Introduction

<u>The problem statement:</u> Help find neighborhoods in Toronto, ON that are similar to a given neighborhood in New York.

<u>Who will be interested:</u> This can be used by relocation agencies to help people who are looking to move to Toronto from New York.

Background: Toronto is a fast growing city in North America. Having said so, there are loads of new opportunities that are sprawling across Toronto that is of interest to people. This has led to a recent growth in immigration to the city. As per this site; of all immigrants in Ontario, 7 out of 10 lived in Toronto. This has led to many immigration services that cater to the city of Toronto,ON. This has also led to a rich culturally diverse Toronto. Huffington Post also came up with this widely read article highlighting the migration from New York to Toronto. Upon reading the article, one thing that strikes is that people do not just move because of new opportunity, but also factor in the lifestyle. Rising cultural diversity of Toronto has been a magnet for people of culturally-diverse New York. This is something relocation agencies cash upon. They have come up with lots of services that help people explore their future neighborhood. We intend to come up with a smart solution that will provide an impetus to this effort. Our algorithm will factor in various lifestyle pointers of a neighborhood and use machine learning to find localities that have matching cultural and lifestyle offerings. This will help find neighborhoods in Toronto, ON that are similar to a given neighborhood in New York.

Data

The data for 2 cities: Toronto and New York will be used to compare neighborhoods, and then we rank the neighborhoods from the selected boroughs for the cities. We will use the previous assignments to retrieve the neighborhood and geo coordinates for New York and Toronto. We will use Machine Learning (unsupervised learning) to cluster the neighborhoods from the two cities. Data sources are *newyork data.json* & the Toronto Wiki page.

Data sources:

- New York city data: https://gist.github.com/0cd2d7265973edb82dbf9ef2486c9ca1
- Toronto city data: Web scraping
 https://en.wikipedia.org/wiki/List_of_postal_codes_of_Canada: M
- FourSquare API to get neighbourhood details for each city

Methodology

We will follow the following steps:

1. Create a dataset that holds the Geo-coordinates for Toronto's neighborhood

Use BeautifulSoup package to perform web scraping on Toronto Wiki page to build the following dataset.

| | Borough | Neighbourhood | Latitude | Longitude |
|----|-----------------|-------------------------------|-----------|------------|
| 37 | East Toronto | The Beaches | 43.676357 | -79.293031 |
| 41 | East Toronto | The Danforth West,Riverdale | 43.679557 | -79.352188 |
| 42 | East Toronto | The Beaches West,India Bazaar | 43.668999 | -79.315572 |
| 43 | East Toronto | Studio District | 43.659526 | -79.340923 |
| 44 | Central Toronto | Lawrence Park | 43.728020 | -79.388790 |

Then, we will further explore the city of Toronto. The following unclustered map view is a representation of it.



2. Use Foursquare APIs to get venues for each of the Toronto's neighborhoods

Next, we use the Foursquare's venues API to get nearby venues. We will capture the following data points: 'Neighbourhood', 'Neighbourhood Latitude', 'Neighbourhood Longitude', 'Venue', 'Venue Latitude', 'Venue Longitude', and 'Venue Category'. A snapshot of the dataset looks like the following. This dataset will form the basis for k-means clustering which we will illustrate later.

| | Neighbourhood | Airport | Airport Food Court | Airport Gate | | | Airport Terminal | American Restaurant | Antique Shop | Aquarium | Theme Restaurant | Thrift / Vintage Store | | Trail | Tra Stati |
|---|---------------|---------|--------------------------|-----------------|---|---|---------------------|------------------------|-----------------|----------|-------------------------|------------------------------|---|-------|--------------|
| 0 | The Beaches | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | |
| 1 | The Beaches | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| 2 | The Beaches | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| 3 | The Beaches | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| 4 | The Beaches | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |

5 rows × 194 columns

3. Sort through the data to identify top 10 common venue categories for each of the Toronto's neighborhoods

Dataset snapshot is given below for your reference.

| | Neighbourhood | 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 | Adelaide,King,Richmond | Steakhouse | Asian Restaurant | Café | Pizza Place | Hotel | Neighborhood | Lounge | Burger Joint | Seafood Restaurant | Smoke Shop |
| 1 | Berczy Park | Seafood Restaurant | Coffee Shop | Cocktail Bar | Beer Bar | Café | Farmers Market | Greek Restaurant | Jazz Club | Basketball Stadium | Fish Marke |
| 2 | Brockton,Exhibition Place,Parkdale Village | Coffee Shop | Breakfast Spot | Café | Climbing Gym | Stadium | Burrito Place | Restaurant | Caribbean Restaurant | Pet Store | Baker |
| 3 | Business Reply Mail Processing Centre 969 Eastern | Yoga Studio | Fast Food Restaurant | Park | Comic Shop | Pizza Place | Butcher | Burrito Place | Recording Studio | Restaurant | Brewery |
| 4 | CN Tower, Bathurst Quay, Island airport, Harbourf | Airport Lounge | Airport Service | Airport Terminal | Harbor / Marina | Sculpture Garden | Airport Food Court | Airport Gate | Bar | Boat or Ferry | Boutique |

4. Perform the above for New York's neighborhoods

Same steps are performed for the city of New York. For conciseness, the final datasets will look something the the following

| | Neighbourhood | Accessories Store | Adult Boutique | Afghan Restaurant | African Restaurant | American Restaurant | | Antique Shop | Arcade | Arepa Restaurant | Warehouse Store | Waste Facility | Wate |
|---|---------------|----------------------|-------------------|----------------------|-----------------------|------------------------|---|-----------------|--------|---------------------|------------------------|-------------------|------|
| 0 | Wakefield | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| 1 | Wakefield | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| 2 | Wakefield | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| 3 | Wakefield | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| 4 | Wakefield | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |

5 rows × 380 columns

| | Neighbourhood | 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 | Allerton | Pizza Place | Pharmacy | Spa | Deli / Bodega | Supermarket | Department Store | Fried Chicken Joint | Breakfast Spot | Bus Station | Gas Station |
| 1 | Annadale | Pizza Place | Park | Sports Bar | Restaurant | Food | Diner | Train Station | Pharmacy | Field | Event Space |
| 2 | Arden Heights | Pharmacy | Coffee Shop | Pizza Place | Bus Stop | Yoga Studio | Financial or Legal Service | Factory | Falafel Restaurant | Farm | Farmers Market |
| 3 | Arlington | Bus Stop | Deli / Bodega | American Restaurant | Boat or Ferry | Food | Grocery Store | Fish Market | Farm | Farmers Market | Fast Food Restaurant |
| 4 | Arrochar | Deli / Bodega | Pizza Place | Italian Restaurant | Bus Stop | Athletics & Sports | Middle Eastern Restaurant | Bagel Shop | Liquor Store | Supermarket | Hotel |

5. This step will be the input. Select a neighborhood in NY for which we are looking for lookalikes in Toronto. Here, we chose Chelsea, NY.

| | Neighbourhood | Airport | Airport Food Court | Airport Gate | Airport Lounge | Airport Service | Airport Terminal | American Restaurant | Antique Shop | Aquarium | Veterinarian | Video Store | Warehouse Store | Waste Facility | |
|----|---------------|---------|--------------------------|-----------------|-------------------|--------------------|---------------------|------------------------|-----------------|----------|------------------|----------------|--------------------|-------------------|---|
| 38 | Chelsea | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.029412 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | , |

6. Use K-means on dataset that has all Toronto's neighborhoods plus this neighborhood. Then find the cluster which has the NY neighborhood in it and list all Toronto neighborhoods there. Following dataset shows each neighborhood in Toronto with its assigned cluster label.

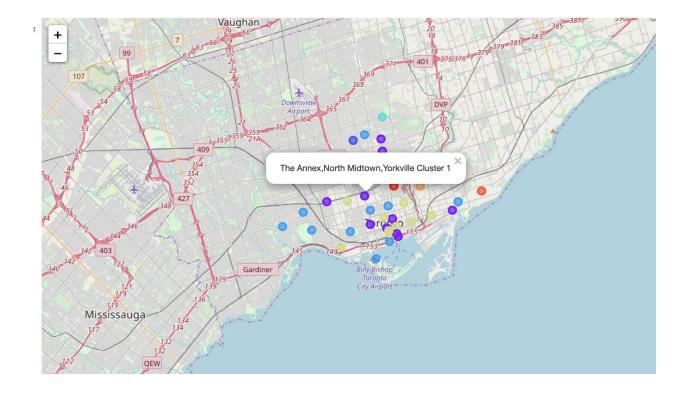
| | Borough | Neighbourhood | Latitude | Longitude | Cluster Labels | 1st Most Common Venue | 2nd Most Common Venue | 3rd Most Common Venue | 4th Most Common Venue | 5th Most Common Venue | 6th Most Common Venue | 7th Most Common Venue | 8 C |
|---|--------------------|-------------------------------------|-----------|------------|-------------------|-----------------------------|--------------------------------|-----------------------------|-----------------------------|-----------------------------|---------------------------------|-----------------------------|----------|
| 0 | East Toronto | The Beaches | 43.676357 | -79.293031 | 9 | Neighborhood | Other Great Outdoors | Health Food Store | Trail | Pub | Cuban Restaurant | Ethiopian Restaurant | E Re |
| 1 | East Toronto | The Danforth West,Riverdale | 43.679557 | -79.352188 | 8 | Greek Restaurant | Ice Cream Shop | Italian Restaurant | Yoga Studio | Bookstore | Restaurant | Spa | |
| 2 | East Toronto | The Beaches West,India Bazaar | 43.668999 | -79.315572 | 3 | Park | Pet Store | Ice Cream Shop | Liquor Store | Sandwich Place | Burger Joint | Fast Food Restaurant | |
| 3 | East Toronto | Studio District | 43.659526 | -79.340923 | 7 | Café | Coffee Shop | Bakery | Italian Restaurant | American Restaurant | Middle Eastern Restaurant | Stationery Store | |
| 4 | Central Toronto | Lawrence Park | 43.728020 | -79.388790 | 4 | Bus Line | Park | Swim School | Dance Studio | Falafel Restaurant | Ethiopian Restaurant | Eastern European | D Re: |

Results

For Chelsea, NY, we found 10 lookalike neighborhoods in Toronto. They are listed below:

| data_: | index | |
|--------|----------|---|
| 0 | | Adelaide, King, Richmond |
| 1 | | Berczy Park |
| 3 | Business | Reply Mail Processing Centre 969 Eastern |
| 7 | | Chinatown, Grange Park, Kensington Market |
| 11 | | Davisville |
| 12 | | Davisville North |
| 15 | | Dovercourt Village, Dufferin |
| 30 | | Ryerson, Garden District |
| 32 | | Stn A PO Boxes 25 The Esplanade |
| 34 | | The Annex, North Midtown, Yorkville |

Also, if we want to visualize them in maps, we can see them as below (marked in purple)



Discussion

We find that k-means is a very powerful technique to compare neighborhoods. For this algorithm to be successful, we need as much data as possible available for both the cities that speaks about the lifestyle of those areas. Then, we can run ML unsupervised K-means algorithm to find lookalikes.

Please note that this algorithm can be generalized to compare any two cities, given the data is available as mentioned above.

Conclusion

For Chelsea,NY we were able to find lookalike neighborhoods in Toronto, ON. We based it off several lifestyle parameters for the neighborhoods and leveraged Foursquare APIs for the same. This is a powerful algorithm that will help relocation agencies zero in on localities that will fit the bill for their clients. If correctly incorporated in their client onboarding process, this algorithm can have potential positive impacts on the bottom line.