```
In [1]: import numpy as np
    import pandas as pd
    import matplotlib.pyplot as plt
    import plotly.express as px
    import plotly.graph_objects as go
    import pandas as pd
    from sklearn import datasets, linear_model
    from sklearn.model_selection import train_test_split
    from matplotlib import pyplot as plt
    from kmodes.kmodes import KModes
    import seaborn as sns
    from scipy import stats
    from sklearn.linear_model import LinearRegression
    from sklearn import preprocessing
```

In [2]: #pip install kmodes

```
In [2]: # imports the dataset
df = pd.read_csv("sf_airbnb_listings.csv", sep=",", header=None, engine='python', encoding="utf-8-sig")
```

```
In [3]: header = df.iloc[0]
    # take the rest of your data minus the header row
    df = df[1:]
    # set the header row as the df header
    df.columns = header
    pd.set_option('display.max_rows', 7500)
    pd.set_option('display.max_columns', 106)
    df
```

	id	listing_url	scrape_id	last_scraped	name	summary	space	description
1	958	https://www.airbnb.com/rooms/958	2.02E+13	6/2/2019	Bright, Modern Garden Unit - 1BR/1B	New update: the house next door is under const	Newly remodeled, modern, and bright garden uni	New update: the house next door is under const
2	5858	https://www.airbnb.com/rooms/5858	2.02E+13	6/2/2019	Creative Sanctuary	NaN	We live in a large Victorian house on a quiet	We live in a large Victorian house on a quiet
3	7918	https://www.airbnb.com/rooms/7918	2.02E+13	6/2/2019	A Friendly Room - UCSF/USF - San Francisco	Nice and good public transportation. 7 minute	Room rental- sunny view room/sink/Wi Fi (inner	Nice and good public transportation. 7 minute
4	8142	https://www.airbnb.com/rooms/8142	2.02E+13	6/2/2019	Friendly Room Apt. Style - UCSF/USF - San Franc	Nice and good public transportation. 7 minute	Room rental Sunny view Rm/Wi- Fi/TV/sink/large 	Nice and good public transportation. 7 minute
5	8339	https://www.airbnb.com/rooms/8339	2.02E+13	6/2/2019	Historic Alamo Square Victorian	Pls email before booking. Interior featured i	Please send us a quick message before booking 	Pls email before booking. Interior featured i
7571	35284961	https://www.airbnb.com/rooms/35284961	2.02E+13	6/2/2019	Brand New Designer 2 BR SF Condo	Luxury spacious 2 bedroom condo located in SF,	Private dedicated entrance NEST temperature c	Luxury spacious 2 bedroom condo located in SF,
7572	35285751	https://www.airbnb.com/rooms/35285751	2.02E+13	6/2/2019	Beautiful 1x1 in Historic Mission Tudor Building	A beautifully remodeled one bedroom in a great	NaN	A beautifully remodeled one bedroom in a great

		9		.mot_co.mpon		• • • • • • • • • • • • • • • • • • • •	ориос	
7573	35286441	https://www.airbnb.com/rooms/35286441	2.02E+13	6/2/2019	Beautiful Queen Victorian in the heart of Mission	Our place is a charming Victorian located in t	The house is a quintessential remodeled Victor	Our place is a charming Victorian located in t
7574	35288483	https://www.airbnb.com/rooms/35288483	2.02E+13	6/2/2019	New comfortable, convenient place for family	This new place is comfortable, with easy commu	NaN	This new place is comfortable, with easy commu
7575	35291911	https://www.airbnb.com/rooms/35291911	2.02E+13	6/2/2019	Spacious 2bdrm/2bath in the heart of SF	Freshly remodeled in May 2019, 2 bedroom 2 ba	- Centrally located - Steps away from 16th and	Freshly remodeled in May 2019, 2 bedroom 2 ba

name

summary

description

space

listing_url scrape_id last_scraped

7575 rows × 106 columns

id

```
In [4]: df['zipcode'] = df.zipcode.astype('category')
    df['latitude'] = df.latitude.astype('category')
    df['longitude'] = df.longitude.astype('category')
    df['maximum_nights'] = df.maximum_nights.astype('category')
    df['minimum_minimum_nights'] = df.minimum_minimum_nights.astype('category')
    df['amenities'] = df.amenities.astype('category')
    df['bed_type'] = df.bed_type.astype('category')
    df['property_type'] = df.property_type.astype('category')

# df['neighbourhood'] = df.neighbourhood.astype(int)
# df['room_type'] = df.room_type.astype(int)
```

In [5]: df.dtypes

Out[5]: 0 object id listing url object scrape id object object last_scraped object name object summary object space description object experiences offered object neighborhood overview object object notes object transit access object object interaction house rules object thumbnail url object medium url object picture url object xl picture url object object host_id object host_url object host_name host since object host location object host about object object host response time host_response_rate object host_acceptance_rate object object host_is_superhost host_thumbnail_url object host_picture_url object host neighbourhood object host listings count object host total listings count object host verifications object host_has_profile_pic object host identity verified object street object neighbourhood object neighbourhood cleansed object neighbourhood_group_cleansed object

city

object

state	object
zipcode	category
market	object
smart_location	object
country_code	object
country	object
latitude	category
longitude	category
is_location_exact	object
property_type	category
room_type	object
accommodates	•
	object object
bathrooms bedrooms	object
beds	object
	object
bed_type	category
amenities	category
square_feet	object
price	object
weekly_price	object
monthly_price	object
security_deposit	object
cleaning_fee	object
guests_included	object
extra_people	object
minimum_nights	object
maximum_nights	category
minimum_minimum_nights	category
maximum_minimum_nights	object
minimum_maximum_nights	object
maximum_maximum_nights	object
minimum_nights_avg_ntm	object
maximum_nights_avg_ntm	object
calendar_updated	object
has_availability	object
availability_30	object
availability_60	object
availability_90	object
availability_365	object
calendar_last_scraped	object
number_of_reviews	object
number_of_reviews_ltm	object
first_review	object

last_review	object
review_scores_rating	object
review_scores_accuracy	object
review_scores_cleanliness	object
review_scores_checkin	object
review_scores_communication	object
review_scores_location	object
review_scores_value	object
requires_license	object
license	object
jurisdiction_names	object
<pre>instant_bookable</pre>	object
<pre>is_business_travel_ready</pre>	object
cancellation_policy	object
require_guest_profile_picture	object
require_guest_phone_verification	object
<pre>calculated_host_listings_count</pre>	object
<pre>calculated_host_listings_count_entire_homes</pre>	object
<pre>calculated_host_listings_count_private_rooms</pre>	object
<pre>calculated_host_listings_count_shared_rooms</pre>	object
reviews_per_month	object
dtype: object	

In [6]:

columns="host_id host_listings_count host_total_listings_count accommodates bathrooms bedrooms beds price wee kly_price monthly_price security_deposit cleaning_fee guests_included minimum_nights maximum_minimum_nights m inimum_maximum_nights maximum_mights minimum_nights_avg_ntm maximum_nights_avg_ntm availability_30 av ailability_60 availability_90 availability_365 number_of_reviews number_of_reviews_ltm review_scores_rating r eview_scores_accuracy review_scores_cleanliness review_scores_checkin review_scores_communication review_scores_location review_scores_value calculated_host_listings_count_calculated_host_listings_count_entire_homes calculated_host_listings_count_shared_rooms neighbourhood room_typ e reviews_per_month".split()

```
In [7]: columns
Out[7]: ['host_id',
          'host listings count',
          'host_total_listings_count',
          'accommodates',
          'bathrooms',
          'bedrooms',
          'beds',
          'price',
          'weekly price',
          'monthly price',
          'security_deposit',
          'cleaning fee',
          'guests included',
          'minimum nights',
          'maximum_minimum_nights',
          'minimum_maximum_nights',
          'maximum maximum nights',
          'minimum_nights_avg_ntm',
          'maximum_nights_avg_ntm',
          'availability 30',
          'availability 60',
          'availability 90',
          'availability 365',
          'number of reviews',
          'number of reviews ltm',
          'review_scores_rating',
          'review_scores_accuracy',
          'review scores cleanliness',
          'review scores checkin',
          'review scores communication',
          'review scores location',
          'review scores value',
          'calculated_host_listings_count',
          'calculated_host_listings_count_entire_homes',
          'calculated_host_listings_count_private_rooms',
          'calculated_host_listings_count_shared_rooms',
          'neighbourhood',
          'room type',
          'reviews_per_month']
```

0 1 [0]		
Out[8]:	host_id	object
	host_listings_count	object
	host_total_listings_count	object
	accommodates	object
	bathrooms	object
	bedrooms	object
	beds	object
	price	object
	weekly_price	object
	monthly_price	object
	security_deposit	object
	cleaning_fee	object
	<pre>guests_included</pre>	object
	minimum_nights	object
	maximum_minimum_nights	object
	minimum_maximum_nights	object
	maximum_maximum_nights	object
	minimum_nights_avg_ntm	object
	<pre>maximum_nights_avg_ntm</pre>	object
	availability_30	object
	availability_60	object
	availability_90	object
	availability_365	object
	number_of_reviews	object
	number_of_reviews_ltm	object
	review_scores_rating	object
	review_scores_accuracy	object
	review_scores_cleanliness	object
	review_scores_checkin	object
	review_scores_communication	object
	review_scores_location	object
	review_scores_value	object
	calculated_host_listings_count	object
	<pre>calculated_host_listings_count_entire_homes</pre>	object
	calculated_host_listings_count_private_rooms	object
	calculated_host_listings_count_shared_rooms	object
	neighbourhood	object
	room_type	object
	reviews_per_month	object
	dtype: object	J
	, i	

```
In [85]: # transforms categorical valuses in column to numeric
    le = preprocessing.LabelEncoder()
    df2['neighbourhood'] = le.fit_transform(df2.neighbourhood.values)
    df2['room_type'] = le.fit_transform(df2.room_type.values)
    df2.fillna(0, inplace=True)
    #df2.to_csv('df2.csv')
    df2
```

Out[85]:

	host_id	host_listings_count	host_total_listings_count	accommodates	bathrooms	bedrooms	beds	price	weekly_price	mon
1	1169	1.0	1.0	3.0	1.0	1.0	2.0	170.0	1120.0	
2	8904	2.0	2.0	5.0	1.0	2.0	3.0	235.0	1600.0	
3	21994	10.0	10.0	2.0	4.0	1.0	1.0	65.0	485.0	
4	21994	10.0	10.0	2.0	4.0	1.0	1.0	65.0	490.0	
5	24215	2.0	2.0	5.0	1.5	2.0	2.0	685.0	0	
7571	94857021	2.0	2.0	2.0	1.0	2.0	2.0	475.0	0	
7572	4430421	92.0	92.0	3.0	1.0	1.0	1.0	115.0	0	
7573	50247302	2.0	2.0	6.0	1.5	2.0	2.0	500.0	0	
7574	163879334	3.0	3.0	6.0	1.0	2.0	3.0	180.0	0	
7575	236978	3.0	3.0	4.0	2.0	2.0	2.0	300.0	0	

7575 rows × 39 columns

In [97]:

columns2="host_id host_listings_count host_total_listings_count accommodates bathrooms bedrooms beds weekly_p
rice monthly_price security_deposit cleaning_fee guests_included minimum_nights mximum_nights minimum_mimimum
_nights maximum_minimum_nights minimum_maximum_nights maximum_nights minimum_nights_avg_ntm maximum_n
ights_avg_ntm availability_30 availability_60 availability_90 availability_365 number_of_reviews number_of_re
views_ltm review_scores_rating review_scores_accuracy review_scores_cleanliness review_scores_checkin review_
scores_communication review_scores_location review_scores_value calculated_host_listings_count_calculated_host
_listings_count_entire_homes calculated_host_listings_count_private_rooms calculated_host_listings_count_sha
red_rooms_neighbourhood_room_type_price".split()

In [10]: df3=pd.DataFrame(df, columns=columns)
 df3

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			_		_

	host_id	host_listings_count	host_total_listings_count	accommodates	bathrooms	bedrooms	beds	price	weekly_price	mon
1	1169	1.0	1.0	3.0	1.0	1.0	2.0	170.0	1120.0	
2	8904	2.0	2.0	5.0	1.0	2.0	3.0	235.0	1600.0	
3	21994	10.0	10.0	2.0	4.0	1.0	1.0	65.0	485.0	
4	21994	10.0	10.0	2.0	4.0	1.0	1.0	65.0	490.0	
5	24215	2.0	2.0	5.0	1.5	2.0	2.0	685.0	NaN	
7571	94857021	2.0	2.0	2.0	1.0	2.0	2.0	475.0	NaN	
7572	4430421	92.0	92.0	3.0	1.0	1.0	1.0	115.0	NaN	
7573	50247302	2.0	2.0	6.0	1.5	2.0	2.0	500.0	NaN	
7574	163879334	3.0	3.0	6.0	1.0	2.0	3.0	180.0	NaN	
7575	236978	3.0	3.0	4.0	2.0	2.0	2.0	300.0	NaN	

7575 rows × 39 columns

4

In [11]: df3 = df3.dropna(axis=1)
 df3

Out[11]:

	host_id	host_listings_count	host_total_listings_count	accommodates	price	guests_included	minimum_nights	maximum_min
1	1169	1.0	1.0	3.0	170.0	2.0	1.0	
2	8904	2.0	2.0	5.0	235.0	2.0	30.0	
3	21994	10.0	10.0	2.0	65.0	1.0	32.0	
4	21994	10.0	10.0	2.0	65.0	1.0	32.0	
5	24215	2.0	2.0	5.0	685.0	2.0	4.0	
7571	94857021	2.0	2.0	2.0	475.0	1.0	3.0	
7572	4430421	92.0	92.0	3.0	115.0	1.0	30.0	
7573	50247302	2.0	2.0	6.0	500.0	4.0	1.0	
7574	163879334	3.0	3.0	6.0	180.0	4.0	30.0	
7575	236978	3.0	3.0	4.0	300.0	4.0	1.0	
7575 r	owe x 24 co	olumno						

7575 rows × 24 columns

```
In [12]: pd.set_option('display.max_rows', 7500)
    pd.set_option('display.max_columns', 106)
    df3
```

Out[12]:

	host_id	host_listings_count	host_total_listings_count	accommodates	price	guests_included	minimum_nights	maximum_min
1	1169	1.0	1.0	3.0	170.0	2.0	1.0	
2	8904	2.0	2.0	5.0	235.0	2.0	30.0	
3	21994	10.0	10.0	2.0	65.0	1.0	32.0	
4	21994	10.0	10.0	2.0	65.0	1.0	32.0	
5	24215	2.0	2.0	5.0	685.0	2.0	4.0	
7571	94857021	2.0	2.0	2.0	475.0	1.0	3.0	
7572	4430421	92.0	92.0	3.0	115.0	1.0	30.0	
7573	50247302	2.0	2.0	6.0	500.0	4.0	1.0	
7574	163879334	3.0	3.0	6.0	180.0	4.0	30.0	
7575	236978	3.0	3.0	4.0	300.0	4.0	1.0	

7575 rows × 24 columns

```
In [13]: df3.dtypes
Out[13]: host id
                                                          object
         host_listings_count
                                                          object
         host_total_listings_count
                                                          object
                                                          object
         accommodates
                                                          object
         price
         guests_included
                                                          object
         minimum nights
                                                          object
         maximum minimum nights
                                                          object
         minimum_maximum_nights
                                                          object
         maximum_maximum_nights
                                                          object
         minimum_nights_avg_ntm
                                                          object
         maximum_nights_avg_ntm
                                                          object
         availability 30
                                                          object
         availability 60
                                                          object
         availability 90
                                                          object
         availability_365
                                                          object
         number of reviews
                                                          object
         number of reviews ltm
                                                          object
         calculated_host_listings_count
                                                          object
         calculated_host_listings_count_entire_homes
                                                          object
         calculated_host_listings_count_private_rooms
                                                          object
         calculated host listings count shared rooms
                                                          object
         neighbourhood
                                                          object
         room_type
                                                          object
         dtype: object
```

categorical data

In [57]:

```
In [730]: data = df3

# model
km = KModes(n_clusters=5, init='Huang', n_init=5, verbose=1)
clusters = km.fit_predict(data)

# Print the results of clustering centroids
print(km.cluster_centroids_)
```

```
Init: initializing centroids
Init: initializing clusters
Starting iterations...
Run 1, iteration: 1/100, moves: 2418, cost: 129298.0
Run 1, iteration: 2/100, moves: 111, cost: 129289.0
Run 1, iteration: 3/100, moves: 1, cost: 129289.0
Init: initializing centroids
Init: initializing clusters
Starting iterations...
Run 2, iteration: 1/100, moves: 2060, cost: 129841.0
Run 2, iteration: 2/100, moves: 512, cost: 129553.0
Run 2, iteration: 3/100, moves: 110, cost: 129553.0
Init: initializing centroids
Init: initializing clusters
Starting iterations...
Run 3, iteration: 1/100, moves: 2735, cost: 129828.0
Run 3, iteration: 2/100, moves: 477, cost: 129770.0
Run 3, iteration: 3/100, moves: 23, cost: 129770.0
Init: initializing centroids
Init: initializing clusters
Starting iterations...
Run 4, iteration: 1/100, moves: 2863, cost: 129566.0
Run 4, iteration: 2/100, moves: 403, cost: 129408.0
Run 4, iteration: 3/100, moves: 134, cost: 129404.0
Run 4, iteration: 4/100, moves: 1, cost: 129404.0
Init: initializing centroids
Init: initializing clusters
Starting iterations...
Run 5, iteration: 1/100, moves: 1958, cost: 130072.0
Run 5, iteration: 2/100, moves: 74, cost: 130072.0
Best run was number 1
[['173206762' '2.0' '2.0' '2.0'
  '{TV,Elevator,Heating,Smoke detector,Essentials}' 'Real Bed' 'House'
  '37.75369' '-122.40637' '100.0' '1.0' '30.0' '30.0' '1125.0' '1125.0'
  '30.0' '1125.0' '0.0' '0.0' '0.0' '0.0' '0.0' '0.0' '2.0' '0.0' '1.0'
  '0.0' 'Mission District' 'Private room']
 ['55782784' '1.0' '1.0' '2.0'
  '{TV,Cable TV,Air conditioning,Paid parking off premises,Gym,Elevator,Heating,Family/kid friendly,Washer,Dr
yer, Smoke detector, Carbon monoxide detector, Essentials, Shampoo, 24-hour check-in, Hangers, Hair dryer, Iron, Self
check-in,Building staff,Hot water,Luggage dropoff allowed,Paid parking on premises}'
  'Real Bed' 'House' '37.78995' '-122.40956' '250.0' '1.0' '2.0' '2.0'
  '14.0' '14.0' '2.0' '14.0' '0.0' '0.0' '0.0' '0.0' '1.0' '1.0' '1.0'
  '1.0' '0.0' '0.0' 'Bernal Heights' 'Entire home/apt']
```

```
['117141107' '2.0' '2.0' '2.0'
  '{TV,Cable TV,Internet,Wifi,Air conditioning,Gym,Elevator,Hot tub,Heating,Smoke detector,Carbon monoxide de
tector, First aid kit, Fire extinguisher, Essentials, Shampoo, Lock on bedroom door, Hangers, Hair dryer, Iron, Laptop
friendly workspace, Self check-in, Building staff, Private entrance, Pack , Äôn Play/travel crib, Hot water, Bed lin
ens,Extra pillows and blankets,Microwave,Coffee maker,Refrigerator,Dishes and silverware,Garden or backyard,L
uggage dropoff allowed,Wide hallways,Wide entrance for guests,Flat path to guest entrance,Wide entrance,Extra
space around bed, Accessible-height toilet, Wide clearance to shower, toilet, Paid parking on premises, Fixed gra
b bars for shower, Fixed grab bars for toilet, Roll-in shower}'
  'Real Bed' 'Apartment' '37.77981' '-122.40826' '100.0' '1.0' '1.0'
  '1.0' '1125.0' '1125.0' '1.0' '1125.0' '30.0' '60.0' '90.0' '365.0'
  '0.0' '0.0' '2.0' '0.0' '1.0' '0.0' 'Downtown' 'Private room']
 ['48005494' '1235.0' '1235.0' '2.0'
  Sert (TV,Internet,Wifi,Kitchen,Pets allowed,Heating,Washer,Dryer,Smoke detector,Carbon monoxide detector, '(TV,
ials, Shampoo, Hangers, Hair dryer, Iron, Laptop friendly workspace, Private entrance }'
  'Real Bed' 'Apartment' '37.77296' '-122.40798' '140.0' '1.0' '30.0'
  '30.0' '1125.0' '1125.0' '30.0' '1125.0' '0.0' '0.0' '0.0' '365.0'
  '0.0' '0.0' '241.0' '241.0' '0.0' '0.0' 'SoMa' 'Entire home/apt']
 ['219930816' '1.0' '1.0' '4.0'
  '{TV,Cable TV,Wifi,Kitchen,Pets allowed,Elevator,Free street parking,Heating,Washer,Dryer,Smoke detector,Ca
rbon monoxide detector, Fire extinguisher, Essentials, Shampoo, Hangers, Hair dryer, Iron, Laptop friendly workspac
e,Private living room,Hot water,Bed linens,Coffee maker,Refrigerator,Dishwasher,Dishes and silverware,Cooking
basics,Oven,Stove,BBQ grill,Patio or balcony,Long term stays allowed,Host greets you}'
  'Real Bed' 'Apartment' '37.75909' '-122.41243' '150.0' '1.0' '30.0'
  '30.0' '1125.0' '1125.0' '30.0' '1125.0' '0.0' '0.0' '0.0' '0.0' '0.0'
  '0.0' '1.0' '1.0' '0.0' '0.0' 'Mission District' 'Entire home/apt']]
# Linear Regression
```

In [58]:

In [115]: columns2="host id host listings count host total listings count accommodates bathrooms bedrooms beds weekly p rice monthly price security deposit cleaning fee guests included minimum nights mximum nights mimimum mimimum nights maximum minimum nights minimum maximum nights maximum maximum nights minimum nights avg ntm maximum n ights avg ntm availability 30 availability 60 availability 90 availability 365 number of reviews number of re views ltm review scores rating review scores accuracy review scores cleanliness review scores checkin review scores communication review scores location review scores value calculated host listings count calculated hos t_listings_count_entire_homes calculated_host_listings_count_private_rooms calculated_host_listings_count_sha red rooms neighbourhood room type reviews per month".split()

```
In [117]: | target = df2['price']
```

In [118]: DF=pd.DataFrame(df2, columns=columns2)

Out[118]:

	host_id	host_listings_count	host_total_listings_count	accommodates	bathrooms	bedrooms	beds	weekly_price	monthly_pri
1	1169	1.0	1.0	3.0	1.0	1.0	2.0	1120.0	4200
2	8904	2.0	2.0	5.0	1.0	2.0	3.0	1600.0	550(
3	21994	10.0	10.0	2.0	4.0	1.0	1.0	485.0	168
4	21994	10.0	10.0	2.0	4.0	1.0	1.0	490.0	168
5	24215	2.0	2.0	5.0	1.5	2.0	2.0	0	
•••									
7571	94857021	2.0	2.0	2.0	1.0	2.0	2.0	0	
7572	4430421	92.0	92.0	3.0	1.0	1.0	1.0	0	
7573	50247302	2.0	2.0	6.0	1.5	2.0	2.0	0	
7574	163879334	3.0	3.0	6.0	1.0	2.0	3.0	0	
7575	236978	3.0	3.0	4.0	2.0	2.0	2.0	0	

7575 rows × 40 columns

```
In [119]: DF1 = DF.dropna(axis=1)
    DF1
```

Out[119]:

host_id	host_listings_count	host_total_listings_count	accommodates	bathrooms	bedrooms	beds	weekly_price	monthly_pri
1169	1.0	1.0	3.0	1.0	1.0	2.0	1120.0	4200
8904	2.0	2.0	5.0	1.0	2.0	3.0	1600.0	5500
21994	10.0	10.0	2.0	4.0	1.0	1.0	485.0	168
21994	10.0	10.0	2.0	4.0	1.0	1.0	490.0	168
24215	2.0	2.0	5.0	1.5	2.0	2.0	0	
94857021	2.0	2.0	2.0	1.0	2.0	2.0	0	
4430421	92.0	92.0	3.0	1.0	1.0	1.0	0	
50247302	2.0	2.0	6.0	1.5	2.0	2.0	0	
163879334	3.0	3.0	6.0	1.0	2.0	3.0	0	
236978	3.0	3.0	4.0	2.0	2.0	2.0	0	
	1169 8904 21994 21994 24215 94857021 4430421 50247302 163879334	1169 1.0 8904 2.0 21994 10.0 21994 10.0 24215 2.0 94857021 2.0 4430421 92.0 50247302 2.0 163879334 3.0	1169 1.0 1.0 8904 2.0 2.0 21994 10.0 10.0 24215 2.0 2.0 94857021 2.0 2.0 4430421 92.0 92.0 50247302 2.0 2.0 163879334 3.0 3.0	1169 1.0 1.0 3.0 8904 2.0 2.0 5.0 21994 10.0 10.0 2.0 24215 2.0 2.0 5.0 94857021 2.0 2.0 2.0 3.0 4430421 92.0 92.0 3.0 50247302 2.0 2.0 6.0 163879334 3.0 3.0 6.0	1169 1.0 1.0 3.0 1.0 8904 2.0 2.0 5.0 1.0 21994 10.0 10.0 2.0 4.0 21994 10.0 10.0 2.0 4.0 24215 2.0 2.0 5.0 1.5 94857021 2.0 2.0 2.0 1.0 4430421 92.0 92.0 3.0 1.0 50247302 2.0 2.0 6.0 1.5 163879334 3.0 3.0 6.0 1.0	1169 1.0 1.0 3.0 1.0 1.0 8904 2.0 2.0 5.0 1.0 2.0 21994 10.0 10.0 2.0 4.0 1.0 21994 10.0 10.0 2.0 4.0 1.0 24215 2.0 2.0 5.0 1.5 2.0	1169 1.0 1.0 3.0 1.0 1.0 2.0 8904 2.0 2.0 5.0 1.0 2.0 3.0 21994 10.0 10.0 2.0 4.0 1.0 1.0 21994 10.0 10.0 2.0 4.0 1.0 1.0 24215 2.0 2.0 5.0 1.5 2.0 2.0	1169 1.0 1.0 3.0 1.0 1.0 2.0 1120.0 8904 2.0 2.0 5.0 1.0 2.0 3.0 1600.0 21994 10.0 10.0 2.0 4.0 1.0 1.0 485.0 21994 10.0 10.0 2.0 4.0 1.0 1.0 490.0 24215 2.0 2.0 5.0 1.5 2.0 2.0 0

7575 rows × 38 columns

```
In [120]: y=target
```

```
In [121]: X_train, X_test, y_train, y_test = train_test_split(DF1, y, test_size=0.40)
    print(X_train.shape, y_train.shape)
    print(X_test.shape, y_test.shape)
```

```
(4545, 38) (4545,)
(3030, 38) (3030,)
```

```
In [122]: lm = linear_model.LinearRegression()
    model = lm.fit(X_train, y_train)
    predictions = lm.predict(X_test)
```

```
In [124]: plt.scatter(y_test, predictions)
    plt.xlabel('True Values')
    plt.ylabel('Predictions')
    plt.title('Predicted')
    plt.xticks(rotation=45)
```

```
Out[124]: ([0,
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[Text(0, 0, ''),
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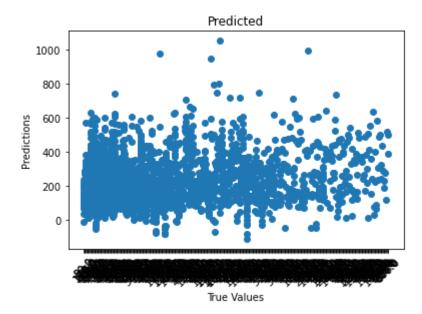
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Text(0, 0, ''),
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Text(0, 0, ''),
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Text(0, 0, ''),
Text(0, 0, '')])
```



In [125]: print('Score:', model.score(X_test, y_test))

Score: 0.28478289270098456

In []: # Linear Regression MOdel 2

Out[136]:

	host_id	host_listings_count	host_total_listings_count	accommodates	bathrooms	bedrooms	beds	price	weekly_price	mon
1	1169	1.0	1.0	3.0	1.0	1.0	2.0	170.0	1120.0	
2	8904	2.0	2.0	5.0	1.0	2.0	3.0	235.0	1600.0	
3	21994	10.0	10.0	2.0	4.0	1.0	1.0	65.0	485.0	
4	21994	10.0	10.0	2.0	4.0	1.0	1.0	65.0	490.0	
5	24215	2.0	2.0	5.0	1.5	2.0	2.0	685.0	0	
7571	94857021	2.0	2.0	2.0	1.0	2.0	2.0	475.0	0	
7572	4430421	92.0	92.0	3.0	1.0	1.0	1.0	115.0	0	
7573	50247302	2.0	2.0	6.0	1.5	2.0	2.0	500.0	0	
7574	163879334	3.0	3.0	6.0	1.0	2.0	3.0	180.0	0	
7575	236978	3.0	3.0	4.0	2.0	2.0	2.0	300.0	0	

7575 rows × 39 columns

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.

```
In [137]: df2.dtypes
Out[137]: host_id
                                                            object
          host listings count
                                                            object
          host total listings count
                                                            object
           accommodates
                                                            object
                                                            object
           bathrooms
                                                            object
           bedrooms
                                                            object
           beds
                                                            object
           price
          weekly price
                                                            object
          monthly price
                                                            object
          security deposit
                                                            object
          cleaning fee
                                                            object
          guests included
                                                            object
          minimum nights
                                                            object
          maximum minimum nights
                                                            object
          minimum maximum nights
                                                            object
                                                            object
          maximum maximum nights
          minimum_nights_avg_ntm
                                                            object
          maximum nights avg ntm
                                                            object
          availability 30
                                                            object
          availability 60
                                                            object
          availability 90
                                                            object
          availability 365
                                                            object
          number of reviews
                                                            object
          number of reviews ltm
                                                            object
           review scores rating
                                                            object
           review scores accuracy
                                                            object
          review scores cleanliness
                                                            object
          review scores checkin
                                                            object
          review scores communication
                                                            object
          review scores location
                                                            object
          review scores value
                                                            object
          calculated host listings count
                                                            object
          calculated_host_listings_count_entire_homes
                                                            object
           calculated_host_listings_count_private_rooms
                                                            object
           calculated host listings count shared rooms
                                                            object
          neighbourhood
                                                             int64
           room type
                                                             int64
           reviews per month
                                                            object
          dtype: object
```

```
In [138]: | df2['host id'] = le.fit transform(df2.host id.values)
          df2['host listings count'] = le.fit transform(df2.host listings count.values)
          df2['host total listings count'] = le.fit transform(df2.host total listings count.values)
          df2['accommodates'] = le.fit transform(df2.accommodates.values)
          df2['price'] = le.fit transform(df2.price.values)
          df2['guests included'] = le.fit transform(df2.guests included.values)
          df2['guests included'] = le.fit transform(df2.guests included.values)
          df2['minimum nights'] = le.fit transform(df2.minimum nights.values)
          df2['maximum minimum nights'] = le.fit transform(df2.maximum minimum nights.values)
          df2['minimum maximum nights'] = le.fit transform(df2.minimum maximum nights.values)
          df2['maximum maximum nights '] = le.fit transform(df2.maximum maximum nights .values)
          df2['minimum nights avg ntm'] = le.fit transform(df2.minimum nights avg ntm.values)
          df2['maximum nights avg ntm'] = le.fit transform(df2.maximum nights avg ntm.values)
          df2['availability 30'] = le.fit transform(df2.availability 30.values)
          df2['availability 60'] = le.fit transform(df2.availability 60.values)
          df2['availability 90'] = le.fit transform(df2.availability 90.values)
          df2['availability 365'] = le.fit transform(df2.availability 365.values)
          df2['number of reviews'] = le.fit transform(df2.number of reviews.values)
          df2['number of reviews ltm'] = le.fit transform(df2.number of reviews ltm.values)
          df2['calculated host listings count'] = le.fit transform(df2.calculated host listings count.values)
          df2['calculated host listings count entire homes '] = le.fit transform(df2.calculated host listings count ent
          ire homes .values)
          df2['calculated host listings count private rooms'] = le.fit transform(df2.calculated host listings count pri
          vate rooms.values)
          df2['calculated host listings count shared rooms'] = le.fit transform(df2.calculated host listings count shared
          ed rooms.values)
```

In [139]: df2.dtypes

Out[139]:	host id	in+22
out[139].	host_id host_listings_count	int32 int32
	host_total_listings_count	int32
	accommodates	int32
	bathrooms	object
	bedrooms	object
	beds	object
	price	int32
	weekly_price	object
	monthly_price	object
	security_deposit	object
	cleaning_fee	object
	guests_included	int64
	minimum_nights	int32
	maximum_minimum_nights	int32
	minimum maximum nights	int32
	maximum maximum nights	object
	minimum_nights_avg_ntm	int32
	maximum_nights_avg_ntm	int32
	availability_30	int32
	availability 60	int32
	availability_90	int32
	availability_365	int32
	number_of_reviews	int32
	number_of_reviews_ltm	int32
	review_scores_rating	object
	review_scores_accuracy	object
	review_scores_cleanliness	object
	review_scores_checkin	object
	review_scores_communication	object
	review_scores_location	object
	review scores value	object
	calculated_host_listings_count	int32
	calculated_host_listings_count_entire_homes	object
	<pre>calculated_host_listings_count_private_rooms</pre>	int32
	calculated_host_listings_count_shared_rooms	int32
	neighbourhood	int64
	room_type	int64
	reviews_per_month	object
	maximum_maximum_nights	int32
	<pre>calculated_host_listings_count_entire_homes</pre>	int32
	dtype: object	

Number of coeffiients: 40

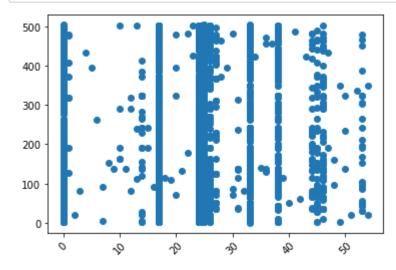
```
In [145]: pd.DataFrame(zip(X.columns, lm.coef_), columns = ['features', 'estimatedCoefficients'])
```

Out[145]:

	features	estimatedCoefficients
0	host_id	0.002568
1	host_listings_count	0.218014
2	host_total_listings_count	0.218014
3	accommodates	-5.235693
4	bathrooms	16.185030
5	bedrooms	20.502325
6	beds	7.485358
7	weekly_price	0.003900
8	monthly_price	-0.002278
9	security_deposit	-0.010565
10	cleaning_fee	0.092709
11	guests_included	-3.305059
12	minimum_nights	0.683907
13	maximum_minimum_nights	0.129070
14	minimum_maximum_nights	-0.103230
15	maximum_maximum_nights	0.000002
16	minimum_nights_avg_ntm	-0.223200
17	maximum_nights_avg_ntm	0.302968
18	availability_30	-0.198812
19	availability_60	0.056494
20	availability_90	-0.110744
21	availability_365	0.032356
22	number_of_reviews	0.004312
23	number_of_reviews_ltm	-0.010657
24	review_scores_rating	-1.098829
25	review_scores_accuracy	11.628345

	features	estimatedCoefficients
26	review_scores_cleanliness	-3.602554
27	review_scores_checkin	11.602738
28	review_scores_communication	9.640296
29	review_scores_location	-13.917118
30	review_scores_value	-4.477288
31	calculated_host_listings_count	0.404228
32	calculated_host_listings_count_entire_homes	-0.307295
33	calculated_host_listings_count_private_rooms	1.704368
34	calculated_host_listings_count_shared_rooms	-0.853777
35	neighbourhood	-0.039407
36	room_type	41.415688
37	reviews_per_month	-4.036389
38	maximum_maximum_nights	-0.151252
39	calculated_host_listings_count_entire_homes	-1.175656

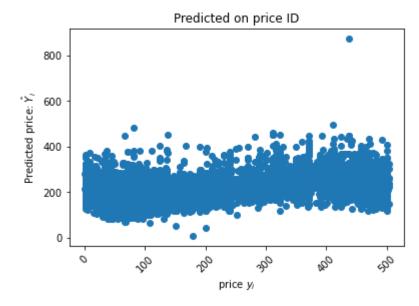
```
In [146]: # True PLot
    plt.scatter(df2.minimum_nights, df2.price)
    plt.xlabel('')
    plt.ylabel('')
    plt.title('')
    plt.xticks(rotation=45)
    plt.show()
```



```
In [147]: lm.predict(X)[0:5]
```

Out[147]: array([162.42074521, 204.01203772, 321.55025648, 353.99479439, 210.71661718])

```
In [148]: # Prediction PLot
    plt.scatter(df2.price, lm.predict(X))
    plt.xlabel('price $y_i$')
    plt.ylabel('Predicted price: $\hat{Y}_i$')
    plt.title('Predicted on price ID')
    plt.xticks(rotation=45)
    plt.show()
```



```
In [149]: mseFull = np.mean((df2.price - lm.predict(X)) ** 2)
    print(mseFull)
```

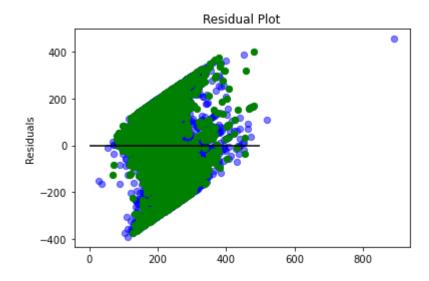
22110.75385550316

```
In [150]: v = np.var(X)
          print("variance", v)
          variance host id
                                                                     1.442344e+06
          host listings count
                                                           3.565887e+02
          host total listings count
                                                           3.565887e+02
          accommodates
                                                           1.003424e+01
          guests included
                                                           6.480794e+00
          minimum nights
                                                           1.206550e+02
          maximum minimum nights
                                                           1.706717e+03
          minimum maximum nights
                                                           1.867289e+03
          minimum nights avg ntm
                                                           2.352391e+03
          maximum nights avg ntm
                                                           4.375798e+03
          availability 30
                                                           1.228940e+02
          availability 60
                                                           4.484524e+02
          availability 90
                                                           9.087368e+02
          availability 365
                                                           1.466309e+04
          number of reviews
                                                           1.988508e+04
          number of reviews ltm
                                                           1.350129e+03
          calculated host listings count
                                                           1.325670e+02
          calculated host listings count private rooms
                                                           3.688758e+01
          calculated host listings count shared rooms
                                                           3.260231e+00
          neighbourhood
                                                           2.516769e+02
          room type
                                                           3.040613e-01
          maximum maximum nights
                                                           5.788197e+03
          calculated host listings count entire homes
                                                           4.803761e+01
          dtype: float64
In [151]:
          lm = LinearRegression()
          lm.fit(X[['minimum nights']], df2.price)
Out[151]: LinearRegression()
          mse2 = np.mean((df2.price - lm.predict(X[['minimum nights']])) ** 2)
In [155]:
          mse2
Out[155]: 25394.1741190435
```

```
In [156]: | X_train, X_test, Y_train, Y_test = train_test_split(
              X, df2.price, test_size=.33, random_state=1000)
          print(X_train.shape)
          print(X_test.shape)
          print(Y train.shape)
          print(Y test.shape)
          (5075, 40)
          (2500, 40)
          (5075,)
          (2500,)
In [157]: lm=LinearRegression()
          lm.fit(X train, Y train)
          pred train = lm.predict(X train)
          pred test = lm.predict(X test)
In [158]: | print("Fit a model X_train, and calculate MSE with Y_train:"), np.mean((Y_train-lm.predict(X_train)) ** 2)
          print("Fit a model X train, and calculate MSE with X test, Y test:"), np.mean((Y test-lm.predict(X test)) **
          2)
          Fit a model X_train, and calculate MSE with Y_train:
          Fit a model X_train, and calculate MSE with X_test, Y_test:
Out[158]: (None, 22895.8325980217)
```

```
In [159]: plt.scatter(lm.predict(X_train), lm.predict(X_train) - Y_train, c='b', s=40, alpha=0.5)
    plt.scatter(lm.predict(X_test), lm.predict(X_test) - Y_test, c='g', s=40)
    plt.hlines(y=0, xmin=0, xmax=500, color="black")
    plt.title('Residual Plot')
    plt.ylabel('Residuals')
```

Out[159]: Text(0, 0.5, 'Residuals')



```
In [ ]: # Decision Tree
```

```
In [37]: from sklearn.model_selection import train_test_split
    from sklearn.tree import DecisionTreeClassifier
    from sklearn.metrics import classification_report, confusion_matrix
    from sklearn import metrics
    from sklearn.tree import export_graphviz
    from IPython.display import Image
    from sklearn import tree
```

```
In [67]: df4 = pd.read_csv("sf_airbnb_listings.csv", sep=",", header=None, engine='python', encoding="utf-8-sig")
```

```
In [68]: header = df4.iloc[0]
# take the rest of your data minus the header row
df4 = df4[1:]
# set the header row as the df header
df4.columns = header
pd.set_option('display.max_rows', 7500)
pd.set_option('display.max_columns', 106)
df4
```

	id	listing_url	scrape_id	last_scraped	name	summary	space	description
	1 958	https://www.airbnb.com/rooms/958	2.02E+13	6/2/2019	Bright, Modern Garden Unit - 1BR/1B	New update: the house next door is under const	Newly remodeled, modern, and bright garden uni	New update: the house next door is under const
	2 5858	https://www.airbnb.com/rooms/5858	2.02E+13	6/2/2019	Creative Sanctuary	NaN	We live in a large Victorian house on a quiet	We live in a large Victorian house on a quiet
	3 7918	https://www.airbnb.com/rooms/7918	2.02E+13	6/2/2019	A Friendly Room - UCSF/USF - San Francisco	Nice and good public transportation. 7 minute	Room rental- sunny view room/sink/Wi Fi (inner	Nice and good public transportation. 7 minute
,	4 8142	https://www.airbnb.com/rooms/8142	2.02E+13	6/2/2019	Friendly Room Apt. Style - UCSF/USF - San Franc	Nice and good public transportation. 7 minute	Room rental Sunny view Rm/Wi- Fi/TV/sink/large 	Nice and good public transportation. 7 minute
	5 8339	https://www.airbnb.com/rooms/8339	2.02E+13	6/2/2019	Historic Alamo Square Victorian	Pls email before booking. Interior featured i	Please send us a quick message before booking 	Pls email before booking. Interior featured i
757	1 35284961	https://www.airbnb.com/rooms/35284961	2.02E+13	6/2/2019	Brand New Designer 2 BR SF Condo	Luxury spacious 2 bedroom condo located in SF,	Private dedicated entrance NEST temperature c	Luxury spacious 2 bedroom condo located in SF,
757	2 35285751	https://www.airbnb.com/rooms/35285751	2.02E+13	6/2/2019	Beautiful 1x1 in Historic Mission Tudor Building	A beautifully remodeled one bedroom in a great	NaN	A beautifully remodeled one bedroom in a great

	id	listing_url	scrape_id	last_scraped	name	summary	space	description
7573	35286441	https://www.airbnb.com/rooms/35286441	2.02E+13	6/2/2019	Beautiful Queen Victorian in the heart of Mission	Our place is a charming Victorian located in t	The house is a quintessential remodeled Victor	Our place is a charming Victorian located in t
7574	35288483	https://www.airbnb.com/rooms/35288483	2.02E+13	6/2/2019	New comfortable, convenient place for family	This new place is comfortable, with easy commu	NaN	This new place is comfortable, with easy commu
7575	35291911	https://www.airbnb.com/rooms/35291911	2.02E+13	6/2/2019	Spacious 2bdrm/2bath in the heart of SF	Freshly remodeled in May 2019, 2 bedroom 2 ba	- Centrally located - Steps away from 16th and	Freshly remodeled in May 2019, 2 bedroom 2 ba

7575 rows × 106 columns

4

•

In [225]: columns4="host_listings_count accommodates host_response_rate bedrooms beds guests_included maximum_nights mi
 nimum_nights availability_30 availability_365 number_of_reviews review_scores_rating price weekly_price mont
 hly_price security_deposit cleaning_fee room_type reviews_per_month".split()
 columns5="host_id host_listings_count accommodates bathrooms bedrooms beds guests_included minimum_nights ava
 ilability_30 availability_365 number_of_reviews review_scores_rating neighbourhood room_type reviews_per_mo
 nth".split()
 df6=pd.DataFrame(df4, columns=columns4)
 df6.fillna(0, inplace=True)
 df6
#df6.to_csv('df6.csv')

Out[225]:

	host_listings_count	accommodates	host_response_rate	bedrooms	beds	guests_included	maximum_nights	minimum_nights	а
1	1.0	3.0	100%	1.0	2.0	2.0	30.0	1.0	
2	2.0	5.0	100%	2.0	3.0	2.0	60.0	30.0	
3	10.0	2.0	100%	1.0	1.0	1.0	60.0	32.0	
4	10.0	2.0	100%	1.0	1.0	1.0	90.0	32.0	
5	2.0	5.0	100%	2.0	2.0	2.0	1125.0	4.0	
7571	2.0	2.0	100%	2.0	2.0	1.0	1125.0	3.0	
7572	92.0	3.0	99%	1.0	1.0	1.0	150.0	30.0	
7573	2.0	6.0	100%	2.0	2.0	4.0	10.0	1.0	
7574	3.0	6.0	100%	2.0	3.0	4.0	1125.0	30.0	
7575	3.0	4.0	100%	2.0	2.0	4.0	1125.0	1.0	

7575 rows × 19 columns

Out[226]:

	host_listings_count	accommodates	host_response_rate	bedrooms	beds	guests_included	maximum_nights	minimum_nights	а
1	1.0	3.0	1.00	1.0	2.0	2.0	30.0	1.0	
2	2.0	5.0	1.00	2.0	3.0	2.0	60.0	30.0	
3	10.0	2.0	1.00	1.0	1.0	1.0	60.0	32.0	
4	10.0	2.0	1.00	1.0	1.0	1.0	90.0	32.0	
5	2.0	5.0	1.00	2.0	2.0	2.0	1125.0	4.0	
7571	2.0	2.0	1.00	2.0	2.0	1.0	1125.0	3.0	
7572	92.0	3.0	0.99	1.0	1.0	1.0	150.0	30.0	
7573	2.0	6.0	1.00	2.0	2.0	4.0	10.0	1.0	
7574	3.0	6.0	1.00	2.0	3.0	4.0	1125.0	30.0	
7575	3.0	4.0	1.00	2.0	2.0	4.0	1125.0	1.0	

7575 rows × 19 columns

•

In [227]: df6 = df6.dropna(axis=1)
 df6

Out[227]:

	host_listings_count	accommodates	bedrooms	beds	guests_included	maximum_nights	minimum_nights	availability_30	availab
1	1.0	3.0	1.0	2.0	2.0	30.0	1.0	1.0	
2	2.0	5.0	2.0	3.0	2.0	60.0	30.0	0.0	
3	10.0	2.0	1.0	1.0	1.0	60.0	32.0	30.0	
4	10.0	2.0	1.0	1.0	1.0	90.0	32.0	11.0	
5	2.0	5.0	2.0	2.0	2.0	1125.0	4.0	30.0	
7571	2.0	2.0	2.0	2.0	1.0	1125.0	3.0	26.0	
7572	92.0	3.0	1.0	1.0	1.0	150.0	30.0	23.0	
7573	2.0	6.0	2.0	2.0	4.0	10.0	1.0	7.0	
7574	3.0	6.0	2.0	3.0	4.0	1125.0	30.0	16.0	
7575	3.0	4.0	2.0	2.0	4.0	1125.0	1.0	19.0	

7575 rows × 18 columns

In [228]: main_columns = columns4
X = df6 # main data
y = df.neighbourhood # Target variable

In [229]: df6.shape

Out[229]: (7575, 18)

In [230]: X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=.40, random_state=2000)

Out[231]: DecisionTreeClassifier(max_depth=2)

```
In [232]: y_pred = classifier.predict(X_test)
print("Accuracy:",metrics.accuracy_score(y_test, y_pred)) # returns the accuracy
```

Accuracy: 0.14785478547854786

In [233]: print(confusion_matrix(y_test, y_pred))
print(classification_report(y_test, y_pred))

```
[[0 0 0 ... 0 0 0]
[0 0 0 ... 0 0 0]
 [0 0 0 ... 0 0 0]
 [0 0 0 ... 0 0 0]
 [0 0 0 ... 0 0 0]
 [0 0 0 ... 0 0 0]]
                         precision
                                       recall f1-score
                                                           support
         Alamo Square
                              0.00
                                         0.00
                                                    0.00
                                                                 23
       Balboa Terrace
                              0.00
                                         0.00
                                                    0.00
                                                                 16
                              0.00
               Bayview
                                         0.00
                                                    0.00
                                                                 78
                              0.00
                                                    0.00
                                                                165
       Bernal Heights
                                         0.00
             Chinatown
                              0.00
                                         0.00
                                                    0.00
                                                                 22
         Civic Center
                              0.00
                                         0.00
                                                    0.00
                                                                  6
                                                                 48
          Cole Valley
                              0.00
                                         0.00
                                                    0.00
                                                    0.00
           Cow Hollow
                              0.00
                                         0.00
                                                                 25
       Crocker Amazon
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                                                    0.00
                                                                 45
             Daly City
                              0.00
                                         0.00
                                                    0.00
                                                                  1
      Diamond Heights
                              0.00
                                         0.00
                                                    0.00
                                                                  8
                                                    0.00
                                                                15
              Dogpatch
                              0.00
                                         0.00
              Downtown
                              0.34
                                         0.58
                                                    0.43
                                                                146
                              0.00
      Duboce Triangle
                                         0.00
                                                    0.00
                                                                 47
             Excelsion
                              0.00
                                         0.00
                                                    0.00
                                                                 45
   Financial District
                              0.00
                                         0.00
                                                    0.00
                                                                 32
   Fisherman''s Wharf
                              0.00
                                         0.00
                                                    0.00
                                                                 24
                                                                  5
          Forest Hill
                              0.00
                                         0.00
                                                    0.00
                              0.00
             Glen Park
                                         0.00
                                                    0.00
                                                                 34
       Haight-Ashbury
                              0.00
                                         0.00
                                                    0.00
                                                                 70
         Hayes Valley
                              0.00
                                         0.00
                                                    0.00
                                                                 32
             Ingleside
                              0.00
                                         0.00
                                                    0.00
                                                                 19
                                                                 59
         Inner Sunset
                              0.00
                                         0.00
                                                    0.00
                              0.00
                                                    0.00
                                                                  5
             Japantown
                                         0.00
             Lakeshore
                              0.00
                                         0.00
                                                    0.00
                                                                 25
         Lower Haight
                              0.00
                                         0.00
                                                    0.00
                                                                 32
                              0.00
                                                    0.00
                Marina
                                         0.00
                                                                 37
                              0.00
                                                    0.00
                                                                19
          Mission Bay
                                         0.00
     Mission District
                              0.12
                                         0.74
                                                    0.20
                                                                296
      Mission Terrace
                              0.00
                                         0.00
                                                    0.00
                                                                 30
                              0.00
              Nob Hill
                                         0.00
                                                    0.00
                                                                133
           Noe Valley
                              0.00
                                         0.00
                                                    0.00
                                                                158
                              0.00
                                                                17
          North Beach
                                         0.00
                                                    0.00
             Oceanview 0
                              0.00
                                         0.00
                                                    0.00
                                                                 19
```

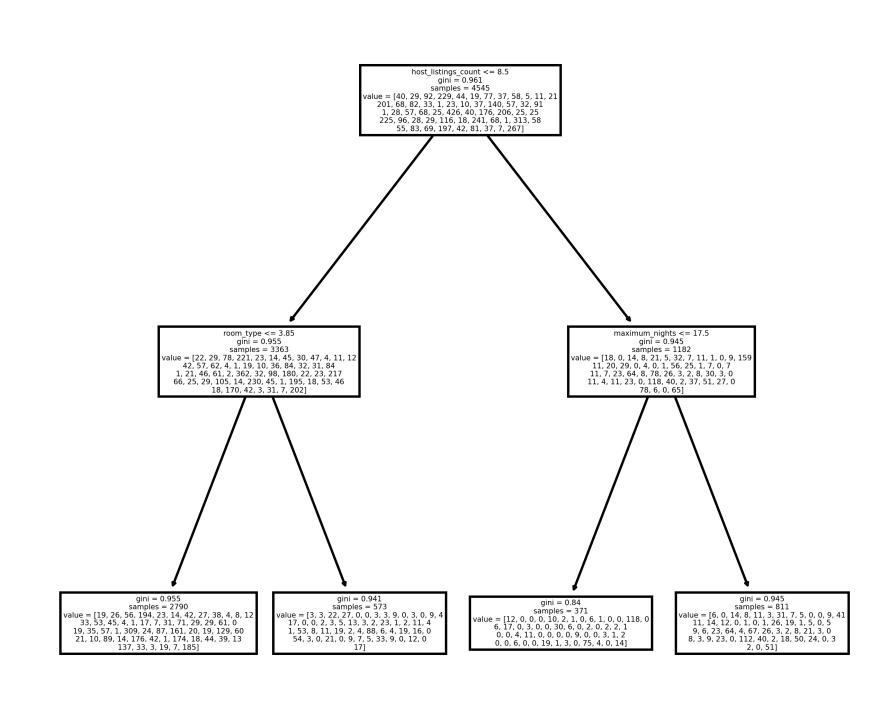
Outer Sunset	0.13	0.38	0.20	136
Pacific Heights	0.00	0.00	0.00	83
Parkside	0.00	0.00	0.00	16
Portola	0.00	0.00	0.00	17
Potrero Hill	0.00	0.00	0.00	88
Presidio	0.00	0.00	0.00	1
Presidio Heights	0.00	0.00	0.00	13
Richmond District	0.00	0.00	0.00	121
Russian Hill	0.00	0.00	0.00	40
Sea Cliff	0.00	0.00	0.00	2
SoMa	0.17	0.43	0.24	213
South Beach	0.00	0.43	0.00	42
				· -
Sunnyside	0.00	0.00	0.00	40
Telegraph Hill	0.00	0.00	0.00	51
Tenderloin	0.00	0.00	0.00	39
The Castro	0.00	0.00	0.00	116
Twin Peaks	0.00	0.00	0.00	25
Union Square	0.00	0.00	0.00	54
Visitacion Valley	0.00	0.00	0.00	22
West Portal	0.00	0.00	0.00	4
Western Addition/NOPA	0.00	0.00	0.00	171
accuracy			0.15	3030
macro avg	0.01	0.04	0.02	3030
weighted avg	0.05	0.15	0.07	3030
- 0 0-0				

C:\Users\kevin\Anaconda3\envs\r-tutorial\lib\site-packages\sklearn\metrics_classification.py:1221: Undefined
MetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted sample
s. Use `zero_division` parameter to control this behavior.
 _warn_prf(average, modifier, msg_start, len(result))

```
In [234]: fig, axes = plt.subplots(nrows = 1,ncols = 1,figsize = (6,6), dpi=500)
    tree.plot_tree(classifier, feature_names = main_columns, filled=False) # plots the tree
```

Out[234]: [Text(1162.5, 1887.5, 'host listings count <= 8.5\ngini = 0.961\nsamples = 4545\nvalue = [40, 29, 92, 229, 4 4, 19, 77, 37, 58, 5, 11, 21\n201, 68, 82, 33, 1, 23, 10, 37, 140, 57, 32, 91\n1, 28, 57, 68, 25, 426, 40, 17 6, 206, 25, 25\n225, 96, 28, 29, 116, 18, 241, 68, 1, 313, 58\n55, 83, 69, 197, 42, 81, 37, 7, 267]'), Text(581.25, 1132.5, 'room type \leq 3.85\ngini = 0.955\nsamples = 3363\nvalue = [22, 29, 78, 221, 23, 14, 45, 30, 47, 4, 11, 12×57 , 62, 4, 1, 19, 10, 36, 84, 32, 31, 84×1 , 21, 46, 61, 2, 362, 32, 98, 180, 22, 23, 217\n66, 25, 29, 105, 14, 230, 45, 1, 195, 18, 53, 46\n18, 170, 42, 3, 31, 7, 202]'), Text(290.625, 377.5, 'gini = 0.955\nsamples = 2790\nvalue = $[19, 26, 56, 194, 23, 14, 42, 27, 38, 4, 8, 12\n$ 33, 53, 45, 4, 1, 17, 7, 31, 71, 29, 29, 61, 0×19 , 35, 57, 1, 309, 24, 87, 161, 20, 19, 129, 60×19 , 10, 89, 14, 176, 42, 1, 174, 18, 44, 39, 13\n137, 33, 3, 19, 7, 185]'), Text(871.875, 377.5, 'gini = 0.941\nsamples = 573\nvalue = $[3, 3, 22, 27, 0, 0, 3, 3, 9, 0, 3, 0, 9, 4\n17,$ 5, 33, 9, 0, 12, 0\n17]'), Text(1743.75, 1132.5, 'maximum nights <= 17.5\ngini = 0.945\nsamples = 1182\nvalue = [18, 0, 14, 8, 21, 5, 3 2, 7, 11, 1, 0, 9, 159\n11, 20, 29, 0, 4, 0, 1, 56, 25, 1, 7, 0, 7\n11, 7, 23, 64, 8, 78, 26, 3, 2, 8, 30, 3, 0×11 , 4, 11, 23, 0, 118, 40, 2, 37, 51, 27, 0×78 , 6, 0, 65]'), Text(1453.125, 377.5, 'gini = 0.84\nsamples = 371\nvalue = [12, 0, 0, 0, 10, 2, 1, 0, 6, 1, 0, 0, 118, 0\n6, 0, 75, 4, 0, 14]'), Text(2034.375, 377.5, 'gini = 0.945\nsamples = 811\nvalue = [6, 0, 14, 8, 11, 3, 31, 7, 5, 0, 0, 9, 41\n11, 14, 12, 0, 1, 0, 1, 26, 19, 1, 5, 0, 5\n9, 6, 23, 64, 4, 67, 26, 3, 2, 8, 21, 3, 0\n8, 3, 9, 23, 0, 112, 40,

2, 18, 50, 24, 0, 3\n2, 0, 51]')]



In []:	
In []:	