Neighborhood Segmentation & Clustering Project Report

Introduction

The primary objective of this project was to process and perform thorough analysis on data obtained from multiple sources. This will be done in order to make educated and data-driven conclusions on a specific aspect of the Greater Toronto Area.

The business problem chosen was to find the best location in the GTA to open a bicycle store based on a few specific criteria. The measures that would be observed to determine the desirability of a location are as follows; **the number of recorded bike thefts in a neighborhood, the number of already existing bike stores in a neighborhood, and the average price of bikes being stolen in a neighborhood.**

The reasoning for choosing the aforementioned criteria as the primary factors when selecting a location stems from our team's rationale, which is as follows; the *more* thefts in an area is better as people will require new bikes more often, the *lower* number of already existing stores is better as that would entail less business competition, and a *higher* average bike cost is better as it is an indication that people would be willing to pay a higher price when purchasing a new bicycle.

Explanation of Data and Sources

The sources being utilized to obtain the necessary data for this project comes from the **Foursquare API** and the **city of Toronto website**.

The Foursquare API would provide the necessary data regarding already existing bicycle stores. More specifically, the Foursquare 'Places' API returns location data in an easily accessible and highly scalable manner. This API provides thorough geolocation data, allowing users to draw rich details about venues within a range of locations. The API requires the creation of a developer account for use, which afterwards a user may access an endpoint to communicate with. The user passes numerous parameters to the endpoint in order to specify the data desired, such as coordinates, radius, venue category id, and so on.

The venue category id chosen to retrieve data from was **17119**. This venue id pertains to the **Retail > Sporting Goods Retail > Bicycle Store** category. The base latitude and longitude passed was near the center of the city of Toronto, with a 15000 meter radius. This radius would cover a majority of Toronto, whilst not crossing into the Mississauga, Vaughan, Markham, or Pickering regions. Shown below are images displaying the selection of a radius and the code used to make a request to the API endpoint.

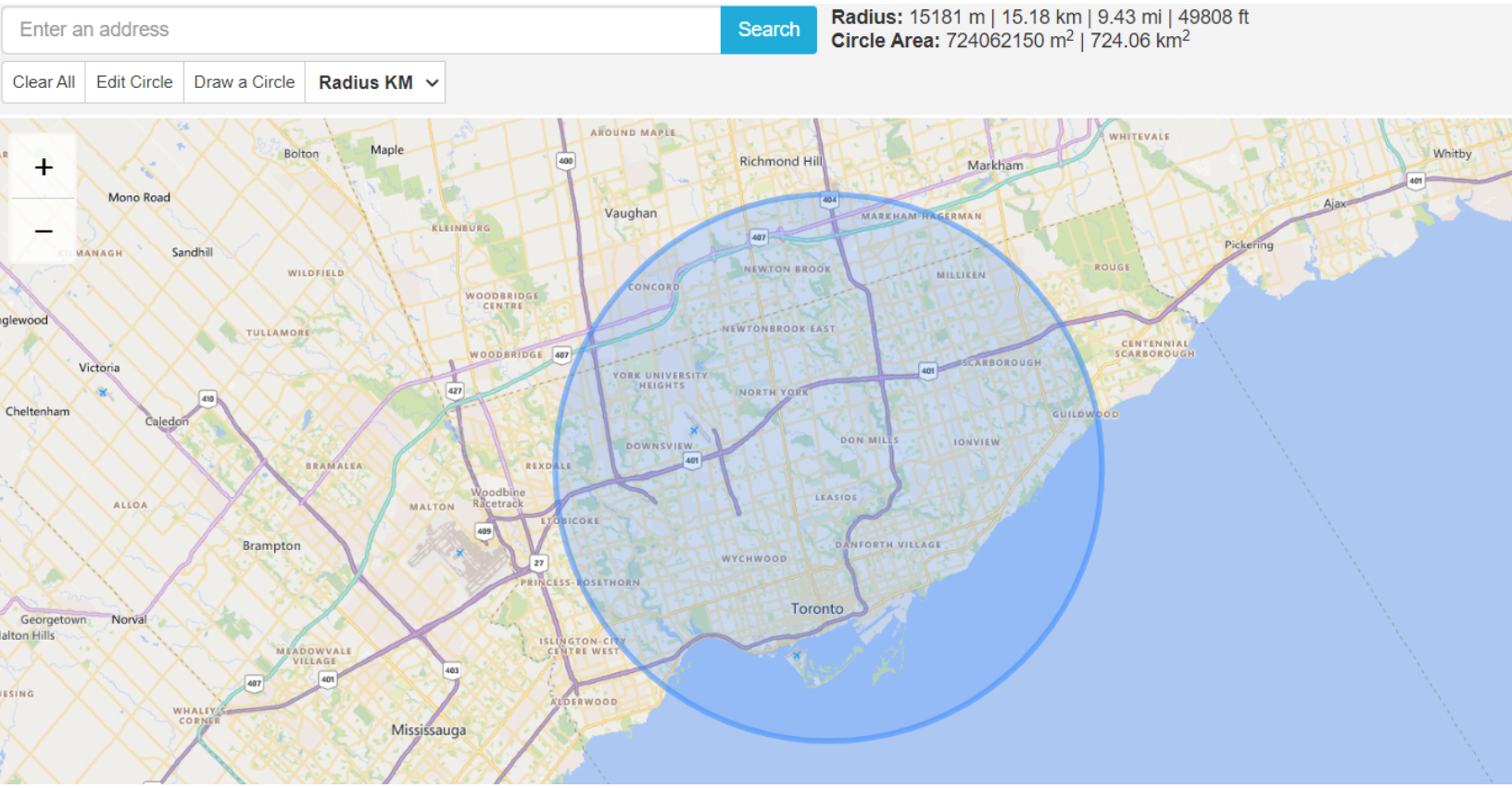


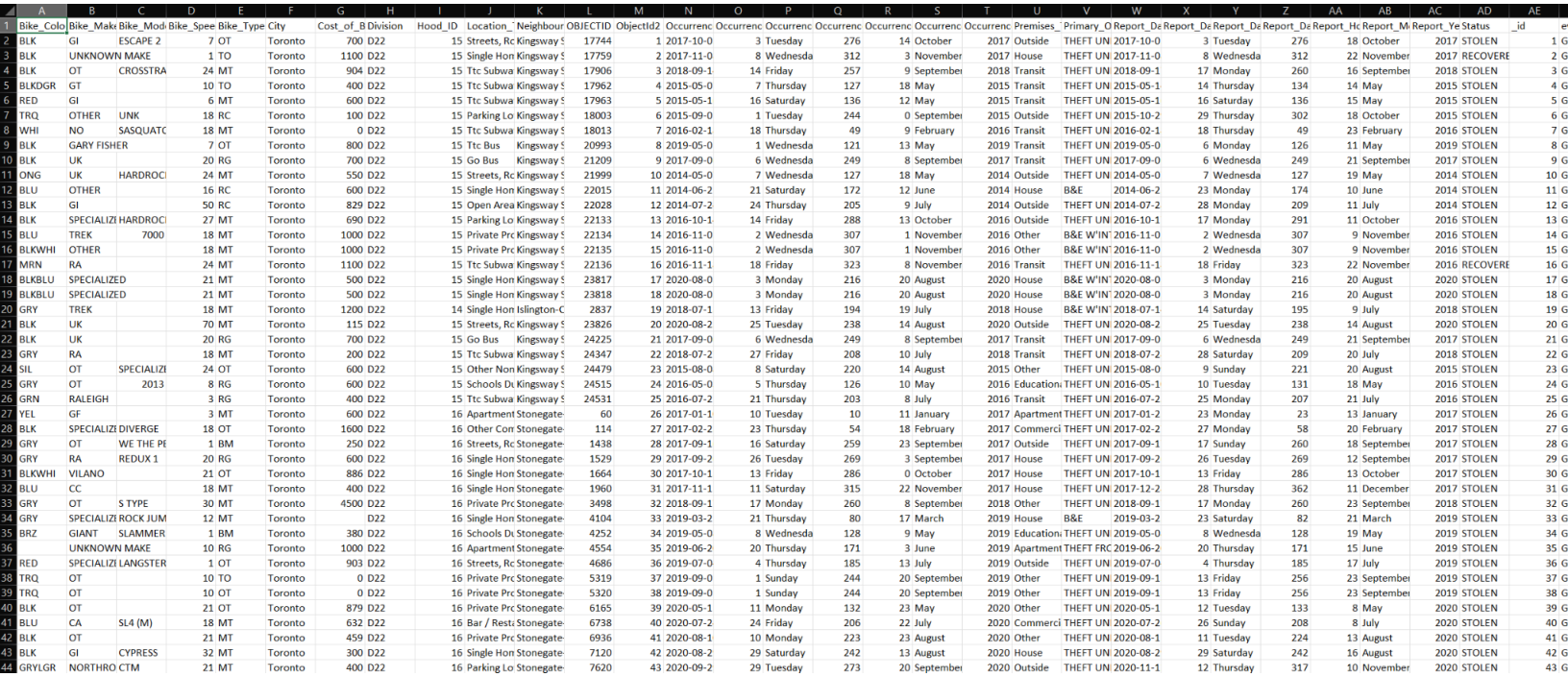
Figure 1

```python
from textwrap import indent
import requests
import json

url = "https://api.foursquare.com/v3/places/search?ll=43.69%2C-79.33&radius=15000&categories=17119&limit=50"

headers = {
    "Accept": "application/json",
    "Authorization": "fsq37aiTLwAGMwc0LBG0ob2Sb22qNqfeOzO1G7w624eeVfc="
}

response = requests.request("GET", url, headers=headers)

#print(response.text)
data = json.loads(response.text)


with open('FoursquareData.json', 'w', encoding='utf-8') as f:
    json.dump(data, f, ensure_ascii=False, indent=4)
```

Figure 2

Due to the limitations of the API endpoint, the maximum number of bicycle stores that could be returned was 50. As a result, this imposes a constraint on the data our team will be working with, as the number of points will be limited by the API call.

The city of Toronto website contains an **open data portal** which provides access to a large collection of data catalogs. The city of Toronto website provided the necessary data regarding bicycle theft, which included details such as the neighborhood the bike was stolen in, the cost of the bike, date information, and so on. This data was provided as a **CSV** file, titled **bicycle_thefts.csv** in the project folder.



	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y	Z	AA	AB	AC	AD	AE
1	Bike_Colo	Bike_Make	Bike_Mod	Bike_Spee	Bike_Type	City	Cost_of_B	Division	Hood_ID	Location_	Neighbour	OBJECTID	ObjectId2	Occurrenc	Occurrenc	Occurrenc	Occurrenc	Occurrenc	Occurrenc	Occurrenc	Premises_	Primary_O	Report_Da	Report_Da	Report_Da	Report_Da	Report_Ho	Report_Mo	Report_Ye	Status	_id	e
2	BLK	GI	ESCAPE 2	7	OT	Toronto	700	D22	15	Streets, Rc	Kingsway S	17744	1	2017-10-0	3	Tuesday	276	14	October	2017	Outside	THEFT UN	2017-10-0	3	Tuesday	276	18	October	2017	STOLEN	1	G
3	BLK	UNKNOWN	MAKE	1	TO	Toronto	1100	D22	15	Single Hon	Kingsway S	17759	2	2017-11-0	8	Wednesda	312	3	November	2017	House	THEFT UN	2017-11-0	8	Wednesda	312	22	November	2017	RECOVERE	2	G
4	BLK	OT	CROSSTRA	24	MT	Toronto	904	D22	15	Ttc Subwa	Kingsway S	17906	3	2018-09-1	14	Friday	257	9	September	2018	Transit	THEFT UN	2018-09-1	17	Monday	260	16	September	2018	STOLEN	3	G
5	BLKDGR	GT		10	TO	Toronto	400	D22	15	Ttc Subwa	Kingsway S	17962	4	2015-05-0	7	Thursday	127	18	May	2015	Transit	THEFT UN	2015-05-1	14	Thursday	134	14	May	2015	STOLEN	4	G
6	RED	GI		6	MT	Toronto	600	D22	15	Ttc Subwa	Kingsway S	17963	5	2015-05-1	16	Saturday	136	12	May	2015	Transit	THEFT UN	2015-05-1	16	Saturday	136	15	May	2015	STOLEN	5	G
7	TRQ	OTHER	UNK	18	RC	Toronto	100	D22	15	Parking Lo	Kingsway S	18003	6	2015-09-0	1	Tuesday	244	0	September	2015	Outside	THEFT UN	2015-10-2	29	Thursday	302	18	October	2015	STOLEN	6	G
8	WHI	NO	SASQUATC	18	MT	Toronto	0	D22	15	Ttc Subwa	Kingsway S	18013	7	2016-02-1	18	Thursday	49	9	February	2016	Transit	THEFT UN	2016-02-1	18	Thursday	49	23	February	2016	STOLEN	7	G
9	BLK	GARY FISHER		7	OT	Toronto	800	D22	15	Ttc Bus	Kingsway S	20993	8	2019-05-0	1	Wednesda	121	13	May	2019	Transit	THEFT UN	2019-05-0	6	Monday	126	11	May	2019	STOLEN	8	G
10	BLK	UK		20	RG	Toronto	700	D22	15	Go Bus	Kingsway S	21209	9	2017-09-0	6	Wednesda	249	8	September	2017	Transit	THEFT UN	2017-09-0	6	Wednesda	249	21	September	2017	STOLEN	9	G
11	ONG	UK	HARDROCI	24	MT	Toronto	550	D22	15	Streets, Rc	Kingsway S	21999	10	2014-05-0	7	Wednesda	127	18	May	2014	Outside	THEFT UN	2014-05-0	7	Wednesda	127	19	May	2014	STOLEN	10	G
12	BLU	OTHER		16	RC	Toronto	600	D22	15	Single Hon	Kingsway S	22015	11	2014-06-2	21	Saturday	172	12	June	2014	House	B&E	2014-06-2	23	Monday	174	10	June	2014	STOLEN	11	G
13	BLK	GI		50	RC	Toronto	829	D22	15	Open Area	Kingsway S	22028	12	2014-07-2	24	Thursday	205	9	July	2014	Outside	THEFT UN	2014-07-2	28	Monday	209	11	July	2014	STOLEN	12	G
14	BLK	SPECIALIZI	HARDROCI	27	MT	Toronto	690	D22	15	Parking Lo	Kingsway S	22133	13	2016-10-1	14	Friday	288	13	October	2016	Outside	THEFT UN	2016-10-1	17	Monday	291	11	October	2016	STOLEN	13	G
15	BLU	TREK	7000	18	MT	Toronto	1000	D22	15	Private Prc	Kingsway S	22134	14	2016-11-0	2	Wednesda	307	1	November	2016	Other	B&E W'IN	2016-11-0	2	Wednesda	307	9	November	2016	STOLEN	14	G
16	BLKWHI	OTHER		18	MT	Toronto	1000	D22	15	Private Prc	Kingsway S	22135	15	2016-11-0	2	Wednesda	307	1	November	2016	Other	B&E W'IN	2016-11-0	2	Wednesda	307	9	November	2016	STOLEN	15	G
17	MRN	RA		24	MT	Toronto	1100	D22	15	Ttc Subwa	Kingsway S	22136	16	2016-11-1	18	Friday	323	8	November	2016	Transit	THEFT UN	2016-11-1	18	Friday	323	22	November	2016	RECOVERE	16	G
18	BLKBLU	SPECIALIZED		21	MT	Toronto	500	D22	15	Single Hon	Kingsway S	23817	17	2020-08-0	3	Monday	216	20	August	2020	House	B&E W'IN	2020-08-0	3	Monday	216	20	August	2020	STOLEN	17	G
19	BLKBLU	SPECIALIZED		21	MT	Toronto	500	D22	15	Single Hon	Kingsway S	23818	18	2020-08-0	3	Monday	216	20	August	2020	House	B&E W'IN	2020-08-0	3	Monday	216	20	August	2020	STOLEN	18	G
20	GRY	TREK		18	MT	Toronto	1200	D22	14	Single Hon	Islington-C	2837	19	2018-07-1	13	Friday	194	19	July	2018	House	B&E W'IN	2018-07-1	14	Saturday	195	9	July	2018	STOLEN	19	G
21	BLK	UK		70	MT	Toronto	115	D22	15	Streets, Rc	Kingsway S	23826	20	2020-08-2	25	Tuesday	238	14	August	2020	Outside	THEFT UN	2020-08-2	25	Tuesday	238	14	August	2020	STOLEN	20	G
22	BLK	UK		20	RG	Toronto	700	D22	15	Go Bus	Kingsway S	24225	21	2017-09-0	6	Wednesda	249	8	September	2017	Transit	THEFT UN	2017-09-0	6	Wednesda	249	21	September	2017	STOLEN	21	G
23	GRY	RA		18	MT	Toronto	200	D22	15	Ttc Subwa	Kingsway S	24347	22	2018-07-2	27	Friday	208	10	July	2018	Transit	THEFT UN	2018-07-2	28	Saturday	209	20	July	2018	STOLEN	22	G
24	SIL	OT	SPECIALIZI	24	OT	Toronto	600	D22	15	Other Non	Kingsway S	24479	23	2015-08-0	8	Saturday	220	14	August	2015	Other	THEFT UN	2015-08-0	9	Sunday	221	20	August	2015	STOLEN	23	G
25	GRY	OT	2013	8	RG	Toronto	600	D22	15	Schools Dc	Kingsway S	24515	24	2016-05-0	5	Thursday	126	10	May	2016	Educationa	THEFT UN	2016-05-1	10	Tuesday	131	18	May	2016	STOLEN	24	G
26	GRN	RALEIGH		3	RG	Toronto	400	D22	15	Ttc Subwa	Kingsway S	24531	25	2016-07-2	21	Thursday	203	8	July	2016	Transit	THEFT UN	2016-07-2	25	Monday	207	21	July	2016	STOLEN	25	G
27	YEL	GF		3	MT	Toronto	600	D22	16	Apartment	Stonegate-	60	26	2017-01-1	10	Tuesday	10	11	January	2017	Apartment	THEFT UN	2017-01-2	23	Monday	23	13	January	2017	STOLEN	26	G
28	BLK	SPECIALIZI	DIVERGE	18	OT	Toronto	1600	D22	16	Other Con	Stonegate-	114	27	2017-02-2	23	Thursday	54	18	February	2017	Commerci	THEFT UN	2017-02-2	27	Monday	58	20	February	2017	STOLEN	27	G
29	GRY	OT	WE THE PE	1	BM	Toronto	250	D22	16	Streets, Rc	Stonegate-	1438	28	2017-09-1	16	Saturday	259	23	September	2017	Outside	THEFT UN	2017-09-1	17	Sunday	260	18	September	2017	STOLEN	28	G
30	GRY	RA	REDUX 1	20	RG	Toronto	600	D22	16	Single Hon	Stonegate-	1529	29	2017-09-2	26	Tuesday	269	3	September	2017	House	THEFT UN	2017-09-2	26	Tuesday	269	12	September	2017	STOLEN	29	G
31	BLKWHI	VILANO		21	OT	Toronto	886	D22	16	Single Hon	Stonegate-	1664	30	2017-10-1	13	Friday	286	0	October	2017	House	THEFT UN	2017-10-1	13	Friday	286	13	October	2017	STOLEN	30	G
32	BLU	CC		18	MT	Toronto	400	D22	16	Single Hon	Stonegate-	1960	31	2017-11-1	11	Saturday	315	22	November	2017	House	THEFT UN	2017-12-2	28	Thursday	362	11	December	2017	STOLEN	31	G
33	GRY	OT	S TYPE	30	MT	Toronto	4500	D22	16	Private Prc	Stonegate-	3498	32	2018-09-1	17	Monday	260	8	September	2018	Other	THEFT UN	2018-09-1	17	Monday	260	23	September	2018	STOLEN	32	G
34	GRY	SPECIALIZI	ROCK JUM	12	MT	Toronto		D22	16	Single Hon	Stonegate-	4104	33	2019-03-2	21	Thursday	80	17	March	2019	House	B&E	2019-03-2	23	Saturday	82	21	March	2019	STOLEN	33	G
35	BRZ	GIANT	SLAMMER	1	BM	Toronto	380	D22	16	Schools Dc	Stonegate-	4252	34	2019-05-0	8	Wednesda	128	9	May	2019	Educationa	THEFT UN	2019-05-0	8	Wednesda	128	19	May	2019	STOLEN	34	G
36		UNKNOWN	MAKE	10	RG	Toronto	1000	D22	16	Apartment	Stonegate-	4554	35	2019-06-2	20	Thursday	171	3	June	2019	Apartment	THEFT FRC	2019-06-2	20	Thursday	171	15	June	2019	STOLEN	35	G
37	RED	SPECIALIZI	LANGSTER	1	OT	Toronto	903	D22	16	Streets, Rc	Stonegate-	4686	36	2019-07-0	4	Thursday	185	13	July	2019	Outside	THEFT UN	2019-07-0	4	Thursday	185	17	July	2019	STOLEN	36	G
38	TRQ	OT		10	TO	Toronto	0	D22	16	Private Prc	Stonegate-	5319	37	2019-09-0	1	Sunday	244	20	September	2019	Other	THEFT UN	2019-09-1	13	Friday	256	23	September	2019	STOLEN	37	G
39	TRQ	OT		10	OT	Toronto	0	D22	16	Private Prc	Stonegate-	5320	38	2019-09-0	1	Sunday	244	20	September	2019	Other	THEFT UN	2019-09-1	13	Friday	256	23	September	2019	STOLEN	38	G
40	BLK	OT		21	OT	Toronto	879	D22	16	Private Prc	Stonegate-	6165	39	2020-05-1	11	Monday	132	23	May	2020	Other	THEFT UN	2020-05-1	12	Tuesday	133	8	May	2020	STOLEN	39	G
41	BLU	CA	SL4 (M)	18	MT	Toronto	632	D22	16	Bar / Rest	Stonegate-	6738	40	2020-07-2	24	Friday	206	22	July	2020	Commerci	THEFT UN	2020-07-2	26	Sunday	208	8	July	2020	STOLEN	40	G
42	BLK	OT		21	MT	Toronto	459	D22	16	Private Prc	Stonegate-	6936	41	2020-08-1	10	Monday	223	23	August	2020	Other	THEFT UN	2020-08-1	11	Tuesday	224	13	August	2020	STOLEN	41	G
43	BLK	GI	CYPRESS	32	MT	Toronto	300	D22	16	Single Hon	Stonegate-	7120	42	2020-08-2	29	Saturday	242	13	August	2020	House	THEFT UN	2020-08-2	29	Saturday	242	16	August	2020	STOLEN	42	G
44	GRYLGR	NORTHRO	CTM	21	MT	Toronto	400	D22	16	Parking Lo	Stonegate-	7620	43	2020-09-2	29	Tuesday	273	20	September	2020	Outside	THEFT UN	2020-11-1	12	Thursday	317	10	November	2020	STOLEN	43	G

Figure 3

Methodology and Process

After retrieving the data from the Foursquare api endpoint, the data was saved into a JSON file called **FoursquareData.json**. Each JSON object represents a venue and consists of various information about itself. In this case, each venue is a bicycle shop. Below is a sample JSON object from the file.


```
"fsq_id": "4bd5eae16798ef3b9d3a648d",
"categories": [
    {
        "id": 17119,
        "name": "Bicycle Store",
        "icon": {
            "prefix": "https://ss3.4sqi.net/img/categories_v2/shops/bikeshop_",
            "suffix": ".png"
        }
    }
],
"chains": [],
"distance": 2842,
"geocodes": {
```

```
    "main": {
        "latitude": 43.678605,
        "longitude": -79.298545
    },
    "roof": {
        "latitude": 43.678605,
        "longitude": -79.298545
    }
},
"location": {
    "address": "615 Kingston Rd",
    "country": "CA",
    "cross_street": "at Main St",
    "formatted_address": "615 Kingston Rd (at Main St), Toronto ON M4E 1R3",
    "locality": "Toronto",
    "neighborhood": [
        "East York"
    ],
    "postcode": "M4E 1R3",
    "region": "ON"
},
"name": "Cycle Solutions",
"related_places": {},
"timezone": "America/Toronto"
```


Figure 4

As seen above, each bicycle shop has an associated latitude and longitude, which will be used to obtain further neighborhood information about each location. Whilst each bicycle shop has a neighborhood name, they do not have an associated neighborhood id, which is essential to merge the shop data with the bicycle theft data by location. Opposed to doing this manually, our team decided to use already existing geojson data to help group bicycle shops into neighborhoods using their longitudes and latitudes.

Our team found a geojson file online, titled **Neighborhoods.json**, which already had the Greater Toronto Area partitioned into polygonal regions with defined geometry and coordinate data. Furthermore, this file also had ids associated with each geographical neighborhood, which is exactly what was required to group our bicycle shops into neighborhoods.

Below is a visual representation of Neighborhoods.json in its geojson form.

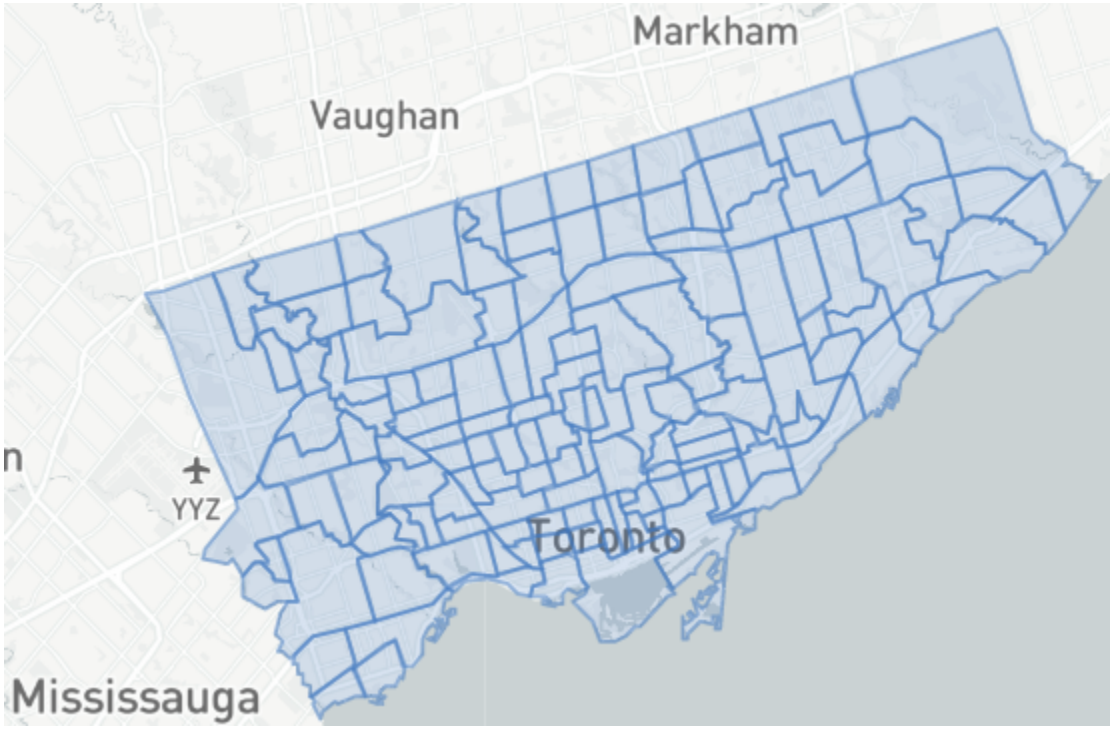


Figure 5

Leveraging the data provided by Neighborhoods.json, the coordinates of each bicycle shop were partitioned into neighborhoods. The process was performed in the **fqapi_to_csv.py** file as shown below.

Figure 6

```
import pandas as pd
import json
from shapely.geometry import shape, Point

bicycle_shop_coordinates_du = open("bicycle_shop_coordinates.csv", "w")

points_with_hood_id = []

data = json.load(open("FoursquareData.json", "r"))
for i in data["results"]:
    lat = i["geocodes"]["main"]["latitude"]
    lon = i["geocodes"]["main"]["longitude"]
    points_with_hood_id.append( { "point": Point(lon, lat), "hood_id": None, "lon": lon, "lat": lat } )

with open("Neighbourhoods.json", "r") as f:
    geojs = json.load(f)

for feature in geojs["features"]:
    polygon = shape(feature["geometry"])
    for point in points_with_hood_id:
        print(point["point"])
        if polygon.contains(point["point"]):
            point["hood_id"] = feature["properties"]["AREA_SHORT_CODE"]

for p in points_with_hood_id:
    bicycle_shop_coordinates_du.write(f"{p['lat']},{p['lon']},{p['hood_id']}")
    bicycle_shop_coordinates_du.write("\n")
```

After this partitioning took place, the resulting data was saved to a CSV titled **bicycle_shop_coordinates.csv**, which can be seen below.

	A	B	C
1	latitude	longtitude	hood_id
2	43.67861	-79.2985	63
3	43.65945	-79.4384	93
4	43.70011	-79.4552	108
5	43.67967	-79.3904	98
6	43.65921	-79.4393	93
7	43.66598	-79.408	95
8	43.6654	-79.4913	89
9	43.71248	-79.36	55
10	43.71636	-79.4001	99
11	43.77294	-79.2541	127
12	43.67908	-79.3434	69
13	43.66616	-79.3179	65
14	43.66646	-79.3426	70
15	43.66982	-79.3004	63
16	43.70914	-79.3627	55
17	43.65825	-79.352	70
18	43.65368	-79.3539	77
19	43.66065	-79.3706	73
20	43.65486	-79.3686	73
21	43.73541	-79.345	42
22	43.69995	-79.3972	100
23	43.71526	-79.3999	99
24	43.66051	-79.3999	79
25	43.66293	-79.4036	79
26	43.65559	-79.3988	78

Figure 7

The complete file consisted of 50 indexes, pertaining to the 50 bicycle shops retrieved from the Foursquare API. As shown, there are now neighborhood ids associated with each shop.

Now that all the necessary data had an associated neighborhood id, our team could then proceed to merge the data. All the merging and processing of the remaining data took place in the **data_process.py** file. As such, all the following screenshots were taken from that file until stated otherwise.

As one of the criteria for assessing the desirability of a neighborhood was the number of already existing bike stores, it was necessary to retrieve the number of stores already present in each neighborhood (this is why we required bike stores to have an associated neighborhood id). As stated before, the *lower* number of already existing stores is better as that would entail less business competition.

Shown below is the process of calculating the number of instances of an already existing bike store per neighborhood id.

```
from operator import index
import pandas as pd

df = pd.read_csv (r"bicycle_shop_coordinates.csv")

predata = {
    'hood_id': [],
    'number of bike shops': []
}

#Add stores to list while counting the number of instances a store appears in the same hood
hood_store_count = {}
for hood in df['hood_id']:
    if hood not in hood_store_count:
        hood_store_count[hood] = 1
    else:
        hood_store_count[hood] += 1

#Only keep unique instances of a hood
df = df.drop_duplicates(subset='hood_id')
df.reset_index(drop=True, inplace=True)

for key, value in hood_store_count.items():
  predata['hood_id'].append(key)
  predata['number of bike shops'].append(value)

df_revised = pd.DataFrame(predata)

#Add geodata to revised df
df_revised['latitude'] = df['latitude']
df_revised['longtitude'] = df['longtitude']
```

Figure 8

As numerous stores may have been in a single neighborhood, duplicate instances of a neighborhood id were removed by grouping them together, allowing the number of stores per neighborhood to be easily calculated. Grouping the stores into neighborhoods resulted in a reduction of 50 indexes in the data frame to 31, indicating that 19 of the 50 stores shared a common neighborhood id. After finding the number of existing bike stores per neighborhood, it was time to move onto the next criteria: the number of recorded bike thefts per neighborhood. As stated before, the *more* thefts in an area is better as people will require new bikes more often. Shown below is the process for obtaining the number of bike thefts per neighborhood id.

```
theft_data = pd.read_csv (r"bicycle_thefts.csv")
predata['bike_thefts'] = [0]*len(predata['hood_id'])

#Get number of bike thefts per hood
index= 0
for hood_id in theft_data['Hood_ID']:
    try:
        theft_data['Hood_ID'][index] = int(hood_id)
    except Exception:
        theft_data.drop(df.index[index])
        index += 1
        continue

    if int(hood_id) in predata['hood_id']:
        i = predata['hood_id'].index(int(hood_id))
        predata['bike_thefts'][i] += 1

df_revised['bike_thefts'] = predata['bike_thefts']
```

Figure 9

Upon obtaining the number of recorded bike thefts per neighborhood, the code for satisfying the final criteria was developed; the average price of a purchased bicycle per neighborhood. As stated before, a *higher* average bike cost is better as it is an indication that people would be willing to pay a higher price when purchasing a new bicycle.

Shown below is the process utilized to obtain the average price of a bicycle per neighborhood id.

```
#Clean the data
theft_data = theft_data[theft_data.Cost_of_Bike != 0]
theft_data = theft_data[theft_data.Cost_of_Bike != '']
theft_data = theft_data[theft_data.Hood_ID != 'NSA']

#Get average bike cost per hood
bike_costs = (theft_data.groupby(['Hood_ID', 'Cost_of_Bike'], as_index=False).mean().groupby('Hood_ID')['Cost_of_Bike'].mean()).to_frame().T

#Add bike costs to revised dataframe
avg_bike_cost = []
for hood_id in df_revised["hood_id"]:
    avg_bike_cost.append(list(bike_costs[str(hood_id)])[0])

df_revised["average_bicycle_cost"] = avg_bike_cost
predata['average_bicycle_cost'] = df_revised['average_bicycle_cost'].tolist()
```

Figure 10

As all of the required data was collected and merged into a single dataframe, a method of quantifying a neighborhood's desirability was necessary. A simple formula for the scoring metric was devised, as shown below.

$$SCORE_{desirability} = \frac{Number\ of\ thefts_{neighborhood\ n} \times Average\ Cost\ of\ Bicycle_{neighborhood\ n}}{Number\ of\ Already\ Existing\ Stores_{neighborhood\ n}}$$

The scoring metric created was a rough measure of a neighborhood's **monetary profitability**. Keeping this in mind, the devised scoring metric would have to be coherent to provide the highest scores to what is seen as the most profitable neighborhoods according to the established criteria. As the number of bike thefts and the average cost of a bicycle were seen as positive drivers, those factors were multiplied. As the number of already existing bicycle stores was seen as a negative driver, that was a dividing factor in the scoring metric.

Using the scoring metric above, a score was assigned to each neighborhood to signify its desirability with respect to each of the three criteria. These scores would be vital for plotting and analyzing the data collected. After assigning scores, each neighborhood id was also matched with its respective name retrieved from the bicycle_thefts.csv file. These names would be used for labels when visualizing the data. These scores were added to the finalized dataframe, and all the merged data was exported as a CSV to plot and map the results of the data processing, in a file titled **processed_data.csv**. The process for these steps are shown below.

Figure 11

```
predata['score'] = [0]*len(predata['hood_id'])
#Produce scores for each naighborhood
for i in range(0, len(predata['hood_id'])):
    score = predata['bike_thefts'][i]*predata['average_bicycle_cost'][i] / predata['number of bike shops'][i]
    predata['score'][i] = round(score ,2)

df_revised['score'] = predata['score']



#Obtain neighborhood name information
predata['neighborhood'] = []
hood_names = theft_data['NeighbourhoodName'].tolist()
hoodlist = theft_data['Hood_ID'].tolist()
for hood in predata['hood_id']:
    common_index = hoodlist.index(str(hood))
    predata['neighborhood'].append(hood_names[common_index])
df_revised['neighborhood'] = predata['neighborhood']

#Export to CSV
print(df_revised)
df_revised.to_csv("processed_data.csv")
```

Results

The results of the data processing and analysis will be represented in two formats. Contained within the **heatmap.py** file, the first will be a **heat map visualization** of the results to more easily signify the desirability of a specific neighborhood. The heat map will contain a marker indicating the location of a neighborhood, and the weight of each marker will be directly proportional to the score of a neighborhood. Furthermore, the heat map exhibits dynamic granularity, showing finer detail the more zoomed in it is. The following was used to develop the heat map and export it as an html, titled **heatmap.html**.

```
import pandas as pd
import folium
from folium.plugins import HeatMap, MarkerCluster

df = pd.read_csv (r"processed_data.csv")

#---------------------------------HEATMAP-------------------------------------#

map = folium.Map(location=[43.728136,-79.384666], zoom_start=11)
cluster = MarkerCluster().add_to(map)

coordinates = [list(items) for items in zip(df['latitude'], df['longtitude'])]

index = 0
for i in range(len(coordinates)):
    folium.Marker(coordinates[i], popup= f"""
        Neighborhood: {df['neighborhood'][index]}\n
        Hood ID: {df['hood_id'][index]}\n
        Score: {df['score'][index]}
        """).add_to(cluster)

    index += 1

max_score = df['score'].max()

lat = df['latitude']
long = df['longtitude']
weight = df['score']

data = []

for i in range(0, len(weight)):
    data.append([lat[i], long[i], weight[i]])

HeatMap(data).add_to(map)

map.save("heatmap.html")
```

Figure 12

The following is presented when viewing heatmap.html

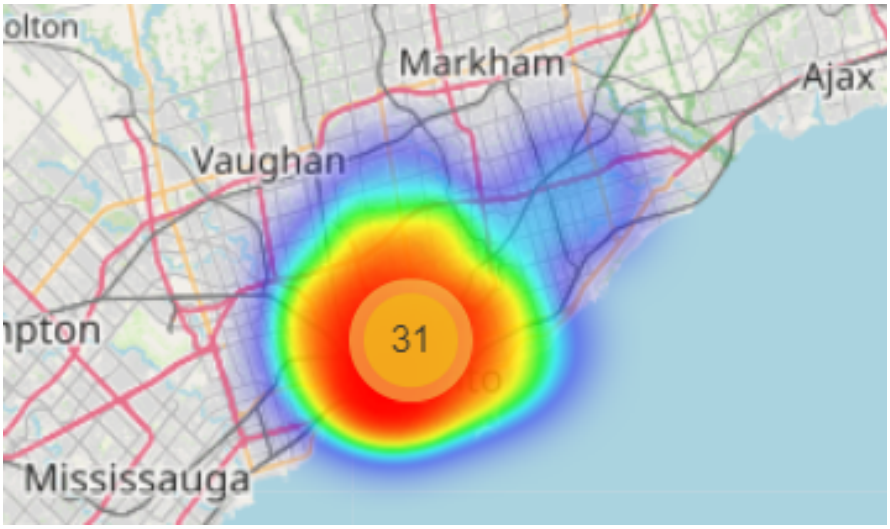


Figure 13

The number 31 in the above image represents the 31 neighborhoods being examined for desirability. Upon zooming in, the granularity of the heat map increases. The following images show the granularity of the heat map increasing every level zoomed in.

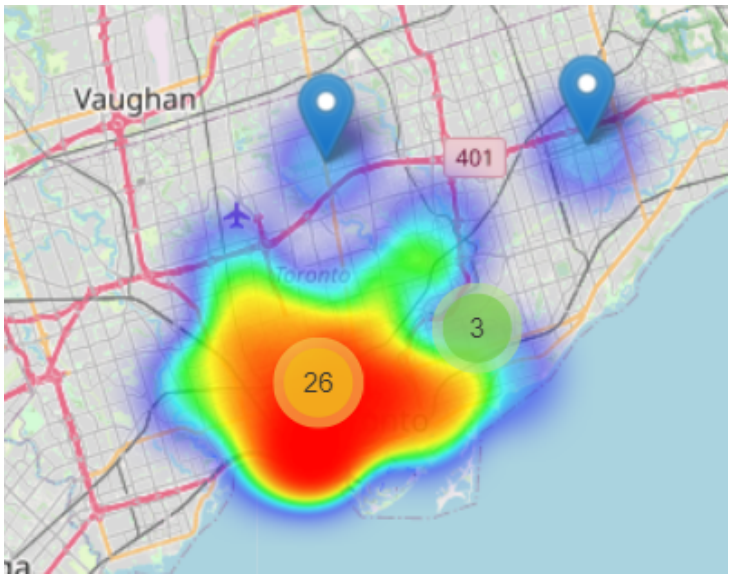


Figure 14

As shown above, every level zoomed in reveals more clusters of neighborhoods. The heat surrounding clusters of neighborhoods signifies the desirability of said cluster of neighborhoods based on the scores assigned to them. The higher the heat, the higher the score associated with those neighborhoods. As such, the most desirable neighborhoods will contain the most heat in the surrounding area.

Also evident from the image, zooming in results in some neighborhood markers being revealed as they are more distant from other clusters.

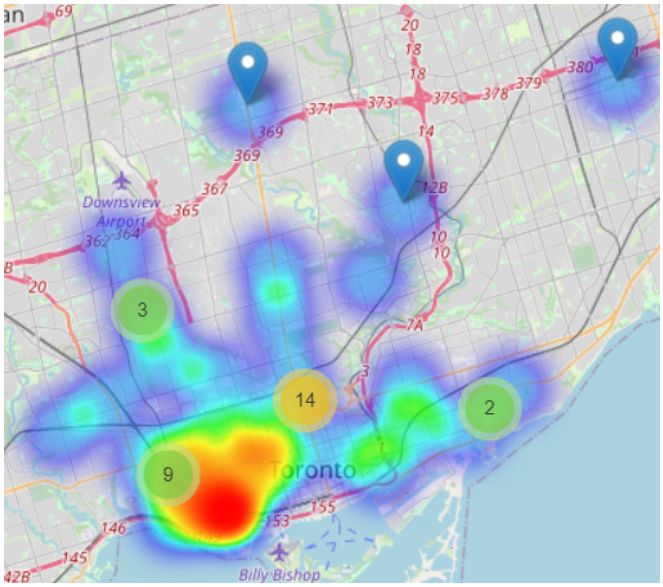


Figure 15

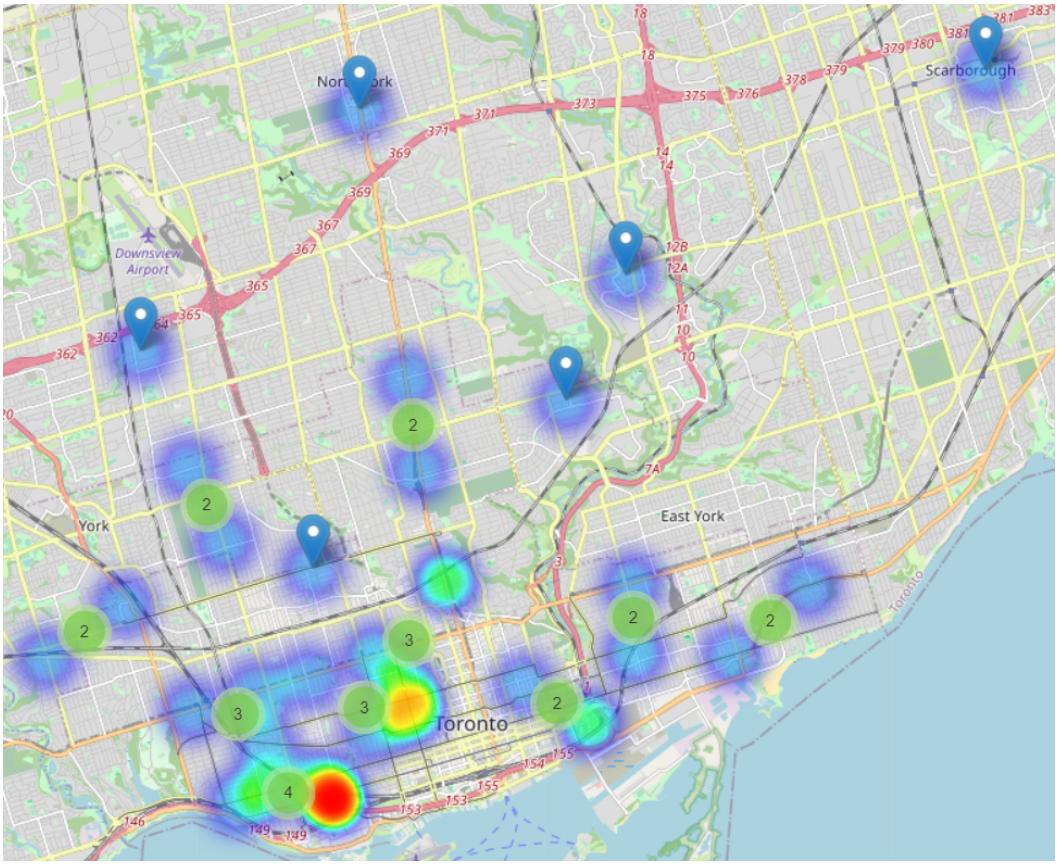


Figure 16

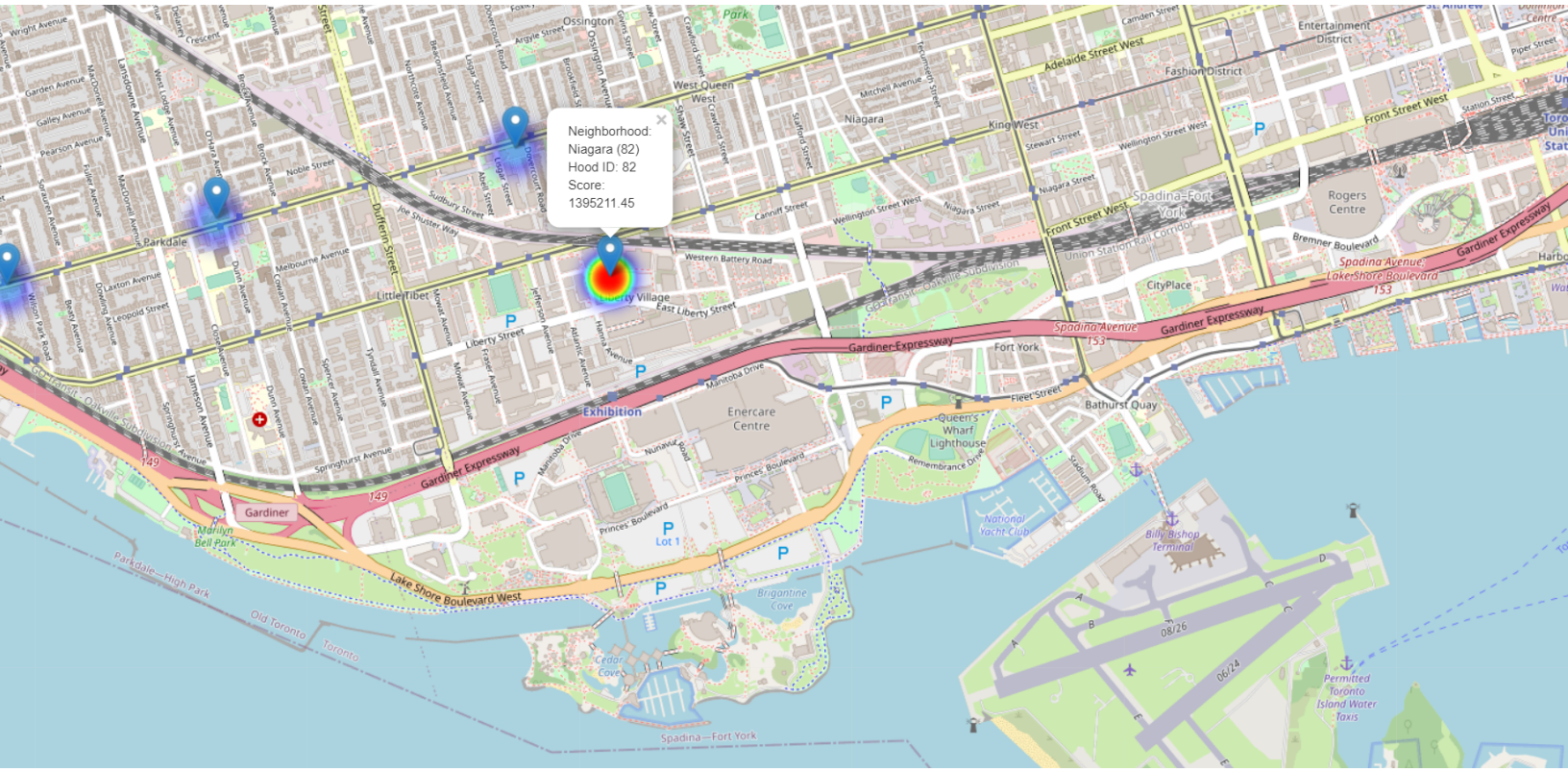


Figure 17

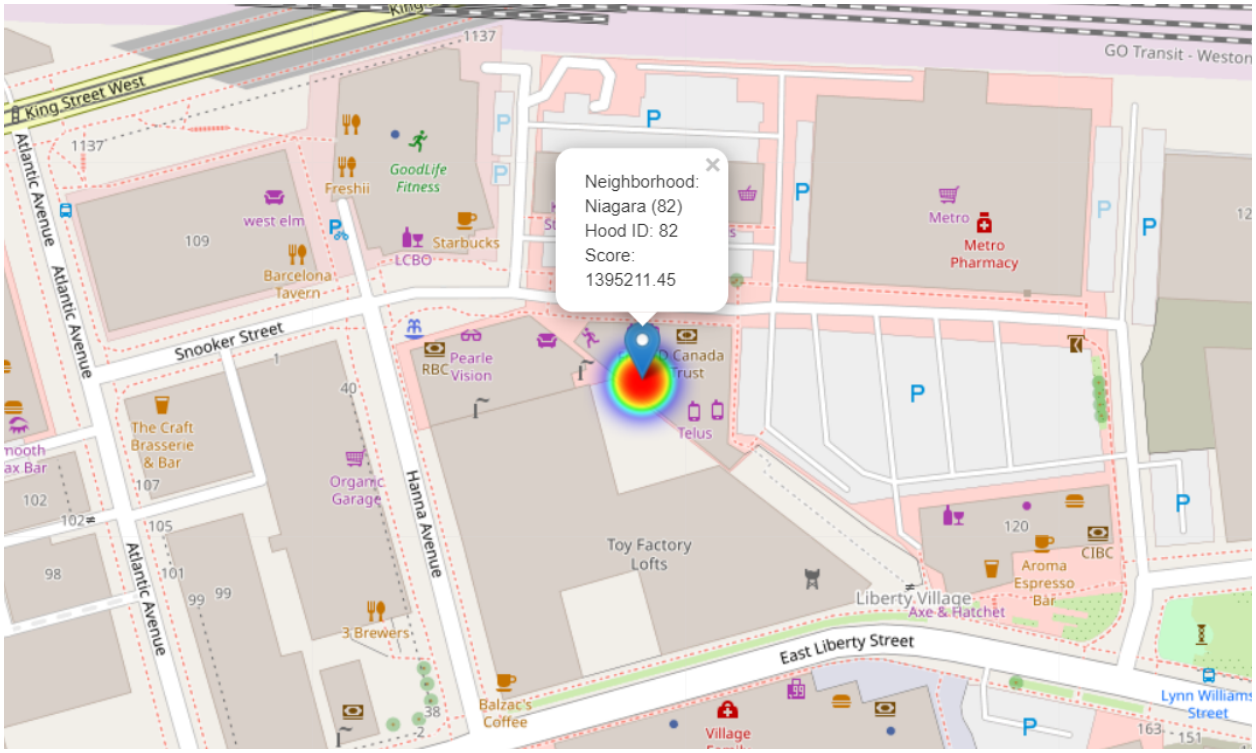


Figure 18

The second method of analyzing the collected data, contained within **kmeans_clustering.ipynb**, utilizes **k-means clustering** to plot the data and cluster them into meaningful groups. The general idea behind k-means clustering is to group the data points into “k” groups based on similarities in data, more specifically, the euclidean distances between the data points and predefined centroids for each cluster. All the points assigned to a cluster are collected and have the mean value amongst them calculated, and the euclidean distance from these means determine which cluster a point belongs to. This form of clustering is a more simple method of clustering, but is an efficient way to easily segment and group data in order to extract useful information from a dataset.

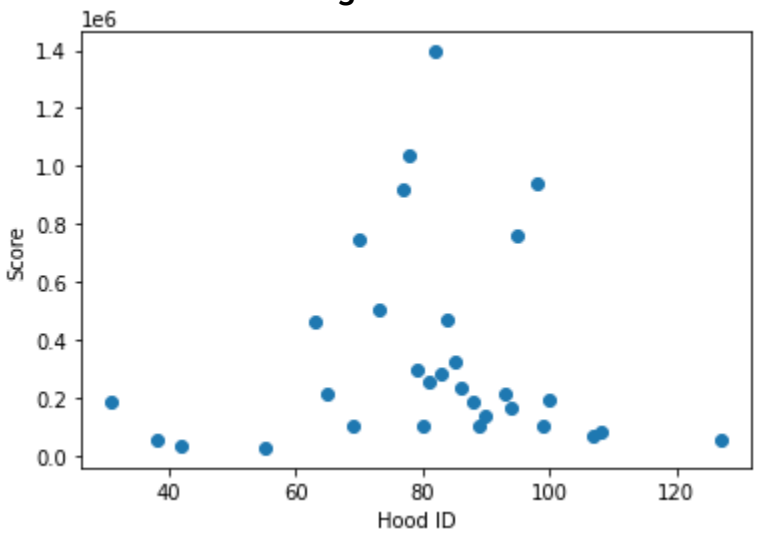
When initially plotting the collected data, our team decided the best scales to use for each axis would be the **Hood IDs** and the **Scores**. This would allow neighborhoods, represented by their hood id, to be segmented by their level of desirability, i.e. their respective scores. In order to view the data before clustering, the following code was used to plot neighborhoods against their desirability.

```
import pandas as pd
from matplotlib import pyplot as plt

cluster_data = pd.read_csv("processed_data.csv")

plt.xlabel("Hood ID")
plt.ylabel("Score")
plt.scatter(cluster_data["hood_id"], cluster_data["score"])
```

Figure 19

Before clustering, the following graph represents hood ids vs their score.

Figure 20



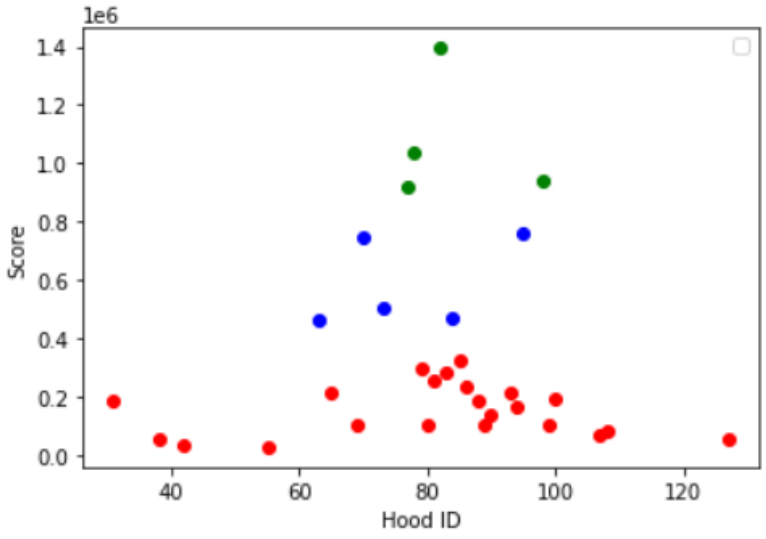
From examining the above plot, our team believed the points could be clustered into 3 groups, each cluster representing three general levels of desirability. The following code was used to segment the dataset of hood ids vs their scores into 3 distinct clusters using the k-means clustering algorithm and export it to a CSV.

```
from sklearn.cluster import KMeans
import pandas as pd
from sklearn.preprocessing import MinMaxScaler
from matplotlib import pyplot as plt

cluster_data = pd.read_csv("processed_data.csv")

km = KMeans(n_clusters=3)

y_predicted = km.fit_predict(cluster_data[["hood_id", "score"]])

cluster_data["cluster"] = y_predicted

df1 = cluster_data[cluster_data.cluster == 0]
df2 =cluster_data[cluster_data.cluster == 1]
df3=cluster_data[cluster_data.cluster == 2]

plt.scatter( df1["hood_id"], df1["score"], color="red")
plt.scatter(df2["hood_id"], df2["score"], color="green")
plt.scatter(df3["hood_id"], df3["score"], color="blue")

plt.xlabel("Hood ID")
plt.ylabel("Score")
plt.legend()

df = pd.DataFrame(cluster_data[["hood_id", "neighborhood", "score", "cluster"]])
print(df)
df.to_csv("segmented_neighborhoods.csv")
```

Figure 21

The following plot is the result of segmenting the data into 3 clusters.

Figure 22



The following is the list of neighborhoods and the cluster they have been segmented into, captured from the **segmented_neighborhoods.csv** file. **The green data points are a part of cluster 1, the blue data points are a part of cluster 2, and the red data points are a part of cluster 0**.

	A	B	C	D	E
1		hood_id	neighborhood	score	cluster
2	0	63	The Beaches (63)	465570.93	2
3	1	93	Dovercourt-Wallace Emerson-Junction (93)	212023.86	0
4	2	108	Briar Hill-Belgravia (108)	81731.82	0
5	3	98	Rosedale-Moore Park (98)	944045.29	1
6	4	95	Annex (95)	761499.1	2
7	5	89	Runnymede-Bloor West Village (89)	105552.68	0
8	6	55	Thorncliffe Park (55)	28604.05	0
9	7	99	Mount Pleasant East (99)	105881.15	0
10	8	127	Bendale (127)	58773	0
11	9	69	Blake-Jones (69)	101675.1	0
12	10	65	Greenwood-Coxwell (65)	217697.56	0
13	11	70	South Riverdale (70)	750123.69	2
14	12	77	Waterfront Communities-The Island (77)	919067.42	1
15	13	73	Moss Park (73)	503606.5	2
16	14	42	Banbury-Don Mills (42)	37013.85	0
17	15	100	Yonge-Eglinton (100)	192190.91	0
18	16	79	University (79)	294202.3	0
19	17	78	Kensington-Chinatown (78)	1037767.84	1
20	18	81	Trinity-Bellwoods (81)	253224.99	0
21	19	94	Wychwood (94)	163849.23	0
22	20	80	Palmerston-Little Italy (80)	107514.37	0
23	21	82	Niagara (82)	1395211.45	1
24	22	84	Little Portugal (84)	472313.02	2
25	23	107	Oakwood Village (107)	72653.93	0
26	24	83	Dufferin Grove (83)	282152.62	0
27	25	86	Roncesvalles (86)	234449.13	0
28	26	38	Lansing-Westgate (38)	55167.43	0
29	27	88	High Park North (88)	188693.86	0
30	28	85	South Parkdale (85)	327063.59	0
31	29	90	Junction Area (90)	137578.55	0
32	30	31	Yorkdale-Glen Park (31)	187134.94	0

Figure 23

Discussion and Conclusion

This section of the report will discuss the findings of the **Results** section, first assessing the results of the heat map visualization of the data, followed by analyzing the results of segmenting and clustering the plot of hood id vs score.

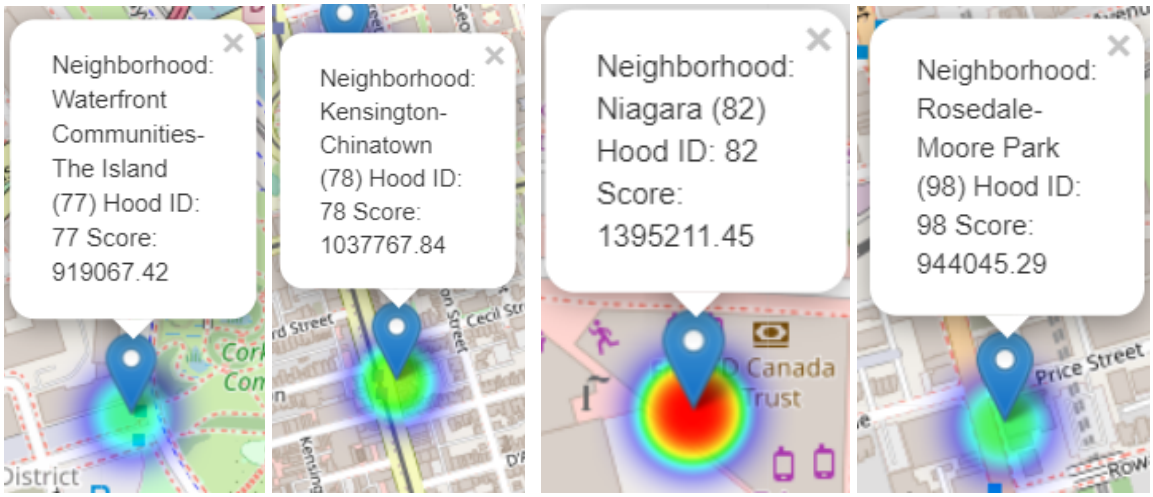
As shown in **Figure 15**, the most desirable locations to open a bicycle store according to our team's criteria reside in the south-western corner of the downtown Toronto area. This is evident by the most concentration of heat in that area, which is directly proportional to the score exhibited by a neighborhood. There is a cluster of 9 neighborhoods in that region which are potential candidates for the most desirable location. Zooming in further, the heat map dynamically adjusts its level of granularity and segments the neighborhoods into smaller clusters., as shown in **Figure 16**. This reveals more specific locations of neighborhoods that would be the most desirable for our team to open a bicycle store. One of those regions contains a cluster of 4 candidates, and the other contains a cluster of 3 candidates, as shown below in more detail.

Figure 24

Upon zooming in another 3 levels, the clusters are eventually broken down into individual neighborhood markers, which indicate the desirability of each specific neighborhood id. As shown in **Figure 18**, the most desirable neighborhood to open a bicycle store in, according to our team's scoring criteria, is the **Niagara** neighborhood with neighborhood id **82** and a score of **1395211.45**. As shown in **Figure 17**, this neighborhood resides near the Toronto **downtown waterfront area**, not too distant from **Centre Island** and the **National Yacht Club**.

Based on our team's personal experience, this "most desirable" has a high number of bicycle riders in the area, particularly due to the concentration of bike stalls in the vicinity. Furthermore, due to the location being near the waterfront area, the weather conditions are typically optimal for bike riding. This shows that the results obtained from the heat map visualization align with real life trends, reflecting the success of the data analysis performed.

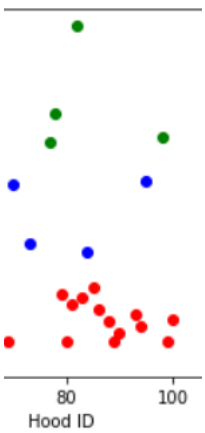
Observing the next few most desirable neighborhoods, our team began to notice a trend among the best candidates.



As shown in the images above, the most desirable neighborhoods have a neighborhood id within the high 70s to 100 range, and neighborhoods lower than that, such as the 50s and 60s ranges, do not present nearly as high of a score. This observation is further reinforced in **Figure 16**, showing how the neighborhoods with the highest scores are within the same general region.

Now it is time to analyze the data resulting from the k-means clustering performed on the plot of neighborhood ids vs their respective scores. As shown in **Figure 22**, the data was segmented into 3 clusters, represented by 3 different colors. From observing the clustered data, it is evident that the least desirable neighborhoods belong to the red cluster (cluster 0), the more “middle of the road” neighborhoods belong to the blue cluster (cluster 2), and the most desirable neighborhoods belong to the green cluster (cluster 1). As our team will obviously want to pick the neighborhoods with the highest scores, our primary focus falls upon the green cluster.

When further inspecting the green cluster (cluster 1), the correlation between the two representations of our results is immediately apparent. The neighborhood ids with the highest desirabilities fall between the high 70s and 100, directly matching our observations from the heat map. Shown below is a segment of the cluster data outlining this.



When taking a look at the CSV output of this clustered data, as shown in **Figure 23**, the neighborhoods belonging to the green cluster (cluster 1) can be grouped to easily view the most desirable neighborhoods as shown in the image below.

B	C	D	E
hood_id	neighborhood	score	cluster
98	Rosedale-Moore Park (98)	944045.29	1
77	Waterfront Communities-The Island (77)	919067.42	1
78	Kensington-Chinatown (78)	1037767.84	1
82	Niagara (82)	1395211.45	1

Once again, these results align perfectly with the observations made when inspecting the heat map visualization of the data, showing consistency amongst the process. From the clustered data, it can also be determined that the best neighborhood to open a bicycle store according to our team's criteria, is the **Niagara** neighborhood with neighborhood id **82**.

In conclusion, this project has been a resounding success. Our team was able to successfully satisfy the original business problem set out, which was to find the best neighborhood to open a bicycle store based on the following criteria; the *more* thefts in an area is better as people will require new bikes more often, the *lower* number of already existing stores is better as that would entail less business competition, and a *higher* average bike cost is better as it is an indication that people would be willing to pay a higher price when purchasing a new bicycle.

Our team was able to sufficiently process the data and put it into formats to easily interpret and perform further analysis on. After collecting all the necessary data, our team was able to represent our findings in multiple formats with a high degree of effectiveness and accuracy. Furthermore, the conclusions resulting from this project have not only been consistent and coherent, but have also aligned with real life trends and patterns, showing the validity of our team's process and the success of this project.