Processed_VG_Reviews_final

December 10, 2022

0.1 Work done by Karthik Raj (SSID: 3035366972)

[1]:
```
import pandas as pd
import gzip
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
def parse(path):
    g = gzip.open(path, 'rb')
    for l in g:
        yield json.loads(l)

def getDF(path):
    i = 0
    df = {}
    for d in parse(path):
        df[i] = d
        i += 1
    return pd.DataFrame.from_dict(df, orient='index')
```

[2]:
```
# Loading in the reviews of products
df_rev = getDF('Video_Games_5.json.gz')
```

[3]:
```
display(df_rev.shape)
display(df_rev.dtypes)
df_rev.head()
```

```
(497577, 12)
```

```
overall           float64
verified             bool
reviewTime         object
reviewerID         object
asin               object
reviewerName       object
reviewText         object
summary            object
unixReviewTime      int64
```

```
vote              object
style             object
image             object
dtype: object
```

[3]:
```
   overall  verified   reviewTime      reviewerID        asin  \
0      5.0      True  10 17, 2015  A1HP7NVNPFMA4N  0700026657
1      4.0     False  07 27, 2015  A1JGAP0185YJI6  0700026657
2      3.0      True  02 23, 2015  A1YJWEXHQBWK2B  0700026657
3      2.0      True  02 20, 2015  A2204E1TH211HT  0700026657
4      5.0      True  12 25, 2014  A2RF5B5H74JLPE  0700026657

        reviewerName                                         reviewText  \
0        Ambrosia075  This game is a bit hard to get the hang of, bu…
1             travis  I played it a while but it was alright. The st…
2  Vincent G. Mezera                                          ok game.
3        Grandma KR  found the game a bit too complicated, not what…
4                jon  great game, I love it and have played it since…

                                    summary  unixReviewTime vote style  \
0                but when you do it's great.      1445040000  NaN   NaN
1  But in spite of that it was fun, I liked it      1437955200  NaN   NaN
2                                Three Stars      1424649600  NaN   NaN
3                                  Two Stars      1424390400  NaN   NaN
4                           love this game      1419465600  NaN   NaN

  image
0   NaN
1   NaN
2   NaN
3   NaN
4   NaN
```

1 Processing Reviews DataFrame

1.1 Conversion of Votes to INT Data Type

[4]:
```
df_rev['vote'] = df_rev['vote'].str.replace(',', '')
df_rev['vote'].fillna(0, inplace = True)
df_rev['vote'] = df_rev['vote'].astype(int)
```

[5]:
```
# Find the range of votes
df_rev['vote'].describe()
```

[5]:
```
count    497577.000000
mean          2.308280
std          17.133128
min           0.000000
25%           0.000000
50%           0.000000
75%           0.000000
max        2474.000000
Name: vote, dtype: float64
```

[6]:
```
display(df_rev.dtypes)
```

```
overall           float64
verified             bool
reviewTime         object
reviewerID         object
asin               object
reviewerName       object
reviewText         object
summary            object
unixReviewTime      int64
vote                int64
style              object
image              object
dtype: object
```

1.2 Filter unverified

[7]:
```
df_verif = df_rev[df_rev['verified'] == True]
display(df_verif.shape)
df_verif.head()
```

```
(332645, 12)
```

[7]:

	overall	verified	reviewTime	reviewerID	asin	reviewerName	reviewText
0	5.0	True	10 17, 2015	A1HP7NVNPFMA4N	0700026657	Ambrosia075	This game is a bit hard to get the hang of, bu…
2	3.0	True	02 23, 2015	A1YJWEXHQBWK2B	0700026657	Vincent G. Mezera	ok game.
3	2.0	True	02 20, 2015	A2204E1TH211HT	0700026657	Grandma KR	found the game a bit too complicated, not what…
4	5.0	True	12 25, 2014	A2RF5B5H74JLPE	0700026657	jon	great game, I love it and have played it since…
5	4.0	True	11 13, 2014	A11V6ZJ2FVQY1D	0700026657	IBRAHIM ALBADI	i liked a lot some time that i haven't play a …

```
                       summary  unixReviewTime  vote style image
0  but when you do it's great.      1445040000     0   NaN   NaN
2                   Three Stars      1424649600     0   NaN   NaN
3                     Two Stars      1424390400     0   NaN   NaN
4                love this game      1419465600     0   NaN   NaN
5                     Anno 2070      1415836800     0   NaN   NaN
```

1.3 Checking to see if worthwhile creating average rating from solely reviews with nonzero Helpfulness Votes

[8]:
```
df_verif['vote'].describe()
```

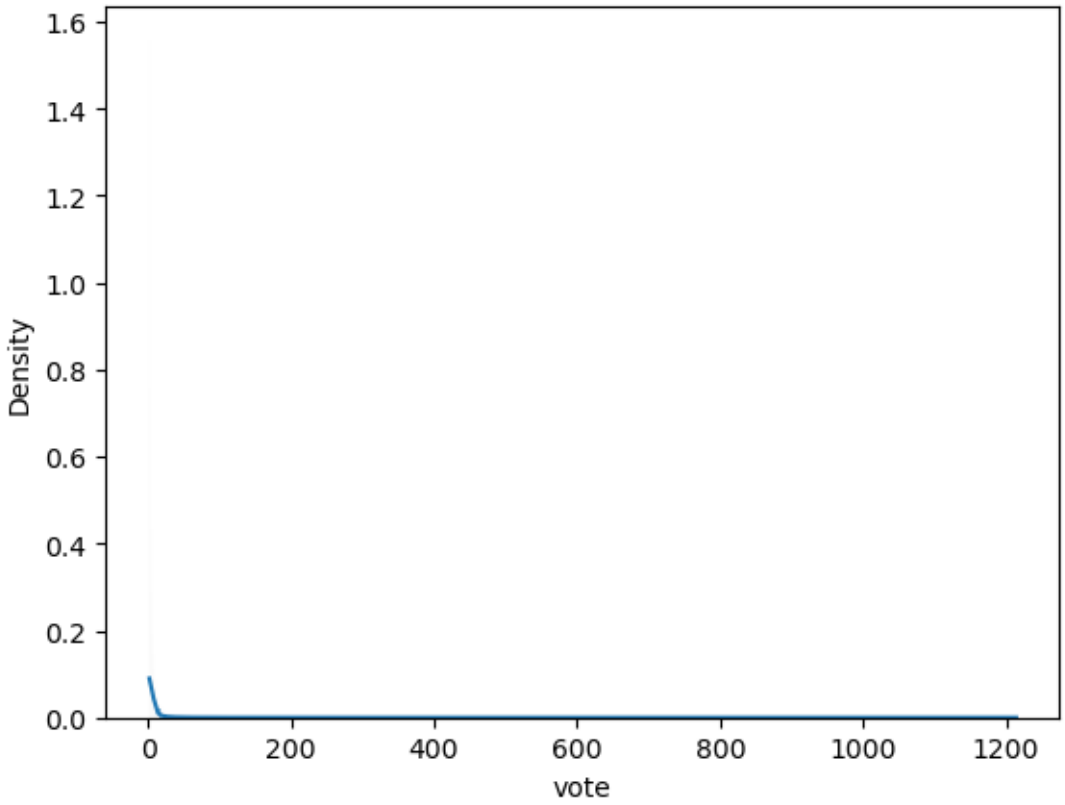
[8]:
```
count    332645.000000
mean          0.902725
std           9.051633
min           0.000000
25%           0.000000
50%           0.000000
75%           0.000000
max        1214.000000
Name: vote, dtype: float64
```

[9]:
```
df_nonz_helpf = df_verif[df_verif['vote'] > 0]
df_nonz_helpf['vote'].describe()
```

[9]:
```
count    37619.000000
mean         7.982323
std         25.845426
min          2.000000
25%          2.000000
50%          3.000000
75%          6.000000
max       1214.000000
Name: vote, dtype: float64
```

[10]:
```
sns.histplot(df_nonz_helpf['vote'], stat = 'density', kde = True)
```

[10]:
```
<AxesSubplot:xlabel='vote', ylabel='Density'>
```



[11]:
```
# Losing 89% of the data if just rolling with nonzero helpfulness reviews so␣
 ↪not worth
(display('Proportion of Reviews with Nonzero Helpfulness ' +
        str(df_nonz_helpf.shape[0] / df_verif.shape[0])))
```

```
'Proportion of Reviews with Nonzero Helpfulness 0.1130905319484736'
```

1.4 Creating Average Rating Column for Each Product Regardless of Helpfulness

[12]:
```
# Losing 7K of products if average is computed solely from helpful reviews
z_helpf_avg = df_verif.groupby('asin').agg({'overall' : np.mean})
z_helpf_avg.rename(columns = {'overall' :'avg_rating_unf'}, inplace = True)
z_helpf_avg
```

[12]:

asin	avg_rating_unf
0700026398	3.200000
0700026657	4.200000
0700099867	3.181818

```
0804161380        4.812500
3828770193        4.200000
…                    …
B01HFRICLE        4.384615
B01HGPUTCA        4.600000
B01HH6JEOC        4.000000
B01HIZF7XE        4.657143
B01HIZGKOE        3.500000

[17099 rows x 1 columns]
```

1.5 Data Cleaning

[13]:
```
# Checking proportion of NaNs in their respective columns
df_verif.isna().sum() / df_verif.shape[0]
```

[13]:
```
overall           0.000000
verified          0.000000
reviewTime        0.000000
reviewerID        0.000000
asin              0.000000
reviewerName      0.000180
reviewText        0.000424
summary           0.000265
unixReviewTime    0.000000
vote              0.000000
style             0.425721
image             0.992830
dtype: float64
```

[14]:
```
dfcl_verif = df_verif.drop(columns = ['image', 'style', 'unixReviewTime',␣
 ↪'reviewTime', 'verified'])
dfcl_verif.head()
```

[14]:
```
   overall      reviewerID        asin       reviewerName  \
0      5.0  A1HP7NVNPFMA4N  0700026657        Ambrosia075
2      3.0  A1YJWEXHQBWK2B  0700026657  Vincent G. Mezera
3      2.0  A2204E1TH211HT  0700026657         Grandma KR
4      5.0  A2RF5B5H74JLPE  0700026657                jon
5      4.0  A11V6ZJ2FVQY1D  0700026657     IBRAHIM ALBADI

                                          reviewText  \
0  This game is a bit hard to get the hang of, bu…
2                                          ok game.
3  found the game a bit too complicated, not what…
4  great game, I love it and have played it since…
```

```
5  i liked a lot some time that i haven't play a …

                      summary  vote
0  but when you do it's great.     0
2                  Three Stars     0
3                    Two Stars     0
4               love this game     0
5                    Anno 2070     0
```

2 Creating Column of the Review Counts

[15]:
```
count_df = dfcl_verif.groupby('asin').size().to_frame(name = 'count')
count_df.head()
```

[15]:
```
            count
asin
0700026398      5
0700026657     10
0700099867     22
0804161380     48
3828770193      5
```

3 Making Final Dataset

[16]:
```
dfcl_verif.set_index('asin', inplace = True)
```

[17]:
```
df_cnt_rev = pd.merge(dfcl_verif,count_df, left_index = True, right_index =␣
 ↪True)
df_cnt_rev.head()
```

[17]:
```
            overall      reviewerID     reviewerName  \
asin
0700026398      1.0  A1NQ759X8WPIVV             Lynn
0700026398      4.0  A2RGUDIF7VB7JZ  Johnathan Scott
0700026398      4.0  A2FTI5YE727I78  CubOfJudahsLion
0700026398      2.0  A2IPY9UTB8JEU5  Emelinda Willis
0700026398      5.0   AK9YPIL2TWL24       David Neil

                                                reviewText  \
asin
0700026398  I'm sure I would love the game, if I could pla…
0700026398                                          Good game
0700026398  This installment introduces some unusual eleme…
```

```
0700026398  This game requires that you open an online acc…
0700026398                            great game! go agent 47!

                                                      summary  vote  count
asin
0700026398                                     Requires steam     0      5
0700026398                                        Four Stars     0      5
0700026398  I like him having some motivation to pursue a …     0      5
0700026398  Requires constant online access. This is only …     0      5
0700026398                                        Five Stars     0      5
```

[18]:
```
df_all_cl = pd.merge(df_cnt_rev,z_helpf_avg, left_index = True, right_index =␣
 ↪True)
df_all_cl.head()
```

[18]:
```
            overall      reviewerID     reviewerName  \
asin
0700026398      1.0  A1NQ759X8WPIVV             Lynn
0700026398      4.0  A2RGUDIF7VB7JZ  Johnathan Scott
0700026398      4.0  A2FTI5YE727I78  CubOfJudahsLion
0700026398      2.0  A2IPY9UTB8JEU5  Emelinda Willis
0700026398      5.0   AK9YPIL2TWL24       David Neil

                                                reviewText  \
asin
0700026398  I'm sure I would love the game, if I could pla…
0700026398                                        Good game
0700026398  This installment introduces some unusual eleme…
0700026398  This game requires that you open an online acc…
0700026398                            great game! go agent 47!

                                                      summary  vote  count  \
asin
0700026398                                     Requires steam     0      5
0700026398                                        Four Stars     0      5
0700026398  I like him having some motivation to pursue a …     0      5
0700026398  Requires constant online access. This is only …     0      5
0700026398                                        Five Stars     0      5

            avg_rating_unf
asin
0700026398             3.2
0700026398             3.2
0700026398             3.2
0700026398             3.2
0700026398             3.2
```

[19]:
```
df_all_cl.to_csv('vg_ratings.csv')
```

Sentiment_Predict_Avg_Rating_fin

December 10, 2022

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import sklearn
!pip install nltk
import nltk
nltk.download('punkt')
```

```
Requirement already satisfied: nltk in
/srv/conda/envs/notebook/lib/python3.9/site-packages (3.7)
Requirement already satisfied: joblib in
/srv/conda/envs/notebook/lib/python3.9/site-packages (from nltk) (1.2.0)
Requirement already satisfied: tqdm in
/srv/conda/envs/notebook/lib/python3.9/site-packages (from nltk) (4.64.0)
Requirement already satisfied: click in
/srv/conda/envs/notebook/lib/python3.9/site-packages (from nltk) (8.1.3)
Requirement already satisfied: regex>=2021.8.3 in
/srv/conda/envs/notebook/lib/python3.9/site-packages (from nltk) (2022.10.31)
```

```
[nltk_data] Downloading package punkt to /home/jovyan/nltk_data…
[nltk_data]   Package punkt is already up-to-date!
```

[1]:
```
True
```

1 Is the Sentiment in Reviews a Viable Predictor for the Average Rating of Products?

The goal of this analysis is to assess whether the sentiment noted in reviews of products with at least a certain minimum number of reviews is a viable predictor of the average rating of those products. If this is the case, can the sentiment in reviews of samples (chosen in a specific manner) of the dataset serve as viable estimators of the average rating of the products.

2 Reviews Dataset Analysis

[2]:
```
df_revs = pd.read_csv('vg_ratings.csv')
display(df_revs.shape)
df_revs.head()
```

```
(332645, 9)
```

[2]:

	asin	overall	reviewerID	reviewerName	reviewText	summary	vote	count	avg_rating_unf
0	0700026398	1.0	A1NQ759X8WPIVV	Lynn	I'm sure I would love the game, if I could pla…	Requires steam	0	5	3.2
1	0700026398	4.0	A2RGUDIF7VB7JZ	Johnathan Scott	Good game	Four Stars	0	5	3.2
2	0700026398	4.0	A2FTI5YE727I78	CubOfJudahsLion	This installment introduces some unusual eleme…	I like him having some motivation to pursue a …	0	5	3.2
3	0700026398	2.0	A2IPY9UTB8JEU5	Emelinda Willis	This game requires that you open an online acc…	Requires constant online access. This is only …	0	5	3.2
4	0700026398	5.0	AK9YPIL2TWL24	David Neil	great game! go agent 47!	Five Stars	0	5	3.2

2.1 Determine Frequency Distribution of 1,2,3,4 and 5 Star Reviews

[3]:
```
df_revs['vote'].value_counts()
```

[3]:
```
0      295026
2       13981
3        6797
4        3864
5        2588
```

```
        …
138         1
182         1
166         1
500         1
282         1
Name: vote, Length: 264, dtype: int64
```

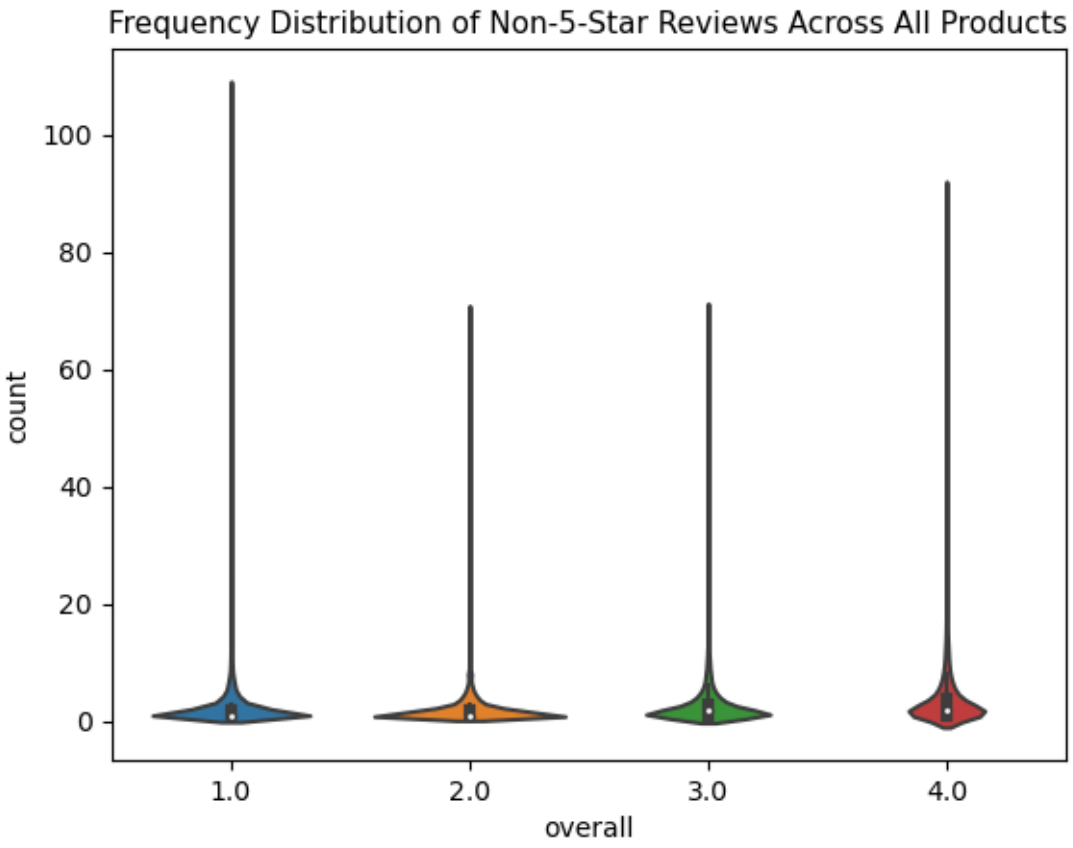
[4]:
```
count_ratings_df = df_revs.groupby(['asin', 'overall']).count()[['count']].
↪reset_index()
count_ratings_df
```

[4]:

	asin	overall	count
0	0700026398	1.0	1
1	0700026398	2.0	1
2	0700026398	4.0	2
3	0700026398	5.0	1
4	0700026657	2.0	1
…	…	…	…
50910	B01HIZF7XE	5.0	25
50911	B01HIZGKOE	2.0	2
50912	B01HIZGKOE	3.0	1
50913	B01HIZGKOE	4.0	1
50914	B01HIZGKOE	5.0	2

[50915 rows x 3 columns]

[5]:
```
# Did not plot
sns.violinplot(data = count_ratings_df[count_ratings_df['overall'] != 5], x =␣
↪'overall', y = 'count')
plt.title('Frequency Distribution of Non-5-Star Reviews Across All Products',␣
↪fontsize = 11);
```



Did not plot the distribution for the counts of 5 star reviews alongside the counts of 1,2,3, and 4 star reviews because there is a much larger distribution for the 5 star reviews. The plot does illustrate how the distribution of the counts of non-5 star review are comparable.

[6]:
```
df_neat_ratings_counts = pd.pivot_table(data = count_ratings_df, index =␣
↪'asin', columns = 'overall', values = 'count')
df_neat_ratings_counts.fillna(0, inplace = True)
df_neat_ratings_counts.head()
```

[6]:

overall	1.0	2.0	3.0	4.0	5.0
asin					
0700026398	1.0	1.0	0.0	2.0	1.0
0700026657	0.0	1.0	1.0	3.0	5.0
0700099867	6.0	2.0	3.0	4.0	7.0
0804161380	0.0	1.0	0.0	6.0	41.0
3828770193	0.0	0.0	1.0	2.0	2.0

[7]:
```
# Run below only once since will overwrite num_review column
df_neat_ratings_counts['num_reviews'] = df_neat_ratings_counts.sum(axis = 1)
display('Number of Products: ' + str(df_neat_ratings_counts.shape[0]))
```

```
df_neat_ratings_counts
```

```
'Number of Products: 17099'
```

[7]:
```
overall     1.0  2.0  3.0  4.0   5.0  num_reviews
asin
0700026398  1.0  1.0  0.0  2.0   1.0          5.0
0700026657  0.0  1.0  1.0  3.0   5.0         10.0
0700099867  6.0  2.0  3.0  4.0   7.0         22.0
0804161380  0.0  1.0  0.0  6.0  41.0         48.0
3828770193  0.0  0.0  1.0  2.0   2.0          5.0
…           …    …    …    …     …            …
B01HFRICLE  0.0  0.0  2.0  4.0   7.0         13.0
B01HGPUTCA  0.0  0.0  0.0  2.0   3.0          5.0
B01HH6JEOC  0.0  0.0  3.0  1.0   3.0          7.0
B01HIZF7XE  0.0  0.0  2.0  8.0  25.0         35.0
B01HIZGKOE  0.0  2.0  1.0  1.0   2.0          6.0

[17099 rows x 6 columns]
```

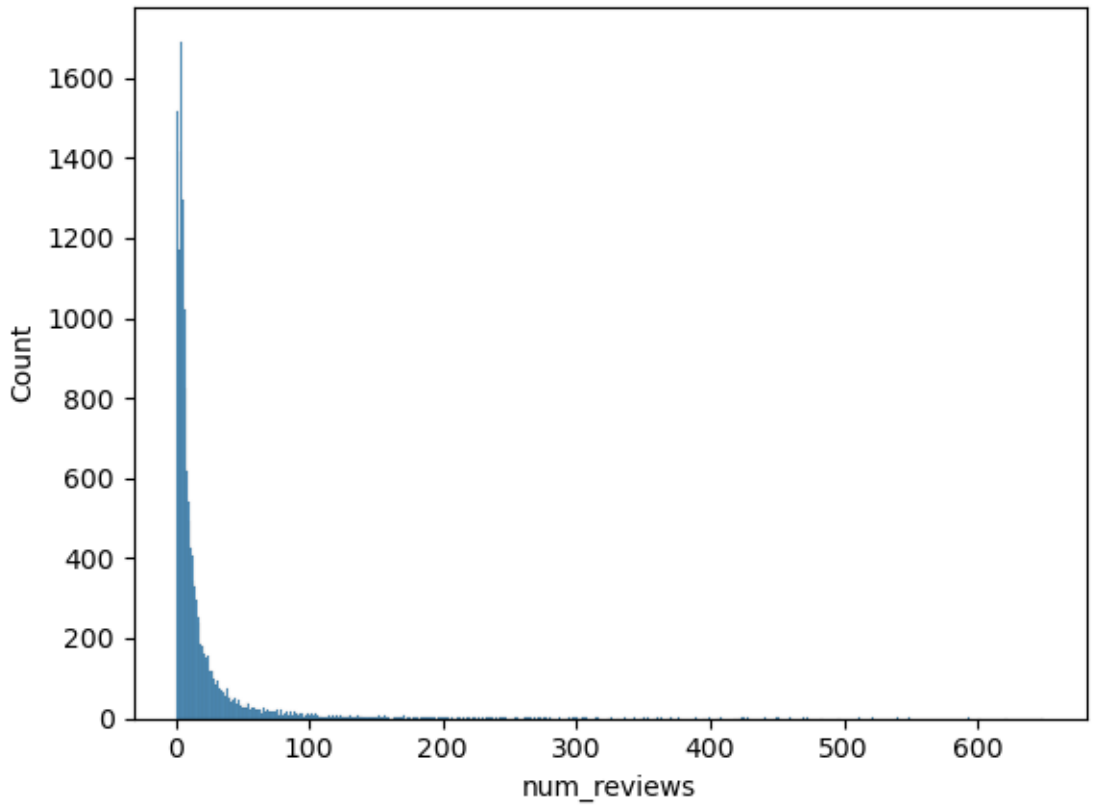
[8]:
```
# Displaying general statistics for frequency distributions of all review types␣
  ↪and for number of reviews per product
df_neat_ratings_counts.describe()
```

[8]:
```
overall           1.0           2.0           3.0           4.0           5.0  \
count    17099.000000  17099.000000  17099.000000  17099.000000  17099.000000
mean         0.889058      0.708813      1.636236      3.209895     13.010059
std          2.253402      1.740458      3.292656      6.059071     27.583163
min          0.000000      0.000000      0.000000      0.000000      0.000000
25%          0.000000      0.000000      0.000000      0.000000      3.000000
50%          0.000000      0.000000      1.000000      1.000000      5.000000
75%          1.000000      1.000000      2.000000      3.000000     12.000000
max        108.000000     70.000000     70.000000     90.000000    513.000000

overall   num_reviews
count    17099.000000
mean        19.454062
std         37.611545
min          1.000000
25%          5.000000
50%          8.000000
75%         18.000000
max        649.000000
```

2.1.1 Distribution of Number of Reviews

[9]:
```
sns.histplot(data = df_neat_ratings_counts, x = 'num_reviews');
```



2.1.2 Using 25th Percentile of the Number of Reviews as Cutoff for Products kept in Sentiment Analysis

[10]:
```
perc = np.percentile(df_neat_ratings_counts['num_reviews'], 25)
perc
```

[10]: 5.0

[11]:
```
df_des_revs = df_neat_ratings_counts[df_neat_ratings_counts['num_reviews'] >=␣
↪perc]
display(df_des_revs.shape)
df_des_revs.head()
```

```
(12992, 6)
```

[11]:
asin	overall	1.0	2.0	3.0	4.0	5.0	num_reviews
0700026398		1.0	1.0	0.0	2.0	1.0	5.0
0700026657		0.0	1.0	1.0	3.0	5.0	10.0
0700099867		6.0	2.0	3.0	4.0	7.0	22.0
0804161380		0.0	1.0	0.0	6.0	41.0	48.0
3828770193		0.0	0.0	1.0	2.0	2.0	5.0

[12]:
```
display('Number of Products: ' + str(df_neat_ratings_counts.shape[0]))
display('New Number of Products who meet desired cutoff of at least 5 reviews:␣
 ↪' + str(df_des_revs.shape[0]))
```

```
'Number of Products: 17099'
```

```
'New Number of Products who meet desired cutoff of at least 5 reviews: 12992'
```

2.2 Sentiment Analysis on Reviews of Products who meet minimum Number of Reviews Threshold

[13]:
```
# Isolate desired portion of the dataset, keeping products with at least 5␣
 ↪(25th percentile) reviews
df_iso_25 = df_revs[df_revs['count'] >= perc]
display(df_iso_25.shape)
df_iso_25.head()
```

```
(321066, 9)
```

[13]:

	asin	overall	reviewerID	reviewerName	reviewText	summary	vote	count
0	0700026398	1.0	A1NQ759X8WPIVV	Lynn	I'm sure I would love the game, if I could pla…	Requires steam	0	5
1	0700026398	4.0	A2RGUDIF7VB7JZ	Johnathan Scott	Good game	Four Stars	0	5
2	0700026398	4.0	A2FTI5YE727I78	CubOfJudahsLion	This installment introduces some unusual eleme…	I like him having some motivation to pursue a …	0	5
3	0700026398	2.0	A2IPY9UTB8JEU5	Emelinda Willis	This game requires that you open an online acc…	Requires constant online access. This is only …	0	5
4	0700026398	5.0	AK9YPIL2TWL24	David Neil	great game! go agent 47!	Five Stars	0	5

```
   avg_rating_unf
0             3.2
1             3.2
2             3.2
3             3.2
4             3.2
```

3 Isolate desired portion of the dataset, only obtaining reviews of products with more than or equal to 5, 5 star reviews

#iso_25th percentile df_iso_25 = pd.merge(df_revs.set_index('asin'), df_des_revs['num_reviews'], left_index= True, right_index = True) display(df_iso_25.shape) df_iso_25.head() # Used products

3.1 Checking to see how many NANs

[14]:
```
df_iso_25.isna().sum()
```

[14]:
```
asin              0
overall           0
reviewerID        0
reviewerName    163
reviewText      143
summary          86
vote              0
count             0
avg_rating_unf    0
dtype: int64
```

[15]:
```
# Checking to see what is in the columns where reviewText is Nan
df_iso_25[df_iso_25['reviewText'].isna()]
```

[15]:
```
              asin  overall      reviewerID     reviewerName reviewText  \
505     B000006RGR      5.0  A3N9BKUHN4B6J2  mohamedalkuwari        NaN
522     B000006RGS      5.0  A3N9BKUHN4B6J2  mohamedalkuwari        NaN
3031    B00001ZT9E      5.0  A3N9BKUHN4B6J2  mohamedalkuwari        NaN
3841    B00002R28F      5.0  A2XIJG9EJFW1U7          Mahmood        NaN
6252    B000031KJM      5.0  A1G2R5DGP0545K        NickStRRR        NaN
…              …      …              …              …        …
320363  B01AC3ZD06      5.0  A3SBULFV1ZKFYU   pedro martinez        NaN
323355  B01CEFXCE4      1.0  A1230IVR534KIH           Nathan        NaN
323786  B01CKGI4RM      5.0  A3SBULFV1ZKFYU   pedro martinez        NaN
329160  B01GKGVI8U      5.0  A1BNU92K69LUMC           valone        NaN
```

```
331955  B01GWGX74Q      3.0  A1EX60VJE83FDC      Wonyong Lee        NaN

                                                  summary  vote  count  \
505                                           Five Stars     0     11
522                                           Five Stars     0     20
3031                                          Five Stars     0      7
3841                                          Five Stars     0     12
6252                                          Five Stars     0     30
…                                                    …    …     …
320363                                        Five Stars     0     87
323355  Instructions from website are in chinease crap     0     12
323786                                        Five Stars     0     60
329160                                        Five Stars     0    171
331955                                       Three Stars     0     27

        avg_rating_unf
505           4.636364
522           4.450000
3031          4.285714
3841          4.500000
6252          4.733333
…                  …
320363        4.919540
323355        3.416667
323786        4.400000
329160        4.567251
331955        4.666667

[143 rows x 9 columns]
```

[16]:
```
# Dont know how there can be a summary if the reviewText is empty so just going␣
↪to drop these reviews later on
df_iso_25[df_iso_25['reviewText'].isna()]['summary'].value_counts()
```

[16]:
```
Five Stars                                                121
Four Stars                                                  4
Three Stars                                                 4
Unhappy.                                                    1
One Star                                                    1
Could of been alittle longer but still fun to play          1
Cool                                                        1
Good replacement that is all.                               1
Very nice                                                   1
Awesome.                                                    1
Great skin for the price                                    1
Instructions from website are in chinease crap              1
Name: summary, dtype: int64
```

[17]:
```
df_iso_25[df_iso_25['summary'].isna()]
```

[17]:

	asin	overall	reviewerID	reviewerName	reviewText	summary	vote	count	avg_rating_unf
1295	B00000I1C1	5.0	A38D4I8SWY6MU1	Marilyn Tyree	Awesome	NaN	0	17	4.764706
6605	B000035XLE	2.0	A21D3NZNORHY74	Gerson	The supposed included poster was missing bumme…	NaN	0	13	4.307692
10108	B00004TN8R	5.0	A38D4I8SWY6MU1	Marilyn Tyree	Awesome	NaN	0	13	4.307692
12428	B00005A4X6	5.0	A2LPD0V7XIKIRL	Xander	Really good game which I didn't expect because…	NaN	0	15	4.133333
13195	B00005CDR8	5.0	A1OLI6ZBZWDSBO	WAEL M BEDEER	very good :) thanks >	NaN	0	33	4.666667
…	…	…	…	…	…	…	…	…	…
325226	B01DPUVMFS	5.0	A3R7ZCCLNJMBOI	jim burton	Good	NaN	0	25	3.920000
325556	B01E38YIJI	5.0	A3UGILCWBKAR1H	Agent Cooper	Love it	NaN	0	26	3.807692
325731	B01EAG0VCG	5.0	A34G07PW0P6G8V	Edgar	Perfect!	NaN	0	15	4.933333
326694	B01EZAA2ZI	5.0	A1DQJ26EQ1XNP0	RCN001	MODERN WARFARE REMASTERED. ALL I HAVE TO SAY!	NaN	0	123	3.731707
327880	B01FT72NOO	5.0	A3HTQRWBZQ745	Michal Foster	Don't listen to the buthurt fanboys. This game…	NaN	0	31	2.935484

[86 rows x 9 columns]

3.2 Testing nltk (Package for Sentiment Analysis)

[18]:
```
# Set up for Sentiment Scores
nltk.download('vader_lexicon')
nltk.download('punkt')
nltk.download('averaged_perceptron_tagger')
from nltk.sentiment.vader import SentimentIntensityAnalyzer

sid = SentimentIntensityAnalyzer()
```

```
[nltk_data] Downloading package vader_lexicon to
[nltk_data]     /home/jovyan/nltk_data…
[nltk_data]   Package vader_lexicon is already up-to-date!
[nltk_data] Downloading package punkt to /home/jovyan/nltk_data…
[nltk_data]   Package punkt is already up-to-date!
[nltk_data] Downloading package averaged_perceptron_tagger to
[nltk_data]     /home/jovyan/nltk_data…
[nltk_data]   Package averaged_perceptron_tagger is already up-to-
[nltk_data]       date!
```

[19]:
```
rng_row = df_iso_25.sample(1)
display(rng_row)
ex_text = ''.join(rng_row['reviewText'].values)
ex_text
```

```
             asin  overall      reviewerID reviewerName  \
122572  B002EE5SAC      4.0  A32M8IN9X7F8GB      Phantos

                                                reviewText  \
122572  Although this isn't the best fighting game in …

                        summary  vote  count  avg_rating_unf
122572  Fun with cool characters     0     34        4.823529
```

[19]:
```
"Although this isn't the best fighting game in the world, there are lots of
characters here and it is a lot of fun. It works with the Wiimote but I got some
arcade-style pads for it and it's more fun to play that way. You can also use
Gamecube controllers with this although the arcade sticks are still easier and
more fun. This may be the best fighting game for the Wii."
```

[20]:
```
# Empty Strings have a compound score of 0, so fine to keep empty strings and␣
 ↪should replace NANs in summary as empty strings
sid.polarity_scores('')
```

[20]:
```
{'neg': 0.0, 'neu': 0.0, 'pos': 0.0, 'compound': 0.0}
```

[21]:
```
sid.polarity_scores('good game')
```

[21]: {'neg': 0.0, 'neu': 0.256, 'pos': 0.744, 'compound': 0.4404}

[22]:
```
sid.polarity_scores('good game!')
```

[22]: {'neg': 0.0, 'neu': 0.239, 'pos': 0.761, 'compound': 0.4926}

[23]:
```
sid.polarity_scores('GOOD GAME!')
```

[23]: {'neg': 0.0, 'neu': 0.239, 'pos': 0.761, 'compound': 0.4926}

[24]:
```
sid.polarity_scores(':)')
```

[24]: {'neg': 0.0, 'neu': 0.0, 'pos': 1.0, 'compound': 0.4588}

[25]:
```
sid.polarity_scores(ex_text)
```

[25]: {'neg': 0.075, 'neu': 0.676, 'pos': 0.249, 'compound': 0.9406}

Findings: 1. Empty Strings have a compound score of 0, so fine to keep empty strings and should replace NANs in summary as empty strings 2. NTLK takes into account punctuation, and emojis, but surprised capitalization of words is not factored in
4. Large amount of text inflates neutral score and corresponding compound score. Thus, I need to split reviews who contain multiple sentences into separate sentences and compute average sentiment for all of those sentences. This average sentiment value will be the corresponding sentiment score for that review 5. Quickness of shipping is factored into review as well

3.3 Dealing with NANs in the reviewText & summary columns; Drop Reviewer Identification columns

[26]:
```
df_iso_25.dropna(subset = ['reviewText'], inplace = True)
df_iso_25['summary'].fillna('', inplace = True)
df_iso_25.drop(columns = ['reviewerID', 'reviewerName'], inplace = True)
df_iso_25.isna().sum()
```

```
/tmp/ipykernel_3329/2966590079.py:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df_iso_25.dropna(subset = ['reviewText'], inplace = True)
/tmp/ipykernel_3329/2966590079.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df_iso_25['summary'].fillna('', inplace = True)
/tmp/ipykernel_3329/2966590079.py:3: SettingWithCopyWarning:
```

```
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df_iso_25.drop(columns = ['reviewerID', 'reviewerName'], inplace = True)
```

[26]:
```
asin              0
overall           0
reviewText        0
summary           0
vote              0
count             0
avg_rating_unf    0
dtype: int64
```

[27]:
```
# Testing package function which splits reviews into multiple sentences
nltk.sent_tokenize(df_iso_25.iloc[3]['reviewText'])
```

[27]:
```
['This game requires that you open an online account to play the game.',
 'A constant online source is required.',
 'Gave the game away.']
```

3.4 Computing Polarity Scores for All Reviews of Chosen Products

[28]:
```
def sent_hand_mult(x):
    all_scores = [sid.polarity_scores(str(uno)) for uno in x]
    neg_mean = np.mean([sent['neg'] for sent in all_scores])
    neu_mean = np.mean([sent['neu'] for sent in all_scores])
    pos_mean = np.mean([sent['pos'] for sent in all_scores])
    cmp_mean = np.mean([sent['compound'] for sent in all_scores])
    return {'neg_mean' : neg_mean, 'neu_mean' : neu_mean, 'pos_mean' :␣
 ↪pos_mean, 'cmp_mean' : cmp_mean}
```

[29]:
```
atemp = df_iso_25['reviewText'].apply(lambda x: nltk.sent_tokenize(x)).
 ↪to_frame()
```

[30]:
```
atemp['Sem_Scores'] = atemp['reviewText'].apply(sent_hand_mult)
```

[31]:
```
atemp['cmp_scores'] = atemp['Sem_Scores'].apply(lambda x: x['cmp_mean'])
```

[32]:
```
atemp['neg_scores'] = atemp['Sem_Scores'].apply(lambda x: x['neg_mean'])
atemp['neu_scores'] = atemp['Sem_Scores'].apply(lambda x: x['neu_mean'])
atemp['pos_scores'] = atemp['Sem_Scores'].apply(lambda x: x['pos_mean'])
```

[33]:
```
atemp.reset_index(inplace = True)
df_iso_25.reset_index(inplace = True)
```

[34]:
```
atemp.head()
```

[34]:
```
   index                                         reviewText  \
0      0  [I'm sure I would love the game, if I could pl…
1      1                                        [Good game]
2      2  [This installment introduces some unusual elem…
3      3  [This game requires that you open an online ac…
4      4                      [great game!, go agent 47!]

                                          Sem_Scores  cmp_scores  neg_scores  \
0  {'neg_mean': 0.07844444444444444, 'neu_mean': …    0.131311    0.078444
1  {'neg_mean': 0.0, 'neu_mean': 0.256, 'pos_mean…    0.440400    0.000000
2  {'neg_mean': 0.1554, 'neu_mean': 0.748, 'pos_m…   -0.169680    0.155400
3  {'neg_mean': 0.0, 'neu_mean': 0.94433333333333…    0.113333    0.000000
4  {'neg_mean': 0.0, 'neu_mean': 0.5925, 'pos_mea…    0.329400    0.000000

   neu_scores  pos_scores
0    0.778889    0.142667
1    0.256000    0.744000
2    0.748000    0.096400
3    0.944333    0.055667
4    0.592500    0.407500
```

[35]:
```
# Range of cmp scores from -1 to 1
atemp['cmp_scores'].describe()
```

[35]:
```
count    320923.000000
mean          0.343672
std           0.307673
min          -0.998600
25%           0.128297
50%           0.365500
75%           0.585900
max           0.999200
Name: cmp_scores, dtype: float64
```

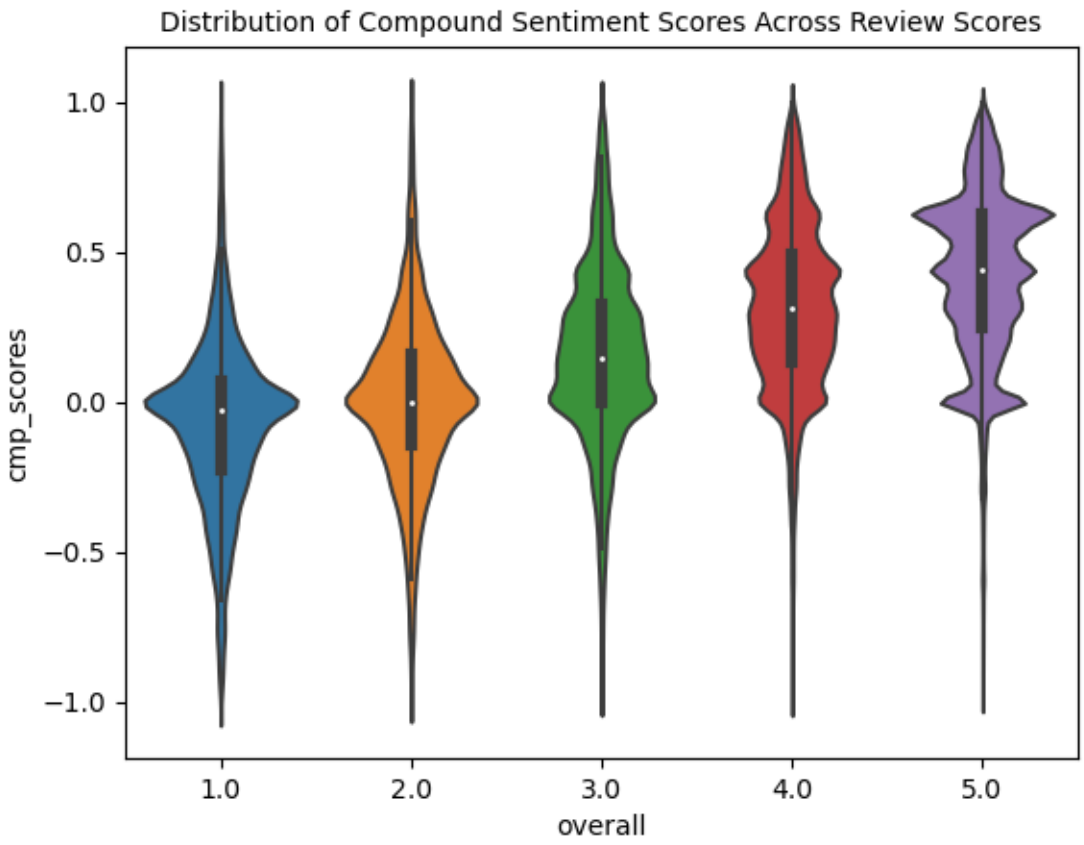
[36]:
```
df_iso_25 = pd.concat([df_iso_25, atemp[['Sem_Scores', 'cmp_scores',␣
 ↪'neg_scores', 'neu_scores', 'pos_scores']]], axis = 1).drop(columns =␣
 ↪'index')
display(df_iso_25.shape)
df_iso_25.head()
```

```
(320923, 12)
```

[36]:

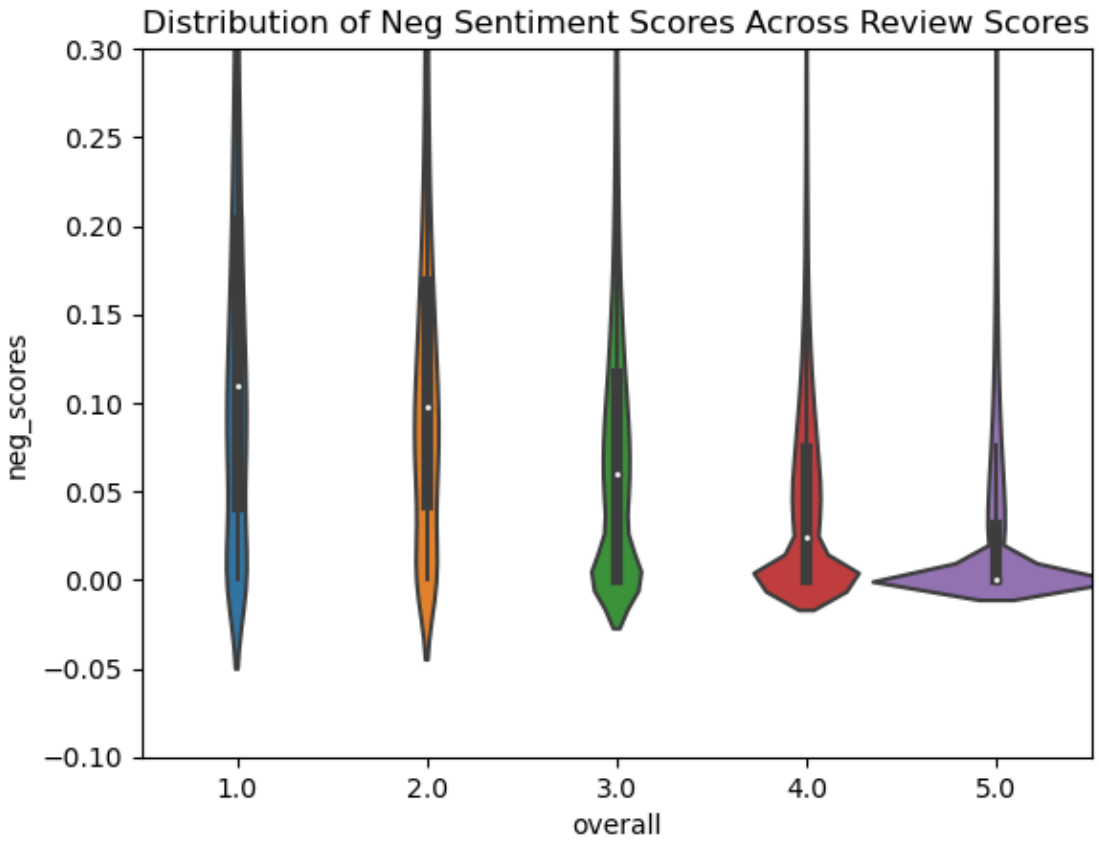
	asin	overall	reviewText	summary	vote	count	avg_rating_unf	Sem_Scores	cmp_scores	neg_scores	neu_scores	pos_scores
0	0700026398	1.0	I'm sure I would love the game, if I could pla…	Requires steam	0	5	3.2	{'neg_mean': 0.07844444444444444, 'neu_mean': …	0.131311	0.078444	0.778889	0.142667
1	0700026398	4.0	Good game	Four Stars	0	5	3.2	{'neg_mean': 0.0, 'neu_mean': 0.256, 'pos_mean…	0.440400	0.000000	0.256000	0.744000
2	0700026398	4.0	This installment introduces some unusual eleme…	I like him having some motivation to pursue a …	0	5	3.2	{'neg_mean': 0.1554, 'neu_mean': 0.748, 'pos_m…	-0.169680	0.155400	0.748000	0.096400
3	0700026398	2.0	This game requires that you open an online acc…	Requires constant online access. This is only …	0	5	3.2	{'neg_mean': 0.0, 'neu_mean': 0.94433333333333…	0.113333	0.000000	0.944333	0.055667
4	0700026398	5.0	great game! go agent 47!	Five Stars	0	5	3.2	{'neg_mean': 0.0, 'neu_mean': 0.5925, 'pos_mea…	0.329400	0.000000	0.592500	0.407500

[37]:
```
sns.violinplot(data = df_iso_25, y = 'cmp_scores', x = 'overall');
plt.title('Distribution of Compound Sentiment Scores Across Review Scores',␣
 ↪fontsize = 10);
```



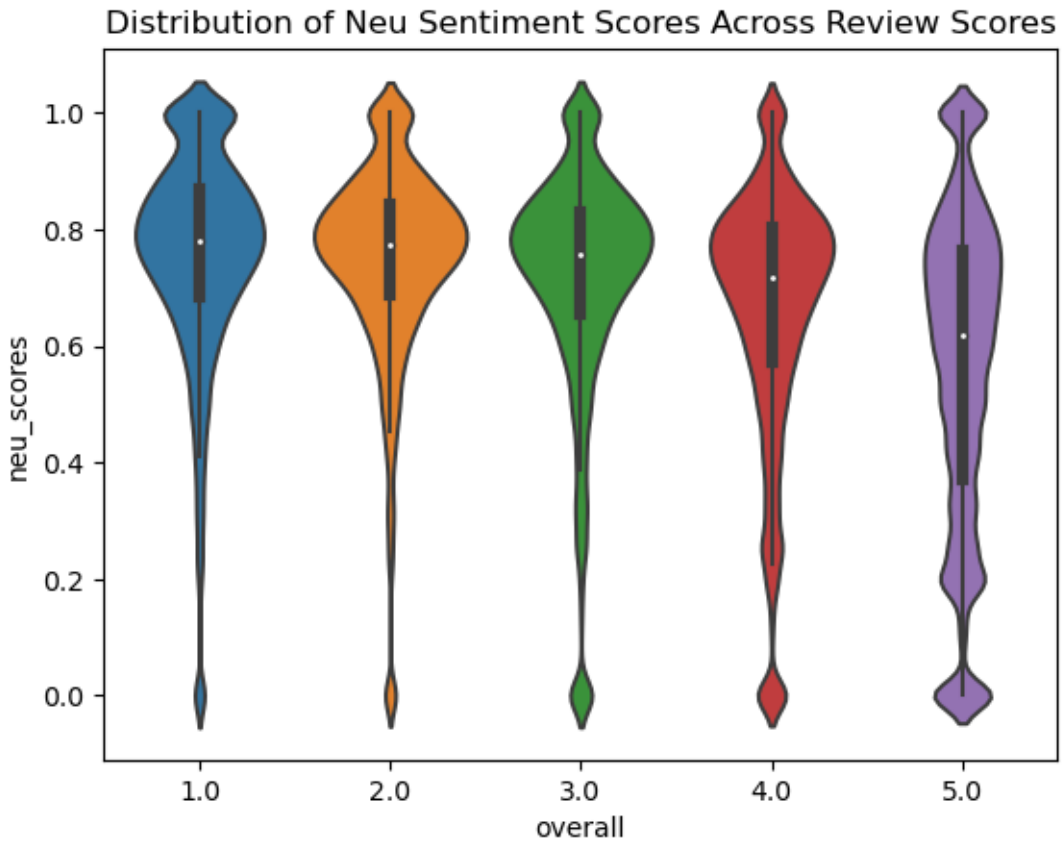
Clear variation in the compound sentiment scores across 1,2,3,4,5 star reviews implying the average compound sentiment score for a product should be a good predictor for the product's average rating

[38]:
```
ax = sns.violinplot(data = df_iso_25, y = 'neg_scores', x = 'overall', width =␣
↪1.3);
ax.set(ylim=(-0.1, 0.3))
plt.title('Distribution of Neg Sentiment Scores Across Review Scores');
```



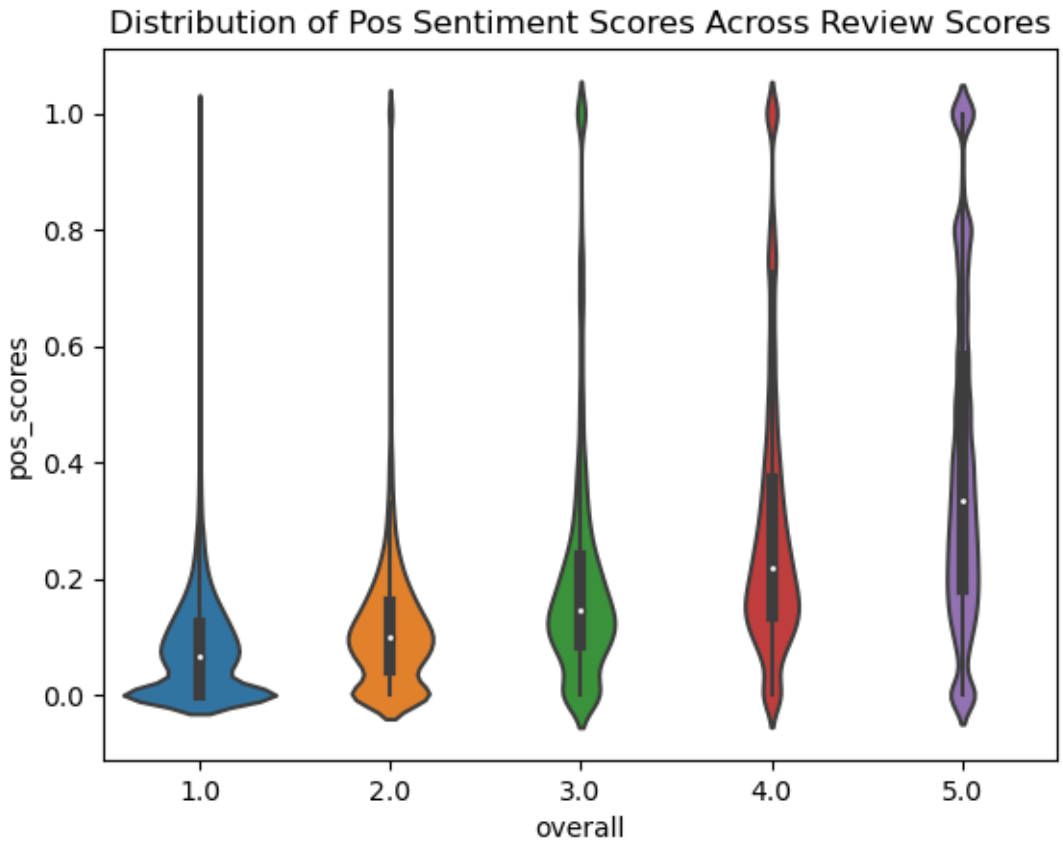
Hard to tell, but there is good variation in the negative sentiment scores across 1,2,3,4,5 star reviews implying the average negative sentiment score for a product may be a decent predictor for the product's average rating. Attempting to give a zoomed-in view of the violinplot.

[39]:
```
sns.violinplot(data = df_iso_25, y = 'neu_scores', x = 'overall');
plt.title('Distribution of Neu Sentiment Scores Across Review Scores');
```



Not great variation in the neutral sentiment scores across 1,2,3,4,5 star reviews implying the average neutral sentiment score for a product may not be a good predictor for the product's average rating

[40]:
```
sns.violinplot(data = df_iso_25, y = 'pos_scores', x = 'overall');
plt.title('Distribution of Pos Sentiment Scores Across Review Scores');
```



Good variation in the positive sentiment scores across 1,2,3,4,5 star reviews implying the average positive sentiment score for a product may be a good predictor for the product's average rating.

[41]:
```
df_iso_25.corr()
```

[41]:
```
                 overall      vote     count  avg_rating_unf  cmp_scores  \
overall         1.000000 -0.046292  0.059350        0.366315    0.446084
vote           -0.046292  1.000000 -0.004391       -0.029636   -0.049868
count           0.059350 -0.004391  1.000000        0.162033    0.003549
avg_rating_unf  0.366315 -0.029636  0.162033        1.000000    0.178020
cmp_scores      0.446084 -0.049868  0.003549        0.178020    1.000000
neg_scores     -0.365749  0.020099 -0.012655       -0.143911   -0.575941
neu_scores     -0.239580  0.064048 -0.019385       -0.096454   -0.461497
pos_scores      0.337308 -0.065081  0.021114        0.133932    0.638324

                neg_scores  neu_scores  pos_scores
overall          -0.365749   -0.239580    0.337308
vote              0.020099    0.064048   -0.065081
count            -0.012655   -0.019385    0.021114
```

```
avg_rating_unf   -0.143911   -0.096454    0.133932
cmp_scores       -0.575941   -0.461497    0.638324
neg_scores        1.000000    0.028553   -0.340591
neu_scores        0.028553    1.000000   -0.920133
pos_scores       -0.340591   -0.920133    1.000000
```

[42]:
```
# Correlation with mean of each respective product's reviews sentiment scores
df_iso_25.groupby('asin').mean().corr()
```

[42]:
```
                 overall      vote     count  avg_rating_unf  cmp_scores  \
overall         1.000000 -0.122230  0.094482        0.999937    0.565701
vote           -0.122230  1.000000  0.001668       -0.122244   -0.137482
count           0.094482  0.001668  1.000000        0.094523    0.014561
avg_rating_unf  0.999937 -0.122244  0.094523        1.000000    0.565603
cmp_scores      0.565701 -0.137482  0.014561        0.565603    1.000000
neg_scores     -0.475573  0.063746 -0.015366       -0.475265   -0.630402
neu_scores     -0.298069  0.180929 -0.029945       -0.298279   -0.526161
pos_scores      0.413724 -0.187075  0.031025        0.413821    0.687622

                neg_scores  neu_scores  pos_scores
overall          -0.475573   -0.298069    0.413724
vote              0.063746    0.180929   -0.187075
count            -0.015366   -0.029945    0.031025
avg_rating_unf   -0.475265   -0.298279    0.413821
cmp_scores       -0.630402   -0.526161    0.687622
neg_scores        1.000000    0.102687   -0.385825
neu_scores        0.102687    1.000000   -0.938676
pos_scores       -0.385825   -0.938676    1.000000
```

In this step, I am taking the groupby and mean to see the correlation of the mean sentiment scores from all reviews of each product with the product's average rating. As expected, average rating has a higher correlation of 0.57 with the mean compound sentiment scores than for each product's individual review's sentiment scores.

The next few phases of the analysis are focused on using various hypotheses to generate various samples of the dataset and see if their respective mean compound sentiment scores' correlation with the average product rating is comparable to the correlation value noted for the entire dataset.

3.5 Is looking at only 5 star reviews or non 5 star reviews sufficient to predict product's average rating?

[43]:
```
# Looking purely at the non 5 star reviews of those products
df_iso_25_nrevs5 = df_iso_25[df_iso_25['overall'] != 5.0]
display(df_iso_25_nrevs5.shape)
df_iso_25_nrevs5
```

(105531, 12)

[43]:

	asin	overall	reviewText	summary	vote	count	avg_rating_unf	Sem_Scores
0	0700026398	1.0	I'm sure I would love the game, if I could pla…	Requires steam	0	5	3.200000	{'neg_mean': 0.07844444444444444, 'neu_mean': …
1	0700026398	4.0	Good game	Four Stars	0	5	3.200000	{'neg_mean': 0.0, 'neu_mean': 0.256, 'pos_mean…
2	0700026398	4.0	This installment introduces some unusual eleme…	I like him having some motivation to pursue a …	0	5	3.200000	{'neg_mean': 0.1554, 'neu_mean': 0.748, 'pos_m…
3	0700026398	2.0	This game requires that you open an online acc…	Requires constant online access. This is only …	0	5	3.200000	{'neg_mean': 0.0, 'neu_mean': 0.94433333333333…
6	0700026657	3.0	ok game.	Three Stars	0	10	4.200000	{'neg_mean': 0.0, 'neu_mean': 0.312, 'pos_mean…
…	…	…	…	…	…	…	…	…
320916	B01HIZF7XE	4.0	A little disappointed that Bioshock 1 doesn't …	Great Graphics, Crappy Sound	4	35		
320917	B01HIZGKOE	4.0	Good game	Four Stars	0	6		
320919	B01HIZGKOE	3.0	Can't expect too much from this game, the WW2 …	the WW2 stuff is pretty good, fun missions	2	6		
320920	B01HIZGKOE	2.0	It's ok. Still cant use PS4 Hotas joy stick.	Still cant use PS4 Hotas joy stick.	0	6		
320922	B01HIZGKOE	2.0	The graphics are terrible, it looks like ps2 g…	Not as good as I expected it to be	0	6		

```
…                …                                                    …
320916        4.657143  {'neg_mean': 0.076, 'neu_mean': 0.643666666666…
320917        3.500000  {'neg_mean': 0.0, 'neu_mean': 0.256, 'pos_mean…
320919        3.500000  {'neg_mean': 0.09, 'neu_mean': 0.638, 'pos_mea…
320920        3.500000  {'neg_mean': 0.0, 'neu_mean': 0.46199999999999…
320922        3.500000  {'neg_mean': 0.1795, 'neu_mean': 0.6825, 'pos_…

        cmp_scores  neg_scores  neu_scores  pos_scores
0         0.131311    0.078444    0.778889    0.142667
1         0.440400    0.000000    0.256000    0.744000
2        -0.169680    0.155400    0.748000    0.096400
3         0.113333    0.000000    0.944333    0.055667
6         0.296000    0.000000    0.312000    0.688000
…              …           …           …           …
320916    0.480500    0.076000    0.643667    0.280667
320917    0.440400    0.000000    0.256000    0.744000
320919    0.743000    0.090000    0.638000    0.272000
320920    0.440950    0.000000    0.462000    0.538000
320922   -0.153400    0.179500    0.682500    0.138000

[105531 rows x 12 columns]
```

[44]:
```
df_iso_25_revs5 = df_iso_25[df_iso_25['overall'] == 5.0]
display(df_iso_25_revs5.shape)
df_iso_25_revs5.head()
```

```
(215392, 12)
```

[44]:
```
          asin  overall                                         reviewText  \
4   0700026398      5.0                          great game! go agent 47!
5   0700026657      5.0  This game is a bit hard to get the hang of, bu…
8   0700026657      5.0  great game, I love it and have played it since…
10  0700026657      5.0  I bought this game thinking it would be pretty…
11  0700026657      5.0  I have played the old anno 1701 AND 1503.  thi…

                                          summary  vote  count  \
4                                     Five Stars     0      5
5                     but when you do it's great.     0     10
8                                 love this game     0     10
10  A very good game balance of skill with depth o…     0     10
11                    Anno 2070 more like anno 1701     0     10

    avg_rating_unf                                         Sem_Scores  \
4              3.2  {'neg_mean': 0.0, 'neu_mean': 0.5925, 'pos_mea…
5              4.2  {'neg_mean': 0.058, 'neu_mean': 0.671, 'pos_me…
8              4.2  {'neg_mean': 0.0, 'neu_mean': 0.428, 'pos_mean…
10             4.2  {'neg_mean': 0.12616666666666668, 'neu_mean': …
```

```
11             4.2  {'neg_mean': 0.009111111111111111, 'neu_mean':…
```

	cmp_scores	neg_scores	neu_scores	pos_scores
4	0.329400	0.000000	0.592500	0.407500
5	0.754300	0.058000	0.671000	0.271000
8	0.893400	0.000000	0.428000	0.572000
10	0.096050	0.126167	0.755167	0.118833
11	0.223867	0.009111	0.897000	0.093889

[45]:
```
df_iso_25_revs5.corr().fillna(0)
```

[45]:

	overall	vote	count	avg_rating_unf	cmp_scores	\
overall	0.0	0.000000	0.000000	0.000000	0.000000	
vote	0.0	1.000000	-0.008092	-0.007746	-0.045497	
count	0.0	-0.008092	1.000000	0.119785	-0.022315	
avg_rating_unf	0.0	-0.007746	0.119785	1.000000	0.021819	
cmp_scores	0.0	-0.045497	-0.022315	0.021819	1.000000	
neg_scores	0.0	0.020903	0.004364	-0.023242	-0.472637	
neu_scores	0.0	0.062614	-0.003958	0.001796	-0.479402	
pos_scores	0.0	-0.063090	0.002114	0.002610	0.601676	

	neg_scores	neu_scores	pos_scores
overall	0.000000	0.000000	0.000000
vote	0.020903	0.062614	-0.063090
count	0.004364	-0.003958	0.002114
avg_rating_unf	-0.023242	0.001796	0.002610
cmp_scores	-0.472637	-0.479402	0.601676
neg_scores	1.000000	0.059392	-0.284119
neu_scores	0.059392	1.000000	-0.939261
pos_scores	-0.284119	-0.939261	1.000000

[46]:
```
df_iso_25_revs5.groupby('asin').mean().corr().fillna(0)
```

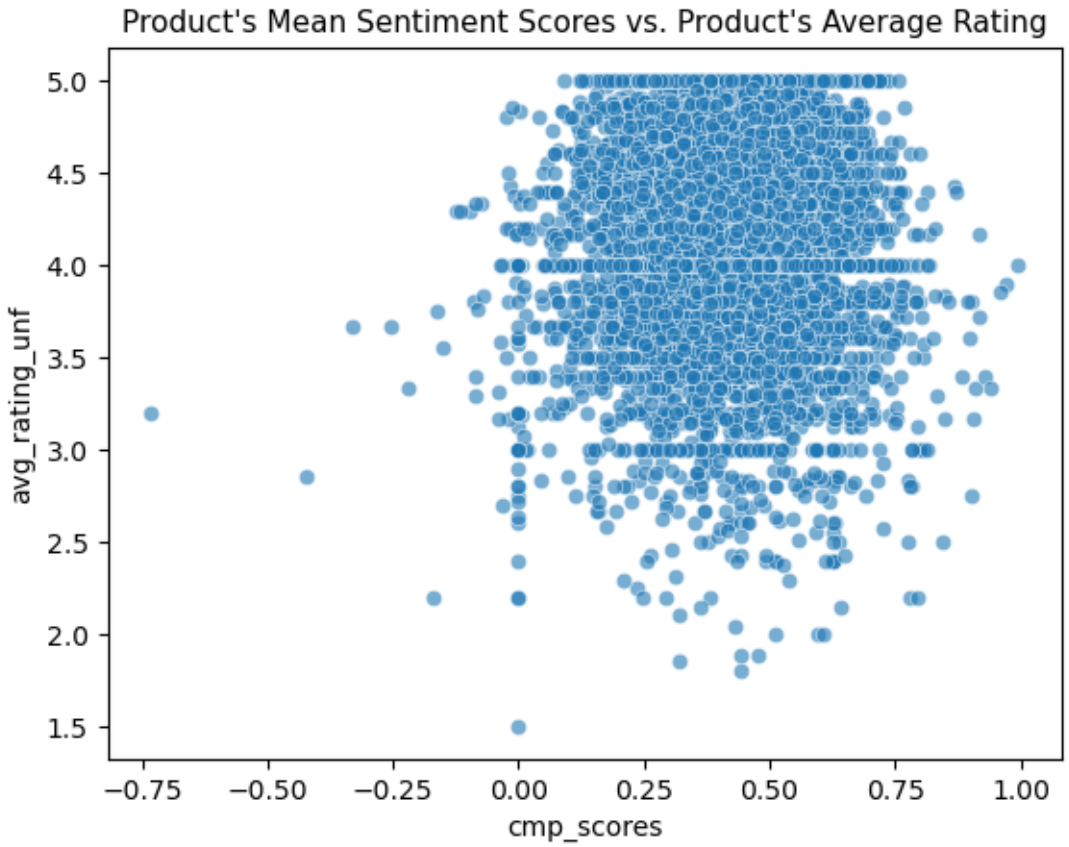
[46]:

	overall	vote	count	avg_rating_unf	cmp_scores	\
overall	0.0	0.000000	0.000000	0.000000	0.000000	
vote	0.0	1.000000	-0.002380	-0.027433	-0.098201	
count	0.0	-0.002380	1.000000	0.088150	-0.023688	
avg_rating_unf	0.0	-0.027433	0.088150	1.000000	0.048739	
cmp_scores	0.0	-0.098201	-0.023688	0.048739	1.000000	
neg_scores	0.0	0.050158	0.017356	-0.015799	-0.493213	
neu_scores	0.0	0.141887	-0.000536	0.009445	-0.514828	
pos_scores	0.0	-0.144529	-0.003513	-0.007513	0.617643	

	neg_scores	neu_scores	pos_scores
overall	0.000000	0.000000	0.000000
vote	0.050158	0.141887	-0.144529
count	0.017356	-0.000536	-0.003513

```
avg_rating_unf    -0.015799    0.009445   -0.007513
cmp_scores        -0.493213   -0.514828    0.617643
neg_scores         1.000000    0.140663   -0.332480
neu_scores         0.140663    1.000000   -0.952575
pos_scores        -0.332480   -0.952575    1.000000
```

[47]:
```
sns.scatterplot(data = df_iso_25_revs5.groupby('asin').mean(), x ='cmp_scores',␣
↪y = 'avg_rating_unf', alpha = 0.6)
plt.title('Product\'s Mean Sentiment Scores vs. Product\'s Average Rating',␣
↪fontsize = 11);
```



No correlation of overall with other features since overall, which represents a review's rating, is 5 for all products. Also, after looking at the correlation of the mean average compound sentiment score from all reviews of a product with that product's average rating, it is clear from the correlation value of 0.05 that there is not enough inherent variation in the mean sentiment scores for the reviews of each product to match the entire range of average product ratings. ***This sample is also two-thirds of the entire dataset, so it shows the size of the sample does not matter as much as the quality of the sample.***

[48]:
```
# Irrational to look only at the 5 star reviews to predict rating, much lower␣
↪correlation value
df_iso_25_nrevs5.corr()
```

[48]:

	overall	vote	count	avg_rating_unf	cmp_scores	\
overall	1.000000	-0.047870	0.021315	0.300556	0.461154	
vote	-0.047870	1.000000	0.007811	-0.034418	-0.034240	
count	0.021315	0.007811	1.000000	0.209351	-0.018040	
avg_rating_unf	0.300556	-0.034418	0.209351	1.000000	0.148897	
cmp_scores	0.461154	-0.034240	-0.018040	0.148897	1.000000	
neg_scores	-0.329801	0.002808	0.007344	-0.100654	-0.614665	
neu_scores	-0.181153	0.053895	-0.006152	-0.083233	-0.296396	
pos_scores	0.353114	-0.052568	0.001525	0.133898	0.617125	

	neg_scores	neu_scores	pos_scores
overall	-0.329801	-0.181153	0.353114
vote	0.002808	0.053895	-0.052568
count	0.007344	-0.006152	0.001525
avg_rating_unf	-0.100654	-0.083233	0.133898
cmp_scores	-0.614665	-0.296396	0.617125
neg_scores	1.000000	-0.193674	-0.331657
neu_scores	-0.193674	1.000000	-0.839907
pos_scores	-0.331657	-0.839907	1.000000

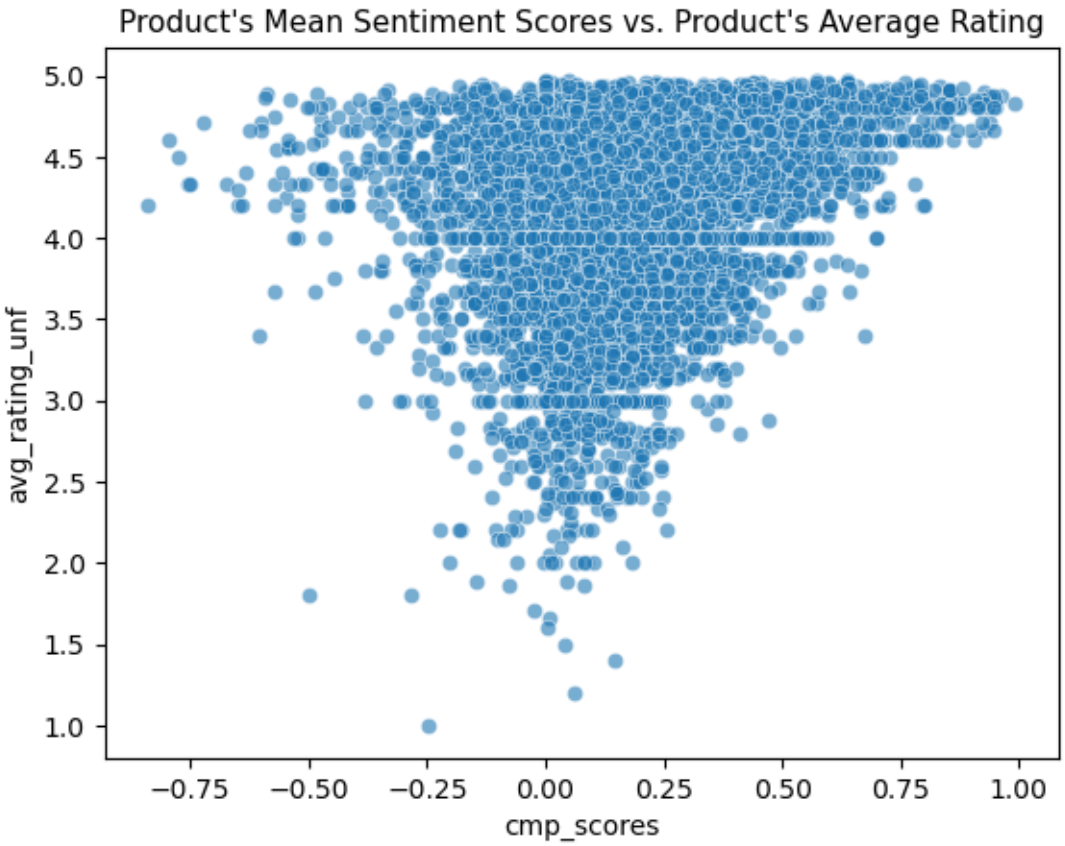
[49]:
```
# Non-5 star reviews have similar correlation when not averaged, but don't gain␣
↪as much when averaged
df_iso_25_nrevs5.groupby('asin').mean().corr()
```

[49]:

	overall	vote	count	avg_rating_unf	cmp_scores	\
overall	1.000000	-0.053718	0.046720	0.598810	0.492615	
vote	-0.053718	1.000000	0.015811	-0.086057	-0.061414	
count	0.046720	0.015811	1.000000	0.126384	-0.011235	
avg_rating_unf	0.598810	-0.086057	0.126384	1.000000	0.306612	
cmp_scores	0.492615	-0.061414	-0.011235	0.306612	1.000000	
neg_scores	-0.349789	0.004708	0.010289	-0.222861	-0.606974	
neu_scores	-0.201961	0.104957	-0.015412	-0.136380	-0.354713	
pos_scores	0.371397	-0.101408	0.008621	0.243133	0.641865	

	neg_scores	neu_scores	pos_scores
overall	-0.349789	-0.201961	0.371397
vote	0.004708	0.104957	-0.101408
count	0.010289	-0.015412	0.008621
avg_rating_unf	-0.222861	-0.136380	0.243133
cmp_scores	-0.606974	-0.354713	0.641865
neg_scores	1.000000	-0.164681	-0.324245
neu_scores	-0.164681	1.000000	-0.864721
pos_scores	-0.324245	-0.864721	1.000000

[50]:
```
sns.scatterplot(data = df_iso_25_nrevs5.groupby('asin').mean(), x␣
↪='cmp_scores', y = 'avg_rating_unf', alpha = 0.6)
plt.title('Product\'s Mean Sentiment Scores vs. Product\'s Average Rating',␣
↪fontsize = 11);
```



After looking at the correlation of the mean average compound sentiment score from all reviews of a product with that product's average rating, it is clear from the correlation value of 0.30 that there is decent inherent variation in the mean sentiment scores for the reviews of each product to match the entire range of average product ratings. ***This sample is also one-third of the entire dataset, so it shows the size of the sample does not matter as much as the quality of the sample.***

3.6 Sample Text from Non-5-Star Reviews and 5 Star Reviews

[51]:
```
df_iso_25_nrevs5['reviewText'].value_counts()
```

[51]:
```
good
590
ok
```

```
471
Good
286
good game
205
Good game
139
  …
The first game is way better than this one buy that one instead i say
1
You are an apprentice of the force.  Make your way through the death star
battling enemies and learning old and new skills.  This game is a great choice
for any Star Wars or Science Fiction fan.
1
Terrible port.
1
Good game, it could use better graphics though.
1
The graphics are terrible, it looks like ps2 graphics, the flight controls
aren't all that good. The platinum trophy for Air Conflicts: Vietnam is
unachievable, as it requires online play which nobody appears to be playing this
game online      1
Name: reviewText, Length: 91905, dtype: int64
```

[52]:
```
df_iso_25_revs5['reviewText'].value_counts()
```

[52]:
```
good
1499
great
1330
Excellent
1136
Great
1131
Good
1095
                                                    …
Thses games are very fun and thrilling to play.two player mode is great with
family and kids. Its exciting and unique. Love the Move games
1
great sing along
1
Bought for 12 year old and she loves it
1
If you love Glee and you love to sing, then this is the best game for you. I
bought this for myself after my kids broke the first copy I had. Great songs,
great play modes and hours of fun with my family.       1
```

```
I am a big fan of aviation flight simulations and was very impressed with this
game.  The graphics are good.  I have no doubt it will provide hours of
entertainment.                                                        1
Name: reviewText, Length: 152679, dtype: int64
```

4 Quick Asides

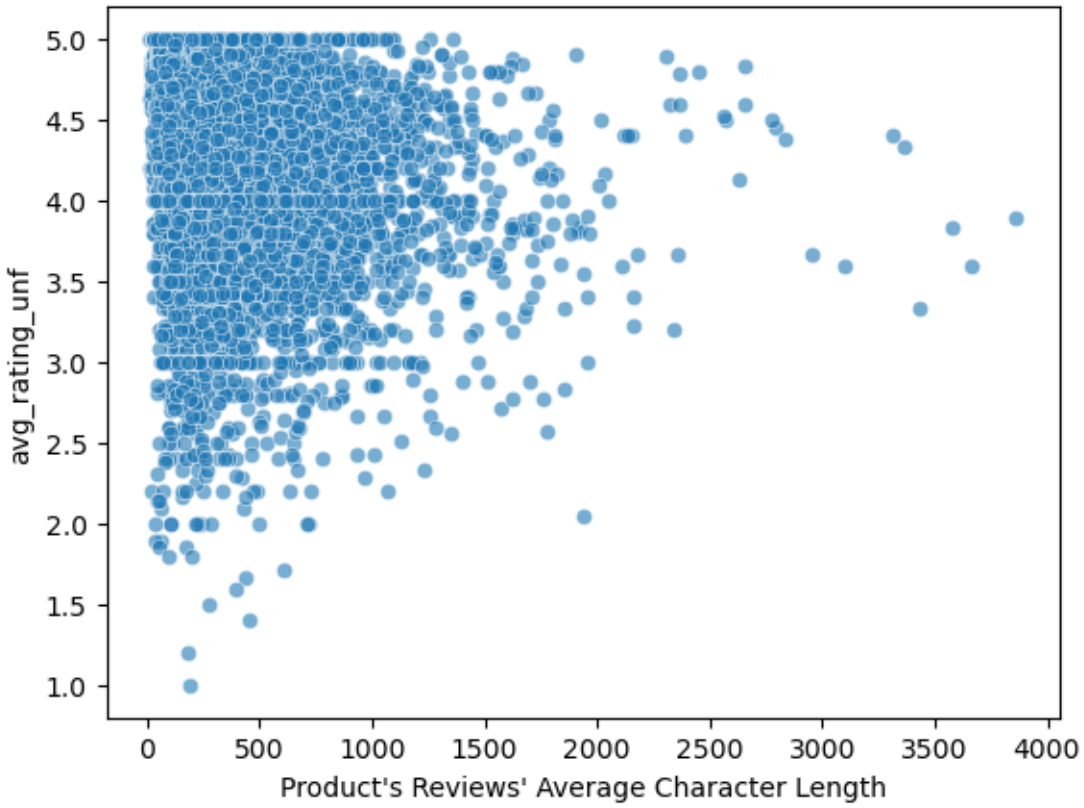
4.1 Seeing if Product's Reviews Average Length of ReviewText is correlated with the Product's Average Rating

[53]:
```
df_iso_25['Review_Ch_Len'] = df_iso_25['reviewText'].str.len()
```

[54]:
```
df_iso_25['Review_Ch_Len'].describe()
```

[54]:
```
count    320923.000000
mean        332.212743
std         768.754183
min           1.000000
25%          30.000000
50%         117.000000
75%         300.000000
max       32457.000000
Name: Review_Ch_Len, dtype: float64
```

[55]:
```
sns.scatterplot(data = df_iso_25.groupby('asin').mean(), x = 'Review_Ch_Len', y␣
↪= 'avg_rating_unf', alpha = 0.6)
plt.xlabel('Product\'s Reviews\' Average Character Length');
```



[56]:
```
df_iso_25.groupby('asin').mean().corr()
```

[56]:
```
                 overall      vote     count  avg_rating_unf  cmp_scores  \
overall         1.000000 -0.122230  0.094482        0.999937    0.565701
vote           -0.122230  1.000000  0.001668       -0.122244   -0.137482
count           0.094482  0.001668  1.000000        0.094523    0.014561
avg_rating_unf  0.999937 -0.122244  0.094523        1.000000    0.565603
cmp_scores      0.565701 -0.137482  0.014561        0.565603    1.000000
neg_scores     -0.475573  0.063746 -0.015366       -0.475265   -0.630402
neu_scores     -0.298069  0.180929 -0.029945       -0.298279   -0.526161
pos_scores      0.413724 -0.187075  0.031025        0.413821    0.687622
Review_Ch_Len  -0.196665  0.398017  0.006320       -0.196722   -0.279827

                neg_scores  neu_scores  pos_scores  Review_Ch_Len
overall          -0.475573   -0.298069    0.413724      -0.196665
vote              0.063746    0.180929   -0.187075       0.398017
count            -0.015366   -0.029945    0.031025       0.006320
avg_rating_unf   -0.475265   -0.298279    0.413821      -0.196722
cmp_scores       -0.630402   -0.526161    0.687622      -0.279827
neg_scores        1.000000    0.102687   -0.385825       0.191251
neu_scores        0.102687    1.000000   -0.938676       0.389890
```

```
pos_scores       -0.385825   -0.938676    1.000000      -0.410350
Review_Ch_Len     0.191251    0.389890   -0.410350       1.000000
```

4.2 Noticing Product's Sentiment Score not only reflects product quality, but also quickness of shipping

[57]:
```
df_iso_25[df_iso_25['reviewText'].str.contains('ship')][['reviewText',␣
 ↪'avg_rating_unf']]
```

[57]:
```
                                                reviewText  avg_rating_unf
19      1st shipment received a book instead of the ga…        3.181818
30      Installing the game was a struggle (because of…        3.181818
44      great set of guides. no shipping damage. all b…        4.812500
83      I have been looking forward to receiving this …        4.812500
156     My son sayes he is still learning how to custo…        3.833333
…                                                     …             …
320576              Item was as described\nFast shipping!        4.840000
320582                           Great buy fast shipping         4.840000
320598              My daughter likes it.  Fast shipping.        4.840000
320643  i love this game it fun playing this it was ni…        4.666667
320685  I got tired of waiting for one of these to be …        3.795918

[7413 rows x 2 columns]
```

[58]:
```
# Proportion of reviews discussing shipping
df_iso_25[df_iso_25['reviewText'].str.contains('ship')][['reviewText',␣
 ↪'avg_rating_unf']].shape[0] / df_iso_25.shape[0]
```

[58]:
```
0.02309899882526338
```

Not a really strict analysis, but it is clear that some product reviews not only reflect product quality, but the quickness of shipping. Fast shipping will increase the rating, but slow shipping will decrease the rating.

4.3 Do helpful reviews (reviews with nonzero helpfulness votes) have good correlation with the product's average rating?

[59]:
```
# Product Arrival also contributes to score, but does not really reflect␣
 ↪product quality
# Rating is sum of arrival efficiency, quality, usability,
temp = df_iso_25[df_iso_25['vote'] != 0]
display('Original Shape: ' + str(df_iso_25.shape))
display('New Shape: ' + str(temp.shape))
temp.head()
```

```
'Original Shape: (320923, 13)'

'New Shape: (36016, 13)'
```

[59]:
```
           asin  overall                                         reviewText  \
15   0700099867      5.0  Loved playing Dirt 2 and I thought the graphic…
16   0700099867      4.0  I had Dirt 2 on Xbox 360 and it was an okay ga…
22   0700099867      1.0  DiRT 2 was like this.  I'm becoming more & mor…
30   0700099867      1.0  Installing the game was a struggle (because of…
31   0700099867      3.0  This is a pretty fun game, but you have to buy…

                                      summary  vote  count  avg_rating_unf  \
15  A step up from Dirt 2 and that is terrific!    11     22        3.181818
16                                      DIRT 3     2     22        3.181818
22                The first one was much better.     7     22        3.181818
30     Pay to unlock content? I don't think so.     9     22        3.181818
31                                         Fun    13     22        3.181818

                                         Sem_Scores  cmp_scores  neg_scores  \
15  {'neg_mean': 0.10300000000000001, 'neu_mean': …    0.436475    0.103000
16  {'neg_mean': 0.0645, 'neu_mean': 0.65450000000…    0.324017    0.064500
22  {'neg_mean': 0.12059259259259258, 'neu_mean': …   -0.003444    0.120593
30  {'neg_mean': 0.0887, 'neu_mean': 0.7654, 'pos_…    0.090880    0.088700
31  {'neg_mean': 0.08225, 'neu_mean': 0.82025, 'po…    0.157300    0.082250

    neu_scores  pos_scores  Review_Ch_Len
15    0.556000    0.340500            431
16    0.654500    0.281000            294
22    0.769741    0.109667           1652
30    0.765400    0.145900            787
31    0.820250    0.097500            743
```

[60]:
```
# How many products have reviews with nonzero helpfulness; appears to be 9094 products;
# some products have drastically more reviews with nonzero helpfulness than others
temp['asin'].value_counts()
```

[60]:
```
B00178630A    288
B000ZKA0J6    120
B00KSQHX1K    104
B00ZQC73O8    101
B00ZQB28XK     86
             ...
B001NTBWK4      1
B001NQB658      1
B001NPCTDC      1
B00HPU96FI      1
```

```
B0055UCIE6      1
Name: asin, Length: 9094, dtype: int64
```

[61]:
```
# Seeing the text in a helpful review
temp.iloc[9]['reviewText']
```

[61]:
```
"it was fun finding the differences in the pictures, but it got boring when the
same pictures kept comming up. it would have been better NOT to have a time
limit on these games.  that just makes it harder and frustrating for beginners
like me.  i am handicapped and disabled and don't move that fast.  also i just
turned 61, so i'm not that fast mentally either.  there should be an option to
choose if you want it to be timed or not.  there should be that option on ALL
games."
```

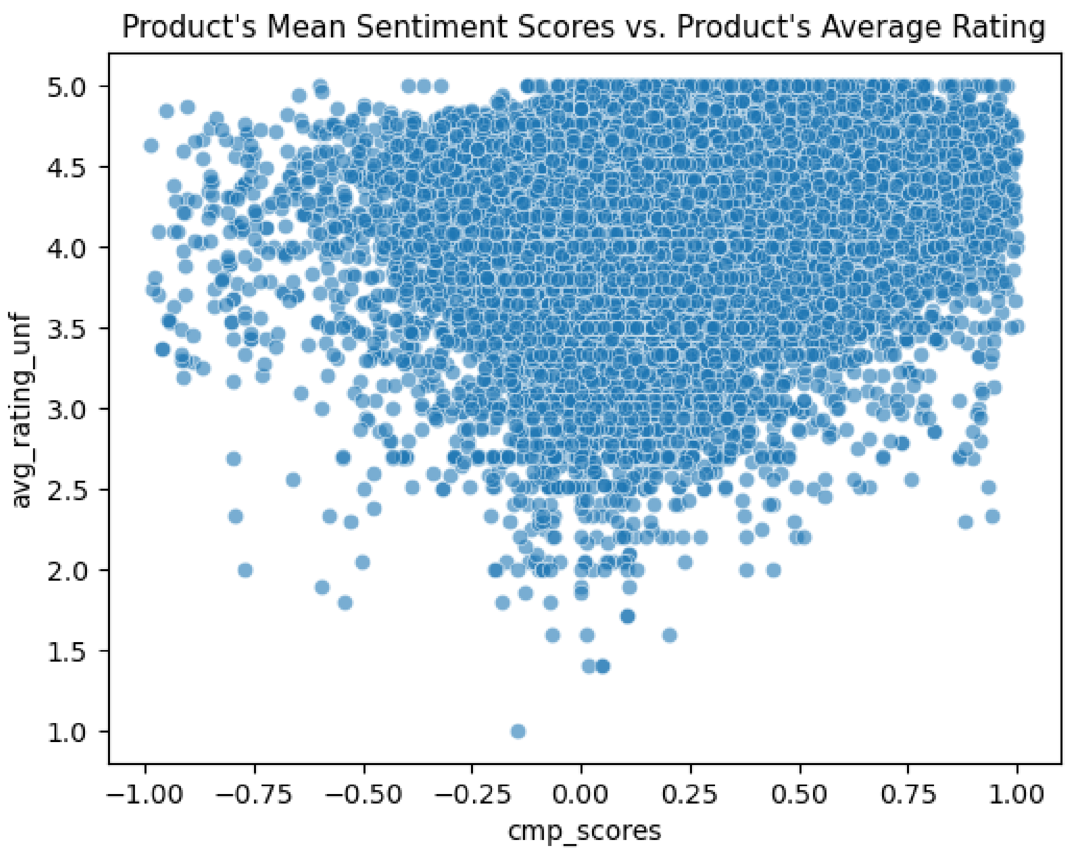
[62]:
```
temp.corr()
```

[62]:

	overall	vote	count	avg_rating_unf	cmp_scores	\
overall	1.000000	0.000183	-0.052556	0.381661	0.501339	
vote	0.000183	1.000000	0.021472	-0.001272	-0.030621	
count	-0.052556	0.021472	1.000000	0.097994	-0.052204	
avg_rating_unf	0.381661	-0.001272	0.097994	1.000000	0.204522	
cmp_scores	0.501339	-0.030621	-0.052204	0.204522	1.000000	
neg_scores	-0.417091	-0.014658	0.059733	-0.162601	-0.647466	
neu_scores	-0.154914	0.075016	-0.018076	-0.057300	-0.321144	
pos_scores	0.389103	-0.062231	-0.020191	0.145644	0.694273	
Review_Ch_Len	0.006654	0.200063	0.025669	-0.015654	-0.148549	

	neg_scores	neu_scores	pos_scores	Review_Ch_Len
overall	-0.417091	-0.154914	0.389103	0.006654
vote	-0.014658	0.075016	-0.062231	0.200063
count	0.059733	-0.018076	-0.020191	0.025669
avg_rating_unf	-0.162601	-0.057300	0.145644	-0.015654
cmp_scores	-0.647466	-0.321144	0.694273	-0.148549
neg_scores	1.000000	-0.220478	-0.342512	0.032304
neu_scores	-0.220478	1.000000	-0.798938	0.220994
pos_scores	-0.342512	-0.798938	1.000000	-0.222328
Review_Ch_Len	0.032304	0.220994	-0.222328	1.000000

[63]:
```
sns.scatterplot(data = temp, x ='cmp_scores', y = 'avg_rating_unf', alpha = 0.6)
plt.title('Product\'s Mean Sentiment Scores vs. Product\'s Average Rating',␣
 ↪fontsize = 11);
```



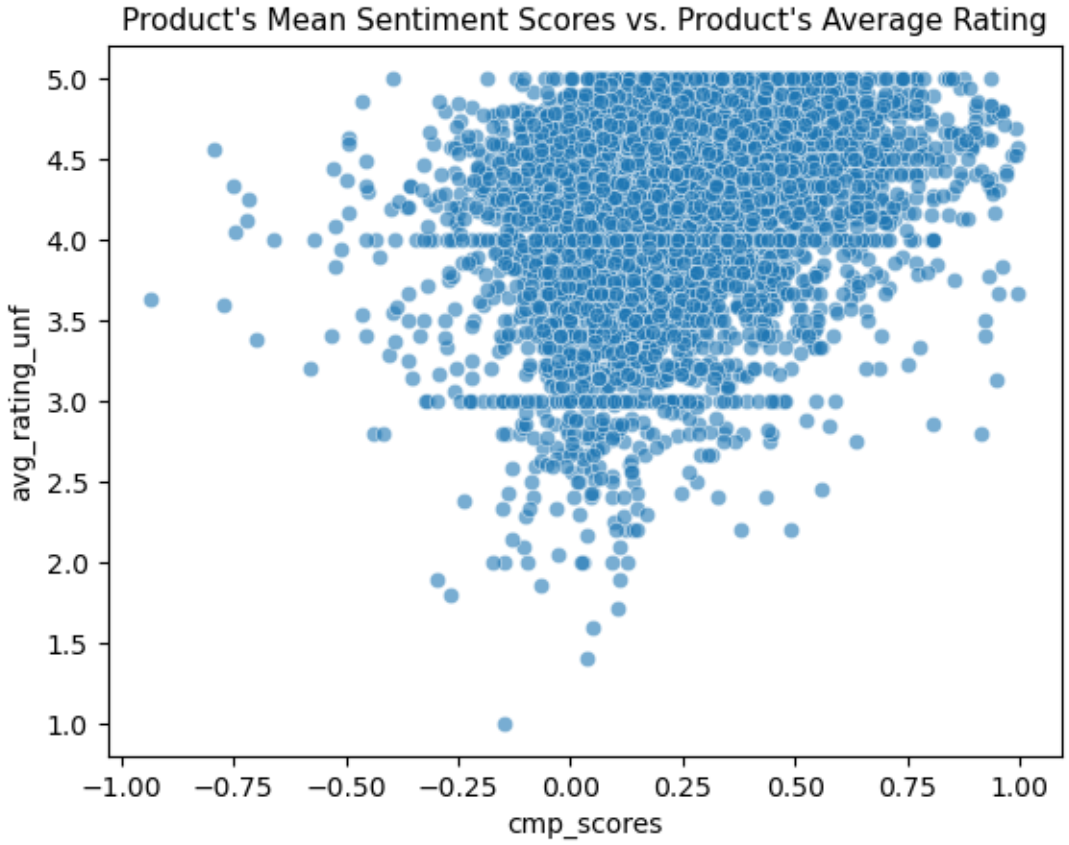
[64]:
```
temp.groupby('asin').mean().corr()
```

[64]:
```
                overall      vote     count  avg_rating_unf  cmp_scores  \
overall        1.000000 -0.018158 -0.037958        0.542925    0.497904
vote          -0.018158  1.000000  0.065452       -0.023018   -0.058211
count         -0.037958  0.065452  1.000000        0.132574   -0.057731
avg_rating_unf 0.542925 -0.023018  0.132574        1.000000    0.283320
cmp_scores     0.497904 -0.058211 -0.057731        0.283320    1.000000
neg_scores    -0.411842 -0.015198  0.061520       -0.227822   -0.643780
neu_scores    -0.194543  0.123219  0.003973       -0.109269   -0.385507
pos_scores     0.396587 -0.107336 -0.039110        0.214469    0.708571
Review_Ch_Len -0.029343  0.222379  0.040604       -0.024155   -0.195454

                neg_scores  neu_scores  pos_scores  Review_Ch_Len
overall          -0.411842   -0.194543    0.396587      -0.029343
vote             -0.015198    0.123219   -0.107336       0.222379
count             0.061520    0.003973   -0.039110       0.040604
avg_rating_unf   -0.227822   -0.109269    0.214469      -0.024155
cmp_scores       -0.643780   -0.385507    0.708571      -0.195454
neg_scores        1.000000   -0.166490   -0.335126       0.093679
```

neu_scores	-0.166490	1.000000	-0.834840	0.233263
pos_scores	-0.335126	-0.834840	1.000000	-0.262583
Review_Ch_Len	0.093679	0.233263	-0.262583	1.000000

[65]:
```
sns.scatterplot(data = temp.groupby('asin').mean(), x ='cmp_scores', y =␣
↪'avg_rating_unf', alpha = 0.6)
plt.title('Product\'s Mean Sentiment Scores vs. Product\'s Average Rating',␣
↪fontsize = 11);
```



[66]:
```
temp.shape[0] / df_iso_25.shape[0]
```

[66]: 0.11222629727380089

After looking at the correlation of the mean average compound sentiment score from all reviews of a product with that product's average rating, it is clear from the correlation value of 0.28 that there is decent inherent variation in the mean sentiment scores for the reviews of each product to match the entire range of average product ratings. ***This sample is also 11% of the entire dataset, so it shows the size of the sample does not matter as much as the quality of the sample.***

Future Work: Looking to see if there are some keywords in the helpful reviews that

may be correlated with average rating 1. Will probably start with creating an adjective frequency distribution amongst the helpful reviews

4.4 Generate final matrix for linear regression model

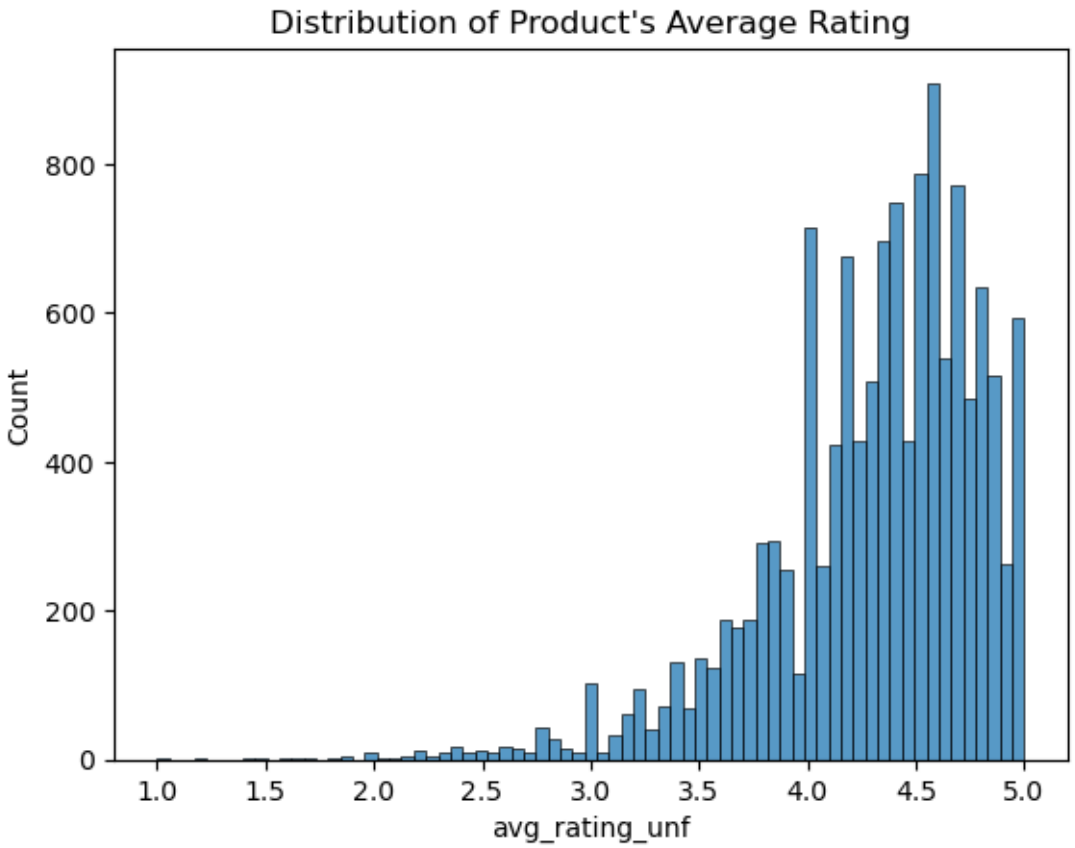
[67]:
```
final_data = (df_iso_25.groupby('asin').agg(np.mean)
              [['avg_rating_unf', 'cmp_scores', 'pos_scores',␣
 ↪'neg_scores','neu_scores', 'Review_Ch_Len']])
final_data
```

[67]:

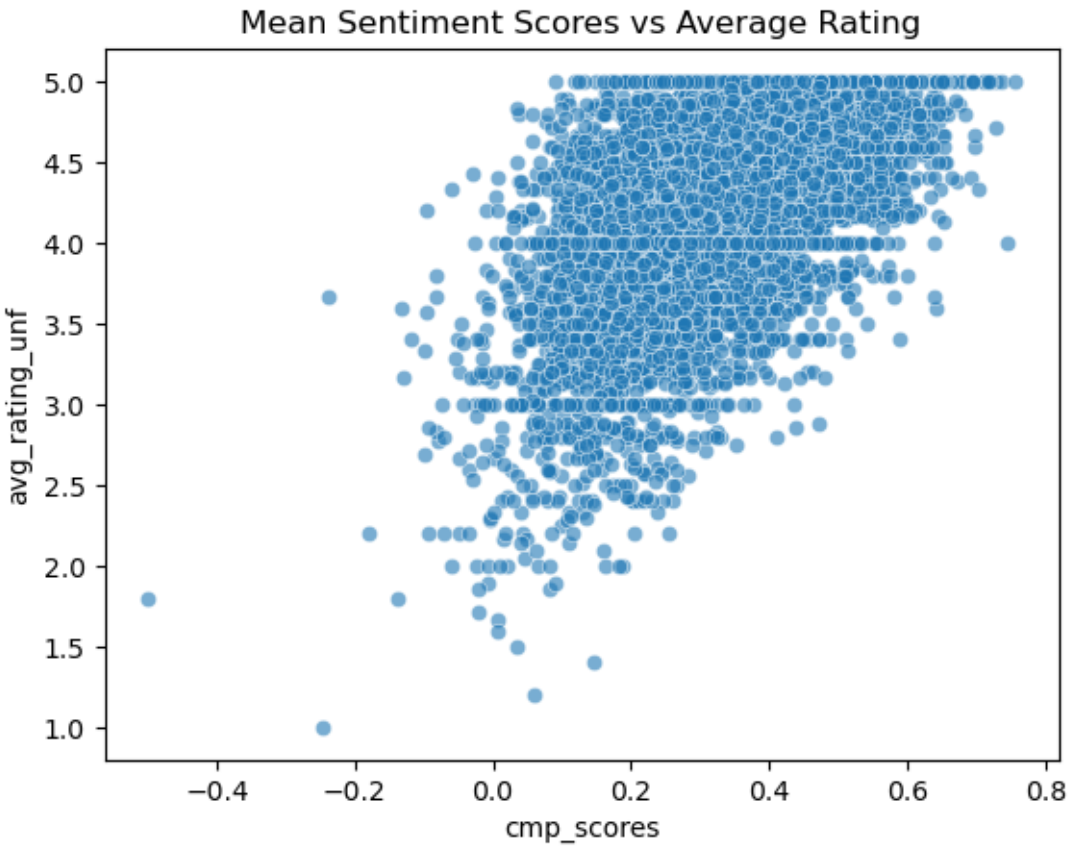
asin	avg_rating_unf	cmp_scores	pos_scores	neg_scores	neu_scores	Review_Ch_Len
0700026398	3.200000	0.168953	0.289247	0.046769	0.663944	305.400000
0700026657	4.200000	0.464753	0.358039	0.038861	0.603167	242.000000
0700099867	3.181818	0.088304	0.211982	0.107430	0.674078	560.454545
0804161380	4.812500	0.460995	0.320402	0.023715	0.655866	413.791667
3828770193	4.200000	0.247624	0.281919	0.043267	0.674814	158.800000
…	…	…	…	…	…	…
B01HFRICLE	4.384615	0.224725	0.162128	0.040874	0.777774	312.000000
B01HGPUTCA	4.600000	0.215997	0.203962	0.081818	0.714220	825.800000
B01HH6JEOC	4.000000	0.263924	0.364452	0.026722	0.608790	268.857143
B01HIZF7XE	4.657143	0.400580	0.311334	0.075038	0.599333	502.514286
B01HIZGKOE	3.500000	0.374608	0.505389	0.064250	0.430306	102.833333

[12992 rows x 6 columns]

[68]:
```
sns.histplot(data = final_data, x = 'avg_rating_unf');
plt.title('Distribution of Product\'s Average Rating');
```



[69]:
```
sns.scatterplot(data = final_data, x = 'cmp_scores', y = 'avg_rating_unf',␣
↪alpha = 0.6);
plt.title('Mean Sentiment Scores vs Average Rating');
```



[70]:
```
final_data.corr()
```

[70]:
```
                avg_rating_unf  cmp_scores  pos_scores  neg_scores  \
avg_rating_unf        1.000000    0.565603    0.413821   -0.475265
cmp_scores            0.565603    1.000000    0.687622   -0.630402
pos_scores            0.413821    0.687622    1.000000   -0.385825
neg_scores           -0.475265   -0.630402   -0.385825    1.000000
neu_scores           -0.298279   -0.526161   -0.938676    0.102687
Review_Ch_Len        -0.196722   -0.279827   -0.410350    0.191251

                neu_scores  Review_Ch_Len
avg_rating_unf   -0.298279      -0.196722
cmp_scores       -0.526161      -0.279827
pos_scores       -0.938676      -0.410350
neg_scores        0.102687       0.191251
neu_scores        1.000000       0.389890
Review_Ch_Len     0.389890       1.000000
```

4.5 Linear Regression Model without Intercept

[71]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = (train_test_split(
    final_data[['cmp_scores', 'neu_scores']], final_data['avg_rating_unf'],
    test_size=0.20, random_state=42))
```

[72]:
```
from sklearn import linear_model as lm
linear_model = lm.LinearRegression(fit_intercept= False)
linear_model.fit(X_train, y_train)
y_train_pred = linear_model.predict(X_train)
y_test_pred = linear_model.predict(X_test)
```

[73]:
```
from sklearn.model_selection import cross_val_score
scores = cross_val_score(linear_model, X_train, y_train, cv=5,␣
 ↪scoring='neg_mean_squared_error')
scores * -1
```

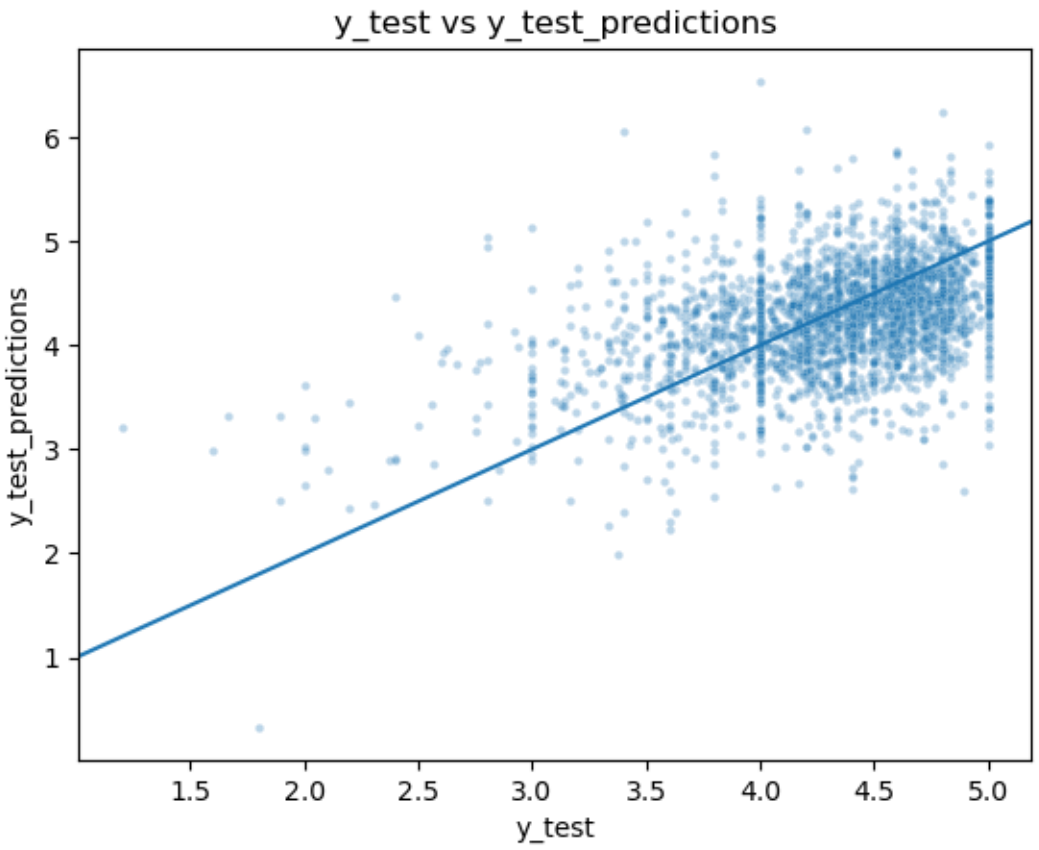
[73]:
```
array([0.30183986, 0.30346264, 0.29137777, 0.30624705, 0.30532351])
```

[74]:
```
from sklearn.metrics import mean_squared_error
display(mean_squared_error(y_train, y_train_pred))
display(mean_squared_error(y_test, y_test_pred))
```

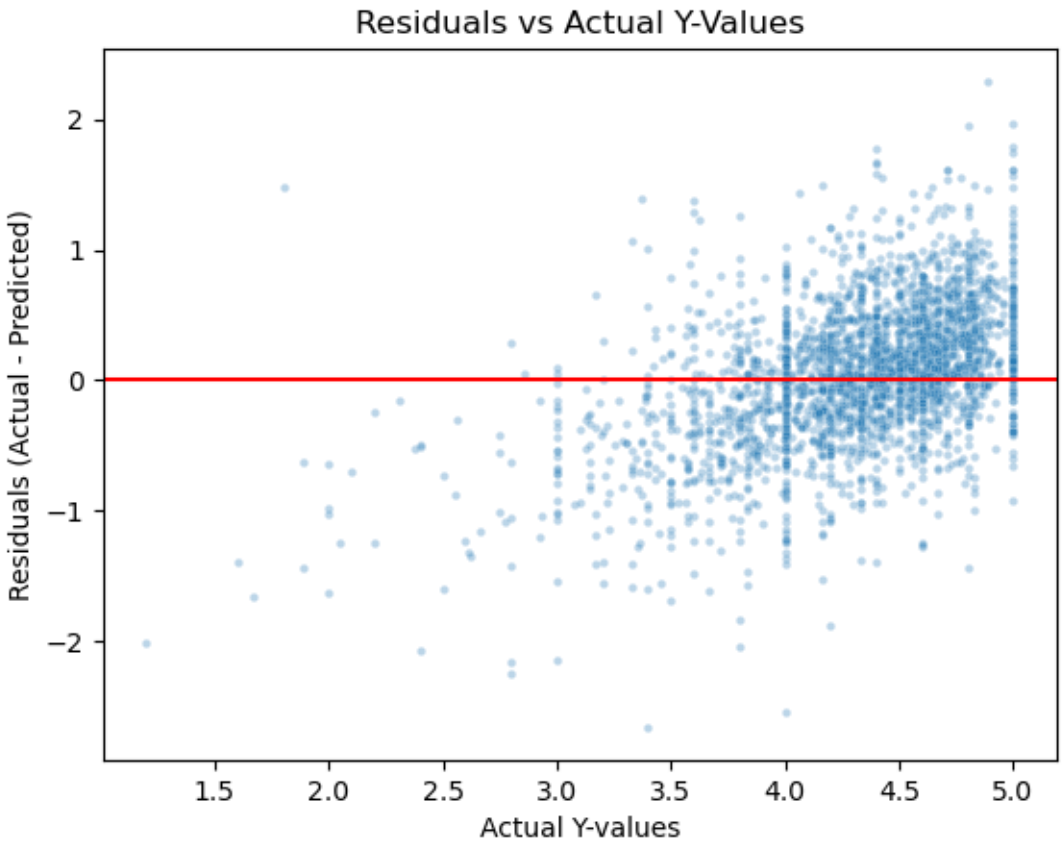
```
0.3014687289110116
```

```
0.3040461216868561
```

[75]:
```
sns.scatterplot(x = y_test, y = y_test_pred, alpha = 0.3, s = 10)
plt.axline((2.5,2.5), slope = 1)
plt.xlabel('y_test')
plt.ylabel('y_test_predictions')
plt.title('y_test vs y_test_predictions');
```



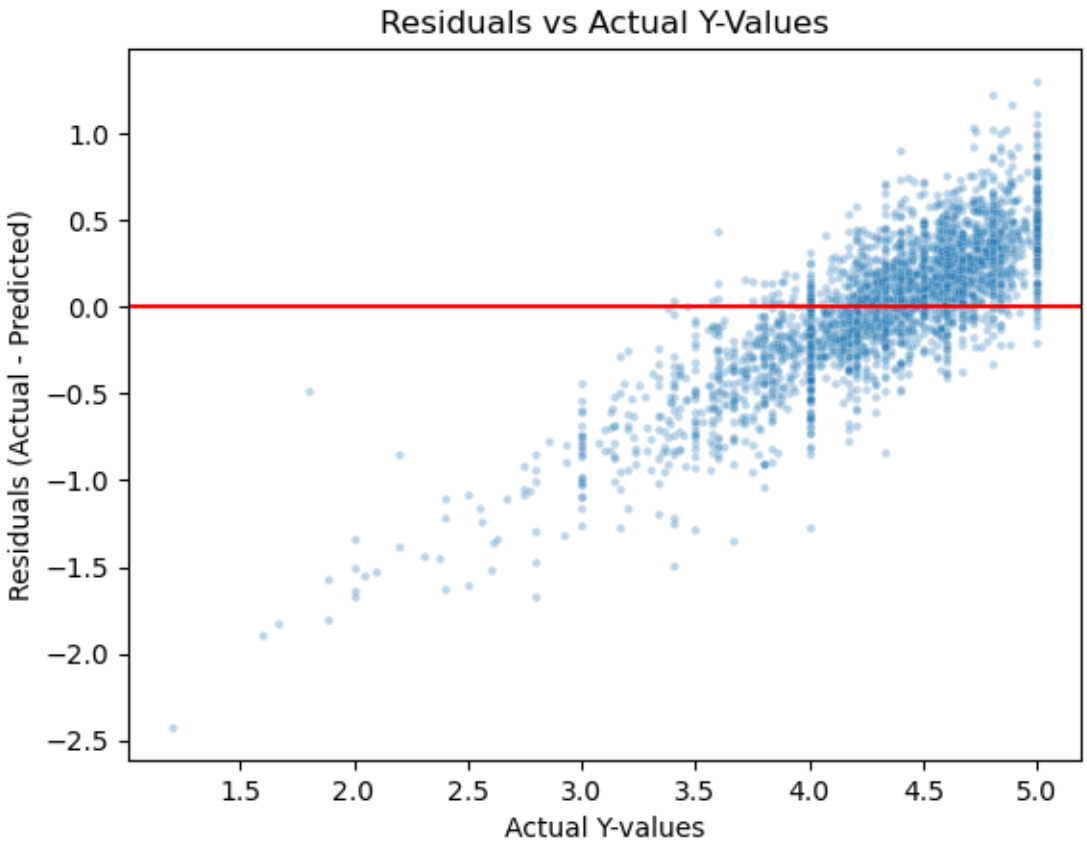
[76]:
```
sns.scatterplot(y = y_test - y_test_pred, x = y_test, alpha = 0.3, s = 10)
plt.axhline(0, color = 'r')
plt.title('Residuals vs Actual Y-Values')
plt.xlabel('Actual Y-values')
plt.ylabel('Residuals (Actual - Predicted)');
```



4.5.1 With Intercept

[77]:
```
linear_model = lm.LinearRegression(fit_intercept= True)
linear_model.fit(X_train, y_train)
y_train_pred = linear_model.predict(X_train)
y_test_pred = linear_model.predict(X_test)
```

[78]:
```
sns.scatterplot(y = y_test - y_test_pred, x = y_test, alpha = 0.3, s = 10)
plt.axhline(0, color = 'r')
plt.title('Residuals vs Actual Y-Values')
plt.xlabel('Actual Y-values')
plt.ylabel('Residuals (Actual - Predicted)');
```



4.6 Modeling Thoughts:

1. Even though using no regularization, cross validation highlights that there isnt an inherent bias in training dataset since the cross validation mean squared error scores are consistent with the final training mean squared error value.
2. Used neutral sentiment score as a predictor since although it was the second lowest in terms of magnitude of correlation with the product's average rating, it had the lowest correlation with compound sentiment score. Independence is greater in importance for improving model performance than largest correlation with target variable.
3. Did not end up using Average Review Character Length for each product as a predictor since it had little change (0.02) on the mean squared error and did not want to risk overfitting with no regularization being used.

4.7 Residual Plot Thoughts:

1. Seem to be consistently overpredicting average ratings less than 4.0 and for the most part, underpredicting ratings greater than 4.0

2. Removed intercept because it led to an extremely strong positively correlated pattern in the residual plot, highlighting regions of overpredicting for average rating less than 4 and underpredicting for average rating greater than 4.

4.8 Discussion & Final Thoughts

1. Clearly, model is not perfect, but seems to be doing a good job in using the inherent relationship between the reviews' sentiment scores and the product's rating to make predictions on the average rating of the product.
2. Average product rating does not only reflect product quality, but also quickness in shipping
3. Should look into use of regularization to build a more robust model once I start adding more features.
4. Need to see how and why the sample of only helpful reviews have good (with respect to other samples of the data) correlation with the product's average rating. > Potential Approach: Determine frequency distribution of adjectives used in helpful reviews and see the top few adjectives used to describe products. The next step would be to create a feature containing the average frequency of the use of these words in the reviews for a product. The assessment of the quality of this feature would be its correlation with the product's average rating.

Let me know thoughts on other features to potentially analyze or any issues in the analysis. This work was done entirely by Karthik Raj (SSID: 3035366972). Thank you for reading this report in its entirety!