Amazon Fine Food Reviews

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:
```
#Let's read the csv file.
df = pd.read_csv(r"D:\Sentiment Analysis\Reviews.csv")
```

In [3]:
```
#Printing first 5 columns from our data frame
df.head()
```

Out[3]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenomi
0	1	B001E4KFG0	A3SGXH7AUHU8GW	delmartian	1	
1	2	B00813GRG4	A1D87F6ZCVE5NK	dll pa	0	
2	3	B000LQOCH0	ABXLMWJIXXAIN	Natalia Corres "Natalia Corres"	1	
3	4	B000UA0QIQ	A395BORC6FGVXV	Karl	3	
4	5	B006K2ZZ7K	A1UQRSCLF8GW1T	Michael D. Bigham "M. Wassir"	0	

In [4]:
```
#Observing the shape of our data frame.
df.shape
```

Out[4]:
```
(568454, 10)
```

- We have 10 features and 568454 data points.

In [5]:
```
#Observing the lables of each column.
print(df.keys())
```

```
Index(['Id', 'ProductId', 'UserId', 'ProfileName', 'HelpfulnessNumerator',
       'HelpfulnessDenominator', 'Score', 'Time', 'Summary', 'Text'],
      dtype='object')
```

In [6]:
```
#Lets check for missing values.
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 568454 entries, 0 to 568453
Data columns (total 10 columns):
 #   Column                  Non-Null Count   Dtype 
---  ------                  --------------   ----- 
 0   Id                      568454 non-null  int64 
 1   ProductId               568454 non-null  object
 2   UserId                  568454 non-null  object
 3   ProfileName             568438 non-null  object
 4   HelpfulnessNumerator    568454 non-null  int64 
 5   HelpfulnessDenominator  568454 non-null  int64 
 6   Score                   568454 non-null  int64 
 7   Time                    568454 non-null  int64 
 8   Summary                 568427 non-null  object
 9   Text                    568454 non-null  object
dtypes: int64(5), object(5)
memory usage: 43.4+ MB
```

- Observe that there are some missing values in "ProfileName" and "Summary" columns

In [7]:
```
df.describe()
```

Out[7]:

	Id	HelpfulnessNumerator	HelpfulnessDenominator	Score	Ti
count	568454.000000	568454.000000	568454.00000	568454.000000	5.684540e+
mean	284227.500000	1.743817	2.22881	4.183199	1.296257e+
std	164098.679298	7.636513	8.28974	1.310436	4.804331e+
min	1.000000	0.000000	0.00000	1.000000	9.393408e+
25%	142114.250000	0.000000	0.00000	4.000000	1.271290e+
50%	284227.500000	0.000000	1.00000	5.000000	1.311120e+
75%	426340.750000	2.000000	2.00000	5.000000	1.332720e+
max	568454.000000	866.000000	923.00000	5.000000	1.351210e+

- Observe that more than 75% of our data is belonging to positive
- Class, i.e. we have imbalanced dataset.

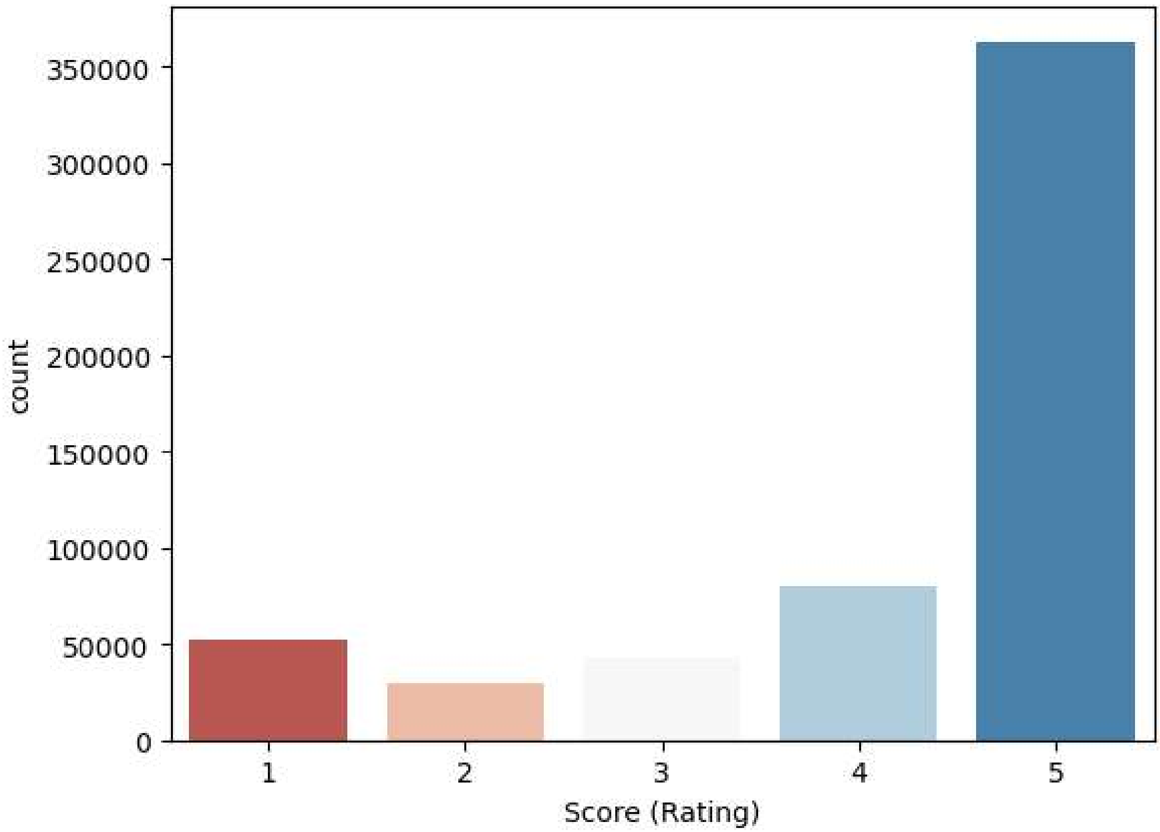
In [8]:
```
#Let's do the value count on "Scores".
df.Score.value_counts()
```

Out[8]:
```
5    363122
4     80655
1     52268
3     42640
2     29769
Name: Score, dtype: int64
```

Exploratory Data Analysis

- Till now we saw that 5-star reviews consists of large proportion (64%) of all reviews.
- The next most prevalent rating 4-star (14%), followed by 1-star(9%), 3-star(8%) and finally 2-star review (5%).
- Note that we have 10 features and 568454 data points. There are some missing values in "ProfileName" and "Summary" columns. More than 75% of our data is belonging to positive class(Score = 4,5), i.e. we have imbalanced dataset.

In [9]:
```
plt.figure()
sns.countplot(x = "Score", data = df, palette= 'RdBu')
plt.xlabel('Score (Rating)')
plt.show()
```



Creating a new dataframe

In [10]:
```
#copying the original dataframe to 'temp_df'.
temp_df = df[['UserId','HelpfulnessNumerator','HelpfulnessDenominator', 'Summa

#Adding new features to dataframe.
temp_df["Sentiment"] = temp_df["Score"].apply(lambda score: "positive" if scor
temp_df["Usefulness"] = (temp_df["HelpfulnessNumerator"]/temp_df["HelpfulnessD

#Lets now observe the shape of our new dataframe.
temp_df.shape
```

Out[10]: (568454, 8)

In [11]:
```
temp_df.describe()
```

Out[11]:

	HelpfulnessNumerator	HelpfulnessDenominator	Score
count	568454.000000	568454.00000	568454.000000
mean	1.743817	2.22881	4.183199
std	7.636513	8.28974	1.310436
min	0.000000	0.00000	1.000000
25%	0.000000	0.00000	4.000000
50%	0.000000	1.00000	5.000000
75%	2.000000	2.00000	5.000000
max	866.000000	923.00000	5.000000

In [12]:
```
temp_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 568454 entries, 0 to 568453
Data columns (total 8 columns):
 #   Column                  Non-Null Count   Dtype 
---  ------                  --------------   ----- 
 0   UserId                  568454 non-null  object
 1   HelpfulnessNumerator    568454 non-null  int64 
 2   HelpfulnessDenominator  568454 non-null  int64 
 3   Summary                 568427 non-null  object
 4   Text                    568454 non-null  object
 5   Score                   568454 non-null  int64 
 6   Sentiment               568454 non-null  object
 7   Usefulness              568454 non-null  object
dtypes: int64(3), object(5)
memory usage: 34.7+ MB
```

In [13]:
```
#Let's view the dataframe when Score = 5
temp_df[temp_df.Score == 5].head(10)
```

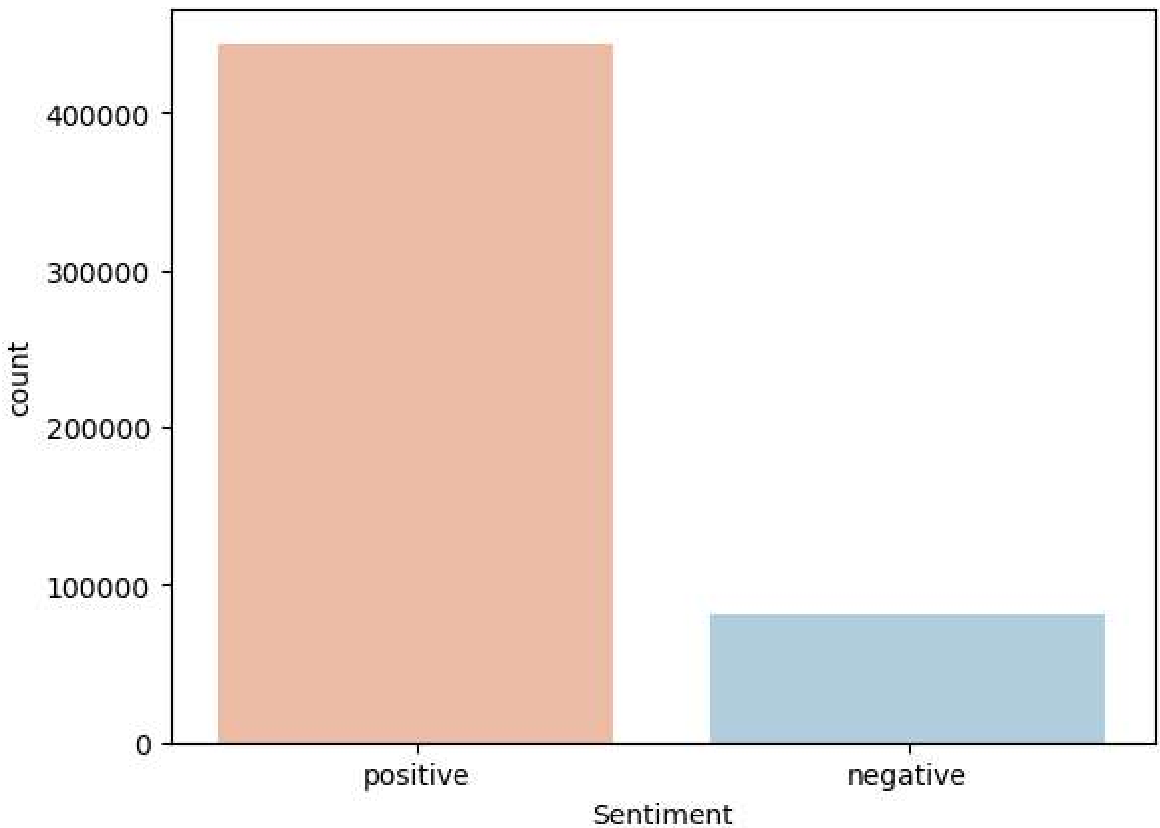
Out[13]:

	UserId	HelpfulnessNumerator	HelpfulnessDenominator	Summary	Text	S
0	A3SGXH7AUHU8GW	1	1	Good Quality Dog Food	I have bought several of the Vitality canned d...	
4	A1UQRSCLF8GW1T	0	0	Great taffy	Great taffy at a great price. There was a wid...	
6	A1SP2KVKFXXRU1	0	0	Great! Just as good as the expensive brands!	This saltwater taffy had great flavors and was...	
7	A3JRGQVEQN31IQ	0	0	Wonderful, tasty taffy	This taffy is so good. It is very soft and ch...	
8	A1MZYO9TZK0BBI	1	1	Yay Barley	Right now I'm mostly just sprouting this so my...	
9	A21BT40VZCCYT4	0	0	Healthy Dog Food	This is a very healthy dog food. Good for thei...	
10	A3HDKO7OW0QNK4	1	1	The Best Hot Sauce in the World	I don't know if it's the cactus or the tequila...	
11	A2725IB4YY9JEB	4	4	My cats LOVE this "diet" food better than thei...	One of my boys needed to lose some weight and ...	
14	A2MUGFV2TDQ47K	4	5	Strawberry Twizzlers - Yummy	The Strawberry Twizzlers are my guilty pleasur...	

	UserId	HelpfulnessNumerator	HelpfulnessDenominator	Summary	Text	S
15	A1CZX3CP8IKQIJ	4	5	Lots of twizzlers, just what you expect.	My daughter loves twizzlers and this shipment ...	

Positive reviews are very common

In [14]:
```
sns.countplot(x = 'Sentiment', order = ["positive", "negative"], data = temp_d
plt.xlabel('Sentiment')
plt.show()
```



In [15]:
```
temp_df.Sentiment.value_counts()
```

Out[15]:
```
positive       443777
negative        82037
not defined     42640
Name: Sentiment, dtype: int64
```

- Therefore we could conclude that the positive reviews are way more than the negative reviews.

Popular words in Review

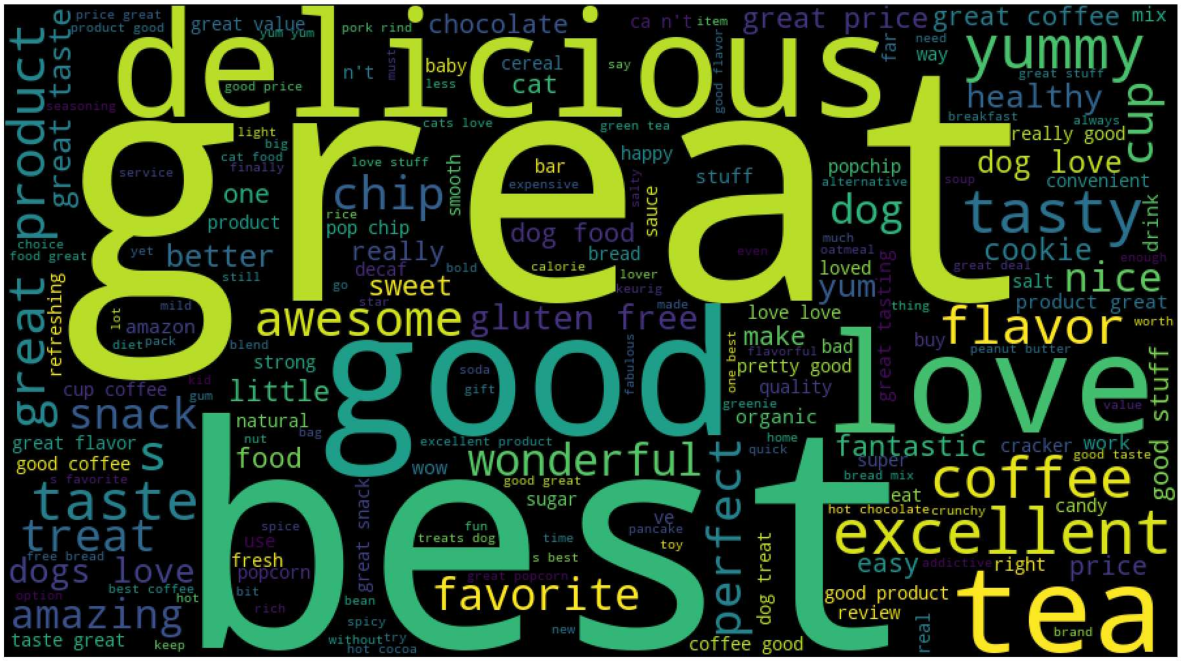
A look at the post popular words in positive (4-5 stars) and negative (1-2 stars) reviews shows that both positive and negative reviews share many popular words such as "coffee", "taste", "flavor", "price", "good" and "product". The words "good", "great", "love", "favorite" and "find" are indicative of positive reviews, while negative reviews contain words such as "didn't" and "disappointed" but these distinguishing words appear less frequently than distinguishing words in positive reviews.

In [16]:
```
pos = temp_df.loc[temp_df['Sentiment'] == 'positive']
pos = pos[0:25000]

neg = temp_df.loc[temp_df['Sentiment'] == 'negative']
neg = neg[0:25000]
```

In [17]:
```
import nltk
from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize
from wordcloud import WordCloud
import string
import matplotlib.pyplot as plt

def create_Word_Corpus(temp):
    words_corpus = ''
    for val in temp["Summary"]:
        text = str(val).lower()
        tokens = []
        tokens = word_tokenize(text)
        tokens = [word for word in tokens if word not in stopwords.words('engl
        for words in tokens:
            words_corpus = words_corpus + ' ' + words
    return words_corpus

#Generate a word cloud image
pos_wordcloud = WordCloud(width = 900, height = 500).generate(create_Word_Corp
neg_wordcloud = WordCloud(width = 900, height = 500).generate(create_Word_Corp
```

In [18]:
```
#Plot cloud
def plot_Cloud(wordCloud):
    plt.figure(figsize=(20,10), facecolor ='w')
    plt.imshow(wordCloud)
    plt.axis("off")
    plt.tight_layout(pad=0)
    plt.show()
    plt.savefig('wordClouds.png', facecolor= 'w', bbox_inches = 'tight')
```

In [19]:
```
#Visuallizing popular positive words
plot_Cloud(pos_wordcloud)
```



<Figure size 640x480 with 0 Axes>

In [20]:
```
#Visuallizing popular negative words
plot_Cloud(neg_wordcloud)
```

<Figure size 640x480 with 0 Axes>

Helpfulness

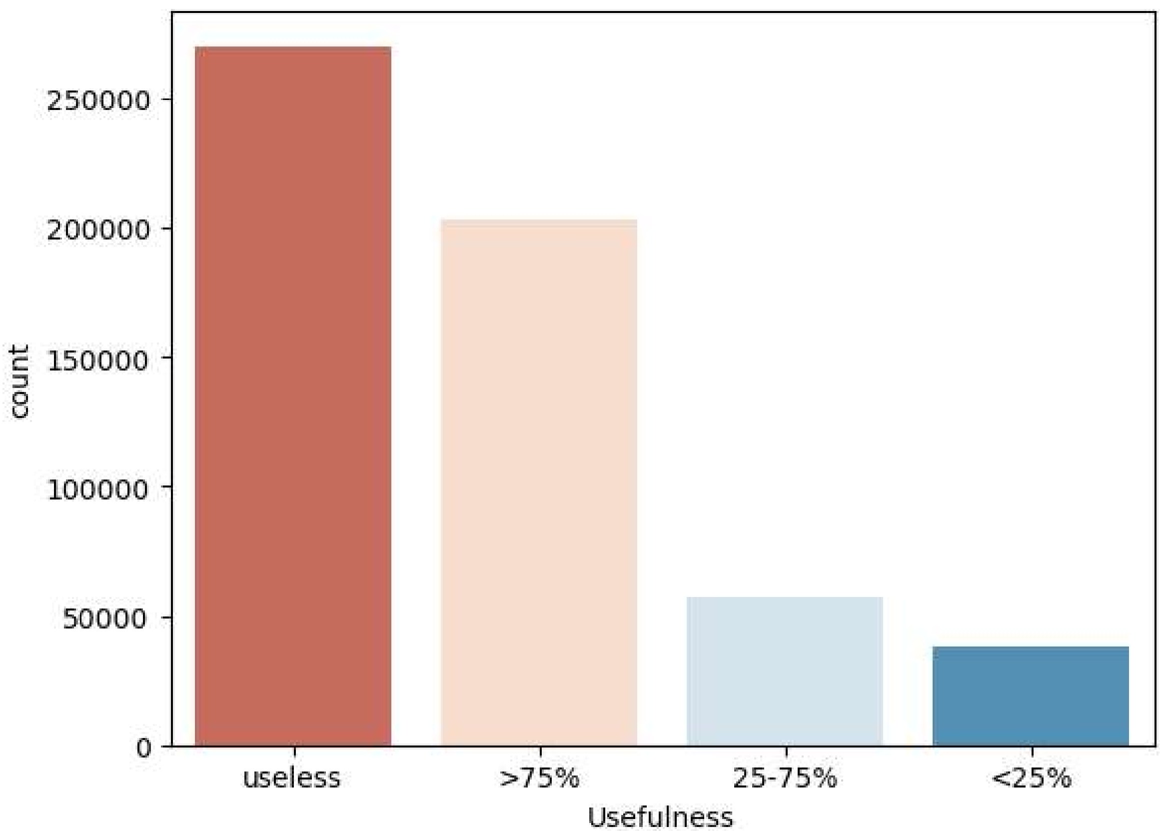
How many reviews are helpful?

- Among all reviews, almost half(50%) are not voted on at all.
- Among reviews that are voted on, helpful reviews(>75%) are the most common

In [21]:
```
#Checking the value count for 'Usefulness'
temp_df.Usefulness.value_counts()
```

Out[21]:
```
useless    270052
>75%       202836
25-75%      57286
<25%        38280
Name: Usefulness, dtype: int64
```

In [22]:
```
sns.countplot(x='Usefulness', order=['useless', '>75%', '25-75%', '<25%'], dat
plt.xlabel('Usefulness')
plt.show()
```



Positive reviews are found more helpful

As the rating becomes more positive, the reviews become more helpful(and less unhelpful).

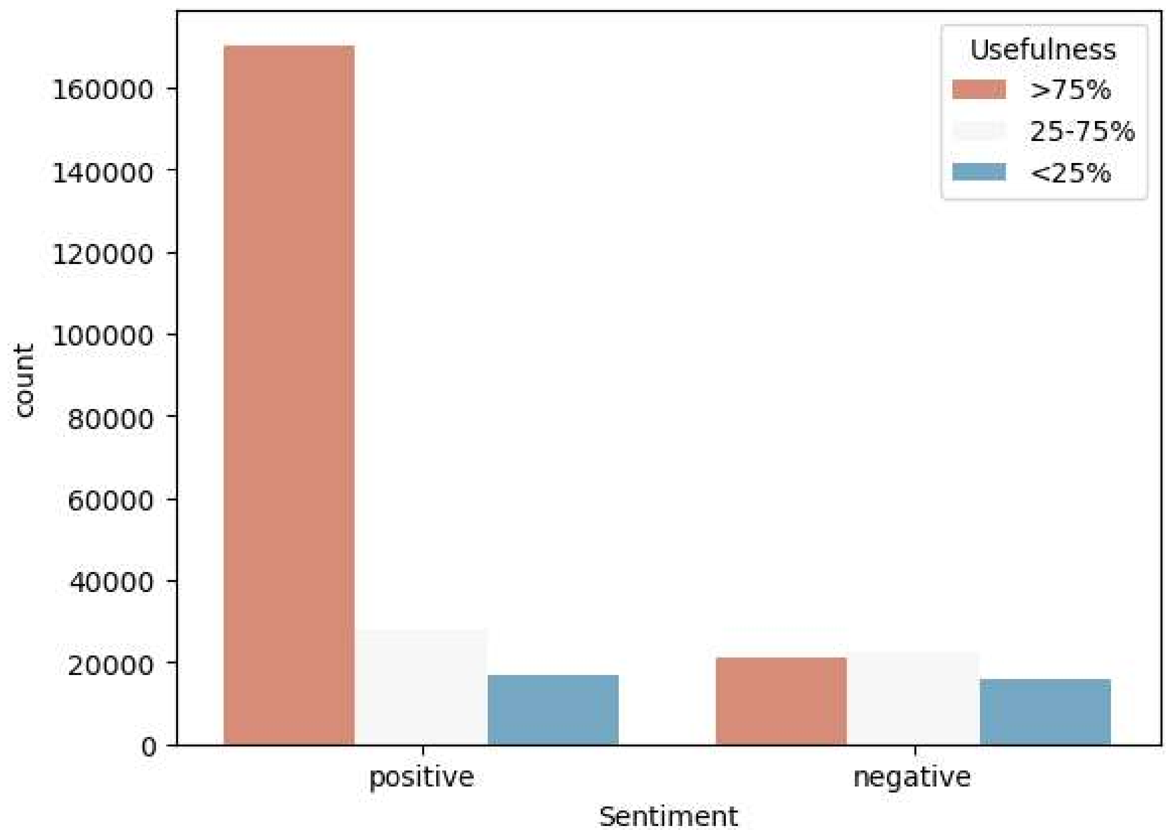
In [23]:
```
temp_df[temp_df.Score==5].Usefulness.value_counts()
```

Out[23]:
```
useless    186743
>75%       142954
25-75%      21314
<25%        12111
Name: Usefulness, dtype: int64
```

In [24]:
```
temp_df[temp_df.Score==2].Usefulness.value_counts()
```

Out[24]:
```
useless    10604
>75%        7423
25-75%      6693
<25%        5049
Name: Usefulness, dtype: int64
```

In [25]:
```
sns.countplot(x='Sentiment', hue='Usefulness', order=["positive", "negative"],
plt.xlabel('Sentiment')
plt.show()
```



- Therefore positive reviews are more helpful.

Word Count

In [26]:
```
temp_df["text_word_count"] = temp_df["Text"].apply(lambda text: len(text.split
```

In [27]:
```
temp_df.head()
```

Out[27]:

	UserId	HelpfulnessNumerator	HelpfulnessDenominator	Summary	Text	Sc
0	A3SGXH7AUHU8GW	1	1	Good Quality Dog Food	I have bought several of the Vitality canned d...	
1	A1D87F6ZCVE5NK	0	0	Not as Advertised	Product arrived labeled as Jumbo Salted Peanut...	
2	ABXLMWJIXXAIN	1	1	"Delight" says it all	This is a confection that has been around a fe...	
3	A395BORC6FGVXV	3	3	Cough Medicine	If you are looking for the secret ingredient i...	
4	A1UQRSCLF8GW1T	0	0	Great taffy	Great taffy at a great price. There was a wid...	

In [28]:
```
temp_df[temp_df.Score==5].text_word_count.median()
```

Out[28]: 52.0

In [29]:
```
temp_df[temp_df.Score==4].text_word_count.median()
```

Out[29]: 65.0

In [30]:
```
temp_df[temp_df.Score==3].text_word_count.median()
```

Out[30]: 70.0

In [31]:
```
temp_df[temp_df.Score==2].text_word_count.median()
```

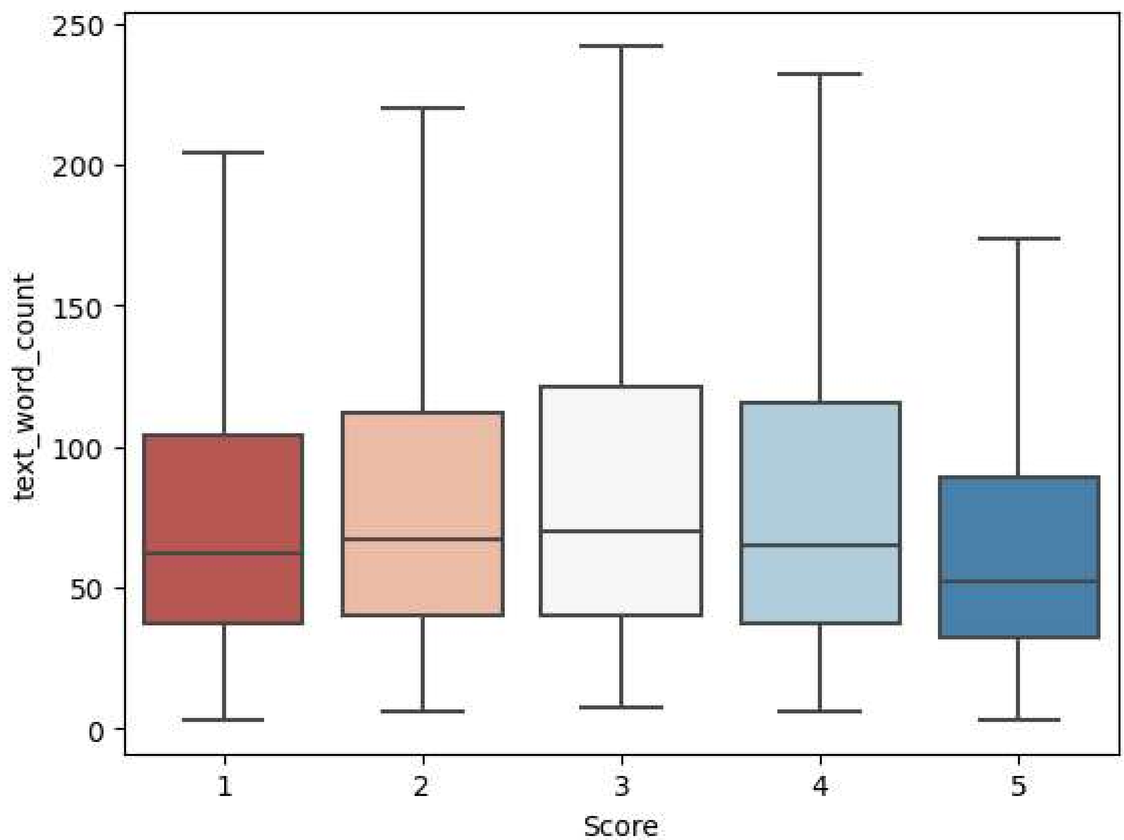
Out[31]:
```
67.0
```

In [32]:
```
temp_df[temp_df.Score==1].text_word_count.median()
```

Out[32]:
```
62.0
```

In [33]:
```
sns.boxplot(x='Score', y='text_word_count', data=temp_df, palette= 'RdBu', shc
```

Out[33]:
```
<AxesSubplot:xlabel='Score', ylabel='text_word_count'>
```

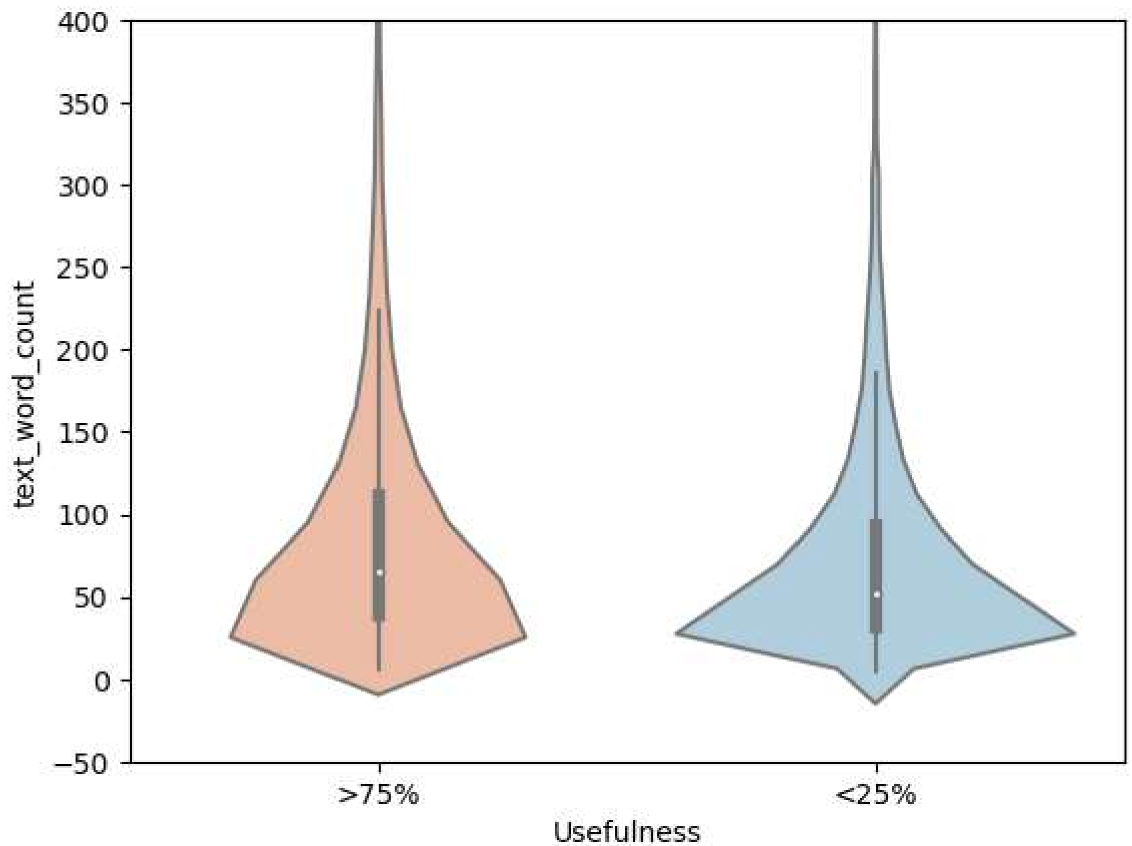


Observations: 5-star reviews had the lowest median word count(52 words), while 3-star reviews had the largest median word count(70 words).

How does word count relate to helpfulness?

The word counts for helpful reviews and not helpful reviews have a similar distribution with the greatest concentration of reviews of approximately 25 words. However, not helpful reviews have a larger concentration of reviews with low word count and helpful reviews have more longer reviews. Helpful reviews have a higher median word count(67 words) than not helpful reviews(54 words).

In [34]:
```
sns.violinplot(x='Usefulness', y='text_word_count', order= [">75%", "<25%"], c
plt.ylim(-50, 400)
plt.show()
```



Frequency of reviewers

Using UserId's, one can recognize repeat reviewers. Reviewers that have reviewed over 50 products account for over 5% of all reviews in the database. We will call such reviewers frequent reviewers. (The cutoff choice of 50, as opposed to another choice, seemed to not have a large impact on the results).

In [35]:
```
x = temp_df.UserId.value_counts()
x.to_dict()
print("Converted series to dictonary")
```

```
Converted series to dictonary
```

In [36]:
```
temp_df["reviewer_freq"] = temp_df["UserId"].apply(lambda counts: "Frequent (>
```

In [37]:
```
temp_df.head()
```

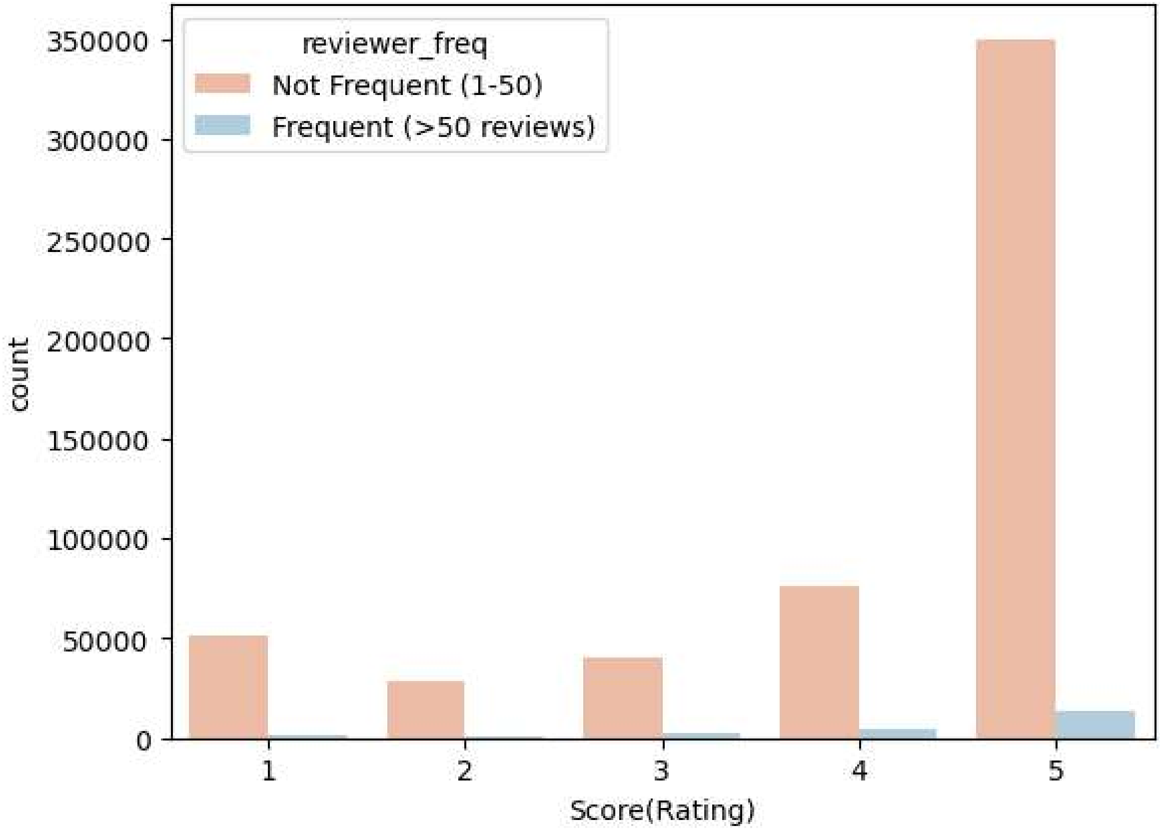
Out[37]:

	UserId	HelpfulnessNumerator	HelpfulnessDenominator	Summary	Text	Sc
0	A3SGXH7AUHU8GW	1	1	Good Quality Dog Food	I have bought several of the Vitality canned d...	
1	A1D87F6ZCVE5NK	0	0	Not as Advertised	Product arrived labeled as Jumbo Salted Peanut...	
2	ABXLMWJIXXAIN	1	1	"Delight" says it all	This is a confection that has been around a fe...	
3	A395BORC6FGVXV	3	3	Cough Medicine	If you are looking for the secret ingredient i...	
4	A1UQRSCLF8GW1T	0	0	Great taffy	Great taffy at a great price. There was a wid...	

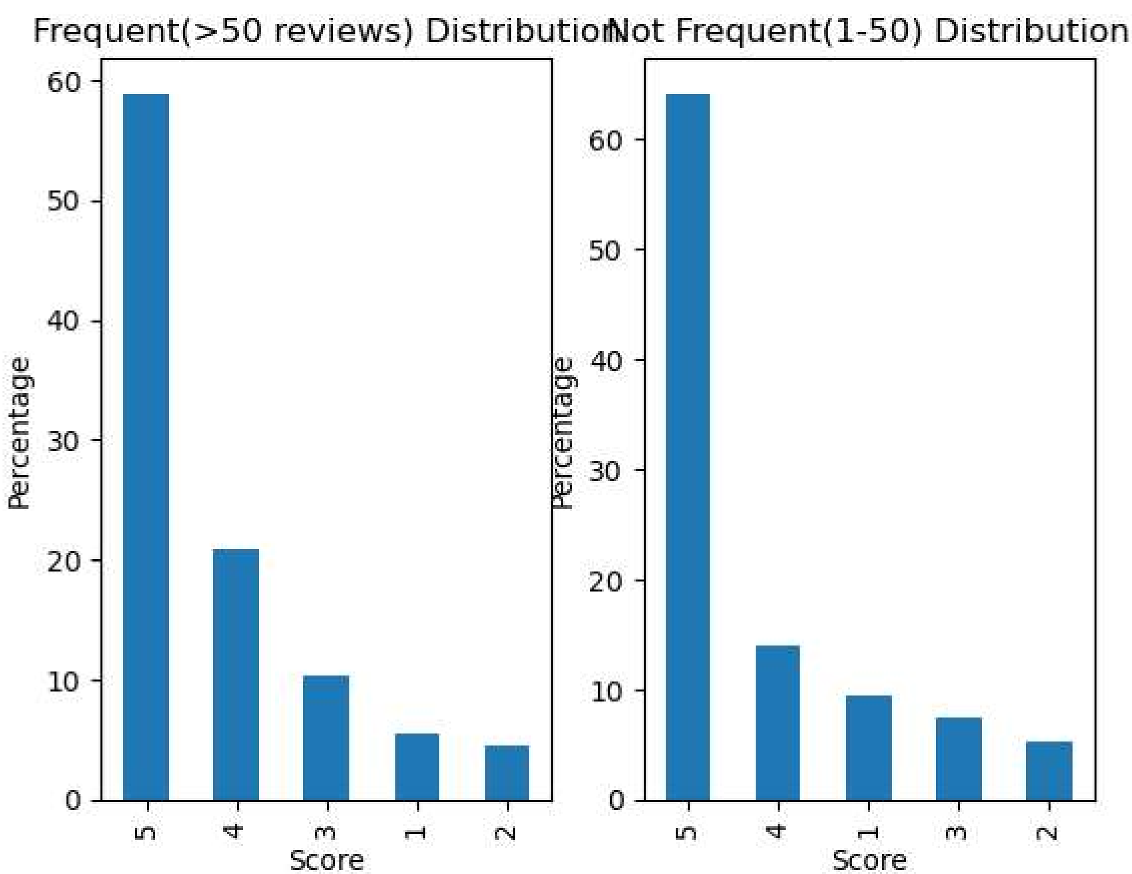
Are frequent reviewers more discerning?

The distribution of ratings among frequent reviewers is similar to that of all reviews. However, we can see that frequent reviewers give less 5-star reviews and less 1-star review. Frequent users appear to be more discerning in the sense that they give less extreme reviews than infrequent reviews.

In [38]:
```
ax = sns.countplot(x = 'Score', hue= 'reviewer_freq', data= temp_df, palette =
ax.set_xlabel('Score(Rating)')
plt.show()
```



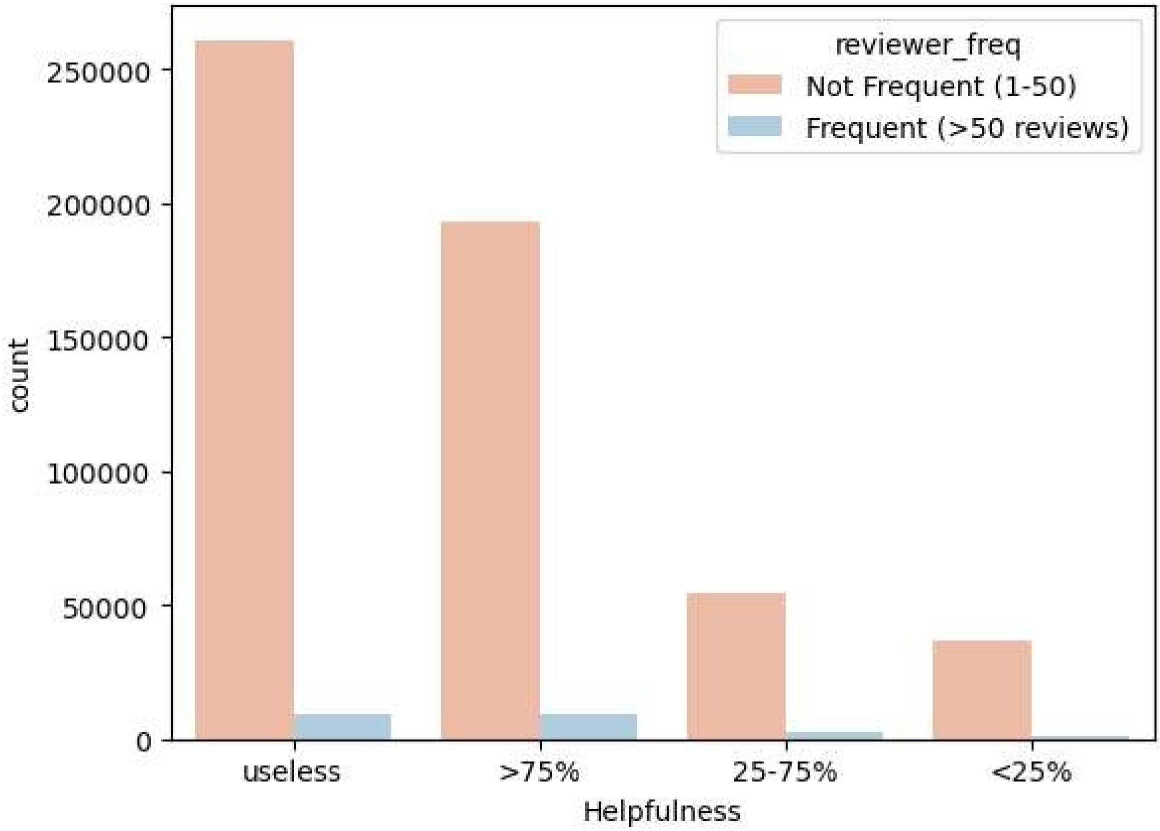
In [39]:
```
y = temp_df[temp_df.reviewer_freq=="Frequent (>50 reviews)"].Score.value_count
z = temp_df[temp_df.reviewer_freq=="Not Frequent (1-50)"].Score.value_counts()

tot_y = y.sum()

y = (y/tot_y)*100

tot_z = z.sum()

z = (z/tot_z)*100

ax1 = plt.subplot(121)
y.plot(kind="bar",ax=ax1)
plt.xlabel("Score")
plt.ylabel("Percentage")
plt.title("Frequent(>50 reviews) Distribution")

ax2 = plt.subplot(122)
z.plot(kind="bar",ax=ax2)
plt.xlabel("Score")
plt.ylabel("Percentage")
plt.title("Not Frequent(1-50) Distribution")
plt.show()
```



Are frequent reviewers more helpful?

The distribution of helpfulness for frequent reviewers is similar to that of all reviews. However, frequent reviewers are more likely to have their review voted on and when voted on, more likely to be voted helpful, and less likely to be unhelpful.

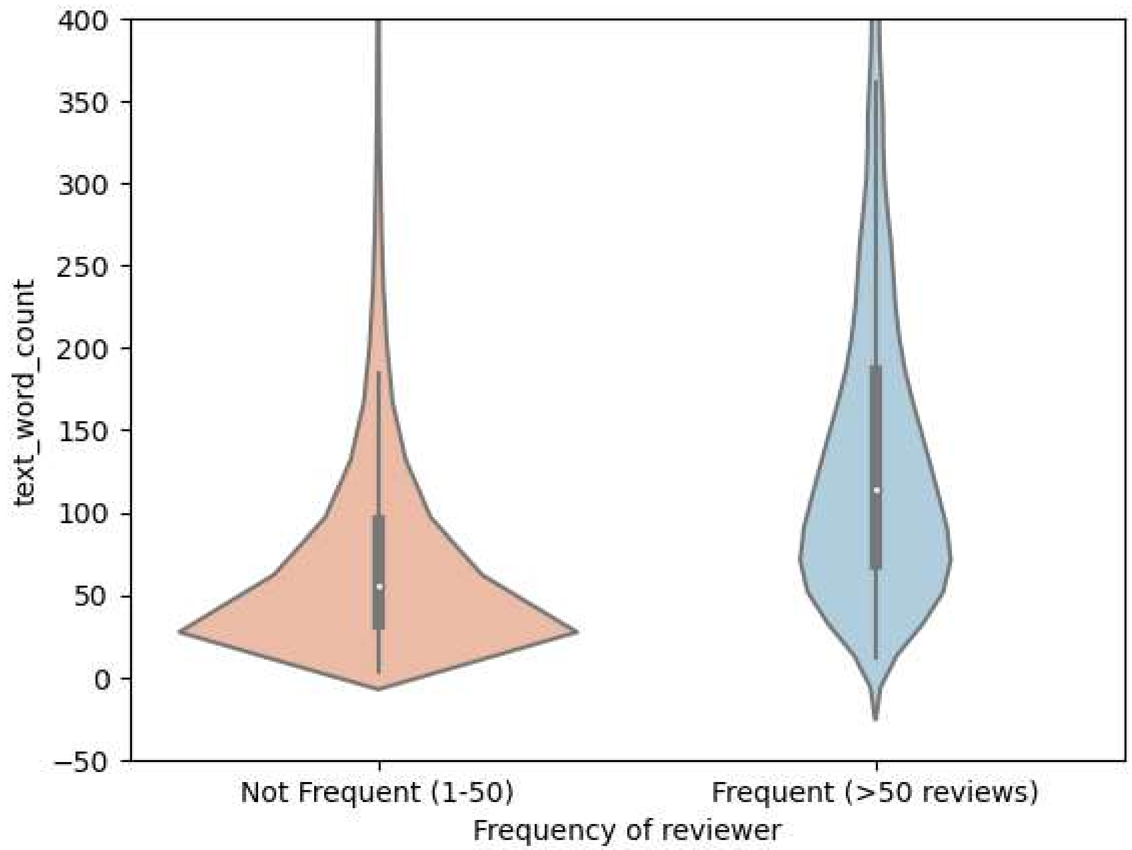
In [40]:
```
sns.countplot(x='Usefulness', order=['useless', '>75%', '25-75%', '<25%'], hue
plt.xlabel('Helpfulness')
plt.show()
```



Are frequent reviewers more verbose?

The distributions of word counts for frequent and infrequent reviews shows that infrequent reviewers have a large amount of reviews of low word count. On the other hand, the largest concentration of word count is higher for frequent reviewers than for infrequent reviews. Moreover, the median word count for frequent reviewers is higher than the median for infrequent reviewers.

In [41]:
```
sns.violinplot(x='reviewer_freq', y='text_word_count', data=temp_df, palette=
plt.xlabel('Frequency of reviewer')
plt.ylim(-50,400)
plt.show()
```



Conclusion

- Positive reviews are very common.
- POsitive reviews are shorter.
- Longer reviews are more helpful.
- Despite being more common and shorter, positive reviews are found more helpful.
- Frequent reviewrs are more discerning in their ratings, write longer reviews and write more helpful reviews.