proj1b

May 15, 2020

```
[1]: # Initialize OK
from client.api.notebook import Notebook
ok = Notebook('proj1b.ok')
```

```
=====================================================================
Assignment: proj1b
OK, version v1.13.11
=====================================================================
```

1 Project 1 Part B

1.1 Due Date: Monday, Feb 24th, 11:59PM

1.2 Collaboration Policy

Data science is a collaborative activity. While you may talk with others about the homework, we ask that you **write your solutions individually**. If you do discuss the assignments with others please **include their names** below.

Collaborators: *list collaborators here*

1.3 Scoring Breakdown

Question	Points
1a	1
1b	2
1ci	3
1cii	1
2a	2
2b	1
2ci	4
2cii	2
2d	2
2e	1

Question	Points
2f	1
2g	3
3a	3
3b	4
3c	1
3d	2
4	5
Total	38

First we import the relevant libraries for this project.

[2]:
```
import pickle
import matplotlib
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import seaborn as sns
sns.set()
plt.style.use('fivethirtyeight')
```

In the following cell, we will load the cleaned data from Part A of Project 1. Note that we will be using the relevant data files based on the staff solution.

[3]:
```
ins = pickle.load(open('./data/ins.p', 'rb'))
vio = pickle.load(open('./data/vio.p', 'rb'))
ins2vio = pickle.load(open('./data/ins2vio.p', 'rb'))
bus = pickle.load(open('./data/bus.p', 'rb'))
```

Note: For all parts of this project requiring you to produce a visualization, we won't be enforcing any specific size on the plots you make, as long as they are clear (i.e. no overlaps) and follow the specifications.

[4]:
```
ins
```

[4]:
```
                    iid                    date  score                 type  \
0       100010_20190329  03/29/2019 12:00:00 AM     -1     New Construction
1       100010_20190403  04/03/2019 12:00:00 AM    100  Routine - Unscheduled
2       100017_20190417  04/17/2019 12:00:00 AM     -1        New Ownership
3       100017_20190816  08/16/2019 12:00:00 AM     91  Routine - Unscheduled
4       100017_20190826  08/26/2019 12:00:00 AM     -1  Reinspection/Followup
…                   …                       …    …                    …
26658      999_20180924  09/24/2018 12:00:00 AM     -1    Routine - Scheduled
26659      999_20181102  11/02/2018 12:00:00 AM     -1  Reinspection/Followup
26660      999_20190909  09/09/2019 12:00:00 AM     80  Routine - Unscheduled
26661       99_20171207  12/07/2017 12:00:00 AM     82  Routine - Unscheduled
26662       99_20180808  08/08/2018 12:00:00 AM     84  Routine - Unscheduled
```

```
          bid  timestamp  year Missing Score
0      100010 2019-03-29  2019          True
1      100010 2019-04-03  2019         False
2      100017 2019-04-17  2019          True
3      100017 2019-08-16  2019         False
4      100017 2019-08-26  2019          True
…        …          …    …           …
26658     999 2018-09-24  2018          True
26659     999 2018-11-02  2018          True
26660     999 2019-09-09  2019         False
26661      99 2017-12-07  2017         False
26662      99 2018-08-08  2018         False

[26663 rows x 8 columns]
```

[5]:
```
ins = ins[ins['score'] >= 0]
```

[6]:
```
ins
```

[6]:
```
                   iid                    date  score                 type  \
1      100010_20190403  04/03/2019 12:00:00 AM    100  Routine - Unscheduled
3      100017_20190816  08/16/2019 12:00:00 AM     91  Routine - Unscheduled
15     100041_20190520  05/20/2019 12:00:00 AM     83  Routine - Unscheduled
20     100055_20190425  04/25/2019 12:00:00 AM     98  Routine - Unscheduled
21     100055_20190912  09/12/2019 12:00:00 AM     82  Routine - Unscheduled
…                …                         …    …                    …
26654     999_20170714  07/14/2017 12:00:00 AM     77  Routine - Unscheduled
26656     999_20180123  01/23/2018 12:00:00 AM     80  Routine - Unscheduled
26660     999_20190909  09/09/2019 12:00:00 AM     80  Routine - Unscheduled
26661      99_20171207  12/07/2017 12:00:00 AM     82  Routine - Unscheduled
26662      99_20180808  08/08/2018 12:00:00 AM     84  Routine - Unscheduled

          bid  timestamp  year Missing Score
1      100010 2019-04-03  2019         False
3      100017 2019-08-16  2019         False
15     100041 2019-05-20  2019         False
20     100055 2019-04-25  2019         False
21     100055 2019-09-12  2019         False
…        …          …    …           …
26654     999 2017-07-14  2017         False
26656     999 2018-01-23  2018         False
26660     999 2019-09-09  2019         False
26661      99 2017-12-07  2017         False
26662      99 2018-08-08  2018         False

[14031 rows x 8 columns]
```

[7]:
```
vio
```

[7]:
```
                                          description  risk_category     vid
0   Consumer advisory not provided for raw or unde…  Moderate Risk  103128
1                 Contaminated or adulterated food      High Risk  103108
2            Discharge from employee nose mouth or eye  Moderate Risk  103117
3                       Employee eating or smoking  Moderate Risk  103118
4                           Food in poor condition  Moderate Risk  103123
..                                             …            …      …
60  Unclean unmaintained or improperly constructed…       Low Risk  103152
61                       Unpermitted food facility       Low Risk  103158
62          Unsanitary employee garments hair or nails       Low Risk  103136
63  Wiping cloths not clean or properly stored or …       Low Risk  103149
64                           Worker safety hazards       Low Risk  103159

[65 rows x 3 columns]
```

[8]:
```
ins2vio
```

[8]:
```
                   iid     vid
0       97975_20190725  103124
1       85986_20161011  103114
2       95754_20190327  103124
3       77005_20170429  103120
4        4794_20181030  103138
…                  …       …
40205   76958_20180919  103119
40206   80305_20190411  103149
40207   80233_20190417  103133
40208  100216_20190321  103119
40209   79430_20190418  103109

[40210 rows x 2 columns]
```

[9]:
```
bus
```

[9]:
```
         bid                         name                address  \
0       1000         HEUNG YUEN RESTAURANT           3279 22nd St
1     100010           ILLY CAFFE SF_PIER 39        PIER 39  K-106-B
2     100017  AMICI'S EAST COAST PIZZERIA            475 06th St
3     100026                LOCAL CATERING        1566 CARROLL AVE
4     100030              OUI OUI! MACARON  2200 JERROLD AVE STE C
…        …                           …                     …
6248   99948             SUSIECAKES BAKERY       3509 CALIFORNIA ST
6249   99988                 HINODEYA SOMA      303 02nd ST STE 102
6250   99991                       TON TON            422 GEARY ST
6251   99992     URBAN EXPRESS KITCHENS LLC            475 06th ST
```

```
6252   99993            THE BRIXTON SOUTH            701 02nd St

               city state postal_code     latitude    longitude  phone_number  \
0     San Francisco    CA       94110    37.755282  -122.420493         -9999
1     San Francisco    CA       94133 -9999.000000 -9999.000000   14154827284
2     San Francisco    CA       94103 -9999.000000 -9999.000000   14155279839
3     San Francisco    CA       94124 -9999.000000 -9999.000000   14155860315
4     San Francisco    CA       94124 -9999.000000 -9999.000000   14159702675
…               …   …         …          …            …           …
6248  San Francisco    CA       94118 -9999.000000 -9999.000000   14150452253
6249  San Francisco    CA       94107 -9999.000000 -9999.000000         -9999
6250  San Francisco    CA       94102 -9999.000000 -9999.000000   14155531280
6251  San Francisco    CA       94103 -9999.000000 -9999.000000   14150368085
6252  San Francisco    CA       94102 -9999.000000 -9999.000000   14158315871

     postal5
0      94110
1      94133
2      94103
3      94124
4      94124
…        …
6248   94118
6249   94107
6250   94102
6251   94103
6252   94102

[6253 rows x 10 columns]
```

[10]:
```python
filtered = ins[ins['score'] != -1]
filtered
```

[10]:
```
                   iid                    date  score                 type  \
1      100010_20190403  04/03/2019 12:00:00 AM    100  Routine - Unscheduled
3      100017_20190816  08/16/2019 12:00:00 AM     91  Routine - Unscheduled
15     100041_20190520  05/20/2019 12:00:00 AM     83  Routine - Unscheduled
20     100055_20190425  04/25/2019 12:00:00 AM     98  Routine - Unscheduled
21     100055_20190912  09/12/2019 12:00:00 AM     82  Routine - Unscheduled
…                  …                      …    …                     …
26654     999_20170714  07/14/2017 12:00:00 AM     77  Routine - Unscheduled
26656     999_20180123  01/23/2018 12:00:00 AM     80  Routine - Unscheduled
26660     999_20190909  09/09/2019 12:00:00 AM     80  Routine - Unscheduled
26661      99_20171207  12/07/2017 12:00:00 AM     82  Routine - Unscheduled
26662      99_20180808  08/08/2018 12:00:00 AM     84  Routine - Unscheduled

          bid  timestamp  year Missing Score
```

```
1       100010 2019-04-03  2019         False
3       100017 2019-08-16  2019         False
15      100041 2019-05-20  2019         False
20      100055 2019-04-25  2019         False
21      100055 2019-09-12  2019         False
…         …         …    …            …
26654      999 2017-07-14  2017         False
26656      999 2018-01-23  2018         False
26660      999 2019-09-09  2019         False
26661       99 2017-12-07  2017         False
26662       99 2018-08-08  2018         False

[14031 rows x 8 columns]
```

[11]:
```
filtered['score'].value_counts()
```

[11]:
```
100    1993
96     1681
92     1260
94     1250
90     1085
98     1080
88      659
86      516
87      513
85      453
89      395
83      367
81      286
93      277
84      276
91      268
82      240
80      197
79      178
78      149
77      128
75      120
76      111
74      101
72       77
73       69
71       63
70       48
68       29
69       28
65       25
```

```
67       24
66       16
64       15
63       11
62       10
60        7
59        5
61        5
58        4
57        4
55        3
51        1
45        1
46        1
54        1
48        1
Name: score, dtype: int64
```

[12]:
```
ins['score']
```

[12]:
```
1         100
3          91
15         83
20         98
21         82
         …
26654      77
26656      80
26660      80
26661      82
26662      84
Name: score, Length: 14031, dtype: int64
```

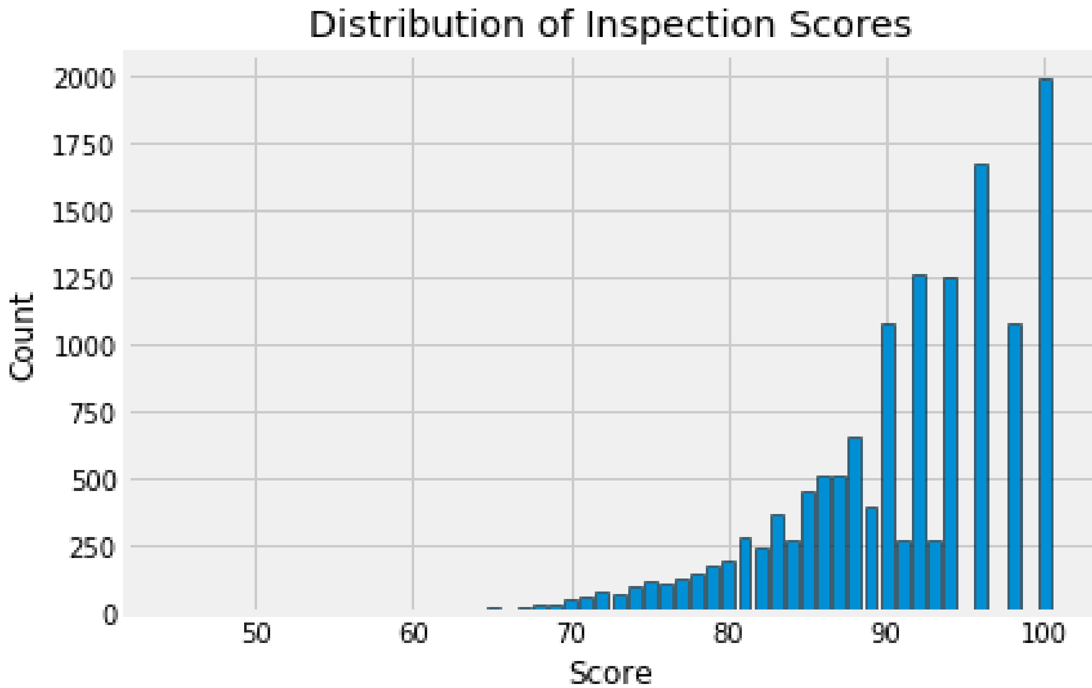
1.4 1: Explore Inspection Scores

In this first part we explore some of the basic inspection score values visually.

1.4.1 Question 1a

Let's look at the distribution of inspection scores. As we saw before when we called head on this data frame, inspection scores appear to be integer values. The discreteness of this variable means that we can use a barplot to visualize the distribution of the inspection score. Make a bar plot of the counts of the number of inspections receiving each score.

It should look like the image below. It does not need to look exactly the same (e.g., no grid), but make sure that all labels and axes are correct.



You might find this matplotlib.pyplot tutorial useful. Key syntax that you'll need:

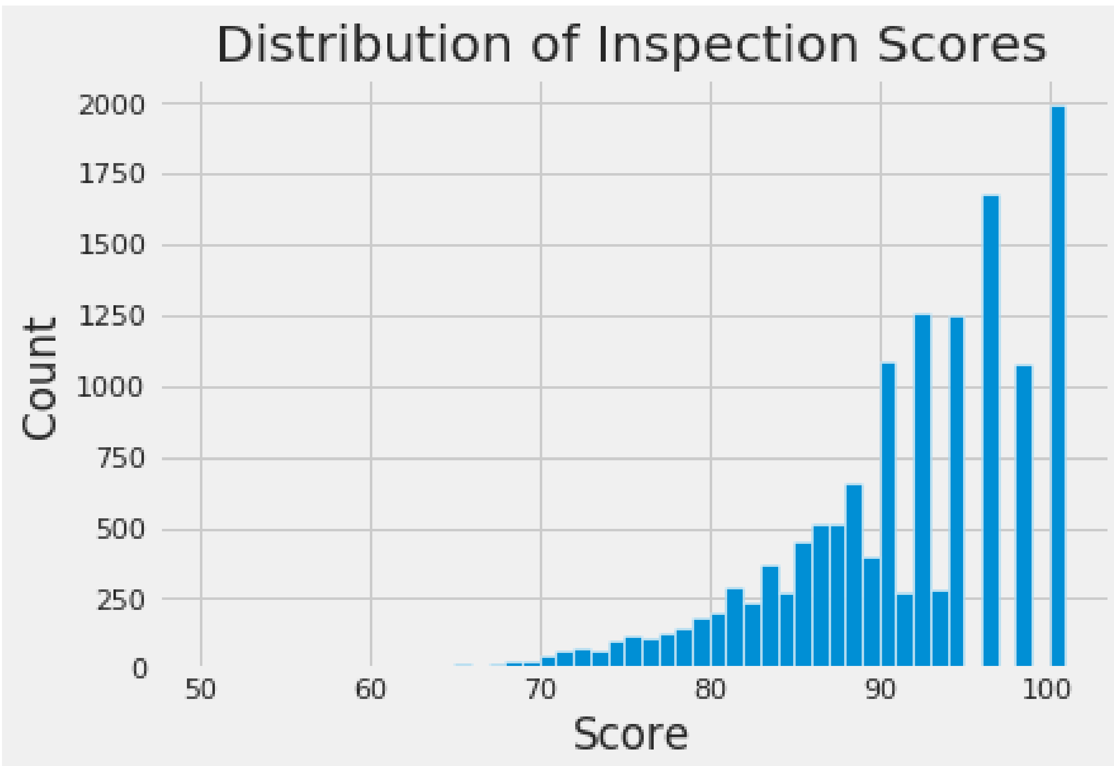
```
plt.bar
plt.xlabel
plt.ylabel
plt.title
```

Note: If you want to use another plotting library for your plots (e.g. plotly, sns) you are welcome to use that library instead so long as it works on DataHub. If you use seaborn sns.countplot(), you may need to manually set what to display on xticks.

[13]:
```
# # names = ['group_a', 'group_b', 'group_c']
# # values = [1, 10, 100]
# # plt.figure(figsize=(9, 3))
# # plt.bar(names, values)

# filtered = ins[ins['score'] != -1]
# names = [0, 50, 60, 70, 80, 90, 100]
# values = [250,500,750,1000,1250, 1500, 1750, 2000]

# plt.bar(names, height=values)

# plt.xlabel('Score')
# plt.ylabel('Count')
# plt.title('Distribution of Inspection Scores')
```

```python
bw_bins = range(50, 102, 1)
plt = filtered['score'].hist(bins=bw_bins, ec='w')
plt.set_xlabel('Score')
plt.set_ylabel('Count')
plt.set_title('Distribution of Inspection Scores')
```

[13]: Text(0.5, 1.0, 'Distribution of Inspection Scores')



1.4.2 Question 1b

Describe the qualities of the distribution of the inspections scores based on your bar plot. Consider the mode(s), symmetry, tails, gaps, and anomalous values. Are there any unusual features of this distribution? What do your observations imply about the scores?

Answer: + Modes: the great frequency of number score 100 (Peak) shows that there are more than 2000 restaurants that have perfect score. This is the highest/tallest amount of data we have in our graph.

- Symmetry: (negatively) Skewed LEFT distribution. The bulk of the observations are medium/large, with a few observations that are much smaller than the rest. For example, the score of 90, 92, 94, 96, 98, 100 are greatly higher than all other scores; and as we can see, the scores below 85 are much smaller than the rest. It follows the Pareto principle (also known as 80/20 rule), which states that "roughly 80% of the effects come from 20 % of the causes".
- Tails: the left tail (smaller values on the left) is much longer than the right tail (larger values on the right).
- Gaps: As we can see, there are no values/data for the restaurant scores of 95, 97, 99. Even though there are no outliers in this graph, there exists gaps between some of the largest score we have in the data.
- Anomalous values: as observed from the graph and the series below, there are no score of 95, 97, 99 in our data of restaurants.
- Observations: there are 3 unusual features of this distribution. Firstly, we observe that there are no (or very little) restaurants that have score lower than 65. Secondly, there are 3 anomalous score values on the graph: 95, 97, and 99: there are no restaurants that have this scores. Lastly, the score of 91 and 93 are greatly lower than its adjacent scores, including 90, 92, 94, 96, 98, 100.
- Implications: from observations, the restaurant food safety scores for restaurants in San Francisco has some restrictions for scores above 90 and below 65.

[14]:
```
filtered['score'].value_counts()
```

[14]:
```
100    1993
96     1681
92     1260
94     1250
90     1085
98     1080
88      659
86      516
87      513
85      453
89      395
83      367
81      286
93      277
84      276
91      268
82      240
80      197
79      178
78      149
77      128
75      120
```

```
76      111
74      101
72       77
73       69
71       63
70       48
68       29
69       28
65       25
67       24
66       16
64       15
63       11
62       10
60        7
59        5
61        5
58        4
57        4
55        3
51        1
45        1
46        1
54        1
48        1
Name: score, dtype: int64
```

1.4.3 Question 1c

Let's figure out which restaurants had the worst scores ever (single lowest score). Let's start by creating a new dataframe called `ins_named`. It should be exactly the same as ins, except that it should have the name and address of every business, as determined by the bus dataframe. If a `business_id` in ins does not exist in bus, the name and address should be given as `NaN`.

Hint: Use the merge method to join the ins dataframe with the appropriate portion of the bus dataframe. See the official documentation on how to use merge.

Note: For quick reference, a pandas left join keeps the keys from the left frame, so if ins is the left frame, all the keys from ins are kept and if a set of these keys don't have matches in the other frame, the columns from the other frame for these "unmatched" key rows contains NaNs.

[15]:
```
ins_named = pd.merge(ins, bus.drop(columns=['city','state','postal_code',␣
 ↪'latitude',
            'longitude', 'phone_number','postal5']), how='left')
ins_named
```

```
[15]:                  iid                    date  score                  type  \
0      100010_20190403  04/03/2019 12:00:00 AM    100  Routine - Unscheduled
1      100017_20190816  08/16/2019 12:00:00 AM     91  Routine - Unscheduled
2      100041_20190520  05/20/2019 12:00:00 AM     83  Routine - Unscheduled
3      100055_20190425  04/25/2019 12:00:00 AM     98  Routine - Unscheduled
4      100055_20190912  09/12/2019 12:00:00 AM     82  Routine - Unscheduled
…                  …                       …    …                     …
14026     999_20170714  07/14/2017 12:00:00 AM     77  Routine - Unscheduled
14027     999_20180123  01/23/2018 12:00:00 AM     80  Routine - Unscheduled
14028     999_20190909  09/09/2019 12:00:00 AM     80  Routine - Unscheduled
14029      99_20171207  12/07/2017 12:00:00 AM     82  Routine - Unscheduled
14030      99_20180808  08/08/2018 12:00:00 AM     84  Routine - Unscheduled

          bid  timestamp  year Missing Score                         name  \
0      100010 2019-04-03  2019         False        ILLY CAFFE SF_PIER 39
1      100017 2019-08-16  2019         False    AMICI'S EAST COAST PIZZERIA
2      100041 2019-05-20  2019         False               UNCLE LEE CAFE
3      100055 2019-04-25  2019         False                Twirl and Dip
4      100055 2019-09-12  2019         False                Twirl and Dip
…        …         …    …           …                          …
14026     999 2017-07-14  2017         False           SERRANO'S PIZZA II
14027     999 2018-01-23  2018         False           SERRANO'S PIZZA II
14028     999 2019-09-09  2019         False           SERRANO'S PIZZA II
14029      99 2017-12-07  2017         False  J & M A-1 CAFE RESTAURANT LLC
14030      99 2018-08-08  2018         False  J & M A-1 CAFE RESTAURANT LLC

                             address
0                  PIER 39  K-106-B
1                       475 06th St
2                    3608 BALBOA ST
3      335 Martin Luther King Jr. Dr
4      335 Martin Luther King Jr. Dr
…                                …
14026                  3274 21st St
14027                  3274 21st St
14028                  3274 21st St
14029                   779 Clay St
14030                   779 Clay St

[14031 rows x 10 columns]
```

```
[16]: ok.grade("q1ci");
```

```
~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~
Running tests

---------------------------------------------------------------------
```

```
Test summary
    Passed: 3
    Failed: 0
[ooooooooook] 100.0% passed
```

[17]:

```
worst_restaurant = ins_named[ins_named['score'] > 0].sort_values(by='score',␣
↪ascending=True)
worst_restaurant.head(20)
```

[17]:

```
                    iid                    date  score                   type  \
10898  86718_20180522  05/22/2018 12:00:00 AM     45  Routine - Unscheduled
291     1154_20190327  03/27/2019 12:00:00 AM     46  Routine - Unscheduled
236    10877_20190701  07/01/2019 12:00:00 AM     48  Routine - Unscheduled
6433   67237_20180914  09/14/2018 12:00:00 AM     51  Routine - Unscheduled
10285  84590_20181001  10/01/2018 12:00:00 AM     54  Routine - Unscheduled
5065   59828_20190820  08/20/2019 12:00:00 AM     55  Routine - Unscheduled
7423   71310_20181203  12/03/2018 12:00:00 AM     55  Routine - Unscheduled
12390  91843_20180822  08/22/2018 12:00:00 AM     55  Routine - Unscheduled
12028  90622_20180821  08/21/2018 12:00:00 AM     57  Routine - Unscheduled
7446   71440_20161121  11/21/2016 12:00:00 AM     57  Routine - Unscheduled
6954   69282_20190123  01/23/2019 12:00:00 AM     57  Routine - Unscheduled
6353   66961_20170724  07/24/2017 12:00:00 AM     57  Routine - Unscheduled
6333   66874_20170315  03/15/2017 12:00:00 AM     58  Routine - Unscheduled
9204   80316_20190703  07/03/2019 12:00:00 AM     58  Routine - Unscheduled
12943  94351_20190508  05/08/2019 12:00:00 AM     58  Routine - Unscheduled
9410     811_20190326  03/26/2019 12:00:00 AM     58  Routine - Unscheduled
7374   71008_20190820  08/20/2019 12:00:00 AM     59  Routine - Unscheduled
6487   67564_20161108  11/08/2016 12:00:00 AM     59  Routine - Unscheduled
2135    3167_20180613  06/13/2018 12:00:00 AM     59  Routine - Unscheduled
9170   80242_20170501  05/01/2017 12:00:00 AM     59  Routine - Unscheduled

         bid  timestamp  year Missing Score  \
10898  86718 2018-05-22  2018         False
291     1154 2019-03-27  2019         False
236    10877 2019-07-01  2019         False
6433   67237 2018-09-14  2018         False
10285  84590 2018-10-01  2018         False
5065   59828 2019-08-20  2019         False
7423   71310 2018-12-03  2018         False
12390  91843 2018-08-22  2018         False
12028  90622 2018-08-21  2018         False
7446   71440 2016-11-21  2016         False
6954   69282 2019-01-23  2019         False
6353   66961 2017-07-24  2017         False
6333   66874 2017-03-15  2017         False
9204   80316 2019-07-03  2019         False
```

```
12943  94351 2019-05-08  2019          False
9410     811 2019-03-26  2019          False
7374   71008 2019-08-20  2019          False
6487   67564 2016-11-08  2016          False
2135    3167 2018-06-13  2018          False
9170   80242 2017-05-01  2017          False

                                    name            address
10898                           Lollipot     890 Taraval St
291                  SUNFLOWER RESTAURANT    506 Valencia St
236                      CHINA FIRST INC.     336 CLEMENT ST
6433                              La Jefa  445 Bayshore Blvd
10285                        Chaat Corner         320 3rd St
5065                       Tip Top Market         84 Turk St
7423   Golden King Vietnamese Restaurant        757 Clay St
12390             Hello Sandwich & Noodle      426 Larkin St
12028                      Taqueria Lolita     750 Phelps St
7446           New Garden Restaurant, Inc.     716 Kearny St
6954          New Jumbo Seafood Restaurant   1532 NORIEGA St
6353                     Mi Tierra Market    2023 MISSION St
6333          Peninsula Seafood Restaurant    641 Jackson St
9204                   Kingdom of Dumpling   1713 Taraval St
12943                          VBowls LLC    1200 Vermont St
9410                      EDEN PLAZA CAFE    600 HARRISON St
7374                     House of Pancakes       937 TARAVAL
6487                                ITHAI       720 Post St
2135                          MING'S DINER   2129 Taraval St
9170                 Wing Lee BBQ Restaurant   501 Clement St.
```

1.4.4 Use the cell above to identify the restaurant with the lowest inspection scores ever. Be sure to include the name of the restaurant as part of your answer in the cell below. You can also head to yelp.com and look up the reviews page for this restaurant. Feel free to add anything interesting you want to share.

Answer:

- The restaurant with the lowest inspection scores ever: Lollipot

[18]:
```
ins[ins['bid']==86718]
```

[18]:
```
                 iid                    date  score                   type  \
19076  86718_20161116  11/16/2016 12:00:00 AM     90  Routine - Unscheduled
19077  86718_20180522  05/22/2018 12:00:00 AM     45  Routine - Unscheduled
19079  86718_20181005  10/05/2018 12:00:00 AM     90  Routine - Unscheduled

         bid  timestamp  year Missing Score
19076  86718 2016-11-16  2016         False
```

```
19077   86718 2018-05-22   2018          False
19079   86718 2018-10-05   2018          False
```

1.5 2: Restaurant Ratings Over Time

Let's consider various scenarios involving restaurants with multiple ratings over time.

1.5.1 Question 2a

Let's see which restaurant has had the most extreme improvement in its rating, aka scores. Let the "swing" of a restaurant be defined as the difference between its highest-ever and lowest-ever rating. **Only consider restaurants with at least 3 ratings, aka rated for at least 3 times (3 scores)!** Using whatever technique you want to use, assign `max_swing` to the name of restaurant that has the maximum swing.

Note: The "swing" is of a specific business. There might be some restaurants with multiple locations; each location has its own "swing".

The city would like to know if the state of food safety has been getting better, worse, or about average. This is a pretty vague and broad question, which you should expect as part of your future job as a data scientist! However for the ease of grading for this assignment, we are going to guide you through it and offer some specific directions to consider.

[19]:
```
ins_valid = ins_named[ins_named['score'] > 0]
more_than_3 = ins_valid.groupby(['bid'],
                      as_index=False).filter(lambda x: x['bid'].count() >= 3)
def ammd(series):
    return max(series) - min(series)

swings = more_than_3.groupby(['bid']).agg(ammd)

max_swing_info = swings[swings['score'] == max(swings['score'])]
#return 86718 as bid of a df that has max(ammd) of score

more_than_3[more_than_3['bid'] == max_swing_info.index[0]]['name']
# return the name of the business that has bid = 86718

max_swing = 'Lollipot'

max_swing
```

[19]:
```
'Lollipot'
```

[20]:
```
ok.grade("q2a");
```

```
~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~
Running tests

---------------------------------------------------------------------
Test summary
    Passed: 1
    Failed: 0
[ooooooooook] 100.0% passed
```

[21]:
```
ins[ins['bid'] == 45]
```

[21]:
```
              iid                    date  score                  type  bid  \
6971  45_20170307  03/07/2017 12:00:00 AM     88  Routine - Unscheduled   45
6972  45_20170914  09/14/2017 12:00:00 AM     85  Routine - Unscheduled   45
6973  45_20180529  05/29/2018 12:00:00 AM     88  Routine - Unscheduled   45
6974  45_20190404  04/04/2019 12:00:00 AM     92  Routine - Unscheduled   45

      timestamp  year Missing Score
6971 2017-03-07  2017         False
6972 2017-09-14  2017         False
6973 2018-05-29  2018         False
6974 2019-04-04  2019         False
```

1.5.2 Question 2b

To get a sense of the number of times each restaurant has been inspected, create a multi-indexed dataframe called `inspections_by_id_and_year` where each row corresponds to data about a given business in a single year, and there is a single data column named count that represents the number of inspections for that business in that year. The first index in the MultiIndex should be on `bid`, and the second should be on year.

An example row in this dataframe might look tell you that `bid` is 573, `year` is 2017, and `count` is 4.

Hint: Use `groupby` to group based on both the `bid` and the `year`.

Hint: Use `rename` to change the name of the column to count.

[22]:
```
ins_valid = ins_named[ins_named['score'] > 0]
id_and_year = ins_valid.groupby(['bid', 'year'], as_index=False).agg(len)
id_and_year.drop(columns=['iid','date', 'score', 'type', 'timestamp',
                          'Missing Score','address'], inplace=True)
id_and_year.rename(columns={'name':'count'}, inplace=True)
id_and_year

inspections_by_id_and_year = pd.pivot_table(id_and_year, values=['count'],
```

```
                              index=['bid','year'])


inspections_by_id_and_year.head(50)
```

[22]:

```
          count
bid year
19  2017      1
    2018      1
24  2016      1
    2017      1
    2019      1
31  2018      1
    2019      1
45  2017      2
    2018      1
    2019      1
48  2018      2
54  2017      1
    2018      1
58  2017      1
    2018      1
    2019      1
61  2017      2
    2018      1
66  2017      1
    2018      2
73  2017      1
    2019      2
76  2016      1
    2017      1
    2019      1
77  2016      1
    2017      1
    2019      1
80  2017      1
    2018      1
88  2017      2
    2018      1
95  2017      2
    2018      1
    2019      1
98  2017      1
    2019      1
99  2017      1
    2018      1
101 2017      1
```

```
     2018       1
102  2016       1
     2017       1
     2018       1
     2019       1
108  2018       1
     2019       1
116  2017       1
     2019       2
121  2017       1
```

[23]:
```
ok.grade("q2b");
```

```
~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~
Running tests

---------------------------------------------------------------------
Test summary
    Passed: 2
    Failed: 0
[ooooooooook] 100.0% passed
```

You should see that some businesses are inspected many times in a single year. Let's get a sense of the distribution of the counts of the number of inspections by calling `value_counts`. There are quite a lot of businesses with 2 inspections in the same year, so it seems like it might be interesting to see what we can learn from such businesses.

[24]:
```
inspections_by_id_and_year['count'].value_counts()
```

[24]:
```
1    10580
2     1688
3       25
Name: count, dtype: int64
```

1.5.3 Question 2c

What's the relationship between the first and second scores for the businesses with 2 inspections in a year? Do they typically improve? For simplicity, let's focus on only 2018 for this problem, using `ins2018` data frame that will be created for you below.

First, make a dataframe called `scores_pairs_by_business` indexed by `business_id` (containing only businesses with exactly 2 inspections in 2018). This dataframe contains the field score_pair consisting of the score pairs ordered chronologically [first_score, second_score].

Plot these scores. That is, make a scatter plot to display these pairs of scores. Include on the plot a reference line with slope 1.

You may find the functions `sort_values`, `groupby`, `filter` and `agg` helpful, though not all necessary.

The first few rows of the resulting table should look something like:

	score_pair
bid	
48	[94, 87]
66	[98, 98]
146	[81, 90]
184	[90, 96]
273	[83, 84]

In the cell below, create `scores_pairs_by_business` as described above.

Note: Each score pair must be a list type; numpy arrays will not pass the autograder.

Hint: Use the filter method from lecture 5 to create a new dataframe that only contains restaurants that received exactly 2 inspections.

Hint: Our code that creates the needed DataFrame is a single line of code that uses `sort_values`, `groupby`, `filter`, `groupby`, `agg`, and `rename` in that order. Your answer does not need to use these exact methods.

[25]:
```
ins2018 = ins[ins['year'] == 2018]
# Create the dataframe here

scores_pairs_by_business = ins2018.sort_values(by=['date']).groupby(['bid'
        ,'year']).filter(lambda x: x['bid'].size == 2).groupby(['bid']).
 ↪agg(lambda x:
           x.tolist()).drop(columns=['iid','date','type','timestamp','year',
        'Missing Score']).rename(columns={'score':'score_pair'})
scores_pairs_by_business
```

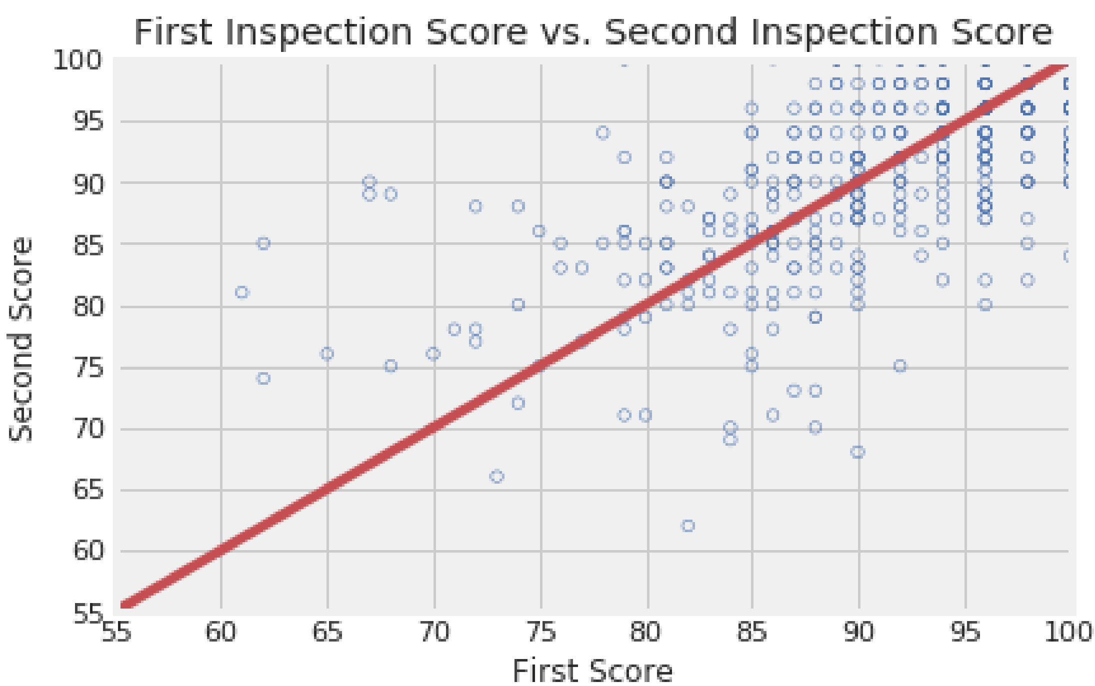
[25]:
```
       score_pair
bid
48       [94, 87]
66       [98, 98]
146      [81, 90]
184      [90, 96]
273      [83, 84]
…             …
95621  [100, 100]
95628    [75, 75]
95674   [100, 96]
95761    [91, 87]
95764   [100, 92]
```

[535 rows x 1 columns]

[26]:
```
ok.grade("q2ci");
```

```
~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~
Running tests

---------------------------------------------------------------------
Test summary
    Passed: 2
    Failed: 0
[ooooooooook] 100.0% passed
```

Now, create your scatter plot in the cell below. It does not need to look exactly the same (e.g., no grid) as the sample below, but make sure that all labels, axes and data itself are correct.



Key pieces of syntax you'll need:

`plt.scatter` plots a set of points. Use `facecolors='none'` and `edgecolors=b` to make circle markers with blue borders.

`plt.plot` for the reference line.

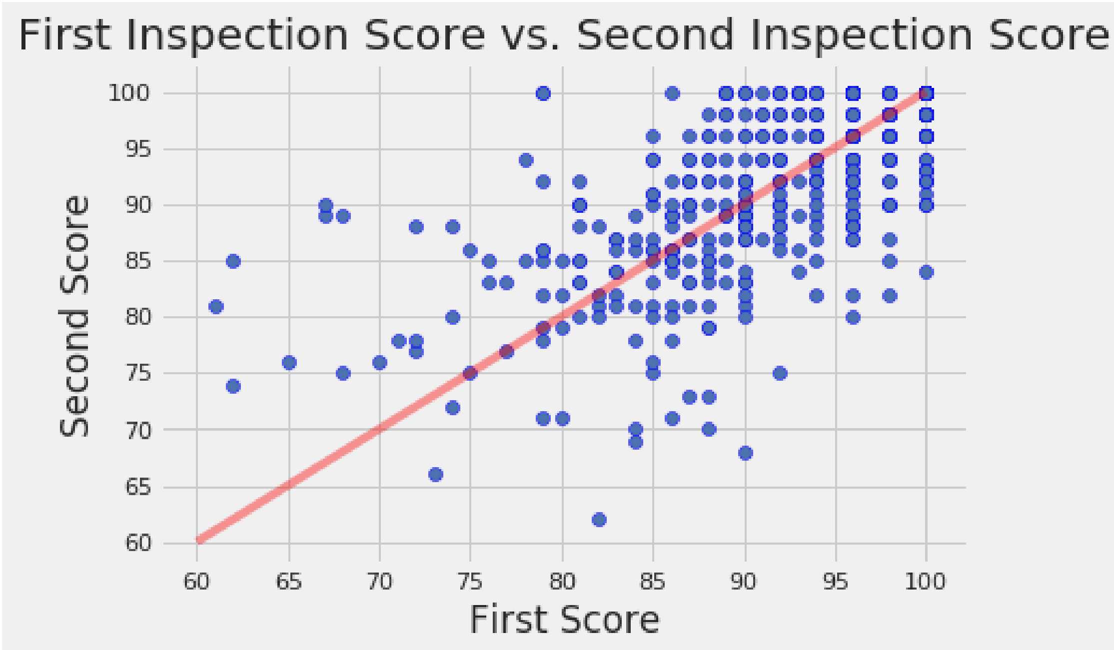
`plt.xlabel`, `plt.ylabel`, `plt.axis`, and `plt.title`.

Note: If you want to use another plotting library for your plots (e.g. `plotly`, `sns`) you are welcome to use that library instead so long as it works on DataHub.

Hint: You may find it convenient to use the `zip()` function to unzip scores in the list.

[27]:
```python
import matplotlib.pyplot as plt
# bw_bins = range(50, 102, 1)
# plt = filtered['score'].hist(bins=bw_bins, ec='w')
# plt.set_xlabel('Score')
# plt.set_ylabel('Count')
# plt.set_title('Distribution of Inspection Scores')

plt.figure()

x = np.linspace(60,100,5)
y = x
plt.plot(x, y, color = 'red', alpha=0.4)

score1 = [scores_pairs_by_business['score_pair'][i][0]
          for i in scores_pairs_by_business.index
          if abs(scores_pairs_by_business['score_pair'][i][0] -
            scores_pairs_by_business['score_pair'][i][1]) <= 30]

score2 = [scores_pairs_by_business['score_pair'][i][1]
          for i in scores_pairs_by_business.index
        if abs(scores_pairs_by_business['score_pair'][i][0] -
            scores_pairs_by_business['score_pair'][i][1]) <= 30]

plt.scatter(score1, score2, c='b', marker='o',
            facecolors='none', edgecolors='blue')


plt.xlabel('First Score')
plt.ylabel('Second Score')
plt.title('First Inspection Score vs. Second Inspection Score')
```

[27]:
```
Text(0.5, 1.0, 'First Inspection Score vs. Second Inspection Score')
```

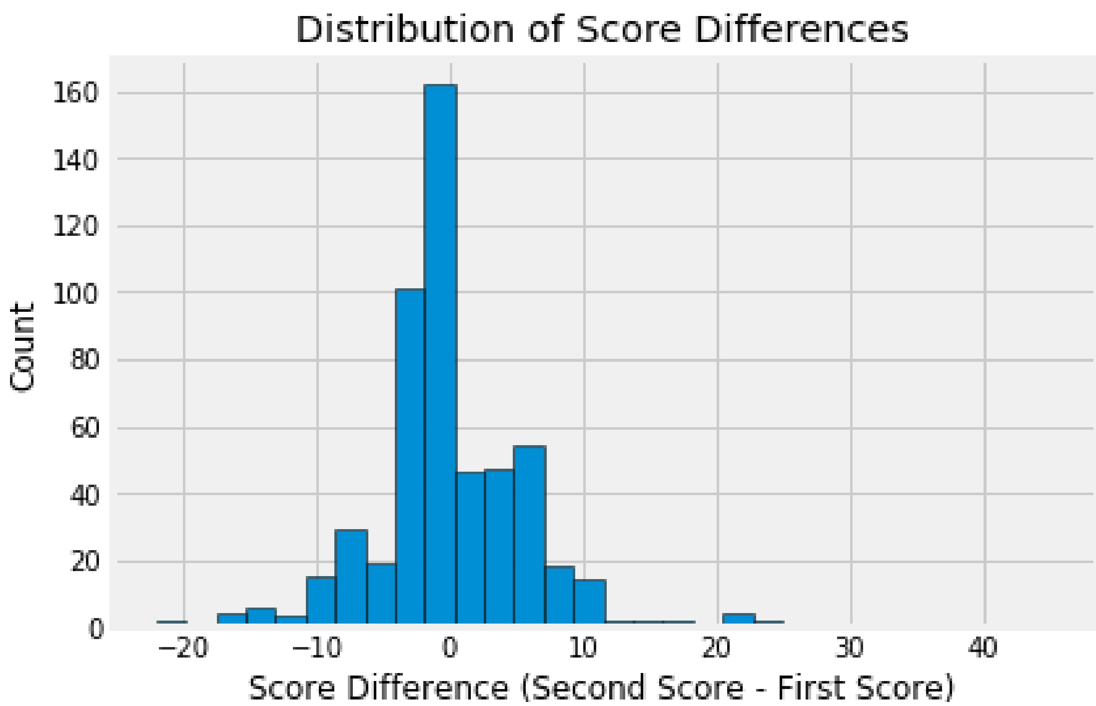


[ ]:

1.5.4 Question 2d

Another way to compare the scores from the two inspections is to examine the difference in scores. Subtract the first score from the second in `scores_pairs_by_business`. Make a histogram of these differences in the scores. We might expect these differences to be positive, indicating an improvement from the first to the second inspection.

The histogram should look like this:



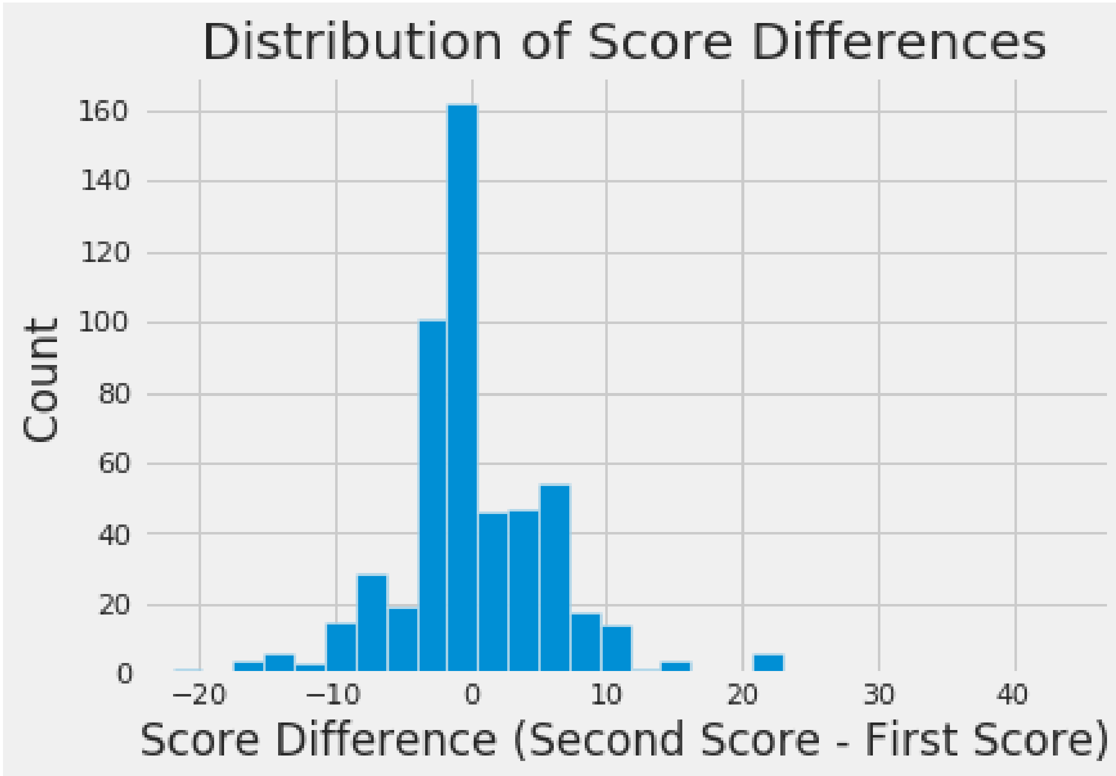
Hint: Use `second_score` and `first_score` created in the scatter plot code above.

Hint: Convert the scores into numpy arrays to make them easier to deal with.

Hint: Use `plt.hist()` Try changing the number of bins when you call `plt.hist()`.

[28]:
```
first_score = np.asarray(score1)
second_score = np.asarray(score2)

plt.hist(second_score-first_score, bins=20)
plt.xlabel('Score Difference (Second Score - First Score)')
plt.ylabel('Count')
plt.title('Distribution of Score Differences')
plt.xlim(right=47)
```

[28]:
```
(-24.25, 47)
```



[29]:
```
score_diff = [score2[i]-score1[i] for i in range(len(score1))]
num_improved = [s for s in score_diff if s > 0]
num_failed = [s for s in score_diff if s < 0]
num_stayed = [s for s in score_diff if s == 0]
print('score_improved: ', len(num_improved))
print('score_failed: ', len(num_failed))
print('score_stayed: ', len(num_stayed))
```

```
score_improved:  192
score_failed:  196
score_stayed:  146
```

[30]:
```
len(score2)
```

[30]: 534

[31]:
```
192+196+146
```

[31]: 534

1.5.5

1.5.6 Question 2e

If restaurants' scores tend to improve from the first to the second inspection, what do you expect to see in the scatter plot that you made in question 2c? What do you oberve from the plot? Are your observations consistent with your expectations?

Hint: What does the slope represent?

- Answer:
- The slope is represented as the difference between first and second scores. If a point is in the upper part of the graph from the slope, it means that the restaurant improves its point. Else if a point is in the lower part of the graph from the slope, the retaurant detoriates its point.
- If restaurants' scores tend to improve from the first to the second inspection, we can expect to see there exists more points in the upper half of the graph (improvement). In other words, the density of the points in the lower-half of the graph will be more scare than the points in the upper-half.
- We can observe from the graph that the scores that improved or stayed as their first scores (sum of diff(s2-s1) >= 0) are more than the score that detoriated (sum of diff(s2-s1) < 0). We can check this using list comprehension as the cell below. However, if we only compare the points that differ in its first and second time of inspection, we can see that the total points of detoriation are more than the total points of improvement.
- This means that the food safety inspection in SF is very strict in its rules. Or restaurants made their mistakes and were reported by its clients. My observations are consistent with my expectations.

[32]:
```
score_diff = [score2[i]-score1[i] for i in range(len(score1))]
num_improved = [s for s in score_diff if s > 0]
num_failed = [s for s in score_diff if s < 0]
num_stayed = [s for s in score_diff if s == 0]
print('score_improved: ', len(num_improved))     #print 192
print('score_failed: ', len(num_failed))         #print 196
print('score_stayed: ', len(num_stayed))         #print 146
```

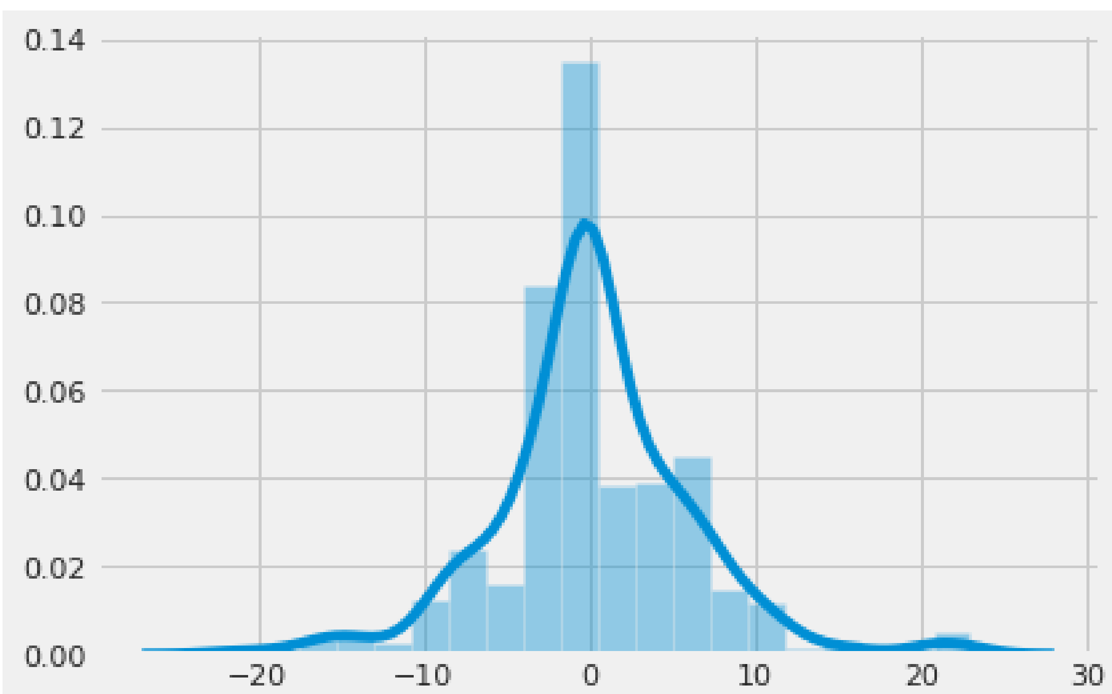
```
score_improved:  192
score_failed:  196
score_stayed:  146
```

1.5.7 Question 2f

If a restaurant's score improves from the first to the second inspection, how would this be reflected in the histogram of the difference in the scores that you made in question 2d? What do you oberve from the plot? Are your observations consistent with your expectations? Explain your observations in the language of Statistics: for instance, the center, the spread, the deviation etc.

- Answer:
- If a restaurant's score improves from the first to the second inspection, we can expect a reflection in the histogram above in the way that this retaurant's score will appear on the right hand side of the score difference 0.
- We can observe from the plot that the total restaurants that does not change their scores have highest counts. Meaning this diff(s2-s1)=0 is the PEAK(mode) of the graph. This is also the center of the graph. Meaning the total number of restaurants that did not change their scores is the highest amongst all retaurants that changed their scores.
- The spread of the graph: this graph has narrow distribution between its score, as we can see in the below graph. The range of scores is mostly in [-10,10].
- As we calculated in the cells below, the standard deviation of this graph is ~5.9. This is a high standard deviation, which indicates that the score values are spread out over the range[-10,10].
- My observations are consistent with my expectations, as explained in part 2e above.

[33]:
```
sns.distplot(second_score-first_score, bins = 20);
```



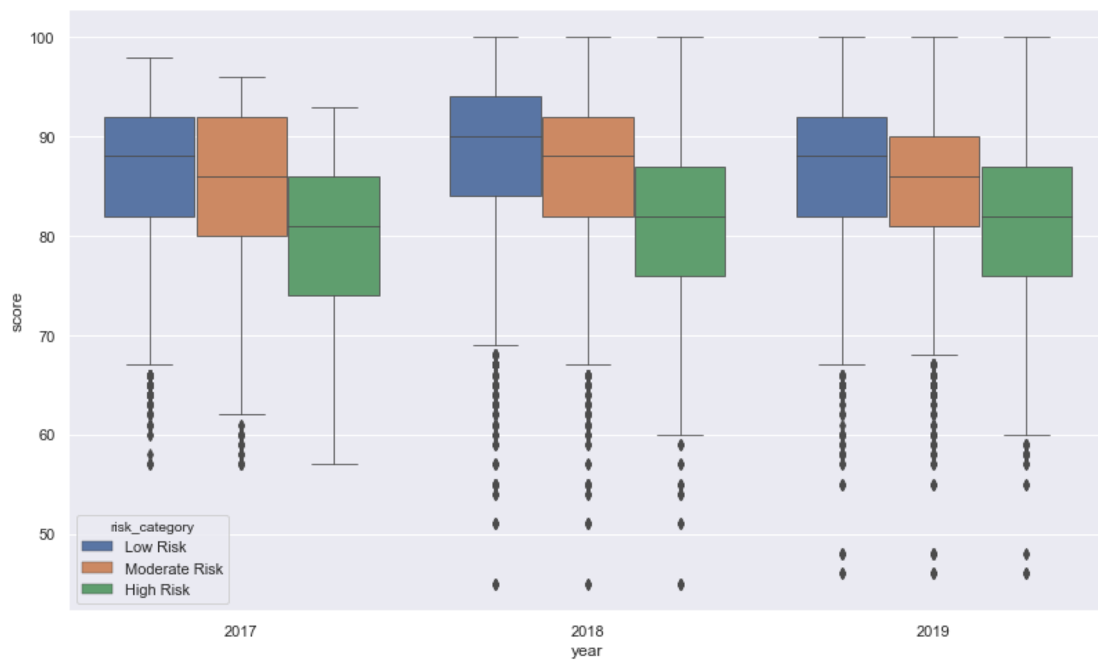
```
[34]: np.std(second_score-first_score)
```

```
[34]: 5.9224832315596565
```

1.5.8 Question 2g

To wrap up our analysis of the restaurant ratings over time, one final metric we will be looking at is the distribution of restaurant scores over time. Create a side-by-side boxplot that shows the distribution of these scores for each different risk category from 2017 to 2019. Use a figure size of at least 12 by 8.

The boxplot should look similar to the sample below:

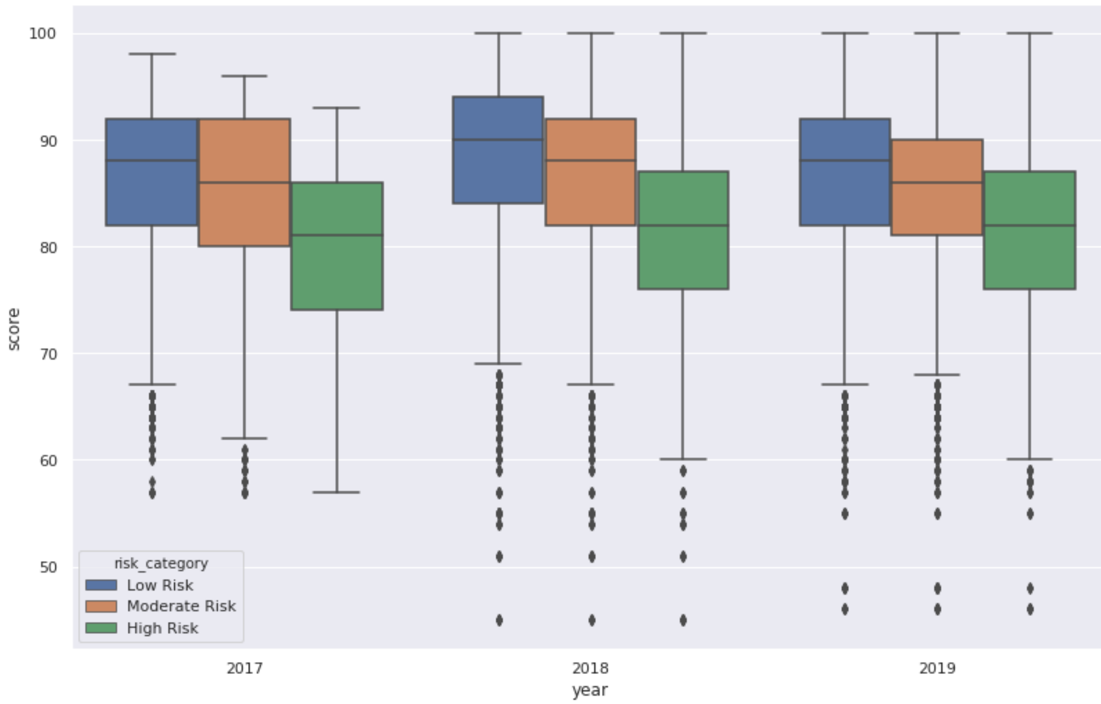


Hint: Use `sns.boxplot()`. Try taking a look at the first several parameters.

Hint: Use `plt.figure()` to adjust the figure size of your plot.

```
[35]: # Do not modify this line
sns.set()
plt.figure(figsize=(12,8))
m1 = pd.merge(ins.drop(columns=['date', 'bid', 'timestamp', 'type', 'Missing␣
 ↪Score']), ins2vio, how='left')
m2 = pd.merge(m1, vio, how='left')
m2 = m2[m2['year'] > 2016]
```

```
ax = sns.boxplot(x='year', y='score', hue='risk_category', data=m2,
                 hue_order=['Low Risk', 'Moderate Risk', 'High Risk'])
```



1.6 Question 3 Interpreting Visualizations

1.6.1 Question 3a

Given a set of data points (`x[i]`, `y[i]`, `c[i]`), a hexbin plot is a visualization of what the aggregated quantity of `c[i]` values are for each coordinate (`x[i]`, `y[i]`).

For example, given the following toy dataset:

x	y	c
1	0	3
1	0	4
1	0	5
2	1	1
2	1	2
3	-1	3

Assume the aggregate function we are using here is `np.size`, for each coordinate (x, y), we will be counting how many c values there are for that coordinate. Specifically,

- For the coordinate (x = 1, y = 0), we will have an aggregated value of 3 for c because there are three entires corresponding to (x = 1, y = 0).
- For the coordinate (x = 2, y = 1), we will have an aggregated value of 2 for c.
- For the coordinate (x = 3, y = -1) we will have an aggregated value of 1 for c.

These aggregated c values will be used to determine the intensity of the color that we assign to each hexigonal bin. It is also important to see that when the bins have the same size, counting the number of occurrences of c is equivalent to determining the density of c for each coordinate.

In the context of restaurant ratings, we can choose our `x[i]`, `y[i]`, `c[i]` values to be the longitude, latitude, and inspection score for each restaurant in San Francisco respectively. Since `x[i]` and `y[i]` also encode the geolocation of each restaurant, we can produce a geospatial hexbin plot that maps the density of scores to different locations within the city.

In order to produce the geospatial plot, we need to make sure we have all the data we need to create the plot. First, create a DataFrame `rated_geo` that includes the `longitude`, `latitude`, and `score` for each restaurant.

Hint: Note that not all the current data we have are actually valid. Some scores might be negative, and some longitude and latitudes are also invalid coordinates on Earth. Make sure to filter out those values in your resulting DataFrame.

Hint: Note that we are only concerned with the restaurant in the San Francisco region, so make sure that when you are filtering out the `latitude` and `longitude` columns, the range you provide in the flitering statement **makes sense** with the latitude and longitude of an actual location from San Francisco. **Don't worry too much about the how strict the bound needs to be**; as long as you cover all of San Francisco, you should be able to reproduce the same results we have for this question.

[36]:
```
valid_inspection = pd.merge(
        bus.drop(columns=['city','state','postal_code',
                          'phone_number','postal5', 'name']),
        ins.drop(columns=['iid', 'date','type', 'Missing Score']), how='left')

valid_inspection = valid_inspection[(valid_inspection['score'] >= 0)
         & (valid_inspection['longitude'] > -9999) &␣
 ↪(valid_inspection['latitude'] > -9999)]

rated_geo = valid_inspection.drop(columns=['bid','address','timestamp','year'])
rated_geo = rated_geo[rated_geo['longitude'] != 0]

rated_geo
```

[36]:

	latitude	longitude	score
0	37.755282	-122.420493	74.0
1	37.755282	-122.420493	76.0
2	37.755282	-122.420493	72.0

```
30     37.752158 -122.420362   85.0
31     37.752158 -122.420362   90.0
…          …          …     …
14492  37.780934 -122.399772   80.0
14493  37.780934 -122.399772   88.0
14552  37.756997 -122.420534   77.0
14553  37.756997 -122.420534   80.0
14554  37.756997 -122.420534   80.0

[7394 rows x 3 columns]
```

[37]:

```
ok.grade("q3a");
```

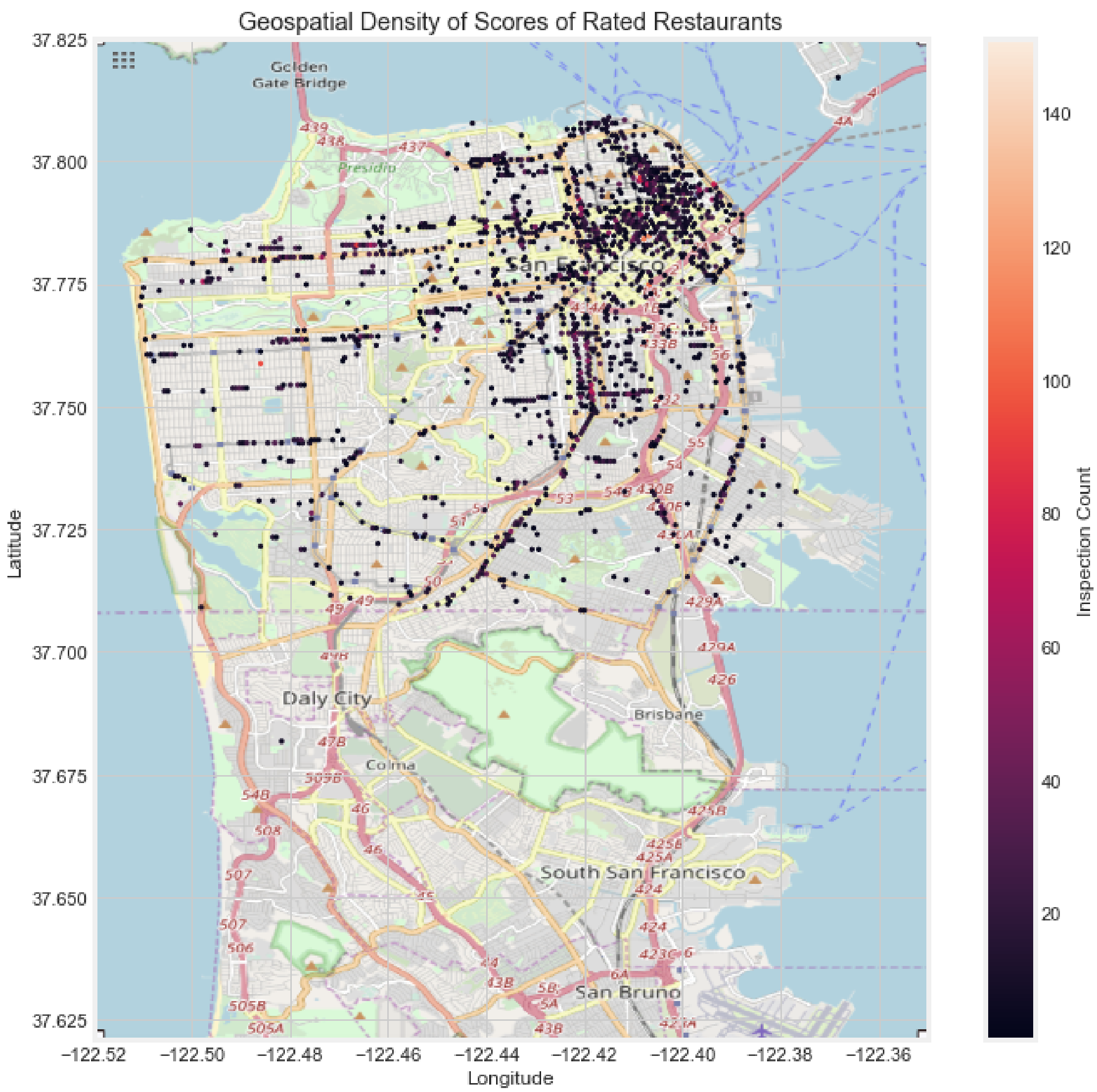
```
~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~
Running tests

---------------------------------------------------------------------
q3a > Suite 1 > Case 3

>>> (rated_geo.shape[0] > 20000) and (rated_geo.shape[0] < 25000) == True
False

# Error: expected
#     True
# but got
#     False

Run only this test case with "python3 ok -q q3a --suite 1 --case 3"
---------------------------------------------------------------------
Test summary
    Passed: 2
    Failed: 1
[ooooook…] 66.7% passed
```

1.6.2 Question 3b

Now that we have our DataFrame ready, we can start creating our geospatial hexbin plot.

Using the `rated_geo` DataFrame from 3a, produce a geospatial hexbin plot that shows the inspection count for all restaurant locations in San Francisco.

Your plot should look similar to the one below:



Hint: Use `pd.DataFrame.plot.hexbin()` or `plt.hexbin()` to create the hexbin plot.

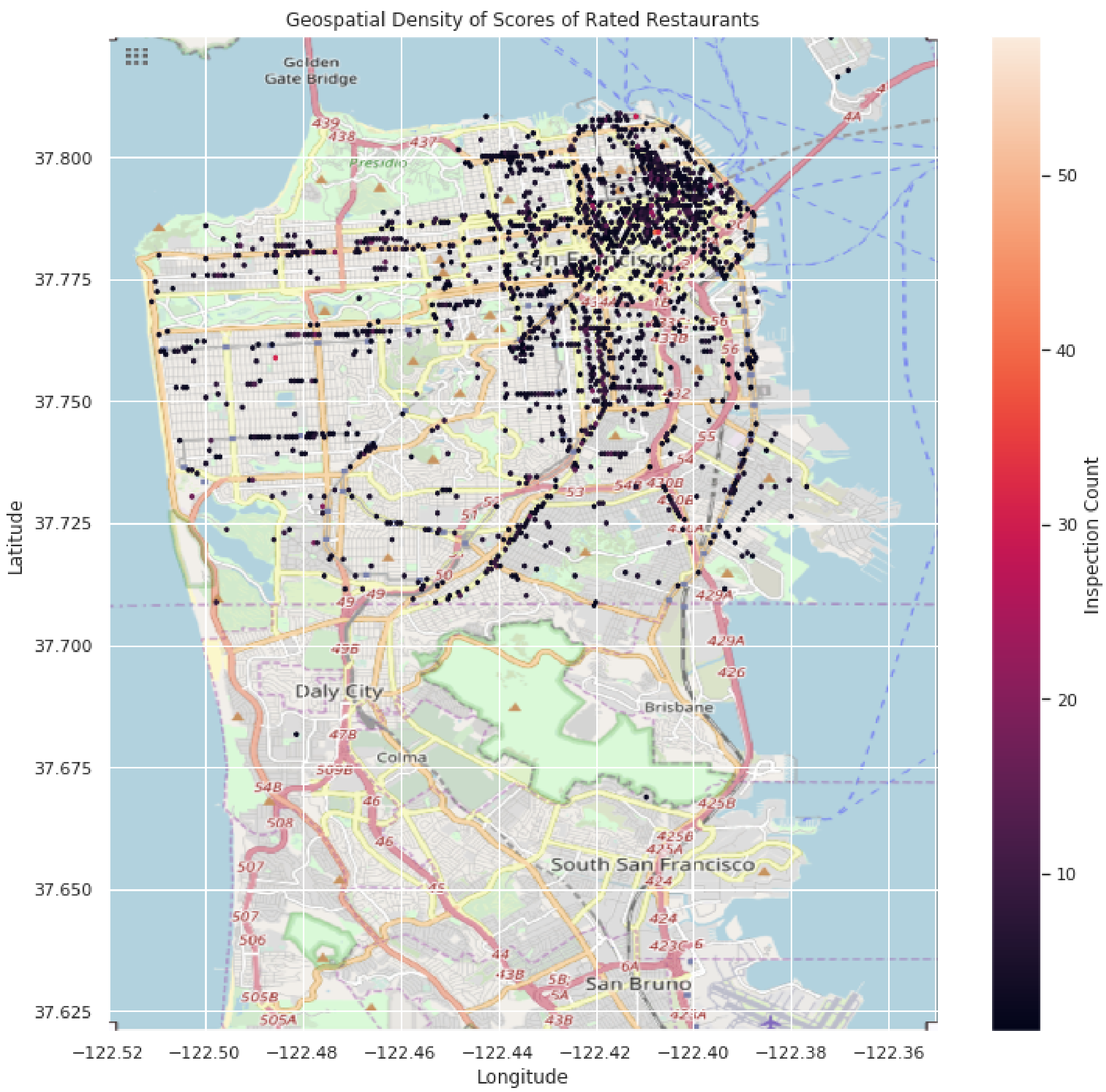
Hint: For the 2 functions we mentioned above, try looking at the parameter `reduce_C_function`, which determines the aggregate function for the hexbin plot.

Hint: Use `fig.colorbar()` to create the color bar to the right of the hexbin plot.

Hint: Try using a `gridsize` of 200 when creating your hexbin plot; it makes the plot cleaner.

[38]:
```
# DO NOT MODIFY THIS BLOCK
min_lon = rated_geo['longitude'].min()
max_lon = rated_geo['longitude'].max()
min_lat = rated_geo['latitude'].min()
max_lat = rated_geo['latitude'].max()
max_score = rated_geo['score'].max()
min_score = rated_geo['score'].min()
bound = ((min_lon, max_lon, min_lat, max_lat))
```

```python
min_lon, max_lon, min_lat, max_lat
map_bound = ((-122.5200, -122.3500, 37.6209, 37.8249))
# DO NOT MODIFY THIS BLOCK

# Read in the base map and setting up subplot
# DO NOT MODIFY THESE LINES
basemap = plt.imread('./data/sf.png')
fig, ax = plt.subplots(figsize = (11,11))
ax.set_xlim(map_bound[0],map_bound[1])
ax.set_ylim(map_bound[2],map_bound[3])
# DO NOT MODIFY THESE LINES


# Create the hexbin plot
ax.set_xlabel('Longitude')
ax.set_ylabel('Latitude')
ax.set_title('Geospatial Density of Scores of Rated Restaurants')

clm = ax.hexbin(x= rated_geo['longitude'], y=rated_geo['latitude'],
        C=rated_geo['score'], reduce_C_function=np.size,
                gridsize=200)

fig.colorbar(clm, label='Inspection Count')
#The reason the Inspection Count was off by 90 was because I only joined 2␣
↪tables


# Setting aspect ratio and plotting the hexbins on top of the base map layer
# DO NOT MODIFY THIS LINE
ax.imshow(basemap, zorder=0, extent = map_bound, aspect= 'equal');
# DO NOT MODIFY THIS LINE
```



1.6.3

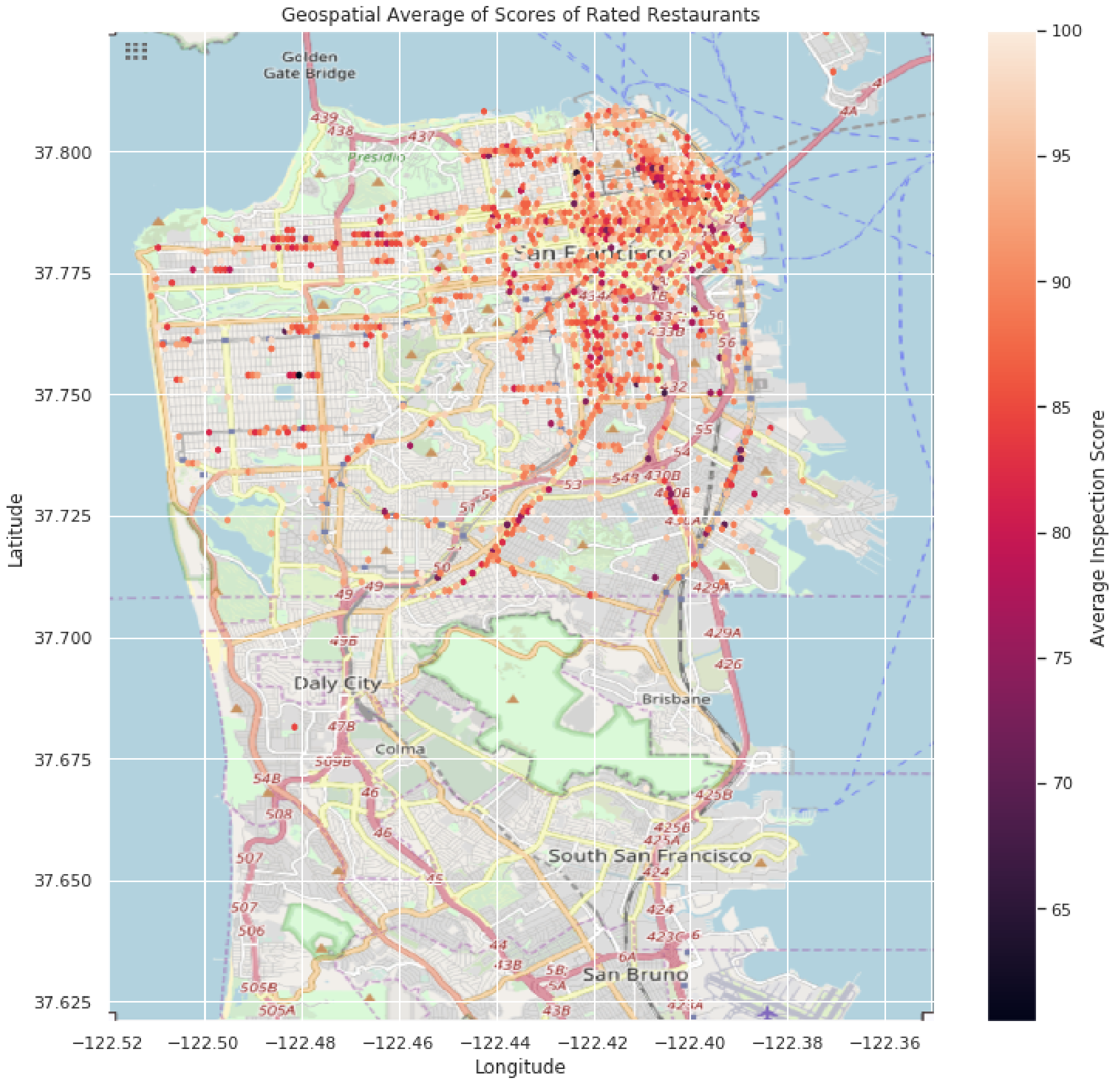
1.6.4 Question 3c

Now that we've created our geospatial hexbin plot for the density of inspection scores for restaurants in San Francisco, let's also create another hexbin plot that visualizes the **average inspection scores** for restaurants in San Francisco.

Hint: If you set up everything correctly in 3b, you should only need to change 1 parameter here to produce the plot.

[39]:

```
# Read in the base map and setting up subplot
# DO NOT MODIFY THESE LINES
basemap = plt.imread('./data/sf.png')
fig, ax = plt.subplots(figsize = (11,11))
ax.set_xlim(map_bound[0],map_bound[1])
ax.set_ylim(map_bound[2],map_bound[3])
# DO NOT MODIFY THESE LINES

# Create the hexbin plot
ax.set_xlabel('Longitude')
ax.set_ylabel('Latitude')
ax.set_title('Geospatial Average of Scores of Rated Restaurants')
clm = ax.hexbin(x= rated_geo['longitude'], y=rated_geo['latitude'],
        C=rated_geo['score'], reduce_C_function=np.mean,
                gridsize=150)
fig.colorbar(clm, label='Average Inspection Score')



# Setting aspect ratio and plotting the hexbins on top of the base map layer
# DO NOT MODIFY THIS LINE
ax.imshow(basemap, zorder=0, extent = map_bound, aspect= 'equal');
# DO NOT MODIFY THIS LINE
```



1.6.5 Question 3d

Given the 2 hexbin plots you have just created above, did you notice any connection between the first plot where we aggregate over the **inspection count** and the second plot where we aggregate over the **inspection mean**? In several sentences, comment your observations in the cell below.

Here're some of the questions that might be interesting to address in your response:

- Roughly speaking, did you notice any of the actual locations (districts/places of interest) where inspection tends to be more frequent? What about the locations where the average inspection score tends to be low?

- Is there any connection between the locations where there are more inspections and the locations where the average inspection score is low?
- What have might led to the connections that you've identified?

- Answer: The connection between the first plot where we aggregate over the INSPECTION COUNT and the second plot where we aggregate over the INSPECTION MEAN:

- Firstly, the first we can notice immediately is that most restaurants tend to be located in downtown SF. This is understandable because downtown of SF is the center of entertainment, business, and skyscrapers. Moreover, people usually visit SF near the piers where they can see all the fantastic view of the city. This is the reason why inspection tends to be more frequent in places near downtown SF, and more scarce outside the downtown.

- Secondly, the locations where average inspection score tends to be low are near the piers (not necessarily near downtown SF). Where there are more inspections (North-East side of downtown SF, near the piers and China Town), the average inspection score tends to be lower than those places where there are fewer inspections. This might be because people tend to be in places near downtown (large population), which makes it harder to keep food safe and cleaned since restaurant employees have to work extremely harder.

- However, we can see that in the North and North-West sides, the average score of restaurants tends to be very high (more than 90). This can be the result of fewer inspections and smaller population.

- As analyzed above, the reasons for those connections might be because of many factors: population density, environment near the Piers, people's hygiene awareness, or the diverse culture of the downtown of SF.

1.7 Summary of Inspections Data

We have done a lot in this project! Below are some examples of what we have learned about the inspections data through some cool visualizations!

- We found that the records are at the inspection level and that we have inspections for multiple years.
- We also found that many restaurants have more than one inspection a year.
- By joining the business and inspection data, we identified the name of the restaurant with the worst rating and optionally the names of the restaurants with the best rating.
- We identified the restaurant that had the largest swing in rating over time.
- We also examined the change of scores over time! Many restaurants are not actually doing better.
- We created cool hexbin plots to relate the ratings with the location of restaurants! Now we know where to go if we want good food!

1.8 Question 4 Create some more cool visualizations!

It is your turn now! Play with the data, and try to produce some visualizations to answer one question that you find interesting regarding the data. You might want to use `merge`/`groupby`/`pivot` to process the data before creating visualizations.

Please show your work in the cells below (feel free to use extra cells if you want), and describe in words what you found in the same cell. This question will be graded leniently, but good solutions may be used to create future homework problems.

1.8.1 Grading

Since the assignment is more open ended, we will have a more relaxed rubric, classifying your answers into the following three categories:

- **Great** (4-5 points): The chart is well designed, and the data computation is correct. The text written articulates a reasonable metric and correctly describes the relevant insight and answer to the question you are interested in.
- **Passing** (3-4 points): A chart is produced but with some flaws such as bad encoding. The text written is incomplete but makes some sense.
- **Unsatisfactory** (<= 2 points): No chart is created, or a chart with completely wrong results.

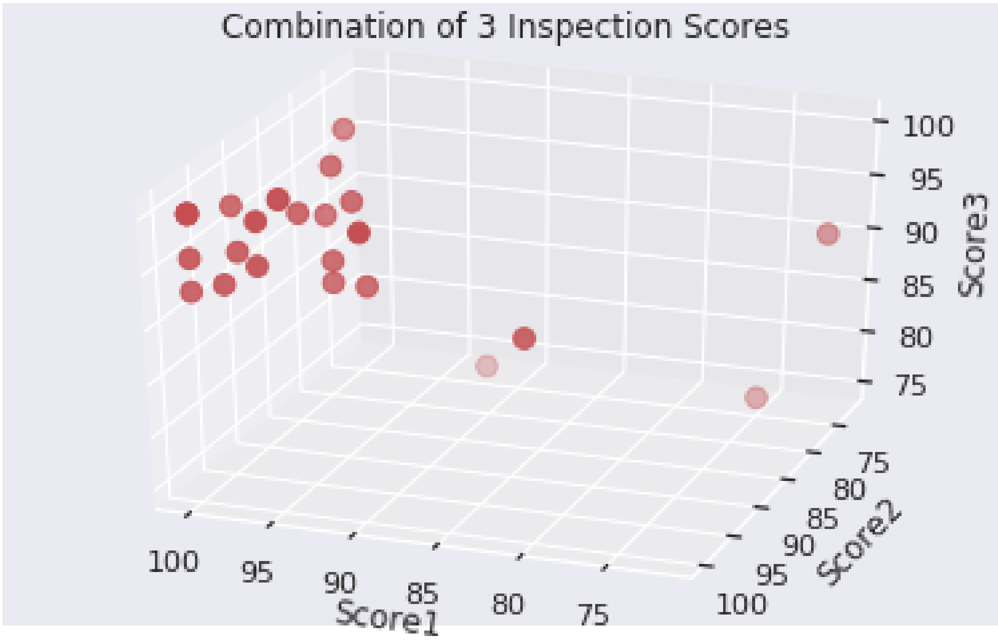
We will lean towards being generous with the grading. We might also either discuss in discussion or post on Piazza some examplar analysis you have done (with your permission)!

You should have the following in your answers: * a few visualizations; Please limit your visualizations to 5 plots. * a few sentences (not too long please!)

Please note that you will only receive support in OH and Piazza for Matplotlib and seaborn questions. However, you may use some other Python libraries to help you create you visualizations. If you do so, make sure it is compatible with the PDF export (e.g., Plotly does not create PDFs properly, which we need for Gradescope).

[40]:
```python
# YOUR DATA PROCESSING AND PLOTTING HERE
from mpl_toolkits.mplot3d import Axes3D

scores_triples_by_business = ins.sort_values(by=['date']).groupby(['bid'
        ,'year']).filter(lambda x: x['bid'].size == 3).groupby(['bid']).
 ↪agg(lambda x:
           x.tolist()).drop(columns=['iid','date','type','timestamp','year',
        'Missing Score']).rename(columns={'score':'score_triple'})

score1 = [scores_triples_by_business['score_triple'][i][0]
          for i in scores_triples_by_business.index
          if np.average(scores_triples_by_business['score_triple'][i][0]
            + scores_triples_by_business['score_triple'][i][1]
            + scores_triples_by_business['score_triple'][i][2]) >= 70]

score2 = [scores_triples_by_business['score_triple'][i][1]
          for i in scores_triples_by_business.index
        if abs(scores_triples_by_business['score_triple'][i][0]
            + scores_triples_by_business['score_triple'][i][1]
            + scores_triples_by_business['score_triple'][i][2]) >= 70]
```

```
score3 = [scores_triples_by_business['score_triple'][i][2]
          for i in scores_triples_by_business.index
          if abs(scores_triples_by_business['score_triple'][i][0]
            + scores_triples_by_business['score_triple'][i][1]
            + scores_triples_by_business['score_triple'][i][2]) >= 70]

fig = plt.figure()
ax = fig.add_subplot(111, projection='3d')
clm = ax.scatter(score1, score2, score3, c='r', s=60, marker='o',
             facecolors='none', edgecolors='r')

ax.set_xlabel('Score1')
ax.set_ylabel('Score2')
ax.set_zlabel('Score3')
ax.set_title('Combination of 3 Inspection Scores')
ax.view_init(30, 110)
plt.show()


# YOUR EXPLANATION HERE (in a comment):

# We now take a look at restaurants that have 3 inspection scores from␣
↪2016-2019.
# As we can see from the 3D graph below, most inspection scores are consistent.
# There are only 3 restaurants that have inconsisent scores of (72,72,90);␣
↪(92,75,75);
# (98, 82, 100). We can also take a look at the data frame below to see the␣
↪triples
# of restaurants score.
```



[41]:
```
scores_triples_by_business
```

[41]:

	score_triple
bid	
3838	[72, 72, 90]
4686	[94, 94, 92]
5528	[100, 100, 100]
5544	[100, 100, 100]
5823	[96, 89, 100]
5854	[98, 92, 98]
5855	[90, 100, 100]
5959	[98, 100, 94]
7649	[98, 92, 98]
7663	[94, 94, 94]
12970	[98, 82, 100]
32570	[82, 96, 90]
34434	[92, 75, 75]
65674	[75, 75, 75]
68974	[98, 98, 96]
81539	[94, 91, 98]
83755	[96, 100, 100]
86301	[96, 90, 96]
88862	[96, 94, 98]
89086	[92, 94, 92]
89678	[100, 94, 98]
91564	[100, 100, 96]

```
94938    [96, 100, 96]
94980  [100, 100, 100]
95253   [100, 100, 93]
```

[42]:
```
#Another interesting fact: WHERE ARE RESTAURANTS USUALLY INSPECTED THRICE?
#Data Manipulation
bid = scores_triples_by_business.index
scores_triples_by_business.index = [i for i in␣
 ↪range(len(scores_triples_by_business.index))]
scores_triples_by_business['bid'] = bid
scores_triples_by_business
```

[42]:
```
       score_triple    bid
0      [72, 72, 90]   3838
1      [94, 94, 92]   4686
2   [100, 100, 100]   5528
3   [100, 100, 100]   5544
4     [96, 89, 100]   5823
5      [98, 92, 98]   5854
6    [90, 100, 100]   5855
7     [98, 100, 94]   5959
8      [98, 92, 98]   7649
9      [94, 94, 94]   7663
10    [98, 82, 100]  12970
11     [82, 96, 90]  32570
12     [92, 75, 75]  34434
13     [75, 75, 75]  65674
14     [98, 98, 96]  68974
15     [94, 91, 98]  81539
16   [96, 100, 100]  83755
17     [96, 90, 96]  86301
18     [96, 94, 98]  88862
19     [92, 94, 92]  89086
20    [100, 94, 98]  89678
21   [100, 100, 96]  91564
22    [96, 100, 96]  94938
23  [100, 100, 100]  94980
24   [100, 100, 93]  95253
```

[43]:
```
triple_locs = pd.merge(scores_triples_by_business, bus.drop(
    columns=['city','state','postal_code', 'latitude','longitude',␣
 ↪'phone_number']), how='left')
triple_locs
```

[43]:
```
       score_triple    bid                                          name  \
0      [72, 72, 90]   3838                                   CAFE PICARO
1      [94, 94, 92]   4686                                   RICE GARDEN
```

2	[100, 100, 100]	5528	AT&T - Juma Cart 1 - Ice Cream
3	[100, 100, 100]	5544	AT&T - Juma Cart 1 - Coffee
4	[96, 89, 100]	5823	WEBSTER ELEMENTARY SCHOOL
5	[98, 92, 98]	5854	Gateway High/Kip Schools
6	[90, 100, 100]	5855	SOTA (SCHOOL OF THE ARTS)
7	[98, 100, 94]	5959	ST. JOHN'S SNACK BAR
8	[98, 92, 98]	7649	SERV U MARKET
9	[94, 94, 94]	7663	GGP MARKET
10	[98, 82, 100]	12970	LA COCINA
11	[82, 96, 90]	32570	Liang's Food
12	[92, 75, 75]	34434	Fang's
13	[75, 75, 75]	65674	Subway Sandwiches #25379
14	[98, 98, 96]	68974	Sushi Avenue Inc
15	[94, 91, 98]	81539	Fayes
16	[96, 100, 100]	83755	Heyday
17	[96, 90, 96]	86301	Cafe Murano
18	[96, 94, 98]	88862	Piece of Heaven
19	[92, 94, 92]	89086	Allegro Romano
20	[100, 94, 98]	89678	Bonito Poke
21	[100, 100, 96]	91564	Guckenheimer 1142.01
22	[96, 100, 96]	94938	94938 Anchor Grill Cart
23	[100, 100, 100]	94980	94980 Orlandos' Caribbean BBQ
24	[100, 100, 93]	95253	95253 C&C Concessions/Portable 142 Lemonade Cart

	address	postal5
0	3120 16th St	94103
1	1515 SLOAT Blvd	94132
2	24 WILLIE MAYS PLAZA	94107
3	24 WILLIE MAYS PLAZA	94107
4	465 MISSOURI St	94107
5	1430 Scott St	94115
6	555 Portola Dr	94131
7	925 CHENERY St	94131
8	2750 21st St	94110
9	2948 24th St	94110
10	2948 FOLSOM STREET	94110
11	1145 Stockton St	94133
12	660 Howard St	94105
13	30 02nd St	94105
14	1515 Sloat Blvd	94132
15	3614 18th St	94110
16	555 Mission St	94105
17	2301 Bryant St	94110
18	1380 Sutter St	94109
19	1701 Jones St	94109
20	2277 Shafter Ave	None
21	1 Market St.	94105

```
22         24 Willie Mays Pl Upper CF Sec 143   94107
23  24 Willie Mays Pl Upper Cent Fd  Sect 142   94107
24   24 Willie Mays Pl Upper Cent Fd Sect 142   94107
```

[44]:
```
triple_locs.groupby('postal5').agg(np.size)
```

[44]:

postal5	score_triple	bid	name	address
94103	1	1	1	1
94105	4	4	4	4
94107	6	6	6	6
94109	2	2	2	2
94110	5	5	5	5
94115	1	1	1	1
94131	2	2	2	2
94132	2	2	2	2
94133	1	1	1	1

[45]:
```
# YOUR EXPLANATION HERE (in a comment):
# Based on this link that shows the zipcode of SF:
# http://www.healthysf.org/bdi/outcomes/zipmap.htm
# We can see that most restaurants that have been
# inspected thrice located near the piers of SF.
```

[46]:
```
# THIS CELL AND ANY CELLS ADDED BELOW WILL NOT BE GRADED
```

1.9 Congratulations! You have finished Part B of Project 1!

2 Submit

Make sure you have run all cells in your notebook in order before running the cell below, so that all images/graphs appear in the output. **Please save before submitting!**

[47]:
```
# Save your notebook first, then run this cell to submit.
import jassign.to_pdf
jassign.to_pdf.generate_pdf('proj1b.ipynb', 'proj1b.pdf')
ok.submit()
```

```
Generating PDF…
Saved proj1b.pdf

<IPython.core.display.Javascript object>


<IPython.core.display.Javascript object>
```

```
Saving notebook…

ERROR  | auth.py:91 | {'error': 'invalid_grant'}

Saved 'proj1b.ipynb'.
Performing authentication
Please enter your bCourses email.
bCourses email: letantruong32@berkeley.edu

Copy the following URL and open it in a web browser. To copy,
highlight the URL, right-click, and select "Copy".

https://okpy.org/client/login/

After logging in, copy the code from the web page, paste it below,
and press Enter. To paste, right-click and select "Paste".

Paste your code here: hnW6PKTBnc4ynGwLeAgI3s03Gp3piA
Successfully logged in as letantruong32@berkeley.edu
Submit… 100% complete
Submission successful for user: letantruong32@berkeley.edu
URL: https://okpy.org/cal/data100/sp20/proj1b/submissions/w0JgDr
```

[ ]:

```

```