AIRBNB - PREDICTING RENTAL PRICES IN SYDNEY

This statistical project aims to explore the key factors that affect the rental prices of properties, which are listed on Airbnb, in Sydney and apply multiple fundamental machine learning models to predict the future price on the data collected. The models we used are multitple linear regression, gradient descent regression, ridge regression, descision tree regression and random forest.

The data description: The data set I used in this project is called the 'listing' dataset, which is released on July 10th 2019, and being publicly available on Inside Airbnb website.
_ URL (Inside Airbnb): http://insideairbnb.com/
_ Description: 106 columns and 38080 rows.
_ Date released: July 10th 2019

In this project, there are four main stages: (1) preprocessing data, (2) exploratory data analysis, (3) model training, prediction and evaluation, and (4) result interpretations.

Stage 1: Preprocessing Data

_ First we import necessary libraries for later use and dataset to be processed:

In [2]:
```
''' STAGE 1: DATA PREPROCESSING '''
# Import Libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings("ignore")
%matplotlib inline
```

In [2]:
```
# Load listing airbnb dataset
listing = pd.read_csv('D:/Data/Airbnb/2019-7-10/listings.csv')
```

_ We would like to adjust the viewing option of dataframe-type output as follow:

In [4]:
```
# Adjust the data view setting to check full data
pd.set_option('display.max_rows', 30)
pd.set_option('display.max_columns', 50)
pd.set_option('display.width', 100)
```

_ Let's take a quick look over summary statistics of features in dataset. Notice here, categorical features and features with missing values will show *NaN* value:

In [4]:
```
# Describe data
print(listing.shape)  # dimension of data
pd.DataFrame(listing.describe()).iloc[1:,:]  # summary statistics of data
```

(38080, 106)

Out[4]:

	id	scrape_id	thumbnail_url	medium_url	xl_picture_url	host_ic
mean	2.097697e+07	2.019071e+13	NaN	NaN	NaN	7.601631e+07
std	9.911534e+06	9.828254e+00	NaN	NaN	NaN	7.480652e+07
min	1.115600e+04	2.019071e+13	NaN	NaN	NaN	1.289400e+04
25%	1.334910e+07	2.019071e+13	NaN	NaN	NaN	1.573907e+07
50%	2.187017e+07	2.019071e+13	NaN	NaN	NaN	4.676120e+07
75%	2.999565e+07	2.019071e+13	NaN	NaN	NaN	1.220192e+08
max	3.656555e+07	2.019071e+13	NaN	NaN	NaN	2.747278e+08

_ We will check the percentage of missing values contained in each feature.

In [5]:
```
## 1.1 Detecting Missing Data
nrow = listing.shape[0]  # row dimension
ncol = listing.shape[1]  # column dimension
missfrq = listing.isnull().sum()/nrow  # returns frequency(in proportion)of missing
missfrq = pd.DataFrame(missfrq)   # transform into dataframe
missfrq = missfrq.rename(columns = {0:'Frequency'})  # add 'frequency' name to colu
pd.DataFrame(missfrq).head(10)
```

Out[5]:

	Frequency
id	0.000000
listing_url	0.000000
scrape_id	0.000000
last_scraped	0.000000
name	0.000341
summary	0.034769
space	0.299501
description	0.021586
experiences_offered	0.000000
neighborhood_overview	0.384506

_ The table above is a summary of missing values frequencies of every feature in the data. Below we will extract the high missing value rate (> 10%) and drop them.

In [6]:
```
# Detect features with missing values frequency > 0.1
misshigh = missfrq[missfrq['Frequency']>0.1].copy()  # Select those frequency value
pd.DataFrame(misshigh).head(10)   # Show the first 10 rows
```

Out[6]:

	Frequency
space	0.299501
neighborhood_overview	0.384506
notes	0.590678
transit	0.376654
access	0.423293
interaction	0.420273
house_rules	0.415966
thumbnail_url	1.000000
medium_url	1.000000
xl_picture_url	1.000000

_ Now, we will drop features that have high frequency values.

In [7]:
```
# Remove all features have missing values frequency > 0.1
VarDrop = misshigh.index   # store the names of features to be dropped
listing = listing.drop(VarDrop, axis = 1)  # drop features that have high missing v
print(listing.shape)   # current dimension of dataset
```

```
(38080, 72)
```

_ Next, we will impute missing values for the remaining features in the data: We will first subset the features that have missing values rate > 0% and < 10% from the *missfrq* table above, and then consider keeping only useful features.

In [8]:
```
## (1.2) Impute Missing values for remaining features in listing
# Subset features that have missing values proportion less than 10%:
missImpute = missfrq[missfrq['Frequency'] != 0].copy()
missImpute = missImpute[missImpute['Frequency'] <= 0.1]  # Select those features wi
pd.DataFrame(missImpute)
```

Out[8]:

	Frequency
name	0.000341
summary	0.034769
description	0.021586
host_name	0.000683
host_since	0.000683
host_location	0.001891
host_is_superhost	0.000683
host_thumbnail_url	0.000683
host_picture_url	0.000683
host_listings_count	0.000683
host_total_listings_count	0.000683
host_has_profile_pic	0.000683
host_identity_verified	0.000683
city	0.000709
state	0.007169
zipcode	0.003703
market	0.001786
bathrooms	0.000578
bedrooms	0.000236
beds	0.001287
cancellation_policy	0.000026

_ As there are many unnecessary features that can complicate the analysis, so we will remove all of them.

In [9]:

```
'''There are some unnecessary features such as host_thumbnail_url, host_picture_url
state (all NSW). We will remove these features.
'''
drop = ['host_thumbnail_url','host_picture_url','city','state','host_location','hos
        'market','name','host_name','zipcode']
listing = listing.drop(drop,axis = 1)
missImpute = missImpute.drop(drop,axis=0)
```

_ Next is to separate the continuous features and categorical features that have missing data.

In [10]:
```
''' We want to separate continuous and categorical features for missing values impu
    Notice that pd.data.describe() only works for continous variable. So we can sub
    dataframe
'''
missing = listing[missImpute.index].copy()  # Subset out missing features
contmiss = missing.describe().columns.values  # Get continuous features with missin
catemiss = missImpute.drop(contmiss,axis=0).index.values  # Get categorical feature
```

In [11]:
```
# Check features
print(contmiss)
print(catemiss)
```

```
['host_listings_count' 'host_total_listings_count' 'bathrooms' 'bedrooms'
 'beds']
['host_is_superhost' 'host_has_profile_pic' 'host_identity_verified'
 'cancellation_policy']
```

_ As the mean is easily influenced by large values in the data and hence sometimes results in misleading, it is not recommended for imputation. The median is more robust in measuring central of tendency but this may not represent a major proportion of the data values. We want to impute missing values with some appropriate data that might not change the characteristics in the data. As the proportions of missing data of all considered features are less than 10%, so using the mode value for imputation could be appropriate (for both continuous and categorical features).

In [12]:
```
# Impute missing values for continuous features with their mode values
for word in contmiss:
    listing[word] = listing[word].fillna(listing[word].mode()[0])
# Impute missing values for categorical features with their mode value
import operator
for word in catemiss:
    mode = max(dict(listing[word].value_counts()).items(), key=operator.itemgetter(
    listing[word] = listing[word].fillna(value = mode)
```

_ Next, we will check to see whether there is any duplicated data. Notice that one listing's 'id' can have many 'host_id' because one owner may have many properties for rent. But duplication for array value ['id' , 'host_id'] might be in check.

In [13]:
```
listing.isnull().sum().unique()  # Check to see whether there are any features with
```

Out[13]:
```
array([0], dtype=int64)
```

In [14]:
```
## (1.3) Checking for duplication
listing.duplicated(['id','host_id']).unique()  # No duplication
```

Out[14]:
```
array([False])
```

In [15]:
```
listing.duplicated(['id']).unique()  # No duplication
```

Out[15]:
```
array([False])
```

In [16]:
```
listing.duplicated(['host_id']).unique()  # There are duplications but it doesn't m
                                          # 1 property
```

Out[16]: array([False, True])

In [28]:
```
listing.duplicated().unique()  # there is no exact duplicate of row
```

Out[28]: array([False])

_ Some other features adjustments will be made for easier modelling later on:

In [17]:
```
## (1.4) Text feature adjustments and redundant features remove
# Remove redundant features
dropvar = ['listing_url','scrape_id','last_scraped','experiences_offered','picture_
           'calendar_last_scraped','street','smart_location','id','host_id','country
           'amenities','host_verifications']
```

_ As we will see below the two features "street" and "smart_location" referring to the same location. So we will drop one feature while remaining the other. As in our example, we will drop "street" (which has been included on the "dropvar" above.

In [18]:
```
# Store 'street' feature in a variable
street = listing['street'].copy()
```

In [19]:
```
# Keep only names of suburbs of NSW and ignore the term 'NSM, Australia'
for i in range(nrow):
    street[i] = street[i].split(",")[0]
```

In [20]:
```
# Store 'smart_location' in a variable
smart_location = listing['smart_location'].copy()
```

In [21]:
```
# Keep only names of suburbs of NSW and ignore the term 'NSM, Australia'
for i in range(nrow):
    smart_location[i] = smart_location[i].split(",")[0]
```

In [22]:
```
'''
We notice below here is that 'smart_location' and 'street' are identical. So we wil
 'smart_location' for analysis.
'''
(smart_location == street).unique() # as these two features are idential we will re
```

Out[22]: array([True])

In [23]:
```
listing = listing.drop(dropvar,axis = 1)
```

In [24]:
```
# Store adjusted features in listing dataset
listing['smart_location'] = smart_location
```

We can export out cleansed data into a CSV file for stage 2 analysis.

In [26]:
```
listing.to_csv("D:/Data/Airbnb/cleansed_listing.csv")
```

Stage 2: Exploratory Data Analysis - Data Featuring, Analysis, Visualization and Dashboard

In this stage, we will conduct statistical analysis, correlation matrix, visualization for the data.

In [3]:
```
''' STAGE II:  EXPLORATORY DATA ANALYSIS '''
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from scipy import stats
import seaborn as sns
from sklearn.model_selection import train_test_split
%matplotlib inline
```

In [6]:
```
# Import cleansed listing data for analysis
listing = pd.read_csv("D:/Data/Airbnb/cleansed_listing.csv")
```

_ One thing we noticed from the data is that the value in "price" feature contain the '$' symbol and "extra_people" feature has values in non-numeric type. So we will transform these features into appropriate format.

In [7]:
```
# Make a copy of listing
listcop = listing.copy()
```

We now create a function to fix the *price* and *extra_people* variables into appropriate format.

In [8]:
```
# Create a function to transform entries in 'price' and 'extra_people' values into
import string
def clear_punctuation(s):
    clear_string = ""
    for symbol in s:
        if symbol not in string.punctuation:
            clear_string += symbol
    return clear_string

# Other method also works (for this case):
#
#  1.    string_punctuation = "$,"
#  2.    def remove_punctuation(s):
#  3.       no_punct = ""
#  4.       for letter in s:
#  5.          if letter not in string_punctuation:
#  6.             no_punct += letter
#  7.       return no_punct  '''
```

Now we can use the defined function to convert data

In [9]:
```
nrow = listing.shape[0]  # row dimension
ncol = listing.shape[1]  # column dimension
# Store 'price' feature in target
target = listcop['price'].copy()
extra_people = listcop['extra_people'].copy()

# Transforming use loop
for i in range(nrow):
    target[i] = int(clear_punctuation(target[i]))/100
    extra_people[i] = int(clear_punctuation(extra_people[i]))/100

# Storing transformed data in listing data
listcop = listcop.drop(['price'],axis=1)
listcop = listcop.drop(['extra_people'],axis=1)
listcop['price'] = target
listcop['extra_people'] = extra_people
listcop = listcop[listcop['price'] != 0]  # drop rows with 0 price

# Convert 'price' and 'extra_people' into numeric type
listcop['price'] = listcop.price.astype(float)
listcop['extra_people'] = listcop.extra_people.astype(float)

# Reset index for the listcop data
listcop = listcop.reset_index(drop=True)
```

We can create a new feature called 'Haversine distance' based on the latitude and longitude available. This can provide some usefull insights as the rental price might be high or low in some specific suburbs away from Sydney Central Station.

In [13]:
```
'''

from numpy import arcsin
from math import sin, cos, sqrt, radians
## Calculate distance from Sydney CBD
SydLong = listcop[listcop['neighbourhood_cleansed']=='Sydney']['longitude']
SydLat = listcop[listcop['neighbourhood_cleansed']=='Sydney']['latitude']
SydLong_avg = np.mean(SydLong)
SydLat_avg = np.mean(SydLat)

## Create train_distance feature for training set
list_lat = listcop['latitude'].copy().reset_index()
list_long = listcop['longitude'].copy().reset_index()

# Haversine Distance
R = 6373.0  # approximate the earth radius in km
list_distance = [None]*len(list_lat)
for i in range(len(list_lat)):
    CBDlat = radians(SydLat_avg)
    CBDlon = radians(SydLong_avg)
    lat = radians(list_lat['latitude'][i])
    lon = radians(list_long['longitude'][i])
    dlon = lon - CBDlon
    dlat = lat - CBDlat
    haversine = sin(dlat / 2)**2 + cos(CBDlat) * cos(lat) * sin(dlon / 2)**2
```

```
    list_distance[i] = 2 * R * arcsin(sqrt(haversine))

# Add Haversine distance feature to 'listing' dataset
listcop['Haversine_distance'] = list_distance
listcop = listcop.drop(['latitude','longitude'],axis=1)  # drop 'latitude' and 'lon

'''
```

The above code is good but we can use *haversine_distances* function from scikit-learn library to get "Haversine_distance"

In [74]:
```
## We can calculate Haversine distance from scikit-learn library
from sklearn.metrics.pairwise import haversine_distances
from math import radians
# The coordinates of Sydney central station
SydSta_coord = [151.2070,-33.8832]
SydSta_in_radians = [radians(_) for _ in SydSta_coord]  # radians value of Sydney c

listcop_coord = listcop[["longitude","latitude"]].values  # an array values of all

result=[] # empty list
# appending haversine distance calculated to result
for i in range(len(listcop_coord)):
    coord = listcop_coord[i]
    data_in_radians = [radians(_) for _ in coord]
    result.append((haversine_distances([SydSta_in_radians, data_in_radians])* 63710

listcop["Haversine_distance"] = result
```

In [75]:
```
listcop["Haversine_distance"]
```

Out[75]:
```
0         2.569058
1         2.431575
2        10.066189
3         1.094128
4         4.475645
           ...
38070     2.575141
38071     1.414878
38072     2.409054
38073     7.292873
38074    10.566450
Name: Haversine_distance, Length: 38075, dtype: float64
```

latitude and longitude information are no longer needed so we will drop them

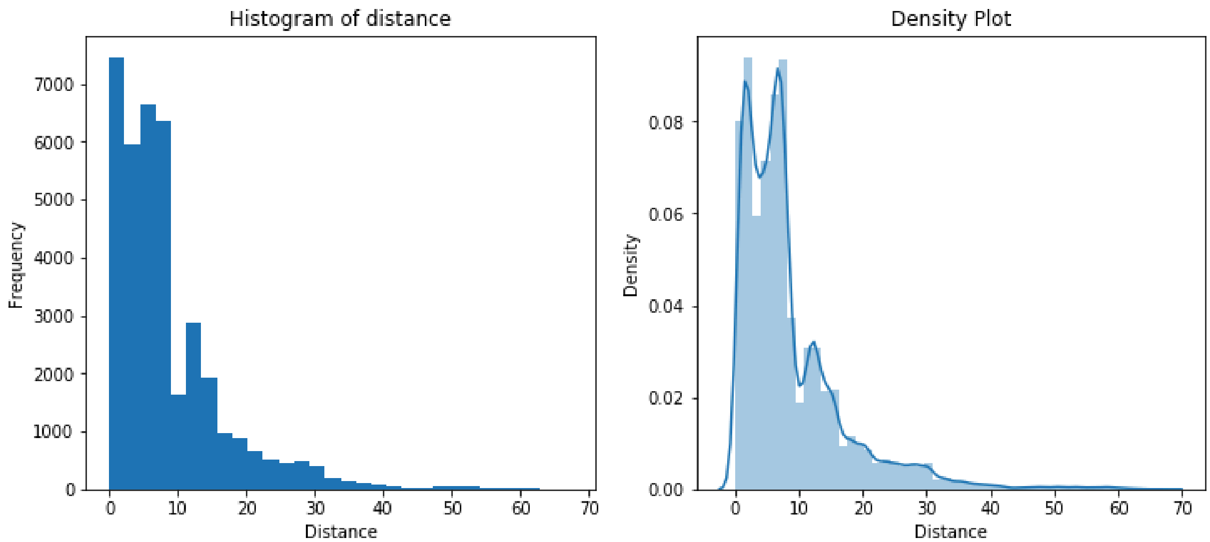
In [76]:
```
listcop = listcop.drop(['latitude','longitude'],axis=1)  # drop 'latitude' and 'lon
```

Here below are some visualizations of Haversine distance:

In [79]:
```
## Visualization of Haversine distance
plt.figure(figsize=(12,5))
plt.subplot(121)
plt.hist(listcop["Haversine_distance"],bins=30)
```

```
plt.title('Histogram of distance')
plt.xlabel('Distance')
plt.ylabel('Frequency')
plt.subplot(122,)
sns.distplot(listcop["Haversine_distance"])
plt.title('Density Plot')
plt.xlabel('Distance')
plt.ylabel('Density')
```

Out[79]: Text(0, 0.5, 'Density')

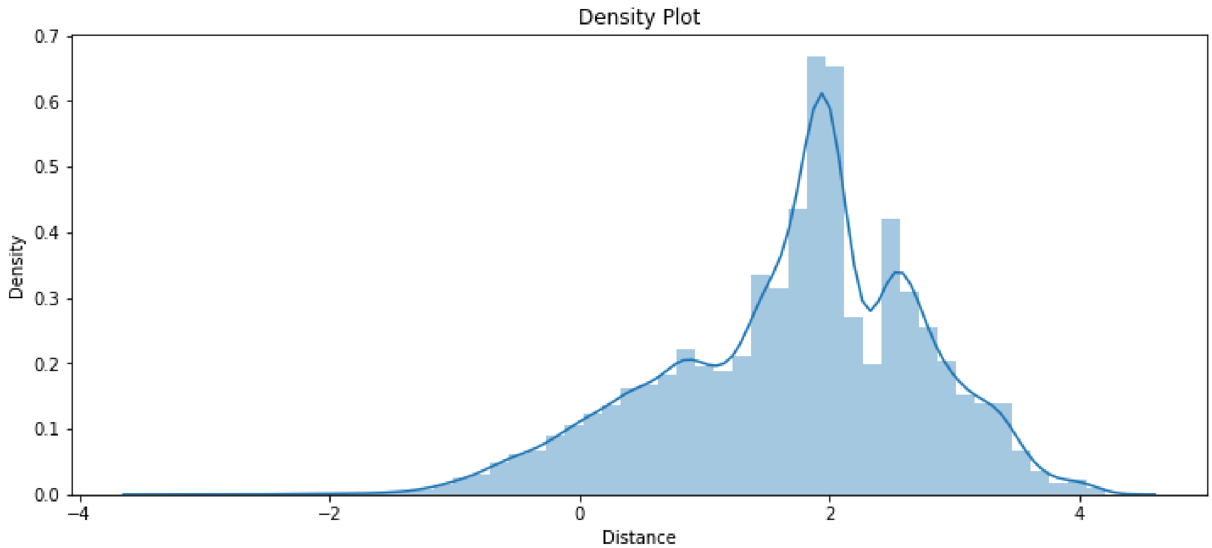


We can see the distribution is heavily right skewed. Hence, we could consider to log transform this feature.

In [80]:
```
## Using log-transform for the Haversine distance
listcop['Log_Haversine_Distance'] = np.log(listcop['Haversine_distance'])
```

In [81]:
```
# Plot log of Haversine distance
plt.figure(figsize=(12,5))
sns.distplot(listcop['Log_Haversine_Distance'])
plt.title('Density Plot')
plt.xlabel('Distance')
plt.ylabel('Density')
```

Out[81]: Text(0, 0.5, 'Density')

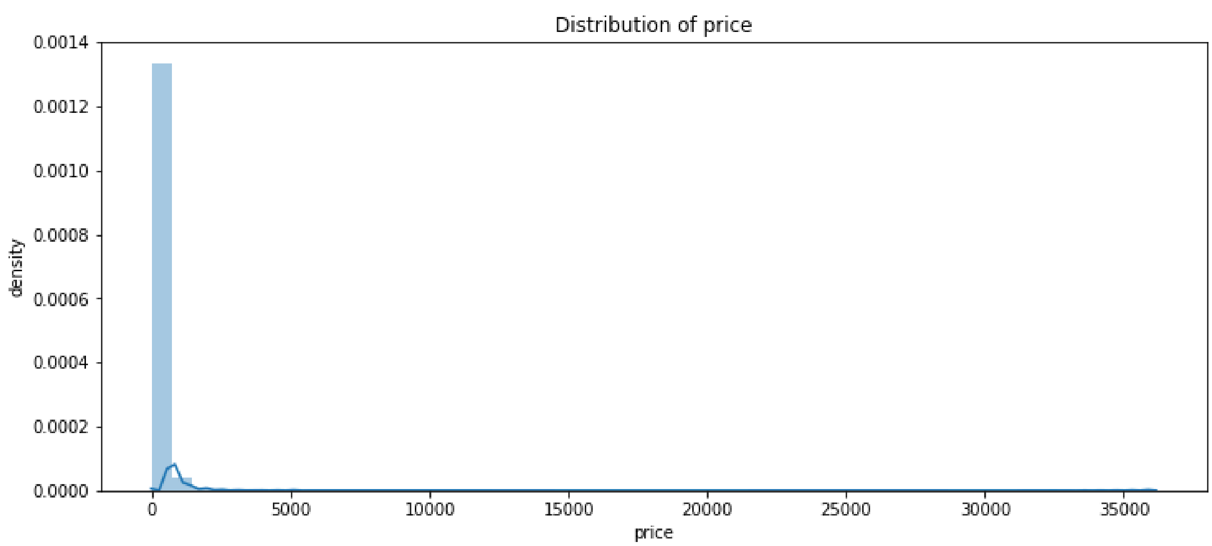


The distribution of this continuous variable seems reasonably normal

Lets also check the distribution of target "price" :

In [14]:
```
plt.figure(figsize=(12,5))
sns.distplot(listcop.price)
plt.title('Distribution of price')
plt.xlabel('price')
plt.ylabel('density')
```

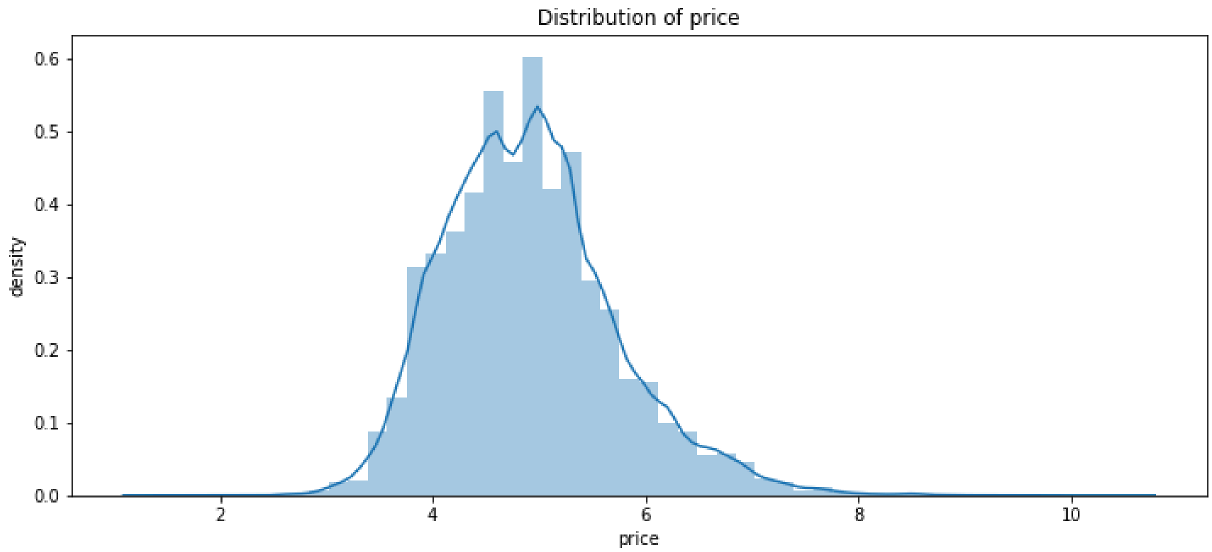
Out[14]:
```
Text(0, 0.5, 'density')
```



The distribution is heavily right skewed. We should try log-transform the *price* for the ease of further analysis.

In [15]:
```
plt.figure(figsize=(12,5))
sns.distplot(np.log(listcop.price))
plt.title('Distribution of price')
plt.xlabel('price')
plt.ylabel('density')
```

Out[15]: Text(0, 0.5, 'density')



Log-transformed price makes the distribution seems approximately normal. And this could be easier for later modeling steps.

In [85]:
```
## Log transform the price
listcop['log_price'] = np.log(listcop['price']+1)
```

1. Categorical Data Analysis

In [86]:
```
listcop.head()
```

Out[86]:

	host_is_superhost	host_listings_count	host_total_listings_count	host_has_profile_pic	host
0	f	1	1	t	
1	t	2	2	t	
2	f	2	2	t	
3	f	3	3	t	
4	t	2	2	t	

In [84]:
```
## Get a quick frequency counts
cate_summary = pd.DataFrame(columns=['categorical feature','frequency distribution'
for name in listcop.columns.values:
    if name not in listcop.describe().columns.values:
        cate_summary = cate_summary.append({'categorical feature':name,
                                            'frequency distribution':dict(listcop[n
cate_summary
```

Out[84]:

	categorical feature	frequency distribution
0	host_is_superhost	{'f': 32596, 't': 5479}
1	host_has_profile_pic	{'t': 37988, 'f': 87}
2	host_identity_verified	{'f': 23688, 't': 14387}
3	neighbourhood_cleansed	{'Sydney': 9745, 'Waverley': 5437, 'Randwick':...
4	is_location_exact	{'t': 28088, 'f': 9987}
5	property_type	{'Apartment': 22404, 'House': 10140, 'Townhous...
6	room_type	{'Entire home/apt': 23410, 'Private room': 139...
7	bed_type	{'Real Bed': 37901, 'Pull-out Sofa': 93, 'Futo...
8	calendar_updated	{'today': 5890, '2 months ago': 1792, '3 month...
9	has_availability	{'t': 38075}
10	requires_license	{'f': 38075}
11	instant_bookable	{'f': 21147, 't': 16928}
12	is_business_travel_ready	{'f': 38075}
13	cancellation_policy	{'strict_14_with_grace_period': 15365, 'flexib...
14	require_guest_profile_picture	{'f': 37870, 't': 205}
15	require_guest_phone_verification	{'f': 37829, 't': 246}
16	smart_location	{'Bondi Beach': 1953, 'Surry Hills': 1367, 'Ma...

As we can see that *host_is_superhost, host_has_profile_pic, has_availability, requires_license, is_business_travel_ready, require_guest_profile_picture, require_guest_phone_verification* has significant amount of either 'True' or 'False' and some of them have all values are 'True' or 'False'. So, these variables are reduncdant features and should be dropped from our dataset.

In [87]:
```
## Dropping some reduncdant features
listcop = listcop.drop(["host_is_superhost","host_has_profile_pic","has_availabilit
                        "is_business_travel_ready","require_guest_profile_picture",
```

What is the distribution of property type?

In [88]:
```
tab = pd.DataFrame(listcop['property_type'].value_counts()).rename(columns={"proper
tab["Frequency"] = tab["Counts"]/sum(tab["Counts"])*100
tab.head(20)
```

Out[88]:

	Counts	Frequency
Apartment	22404	58.841760
House	10140	26.631648
Townhouse	1727	4.535785
Condominium	760	1.996060
Guest suite	549	1.441891
Guesthouse	444	1.166120
Villa	300	0.787919
Serviced apartment	296	0.777413
Loft	235	0.617203
Bed and breakfast	206	0.541037
Boutique hotel	193	0.506894
Bungalow	193	0.506894
Cottage	142	0.372948
Hostel	112	0.294156
Other	78	0.204859
Cabin	78	0.204859
Hotel	43	0.112935
Tiny house	41	0.107682
Boat	29	0.076165
Camper/RV	22	0.057781

From the frequency table, we can see that most property listings on Airbnb in Sydney are Apartments and Houses, which accounts for about 58.84% and 26.63%, respectively.
Other property listings are much less frequent, so we can consider grouping these properties into one group, e.g. "*Other Types*".

In [89]:
```
## Grouping property types other than Apartment and House into "Other Types"
listcop['property_type'][(listcop.property_type!="Apartment") & (listcop.property_t
listcop["property_type"].unique()
```

Out[89]: `array(['Apartment', 'Other Types', 'House'], dtype=object)`

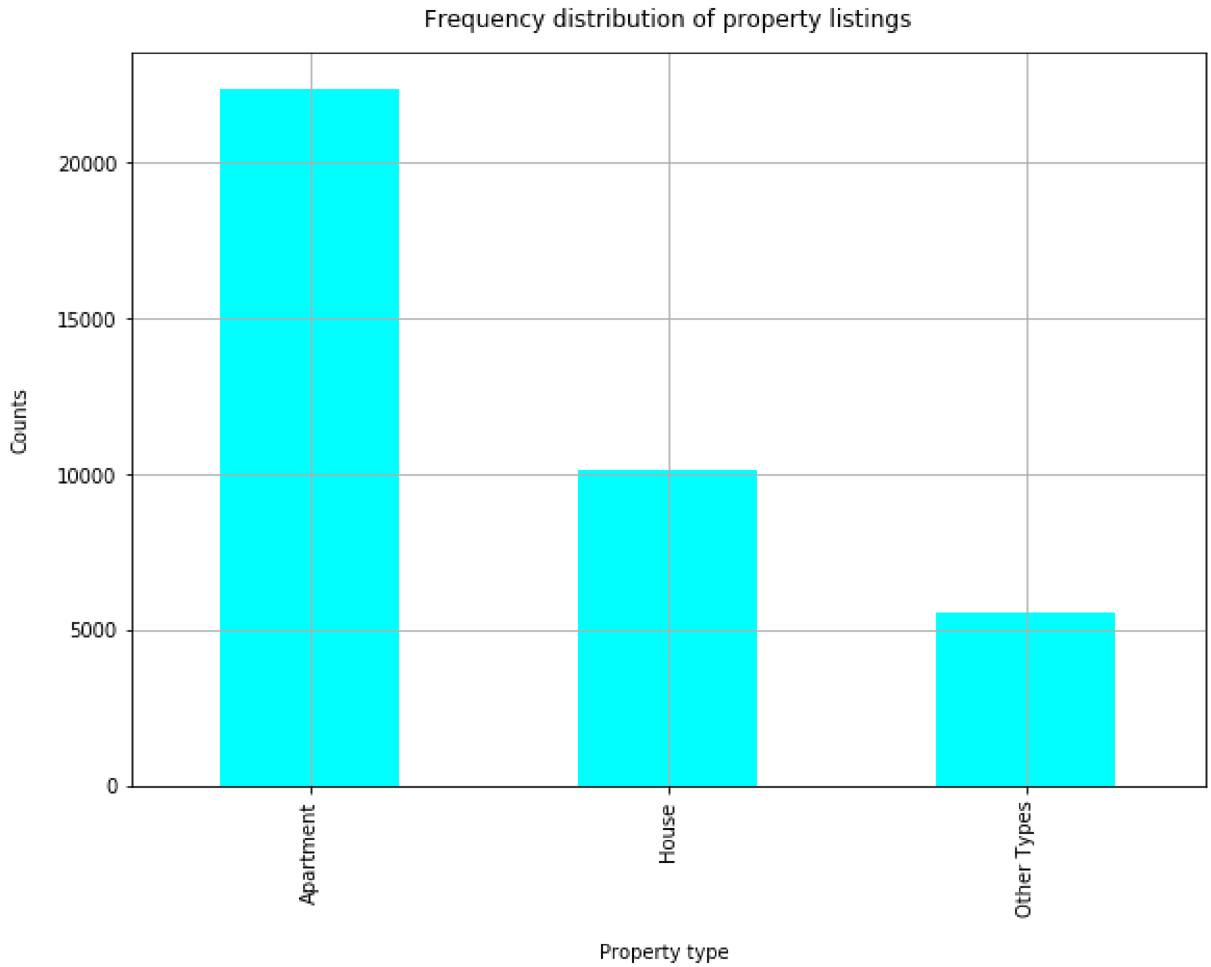
In [90]:
```
# Checking the groupings distribution of property listing
tab1 = pd.DataFrame(listcop['property_type'].value_counts()).rename(columns={"prope
tab1["Frequency"] = tab1["Counts"]/sum(tab1["Counts"])*100
tab1
```

Out[90]:

	Counts	Frequency
Apartment	22404	58.841760
House	10140	26.631648
Other Types	5531	14.526592

In [23]:
```
# Barplot of the top 15 wanted property
listcop['property_type'].value_counts().plot(kind='bar',figsize=(10,7), color = "cy
plt.xlabel("Property type ", labelpad=14)
plt.ylabel("Counts", labelpad=14)
plt.title("Frequency distribution of property listings", y=1.02)
```

Out[23]: Text(0.5, 1.02, 'Frequency distribution of property listings')



Room type by property type:

In [91]:
```
# frequency table
tab2 = pd.crosstab(listcop['property_type'], listcop['room_type'], margins=True, ma
tab2[tab2['Total']>=100]
```

Out[91]:

room_type property_type	Entire home/apt	Private room	Shared room	Total
Apartment	14945	7051	408	22404
House	5444	4500	196	10140
Other Types	3021	2372	138	5531
Total	23410	13923	742	38075

In [25]:

```
# Proportion table
tab2.div(tab2.Total.astype(float),axis=0)
```

Out[25]:

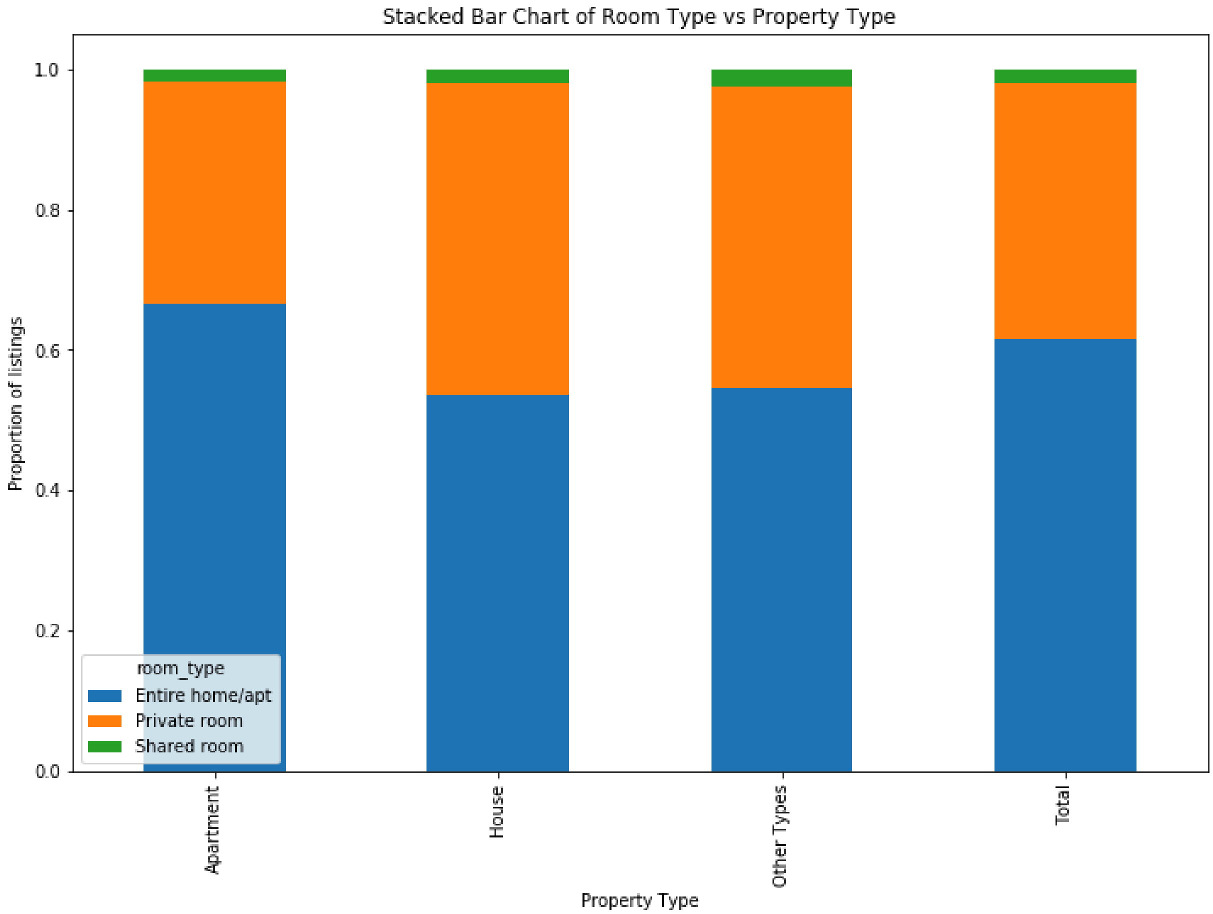
room_type property_type	Entire home/apt	Private room	Shared room	Total
Apartment	0.667068	0.314721	0.018211	1.0
House	0.536884	0.443787	0.019329	1.0
Other Types	0.546194	0.428856	0.024950	1.0
Total	0.614839	0.365673	0.019488	1.0

In [21]:

```
## Visualize the result
tab2.div(tab2.Total.astype(float),axis=0).iloc[:,0:3].plot(figsize=(12,8),kind='bar
plt.title("Stacked Bar Chart of Room Type vs Property Type")
plt.xlabel("Property Type")
plt.ylabel("Proportion of listings")
```

Out[21]:

```
Text(0, 0.5, 'Proportion of listings')
```



In [26]:
```
## Chi-square test
from scipy.stats import chi2_contingency
stat, p, dof, expected = chi2_contingency(tab2.iloc[0:3,0:3])

# Interpret p-value
alpha = 0.05
print("p value is " + str(p))
if p <= alpha:
    print('Dependent (reject H0): The two variables are dependent')
else:
    print('Independent (H0 holds true): Two variables might be independent')
```

```
p value is 2.0555747653886704e-137
Dependent (reject H0): The two variables are dependent
```

We can see that most people in Sydney list their entire apartment or property for rent in all kinds of property while the second most popular room type for rent is private room.
And it also seems that room types and property types are dependent variables. This might not be a good news for modeling step. Later on, we will check the dependency among categorical variables in the data.

Bed type distribution by property type:

In [92]:
```
# Frequency table
tab3 = pd.crosstab(listcop['property_type'],listcop['bed_type'], margins=True, marg
tab3[tab3['Total'] >= 100]
```

Out[92]:

bed_type property_type	Airbed	Couch	Futon	Pull-out Sofa	Real Bed	Total
Apartment	13	9	28	59	22295	22404
House	3	3	9	13	10112	10140
Other Types	10	2	4	21	5494	5531
Total	26	14	41	93	37901	38075

In [24]:

```
# Proportion table
tab3.div(tab3.Total.astype(float), axis=0)
```

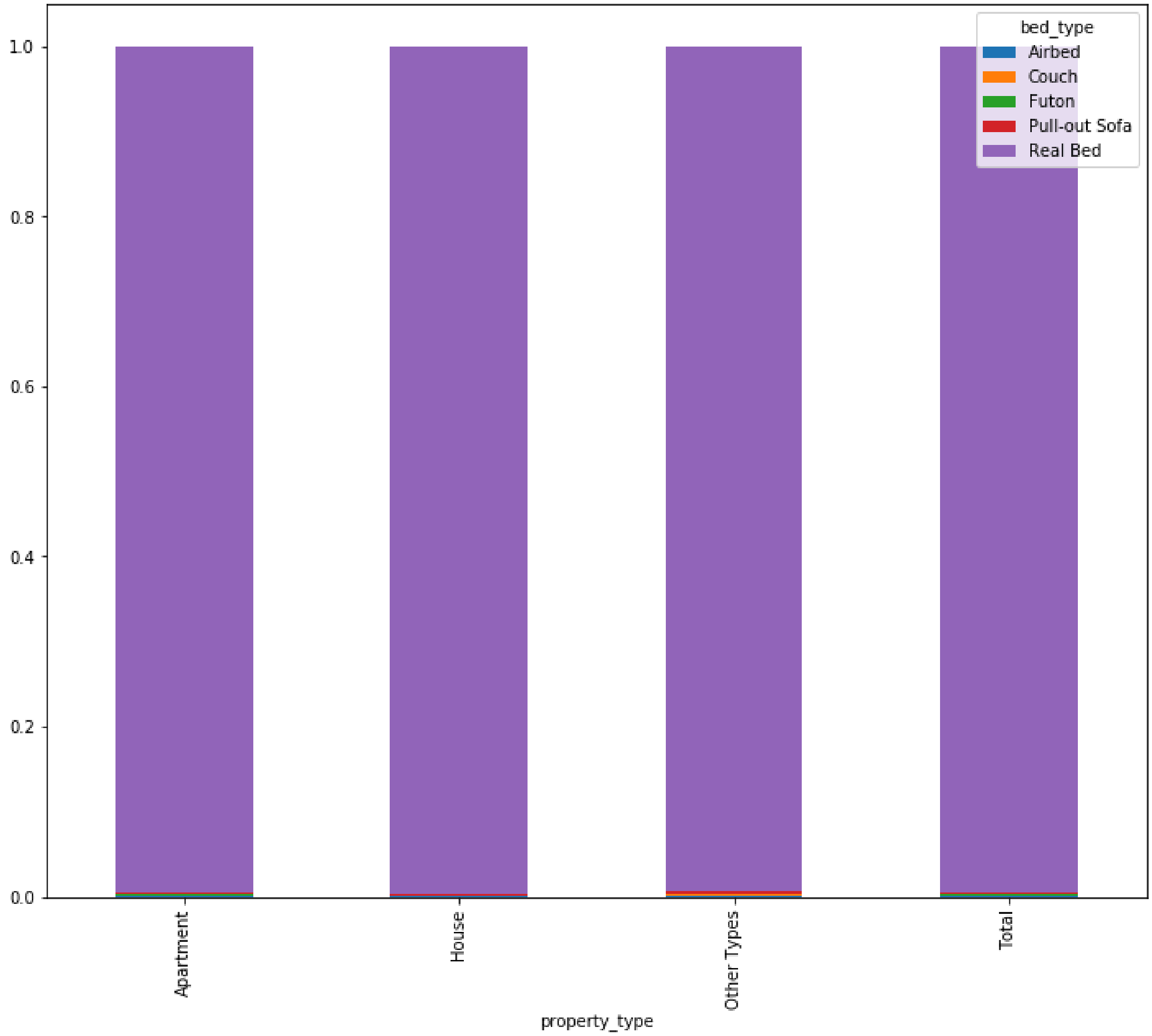
Out[24]:

bed_type property_type	Airbed	Couch	Futon	Pull-out Sofa	Real Bed	Total
Apartment	0.000580	0.000402	0.001250	0.002633	0.995135	1.0
House	0.000296	0.000296	0.000888	0.001282	0.997239	1.0
Other Types	0.001808	0.000362	0.000723	0.003797	0.993310	1.0
Total	0.000683	0.000368	0.001077	0.002443	0.995430	1.0

In [25]:

```
# Visualization
tab3.div(tab3.Total.astype(float), axis=0).iloc[:,0:5].plot(figsize=(12,10),kind='b
```

Out[25]: `<matplotlib.axes._subplots.AxesSubplot at 0x1acbe06a390>`



It is also obvious that the most popular bed type is real bed. And because the proportion of real bed accounts for about 99% of the whole data so this variable may not be so informative and could be reduncdant. Hence, we might consider to drop this variable off the dataset.

In [93]:
```
# Dropping the bed type variable
listcop = listcop.drop("bed_type",axis=1)
```

See the frequency table of cancelation policy:

In [94]:
```
tab4 = pd.DataFrame(listcop['cancellation_policy'].value_counts()).rename(columns={
tab4
```

Out[94]:

	Counts
strict_14_with_grace_period	15365
flexible	13922
moderate	8587
super_strict_60	111
super_strict_30	67
luxury_super_strict_125	8
luxury_no_refund	7
luxury_moderate	7
luxury_super_strict_95	1

As we can see that we can group the the last cancellation policies into one group with *moderate* policy

In [95]:
```
# Grouping the cancellation policy types in listing data.
listcop['cancellation_policy'][(listcop.cancellation_policy!="strict_14_with_grace_
                                (listcop.cancellation_policy!="flexible")]="Moderate
listcop["cancellation_policy"].unique()
```

Out[95]:
```
array(['Moderate and other types', 'strict_14_with_grace_period',
       'flexible'], dtype=object)
```

See the cross frequency table of cancellation policy and property type:

In [96]:
```
# Frequency table
tab5 = pd.crosstab(listcop['property_type'], listcop['cancellation_policy'], margin
tab5
```

Out[96]:

cancellation_policy	Moderate and other types	flexible	strict_14_with_grace_period	Total
property_type				
Apartment	5222	8159	9023	22404
House	2086	3733	4321	10140
Other Types	1480	2030	2021	5531
Total	8788	13922	15365	38075

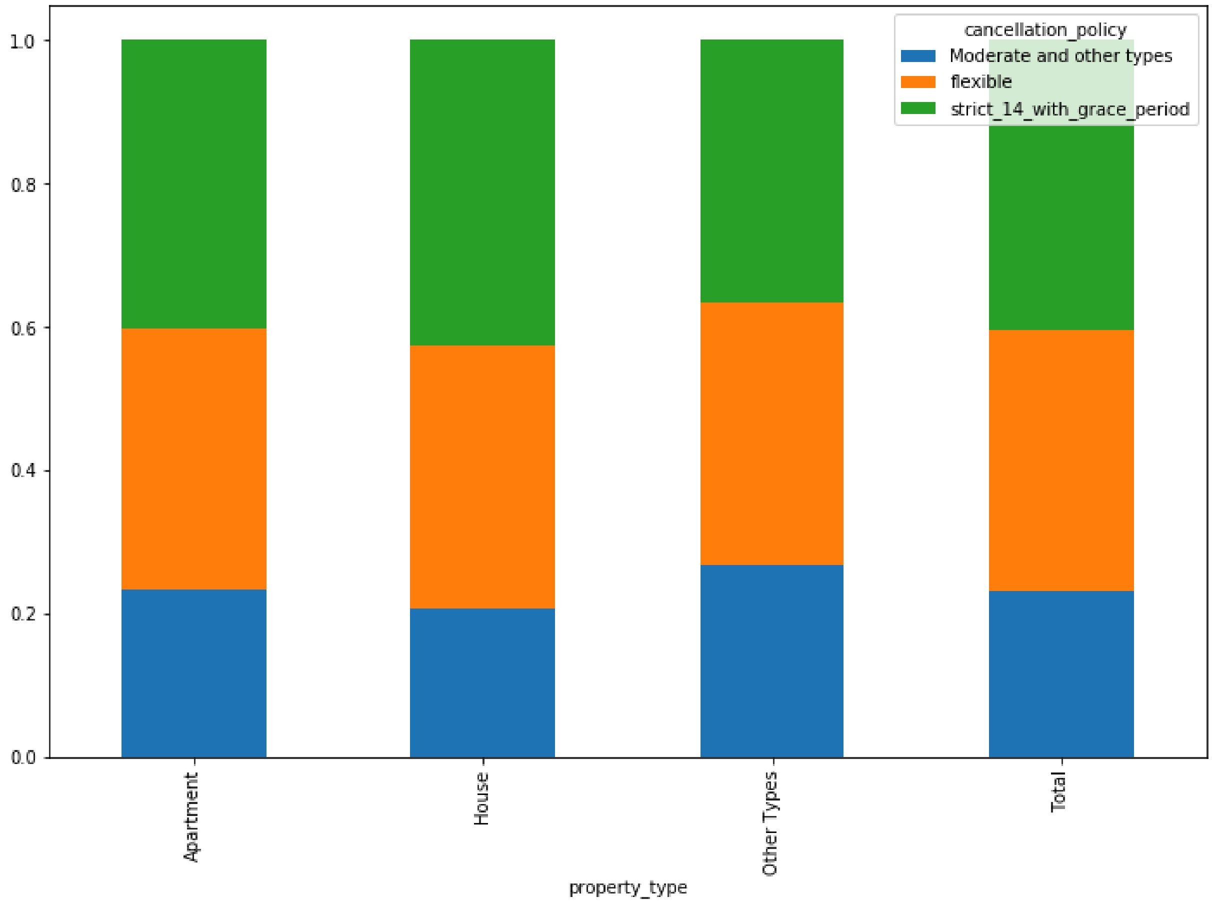
In [32]:
```
# Proportion table
tab5.div(tab5.Total.astype(float), axis=0).iloc[:,0:3]*100
```

Out[32]:

cancellation_policy	Moderate and other types	flexible	strict_14_with_grace_period
property_type			
Apartment	23.308338	36.417604	40.274058
House	20.571992	36.814596	42.613412
Other Types	26.758272	36.702224	36.539505
Total	23.080762	36.564675	40.354563

In [31]:
```
# Visualization
tab5.div(tab5.Total.astype(float), axis=0).iloc[:,0:3].plot(figsize=(12,8),kind='ba
```

Out[31]: <matplotlib.axes._subplots.AxesSubplot at 0x1acbe1ce668>



Apartments with strict and flexible policy types are the most commonly listed. The second most common one is House with strict and flexible policy.
The variability of policy types among property types is not significantly different

In [33]:
```
listcop['calendar_updated'].unique()  ## check categories in "calendar_updated"
```

Out[33]:
```
array(['5 weeks ago', '3 days ago', '2 months ago', '4 days ago',
       '3 months ago', '4 months ago', 'a week ago', 'today',
       '26 months ago', '30 months ago', '10 months ago', 'yesterday',
       '6 weeks ago', '13 months ago', '2 weeks ago', '15 months ago',
       '37 months ago', '5 months ago', '11 months ago', '20 months ago',
       '4 weeks ago', '5 days ago', '41 months ago', '19 months ago',
       '7 months ago', '3 weeks ago', '17 months ago', '31 months ago',
       '33 months ago', '8 months ago', '57 months ago', '70 months ago',
       '28 months ago', '34 months ago', '21 months ago', '16 months ago',
       '6 days ago', '49 months ago', '6 months ago', '46 months ago',
       '32 months ago', '12 months ago', '43 months ago', '27 months ago',
       '29 months ago', '9 months ago', '7 weeks ago', '23 months ago',
       '40 months ago', '45 months ago', '1 week ago', '18 months ago',
       '47 months ago', '59 months ago', '44 months ago', '48 months ago',
       '83 months ago', 'never', '35 months ago', '39 months ago',
       '36 months ago', '2 days ago', '25 months ago', '22 months ago',
       '14 months ago', '56 months ago', '24 months ago', '74 months ago',
       '53 months ago', '62 months ago', '38 months ago', '42 months ago',
       '50 months ago', '69 months ago', '51 months ago', '63 months ago',
       '68 months ago', '67 months ago', '61 months ago', '54 months ago',
       '58 months ago', '60 months ago', '52 months ago', '55 months ago'],
      dtype=object)
```

As we can see there are so much categories in this "calendar_updated" variable. So, we definitely need to group them for better analysis and modeling.
Below here we will see the frequency counts of this variable

In [34]:
```
listcop["calendar_updated"].value_counts()/sum(listcop["calendar_updated"].value_co
```

Out[34]:
```
today             15.469468
2 months ago       4.706500
3 months ago       4.496389
2 weeks ago        4.480630
a week ago         4.459619
                    ...
83 months ago      0.002626
74 months ago      0.002626
70 months ago      0.002626
60 months ago      0.002626
69 months ago      0.002626
Name: calendar_updated, Length: 84, dtype: float64
```

As we can see the proportion in most categories, except "today", are less than 5%. It is suggested we need to group these categories by some logic.

- group 1: 'yesterday', 'today' (or "recently updated")
- group 2: 2-6 days
- group 3: 1-7 weeks
- group 4: 2-6 months
- group 5: >6-12 months
- group 6: >12-24 months
- group 7: >24 months or never

In [ ]:
```
'''

## Grouping the levels in 'calendar_updated'  (BUT CODE IS NOT RECOMMENDED)
for i in range(len(listcop['calendar_updated'])):
    word = listcop.calendar_updated[i].split()
    if len(word) == 1:
        if word[0] =='yesterday' or word[0] == 'today':
            word = 'most recently updated'
    else:
        if word[0] == 'a': word[0]='1'
        if word[1]=='days' or word[1] =='day':
            word = '2-6 days'
        if word[1]=='week' or word[1] == 'weeks':
            word = '1-7 weeks'
        if word[1] == 'months' or word[1] == 'month':
            if int(word[0]) <= 6:
                word = '2-6 months'
            elif int(word[0]) <=12:
                word = '>6-12 months'
            elif int(word[0]) <= 24:
                word = '>12-24 months'
            else:
                word = '>24 months or never'
    listcop.calendar_updated[i] = word

'''
```

But above code is terrible and we can do as following:

In [97]:
```
#### Categorization of "neighbourhood_cleansed"

listcop['calendar_updated'][listcop['calendar_updated'].str[0]=='a']=listcop['calen
# replace every word "a..." by '1'

listcop['calendar_updated'][(listcop['calendar_updated']=="yesterday") |
                            (listcop['calendar_updated']=="today")]="recently updat

listcop['calendar_updated'][(listcop['calendar_updated'].str.contains("day")) & (li
                            (listcop['calendar_updated']!="today")]="2-6 days"

listcop['calendar_updated'][listcop['calendar_updated'].str.contains("week")]="1-7

index1 = listcop['calendar_updated'][listcop['calendar_updated'].str.contains("mont
    [listcop['calendar_updated'].str.contains("month")].str[0:2].astype(int)<=6].in

index2 = listcop['calendar_updated'][listcop['calendar_updated'].str.contains("mont
    (listcop['calendar_updated'][listcop['calendar_updated'].str.contains("month")]
     &
     (listcop['calendar_updated'][listcop['calendar_updated'].str.contains("month")

index3 = listcop['calendar_updated'][listcop['calendar_updated'].str.contains("mont
    (listcop['calendar_updated'][listcop['calendar_updated'].str.contains("month")]
     &
    (listcop['calendar_updated'][listcop['calendar_updated'].str.contains("month")]
```

```
index4 = listcop['calendar_updated'][listcop['calendar_updated'].str.contains("mont
    [listcop['calendar_updated'].str.contains("month")].str[0:2].astype(int)>24].in

listcop.loc[index1,'calendar_updated']="2-6 months"

listcop.loc[index2,'calendar_updated']=">6-12 months"

listcop.loc[index3,'calendar_updated']=">12-24 months"

listcop.loc[index4,'calendar_updated']=">24 months or never"

listcop['calendar_updated'][listcop['calendar_updated']=="never"]=">24 months or ne

# Check categories
listcop['calendar_updated'].unique()
```

Out[97]:
```
array(['1-7 weeks', '2-6 days', '2-6 months', 'recently updated',
       '>24 months or never', '>6-12 months', '>12-24 months'],
      dtype=object)
```

In [36]:
```
## Checking levels of "neighbourhood_cleansed"
listcop['neighbourhood_cleansed'].unique()
```

Out[36]:
```
array(['Sydney', 'Manly', 'Leichhardt', 'Woollahra', 'North Sydney',
       'Waverley', 'Mosman', 'Pittwater', 'Lane Cove', 'Marrickville',
       'Hornsby', 'Warringah', 'Rockdale', 'Randwick', 'Sutherland Shire',
       'Ku-Ring-Gai', 'Strathfield', 'Canterbury', 'Blacktown',
       'Willoughby', 'Auburn', 'Canada Bay', 'The Hills Shire',
       'Ashfield', 'Parramatta', 'Hurstville', 'Ryde', 'Botany Bay',
       'Holroyd', 'Penrith', 'Bankstown', 'Hunters Hill', 'Burwood',
       'Campbelltown', 'Camden', 'Liverpool', 'City Of Kogarah',
       'Fairfield'], dtype=object)
```

This categorical variable also has too many levels. Again, we could check the proportion distribution of these categories and group them appropriately

In [69]:
```
## Proportion table of "neighbourhood_cleansed"
pd.DataFrame(listcop['neighbourhood_cleansed'].value_counts()/
    sum(listcop['neighbourhood_cleansed'].value_counts())*100).rename_axis("neighbo
    columns={"neighbourhood_cleansed":"Proportion"})
```

Out[69]:

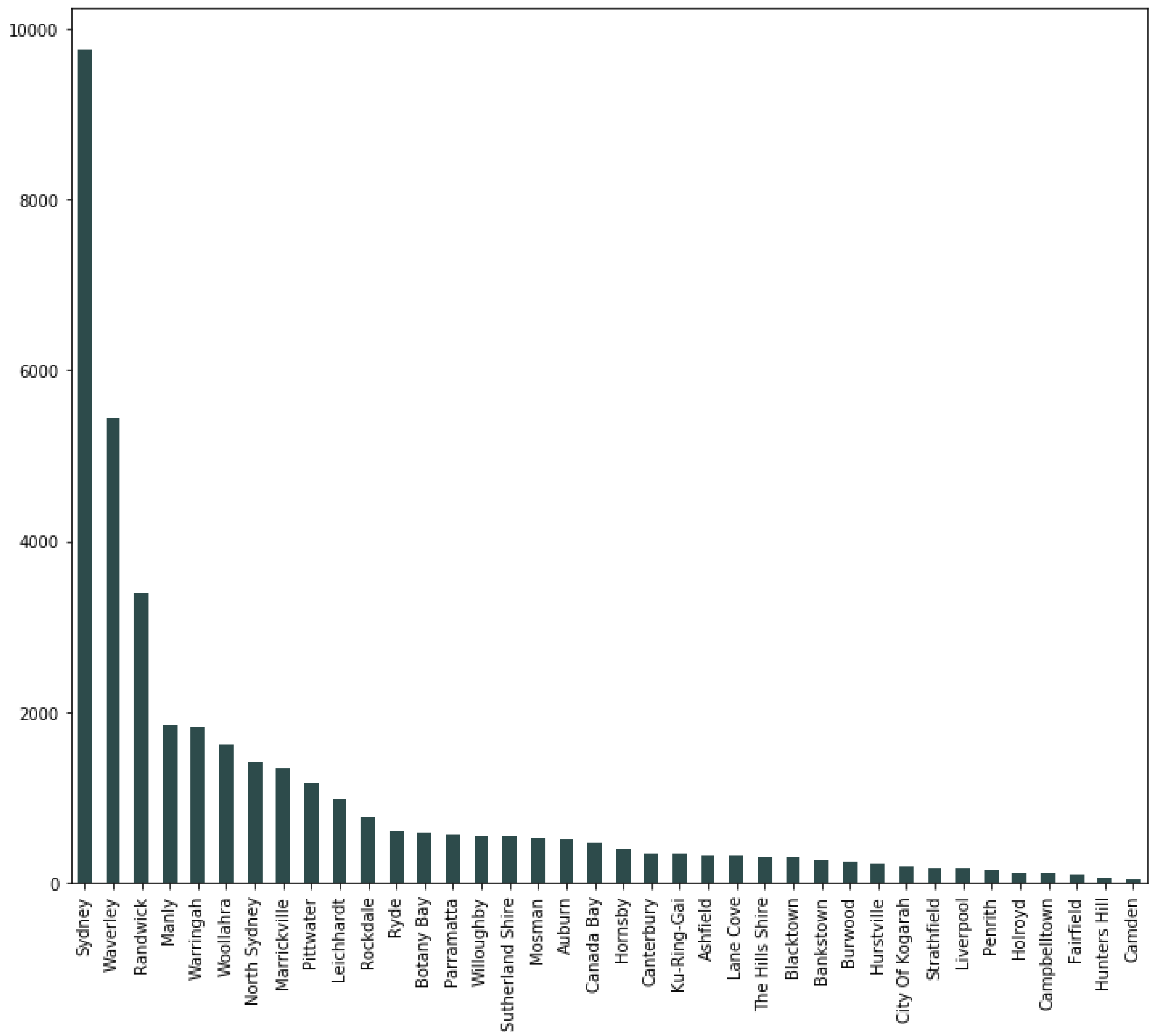
	Proportion
neighborhoods	
Sydney	25.594222
Waverley	14.279711
Randwick	8.916612
Manly	4.864084
Warringah	4.774787
Woollahra	4.265266
North Sydney	3.697965
Marrickville	3.495732
Pittwater	3.091267
Leichhardt	2.592252
Rockdale	2.006566
Ryde	1.604728
Botany Bay	1.544320
Parramatta	1.481287
Willoughby	1.452397
...	...
Lane Cove	0.822062
The Hills Shire	0.806303
Blacktown	0.793171
Bankstown	0.677610
Burwood	0.651346
Hurstville	0.604071
City Of Kogarah	0.496389
Strathfield	0.464872
Liverpool	0.428102
Penrith	0.380827
Holroyd	0.315167
Campbelltown	0.288903
Fairfield	0.228496

	Proportion
neighborhoods	
Hunters Hill	0.173342
Camden	0.120814

38 rows × 1 columns

In [77]:
```
listcop['neighbourhood_cleansed'].value_counts().plot.bar(figsize=(12,10), color="d
```

Out[77]: <matplotlib.axes._subplots.AxesSubplot at 0x1acc043a438>



As presented above, most listing properties are located in "Sydney Central" while the second and third most listings lies in "Waverley" and "Randwick".

Grouping "neighbourhood_cleansed", we can use the ***k-means*** algorithm from scikit-learn library. This algorithm simply:

- Step 1: First initially assigned random k data points as centroids.

- Step 2: Then based on similarity measure (i.e. Euclidean distance) between each data point in dataset to each centroid, the data will be assigned to the cluster which have the closest centroid to that data point.
- Step 3: After that the new centroid will be recalculated in each cluster and and the step 2 will be redo again.
- Step 4: Step 2 and 3 above will be repeated until no significant changes in centroid values observed.

This algorithm will be applied to the Haversine distance and based on the clusters implied, we will group places in "neighbourhood cleansed" accordingly on the corresponding index.

In [106…

```
## K-means clustering for the "neighbourhood_cleansed" grouping based on "Haversine
from sklearn.cluster import KMeans
X = np.array(listcop['Haversine_distance'].copy())
kmeans = KMeans(n_clusters=3, random_state=0).fit(X.reshape(-1,1))
kmeans.labels_
```

Out[106…

```
array([1, 1, 0, ..., 1, 1, 0])
```

In [108…

```
## Checking frequency distribution among groups implied
kmeans_labels = kmeans.labels_.copy()
groups_table = pd.concat([listcop['neighbourhood_cleansed'],pd.Series(kmeans_labels
pd.DataFrame(groups_table["Labels"].value_counts()/sum(groups_table["Labels"].value
    columns={"Labels":"Frequency"})
```

Out[108…

	Frequency
1	70.600131
0	22.991464
2	6.408404

As we can see the frequency proportion seems ok and can be used for later modelling. The smallest proportion observed is > 5%, which is good.

In [109…

```
## Check the detail places of each group
group1 = groups_table["neighbourhood_cleansed"][groups_table["Labels"]==0].unique()
group2 = groups_table["neighbourhood_cleansed"][groups_table["Labels"]==1].unique()
group3 = groups_table["neighbourhood_cleansed"][groups_table["Labels"]==2].unique()
## See 4 groups results
print(group1)
print(group2)
print(group3)
```

```
['Manly' 'Hornsby' 'Warringah' 'Sutherland Shire' 'Ku-Ring-Gai'
 'Pittwater' 'Strathfield' 'Canterbury' 'Auburn' 'Parramatta' 'Hurstville'
 'Randwick' 'Ryde' 'Bankstown' 'Rockdale' 'Burwood' 'Canada Bay'
 'City Of Kogarah' 'Willoughby' 'Ashfield' 'Hunters Hill'
 'The Hills Shire' 'Holroyd' 'Lane Cove']
['Sydney' 'Leichhardt' 'Woollahra' 'North Sydney' 'Waverley' 'Mosman'
 'Lane Cove' 'Marrickville' 'Rockdale' 'Randwick' 'Willoughby'
 'Canada Bay' 'Ashfield' 'Botany Bay' 'Manly' 'Hunters Hill' 'Canterbury'
 'Ryde']
['Pittwater' 'Blacktown' 'The Hills Shire' 'Holroyd' 'Penrith' 'Warringah'
 'Hornsby' 'Campbelltown' 'Parramatta' 'Camden' 'Sutherland Shire'
 'Liverpool' 'Bankstown' 'Fairfield']
```

As the "Haversine distance" we measure here is the distance away from the Sydney central station. So, we would like to group the places in "neighbourhood_cleansed" according to the distance away from the Sydney central station.

In [112…

```
## The centroid of each cluster
kmeans.cluster_centers_
```

Out[112…

```
array([[14.81106699],
       [ 4.50900554],
       [32.60237224]])
```

As we can see that the group 1 contains places that are 14.81 km away from Sydney central station in average, group 2 contains places that are 4.5 km away from central station in average and group 3 contains places that are 32.6 km away from central station in average.

In [117…

```
# New groups_table
groups_table = pd.concat([groups_table,listcop["Haversine_distance"]], axis=1)
```

In [120…

```
## Getting the distances that is closest and farthest to the centroid in each clust
print("group 1 min is ",min(groups_table["Haversine_distance"][groups_table["Labels
     max(groups_table["Haversine_distance"][groups_table["Labels"]==0]))
print("group 2 min is ",min(groups_table["Haversine_distance"][groups_table["Labels
     max(groups_table["Haversine_distance"][groups_table["Labels"]==1]))
print("group 3 min is ",min(groups_table["Haversine_distance"][groups_table["Labels
     max(groups_table["Haversine_distance"][groups_table["Labels"]==2]))
```

```
group 1 min is  9.663634116070034  and max is  23.697489433627812
group 2 min is  0.03844540843699184  and max is  9.658456317183429
group 3 min is  23.707533576615553  and max is  67.41975757256199
```

So, we can overall group levels in "neighbourhood_cleansed" as following:

- group 1: 9.66-23.69 km away from central station
- group 2: 0.04-9.65 km away from central station
- group 3: 23.70-67.42 km away from central station

In [121…

```
##  Grouping levels in "neighbourhood_cleansed" and rename as "Distance_to_CentralS
for word in group1:
    listcop['neighbourhood_cleansed'] = listcop['neighbourhood_cleansed'].replace(w
for word in group2:
```

```
    listcop['neighbourhood_cleansed'] = listcop['neighbourhood_cleansed'].replace(w
for word in group3:
    listcop['neighbourhood_cleansed'] = listcop['neighbourhood_cleansed'].replace(w

listcop.rename(columns={"neighbourhood_cleansed":"Distance_to_CentralStation"}, inp
```

In [125…

```
listcop['Distance_to_CentralStation'].unique()
```

Out[125…

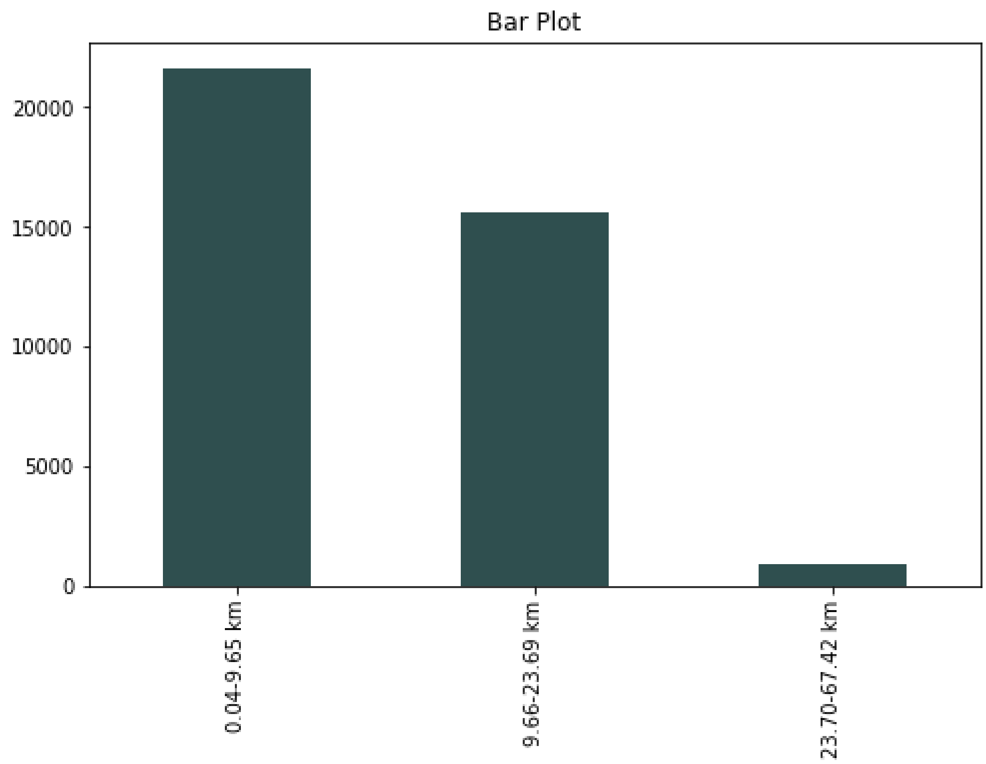
```
array(['0.04-9.65 km', '9.66-23.69 km', '23.70-67.42 km'], dtype=object)
```

In [126…

```
# Visualization
plt.figure(figsize=(8,5))
listcop['Distance_to_CentralStation'].value_counts().plot.bar(color='darkslategrey'
plt.title('Bar Plot')
```

Out[126…

```
Text(0.5, 1.0, 'Bar Plot')
```



In [90]:

```
## Single-Linkage clustering for "neighbourhood_cleansed" grouping based on "Havers
```

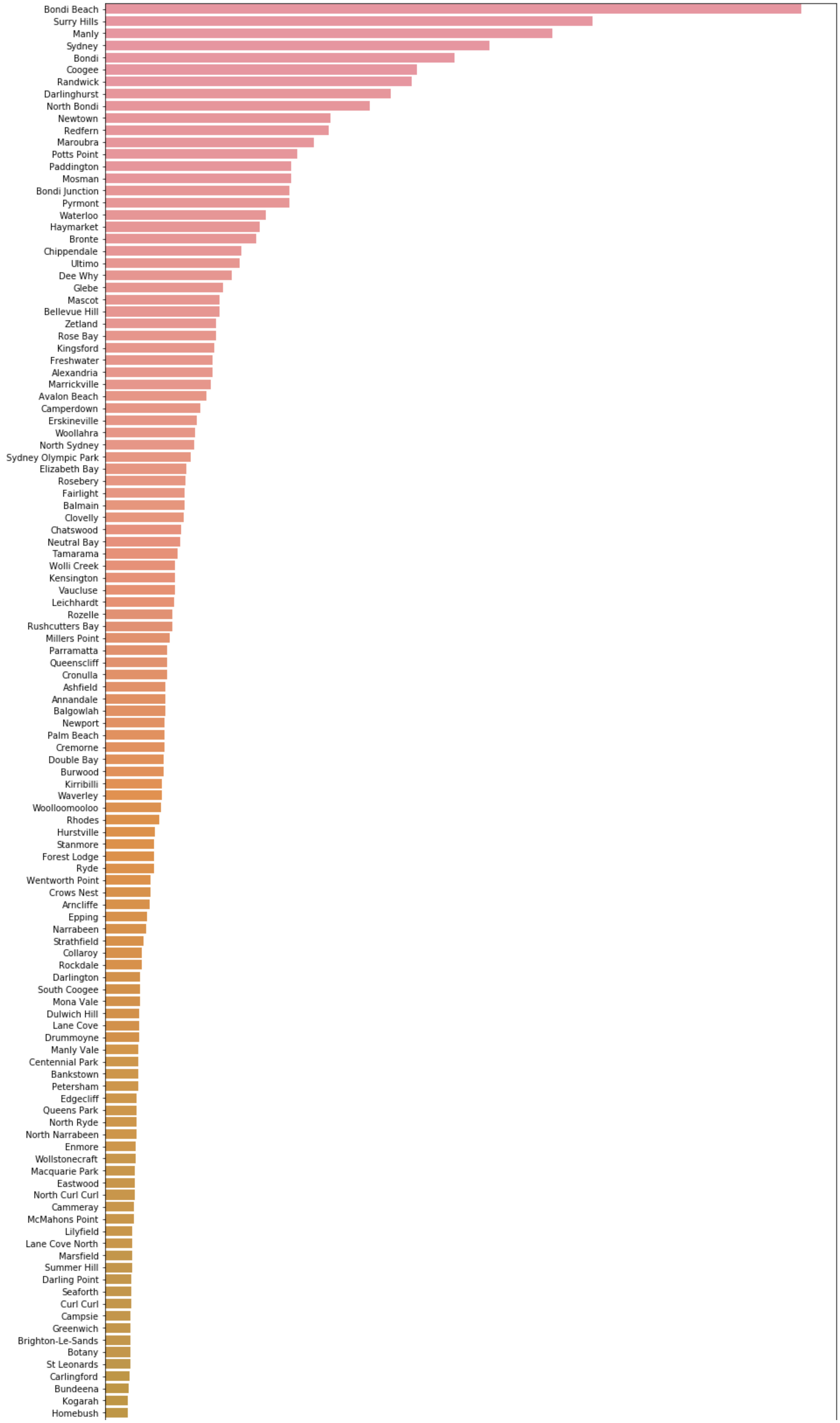
Next we move to grouping "smart_location". And again, we can use k-means algorithm to group "smart_location" based on the cluser implied from Haversine distance calculated.

In [128…

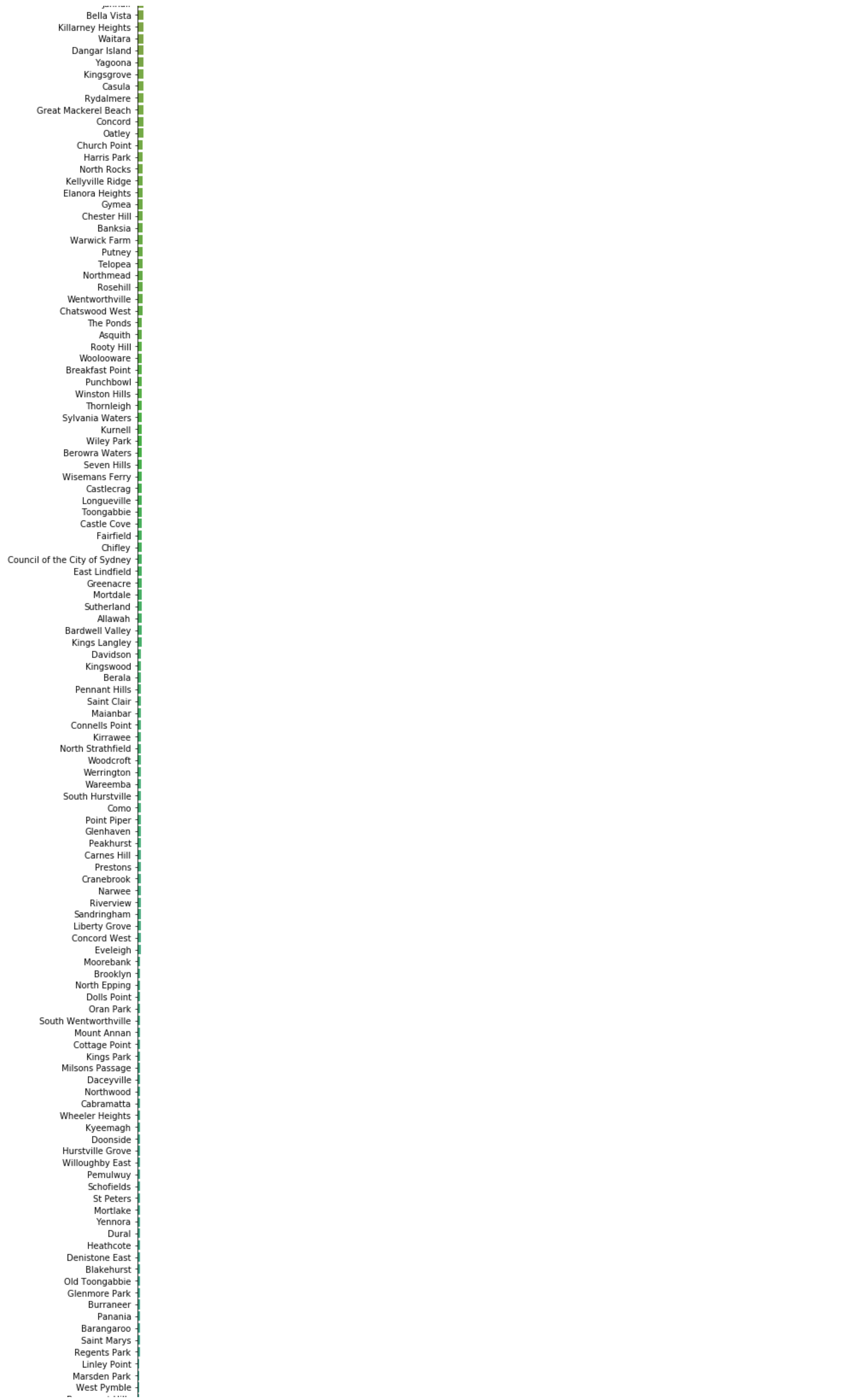
```
# Table of frequency of 'smart_location'
Locfreq = listcop['smart_location'].value_counts().reset_index()
# Rename columns of Locfreq
Locfreq=Locfreq.rename(columns={'index':'smart_location','smart_location':'frequenc
# Barplot of 'smart_location'
plt.figure(figsize=(15,200))
ax = sns.barplot(x='frequency', y='smart_location', data=Locfreq)
ax.set_xlabel('frequency')
```

Out[128…

```
Text(0.5, 0, 'frequency')
```


Bondi Beach
Surry Hills
Manly
Sydney
Bondi
Coogee
Randwick
Darlinghurst
North Bondi
Newtown
Redfern
Maroubra
Potts Point
Paddington
Mosman
Bondi Junction
Pyrmont
Waterloo
Haymarket
Bronte
Chippendale
Ultimo
Dee Why
Glebe
Mascot
Bellevue Hill
Zetland
Rose Bay
Kingsford
Freshwater
Alexandria
Marrickville
Avalon Beach
Camperdown
Erskineville
Woollahra
North Sydney
Sydney Olympic Park
Elizabeth Bay
Rosebery
Fairlight
Balmain
Clovelly
Chatswood
Neutral Bay
Tamarama
Wolli Creek
Kensington
Vaucluse
Leichhardt
Rozelle
Rushcutters Bay
Millers Point
Parramatta
Queenscliff
Cronulla
Ashfield
Annandale
Balgowlah
Newport
Palm Beach
Cremorne
Double Bay
Burwood
Kirribilli
Waverley
Woolloomooloo
Rhodes
Hurstville
Stanmore
Forest Lodge
Ryde
Wentworth Point
Crows Nest
Arncliffe
Epping
Narrabeen
Strathfield
Collaroy
Rockdale
Darlington
South Coogee
Mona Vale
Dulwich Hill
Lane Cove
Drummoyne
Manly Vale
Centennial Park
Bankstown
Petersham
Edgecliff
Queens Park
North Ryde
North Narrabeen
Enmore
Wollstonecraft
Macquarie Park
Eastwood
North Curl Curl
Cammeray
McMahons Point
Lilyfield
Lane Cove North
Marsfield
Summer Hill
Darling Point
Seaforth
Curl Curl
Campsie
Greenwich
Brighton-Le-Sands
Botany
St Leonards
Carlingford
Bundeena
Kogarah
Homebush


Dover Heights
Birchgrove
Warriewood
Allambie Heights
Sydney
Hornsby
Canterbury
Roseville
Liverpool
Frenchs Forest
North Balgowlah
Castle Hill
North Manly
Saint Peters
Artarmon
Gladesville
Little Bay
Cremorne Point
Croydon
Homebush West
Balgowlah Heights
Balmain East
Willoughby
Baulkham Hills
Riverwood
Earlwood
Blacktown
Matraville
Beverly Hills
Auburn
Bexley
Milsons Point
Lewisham
Beacon Hill
Lidcombe
Sans Souci
Naremburn
Hunters Hill
Beaconsfield
Hillsdale
Bilgola Plateau
Eastgardens
Whale Beach
Eastlakes
Westmead
West Ryde
Glenwood
Merrylands
Pymble
Lindfield
Waverton
Padstow
Turrella
Gordon
Avalon
Wahroonga
Guildford
Malabar
Ermington
Killara
North Parramatta
Brookvale
Collaroy Plateau
Chiswick
The Rocks
Turramurra
Cromer
Clareville
Saint Leonards
Tempe
Quakers Hill
Lane Cove West
Lavender Bay
Five Dock
Clontarf
Miranda
Forestville
Glenfield
Meadowbank
Belrose
Bilgola Beach
Granville
Belmore
Kellyville
Penrith
Cherrybrook
Beecroft
West Pennant Hills
Campbelltown
Pagewood
Watsons Bay
Lakemba
Northbridge
Hurlstone Park
Monterey
NSW
Haberfield
Bayview
Revesby
Scotland Island
Abbotsford
Saint Ives
Newington
Caringbah
Sylvania
Croydon Park
North Willoughby
Sydenham
Penshurst
Caringbah South
Dawes Point
Russell Lea
Dundas Valley
Kurraba Point
Narraweena
Rouse Hill
Carlton


Bella Vista
Killarney Heights
Waitara
Dangar Island
Yagoona
Kingsgrove
Casula
Rydalmere
Great Mackerel Beach
Concord
Oatley
Church Point
Harris Park
North Rocks
Kellyville Ridge
Elanora Heights
Gymea
Chester Hill
Banksia
Warwick Farm
Putney
Telopea
Northmead
Rosehill
Wentworthville
Chatswood West
The Ponds
Asquith
Rooty Hill
Woolooware
Breakfast Point
Punchbowl
Winston Hills
Thornleigh
Sylvania Waters
Kurnell
Wiley Park
Berowra Waters
Seven Hills
Wisemans Ferry
Castlecrag
Longueville
Toongabbie
Castle Cove
Fairfield
Chifley
Council of the City of Sydney
East Lindfield
Greenacre
Mortdale
Sutherland
Allawah
Bardwell Valley
Kings Langley
Davidson
Kingswood
Berala
Pennant Hills
Saint Clair
Maianbar
Connells Point
Kirrawee
North Strathfield
Woodcroft
Werrington
Wareemba
South Hurstville
Como
Point Piper
Glenhaven
Peakhurst
Carnes Hill
Prestons
Cranebrook
Narwee
Riverview
Sandringham
Liberty Grove
Concord West
Eveleigh
Moorebank
Brooklyn
North Epping
Dolls Point
Oran Park
South Wentworthville
Mount Annan
Cottage Point
Kings Park
Milsons Passage
Daceyville
Northwood
Cabramatta
Wheeler Heights
Kyeemagh
Doonside
Hurstville Grove
Willoughby East
Pemulwuy
Schofields
St Peters
Mortlake
Yennora
Dural
Heathcote
Denistone East
Blakehurst
Old Toongabbie
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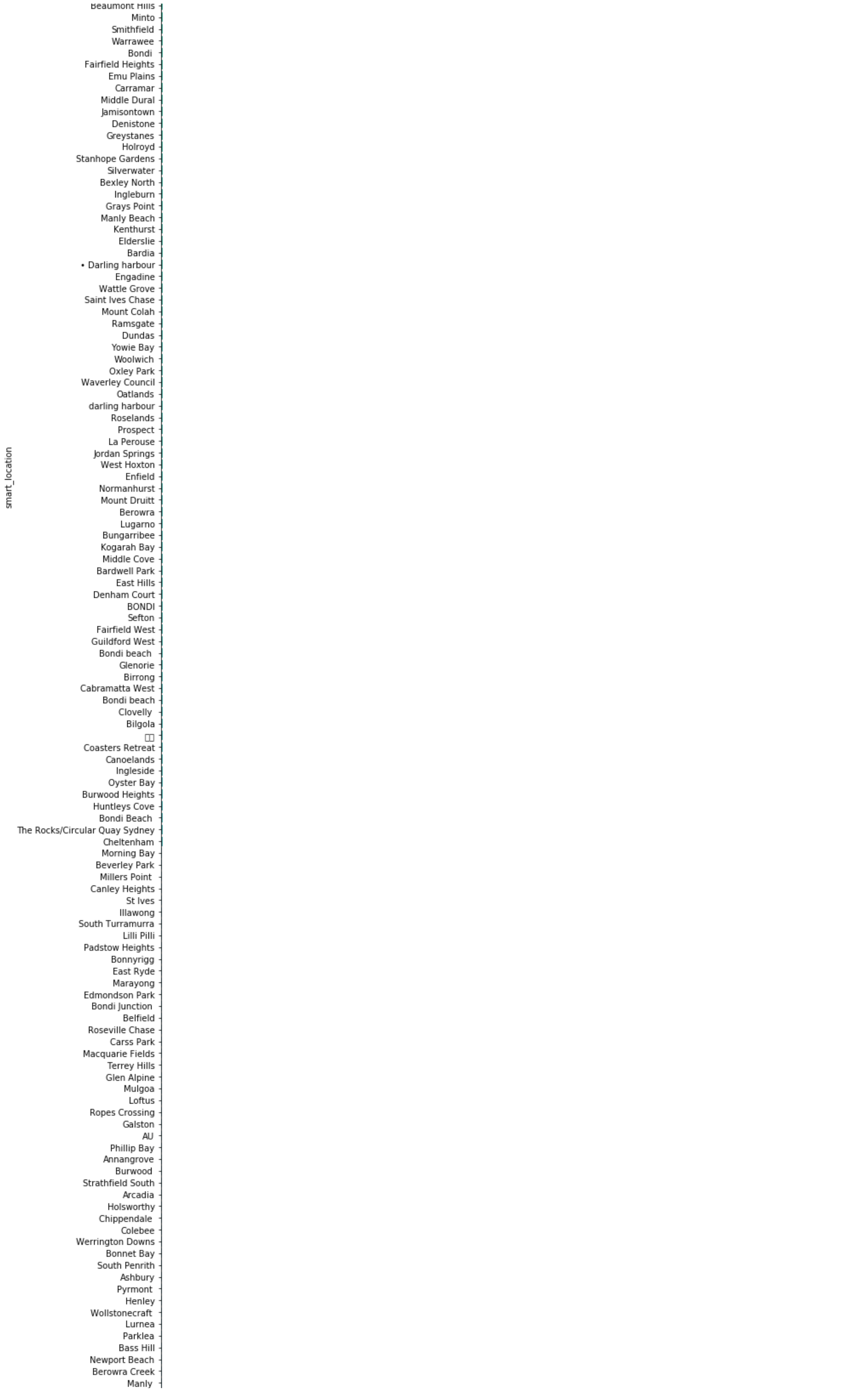
Burraneer
Panania
Barangaroo
Saint Marys
Regents Park
Linley Point
Marsden Park
West Pymble


Beaumont Hills
Minto
Smithfield
Warrawee
Bondi
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Emu Plains
Carramar
Middle Dural
Jamisontown
Denistone
Greystanes
Holroyd
Stanhope Gardens
Silverwater
Bexley North
Ingleburn
Grays Point
Manly Beach
Kenthurst
Elderslie
Bardia
• Darling harbour
Engadine
Wattle Grove
Saint Ives Chase
Mount Colah
Ramsgate
Dundas
Yowie Bay
Woolwich
Oxley Park
Waverley Council
Oatlands
darling harbour
Roselands
Prospect
La Perouse
Jordan Springs
West Hoxton
Enfield
Normanhurst
Mount Druitt
Berowra
Lugarno
Bungarribee
Kogarah Bay
Middle Cove
Bardwell Park
East Hills
Denham Court
BONDI
Sefton
Fairfield West
Guildford West
Bondi beach
Glenorie
Birrong
Cabramatta West
Bondi beach
Clovelly
Bilgola
Coasters Retreat
Canoelands
Ingleside
Oyster Bay
Burwood Heights
Huntleys Cove
Bondi Beach
The Rocks/Circular Quay Sydney
Cheltenham
Morning Bay
Beverley Park
Millers Point
Canley Heights
St Ives
Illawong
South Turramurra
Lilli Pilli
Padstow Heights
Bonnyrigg
East Ryde
Marayong
Edmondson Park
Bondi Junction
Belfield
Roseville Chase
Carss Park
Macquarie Fields
Terrey Hills
Glen Alpine
Mulgoa
Loftus
Ropes Crossing
Galston
AU
Phillip Bay
Annangrove
Burwood
Strathfield South
Arcadia
Holsworthy
Chippendale
Colebee
Werrington Downs
Bonnet Bay
South Penrith
Ashbury
Pyrmont
Henley
Wollstonecraft
Lurnea
Parklea
Bass Hill
Newport Beach
Berowra Creek
Manly
smart_location


Eastern Creek
Constitution Hill
Plumpton
Duffys Forest
Condell Park
Luddenham
Raby
North Wahroonga
Gymea Bay
Randwick City Council
Bossley Park
Bankstwoen
Leumeah
Chipping Norton
Sandy Point
Bonnyrigg Heights
Catherine Field
Tennyson Point
Waterloo
North Turramurra
Old Guildford
Yarrawarrah
Canley Vale
Leppington
Blair Athol
Woodbine
Cobbitty
Wentworth Point
Randwick
Taren Point
Cattai
Lalor Park
Dean Park
Rodd Point
Hornsby Heights
Berowra Heights
Kareela
Artarmon
Sydney City
Potts Point
Elvina Bay
Canada Bay
Rushcutters Bay
Westleigh
Botany Bay
St Pauls
Spring Farm
Clemton Park
Mount Pritchard
Rossmore
Waterfall
Picnic Point
Melrose Park
Neutral Bay
Rockdale City Council
Horningsea Park
Emu Heights
Lower Portland
Oakhurst
North Bondi
Gunderman
Auburn
Ramsgate Beach
Cabarita
Hammondville
Revesby Heights
Acacia Gardens
Harrington Park
North St Marys
Gregory Hills
Lovett Bay
East Killara
Pittwater Council
Oxford Falls
Cartwright
Wolli Creek
Surry Hills
Peakhurst Heights
Bangor
Darlinghurst
Balmoral Beach
Potts Hill
Wentworth point
Sydney CBD
Saint Helens Park
Bankstown
Bronte
Lewisham
Mount Kuring-Gai
City of Canada Bay Council
Kellyville Sydney
Castlereagh
Colyton
Villawood
Merrylands West
Coogee
Marrickville
Pendle Hill
Meadowbank
Leonay
Alexandria
Eastgardens
Warriewood Beach
Bradbury
Greenhills Beach
Paddington
Southport
Abbotsbury
Allawah
Saint Andrews
Redfern NSW 2016
North Parramatta
Darlinghurst Sydney
waterloo
Parramatta
Brighton Le Sands
Redfern


Queens park
Londonderry
Lansvale
Cambridge Gardens
Sydney berowra Heights
wenworth point
Bar Point
Rozelle Sydney
St Ives Chase
Kirribilli
Ku-Ring-Gai Chase
camperdown
Milsons point
Kyle Bay
Ku-Ring-Gai Council
Maroubra beach
Cambridge Park
Prairiewood
Watson's Bay
Huntleys Point
Glen Waverley
Port Jackson
pyrmont
GREYSTANES
MANLY
North Sydney NSW 2060
Neutral Bay
Erskine Park
Riverstone
Macquarie Links
Warriewood DC
Melbourne
Rockdale
Rockdale
Forest lodge
Fairlight
Potts point
Campsie
Dee Why Beach
Bilgola / Avalon
Minchinbury
North Curl Curl (near Manly)
norfolk rd.
North Epping
Kogarah
Bondi junction
CAMPERDOWN
Rose bay
Bringelly
Darlington Sydney
brookvale
Paddington/Woollahra
Dolans Bay
Denistone West
Berowra waters
Balmain / Birchgrove
Hurstville
Waterloo DC
Dover heights
Surry Hills Sydney
Eschol Park
North Sydney / Waverton
Darlington
Claymore
Sydney Olympic Park
Gledswood Hills
Bondi Junction Sydney
Bellevue Hill (Double Bay side).
Agnes Banks
Queens Park
Box Hill
Manahan
SYDNEY
Minto Heights
St Clair
Allambie Heights
Parramatta City Council
Kensignton
Great Mackeral beach
Menai
Middleton Grange
Auburn City Council
East Redfern
Berrilee
Kingsford
Hebersham
Haberfield
Kemps Creek
warriewood Beach
Llandilo
Pitt Town
North Ryde
Bankstown City Council
zetland
Bellevue hill
Ashfield
Woronora
North Bondi Beach
Orchard Hills
Barangaroo
Coogee beach
South Maroota
St. Leonards
Kings Cross
Ashfield Sydney
Fairlight (Manly)
Ambarvale
Homebush west
Mccarrs Creek
Northern Beaches
Allawah/Carlton
Waverley
Oran park
Saint Johns Park
palm beach
Willoughby City Council
Maroubra Beach
Frenchs Forest East
Редферн

From the barplot, we can roughly see four separated groups of locations:

In [129…

```
# Grouping in smart_location
group1 = Locfreq[Locfreq['frequency']>300]['smart_location'].unique()
group2 = Locfreq[(Locfreq['frequency']<=300) & (Locfreq['frequency'] >100)]['smart_
group3 = Locfreq[(Locfreq['frequency']<=100) & (Locfreq['frequency'] >10)]['smart_l
group4 = Locfreq[Locfreq['frequency']<=10]['smart_location'].unique()
```

In [130…

```
# Frequency observed within each group
print(sum(Locfreq[Locfreq['frequency']>300]['frequency']))
print(sum(Locfreq[(Locfreq['frequency']<=300) & (Locfreq['frequency'] >100)]['frequ
print(sum(Locfreq[(Locfreq['frequency']<=100) & (Locfreq['frequency'] >10)]['freque
print(sum(Locfreq[Locfreq['frequency']<=10]['frequency']))
```

```
19325
8939
8325
1486
```

We will modify the location groups as:

_ Top group: frequency > 300

_ 1st Middle group: 100 < frequency <= 300

_ 2nd Middle group: 10 < frequency <= 100

_ Bottom group: frequency <= 10

In [131…

```
# Modify level of 'smart_location'
for word in group1:
    listcop['smart_location'] = listcop['smart_location'].replace(word,'Top group')
for word in group2:
    listcop['smart_location'] = listcop['smart_location'].replace(word,'1st Middle 
for word in group3:
    listcop['smart_location'] = listcop['smart_location'].replace(word,'2nd Middle 
for word in group4:
    listcop['smart_location'] = listcop['smart_location'].replace(word,'Bottom grou
```

In [132…

```
listcop['smart_location'].unique()
```

Out[132…

```
array(['Top group', '1st Middle group', '2nd Middle group',
       'Bottom group'], dtype=object)
```

In [143…

```
## Current categorical variables in data
listcop.drop(listcop.describe().columns,axis=1).columns
```

Out[143…

```
Index(['host_identity_verified', 'Distance_to_CentralStation', 'is_location_exac
t',
       'property_type', 'room_type', 'calendar_updated', 'instant_bookable', 'canc
ellation_policy',
       'smart_location'],
      dtype='object')
```

In [84]:

```
## Current columns in the listcop data
listcop.columns
```

Out[84]:
```
Index(['host_listings_count', 'host_total_listings_count', 'host_identity_verifie
d',
       'neighbourhood_cleansed', 'is_location_exact', 'property_type', 'room_typ
e', 'accommodates',
       'bathrooms', 'bedrooms', 'beds', 'guests_included', 'minimum_nights', 'maxi
mum_nights',
       'minimum_minimum_nights', 'maximum_minimum_nights', 'minimum_maximum_night
s',
       'maximum_maximum_nights', 'minimum_nights_avg_ntm', 'maximum_nights_avg_nt
m',
       'calendar_updated', 'availability_30', 'availability_60', 'availability_9
0',
       'availability_365', 'number_of_reviews', 'number_of_reviews_ltm', 'instant_
bookable',
       'cancellation_policy', 'calculated_host_listings_count',
       'calculated_host_listings_count_entire_homes',
       'calculated_host_listings_count_private_rooms',
       'calculated_host_listings_count_shared_rooms', 'smart_location', 'extra_peo
ple',
       'Log_Haversine_Distance', 'log_price', 'price'],
      dtype='object')
```

2. Continuous Data Analysis

Average sale price by different property types

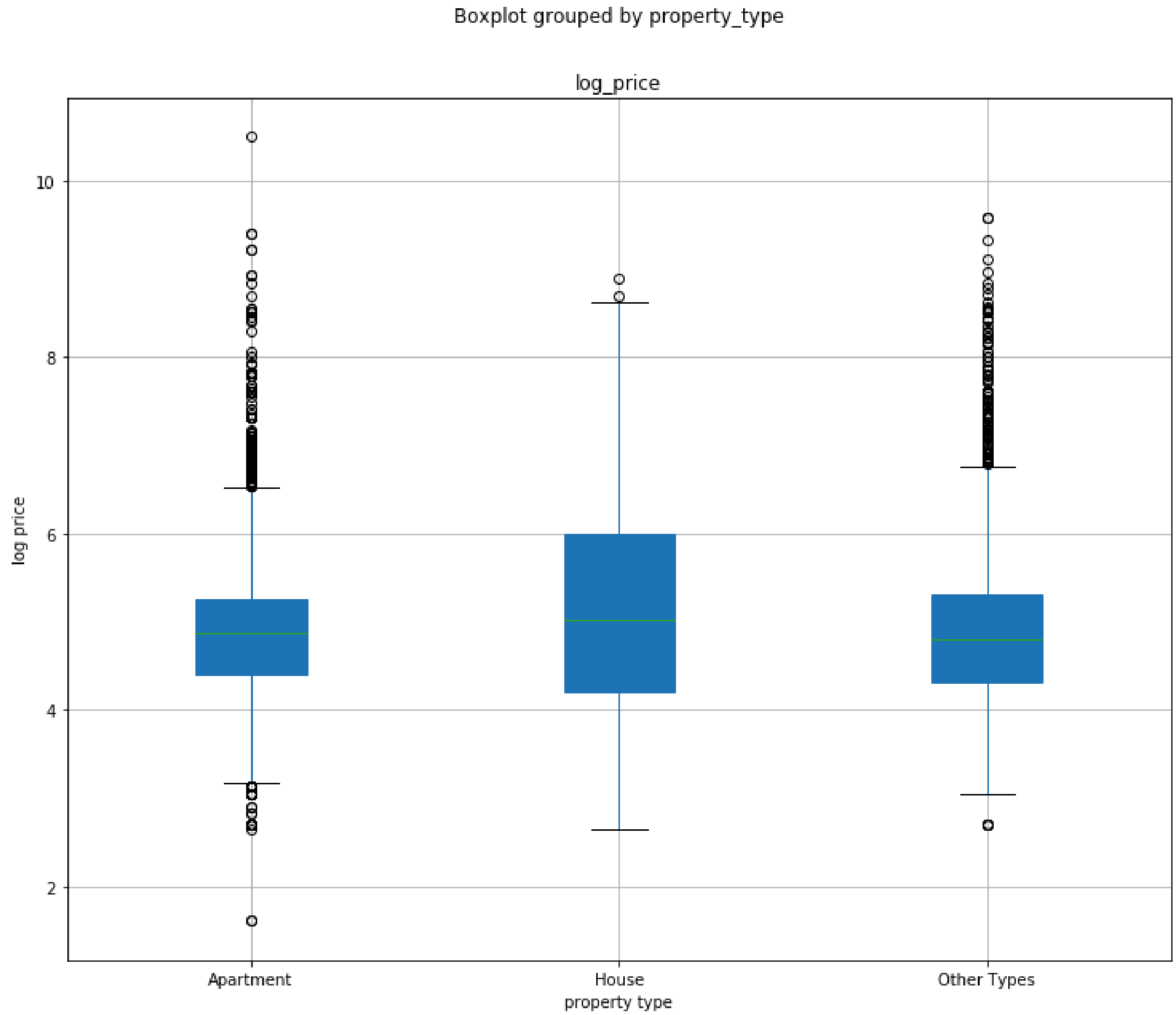
In [63]:
```
listcop[["property_type","price"]].groupby("property_type").mean()
```

Out[63]:

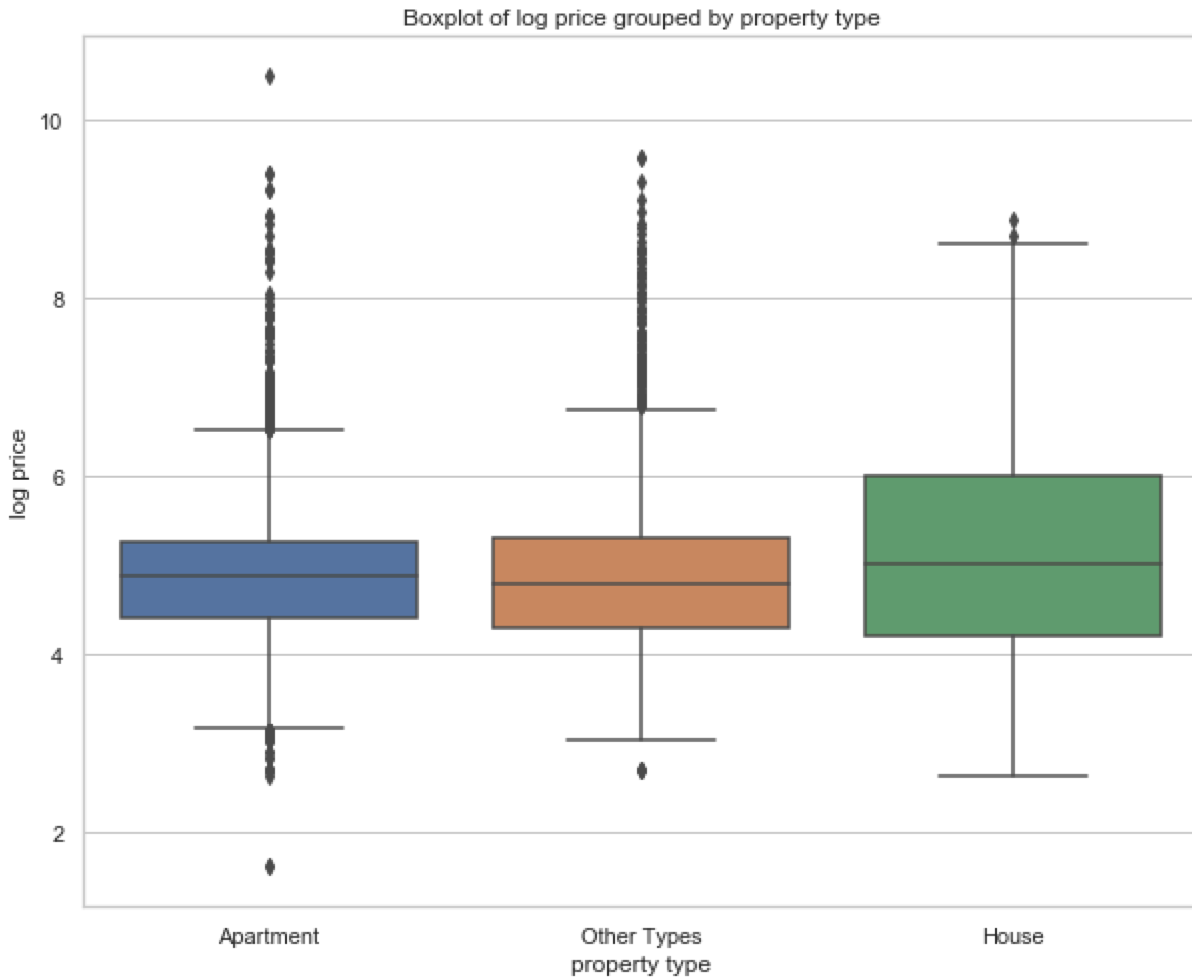
	price
property_type	
Apartment	163.496831
House	299.772189
Other Types	205.118062

In [62]:
```
## Visualization by matplotlib
listcop[['log_price','property_type']].boxplot(figsize=(12,10),by='property_type',
plt.xlabel('property type')
plt.ylabel('log price')
```

Out[62]:
```
Text(0, 0.5, 'log price')
```



In [77]:
```
## Visualization by seaborn
plt.figure(figsize=(10,8))
ax = sns.boxplot(y=listcop.log_price, x=listcop.property_type, linewidth=1.5)
ax.set(ylabel="log price",xlabel="property type", title="Boxplot of log price group
sns.set(style="whitegrid")
```



It can be seen that the variability in price among property types seems not be significantly different from each other. Houses have a wider spread of variability in prices than other properties. The average rental price for house is higher than for apartment and other types of property.

In [149…
```
listcop.drop(["Haversine_distance"],axis=1,inplace = True)
```

3. Correlation and dependence analysis

Now we will separate target data and feature data:

In [150…
```
# Store target and features set
y = listcop['price'].copy()
X = listcop.drop(['price'],axis=1).copy()
```

We will conduct analysis of some continuous variables below:

In [151…
```
## (2.1) Continuous Variables Analysis
contnames = X.describe().columns.values  # continuous feature names
catenames = X.drop(contnames,axis=1).columns.values  # categorical feature names
X_cont = X[contnames].copy()
```

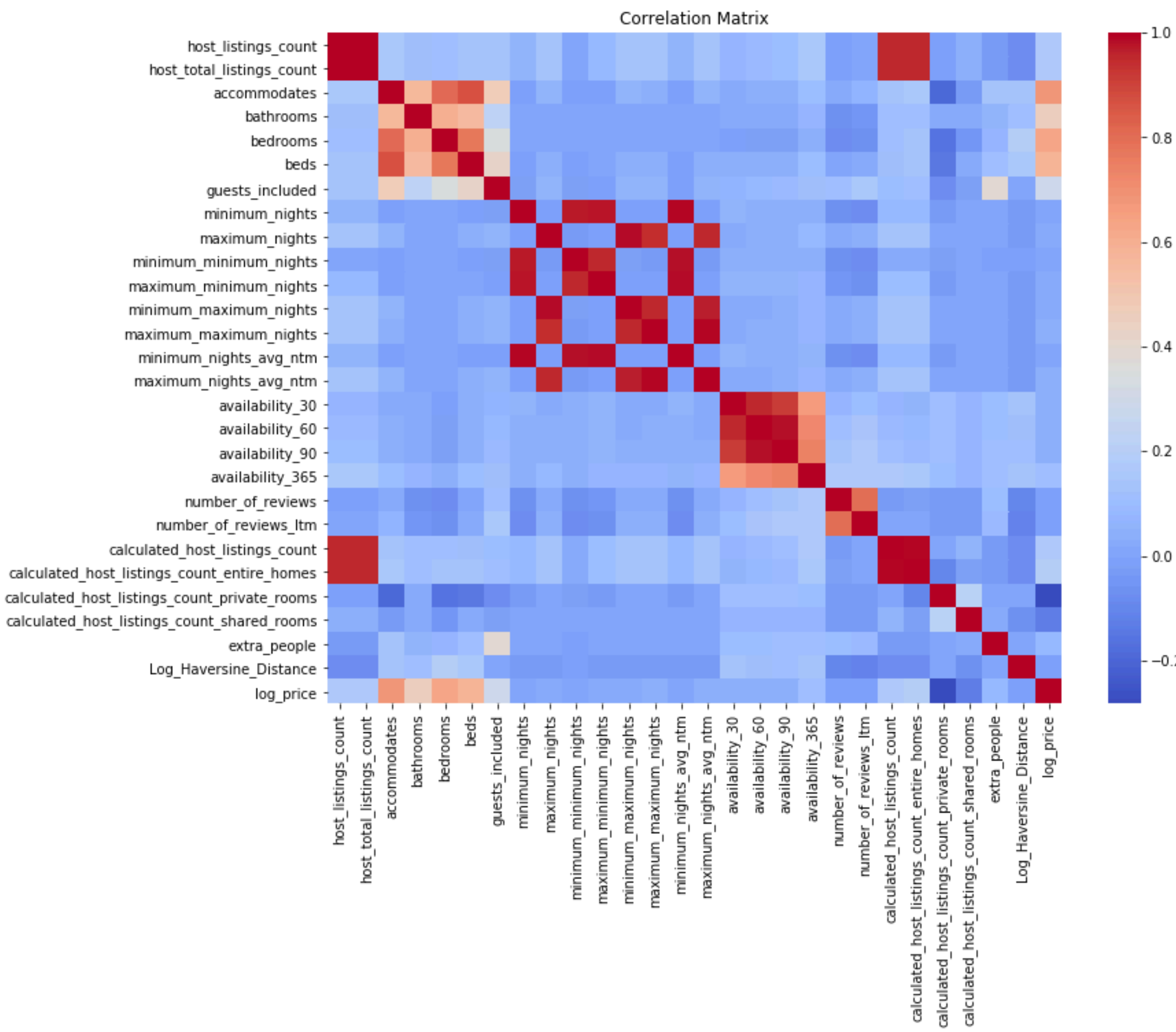
_ Correlation matrix plot:

In [152…

```
# Correlation matrix between continuous variables
corplot = X_cont.corr()
# Plot correlation matrix
plt.figure(1,figsize = (12,9))
sns.heatmap(corplot,cmap='coolwarm')
plt.title('Correlation Matrix')
```

Out[152…

```
Text(0.5, 1, 'Correlation Matrix')
```



Next, we will subset out the highly correlated features (>75%):

In [153…

```
# We will see high correlation values (>0.75)
tri_upper = pd.DataFrame(np.triu(corplot,k=1))  # an upper triangular part of corre
tri_upper.columns = contnames # set names of this triangular matrix matched with co
# Choose out feature columns that have high correlation value (>0.75)
highcorr = ['host_listings_count']
for word in contnames:
    if any(tri_upper[word] >= 0.75):
        highcorr.append(word)
highcorr
```

Out[153…

```
['host_listings_count',
 'host_total_listings_count',
 'bedrooms',
 'beds',
 'minimum_minimum_nights',
 'maximum_minimum_nights',
 'minimum_maximum_nights',
 'maximum_maximum_nights',
 'minimum_nights_avg_ntm',
 'maximum_nights_avg_ntm',
 'availability_60',
 'availability_90',
 'number_of_reviews_ltm',
 'calculated_host_listings_count',
 'calculated_host_listings_count_entire_homes']
```

We will keep bedrooms, beds, availability_60, availability_90 as these features might provides useful realtionship with target feature. We will drop remaining high correlated features.

In [154…

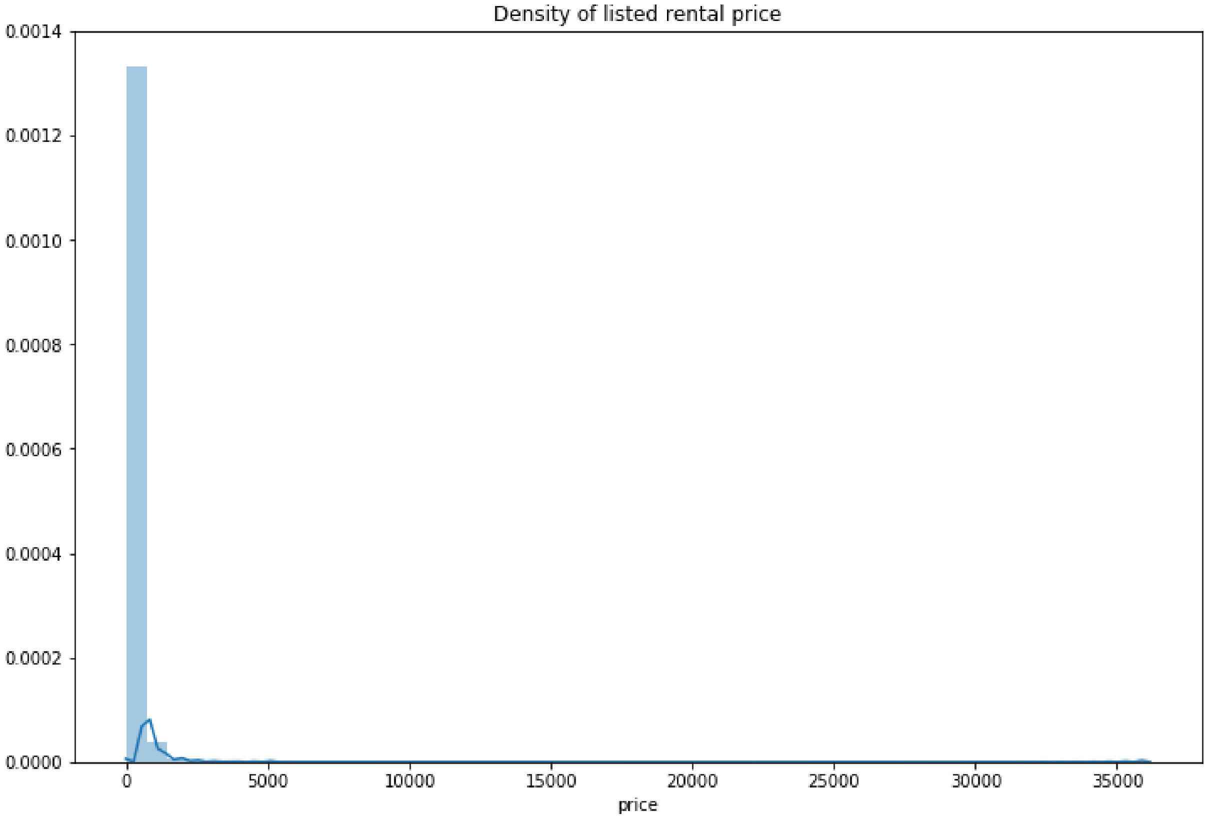
```
# Drop high correlated variables
X = X.drop(['host_total_listings_count','beds','minimum_minimum_nights','maximum_mi
                        'minimum_maximum_nights','maximum_maximum_nights','maximum_
                        'availability_90','number_of_reviews_ltm','calculated_host_
                        'calculated_host_listings_count_entire_homes'],axis=1)

X_cont = X_cont.drop(['host_total_listings_count','beds','minimum_minimum_nights','
                        'minimum_maximum_nights','maximum_maximum_nights','maximum_
                        'availability_90','number_of_reviews_ltm','calculated_host_
                        'calculated_host_listings_count_entire_homes'],axis=1)
```

In [155…

```
# Density plot of target variable
plt.figure(2,figsize = (12,8))
sns.distplot(y)
plt.title('Density of listed rental price')
```

Out[155…

```
Text(0.5, 1.0, 'Density of listed rental price')
```



Clearly, from the histogram and density plot above, we can see the target variable is extremely right-skewed. This would highly recommend transformation of target features. We will try log-transformation.

In [156…

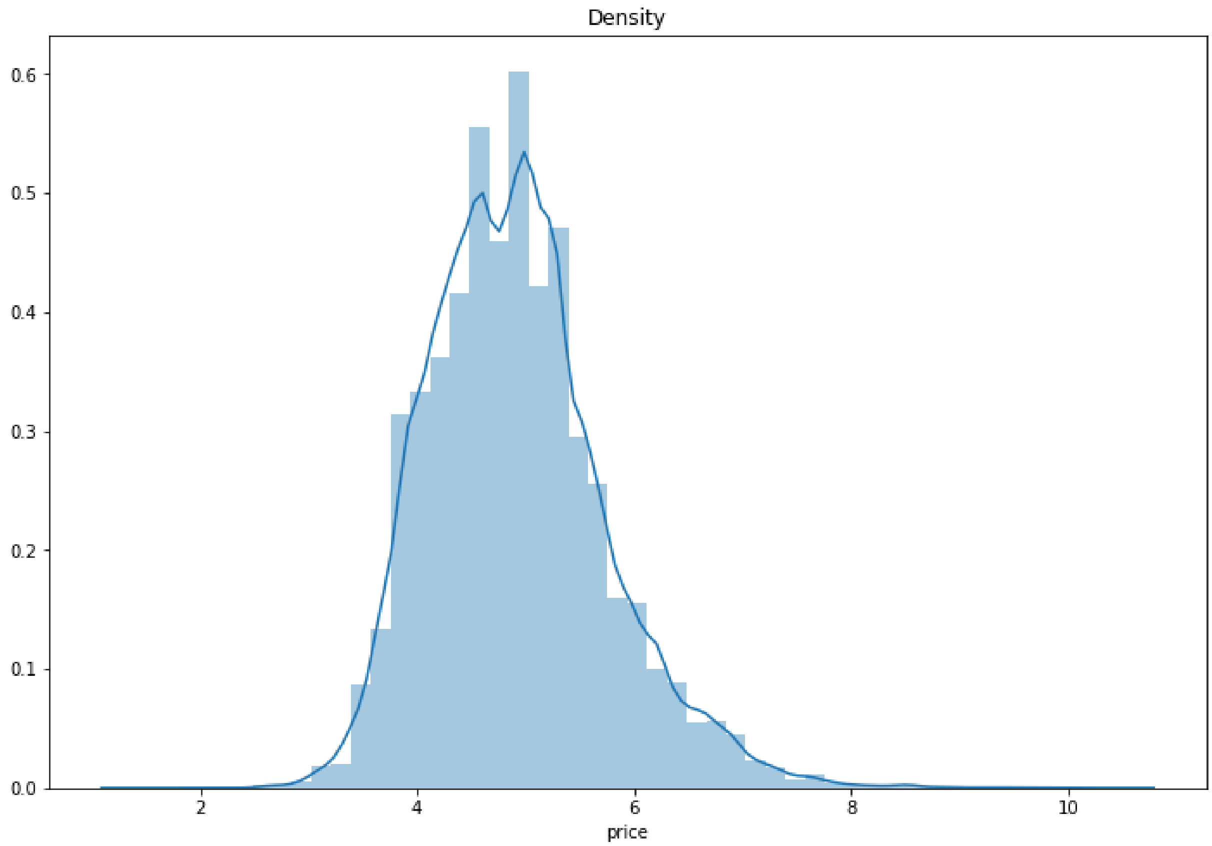
```
# Try transform target variable
y_log = y.apply(lambda x: np.log(x))
```

In [157…

```
# Plot with new log-transformed target feature
plt.figure(2,figsize = (12,8))
sns.distplot(y_log)
plt.title('Density')
```

Out[157…

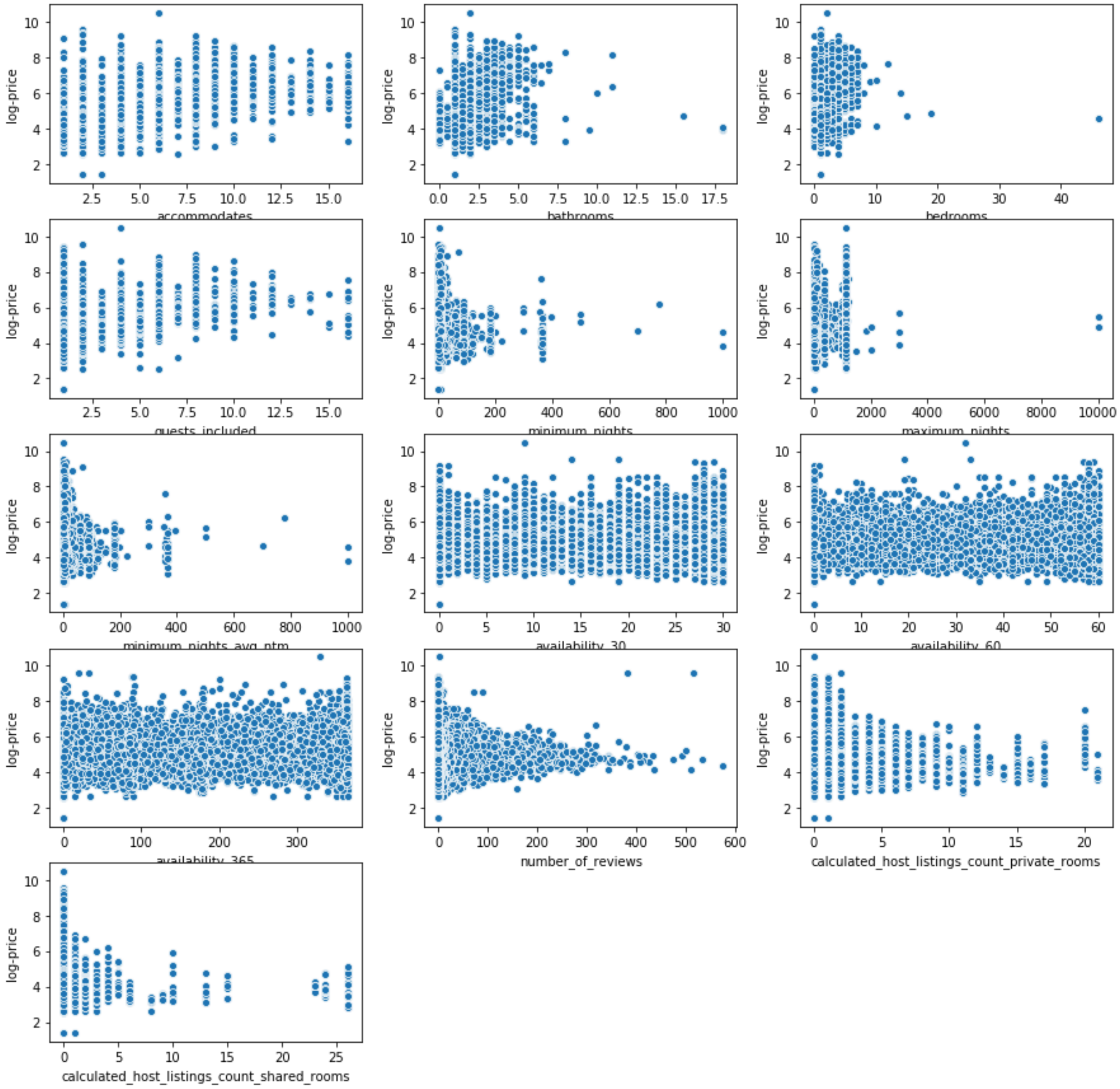
```
Text(0.5, 1.0, 'Density')
```



Clearly the histogram and density plot of log-transformed target feature seems closer to normal distribution now. The density plot and histogram plot of log-transformed target seems reasonably good.

In [158…

```
# Scatterplot of continuous features with log-target variable
contplot = X_cont.copy()
contplot['log-price'] = y_log
plt.figure(figsize=(15,15))
for i in range(1, 14):
    plt.subplot(5, 3, i)
    word = contplot.columns.values[i]
    sns.scatterplot(x=word,y="log-price",data=contplot)
### Or alternatively,
#   f = plt.figure(figsize=(12,7))
#   for i in range(1, 15):
#       f.add_subplot(5, 3, i)
#       word = contplot.columns.values[i]
#       sns.scatterplot(x=word,y="log-price",data=contplot)
```



In [ ]:
```
X.drop(["log_price"],axis=1,inplace=True)  # drop log price
```

In [176…
```
# Output data to computer
# X.to_csv("D:/Data/Airbnb/X.csv", index=False)
# y.to_csv("D:/Data/Airbnb/y.csv", index=False)
```

Stage 3: Model Fitting

In this stage, we will try different statistical models in fitting "cleaned" data. The models examined in our project includes Linear Regression, Ridge Regression, Decision Trees, and Random Forest.

In [1]:
```
''' STAGE III: MODEL FITTING '''
from sklearn.model_selection import train_test_split
import pandas as pd
import numpy as np
# Import processed data from computer
```

```
dat = pd.read_csv("D:/Data/Airbnb/X.csv")    # dat = X.copy()
tar = pd.read_csv("D:/Data/Airbnb/y.csv")
tar_log = tar.apply(lambda x: np.log(x))
```

In [2]:
```
# Or if we continue use directly data from Stage 2:
# dat = X.copy()
# tar = y.copy()
```

In [4]:
```
# Adjust the data view setting to check full data
pd.set_option('display.max_rows', 53)
pd.set_option('display.max_columns', 50)
pd.set_option('display.width', 100)
```

Before moving to modelling part, we need to encode any categorical variables in dataset.

In [5]:
```
'''One-Hot Encoding for categorical features '''
# One-Hot Encoder for data using pd.get_dummies
contnames = dat.describe().columns.values
catenames = dat.drop(contnames,axis=1).columns.values
dat = pd.get_dummies(dat,columns=catenames)
dat.head(10)
```

Out[5]:

	host_listings_count	accommodates	bathrooms	bedrooms	guests_included	minimum_n
0	1	1	1.0	1	1	
1	2	2	1.0	1	2	
2	2	6	3.0	3	6	
3	3	2	1.0	1	1	
4	2	8	2.0	4	6	
5	1	2	1.0	1	1	
6	2	2	1.0	0	2	
7	1	2	1.0	1	1	
8	1	2	1.0	1	1	
9	1	2	1.0	1	2	

Now, we split the data into training and test data.

In [6]:
```
# Splitting data
dat_train, dat_test, tar_train, tar_test = train_test_split(dat, tar_log, test_size
```

But before fitting model, we need to standardizing continous variables

In [7]:
```
# Standardizing continuous variables
from sklearn.preprocessing import StandardScaler
```

```
scaler = StandardScaler()
dat_train[contnames] = scaler.fit_transform(dat_train[contnames])
dat_test[contnames] = scaler.fit_transform(dat_test[contnames])
```

1. Linear Regression Model

In [8]:
```
'''(1): Linear Regression'''
# Import libraries
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
from sklearn.linear_model import LinearRegression
from statsmodels.formula.api import ols
from sklearn.model_selection import cross_val_score
from sklearn.metrics import mean_squared_error,mean_squared_log_error, mean_absolut
```

In [16]:
```
# Create a linear regression object and fit model to data
ols = LinearRegression()
ols.fit(dat_train,tar_train)
# View intercept
ols_intercept = ols.intercept_
# View feature coefficients
ols_coef = ols.coef_
ols_coef = ols_coef.tolist()
ols_coef[0].insert(0, ols_intercept[0])  # Add intercept to the coefficient output
# Make prediction
ols_testpred = ols.predict(dat_test)
# R-Square
R_squared = ols.score(dat_train,tar_train)
print('R-squared: %.2f' % R_squared)
# mean square error
MSE = mean_squared_error(tar_test,ols_testpred)
print('MSE: {}'.format(MSE))
RMSE = np.sqrt(mean_squared_error(tar_test,ols_testpred))
print('RMSE: {}'.format(RMSE))
```

```
R-squared: 0.66
MSE: 0.2372682483477713
RMSE: 0.4871018870295734
```

In [17]:
```
# Coefficients of OLS output (with intercept)
feature_names = list(dat_train.columns.values)
feature_names.insert(0,'Intercept')
pd.DataFrame(ols_coef, columns = feature_names, index = ['OLS_Coefficients']).T.hea
```

Out[17]:

	OLS_Coefficients
Intercept	2.387661e+11
host_listings_count	3.354641e-02
accommodates	1.989030e-01
bathrooms	8.446641e-02
bedrooms	1.899096e-01
guests_included	-3.551111e-02
minimum_nights	-5.762749e-02
maximum_nights	-2.296546e-05
minimum_nights_avg_ntm	3.998696e-02
availability_30	8.450900e-02
availability_60	-2.836635e-02
availability_365	6.719340e-02
number_of_reviews	-2.665603e-02
calculated_host_listings_count_private_rooms	-2.064697e-02
calculated_host_listings_count_shared_rooms	-3.128267e-02
extra_people	1.588872e-02
Log_Haversine_Distance	-5.098876e-03
host_identity_verified_f	1.211259e+09
host_identity_verified_t	1.211259e+09
Distance_to_CentralStation_0.04-9.65 km	1.983584e+10
Distance_to_CentralStation_23.70-67.42 km	1.983584e+10
Distance_to_CentralStation_9.66-23.69 km	1.983584e+10
is_location_exact_f	5.702898e+09
is_location_exact_t	5.702898e+09
property_type_Apartment	-1.643872e+10
property_type_House	-1.643872e+10
property_type_Other Types	-1.643872e+10
room_type_Entire home/apt	8.108234e+10
room_type_Private room	8.108234e+10
room_type_Shared room	8.108234e+10

	OLS_Coefficients
calendar_updated_1-7 weeks	-1.460285e+11
calendar_updated_2-6 days	-1.460285e+11
calendar_updated_2-6 months	-1.460285e+11
calendar_updated_>12-24 months	-1.460285e+11
calendar_updated_>24 months or never	-1.460285e+11
calendar_updated_>6-12 months	-1.460285e+11
calendar_updated_recently updated	-1.460285e+11
instant_bookable_f	-7.403519e+10
instant_bookable_t	-7.403519e+10
cancellation_policy_Moderate and other types	-7.965845e+10
cancellation_policy_flexible	-7.965845e+10
cancellation_policy_strict_14_with_grace_period	-7.965845e+10
smart_location_1st Middle group	-3.043766e+10
smart_location_2nd Middle group	-3.043766e+10
smart_location_Bottom group	-3.043766e+10
smart_location_Top group	-3.043766e+10

In [18]:

```
## The error rates of linear regression (OLS) model over both training and test set
ols_trainpred = ols.predict(dat_train)
# linear regression (OLS) training error
ols_train_error = [
    mean_squared_error(ols_trainpred, tar_train),
    mean_squared_log_error(ols_trainpred, tar_train),
    mean_absolute_error(ols_trainpred, tar_train)
]
# linear regression (OLS) test error
ols_test_error = [
    mean_squared_error(ols_testpred, tar_test),
    mean_squared_log_error(ols_testpred, tar_test),
    mean_absolute_error(ols_testpred, tar_test)
]
# error rate table of linear regression (OLS)
ols_scores = pd.DataFrame([ols_train_error,ols_test_error],columns=["MSE","MSLE","M
ols_scores
```

Out[18]:

	MSE	MSLE	MAE
train	0.221331	0.006135	0.346287
test	0.237268	0.006393	0.351179

2. Stochastic Gradient Descent

In [38]:
```
'''(2): Stochastic Gradient Descent'''
from sklearn.linear_model import SGDRegressor
sgd = SGDRegressor(loss ='squared_loss')
sgd.fit(dat_train, tar_train)
sgd_testpred = sgd.predict(dat_test)
# Using cross validation k = 5
sgd_scores = cross_val_score(sgd, dat_train, tar_train, cv=5)
print(sgd_scores)
# mean square error
print('MSE: {}'.format(mean_squared_error(tar_test,sgd_testpred)))
print('RMSE: {}'.format(np.sqrt(mean_squared_error(tar_test,sgd_testpred))))
```

```
[0.65572732 0.63741729 0.6642508  0.65037233 0.67352382]
MSE: 0.24325848729782476
RMSE: 0.4932124160012851
```

In [10]:
```
## The error rates of stochastic gradient descent over both training and test set
sgd_trainpred = sgd.predict(dat_train)
# stochastic gradient descent training error
sgd_train_error = [
    mean_squared_error(sgd_trainpred, tar_train),
    mean_squared_log_error(sgd_trainpred, tar_train),
    mean_absolute_error(sgd_trainpred, tar_train)
]
# stochastic gradient descent test error
sgd_test_error = [
    mean_squared_error(sgd_testpred, tar_test),
    mean_squared_log_error(sgd_testpred, tar_test),
    mean_absolute_error(sgd_testpred, tar_test)
]
# error rate table of stochastic gradient descent
sgd_scores = pd.DataFrame([sgd_train_error,sgd_test_error],columns=["MSE","MSLE","M
sgd_scores
```

Out[10]:

	MSE	MSLE	MAE
train	0.222941	0.006167	0.347219
test	0.239540	0.006436	0.352535

3. Ridge Regression

In [12]:
```
'''(3): Ridge Regression'''
from sklearn.linear_model import Ridge
ridge = Ridge()
ridge.fit(dat_train,tar_train)  # create models
ridge_testpred = ridge.predict(dat_test) # predictions
# R-Square
print('R-squared: %.2f' % ridge.score(dat_test,tar_test))
# mean square error
print('MSE: {}'.format(mean_squared_error(ridge_testpred,tar_test)))
```

```
R-squared: 0.64
MSE: 0.2372624962669653
```

In [13]:
```python
## The error rates of ridge regression model over both training and test set
ridge_trainpred = ridge.predict(dat_train)
# ridge regression training error
ridge_train_error = [
    mean_squared_error(ridge_trainpred, tar_train),
    mean_squared_log_error(ridge_trainpred, tar_train),
    mean_absolute_error(ridge_trainpred, tar_train)
]
# ridge regression test error
ridge_test_error = [
    mean_squared_error(ridge_testpred, tar_test),
    mean_squared_log_error(ridge_testpred, tar_test),
    mean_absolute_error(ridge_testpred, tar_test)
]
# error rate table of ridge regression
ridge_scores = pd.DataFrame([ridge_train_error,ridge_test_error],columns=["MSE","MS
ridge_scores
```

Out[13]:

	MSE	MSLE	MAE
train	0.221331	0.006135	0.346290
test	0.237262	0.006393	0.351182

4. Decision Tree

In [28]:
```python
'''(4): Decision Tree'''
from sklearn.tree import DecisionTreeRegressor
tree = DecisionTreeRegressor(criterion='mse',   # Initialize and fit regressor
                             max_depth=6)
tree.fit(dat_train,tar_train)
tree_testpred = tree.predict(dat_test)
# mean squared error
print('MSE: {}'.format(mean_squared_error(tree_testpred,tar_test)))
```

```
MSE: 0.22544961235419086
```

In [29]:
```python
## The error rates of decision tree model over both training and test set
tree_trainpred = tree.predict(dat_train)
# decision tree training error
tree_train_error = [
    mean_squared_error(tree_trainpred, tar_train),
    mean_squared_log_error(tree_trainpred, tar_train),
    mean_absolute_error(tree_trainpred, tar_train)
]
# decision tree test error
tree_test_error = [
    mean_squared_error(tree_testpred, tar_test),
    mean_squared_log_error(tree_testpred, tar_test),
    mean_absolute_error(tree_testpred, tar_test)
]
# error rate table of decision tree
```

```
tree_scores = pd.DataFrame([tree_train_error,tree_test_error],columns=["MSE","MSLE"
tree_scores
```

Out[29]:

	MSE	MSLE	MAE
train	0.208947	0.005798	0.335657
test	0.225450	0.006116	0.343320

5. Gradient Boosting Regression

In [41]:
```
'''(5): Gradient Boosting '''
from sklearn.ensemble import GradientBoostingRegressor
# evaluate the model
gbr = GradientBoostingRegressor()
gbr.fit(dat_train, tar_train)
# make a single prediction
gbr_testpred = gbr.predict(dat_test)
# mean squared error
print('MSE: {}'.format(mean_squared_error(gbr_testpred,tar_test)))
```

```
MSE: 0.1974184303740817
```

In [42]:
```
## The error rates of gradient boosting regression over both training and test set
gbr_trainpred = gbr.predict(dat_train)
# gradient boosting regression training error
gbr_train_error = [
    mean_squared_error(gbr_trainpred, tar_train),
    mean_squared_log_error(gbr_trainpred, tar_train),
    mean_absolute_error(gbr_trainpred, tar_train)
]
# gradient boosting regression test error
gbr_test_error = [
    mean_squared_error(gbr_testpred, tar_test),
    mean_squared_log_error(gbr_testpred, tar_test),
    mean_absolute_error(gbr_testpred, tar_test)
]
# error rate table of gradient boosting regression
gbr_scores = pd.DataFrame([gbr_train_error,gbr_test_error],columns=["MSE","MSLE","M
gbr_scores
```

Out[42]:

	MSE	MSLE	MAE
train	0.176628	0.004928	0.308308
test	0.197418	0.005413	0.321578

6. Extreme Gradient Boosting (XGBoost)

In [48]:
```
'''(6): Extreme Gradient Boosting '''
from xgboost import XGBRegressor
# evaluate the model
xgb = XGBRegressor(objective='reg:squarederror')
xgb.fit(dat_train, tar_train)
```

```
xgb_testpred = xgb.predict(dat_test)
# mean squared error
print('MSE: {}'.format(mean_squared_error(xgb_testpred,tar_test)))
```

MSE: 0.19580418257283413

In [49]:
```
## The error rates of extreme gradient boosting regression over both training and t
xgb_trainpred = xgb.predict(dat_train)
# extreme gradient boosting regression training error
xgb_train_error = [
    mean_squared_error(xgb_trainpred, tar_train),
    mean_squared_log_error(xgb_trainpred, tar_train),
    mean_absolute_error(xgb_trainpred, tar_train)
]
# extreme gradient boosting regression test error
xgb_test_error = [
    mean_squared_error(xgb_testpred, tar_test),
    mean_squared_log_error(xgb_testpred, tar_test),
    mean_absolute_error(xgb_testpred, tar_test)
]
# error rate table of extreme gradient boosting regression
xgb_scores = pd.DataFrame([xgb_train_error,xgb_test_error],columns=["MSE","MSLE","M
xgb_scores
```

Out[49]:

	MSE	MSLE	MAE
train	0.176972	0.004938	0.308273
test	0.195804	0.005363	0.320333

7. Random Forest

In [14]:
```
'''(7): Random Forest '''
from sklearn.ensemble import RandomForestRegressor
rfr = RandomForestRegressor(n_estimators = 100, random_state = 0)
rfr.fit(dat_train, tar_train) # create model
rfr_testpred = rfr.predict(dat_test)  # Predictions of test set
# mean squared error
print('MSE: {}'.format(mean_squared_error(rfr_testpred,tar_test)))
```

MSE: 0.19366256391688466

In [15]:
```
## The error rates of random forest model over both training and test set
rfr_trainpred = rfr.predict(dat_train)
# random forest training error
rfr_train_error = [
    mean_squared_error(rfr_trainpred, tar_train),
    mean_squared_log_error(rfr_trainpred, tar_train),
    mean_absolute_error(rfr_trainpred, tar_train)
]
# random forest test error
rfr_test_error = [
    mean_squared_error(rfr_testpred, tar_test),
    mean_squared_log_error(rfr_testpred, tar_test),
    mean_absolute_error(rfr_testpred, tar_test)
]
```

```
# error rate table of random forest
rfr_scores = pd.DataFrame([rfr_train_error,rfr_test_error],columns=["MSE","MSLE","M
rfr_scores
```

Out[15]:

	MSE	MSLE	MAE
train	0.024950	0.000699	0.113321
test	0.193663	0.005296	0.314582

Clearly, the gradient boosting regression and extreme gradient boosting model above out-performs other models with the mean squared error less than 20% on both training and test set.

However, the extreme gradient boosting (XGBoost) perform slightly better than the gradient boosting model on the test set and it is also faster. Hence, we will use the result from extreme gradient boosting for our prediction.

- The random forest model clearly overfit the data when the error on the training set is pretty low compared to the result on the test set.
- Linear regression, ridge regression, stochastic gradient descent and decision tree have similar performance and do not overfitting the models. Overall, their predictions are good but not as good as gradient boosting models.

Stage 4: Result Interpretations

First, we want to make a backup for our data set

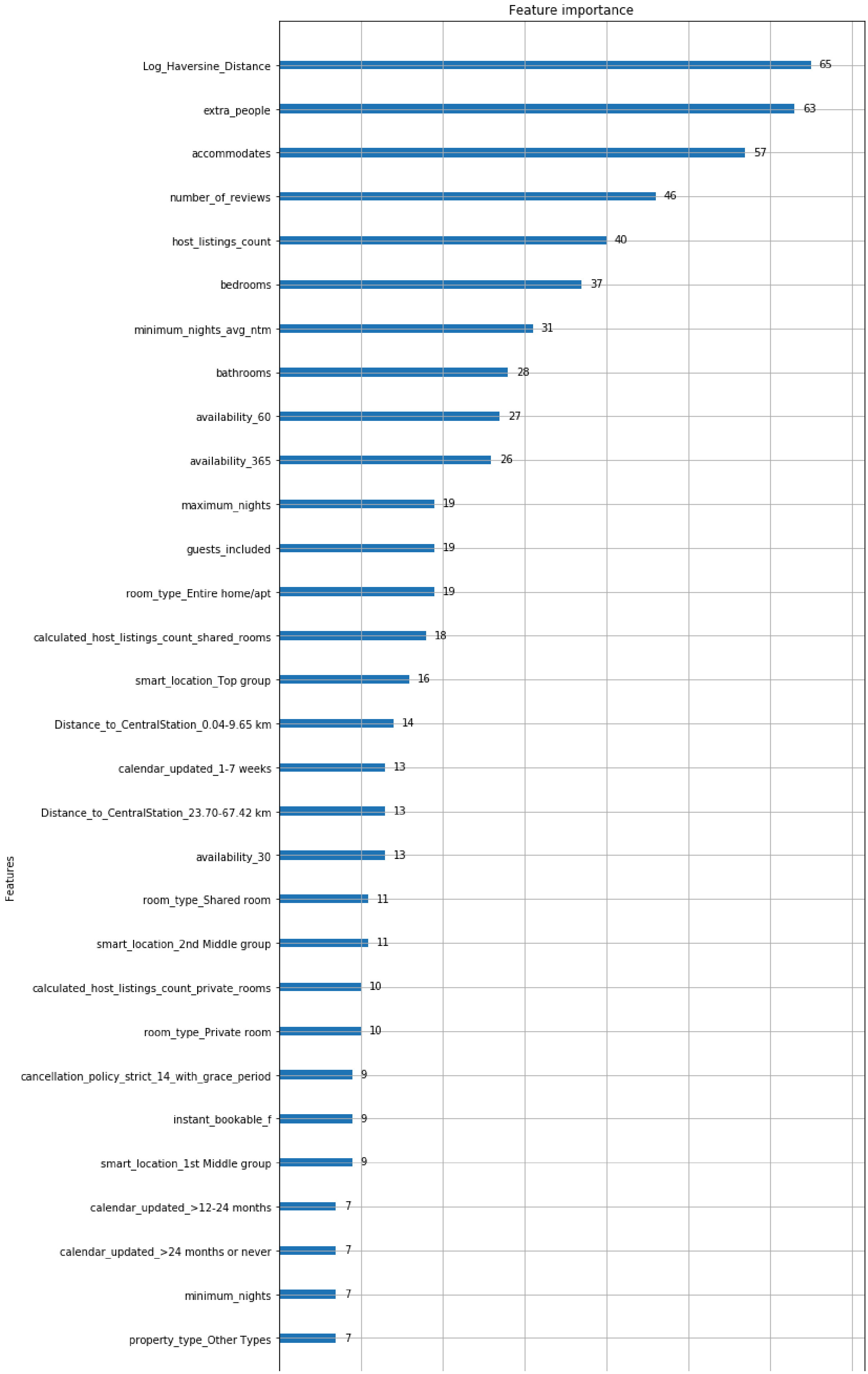
In [54]:
```
dat_backup = dat.copy()
test_cop = dat_test.copy() # copy a backup of feature test set
test_cop["target"]=np.exp(xgb_testpred)  # transform log price into original price
test_cop.reset_index(drop=True, inplace=True)   # reset index of test_cop
obs_tar = tar_test.copy()  # copy a backup of target in test set
obs_tar.reset_index(drop=True, inplace=True)  # reset index of obs_tar
```

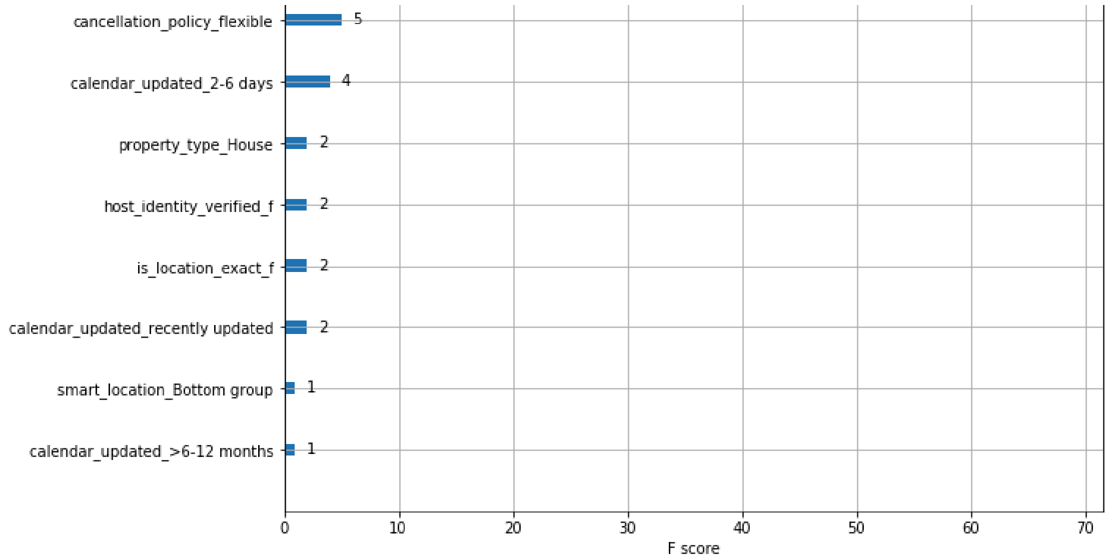
In [55]:
```
# Fit extreme gradient boosting to the whole data set
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
dat_backup[contnames] = scaler.fit_transform(dat_backup[contnames])

from xgboost import XGBRegressor
# evaluate the model
xgb = XGBRegressor(objective='reg:squarederror')
xgb.fit(dat_backup, tar_log)
logprice_pred = xgb.predict(dat_backup)
# mean squared error
print('MSE: {}'.format(mean_squared_error(logprice_pred,tar_log)))
```

```
MSE: 0.18022692625727782
```

In [72]:
```
## Feature importance
from xgboost import plot_importance
fig, ax = plt.subplots(figsize=(10,30))
plot_importance(xgb, ax=ax)
```

```
Out[72]: <matplotlib.axes._subplots.AxesSubplot at 0x1b21cbec548>
```


Feature importance
Features
Log_Haversine_Distance 65
extra_people 63
accommodates 57
number_of_reviews 46
host_listings_count 40
bedrooms 37
minimum_nights_avg_ntm 31
bathrooms 28
availability_60 27
availability_365 26
maximum_nights 19
guests_included 19
room_type_Entire home/apt 19
calculated_host_listings_count_shared_rooms 18
smart_location_Top group 16
Distance_to_CentralStation_0.04-9.65 km 14
calendar_updated_1-7 weeks 13
Distance_to_CentralStation_23.70-67.42 km 13
availability_30 13
room_type_Shared room 11
smart_location_2nd Middle group 11
calculated_host_listings_count_private_rooms 10
room_type_Private room 10
cancellation_policy_strict_14_with_grace_period 9
instant_bookable_f 9
smart_location_1st Middle group 9
calendar_updated_>12-24 months 7
calendar_updated_>24 months or never 7
minimum_nights 7
property_type_Other Types 7

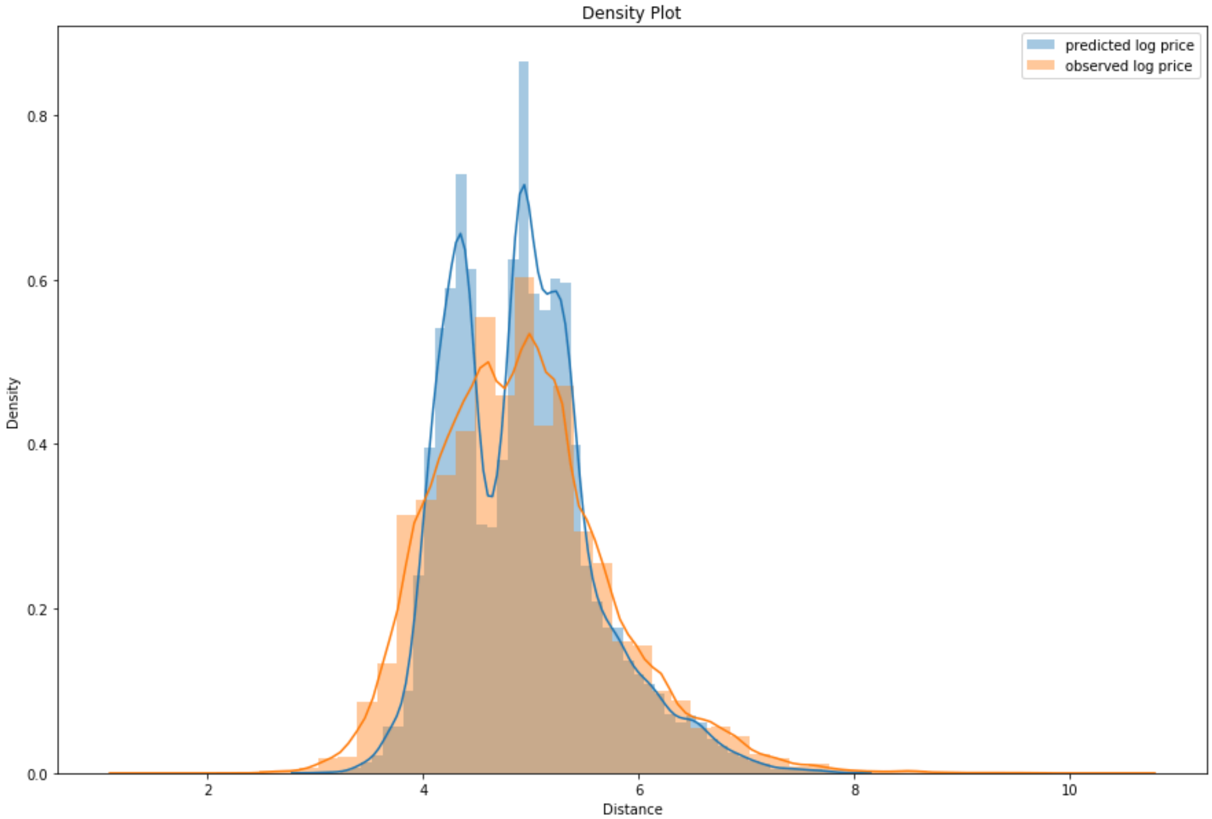


As we can see, those features that mostly affect the rental price prediction would be:

- 'Log_Haversine_Distance': which is the distance of the listed property to Sydney central station
- 'extra_people'
- 'accommodates'
- 'number of reviews'
- 'host_listings_count'
- 'bedrooms'

In [73]:
```
# Visualize distribution of log rental price
plt.figure(figsize=(15,10))
sns.distplot(logprice_pred)
sns.distplot(tar_log)
plt.title('Density Plot')
plt.legend(labels=["predicted log price", "observed log price"])
plt.xlabel('Distance')
plt.ylabel('Density')
```

Out[73]:
```
Text(0, 0.5, 'Density')
```

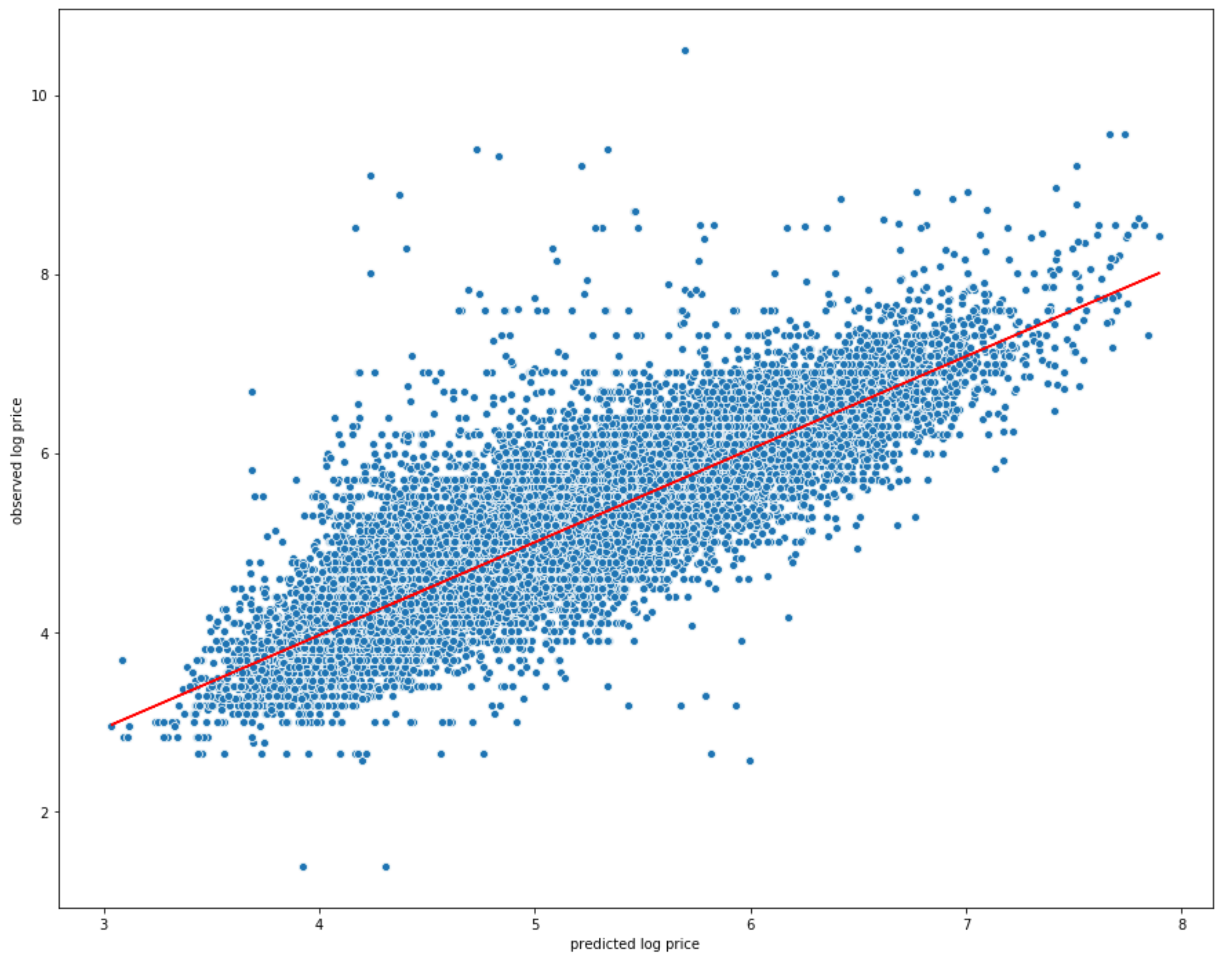


In [172…

```
# Scatterplot of log price
plt.figure(figsize=(15,12))
sns.scatterplot(x = logprice_pred, y = tar_log["price"])
plt.xlabel("predicted log price")
plt.ylabel("observed log price")

## add regression line manually
m, b = np.polyfit(logprice_pred, tar_log["price"], 1) #obtain m (slope) and b(inter
plt.plot(logprice_pred, m*logprice_pred+b, color='red')
```

Out[172…

```
[<matplotlib.lines.Line2D at 0x1b223400b48>]
```



As we can see from above that there is a strongly linear correlated relationship. And the Pearson's correlation can be estimated at:

In [179…

```
from sklearn.metrics import r2_score
from scipy.stats import pearsonr
print("Pearson Correlation: {}".format(pearsonr(logprice_pred, tar_log["price"])[0]
print("R squared: {}".format(r2_score(tar_log["price"],logprice_pred)))
```

```
Pearson Correlation: 0.8519649905580591
R squared: 0.7248621452987566
```

Hence, our predicted results seem reasonable. Here below is the basic summary of our prediction

In [201…

```
## Summary statistic
price_predicted = np.exp(logprice_pred)
price_summary = pd.DataFrame([list(price_predicted), list(tar["price"])],
                             index=["predicted price", "observed price"]).T
price_summary.describe()
```

Out[201…

	predicted price	observed price
count	38075.000000	38075.000000
mean	176.516556	205.835351
std	172.602332	389.216801
min	20.862516	4.000000
25%	79.401684	75.000000
50%	134.655548	130.000000
75%	198.705505	210.000000
max	2689.312500	36128.000000