Sentiment Analysis on Amazon Fine Food Reviews:

Introduction:

In this project, I produced a sentiment analysis covering over 500,000 reviews from an Amazon Fine Food Review dataset. I classified all positive and negative customer reviews and then created word clouds, plotly visualizations, and a text classification model to display my analysis further.

Data :

For this project, I used the Amazon Fine Food Review dataset found on Kaggle.

In [1]:
```
# Imports
import pandas as pd
import numpy as np
import seaborn as sns
import nltk
from nltk import word_tokenize, sent_tokenize
from nltk.corpus import stopwords

%matplotlib inline
import matplotlib.pyplot as plt
from plotly.offline import download_plotlyjs, init_notebook_mode, plot, iplot
init_notebook_mode(connected=True)
import cufflinks as cf
cf.go_offline()

import plotly.express as px
import re
def plot_cloud(wordcloud):
    plt.figure(figsize=(40, 30))
    plt.imshow(wordcloud)
    plt.axis("off");
from wordcloud import WordCloud, STOPWORDS
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.model_selection import train_test_split
from sklearn.naive_bayes import MultinomialNB
from sklearn import metrics

def __iter__(self): return 0

print("All imports installed...!")
```

```
All imports installed...!
```

In [2]:
```
amazon = pd.read_csv('Reviews.csv')
amazon.head()
```

Out[2]:

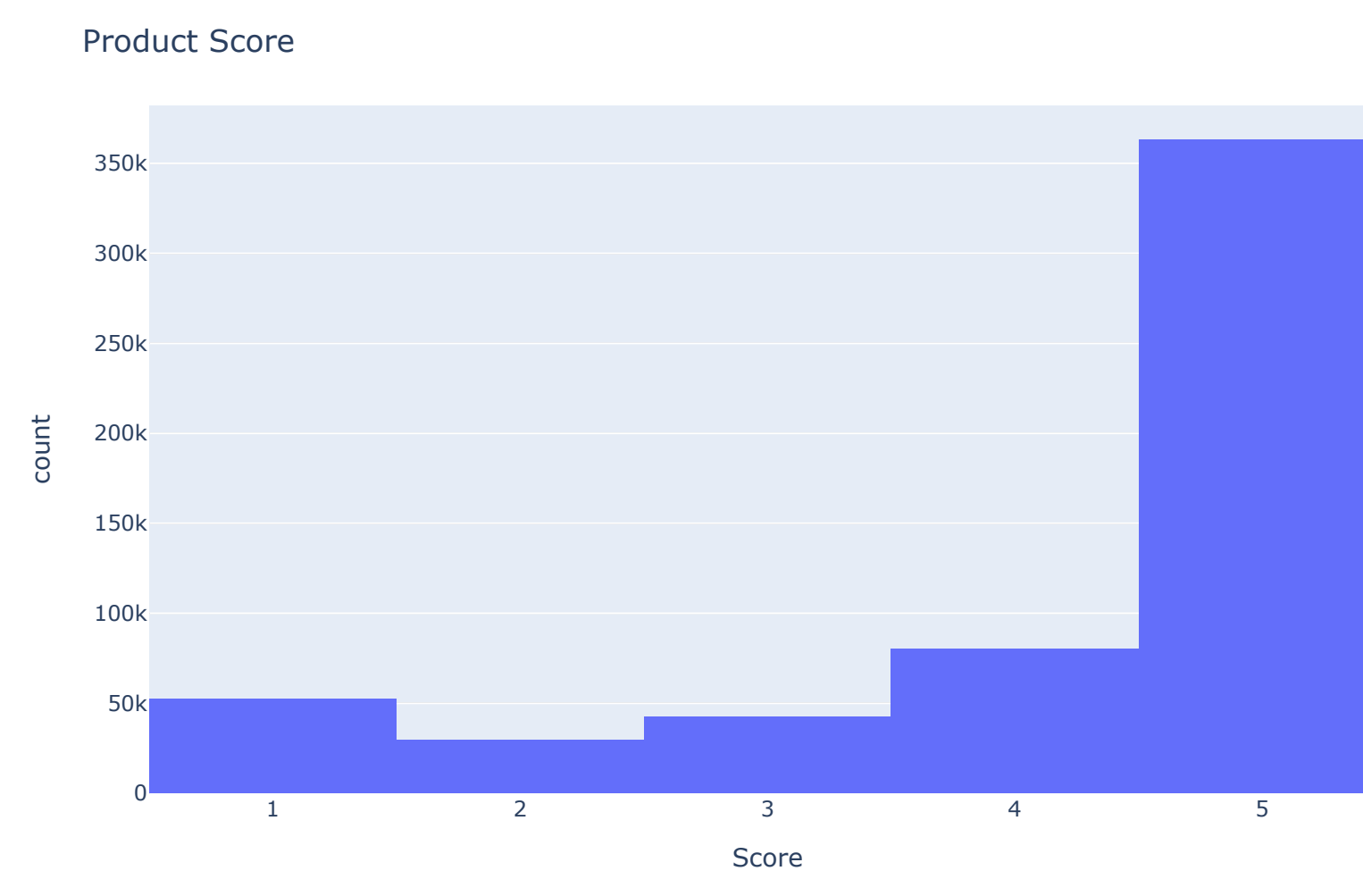
	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	Summary
0	1	B001E4KFG0	A3SGXH7AUHU8GW	delmartian	1	1	5	1303862400	Good Quality Dog Food
1	2	B00813GRG4	A1D87F6ZCVE5NK	dll pa	0	0	1	1346976000	Not as Advertised
2	3	B000LQOCH0	ABXLMWJIXXAIN	Natalia Corres "Natalia Corres"	1	1	4	1219017600	"Delight" says it all
3	4	B000UA0QIQ	A395BORC6FGVXV	Karl	3	3	2	1307923200	Cough Medicine
4	5	B006K2ZZ7K	A1UQRSCLF8GW1T	Michael D. Bigham "M. Wassir"	0	0	5	1350777600	Great taffy

Methodology:

To prepare for this analysis, I visualized the product scores from the dataset in a histogram using the plotly library.

In [3]:
```
# Visualizing Product Scores - Histogram

fig = px.histogram(amazon, x="Score")
fig.update_layout(title_text = "Product Score")
fig.show()
```



From the blue histogram, we can see more positive customer ratings than negative. Therefore, the majority of Amazon's product reviews are positive.

Next, I created a word cloud to show the most frequently used words in the text (review) column.

Review Word Cloud

In [4]:
```
text = " ".join(review for review in amazon.Text)

# Removing errors in Text column
stopwords = set(STOPWORDS)
stopwords.update(["br", "href"])

wordcloud = WordCloud(width = 3000, height = 2000, random_state = 1, stopwords=stopwords, background_color = "v

plot_cloud(wordcloud)
```

Next, I added a sentiment column by classifying only positive and negative reviews using the dataset's 'Score' column. For this sentiment, I categorized all positive reviews as scores > 3, negative for scores < 3, and dropped all neutral scores, which = 3. Note, the sentiment column will later be used as training data for the sentiment classification model.

In [5]:
```
amazon = amazon[amazon.Score != 3]

# Postive = 1
# Negative = -1

amazon ["Sentiment"] = amazon["Score"].apply(lambda x: -1 if x < 3 else +1)

amazon.head()
```

Out[5]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	Summary
0	1	B001E4KFG0	A3SGXH7AUHU8GW	delmartian	1	1	5	1303862400	Good Quality Dog Food
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2	3	B000LQOCH0	ABXLMWJIXXAIN	Natalia Corres "Natalia Corres"	1	1	4	1219017600	"Delight" says it all
3	4	B000UA0QIQ	A395BORC6FGVXV	Karl	3	3	2	1307923200	Cough Medicine
4	5	B006K2ZZ7K	A1UQRSCLF8GW1T	Michael D. Bigham "M. Wassir"	0	0	5	1350777600	Great taffy

After building the sentiment column, I also created word clouds to display the most frequently used words for both positive and negative product reviews, respectfully. In addition, I made a product sentiment histogram to show the distribution of reviews with sentiment across the dataset.

In [6]:
```
# Postive Word Cloud

positive = amazon[amazon["Sentiment"] == 1]

text = " ".join(review for review in positive.Text)

text = text.replace('\n', "")

stopwords = set(STOPWORDS)
stopwords.update(["br", "href"])

wordcloud.postive = WordCloud(width = 3000, height = 2000, random_state = 1, stopwords=stopwords, background_co

plot_cloud(wordcloud.postive)
```

In [7]:
```
# Negative Word Cloud

negative = amazon[amazon["Sentiment"] == -1]

text = " ".join(review for review in negative.Text)

text = text.replace('\n', "")

stopwords = set(STOPWORDS)
stopwords.update(["good", "great", "br", "href"])

wordcloud.negative = WordCloud(width = 3000, height = 2000, random_state = 1, stopwords=stopwords, background_c

plot_cloud(wordcloud.negative)
```

Product Sentiment Histogram

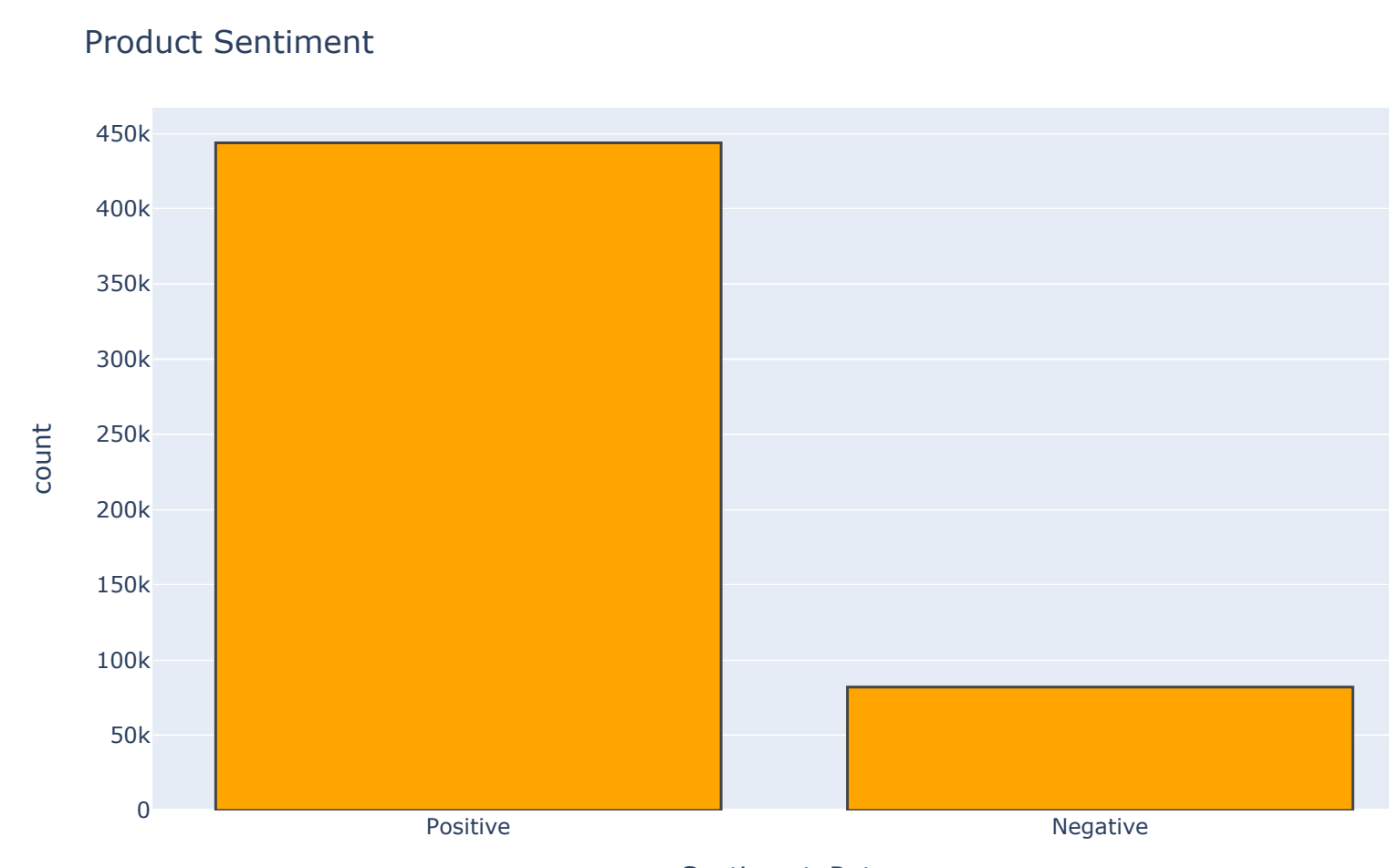
In [8]:
```
amazon ["Sentiment_Rate"] = amazon["Sentiment"].apply(lambda x: "Negative" if x == -1 else "Positive")

fig = px.histogram(amazon, x = "Sentiment_Rate")

fig.update_traces(marker_color = 'orange', marker_line_width=1.5)

fig.update_layout(title_text = "Product Sentiment")

fig.show()
```



From the orange histogram, we can see that the product sentiment is more positive than negative.

Finally, I created a text classification model to train and establish the accuracy of my data. I start by pre-processing the textual data using NLTK to remove special characters, lowercasing text, and stopwords. Then, I test the accuracy of the sentiment model by performing the Multi Nominal Naive Bayes Classification function using the scikit-learn library.

In [9]:
```
amazon.Summary = amazon['Summary'].str.replace('[^\w\s]','')

amazon.head()
```

```
<ipython-input-9-a813c68aaaa4>:1: FutureWarning:

The default value of regex will change from True to False in a future version.
```

Out[9]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	Summary
0	1	B001E4KFG0	A3SGXH7AUHU8GW	delmartian	1	1	5	1303862400	Good Quality Dog Food
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In [10]:
```
sentiment_df = amazon[["Summary", "Sentiment"]]

sentiment_df.head()
```

Out[10]:

	Summary	Sentiment
0	Good Quality Dog Food	1
1	Not as Advertised	-1
2	Delight says it all	1
3	Cough Medicine	-1
4	Great taffy	1

Data Pre-Processing

In [11]:
```
df = sentiment_df

df["Summary"] = df["Summary"].astype(str)

# Change to lowercasing for all text reviews in 'Summary'

df["Summary"] = df["Summary"].apply(lambda x: " ".join(x.lower() for x in x.split()))

stop = set(stopwords)

df["Summary"] = df["Summary"].apply(lambda x: " ".join(x for x in x.split() if x not in stop ))
```

In [12]:
```
cv = CountVectorizer(token_pattern=r'\b\w+\b')
text_counts = cv.fit_transform(df["Summary"])

X_train, X_test, y_train, y_test = train_test_split(
    text_counts, df["Sentiment"], test_size=0.3, random_state=1)

# Multinomial Naive Bayes Model
clf = MultinomialNB().fit(X_train, y_train)
predicted= clf.predict(X_test)


print("Multinomial Naive Bayes Accuracy:",metrics.accuracy_score(y_test, predicted))
```

```
Multinomial Naive Bayes Accuracy: 0.9048654473992837
```

As a result, the overall classification rate has an approx. 90.5% accuracy!