Project One

Introduction

In this assignment I will be exploring Airbnb rental price data in New York City. Specifically, I am interest in answering, "How does the room type and location of an Airbnb listing affect it's price, in New York City?"

The data set I will be working with is from Inside Airbnb, retrieved from http://insideairbnb.com/index.html (http://insideairbnb.com/index.html).

To be more specific my response variable(Y) will the price in dollars per night of an New York City Airbnb.

My first explanatory variable(X1) will the type of room the listing is for, I will investigate the types later on in the assignment.

My second explanatory variable(X2) will be the the location of the listing. I will be using the neighourhood of New York City the listing is in to classify location.

In the data room_type is the room type of the listing and neighbourhood_group is the neighbourhood of New York City the listing is located in.

In [ ]:
```
# Uncomment following line to install on colab
! pip install qeds fiona geopandas xgboost gensim folium pyLDAvis descartes py
geos rtree
```

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Requirement already satisfied: qeds in /usr/local/lib/python3.7/dist-packages
(0.7.0)
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packages (from sympy->quantecon->qeds) (1.2.1)
ERROR: Operation cancelled by user
```

In [ ]:

```python
# Import Libraries
import numpy as np
import pandas as pd
pd.options.mode.chained_assignment = None

import matplotlib.pyplot as plt
from google.colab import files

import geopandas as gpd

from shapely.geometry import Point

import matplotlib.cm as cm
from matplotlib.colors import Normalize

%matplotlib inline
```

In [ ]:

```
# read the data in using pandas
data_raw=pd.read_csv('AB_NYC_2019.csv')

data_raw = pd.DataFrame(data_raw)

# let's take a look at the top 5 rows of our raw data set
data_raw.head()
```

Out[ ]:

	id	name	host_id	host_name	neighbourhood_group	neighbourhood	latitude
0	2539	Clean & quiet apt home by the park	2787	John	Brooklyn	Kensington	40.64749
1	2595	Skylit Midtown Castle	2845	Jennifer	Manhattan	Midtown	40.75362
2	3647	THE VILLAGE OF HARLEM....NEW YORK !	4632	Elisabeth	Manhattan	Harlem	40.80902
3	3831	Cozy Entire Floor of Brownstone	4869	LisaRoxanne	Brooklyn	Clinton Hill	40.68514
4	5022	Entire Apt: Spacious Studio/Loft by central park	7192	Laura	Manhattan	East Harlem	40.79851

Cleaning Data

In [ ]:

```
# Let's take create a subset of the dataframe to only include the columns we w
ill need

data = data_raw[["id", "price", "room_type", 'neighbourhood_group']]
data.head()

# Below we can see that our new data only has the 4 columns we need.
```

Out[ ]:

	id	price	room_type	neighbourhood_group
0	2539	149	Private room	Brooklyn
1	2595	225	Entire home/apt	Manhattan
2	3647	150	Private room	Manhattan
3	3831	89	Entire home/apt	Brooklyn
4	5022	80	Entire home/apt	Manhattan

In [ ]:
```
# taking a look at the types of our data
data.dtypes
```

Out[ ]:
```
id                       int64
price                    int64
room_type               object
neighbourhood_group     object
dtype: object
```

We see that id, price are numerical data while room_type and neighbourhood_group are categorical data

In [ ]:
```
# Clean our data by droping rows with a nans in any of the columns
print("There are {} missing values in the data set".format(data_raw.isnull().v
alues.sum()))

data_no_na = data.dropna(axis=0, how='any')
```

```
There are 20141 missing values in the data set
```

Summary Statistics

In [ ]:
```
# Lets pull up the summary statistics of our data
data.describe().T
```

Out[ ]:

	count	mean	std	min	25%	50%	75%	m
id	48895.0	1.901714e+07	1.098311e+07	2539.0	9471945.0	19677284.0	29152178.5	36487245
price	48895.0	1.527207e+02	2.401542e+02	0.0	69.0	106.0	175.0	10000

First we can see that we have 48895 observations in the data set. We see that the mean price of Airbnb listing is for 152 dollars per night. The standard deviation of prices is 240. Interestingly, the cheapest listing is for 0 a night, which may be human error, and the most expensive listing is for 10000 dollars a night. We are also given the 25%, 50% and 75% percentiles.

We can ignore the id as the values are meaningless and is only used for identification.

In [ ]:
```
# Unique values for room_type and neighbour_hood group

print("There are {} unique room_types in the data which are are: {}".format(data['room_type'].nunique() ,data['room_type'].unique()))
print("There are {} unique neighbourhood_groups in the data which are: {} ".format(data['neighbourhood_group'].nunique(), data['neighbourhood_group'].unique()))
```

```
There are 3 unique room_types in the data which are are: ['Private room' 'Entire home/apt' 'Shared room']
There are 5 unique neighbourhood_groups in the data which are: ['Brooklyn' 'Manhattan' 'Queens' 'Staten Island' 'Bronx']
```

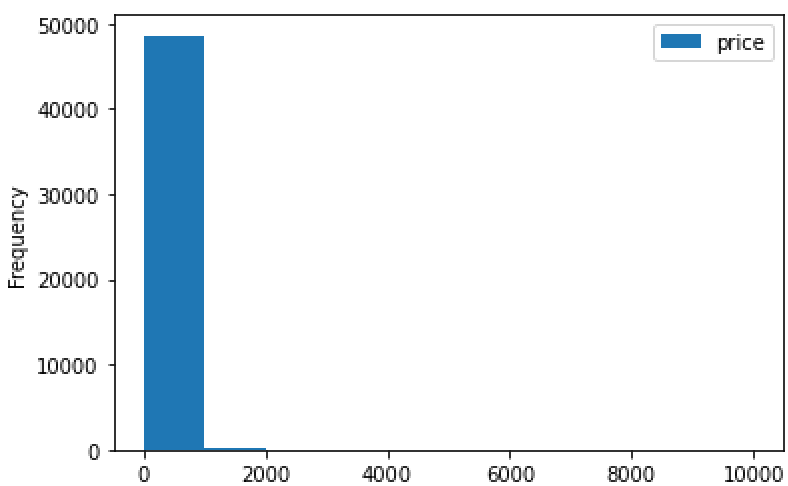
We can see that there are 3 unique room types in the data which are 'Private room,' 'Entire home/apt' and 'Shared room'. Entire home/apt means that the entire unit is listed, whether it was a home or apartment.

There are 5 unique New York City neighbourhoods in our data which are; 'Brooklyn', 'Manhattan','Queens', 'Staten Island' and 'Bronx'.

Histogram of Price, Room type and Neighbourhood

In [ ]:
```
data[['price']].plot(kind='hist')
```

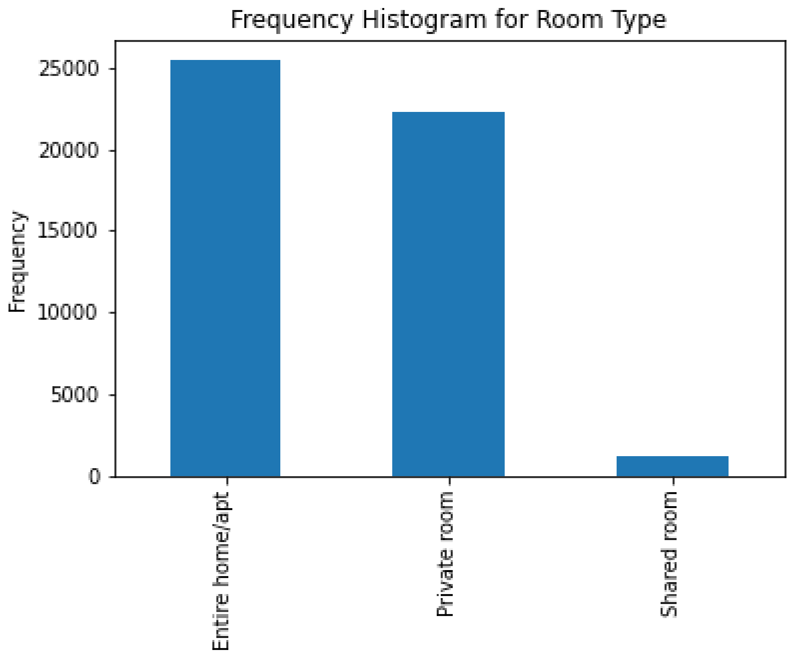
Out[ ]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f3a33339190>
```



We can see that the majority of listings fall below 1000 dollars per night price. There seems to be a few listing between 1000 and 2000 dollars a night and very few listings over the price of 2000 per night.

In [ ]:
```
data['room_type'].value_counts().plot(kind='bar')
plt.title("Frequency Histogram for Room Type")
plt.ylabel("Frequency")
```

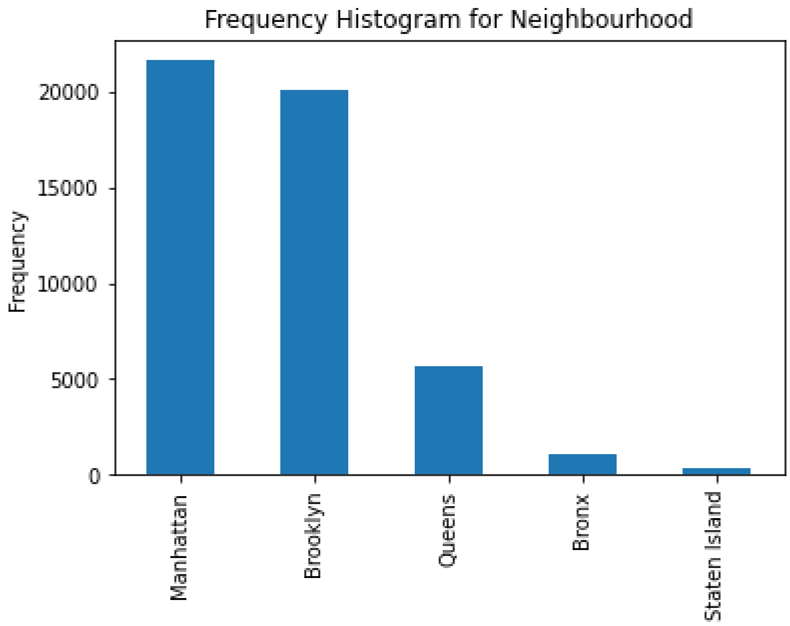
Out[ ]:
```
Text(0, 0.5, 'Frequency')
```



From the histogram above, we note that most listings in New York City is for the entire home/apartment. The second most popular listed room type are private rooms and the least popular, by far, are shared rooms. This suggests that many hosts understand the value of privacy for customers.

In [ ]:
```
data['neighbourhood_group'].value_counts().plot(kind='bar')
plt.title("Frequency Histogram for Neighbourhood")
plt.ylabel("Frequency")
```

Out[ ]:
```
Text(0, 0.5, 'Frequency')
```



From the histogram above, we can see the number of listings in each neighbourhood in New York City. In descending order; Manhattan, Brooklyn, Queens, Bronx and Staten Island. The majority of listings are found in either Manhattan and Brooklyn, this may suggest that Manhattan and Brooklyn are popular tourist destinations which high demand for AirBnbs.

Visualizing Price to Room Type and Price to Neighbourhood

In [ ]:

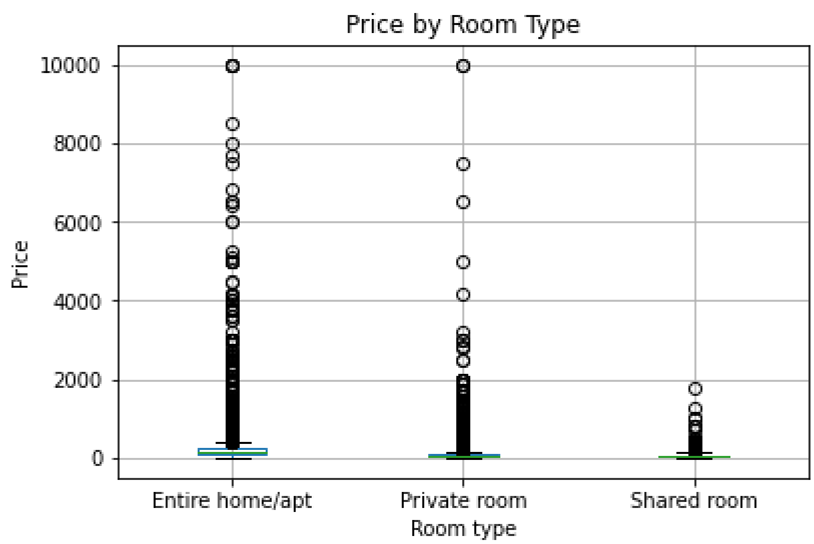
```
# Since room_type is a categorical data, lets creates a boxplot to take a look
# at how price differs by room_type

data.boxplot(column = 'price', by = "room_type")
plt.xlabel("Room type")
plt.ylabel("Price")
plt.title("Price by Room Type")
plt.suptitle("")
```

```
/usr/local/lib/python3.7/dist-packages/numpy/core/_asarray.py:83: VisibleDepr
ecationWarning: Creating an ndarray from ragged nested sequences (which is a
list-or-tuple of lists-or-tuples-or ndarrays with different lengths or shape
s) is deprecated. If you meant to do this, you must specify 'dtype=object' wh
en creating the ndarray
  return array(a, dtype, copy=False, order=order)
```

Out[ ]:

```
Text(0.5, 0.98, '')
```

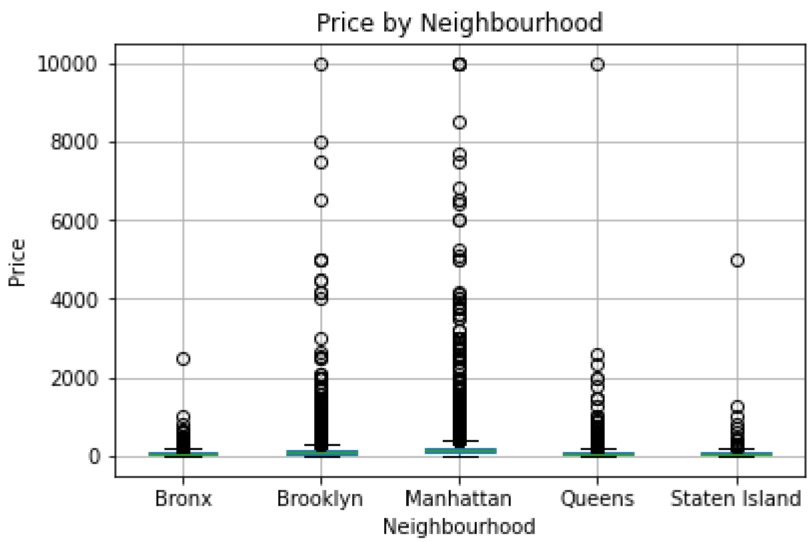


In the plot above, we can see how price differs by room type. There seems to be a larger variation in prices for listings of the entire home/apartment and private room type compared to shared rooms which are all under 2000 dollars a night. There are more expensive listings for the entire home/apartment compared to private rooms. This make sense as we expect consumers are willing to pay more for more privacy and a larger space. For all three room types, the majority of the room prices are far below 2000.

In [ ]:
```
data.boxplot(column = 'price', by = "neighbourhood_group")
plt.xlabel("Neighbourhood")
plt.ylabel("Price")
plt.title("Price by Neighbourhood")
plt.suptitle("")
```

```
/usr/local/lib/python3.7/dist-packages/numpy/core/_asarray.py:83: VisibleDepr
ecationWarning: Creating an ndarray from ragged nested sequences (which is a
list-or-tuple of lists-or-tuples-or ndarrays with different lengths or shape
s) is deprecated. If you meant to do this, you must specify 'dtype=object' wh
en creating the ndarray
  return array(a, dtype, copy=False, order=order)
```

Out[ ]:
```
Text(0.5, 0.98, '')
```



In the plot above, we can see how price differs between the neighbourhoods of New York City. The majority of listings in the Bronx, Queens and Staten Island fall below 2000, which a few exceptions. Although the majority of listings are similar across all neighourhoods, Brooklyn and Manhattan have a number of listings over 2000 dollar listing price. As we saw before, Brooklyn and Manhattan were the most popular in terms of listings, so it may not come as a surprise that there are out outliers in Brooklyn and Manhattan.

Summary

In first project, I found interesting results on how pricing of a Airbnbs listing is affected why its room type and its neighbourhood in New York City. We found that there is a larger variation in prices for Airbnb listings of entire homes/apartments and private rooms compared to shared rooms. I also discovered that we see an greater variation in prices for listings in Brooklyn and Manhattan compared to listings in Bronx, Queens and Staten Island. We discovered that Brooklyn and Manhattan were the neighbourhoods with the most listings. We also discovered that there was many more entire homes/apartments and private room listed compared to shared rooms and they also had more expensive options which may suggest that consumers demand for and value privacy.

Future Steps

In the future I would want to look into fitting a linear model that predicts the price provided a Airbnb's listing and room type. I would want to analyze my model to reach a conclusion for my research question of what is the effect a Airbnb listing's room type and neighbourhood has on its price.

Project 2

Part 1 - Addressing Comments in Project 1

Abstract

In this assignment I will be exploring Airbnb rental price data in New York City. Specifically, my key question of interest is "How does Airbnb listing prices differ between room types and the different bourghs of New York City?"

The data set I will be working with is from Inside Airbnb, retrieved from http://insideairbnb.com/index.html (http://insideairbnb.com/index.html).

Defining Variables

To be more specific, my response variable(Y) will the price in dollars per night of an New York City Airbnb.

My first explanatory variable(X1) will the type of room the listing is for, I will investigate the different room types later on in the assignment.

My second explanatory variable(X2) will be the the location of the listing. To classify location, I will be using the borough in New York City for which the listing is located.

In the data room_type is the room type of the listing and neighbourhood_group is the neighbourhood of New York City the listing is located in.

Road Map

In the first part of this notebook I will be importing the required libraries and load in the required data. Next, I will clean our data set, run summary statistics and visualize key variables in the data set. Finally, I will prepare our data to create visualiations through maps of how price differs between location and room types.

Setup

In [ ]:
```
# Uncomment following line to install on colab
! pip install qeds fiona geopandas xgboost gensim folium pyLDAvis descartes py
geos rtree
```

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Requirement already satisfied: qeds in /usr/local/lib/python3.7/dist-packages
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ges (from fiona) (2020.12.5)
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dist-packages (from gensim) (4.2.0)
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-packages (from folium) (0.4.2)
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es (from folium) (2.11.3)
Requirement already satisfied: wheel>=0.23.0 in /usr/local/lib/python3.7/dist
-packages (from pyLDAvis) (0.36.2)
Requirement already satisfied: joblib>=0.8.4 in /usr/local/lib/python3.7/dist
-packages (from pyLDAvis) (1.0.1)
Requirement already satisfied: future in /usr/local/lib/python3.7/dist-packag
es (from pyLDAvis) (0.16.0)
Requirement already satisfied: funcy in /usr/local/lib/python3.7/dist-package
s (from pyLDAvis) (1.15)
Requirement already satisfied: numexpr in /usr/local/lib/python3.7/dist-packa
ges (from pyLDAvis) (2.7.2)
Requirement already satisfied: more-itertools in /usr/local/lib/python3.7/dis
t-packages (from quandl->qeds) (8.7.0)
Requirement already satisfied: python-dateutil in /usr/local/lib/python3.7/di
st-packages (from quandl->qeds) (2.8.1)
Requirement already satisfied: inflection>=0.3.1 in /usr/local/lib/python3.7/
dist-packages (from quandl->qeds) (0.5.1)
Requirement already satisfied: numba>=0.38 in /usr/local/lib/python3.7/dist-p
ackages (from quantecon->qeds) (0.51.2)
Requirement already satisfied: sympy in /usr/local/lib/python3.7/dist-package
s (from quantecon->qeds) (1.7.1)
Requirement already satisfied: retrying>=1.3.3 in /usr/local/lib/python3.7/di
st-packages (from plotly->qeds) (1.3.3)
Requirement already satisfied: lxml in /usr/local/lib/python3.7/dist-packages
(from pandas-datareader->qeds) (4.2.6)
Requirement already satisfied: pytz>=2017.2 in /usr/local/lib/python3.7/dist-
packages (from pandas->qeds) (2018.9)
Requirement already satisfied: chardet<4,>=3.0.2 in /usr/local/lib/python3.7/
dist-packages (from requests->qeds) (3.0.4)
Requirement already satisfied: idna<3,>=2.5 in /usr/local/lib/python3.7/dist-
packages (from requests->qeds) (2.10)
Requirement already satisfied: urllib3!=1.25.0,!=1.25.1,<1.26,>=1.21.1 in /us
r/local/lib/python3.7/dist-packages (from requests->qeds) (1.24.3)
Requirement already satisfied: patsy>=0.4.0 in /usr/local/lib/python3.7/dist-
packages (from statsmodels->qeds) (0.5.1)
Requirement already satisfied: jdcal in /usr/local/lib/python3.7/dist-package
s (from openpyxl->qeds) (1.4.1)
Requirement already satisfied: et-xmlfile in /usr/local/lib/python3.7/dist-pa
ckages (from openpyxl->qeds) (1.0.1)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.7/dist-
packages (from matplotlib->qeds) (0.10.0)
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.1 in /u
sr/local/lib/python3.7/dist-packages (from matplotlib->qeds) (2.4.7)
```

```
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.7/
dist-packages (from matplotlib->qeds) (1.3.1)
Requirement already satisfied: MarkupSafe>=0.23 in /usr/local/lib/python3.7/d
ist-packages (from jinja2->folium) (1.1.1)
Requirement already satisfied: llvmlite<0.35,>=0.34.0.dev0 in /usr/local/lib/
python3.7/dist-packages (from numba>=0.38->quantecon->qeds) (0.34.0)
Requirement already satisfied: setuptools in /usr/local/lib/python3.7/dist-pa
ckages (from numba>=0.38->quantecon->qeds) (54.0.0)
Requirement already satisfied: mpmath>=0.19 in /usr/local/lib/python3.7/dist-
packages (from sympy->quantecon->qeds) (1.2.1)
```

In [ ]:

```
# Import Libraries
import numpy as np
np.warnings.filterwarnings('ignore', category=np.VisibleDeprecationWarning)
import pandas as pd
pd.options.mode.chained_assignment = None

import matplotlib.pyplot as plt
from google.colab import files

import geopandas as gpd

from shapely.geometry import Point

import matplotlib.cm as cm
from matplotlib.colors import Normalize
import matplotlib as mpl

%matplotlib inline
```

Reading and preping dataframes

In [ ]:

```
# read the data in using pandas
data_raw=pd.read_csv('AB_NYC_2019.csv')

data_raw = pd.DataFrame(data_raw)

# filter the rows we need
data = data_raw[["id", "price", "room_type", 'neighbourhood_group', 'neighbour
hood', 'latitude', 'longitude']]

data.head(2)
# Below we can see that our new data only has the columns we need.
```

Out[ ]:

	id	price	room_type	neighbourhood_group	neighbourhood	latitude	longitude
0	2539	149	Private room	Brooklyn	Kensington	40.64749	-73.97237
1	2595	225	Entire home/apt	Manhattan	Midtown	40.75362	-73.98377

In [ ]:
```
# taking a look at the types of our data
data.dtypes
```

Out[ ]:
```
id                       int64
price                    int64
room_type               object
neighbourhood_group     object
neighbourhood           object
latitude               float64
longitude              float64
dtype: object
```

We see that id, price are numerical data while room_type and neighbourhood_group are categorical data

In [ ]:
```
# Clean our data by droping rows with a nans in any of the columns
print("There are {} missing values in the data set".format(data.isnull().value
s.sum()))
```

```
There are 0 missing values in the data set
```

Since there are 0 missing values in our filtered data set, we do not need to drop any rows!

In [ ]:
```
# Get discriptive statistics of Y variable: Listing price
data.price.describe()
```

Out[ ]:
```
count    48895.000000
mean       152.720687
std        240.154170
min          0.000000
25%         69.000000
50%        106.000000
75%        175.000000
max      10000.000000
Name: price, dtype: float64
```

First we can see that we have 48895 observations in the data set. We see that the mean price of Airbnb listing is for 152 dollars per night. The standard deviation of prices is 240. Interestingly, the cheapest listing is for 0 a night, which may be human error, and the most expensive listing is for 10000 dollars a night. We are also given the 25%, 50% and 75% percentiles.

We can ignore other numerical columns such as id, latitude and longitude as the summary statistics are meaningless.

We notice that the 75% percentile price is 175, while the max is 100000. This suggets that we may have some outliers in our data. Let's take a look at the the different quantiles of our price data.

In [ ]:
```
data.price.quantile(np.arange(0,1.01,0.05))
```

Out[ ]:
```
0.00        0.0
0.05       40.0
0.10       49.0
0.15       55.0
0.20       60.0
0.25       69.0
0.30       75.0
0.35       81.0
0.40       90.0
0.45      100.0
0.50      106.0
0.55      120.0
0.60      130.0
0.65      149.0
0.70      155.0
0.75      175.0
0.80      200.0
0.85      225.0
0.90      269.0
0.95      355.0
1.00    10000.0
Name: price, dtype: float64
```

We see that 355 dollars per night is the 95% percentile of our data. This means that only 5% of listings were within the 355 to 10000 dollar range, while 95% of lisings prices were less 355 dollars. Let's drop the outliers at the 95th percentile to get better visualization of our data.

In [ ]:
```
# filter data set
data_95th = data.query("price <= 355")
```

In [ ]:
```
# Unique values for room_type and neighbour_hood group

print("There are {} unique room_types in the data which are are: {}".format(da
ta['room_type'].nunique() ,data['room_type'].unique()))
print("There are {} unique neighbourhood_groups in the data which are: {} ".fo
rmat(data['neighbourhood_group'].nunique(), data['neighbourhood_group'].unique
()))
```

```
There are 3 unique room_types in the data which are are: ['Private room' 'Ent
ire home/apt' 'Shared room']
There are 5 unique neighbourhood_groups in the data which are: ['Brooklyn' 'M
anhattan' 'Queens' 'Staten Island' 'Bronx']
```

We can see that there are 3 unique room types in the data which are 'Private room,' 'Entire home/apt' and 'Shared room'. Entire home/apt means that the entire unit is listed, whether it was a home or apartment.

There are 5 unique New York City boroughs in our data, which are; 'Brooklyn', 'Manhattan','Queens', 'Staten Island' and 'Bronx'.

Summary Statistics and Data Exploration

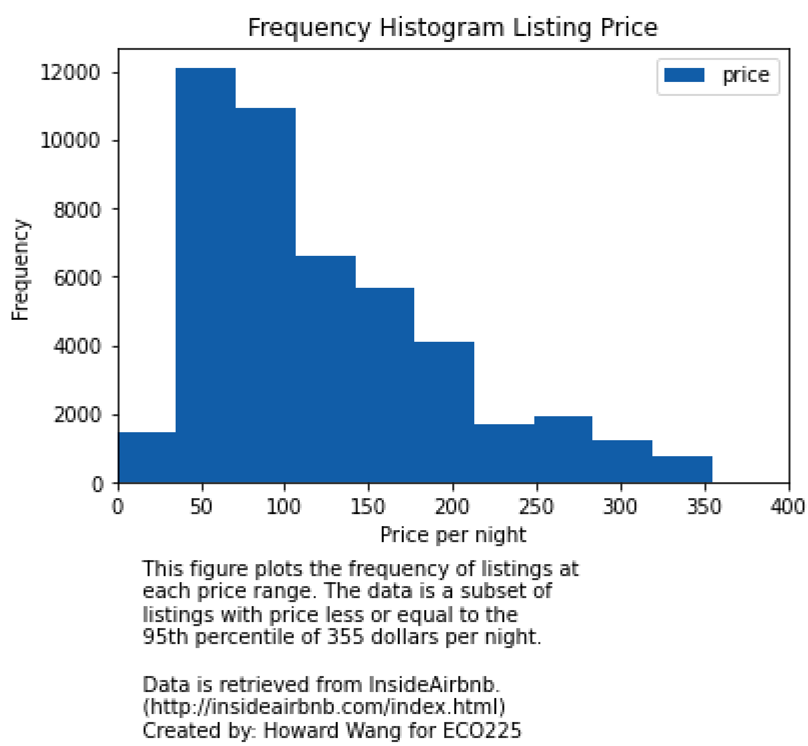
In [ ]:
```
txt = '''
    This figure plots the frequency of listings at
    each price range. The data is a subset of
    listings with price less or equal to the
    95th percentile of 355 dollars per night.

    Data is retrieved from InsideAirbnb.
    (http://insideairbnb.com/index.html)
    Created by: Howard Wang for ECO225
    '''



data_95th[['price']].plot(kind='hist',color="#115DA8")
plt.title("Frequency Histogram Listing Price")
plt.xlabel("Price per night")
plt.xlim(0, 400)
plt.text(0.1,-8100, txt)
```

Out[ ]:
```
Text(0.1, -8100, '\n    This figure plots the frequency of listings at\n    e
ach price range. The data is a subset of\n    listings with price less or equ
al to the\n    95th percentile of 355 dollars per night.\n    \n    Data is r
etrieved from InsideAirbnb.\n    (http://insideairbnb.com/index.html)\n    Cr
eated by: Howard Wang for ECO225\n    ')
```



We can see that there is the largest number from listings between the 50 to 100 dollar range. Also note that there is a decreasing number of listings as price increases. This suggets that hosts understand consumers are price sensitive.

In [ ]:
```
txt = '''
    This figure shows the total number of AirBnb listings
    by room type in NYC.

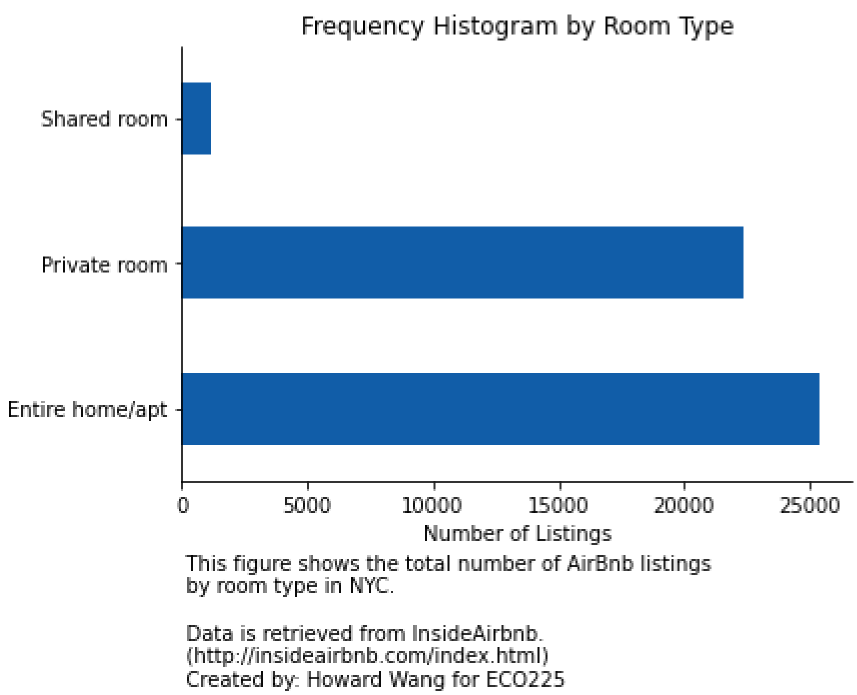
    Data is retrieved from InsideAirbnb.
    (http://insideairbnb.com/index.html)
    Created by: Howard Wang for ECO225
    '''

fig, ax = plt.subplots()
data['room_type'].value_counts().plot(kind='barh', ax=ax, color="#115DA8")
ax.spines['right'].set_visible(False)
ax.spines['top'].set_visible(False)
ax.set_title("Frequency Histogram by Room Type")

ax.set_xlabel("Number of Listings")
#plt.grid(axis='x')

fig.text(0.1,-0.27,txt)
```

Out[ ]:
```
Text(0.1, -0.27, '\n    This figure shows the total number of AirBnb listings
\n    by room type in NYC.\n    \n    Data is retrieved from InsideAirbnb.\n
(http://insideairbnb.com/index.html)\n    Created by: Howard Wang for ECO225
\n    ')
```



From the histogram above, we note that most listings in New York City are for the entire home/apartment. The second most popular listed room type are private rooms and the least popular, by far, are shared rooms. This suggests that many hosts understand the value of privacy for customers.

In [ ]:
```
txt = '''
    This figure shows the total number of AirBnb listings
    in the Boroughs of NYC.

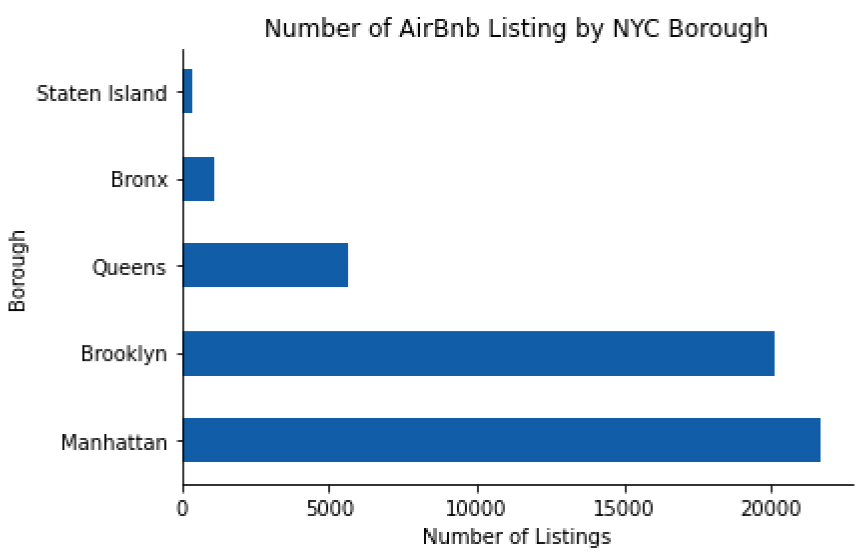
    Data is retrieved from InsideAirbnb.
    (http://insideairbnb.com/index.html)
    Created by: Howard Wang for ECO225
    '''

fig, ax = plt.subplots()
data['neighbourhood_group'].value_counts().plot(kind='barh', ax=ax, color="#11
5DA8")
ax.spines['right'].set_visible(False)
ax.spines['top'].set_visible(False)
ax.set_title("Number of AirBnb Listing by NYC Borough")

ax.set_xlabel("Number of Listings")
ax.set_ylabel("Borough")
#plt.grid(axis='x')


fig.text(0.1,-0.27,txt)
```

Out[ ]:
```
Text(0.1, -0.27, '\n    This figure shows the total number of AirBnb listings
\n    in the Boroughs of NYC.\n    \n    Data is retrieved from InsideAirbn
b.\n    (http://insideairbnb.com/index.html)\n    Created by: Howard Wang for
ECO225\n    ')
```



This figure shows the total number of AirBnb listings
in the Boroughs of NYC.

Data is retrieved from InsideAirbnb.
(http://insideairbnb.com/index.html)
Created by: Howard Wang for ECO225

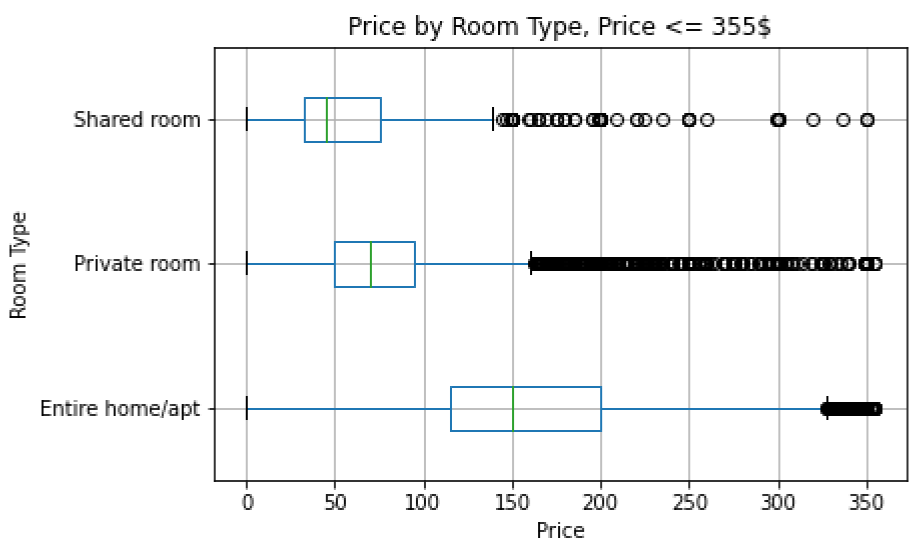
From the histogram above, we can see the number of listings in each neighbourhood in New York City. In descending order; Manhattan, Brooklyn, Queens, Bronx and Staten Island. The majority of listings are found in either Manhattan and Brooklyn, this may suggest that Manhattan and Brooklyn have high population which leads to the high demand for AirBnbs. We will be exploring this later in the project.

Visualizing Price to Room Type and Price to Neighbourhood

In [ ]:
```
# Since room_type is a categorical data, lets creates a boxplot to take a look
# at how price differs by room_type

data_95th.boxplot(column = 'price', by = "room_type", vert=False)
plt.xlabel("Price")
plt.ylabel("Room Type")
plt.title("Price by Room Type, Price <= 355$")
plt.suptitle("")
```

Out[ ]:
```
Text(0.5, 0.98, '')
```

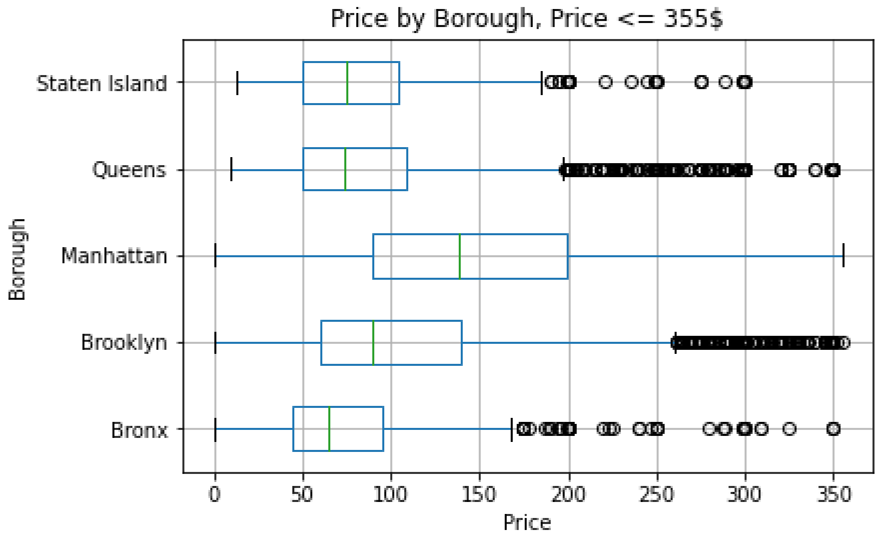


In the plot above, we can see how price differs by room type. There seems to be a larger variation in prices for listings of the entire home/apartment and private room type compared to shared rooms. The median listing price for entire home/apartment are higher compared to private rooms. Private rooms in turn have a higher median listing price compared to shared rooms. This make sense as we expect consumers are willing to pay more for more privacy and a larger space. We note that shared rooms have the median of around 40 dollars per night, private rooms at around 70 dollars per night and entire home/apartments at around 150 dollars per night.

We are using a filtered data set to remove the outliers by filtering the data for price to less than 355 dollars per night, which is the 95th percentile. The plots would be very zoomed out otherwise.

In [ ]:
```
data_95th.boxplot(column = 'price', by = "neighbourhood_group", vert=False)
plt.xlabel("Price")
plt.ylabel("Borough")
plt.title("Price by Borough, Price <= 355$")
plt.suptitle("")
```

Out[ ]:
```
Text(0.5, 0.98, '')
```



In the plot above, we can see how price differs between the boroughs of New York City. Although the majority of listings are similar across Staten Island, Queens, Brooklyn and Bronx, Manhattan stands out with the only median price above 100 dollars per night. Manhattan has the widest IQR range meaning Manhattan has the largest variation of prices between all five boroughs. Brooklyn trailed with the second highest median price. Staten Island and Queens had similar median prices but Queens had more variations in prices and more outliers. Finally, Bronx had the lowest median listing price and a small IQR range, suggesting that Airbnbs in Bronx are generally cheaper compared to another borough in NYC.

We are using a filtered data set to remove the outliers by filtering the data for price to less than 355 dollars per night, which is the 95th percentile. The plots would be very zoomed out otherwise.

Part 2 Question and Message

The Question: How does the room type and location of an Airbnb listing affect its listing price?

The Message: So far, we've seen how the room type of the listing affects it's prices. Generally, entire homes/apartments have a higher lising price compared to private rooms which is followed by shared rooms. We've also seen that generally, Manhattan listings are the most expensive followed by Brooklyn. Staten Island and Queens have similar median prices and the Bronx has the lowest.

In part 3 we will create maps that of NYC that illustrate how price differs in NYC in general. We will also group listings by room type and create separate maps for each.

Part 3 Maps

In [ ]:
```
# read in county shape data
county_df = gpd.read_file("https://www2.census.gov/geo/tiger/TIGER2019/COUNTY/
tl_2019_us_county.zip")
county_df.head(2)
```

Out[ ]:

	STATEFP	COUNTYFP	COUNTYNS	GEOID	NAME	NAMELSAD	LSAD	CLASSFP	MTFC(
0	31	039	00835841	31039	Cuming	Cuming County	06	H1	G402(
1	53	069	01513275	53069	Wahkiakum	Wahkiakum County	06	H1	G402(

In [ ]:
```
# create a geometry column used as that applies Point function to longitude an
d latitude
data["geometry"] = list(zip(data.longitude, data.latitude))
data["geometry"] = data["geometry"].apply(Point)

# create a geodataframe from our pandas dataframe
gdf = gpd.GeoDataFrame(data, crs= 4326, geometry="geometry")

gdf.head(2)
```

Out[ ]:

	id	price	room_type	neighbourhood_group	neighbourhood	latitude	longitude	geometry
0	2539	149	Private room	Brooklyn	Kensington	40.64749	-73.97237	POINT (-73.9723 40.64749
1	2595	225	Entire home/apt	Manhattan	Midtown	40.75362	-73.98377	POINT (-73.9837 40.75362

In [ ]:
```
# Filtered by GEOID for the 5 boughs of NYC
county_df = county_df.query("GEOID in ['36005', '36047', '36061', '36081', '36
085']")

# made naming changes to match county data with airbnb data
county_df["NAME"].replace({
    "Kings": "Brooklyn",
    "New York": "Manhattan",
    "Richmond": "Staten Island"}, inplace = True)

county_df
```

Out[ ]:

	STATEFP	COUNTYFP	COUNTYNS	GEOID	NAME	NAMELSAD	LSAD	CLASSFP	MTF
1399	36	085	00974141	36085	Staten Island	Richmond County	06	H6	G4
2333	36	081	00974139	36081	Queens	Queens County	06	H6	G4
2409	36	047	00974122	36047	Brooklyn	Kings County	06	H6	G4
2446	36	061	00974129	36061	Manhattan	New York County	06	H6	G4
3162	36	005	00974101	36005	Bronx	Bronx County	06	H6	G4

In [ ]:

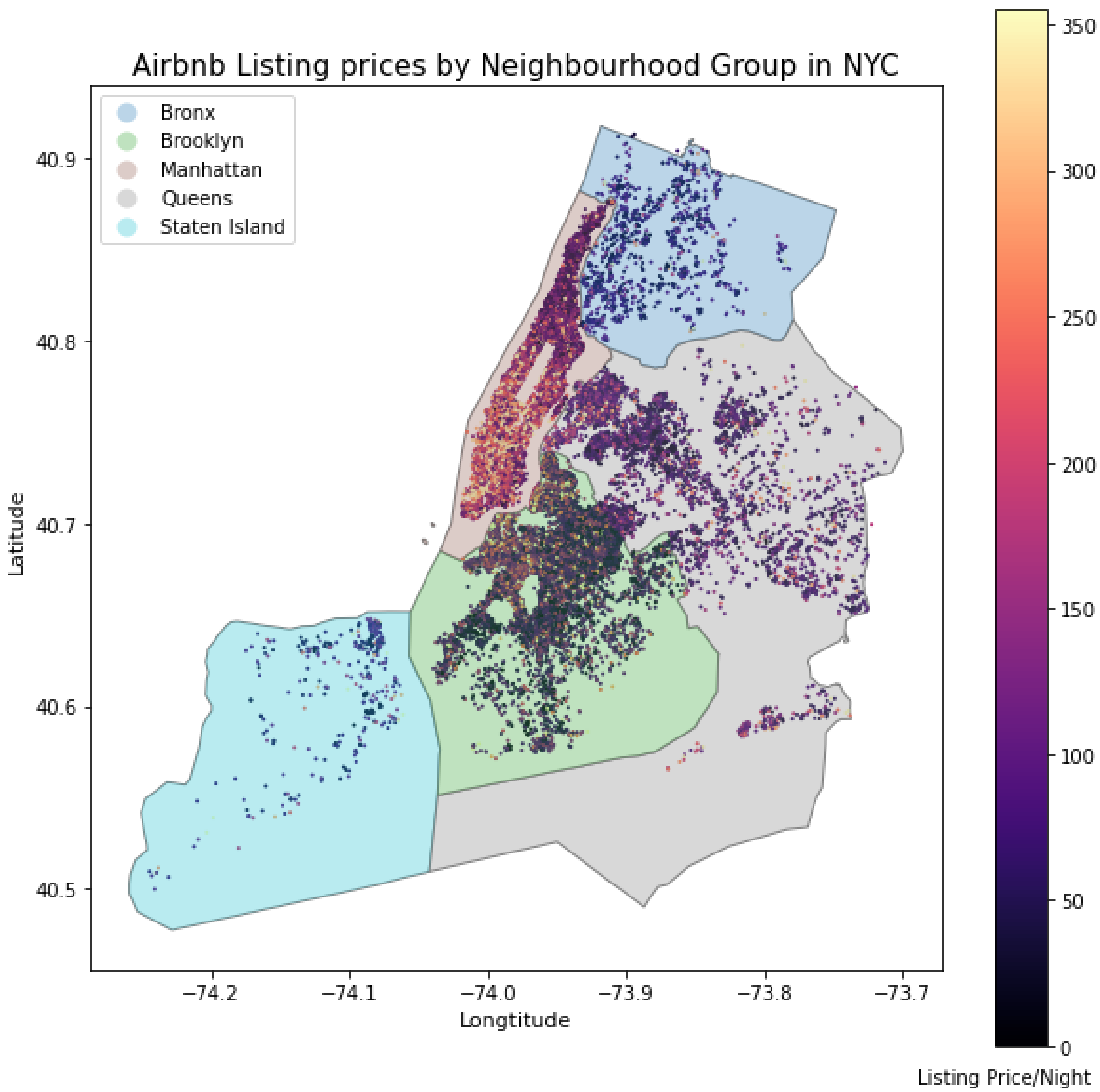
```
# Plot listings and prices on map
fig, gax = plt.subplots(figsize=(10, 10))
county_df.plot(ax=gax, edgecolor = 'grey', color='white')
gdf.plot(ax=gax, column = 'price',  vmin=0, vmax=355, markersize = .9, legend
= True, cmap='magma')

county_df.plot(column = "NAME", legend = True, alpha = 0.3, ax = gax)
gax.set_title("Airbnb Listing prices by Neighbourhood Group in NYC", fontsize
= 15)

gax.annotate('Listing Price/Night',xy=(0.78, 0.06),  xycoords='figure fractio
n')

gax.set_ylabel("Latitude", fontsize = 11)
gax.set_xlabel("Longtitude", fontsize = 11)
```

Out[ ]: Text(0.5, 109.01504300107274, 'Longtitude')



We can see from the plot above that listings in Brooklyn and Manhattan had a wide range of prices. Airbnbs' with a low and high listings prices were found in Manhattan and Brooklyn, while Bronx, Staten Island and Queens mainly had cheaper listings. South Manhattan stands out with the most number of listings with high listing prices. North Brooklyn also had a number of high priced Airbnbs, suggesting that the demand for Airbnbs in North Brooklyn and South Manhattan are high.

In [ ]:
```
# Now lets take a look at how the average listing price looks
fig, gax = plt.subplots(1, 3, figsize=(20,20), constrained_layout=True)

for ax in gax.reshape(-1):
  county_df.plot(ax = ax, edgecolor = "grey", color = "white")
  county_df.plot(column = "NAME", legend = True, alpha = .3, ax = ax)

# filter and map entire hooms/apt
ent_room = gdf.query("room_type == 'Entire home/apt'")
ent_room.plot(ax=gax[0], column = 'price',  vmin=0, vmax=355, markersize = .9,
cmap='magma')

# filter and map entire private
pri_room = gdf.query("room_type == 'Private room'")
pri_room.plot(ax=gax[1], column = 'price',  vmin=0, vmax=355, markersize = .9,
cmap='magma')

# filter and map entire shared room
shared_room = gdf.query("room_type == 'Shared room'")
shared_room.plot(ax=gax[2], column = 'price',  vmin=0, vmax=355, markersize =
.9, cmap='magma')

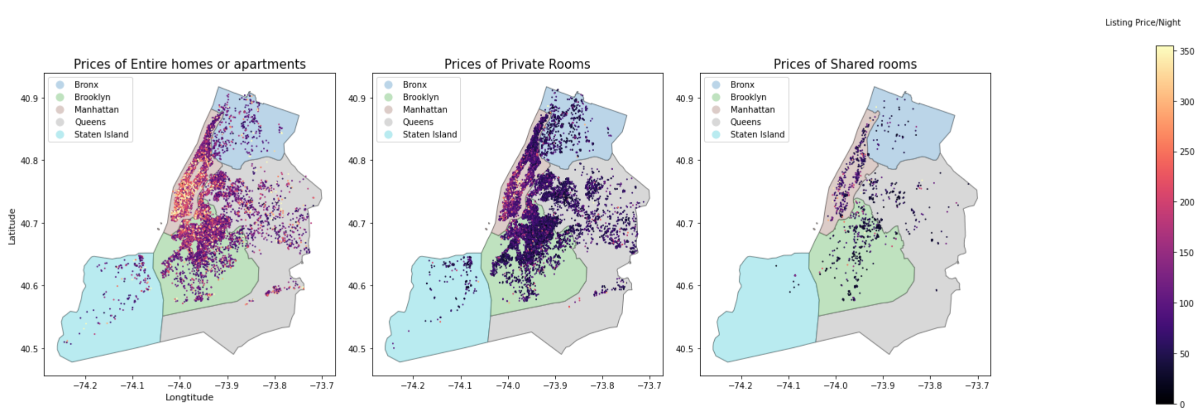
# Add a color bar to the far left graph
norm_95th = Normalize(vmin=0, vmax=355, clip=True)
col_bar = cm.ScalarMappable(norm=norm_95th, cmap='magma')
fig.colorbar(col_bar, ax = gax[2], location="right", shrink = 0.3)

# add titles
gax[0].set_title("Prices of Entire homes or apartments", fontsize = 15)
gax[1].set_title("Prices of Private Rooms", fontsize = 15)
gax[2].set_title("Prices of Shared rooms", fontsize = 15)

# add axis
gax[0].set_ylabel("Latitude", fontsize = 11)
gax[0].set_xlabel("Longtitude", fontsize = 11)

gax[2].annotate('Listing Price/Night',xy=(0.92, 0.76),  xycoords='figure fract
ion')
```

Out[ ]:
```
Text(0.92, 0.76, 'Listing Price/Night')
```



The figure above confirms that the majority of listings were for entire homes and apartments followed by private rooms and finally shared rooms were the least popular listings. Listings of the entire homes or apartments were mainly listed for higher prices. Although there were private rooms and shared rooms with high listings prices, the majority of listings were for the lower end of prices. This does not come as a surprise as we think people value privacy and are willing to pay more for it.

Bonus Interactive Map

In [ ]:

```
# getting the mean listing price by neighbourhood
mean_neighbourhood = gdf.groupby('neighbourhood_group').mean()
mean_neighbourhood.reset_index(inplace=True)
mean_neighbourhood = mean_neighbourhood[['neighbourhood_group',"price"]]
mean_neighbourhood.rename(columns={'price': 'average_neighbourhood_price'}, inplace=True)

#rename column and join to add as a column in county_df
county_df.rename(columns={'NAME' : 'neighbourhood_group'}, inplace=True)
county_df = county_df.merge(mean_neighbourhood, how='left', on = 'neighbourhood_group')

# print our average prices
print(county_df['average_neighbourhood_price'])

# print out mean price
print(np.mean(county_df['average_neighbourhood_price']))
```

```
0    114.812332
1     99.517649
2    124.383207
3    196.875814
4     87.496792
Name: average_neighbourhood_price, dtype: float64
124.61715890102955
```

In [ ]:

```
from bokeh.io import output_notebook
from bokeh.plotting import figure, ColumnDataSource, save
from bokeh.io import output_notebook, show, output_file
from bokeh.models import GeoJSONDataSource, LinearColorMapper, ColorBar, HoverTool
from bokeh.palettes import brewer

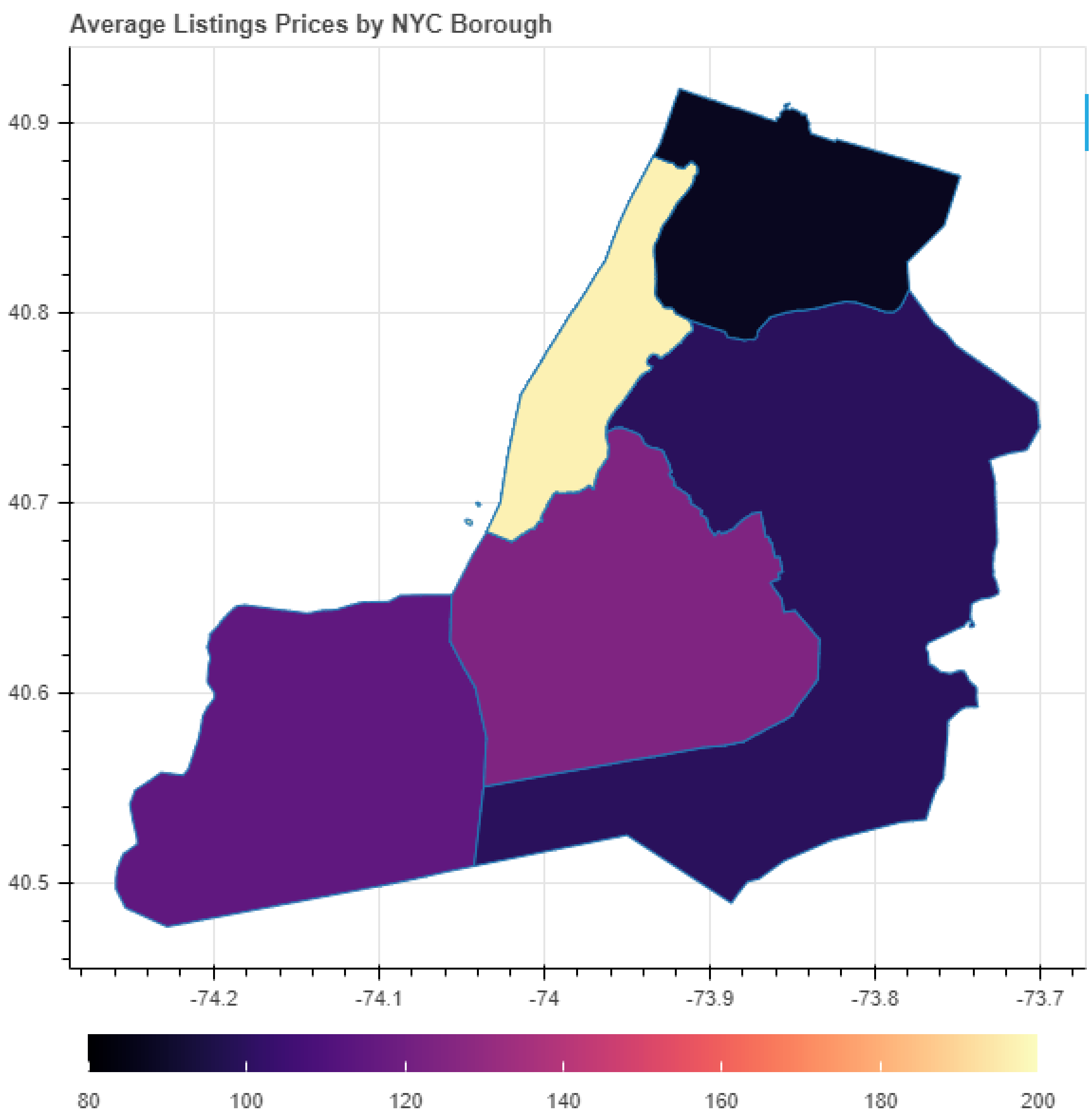
from bokeh.resources import INLINE
output_notebook(INLINE)
import json
```

In [ ]:

```
#Convert data to geojson for bokeh
county_geojson=GeoJSONDataSource(geojson=county_df.to_json())
```

In [ ]:
```
color_mapper = LinearColorMapper(palette = 'Magma256', low =80 , high = 200)
color_bar = ColorBar(color_mapper=color_mapper, label_standoff=8,width = 500, height = 20,
                     border_line_color=None,location = (0,0), orientation = 'horizontal')
hover = HoverTool(tooltips = [('Borough','@neighbourhood_group'),('Average Price', '@average_neighbourhood_price')])

p = figure(title="Average Listings Prices by NYC Borough", tools=[hover])
p.patches("xs","ys",source=county_geojson,
          fill_color = {'field' :'average_neighbourhood_price', 'transform' : color_mapper})
p.add_layout(color_bar, 'below')
#output_file('prj2_Interactive_fig_hwang.html', mode='inline')
show(p)
```



(http

PLEASE USE THE LINK BELOW The link below is to a github repository which hosts the HTML to the interactive figure. Please download the HTML file to access figure.

https://github.com/hwang-UofT/eco225_pro2 (https://github.com/hwang-UofT/eco225_pro2)

Bonus - Additional Data Set

Let's now pull a dataset containing population estimates for the Boroughs of NYC on July 1, 2019.

We will clean the data and then merge in data with our county data set which includes the unique borough names and geometry data.

We would be able to calculate the population density of each NYC borough and map the results to see the relationship between population density and Airbnb listing price.

This data set is retrived from the United States Census Bureau.
https://www.census.gov/quickfacts/fact/table/newyorkcitynewyork,bronxcountybronxboroughnewyork,kingscountyb
(https://www.census.gov/quickfacts/fact/table/newyorkcitynewyork,bronxcountybronxboroughnewyork,kingscountyb

In [ ]:
```
population_df = pd.read_csv("QuickFacts Mar-04-2021.csv")
population_df.head()
```

Out[ ]:

	Fact	Fact Note	New York city, New York	Value Note for New York city, New York	Bronx County (Bronx Borough), New York	Value Note for Bronx County (Bronx Borough), New York	Kings County (Brooklyn Borough), New York	Value Note for Kings County (Brooklyn Borough), New York	New York County (Manhattan Borough), New York
0	Population estimates, July 1, 2019, (V2019)	NaN	8,336,817	NaN	1,418,207	NaN	2,559,903	NaN	1,628,706
1	Population estimates base, April 1, 2010, (V2...	NaN	8,175,031	NaN	1,384,580	NaN	2,504,721	NaN	1,586,381
2	Population, percent change - April 1, 2010 (es...	NaN	2.0%	NaN	2.4%	NaN	2.2%	NaN	2.7%
3	Population, Census, April 1, 2010	NaN	8,175,133	NaN	1,385,108	NaN	2,504,700	NaN	1,585,873
4	Persons under 5 years, percent	NaN	6.5%	NaN	7.1%	NaN	7.1%	NaN	4.7%

In [ ]:
```
# isolate first row
population_df = population_df.iloc[[0]]
population_df = population_df.T.reset_index()
# rename columns
population_df = population_df.rename(columns={"index":"neighbourhood_group", 0
:'population_2019'})

#drop NAs
population_df.dropna(inplace=True)

# drop rows we dont need
population_df.drop([0,2], inplace=True)
population_df
```

Out[ ]:

	neighbourhood_group	population_2019
4	Bronx County (Bronx Borough), New York	1,418,207
6	Kings County (Brooklyn Borough), New York	2,559,903
8	New York County (Manhattan Borough), New York	1,628,706
10	Queens County (Queens Borough), New York	2,253,858
12	Richmond County (Staten Island Borough), New York	476,143

In [ ]:
```
# made naming changes to match county data with airbnb data
population_df["neighbourhood_group"].replace({
    "Bronx County (Bronx Borough), New York": "Bronx",
    "Kings County (Brooklyn Borough), New York": "Brooklyn",
    "New York County (Manhattan Borough), New York": "Manhattan",
    "Queens County (Queens Borough), New York": "Queens",
    "Richmond County (Staten Island Borough), New York": "Staten Island"}, inp
lace = True)
population_df
```

Out[ ]:

	neighbourhood_group	population_2019
4	Bronx	1,418,207
6	Brooklyn	2,559,903
8	Manhattan	1,628,706
10	Queens	2,253,858
12	Staten Island	476,143

In [ ]:

```
# Merge with airbnb dataset

# add population column
merged_county = county_df.merge(population_df, how='left', left_on="NAME", rig
ht_on="neighbourhood_group")

# add area column
merged_county["Area"] = merged_county.geometry.area

merged_county["population_2019"] = merged_county["population_2019"].str.replac
e(',', '').astype(float)
merged_county["Pop_Density"] = merged_county["population_2019"]/merged_county[
"Area"]

merged_county.head()
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:7: UserWarning:
Geometry is in a geographic CRS. Results from 'area' are likely incorrect. Us
e 'GeoSeries.to_crs()' to re-project geometries to a projected CRS before thi
s operation.

  import sys
```

Out[ ]:

	STATEFP	COUNTYFP	COUNTYNS	GEOID	NAME	NAMELSAD	LSAD	CLASSFP	MTFCC
0	36	085	00974141	36085	Staten Island	Richmond County	06	H6	G4020
1	36	081	00974139	36081	Queens	Queens County	06	H6	G4020
2	36	047	00974122	36047	Brooklyn	Kings County	06	H6	G4020
3	36	061	00974129	36061	Manhattan	New York County	06	H6	G4020
4	36	005	00974101	36005	Bronx	Bronx County	06	H6	G4020

In [ ]:
```
fig, gax = plt.subplots(figsize=(10,10))
merged_county.plot(ax = gax, column="Pop_Density", cmap="Blues", edgecolor = 'grey', legend=True)

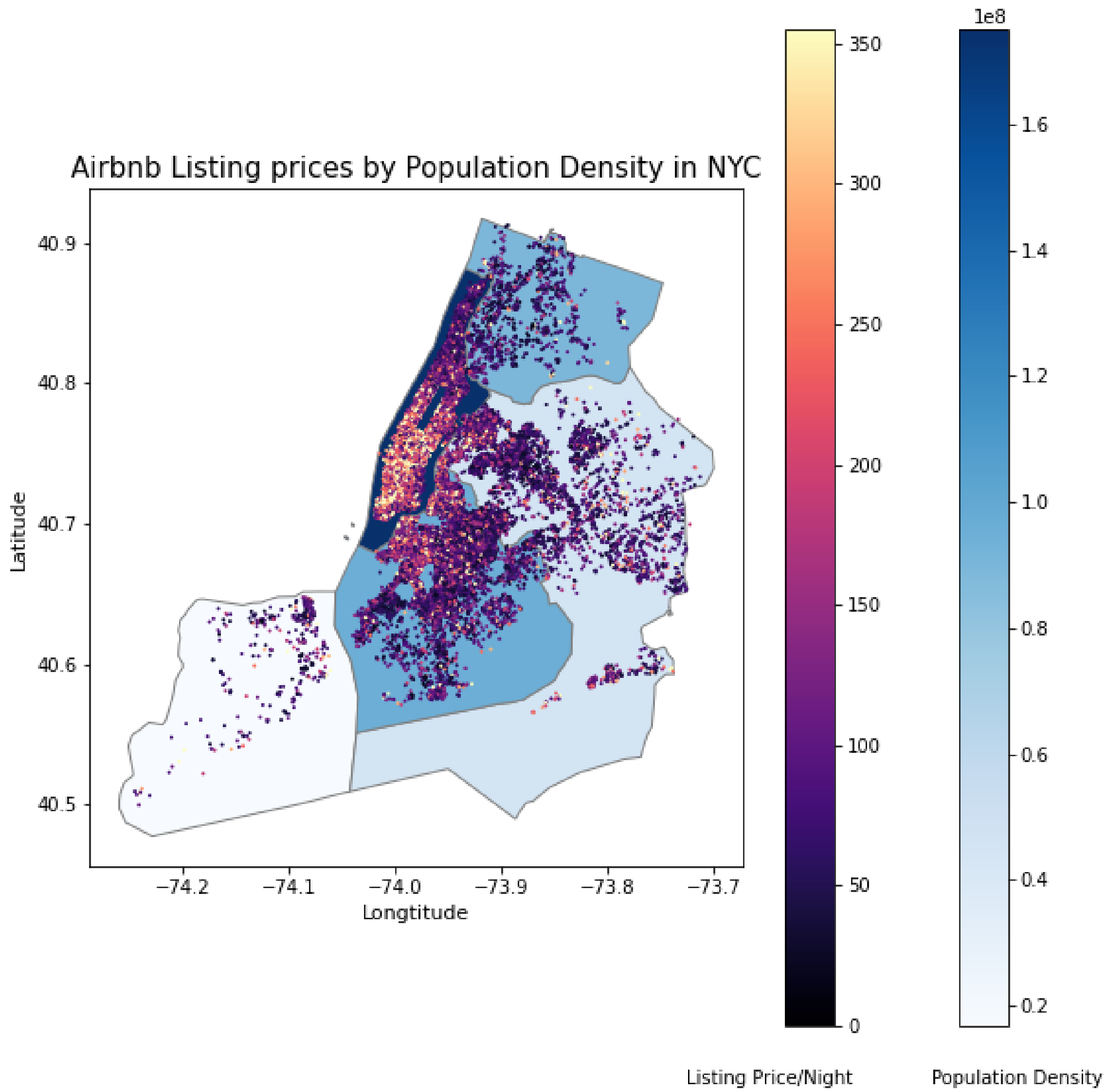
gdf.plot(ax=gax, column = 'price',  vmin=0, vmax=355, markersize = .9, legend = True, cmap='magma')

gax.set_title("Airbnb Listing prices by Population Density in NYC", fontsize = 15)

gax.annotate('Listing Price/Night',xy=(0.59, 0.05),  xycoords='figure fraction')
gax.annotate('Population Density',xy=(0.8, 0.05),  xycoords='figure fraction')

gax.set_ylabel("Latitude", fontsize = 11)
gax.set_xlabel("Longtitude", fontsize = 11)
```

Out[ ]: Text(0.5, 155.34715325001977, 'Longtitude')



We can see that Manhattan and Brooklyn are the highest population desentiy levels and have a number of high priced airbnb listings. Similarily, Bronx has the lowest population density and generally lower price. This aligns with our preivous findings that Bronx had the lowest median price and Manhattan had the highest. This suggests that Population density might have a positive relationship with Airbnb price listings. The high population density suggests that there are more demand for places to sleep / live in compared to low population density places. This naturally means, a higher demand for housing and a higher price as we see in the data.

Conclusion and Future Steps

In the second project, I made changes based on the comments I receieved in project 1. I fine tuned my graphs and updated my anaylses on my visualizations. I created visualizations that illustrate how price differs between entire homes/apartments, private rooms and shared rooms on a map of NYC. I also made a map on NYC containing all listings in each of the boroughs. We discovered that the median listing price and the variation in listing price was highest in listings for entire homes/apartments. Median and variation in listing price decreased in private rooms and was the lowest in shared rooms. We discovered that Manhattan had both the highest and largest variation in listing prices. Brooklyn had the second highest median listing price while Queens and Staten Island had similar median prices and Bronx had the lowest. South Manhattan stands out with the most number of listings with high listing prices. North Brooklyn also had a number of high priced Airbnbs suggesting that the demand for Airbnbs in North Brooklyn and South Manhattan are high.

I also combined a NYC borough population estimate data to calculate the population density of the boroughs. I created a map that illustrated higher population density boroughs generally had higher listing prices.

Future Steps

In the future I would want to look into fitting a linear model that predicts the price provided a Airbnb's listing and room type. I would want to analyze my model to reach a conclusion for my research question of what is the effect a Airbnb listing's room type and neighbourhood has on its price. I would do this by testing the significance of my coefficient estimates for predicting listing price.