Real Estate in New York City

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1. Introduction

1.1 Background

Toronto is known as an international center of finance, arts, culture, and business as well as being known as one of the most multicultural cities in the world. Toronto is the provincial capital of Ontario and the most populous city in Canada, with a population of 2,731,571 as of 2016.[2] In comparison, New York City is the most populous city in the United States with an estimated 2018 population of 8,398,748. In addition, New York City is known as a global power city and renowned as the financial, cultural, and media capital of the world.[3]

For Alphabet Inc., parent company of Google Inc., both New York City and Toronto are important cities. Google's Toronto Offices serve as a hub-office for many members of the company's creative team and salespeople. Engineers and computer scientists at the Google office in Toronto work on many of Google's well known products and services. In addition, in August 2019 Google announced it would be expanding office space in the financial district of Toronto.[4] New York is home to Google's second largest office in the Chelsea neighborhood of Manhattan. "Engineers work on Google Drive, Search, AdWords, and Maps, and the large sales team works with clients that include media companies and ad agencies."[1]

1.2 Business Problem

For Real Estate Agents, determining the best area or neighborhood and finding a client's perfect home at the right place can be the most difficult and time consuming aspect. To complete this task, an agent may spend countless hours on researching and showing clients homes or may pay significant amounts of money to hire employees to conduct research and/or pay for expensive subscriptions to companies that aggregate statistical data.

As a Real Estate Agent in New York City, a client has contacted me who has accepted a job offer at Google's NYC office and is relocating from Toronto. The client is ready to make an offer on their new condo/co-op as quickly as possible. This project will help to understand the diversity of each neighborhood analyzed by leveraging venue data from Foursquare's Places API and k-means clustering unsupervised machine learning algorithm. The objective of this project will be to propose the 3 best listings I can find for my client who will be arriving next week and is ready to buy their new home. The client would like to buy a condo/co-op in a neighborhood most

similar to the one they live in now, as similar as possible in price/size to the one they have now, and closest to Google's NYC office building.
The apartment in Toronto they are moving from is a 2 bedroom & 2 bathroom condo listed for C$899,000 in the Downtown Toronto (Old Toronto) neighborhood of Toronto, ON, Canada.
The current home address is: 1 A The Esplanade Ave # 2008, Toronto, ON, M5E 0A8.
Google's NYC office building address is: 75 9th Ave, New York, NY 10011.

1.3 Interest

The primary stakeholders, interested in a new way to use quantifiable analysis to understand and profile a neighborhood would be Real Estate Agents and Real Estate Buyers. Previously, neighborhood profiles have always been aggregated and compared based on historic, statistical, and/or demographic information. However, I believe a new approach based on venues and often they're visited for creating neighborhood profiles in order to compare other neighborhood profiles can provide a basis for a much more accurate area profile.

2. Data Collection and Cleaning

2.1 Data Sources

The data sources I utilized are; New York City Dataset, Toronto Dataset, Toronto Longitude and Latitude Coordinates Dataset, Foursquare API, and the Zillow API. The New York City Dataset, Toronto Dataset, and Toronto Longitude and Latitude Coordinates Dataset were used to create the Manhattan data frame and Toronto data frame containing neighborhood names and each corresponding latitudes and longitudes. Utilizing the Foursquare API, I collected data on nearby venues and the frequency they are visited in order to create neighborhood profiles which could be compared to find the optimal neighborhood for the client. The Zillow API was used to determine three proposed listings in the optimal new neighborhood for the client moving from Toronto.

2.1 Data Collection and Cleaning

In order to address the business problem, it was necessary to gather the neighborhood names and corresponding latitudes and longitudes for Toronto, Ontario and New York, NY. The New York City Dataset contained a complete list of New York City Boroughs, Neighborhoods, and their corresponding latitudes and longitudes. I then formatted the New York City Dataset into a new Manhattan data frame that only contained the neighborhood names and corresponding latitudes and longitudes Manhattan.

	Borough	Neighborhood	Latitude	Longitude
0	Manhattan	Marble Hill	40.876551	-73.910660
1	Manhattan	Chinatown	40.715618	-73.994279
2	Manhattan	Washington Heights	40.851903	-73.936900
3	Manhattan	Inwood	40.867684	-73.921210
4	Manhattan	Hamilton Heights	40.823604	-73.949688

To create the data frame Toronto, I scraped two datasets; the Toronto Dataset and the Toronto Longitude and Latitude Coordinates Dataset, including only boroughs that contained the word Toronto and each corresponding postal code, borough name, neighborhood name, latitude and longitude.

	Postalcode	Borough	Neighborhood	Latitude	Longitude
0	M4E	East Toronto	The Beaches	43.676357	-79.293031
1	M4K	East Toronto	The Danforth West, Riverdale	43.679557	-79.352188
2	M4L	East Toronto	The Beaches West, India Bazaar	43.668999	-79.315572
3	M4M	East Toronto	Studio District	43.659526	-79.340923
4	M4N	Central Toronto	Lawrence Park	43.728020	-79.388790

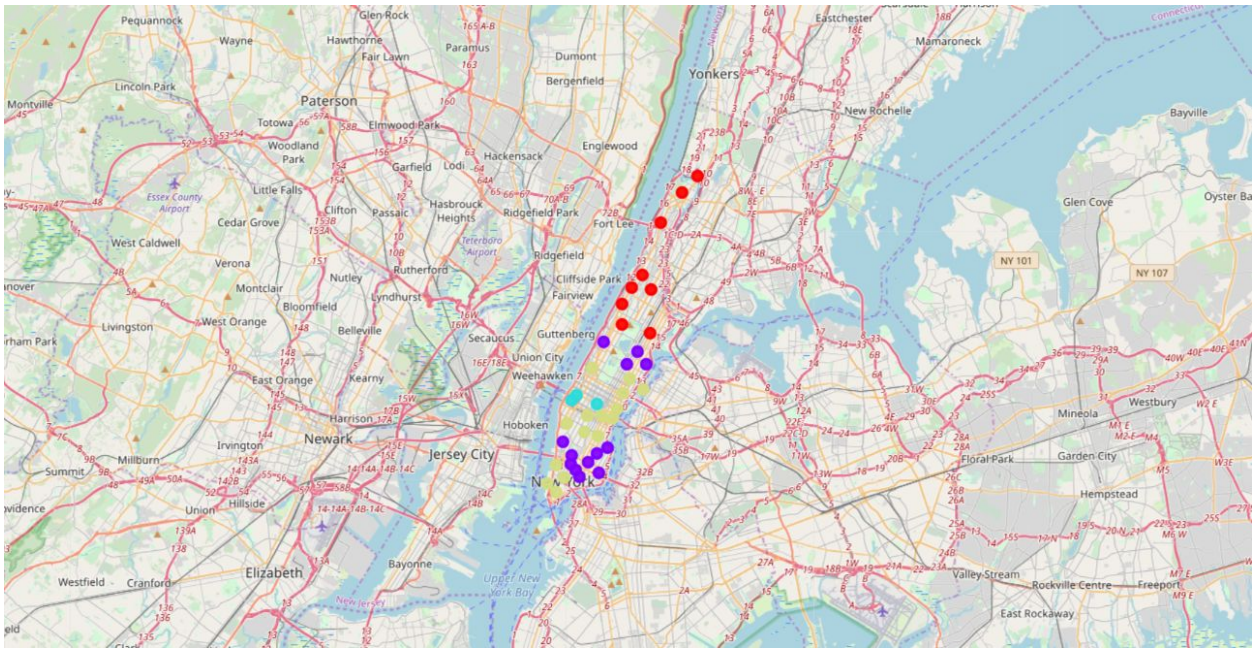
Utilizing the Foursquare API, I analyzed each Manhattan neighborhood creating a new data frame with the top 15 most common venues.

	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	11th Most Common Venue	12th Most Common Venue	13th Most Common Venue	14th Most Common Venue	15th Most Common Venue
0	Battery Park City	Park	Coffee Shop	Gym / Fitness Center	Wine Shop	Hotel	Memorial Site	Falafel Restaurant	Gym	Plaza	Monument / Landmark	Cocktail Bar	Pizza Place	Bookstore	Scenic Lookout	Dog Run
1	Carnegie Hill	Coffee Shop	Yoga Studio	Exhibit	Gym / Fitness Center	Art Museum	Wine Shop	Café	Pizza Place	Bakery	French Restaurant	Italian Restaurant	Bookstore	Bar	Salon / Barbershop	American Restaurant
2	Central Harlem	Southern / Soul Food Restaurant	Yoga Studio	Coffee Shop	Cocktail Bar	Mexican Restaurant	American Restaurant	Café	Juice Bar	Pizza Place	Bar	French Restaurant	Park	Wine Shop	Indian Restaurant	Caribbean Restaurant
3	Chelsea	Art Gallery	Yoga Studio	Gym / Fitness Center	Park	Seafood Restaurant	Bakery	Coffee Shop	Sushi Restaurant	Japanese Restaurant	New American Restaurant	Cycle Studio	Tapas Restaurant	Gym	Hotel	Scenic Lookout
4	Chinatown	Hotel	Cocktail Bar	Pizza Place	Bakery	Coffee Shop	Ice Cream Shop	Spa	Chinese Restaurant	Mediterranean Restaurant	Sandwich Place	Jewelry Store	Gift Shop	Rock Club	Thai Restaurant	Yoga Studio

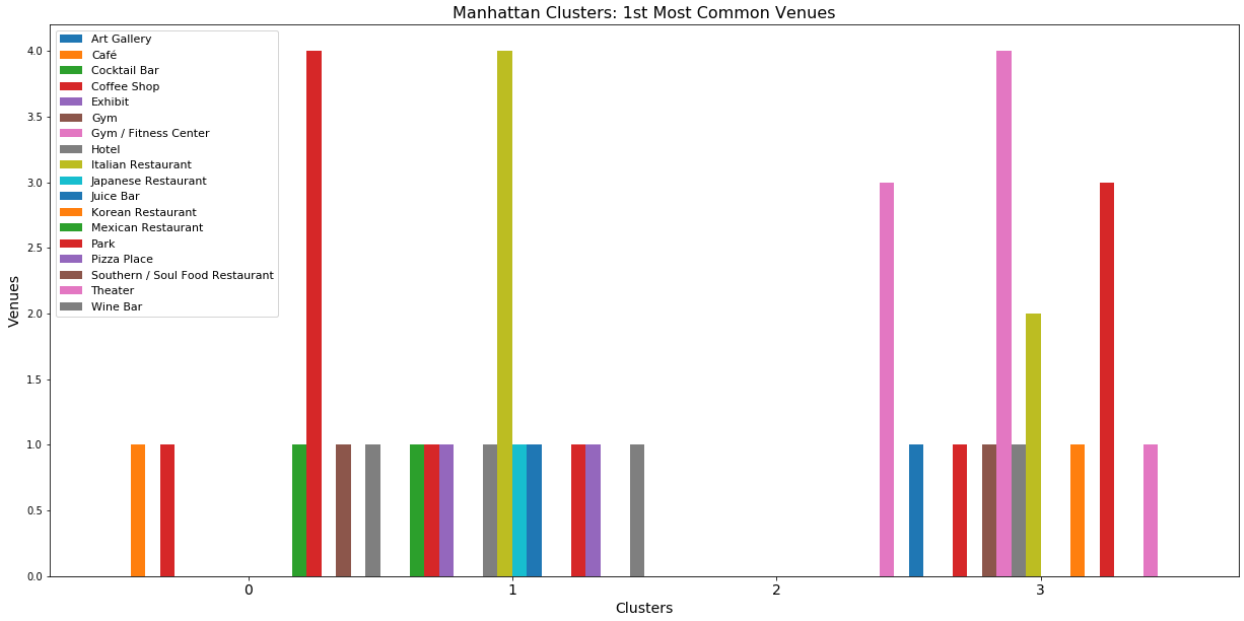
To create the desired neighborhood profiles based on nearby venues and the frequencies visited, I used k-means clustering to create four clusters for the neighborhoods in Manhattan.

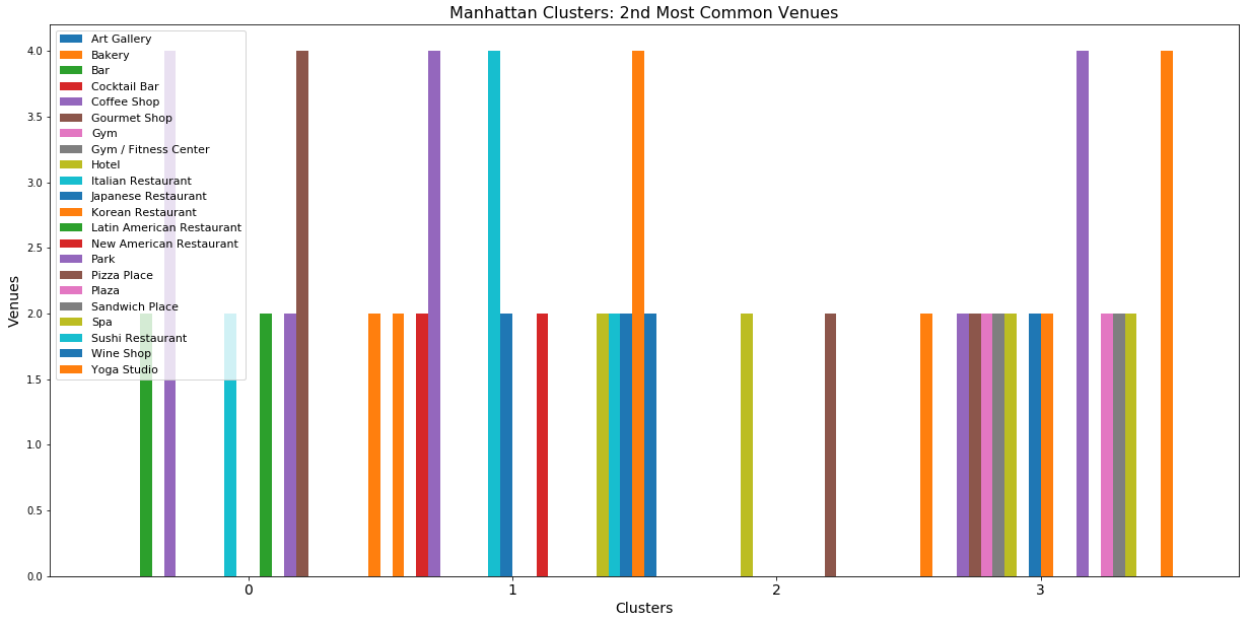
	Borough	Neighborhood	Latitude	Longitude	Cluster Labels	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue	6th Most Common Venue	7th Most Common Venue	8th Most Common Venue	9th Most Common Venue	10th Most Common Venue	11th Most Common Venue	12th Most Common Venue	13th Most Common Venue	14th Most Common Venue	15th Most Common Venue
0	Manhattan	Marble Hill	40.876551	-73.910660	0	Mexican Restaurant	Pizza Place	Park	Café	Bakery	Coffee Shop	Bar	Diner	Latin American Restaurant	Donut Shop	Deli / Bodega	Wine Shop	Thai Restaurant	Restaurant	Scenic Lookout
1	Manhattan	Chinatown	40.715618	-73.994279	1	Hotel	Cocktail Bar	Pizza Place	Bakery	Coffee Shop	Ice Cream Shop	Spa	Chinese Restaurant	Mediterranean Restaurant	Sandwich Place	Jewelry Store	Gift Shop	Rock Club	Thai Restaurant	Yoga Studio
2	Manhattan	Washington Heights	40.851903	-73.936900	0	Park	Pizza Place	Bakery	Latin American Restaurant	Café	Mexican Restaurant	Coffee Shop	Wine Shop	Tapas Restaurant	Spanish Restaurant	Bar	Scenic Lookout	Sandwich Place	Grocery Store	Mobile Phone Shop
3	Manhattan	Inwood	40.867684	-73.921210	0	Wine Bar	Latin American Restaurant	Mexican Restaurant	Pizza Place	Park	Deli / Bodega	Café	Spanish Restaurant	Lounge	Bar	Bakery	Playground	Restaurant	Wine Shop	Frozen Yogurt Shop
4	Manhattan	Hamilton Heights	40.823604	-73.949688	0	Coffee Shop	Bar	Yoga Studio	Park	Italian Restaurant	Mexican Restaurant	Cocktail Bar	Deli / Bodega	Seafood Restaurant	Café	French Restaurant	Pizza Place	Scenic Lookout	Ethiopian Restaurant	Pool

Manhattan Clusters Map:



To better visualize the data gathered about the Manhattan neighborhoods, I created two bar plots for the 1st and 2nd most common venues.





Two lists were created for the clustered Manhattan neighborhoods in order to find the neighborhood most similar to the client's current neighborhood in Toronto.

	Cluster, Manhattan	1st Most Common Venues
0	0	Coffee Shop, Kor. Rest., South. Rest., Mex. Re...
1	1	Ital. Rest., Wine Bar, Jap. Rest., Juice Bar, ...
2	2	Theater, Juice Bar, Park, South. Rest., Ital. ...
3	3	Kor. Rest., Park, Gym

	Cluster, Manhattan	2nd Most Common Venues
0	0	Bar, Coffee Shop, Sushi Rest., Park, Latin Res...
1	1	Yoga Studio, New Amer. Rest., Park, Ital. Rest...
2	2	Spa, Yoga Studio, Pizza Place, Park, Plaza, Sa...
3	3	Yoga Studio, Park, Plaza, Sandwich Place, Spa

Utilizing the Foursquare API, I analyzed each Toronto neighborhood creating a new data frame with the top 15 most common venues.

	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	11th Most Common Venue	12th Most Common Venue	13th Most Common Venue	14th Most Common Venue	15th Most Common Venue
0	Adelaide, King, Richmond	Coffee Shop	Hotel	Café	Pizza Place	Theater	Gastropub	Beer Bar	Japanese Restaurant	Gym	Plaza	Breakfast Spot	Seafood Restaurant	Italian Restaurant	Steakhouse	Movie Theater
1	Berczy Park	Coffee Shop	Café	Park	Restaurant	Japanese Restaurant	Hotel	Beer Bar	Gastropub	Italian Restaurant	Liquor Store	Bakery	Farmers Market	Gym	New American Restaurant	American Restaurant
2	Brockton, Exhibition Place, Parkdale Village	Café	Restaurant	Coffee Shop	Bar	Furniture / Home Store	Gift Shop	Park	Bakery	Tibetan Restaurant	New American Restaurant	Tea Room	Japanese Restaurant	Theater	Theme Park	Athletics & Sports
3	Business Reply Mail Processing Centre 969 Eastern	Coffee Shop	Brewery	Café	Park	Indian Restaurant	Pizza Place	Italian Restaurant	Diner	Beach	Bakery	Sushi Restaurant	Grocery Store	Pet Store	Bar	American Restaurant
4	CN Tower, Bathurst Quay, Island airport, Harbo...	Park	Café	Coffee Shop	Gym	Harbor / Marina	Boat or Ferry	Scenic Lookout	Pizza Place	Bar	Hotel	Restaurant	Track	Brewery	Pub	Sushi Restaurant

To create neighborhood profiles based on nearby venues and the frequencies visited, I used k-means clustering to create four clusters for the neighborhoods in Toronto. Focusing on the client's current neighborhood, the Esplanade, I created two bar plots that included the most commonly frequented venues in the neighborhood. This resulted in a list of the 1st and 2nd most commonly frequented venues to be compared with the neighborhoods in Manhattan.

	Esplanade 1st & 2nd Most Common Venues	Venues
0	1	Coffee Shop, Hotel
1	2	Cafe, Hotel, Coffee Shop, Jap. Rest., Park

Toronto Clusters Map:

3. Methodology & Analysis

3.1 Methodology

Utilizing the data gathered from the Foursquare API, this project aims to assist a Real Estate agent in determining a neighborhood in Manhattan most similar to the client's current neighborhood in Toronto. By leveraging venue data from Foursquare's Places API and k-means clustering unsupervised machine learning algorithm, we can better understand the diversity of each neighborhood and easily find the most similar Manhattan neighborhood.

First, we collected from the New York City Dataset, a list of Boroughs and Neighborhoods in New York City. We then created a dataframe listing all the neighborhoods within Manhattan and their corresponding latitudes and longitudes, excluding all other boroughs, which we could use to analyze using the Foursquare API. Second, we performed the same procedure to compose a dataframe that listed the neighborhoods in Toronto that only contained the word Toronto and their corresponding latitudes and longitudes. We did this by first creating a dataframe from the Toronto Dataset and joining it with the Toronto Longitude and Latitude Coordinates Dataset, excluding the neighborhoods that did not contain the word Toronto.

Third, using the Foursquare API, we extracted information on the venues in Manhattan. We then created Manhattan neighborhood profiles by using the frequency the venues are visited and k-means clustering machine learning algorithm to compare and contrast the profiles created of each neighborhood. Fourth, using the Foursquare API, we extracted information on the venues in

Toronto. We then created Toronto neighborhood profiles by using the frequency the venues are visited and k-means clustering machine learning algorithm to compare and contrast the profiles created of each neighborhood. Focusing on the client's current neighborhood, The Esplanade, we were able to create a neighborhood profile that included the 1st and 2nd most common venues.

Next, we will analyze the Manhattan neighborhood profiles we created based on the most frequented venues in each neighborhood. We will compare the Manhattan neighborhood profiles of each of the four clusters with the Toronto the Esplanade neighborhood profile. We will then identify which Manhattan neighborhood most closely matches the characteristics of The Esplanade neighborhood and propose to the client three current houses within the optimal neighborhood using the Zillow API. Lastly, we will discuss and reasons why the optimal Manhattan neighborhood and three homes to propose to the client were selected.

3.2 Analysis

The Neighborhood Profile of the Client's Current Neighborhood in Toronto, the Esplanade:

	Borough	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	9th Most Common Venue	10th Most Common Venue	11th Most Common Venue	12th Most Common Venue	13th Most Common Venue	14th Most Common Venue	15th Most Common Venue
11	Downtown Toronto	0	Coffee Shop	Café	Park	Gastropub	Thai Restaurant	Diner	Restaurant	Japanese Restaurant	Pub	Dance Studio	Ramen Restaurant	Ice Cream Shop	Breakfast Spot	Pool	Gay Bar
12	Downtown Toronto	0	Coffee Shop	Park	Café	Japanese Restaurant	Italian Restaurant	Gym	Men's Store	Gastropub	Gay Bar	Diner	Gourmet Shop	Comic Shop	Thai Restaurant	Pizza Place	Ramen Restaurant
14	Downtown Toronto	0	Coffee Shop	Japanese Restaurant	Café	Gastropub	Gym	Seafood Restaurant	Restaurant	Cosmetics Shop	Ramen Restaurant	Pizza Place	Plaza	Burrito Place	Steakhouse	Hotel	Tea Room
15	Downtown Toronto	0	Coffee Shop	Café	Hotel	Restaurant	Seafood Restaurant	Gastropub	Italian Restaurant	Steakhouse	Beer Bar	Clothing Store	Breakfast Spot	Bakery	Gym	Pizza Place	Cosmetics Shop
16	Downtown Toronto	0	Coffee Shop	Café	Park	Restaurant	Japanese Restaurant	Hotel	Beer Bar	Gastropub	Italian Restaurant	Liquor Store	Bakery	Farmers Market	Gym	New American Restaurant	American Restaurant
17	Downtown Toronto	0	Coffee Shop	Café	Ramen Restaurant	Pizza Place	Japanese Restaurant	Restaurant	Gastropub	Sushi Restaurant	Bookstore	Yoga Studio	Breakfast Spot	Park	Steakhouse	Mexican Restaurant	Dance Studio
18	Downtown Toronto	0	Coffee Shop	Hotel	Café	Pizza Place	Theater	Gastropub	Beer Bar	Japanese Restaurant	Gym	Plaza	Breakfast Spot	Seafood Restaurant	Italian Restaurant	Steakhouse	Movie Theater
19	Downtown Toronto	0	Coffee Shop	Café	Hotel	Park	Japanese Restaurant	Steakhouse	Italian Restaurant	Gym	Aquarium	Bar	Theater	Salad Place	Baseball Stadium	Deli / Bodega	Restaurant
20	Downtown Toronto	0	Coffee Shop	Hotel	Café	Italian Restaurant	Theater	Steakhouse	Concert Hall	Farmers Market	Salad Place	Lounge	Japanese Restaurant	Plaza	Thai Restaurant	Monument / Landmark	Gastropub
21	Downtown Toronto	0	Coffee Shop	Café	Hotel	Japanese Restaurant	Gastropub	Italian Restaurant	Beer Bar	Steakhouse	Theater	Farmers Market	Seafood Restaurant	Concert Hall	Vegetarian / Vegan Restaurant	Lounge	Plaza
28	Downtown Toronto	0	Coffee Shop	Café	Hotel	Japanese Restaurant	Restaurant	Gastropub	Beer Bar	Steakhouse	Seafood Restaurant	Italian Restaurant	Park	Salad Place	Gym	American Restaurant	Deli / Bodega
29	Downtown Toronto	0	Hotel	Coffee Shop	Café	Theater	Steakhouse	Farmers Market	Lounge	Plaza	Salad Place	Italian Restaurant	Concert Hall	Park	Thai Restaurant	Beer Bar	Gastropub
37	Downtown Toronto	0	Coffee Shop	Japanese Restaurant	Park	Restaurant	Italian Restaurant	Ramen Restaurant	Pizza Place	Thai Restaurant	Gastropub	Breakfast Spot	Dance Studio	Sushi Restaurant	Tea Room	Bookstore	Gay Bar

	Esplanade 1st & 2nd Most Common Venues	Venues
0	1	Coffee Shop, Hotel
1	2	Cafe, Hotel, Coffee Shop, Jap. Rest., Park

Manhattan Neighborhood Clusters:

	Cluster, Manhattan	1st Most Common Venues
0	0	Coffee Shop, Kor. Rest., South. Rest., Mex. Re...
1	1	Ital. Rest., Wine Bar, Jap. Rest., Juice Bar, ...
2	2	Theater, Juice Bar, Park, South. Rest., Ital. ...
3	3	Kor. Rest., Park, Gym

	Cluster, Manhattan	2nd Most Common Venues
0	0	Bar, Coffee Shop, Sushi Rest., Park, Latin Res...
1	1	Yoga Studio, New Amer. Rest., Park, Ital. Rest...
2	2	Spa, Yoga Studio, Pizza Place, Park, Plaza, Sa...
3	3	Yoga Studio, Park, Plaza, Sandwich Place, Spa

Comparing the Manhattan Neighborhood Clusters to the Esplanade Profile:

	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	11th Most Common Venue	12th Most Common Venue	13th Most Common Venue	14th Most Common Venue	15th Most Common Venue
1	Chinatown	Chinese Restaurant	American Restaurant	Vietnamese Restaurant	Cocktail Bar	Salon / Barbershop	Spa	Bakery	Optical Shop	Hotpot Restaurant	Asian Restaurant	Boutique	Bubble Tea Shop	Malay Restaurant	Ice Cream Shop	Noodle House
6	Central Harlem	Cosmetics Shop	African Restaurant	American Restaurant	Bar	French Restaurant	Seafood Restaurant	Chinese Restaurant	Café	Tapas Restaurant	Market	Bookstore	Boutique	Fried Chicken Joint	Spa	Southern / Soul Food Restaurant
8	Upper East Side	Italian Restaurant	Exhibit	Art Gallery	Bakery	Juice Bar	Coffee Shop	Gym / Fitness Center	Pizza Place	French Restaurant	Hotel	Yoga Studio	Sushi Restaurant	Grocery Store	Cocktail Bar	Boutique
11	Roosevelt Island	Sandwich Place	Park	Dog Run	Farmers Market	Gym / Fitness Center	Kosher Restaurant	Coffee Shop	Greek Restaurant	Liquor Store	Supermarket	Dry Cleaner	School	Soccer Field	Bus Line	Café
13	Lincoln Square	Café	Theater	Plaza	Concert Hall	Italian Restaurant	Performing Arts Venue	Gym / Fitness Center	Gym	American Restaurant	Clothing Store	Indie Movie Theater	French Restaurant	Movie Theater	Cosmetics Shop	Cycle Studio
14	Clinton	Theater	Gym / Fitness Center	Italian Restaurant	Spa	American Restaurant	Coffee Shop	Sandwich Place	Wine Shop	Hotel	Gym	Fried Chicken Joint	Mediterranean Restaurant	Lounge	Cocktail Bar	Food Court
15	Midtown	Hotel	Sporting Goods Shop	Coffee Shop	Theater	Clothing Store	Bookstore	French Restaurant	Steakhouse	Food Truck	Bakery	Japanese Restaurant	Café	Tailor Shop	Chinese Restaurant	Cocktail Bar
16	Murray Hill	Coffee Shop	Sandwich Place	Hotel	American Restaurant	Japanese Restaurant	Sushi Restaurant	Italian Restaurant	Bar	Gym / Fitness Center	Pizza Place	Bagel Shop	Mediterranean Restaurant	Martial Arts Dojo	French Restaurant	Restaurant
17	Chelsea	Coffee Shop	Bakery	Italian Restaurant	Ice Cream Shop	American Restaurant	Nightclub	Hotel	Bookstore	Market	Sushi Restaurant	Men's Store	Seafood Restaurant	Tapas Restaurant	Japanese Restaurant	Theater
21	Tribeca	American Restaurant	Park	Italian Restaurant	Café	Spa	Wine Shop	Wine Bar	Coffee Shop	Greek Restaurant	Men's Store	Cocktail Bar	Burger Joint	Bakery	Boutique	Hotel
24	West Village	Italian Restaurant	New American Restaurant	Cosmetics Shop	Wine Bar	American Restaurant	Cocktail Bar	Park	Bakery	Jazz Club	Theater	Coffee Shop	Japanese Restaurant	Boutique	Pizza Place	Chinese Restaurant
29	Financial District	Coffee Shop	Bar	American Restaurant	Hotel	Pizza Place	Food Truck	Gym	Gym / Fitness Center	Cocktail Bar	Steakhouse	Wine Shop	Italian Restaurant	Jewelry Store	Event Space	Falafel Restaurant
32	Civic Center	Gym / Fitness Center	Hotel	Sandwich Place	Coffee Shop	French Restaurant	Bakery	Cocktail Bar	Italian Restaurant	Yoga Studio	Spa	Park	American Restaurant	Hotel Bar	Gym	Wine Shop
33	Midtown South	Korean Restaurant	Japanese Restaurant	Hotel Bar	Coffee Shop	Hotel	Dessert Shop	American Restaurant	Cosmetics Shop	Cocktail Bar	Vegetarian / Vegan Restaurant	Salad Place	Clothing Store	Gym / Fitness Center	Lingerie Store	Burger Joint
34	Sutton Place	Gym / Fitness Center	Furniture / Home Store	Italian Restaurant	Gym	Yoga Studio	Indian Restaurant	Latin American Restaurant	Department Store	Juice Bar	French Restaurant	Beer Garden	Beer Bar	Chinese Restaurant	Bakery	Grocery Store
38	Flatiron	Yoga Studio	Café	Gym / Fitness Center	Japanese Restaurant	American Restaurant	Cycle Studio	Mediterranean Restaurant	Salon / Barbershop	Clothing Store	Coffee Shop	Cosmetics Shop	Spa	New American Restaurant	Dessert Shop	Toy / Game Store
39	Hudson Yards	American Restaurant	Italian Restaurant	Coffee Shop	Café	Hotel	Gym / Fitness Center	Spanish Restaurant	Burger Joint	Thai Restaurant	Restaurant	Bar	Gym	Boat or Ferry	Park	Dog Run

It appears the Flatiron District neighborhood would be most similar to the Esplanade and closest to the client's future work at the Google office in Chelsea.

Using the Zillow API, we will determine three current listings for a co-op/condo in the Flatiron District to propose to the client:

Listing 1: 16 West 16th Street, APT 7AS, New York, NY, 10011. Type: Cooperative. 1 Bedroom & 1 Bath. 750 sq. ft. Price: $965,000.

Listing 2: 61 Irving Place, APT 1D, New York, NY, 10003. Type: Cooperative. 1 Bedroom & 1 Bath. 950 sq. ft. Price: $999,000.

Listing 3: 21 E 22nd Street, APT 2A, New York, NY, 10010. Type: Cooperative. 0 Bedroom & 1 Bath. 925 sq. ft. Price: $925,000.

4. Results and Discussion

As our analysis has shown that the Esplanade neighborhood profile when compared to Manhattan neighborhood profiles we created, most closely matches the Flatiron District neighborhood. The neighborhood profiles were created based on K-Means Clustering, a form of unsupervised machine learning, along with venue frequency data gathered by using the Foursquare API. The Flatiron District neighborhood appeared to be most comparable to the Esplanade neighborhood in terms of venue frequency and would also be a short commute to client's future employment at the Google office in Chelsea. Based on the results, the Chelsea neighborhood appeared to be a close tie for second. Based on this information we gathered using

the Zillow API 3 listings, most similar to the client's current home at 1 A The Esplanade Ave # 2008, Toronto, ON, M5E 0A8. While the client's current home is a 2 bedroom & 2 bathroom condo, listed for C$899,000, almost all 2 bedroom & 2 bathroom condos listed in the Flatiron District were priced significantly higher. The three listings proposed were based first on price and then on sq. ft. and number of bedrooms and bathrooms. Of the three listings, Listing 1 appeared to be the best fit for the client.

The resulting Manhattan neighborhoods listed in cluster 1 (cluster 0) contained the largest number of potential optimal neighborhoods based on the number and frequency of venues. I believe the information gathered, joined with other demographics and statistics not explored in this project, would determine which of the potential neighborhoods would be the very best match. The purpose of this analysis, to create neighborhood profiles based on data gathered via the Foursquare API, was to demonstrate and provide information on areas in Manhattan that might closely match the client's current neighborhood in Toronto. The recommended neighborhood should be considered as a starting point for a more detailed analysis which may result in a location where many other factors have been taken into account.

5. Conclusion

As our analysis has shown that the Esplanade neighborhood profile when compared to Manhattan neighborhood profiles we created, most closely matches the Flatiron District neighborhood. The neighborhood profiles were created based on K-Means Clustering, a form of unsupervised machine learning, along with venue frequency data gathered by using the Foursquare API. While each neighborhood profile was based on the venue frequency from Foursquare, there are many other demographics and statistics that could be applied in creating neighborhood profiles.

The primary stakeholders, interested in a new way to use quantifiable analysis to understand and profile a neighborhood would be Real Estate Agents and Real Estate Buyers. Previously neighborhood profiles have always been aggregated and compared based on historic, statistical, and/or demographic information. However, I believe a new approach based on venues and often they’re visited for creating neighborhood profiles in order to compare other neighborhood profiles can provide a basis for a much more accurate area profile.

The area in Manhattan determined to be most similar to the client's current neighborhood in Toronto, the Esplanade, is the Flatiron District.

As a Real Estate Agent in New York City, the three listings I would propose that are most similar to client's current home are:

Listing 1: 16 West 16th Street, APT 7AS, New York, NY, 10011. Type: Cooperative. 1 Bedroom & 1 Bath. 750 sq. ft. Price: $965,000.

Listing 2: 61 Irving Place, APT 1D, New York, NY, 10003. Type: Cooperative. 1 Bedroom & 1 Bath. 950 sq. ft. Price: $999,000.

Listing 3: 21 E 22nd Street, APT 2A, New York, NY, 10010. Type: Cooperative. 0 Bedroom & 1 Bath. 925 sq. ft. Price: $925,000.

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