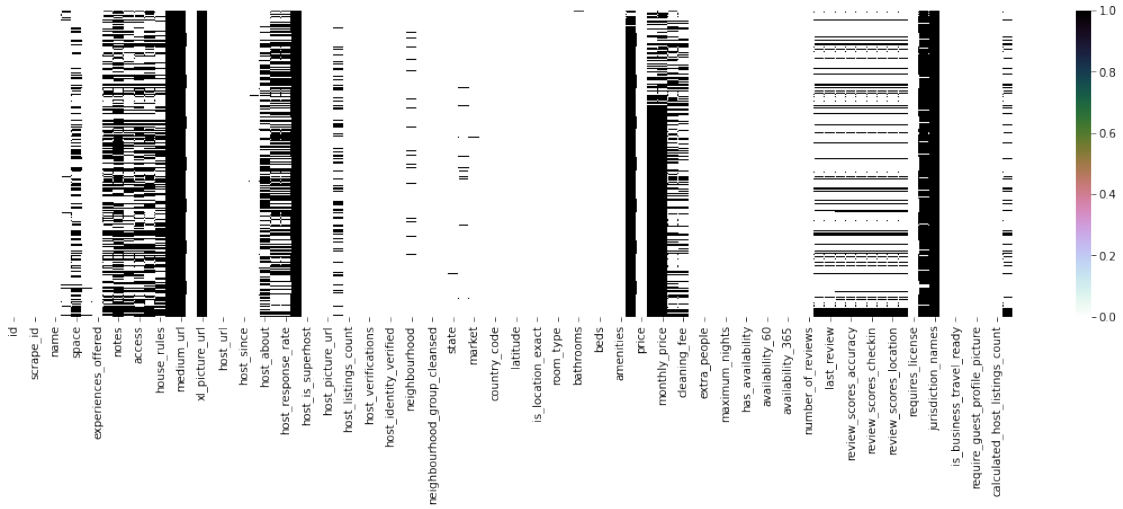
airbnb-berlin-cost-prediction

April 30, 2020

[597]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
```

[545]:
```
pd.options.display.max_columns = None
pd.options.display.max_rows = None
df = pd.read_csv("./berlin-airbnb-data/listings_summary.csv")
```

[546]:
```
#source : https://www.kaggle.com/mhmdpkts/
 ↪predict-price-ann-data-cleaning-future-engineering
fig, ax = plt.subplots(figsize = (20, 5))
sns.heatmap(df.isna(), cmap = "cubehelix_r", yticklabels='')
plt.show()
```



A simple heat map shows the state of missing values, a presence of black line shows that a value is missing. From a quick observation we find that some columns have a large amount of data missing in them. We will verify this numerically,

[547]:
```
#Calculate the percentage of the missing values in
((len(df)-df.count())/len(df)*100).sort_values(ascending = False)
```

[547]:
```
xl_picture_url                100.000000
jurisdiction_names            100.000000
thumbnail_url                 100.000000
medium_url                    100.000000
host_acceptance_rate          100.000000
square_feet                    98.022348
license                        92.736786
monthly_price                  88.209471
weekly_price                   83.677723
notes                          68.007272
host_response_rate             57.178964
host_response_time             57.174530
interaction                    53.857751
access                         51.946612
host_about                     50.385775
house_rules                    49.232884
neighborhood_overview          48.829372
transit                        42.195814
security_deposit               41.508514
space                          37.832565
cleaning_fee                   31.686768
host_neighbourhood             22.587797
review_scores_value            19.665662
review_scores_checkin          19.652359
review_scores_location         19.647925
review_scores_communication    19.590280
review_scores_accuracy         19.572543
review_scores_cleanliness      19.559241
review_scores_rating           19.461689
reviews_per_month              17.355445
first_review                   17.355445
last_review                    17.328840
neighbourhood                   5.015076
summary                         4.270131
zipcode                         2.908833
description                     0.900142
host_location                   0.514367
state                           0.372473
market                          0.279354
name                            0.261618
beds                            0.177368
bathrooms                       0.141894
host_is_superhost               0.115289
host_listings_count             0.115289
```

host_total_listings_count	0.115289
host_identity_verified	0.115289
host_picture_url	0.115289
host_thumbnail_url	0.115289
host_has_profile_pic	0.115289
host_since	0.115289
host_name	0.115289
bedrooms	0.079816
city	0.022171
scrape_id	0.000000
last_scraped	0.000000
picture_url	0.000000
listing_url	0.000000
host_url	0.000000
host_id	0.000000
experiences_offered	0.000000
host_verifications	0.000000
country	0.000000
street	0.000000
calendar_last_scraped	0.000000
calendar_updated	0.000000
has_availability	0.000000
availability_30	0.000000
availability_60	0.000000
availability_90	0.000000
availability_365	0.000000
number_of_reviews	0.000000
neighbourhood_cleansed	0.000000
requires_license	0.000000
instant_bookable	0.000000
is_business_travel_ready	0.000000
cancellation_policy	0.000000
require_guest_profile_picture	0.000000
require_guest_phone_verification	0.000000
maximum_nights	0.000000
minimum_nights	0.000000
extra_people	0.000000
guests_included	0.000000
price	0.000000
amenities	0.000000
bed_type	0.000000
accommodates	0.000000
room_type	0.000000
property_type	0.000000
is_location_exact	0.000000
longitude	0.000000
latitude	0.000000

```
calculated_host_listings_count        0.000000
country_code                          0.000000
smart_location                        0.000000
neighbourhood_group_cleansed          0.000000
id                                    0.000000
dtype: float64
```

High percentage of missing values are present in some columns, we are going to cut down any columns that have more than 40% of data missing in them.

[548]:
```
col_list_to_drop = []

columns = df.columns
length = len(df)
for i in columns:
    rate = round(df[i].isna().sum()/length,3)
    if rate > 0.45:
        col_list_to_drop.append(i)
```

For our analysis, we are not going to need any data related to host's personnel details. Nether do we have any value with the available url's. Since we are not going to perform any form of text processing, we will delete all those columns that have either textual data, are related to host's personnel details and contain textual data in them. Since the work is to predict the pricing of a new hosting, we will not use the columns related to the reviews, as its expected to have not reviews at the time of publishing the property for first time. The location details are provided using features like lattitude, longitude, street names, city and others. For our modeling we would not be using the details of city, since this data is assumed to be of Berlin.

The availability would not help to provide a cost estimation, the availability could be instead used to calculate the earning of a host.

[549]:
```
col_list_to_drop .extend (["id",
                           "listing_url",
                           "smart_location",
                           "street",
                           "city",
                           "state",
                           "market",
                           "host_total_listings_count",
                           "scrape_id",
                           "experiences_offered",
                           "last_scraped",
                           "name",
                           "host_acceptance_rate",
                           "summary",
                           "space",
                           "description",
                           "neighborhood_overview",
```

```
                    "notes",
                    "transit",
                    "access",
                    "interaction",
                    "house_rules",
                    "thumbnail_url",
                    "medium_url",
                    "picture_url",
                    "xl_picture_url",
                    "availability_30",
                    "availability_60",
                    "availability_90",
                    "availability_365",
                    "host_id",
                    "host_url",
                    "host_name",
                    "host_since",
                    "host_location",
                    "host_about",
                    "host_response_time",
                    "host_response_rate",
                    "host_thumbnail_url",
                    "host_picture_url",
                    "host_neighbourhood",
                    "host_listings_count",
                    "host_verifications",
                    "host_has_profile_pic",
                    "host_identity_verified",
                    "calendar_updated",
                    "calendar_last_scraped",
                    "first_review",
                    "last_review",
                    "license",
                    "jurisdiction_names",
                    "require_guest_profile_picture",
                    "requires_license",
                    "is_location_exact",
                    "require_guest_phone_verification",
                    "calculated_host_listings_count",
                    "review_scores_value",
                    "review_scores_rating",
                    "review_scores_accuracy",
                    "review_scores_cleanliness",
                    "reviews_per_month",
                    "review_scores_checkin",
                    "review_scores_communication",
                    "review_scores_location",
```

```
                          "review_scores_value"])

df.drop(list(set(col_list_to_drop)), axis=1, inplace=True)
```

[550]:
```
df.describe(include="all")
```

[550]:

	host_is_superhost	neighbourhood	neighbourhood_cleansed	\
count	22526	21421	22552	
unique	2	91	136	
top	f	Neukölln	Tempelhofer Vorstadt	
freq	19515	3209	1325	
mean	NaN	NaN	NaN	
std	NaN	NaN	NaN	
min	NaN	NaN	NaN	
25%	NaN	NaN	NaN	
50%	NaN	NaN	NaN	
75%	NaN	NaN	NaN	
max	NaN	NaN	NaN	

	neighbourhood_group_cleansed	zipcode	country_code	country	\
count	22552	21896	22552	22552	
unique	12	215	1	1	
top	Friedrichshain-Kreuzberg	10245	DE	Germany	
freq	5497	855	22552	22552	
mean	NaN	NaN	NaN	NaN	
std	NaN	NaN	NaN	NaN	
min	NaN	NaN	NaN	NaN	
25%	NaN	NaN	NaN	NaN	
50%	NaN	NaN	NaN	NaN	
75%	NaN	NaN	NaN	NaN	
max	NaN	NaN	NaN	NaN	

	latitude	longitude	property_type	room_type	accommodates	\
count	22552.000000	22552.000000	22552	22552	22552.000000	
unique	NaN	NaN	33	3	NaN	
top	NaN	NaN	Apartment	Private room	NaN	
freq	NaN	NaN	20225	11534	NaN	
mean	52.509824	13.406107	NaN	NaN	2.637460	
std	0.030825	0.057964	NaN	NaN	1.510548	
min	52.345803	13.103557	NaN	NaN	1.000000	
25%	52.489065	13.375411	NaN	NaN	2.000000	
50%	52.509079	13.416779	NaN	NaN	2.000000	
75%	52.532669	13.439259	NaN	NaN	3.000000	
max	52.651670	13.757642	NaN	NaN	16.000000	

	bathrooms	bedrooms	beds	bed_type	amenities	price	\
count	22520.000000	22534.000000	22512.000000	22552	22552	22552	

unique	NaN	NaN	NaN	5	19985	295
top	NaN	NaN	NaN	Real Bed	{}	$30.00
freq	NaN	NaN	NaN	21766	75	1387
mean	1.092695	1.161134	1.620558	NaN	NaN	NaN
std	0.329894	0.646156	1.174840	NaN	NaN	NaN
min	0.000000	0.000000	0.000000	NaN	NaN	NaN
25%	1.000000	1.000000	1.000000	NaN	NaN	NaN
50%	1.000000	1.000000	1.000000	NaN	NaN	NaN
75%	1.000000	1.000000	2.000000	NaN	NaN	NaN
max	8.500000	12.000000	22.000000	NaN	NaN	NaN

	security_deposit	cleaning_fee	guests_included	extra_people	\
count	13191	15406	22552.000000	22552	
unique	142	112	NaN	65	
top	$0.00	$0.00	NaN	$0.00	
freq	5319	1865	NaN	10863	
mean	NaN	NaN	1.332121	NaN	
std	NaN	NaN	0.835034	NaN	
min	NaN	NaN	1.000000	NaN	
25%	NaN	NaN	1.000000	NaN	
50%	NaN	NaN	1.000000	NaN	
75%	NaN	NaN	1.000000	NaN	
max	NaN	NaN	16.000000	NaN	

	minimum_nights	maximum_nights	has_availability	number_of_reviews	\
count	22552.000000	2.255200e+04	22552	22552.000000	
unique	NaN	NaN	1	NaN	
top	NaN	NaN	t	NaN	
freq	NaN	NaN	22552	NaN	
mean	7.157059	1.030505e+05	NaN	17.840679	
std	40.665073	9.640519e+06	NaN	36.769624	
min	1.000000	1.000000e+00	NaN	0.000000	
25%	2.000000	2.000000e+01	NaN	1.000000	
50%	2.000000	1.124000e+03	NaN	5.000000	
75%	4.000000	1.125000e+03	NaN	16.000000	
max	5000.000000	1.000000e+09	NaN	498.000000	

	instant_bookable	is_business_travel_ready	cancellation_policy
count	22552	22552	22552
unique	2	1	5
top	f	f	flexible
freq	15518	22552	9102
mean	NaN	NaN	NaN
std	NaN	NaN	NaN
min	NaN	NaN	NaN
25%	NaN	NaN	NaN
50%	NaN	NaN	NaN

```
75%                  NaN                      NaN                  NaN
max                  NaN                      NaN                  NaN
```

For simplicity, we are going to check the neighbourhood based grouping.

[551]:
```
neighbourhood_columns = ['neighbourhood', 'neighbourhood_cleansed',␣
↪'neighbourhood_group_cleansed', 'zipcode', 'country_code', 'country']
df.drop(neighbourhood_columns, axis=1, inplace=True)
col_list_to_drop.extend(neighbourhood_columns)
```

We will drop those columns that are categorical and have no unique values.

[552]:
```
for col in df.columns:
    if len(df[col].unique()) == 1:
        print("Dropping Column {}".format(col))
        df.drop(col, axis=1, inplace=True)
```

```
Dropping Column has_availability
Dropping Column is_business_travel_ready
```

We are going to filter the columns that depict prices, from the above summary details of all columns we have the following columns that describe prices “price”, “weekly_price”, “monthly_price”, “security_deposit”,“cleaning_fee”, “extra_people”.

[553]:
```
df.describe(include="all")
```

[553]:

```
       host_is_superhost      latitude     longitude property_type  \
count              22526  22552.000000  22552.000000         22552
unique                 2           NaN           NaN            33
top                    f           NaN           NaN     Apartment
freq               19515           NaN           NaN         20225
mean                 NaN     52.509824     13.406107           NaN
std                  NaN      0.030825      0.057964           NaN
min                  NaN     52.345803     13.103557           NaN
25%                  NaN     52.489065     13.375411           NaN
50%                  NaN     52.509079     13.416779           NaN
75%                  NaN     52.532669     13.439259           NaN
max                  NaN     52.651670     13.757642           NaN

           room_type  accommodates     bathrooms      bedrooms          beds  \
count          22552  22552.000000  22520.000000  22534.000000  22512.000000
unique             3           NaN           NaN           NaN           NaN
top     Private room           NaN           NaN           NaN           NaN
freq           11534           NaN           NaN           NaN           NaN
mean             NaN      2.637460      1.092695      1.161134      1.620558
std              NaN      1.510548      0.329894      0.646156      1.174840
min              NaN      1.000000      0.000000      0.000000      0.000000
25%              NaN      2.000000      1.000000      1.000000      1.000000
```

```
50%              NaN      2.000000      1.000000      1.000000      1.000000
75%              NaN      3.000000      1.000000      1.000000      2.000000
max              NaN     16.000000      8.500000     12.000000     22.000000

        bed_type amenities   price security_deposit cleaning_fee  \
count      22552     22552   22552            13191        15406
unique         5     19985     295              142          112
top     Real Bed        {}  $30.00            $0.00        $0.00
freq       21766        75    1387             5319         1865
mean         NaN       NaN     NaN              NaN          NaN
std          NaN       NaN     NaN              NaN          NaN
min          NaN       NaN     NaN              NaN          NaN
25%          NaN       NaN     NaN              NaN          NaN
50%          NaN       NaN     NaN              NaN          NaN
75%          NaN       NaN     NaN              NaN          NaN
max          NaN       NaN     NaN              NaN          NaN

        guests_included extra_people  minimum_nights  maximum_nights  \
count      22552.000000        22552    22552.000000    2.255200e+04
unique              NaN           65             NaN             NaN
top                 NaN        $0.00             NaN             NaN
freq                NaN        10863             NaN             NaN
mean           1.332121          NaN        7.157059    1.030505e+05
std            0.835034          NaN       40.665073    9.640519e+06
min            1.000000          NaN        1.000000    1.000000e+00
25%            1.000000          NaN        2.000000    2.000000e+01
50%            1.000000          NaN        2.000000    1.124000e+03
75%            1.000000          NaN        4.000000    1.125000e+03
max           16.000000          NaN     5000.000000    1.000000e+09

        number_of_reviews instant_bookable cancellation_policy
count        22552.000000            22552               22552
unique                NaN                2                   5
top                   NaN                f            flexible
freq                  NaN            15518                9102
mean            17.840679              NaN                 NaN
std             36.769624              NaN                 NaN
min              0.000000              NaN                 NaN
25%              1.000000              NaN                 NaN
50%              5.000000              NaN                 NaN
75%             16.000000              NaN                 NaN
max            498.000000              NaN                 NaN
```

[554]:
```
df.price = df.price.str.replace('$', '').str.replace(',', '').astype(float)
df.cleaning_fee = df.cleaning_fee.str.replace('$', '').str.replace(',', '').
 ↪astype(float)
```

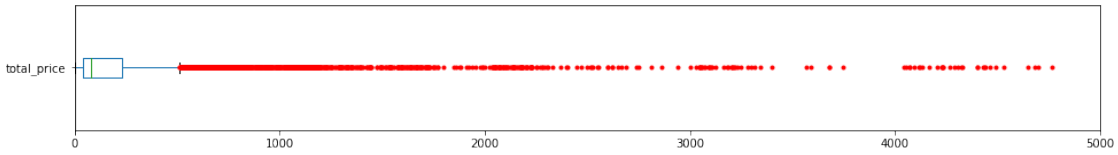
```
df.security_deposit = df.security_deposit.str.replace('$', '').str.replace(',',␣
↪'').astype(float)
df.extra_people = df.extra_people.str.replace('$', '').str.replace(',', '').
↪astype(float)
```

[555]:
```
print(df['price'].isna().sum())
print(df['cleaning_fee'].isna().sum())
print(df['security_deposit'].isna().sum())
print(df['extra_people'].isna().sum())
```

```
0
7146
9361
0
```

Replacing all the missing values of cleaning fee and security deposit to zero and merging the price, cleaning_fee and security_deposit columns. The resultant total_price shows a skewed distribution, with not much data beyond 5000 Euros. Dropping all rows that have price columns either set to 0 or are greater than 5000

[556]:
```
df['cleaning_fee'].fillna(0, inplace=True)
df['security_deposit'].fillna(0, inplace=True)
df['total_price'] = df['price'] + df['cleaning_fee'] + df['security_deposit']
red_square = dict(markerfacecolor='r', markeredgecolor='r', marker='.')
df['total_price'].plot(kind='box', xlim=(0, 5000), vert=False,␣
↪flierprops=red_square, figsize=(16,2))
df.drop(df[ (df.price > 5000) | (df.price == 0) ].index, axis=0, inplace=True)
#drop the columns that were merged
df.drop(['cleaning_fee', 'security_deposit', 'price'], inplace=True, axis = 1)
```



[557]:
```
df.describe(include="all")
```

[557]:

	host_is_superhost	latitude	longitude	property_type
count	22496	22521.000000	22521.000000	22521
unique	2	NaN	NaN	33
top	f	NaN	NaN	Apartment
freq	19486	NaN	NaN	20216
mean	NaN	52.509840	13.406166	NaN
std	NaN	0.030836	0.057948	NaN
min	NaN	52.345803	13.103557	NaN

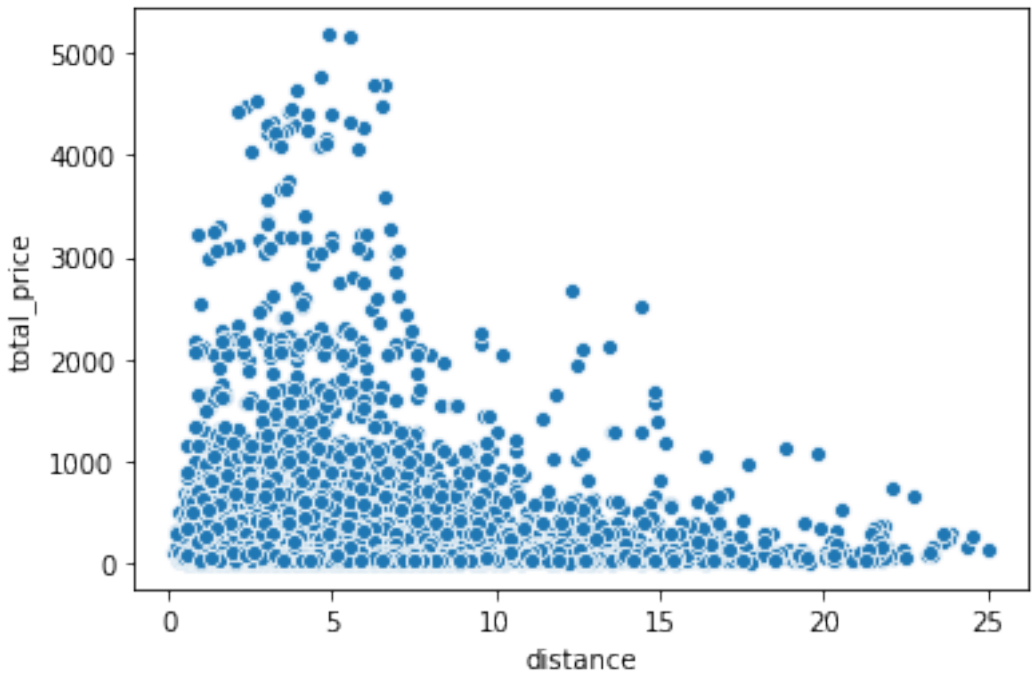
```
25%                  NaN     52.489056     13.375606           NaN
50%                  NaN     52.509117     13.416834           NaN
75%                  NaN     52.532678     13.439284           NaN
max                  NaN     52.651670     13.757642           NaN

          room_type  accommodates     bathrooms      bedrooms          beds  \
count         22521  22521.000000  22489.000000  22503.000000  22481.000000
unique            3           NaN           NaN           NaN           NaN
top     Private room           NaN           NaN           NaN           NaN
freq          11508           NaN           NaN           NaN           NaN
mean            NaN      2.637361      1.092712      1.161045      1.620568
std             NaN      1.509021      0.329983      0.645998      1.173845
min             NaN      1.000000      0.000000      0.000000      0.000000
25%             NaN      2.000000      1.000000      1.000000      1.000000
50%             NaN      2.000000      1.000000      1.000000      1.000000
75%             NaN      3.000000      1.000000      1.000000      2.000000
max             NaN     16.000000      8.500000     12.000000     22.000000

        bed_type amenities  guests_included  extra_people  minimum_nights  \
count      22521     22521     22521.000000  22521.000000    22521.000000
unique         5     19970              NaN           NaN             NaN
top     Real Bed        {}              NaN           NaN             NaN
freq       21735        74              NaN           NaN             NaN
mean         NaN       NaN         1.331380      8.265397        7.160384
std          NaN       NaN         0.834745     11.155132       40.687817
min          NaN       NaN         1.000000      0.000000        1.000000
25%          NaN       NaN         1.000000      0.000000        2.000000
50%          NaN       NaN         1.000000      5.000000        2.000000
75%          NaN       NaN         1.000000     15.000000        4.000000
max          NaN       NaN        16.000000    250.000000     5000.000000

        maximum_nights  number_of_reviews instant_bookable  \
count     2.252100e+04       22521.000000            22521
unique             NaN                NaN                2
top                NaN                NaN                f
freq               NaN                NaN            15508
mean      1.031910e+05          17.859420              NaN
std       9.647152e+06          36.788259              NaN
min       1.000000e+00           0.000000              NaN
25%       2.000000e+01           1.000000              NaN
50%       1.124000e+03           5.000000              NaN
75%       1.125000e+03          16.000000              NaN
max       1.000000e+09         498.000000              NaN

       cancellation_policy   total_price
count                22521  22521.000000
unique                   5           NaN
```

```
top              flexible           NaN
freq                9080           NaN
mean                 NaN    197.062386
std                  NaN    336.835524
min                  NaN      8.000000
25%                  NaN     41.000000
50%                  NaN     80.000000
75%                  NaN    228.000000
max                  NaN   5180.000000
```

[ ]:

[558]:
```
#source : https://www.kaggle.com/mhmdpkts/
 ↪predict-price-ann-data-cleaning-future-engineering
#create distance feature from latitude and longtitude
from geopy.distance import great_circle
def distance_from_berlin(lat, lon):
    berlin_centre = (52.5027778, 13.404166666666667)
    record = (lat, lon)
    #returns surface distance in kilometers
    return great_circle(berlin_centre, record).km

#add distanse dataset
df['distance'] = df.apply(lambda x: distance_from_berlin(x.latitude, x.
 ↪longitude), axis=1)
df.drop(['latitude', 'longitude'], inplace=True, axis=1)
```

[559]:
```
sns.scatterplot(x=df['distance'], y = df['total_price'])
plt.show()
```



Observation : With the increase in distance from the center, we find the prices going comparatively down.

[560]:
```
#Generate a Categorical and Numerical Column List
numerical_columns = []
categoical_columns = []
for column in df.columns:
    if df[column].dtype == 'object':
        categoical_columns.append(column)
    else:
        numerical_columns.append(column)
```

[561]:
```
df.describe(include="all")
```

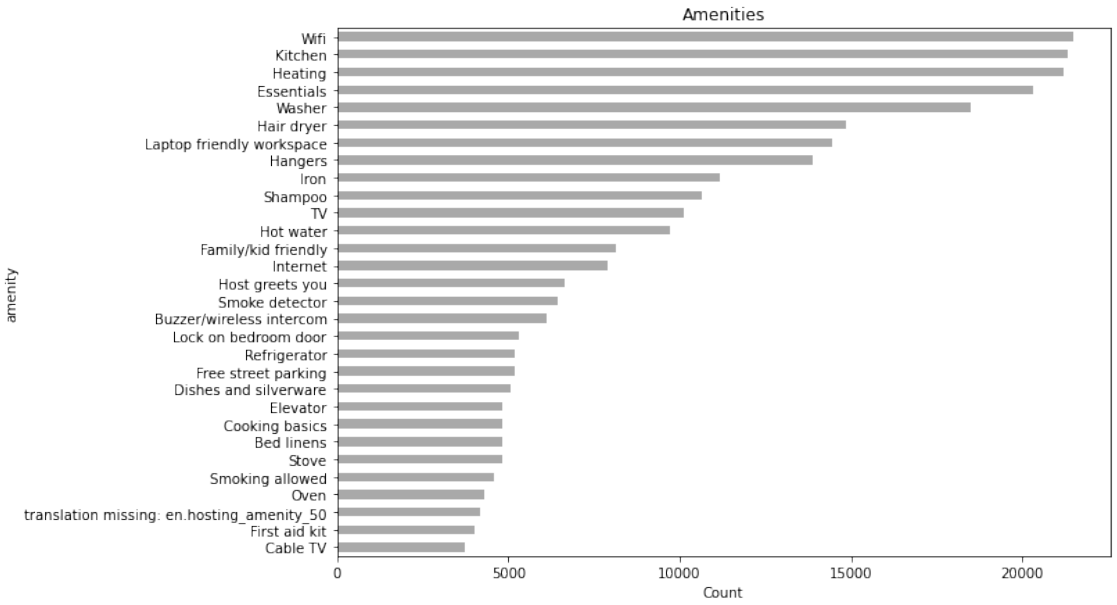
[561]:

	host_is_superhost	property_type	room_type	accommodates	\
count	22496	22521	22521	22521.000000	
unique	2	33	3	NaN	
top	f	Apartment	Private room	NaN	
freq	19486	20216	11508	NaN	
mean	NaN	NaN	NaN	2.637361	
std	NaN	NaN	NaN	1.509021	
min	NaN	NaN	NaN	1.000000	
25%	NaN	NaN	NaN	2.000000	
50%	NaN	NaN	NaN	2.000000	
75%	NaN	NaN	NaN	3.000000	

```
max                 NaN           NaN           NaN     16.000000

          bathrooms      bedrooms          beds  bed_type amenities  \
count   22489.000000  22503.000000  22481.000000     22521     22521
unique           NaN           NaN           NaN         5     19970
top              NaN           NaN           NaN  Real Bed        {}
freq             NaN           NaN           NaN     21735        74
mean        1.092712      1.161045      1.620568       NaN       NaN
std         0.329983      0.645998      1.173845       NaN       NaN
min         0.000000      0.000000      0.000000       NaN       NaN
25%         1.000000      1.000000      1.000000       NaN       NaN
50%         1.000000      1.000000      1.000000       NaN       NaN
75%         1.000000      1.000000      2.000000       NaN       NaN
max         8.500000     12.000000     22.000000       NaN       NaN

        guests_included  extra_people  minimum_nights  maximum_nights  \
count      22521.000000  22521.000000    22521.000000    2.252100e+04
unique              NaN           NaN             NaN             NaN
top                 NaN           NaN             NaN             NaN
freq                NaN           NaN             NaN             NaN
mean           1.331380      8.265397        7.160384    1.031910e+05
std            0.834745     11.155132       40.687817    9.647152e+06
min            1.000000      0.000000        1.000000    1.000000e+00
25%            1.000000      0.000000        2.000000    2.000000e+01
50%            1.000000      5.000000        2.000000    1.124000e+03
75%            1.000000     15.000000        4.000000    1.125000e+03
max           16.000000    250.000000     5000.000000    1.000000e+09

        number_of_reviews instant_bookable cancellation_policy   total_price  \
count        22521.000000            22521                22521  22521.000000
unique                NaN                2                    5           NaN
top                   NaN                f             flexible           NaN
freq                  NaN            15508                 9080           NaN
mean            17.859420              NaN                  NaN    197.062386
std             36.788259              NaN                  NaN    336.835524
min              0.000000              NaN                  NaN      8.000000
25%              1.000000              NaN                  NaN     41.000000
50%              5.000000              NaN                  NaN     80.000000
75%             16.000000              NaN                  NaN    228.000000
max            498.000000              NaN                  NaN   5180.000000

           distance
count   22521.000000
unique           NaN
top              NaN
freq             NaN
mean        4.547260
```

```
std          2.664719
min          0.198956
25%          2.976668
50%          4.088234
75%          5.550559
max         25.012109
```

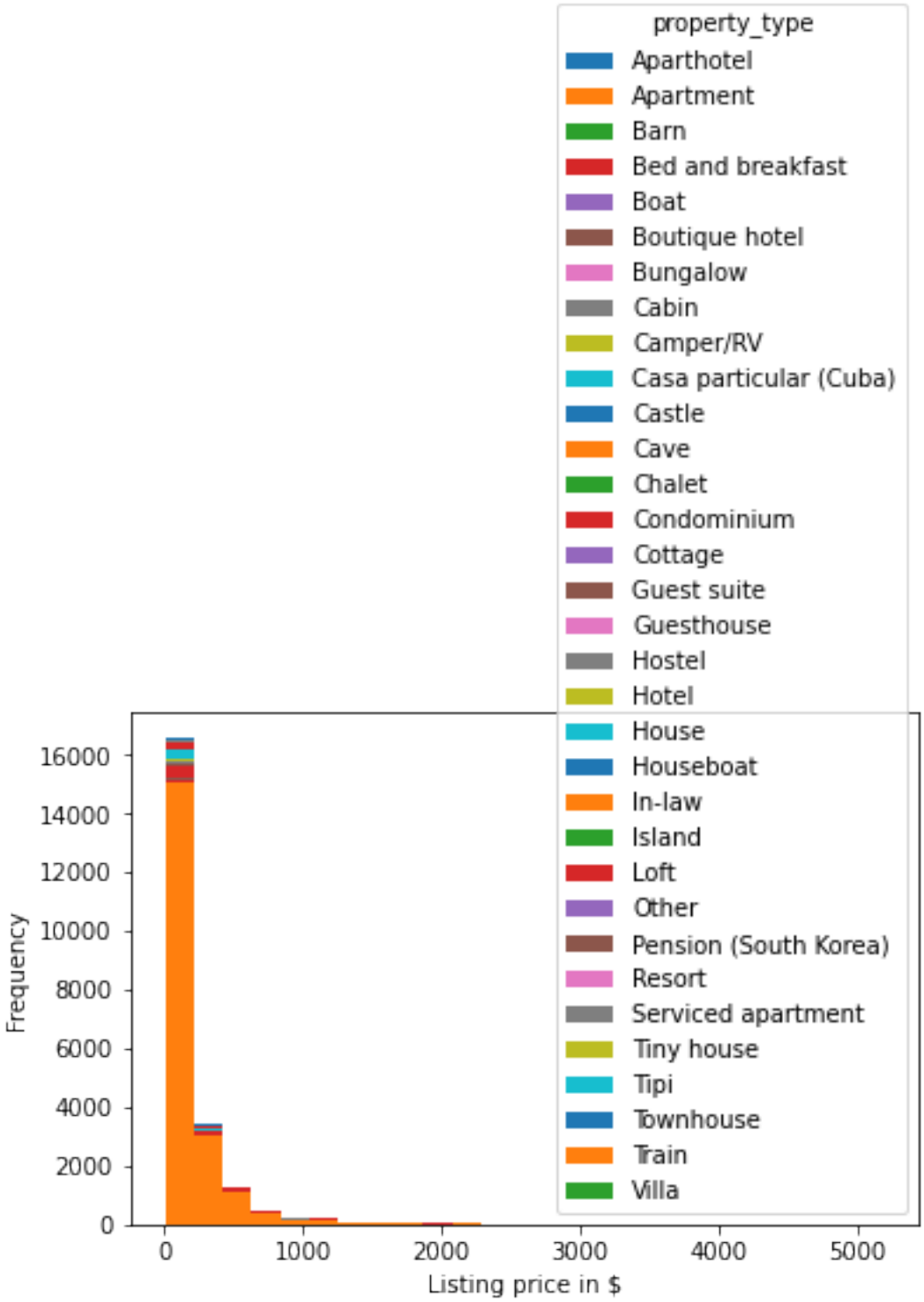
[562]:
```
#source https://www.kaggle.com/brittabettendorf/
 ↪predicting-prices-xgboost-feature-engineering
from collections import Counter
results = Counter()
df['amenities'].str.strip('{}')\
               .str.replace('"', '')\
               .str.lstrip('\"')\
               .str.rstrip('\"')\
               .str.split(',')\
               .apply(results.update)

results.most_common(30)
sub_df = pd.DataFrame(results.most_common(30), columns=['amenity', 'count'])
# plot the Top 20
sub_df.sort_values(by=['count'], ascending=True).plot(kind='barh', x='amenity',␣
 ↪y='count',
                                                      figsize=(10,7),␣
 ↪legend=False, color='darkgrey',
                                                      title='Amenities')
plt.xlabel('Count');
```



[563]:
```
df['Laptop_friendly_workspace'] = df['amenities'].str.contains('Laptop friendly␣
↪workspace')
df['TV'] = df['amenities'].str.contains('TV')
df['Family_kid_friendly'] = df['amenities'].str.contains('Family/kid friendly')
df['Host_greets_you'] = df['amenities'].str.contains('Host greets you')
df['Smoking_allowed'] = df['amenities'].str.contains('Smoking allowed')
df.drop(['amenities'], axis=1, inplace=True)
```

[ ]:
```
```

[564]:
```
df.pivot(columns = 'property_type', values = 'total_price').plot.hist(stacked =␣
↪True, bins=25)
plt.xlabel('Listing price in $')
plt.show()
```

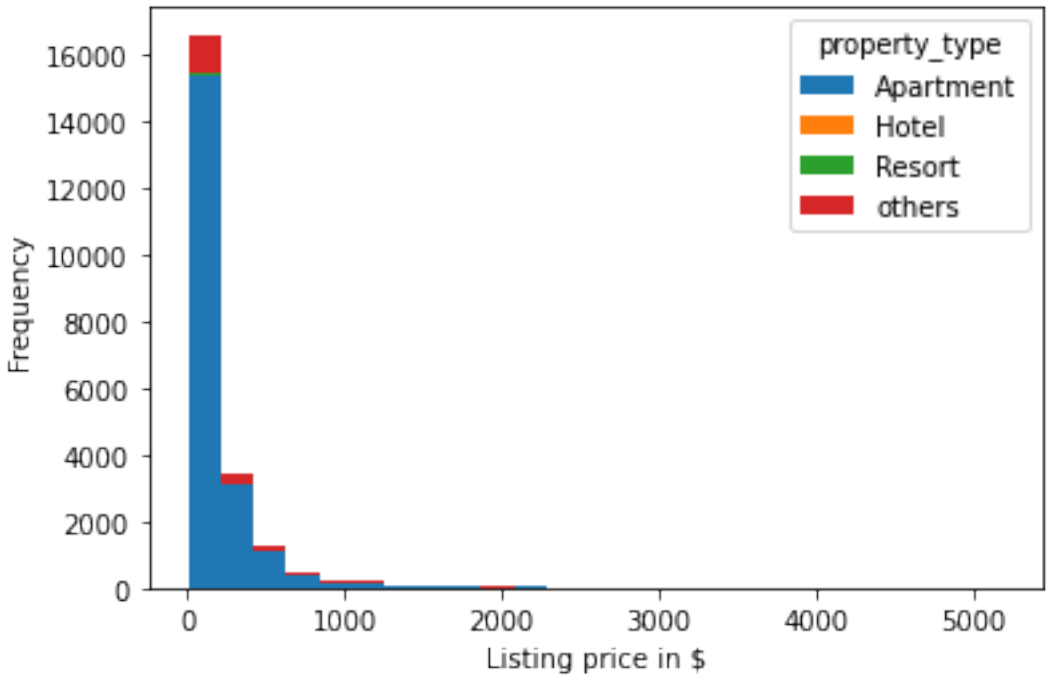

property_type
Aparthotel
Apartment
Barn
Bed and breakfast
Boat
Boutique hotel
Bungalow
Cabin
Camper/RV
Casa particular (Cuba)
Castle
Cave
Chalet
Condominium
Cottage
Guest suite
Guesthouse
Hostel
Hotel
House
Houseboat
In-law
Island
Loft
Other
Pension (South Korea)
Resort
Serviced apartment
Tiny house
Tipi
Townhouse
Train
Villa
Frequency
0
2000
4000
6000
8000
10000
12000
14000
16000
0
1000
2000
3000
4000
5000
Listing price in $

[565]:

```
property_mapping = {'Guesthouse':'Guesthouse', 'Apartment':'Apartment',␣
 ↪'Condominium':'others', 'Loft':'others','House':'Apartment','Serviced␣
 ↪apartment':'others','Townhouse':'others','Boutique hotel':'others','Bed and␣
 ↪breakfast':'others',
                    'Bungalow':'others','Boat':'others','Guest suite':
 ↪'others','Other':'others','Island':'others',
                    'Hostel':'others','Train':'others','Camper/RV':
 ↪'others','Houseboat':'others','Cabin':'others',
                    'Cottage':'others','Tiny house':'others','Chalet':
 ↪'others','Castle':'others','Villa':'others',
                    'Aparthotel':'others','Hotel':'Hotel','Tipi':
 ↪'others','Resort':'Resort','In-law':'others',
                    'Cave':'others','Barn':'others','Pension (South Korea)':
 ↪'others','Guesthouse':'others','Casa particular (Cuba)':'others','others':
 ↪'others'}
df['property_type']=df['property_type'].map(property_mapping)
```

Different property_types can be merged in to a smaller categorical set.

[566]:
```
df['property_type'].unique()
df.pivot(columns = 'property_type', values = 'total_price').plot.hist(stacked =␣
 ↪True, bins=25)
plt.xlabel('Listing price in $')
plt.show()
```



[567]:
```
df.head()
```

[567]:

	host_is_superhost	property_type	room_type	accommodates	bathrooms
0	t	others	Entire home/apt	3	1.0
1	f	Apartment	Private room	2	1.0
2	f	Apartment	Entire home/apt	4	1.0
3	f	Apartment	Private room	2	1.0
4	t	Apartment	Private room	2	1.0

	bedrooms	beds	bed_type	guests_included	extra_people
0	1.0	2.0	Real Bed	1	28.0
1	1.0	1.0	Real Bed	1	0.0
2	1.0	2.0	Real Bed	2	20.0
3	1.0	1.0	Pull-out Sofa	1	18.0
4	1.0	2.0	Real Bed	1	24.0

	minimum_nights	maximum_nights	number_of_reviews	instant_bookable
0	4	1125	118	f
1	2	40	6	f
2	62	1125	143	t
3	5	360	25	f
4	2	10	197	f

	cancellation_policy	total_price	distance
0	strict_14_with_grace_period	290.0	3.533182
1	flexible	17.0	5.085573
2	strict_14_with_grace_period	340.0	3.695677
3	strict_14_with_grace_period	306.0	3.755285
4	moderate	42.0	4.550423

	Laptop_friendly_workspace	TV	Family_kid_friendly	Host_greets_you
0	True	True	True	False
1	True	False	False	False
2	True	False	True	False
3	True	False	False	True
4	True	False	True	False

	Smoking_allowed
0	False
1	False
2	False
3	False
4	False

[ ]:

[568]:
```
#convert all boolean to integer 0 or 1
def object2bool(x):
    if x=="t" or x=="T" or x==True:
        return 1.0
    elif x=="f" or x=="F" or x==False:
        return 0.0
    else:
        return None
```

[569]:
```
for i in ["host_is_superhost", "instant_bookable",␣
↪"Laptop_friendly_workspace","TV","Family_kid_friendly","Host_greets_you","Smoking_allowed"]
↪
    df[i] = df[i].map(object2bool)
```

[570]:
```
#now fill the missing values with 0
df.beds.fillna(0,inplace=True)
df.bedrooms.fillna(0,inplace=True)
df.bathrooms.fillna(0,inplace=True)
```

[571]:
```
#Convert all categorical values in to numerical
#nominal_categorical bed_type and property_type
for i in ["bed_type","property_type","cancellation_policy","room_type"]:
    x = df[[i]]
    x.room_type = pd.Categorical(x[i])
    df.drop([i], inplace=True, axis=1)
    dummies = pd.get_dummies(x, prefix = i)
    df = pd.concat([df,dummies], axis=1)
```

```
/home/arunhiremath/sfsu/data_mining/venv/lib/python3.6/site-
packages/ipykernel_launcher.py:5: UserWarning: Pandas doesn't allow columns to
be created via a new attribute name - see https://pandas.pydata.org/pandas-
docs/stable/indexing.html#attribute-access
  """
/home/arunhiremath/sfsu/data_mining/venv/lib/python3.6/site-
packages/pandas/core/generic.py:5303: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  self[name] = value
```

[ ]:
```

```

[572]:
```
#Calculate the percentage of the missing values in
((len(df)-df.count())/len(df)*100).sort_values(ascending = False)
```

[572]:
```
host_is_superhost                                  0.111008
maximum_nights                                     0.000000
TV                                                 0.000000
Laptop_friendly_workspace                          0.000000
distance                                           0.000000
total_price                                        0.000000
instant_bookable                                   0.000000
number_of_reviews                                  0.000000
minimum_nights                                     0.000000
Host_greets_you                                    0.000000
extra_people                                       0.000000
guests_included                                    0.000000
beds                                               0.000000
bedrooms                                           0.000000
bathrooms                                          0.000000
accommodates                                       0.000000
Family_kid_friendly                                0.000000
room_type_Shared room                              0.000000
room_type_Private room                             0.000000
property_type_others                               0.000000
room_type_Entire home/apt                          0.000000
cancellation_policy_super_strict_60                0.000000
cancellation_policy_super_strict_30                0.000000
cancellation_policy_strict_14_with_grace_period    0.000000
cancellation_policy_moderate                       0.000000
cancellation_policy_flexible                       0.000000
property_type_Resort                               0.000000
bed_type_Airbed                                    0.000000
property_type_Hotel                                0.000000
property_type_Apartment                            0.000000
bed_type_Real Bed                                  0.000000
bed_type_Pull-out Sofa                             0.000000
bed_type_Futon                                     0.000000
bed_type_Couch                                     0.000000
Smoking_allowed                                    0.000000
dtype: float64
```

[573]:
```
#detect outliers
#outlier detection with z score
def detect_outlier(data_1):
    feature_outliers=[]
    threshold=7
    mean_1 = np.mean(data_1)
    std_1 =np.std(data_1)

    counter=0
    for y in data_1:
```

```
        z_score= (y - mean_1)/std_1
        if np.abs(z_score) > threshold:
            feature_outliers.append(counter)
        counter += 1
    return feature_outliers
```

[576]:
```
outliers = np.array([])
print("--Feature and Outlier Counts--\n")
for i in df.columns:
    f_out = detect_outlier(df[i])
    outliers = np.concatenate((outliers,np.asarray(f_out)))
    print(i ," outlier count :",len(f_out))

outliers = np.unique(outliers,0)
print("Total Unique Outlier Index Count:",len(outliers))
```

```
--Feature and Outlier Counts--

host_is_superhost  outlier count : 0
accommodates  outlier count : 36
bathrooms  outlier count : 29
bedrooms  outlier count : 20
beds  outlier count : 47
guests_included  outlier count : 52
extra_people  outlier count : 28
minimum_nights  outlier count : 18
maximum_nights  outlier count : 3
number_of_reviews  outlier count : 60
instant_bookable  outlier count : 0
total_price  outlier count : 82
distance  outlier count : 10
Laptop_friendly_workspace  outlier count : 0
TV  outlier count : 0
Family_kid_friendly  outlier count : 0
Host_greets_you  outlier count : 0
Smoking_allowed  outlier count : 0
bed_type_Airbed  outlier count : 23
bed_type_Couch  outlier count : 72
bed_type_Futon  outlier count : 240
bed_type_Pull-out Sofa  outlier count : 0
bed_type_Real Bed  outlier count : 0
property_type_Apartment  outlier count : 0
property_type_Hotel  outlier count : 31
property_type_Resort  outlier count : 3
property_type_others  outlier count : 0
cancellation_policy_flexible  outlier count : 0
cancellation_policy_moderate  outlier count : 0
```

```
cancellation_policy_strict_14_with_grace_period  outlier count : 0
cancellation_policy_super_strict_30  outlier count : 53
cancellation_policy_super_strict_60  outlier count : 14
room_type_Entire home/apt  outlier count : 0
room_type_Private room  outlier count : 0
room_type_Shared room  outlier count : 296
Total Unique Outlier Index Count: 1013
```

[580]:
```
clean_data = df.drop(outliers,axis=0)
clean_data.describe()
```

[580]:

	host_is_superhost	accommodates	bathrooms	bedrooms	\
count	21484.000000	21508.000000	21508.000000	21508.000000	
mean	0.133122	2.625628	1.088897	1.159336	
std	0.339715	1.464694	0.312926	0.639407	
min	0.000000	1.000000	0.000000	0.000000	
25%	0.000000	2.000000	1.000000	1.000000	
50%	0.000000	2.000000	1.000000	1.000000	
75%	0.000000	3.000000	1.000000	1.000000	
max	1.000000	16.000000	8.500000	12.000000	

	beds	guests_included	extra_people	minimum_nights	\
count	21508.000000	21508.000000	21508.000000	21508.000000	
mean	1.605635	1.325925	8.205691	6.828575	
std	1.129438	0.798336	10.993609	21.020639	
min	0.000000	1.000000	0.000000	1.000000	
25%	1.000000	1.000000	0.000000	2.000000	
50%	1.000000	1.000000	5.000000	3.000000	
75%	2.000000	1.000000	15.000000	4.000000	
max	22.000000	16.000000	250.000000	1000.000000	

	maximum_nights	number_of_reviews	instant_bookable	total_price	\
count	2.150800e+04	21508.000000	21508.000000	21508.000000	
mean	6.152696e+04	16.994421	0.311047	196.176306	
std	7.138766e+06	33.017884	0.462933	329.751018	
min	1.000000e+00	0.000000	0.000000	8.000000	
25%	2.000000e+01	1.000000	0.000000	42.000000	
50%	1.124000e+03	5.000000	0.000000	80.000000	
75%	1.125000e+03	16.000000	1.000000	229.000000	
max	1.000000e+09	305.000000	1.000000	5180.000000	

	distance	Laptop_friendly_workspace	TV	\
count	21508.000000	21508.000000	21508.000000	
mean	4.555035	0.642598	0.453738	
std	2.667428	0.479246	0.497867	
min	0.198956	0.000000	0.000000	
25%	2.982166	0.000000	0.000000	

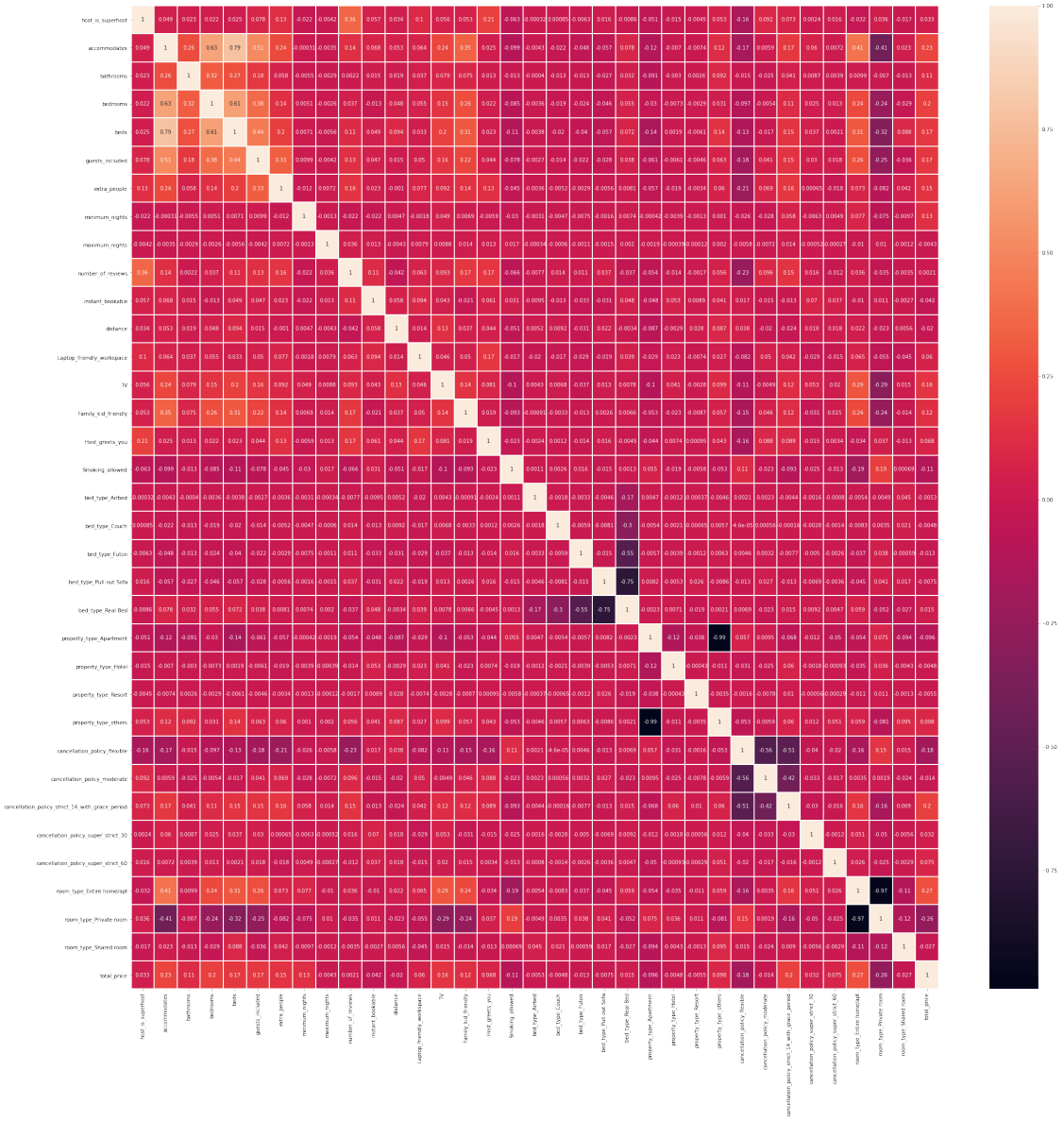
```
50%        4.091531                   1.000000      0.000000
75%        5.558063                   1.000000      1.000000
max       25.012109                   1.000000      1.000000

       Family_kid_friendly  Host_greets_you  Smoking_allowed  bed_type_Airbed  \
count         21508.000000     21508.000000     21508.000000     21508.000000
mean              0.361121         0.296355         0.203831         0.000465
std               0.480337         0.456660         0.402854         0.021558
min               0.000000         0.000000         0.000000         0.000000
25%               0.000000         0.000000         0.000000         0.000000
50%               0.000000         0.000000         0.000000         0.000000
75%               1.000000         1.000000         0.000000         0.000000
max               1.000000         1.000000         1.000000         1.000000

       bed_type_Couch  bed_type_Futon  bed_type_Pull-out Sofa  \
count    21508.000000    21508.000000            21508.000000
mean         0.001581        0.004417                0.020086
std          0.039729        0.066315                0.140296
min          0.000000        0.000000                0.000000
25%          0.000000        0.000000                0.000000
50%          0.000000        0.000000                0.000000
75%          0.000000        0.000000                0.000000
max          1.000000        1.000000                1.000000

       bed_type_Real Bed  property_type_Apartment  property_type_Hotel  \
count       21508.000000              21508.000000         21508.000000
mean            0.973452                  0.916822             0.001395
std             0.160763                  0.276158             0.037322
min             0.000000                  0.000000             0.000000
25%             1.000000                  1.000000             0.000000
50%             1.000000                  1.000000             0.000000
75%             1.000000                  1.000000             0.000000
max             1.000000                  1.000000             1.000000

       property_type_Resort  property_type_others  \
count          21508.000000          21508.000000
mean               0.000139              0.081644
std                0.011810              0.273828
min                0.000000              0.000000
25%                0.000000              0.000000
50%                0.000000              0.000000
75%                0.000000              0.000000
max                1.000000              1.000000

       cancellation_policy_flexible  cancellation_policy_moderate  \
count                  21508.000000                  21508.000000
mean                       0.403943                      0.315789
```

```
std                          0.490698                      0.464840
min                          0.000000                      0.000000
25%                          0.000000                      0.000000
50%                          0.000000                      0.000000
75%                          1.000000                      1.000000
max                          1.000000                      1.000000

       cancellation_policy_strict_14_with_grace_period  \
count                                     21508.000000
mean                                          0.278176
std                                           0.448111
min                                           0.000000
25%                                           0.000000
50%                                           0.000000
75%                                           1.000000
max                                           1.000000

       cancellation_policy_super_strict_30  \
count                          21508.000000
mean                               0.001488
std                                0.038544
min                                0.000000
25%                                0.000000
50%                                0.000000
75%                                0.000000
max                                1.000000

       cancellation_policy_super_strict_60  room_type_Entire home/apt  \
count                          21508.000000                21508.000000
mean                               0.000604                    0.476985
std                                0.024578                    0.499482
min                                0.000000                    0.000000
25%                                0.000000                    0.000000
50%                                0.000000                    0.000000
75%                                0.000000                    1.000000
max                                1.000000                    1.000000

       room_type_Private room  room_type_Shared room
count            21508.000000           21508.000000
mean                 0.512693               0.010322
std                  0.499850               0.101073
min                  0.000000               0.000000
25%                  0.000000               0.000000
50%                  1.000000               0.000000
75%                  1.000000               0.000000
max                  1.000000               1.000000
```

[589]:
```
#rearrange columns, push total_price to the end
column_list = [col for col in df.columns if col != "total_price"]
column_list.append("total_price")
df = df[column_list]
column_list.pop()
```

[589]:
```
'total_price'
```

[587]:
```
f, ax = plt.subplots( figsize=(35,35) )
sns.heatmap(df.corr(),annot=True,linewidths=1)
plt.show()
```



[ ]:
```
# import train_test_split function
from sklearn.model_selection import train_test_split
# import metrics
from sklearn.metrics import mean_squared_error, r2_score

import re
import xgboost as xgb

import warnings
warnings.filterwarnings("ignore")

# split our data
X_train, X_test, y_train, y_test = train_test_split(df[column_list],␣
 ↪df['total_price'], test_size=0.2)
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test  = sc.transform(X_test)
booster = xgb.XGBRegressor()
from sklearn.model_selection import GridSearchCV

# create Grid
param_grid = {'n_estimators': [100, 150, 200],
              'learning_rate': [0.01, 0.05, 0.1],
              'max_depth': [3, 4, 5, 6, 7],
              'colsample_bytree': [0.6, 0.7, 1],
              'gamma': [0.0, 0.1, 0.2]}

# instantiate the tuned random forest
booster_grid_search = GridSearchCV(booster, param_grid, cv=3, n_jobs=-1)

# train the tuned random forest
booster_grid_search.fit(X_train, y_train)

# print best estimator parameters found during the grid search
print(booster_grid_search.best_params_)
```

[596]:
```
# instantiate xgboost with best parameters
booster = xgb.XGBRegressor(colsample_bytree=0.7, gamma=0.2, learning_rate=0.1,
                           max_depth=6, n_estimators=200, random_state=4)

# train
booster.fit(X_train, y_train)

# predict
y_pred_train = booster.predict(X_train)
y_pred_test = booster.predict(X_test)
```

```
      ␣
↪--------------------------------------------------------------------------

       KeyboardInterrupt                         Traceback (most recent call␣
↪last)

       <ipython-input-596-e354759097d0> in <module>
         4
         5 # train
   ----> 6 booster.fit(X_train, y_train)
         7
         8 # predict


       ~/sfsu/data_mining/venv/lib/python3.6/site-packages/xgboost/sklearn.py␣
↪in fit(self, X, y, sample_weight, base_margin, eval_set, eval_metric,␣
↪early_stopping_rounds, verbose, xgb_model, sample_weight_eval_set, callbacks)
       547                               evals_result=evals_result, obj=obj,␣
↪feval=feval,
       548                               verbose_eval=verbose,␣
↪xgb_model=xgb_model,
   --> 549                               callbacks=callbacks)
       550
       551         if evals_result:


       ~/sfsu/data_mining/venv/lib/python3.6/site-packages/xgboost/training.py␣
↪in train(params, dtrain, num_boost_round, evals, obj, feval, maximize,␣
↪early_stopping_rounds, evals_result, verbose_eval, xgb_model, callbacks)
       207                             evals=evals,
       208                             obj=obj, feval=feval,
   --> 209                             xgb_model=xgb_model, callbacks=callbacks)
       210
       211


       ~/sfsu/data_mining/venv/lib/python3.6/site-packages/xgboost/training.py␣
↪in _train_internal(params, dtrain, num_boost_round, evals, obj, feval,␣
↪xgb_model, callbacks)
        72         # Skip the first update if it is a recovery step.
        73         if version % 2 == 0:
   ---> 74             bst.update(dtrain, i, obj)
        75             bst.save_rabit_checkpoint()
        76             version += 1
```

```
~/sfsu/data_mining/venv/lib/python3.6/site-packages/xgboost/core.py in␣
↪update(self, dtrain, iteration, fobj)
      1247             _check_call(_LIB.XGBoosterUpdateOneIter(self.handle,
      1248                                                     ctypes.
↪c_int(iteration),
   -> 1249                                                     dtrain.handle))
      1250         else:
      1251             pred = self.predict(dtrain, training=True)


KeyboardInterrupt:
```

[ ]:
```
RMSE = np.sqrt(mean_squared_error(y_test, y_pred_test))
print(f"RMSE: {round(RMSE, 4)}")
```

[ ]:
```
r2 = r2_score(y_test, y_pred_test)
r2
print(f"r2: {round(r2, 4)}")
```

[ ]:

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[507]:

```
['accommodates', 'bathrooms', 'bedrooms', 'beds', 'guests_included',
'extra_people', 'minimum_nights', 'maximum_nights', 'number_of_reviews',
'total_price', 'distance']
['host_is_superhost', 'property_type', 'room_type', 'bed_type', 'amenities',
'instant_bookable', 'cancellation_policy']
```

[508]:

[508]:

	accommodates	bathrooms	bedrooms	beds	\
count	22521.000000	22521.000000	22521.000000	22521.000000	
mean	2.637361	1.091159	1.160117	1.617690	
std	1.509021	0.332308	0.646572	1.174785	
min	1.000000	0.000000	0.000000	0.000000	
25%	2.000000	1.000000	1.000000	1.000000	
50%	2.000000	1.000000	1.000000	1.000000	
75%	3.000000	1.000000	1.000000	2.000000	
max	16.000000	8.500000	12.000000	22.000000	

	guests_included	extra_people	minimum_nights	maximum_nights	\

```
count     22521.000000  22521.000000    22521.000000    2.252100e+04
mean          1.331380      8.265397        7.160384    1.031910e+05
std           0.834745     11.155132       40.687817    9.647152e+06
min           1.000000      0.000000        1.000000    1.000000e+00
25%           1.000000      0.000000        2.000000    2.000000e+01
50%           1.000000      5.000000        2.000000    1.124000e+03
75%           1.000000     15.000000        4.000000    1.125000e+03
max          16.000000    250.000000     5000.000000    1.000000e+09

       number_of_reviews   total_price      distance
count       22521.000000  22521.000000  22521.000000
mean           17.859420    197.062386      4.547260
std            36.788259    336.835524      2.664719
min             0.000000      8.000000      0.198956
25%             1.000000     41.000000      2.976668
50%             5.000000     80.000000      4.088234
75%            16.000000    228.000000      5.550559
max           498.000000   5180.000000     25.012109
```

[509]:

```
      ␣
↪---------------------------------------------------------------------------

       KeyError                                  Traceback (most recent call␣
↪last)

       <ipython-input-509-ed0859335248> in <module>
   ----> 1 df[categoical_columns].describe()


       ~/sfsu/data_mining/venv/lib/python3.6/site-packages/pandas/core/frame.py␣
↪in __getitem__(self, key)
      2804             if is_iterator(key):
      2805                 key = list(key)
   -> 2806             indexer = self.loc._get_listlike_indexer(key, axis=1,␣
↪raise_missing=True)[1]
      2807
      2808         # take() does not accept boolean indexers


       ~/sfsu/data_mining/venv/lib/python3.6/site-packages/pandas/core/indexing.
↪py in _get_listlike_indexer(self, key, axis, raise_missing)
      1551
      1552         self._validate_read_indexer(
```

```
   -> 1553             keyarr, indexer, o._get_axis_number(axis),␣
↪raise_missing=raise_missing
      1554         )
      1555         return keyarr, indexer


       ~/sfsu/data_mining/venv/lib/python3.6/site-packages/pandas/core/indexing.
↪py in _validate_read_indexer(self, key, indexer, axis, raise_missing)
      1644             if not (self.name == "loc" and not raise_missing):
      1645                 not_found = list(set(key) - set(ax))
   -> 1646                 raise KeyError(f"{not_found} not in index")
      1647
      1648             # we skip the warning on Categorical/Interval


       KeyError: "['bed_type', 'property_type', 'amenities',␣
↪'cancellation_policy'] not in index"
```

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