Analysis of Airbnb listings and rent prices of metropolises in US

- NYC, Boston, San Francisco, and Seattle

A project submitted in partial fulfillment of the requirements for ECON-UB 232, Data Bootcamp

May 2020

Contents

Introduction

AirBed and Breakfast, also known as Airbnb, is an American online marketplace company based in San Francisco, California, United States. The service Airbnb offer is mainly arrangement for lodging, primarily homestays, or tourism experiences. Founded in August 2008, Airbnb has brought unprecedented strong competition to traditional hotel industry. In fact, the company does not own any of the real estate listings, nor does it host events; it acts as a broker, receiving commission fee from each booking. On the one

hand, this novel business model provides tourists with economic-friendly choice of living; on the other hand, renting idle rooms or houses to people in need is better for resource allocation, as well as creating additional revenues for household.

In the past few years, Airbnb has attracted 45.6 million users in total. Diversified background of hosts make the characteristics of Airbnb rooms very complicated. Besides, the pricing of Airbnb is always a hot topic. For hosts, they want to learn about the charactistics and prices of Airbnb rooms in the city so that they can improve their houses accordingly, set suitable prices for their houses, and get more profits. For guests, they want to spend time in cost-effective houses with their favorite characteristics.

In this project, we analyze and visualize characteristics of Airbnb rooms in for major American cities, New York City, Boston, San Francisco and Seattle (two on the east coast and two on the west coast). We compare the prices and run regressions to figure out the relationship between different factors and prices, then pick out the significant variables. Last but not least, we apply machine learning tools to train the model and make prediction for prices. We also do cross-city comparison so that people can get the sense of different and similar patterns in different cities. From our project, hosts can learn the patterns of rooms in different cities, and set proper prices according to different contributions of factors. Guests can have an overview of Airbnb houses in their destination, and choose a house which maximize their utility.

Hopefully this project will contribute to this rapidly growing industry, establish a fair and healthy market, do good to the resource allocation, and help both guests and hosts to make the optimized desicions.

In [288…
```
import pandas as pd
import numpy as np
import matplotlib as mpl
import matplotlib.pyplot as plt
import matplotlib.image as img
from PIL import Image
import requests
from io import BytesIO
import seaborn as sns
from scipy.stats import norm
from scipy import stats
%matplotlib inline
```

Preset Functions

For convenience in repetitive implementation for different cities.

In [289…
```
# import dataset
def import_df(web):
    df = pd.read_csv(web)
    df['price'] = df['price'].str.replace('$','')
    df['price'] = df['price'].str.replace(',','').astype(float)
    return df
```

In [290…
```
# import the image
def import_img(web):
    response = requests.get(web)
    img = Image.open(BytesIO(response.content))
    return img
```

In [291…
```
# get the max/min value of longitude and latitude
def area(df):
    xl=df['longitude'].min()
    xh=df['longitude'].max()
    yl=df['latitude'].min()
    yh=df['latitude'].max()
    return xl,xh,yl,yh
```

In [292…
```
# get the overall geographic location for all houses
def location(city,df,sqrt,colorsize,figsize1,figsize2):
    mpl.rcParams.update(mpl.rcParamsDefault)
    %matplotlib inline
```

```
    cmap = plt.cm.coolwarm
    n = mpl.colors.Normalize()
    fig,ax = plt.subplots(figsize=(figsize1,figsize2))
    df.plot.scatter(ax=ax,x='longitude',y='latitude',s=df['price']**sqrt,
                    color=cmap(n(df['price'].values)*colorsize))
    ax.set_xlim(df['longitude'].min()-0.01,df['longitude'].max()+0.01)
    ax.set_ylim(df['latitude'].min()-0.01,df['latitude'].max()+0.01)
    ax.set_xlabel('Longitude')
    ax.set_ylabel('Latitude')
    ax.set_title(city+' Airbnb Locations',size=14,fontweight='bold')
    return fig,ax
```

In [293…

```
# get the geographic location under each room type category
def room_type_location(df,sqrt,colorsize,figsize1,figsize2):
    mpl.rcParams.update(mpl.rcParamsDefault)
    %matplotlib inline

    rtype = df.groupby(['id','room_type','latitude','longitude'],as_index=False)[['price
    types = df['room_type'].unique()
    num = len(types)
    cmap = plt.cm.coolwarm
    n = mpl.colors.Normalize()
    fig,ax = plt.subplots(1,num,figsize=(figsize1*num,figsize2))
    for i in range(0,num):
        tprice = rtype.loc[rtype['room_type']==types[i],:]
        tprice.plot.scatter(ax=ax[i],x='longitude',y='latitude',s=tprice['price']**sqrt,
                            color=cmap(n(tprice['price'].values)*colorsize))
        ax[i].set_xlim(df['longitude'].min()-0.01,df['longitude'].max()+0.01)
        ax[i].set_ylim(df['latitude'].min()-0.01,df['latitude'].max()+0.01)
        ax[i].set_title(types[i],size=13,fontweight='bold')
        ax[i].set_xlabel('Longitude')
        ax[i].set_ylabel('Latitude')
    return fig,ax
```

In [294…

```
# get the top 10 hosts with the most house listings
def top_hosts(city,df):
    top_host = df['host_id'].value_counts()[:10]
    ax = sns.barplot(top_host.index, top_host.values,order=top_host.index)
    ax.set_xticklabels(ax.get_xticklabels(),rotation=45)
    ax.set_title('Hosts with the most listings in '+city,size=14,fontweight='bold')
    ax.set_ylabel('Count of listings')
    ax.set_xlabel('Host IDs')
```

In [295…

```
# count number of listings in each neighbourhood
def count_nei(city,df):
    mpl.rcParams.update(mpl.rcParamsDefault)
    %matplotlib inline
    fig,ax = plt.subplots(figsize=(18,5))
    ax = sns.countplot(x='neighbourhood',data=df)
    ax.set_xlabel('Neighbourhood group')
    ax.set_ylabel('Count')
    ax.set_title('Counts of listings in neighbourhoods',fontsize=14,fontweight='bold')
    ax.set_xticklabels(ax.get_xticklabels(),rotation=90)
    return fig,ax
```

In [296…

```
# plot pie charts for number of listings in each neighbourhood
def nei_pie(city,df):
    if city == 'NYC':
        labels = df.neighbourhood_group.value_counts().index
        sizes = df.neighbourhood_group.value_counts().values
        explode = (0.1, 0.2, 0.3, 0.4, 0.6)
    else:
        labels = df.neighbourhood.value_counts().index
        sizes = df.neighbourhood.value_counts().values
        explode = np.full(len(sizes),0.1)
    fig, ax = plt.subplots()
    wedges, texts, autotexts = ax.pie(sizes, explode=explode,labels=labels, autopct='%1.
                                      shadow=True, startangle=90)
    ax.axis('equal')  # Equal aspect ratio ensures that pie is drawn as a circle.
    ax.set_title('Most rented neighbourhood group pie chart',size=12,fontweight='bold')
```

```
    ax.legend(wedges, labels,
              title='Neighbourhood groups',
              loc='center left',
              bbox_to_anchor=(1, 0, 0.5, 1))
    return ax
```

In [297…

```
# get price distribution of each neighbourhood
def nei_stats(city,df):
    if city == 'NYC':
        col = 'neighbourhood_group'
    else:
        col = 'neighbourhood'
    nei = df[col].unique()
    price_list = []
    for n in nei:
        sub = df.loc[df[col] == n]
        sub_price = sub[['price']]
        price_list.append(sub_price)
    stats_list = []
    for p in price_list:
        i = p.describe(percentiles=[.25, .50, .75])
        i = i.iloc[3:]
        i.reset_index(inplace=True)
        i.rename(columns={'index':'Stats'},inplace=True)
        stats_list.append(i)
    # change names of the price column to the area name
    for i in range(0,len(nei)):
        stats_list[i].rename(columns={'price':nei[i]},inplace=True)

    # finilize dataframe for final view
    stats_df = stats_list
    stats_df = [df.set_index('Stats') for df in stats_df]
    stats_df = stats_df[0].join(stats_df[1:])
    stats_df
    return stats_df

# use violinplot to show density and distribtuion of prices
def plot_distribution(city,df,dropv):
    if city == 'NYC':
        col = 'neighbourhood_group'
        angel = 0
    else:
        col = 'neighbourhood'
        angel = 45
    # create a sub-dataframe with no extreme values / less than 500
    no_extreme = df[df.price < dropv]
    ax = sns.violinplot(data=no_extreme,x=col,y='price')
    ax.set_xlabel('Neighbourhood group')
    ax.set_ylabel('Price')
    ax.set_title('Density and distribution of prices for each neighbourhood group',fontv
    ax.set_xticklabels(ax.get_xticklabels(),rotation=angel)
    return fig,ax
```

In [298…

```
# get top 10 neighborhoods with the most listings
def top_nei(city,df):
    nbhd = df.neighbourhood.value_counts()[:10]
    figure,ax = plt.subplots(figsize=(6,4))
    x = list(nbhd.index)
    y = list(nbhd.values)
    ax = sns.barplot(y,x)
    ax.set_title('Most Popular Neighbourhood in '+city,size=14,fontweight='bold')
    ax.set_ylabel("Neighbourhood area")
    ax.set_xlabel("Number of guest hosted in this Area")
    return fig,ax
```

In [299…

```
# get the number of rooms under each room type in the top 10 neighborhoods
def top_nei_room_type(city,df):
    top10nei = df.neighbourhood.value_counts()[:10].index
    top10nei_df = df.loc[df['neighbourhood'].isin(top10nei)]
    if city == 'NYC':
        ax = sns.catplot(x='neighbourhood',col='room_type',hue='neighbourhood_group',dat
```

```
    else:
        ax = sns.catplot(x='neighbourhood',col='room_type',data=top10nei_df,kind='count
    ax.set_xticklabels(rotation=45)
    return ax
```

In [300…
```
# use colormap to display avaialbility_365
def ava365(city,df,figsize1,figsize2):
    fig,ax = plt.subplots(figsize=(figsize1,figsize2))
    df.plot(kind='scatter', x='longitude', y='latitude', label='availability_365', c='av
    ax.set_title('Availability of rooms in '+city,size=14,fontweight='bold')
    ax.set_xlabel('Longitude')
    ax.set_ylabel('Latitude')
    ax.legend().remove()
    return fig,ax
```

➢ NYC

1. Data

1.1 Data Cleaning

In [301…
```
url1 = 'https://raw.githubusercontent.com/kristallqiu99/'
url2 = 'data_bootcamp_final_project/master/nyc_data/AB_NYC_2019.csv'
nyc = pd.read_csv(url1+url2,index_col=0)
```

In [302…
```
nyc.head(5)
```

Out[302…

	id	name	host_id	host_name	neighbourhood_group	neighbourhood	latitude	longitude
0	2539	Clean & quiet apt home by the park	2787	John	Brooklyn	Kensington	40.64749	-73.97237
1	2595	Skylit Midtown Castle	2845	Jennifer	Manhattan	Midtown	40.75362	-73.98377
2	3647	THE VILLAGE OF HARLEM....NEW YORK !	4632	Elisabeth	Manhattan	Harlem	40.80902	-73.94190
3	3831	Cozy Entire Floor of Brownstone	4869	LisaRoxanne	Brooklyn	Clinton Hill	40.68514	-73.95976
4	5022	Entire Apt: Spacious Studio/Loft by central park	7192	Laura	Manhattan	East Harlem	40.79851	-73.94399

In [303…
```
nyc.dtypes
```

Out[303…
```
id                                  int64
name                               object
host_id                             int64
host_name                          object
neighbourhood_group                object
neighbourhood                      object
latitude                          float64
longitude                         float64
room_type                          object
price                               int64
minimum_nights                      int64
number_of_reviews                   int64
last_review                        object
reviews_per_month                 float64
calculated_host_listings_count      int64
availability_365                    int64
dtype: object
```

In [304…
```
nyc.isnull().sum()
```

Out[304…
```
id                                  0
name                               16
host_id                             0
host_name                          21
neighbourhood_group                 0
neighbourhood                       0
latitude                            0
longitude                           0
room_type                           0
price                               0
minimum_nights                      0
number_of_reviews                   0
last_review                     10052
reviews_per_month               10052
calculated_host_listings_count      0
availability_365                    0
dtype: int64
```

In [305…
```
nyc.drop(['name','host_name','last_review'],axis = 1,inplace=True)
nyc = nyc.dropna(subset=['reviews_per_month'])
nyc = nyc.loc[nyc['price']>0,:]
nyc.describe()
```

Out[305…

	id	host_id	latitude	longitude	price	minimum_nights	numbe
count	3.883300e+04	3.883300e+04	38833.000000	38833.000000	38833.000000	38833.000000	38
mean	1.809583e+07	6.423943e+07	40.728139	-73.951156	142.354595	5.867561	
std	1.069500e+07	7.589466e+07	0.054992	0.046697	196.957737	17.386070	
min	2.539000e+03	2.438000e+03	40.506410	-74.244420	10.000000	1.000000	
25%	8.719522e+06	7.033514e+06	40.688640	-73.982470	69.000000	1.000000	
50%	1.886923e+07	2.837092e+07	40.721720	-73.954810	101.000000	2.000000	
75%	2.755799e+07	1.018090e+08	40.763000	-73.935020	170.000000	4.000000	
max	3.645581e+07	2.738417e+08	40.913060	-73.712990	10000.000000	1250.000000	

2. Exploratory Data Analysis

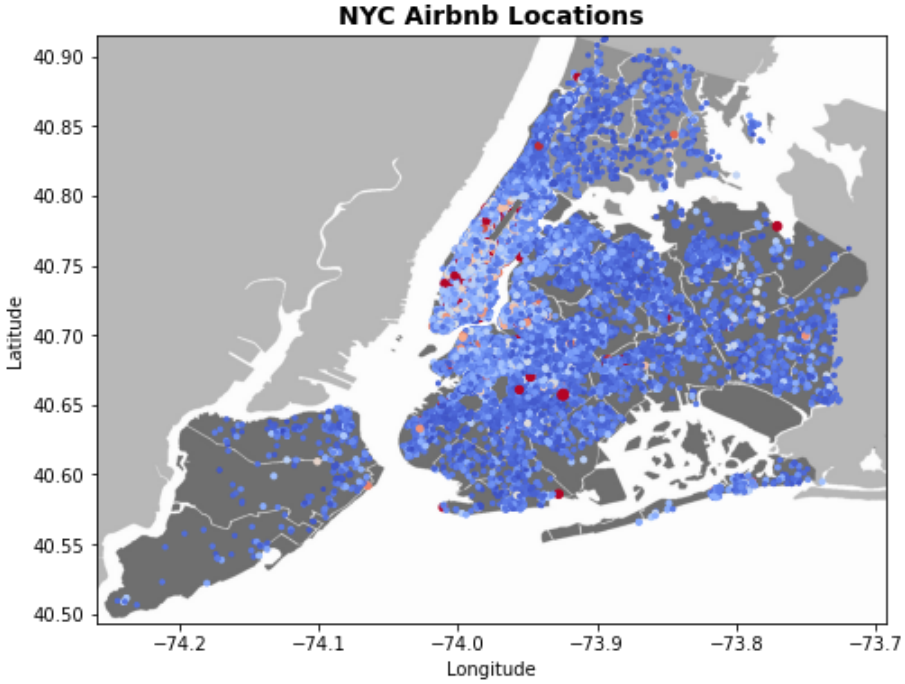
2.1 Data Visualization

2.1.1 Location

In [306…
```
mpl.rcParams.update(mpl.rcParamsDefault)
%matplotlib inline

response = requests.get('https://raw.githubusercontent.com/kristallqiu99/data_bootcamp_f
img_nyc = Image.open(BytesIO(response.content))

cmap = plt.cm.coolwarm
n = mpl.colors.Normalize()

fig,ax = plt.subplots(figsize=(8,6))

xl=nyc['longitude'].min()-0.015
xh=nyc['longitude'].max()+0.02
yl=nyc['latitude'].min()-0.013
yh=nyc['latitude'].max()+0.0025

ax.imshow(img_nyc,extent=[xl,xh,yl,yh])

nyc.plot.scatter(ax = ax,x = 'longitude',y = 'latitude',s = nyc['price']**0.4,
                 color = cmap(n(nyc['price'].values)*13))

ax.set_xlim(xl,xh)
```

```
ax.set_ylim(yl,yh)
ax.set_xlabel('Longitude')
ax.set_ylabel('Latitude')
ax.set_title('NYC Airbnb Locations',size=14,fontweight='bold')
```

Out[306… `Text(0.5, 1.0, 'NYC Airbnb Locations')`



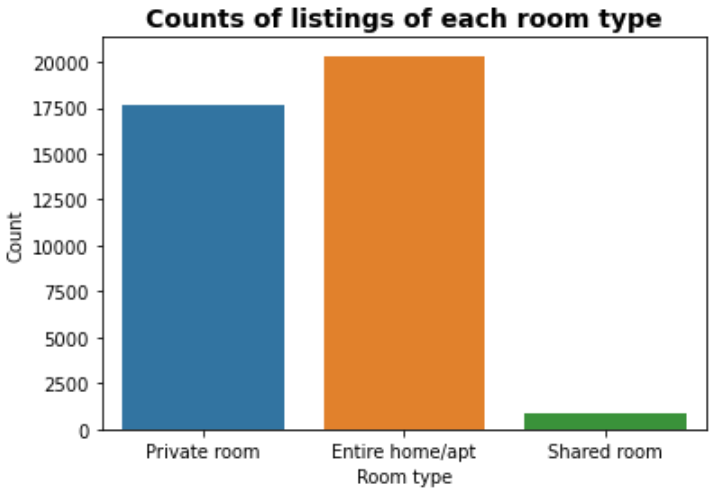
In the plot above, the most expensive houses are plotted in red dots and the cheaper ones are plotted in light blue. We learn surprisingly that in NYC, the most expensive Airbnb houses are located dispersedly, instead of clustering in one specific area.

2.1.2 Room Type

a) Number of listings of each room type

In [307…

```
ax = sns.countplot(data=nyc,x='room_type')
ax.set_xlabel('Room type')
ax.set_ylabel('Count')
ax.set_title('Counts of listings of each room type',size=14,fontweight='bold')
current_palette = sns.color_palette()
```



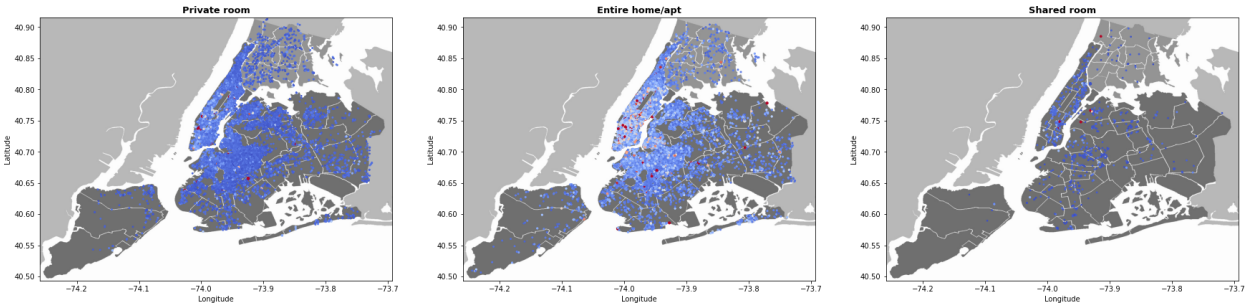
From the bar chart above, we know that there are very few shared room as Airbnb offerings in NYC. There are two major room types in NYC, private room and entire home types, relatively of the same number.

b) Spread

In [308…

```
mpl.rcParams.update(mpl.rcParamsDefault)
%matplotlib inline
```

```
rtype = nyc.groupby(['id','room_type','latitude','longitude'],as_index=False)[['price']]
rtype
type = nyc['room_type'].unique()
num = len(type)
cmap = plt.cm.coolwarm
n = mpl.colors.Normalize()
fig,ax = plt.subplots(1,num,figsize=(10*num,14))
for i in range(0,num):
    tprice = rtype.loc[rtype['room_type']==type[i],:]
    tprice.plot.scatter(ax=ax[i],x='longitude',y='latitude',s=tprice['price']**0.3,
                        color=cmap(n(tprice['price'].values)*13))
    ax[i].set_title(type[i],size=13,fontweight='bold')
    ax[i].set_xlabel('Longitude')
    ax[i].set_ylabel('Latitude')
    ax[i].imshow(img_nyc,extent=[xl,xh,yl,yh])
```



Those two major room types distribute evenly in NYC, and their locations don't follow some certain patterns.

2.1.3 Host

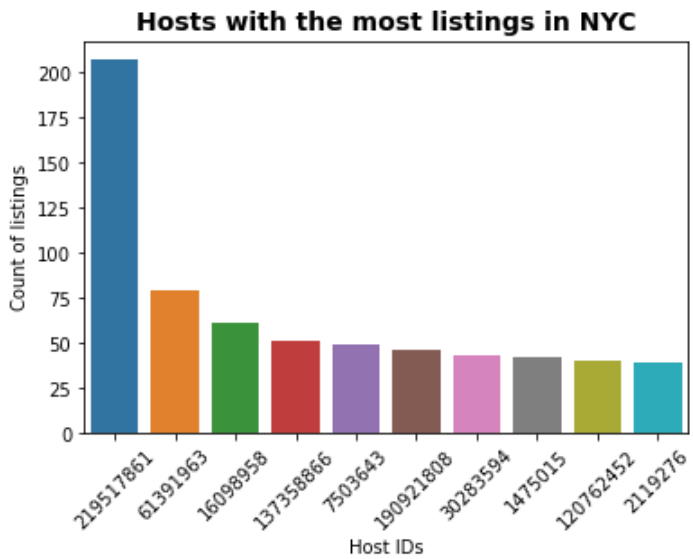
In [309…

```
top_host = nyc['host_id'].value_counts()[:10]
ax = sns.barplot(top_host.index, top_host.values,order=top_host.index)
ax.set_xticklabels(ax.get_xticklabels(),rotation=45)
ax.set_title('Hosts with the most listings in NYC',size=14,fontweight='bold')
ax.set_ylabel('Count of listings')
ax.set_xlabel('Host IDs')
```

```
/Users/kristallqiu/opt/anaconda3/lib/python3.8/site-packages/seaborn/_decorators.py:36:
FutureWarning: Pass the following variables as keyword args: x, y. From version 0.12, th
e only valid positional argument will be `data`, and passing other arguments without an
explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

Out[309…

```
Text(0.5, 0, 'Host IDs')
```

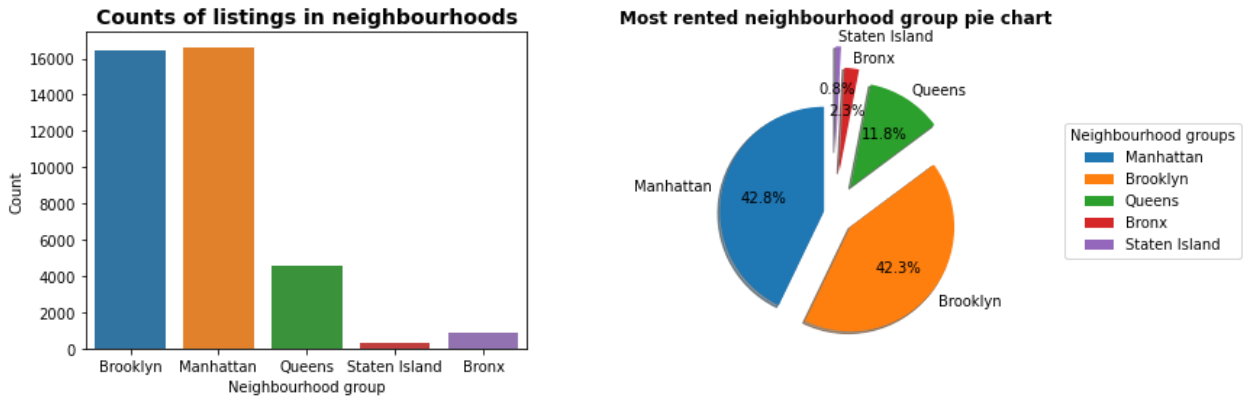


We notice that there is one host with a significantly high number of listings than other hosts in NYC, who has more than 200 listings. After that, other hosts all have listings fewer than 100 and the number doesn't different much from each other.

2.1.4 Neighbourhood

In [310…
```
fig, ax = plt.subplots(1,2,figsize=(12,4))
# bar chart
sns.countplot(x='neighbourhood_group',data=nyc,ax=ax[0])
ax[0].set_xlabel('Neighbourhood group')
ax[0].set_ylabel('Count')
ax[0].set_title('Counts of listings in neighbourhoods',fontsize=14,fontweight='bold')
current_palette = sns.color_palette()

# pie chart
labels = nyc.neighbourhood_group.value_counts().index
sizes = nyc.neighbourhood_group.value_counts().values
explode = (0.1, 0.2, 0.3, 0.4, 0.6)

wedges, texts, autotexts = ax[1].pie(sizes, explode=explode,labels=labels, autopct='%1.1
                                     shadow=True, startangle=90)
ax[1].axis('equal')  # Equal aspect ratio ensures that pie is drawn as a circle.
ax[1].set_title('Most rented neighbourhood group pie chart',size=12,fontweight='bold')
ax[1].legend(wedges, labels,
          title='Neighbourhood groups',
          loc='center left',
          bbox_to_anchor=(1, 0, 0.5, 1))
```

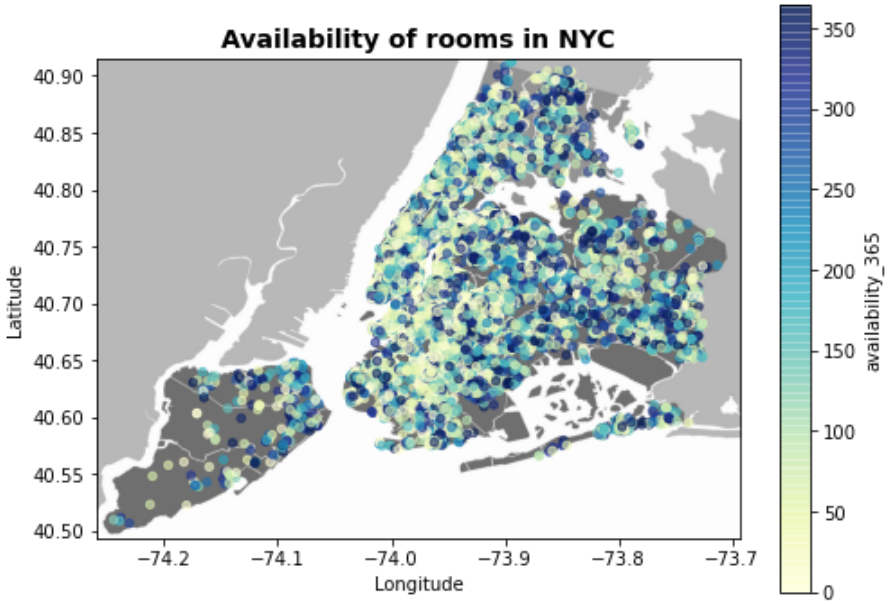
Out[310… <matplotlib.legend.Legend at 0x7f88ecab6670>



From the pie chart and bar chart above, we learn that most Airbnb houses are located in Manhattan and Brooklyn, where there are more scenery spots and places for fun.

2.1.5 Availability

In [311…
```
fig,ax = plt.subplots(figsize=(8,6))
nyc.plot(kind='scatter', x='longitude', y='latitude', label='availability_365',
         c='availability_365', cmap='YlGnBu', alpha=0.6,colorbar=True,ax=ax)
xl=nyc['longitude'].min()-0.015
xh=nyc['longitude'].max()+0.02
yl=nyc['latitude'].min()-0.013
yh=nyc['latitude'].max()+0.0025
ax.imshow(img_nyc,extent=[xl,xh,yl,yh])
ax.set_xlabel('Longitude')
ax.set_ylabel('Latitude')
ax.set_title('Availability of rooms in NYC',size=14,fontweight='bold')
ax.legend().remove()
```



In this graph, we plot the availability of rooms in NYC. We notice that most rooms are available for fewer than 200 days per year, while there are a few houses that are available for the whole year. We guess that most rooms are made available during peak tourist seasons, but during the tourist-off season, some rooms will not be available since there isn't a very large demand in the market.

2.2 Data Analysis

2.2.1 Price with room types

In [312…

```
rtype = nyc['room_type'].unique()
price_list = []
for n in rtype:
    sub = nyc.loc[nyc['room_type'] == n]
    sub_price = sub[['price']]
    price_list.append(sub_price)
stats_list = []
for p in price_list:
    i = p.describe(percentiles=[.25, .50, .75])
    i = i.iloc[3:]
    i.reset_index(inplace=True)
    i.rename(columns={'index':'Stats'},inplace=True)
    stats_list.append(i)
# change names of the price column to the area name
for i in range(0,len(rtype)):
    stats_list[i].rename(columns={'price':rtype[i]},inplace=True)
# finilize dataframe for final view
stats_df = stats_list
stats_df = [df.set_index('Stats') for df in stats_df]
stats_df = stats_df[0].join(stats_df[1:])
stats_df
```

Out[312…

Stats	Private room	Entire home/apt	Shared room
min	10.0	10.0	10.0
25%	50.0	116.0	32.0
50%	70.0	151.0	45.0
75%	94.0	220.0	70.0
max	10000.0	10000.0	1800.0

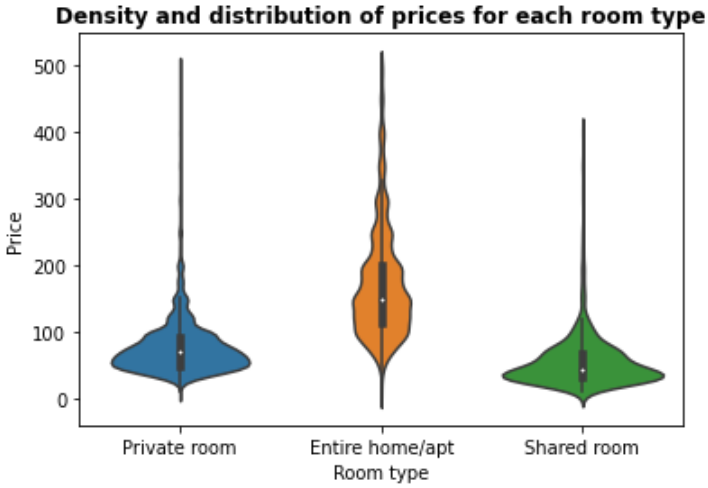
a) Density distribution

In [313…

```
no_extreme = nyc[nyc.price < 500]
ax = sns.violinplot(data=no_extreme,x='room_type',y='price')
```

```
ax.set_xlabel('Room type')
ax.set_ylabel('Price')
ax.set_title('Density and distribution of prices for each room type',fontweight='bold')
```

Out[313… `Text(0.5, 1.0, 'Density and distribution of prices for each room type')`

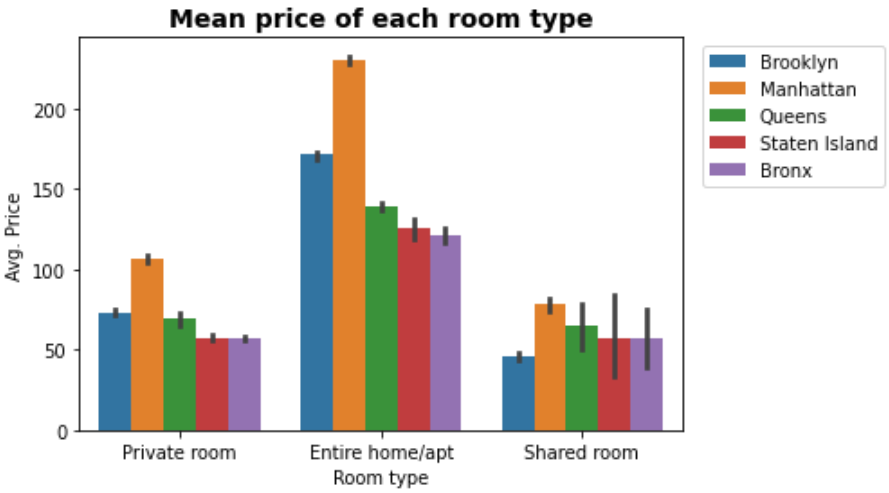


From the density distribution, we know that hosts charge a higher price for entire home/apt room type, ranging from less than 100 dollars to more than 300 dollars, even to 400 dollars. On the contrary, most private rooms and shared rooms are charged a price of fewer than 100 dollars per day.

b) Compare & Contrast - Neighbourhood

In [314…
```
ax = sns.barplot(data=nyc,x='room_type',y='price',hue='neighbourhood_group',ci=68)
ax.legend(bbox_to_anchor=(1, 0, 0.35, 1))
ax.set_xlabel('Room type')
ax.set_ylabel('Avg. Price')
ax.set_title('Mean price of each room type',fontsize=14,fontweight ='bold')
```

Out[314… `Text(0.5, 1.0, 'Mean price of each room type')`



We learn from this graph that regardless the room type, the mean price of rooms in Manhattan is much higher than that of rooms in other boroughs.

2.2.2 Price with neighbourhoods

In [315…
```
nei_stats('NYC',nyc)
```

Out[315…

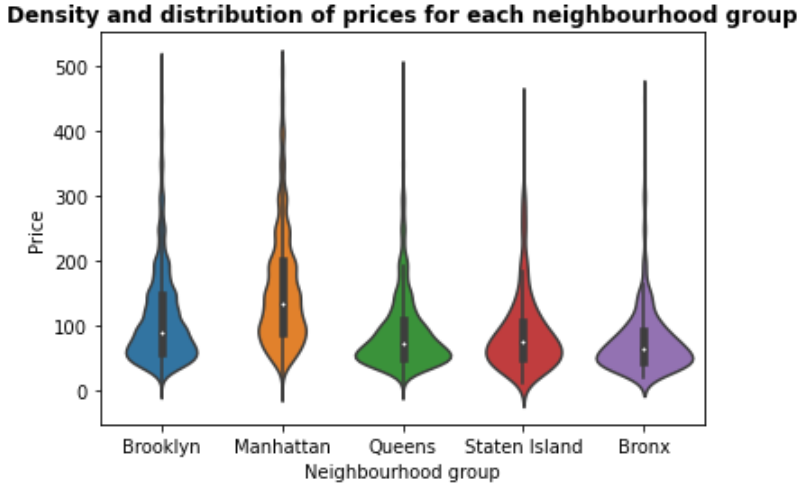
Stats	Brooklyn	Manhattan	Queens	Staten Island	Bronx
min	10.0	10.0	10.0	13.0	20.0
25%	60.0	90.0	50.0	50.0	45.0
50%	94.0	140.0	72.0	75.0	65.0

Stats	Brooklyn	Manhattan	Queens	Staten Island	Bronx
75%	150.0	200.0	109.0	105.0	95.0
max	10000.0	9999.0	10000.0	625.0	800.0

a) Density distribution

In [316…
```
plot_distribution('NYC',nyc,500)
```

Out[316…
```
(<Figure size 576x432 with 2 Axes>,
 <AxesSubplot:title={'center':'Density and distribution of prices for each neighbourhood group'}, xlabel='Neighbourhood group', ylabel='Price'>)
```

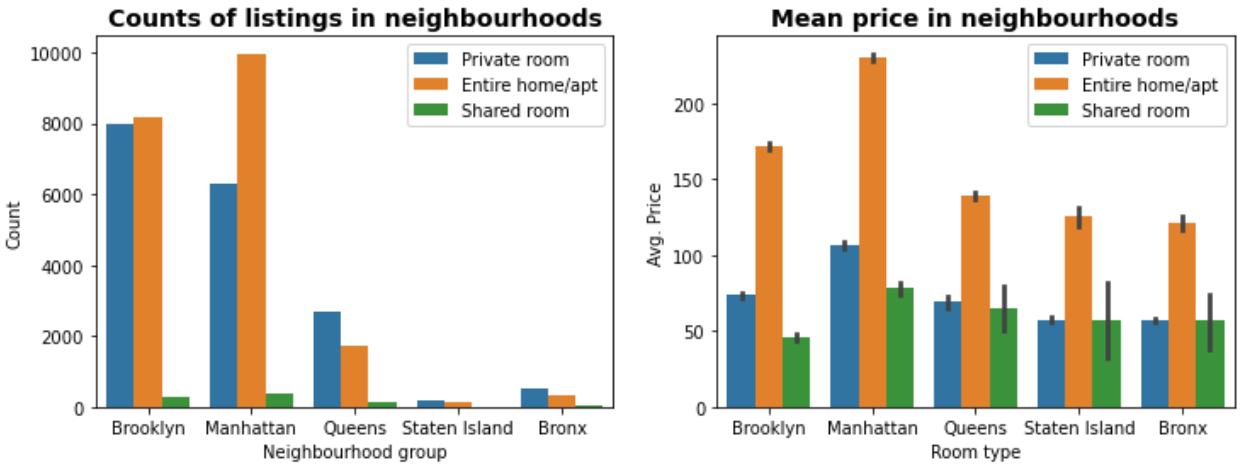


In this graph, we plot the density and distribution of prices for each neighbourhood group. As before, the prices in Manhattan vary the most, while the prices in other districts are more concentrated.

b) Compare & Contrast - Room Type

In [317…
```
figure,ax = plt.subplots(1,2,figsize=(12,4))
sns.countplot(data=nyc,x='neighbourhood_group',hue='room_type',palette=current_palette,a
ax[0].set_title('Counts of listings in neighbourhoods',fontsize=14,fontweight ='bold')
ax[0].set_xlabel('Neighbourhood group')
ax[0].set_ylabel('Count')
ax[0].legend()

sns.barplot(data=nyc,x='neighbourhood_group',y='price',hue='room_type',ci=68,ax=ax[1],pa
ax[1].legend(bbox_to_anchor=(1, 0, 0, 1))
ax[1].set_title('Mean price in neighbourhoods',fontsize=14,fontweight ='bold')
ax[1].set_xlabel('Room type')
ax[1].set_ylabel('Avg. Price')
```

Out[317…
```
Text(0, 0.5, 'Avg. Price')
```



Here with the comparison of count of listings and mean price, we notice that the mean price in Manhattan, especially mean price for entire home/apt, is much higher than mean price in other

districts. Manhattan has most counts of listings of entire home/apt, too.

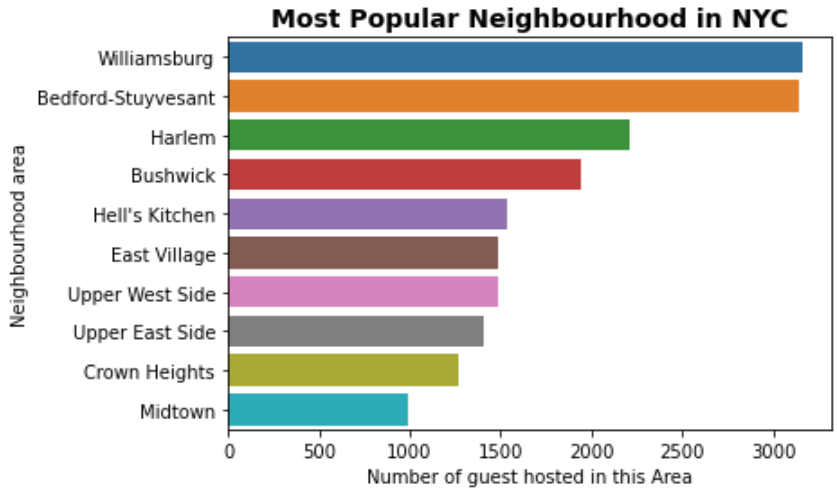
2.2.3 Neighbourhood Exploration

a) Popular neighbourhoods

In [318…
```
nbhd = nyc.neighbourhood.value_counts()[:10]
figure,ax = plt.subplots(figsize=(6,4))
x = list(nbhd.index)
y = list(nbhd.values)
ax = sns.barplot(y,x)
ax.set_title('Most Popular Neighbourhood in NYC',size=14,fontweight='bold')
ax.set_ylabel("Neighbourhood area")
ax.set_xlabel("Number of guest hosted in this Area")
```

```
/Users/kristallqiu/opt/anaconda3/lib/python3.8/site-packages/seaborn/_decorators.py:36:
FutureWarning: Pass the following variables as keyword args: x, y. From version 0.12, th
e only valid positional argument will be `data`, and passing other arguments without an
explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

Out[318… `Text(0.5, 0, 'Number of guest hosted in this Area')`

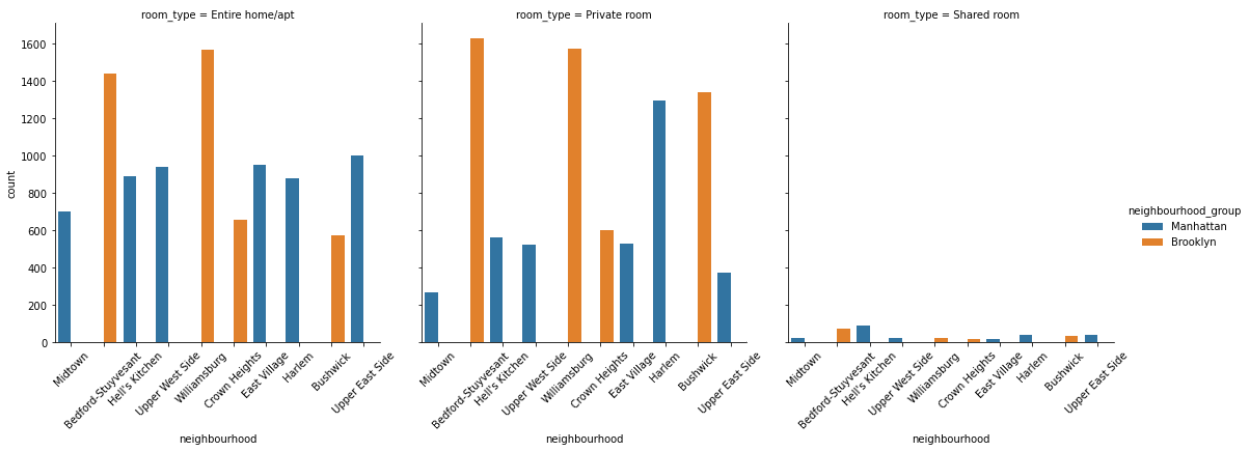


We list top ten most popular neighbourhood in NYC in this horizontal bar chart. There are many names that we are familier with; and we learn that the most popular neighbourhood are mostly located in Manhattan.

b) Room type within popular neighbourhoods

In [319…
```
top10nei = nyc.neighbourhood.value_counts()[:10].index
top10nei_df = nyc.loc[nyc['neighbourhood'].isin(top10nei)]
ax = sns.catplot(x='neighbourhood',col='room_type',hue='neighbourhood_group',data=top10r
ax.set_xticklabels(rotation=45)
```

Out[319… `<seaborn.axisgrid.FacetGrid at 0x7f88b113d700>`



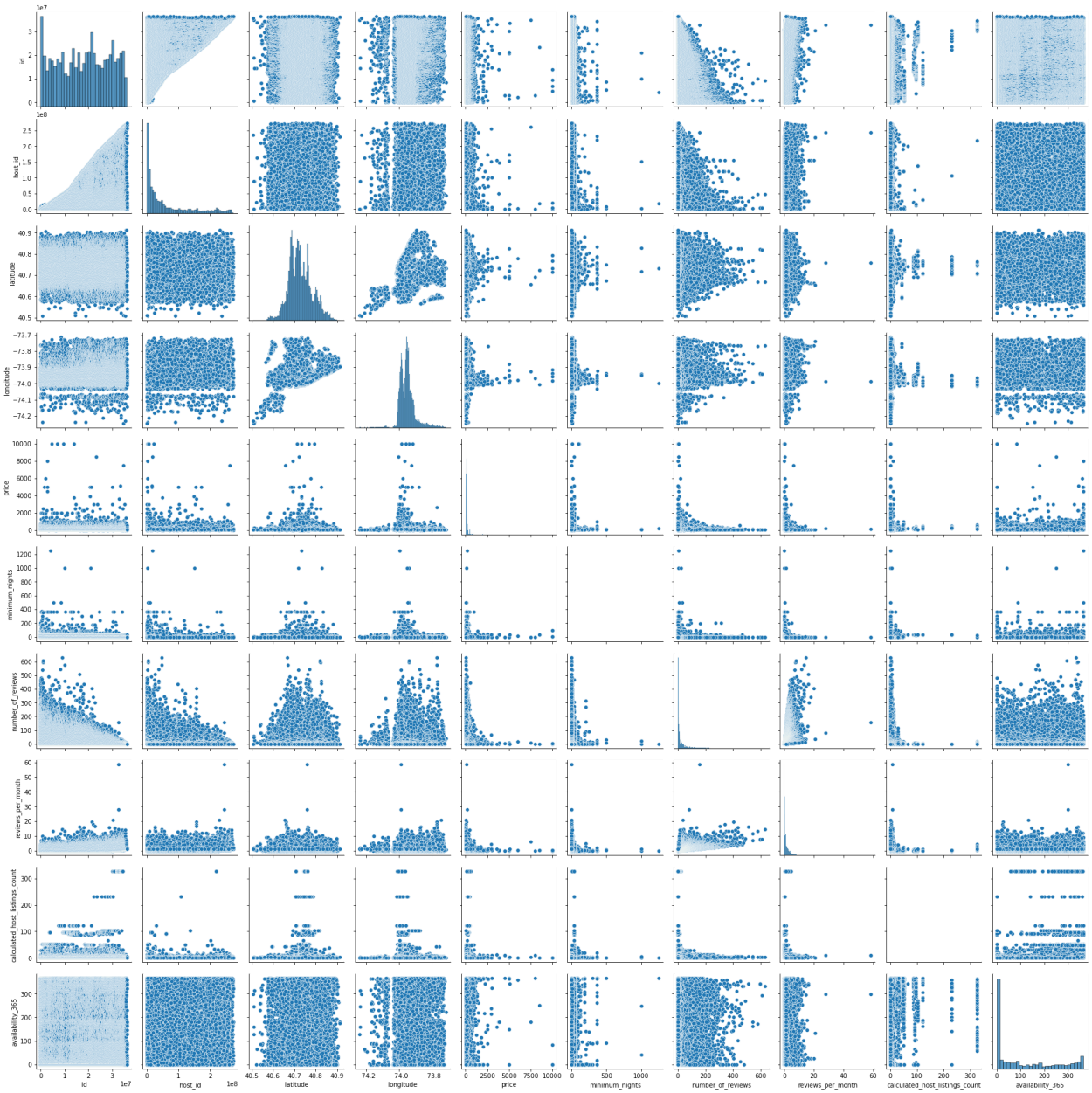
Based on the top ten popular neighborhood we selected before, we picture the room types information in these neighborhoods for readers' reference. Guests can know the distribution of their favourite room type in popular neighborhoods, so that they can make the decisions more easily.

3. Descriptive Data Analysis

3.1 Pairplot of each variable

In [320…
```
sns.pairplot(nyc)
```

Out[320…
```
<seaborn.axisgrid.PairGrid at 0x7f88b2f6bcd0>
```



We can see the correltation between each variable. It does not make sense as many of them are categorical data and interrelated. We can also observe that there are extreme values of price so we may need to drop those extreme values.

4. Predictive Data Analysis

In [321…
```
# encode string values
model = nyc.copy()
model['neighbourhood_group']= model['neighbourhood_group'].astype("category").cat.codes
model['neighbourhood'] = model['neighbourhood'].astype("category").cat.codes
model['room_type'] = model['room_type'].astype("category").cat.codes

mean = model['reviews_per_month'].mean()
model['reviews_per_month'].fillna(mean, inplace=True)

model['log_price'] = np.log(model.price+1)
```

```
model = model.drop(columns=['id' ,'host_id','price']) # delete price column

model.isnull().sum()
```

Out[321…
```
neighbourhood_group                0
neighbourhood                      0
latitude                           0
longitude                          0
room_type                          0
minimum_nights                     0
number_of_reviews                  0
reviews_per_month                  0
calculated_host_listings_count     0
availability_365                   0
log_price                          0
dtype: int64
```

Value Reference

In [322…
```
nycVF = {}
nycd = ['neighbourhood_group','room_type']
for c in nycd:
    nycVF = {}
    for i in model[c].unique():
        indx = model[model[c]==i].index.values[0]
        nycVF[i] = nyc[c][indx]
    print(c.capitalize(),'\n',dict(sorted(nycVF.items())))
```

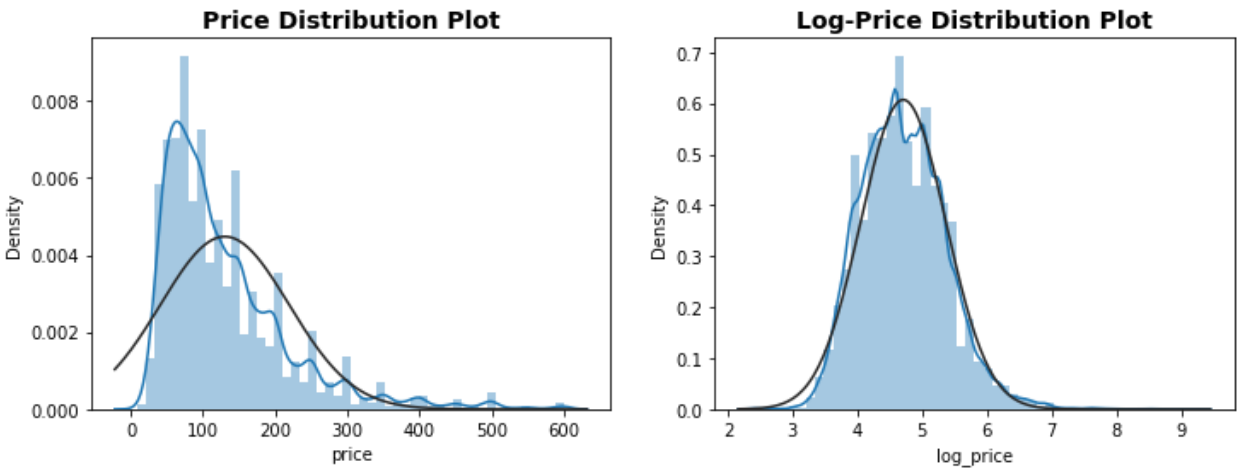
```
Neighbourhood_group
 {0: 'Bronx', 1: 'Brooklyn', 2: 'Manhattan', 3: 'Queens', 4: 'Staten Island'}
Room_type
 {0: 'Entire home/apt', 1: 'Private room', 2: 'Shared room'}
```

4.1 Probability distribution

In [323…
```
fig,ax = plt.subplots(1,2,figsize=(12,4))
sns.distplot(nyc.loc[nyc['price']<=600]['price'],fit=norm, ax=ax[0]) # drop extreme valu
ax[0].set_title("Price Distribution Plot",size=14, weight='bold')
sns.distplot(model['log_price'],fit=norm,ax=ax[1])
ax[1].set_title("Log-Price Distribution Plot",size=14, weight='bold')
```

```
/Users/kristallqiu/opt/anaconda3/lib/python3.8/site-packages/seaborn/distributions.py:25
51: FutureWarning: `distplot` is a deprecated function and will be removed in a future v
ersion. Please adapt your code to use either `displot` (a figure-level function with sim
ilar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
/Users/kristallqiu/opt/anaconda3/lib/python3.8/site-packages/seaborn/distributions.py:25
51: FutureWarning: `distplot` is a deprecated function and will be removed in a future v
ersion. Please adapt your code to use either `displot` (a figure-level function with sim
ilar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

Out[323…
```
Text(0.5, 1.0, 'Log-Price Distribution Plot')
```

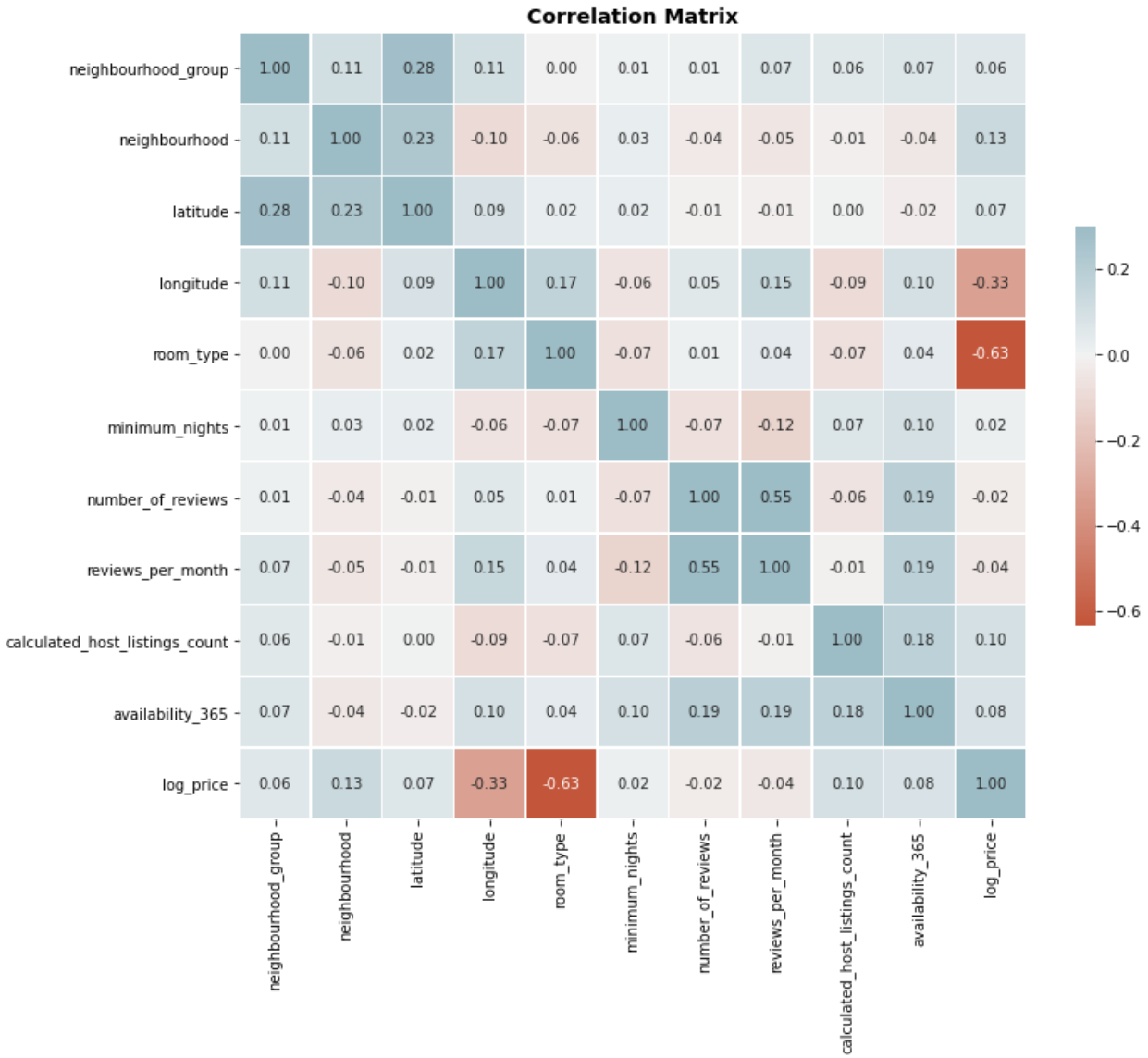


We learn that the log-price distribution is approximately normal, with a mean close to 5.

4.2 Correlation

In [324…
```
plt.figure(figsize=(12,10))
palette = sns.diverging_palette(20, 220, n=256)
corr=model.corr(method='pearson')
sns.heatmap(corr, annot=True, fmt=".2f", cmap=palette, vmax=.3, center=0,
            square=True, linewidths=.5, cbar_kws={"shrink": .5}).set(ylim=(11, 0))
plt.title("Correlation Matrix",size=14, weight='bold')
```

Out[324…
```
Text(0.5, 1.0, 'Correlation Matrix')
```



In this correlation matrix we calculate and display the correlation between different variables. The hosts can easily find the relationship between variables and make the optimized investment decisions.

4.3 Regression

In [325…
```
model['price'] = nyc['price']
model.head(5)
```

Out[325…

	neighbourhood_group	neighbourhood	latitude	longitude	room_type	minimum_nights	number_of_revi
0	1	107	40.64749	-73.97237	1	1	
1	2	126	40.75362	-73.98377	0	1	
3	1	41	40.68514	-73.95976	0	1	
4	2	61	40.79851	-73.94399	0	10	
5	2	136	40.74767	-73.97500	0	3	

4.3.1 Linear Regression

In [326…
```
import statsmodels.formula.api as smf
```

a) Price - all variables

In [327…
```
reg_price = smf.ols('price ~  neighbourhood_group +room_type +  availability_365 + numbe
                    ,data=model).fit()

print(reg_price.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.091
Model:                            OLS   Adj. R-squared:                  0.091
Method:                 Least Squares   F-statistic:                     646.4
Date:                Wed, 04 Nov 2020   Prob (F-statistic):               0.00
Time:                        11:43:13   Log-Likelihood:            -2.5841e+05
No. Observations:               38833   AIC:                         5.168e+05
Df Residuals:                   38826   BIC:                         5.169e+05
Df Model:                           6
Covariance Type:            nonrobust
================================================================================
==========
                                   coef    std err          t      P>|t|      [0.025
0.975]
--------------------------------------------------------------------------------
----------
Intercept                      170.4157      2.635     64.676      0.000     165.251
175.580
neighbourhood_group              8.0991      1.291      6.272      0.000       5.568
10.630
room_type                     -102.9268      1.768    -58.224      0.000    -106.392
-99.462
availability_365                 0.1477      0.008     19.168      0.000       0.133
0.163
number_of_reviews               -0.1766      0.024     -7.374      0.000      -0.223
-0.130
calculated_host_listings_count   0.0824      0.037      2.216      0.027       0.010
0.155
reviews_per_month               -1.8182      0.685     -2.656      0.008      -3.160
-0.476
==============================================================================
Omnibus:                    96312.864   Durbin-Watson:                   1.929
Prob(Omnibus):                  0.000   Jarque-Bera (JB):       2113631475.472
Skew:                          26.749   Prob(JB):                         0.00
Kurtosis:                    1144.678   Cond. No.                         534.
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specifi
ed.
```

Here we run an ordinary least square regression for price on several factors that we think may influence the price of Airbnb. We have H0: beta = 0 against H1: beta != 0 for every beta in this regression model. According to the output table, the P-value of reviews_per_month is bigger than 5%, which means that we don't reject H0 against H1. There is no evidence that the effect of reviews_per_month is significant to the price of Airbnb house and we should drop it.

a) Price - drop reviews_per_month

In [328…
```
reg_price = smf.ols('price ~  neighbourhood_group +room_type +  availability_365 + numbe
                    ,data=model).fit()

print(reg_price.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.091
Model:                            OLS   Adj. R-squared:                  0.091
Method:                 Least Squares   F-statistic:                     774.2
Date:                Wed, 04 Nov 2020   Prob (F-statistic):               0.00
Time:                        11:43:13   Log-Likelihood:            -2.5841e+05
No. Observations:               38833   AIC:                         5.168e+05
Df Residuals:                   38827   BIC:                         5.169e+05
Df Model:                           5
```

```
Covariance Type:            nonrobust
==============================================================================================
                                 coef    std err          t      P>|t|      [0.025
0.975]
----------------------------------------------------------------------------------------------
Intercept                    169.6320      2.619     64.781      0.000     164.500
174.764
neighbourhood_group            7.8472      1.288      6.093      0.000       5.323
10.371
room_type                   -103.1122      1.767    -58.370      0.000    -106.575
-99.650
availability_365               0.1459      0.008     19.008      0.000       0.131
0.161
number_of_reviews             -0.2104      0.020    -10.387      0.000      -0.250
-0.171
calculated_host_listings_count     0.0815      0.037      2.192      0.028       0.009
0.154
==============================================================================
Omnibus:                    96314.167   Durbin-Watson:                   1.929
Prob(Omnibus):                  0.000   Jarque-Bera (JB):       2113557368.908
Skew:                          26.750   Prob(JB):                         0.00
Kurtosis:                    1144.658   Cond. No.                         532.
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specifi
ed.
```

Here we run an ordinary least square regression for log_price on several x variables. We have H0: beta = 0 against H1: beta != 0 for every beta in this regression model. This time each veriable is significant at 5% level.

And, we can get price = 169.6320 + neighbourhood_group *7.8472* - *room_type* 103.1122 + availability_365 *0.1459* - *number_of_reviews* 0.2104 + calculated_host_listings_count* 0.0815

And from this, we can find that availability make the largest contribution to a relative higher price.

b) Log price

In [329…

```
reg_logprice = smf.ols('log_price ~  neighbourhood_group +room_type +  availability_365
                    ,data=model).fit()
print(reg_logprice.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:              log_price   R-squared:                       0.418
Model:                            OLS   Adj. R-squared:                  0.418
Method:                 Least Squares   F-statistic:                     4641.
Date:                Wed, 04 Nov 2020   Prob (F-statistic):               0.00
Time:                        11:43:13   Log-Likelihood:                -28305.
No. Observations:               38833   AIC:                         5.662e+04
Df Residuals:                   38826   BIC:                         5.668e+04
Df Model:                           6
Covariance Type:            nonrobust
==============================================================================================
                                 coef    std err          t      P>|t|      [0.025
0.975]
----------------------------------------------------------------------------------------------
Intercept                      4.9685      0.007    706.053      0.000       4.955
4.982
neighbourhood_group            0.0483      0.003     14.011      0.000       0.042
0.055
room_type                     -0.7690      0.005   -162.890      0.000      -0.778
-0.760
availability_365               0.0005   2.06e-05     25.496      0.000       0.000
0.001
number_of_reviews             -0.0003   6.39e-05     -5.311      0.000      -0.000
-0.000
calculated_host_listings_count     0.0009   9.93e-05      8.568      0.000       0.001
0.001
reviews_per_month             -0.0089      0.002     -4.880      0.000      -0.013
-0.005
==============================================================================
```

```
Omnibus:                       7731.513   Durbin-Watson:                   1.913
Prob(Omnibus):                    0.000   Jarque-Bera (JB):            29414.787
Skew:                             0.961   Prob(JB):                         0.00
Kurtosis:                         6.806   Cond. No.                          534.
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specifi
ed.
```

We run the OLS regression for log_price again and the remained variables are all significant.

Therefore, we can get log_price = 4.9375 - 0.762 *room_type* - *0.0056* reviews_per_month + 0.001 *neighbourhood* + *0.0006* availability_365 - 0.0004*number_of_reviews* + *calculated_how_listings_count* 0.0009 - reviews_per_month*0.0056

We find that neighbour has the greatest relevance of the log_price.

4.3.2 ML

From the linear regression we found that log_price is a better dependent variable to predict.

In [330…
```
from sklearn.model_selection import train_test_split
```

In [331…
```
X_train1, X_test1, y_train1, y_test1 = train_test_split(model[['room_type']].values, mod
                                                test_size=0.25, random_state=0)
```

a) K-Nearest Neighbors

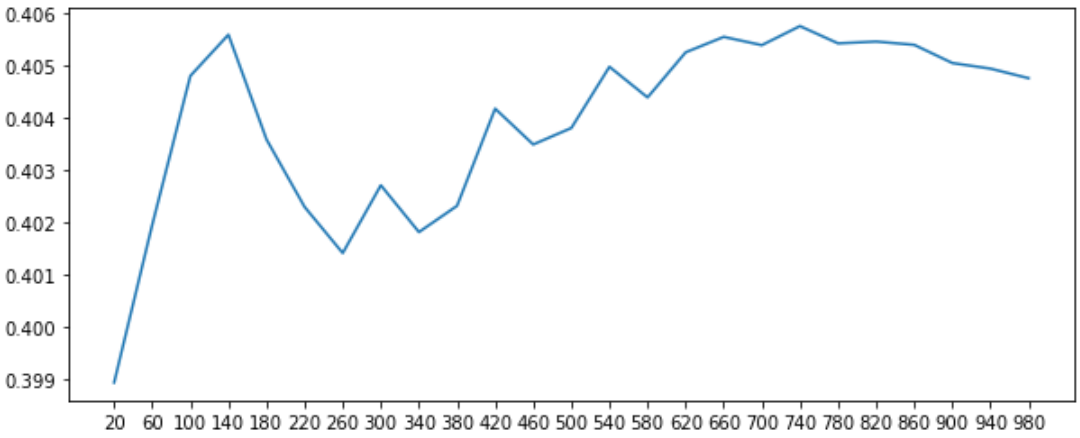
In [332…
```
from sklearn.neighbors import KNeighborsRegressor as knn
from sklearn.model_selection import cross_val_score
```

In [333…
```
scores = pd.Series()
for i in range(20,1000,40):
    scores[str(i)] = cross_val_score(knn(n_neighbors=i),
                     X_train1, y_train1,cv=5).mean()
indx = scores.idxmax()
```

```
<ipython-input-333-a95900ce99d7>:1: DeprecationWarning: The default dtype for empty Seri
es will be 'object' instead of 'float64' in a future version. Specify a dtype explicitly
to silence this warning.
  scores = pd.Series()
```

In [334…
```
fig,ax = plt.subplots(figsize=(10,4))
plt.plot(scores.index,scores.values)
```

Out[334…
```
[<matplotlib.lines.Line2D at 0x7f88ff245340>]
```



In [335…
```
skl_knn = knn(n_neighbors=int(indx)).fit(X_train1, y_train1)
knn_score1 = skl_knn.score(X_test1, y_test1)
print(knn_score1)
```

```
0.41313093103436194
```

b) Random Forest

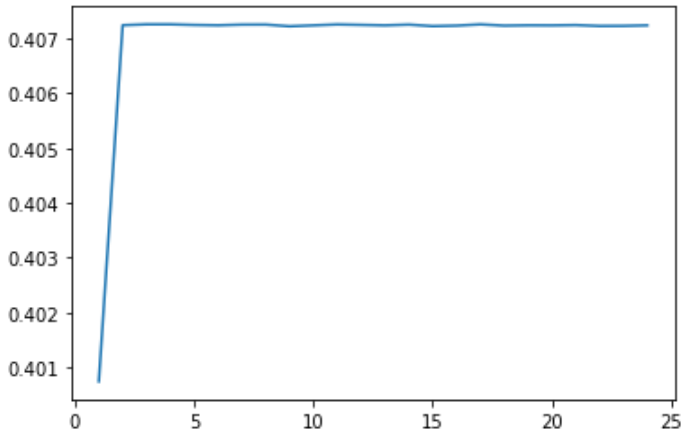
In [336…
```
from sklearn.ensemble import RandomForestRegressor as rf
```

In [337…
```
cross_val_score(rf(n_estimators=100,max_depth=3),X_train1, y_train1.ravel(),cv=5).mean()
```

Out[337… 0.4072375187490146

In [338…
```
cv_scores = pd.DataFrame()
for i in range(1,25):
    cv_scores.loc[i,'rf'] = cross_val_score(rf(n_estimators=100,max_depth=i),X_train1, y
```

In [339…
```
ax = cv_scores.plot()
ax.get_legend().remove()
```



In [340…
```
indx = scores.idxmax()
skl_rf = rf(n_estimators=100,max_depth=int(indx)).fit(X_train1, y_train1.ravel())
skl_rf.predict(X_test1)
rf_score1 = skl_rf.score(X_test1,y_test1)
print(rf_score1)
```

0.4136244486236249

In [341…
```
score_table = pd.DataFrame({'K Nearest Neighbors':[knn_score1],'Random Forest':[rf_score
score_table = score_table.T
score_table.columns = ['Score']
score_table
```

Out[341…

	Score
K Nearest Neighbors	0.413131
Random Forest	0.413624

As we can see from above table, for log_price, we should choose Random Forest as the score of this model is the highest, compared to KNN.

Rank score for log_price : Random Forest > KNN

Possiable reason for a relative low score for both is that log_price also should be dependent on some features not containing in the dataFrame as well, such as environment, surroundings or quality of the room and so on.

➢ Boston

1. Data

1.1 Data Cleaning

In [342…
```
bos=import_df('https://raw.githubusercontent.com/kristallqiu99/' +
              'data_bootcamp_final_project/master/boston_data/AB_BOS_2016.csv')
bos.head(5)
```

Out[342…

	Unnamed: 0	id	listing_url	scrape_id	last_scraped	name	s
0	0	12147973	https://www.airbnb.com/rooms/12147973	20160906204935	2016-09-07	Sunny Bungalow in the City	
1	1	3075044	https://www.airbnb.com/rooms/3075044	20160906204935	2016-09-07	Charming room in pet friendly apt	
2	2	6976	https://www.airbnb.com/rooms/6976	20160906204935	2016-09-07	Mexican Folk Art Haven in Boston	C
3	3	1436513	https://www.airbnb.com/rooms/1436513	20160906204935	2016-09-07	Spacious Sunny Bedroom Suite in Historic Home	e
4	4	7651065	https://www.airbnb.com/rooms/7651065	20160906204935	2016-09-07	Come Home to Boston	N

5 rows × 96 columns

In [343…
```
bos.dtypes
```

Out[343…
```
Unnamed: 0                           int64
id                                   int64
listing_url                         object
scrape_id                            int64
last_scraped                        object
                                     ...
cancellation_policy                 object
require_guest_profile_picture       object
require_guest_phone_verification    object
calculated_host_listings_count       int64
reviews_per_month                  float64
Length: 96, dtype: object
```

In [344…
```
var_col = ['id','host_id','host_since','host_response_time',
       'host_response_rate', 'host_acceptance_rate', 'host_is_superhost',
       'host_listings_count', 'host_total_listings_count','host_has_profile_pic', 'host_
       'street', 'neighbourhood_cleansed','latitude', 'longitude','property_type', 'roor
       'bathrooms', 'bedrooms', 'beds', 'bed_type','price','guests_included',
        'extra_people', 'minimum_nights','maximum_nights','availability_365',
        'number_of_reviews','cancellation_policy',
       'require_guest_profile_picture', 'require_guest_phone_verification',
       'calculated_host_listings_count','reviews_per_month']
bos = bos.loc[:,var_col]
bos.rename(columns={'neighbourhood_cleansed':'neighbourhood'}, inplace=True)
```

In [345…
```
bos.isnull().sum()
```

Out[345…
```
id                                  0
host_id                             0
host_since                          0
```

```
host_response_time                  471
host_response_rate                  471
host_acceptance_rate                471
host_is_superhost                     0
host_listings_count                   0
host_total_listings_count             0
host_has_profile_pic                  0
host_identity_verified                0
street                                0
neighbourhood                         0
latitude                              0
longitude                             0
property_type                         3
room_type                             0
accommodates                          0
bathrooms                            14
bedrooms                             10
beds                                  9
bed_type                              0
price                                 0
guests_included                       0
extra_people                          0
minimum_nights                        0
maximum_nights                        0
availability_365                      0
number_of_reviews                     0
cancellation_policy                   0
require_guest_profile_picture         0
require_guest_phone_verification      0
calculated_host_listings_count        0
reviews_per_month                   756
dtype: int64
```

In [346…
```
bos = bos.dropna(subset=['reviews_per_month','host_response_time','host_response_rate',
```

In [347…
```
bos
```

Out[347…

	id	host_id	host_since	host_response_time	host_response_rate	host_acceptance_rate	ho
1	3075044	2572247	2012-06-07	within an hour	100%	100%	
2	6976	16701	2009-05-11	within a few hours	100%	88%	
3	1436513	6031442	2013-04-21	within a few hours	100%	50%	
4	7651065	15396970	2014-05-11	within an hour	100%	100%	
5	12386020	64200298	2016-03-23	within a few hours	100%	95%	
...	...	...	...	...	...	...	
3574	14743129	91855319	2016-08-25	within an hour	100%	100%	
3575	5280827	19246369	2014-07-31	within an hour	96%	100%	
3578	14536322	78459716	2016-06-18	within an hour	100%	100%	
3580	8373729	19246369	2014-07-31	within an hour	96%	100%	
3583	14603878	74318064	2016-05-27	within an hour	100%	96%	

2593 rows × 34 columns

In [348…
```
bos.describe()
```

Out[348…

	id	host_id	host_listings_count	host_total_listings_count	latitude	longitu

	id	host_id	host_listings_count	host_total_listings_count	latitude	longitu
count	2.593000e+03	2.593000e+03	2593.000000	2593.000000	2593.000000	2593.0000
mean	7.720118e+06	2.307167e+07	46.735442	46.735442	42.338866	-71.0833
std	4.490205e+06	2.234577e+07	145.530247	145.530247	0.025334	0.0314
min	3.353000e+03	4.240000e+03	1.000000	1.000000	42.235942	-71.1714
25%	4.032126e+06	5.052732e+06	1.000000	1.000000	42.325530	-71.1040
50%	7.840131e+06	1.644292e+07	2.000000	2.000000	42.344829	-71.0770
75%	1.205282e+07	3.332387e+07	7.000000	7.000000	42.355024	-71.0616
max	1.484378e+07	9.185532e+07	749.000000	749.000000	42.389982	-71.0001

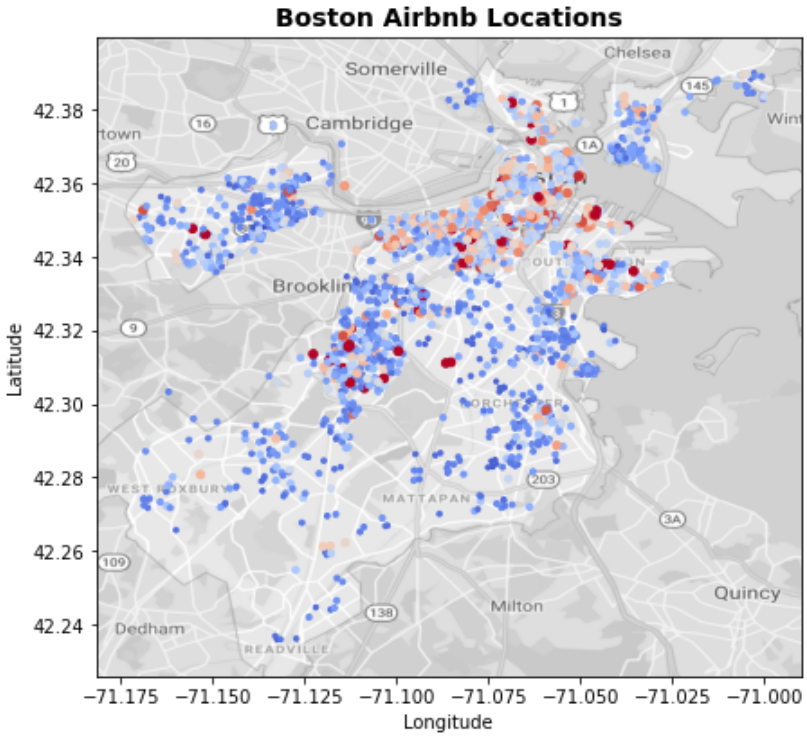
2. Exploratory Data Analysis

2.1 Data Visualization

2.1.1 Location

In [349…
```
fig,ax = location('Boston', bos,0.5,3,7,7)
xl,xh,yl,yh = area(bos)
img_bos = import_img('https://raw.githubusercontent.com/kristallqiu99/' +
                     'data_bootcamp_final_project/master/boston_data/BOS_map.png')
ax.imshow(img_bos,extent=[xl-0.02,xh+0.01,yl-0.01,yh+0.01])
```

Out[349…
```
<matplotlib.image.AxesImage at 0x7f889c83eb50>
```



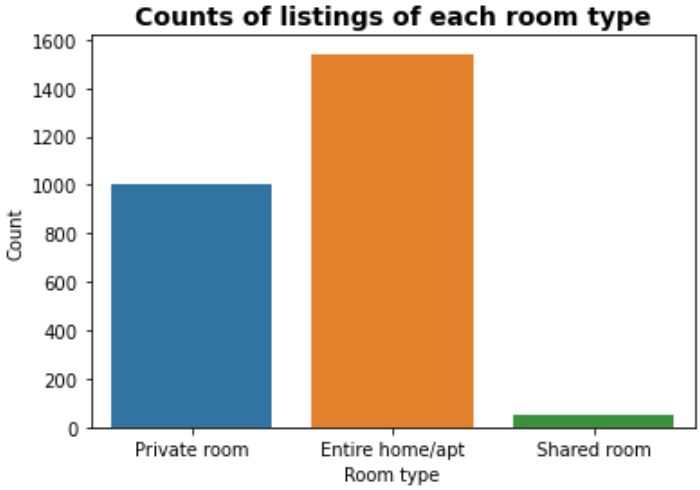
In the plot above, the most expensive houses are plotted in red dots and the cheaper ones are plotted in light blue. We find that the most expensive houses usually locate in Back Bay area.

2.1.2 Room Type

a) Number of listings of each room type

In [350…
```
ax = sns.countplot(data=bos,x='room_type')
ax.set_xlabel('Room type')
ax.set_ylabel('Count')
```

```
ax.set_title('Counts of listings of each room type',size=14,fontweight='bold')
current_palette = sns.color_palette()
```

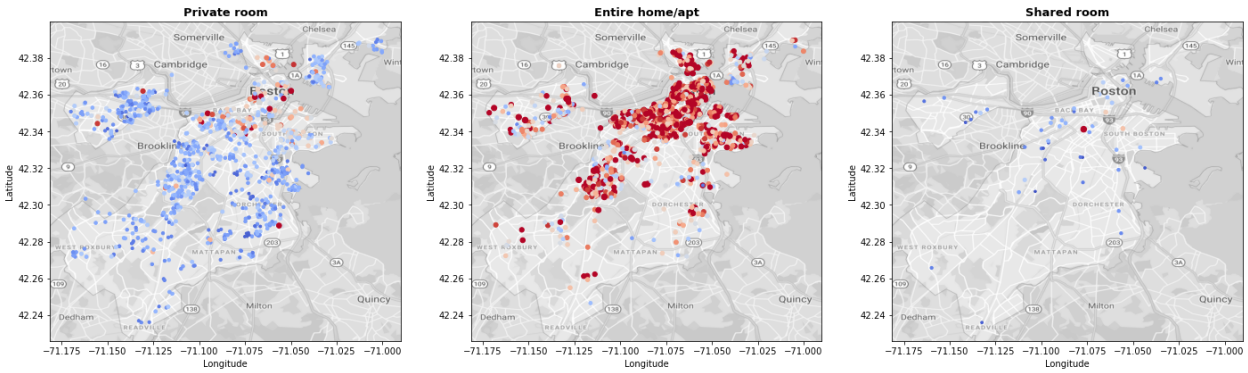


From the bar chart above, we know that there are very few shared room as Airbnb offerings in boston, just like NYC. The entire room/apt has the highest counts of listings, with a number of almost 1600.

b) Spread

In [351…

```
fig,ax = room_type_location(bos,0.6,1.5,8,8)
for i in range(0,len(bos['room_type'].unique())):
    ax[i].imshow(img_bos,extent=[xl-0.02,xh+0.01,yl-0.01,yh+0.01])
```



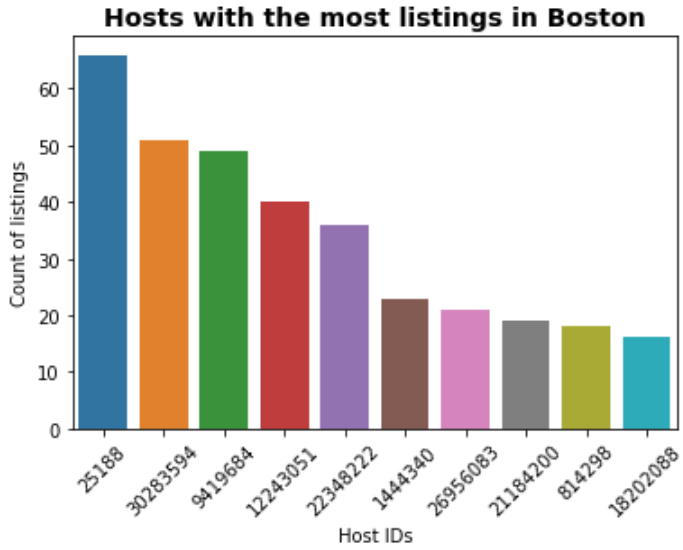
From the plot above, we notice that the private room are very widespread. But the entire home/apt mostly locate in Back Bay area.

2.1.3 Host

In [352…

```
top_hosts('Boston',bos)
```

```
/Users/kristallqiu/opt/anaconda3/lib/python3.8/site-packages/seaborn/_decorators.py:36:
FutureWarning: Pass the following variables as keyword args: x, y. From version 0.12, th
e only valid positional argument will be `data`, and passing other arguments without an
explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

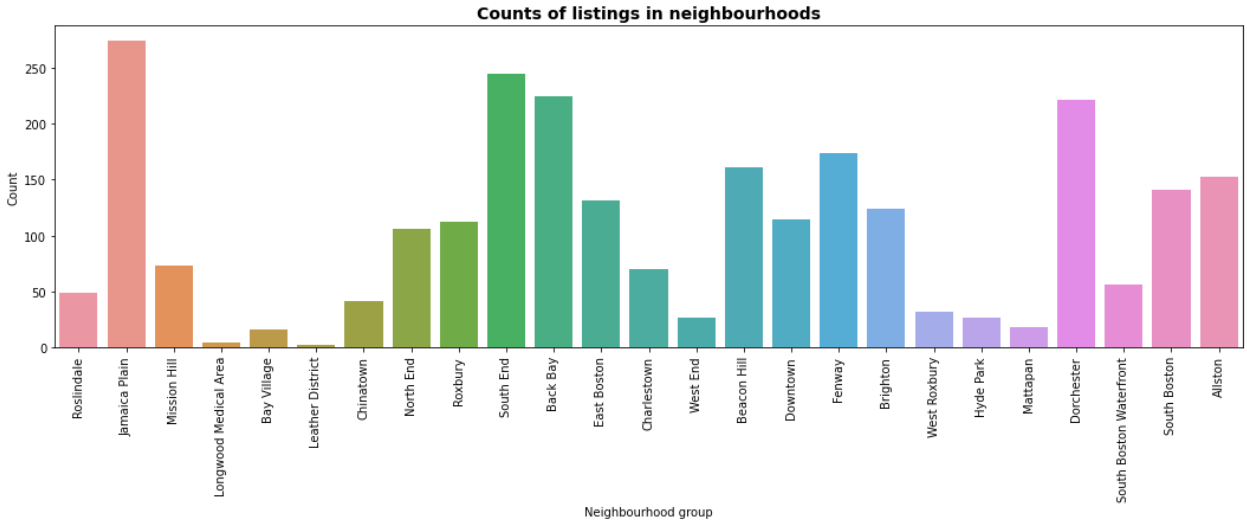


We notice that there is one host with more than 60 listings. Four hosts are in the second tier, having listings from 30 to 50. The difference between number of hosts are not so big as NYC.

2.1.4 Neighbourhood

In [353…
```
count_nei('Boston',bos)
```

Out[353…
```
(<Figure size 1296x360 with 1 Axes>,
 <AxesSubplot:title={'center':'Counts of listings in neighbourhoods'}, xlabel='Neighbourhood group', ylabel='Count'>)
```

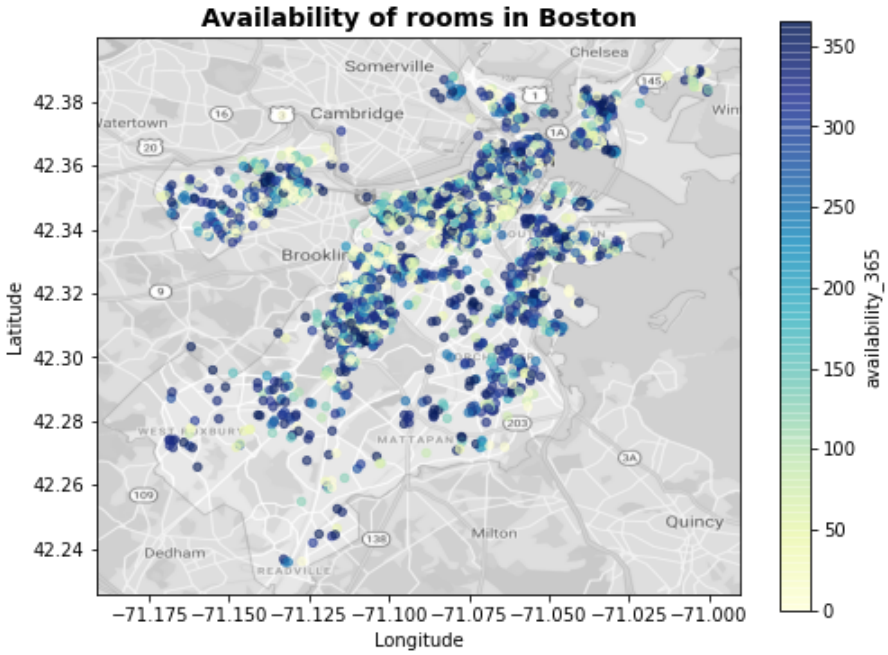


From the bar chart above, we learn that there are more neighborhoods in Boston than in New York. The neighbourhoods with most listings are: Jamaica Plain, South End, Back Bay, and Dorchester. There are many neighborhoods with fewer than 50 listings, too.

2.1.5 Availability

In [354…
```
fig,ax = ava365('Boston',bos,8,6)
ax.imshow(img_bos,extent=[xl-0.02,xh+0.01,yl-0.01,yh+0.01])
```

Out[354…
```
<matplotlib.image.AxesImage at 0x7f889c689850>
```



In this graph, we plot the availability of rooms in Boston. We notice that most rooms are available for more than 200 days per year, which is very different from the situation in NYC. We guess that the total number of listings in Boston is smaller, so there is less competition in this market.

2.2 Data Analysis

2.2.1 Price with room types

In [355…

```
rtype = bos['room_type'].unique()
price_list = []
for n in rtype:
    sub = bos.loc[bos['room_type'] == n]
    sub_price = sub[['price']]
    price_list.append(sub_price)
stats_list = []
for p in price_list:
    i = p.describe(percentiles=[.25, .50, .75])
    i = i.iloc[3:]
    i.reset_index(inplace=True)
    i.rename(columns={'index':'Stats'},inplace=True)
    stats_list.append(i)
# change names of the price column to the area name
for i in range(0,len(rtype)):
    stats_list[i].rename(columns={'price':rtype[i]},inplace=True)
# finilize dataframe for final view
stats_df = stats_list
stats_df = [df.set_index('Stats') for df in stats_df]
stats_df = stats_df[0].join(stats_df[1:])
stats_df
```

Out[355…

Stats	Private room	Entire home/apt	Shared room
min	20.0	11.0	22.00
25%	65.0	150.0	45.00
50%	79.0	199.0	60.00
75%	100.0	269.0	84.75
max	350.0	1300.0	500.00

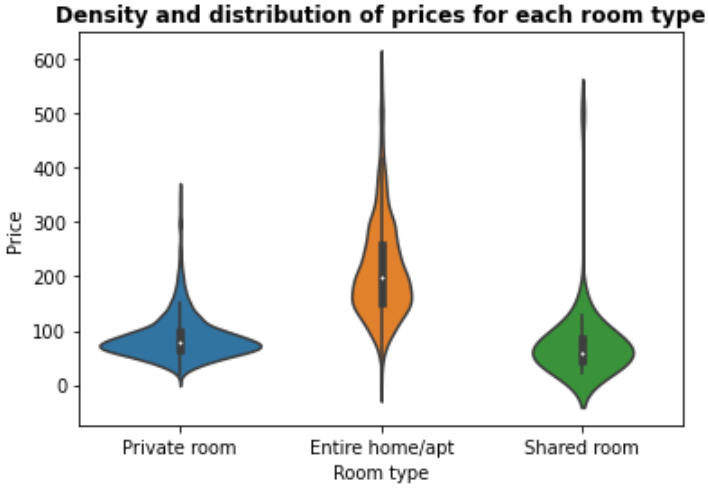
a) Density distribution

In [356…

```
no_extreme = bos[bos.price < 600]
```

```
ax = sns.violinplot(data=no_extreme,x='room_type',y='price')
ax.set_xlabel('Room type')
ax.set_ylabel('Price')
ax.set_title('Density and distribution of prices for each room type',fontweight='bold')
```

Out[356… `Text(0.5, 1.0, 'Density and distribution of prices for each room type')`



From the density distribution, we know that hosts charge a higher price for entire home/apt room type, ranging from less than 100 dollars to more than 300 dollars, even to 500 dollars. On the contrary, most private rooms and shared rooms are charged a price of fewer than 100 dollars per day. This is consistent with our observation of NYC.

2.2.2 Price with neighbourhoods

In [357…
```
nei_stats('BOS',bos)
```

Out[357…

Stats	Roslindale	Jamaica Plain	Mission Hill	Longwood Medical Area	Bay Village	Leather District	Chinatown	North End	Roxbury	South End	…
min	40.0	22.0	27.0	84.00	90.0	159.00	80.0	60.0	22.0	67.0	…
25%	60.0	75.0	65.0	84.00	135.5	216.75	159.0	135.0	75.0	150.0	…
50%	75.0	99.5	85.0	116.50	184.0	274.50	255.0	175.0	99.5	189.0	…
75%	100.0	168.0	140.0	179.75	362.5	332.25	299.0	207.5	167.0	240.0	…
max	285.0	750.0	399.0	272.00	500.0	390.00	399.0	425.0	650.0	1300.0	…

5 rows × 25 columns

In [358…
```
fig,ax = plt.subplots(figsize=(30,5))
plot_distribution('Boston',bos,600)
```

Out[358…
```
(<Figure size 2160x360 with 1 Axes>,
 <AxesSubplot:title={'center':'Density and distribution of prices for each neighbourhood
group'}, xlabel='Neighbourhood group', ylabel='Price'>)
```

In this graph, we plot the density and distribution of prices for each neighbourhood group. We notice that in Boston, the prices vary much more than in NYC, since some violin plots are super slim and long, while others are concentrated and short.

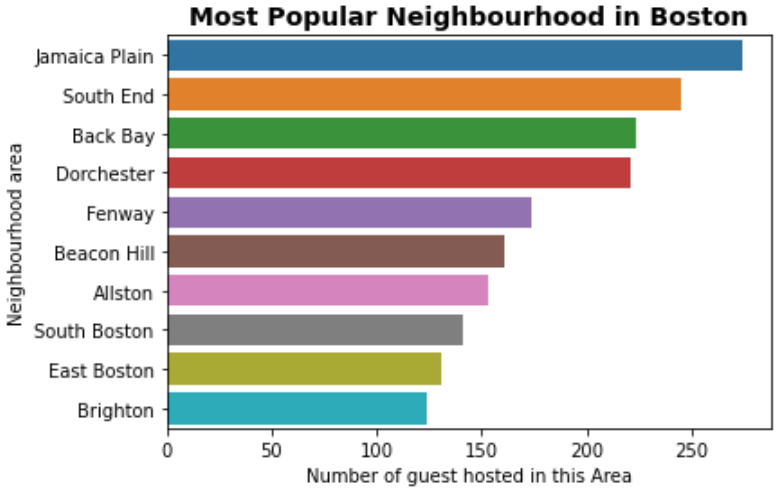
2.2.3 Neighbourhood Exploration

a) Popular neighbourhoods

In [359…
```
top_nei('Boston',bos)
```

```
/Users/kristallqiu/opt/anaconda3/lib/python3.8/site-packages/seaborn/_decorators.py:36:
FutureWarning: Pass the following variables as keyword args: x, y. From version 0.12, th
e only valid positional argument will be `data`, and passing other arguments without an
explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

Out[359…
```
(<Figure size 2160x360 with 1 Axes>,
 <AxesSubplot:title={'center':'Most Popular Neighbourhood in Boston'}, xlabel='Number of
guest hosted in this Area', ylabel='Neighbourhood area'>)
```

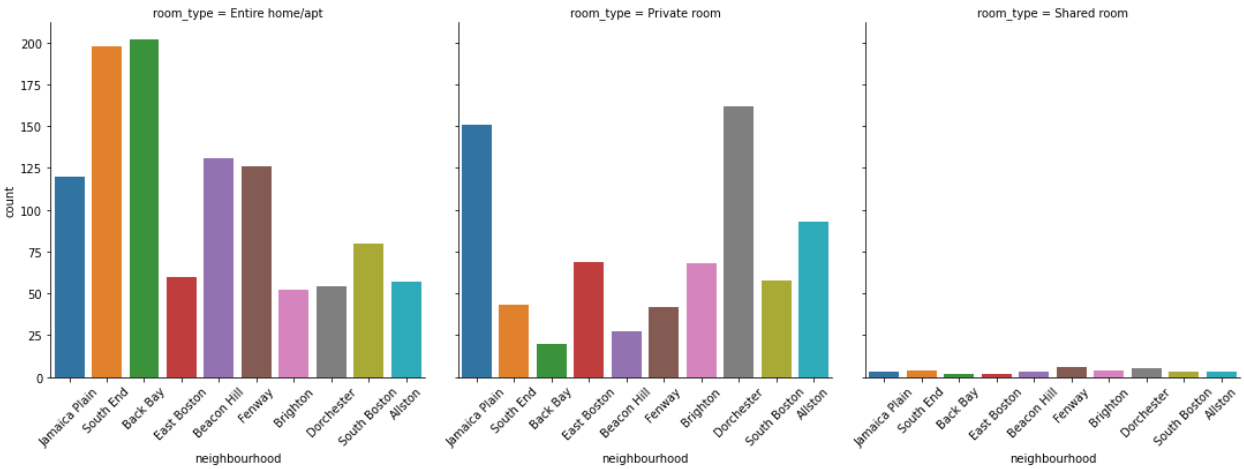


We list top ten most popular neighbourhood in Boston in this horizontal bar chart. The most popular neighbourhood in Boston is Jamaica Plain, but the popularity doesn't vary that much as in NYC.

b) Room type within popular neighbourhoods

In [360…
```
top_nei_room_type('BOS',bos)
```

Out[360…
```
<seaborn.axisgrid.FacetGrid at 0x7f887d93c670>
```



Based on the top ten popular neighborhood we selected before, we picture the room types information in these neighborhoods for readers' reference. Guests can know the distribution of their favourite room type in popular neighborhoods, so that they can make the decisions more easily.

3. Descriptive Data Analysis

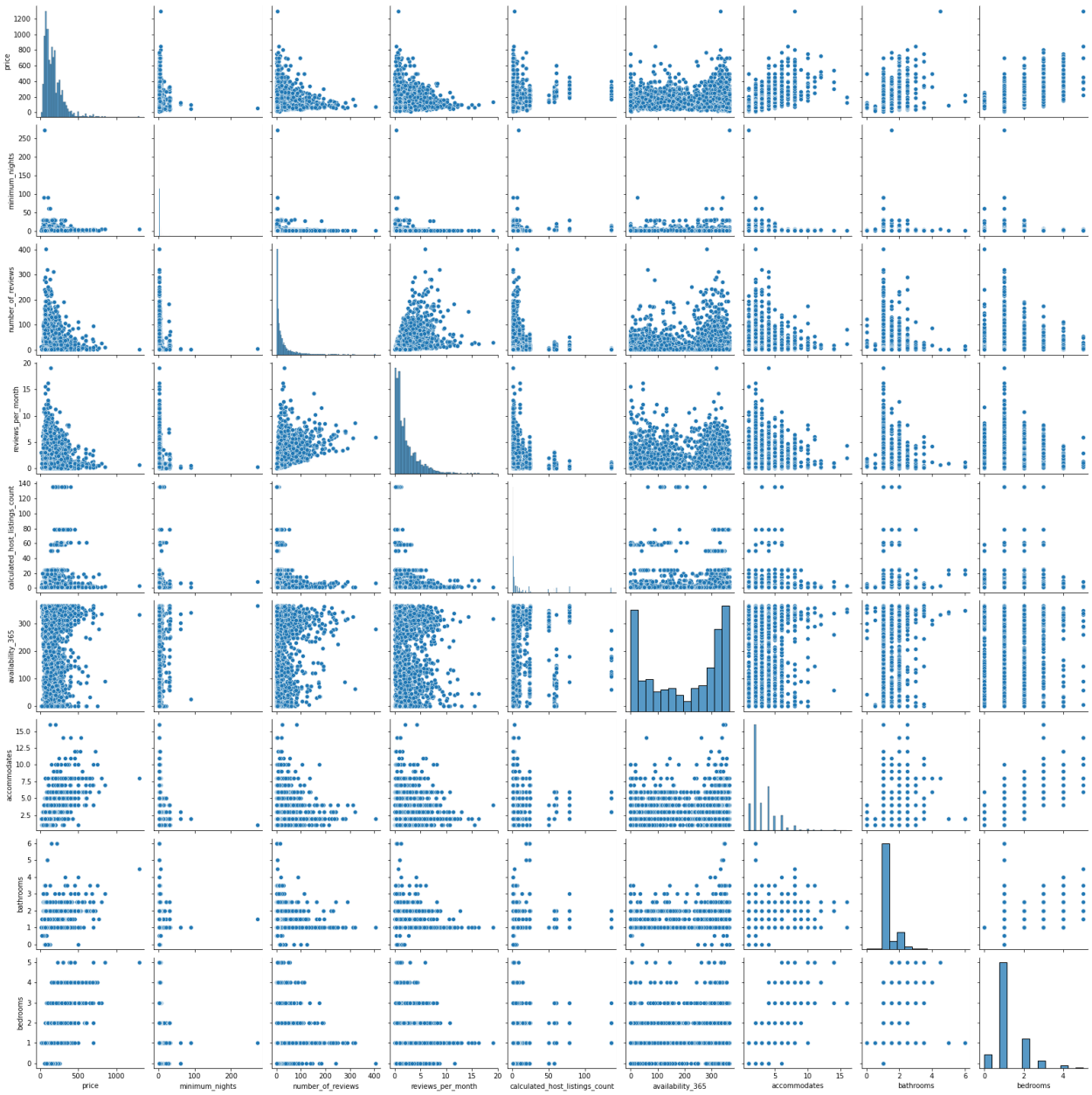
3.1 Pairplot of each variable

In [361…
```
vc = list(nyc.columns)
for i in ['id','host_id','neighbourhood_group','latitude', 'longitude']:
    vc.remove(i)
```

```
for j in ['accommodates', 'bathrooms', 'bedrooms']:
    vc.append(j)

pp2 = bos.loc[:,vc]
sns.pairplot(pp2)
```

Out[361…

```
<seaborn.axisgrid.PairGrid at 0x7f887ec85a90>
```



We can see the correltation between each variable. It does not make sense as many of them are categorical data

4. Predictive Data Analysis

In [362…

```
bos.columns
```

Out[362…

```
Index(['id', 'host_id', 'host_since', 'host_response_time',
       'host_response_rate', 'host_acceptance_rate', 'host_is_superhost',
       'host_listings_count', 'host_total_listings_count',
       'host_has_profile_pic', 'host_identity_verified', 'street',
       'neighbourhood', 'latitude', 'longitude', 'property_type', 'room_type',
       'accommodates', 'bathrooms', 'bedrooms', 'beds', 'bed_type', 'price',
       'guests_included', 'extra_people', 'minimum_nights', 'maximum_nights',
       'availability_365', 'number_of_reviews', 'cancellation_policy',
       'require_guest_profile_picture', 'require_guest_phone_verification',
       'calculated_host_listings_count', 'reviews_per_month'],
      dtype='object')
```

In [363…

```
model2 = bos.loc[:,:].copy()
model2['neighbourhood'] = model2['neighbourhood'].astype("category").cat.codes
model2['room_type'] = model2['room_type'].astype("category").cat.codes
model2['host_response_time'] = model2['host_response_time'].astype("category").cat.codes
model2['host_response_rate'] = model2['host_response_rate'].str.replace('%','').astype(i
model2['host_acceptance_rate'] = model2['host_acceptance_rate'].str.replace('%','').asty

model2['host_response_rate'] = model2['host_response_rate']/100
model2['host_acceptance_rate'] = model2['host_acceptance_rate']/100

tf = ['host_is_superhost','host_has_profile_pic','host_identity_verified',
      'require_guest_profile_picture','require_guest_phone_verification']
for c in tf:
    model2[c] = model2[c].replace('t',1)
    model2[c] = model2[c].replace('f',0)

cancel = ['flexible','moderate','strict', 'super_strict_30']
for i in range(0,len(cancel)):
    model2['cancellation_policy'] = model2['cancellation_policy'].replace(cancel[i],i)


model2['extra_people'] = model2['extra_people'].str.replace('$','').astype(float)
model2['property_type'] = model2['property_type'].astype("category").cat.codes
model2['bed_type'] = model2['bed_type'].astype("category").cat.codes

mean = model2['reviews_per_month'].mean()
model2['reviews_per_month'].fillna(mean, inplace=True)

model2['log_price'] = np.log(model2.price+1)

model2 = model2.drop(columns=['id' ,'host_id','price','host_since','street']) # delete p

model2.isnull().sum()
```

Out[363…

```
host_response_time                 0
host_response_rate                 0
host_acceptance_rate               0
host_is_superhost                  0
host_listings_count                0
host_total_listings_count          0
host_has_profile_pic               0
host_identity_verified             0
neighbourhood                      0
latitude                           0
longitude                          0
property_type                      0
room_type                          0
accommodates                       0
bathrooms                         12
bedrooms                           8
beds                               6
bed_type                           0
guests_included                    0
extra_people                       0
minimum_nights                     0
maximum_nights                     0
availability_365                   0
number_of_reviews                  0
cancellation_policy                0
require_guest_profile_picture      0
require_guest_phone_verification   0
calculated_host_listings_count     0
reviews_per_month                  0
log_price                          0
dtype: int64
```

Value Reference

In [364…

```
bosVF = {}
bosd = ['neighbourhood','room_type','host_response_time',
        'host_is_superhost','cancellation_policy','property_type','bed_type']
for c in bosd:
    bosVF = {}
    for i in model2[c].unique():
```

```
        indx = model2[model2[c]==i].index.values[0]
        bosVF[i] = bos[c][indx]
    print(c.capitalize(),'\n',dict(sorted(bosVF.items())))
```

```
Neighbourhood
 {0: 'Allston', 1: 'Back Bay', 2: 'Bay Village', 3: 'Beacon Hill', 4: 'Brighton', 5: 'Ch
arlestown', 6: 'Chinatown', 7: 'Dorchester', 8: 'Downtown', 9: 'East Boston', 10: 'Fenwa
y', 11: 'Hyde Park', 12: 'Jamaica Plain', 13: 'Leather District', 14: 'Longwood Medical
Area', 15: 'Mattapan', 16: 'Mission Hill', 17: 'North End', 18: 'Roslindale', 19: 'Roxbu
ry', 20: 'South Boston', 21: 'South Boston Waterfront', 22: 'South End', 23: 'West End',
24: 'West Roxbury'}
Room_type
 {0: 'Entire home/apt', 1: 'Private room', 2: 'Shared room'}
Host_response_time
 {0: 'a few days or more', 1: 'within a day', 2: 'within a few hours', 3: 'within an hou
r'}
Host_is_superhost
 {0: 'f', 1: 't'}
Cancellation_policy
 {0: 'flexible', 1: 'moderate', 2: 'strict', 3: 'super_strict_30'}
Property_type
 {-1: nan, 0: 'Apartment', 1: 'Bed & Breakfast', 2: 'Boat', 3: 'Condominium', 4: 'Dorm',
5: 'Entire Floor', 6: 'Guesthouse', 7: 'House', 8: 'Loft', 9: 'Other', 10: 'Townhouse',
11: 'Villa'}
Bed_type
 {0: 'Airbed', 1: 'Couch', 2: 'Futon', 3: 'Pull-out Sofa', 4: 'Real Bed'}
```

In [365…

```
model2
```

Out[365…

	host_response_time	host_response_rate	host_acceptance_rate	host_is_superhost	host_listings_count
1	3	1.00	1.00	0	1
2	2	1.00	0.88	1	1
3	2	1.00	0.50	0	1
4	3	1.00	1.00	1	1
5	2	1.00	0.95	1	2
...	...	...	...	...	...
3574	3	1.00	1.00	0	2
3575	3	0.96	1.00	0	28
3578	3	1.00	1.00	0	4
3580	3	0.96	1.00	0	28
3583	3	1.00	0.96	0	4

2593 rows × 30 columns

4.1 Probability distribution

In [366…

```
keep_col2 = ['host_response_rate', 'host_acceptance_rate','neighbourhood',
        'property_type', 'room_type', 'accommodates',
       'bathrooms', 'bedrooms', 'beds', 'bed_type', 'extra_people',
        'availability_365', 'number_of_reviews', 'cancellation_policy',
        'calculated_host_listings_count', 'reviews_per_month', 'log_price']
```

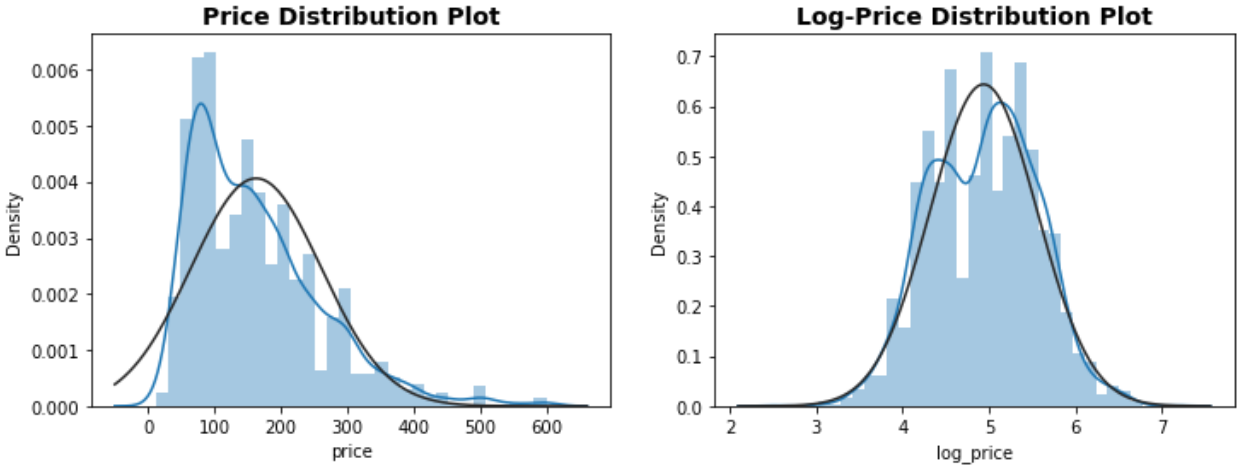
In [367…

```
fig,ax = plt.subplots(1,2,figsize=(12,4))
sns.distplot(bos.loc[bos['price']<=600]['price'],fit=norm, ax=ax[0]) # drop extreme valu
ax[0].set_title("Price Distribution Plot",size=14, weight='bold')
sns.distplot(model2['log_price'],fit=norm,ax=ax[1])
ax[1].set_title("Log-Price Distribution Plot",size=14, weight='bold')
```

```
/Users/kristallqiu/opt/anaconda3/lib/python3.8/site-packages/seaborn/distributions.py:25
51: FutureWarning: `distplot` is a deprecated function and will be removed in a future v
ersion. Please adapt your code to use either `displot` (a figure-level function with sim
ilar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
/Users/kristallqiu/opt/anaconda3/lib/python3.8/site-packages/seaborn/distributions.py:25
```

```
51: FutureWarning: `distplot` is a deprecated function and will be removed in a future v
ersion. Please adapt your code to use either `displot` (a figure-level function with sim
ilar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

Out[367… `Text(0.5, 1.0, 'Log-Price Distribution Plot')`



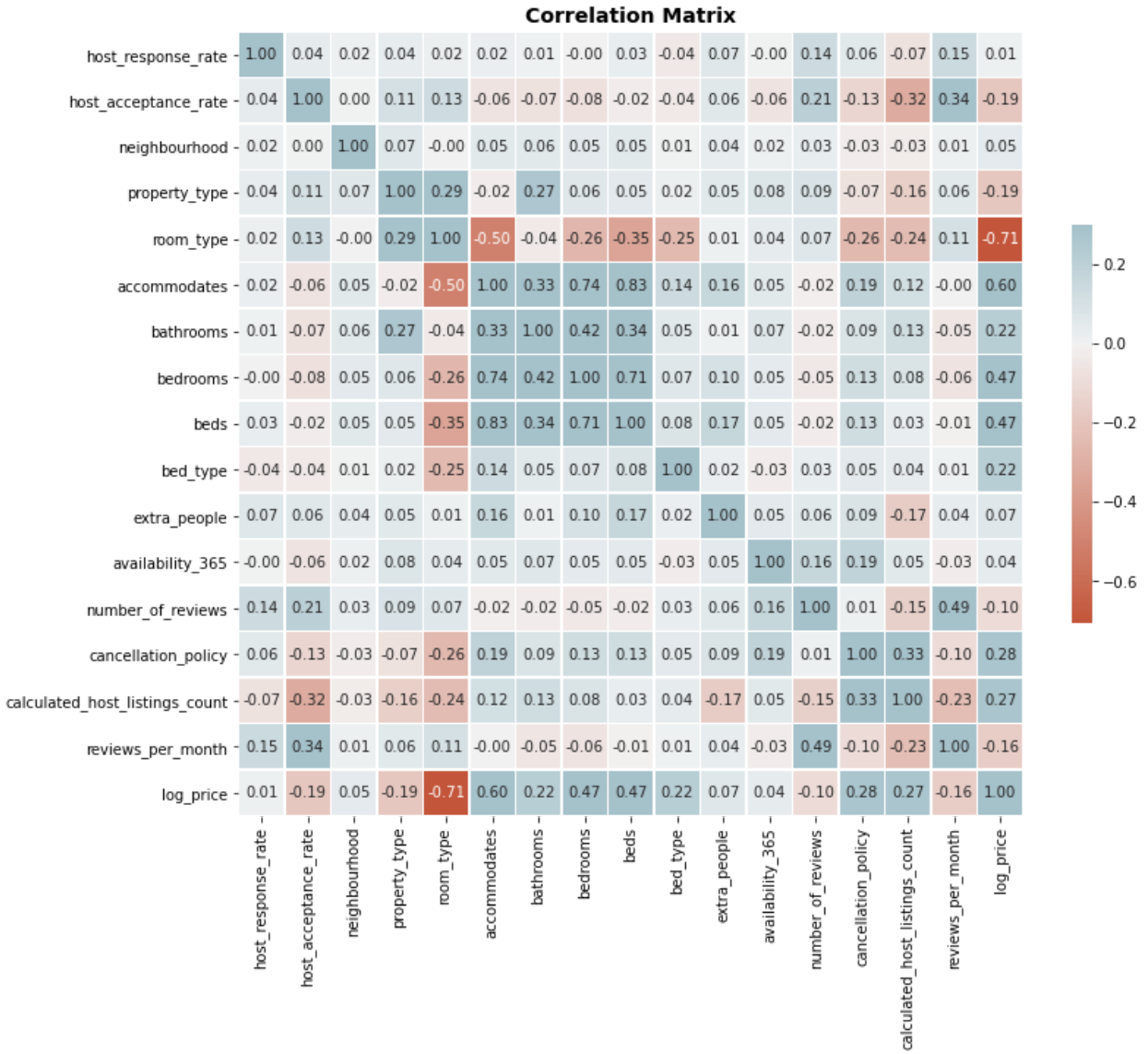
From the log_price distribution plot we learn that the distribution of log_price is approximately normal, also with a mean a little bit less than 5.

4.2 Correlation

In [368…

```
import statsmodels.formula.api as smf
col_df2 = model2.loc[:,keep_col2]
plt.figure(figsize=(12,10))
palette = sns.diverging_palette(20, 220, n=256)
corr=col_df2.corr(method='pearson')
sns.heatmap(corr, annot=True, fmt=".2f", cmap=palette, vmax=.3, center=0,
            square=True, linewidths=.5, cbar_kws={"shrink": .5}).set(ylim=(17, 0))
plt.title("Correlation Matrix",size=14, weight='bold')
```

Out[368… `Text(0.5, 1.0, 'Correlation Matrix')`



In this correlation matrix we calculate and display the correlation between different variables. The hosts can easily find the relationship between variables and make the optimized investment decisions.

4.3 Regression

In [369…

```
model2['price'] = bos['price']
model2
```

Out[369…

	host_response_time	host_response_rate	host_acceptance_rate	host_is_superhost	host_listings_count
1	3	1.00	1.00	0	1
2	2	1.00	0.88	1	1
3	2	1.00	0.50	0	1
4	3	1.00	1.00	1	1
5	2	1.00	0.95	1	2
...	...	...	...	...	...
3574	3	1.00	1.00	0	2
3575	3	0.96	1.00	0	28
3578	3	1.00	1.00	0	4
3580	3	0.96	1.00	0	28
3583	3	1.00	0.96	0	4

2593 rows × 31 columns

4.3.1 Linear Regression

In [370…
```
import statsmodels.formula.api as smf
```

a) Price - all variables

In [371…
```
reg_price = smf.ols('price ~ host_response_rate + host_acceptance_rate + neighbourhood +
                    ,data=model2).fit()

print(reg_price.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.559
Model:                            OLS   Adj. R-squared:                  0.557
Method:                 Least Squares   F-statistic:                     202.6
Date:                Wed, 04 Nov 2020   Prob (F-statistic):               0.00
Time:                        11:48:37   Log-Likelihood:                -14700.
No. Observations:                2571   AIC:                         2.943e+04
Df Residuals:                    2554   BIC:                         2.953e+04
Df Model:                          16
Covariance Type:            nonrobust
================================================================================
==========
                                   coef    std err          t      P>|t|      [0.025
0.975]
--------------------------------------------------------------------------------
----------
Intercept                       55.6980     19.573      2.846      0.004      17.318
94.078
host_response_rate              33.9811     13.150      2.584      0.010       8.195
59.767
host_acceptance_rate           -11.4311      7.583     -1.507      0.132     -26.301
3.439
neighbourhood                    0.0069      0.200      0.034      0.973      -0.386
0.400
property_type                   -1.8969      0.542     -3.503      0.000      -2.959
-0.835
room_type                      -80.3650      3.620    -22.198      0.000     -87.464
-73.266
accommodates                     5.1091      1.720      2.971      0.003       1.737
8.481
bathrooms                       32.7906      3.372      9.724      0.000      26.178
39.403
bedrooms                        39.9702      3.047     13.118      0.000      33.996
45.945
beds                             5.9854      2.554      2.344      0.019       0.978
10.993
bed_type                         0.9628      2.953      0.326      0.744      -4.828
6.753
extra_people                     0.0848      0.076      1.112      0.266      -0.065
0.234
availability_365                 0.0416      0.011      3.706      0.000       0.020
0.064
number_of_reviews               -0.1068      0.044     -2.443      0.015      -0.193
-0.021
cancellation_policy              3.7307      1.950      1.913      0.056      -0.094
7.555
calculated_host_listings_count   0.2393      0.070      3.435      0.001       0.103
0.376
reviews_per_month               -3.3267      0.824     -4.039      0.000      -4.942
-1.712
==============================================================================
Omnibus:                     1138.443   Durbin-Watson:                   1.668
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            13324.979
Skew:                           1.775   Prob(JB):                         0.00
Kurtosis:                      13.573   Cond. No.                     3.66e+03
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specifi
ed.
[2] The condition number is large, 3.66e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
```

Here we run an ordinary least square regression for price on several factors that we think may influence the price of Airbnb. We have H0: beta = 0 against H1: beta != 0 for every beta in this regression model. According to the output table, the P-values of host_acceptance_rate, neighbourhood, bed_type, extra_people, cancellation_policy are bigger than 5%, which means that we don't reject H0 against H1. There is no evidence that the effect of host_acceptance_rate, neighbourhood, bed_type, extra_people, cancellation_policy is significant to the price of Airbnb house and we should drop them.

a) Price - drop variables

In [372…

```
reg_price = smf.ols('price ~ host_response_rate +property_type + room_type + accommodate
                    ,data=model2).fit()

print(reg_price.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.558
Model:                            OLS   Adj. R-squared:                  0.556
Method:                 Least Squares   F-statistic:                     293.7
Date:                Wed, 04 Nov 2020   Prob (F-statistic):               0.00
Time:                        11:48:37   Log-Likelihood:                -14704.
No. Observations:                2571   AIC:                         2.943e+04
Df Residuals:                    2559   BIC:                         2.950e+04
Df Model:                          11
Covariance Type:            nonrobust
================================================================================
==========
                                   coef    std err          t      P>|t|      [0.025
0.975]
--------------------------------------------------------------------------------
----------
Intercept                       51.3141     13.287      3.862      0.000      25.260
77.369
host_response_rate              37.1538     13.078      2.841      0.005      11.510
62.798
property_type                   -1.9062      0.538     -3.543      0.000      -2.961
-0.851
room_type                      -81.4652      3.478    -23.420      0.000     -88.286
-74.644
accommodates                     5.4658      1.710      3.197      0.001       2.113
8.819
bathrooms                       32.8821      3.366      9.768      0.000      26.281
39.483
bedrooms                        40.0036      3.043     13.144      0.000      34.036
45.971
beds                             5.9266      2.549      2.325      0.020       0.929
10.924
availability_365                 0.0467      0.011      4.226      0.000       0.025
0.068
number_of_reviews               -0.1042      0.044     -2.392      0.017      -0.190
-0.019
calculated_host_listings_count   0.2824      0.065      4.352      0.000       0.155
0.410
reviews_per_month               -3.7074      0.802     -4.624      0.000      -5.280
-2.135
==============================================================================
Omnibus:                     1129.095   Durbin-Watson:                   1.660
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            13015.463
Skew:                           1.762   Prob(JB):                         0.00
Kurtosis:                      13.444   Cond. No.                     3.03e+03
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specifi
ed.
[2] The condition number is large, 3.03e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
```

And, we can get price = 51.3141 + 37.1538 *host_response_rate* - *property_type* 1.962-room_type *81.4652 + accommodates* 5.4658 + bathrooms *32.8821 + bedrooms* 40.0036 + beds *5.9266+availability_365* 0.0467-number_of_reviews *0.1042 + calculated_host_listings_count* 0.2824 - reviews_per_month* 3.7074

And from this, we can find that bedrooms make the largest contribution to a relative higher price.

b) log_price - all vairables

In [373…

```
reg_price = smf.ols('log_price ~ host_response_rate + host_acceptance_rate + neighbourhc
                    ,data=model2).fit()

print(reg_price.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:              log_price   R-squared:                       0.623
Model:                            OLS   Adj. R-squared:                  0.621
Method:                 Least Squares   F-statistic:                     263.9
Date:                Wed, 04 Nov 2020   Prob (F-statistic):               0.00
Time:                        11:48:37   Log-Likelihood:                -1165.0
No. Observations:                2571   AIC:                             2364.
Df Residuals:                    2554   BIC:                             2464.
Df Model:                          16
Covariance Type:            nonrobust
================================================================================
==========
                                   coef    std err          t      P>|t|      [0.025
0.975]
--------------------------------------------------------------------------------
----------
Intercept                        4.3489      0.101     42.957      0.000       4.150
4.547
host_response_rate               0.2018      0.068      2.967      0.003       0.068
0.335
host_acceptance_rate            -0.0982      0.039     -2.503      0.012      -0.175
-0.021
neighbourhood                    0.0024      0.001      2.348      0.019       0.000
0.004
property_type                   -0.0116      0.003     -4.158      0.000      -0.017
-0.006
room_type                       -0.6016      0.019    -32.128      0.000      -0.638
-0.565
accommodates                     0.0539      0.009      6.058      0.000       0.036
0.071
bathrooms                        0.0865      0.017      4.958      0.000       0.052
0.121
bedrooms                         0.1324      0.016      8.399      0.000       0.101
0.163
beds                            -0.0024      0.013     -0.184      0.854      -0.028
0.023
bed_type                         0.0603      0.015      3.946      0.000       0.030
0.090
extra_people                     0.0013      0.000      3.312      0.001       0.001
0.002
availability_365                 0.0001   5.81e-05      2.454      0.014    2.86e-05
0.000
number_of_reviews               -0.0004      0.000     -1.761      0.078      -0.001
4.52e-05
cancellation_policy              0.0278      0.010      2.756      0.006       0.008
0.048
calculated_host_listings_count   0.0017      0.000      4.645      0.000       0.001
0.002
reviews_per_month               -0.0140      0.004     -3.292      0.001      -0.022
-0.006
==============================================================================
Omnibus:                      127.851   Durbin-Watson:                   1.572
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              443.259
Skew:                           0.095   Prob(JB):                     5.59e-97
Kurtosis:                       5.025   Cond. No.                     3.66e+03
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specifi
ed.
[2] The condition number is large, 3.66e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
```

Here we run an ordinary least square regression for price on several factors again after drop those variables. We have H0: beta = 0 against H1: beta != 0 for every beta in this regression model. According to the output table, the P-value of beds and number_of_reviews are bigger than 5%, which means that we don't reject H0 against H1. There is no evidence that the effect of beds and number_of_reviews is significant to the price of Airbnb house and we should drop them.

b) log_price - drop variables

In [374…

```
reg_price = smf.ols('log_price ~ host_response_rate + host_acceptance_rate + neighbourhc
                    ,data=model2).fit()

print(reg_price.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:              log_price   R-squared:                       0.623
Model:                            OLS   Adj. R-squared:                  0.621
Method:                 Least Squares   F-statistic:                     301.7
Date:                Wed, 04 Nov 2020   Prob (F-statistic):               0.00
Time:                        11:48:37   Log-Likelihood:                -1167.0
No. Observations:                2573   AIC:                             2364.
Df Residuals:                    2558   BIC:                             2452.
Df Model:                          14
Covariance Type:            nonrobust
================================================================================
==========
                                   coef    std err          t      P>|t|      [0.025
0.975]
--------------------------------------------------------------------------------
----------
Intercept                        4.3660      0.101     43.310      0.000       4.168
4.564
host_response_rate               0.1932      0.068      2.848      0.004       0.060
0.326
host_acceptance_rate            -0.1030      0.039     -2.633      0.009      -0.180
-0.026
neighbourhood                    0.0024      0.001      2.335      0.020       0.000
0.004
property_type                   -0.0120      0.003     -4.293      0.000      -0.017
-0.007
room_type                       -0.6015      0.019    -32.140      0.000      -0.638
-0.565
accommodates                     0.0531      0.007      7.466      0.000       0.039
0.067
bathrooms                        0.0868      0.017      4.987      0.000       0.053
0.121
bedrooms                         0.1320      0.015      8.580      0.000       0.102
0.162
bed_type                         0.0594      0.015      3.892      0.000       0.029
0.089
extra_people                     0.0013      0.000      3.277      0.001       0.001
0.002
availability_365                 0.0001    5.7e-05      2.133      0.033    9.81e-06
0.000
cancellation_policy              0.0268      0.010      2.661      0.008       0.007
0.047
calculated_host_listings_count   0.0017      0.000      4.744      0.000       0.001
0.002
reviews_per_month               -0.0173      0.004     -4.536      0.000      -0.025
-0.010
==============================================================================
Omnibus:                      127.260   Durbin-Watson:                   1.573
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              435.697
Skew:                           0.102   Prob(JB):                     2.45e-95
Kurtosis:                       5.006   Cond. No.                     3.63e+03
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specifi
ed.
[2] The condition number is large, 3.63e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
```

And, we can get log_price = 4.5540 + host_response_rate *0.2136* - *property_type* 0.0107-room_type *0.6220* + *accommodates* 0.0593 + bathrooms *0.0890* + *bedrooms* 0.1315 - beds *0.0031* + *availability_365* 0.0002 + calculated_host_listings_count *0.0019* - *reviews_per_month* 0.0201

We find that different from price, host_reponse_rate has the greatest relevance of the log_price.

We run linear regression on log_price against the factors remained.

4.3.2 ML

From the linear regression we found that log_price is a better dependent variable to predict.

In [375…
```
from sklearn.model_selection import train_test_split
```

In [376…
```
X_train2, X_test2, y_train2, y_test2 = train_test_split(model2[['room_type']].values, mo
                                                        test_size=0.25, random_state=0)
```

a) K-Nearest Neighbors

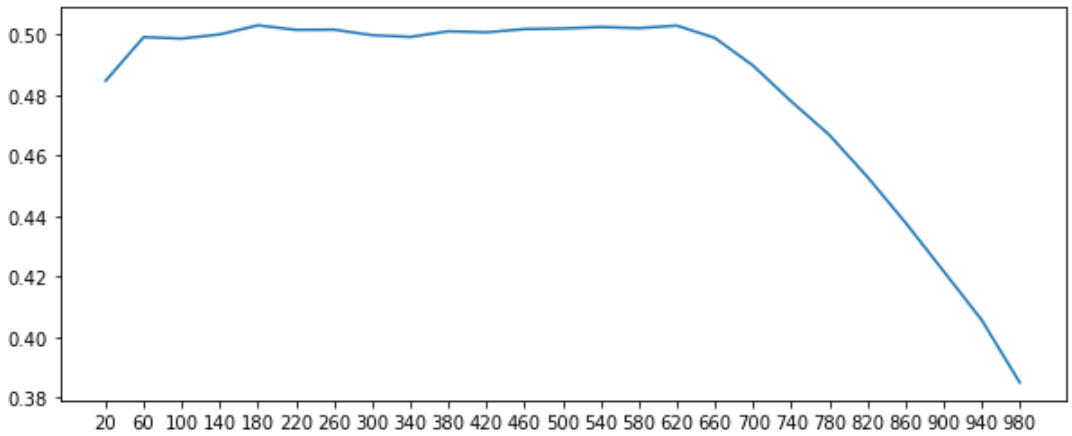
In [377…
```
from sklearn.neighbors import KNeighborsRegressor as knn
from sklearn.model_selection import cross_val_score
```

In [378…
```
scores = pd.Series()
for i in range(20,1000,40):
    scores[str(i)] = cross_val_score(knn(n_neighbors=i),
                     X_train2, y_train2,cv=5).mean()
indx = scores.idxmax()
```

```
<ipython-input-378-8d5994fa6407>:1: DeprecationWarning: The default dtype for empty Seri
es will be 'object' instead of 'float64' in a future version. Specify a dtype explicitly
to silence this warning.
  scores = pd.Series()
```

In [379…
```
fig,ax = plt.subplots(figsize=(10,4))
plt.plot(scores.index,scores.values)
```

Out[379…
```
[<matplotlib.lines.Line2D at 0x7f889cf3ef40>]
```



In [380…
```
skl_knn = knn(n_neighbors=int(indx)).fit(X_train2, y_train2)
knn_score2 = skl_knn.score(X_test2, y_test2)
print(knn_score2)
```

```
0.5225235361166825
```

b) Random Forest

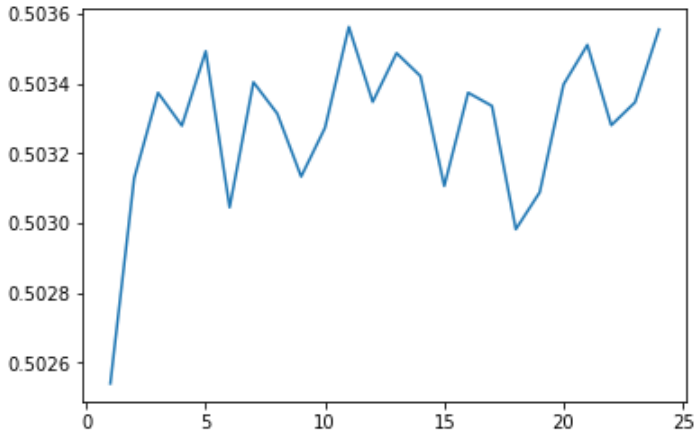
In [381…
```
from sklearn.ensemble import RandomForestRegressor as rf
```

In [382…
```
cross_val_score(rf(n_estimators=100,max_depth=3),X_train2, y_train2.ravel(),cv=5).mean()
```

Out[382…
```
0.5032555039276142
```

In [383…
```
cv_scores = pd.DataFrame()
for i in range(1,25):
    cv_scores.loc[i,'rf'] = cross_val_score(rf(n_estimators=100,max_depth=i),X_train2, y
```

In [384…
```
ax = cv_scores.plot()
ax.get_legend().remove()
```



In [385…
```
indx = scores.idxmax()
skl_rf = rf(n_estimators=100,max_depth=int(indx)).fit(X_train2, y_train2.ravel())
skl_rf.predict(X_test2)
rf_score2 = skl_rf.score(X_test2,y_test2)
print(rf_score2)
```

```
0.5302768258666375
```

In [386…
```
score_table = pd.DataFrame({'K Nearest Neighbors':[knn_score2],'Random Forest':[rf_score
score_table = score_table.T
score_table.columns = ['Score']
score_table
```

Out[386…

	Score
K Nearest Neighbors	0.522524
Random Forest	0.530277

As we can see from above table, for log_price, we should chooseRandom Forest as the score of this model is the highest, compared to K Nearest Neighbors.

Rank score for log_price : Random Forest > KNN

➢ San Francisco

1. Data

1.1 Data Description

In [387…
```
sf = import_df('https://raw.githubusercontent.com/kristallqiu99/' +
               'data_bootcamp_final_project/master/sanfrancisco_data/AB_SF_2019.csv')
```

1.2 Data Cleaning

In [388…
```
sf.head()
```

Out[388…

	Unnamed: 0	id	last_scraped	name	space	description	neighborhood_overview	notes
0	0	958	10/14/19	Bright, Modern Garden Unit - 1BR/1B	Newly remodeled, modern, and bright garden uni...	New update: the house next door is under const...	*Quiet cul de sac in friendly neighborhood *St...	Due to the fact that we have children and a do...

	Unnamed: 0	id	last_scraped	name	space	description	neighborhood_overview	notes
1	1	3850	10/14/19	Charming room for two	This room can fit two people. Nobody else will...	Your own private room plus access to a shared ...	This is a quiet, safe neighborhood on a substa...	House Rule footnotes: 1.\tI don't allow check ...
2	2	5858	10/14/19	Creative Sanctuary	We live in a large Victorian house on a quiet ...	We live in a large Victorian house on a quiet ...	I love how our neighborhood feels quiet but is...	All the furniture in the house was handmade so...
3	3	7918	10/14/19	A Friendly Room - UCSF/USF - San Francisco	Settle down, S.F. resident, student, hospital,...	Nice and good public transportation. 7 minute...	Shopping old town, restaurants, McDonald, Whol...	Wi-Fi signal in common areas. Large eat in k...
4	4	8142	10/14/19	Friendly Room Apt. Style - UCSF/USF - San Franc...	Settle down, S.F. resident, student, hospital,...	Nice and good public transportation. 7 minute...	NaN	Wi-Fi signal in common areas. Large eat in k...

5 rows × 59 columns

In [389…
```
var_col2 = []
for var in var_col:
    if var in sf.columns:
        var_col2.append(var)
    else:
        print(var)
```

```
host_since
host_response_time
host_acceptance_rate
host_is_superhost
host_listings_count
street
number_of_reviews
cancellation_policy
```

In [390…
```
sf = sf.loc[:,var_col2]
sf.rename(columns={'neighbourhood_cleansed':'neighbourhood'}, inplace=True)
```

In [391…
```
sf.isnull().sum()
```

Out[391…
```
id                              0
host_id                         0
host_response_rate             927
host_total_listings_count        8
host_has_profile_pic             8
host_identity_verified           8
neighbourhood                    0
latitude                         0
longitude                        0
property_type                    0
room_type                        0
accommodates                     0
bathrooms                       12
bedrooms                         4
beds                             9
bed_type                         0
price                            0
guests_included                  0
extra_people                     0
minimum_nights                   0
maximum_nights                   0
```

```
availability_365                          0
require_guest_profile_picture             0
require_guest_phone_verification          0
calculated_host_listings_count            0
reviews_per_month                      1605
dtype: int64
```

In [392…
```
sf.dropna(subset=['reviews_per_month','host_response_rate'],inplace=True)
sf
```

Out[392…

	id	host_id	host_response_rate	host_total_listings_count	host_has_profile_pic	host_ident
0	958	1169	100%	1.0	t	
1	3850	4921	100%	2.0	t	
2	5858	8904	80%	2.0	t	
3	7918	21994	86%	10.0	t	
4	8142	21994	86%	10.0	t	
...	...	...	...	...	...	
7978	38984642	25150753	100%	1.0	t	
7979	38985258	298699757	100%	0.0	t	
7998	39059847	222647651	100%	0.0	t	
8042	39225180	534450	90%	0.0	t	
8053	39258642	158118568	83%	0.0	t	

5811 rows × 26 columns

In [393…
```
sf.describe()
```

Out[393…

	id	host_id	host_total_listings_count	latitude	longitude	accommodates	5
count	5.811000e+03	5.811000e+03	5811.000000	5811.000000	5811.000000	5811.000000	
mean	1.793677e+07	5.145251e+07	50.918258	37.764079	-122.431986	3.164516	
std	1.176556e+07	7.156662e+07	250.678348	0.023110	0.027429	1.920302	
min	9.580000e+02	4.600000e+01	0.000000	37.704740	-122.513060	1.000000	
25%	6.914396e+06	3.832588e+06	1.000000	37.748545	-122.444835	2.000000	
50%	1.866994e+07	1.704204e+07	2.000000	37.764760	-122.426500	2.000000	
75%	2.803957e+07	6.734331e+07	6.000000	37.782875	-122.411225	4.000000	
max	3.925864e+07	2.986998e+08	1735.000000	37.810310	-122.370430	16.000000	

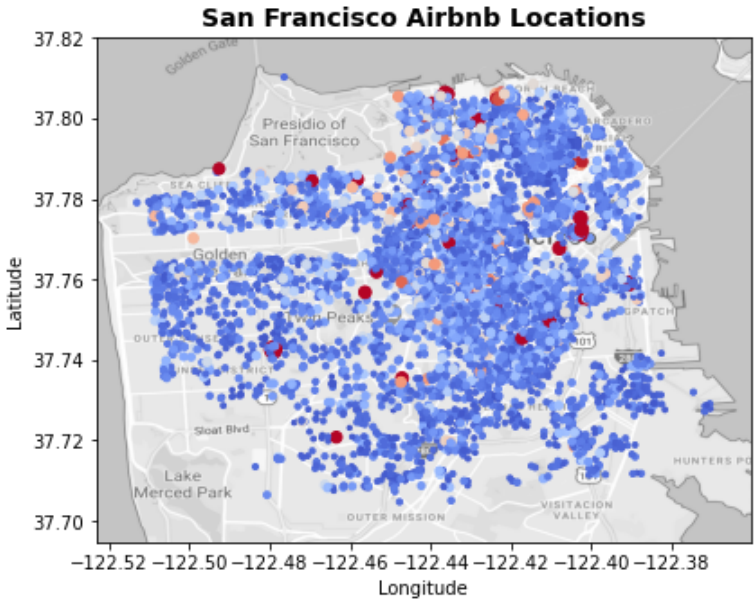
2. Exploratory Data Analysis

2.1 Data Visualization

2.1.1 Location

In [394…
```
fig,ax = location('San Francisco',sf,0.5,6,6.5,6)
xl,xh,yl,yh = area(sf)
img_sf = import_img('https://raw.githubusercontent.com/kristallqiu99/' +
                    'data_bootcamp_final_project/master/sanfrancisco_data/SF_map.png')
ax.imshow(img_sf,extent=[xl-0.025,xh+0.03,yl-0.015,yh+0.03])
```

Out[394…
```
<matplotlib.image.AxesImage at 0x7f889cce62e0>
```



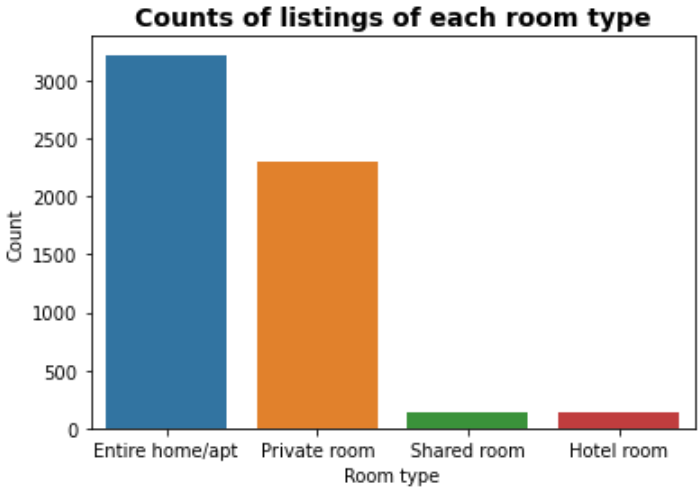
In the plot above, the most expensive houses are plotted in red dots and the cheaper ones are plotted in light blue. We learn that in San Francisco, just like in NYC, the most expensive Airbnb houses are located dispersedly, instead of clustering in one specific area.

2.1.2 Room Type

a) Number of listings of each room type

In [395…

```
ax = sns.countplot(data=sf,x='room_type')
ax.set_xlabel('Room type')
ax.set_ylabel('Count')
ax.set_title('Counts of listings of each room type',size=14,fontweight='bold')
current_palette = sns.color_palette()
```

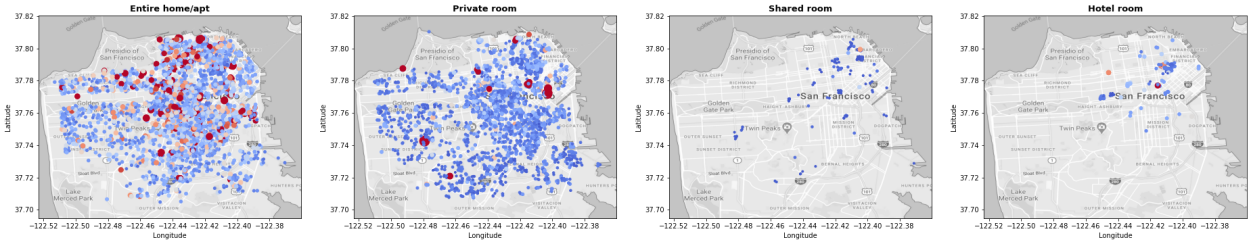


From the bar chart above, we know that there are very few shared room as Airbnb offerings in San Francisco. Although there are very few hotel rooms in San Francisco, it is the only city who has this room type among the four major US cities. The major types in San Francisco, entire home/apt is the more than private room, with more than 3500 offerings.

b) Spread

In [396…

```
fig,ax = room_type_location(sf,0.6,6,8,8)
for i in range(0,len(sf['room_type'].unique())):
    ax[i].imshow(img_sf,extent=[xl-0.025,xh+0.03,yl-0.015,yh+0.03])
```

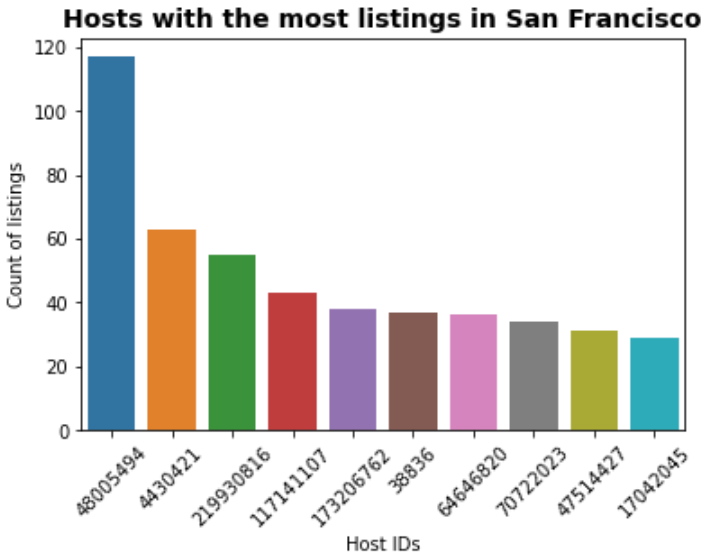


Those two major room types distribute evenly in San Francisco, and their locations don't follow some certain patterns.

2.1.3 Host

In [397…
```
top_hosts('San Francisco',sf)
```

```
/Users/kristallqiu/opt/anaconda3/lib/python3.8/site-packages/seaborn/_decorators.py:36:
FutureWarning: Pass the following variables as keyword args: x, y. From version 0.12, th
e only valid positional argument will be `data`, and passing other arguments without an
explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

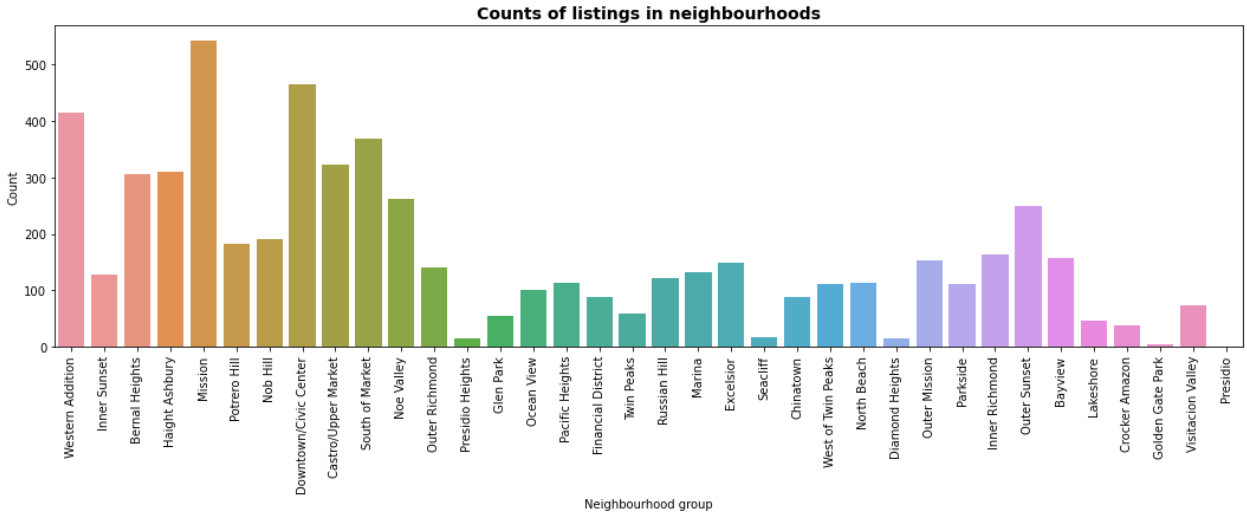


We notice that there is one host with a significantly high number of listings than other hosts in San Francisco, which has listings almost twice as the second host. After that, other hosts all have listings fewer than 70 and the number doesn't different much from each other.

2.1.4 Neighbourhood

In [398…
```
count_nei('San Francisco',sf)
```

Out[398…
```
(<Figure size 1296x360 with 1 Axes>,
 <AxesSubplot:title={'center':'Counts of listings in neighbourhoods'}, xlabel='Neighbour
hood group', ylabel='Count'>)
```

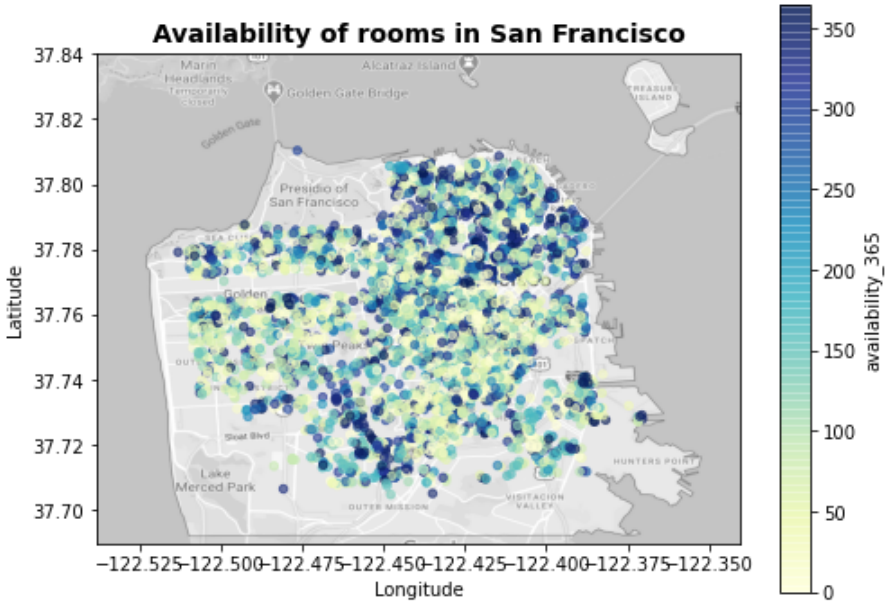


From the bar chart above, we learn that most Airbnb houses are located in Mission, followed by Downtown and Western Addition.

2.1.5 Availability

In [399…
```
fig,ax = ava365('San Francisco',sf,8,6)
ax.imshow(img_sf,extent=[xl-0.025,xh+0.03,yl-0.015,yh+0.03])
```

Out[399…
```
<matplotlib.image.AxesImage at 0x7f8886f01760>
```



In this graph, we plot the availability of rooms in San Francisco. We notice that most rooms are available for fewer than 200 days per year, while there are a few houses that are available for the whole year. We guess that most rooms are made available during peak tourist seasons, but during the tourist-off season, some rooms will not be available since there isn't a very large demand in the market, which is the same as NYC.

2.2 Data Analysis

2.2.1 Price with room types

In [400…
```
rtype = sf['room_type'].unique()
price_list = []
for n in rtype:
    sub = sf.loc[sf['room_type'] == n]
    sub_price = sub[['price']]
    price_list.append(sub_price)
stats_list = []
for p in price_list:
    i = p.describe(percentiles=[.25, .50, .75])
    i = i.iloc[3:]
    i.reset_index(inplace=True)
    i.rename(columns={'index':'Stats'},inplace=True)
    stats_list.append(i)
# change names of the price column to the area name
for i in range(0,len(rtype)):
    stats_list[i].rename(columns={'price':rtype[i]},inplace=True)
# finilize dataframe for final view
stats_df = stats_list
stats_df = [df.set_index('Stats') for df in stats_df]
stats_df = stats_df[0].join(stats_df[1:])
stats_df
```

Out[400…

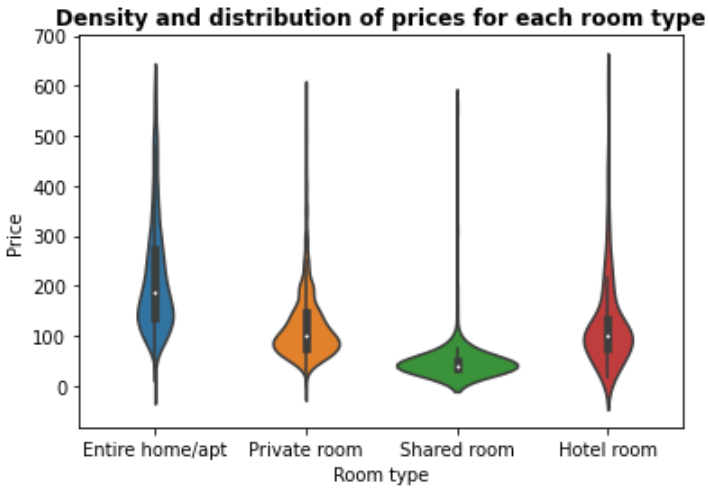
Stats	Entire home/apt	Private room	Shared room	Hotel room
min	10.0	0.0	27.0	19.00
25%	139.0	76.0	34.0	75.00

Stats	Entire home/apt	Private room	Shared room	Hotel room
50%	195.0	100.0	40.5	100.00
75%	300.0	149.0	50.0	152.25
max	4500.0	8000.0	555.0	999.00

a) Density distribution

In [401…
```
no_extreme = sf[sf.price < 600]
ax = sns.violinplot(data=no_extreme,x='room_type',y='price')
ax.set_xlabel('Room type')
ax.set_ylabel('Price')
ax.set_title('Density and distribution of prices for each room type',fontweight='bold')
```

Out[401… `Text(0.5, 1.0, 'Density and distribution of prices for each room type')`



From the density distribution, we know that hosts charge a higher price for entire home/apt room type, ranging from less than 100 dollars to more than 400 dollars, even to 500 dollars. On the contrary, most private rooms and hotel rooms are charged a price of around 100 dollars per day. The shared rooms are the cheapest, which are less than 100 dollars.

2.2.2 Price with neighbourhoods

In [402…
```
nei_stats('San Francisco',sf)
```

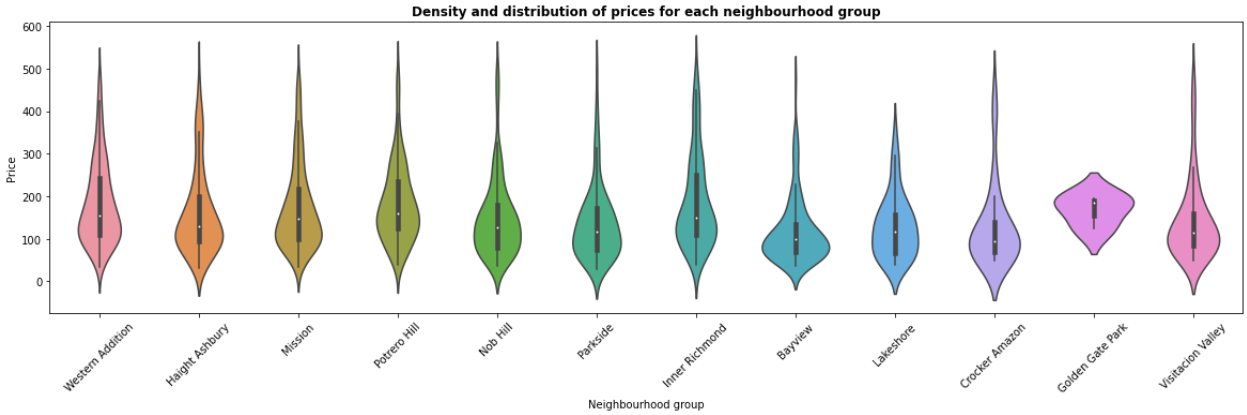
Out[402…

Stats	Western Addition	Inner Sunset	Bernal Heights	Haight Ashbury	Mission	Potrero Hill	Nob Hill	Downtown/Civic Center	Castro/Upper Market	Sou Marl
min	33.0	47.0	0.0	31.00	33.0	39.0	37.0	19.0	10.00	32
25%	110.0	105.0	100.0	99.00	100.0	125.0	82.0	80.0	119.00	125
50%	173.5	150.0	145.0	139.00	150.0	175.0	134.0	117.5	175.00	171
75%	275.0	250.0	219.0	223.75	245.0	271.0	189.0	199.0	283.75	242
max	3000.0	2000.0	1850.0	1800.00	2500.0	4500.0	1250.0	1200.0	1450.00	2999

5 rows × 36 columns

a) Density distribution

In [403…
```
sfnei = ['Western Addition','Haight Ashbury','Mission','Potrero Hill','Nob Hill','Golder
        'Parkside','Inner Richmond','Visitacion Valley','Bayview','Lakeshore','Crocker A
sf_density = sf.loc[sf['neighbourhood'].isin(sfnei),:]
fig,ax = plt.subplots(figsize=(20,5))
ax = plot_distribution('San Francisco',sf_density,500)
```



We see the prices vary a lot in some neighborhood, and price of rooms in inner richmond vary the most.

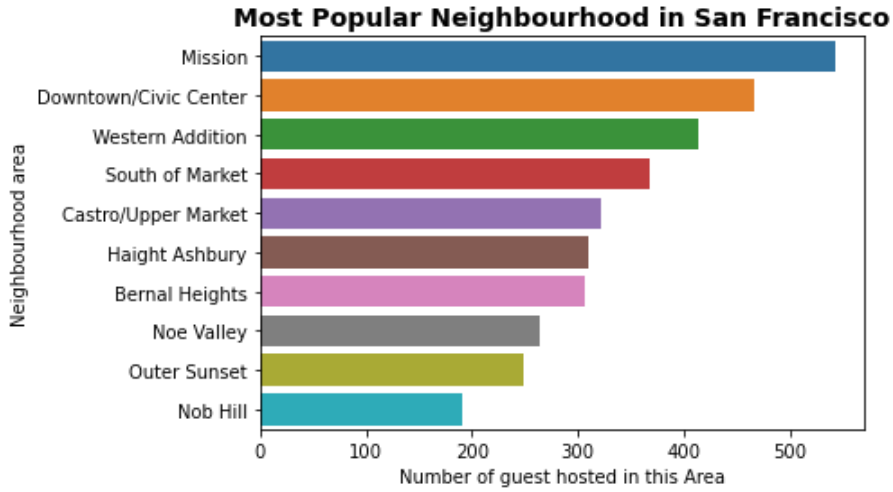
2.2.3 Neighbourhood Exploration

a) Popular neighbourhoods

In [404…
```
top_nei('San Francisco',sf)
```

```
/Users/kristallqiu/opt/anaconda3/lib/python3.8/site-packages/seaborn/_decorators.py:36:
FutureWarning: Pass the following variables as keyword args: x, y. From version 0.12, th
e only valid positional argument will be `data`, and passing other arguments without an
explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

Out[404…
```
(<Figure size 1440x360 with 1 Axes>,
 <AxesSubplot:title={'center':'Most Popular Neighbourhood in San Francisco'}, xlabel='Nu
mber of guest hosted in this Area', ylabel='Neighbourhood area'>)
```

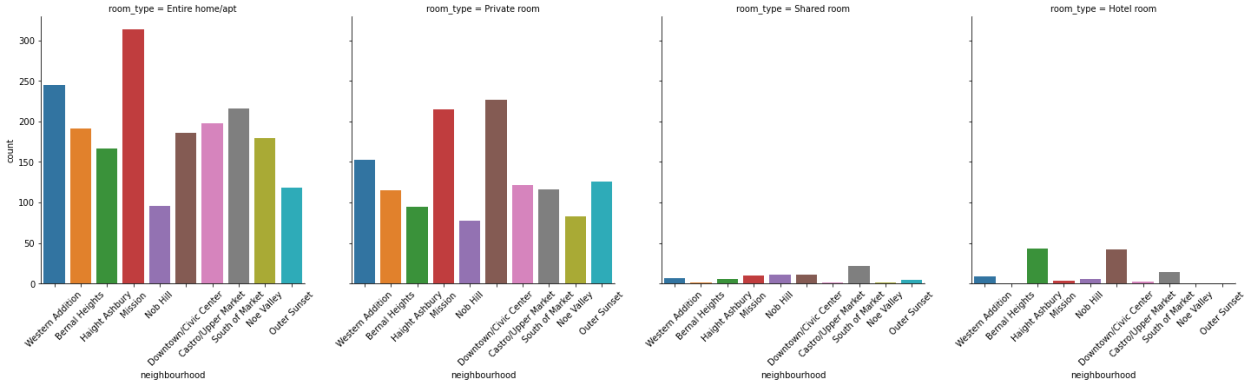


We list top ten most popular neighbourhood in San Francisco in this horizontal bar chart. The most popular one is Mission, followed by Downtown and Western Addition.

b) Room type within popular neighbourhoods

In [405…
```
top_nei_room_type('San Francisco',sf)
```

Out[405…
```
<seaborn.axisgrid.FacetGrid at 0x7f888799d790>
```



Based on the top ten popular neighborhood we selected before, we picture the room types information in these neighborhoods for readers' reference. Guests can know the distribution of their favourite room type in popular neighborhoods, so that they can make the decisions more easily.

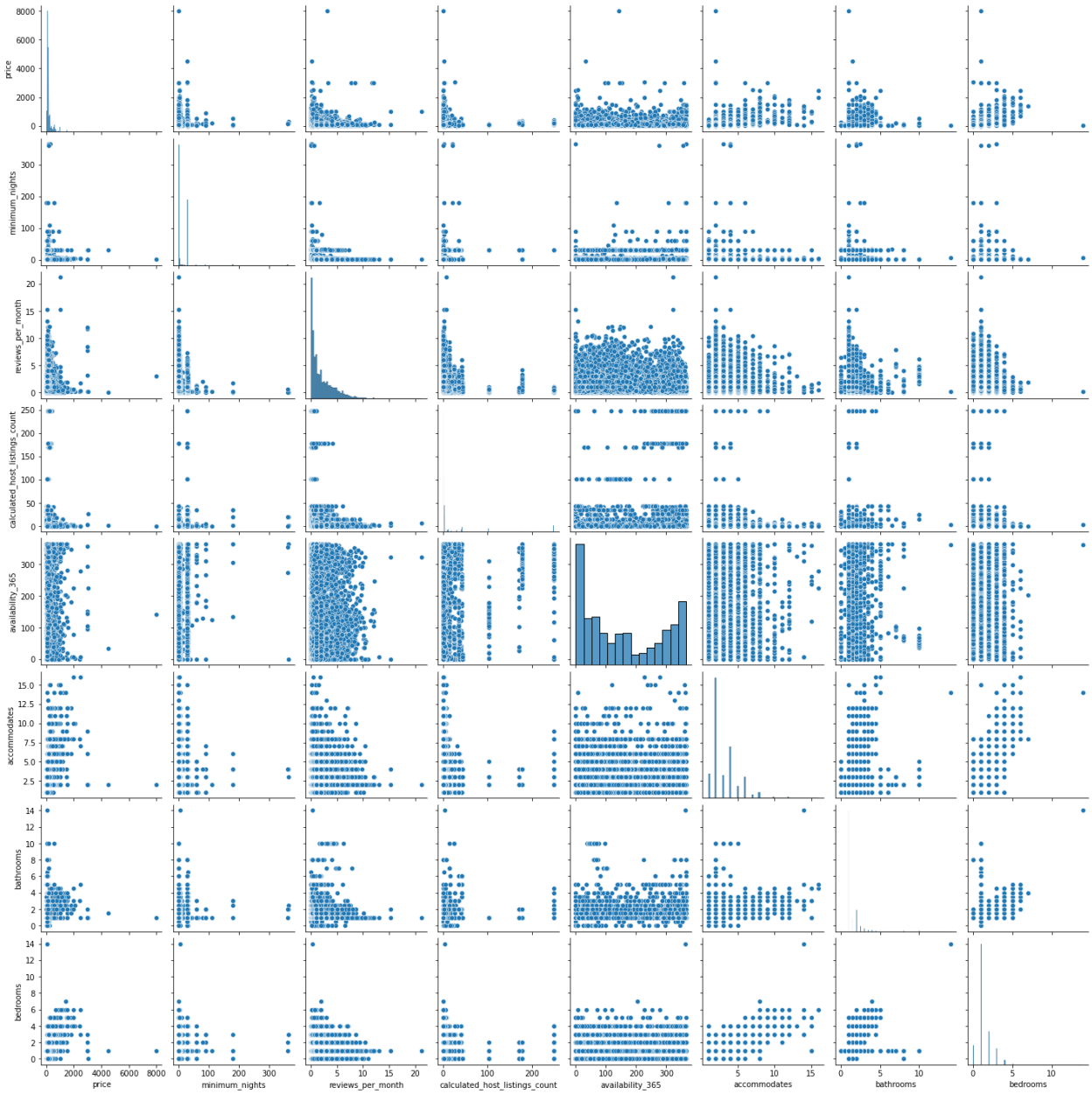
3. Descriptive Data Analysis

3.1 Pairplot of each variable

In [406…

```
vc = list(nyc.columns)
for i in ['id','host_id','neighbourhood_group','latitude', 'longitude','number_of_reviev
    vc.remove(i)
for j in ['accommodates', 'bathrooms', 'bedrooms']:
    vc.append(j)

pp3 = sf.loc[:,vc]
sns.pairplot(pp3)
```

Out[406… <seaborn.axisgrid.PairGrid at 0x7f88879637f0>



We can see the correltation between each variable. It does not make sense as many of them are categorical data

4. Predictive Data Analysis

In [407…
```
sf.columns
```

Out[407…
```
Index(['id', 'host_id', 'host_response_rate', 'host_total_listings_count',
       'host_has_profile_pic', 'host_identity_verified', 'neighbourhood',
       'latitude', 'longitude', 'property_type', 'room_type', 'accommodates',
       'bathrooms', 'bedrooms', 'beds', 'bed_type', 'price', 'guests_included',
       'extra_people', 'minimum_nights', 'maximum_nights', 'availability_365',
       'require_guest_profile_picture', 'require_guest_phone_verification',
       'calculated_host_listings_count', 'reviews_per_month'],
      dtype='object')
```

In [408…
```
model3 = sf.loc[:,:].copy()
model3['neighbourhood'] = model3['neighbourhood'].astype("category").cat.codes
model3['room_type'] = model3['room_type'].astype("category").cat.codes

model3['host_response_rate'] = model3['host_response_rate'].str.replace('%','').astype(i
model3['host_response_rate'] = model3['host_response_rate']/100

tf = ['host_has_profile_pic','host_identity_verified',
      'require_guest_profile_picture','require_guest_phone_verification']
for c in tf:
    model3[c] = model3[c].replace('t',1)
```

```
    model3[c] = model3[c].replace('f',0)

model3['bed_type'] = model3['bed_type'].astype("category").cat.codes
model3['extra_people'] = model3['extra_people'].str.replace('$','').astype(float)
model3['property_type'] = model3['property_type'].astype("category").cat.codes


mean = model3['reviews_per_month'].mean()
model3['reviews_per_month'].fillna(mean, inplace=True)

model3['log_price'] = np.log(model3.price+1)

model3 = model3.drop(columns=['id','host_id','price','latitude','longitude','minimum_nig

model3.isnull().sum()
```

Out[408…

```
host_response_rate                  0
host_total_listings_count           0
host_has_profile_pic                0
host_identity_verified              0
neighbourhood                       0
property_type                       0
room_type                           0
accommodates                        0
bathrooms                          11
bedrooms                            1
beds                                5
bed_type                            0
guests_included                     0
extra_people                        0
availability_365                    0
require_guest_profile_picture       0
require_guest_phone_verification    0
calculated_host_listings_count      0
reviews_per_month                   0
log_price                           0
dtype: int64
```

In [409…

```
model3.columns
```

Out[409…

```
Index(['host_response_rate', 'host_total_listings_count',
       'host_has_profile_pic', 'host_identity_verified', 'neighbourhood',
       'property_type', 'room_type', 'accommodates', 'bathrooms', 'bedrooms',
       'beds', 'bed_type', 'guests_included', 'extra_people',
       'availability_365', 'require_guest_profile_picture',
       'require_guest_phone_verification', 'calculated_host_listings_count',
       'reviews_per_month', 'log_price'],
      dtype='object')
```

Value Reference

In [410…

```
sfVF = {}
sfd = ['neighbourhood','room_type','host_has_profile_pic','property_type','bed_type']
for c in sfd:
    sfVF = {}
    for i in model3[c].unique():
        indx = model3[model3[c]==i].index.values[0]
        sfVF[i] = sf[c][indx]
    print(c.capitalize(),'\n',dict(sorted(sfVF.items())))
```

```
Neighbourhood
 {0: 'Bayview', 1: 'Bernal Heights', 2: 'Castro/Upper Market', 3: 'Chinatown', 4: 'Crock
er Amazon', 5: 'Diamond Heights', 6: 'Downtown/Civic Center', 7: 'Excelsior', 8: 'Financ
ial District', 9: 'Glen Park', 10: 'Golden Gate Park', 11: 'Haight Ashbury', 12: 'Inner
Richmond', 13: 'Inner Sunset', 14: 'Lakeshore', 15: 'Marina', 16: 'Mission', 17: 'Nob Hi
ll', 18: 'Noe Valley', 19: 'North Beach', 20: 'Ocean View', 21: 'Outer Mission', 22: 'Ou
ter Richmond', 23: 'Outer Sunset', 24: 'Pacific Heights', 25: 'Parkside', 26: 'Potrero H
ill', 27: 'Presidio', 28: 'Presidio Heights', 29: 'Russian Hill', 30: 'Seacliff', 31: 'S
outh of Market', 32: 'Twin Peaks', 33: 'Visitacion Valley', 34: 'West of Twin Peaks', 3
5: 'Western Addition'}
Room_type
 {0: 'Entire home/apt', 1: 'Hotel room', 2: 'Private room', 3: 'Shared room'}
Host_has_profile_pic
 {0: 'f', 1: 't'}
Property_type
 {0: 'Aparthotel', 1: 'Apartment', 2: 'Bed and breakfast', 3: 'Boutique hotel', 4: 'Bung
```

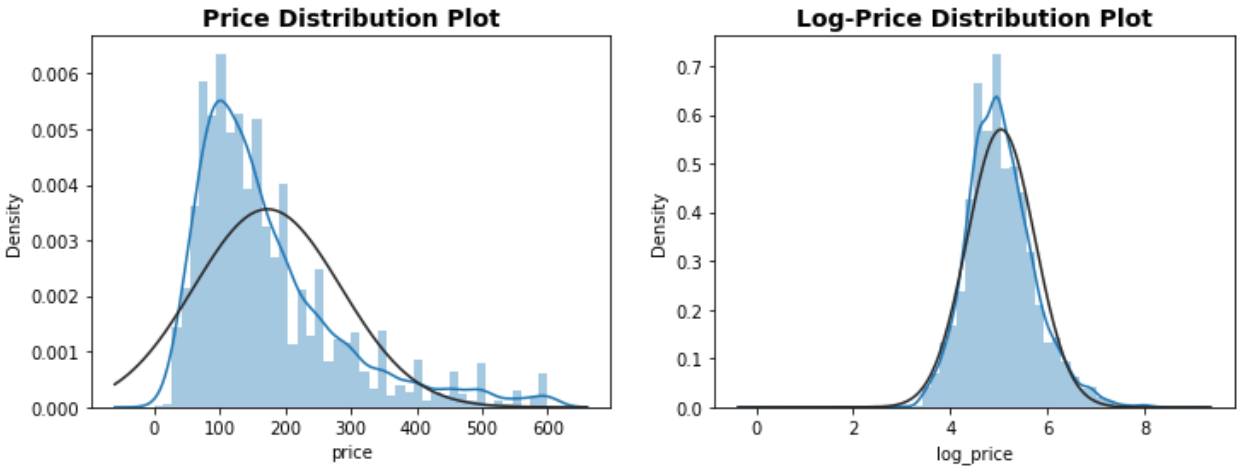
```
alow', 5: 'Cabin', 6: 'Castle', 7: 'Condominium', 8: 'Cottage', 9: 'Dome house', 10: 'Ea
rth house', 11: 'Guest suite', 12: 'Guesthouse', 13: 'Hostel', 14: 'Hotel', 15: 'House',
16: 'In-law', 17: 'Loft', 18: 'Other', 19: 'Resort', 20: 'Serviced apartment', 21: 'Tiny
house', 22: 'Townhouse', 23: 'Villa'}
Bed_type
 {0: 'Airbed', 1: 'Couch', 2: 'Futon', 3: 'Pull-out Sofa', 4: 'Real Bed'}
```

4.1 Probability distribution

In [411…
```
fig,ax = plt.subplots(1,2,figsize=(12,4))
sns.distplot(sf.loc[sf['price']<=600]['price'],fit=norm, ax=ax[0]) # drop extreme values
ax[0].set_title("Price Distribution Plot",size=14, weight='bold')
sns.distplot(model3['log_price'],fit=norm,ax=ax[1])
ax[1].set_title("Log-Price Distribution Plot",size=14, weight='bold')
```

```
/Users/kristallqiu/opt/anaconda3/lib/python3.8/site-packages/seaborn/distributions.py:25
51: FutureWarning: `distplot` is a deprecated function and will be removed in a future v
ersion. Please adapt your code to use either `displot` (a figure-level function with sim
ilar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
/Users/kristallqiu/opt/anaconda3/lib/python3.8/site-packages/seaborn/distributions.py:25
51: FutureWarning: `distplot` is a deprecated function and will be removed in a future v
ersion. Please adapt your code to use either `displot` (a figure-level function with sim
ilar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

Out[411… `Text(0.5, 1.0, 'Log-Price Distribution Plot')`



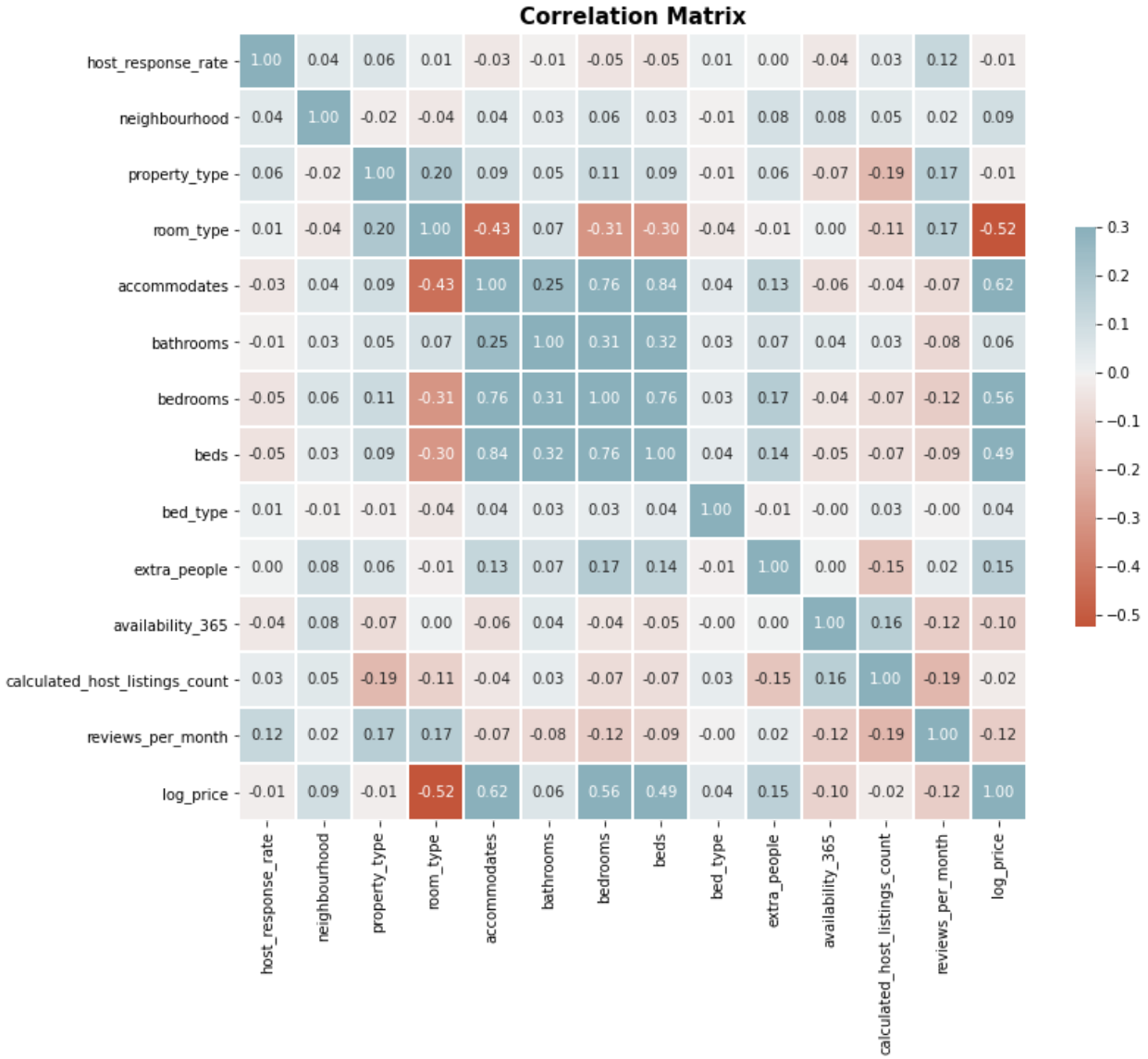
We learn from the log_price distribution plot that the log_price of San Francisco is also aprroximitely normally distributed with a mean around 5. But it is less deviated, since we can know that the standard deviation is smaller than that of NYC and Boston.

4.2 Correlation

In [412…
```
keep_col3 = ['host_response_rate', 'neighbourhood',
       'property_type', 'room_type', 'accommodates',
      'bathrooms', 'bedrooms', 'beds', 'bed_type', 'extra_people','availability_365',
       'calculated_host_listings_count', 'reviews_per_month', 'log_price']
```

In [413…
```
cordf3 = model3.loc[:,keep_col3]
plt.figure(figsize=(12,10))
palette = sns.diverging_palette(20, 220, n=256)
corr = cordf3.corr(method='pearson')
sns.heatmap(corr, annot=True, fmt=".2f", cmap=palette, vmax=.3, center=0,
            square=True, linewidths=1, cbar_kws={"shrink": .5}).set(ylim=(14, 0))
plt.title("Correlation Matrix",size=15, weight='bold')
```

Out[413… `Text(0.5, 1.0, 'Correlation Matrix')`



In this correlation matrix we calculate and display the correlation between different variables. The hosts can easily find the relationship between variables and make the optimized investment decisions.

4.3 Regression

In [414…]
```
model3['price'] = sf['price']
model3.head(5)
```

Out[414…]

	host_response_rate	host_total_listings_count	host_has_profile_pic	host_identity_verified	neighbourhood
0	1.00	1.0	1	1	35
1	1.00	2.0	1	1	13
2	0.80	2.0	1	1	1
3	0.86	10.0	1	1	11
4	0.86	10.0	1	1	11

5 rows × 21 columns

4.3.1 Linear Regression

In [415…]
```
import statsmodels.formula.api as smf
```

a) Price - all vairables

In [416…]
```
reg_price = smf.ols('price ~ host_response_rate + neighbourhood + property_type + room_t
```

```
                    ,data=model3).fit()
print(reg_price.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.265
Model:                            OLS   Adj. R-squared:                  0.264
Method:                 Least Squares   F-statistic:                     160.7
Date:                Wed, 04 Nov 2020   Prob (F-statistic):               0.00
Time:                        11:51:13   Log-Likelihood:                -39267.
No. Observations:                5794   AIC:                         7.856e+04
Df Residuals:                    5780   BIC:                         7.866e+04
Df Model:                          13
Covariance Type:            nonrobust
==============================================================================
==========
                                 coef    std err          t      P>|t|      [0.025
0.975]
------------------------------------------------------------------------------
----------
Intercept                     37.6729     53.449      0.705      0.481     -67.107
142.453
host_response_rate           -22.7203     26.617     -0.854      0.393     -74.899
29.459
neighbourhood                  1.1781      0.265      4.442      0.000       0.658
1.698
property_type                  0.5854      0.450      1.301      0.193      -0.297
1.468
room_type                    -22.6943      3.280     -6.920      0.000     -29.124
-16.265
accommodates                  43.2848      3.006     14.400      0.000      37.392
49.177
bathrooms                      6.3754      3.194      1.996      0.046       0.114
12.637
bedrooms                      56.7179      5.089     11.144      0.000      46.741
66.695
beds                         -21.6089      4.745     -4.554      0.000     -30.910
-12.307
bed_type                       3.4368     11.635      0.295      0.768     -19.373
26.246
extra_people                   0.5844      0.092      6.383      0.000       0.405
0.764
availability_365              -0.0589      0.022     -2.658      0.008      -0.102
-0.015
calculated_host_listings_count   -0.1817      0.073     -2.494      0.013      -0.324
-0.039
reviews_per_month             -5.1440      1.390     -3.701      0.000      -7.868
-2.420
==============================================================================
Omnibus:                    10974.180   Durbin-Watson:                   1.883
Prob(Omnibus):                  0.000   Jarque-Bera (JB):         37662938.173
Skew:                          14.165   Prob(JB):                         0.00
Kurtosis:                     396.961   Cond. No.                     4.07e+03
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specifi
ed.
[2] The condition number is large, 4.07e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
```

Here we run an ordinary least square regression for price on several factors that we think may influence the price of Airbnb. We have H0: beta = 0 against H1: beta != 0 for every beta in this regression model. According to the output table, the P-value of host_response_rate, property_type and bed_type are bigger than 5%, which means that we don't reject H0 against H1. There is no evidence that the effect of host_response_rate, property_type and bed_type is significant to the price of Airbnb house and we should drop them.

a) Price - drop vairables

In [417…

```
reg_price = smf.ols('price ~ neighbourhood + room_type + accommodates + bathrooms + bedr
                    ,data=model3).fit()
print(reg_price.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.265
```

```
Model:                            OLS   Adj. R-squared:                  0.264
Method:                 Least Squares   F-statistic:                     208.6
Date:                Wed, 04 Nov 2020   Prob (F-statistic):               0.00
Time:                        11:51:13   Log-Likelihood:                -39269.
No. Observations:                5794   AIC:                         7.856e+04
Df Residuals:                    5783   BIC:                         7.863e+04
Df Model:                          10
Covariance Type:            nonrobust
================================================================================
==========
                                   coef    std err          t      P>|t|      [0.025
0.975]
--------------------------------------------------------------------------------
----------
Intercept                       32.2892      9.824      3.287      0.001      13.031
51.547
neighbourhood                    1.1614      0.265      4.384      0.000       0.642
1.681
room_type                      -21.7462      3.197     -6.801      0.000     -28.014
-15.478
accommodates                    43.5271      2.998     14.519      0.000      37.650
49.404
bathrooms                        6.2908      3.192      1.971      0.049       0.033
12.549
bedrooms                        57.2326      5.076     11.275      0.000      47.281
67.184
beds                           -21.5573      4.742     -4.546      0.000     -30.853
-12.262
extra_people                     0.5845      0.092      6.387      0.000       0.405
0.764
availability_365                -0.0590      0.022     -2.665      0.008      -0.102
-0.016
calculated_host_listings_count  -0.1959      0.072     -2.715      0.007      -0.337
-0.054
reviews_per_month               -5.0715      1.371     -3.699      0.000      -7.759
-2.384
==============================================================================
Omnibus:                    10970.510   Durbin-Watson:                   1.882
Prob(Omnibus):                  0.000   Jarque-Bera (JB):         37637719.551
Skew:                          14.154   Prob(JB):                         0.00
Kurtosis:                     396.830   Cond. No.                         727.
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specifi
ed.
```

After dropping those variables, we run the linear regression again to do the selection process for the second time. The remained variables are all significant at 5% level.

And, we can get price = 32.2892 + 1.1614 *neighbourhood* - *room_type* 21.7462 + accommodates *43.5271* - *bathrooms* 6.2908 + bedrooms *57.2326* - *beds* 21.5573 + extra_people *0.5845* - *availability_365* 0.0590 - calculated_host_listings_count *0.1959* - *reviews_per_month* 5.0715

We find that different from price, bedrooms has the greatest relevance of the price.

b) Log price - all variables

In [418…

```
reg_price = smf.ols('log_price ~ host_response_rate + neighbourhood + property_type + rc
                    ,data=model3).fit()
print(reg_price.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:              log_price   R-squared:                       0.512
Model:                            OLS   Adj. R-squared:                  0.511
Method:                 Least Squares   F-statistic:                     467.3
Date:                Wed, 04 Nov 2020   Prob (F-statistic):               0.00
Time:                        11:51:13   Log-Likelihood:                -4053.8
No. Observations:                5794   AIC:                             8136.
Df Residuals:                    5780   BIC:                             8229.
Df Model:                          13
Covariance Type:            nonrobust
================================================================================
==========
                                   coef    std err          t      P>|t|      [0.025
0.975]
```

```
------------------------------------------------------------------------------
----------
Intercept                          4.5228      0.123     36.893      0.000        4.282
4.763
host_response_rate                 0.0655      0.061      1.073      0.283       -0.054
0.185
neighbourhood                      0.0035      0.001      5.815      0.000        0.002
0.005
property_type                     -0.0009      0.001     -0.882      0.378       -0.003
0.001
room_type                         -0.1991      0.008    -26.466      0.000       -0.214
-0.184
accommodates                       0.1501      0.007     21.779      0.000        0.137
0.164
bathrooms                         -0.0453      0.007     -6.188      0.000       -0.060
-0.031
bedrooms                           0.2017      0.012     17.282      0.000        0.179
0.225
beds                              -0.0870      0.011     -7.995      0.000       -0.108
-0.066
bed_type                           0.0319      0.027      1.194      0.233       -0.020
0.084
extra_people                       0.0016      0.000      7.708      0.000        0.001
0.002
availability_365                  -0.0004   5.08e-05     -8.580      0.000       -0.001
-0.000
calculated_host_listings_count    -0.0003      0.000     -1.797      0.072       -0.001
2.72e-05
reviews_per_month                 -0.0146      0.003     -4.594      0.000       -0.021
-0.008
==============================================================================
Omnibus:                     1152.024   Durbin-Watson:                   1.809
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             9800.444
Skew:                           0.710   Prob(JB):                         0.00
Kurtosis:                       9.211   Cond. No.                     4.07e+03
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specifi
ed.
[2] The condition number is large, 4.07e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
```

Here we run an ordinary least square regression for log_price on several factors that we think may influence the price of Airbnb. We have H0: beta = 0 against H1: beta != 0 for every beta in this regression model. According to the output table, the P-value of host_response_rate, property_type, bed_type and calculated_host_listings_count are bigger than 5%, which means that we don't reject H0 against H1. There is no evidence that the effect of host_response_rate, property_type, bed_type and calculated_host_listings_count is significant to the price of Airbnb house and we should drop them.

B) Log price - drop variables

In [419…

```
reg_price = smf.ols('log_price ~ neighbourhood + room_type + accommodates + bathrooms +
                    ,data=model3).fit()
print(reg_price.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:              log_price   R-squared:                       0.512
Model:                            OLS   Adj. R-squared:                  0.511
Method:                 Least Squares   F-statistic:                     674.2
Date:                Wed, 04 Nov 2020   Prob (F-statistic):               0.00
Time:                        11:51:13   Log-Likelihood:                -4056.7
No. Observations:                5794   AIC:                             8133.
Df Residuals:                    5784   BIC:                             8200.
Df Model:                           9
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept      4.7019      0.022    211.316      0.000       4.658       4.745
neighbourhood  0.0035      0.001      5.790      0.000       0.002       0.005
room_type     -0.1996      0.007    -27.367      0.000      -0.214      -0.185
accommodates   0.1496      0.007     21.762      0.000       0.136       0.163
bathrooms     -0.0457      0.007     -6.256      0.000      -0.060      -0.031
bedrooms       0.2020      0.012     17.379      0.000       0.179       0.225
beds          -0.0864      0.011     -7.948      0.000      -0.108      -0.065
```

```
extra_people           0.0017      0.000      7.994      0.000       0.001       0.002
availability_365      -0.0004   5.03e-05     -8.907      0.000      -0.001      -0.000
reviews_per_month     -0.0137      0.003     -4.409      0.000      -0.020      -0.008
==============================================================================
Omnibus:                     1153.943   Durbin-Watson:                   1.812
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             9806.503
Skew:                           0.712   Prob(JB):                         0.00
Kurtosis:                       9.213   Cond. No.                         716.
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specifi
ed.
```

After dropping those variables, we run the linear regression again to do the selection process for the second time. The remained variables are all significant at 5% level.

And, we can get log_price = 4.7019 + 0.0035 *neighbourhood* - *room_type* 0.1996 + accommodates *0.1496* - *bathrooms* 0.0457 + bedrooms *0.2020* - *beds* 0.0864 + extra_people *0.0017* - *availability_365* 0.0004 - reviews_per_month* 0.0137

We find that different from price, bedrooms has the greatest relevance of the log_price.

4.3.2 ML

From the linear regression we found that log_price is a better dependent variable to predict.

In [420…
```
from sklearn.model_selection import train_test_split
```

In [421…
```
X_train3, X_test3, y_train3, y_test3 = train_test_split(model3[['room_type']].values, mo
                                                        test_size=0.25, random_state=0)
```

a) K-Nearest Neighbors

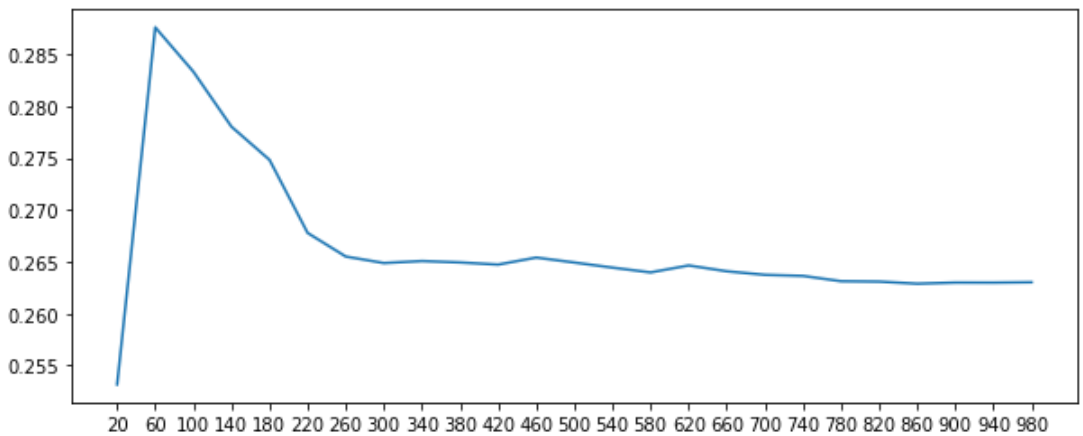
In [422…
```
from sklearn.neighbors import KNeighborsRegressor as knn
from sklearn.model_selection import cross_val_score
```

In [423…
```
scores = pd.Series()
for i in range(20,1000,40):
    scores[str(i)] = cross_val_score(knn(n_neighbors=i),
                     X_train3, y_train3,cv=5).mean()
indx = scores.idxmax()
```

```
<ipython-input-423-ff3c0d8f2030>:1: DeprecationWarning: The default dtype for empty Seri
es will be 'object' instead of 'float64' in a future version. Specify a dtype explicitly
to silence this warning.
  scores = pd.Series()
```

In [424…
```
fig,ax = plt.subplots(figsize=(10,4))
plt.plot(scores.index,scores.values)
```

Out[424…
```
[<matplotlib.lines.Line2D at 0x7f8891dc1550>]
```



In [425…
```
skl_knn = knn(n_neighbors=int(indx)).fit(X_train3, y_train3)
knn_score3 = skl_knn.score(X_test3, y_test3)
print(knn_score3)
```

```
0.2732330467557673
```

b) Random Forest

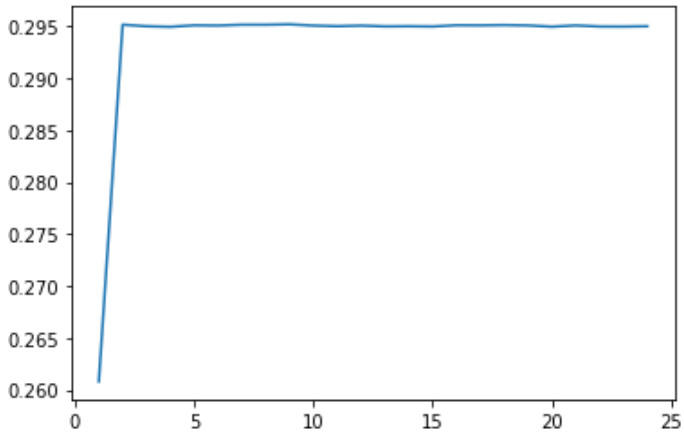
In [426…
```
from sklearn.ensemble import RandomForestRegressor as rf
```

In [427…
```
cross_val_score(rf(n_estimators=100,max_depth=3),X_train3, y_train3.ravel(),cv=5).mean()
```

Out[427…
```
0.2950210431373713
```

In [428…
```
cv_scores = pd.DataFrame()
for i in range(1,25):
    cv_scores.loc[i,'rf'] = cross_val_score(rf(n_estimators=100,max_depth=i),X_train3, y
```

In [429…
```
ax = cv_scores.plot()
ax.get_legend().remove()
```



In [430…
```
indx = scores.idxmax()
skl_rf = rf(n_estimators=100,max_depth=int(indx)).fit(X_train3, y_train3.ravel())
skl_rf.predict(X_test3)
rf_score3 = skl_rf.score(X_test3,y_test3)
print(rf_score3)
```

```
0.28304609141619497
```

In [431…
```
score_table = pd.DataFrame({'K Nearest Neighbors':[knn_score3],'Random Forest':[rf_score
score_table = score_table.T
score_table.columns = ['Score']
score_table
```

Out[431…

	Score
K Nearest Neighbors	0.273233
Random Forest	0.283046

As we can see from above table, for log_price, we should choose Random Forest as the score of this model is the highest, compared to K Nearest Neighbors.

Rank score for log_price : Random Forest > KNN

Possiable reason for a relative low score for both is that log_price should be dependent on some features not containing in the dataFrame as well, such as environment, surroundings or quality of the room.

➢ Seattle

1. Data

1.1 Data Description

In [432…
```
sea = import_df('https://raw.githubusercontent.com/kristallqiu99/' +
                'data_bootcamp_final_project/master/seattle_data/AB_SEA_2016.csv')
sea.drop(sea.columns[0],axis = 1,inplace=True)
sea.head(5)
```

Out[432…

	id	listing_url	scrape_id	last_scraped	name	summary
0	241032	https://www.airbnb.com/rooms/241032	20160104002432	2016-01-04	Stylish Queen Anne Apartment	NaN
1	953595	https://www.airbnb.com/rooms/953595	20160104002432	2016-01-04	Bright & Airy Queen Anne Apartment	Chemically sensitive? We've removed the irrita...
2	3308979	https://www.airbnb.com/rooms/3308979	20160104002432	2016-01-04	New Modern House-Amazing water view	New modern house built in 2013. Spectacular s...
3	7421966	https://www.airbnb.com/rooms/7421966	20160104002432	2016-01-04	Queen Anne Chateau	A charming apartment that sits atop Queen Anne...
4	278830	https://www.airbnb.com/rooms/278830	20160104002432	2016-01-04	Charming craftsman 3 bdm house	Cozy family craftman house in beautiful neighb...

5 rows × 92 columns

In [433…
```
sea.isnull().sum()
```

Out[433…
```
id                                  0
listing_url                         0
scrape_id                           0
last_scraped                        0
name                                0
                                 ...
cancellation_policy                 0
require_guest_profile_picture       0
require_guest_phone_verification    0
calculated_host_listings_count      0
reviews_per_month                 627
Length: 92, dtype: int64
```

1.2 Data Cleaning

In [434…
```
var_col3 = var_col.copy()
```

In [435…
```
i = var_col3.index('neighbourhood_cleansed')
var_col3[i]='neighbourhood_group_cleansed'
sea = sea.loc[:,var_col3]
sea.rename(columns={'neighbourhood_group_cleansed':'neighbourhood'}, inplace=True)
```

In [436…
```
sea.isnull().sum()
```

Out[436…
```
id                                  0
host_id                             0
host_since                          2
host_response_time                523
host_response_rate                523
host_acceptance_rate              773
host_is_superhost                   2
```

```
host_listings_count                 2
host_total_listings_count           2
host_has_profile_pic                2
host_identity_verified              2
street                              0
neighbourhood                       0
latitude                            0
longitude                           0
property_type                       1
room_type                           0
accommodates                        0
bathrooms                          16
bedrooms                            6
beds                                1
bed_type                            0
price                               0
guests_included                     0
extra_people                        0
minimum_nights                      0
maximum_nights                      0
availability_365                    0
number_of_reviews                   0
cancellation_policy                 0
require_guest_profile_picture       0
require_guest_phone_verification    0
calculated_host_listings_count      0
reviews_per_month                 627
dtype: int64
```

In [437…
```
sea.dropna(subset=['reviews_per_month'],inplace=True)
```

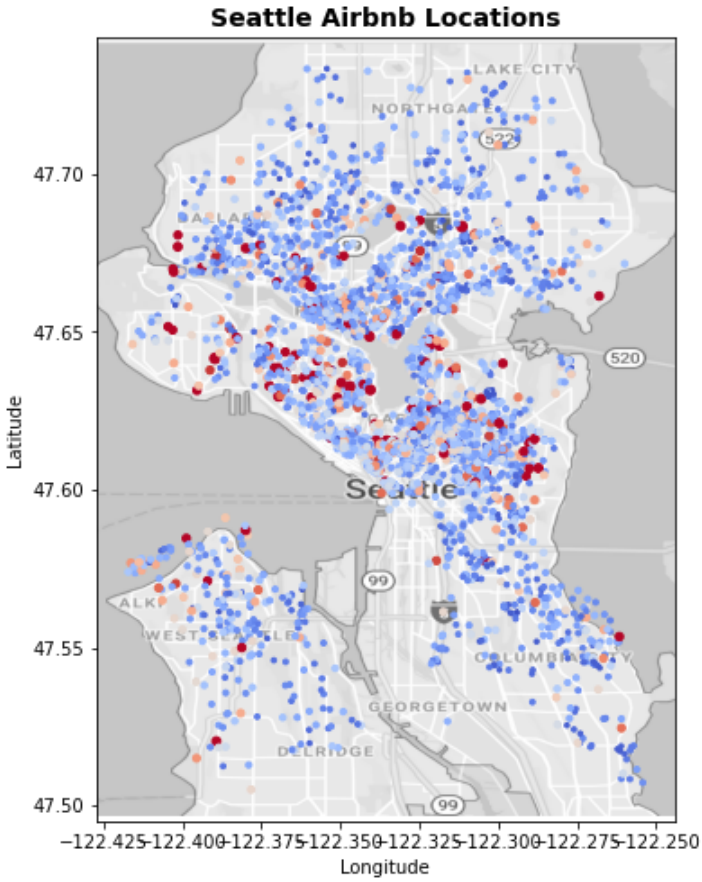
2. Exploratory Data Analysis

2.1 Data Visualization

2.1.1 Location

In [438…
```
xl,xh,yl,yh = area(sea)
fig,ax = location('Seattle',sea,0.5,3,12,8)
img_sea = import_img('https://raw.githubusercontent.com/kristallqiu99/' +
                     'data_bootcamp_final_project/master/seattle_data/SEA_map.png')
ax.imshow(img_sea,extent=[xl-0.085,xh+0.075,yl-0.0085,yh+0.009])
```

Out[438…
```
<matplotlib.image.AxesImage at 0x7f88912aa940>
```



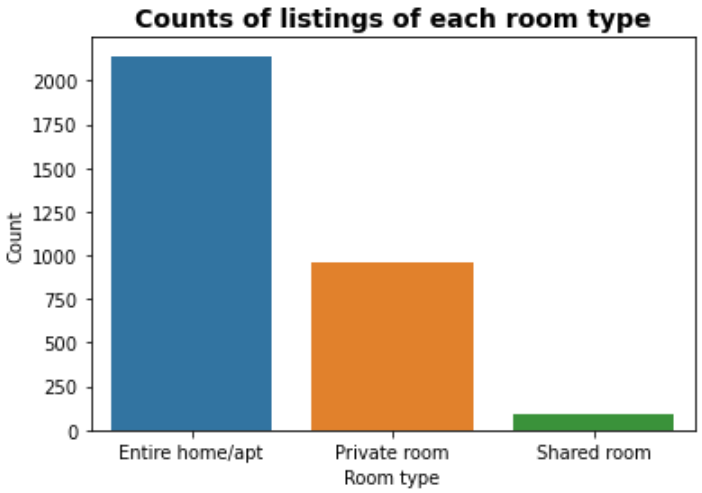
In the plot above, the most expensive houses are plotted in red dots and the cheaper ones are plotted in light blue. We learn that in Seattle, the most expensive Airbnb houses are located mostly in Greenwood, Green Lake, University District, Walling Ford, Queen Anne and East Lake (from the north to the south).

2.1.2 Room Type

a) Number of listings of each room type

In [439…

```
ax = sns.countplot(data=sea,x='room_type')
ax.set_xlabel('Room type')
ax.set_ylabel('Count')
ax.set_title('Counts of listings of each room type',size=14,fontweight='bold')
current_palette = sns.color_palette()
```



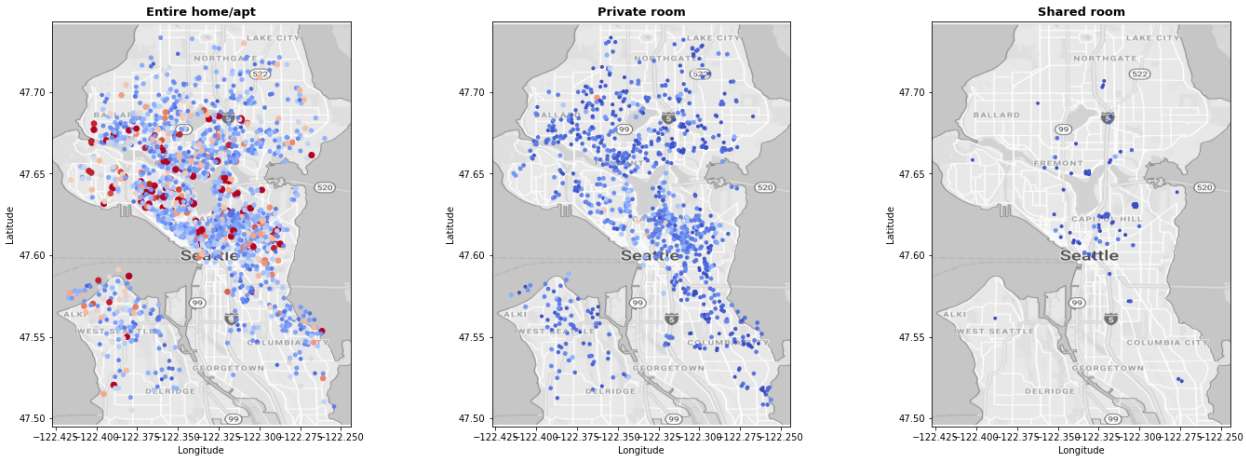
From the bar chart above, there is a significantly higher number of entire home/apt. Meanwhile, the number of shared room is low as in other cities.

b) Spread

In [440…

```
fig,ax = room_type_location(sea,0.6,3,8,8)
for i in range(0,len(sea['room_type'].unique())):
```

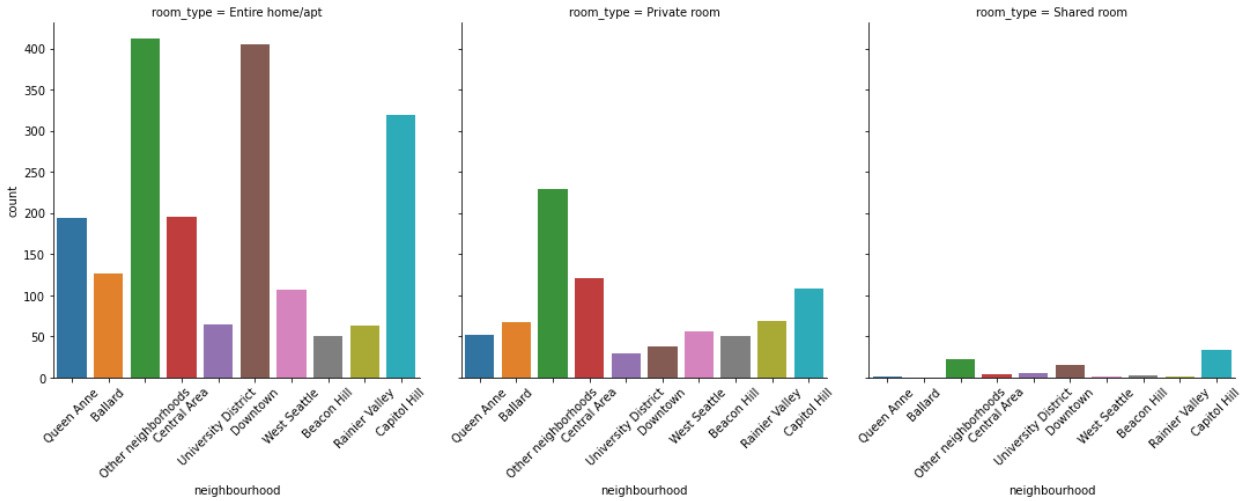
```
    ax[i].imshow(img_sea,extent=[xl-0.085,xh+0.075,yl-0.009,yh+0.009])
```



Those two major room types distribute evenly in Seattle, and their locations don't follow some certain patterns.

In [441…
```
top_nei_room_type('Seattle',sea)
```

Out[441…
```
<seaborn.axisgrid.FacetGrid at 0x7f88926e1fa0>
```

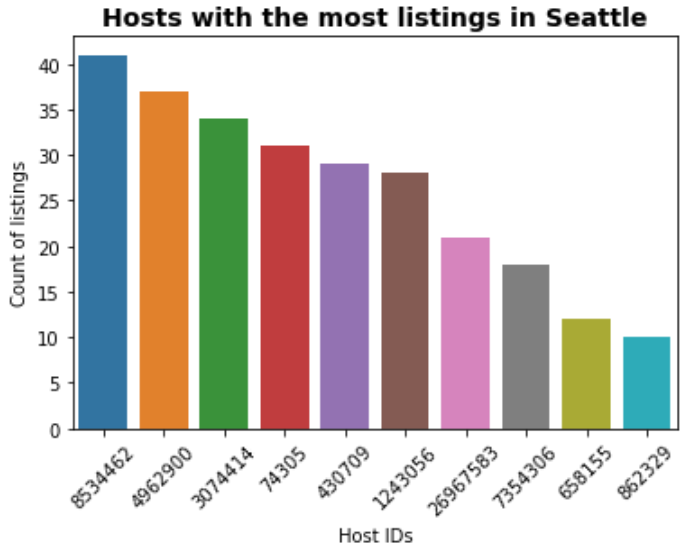


From the plot above, we learn that Downtown and Capital Hill have much more entire home/apt than other neighborhoods do.

2.1.3 Host

In [442…
```
top_hosts('Seattle',sea)
```

```
/Users/kristallqiu/opt/anaconda3/lib/python3.8/site-packages/seaborn/_decorators.py:36:
FutureWarning: Pass the following variables as keyword args: x, y. From version 0.12, th
e only valid positional argument will be `data`, and passing other arguments without an
explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

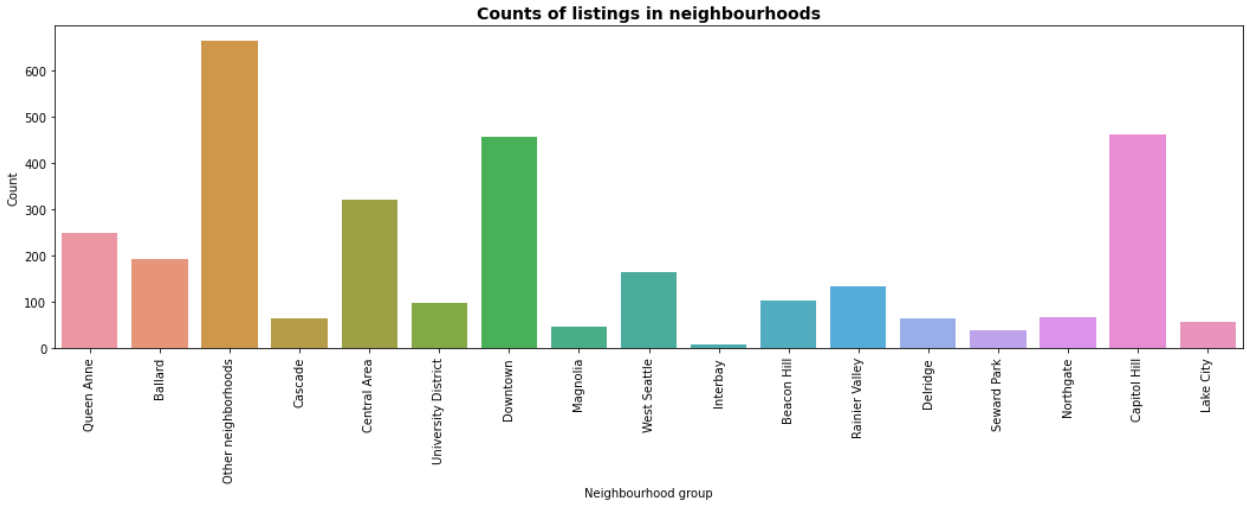


We notice that the number of listing is strictly decreasing among hosts. But there isn't one specific host who has a super big competitive advantage.

2.1.4 Neighbourhood

In [443…
```
count_nei('Seattle',sea)
```

Out[443…
```
(<Figure size 1296x360 with 1 Axes>,
 <AxesSubplot:title={'center':'Counts of listings in neighbourhoods'}, xlabel='Neighbourhood group', ylabel='Count'>)
```

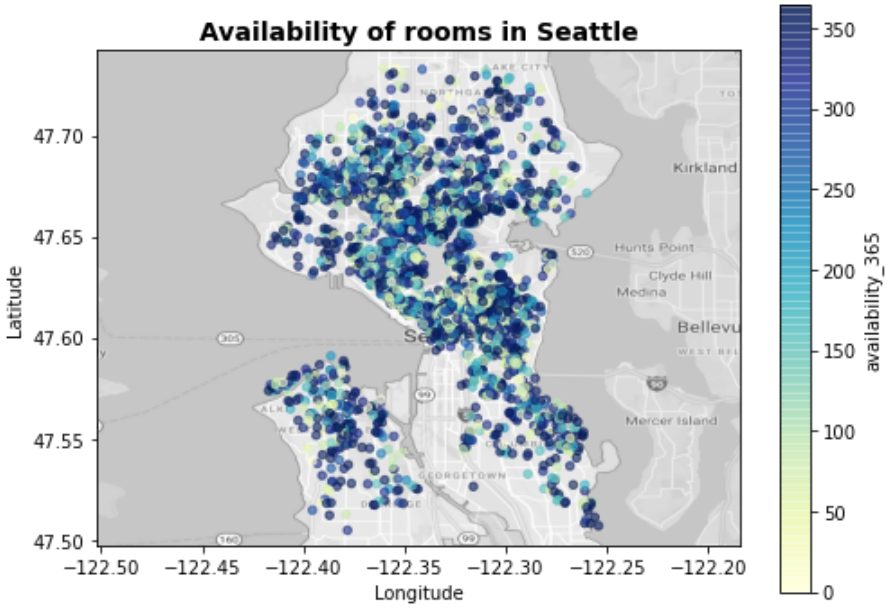


Since there are 87 neighborhoods in Seattle, we pick out major ones and classify all other neighborhoods as "other neighborhoods". From the bar chart above, we learn that most Airbnb houses are located in Downtown, Central Area and Capitol Hill. The Airbnb rooms are very dispersed in other districts. That is very different the scenario of NYC.

2.1.5 Availability

In [444…
```
fig,ax = ava365('Seattle',sea,8,6)
ax.imshow(img_sea,extent=[xl-0.085,xh+0.07,yl-0.008,yh+0.009])
```

Out[444…
```
<matplotlib.image.AxesImage at 0x7f8893439820>
```



In this graph, we plot the availability of rooms in Seattle. We notice that most rooms are available for more than 200 days per year. The situation is kind of similar to Boston, we also guess there is less competition in Boston.

2.2 Data Analysis

2.2.1 Price with room types

In [445…

```
rtype = sea['room_type'].unique()
price_list = []
for n in rtype:
    sub = sea.loc[sea['room_type'] == n]
    sub_price = sub[['price']]
    price_list.append(sub_price)
stats_list = []
for p in price_list:
    i = p.describe(percentiles=[.25, .50, .75])
    i = i.iloc[3:]
    i.reset_index(inplace=True)
    i.rename(columns={'index':'Stats'},inplace=True)
    stats_list.append(i)
# change names of the price column to the area name
for i in range(0,len(rtype)):
    stats_list[i].rename(columns={'price':rtype[i]},inplace=True)
# finilize dataframe for final view
stats_df = stats_list
stats_df = [df.set_index('Stats') for df in stats_df]
stats_df = stats_df[0].join(stats_df[1:])
stats_df
```

Out[445…

Stats	Entire home/apt	Private room	Shared room
min	39.0	25.0	22.0
25%	99.0	55.0	33.0
50%	126.0	68.0	40.0
75%	175.0	85.0	53.0
max	1000.0	280.0	118.0

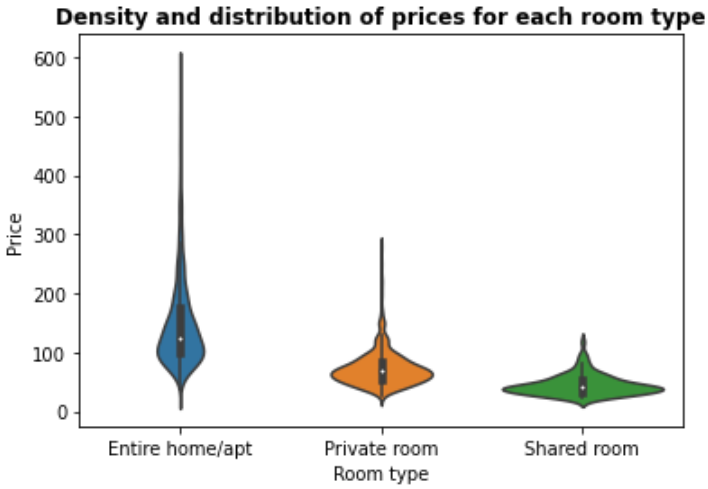
a) Density distribution

In [446…

```
no_extreme = sea[sea.price < 600]
ax = sns.violinplot(data=no_extreme,x='room_type',y='price')
ax.set_xlabel('Room type')
```

```
ax.set_ylabel('Price')
ax.set_title('Density and distribution of prices for each room type',fontweight='bold')
```

Out[446… `Text(0.5, 1.0, 'Density and distribution of prices for each room type')`



This graph is clear to show that hosts charge different prices for different room types. The cheapest room is shared room, and price of the entire home/apt can go beyond 100 dollar.

2.2.2 Price with neighbourhoods

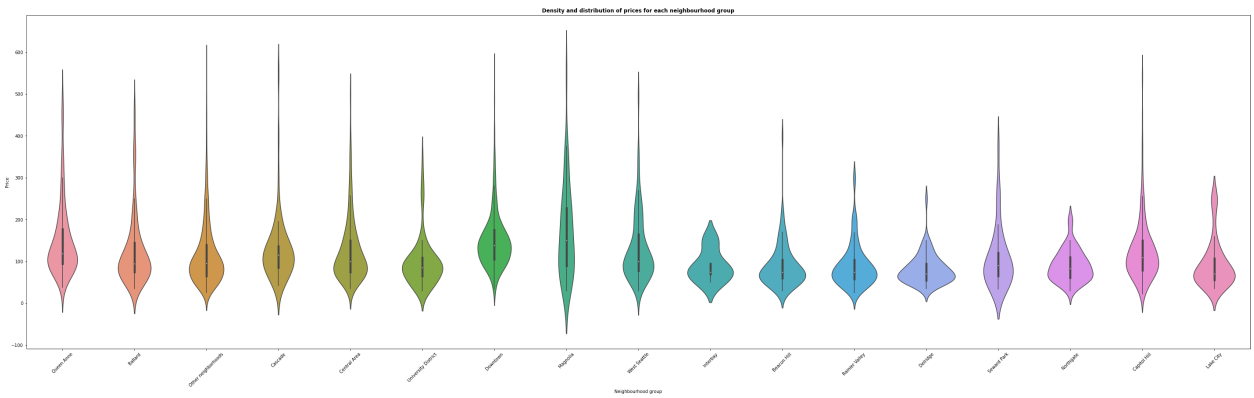
In [447…
```
nei_stats('Seattle',sea)
```

Out[447…

Stats	Queen Anne	Ballard	Other neighborhoods	Cascade	Central Area	University District	Downtown	Magnolia	West Seattle	Interba
min	38.00	35.0	25.0	42.0	35.0	30.0	35.00	30.0	30.0	50
25%	95.00	75.0	65.0	85.0	75.0	65.0	105.25	91.5	77.5	69
50%	120.00	95.0	96.0	115.0	100.0	85.0	139.00	150.0	100.0	75
75%	189.25	145.0	140.0	140.0	150.0	109.0	175.00	228.5	165.0	95
max	975.00	475.0	1000.0	775.0	500.0	350.0	999.00	950.0	495.0	150

a) Density distribution

In [448…
```
fig,ax = plt.subplots(figsize=(50,14))
ax = plot_distribution('Seattle',sea,600)
```



We see the prices vary a lot in some neighborhoods, especially Magnolia. Also, the gap between most expensive one and the cheapest one is much bigger in these districts. We guess there is a very diversed portfolio in these neighborhoods so that we have rooms that meet different people's need.

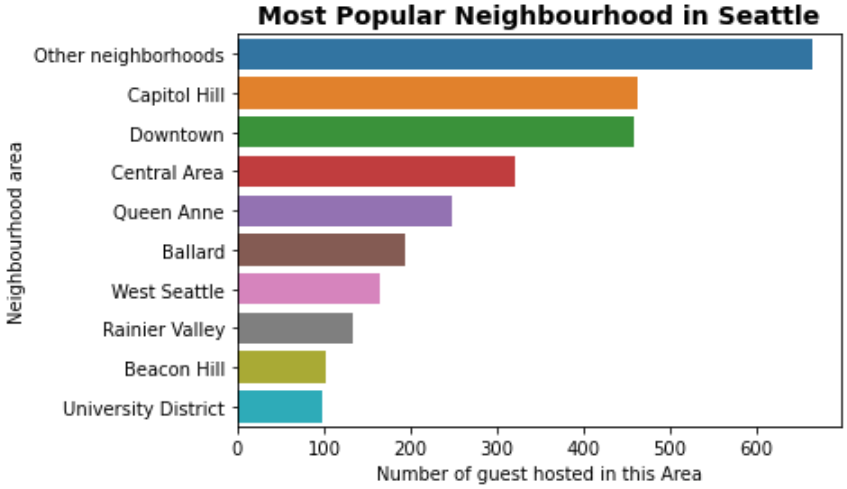
2.2.3 Neighbourhood Exploration

a) Popular Neighbourhood

In [449…
```
top_nei('Seattle',sea)
```

```
/Users/kristallqiu/opt/anaconda3/lib/python3.8/site-packages/seaborn/_decorators.py:36: FutureWarning: Pass the following variables as keyword args: x, y. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

Out[449…
```
(<Figure size 3600x1008 with 1 Axes>,
 <AxesSubplot:title={'center':'Most Popular Neighbourhood in Seattle'}, xlabel='Number of guest hosted in this Area', ylabel='Neighbourhood area'>)
```

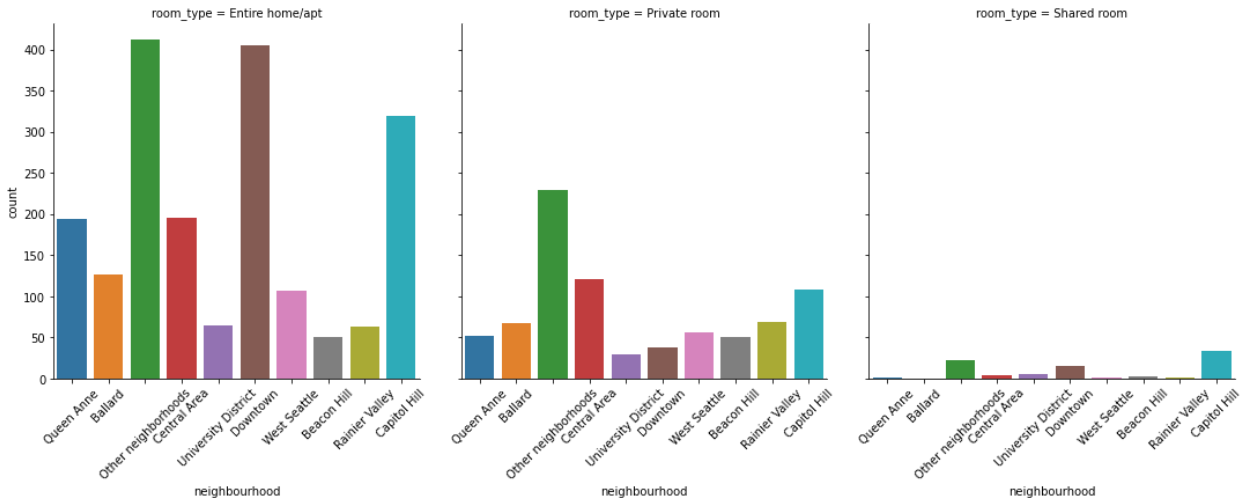


Since there are 87 neighborhoods in Seattle, we pick out major ones and classify all other neighborhoods as "other neighborhoods". We can see that Capitol Hill and Downtown are the most popular neighborhoods in Seattle, with Central Area in the third place.

b) Room type within popular neighbourhoods

In [450…
```
top_nei_room_type('Seattle',sea)
```

Out[450…
```
<seaborn.axisgrid.FacetGrid at 0x7f8894e91ca0>
```



Based on the top ten popular neighborhood we selected before, we picture the room types information in these neighborhoods for readers' reference. Guests can know the distribution of their favourite room type in popular neighborhoods, so that they can make the decisions more easily. We notice that Downtown and Capital Hill have an extremely high number of entire home/apt. Since there are 87 neighborhoods in Seattle, we pick out major ones and classify all other neighborhoods as "other neighborhoods".

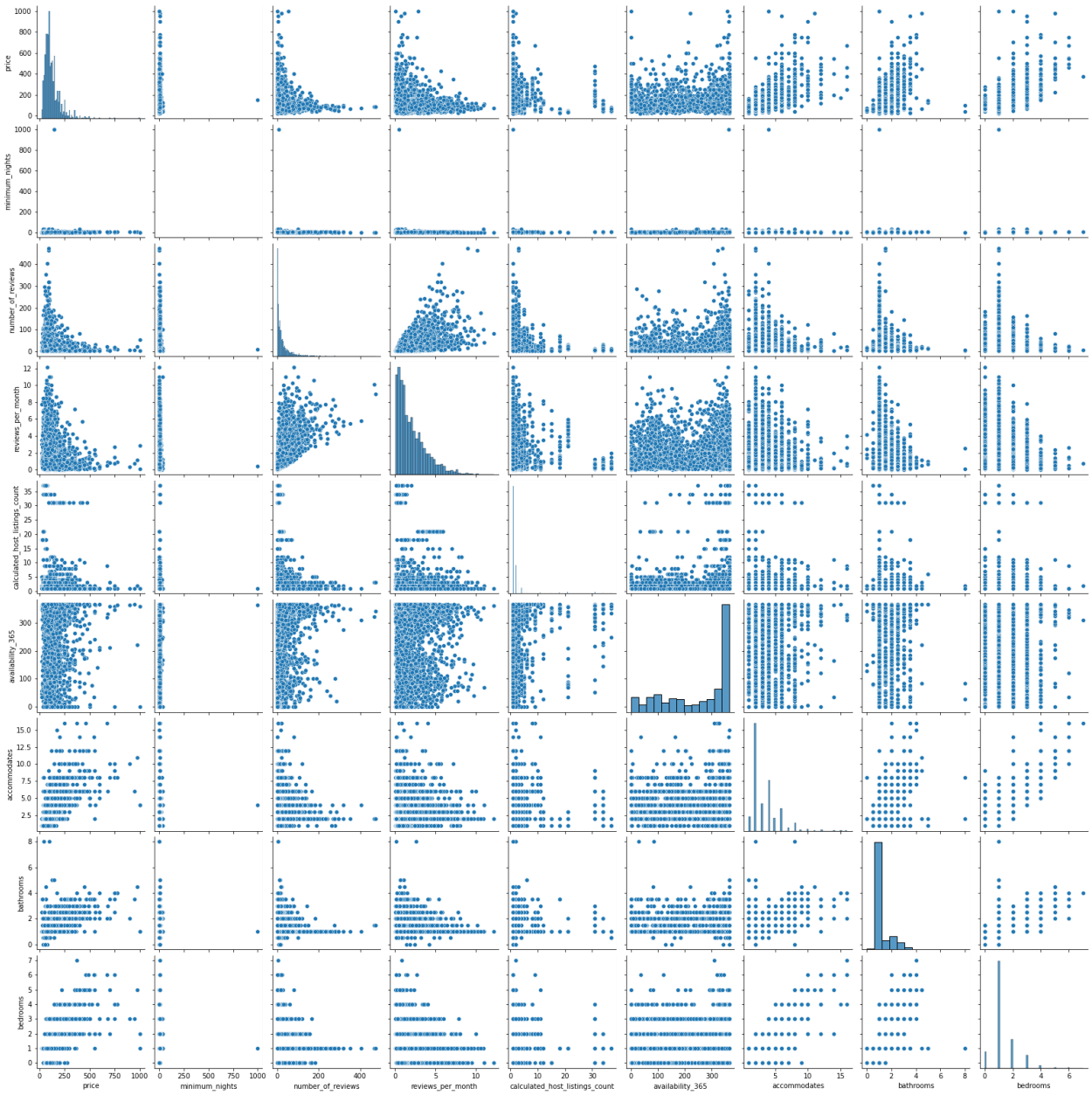
3. Descriptive Data Analysis

3.1 Pairplot of each variable

In [451…
```
vc = list(nyc.columns)
for i in ['id','host_id','neighbourhood_group','latitude', 'longitude']:
    vc.remove(i)
```

```
for j in ['accommodates', 'bathrooms', 'bedrooms']:
    vc.append(j)

pp4 = sea.loc[:,vc]
sns.pairplot(pp4)
```

Out[451… <seaborn.axisgrid.PairGrid at 0x7f88952ae280>



We can see the correltation between each variable. It does not make sense as many of them are categorical data

4. Predictive Data Analysis

In [452…

```
model4 = sea.dropna().loc[:,:].copy()
model4['neighbourhood'] = model4['neighbourhood'].astype("category").cat.codes
model4['room_type'] = model4['room_type'].astype("category").cat.codes
model4['host_response_time'] = model4['host_response_time'].astype("category").cat.codes

model4['host_response_rate'] = model4['host_response_rate'].str.replace('%','').astype(i
model4['host_acceptance_rate'] = model4['host_acceptance_rate'].str.replace('%','').asty
model4['host_response_rate'] = model4['host_response_rate']/100
model4['host_acceptance_rate'] = model4['host_acceptance_rate']/100

tf = ['host_is_superhost','host_has_profile_pic','host_identity_verified',
      'require_guest_profile_picture','require_guest_phone_verification']
for c in tf:
    model4[c] = model4[c].replace('t',1)
```

```
    model4[c] = model4[c].replace('f',0)

cancel = ['flexible','moderate','strict', 'super_strict_30']
for i in range(0,len(cancel)):
    model4['cancellation_policy'] = model4['cancellation_policy'].replace(cancel[i],i)

mean = model4['reviews_per_month'].mean()
model4['reviews_per_month'].fillna(mean, inplace=True)

model4['extra_people'] = model4['extra_people'].str.replace('$','').astype(float)
model4['property_type'] = model4['property_type'].astype("category").cat.codes
model4['bed_type'] = model4['bed_type'].astype("category").cat.codes

model4['log_price'] = np.log(model4.price+1)

model4 = model4.drop(columns=['id' ,'host_id','price','host_since','street']) # delete p

model4.isnull().sum()
```

Out[452…

```
host_response_time                 0
host_response_rate                 0
host_acceptance_rate               0
host_is_superhost                  0
host_listings_count                0
host_total_listings_count          0
host_has_profile_pic               0
host_identity_verified             0
neighbourhood                      0
latitude                           0
longitude                          0
property_type                      0
room_type                          0
accommodates                       0
bathrooms                          0
bedrooms                           0
beds                               0
bed_type                           0
guests_included                    0
extra_people                       0
minimum_nights                     0
maximum_nights                     0
availability_365                   0
number_of_reviews                  0
cancellation_policy                0
require_guest_profile_picture      0
require_guest_phone_verification   0
calculated_host_listings_count     0
reviews_per_month                  0
log_price                          0
dtype: int64
```

Value Reference

In [453…

```
seaVF = {}
sead = ['neighbourhood','room_type','host_response_time',
        'host_is_superhost','cancellation_policy','property_type','bed_type']
for c in sead:
    seaVF = {}
    for i in model4[c].unique():
        indx = model4[model4[c]==i].index.values[0]
        seaVF[i] = sea[c][indx]
    print(c.capitalize(),'\n',dict(sorted(seaVF.items())))
```

```
Neighbourhood
 {0: 'Ballard', 1: 'Beacon Hill', 2: 'Capitol Hill', 3: 'Cascade', 4: 'Central Area', 5:
'Delridge', 6: 'Downtown', 7: 'Interbay', 8: 'Lake City', 9: 'Magnolia', 10: 'Northgat
e', 11: 'Other neighborhoods', 12: 'Queen Anne', 13: 'Rainier Valley', 14: 'Seward Par
k', 15: 'University District', 16: 'West Seattle'}
Room_type
 {0: 'Entire home/apt', 1: 'Private room', 2: 'Shared room'}
Host_response_time
 {0: 'a few days or more', 1: 'within a day', 2: 'within a few hours', 3: 'within an hou
r'}
Host_is_superhost
 {0: 'f', 1: 't'}
Cancellation policy
```

```
 {0: 'flexible', 1: 'moderate', 2: 'strict'}
Property_type
 {0: 'Apartment', 1: 'Bed & Breakfast', 2: 'Boat', 3: 'Bungalow', 4: 'Cabin', 5: 'Campe
r/RV', 6: 'Chalet', 7: 'Condominium', 8: 'Dorm', 9: 'House', 10: 'Loft', 11: 'Other', 1
2: 'Tent', 13: 'Townhouse', 14: 'Treehouse', 15: 'Yurt'}
Bed_type
 {0: 'Airbed', 1: 'Couch', 2: 'Futon', 3: 'Pull-out Sofa', 4: 'Real Bed'}
```

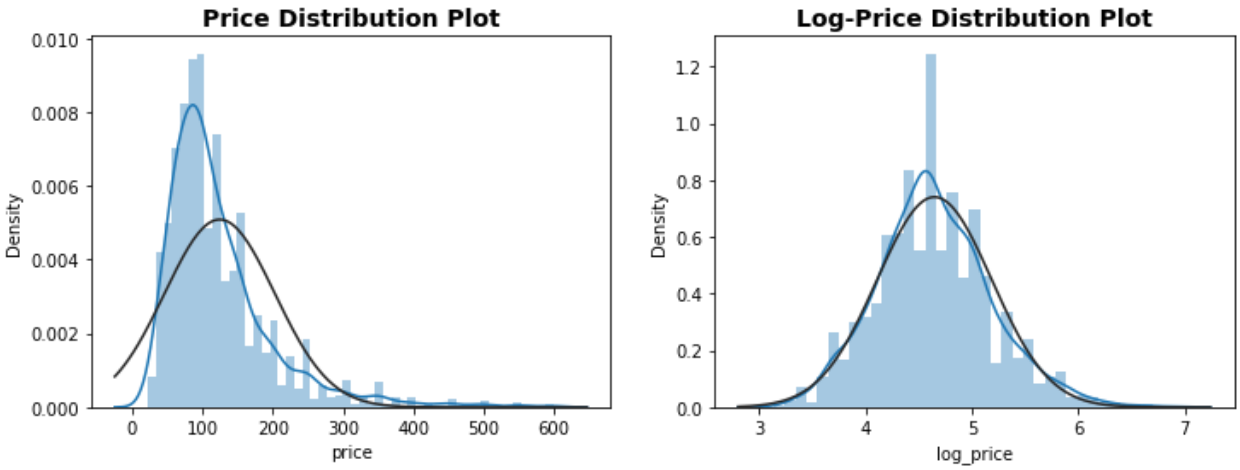
4. Predictive Data Analysis

4.1 Probability distribution

In [454…
```
fig,ax = plt.subplots(1,2,figsize=(12,4))
sns.distplot(sea.loc[sea['price']<=600]['price'],fit=norm, ax=ax[0]) # drop extreme valu
ax[0].set_title("Price Distribution Plot",size=14, weight='bold')
sns.distplot(model4['log_price'],fit=norm,ax=ax[1])
ax[1].set_title("Log-Price Distribution Plot",size=14, weight='bold')
```

```
/Users/kristallqiu/opt/anaconda3/lib/python3.8/site-packages/seaborn/distributions.py:25
51: FutureWarning: `distplot` is a deprecated function and will be removed in a future v
ersion. Please adapt your code to use either `displot` (a figure-level function with sim
ilar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
/Users/kristallqiu/opt/anaconda3/lib/python3.8/site-packages/seaborn/distributions.py:25
51: FutureWarning: `distplot` is a deprecated function and will be removed in a future v
ersion. Please adapt your code to use either `displot` (a figure-level function with sim
ilar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

Out[454… `Text(0.5, 1.0, 'Log-Price Distribution Plot')`

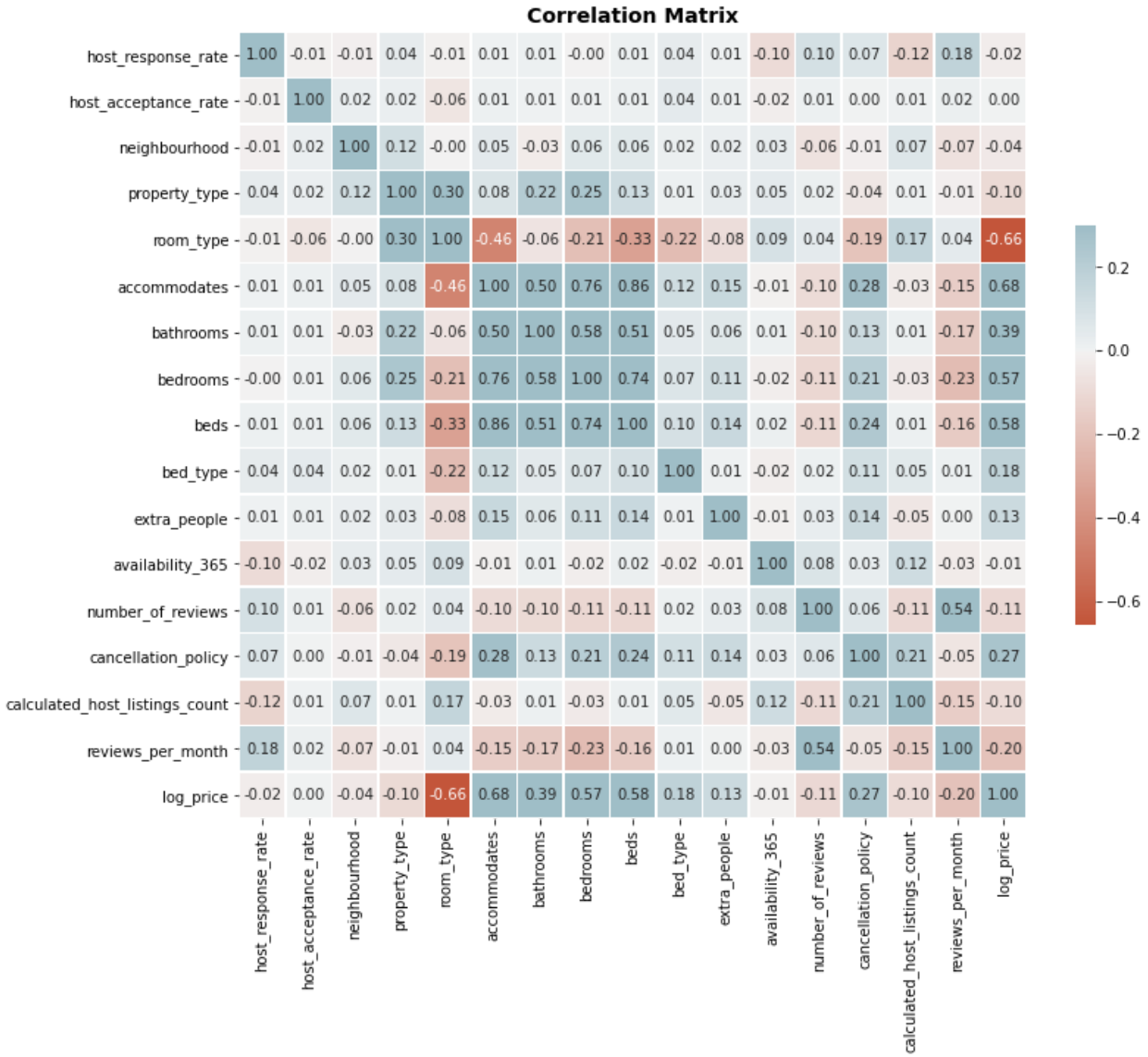


It is also true that the log_price is approximitely normol distributed. However, this time it is a little bit right skewed.

4.2 Correlation

In [455…
```
keep_col = ['host_response_rate', 'host_acceptance_rate','neighbourhood',
        'property_type', 'room_type', 'accommodates',
       'bathrooms', 'bedrooms', 'beds', 'bed_type', 'extra_people',
        'availability_365', 'number_of_reviews', 'cancellation_policy',
        'calculated_host_listings_count', 'reviews_per_month', 'log_price']
col_df4 = model4.loc[:,keep_col]
plt.figure(figsize=(12,10))
palette = sns.diverging_palette(20, 220, n=256)
corr=col_df4.corr(method='pearson')
sns.heatmap(corr, annot=True, fmt=".2f", cmap=palette, vmax=.3, center=0,
            square=True, linewidths=.5, cbar_kws={"shrink": .5}).set(ylim=(17, 0))
plt.title("Correlation Matrix",size=14, weight='bold')
```

Out[455… `Text(0.5, 1.0, 'Correlation Matrix')`



In this correlation matrix we calculate and display the correlation between different variables. The hosts can easily find the relationship between variables and make the optimized investment decisions.

4.3 Regression

In [456…
```
model4['price'] = sea.dropna().loc[:,['price']]
```

4.3.1 Linear Regression

In [457…
```
import statsmodels.formula.api as smf
```

a) Price - all variables

In [458…
```
reg_price = smf.ols('price ~ host_response_rate + host_acceptance_rate + neighbourhood +
                    ,data=model4).fit()
print(reg_price.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.581
Model:                            OLS   Adj. R-squared:                  0.578
Method:                 Least Squares   F-statistic:                     229.8
Date:                Wed, 04 Nov 2020   Prob (F-statistic):               0.00
Time:                        11:54:39   Log-Likelihood:                -14384.
No. Observations:                2671   AIC:                         2.880e+04
Df Residuals:                    2654   BIC:                         2.890e+04
Df Model:                          16
Covariance Type:            nonrobust
==============================================================================
==========
```

```
                                   coef    std err          t      P>|t|      [0.025
0.975]
------------------------------------------------------------------------------------
----------
Intercept                       107.6454     54.808      1.964      0.050       0.175
215.116
host_response_rate              -15.2809      9.762     -1.565      0.118     -34.423
3.861
host_acceptance_rate            -55.5318     53.185     -1.044      0.297    -159.820
48.757
neighbourhood                    -0.8526      0.219     -3.891      0.000      -1.282
-0.423
property_type                    -0.8905      0.253     -3.520      0.000      -1.386
-0.394
room_type                       -39.5868      2.436    -16.253      0.000     -44.363
-34.811
accommodates                     7.4357      1.203      6.181      0.000       5.077
9.795
bathrooms                       27.9597      2.199     12.716      0.000      23.648
32.271
bedrooms                        27.2998      2.129     12.823      0.000      23.125
31.474
beds                             2.6378      1.834      1.438      0.151      -0.959
6.235
bed_type                         0.7454      2.443      0.305      0.760      -4.044
5.535
extra_people                     0.2017      0.060      3.348      0.001       0.084
0.320
availability_365                 0.0141      0.009      1.628      0.104      -0.003
0.031
number_of_reviews               -0.0322      0.030     -1.091      0.275      -0.090
0.026
cancellation_policy              4.4186      1.446      3.055      0.002       1.583
7.255
calculated_host_listings_count   0.0661      0.174      0.379      0.705      -0.276
0.408
reviews_per_month               -1.8424      0.683     -2.698      0.007      -3.181
-0.504
==============================================================================
Omnibus:                     2398.080   Durbin-Watson:                   1.856
Prob(Omnibus):                  0.000   Jarque-Bera (JB):           219825.723
Skew:                           3.847   Prob(JB):                         0.00
Kurtosis:                      46.772   Cond. No.                     2.08e+04
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specifi
ed.
[2] The condition number is large, 2.08e+04. This might indicate that there are
strong multicollinearity or other numerical problems.
```

Here we run an ordinary least square regression for price on several factors that we think may influence the price of Airbnb. We have H0: beta = 0 against H1: beta != 0 for every beta in this regression model. According to the output table, the P-value of host_response_rate, host_response_rate, beds, beds_type, avaiability_365, number_of_reviews and calculated_host_listings_count are bigger than 5%, which means that we don't reject H0 against H1. There is no evidence that the effect of host_response_rate, host_response_rate, beds, beds_type, avaiability_365, number_of_reviews and calculated_host_listings_countis significant to the price of Airbnb house and we should drop them.

a) Price - drop variables

In [459…

```
reg_price = smf.ols('price ~ neighbourhood + property_type + room_type + accommodates +
                    ,data=model4).fit()
print(reg_price.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.579
Model:                            OLS   Adj. R-squared:                  0.578
Method:                 Least Squares   F-statistic:                     406.8
Date:                Wed, 04 Nov 2020   Prob (F-statistic):               0.00
Time:                        11:54:39   Log-Likelihood:                -14389.
No. Observations:                2671   AIC:                         2.880e+04
Df Residuals:                    2661   BIC:                         2.886e+04
Df Model:                           9
Covariance Type:            nonrobust
```

```
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept      44.0854      3.980     11.076      0.000      36.280      51.890
neighbourhood  -0.8220      0.218     -3.765      0.000      -1.250      -0.394
property_type  -0.9107      0.252     -3.619      0.000      -1.404      -0.417
room_type     -38.7602      2.315    -16.742      0.000     -43.300     -34.220
accommodates    8.7267      0.920      9.482      0.000       6.922      10.531
bathrooms      28.2083      2.192     12.869      0.000      23.910      32.506
bedrooms       27.5542      2.074     13.288      0.000      23.488      31.620
extra_people    0.2003      0.060      3.334      0.001       0.082       0.318
cancellation_policy     4.3426      1.378      3.152      0.002       1.641       7.044
reviews_per_month      -2.4800      0.569     -4.361      0.000      -3.595      -1.365
==============================================================================
Omnibus:                     2378.342   Durbin-Watson:                   1.853
Prob(Omnibus):                  0.000   Jarque-Bera (JB):           210103.216
Skew:                           3.807   Prob(JB):                         0.00
Kurtosis:                      45.777   Cond. No.                         89.0
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specifi
ed.
```

After dropping those insignificant variables, we run the linear regression again. This time we find all remained variables significant at 5% level, as we expected.

And, we can get price = 44.0854 - neighbour *0.8220* - *property_type* 0.9107 - room_type *38.7602* + *accommodates* 8.7267 + bathrooms *28.2083* + *bedrooms* 27.5542 + extra_people *0.20034* + *cancellation_policy* 4.3426 - reviews_per_month* 2.4800

And from this, we can find that bedrooms make the largest contribution to a relative higher price.

b) Log price - all variables

In [460…
```
reg_price = smf.ols('log_price ~ host_response_rate + host_acceptance_rate + neighbourhc
                    ,data=model4).fit()
print(reg_price.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:              log_price   R-squared:                       0.674
Model:                            OLS   Adj. R-squared:                  0.672
Method:                 Least Squares   F-statistic:                     342.3
Date:                Wed, 04 Nov 2020   Prob (F-statistic):               0.00
Time:                        11:54:39   Log-Likelihood:                -643.73
No. Observations:                2671   AIC:                             1321.
Df Residuals:                    2654   BIC:                             1422.
Df Model:                          16
Covariance Type:            nonrobust
==============================================================================
==========
                                 coef    std err          t      P>|t|      [0.025
0.975]
------------------------------------------------------------------------------
----------
Intercept                     5.0146      0.320     15.686      0.000       4.388
5.641
host_response_rate           -0.0929      0.057     -1.632      0.103      -0.205
0.019
host_acceptance_rate         -0.7341      0.310     -2.366      0.018      -1.342
-0.126
neighbourhood                -0.0068      0.001     -5.292      0.000      -0.009
-0.004
property_type                -0.0066      0.001     -4.470      0.000      -0.009
-0.004
room_type                    -0.4604      0.014    -32.405      0.000      -0.488
-0.433
accommodates                  0.0604      0.007      8.612      0.000       0.047
0.074
bathrooms                     0.1031      0.013      8.036      0.000       0.078
0.128
bedrooms                      0.1489      0.012     11.990      0.000       0.125
0.173
```

```
beds                              -0.0095      0.011     -0.888      0.374      -0.030
0.011
bed_type                           0.0417      0.014      2.926      0.003       0.014
0.070
extra_people                       0.0008      0.000      2.357      0.019       0.000
0.002
availability_365                   0.0002   5.06e-05      3.893      0.000    9.78e-05
0.000
number_of_reviews               1.929e-05      0.000      0.112      0.911      -0.000
0.000
cancellation_policy                0.0304      0.008      3.608      0.000       0.014
0.047
calculated_host_listings_count    -0.0023      0.001     -2.244      0.025      -0.004
-0.000
reviews_per_month                 -0.0228      0.004     -5.735      0.000      -0.031
-0.015
==============================================================================
Omnibus:                      107.615   Durbin-Watson:                   1.688
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              191.010
Skew:                           0.320   Prob(JB):                     3.33e-42
Kurtosis:                       4.143   Cond. No.                     2.08e+04
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specifi
ed.
[2] The condition number is large, 2.08e+04. This might indicate that there are
strong multicollinearity or other numerical problems.
```

Here we run an ordinary least square regression for log_price on several factors that we think may influence the price of Airbnb. We have H0: beta = 0 against H1: beta != 0 for every beta in this regression model. According to the output table, the P-value of host_response_rate,beds, and number_of _reviews are bigger than 5%, which means that we don't reject H0 against H1. There is no evidence that the effect of rhost_response_rate,beds, and number_of _reviews is significant to the price of Airbnb house and we should drop them.

b) Log price - drop variables

In [461…

```
reg_price = smf.ols('price ~ host_acceptance_rate + neighbourhood + property_type + roor
                    ,data=model4).fit()
print(reg_price.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.580
Model:                            OLS   Adj. R-squared:                  0.578
Method:                 Least Squares   F-statistic:                     282.1
Date:                Wed, 04 Nov 2020   Prob (F-statistic):               0.00
Time:                        11:54:39   Log-Likelihood:                -14387.
No. Observations:                2671   AIC:                         2.880e+04
Df Residuals:                    2657   BIC:                         2.888e+04
Df Model:                          13
Covariance Type:            nonrobust
==============================================================================
==========
                                 coef    std err          t      P>|t|      [0.025
0.975]
------------------------------------------------------------------------------
----------
Intercept                     92.5261     53.995      1.714      0.087     -13.351
198.403
host_acceptance_rate         -54.2653     53.206     -1.020      0.308    -158.594
50.063
neighbourhood                 -0.8423      0.219     -3.845      0.000      -1.272
-0.413
property_type                 -0.9071      0.253     -3.588      0.000      -1.403
-0.411
room_type                    -39.5514      2.434    -16.248      0.000     -44.325
-34.778
accommodates                  8.6001      0.923      9.321      0.000       6.791
10.409
bathrooms                    28.1637      2.192     12.846      0.000      23.865
32.463
bedrooms                     27.8658      2.083     13.381      0.000      23.782
31.949
bed_type                      0.5936      2.442      0.243      0.808      -4.196
5.383
```

```
extra_people                        0.2054      0.060      3.410      0.001       0.087
0.323
availability_365                    0.0148      0.009      1.722      0.085      -0.002
0.032
cancellation_policy                 3.9372      1.428      2.757      0.006       1.137
6.737
calculated_host_listings_count      0.1262      0.173      0.731      0.465      -0.212
0.465
reviews_per_month                  -2.3736      0.577     -4.113      0.000      -3.505
-1.242
==============================================================================
Omnibus:                     2392.638   Durbin-Watson:                   1.852
Prob(Omnibus):                  0.000   Jarque-Bera (JB):           215835.217
Skew:                           3.839   Prob(JB):                         0.00
Kurtosis:                      46.364   Cond. No.                      2.06e+04
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specifi
ed.
[2] The condition number is large, 2.06e+04. This might indicate that there are
strong multicollinearity or other numerical problems.
```

After dropping those insignificant variables, we run the linear regression again. This time we find all remained variables significant at 5% level, as we expected.

And, we can get log_price = 4.9270 - 0.7283 *host_acceptance_rate* - *0.0068* neighbourhood - property_type *0.0067* - *room_type* 0.4613 + accommodates *0.0564* + *bathrooms* 0.1016 + bedrooms *0.1469* + *bed_type* 0.0410 + extra_people *0.0008* + *availability_365* 0.0002 + cancellation_policy *0.0294* - *calculated_host_listings_count* 0.0022 - reviews_per_month* 0.0235

We find that different from price, bedrooms has the greatest relevance of the log_price.

4.3.2 ML

From the linear regression we found that log_price is a better dependent variable to predict.

In [462…
```
from sklearn.model_selection import train_test_split
```

In [463…
```
X_train4, X_test4, y_train4, y_test4 = train_test_split(model4[['room_type']].values, mo
                                                        test_size=0.25, random_state=0)
```

a) K-Nearest Neighbors

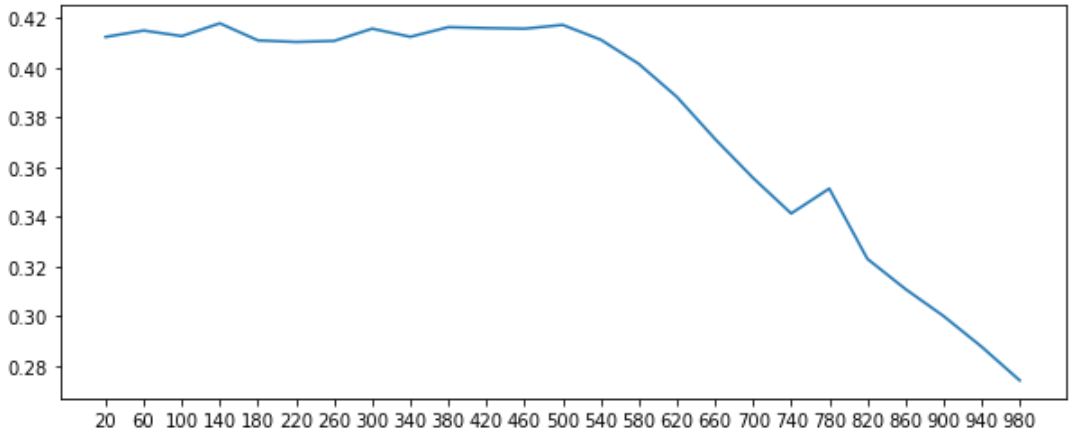
In [464…
```
from sklearn.neighbors import KNeighborsRegressor as knn
from sklearn.model_selection import cross_val_score
```

In [465…
```
scores = pd.Series()
for i in range(20,1000,40):
    scores[str(i)] = cross_val_score(knn(n_neighbors=i),
                     X_train4, y_train4,cv=5).mean()
indx = scores.idxmax()
```

```
<ipython-input-465-c488bb7d7dc7>:1: DeprecationWarning: The default dtype for empty Seri
es will be 'object' instead of 'float64' in a future version. Specify a dtype explicitly
to silence this warning.
  scores = pd.Series()
```

In [466…
```
fig,ax = plt.subplots(figsize=(10,4))
plt.plot(scores.index,scores.values)
```

Out[466…
```
[<matplotlib.lines.Line2D at 0x7f88897de1f0>]
```



In [467…
```
skl_knn = knn(n_neighbors=int(indx)).fit(X_train4, y_train4)
knn_score4 = skl_knn.score(X_test4, y_test4)
print(knn_score4)
```

```
0.41371362563147795
```

b) Random Forest

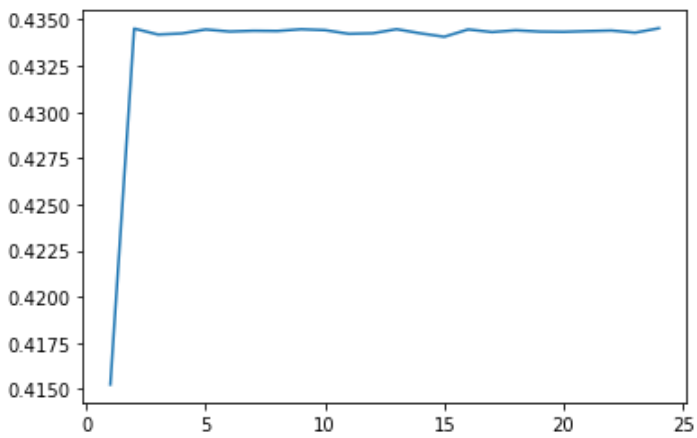
In [468…
```
from sklearn.ensemble import RandomForestRegressor as rf
```

In [469…
```
cross_val_score(rf(n_estimators=100,max_depth=3),X_train4, y_train4.ravel(),cv=5).mean()
```

Out[469…
```
0.4343007642316056
```

In [470…
```
cv_scores = pd.DataFrame()
for i in range(1,25):
    cv_scores.loc[i,'rf'] = cross_val_score(rf(n_estimators=100,max_depth=i),X_train4, y
```

In [471…
```
ax = cv_scores.plot()
ax.get_legend().remove()
```



In [472…
```
indx = scores.idxmax()
skl_rf = rf(n_estimators=100,max_depth=int(indx)).fit(X_train4, y_train4.ravel())
skl_rf.predict(X_test4)
rf_score4 = skl_rf.score(X_test4,y_test4)
print(rf_score4)
```

```
0.41838139640368466
```

In [473…
```
score_table = pd.DataFrame({'K Nearest Neighbors':[knn_score4],'Random Forest':[rf_score
score_table = score_table.T
score_table.columns = ['Score']
score_table
```

Out[473…

	Score
K Nearest Neighbors	0.413714

	Score
Random Forest	0.418381

As we can see from above table, for log_price, we should choose Random Forest as the score of this model is the highest, compared to K Nearest Neighbors.

Rank score for log_price : Random Forest > KNN

Possiable reason for a relative low score for both is that log_price should be dependent on some features not containing in the dataFrame as well, such as environment, surroundings or quality of the room.

5. Cross-city comparison

5.1 Data Cleaning & Filtering

In [474…
```
nyc.columns
```

Out[474…
```
Index(['id', 'host_id', 'neighbourhood_group', 'neighbourhood', 'latitude',
       'longitude', 'room_type', 'price', 'minimum_nights',
       'number_of_reviews', 'reviews_per_month',
       'calculated_host_listings_count', 'availability_365'],
      dtype='object')
```

NYC Data

'neighbourhood_group'

In [475…
```
nyc1 = nyc.copy()
nyc1 = nyc1.loc[:,['id', 'neighbourhood', 'room_type', 'price', 'minimum_nights',
       'reviews_per_month','calculated_host_listings_count', 'availability_365']]
nyc1['city'] = np.array(['New York']*len(nyc))
```

Boston Data

In [476…
```
'neighbourhood_group' in bos.columns
```

Out[476…
```
False
```

In [477…
```
bos1 = bos.copy()
bos1 = bos1.loc[:,['id', 'neighbourhood', 'room_type', 'price', 'minimum_nights',
       'reviews_per_month','calculated_host_listings_count', 'availability_365']]
bos1['city'] = np.array(['Boston']*len(bos))
```

San Francisco Data

'neighbourhood_group'

In [478…
```
sf1 = sf.copy()
sf1 = sf1.loc[:,['id', 'neighbourhood', 'room_type', 'price', 'minimum_nights',
       'reviews_per_month','calculated_host_listings_count', 'availability_365']]
sf1['city'] = np.array(['San Francisco']*len(sf))
```

Seattle Data

'neighbourhood_group'

In [479…
```
sea1 = sea.copy()
sea1 = sea1.loc[:,['id','neighbourhood', 'room_type', 'price', 'minimum_nights',
       'reviews_per_month','calculated_host_listings_count', 'availability_365']]
sea1['city'] = np.array(['Seattle']*len(sea))
```

Merging Data

In [480…
```
merged = pd.concat([nyc1,bos1,sf1,sea1],sort=False)
```

In [481…
```
merged
```

Out[481…

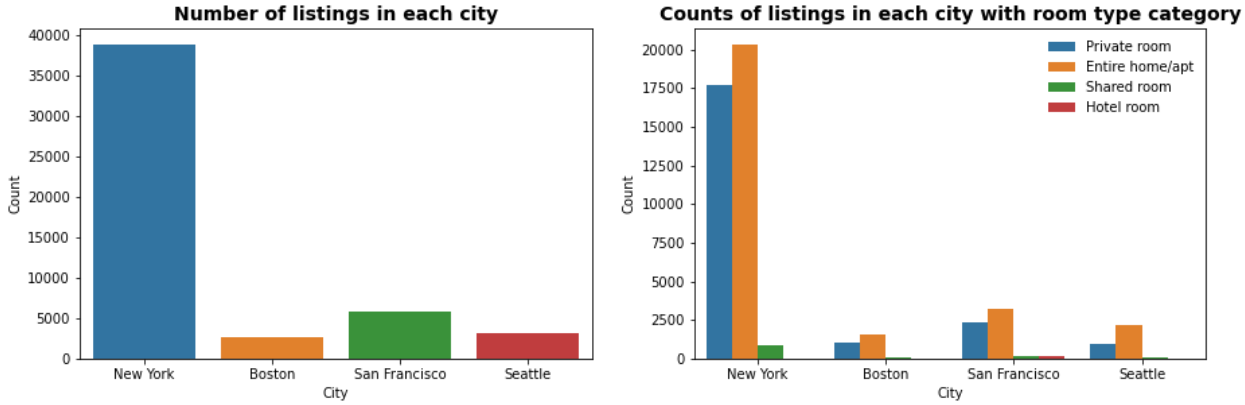
	id	neighbourhood	room_type	price	minimum_nights	reviews_per_month	calculated_host_lis
0	2539	Kensington	Private room	149.0	1	0.21	
1	2595	Midtown	Entire home/apt	225.0	1	0.38	
3	3831	Clinton Hill	Entire home/apt	89.0	1	4.64	
4	5022	East Harlem	Entire home/apt	80.0	10	0.10	
5	5099	Murray Hill	Entire home/apt	200.0	3	0.59	
...	...	...	...	...	...	...	...
3810	262764	Other neighborhoods	Entire home/apt	154.0	2	1.56	
3811	8578490	Other neighborhoods	Entire home/apt	65.0	1	0.63	
3812	3383329	Other neighborhoods	Entire home/apt	95.0	3	4.01	
3813	8101950	Other neighborhoods	Entire home/apt	359.0	3	0.30	
3814	8902327	Capitol Hill	Entire home/apt	79.0	2	2.00	

50428 rows × 9 columns

5.2 Listings comparison

In [482…
```
figure,ax = plt.subplots(1,2,figsize=(15,4.5))
sns.countplot(x='city',data=merged,ax=ax[0])
ax[0].set_xlabel('City')
ax[0].set_ylabel('Count')
ax[0].set_title('Number of listings in each city',size=14,fontweight='bold')
sns.countplot(data=merged,x='city',hue='room_type',palette=current_palette,ax=ax[1])
ax[1].set_title('Counts of listings in each city with room type category',fontsize=14,fc
ax[1].set_xlabel('City')
ax[1].set_ylabel('Count')
ax[1].legend(frameon=False)
```

Out[482…
```
<matplotlib.legend.Legend at 0x7f888637c4c0>
```



From the bar chart, we observe that there is almost 40000 listings in NYC, which is almost ten times as high as in other cities.

5.3 Density and distribution of prices comparison

In [483…

```
city = merged['city'].unique()
price_list = []
for c in city:
    sub = merged.loc[merged['city'] == c]
    sub_price = sub[['price']]
    price_list.append(sub_price)
stats = []
for p in price_list:
    i = p.describe(percentiles=[.25, .50, .75])
    i = i.iloc[3:]
    i.reset_index(inplace=True)
    i.rename(columns={'index':'Stats'},inplace=True)
    stats.append(i)
# change names of the price column to the area name
for i in range(0,len(city)):
    stats[i].rename(columns={'price':city[i]},inplace=True)

# finilize dataframe for final view
stats_df = stats
stats_df = [df.set_index('Stats') for df in stats_df]
stats_df = stats_df[0].join(stats_df[1:])
stats_df
```

Out[483…

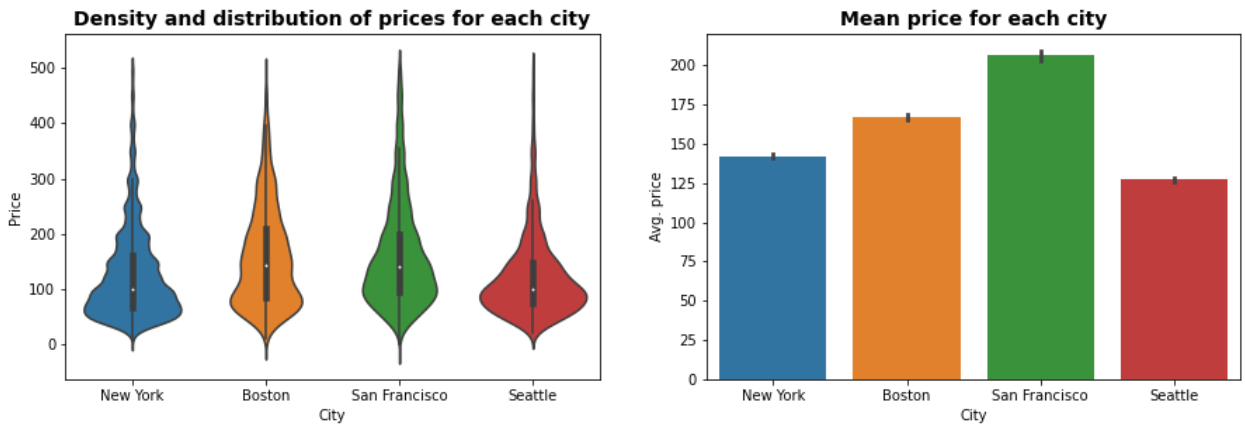
Stats	New York	Boston	San Francisco	Seattle
min	10.0	11.0	0.0	22.0
25%	69.0	85.0	99.0	75.0
50%	101.0	147.0	147.0	100.0
75%	170.0	219.0	230.0	150.0
max	10000.0	1300.0	8000.0	1000.0

In [484…

```
no_extreme = merged[merged.price < 500]
figure,ax = plt.subplots(1,2,figsize=(15,4.5))
sns.violinplot(data=no_extreme,x='city',y='price',ax=ax[0])
ax[0].set_xlabel('City')
ax[0].set_ylabel('Price')
ax[0].set_title('Density and distribution of prices for each city',size=14, fontweight=
sns.barplot(x='city', y='price', data=merged, ci=68,ax=ax[1])
ax[1].set_xlabel('City')
ax[1].set_ylabel('Avg. price')
ax[1].set_title('Mean price for each city',size=14, fontweight='bold')
```

Out[484…

```
Text(0.5, 1.0, 'Mean price for each city')
```



In [485…

```
mean = pd.DataFrame()
mean.loc['avg_price','New York'] = nyc['price'].mean()
mean.loc['avg_availability_365','New York'] = nyc['availability_365'].mean()
mean.loc['avg_price','San Francisco'] = sf['price'].mean()
```

```
mean.loc['avg_availability_365','San Francisco'] = sf['availability_365'].mean()
mean.loc['avg_price','Boston'] = bos['price'].mean()
mean.loc['avg_availability_365','Boston'] = bos['availability_365'].mean()
mean.loc['avg_price','Seattle'] = sea['price'].mean()
mean.loc['avg_availability_365','Seattle'] = sea['availability_365'].mean()
mean.loc[['avg_price'],:]
```

Out[485…

	New York	San Francisco	Boston	Seattle
avg_price	142.354595	206.403717	167.139992	127.098402

Surprisingly, San Francisco has the highest mean price, while actually most houses in NYC are of less than 100 dollars, which is the lowest among four cities.

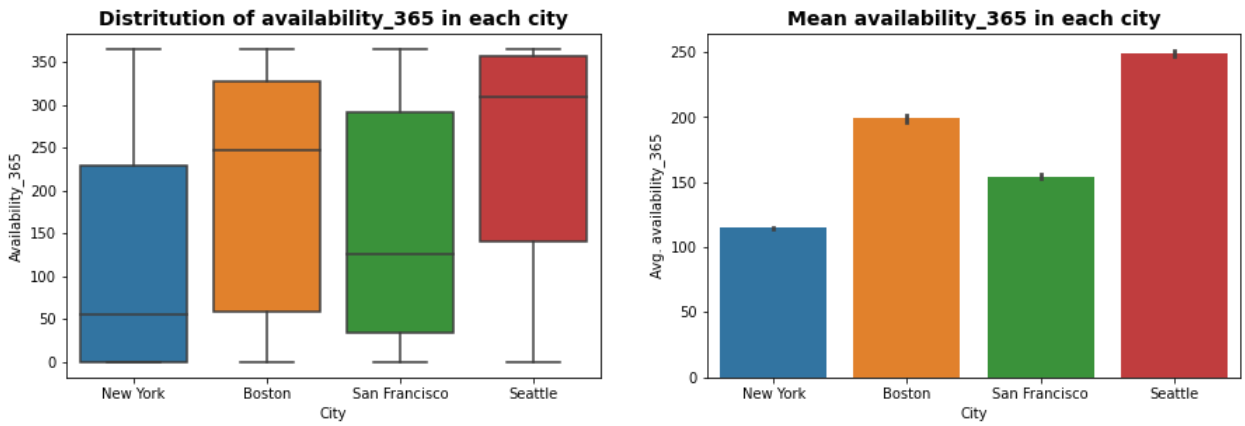
5.4 Availability comparison

In [486…

```
figure,ax = plt.subplots(1,2,figsize=(15,4.5))
sns.boxplot(x='city',y='availability_365',data=merged,ax=ax[0])
ax[0].set_xlabel('City')
ax[0].set_ylabel('Availability_365')
ax[0].set_title('Distritution of availability_365 in each city',size=14,fontweight='bold
sns.barplot(x='city', y='availability_365', data=merged, ci=68,ax=ax[1])
ax[1].set_xlabel('City')
ax[1].set_ylabel('Avg. availability_365')
ax[1].set_title('Mean availability_365 in each city',size=14,fontweight='bold')
mean.loc[['avg_availability_365'],:]
```

Out[486…

	New York	San Francisco	Boston	Seattle
avg_availability_365	114.878222	154.489072	198.947551	249.193356



NYC has the lowest availability in a year, while average availability in Seattle is almost 250 days. We guess that the NYC market is super competitive, so many hosts will take a different strategy in seasons when there are few tourists to reduce the cost.

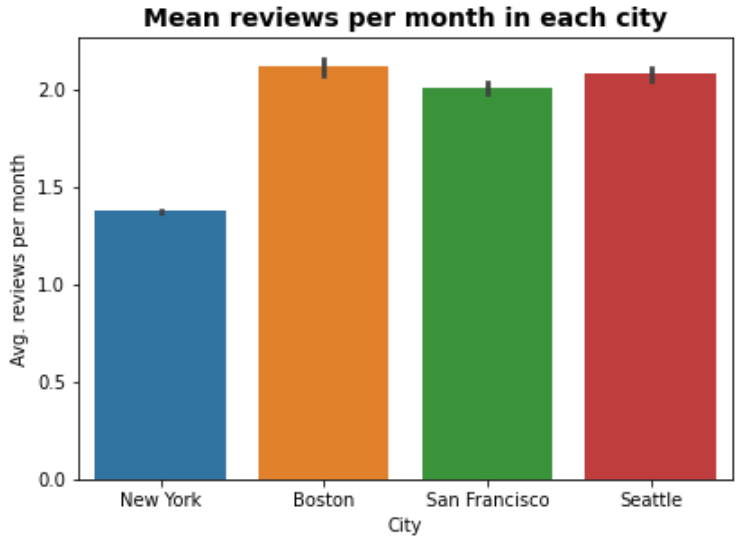
5.5 Reviews comparison

In [487…

```
fig,ax=plt.subplots(figsize=(6.5,4.5))
sns.barplot(x='city', y='reviews_per_month', data=merged, ci=68,ax=ax)
ax.set_xlabel('City')
ax.set_ylabel('Avg. reviews per month')
ax.set_title('Mean reviews per month in each city',size=14,fontweight='bold')
```

Out[487…

```
Text(0.5, 1.0, 'Mean reviews per month in each city')
```



From this bar chart, we know that Boston, San Francisco and Seattle almost have the same mean reviews per month. However, this statistics is much lower in NYC. We wonder if NYC hosts will have some effective tools to facilitate the communication between them and the guests.

5.6 Overall Conclusion for Machine Learning

In [488…

```
scoreTable = {'K Nearest Neighbors': [0.413131,0.522524,0.273233,0.413714],
'Random Forest': [0.413631,0.530373,0.283049,0.418031]}
scoreTable = pd.DataFrame(scoreTable)
scoreTable["Prediction"] = list(["NYC","BOS","SF","SEA"])
scoreTable = scoreTable.set_index("Prediction")
scoreTable = scoreTable.T
scoreTable
```

Out[488…

Prediction	NYC	BOS	SF	SEA
K Nearest Neighbors	0.413131	0.522524	0.273233	0.413714
Random Forest	0.413631	0.530373	0.283049	0.418031

For NYC , we should use Random Forest model as the score of Linear Regression (0.413531) is higher than the score of K Nearest Neighbors (0.413131). And, we find that in NYC, neighbour has the greatest relevance of the log_price.

For BOS, we should use Random Forest model as the score of Linear Regression (0.530373) is higher than the score of K Nearest Neighbors (0.522524). We find that in BOS, host_reponse_rate has the greatest relevance of the log_price.

For SF, we should use Random Forest model as the score of Linear Regression (0.283049) is higher than the score of K Nearest Neighbors (0.273233). We find that in SF, bedrooms has the greatest relevance of the log_price.

For BOS, we should use Random Forest model as the score of Linear Regression (0.418031) is higher than the score of K Nearest Neighbors (0.413714). We find that in SEA, bedrooms has the greatest relevance of the log_price

6. Conclusion

In the project, we display many characteristics of Airbnb rooms including location, price and availablility in four major American cities, so that both guests and hosts can have a whole picture of this industry in these cities. We see that although there are minor differences, most Airbnb rooms follow similar patterns such as in room types, in log_prices, and so on.

By running regression, we figure out different significant variables that influence prices in different cities. We notice that many variables play different roles in different cities. Therefore, based on the result, hosts can pick the variable which contributes the most to the price increase and invest in this aspect. This help hosts to avoid wasting money and time on developing attributes that have low weight or low variance in guests' perception.

We apply machine learning to those four datasets, making predictions based on Random Forest or KNN. According to scores attached to those methods, we pick the most suitable method for each city's dataset.

Finally, we make comparison between NYC, Boston, San Francisco and Seattle. One thing we notice is that the mean availablility in New York is very low while that in Seattle is higher than other cities. However, there are a significantly higher number of listings in NYC. This is a reflection of the market situation. We assume that the NYC market is super competitive, so many hosts will take a different strategy in seasons when there are few tourists to reduce the cost. In future projects, we can go deeper in this topic and analyze the reason behind this interesting observation.

Reference

Dataset & some inspiration:

NYC : https://www.kaggle.com/dgomonov/new-york-city-airbnb-open-data

BOS : https://www.kaggle.com/airbnb/boston

SF : http://insideairbnb.com/get-the-data.html

SEA : https://www.kaggle.com/airbnb/seattle