CAPSTONE PROJECT THE BATTLE OF NEIGHBORHOODS



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Description of the problem

The Manhattan borough is one of the best known and most visited in New York, in which more than 90% of the main actions of the city are concentrated: the Empire State Bulding, the Rockefeller Center, the Chrysler Building and the incredible Times Square, to name a few.

In addition to its wonderful tourist and commercial attraction, it is an ideal place to live, surrounded by the Hudson (west) and Harlem (north) rivers. Each person is different, with different tastes and interests, and these are really important factors when buying an apartment. It is also necessary to know the environment and the places that are in the surroundings of the new home, since these provide an overview of the quality of life that can be had there and is a very valuable element to promote the purchase of real estate goods.

That is why a person before buying an apartment in Manhattan asks the following question: how to consider and choose the best neighborhood to live in Manhattan according to the main places that surround the area?

Data

Two different sources were taken as reference for the elaboration of this project:

The first comes from the renowned Kaggle site. A record was selected for each building or construction unit (apartment, residence, etc.) sold on the New York City property market, over a 12-month period, specifically September 2016 to the same month in 2017.
 https://www.kaggle.com/new-york-city/nyc-property-sales

The dataset in Kaggle corresponds to a modified version of the New York City Department of Finance that considered continuous sales information.

https://www1.nyc.gov/site/finance/taxes/property-rolling-sales-data.page

The data set is made up of:

- **BOROUGH:** a digit code for the borough where the property is located. Manhattan (1), Bronx (2), Brooklyn (3), Queens (4), and Staten Island (5).
- NEIGHBORHOOD
- BUILDING CLASS CATEGORY
- TAX CLASS AT PRESENT
- BLOC
- LOT
- EASE-MENT
- BUILDING CLASS AT PRESENT
- ADDRESS
- APARTMENT NUMBER
- ZIP CODE
- RESIDENTIAL UNITS
- COMMERCIAL UNITS
- TOTAL UNITS

- LAND SQUARE FEET
- GROSS SQUARE FEET
- YEAR BUILT
- TAX CLASS AT TIME OF SALE
- BUILDING CLASS AT TIME OF SALE
- SALE PRICE
- SALE DATE
- The second source was taken from Foursquare, through its developer API. Foursquare is a specialized location technology platform dedicated to improving the way people move around the real world. It is a service based on web location applied to social networks. From it we drew the busiest places around the Manhattan borough neighborhoods. https://es.foursquare.com/

Methodology

This project was based on a series of steps for its preparation, below you can see them in detail:

- Data processing

Once the data was loaded, it was advanced in its processing in order to obtain the information without elements that could affect it. Fortunately, the selected data set was already processed for the use we would give it.

	Unnamed: 0	BOROUGH	NEIGHBORHOOD	BUILDING CLASS CATEGORY	CLASS AT PRESENT	BLOCK	LOT	EASE- MENT	BUILDING CLASS AT PRESENT	ADDRESS	APARTMENT NUMBER	CODE	RESIDENTIAL UNITS	CON
0	.4	1.0	ALPHABET CITY	07 RENTALS - WALKUP APARTMENTS	2A	392.0	6.0		C2	AVENUE B		10009.0	5.0	1
1	5	1.0	ALPHABET CITY	07 RENTALS - WALKUP APARTMENTS	2	399.0	25.0		C7	234 EAST 4TH STREET		10009.0	28.0	
2	6	1.0	ALPHABET CITY	07 RENTALS - WALKUP APARTMENTS	2	399.0	39.0		C7	197 EAST 3RD STREET		10009.0	16.0	
3	.7	1.0	ALPHABET CITY	07 RENTALS - WALKUP APARTMENTS	28	402.0	21.0		04	154 EAST 7TH STREET		10009.0	10.0	
4		1.0	ALPHABET CITY	07 RENTALS - WALKUP APARTMENTS	2A	404.0	55.0		CZ	301 EAST 10TH STREET		10009.0	6.0	
1									-					+

Figure 1. First 5 observations of original data..

The columns chosen to work correspond to borough and neighborhood.

	BOROUGH	NEIGHBORHOOD
0	1.0	ALPHABET CITY
1	1.0	ALPHABET CITY
2	1.0	ALPHABET CITY
3	1.0	ALPHABET CITY
4	1.0	ALPHABET CITY

Figure 2. First 5 observations of Borough and Neighborhood.

Subsequently, it was filtered by borough and number 1, Manhattan was chosen. After this, it was grouped by neighborhoods and the number of houses sold in each neighborhood was counted.

HOUSES SOLD

NEIGHBORHOOD

139	ALPHABET CITY
487	CHELSEA
114	CHINATOWN
296	CIVIC CENTER
278	CLINTON
105	EAST VILLAGE
92	FASHION
470	FINANCIAL

Figure 3. First 5 observations grouped by Neighborhood.

Once grouped and with the number of houses sold, the index was reset to be able to use said column later.

	NEIGHBORHOOD	HOUSES SOLD
0	ALPHABET CITY	139
1	CHELSEA	487
2	CHINATOWN	114
3	CIVIC CENTER	296
4	CLINTON	278

Figure 4. First 5 observations of Neighborhood and house sold with index reset.

A new dataframe was created in which the geographical coordinates were added by means of the 'Geolocator' package of each of the neighborhoods of the Manhattan borough, the name of the neighborhood 'Midtown CBD' was changed to 'Midtown' and 'Washington Heights Lower',' Washington Heights Upper 'to' Washington Heights'. One of the difficulties in this stage of the process was that the package generated an error when trying to get the coordinates.

	NEIGHBORHOOD	LATITUDE	LONGITUDE
0	ALPHABET CITY	40.725102	-73.979583
1	CHELSEA	40.746491	-74.001528
2	CHINATOWN	40.716491	-73.996250
3	CIVIC CENTER	40.713679	-74.002404
4	CLINTON	43.048403	-75.378503

Figure 5. First 5 observations of Neighborhoods with their latitude and longitude.

Then, the dataframe was merged with the number of houses sold along with the geographic coordinates.

	NEIGHBORHOOD	HOUSES SOLD	LATITUDE	LONGITUDE
0	ALPHABET CITY	139	40.725102	-73.979583
1	CHELSEA	487	40.746491	-74.001528
2	CHINATOWN	114	40.716491	-73.996250
3	CIVIC CENTER	296	40.713679	-74.002404
4	CLINTON	278	43.048403	-75.378503

Figure 6. First 5 observations merged.

Repeated coordinates are presented in this dataframe, since the 'Geolocator' package did not know how to differentiate between 'UPPER EAST SIDE (59-79)', 'UPPER EAST SIDE (79-96)', 'UPPER EAST SIDE (96-110) 'and' UPPER WEST SIDE (59-79) ',' UPPER WEST SIDE (79-96) ',' UPPER WEST SIDE (96-116) ', also happened with' WASHINGTON HEIGHTS 'due to the modification that was made. Select one observation for each of the three neighborhoods with the sum of the houses sold.

28	UPPER EAST SIDE	1387	40.773702	-73.964120
29	UPPER WEST SIDE	1350	40.787045	-73.975416
30	WASHINGTON HEIGHTS	156	40.840198	-73.940221

Figure 7. Observations changed.

Once the neighborhood data was collected, they were plotted on a map using the por Folium 'package. Three neighborhoods that were very far apart and outside the Manhattan borough were observed, being possible errors of the original data, therefore, the Clinton, Javits Center and Murray Hill neighborhoods were eliminated from our data.

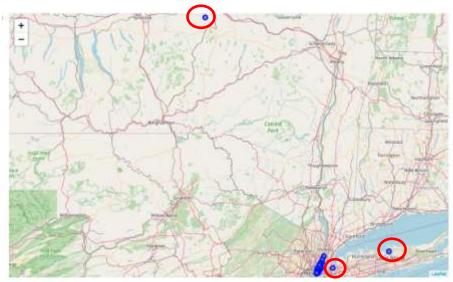


Figure 8. Map of New York with the neighborhoods.

Once deleted, it was possible to find the neighborhoods that would be used in the model.



Figure 9. Map of New York with some neighborhoods elimated.

We graph the number of homes sold by neighborhood in the data period:

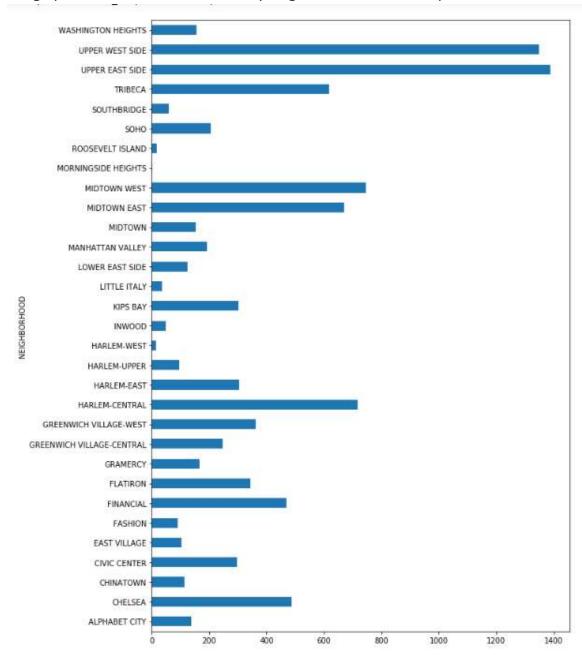


Figure 10. Number of houses sold by Neighborhood.

In addition, a dataframe was created with the price of the houses sold in the neighborhoods. To do this, first the object price column had to be transformed to 'Float64', and the boxes replaced with '-' with NaN. To then eliminate the boxes with missing values and thus calculate the average price of houses sold by neighborhood.

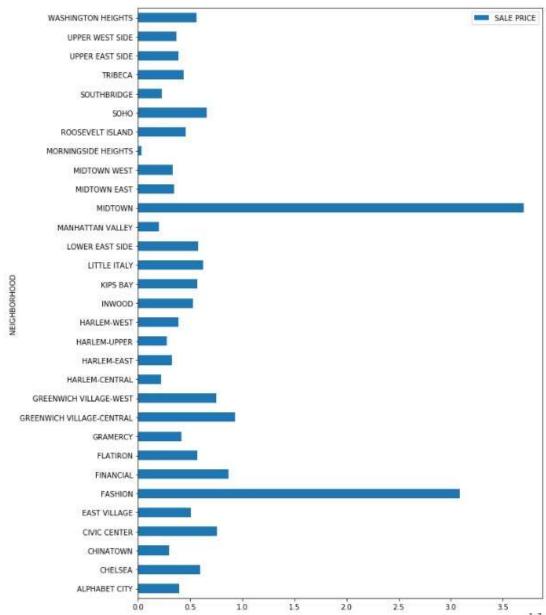


Figure 11. Average price of houses sold by neighborhood.

Already with the coordinate data we proceed to connect with foursquare to obtain the main venues by neighborhood. Then, they were transformed into dummy variables (from categorical to numeric), and a column was created for each of the categories or venues.

Turkish taurant	Ukrainian Restaurant	Used Bookstore	Vegetarian / Vegan Restaurant	Veterinarian	Video Game Store	Vietnamese Restaurant	Waterfront	Whisky Bar	Wine Bar	Wine Shop	Wings Joint	Women's Store	Yoga Studio	Neighborhood
0	0	0	0	0	0	0	0	0	0	0	0	0	0	ALPHABET CITY
0	0	0	0	0	0	0	0	0	0	0	0	0	0	ALPHABET CITY
0	0	0	0	0	0	0	0	0	0	0	0	0	0	ALPHABET CITY
0	0	0	0	0	0	0	0	0	1	0	0	0	0	ALPHABET CITY
0	0	0	0	0	0	0	0	0	0	0	0	0	0	ALPHABET CITY
)

Figure 12. First 5 observations of the dataframe with variables dummies.

Subsequently, they were grouped by neighborhood and the mean by category was determined.

	Neighborhood	African Restaurant	American Restaurant	Amphitheater	Animal Shelter	Antique Shop	Arcade	Arepa Restaurant	Argentinian Restaurant	Art Gallery	Art Museum	Arts & Crafts Store	Asian Restaurant	Athletic & Spor
0	ALPHABET CITY	0.00	0.010000	0.00	0.00	0.00	0.000000	0.00	0.010000	0.010000	0.000000	0.00	0.010000	0.0000
1	CHELSEA	0.00	0.022472	0.00	0.00	0.00	0.000000	0.00	0.011236	0.382022	0.000000	0.00	0.000000	0.0000
2	CHINATOWN	0.00	0.000000	0.00	0.01	0.00	0.000000	0.00	0.000000	0.000000	0.000000	0.00	0.010000	0.0000
3	CIVIC CENTER	0.00	0.026667	0.00	0.00	0.00	0.000000	0.00	0.000000	0.000000	0.000000	0.00	0.000000	0.0000
4	EAST VILLAGE	0.00	0.020000	0.00	0.00	0.00	0.000000	0.01	0.000000	0.010000	0.000000	0.01	0.010000	0.0000

Figure 13. First 5 observations of the dataframe with variables dummies grouped by neighborhodd.

Then a dataframe was created with the ten busiest places for each neighborhood.

	Neighborhood	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue	6th Most Common Venue	7th Most Common Venue	8th Most Common Venue	9th Most Common Venue	10th Most Common Venue
0	ALPHABET CITY	Cocktail Bar	Bar	Wine Bar	Coffee Shop	Garden	Italian Restaurant	Salon / Barbershop	Pizza Place	Beer Bar	Bookstore
1	CHELSEA	Art Gallery	Café	Gym / Fitness Center	Thai Restaurant	Ice Cream Shop	Grocery Store	Park	Coffee Shop	Bagel Shop	American Restaurant
2	CHINATOWN	Chinese Restaurant	Bakery	Bubble Tea Shop	Sandwich Place	Salon / Barbershop	Vietnamese Restaurant	Spa	Ice Cream Shop	Optical Shop	Cocktail Bar
3	CIVIC CENTER	Chinese Restaurant	Bubble Tea Shop	Dim Sum Restaurant	Park	Coffee Shop	Dessert Shop	Gym	Optical Shop	Cocktail Bar	Cantonese Restaurant
4	EAST VILLAGE	Japanese Restaurant	Grocery Store	Dessert Shop	Pizza Place	Bar	Vietnamese Restaurant	Sushi Restaurant	Vegetarian / Vegan Restaurant	loe Cream Shop	Coffee Shop

Figure 14. First 5 observations of the dataframe grouped by neighborhood with the top 10 of venues.

Model Creation

Because this corresponded to a classification problem, Unsupervised Machine Learning, specifically the Kmeans Model, was used to establish five clusters.

Figure 15. Code of Kmeans model.

Once with the clusters already created, the processed table was merged with the table of the main venues, in addition to the cluster type.

	NEIGHBORHOOD	HOUSES SOLD	LATITUDE	LONGITUDE	Cluster Labels	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue	6th Most Common Venue	7th Most Common Venue	8th Most Common Venue
0	ALPHABET CITY	139	40.725102	-73.979583	0	Cocktail Bar	Bar	Wine Bar	Coffee Shop	Garden	Italian Restaurant	Salon / Barbershop	Pizza Place
1	CHELSEA	487	40.746491	-74.001528	1	Art Gallery	Café	Gym / Fitness Center	Thai Restaurant	loe Cream Shop	Grocery Store	Park	Coffee Shop
2	CHINATOWN	114	40.716491	-73.996250	2	Chinese Restaurant	Bakery	Bubble Tea Shop	Sandwich Place	Salon / Barbershop	Vietnamese Restaurant	Spa	loe Cream Shop
3	CIVIC CENTER	296	40.713879	-74.002404	0	Chinese Restaurant	Bubble Tea Shop	Dim Sum Restaurant	Park	Coffee Shop	Dessert Shop	Gym	Optical Shop
4	EAST VILLAGE	105	40.729269	-73.987361	0	Japanese Restaurant	Grocery Store	Dessert Shop	Pizza Place	Bar	Vietnamese Restaurant	Sushi Restaurant	Vegetarian / Vegan Restaurant

Figure 16. First 5 observations of the dat frame grouped by neighborhood with their label.

Results and discussions

After completing the modeling, which resulted in five clusters each with the top 10 busiest locations in each neighborhood, they were categorized as follows:



Figure 17. New York map with labeled neighborhoods

- **Cluster 1:** in these neighborhoods the most frequented places correspond to restaurants and bars, which could be an option for singles, young couples or foodies.

	NEIGHBORHOOD	HOUSES SOLD	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue	6th Most Common Venue	7th Most Common Venue	8th Most Common Venue	9th Most Common Venue	10th Most Common Venue
0	ALPHABET CITY	139	Cocktail Bar	Bar	Wine Bar	Coffee Shop	Garden	Italian Restaurant	Salon / Barbershop	Pizza Place	Beer Bar	Bookstore
3	CIVIC CENTER	296	Chinese Restaurant	Bubble Tea Shop	Dim Sum Restaurant	Park	Coffee Shop	Dessert Shop	Gym	Optical Shop	Cocktail Bar	Cantonese Restaurant
4	EAST VILLAGE	105	Japanese Restaurant	Grocery Store	Dessert Shop	Pizza Place	Bar	Vietnamese Restaurant	Sushi Restaurant	Vegetarian / Vegan Restaurant	loe Cream Shop	Coffee Shop
8	GRAMERCY	167	Italian Restaurant	American Restaurant	Pizza Place	Bar	Wine Shop	Bagel Shop	Coffee Shop	Spa	Grocery Store	Hotel
9	GREENWICH VILLAGE- CENTRAL	247	American Restaurant	Italian Restaurant	Coffee Shop	Cocktail Bar	Pizza Place	Bakery	Sandwich Place	Speakeasy	Jazz Club	loe Cream Shop
16	KIPS BAY	303	Bar	loe Cream Shop	American Restaurant	Bagel Shop	Italian Restaurant	Grocery Store	Coffee Shop	Pizza Place	Yoga Studio	Convenience Store
18	LOWER EAST SIDE	128	Mexican Restaurant	Café	Cocktail Bar	Coffee Shop	American Restaurant	Ice Cream Shop	Sandwich Place	Chinese Restaurant	Bakery	Bar
19	MANHATTAN VALLEY	193	Chinese Restaurant	Coffee Shop	Bar	Yoga Studio	Bistro	Bubble Tea Shop	American Restaurant	Grocery Store	Bagel Shop	Bank
29	UPPER WEST SIDE	1350	American Restaurant	Bar	Coffee Shop	Wine Bar	Dessert Shop	Bakery	Italian Restaurant	Pizza Place	Seafood Restaurant	Bagel Shop

Figure 18. First Cluster.

- **Cluster 2:** The main places that surround these neighborhoods are conformed by art galleries and cafeterias. It could be an alternative for young university students, singles or adults who enjoy the arts and the wonders of a quiet life.

N	NEIGHBORHOOD	HOUSES SOLD	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue	6th Most Common Venue	7th Most Common Venue	8th Most Common Venue	9th Most Common Venue	10th Most Common Venue
1	CHELSEA	487	Art Gallery	Café	Gym / Fitness Center	Thai Restaurant	loe Cream Shop	Grocery Store	Park	Coffee Shop	Bagel Shop	American Restaurant

Figure 19. Second cluster.

- **Cluster 3:** These neighborhoods have very crowded places around them and are mainly characterized by the diversity between them. Ideal for professionals or contemporary couples with high financial income and whose routine is quite dynamic.

	NEIGHBORHOOD	HOUSES SOLD	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue	6th Most Common Venue	7th Most Common Venue	8th Most Common Venue	9th Most Common Venue	10th M Comn Ver
2	CHINATOWN	114	Chinese Restaurant	Bakery	Bubble Tea Shop	Sandwich Place	Salon / Barbershop	Vietnamese Restaurant	Spa	Ice Cream Shop	Optical Shop	Cocktail
5	FASHION	92	Coffee Shop	Gym / Fitness Center	Hotel	Boxing Gym	Grocery Store	Lounge	Yoga Studio	Bakery	Donut Shop	Miscellane SI
6	FINANCIAL	470	Coffee Shop	Pizza Place	American Restaurant	Gym	Italian Restaurant	Gym / Fitness Center	Steakhouse	Bar	Falafel Restaurant	Juice
7	FLATIRON	345	Japanese Restaurant	Spa	American Restaurant	Gym / Fitness Center	Gym	Café	Italian Restaurant	Mediterranean Restaurant	Cosmetics Shop	Juice
10	GREENWICH VILLAGE-WEST	363	American Restaurant	Coffee Shop	Yoga Studio	Steakhouse	loe Cream Shop	Gym / Fitness Center	Italian Restaurant	Sandwich Place	Cocktail Bar	Salad Pl
17	LITTLE ITALY	37	Spa	Chinese Restaurant	loe Cream Shop	Bubble Tea Shop	Mediterranean Restaurant	Bakery	Italian Restaurant	Thai Restaurant	Pizza Place	Sandv Pl:
20	MIDTOWN	154	Hotel	Indian Restaurant	Food & Drink Shop	Theater	Sushi Restaurant	Hotel Bar	Art Museum	Vegetarian / Vegan Restaurant	Steakhouse	Pl
21	MIDTOWN EAST	671	Hotel	Coffee Shop	Salon / Barbershop	Boutique	Art Museum	Gym / Fitness Center	Jewelry Store	Sandwich Place	Chinese Restaurant	\$
24	ROOSEVELT ISLAND	19	Baseball Field	Park	Playground	Scenic Lookout	Restaurant	Dog Run	Liquor Store	Supermarket	Sandwich Place	Sch
25	SOHO	205	Italian Restaurant	Mediterranean Restaurant	Coffee Shop	Sandwich Place	loe Cream Shop	Bakery	Pizza Place	Cosmetics Shop	Clothing Store	Salı Barbersi
26	SOUTHBRIDGE	60	Italian Restaurant	American Restaurant	Café	Coffee Shop	Sandwich Place	Pizza Place	Hotel	Falafel Restaurant	Juice Bar	
27	TRIBECA	617	Gym / Fitness Center	Coffee Shop	Italian Restaurant	Bakery	Gym	Spa	American Restaurant	Steakhouse	Sushi Restaurant	Cocktail
28	UPPER EAST SIDE	1387	Italian Restaurant	Art Museum	Clothing Store	French Restaurant	Outdoor Sculpture	Coffee Shop	Boutique	Women's Store	Café	Steakho

Figure 20. Third cluster.

- **Cluster 4:** The busiest places in these neighborhoods are primarily beauty salons, clothing stores, tech shops, and theme restaurants. An ideal option for professional women who pursue a good lifestyle and enjoy international cuisine.

	NEIGHBORHOOD	HOUSES SOLD	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue	6th Most Common Venue	7th Most Common Venue	8th Most Common Venue	9th Most Common Venue	10th Most Common Venue
11	HARLEM- CENTRAL	718	Cosmetics Shop	Mobile Phone Shop	Clothing Store	African Restaurant	Burger Joint	Theater	Southern / Soul Food Restaurant	Pizza Place	Mexican Restaurant	French Restaurant
12	HARLEM-EAST	306	Cosmetics Shop	Mobile Phone Shop	Clothing Store	African Restaurant	Burger Joint	Theater	Southern / Soul Food Restaurant	Pizza Place	Mexican Restaurant	French Restaurant
13	HARLEM-UPPER	97	Cosmetics Shop	Mobile Phone Shop	Clothing Store	African Restaurant	Burger Joint	Theater	Southern / Soul Food Restaurant	Pizza Place	Mexican Restaurant	French Restaurant
14	HARLEM-WEST	14	Cosmetics Shop	Mobile Phone Shop	Clothing Store	African Restaurant	Burger Joint	Theater	Southern / Soul Food Restaurant	Pizza Place	Mexican Restaurant	French Restaurant

Figure 21. Fourth cluster.

When analyzing this cluster in greater depth, an error was noted in the processing since in the four neighborhoods that compose it, the same coordinate was used, thus deriving repeated information. This does not mean that the cluster is wrong, but rather that it is made up of the sum of the houses sold in a single neighborhood.

- **Cluster 5:** The main places that surround these neighborhoods are made up of parks, cafes, bookstores and wine shops. It could be an alternative for families with children, retired adults who enjoy outdoor walks or a wine tasting.

	NEIGHBORHOOD	HOUSES SOLD	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue	6th Most Common Venue	7th Most Common Venue	8th Most Common Venue	9th Most Common Venue	10th Most Common Venue
15	INWOOD	50	Café	Mexican Restaurant	Park	Spanish Restaurant	American Restaurant	Wine Shop	Wine Bar	Bakery	Frozen Yogurt Shop	Chinese Restaurant
22	MIDTOWN WEST	746	Mexican Restaurant	Thai Restaurant	Italian Restaurant	Coffee Shop	Theater	Wine Shop	Gym	Wine Bar	Gourmet Shop	Pizza Place
23	MORNINGSIDE HEIGHTS	2	Deli / Bodega	Sandwich Place	Coffee Shop	Mexican Restaurant	Italian Restaurant	Café	Chinese Restaurant	Pharmacy	Park	College Cafeteria
30	WASHINGTON HEIGHTS	158	Pizza Place	Latin American Restaurant	Mexican Restaurant	Bookstore	Chinese Restaurant	Bakery	Coffee Shop	Thai Restaurant	Korean Restaurant	Park

Figure 22. Fifth cluster.

Additionally, it was possible to determine that the residents with the highest demand and probably the most accessible, correspond to those of **cluster 1**.

NEIGHBORHOOD

UPPER EAST SIDE 1387

UPPER WEST SIDE 1350

MIDTOWN WEST 746

HARLEM-CENTRAL 718

MIDTOWN EAST 671

Name: HOUSES SOLD, dtype: int64

Figure 23. Top 5 neighborhoods with best-selling houses.

Also, the first 4 most expensive neighborhoods in the Manhattan borough belong to cluster 3, this may be due to the fact that it is the most visited area.



Figure 24. Top 5 Neighborhoods with average most expensive houses sold.

Conclusion

After collecting the information, grouping it and analyzing it, it was possible to categorize the different neighborhoods that make up the Manhattan borough, in this way the possible buyers or tenants will be able to consider and make the best decision when purchasing or renting an apartment. Choosing the neighborhood that best suits your tastes, interests or needs, depending on the places to go in the vicinity of the neighborhood.

In addition, this could lead to great opportunities for the Manhattan real estate sector, it would contribute as an important resource in the final consideration or purchase stage, since it would add value to the property to be promoted.

Also, it is important to highlight that in carrying out this type of modeling, an exhaustive review of the data entered is essential for its execution, since a minimum error could alter the results.