Capstone Project on Coursera

# Research on Location Selection of Street Stores in Toronto

PENGKUN APRIL 22TH

# Introduction

- A long time ago, I read a report by chance. Researchers at the University of Cambridge have analyzed the 620,000 check-in data related to Starbucks and McDonald's users posted on Twitter within 5 months, combined with traditional location characteristics, using machine learning algorithms to get a result: Foursquare check-in data helps Starbucks chose a better store.
- This study found that even with these differences, no matter which chain store is targeted, the combination of traditional geographic features and the flow of people based on Foursquare's check-in data analysis can get the best prediction results.
- Therefore, based on the research results of the report talked above. My Capstone Project will sort out the most popular types of stores in Toronto’s neighborhoods, and form a sorted list to provide useful reference for the location selection of the new stores. Furthermore, different types of stores have different location strategies, some radical and some conservative. But no matter what type, you can get reference from the results of this capstone project.

# Data Description
## Importing Dataset

| | Postal code | Borough | Neighborhood |
|---|---|---|---|
| 0 | M1A | Not assigned | NaN |
| 1 | M2A | Not assigned | NaN |
| 2 | M3A | North York | Parkwoods |
| 3 | M4A | North York | Victoria Village |
| 4 | M5A | Downtown Toronto | Regent Park / Harbourfront |

- The data used by Capstone Project mainly includes three parts. The first is Toronto 's postal codes data, which mainly includes the three fields of Postal code, Borough, and Neighborhood. The second is to integrate postal codes data with GPS data to form a table with longitude and latitude. The third is the data obtained from Foursquare, the latitude and longitude of each Venue and the type of store from each Neighborhood, so that the space can be visualized more conveniently.

# Data Description
## Cleaning the Data

- Then the data cleaning is needed, for the following reasons:
- More than one neighborhood can exist in one postal code area. For example, in the table on the Wikipedia page, M5A is listed twice and has two neighborhoods: Harbourfront and Regent Park. These two rows will be combined into one row with the neighborhoods separated with a comma as shown in row 11 in the above table.
- If a cell has a borough but a Not assigned neighborhood, then the neighborhood will be the same as the borough.

| | PostalCode | Borough | Neighborhood |
|---|---|---|---|
| 0 | M3A | North York | Parkwoods |
| 1 | M4A | North York | Victoria Village |
| 2 | M5A | Downtown Toronto | Regent Park, Harbourfront |
| 3 | M6A | North York | Lawrence Manor, Lawrence Heights |
| 4 | M7A | Downtown Toronto | Queen's Park, Ontario Provincial Government |
| 5 | M9A | Etobicoke | Islington Avenue |

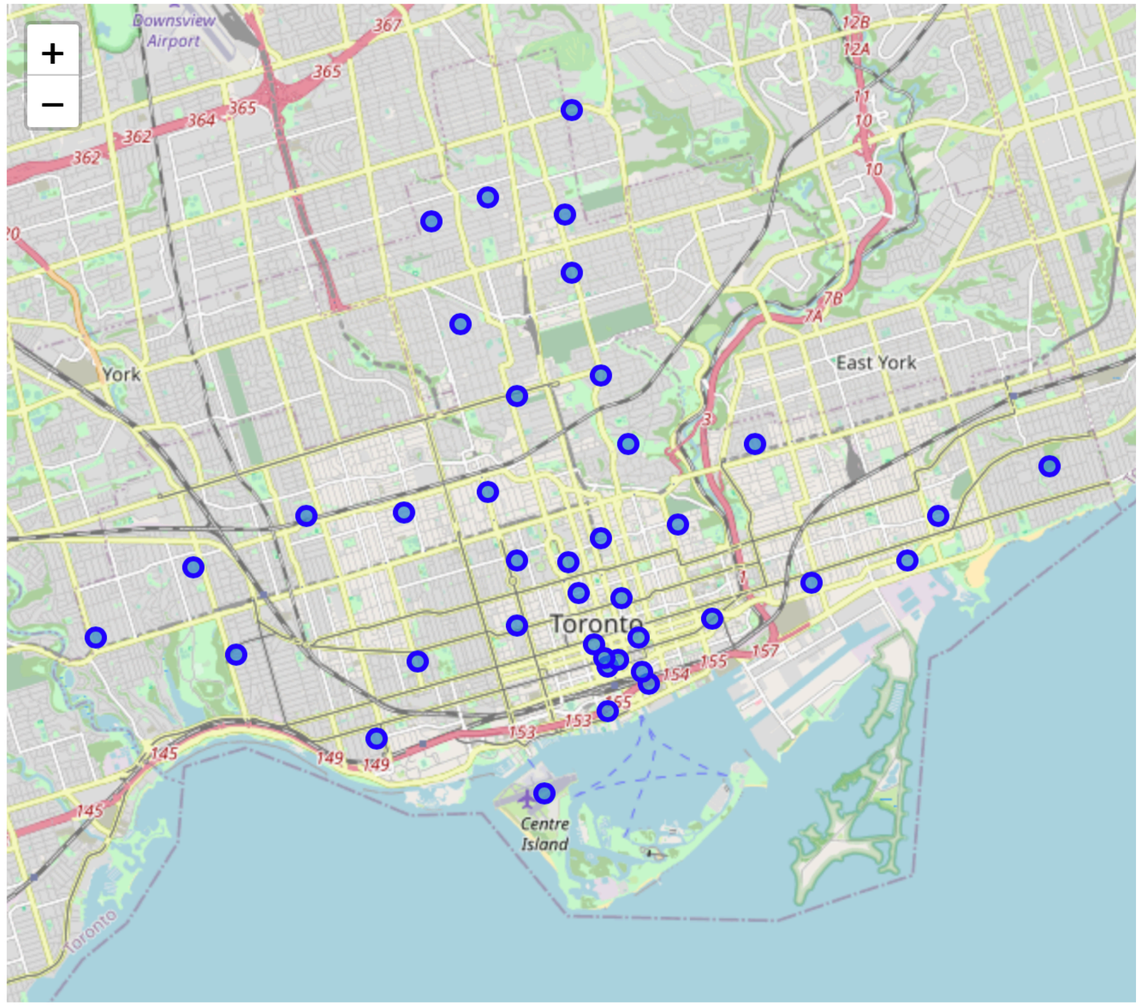
| | Postal Code | Latitude | Longitude |
|---|---|---|---|
| 0 | M1B | 43.806686 | -79.194353 |
| 1 | M1C | 43.784535 | -79.160497 |
| 2 | M1E | 43.763573 | -79.188711 |
| 3 | M1G | 43.770992 | -79.216917 |
| 4 | M1H | 43.773136 | -79.239476 |

| | PostalCode | Borough | Neighborhood | Latitude | Longitude |
|---|---|---|---|---|---|
| **0** | M3A | North York | Parkwoods | 43.753259 | -79.329656 |
| **1** | M4A | North York | Victoria Village | 43.725882 | -79.315572 |
| **2** | M5A | Downtown Toronto | Regent Park, Harbourfront | 43.654260 | -79.360636 |
| **3** | M6A | North York | Lawrence Manor, Lawrence Heights | 43.718518 | -79.464763 |
| **4** | M7A | Downtown Toronto | Queen's Park, Ontario Provincial Government | 43.662301 | -79.389494 |
| **5** | M9A | Etobicoke | Islington Avenue | 43.667856 | -79.532242 |

# Selecting Toronto data and data visualization

- Filter the data table obtained in the previous section, and only keep the data of Toronto, as shown in the right table. Both borough and neighborhood in the table are in Toronto. The dataframe has 4 boroughs and 39 neighborhoods. By this way, we only keep the data that we should pay attention to.

- Next, We use the folium function to draw the map, the geographical coordinates of Toronto are 43.6534817, -79.3839347. So we can get the data visualization of the neighborhoods of Toronto



# Methodology

# Getting Foursquare Data

- irst, we define Foursquare credentials and version by adding the CLIENT_ID, CLIENT_SECRET and VERSION. Next, we get the top 100 venues that are in the first neighborhood within a radius of 500 meters. The result file returned through the API interface is in json format, and the data structure is shown in the figure.


```
{'meta': {'code': 200, 'requestId': '5ea03711c8cff26793583533'},
 'response': {'suggestedFilters': {'header': 'Tap to show:',
   'filters': [{'name': 'Open now', 'key': 'openNow'}]},
  'headerLocation': 'Corktown',
  'headerFullLocation': 'Corktown, Toronto',
  'headerLocationGranularity': 'neighborhood',
  'totalResults': 48,
  'suggestedBounds': {'ne': {'lat': 43.6587599045, 'lng': -79.3544279001486},
   'sw': {'lat': 43.6497598955, 'lng': -79.36684389985142}},
  'groups': [{'type': 'Recommended Places',
    'name': 'recommended',
    'items': [{'reasons': {'count': 0,
       'items': [{'summary': 'This spot is popular',
         'type': 'general',
         'reasonName': 'globalInteractionReason'}]},
      'venue': {'id': '54ea41ad498e9a11e9e13308',
       'name': 'Roselle Desserts',
       'location': {'address': '362 King St E',
```

# Getting Foursquare Data

- As we know, all the information is in the items key. Before we proceed, let's borrow the get_category_type function from the Foursquare lab. Now we are ready to clean the json and structure it into a pandas dataframe. we know the number of venues were returned by Foursquare. 48 venues were returned by Foursquare.

```
# function that extracts the category of the venue
def get_category_type(row):
    try:
        categories_list = row['categories']
    except:
        categories_list = row['venue.categories']

    if len(categories_list) == 0:
        return None
    else:
        return categories_list[0]['name']
```

# Explore Neighborhoods in Toronto

```
def getNearbyVenues(names, latitudes, longitudes, radius=500):

    venues_list=[]
    for name, lat, lng in zip(names, latitudes, longitudes):
        print(name)

        # create the API request URL
        url = 'https://api.foursquare.com/v2/venues/explore?&client_id={}&client_secret={}&ll={},{
            CLIENT_ID,
            CLIENT_SECRET,
            lat,
            lng,
            VERSION,
            radius,
            LIMIT)

        # make the GET request
        results = requests.get(url).json()["response"]['groups'][0]['items']

        # return only relevant information for each nearby venue
        venues_list.append([(
            name,
            lat,
            lng,
            v['venue']['name'],
            v['venue']['location']['lat'],
            v['venue']['location']['lng'],
            v['venue']['categories'][0]['name']) for v in results])

    nearby_venues = pd.DataFrame([item for venue_list in venues_list for item in venue_list])
    nearby_venues.columns = ['Neighborhood',
                   'Neighborhood Latitude',
                   'Neighborhood Longitude',
                   'Venue',
                   'Venue Latitude',
                   'Venue Longitude',
                   'Venue Category']

    return(nearby_venues)
```

- Firstly, we create a function to repeat the same process to all the neighborhoods in Toronto.
- Then we run the above function on each neighborhood and create a new dataframe called toronto_venues. The size of the resulting dataframe is (1612, 7). There are 230 uniques categories.

# Analyze Each Neighborhood

```
----Berczy Park----
                venue  freq
0          Coffee Shop  0.07
1         Cocktail Bar  0.05
2  Italian Restaurant  0.03
3               Bakery  0.03
4                 Café  0.03
```

- Analyze Each Neighborhood, let's group rows by neighborhood and by taking the mean of the frequency of occurrence of each category. And printing each neighborhood along with the top 5 most common venues.

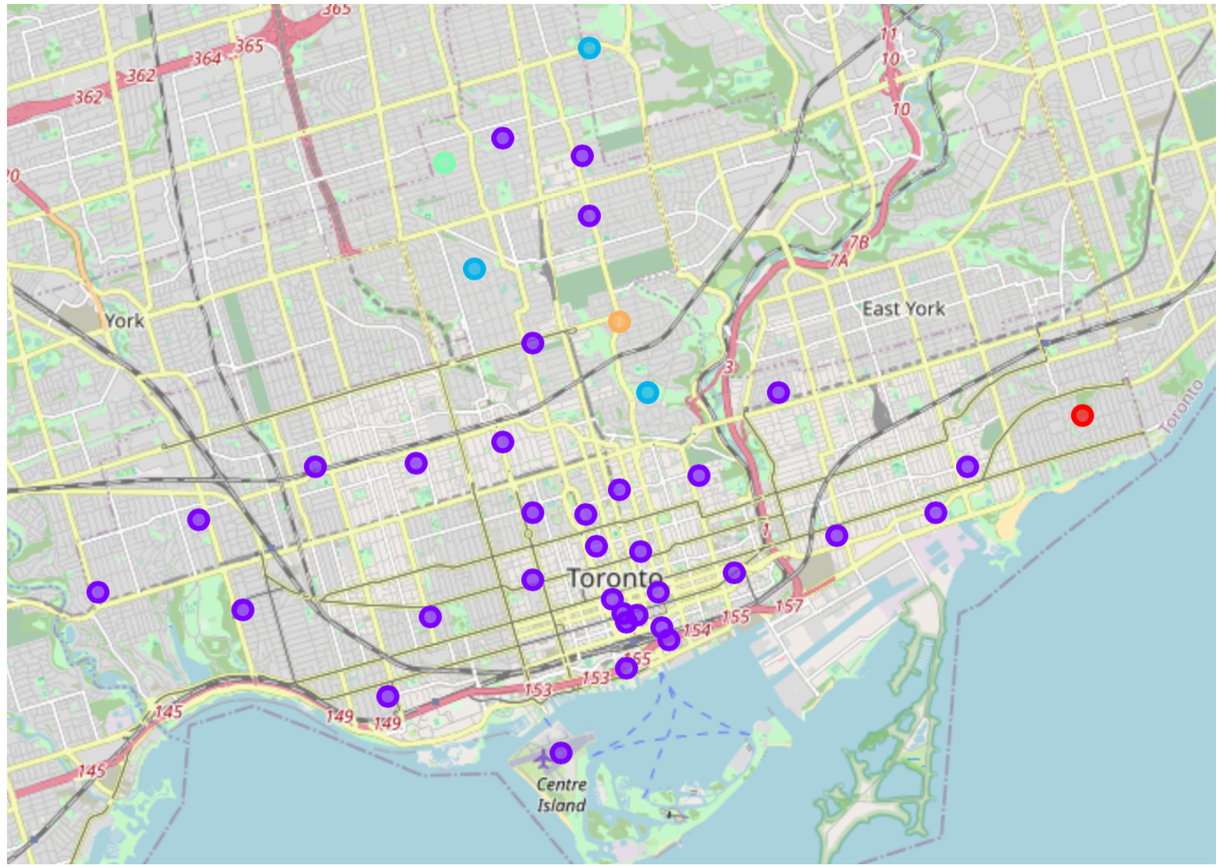
# Analyze Each Neighborhood

| | 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 | Berczy Park | Coffee Shop | Cocktail Bar | Cheese Shop | Farmers Market | Seafood Restaurant | Bakery | Restaurant | Italian Restaurant | Café | Beer Bar |
| 1 | Brockton, Parkdale Village, Exhibition Place | Café | Coffee Shop | Breakfast Spot | Gym | Bakery | Convenience Store | Performing Arts Venue | Pet Store | Climbing Gym | Restaurant |
| 2 | Business reply mail Processing CentrE | Yoga Studio | Spa | Garden Center | Garden | Fast Food Restaurant | Farmers Market | Light Rail Station | Comic Shop | Pizza Place | Butcher |
| 3 | CN Tower, King and Spadina, Railway Lands, Har... | Airport Service | Airport Lounge | Airport Terminal | Sculpture Garden | Plane | Airport | Airport Food Court | Rental Car Location | Boutique | Harbor / Marina |
| 4 | Central Bay Street | Coffee Shop | Italian Restaurant | Sandwich Place | Café | Salad Place | Fried Chicken Joint | Bubble Tea Shop | Burger Joint | Japanese Restaurant | Ice Cream Shop |

- Next, we put that into a pandas dataframe. First, we write a function to sort the venues in descending order. Then we create the new dataframe and display the top 10 venues for each neighborhood. Result is shown in the following table.
-

# Cluster Neighborhoods

- Run k-means to cluster the neighborhood into 5 clusters. Set number of clusters equals to 5, run k-means clustering, and check cluster labels generated for each row in the dataframe. We create a new dataframe that includes the cluster as well as the top 10 venues for each neighborhood. Adding clustering labels and merging toronto_grouped with toronto_data to add latitude/longitude for each neighborhood. Check the last columns, and in the final part, we visualize the resulting clusters.



# Results

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# Cluster 1

| | 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 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **4** | East Toronto | 0 | Health Food Store | Trail | Pub | Women's Store | Department Store | Ethiopian Restaurant | Electronics Store | Eastern European Restaurant | Dumpling Restaurant | Donut Shop |

# Cluster 2

| | 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 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | Downtown Toronto | 1 | Coffee Shop | Pub | Bakery | Park | Breakfast Spot | Restaurant | Café | Theater | Mexican Restaurant | Shoe Store |
| **1** | Downtown Toronto | 1 | Coffee Shop | Diner | Sushi Restaurant | Gym | Restaurant | Park | Mexican Restaurant | Juice Bar | Italian Restaurant | Hobby Shop |
| **2** | Downtown Toronto | 1 | Clothing Store | Coffee Shop | Café | Restaurant | Japanese Restaurant | Bubble Tea Shop | Cosmetics Shop | Middle Eastern Restaurant | Tea Room | Bookstore |
| **3** | Downtown Toronto | 1 | Coffee Shop | Café | Cocktail Bar | Gastropub | Hotel | Italian Restaurant | American Restaurant | Seafood Restaurant | Farmers Market | Department Store |
| **5** | Downtown Toronto | 1 | Coffee Shop | Cocktail Bar | Cheese Shop | Farmers Market | Seafood Restaurant | Bakery | Restaurant | Italian Restaurant | Café | Beer Bar |

# Cluster 3

| | 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 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **18** | Central Toronto | 2 | Park | Bus Line | Swim School | Falafel Restaurant | Event Space | Ethiopian Restaurant | Electronics Store | Eastern European Restaurant | Dumpling Restaurant | Donut Shop |
| **21** | Central Toronto | 2 | Park | Jewelry Store | Home Service | Trail | Sushi Restaurant | Eastern European Restaurant | Dumpling Restaurant | Electronics Store | Department Store | Doner Restaurant |
| **33** | Downtown Toronto | 2 | Park | Playground | Trail | Deli / Bodega | Ethiopian Restaurant | Electronics Store | Eastern European Restaurant | Dumpling Restaurant | Donut Shop | Doner Restaurant |

# Cluster 4

| | 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 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **19** | Central Toronto | 3 | Garden | Women's Store | Department Store | Event Space | Ethiopian Restaurant | Electronics Store | Eastern European Restaurant | Dumpling Restaurant | Donut Shop | Doner Restaurant |

# Cluster 5

| | 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 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **29** | Central Toronto | 4 | Playground | Women's Store | Department Store | Event Space | Ethiopian Restaurant | Electronics Store | Eastern European Restaurant | Dumpling Restaurant | Donut Shop | Doner Restaurant |

# Discussion

- Combining the above analysis, we can know that the most popular types of stores among clusters vary widely. But there are extremely high similarities in the same cluster. This has important strategic significance for the selection of new stores. Through analysis, the company can set its own operation and location strategy, choose to participate in fierce competition, or stay away from the same type of store, and go to a store that has not yet been developed. region. It all depends on the company's decision, but our use of data can provide strong support for the company's decision. This is also the most important significance of this report.

# Conclusions

- The conclusion is that through Foursquare data, combined with machine learning and cluster analysis, when the company decides to open a new chain store, it can combine its own location strategy to find the most suitable store area.