AIRBNB NEW YORK CITY PRICING DYNAMICS

Data Bootcamp Final Project

Principal Investigators : Samantha Warsop & Brittany Miu

Email: sw3469@nyu.edu bm2352@nyu.edu

This project will explore how pricing differs across Airbnbs and the influences it has on demand. We will also explore the seasonal pattern of airbnb prices in New York City and the effects it has on travel. As an example, in New York City, Airbnb prices across different neighbourhood groups such as Manhattan, Brooklyn, Queens, Staten Island, and the Bronx might differ. We can look at how pricing varies across these different neighbourhood groups in terms of the number of the listings and property type available.

The key element of the project is the use of Airbnb's data, providing access to measures such as prices, number of listings, property type, etc. in New York. Detailed of this dataset are described below in the data report.

There will be three different sections in this project:

1. Basic Data Analysis

This section will have different summary statistics describing the number of listings and property type in each neighbourhood group.

2. Pricing Effect on Demand for Airbnbs in New York City

This section will explore how prices differ across different neighbourhood groups and discover what factors prices are dependent on. We will have visualizations such as a map to indicate where entire apartments/homes are most prevalent. There will be a bar chart illustrating the average prices in each neighbourhood. By analyzing the number of listings and prices per neighbourhood, we can find out which neighbourhood is the most optimal.

3. Seasonal Pattern of Prices

The last will explore how prices vary across different seasons. We plan to have visualizations showing how prices change over the year and provide explanations as to why. For example, airbnb prices during the holidays might be more expensive than during non-holidays.

Overview:

The data behind our project comes from insideairbnb (http://insideairbnb.com/get-the-data.html) . Their New York city data (http://insideairbnb.com/new-york-city/) provides access to information on room types, availability, activity, as well as listings per host.

Important Variables:

The key series that we must retrive is within insideairbnb's data on New York city data (http://insideairbnb.com/new-york-city/). This data provides the airbnb locations, as well as pricing, which will allow us to determine answers to both analysis part one and two. This data combined with utalizing datetime and holiday functions will allow us to analyze Airbnb's seasonal pattern of prices.

Access:

We will use insideairbnb to download and acess the data. Below we will demonstrate that we have the ability to access the data. NOTE: csv files could not be uploaded to github due to the file size. Files are in a flashdrive left at your office.

Requisite Packages:

Below we will bring in the packages we need:

In [1]:

```
import pandas as pd
import numpy as np #numerical analysis
import matplotlib.pyplot as plt #plotting
import geopandas as gpd #geospatial data in python
import os #manipulate paths
from datetime import date #maniupulating dates and times
import datetime
import holidays #generate country specific sets of holidays
import calendar #useful functions related to the calendar
from mpl_toolkits.axes_grid1.inset_locator import zoomed_inset_axes #maniupula
te data to get zoomed in picture
from mpl_toolkits.axes_grid1.inset_locator import mark_inset
```

Cleaned Data:

Data that was cleaned in a separate notebook can be accessed in our Data Report (https://github.com/brittanymiu/data_bootcamp_final_project/blob/master/Airbnb_Data%20Report_Saman

NOTE: csv files could not be uploaded to github due to the file size. Files are in a flashdrive left at your office.

In [2]:

```
file= "/Users/SamanthaWarsop 1/Airbnb New York/clean_listings.csv"
```

In [4]:

```
#listings csv is going to be used in analysis part one and two
listings = pd.read_csv(file)
```

```
/anaconda3/lib/python3.7/site-packages/IPython/core/interactiveshe
ll.py:3020: DtypeWarning: Columns (12) have mixed types. Specify d
type option on import or set low_memory=False.
  interactivity=interactivity, compiler=compiler, result=result)
```

In [5]:

```
listings.head()
```

Out[5]:

	Unnamed: 0	listing_id	experiences_offered	host_id	host_acceptance_rate	host_is_supe
0	0	1742654	none	9173924	0.0	
1	2	15984984	none	9737900	0.0	
2	3	13820083	none	31829334	0.0	
3	4	6170979	none	31104121	0.0	
4	5	27283214	none	3508466	0.0	

5 rows × 53 columns

In [6]:

```
calendar_file = "/Users/SamanthaWarsop 1/Airbnb New York/clean_calendar.csv"
```

In [7]:

```
#calendar csv will be used in analysis part three
calendar_df = pd.read_csv(calendar_file)
```

In [8]:

```
calendar_df.head()
```

Out[8]:

	Unnamed: 0	listing_id	date	available	price	minimum_nights	maximum_nights	Year	M
0	0	36647	2019-03-07	f	69.0	2.0	730.0	2019	
1	1	36647	2019-03-08	f	69.0	2.0	730.0	2019	
2	2	36647	2019-03-09	f	69.0	2.0	730.0	2019	
3	3	36647	2019-03-10	f	69.0	2.0	730.0	2019	
4	4	36647	2019-03-11	f	69.0	2.0	730.0	2019	

In [9]:

```
#listings_calendar csv will be used in analysis part three
listings_calendar_file = "/Users/brittanymiu/Airbnb New York/listings_calendar
.csv"
```

In [10]:

```
listings_calendar = pd.read_csv(listings_calendar_file)
```

```
/anaconda3/lib/python3.7/site-packages/IPython/core/interactiveshe
ll.py:3020: DtypeWarning: Columns (12,27,28) have mixed types. Spe
cify dtype option on import or set low_memory=False.
  interactivity=interactivity, compiler=compiler, result=result)
```

In [11]:

```
listings_calendar.head()
```

Out[11]:

	Unnamed: 0	listing_id	experiences_offered	host_id	host_acceptance_rate	host_is_sup
0	0	1742654	none	9173924.0	0.0	
1	1	1742654	none	9173924.0	0.0	
2	2	1742654	none	9173924.0	0.0	
3	3	1742654	none	9173924.0	0.0	
4	4	1742654	none	9173924.0	0.0	

5 rows × 61 columns

ANALYSIS PART ONE

BASIC DATA ANALYSIS

Before we look at airbnb prices, we are first going to look at the number of listings and room type in each neighborhood group.

In [12]:

```
#finding the number of listings for each neighbourhood group
neighborhood_group_df = listings.groupby('neighbourhood_group_cleansed').listi
ng_id.count()
neighborhood_group_df = neighborhood_group_df.reset_index()
neighborhood_group_df = neighborhood_group_df.rename(columns={'listing_id':'Nu
mber_of_Listings'})
neighborhood_group_df
```

Out[12]:

	neighbourhood_group_cleansed	Number_of_Listings
0	Bronx	745
1	Brooklyn	14555
2	Manhattan	13817
3	Queens	3969
4	Staten Island	257

In [13]:

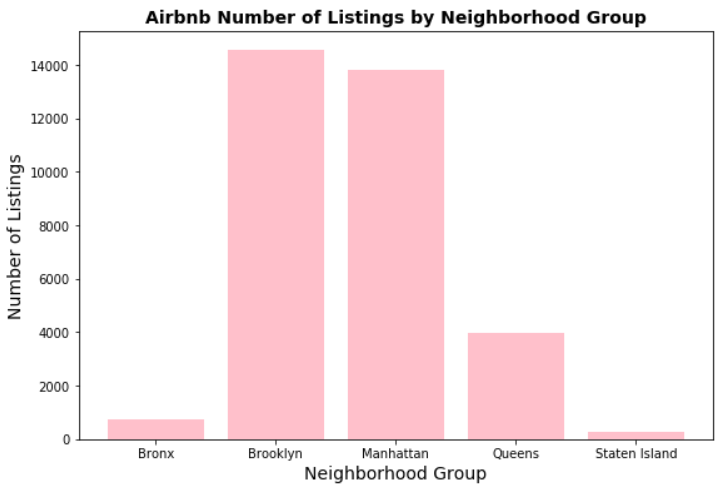
```
#finding the number of room types
room_type = listings.groupby('room_type').listing_id.count()
room_type = room_type.reset_index()
room_type = room_type.rename(columns = {'listing_id': 'room_count'})
room_type
```

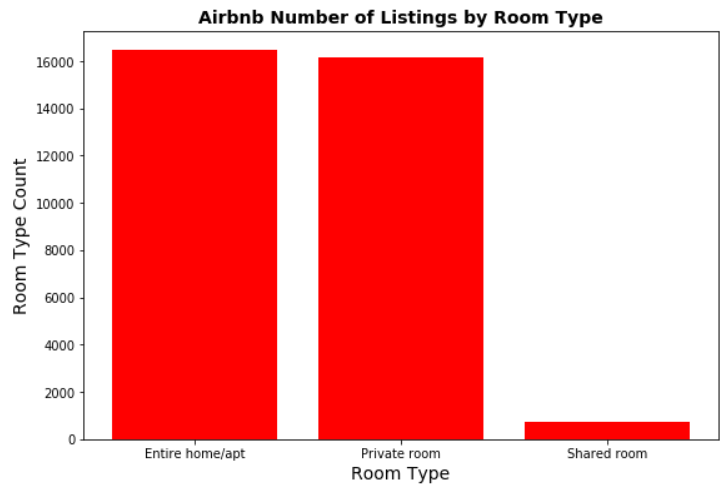
Out[13]:

	room_type	room_count
0	Entire home/apt	16467
1	Private room	16139
2	Shared room	737

In [14]:

```
fig, ax = plt.subplots(nrows = 1, ncols = 2, sharex = False, figsize = (20,6))

ax[0].bar(neighborhood_group_df.neighbourhood_group_cleansed, neighborhood_gro
up_df.Number_of_Listings, color = "pink")

ax[0].set_title("Airbnb Number of Listings by Neighborhood Group", fontsize =
14, fontweight = "bold")

ax[0].set_ylabel("Number of Listings", fontsize = 14,)
ax[0].set_xlabel("Neighborhood Group", fontsize = 14,)

ax[1].bar(room_type.room_type, room_type.room_count, color = "red")

ax[1].set_title("Airbnb Number of Listings by Room Type", fontsize = 14, fontw
eight = "bold")

ax[1].set_ylabel("Room Type Count", fontsize = 14,)
ax[1].set_xlabel("Room Type", fontsize = 14,)

plt.show()
```





In [15]:

```
#finding the number of listings for each room type in each neighbourhood group
neighborhood_room = listings.groupby(['neighbourhood_group_cleansed', 'room_type']).listing_id.count()
neighborhood_room = neighborhood_room.reset_index()
neighborhood_room = neighborhood_room.rename(columns={'listing_id':'Number_of_Listings'})
neighborhood_room.set_index(['neighbourhood_group_cleansed', 'room_type'])
neighborhood_room
```

Out[15]:

	neighbourhood_group_cleansed	room_type	Number_of_Listings
0	Bronx	Entire home/apt	226
1	Bronx	Private room	486
2	Bronx	Shared room	33
3	Brooklyn	Entire home/apt	6976
4	Brooklyn	Private room	7308
5	Brooklyn	Shared room	271
6	Manhattan	Entire home/apt	7742
7	Manhattan	Private room	5775
8	Manhattan	Shared room	300
9	Queens	Entire home/apt	1406
10	Queens	Private room	2432
11	Queens	Shared room	131
12	Staten Island	Entire home/apt	117
13	Staten Island	Private room	138
14	Staten Island	Shared room	2

In [16]:

```
#creating a map
#NYC shape file is from Professor Michael Waugh's Data Bootcamp course
cwd = os.getcwd()
```

In [17]:

```
shape_file = cwd + "/shape_file/ZIP_CODE_040114.shx"
```

In [18]:

```
shape_file
```

Out[18]:

```
'/Users/brittanymiu/Airbnb New York/shape_file/ZIP_CODE_040114.shx
'
```

In [19]:

```
nyc_map = gpd.read_file(shape_file)
```

In [20]:

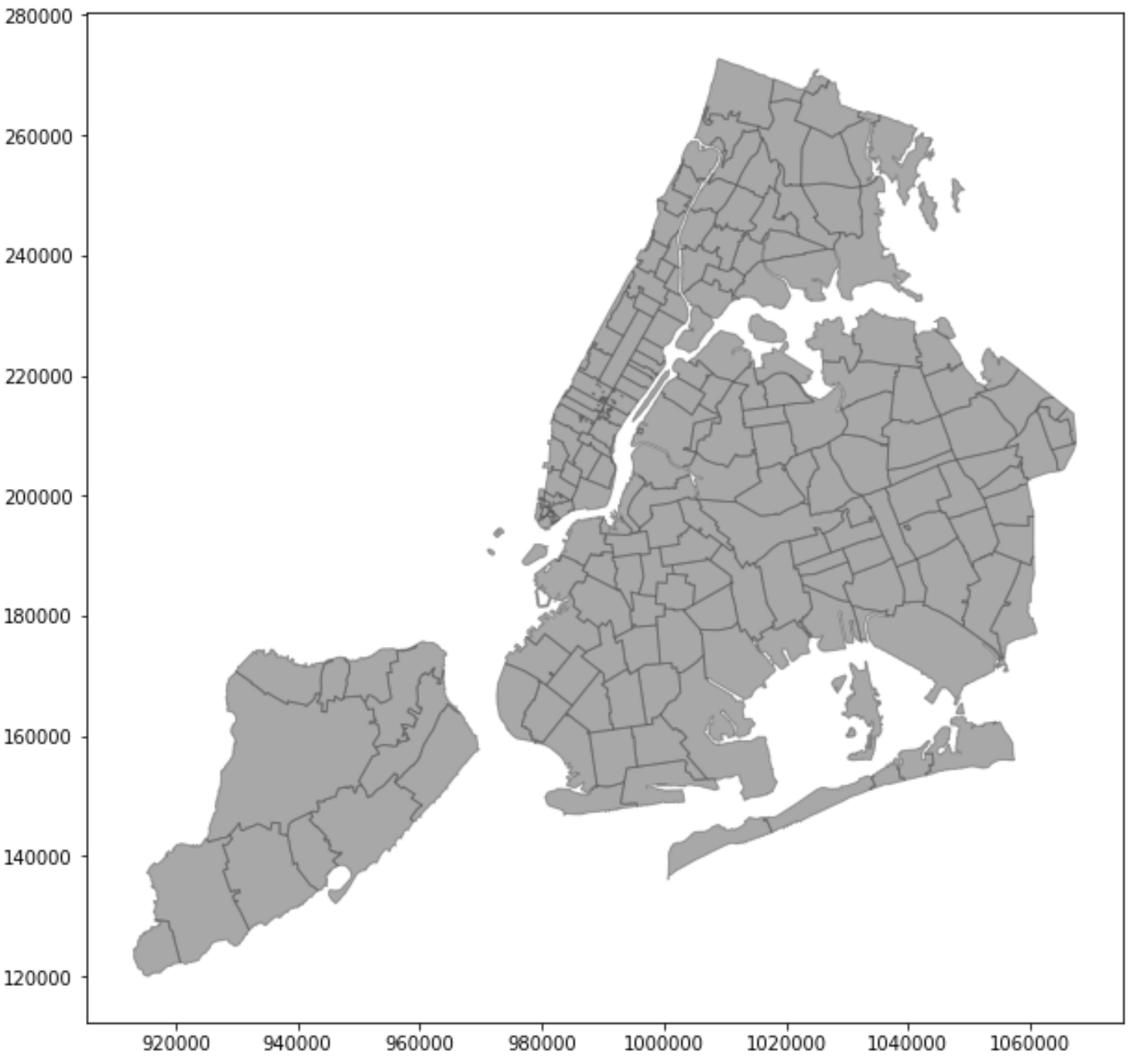
```
nyc_map.head()
```

Out[20]:

	ZIPCODE	BLDGZIP	PO_NAME	POPULATION	AREA	STATE	COUNTY	ST_FIPS
0	11436	0	Jamaica	18681.0	2.269930e+07	NY	Queens	36
1	11213	0	Brooklyn	62426.0	2.963100e+07	NY	Kings	36
2	11212	0	Brooklyn	83866.0	4.197210e+07	NY	Kings	36
3	11225	0	Brooklyn	56527.0	2.369863e+07	NY	Kings	36
4	11218	0	Brooklyn	72280.0	3.686880e+07	NY	Kings	36

In [21]:

```
fig, ax = plt.subplots(figsize=(10,10))
gpd.plotting.plot_polygon_collection(ax,
                                     nyc_map['geometry'],
                                     linewidth=0.9,
                                     edgecolor='#B9EBE3',
                                     alpha=0.5,
                                     color='#525252');
```



In [22]:

```
#looking at the number of neigborhoods in NYC
listings.neighbourhood_cleansed.value_counts()
```

Out[22]:

```
Williamsburg                2850
Bedford-Stuyvesant          2789
Harlem                      1992
Bushwick                    1733
Hell's Kitchen              1273
East Village                1270
Upper West Side             1227
Crown Heights               1135
Upper East Side             1061
```

```
East Harlem                  825

Greenpoint                   753
Midtown                      734
Lower East Side              639
Washington Heights           628
Chelsea                      625
Astoria                      603
West Village                 472
Flatbush                     451
Clinton Hill                 413
Prospect-Lefferts Gardens    392
Long Island City             366
Park Slope                   366
East Flatbush                362
Flushing                     341
Financial District           322
Fort Greene                  318
Murray Hill                  286
Sunset Park                  283
Ridgewood                    283
Chinatown                    273
                             ...
Graniteville                   3
Jamaica Hills                  3
Mill Basin                     3
Rosebank                       3
Todt Hill                      3
Emerson Hill                   3
Eltingville                    2
Little Neck                    2
Holliswood                     2
Arden Heights                  2
Breezy Point                   2
Westerleigh                    2
North Riverdale                2
Neponsit                       2
Howland Hook                   2
Lighthouse Hill                2
Glen Oaks                      2
Castle Hill                    2
Silver Lake                    2
Co-op City                     2
Huguenot                       2
Grant City                     2
Prince's Bay                   1
Castleton Corners              1
New Dorp Beach                 1
Bay Terrace, Staten Island     1
Willowbrook                    1
Rossville                      1
Olinville                      1
Richmondtown                   1
Name: neighbourhood_cleansed, Length: 219, dtype: int64
```

In [23]:

```
#assigning id to each neighbourhood_clensed
listings = listings.assign(neighbourhood_cleansed_id=listings['neighbourhood_c
leansed'].astype('category').cat.codes)
```

In [24]:

```
#creating a new data frame of stats grouped by neighbourhood_cleansed_id
listings_stats = listings.groupby(['neighbourhood_cleansed_id'])
agg = pd.core.groupby.GroupBy.aggregate
avg_price = listings_stats['price'].agg(np.mean)
avg_eval_loc = listings_stats['review_scores_location'].agg(np.mean)
avg_eval_val = listings_stats["review_scores_rating"].agg(np.mean)
listings_count = listings_stats['listing_id'].agg('count')
```

In [25]:

```
listings_stats_df = pd.DataFrame({'neighbourhood_cleansed_id':avg_price.index,
                                  'count': listings_count.values,
                                  'mean_price':avg_price.values,
                                 'eval_mean':avg_eval_loc.values,
                                  'eval_mean_val':avg_eval_val.values})
listings_stats_df.head()
```

Out[25]:

	neighbourhood_cleansed_id	count	mean_price	eval_mean	eval_mean_val
0	0	33	91.727273	9.303030	94.636364
1	1	2	62.000000	9.500000	92.000000
2	2	19	108.631579	9.578947	95.947368
3	3	60	165.383333	9.383333	95.316667
4	4	603	120.338308	9.630182	94.663350

In [26]:

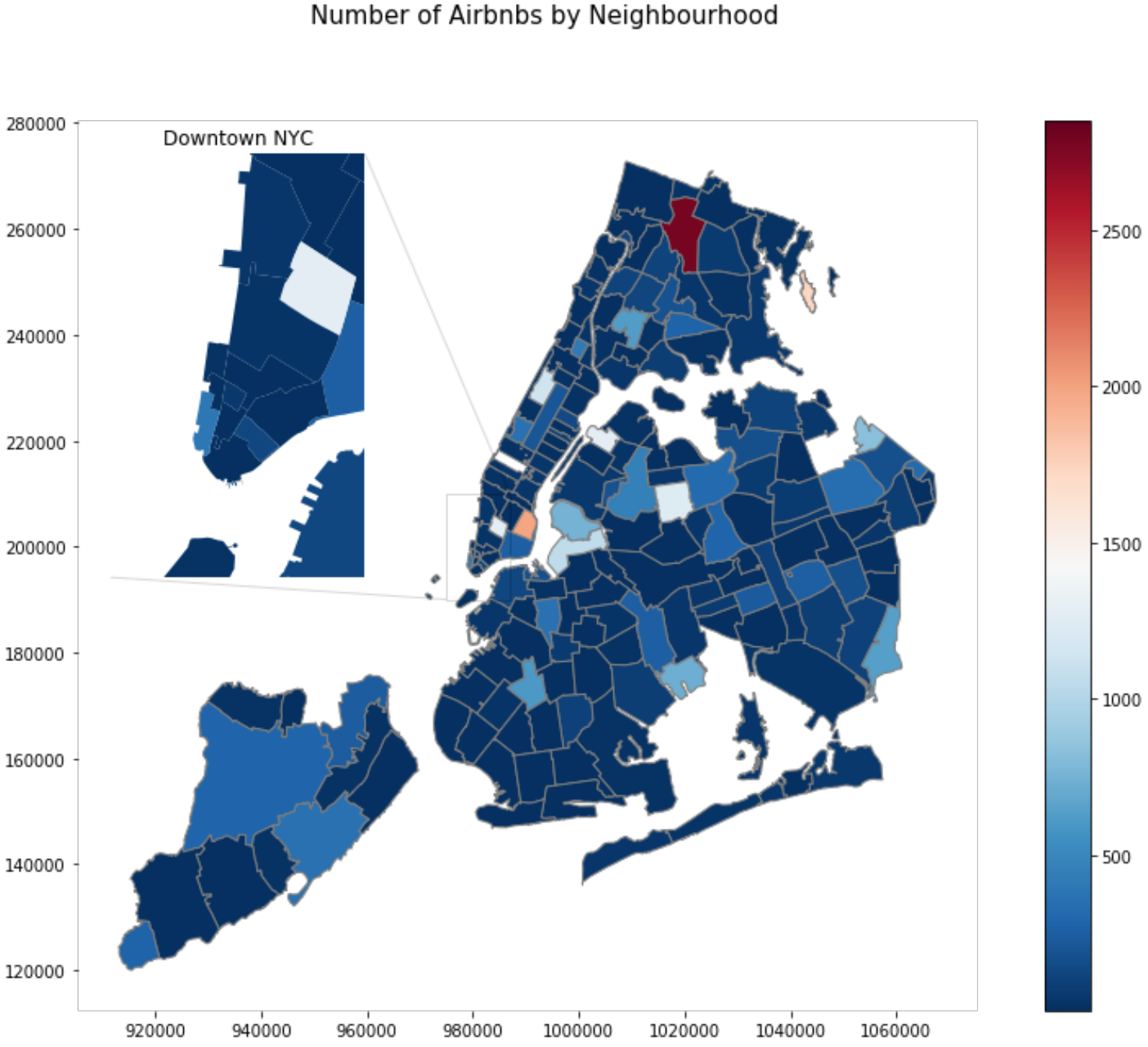
```
#creating a new data frame with geometric coordinates
crs = nyc_map.crs
gdf_listings = gpd.GeoDataFrame(listings_stats_df, crs=crs, geometry=nyc_map['
geometry'])
gdf_listings.head()
```

Out[26]:

	neighbourhood_cleansed_id	count	mean_price	eval_mean	eval_mean_val	g
0	0	33	91.727273	9.303030	94.636364	P ((1038098.25 188138.3800(
1	1	2	62.000000	9.500000	92.000000	P ((1001613.71 186926.43951
2	2	19	108.631579	9.578947	95.947368	P ((1011174.27 183696.3377
3	3	60	165.383333	9.383333	95.316667	P ((995908.365 183617.6128(
4	4	603	120.338308	9.630182	94.663350	P ((991997.113 176307.49586

In [27]:

```
#creating a map showing the number of airbnbs
fig, ax = plt.subplots(figsize=(15,10));

gdf_listings.plot(ax = ax, edgecolor='tab:grey', column = 'count', cmap='RdBu_
r', legend = True)

ax.spines["right"].set_visible(False)
ax.spines["top"].set_visible(False)
ax.spines["left"].set_visible(False)
ax.spines["bottom"].set_visible(False)

fig.suptitle("Number of Airbnbs by Neighbourhood", fontsize = 15)

#code for zoomed in picture of Downtown NYC is from Professor Michael Waugh's
class Data Bootcamp
axins = zoomed_inset_axes(ax,
                          4,
                          loc=2,
                          borderpad=2)

gdf_listings.plot(ax = axins, column='count', cmap='RdBu_r')

x1, x2, y1, y2 = 975000, 987000, 190000, 210000
axins.set_xlim(x1, x2)
axins.set_ylim(y1, y2)

axins.set_title("Downtown NYC")

mark_inset(ax, axins, loc1=3, loc2=1, alpha = 0.15)

axins.spines["right"].set_visible(False)
axins.spines["top"].set_visible(False)
axins.spines["left"].set_visible(False)
axins.spines["bottom"].set_visible(False)

axins.get_xaxis().set_visible(False)
axins.get_yaxis().set_visible(False)

plt.show()
```



Based on our findings so far, Brooklyn has the most listings, followed by Manhattan. Staten Island has the fewest listings. In terms of the number of listings, Brooklyn and Manhattan are the most competitive markets for Airbnbs and Staten Island is the least competitive market. To go more in depth on the type of listings each neighborhood group has, we also looked at the room type. Manhattan has the most number of entire homes/apartments, followed by Brooklyn in New York City.

Entire homes/apartments are generally more expensive than private rooms and shared rooms which may explain the price discrepancy between neighborhood groups, which we will look further in the next section. An interesting finding is that Brooklyn has more private room listings than entire home/apartments.

Based on the map, we can see that the number of Airbnbs in each neighborhood in New York City range from 100 to 200. There are some neighborhood groups that have more than 500 listings. We can also see that in different parts of Manhattan, there are more than 1500 listings.

ANALYSIS PART TWO

PRICING EFFECT ON DEMAND FOR AIRBNBS IN NEW YORK CITY

This section will go more in depth into the pricing and evaluate what factors prices are dependent on.

In [28]:

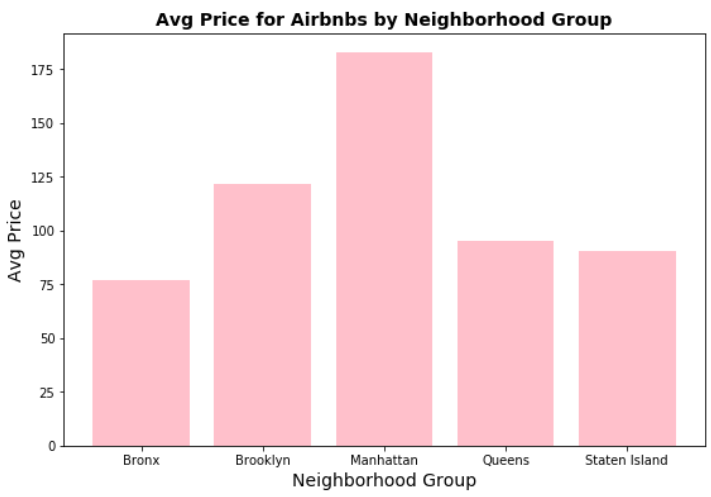
```
#finding the average price for each neighborhood group
avg_price = listings.groupby('neighbourhood_group_cleansed').price.mean()
avg_price = avg_price.reset_index()
avg_price = avg_price.rename(columns={'price':'Average_Price'})
avg_price = avg_price.sort_values('Average_Price',ascending=[0])
combo = pd.merge(neighborhood_group_df, avg_price ,on='neighbourhood_group_cleansed')
combo.head()
```

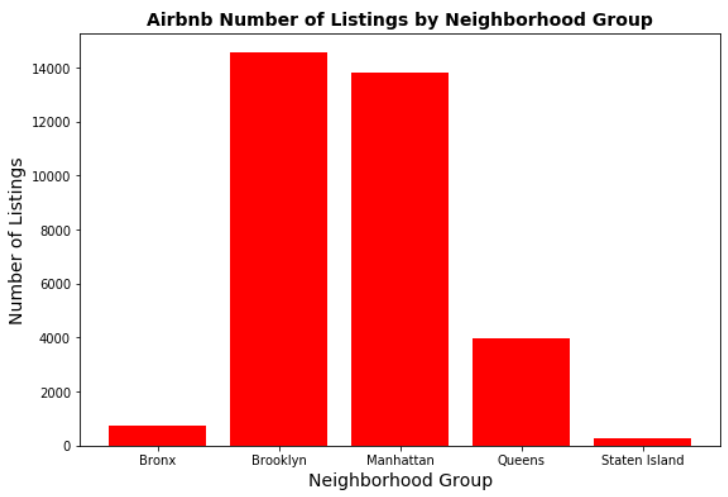
Out[28]:

	neighbourhood_group_cleansed	Number_of_Listings	Average_Price
0	Bronx	745	76.789262
1	Brooklyn	14555	121.322363
2	Manhattan	13817	182.661142
3	Queens	3969	95.002268
4	Staten Island	257	90.287938

In [29]:

```
fig, ax = plt.subplots(nrows = 1, ncols = 2, sharex = False, figsize = (20,6))

ax[0].bar(combo.neighbourhood_group_cleansed, combo.Average_Price, color = "pi
nk")

ax[0].set_title("Avg Price for Airbnbs by Neighborhood Group", fontsize = 14,
fontweight = "bold")

ax[0].set_ylabel("Avg Price", fontsize = 14,)
ax[0].set_xlabel("Neighborhood Group", fontsize = 14,)

ax[1].bar(combo.neighbourhood_group_cleansed, combo.Number_of_Listings, color
= 'red')

ax[1].set_title("Airbnb Number of Listings by Neighborhood Group", fontsize =
14, fontweight = 'bold')

ax[1].set_ylabel("Number of Listings", fontsize = 14,)
ax[1].set_xlabel("Neighborhood Group", fontsize = 14,)

plt.show()
```





In [30]:

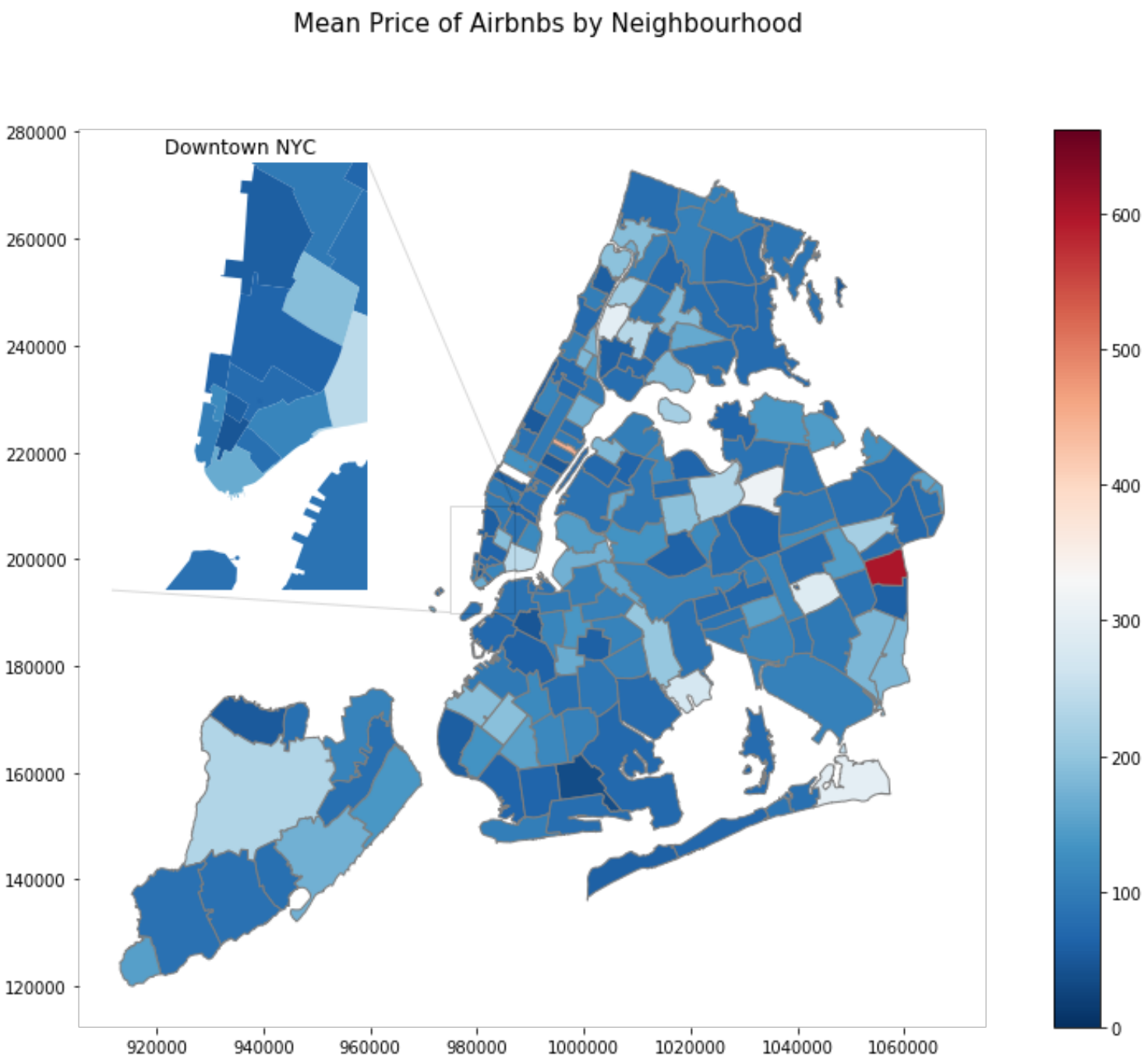
```
#finding the average price for each room type in each neighbourhood group
neighborhood_price = listings.groupby(['neighbourhood_group_cleansed','room_ty
pe']).price.mean()
neighborhood_price = neighborhood_price.reset_index()
neighborhood_price = neighborhood_price.sort_values('price',ascending=[0])
neighborhood_price
```

Out[30]:

	neighbourhood_group_cleansed	room_type	price
6	Manhattan	Entire home/apt	245.195040
3	Brooklyn	Entire home/apt	177.024799
9	Queens	Entire home/apt	142.449502
12	Staten Island	Entire home/apt	130.965812
0	Bronx	Entire home/apt	119.712389
14	Staten Island	Shared room	112.500000
7	Manhattan	Private room	104.247273
8	Manhattan	Shared room	78.336667
4	Brooklyn	Private room	70.967570
10	Queens	Private room	69.506990
2	Bronx	Shared room	63.000000
11	Queens	Shared room	59.076336
1	Bronx	Private room	57.765432
13	Staten Island	Private room	55.478261
5	Brooklyn	Shared room	45.354244

In [31]:

```
#a map showing the mean price in each neighbourhood
fig, ax = plt.subplots(figsize=(15,10));

gdf_listings.plot(ax = ax, edgecolor='tab:grey', column = 'mean_price', cmap='
RdBu_r', vmin=0, vmax=1.1*gdf_listings.mean_price.max(), legend = True)

ax.spines["right"].set_visible(False)
ax.spines["top"].set_visible(False)
ax.spines["left"].set_visible(False)
ax.spines["bottom"].set_visible(False)

fig.suptitle("Mean Price of Airbnbs by Neighbourhood", fontsize = 15)

#code for zoomed in picture of Downtown NYC is from Professor Michael Waugh's
class Data Bootcamp
axins = zoomed_inset_axes(ax,
                          4,
                          loc=2,
                          borderpad=2)

gdf_listings.plot(ax = axins, column='mean_price', vmin=0, vmax=1.1*gdf_listin
gs.mean_price.max(), cmap='RdBu_r')

x1, x2, y1, y2 = 975000, 987000, 190000, 210000
axins.set_xlim(x1, x2)
axins.set_ylim(y1, y2)

axins.set_title("Downtown NYC")

mark_inset(ax, axins, loc1=3, loc2=1, alpha = 0.15)

axins.spines["right"].set_visible(False)
axins.spines["top"].set_visible(False)
axins.spines["left"].set_visible(False)
axins.spines["bottom"].set_visible(False)

axins.get_xaxis().set_visible(False)
axins.get_yaxis().set_visible(False)
plt.show()
```



Airbnbs in Manhattan are the most expensive, followed by airbnbs in Brooklyn. As for room type, entire homes/apt are the most expensive. Manhattan airbnbs with entire homes/apt are the most expensive in New York City, priced at 245.2 dollars.

Prices of shared rooms and private rooms vary depending on location. An interesting find is that some shared rooms are more expensive than private rooms. This means that another variable such as location is a more important determining factor for price. Shared rooms in Staten Island are more expensive than private rooms in Manhattan. The cheapest airbnb listing in New York City is a shared room in Brooklyn.

We are also able to conclude that on average the majority of the listings are between 100-300 dollars, with the exception of Astoria where there is a listing for 10,000 dollars per night, which is skewing the averages.

In [32]:

```
#a heatmap to evaluate the relationship between prices and property type and r
oom type
#code for seaborn heatmap is from https://seaborn.pydata.org/generated/seaborn
.heatmap.html
#and http://alanpryorjr.com/visualizations/seaborn/heatmap/heatmap/
import seaborn as sns
plt.figure(figsize=(12,12))
sns.heatmap(listings.groupby([
        'property_type', 'room_type']).price.mean().unstack(),annot=True, fmt=
".0f")
```

Out[32]:

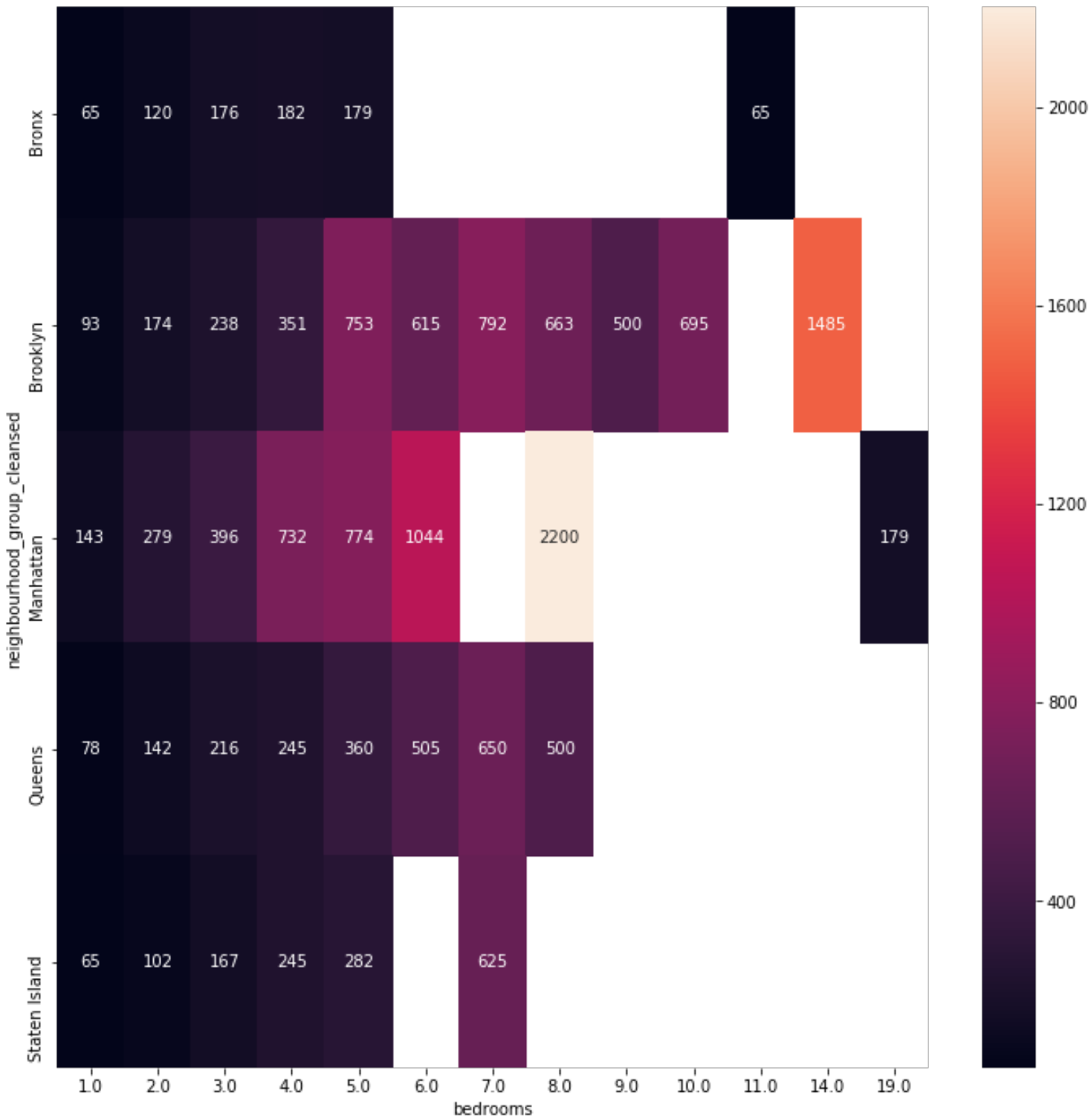
```
<matplotlib.axes._subplots.AxesSubplot at 0x12af10cf8>
```

In [33]:

```
#a heat map to evaluate the relationship between prices and neighbourhood grou
p and bedrooms
plt.figure(figsize=(12,12))
sns.heatmap(listings.groupby([
        'neighbourhood_group_cleansed', 'bedrooms']).price.mean().unstack(),an
not=True, fmt=".0f")
```

Out[33]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x12deb5e10>
```



Through this we are able to determine that pricing varies largely with the amount of bedrooms in a listing, as well as the location. It can be seen that Manahatan has the highest number of not only single bedroom listing, but also the only neighborhood with 19 bedroom listings. Brooklyn has an extremely high amount of larger bedroom listing, which makes sense as they had the highest number of listings on airbnb- specifically private room listings within a larger listing.

Prices also vary depending on property type. We can see that there is an airbnb listing priced at 1100 dollars, which makes sense because the airbnb listing is a hotel.

In [34]:

```
#analyzing the availablility of airbnbs
availability_365 = listings[['neighbourhood_group_cleansed', 'availability_365
']]
availability_365 = availability_365.groupby(['neighbourhood_group_cleansed']).
mean()
availability_365
```

Out[34]:

neighbourhood_group_cleansed	availability_365
Bronx	175.614765
Brooklyn	105.076537
Manhattan	108.267569
Queens	151.961451
Staten Island	205.392996

In [35]:

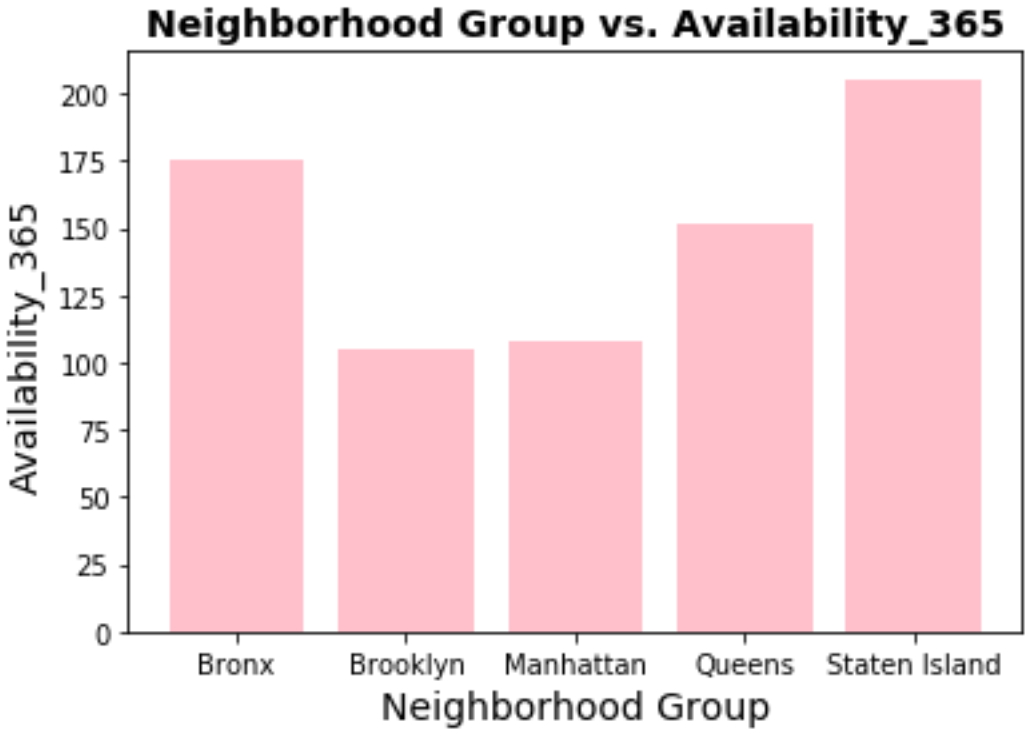
```
#combining the average price and availability
new_availability_365 = availability_365.reset_index()
availability_price = pd.merge(new_availability_365, avg_price ,on='neighbourhood_group_cleansed')
availability_price
```

Out[35]:

	neighbourhood_group_cleansed	availability_365	Average_Price
0	Bronx	175.614765	76.789262
1	Brooklyn	105.076537	121.322363
2	Manhattan	108.267569	182.661142
3	Queens	151.961451	95.002268
4	Staten Island	205.392996	90.287938

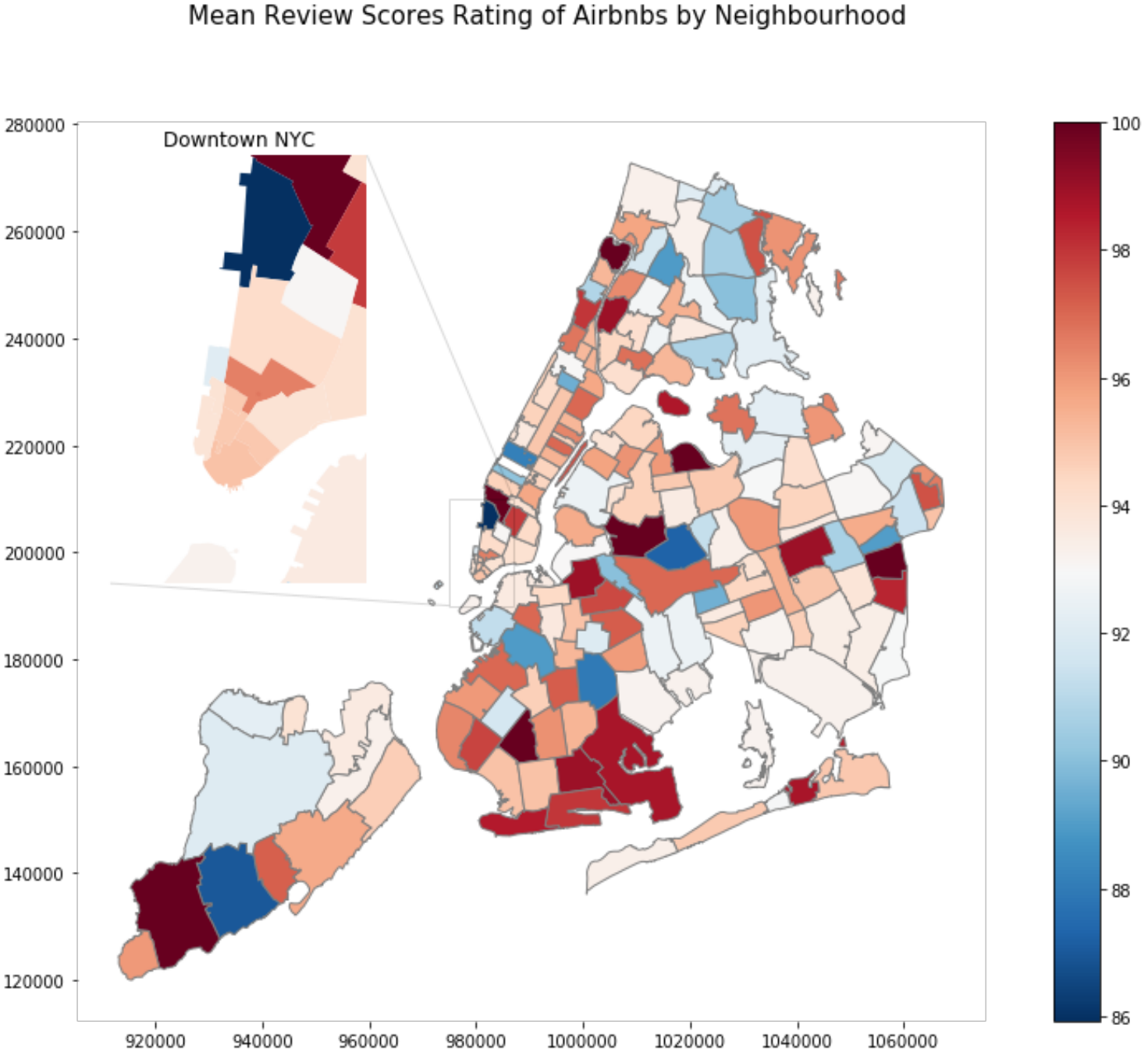
In [36]:

```
fig, ax = plt.subplots()

ax.bar(availability_365.index, availability_365.availability_365, color = "pink")

ax.set_title("Neighborhood Group vs. Availability_365", fontsize = 14, fontweight = "bold")

ax.set_ylabel("Availability_365", fontsize = 14,)
ax.set_xlabel("Neighborhood Group", fontsize = 14,)

plt.show()
```



In [37]:

```
#a map showing the mean review scores for each neighbourhood
fig, ax = plt.subplots(figsize=(15,10));

gdf_listings.plot(ax = ax, edgecolor='tab:grey', column = 'eval_mean_val', cma
p='RdBu_r', legend = True)

ax.spines["right"].set_visible(False)
ax.spines["top"].set_visible(False)
ax.spines["left"].set_visible(False)
ax.spines["bottom"].set_visible(False)

fig.suptitle("Mean Review Scores Rating of Airbnbs by Neighbourhood", fontsize
= 15)

#code for zoomed in picture of Downtown NYC is from Mike's class Data Bootcamp
axins = zoomed_inset_axes(ax,
                          4,
                          loc=2,
                          borderpad=2)

gdf_listings.plot(ax = axins, column='eval_mean_val', cmap='RdBu_r')

x1, x2, y1, y2 = 975000, 987000, 190000, 210000
axins.set_xlim(x1, x2)
axins.set_ylim(y1, y2)

axins.set_title("Downtown NYC")

mark_inset(ax, axins, loc1=3, loc2=1, alpha = 0.15)

axins.spines["right"].set_visible(False)
axins.spines["top"].set_visible(False)
axins.spines["left"].set_visible(False)
axins.spines["bottom"].set_visible(False)

axins.get_xaxis().set_visible(False)
axins.get_yaxis().set_visible(False)

plt.show()
```



We are able to determine that the higher the availbility the lower the average price. Staten island has the highest availability and therefore it also has the lowest average price. Manhattan and Brooklyn have relatively similar availability, however Brooklyn's average price is much lower than Manhattan. This could be due to location factors, and as mentioned above Brooklyn has more private rooms available than entire apartments/homes than Manhattan which are often cheaper to book.

Further, the majority of review scores for all of the nieghborhoods are relitively high. This shows that there is not a strong relationship between average review and price level. This makes sense due to Airbnbs business model, where listings rely on high costumer reviews in order to stay active. Overall location has the highest effect on pricing for Airbnbs in New York.

ANALYSIS PART THREE

SEASONAL PATTERN OF PRICES

The last will explore how prices vary across different seasons. We plan to have visualizations showing how prices change over the year and provide explanations as to how this affects Airbnb prices. For example, airbnb prices during the holidays might be more expensive than during non-holidays.

In [38]:

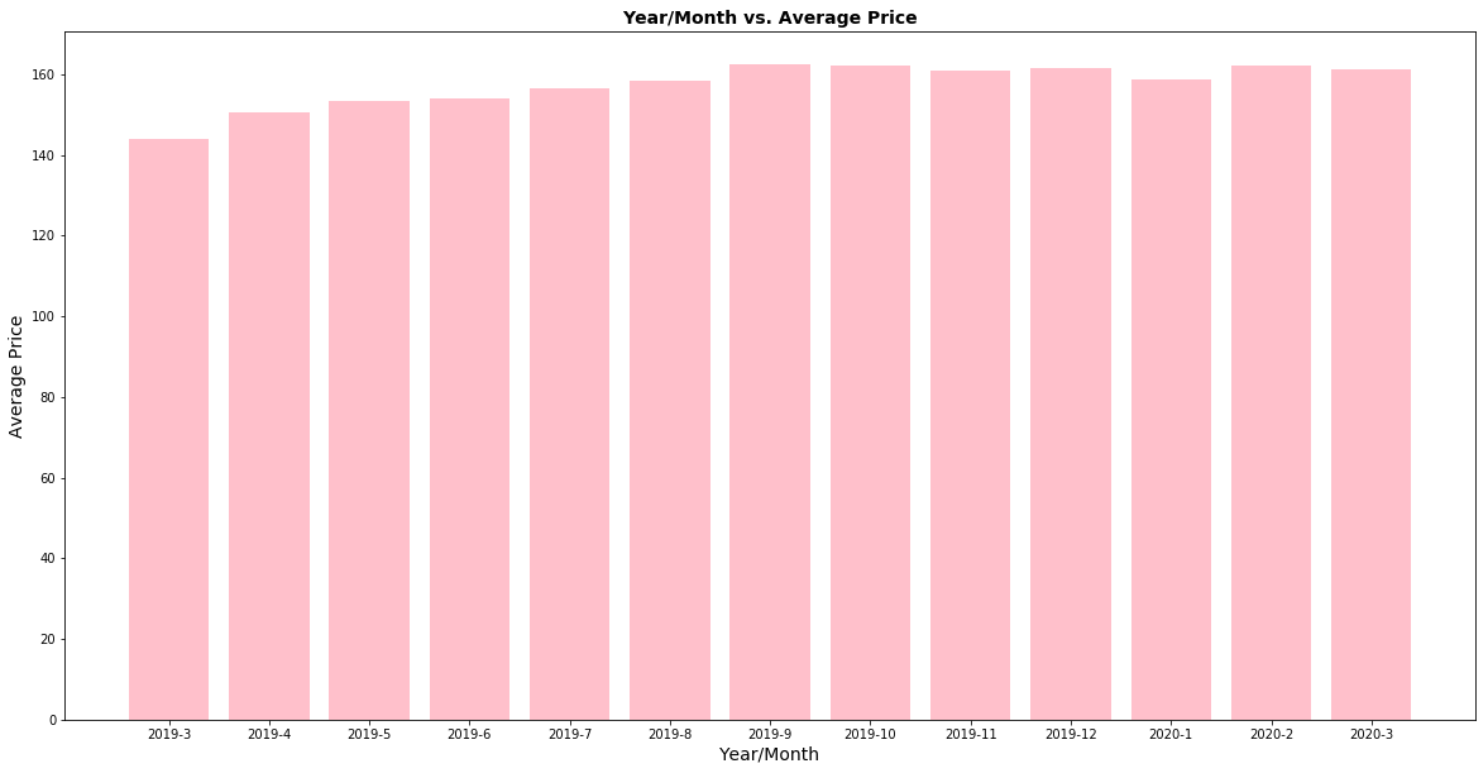
```
#using the clean_calendar csv to evaluate prices over the year
year=calendar_df.groupby(['Year','Month']).price.mean()
year=year.reset_index()
year=year.rename(columns={'price':'Average_Price'})
year['Year_Month']=year['Year'].map(str) + "-" + year['Month'].map(str)
year.head()
```

Out[38]:

	Year	Month	Average_Price	Year_Month
0	2019	3	143.946696	2019-3
1	2019	4	150.627914	2019-4
2	2019	5	153.468202	2019-5
3	2019	6	153.986027	2019-6
4	2019	7	156.497352	2019-7

In [39]:

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

ax.bar(year.Year_Month, year.Average_Price, color = "pink")

ax.set_title("Year/Month vs. Average Price", fontsize = 14, fontweight = "bold
")

ax.set_ylabel("Average Price", fontsize = 14,)
ax.set_xlabel("Year/Month", fontsize = 14,)

plt.show()
```



In [40]:

```
#using the listings_calendar csv to evaluate prices across the year in specifi
c neighbourhoods
calendar_price = listings_calendar[['neighbourhood_group_cleansed', 'date', 'p
rice_y', "Year", "Month", "Day"]]
calendar_price.head()
```

Out[40]:

	neighbourhood_group_cleansed	date	price_y	Year	Month	Day
0	Manhattan	2019-03-06	185.0	2019	3	6
1	Manhattan	2019-03-07	185.0	2019	3	7
2	Manhattan	2019-03-08	185.0	2019	3	8
3	Manhattan	2019-03-09	185.0	2019	3	9
4	Manhattan	2019-03-10	185.0	2019	3	10

In [41]:

```
#finding the prices across the year in Manhattan
manhattan_calendar_price = calendar_price.loc[calendar_price['neighbourhood_group_cleansed'] == "Manhattan"]
manhattan_calendar_price.head()
```

Out[41]:

	neighbourhood_group_cleansed	date	price_y	Year	Month	Day
0	Manhattan	2019-03-06	185.0	2019	3	6
1	Manhattan	2019-03-07	185.0	2019	3	7
2	Manhattan	2019-03-08	185.0	2019	3	8
3	Manhattan	2019-03-09	185.0	2019	3	9
4	Manhattan	2019-03-10	185.0	2019	3	10

In [42]:

```
#finding the average prices per month in Mahattan
manhattan_year=manhattan_calendar_price.groupby(['Year','Month']).price_y.mean()
manhattan_year=manhattan_year.reset_index()
manhattan_year=manhattan_year.rename(columns={'price_y':'Average_Price'})
manhattan_year['Year_Month']=manhattan_year['Year'].map(str) + "-" + manhattan_year['Month'].map(str)
manhattan_year.head()
```

Out[42]:

	Year	Month	Average_Price	Year_Month
0	2019	3	169.821029	2019-3
1	2019	4	181.867487	2019-4
2	2019	5	186.553212	2019-5
3	2019	6	187.258937	2019-6
4	2019	7	190.420792	2019-7

In [43]:

```
#finding the prices across the year in Brooklyn
brooklyn_calendar_price = calendar_price.loc[calendar_price['neighbourhood_group_cleansed'] == "Brooklyn"]
brooklyn_calendar_price.head()
```

Out[43]:

	neighbourhood_group_cleansed	date	price_y	Year	Month	Day
365	Brooklyn	2019-03-06	180.0	2019	3	6
366	Brooklyn	2019-03-07	180.0	2019	3	7
367	Brooklyn	2019-03-08	180.0	2019	3	8
368	Brooklyn	2019-03-09	180.0	2019	3	9
369	Brooklyn	2019-03-10	180.0	2019	3	10

In [44]:

```
#finding the average prices per month in Brooklyn
brooklyn_year=brooklyn_calendar_price.groupby(['Year','Month']).price_y.mean()
brooklyn_year=brooklyn_year.reset_index()
brooklyn_year=brooklyn_year.rename(columns={'price_y':'Average_Price'})
brooklyn_year['Year_Month']=brooklyn_year['Year'].map(str) + "-" + brooklyn_year['Month'].map(str)
brooklyn_year.head()
```

Out[44]:

	Year	Month	Average_Price	Year_Month
0	2019	3	115.851354	2019-3
1	2019	4	119.921534	2019-4
2	2019	5	121.870839	2019-5
3	2019	6	122.288361	2019-6
4	2019	7	124.569803	2019-7

In [45]:

```
#finding the prices across the year in Queens
queens_calendar_price = calendar_price.loc[calendar_price['neighbourhood_group_cleansed'] == "Queens"]
queens_calendar_price.head()
```

Out[45]:

	neighbourhood_group_cleansed	date	price_y	Year	Month	Day
23360	Queens	2019-03-07	135.0	2019	3	7
23361	Queens	2019-03-08	135.0	2019	3	8
23362	Queens	2019-03-09	135.0	2019	3	9
23363	Queens	2019-03-10	135.0	2019	3	10
23364	Queens	2019-03-11	135.0	2019	3	11

In [46]:

```
#finding the average prices per month in Queens
queens_year=queens_calendar_price.groupby(['Year','Month']).price_y.mean()
queens_year=queens_year.reset_index()
queens_year=queens_year.rename(columns={'price_y':'Average_Price'})
queens_year['Year_Month']=queens_year['Year'].map(str) + "-" + queens_year['Month'].map(str)
queens_year.head()
```

Out[46]:

	Year	Month	Average_Price	Year_Month
0	2019	3	89.887583	2019-3
1	2019	4	93.110099	2019-4
2	2019	5	94.921426	2019-5
3	2019	6	95.476400	2019-6
4	2019	7	97.135946	2019-7

In [47]:

```
#finding the prices across the years in the Bronx
bronx_calendar_price = calendar_price.loc[calendar_price['neighbourhood_group_
cleansed'] == "Bronx"]
bronx_calendar_price.head()
```

Out[47]:

	neighbourhood_group_cleansed	date	price_y	Year	Month	Day
24820	Bronx	2019-03-07	78.0	2019	3	7
24821	Bronx	2019-03-08	78.0	2019	3	8
24822	Bronx	2019-03-09	78.0	2019	3	9
24823	Bronx	2019-03-10	78.0	2019	3	10
24824	Bronx	2019-03-11	78.0	2019	3	11

In [48]:

```
#finding the average prices per month in the Bronx
bronx_year=bronx_calendar_price.groupby(['Year','Month']).price_y.mean()
bronx_year=bronx_year.reset_index()
bronx_year=bronx_year.rename(columns={'price_y':'Average_Price'})
bronx_year['Year_Month']=bronx_year['Year'].map(str) + "-" + bronx_year['Month
'].map(str)
bronx_year.head()
```

Out[48]:

	Year	Month	Average_Price	Year_Month
0	2019	3	73.898228	2019-3
1	2019	4	75.745907	2019-4
2	2019	5	76.685675	2019-5
3	2019	6	77.036292	2019-6
4	2019	7	78.915346	2019-7

In [49]:

```
#finding the prices across the year in Staten Island
statenisland_calendar_price = calendar_price.loc[calendar_price['neighbourhood_group_cleansed'] == "Staten Island"]
statenisland_calendar_price.head()
```

Out[49]:

	neighbourhood_group_cleansed	date	price_y	Year	Month	Day
55115	Staten Island	2019-03-07	45.0	2019	3	7
55116	Staten Island	2019-03-08	45.0	2019	3	8
55117	Staten Island	2019-03-09	45.0	2019	3	9
55118	Staten Island	2019-03-10	45.0	2019	3	10
55119	Staten Island	2019-03-11	45.0	2019	3	11

In [50]:

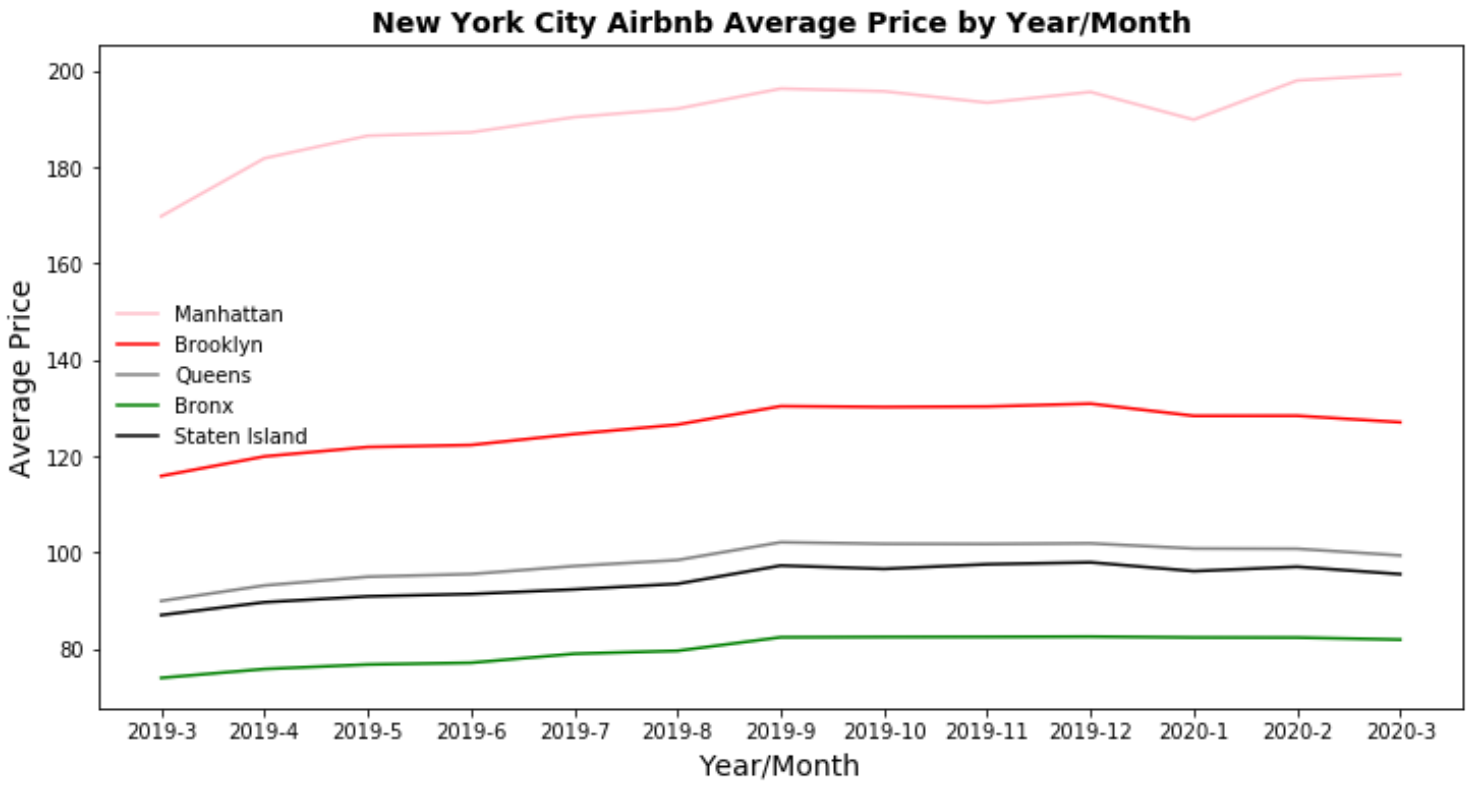
```
#finding the prices per month in Staten Island
statenisland_year=statenisland_calendar_price.groupby(['Year','Month']).price_y.mean()
statenisland_year=statenisland_year.reset_index()
statenisland_year=statenisland_year.rename(columns={'price_y':'Average_Price'})
statenisland_year['Year_Month']=statenisland_year['Year'].map(str) + "-" + statenisland_year['Month'].map(str)
statenisland_year.head()
```

Out[50]:

	Year	Month	Average_Price	Year_Month
0	2019	3	86.956062	2019-3
1	2019	4	89.622129	2019-4
2	2019	5	90.842640	2019-5
3	2019	6	91.332773	2019-6
4	2019	7	92.292356	2019-7

In [51]:

```
#a plot to show the prices per month of Airbnbs in each neighbourhood group
fig, ax = plt.subplots(figsize = (12,6))

ax.plot(manhattan_year.Year_Month, manhattan_year.Average_Price, label = "Manh
attan", color = "pink")
ax.plot(brooklyn_year.Year_Month, brooklyn_year.Average_Price, label = "Brookl
yn", color = "red")
ax.plot(queens_year.Year_Month, queens_year.Average_Price, label = "Queens", c
olor = "grey")
ax.plot(bronx_year.Year_Month, bronx_year.Average_Price, label = "Bronx", colo
r = 'green')
ax.plot(statenisland_year.Year_Month, statenisland_year.Average_Price, label='
Staten Island', color = "black")

ax.legend(frameon=False)

ax.set_title("New York City Airbnb Average Price by Year/Month", fontsize = 14
, fontweight = "bold")

ax.set_ylabel("Average Price", fontsize = 14,)
ax.set_xlabel("Year/Month", fontsize = 14,)

plt.show()
```



In [52]:

```
#information about holidays module is from https://pypi.org/project/holidays/
and
#https://www.geeksforgeeks.org/python-holidays-library/
#help with the code is from https://stackoverflow.com/questions/2394235/detect
ing-a-us-holiday and
#https://stackoverflow.com/questions/29688899/pandas-checking-if-a-date-is-a-h
oliday-and-assigning-boolean-value
#adding name of day, holiday, and US holiday name to the calendar dataframe
#If it is a holiday, it will be True and holiday name will be shown
us_holidays = holidays.US()
calendar_df.fillna(0, inplace=True)
calendar_df['day_Name']='default' #Default to calendars with Monday as the fir
st day of the week, and Sunday as the last
calendar_df['holiday']='False'
calendar_df['us_holidays_name']='working'
for index,row in calendar_df.iterrows():
    sdate = datetime.date(int(row['Year']),int(row['Month']),int(row['Day']))
#creating date in the format Year-Month-Day
    vall=date(int(row['Year']),int(row['Month']),int(row['Day'])) in us_holida
ys #checking date to see if its a holiday
    calendar_df.set_value(index,'day_Name',calendar.day_name[sdate.weekday()])
#getting the day of the week
    calendar_df.set_value(index,'holiday',vall) #getting True or False
    calendar_df.set_value(index,'us_holidays_name',us_holidays.get(sdate)) #ge
tting the name of holiday
```

```
/anaconda3/lib/python3.7/site-packages/ipykernel_launcher.py:15: F
utureWarning: set_value is deprecated and will be removed in a fut
ure release. Please use .at[] or .iat[] accessors instead
  from ipykernel import kernelapp as app
/anaconda3/lib/python3.7/site-packages/ipykernel_launcher.py:16: F
utureWarning: set_value is deprecated and will be removed in a fut
ure release. Please use .at[] or .iat[] accessors instead
  app.launch_new_instance()
/anaconda3/lib/python3.7/site-packages/ipykernel_launcher.py:17: F
utureWarning: set_value is deprecated and will be removed in a fut
ure release. Please use .at[] or .iat[] accessors instead
```

In [53]:

```
calendar_df.head()
```

Out[53]:

	Unnamed: 0	listing_id	date	available	price	minimum_nights	maximum_nights	Year	M
0	0	36647	2019-03-07	f	69.0	2.0	730.0	2019	
1	1	36647	2019-03-08	f	69.0	2.0	730.0	2019	
2	2	36647	2019-03-09	f	69.0	2.0	730.0	2019	
3	3	36647	2019-03-10	f	69.0	2.0	730.0	2019	
4	4	36647	2019-03-11	f	69.0	2.0	730.0	2019	

In [54]:

```
#finding average price for the day of the week
#assigning numbers to the day of the week - Monday:1, Tuesday:2, etc.
calendar_day=calendar_df.groupby('day_Name').price.mean()
calendar_day=calendar_day.reset_index()
calendar_day['day_num']=0

for index,row in calendar_day.iterrows():
    if row['day_Name']=='Monday':
        calendar_day.set_value(index,'day_num',1)
    if row['day_Name']=='Tuesday':
        calendar_day.set_value(index,'day_num',2)
    if row['day_Name']=='Wednesday':
        calendar_day.set_value(index,'day_num',3)
    if row['day_Name']=='Thursday':
        calendar_day.set_value(index,'day_num',4)
    if row['day_Name']=='Friday':
        calendar_day.set_value(index,'day_num',5)
    if row['day_Name']=='Saturday':
        calendar_day.set_value(index,'day_num',6)
    if row['day_Name']=='Sunday':
        calendar_day.set_value(index,'day_num',7)
calendar_day=calendar_day.sort_values('day_num',ascending=[1])
calendar_day=calendar_day.rename(columns={'price':'Average_Price'})
calendar_day
```

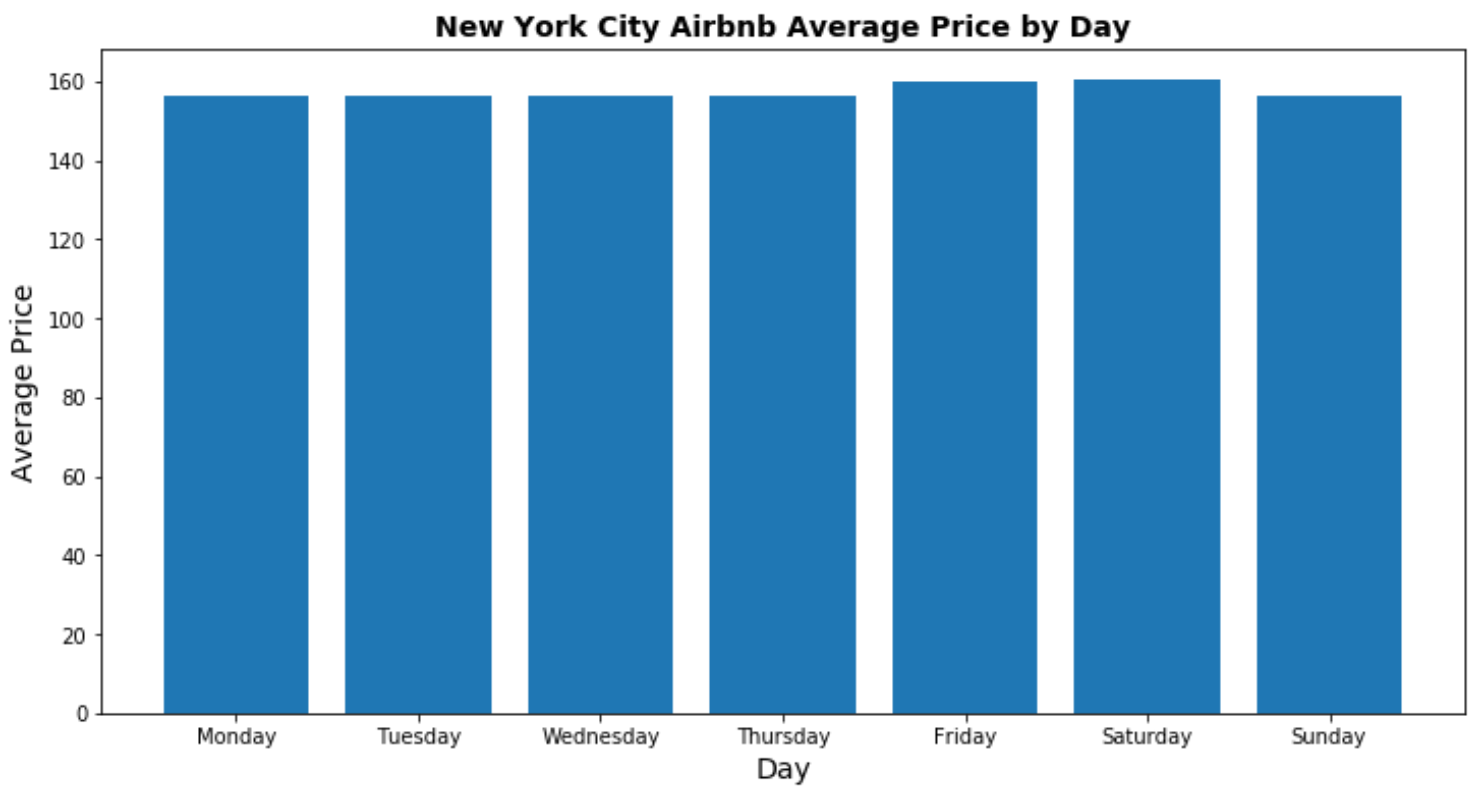
```
/anaconda3/lib/python3.7/site-packages/ipykernel_launcher.py:15: F
utureWarning: set_value is deprecated and will be removed in a fut
ure release. Please use .at[] or .iat[] accessors instead
  from ipykernel import kernelapp as app
/anaconda3/lib/python3.7/site-packages/ipykernel_launcher.py:7: Fu
tureWarning: set_value is deprecated and will be removed in a futu
re release. Please use .at[] or .iat[] accessors instead
  import sys
/anaconda3/lib/python3.7/site-packages/ipykernel_launcher.py:17: F
utureWarning: set_value is deprecated and will be removed in a fut
ure release. Please use .at[] or .iat[] accessors instead
/anaconda3/lib/python3.7/site-packages/ipykernel_launcher.py:19: F
utureWarning: set_value is deprecated and will be removed in a fut
ure release. Please use .at[] or .iat[] accessors instead
/anaconda3/lib/python3.7/site-packages/ipykernel_launcher.py:13: F
utureWarning: set_value is deprecated and will be removed in a fut
ure release. Please use .at[] or .iat[] accessors instead
  del sys.path[0]
/anaconda3/lib/python3.7/site-packages/ipykernel_launcher.py:9: Fu
tureWarning: set_value is deprecated and will be removed in a futu
re release. Please use .at[] or .iat[] accessors instead
  if __name__ == '__main__':
/anaconda3/lib/python3.7/site-packages/ipykernel_launcher.py:11: F
utureWarning: set_value is deprecated and will be removed in a fut
ure release. Please use .at[] or .iat[] accessors instead
  # This is added back by InteractiveShellApp.init_path()
```

Out[54]:

	day_Name	Average_Price	day_num
1	Monday	156.102005	1
5	Tuesday	156.171415	2
6	Wednesday	156.144117	3
4	Thursday	156.050243	4
0	Friday	160.112917	5
2	Saturday	160.339375	6
3	Sunday	156.298016	7

In [55]:

```
fig, ax = plt.subplots(figsize = (12,6))

ax.bar(calendar_day.day_Name, calendar_day.Average_Price)

ax.set_title("New York City Airbnb Average Price by Day", fontsize = 14, fontw
eight = "bold")

ax.set_ylabel("Average Price", fontsize = 14,)
ax.set_xlabel("Day", fontsize = 14,)

plt.show()
```



In [56]:

```
#finding the number of listings during a given holiday
holiday_df=calendar_df.groupby('us_holidays_name').listing_id.count()
holiday_df=holiday_df.reset_index()
holiday_df=holiday_df.sort_values('listing_id',ascending=[0])
holiday_df
```

Out[56]:

	us_holidays_name	listing_id
0	Christmas Day	49748
1	Columbus Day	49748
4	Martin Luther King, Jr. Day	49748
6	New Year's Day	49748
7	Thanksgiving	49748
8	Veterans Day	49748
9	Washington's Birthday	49748
2	Independence Day	49747
3	Labor Day	49747
5	Memorial Day	49747

In [57]:

```
#finding the average price of an Airbnb during a given holiday
holiday_price_df=calendar_df.groupby('us_holidays_name').price.mean()
holiday_price_df=holiday_price_df.reset_index()
holiday_price_df=holiday_price_df.sort_values('price',ascending=[0])

holiday_price_df.head(10)
```

Out[57]:

	us_holidays_name	price
6	New Year's Day	162.423153
0	Christmas Day	162.239387
9	Washington's Birthday	160.791710
1	Columbus Day	160.780835
3	Labor Day	160.468269
7	Thanksgiving	159.833360
8	Veterans Day	159.151182
4	Martin Luther King, Jr. Day	157.423112
2	Independence Day	154.759463
5	Memorial Day	152.030052

In [58]:

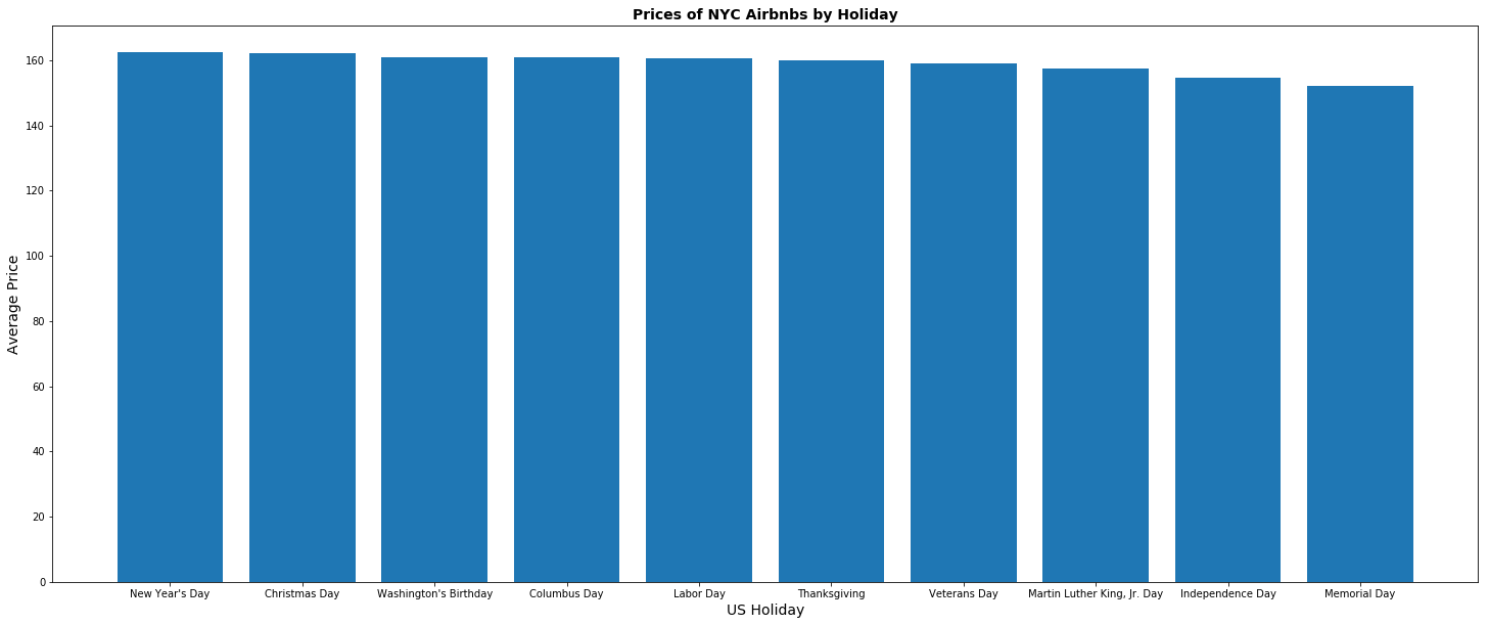
```
#combining two dataframes
holiday_listings_price=pd.merge(holiday_df,holiday_price_df,on='us_holidays_name')
holiday_listings_price=holiday_listings_price.rename(columns={'listing_id':'number_Of_listings'})
holiday_listings_price=holiday_listings_price.rename(columns={'price':'average_price'})
holiday_listings_price
```

Out[58]:

	us_holidays_name	number_Of_listings	average_price
0	Christmas Day	49748	162.239387
1	Columbus Day	49748	160.780835
2	Martin Luther King, Jr. Day	49748	157.423112
3	New Year's Day	49748	162.423153
4	Thanksgiving	49748	159.833360
5	Veterans Day	49748	159.151182
6	Washington's Birthday	49748	160.791710
7	Independence Day	49747	154.759463
8	Labor Day	49747	160.468269
9	Memorial Day	49747	152.030052

In [59]:

```
fig, ax = plt.subplots(figsize = (25,10))

ax.bar(holiday_price_df.us_holidays_name, holiday_price_df.price)

ax.set_title("Prices of NYC Airbnbs by Holiday", fontsize = 14, fontweight = "
bold")

ax.set_ylabel("Average Price", fontsize = 14,)
ax.set_xlabel("US Holiday", fontsize = 14,)

plt.show()
```



We are able to conclude that the average listing price does not show a high degree of seasonality. Prices are relatively consistent throughout the year. The data shows a general upward trend in all of the neighborhoods, with prices increasing during the March until December. Manhattan airbnb prices fluctuate the most throughout the year.

There is also no significant difference between prices during each day of the week. Friday and Saturday prices are a little more expensive, priced at 160 dollars opposed to 156 dollars.

Holiday pricing is slighlty more expensive, but again the data does not show significant seasonality. Airbnb prices during the New Year's are the most expensive at 162.4 dollars. The summer holidays on average are less expensive than the winter holidays. A possible explanation for this could be the lower levels of tourism in the hotter months.

SUMMARY

To summarize our findings, we were able to determine that Airbnbs pricing is dependent on location as well as room type and property type. Further, seasonality does not have a strong affect on Airbnbs pricing levels in New York City. Overall, Airbnbs data shows a strong upward trend in terms of pricing on average for all of locations at any season.

If a host is interested in investing a property for Airbnb, we would offer the following recommendations based on our findings:

1. Invest in a property in Manhattan or Brooklyn to get maximum revenue from Airbnb

2. Make sure your Airbnb is available and listed during the winter months.

3. Keep in mind that Airbnbs have more demand on Friday and the weekends.

3. Make sure your property/listing is in excellent condition as reviews are an important consideration factor for travelers/guests.