Airbnb Data Analysis of Popular Cities in The US

In this project, we would like to extract and analyze some useful information from the dataset using Kaggle website for some prospective Airbnb hosts. This report will go through some questions that we concerned and answered with visuals (Boxplots, Scatter Plots, Basemap, Heatmap, and graphs etc.) and statistical summaries using Machine Learning algorithms.

Before the Analysis:

This is what our dataset looks like:

Out[1]:

	id	log_price	property_type	room_type	amenities	accommodates	bathrooms	bed_type	cancellation_policy	cleaning_fee	...	latitud
0	6901257	5.010635	Apartment	Entire home/apt	{"Wireless Internet","Air conditioning",Kitche...	3	1.0	Real Bed	strict	True	...	40.69652
1	6304928	5.129899	Apartment	Entire home/apt	{"Wireless Internet","Air conditioning",Kitche...	7	1.0	Real Bed	strict	True	...	40.76611
2	7919400	4.976734	Apartment	Entire home/apt	{TV,"Cable TV","Wireless Internet","Air condit...	5	1.0	Real Bed	moderate	True	...	40.80811
3	13418779	6.620073	House	Entire home/apt	{TV,"Cable TV",Internet,"Wireless Internet",Ki...	4	1.0	Real Bed	flexible	True	...	37.77200
4	3808709	4.744932	Apartment	Entire home/apt	{TV,Internet,"Wireless Internet","Air conditio...	2	1.0	Real Bed	moderate	True	...	38.92562
5	12422935	4.442651	Apartment	Private room	{TV,"Wireless Internet",Heating,"Smoke detecto...	2	1.0	Real Bed	strict	True	...	37.75316
6	11825529	4.418841	Apartment	Entire home/apt	{TV,Internet,"Wireless Internet","Air conditio...	3	1.0	Real Bed	moderate	True	...	33.98045
7	13971273	4.787492	Condominium	Entire home/apt	{TV,"Cable TV","Wireless Internet","Wheelchair...	2	1.0	Real Bed	moderate	True	...	34.04673
8	180792	4.787492	House	Private room	{TV,"Cable TV","Wireless Internet","Pets live ...	2	1.0	Real Bed	moderate	True	...	37.78112

In our dataset, we have found a lot of missing variable in multiple columns like bathrooms and first_reviews, which we would replace them with 0.

```python
#Show which column has missing values and how many missing values that vari
print(mydata.isna().sum()[mydata.isna().sum() > 0])
```

```
bathrooms                 200
first_review            15864
host_has_profile_pic      188
host_identity_verified    188
host_response_rate      18299
host_since                188
last_review             15827
neighbourhood            6872
review_scores_rating    16722
thumbnail_url            8216
zipcode                   966
bedrooms                   91
beds                      131
dtype: int64
```

Other than missing variable, We have fixed the cities are mislabeled with wrong zipcodes.

```python
#Assign the specific zipcode area into the zipcode (it contains the '-' in
if any(mydata.zipcode.str.contains("-")):
    mydata.zipcode = mydata.zipcode.str.partition('-')[0].str.strip()
else:
    mydata.zipcode = mydata.zipcode
#Remove unnecessary zipcode data that are mislabeled.
mydata.zipcode = mydata.loc[(mydata.zipcode.str.len() <6) & (mydata.zipcode
#Fix the mislabeled data that has the city from 'NYC' to 'LA' where the zip
mydata.loc[mydata.zipcode == '10023', 'city'] = 'NYC'
mydata.loc[mydata.zipcode == '10023', 'city'].value_counts()
#Replace the data that has NaN values with 0
mydata = mydata.fillna(0)
```

We also extract the year of the host_since column into a new column called year, which can be used in the later analysis. During this process, we found out that some variables in host_since with year of 1970, so we dropped the mislabeled years.

```python
#Extract the year from the host_since variable then assign it to the new va
mydata['host_since'] = pd.to_datetime(mydata['host_since'])
mydata['year']=mydata['host_since'].apply(lambda x: x.year)
print(mydata.year.value_counts())
#Drop the mydata that has the year of 1970 since they are mislabeled - wron
mydata = mydata[mydata['year'] != 1970]
```

```
2015    15594
2014    13690
2016    13190
2013    10729
2012     8308
2017     4970
2011     4887
2010     1766
2009      698
1970      188
2008       91
Name: year, dtype: int64
```

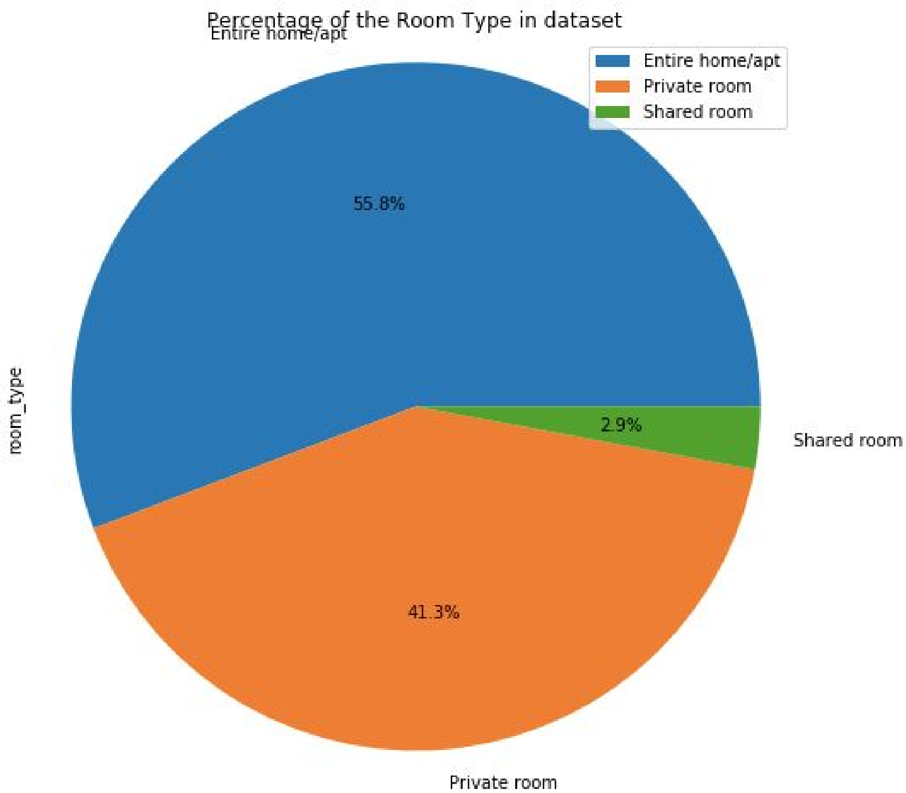
Project Summary Questions that our group wants to analyze:

- What are the most popular room types in Airbnb?
- Which area has the maximum listing on Airbnb? (base map)
- Which area has the maximum listing on Airbnb? (zip code)
- What Cancellation policy should hosts set up for their listing?
- What price to set for the daily rate?
- What amenities should be installed in the listing? (included cleaning fee) And Display listing thumbnail images
- Which cities has the most review score in our dataset?
- What is the popular number of accommodations, bedroom, beds and bathroom when customers are searching for listings?
- MACHINE LEARNING CLASSIFICATION ALGORITHM:
    - Fitting a Linear Regression Model
        - Using Numeric Independent Variables
            - OLS Regression Model on Multiple Independent Variables:
                - Using Cross Validation to Predict the Estimates of Y
                - Using Cross Validation to Get the Mean RMS Error
            - OLS Regression Model on Single Independent Variable:
                - Using Cross Validation to Predict the Estimates of Y
                - Using Cross Validation to Get the Mean RMS Error
            - Which OLS Regression Model to Choose that Gives the Best Results/Prediction on Y (log_price)?
        - Using Categorical Independent Variables
            - OLS Regression Model on Multiple Independent Variables:
                - Using Cross Validation to Predict the Estimates of Y
                - Using Cross Validation to Get the Mean RMS Error
            - OLS Regression Model on Single Independent Variable:
                - Using Cross Validation to Predict the Estimates of Y
                - Using Cross Validation to Get the Mean RMS Error
            - Which OLS Regression Model to Choose that Gives the Best Results/Prediction on Y (log_price)?
        - Representing an Interaction Using Interactive Dataframe Between Related Variables
            - Interactive Dataframe that represents the relationship between The Number of Reviews and The Review Score Rating:
                - Using Cross Validation to Predict the Estimates of Y
                - Using Cross Validation to Get the Mean RMS Error
            - Interactive Dataframe that Represents The Relationship Between The Number of Reviews and The Review Score Rating, As Well as the Relationship Between Bathrooms, Bedrooms, and Beds:
                - Using Cross Validation to Predict the Estimates of Y:
                - Using Cross Validation to Get the Mean RMS Error:

        - Which OLS Regression Model to Choose that Gives the Best Results/Prediction on Y (log_price)?
    - Fitting A Logistic Regression Model
        - Predicting the Probability of A dependent variable (Y)
        - Evaluating the Accuracy of a Logistic Regression Classification Using Confusion Matrix
        - Plot the ROC Curve of a Logistic Regression Classification Model

Question 1:

What are the most popular room types in Airbnb?

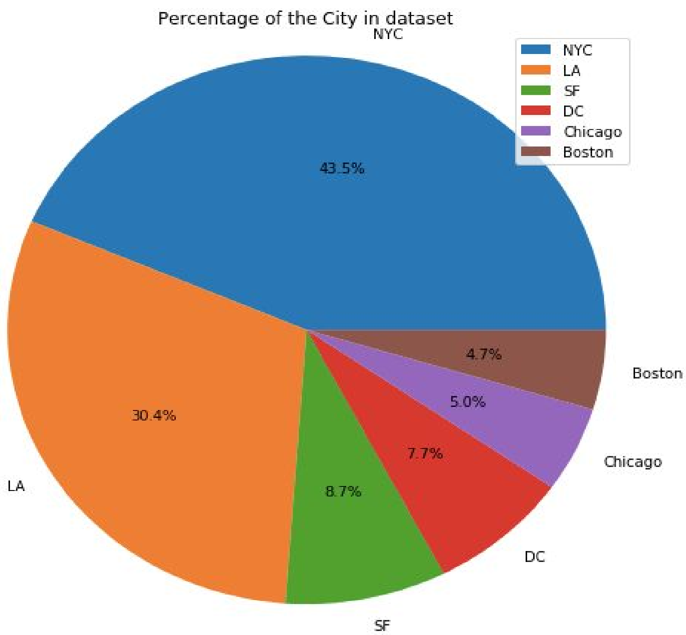


Understanding the competition in the market is important to prospective hosts, which can help with adjusting the price of listing. The pie chart above shows the 3 basic room types that people will look for when they are searching for properties with its percentage. Accordingly, entire home/apt are rented out the most. Prospective hosts can consider putting their entire home/ apt as a listing on Airbnb for higher reservation search.

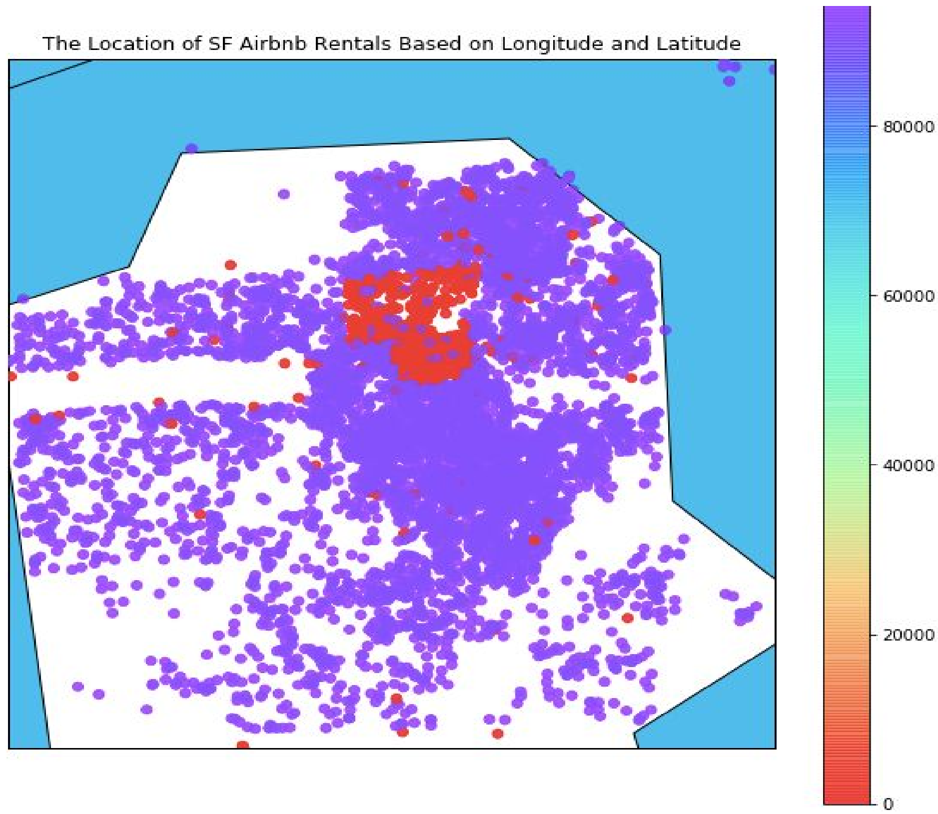
Question 2:

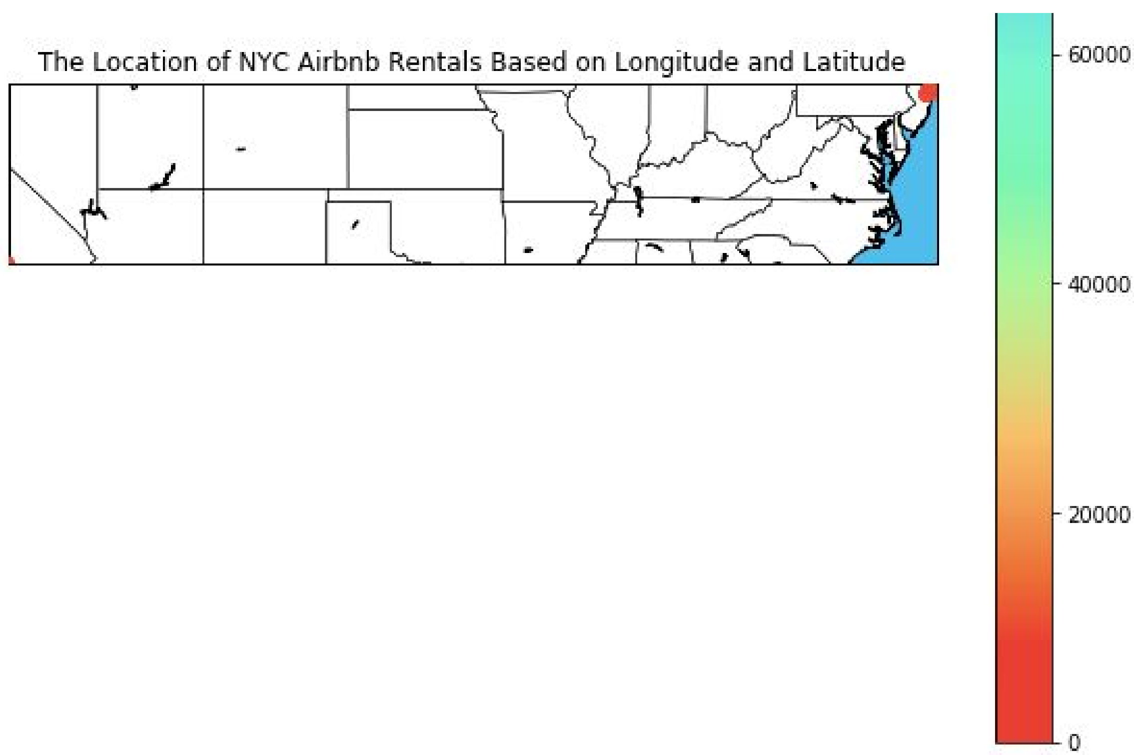
Which area has the maximum listing on Airbnb? (base map)

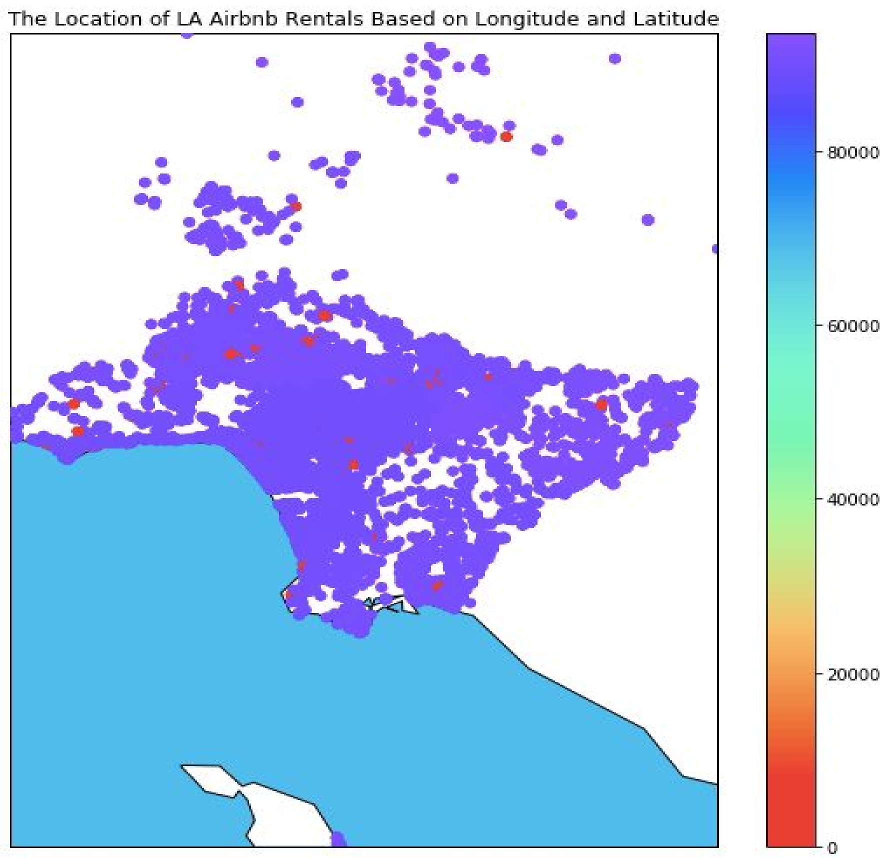
In order to answer this question, we have made a pie chart and 5 different base maps according to the popular cities in our dataset. The pie chart gives the general idea of which cities has the most listings on Airbnb, which New York City has the most and Boston has the least. Other than the number of listings, we would like to show the concentration of the listings in each city according to their longitude and latitude. The reason for splitting the map according to cities is location information columns like longitude and latitude have too much data to process, which will take a while to plot everything into a single base map. Here is the pie chart and base maps of our 5 cities:

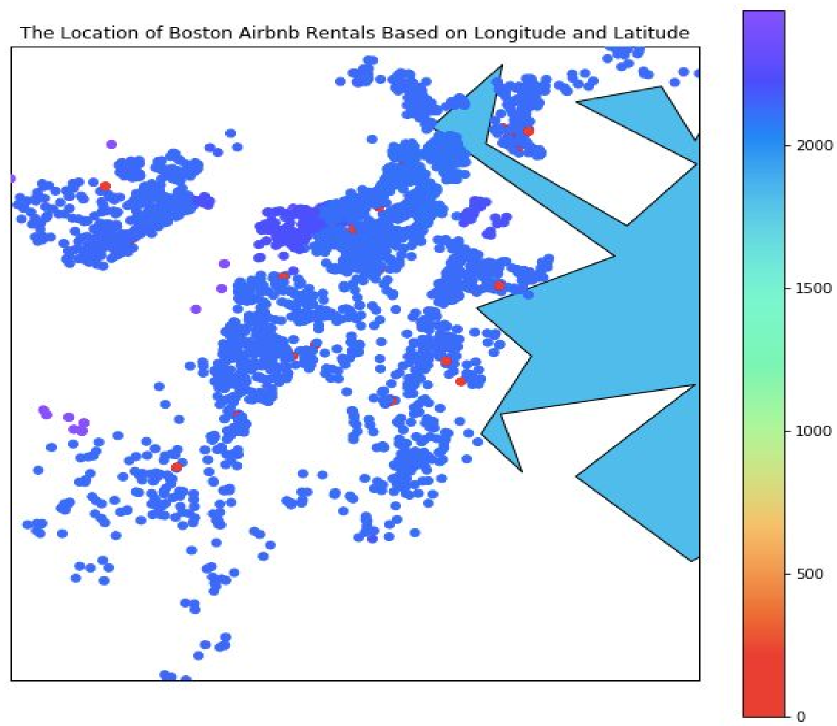


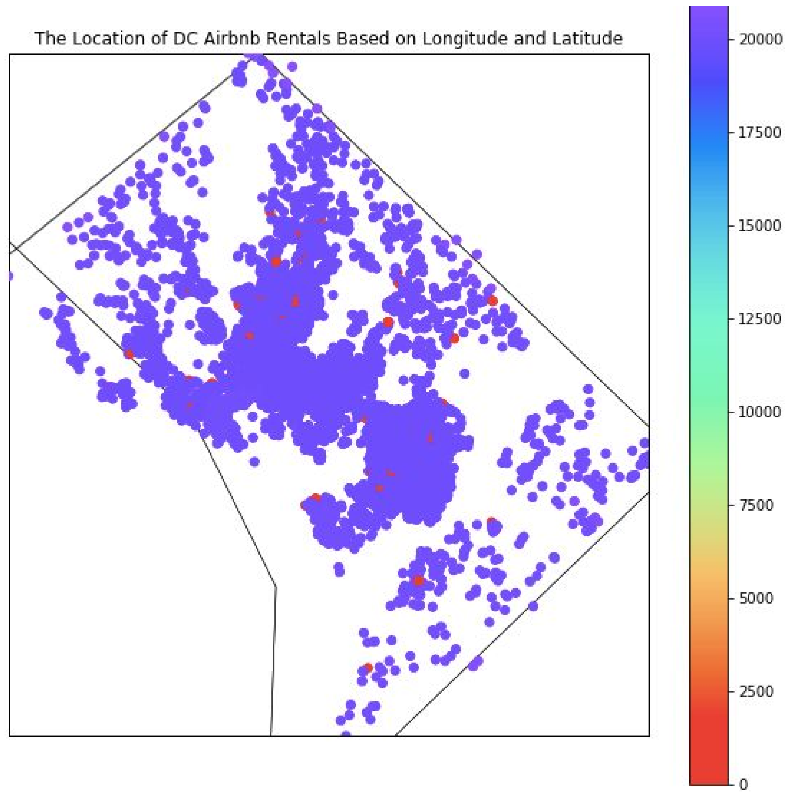

```
sf_data = mydata[mydata.city == 'SF']
import matplotlib.cm
from mpl_toolkits.basemap import Basemap
sf_lon = sf_data.longitude.values
sf_lat = sf_data.latitude.values
#Create the basemap of Airbnb rentals in SF using their longitude and latit
sf_m = Basemap(llcrnrlon=min(sf_lon), llcrnrlat=min(sf_lat), urcrnrlon=max(
            lon_0=(max(sf_lon)-min(sf_lon)), projection='merc', resolution
plt.figure(figsize=(10,10))
sf_m.drawcoastlines()
sf_m.drawcountries()
sf_m.drawstates()
sf_m.drawmapboundary(fill_color='#46bcec')
sf_m.fillcontinents(color = 'white',lake_color='#46bcec')
# Convert latitude and longitude to map projection coordinates
sf_lons, sf_lats = sf_m(sf_lon, sf_lat)
# Plot the scatter points onto the basemap with the color based on the zipc
sf_m.scatter(sf_lons, sf_lats, c = sf_data.zipcode, marker = 'o', cmap ='ra
plt.title('The Location of SF Airbnb Rentals Based on Longitude and Latitud
plt.colorbar()
plt.show()
```

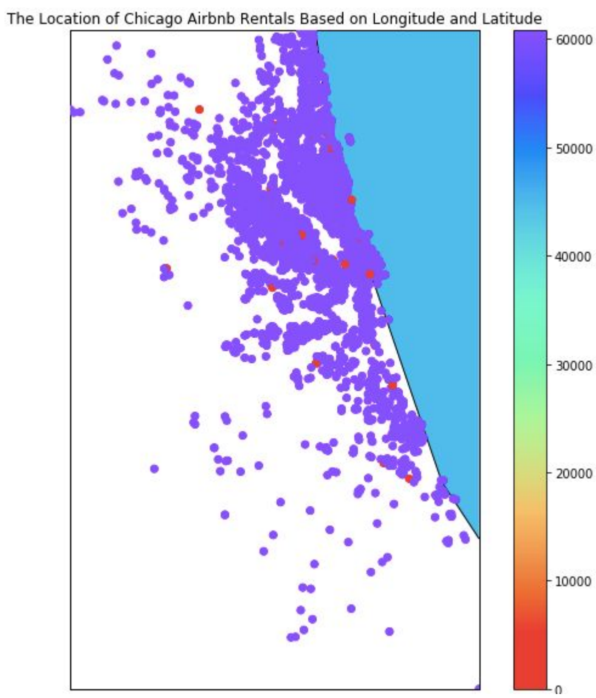

The Location of SF Airbnb Rentals Based on Longitude and Latitude
80000
60000
40000
20000
0


The Location of NYC Airbnb Rentals Based on Longitude and Latitude
60000
40000
20000
0


The Location of LA Airbnb Rentals Based on Longitude and Latitude
80000
60000
40000
20000
0


The Location of Boston Airbnb Rentals Based on Longitude and Latitude
2000
1500
1000
500
0



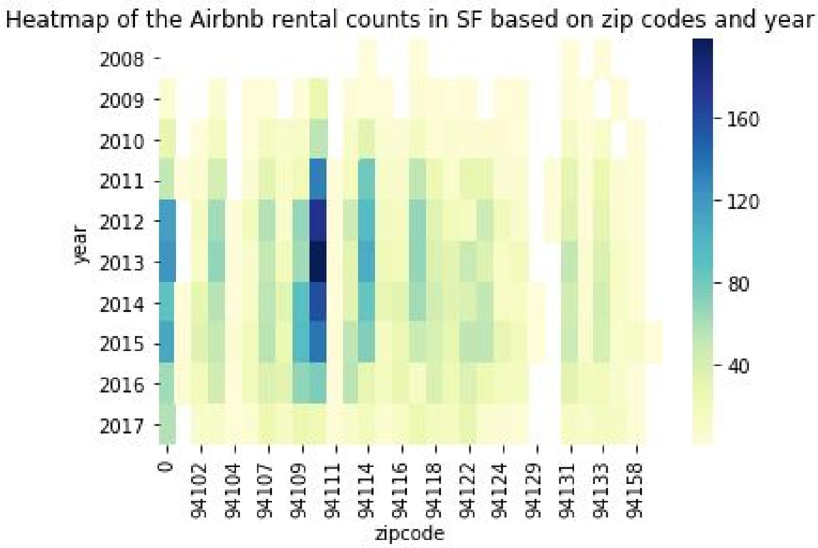


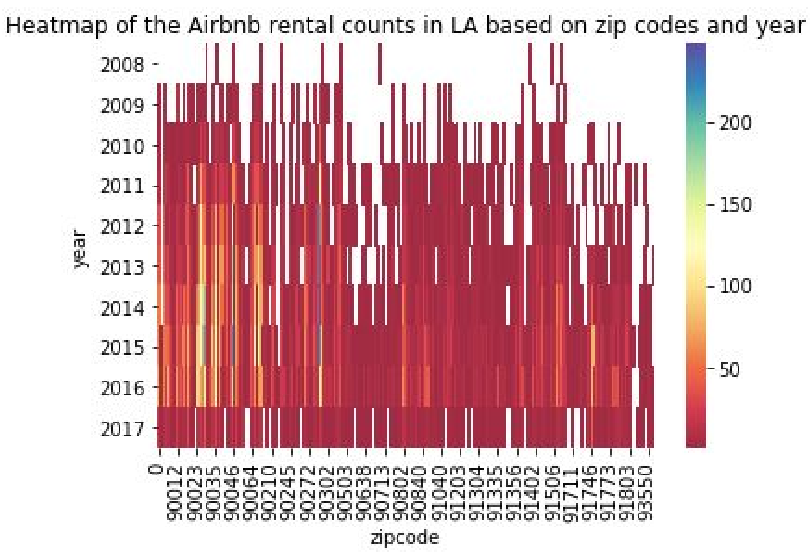
From the base maps, we can see that most of the listings are concentrated next to the ocean, which can attract more people to make reservations with the beautiful views. In DC and Boston, we can see listings are more concentrated in the center of the city, which we assume the concentrated areas are so close to the tourist sightseeing places or downtown of the cities.

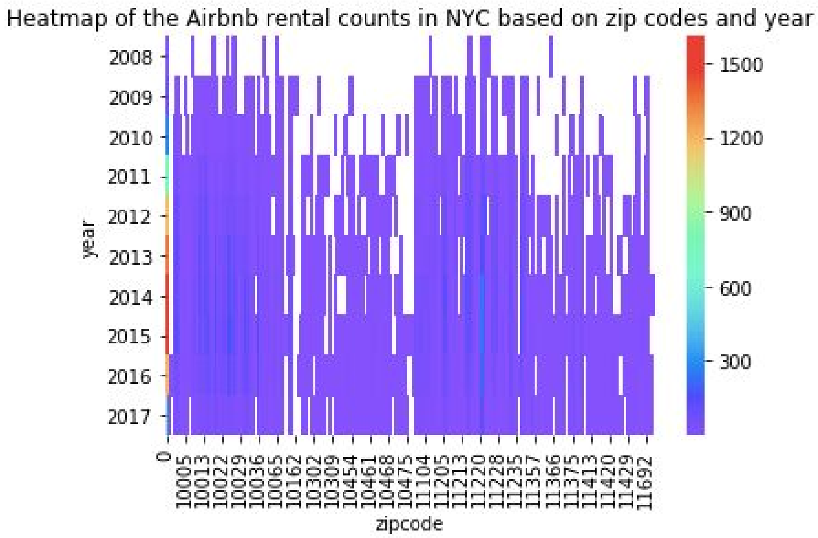
Question 3:

Which area has the maximum listing on Airbnb? (zip code)

Other than visualizing on the map, we can also find the specific zip code which has the most listing in the dataset. According to this question, we chose SF, NYC, and LA as the cities to investigate. Heatmap is the method that we would like to show the relationship between zip code and years. Here are our heatmaps:



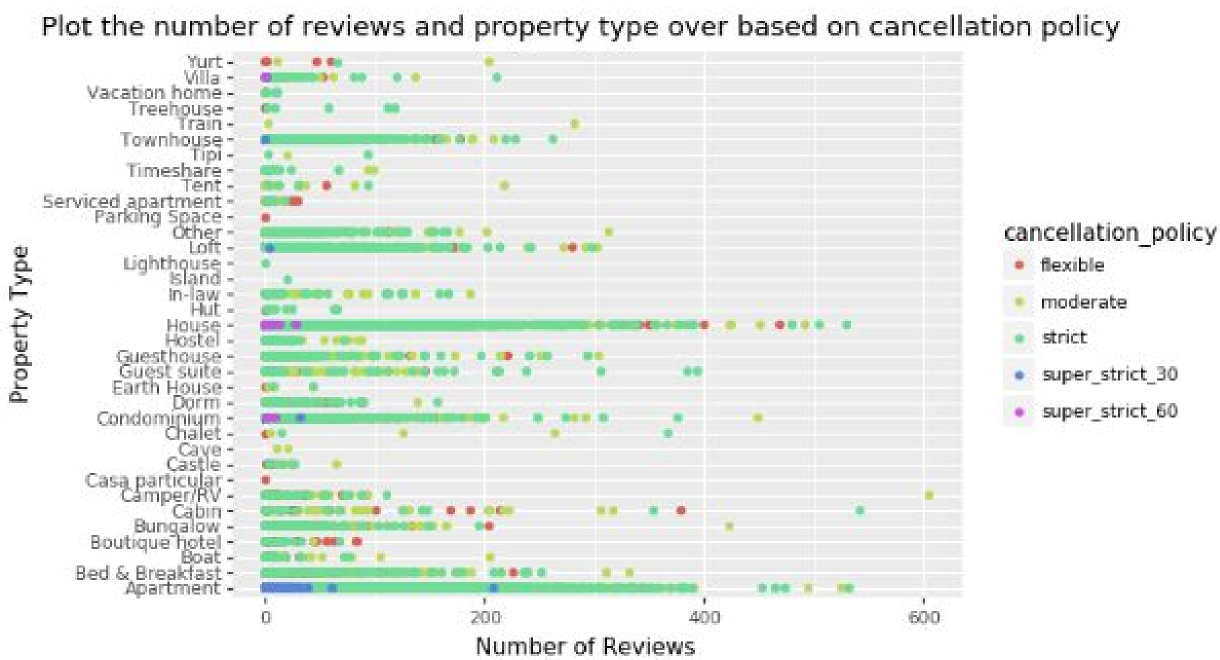




Question 4:

What Cancellation policy should hosts set up for their listing?

Cancellation policy is a rule that protects hosts when customers cancel their reservation. When customers cancel booking at the very last minutes, hosts may not be able to find a new customer for replacement.



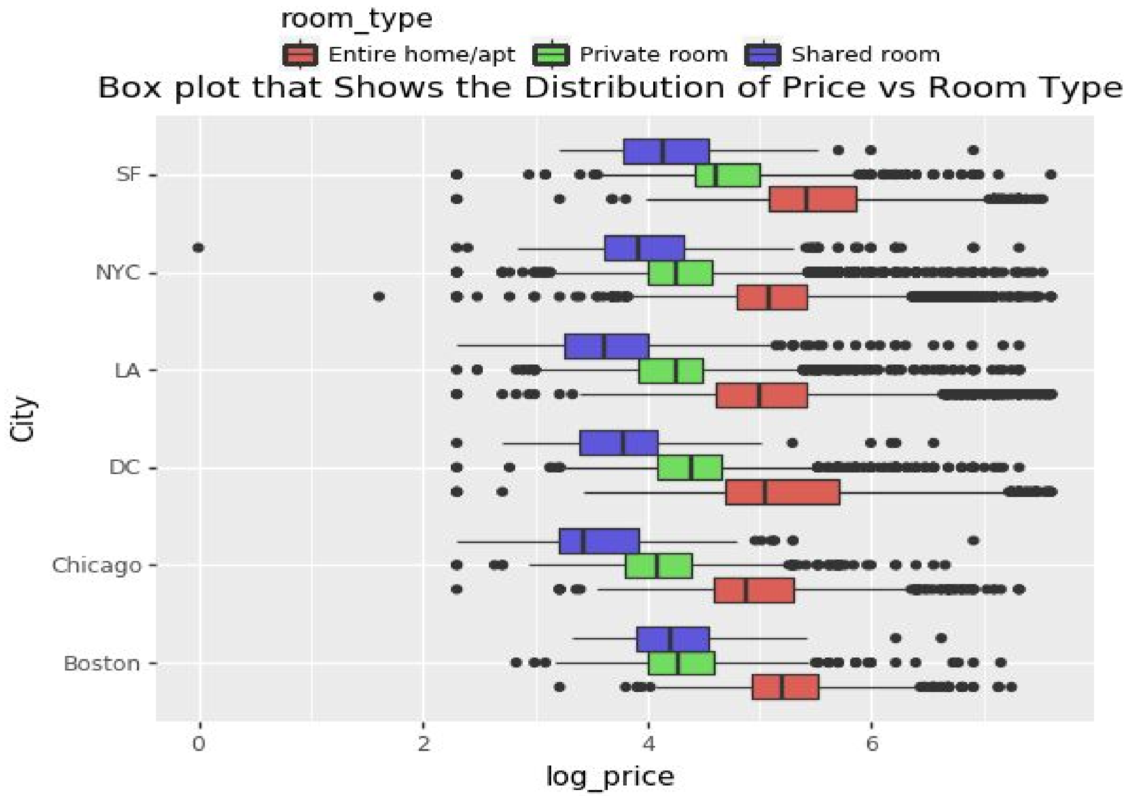
Based on the plot, apartment and house have the most number of reviews about the Airbnb from the customers, and we can tell that most of the property type has the strict the cancelation policy.

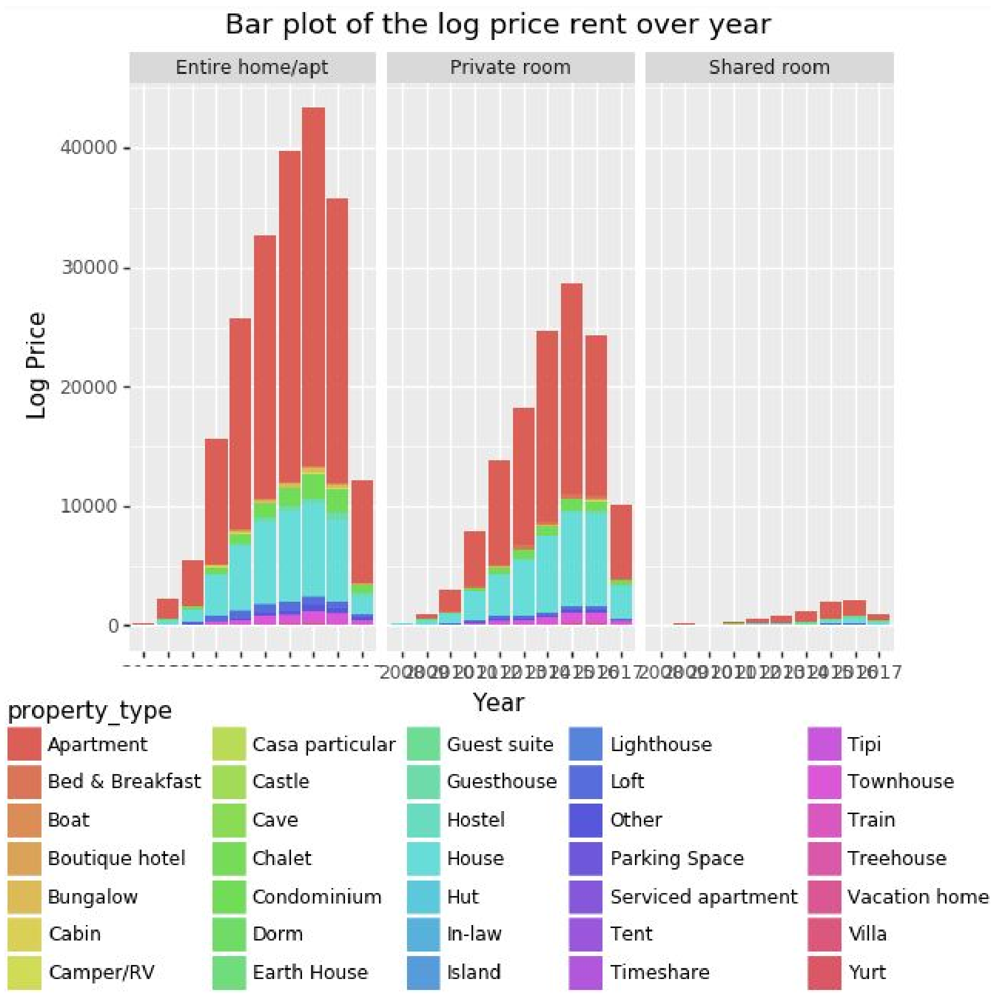
The property type Parking Space has the most flexible cancellation policy, but it also has the least reviews. Property type apartment has the most reviews and also has a strict cancellation policy. For apartments, Some lot of hosts decided to set their cancellation policy to super strict 30.

Question 5:

What price to set for the daily rate?

We can determine the most acceptable price of a listing base on the review rating score. If the listing has a higher review score, which means customers are happy with the price and quality of staying. We will use scatter plot, bar chart and boxplot to show the relationship between review scores, price and room types.


room_type
Entire home/apt
Private room
Shared room
Box plot that Shows the Distribution of Price vs Room Type
City
SF
NYC
LA
DC
Chicago
Boston
0
2
4
6
log_price


Bar plot of the log price rent over year
Entire home/apt
Private room
Shared room
Log Price
40000
30000
20000
10000
0
Year
property_type
Apartment
Bed & Breakfast
Boat
Boutique hotel
Bungalow
Cabin
Camper/RV
Casa particular
Castle
Cave
Chalet
Condominium
Dorm
Earth House
Guest suite
Guesthouse
Hostel
House
Hut
In-law
Island
Lighthouse
Loft
Other
Parking Space
Serviced apartment
Tent
Timeshare
Tipi
Townhouse
Train
Treehouse
Vacation home
Villa
Yurt

From the Review scores and price plot, we can see all the score 100 listing are having a price from 1.7 to 7.6. This data gives the general idea of how price distributes in review scores. We also use boxplot with price vs room in all cities to get the more accurate numbers of the most acceptable price. Most of the houses are having an average log_price above 5. All the room type in Chicago has the least average price, so hosts can adjust the price according to the city of property. This bar chart shows that the log price reaches its peaks in 2015, and the 4 property types that Airbnb rents out the most are apartments, houses, condos then townhouses where entire home/apt are rented the most, the private room and shared room correspondingly.

Question 6:

What amenities should be installed in the listing? (included cleaning fee) And Display Listing Thumbnail Images

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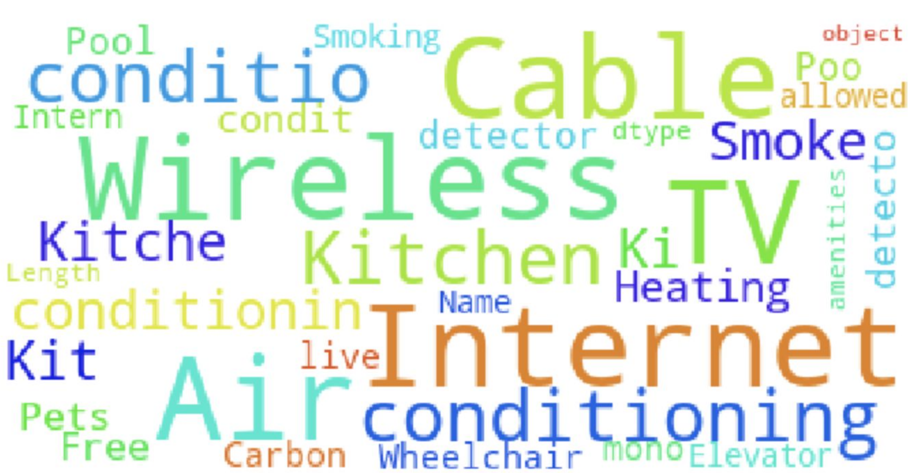
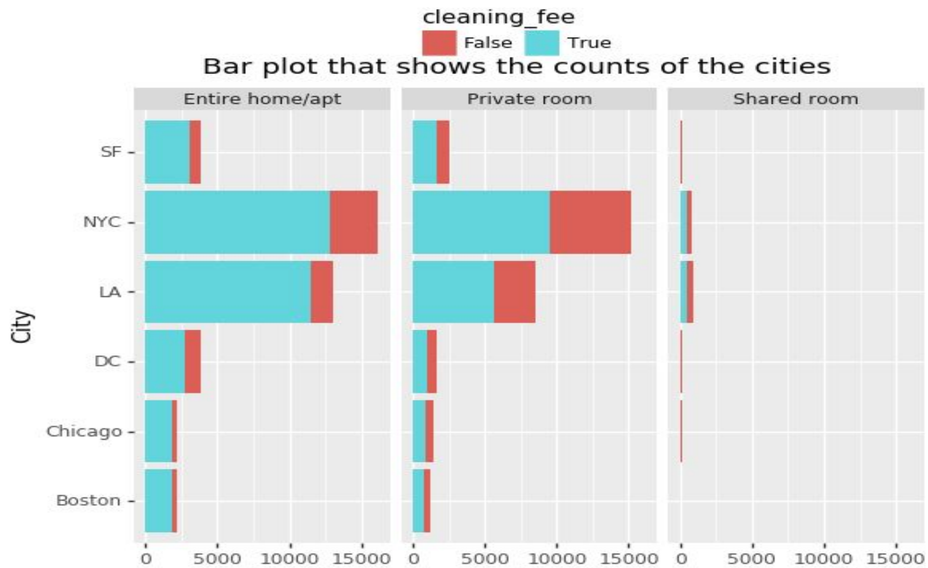
We decided to use the word cloud to show the most common amenities in the listings in our dataset. Here is our word cloud:

```
#Word Cloud for Amenities
from os import path
from PIL import Image
from wordcloud import WordCloud, STOPWORDS, ImageColorGenerator

def generate_wordcloud(data, title = None):
    """ This function helps generate the wordcloud of the dataset column th
        Parameter:
            The dataset column
    """
    wordcloud = WordCloud(background_color ='white', max_font_size=50, max_
    fig = plt.figure(1,figsize=(12,12))
    plt.imshow(wordcloud)
    plt.axis("off")
    plt.show()

generate_wordcloud(mydata['amenities'])
```



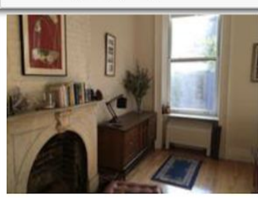


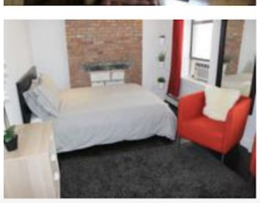
Based on the WordCloud plot above, it shows that ‘Wireless’, ‘Internet’, and 'Cable' are the most common amenities in all the Airbnb listing posts. Other than amenities, most of the hosts on Airbnb acquire customers to pay cleaning fees when they make reservations, which prospective hosts can use this as a preference.

Since the dataset has the variable called thumbnail URL where it contains the URL link, Im trying to show to first few pictures using the Python Image Library package.
So to show the image, I remove all the 0 from that column in order to open the image using URL as it only reads the strings. Then I display the first few images that indicates the thumbnail of the Airbnb rental post.

In [49]:

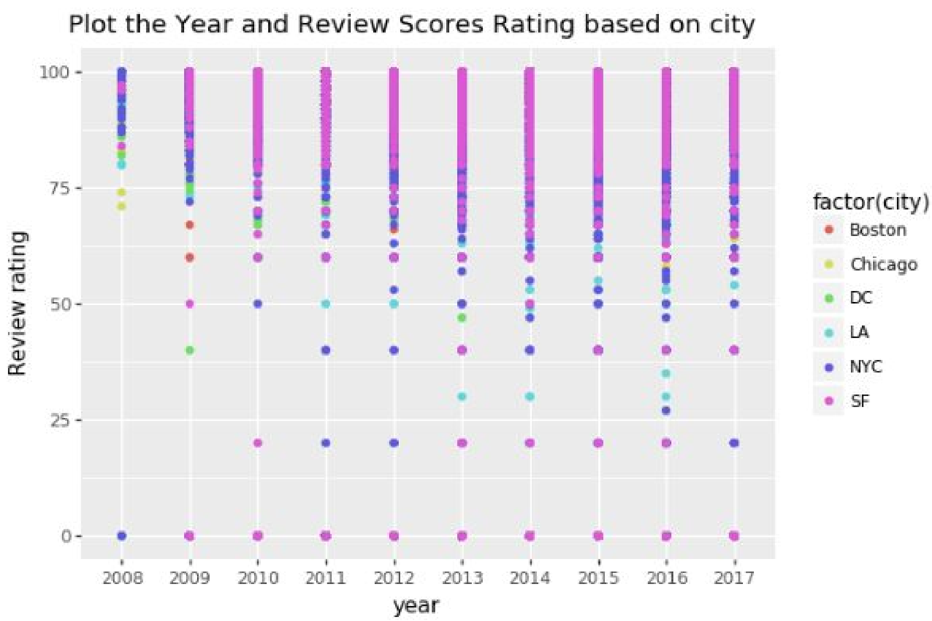
```
rows20 = mydata[0:20]
rows20
from urllib.request import urlopen
from PIL import Image
from IPython.display import display
#Image.open(urlopen(rows20.thumbnail_url.values[0:20]))

new_list = [i for i in rows20.thumbnail_url.values.tolist()]
for i in new_list:
    if i == 0:
        new_list.remove(i)
for x in range(len(new_list)):
    img = Image.open(urlopen(new_list[x]))
    display(img)
```





Question 7:

Which cities has the most review score in our dataset?

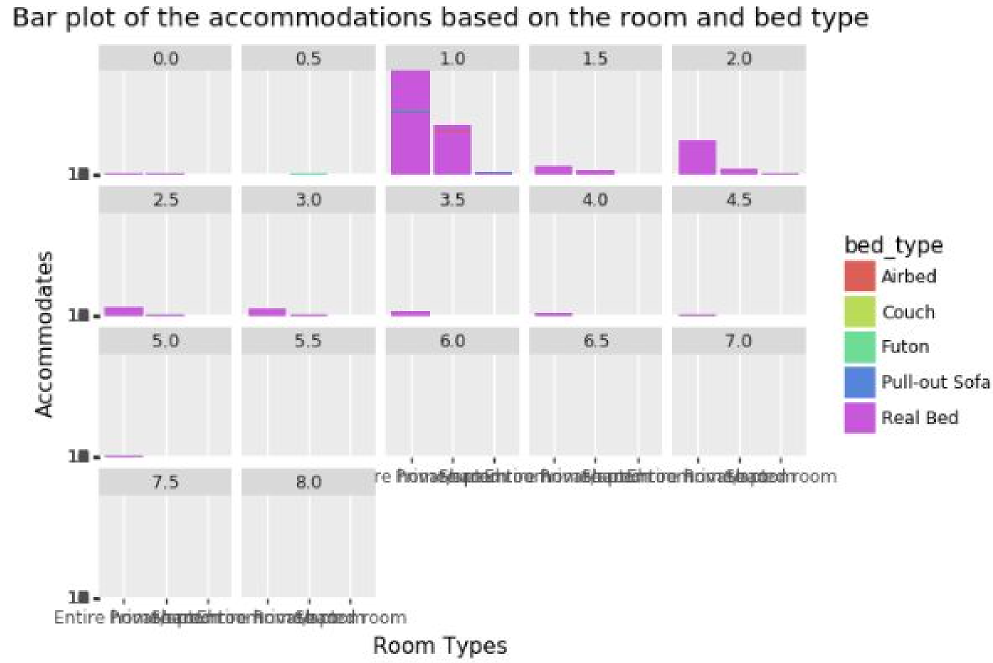


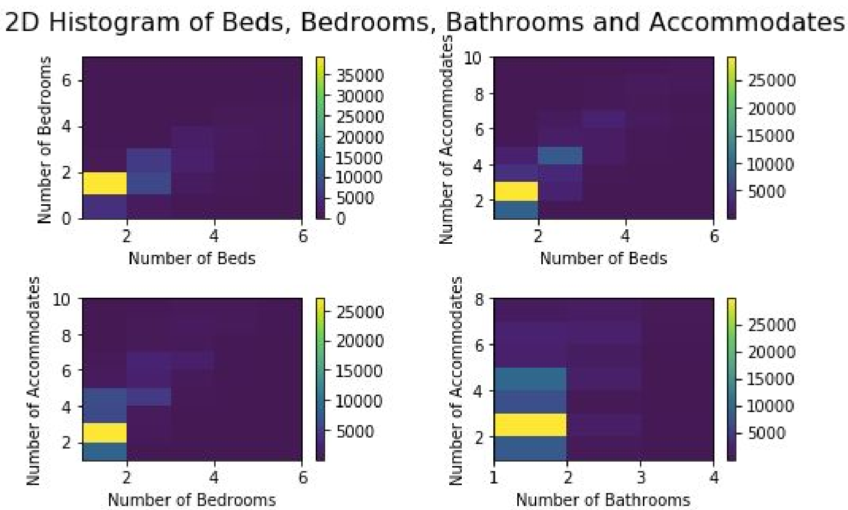
Based on the plot we can tell the SF had the most review score rating of Airbnb from 2010-2017 which is over 60 scores of ratings .
We can tell that the Airbnb reviews of each city increased more during 2010-2017 as people started using AirBnb more and more.

Question 8:

What is the popular number of accommodations, bedroom, beds and bathroom when customers are searching for listings?

Accommodations and number of beds are the things that customers are concerning the most. In order to investigate the relationship between accommodations and beds, we created bar plot and 2D Histogram with different combination between, number of beds, bedrooms, bathroom and accommodation. Here is our plots:





The ggplot above shows that most of the Airbnb rentals have real beds instead of airbed, couch or pull-out sofa ... and they mostly have entire home/apartment then private room with the majority of either 1 or 2 bathrooms. From the histogram, we can also see that the yellow parts have the most search by customers. Most of the customers are looking for 1-2 rooms, 1-2 bed, 2-3 accommodates and 1-2 bathrooms.

MACHINE LEARNING CLASSIFICATION ALGORITHM:

FITTING A LINEAR REGRESSION MODEL

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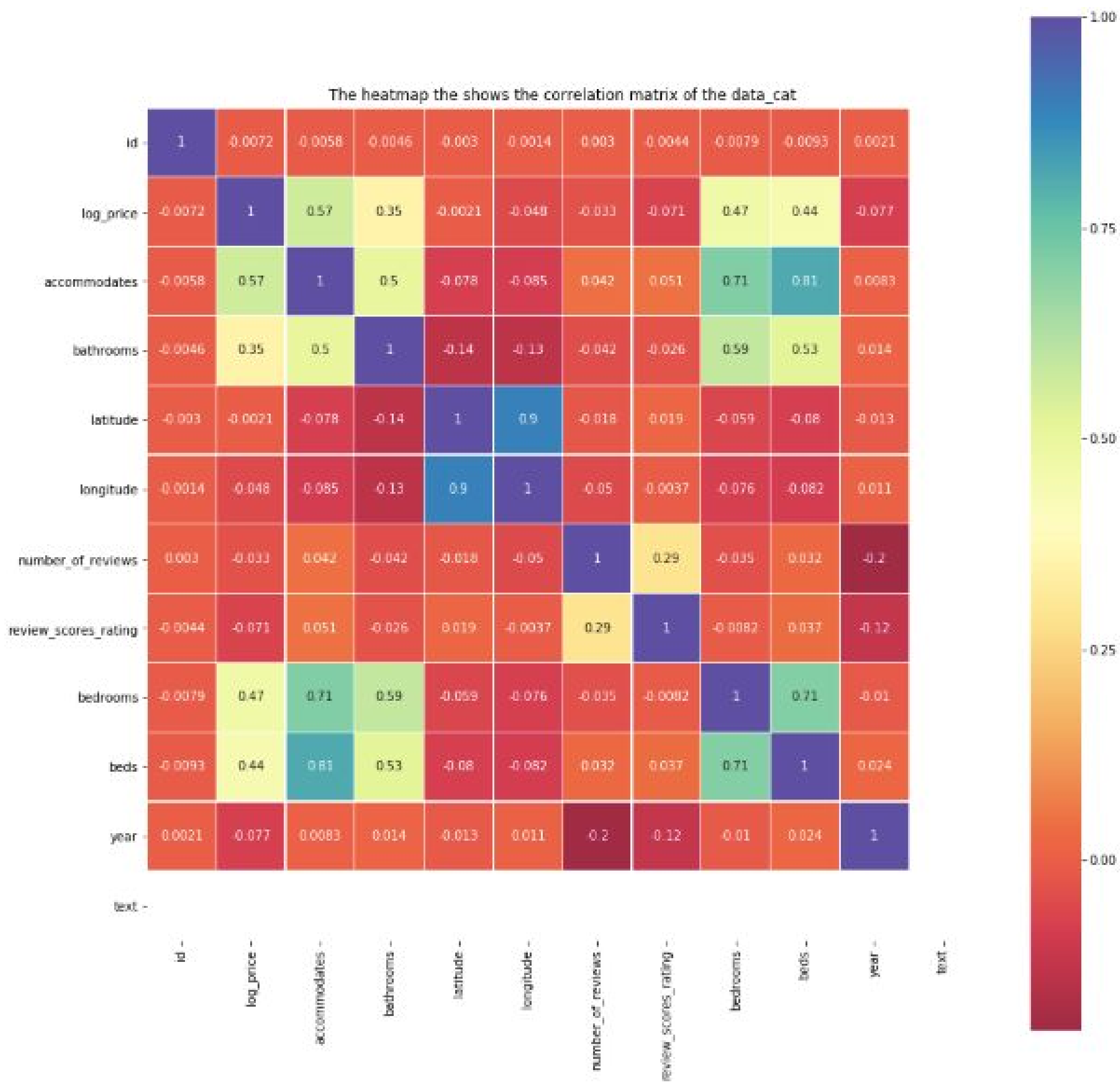
1. Using Numeric Independent Variables:



Based on the heatmap of the correlation matrix above, we can see that id, latitude, longitude, number_of_reviews, review_scores_rating, year and text doesn't have that much impact on the log_price variables since the its correlation matrix value are very low.
So We decide to drop the unrelated/unneccessary variables out of the new dataframe.

OLS Regression Model on Multiple Independent Variables:

```
import statsmodels.api as sm
import statsmodels as statm
from statsmodels.formula.api import ols
from sklearn.linear_model import LinearRegression
from sklearn import linear_model

def model_df(df):
    """ Fit the linear regression model onto the dataframe
        Parameters:
            The dataframe that contains the independent variables
        Return:
            The linear regression model that was fit into the dataframe
   """
    #Add the columns of ones to an array
    x = sm.add_constant(df)
    y_new = mydata[['log_price']]
    y = y_new
    # Fit the linear model
    model = linear_model.LinearRegression()
    results = model.fit(x, y)
    model = sm.OLS(y, x)
    ret = model.fit()
    return ret

#Fit the linear regression model on the data_num dataframe
#Get the summary of the new model
model_df(data_num.drop(['log_price'],axis=1)).summary()
```

OLS Regression Results

Dep. Variable:	log_price	**R-squared:**	0.339
Model:	OLS	**Adj. R-squared:**	0.339
Method:	Least Squares	**F-statistic:**	9495.
Date:	Sun, 09 Dec 2018	**Prob (F-statistic):**	0.00
Time:	06:40:24	**Log-Likelihood:**	-65037.
No. Observations:	73923	**AIC:**	1.301e+05
Df Residuals:	73918	**BIC:**	1.301e+05
Df Model:	4		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	4.0902	0.005	801.507	0.000	4.080	4.100
accommodates	0.1789	0.002	99.568	0.000	0.175	0.182
bathrooms	0.0815	0.005	17.644	0.000	0.072	0.091
bedrooms	0.1228	0.004	30.758	0.000	0.115	0.131
beds	-0.0752	0.003	-24.249	0.000	-0.081	-0.069

Omnibus:	3115.442	**Durbin-Watson:**	2.004
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	7036.212
Skew:	0.268	**Prob(JB):**	0.00
Kurtosis:	4.413	**Cond. No.**	13.9

Using Cross Validation to Predict the Estimates of Y:

```
from sklearn.metrics import mean_squared_error, make_scorer
from sklearn.model_selection import cross_val_score, cross_val_predict
def cross_val_pre(df):
    """ The funtion helps predict the cross-validated estimates for each input data point
        Parameters:
                The dataset that contains the independent variables
        Return:
                The prediction estimate of y (dependent variable) for each input data point
   """
    data_num =df
    x = np.array(data_num.drop(['log_price'],axis=1), dtype=pd.Series)
    y = np.array(data_num['log_price'], dtype=pd.Series)
    model = linear_model.LinearRegression()
    y_pred = cross_val_predict(model, x, y, cv=5)
    return y_pred

#Predict the log_price variable using 4 independent variables and show the first 5
cross_val_pre(data_num)[0:5]
```

```
array([4.75474136, 5.55995482, 4.96091934, 4.97892045, 4.45522362])
```

Based on the Cross Validation, we get the estimates of Y prediction on log_price variable using 4 independent variable, and the log_price prediction for the first 5 Airbnb rentals are 4.75474136, 5.55995482, 4.96091934, 4.97892045, 4.45522362.

Using Cross Validation to Get the Mean RMS Error:

```
def rms_error_mean(df):
    """ The funtion helps calculate the Cross Validation Error of the model fitted
        Parameters:
                The dataset that contains the independent variables
        Return:
                The mean squared error
   """
    data_num = df
    x = np.array(data_num.drop(['log_price'],axis=1), dtype=pd.Series)
    y = np.array(data_num['log_price'], dtype=pd.Series)
    model = linear_model.LinearRegression()
    ms_error= cross_val_score(model, x, y, cv=5, scoring = make_scorer(mean_squared_error))
    rms_err = np.sqrt(ms_error)
    return rms_err.mean()
#Get the Mean of RMS Error for the dataframe with numeric columns
rms_error_mean(data_num)
```

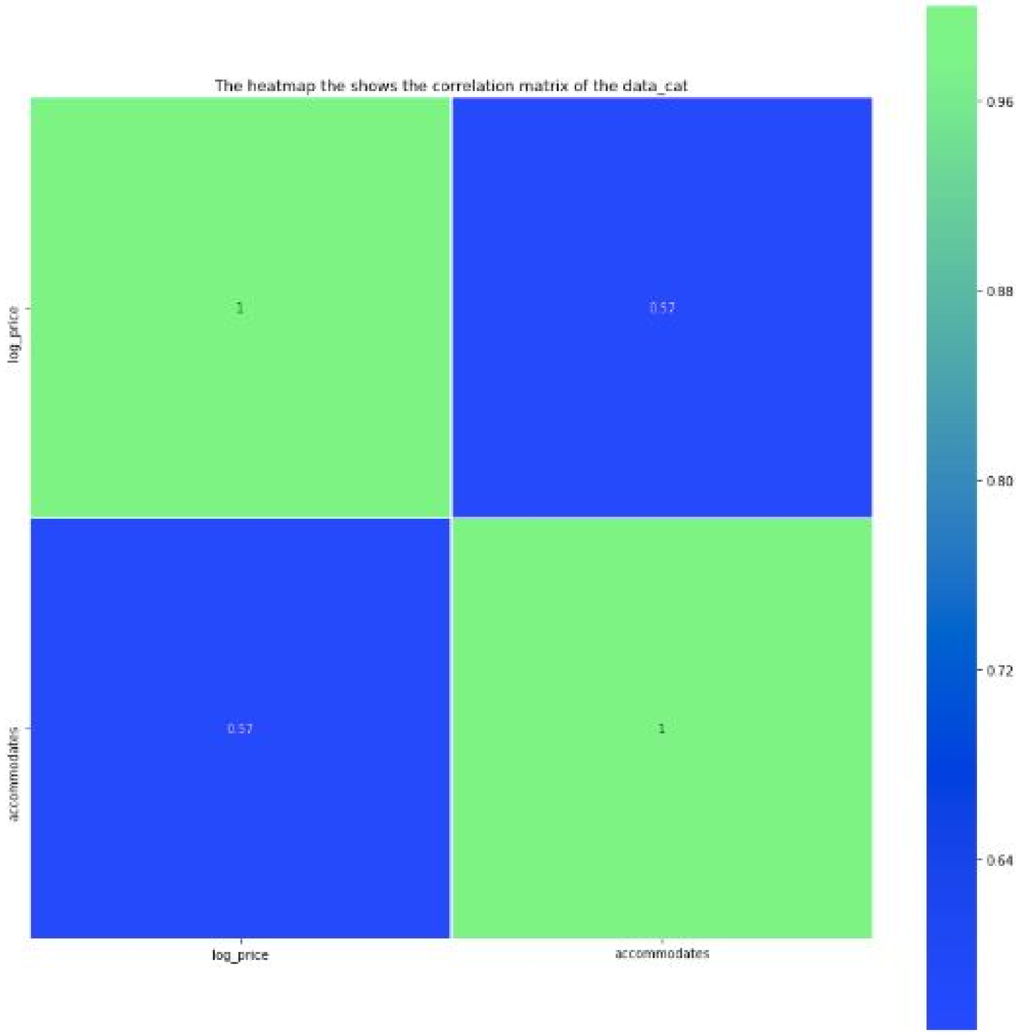
```
0.5833076807527344
```

Based on the RMSE prediction above, using 4 independent variables (accommodates,bathrooms, bedrooms, beds) gives us the RMS Error of 0.5833076807527344. Since the correlation between log price and bathrooms, bedrooms, beds are relatively smaller (0.35, 0.47, 0.44 correspondingly) than the correlation between log_price and accommodates (0.57) we decide to drop the three variables that have low correlation to log_price in the dataframe.
Then fit into the OLS Regression Model using Single Independent Variable and get the summary of the new model.

OLS Regression Model on Single Independent Variable:

```
#Drop the bathrooms, bedrooms, beds variables out of the new numeric dataframe.
data_num = data_num.drop(['bathrooms', 'bedrooms', 'beds'], axis=1)
```

```
#Plot the correlation matrix of the new data.
plt.figure(figsize=(15, 15))
sns.heatmap(data_num.corr(),linewidths=0.25,vmax=1.0,square=True,cmap="winter", linecolor='w',ar
plt.title('The heatmap the shows the correlation matrix of the data_cat')
plt.show()
```



```
#Fit the linear regression model on the new data_num dataframe
#with only log_price as dependent variable and accommodates as independent variable.
#Get the summary of the new model
model_df(data_num.drop(['log_price'],axis=1)).summary()
```

OLS Regression Results

Dep. Variable:	log_price	**R-squared:**	0.322
Model:	OLS	**Adj. R-squared:**	0.322
Method:	Least Squares	**F-statistic:**	3.516e+04
Date:	Sun, 09 Dec 2018	**Prob (F-statistic):**	0.00
Time:	06:40:47	**Log-Likelihood:**	-65981.
No. Observations:	73923	**AIC:**	1.320e+05
Df Residuals:	73921	**BIC:**	1.320e+05
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	4.1854	0.004	1086.075	0.000	4.178	4.193
accommodates	0.1891	0.001	187.508	0.000	0.187	0.191

Omnibus:	3637.542	**Durbin-Watson:**	2.003
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	9772.161
Skew:	0.258	**Prob(JB):**	0.00
Kurtosis:	4.705	**Cond. No.**	7.10

Using Cross Validation to Predict the Estimates of Y:

```
#Predict the log_price variable using a single independent variable and show the first 5
cross_val_pre(data_num)[0:5]
```

```
array([4.75204655, 5.50768929, 5.12986792, 4.94095724, 4.56313587])
```

Based on the Cross Validation, we get the estimates of Y prediction on log_price variable using a single independent variable, and the log_price prediction for the first 5 Airbnb rentals are 4.75204655, 5.50768929, 5.12986792, 4.94095724, 4.56313587

Using Cross Validation to Get the Mean RMS Error:

```
#Get the Mean of RMS Error for the dataframe with numeric columns
rmse_pred(data_num)
```

```
0.5907458857938345
```

Based on the RMSE prediction above, using only single independent variable (accommodates) gives us the RMS Error of 0.5907458857938345

Which OLS Regression Model to Choose that Gives the Best Results/Prediction on Y (log_price)?

Based on the two prediction for the estimates of Y using OLS Regression Model:
Using 4 independent varialbles gives us the Y estimates (first 5): 4.75474136, 5.55995482, 4.96091934, 4.97892045, 4.45522362 with the Mean RMS Error of 0.5833076807527344.
Using a single independent varialble gives us the Y estimates (first 5): 44.75204655, 5.50768929, 5.12986792, 4.94095724, 4.56313587 with the Mean RMS Error of 0.5907458857938345.
Comparing with the actual log_price rent ratio (first 5) above, Fitting the OLS Linear Regression with 4 Independent Variables gives us a better and more exact prediction of Y estimates with the lower Mean RMS Error.

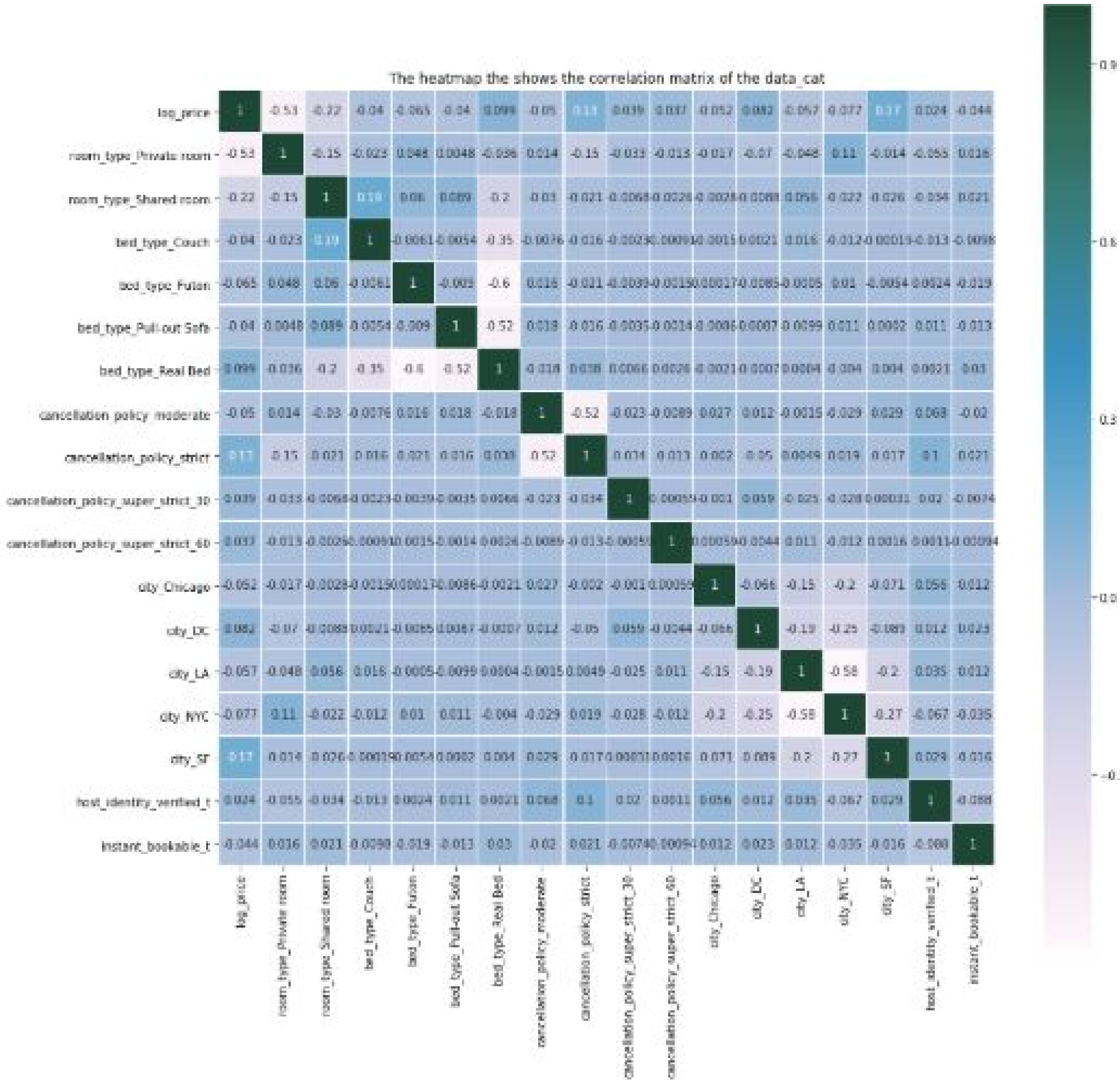
---

2. Using Categorical Independent Variables:

```
#Create new dataframe that has the columns of just numeric type.
print(mydata.room_type.value_counts())
print(mydata.bed_type.value_counts())
print(mydata.cancellation_policy.value_counts())
print(mydata.city.value_counts())
print(mydata.host_identity_verified.value_counts())
print(mydata.instant_bookable.value_counts())
```

```
Entire home/apt    41223
Private room       30539
Shared room         2161
Name: room_type, dtype: int64
Real Bed         71847
Futon              750
Pull-out Sofa      582
Airbed             477
Couch              267
Name: bed_type, dtype: int64
strict             32296
flexible           22484
moderate           19014
super_strict_30      112
super_strict_60       17
Name: cancellation_policy, dtype: int64
NYC        32174
LA         22443
SF          6432
DC          5687
Chicago     3719
Boston      3468
Name: city, dtype: int64
t    49748
f    24175
Name: host_identity_verified, dtype: int64
f    54515
t    19408
Name: instant_bookable, dtype: int64
```

Since room_type with Entire Home/Apt, bed_type with Real Bed, cancellation_policy with strict, city with NYC, host_identity_verified with True and instant_bookable with False have higher percentage compared to other types, we create the dummy variables and add to new categorical data frame since these variables listed above don't give new information, hence drop it for the fitting linear model process.



OLS Regression Model on Multiple Independent Variables:

OLS Regression Results

Dep. Variable:	log_price	**R-squared:**	0.410
Model:	OLS	**Adj. R-squared:**	0.410
Method:	Least Squares	**F-statistic:**	3023.
Date:	Sun, 09 Dec 2018	**Prob (F-statistic):**	0.00
Time:	06:41:08	**Log-Likelihood:**	-60851.
No. Observations:	73923	**AIC:**	1.217e+05
Df Residuals:	73905	**BIC:**	1.219e+05
Df Model:	17		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	5.1578	0.027	188.654	0.000	5.104	5.211
room_type_Private room	-0.8242	0.004	-192.893	0.000	-0.833	-0.816
room_type_Shared room	-1.2678	0.013	-100.555	0.000	-1.292	-1.243
bed_type_Couch	0.1363	0.042	3.215	0.001	0.053	0.219
bed_type_Futon	-0.0513	0.032	-1.586	0.113	-0.115	0.012
bed_type_Pull-out Sofa	-0.0104	0.034	-0.305	0.760	-0.077	0.056
bed_type_Real Bed	0.0757	0.025	2.972	0.003	0.026	0.126
cancellation_policy_moderate	-0.0632	0.006	-11.458	0.000	-0.074	-0.052
cancellation_policy_strict	0.0393	0.005	7.954	0.000	0.030	0.049
cancellation_policy_super_strict_30	0.2610	0.052	4.978	0.000	0.158	0.364
cancellation_policy_super_strict_60	1.3930	0.134	10.413	0.000	1.131	1.655
city_Chicago	-0.2254	0.013	-17.265	0.000	-0.251	-0.200
city_DC	0.0656	0.012	5.507	0.000	0.042	0.089
city_LA	-0.1112	0.010	-11.013	0.000	-0.131	-0.091
city_NYC	-0.0606	0.010	-6.131	0.000	-0.080	-0.041
city_SF	0.3168	0.012	27.200	0.000	0.294	0.340
host_identity_verified_t	-0.0317	0.004	-7.144	0.000	-0.040	-0.023
instant_bookable_t	-0.0494	0.005	-10.655	0.000	-0.059	-0.040

Omnibus:	10454.202	**Durbin-Watson:**	2.003
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	22772.558
Skew:	0.850	**Prob(JB):**	0.00
Kurtosis:	5.122	**Cond. No.**	119.

Using Cross Validation to Predict the Estimates of Y:

```
#Predict the log_price variable using 18 independent variables and show the first 5
cross_val_pre(data_cat)[0:5]
```

```
array([5.18154003, 5.16357256, 5.03094156, 5.5143574 , 5.1471185 ])
```

Based on the Cross Validation, we get the estimates of Y prediction on log_price variable using 18 independent variables, and the log_price prediction for the first 5 Airbnb rentals are 5.18154003, 5.16357256, 5.03094156, 5.5143574 , 5.1471185

Using Cross Validation to Get the Mean RMS Error:

```
#Get the Mean of RMS Error for the dataframe with categorical columns
rms_error_mean(data_cat)
```

```
0.5512963783867209
```

Based on the RMSE prediction above, using 18 independent variables gives us the RMS Error of 0.5512963783867209

Based on the Correlation matrix above, we can see that the correlation between log_price and city_SF is the highest for the categorical variable (0.17).
So we decide to fit the OLS regression model using city_SF as a single independent variable and log_price as dependent variable.

OLS Regression Model on Single Independent Variable:

```
#Subset the only neccessary variables (dependent: log_price, independent: city_SF) into the new
data_cat2 = data_cat[['log_price','city_SF']]
#Fit the linear regression model on the new data_cat dataframe
#with only log_price as dependent variable and city_SF as independent variable.
#Get the summary of the new model
model_df(data_cat2.drop(['log_price'],axis=1)).summary()
```

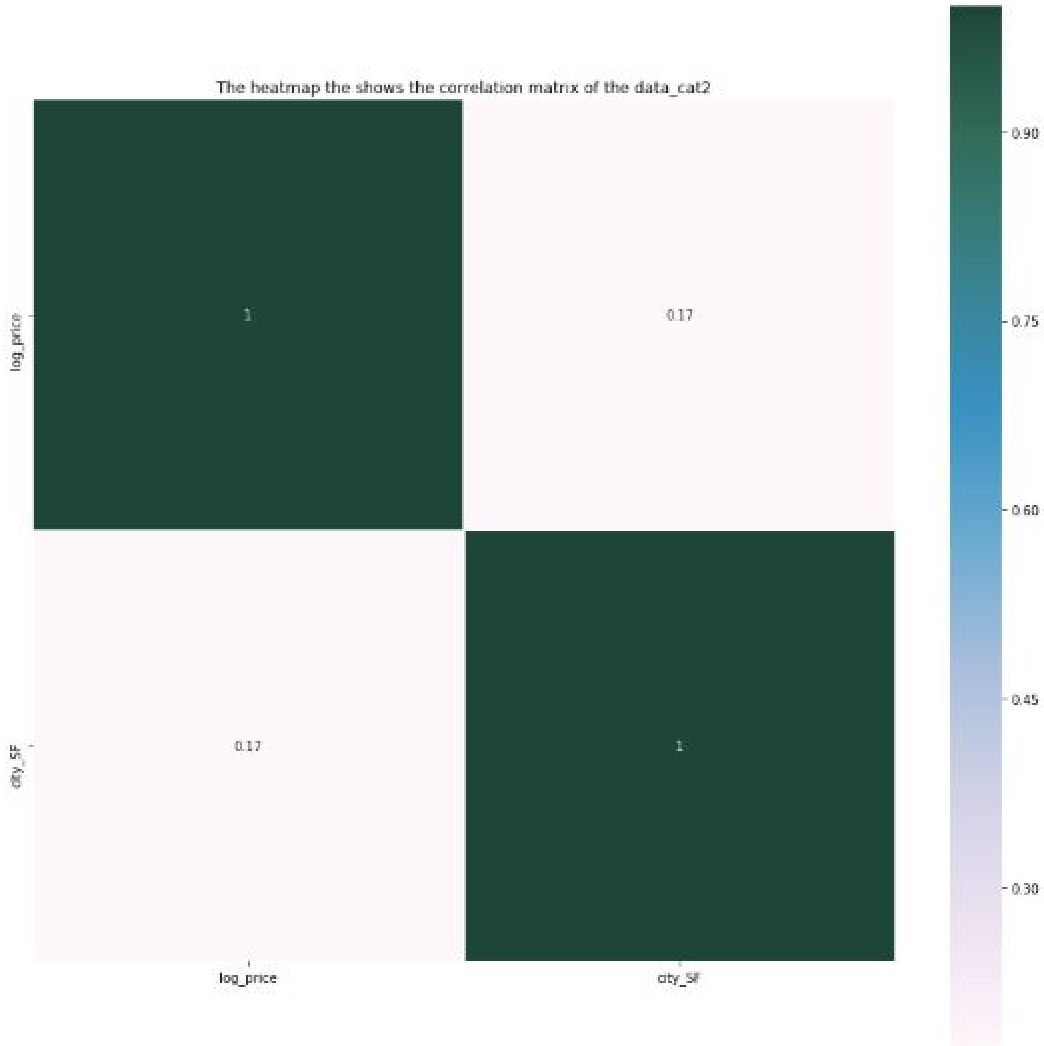
OLS Regression Results

Dep. Variable:	log_price	**R-squared:**	0.028
Model:	OLS	**Adj. R-squared:**	0.028
Method:	Least Squares	**F-statistic:**	2117.
Date:	Sun, 09 Dec 2018	**Prob (F-statistic):**	0.00
Time:	06:41:18	**Log-Likelihood:**	-79319.
No. Observations:	73923	**AIC:**	1.586e+05
Df Residuals:	73921	**BIC:**	1.587e+05
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	4.7452	0.003	1742.267	0.000	4.740	4.751
city_SF	0.4248	0.009	46.007	0.000	0.407	0.443

Omnibus:	4024.326	**Durbin-Watson:**	1.992
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	5182.127
Skew:	0.535	**Prob(JB):**	0.00
Kurtosis:	3.733	**Cond. No.**	3.58

```
#Plot the correlation matrix of the new data.
plt.figure(figsize=(15, 15))
sns.heatmap(data_cat2.corr(),linewidths=0.25,vmax=1.0,square=True,cmap="PuBuGn", linecolor='w',a
plt.title('The heatmap the shows the correlation matrix of the data_cat2')
plt.show()
```



Using Cross Validation to Predict the Estimates of Y:

```
#Predict the log_price variable using a single independent variable and show the first 5
cross_val_pre(data_cat2)[0:5]
```

```
array([4.74548765, 4.74548765, 4.74548765, 5.16881472, 4.74548765])
```

Based on the Cross Validation, we get the estimates of Y prediction on log_price variable using a single independent variable (city_SF), and the log_price prediction for the first 5 Airbnb rentals are 4.74548765, 4.74548765, 4.74548765, 5.16881472, 4.74548765

Using Cross Validation to Get the Mean RMS Error:

```
#Get the Mean of RMS Error for the dataframe with categorical columns
rmse_pred(data_cat2)
```

```
0.7075375283967854
```

Based on the RMSE prediction above, using only single independent variable (city_SF) gives us the RMS Error of 0.7075375283967854

```
mydata.log_price[0:5]
```

```
0    5.010635
1    5.129899
2    4.976734
3    6.620073
4    4.744932
```

Which OLS Regression Model to Choose that Gives the Best Results/Prediction on Y (log_price)?

Based on the two prediction for the estimates of Y using OLS Regression Model:
Using 18 independent varialbles gives us the Y estimates (first 5): 5.18154003, 5.16357256, 5.03094156, 5.5143574 , 5.1471185 with the Mean RMS Error of 0.5512963783867209.
Using a single independent varialble gives us the Y estimates (first 5):4.74548765, 4.74548765, 4.74548765, 5.16881472, 4.74548765 with the Mean RMS Error of 0.7075375283967854.
Comparing with the actual log_price rent ratio (first 5) above, Fitting the OLS Linear Regression with 18 Independent Variables gives us a better and more exact prediction of Y estimates with the lower Mean RMS Error.

REPRESENTING AN INTERACTION USING INTERACTIVE DATAFRAME BETWEEN RELATED VARIABLES:

Interactive Dataframe that represents the relationship between The Number of Reviews and The Review Score Rating:

```
#Create a new Interaction Dataframe that Adds the Review Score Rating and Numbers Columns that
inter_df= pd.DataFrame()
inter_df['number_of_reviews']=mydata['number_of_reviews']
inter_df['review_scores_rating']=mydata['review_scores_rating']
inter_df['review_num_with_ratings']=mydata['number_of_reviews']*mydata['review_scores_rating']
#Fit the linear regression model on the new inter_df dataframe
#with number_of_reviews, review_scores_rating and review_num_with_ratings as independent variab
#Get the summary of the new model
model_df(inter_df).summary()
```

OLS Regression Results

Dep. Variable:	log_price	**R-squared:**	0.008
Model:	OLS	**Adj. R-squared:**	0.008
Method:	Least Squares	**F-statistic:**	206.9
Date:	Sun, 09 Dec 2018	**Prob (F-statistic):**	1.27e-133
Time:	06:41:33	**Log-Likelihood:**	-80054.
No. Observations:	73923	**AIC:**	1.601e+05
Df Residuals:	73919	**BIC:**	1.602e+05
Df Model:	3		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	4.8815	0.005	889.638	0.000	4.871	4.892
number_of_reviews	-0.0210	0.001	-15.572	0.000	-0.024	-0.018
review_scores_rating	-0.0013	6.91e-05	-18.602	0.000	-0.001	-0.001
review_num_with_ratings	0.0002	1.43e-05	15.414	0.000	0.000	0.000

Omnibus:	3055.065	**Durbin-Watson:**	1.993
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	3682.832
Skew:	0.468	**Prob(JB):**	0.00
Kurtosis:	3.566	**Cond. No.**	8.52e+03

```
#Merging the two dataframe: data_cat and inter_df
data_cat3= pd.concat([data_cat,inter_df],axis=1)
#Fit the linear regression model on the new data_cat3 dataframe
#Get the summary of the new model
model_df(data_cat3.drop(['log_price'], axis = 1)).summary()
```

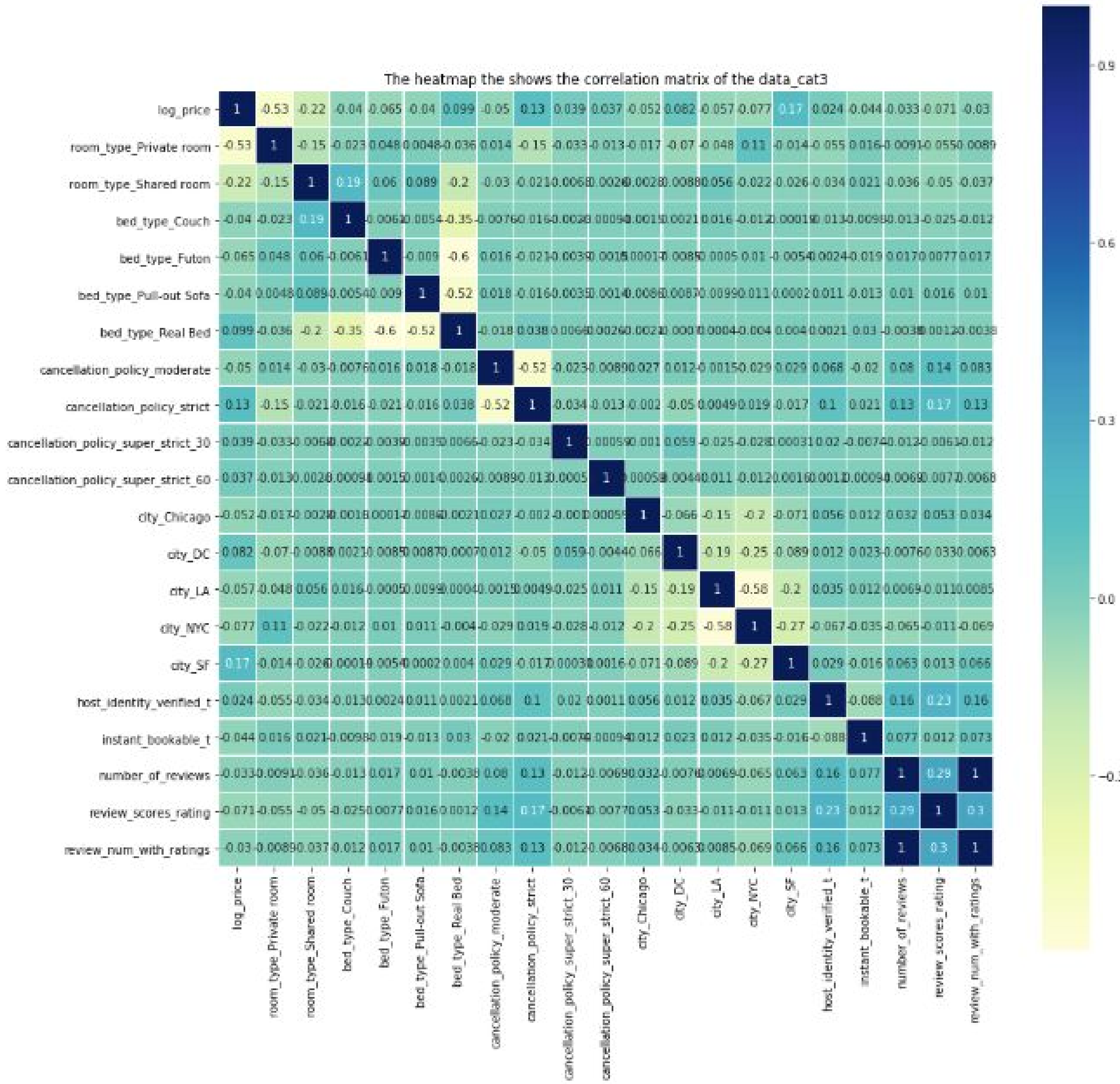
OLS Regression Results

Dep. Variable:	log_price	**R-squared:**	0.427
Model:	OLS	**Adj. R-squared:**	0.427
Method:	Least Squares	**F-statistic:**	2756.
Date:	Sun, 09 Dec 2018	**Prob (F-statistic):**	0.00
Time:	06:41:49	**Log-Likelihood:**	-59769.
No. Observations:	73923	**AIC:**	1.196e+05
Df Residuals:	73902	**BIC:**	1.198e+05
Df Model:	20		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	5.2666	0.027	194.498	0.000	5.214	5.320
room_type_Private room	-0.8259	0.004	-196.017	0.000	-0.834	-0.818
room_type_Shared room	-1.2828	0.012	-103.167	0.000	-1.307	-1.258
bed_type_Couch	0.1222	0.042	2.926	0.003	0.040	0.204
bed_type_Futon	-0.0333	0.032	-1.045	0.296	-0.096	0.029
bed_type_Pull-out Sofa	0.0121	0.034	0.360	0.719	-0.054	0.078
bed_type_Real Bed	0.0774	0.025	3.085	0.002	0.028	0.127
cancellation_policy_moderate	-0.0022	0.006	-0.383	0.702	-0.013	0.009
cancellation_policy_strict	0.1031	0.005	20.305	0.000	0.093	0.113
cancellation_policy_super_strict_30	0.2851	0.052	5.517	0.000	0.184	0.386
cancellation_policy_super_strict_60	1.3788	0.132	10.459	0.000	1.120	1.637
city_Chicago	-0.2223	0.013	-17.276	0.000	-0.247	-0.197
city_DC	0.0457	0.012	3.887	0.000	0.023	0.069
city_LA	-0.1240	0.010	-12.456	0.000	-0.143	-0.104
city_NYC	-0.0668	0.010	-6.848	0.000	-0.086	-0.048
city_SF	0.3070	0.011	26.722	0.000	0.284	0.329
host_identity_verified_t	0.0051	0.004	1.145	0.252	-0.004	0.014
instant_bookable_t	-0.0338	0.005	-7.342	0.000	-0.043	-0.025
number_of_reviews	-0.0199	0.001	-19.187	0.000	-0.022	-0.018
review_scores_rating	-0.0022	5.53e-05	-40.051	0.000	-0.002	-0.002
review_num_with_ratings	0.0002	1.1e-05	18.688	0.000	0.000	0.000

Omnibus:	8808.951	**Durbin-Watson:**	2.003
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	18339.689
Skew:	0.748	**Prob(JB):**	0.00
Kurtosis:	4.929	**Cond. No.**	2.69e+05

```
#Plot the correlation matrix of the new data.
plt.figure(figsize=(15, 15))
sns.heatmap(data_cat3.corr(),linewidths=0.25,vmax=1.0,square=True,cmap="YlGnBu", linecolor='w',annot=True)
plt.title('The heatmap the shows the correlation matrix of the data_cat3')
plt.show()
```



Using Cross Validation to Predict the Estimates of Y:

```
#Predict the log_price variable using a single independent variable and show the first 5
cross_val_pre(data_cat3)[0:5]
```

```
array([5.1654721 , 5.13577557, 5.0350876 , 5.65501961, 5.22050827])
```

Based on the Cross Validation, we get the estimates of Y prediction on log_price variable using 20 independent variables that includes the one that shows the relationship between number_of_reviews and review_scores_rating, and the log_price prediction for the first 5 Airbnb rentals are 5.1654721 , 5.13577557, 5.0350876 , 5.65501961, 5.22050827

Using Cross Validation to Get the Mean RMS Error:

```
#Get the Mean of RMS Error for the first interactive dataframe
rmse_pred(data_cat3)
```

```
0.5433327731350455
```

Based on the RMSE prediction above, using only 20 independent variables that includes the one that shows the relationship between number_of_reviews and review_scores_rating gives us the RMS Error of 0.5433327731350455

Interactive Dataframe that Represents The Relationship Between The Number of Reviews and The Review Score Rating, As Well as the Relationship Between Bathrooms, Bedrooms, and Beds:

```
#Create a new Interaction Dataframe that Adds the Bathrooms, Bedrooms, and Beds that Shows Thei
inter_df2= pd.DataFrame()
inter_df2['bathrooms']=mydata['bathrooms']
inter_df2['bedrooms']=mydata['bedrooms']
inter_df2['beds']=mydata['beds']
inter_df2['bthrm_bdrm_bd']=mydata['bathrooms']*mydata['bedrooms']*mydata['beds']
#Fit the linear regression model on the new inter_df2 dataframe
#with bathrooms, bedrooms, beds, and bthrm_bdrm_bd as independent variables.
#Get the summary of the new model
model_df(inter_df2).summary()
```

OLS Regression Results

Dep. Variable:	log_price	**R-squared:**	0.253
Model:	OLS	**Adj. R-squared:**	0.253
Method:	Least Squares	**F-statistic:**	6262.
Date:	Sun, 09 Dec 2018	**Prob (F-statistic):**	0.00
Time:	06:42:07	**Log-Likelihood:**	-69577.
No. Observations:	73923	**AIC:**	1.392e+05
Df Residuals:	73918	**BIC:**	1.392e+05
Df Model:	4		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	4.1059	0.007	630.467	0.000	4.093	4.119
bathrooms	0.1286	0.005	24.791	0.000	0.118	0.139
bedrooms	0.2500	0.004	60.610	0.000	0.242	0.258
beds	0.1251	0.003	45.297	0.000	0.120	0.130
bthrm_bdrm_bd	-0.0022	0.000	-15.004	0.000	-0.002	-0.002

Omnibus:	2333.966	**Durbin-Watson:**	2.001
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	5462.425
Skew:	0.162	**Prob(JB):**	0.00
Kurtosis:	4.292	**Cond. No.**	77.7

```
#Merging the two dataframe: data_cat3 and inter_df2
data_cat4= pd.concat([data_cat3,inter_df2],axis=1)
#Fit the linear regression model on the new data_cat4 dataframe
#Get the summary of the new model
model_df(data_cat4.drop(['log_price'], axis = 1)).summary()
```

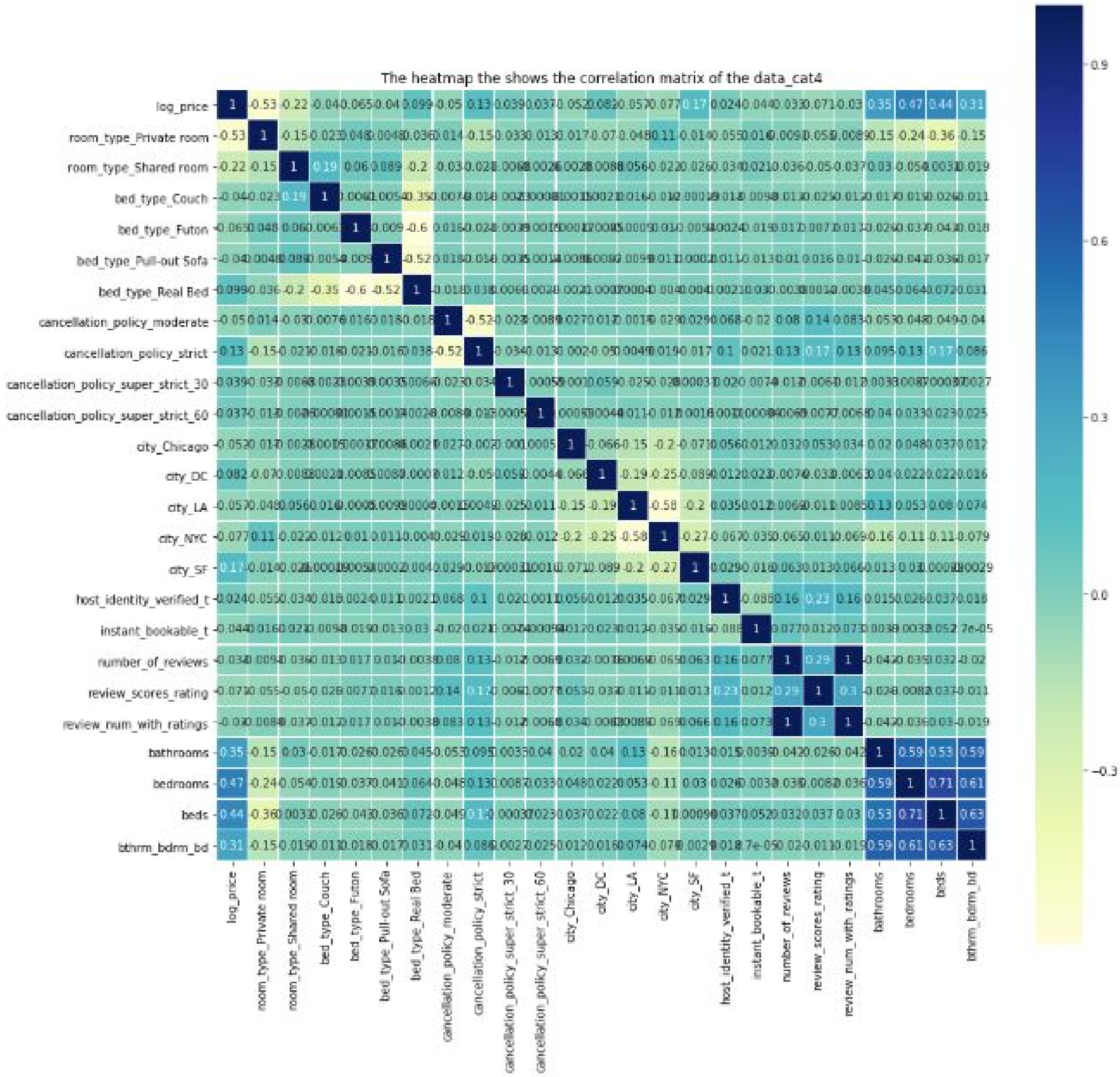
OLS Regression Results

Dep. Variable:	log_price	**R-squared:**	0.544
Model:	OLS	**Adj. R-squared:**	0.544
Method:	Least Squares	**F-statistic:**	3680.
Date:	Sun, 09 Dec 2018	**Prob (F-statistic):**	0.00
Time:	06:42:17	**Log-Likelihood:**	-51299.
No. Observations:	73923	**AIC:**	1.026e+05
Df Residuals:	73898	**BIC:**	1.029e+05
Df Model:	24		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	4.7639	0.025	193.610	0.000	4.716	4.812
room_type_Private room	-0.7022	0.004	-175.044	0.000	-0.710	-0.694
room_type_Shared room	-1.2038	0.011	-107.885	0.000	-1.226	-1.182
bed_type_Couch	0.1473	0.037	3.955	0.000	0.074	0.220
bed_type_Futon	-0.0363	0.028	-1.278	0.201	-0.092	0.019
bed_type_Pull-out Sofa	0.0464	0.030	1.550	0.121	-0.012	0.105
bed_type_Real Bed	0.0204	0.022	0.911	0.362	-0.023	0.064
cancellation_policy_moderate	-0.0126	0.005	-2.503	0.012	-0.022	-0.003
cancellation_policy_strict	0.0368	0.005	8.079	0.000	0.028	0.046
cancellation_policy_super_strict_30	0.2829	0.046	6.138	0.000	0.193	0.373
cancellation_policy_super_strict_60	0.7744	0.118	6.582	0.000	0.544	1.005
city_Chicago	-0.2630	0.011	-22.911	0.000	-0.285	-0.240
city_DC	0.0354	0.010	3.376	0.001	0.015	0.056
city_LA	-0.1486	0.009	-16.712	0.000	-0.166	-0.131
city_NYC	-0.0227	0.009	-2.605	0.009	-0.040	-0.006
city_SF	0.2929	0.010	28.591	0.000	0.273	0.313
host_identity_verified_t	0.0018	0.004	0.462	0.644	-0.006	0.010
instant_bookable_t	-0.0392	0.004	-9.518	0.000	-0.047	-0.031
number_of_reviews	-0.0208	0.001	-22.509	0.000	-0.023	-0.019
review_scores_rating	-0.0020	4.94e-05	-40.276	0.000	-0.002	-0.002
review_num_with_ratings	0.0002	9.81e-06	22.352	0.000	0.000	0.000
bathrooms	0.1685	0.004	41.054	0.000	0.160	0.177
bedrooms	0.1984	0.003	60.960	0.000	0.192	0.205
beds	0.0312	0.002	13.638	0.000	0.027	0.036
bthrm_bdrm_bd	-0.0007	0.000	-6.184	0.000	-0.001	-0.000

Omnibus:	7625.387	**Durbin-Watson:**	2.010
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	21978.805
Skew:	0.564	**Prob(JB):**	0.00
Kurtosis:	5.421	**Cond. No.**	2.69e+05

```
#Plot the correlation matrix of the new data.
plt.figure(figsize=(15, 15))
sns.heatmap(data_cat4.corr(),linewidths=0.25,vmax=1.0,square=True,cmap="YlGnBu", linecolor='w',annot=True)
plt.title('The heatmap the shows the correlation matrix of the data_cat4')
plt.show()
```



Using Cross Validation to Predict the Estimate of Y:

```
#Predict the log_price variable using 24 independent variables and show the first 5
cross_val_pre(data_cat4)[0:5]
```

```
array([4.99987162, 5.42073906, 4.98276235, 5.69938209, 4.83734156])
```

Based on the Cross Validation, we get the estimates of Y prediction on log_price variable using 24 independent variables that includes the one that shows the relationship between number_of_reviews and review_scores_rating, as Well as the Relationship Between

Bathrooms, Bedrooms, and Beds, and the log_price prediction for the first 5 Airbnb rentals are 4.99987162, 5.42073906, 4.98276235, 5.69938209, 4.83734156

Using Cross Validation to Get the Mean RMS Error:

```
#Get the Mean of RMS Error for the first interactive dataframe
rmse_pred(data_cat4)
```

```
0.4845555842193157
```

Based on the RMSE prediction above, using only 24 independent variables that includes the one that shows the relationship between number_of_reviews and review_scores_rating, as Well as the Relationship Between Bathrooms, Bedrooms, and Beds, gives us the RMS Error of 0.4845555842193157

Which OLS Regression Model to Choose that Gives the Best Results/Prediction on Y (log_price) Using Interactive Dataframe?

Based on the two prediction for the estimates of Y using OLS Regression Model:
Using 20 independent varialbles gives us the Y estimates (first 5): 5.1654721 , 5.13577557, 5.0350876 , 5.65501961, 5.22050827 with the Mean RMS Error of 0.5433327731350455.
Using 24 independent varialbles gives us the Y estimates (first 5): 4.99987162, 5.42073906, 4.98276235, 5.69938209, 4.83734156with the Mean RMS Error of 0.4845555842193157.
Comparing with the actual log_price rent ratio (first 5) , Fitting the OLS Linear Regression with 24 Independent Variables Using interactive dataframe gives us a better and more exact prediction of Y estimates with the lower Mean RMS Error.
The model with 24 independent variables using the interactive dataframe is the best model, not to mention it has the highest R2 value out of all models fitted.

**FITTING LOGISTIC REGRESSION MODEL:

```
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
#Assign the data_cat dataframe into new dataframe used for classification
class_df = data_cat
#Based on the mean of the log price of the data_cat df, assign the value 0 or 1 to the class_df
class_df.loc[class_df.log_price > np.mean(data_cat.log_price), 'log_price'] = 1
class_df.loc[class_df.log_price <= np.mean(data_cat.log_price), 'log_price'] = 0
#Create 2 dataframe, one for Y(dependent variable), one for X(independent variables)
class_df_targety= class_df['log_price']
class_df_x=class_df.drop(['log_price'],axis=1)
```

```
#Using the train_test_split function to split the testing and training data for X and Y datafra
x_training, x_testing, y_training, y_testing = train_test_split(class_df_x, class_df_targety, te
#Fit the logistic regression on the training and testing dataset of X and Y
log_model= LogisticRegression()
log_fit = log_model.fit(x_training.astype(int),y_training.astype(int))
```

Predicting the Probability of A dependent variable (Y):

```
from sklearn.metrics import classification_report
#Using the predict() function to predict the y estimates based on the testing set of X
prediction_y = log_model.predict(x_testing.astype(int))
#Building a text report showing the main classification metrics
print(classification_report(y_testing.astype(int), prediction_y.astype(int)))
print('The Logistic Regression Classifier on the testing set has the accuracy of : {:.2f}'.form
```

```
             precision    recall  f1-score   support

          0       0.74      0.86      0.80      7137
          1       0.85      0.72      0.78      7648

avg / total       0.80      0.79      0.79     14785

The Logistic Regression Classifier on the testing set has the accuracy of : 0.79
```

Evaluating the Accuracy of a Logistic Regression Classification Using Confusion Matrix:

```
from sklearn.metrics import confusion_matrix
#Find the confusion matrix that evaluates the accuracy of the classification
confusion_matrix = confusion_matrix(y_testing.astype(int), prediction_y.astype(int))
confusion_matrix
```

```
array([[6138,  999],
       [2109, 5539]])
```

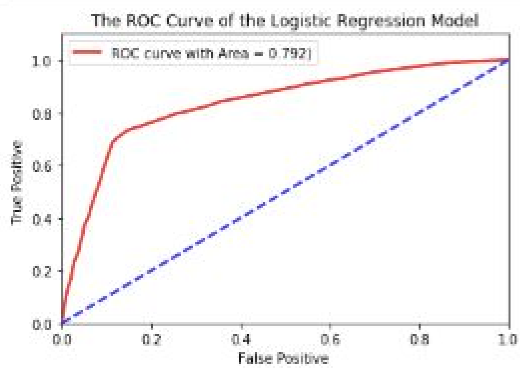
Based on the Confusion Matrix obtained above, we can conclude that:
There are 6138 + 5539 = 11677 correct predictions and there are 999 + 2109 = 3108 incorrect predictions using Logistic Regression classification.

Plot the ROC Curve of a Logistic Regression Classification Model:

```
from sklearn.metrics import roc_curve, roc_auc_score
#Computing false, true positive rates and the thresholds using roc_curve() function
fpr, tpr, thresholds = roc_curve(y_testing.astype(int), log_model.predict_proba(x_testing.astype
#Computing the Area Under the Receiver Operating Characteristic Curve (ROC AUC) from prediction
area_under_roc_auc = roc_auc_score(y_testing.astype(int), log_model.predict(x_testing.astype(int
print('The Area under the ROC AUC from the prediction scores is : ', area_under_roc_auc)
```

```
The Area under the ROC AUC from the prediction scores is :  0.792133426240061
```

```
#Make the plot that shows the ROC curve of the logistic regression model
plt.figure()
plt.plot(fpr, tpr, color='red', lw=2, label='ROC curve with Area = %0.3f)' % area_under_roc_auc)
plt.plot([0, 1], [0, 1],color='blue', lw=2, linestyle='--')
plt.xlabel('False Positive ')
plt.ylabel('True Positive ')
plt.title('The ROC Curve of the Logistic Regression Model')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.10])
plt.legend(loc = 'top')
plt.show()
```



Based on the ROC Curve of the Logistic Regression model above:
The blue line shows the ROC curve of a random classifier while a red line shows the ROC curve with the area under the ROC curve of the logistic model (Area = 0.792).
The further the ROC curve(red line) is from the blue line, the better the logistic regression model is.