Airbnb Price Prediction Challenge

CMP461 - Big Data

[Phase 2]

Team no. 5

Team members

Khaled Amgad
Section:1, B.N.:15
khaled.mohamed98@eng-st.cu.edu.eg

Sofyan Mahmoud
Section:1, B.N.:25
sofyan.alsayed98@eng-st.cu.edu.eg

Mohamed Mokhtar
Section:2, B.N.:17
mohamed.mahmoud98@eng-st.cu.e…

Nour Nasser
Section:2, B.N.:30
nour.mohamed98@eng-st.cu.edu.eg

Table of Contents

Problem definition

Airbnb, Inc. operates an online marketplace for lodging, primarily homestays for vacation rentals, and tourism activities. It is based in San Francisco, California.
Our problem is going to be analysis and exploration on the given dataset we provided in the proposal and modeling the data in order to predict the price of an instance.

Data overview

The dataset consists of 74,111 entries, splitted into the following groups of data types.

Attributes description

Name	type	description
property_type	CATEG.	the instance type e.g. apartment, bed or house, etc.
room_type	CATEG.	type of the room, e.g. shared room or entire house.
bed_type	CATEG.	type of the bed e.g. real bed or sofa.
cancellation_policy	CATEG.	description if you want to cancel reservations e.g strict.
city	CATEG.	the name of the city where property there.
neighbourhood	CATEG.	neighbourhood city/popular place name.
host_since	DATE	date of the host creation account.
first_review	DATE	data of the review of the first guest made.
last_review	DATE	last date of the review on this property.
name	STRING	title of the property.
description	STRING	the host description about the property.
thumbnail_url	STRING	picture url of the property.
Id	INT	unique identifier for each instance of a host.
accommodates	INT	number of people can live in the property.
bathrooms	INT	number of bathrooms in the property.
host_response_rate	INT	percentage of the response rate of the host.
bedrooms	INT	number of bedrooms on the house/property.
beds	INT	number of beds on the property.
number_of_reviews	INT	number of reviews on this property.
zipcode	INT	postal code for this property.
log_price	FLOAT	logarithm value of the price of each item.
latitude	FLOAT	coordinates at geographic coordinate system.
longitude	FLOAT	coordinates at geographic coordinate system.
review_scores_rating	FLOAT	score rate on this property.
cleaning_fee	BOOL	whether there is a fee for cleaning or not.
host_has_profile_pic	BOOL	whether the host has a profile picture or not.
host_identity_verified	BOOL	whether the host has verified id on the website or not.
instant_bookable	BOOL	whether you can book this instance or not.
amenities	ARRAY	list of entertainment objects in the property e.g. WIFI.

Data Exploration and Visualization

In this section, we will go through the most important and non clear attributes to describe what values are available for it. First will discuss the object attributes then the numerical and boolean and finally the array

Categorical type attributes

Property type

This attribute can be one of the following which described on the bar plot values, describes the host's instance type and their occurrences

Stats and top property type

Unique	35
Top	Apartment
Freq	49003

Top 5 frequent property types

1. Apartment
2. House
3. Condominium
4. Townhouse
5. Loft

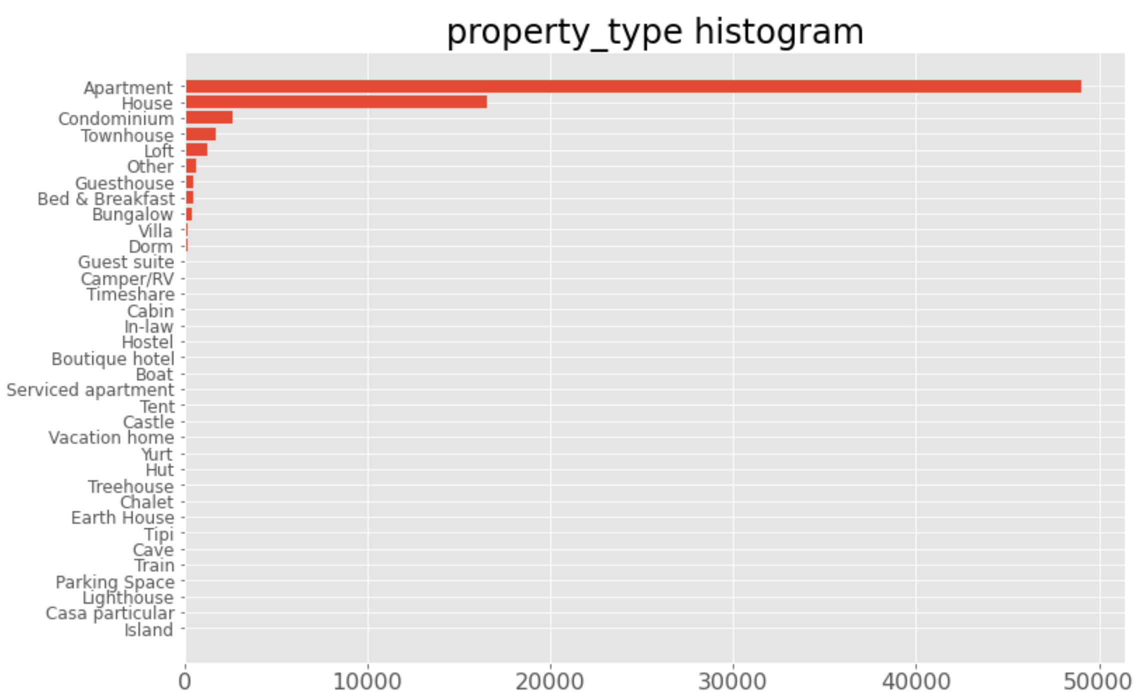


Fig. 1 Property type bar plot

Room type

This attribute can be 'Entire home/apt' or 'Private room' or 'Shared room' as we can see that from the bar plot described below

Stats and top room type

Unique	3
Top	Entire home/apt
Freq	41310

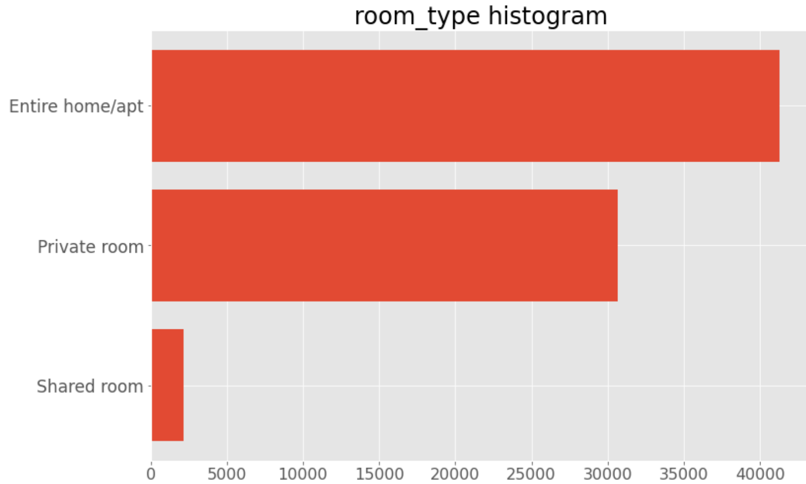


Fig. 2 Room type bar plot

Bed type

Stats and top bed type

Unique	5
Top	Real Bed
Freq	72028

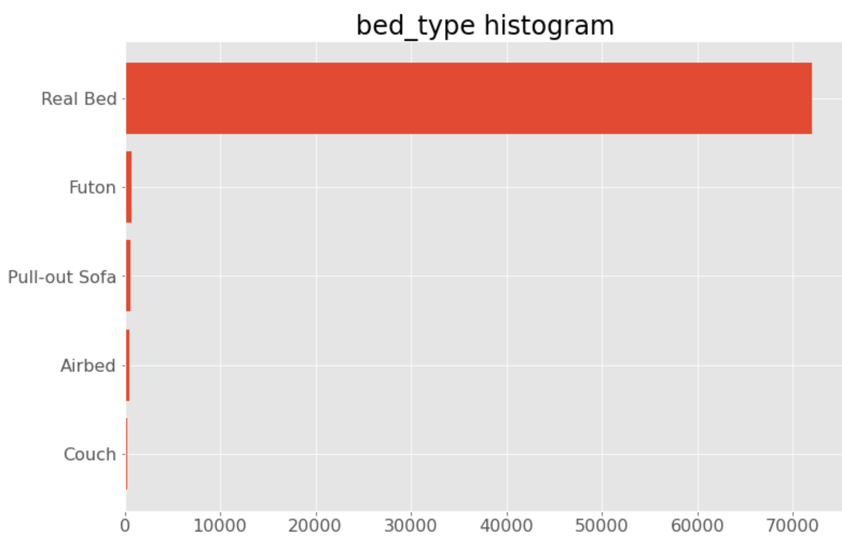


Fig. 3 Bed type histogram

Cancelation policy

The following is pie chart shows the different types of cancellation policies exist, it can be one of the following ['strict', 'flexible', 'moderate', 'super_strict_30', 'super_strict_60']

Stats and top cancelation policy

Unique	5
Top	strict
Freq	32374

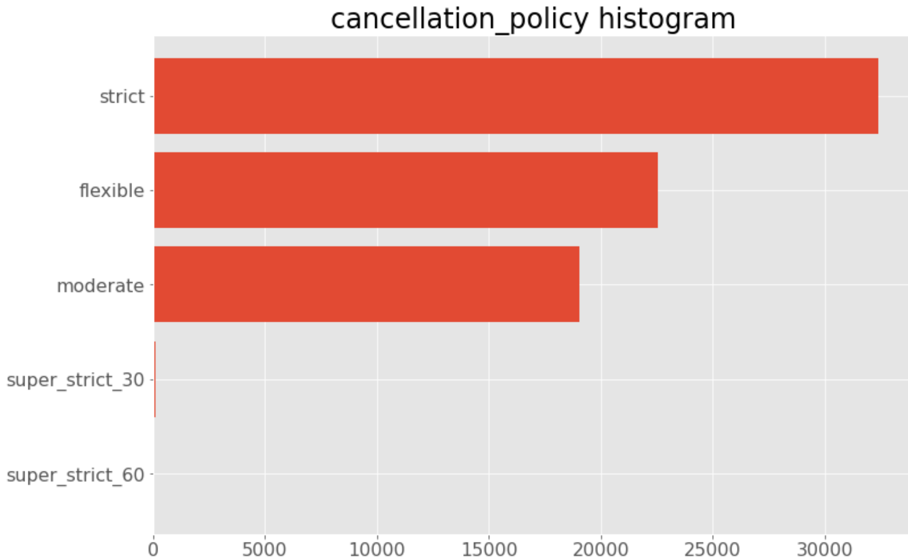


Fig. 4 cancelation policy histogram

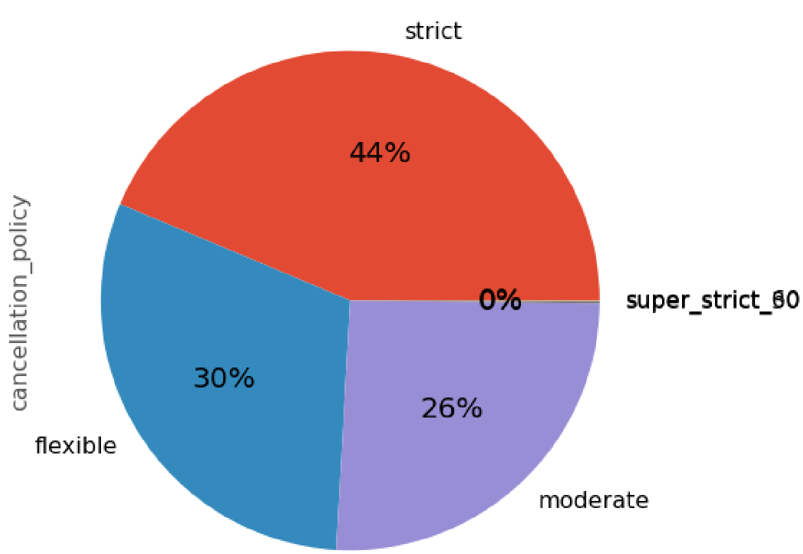


Fig. 5 cancelation policy pie chart

City

The city where the property exists we find that is categorical and have the following attributes as mentioned on the plots

Stats and top city

Unique	6
Top	NYC
Freq	32349

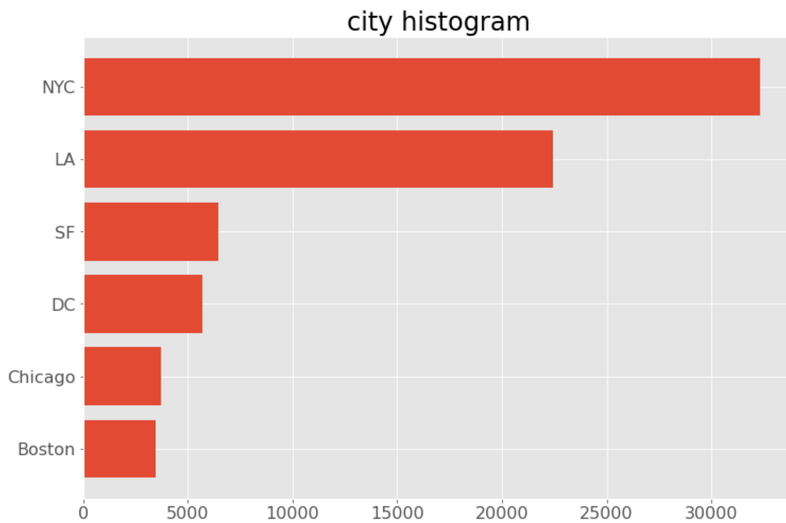


Fig. 6 city histogram

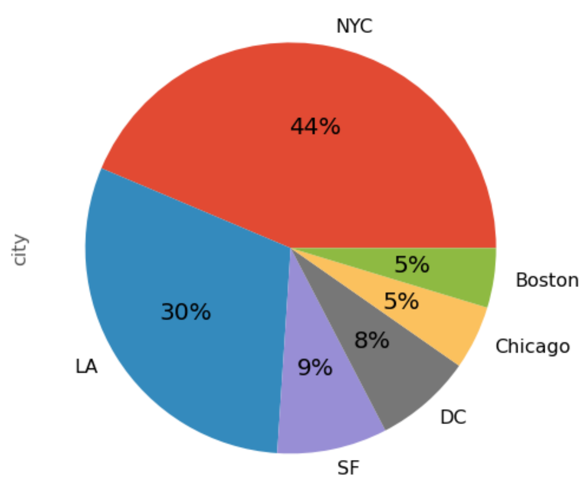


Fig. 7 city pie chart

Neighbourhood

Stats and top neighbourhood

Unique	619
Top	Williamsburg
Freq	2862

Top 5 neighbourhood

1. Williamsburg
2. Bedford-Stuyvesant
3. Bushwick
4. Upper West Side
5. Mid-Wilshire

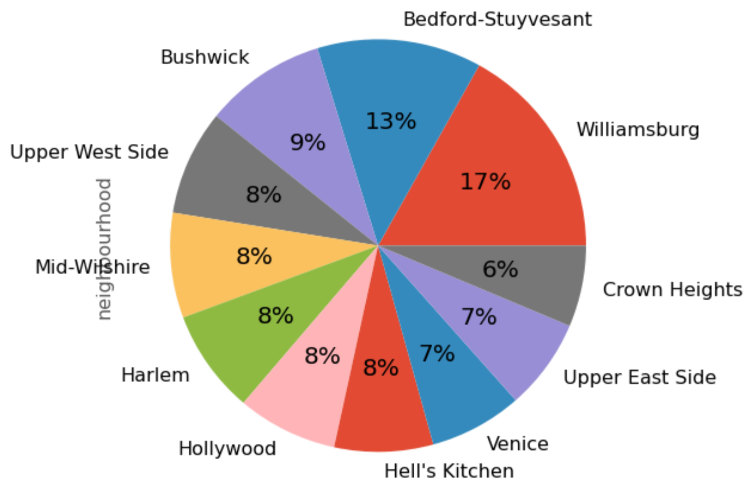


Fig. 8 neighbourhood places has more than 1000 frequency pie chart

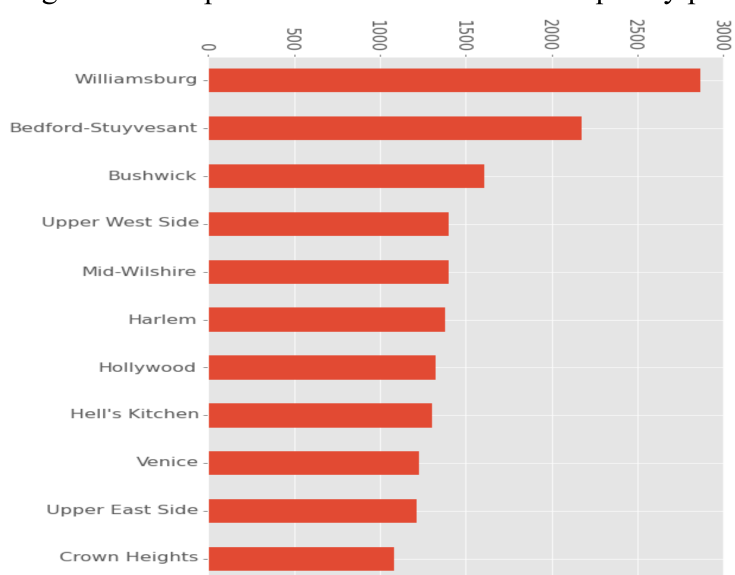


Fig. 9 neighbourhood places has more than 1000 frequency bar chart

Date type attributes

Host since

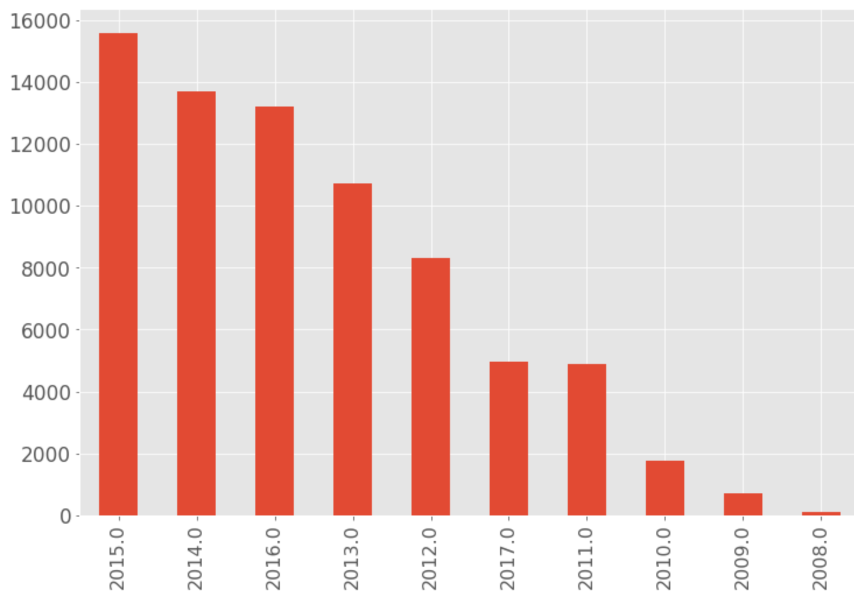


Fig. 10 frequency of host since years of hosts created

First review

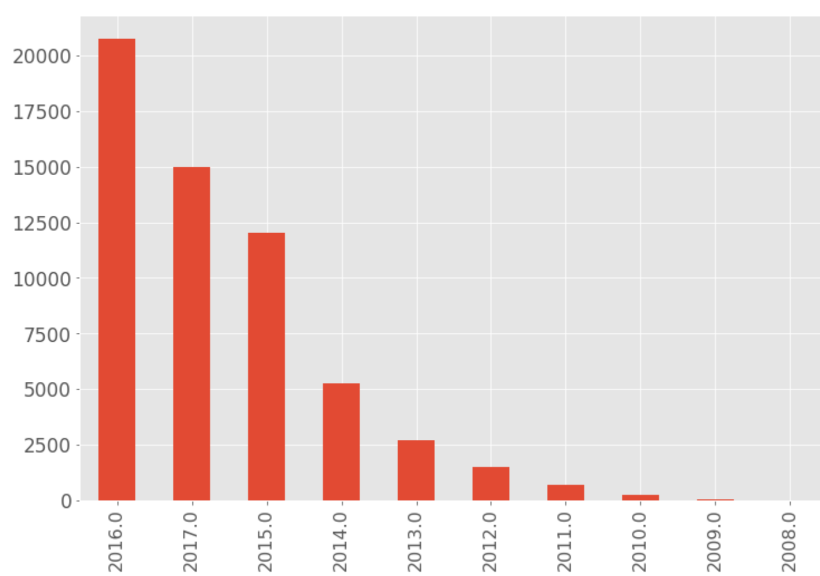


Fig. 11 histogram of years of first reviews

Last review

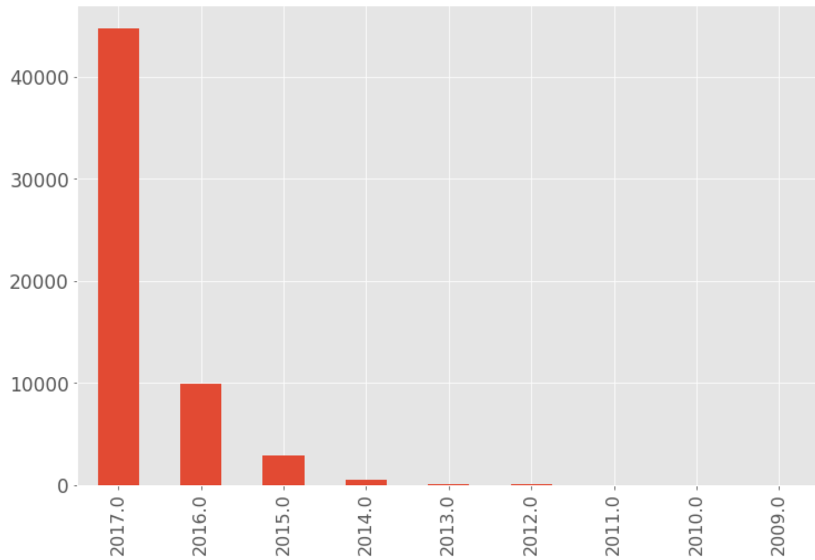


Fig. 12 neighbourhood places has more than 1000 frequency bar chart

Numerical type attributes

Accommodates

Number of people can live in the property.
We can see that most of the property instances / apartments has 2 accommodates available.

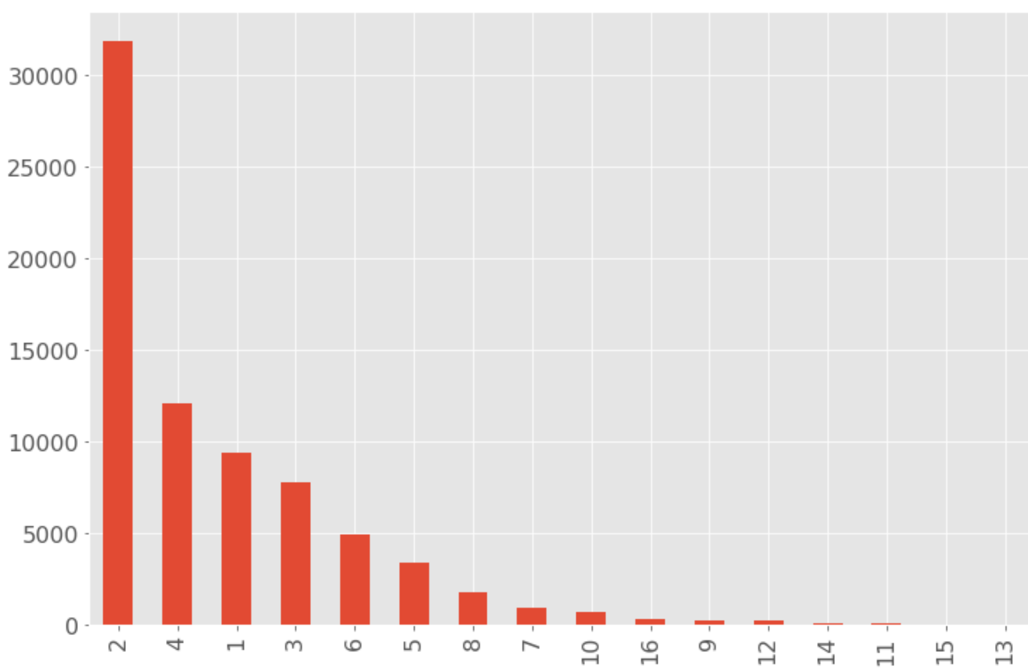


Fig. 13 Number of instances has available accommodates count

Bathrooms

Number of bathrooms in the property.

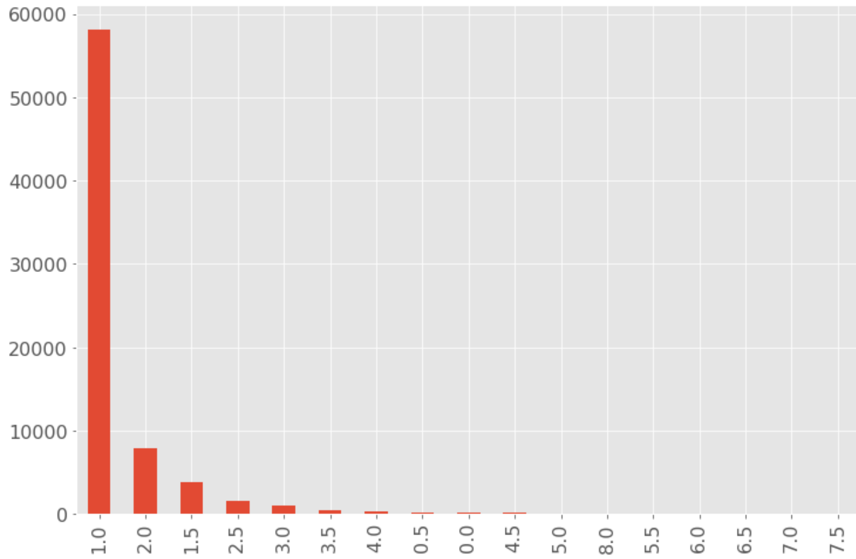


Fig. 14 property count (y-axis) and bathrooms count (x-axis)

Host response rate

Percentage of the response rate of the host.

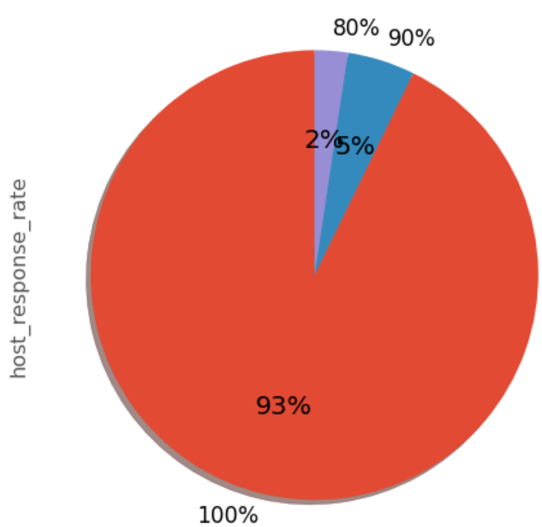


Fig. 15 Top 3 responses rates percentage

Bedrooms

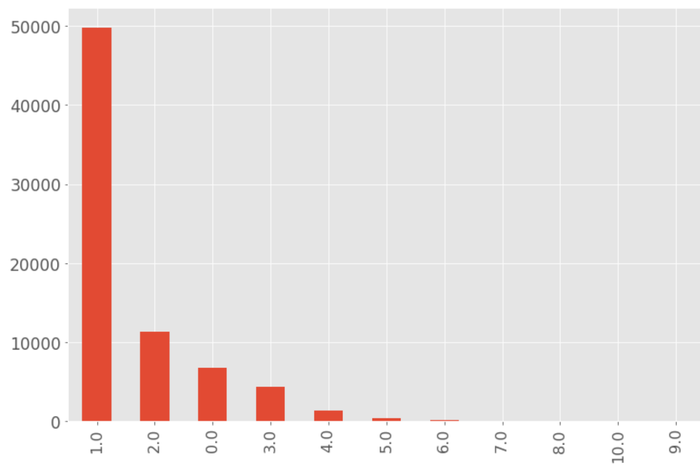


Fig. 16 Number of bedrooms (x-axis) count, frequency; Most frequent bedrooms count is 1

Beds

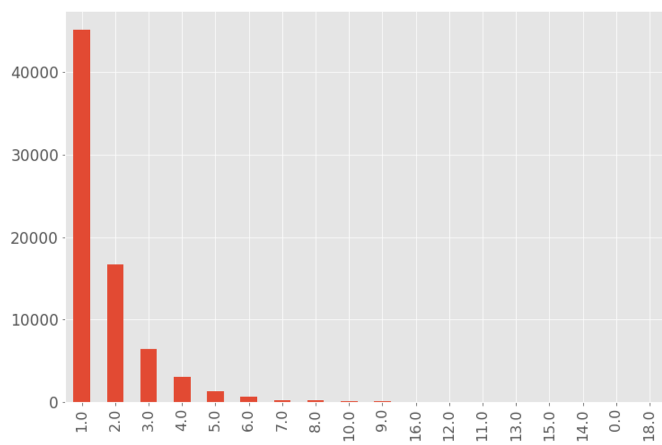


Fig. 16 Number of bed (x-axis) count, frequency; Most frequent beds count is 1

Number of reviews

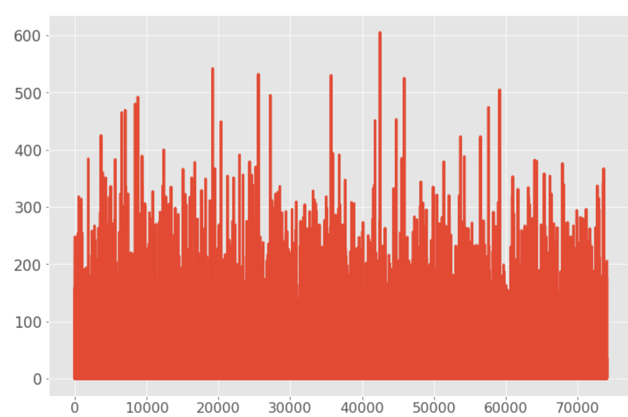


Fig. 18 Number of reviews for each property id

Log price

logarithm value of the price of each item

Stats

mean	4.782069	std	0.717394
min	0.000000	max	7.600402

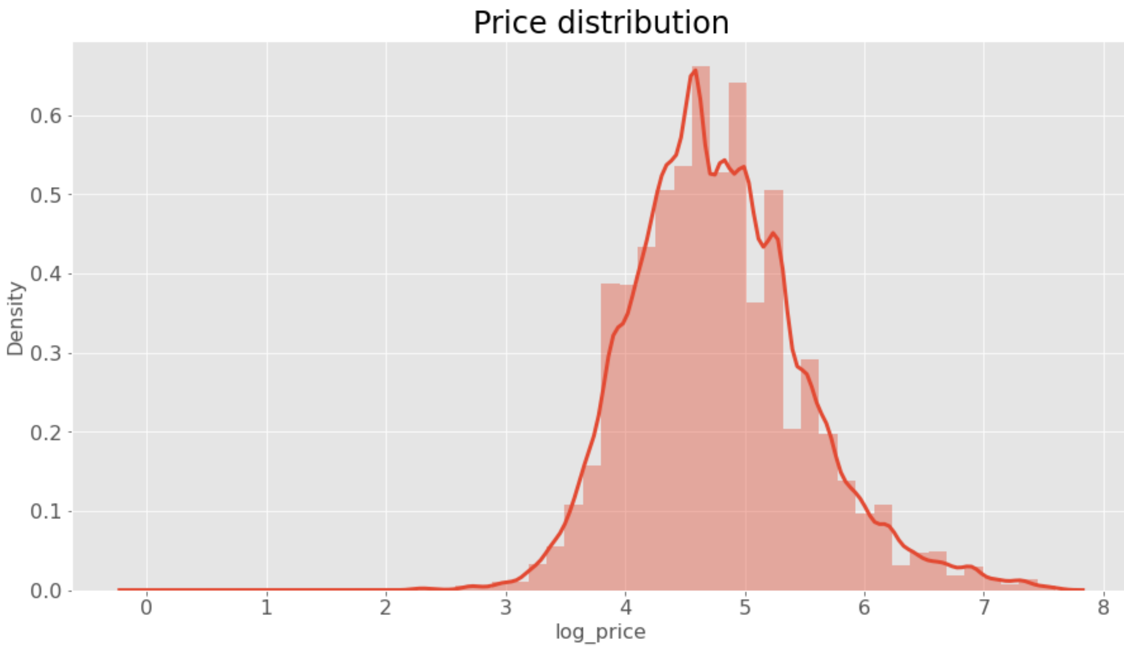


Fig. 19 Distribution of the log pricey field on all data

Review scores rating

Score rate on each property

Stats

mean	94.067365	std	7.836556
min	20.000000	max	100.000000

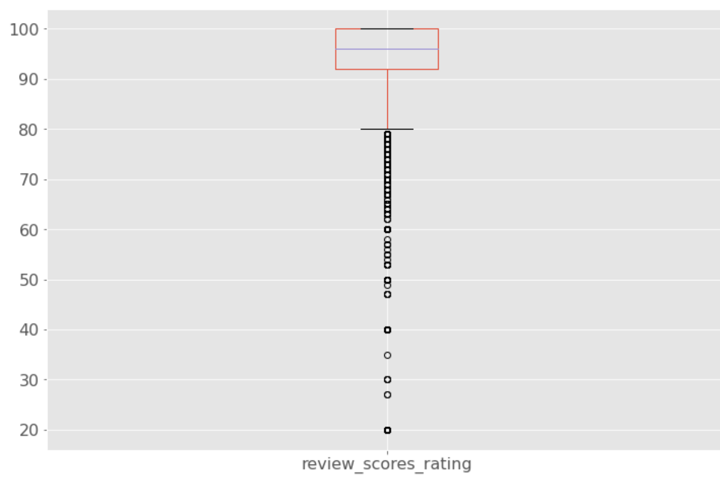


Fig. 20 Box plot for review scoring rate

Boolean type attributes

Cleaning fee

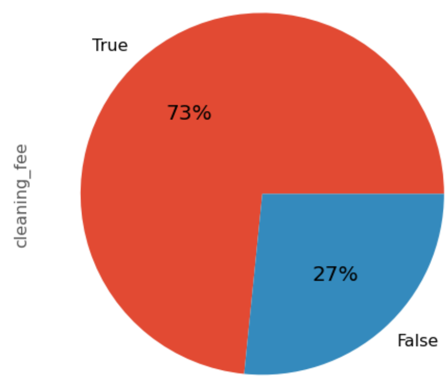


Fig. 21 Cleaning fees pie chart

Host has profile picture

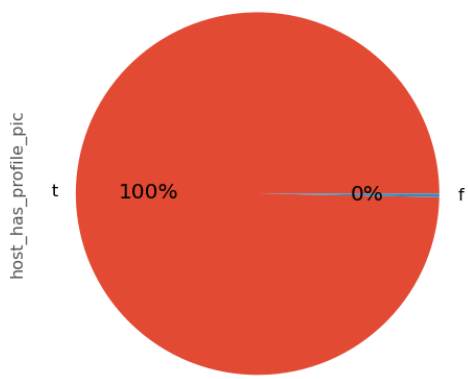


Fig. 22 Host has profile picture pie chart

Host identity verified

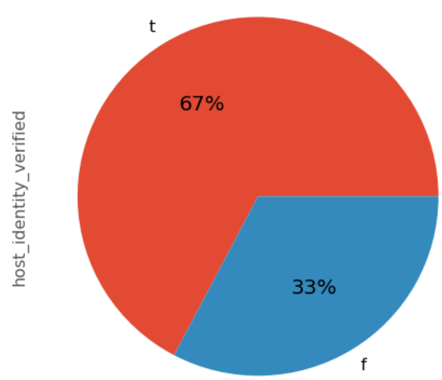


Fig. 23 Host has identity verified

Instant bookable

whether you can book this instance or not in the current time.

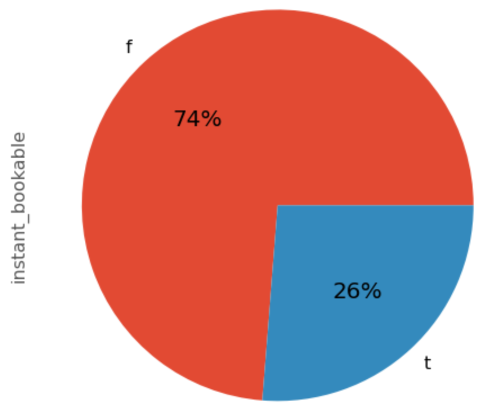


Fig. 24 Instant bookable pie chart

Composite type attributes

Amenities

For each property there is a list of entertainment objects and amenities in the property e.g. [WIFI, telephone, washing machine, etc.]
Here is the following are the set of items can be exist on those arrays
Those are top 20 attributes
We can conclude that Wireless Internet and Kitchen are the most two supported in any property

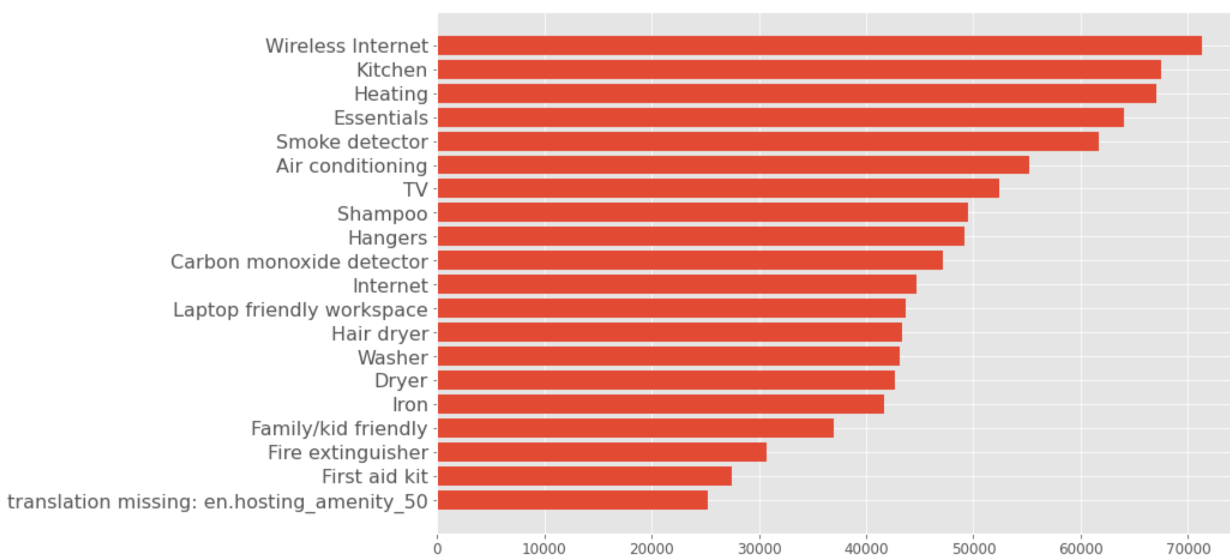
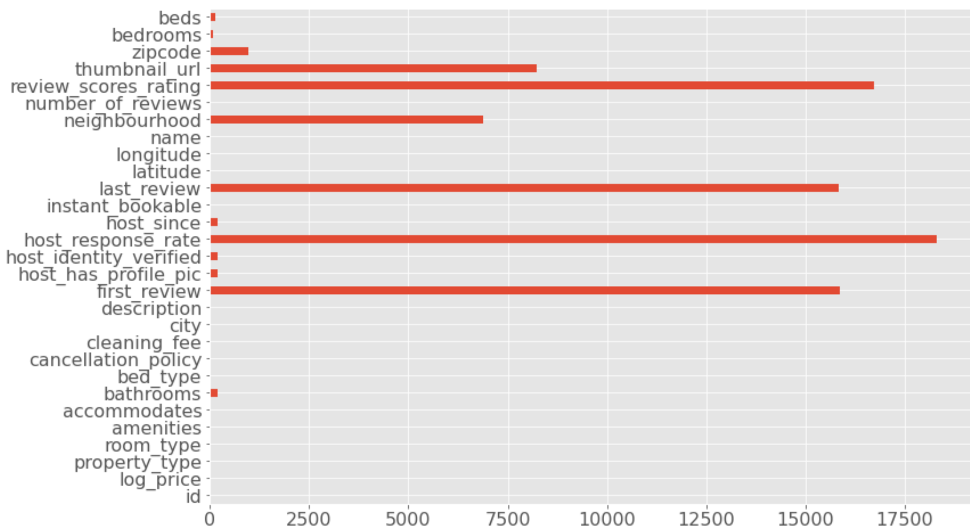


Fig. 25 Amenities array items spreaded and their frequencies

Pre-processing and Features Extraction

Missing data columns stats and Handling

We notice that the range of missing data is maximum about 18,000 and it is recorded in host response rate which can be replaced with the mean of the rest values as well as the numerical values can be replaced with their column's mean.




```
id                            0
log_price                     0
property_type                 0
room_type                     0
amenities                     0
accommodates                  0
bathrooms                   200
bed_type                      0
cancellation_policy           0
cleaning_fee                  0
city                          0
description                   0
first_review              15864
host_has_profile_pic        188
host_identity_verified      188
host_response_rate        18299
host_since                  188
instant_bookable              0
last_review               15827
latitude                      0
longitude                     0
name                          0
neighbourhood              6872
number_of_reviews             0
review_scores_rating      16722
thumbnail_url              8216
zipcode                     966
bedrooms                     91
beds                        131
```

Fig. 26 Null entries of each column count

Remove not needed columns which is not related to our problem it

The following list are the columns will be dropped

1. Id
2. Description
3. First review
4. Last review
5. Host since
6. Host has profile picture
7. Name
8. Thumbnail url
9. Zip code
10. Neighbourhood

Regarding the description and the name and any textual field if first review and last review text are provided, we can mention a method of making use of those columns and it may be used in our future plan as well. We can make sentiment analysis on them and replace both of them with a boolean representing whether this review was positive or negative. The rest of variables are removed for simplicity like neighbourhood and the dates above because it has a wide range of values.

Heatmap and correlation between the numerical data

Dependency and correlation between attributes and each other and extract more information about the data and select the attributes to be used in price prediction. (On data before preprocessing)

Fig. 27 Heatmap of correlation between columns and each other

Handling categorical and composite attributes

The only composite attribute we have is the amenities and it is a string represents a list of additional features/entertainment objects on the property, so to represent that in our data, we have used the count of those list to represent that variable

Normalization and splitting the dataset

In this part we will make the data normalization wherever it is needed in order to use it for some models that require this step. Data is splitted into 80% training and 20% validation.

Data associations and Insights

Longitude and latitude with respect to price heat location map

Here we see the most expensive apartments who are on the side of the see

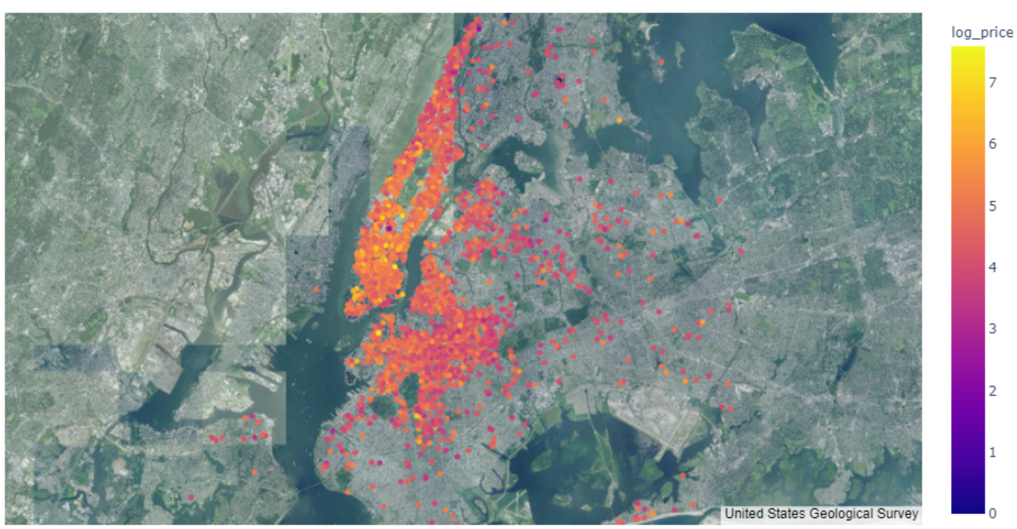


Fig. 28 New york city with longitude and latitude heated with prices

Relation between price and city

Fig. 29 Insights between cities and the price (relation)

Relation between price and cancellation policy

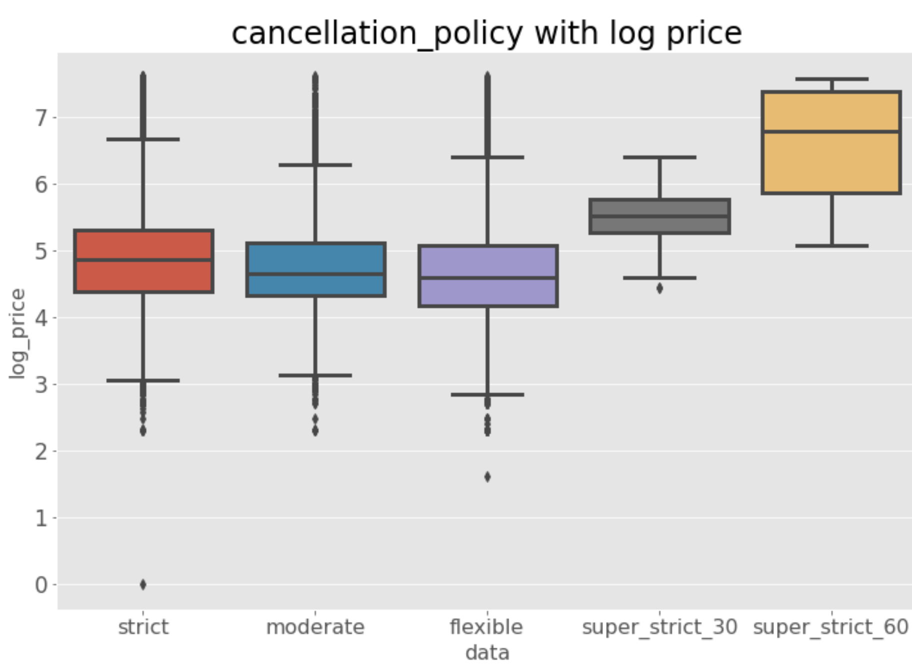


Fig. 30 Insights between cancelation policy and the price (relation)

Relation between price and bed type

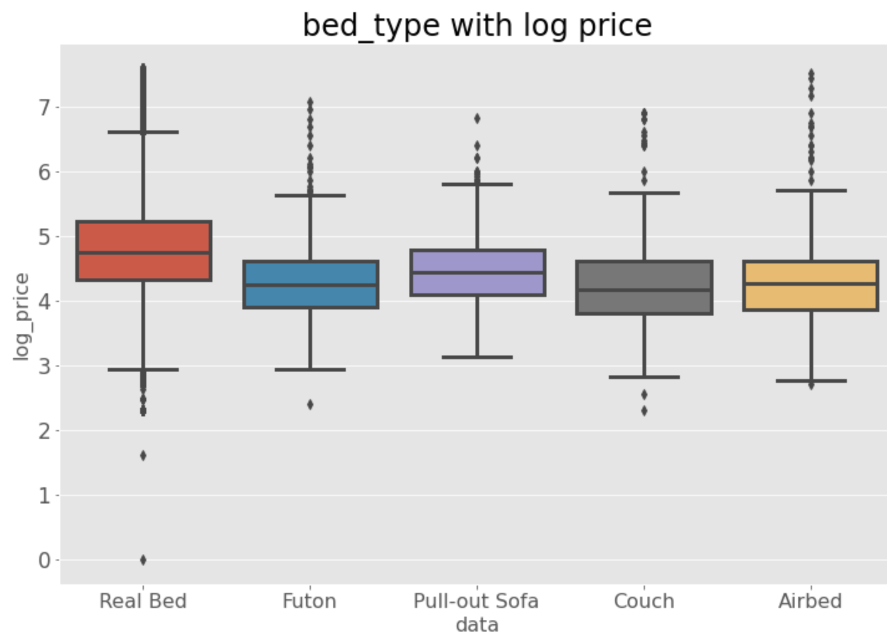


Fig. 31 Insights between bed types and the price (relation)

Relation between price and room type

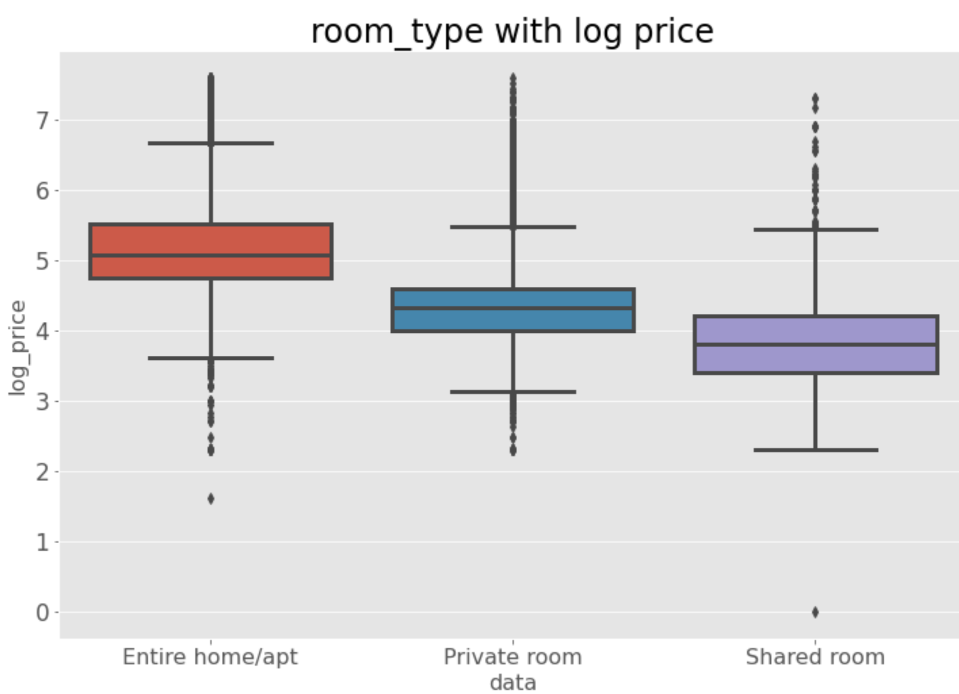


Fig. 32 Insights between room types and the price (relation)

Support of some of common property types

Most common type is apartment

```
Support of Apartment 0.661210886373143
Support of House 0.22278744046093021
Support of Condominium 0.03586512123706333
Support of Loft 0.01678563236226741
Support of Townhouse 0.022830618936460174
Support of Hostel 0.0009445291522176195
Support of Guest suite 0.0016596726531823887
```

Support of city variable on the dataset

Most common city is New york city

```
['NYC' 'SF' 'DC' 'LA' 'Chicago' 'Boston']
Support of NYC 0.43649390778696817
Support of SF 0.08681572236240234
Support of DC 0.07674974025448314
Support of LA 0.302964472210603
Support of Chicago 0.050181484529961816
Support of Boston 0.04679467285558149
```

Support of boolean variables and their associations

Cleaning fee is very common on most of the dataset and the host is being identified

support	itemsets
0.734075	(cleaning_fee)
0.671263	(host_identity_verified)
0.262458	(instant_bookable)
0.526359	(host_identity_verified, cleaning_fee)
0.194613	(instant_bookable, cleaning_fee)
0.158168	(host_identity_verified, instant_bookable)
0.126837	(host_identity_verified, instant_bookable, cle...

Model selection and tuning and Results

The best outcome came for the **XGBoost regressor**, and got a very good MSE with respect to the published ones on the competition and near to some of them and higher than some others which is good as well as we have tried **RandomForestRegressor** and tuning done on it had very similar results but was a bit less than it as well as trying **Linear Regression** but it was less than them.

Training MSE: 0.2005
Validation MSE: 0.201

Training r2: 0.6092
Validation r2: 0.6139

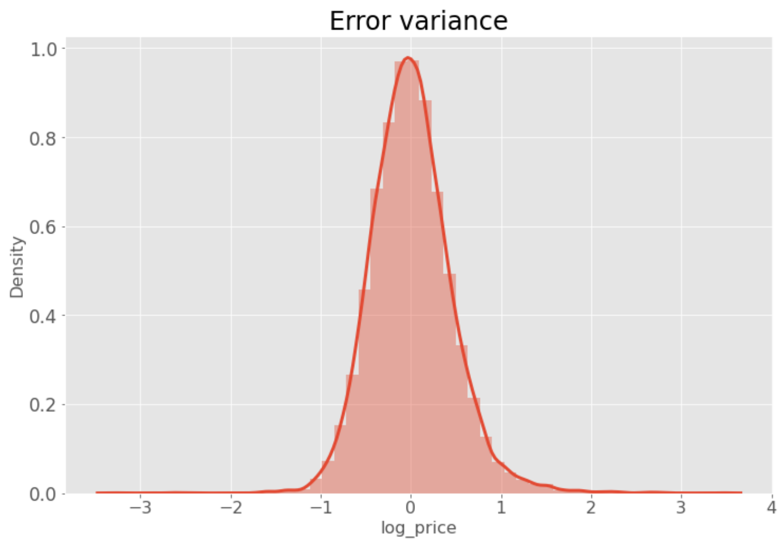


Fig. 30 Error variance of the XGBoost regressor

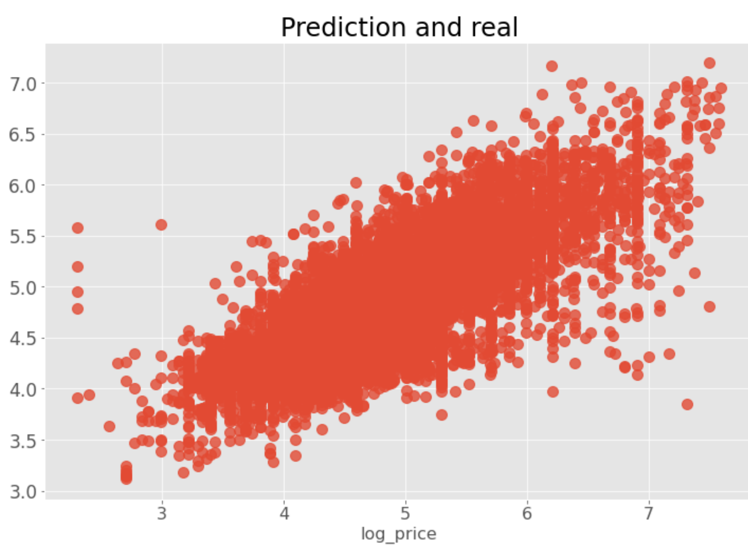


Fig. 31 Predicted price versus real price scatter plot

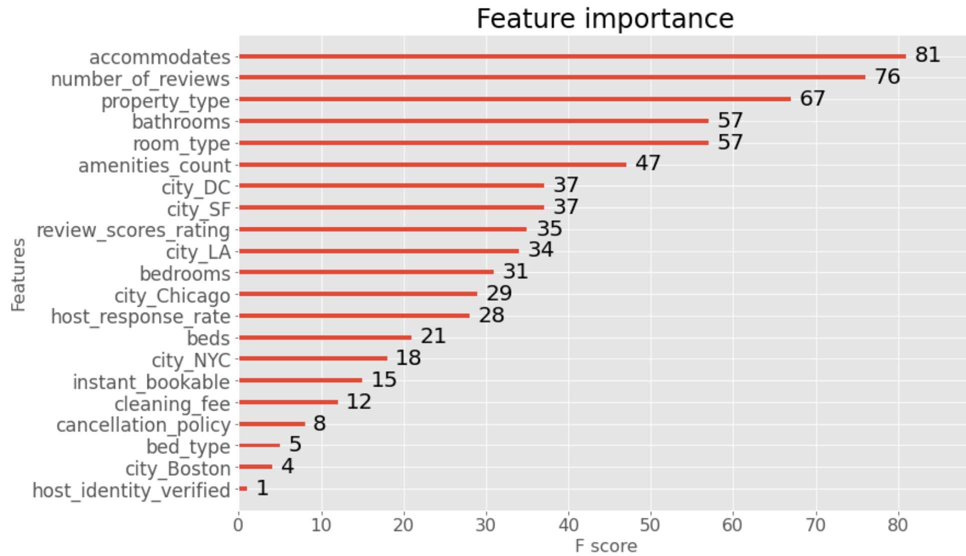


Fig. 32 Features importance on each used feature on XGboost regressor

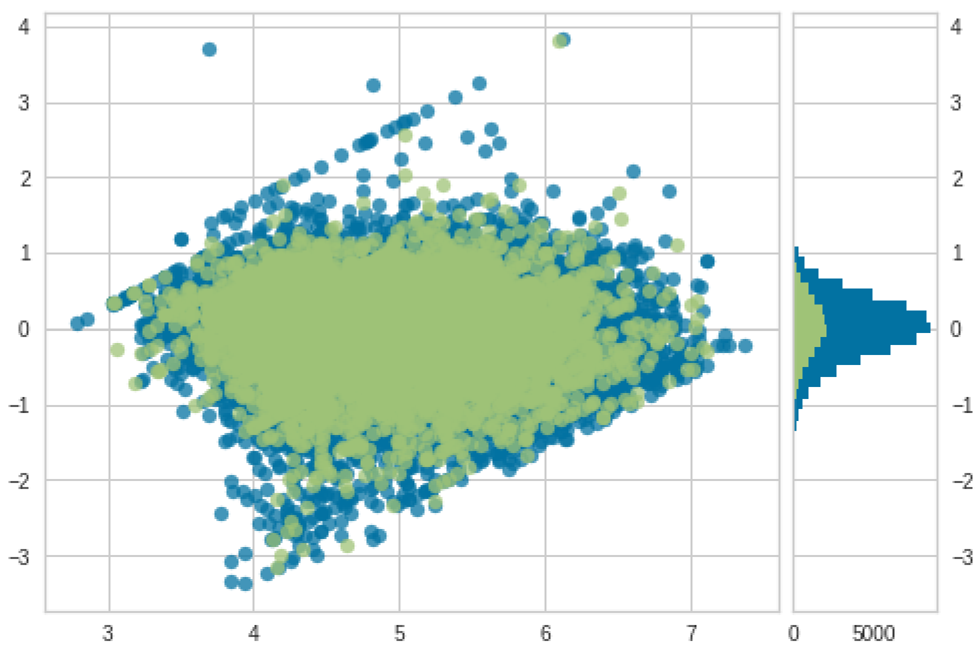


Fig. 33 Residual plot for the validation (green) and training (blue) data and their variance

Future work

- Use reviews dataset on each property and making sentiment analysis on them in order to add new feature to each property
- Using more larger dataset consists of multiple places and countries