BUSA8001_Team21_Final

November 4, 2022

BUSA8001 Group Assignment - Predicting Airbnb Listing Prices in Melbourne

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Kaggle Competition Ends: Friday, 4 November 2022 @ 3:00pm (Week 13)
Assignment Due Date on iLearn: Friday, 4 November 2022 @ 11.59pm (Week 13)

Overview:

- In the group assignment you will form a team of up to 3 students (minimum 2) and participate in a forecasting competition on Kaggle
- The goal is to predict listed prices of Airbnb properties in Melbourne based on various Airbnb characteristics and regression models
- You will:
  - Write a problem statement and perform Exploratory Data Analysis
  - Clean up data, deal with categorical features and missing observations, and create new variables (feature engineering)
  - Construct and tune forecasting models, produce forecasts and submit your predictions to Kaggle
  - Each member of the team will record a video presentation of their work
  - Marks will be awarded producing a prediction in the top 5 positions of their unit as well as for reaching the highest ranking on Kaggle amongst all teams.

Instructions:

- Form a team of 3 students (minimum 2 students)
- Each team member needs to join https://www.kaggle.com
- Choose a team leader and form a team in the competition `https://www.kaggle.com/t/0854c07cc3ac4037920a9fa4cdebacd1`
  - Team leader to click on `team` and join and invite other team members to join
  - Your **team's name must start** with your unit code, for instance you could have a team called BUSA8001_masterful_geniuses
- All team members should work on all the tasks listed below however

- **Choose a team member who will be responsible for one of each of the 3 tasks listed below**

Marks:

- Total Marks: 40
- Your individual mark will consist of:
  - 50% x overall assignment mark + 45% x mark for the task that you are responsible for + 5% x mark received from your teammates for your effort in group work
- 7 marks will be deducted from each Task for which there is no video presentation

Competition Marks:

- 2 marks: Ranking in the top 5 places of your unit on Kaggle (make sure you name your team as instructed above)

- 2 marks: Reaching the first place in your unit (make sure you name your team as instructed above)

Submissions:

1. On Kaggle: submit your team's forecast in order to be ranked by Kaggle
   - Can do this as many times as necessary while building their model

2. On iLearn **only team leader to submit** this Jupyter notebook re-named `Group_Assignment_Team_Name.ipynb` where Team_Name is your team's name on Kaggle
   - The Jupyter notebook must contain team members names/ID numbers, and team name in the competition
   - Provide answers to the 3 Tasks below in the allocated cells including all codes/outputs/writeups
   - One 15 minute video recording of your work
     - Each team member to provide a 5 minute presentation of the Task that they led (it is best to jointly record your video using Zoom)
     - When recording your video make sure your face is visible, that you share your Jupyter Notebook and explain everything you've done in the submitted Jupyter notebook on screen
     - 7 marks will be deducted from each Task for which there is no video presentation or if you don't follow the above instructions
3. On iLearn each student needs to submit a file with their teammates' names, ID number and a mark for their group effort (out of 100%)

Fill out the following information

For each team member provide name, Student ID number and which task is performed below

- Team Name on Kaggle: `BUSA8001_Team21`
- Team Leader and Team Member 1: `Michelle Melisa Flood 47106905 (Worked on all 3 tasks)`
- Team Member 2: `Smriti Pradhananga 46188290 (Worked on all 3 tasks)`
- Team Member 3: `Nishant Somani 46308326 (Worked on all 3 tasks)`

Task 1: Problem Description and Initial Data Analysis

1. Read the Competition Overview on Kaggle https://www.kaggle.com/t/0854c07cc3ac4037920a9fa4cdebacd1
2. Referring to Competition Overview and the data provided on Kaggle write about a 500 words **Problem Description** focusing on key points that will need to be addressed as first steps in Tasks 2 and 3 below, using the following headings:
   - Forecasting Problem
   - Evaluation Criteria
   - Types of Variables/Features
   - Data summary and main data characteristics
   - Missing Values (only explain what you found at this stage)
   - Note: you should **not** discuss any specific predictive algorithms at this stage.

Total Marks: 12

0.0.1 Problem Description

This analysis aims to examine the data of Melbourne Airbnb in regards to several characteristics of the already listed properties and determine prices for new properties.

Forecasting Problem

- One of the main problem during the forecasting of price is that there are 61 variables in the dataset including the price. Due to which, the accuracy of predicting price will decrease.
- Another problem includes the large volume of the dataset. There are 7000 training entries and 3000 entries requires to be predicted.

Evaluation Criteria The prediction accuracy of the dataset is evaluated in terms of root-mean-square error (RMSE). RMSE is the residuals' standard deviation (prediction errors). Residuals are a measure of how far away data points are from the regression line. It is a measure of how spread out these residuals are. In other words, it indicates how concentrated the data is around the best fit line.

Types of Variables/Features

Data Summary and main data characteristics

Missing Values

Task 2: Data Cleaning, Missing Observations and Feature Engineering

- In this task you will follow a set of instructions/questions listed below.
- Make sure you **explain** each step you do both in Markdown text and on your video.
  - Do not just read out your commands without exaplaining what they do and why you used them

Total Marks: 12

[1]:
```
#importing libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import math

#hide warnings
import warnings
warnings.filterwarnings('ignore')
```

[2]:
```
#reading the files
df_train = pd.read_csv('data/train.csv')
df_test = pd.read_csv('data/test.csv')
```

Minimum and Maximum nights

[3]:
```
#looking into minimum and maximum nights
df_train[['minimum_nights', 'maximum_nights', 'minimum_minimum_nights',␣
↪'maximum_minimum_nights', 'minimum_nights_avg_ntm']].corr(method = 'pearson')
```

[3]:
```
                        minimum_nights  maximum_nights  \
minimum_nights                1.000000        0.006795
maximum_nights                0.006795        1.000000
minimum_minimum_nights        0.888391        0.006888
maximum_minimum_nights        0.988808        0.005681
minimum_nights_avg_ntm        0.988371        0.006277

                        minimum_minimum_nights  maximum_minimum_nights  \
minimum_nights                        0.888391                0.988808
maximum_nights                        0.006888                0.005681
minimum_minimum_nights                1.000000                0.880834
maximum_minimum_nights                0.880834                1.000000
minimum_nights_avg_ntm                0.937815                0.985033

                        minimum_nights_avg_ntm
minimum_nights                        0.988371
maximum_nights                        0.006277
minimum_minimum_nights                0.937815
maximum_minimum_nights                0.985033
minimum_nights_avg_ntm                1.000000
```

Various columns for minimum and maximum night stays are included in the dataset. Out of which, two main night stays will be used, due to minor differences amongst each other. For instance, minimum_nights and minimum_minimum_nights, here, the latter supposedly refers to the fact that minimum and maximum night stays can differ throughout the year. Therefore, only the default (i.e. most frequently used) min/max night stay values will be used.

[4]:
```
#dropping highly correlated maximum and minimum nights
cols_to_drop = ['minimum_minimum_nights', 'maximum_minimum_nights',␣
↪'minimum_maximum_nights',
                 'maximum_maximum_nights', 'minimum_nights_avg_ntm',␣
↪'maximum_nights_avg_ntm']
df_train = df_train.drop(cols_to_drop, axis = 1)
df_test = df_test.drop(cols_to_drop, axis = 1)
```

Availability

[5]:
```
#availablity columns
df_train[['availability_30', 'availability_60', 'availability_90',␣
↪'availability_365']].corr()
```

[5]:
```
                  availability_30  availability_60  availability_90  \
availability_30          1.000000         0.917517         0.844934
availability_60          0.917517         1.000000         0.961328
availability_90          0.844934         0.961328         1.000000
availability_365         0.451333         0.507560         0.545400

                  availability_365
availability_30           0.451333
availability_60           0.507560
availability_90           0.545400
availability_365          1.000000
```

Likewise, there are numerous measures of availability that highly correlates with each other. Thus, one will be kept, and it will be keep availability_365 as this one is the less correlated with other variables.

[6]:
```
#dropping highly correlated availability
cols_to_drop = ['availability_30', 'availability_60', 'availability_90']
df_train = df_train.drop(cols_to_drop, axis = 1)
df_test = df_test.drop(cols_to_drop, axis = 1)
```

Reviews

[7]:
```
#review columns
df_train[['number_of_reviews_ltm', 'reviews_per_month',␣
↪'number_of_reviews','number_of_reviews_l30d']].corr()
```

[7]:
```
                        number_of_reviews_ltm  reviews_per_month  \
number_of_reviews_ltm                1.000000           0.894179
reviews_per_month                    0.894179           1.000000
number_of_reviews                    0.622978           0.684857
number_of_reviews_l30d               0.789573           0.731521
```

```
                           number_of_reviews  number_of_reviews_l30d
number_of_reviews_ltm               0.622978                0.789573
reviews_per_month                   0.684857                0.731521
number_of_reviews                   1.000000                0.498111
number_of_reviews_l30d              0.498111                1.000000
```

number_of_reviews_ltm and reviews_per_month will be highly correlated with number_of_reviews and thus will be dropped.

[8]:
```python
#dropping highly correlated review columns
cols_to_drop = ['number_of_reviews_ltm', 'number_of_reviews_l30d',␣
 ↪'reviews_per_month']
df_train = df_train.drop(cols_to_drop, axis = 1)
df_test = df_test.drop(cols_to_drop, axis = 1)
```

Dropping irrelevant columns There are many variables that relates to host and not the property, so we will be dropping them. Likewise, there are irrelevant information on source, description etc. which would not predict the price accurately.

[9]:
```python
#dropping irrelevant columns
cols_to_drop1 = ['source', 'name', 'description','neighborhood_overview',␣
 ↪'host_name', 'host_since', 'host_location',
                'host_about', 'host_neighbourhood', 'host_has_profile_pic',␣
 ↪'neighbourhood', 'latitude',
                'longitude', 'has_availability','first_review',␣
 ↪'calculated_host_listings_count',␣
 ↪'calculated_host_listings_count_entire_homes',
                'calculated_host_listings_count_private_rooms',␣
 ↪'calculated_host_listings_count_shared_rooms', 'host_verifications']

df_train = df_train.drop(cols_to_drop1, axis = 1)
df_test = df_test.drop(cols_to_drop1, axis = 1)

#replacing columns with f as 0 and t as 1
df_train.replace({'f': 0, 't': 1}, inplace = True)
df_test.replace({'f': 0, 't': 1}, inplace = True)
```

Task 2, Question 1:

Clean **all** numerical features and the target variable `price` so that they can be used in training algorithms. For instance, `host_response_rate` feature is in object format containing both numerical values and text. Extract numerical values (or equivalently eliminate the text) so that the numerical values can be used as a regular feature. (2 marks)

Price

```
[10]: #replacing string characters from the price column
df_train['price'] = df_train['price'].str.replace('$','')
df_train['price'] = df_train['price'].str.replace(',','')

#converting the price column into numeric
df_train["price"] = pd.to_numeric(df_train["price"])
```

Host Response Rate and Host Acceptance Rate

```
[11]: #replacing string characters from columns
df_train['host_response_rate'] = df_train['host_response_rate'].str.
 ↪replace('%','')
df_test['host_response_rate'] = df_test['host_response_rate'].str.
 ↪replace('%','')
df_train['host_acceptance_rate'] = df_train['host_acceptance_rate'].str.
 ↪replace('%','')
df_test['host_acceptance_rate'] = df_test['host_acceptance_rate'].str.
 ↪replace('%','')

#converting columns into numeric
df_train["host_response_rate"] = pd.to_numeric(df_train["host_response_rate"])
df_test["host_response_rate"] = pd.to_numeric(df_test["host_response_rate"])
df_train["host_acceptance_rate"] = pd.
 ↪to_numeric(df_train["host_acceptance_rate"])
df_test["host_acceptance_rate"] = pd.to_numeric(df_test["host_acceptance_rate"])
```

```
[12]: #converting rates into scores out of 5 as reviews are also rated out of 5,␣
 ↪maintaining uniformity
df_train["host_response_rate"] = ((df_train["host_response_rate"])/100)*5
df_test["host_response_rate"] = ((df_test["host_response_rate"])/100)*5
df_train["host_acceptance_rate"] = ((df_train["host_acceptance_rate"])/100)*5
df_test["host_acceptance_rate"] = ((df_test["host_acceptance_rate"])/100)*5
```

Task 2, Question 2 Create at least 4 new features from existing features which contain multiple items of information, e.g. creating `email`, `phone`, `work_email`, etc. from feature `host_verifications`. (2 marks)

Bathroom

```
[13]: #split bathrooms into 2 new columns called num_bathrooms and private_bathroom
df_train[['num_bathrooms','private_bathroom','column3']] = df_train.bathrooms.
 ↪str.split(" ", expand = True)
df_test[['num_bathrooms','private_bathroom','column3']] = df_test.bathrooms.str.
 ↪split(" ", expand = True)

#drop excess column
del df_train['column3']
del df_test['column3']
```

```
#encode values so shared bathroom shows 0 and private bathroom shows 1 in the␣
↪private_bathroom column (not mentioned also indicates 1)
df_train['private_bathroom'] = df_train['private_bathroom'].replace(['shared',␣
↪'bath', 'baths', 'private', None], [0, 1, 1, 1, 1])
df_train['private_bathroom'][df_train.num_bathrooms == 'Private'] = 1
df_train['private_bathroom'][df_train.num_bathrooms == 'Shared'] = 0

#change the num_bathrooms of rows that its bathrooms variable does not start␣
↪with a number
df_train['num_bathrooms'] = df_train['num_bathrooms'].replace(['Half-bath',␣
↪'Private', 'Shared'], 0.5)

#do the same for the testing dataset
df_test['private_bathroom'] = df_test['private_bathroom'].replace(['shared',␣
↪'bath', 'baths', 'private', None], [0, 1, 1, 1, 1])
df_test['private_bathroom'][df_test.num_bathrooms == 'Private'] = 1
df_test['private_bathroom'][df_test.num_bathrooms == 'Shared'] = 0
df_test['num_bathrooms'] = df_test['num_bathrooms'].replace(['Half-bath',␣
↪'Private', 'Shared'], 0.5)

#convert to a suitable data type
df_train['num_bathrooms'] = pd.to_numeric(df_train['num_bathrooms'])
df_train['private_bathroom'] = df_train['private_bathroom'].astype(int)
df_test['num_bathrooms'] = pd.to_numeric(df_test['num_bathrooms'])
df_test['private_bathroom'] = df_test['private_bathroom'].astype(int)
```

Review columns

[14]:
```
#adding the review colums and getting their average
sum_review_train = df_train['review_scores_rating'] +␣
↪df_train['review_scores_accuracy'] + df_train['review_scores_cleanliness'] +␣
↪df_train['review_scores_checkin'] + df_train['review_scores_communication']␣
↪+ df_train['review_scores_location'] + df_train['review_scores_value']
average_review_train = sum_review_train/7
average_review_train = average_review_train.to_frame(name = 'average_review')
df_train = df_train.join(average_review_train)

#do the same for testing dataset
sum_review_test = df_test['review_scores_rating'] +␣
↪df_test['review_scores_accuracy'] + df_test['review_scores_cleanliness'] +␣
↪df_test['review_scores_checkin'] + df_test['review_scores_communication'] +␣
↪df_test['review_scores_location'] + df_test['review_scores_value']
average_review_test = sum_review_test/7
average_review_test = average_review_test.to_frame(name = 'average_review')
df_test = df_test.join(average_review_test)
```

Amenities

[15]:
```
#create new amenities columns
df_train.loc[df_train['amenities'].str.contains('Air conditioning|Central air␣
↪conditioning'), 'air_conditioning'] = 1
df_train.loc[df_train['amenities'].str.contains('BBQ grill|Fire pit|Propane␣
↪barbeque'), 'bbq'] = 1
df_train.loc[df_train['amenities'].str.contains('Beach view|Beachfront|Lake␣
↪access|Mountain view|Ski-in/Ski-out|Waterfront'), 'nature_and_views'] = 1
df_train.loc[df_train['amenities'].str.contains('Breakfast'), 'breakfast'] = 1
df_train.loc[df_train['amenities'].str.contains('Cooking basics'),␣
↪'cooking_basics'] = 1
df_train.loc[df_train['amenities'].str.contains('Dishwasher|Dryer|Washer'),␣
↪'appliance'] = 1
df_train.loc[df_train['amenities'].str.contains('Exercise equipment|Gym|gym'),␣
↪'gym'] = 1
df_train.loc[df_train['amenities'].str.contains('Family/kid␣
↪friendly|Children|children'), 'child_friendly'] = 1
df_train.loc[df_train['amenities'].str.contains('parking'), 'parking'] = 1
df_train.loc[df_train['amenities'].str.contains('Garden|Outdoor|Sun␣
↪loungers|Terrace|Balcony|Patio'), 'outdoor_space'] = 1
df_train.loc[df_train['amenities'].str.contains('Hot tub|Jetted tub|hot␣
↪tub|Sauna|Pool|pool'), 'hot_tub_sauna_or_pool'] = 1

#replacing nulls with zeros for new amenities columns and changing the data␣
↪type to int
cols_to_replace_nulls = df_train.iloc[:,32:].columns
df_train[cols_to_replace_nulls] = df_train[cols_to_replace_nulls].fillna(0)
df_train[cols_to_replace_nulls] = df_train[cols_to_replace_nulls].astype(int)

#do the same for the testing dataset
df_test.loc[df_test['amenities'].str.contains('Air conditioning|Central air␣
↪conditioning'), 'air_conditioning'] = 1
df_test.loc[df_test['amenities'].str.contains('BBQ grill|Fire pit|Propane␣
↪barbeque'), 'bbq'] = 1
df_test.loc[df_test['amenities'].str.contains('Beach view|Beachfront|Lake␣
↪access|Mountain view|Ski-in/Ski-out|Waterfront'), 'nature_and_views'] = 1
df_test.loc[df_test['amenities'].str.contains('Breakfast'), 'breakfast'] = 1
df_test.loc[df_test['amenities'].str.contains('Cooking basics'),␣
↪'cooking_basics'] = 1
df_test.loc[df_test['amenities'].str.contains('Dishwasher|Dryer|Washer'),␣
↪'appliance'] = 1
df_test.loc[df_test['amenities'].str.contains('Exercise equipment|Gym|gym'),␣
↪'gym'] = 1
df_test.loc[df_test['amenities'].str.contains('Family/kid␣
↪friendly|Children|children'), 'child_friendly'] = 1
```

```
df_test.loc[df_test['amenities'].str.contains('parking'), 'parking'] = 1
df_test.loc[df_test['amenities'].str.contains('Garden|Outdoor|Sun␣
↪loungers|Terrace|Balcony|Patio'), 'outdoor_space'] = 1
df_test.loc[df_test['amenities'].str.contains('Hot tub|Jetted tub|hot␣
↪tub|Sauna|Pool|pool'), 'hot_tub_sauna_or_pool'] = 1

cols_to_replace_nulls = df_test.iloc[:,31:].columns
df_test[cols_to_replace_nulls] = df_test[cols_to_replace_nulls].fillna(0)
df_test[cols_to_replace_nulls] = df_test[cols_to_replace_nulls].astype(int)
```

[16]:
```
#sum the total number of main amenities
df_train['sum_amenities'] = df_train['air_conditioning'] + df_train['bbq'] +␣
↪df_train['nature_and_views'] + df_train['breakfast'] +␣
↪df_train['cooking_basics'] + df_train['appliance'] + df_train['gym'] +␣
↪df_train['child_friendly'] + df_train['parking'] + df_train['outdoor_space']␣
↪+ df_train['hot_tub_sauna_or_pool']
df_test['sum_amenities'] = df_test['air_conditioning'] + df_test['bbq'] +␣
↪df_test['nature_and_views'] + df_test['breakfast'] +␣
↪df_test['cooking_basics'] + df_test['appliance'] + df_test['gym'] +␣
↪df_test['child_friendly'] + df_test['parking'] + df_test['outdoor_space'] +␣
↪df_test['hot_tub_sauna_or_pool']

#drop columns after encoding
cols_to_drop2 = ['air_conditioning', 'bbq', 'nature_and_views', 'breakfast',␣
↪'cooking_basics', 'appliance', 'gym',
                 'child_friendly', 'parking', 'outdoor_space',␣
↪'hot_tub_sauna_or_pool', 'bathrooms']

df_train = df_train.drop(cols_to_drop2, axis=1)
df_test = df_test.drop(cols_to_drop2, axis=1)
```

[17]:
```
#counting the number of amenities and adding it to the n_amenities column
df_train['n_amenities'] = df_train['amenities'].apply(lambda x: len(x.
↪replace('{', '').replace('{', '').\
                                                                            ␣
↪replace('"', '').split(',')))

df_test['n_amenities'] = df_test['amenities'].apply(lambda x: len(x.
↪replace('{', '').replace('{', '').\
                                                                            ␣
↪replace('"', '').split(',')))

#drop columns after encoding
cols_to_drop3 = ['review_scores_rating', 'review_scores_accuracy',␣
↪'review_scores_cleanliness', 'review_scores_checkin',
```

```
                 'review_scores_communication', 'review_scores_location',␣
↪'review_scores_value', 'amenities']

df_train = df_train.drop(cols_to_drop3, axis=1)
df_test = df_test.drop(cols_to_drop3, axis=1)
```

Review Dates

[18]:
```
#convert last_review to datetime
df_train.last_review = pd.to_datetime(df_train.last_review)

#calculate the number of days since last_review from 1st Nov 2022
df_train['since_last_review'] = (pd.datetime(2022, 11, 1) - df_train.
↪last_review).astype('timedelta64[D]')

#do the same for the testing dataset
df_test.last_review = pd.to_datetime(df_test.last_review)
df_test['since_last_review'] = (pd.datetime(2022, 11, 1) - df_test.last_review).
↪astype('timedelta64[D]')
```

Task 2, Question 3: Impute missing values for all features in both training and test datasets. (3 marks)

Filling missing values from the dataset

[19]:
```
#interpulate missing values with a median for numerical variables
for col in ['host_response_rate', 'host_acceptance_rate', 'bedrooms', 'beds',␣
↪'num_bathrooms', 'since_last_review','availability_365']:
            df_train[col].fillna(df_train[col].median(), inplace = True)

for col in ['host_response_rate', 'host_acceptance_rate', 'bedrooms',␣
↪'beds','num_bathrooms', 'since_last_review','availability_365']:
            df_test[col].fillna(df_test[col].median(), inplace = True)

#interpulate missing values with mode for categorical variables
cols_mode = ['host_response_time', 'neighbourhood_cleansed', 'property_type',␣
↪'room_type']
df_train[cols_mode] = df_train[cols_mode].fillna(df_train.mode().iloc[0])
df_test[cols_mode] = df_test[cols_mode].fillna(df_test.mode().iloc[0])

#for this column, NA means 0
df_train['sum_amenities'] = df_train['sum_amenities'].fillna(0)
df_test['sum_amenities'] = df_test['sum_amenities'].fillna(0)
```

Task 2, Question 4: Encode all categorical variables appropriately as discussed in class.

Where a categorical feature contains more than 5 unique values, map the features into 5 most frequent values + ‘other’ and then encode appropriately. For instance, you could group then map `property_type` into 5 basic types + ‘other’: [entire rental unit, private room, entire room, entire towehouse, shared room, other] and then encode. (2 marks)

Property type

[20]:
```
#replace other than the top 4 property_type with 'OtherPropertyType'
df_train.loc[~df_train.property_type.isin(['Entire rental unit',
                                            'Entire home',
                                            'Private room in home',
                                            'Private room in rental unit']),␣
 ↪'property_type'] = 'OtherPropertyType'
df_test.loc[~df_test.property_type.isin(['Entire rental unit',
                                          'Entire home',
                                          'Private room in home',
                                          'Private room in rental unit']),␣
 ↪'property_type'] = 'OtherPropertyType'
```

Neighbourhood Cleansed

[21]:
```
#replace other than the top 5 neighbourhood_cleansed with 'OtherNeighbourhood'
df_train.loc[~df_train.neighbourhood_cleansed.isin(['Melbourne',
                                                     'Port Phillip',
                                                     'Yarra Ranges',
                                                     'Yarra',
                                                     'Stonnington']),␣
 ↪'neighbourhood_cleansed'] = 'OtherNeighbourhood'
df_test.loc[~df_test.neighbourhood_cleansed.isin(['Melbourne',
                                                   'Port Phillip',
                                                   'Yarra Ranges',
                                                   'Yarra',
                                                   'Stonnington']),␣
 ↪'neighbourhood_cleansed'] = 'OtherNeighbourhood'
```

Host Response Time

[22]:
```
#mapping integer to host_response_time
host_response_time_mapping = {'within an hour':4, 'within a few hours':3,␣
 ↪'within a day':2, 'a few days or more':1}
df_train['host_response_time'] = df_train['host_response_time'].
 ↪map(host_response_time_mapping)
df_test['host_response_time'] = df_test['host_response_time'].
 ↪map(host_response_time_mapping)
```

[23]:
```
#one_hot encoding the neighbourhood_cleansed column
one_hot3 = pd.get_dummies(df_train[['neighbourhood_cleansed']])
one_hot3.rename(columns = {'neighbourhood_cleansed_Melbourne':'Melbourne',
                           'neighbourhood_cleansed_Port Phillip':'Port Phillip',
                           'neighbourhood_cleansed_Yarra Ranges':'Yarra Ranges',
                           'neighbourhood_cleansed_Yarra':'Yarra',
```

```
                           'neighbourhood_cleansed_Stonnington':'Stonnington',
                           'neighbourhood_cleansed_OtherNeighbourhood':
 ↪'OtherNeighbourhood'}, inplace = True)
df_train = pd.concat([df_train, one_hot3], axis=1)

#do the same for testing dataset
one_hot4 = pd.get_dummies(df_test[['neighbourhood_cleansed']])
one_hot4.rename(columns = {'neighbourhood_cleansed_Melbourne':'Melbourne',
                           'neighbourhood_cleansed_Port Phillip':'Port Phillip',
                           'neighbourhood_cleansed_Yarra Ranges':'Yarra Ranges',
                           'neighbourhood_cleansed_Yarra':'Yarra',
                           'neighbourhood_cleansed_Stonnington':'Stonnington',
                           'neighbourhood_cleansed_OtherNeighbourhood':
 ↪'OtherNeighbourhood'}, inplace = True)
df_test = pd.concat([df_test, one_hot4], axis=1)

#drop columns after encoding
df_train = df_train.drop(['neighbourhood_cleansed'], axis=1)
df_test = df_test.drop(['neighbourhood_cleansed'], axis=1)
```

Room type

[24]:
```
#mapping integer to room_type
room_type_mapping = {'Entire home/apt':4, 'Hotel room':3, 'Private room':2,␣
 ↪'Shared room':1}
df_train['room_type'] = df_train['room_type'].map(room_type_mapping)
df_test['room_type'] = df_test['room_type'].map(room_type_mapping)
```

Property type

[25]:
```
#one_hot encoding the property_type column
one_hot1 = pd.get_dummies(df_train[['property_type']])
one_hot1.rename(columns = {'property_type_Entire home':'Entire home',
                           'property_type_Entire rental unit':'Entire rental␣
 ↪unit',
                           'property_type_OtherPropertyType':
 ↪'OtherPropertyType',
                           'property_type_Private room in home':'Private room␣
 ↪in home',
                           'property_type_Private room in rental unit':'Private␣
 ↪room in rental unit'}, inplace = True)
df_train = pd.concat([df_train, one_hot1], axis=1)

#do the same for testing dataset
one_hot2 = pd.get_dummies(df_test[['property_type']])
one_hot2.rename(columns = {'property_type_Entire home':'Entire home',
```

```
                                'property_type_Entire rental unit':'Entire rental␣
↪unit',
                                'property_type_OtherPropertyType':
↪'OtherPropertyType',
                                'property_type_Private room in home':'Private room␣
↪in home',
                                'property_type_Private room in rental unit':'Private␣
↪room in rental unit'}, inplace = True)
df_test = pd.concat([df_test, one_hot2], axis=1)

#drop columns after encoding
df_train = df_train.drop(['property_type'], axis=1)
df_test = df_test.drop(['property_type'], axis=1)
```

[26]:
```
df_train['Entire home']=np.where(df_train['Entire home'] ==1, 5,␣
↪df_train['Entire home'])
df_train['Entire rental unit']=np.where(df_train['Entire rental unit'] ==1, 5,␣
↪df_train['Entire rental unit'])
df_train['Private room in home']=np.where(df_train['Private room in home'] ==1,␣
↪3, df_train['Private room in home'])
df_train['Private room in rental unit']=np.where(df_train['Private room in␣
↪rental unit'] ==1, 4, df_train['Private room in rental unit'])
df_train['Sum_property_type']=df_train['Entire home']+df_train['Entire rental␣
↪unit']+df_train['Private room in home']+df_train['Private room in rental␣
↪unit']+df_train['OtherPropertyType']
#print(df_train['Sum_property_type'])

df_test['Entire home']=np.where(df_test['Entire home'] ==1, 5, df_test['Entire␣
↪home'])
df_test['Entire rental unit']=np.where(df_test['Entire rental unit'] ==1, 5,␣
↪df_test['Entire rental unit'])
df_test['Private room in home']=np.where(df_test['Private room in home'] ==1,␣
↪3, df_test['Private room in home'])
df_test['Private room in rental unit']=np.where(df_test['Private room in rental␣
↪unit'] ==1, 4, df_test['Private room in rental unit'])
df_test['Sum_property_type']=df_test['Entire home']+df_test['Entire rental␣
↪unit']+df_test['Private room in home']+df_test['Private room in rental␣
↪unit']+df_test['OtherPropertyType']
#print(df_test['Sum_property_type'])

df_train.drop(['Entire home','Entire rental unit','Private room in␣
↪home','Private room in rental␣
↪unit','OtherPropertyType','Sum_property_type'],axis=1)
df_test.drop(['Entire home','Entire rental unit','Private room in␣
↪home','Private room in rental␣
↪unit','OtherPropertyType','Sum_property_type'],axis=1)
```

[26]:
```
        ID  host_response_time  host_response_rate  host_acceptance_rate  \
0     7000                   4                 5.0                  5.00
1     7001                   4                 5.0                  4.55
2     7002                   2                 3.0                  4.35
3     7003                   4                 5.0                  5.00
4     7004                   4                 5.0                  4.90
…      …                   …                  …                    …
2995  9995                   4                 5.0                  4.90
2996  9996                   4                 5.0                  4.90
2997  9997                   4                 5.0                  4.90
2998  9998                   4                 5.0                  4.90
2999  9999                   4                 5.0                  4.90

      host_is_superhost  host_listings_count  host_identity_verified  \
0                     0                  6.0                       1
1                     1                  1.0                       1
2                     0                  1.0                       1
3                     0                  6.0                       1
4                     1                 12.0                       1
…                   …                   …                      …
2995                  0                  2.0                       1
2996                  0                  1.0                       1
2997                  0                  1.0                       1
2998                  0                  1.0                       1
2999                  0                  1.0                       0

      room_type  accommodates  bedrooms  …  average_review  sum_amenities  \
0             2             2       1.0  …        4.937143              4
1             4             2       1.0  …        4.954286              3
2             4             2       1.0  …        4.744286              4
3             2             2       1.0  …        4.285714              4
4             4             2       1.0  …        4.778571              4
…          …            …          …  …             …              …
2995          2             2       1.0  …        4.964286              4
2996          2             2       1.0  …        4.902857              5
2997          2             1       1.0  …        4.898571              2
2998          4             2       1.0  …        4.945714              3
2999          4             6       4.0  …        5.000000              3

      n_amenities  since_last_review  Melbourne OtherNeighbourhood  \
0              57              107.0          0                  1
1              51               59.0          0                  0
2              40               72.0          0                  1
3              50              335.0          0                  1
4              49               73.0          0                  0
…            …                …        …                …
2995           13             1537.0          1                  0
```

```
2996          29          959.0          1                    0
2997          14         1625.0          0                    0
2998          20          960.0          0                    0
2999          20         1035.0          1                    0

      Port Phillip  Stonnington  Yarra  Yarra Ranges
0                0            0      0             0
1                0            0      1             0
2                0            0      0             0
3                0            0      0             0
4                1            0      0             0
…              …          …    …           …
2995             0            0      0             0
2996             0            0      0             0
2997             0            0      1             0
2998             0            0      1             0
2999             0            0      0             0

[3000 rows x 29 columns]
```

Task 2, Question 5: Perform any other actions you think need to be done on the data before constructing predictive models, and clearly explain what you have done. (1 marks)

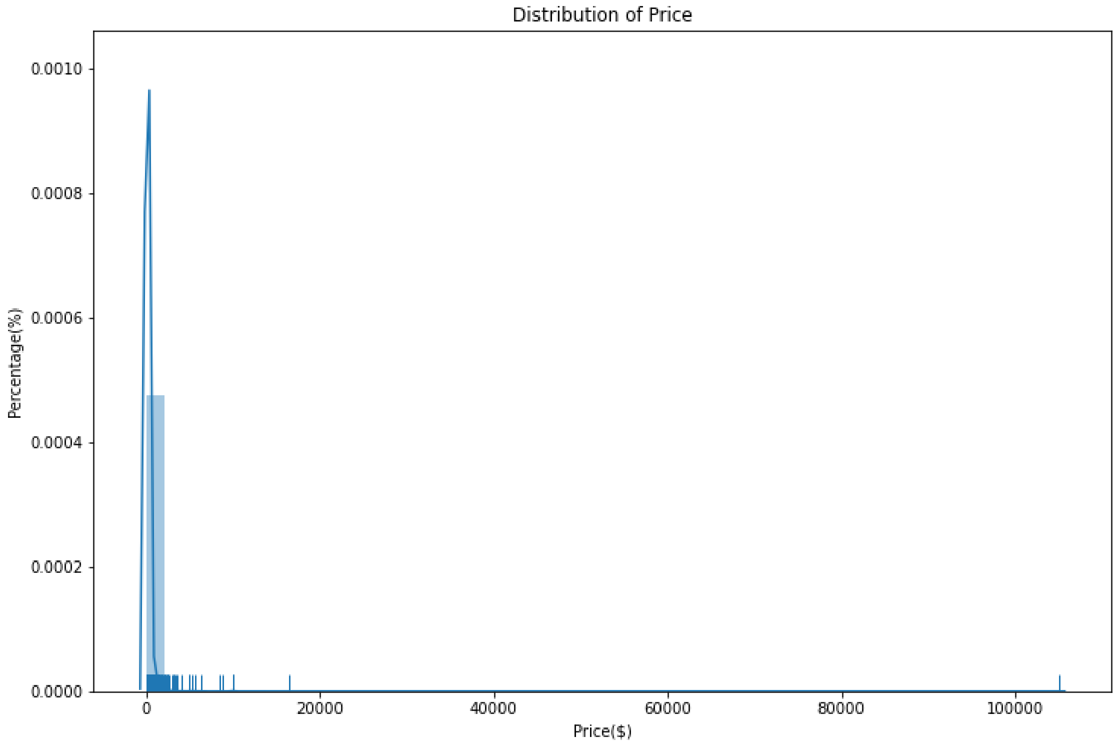
Task 2, Question 6: Perform exploratory data analysis to measure the relationship between the features and the target and write up your findings. (2 marks)

Distribution of price

With price being our target variable, we shall see the distribution of price in the dataset.

[27]:
```
plt.figure(figsize=(12,8))
sns.distplot(df_train['price'],rug=True)
plt.title('Distribution of Price')
plt.xlabel('Price($)')
plt.ylabel('Percentage(%)')
```

[27]:
```
Text(0, 0.5, 'Percentage(%)')
```

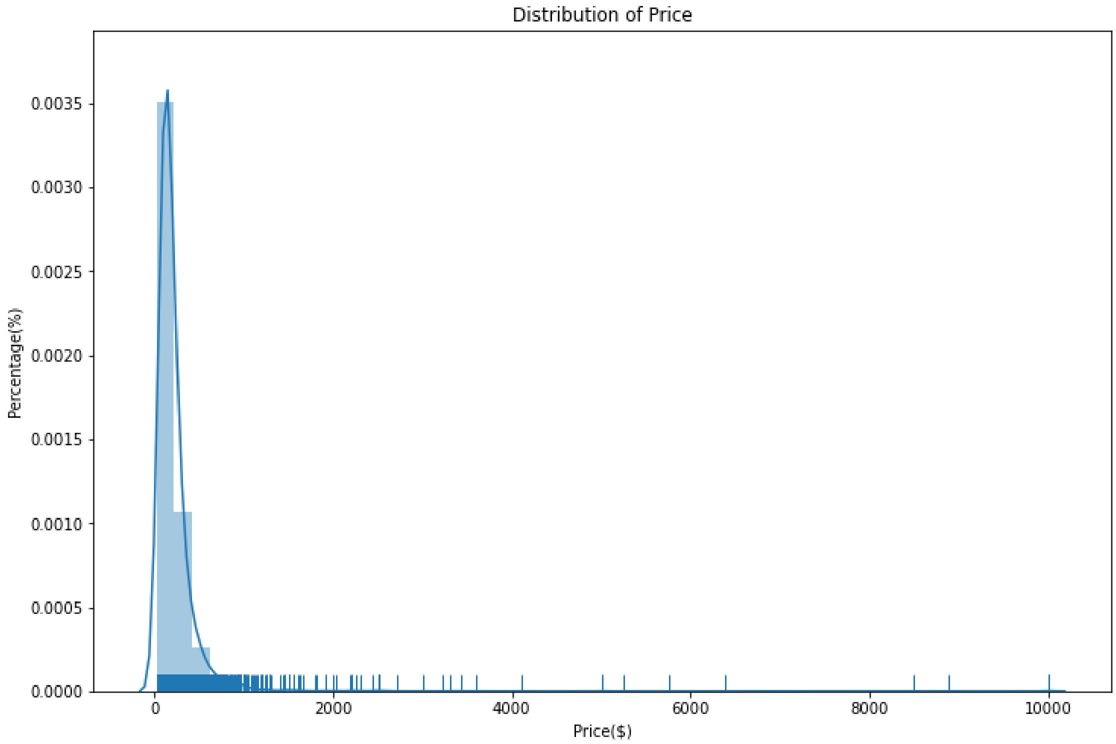


Here, the lines represents the price in those coordinates. We observe that there are few outliers in the dataset and thus we shall drop these rows containing the outliers.

[28]:
```
#drop price outliers
df_train.drop(df_train[df_train.price > 10000].index, inplace=True)
```

[29]:
```
plt.figure(figsize=(12,8))
sns.distplot(df_train['price'],rug=True)
plt.title('Distribution of Price')
plt.xlabel('Price($)')
plt.ylabel('Percentage(%)')
```

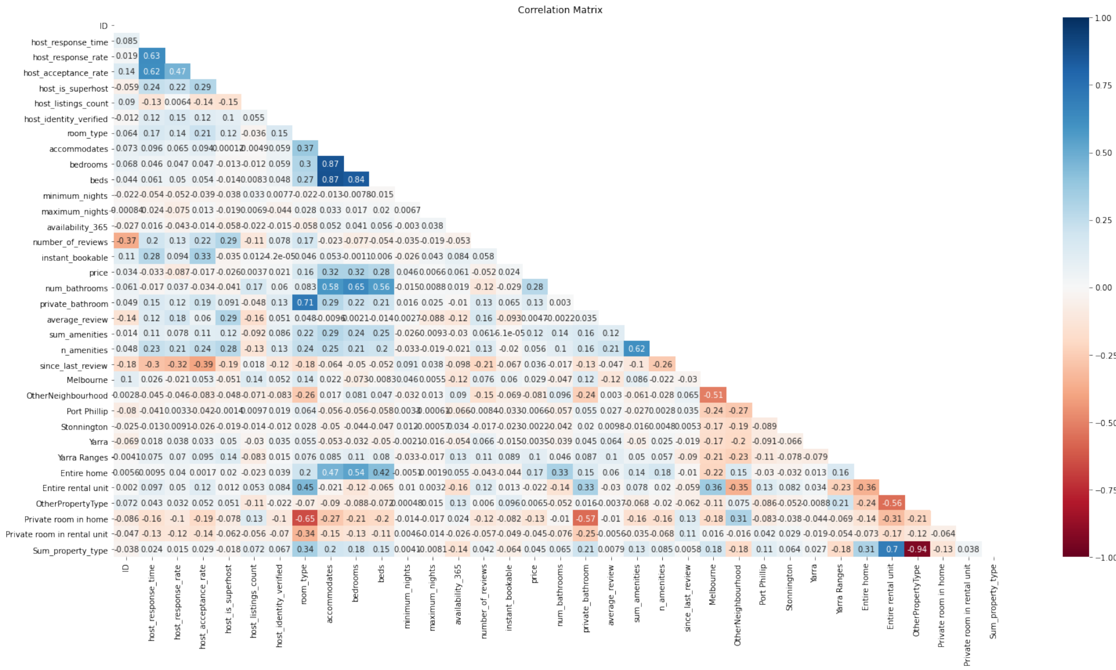
[29]: Text(0, 0.5, 'Percentage(%)')



Now, we can observe the distribution of price much better. We still see the varying of price range but we shall not consider them as outliers as the property type contained in the dataset are worth the prices.

Correlation Matrix

[30]:
```
plt.figure(figsize=(22, 12))
mask = np.triu(np.ones_like(df_train.corr(), dtype=np.bool))
s = sns.heatmap(df_train.corr(),
                annot=True,
                mask=mask,
                cmap='RdBu',
                vmin=-1,
                vmax=1)
s.set_xticklabels(s.get_xticklabels(), rotation=90)
plt.title('Correlation Matrix')
plt.tight_layout()
plt.show()
```

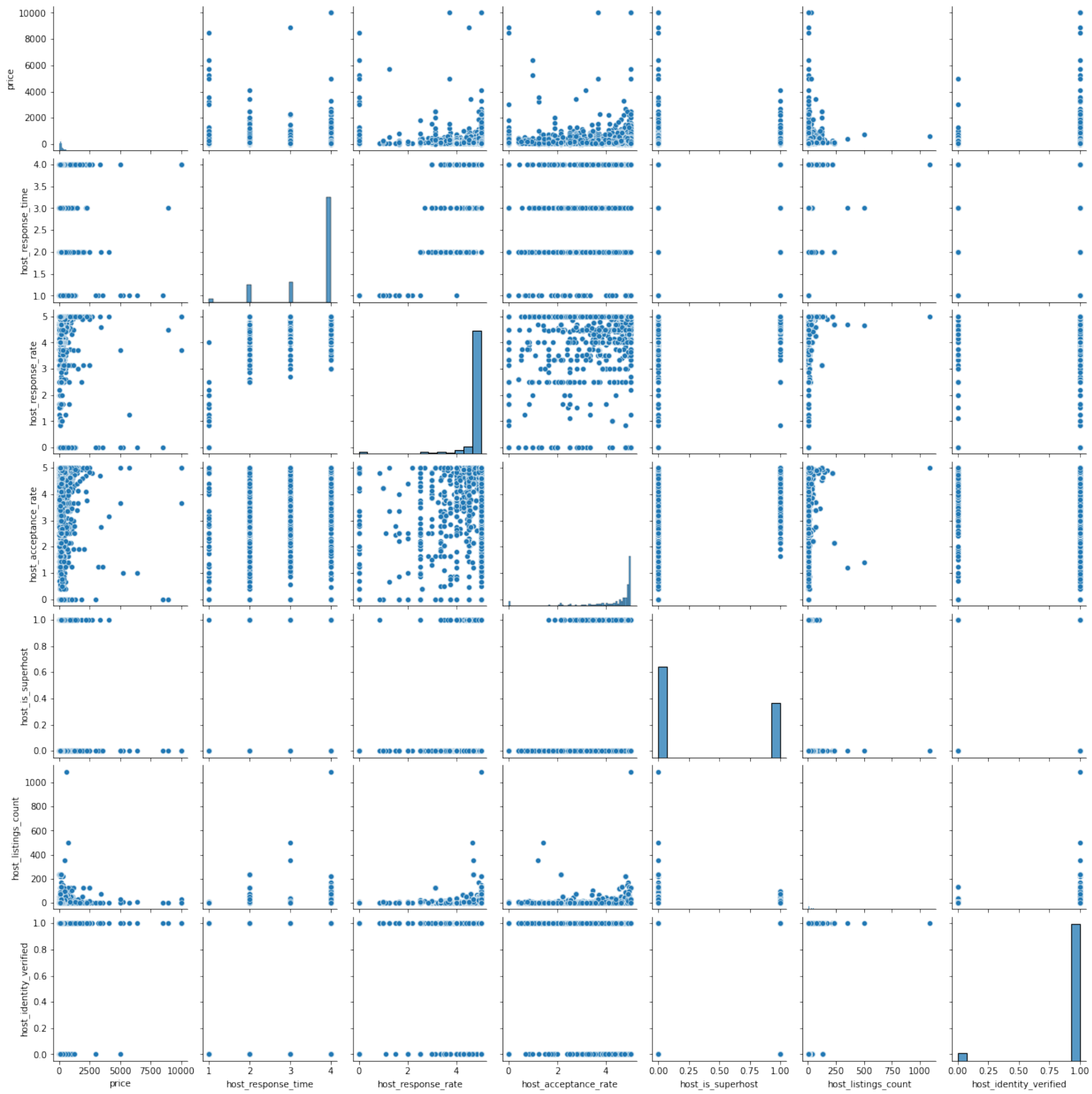


The figure above shows us the correlation matrix among the variables in the dataset. Here we can observe that Sum_property_type and OtherPropertyType has the lowest (-0.94) correlation. Whereas, accommodates and beds have the highest correlation of 0.87, which makes sense as we need more beds if more people would like to stay at the property. We know that correlation matrix does not define non-linear relationships well, so we shall plot the variables to have a further clarification on the variables.

Pair plots

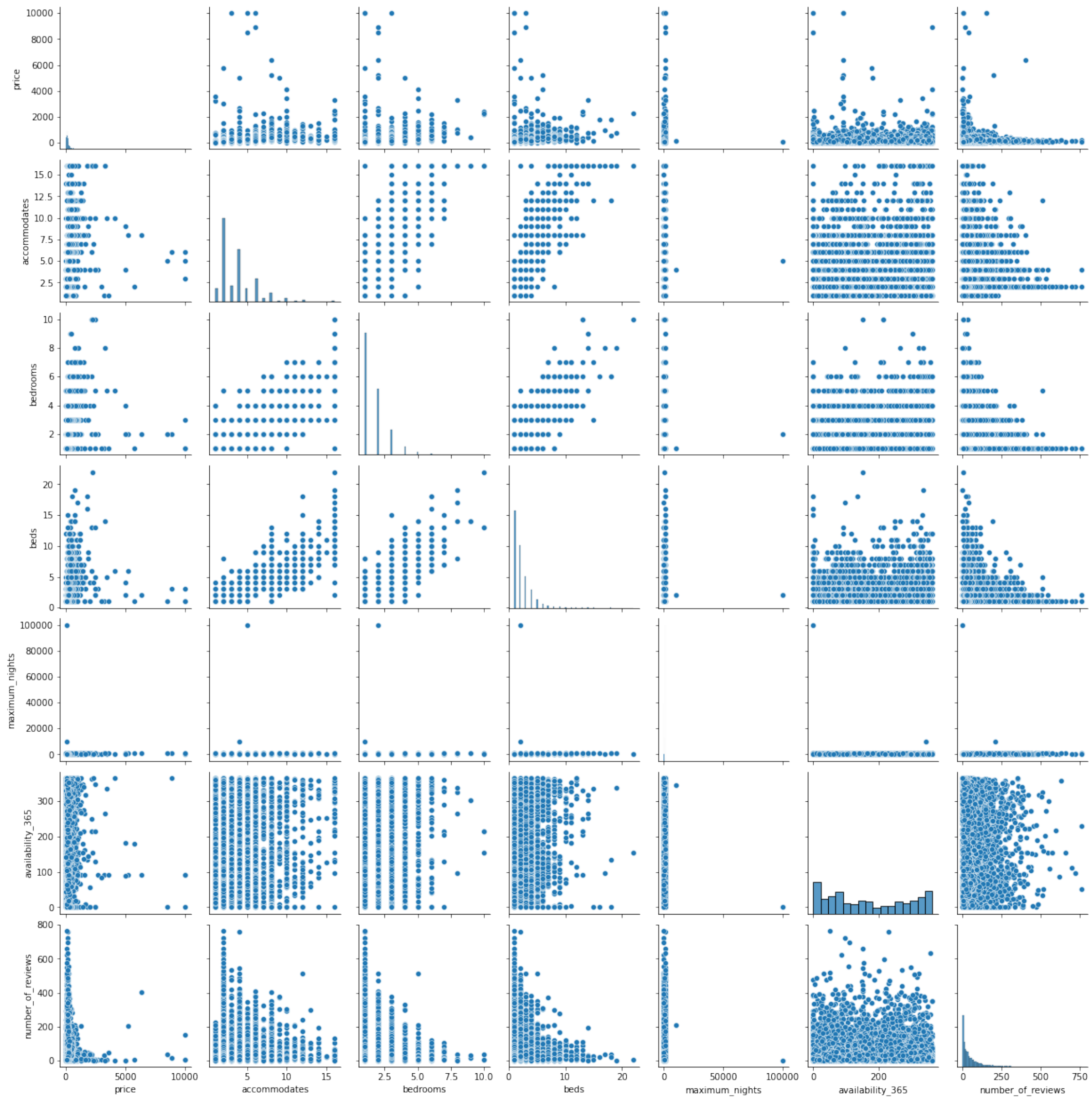
[55]:
```
cols =␣
 ↪['price','host_response_time','host_response_rate','host_acceptance_rate','host_is_superhos
       'host_identity_verified']
plt.figure()
sns.pairplot(df_train[cols])
plt.show()
```

```
<Figure size 432x288 with 0 Axes>
```



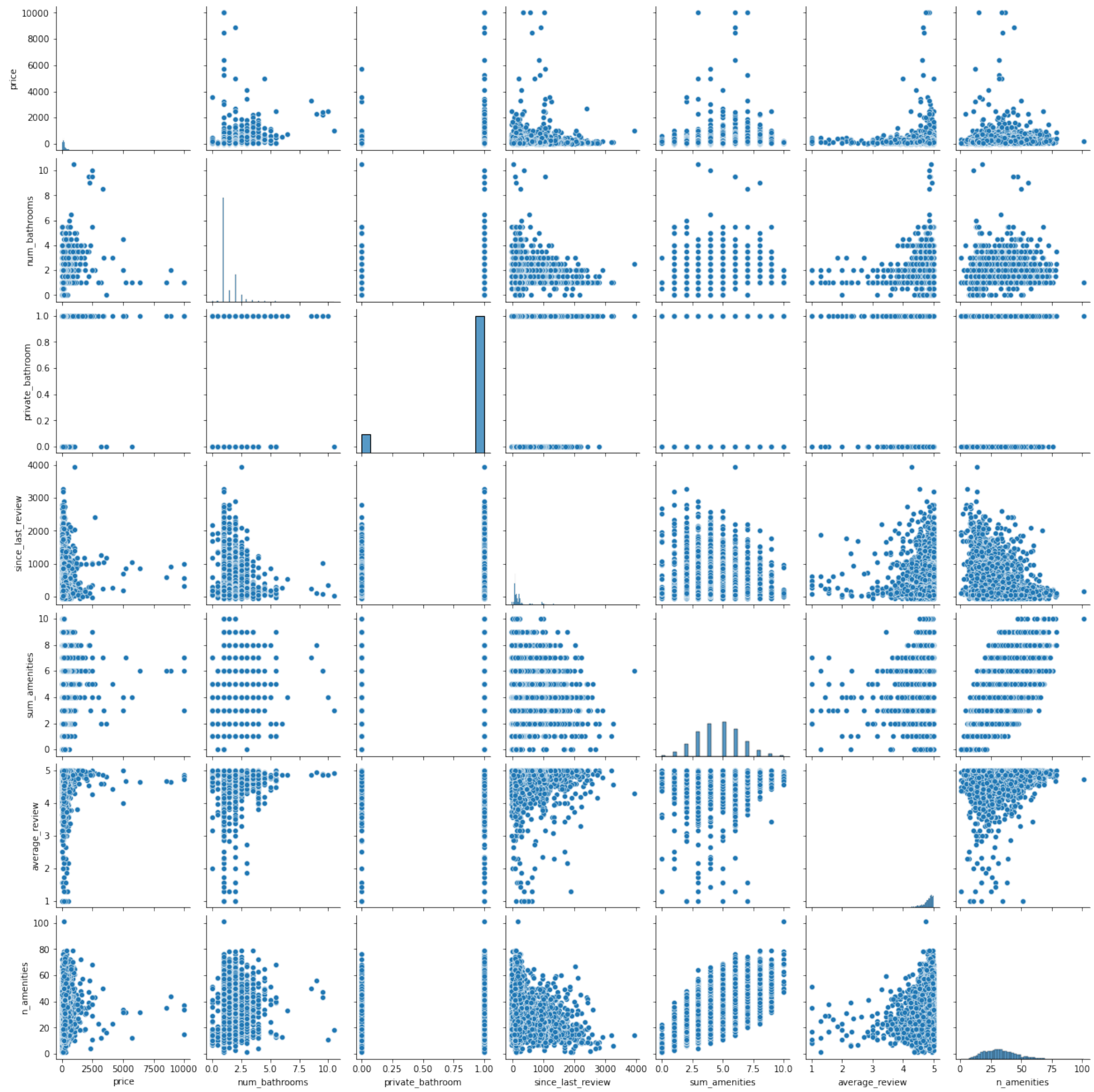

```
[56]: cols =␣
       ↪['price','accommodates','bedrooms','beds','maximum_nights','availability_365','number_of_re
      plt.figure()
      sns.pairplot(df_train[cols])
      plt.show()
```

<Figure size 432x288 with 0 Axes>




```
[57]: cols =␣
       ↪['price','num_bathrooms','private_bathroom','since_last_review','sum_amenities','average_re
      plt.figure()
      cols_to_plot = df_train.columns[1:3].tolist() + ['price'] #explicitly add price␣
       ↪column
      sns.pairplot(df_train[cols])
      plt.show()
```

<Figure size 432x288 with 0 Axes>



From the three plots above, we see that there is not a significant linear relationship among price and the variables, but has mostly spread throughout. With this in mind, during the modelling we shall use non-linear models to impute the value of price.

Task 3: Fit and tune a forecasting model/Submit predictions/Report score and ranking

Make sure you **clearly explain each step** you do, both in text and on the recoded video.

1. Build a machine learning (ML) regression model taking into account the outcomes of Tasks 1 & 2 (Explain carefully)
2. Fit the model and tune hyperparameters via cross-validation: make sure you comment and explain each step clearly

3. Create predictions using the test dataset and submit your predictions on Kaggle's competition page
4. Provide Kaggle ranking and **score** (screenshot your best submission) and Comment
5. Make sure your Python code works, so that a marker that can replicate your all of your results and obtain the same RMSE from Kaggle

- Hint: to perform well you will need to iterate Task 3, building and tuning various models in order to find the best one.

Total Marks: 12

[34]:
```python
df_train.info()
# df_train.to_excel('data_clean_train.xlsx', header=True)
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 6998 entries, 0 to 6999
Data columns (total 36 columns):
 #   Column                     Non-Null Count  Dtype
---  ------                     --------------  -----
 0   ID                         6998 non-null   int64
 1   host_response_time         6998 non-null   int64
 2   host_response_rate         6998 non-null   float64
 3   host_acceptance_rate       6998 non-null   float64
 4   host_is_superhost          6998 non-null   int64
 5   host_listings_count        6998 non-null   int64
 6   host_identity_verified     6998 non-null   int64
 7   room_type                  6998 non-null   int64
 8   accommodates               6998 non-null   int64
 9   bedrooms                   6998 non-null   float64
 10  beds                       6998 non-null   float64
 11  minimum_nights             6998 non-null   int64
 12  maximum_nights             6998 non-null   int64
 13  availability_365           6998 non-null   float64
 14  number_of_reviews          6998 non-null   int64
 15  last_review                6998 non-null   datetime64[ns]
 16  instant_bookable           6998 non-null   int64
 17  price                      6998 non-null   float64
 18  num_bathrooms              6998 non-null   float64
 19  private_bathroom           6998 non-null   int64
 20  average_review             6971 non-null   float64
 21  sum_amenities              6998 non-null   int64
 22  n_amenities                6998 non-null   int64
 23  since_last_review          6998 non-null   float64
 24  Melbourne                  6998 non-null   uint8
 25  OtherNeighbourhood         6998 non-null   uint8
 26  Port Phillip               6998 non-null   uint8
 27  Stonnington                6998 non-null   uint8
 28  Yarra                      6998 non-null   uint8
 29  Yarra Ranges               6998 non-null   uint8
```

```
 30  Entire home                 6998 non-null   uint8
 31  Entire rental unit          6998 non-null   uint8
 32  OtherPropertyType           6998 non-null   uint8
 33  Private room in home        6998 non-null   uint8
 34  Private room in rental unit 6998 non-null   uint8
 35  Sum_property_type           6998 non-null   uint8
dtypes: datetime64[ns](1), float64(9), int64(14), uint8(12)
memory usage: 1.4 MB
```

[35]:
```python
df_test.info()
# df_test.to_excel('data_clean_test.xlsx', header=True)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3000 entries, 0 to 2999
Data columns (total 35 columns):
 #   Column                      Non-Null Count  Dtype
---  ------                      --------------  -----
 0   ID                          3000 non-null   int64
 1   host_response_time          3000 non-null   int64
 2   host_response_rate          3000 non-null   float64
 3   host_acceptance_rate        3000 non-null   float64
 4   host_is_superhost           3000 non-null   int64
 5   host_listings_count         3000 non-null   float64
 6   host_identity_verified      3000 non-null   int64
 7   room_type                   3000 non-null   int64
 8   accommodates                3000 non-null   int64
 9   bedrooms                    3000 non-null   float64
 10  beds                        3000 non-null   float64
 11  minimum_nights              3000 non-null   int64
 12  maximum_nights              3000 non-null   int64
 13  availability_365            3000 non-null   float64
 14  number_of_reviews           3000 non-null   int64
 15  last_review                 2877 non-null   datetime64[ns]
 16  instant_bookable            3000 non-null   int64
 17  num_bathrooms               3000 non-null   float64
 18  private_bathroom            3000 non-null   int64
 19  average_review              2858 non-null   float64
 20  sum_amenities               3000 non-null   int64
 21  n_amenities                 3000 non-null   int64
 22  since_last_review           3000 non-null   float64
 23  Melbourne                   3000 non-null   uint8
 24  OtherNeighbourhood          3000 non-null   uint8
 25  Port Phillip                3000 non-null   uint8
 26  Stonnington                 3000 non-null   uint8
 27  Yarra                       3000 non-null   uint8
 28  Yarra Ranges                3000 non-null   uint8
 29  Entire home                 3000 non-null   uint8
 30  Entire rental unit          3000 non-null   uint8
```

```
 31   OtherPropertyType            3000 non-null   uint8
 32   Private room in home         3000 non-null   uint8
 33   Private room in rental unit  3000 non-null   uint8
 34   Sum_property_type            3000 non-null   uint8
dtypes: datetime64[ns](1), float64(9), int64(13), uint8(12)
memory usage: 574.3 KB
```

[36]:
```
#from above, we can still see irrelevant columns so dropping them
cols_to_drop1 = ['Stonnington', 'Port Phillip', 'OtherNeighbourhood',␣
 ↪'instant_bookable','minimum_nights','last_review']

df_train = df_train.drop(cols_to_drop1, axis = 1)
df_test = df_test.drop(cols_to_drop1, axis = 1)
```

[37]:
```
#preparing training and testing datasets
X_train = df_train.drop(['price','ID', 'average_review', 'maximum_nights'],␣
 ↪axis=1).values
y_train = df_train.price.values
X_test = df_test.drop(['ID', 'average_review','maximum_nights'], axis=1).values
```

Importing libraries for prediction models

[38]:
```
#importing libraries
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import validation_curve
from sklearn.metrics import mean_squared_error
from sklearn.model_selection import GridSearchCV, KFold

from sklearn.linear_model import LinearRegression
from sklearn.linear_model import RANSACRegressor
from sklearn.linear_model import Ridge
from sklearn.linear_model import Lasso
from sklearn.linear_model import ElasticNet
from sklearn.ensemble import RandomForestRegressor
from sklearn.svm import SVR
from sklearn.pipeline import make_pipeline

#scaling data
sc = StandardScaler()
X_train_scaled = sc.fit_transform(X_train)
X_test_scaled = sc.transform(X_test)
```

After several runs of the algorithms, we found that scaling the data did not increase the accuracy so we shall not be using the scaled data.

Simple Linear Regression

```
[39]: slr = LinearRegression().fit(X_train, y_train)

      #Create grid for Linear Regression
      slr_param_grid = {'fit_intercept': ['False', 'True'],
                        'normalize': ['False', True]}

      # K-fold on training
      slr_grid_search = GridSearchCV(slr, slr_param_grid, cv=KFold(n_splits=10,␣
       ↪random_state=8,shuffle=True), return_train_score=True)
      slr_grid_search.fit(X_train, y_train)
      slr_predicted = slr_grid_search.predict(X_test)

      # Evaluation
      print('Best fit_intercept: ' + slr_grid_search.best_params_['fit_intercept'])
      print('Best normalize: ' , slr_grid_search.best_params_['normalize'])
```

```
Best fit_intercept: False
Best normalize:  True
```

```
[40]: #use Linear Regression
      slr = LinearRegression(fit_intercept=False, normalize=True)
      slr.fit(X_train, y_train)
      y_train_pred_slr = slr.predict(X_train)
      print(f'RMSE train: {math.sqrt(mean_squared_error(y_train, y_train_pred_slr)):.
       ↪3f}')

      # y_test_pred_slr = slr.predict(X_test)
```

```
RMSE train: 330.098
```

RANSAC Regression

```
[41]: #use RANSAC Regressor
      ransac = RANSACRegressor(LinearRegression(),
                               max_trials=200,
                               min_samples=90,
                               residual_threshold=5.0,
                               random_state=5)
      ransac.fit(X_train, y_train)
      y_train_pred_ransac = ransac.predict(X_train)
      print(f'RMSE train: {math.sqrt(mean_squared_error(y_train,␣
       ↪y_train_pred_ransac)):.3f}')
```

```
RMSE train: 344.633
```

Ridge Regression

```
[42]: ridge = Ridge()

#Create grid for Ridge
ridge_param_grid = {'alpha': [0.001, 0.01, 0.1, 1, 10, 100]}

# K-fold on training
ridge_grid_search = GridSearchCV(ridge, ridge_param_grid, cv=KFold(n_splits=10,␣
↪random_state=8,shuffle=True), return_train_score=True)
ridge_grid_search.fit(X_train, y_train)
ridge_predicted = ridge_grid_search.predict(X_test)

# Evaluation
print('Best alpha: ' + str(ridge_grid_search.best_params_['alpha']))
```

```
Best alpha: 100
```

```
[43]: #use Ridge Regressor
ridge = Ridge(alpha=100)
ridge.fit(X_train, y_train)
y_train_pred_ridge = ridge.predict(X_train)
print(f'RMSE train: {math.sqrt(mean_squared_error(y_train, y_train_pred_ridge)):
↪.3f}')

# y_test_pred_ridge = ridge.predict(X_test)
```

```
RMSE train: 330.167
```

Lasso Regression

```
[44]: lasso = Lasso()

#Create grid for lasso
lasso_param_grid = {'alpha': [0.001, 0.01, 0.1, 1, 10, 100]}

# K-fold on training
lasso_grid_search = GridSearchCV(lasso, lasso_param_grid, cv=KFold(n_splits=10,␣
↪random_state=8,shuffle=True), return_train_score=True)
lasso_grid_search.fit(X_train, y_train)
lasso_predicted = lasso_grid_search.predict(X_test)

# Evaluation
print('Best alpha: ' + str(lasso_grid_search.best_params_['alpha']))
```

```
Best alpha: 1
```

```
[45]: #use Lasso Regressor
lasso = Lasso(alpha=1)
lasso.fit(X_train, y_train)
```

```
y_train_pred_lasso = lasso.predict(X_train)
print(f'RMSE train: {math.sqrt(mean_squared_error(y_train, y_train_pred_lasso)):
↪.3f}')

# y_test_pred_lasso = lasso.predict(X_test)
```

```
RMSE train: 330.224
```

Elastic Net

[46]:
```
elasticnet = ElasticNet()

#Create grid for ElasticNet
elasticnet_param_grid = {'alpha': [0.001, 0.01, 0.1, 1, 10, 100],
                        'l1_ratio': [0.001, 0.01, 0.1, 1, 10, 100]}

# K-fold on training
elasticnet_grid_search = GridSearchCV(elasticnet, elasticnet_param_grid,␣
↪cv=KFold(n_splits=10, random_state=8,shuffle=True), return_train_score=True)
elasticnet_grid_search.fit(X_train, y_train)
elasticnet_predicted = elasticnet_grid_search.predict(X_test)

# Evaluation
print('Best alpha: ' + str(elasticnet_grid_search.best_params_['alpha']))
print('Best l1_ratio: ' + str(elasticnet_grid_search.best_params_['l1_ratio']))
```

```
Best alpha: 1
Best l1_ratio: 1
```

[47]:
```
#use ElasticNet Regressor
elasticnet = ElasticNet(alpha=1, l1_ratio=1)
elasticnet.fit(X_train, y_train)
y_train_pred_elasticnet = elasticnet.predict(X_train)
print(f'RMSE train: {math.sqrt(mean_squared_error(y_train,␣
↪y_train_pred_elasticnet)):.3f}')

# y_test_pred_elasticnet = elasticnet.predict(X_test)
```

```
RMSE train: 330.224
```

Support Vector Machines (SVMs)

[48]:
```
from sklearn import svm
from sklearn.svm import SVC
from sklearn.metrics import mean_absolute_percentage_error

from sklearn.metrics import mean_absolute_error
from sklearn.model_selection import train_test_split
```

```
model_SVR = svm.SVR()
model_SVR.fit(X_train,y_train)
Y_pred = model_SVR.predict(X_train)
print(f'RMSE train: {math.sqrt(mean_squared_error(y_train, Y_pred)):.3f}')
Y_pred = model_SVR.predict(X_test)
```

```
RMSE train: 362.819
```

Stacking Regressor

[49]:
```
#!pip install mlxtend

forest = RandomForestRegressor()

from mlxtend.regressor import StackingCVRegressor

models = [elasticnet, ridge, forest]

stack = StackingCVRegressor(models, meta_regressor = Ridge(), cv=10)
stack.fit(X_train, y_train)
```

[49]:
```
StackingCVRegressor(cv=10, meta_regressor=Ridge(),
                    regressors=[ElasticNet(alpha=1, l1_ratio=1),
                                Ridge(alpha=100), RandomForestRegressor()])
```

[50]:
```
stack_predicted = stack.predict(X_test)
print(stack.get_params)
#print('Training set score: {:.04f}'.format(stack.best_score_))
```

```
<bound method StackingCVRegressor.get_params of StackingCVRegressor(cv=10,
meta_regressor=Ridge(),
                    regressors=[ElasticNet(alpha=1, l1_ratio=1),
                                Ridge(alpha=100), RandomForestRegressor()])>
```

[51]:
```
stack.fit(X_train, y_train)
y_train_pred_stack = stack.predict(X_train)
print(f'RMSE train: {math.sqrt(mean_squared_error(y_train, y_train_pred_stack)):
 ↪.3f}')
```

```
RMSE train: 203.132
```

Random Forest Regressor

[52]:
```
# forest = RandomForestRegressor()

# # Create the parameter grid based on the results of random search
# forest_param_grid  = {'criterion': ['mse', 'mae'],
#               'min_samples_split': [2, 5, 10],
#               'max_depth': ['None', 2, 6, 8],
```

```
#              'min_samples_leaf': [1, 5, 10],
#              'max_leaf_nodes': ['None', 5, 20]}

# # Instantiate the grid search model
# forest_grid_search = GridSearchCV(forest,forest_param_grid)
# forest_grid_search.fit(X_train, y_train)
# forest_predicted = forest_grid_search.predict(X_test)
```

[53]:
```
#use RandomForest Regressor
forest = RandomForestRegressor(n_estimators=1000,
                               criterion='mse',
                               n_jobs=-1, random_state=1)
forest.fit(X_train, y_train)
y_train_pred_forest = forest.predict(X_train)
print(f'RMSE train: {math.sqrt(mean_squared_error(y_train,␣
 ↪y_train_pred_forest)):.3f}')

y_test_pred_forest = forest.predict(X_test)
```

```
RMSE train: 121.826
```

[54]:
```
#import result
df = pd.DataFrame(y_test_pred_forest, columns = ['price'])
df['ID'] = df_test['ID']

def swap_columns(df, col1, col2):
    col_list = list(df.columns)
    x, y = col_list.index(col1), col_list.index(col2)
    col_list[y], col_list[x] = col_list[x], col_list[y]
    df = df[col_list]
    return df

df = swap_columns(df, 'price', 'ID')
df['price'] = round(df.price, 2)
df.to_csv('result.csv', index=False)
```

[ ]:
```
```