# The Battle of Neighborhoods:
## Find the best place to stay in New York City

Applied Data Science Capstone Project

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## Table of contents



## Introduction: Business Problem

### Background

According the latest *NYC&Company* release New York City welcomed about 65.2 million tourists in 2018 year - 51.6 million domestic and 13.5 million international visitors. And these numbers are continuously increasing from year to year [1].

New York City has the largest selection of lodging choices in the country – from the hostels to the luxury hotels. The prices vary from 100$ till several thousand dollars with average price 292 USD per night.

The Hotel Occupancy rate is also high – in 2018 year it was 88% [2].
Visitors prefer short stays that are often over weekends - averaging 2.4 nights [3].

## Problem description

In New York City there are almost 300 hotels with over 75,000 hotel rooms and Airbnb has more than 50,000 apartment listings in New York City in 2018 year - it can be hard to find the right fit or know how much you will get with your money.

In this project we will try to find the most optimal neighbourhoods on Manhattan where a tourist can rent an accommodation via Airbnb service and have a pleasant stay in NYC and a possibility to attend the most visited attractions like Central Park, Times Square and so on.

## Target Audience

This investigation would interest New York City's visitors who prefers short stays (from 1 night) and wants to select the best neighborhoods on Manhattan, New York.

## Success Criteria

The success criteria of this project will be a recommendation with the set of apartments clusters have the best score calculated based on

- Accommodation price with fees;
- Location of the accommodation;
- Venues in radius of 1000 meters from the accommodation;
- Crime rate in radius of 100 meters from the accommodation.

# Data

## Initial datasets

In our investigation we will use the free and public available datasets.
We will try to evaluate available Airbnb 2019-year accommodations on Manhattan, New York and define the most reasonable apartments sets (clusters) for the visitors.

Based on definition of our problem, we suppose that factors that will help us are:
- accommodation’s average price per person by the neighborhood;
- number of tourist attractions near the accommodation;
- number of crimes nearby the accommodation.

**Airbnb New York City apartment listing**

http://data.insideairbnb.com/united-states/ny/new-york-city/2019-12-04/data/listings.csv.gz

It is available below under a *Creative Commons CC0 1.0 Universal (CC0 1.0) "Public Domain Dedication" license.*

Initially data contains 50,599 rows and 106 columns with the information about available accommodations – name, borough, neighborhood, price per night, cleaning fee, minimum nights, guest number and so on.

For our project records were filtered as

- Borough - Manhattan, New York only;
- Number of reviews >= 10;
- Availability >= 10 days/year;
- Last Scraped/Reviewed later than 2019-10-01;
- Minimum nights >= 1;
- Excluded Hostels and Camper/RV;
- Excluded Shared rooms.

After filter was applied, we have 2,356 accommodations in our data set:

| id | listing_url | scrape_id | last_scraped | name | summary | space | description | experiences_offered | neighborhood_overview | notes | transit | acces |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 5178 | https://www.airbnb.com/rooms/5178 | 20191204162729 | 2019-12-05 | Large Furnished Room Near B'way | Please don't expect the luxury here just a basic room in the center of Manhattan. | You will use one large, furnished, private room of a two-bedroom apartment and share a bathroom with the host. The apartment is located a few blocks away from Central Park between 8th and 9th Avenue. The closest subway station is Columbus Circle 59th Street. Great restaurants, Broadway and all transportation are easily accessible. The cost of the room is *79pernight. Weeklyrateisavailable. Thereisa* 12.00 fee per guest. The apartment also features hardwood floors and a second-floor walk-up. There is a full-sized bed,TV, microwave, and a small refrigerator as well as other appliances. Wired internet, WIFI, TV, electric heat, bed sheets and towels are included. A kitchen is available in the living room. You can come in any time except midnight. Basic check in/out time is 12pm. I am flexible on the schedule so please ask. Please nore that the living room is a private place for the host. Also, because the place is close to the street, there is some traffic noise from ou | Please don't expect the luxury here just a basic room in the center of Manhattan. You will use one large, furnished, private room of a two-bedroom apartment and share a bathroom with the host. The apartment is located a few blocks away from Central Park between 8th and 9th Avenue. The closest subway station is Columbus Circle 59th Street. Great restaurants, Broadway and all transportation are easily accessible. The cost of the room is *79pernight. Weeklyrateisavailable. Thereisa*12.00 fee per guest. The apartment also features hardwood floors and a second-floor walk-up. There is a full-sized bed,TV, microwave, and a small refrigerator as well as other appliances. Wired internet, WIFI, TV, electric heat, bed sheets and towels are included. A kitchen is available in the living room. You can come in any time except midnight. Basic check in/out time is 12pm. I am flexible on the schedule so please ask. Please nore that the living room is a private place for the host. A | none | Theater district, many restaurants around here. | Reservation should be made at least a few days before the date of arrival. No reservation for the day will be taken so please do not ask availablity for "tonight". Also one night stay is set a higher price per host discretion. | NaN | Bathroom i shared with th host but th kitchen is no i the commor area |

**Neighborhood Tabulation Areas**

https://data.cityofnewyork.us/api/geospatial/cpf4-rkhq?method=export&format=GeoJSON

This dataset contains MultiPolygon GIS data with the coordinates of each NYC neighborhood. We will use these data for the maps and for the mapping of Airbnb neighborhoods because Airbnb has different neighborhoods structure.

**Foursquare API data about venues** - food places, museums, galleries, shopping centers, sightseeing attractions, concert halls and so on. We will check Top-50 venues for the Top-100 Manhattan's Airbnb accommodations in radius of 1000 meters.

**New York Police Crime Records**
https://data.cityofnewyork.us/api/views/5uac-w243/rows.csv?accessType=DOWNLOAD
We will use this statistic during our apartment evaluation. Originally it contains 461,711 rows and 35 columns.
We filter this dataset by
- Borough – *Manhattan, New York* only;
- Crime type – *FELONY* and *MISDEMEANOR*.

After filtering we have 101,086 crimes records for Manhattan in 2019 year.
This dataset contains NYC Precincts column which is not the same as Neighborhood Tabulation Areas. We need to define the NYC Neighborhood name by the latitude/longitude of each crime record from this dataset.

| | CMPLNT_NUM | ADDR_PCT_CD | BORO_NM | CMPLNT_FR_DT | CMPLNT_FR_TM | CMPLNT_TO_DT | CMPLNT_TO_TM | CRM_ATPT_CPTD_CD | HADEVELOPT | HOUSING_PSA | JURISDICTION_CODE | JURIS_DESC | KY_CD | LAW_CAT_CD | LOC_OF_OCCUR_DESC | OFNS_DESC | PARKS_NM | PATROL_BORO | PD_CD | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 289837961 | 25 | MANHATTAN | 30.12.19 | 08:30:00 PM | 31.12.19 | 10:00:00 AM | COMPLETED | NaN | NaN | 0.0 | N.Y. POLICE DEPT | 341 | MISDEMEANOR | INSIDE | PETIT LARCENY | NaN | PATROL BORO MAN NORTH | 338.0 | LARCI BUI |
| 4 | 299841674 | 18 | MANHATTAN | 30.12.19 | 03:30:00 PM | 30.12.19 | 04:50:00 PM | COMPLETED | NaN | NaN | 0.0 | N.Y. POLICE DEPT | 341 | MISDEMEANOR | NaN | PETIT LARCENY | NaN | PATROL BORO MAN SOUTH | 301.0 | LARCI BY A |
| 3 | 227601821 | 18 | MANHATTAN | 29.12.19 | 12:30:00 PM | 29.12.19 | 01:30:00 PM | COMPLETED | NaN | NaN | 0.0 | N.Y. POLICE DEPT | 233 | MISDEMEANOR | NaN | SEX CRIMES | NaN | PATROL BORO MAN SOUTH | 175.0 | SEXUA |
| 1 | 754294853 | 19 | MANHATTAN | 28.12.19 | 11:30:00 AM | 28.12.19 | 05:00:00 PM | COMPLETED | NaN | NaN | 0.0 | N.Y. POLICE DEPT | 109 | FELONY | INSIDE | GRAND LARCENY | NaN | PATROL BORO MAN NORTH | 407.0 | LARCEN BY DI |
| 5 | 365001231 | 26 | MANHATTAN | 25.12.19 | 05:10:00 PM | 25.12.19 | 05:15:00 PM | COMPLETED | NaN | NaN | 0.0 | N.Y. POLICE DEPT | 341 | MISDEMEANOR | NaN | PETIT LARCENY | NaN | PATROL BORO MAN NORTH | 321.0 | LARCI FR |

# Data Cleaning and Feature Engineering

**Airbnb**

We do not need all columns from the original dataset so let's create a subset of the needed columns:

• id - listing identifier;

• *name* - accommodation's name;

• *last_review* - accommodation's last review date;

• *listing_url* - accommodation's URL;

• *picture_url* - accommodation's picture URL;

• *neighbourhood_group_cleansed* - NYC Borough's name. e.g. Manhattan, Bronx. We will use accommodations only from Manhattan;

• *neighbourhood_cleansed* - Airbnb Neighborhood's name, e.g. Hell's Kitchen.

***These Names are not the same as NYC Neighborhood Tabulation Areas;***

• *review_scores_rating* - accommodation's weighted sum of other scores- *review_scores_location, review_scores_value*

• *latitude* - accommodation's latitude;

• *longitude* - accommodation's longitude;

• *property_type* - accommodation's type e.g. Entire home/Apt, Private Room. ***We exclude Hostels and Camper/RV****;*

• *room_type* - accommodation's room type. **We exclude Shared rooms**;

• *accommodates* - number of persons allowed. We use this value to calculate *price_per_person* custom column;

• *bathrooms* - number of bathrooms. Keep it for informative reasons;

• *bedrooms* - number of bedrooms. Keep it for informative reasons;

• *square_feet* - accommodation's size. Keep it for informative reasons;

• *price* - price per night;

• *security_deposit* - security deposit;

• *cleaning_fee* - additional fee. We will use it to calculate **full_price** per night for the accommodation;

• *minimum nights* - minimum nights for rent. We use accommodations with 1 or 2 minimum nights;

• *number_of_reviews_ltm* - number of reviews for the last month. Keep it for informative reasons;

• *reviews_per_month* - average number of reviews per month. Keep it for informative reasons;

• *number_of_reviews_ltm* - overall number of reviews. Keep it for informative reasons;

• *availability_365* - available days/year.

Now we should clean different *Prices* columns:

- fill in empty values;
- convert *String* to *Float*, e.g. $2,100.00 => 2100.00.

| id | name | last_review | listing_url | picture_url | neighbourhood_group_cleansed | neighbourhood_cleansed | review_scores_rating | latitude | longitude | property_type | room_type | accommodates | bathrooms | bedrooms | square_feet | price | security_deposit |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 5178 | Large Furnished Room Near B'way | 2019-11-21 | https://www.airbnb.com/rooms/5178 | https://a0.muscache.com/im/pictures/12065/f070997b_original.jpg?aki_policy=large | Manhattan | Hell's Kitchen | 84.0 | 40.76489 | -73.98493 | Apartment | Private room | 2 | 1 | 1 | 0 | 79.0 | 0.0 |
| 7322 | Chelsea Perfect by Doti, an AIRBNB Super Host! | 2019-11-16 | https://www.airbnb.com/rooms/7322 | https://a0.muscache.com/im/pictures/23207/33258e91_original.jpg?aki_policy=large | Manhattan | Chelsea | 96.0 | 40.74192 | -73.99501 | Apartment | Private room | 3 | 1 | 1 | 0 | 120.0 | 0.0 |
| 9704 | Spacious 1 bedroom in luxe building | 2019-11-09 | https://www.airbnb.com/rooms/9704 | https://a0.muscache.com/im/pictures/38418/569b54fd_original.jpg?aki_policy=large | Manhattan | Harlem | 98.0 | 40.81305 | -73.95466 | Apartment | Private room | 2 | 1 | 1 | 900 | 52.0 | 150.0 |
| 12192 | ENJOY Downtown NYC! | 2019-11-13 | https://www.airbnb.com/rooms/12192 | https://a0.muscache.com/im/pictures/93658190/67480448_original.jpg?aki_policy=large | Manhattan | East Village | 88.0 | 40.72290 | -73.98199 | Apartment | Private room | 2 | 1 | 1 | 0 | 68.0 | 100.0 |
| 15711 | 2 bedroom - Upper East Side- great for kids | 2019-11-24 | https://www.airbnb.com/rooms/15711 | https://a0.muscache.com/im/pictures/c444be23-6b18-4094-b2c7-cee811c08c9c.jpg?aki_policy=large | Manhattan | Upper East Side | 93.0 | 40.77065 | -73.95269 | Apartment | Entire home/apt | 6 | 1 | 2 | 0 | 250.0 | 500.0 |

## Airbnb Features Engineering

Now we are going to add some new features (columns) to our Airbnb dataset:

• **full_price** - *price* + *cleaning_fee*. Airbnb *price* column could be misleading because it does not include mandatory cleaning fee price;

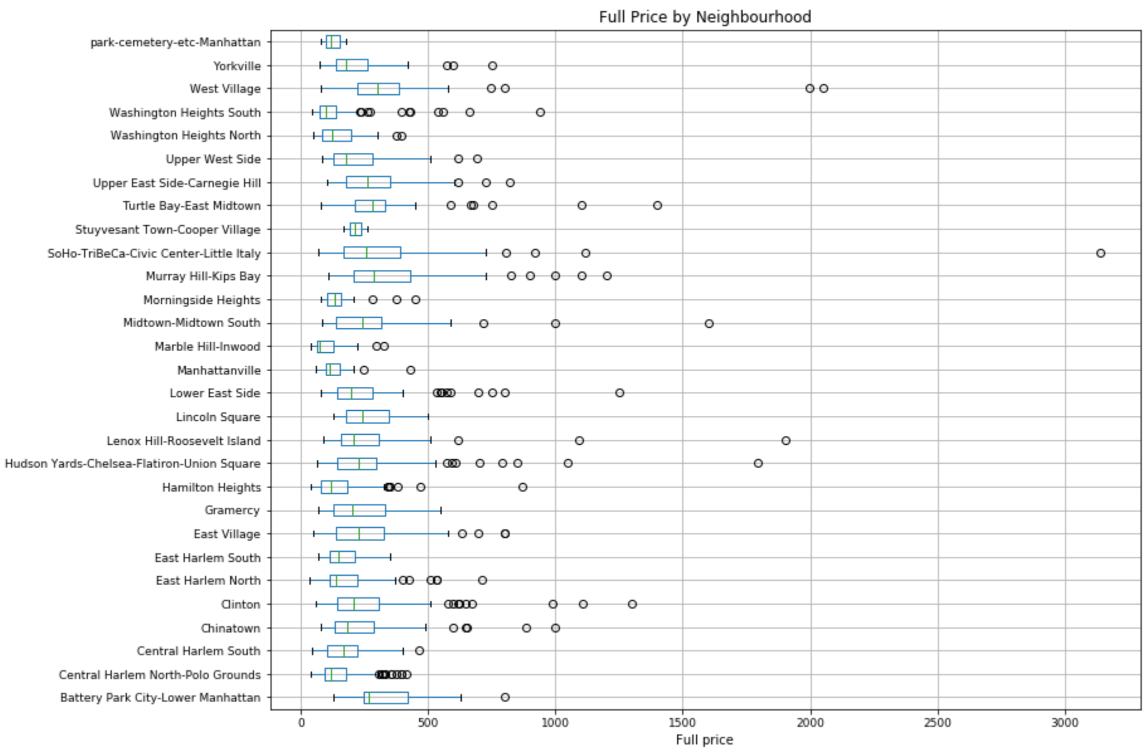
• **price_per_person** - (price + cleaning_fee)/accommodates;

• **tab_area** from *New York Area Tabulation Name* dataset to our *Airbnb* data set because Neighborhoods' names are quite different in these data sets. We use custom *define_tab_area* function which returns *New York Area Tabulation Name* for each Airbnb accommodation's latitude/longitude pair;

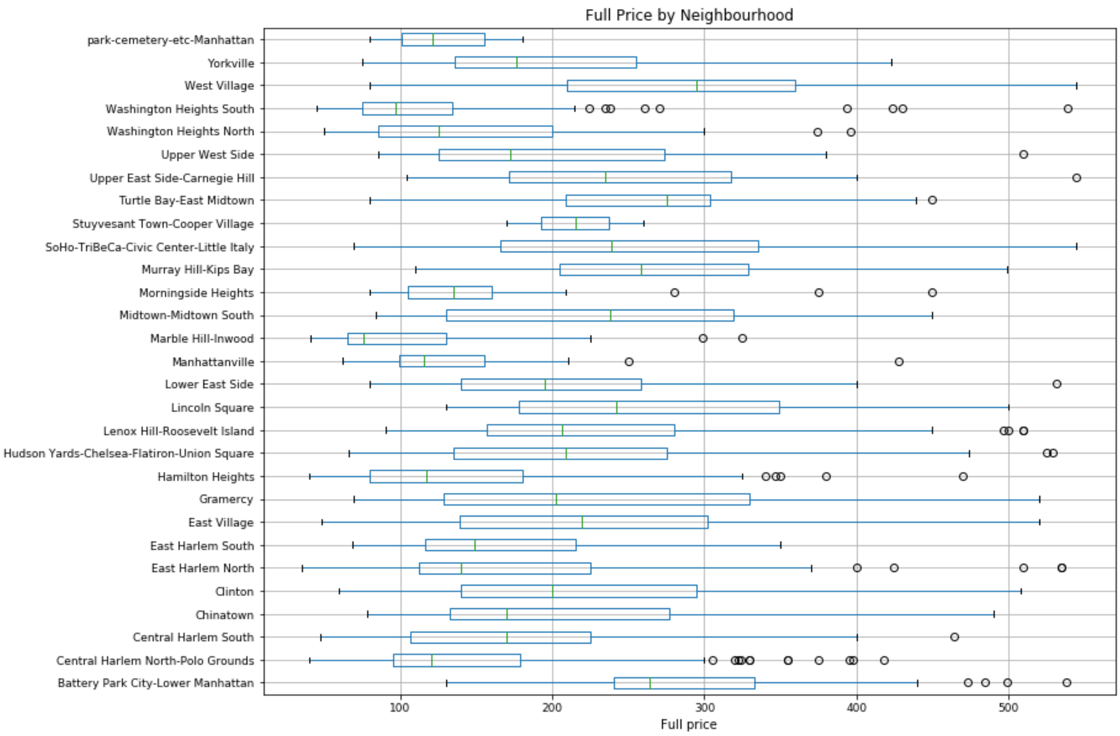
• **crimes** - calculate the number of crimes in radius of 100 meters from each accommodation. This calculation takes 25-50 munities in Python.

## Airbnb Outliers

Check for outliers for the *Full price* column:



In the chart above we can see some outliers - observation points that are distant from other observations. In our case they are the indication of variance in the data. Let's remove these outliers via IQR method.
After removing the outliers, a new Barchart looks like this




So finally, we got 2,252 rows and 28 columns for the Airbnb dataset.

**Neighborhood Tabulation Areas**

*'Neighborhood Tabulation Areas.geojson'* file contains only polygon area coordinates for each Neighborhoods. So, we need to

• remove neighborhoods outside Manhattan;

• calculate Centroid points ('latitude', 'longitude') for each Neighborhood.

For used **Nominatim** service to detect Centroid points for each Neighborhood and then made some manual correction because Nominatim service is not quite accurate.

| Neighborhood | Latitude | Longitude |
|---|---|---|
| Manhattanville | 40.815778 | -73.951554 |
| Clinton | 40.764423 | -73.992392 |
| Chinatown | 40.715100 | -73.995500 |
| Battery Park City-Lower Manhattan | 40.706784 | -74.010147 |
| Lincoln Square | 40.772319 | -73.984401 |

**New York Police Crime Records**

We are interested in crimes only for Manhattan and types are 'Felony' or 'Misdemeanor'. After filtering we have 101,086 crimes records for Manhattan in 2019 year.
We keep all columns, but it's needed to convert Latitude and Longitude columns from *String* to *Float.*
We added **tab_area** column (New York Area Tabulation Name) to NYC Manhattan Crimes data set because we need to display **Crime Rate** Information on the New York Area Tabulation Map.
And removed *'Not defined'* values for *tab_area* column as they do not belong to Manhattan.

# Methodology

In this project we are trying to detect Manhattan's Neighborhoods that have accommodations for rent with positive reviews, reasonable prices, low number of crimes and tourists' attractions nearby.
In the first step we have collected the following data:
• Airbnb Accommodations with their NYC Tabulation Area (official neighborhood names);
• Airbnb Accommodation's number of crimes nearby;
• Defined NYC Tabulation Area (official neighborhood name) for each Manhattan's crime case.

The second step in our analysis will be a calculation and exploration different neighborhoods of Manhattan. We will explore the following characteristics:
• number of crimes in the area;
• average price per person;
• number of accommodations available.

In the third and final step we will
• select Top-100 Airbnb accommodations based on summary rating, number of crimes and price per person, and
• invoke Foursquare API to find Top accommodations' nearby venues
• create and investigate clusters (using k-means clustering) for our accommodations to make some recommendations to our tourists.

# Analysis

In this section, we will explore the cleansed data and visualize them. Then, we will conduct cluster analysis to try to classify Manhattan's NYC Airbnb Neighborhoods.

**Average Price per Person Neighborhoods**

Calculate **average price_per_person**, **average crimes rate** and **number of accommodations** for each Airbnb neighborhoods.

Top-5 Neighborhoods with Highest average *Price per Person* in 2019 year:

- West Village - 112.85 USD - 88 accommodations
- Lincoln Square - 112.51 USD - 20 accommodations
- Stuyvesant Town-Cooper Village - 107.5 USD - 2 accommodations
- SoHo-TriBeCa-Civic Center-Little Italy - 105.38 USD - 81 accommodations
- Upper East Side-Carnegie Hill - 96.98 USD - 24 accommodations

Top-5 Neighborhoods with Lowest average *Price per Person* in 2019 year:

- Marble Hill-Inwood - 45.48 USD - 25 accommodations
- Washington Heights South - 46.79 USD - 82 accommodations
- Washington Heights North - 54.74 USD - 53 accommodations
- Central Harlem North-Polo Grounds - 57 USD - 132 accommodations
- Manhattanville - 59.75 USD - 25 accommodations

**Crime Rate Neighborhoods**

Top-5 Neighborhoods with the Highest Crime level in 2019 year:

- Midtown-Midtown South - 10,397
- Hudson Yards-Chelsea-Flatiron-Union Square - 7,788
- East Harlem North - 6,221
- Central Harlem North-Polo Grounds - 5,186
- SoHo-TriBeCa-Civic Center-Little Italy - 4,789

Top-5 Neighborhoods with the Lowest Crime level in 2019 year:

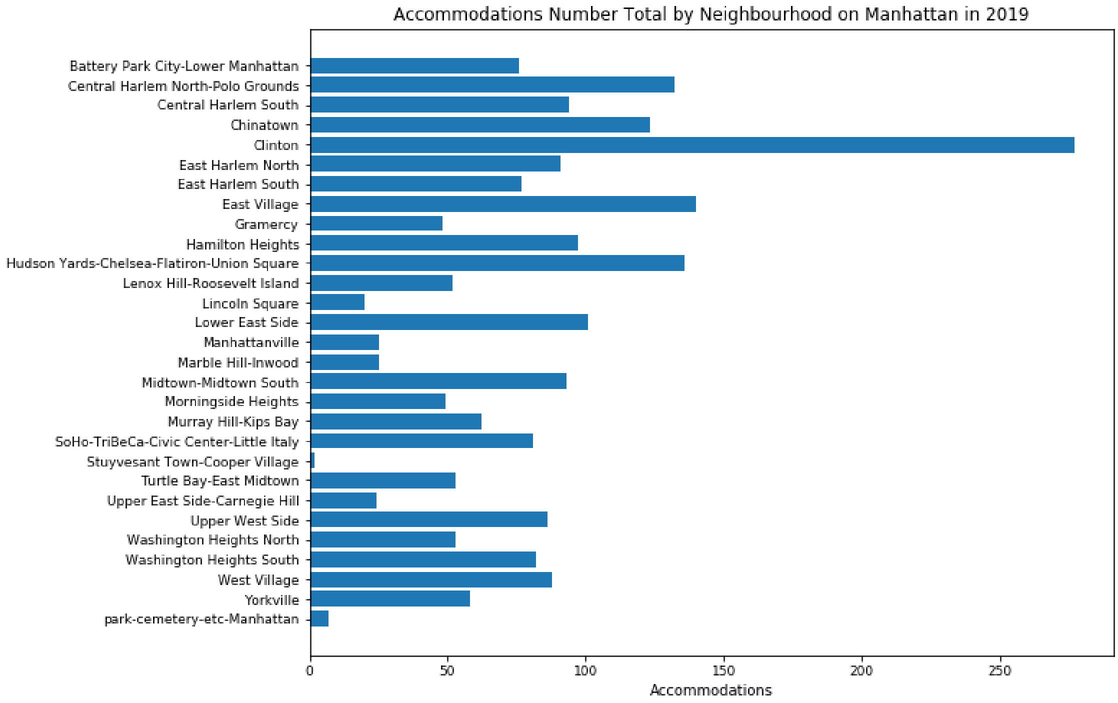
- Stuyvesant Town-Cooper Village - 145
- park-cemetery-etc-Manhattan - - 1,213
- Lenox Hill-Roosevelt Island - 1,604
- Manhattanville - 1,832
- Yorkville - 1,898

## All data

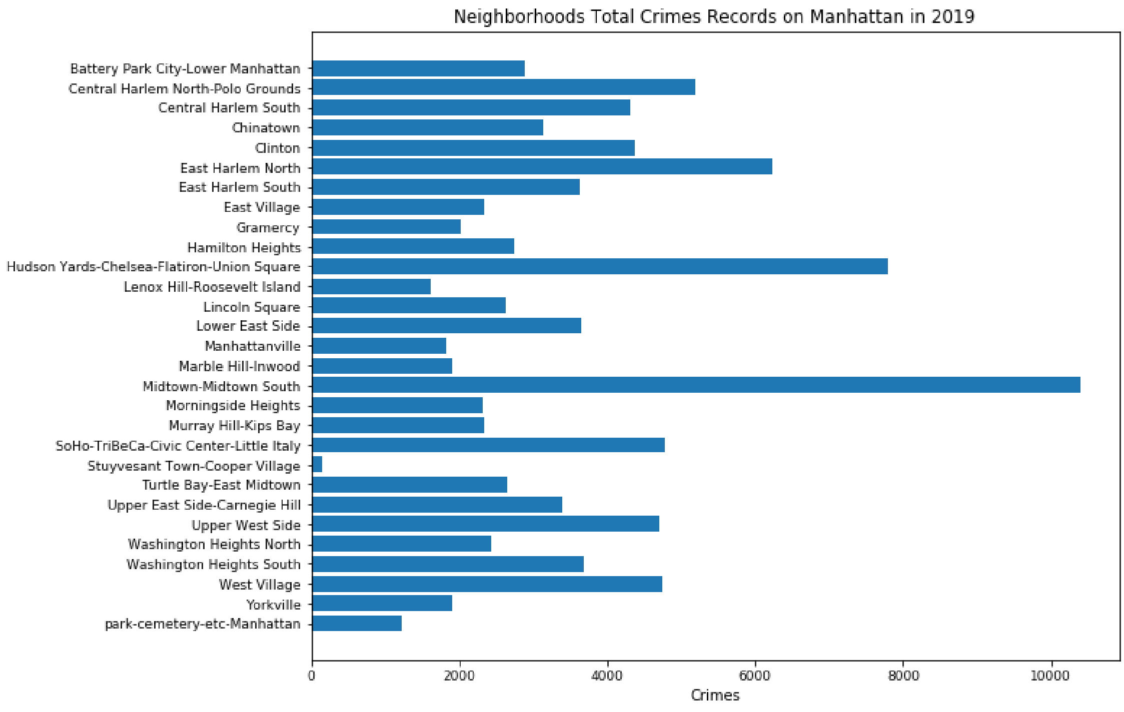
| tab_area | mean_price_per_person | accommodates | mean_crimes |
|---|---|---|---|
| Marble Hill-Inwood | 45.475238 | 25 | 54.440000 |
| Washington Heights South | 46.793172 | 82 | 57.682927 |
| Washington Heights North | 54.738050 | 53 | 50.886792 |
| Central Harlem North-Polo Grounds | 57.038497 | 132 | 73.265152 |
| Manhattanville | 59.746667 | 25 | 70.520000 |
| Hamilton Heights | 60.069404 | 97 | 66.206186 |
| park-cemetery-etc-Manhattan | 61.404762 | 7 | 13.428571 |
| East Harlem North | 62.275497 | 91 | 104.824176 |
| East Harlem South | 64.950000 | 77 | 90.051948 |
| Central Harlem South | 67.000823 | 94 | 87.148936 |
| Morningside Heights | 71.386054 | 49 | 56.204082 |
| Upper West Side | 78.127907 | 86 | 57.813953 |
| Midtown-Midtown South | 81.491705 | 93 | 139.000000 |
| Battery Park City-Lower Manhattan | 82.133130 | 76 | 90.394737 |
| Chinatown | 82.362703 | 123 | 93.081301 |
| Clinton | 84.308819 | 277 | 84.314079 |
| East Village | 84.842758 | 140 | 74.385714 |
| Lower East Side | 88.452617 | 101 | 72.415842 |
| Hudson Yards-Chelsea-Flatiron-Union Square | 88.591179 | 136 | 77.816176 |
| Yorkville | 89.692529 | 58 | 65.000000 |
| Murray Hill-Kips Bay | 90.410167 | 62 | 48.016129 |
| Gramercy | 94.364931 | 48 | 84.791667 |
| Turtle Bay-East Midtown | 94.817296 | 53 | 60.509434 |
| Lenox Hill-Roosevelt Island | 96.636218 | 52 | 45.019231 |
| Upper East Side-Carnegie Hill | 96.988889 | 24 | 62.833333 |
| SoHo-TriBeCa-Civic Center-Little Italy | 105.384002 | 81 | 71.962963 |
| Stuyvesant Town-Cooper Village | 107.500000 | 2 | 47.000000 |
| Lincoln Square | 112.514286 | 20 | 87.300000 |
| West Village | 112.854167 | 88 | 99.863636 |

# NYC Manhattan's Neighborhoods Analysis Charts

## Apartments Total by Neighborhood Chart



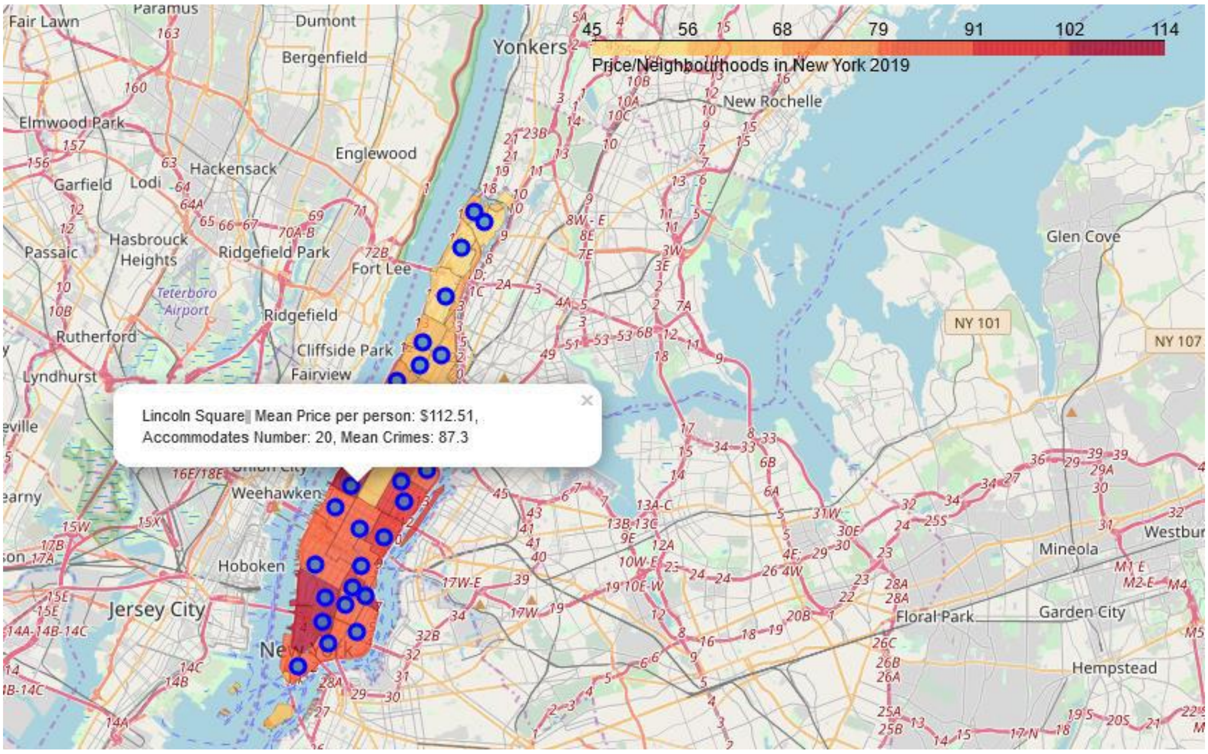

## Neighborhoods Crimes Records Chart



## NYC Manhattan's Neighborhoods Analysis Maps

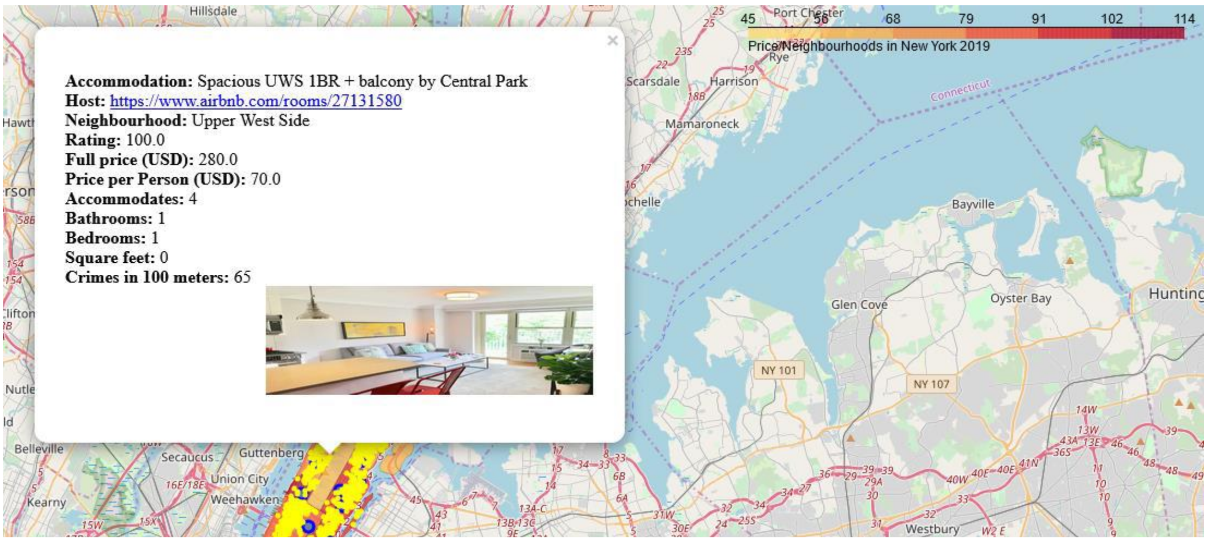
We created several maps to visualize our results and help the user select needed lodges.

### NYC Tabulation Area Neighborhoods Average Prices per Person on Manhattan in 2019 Map



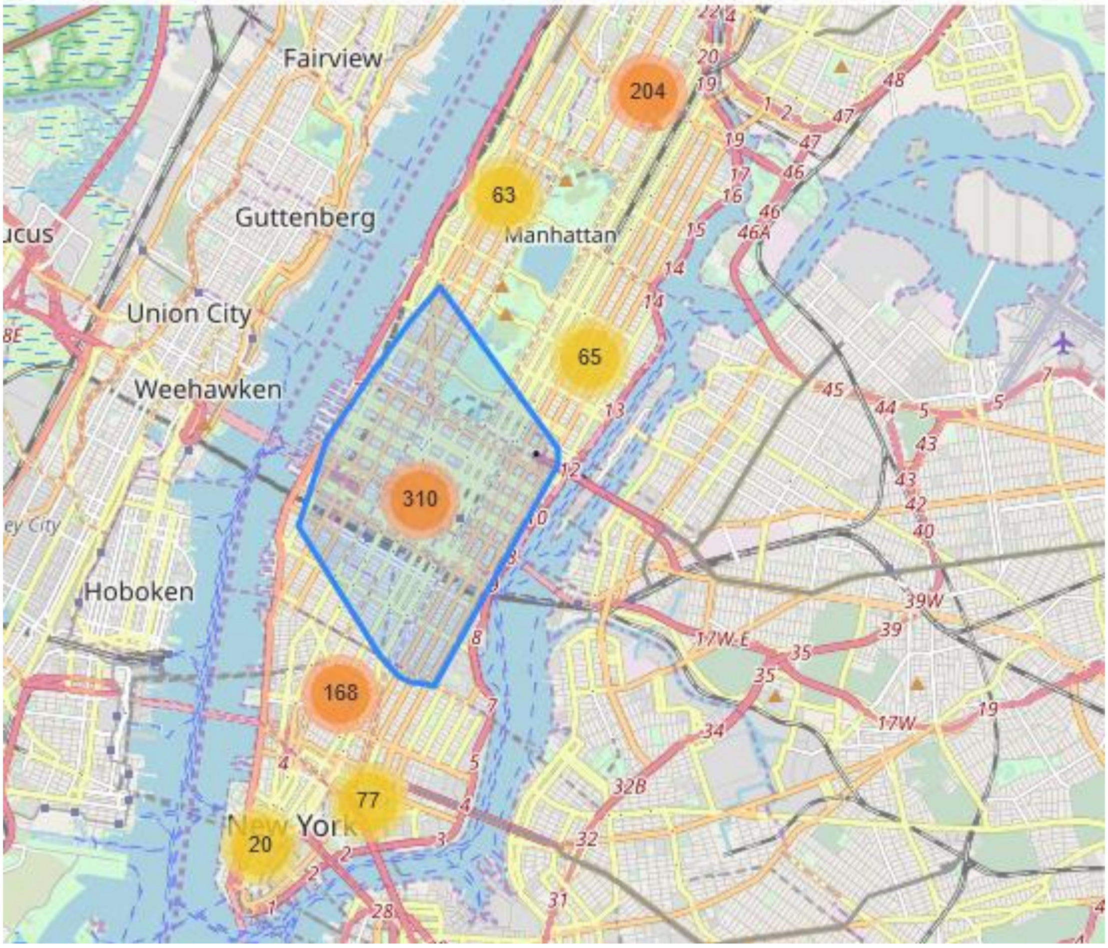

### Accommodations Detailed Info Map

We put all our Airbnb accommodations on the Map - so the user can easily review them.



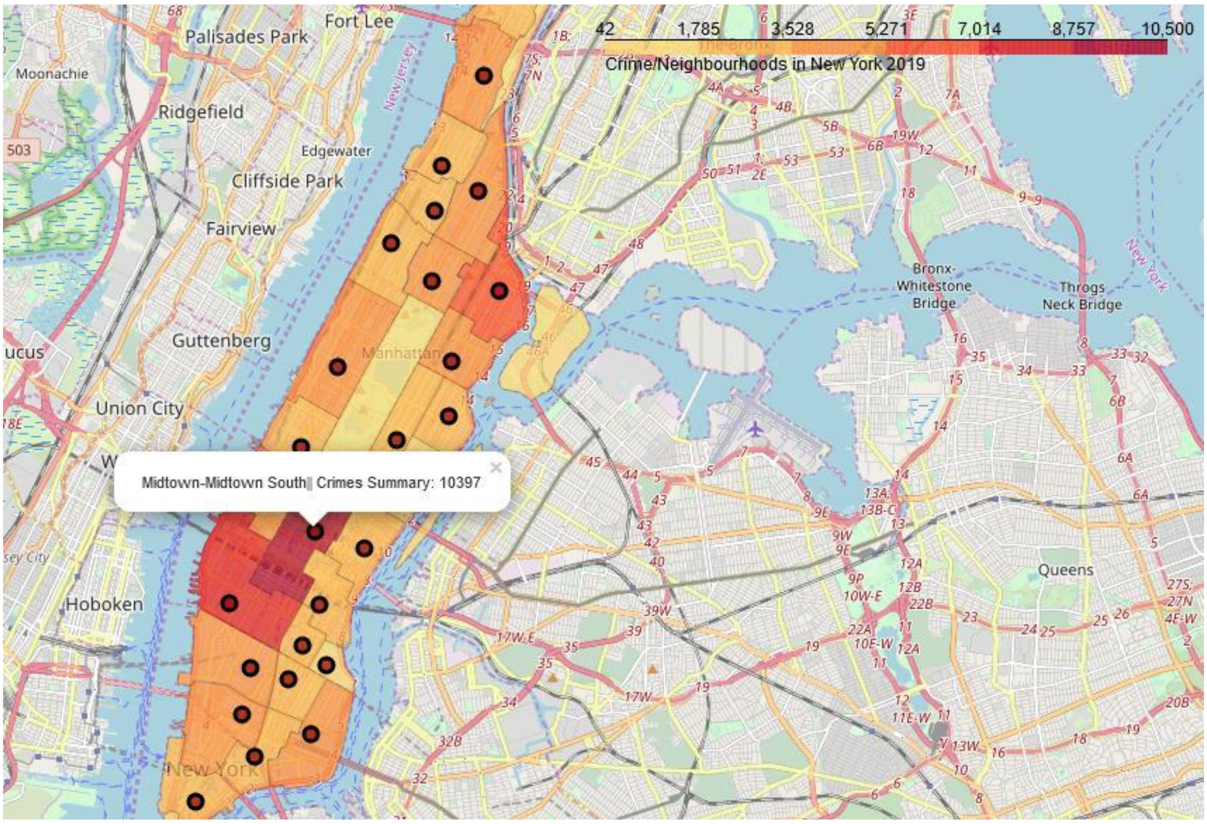
**Crimes Cluster Map**

Cluster Map of **1000 crimes** by Neighborhood from *New York Police Crime* data set.



**Summary Crimes by Neighborhoods Map**

In this map we depict the summary number of crimes for each neighborhood on Manhattan for 2019 year.



## Foursquare API Neighborhoods Analysis

Because of the Foursquare API limitations for free usage lets analyze Top-100 Accommodations from the Airbnb data set. We define Top-3 Venue Categories for each accommodation in radius of 1000 meters. Then we will try to define the 3 clusters for these accommodations.

Let’s choose Top Accommodations by

• review_scores_rating - overall accommodations rating - from maximum 100 to lower values
• full_price - from lower price to higher
• price_per_person - from lower price to higher
• crimes - from lower number to higher

roll output; double click to hide

| | name | tab_area | neighbourhood_cleansed | latitude | longitude | review_scores_rating | property_type | room_type | accommodates | full_price | price_per_person | crimes | listing_url | picture_url | bathrooms | bedrooms | square_feet |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Private Bedroom in Cozy Hamilton Heights Apartment | Hamilton Heights | Harlem | 40.82749 | -73.94461 | 100.0 | Apartment | Private room | 2 | 54.0 | 27.0 | 34 | https://www.airbnb.com /rooms/34770173 | https://a0.muscache.com/im/pictures/aff6d2a3-b6f6-491f-84b3-1e6d2ff35115.jpg?aki_policy=large | 1 | 1 | 0 |
| | Mr. B - Room Apartment in NYC | Washington Heights South | Washington Heights | 40.84377 | -73.94094 | 100.0 | Apartment | Private room | 1 | 67.0 | 67.0 | 32 | https://www.airbnb.com /rooms/32589616 | https://a0.muscache.com/im/pictures/88aec7e7-eb04-417d-9c42-43a33d4b9426.jpg?aki_policy=large | 1 | 1 | 0 |
| | master bedroom/NYC/The Heights | Washington Heights North | Washington Heights | 40.84911 | -73.93097 | 100.0 | Apartment | Private room | 2 | 74.0 | 37.0 | 78 | https://www.airbnb.com /rooms/26303788 | https://a0.muscache.com/im/pictures/fcc9077f-fab7-4c8f-a62c-1b7340fcaa30.jpg?aki_policy=large | 1 | 1 | 0 |
| | Little Safe Haven | Hamilton Heights | Harlem | 40.82494 | -73.94280 | 100.0 | Apartment | Private room | 1 | 80.0 | 80.0 | 43 | https://www.airbnb.com /rooms/29205817 | https://a0.muscache.com/im/pictures/97143bde-79c7-4112-8bfa-fb219529c4e6.jpg?aki_policy=large | 1 | 1 | 0 |
| | One cozy private BR close to the mecca of shopping | Turtle Bay-East Midtown | Midtown | 40.76026 | -73.96590 | 100.0 | Apartment | Private room | 1 | 80.0 | 80.0 | 64 | https://www.airbnb.com /rooms/13246804 | https://a0.muscache.com/im/pictures/b4722160-be37-4701-a2e5-36cfe38f7a27.jpg?aki_policy=large | 1 | 2 | 0 |

We define our custom Top-Level categories for Venues

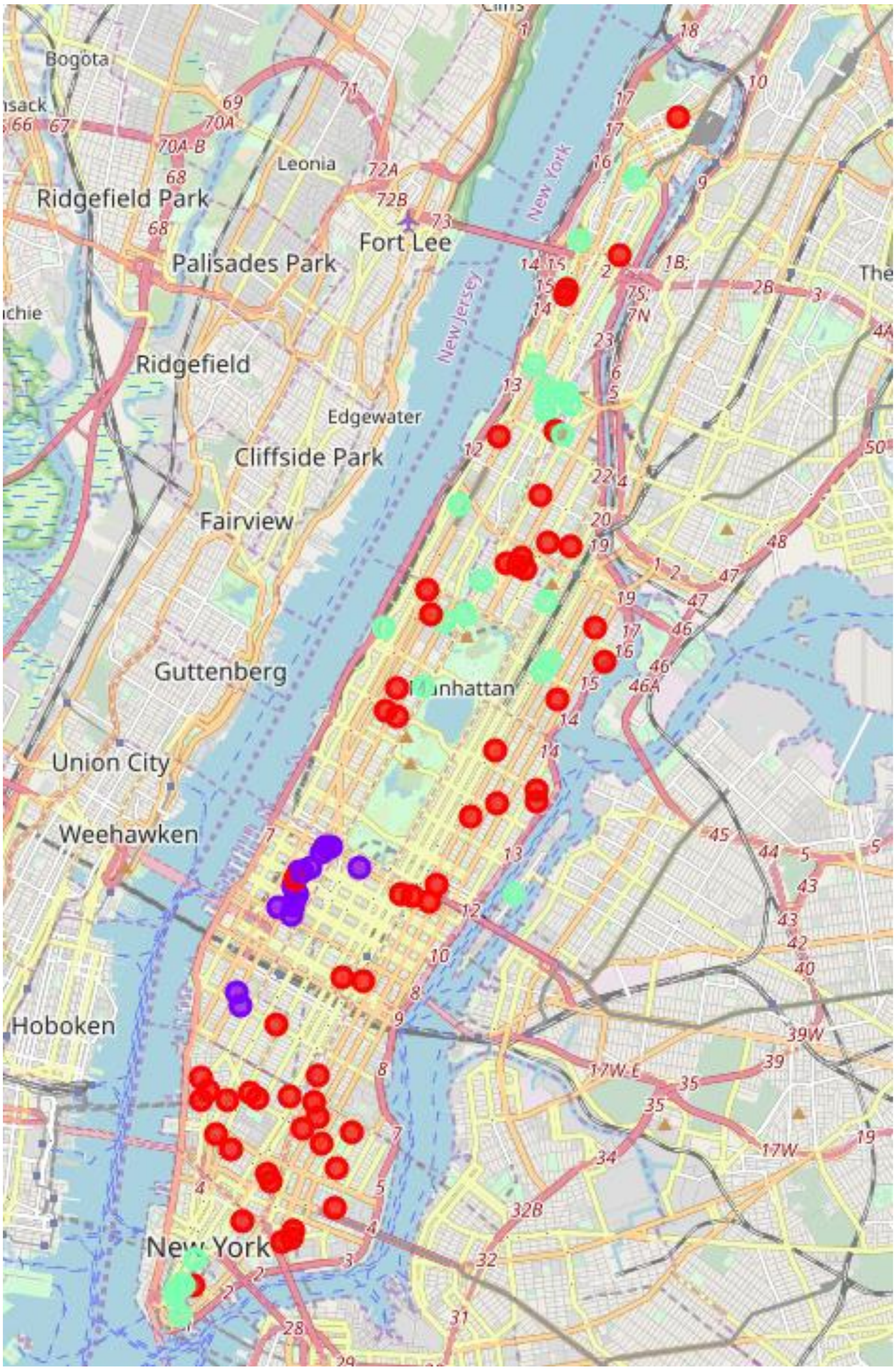
```
fine_art_cat = ['Art','Arts','Museum', 'Library','Exhibit','Gallery']
eat_place_cat = ['Restaurant','Steakhouse']
shopping_cat = ['Shopping Mall','Market','Boutique']
outdoor_cat = ['Sculpture Garden','Scenic Lookout','Roof Deck','Outdoor Sculpture','Monument / Landmark',
               'Memorial Site','Lighthouse','Historic Site','Harbor / Marina','Fountain','Event Space','Bridge',
               'Waterfront','Church','Building','Garden','Historic Site','Lake','Park',
               'Pier','Rest Area','River','Synagogue','Field']
entertainment_cat = ['Nightclub','Circus','Club', 'Stadium', 'Karaoke Bar', 'Pub','Theater','Opera', 'Concert', 'Zoo']

#Join all categories' values in one
tourists_categories = fine_art_cat + eat_place_cat + shopping_cat + outdoor_cat +entertainment_cat
```

Calculate the Top-3 Venues Categories for each accommodation.

Then run k-means to cluster the neighborhood into 3 clusters.

| Cluster Labels | name | 1st Most Common Venue | 2nd Most Common Venue | 3rd Most Common Venue | 1st Most Common Venue Share | 2nd Most Common Venue Share | 3rd Most Common Venue Share |
|---|---|---|---|---|---|---|---|
| 1 | **Stylish, Quiet, Centrally Located (9th & 52nd) | Food Place | Entertainment | Fine Art | 0.62 | 0.35 | 0.04 |
| 2 | 157-C | Food Place | Sightseeing | Fine Art | 0.52 | 0.29 | 0.14 |
| 2 | A neat bedroom in a cozy 3-bedroom apartment | Food Place | Sightseeing | Shopping | 0.48 | 0.41 | 0.04 |
| 0 | Art filled peaceful paradise EV Union Square | Food Place | Sightseeing | Shopping | 0.71 | 0.07 | 0.07 |
| 0 | Artsy Parisian Apt in Greenwich Village | Food Place | Entertainment | Sightseeing | 0.65 | 0.26 | 0.09 |

Now, we can examine each cluster and determine our custom venue categories that distinguish each cluster.




**Cluster 0 – Mix (red dots)** characteristics:

• average *price_per_person*

• average *crimes* rate

• second top Common Venue Category has a Mix of all kind of Categories

• contains 58% from all top accommodations

| | review_scores_rating | accommodates | full_price | price_per_person | crimes | bathrooms | bedrooms | Cluster Labels |
|---|---|---|---|---|---|---|---|---|
| count | 58.0 | 58.000000 | 58.000000 | 58.000000 | 58.000000 | 58.000000 | 58.000000 | 58.0 |
| mean | 100.0 | 2.189655 | 229.068966 | 109.554023 | 67.051724 | 1.051724 | 1.034483 | 0.0 |
| std | 0.0 | 0.907220 | 117.766028 | 48.078871 | 57.990750 | 0.291542 | 0.417407 | 0.0 |
| min | 100.0 | 1.000000 | 67.000000 | 37.000000 | 3.000000 | 0.000000 | 0.000000 | 0.0 |
| 25% | 100.0 | 2.000000 | 132.250000 | 71.250000 | 37.250000 | 1.000000 | 1.000000 | 0.0 |
| 50% | 100.0 | 2.000000 | 202.500000 | 99.166667 | 49.500000 | 1.000000 | 1.000000 | 0.0 |
| 75% | 100.0 | 2.750000 | 301.750000 | 140.125000 | 78.000000 | 1.000000 | 1.000000 | 0.0 |
| max | 100.0 | 5.000000 | 519.000000 | 259.500000 | 385.000000 | 2.000000 | 2.000000 | 0.0 |

**Cluster 1 – Entertainment (blue dots)** characteristics:
- highest average *price_per_person* among all clusters
- highest average *crimes* rate among all clusters
- *Entertainment* is 1st and the 2nd Top Common Venue Categories
- contains 15% from all top accommodations

| | review_scores_rating | accommodates | full_price | price_per_person | crimes | bathrooms | bedrooms | Cluster Labels |
|---|---|---|---|---|---|---|---|---|
| count | 15.0 | 15.000000 | 15.000000 | 15.000000 | 15.000000 | 15.0 | 15.000000 | 15.0 |
| mean | 100.0 | 2.666667 | 273.733333 | 111.403333 | 102.000000 | 1.0 | 0.866667 | 1.0 |
| std | 0.0 | 1.175139 | 96.230725 | 40.353361 | 64.378346 | 0.0 | 0.516398 | 0.0 |
| min | 100.0 | 1.000000 | 110.000000 | 55.000000 | 23.000000 | 1.0 | 0.000000 | 1.0 |
| 25% | 100.0 | 2.000000 | 210.000000 | 79.650000 | 61.000000 | 1.0 | 1.000000 | 1.0 |
| 50% | 100.0 | 2.000000 | 275.000000 | 105.000000 | 74.000000 | 1.0 | 1.000000 | 1.0 |
| 75% | 100.0 | 4.000000 | 329.500000 | 137.500000 | 130.500000 | 1.0 | 1.000000 | 1.0 |
| max | 100.0 | 5.000000 | 420.000000 | 200.000000 | 257.000000 | 1.0 | 2.000000 | 1.0 |

**Cluster 2 – Sightseeing (light-green dots)** characteristics:
- lowest average *price_per_person*
- lowest *crimes* rate among all clusters
- *Sightseeing* is the second top Common Venue Category
- contains 27% from all top accommodations

| | review_scores_rating | accommodates | full_price | price_per_person | crimes | bathrooms | bedrooms | Cluster Labels |
|---|---|---|---|---|---|---|---|---|
| count | 27.000000 | 27.000000 | 27.000000 | 27.000000 | 27.000000 | 27.000000 | 27.000000 | 27.0 |
| mean | 99.925926 | 3.148148 | 182.074074 | 58.638889 | 65.037037 | 1.185185 | 1.111111 | 2.0 |
| std | 0.266880 | 1.974914 | 112.167775 | 17.109439 | 43.882256 | 0.483341 | 0.506370 | 0.0 |
| min | 99.000000 | 1.000000 | 54.000000 | 27.000000 | 4.000000 | 1.000000 | 0.000000 | 2.0 |
| 25% | 100.000000 | 2.000000 | 88.500000 | 46.000000 | 33.000000 | 1.000000 | 1.000000 | 2.0 |
| 50% | 100.000000 | 2.000000 | 158.000000 | 57.000000 | 62.000000 | 1.000000 | 1.000000 | 2.0 |
| 75% | 100.000000 | 4.000000 | 260.500000 | 65.125000 | 82.500000 | 1.000000 | 1.000000 | 2.0 |
| max | 100.000000 | 10.000000 | 470.000000 | 100.000000 | 175.000000 | 3.000000 | 3.000000 | 2.0 |

# Results and Discussion

During the analysis, three clusters were defined. All clusters have a 'Food Place' category as the First Common Venues. This is what we have in common among our clusters.

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- average **Price per person;**
- average **Crimes Rate;**
- the second Common Venues;
- number of available Airbnb accommodations;
- neighborhoods location.

**Cluster 0 – Mix** is the most generic cluster - it has a

- average price_per_person - $110;
- average crimes rate - 67 (but very varying - depends on the neighborhood, from 3 to 385 crime cases in radius of 100 meters from the accommodation);
- mix of all Venue Categories (Fine Arts, Shopping, Entertainment);
- contains 58% from all accommodations selected from analysis (Top-100 Airbnb accommodations);
- spreads almost on all Manhattan's areas.

**Cluster 1 - Entertainment** is the smallest cluster with the following qualities (Nightclub, Stadium, Pub, Theater, Concert and so on):

- highest average *price_per_person* among all clusters - $111;
- highest average *crimes* rate among all clusters – 102;
- *Entertainment* is 1st and the 2nd Top Common Venue Categories;
- contains 15% from all top accommodations (Top-100 Airbnb accommodations);
- spreads on *Chelsea, Hell's Kitchen, and Midtown* Airbnb's Neighborhoods.

**Cluster 2 - Sightseeing** is the cheapest one with many Sightseeing attractions nearby (Monument/Landmark, Memorial Site, Historic Site, Lake, Park, Pier, and so on)

- lowest average price_per_person - $59;
- lowest crimes rate among all clusters – 65;
- *Sightseeing* is the second top Common Venue Category;
- contains 27% from all top accommodations (Top-100 Airbnb accommodations);
- spreads on *East Harlem, Financial District, Harlem, Inwood, Morningside Heights, Roosevelt Island, Upper West Side, Washington Heights, West Village.*

We identified three clusters from which a visitor could choose an appropriate accommodation based on his/her preferences or needs.

**Top Neighborhoods Statistics**

Top-5 Neighborhoods with Lowest average *Price per Person* in 2019 year:

| | |
|---|---|
| • Marble Hill-Inwood | - 45.48 USD - 25 accommodations |
| • Washington Heights South | - 46.79 USD - 82 accommodations |
| • Washington Heights North | - 54.74 USD - 53 accommodations |
| • Central Harlem North-Polo Grounds | - 57 USD - 132 accommodations |
| • Manhattanville | - 59.75 USD - 25 accommodations |

Top-5 Neighborhoods with the Lowest *Crime level* in 2019 year:

| | |
|---|---|
| • Stuyvesant Town-Cooper Village | - 145 |
| • park-cemetery-etc-Manhattan - | - 1,213 |
| • Lenox Hill-Roosevelt Island | - 1,604 |
| • Manhattanville | - 1,832 |
| • Yorkville | - 1,898 |

**Limitations**

- We limited our investigation by Manhattan Borough only;

- Foursquare free account has a limitation of 950 calls/day so maybe it's worth to upgrade our free account to analyze Top-1000 Airbnb accommodations instead of Top-100.

# Conclusion

To conclude, the basic data analysis was performed to identify Manhattan's Neighborhoods clusters for a short stay visit. During the analysis, we cleansed and investigated Manhattan Neighborhoods' datasets, found some statistical characteristics and visualize them.

The aim of this project is to help Manhattan visitors select the Airbnb neighborhoods where to stay based on the most common venues, price policy, and safety characteristics:
• if a person is interested in **entertainment** (Nightlife, Pubs, Concerts, Movies) we recommend paying attention for accommodations from the *Cluster 1 - Entertainment*: *Chelsea, Hell's Kitchen, and Midtown* Airbnb's Neighborhoods. But the person should take into the consideration the high prices and crime rate for this location;

• if a person is looking for a neighborhood with **lower prices** and nice views nearby, we recommend looking at *Cluster 2 - Sightseeing*: *Chelsea, Hell's Kitchen, and Midtown Airbnb's Neighborhoods*;

• if a person **does not have any preferences** - investigate proposals from *Cluster 0 - Mix*. It has average prices and spreads over almost all Manhattan's neighborhood.

**Areas of improvement**

 We could include the other NYC Boroughs - The Bronx, Brooklyn, Queens, and Staten Island;
• We also could utilize other services like Google API to find nearby Venues;
• We have not analyzed the Hotels. It's very big chunk but we have not found any fresh public data sets about hotels accommodations with rating.

# References

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