DC AirBnB Listing Analysis

September 17, 2020

1 Airbnb Washington DC Project

1.1 Part ii: Understanding the factors determining price of listing

1.2 Data set: InsideAirbnb - Washington D.C.

1.2.1 Lok Tin Kevin Chan

Airbnb is a platform economy that facilitate digital interactions between real estate owners and customers for short to mid-term stay. The aim of the project is to explore Airbnb's in Washington DC and gain a better understanding:

```
1) What do users care about during their Airbnb Stay?
2) What factors affect listing price of an Airbnb listing?
```

This second part of the project aims to understand what are the relationship that affects the price per night for listing in Washington DC by analysis the listings.csv file in InsideAirBnB dataset.

The dataset is collected through web scrapping publicly available information on Airbnb website. As of the date analysis the data is updated to from 2015 to September 2019.

[15]:
```
# Importing libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import pandas_profiling
import geopandas as geopd
import seaborn as sns
import datetime as dt
import spacy
import en_core_web_lg
import string
import nltk
import sklearn

from sklearn.model_selection import train_test_split
from sklearn.feature_extraction.text import CountVectorizer, TfidfTransformer
from sklearn.model_selection import KFold
from sklearn.model_selection import cross_val_score
from wordcloud import WordCloud, STOPWORDS
from nltk.corpus import stopwords
```

```python
from geopy.distance import geodesic
from collections import Counter
from math import sqrt
from xgboost import XGBRegressor
from spacy.lang.en.stop_words import STOP_WORDS
from scipy import sparse
from eli5 import show_weights

pd.options.mode.chained_assignment = None
```

[3]:
```python
# import dataset [listing.csv] for data cleaning and eda

df = pd.read_csv("../0_Data/listings.csv")
```

```
C:\Users\User\Anaconda3\lib\site-packages\IPython\core\interactiveshell.py:3063:
DtypeWarning: Columns (61,62) have mixed types.Specify dtype option on import or
set low_memory=False.
  interactivity=interactivity, compiler=compiler, result=result)
```

[193]:
```python
# Taking a peak at sample of the raw data
df.head(5)
```

[193]:
```
     id                      listing_url        scrape_id last_scraped  \
0  3344  https://www.airbnb.com/rooms/3344  20190922191721   2019-09-22
1  3362  https://www.airbnb.com/rooms/3362  20190922191721   2019-09-22
2  3662  https://www.airbnb.com/rooms/3662  20190922191721   2019-09-22
3  3670  https://www.airbnb.com/rooms/3670  20190922191721   2019-09-22
4  3686  https://www.airbnb.com/rooms/3686  20190922191721   2019-09-22

                                             name  \
0                White House/Center City, 1 roommate
1  Convention Center Rowhouse & In Law: 2 Units, 4BR
2                                  Vita's Hideaway II
3                 Beautiful Sun-Lit U Street 1BR/1BA
4                                     Vita's Hideaway

                                           summary  \
0  This listing is for one roommate in a 2BR/2BA …
1  An architect-designed rowhouse featuring a lar…
2  IMPORTANT NOTES * Carefully read and be sure t…
3  Convenient location perfect for business trave…
4  IMPORTANT NOTES * Carefully read and be sure t…

                                             space  \
0  You have found The One, but be sure to message…
1  This listing features our 19th century Victori…
2  IMPORTANT NOTES * Airbnb keeps accurate track …
```

```
3  Sunny, bright private room. Includes a queen s…
4  IMPORTANT NOTES * Airbnb keeps accurate track …

                                        description experiences_offered  \
0  This listing is for one roommate in a 2BR/2BA …                none
1  An architect-designed rowhouse featuring a lar…                none
2  IMPORTANT NOTES * Carefully read and be sure t…                none
3  Convenient location perfect for business trave…                none
4  IMPORTANT NOTES * Carefully read and be sure t…                none

                             neighborhood_overview  … instant_bookable  \
0  This is the hottest neighborhood in D.C. at th…  …                t
1                                              NaN  …                t
2  We love that our neighborhood is up and coming…  …                f
3  We are nicely situated on a quiet residential …  …                f
4  We love that our neighborhood is up and coming…  …                f

  is_business_travel_ready          cancellation_policy  \
0                        f                     moderate
1                        f  strict_14_with_grace_period
2                        f                     moderate
3                        f  strict_14_with_grace_period
4                        f                     moderate

  require_guest_profile_picture require_guest_phone_verification  \
0                             f                                f
1                             f                                f
2                             f                                f
3                             f                                f
4                             f                                f

   calculated_host_listings_count  \
0                               2
1                               5
2                               3
3                               1
4                               3

   calculated_host_listings_count_entire_homes  \
0                                            1
1                                            5
2                                            0
3                                            0
4                                            0

  calculated_host_listings_count_private_rooms  \
0                                            1
```

```
1                                              0
2                                              3
3                                              1
4                                              3

   calculated_host_listings_count_shared_rooms  reviews_per_month
0                                            0               0.09
1                                            0               1.32
2                                            0               0.35
3                                            0               1.44
4                                            0               0.66

[5 rows x 106 columns]
```

1.2.2 Metadata Information

id = unique ID for the listing

listing url = link to AirBnB listing

scrape id = Date and time it was scraped

name = Name of the listing

summary = brief description of the listing

Space = additional description

description = full description

neighborhood = Neighborhood where the listing is located

Cancellation policy = policy for cancellation

host_id = unique ID for host

host_name = host name

host_description = description of host

calculated_host_listings_count = number of listing assoicated with unique id for the host

latitude = latitude of location

longtitude = longtitude of location

property type = type of property

room type = type of room for rent

price = price per night for listing

bedrooms = number of bedrooms

bathrooms = number of bathrooms

beds = number of beds

number_of_reviews = total number of review left at listing

last review = Date of the lastest review

1.2.3 Data cleaning

[4]:
```
# data cleaning part i

# Only keeping columns that are interesting and relevant to analysis
df_clean = df.iloc[:
↪,[0,4,5,19,21,24,28,32,39,48,49,51,52,53,54,55,56,60,82,85,86]]

# convert superhost to from t/f to 0 = false and 1 = true

df_clean['host_is_superhost'] = df_clean['host_is_superhost'].map({'t':1,'f':0})

# convert last review from object to date

df_clean['last_review'] = pd.to_datetime(df_clean['last_review'], format =␣
↪"%Y-%M-%d")

# Convert price into numerical value by remove $ symbol

df_clean['price'] = df_clean['price'].replace('[\$,]', '', regex=True).
↪astype(float)

# Shortening the Neightbourhood_clean by shortening the name

neighbourhood_shortened = {'Downtown, Chinatown, Penn Quarters, Mount Vernon␣
↪Square, North Capitol Street':
                            'Downtown',
                            'Shaw, Logan Circle': 'Shaw',
                            'Historic Anacostia': 'Anacostia',
                            'Howard University, Le Droit Park, Cardozo/Shaw':␣
↪'Howard U',
                            'Columbia Heights, Mt. Pleasant, Pleasant Plains,␣
↪Park View': 'Columbia Heights',
                            'Capitol Hill, Lincoln Park': 'Capitol Hill',
                            'Eastland Gardens, Kenilworth': 'Eastland Gardens',
                            'Ivy City, Arboretum, Trinidad, Carver Langston':␣
↪'Ivy City',
                            'Kalorama Heights, Adams Morgan, Lanier Heights':␣
↪'Adams Morgan',
                            'Dupont Circle, Connecticut Avenue/K Street':␣
↪'Dupont Circle',
                            'Cathedral Heights, McLean Gardens, Glover Park':␣
↪'Cathedral Heights',
```

```
                            'Brightwood Park, Crestwood, Petworth': 'Brightwood␣
↪Park',
                            'Union Station, Stanton Park, Kingman Park': 'Union␣
↪Station',
                            'Southwest Employment Area, Southwest/Waterfront,␣
↪Fort McNair, Buzzard Point': 'Southwest',
                            'Edgewood, Bloomingdale, Truxton Circle, Eckington':
↪ 'Edgewood',
                            'Takoma, Brightwood, Manor Park': 'Takoma',
                            'Friendship Heights, American University Park,␣
↪Tenleytown': 'Friendship Heights',
                            'Spring Valley, Palisades, Wesley Heights, Foxhall␣
↪Crescent, Foxhall Village, Georgetown Reservoir':
                            'Spring Valley',
                            'Capitol View, Marshall Heights, Benning Heights':␣
↪'Capitol View',
                            'Congress Heights, Bellevue, Washington Highlands':␣
↪'Congress Heights',
                            'Brookland, Brentwood, Langdon': 'Brookland',
                            'Colonial Village, Shepherd Park, North Portal␣
↪Estates': 'Colonial Village',
                            'Sheridan, Barry Farm, Buena Vista': 'Sheridan',
                            'Lamont Riggs, Queens Chapel, Fort Totten, Pleasant␣
↪Hill': 'Lamont Riggs',
                            'Georgetown, Burleith/Hillandale': 'Georgetown',
                            'Cleveland Park, Woodley Park, Massachusetts Avenue␣
↪Heights, Woodland-Normanstone Terrace':
                            'Cleveland Park',
                            'West End, Foggy Bottom, GWU': 'West End',
                            'North Cleveland Park, Forest Hills, Van Ness':␣
↪'Van Ness',
                            'Douglas, Shipley Terrace': 'Douglas',
                            'River Terrace, Benning, Greenway, Dupont Park':␣
↪'River Terrace',
                            'North Michigan Park, Michigan Park, University␣
↪Heights': 'North Michigan Park',
                            'Hawthorne, Barnaby Woods, Chevy Chase':␣
↪'Hawthorne',
                            'Woodridge, Fort Lincoln, Gateway': 'Woodridge',
                            'Twining, Fairlawn, Randle Highlands, Penn Branch,␣
↪Fort Davis Park, Fort Dupont': 'Twining',
                            'Fairfax Village, Naylor Gardens, Hillcrest, Summit␣
↪Park': 'Fairfax Village',
                            'Deanwood, Burrville, Grant Park, Lincoln Heights,␣
↪Fairmont Heights': 'Deanwood',
                            'Mayfair, Hillbrook, Mahaning Heights': 'Mayfair',
```

```
                             'Near Southeast, Navy Yard': 'Navy Yard',
                             'Woodland/Fort Stanton, Garfield Heights, Knox␣
↪Hill': 'Woodland/Fort Stanton'}

df_clean['neighbourhood_cleansed'] = df_clean['neighbourhood_cleansed'].
↪replace(neighbourhood_shortened)
```

[5]:
```
# Data cleaning part ii

# Check for null values

df_clean.isnull().sum()

# filling in the one single missing value of superhost (id:3890435 manual check)

df_clean['host_is_superhost'].fillna(0, inplace=True)

# filling in three missing names (id: 6984846, 8320890, 16269511 manual check )

df_clean.loc[df_clean['id'] == 6984846, 'name'] = 'Entire apartment hosted by␣
↪Paula'
df_clean.loc[df_clean['id']==8320890, 'name'] = 'NA'
df_clean.loc[df_clean['id']==16269511, 'name'] ='Entire guesthouse hosted by␣
↪Christina'

# filling in the one single missing host name and list count (id: 3890435␣
↪manual check)

df_clean.loc[df_clean['id']==3890435, 'host_name'] ='Liz'
df_clean.loc[df_clean['id']==3890435, 'host_listings_count'] = 1

# filling in empty bathrooms, bedrooms, beds to be zero as meaning none is␣
↪provided if NAN
df_clean['bathrooms'].fillna(0, inplace=True)
df_clean['bedrooms'].fillna(0, inplace=True)
df_clean['beds'].fillna(0, inplace=True)

df_clean['summary'].fillna("missing", inplace = True)
```

1.2.4 Profile Report

From our profile report that are 9189 listing with 12 numerical variables, 7 categorical, 1 Date and 1 text after cleaning the dataset.

Taking a deeper look at the variables, it is interesting to note the following observations:

- There are 6076 distinct host with 49% of the host having only one listing and 14.7% having two listing. Interestingly though there is one host with 1795 listing (host name: Zeus)

- 45% of the listing has property type Apartment with entire apartment room type (71%) to be most common for listing.
- distribution of listing across the neighborhood are quite even with Columbia Heights and Union station (~10%)

Looking the correlation of Price to other variable, we can note that:

- Price is positively correlated to accommodates, bathrooms, beds, bedrooms (which are related to size), number of listing per host (though maybe skewed by Zeus)
- more interestingly Price is negatively correlated to is whether host is superhot. Which may indicate that superhot are more realistic at pricing their listing.

[19]:
```
# Getting an idea of the distribution of the dataset
pandas_profiling.ProfileReport(df_clean)
# Correlation map is at the end of the report
```

```
HBox(children=(FloatProgress(value=0.0, description='Summarize dataset', max=35.0, style=Progre
```

```
HBox(children=(FloatProgress(value=0.0, description='Generate report structure', max=1.0, style
```

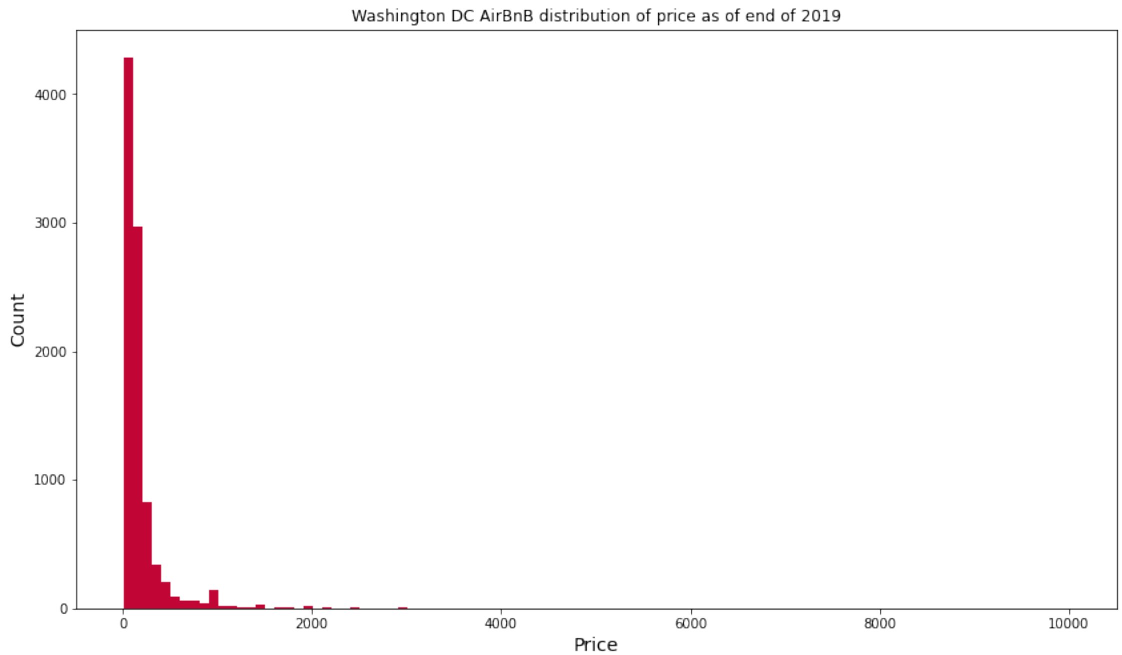
```
HBox(children=(FloatProgress(value=0.0, description='Render HTML', max=1.0, style=ProgressStyle
```

```
<IPython.core.display.HTML object>
```

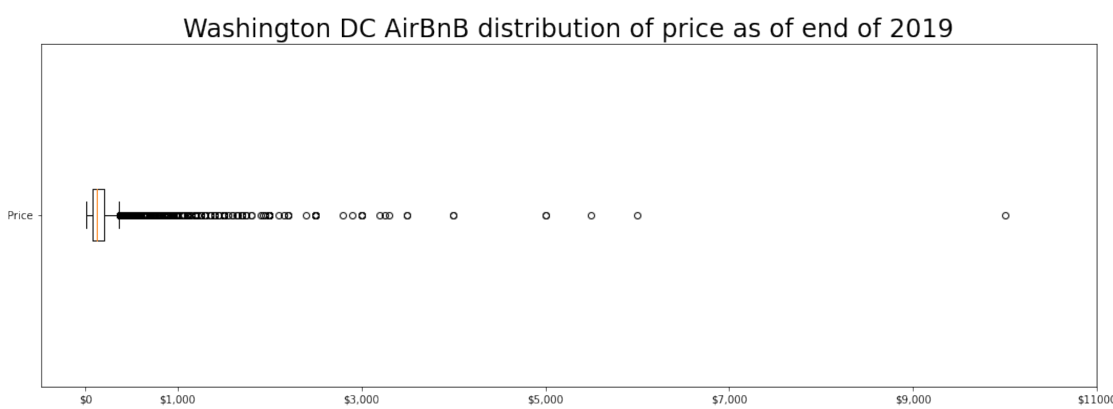
[19]:

1.2.5 Explortatory Data Analysis

[10]:
```
# First lets take a deeper look at price

#config the plot size for better display
plt.figure(figsize=(14, 8))

## distribution of price
plt.hist(df_clean['price'], bins = 100, color = '#c10534')
plt.title('Washington DC AirBnB distribution of price as of end of 2019')
plt.xlabel('Price', fontdict={'fontsize': 14})
plt.ylabel('Count', fontdict={'fontsize': 14});
```



[11]:
```python
# Configure the plot area
plt.figure(figsize=(18, 6))

#boxplot
plt.boxplot(df_clean['price'], vert=False)
plt.title('Washington DC AirBnB distribution of price as of end of 2019',
 ↪fontdict={'fontsize': 24})
plt.yticks(ticks=[1], labels=['Price'])
plt.xticks(ticks=[0, 1000, 3000, 5000, 7000, 9000, 11000], labels=['$0',
 ↪'$1,000', '$3,000', '$5,000', '$7,000','$9,000','$11000']);
```



From the above bar and box chart, we can observe that majority of the listing has price in range between \$0 to \$600 and around 400 listing that has price per night greater than \$600 dollars. Lets first take a look at listing that greater than \$3000 to see whether there is a reasoning behind them.

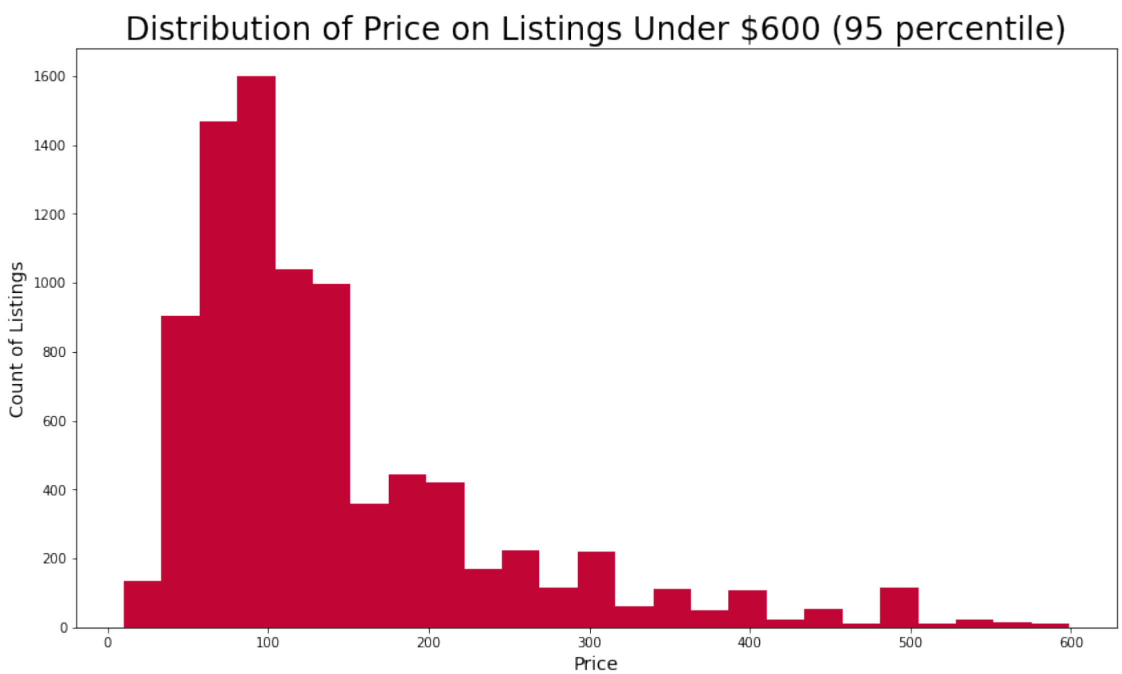
[12]:
```python
# Lets take a look at listing greater than 3000
df_clean[df_clean['price'] > 3000]
```

[12]:
```
            id                                            name  \
2215  12017374              Bright and Charming 2 Bedroom. Hear
2747  14507861               Entire Capitol Hill Home - 5BR/4BA
2844  15054700                    Historic Georgetown Residence
3171  15996618  Large Capitol Hill 3B/3.5BA for the Inauguration!
3602  16466316       Huge Home Presidential Inauguration week 2017
3671  16532102     Entire House at Centrally-located Logan Circle!
3820  16634189                        Good Space for Good People
3860  16661573                                 Inaguration Palace
3937  16709404          Walk to Inauguration from Our Hill Rowhouse!
4024  16769736             Gorgeous Georgian embassy-like home in DC
7398  30939691                        Casa en el Chorro, La Tana
7746  32741852             Luxurious and Historic Georgetown Mansion

                                                summary    host_id host_name  \
2215  AVAILABLE: JUNE, JULY, AND AUGUST. Beautiful 2…     683757    Alison
2747  Historic Federal Row Home on Safest Street on …   19521188    Adrian
2844  Historic neoclassical empire four story home i…   95158537   Lindsey
3171  Welcome to Capitol Hill for Inauguration weeke…   11077252   Emerson
3602  My place is close to DOWNTOWN WASHINGTON DC FO…  108042585    Hansel
3671  Our house is located in the historic Logan Cir…   37551897     Paula
3820  Beautiful three bedroom penthouse duplex, 1900…   77013163     Janai
3860  You'll love the short walk to downtown, the am…   18880505    Andrew
3937  Historic 3-story row house in the heart of Cap…   82205754    Nathan
4024  Gorgeous modern Georgian home in an exclusive …   49351903      Rosa
7398  Hermosa casa en el Chorro, ubicada a dos cuadr…  230409838   Gabriel
7746  This majestic Georgetown mansion is in the fin…  101353697     Cathy

                                             host_about  host_is_superhost  \
2215  My name is Alison Schuyler Ogden. Check me out…                0.0
2747                                                NaN                0.0
2844                                                NaN                0.0
3171                                                NaN                0.0
3602                                                NaN                0.0
3671  Hi! We're the Luceros - we're a family of four…                0.0
3820  I'd like to share the comfort and peace I enjo…                0.0
3860                                                NaN                0.0
3937                                                NaN                0.0
4024                                                NaN                0.0
7398                                                NaN                0.0
7746                                                NaN                0.0
```

```
      host_listings_count neighbourhood_cleansed  latitude  …  \
2215                  1.0           Adams Morgan  38.92355  …
2747                  2.0           Capitol Hill  38.88389  …
2844                  1.0             Georgetown  38.90886  …
3171                  1.0          Union Station  38.89776  …
3602                  1.0           Lamont Riggs  38.96371  …
3671                  1.0                   Shaw  38.90946  …
3820                  1.0               Downtown  38.90248  …
3860                  2.0                   Shaw  38.91200  …
3937                  1.0          Union Station  38.89277  …
4024                  1.0          Spring Valley  38.92245  …
7398                  1.0          River Terrace  38.89162  …
7746                  6.0             Georgetown  38.91131  …

      property_type        room_type accommodates  bathrooms  bedrooms  beds  \
2215      Apartment  Entire home/apt            4        1.0       2.0   2.0
2747          House  Entire home/apt           12        3.0       4.0   8.0
2844          House  Entire home/apt            8        6.5       4.0   5.0
3171          House  Entire home/apt           10        3.5       3.0   5.0
3602          House  Entire home/apt           10        3.5       4.0   4.0
3671          House  Entire home/apt            8        2.0       4.0   4.0
3820      Apartment  Entire home/apt            5        3.0       3.0   3.0
3860          House  Entire home/apt           16        2.0       6.0   8.0
3937          House  Entire home/apt            8        2.5       4.0   4.0
4024          House  Entire home/apt            8        5.5       4.0   4.0
7398          House  Entire home/apt            6        2.5       3.0   5.0
7746          House  Entire home/apt           10       10.0       6.0   9.0

        price  number_of_reviews         last_review review_scores_rating
2215   3200.0                  0                 NaT                  NaN
2747   5995.0                  0                 NaT                  NaN
2844  10000.0                  0                 NaT                  NaN
3171   4000.0                  0                 NaT                  NaN
3602   3500.0                  0                 NaT                  NaN
3671   4000.0                  0                 NaT                  NaN
3820   5500.0                  0                 NaT                  NaN
3860   5000.0                  0                 NaT                  NaN
3937   3250.0                  0                 NaT                  NaN
4024   5000.0                  0                 NaT                  NaN
7398   3300.0                  0                 NaT                  NaN
7746   3500.0                  2 2019-01-21 00:05:00                100.0

[12 rows x 21 columns]
```

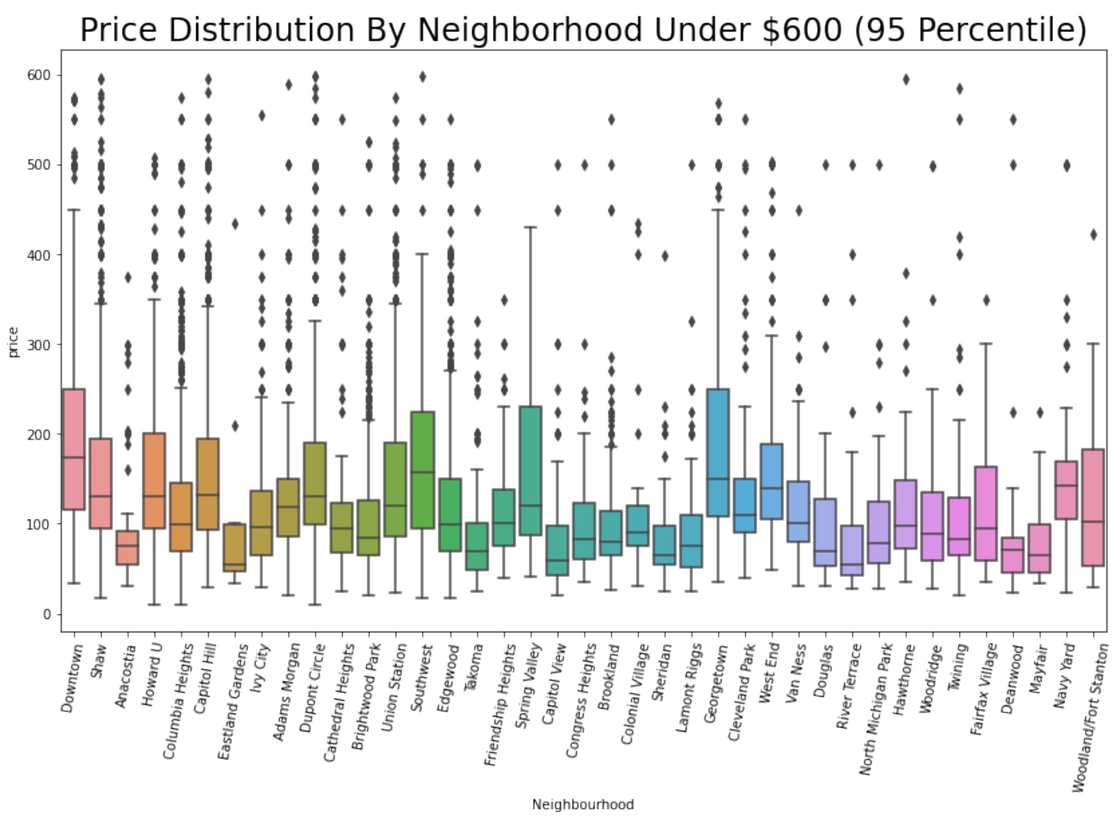
From the above we can see that these listing are large houses / mansions that are for rent and that other than id: 32741852 that has 2 reviews, all other listing greater than \$3000 per night has no review and compared to the 95 percentile of \$197 per night can be considered as outlier for further eda on price to allow us to have a better understanding of price of Airbnb listing in DC without skewed by the outliers.

[7]:
```
# Subset the dataframe to ignore outlier prices
df_c_price = df_clean[df_clean['price']<600]

# Configure the plot area for better viewing
plt.figure(figsize=(14, 8))

# Histrogram plot
plt.hist(df_c_price['price'], bins=25, color='#c10534')
plt.title('Distribution of Price on Listings Under $600 (95 percentile)',␣
↪fontdict={'fontsize': 24})
plt.xlabel('Price', fontdict={'fontsize': 14})
plt.ylabel('Count of Listings', fontdict={'fontsize': 14});

# Save the figure image to file
plt.savefig('../3_Figures/Price Histrogram.png')

# a right skewed distribution of price
```



1.2.6 Location

[218]:
```python
# Does Location affect the price?

plt.figure(figsize=(14, 8))

#boxplot
sns.boxplot(x='neighbourhood_cleansed', y='price', data=df_c_price);
plt.title('Price Distribution By Neighborhood Under $600 (95 Percentile)',␣
 ↪size=24)
plt.xticks(rotation=80)
plt.xlabel("Neighbourhood")

# save figure image to file
plt.savefig('../3_Figures/Price Box by neighborhood.png')
```



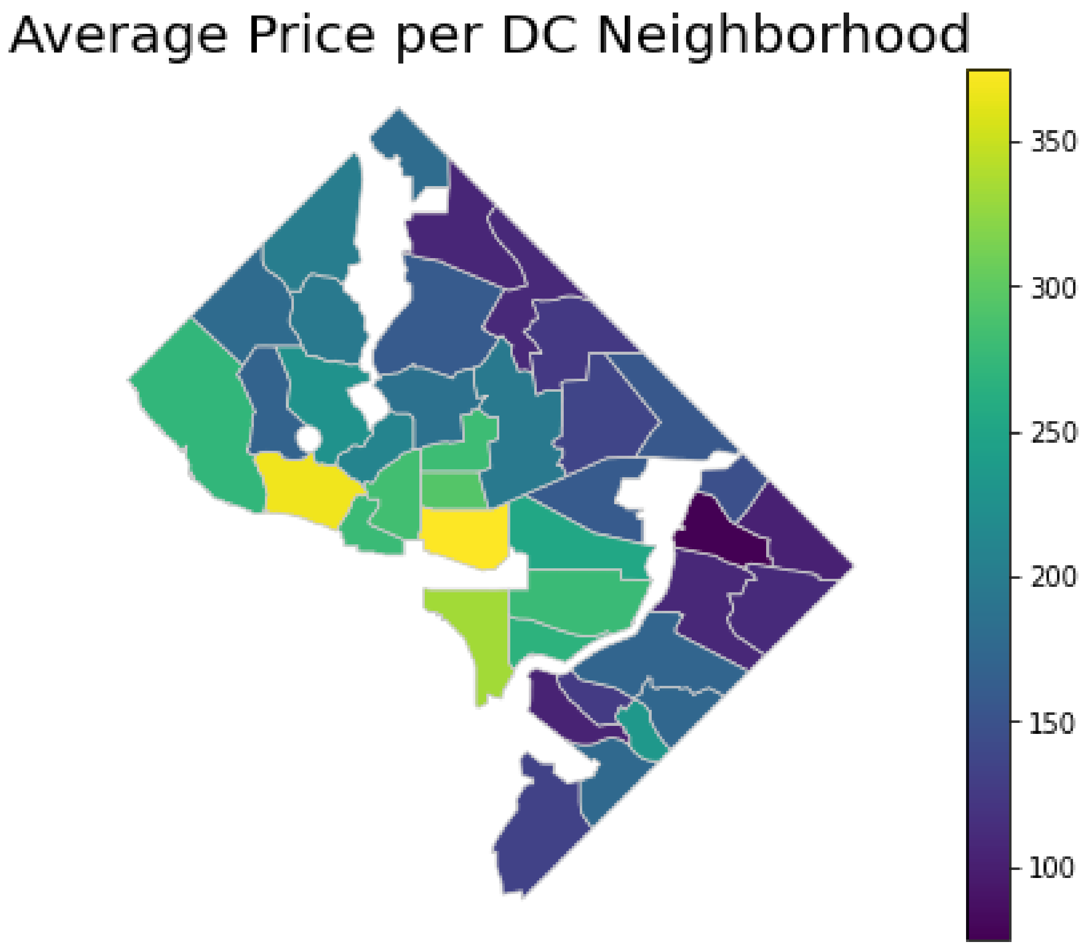
[216]:
```python
# Visalize the average price and standard deviation of Price by neighboorhood
# Calculate the average price per neighbourhood
mean_Price = pd.DataFrame(df_c_price.groupby('neighbourhood_cleansed')['price'].
 ↪mean().round(2))
# Calculate the std per neighbourhood
```

```
std_Price = pd.DataFrame(df_c_price.groupby('neighbourhood_cleansed')['price'].
 ↪std().round(2))

# Read-in the geographic information in geojson file
df_map = geopd.read_file('../0_Data/neighbourhoods.geojson')

# Replace the names to shortened version
df_map['neighbourhood'] = df_map['neighbourhood'].
 ↪replace(neighbourhood_shortened)

#Join the calculated values with geographic information
df_map_ = df_map.set_index('neighbourhood').join(mean_Price)
df_map_2 = df_map.set_index('neighbourhood').join(std_Price)

# Calculate the coordinates of the each neighborhood
df_map['coords'] = df_map['geometry'].apply(lambda x: x.representative_point().
 ↪coords[:])
df_map['coords'] = [coords[0] for coords in df_map['coords']]
```

[213]:

```
## Average Price DC Map

# Define variables
variable = 'price'
tempt = 'neighbourhood'

# Configure the plot area for viewing
plt.figure(figsize=(20, 20))
fig, ax = plt.subplots(1, figsize=(10, 6))

# create map
df_map_.plot(column=variable, linewidth=0.8, ax=ax, edgecolor='0.8')

ax.axis('off')
ax.set_title('Average Price per DC Neighborhood', fontdict={'fontsize': '20',␣
 ↪'fontweight': '2'})

# Create colorbar as a legend
vmin, vmax = 75, 375
sm = plt.cm.ScalarMappable( norm=plt.Normalize(vmin=vmin, vmax=vmax))
sm._A = []
cbar = fig.colorbar(sm)


plt.show();

#save figure image to file
plt.savefig('../3_Figures/Average Price per neighborhood.png')
```

<Figure size 1440x1440 with 0 Axes>



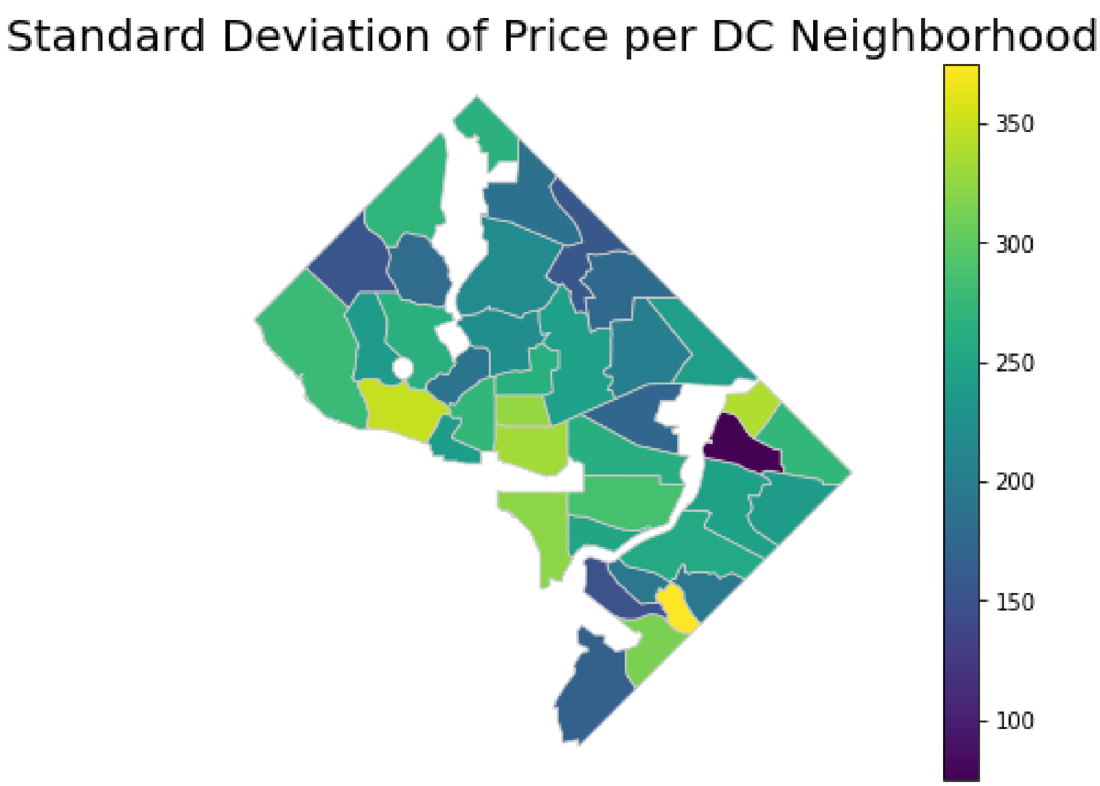
<Figure size 432x288 with 0 Axes>

From the boxplot and the map, we can observe that most expensive neighboorhood on average for AirBnB is Georgetown and Southwest neighborhood followed by capital hill area, while the least expensive neightborhood on average is Mayfair.

[215]:
```
## standard deviation of Price



# Define variables
variable = 'price'
tempt = 'neighbourhood'



# Configure the plot area for viewing
```

```
plt.figure(figsize=(20, 20))
fig, ax = plt.subplots(1, figsize=(10, 6))

# Plot the map
df_map_2.plot(column=variable, linewidth=0.8, ax=ax, edgecolor='0.8')
ax.axis('off')
ax.set_title('Standard Deviation of Price per DC Neighborhood',␣
↪fontdict={'fontsize': '20', 'fontweight': '2'})
vmin, vmax = 75, 375
sm = plt.cm.ScalarMappable(norm=plt.Normalize(vmin=vmin, vmax=vmax))
sm._A = []
cbar = fig.colorbar(sm)


plt.show();


#Save figure image to file
plt.savefig('../3_Figures/std Price per neighborhood.png')
```

```
<Figure size 1440x1440 with 0 Axes>
```



```
<Figure size 432x288 with 0 Axes>
```

Neighbourhood with the largest standard deviation of price is Woodland/Fort Stanton ($129) and the least is Mayfair (\$45)

From the above maps and charts, we can see that there seems to be a trend that closer the listing is to National Mall, the more expensive it is, thus we create a variable to calculate the distance from of the listing to national mall (in miles).

[217]:
```
# Calculate distance from the National Mall to each Airbnb and use that as a␣
↪variable

# define lat and long of the national mall (coordinates taken from Google maps)
lat_nationalmall = 38.889770
lon_nationalmall = -77.023653

df_c_price['lat_nationalmall'] = lat_nationalmall
df_c_price['lon_nationalmall'] = lon_nationalmall

# create a new column that displays the distance between the listing and the␣
↪national mall using vincenty forumla
df_c_price['distance_mall'] = df_c_price.apply(lambda x:␣
↪geodesic((x['latitude'], x['longitude']),
                                                                    ␣
↪(lat_nationalmall, lon_nationalmall)).miles, axis=1)

df_c_price.drop(['lat_nationalmall','lon_nationalmall'], axis = 1, inplace =␣
↪True)

# The distance to mall shows negative correlation, thus the farther away from␣
↪national mall the more expensive it is though not very strong.
np.corrcoef(df_c_price['price'],df_c_price['distance_mall'])
```

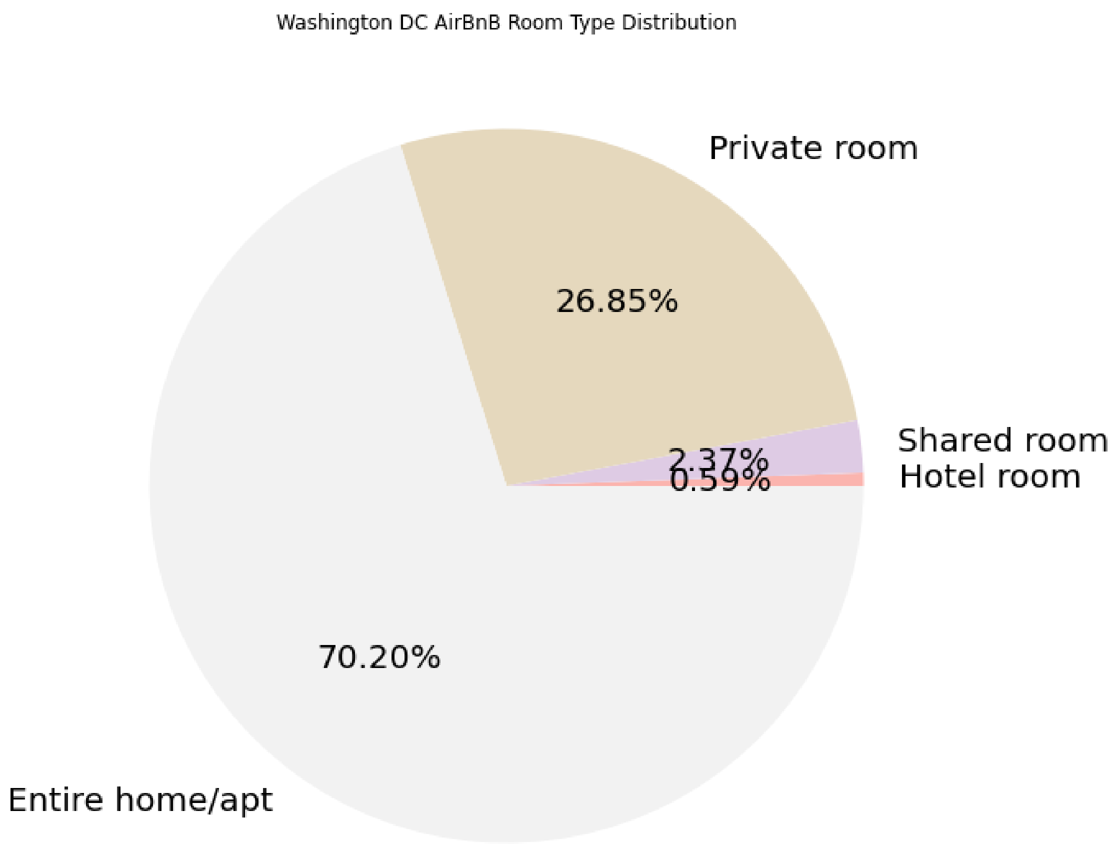
[217]:
```
array([[ 1.        , -0.22719722],
       [-0.22719722,  1.        ]])
```

1.2.7 Room Type and Apartment Type

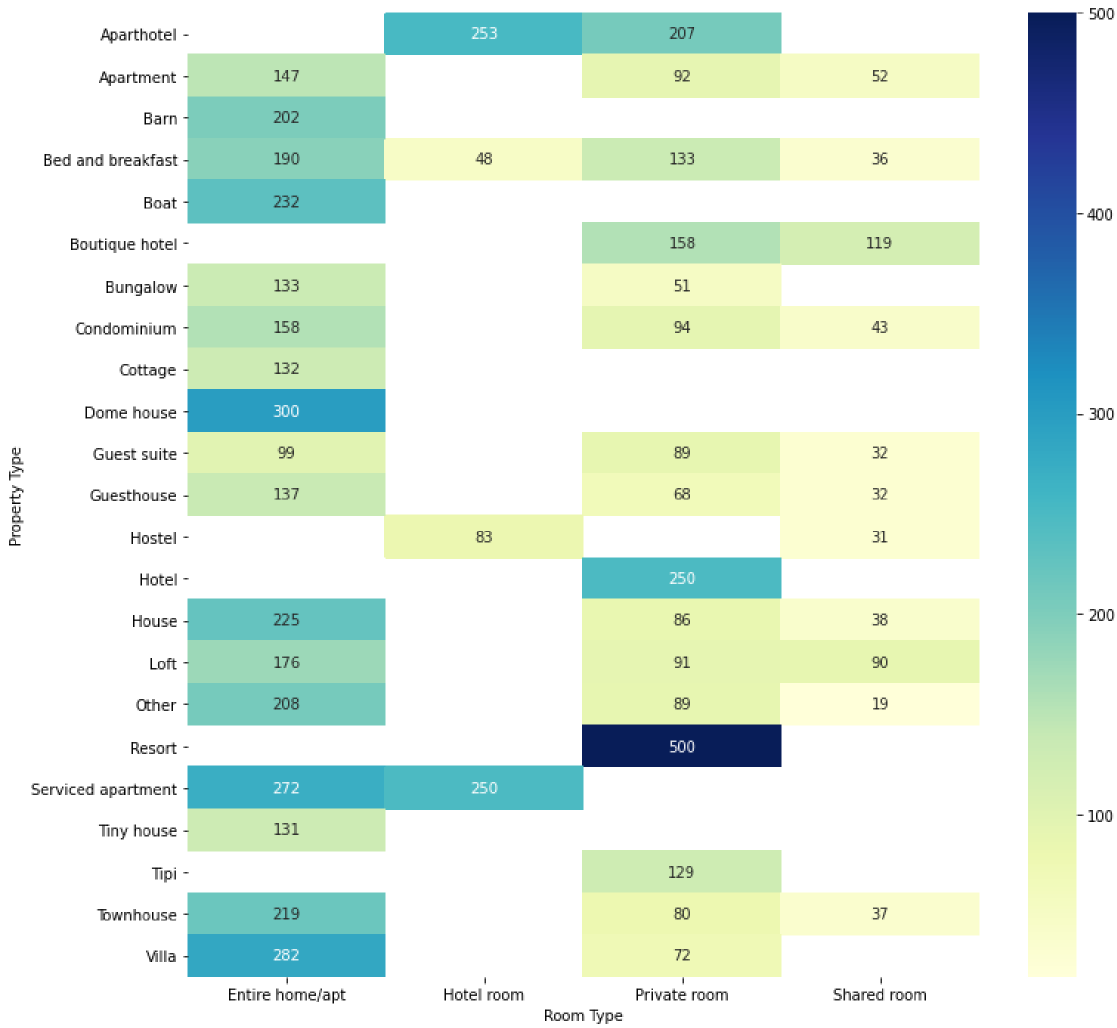
[18]:
```
# Does the room type / apartment type affect price as well?
df_c_price.groupby('room_type').id.count()
```

[18]:
```
room_type
Entire home/apt    6103
Hotel room           51
Private room       2334
Shared room         206
Name: id, dtype: int64
```

[19]:
```
#Declare variable
room = df_c_price.room_type
r = Counter(room)

#piechart
room_df = pd.DataFrame.from_dict(r, orient='index').sort_values(by=0)
room_df.columns = ['room_type']
room_df.plot.pie(y = 'room_type',
                 colormap = 'Pastel1',
                 figsize=(10,10),
                 fontsize = 20, autopct = '%.2f%%',
                 legend = False,
                 title = 'Washington DC AirBnB Room Type Distribution')
#remove y label
plt.ylabel("")

#save figure image to file
plt.savefig('../3_Figures/roomtype.png')
```



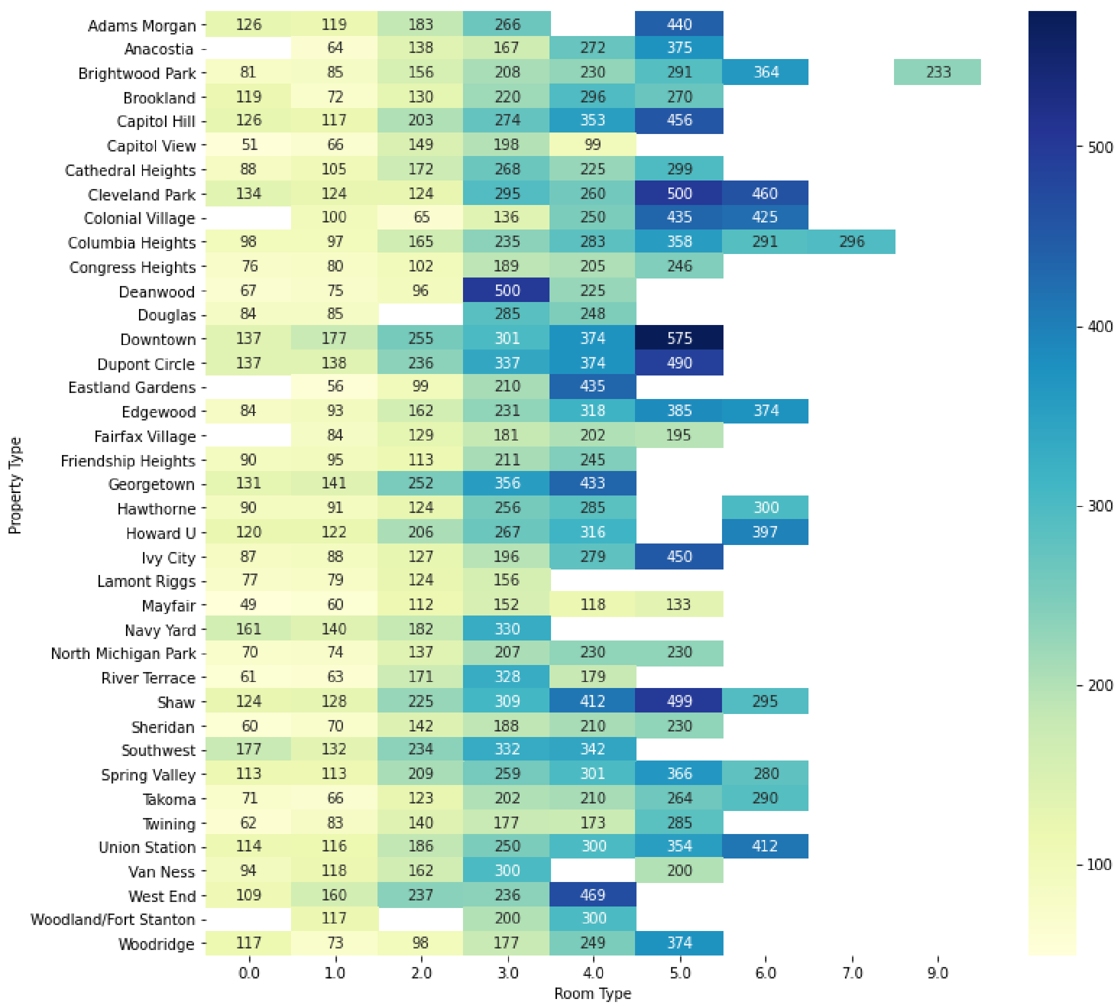
[21]:
```
# Heatmap of room type and property type and its relationship to price

# configure the area for viewing
plt.figure(figsize=(12,12))

# heatmap
sns.heatmap(df_c_price.groupby([
        'property_type', 'room_type']).price.mean().unstack(),annot=True, fmt=".
↪0f", cmap="YlGnBu")
plt.ylabel('Property Type')
plt.xlabel('Room Type')
plt.savefig('../3_Figures/heatmap1.png')
```



The above heatmap all the listing price broken down by property type and room type. This chart gives us a much better understanding of the price breakdown in DC based on property type and room type. It can be observed that private room in resort type is the most expensive. For property type that Entire home/aprt for those that have the option is the most expensive as expected.

Property type and room type plays a strong role in deciding price of a listing.

[22]:
```python
# Configure the area for viewing
plt.figure(figsize=(12,12))

# Heatmap
sns.heatmap(df_c_price.groupby([
        'neighbourhood_cleansed', 'bedrooms']).price.mean().
 ↪unstack(),annot=True, fmt=".0f", cmap="YlGnBu")
plt.ylabel('Property Type')
plt.xlabel('Room Type')

# save figure image to file
plt.savefig('../3_Figures/heatmap2.png')
```



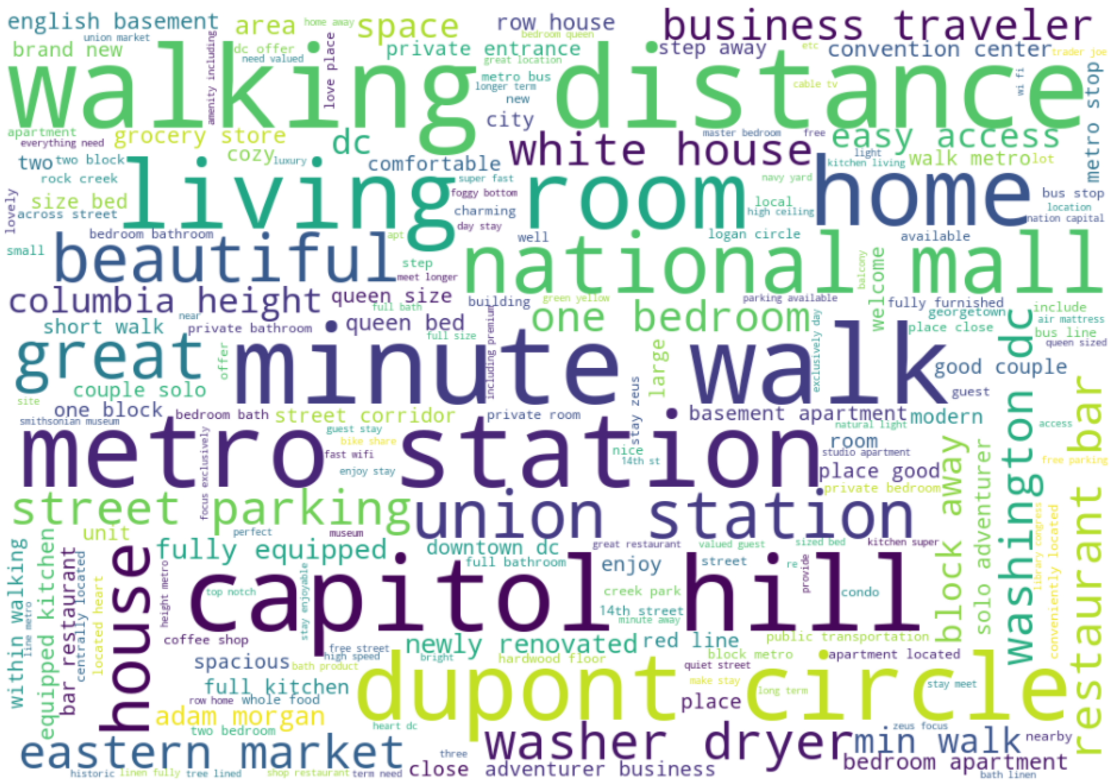
It can be analyzed that with the increase in the number of bedrooms price of listing increases.Although, it depends upon the neighbourhood as well.

1.2.8 Summary

What are the most commonly used phase in summary that host use to catch the eye of end users?

[21]:
```
# Subset the dataframe and organize
summaryDF = df_c_price[['summary','price']]
summaryDF = summaryDF[pd.notnull(summaryDF['summary'])]
summaryDF = summaryDF[summaryDF['summary']!=0]
# Sort the subset by ascending order of price
summaryDF = summaryDF.sort_values('price',ascending=[0])

words=''
for index,row in summaryDF.iterrows():
    words += row['summary']

# Clean the summary for wordcloud
string_punctuation = string.punctuation #Remove puncuation
ignoreChar=['\r','\n','',' ',"'s","dc"] #ignore characters
nums=['0','1','2','3','4','5','6','7','8','9'] #ignore numbers
summary_data=nltk.word_tokenize(words)
words_only = [l.lower() for l in summary_data if l not in string_punctuation if␣
↪l not in ignoreChar if l not in nums]
filtered_data=[word for word in words_only if word not in stopwords.
↪words('english')] #Remove stop words
wnl = nltk.WordNetLemmatizer()
final_data=[wnl.lemmatize(data) for data in filtered_data]
final_words=' '.join(final_data)
```

[22]:
```
# Generate the wordcloud
wordcloud = WordCloud(width = 1000, height = 700,  background_color='white').
↪generate(final_words)

#config the area for viewing
plt.figure(figsize=(18,12))

#plot the wordcloud
plt.imshow(wordcloud)
plt.axis("off")
plt.show()

# save the wordcloud image to file
plt.savefig('../3_Figures/wordcloud.png')
```



<Figure size 432x288 with 0 Axes>

From the above word cloud, we can see that in summary section, most host owners that has a higher price list mentions most about it's location relative to sightseeing spots (e.g. National Mall, Capital Hill), transport (metro station) then followed by amenities it provides. This thus further emphasis that location, location and location matters strongly when determining the price per night for Airbnb listings in Washington DC.

1.2.9 Prediction Model of Price

The following below is a simple attempt at modelling price with the dataset though it is quite sub-par and should be improved in future iterations.

[8]:
```
# Subset the data into modelable data (dropping id, name, dates)
df_model = df_c_price.
 ↪drop(['id','name','summary','host_id','host_name','host_about','last_review'],␣
 ↪axis = 1)
# Add dummy variables to neighbourhood, property type and roomtype
df_model = pd.get_dummies(df_model,␣
 ↪columns=["neighbourhood_cleansed","property_type",'room_type'])

# show the summary stats for the subset dataset
```

```
df_model.describe().T
```

[8]:

```
                          count       mean         std       min        25%  \
host_is_superhost        8694.0   0.340695    0.473970   0.00000   0.000000
host_listings_count      8694.0  51.161261  240.116399   0.00000   1.000000
latitude                 8694.0  38.912190    0.023578  38.82037  38.899513
longitude                8694.0 -77.017407    0.029267 -77.12128 -77.036560
accommodates             8694.0   3.595698    2.258918   1.00000   2.000000
…                           …         …           …         …          …
property_type_Villa      8694.0   0.000920    0.030322   0.00000   0.000000
room_type_Entire home/apt 8694.0   0.701978    0.457415   0.00000   0.000000
room_type_Hotel room     8694.0   0.005866    0.076370   0.00000   0.000000
room_type_Private room   8694.0   0.268461    0.443184   0.00000   0.000000
room_type_Shared room    8694.0   0.023695    0.152104   0.00000   0.000000

                                50%       75%         max
host_is_superhost          0.000000   1.00000     1.00000
host_listings_count        2.000000   4.00000  1795.00000
latitude                  38.911470  38.92523    38.99549
longitude                -77.019955 -76.99698   -76.90482
accommodates               3.000000   4.00000    17.00000
…                               …         …          …
property_type_Villa        0.000000   0.00000     1.00000
room_type_Entire home/apt  1.000000   1.00000     1.00000
room_type_Hotel room       0.000000   0.00000     1.00000
room_type_Private room     0.000000   1.00000     1.00000
room_type_Shared room      0.000000   0.00000     1.00000

[77 rows x 8 columns]
```

[10]:

```
# Let y = Price
y = df_model['price'].values

#Remove Price from subset dataset
del df_model['price']

# Let x be the remainig chosen values
X  = df_model.values
```

[18]:

```
# Model using XGBOOST
xgb_model = XGBRegressor(n_estimators= 150,
 max_depth=5)

kfold = KFold(n_splits=10, random_state=1994)
results = cross_val_score(xgb_model, X, y, cv=kfold)
```

```python
# Get the model training score
print("Accuracy: %.2f%% (%.2f%%)" % (results.mean()*100, results.std()*100))
```

```
C:\Users\User\Anaconda3\lib\site-packages\sklearn\model_selection\_split.py:297:
FutureWarning: Setting a random_state has no effect since shuffle is False. This
will raise an error in 0.24. You should leave random_state to its default
(None), or set shuffle=True.
  FutureWarning
```

```
[08:38:38] WARNING: src/objective/regression_obj.cu:152: reg:linear is now
deprecated in favor of reg:squarederror.
[08:38:40] WARNING: src/objective/regression_obj.cu:152: reg:linear is now
deprecated in favor of reg:squarederror.
[08:38:42] WARNING: src/objective/regression_obj.cu:152: reg:linear is now
deprecated in favor of reg:squarederror.
[08:38:44] WARNING: src/objective/regression_obj.cu:152: reg:linear is now
deprecated in favor of reg:squarederror.
[08:38:46] WARNING: src/objective/regression_obj.cu:152: reg:linear is now
deprecated in favor of reg:squarederror.
[08:38:48] WARNING: src/objective/regression_obj.cu:152: reg:linear is now
deprecated in favor of reg:squarederror.
[08:38:50] WARNING: src/objective/regression_obj.cu:152: reg:linear is now
deprecated in favor of reg:squarederror.
[08:38:52] WARNING: src/objective/regression_obj.cu:152: reg:linear is now
deprecated in favor of reg:squarederror.
[08:38:54] WARNING: src/objective/regression_obj.cu:152: reg:linear is now
deprecated in favor of reg:squarederror.
[08:38:56] WARNING: src/objective/regression_obj.cu:152: reg:linear is now
deprecated in favor of reg:squarederror.
Accuracy: 48.17% (10.18%)
```

Tested including Document Term Matrix with summary and yield a similar results (as summary maybe already capture by distance and neighboorhood factors)

For future improvements: - Conduct parameter tuning for XGBoost - Conduct test with different models - Conduct ensemble learning

```
[ ]:
```