Airbnb_Listings

March 13, 2020

In [1]:
```
import pandas as pd
import pathlib, itertools
import numpy as np
import seaborn as sns
from sklearn import preprocessing
import matplotlib
import matplotlib.pyplot as plt
import statsmodels
import statsmodels.api as sm
import scipy.stats as stats
import math
from sklearn.cluster import KMeans
import ipyvolume as ipv
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import OneHotEncoder
from sklearn.preprocessing import RobustScaler
from sklearn.model_selection import train_test_split
from sklearn import datasets, linear_model
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.model_selection import GridSearchCV
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import PolynomialFeatures
from sklearn.ensemble import AdaBoostRegressor
from sklearn.decomposition import PCA
from sklearn.preprocessing import normalize
from sklearn.feature_extraction.text import CountVectorizer
from xgboost import XGBRegressor
```

In [2]:
```
HOME_DIR = pathlib.Path.home()
CW_DIR = pathlib.Path.cwd()#sets current working directory
plt.rcParams["axes.labelsize"] = 12#default plot size
```

In [3]:
```
listings=pd.read_csv('listings.csv')#reads data
```

In [4]:
```
listings.head()#shows top listings
```

Out[4]:
```
     id                                          name  host_id  \
0  2595                         Skylit Midtown Castle     2845
```

```
1  3647               THE VILLAGE OF HARLEM...NEW YORK !     4632
2  3831                   Cozy Entire Floor of Brownstone     4869
3  5022  Entire Apt: Spacious Studio/Loft by central park     7192
4  5099         Large Cozy 1 BR Apartment In Midtown East     7322

     host_name neighbourhood_group neighbourhood  latitude  longitude  \
0     Jennifer           Manhattan       Midtown  40.75362  -73.98377
1    Elisabeth           Manhattan        Harlem  40.80902  -73.94190
2  LisaRoxanne            Brooklyn  Clinton Hill  40.68514  -73.95976
3        Laura           Manhattan   East Harlem  40.79851  -73.94399
4        Chris           Manhattan   Murray Hill  40.74767  -73.97500

         room_type  minimum_nights  calculated_host_listings_count  \
0  Entire home/apt               1                               2
1     Private room               3                               1
2  Entire home/apt               1                               1
3  Entire home/apt              10                               1
4  Entire home/apt               3                               1

   availability_365  number_of_reviews  reviews_per_month  price
0               288                 46               0.39    225
1               365                  0                NaN    150
2               212                274               4.64     89
3                 0                  9               0.10     80
4               127                 75               0.60    200
```

In [5]:
```
def anynans(X):
    return np.isnan(X).any()#shows if there are nulls
```

In [6]:
```
listings.dtypes#returns data types
```

Out[6]:
```
id                                  int64
name                               object
host_id                             int64
host_name                          object
neighbourhood_group                object
neighbourhood                      object
latitude                          float64
longitude                         float64
room_type                          object
minimum_nights                      int64
calculated_host_listings_count      int64
availability_365                    int64
number_of_reviews                   int64
reviews_per_month                 float64
price                               int64
dtype: object
```

In [7]:
```
percent_missing = listings.isnull().sum() * 100 / len(listings)
```

In [8]: print(percent_missing)#returns percentage missing in each column

```
id                                 0.000000
name                               0.032744
host_id                            0.000000
host_name                          0.036837
neighbourhood_group                0.000000
neighbourhood                      0.000000
latitude                           0.000000
longitude                          0.000000
room_type                          0.000000
minimum_nights                     0.000000
calculated_host_listings_count     0.000000
availability_365                   0.000000
number_of_reviews                  0.000000
reviews_per_month                 20.733055
price                              0.000000
dtype: float64
```

In [9]: print(listings.isnull().sum())#host name is not useful to us since we have host_id

```
id                                    0
name                                 16
host_id                               0
host_name                            18
neighbourhood_group                   0
neighbourhood                         0
latitude                              0
longitude                             0
room_type                             0
minimum_nights                        0
calculated_host_listings_count        0
availability_365                      0
number_of_reviews                     0
reviews_per_month                 10131
price                                 0
dtype: int64
```

In [10]: #listings.agg(['count', 'size', 'nunique'])
listings.describe()#description stats

Out[10]:

	id	host_id	latitude	longitude	minimum_nights \
count	4.886400e+04	4.886400e+04	48864.000000	48864.000000	48864.000000
mean	1.940851e+07	6.943161e+07	40.728664	-73.951850	7.093116
std	1.124290e+07	8.058217e+07	0.054794	0.046440	20.264170
min	2.595000e+03	2.438000e+03	40.499790	-74.244420	1.000000
25%	9.577635e+06	8.048590e+06	40.689797	-73.982952	1.000000

```
50%    1.994839e+07  3.168654e+07     40.722880    -73.955510        2.000000
75%    2.974014e+07  1.096553e+08     40.762970    -73.935628        5.000000
max    3.749909e+07  2.830244e+08     40.912400    -73.712990     1250.000000

       calculated_host_listings_count  availability_365  number_of_reviews  \
count                    48864.000000      48864.000000       48864.000000
mean                         7.438278        112.483505          23.392191
std                         34.949053        132.373994          44.939690
min                          1.000000          0.000000           0.000000
25%                          1.000000          0.000000           1.000000
50%                          1.000000         41.000000           5.000000
75%                          2.000000        232.000000          24.000000
max                        343.000000        365.000000         639.000000

       reviews_per_month         price
count       38733.000000  48864.000000
mean            1.365694    151.453176
std             1.692891    236.585525
min             0.010000      0.000000
25%             0.190000     69.000000
50%             0.710000    105.000000
75%             2.000000    175.000000
max            66.610000  10000.000000
```

```
In [11]: listings.agg(['count', 'size', 'nunique'])#shows the count, size and number of unique
         #host_name: alot of people with the same first name
         #lim
```

```
Out[11]:             id   name  host_id  host_name  neighbourhood_group  neighbourhood  \
         count    48864  48848    48864      48846                48864          48864
         size     48864  48864    48864      48864                48864          48864
         nunique  48864  47894    37384      11407                    5            222

                  latitude  longitude  room_type  minimum_nights  \
         count       48864      48864      48864           48864
         size        48864      48864      48864           48864
         nunique     19103      14816          3             113

                  calculated_host_listings_count  availability_365  number_of_reviews  \
         count                             48864             48864              48864
         size                              48864             48864              48864
         nunique                              46               366                392

                  reviews_per_month  price
         count                38733  48864
         size                 48864  48864
         nunique                952    667
```

```
In [12]: print(listings[listings['name'].isnull()])#to determine if name is MCAR
```

	id	name	host_id	host_name	neighbourhood_group	\
2787	1615764	NaN	6676776	Peter	Manhattan	
3608	2232600	NaN	11395220	Anna	Manhattan	
5661	4209595	NaN	20700823	Jesse	Manhattan	
5865	4370230	NaN	22686810	Michaël	Manhattan	
6148	4581788	NaN	21600904	Lucie	Brooklyn	
6439	4756856	NaN	1832442	Carolina	Brooklyn	
6477	4774658	NaN	24625694	Josh	Manhattan	
8686	6782407	NaN	31147528	Huei-Yin	Brooklyn	
11763	9325951	NaN	33377685	Jonathan	Manhattan	
12598	9787590	NaN	50448556	Miguel	Manhattan	
12834	9885866	NaN	37306329	Juliette	Manhattan	
13171	10052289	NaN	49522403	Vanessa	Brooklyn	
15557	12797684	NaN	69715276	Yan	Manhattan	
15803	12988898	NaN	71552588	Andrea	Bronx	
17750	14135050	NaN	85288337	Jeff	Brooklyn	
28372	22275821	NaN	49662398	Kathleen	Brooklyn	

	neighbourhood	latitude	longitude	room_type	\
2787	Battery Park City	40.71239	-74.01620	Entire home/apt	
3608	East Village	40.73215	-73.98821	Entire home/apt	
5661	Greenwich Village	40.73473	-73.99244	Entire home/apt	
5865	Nolita	40.72046	-73.99550	Entire home/apt	
6148	Williamsburg	40.71370	-73.94378	Private room	
6439	Bushwick	40.70046	-73.92825	Private room	
6477	Washington Heights	40.85198	-73.93108	Private room	
8686	Williamsburg	40.71354	-73.93882	Private room	
11763	Hell's Kitchen	40.76436	-73.98573	Entire home/apt	
12598	Harlem	40.80316	-73.95189	Entire home/apt	
12834	Chinatown	40.71632	-73.99328	Private room	
13171	Brownsville	40.66409	-73.92314	Private room	
15557	Upper West Side	40.79843	-73.96404	Private room	
15803	Fordham	40.86032	-73.88493	Shared room	
17750	Bedford-Stuyvesant	40.69421	-73.93234	Private room	
28372	Bushwick	40.69546	-73.92741	Entire home/apt	

	minimum_nights	calculated_host_listings_count	availability_365	\
2787	1000	1	362	
3608	1	1	51	
5661	1	1	0	
5865	7	1	0	
6148	1	1	0	
6439	1	1	0	
6477	1	1	0	
8686	1	1	0	
11763	4	1	0	
12598	5	5	0	
12834	4	1	0	

```
13171             3                              1            362
15557             1                              2              0
15803             1                              1            365
17750             3                              1              0
28372             4                              1              0

       number_of_reviews  reviews_per_month  price
2787                   0                NaN    400
3608                  28               0.44    200
5661                   1               0.02    225
5865                   5               0.09    215
6148                   0                NaN    150
6439                   0                NaN     70
6477                   0                NaN     40
8686                   0                NaN     45
11763                  1               0.02    190
12598                  0                NaN    300
12834                  0                NaN     67
13171                  3               0.07     50
15557                  0                NaN    100
15803                  0                NaN    130
17750                  0                NaN     70
28372                  5               0.26    110
```

In [13]:
```
missing_host_id=listings[listings['name'].isnull()]['host_id']
```

In [14]:
```
missing_host_id=missing_host_id.to_numpy()

#print(listings[listings['host_id']==missing_host_id])
```

In [15]:
```
listings.loc[listings['host_id'].isin(missing_host_id)]#seems to be missing completel
```

Out[15]:
```
            id                     name   host_id host_name  \
2787   1615764                      NaN   6676776     Peter
3608   2232600                      NaN  11395220      Anna
5661   4209595                      NaN  20700823     Jesse
5865   4370230                      NaN  22686810   Michaël
6148   4581788                      NaN  21600904     Lucie
6439   4756856                      NaN   1832442  Carolina
6477   4774658                      NaN  24625694      Josh
8686   6782407                      NaN  31147528  Huei-Yin
11763  9325951                      NaN  33377685  Jonathan
12598  9787590                      NaN  50448556    Miguel
12601  9788141           Bedroom in UWS  50448556    Miguel
12604  9790098  Bedroom in UWS 118th st  50448556    Miguel
12834  9885866                      NaN  37306329  Juliette
12846  9896731           BEDROOM IN UWS  50448556    Miguel
12865  9902915           BEDROOM IN UWS  50448556    Miguel
```

13171	10052289	NaN	49522403	Vanessa
15557	12797684	NaN	69715276	Yan
15558	12797920	Large Bedroom near Subway	69715276	Yan
15803	12988898	NaN	71552588	Andrea
17750	14135050	NaN	85288337	Jeff
28372	22275821	NaN	49662398	Kathleen

	neighbourhood_group	neighbourhood	latitude	longitude \
2787	Manhattan	Battery Park City	40.71239	-74.01620
3608	Manhattan	East Village	40.73215	-73.98821
5661	Manhattan	Greenwich Village	40.73473	-73.99244
5865	Manhattan	Nolita	40.72046	-73.99550
6148	Brooklyn	Williamsburg	40.71370	-73.94378
6439	Brooklyn	Bushwick	40.70046	-73.92825
6477	Manhattan	Washington Heights	40.85198	-73.93108
8686	Brooklyn	Williamsburg	40.71354	-73.93882
11763	Manhattan	Hell's Kitchen	40.76436	-73.98573
12598	Manhattan	Harlem	40.80316	-73.95189
12601	Manhattan	Harlem	40.80518	-73.95099
12604	Manhattan	Harlem	40.80345	-73.95067
12834	Manhattan	Chinatown	40.71632	-73.99328
12846	Manhattan	Harlem	40.80489	-73.95171
12865	Manhattan	Harlem	40.80519	-73.95091
13171	Brooklyn	Brownsville	40.66409	-73.92314
15557	Manhattan	Upper West Side	40.79843	-73.96404
15558	Manhattan	Upper West Side	40.79806	-73.96167
15803	Bronx	Fordham	40.86032	-73.88493
17750	Brooklyn	Bedford-Stuyvesant	40.69421	-73.93234
28372	Brooklyn	Bushwick	40.69546	-73.92741

	room_type	minimum_nights	calculated_host_listings_count \
2787	Entire home/apt	1000	1
3608	Entire home/apt	1	1
5661	Entire home/apt	1	1
5865	Entire home/apt	7	1
6148	Private room	1	1
6439	Private room	1	1
6477	Private room	1	1
8686	Private room	1	1
11763	Entire home/apt	4	1
12598	Entire home/apt	5	5
12601	Private room	1	5
12604	Private room	1	5
12834	Private room	4	1
12846	Private room	2	5
12865	Private room	6	5
13171	Private room	3	1
15557	Private room	1	2

```
15558     Private room              1                               2
15803      Shared room              1                               1
17750     Private room              3                               1
28372  Entire home/apt              4                               1

       availability_365  number_of_reviews  reviews_per_month  price
2787                362                  0                NaN    400
3608                 51                 28               0.44    200
5661                  0                  1               0.02    225
5865                  0                  5               0.09    215
6148                  0                  0                NaN    150
6439                  0                  0                NaN     70
6477                  0                  0                NaN     40
8686                  0                  0                NaN     45
11763                 0                  1               0.02    190
12598                 0                  0                NaN    300
12601                 0                  1               0.02    100
12604                 0                  0                NaN    200
12834                 0                  0                NaN     67
12846                 0                  1               0.02    100
12865                 0                  0                NaN    100
13171               362                  3               0.07     50
15557                 0                  0                NaN    100
15558                 0                  1               0.03    100
15803               365                  0                NaN    130
17750                 0                  0                NaN     70
28372                 0                  5               0.26    110
```

```
In [16]: listings.drop(['id','host_name'], axis=1, inplace=True)#the id and the host_name are
         #trans_listings = listings[listings['name'].notnull()]
```

```
In [17]: print(listings[listings['reviews_per_month'].isnull()])#Nan reviews_per_month values
```

```
                                              name    host_id  \
1                     THE VILLAGE OF HARLEM...NEW YORK !       4632
18                   Huge 2 BR Upper East  Cental Park      17985
24      Magnifique Suite au N de Manhattan - vue Cloitres      26394
34                         Clean and Quiet in Brooklyn       7355
36                            Country space in the city      45445
...                                                ...        ...
48859                            Overnighter / Weekender  283024389
48860                        East Harlem's Best Kept Secret     299391
48861   Perfect, Brand New 1 Bedroom Apartment In Midtown  113464126
48862                  Large bedroom overlooking Riverside    7941569
48863  Brand New Spacious 1 Bedroom Apt In Hells Kitchen  132699715

      neighbourhood_group        neighbourhood  latitude  longitude  \
1               Manhattan               Harlem  40.80902  -73.94190
```

```
18             Manhattan         East Harlem  40.79685  -73.94872
24             Manhattan              Inwood  40.86754  -73.92639
34              Brooklyn  Bedford-Stuyvesant  40.68876  -73.94312
36              Brooklyn            Flatbush  40.63702  -73.96327
...                  ...                 ...       ...        ...
48859             Queens             Astoria  40.77321  -73.92567
48860          Manhattan         East Harlem  40.80504  -73.93774
48861          Manhattan      Hell's Kitchen  40.76207  -73.98818
48862          Manhattan Morningside Heights  40.81574  -73.95931
48863          Manhattan      Hell's Kitchen  40.76825  -73.98972

             room_type  minimum_nights  calculated_host_listings_count  \
1         Private room               3                               1
18     Entire home/apt               7                               2
24        Private room               4                               1
34        Private room               5                               1
36        Private room               1                               1
...                ...             ...                             ...
48859      Shared room               1                               1
48860     Private room               2                               1
48861  Entire home/apt               1                               1
48862     Private room               1                               1
48863  Entire home/apt               1                               1

       availability_365  number_of_reviews  reviews_per_month  price
1                   365                  0                NaN    150
18                  275                  0                NaN    190
24                    0                  0                NaN     80
34                    0                  0                NaN     35
36                  365                  0                NaN    150
...                 ...                ...                ...    ...
48859                53                  0                NaN     65
48860                53                  0                NaN     60
48861               105                  0                NaN    239
48862                14                  0                NaN     75
48863                74                  0                NaN    239

[10131 rows x 13 columns]
```

```
In [18]: listings[listings['reviews_per_month'].isnull()].agg(['count', 'size', 'nunique'])
```

```
Out[18]:           name  host_id  neighbourhood_group  neighbourhood  latitude  \
         count    10121    10131                10131          10131     10131
         size     10131    10131                10131          10131     10131
         nunique   9971     8263                    5            191      7644

                  longitude  room_type  minimum_nights  calculated_host_listings_count  \
```

```
count        10131     10131          10131                          10131
size         10131     10131          10131                          10131
nunique       6667         3             88                             43

         availability_365  number_of_reviews  reviews_per_month  price
count               10131              10131                  0  10131
size                10131              10131              10131  10131
nunique               365                  1                  0    513
```

```
In [19]: listings.fillna({'reviews_per_month':0.00}, inplace=True)#the number of reviews for a
         #values are all 0. Hence, it is logical to assume that the reviews per month should a

In [20]: listings_copy=listings.copy()#one dataframe for testing without text featurs
         listings['name'] = listings['name'].fillna('')#one dataframe for testing WITH text fe

In [21]: listings_copy=listings_copy.drop(columns=['name'])#doing one analysis WITHOUT text fe

In [22]: percent_missing = listings.isnull().sum() * 100 / len(listings)
         percent_missing_copy=listings_copy.isnull().sum() * 100 / len(listings_copy)

In [23]: print(percent_missing)#confirms if missing values were cleaned up
```

```
name                              0.0
host_id                           0.0
neighbourhood_group               0.0
neighbourhood                     0.0
latitude                          0.0
longitude                         0.0
room_type                         0.0
minimum_nights                    0.0
calculated_host_listings_count    0.0
availability_365                  0.0
number_of_reviews                 0.0
reviews_per_month                 0.0
price                             0.0
dtype: float64
```

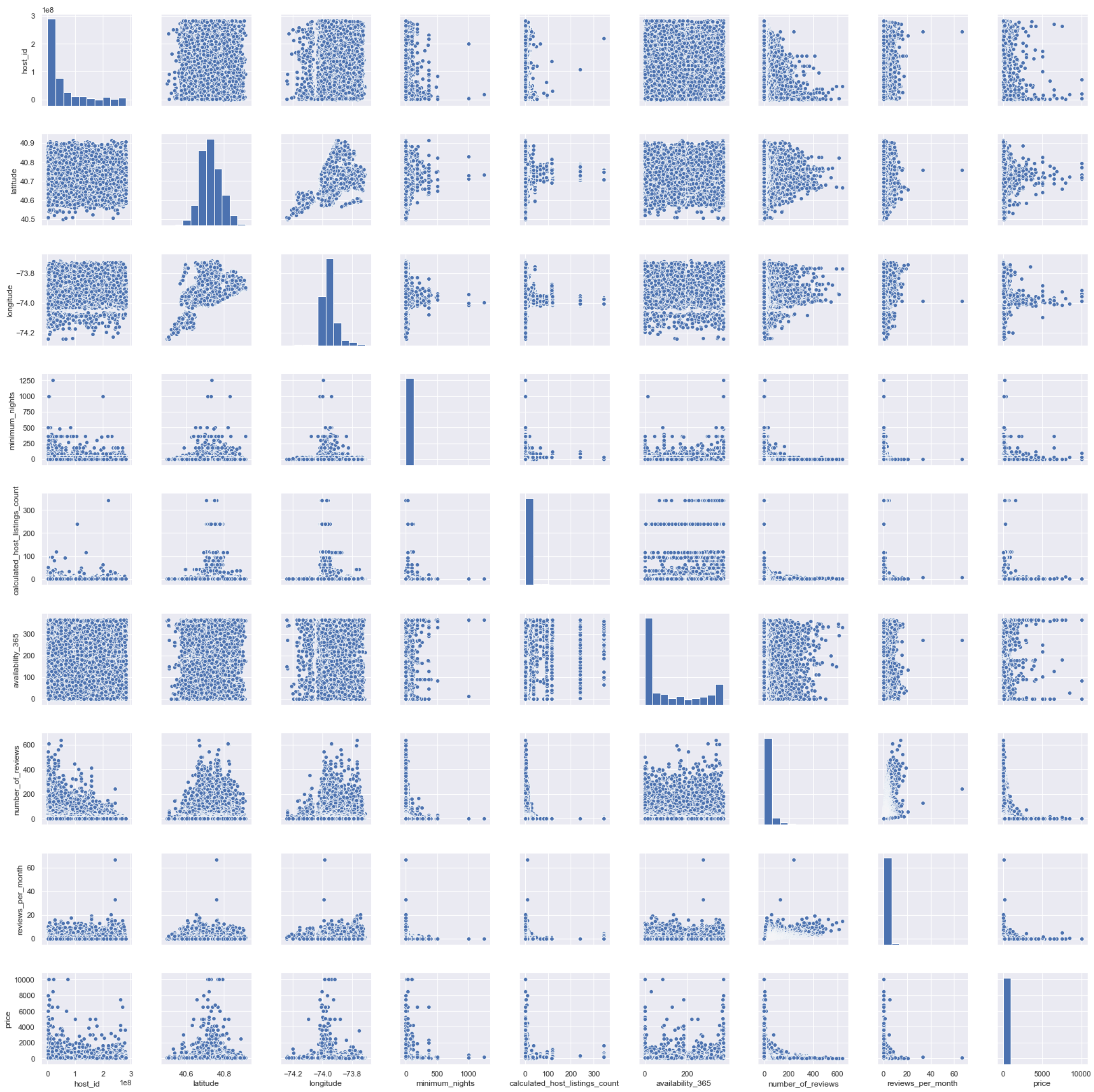
```
In [24]: print(percent_missing_copy)
```

```
host_id                           0.0
neighbourhood_group               0.0
neighbourhood                     0.0
latitude                          0.0
longitude                         0.0
room_type                         0.0
minimum_nights                    0.0
calculated_host_listings_count    0.0
availability_365                  0.0
```

```
number_of_reviews                 0.0
reviews_per_month                 0.0
price                             0.0
dtype: float64
```

```
In [25]: sns.set()
         sns.pairplot(listings)#does a scatterplot of each feature with other features to see
```

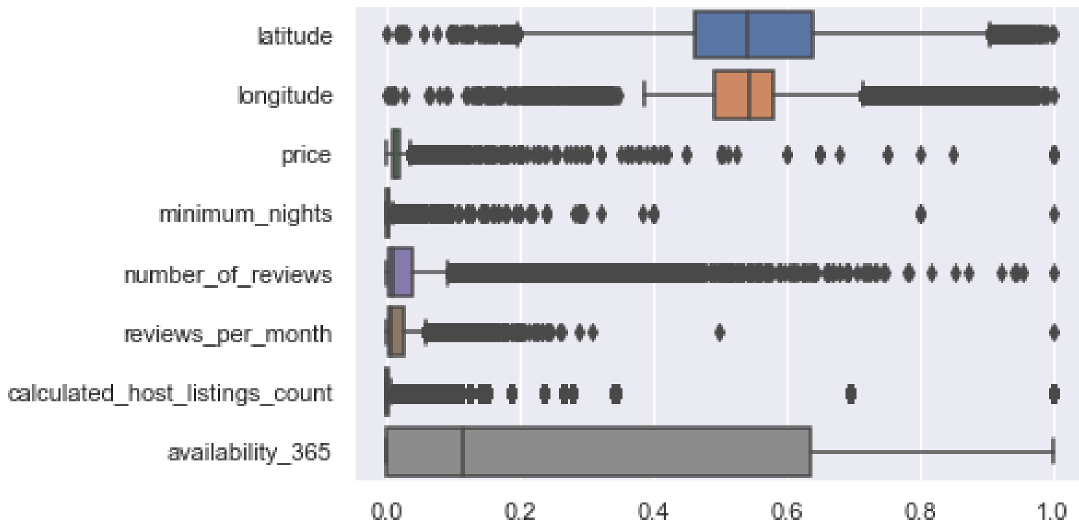
```
Out[25]: <seaborn.axisgrid.PairGrid at 0x177092acf98>
```




```
In [26]: scaler = preprocessing.MinMaxScaler()
         features = ['latitude','longitude','price','minimum_nights','number_of_reviews','revie
         scaled = pd.DataFrame(scaler.fit_transform(listings[features]), columns=features)
```

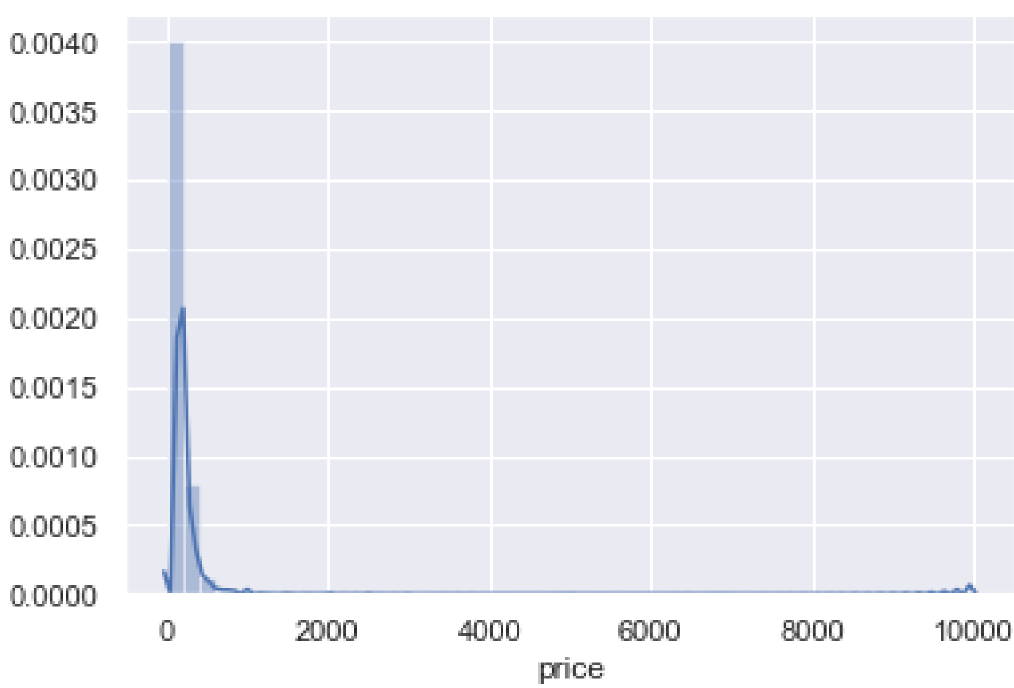
```
sns.boxplot(data=scaled, orient='h')
#Latitude and longitude have normal distributions. The other variables are skewed to
```

Out[26]: <matplotlib.axes._subplots.AxesSubplot at 0x1770eacb6d8>

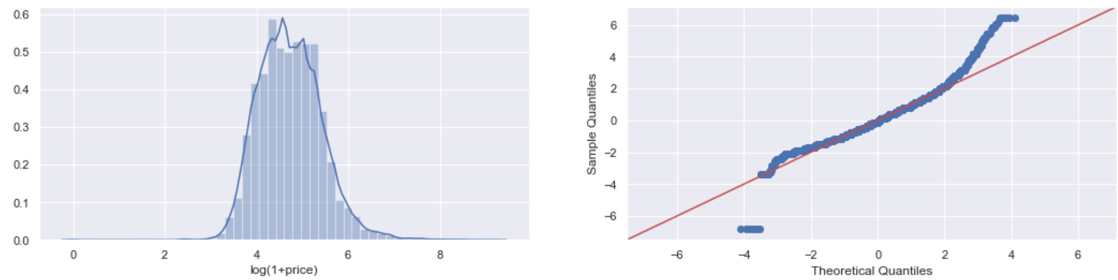


In [27]:
```
#price, minimum nights, number of reviews, reviews_per_month, and calculated_host_lis
sns.distplot(listings['price'])#shows outliers
```

Out[27]: <matplotlib.axes._subplots.AxesSubplot at 0x1770eab4828>

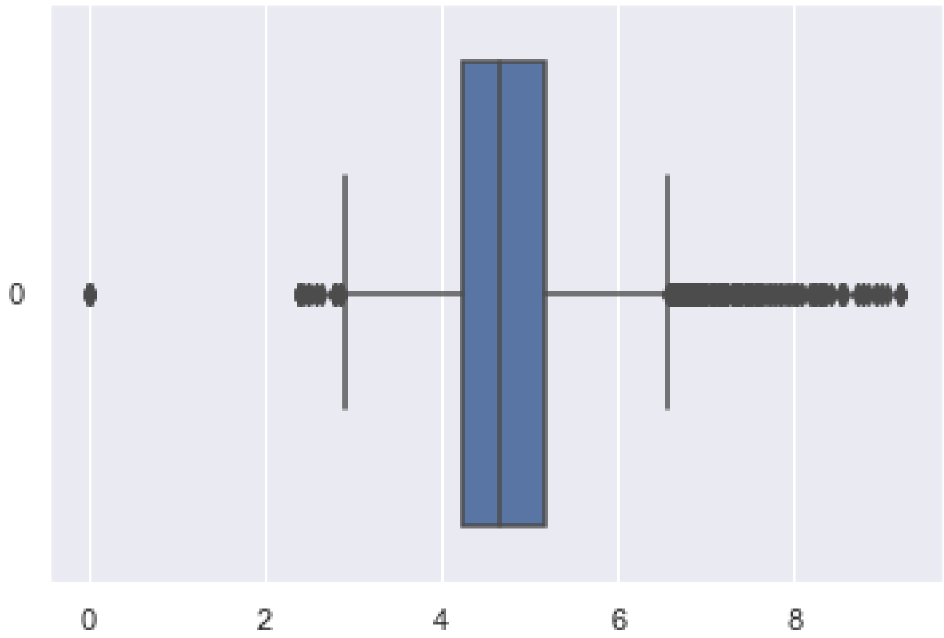


In [28]:
```
fig, axes = plt.subplots(1,2, figsize=(18,4))
sns.distplot(np.log1p(listings['price']), ax=axes[0])
axes[0].set_xlabel('log(1+price)')
sm.qqplot(np.log1p(listings['price']), stats.norm, fit=True, line='45', ax=axes[1]);#
#of target variable in order to maintain homoskedasticity assumption for linear regre
```



In [29]:
```
listings['price']=np.log1p(listings['price'])
sns.boxplot(data=listings['price'], orient='h')#shows new and transformed box plot
```

Out[29]: <matplotlib.axes._subplots.AxesSubplot at 0x177102af160>



In [30]:
```
listings=listings[listings['price']>0] #dropping the 0 price
listings_copy=listings_copy[listings_copy['price']>0] #dropping the 0 price entry
Q1 = listings['price'].quantile(0.25)
Q3 = listings['price'].quantile(0.75)
IQR = Q3 - Q1
print(len(listings[(listings['price'] < (Q1 - 1.5 * IQR)) |(listings['price'] > (Q3 +
#gets a sense for how many price outliers there are
```

```
598
```

In [31]:
```
x = np.cos(listings['latitude']) * np.cos(listings['longitude'])
y = np.cos(listings['latitude']) * np.sin(listings['longitude'])
z = np.sin(listings['latitude'])
df2=listings_copy.copy()
listings['x']=x
listings['y']=y
listings['z']=z
listings_copy['x']=x
listings_copy['y']=y
listings_copy['z']=z
#transforms latitude and longitude into x,y,z coordinates since latitude and longitud
```

```
c:\users\ajeet\appdata\local\programs\python\python36\lib\site-packages\ipykernel_launcher.py:5
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: http://pandas.pydata.org/pandas-docs/stable/user_guide/in
  """
c:\users\ajeet\appdata\local\programs\python\python36\lib\site-packages\ipykernel_launcher.py:6
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: http://pandas.pydata.org/pandas-docs/stable/user_guide/in

c:\users\ajeet\appdata\local\programs\python\python36\lib\site-packages\ipykernel_launcher.py:7
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: http://pandas.pydata.org/pandas-docs/stable/user_guide/in
  import sys
```

In [32]:
```
listings['x'].describe()#summary stats for x
```

Out[32]:
```
count    48854.000000
mean        -0.123020
std          0.045586
min         -0.382992
```

```
25%         -0.153860
50%         -0.126742
75%         -0.107171
max          0.113532
Name: x, dtype: float64
```

```
In [33]: listings['y'].describe()#summary stats for y
```

```
Out[33]: count    48854.000000
mean        -0.983510
std          0.008475
min         -0.999996
25%         -0.989320
50%         -0.983878
75%         -0.979613
max         -0.863053
Name: y, dtype: float64
```

```
In [34]: listings['z'].describe()#summary stats for z
```

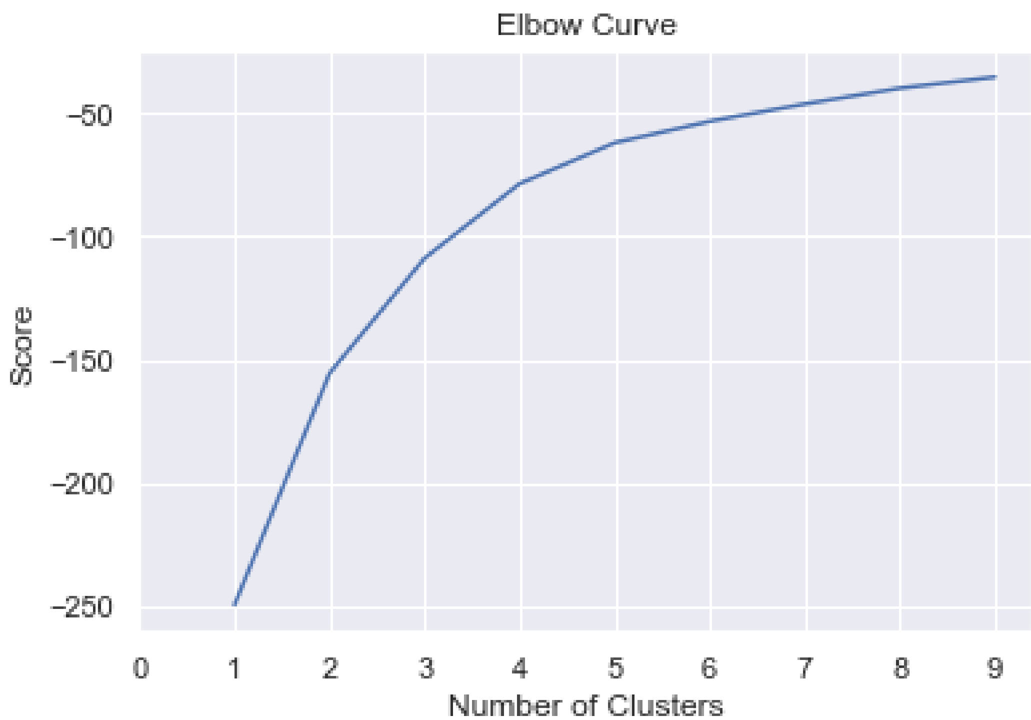
```
Out[34]: count    48854.000000
mean         0.111639
std          0.054408
min         -0.071634
25%          0.077656
50%          0.117532
75%          0.150332
max          0.334349
Name: z, dtype: float64
```

```
In [35]: fig = ipv.figure(height=600, width=600, layout={'width':'100%', 'height':'100%'})
         scatter = ipv.scatter(x, y, z, size=1, marker="sphere")
         #ipv.quickscatter(x, y, z, size=1, marker="sphere")
         ipv.xyzlim(-0.5, 0.5)
         display(fig)#shows 3-D representation of New York plotted. The z-statistic could be i
         #up could cost more intuitively
```

```
Figure(camera=PerspectiveCamera(fov=46.0, position=(0.0, 0.0, 2.0), quaternion=(0.0, 0.0, 0.0,
```

```
In [36]: clusters = range(1,10)
         kmeans = [KMeans(n_clusters=i) for i in clusters]
         Z_axis = listings[['x','y','z']]
         #X_axis = listings[['longitude']]
         score = [kmeans[i].fit(Z_axis).score(Z_axis) for i in range(len(kmeans))]
         # Visualize
         x = [0,1,2,3,4,5,6,7,8,9]
         # create an index for each tick position
         xi = list(range(len(x)))
```

```
    plt.plot(clusters, score)
    plt.xlabel('Number of Clusters')
    plt.ylabel('Score')
    plt.xticks(xi,x)
    plt.title('Elbow Curve')
    plt.show()
    print(listings.columns)#using clustering approach to group (x,y,z) points that are cl
```




```
Index(['name', 'host_id', 'neighbourhood_group', 'neighbourhood', 'latitude',
       'longitude', 'room_type', 'minimum_nights',
       'calculated_host_listings_count', 'availability_365',
       'number_of_reviews', 'reviews_per_month', 'price', 'x', 'y', 'z'],
      dtype='object')
```

```
In [37]: #While there is no obvious number of clusters to use from the elbow graph above, the 
```

```
In [39]: kmeans = KMeans(n_clusters = 4, init ='k-means++')
         kmeans.fit(listings[listings.columns[13:16]]) # Compute k-means clustering.
         listings['cluster_label'] = kmeans.fit_predict(listings[listings.columns[13:16]])
         listings_copy['cluster_label']=kmeans.fit_predict(listings_copy[listings_copy.columns
         #coordinate based on proximity
         centers = kmeans.cluster_centers_ # Coordinates of cluster centers.
         labels = kmeans.predict(listings[listings.columns[13:16]]) # Labels of each point
         listings.head(10)
```

```
c:\users\ajeet\appdata\local\programs\python\python36\lib\site-packages\ipykernel_launcher.py:3
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: http://pandas.pydata.org/pandas-docs/stable/user_guide/in
  This is separate from the ipykernel package so we can avoid doing imports until
```

Out[39]:

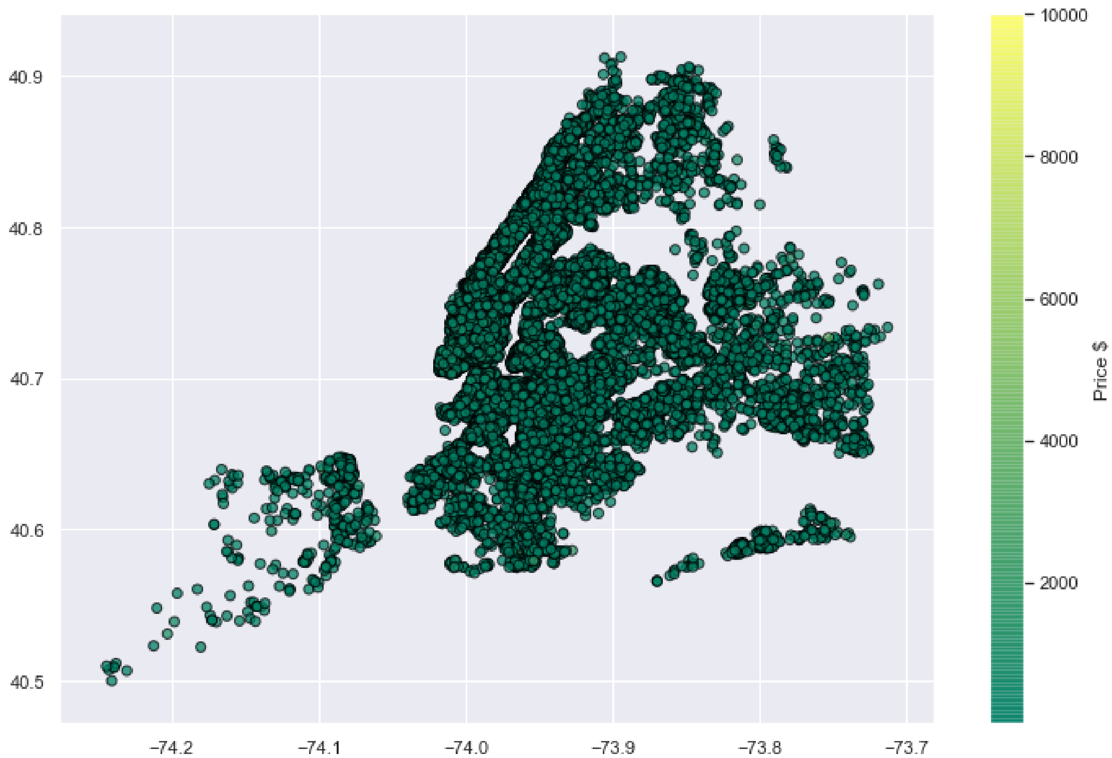
```
                                               name  host_id  \
0                                Skylit Midtown Castle     2845
1                    THE VILLAGE OF HARLEM...NEW YORK !     4632
2                        Cozy Entire Floor of Brownstone     4869
3  Entire Apt: Spacious Studio/Loft by central park     7192
4          Large Cozy 1 BR Apartment In Midtown East     7322
5                                      BlissArtsSpace!     7356
6                     Large Furnished Room Near B'way      8967
7                   Cozy Clean Guest Room - Family Apt     7490
8                                       Best Hideaway     7516
9                   Cute & Cozy Lower East Side 1 bdrm     7549

  neighbourhood_group       neighbourhood  latitude  longitude  \
0           Manhattan             Midtown  40.75362  -73.98377
1           Manhattan              Harlem  40.80902  -73.94190
2            Brooklyn        Clinton Hill  40.68514  -73.95976
3           Manhattan         East Harlem  40.79851  -73.94399
4           Manhattan         Murray Hill  40.74767  -73.97500
5            Brooklyn  Bedford-Stuyvesant  40.68688  -73.95596
6           Manhattan      Hell's Kitchen  40.76489  -73.98493
7           Manhattan     Upper West Side  40.80178  -73.96723
8           Manhattan        East Village  40.72764  -73.97949
9           Manhattan           Chinatown  40.71344  -73.99037

         room_type  minimum_nights  calculated_host_listings_count  \
0  Entire home/apt               1                               2
1     Private room               3                               1
2  Entire home/apt               1                               1
3  Entire home/apt              10                               1
4  Entire home/apt               3                               1
5     Private room              45                               1
6     Private room               2                               1
7     Private room               2                               1
8  Entire home/apt              30                               1
9  Entire home/apt               1                               4

   availability_365  number_of_reviews  reviews_per_month     price         x  \
0               288                 46               0.39  5.420535 -0.155116
1               365                  0               0.00  5.017280 -0.114165
2               212                274               4.64  4.499810 -0.130353
```

```
3              0                 9              0.10  4.394449 -0.116195
4            127                75              0.60  5.303305 -0.146402
5              0                49              0.39  4.110874 -0.126666
6            239               434              3.48  4.382027 -0.156402
7              0               118              0.98  4.382027 -0.139242
8            322                94              0.74  4.762174 -0.150510
9              0               161              1.33  5.017280 -0.160911

          y         z  cluster_label
0 -0.984060  0.086974              3
1 -0.992957  0.031679              1
2 -0.979287  0.154938              0
3 -0.992330  0.042182              1
4 -0.984853  0.092900              3
5 -0.980041  0.153219              0
6 -0.984785  0.075742              3
7 -0.989493  0.038915              1
8 -0.982149  0.112824              3
9 -0.978774  0.126921              3
```

In [40]:
```python
listings = listings.drop(columns=['latitude','longitude','x','y','z'])
listings_copy=listings_copy.drop(columns=['latitude','longitude','x','y','z'])
print(listings.columns)
print(listings_copy.columns)#shows columns
```

```
Index(['name', 'host_id', 'neighbourhood_group', 'neighbourhood', 'room_type',
       'minimum_nights', 'calculated_host_listings_count', 'availability_365',
       'number_of_reviews', 'reviews_per_month', 'price', 'cluster_label'],
      dtype='object')
Index(['host_id', 'neighbourhood_group', 'neighbourhood', 'room_type',
       'minimum_nights', 'calculated_host_listings_count', 'availability_365',
       'number_of_reviews', 'reviews_per_month', 'price', 'cluster_label'],
      dtype='object')
```

In [41]:
```python
plt.figure(figsize=(12, 8))
plt.scatter(df2.longitude, df2.latitude, c=df2.price, cmap='summer', edgecolor='black

cbar = plt.colorbar()
cbar.set_label('Price $')#there does not seem to be a high correlation between latitu
#but perhaps the more expensive areas are covered by the green dots. The z coordinate
```




```
In [42]: Q1 = listings['availability_365'].quantile(0.25)
         Q3 = listings['availability_365'].quantile(0.75)
         IQR = Q3 - Q1
         print(len(listings[(listings['availability_365'] < (Q1 - 1.5 * IQR)) |(listings['avail
         #shows outliers
```

0

```
In [43]: Q1 = listings['number_of_reviews'].quantile(0.25)
         Q3 = listings['number_of_reviews'].quantile(0.75)
         IQR = Q3 - Q1
         print(len(listings[(listings['number_of_reviews'] < (Q1 - 1.5 * IQR)) |(listings['numb
         #shows outliers
```

6034

```
In [44]: Q1 = listings['reviews_per_month'].quantile(0.25)
         Q3 = listings['reviews_per_month'].quantile(0.75)
         IQR = Q3 - Q1
         print(len(listings[(listings['reviews_per_month'] < (Q1 - 1.5 * IQR)) |(listings['rev
         #shows outliers
```

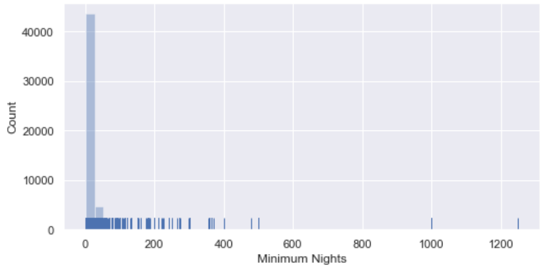
3419

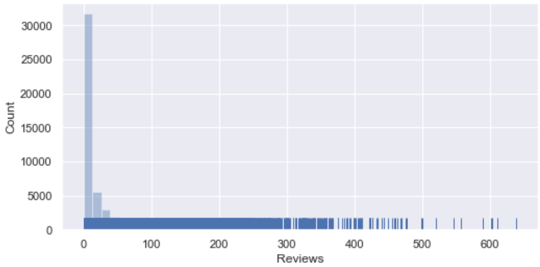
In [45]:
```
Q1 = listings['calculated_host_listings_count'].quantile(0.25)
Q3 = listings['calculated_host_listings_count'].quantile(0.75)
IQR = Q3 - Q1
print(len(listings[(listings['calculated_host_listings_count'] < (Q1 - 1.5 * IQR)) |(
#shows outliers
```

7076

In [46]:
```
fig, axes = plt.subplots(1,2, figsize=(18,4))

sns.distplot(listings['minimum_nights'], kde=False, rug=True, ax = axes[0])
axes[0].set_xlabel('Minimum Nights')
axes[0].set_ylabel('Count')

sns.distplot(listings['number_of_reviews'], kde=False, rug=True, ax = axes[1])
axes[1].set_xlabel('Reviews')
axes[1].set_ylabel('Count')
#both are heavily skewed to the right. I am thinking to get rid of any minimum night
#make
```

Out[46]: Text(0, 0.5, 'Count')



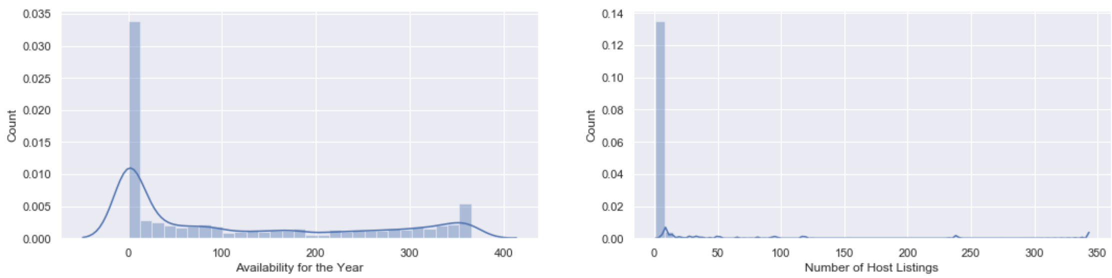


In [48]:
```
df3=listings_copy.copy()
listings=listings[listings['minimum_nights']<=365]
listings_copy=listings_copy[listings_copy['minimum_nights']<=365]#removing data point
#365. this does not make sense and I am assuming that the stay cannot be longer than
```

In [49]:
```
fig, axes = plt.subplots(1,2, figsize=(18,4))

sns.distplot(listings['availability_365'], ax = axes[0])
axes[0].set_xlabel('Availability for the Year')
axes[0].set_ylabel('Count')
```

```
sns.distplot(listings['calculated_host_listings_count'], ax = axes[1])
axes[1].set_xlabel('Number of Host Listings')
axes[1].set_ylabel('Count')#shows distribution of availability and host listings
```

Out[49]: Text(0, 0.5, 'Count')




```
In [50]: a=[len(listings[listings['minimum_nights']<3])/len(listings),
         len(listings[listings['calculated_host_listings_count']<2])/len(listings),
         len(listings[listings['number_of_reviews']<5])/len(listings),
         len(listings[listings['availability_365']<6])/len(listings),
         len(listings[listings['reviews_per_month']<1])/len(listings)]
         for i in a:
             print(i)#playing with the numbers to see what percentage of observations are comp
```

```
0.5006449499396
0.6590364652648389
0.4744374603304601
0.39651112794578325
0.6604492127515816
```

```
In [51]: df3=listings.copy()
         listings['low_avail'] = listings['availability_365']<6#creates piece-wise element to
         #since they are heavily skewed to the right. Takes high small frequencies and makes t
         listings['low_nights'] = listings['minimum_nights']< 3
         listings['no_reviews'] = listings['reviews_per_month']==0
         listings['low_reviews'] = listings['number_of_reviews']<5#since the distributions are
         #wise element to the regression by weighting lower values more
```

```
In [52]: listings.groupby('neighbourhood_group', as_index=False)['price'].mean().sort_values(b
         #Staten Island, Queens, Bronx
```

Out[52]:

	neighbourhood_group	price
0	Bronx	4.263594
3	Queens	4.379170
4	Staten Island	4.397977
1	Brooklyn	4.578436
2	Manhattan	5.005256

In [53]:
```
listings.groupby('neighbourhood', as_index=False)['price'].mean().sort_values(by=['pri
#within each borough, there is a variation in the price of the Airbnb. So it would be
```

Out[53]:
```
         neighbourhood     price
88        Graniteville  3.660594
27         Bull's Head  3.780475
197            Tremont  3.840318
136         Mount Eden  3.901788
103        Hunts Point  3.908886
..                 ...       ...
216        Willowbrook  5.703782
198            Tribeca  5.733462
220            Woodrow  6.552508
83      Fort Wadsworth  6.685861
51        Country Club  6.908755

[222 rows x 2 columns]
```

In [ ]:

In [54]:
```
df4=listings.copy()

listings['area']=listings['neighbourhood'] + ',' + listings['neighbourhood_group']#me
#space
```

In [55]:
```
listings_copy['area']=listings_copy['neighbourhood'] + ',' + listings_copy['neighbour
listings_copy=listings_copy.drop(columns=['neighbourhood','neighbourhood_group'])
listings=listings.drop(columns=['neighbourhood','neighbourhood_group'])
```

In [56]:
```
listings.groupby('area', as_index=False)['price'].mean().sort_values(by=['price'])#sh
```

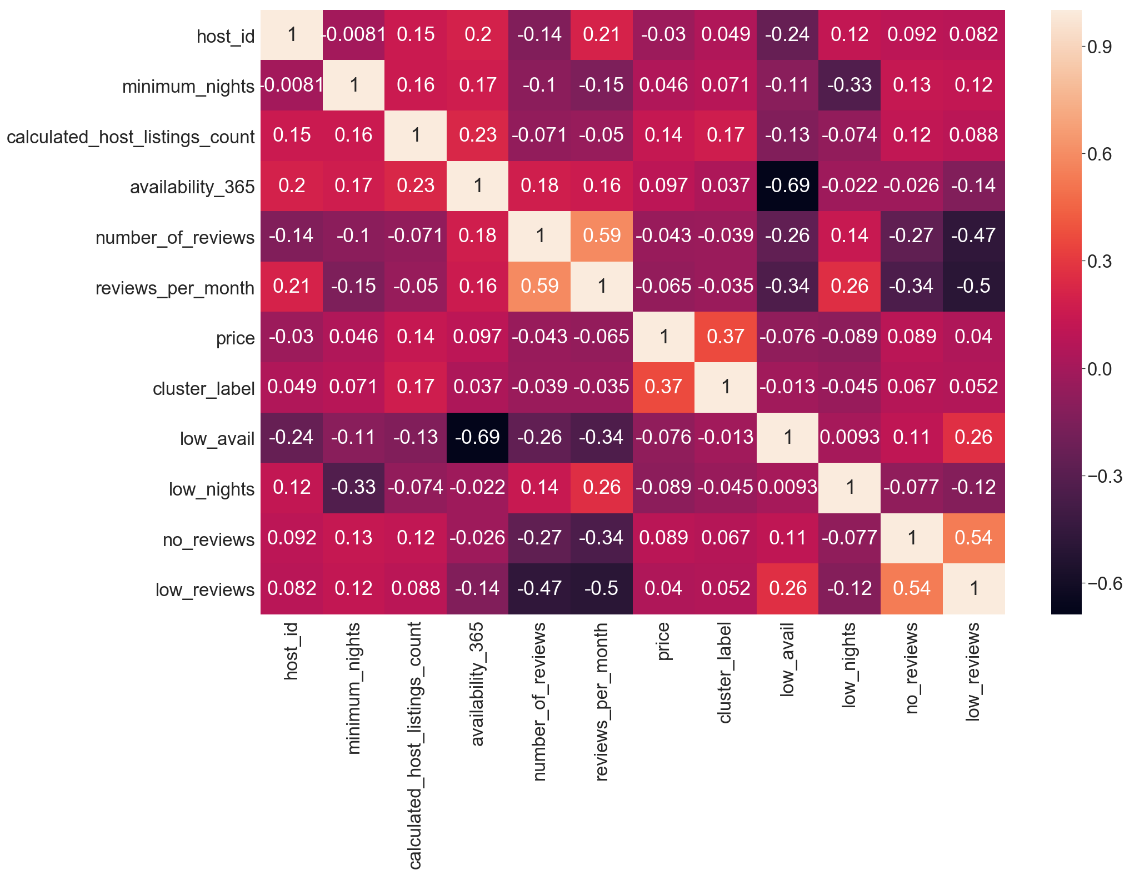
Out[56]:
```
                              area     price
88       Graniteville,Staten Island  3.660594
27        Bull's Head,Staten Island  3.780475
197                   Tremont,Bronx  3.840318
136                Mount Eden,Bronx  3.901788
103               Hunts Point,Bronx  3.908886
..                              ...       ...
216       Willowbrook,Staten Island  5.703782
198               Tribeca,Manhattan  5.733462
220           Woodrow,Staten Island  6.552508
83     Fort Wadsworth,Staten Island  6.685861
51               Country Club,Bronx  6.908755

[222 rows x 2 columns]
```

In [57]:
```
#As seen from here, some of the cheapest and most expensive AirBnBs are in the Bronx
#within boroughs
listings.columns
```

Out[57]: Index(['name', 'host_id', 'room_type', 'minimum_nights',
       'calculated_host_listings_count', 'availability_365',
       'number_of_reviews', 'reviews_per_month', 'price', 'cluster_label',
       'low_avail', 'low_nights', 'no_reviews', 'low_reviews', 'area'],
      dtype='object')

In [59]:
```
sns.set(font_scale=3)
plt.figure(figsize=(30, 20))
sns.heatmap(listings.corr(), annot=True)#shows heatmap. No highly correlated variable
#number_of_reviews and reviews_per_month seem to be correlated which makes since sinc
```

Out[59]: <matplotlib.axes._subplots.AxesSubplot at 0x1771b6c0dd8>



	host_id	minimum_nights	calculated_host_listings_count	availability_365	number_of_reviews	reviews_per_month	price	cluster_label	low_avail	low_nights	no_reviews	low_reviews
host_id	1	-0.0081	0.15	0.2	-0.14	0.21	-0.03	0.049	-0.24	0.12	0.092	0.082
minimum_nights	-0.0081	1	0.16	0.17	-0.1	-0.15	0.046	0.071	-0.11	-0.33	0.13	0.12
calculated_host_listings_count	0.15	0.16	1	0.23	-0.071	-0.05	0.14	0.17	-0.13	-0.074	0.12	0.088
availability_365	0.2	0.17	0.23	1	0.18	0.16	0.097	0.037	-0.69	-0.022	-0.026	-0.14
number_of_reviews	-0.14	-0.1	-0.071	0.18	1	0.59	-0.043	-0.039	-0.26	0.14	-0.27	-0.47
reviews_per_month	0.21	-0.15	-0.05	0.16	0.59	1	-0.065	-0.035	-0.34	0.26	-0.34	-0.5
price	-0.03	0.046	0.14	0.097	-0.043	-0.065	1	0.37	-0.076	-0.089	0.089	0.04
cluster_label	0.049	0.071	0.17	0.037	-0.039	-0.035	0.37	1	-0.013	-0.045	0.067	0.052
low_avail	-0.24	-0.11	-0.13	-0.69	-0.26	-0.34	-0.076	-0.013	1	0.0093	0.11	0.26
low_nights	0.12	-0.33	-0.074	-0.022	0.14	0.26	-0.089	-0.045	0.0093	1	-0.077	-0.12
no_reviews	0.092	0.13	0.12	-0.026	-0.27	-0.34	0.089	0.067	0.11	-0.077	1	0.54
low_reviews	0.082	0.12	0.088	-0.14	-0.47	-0.5	0.04	0.052	0.26	-0.12	0.54	1

In [60]:
```
listings.dtypes
```

Out[60]:
```
name                               object
host_id                             int64
room_type                          object
minimum_nights                      int64
calculated_host_listings_count      int64
availability_365                    int64
```

```
number_of_reviews                    int64
reviews_per_month                  float64
price                              float64
cluster_label                        int32
low_avail                             bool
low_nights                            bool
no_reviews                            bool
low_reviews                           bool
area                                object
dtype: object
```

In [61]:
```
listings.head()
```

Out[61]:
```
                                             name  host_id        room_type  \
0                           Skylit Midtown Castle     2845  Entire home/apt
1             THE VILLAGE OF HARLEM...NEW YORK !     4632     Private room
2                 Cozy Entire Floor of Brownstone     4869  Entire home/apt
3  Entire Apt: Spacious Studio/Loft by central park     7192  Entire home/apt
4         Large Cozy 1 BR Apartment In Midtown East     7322  Entire home/apt

   minimum_nights  calculated_host_listings_count  availability_365  \
0               1                               2               288
1               3                               1               365
2               1                               1               212
3              10                               1                 0
4               3                               1               127

   number_of_reviews  reviews_per_month     price  cluster_label  low_avail  \
0                 46               0.39  5.420535              3      False
1                  0               0.00  5.017280              1      False
2                274               4.64  4.499810              0      False
3                  9               0.10  4.394449              1       True
4                 75               0.60  5.303305              3      False

   low_nights  no_reviews  low_reviews                   area
0        True       False        False      Midtown,Manhattan
1       False        True         True       Harlem,Manhattan
2        True       False        False  Clinton Hill,Brooklyn
3       False       False        False  East Harlem,Manhattan
4       False       False        False  Murray Hill,Manhattan
```

In [62]:
```
listings.low_avail=listings.low_avail.astype(int)
listings.low_nights=listings.low_nights.astype(int)
listings.no_reviews=listings.no_reviews.astype(int)
listings.low_reviews=listings.low_reviews.astype(int)#converts booleans to 0s and 1
categorical_features = listings[['room_type','cluster_label','area']]

categorical_features = pd.get_dummies(categorical_features)
```

```
numerical_features =  listings.drop(columns=['room_type','cluster_label','area'], axis
y = numerical_features.price
numerical_features = numerical_features.drop(['price'], axis=1)#separates categorical
#makes price variable the y vector.
```

In [63]:
```
categorical_features.columns
```

Out[63]:
```
Index(['cluster_label', 'room_type_Entire home/apt', 'room_type_Private room',
       'room_type_Shared room', 'area_Allerton,Bronx',
       'area_Arden Heights,Staten Island', 'area_Arrochar,Staten Island',
       'area_Arverne,Queens', 'area_Astoria,Queens',
       'area_Bath Beach,Brooklyn',
       ...
       'area_Westerleigh,Staten Island', 'area_Whitestone,Queens',
       'area_Williamsbridge,Bronx', 'area_Williamsburg,Brooklyn',
       'area_Willowbrook,Staten Island', 'area_Windsor Terrace,Brooklyn',
       'area_Woodhaven,Queens', 'area_Woodlawn,Bronx',
       'area_Woodrow,Staten Island', 'area_Woodside,Queens'],
      dtype='object', length=226)
```

In [64]:
```
one_hot = pd.get_dummies(categorical_features['cluster_label'])#one hot encodes clust
```

In [65]:
```
print(one_hot)
```

```
       0  1  2  3
0      0  0  0  1
1      0  1  0  0
2      1  0  0  0
3      0  1  0  0
4      0  0  0  1
...   .. .. .. ..
48859  0  1  0  0
48860  0  1  0  0
48861  0  0  0  1
48862  0  1  0  0
48863  0  0  0  1

[48841 rows x 4 columns]
```

In [66]:
```
categorical_features=categorical_features.drop(columns=['cluster_label'])
categorical_features=categorical_features.join(one_hot)
```

In [67]:
```
categorical_features.head()
```

Out[67]:
```
   room_type_Entire home/apt  room_type_Private room  room_type_Shared room  \
0                          1                       0                      0
```

```
1                       0                       1                      0
2                       1                       0                      0
3                       1                       0                      0
4                       1                       0                      0

   area_Allerton,Bronx  area_Arden Heights,Staten Island  \
0                    0                                 0
1                    0                                 0
2                    0                                 0
3                    0                                 0
4                    0                                 0

   area_Arrochar,Staten Island  area_Arverne,Queens  area_Astoria,Queens  \
0                            0                    0                    0
1                            0                    0                    0
2                            0                    0                    0
3                            0                    0                    0
4                            0                    0                    0

   area_Bath Beach,Brooklyn  area_Battery Park City,Manhattan  ...  \
0                         0                                 0  ...
1                         0                                 0  ...
2                         0                                 0  ...
3                         0                                 0  ...
4                         0                                 0  ...

   area_Willowbrook,Staten Island  area_Windsor Terrace,Brooklyn  \
0                               0                              0
1                               0                              0
2                               0                              0
3                               0                              0
4                               0                              0

   area_Woodhaven,Queens  area_Woodlawn,Bronx  area_Woodrow,Staten Island  \
0                      0                    0                           0
1                      0                    0                           0
2                      0                    0                           0
3                      0                    0                           0
4                      0                    0                           0

   area_Woodside,Queens  0  1  2  3
0                     0  0  0  0  1
1                     0  0  1  0  0
2                     0  1  0  0  0
3                     0  0  1  0  0
4                     0  0  0  0  1

[5 rows x 229 columns]
```

In [68]:
```
numerical_text=numerical_features.copy()
numerical_features = numerical_features.drop(['host_id','name'], axis=1)#drops 'name'
```

In [69]:
```
transformer = RobustScaler().fit(numerical_features)
numerical_features=transformer.transform(numerical_features)#uses robust scaler to ac
#and target distributions
```

In [70]:
```
columns=['minimum_nights', 'calculated_host_listings_count','availability_365','numbe
numerical_df = pd.DataFrame({'minimum_nights': numerical_features[:, 0], 'calculated_
                             'availability_365': numerical_features[:, 2], 'number_of_
                             'reviews_per_month': numerical_features[:, 4]})
#numerical_features=np.concatenate((numerical_features, categorical_features_one_hot)
print(numerical_features)
#numerical_df=pd.DataFrame(data=numerical_features, columns=columns)
#X=pd.concat([numerical_df, categorical_features], axis=1)
```

```
[[-0.25        1.          1.06465517 ...  0.          0.
   0.        ]
 [ 0.25        0.          1.39655172 ... -1.          1.
   1.        ]
 [-0.25        0.          0.73706897 ...  0.          0.
   0.        ]
 ...
 [-0.25        0.          0.27586207 ...  0.          1.
   1.        ]
 [-0.25        0.         -0.11637931 ...  0.          1.
   1.        ]
 [-0.25        0.          0.14224138 ...  0.          1.
   1.        ]]
```

In [72]:
```
#X.isnull().sum()
```

In [73]:
```
#percent_missing = listings.isnull().sum() * 100 / len(listings)
#print(X[X.isnull()])
#X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_stat
numerical_df.dtypes
```

Out[73]:
```
minimum_nights                    float64
calculated_host_listings_count    float64
availability_365                  float64
number_of_reviews                 float64
reviews_per_month                 float64
dtype: object
```

In [74]:
```
categorical_features.dtypes
categorical_float_df=categorical_features.apply(pd.to_numeric, errors='coerce')
categorical_float_df.dtypes
```

Out[74]: room_type_Entire home/apt   uint8
         room_type_Private room   uint8
         room_type_Shared room   uint8
         area_Allerton,Bronx   uint8
         area_Arden Heights,Staten Island   uint8
                                            ...
         area_Woodside,Queens   uint8
         0   uint8
         1   uint8
         2   uint8
         3   uint8
         Length: 229, dtype: object

```
In [75]: y.isnull().sum()#checking to make sure that there are no nulls
```

Out[75]: 0

```
In [79]: X=np.concatenate((numerical_features, categorical_features), axis=1)#creates X
         #X=pd.concat([numerical_df,categorical_features], axis=0)
         #numerical_df.shape
         #X=numerical_df.combine(categorical_features)
```

```
In [80]: #X.isnull().sum()
```

```
In [81]: X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state
         #with a training size of 30% of dataset
```

```
In [92]: #Simple Linear Model
         regression=linear_model.LinearRegression()#linear regression model
         regression.fit(X_train, y_train)#fits training set
         lin_y_pred=regression.predict(X_test)#predicts test set
         lin_y_pred_train=regression.predict(X_train)
         print('R^2 For Training Set: %.2f'
               % regression.score(X_train, y_train))#R^2 score for training set
         print('Mean squared error for Test Set: %.2f'
               % mean_squared_error(y_test, lin_y_pred))#test set prediction
         print('Mean squared error for Train Set: %.2f'
               % mean_squared_error(y_train, lin_y_pred_train))
```

```
R^2 For Training Set: 0.56
Mean squared error for Test Set: 8164121273.22
Mean squared error for Train Set: 0.21
```

```
In [93]: regression.coef_
```

```
Out[93]: array([-9.64923499e-03, -5.20295224e-04,  1.21439993e-01, -1.15034544e-02,
                -1.37664009e-02, -1.06201598e-01,  8.02025463e-02,  1.31515985e-01,
                -1.43628021e-03, -1.33528193e+10, -1.33528193e+10, -1.33528193e+10,
```

-6.31476802e+06, -6.31476834e+06, -6.31476804e+06, -6.31476774e+06,
-6.31476786e+06, -6.31476804e+06, -6.31476741e+06, -6.31476790e+06,
-6.31476800e+06, -6.31476703e+06, -6.31476802e+06, -6.31476804e+06,
-6.31476794e+06, -6.31476785e+06, -6.31476766e+06, -6.31476803e+06,
-6.31476814e+06, -6.31476812e+06, -6.31476798e+06, -6.31476751e+06,
-6.31476813e+06, -6.31476669e+06, -6.31476785e+06, -6.31476784e+06,
-6.31476839e+06, -6.31476747e+06, -6.31476801e+06, -6.31476825e+06,
-6.31476791e+06, -6.31476801e+06, -6.31476797e+06, -6.31476751e+06,
-6.31476781e+06, -6.31476720e+06, -6.31476739e+06, -6.31476761e+06,
-6.31476789e+06, -6.31476758e+06, -6.31476817e+06, -6.31476792e+06,
-6.31476803e+06, -6.31476756e+06, -6.31476811e+06, -6.31476736e+06,
-6.31476816e+06, -6.31476767e+06, -6.31476827e+06, -6.31476804e+06,
-6.31476803e+06, -6.31476792e+06, -6.31476818e+06, -6.31476499e+06,
-6.31476783e+06, -6.31476800e+06, -6.31476746e+06, -6.31476789e+06,
-6.31476808e+06, -6.31476808e+06, -6.31476757e+06, -6.31476806e+06,
-6.31476804e+06, -6.31476796e+06, -6.31476766e+06, -6.31476771e+06,
-6.31476808e+06, -6.31476753e+06, -6.31476789e+06, -6.31476825e+06,
-6.31476802e+06, -6.31476804e+06, -6.31476804e+06, -6.31476810e+06,
-6.31476805e+06, -6.31476804e+06, -6.31476740e+06, -6.31476794e+06,
-6.31476723e+06, -6.31476803e+06, -6.31476794e+06, -6.31476805e+06,
-6.31476786e+06, -6.31476755e+06, -6.31476791e+06, -6.31476629e+06,
-6.31476800e+06, -6.31476804e+06, -6.31476752e+06, -6.31476746e+06,
-6.31476877e+06, -6.31476844e+06, -6.31476810e+06, -6.31476774e+06,
-6.31476776e+06, -6.31476735e+06, -6.31476796e+06, -6.31476773e+06,
-6.31476745e+06, -6.31476817e+06, -6.31476788e+06, -6.31476729e+06,
-6.31476782e+06, -6.31476799e+06, -6.31476837e+06, -6.31476830e+06,
-6.31476798e+06, -6.31476801e+06, -6.31476771e+06, -6.31476782e+06,
-6.31476797e+06, -6.31476793e+06, -6.31476786e+06, -6.31476789e+06,
-6.31476797e+06, -6.31476755e+06, -6.31476814e+06, -6.31476802e+06,
-6.31476757e+06, -6.31476802e+06, -6.31476777e+06, -6.31476795e+06,
-6.31476757e+06, -6.31476818e+06, -6.31476795e+06, -6.31476830e+06,
-6.31476807e+06, -6.31476838e+06, -6.31476801e+06, -6.31476808e+06,
-6.31476728e+06, -6.31476804e+06, -6.31476794e+06, -6.31476766e+06,
-6.31476806e+06, -6.31476819e+06, -6.31476807e+06, -6.31476798e+06,
-6.31476828e+06, -6.31476809e+06, -6.31476747e+06, -6.31476753e+06,
-6.31476747e+06, -6.31476772e+06, -6.31476838e+06, -6.31476872e+06,
-6.31476816e+06, -6.31476718e+06, -6.31476746e+06, -6.31476775e+06,
-6.31476811e+06, -6.31476812e+06, -6.31476751e+06, -6.31476809e+06,
-6.31476748e+06, -6.31476816e+06, -6.31476825e+06, -6.31476813e+06,
-6.31476790e+06, -6.31476836e+06, -6.31476785e+06, -6.31476758e+06,
-6.31476790e+06, -6.31476816e+06, -6.31476835e+06, -6.31476767e+06,
-6.31476804e+06, -6.31476806e+06, -6.31476799e+06, -6.31476805e+06,
-6.31476677e+06, -6.31476792e+06, -6.31476767e+06, -6.31476782e+06,
-6.31476808e+06, -6.31476834e+06, -6.31476806e+06, -6.31476689e+06,
-6.31476795e+06, -6.31476794e+06, -6.31476803e+06, -6.31476732e+06,
-6.31476837e+06, -6.31476814e+06, -6.31476807e+06, -6.31476760e+06,
-6.31476792e+06, -6.31476806e+06, -6.31476805e+06, -6.31476781e+06,
-6.31476795e+06, -6.31476747e+06, -6.31476802e+06, -6.31476790e+06,

```
                -6.31476734e+06, -6.31476790e+06, -6.31476765e+06, -6.31476823e+06,
                -6.31476793e+06, -6.31476840e+06, -6.31476703e+06, -6.31476760e+06,
                -6.31476785e+06, -6.31476820e+06, -6.31476753e+06, -6.31476746e+06,
                -6.31476812e+06, -6.31476740e+06, -6.31476816e+06, -6.31476791e+06,
                -6.31476817e+06,  1.94289029e-16, -6.31476733e+06, -6.31476810e+06,
                -6.31476814e+06, -6.31476788e+06, -6.31476815e+06, -6.31476760e+06,
                -2.77555756e-17, -6.31476774e+06, -6.31476807e+06, -6.31476819e+06,
                -6.31476613e+06, -6.31476802e+06, -7.54476986e+08, -7.54476986e+08,
                -7.54476986e+08, -7.54476985e+08])
```

```
In [94]: lasso_params={'alpha':[0.001, 0.005, 0.0075, 0.01]}
         #pipe2 = Pipeline([('poly', PolynomialFeatures()),
         #                  ('fit', linear_model.Lasso())])
         #lasso=GridSearchCV(pipe2, param_grid=lasso_params).fit(X_train, y_train).best_estima
         lasso= GridSearchCV(linear_model.Lasso(), param_grid=lasso_params).fit(X_train, y_tra
         print(lasso.best_estimator_)#shows best performing model parameters
         lasso_y_pred=lasso.predict(X_test)#predicts test
         lasso_y_pred_train=lasso.predict(X_train)
         print('R^2 For Training Set: %.2f'
               % lasso.score(X_train, y_train))
         print('Mean squared error for Test Set: %.2f'
               % mean_squared_error(y_test, lasso_y_pred))#0.23 mean squared error for Lasso m
         print('Mean squared error for Train Set: %.2f'
               % mean_squared_error(y_train, lasso_y_pred_train))
```

```
Lasso(alpha=0.001, copy_X=True, fit_intercept=True, max_iter=1000,
      normalize=False, positive=False, precompute=False, random_state=None,
      selection='cyclic', tol=0.0001, warm_start=False)
R^2 For Training Set: 0.53
Mean squared error for Test Set: 0.23
Mean squared error for Train Set: 0.22
```

```
In [95]: ridge_params = {'alpha':[1.5,1.6,1.7,1.8,1.9,2]}

         #lasso=GridSearchCV(pipe2, param_grid=lasso_params).fit(X_train, y_train).best_estima
         ridge=GridSearchCV(linear_model.Ridge(), param_grid=ridge_params).fit(X_train, y_trai
         print(ridge.best_estimator_)
         ridge_y_pred=ridge.predict(X_test)
         ridge_y_pred_train=ridge.predict(X_train)
         print('R^2 For Training Set: %.2f'
               % lasso.score(X_train, y_train))
         print('Mean squared error for Test Set: %.2f'
               % mean_squared_error(y_test, ridge_y_pred))#0.22 mean squared error for Ridge
         print('Mean squared error for Train Set: %.2f'
               % mean_squared_error(y_train, ridge_y_pred_train))#0.22 mean squared error for
```

```
Ridge(alpha=2, copy_X=True, fit_intercept=True, max_iter=None, normalize=False,
      random_state=None, solver='auto', tol=0.001)
```

```
R^2 For Training Set: 0.53
Mean squared error for Test Set: 0.22
Mean squared error for Train Set: 0.21
```

```
In [96]: regr = AdaBoostRegressor(random_state=0, n_estimators=150)
         regr.fit(X_train, y_train)
         boost_y_pred=regr.predict(X_test)
         boost_y_pred_train=regr.predict(X_train)
         print('R^2 For Training Set for Test Set: %.2f'
               % regr.score(X_train, y_train))
         print('Mean squared error for Test Set: %.2f'
               % mean_squared_error(y_test, boost_y_pred))#Boost regressor
         print('Mean squared error for Test Set: %.2f'
               % mean_squared_error(y_train, boost_y_pred_train))
```

```
R^2 For Training Set for Test Set: 0.14
Mean squared error for Test Set: 0.41
Mean squared error for Test Set: 0.41
```

```
In [87]: pca = PCA(n_components=2)
         X_red=pca.fit_transform(X_train)
         print(pca.explained_variance_ratio_.cumsum())#2 component PCA
```

```
[0.98020052 0.99358823]
```

```
In [97]: regression=linear_model.LinearRegression()
         regression.fit(X_red, y_train)
         X_test_red=pca.transform(X_test)
         pca_y_pred=regression.predict(X_test_red)
         pca_y_pred_train=regression.predict(X_red)
         print('R^2 For Training Set: %.2f'
               % regression.score(X_red, y_train))
         print('Mean squared error for Test Set: %.2f'
               % mean_squared_error(y_test, pca_y_pred))#0.46 mean squared error. Performed po
         print('Mean squared error for Train Set: %.2f'
               % mean_squared_error(y_train, pca_y_pred_train))
```

```
R^2 For Training Set: 0.02
Mean squared error for Test Set: 0.46
Mean squared error for Train Set: 0.47
```

```
In [89]: xgb = XGBRegressor()
         parameters = {'nthread':[4], #when use hyperthread, xgboost may become slower
                       'objective':['reg:linear'],
                       'learning_rate': [.03, 0.05, .07], #so called `eta` value
```

```
                    'max_depth': [7, 8, 9],
                    'min_child_weight': [4],
                    'silent': [1],
                    'subsample': [0.7],
                    'colsample_bytree': [0.7],
                    'n_estimators': [250]}
xgb_grid = GridSearchCV(xgb,
                        parameters,
                        cv = 2,
                        n_jobs = 5,
                        verbose=True)
xgb_grid.fit(X_train,y_train)
```

```
Fitting 2 folds for each of 9 candidates, totalling 18 fits


[Parallel(n_jobs=5)]: Using backend LokyBackend with 5 concurrent workers.
[Parallel(n_jobs=5)]: Done  18 out of  18 | elapsed:  4.8min finished
c:\users\ajeet\appdata\local\programs\python\python36\lib\site-packages\xgboost\core.py:587: Fu
  if getattr(data, 'base', None) is not None and \
```

Out[89]:
```
GridSearchCV(cv=2, error_score=nan,
             estimator=XGBRegressor(base_score=0.5, booster='gbtree',
                                    colsample_bylevel=1, colsample_bynode=1,
                                    colsample_bytree=1, gamma=0,
                                    importance_type='gain', learning_rate=0.1,
                                    max_delta_step=0, max_depth=3,
                                    min_child_weight=1, missing=None,
                                    n_estimators=100, n_jobs=1, nthread=None,
                                    objective='reg:linear', random_state=0,
                                    reg_alpha=0, reg_...
                                    scale_pos_weight=1, seed=None, silent=None,
                                    subsample=1, verbosity=1),
             iid='deprecated', n_jobs=5,
             param_grid={'colsample_bytree': [0.7],
                         'learning_rate': [0.03, 0.05, 0.07],
                         'max_depth': [7, 8, 9], 'min_child_weight': [4],
                         'n_estimators': [250], 'nthread': [4],
                         'objective': ['reg:linear'], 'silent': [1],
                         'subsample': [0.7]},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
             scoring=None, verbose=True)
```

In [90]:
```
print(xgb_grid.best_params_)
```

```
{'colsample_bytree': 0.7, 'learning_rate': 0.05, 'max_depth': 9, 'min_child_weight': 4, 'n_est
```

```
In [98]: xgb_pred=xgb_grid.predict(X_test)
         xgb_pred_train=xgb_grid.predict(X_train)
         print('R^2 For Training Set: %.2f'
               % xgb_grid.score(X_train, y_train))
         print('Mean squared error for Test Set: %.2f'
               % mean_squared_error(y_test, xgb_pred))
         print('Mean squared error for Train Set: %.2f'
               % mean_squared_error(y_train, xgb_pred_train))
```

```
R^2 For Training Set: 0.67
Mean squared error for Test Set: 0.19
Mean squared error for Train Set: 0.16
```

```
In [ ]: #The best performing model was the XGBoost Regressor with a 0.03 learning rate, a max_
```

```
In [ ]:
```

```
In [ ]:
```

```
In [ ]:
```