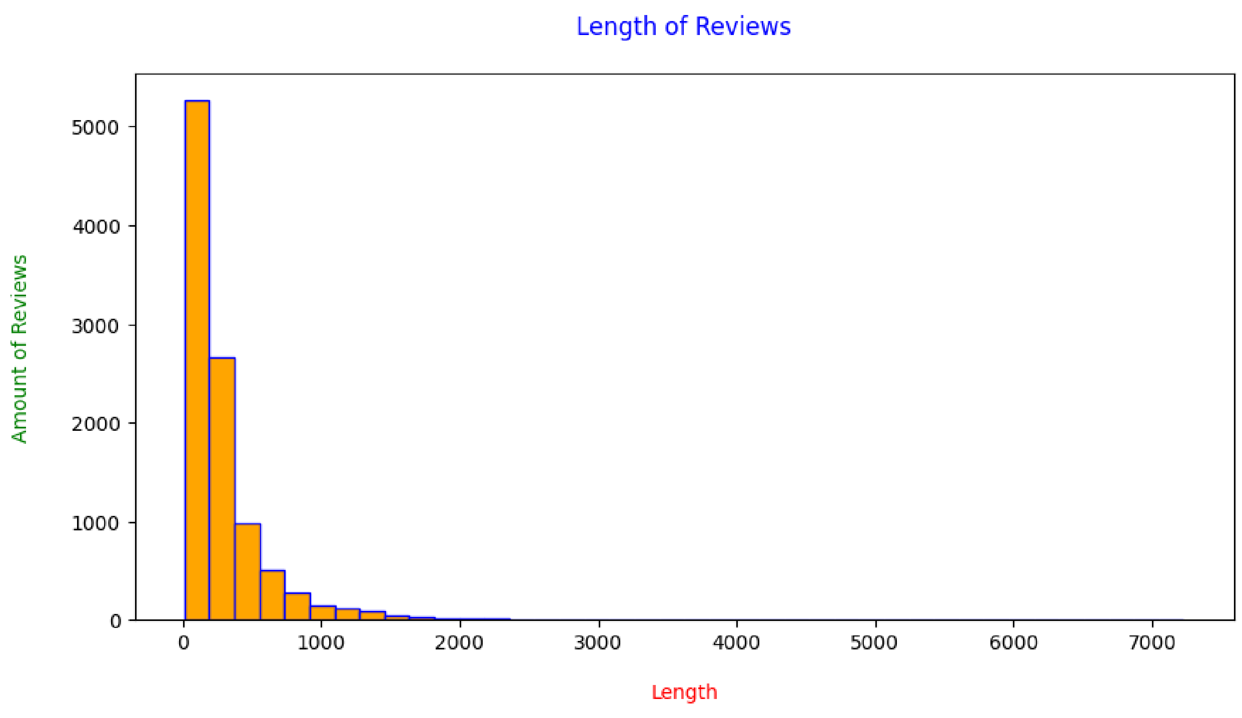
Reviews with negative polarity will be in range of [-1, 0), neutral ones will be 0.0, and positive reviews will have the range of (0, 1].

From the histogram above, we know that most of the reviews are distributed in positive sentiments, meaning that what we extracted from our analysis before is true. Statistically, this histogram shows that our data is normally distributed, but not with standard distribution. In conclusion, we know for sure that our analysis about the amount of sentiments from the reviews is correct and corresponds to the histogram above.

Review Length

```
dataset["length"] = dataset["reviews"].astype(str).apply(len)
```

```
dataset["length"].plot(kind = "hist", bins = 40, edgecolor = "blue", linewidth = 1, color = "orange", figsize = (10,5))
plt.title("Length of Reviews", color = "blue", pad = 20)
plt.xlabel("Length", labelpad = 15, color = "red")
plt.ylabel("Amount of Reviews", labelpad = 20, color = "green")

plt.show()
```

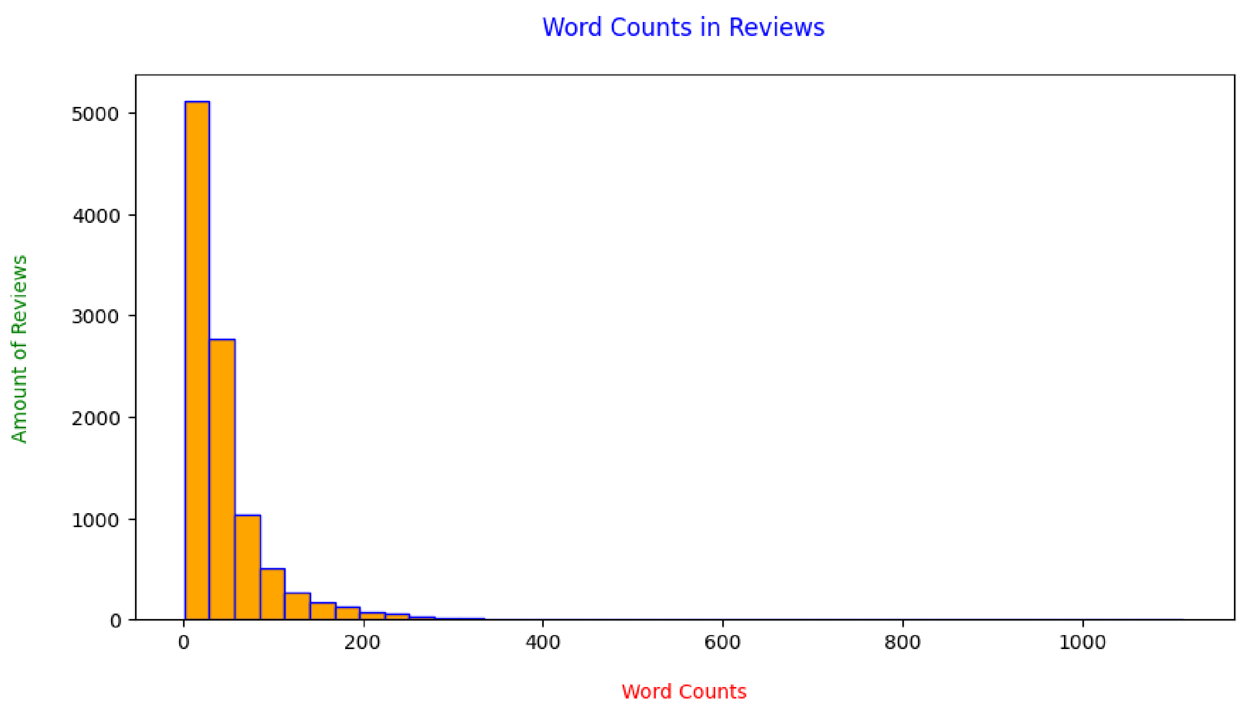


Based on this, we know that our review has text length between approximately 0-1000 characters. The distribution itself has positive skewness, or in other words it is skewed right, and this means that our reviews rarely has larger length than 1000 characters. Of course, the review that we use here is affected by the text preprocessing phase, so the length might not be the actual value of the review itself as some words might have been omitted already. This will also have the same effect when we count the tatal of words in our reviews.

Word Counts

```
dataset["word_counts"] = dataset["reviews"].apply(lambda x: len(str(x).split()))
```

```
dataset["word_counts"].plot(kind = "hist", bins = 40, edgecolor = "blue", linewidth = 1, color = "orange", figsize = (10,5))
plt.title("Word Counts in Reviews", color = "blue", pad = 20)
plt.xlabel("Word Counts", labelpad = 15, color = "red")
plt.ylabel("Amount of Reviews", labelpad = 20, color = "green")

plt.show()
```



From the figure above, we infer that most of the reviews consist of 0-200 words. Just like before, the distribution is skewed right and the calculation is affected by our text preprocessing phase before.

N-Gram Analysis

N-Gram Function

```
def Gram_Analysis(Corpus, Gram, N):
  # Vectorizer
  Vectorizer = CountVectorizer(stop_words = Stopwords, ngram_range=(Gram,Gram))

  # N-Grams Matrix
  ngrams = Vectorizer.fit_transform(Corpus)

  # N-Grams Frequency
  Count = ngrams.sum(axis=0)

  # List of Words
  words = [(word, Count[0, idx]) for word, idx in Vectorizer.vocabulary_.items()]

  # Sort Descending With Key = Count
  words = sorted(words, key = lambda x:x[1], reverse = True)

  return words[:N]
```

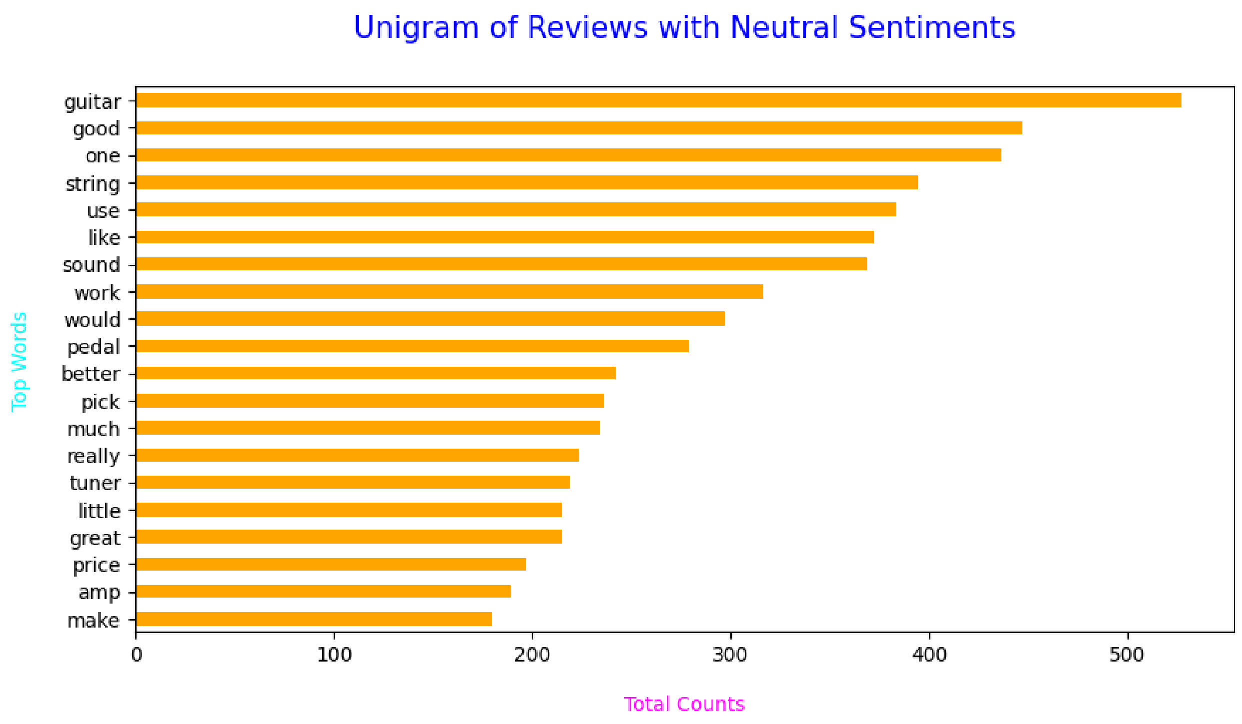
Filter The DataFrame Based On Sentiments

```
# Use dropna() so the base DataFrame is not affected
Positive = dataset[dataset["sentiment"] == "Positive"].dropna()
Neutral = dataset[dataset["sentiment"] == "Neutral"].dropna()
Negative = dataset[dataset["sentiment"] == "Negative"].dropna()
```

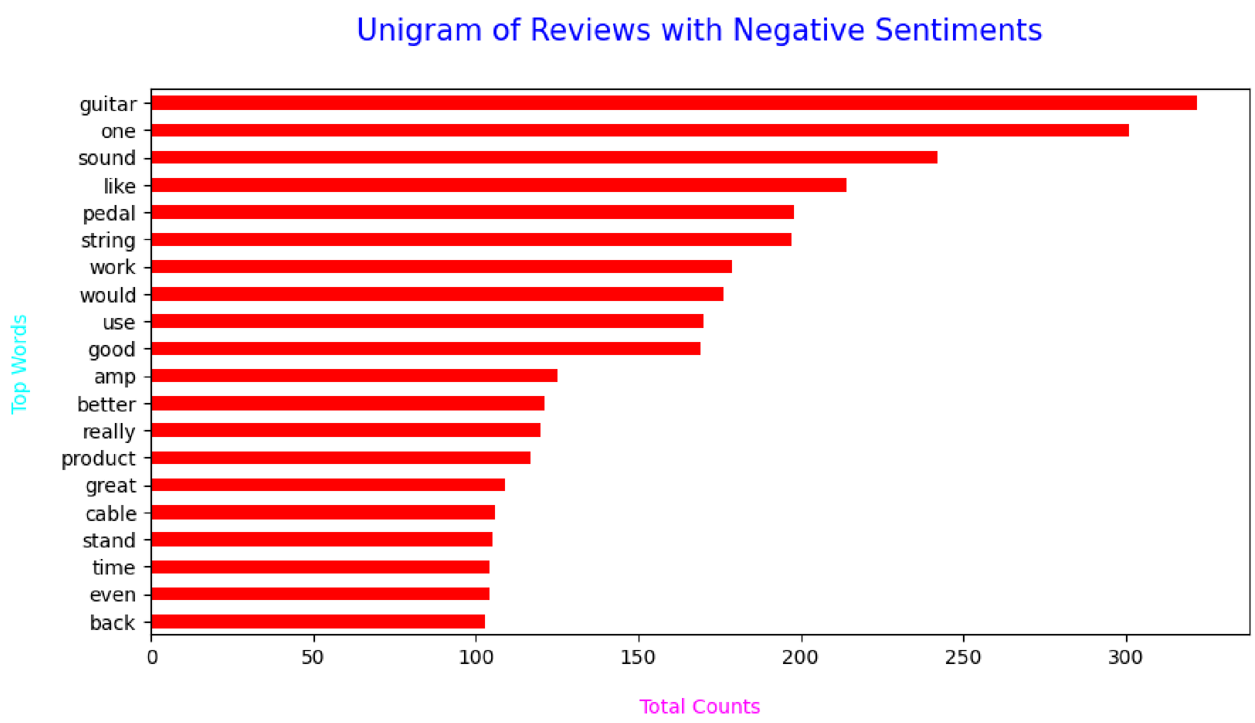
Unigram of Reviews Based on Sentiments

```
from sklearn.feature_extraction.text import CountVectorizer
import matplotlib.pyplot as plt
import pandas as pd
```

```
from sklearn.feature_extraction.text import CountVectorizer
import matplotlib.pyplot as plt
import pandas as pd

# Define stop words as a list
Stopwords = ['an', 'if', 'for', 'amongst', 'seeming', 'themselves', 'before', 'about', 'around', 'name',
             'their', 'nine', 'last', 'everyone', 'thin', 'that', 'on', 'except', 'his', 'off', 'become',
             'is', 'wherein', 'along', 'cannot', 'nothing', 'thereafter', 'etc', 'own', 'to', 'five', 'its',
             'the', 'ever', 'interest', 'such', 'none', 'get', 'them', 'down', 'found', 'onto', 'not', 'me',
             'both', 'almost', 'my', 'others', 'alone', 'twenty', 'between', 'somewhere', 'top', 'former',
             'anyhow', 'no', 'most', 'bottom', 'becoming', 'whom', 'through', 'into', 'anyone', 'been', 'we',
             'will', 'everywhere', 'whereas', 'indeed', 'but', 'again', 'behind', 'seems', 'forty', 'find',
             'whether', 'at', 'any', 'mine', 'may', 'latter', 'so', 'below', 'describe', 'un', 'hereupon',
             'anyway', 'have', 'enough', 'four', 'up', 'someone', 'noone', 'whereupon', 'her', 'had',
             'wherever', 'another', 'towards', 'already', 'as', 'therein', 'yours', 'thus', 'keep', 'eleven',
             'many', 'several', 'either', 'six', 'do', 'cry', 'during', 'now', 'what', 'whenever', 'toward',
             'ltd', 'meanwhile', 'yourself', 'all', 'over', 'in', 'first', 'this', 'else', 'without', 'fifteen',
             'you', 'being', 'go', 'thick', 'herein', 'well', 'whence', 'once', 'might', 'beforehand', 'mill',
             'more', 'somehow', 'too', 'inc', 'because', 'itself', 'formerly', 'from', 'elsewhere', 'take', 'a']

# Gram Analysis function
def Gram_Analysis(Corpus, Gram, N):
    # Vectorizer
    Vectorizer = CountVectorizer(stop_words=Stopwords, ngram_range=(Gram, Gram))

    # N-Grams Matrix
    X = Vectorizer.fit_transform(Corpus)

    # Sum of N-Grams
    N_Grams = X.sum(axis=0)

    # Extracting N-Grams
    Words = [(word, N_Grams[0, idx]) for word, idx in Vectorizer.vocabulary_.items()]

    # Sorting
    Words = sorted(Words, key=lambda x: x[1], reverse=True)

    return Words[:N]

# Finding Unigram
words = Gram_Analysis(Neutral["reviews"], 1, 20)
Unigram = pd.DataFrame(words, columns=["Words", "Counts"])

# Visualization
Unigram.groupby("Words").sum()["Counts"].sort_values().plot(kind="barh", color="orange", figsize=(10, 5))
plt.title("Unigram of Reviews with Neutral Sentiments", loc="center", fontsize=15, color="blue", pad=25)
plt.xlabel("Total Counts", color="magenta", fontsize=10, labelpad=15)
plt.xticks(rotation=0)
plt.ylabel("Top Words", color="cyan", fontsize=10, labelpad=15)
plt.show()
```



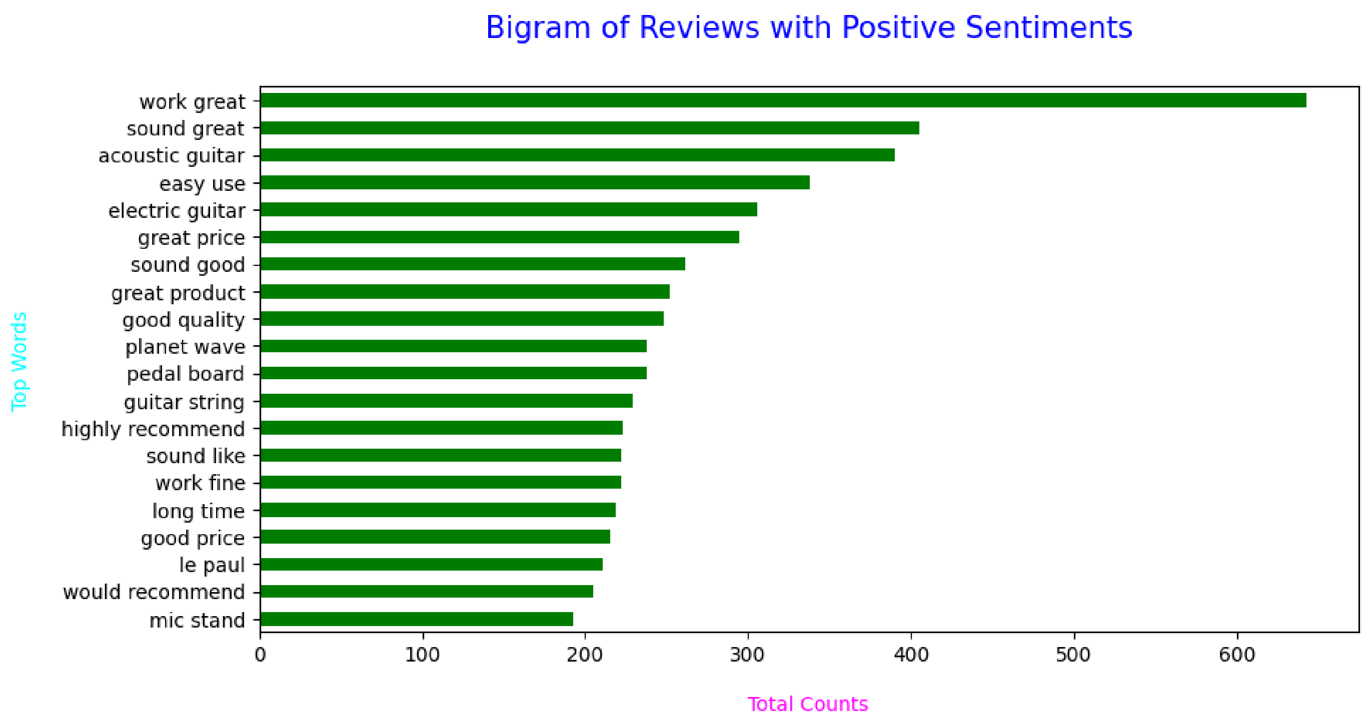

```
# Finding Unigram
words = Gram_Analysis(Negative["reviews"], 1, 20)
Unigram = pd.DataFrame(words, columns = ["Words", "Counts"])

# Visualization
Unigram.groupby("Words").sum()["Counts"].sort_values().plot(kind = "barh", color = "red", figsize = (10, 5))
plt.title("Unigram of Reviews with Negative Sentiments", loc = "center", fontsize = 15, color = "blue", pad = 25)
plt.xlabel("Total Counts", color = "magenta", fontsize = 10, labelpad = 15)
plt.xticks(rotation = 0)
plt.ylabel("Top Words", color = "cyan", fontsize = 10, labelpad = 15)
plt.show()
```



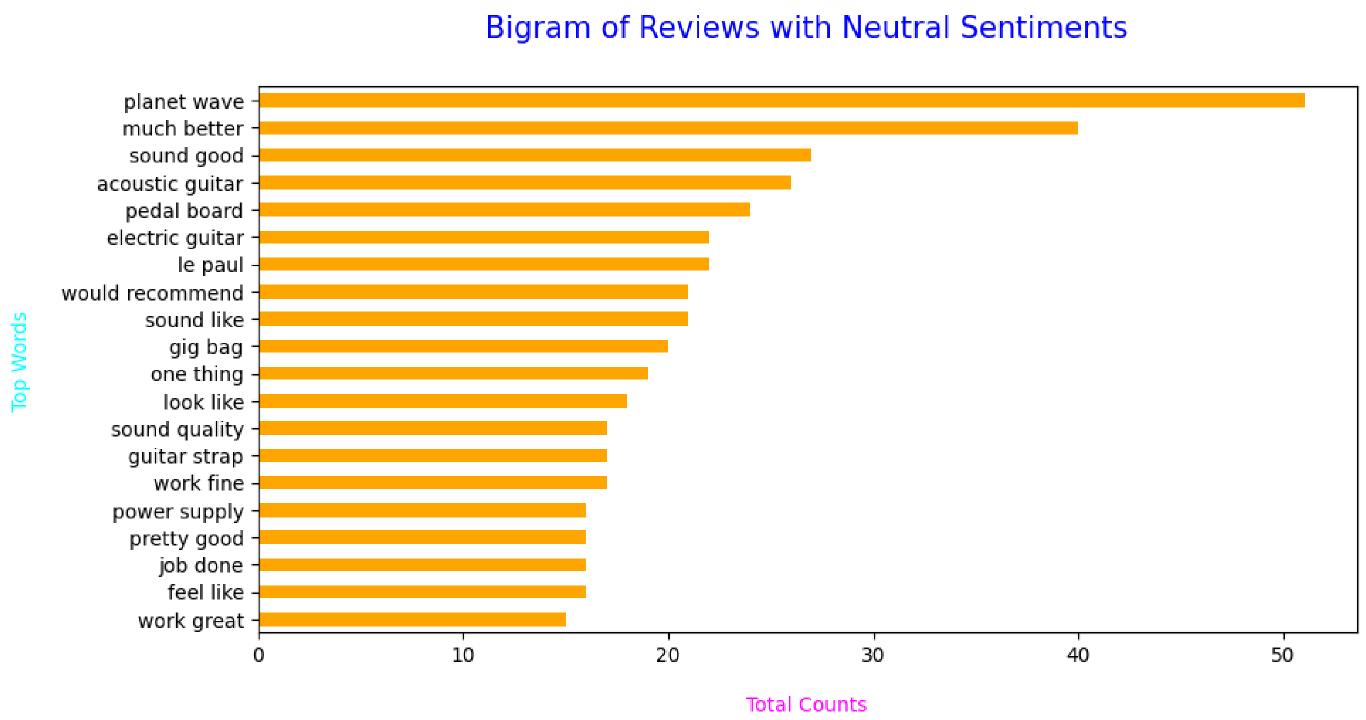
These unigrams are not really accurate, because we can clearly see that even for postive sentiments, the top unigram is the wird guitar which is an object, though from here we might know that the most frequently bought items are guitars or the complement of it. We should try to find the bigram and see how accurate it can describe each sentiments

Bigram of Reviews Based On Sentiments

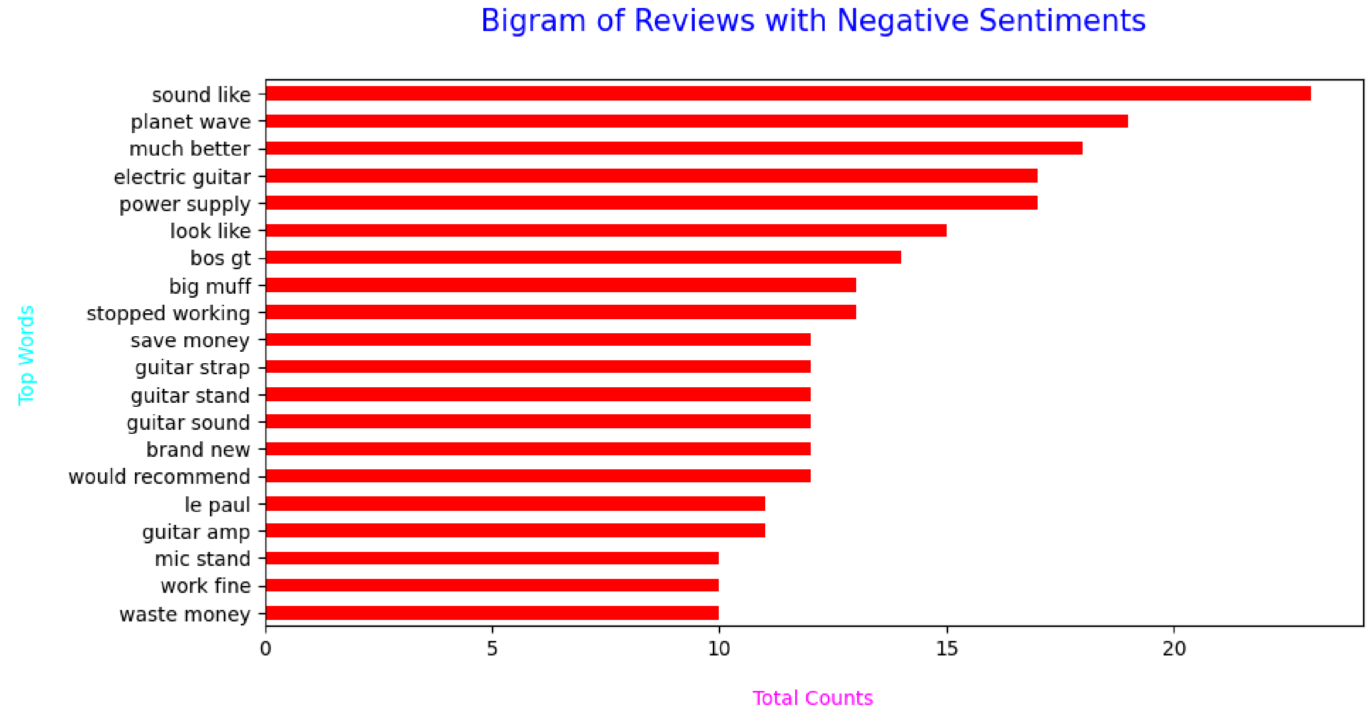
```
# Finding Bigram
words = Gram_Analysis(Positive["reviews"], 2, 20)
Bigram = pd.DataFrame(words, columns = ["Words", "Counts"])

# Visualization
Bigram.groupby("Words").sum()["Counts"].sort_values().plot(kind = "barh", color = "green", figsize = (10, 5))
plt.title("Bigram of Reviews with Positive Sentiments", loc = "center", fontsize = 15, color = "blue", pad = 25)
plt.xlabel("Total Counts", color = "magenta", fontsize = 10, labelpad = 15)
plt.xticks(rotation = 0)
plt.ylabel("Top Words", color = "cyan", fontsize = 10, labelpad = 15)
plt.show()
```




```
# Finding Bigram
words = Gram_Analysis(Neutral["reviews"], 2, 20)
Bigram = pd.DataFrame(words, columns = ["Words", "Counts"])

# Visualization
Bigram.groupby("Words").sum()["Counts"].sort_values().plot(kind = "barh", color = "orange", figsize = (10, 5))
plt.title("Bigram of Reviews with Neutral Sentiments", loc = "center", fontsize = 15, color = "blue", pad = 25)
plt.xlabel("Total Counts", color = "magenta", fontsize = 10, labelpad = 15)
plt.xticks(rotation = 0)
plt.ylabel("Top Words", color = "cyan", fontsize = 10, labelpad = 15)
plt.show()
```



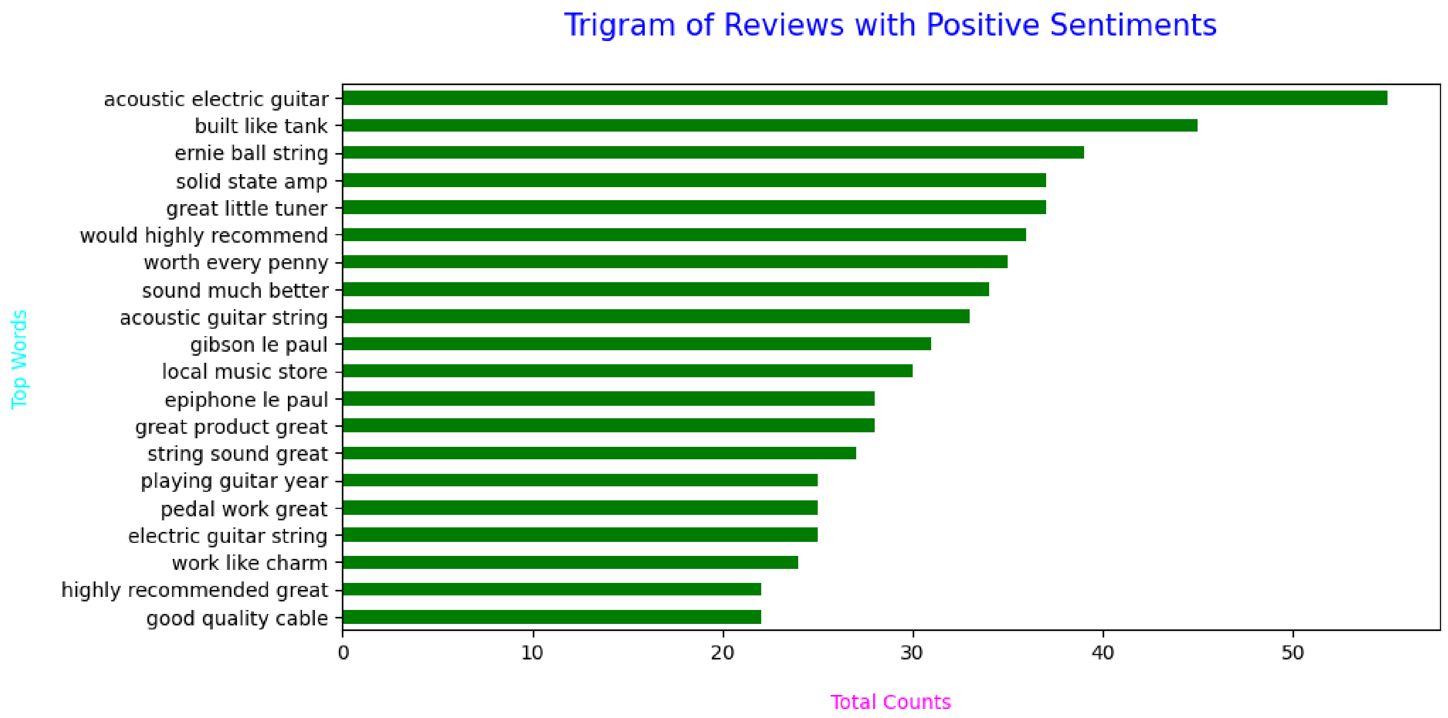

```
# Finding Bigram
words = Gram_Analysis(Negative["reviews"], 2, 20)
Bigram = pd.DataFrame(words, columns = ["Words", "Counts"])

# Visualization
Bigram.groupby("Words").sum()["Counts"].sort_values().plot(kind = "barh", color = "red", figsize = (10, 5))
plt.title("Bigram of Reviews with Negative Sentiments", loc = "center", fontsize = 15, color = "blue", pad = 25)
plt.xlabel("Total Counts", color = "magenta", fontsize = 10, labelpad = 15)
plt.xticks(rotation = 0)
plt.ylabel("Top Words", color = "cyan", fontsize = 10, labelpad = 15)
plt.show()
```



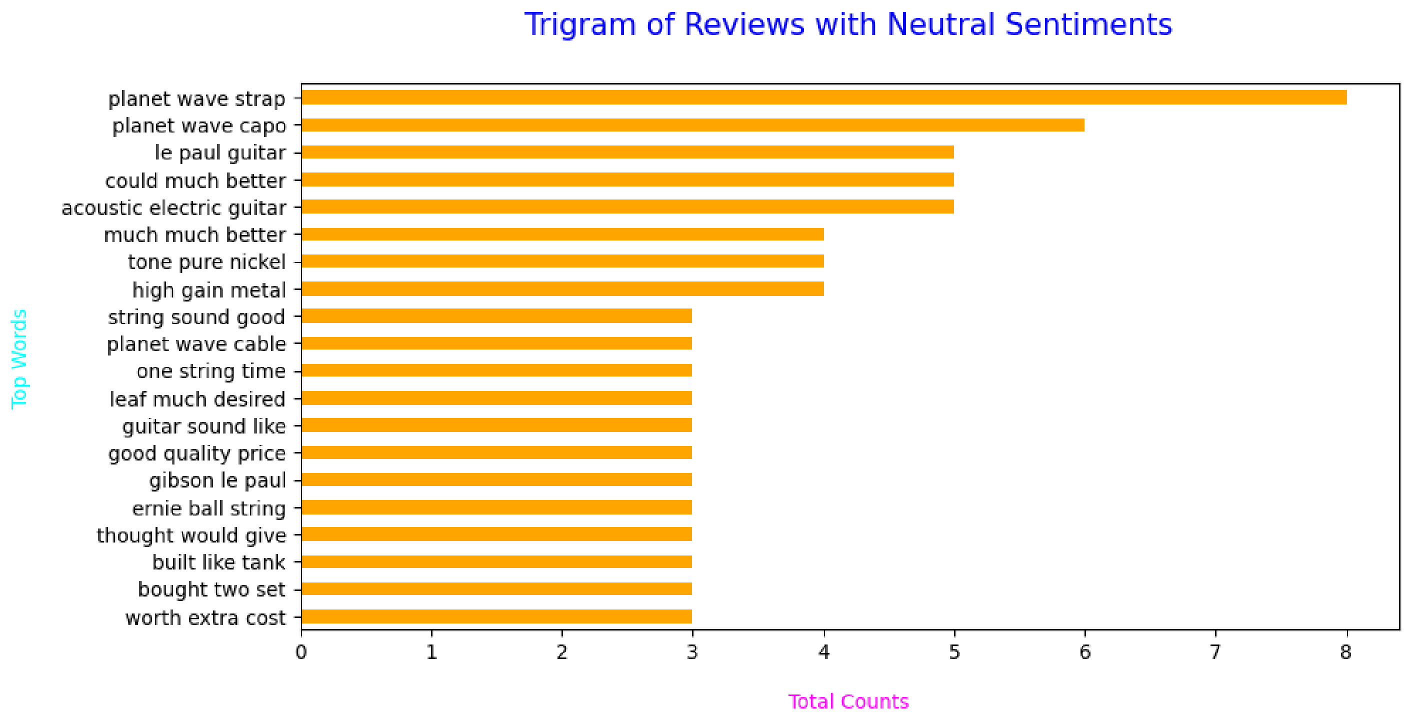
The bigrams work better than the unigrams, because we can actually see some phrases that really describe what a good sentiment is. Although, in some parts we can still see guitar objects as the top words, which make us believe that our interpretation about the most selling items are related to guitars.

Trigram of Reviews Based On Sentiments

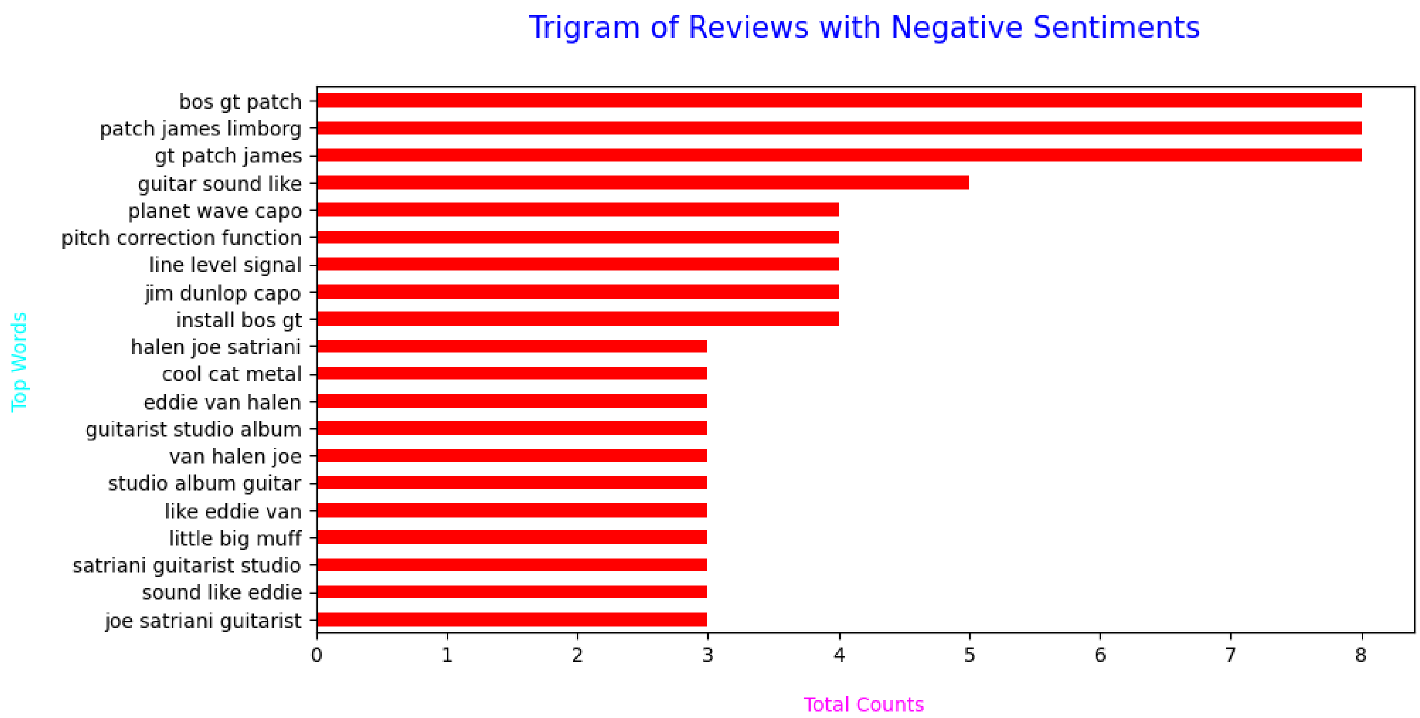
```
# Finding Trigram
words = Gram_Analysis(Positive["reviews"], 3, 20)
Trigram = pd.DataFrame(words, columns = ["Words", "Counts"])

# Visualization
Trigram.groupby("Words").sum()["Counts"].sort_values().plot(kind = "barh", color = "green", figsize = (10, 5))
plt.title("Trigram of Reviews with Positive Sentiments", loc = "center", fontsize = 15, color = "blue", pad = 25)
plt.xlabel("Total Counts", color = "magenta", fontsize = 10, labelpad = 15)
plt.xticks(rotation = 0)
plt.ylabel("Top Words", color = "cyan", fontsize = 10, labelpad = 15)
plt.show()
```




```
# Finding Trigram
words = Gram_Analysis(Neutral["reviews"], 3, 20)
Trigram = pd.DataFrame(words, columns = ["Words", "Counts"])

# Visualization
Trigram.groupby("Words").sum()["Counts"].sort_values().plot(kind = "barh", color = "orange", figsize = (10, 5))
plt.title("Trigram of Reviews with Neutral Sentiments", loc = "center", fontsize = 15, color = "blue", pad = 25)
plt.xlabel("Total Counts", color = "magenta", fontsize = 10, labelpad = 15)
plt.xticks(rotation = 0)
plt.ylabel("Top Words", color = "cyan", fontsize = 10, labelpad = 15)
plt.show()
```




```
# Finding Trigram
words = Gram_Analysis(Negative["reviews"], 3, 20)
Trigram = pd.DataFrame(words, columns = ["Words", "Counts"])

# Visualization
Trigram.groupby("Words").sum()["Counts"].sort_values().plot(kind = "barh", color = "red", figsize = (10, 5))
plt.title("Trigram of Reviews with Negative Sentiments", loc = "center", fontsize = 15, color = "blue", pad = 25)
plt.xlabel("Total Counts", color = "magenta", fontsize = 10, labelpad = 15)
plt.xticks(rotation = 0)
plt.ylabel("Top Words", color = "cyan", fontsize = 10, labelpad = 15)
plt.show()
```



We can say that the trigrams are slightly better to describe each sentiments, although negative trigrams say a lot about bad products which we can infer from the top words above. From the N-Gram Analysis, we can also see how the decision of not removing not in our list of stopwords affects our data as we keep the meaning of negation phrases.

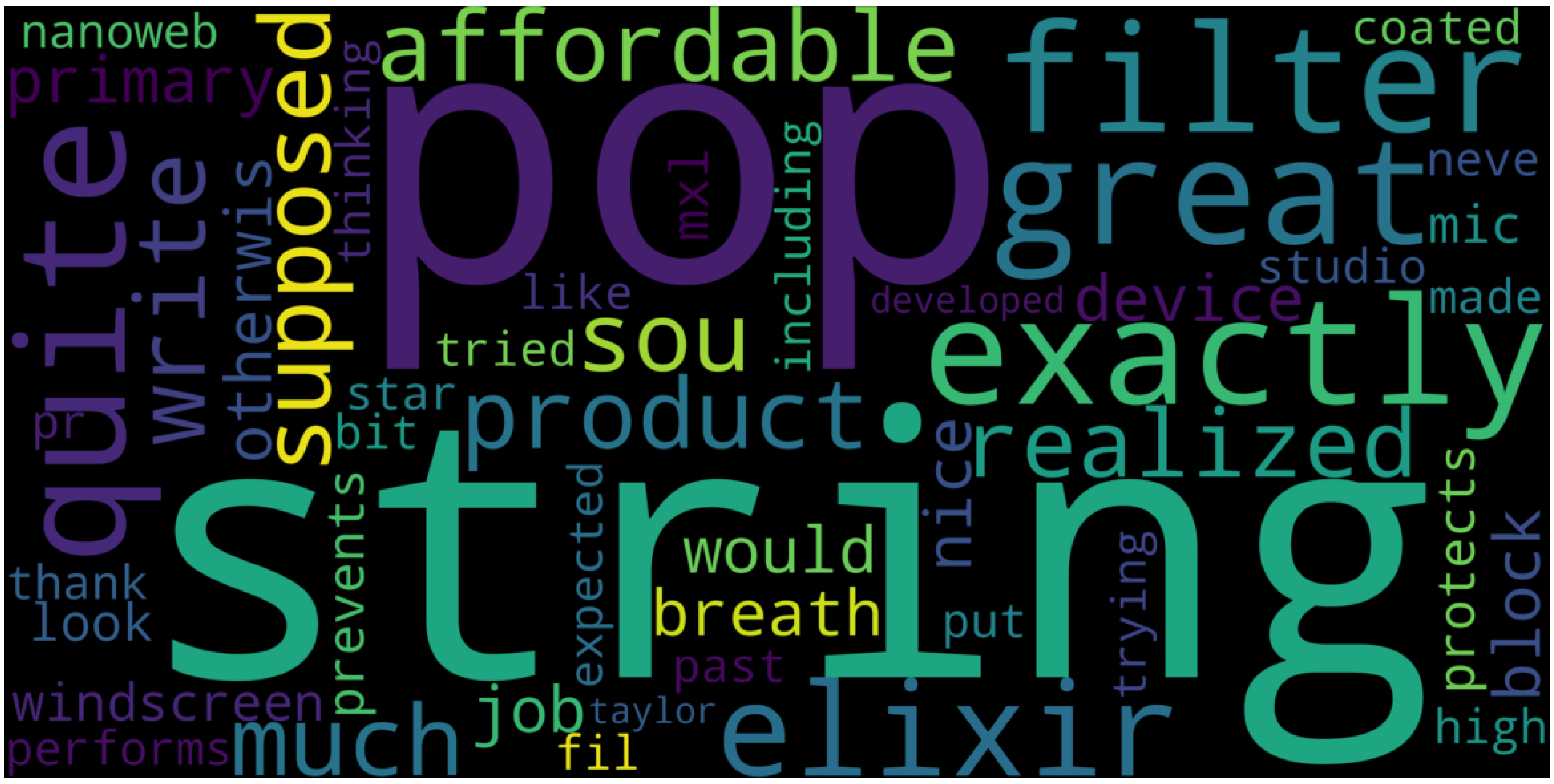
Word Clouds

Word Cloud of Reviews with Positive Sentiments

```
pip install wordcloud
```

```
Requirement already satisfied: wordcloud in /usr/local/lib/python3.10/dist-packages (1.9.3)
Requirement already satisfied: numpy>=1.6.1 in /usr/local/lib/python3.10/dist-packages (from wordcloud) (1.25.2)
Requirement already satisfied: pillow in /usr/local/lib/python3.10/dist-packages (from wordcloud) (9.4.0)
Requirement already satisfied: matplotlib in /usr/local/lib/python3.10/dist-packages (from wordcloud) (3.7.1)
Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib->wordcloud) (1.2.1)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.10/dist-packages (from matplotlib->wordcloud) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib->wordcloud) (4.53.1)
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib->wordcloud) (1.4.5)
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib->wordcloud) (24.1)
Requirement already satisfied: pyparsing>=2.3.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib->wordcloud) (3.1.2)
Requirement already satisfied: python-dateutil>=2.7 in /usr/local/lib/python3.10/dist-packages (from matplotlib->wordcloud) (2.8.2)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.10/dist-packages (from python-dateutil>=2.7->matplotlib->wordcloud) (1.16.0)
```

```
from wordcloud import WordCloud
import matplotlib.pyplot as plt

# Define stop words as a list
Stopwords = ['an', 'if', 'for', 'amongst', 'seeming', 'themselves', 'before', 'about', 'around', 'name',
             'their', 'nine', 'last', 'everyone', 'thin', 'that', 'on', 'except', 'his', 'off', 'become',
             'is', 'wherein', 'along', 'cannot', 'nothing', 'thereafter', 'etc', 'own', 'to', 'five', 'its',
             'the', 'ever', 'interest', 'such', 'none', 'get', 'them', 'down', 'found', 'onto', 'not', 'me',
             'both', 'almost', 'my', 'others', 'alone', 'twenty', 'between', 'somewhere', 'top', 'former',
             'anyhow', 'no', 'most', 'bottom', 'becoming', 'whom', 'through', 'into', 'anyone', 'been', 'we',
             'will', 'everywhere', 'whereas', 'indeed', 'but', 'again', 'behind', 'seems', 'forty', 'find',
             'whether', 'at', 'any', 'mine', 'may', 'latter', 'so', 'below', 'describe', 'un', 'hereupon',
             'anyway', 'have', 'enough', 'four', 'up', 'someone', 'noone', 'whereupon', 'her', 'had',
             'wherever', 'another', 'towards', 'already', 'as', 'therein', 'yours', 'thus', 'keep', 'eleven',
             'many', 'several', 'either', 'six', 'do', 'cry', 'during', 'now', 'what', 'whenever', 'toward',
             'ltd', 'meanwhile', 'yourself', 'all', 'over', 'in', 'first', 'this', 'else', 'without', 'fifteen',
             'you', 'being', 'go', 'thick', 'herein', 'well', 'whence', 'once', 'might', 'beforehand', 'mill',
             'more', 'somehow', 'too', 'inc', 'because', 'itself', 'formerly', 'from', 'elsewhere', 'take', 'a']

# Generate word cloud
wordCloud = WordCloud(max_words=50, width=3000, height=1500, stopwords=Stopwords).generate(str(Positive["reviews"]))

# Plot the word cloud
plt.figure(figsize=(15, 15))
plt.imshow(wordCloud, interpolation="bilinear")
plt.axis("off")
plt.show()
```

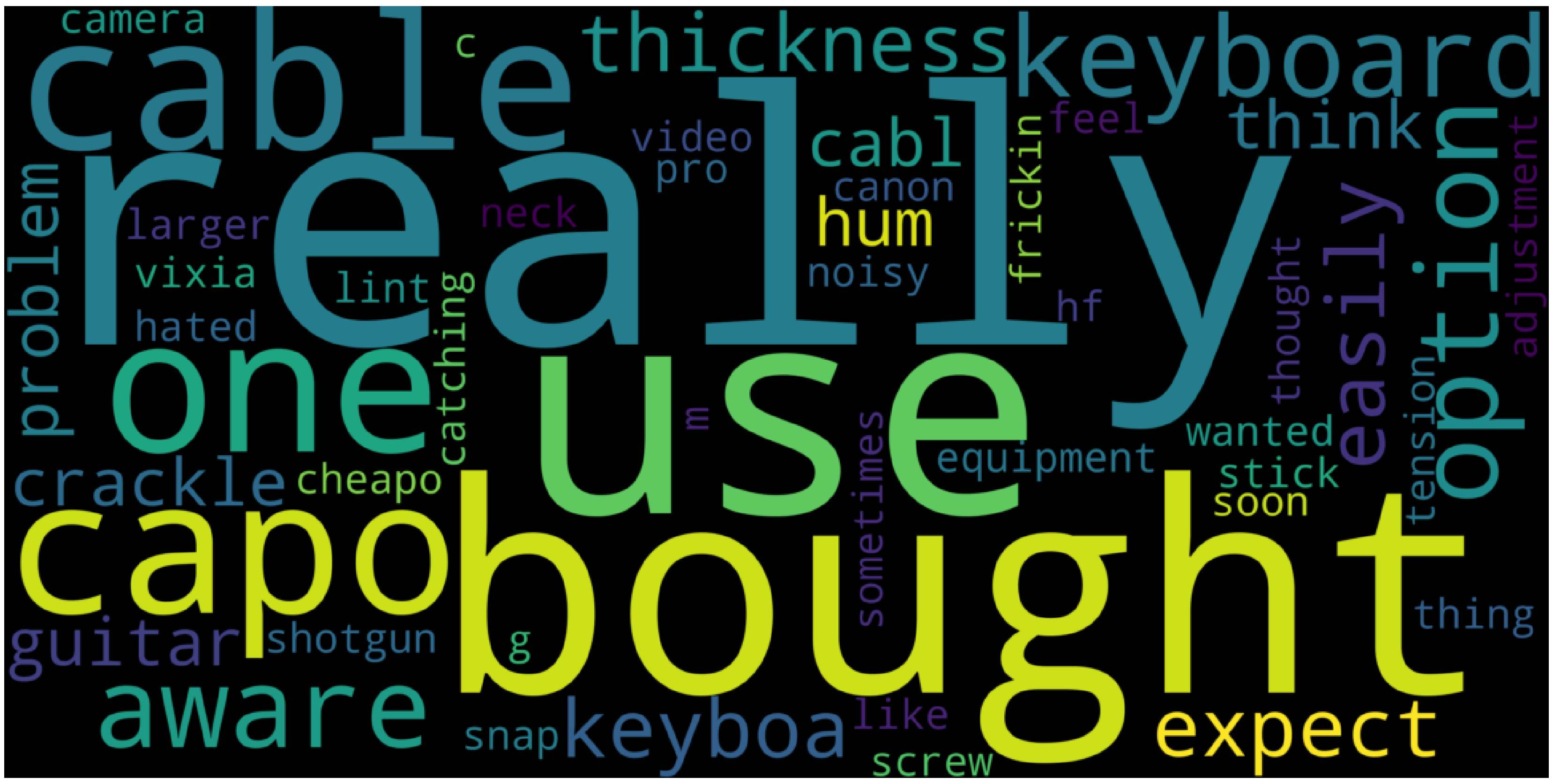


Word Cloud of Reviews with Neutral Sentiments

```
wordCloud = WordCloud(max_words = 50, width = 3000, height = 1500, stopwords = Stopwords).generate(str(Neutral["reviews"]))
plt.figure(figsize = (15, 15))
plt.imshow(wordCloud, interpolation = "bilinear")
plt.axis("off")
plt.show()
```

Word Cloud of Reviews with Negative Sentiments

```
wordCloud = WordCloud(max_words = 50, width = 3000, height = 1500, stopwords = Stopwords).generate(str(Negative["reviews"]))
plt.figure(figsize = (15, 15))
plt.imshow(wordCloud, interpolation = "bilinear")
plt.axis("off")
plt.show()
```



From these word clouds, not only we can see words that really describe our sentiments, but just like our N-Grams Analysis we can see objects being discussed in the reviews given.

Feature Engineering

Drop Insignificant Columns

```
Columns = ["reviewerID", "asin", "reviewerName", "helpful", "unixReviewTime", "reviewTime", "polarity", "length", "word_counts", "overall"]
dataset.drop(columns = Columns, axis = 1, inplace = True)
```

We dropped these columns to make our dataset concise. We now have two columns as our independent variables and the last column as dependent variables. To continue, we must encode our label as a set of numbers corresponding to each categories of it.

Current State of The Dataset

```
dataset.head()
```

	reviews	sentiment
0	not much write exactly supposed filter pop sou...	Positive
1	product exactly quite affordable not realized ...	Positive
2	primary job device block breath would otherwis...	Positive
3	nice windscreen protects mxl mic prevents pop ...	Positive
4	pop filter great look performs like studio fil...	Positive

Next steps: Generate code with dataset | View recommended plots | New interactive sheet

Encoding Our Target Variable

```
Encoder = LabelEncoder()
dataset["sentiment"] = Encoder.fit_transform(dataset["sentiment"])
```

```
dataset["sentiment"].value_counts()
```

```
sentiment
2    9022
1     772
0     467
Name: count, dtype: int64
```

We had successfully encoded our sentiment into numbers so that our model can easily figure it out. From above, we know that the label Positive is encoded into 2, Neutral into 1, and Negative into 0. Now, we have to give importance of each words in the whole review, i.e. giving them weights. We can do this by using TF-IDF (Term Frequency - Inverse Document Frequency) Vectorizer.

TF-IDF Vectorizer

```
# Defining our vectorizer with total words of 5000 and with bigram model
TF_IDF = TfidfVectorizer(max_features = 5000, ngram_range = (2, 2))

# Fitting and transforming our reviews into a matrix of weighed words
# This will be our independent features
X = TF_IDF.fit_transform(dataset["reviews"])

# Check our matrix shape
X.shape
```

```
(10261, 5000)
```

```
# Declaring our target variable
y = dataset["sentiment"]
```

From the shape, we successfully transformed our reviews with TF-IDF Vectorizer of 7000 top bigram words. Now, as we know from before, our data is kind of imbalanced with very little neutral and negative values compared to positive sentiments. We need to balance our dataset before going into modelling process.

Resampling Our Dataset

There are many ways to do resampling to an imbalanced dataset, such as SMOTE and Bootstrap Method. We will use SMOTE (Synthetic Minority Oversampling Technique) that will randomly generate new replicates of our undersampling data to balance our dataset.

```
from collections import Counter
counter = Counter(y)
print(counter)
```

```
Counter({2: 9022, 1: 772, 0: 467})
```

```
Balancer = SMOTE(random_state = 42)
X_final, y_final = Balancer.fit_resample(X, y)
```

```
Counter(y_final)
```

```
Counter({2: 9022, 1: 9022, 0: 9022})
```

Now our data is already balanced as we can see from the counter of each sentiment categories before and after the resampling with SMOTE.

```
#Splitting Our Dataset
```

We splitted our dataset into 75:25 portion respectively for the training and test set.

```
X_train, X_test, y_train, y_test = train_test_split(X_final, y_final, test_size = 0.25, random_state = 42)
```

Model Selection and Evaluation

We do not really know what is the best model that fits our data well. Because of that, we will need to try every classification models available and find the best models using the Confusion Matrix and F1 Score as our main metrics, and the rest of the metrics as our support. First, we should do some cross validation techniques in order to find the best model.

Model Building

We are using K-Fold Cross Validation on our early dataset (before resampling) because the CV itself is not affected by the imbalanced dataset as it splits the dataset and takes into account every validations. If we use the CV on the balanced dataset that we got from resampling we should be able to get similar result.

```
DTree = DecisionTreeClassifier()
LogReg = LogisticRegression()
SVC = SVC()
RForest = RandomForestClassifier()
Bayes = BernoulliNB()
KNN = KNeighborsClassifier()

Models = [DTree, LogReg, SVC, RForest, Bayes, KNN]
Models_Dict = {0: "Decision Tree", 1: "Logistic Regression", 2: "SVC", 3: "Random Forest", 4: "Naive Bayes", 5: "K-Neighbors"}

for i, model in enumerate(Models):
  print("{} Test Accuracy: {}".format(Models_Dict[i], cross_val_score(model, X, y, cv = 10, scoring = "accuracy").mean()))
```

```
Decision Tree Test Accuracy: 0.8178531501316311
Logistic Regression Test Accuracy: 0.8818828283518491
SVC Test Accuracy: 0.8805184008381876
Random Forest Test Accuracy: 0.8774975277640168
Naive Bayes Test Accuracy: 0.8091794454219505
K-Neighbors Test Accuracy: 0.8799336055165503
```

We got six models on our sleeves and from the results of 10-Fold Cross Validation, we know that the Logistic Regression model is the best model with the highest accuracy, slightly beating the SVC. Because of this, we will use the best model in predicting our sentiment, also to tune our parameter and evaluate the end-result of how well the model works.

Hyperparameter Tuning

```
Param = {"C": np.logspace(-4, 4, 50), "penalty": ['l1', 'l2']}
grid_search = GridSearchCV(estimator = LogisticRegression(random_state = 42), param_grid = Param, scoring = "accuracy", cv = 10, verbose = 0, n_jobs = 
```

```
grid_search.fit(X_train, y_train)
best_accuracy = grid_search.best_score_
best_parameters = grid_search.best_params_

print("Best Accuracy: {:.2f} %".format(best_accuracy*100))
print("Best Parameters:", best_parameters)
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/model_selection/_validation.py:425: FitFailedWarning:
500 fits failed out of a total of 1000.
The score on these train-test partitions for these parameters will be set to nan.
If these failures are not expected, you can try to debug them by setting error_score='raise'.

Below are more details about the failures:
--------------------------------------------------------------------------------
500 fits failed with the following error:
Traceback (most recent call last):
  File "/usr/local/lib/python3.10/dist-packages/sklearn/model_selection/_validation.py", line 729, in _fit_and_score
    estimator.fit(X_train, y_train, **fit_params)
  File "/usr/local/lib/python3.10/dist-packages/sklearn/base.py", line 1152, in wrapper
    return fit_method(estimator, *args, **kwargs)
  File "/usr/local/lib/python3.10/dist-packages/sklearn/linear_model/_logistic.py", line 1169, in fit
    solver = _check_solver(self.solver, self.penalty, self.dual)
  File "/usr/local/lib/python3.10/dist-packages/sklearn/linear_model/_logistic.py", line 56, in _check_solver
    raise ValueError(
ValueError: Solver lbfgs supports only 'l2' or 'none' penalties, got l1 penalty.

  warnings.warn(some_fits_failed_message, FitFailedWarning)
/usr/local/lib/python3.10/dist-packages/sklearn/model_selection/_search.py:979: UserWarning: One or more of the test scores are non-finite: [       nan 0.33509045
        nan 0.38351638        nan 0.43243528        nan 0.48711753
        nan 0.54204653        nan 0.59367472        nan 0.64387422
        nan 0.68136331        nan 0.71609422        nan 0.74171103
        nan 0.76314101        nan 0.78126979        nan 0.79112288
        nan 0.79358598        nan 0.79747771        nan 0.80427615
        nan 0.81324213        nan 0.82496699        nan 0.83688869
        nan 0.85161841        nan 0.86516588        nan 0.8765457
        nan 0.88694013        nan 0.89728544        nan 0.90477374
        nan 0.91098105        nan 0.9174837         nan 0.9210306
        nan 0.92152338        nan 0.92162185        nan 0.92285343
        nan 0.92447902        nan 0.92580931        nan 0.92728714
        nan 0.92871574        nan 0.92930702        nan 0.9328046
        nan 0.93462756        nan 0.93625322        nan 0.9373861
        nan 0.93965236        nan 0.94083462        nan 0.9423125
        nan 0.94359346        nan 0.94590868        nan 0.94689393
        nan 0.94797789        nan 0.94832265]
  warnings.warn(
Best Accuracy: 94.83 %
Best Parameters: {'C': 10000.0, 'penalty': 'l2'}
/usr/local/lib/python3.10/dist-packages/sklearn/linear_model/_logistic.py:460: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  n_iter_i = _check_optimize_result(
```

We got a nice accuracy on our training set, which is 94.80% and from our Grid Search, we are also able to find our optimal hyperparameters. It is time to finish our model using these parameters to get the best model of Logistic Regression.

Best Model

```
Classifier = LogisticRegression(random_state = 42, C = 6866.488450042998, penalty = 'l2')
Classifier.fit(X_train, y_train)

Prediction = Classifier.predict(X_test)
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/linear_model/_logistic.py:460: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  n_iter_i = _check_optimize_result(
```

Now that our model is done, we will test our model on our test set. The metrics that we will evaluate is based on this prediction that we made here.

Metrics

Accuracy On Test Set

```
accuracy_score(y_test, Prediction)
```

```
0.9521205851928476
```

Really high accuracy that we got here, 95.21%. Still, we need to look out for the Confusion Matrix and F1 Score to find out about our model performance.

Confusion Matrix

```
ConfusionMatrix = confusion_matrix(y_test, Prediction)
```

Visualizing Our Confusion Matrix

```
# Plotting Function for Confusion Matrix
def plot_cm(cm, classes, title, normalized = False, cmap = plt.cm.Blues):

  plt.imshow(cm, interpolation = "nearest", cmap = cmap)
  plt.title(title, pad = 20)
  plt.colorbar()
  tick_marks = np.arange(len(classes))
  plt.xticks(tick_marks, classes)
  plt.yticks(tick_marks, classes)

  if normalized:
    cm = cm.astype('float') / cm.sum(axis = 1)[: np.newaxis]
    print("Normalized Confusion Matrix")
  else:
    print("Unnormalized Confusion Matrix")

  threshold = cm.max() / 2
  for i in range(cm.shape[0]):
    for j in range(cm.shape[1]):
      plt.text(j, i, cm[i, j], horizontalalignment = "center", color = "white" if cm[i, j] > threshold else "black")
```