p2

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1 Project #1:

What Determines Business' Yelp Ratings in Toronto?
by Thomas Keough

1.1 Introduction

With broad access to review data on websites, online business ratings are becoming increasingly relevant to business owners. This is especially true of service-oriented businesses, such as restaurants, hair salons, and hotels. Customers prefer to visit well-reviewed businesses, which means businesses should care about their online ratings. By extension, this means that both businesses and customers are interested in identifying what causes a business to earn good reviews. This analysis seeks to understand the determinants of online business ratings by using metrics available on Yelp, one of the most popular websites for reviews.

This analysis using data acquired from Kaggle.com. The data was initially published by Yelp as part of a dataset challenge. It was last updated in August 2017 and includes data from 11 cities in four countries, including the USA and Canada. The dataset is composed of files pertaining to business attributes, hours of operation, reviews, check-ins, tips, and users. This analysis merges the files for business attributes, hours of operation, and check-ins for businesses in Toronto, Ontario. The dependent variable is business ratings, measured in Yelp stars. The chosen covariates are business' total number of Yelp reviews, total weekly hours of operation, and daily average number of Yelp check-ins.

The results of this analysis demonstrate that the number of reviews, hours of operation, and number of check-ins are all positively correlated with business ratings. The effect of the number of reviews depends in part on the type of business. It is likely that the effect of hours of operation and number of check-ins also differ depending on the business's industry. In the future, businesses should be grouped by industry to identify if the hours of operation and number of check-ins also depend on the type of business. Further, a control variable for population density should be included in the analysis because the number of reviews and check-ins seem to be biased by the population of a business's postal code region.

1.2 Data Cleaning

(i) Setting Up The Project

Y: Business Rating ('stars')
This analysis seeks to identify the determinants of business ratings using quantitative data gathered from Yelp. The outcome variable is the business rating, which is referred to as "stars" in the dataset.

This variable takes a value between 1 and 5. It is discrete data; potential values must be multiples of 0.5. This analysis includes three covariates of interest.

X1: Number of Reviews (‘review_count’)
The first covariate is the total number of reviews for each business. It is discrete. The review system is an extremely prominent feature of Yelp and is used frequently, so the number of reviews should account for a significant proportion of the variation in business ratings. There are two valid hypotheses for the correlation between the number of reviews with business ratings. For instance, a business that has exceptionally good service can encourage Yelp users to leave positive reviews. This would suggest that the number of reviews is positively associated with business ratings. However, the opposite effect is also feasible; exceptionally poor service may encourage Yelp users to leave negative reviews, meaning the number of reviews would be negatively correlated with business ratings. The dominant hypothesis, should one exist, will manifest itself through an empirical analysis of the relationship between review count and ratings.

X2: Number of Operating Hours per Week (‘wk_op_hours’)
The second covariate is the number of operating hours in a week for a business. Businesses differ largely in hours of operation on a day-to-day basis, so using the weekly total of operating hours will account for those differences across the days of the week. This variable will provide insight on the effect of customer access to businesses, which may be a component in evaluating business quality from the perspective of customers. There are several hypotheses for the direction of the relationship between operating hours and business ratings. It could be that businesses that are open longer throughout the week earn more reviews because they can serve more customers. Therefore, the direction of the relationship would be dependent on the ambiguous effect of the number of reviews on business ratings. Alternatively, businesses that are open for fewer hours per week may instill a sense of exclusivity in its customers. For example, fine dining venues, nightclubs, and other businesses that have limited weekly operating hours may observe more positive reviews because attendees feel exclusive.

X3: Average Number of Check-ins per Day (‘daily_checkin_avg’)
The third covariate is the average number of Yelp check-ins per day. It is important to note that this calculation of the daily check-in average ignores days wherein businesses had zero check-ins. In other words, it is the average number of check-ins for days that had at least one check-in. “Checking in” is a Yelp feature that allows users to inform their Yelp following of the businesses they visit. When a user “checks in” to a business, their attendance is published on their profile. Users can also earn badges and special offers at businesses they check in at. These two components provide increased incentives for Yelp users to visit high-quality businesses; users can show off their attendance at a popular business and potentially earn discounts in the process. Comparatively, poor-quality businesses would have fewer check-ins since users would not want to publish their attendance at them. Therefore, this variable accounts for customer perception of businesses. Therefore, check-ins should be positively correlated with a business’s ratings in theory. An OLS regression that utilizes this covariate and the number of reviews would provide insight on how the number of reviews affects a business’s rating while holding constant the customers’ perception of the business. This would provide insight on the causality of business ratings.

(ii) Data Cleaning

[ ]:
```
import pandas as pd
import matplotlib.pyplot as plt
```

```
import geopandas as gpd
from shapely.geometry import Point
import numpy as np
%matplotlib inline
```

[ ]:
```
# load data
df = pd.read_csv('/Users/thomas/Documents/schoolwork/eco225/yelp_data/
 ↪yelp_business.csv')
df2 = pd.read_csv('/Users/thomas/Documents/schoolwork/eco225/yelp_data/
 ↪yelp_checkin.csv')
df3 = pd.read_csv('/Users/thomas/Documents/schoolwork/eco225/yelp_data/
 ↪yelp_business_hours.csv')

# make copies
bsn_df = df.copy()
checkin_df = df2.copy()
hours_df = df3.copy()
```

[ ]:
```
# build Toronto businesses dataframe:

# make a df for Toronto businesses
tor_bsn = bsn_df.loc[bsn_df['city'] == 'Toronto']

# generate a restaurant dummy
tor_bsn['restaurant'] = tor_bsn['categories'].str.contains('Restaurant').
 ↪astype(int)

# generate a shops dummy
tor_bsn['shop'] = tor_bsn['categories'].str.contains('Shopping').astype(int)

# Incorporate check-in data:

# find average daily checkins for each business
all_checks = checkin_df.groupby('business_id').mean().
 ↪rename(columns={'checkins': 'daily_checkin_avg'})

# inner join on tor_bsn to get checkin data for each business in Toronto
tor_bsn = tor_bsn.merge(all_checks, on='business_id')

# === Incorporate weekly operating hours: ===

# build a function to clean hours_df

def count_hours(operating_hours: str) -> float:
    """Returns a float given a string of the form "HH:MM-HH:MM" that contains a␣
 ↪business's operating hours."""
```

```python
    # if business is closed on the given day:
    if operating_hours == 'None':
        return 0.0

    # '2000-01-01' is needed in the string that is converted to datetime to␣
 ↪avoid being out of pandas' accepted date range
    hours = operating_hours.split('-')
    opn = pd.to_datetime('2000-01-01 ' + hours[0])
    close = pd.to_datetime('2000-01-01 ' + hours[1])

    # if the business is open past midnight:
    if close < opn:
        end_date = '2000-01-02'
    else:
        end_date = '2000-01-01'

    # calculate a timedelta that accounts for hours of operation past midnight
    window = pd.to_timedelta(pd.to_datetime(f'{end_date} ' + hours[1]) - pd.
 ↪to_datetime('2000-01-01 ' + hours[0]))

    # return a float reprsenting the number of hours open in the given day
    return window.total_seconds() / (60 * 60)

# merge hours_df with tor_bsn to avoid running count_hours on unneeded␣
 ↪businesses
tor_bsn = tor_bsn.merge(hours_df, on='business_id')

# generate total weekly operating hours for each Toronto restaurant
tor_bsn['wk_op_hours'] = 0

# sum operating hours for each day - monday thru sunday are columns 8-14
for day in tor_bsn.columns[-8:-1]:
    tor_bsn['wk_op_hours'] += tor_bsn[day].apply(count_hours)

# remove daily operating hours columns
tor_bsn = tor_bsn.drop(columns=['monday', 'tuesday', 'wednesday', 'thursday',␣
 ↪'friday', 'saturday', 'sunday'])

# save cleaned data to csv
# tor_bsn.to_csv('/Users/thomas/Documents/schoolwork/eco225/yelp_data/
 ↪toronto_businesses.csv')

# order columns
tor_bsn = tor_bsn[['business_id', 'name', 'stars', 'review_count',␣
 ↪'daily_checkin_avg', 'wk_op_hours', 'restaurant', 'shop', 'categories']]
```

```
# Toronto dataframe is now clean
tor_bsn
```

```
/var/folders/ms/q_hrvhnj60188mzvbg992ch80000gn/T/ipykernel_8189/4038026341.py:7:
SettingWithCopyWarning:
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_guide/indexing.html#returning-a-view-versus-a-copy
  tor_bsn['restaurant'] =
tor_bsn['categories'].str.contains('Restaurant').astype(int)
/var/folders/ms/q_hrvhnj60188mzvbg992ch80000gn/T/ipykernel_8189/4038026341.py:10
: SettingWithCopyWarning:
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_guide/indexing.html#returning-a-view-versus-a-copy
  tor_bsn['shop'] = tor_bsn['categories'].str.contains('Shopping').astype(int)
```

[ ]:

```
                  business_id                           name  stars  \
0      l09JfMeQ6ynYs5MCJtrcmQ                "Alize Catering"    3.0
1      lHYiCS-y8AFjUitv6MGpxg                     "Starbucks"    4.0
2      VSGcuYDV3q-AAZ9ZPq4fBQ                   "Sportster's"    2.5
3      1K4qrnfyzKzGgJPBEcJaNQ        "Chula Taberna Mexicana"    3.5
4      AtdXq_gu9NTE5rx4ct_dGg                      "DAVIDsTEA"    4.0
…                         …                             …    …
14845  sEAKw3MZkER1u_1fzIeD3g                  "Gol Take-Out"    4.0
14846  1HplwLVbBid-Bgw1sEPGFg        "Dumpling Melody Bistro"    2.0
14847  dWoAayHRyIrkk1dcvBxv3Q          "Art Ink Collective"    3.5
14848  SvW3WsatQWvR8c1iwAD_QA              "Urban House Cafe"    4.0
14849  nGjEV4bnODPk8bcbOC6Aig   "Sweet Serendipity Bake Shop"    4.5

       review_count  daily_checkin_avg  wk_op_hours  restaurant  shop  \
0                12           1.000000         91.0           1     0
1                21           4.577586        115.5           0     0
2                 7           2.125000         70.0           0     0
3                39           1.333333        103.5           1     0
4                 6           1.272727         70.5           0     0
…               …                  …          …         …    …
14845            15           1.000000          0.0           1     0
14846            12           1.125000          0.0           1     0
14847             3           1.000000         43.0           0     1
14848            32           2.000000         91.0           1     0
14849            22           1.000000         45.0           0     0
```

```
                                    categories
0                    Italian;French;Restaurants
1                             Food;Coffee & Tea
2                     Bars;Sports Bars;Nightlife
3        Tiki Bars;Nightlife;Mexican;Restaurants;Bars
4                    Coffee & Tea;Food;Tea Rooms
…                                            …
14845  Food;Restaurants;International Grocery;Ethnic …
14846                           Restaurants;Chinese
14847  Shopping;Beauty & Spas;Piercing;Art Galleries;…
14848  Nightlife;Restaurants;Sandwiches;Bars;Canadian…
14849                                 Bakeries;Food

[14850 rows x 9 columns]
```

1.3 Summary Statistics

[ ]:
```
# generate summary statistics for y, x1, x2, x3
sums = tor_bsn[['stars', 'review_count', 'wk_op_hours', 'daily_checkin_avg']].
↪describe()
sums = sums.rename(columns={'stars': 'Yelp Rating', 'review_count': 'Yelp␣
↪Review Count', 'wk_op_hours': 'Hours of Operation per Week',␣
↪'daily_checkin_avg': 'Average Number of Check-ins per Day'})
sums
```

[ ]:
```
        Yelp Rating  Yelp Review Count  Hours of Operation per Week  \
count  14850.000000       14850.000000                 14850.000000
mean       3.494007          28.295556                    47.315771
std        0.841782          56.253223                    35.878516
min        1.000000           3.000000                     0.000000
25%        3.000000           5.000000                     0.000000
50%        3.500000          10.000000                    54.000000
75%        4.000000          28.000000                    74.500000
max        5.000000        1494.000000                   167.883333

       Average Number of Check-ins per Day
count                         14850.000000
mean                              1.522870
std                               1.090018
min                               1.000000
25%                               1.000000
50%                               1.187500
75%                               1.555556
max                              31.042553
```

Stars

The summary statistics for *stars* indicate that the data is discrete. Moreover, it demonstrates that the minimum and maximum ratings are 1 and 5 respectively. The average review is roughly 3.5 stars. Assuming that an average business should have a rating near the midpoint between the minimum and maxmimum, the mean may indicate that there is a systematic bias towards over-rating businesses by 0.5 stars at the aggregate level. The interquartile range is between 3 and 4 stars, which further suggests this bias; it demonstrates that half of all businesses in Toronto are above the rating midpoint. In other words, only 25% of business can be considered poor-quality (i.e. a rating below 3 stars).

Number of Reviews
There appears to be a great variation in the number of reviews across businesses but it is primarily due to an enormous right skew. The standard deviation (56) is double the mean review count (28). The maximum review count of 1494 is indicative of right skew since it is 53 times larger than the average. Moreover, 75% of all Toronto businesses have 28 reviews or less. This may yield low power in a regression analysis since the vast majority of businesses have very similar review counts, despite the extreme variation suggested by the standard deviation.

Weekly Operating Hours
On average, businesses in Toronto are open for roughly 47 hours per week. The standard deviation is roughly 36 hours per week which indicates that there is a large variation in weekly operating hours across businesses. There are several signs of right skew in this variable, which may be the cause of the large standard deviation. The 50th percentile (54) is larger than the mean, which suggests that outliers on the right side of the distribution are positively biasing the mean. Moreover, this variable's lower bound of zero suggests that most of the variation would occur above the mean. The maximum value observed for this variable is 167.88, which is 0.12 hours less than the total number of hours in a week. This observation may need to be dropped from analysis if it biases the trends of interest, since the vast majority of businesses cannot operate for nearly every hour of the week.

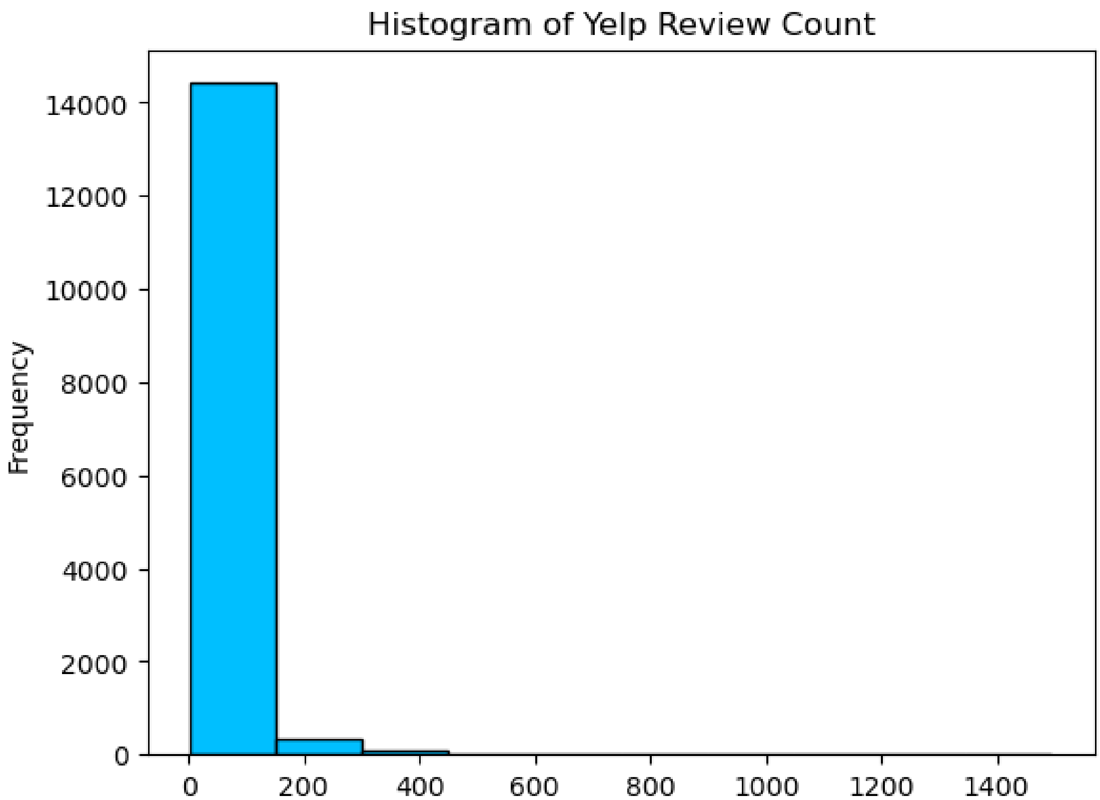
Daily Check-in Average
There is very little variation across businesses in their daily check-in averages. Despite the mean and standard deviations being approximately 1.52 and 1.10 respectively, 75% of the observations lie between 1 and 1.55. There is a significant right skew in this data since the maximum value observed is roughly 31 check-ins on average. This variable may prove irrelevant in a regression analysis due to the uniformity of the data: there is not enough variation to properly calculate how an outcome variable changes given a change in the daily check-in average.

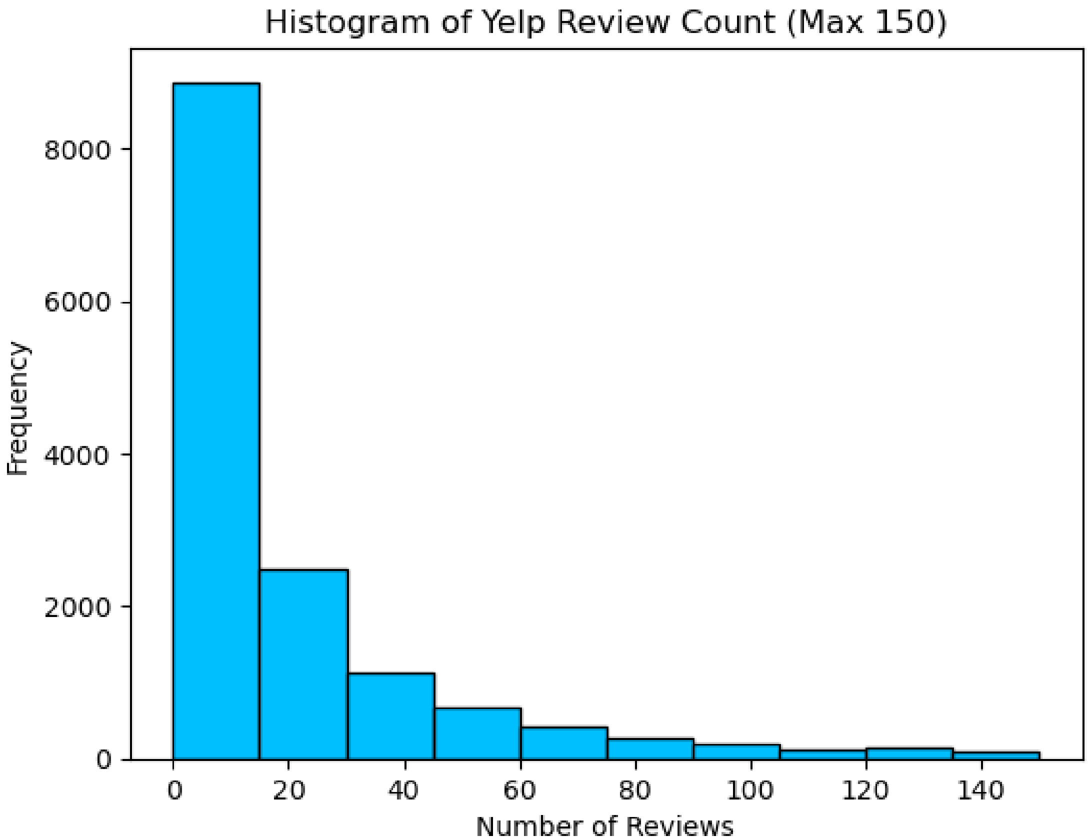
1.4 Plots & Figures

[ ]:
```
# histograms of review_count
fig1, ax1 = plt.subplots()
fig2, ax2 = plt.subplots()

tor_bsn['review_count'].plot(ax=ax1, kind='hist', color='deepskyblue',␣
↪edgecolor='black', grid=False, title='Histogram of Yelp Review Count')
plt.xlabel('Number of Reviews')
```

```
tor_bsn['review_count'].plot(ax=ax2, kind='hist', color='deepskyblue',␣
 ↪edgecolor='black', grid=False, title='Histogram of Yelp Review Count (Max␣
 ↪150)', range=(0,150))
plt.xlabel('Number of Reviews')
```

[ ]: Text(0.5, 0, 'Number of Reviews')





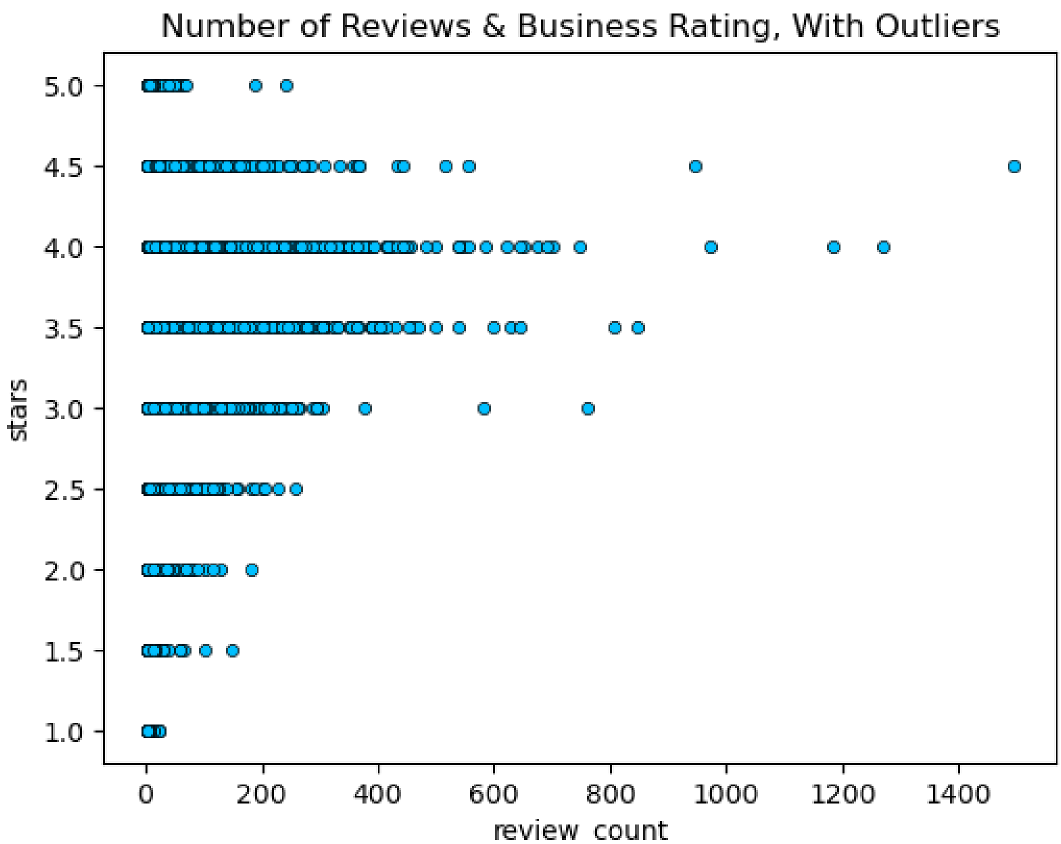
As demonstrated by the summary statistics table, review_count has significant right skew. Ignoring businesses with more than 150 reviews yields a clearer picture: the distribution of reviews is unimodal with a peak between 0 and ~15. Given the lack of variation, the number of reviews may not be a significant determinant of business ratings. In other words, the variation in business ratings cannot be meaningfully explained by the number of reviews alone because the majority of businesses are very similar in this dimension. This variable must be used in a multiple regression alongside additional covariates to generate statistically significant coefficients and identify the relevant determinants of business ratings.

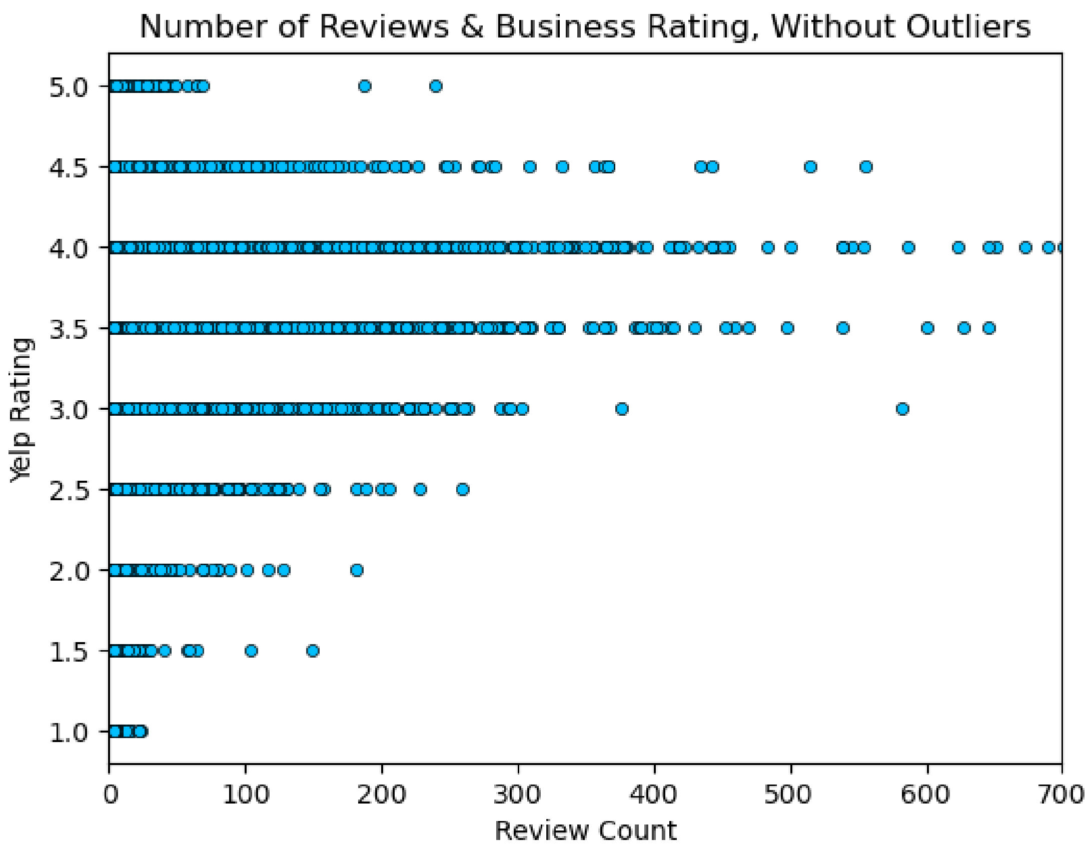
```
[ ]: # relationship between business rating and review count
fig1, ax1 = plt.subplots()
fig2, ax2 = plt.subplots()

tor_bsn.plot(ax=ax1, kind='scatter', c='deepskyblue', edgecolor='black',␣
 ↪x='review_count', y='stars', title='Number of Reviews & Business Rating,␣
 ↪With Outliers', linewidth=0.5)
plt.xlabel('Review Count')
plt.ylabel('Yelp Rating')
```

```
tor_bsn.plot(ax=ax2, kind='scatter', c='deepskyblue', edgecolor='black',␣
 ↪x='review_count', y='stars', xlim=(0,700), title='Number of Reviews &␣
 ↪Business Rating, Without Outliers', linewidth=0.5)
plt.xlabel('Review Count')
plt.ylabel('Yelp Rating')
```

```
/Users/thomas/opt/anaconda3/lib/python3.9/site-
packages/pandas/plotting/_matplotlib/core.py:1114: UserWarning: No data for
colormapping provided via 'c'. Parameters 'cmap' will be ignored
  scatter = ax.scatter(
```

```
[ ]: Text(0, 0.5, 'Yelp Rating')
```



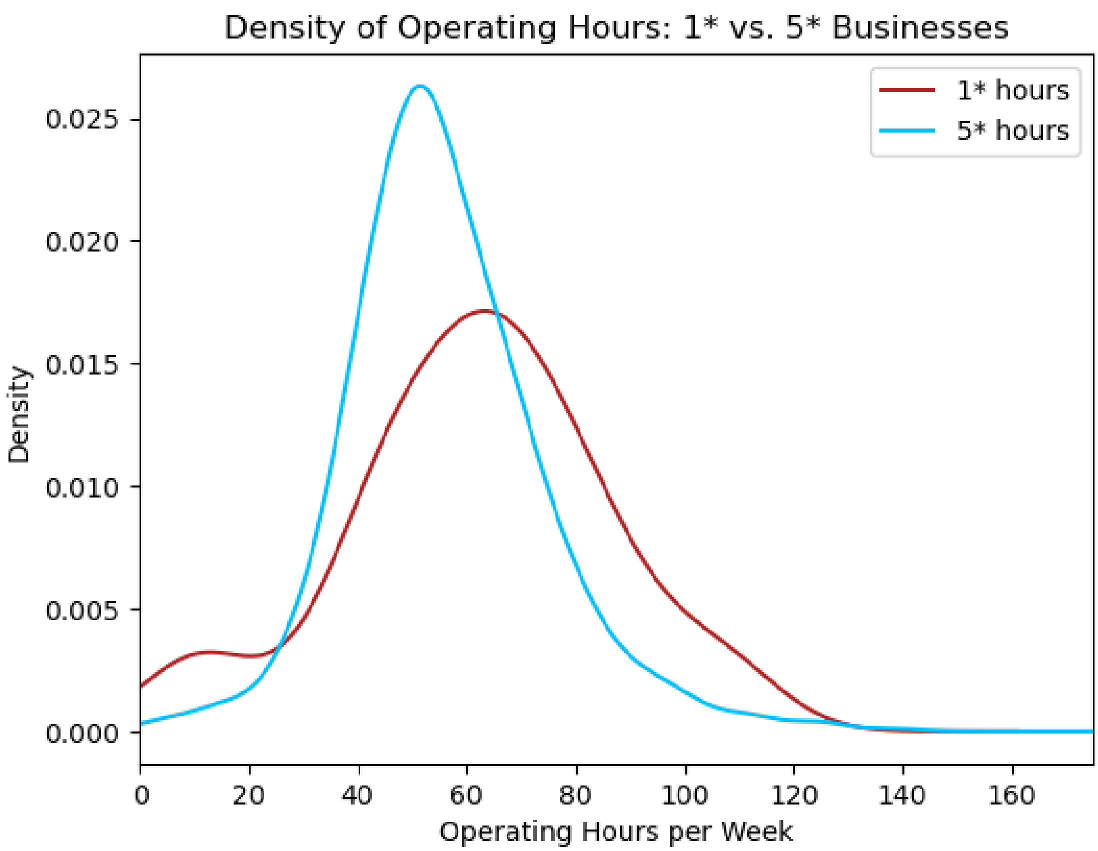


This scatter plot demonstrates that a business's number of reviews is positively correlated with the business's rating. This suggests that the effect of good service dominates the effect of bad service in regard to generating reviews for businesses. If the poorest quality businesses had the greatest number of reviews, then the effect of bad service would dominate. There appears to be non-linearity in this relatationship: the marginal benefit of an additional review decreases significantly between the 200 and 300 review marks. However, this non-linearity may simply be a result of the data for *stars* being discrete. The true effect of the number of reviews on a business's rating is not clear through this plot. Controlling for additional variables, such as the number of checkins on average per day (i.e. customer perception), may present a relationship that differs from the one seen here.

[ ]:
```
# density of operating hours for businesses with 1*, 5* reviews
tor_1s = tor_bsn.groupby('stars').get_group(1).rename(columns={'wk_op_hours':␣
 ↪'1* hours'})
tor_1s = tor_1s[tor_1s['1* hours'] != 0]
tor_5s = tor_bsn.groupby('stars').get_group(5).rename(columns={'wk_op_hours':␣
 ↪'5* hours'})
tor_5s = tor_5s[tor_5s['5* hours'] != 0]
```

```
tor_1s['1* hours'].plot(kind='kde', c='firebrick', legend=True, title='Density␣
↪of Operating Hours: 1* vs. 5* Businesses', xlim=(0,175)).
↪set_xlabel("Operating Hours per Week")
tor_5s['5* hours'].plot(kind='kde', c='deepskyblue', legend=True)
```

```
[ ]: <AxesSubplot: title={'center': 'Density of Operating Hours: 1* vs. 5*
Businesses'}, xlabel='Operating Hours per Week', ylabel='Density'>
```



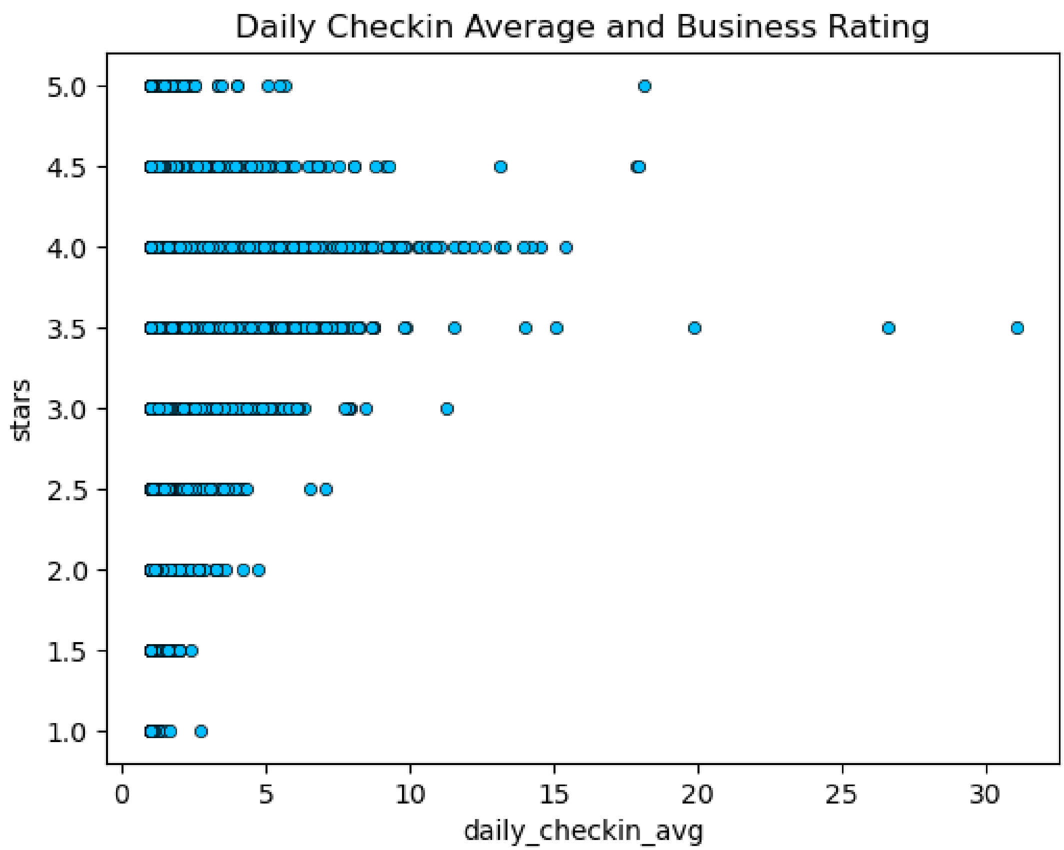
This density plot demonstrates how weekly operating hours differ across businesses at either end of the rating spectrum. Five-star businesses are more likely to have between 45-65 hours of operation in any given week and a narrower spread than one-star businesses. On the contrary, one-star businesses have much more variation and are more likely to have less than 30 hours of operation. This evidences the hypothesis that customer access plays a role in determining business ratings. This density plot ignores businesses that had no weekly operating hours listed on Yelp in order to portray a clearer picture of the spread of operating hours across ratings.

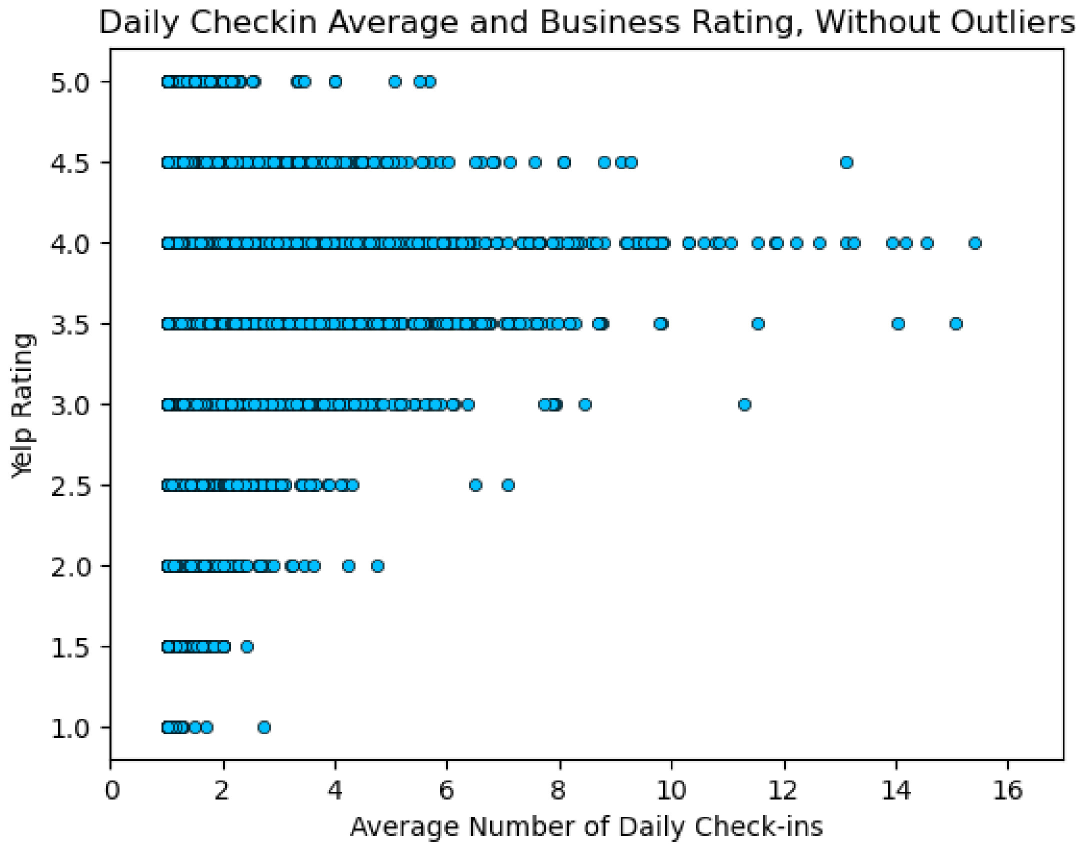
The wider variation in operating hours per week for one-star businesses suggests that there are more one-star businesses than five-star businesses that operate for more than 70 hours per week. This may be random noise, but it could indicate that businesses' hours of operation are weakly correlated with their ratings. In other words, hours of operation may be a poor determinant of business ratings. In order to identify the strength of a correlation between operating hours and ratings, a linear regression should be done with these two variables.

[ ]:
```
# relationship between businsess rating and checkins
fig1, ax1 = plt.subplots()
fig2, ax2 = plt.subplots()

tor_bsn.plot(ax=ax1, kind='scatter', edgecolor='black',  x='daily_checkin_avg',␣
 ↪y='stars', c='deepskyblue', title='Daily Checkin Average and Business␣
 ↪Rating', linewidth=0.5)
plt.xlabel('Average Number of Daily Check-ins')
plt.ylabel('Yelp Rating')

tor_bsn.plot(ax=ax2, kind='scatter', edgecolor='black', x='daily_checkin_avg',␣
 ↪y='stars', c='deepskyblue', title='Daily Checkin Average and Business␣
 ↪Rating, Without Outliers', linewidth=0.5).set_xlim(0, 17)
plt.xlabel('Average Number of Daily Check-ins')
plt.ylabel('Yelp Rating')
```

```
/Users/thomas/opt/anaconda3/lib/python3.9/site-
packages/pandas/plotting/_matplotlib/core.py:1114: UserWarning: No data for
colormapping provided via 'c'. Parameters 'cmap' will be ignored
  scatter = ax.scatter(
```

[ ]:
```
Text(0, 0.5, 'Yelp Rating')
```


Daily Checkin Average and Business Rating
stars
daily_checkin_avg
5.0
4.5
4.0
3.5
3.0
2.5
2.0
1.5
1.0
0
5
10
15
20
25
30



There is a clear positive association between the average number of check-ins per day and the business rating. Non-linearity also appears to be present but this may be a result of business ratings being measured discretely. There are several massive outliers beyond roughly 17 average check-ins per day, which should be excluded from a formal regression analysis as they exacerbate the non-linear trend. Overall, this relationship is very similar to that of the total number of reviews and business ratings. As a result, controlling for both variables in a regression may be redundant and reduce power. The average daily check-in variable is likely to be a worse predictor of business ratings than the count of reviews since it has relatively less variation.

Using the check-in data as a covariate may present issues with reverse causation as well. Assuming customers use the check-in feature to boast about the businesses they visit, a higher Yelp rating would increase the number of check-ins a business receives. This complicates the identification of a causal relationship between these variables because either the business rating or the average number of check-ins must be used as a dependent variable. Though the issue of reverse causation may not be easily solved with the current dataset, a multiple regression including the other covariates (review_count, wk_op_hours) would provide greater insight into the causality of business ratings.

2 Project 2

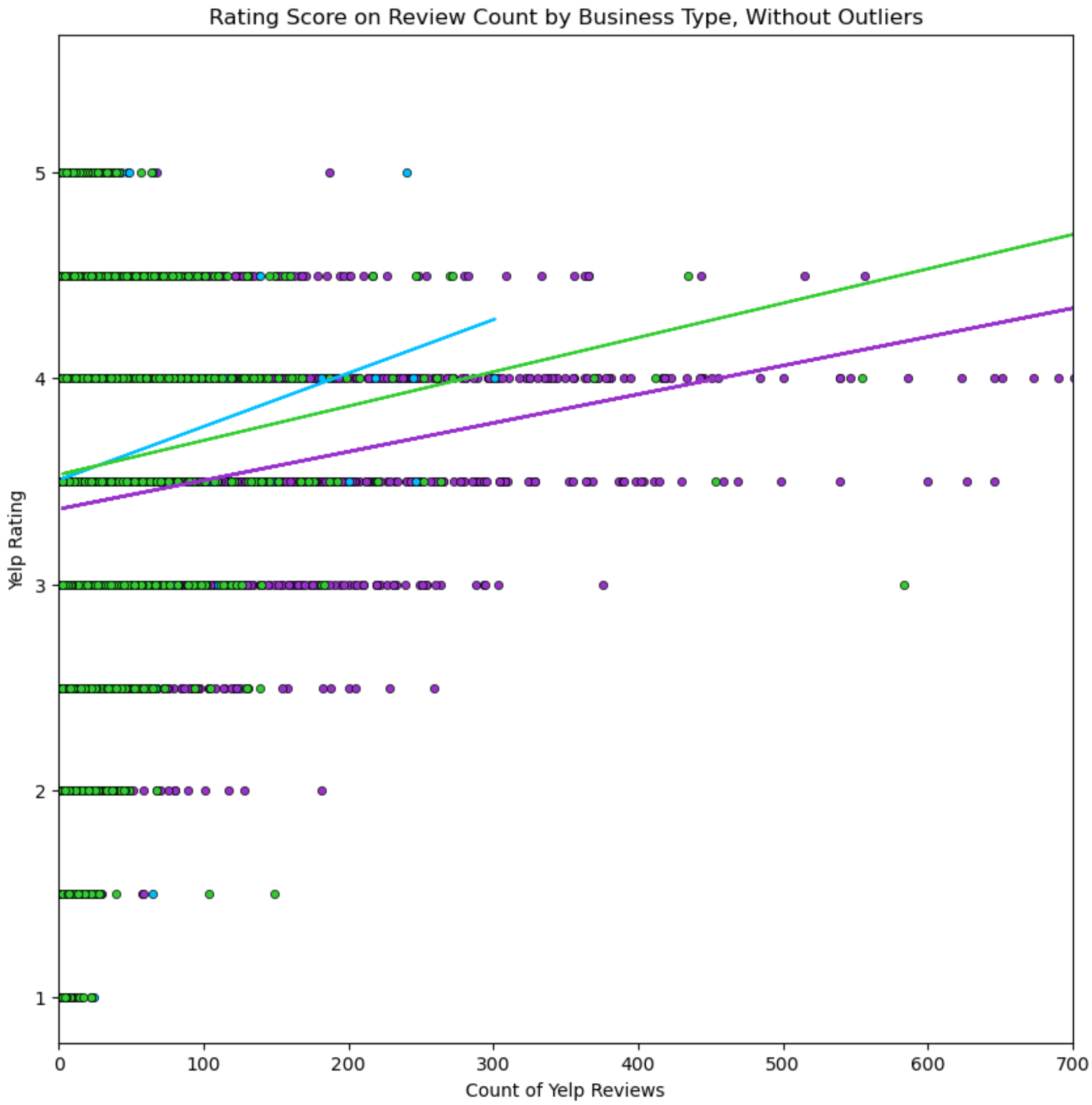
2.1 The Message

What are the most relevant determinants of a business's Yelp Rating, and do they differ depending on the type of business?

```
[ ]: # build scatter plot with stars, review_count for restaurants, shops,␣
     ↪miscellaneous
     fig, ax = plt.subplots(figsize=(10,10))


     not_rst_shop = tor_bsn[tor_bsn['shop'] == 0]
     not_rst_shop = not_rst_shop[not_rst_shop['restaurant'] == 0]

     #     # find variables to graph based on business type
     rst = tor_bsn[['stars', 'review_count']][tor_bsn['restaurant'] == 1]
     shop = tor_bsn[['stars', 'review_count']][tor_bsn['shop'] == 1]
     other = not_rst_shop[['stars', 'review_count']]

     #     # find line of best fit for each set of variables
     rst_x, rst_y = np.polyfit(rst['review_count'], rst['stars'], 1)
     shop_x, shop_y = np.polyfit(shop['review_count'], shop['stars'], 1)
     other_x, other_y = np.polyfit(other['review_count'], other['stars'], 1)

     # store relevant data
     types_d = {'rst': (rst, rst_x, rst_y, 'darkorchid'),
                'shop': (shop, shop_x, shop_y, 'deepskyblue'),
                'other': (other, other_x, other_y, 'limegreen')}

     for _type in types_d:
         data, x, y, col = types_d[_type]
         data.plot(ax=ax, kind='scatter', x='review_count', y='stars', c=col,␣
      ↪edgecolor='black', linewidth=0.5)
         plt.plot(data['review_count'], (x*data['review_count']+y), c=col)

     plt.title('Rating Score on Review Count by Business Type, Without Outliers')
     plt.xlabel('Count of Yelp Reviews')
     plt.ylabel('Yelp Rating')
     plt.xlim(0, 700)
```

```
/Users/thomas/opt/anaconda3/lib/python3.9/site-
packages/pandas/plotting/_matplotlib/core.py:1114: UserWarning: No data for
colormapping provided via 'c'. Parameters 'cmap' will be ignored
  scatter = ax.scatter(
```

```
[ ]: (0.0, 700.0)
```



This scatter plot demonstrates the relationship between a business's count of Yelp reviews and its Yelp rating. Different colours are used to portrary different types of businesses: restaurants are in purple, shops are in green, and miscellaneous (non-shops, non-restaurants) are in blue. Each type of business also has its own line of best fit, which is calculated with the OLS method. This plot ignores outliers that have more than 700 reviews.

The lines of best fit suggest that the relationship between the count of Yelp reviews and the Yelp rating is very similar for restaurants and shops. That is, a restaurant or shop that has ~200 more reviews is observed to have a Yelp rating that is 0.25 stars higher on average. Moreover, restaurants have the lowest average ratings when compared to shops and miscelleaneous businesses. Holding the number of reviews constant, the expected rating for a restaurant is roughly 0.2 stars lower than for a shop or an other. It is unclear why restaurants have the lowest average reviews, but it is likely related to the particularities of the food industry. For instance, poor-quality food may make customers more likely to leave unfavourable reviews compared to poor-quality service at a shop – perhaps because bad food is more tangible.

Businesses that are not restaurants nor shops include industries like hospitality, service, and banking. These types of businesses seem to have the largest positive correlation between their number of reviews and their rating: they are observed to have a 0.5 higher rating when they have ~200 more reviews. These types of businesses also have many fewer reviews than restaurants and shops on average. The miscellaneous business with the most reviews has only ~300 reviews. The correlation's large magnitude may be a result of low sample size, since this graph does not indicate how many observations are in each business category. It could also be that the count of Yelp reviews is truly a more significant determinant of Yelp ratings for miscellaneous businesses because 'good service' in these industries is very tangible; a good haircut, comfortable beds at a hotel, or saving on fees at a bank have the potential to make customers more content than mere retail stores or take-out restuarants.

All in all, this plot provides significant insight with regard to this paper's main message. It demonstrates that the number of Yelp reviews a business has is correlated with its Yelp rating and is therefore a relevant determinant. Moreover, it shows that the effect of a determinant of ratings likely depends on the type of business – at least in the case of review counts.

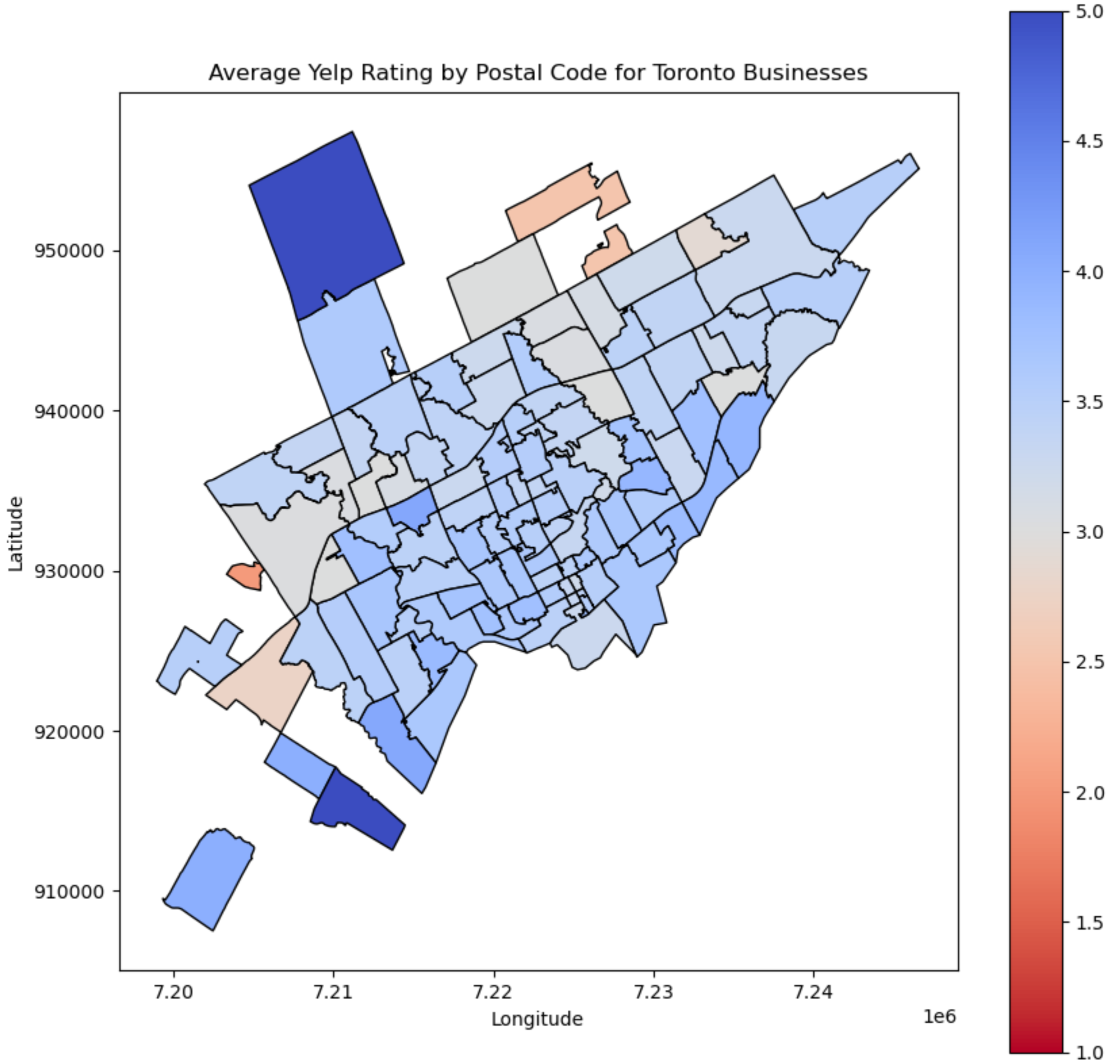
2.2 Maps and Interpretations

[ ]:
```
# use toronto business data with postal code, longitude, latitude columns
df = pd.read_csv('/Users/thomas/Documents/schoolwork/eco225/yelp_data/
 ↪toronto_businesses.csv')
df = df.copy()

# drop irrelevant postal codes
for i in range(2):
    df.drop(df['longitude'].idxmax(), axis=0, inplace=True)

# build geometry column
df['coordinates'] = list(zip(df['longitude'], df['latitude']))
df['coordinates'] = df['coordinates'].apply(Point)
gdf = gpd.GeoDataFrame(df, geometry='coordinates')

# clean postal_code column for merge
gdf['postal_code'] = gdf['postal_code'].str[:3]

# import shp file
toronto = gpd.read_file('/Users/thomas/Documents/schoolwork/eco225/shp/
 ↪lfsa000a21a_e/lfsa000a21a_e.shp')
toronto = toronto.rename(columns={'CFSAUID': 'postal_code'})

# drop more irrelevant postal codes
toronto = toronto[toronto['PRNAME'] == 'Ontario']

# ratings map
```

```
gdf_stars = gdf.groupby('postal_code')[['stars']].mean()
t_stars = toronto.merge(gdf_stars, how='inner', on='postal_code')

# review count map
gdf_reviews = gdf.groupby('postal_code')[['review_count']].mean()
t_reviews = toronto.merge(gdf_reviews, on='postal_code')

# checkins map
gdf_checks = gdf.groupby('postal_code')[['daily_checkin_avg']].mean()
t_checks = toronto.merge(gdf_checks, on='postal_code')
```

[ ]:
```
# plotting code for ratings maps
fig, gax = plt.subplots(figsize=(10,10))
t_stars.plot(ax=gax, edgecolor='black', column='stars', cmap='coolwarm_r',␣
 ↪vmin=1, vmax=5, legend=True)

plt.title('Average Yelp Rating by Postal Code for Toronto Businesses')
plt.xlabel('Longitude')
plt.ylabel('Latitude')
```

[ ]:
```
Text(56.472222222222214, 0.5, 'Latitude')
```

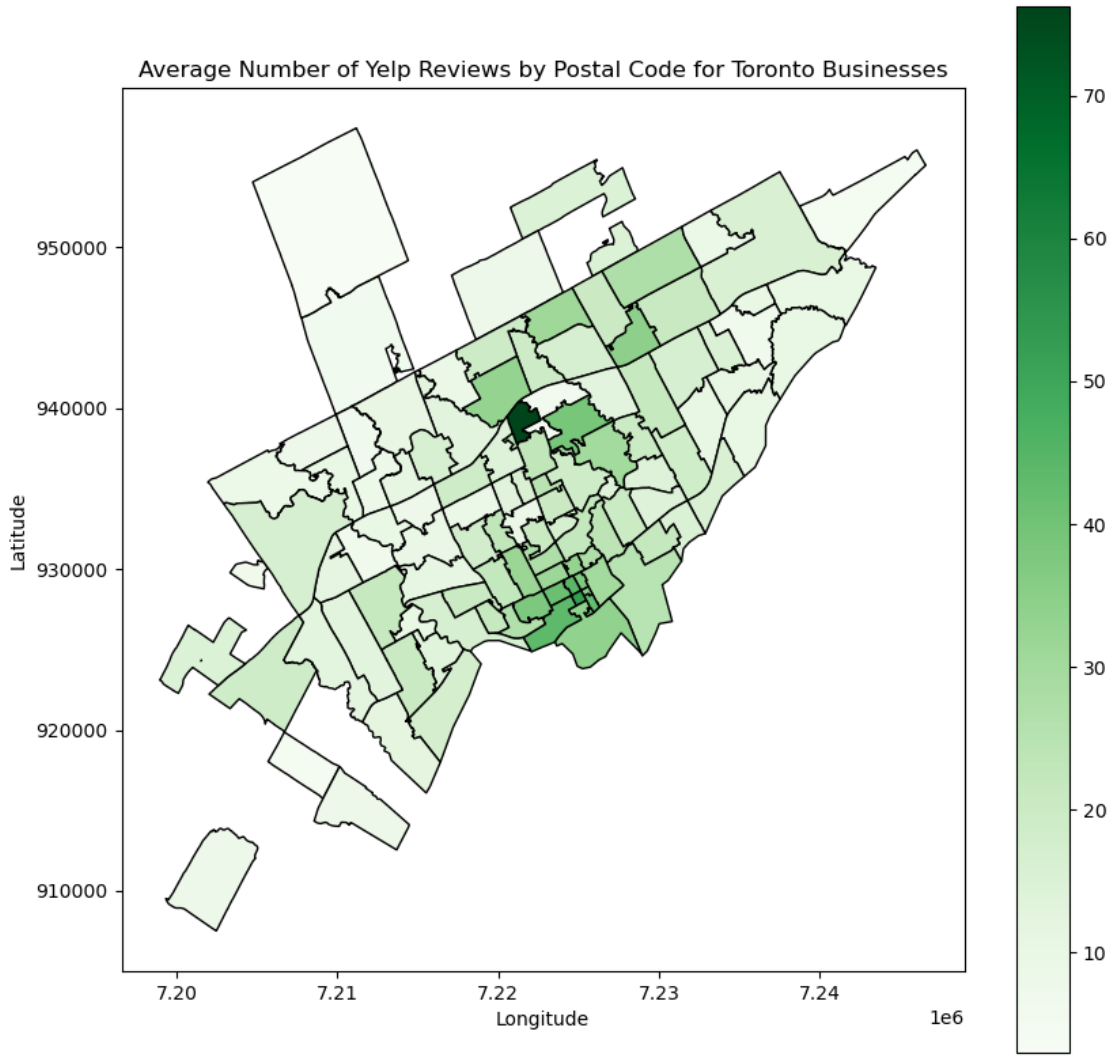


The map of average Yelp ratings by postal code demonstrates that physical geography does not play a significant role in determining Toronto businesses' ratings. Most postal codes have very typical ratings, especially in regions with greater population density. Outliers become more common as distance from downtown increases, but the direction of these outliers seems to be random. This suggests that the prominence of outliers may be the result of each business having relatively fewer reviews. With fewer reviews in these regions, the expected rating is more likely to deviate from the true mean rating.

[ ]:
```
# plotting code for operating hours map
fig, gax = plt.subplots(figsize=(10,10))
t_reviews.plot(ax=gax, edgecolor='black', column='review_count', cmap='Greens',␣
↪legend=True)
```

```
plt.title('Average Number of Yelp Reviews by Postal Code for Toronto␣
  ↪Businesses')
plt.xlabel('Longitude')
plt.ylabel('Latitude')
```

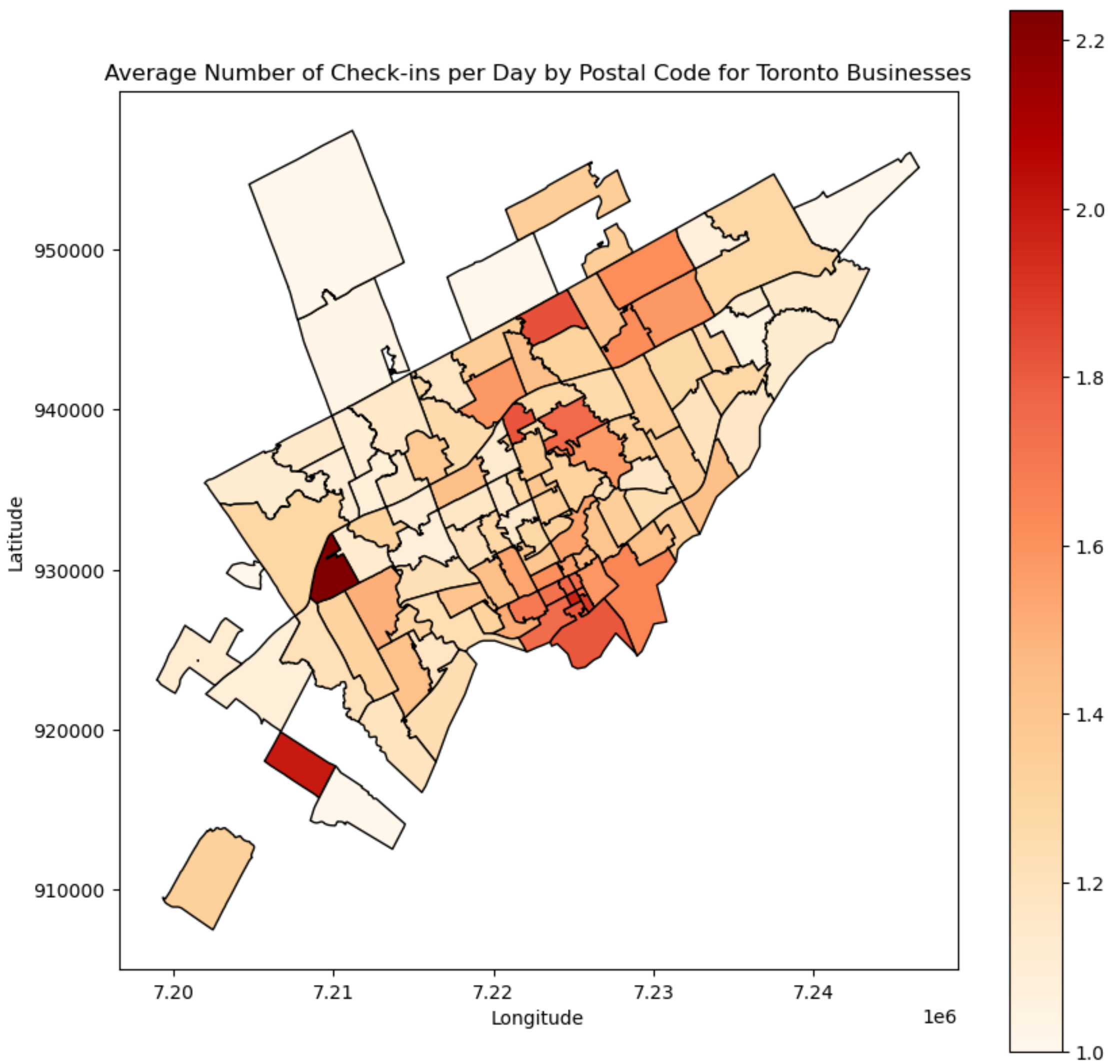
[ ]: Text(56.472222222222214, 0.5, 'Latitude')



Contrary to the map of average Yelp ratings, the average number of Yelp reviews seems to be influenced by geography. The postal codes with the highest average number of reviews are seen in regions with the highest population density, such as those in downtown Toronto. This is rather obvious; businesses that operate in areas with high population density will have more potential customers than thoe in low-density regions. This hints at why this paper has been unable to identify a significant positive correlation between the count of reviews and Yelp ratings: without controlling for population density, businesses in regions with larger populations will see more reviews on average regardless of their actual quality. Including a variable that measures the population for each postal code in a regression with the count of reviews would therefore increase the chances of finding a significant relationship between review count and ratings. The population variable would control for the amount of potential customers that businesses may have, thereby isolating the effect of an additional review on ratings.

```
[ ]: # plotting code for checkins map
fig, gax = plt.subplots(figsize=(10,10))
t_checks.plot(ax=gax, edgecolor='black', column='daily_checkin_avg',␣
 ↪cmap='OrRd', legend=True)

plt.title('Average Number of Check-ins per Day by Postal Code for Toronto␣
 ↪Businesses')
plt.xlabel('Longitude')
plt.ylabel('Latitude')
```

```
[ ]: Text(56.472222222222214, 0.5, 'Latitude')
```



Similar to the map for average number of reviews, the number of Yelp check-ins a business gets appears to be influenced by geography. The businesses that are located in regions of greater population density, such as downtown, have more check-ins per day on average. However, the number of check-ins seems to be much more volatile than the number of reviews. This map has outliers of greater magnitude and with greater frequency since many postal codes outside of downtown seem to have high average daily check-in counts. This is likely because check-ins are used infrequently on Yelp to begin with. It does not take much for a business to have a much higher average number of check-ins, especially when the mean for Toronto is 1.5 per day. One especially passionate customer could raise the average number of check-ins per day by 1 on their own. This hypothetical example is especially plausible for restaurants, since returning customers are commonplace in the food industry.

2.3 Conclusion

This analysis demonstrates that the number of reviews, weekly hours of operation, and average number of check-ins per day all appear to be positively correlated with business ratings in Toronto on Yelp. In other words, high-quality businesses tend to have more reviews, are open for longer, and receive more check-ins on average relative to poor-quality businesses.

However, this conclusion can only be drawn from each covariate's relationship with business ratings alone. In other words, the direction of causality among these variables, if any exists, remains unknown. Further, this analysis has not been able to quantify the effects of each covariate on different types of businesses. It is clear that the number of reviews depends in part on a business's industry, and the same is likely true of operating hours and check-ins. The maps for the number of reviews and check-ins demonstrate that population density in a business's region is likely causing ommitted variable bias. Population should be controlled for in order to yield a more precise estimate of these covariates' effects on ratings. Therefore, this analysis is unable to determine how relevant the chosen covariates are in determining business ratings.

A multiple regression model with these variables would contribute to a better understanding of the causality of business ratings. It allows for control variables which would yield more precision in determining the effects of any individual covariate. Moreover, it would generate an R^2 value to indicate how relevant the covariates are. This would provide insight on whether the total number of reviews and average number of check-ins per day are relevant predictors, considering they have limited variation.