Group 3 NYC AirBnB Data Principle Component Analysis

Step-1: Import Packages, Data Exploration & Cleaning

Intent should be to maximize information content while minimizing the number of dimensions or variables in the datset. Most of the variables in the dataframe have non null values except 'last_review', 'reviews_per_month', and 'license'. These columns are believed to have either little information value, or are believed to have other variables that would explain their effects anyway. Thus the aforementioned columns were removed. In addition all observations with zero values in the 'price' column were removed. It is assumed that the 'price' will be the primary variable of interest.

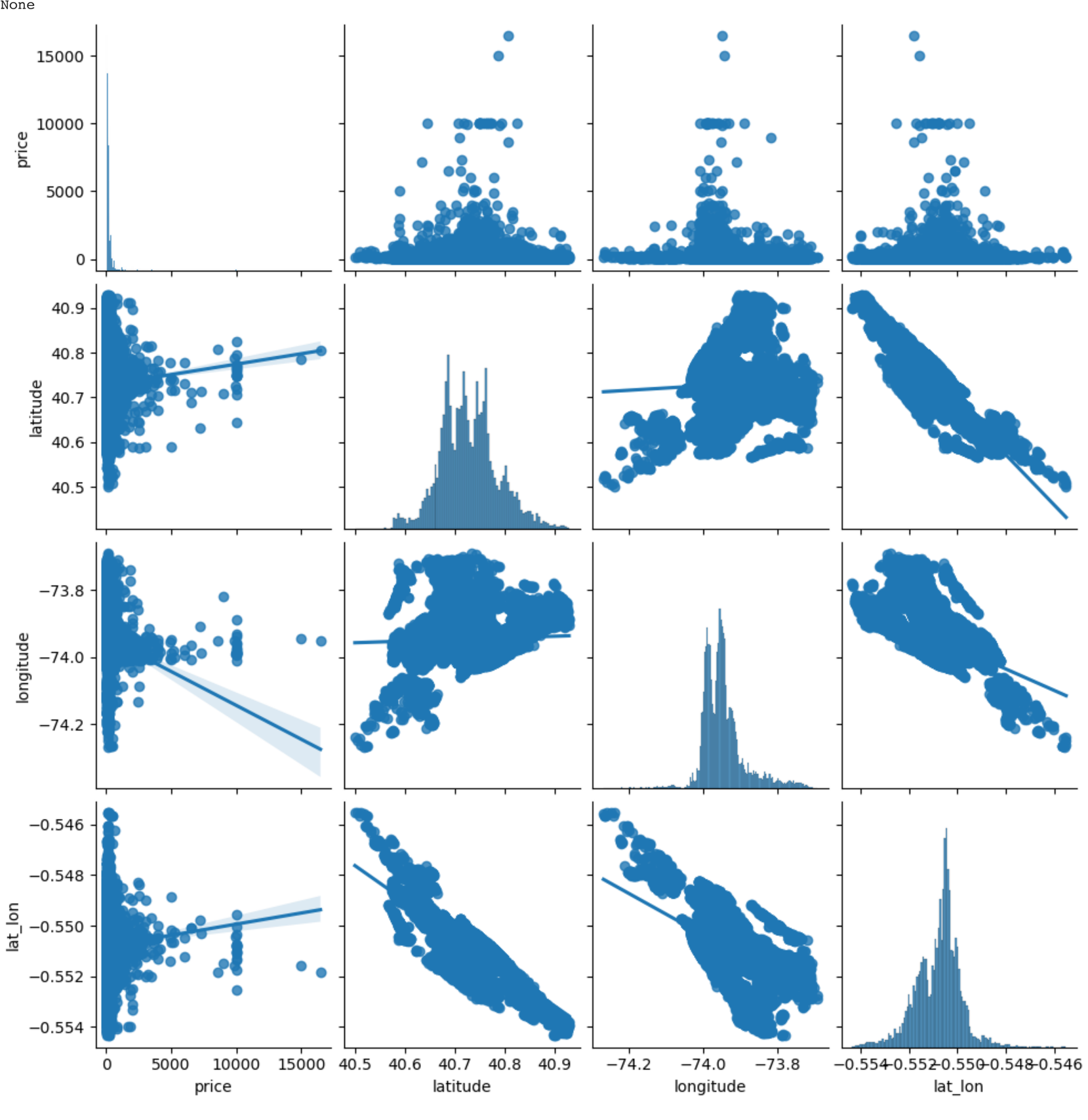
In [1]:
```
import pandas as pd
import numpy as np
from sklearn.decomposition import PCA
import matplotlib.pyplot as plt
from sklearn.preprocessing import scale
import seaborn as sb
import plotly.express as px
```

In [2]:
```
df = pd.read_csv('Grp3Project_InitialData/listings.csv')
display(df.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 39881 entries, 0 to 39880
Data columns (total 18 columns):
 #   Column                          Non-Null Count  Dtype
---  ------                          --------------  -----
 0   id                              39881 non-null  int64
 1   name                            39868 non-null  object
 2   host_id                         39881 non-null  int64
 3   host_name                       39831 non-null  object
 4   neighbourhood_group             39881 non-null  object
 5   neighbourhood                   39881 non-null  object
 6   latitude                        39881 non-null  float64
 7   longitude                       39881 non-null  float64
 8   room_type                       39881 non-null  object
 9   price                           39881 non-null  int64
 10  minimum_nights                  39881 non-null  int64
 11  number_of_reviews               39881 non-null  int64
 12  last_review                     31519 non-null  object
 13  reviews_per_month               31519 non-null  float64
 14  calculated_host_listings_count  39881 non-null  int64
 15  availability_365                39881 non-null  int64
 16  number_of_reviews_ltm           39881 non-null  int64
 17  license                         5 non-null      object
dtypes: float64(3), int64(8), object(7)
memory usage: 5.5+ MB
None
```

In [3]:
```
# remove deemed to be less than useful
df['lat_lon']= df['latitude']/df['longitude']
df = df.drop(['license', 'reviews_per_month','last_review', 'name', 'host_id','neighbourhood', 'host_name'],axis = 1)
df = df.loc[(df['price']> 0)]# Remove all zero values from the price
display(df.info())
sb.pairplot(df[['price','latitude','longitude','lat_lon']], kind="reg")
plt.show()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 39851 entries, 0 to 39880
Data columns (total 12 columns):
 #   Column                          Non-Null Count  Dtype
---  ------                          --------------  -----
 0   id                              39851 non-null  int64
 1   neighbourhood_group             39851 non-null  object
 2   latitude                        39851 non-null  float64
 3   longitude                       39851 non-null  float64
 4   room_type                       39851 non-null  object
 5   price                           39851 non-null  int64
 6   minimum_nights                  39851 non-null  int64
 7   number_of_reviews               39851 non-null  int64
 8   calculated_host_listings_count  39851 non-null  int64
 9   availability_365                39851 non-null  int64
 10  number_of_reviews_ltm           39851 non-null  int64
 11  lat_lon                         39851 non-null  float64
dtypes: float64(3), int64(7), object(2)
memory usage: 4.0+ MB
None
```



The pairplot was developed to gain an understanding of the relationship between 'latitiude', 'longitude', and 'price'. Based on this visualization, that correlation appears to be weak.

Step 2: Determine & Remove the Outliers

Process was to remove all outliers larger than q3 + (1.5 * IQR), or less than or equal to the minimum. In addition the latitude and longitude columns were removed from the dataset and replaced with the transformation 'lat_lon', which is the ratio latitude to longitude. The result reduced the number of observations in the data from 39881 to 36524.

In [4]:
```
df_stats = df.groupby('room_type')['price'].describe()
df_stats.reindex()
display(df_stats)
```

room_type	count	mean	std	min	25%	50%	75%	max
Entire home/apt	22761.0	251.546022	338.044654	10.0	128.00	180.0	275.0	15000.0
Hotel room	172.0	436.470930	282.491141	100.0	258.75	308.0	501.5	1998.0
Private room	16361.0	122.936495	356.373737	10.0	55.00	75.0	110.0	16500.0
Shared room	557.0	119.398564	454.106078	10.0	42.00	66.0	92.0	10000.0

In [5]:
```
# Create Table with outliers
df_stats['IQR'] = df_stats["75%"]- df_stats["25%"]
df_stats['upper_outlier'] = df_stats["75%"] + (1.5 * df_stats['IQR'])
df_stats['lower_outlier'] = df_stats["25%"] - (1.5 * df_stats['IQR'])
display(df_stats)
```

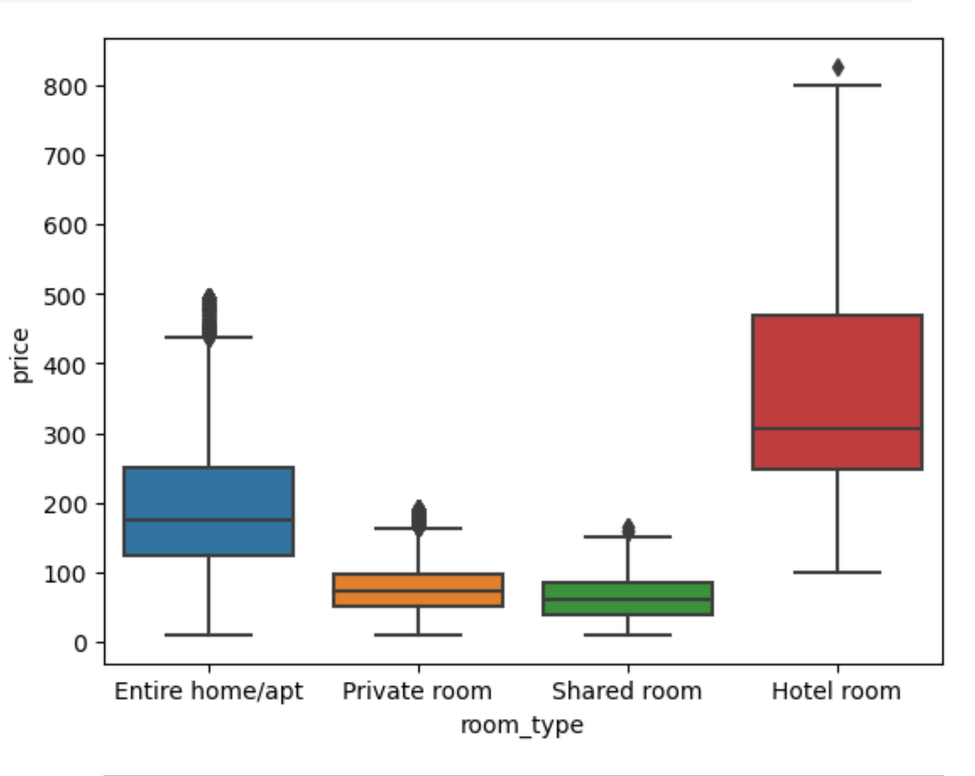
room_type	count	mean	std	min	25%	50%	75%	max	IQR	upper_outlier	lower_outlier
Entire home/apt	22761.0	251.546022	338.044654	10.0	128.00	180.0	275.0	15000.0	147.00	495.500	-92.500
Hotel room	172.0	436.470930	282.491141	100.0	258.75	308.0	501.5	1998.0	242.75	865.625	-105.375
Private room	16361.0	122.936495	356.373737	10.0	55.00	75.0	110.0	16500.0	55.00	192.500	-27.500
Shared room	557.0	119.398564	454.106078	10.0	42.00	66.0	92.0	10000.0	50.00	167.000	-33.000

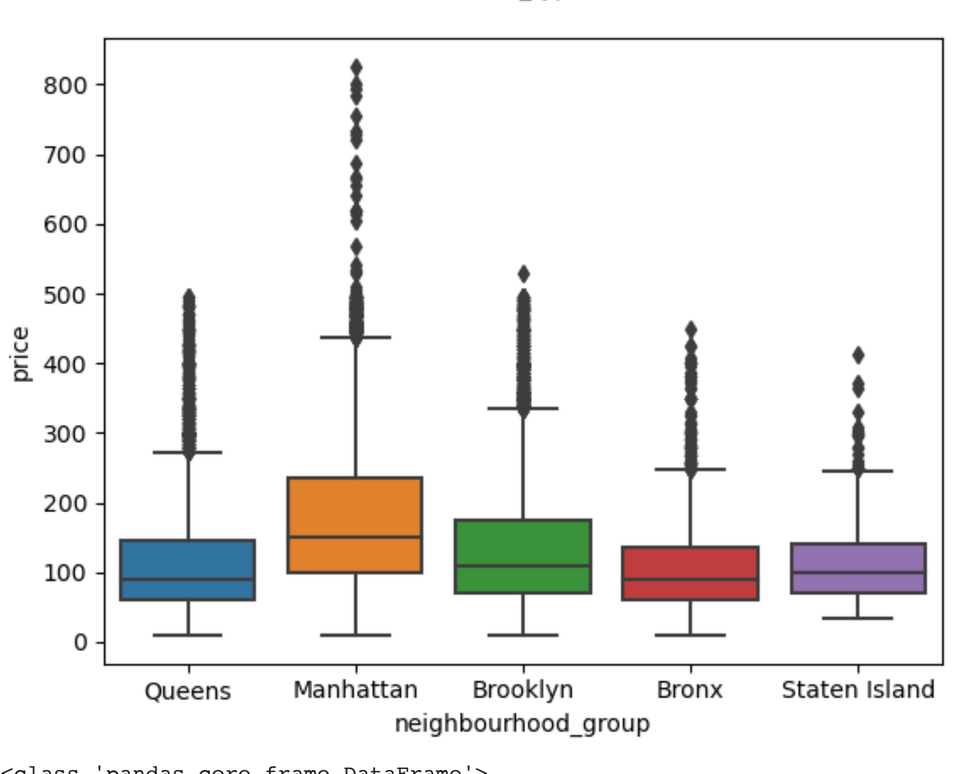
In [6]:
```
df1 = df[(df['room_type'] == "Entire home/apt") & (df['price']>=10) & (df['price']<= 496)]
df2 = df[(df['room_type'] == "Private room") & (df['price']>= 10) & (df['price']<= 192)]
df3 = df[(df['room_type'] == "Shared room") & (df['price']>= 10) & (df['price']<= 167)]
df4 = df[(df['room_type'] == "Hotel room") & (df['price']>= 100) & (df['price']<= 865)]
frames = [df1, df2, df3, df4]
df = pd.concat(frames)

display(df.groupby('neighbourhood_group')['price'].describe())
display(df.groupby('room_type')['price'].describe())
sb.boxplot(y = df['price'], x = df['room_type'])
plt.show()
sb.boxplot(y = df['price'], x = df['neighbourhood_group'])
plt.show()
display(df.info())
display(df.corr())
```

neighbourhood_group	count	mean	std	min	25%	50%	75%	max
Bronx	1530.0	108.036601	68.561010	10.0	60.0	89.0	135.00	450.0
Brooklyn	14192.0	133.914459	88.425233	10.0	69.0	110.0	175.00	529.0
Manhattan	14426.0	180.040690	105.605595	10.0	100.0	150.0	235.00	826.0
Queens	5954.0	114.189620	79.028227	10.0	60.0	90.0	145.00	495.0
Staten Island	422.0	113.646919	61.827482	33.0	69.0	99.5	140.75	412.0

room_type	count	mean	std	min	25%	50%	75%	max
Entire home/apt	21117.0	196.250793	95.382230	10.0	125.0	175.0	250.0	496.0
Hotel room	155.0	363.490323	163.471288	100.0	248.5	307.0	470.0	826.0
Private room	14751.0	78.448648	34.294310	10.0	52.0	72.0	97.0	192.0
Shared room	501.0	66.179641	32.916921	10.0	40.0	60.0	85.0	165.0






```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 36524 entries, 2 to 19816
Data columns (total 12 columns):
 #   Column                          Non-Null Count  Dtype
---  ------                          --------------  -----
 0   id                              36524 non-null  int64
 1   neighbourhood_group             36524 non-null  object
 2   latitude                        36524 non-null  float64
 3   longitude                       36524 non-null  float64
 4   room_type                       36524 non-null  object
 5   price                           36524 non-null  int64
 6   minimum_nights                  36524 non-null  int64
 7   number_of_reviews               36524 non-null  int64
 8   calculated_host_listings_count  36524 non-null  int64
 9   availability_365                36524 non-null  int64
 10  number_of_reviews_ltm           36524 non-null  int64
 11  lat_lon                         36524 non-null  float64
dtypes: float64(3), int64(7), object(2)
memory usage: 3.6+ MB
None
```

	id	latitude	longitude	price	minimum_nights	number_of_reviews	calculated_host_listings_count	availability_365	number_of_reviews_ltm	lat_lon
id	1.000000	-0.006021	0.090372	0.100288	-0.114942	-0.187285	0.041516	0.295017	-0.084761	-0.036796
latitude	-0.006021	1.000000	0.057068	0.023211	0.033942	-0.032738	0.031671	-0.021543	-0.042166	-0.886394
longitude	0.090372	0.057068	1.000000	-0.221445	-0.099553	0.040181	-0.063658	0.143466	0.077105	-0.512761
price	0.100288	0.023211	-0.221445	1.000000	-0.088323	-0.000474	0.152782	0.155715	0.082033	0.082805
minimum_nights	-0.114942	0.033942	-0.099553	-0.088323	1.000000	-0.147075	0.124210	-0.054423	-0.234587	0.017041
number_of_reviews	-0.187285	-0.032738	0.040181	-0.000474	-0.147075	1.000000	-0.096784	0.089859	0.629522	0.009497
calculated_host_listings_count	0.041516	0.031671	-0.063658	0.152782	0.124210	-0.096784	1.000000	0.131778	-0.059441	0.002320
availability_365	0.295017	-0.021543	0.143466	0.155715	-0.054423	0.089859	0.131778	1.000000	0.160993	-0.048121
number_of_reviews_ltm	-0.084761	-0.042166	0.077105	0.082033	-0.234587	0.629522	-0.059441	0.160993	1.000000	0.000450
lat_lon	-0.036796	-0.886394	-0.512761	0.082805	0.017041	0.009497	0.002320	-0.048121	0.000450	1.000000

In [7]:
```
df_select = df[['price','lat_lon','neighbourhood_group','room_type', 'minimum_nights', 'number_of_reviews','calculated_host_listings_count','availability_365','number_of_reviews_ltm']]
df_select.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 36524 entries, 2 to 19816
Data columns (total 9 columns):
 #   Column                          Non-Null Count  Dtype
---  ------                          --------------  -----
 0   price                           36524 non-null  int64
 1   lat_lon                         36524 non-null  float64
 2   neighbourhood_group             36524 non-null  object
 3   room_type                       36524 non-null  object
 4   minimum_nights                  36524 non-null  int64
 5   number_of_reviews               36524 non-null  int64
 6   calculated_host_listings_count  36524 non-null  int64
 7   availability_365                36524 non-null  int64
 8   number_of_reviews_ltm           36524 non-null  int64
dtypes: float64(1), int64(6), object(2)
memory usage: 2.8+ MB
```

Step 3: Incorporate Categorical Variables into the Data and Scale the Dataset

The purpose of this step was to incorporate room type and neighborhood or NYC burrough into the dataset as "dummy variables" using one hot encoding. Also conducted during this step was a targeted correlation between price and the remaining variables.The strongest positive correlations were room types of 'Entire home/apt', neighborhood groups of 'Manhattan' and 365 day availability. Strongest negative correlation was a room type of "Private room". Finally the dataset was normalized.

In [8]:
```
 # One-hot encode the neighbourhood_group column
dfx = pd.concat([df_select,
              pd.get_dummies(df_select['neighbourhood_group'])],axis=1)
```

In [9]:
```
 # One-hot encode the room_type column
X = pd.concat([dfx,
              pd.get_dummies(dfx['room_type'])],axis=1)

# Drop the original categorical column and the response variable
df = X.drop(['neighbourhood_group','room_type'], axis=1)
display(df.info())
display(df[df.columns[0:]].corr()['price'][:].sort_values(ascending=False).to_frame())
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 36524 entries, 2 to 19816
Data columns (total 16 columns):
 #   Column                          Non-Null Count  Dtype
---  ------                          --------------  -----
 0   price                           36524 non-null  int64
 1   lat_lon                         36524 non-null  float64
 2   minimum_nights                  36524 non-null  int64
 3   number_of_reviews               36524 non-null  int64
 4   calculated_host_listings_count  36524 non-null  int64
 5   availability_365                36524 non-null  int64
 6   number_of_reviews_ltm           36524 non-null  int64
 7   Bronx                           36524 non-null  uint8
 8   Brooklyn                        36524 non-null  uint8
 9   Manhattan                       36524 non-null  uint8
 10  Queens                          36524 non-null  uint8
 11  Staten Island                   36524 non-null  uint8
 12  Entire home/apt                 36524 non-null  uint8
 13  Hotel room                      36524 non-null  uint8
 14  Private room                    36524 non-null  uint8
 15  Shared room                     36524 non-null  uint8
dtypes: float64(1), int64(6), uint8(9)
memory usage: 2.5 MB
None
```

	price
price	1.000000
Entire home/apt	0.585895
Manhattan	0.269626
availability_365	0.155715
calculated_host_listings_count	0.152782
Hotel room	0.144978
lat_lon	0.082805
number_of_reviews_ltm	0.082033
number_of_reviews	-0.000474
Staten Island	-0.037760
Bronx	-0.085095
minimum_nights	-0.088323
Shared room	-0.098770
Brooklyn	-0.112220
Queens	-0.151669
Private room	-0.585485

In [10]:
```
X = scale(df)# Normalize the data
display(pd.DataFrame(X).describe().transpose())# Display the normalize data statistics
corr_ = pd.DataFrame(X).corr() #Display the correlation matrix for the normalized data
pd.DataFrame(corr_).style.background_gradient(cmap = 'YlOrRd')
```

	count	mean	std	min	25%	50%	75%	max
0	36524.0	5.539893e-15	1.000014	-1.415415	-0.746793	-0.283901	0.436153	6.978363
1	36524.0	9.434973e-14	1.000014	-3.783566	-0.643971	0.177789	0.568060	5.630077
2	36524.0	-1.498075e-14	1.000014	-0.587472	-0.556147	0.258299	0.320948	38.537241
3	36524.0	3.666876e-16	1.000014	-0.489330	-0.471433	-0.381952	-0.024027	25.997131
4	36524.0	-1.983690e-14	1.000014	-0.263174	-0.263174	-0.263174	-0.228420	7.591338
5	36524.0	7.306705e-15	1.000014	-0.932757	-0.932757	-0.429781	1.028121	1.727913
6	36524.0	7.110498e-15	1.000014	-0.472989	-0.472989	-0.411815	-0.044770	53.849669
7	36524.0	4.900318e-14	1.000014	-0.209098	-0.209098	-0.209098	-0.209098	4.782457
8	36524.0	2.021351e-15	1.000014	-0.797183	-0.797183	-0.797183	1.254417	1.254417
9	36524.0	-1.425716e-14	1.000014	-0.807972	-0.807972	-0.807972	1.237666	1.237666
10	36524.0	1.973372e-14	1.000014	-0.441323	-0.441323	-0.441323	-0.441323	2.265913
11	36524.0	4.617554e-15	1.000014	-0.108116	-0.108116	-0.108116	-0.108116	9.249311
12	36524.0	-1.630806e-13	1.000014	-1.170731	-1.170731	0.854167	0.854167	0.854167
13	36524.0	2.449373e-15	1.000014	-0.065283	-0.065283	-0.065283	-0.065283	15.317921
14	36524.0	-7.222863e-15	1.000014	-0.823098	-0.823098	-0.823098	1.214922	1.214922
15	36524.0	-5.620017e-14	1.000014	-0.117931	-0.117931	-0.117931	-0.117931	8.479516

Out[10]:

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
0	1.000000	0.082805	-0.088323	-0.000474	0.152782	0.155715	0.082033	-0.085095	-0.112220	0.269626	-0.151669	-0.037760	0.585895	0.144978	-0.585485	-0.098770
1	0.082805	1.000000	0.017041	0.009497	0.002320	-0.048121	0.000450	-0.492280	0.576398	-0.236596	-0.273398	0.321136	0.088623	-0.000014	-0.083587	-0.023660
2	-0.088323	0.017041	1.000000	-0.147075	0.124210	-0.054423	-0.234587	-0.060490	-0.018337	0.099410	-0.064700	-0.034070	-0.006647	-0.028905	0.010089	0.001815
3	-0.000474	0.009497	-0.147075	1.000000	-0.096784	0.089859	0.629522	0.006102	0.025945	-0.055635	0.030901	0.017911	0.022851	0.044267	-0.026437	-0.010235
4	0.152782	0.002320	0.124210	-0.096784	1.000000	0.131778	-0.059441	-0.046750	-0.101159	0.114416	0.014788	-0.025462	0.014032	0.001746	-0.008779	-0.023518
5	0.155715	-0.048121	-0.054423	0.089859	0.131778	1.000000	0.160993	0.102307	-0.075341	-0.060966	0.105373	0.066505	0.055361	0.044967	-0.064226	0.010751
6	0.082033	0.000450	-0.234587	0.629522	-0.059441	0.160993	1.000000	0.026521	0.002098	-0.073314	0.071627	0.028496	0.050213	0.022147	-0.049378	-0.017275
7	-0.085095	-0.492280	-0.060490	0.006102	-0.046750	0.102307	0.026521	1.000000	-0.166689	-0.168945	-0.092280	-0.022607	-0.044166	-0.013651	0.042079	0.017640
8	-0.112220	0.576398	-0.018337	0.025945	-0.101159	-0.075341	0.002098	-0.166689	1.000000	-0.644102	-0.351815	-0.086188	-0.048267	-0.047722	0.058642	-0.015778
9	0.269626	-0.236596	0.099410	-0.055635	0.114416	-0.060966	-0.073314	-0.168945	-0.644102	1.000000	-0.356577	-0.087355	0.153711	0.069598	-0.165311	0.005835
10	-0.151669	-0.273398	-0.064700	0.030901	0.014788	0.105373	0.071627	-0.092280	-0.351815	-0.356577	1.000000	-0.047714	-0.118182	-0.019689	0.119996	0.006582
11	-0.037760	0.321136	-0.034070	0.017911	-0.025462	0.066505	0.028496	-0.022607	-0.086188	-0.087355	-0.047714	1.000000	0.008307	-0.007058	-0.004926	-0.010548
12	0.585895	0.088623	-0.006647	0.022851	0.014032	0.055361	0.050213	-0.044166	-0.048267	0.153711	-0.118182	0.008307	1.000000	-0.076429	-0.963626	-0.138066
13	0.144978	-0.000014	-0.028905	0.044267	0.001746	0.044967	0.022147	-0.013651	-0.047722	0.069598	-0.019689	-0.007058	-0.076429	1.000000	-0.053734	-0.007699
14	-0.585485	-0.083587	0.010089	-0.026437	-0.008779	-0.064226	-0.049378	0.042079	0.058642	-0.165311	0.119996	-0.004926	-0.963626	-0.053734	1.000000	-0.097069
15	-0.098770	-0.023660	0.001815	-0.010235	-0.023518	0.010751	-0.017275	0.017640	-0.015778	0.005835	0.006582	-0.010548	-0.138066	-0.007699	-0.097069	1.000000

Step 4: Principal Component Analysis

The PCA was conducted on the normalized data and indicate the following results:

- The most important variables in the dataset are 'price', 'Manhattan', 'Entire home/apt', and 'Private room'
- The least significant variables seem to be 'Hotel room' and 'Queens'.
- Information content in the data is dispersed. There dont seem to be any significant clusters of variability. As indicated by the scree plot and the measures of the cumulative variability, you dont get above 90% of the variability explained until you get to 11 of the 16 principal components. Once you get to roughly 13 principal components, marginal variability apears to go to zero. As evidenced by the correlation matrices and the heatmaps, most of the variables could be considered to have a significant component loading depending on the dimension in which they are viewed. The practical effect of this seems to be that action taken to reduce the dimensionality of the dataset won't add any significant benefits.

In [11]:
```
# Select the number of components
pca1 = PCA(n_components=16)
# Fit the PCA model
pca1.fit(X)
```

Out[11]:
```
PCA(n_components=16)
```

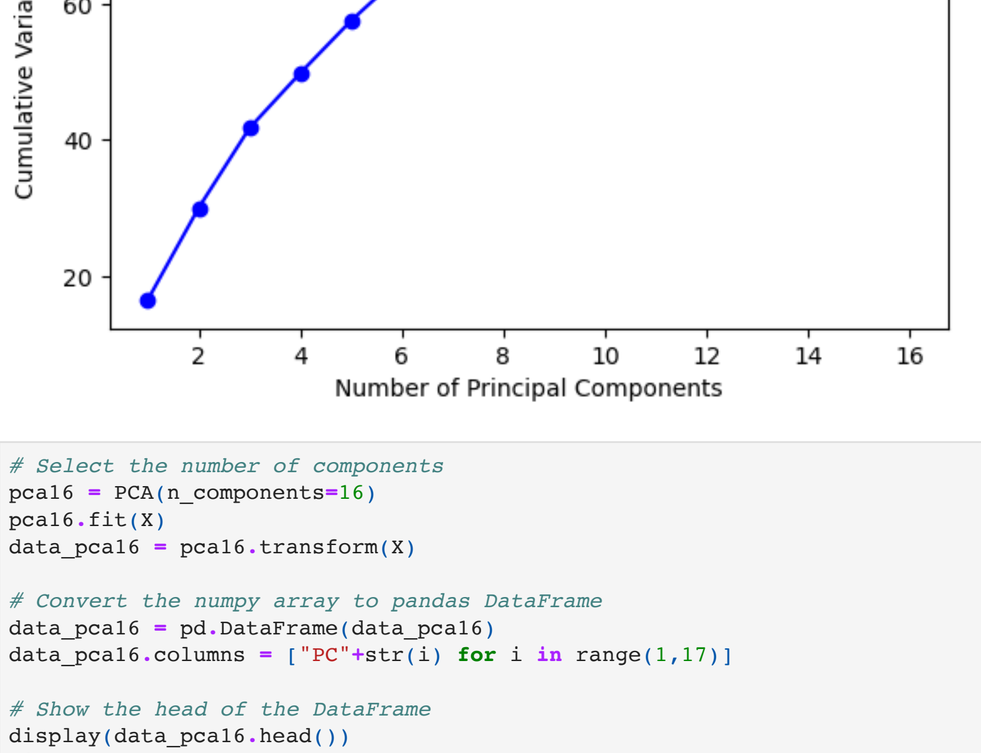
In [12]:
```
#The amount of variance that each PC explains
var = pca1.explained_variance_ratio_
display(var)
```

```
array([1.65195096e-01, 1.34942542e-01, 1.17200904e-01, 8.08398602e-02,
       7.70139078e-02, 6.83907993e-02, 6.70856015e-02, 6.42368108e-02,
       6.33128426e-02, 5.42576742e-02, 4.61935056e-02, 2.61700494e-02,
       2.17283626e-02, 1.34320435e-02, 6.22380475e-33, 5.16641682e-33])
```

In [13]:
```
#Cumulative Variance explains
var1 = np.cumsum(np.round(pca1.explained_variance_ratio_, decimals=4)*100)
display(var1)
```

```
array([16.52, 30.01, 41.73, 49.81, 57.51, 64.35, 71.06, 77.48, 83.81,
       89.24, 93.86, 96.48, 98.65, 99.99, 99.99, 99.99])
```

In [14]:
```
var1 = pd.DataFrame(var1, index=np.arange(1,17))
plt.plot(var1,'-o',color='blue')
plt.title('Scree Plot')
plt.xlabel('Number of Principal Components')
plt.ylabel('Cumulative Variance Explained')
plt.savefig('scree_plot.png',dpi=100,bbox_inches='tight')
plt.show()
```



In [15]:
```
# Select the number of components
pca16 = PCA(n_components=16)
pca16.fit(X)
data_pca16 = pca16.transform(X)

# Convert the numpy array to pandas DataFrame
data_pca16 = pd.DataFrame(data_pca16)
data_pca16.columns = ["PC"+str(i) for i in range(1,17)]

# Show the head of the DataFrame
display(data_pca16.head())
display(data_pca16.corr())
```

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10	PC11	PC12	PC13	PC14	PC15	PC16
0	1.985462	-0.577469	0.687516	-1.269858	-2.613957	-0.497312	-0.356578	0.348281	-0.725955	0.259770	-1.033230	1.721738	-1.038442	0.247408	3.330669e-16	7.771561e-16
1	1.649282	-0.675217	-0.170214	0.425239	-0.003942	0.126435	0.262893	-0.061995	0.360419	0.214147	-1.145967	-0.686522	-0.364044	0.242477	3.330669e-16	-7.216450e-16
2	1.295075	2.063616	-0.424649	-0.932033	-0.293281	0.386445	-0.234463	0.151246	-0.287277	-0.102477	-0.403823	0.576902	-0.259064	0.234949	-2.220446e-16	4.996004e-16
3	0.623319	1.974616	-0.481647	-0.789052	0.378923	-0.226539	-0.271675	0.031405	0.009326	0.479975	0.344678	-0.244835	-0.305966	0.151578	-2.220446e-16	1.110223e-16
4	1.784482	-0.174928	2.224686	1.621296	0.475536	0.107636	-0.095550	-0.043105	1.363229	1.097498	-1.097350	-1.618384	-2.879385	0.585529	7.771561e-16	-8.326673e-16

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10	PC11	PC12	PC13	PC14	PC15	PC16
PC1	1.000000e+00	1.523014e-16	-5.197114e-17	9.291861e-16	-4.821917e-16	9.808515e-16	-2.083315e-16	2.422911e-16	3.451393e-16	1.430505e-15	-1.990741e-16	1.357457e-15	-8.221773e-16	4.365259e-16	0.186571	-0.199935
PC2	1.523014e-16	1.000000e+00	1.836350e-16	-2.551501e-16	-3.359047e-16	-5.094300e-17	1.174007e-16	-9.892546e-18	1.382529e-16	8.108446e-16	-4.979036e-16	-2.945410e-16	1.079519e-16	6.689318e-16	-0.333345	0.081764
PC3	-5.197114e-17	1.836350e-16	1.000000e+00	7.357477e-17	1.987143e-16	-2.004536e-16	-4.495121e-16	1.332121e-17	5.788909e-17	5.434269e-17	7.493605e-17	3.759816e-16	1.784906e-15	5.733677e-16	-0.198341	0.071493
PC4	9.291861e-16	-2.551501e-16	7.357477e-17	1.000000e+00	-8.831691e-18	-4.671867e-16	-3.279430e-16	3.184741e-16	-2.345375e-17	-1.063903e-15	-5.804964e-16	-2.428702e-17	1.259448e-16	-1.636388e-16	0.453665	-0.645487
PC5	-4.821917e-16	-3.359047e-16	1.987143e-16	-8.831691e-18	1.000000e+00	2.192629e-16	2.427761e-16	4.448873e-16	9.724887e-17	3.242284e-16	-5.086496e-16	-2.775468e-16	3.045571e-17	5.346449e-16	0.071309	0.188502
PC6	9.808515e-16	-5.094300e-17	-2.004536e-16	-4.671867e-16	2.192629e-16	1.000000e+00	-3.330281e-16	1.797741e-17	8.215171e-16	6.299404e-16	6.999940e-16	4.284994e-16	-2.101045e-16	9.401530e-16	-0.201788	0.323154
PC7	-2.083315e-16	1.174007e-16	-4.495121e-16	-3.279430e-16	2.427761e-16	-3.330281e-16	1.000000e+00	-7.507384e-16	9.572675e-16	9.259192e-16	6.108923e-16	2.539663e-16	-3.396047e-16	-9.551215e-16	0.106846	-0.182019
PC8	2.422911e-16	-9.892546e-18	1.332121e-17	3.184741e-16	4.448873e-16	1.797741e-17	-7.507384e-16	1.000000e+00	-2.282171e-16	1.143042e-16	-7.572605e-16	-6.436984e-17	-1.146200e-16	2.985484e-16	-0.457940	0.173199
PC9	3.451393e-16	1.382529e-16	5.788909e-17	-2.345375e-17	9.724887e-17	8.215171e-16	9.572675e-16	-2.282171e-16	1.000000e+00	-4.881320e-16	-2.781155e-16	7.277594e-16	-2.123849e-16	3.570321e-16	-0.435207	-0.121227
PC10	1.430505e-15	8.108446e-16	5.434269e-17	-1.063903e-15	3.242284e-16	6.299404e-16	9.259192e-16	1.143042e-16	-4.881320e-16	1.000000e+00	6.590839e-17	2.748950e-16	-7.692103e-17	7.047150e-16	-0.059290	0.104858
PC11	-1.990741e-16	-4.979036e-16	7.493605e-17	-5.804964e-16	-5.086496e-16	6.999940e-16	6.108923e-16	-7.572605e-16	-2.781155e-16	6.590839e-17	1.000000e+00	2.417813e-16	5.868821e-16	-4.642767e-16	-0.158442	0.055199
PC12	1.357457e-15	-2.945410e-16	3.759816e-16	-2.428702e-17	-2.775468e-16	4.284994e-16	2.539663e-16	-6.436984e-17	7.277594e-16	2.748950e-16	2.417813e-16	1.000000e+00	-1.180466e-15	-3.553876e-16	0.087304	0.482589
PC13	-8.221773e-16	1.079519e-16	1.784906e-15	1.259448e-16	3.045571e-17	-2.101045e-16	-3.396047e-16	-1.146200e-16	-2.123849e-16	-7.692103e-17	5.868821e-16	-1.180466e-15	1.000000e+00	8.209378e-16	-0.293488	-0.224303
PC14	4.365259e-16	6.689318e-16	5.733677e-16	-1.636388e-16	5.346449e-16	9.401530e-16	-9.551215e-16	2.985484e-16	3.570321e-16	7.047150e-16	-4.642767e-16	-3.553876e-16	8.209378e-16	1.000000e+00	0.141552	-0.111220
PC15	1.865714e-01	-3.333454e-01	-1.983406e-01	4.536649e-01	7.130877e-02	-2.017885e-01	1.068460e-01	-4.579403e-01	-4.352074e-01	-5.928969e-02	-1.584425e-01	8.730435e-02	-2.934884e-01	1.415518e-01	1.000000	-0.391274
PC16	-1.999345e-01	8.176412e-02	7.149343e-02	-6.454870e-01	1.885020e-01	3.231540e-01	-1.820191e-01	1.731987e-01	-1.212269e-01	1.048579e-01	5.519922e-02	4.825892e-01	-2.243028e-01	-1.112203e-01	-0.391274	1.000000

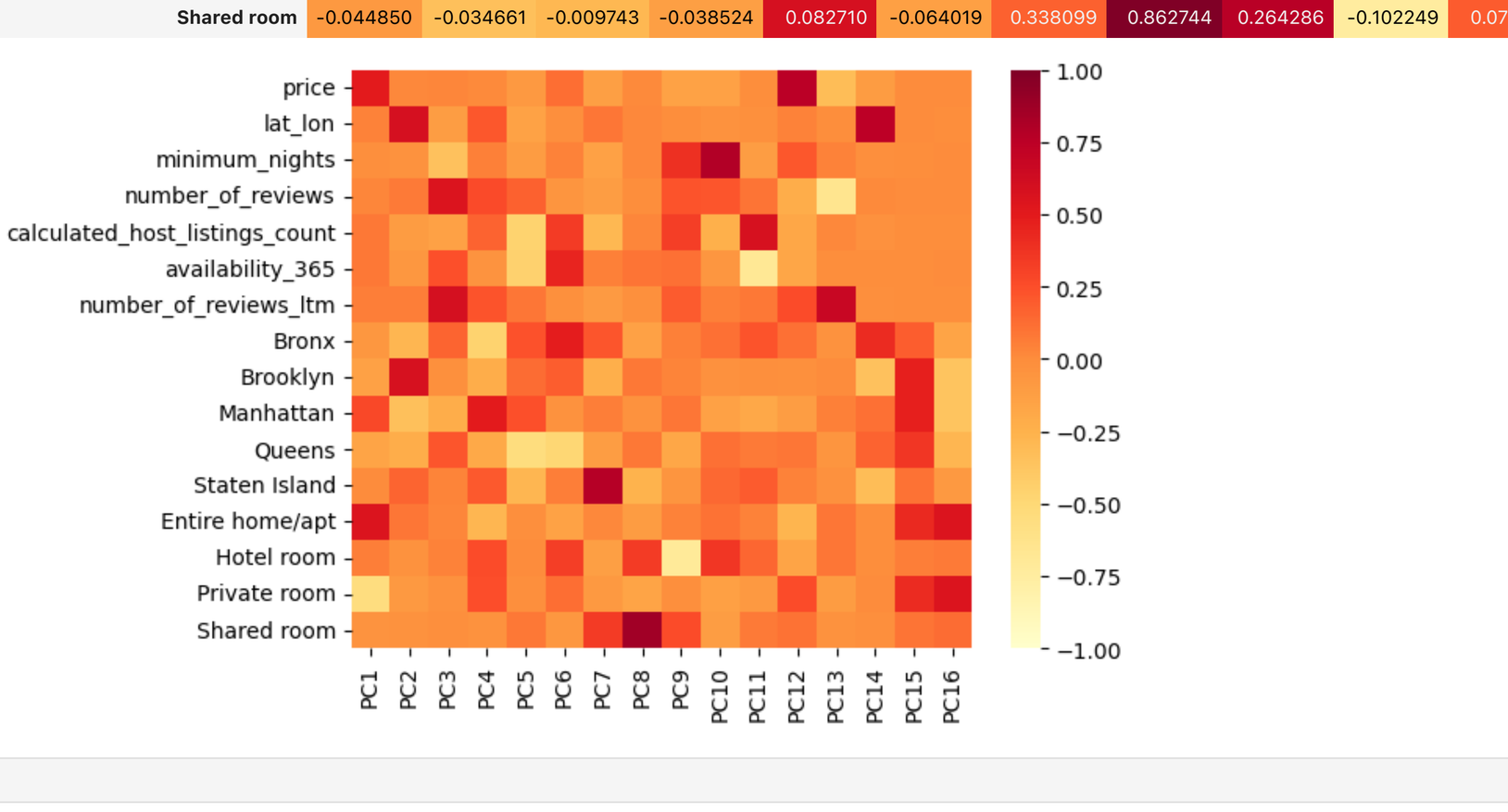
All pairwise combinations are cose to zero which is indicative of no multicollinearity among principal components.

In [16]:
```
# Show the loadings for the 1st components
pca16.components_[[0]]
```

Out[16]:
```
array([[ 0.49436566,  0.04118856, -0.01297004,  0.02628435,  0.08448953,
         0.0832199 ,  0.05627946, -0.06993217, -0.13351556,  0.27544056,
        -0.15112606,  0.0024715 ,  0.55148041,  0.05822177, -0.55213588,
        -0.04485018]])
```

In [17]:
```
corr_16 = pd.DataFrame(pca16.components_.transpose(),
           index=df.loc[:,'price':'Shared room'].columns,
           columns=["PC"+str(i) for i in range(1,17)])
display(pd.DataFrame(corr_16).style.background_gradient(cmap = 'YlOrRd'))
ax = sb.heatmap(corr_16, annot=False, cmap = 'YlOrRd', vmin = -1, vmax = 1)
plt.show()
```

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10	PC11	PC12	PC13	PC14	PC15	PC16
price	0.494366	0.019726	0.024750	0.013123	-0.082987	0.118820	-0.118382	0.012789	-0.142628	-0.134824	-0.003869	0.757667	-0.312720	-0.094119	0.000000	0.000000
lat_lon	0.041189	0.592048	-0.107348	0.218596	-0.141812	-0.011429	0.087850	0.017217	-0.002317	-0.033825	-0.022378	0.042853	-0.000951	0.746145	0.000000	-0.000000
minimum_nights	-0.012970	-0.037755	-0.347262	0.050110	-0.093974	0.040430	-0.133461	0.018612	0.394311	0.796024	-0.103264	0.212317	0.040142	-0.013854	-0.000000	0.000000
number_of_reviews	0.026284	0.071200	0.552707	0.273389	0.175848	-0.049760	-0.104132	-0.007327	0.228779	0.221871	0.094714	-0.212012	-0.643504	0.011531	0.000000	-0.000000
calculated_host_listings_count	0.084490	-0.094115	-0.140241	0.169653	-0.455272	0.337139	-0.288567	0.030013	0.324731	-0.235346	0.581545	-0.173810	0.017159	-0.030162	-0.000000	-0.000000
availability_365	0.083220	-0.065082	0.247721	-0.046817	-0.452562	0.447795	0.051175	0.099129	0.112693	-0.059676	-0.680342	-0.168357	-0.003885	-0.004160	-0.000000	-0.000000
number_of_reviews_ltm	0.056279	0.057868	0.594665	0.230606	0.089309	-0.016554	-0.090609	-0.020525	0.197982	0.054122	0.081691	0.260563	0.673028	-0.011755	-0.000000	-0.000000
Bronx	-0.069932	-0.277898	0.158760	-0.456528	0.241822	0.490120	0.220642	-0.137241	0.047105	0.114314	0.233853	0.109733	-0.035246	0.417605	0.195272	-0.149211
Brooklyn	-0.133516	0.584626	-0.021376	-0.215595	0.127282	0.192071	-0.233596	0.084471	0.035789	-0.027639	-0.014284	-0.016206	0.006306	-0.344373	0.475098	-0.363031
Manhattan	0.275441	-0.341754	-0.218352	0.498337	0.244525	-0.034873	0.055357	-0.037286	0.086747	-0.137065	-0.183061	-0.104373	0.051653	0.113467	0.476482	-0.364089
Queens	-0.151126	-0.215745	0.221086	-0.187960	-0.541923	-0.490624	-0.108984	0.085466	-0.173343	0.114129	0.076264	0.087585	-0.050383	0.168579	0.360039	-0.275112
Staten Island	0.002472	0.163468	0.034519	0.209284	-0.279281	0.060490	0.775292	-0.252848	-0.049195	0.144261	0.200540	0.042905	-0.024820	-0.313886	0.104164	-0.079594
Entire home/apt	0.551480	0.091312	0.024684	-0.274147	-0.008817	-0.147154	0.016972	-0.098540	0.045075	0.103288	0.046521	-0.267217	0.091210	-0.001003	0.423029	0.553617
Hotel room	0.058222	-0.036223	0.046789	0.262682	0.000898	0.322818	-0.122847	0.336009	-0.706331	0.363312	0.149119	-0.150758	0.087164	-0.005353	0.055684	0.072873
Private room	-0.552136	-0.078889	-0.028733	0.250255	-0.010852	0.120515	-0.080953	-0.149850	-0.014439	-0.127852	-0.085020	0.263893	-0.095706	0.004729	0.420305	0.550053
Shared room	-0.044850	-0.034661	-0.009743	-0.038524	0.082710	-0.064019	0.338099	0.862744	0.264286	-0.102249	0.077795	0.105582	-0.032243	-0.012699	0.099633	0.130390



In [ ]: