



# New York City Real State Analysis

## COURSERA CAPSTONE PROJECT

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## Part 1: Introduction

### BACKGROUND

New York City (NYC) is the most populated city in the United States (US), with an estimated population of more than 8 million distributed over more than 300 square miles.

It is also the largest metropolitan area in the US with more than 20 million people, and is composed of five boroughs: Brooklyn, Queens, Manhattan, the Bronx, and Staten Island.

Real estate is a major part in the city economy, as the total value of all NYU passed the \$1 trillion mark in the 2017 fiscal year with an increase of more than 10% over the previous year. NYC is home to some of the world's most valuable real state. [1]

### BUSINESS PROBLEM

An investment on real state in NYC will come with some challenges, and any potential investor will need to be assured of the value of the investments. This value will come from selecting the best neighborhood for a target amount to be invested.

The best neighborhood will depend mainly of the proximity to the venues preferred by the potential investor. Other factors like crime statistics were not considered, assumed not relevant to the higher market segments analyzed in this report.

The question is: How to select the best neighborhood for a given investment amount and the venues preferences of a potential investor.

[1] New York City ([https://en.wikipedia.org/wiki/New\\_York\\_City](https://en.wikipedia.org/wiki/New_York_City))

## Part 2: Data Acquisition

### DATA SOURCES

In order to segment the neighborhoods of NYC and explore them, we need the first dataset. This dataset was extracted from the NYU Spatial Data Repository [2] and contains the 5 boroughs and the 306 neighborhoods as well as the latitude and longitude coordinates of each neighborhood. This dataset was previously used in the course week 3 lab Segmenting and Clustering Neighborhoods in New York City.

The second dataset was extracted from Zillow Research Data [3] and contains a time series of the Zillow Home Value Index (ZHVI), this is a smoothed, seasonally adjusted measure of the typical home value and market changes across a given region and housing type.

The dataset selected from Zillow Research is for the mid-tier condo/coops (typical value in US dollars for homes that fall within 33<sup>rd</sup> to 67<sup>th</sup> percentile range for a given region). The mid-tier condo/coop ZHVI is assumed to be representative of the average home values of a highly dense region with a low percentage of single-family homes.

The third data set was extracted with the Foursquare Developer Application Programming Interface (API) [4] and includes the venues, categories and location data of the neighborhoods requested by the API within a given radius. This dataset was previously used in the course week 2 lab Foursquare API.

### DATA CLEANING

Dataset 1 (from NYU) was extracted first in a json file, and filtered to the features key that contains all relevant data, this data was transformed to a pandas dataframe using loop script in Python (Programming language), see figure 1 for the first five rows of the dataframe.

	Borough	Neighborhood	Latitude	Longitude
0	Bronx	Wakefield	40.894705	-73.847201
1	Bronx	Co-op City	40.874294	-73.829939
2	Bronx	Eastchester	40.887556	-73.827806
3	Bronx	Fieldston	40.895437	-73.905643
4	Bronx	Riverdale	40.890834	-73.912585

Figure 1

Dataset 2 (from Zillow) was extracted first in a Comma Separated Values (CSV) file and transferred directly to a dataframe (read csv method) and filtered to show NYC only, not required columns were dropped and remaining columns were renamed keeping the

neighborhood name as the key index, see figure 2 for the first 5 rows and the last 10 columns of the dataframe.

	2019-09	2019-10	2019-11	2019-12	2020-01	2020-02	2020-03	2020-04	2020-05	2020-06
Neighborhood										
Upper West Side	1233923.0	1226329.0	1228089.0	1234873.0	1232891.0	1228788.0	1218444.0	1218807.0	1214683.0	1210707.0
Upper East Side	929593.0	927350.0	926257.0	927430.0	927683.0	929749.0	925260.0	925438.0	925215.0	933518.0
East New York	341233.0	340846.0	340971.0	340998.0	342076.0	343255.0	344385.0	345332.0	345130.0	345802.0
Washington Heights	566566.0	560402.0	556665.0	552960.0	548861.0	544782.0	541350.0	538371.0	533715.0	531615.0
Astoria	513852.0	514333.0	513360.0	514066.0	514298.0	514380.0	513222.0	513961.0	514368.0	515600.0

Figure 2

Dataset 3 (from Foursquare) was extracted first in a json file, flattened (json normalize method), filtered to the venues and their categories, and keeping the location data, see figure 3 for the first five rows of the dataframe.

	name	categories	lat	lng
0	The Bar Room at Temple Court	Hotel Bar	40.711448	-74.006802
1	The Beekman, A Thompson Hotel	Hotel	40.711173	-74.006702
2	Alba Dry Cleaner & Tailor	Laundry Service	40.711434	-74.006272
3	Gibney Dance Center Downtown	Dance Studio	40.713923	-74.005661
4	The Class by Taryn Toomey	Gym / Fitness Center	40.712753	-74.008734

Figure 3

## FEATURE SELECTION

After cleaning the data, we ended with 3 datasets: the first with 306 neighborhoods and the required location data, the second with 190 neighborhoods and ZHVI 296 months' time series and the third with 10,058 venues, neighborhoods, categories and location data.

The field in common in the 3 datasets is the neighborhood and was selected as the key index to link the 3 datasets. The number of venues and neighborhoods will need to be reduced after the exploratory data analysis.

[2] NYU Spatial Data Repository ([https://geo.nyu.edu/catalog/nyu\\_2451\\_34572](https://geo.nyu.edu/catalog/nyu_2451_34572))

[3] Zillow Research Data (<https://www.zillow.com/research/data/>)

[4] Foursquare Developer (<https://developer.foursquare.com/>)

## Part 3: Exploratory Data Analysis

### NEIGHBORHOODS

For the first dataset we used folium library to create a map of NYC with a marker for each one of the neighborhoods on the dataset see figure 4 for the resulting map.

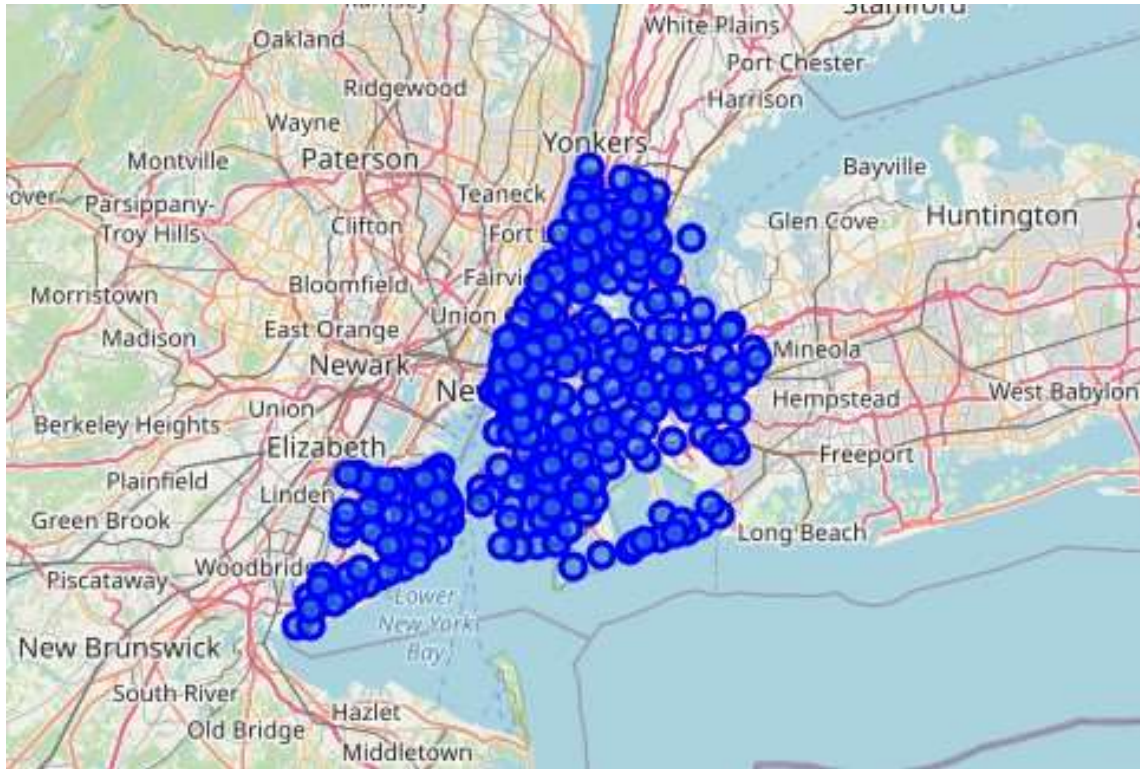


Figure 4

In the course week 3 Lab Segmenting and Clustering Neighborhoods in New York City, we used the k-means (machine learning) algorithm from the scikit learn library to segment and cluster NYC neighborhoods by venues similarity. The results from this exercise were inconclusive and were not repeated for this report, see figure 5 for a map with the clusters in different color markers for the Manhattan borough.



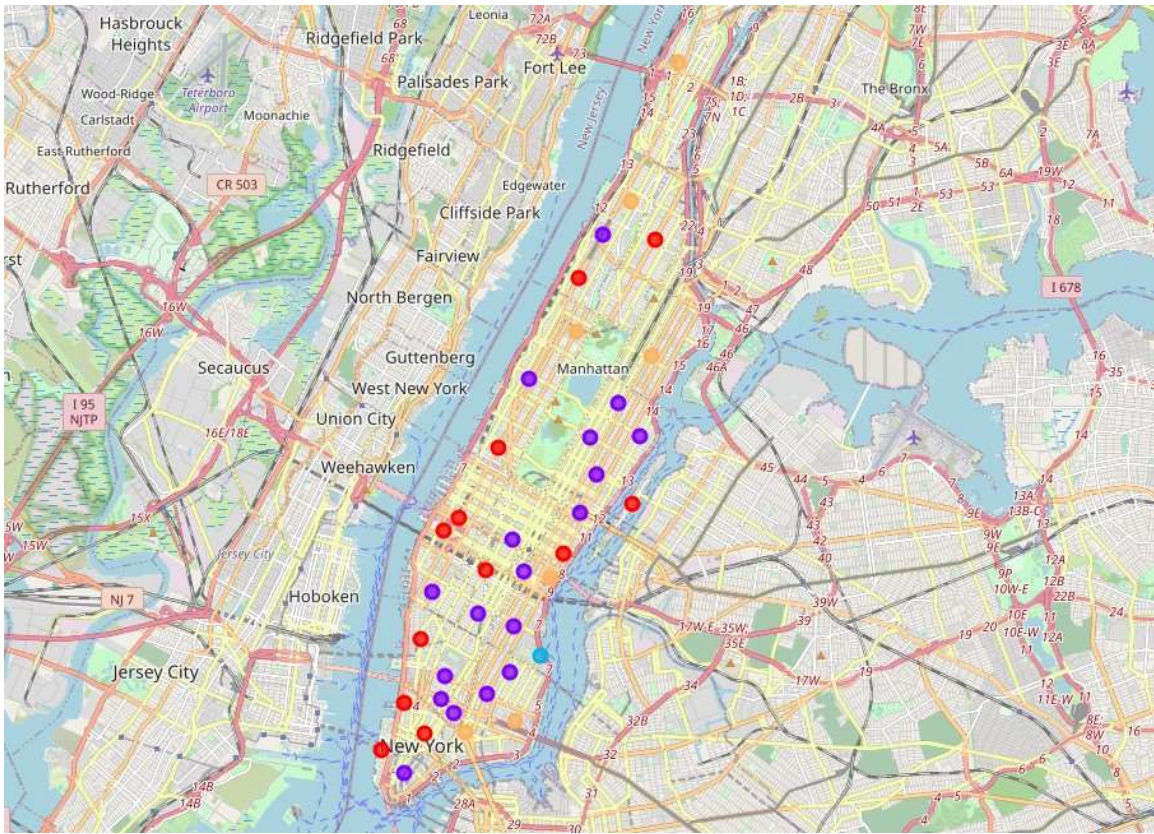


Figure 5

We decided to look for other variables to segment and rank the Neighborhoods.

## VALUE

From the second dataset we used the matplotlib library to create a line plot (graph), and selected the top 30 neighborhoods by the last available month of the ZHVI (Value Index), see figure 6 for a time series of the top 30 neighborhoods by the ZHVI (Value Index).

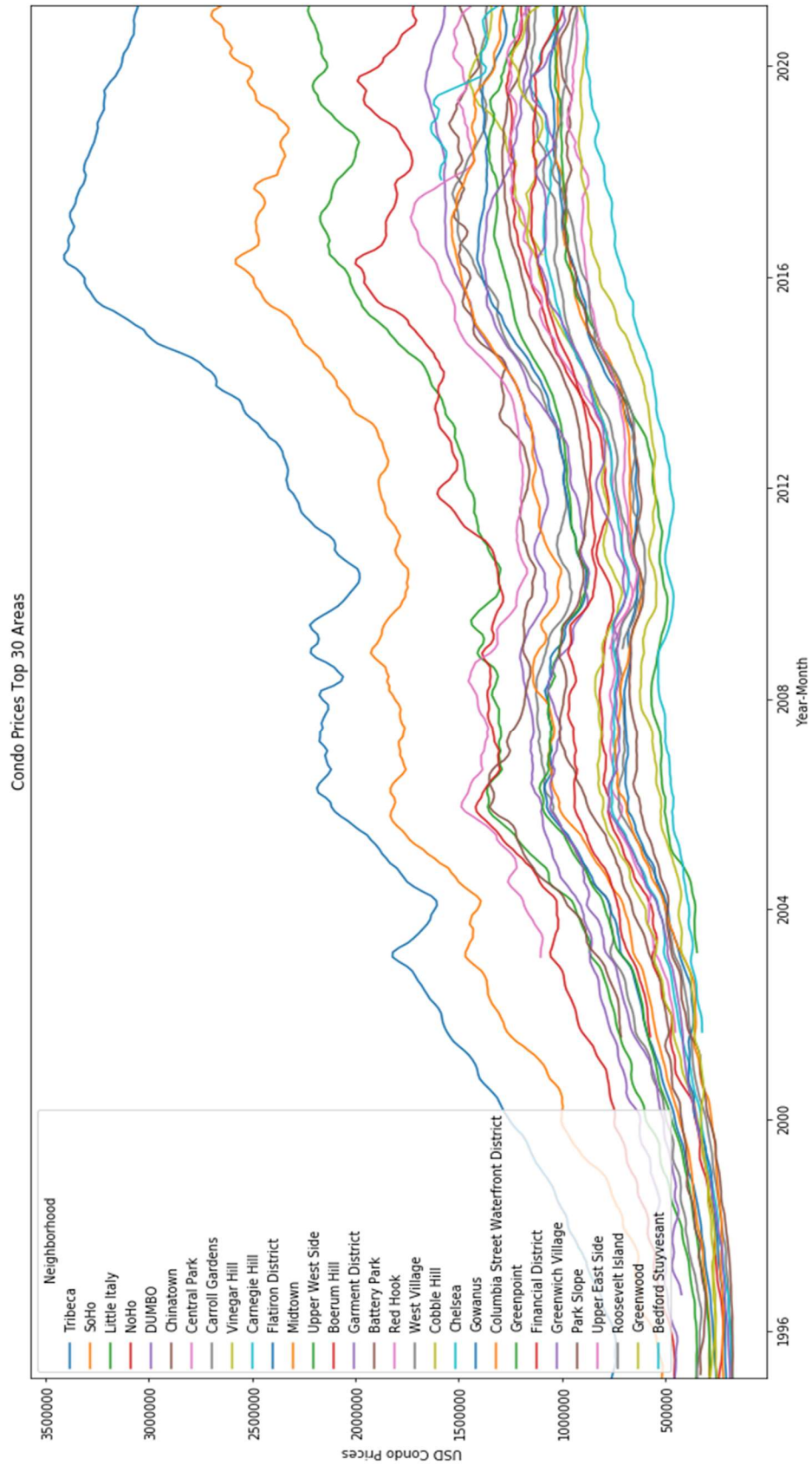


Figure 6

Figure 6

In order to select the best neighborhood and avoid recommending a property in a neighborhood that have declining property values, is important to analyze the trend.

As you can see in figure 6, the most expensive neighborhood (by ZHVI), Tribeca, peaked around 2016 and started a decline, other neighborhood like SoHo or Little Italy continue their trend up, at least until the most recent months, the value index (XHVI) is a lagging indicator and the effect of the COVID-19 Pandemic is not reflected in this values.

The more recent information suggests that the effects of the pandemic will apply a temporary discount of the rental price and create a better investment deals in NYC. The percentage discounts vary by proximity of the unused office space with the biggest discounts in Manhattan according to data from StreetEasy. The biggest rental reductions are in Flatiron (45%), Financial District (42%) and Midtown (40%) neighborhoods [5].

See Figure 7 for Manhattan, Brooklyn, and Queens real estate status as of June 2020.

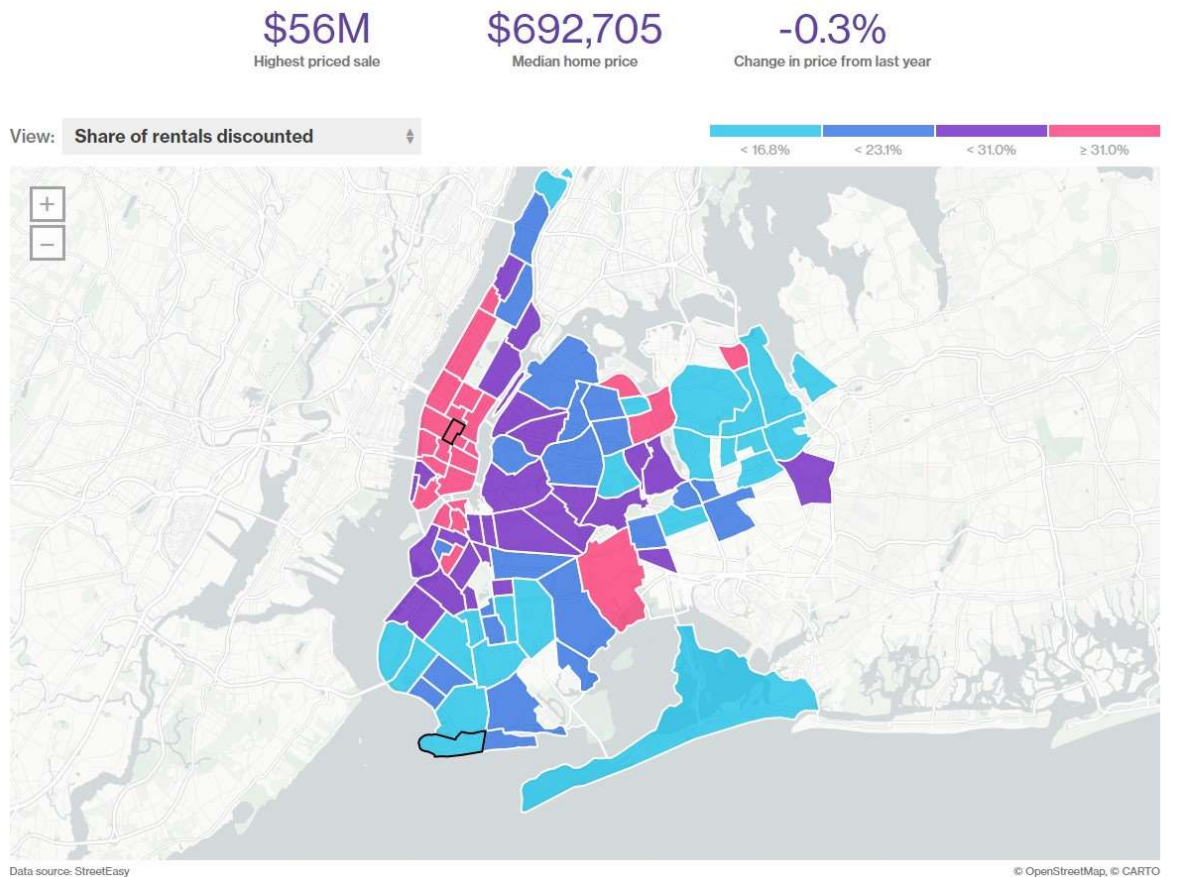


Figure 7



## VENUES

From the third dataset we selected the top 30 neighborhoods by the number of venues, and compared to the neighborhoods in the second dataset, see figure 8 for the top 5 neighborhood by venues (note that foursquare API caps the results to 100 per request).

	Neighborhood Latitude	Neighborhood Longitude	Venue	Venue Latitude	Venue Longitude	Venue Category
<b>Neighborhood</b>						
<b>Murray Hill</b>	147	147	147	147	147	147
<b>Chelsea</b>	105	105	105	105	105	105
<b>Lenox Hill</b>	100	100	100	100	100	100
<b>Little Italy</b>	100	100	100	100	100	100
<b>Chinatown</b>	100	100	100	100	100	100

Figure 8

By combining the datasets we reduced our top neighborhood list to 20 and reduced the number of venues from more than 10,000 to close to 2,000, with 279 unique venue categories, see figure 9 for the top 5 venues in an example neighborhood.

	Neighborhood	Neighborhood Latitude	Neighborhood Longitude	Venue	Venue Latitude	Venue Longitude	Venue Category
<b>753</b>	Belmont	40.857277	-73.888452	Tino's Delicatessen	40.855882	-73.887166	Italian Restaurant
<b>754</b>	Belmont	40.857277	-73.888452	Casa Della Mozzarella	40.855440	-73.887373	Deli / Bodega
<b>755</b>	Belmont	40.857277	-73.888452	Full Moon Pizzeria	40.855506	-73.887557	Pizza Place
<b>756</b>	Belmont	40.857277	-73.888452	DeLillo Pastry Shop	40.855364	-73.887198	Dessert Shop
<b>757</b>	Belmont	40.857277	-73.888452	Gino's Pastry Shop	40.855648	-73.888196	Dessert Shop

See also figure 10 for the updated time series of the now top 20 neighborhoods by the ZHVI (Value Index). As you can see the top neighborhood by venue continue their trend up or have a stable trend.

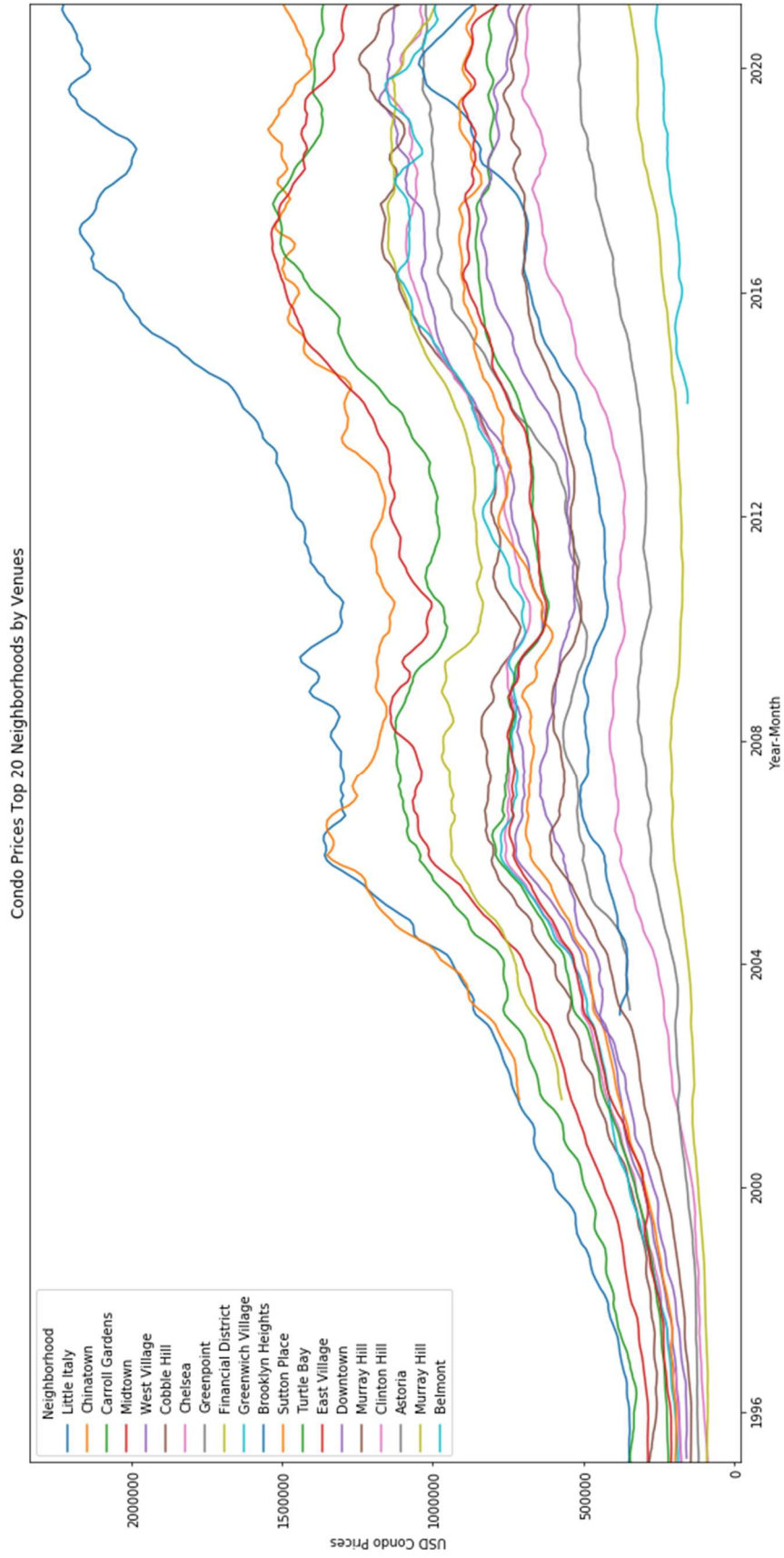


Figure 10

We used the one hot encoding method to analyze each neighborhood. By expanding the dataframe, adding a dummy column for each venue and grouping rows by neighborhood and averaging the occurrences in each category we created a new table with 279 unique venue categories and 19 unique neighborhoods. See Figure 11 for part of the resulting table.

	Neighborhood	Accessories Store	Adult Boutique	American Restaurant	Antique Shop	Arepa Restaurant	Argentinian Restaurant	Art Gallery	Arts & Crafts Store	Asian Restaurant
0	Astoria	0.00	0.00	0.010000	0.00	0.00	0.000000	0.000000	0.000000	0.000000
1	Belmont	0.00	0.00	0.010417	0.00	0.00	0.000000	0.000000	0.000000	0.000000
2	Brooklyn Heights	0.00	0.00	0.010000	0.00	0.00	0.000000	0.000000	0.000000	0.020000
3	Carroll Gardens	0.00	0.00	0.010000	0.00	0.00	0.000000	0.000000	0.010000	0.000000
4	Chelsea	0.00	0.00	0.038095	0.00	0.00	0.000000	0.047619	0.000000	0.009524
5	Chinatown	0.00	0.00	0.030000	0.00	0.00	0.000000	0.000000	0.000000	0.020000
6	Clinton Hill	0.00	0.00	0.000000	0.00	0.00	0.000000	0.010638	0.021277	0.000000
7	Cobble Hill	0.00	0.00	0.010309	0.00	0.00	0.010309	0.010309	0.010309	0.000000
8	Downtown	0.00	0.00	0.020000	0.01	0.00	0.000000	0.000000	0.020000	0.010000
9	East Village	0.00	0.00	0.010000	0.00	0.01	0.010000	0.010000	0.010000	0.000000
10	Financial District	0.00	0.00	0.030000	0.00	0.00	0.000000	0.000000	0.000000	0.000000
11	Greenpoint	0.00	0.00	0.010000	0.00	0.00	0.000000	0.000000	0.000000	0.000000
12	Greenwich Village	0.00	0.00	0.010000	0.00	0.00	0.000000	0.010000	0.000000	0.000000
13	Little Italy	0.00	0.00	0.000000	0.00	0.00	0.000000	0.000000	0.000000	0.000000
14	Midtown	0.00	0.00	0.020000	0.00	0.00	0.000000	0.010000	0.000000	0.000000
15	Murray Hill	0.00	0.00	0.020408	0.00	0.00	0.000000	0.000000	0.000000	0.006803
16	Sutton Place	0.00	0.01	0.010000	0.00	0.00	0.000000	0.000000	0.000000	0.010000
17	Turtle Bay	0.00	0.00	0.020000	0.00	0.00	0.000000	0.000000	0.000000	0.010000
18	West Village	0.01	0.00	0.050000	0.00	0.00	0.000000	0.010000	0.000000	0.000000

Figure 11

[5] NYC Landlords Are Cutting Rents for Apartments Closer to Offices  
<https://www.bloomberg.com/graphics/property-prices/nyc/>

## Part 4: Modeling

### SELECTION

As we mentioned in Part 3, we decided not to use the k-means algorithm for segmenting and clustering the neighborhoods, as this was done in the course week 3 Lab Segmenting and Clustering Neighborhoods in New York City, with inconclusive results.

By analyzing figure 11 we realize that this information can be used in a recommendation system (like Netflix or Amazon recommend movies or books), but we could not get enough information on the preference of the venues from the foursquare API to do a collaborative filtering of the venues, so the model has to be based on the venue content.

So we decided to ask a potential client (tester) to select their venues preferences and simplify the content-based recommendation algorithm to a minimum viable model.

### DEPLOYMENT

Starting from the resulting venues by neighborhoods table shown in figure 11, we modified the functions and scripts used in the course week 3 Lab Segmenting and Clustering Neighborhoods in New York City, and sorted the venues and created a new dataframe with the top ten most common venues by neighborhood as fully shown in figure 12.

The table in figure 12 show the neighborhoods in alphabetical order, a hard copy was shown to a potential client (tester) and used select the top 10 must have venue categories by circling the selected venues from a reduced list.

The top 10 must have preferences provided by the potential client (tester) are: Gym, Mediterranean Restaurant, Mexican Restaurant, Pub, Restaurant, Sandwich Place, Spa, Steakhouse, Sushi Restaurant & Yoga Studio. The provided preferences are a must have and are not in a priority order, so these preferences were given equal weights.

A new table was produced that sort the neighborhoods by the value index (ZHVI), and a hard copy shown to the potential client (tester) with the average condo value index as partially shown in figure 13, so this table confirmed our assumptions that the top neighborhoods by venues are higher in the value index (pricier).

In a simplified (content-based) recommend system algorithm, we simple multiply the potential client (tester) preferences list times the grouped neighborhoods by venue table (figure 11), so given that the preferences have an equal weight of 1, we are simply applying a filter to the table.

A new total weight from the sum of the venues was calculated and multiplied to the value index (ZHVI), a new Ranking was produced dividing the results by the maximum weight.



	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	Astoria	Bar	Middle Eastern Restaurant	Greek Restaurant	Hookah Bar	Indian Restaurant	Seafood Restaurant	Bakery	Mediterranean Restaurant	Café	Gourmet Shop
1	Belmont	Italian Restaurant	Pizza Place	Deli / Bodega	Bakery	Grocery Store	Dessert Shop	Donut Shop	Bank	Café	Shoe Store
2	Brooklyn Heights	Yoga Studio	Park	Deli / Bodega	Italian Restaurant	Cosmetics Shop	Gym	Bakery	Pizza Place	Mexican Restaurant	Ice Cream Shop
3	Carroll Gardens	Italian Restaurant	Coffee Shop	Bakery	Pizza Place	Cocktail Bar	Spa	Bar	Wine Shop	French Restaurant	Food & Drink Shop
4	Chelsea	Coffee Shop	Art Gallery	American Restaurant	Italian Restaurant	Bakery	Ice Cream Shop	Hotel	Seafood Restaurant	Sushi Restaurant	Nightclub
5	Chinatown	Chinese Restaurant	Bakery	Cocktail Bar	Vietnamese Restaurant	Dessert Shop	Spa	American Restaurant	Salon / Barbershop	Noodle House	Optical Shop
6	Clinton Hill	Italian Restaurant	Pizza Place	Thai Restaurant	Wine Shop	Japanese Restaurant	Mexican Restaurant	Chinese Restaurant	Diner	Indian Restaurant	Restaurant
7	Cobble Hill	Playground	Bar	Cocktail Bar	Coffee Shop	Pizza Place	Yoga Studio	Deli / Bodega	Italian Restaurant	Middle Eastern Restaurant	Bike Rental / Bike Share
8	Downtown	Burger Joint	Coffee Shop	Pizza Place	Sandwich Place	Grocery Store	Chinese Restaurant	Bar	French Restaurant	Performing Arts Venue	Cocktail Bar
9	East Village	Bar	Pizza Place	Mexican Restaurant	Ice Cream Shop	Cocktail Bar	Wine Bar	Vietnamese Restaurant	Coffee Shop	Vegetarian / Vegan Restaurant	Korean Restaurant
10	Financial District	Coffee Shop	Pizza Place	Cocktail Bar	Bar	Hotel	Gym / Fitness Center	Salad Place	Café	Steakhouse	Italian Restaurant
11	Greenpoint	Bar	Coffee Shop	Pizza Place	Cocktail Bar	Yoga Studio	Mexican Restaurant	French Restaurant	Deli / Bodega	Flower Shop	Thrift / Vintage Store
12	Greenwich Village	Italian Restaurant	Sushi Restaurant	Café	Clothing Store	Ice Cream Shop	Gym	Dessert Shop	Chinese Restaurant	Indian Restaurant	Bubble Tea Shop
13	Little Italy	Bakery	Café	Italian Restaurant	Bubble Tea Shop	Coffee Shop	Cocktail Bar	Salon / Barbershop	Pizza Place	Mediterranean Restaurant	Ice Cream Shop
14	Midtown	Coffee Shop	Clothing Store	Hotel	Bakery	Theater	Sporting Goods Shop	Sandwich Place	Bookstore	Steakhouse	Gym
15	Murray Hill	Korean Restaurant	Hotel	Coffee Shop	Japanese Restaurant	Sandwich Place	Pizza Place	Bar	Pub	Gym / Fitness Center	Bakery
16	Sutton Place	Italian Restaurant	Coffee Shop	Furniture / Home Store	Park	Pizza Place	Gym / Fitness Center	Bar	Beer Bar	Beer Garden	Chinese Restaurant
17	Turtle Bay	Coffee Shop	Italian Restaurant	Café	Sushi Restaurant	Park	Seafood Restaurant	Japanese Restaurant	French Restaurant	Deli / Bodega	Wine Bar
18	West Village	Italian Restaurant	American Restaurant	New American Restaurant	Cocktail Bar	Wine Bar	Park	Pizza Place	Jazz Club	Cosmetics Shop	Theater

Figure 12

	Neighborhood	condo value index(\$)	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
0	Little Italy	2224698.0	Bakery	Café	Italian Restaurant	Bubble Tea Shop	Coffee Shop	Cocktail Bar	Salon / Barbershop	Pizza Place	Mediterranean Restaurant
1	Chinatown	1494949.0	Chinese Restaurant	Bakery	Cocktail Bar	Vietnamese Restaurant	Dessert Shop	Spa	American Restaurant	Salon / Barbershop	Noodle House
2	Carroll Gardens	1362646.0	Italian Restaurant	Coffee Shop	Bakery	Pizza Place	Cocktail Bar	Spa	Bar	Wine Shop	French Restaurant
3	Midtown	1284458.0	Coffee Shop	Clothing Store	Hotel	Bakery	Theater	Sporting Goods Shop	Sandwich Place	Bookstore	Steakhouse
4	West Village	1125683.0	Italian Restaurant	American Restaurant	New American Restaurant	Cocktail Bar	Wine Bar	Park	Pizza Place	Jazz Club	Cosmetics Shop
5	Cobble Hill	1110841.0	Playground	Bar	Cocktail Bar	Coffee Shop	Pizza Place	Yoga Studio	Deli / Bodega	Italian Restaurant	Middle Eastern Restaurant
6	Chelsea	1037893.0	Coffee Shop	Art Gallery	American Restaurant	Italian Restaurant	Bakery	Ice Cream Shop	Hotel	Seafood Restaurant	Sushi Restaurant
7	Greenpoint	1022042.0	Bar	Coffee Shop	Pizza Place	Cocktail Bar	Yoga Studio	Mexican Restaurant	French Restaurant	Deli / Bodega	Flower Shop
8	Financial District	990869.0	Coffee Shop	Pizza Place	Cocktail Bar	Bar	Hotel	Gym / Fitness Center	Salad Place	Café	Steakhouse
9	Greenwich Village	990262.0	Italian Restaurant	Sushi Restaurant	Café	Clothing Store	Ice Cream Shop	Gym	Dessert Shop	Chinese Restaurant	Indian Restaurant
10	Brooklyn Heights	863929.0	Yoga Studio	Park	Deli / Bodega	Italian Restaurant	Cosmetics Shop	Gym	Bakery	Pizza Place	Mexican Restaurant
11	Sutton Place	860577.0	Italian Restaurant	Coffee Shop	Furniture / Home Store	Park	Pizza Place	Gym / Fitness Center	Bar	Beer Bar	Beer Garden
12	Turtle Bay	791213.0	Coffee Shop	Italian Restaurant	Café	Sushi Restaurant	Park	Seafood Restaurant	Japanese Restaurant	French Restaurant	Deli / Bodega
13	East Village	783746.0	Bar	Pizza Place	Mexican Restaurant	Ice Cream Shop	Cocktail Bar	Wine Bar	Vietnamese Restaurant	Coffee Shop	Vegetarian / Vegan Restaurant
14	Downtown	742593.0	Burger Joint	Coffee Shop	Pizza Place	Sandwich Place	Grocery Store	Chinese Restaurant	Bar	French Restaurant	Performing Arts Venue
15	Murray Hill	697072.0	Korean Restaurant	Hotel	Coffee Shop	Japanese Restaurant	Sandwich Place	Pizza Place	Bar	Pub	Gym / Fitness Center
16	Murray Hill	349385.0	Korean Restaurant	Hotel	Coffee Shop	Japanese Restaurant	Sandwich Place	Pizza Place	Bar	Pub	Gym / Fitness Center
17	Clinton Hill	674418.0	Italian Restaurant	Pizza Place	Thai Restaurant	Wine Shop	Japanese Restaurant	Mexican Restaurant	Chinese Restaurant	Diner	Indian Restaurant
18	Astoria	515600.0	Bar	Middle Eastern Restaurant	Greek Restaurant	Hookah Bar	Indian Restaurant	Seafood Restaurant	Bakery	Mediterranean Restaurant	Café
19	Belmont	254028.0	Italian Restaurant	Pizza Place	Deli / Bodega	Bakery	Grocery Store	Dessert Shop	Donut Shop	Bank	Café

Figure 13

## RESULTS

A neighborhood recommendation ranking with the top neighborhood with a ranking of 1 was produced from the deployment of the simplified venue-based recommender system algorithm, see figure 14 for the results table.

	condo value index(\$)	Total	Ranking
Neighborhood			
Little Italy	2224698.0	0.09	1.00
Midtown	1284458.0	0.15	0.96
Chinatown	1494949.0	0.09	0.67
Financial District	990869.0	0.13	0.64
Greenwich Village	990262.0	0.13	0.64
Greenpoint	1022042.0	0.12	0.61
Cobble Hill	1110841.0	0.10	0.57
Clinton Hill	674418.0	0.16	0.54
Brooklyn Heights	863929.0	0.11	0.47
Murray Hill	697072.0	0.13	0.45
West Village	1125683.0	0.08	0.45
Sutton Place	860577.0	0.10	0.43
Turtle Bay	791213.0	0.10	0.40
Carroll Gardens	1362646.0	0.05	0.34
Astoria	515600.0	0.13	0.33
Downtown	742593.0	0.09	0.33
Chelsea	1037893.0	0.05	0.25
East Village	783746.0	0.06	0.23
Murray Hill	349385.0	0.13	0.23
Belmont	254028.0	0.06	0.08

Figure 14

As shown in Figure 14, the results are as expected, with the total column showing the weights of the preferred venues, and the new ranking produced by these preferences.

Figure 15 show a new map with the selected neighborhoods markers.

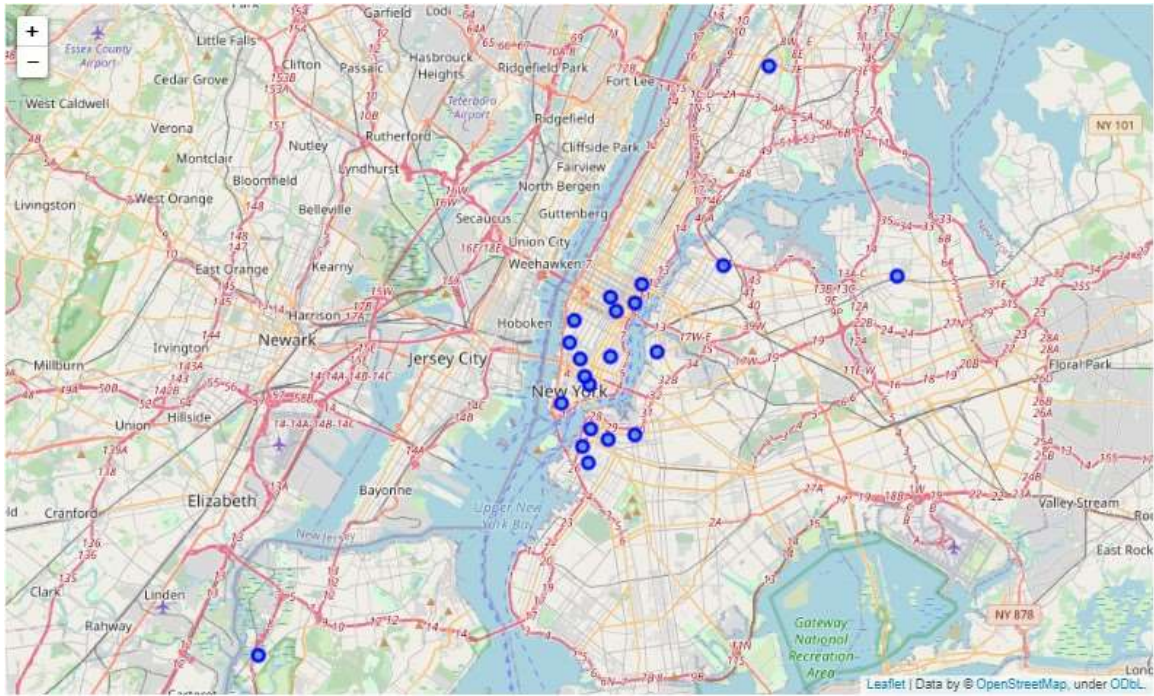


Figure 15

## Part 5: Conclusions

The results of the model differ from the previous rankings calculated by only one variable, either the value index of the maximum number of venues. By adding the potential client (tester) preferences to the calculation we are essentially personalizing the ranking, as this is the intention of a recommender system.

The value of the results is in the differentiation of the rankings, and when a maximum investment cap and their personal venue preferences is provided, we can give to our potential clients the top neighborhoods to consider for an investment. This answer the business question from Part 1: How to select the best neighborhood for a given investment amount and the preferences venues of a potential investor.



## Part 6: Future Work

The rankings are subject to change by the fluctuation of the condo value index, for this report we decided not to use the Zillow forecasts, or the discounts provided by StreetEasy as shown in figure 7. This are theoretical discount and will not be realized until a purchase is made, so we recommend apply them with caution at updating the model.

This model can be applied to other cities, suburbs, or lower market segments, and in these cases the variables that influence the model will differ, we can use crime, or economic data to generate a city-segment specific model.

A full fledge recommender system can be generated by a collaborative filtering of the preferred venues with data acquired from Foursquare or Google.