MIE451/1513 Decision Support System -- Data Science Solution

Be sure to let us know:

i. what location you chose (and remember to sign up on Piazza so there are no duplicates),

ii. what preprocessing steps you implemented

1. **i. Niagara-on-the-lake**
2. **ii. truncate to max 100 reviews per hotel, drop hotels with < 20 reviews**

There were no blank reviews

In [1]:

```
# check the current python version
import sys
print(sys.version)

#Plot
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline

#Data Packages
import math
import pandas as pd
import numpy as np

#Progress bar
from tqdm import tqdm

#Counter
from collections import Counter

#Operation
import operator

#Natural Language Processing Packages
import re
import nltk

## Download Resources
nltk.download("vader_lexicon")
nltk.download("stopwords")
nltk.download("averaged_perceptron_tagger")
nltk.download("wordnet")

from nltk.sentiment import SentimentAnalyzer
from nltk.sentiment.vader import SentimentIntensityAnalyzer
from nltk.sentiment.util import *
from nltk import tokenize
from nltk.corpus import stopwords
from nltk.tag import PerceptronTagger
from nltk.data import find

## Machine Learning
import sklearn
import sklearn.metrics as metrics

## Data Visualization
import folium
```

```
from tabulate import tabulate
from scipy.stats.kde import gaussian_kde

## Geolocation
from geopy.geocoders import Nominatim
from geopy.extra.rate_limiter import RateLimiter
```

```
3.6.9 (default, Oct  8 2020, 12:12:24)
[GCC 8.4.0]
[nltk_data] Downloading package vader_lexicon to /root/nltk_data...
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Unzipping corpora/stopwords.zip.
[nltk_data] Downloading package averaged_perceptron_tagger to
[nltk_data]     /root/nltk_data...
[nltk_data]   Unzipping taggers/averaged_perceptron_tagger.zip.
[nltk_data] Downloading package wordnet to /root/nltk_data...
[nltk_data]   Unzipping corpora/wordnet.zip.
```

```
/usr/local/lib/python3.6/dist-packages/nltk/twitter/__init__.py:20: UserWarning: The twyt
hon library has not been installed. Some functionality from the twitter package will not
be available.
  warnings.warn("The twython library has not been installed. "
```

In [2]:

```
pd.set_option('display.max_columns', None)
pd.set_option('display.expand_frame_repr', False)
pd.set_option('max_colwidth', 500)
```

In [3]:

```
# Use vader to evaluated sentiment of reviews
def evalSentences(sentences, to_df=False, columns=[]):
    #Instantiate an instance to access SentimentIntensityAnalyzer class
    sid = SentimentIntensityAnalyzer()
    pdlist = []
    if to_df:
        for sentence in tqdm(sentences):
            ss = sid.polarity_scores(sentence)
            pdlist.append([sentence]+[ss['compound']])
        reviewDf = pd.DataFrame(pdlist)
        reviewDf.columns = columns
        return reviewDf

    else:
        for sentence in tqdm(sentences):
            print(sentence)
            ss = sid.polarity_scores(sentence)
            for k in sorted(ss):
                print('{0}: {1}, '.format(k, ss[k]), end='')
            print()
```

In [4]:

```
#Read in from pandas
columnNames = ['filePath','hotelName','reviewColumn','ratingScore','groundTruth',
               'date_stamp','streetAddress', 'City',
               'Province','postalCode']

hotelDf = pd.read_csv('https://raw.githubusercontent.com/MIE451-1513-2020/assignment-ds-i
tazap/master/trip-advisor-crawler/reviews_niagara.csv?token=AHTKMHOUHAGC5AUCQCVQZSS7XKHZE
',
                          header=None, names=columnNames)

#clean and get average ratings
hotels = hotelDf.hotelName.unique()
hotel_vader = {}
hotel_ground_truth = {}
for hotel in hotels:
  hotel_count = hotelDf.loc[hotelDf['hotelName'] == hotel].count()[0]
  if hotel_count < 20:
```

```
    hotelDf = hotelDf.loc[hotelDf['hotelName'] != hotel]
    print(hotel)


reviews = hotelDf['reviewColumn'].values

reviewDF = evalSentences(reviews, to_df=True, columns=['reviewCol','vader'])
```

```
Scarlet Tunic Bed and Breakfast
The Byron House
The Tea Cosy Bed and Breakfast
Wishing Well Historic Cottage
Barker House Bed and Breakfast
Lulu&#39;s Bed &amp; Breakfast
Rye Park Manor
Alfred&#39;s Coach House
TwiningRetreat
Heritage Trail Luxury Cottage &amp; Garden Retreat
Niagara On The Lake Furnished Rentals And Suites
Vine Village Apartments
Aaron&#39;s Bed
The Grange at Stag Hollow
The Stocking House Bed and Breakfast
Blue Willow Bed and Breakfast
Sterling House Bed and Breakfast
Beau&#39;s Bungalow
House29 Bed + Breakfast
A La Gallarie Bed and Breakfast
Wellington House B&amp;B
Villa Flora Bed
Le Papillon
Luisa&#39;s Suite Retreat
Royal Manor Bed and Breakfast
```

```
  0%|          | 0/6774 [00:00<?, ?it/s]
```

```
Country Side B&amp;B
Arbour View B&amp;B
Ben Brae-on-the-Park
Under the Arbour Bed and Breakfast
The Loyalist Bed &amp; Breakfast
Fawlty Towers B&amp;B
The Coach Stop
Vineyard Villa Bed &amp; Breakfast
Brock Hollow B&amp;B
DownHome Bed and Breakfast
Historic Locust Grove Canada Bed &amp; Breakfast
Cobblestone Bed and Breakfast
```

```
100%|██████████| 6774/6774 [00:09<00:00, 740.61it/s]
```

Q1 a)

In [5]:

```
#clean and get average ratings
hotels = hotelDf.hotelName.unique()
hotel_vader = {}
hotel_ground_truth = {}
for hotel in hotels:
  hotel_count = hotelDf.loc[hotelDf['hotelName'] == hotel].count()[0]
  reviews = hotelDf.loc[hotelDf['hotelName'] == hotel]['reviewColumn'].values
  eval = evalSentences(reviews, to_df=True, columns=['reviewCol','vader'])
  vader_avg = eval['vader'].mean()
  hotel_vader[hotel] = vader_avg
  hotel_ground_truth[hotel] = hotelDf.loc[hotelDf['hotelName'] == hotel].ratingScore.mea
n() / 5
```

```
100%|██████████| 53/53 [00:00<00:00, 727.66it/s]
100%|██████████| 28/28 [00:00<00:00, 528.44it/s]
100%|██████████| 42/42 [00:00<00:00, 745.65it/s]
```

```
100%|██████████| 58/58 [00:00<00:00, 652.73it/s]
100%|██████████| 38/38 [00:00<00:00, 702.89it/s]
100%|██████████| 25/25 [00:00<00:00, 727.81it/s]
100%|██████████| 100/100 [00:00<00:00, 837.15it/s]
100%|██████████| 50/50 [00:00<00:00, 621.09it/s]
100%|██████████| 100/100 [00:00<00:00, 914.50it/s]
100%|██████████| 100/100 [00:00<00:00, 550.41it/s]
100%|██████████| 100/100 [00:00<00:00, 961.81it/s]
100%|██████████| 100/100 [00:00<00:00, 828.43it/s]
100%|██████████| 70/70 [00:00<00:00, 763.36it/s]
100%|██████████| 45/45 [00:00<00:00, 698.39it/s]
100%|██████████| 100/100 [00:00<00:00, 1071.73it/s]
100%|██████████| 20/20 [00:00<00:00, 718.89it/s]
100%|██████████| 25/25 [00:00<00:00, 853.02it/s]
100%|██████████| 55/55 [00:00<00:00, 726.84it/s]
100%|██████████| 100/100 [00:00<00:00, 656.68it/s]
100%|██████████| 100/100 [00:00<00:00, 657.77it/s]
100%|██████████| 100/100 [00:00<00:00, 797.29it/s]
100%|██████████| 73/73 [00:00<00:00, 737.63it/s]
100%|██████████| 25/25 [00:00<00:00, 689.28it/s]
100%|██████████| 45/45 [00:00<00:00, 730.00it/s]
100%|██████████| 35/35 [00:00<00:00, 807.28it/s]
100%|██████████| 100/100 [00:00<00:00, 718.76it/s]
100%|██████████| 100/100 [00:00<00:00, 633.65it/s]
100%|██████████| 30/30 [00:00<00:00, 752.86it/s]
100%|██████████| 100/100 [00:00<00:00, 831.01it/s]
100%|██████████| 100/100 [00:00<00:00, 675.49it/s]
100%|██████████| 100/100 [00:00<00:00, 662.22it/s]
100%|██████████| 27/27 [00:00<00:00, 877.38it/s]
100%|██████████| 20/20 [00:00<00:00, 584.39it/s]
100%|██████████| 100/100 [00:00<00:00, 563.93it/s]
100%|██████████| 100/100 [00:00<00:00, 650.97it/s]
100%|██████████| 26/26 [00:00<00:00, 780.02it/s]
100%|██████████| 80/80 [00:00<00:00, 655.98it/s]
100%|██████████| 20/20 [00:00<00:00, 627.89it/s]
100%|██████████| 100/100 [00:00<00:00, 1043.97it/s]
100%|██████████| 100/100 [00:00<00:00, 1040.20it/s]
100%|██████████| 100/100 [00:00<00:00, 703.35it/s]
100%|██████████| 100/100 [00:00<00:00, 1067.42it/s]
100%|██████████| 100/100 [00:00<00:00, 607.54it/s]
100%|██████████| 61/61 [00:00<00:00, 519.79it/s]
100%|██████████| 61/61 [00:00<00:00, 609.52it/s]
100%|██████████| 100/100 [00:00<00:00, 653.58it/s]
100%|██████████| 100/100 [00:00<00:00, 774.75it/s]
100%|██████████| 100/100 [00:00<00:00, 743.60it/s]
100%|██████████| 100/100 [00:00<00:00, 644.79it/s]
100%|██████████| 100/100 [00:00<00:00, 850.54it/s]
100%|██████████| 30/30 [00:00<00:00, 685.50it/s]
100%|██████████| 100/100 [00:00<00:00, 738.30it/s]
100%|██████████| 48/48 [00:00<00:00, 564.79it/s]
100%|██████████| 20/20 [00:00<00:00, 533.94it/s]
100%|██████████| 100/100 [00:00<00:00, 523.59it/s]
100%|██████████| 25/25 [00:00<00:00, 625.19it/s]
100%|██████████| 100/100 [00:00<00:00, 789.95it/s]
100%|██████████| 100/100 [00:00<00:00, 870.78it/s]
100%|██████████| 57/57 [00:00<00:00, 855.55it/s]
100%|██████████| 100/100 [00:00<00:00, 1044.95it/s]
100%|██████████| 57/57 [00:00<00:00, 785.37it/s]
100%|██████████| 100/100 [00:00<00:00, 692.37it/s]
100%|██████████| 25/25 [00:00<00:00, 885.53it/s]
100%|██████████| 100/100 [00:00<00:00, 1017.44it/s]
100%|██████████| 100/100 [00:00<00:00, 880.80it/s]
100%|██████████| 45/45 [00:00<00:00, 674.41it/s]
100%|██████████| 100/100 [00:00<00:00, 541.48it/s]
100%|██████████| 90/90 [00:00<00:00, 715.44it/s]
100%|██████████| 55/55 [00:00<00:00, 526.56it/s]
100%|██████████| 80/80 [00:00<00:00, 680.21it/s]
100%|██████████| 65/65 [00:00<00:00, 709.09it/s]
100%|██████████| 95/95 [00:00<00:00, 799.95it/s]
100%|██████████| 100/100 [00:00<00:00, 816.46it/s]
100%|██████████| 100/100 [00:00<00:00, 700.08it/s]
100%|██████████| 20/20 [00:00<00:00, 586.32it/s]
```

```
100%|██████████| 24/24 [00:00<00:00, 745.08it/s]
100%|██████████| 100/100 [00:00<00:00, 888.76it/s]
100%|██████████| 100/100 [00:00<00:00, 680.00it/s]
100%|██████████| 80/80 [00:00<00:00, 766.65it/s]
100%|██████████| 100/100 [00:00<00:00, 724.13it/s]
100%|██████████| 30/30 [00:00<00:00, 632.49it/s]
100%|██████████| 100/100 [00:00<00:00, 638.14it/s]
100%|██████████| 75/75 [00:00<00:00, 562.83it/s]
100%|██████████| 100/100 [00:00<00:00, 745.00it/s]
100%|██████████| 99/99 [00:00<00:00, 736.99it/s]
100%|██████████| 80/80 [00:00<00:00, 1004.68it/s]
100%|██████████| 36/36 [00:00<00:00, 845.13it/s]
100%|██████████| 81/81 [00:00<00:00, 725.56it/s]
100%|██████████| 100/100 [00:00<00:00, 727.11it/s]
100%|██████████| 30/30 [00:00<00:00, 789.66it/s]
100%|██████████| 31/31 [00:00<00:00, 782.50it/s]
100%|██████████| 89/89 [00:00<00:00, 734.58it/s]
100%|██████████| 20/20 [00:00<00:00, 623.07it/s]
100%|██████████| 75/75 [00:00<00:00, 683.68it/s]
```

In [457]:

```python
hotel_vader
import operator
```

Q1 b) i) & ii)

Ranked Vader

In [460]:

```python
sorted_hotel_vader = sorted(hotel_vader.items(), key=operator.itemgetter(1), reverse=True
)
sorted_hotel_vader
```

Out[460]:

```
[('Old Town Country Landing B&amp;B', 0.9817433333333334),
 ('Arcadia House B&amp;B', 0.9738999999999999),
 ('Bruce Manor', 0.9736225),
 ('Kellar House Accommodations', 0.9703724137931037),
 ('Cape House Bed and Breakfast', 0.9688990000000001),
 ('Blue Skies Bed &amp; Breakfast', 0.9684888888888886),
 ('A Lil Bit Of Eden', 0.9679600000000003),
 ('Woodbourne Inn', 0.967813),
 ('In Elegance Bed and Breakfast', 0.967743),
 ('Chalet Bed and Breakfast', 0.9658328767123289),
 ('Historic Wilson-Guy House', 0.9657140350877194),
 ('Darlington House Bed and Breakfast', 0.965418),
 ('The White House Boutique Bed &amp; Breakfast', 0.9640139999999998),
 ('The Stewart House', 0.9632350000000001),
 ('Yolanta&#39;s B&amp;B', 0.9616851851851853),
 ('Two Bees Bed &amp; Breakfast', 0.9616630000000004),
 ('Orchid Inn', 0.9614565656565656),
 ('Serendipity Bed &amp; Breakfast', 0.9614150000000002),
 ('Globetrotters Bed and Breakfast', 0.9607557377049181),
 ('Matisse Bed &amp; Breakfast', 0.9607142857142857),
 ('The Red Coat', 0.9604033707865173),
 ('Brockamour Manor Bed and Breakfast', 0.9601970000000003),
 ('Victoria Gables Bed &amp; Breakfast', 0.9593579999999997),
 ('Historic Lyons House', 0.9591420000000003),
 ('Graystone Bed and Breakfast', 0.9586370000000004),
 ('627 on King Bed and Breakfast', 0.9586319999999999),
 ('WeatherPine Inn', 0.9584350000000001),
 ('The Promenade', 0.9575277777777779),
 ('Greenview Manor, Luxury Bed &amp; Breakfast', 0.9565539999999997),
 ('Abagales Victorian Hot Tubs and Suites Bed and Breakfast',
  0.9563140000000001),
 ('Silver Birches by-the-Lake B&amp;B', 0.9562287500000004),
```

```
('Green Oaks B&amp;B', 0.9559824999999996),
('Hoppy&#39;s Bed &amp; Breakfast', 0.9553180000000002),
('Post House Inn', 0.9537590000000006),
('St. Andrews House Bed &amp; Breakfast', 0.9536346153846154),
('Panache Bed and Breakfast', 0.9534421052631581),
('Bernard Gray Hall Bed and Breakfast', 0.9513160000000002),
('On the 6 Bed and Breakfast', 0.9507400000000005),
('Wine Country Bed &amp; Breakfast', 0.9501370000000002),
('Queen Regent Bed &amp; Breakfast', 0.9498867924528304),
('Abacot Hall Bed &amp; Breakfast', 0.9497529999999997),
('Explorer House Bed &amp; Breakfast', 0.9488939999999997),
('Lakelands Bed and Breakfast', 0.9488190000000002),
('The Pillar and Post Inn, Spa and Conference Centre', 0.948786),
('Antique Slumber B&amp;B', 0.9460680000000005),
('John&#39;s Gate Gourmet Bed and Breakfast', 0.9460419999999999),
('Demi&#39;s Place Bed and Breakfast', 0.9460287500000005),
('Dorchester House Bed and Breakfast', 0.9415600000000002),
('Finlay House', 0.9413409999999999),
('BranCliff Inn', 0.937429),
('Williams Gate Bed and Breakfast Private Suites', 0.9336719999999998),
('Somerset Bed &amp; Breakfast', 0.9330999999999999),
('Via Veneto', 0.9328019999999997),
('Schoolmaster&#39;s House Bed &amp; Breakfast', 0.9287600000000005),
('Harbour House Hotel', 0.928205),
('Maria&#39;s Bed and Breakfast', 0.927039),
('American Loyalist Peter Secord Inn C.1782', 0.9255866666666667),
('Holiday Inn Express &amp; Suites - Niagara-On-The-Lake',
 0.9250828571428571),
('Niagara RV Rentals', 0.9234099999999998),
('Butler Creek House', 0.9207190476190474),
('Lakewinds Country Manor', 0.9169930000000001),
('Copper Dreams Bed and Breakfast', 0.9137155555555553),
('Arnica Bed &amp; Breakfast', 0.9125105263157893),
('Carbonnel Bed &amp; Breakfast', 0.9047869999999998),
('The Doctor&#39;s House B&amp;B', 0.9018499999999999),
('Prince of Wales', 0.8997769999999999),
('Grand Victorian Bed and Breakfast', 0.8983581818181818),
('The Historic Pacific', 0.8955480000000001),
('Queen&#39;s Landing', 0.8910330000000002),
('Best Western Colonel Butler Inn', 0.8902530000000003),
('Simcoe Manor', 0.8889092307692309),
('The Charles Hotel', 0.8861200000000004),
('Shaw Club Hotel', 0.884196),
('The Georgian Residence Luxury Boutique Suites', 0.8824708333333331),
('Cedar Gables Bed and Breakfast', 0.8815440000000001),
('Staybridge Suites Niagara-On-The-Lake', 0.8781355555555554),
('White Oaks Conference Resort &amp; Spa', 0.8701129999999999),
('Old Ivy Walk', 0.8663750000000002),
('Eagle&#39;s Wing Bed and Breakfast', 0.8653583333333335),
('124 on Queen Hotel and Spa', 0.860997),
('Oban Inn', 0.8578600000000002),
('Apple Tree Historic Bed &amp; Breakfast', 0.8549333333333331),
('Olde Angel Inn Hotel and Restaurant', 0.831034),
('The Irish Harp Pub Inn', 0.8295666666666666),
('Clover Field House', 0.8081035714285715),
('Hilton Garden Inn Niagara-on-the-Lake', 0.7799849999999999),
('Moffat Inn', 0.7758730000000003),
('Riverbend Inn and Vineyard', 0.7650819999999997),
('A Pillow and Toast', 0.7281359999999999),
('South Landing Inn', 0.7165280000000002),
('The Old Bank House', 0.6993081967213115),
('King George III Inn', 0.599592),
('Residence &amp; Conference Centres - Niagara on the Lake',
 0.5701072727272727),
('Great Blue Resorts - Vine Ridge Resort Niagara', 0.5597645161290322)]
```

Ranked Ground Truth

In [461]:

```
sorted_hotel_ground_truth = sorted(hotel_ground_truth.items(), key=operator.itemgetter(1)
, reverse=True)
sorted_hotel_ground_truth
```

Out[461]:

```
[('The White House Boutique Bed &amp; Breakfast', 1.0),
 ('Lakelands Bed and Breakfast', 1.0),
 ('Post House Inn', 1.0),
 ('Explorer House Bed &amp; Breakfast', 1.0),
 ('Brockamour Manor Bed and Breakfast', 1.0),
 ('On the 6 Bed and Breakfast', 1.0),
 ('Old Town Country Landing B&amp;B', 1.0),
 ('Greenview Manor, Luxury Bed &amp; Breakfast', 0.998),
 ('Victoria Gables Bed &amp; Breakfast', 0.998),
 ('Graystone Bed and Breakfast', 0.998),
 ('Hoppy&#39;s Bed &amp; Breakfast', 0.998),
 ('Serendipity Bed &amp; Breakfast', 0.998),
 ('Globetrotters Bed and Breakfast', 0.9967213114754099),
 ('Abacot Hall Bed &amp; Breakfast', 0.9960000000000001),
 ('Blue Skies Bed &amp; Breakfast', 0.9950617283950617),
 ('The Promenade', 0.9944444444444445),
 ('Matisse Bed &amp; Breakfast', 0.9942857142857143),
 ('Wine Country Bed &amp; Breakfast', 0.994),
 ('A Lil Bit Of Eden', 0.9933333333333334),
 ('Arcadia House B&amp;B', 0.9933333333333334),
 ('St. Andrews House Bed &amp; Breakfast', 0.9923076923076923),
 ('Two Bees Bed &amp; Breakfast', 0.992),
 ('Woodbourne Inn', 0.992),
 ('Darlington House Bed and Breakfast', 0.992),
 ('The Stewart House', 0.99),
 ('In Elegance Bed and Breakfast', 0.99),
 ('Kellar House Accommodations', 0.9896551724137931),
 ('Panache Bed and Breakfast', 0.9894736842105264),
 ('Chalet Bed and Breakfast', 0.9890410958904109),
 ('Queen Regent Bed &amp; Breakfast', 0.9886792452830189),
 ('Cape House Bed and Breakfast', 0.9880000000000001),
 ('Bruce Manor', 0.9875),
 ('Demi&#39;s Place Bed and Breakfast', 0.9875),
 ('627 on King Bed and Breakfast', 0.986),
 ('Williams Gate Bed and Breakfast Private Suites', 0.986),
 ('Bernard Gray Hall Bed and Breakfast', 0.984),
 ('Silver Birches by-the-Lake B&amp;B', 0.9824999999999999),
 ('Historic Wilson-Guy House', 0.9824561403508772),
 ('WeatherPine Inn', 0.982),
 ('Maria&#39;s Bed and Breakfast', 0.982),
 ('BranCliff Inn', 0.982),
 ('Antique Slumber B&amp;B', 0.9800000000000001),
 ('Historic Lyons House', 0.9800000000000001),
 ('Orchid Inn', 0.9797979797979798),
 ('The Red Coat', 0.9797752808988764),
 ('Yolanta&#39;s B&amp;B', 0.9777777777777779),
 ('Green Oaks B&amp;B', 0.9775),
 ('Cedar Gables Bed and Breakfast', 0.976),
 ('John&#39;s Gate Gourmet Bed and Breakfast', 0.974),
 ('Lakewinds Country Manor', 0.974),
 ('Arnica Bed &amp; Breakfast', 0.9736842105263157),
 ('Butler Creek House', 0.9714285714285713),
 ('Finlay House', 0.97),
 ('Via Veneto', 0.97),
 ('Copper Dreams Bed and Breakfast', 0.9644444444444444),
 ('Abagales Victorian Hot Tubs and Suites Bed and Breakfast', 0.96),
 ('Old Ivy Walk', 0.96),
 ('American Loyalist Peter Secord Inn C.1782', 0.96),
 ('Schoolmaster&#39;s House Bed &amp; Breakfast', 0.9578947368421054),
 ('The Pillar and Post Inn, Spa and Conference Centre', 0.954),
 ('Grand Victorian Bed and Breakfast', 0.9527272727272728),
 ('Carbonnel Bed &amp; Breakfast', 0.952),
 ('The Doctor&#39;s House B&amp;B', 0.95),
 ('The Georgian Residence Luxury Boutique Suites', 0.95),
 ('Holiday Inn Express &amp; Suites - Niagara-On-The-Lake',
  0.9428571428571428),
 ('Somerset Bed &amp; Breakfast', 0.9400000000000001),
```

```
 ('Somerset Bed &amp; Breakfast', 0.9400000000000001),
 ('Staybridge Suites Niagara-On-The-Lake', 0.9377777777777778),
 ('The Historic Pacific', 0.9359999999999999),
 ('Simcoe Manor', 0.9292307692307693),
 ('Prince of Wales', 0.9279999999999999),
 ('Dorchester House Bed and Breakfast', 0.9199999999999999),
 ('Queen&#39;s Landing', 0.916),
 ('124 on Queen Hotel and Spa', 0.916),
 ('White Oaks Conference Resort &amp; Spa', 0.908),
 ('Clover Field House', 0.9071428571428571),
 ('Harbour House Hotel', 0.9039999999999999),
 ('Apple Tree Historic Bed &amp; Breakfast', 0.9022222222222223),
 ('Eagle&#39;s Wing Bed and Breakfast', 0.9),
 ('The Charles Hotel', 0.892),
 ('Olde Angel Inn Hotel and Restaurant', 0.882),
 ('Best Western Colonel Butler Inn', 0.882),
 ('Shaw Club Hotel', 0.8779999999999999),
 ('Oban Inn', 0.874),
 ('Hilton Garden Inn Niagara-on-the-Lake', 0.874),
 ('Niagara RV Rentals', 0.8699999999999999),
 ('The Irish Harp Pub Inn', 0.8622222222222222),
 ('South Landing Inn', 0.8373333333333333),
 ('The Old Bank House', 0.8),
 ('Moffat Inn', 0.798),
 ('A Pillow and Toast', 0.792),
 ('Riverbend Inn and Vineyard', 0.774),
 ('King George III Inn', 0.704),
 ('Great Blue Resorts - Vine Ridge Resort Niagara', 0.6709677419354839),
 ('Residence &amp; Conference Centres - Niagara on the Lake',
  0.6509090909090909)]
```

In [8]:

```python
def prettyprint(dict_list):
  for x in dict_list:
    print(x[0], ":", x[1])
  print("")
```

In [9]:

```python
print("====== Top 5 ======\n")
print("------ Vader ------")
prettyprint(sorted_hotel_vader[:5])
print("------ Ground Truth ------")
prettyprint(sorted_hotel_ground_truth[:5])
print("====== Bottom 5 ======\n")
print("------ Vader ------")
prettyprint(sorted_hotel_vader[-5:])
print("------ Ground Truth ------")
prettyprint(sorted_hotel_ground_truth[-5:])
```

```
====== Top 5 ======

------ Vader ------
Old Town Country Landing B&amp;B : 0.9817433333333334
Arcadia House B&amp;B : 0.9738999999999999
Bruce Manor : 0.9736225
Kellar House Accommodations : 0.9703724137931037
Cape House Bed and Breakfast : 0.9688990000000001

------ Ground Truth ------
The White House Boutique Bed &amp; Breakfast : 1.0
Lakelands Bed and Breakfast : 1.0
Post House Inn : 1.0
Explorer House Bed &amp; Breakfast : 1.0
Brockamour Manor Bed and Breakfast : 1.0

====== Bottom 5 ======

------ Vader ------
South Landing Inn : 0.7165280000000002
The Old Bank House : 0.6993081967213115
```

```
King George III Inn : 0.599592
Residence &amp; Conference Centres - Niagara on the Lake : 0.5701072727272727
Great Blue Resorts - Vine Ridge Resort Niagara : 0.5597645161290322

------ Ground Truth ------
A Pillow and Toast : 0.792
Riverbend Inn and Vineyard : 0.774
King George III Inn : 0.704
Great Blue Resorts - Vine Ridge Resort Niagara : 0.6709677419354839
Residence &amp; Conference Centres - Niagara on the Lake : 0.6509090909090909
```

The ground truth and vader report completely different top 5 hotels. But, upon reviewing the ground truth score for the top 5 vader score hotels, I can see that these top 5 hotels are still extremelty highly rated (98% +) so I think there are just a lot of well-rated hotels:

Old Town Country Landing B&B : 1.0

Arcadia House B&B : 0.9933

Bruce Manor : 0.9875

Kellar House Accommodations : 0.9897

Cape House Bed and Breakfast : 0.9880

The bottom 5 however have more similarities. Vader included 4 out of 5 worst hotels correclty, just in a different order.

I think these results are due to there being a lot of well rated hotels so the ranking may have been off even though the scores were similar. For the worse hotels there aren't many so there is a larger variance in the bottom 5. This makes the bottom 5 easier to rank

Q2 a)

In [10]:

```python
def get_stop_words():
    stop = set(stopwords.words('english'))
    #Add possible Stop Words for Hotel Reviews
    stop.add('hotel')
    stop.add('room')
    stop.add('rooms')
    stop.add('stay')
    stop.add('staff')
    return stop

def getTopKWords(df, kwords):

    stop = get_stop_words()
    counter = Counter()

    reviews = df['reviewCol'].values

    for review in reviews:
            counter.update([word.lower()
                            for word
                            in re.findall(r'\w+', review)
                            if word.lower() not in stop and len(word) > 2])
    topk = counter.most_common(kwords)
    return topk

# Note: You may want to use an NLTK tokenizer instead of a regular expression in the foll
owing
def dataFrameTransformation(hotelDf, reviewDF, topk):
    reviews = reviewDF['reviewCol'].values
    print(len(reviews))
    #Find out if a particular review has the word from topk list
```

```
    freqReview = []
    for i in range(len(reviews)):
        tempCounter = Counter([word.lower() for word in re.findall(r'\w+',reviews[i])])
        topkinReview = [1 if tempCounter[word] > 0 else 0 for (word,wordCount) in topk]
        freqReview.append(topkinReview)


    #Prepare freqReviewDf
    freqReviewDf = pd.DataFrame(freqReview)
    dfName = []
    for c in topk:
        dfName.append(c[0])
    freqReviewDf.columns = dfName
    finalreviewDf = reviewDF.join(freqReviewDf)
    finaldfx = hotelDf[['hotelName','ratingScore','groundTruth']].join(finalreviewDf)
    return finaldfx

def getTopK(df, kwords, label_value, label_column='groundTruth', operation=operator.eq,
value_column='reviewCol'):
    stop = get_stop_words()
    counter = Counter()
    reviews = df.loc[operation(df[label_column],label_value)][value_column]
    for review in reviews:
            counter.update([word.lower()
                            for word
                            in re.findall(r'\w+', review)
                            if word.lower() not in stop and len(word) > 2])
    topk = counter.most_common(kwords)
    return topk
```

In [11]:

```
hotelDf = hotelDf.reset_index()
reviewDF = reviewDF.reset_index()
```

i) positive reviews

In [12]:

```
#We are only intereseted in this three column for overall analysis
topk = getTopKWords(reviewDF, 500)
finaldf = dataFrameTransformation(hotelDf, reviewDF, topk)
itemAnalysisDf = finaldf[['reviewCol','groundTruth','vader']]
topkGroundPos = getTopK(itemAnalysisDf, 50, label_value='positive')
topkGroundPos
```

6774

Out[12]:

```
[('breakfast', 4800),
 ('great', 3164),
 ('niagara', 2441),
 ('stayed', 2318),
 ('comfortable', 2252),
 ('lake', 2113),
 ('clean', 2075),
 ('wonderful', 2001),
 ('would', 1989),
 ('hosts', 1877),
 ('time', 1872),
 ('home', 1858),
 ('place', 1854),
 ('beautiful', 1814),
 ('area', 1730),
 ('house', 1676),
 ('back', 1665),
 ('bed', 1639),
 ('well', 1628),
 ('delicious', 1620),
 ('lovely', 1558),
```

```
 ('location', 1511),
 ('one', 1494),
 ('nice', 1460),
 ('breakfasts', 1451),
 ('made', 1422),
 ('recommend', 1416),
 ('friendly', 1355),
 ('perfect', 1309),
 ('amazing', 1260),
 ('also', 1250),
 ('definitely', 1231),
 ('town', 1202),
 ('day', 1163),
 ('good', 1152),
 ('wine', 1138),
 ('nthe', 1134),
 ('everything', 1114),
 ('inn', 1114),
 ('visit', 1104),
 ('walk', 1095),
 ('like', 1088),
 ('enjoyed', 1084),
 ('food', 1050),
 ('two', 1036),
 ('excellent', 1028),
 ('night', 1022),
 ('experience', 1019),
 ('morning', 1004),
 ('first', 947)]
```

ii) negative reviews

In [13]:

```
topkGroundNeg = getTopK(itemAnalysisDf, 50, label_value='negative')
topkGroundNeg
```

Out[13]:

```
[('would', 289),
 ('one', 266),
 ('breakfast', 250),
 ('night', 193),
 ('time', 163),
 ('bed', 149),
 ('good', 149),
 ('place', 143),
 ('nice', 140),
 ('could', 137),
 ('like', 133),
 ('stayed', 129),
 ('niagara', 127),
 ('nthe', 126),
 ('inn', 126),
 ('small', 124),
 ('get', 120),
 ('two', 117),
 ('great', 113),
 ('area', 106),
 ('back', 106),
 ('told', 101),
 ('service', 99),
 ('also', 98),
 ('clean', 96),
 ('bathroom', 95),
 ('location', 95),
 ('desk', 95),
 ('price', 93),
 ('day', 90),
 ('lake', 90),
 ('food', 89),
```

```
 ('food', 89),
 ('booked', 89),
 ('front', 88),
 ('even', 85),
 ('old', 84),
 ('well', 82),
 ('never', 82),
 ('u2019t', 82),
 ('first', 80),
 ('much', 79),
 ('went', 78),
 ('experience', 78),
 ('door', 77),
 ('little', 77),
 ('morning', 76),
 ('next', 74),
 ('left', 72),
 ('said', 72),
 ('got', 72)]
```

The word "Niagara" is location specific

words in both lists:

In [14]:

```
for (word,count) in topkGroundPos:
  for (word1, count1) in topkGroundNeg:
    if word == word1:
      print(word)
```

```
breakfast
great
niagara
stayed
lake
clean
would
time
place
area
back
bed
well
location
one
nice
also
day
good
nthe
inn
like
food
two
night
experience
morning
first
```

"Niagara" is location specific.

Above are the words that appear in both lists. Most seem to be pretty non-descriptive or nouns that could have been described positively or negatively (if they had a negation) so that makes sense. Some surprising ones are "nice", "good", and "clean" because they seem all positive, but they still makes sense because they could have been used with a negation: "not clean, not nice, etc."

Q2 b)

In [15]:

```
# This grammar is described in the paper by S. N. Kim,
# T. Baldwin, and M.-Y. Kan.
# Evaluating n-gram based evaluation metrics for automatic
# keyphrase extraction.
# Technical report, University of Melbourne, Melbourne 2010.
grammar = r"""
    NBAR:
        {<NN.*|JJ>*<NN.*>}  # Nouns and Adjectives, terminated with Nouns

    NP:
        {<NBAR>}
        {<NBAR><IN><NBAR>}  # Above, connected with in/of/etc...
"""

# to make the results more useable, we clean up the tree results shown above.
lemmatizer = nltk.WordNetLemmatizer()
stemmer = nltk.stem.porter.PorterStemmer()
stopword_list = get_stop_words()

# generator, create item one a time
def get_terms(tree):
    for leaf in leaves(tree):
        term = [normalise(w) for w,t in leaf if acceptable_word(w) ]
        # Phrase only
        if len(term)>1:
            yield term

# generator, generate leaves one by one
def leaves(tree):
    """Finds NP (nounphrase) leaf nodes of a chunk tree."""
    for subtree in tree.subtrees(filter = lambda t: t.label()=='NP' or t.label()=='JJ' o
r t.label()=='RB'):
        yield subtree.leaves()

# stemming, lematizing, lower case...
def normalise(word,lemmatizer=lemmatizer, stemmer=stemmer):
    """Normalises words to lowercase and stems and lemmatizes it."""
    word = word.lower()
    word = stemmer.stem(word)
    word = lemmatizer.lemmatize(word)
    return word

# stop-words and length control
def acceptable_word(word, stopword_list=stopword_list):
    """Checks conditions for acceptable word: length, stopword."""
    accepted = bool(2 <= len(word) <= 40
        and word.lower() not in stopword_list)
    return accepted

# Flatten phrase lists to get tokens for analysis
def flatten_phrase_lists(npTokenList):
    finalList =[]
    for phrase in npTokenList:
        token = ''
        for word in phrase:
            token += word + ' '
        finalList.append(token.rstrip())
    return finalList

def getTopKNP(df, kNPs, label_value):

    counter = Counter()
    df = df.loc[df['groundTruth'] == label_value]
    reviews = df['reviewCol'].values

    for review in reviews:
            counter.update(flatten_phrase_lists([word
                                for word
```

```
                                in get_terms(chunker.parse(pos_tag(re.findall(r'\w+', review
))))
                                ]))
    topk = counter.most_common(kNPs)
    return topk


def NPdataFrameTransformation(hotelDf, reviewDF, topk):
    reviews = reviewDF['reviewCol'].values

    #Find out if a particular review has the word from topk list
    freqReview = []
    for i in range(len(reviews)):
        tempCounter = Counter(flatten_phrase_lists([word
                                    for word
                                    in get_terms(chunker.parse(pos_tag(re.findall(r'
\w+',reviews[i]))))]))
        topkinReview = [1 if tempCounter[word] > 0 else 0 for (word,wordCount) in topk]
        freqReview.append(topkinReview)

    #Prepare freqReviewDf
    freqReviewDf = pd.DataFrame(freqReview)
    dfName = []
    for c in topk:
        dfName.append(c[0])
    freqReviewDf.columns = dfName
    finalreviewDf = reviewDF.join(freqReviewDf)
    finaldfx = hotelDf[['hotelName','ratingScore','groundTruth']].join(finalreviewDf)
    return finaldfx
```

In [16]:

```
# Sample text
text = """The Buddha, the Godhead, resides quite as comfortably in the circuits of a digi
tal
computer or the gears of a cycle transmission as he does at the top of a mountain
or in the petals of a flower. To think otherwise is to demean the Buddha...which is
to demean oneself."""
# Part of Speech Tagging
# Google: https://en.wikipedia.org/wiki/Part-of-speech_tagging
tagger = PerceptronTagger()
pos_tag = tagger.tag
taggedToks = pos_tag(re.findall(r'\w+', text))
taggedToks

# Create phrase tree
chunker = nltk.RegexpParser(grammar)
tree = chunker.parse(taggedToks)
```

ii) positive

In [17]:

```
topk_phrase = getTopKNP(finaldf, 50, label_value='positive')
topk_phrase[:50]
```

Out[17]:

```
[('main street', 266),
 ('first time', 211),
 ('wonder host', 205),
 ('niagara fall', 194),
 ('minut walk', 180),
 ('short walk', 177),
 ('shaw festiv', 173),
 ('delici breakfast', 170),
 ('hot tub', 153),
 ('great place', 135),
 ('next year', 126),
 ('next time', 118),
 ('graciou host', 116),
```

```
 ('graciou host', 116),
 ('great locat', 116),
 ('comfort bed', 111),
 ('front desk', 106),
 ('great host', 104),
 ('great time', 100),
 ('wine tour', 94),
 ('queen street', 90),
 ('cours breakfast', 90),
 ('short drive', 85),
 ('wonder experi', 85),
 ('second floor', 76),
 ('perfect host', 76),
 ('perfect place', 74),
 ('orchid inn', 74),
 ('great experi', 71),
 ('next visit', 70),
 ('excel host', 70),
 ('wine tast', 70),
 ('fresh fruit', 68),
 ('wonder time', 67),
 ('warm welcom', 67),
 ('minut drive', 66),
 ('next morn', 66),
 ('wine countri', 64),
 ('common area', 64),
 ('great breakfast', 64),
 ('beauti home', 63),
 ('local wineri', 62),
 ('first experi', 62),
 ('victoria gabl', 62),
 ('lake ontario', 60),
 ('mani wineri', 60),
 ('amaz breakfast', 60),
 ('golf cours', 59),
 ('gourmet breakfast', 57),
 ('finlay hous', 57),
 ('wonder place', 56)]
```

ii) negative

In [18]:

```
bottomk_phrase = getTopKNP(finaldf, 50, label_value='negative')
bottomk_phrase[:50]
```

Out[18]:

```
[('front desk', 39),
 ('second floor', 16),
 ('niagara fall', 13),
 ('next morn', 11),
 ('first time', 10),
 ('great locat', 10),
 ('main street', 10),
 ('oban inn', 10),
 ('next day', 10),
 ('first night', 9),
 ('park lot', 9),
 ('hot tub', 9),
 ('common area', 8),
 ('shaw festiv', 8),
 ('vintag hotel', 8),
 ('first floor', 8),
 ('hot water', 7),
 ('shaw club', 7),
 ('credit card', 7),
 ('moffat inn', 7),
 ('new owner', 7),
 ('custom servic', 6),
 ('book com', 6),
```

```
 ('mani year', 6),
 ('nice touch', 6),
 ('nice place', 6),
 ('front door', 5),
 ('second night', 5),
 ('confirm email', 5),
 ('sever year', 5),
 ('good locat', 5),
 ('doubl bed', 5),
 ('good size', 5),
 ('queen bed', 5),
 ('bathroom door', 5),
 ('medic suppli', 5),
 ('littl bit', 4),
 ('first morn', 4),
 ('confirm number', 4),
 ('last night', 4),
 ('long weekend', 4),
 ('last minut', 4),
 ('good place', 4),
 ('earli check', 4),
 ('good thing', 4),
 ('queen land', 4),
 ('minut walk', 4),
 ('comfort bed', 4),
 ('great experi', 4),
 ('patio furnitur', 4)]
```

phrases in both lists:

In [19]:

```
for (word,count) in topk_phrase:
  for (word1, count1) in bottomk_phrase:
    if word == word1:
      print(word)
```

```
main street
first time
niagara fall
minut walk
shaw festiv
hot tub
great locat
comfort bed
front desk
second floor
great experi
next morn
common area
```

I did not expec to see "second floor" in the positive list. I guess since the town is in cottage country near wineries and a lake, it is in reference to a lot of B&B hotels. B&B's are often just residential homes with a few rooms to rent out so I guess the second floor of a home would be reserved for that.

The phrases above appear in both lists. I'm surprised to see great location and great experience but i guess there could be a negation (not term) in the negative reviews. I was also suprised to see "shaw festiv" because i wasn't sure what that meant. Upon research I learned there's a local festival called "Shaw Festival" that I guess came up in a lot of reviews. It might be there because people might be visiting the town just to attend the festival so its important to review it.

In [20]:

```
def NPdataFrameTransformation(hotelDf, reviewDF, topk):
    reviews = reviewDF['reviewCol'].values

    #Find out if a particular review has the word from topk list
    freqReview = []
    for i in range(len(reviews)):
```

```
        tempCounter = Counter(flatten_phrase_lists([word
                                                    for word
                                                    in get_terms(chunker.parse(pos_tag(re.findall(r'
\w+',reviews[i]))))]))
        topkinReview = [1 if tempCounter[word] > 0 else 0 for (word,wordCount) in topk]
        freqReview.append(topkinReview)


    #Prepare freqReviewDf
    freqReviewDf = pd.DataFrame(freqReview)
    dfName = []
    for c in topk:
        dfName.append(c[0])
    freqReviewDf.columns = dfName
    finalreviewDf = reviewDF.join(freqReviewDf)
    finaldf = hotelDf[['hotelName','ratingScore','groundTruth']].join(finalreviewDf)
    return finaldf
```

In [21]:

```
finaldf_phrase = NPdataFrameTransformation(hotelDf, reviewDF, topk_phrase)
```

Q2 c)

In [204]:

```
grammar2c = """
  NBAR:
    {<DT>?<NN|NNS>*<VB|VBD>*<RB>*?<JJ|NN.*>}
  NP:
    {<NBAR>}
    {<NBAR><IN><NBAR>}
"""
# Sample text
text = """meal was not very good. no rooms were extremely great. there were no locks. the
front desk was nice"""
# Part of Speech Tagging
# Google: https://en.wikipedia.org/wiki/Part-of-speech_tagging
tagger = PerceptronTagger()
pos_tag = tagger.tag
taggedToks = pos_tag(re.findall(r'\w+', text))
print(taggedToks)
chunker = nltk.RegexpParser(grammar2c)
tree = chunker.parse(taggedToks)
print(chunker)
print(tree)
```

```
[('meal', 'NN'), ('was', 'VBD'), ('not', 'RB'), ('very', 'RB'), ('good', 'JJ'), ('no', 'D
T'), ('rooms', 'NNS'), ('were', 'VBD'), ('extremely', 'RB'), ('great', 'JJ'), ('there', '
EX'), ('were', 'VBD'), ('no', 'DT'), ('locks', 'NNS'), ('the', 'DT'), ('front', 'NN'), ('
desk', 'NN'), ('was', 'VBD'), ('nice', 'JJ')]
chunk.RegexpParser with 2 stages:
RegexpChunkParser with 1 rules:
       <ChunkRule: '<DT>?<NN|NNS>*<VB|VBD>*<RB>*?<JJ|NN.*>'>
RegexpChunkParser with 2 rules:
       <ChunkRule: '<NBAR>'>
       <ChunkRule: '<NBAR><IN><NBAR>'>
(S
  (NP (NBAR meal/NN was/VBD not/RB very/RB good/JJ))
  (NP (NBAR no/DT rooms/NNS were/VBD extremely/RB great/JJ))
  there/EX
  were/VBD
  (NP (NBAR no/DT locks/NNS))
  (NP (NBAR the/DT front/NN desk/NN was/VBD nice/JJ)))
```

i) positive reviews

In [205]:

```python
topk_phrase_2c = getTopKNP(finaldf, 50, label_value='positive')
topk_phrase_2c[:50]
```

Out[205]:

```
[('breakfast delici', 232),
 ('bed comfort', 188),
 ('minut walk', 184),
 ('feel welcom', 136),
 ('everi morn', 123),
 ('make sure', 89),
 ('front desk', 83),
 ('cours breakfast', 79),
 ('golf cours', 72),
 ('gourmet breakfast', 72),
 ('wine tast', 65),
 ('minut drive', 56),
 ('made sure', 55),
 ('wine tour', 53),
 ('anoth coupl', 51),
 ('front porch', 51),
 ('say enough', 50),
 ('spotlessli clean', 49),
 ('breakfast excel', 49),
 ('locat perfect', 47),
 ('extrem comfort', 47),
 ('extrem clean', 47),
 ('breakfast great', 46),
 ('coffe maker', 46),
 ('everi year', 46),
 ('realli nice', 46),
 ('everi day', 44),
 ('feel comfort', 44),
 ('back next', 43),
 ('host friendli', 41),
 ('extrem help', 40),
 ('year old', 39),
 ('food delici', 39),
 ('visit niagara', 38),
 ('breakfast tabl', 38),
 ('breakfast wonder', 37),
 ('min walk', 37),
 ('weekend getaway', 36),
 ('food great', 35),
 ('everi time', 33),
 ('breakfast good', 33),
 ('absolut delici', 33),
 ('wed anniversari', 33),
 ('bike ride', 32),
 ('everi detail', 32),
 ('downtown niagara', 32),
 ('king bed', 32),
 ('bedroom suit', 32),
 ('mini fridg', 31),
 ('park lot', 31)]
```

ii) negative reviews

In [207]:

```python
bottomk_phrase_2c = getTopKNP(finaldf, 50, label_value='negative')
bottomk_phrase_2c[:50]
```

Out[207]:

```
[('front desk', 39),
 ('bed comfort', 11),
 ('park lot', 11),
 ('custom servic', 10),
 ('credit card', 9),
 ('noth special', 6),
```

```
 ('noth special', 6),
 ('brand new', 5),
 ('bed uncomfort', 5),
 ('make sure', 5),
 ('hair dryer', 5),
 ('locat great', 5),
 ('everi year', 4),
 ('confirm number', 4),
 ('coffe maker', 4),
 ('visit niagara', 4),
 ('everi day', 4),
 ('food good', 4),
 ('confirm email', 4),
 ('everi time', 4),
 ('musti smell', 4),
 ('fruit cup', 4),
 ('hear peopl', 4),
 ('bathroom door', 4),
 ('child play', 4),
 ('night sleep', 3),
 ('toilet paper', 3),
 ('book com', 3),
 ('extrem loud', 3),
 ('tv work', 3),
 ('golf club', 3),
 ('water pressur', 3),
 ('absolut beauti', 3),
 ('extrem small', 3),
 ('minut walk', 3),
 ('ice bucket', 3),
 ('water stain', 3),
 ('star experi', 3),
 ('anoth coupl', 3),
 ('wineri tour', 3),
 ('quit good', 3),
 ('car park', 3),
 ('day earli', 3),
 ('lobbi area', 3),
 ('ice machin', 3),
 ('wed anniversari', 3),
 ('plastic tube', 3),
 ('window open', 3),
 ('inch high', 3),
 ('air condit', 3),
 ('ceil fan', 3)]
```

In [208]:

```
c = []
og = []
for (word,count) in topk_phrase_2c:
  c.append(word)
for (word1, count1) in topk_phrase:
  og.append(word1)

for word in c:
  if word not in og:
    print(word)
```

```
breakfast delici
bed comfort
feel welcom
everi morn
make sure
made sure
anoth coupl
front porch
say enough
spotlessli clean
breakfast excel
locat perfect
extrem comfort
extrem clean
```

```
extrem clean
breakfast great
coffe maker
everi year
realli nice
everi day
feel comfort
back next
host friendli
extrem help
year old
food delici
visit niagara
breakfast tabl
breakfast wonder
min walk
weekend getaway
food great
everi time
breakfast good
absolut delici
wed anniversari
bike ride
everi detail
downtown niagara
king bed
bedroom suit
mini fridg
park lot
```

In [209]:

```
for word in og:
  if word not in c:
    print(word)
```

```
main street
first time
wonder host
niagara fall
short walk
shaw festiv
delici breakfast
hot tub
great place
next year
next time
graciou host
great locat
comfort bed
great host
great time
queen street
short drive
wonder experi
second floor
perfect host
perfect place
orchid inn
great experi
next visit
excel host
fresh fruit
wonder time
warm welcom
next morn
wine countri
common area
great breakfast
beauti home
local wineri
first experi
victoria gabl
```

```
victoria gabl
lake ontario
mani wineri
amaz breakfast
finlay hous
wonder place
```

In [211]:

```python
for word in og:
  if word in c:
    print(word)
```

```
minut walk
front desk
wine tour
cours breakfast
wine tast
minut drive
golf cours
gourmet breakfast
```

I used a grammar rule that captured more noun-adjective phrases, and more desriptive words in the negative reviews.

1. **Similarity: both captured the 8 phrases above that happened to be some of the most common phrases in both my grammar list and the provided one. This is good because these are really common noun phrases and were captured in both grammar rules. My grammar rule seems to capture similar noun phrases as the original one in addition to others.**

1. **Difference: My grammar rule captured noun-adjective terms, not just adjective-noun terms like the provided rule. For example, "breakfast wonderful" was captured using my grammar rule but only "wonderful breakfast" would have been captured in the provided one.**

1. **Difference: my grammar rule captured more negative phrases for the bottom reviews such as "musty smell" and "bed uncomfrtable." I found that the original grammar rule didn't have any phrases in the bottom reviews that were clearly negative.**

I think my grammar pattern is more effective because the the negative phrases seem to be more unique to negative reviews. I also think this grammar pattern captures what the original one did + more so it should still hold the most frequent terms as the original. It had phrases with strong adjectives that represent the sentiment of the review more strongly.

Q3 a)

In [27]:

```python
# get Top K mutual information terms from the dataframe
def getMI(topk, df, label_column='groundTruth'):
    miScore = []
    for word in topk:
        miScore.append([word[0]]+[metrics.mutual_info_score(df[label_column], df[word[0]
])])
    miScoredf = pd.DataFrame(miScore).sort_values(1,ascending=0)
    miScoredf.columns = ['Word','MI Score']
    return miScoredf
```

In [28]:

```python
#@title Default title text
miScoredf = getMI(topk, finaldf)
miScoredf[:50]
```

Out[28]:

	Word	MI Score

	Word	MI Score
340	told	0.014722
266	price	0.013877
12	hosts	0.011898
20	delicious	0.010516
100	small	0.008875
228	desk	0.007905
9	wonderful	0.007674
280	however	0.007145
17	one	0.007104
38	night	0.007037
357	said	0.006988
29	perfect	0.006013
176	never	0.005856
137	booked	0.005792
25	breakfasts	0.005412
283	asked	0.005279
11	home	0.004718
220	left	0.004578
406	given	0.004451
198	got	0.004412
4	comfortable	0.004409
484	less	0.004398
30	good	0.004349
68	get	0.004328
302	disappointed	0.004182
31	amazing	0.004094
62	highly	0.003949
332	think	0.003870
13	beautiful	0.003828
165	door	0.003790
117	front	0.003734
49	could	0.003633
111	old	0.003580
383	work	0.003468
310	though	0.003448
174	floor	0.003446
5	would	0.003419
393	open	0.003395
494	air	0.003376
493	reservation	0.003376
363	put	0.003362
431	looked	0.003167
304	nothing	0.003115
143	beautifully	0.003074
479	expect	0.003050

	Word	MI Score
355	although	0.003045
0	breakfast	0.003004
69	bathroom	0.002967
311	still	0.002937
45	enjoyed	0.002926

In [29]:

```
miScoredf[:5]
```

Out[29]:

	Word	MI Score
340	told	0.014722
266	price	0.013877
12	hosts	0.011898
20	delicious	0.010516
100	small	0.008875

A lot of these make sense. The top 5 are reprinted above. I was surprised to see "told" at the top but the more I thought about it the more it describes communication, likely with staff either good or bad. I still don't think it's a very "sentimental" word, but I can see how it could be used by reviewers when describing conversations with hotel staff. People often compare their experience to the "price" they paid so that makes sense to come up. Since there were so many B&B's, it was expected to see "hosts" and "delicisou" because you normally interact with B&B hosts a lot more compared to hotel staff. At B&Bs you usually have a provided breakfast so that explains the word "delicious." Finally, since you rent a room in a hotel, the word "small" makes sense because the size of the room is one of the first things you notice.

Q3 b)

In [219]:

```
finaldf_phrase_2c = NPdataFrameTransformation(hotelDf, reviewDF, topk_phrase_2c)
miScoredf_phrase = getMI(topk_phrase_2c, finaldf_phrase_2c)
miScoredf_phrase[:50]
```

Out[219]:

	Word	MI Score
6	front desk	4.598335e-03
0	breakfast delici	1.435689e-03
49	park lot	1.264790e-03
3	feel welcom	1.134177e-03
7	cours breakfast	6.608491e-04
9	gourmet breakfast	5.935635e-04
4	everi morn	5.928188e-04
2	minut walk	5.038449e-04
12	made sure	4.424727e-04
16	say enough	4.173313e-04
17	spotlessli clean	4.005769e-04
21	extrem clean	3.922016e-04
19	locat perfect	3.922016e-04

	Word	MI Score
22	breakfast great	3.83[illegible]e-04
28	back next	3.587131e-04
30	extrem help	3.336102e-04
35	breakfast wonder	3.085188e-04
36	min walk	2.917976e-04
38	food great	2.917976e-04
41	absolut delici	2.750815e-04
44	everi detail	2.667254e-04
43	bike ride	2.667254e-04
8	golf cours	2.242437e-04
10	wine tast	2.057218e-04
13	wine tour	1.296055e-04
39	everi time	1.282752e-04
18	breakfast excel	1.132204e-04
20	extrem comfort	1.026010e-04
33	visit niagara	8.184427e-05
29	host friendli	7.244298e-05
32	food delici	6.304729e-05
34	breakfast tabl	5.403570e-05
26	everi day	5.363567e-05
37	weekend getaway	4.968667e-05
24	everi year	4.450793e-05
23	coffe maker	4.035365e-05
40	breakfast good	3.733836e-05
42	wed anniversari	3.662323e-05
11	minut drive	3.611998e-05
45	downtown niagara	3.347823e-05
48	mini fridg	2.975924e-05
15	front porch	2.464889e-05
46	king bed	1.954399e-05
27	feel comfort	9.022205e-06
25	realli nice	7.332038e-06
31	year old	2.184829e-06
47	bedroom suit	1.560398e-06
14	anoth coupl	6.284783e-07
1	bed comfort	7.526998e-08
5	make sure	2.355896e-08

Disclaimer

The majority of reviews are positive, so the data is very skewed. The top MI phrases are as a result mainly positive. I will answer this question by analyzing theese positive phrases as indicators of what hotels should continute to do or invest even more resources in to remain well-reviewed. I printed the number of negative vs positive review counts below

In [232]:

```
print('negative reviews:', len(finaldf_phrase_2c.loc[finaldf_phrase_2c['groundTruth'] ==
'negative'].index))
print('positive reviews:', len(finaldf_phrase_2c.loc[finaldf_phrase_2c['groundTruth'] ==
'positive'].index))
```

```
negative reviews: 371
positive reviews: 6403
```

The top phrases made a lot more sense. The top #1 phrase "Front Desk" is definitely something I personally consider as important to my visit anywhere. If the front desk staff are rude it is very noticeable and frustrating, but if they are nice they can be very helpful and give unique recommendations. Since a lot of hotels in Niagara-on-the-lake are B&Bs it makes sense to see NINE phrases relating to food taste because B&Bs often provide breakfasts. It can be a nice addition that people seek out explicitly when booking a hotel. Since Niagara-on-the-lake is a small town in wine country, guests likely drive up, so "park lot" is an important feature to consider. There were also a few phrases about room cleanliness which is obvious why it's importnat.

Some phrases like "wine tour" and "golf course" indicate that although they are part of the town and not individual hotels, hotels can often help guests find out about these local attractions and make arrangemnets.

Another interesting observation were phrases like "made sure" "every detail" "extremly helpful" and "every time" that I think are great examples of describing above and beyond service. Along with the physical parts of a hotel, such as food and parking, the hosts are also exteremly important. Like the front desk, hosts are very prominant in B&Bs as they are usually owners of the house and communicate with the guests much more than a busy city hotel. These phrases indicate that guests notice when a host "makes sure" the guest is receiving good service "ever time" and paying attention to "every detail."

Based on this list I think hotels in this town should continue to focus on:

1. **providing fresh breakfast**
2. **room cleanliness**
3. **high-standard communication with guests (recommendatins, details, etc.)**
4. **information on local attractions such as wine tours and golf courses**

Q4 a)

In [274]:

```
# Simple example of getting pointwise mutual information of a term
def demo_pmiCal(df,word):
    pmilist=[]
    N = df.shape[0]
    for sentiment in ['positive','negative']:
        for word_present in [False,True]:
            px = sum(df['groundTruth']==sentiment)
            py = sum(df[word]==word_present)
            pxy = len(df[(df['groundTruth']==sentiment) & (df[word]==word_present)])

            if pxy==0:#Log 0 cannot happen
                pmi = math.log((pxy+0.0001)*N/(px*py))
            else:
                pmi = math.log(pxy*N/(px*py))

            pmilist.append([sentiment]+[word_present]+[px]+[py]+[pxy]+[pmi])

    # assemble the results into a dataframe
    pmidf = pd.DataFrame(pmilist)
    pmidf.columns = ['sentiment (x)','word_present (y)','px','py','pxy','pmi']
    return pmidf
# Compute PMI for all terms and all possible labels
def pmiForAllCal(df, topk_word, gt_sentiment, label_column='groundTruth'):
    #Try calculate all the pmi for top k and store them into one pmidf dataframe

    index = [x[0] for x in topk_word]
    pmiDf = pd.DataFrame(index=index, columns=['pmi'])
```

```python
    for (word, count) in tqdm(topk_word):
        pmiDf.at[word, 'pmi'] = pmiCalc(df,word,gt_sentiment,label_column)

    return pmiDf


def pmiCalc(df, word, gt_sentiment, label_column='groundTruth'):

    N = df.shape[0]

    px = sum(df[label_column]==gt_sentiment)
    py = sum(df[word]==True)
    pxy = len(df[(df[label_column]==gt_sentiment) & (df[word]==True)])
    if px == 0 or py == 0:
      print('there are no negative reviews')
      pmi = 99
    elif pxy==0:#Log 0 cannot happen
        pmi = math.log((pxy+0.0001)*N/(px*py))
    else:
        pmi = math.log(pxy*N/(px*py))
    return pmi
```

i) positive

In [264]:

```python
pmiposdf = pmiForAllCal(finaldf,topk,'positive')
#Sorted top pmi words for positive reviews
pmiposdf.sort_values('pmi',ascending=0).head(50)
```

```
100%|██████████| 500/500 [00:02<00:00, 175.93it/s]
```

Out[264]:

	pmi
chef	0.0563251
donna	0.0563251
maria	0.0563251
blocks	0.0563251
sandra	0.0563251
spotless	0.0563251
welcomed	0.0563251
beautifully	0.0540022
gracious	0.0534224
immaculate	0.0521843
recommended	0.0520968
hosts	0.0516192
knowledgeable	0.0514351
delicious	0.0512068
exceptional	0.0509051
peaceful	0.050528
bikes	0.0498526
memorable	0.0497244
phyllis	0.0495911
attractions	0.0494522
recommendations	0.0493565
luxurious	0.0487779

	pmi
homemade	0.0484819
perfect	0.0482497
relax	0.0480946
gourmet	0.0477781
john	0.0472204
highly	0.0466632
bike	0.0466163
thanks	0.0465371
fantastic	0.0464922
gardens	0.0460158
appointed	0.0452344
thank	0.0447375
treat	0.0445603
relaxing	0.0445464
detail	0.0444438
wonderful	0.0443202
kent	0.0429021
distance	0.0426129
amazing	0.0423519
breakfasts	0.0419777
incredible	0.0417263
private	0.0409402
delightful	0.0407606
home	0.0397601
enjoyed	0.0392853
welcome	0.0391045
host	0.0386255
shopping	0.0384993

ii) negative

In [36]:

```
#Sorted top pmi words for negative reviews
pminegdf = pmiForAllCal(finaldf,topk,'negative')
pminegdf.sort_values('pmi',ascending=0).head(50)
```

```
100%|██████████| 500/500 [00:02<00:00, 245.92it/s]
```

Out[36]:

	pmi
told	2.03889
price	1.80182
said	1.66104
less	1.54066
however	1.52291
desk	1.51426
reservation	1.48326

	pmi
reservation	1.48326
given	1.47214
air	1.45166
asked	1.40293
expect	1.36667
open	1.34491
looked	1.34142
work	1.33726
think	1.31071
put	1.28951
disappointed	1.27273
building	1.26131
though	1.24391
although	1.23805
small	1.23407
towels	1.22568
left	1.22334
booking	1.22208
used	1.21297
never	1.1999
sleep	1.17207
nothing	1.17159
still	1.17004
got	1.16783
since	1.15255
booked	1.14679
bar	1.12915
fine	1.12631
let	1.11289
side	1.10624
worth	1.08249
wanted	1.0801
ask	1.07779
came	1.05133
door	1.04268
upon	1.04143
floor	1.03435
cold	1.03284
lot	0.9942
thing	0.993622
check	0.983351
long	0.980396
bit	0.969785
front	0.947461

1. For positive reviews, some top PMI words were names, such as "Maria, donna, sandra, john" likely host

names. This is interesting because it probably means that really good hosts were memorable by name and worth mentioning in reviews.

2. I noticed that the negative reviews had a lot of emphasized descriptive adjectives. For example, postivie reviews had "immaculate, beautifully, luxurious, memorable, gourmet, perfect, homemade, gracious, fantastic" while negative reviews only had a few negative adjectives, like "disappointed." Negative review words had more verbs that seem to be describing bad interactions, such as "still, got, expect, never, nothing, asked." It is important to note that the data is skewed in favor of positive reviews so there are less words to choose from
3. Positive review words had more words about location than negative reviews. For example, pos reviews had "shopping, bikes, attractions" but neg reviews didn't mention such things.

Q4 b)

In [237]:

```
# Simple example of getting pointwise mutual information of a term

def demo_pmiCal(df,word):
    pmilist=[]
    N = df.shape[0]
    for sentiment in ['positive','negative']:
        for word_present in [False,True]:
            px = sum(df['groundTruth']==sentiment)
            py = sum(df[word]==word_present)
            pxy = len(df[(df['groundTruth']==sentiment) & (df[word]==word_present)])

            if pxy==0:#Log 0 cannot happen
                pmi = math.log((pxy+0.0001)*N/(px*py))
            else:
                pmi = math.log(pxy*N/(px*py))

            pmilist.append([sentiment]+[word_present]+[px]+[py]+[pxy]+[pmi])

    # assemble the results into a dataframe
    pmidf = pd.DataFrame(pmilist)
    pmidf.columns = ['sentiment (x)','word_present (y)','px','py','pxy','pmi']
    return pmidf
```

i) positive

In [233]:

```
pminegdf_phrase = pmiForAllCal(finaldf_phrase_2c,topk_phrase_2c,'positive')
pminegdf_phrase.sort_values('pmi',ascending=0).head(50)
```

```
100%|██████████| 50/50 [00:00<00:00, 233.85it/s]
```

Out[233]:

	pmi
breakfast wonder	0.0563251
gourmet breakfast	0.0563251
min walk	0.0563251
locat perfect	0.0563251
extrem clean	0.0563251
made sure	0.0563251
breakfast great	0.0563251
everi detail	0.0563251
bike ride	0.0563251

	pmi
spotlessli clean	0.0563251
cours breakfast	0.0563251
absolut delici	0.0563251
back next	0.0563251
extrem help	0.0563251
feel welcom	0.0563251
food great	0.0563251
say enough	0.0563251
breakfast delici	0.052024
everi morn	0.0481618
golf cours	0.0417263
wine tast	0.0410577
minut walk	0.0393275
wine tour	0.0372769
breakfast excel	0.0361224
extrem comfort	0.0352717
host friendli	0.0322276
food delici	0.0310073
breakfast tabl	0.0296569
weekend getaway	0.0289261
breakfast good	0.0264722
downtown niagara	0.0255535
mini fridg	0.0245764
king bed	0.0212338
minut drive	0.020607
front porch	0.0178588
feel comfort	0.0118734
realli nice	0.0108627
year old	0.0063147
make sure	0.000444665
bed comfort	-0.000537738
anoth coupl	-0.0030983
bedroom suit	-0.00619523
coffe maker	-0.0270565
everi year	-0.0288327
wed anniversari	-0.0306863
everi day	-0.0326224
visit niagara	-0.0437583
everi time	-0.0614579
park lot	-0.239941
front desk	-0.289626

ii) negative

In [235]:

```
pminegdf_phrase = pmiForAllCal(finaldf_phrase_2c,topk_phrase_2c,'negative')
pminegdf_phrase.sort_values('pmi',ascending=0).head(50)
```

```
100%|██████████| 50/50 [00:00<00:00, 257.89it/s]
```

Out[235]:

	pmi
front desk	1.67519
park lot	1.54367
everi time	0.70742
visit niagara	0.55327
everi day	0.440792
wed anniversari	0.419738
everi year	0.399119
coffe maker	0.378916
bedroom suit	0.101285
anoth coupl	0.0520135
bed comfort	0.00923542
make sure	-0.00770569
year old	-0.11578
realli nice	-0.20887
feel comfort	-0.230849
front porch	-0.3725
minut drive	-0.445259
king bed	-0.462651
mini fridg	-0.561091
downtown niagara	-0.591863
breakfast good	-0.621716
weekend getaway	-0.706273
breakfast tabl	-0.732941
food delici	-0.784234
host friendli	-0.833025
extrem comfort	-0.966556
breakfast excel	-1.00738
wine tour	-1.06565
minut walk	-1.17853
wine tast	-1.28501
golf cours	-1.32946
everi morn	-1.90754
breakfast delici	-2.54639
bike ride	-9.77143
everi detail	-9.77143
absolut delici	-9.8022
min walk	-9.86104
food great	-9.86104
breakfast wonder	-9.91661
extrem help	-9.99457

	pmi
back next	-10.0669
breakfast great	-10.1343
extrem clean	-10.1558
locat perfect	-10.1558
spotlessli clean	-10.1769
say enough	-10.2177
made sure	-10.276
gourmet breakfast	-10.5684
cours breakfast	-10.6751
feel welcom	-11.211

In [238]:

```
demo_pmiCal(finaldf_phrase_2c, 'front desk')
```

Out[238]:

	sentiment (x)	word_present (y)	px	py	pxy	pmi
0	positive	False	6403	6668	6328	0.003989
1	positive	True	6403	106	75	-0.289626
2	negative	False	371	6668	340	-0.071485
3	negative	True	371	106	31	1.675193

In [239]:

```
demo_pmiCal(finaldf_phrase_2c, 'park lot')
```

Out[239]:

	sentiment (x)	word_present (y)	px	py	pxy	pmi
0	positive	False	6403	6735	6374	0.001235
1	positive	True	6403	39	29	-0.239941
2	negative	False	371	6735	361	-0.021550
3	negative	True	371	39	10	1.543668

1. **"front desk" appeared at the top of the negative reviews list but at the bottom of another. Upon further analysis, I saw that when 'front desk' was present, the pmi was highest thatn the 3 other scenarios above, meaning it was indicative of a negative review. This means that the front desk being rude can really make a negative experience, but if the experience was positive, it doesn't necessarily tell you much. This i sinteresting because 'front desk' appeared a lot in the topk words analysis but its actually not equally indicative in positive and negative reviews.**
2. **"park lot" also had a high pmi in negative reviews which makes sense because if you have problems parking or with car theft etc, your trip can be ruined. But if the parking service is there, it deson't really mean you automtically have a great trip.**
3. **In general, the top pmi phrases list had a lot more high pmi words whereas the bottom list has a lot fo negative words. I think this, again, attributes to the fact that the data is skewed and has much more positive reviews so the analysis has a larger corpus for positive reviews and therefore is more accurate and can pull out these pmi values.**

Q4 c)

Top Hotel

In [246]:

```
hotelDf_top = hotelDf.loc[hotelDf['hotelName']=='The White House Boutique Bed &amp; Brea
kfast'].reset_index()
reviews_top = hotelDf_top['reviewColumn'].values
reviewDF_top = evalSentences(reviews_top, to_df=True, columns=['reviewCol','vader']).res
et_index()
```

```
100%|██████████| 100/100 [00:00<00:00, 772.27it/s]
```

In [248]:

```
topk_top = getTopKWords(reviewDF_top, 500)
finaldf_top = dataFrameTransformation(hotelDf_top, reviewDF_top, topk_top)
```

```
100
```

In [261]:

```
top_pmi_df = pmiForAllCal(finaldf_top,topk_top,'positive')
#Sorted top pmi words for positive reviews
top_pmi_df.sort_values('pmi',ascending=0).head(50)
```

```
100%|██████████| 500/500 [00:00<00:00, 794.26it/s]
```

Out[261]:

	pmi
sonny	0
drive	0
warmth	0
everyone	0
early	0
detail	0
attention	0
catered	0
shopping	0
nthey	0
ample	0
maker	0
travelling	0
impeccable	0
caring	0
left	0
feeling	0
came	0
homemade	0
got	0
late	0
usual	0
welcomed	0
minutes	0
festival	0
job	0
plentiful	0

	pmi
plentiful	0
think	0
guide	0
details	0
sights	0
offer	0
decorated	0
added	0
porch	0
front	0
property	0
hope	0
four	0
exceeded	0
found	0
appreciated	0
cant	0
minute	0
guest	0
fresh	0
set	0
cooked	0
genuinely	0
treated	0

In [275]:

```
top_pmi_df = pmiForAllCal(finaldf_top,topk_top,'negative')
#Sorted top pmi words for positive reviews
top_pmi_df.sort_values('pmi',ascending=0).head(50)
```

```
 40%|████      | 201/500 [00:00<00:00, 674.17it/s]
```

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Out[275]:

	pmi
sonny	99
drive	99
warmth	99
everyone	99
early	99
detail	99
attention	99
catered	99
shopping	99
nthey	99
ample	99
maker	99

	pmi
travelling	99
impeccable	99
caring	99
left	99
feeling	99
came	99
homemade	99
got	99
late	99
usual	99
welcomed	99
minutes	99
festival	99
job	99
plentiful	99
think	99
guide	99
details	99
sights	99
offer	99
decorated	99
added	99
porch	99
front	99
property	99
hope	99
four	99
exceeded	99
found	99
appreciated	99
cant	99
minute	99
guest	99
fresh	99
set	99
cooked	99
genuinely	99
treated	99

This hotel has no negative reviews. Therefore, this analysis is not useful because all pmi values for positive reviews are 0 since there are no negative reviews in the data to even compare to. This means any word or phrase is always in a positive review so you can't comment on how positive it is or how negative it is. All phrases have only one option for sentiment, positive.

In [276]:

```
topk_phrase_4 = getTopKNP(finaldf_top, 50, label_value='positive')
```

```python
finaldf_phrase_4 = NPdataFrameTransformation(hotelDf_top, reviewDF_top, topk_phrase_4)
pminegdf_phrase_4 = pmiForAllCal(finaldf_phrase_4,topk_phrase_4,'positive')
pminegdf_phrase_4.sort_values('pmi',ascending=0).head(50)
```

```
100%|██████████| 50/50 [00:00<00:00, 720.21it/s]
```

Out[276]:

	pmi
host sonni	0
restaur wineri	0
walk distanc	0
town center breakfast	0
wife eleanor	0
breakfast big	0
extrem hospit	0
gave suggest	0
morn highli	0
visit notl	0
visit sunni	0
peopl god	0
bike rental big	0
cours breakfast	0
tub ultra	0
clean amaz	0
home base nice	0
owner judi	0
water sever	0
glass chocol	0
screen tv njudi	0
end boutiqu bed	0
breakfast knowledg	0
atmospher superb	0
choic locat	0
town breakfast delici	0
day delici	0
landscap owner	0
make sure	0
everi morn	0
breakfast delici	0
host judi	0
owner sunni	0
extrem help	0
back next	0
time nthe	0
feel welcom	0
bed comfort	0
host attent	0

spend time	pmi
host help	0
everi morn sonni	0
extrem clean	0
well stock	0
area judi	0
everi way	0
min walk	0
host noth	0
felt safe	0
servic beauti	0

In [277]:

```
pminegdf_phrase_4 = pmiForAllCal(finaldf_phrase_4,topk_phrase_4,'negative')
pminegdf_phrase_4.sort_values('pmi',ascending=0).head(50)
```

```
100%|██████████| 50/50 [00:00<00:00, 624.15it/s]
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there are no negative reviews
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there are no negative reviews
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Out[277]:

	pmi
host sonni	99
restaur wineri	99
walk distanc	99
town center breakfast	99
wife eleanor	99
breakfast big	99
extrem hospit	99
gave suggest	99
morn highli	99
visit notl	99
visit sunni	99
peopl god	99
bike rental big	99
cours breakfast	99
tub ultra	99
clean amaz	99
home base nice	99
owner judi	99
water sever	99
glass chocol	99
screen tv njudi	99
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breakfast knowledg	99
atmospher superb	99
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town breakfast delici	99
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landscap owner	99
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everi morn	99
breakfast delici	99
host judi	99
owner sunni	99
extrem help	99
back next	99
time nthe	99
feel welcom	99
bed comfort	99
host attent	99
spend time	99

	pmi
spend time	99
host help	99
everi morn sonni	99
extrem clean	99
well stock	99
area judi	99
everi way	99
min walk	99
host noth	99
felt safe	99
servic beauti	99

I set pmi = 99 if there is a division by 0

This hotel has no negative reviews. Therefore, this analysis is not useful because all pmi values for positive reviews are 0 since there are no negative reviews in the data to even compare to. This means any word or phrase is always in a positive review so you can't comment on how positive it is or how negative it is.

Worst Hotel - ground truth score of 0.65

In [278]:

```
hotelDf_top = hotelDf.loc[hotelDf['hotelName']=='Residence &amp; Conference Centres - Niagara on the Lake'].reset_index()
reviews_top = hotelDf_top['reviewColumn'].values
reviewDF_top = evalSentences(reviews_top, to_df=True, columns=['reviewCol','vader'])
topk_top = getTopKWords(reviewDF_top, 500)
finaldf_top = dataFrameTransformation(hotelDf_top, reviewDF_top, topk_top)
```

```
100%|██████████| 55/55 [00:00<00:00, 775.91it/s]
```

```
55
```

i) positive

In [280]:

```
worse_pmiposdf = pmiForAllCal(finaldf_top,topk_top,'positive')
#Sorted top pmi words for positive reviews
worse_pmiposdf.sort_values('pmi',ascending=0).head(50)
```

```
100%|██████████| 500/500 [00:00<00:00, 794.03it/s]
```

Out[280]:

	pmi
require	0.675129
able	0.675129
u002fshower	0.675129
hotels	0.675129
entire	0.675129
lovely	0.675129
includes	0.675129
greenhouse	0.675129

	pmi
come	0.675129
agriculture	0.675129
u00e9cor	0.675129
onsite	0.675129
taste	0.675129
thursday	0.675129
brewery	0.675129
buy	0.675129
short	0.675129
kitchenette	0.675129
traveling	0.675129
units	0.675129
session	0.675129
festival	0.675129
residences	0.675129
oven	0.675129
garbages	0.675129
guests	0.675129
stove	0.675129
u002fc	0.675129
sink	0.675129
door	0.675129
first	0.675129
perfect	0.675129
walking	0.675129
distance	0.675129
needed	0.675129
mentioned	0.675129
daily	0.675129
floors	0.675129
four	0.675129
property	0.675129
town	0.675129
local	0.675129
set	0.675129
easy	0.675129
size	0.675129
quite	0.675129
excellent	0.675129
shaw	0.675129
within	0.675129
polite	0.675129

ii) negative

In [287]:

```
worse_pmiposdf = pmiForAllCal(finaldf_top,topk_top,'negative')
#Sorted top pmi words for positive reviews
worse_pmiposdf.sort_values('pmi',ascending=0).head(50)
```

```
100%|██████████| 500/500 [00:00<00:00, 842.22it/s]
```

Out[287]:

	pmi
stuff	0.711496
seemed	0.711496
head	0.711496
however	0.711496
couple	0.711496
busy	0.711496
tightly	0.711496
old	0.711496
covered	0.711496
buffet	0.711496
holes	0.711496
walls	0.711496
money	0.711496
bring	0.711496
spacious	0.711496
blame	0.711496
pool	0.711496
pillow	0.711496
paid	0.711496
street	0.711496
refund	0.711496
slithering	0.711496
black	0.711496
bug	0.711496
adult	0.711496
lit	0.711496
darted	0.711496
downstairs	0.711496
girl	0.711496
keep	0.711496
dog	0.711496
100	0.711496
run	0.711496
discovered	0.711496
web	0.711496
pot	0.711496
employees	0.711496
com	0.711496

	pmi
low	0.711496
fit	0.711496
never	0.711496
please	0.711496
works	0.711496
handy	0.711496
came	0.711496
sheets	0.711496
stains	0.711496
u002fconference	0.711496
updates	0.711496
reservations	0.711496

This hotel still had an average ground truth score of 65% which means that there are still a lot of good reviews. This analysis was more useful here. i could see that the positive reviews discussed nouns like the "shower" and "greenhouse" while negative reviews mentioned "holes" "refund" and "bugs" so does provide a bit more insight on what could be going wrong in this hotel because there are actually an even-ish amount of reviews to gather data on.

In [285]:

```
topk_phrase_4 = getTopKNP(finaldf_top, 50, label_value='positive')
finaldf_phrase_4 = NPdataFrameTransformation(hotelDf_top, reviewDF_top, topk_phrase_4)
pminegdf_phrase_4 = pmiForAllCal(finaldf_phrase_4,topk_phrase_4,'positive')
pminegdf_phrase_4.sort_values('pmi',ascending=0).head(50)
```

```
100%|██████████| 50/50 [00:00<00:00, 751.46it/s]
```

Out[285]:

	pmi
firework place	0.675129
moment hesit	0.675129
downtown niagara	0.675129
say enough good	0.675129
pretti good	0.675129
fruit juic coffe	0.675129
clock nand	0.675129
wineri visit	0.675129
buy realli enjoy	0.675129
brew wine	0.675129
wineri also interest	0.675129
correct choic	0.675129
minut walk	0.675129
famili member graduat	0.675129
seper full	0.675129
close door	0.675129
comput desk chair	0.675129
closet area	0.675129
size fridg microwav	0.675129
kitchen tabl	0.675129

	pmi
internet access	0.675129
morn quit	0.675129
conveni nearbi	0.675129
minut drive	0.675129
also friendli	0.675129
shampoo small	0.675129
bed comfort	0.675129
kitchenett refriger microwav	0.675129
bath u002fshow	0.675129
card key	0.675129
night time clerk	0.675129
continent breakfast	0.675129
grill park	0.675129
housekeep compar	0.675129
star hotel	0.675129
amazingli help	0.675129
u002fc comfort	0.675129
unit nthe locat	0.675129
wineri restaur	0.675129
mid juli	0.675129
noth fanci	0.675129
agricultur collag campu	0.675129
micro breweri	0.675129
wall look	0.675129
bathroom breakfast	0.675129
restaur cleanli friendli	0.675129
student dorm	0.675129
outlet mall	0.387447
bedroom suit	0.387447
front desk	-0.241162

In [286]:

```
pminegdf_phrase_4 = pmiForAllCal(finaldf_phrase_4,topk_phrase_4,'negative')
pminegdf_phrase_4.sort_values('pmi',ascending=0).head(50)
```

```
100%|██████████| 50/50 [00:00<00:00, 791.87it/s]
```

Out[286]:

	pmi
front desk	0.200671
bedroom suit	-0.674798
outlet mall	-0.674798
conveni nearbi	-8.49884
wineri also interest	-8.49884
minut drive	-8.49884
downtown niagara	-8.49884
say enough good	-8.49884

say enough good	-8.49884
	pmi
pretti good	-8.49884
fruit juic coffe	-8.49884
clock nand	-8.49884
wineri visit	-8.49884
buy realli enjoy	-8.49884
brew wine	-8.49884
correct choic	-8.49884
morn quit	-8.49884
moment hesit	-8.49884
famili member graduat	-8.49884
seper full	-8.49884
close door	-8.49884
comput desk chair	-8.49884
closet area	-8.49884
size fridg microwav	-8.49884
kitchen tabl	-8.49884
internet access	-8.49884
minut walk	-8.49884
firework place	-8.49884
amazingli help	-8.49884
restaur cleanli friendli	-8.49884
student dorm	-8.49884
kitchenett refriger microwav	-8.49884
bath u002fshow	-8.49884
card key	-8.49884
night time clerk	-8.49884
continent breakfast	-8.49884
grill park	-8.49884
housekeep compar	-8.49884
star hotel	-8.49884
shampoo small	-8.49884
u002fc comfort	-8.49884
unit nthe locat	-8.49884
wineri restaur	-8.49884
mid juli	-8.49884
noth fanci	-8.49884
agricultur collag campu	-8.49884
micro breweri	-8.49884
wall look	-8.49884
bathroom breakfast	-8.49884
also friendli	-8.49884
bed comfort	-9.19199

Again, the phrase analysis was more useful here. i could see that the positive reviews discussed nouns like the "firework place" and "computer desk chair" while negative reviews mentioned "front desk" so does provide a bit

more insight on what could be going wrong in this hotel because there are actually an even ish amount of reviews to gather data on.

Q5

Note Remember to save a static image of the map in the notebook

Q a) i)

In [49]:

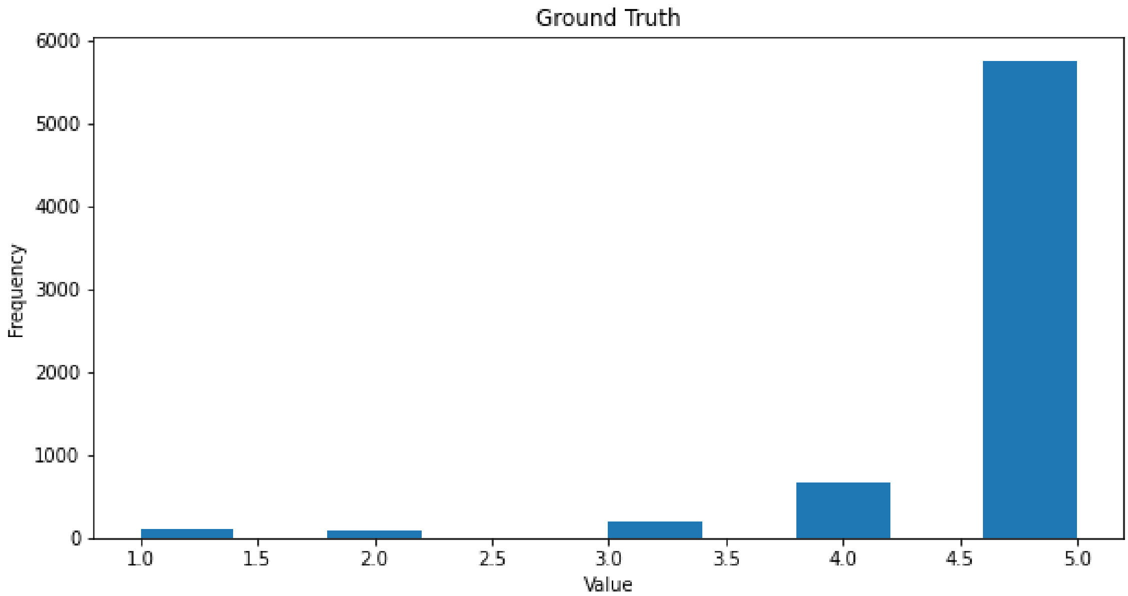
```
def getHistogram(df, measure, title,figsize=(10,5)):
    fig = plt.figure(figsize=figsize)
    plt.title(title)

    if measure=='both':
        x = [df['ratingScore'].values/5]
        y = [df['vader'].values]
        bins = np.linspace(-1, 1, 100)
        plt.hist(x, bins, label='normalized Ground Truth')
        plt.hist(y, bins, label='vader')
        plt.legend(loc='upper right')
        plt.xlabel("Value")
        plt.ylabel("Frequency")
    else:
        plt.hist(df[measure].values)

    plt.xlabel("Value")
    plt.ylabel("Frequency")
```

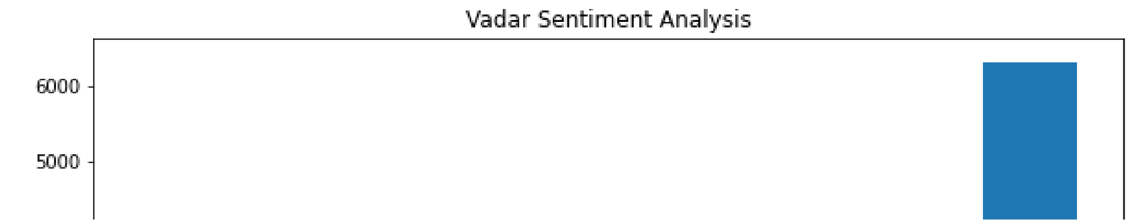
In [50]:

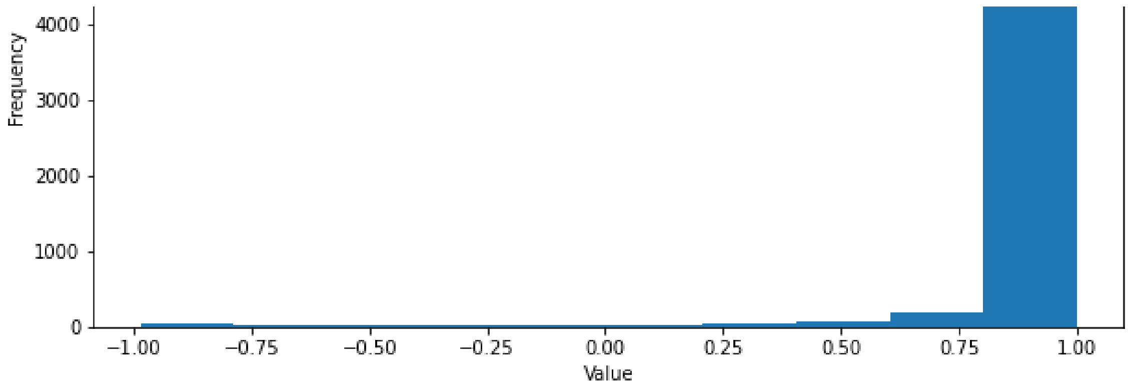
```
#what is the distrubution in ground truth scores like?
getHistogram(finaldf,'ratingScore', 'Ground Truth')
```



In [51]:

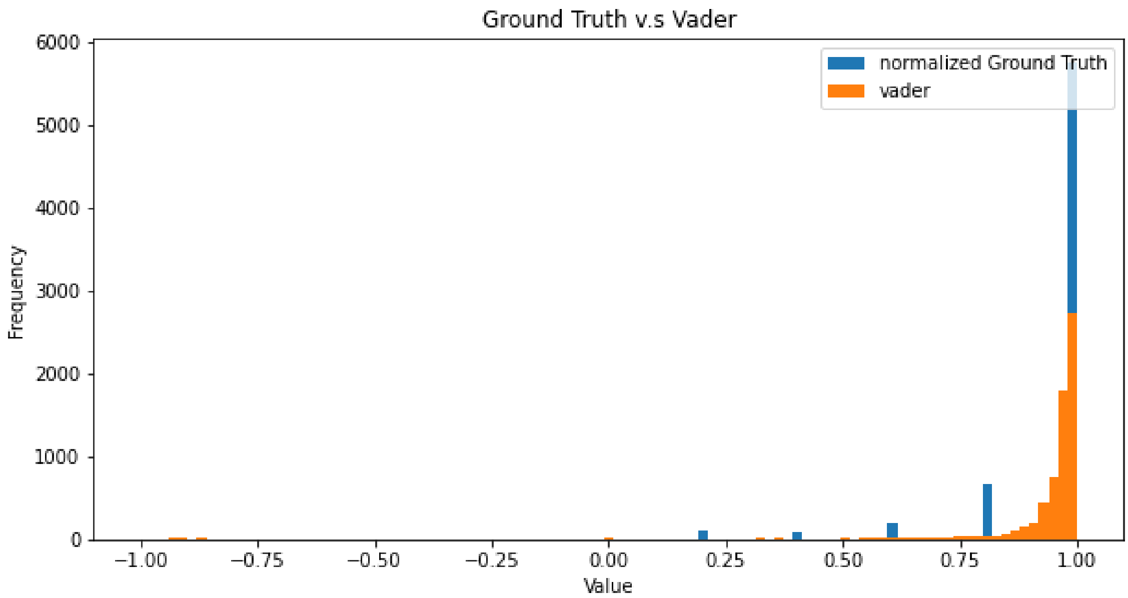
```
# what is the distrubtuion in vader scores like?
getHistogram(finaldf, 'vader', 'Vadar Sentiment Analysis')
```





In [52]:

```
# how do the distrubutions compare between ground truth (normalized) and vader
getHistogram(finaldf, 'both', 'Ground Truth v.s Vader')
```



This explains a lot and is definitely very surprising. There are sooo many positive reviews so it helps me undestand some of my results in previous questions where skewed data affected my findings. I guess Niagara-on-the-lake just has great hotels and happy reviewers.

Q5 a) ii)

In [291]:

```
hotelDf['count'] = 1
```

In [295]:

```
print(len(hotelDf.index))
```

```
6774
```

In [311]:

```
df_grouped = hotelDf.groupby(["hotelName"], as_index=False)["count"].count()
```

In [322]:

```
x=df_grouped['hotelName'].values
y=df_grouped['count'].values
print(y)
index = np.arange(len(x))
```

```
[100 100  30  25 100  50  30 100  90  30  38  25 100  81 100 100  80  42
 100 100  25  73  28  45 100  80  20  24 100 100  61  55 100  31  80 100
```

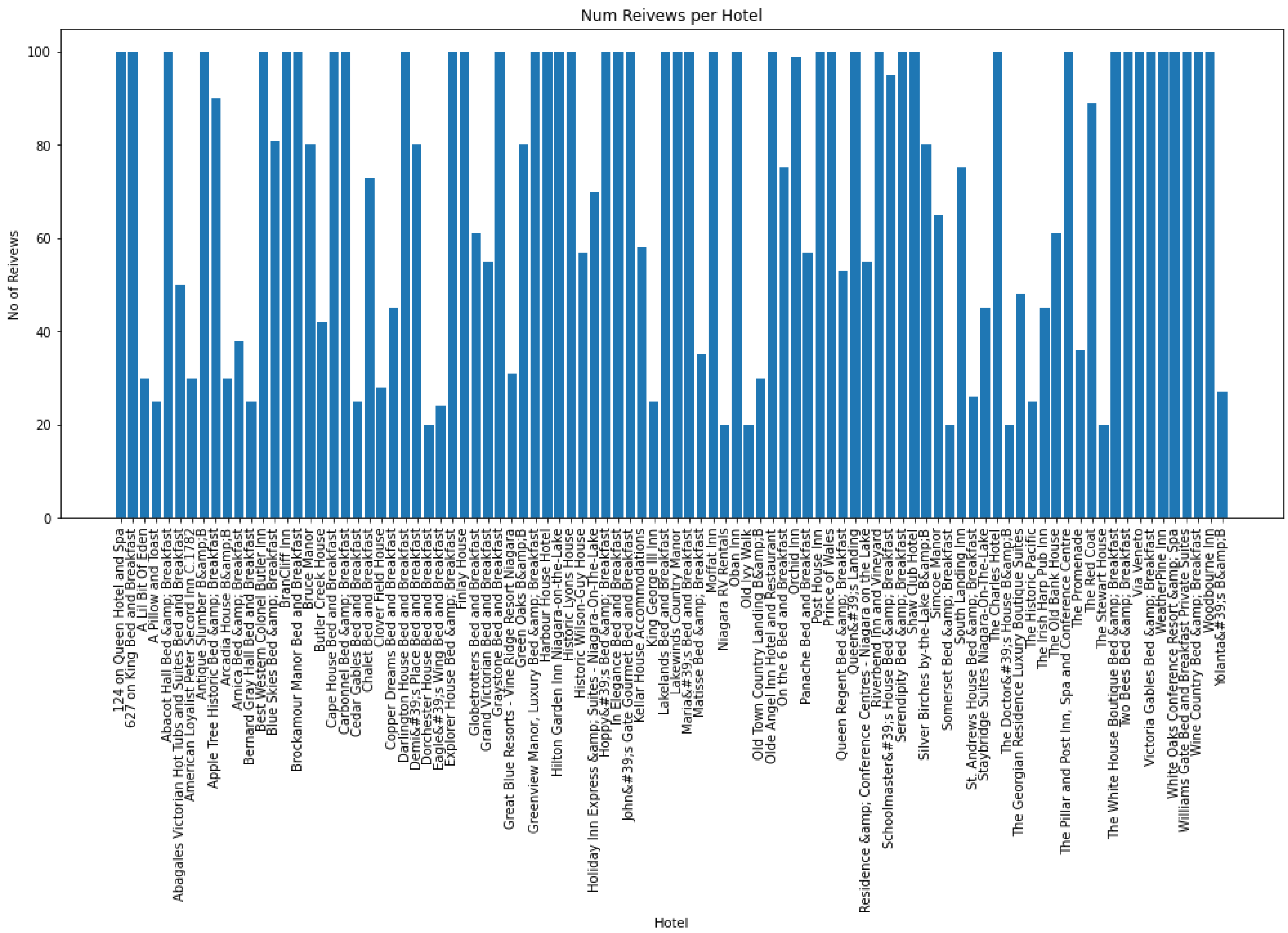
```
 100 100 100  57  70 100 100 100  58  25 100 100 100  35 100  20 100  20
  30 100  75  99  57 100 100  53 100  55 100  95 100 100  80  65  20  75
  26  45 100  20  48  25  45  61 100  36  89  20 100 100 100 100 100 100
 100 100 100  27]
```

In [343]:

```python
def plot_bar_x():
    # this is for plotting purpose
    fig = plt.figure(figsize=(17, 7))
    index = np.arange(len(x))
    plt.bar(index, y)
    plt.xlabel('Hotel', fontsize=10)
    plt.ylabel('No of Reivews', fontsize=10)
    plt.xticks(index, x, fontsize=10, rotation=90)
    plt.title('Num Reivews per Hotel')
    plt.show()
```

In [344]:

```python
plot_bar_x()
```



There are not trends apparent. I only kepy hotels with > 20 reviews and capped the reviews at a max of 100. There is a range for the number of reviews.

Q5 b) i)

In [56]:

```python
def avg_rating_per_hotel(df):
  # average the scores over all hotels, you may need to provide additional filtering
  tempDf = df[['hotelName','vader','ratingScore','reviewCol']]
  tempDf.columns = ['hotelName','AverageVader', 'AverageRatingScore','n_reviews']
  tempDf = tempDf.groupby('hotelName').agg({'AverageVader':'mean', 'AverageRatingScore':
```

```
'mean','n_reviews':'count'})
  return tempDf
```

In [57]:

```
avg_rating_df = avg_rating_per_hotel(finaldf)
avgRatingTop5 = avg_rating_df.reset_index(drop=False)\
                                .sort_values('AverageRatingScore',ascending=False)[['hote
lName','AverageRatingScore']].head(5)
avgRatingTop5
```

Out[57]:

	hotelName	AverageRatingScore
56	On the 6 Bed and Breakfast	5.0
84	The White House Boutique Bed & Breakfast	5.0
59	Post House Inn	5.0
15	Brockamour Manor Bed and Breakfast	5.0
46	Lakelands Bed and Breakfast	5.0

In [58]:

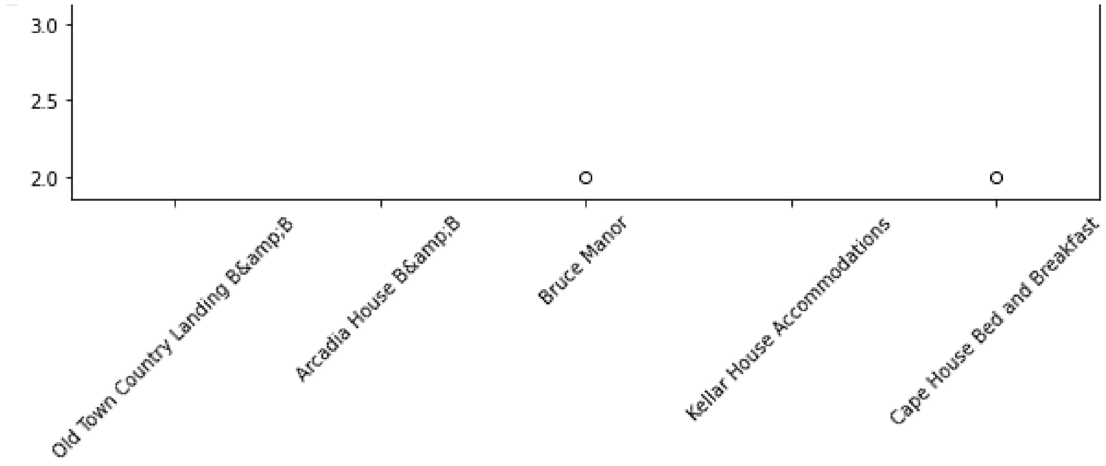
```
avgVaderTop5 = avg_rating_df.reset_index(drop=False)\
                                .sort_values('AverageVader',ascending=False)[['hotelName',
'AverageVader']].head(5)
avgVaderTop5
```

Out[58]:

	hotelName	AverageVader
54	Old Town Country Landing B&B	0.981743
9	Arcadia House B&B	0.973900
16	Bruce Manor	0.973622
44	Kellar House Accommodations	0.970372
18	Cape House Bed and Breakfast	0.968899

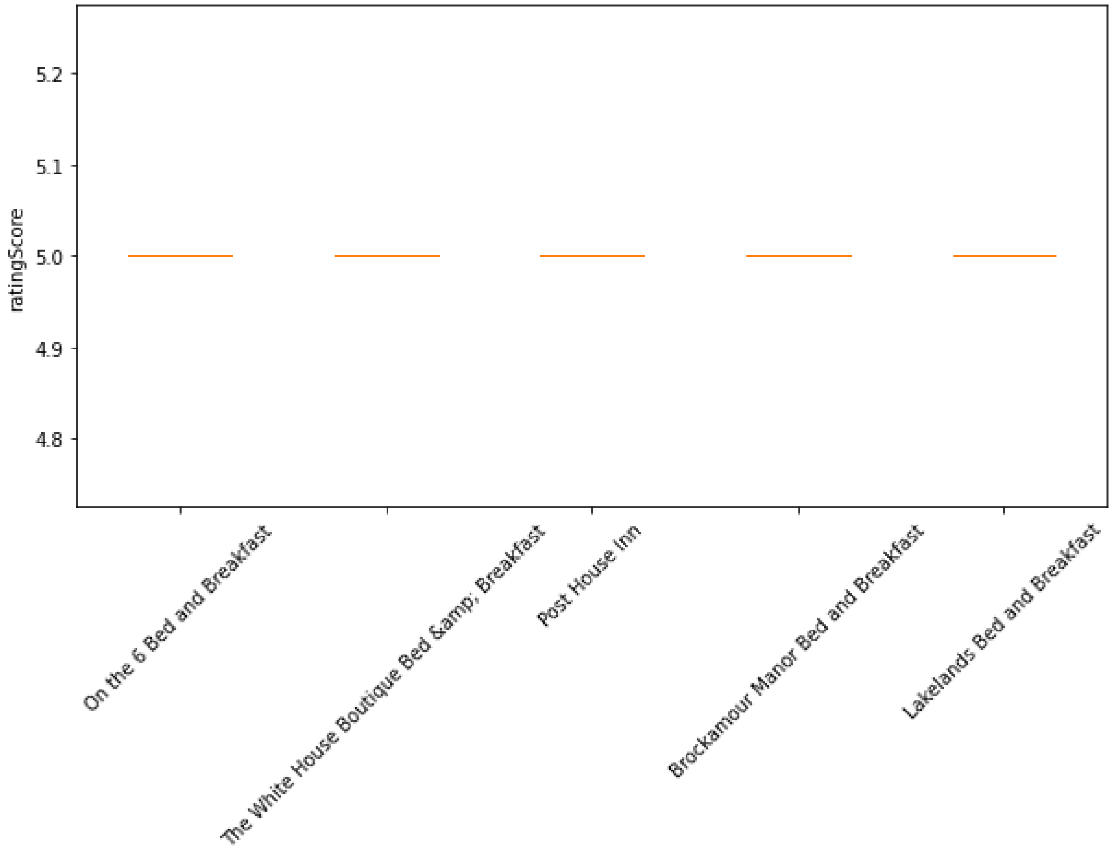
In [59]:

```
# how do the ratings compare for 5 hotels?
five_hotels = avgVaderTop5.hotelName.values

hotel_list = []
for hotel in five_hotels:
  _hotel = finaldf.loc[finaldf['hotelName'] == hotel]['ratingScore']
  hotel_list.append(_hotel)


# multiple box plots on one figure
plt.figure(figsize=(10,5))
plt.boxplot(hotel_list)
plt.xticks(np.arange(1,6), five_hotels,rotation=45)
plt.ylabel('ratingScore')
plt.show()
```



In [60]:

```
# how do the ratings compare for 5 hotels?
five_hotels = avgRatingTop5.hotelName.values

hotel_list = []
for hotel in five_hotels:
  _hotel = finaldf.loc[finaldf['hotelName'] == hotel]['ratingScore']
  hotel_list.append(_hotel)

# multiple box plots on one figure
plt.figure(figsize=(10,5))
plt.boxplot(hotel_list)
plt.xticks(np.arange(1,6), five_hotels,rotation=45)
plt.ylabel('ratingScore')
plt.show()
```



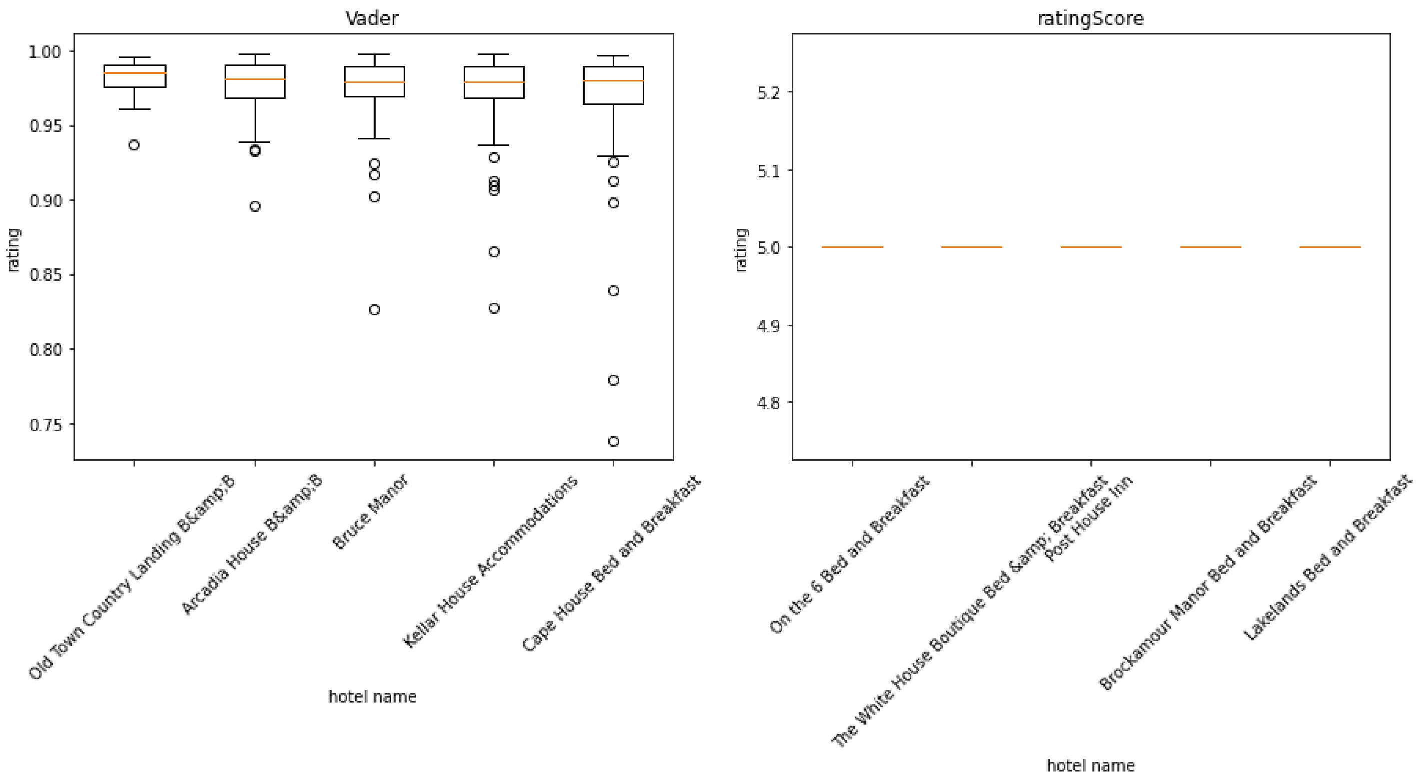
In [359]:

```
fig, ax = plt.subplots(1,2,figsize=(15,5),sharex=False,sharey=False)

# how do the ratings compare for 5 hotels?
five_hotels = avgVaderTop5.hotelName.values

hotel_list = []
for hotel in five_hotels:
```

```
    _hotel = finaldf.loc[finaldf['hotelName'] == hotel]['vader']
    hotel_list.append(_hotel)


# multiple box plots on one figure
ax[0].boxplot(hotel_list)
ax[0].set_title('Vader')
ax[0].set_ylabel('rating')
ax[0].set_xlabel('hotel name')
ax[0].set_xticklabels(five_hotels, fontdict=None, minor=False, rotation=45)

# how do the ratings compare for 5 hotels?
five_hotels = avgRatingTop5.hotelName.values

hotel_list = []
for hotel in five_hotels:
    _hotel = finaldf.loc[finaldf['hotelName'] == hotel]['ratingScore']
    hotel_list.append(_hotel)

ax[1].boxplot(hotel_list)
ax[1].set_title('ratingScore')
ax[1].set_ylabel('rating')
ax[1].set_xlabel('hotel name')
ax[1].set_xticklabels(five_hotels, fontdict=None, minor=False, rotation=45)
# multiple box plots on one figure
```

Out[359]:

```
[Text(0, 0, 'On the 6 Bed and Breakfast'),
 Text(0, 0, 'The White House Boutique Bed &amp; Breakfast'),
 Text(0, 0, 'Post House Inn'),
 Text(0, 0, 'Brockamour Manor Bed and Breakfast'),
 Text(0, 0, 'Lakelands Bed and Breakfast')]
```



Q5 b) ii)

In [61]:

```
avgRatingTop5.mean()
```

Out[61]:

```
AverageRatingScore    5.0
dtype: float64
```

In [62]:

```
avgRatingTop5.var()
```

Out[62]:

```
AverageRatingScore    0.0
dtype: float64
```

In [63]:

```
avgVaderTop5.mean()
```

Out[63]:

```
AverageVader    0.973707
dtype: float64
```

In [64]:

```
avgVaderTop5.var()
```

Out[64]:

```
AverageVader    0.000025
dtype: float64
```

Q5 b) iii)

The mean and variance was more sufficient in this case because the top 5 hotels were nearly perfectly rated so there wasn't much variance that a boxplot would help visualize. The ground truth rating had 0 variance and the Vader rating had a 0.000025 variance so it's not necessarily helpful to visualize a boxplot but usually it is more useful

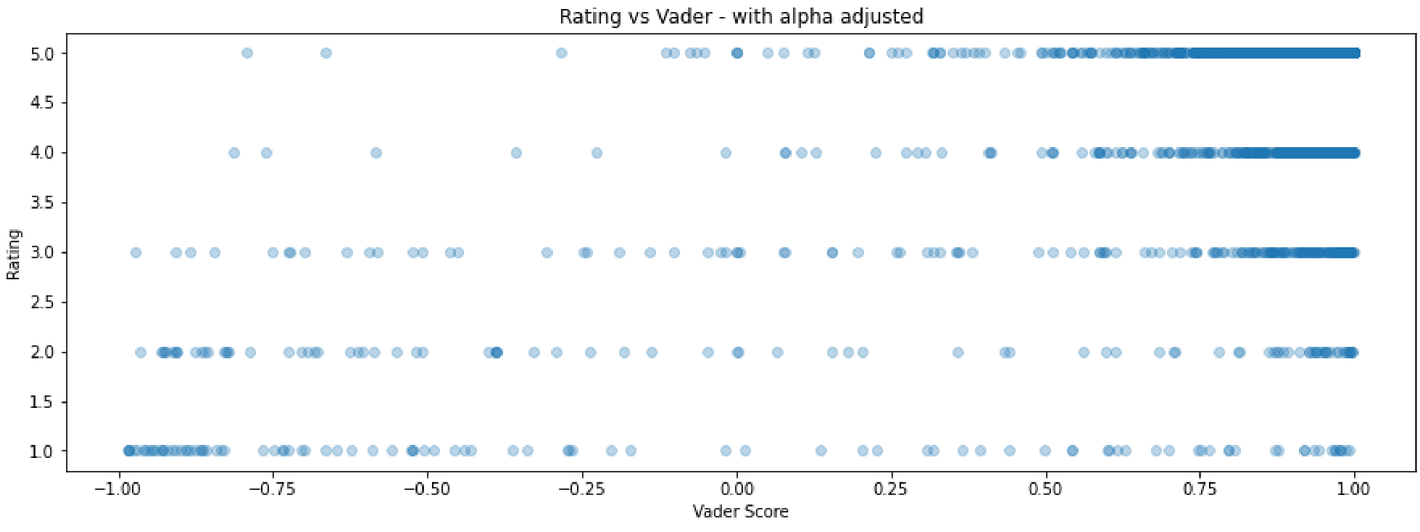
Q5 c) i)

In [360]:

```
fig, ax = plt.subplots(1,1,figsize=(15,5),sharex=False,sharey=False)
rating_scores = finaldf['ratingScore'].values
vader_scores = finaldf['vader'].values
ax.plot(vader_scores, rating_scores,"o", alpha=0.3)

ax.set_title('Rating vs Vader - with alpha adjusted')

ax.set_ylabel('Rating')
ax.set_xlabel('Vader Score')
```

Out[360]:

```
Text(0.5, 0, 'Vader Score')
```

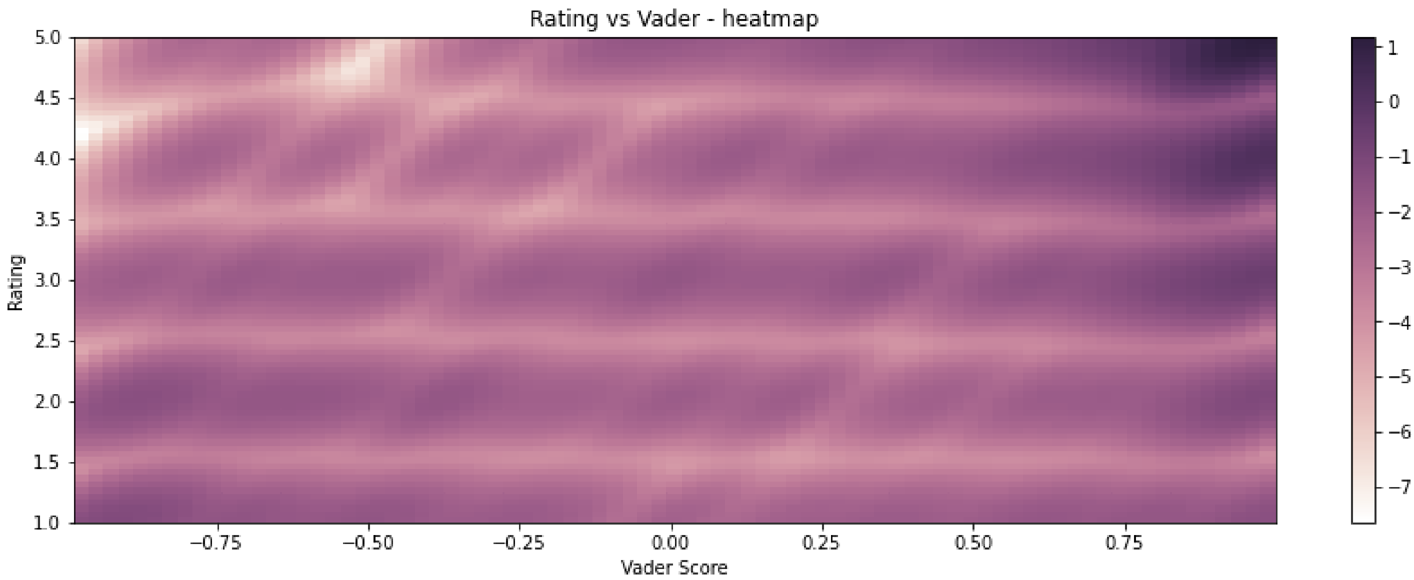


In [361]:

```
k = gaussian_kde(np.vstack([vader_scores, rating_scores]))
xi, yi = np.mgrid[vader_scores.min():vader_scores.max():vader_scores.size**0.5*1j,rating
_scores.min():rating_scores.max():rating_scores.size**0.5*1j]
zi = k(np.vstack([xi.flatten(), yi.flatten()]))

cmap = sns.cubehelix_palette(light=1, as_cmap=True)
fig, (ax1) = plt.subplots(1,1, figsize=(15,5))


b1 = ax1.pcolormesh(xi, yi, np.log10(zi.reshape(xi.shape)), cmap=cmap)

ax1.set_xlim(vader_scores.min(), vader_scores.max())
ax1.set_ylim(rating_scores.min(), rating_scores.max())

ax1.set_xlabel('Vader Score')
ax1.set_ylabel('Rating')

fig.colorbar(b1, ax=ax1)

ax1.set_title('Rating vs Vader - heatmap')
```

Out[361]:

```
Text(0.5, 1.0, 'Rating vs Vader - heatmap')
```



From the scatter plot, it appears that there is clustering in the 2 opposite corners, showing a cluster at poorly rated hotels and well-rated. This shows that the vader score did well in labelling similarly to the gorund truth. There are still a few hotels that vader didn't label 100% correctly but otherwise, it is well calibrated.

Q5 c) ii)

In [67]:

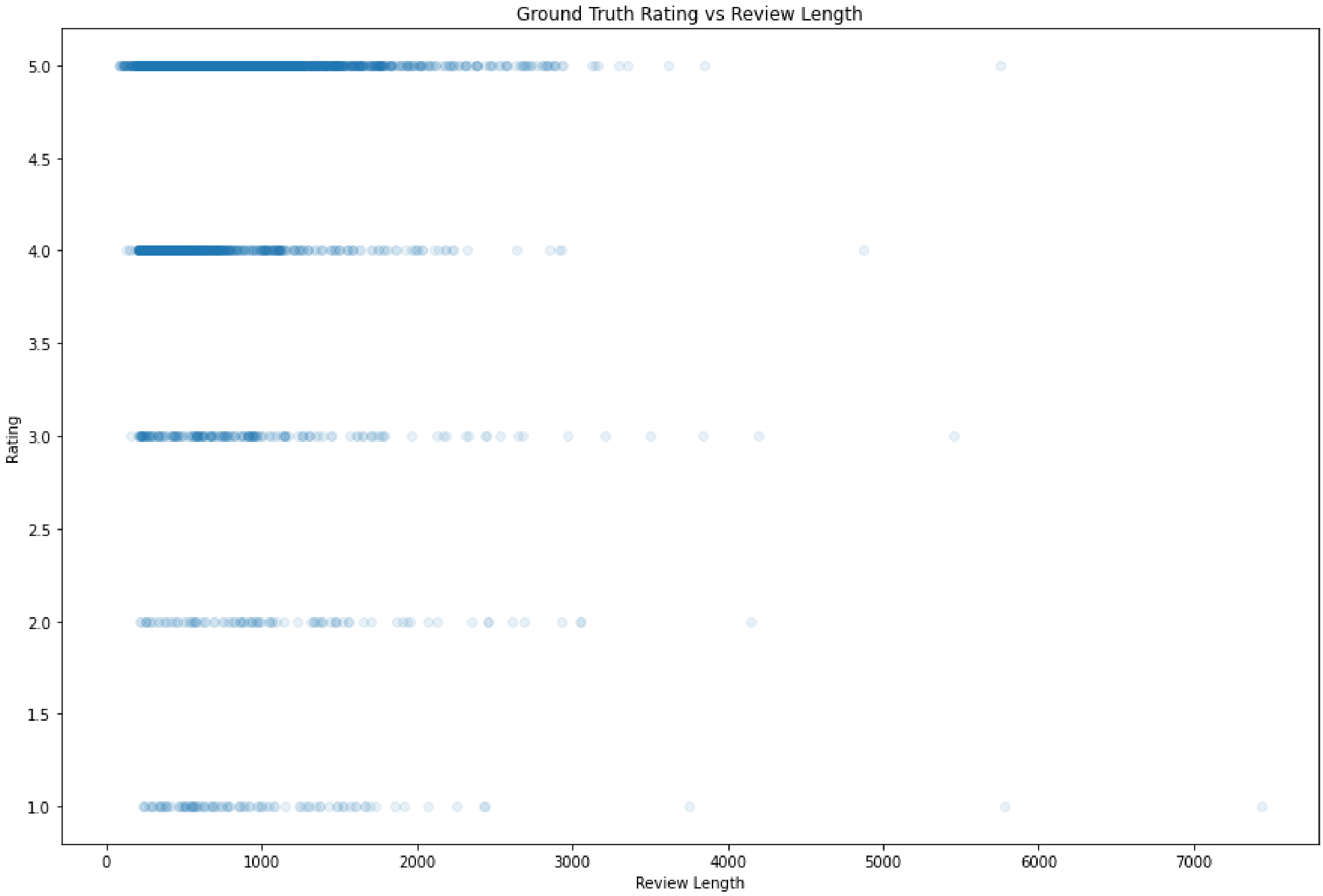
```
finaldf['reviewLength'] = finaldf['reviewCol'].str.len()
```

In [368]:

```
fig, ax = plt.subplots(1,1,figsize=(15,10),sharex=False,sharey=False)
rating_scores = finaldf['ratingScore'].values
reviewLength_scores = finaldf['reviewLength'].values
ax.plot(reviewLength_scores, rating_scores,"o", alpha=0.1)
ax.set_title('Ground Truth Rating vs Review Length')

ax.set_ylabel('Rating')
ax.set_xlabel('Review Length')
```

Out[368]:

```
Text(0.5, 0, 'Review Length')
```

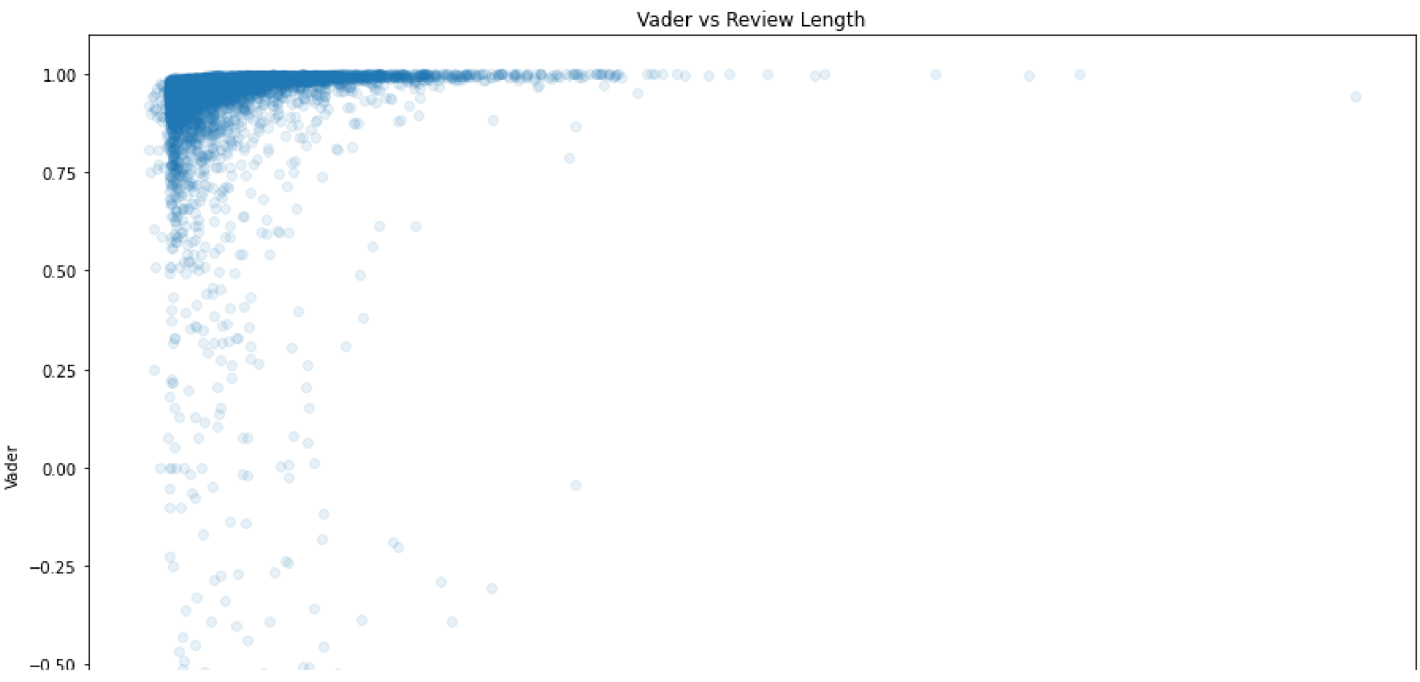


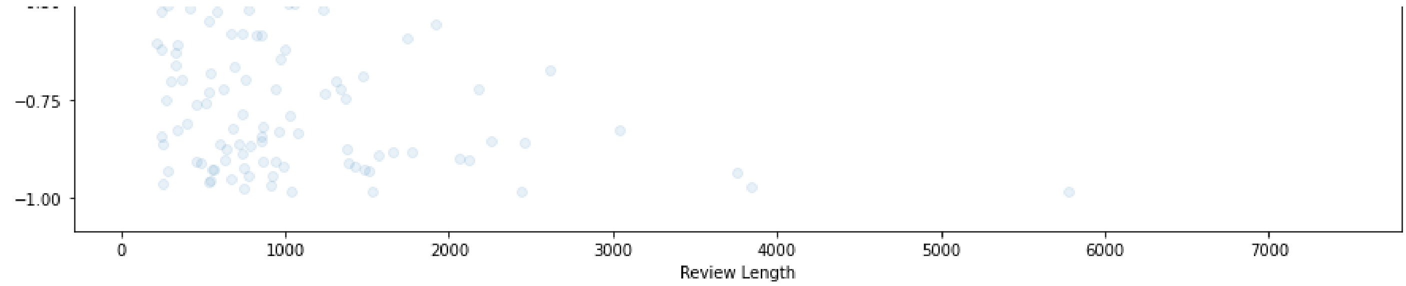
In [367]:

```
fig, ax = plt.subplots(1,1,figsize=(15,10),sharex=False,sharey=False)
rating_scores = finaldf['vader'].values
reviewLength_scores = finaldf['reviewLength'].values
ax.plot(reviewLength_scores, rating_scores,"o", alpha=0.1)

ax.set_title('Vader vs Review Length')
ax.set_ylabel('Vader')
ax.set_xlabel('Review Length')
```

Out[367]:

```
Text(0.5, 0, 'Review Length')
```



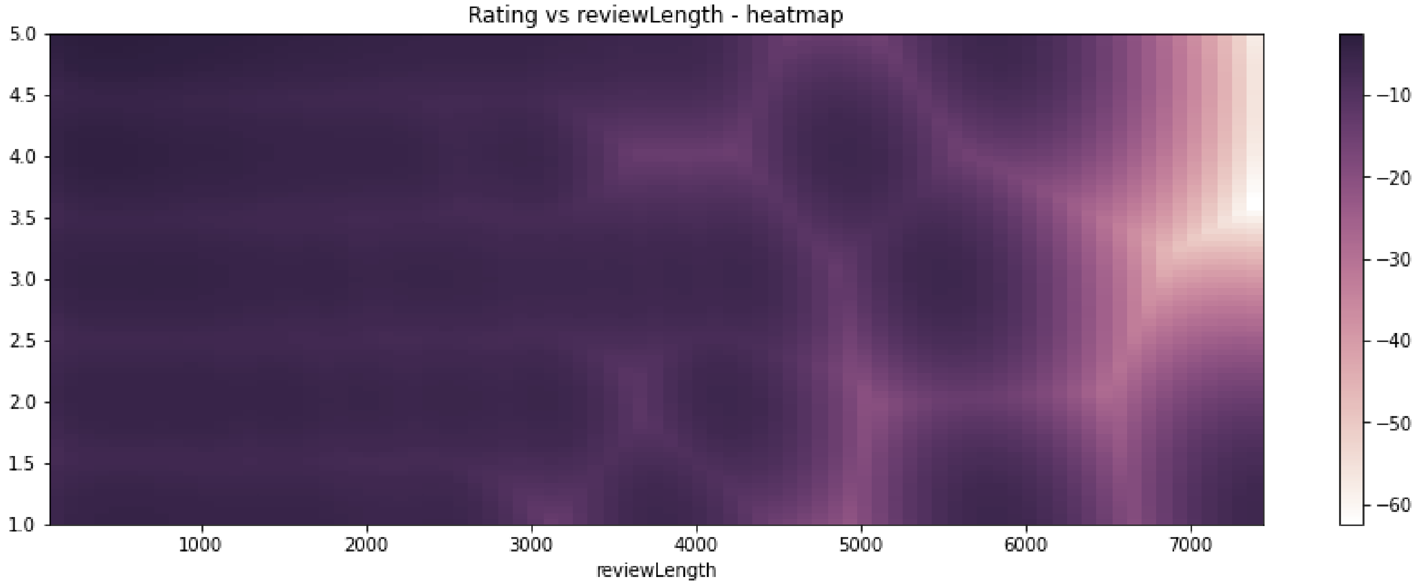


In [374]:

```
k = gaussian_kde(np.vstack([reviewLength_scores, rating_scores]))
xi, yi = np.mgrid[reviewLength_scores.min():reviewLength_scores.max():reviewLength_scores
.size**0.5*1j,rating_scores.min():rating_scores.max():rating_scores.size**0.5*1j]
zi = k(np.vstack([xi.flatten(), yi.flatten()]))

cmap = sns.cubehelix_palette(light=1, as_cmap=True)
fig, (ax1) = plt.subplots(1,1, figsize=(15,5))


b1 = ax1.pcolormesh(xi, yi, np.log10(zi.reshape(xi.shape)), cmap=cmap)

ax1.set_xlim(reviewLength_scores.min(), reviewLength_scores.max())
ax1.set_ylim(rating_scores.min(), rating_scores.max())

ax1.set_xlabel('reviewLength')

ax2.set_xlabel('reviewLength')

fig.colorbar(b1, ax=ax1)
ax1.set_title('Rating vs reviewLength - heatmap')
```

Out[374]:

```
Text(0.5, 1.0, 'Rating vs reviewLength - heatmap')
```



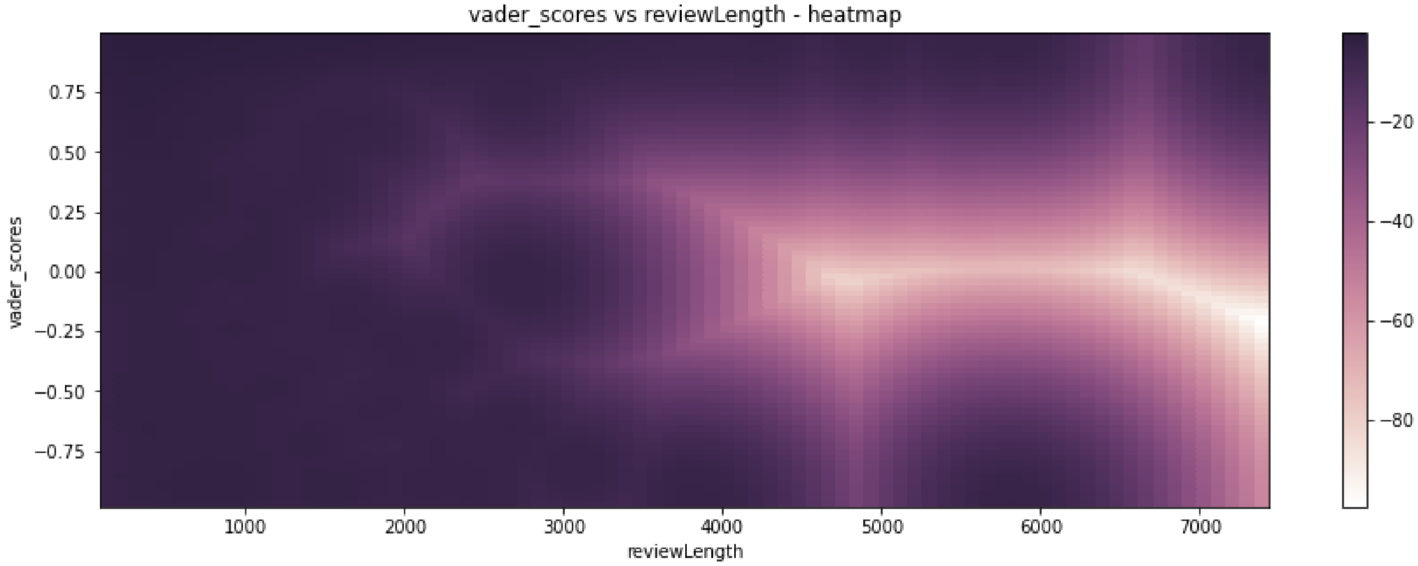
In [375]:

```
k = gaussian_kde(np.vstack([reviewLength_scores, vader_scores]))
xi, yi = np.mgrid[reviewLength_scores.min():reviewLength_scores.max():reviewLength_scores
.size**0.5*1j,vader_scores.min():vader_scores.max():vader_scores.size**0.5*1j]
zi = k(np.vstack([xi.flatten(), yi.flatten()]))

cmap = sns.cubehelix_palette(light=1, as_cmap=True)
fig, (ax1) = plt.subplots(1,1, figsize=(15,5))


b1 = ax1.pcolormesh(xi, yi, np.log10(zi.reshape(xi.shape)), cmap=cmap)

ax1.set_xlim(reviewLength_scores.min(), reviewLength_scores.max())
```

```
ax1.set_ylim(vader_scores.min(), vader_scores.max())

ax1.set_xlabel('reviewLength')
ax1.set_ylabel('vader_scores')

fig.colorbar(b1, ax=ax1)
ax1.set_title('vader_scores vs reviewLength - heatmap')
```

Out[375]:

```
Text(0.5, 1.0, 'vader_scores vs reviewLength - heatmap')
```



It appears that longer reviews typically occur for most positive reviews. Long reviews are generally very rare, based on the graphs. This is intersting because it shows that customers who had a good time really did want to go into detail about their experience.

It also seems like mediocre reviews are on average short. This makes sense because if nothing was very good or bad, there isn't typically much to talk about in a review. I found this interesting and relatable because if I have an average experience I also feel like my review wouldn't really be helpful for readers, I'd just leave a start rating without text personally. Again, the data is really skewed so there are a lot of positive reviews but from what i can tell, this is the only observation I can conclude.

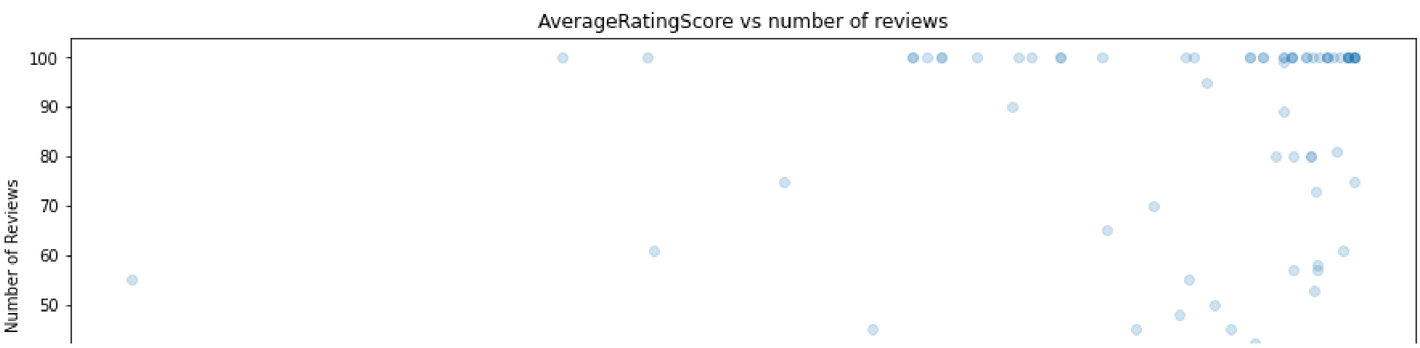
Q5 c) iii)

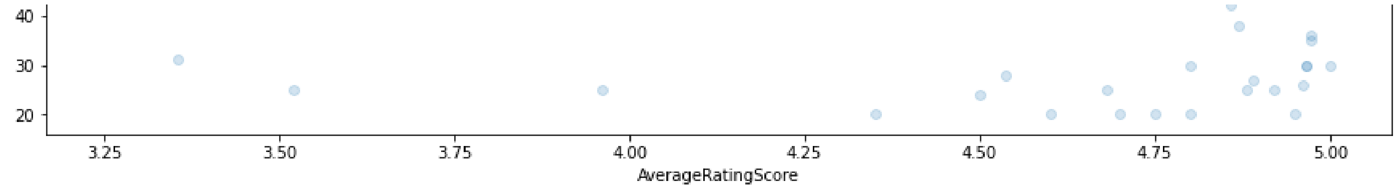
In [377]:

```
fig, ax = plt.subplots(1,1,figsize=(15,5),sharex=False,sharey=False)
rating_scores = avg_rating_df['n_reviews'].values
reviewLength_scores = avg_rating_df['AverageRatingScore'].values
ax.plot(reviewLength_scores, rating_scores,"o", alpha=0.2)
ax.set_title('AverageRatingScore vs number of reviews')

ax.set_ylabel('Number of Reviews')
ax.set_xlabel('AverageRatingScore')
```

Out[377]:

```
Text(0.5, 0, 'AverageRatingScore')
```



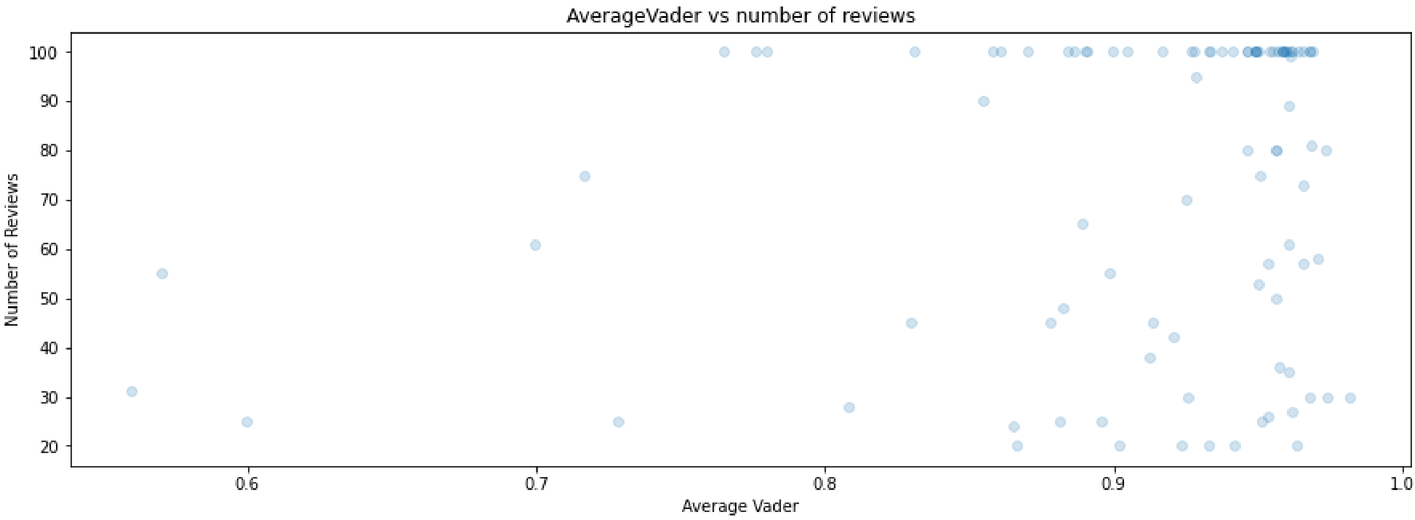


In [378]:

```
fig, ax = plt.subplots(1,1,figsize=(15,5),sharex=False,sharey=False)
rating_scores = avg_rating_df['n_reviews'].values
reviewLength_scores = avg_rating_df['AverageVader'].values
ax.plot(reviewLength_scores, rating_scores,"o", alpha=0.2)
ax.set_title('AverageVader vs number of reviews')

ax.set_ylabel('Number of Reviews')
ax.set_xlabel('Average Vader')
```

Out[378]:

```
Text(0.5, 0, 'Average Vader')
```



From the graphs, it appears that a lot of reviews are more common with higher rated hotels. This is intersting because if the hotel really did do an outstanding job you would likely leave a review. Otherwise, you may just want to move on and forget the experience.

Also, I found it interesting that low rated hotels didn't have a lot of reviews because if you have a particularly bad experience you may feel so strongly about it that you want to review it so others don't visit the hotel. I guess since the low-rated hotels are still not horribly rated (lowest being 0.65) then the experiences were not bad enough to warn other potential visitors.

Q5 d)

In [74]:

```
hotelDfFilled = hotelDf
hotelDfFilled['City'] = hotelDfFilled['City'].fillna('Niagara On The Lake')
```

In [75]:

```
def make_address(row):
  # individual columns need to be combined
  return row['streetAddress']+", "+row['City']+", "+row['Province']

# Need the location for each hotel in a format the tool can handle

geo_rating_df = avg_rating_df\
                           .join(hotelDfFilled.groupby('hotelName')\
                           .agg({'streetAddress':'max','City':'max','Province':'max','post
alCode':'max'}))
```

```
geo_rating_df['formed_address'] = geo_rating_df.apply(make_address , axis=1)
geo_rating_df.tail()
```

Out[75]:

hotelName	AverageVader	AverageRatingScore	n_reviews	streetAddress	City	Province	postalCode	formed_address
White Oaks Conference Resort & Spa	0.870113	4.540000	100	253 Taylor Rd	Niagara On The Lake	Ontario	L0S 1J0	253 Taylor Rd, Niagara On The Lake, Ontario
Williams Gate Bed and Breakfast Private Suites	0.933672	4.930000	100	413 Gate Street	Niagara On The Lake	Ontario	L0S 1J0	413 Gate Street, Niagara On The Lake, Ontario
Wine Country Bed & Breakfast	0.950137	4.970000	100	75 John Street W PO Box 1789	Niagara On The Lake	Ontario	L0S 1J0	75 John Street W PO Box 1789, Niagara On The Lake, Ontario
Woodbourne Inn	0.967813	4.960000	100	214 Four Mile Creek Rd.	Niagara On The Lake	Ontario	L0S 1P0	214 Four Mile Creek Rd., Niagara On The Lake, Ontario
Yolanta's B&B	0.961685	4.888889	27	596 Simcoe St	Niagara On The Lake	Ontario	L0S 1J0	596 Simcoe St, Niagara On The Lake, Ontario

In [76]:

```
# 0 - need to give the tool a generic name.
locator = Nominatim(user_agent='myGeocoder')
# 1 - conveneint function to delay between geocoding calls
geocode = RateLimiter(locator.geocode, min_delay_seconds=1)
# 2 - form the location string
geo_rating_df['location'] = geo_rating_df['formed_address'].apply(geocode)
# 3 - create longitude, laatitude and altitude from location column (returns tuple)
geo_rating_df['point'] = geo_rating_df['location'].apply(lambda loc: tuple(loc.point) if
loc else None)
# 4 - split point column into latitude, longitude and altitude columns
geo_rating_df[['latitude', 'longitude', 'altitude']] = pd.DataFrame(geo_rating_df['point
'].tolist(), index=geo_rating_df.index)

geo_rating_df.head()
```

Out[76]:

hotelName	AverageVader	AverageRatingScore	n_reviews	streetAddress	City	Province	postalCode	formed_address
124 on Queen Hotel and Spa	0.860997	4.580000	100	124 Queen Street	Niagara On The Lake	Ontario	L0S 1J0	124 Queen Street, Niagara On The Lake, Ontario
627 on King Bed and Breakfast	0.958632	4.930000	100	627 King Street PO Box 1092	Niagara On The Lake	Ontario	L0S 1J0	627 King Street PO Box 1092, Niagara On The Lake, Ontario
A Lil Bit Of Eden	0.967960	4.966667	30	420 Line 2 Bradfield Rd.) RR2	Niagara On The Lake	Ontario	L0S 1J0	420 Line 2 Bradfield Rd.) RR2, Niagara On The Lake, Ontario

hotelName	AverageVader	AverageRatingScore	n_reviews	streetAddress	City	Province	postalCode	formed_address
Willow and Toast	0.728136	3.960000	25	8 Garrison Village Dr	Niagara On The Lake	Ontario	L0S 1J0	8 Garrison Village Dr, Niagara On The Lake, Ontario
Abacot Hall Bed & Breakfast	0.949753	4.980000	100	508 Mississauga Street	Niagara On The Lake	Ontario	L0S 1J0	508 Mississauga Street, Niagara On The Lake, Ontario

In [392]:

```
geo_rating_df = geo_rating_df.round({'AverageRatingScore': 1})
```

In [ ]:

```
m = folium.Map([60, 10], tiles='Mapbox Bright', zoom_start=5)
folium.Circle([circle_lat, circle_lon], 150000, fill=True).add_child(folium.Popup('My na
me is Circle')).add_to(m)
folium.map.Marker(
    [circle_lat + 0.5, circle_lon - 1.6],
    icon=DivIcon(
        icon_size=(150,36),
        icon_anchor=(0,0),
        html='<div style="font-size: 24pt">%s</div>' % text,
        )
    ).add_to(m)
m
```

In [425]:

```
map1 = folium.Map(
    location=[43.222296, -79.132129], # <- this will need to be set based on your own hot
els
    tiles='cartodbpositron',
    zoom_start=12,
)


text = 'Test'
circle_lat = 60
circle_lon = 10
geo_rating_df.dropna().apply(lambda row:folium.Circle([row["latitude"], row["longitude"]
], 200, fill=True).add_to(map1), axis=1)

from folium.features import DivIcon
geo_rating_df.dropna().apply(lambda row:folium.Marker(location=[row["latitude"], row["lon
gitude"]], icon=DivIcon(
        icon_size=(150,36),
        icon_anchor=(7,8),
       html='<div style="font-size: 8pt">%s</div>' % row['AverageRatingScore'],
        )).add_to(map1), axis=1)

map1
```

Out[425]:

Make this Notebook Trusted to load map: File -> Trust Notebook

In [426]:

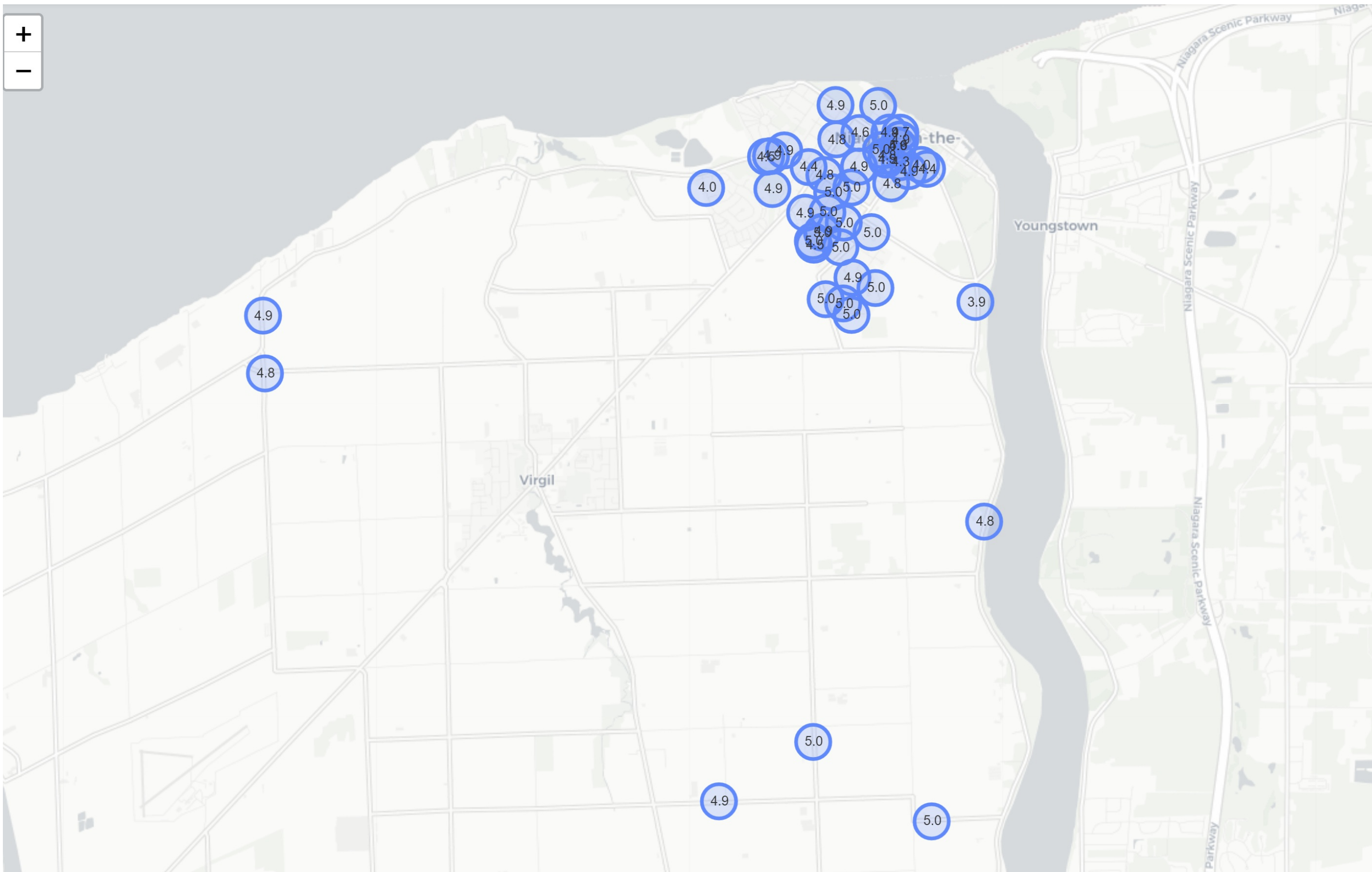
```python
## folium graphs are best saved as screenshot images to be reloaded into the notebook
from IPython.display import Image
Image('capture.PNG')
```

Out[426]:

In [428]:

```python
Image('Capture2.PNG')
```

Out[428]:



It doesn't seem like there is a clear area that has better reviews. I wouldn't avoid staying at any particular geolocation

Q5 e) i)

In [79]:

```
import datetime
from dateutil.relativedelta import relativedelta
def get_past_date(str_days_ago):
    TODAY = datetime.date.today()
    splitted = str_days_ago.split()
    if len(splitted) == 1 and splitted[0].lower() == 'today':
        return str(TODAY.isoformat())
    elif len(splitted) == 1 and splitted[0].lower() == 'yesterday':
        date = TODAY - relativedelta(days=1)
        return str(date.isoformat())
    elif splitted[1].lower() in ['hour', 'hours', 'hr', 'hrs', 'h']:
        date = datetime.datetime.now() - relativedelta(hours=int(splitted[0]))
        return str(date.date().isoformat())
    elif splitted[1].lower() in ['day', 'days', 'd']:
        date = TODAY - relativedelta(days=int(splitted[0]))
        return str(date.isoformat())
    elif splitted[1].lower() in ['wk', 'wks', 'week', 'weeks', 'w']:
        date = TODAY - relativedelta(weeks=int(splitted[0]))
        return str(date.isoformat())
    elif splitted[1].lower() in ['mon', 'mons', 'month', 'months', 'm']:
        date = TODAY - relativedelta(months=int(splitted[0]))
        return str(date.isoformat())
    elif splitted[1].lower() in ['yrs', 'yr', 'years', 'year', 'y']:
        date = TODAY - relativedelta(years=int(splitted[0]))
        return str(splitted)
    else:
        return pd.to_datetime(str_days_ago)
pd.to_datetime("2020-10-4")
```

Out[79]:

```
Timestamp('2020-10-04 00:00:00')
```

In [429]:

```
avg_rating_df = avg_rating_per_hotel(finaldf)
avgRatingTop = avg_rating_df.reset_index(drop=False)\
                                        .sort_values('AverageRatingScore',ascending=False)[['hote
lName','AverageRatingScore']]
avgRatingTop
```

Out[429]:

	hotelName	AverageRatingScore
56	On the 6 Bed and Breakfast	5.000000
84	The White House Boutique Bed & Breakfast	5.000000
59	Post House Inn	5.000000
15	Brockamour Manor Bed and Breakfast	5.000000
46	Lakelands Bed and Breakfast	5.000000
...	...	...
3	A Pillow and Toast	3.960000
64	Riverbend Inn and Vineyard	3.870000
45	King George III Inn	3.520000
33	Great Blue Resorts - Vine Ridge Resort Niagara	3.354839
63	Residence & Conference Centres - Niagara on the Lake	3.254545

94 rows × 2 columns

In [442]:

```
avgRatingTop[43:49]
```

Out[442]:

	hotelName	AverageRatingScore
57	Orchid Inn	4.898990
82	The Red Coat	4.898876
93	Yolanta's B&B	4.888889
34	Green Oaks B&B	4.887500
20	Cedar Gables Bed and Breakfast	4.880000
47	Lakewinds Country Manor	4.870000

In [444]:

```
six_hotels = ['On the 6 Bed and Breakfast', 'The White House Boutique Bed &amp; Breakfast
', 'Green Oaks B&amp;B', 'Orchid Inn','Great Blue Resorts - Vine Ridge Resort Niagara',
'Residence &amp; Conference Centres - Niagara on the Lake']
```

In [445]:

```
hotelDf.loc[hotelDf['hotelName'].isin(six_hotels)].groupby('hotelName')['count'].sum()
```

Out[445]:

```
hotelName
Great Blue Resorts - Vine Ridge Resort Niagara                31
Green Oaks B&amp;B                                             80
On the 6 Bed and Breakfast                                    75
Orchid Inn                                                    99
Residence &amp; Conference Centres - Niagara on the Lake      55
The White House Boutique Bed &amp; Breakfast                   100
Name: count, dtype: int64
```

In [446]:

```
six_hotels
```

Out[446]:

```
['On the 6 Bed and Breakfast',
 'The White House Boutique Bed &amp; Breakfast',
 'Green Oaks B&amp;B',
 'Orchid Inn',
 'Great Blue Resorts - Vine Ridge Resort Niagara',
 'Residence &amp; Conference Centres - Niagara on the Lake']
```

In [447]:

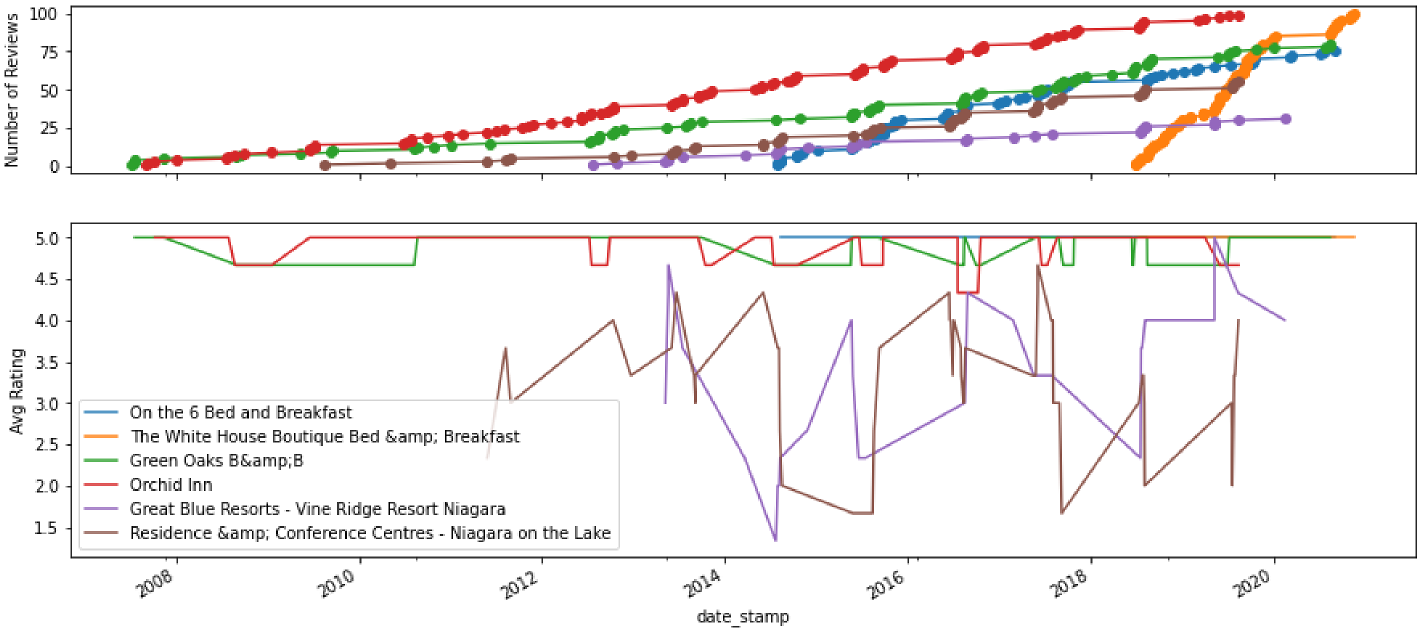
```
# It can be useful to see when reviews were being made and how the ratings changed using
a running mean
fig, ax = plt.subplots(2, 1, figsize=(15,7),
                       sharex=True,
                       gridspec_kw={
                           'height_ratios': [1, 2]})

for hotel in six_hotels:
  _df = hotelDf[hotelDf['hotelName']==hotel]
  for i in _df.index:
    if 'ago' in _df.loc[i, 'date_stamp']:
      x=get_past_date(_df.loc[i, 'date_stamp'])
      _df.loc[i,'date_stamp']= x
  _df = _df[_df['hotelName']==hotel].set_index('date_stamp')

  _df.index = pd.to_datetime(_df.index)
  _df = _df.sort_index()
  _df['count'] = 1
  _df['count'].cumsum().plot(ax=ax[0],label=hotel, marker='o')
  _df['ratingScore'].rolling(3).mean().plot(ax=ax[1],label=hotel)

ax[1].set_ylabel('Avg Rating')
```

```
ax[0].set_ylabel('Number of Reviews')
plt.legend()
```

```
/usr/local/lib/python3.6/dist-packages/pandas/core/indexing.py:1763: SettingWithCopyWarni
ng:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_g
uide/indexing.html#returning-a-view-versus-a-copy
  isetter(loc, value)
```

Out[447]:

```
<matplotlib.legend.Legend at 0x7f236069e400>
```



The top 2 highly rated hotels (blue and orange) were always consistent and top rated, there isn't a change in avg rating over time. The middle 2 were also always top rated although they have more flucuation recently. The bottom 2 fluctuate a lot. There is no increasing or decreasing trend for the bottom 2. This could mean they aren't really doing anything differently to address their lower rating.

Q5 e) ii)

In [450]:

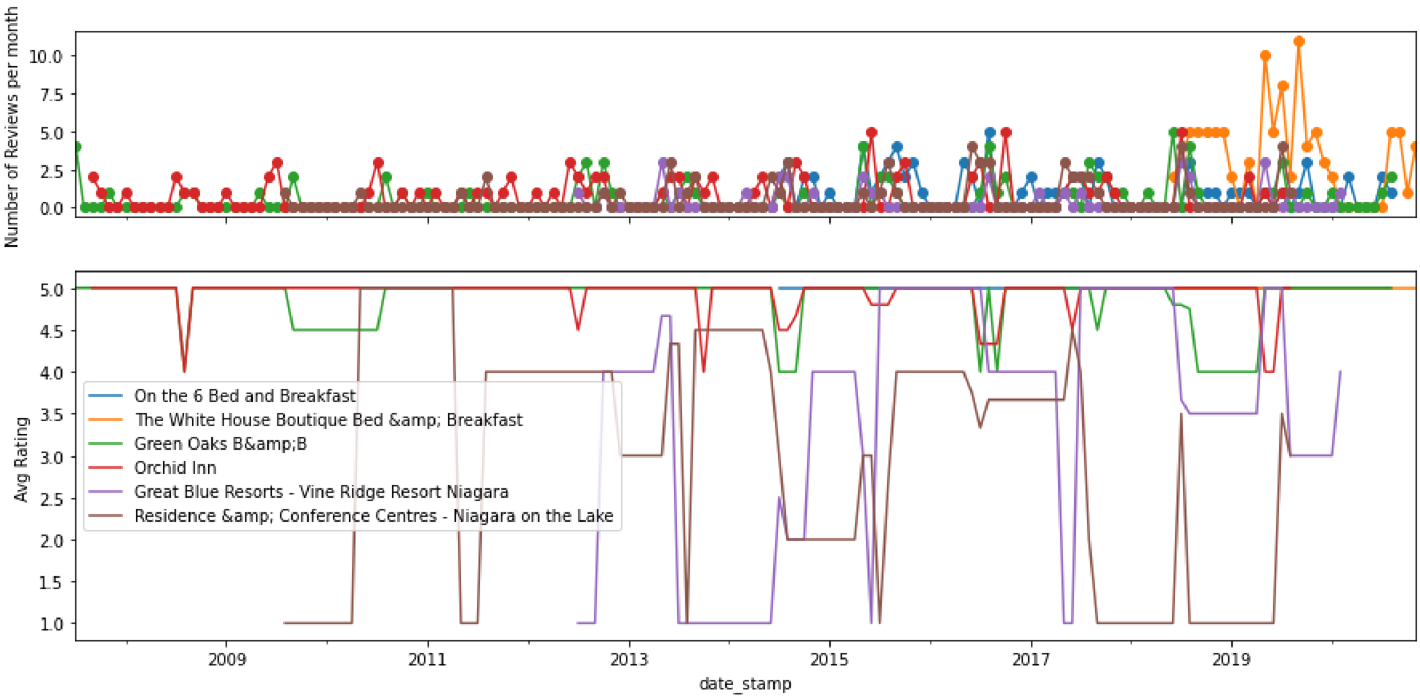
```
# It can be useful to see when reviews were being made and how the ratings changed
fig, ax = plt.subplots(2, 1, figsize=(15,7),
                       sharex=True,
                       gridspec_kw={
                           'height_ratios': [1, 2]})

for hotel in six_hotels:
  _df = hotelDf[hotelDf['hotelName']==hotel]
  for i in _df.index:
    if 'ago' in _df.loc[i, 'date_stamp']:
      x=get_past_date(_df.loc[i, 'date_stamp'])
      _df.loc[i,'date_stamp']= x
  _df = _df[_df['hotelName']==hotel].set_index('date_stamp')

  _df.index = pd.to_datetime(_df.index)
  _df = _df.sort_index()
  _df['count'] = 1
  _df_monthly = _df.groupby(pd.Grouper(freq='M')).agg({'count':'sum','ratingScore':'mean
'})
  _df_monthly['ratingScore'] = _df_monthly['ratingScore'].fillna(method='ffill')  # hold
the last rating constant in months with no reviews
  _df_monthly['count'].plot(ax=ax[0],label=hotel, marker='o')
  _df_monthly['ratingScore'].plot(ax=ax[1],label=hotel)
```

```
ax[1].set_ylabel('Avg Rating')
ax[0].set_ylabel('Number of Reviews per month')
plt.legend()
```

```
/usr/local/lib/python3.6/dist-packages/pandas/core/indexing.py:1763: SettingWithCopyWarni
ng:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_g
uide/indexing.html#returning-a-view-versus-a-copy
  isetter(loc, value)
```

Out[450]:

```
<matplotlib.legend.Legend at 0x7f235fe77438>
```



Top 2 Hotels

In [451]:

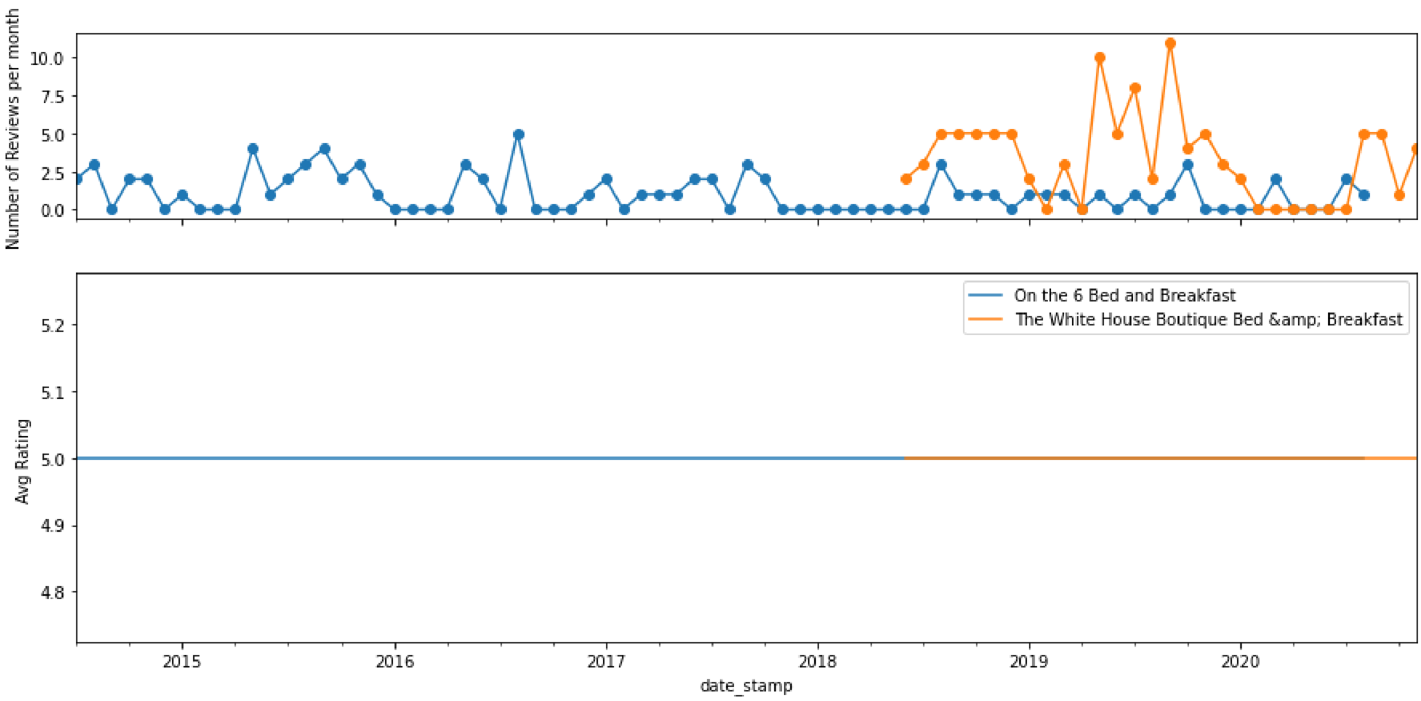
```
# It can be useful to see when reviews were being made and how the ratings changed
fig, ax = plt.subplots(2, 1, figsize=(15,7),
                       sharex=True,
                       gridspec_kw={
                           'height_ratios': [1, 2]})

for hotel in six_hotels[:2]:
  _df = hotelDf[hotelDf['hotelName']==hotel]
  for i in _df.index:
    if 'ago' in _df.loc[i, 'date_stamp']:
      x=get_past_date(_df.loc[i, 'date_stamp'])
      _df.loc[i,'date_stamp']= x
  _df = _df[_df['hotelName']==hotel].set_index('date_stamp')

  _df.index = pd.to_datetime(_df.index)
  _df = _df.sort_index()
  _df['count'] = 1
  _df_monthly = _df.groupby(pd.Grouper(freq='M')).agg({'count':'sum','ratingScore':'mean
'})
  _df_monthly['ratingScore'] = _df_monthly['ratingScore'].fillna(method='ffill') # hold
the last rating constant in months with no reviews
  _df_monthly['count'].plot(ax=ax[0],label=hotel, marker='o')
  _df_monthly['ratingScore'].plot(ax=ax[1],label=hotel)

ax[1].set_ylabel('Avg Rating')
```

```
ax[0].set_ylabel('Number of Reviews per month')
plt.legend()
```

```
/usr/local/lib/python3.6/dist-packages/pandas/core/indexing.py:1763: SettingWithCopyWarni
ng:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_g
uide/indexing.html#returning-a-view-versus-a-copy
  isetter(loc, value)
```

Out[451]:

```
<matplotlib.legend.Legend at 0x7f235fdb6b38>
```



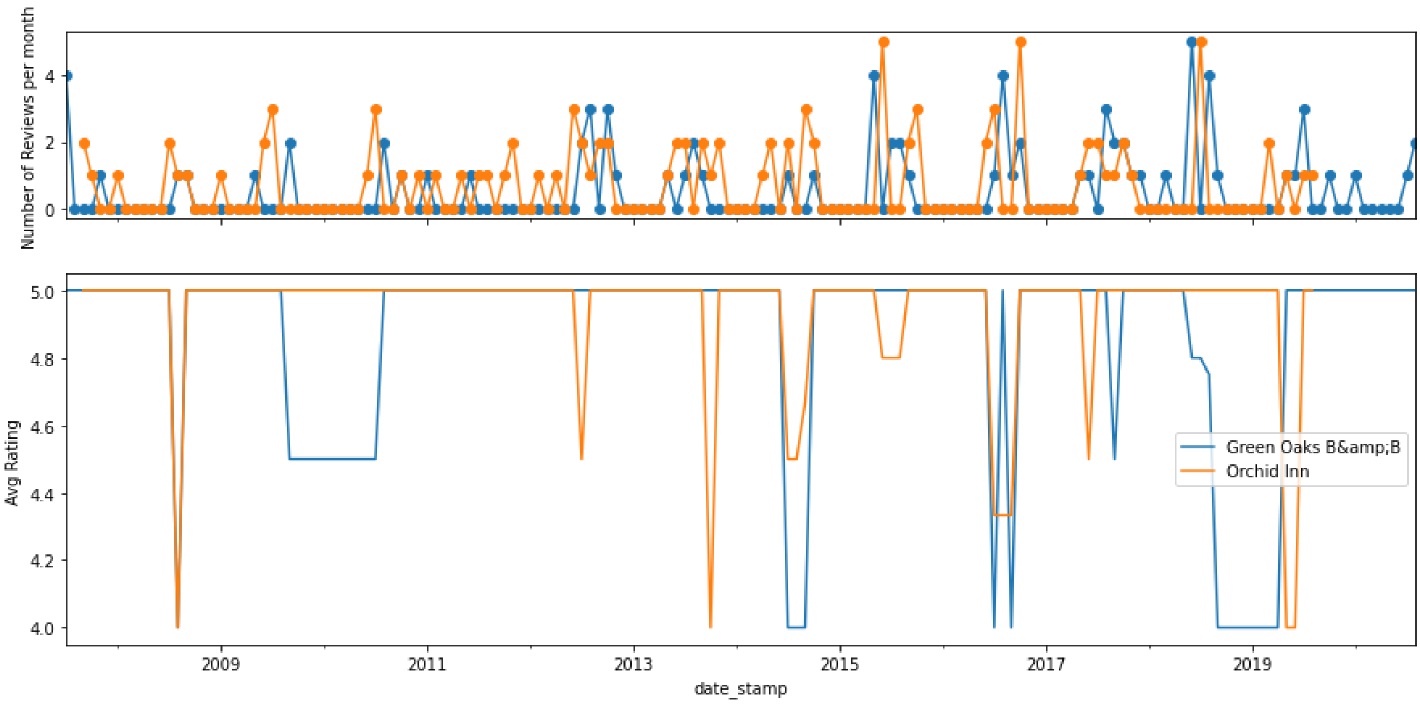
These hotels always have perfect reviews so no comments on the trend can be made here

In [453]:

```
# It can be useful to see when reviews were being made and how the ratings changed
fig, ax = plt.subplots(2, 1, figsize=(15,7),
                       sharex=True,
                       gridspec_kw={
                           'height_ratios': [1, 2]})

for hotel in six_hotels[2:4]:
  _df = hotelDf[hotelDf['hotelName']==hotel]
  for i in _df.index:
    if 'ago' in _df.loc[i, 'date_stamp']:
      x=get_past_date(_df.loc[i, 'date_stamp'])
      _df.loc[i,'date_stamp']= x
  _df = _df[_df['hotelName']==hotel].set_index('date_stamp')

  _df.index = pd.to_datetime(_df.index)
  _df = _df.sort_index()
  _df['count'] = 1
  _df_monthly = _df.groupby(pd.Grouper(freq='M')).agg({'count':'sum','ratingScore':'mean
'})
  _df_monthly['ratingScore'] = _df_monthly['ratingScore'].fillna(method='ffill')  # hold
the last rating constant in months with no reviews
  _df_monthly['count'].plot(ax=ax[0],label=hotel, marker='o')
  _df_monthly['ratingScore'].plot(ax=ax[1],label=hotel)

ax[1].set_ylabel('Avg Rating')
ax[0].set_ylabel('Number of Reviews per month')
plt.legend()
```

Out[453]:

```
<matplotlib.legend.Legend at 0x7f235fac2dd8>
```



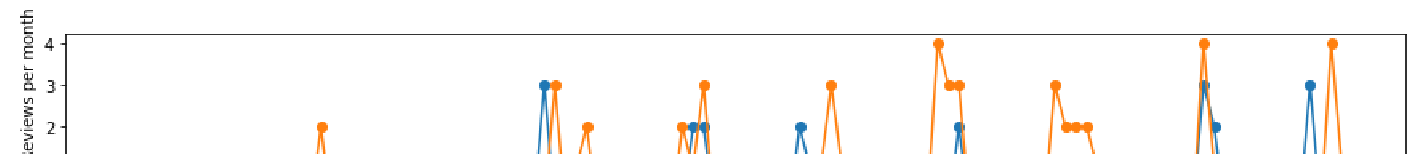
There seems to be a decrease in avg rating whenever there is an increase of reviews that month. This means that maybe these hotels are actually not that great and that comes to light in moths with a lot of reviews. When there is a peak in reviews, there is a large dip in avg rating. A hypothesis for this could be that they are bad at handling a lot of guests at once.

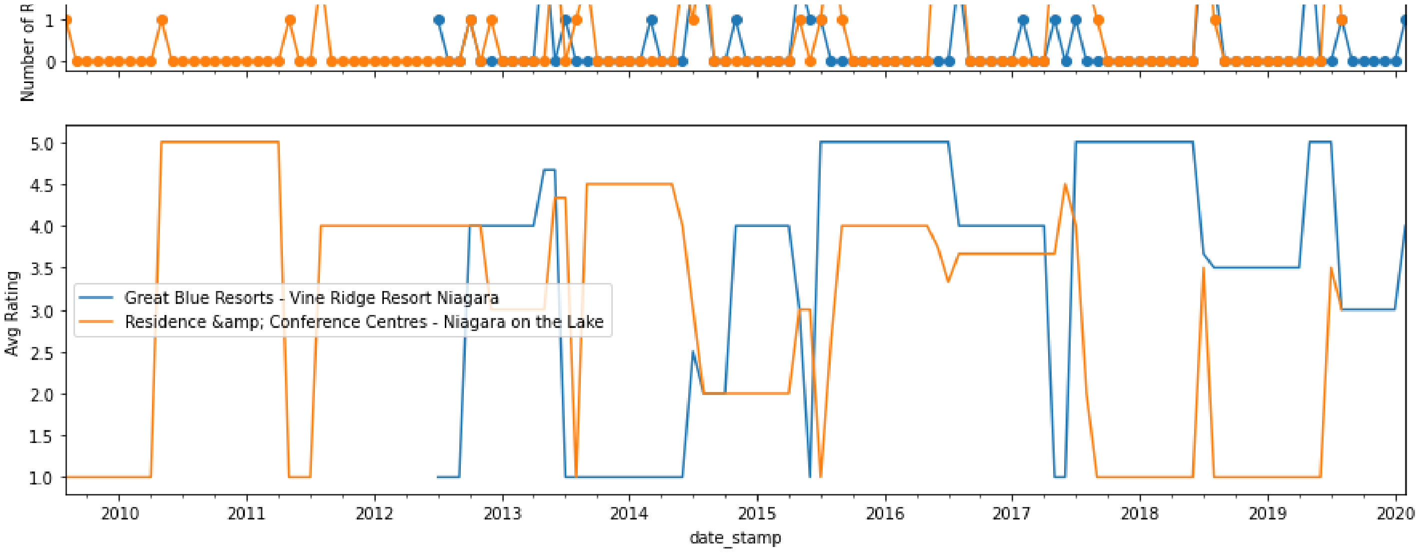
In [456]:

```
# It can be useful to see when reviews were being made and how the ratings changed
fig, ax = plt.subplots(2, 1, figsize=(15,7),
                       sharex=True,
                       gridspec_kw={
                           'height_ratios': [1, 2]})

for hotel in six_hotels[4:6]:
    _df = hotelDf[hotelDf['hotelName']==hotel]
    for i in _df.index:
        if 'ago' in _df.loc[i, 'date_stamp']:
            x=get_past_date(_df.loc[i, 'date_stamp'])
            _df.loc[i,'date_stamp']= x
    _df = _df[_df['hotelName']==hotel].set_index('date_stamp')

    _df.index = pd.to_datetime(_df.index)
    _df = _df.sort_index()
    _df['count'] = 1
    _df_monthly = _df.groupby(pd.Grouper(freq='M')).agg({'count':'sum','ratingScore':'mean
'})
    _df_monthly['ratingScore'] = _df_monthly['ratingScore'].fillna(method='ffill') # hold
the last rating constant in months with no reviews
    _df_monthly['count'].plot(ax=ax[0],label=hotel, marker='o')
    _df_monthly['ratingScore'].plot(ax=ax[1],label=hotel)

ax[1].set_ylabel('Avg Rating')
ax[0].set_ylabel('Number of Reviews per month')
plt.legend()
```

Out[456]:

```
<matplotlib.legend.Legend at 0x7f235f830a20>
```





These hotels have opposite trends for their avg rating (when blue is high, orange is low), a hypothesis could be that perhaps they are better in different seasons. Blue seems to do better in the winter months, where as orange seems to have a peak every summer in the past 3 years.del

I found it really difficult to obvserve a clear trend for this question. I think looking at the orginial graph with all 6 hotels, there seem to be a peak in review rates in the middle-end of the year. This is fall and when local vineyards carry out their harvest. I can hypothesize that this might be the best time to visit Niagara-on-the-lake.