Coursera Capstone Project

Toronto Gamestop

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Introduction

Gamestop is a dominating video game retailer in north America. Gamestop stores are chain stores that sell video games as well as gaming related product.

If someone is going to step into this business and open a Gamestop store, the best strategy is to find the neighborhood in Toronto that has the least competitors, i.e., other Gamestop stores, and the neighborhood that has highest income and population.

Data acquisition and processing

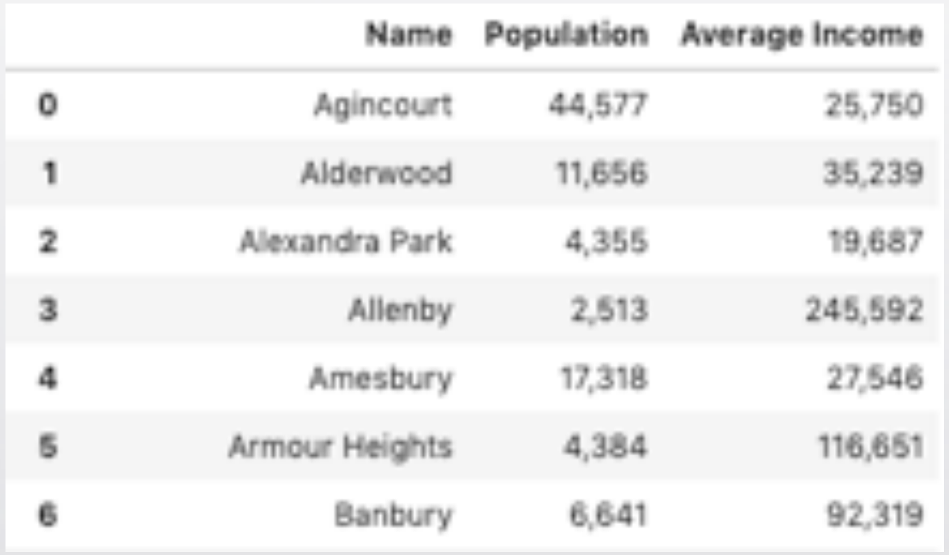
- The Foursquare location data will be used to get the number of Gamestop in each neighborhood.
- Population and average income: https://en.wikipedia.org/wiki/Demographics_of_Toronto_neighbourhoods.
- Foursquare venue categories: https://developer.foursquare.com/docs/resources/categories

  Electronics store: 4bf58dd8d48988d10b951735

  Video game store: 4bf58dd8d48988d122951735

1. Beautifulsoup4

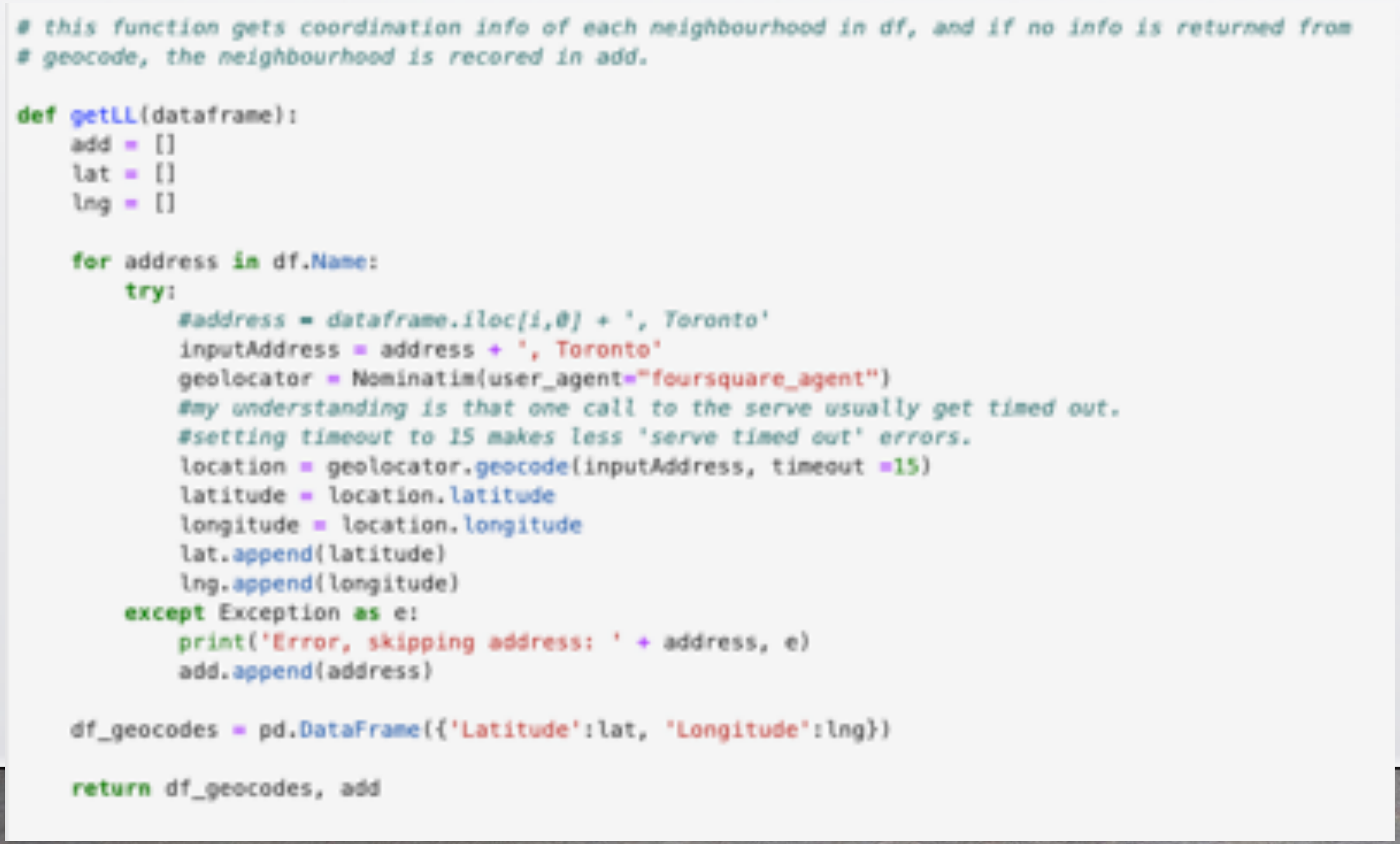
Beautifulsoup4 API is used to create a data-frame containing name of the neighborhoods of Toronto. From it I can get the population and average income to help making decisions.



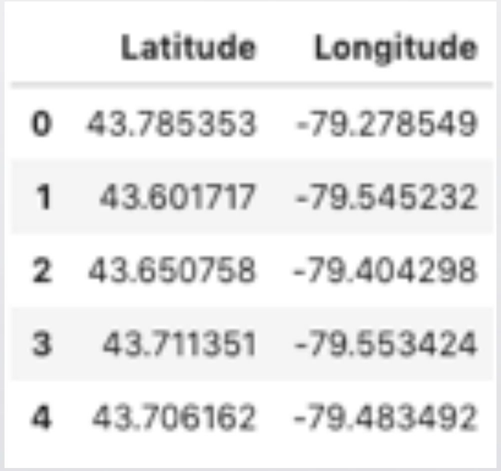
	Name	Population	Average Income
0	Agincourt	44,577	25,750
1	Alderwood	11,656	35,239
2	Alexandra Park	4,355	19,687
3	Allenby	2,513	245,592
4	Amesbury	17,318	27,546
5	Armour Heights	4,384	116,651
6	Banbury	6,641	92,319

2. Google geocode

Generally, the Foursquare API is a good tool of translating from a given latitude and longitude to venues that are nearby. So it is important to first get location info of each neighborhood. Here I am using Google geocode API key to find the coordinates.



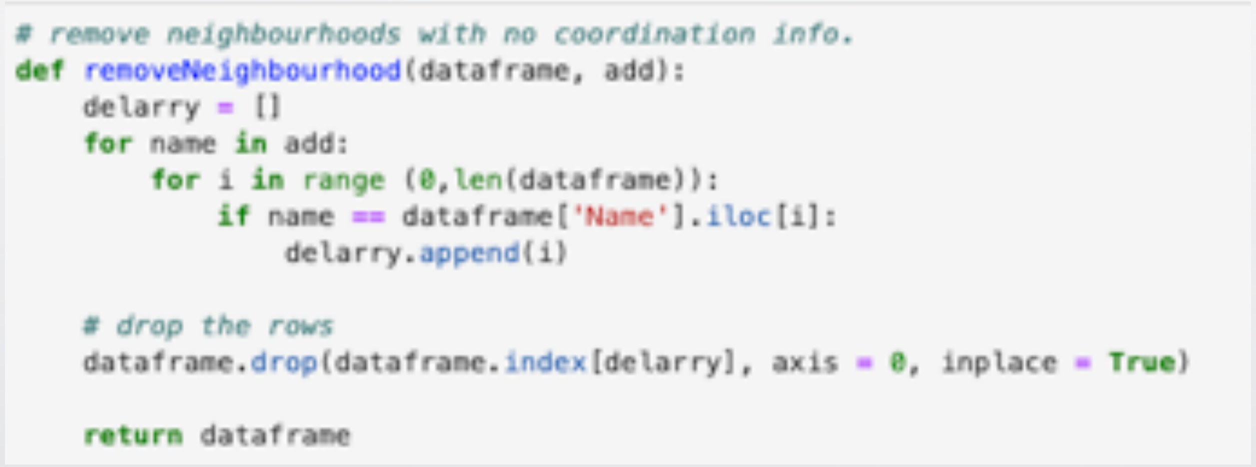
```
# this function gets coordination info of each neighbourhood in df, and if no info is returned from
# geocode, the neighbourhood is recored in add.

def getLL(dataframe):
    add = []
    lat = []
    lng = []

    for address in df.Name:
        try:
            #address = dataframe.iloc[i,0] + ', Toronto'
            inputAddress = address + ', Toronto'
            geolocator = Nominatim(user_agent="foursquare_agent")
            #my understanding is that one call to the serve usually get timed out.
            #setting timeout to 15 makes less 'serve timed out' errors.
            location = geolocator.geocode(inputAddress, timeout =15)
            latitude = location.latitude
            longitude = location.longitude
            lat.append(latitude)
            lng.append(longitude)
        except Exception as e:
            print('Error, skipping address: ' + address, e)
            add.append(address)

    df_geocodes = pd.DataFrame({'Latitude':lat, 'Longitude':lng})

    return df_geocodes, add
```



	Latitude	Longitude
0	43.785353	-79.278549
1	43.601717	-79.545232
2	43.650758	-79.404298
3	43.711351	-79.553424
4	43.706162	-79.483492

2. Google geocode

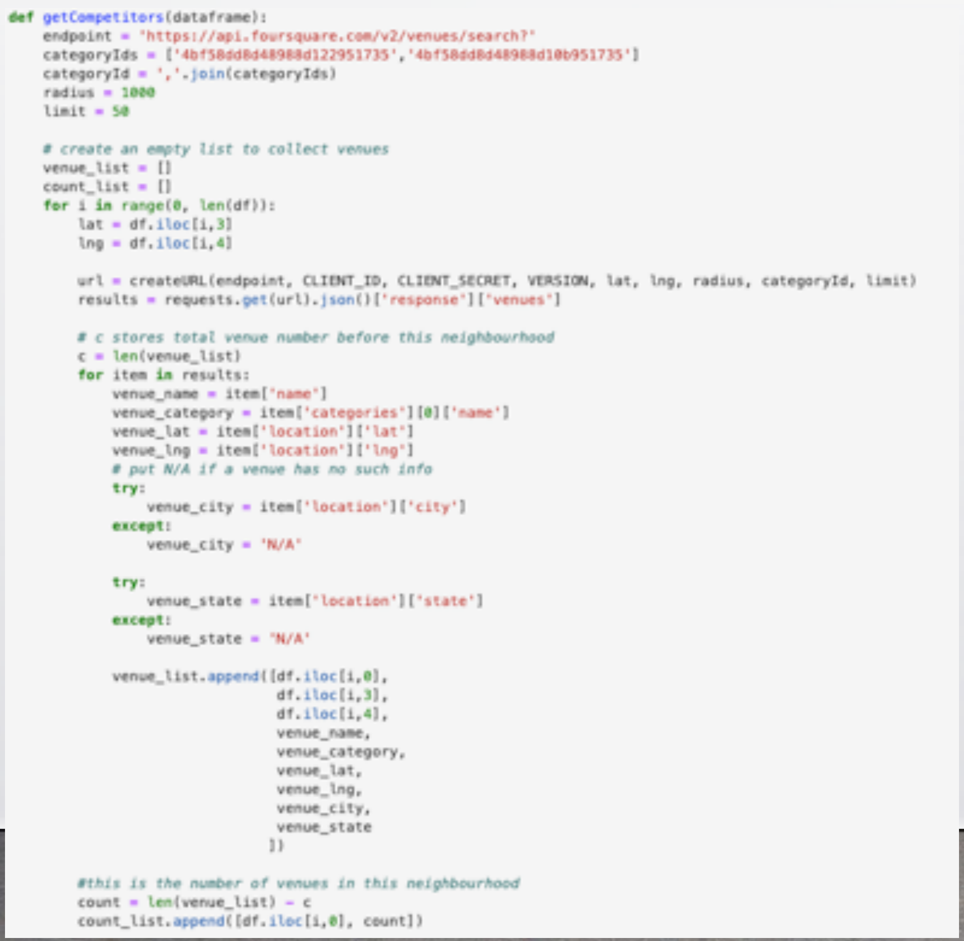
some of the neighbourhoods have no coordination, so I need to remove these neighborhoods from the dataframe with another function.



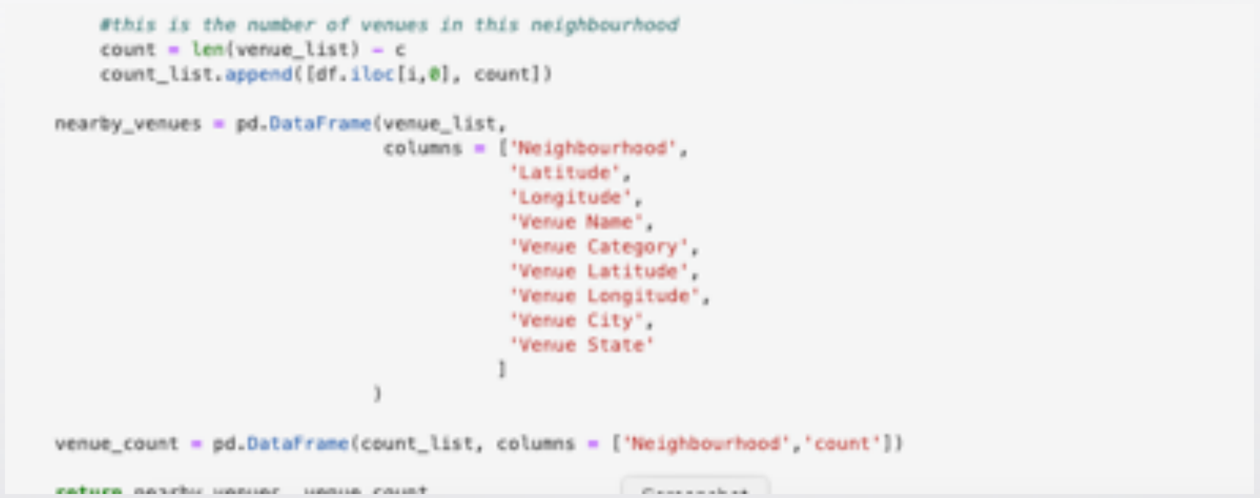
```python
# remove neighbourhoods with no coordination info.
def removeNeighbourhood(dataframe, add):
    delarry = []
    for name in add:
        for i in range (0,len(dataframe)):
            if name == dataframe['Name'].iloc[i]:
                delarry.append(i)

    # drop the rows
    dataframe.drop(dataframe.index[delarry], axis = 0, inplace = True)

    return dataframe
```

3. Foursquare

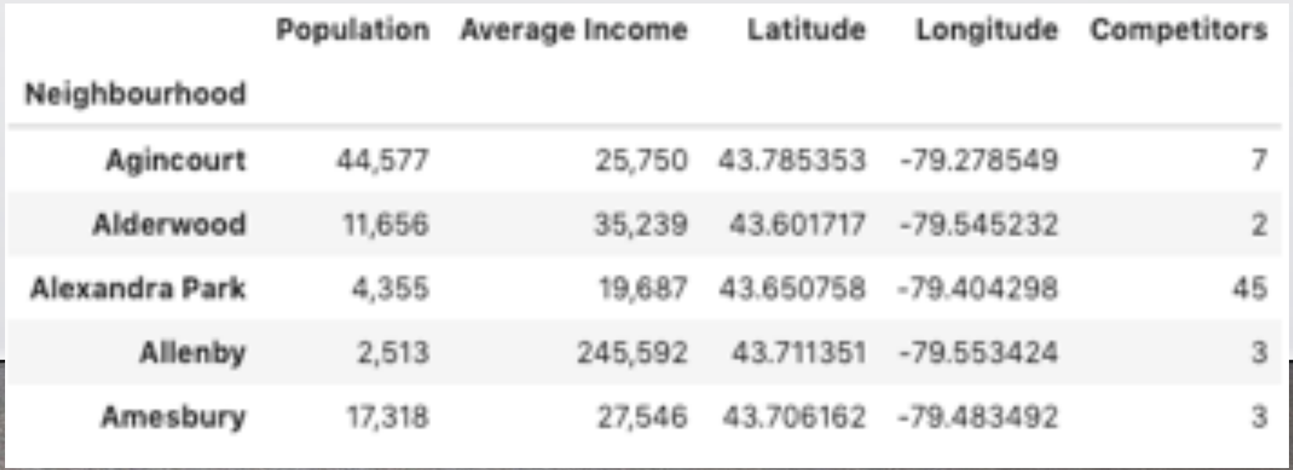
In order to find out how many competitors are there in each neighborhood, I used Foursquare API to request store information. A function was used to recursively request venue information from Foursquare.



```python
def getCompetitors(dataframe):
    endpoint = 'https://api.foursquare.com/v2/venues/search?'
    categoryIds = ['4bf58dd8d48988d122951735','4bf58dd8d48988d10b951735']
    categoryId = ','.join(categoryIds)
    radius = 1000
    limit = 50

    # create an empty list to collect venues
    venue_list = []
    count_list = []
    for i in range(0, len(df)):
        lat = df.iloc[i,3]
        lng = df.iloc[i,4]

        url = createURL(endpoint, CLIENT_ID, CLIENT_SECRET, VERSION, lat, lng, radius, categoryId, limit)
        results = requests.get(url).json()['response']['venues']

        # c stores total venue number before this neighbourhood
        c = len(venue_list)
        for item in results:
            venue_name = item['name']
            venue_category = item['categories'][0]['name']
            venue_lat = item['location']['lat']
            venue_lng = item['location']['lng']
            # put N/A if a venue has no such info
            try:
                venue_city = item['location']['city']
            except:
                venue_city = 'N/A'

            try:
                venue_state = item['location']['state']
            except:
                venue_state = 'N/A'

            venue_list.append([df.iloc[i,0],
                               df.iloc[i,3],
                               df.iloc[i,4],
                               venue_name,
                               venue_category,
                               venue_lat,
                               venue_lng,
                               venue_city,
                               venue_state
                              ])

        #this is the number of venues in this neighbourhood
        count = len(venue_list) - c
        count_list.append([df.iloc[i,0], count])
```



```python
        #this is the number of venues in this neighbourhood
        count = len(venue_list) - c
        count_list.append([df.iloc[i,0], count])

    nearby_venues = pd.DataFrame(venue_list,
                                 columns = ['Neighbourhood',
                                            'Latitude',
                                            'Longitude',
                                            'Venue Name',
                                            'Venue Category',
                                            'Venue Latitude',
                                            'Venue Longitude',
                                            'Venue City',
                                            'Venue State'
                                           ]
                                )

    venue_count = pd.DataFrame(count_list, columns = ['Neighbourhood','count'])

    return nearby_venues, venue_count
```



	Population	Average Income	Latitude	Longitude	Competitors
Neighbourhood					
Agincourt	44,577	25,750	43.785353	-79.278549	7
Alderwood	11,656	35,239	43.601717	-79.545232	2
Alexandra Park	4,355	19,687	43.650758	-79.404298	45
Allenby	2,513	245,592	43.711351	-79.553424	3
Amesbury	17,318	27,546	43.706162	-79.483492	3

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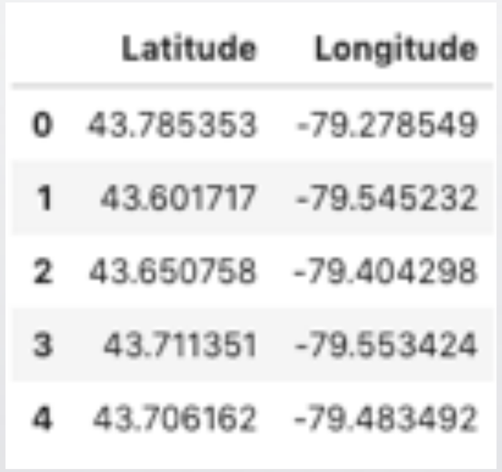

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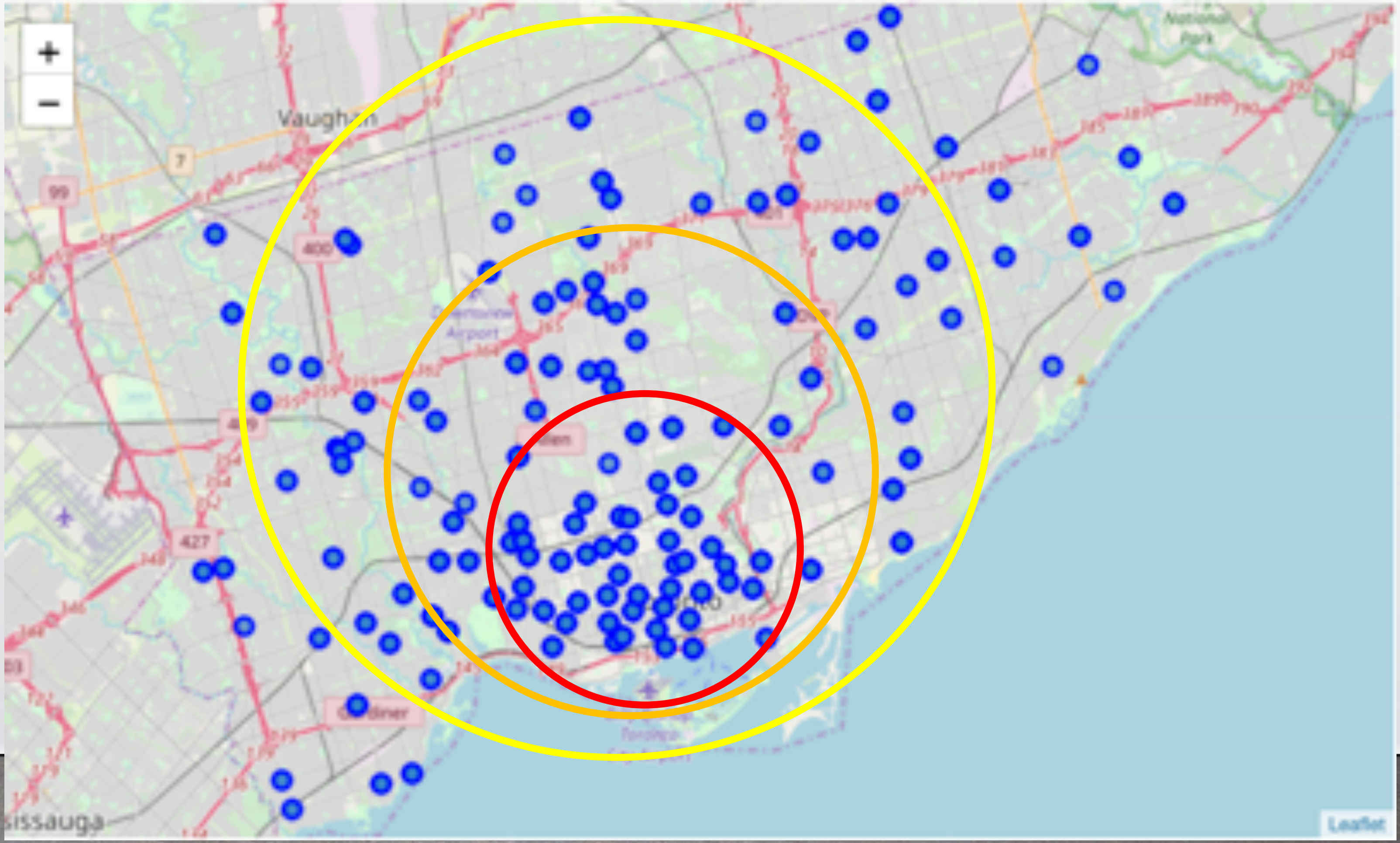
Data visualization

Use folium to pin the venues on the map of Toronto City

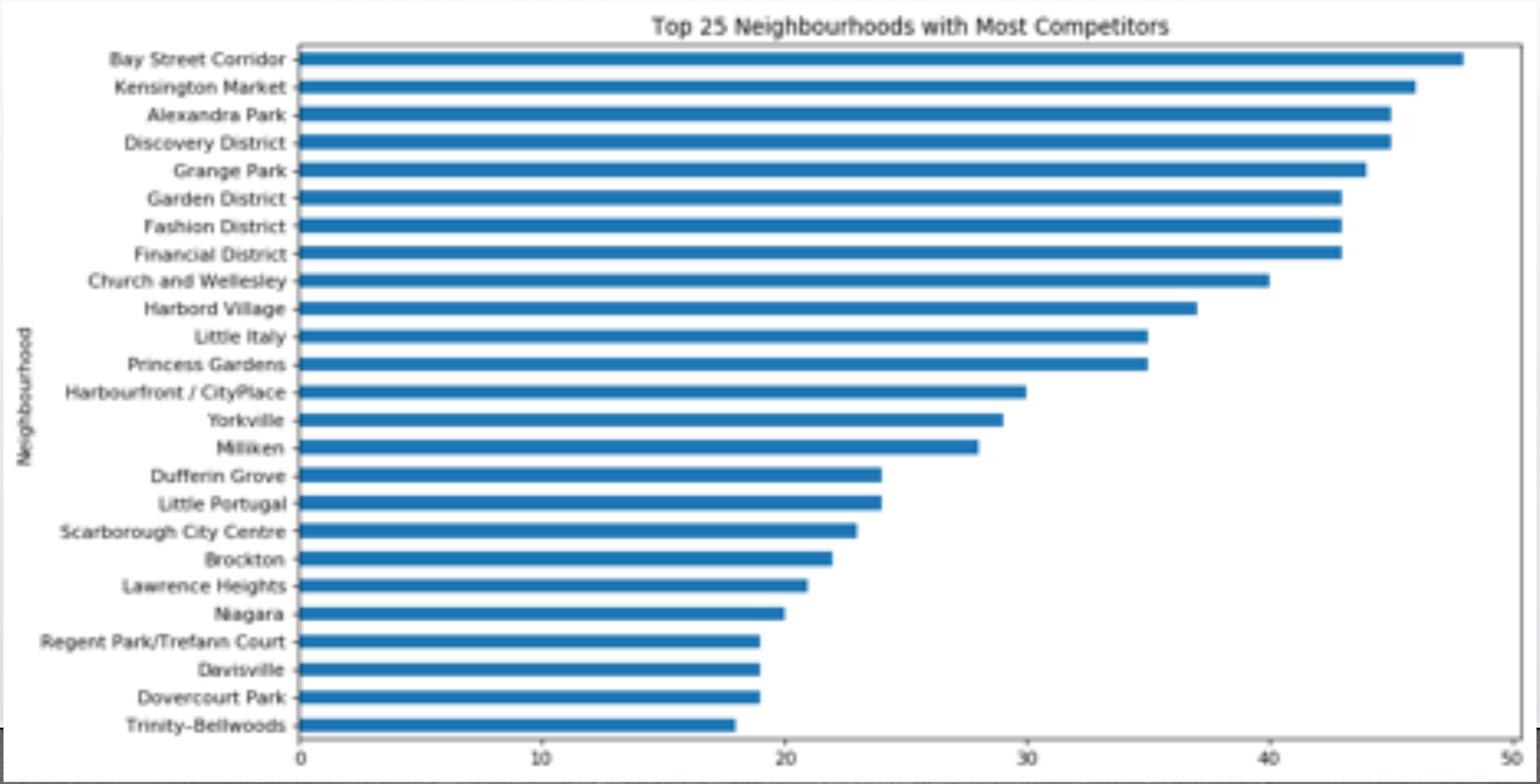
- in the downtown area stores are more densely allocated
- more people and better business environment
- competition is more intense here.



Top 25 neighborhoods with most competitors

As one can see from the top 25 neighborhoods with most video game stores, there are most stores in Bay Street corridor, Kensington Market, Alexandra Park and Discovery District, but the average income of these neighborhoods are not outstanding, therefore it may not be a good idea to open another store in these neighborhoods.

Top 25 neighborhoods with most competitors



Top 25 neighborhoods with most population

From the bar chart of most population, we can see that Old East York is most densely populated. Here if we assume that the composition of video game players is evenly distributed among all Toronto city, then higher population could be an indicator of more potential customers, although we still need to check their consumption strength with other indicators such as income level, average age and land rents.

Top 25 neighborhoods with most population

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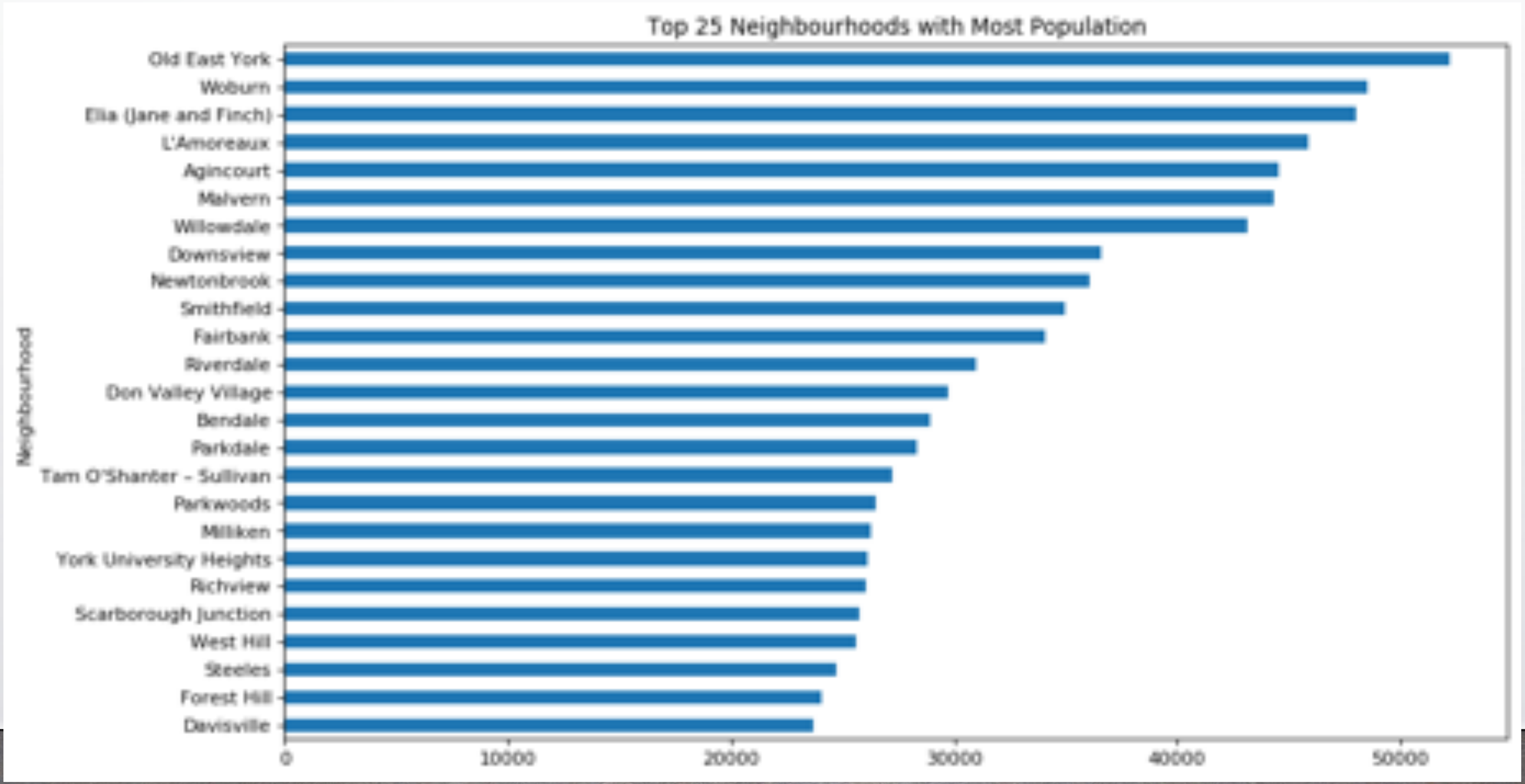

Top 25 neighborhoods with most average income

From the bar chart of most average income, it seems that people in Bridle Path, Allenby, and Hoggs Hollow are wat more better off than the rest Toronto city. This typically indicates that people in these neighborhoods are more budget-free and they tend to spend more money for the leisure purpose since they have loose budgets.

Top 25 neighborhoods with most average income

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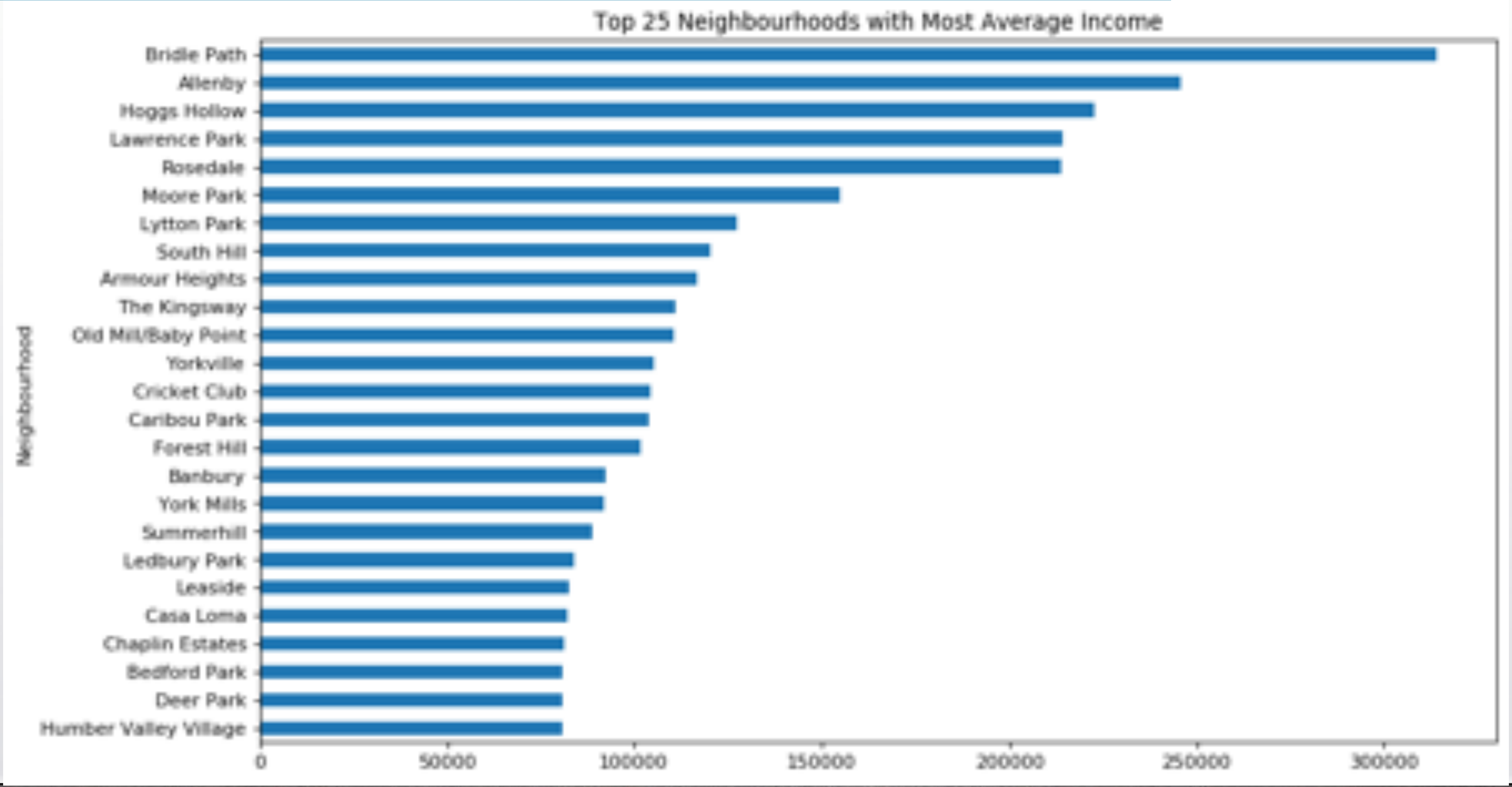

Conclusion

Making a decision is never easy, but it could be more accurate and less ‘random’ with the aid of reliable data.

For investors who want to open a Gamestop store in Toronto City, they need to consider the competition with other brands and small stores, they also need to take the income level and population of local people.

It is also important to keep in mind that these data and information are only for reference, since they only cover one particular year and come from one source. For the purpose of study and exercise the use of data science tools we have also made several assumptions to minimize and simplify the problem that was supposed to be very complicated. Thus one may never simply make decision depend on these results, as sometime unforeseeable deviation from reality could lead to fatal outcomes.

Acknowledgement

My project benefited from these works and tools:

- https://towardsdatascience.com/tuning-in-to-nycs-music-neighborhoods-efb7ae77a4cd¶
- https://developer.foursquare.com/docs/resources/categories
- https://en.wikipedia.org/wiki/Demographics_of_Toronto_neighbourhoods