Business Plan for Opening a New Club in Toronto

I am a data analyst working on research, data collection, collation and analysis, problem solution scenario development, etc. I have a project on business settlement in Toronto, collecting and analyzing data and coming up with recommendations on the problem defined.

1. Problem statement

The owner of popular clubs all over Europe is aiming at opening new branches in other continents, particularly in Toronto, Canada. I am asked to make an analysis and tell him where would it be best to open the clubs. I am also asked to be as specific as possible and name not only boroughs but also neighborhoods which might work the best for club opening. The club owner also mentioned, that the strategy of the company is to settle in areas where the competition is lower, but it's still accessible from more overloaded parts of the city.

2. Research summary

I am starting with the analysis of the problem. Clubs are mainly popular with the youth. Thus I am making a small research on neighborhoods/boroughs of Toronto which have the highest concentration of young people. A number of articles state, that most of the top neighborhoods (such as Yonge and Eglinton, Distillery District, Liberty Village, etc.) for the youth are located in East York. An example of such articles is the following: https://www.torontorentals.com/blog/toronto-neighbourhoods-for-young-professionals.

But as my client mentioned strategy-wise they are aiming at less loaded parts of the city, thus the nest step was to find the borough with lower competition on clubs but at the same time accessible from East-York and surroundings. It was obvious from the research that a potential borough would be Scarborough, which is just 20-minute drive away from East York.

3. Data

Having researched the problem and brought up specifications needed for the analysis, we come to the point of the data. Initially having the location of Toronto, we narrowed it up to Scarborough based on the research. Thus at this point we need to come up with the specific locations (namely neighborhoods) in Scarborough, Toronto where opening a club would be more efficient. And as clubs are mostly visited by young people we need to discover neighborhoods with active youth.

For that we will be concentrated on exploring the most common venues in different neighborhoods of Toronto. Thus we need the following steps of data collection, collation and analysis:

1. All neighborhoods in Toronto with their longitudes and latitudes. We have data on the coordinates of Postal Codes, but as we will need to make the research on the neighborhoods and boroughs, we are to create the necessary database. Thus we will:

a. First the list of the boroughs, neighborhoods and their Postal Codes will be extracted from the following page: https://en.wikipedia.org/wiki/List_of_postal_codes_of_Canada:_M
b. The data will be collated with the geospatial coordinates of the Postal Codes.

2. Based on the database, we will collect data on most common venues with the help of the Foursquare location data.
3. Finally we will use clustering to understand the best neighborhoods of Scarborough for opening a club.

3.1 Data collection and collation

As mentioned in the section above, for the analysis we need to have a database on each of the Toronto neighborhoods with their longitudes and latitudes. We have a database on the coordinates of different neighborhoods, but the thing is that they are mentioned with the postal codes only.

[49]:

	PostalCode	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
5	M1J	43.744734	-79.239476
6	M1K	43.727929	-79.262029
7	M1L	43.711112	-79.284577
8	M1M	43.716316	-79.239476
9	M1N	43.692657	-79.264848
10	M1P	43.757410	-79.273304
11	M1R	43.750072	-79.295849
12	M1S	43.794200	-79.262029
13	M1T	43.781638	-79.304302
14	M1V	43.815252	-79.284577

Thus, we are going to need to add to this data corresponding information on neighborhoods and boroughs. On the Wikipedia page (https://en.wikipedia.org/wiki/List_of_postal_codes_of_Canada:_M) we get a list of all the boroughs and neighborhoods of Toronto, which also have postal codes mentioned. We are going to use the postal codes as references for data collation of two different datasets.

Both databases need to be cleaned and prepared. We start from the wikipedia list.

```
#reading data from the newly created file
dtable=pd.read_csv('list.csv')
#renaming the colomns
dtable=dtable.rename(columns={"Postcode": "PostalCode","Borough": "Borough","Neighbourhood\n": "Neighborhood"})
#removing '\n's from the Neighborhood column values
dtable['Neighborhood'] = dtable['Neighborhood'].str[:-1]
#Filtering 'Not assigned' Boroughs out
dtable=dtable[dtable.Borough != 'Not assigned']
#grouping the values of Neighborhood by PostalCode and setting ',' as a separator
dtable = dtable.groupby(['PostalCode','Borough']).agg(lambda x: ", ".join(x))
#reseting the indexes
dtable.reset_index(level=['PostalCode','Borough'], inplace=True)
#Filling the 'Not assigned' Neighborhood cells with the corresponding values of Borough
dtable.loc[dtable['Neighborhood'] =='Not assigned', 'Neighborhood'] = dtable['Borough']
#cheching the shape
dtable.shape
```

```
(103, 3)
```


The first step will be removing the rows with boroughs valued as “Not assigned”. It is important for us to work with neighbors at Scarborough borough only, thus missing information about the borough makes the data on the specific postal code useless, or even harmful for the analysis.

Secondly, we see that we have repeating postal codes due to the fact that different boroughs refer to the same postal code. Thus we will make sure all the relevant data is grouped by postal codes and the neighborhoods of the later are attached to each other.

And lastly, we also notice a “Not assigned” value in the neighborhood feature. Here we will make sure that all such cases get the value of the corresponding borough.

So now we have a proper database with all postal codes, neighborhoods and boroughs of Toronto.

	PostalCode	Borough	Neighborhood
0	M1B	Scarborough	Rouge, Malvern
1	M1C	Scarborough	Highland Creek, Rouge Hill, Port Union
2	M1E	Scarborough	Guildwood, Morningside, West Hill
3	M1G	Scarborough	Woburn
4	M1H	Scarborough	Cedarbrae
5	M1J	Scarborough	Scarborough Village
6	M1K	Scarborough	East Birchmount Park, Ionview, Kennedy Park
7	M1L	Scarborough	Clairlea, Golden Mile, Oakridge
8	M1M	Scarborough	Cliffcrest, Cliffside, Scarborough Village West
9	M1N	Scarborough	Birch Cliff, Cliffside West

The second dataset also needs to be worked on.

Although it seems from the first sight that it looks quite good, the number of observations is also matching the first dataset, we notice, that the names of our referral feature, namely postal codes, differs from the was it is mentioned in the first dataset. Thus, we rename is to exactly the way it is named in the later.

```
[48]: #reading the file into a df
      df_geo=pd.read_csv('http://cocl.us/Geospatial_data')
      #changing the column name on the one in the inital table
      df_geo=df_geo.rename(columns={"Postal Code": "PostalCode"})
      #merging two tables with respect to their Postal Codes
      dtable_geo= pd.merge(dtable, df_geo, on='PostalCode')
      dtable_geo.shape
```

```
[48]: (103, 5)
```

Afterwards we make the last step and merge the two datasets and receive the final one, which includes 103 observations with 5 features each.

```
[15]: dtable_geo.head(10)
```

[15]:

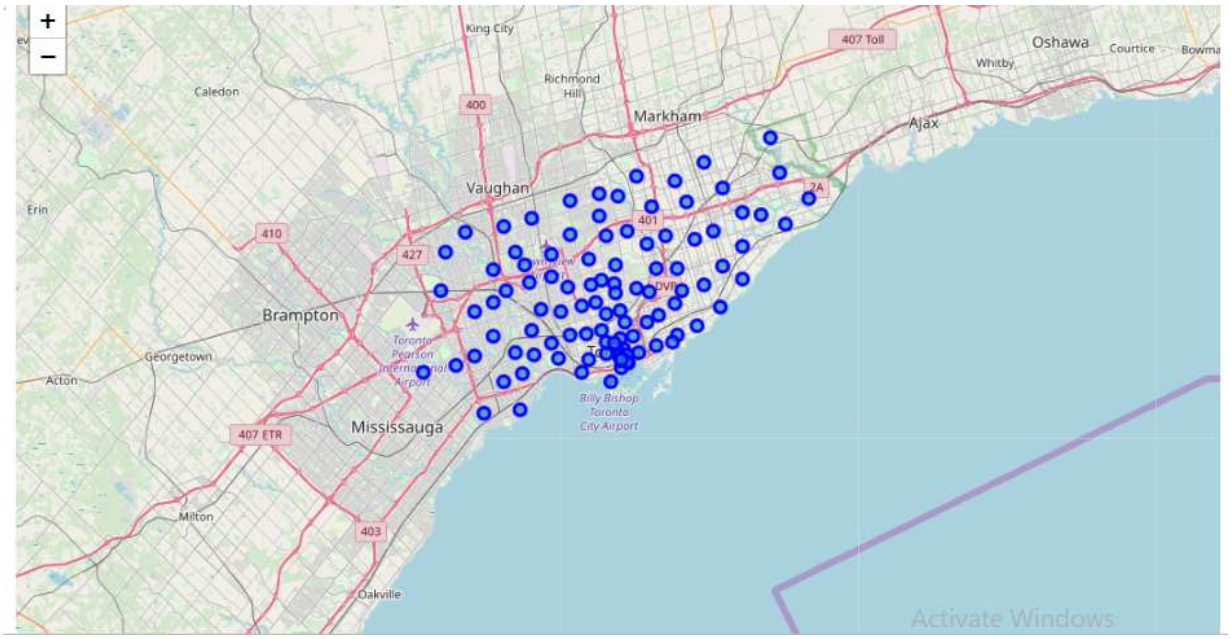
	PostalCode	Borough	Neighborhood	Latitude	Longitude
0	M1B	Scarborough	Rouge, Malvern	43.806686	-79.194353
1	M1C	Scarborough	Highland Creek, Rouge Hill, Port Union	43.784535	-79.160497
2	M1E	Scarborough	Guildwood, Morningside, West Hill	43.763573	-79.188711
3	M1G	Scarborough	Woburn	43.770992	-79.216917
4	M1H	Scarborough	Cedarbrae	43.773136	-79.239476
5	M1J	Scarborough	Scarborough Village	43.744734	-79.239476
6	M1K	Scarborough	East Birchmount Park, Ionview, Kennedy Park	43.727929	-79.262029
7	M1L	Scarborough	Clairlea, Golden Mile, Oakridge	43.711112	-79.284577
8	M1M	Scarborough	Cliffcrest, Cliffside, Scarborough Village West	43.716316	-79.239476
9	M1N	Scarborough	Birch Cliff, Cliffside West	43.692657	-79.264848

Finally, we are importing from the Foursquare database all relevant data on venues in the surroundings of each of the neighborhoods. We are taking top 100 venues only in the radius of 500 meters.

Neighborhood	Neighborhood Latitude	Neighborhood Longitude	Venue	Venue Latitude	Venue Longitude	Venue Category
Agincourt	4	4	4	4	4	4
Agincourt North, L'Amoreaux East, Milliken, Steeles East	3	3	3	3	3	3
Birch Cliff, Cliffside West	4	4	4	4	4	4
Cedarbrae	8	8	8	8	8	8
Clairlea, Golden Mile, Oakridge	10	10	10	10	10	10
Clarks Corners, Sullivan, Tam O'Shanter	10	10	10	10	10	10
Cliffcrest, Cliffside, Scarborough Village West	3	3	3	3	3	3
Dorset Park, Scarborough Town Centre, Wexford Heights	6	6	6	6	6	6
East Birchmount Park, Ionview, Kennedy Park	4	4	4	4	4	4
Guildwood, Morningside, West Hill	9	9	9	9	9	9
Highland Creek, Rouge Hill, Port Union	2	2	2	2	2	2
L'Amoreaux West	12	12	12	12	12	12
Maryvale, Wexford	7	7	7	7	7	7
Rouge, Malvern	2	2	2	2	2	2
Scarborough Village	1	1	1	1	1	1
Woburn	4	4	4	4	4	4

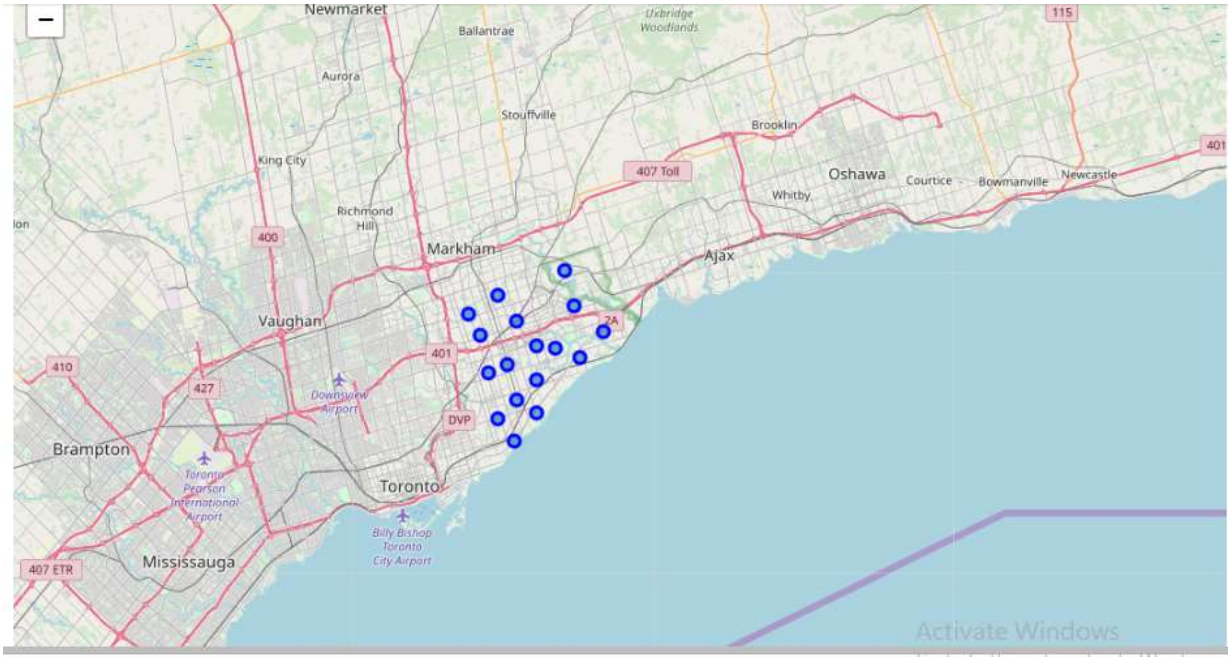
4. Methodology

We are starting with exploratory data analysis. To have the overall image of what we are working with we first are mapping it all down.



The map shows all the neighborhoods in Toronto, Canada.

As we want to concentrate of Scarborough only, we are leaving the neighborhoods in Scarborough only.



If we observe the top 100 venues located within 500meters of the neighborhoods mentioned in the map we will receive 89 venues referring to 53 different categories, such as restaurants, banks, bakeries, bars, etc.

32]:

Neighborhood	Neighborhood Latitude	Neighborhood Longitude	Venue	Venue Latitude	Venue Longitude	Venue Category
Agincourt	4	4	4	4	4	4
Agincourt North, L'Amoreaux East, Milliken, Steeles East	3	3	3	3	3	3
Birch Cliff, Cliffside West	4	4	4	4	4	4
Cedarbrae	8	8	8	8	8	8
Clairlea, Golden Mile, Oakridge	10	10	10	10	10	10
Clarks Corners, Sullivan, Tam O'Shanter	10	10	10	10	10	10
Cliffcrest, Cliffside, Scarborough Village West	3	3	3	3	3	3
Dorset Park, Scarborough Town Centre, Wexford Heights	6	6	6	6	6	6
East Birchmount Park, Ionview, Kennedy Park	4	4	4	4	4	4
Guildwood, Morningside, West Hill	9	9	9	9	9	9
Highland Creek, Rouge Hill, Port Union	2	2	2	2	2	2
L'Amoreaux West	12	12	12	12	12	12
Maryvale, Wexford	7	7	7	7	7	7
Rouge, Malvern	2	2	2	2	2	2
Scarborough Village	1	1	1	1	1	1
Woburn	4	4	4	4	4	4

19]:

```
#now let's see how many unique ones are here
print('There are {} uniques categories.'.format(len(scarborough_venues['Venue Category'].unique())))
```

```
There are 53 uniques categories.
```

What we want to do is to understand which are the most popular venues in each of the neighborhoods. For example, for Agincourt we see that Lounge, Breakfast Spot, Sandwich Place and Chinese Restaurant are the most popular venue types/categories, which are all equally popular (have same occurrence frequencies).

```
----Agincourt----
                venue  freq
0               Lounge  0.25
1      Breakfast Spot  0.25
2      Sandwich Place  0.25
3  Chinese Restaurant  0.25
4  American Restaurant  0.00
```

Playing with the viewing format a little we can observe the most common vanues for each of the neighborhoods in a common table.

	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
0	Agincourt	Lounge	Sandwich Place	Breakfast Spot	Chinese Restaurant	Vietnamese Restaurant	Coffee Shop	General Entertainment	Fried Chicken Joint
1	Agincourt North, L'Amoreaux East, Milliken, St...	Park	Asian Restaurant	Playground	Vietnamese Restaurant	General Entertainment	Fried Chicken Joint	Fast Food Restaurant	Electronics Store
2	Birch Cliff, Cliffside West	General Entertainment	Skating Rink	Café	College Stadium	Vietnamese Restaurant	Coffee Shop	Grocery Store	Fried Chicken Joint
3	Cedarbrae	Caribbean Restaurant	Thai Restaurant	Athletics & Sports	Fried Chicken Joint	Bakery	Bank	Lounge	Hakka Restaurant
4	Clairlea, Golden Mile, Oakridge	Bakery	Bus Line	Intersection	Fast Food Restaurant	Soccer Field	Bus Station	Metro Station	Park

Finally, we are ready to perform the clustering. We are using partitioning-based clustering K-means algorithm, which suggests the set number of mutually exclusive clusters. We are going to opt for 5 clusters, which are presented in the map below. Each color identifies a specific cluster, thus the neighborhoods of the same color are in the same cluster, namely are similar to each other and dissimilar to others.

Now let’s have a closer look at each of the clusters.

Cluster 1. Most common venues in the first cluster mainly include places for some family time,thus I'd call it 'Family'.

[48]:
```
scarborough_merged.loc[scarborough_merged['Cluster Labels'] == 0, scarborough_merged.columns[[2] + list(range(5, scarborough_merged.shape[1]
```

[48]:

	Neighborhood	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
5	Scarborough Village	0	Playground	Vietnamese Restaurant	Chinese Restaurant	Grocery Store	General Entertainment	Fried Chicken Joint	Fast Food Restaurant	Electronics Store
14	Agincourt North, L'Amoreaux East, Milliken, St...	0	Park	Asian Restaurant	Playground	Vietnamese Restaurant	General Entertainment	Fried Chicken Joint	Fast Food Restaurant	Electronics Store

Cluster 2. Here we see, that most of he venues, such as Coffee Shop, Discount Store, Restaurants, etc., are popular with the youth, hence I'll name it 'youth'.

]:
```
scarborough_merged.loc[scarborough_merged['Cluster Labels'] == 1, scarborough_merged.columns[[2] + list(range(5, scarborough_merged.shape[1]
```

]:

	Neighborhood	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
2	Guildwood, Morningside, West Hill	1	Intersection	Breakfast Spot	Mexican Restaurant	Tech Startup	Spa	Electronics Store	Medical Center	Pizza Place
3	Woburn	1	Coffee Shop	Korean Restaurant	Convenience Store	Vietnamese Restaurant	Grocery Store	General Entertainment	Fried Chicken Joint	Fast Food Restaurant
4	Cedarbrae	1	Caribbean Restaurant	Thai Restaurant	Athletics & Sports	Fried Chicken Joint	Bakery	Bank	Lounge	Hakka Restaurant
6	East Birchmount Park, Ionview, Kennedy Park	1	Discount Store	Department Store	Playground	Coffee Shop	Vietnamese Restaurant	Chinese Restaurant	Grocery Store	General Entertainment
7	Clairlea, Golden Mile, Oakridge	1	Bakery	Bus Line	Intersection	Fast Food Restaurant	Soccer Field	Bus Station	Metro Station	Park
9	Birch Cliff, Cliffside West	1	General Entertainment	Skating Rink	Café	College Stadium	Vietnamese Restaurant	Coffee Shop	Grocery Store	Fried Chicken Joint
10	Dorset Park, Scarborough Town Centre, Wexford ...	1	Indian Restaurant	Chinese Restaurant	Latin American Restaurant	Vietnamese Restaurant	Pet Store	Bakery	Grocery Store	General Entertainment
11	Maryvale, Wexford	1	Middle Eastern Restaurant	Auto Garage	Bakery	Shopping Mall	Sandwich Place	Breakfast Spot	Vietnamese Restaurant	College Stadium
12	Agincourt	1	Lounge	Sandwich Place	Breakfast Spot	Chinese Restaurant	Vietnamese Restaurant	Coffee Shop	General Entertainment	Fried Chicken Joint
13	Clarks Corners, Sullivan, Tam O'Shanter	1	Pizza Place	Noodle House	Thai Restaurant	Fried Chicken Joint	Fast Food Restaurant	Italian Restaurant	Bank	Chinese Restaurant
15	L'Amoreaux West	1	Chinese Restaurant	Fast Food Restaurant	Coffee Shop	Grocery Store	Pharmacy	Pizza Place	Breakfast Spot	American Restaurant

Cluster 3. Fast Food Restaurant, Print Shop, Asian Restaurants, Grocery Stores are liked budget-concious visiors, so it's gonna be named as 'Budget-concious'.

[50]:
```
scarborough_merged.loc[scarborough_merged['Cluster Labels'] == 2, scarborough_merged.columns[[2] + list(range(5, scarborough_merged.shape[1]
```

[50]:

	Neighborhood	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
0	Rouge, Malvern	2	Fast Food Restaurant	Print Shop	Vietnamese Restaurant	Chinese Restaurant	Grocery Store	General Entertainment	Fried Chicken Joint	Electronics Store

Cluster 4. Bar,Construction & Landscaping, Restaurants, Coffee Shops,Grocery Stores are of main inerest to man, thus we have here the 'Man' cluster.

[51]:
```
scarborough_merged.loc[scarborough_merged['Cluster Labels'] == 3, scarborough_merged.columns[[2] + list(range(5, scarborough_merged.shape[1]
```

[51]:

	Neighborhood	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
1	Highland Creek, Rouge Hill, Port Union	3	Bar	Construction & Landscaping	Vietnamese Restaurant	Coffee Shop	Grocery Store	General Entertainment	Fried Chicken Joint	Fast Food Restaurant

Cluster 5. And the last cluster with 1st Most Common Venue as motel is named 'traveler'.

[52]:
```
scarborough_merged.loc[scarborough_merged['Cluster Labels'] == 4 , scarborough_merged.columns[[2] + list(range(5, scarborough_merged.shape[1
```

[52]:

	Neighborhood	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
8	Cliffcrest, Cliffside, Scarborough Village West	4	Motel	American Restaurant	Coffee Shop	Grocery Store	General Entertainment	Fried Chicken Joint	Fast Food Restaurant	Electronics Store

As we can see clusters differ depending on main customers/visitor of the most common venues of the cluster. Thus, the names of the clusters are based on the group of the main visitors.

5. Results

Now we have five main clusters as a final result. The most common venues of the neighborhoods in these cluster are Playgrounds, Parks, Restaurants And Grocery Stores. We can conclude that these cluster is mostly popular with families.

The most popular venues In the second cluster turned out to be General Entertainment, Café's, Coffee Shops, Fast Food Restaurants, Discount Stores, Skating Rink, etc. It is obvious, that here the target group are young professionals, students, etc. Thus, we have here the "Youth" cluster.

Fast Food Restaurant, Print Shop, Asian Restaurants, Grocery Stores were the most common venues for the third cluster, which are liked by budget-conscious visitors, so it is going to be named as 'Budget-conscious'.

The fourth cluster might be mainly popular with man, as we can conclude from Bars, Construction & Landscaping, Restaurants, Coffee Shops, Grocery Stores, which are of main interest to man, thus we have here the 'Man' cluster.

And the last fifth cluster is going to be called 'Traveler' due to Motel, General Entertainment, Coffee Shops being the most common venues.

6. Conclusion

Having gone through a long journey of data collection, collation, analysis and visualization, using K-means clustering algorithm and analyzing the results, we received five main groups of neighborhoods:

1. Family
2. Youth
3. Budget-conscious
4. Man
5. Traveler

Our task was to determine the neighbors where it would be most efficient to open a club. Our results make it clear, that the neighborhoods of the cluster “Youth” would be the perfect locations for clubs.

The analysis turned out really successful and hit all mentioned goals. On one hand these neighborhoods were indicating as common ones venues which are popular with the Youth (e.g. General Entertainment, Coffee Shops, Café’s, Discount Stores or Fast Food Restaurants), on the other hand at the same time no clubs were mentioned. Here we meet the strategic decision of the business owner to settle in places with max potential demand and minimal competition.

The map introduces in purple all the neighborhoods which are going to work the best for this case.

7. Future directions

In this work we have segmented our analysis to one borough only. It might be useful to also analyze the data for the whole Toronto area and see if the clusters look similar and the logic behind them can be related to the one noted here.

Another interesting point would be to make the same analysis within the chosen cluster only. This will give us more information about dissimilarities within the clusters and help to make more specific recommendations.