Capstone Project – The Battle of Neighborhoods | Finding a Better Place in Scarborough, Toronto

1. Installing and Importing Python Libraries and Dependencies

```
In [1]:
!pip install geocoder
!pip install folium
Requirement already satisfied: geocoder in /home/untold/anaconda3/lib/python3
.8/site-packages (1.38.1)
Requirement already satisfied: requests in /home/untold/anaconda3/lib/python3
.8/site-packages (from geocoder) (2.24.0)
Requirement already satisfied: six in /home/untold/anaconda3/lib/python3.8/si
te-packages (from geocoder) (1.15.0)
Requirement already satisfied: click in /home/untold/anaconda3/lib/python3.8/
site-packages (from geocoder) (7.1.2)
Requirement already satisfied: ratelim in /home/untold/anaconda3/lib/python3.
8/site-packages (from geocoder) (0.1.6)
Requirement already satisfied: future in /home/untold/anaconda3/lib/python3.8
/site-packages (from geocoder) (0.18.2)
Requirement already satisfied: idna<3,>=2.5 in /home/untold/anaconda3/lib/pyt
hon3.8/site-packages (from requests->geocoder) (2.10)
Requirement already satisfied: chardet<4,>=3.0.2 in /home/untold/anaconda3/li
b/python3.8/site-packages (from requests->geocoder) (3.0.4)
Requirement already satisfied: urllib3!=1.25.0,!=1.25.1,<1.26,>=1.21.1 in /ho
me/untold/anaconda3/lib/python3.8/site-packages (from requests->geocoder) (1.
25.9)
Requirement already satisfied: certifi>=2017.4.17 in /home/untold/anaconda3/1
ib/python3.8/site-packages (from requests->geocoder) (2020.6.20)
Requirement already satisfied: decorator in /home/untold/anaconda3/lib/python
3.8/site-packages (from ratelim->geocoder) (4.4.2)
Requirement already satisfied: folium in /home/untold/anaconda3/lib/python3.8
/site-packages (0.12.0)
Requirement already satisfied: requests in /home/untold/anaconda3/lib/python3
.8/site-packages (from folium) (2.24.0)
Requirement already satisfied: jinja2>=2.9 in /home/untold/anaconda3/lib/pyth
on3.8/site-packages (from folium) (2.11.2)
Requirement already satisfied: branca >= 0.3.0 in /home/untold/anaconda3/lib/py
thon3.8/site-packages (from folium) (0.4.2)
Requirement already satisfied: numpy in /home/untold/anaconda3/lib/python3.8/
site-packages (from folium) (1.18.5)
Requirement already satisfied: idna<3,>=2.5 in /home/untold/anaconda3/lib/pyt
hon3.8/site-packages (from requests->folium) (2.10)
Requirement already satisfied: chardet<4,>=3.0.2 in /home/untold/anaconda3/li
b/python3.8/site-packages (from requests->folium) (3.0.4)
```

```
Requirement already satisfied: urllib3!=1.25.0, !=1.25.1, <1.26, >=1.21.1 in /ho
me/untold/anaconda3/lib/python3.8/site-packages (from requests->folium) (1.25
.9)
Requirement already satisfied: certifi>=2017.4.17 in /home/untold/anaconda3/l
ib/python3.8/site-packages (from requests->folium) (2020.6.20)
Requirement already satisfied: MarkupSafe>=0.23 in /home/untold/anaconda3/lib
/python3.8/site-packages (from jinja2>=2.9->folium) (1.1.1)
Importing Libraries
                                                                         In [2]:
import pandas as pd
import requests
import numpy as np
import geocoder
import folium
import requests
import matplotlib.cm as cm
import matplotlib.colors as colors
import json
import xml
import matplotlib.pyplot as plt
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")
from pandas.io.json import json normalize
from sklearn.cluster import KMeans
from geopy.geocoders import Nominatim
from bs4 import BeautifulSoup
pd.set_option('display.max columns', None)
pd.set option('display.max rows', None)
print("All Required Libraries Imported!")
All Required Libraries Imported!
2. Data Extraction and Cleaning
                    Scraping List of Postal Codes of
      BeautifulSoup
                                                          Given Wikipedia
Link: https://en.wikipedia.org/wiki/List_of_postal_codes_of_Canada:_M
                                                                         In [3]:
url = "https://en.wikipedia.org/wiki/List of postal codes of Canada: M"
extracting data = requests.get(url).text
wiki data = BeautifulSoup(extracting data, 'lxml')
Converting content of PostalCode HTML table as dataframe
                                                                         In [4]:
column names = ['Postalcode', 'Borough', 'Neighborhood']
```

```
toronto = pd.DataFrame(columns = column names)
content = wiki data.find('div', class ='mw-parser-output')
table = content.table.tbody
postcode = 0
borough = 0
neighborhood = 0
for tr in table.find all('tr'):
    i = 0
    for td in tr.find all('td'):
       if i == 0:
            postcode = td.text
            i = i + 1
        elif i == 1:
            borough = td.text
            i = i + 1
        elif i == 2:
            neighborhood = td.text.strip('\n').replace(']','')
    toronto = toronto.append({'Postalcode': postcode, 'Borough': borough, 'Neig
hborhood': neighborhood},ignore index=True)
                                                                        In [5]:
# clean dataframe
toronto = toronto[toronto.Borough!='Not assigned']
toronto = toronto[toronto.Borough!= 0]
toronto.reset index(drop = True, inplace = True)
i = 0
for i in range(0,toronto.shape[0]):
    if toronto.iloc[i][2] == 'Not assigned':
        toronto.iloc[i][2] = toronto.iloc[i][1]
        i = i+1
                                                                        In [6]:
df = toronto.groupby(['Postalcode', 'Borough'])['Neighborhood'].apply(', '.joi
n).reset_index()
df.head()
                                                                        Out[6]:
```

	Po sta lco de	Boro ugh	Neigh borho od
0	M1 A\ n	Not assig ned\n	Not assign ed∖n
1	M1 B\n	Scarb oroug h\n	Malve rn, Rouge
2	M1 C\n	Scarb oroug h\n	Rouge Hill, Port Union , Highl and Creek
3	M1 E\n	Scarb oroug h\n	Guild wood, Morni ngside , West Hill
4	M1 G\ n	Scarb oroug h\n	Wobu rn

In [7]:

	Po sta lco de	B or ou gh	Neig hbor hood
c o u n t	18 0	18 0	180
u n i q u e	18 0	11	100
t o p	M 2K \n	N ot as si gn ed \n	Not assig ned∖n
f r e q	1	77	77

```
In [8]:
df = df.dropna()
empty = 'Not assigned'
df = df[(df.Postalcode != empty ) & (df.Borough != empty) & (df.Neighborhood
!= empty)]
In [9]:
df.head()
Out[9]:
```

	Po sta lco de	Boro ugh	Neigh borho od
0	M1 A\ n	Not assig ned\n	Not assign ed\n
1	M1 B\n	Scarb oroug h\n	Malve rn, Rouge
2	M1 C\n	Scarb oroug h\n	Rouge Hill, Port Union , Highl and Creek
3	M1 E∖n	Scarb oroug h\n	Guild wood, Morni ngside , West Hill
4	M1 G\ n	Scarb oroug h\n	Wobu rn

```
def neighborhood_list(grouped):
    return ', '.join(sorted(grouped['Neighborhood'].tolist()))

grp = df.groupby(['Postalcode', 'Borough'])

df_2 = grp.apply(neighborhood_list).reset_index(name='Neighborhood')
```

Out[11]:

		Out[II].	
	Po sta Ico de	B or ou gh	Neig hbor hood
c o u n t	18 0	18 0	180
u n i q u e	18 0	11	100
t o p	M 2K \n	N ot as si gn ed \n	Not assig ned∖n
f r e q	1	77	77

In [12]:

print(df_2.shape)
df_2.head()
(180, 3)

	Po sta lco de	Boro ugh	Neigh borho od
0	M1 A\ n	Not assig ned\n	Not assign ed\n
1	M1 B\n	Scarb oroug h\n	Malve rn, Rouge
2	M1 C\n	Scarb oroug h\n	Rouge Hill, Port Union , Highl and Creek
3	M1 E∖n	Scarb oroug h\n	Guild wood, Morni ngside , West Hill
4	M1 G\ n	Scarb oroug h\n	Wobu rn

```
In [13]:
```

```
def get_latilong(postal_code):
    lati_long_coords = None
    while(lati_long_coords is None):
        g = geocoder.arcgis('{}, Toronto, Ontario'.format(postal_code))
        lati_long_coords = g.latlng
```

```
get_latilong('M4G')
                                                                          Out[13]:
[43.70902000000066, -79.36348999999996]
                                                                          In [14]:
# Retrieving Postal Code Co-ordinates
postal_codes = df_2['Postalcode']
coords = [ get latilong(postal code) for postal code in postal codes.tolist()
                                                                          In [15]:
# Adding Columns Latitude & Longitude
df coords = pd.DataFrame(coords, columns=['Latitude', 'Longitude'])
df_2['Latitude'] = df_coords['Latitude']
df_2['Longitude'] = df_coords['Longitude']
                                                                          In [16]:
df_2[df_2.Postalcode == 'M5G']
                                                                          Out[16]:
                                          N
          P
                                          e
                                                                           \mathbf{L}
                                                            L
          0
                                          i
                          B
          S
                                          g
                                                            a
                          0
                                                                           n
          t
                                          h
                                                            t
                          r
                                                                           g
          a
                          0
                                                                           i
                                          0
                                                                           t
                          u
          \mathbf{c}
                                          r
                                                            u
                          g
                                                                           u
          0
                                          h
                                                            d
                          h
                                                                           d
          d
                                          0
                                                            e
                                                                           e
          e
                                          0
                                          d
                                                                          In [17]:
df 2.head(10)
```

Out[17]:

return lati_long_coords

	P o s t a l c o d e	B o r o u g h	N e i g h b o r h o o d	L a t i t u d e	L o n g i t u d e
0	M 1 A \ n	N o t a s s i g n e d \ n	N o t a s s i g n e d \ n	4 3 6 4 8 6 9	7 9 3 8 5 4 4
1	M 1 B \ n	S c a r b o r o u g h \ n	M a l v e r n , R o u g e	4 3 8 1 1 3 9	- 7 9 1 9 6 6 2

P o s t a l c o d e	B o r o u g h	N e i g h b o r h o o d	L a t i t u d e	L o n g i t u d
M 1 C \ n	S c a r b o r o u g h \ n	R o u g e H i l l , P o r t U n i o n , H i g h l a n d C r e	4 3 7 8 5 7 4	- 7 9 1 5 8 7 5

	P o s t a l c o d e	B o r o u g h	N e i g h b o r h o o d	L a t i t u d e	L o n g i t u d
			e k 		
3	M 1 E \ n	S c a r b o r o u g h \ n	u i l d w o o d , M o r n i n g s i d e , W e s t H	4 3 7 6 5 7 5	- 7 9 1 7 4 7

	P o s t a l c o d e	B o r o u g h	N e i g h b o r h o d	L a t i t u d e	L o n g i t u d
4	M 1 G \ n	S c a r b o r o u g h \ n	W o b u r	4 3 7 6 8 1 2	- 7 9 2 1 7 6
5	M 1 H \ n	S c a r b o r o u g h	C e d a r b r a e	4 3 7 6 9 4 4	7 9 2 3 8 9 2

	P o s t a l c o d	B o r o u g h	N e i g h b o r h o o d	L a t i t u d e	L o n g i t u d
		n			
6	M 1 J \	S c a r b o r o u g h \	S c a r b o r o u g h V i l a g e	4 3 7 4 4 4 6	7 9 2 3 1 1 7
7	M 1 K \ n	S c a r b o r	K e n n e d	4 3 7 2 5	- 7 9 2 6 4

P o s t a l c o d e	B o r o u g h	N e i g h b o r h o o d	L a t i t u d e	L o n g i t u d
	o u g h \ n	Park, Ionview, East Birchmount Park	8 2	6

	P o s t a l c o d e	B o r o u g h	N e i g h b o r h o d	L a t i t u d e	L o n g i t u d
*	M 1 L \ n	S c a r b o r o u g h \ n	G o l d e n M i l e , C l a i r l e a , O a k r i d g e	4 3 7 1 2 8 9	7 9 2 8 5 0 6

P o s t a l c o d e	B o r o u g h	N e i g h b o r h o o d	L a t i t u d e	L o n g i t u d
M 1 M \ n	S c a r b o r o u g h \ n	C l i f f s i d e , C l i f f c r e s t , S c a r b o r o u g	4 3 7 2 3 6 0	- 7 9 2 3 4 9 6

P o s t a l c o d e	B o r o u g h	N e i g h b o r h o o d	L a t i t u d e	L o n g i t u d
		h V i l a g e W e s t		

In [18]:

0)

```
for lat, lng, nei in zip(df 2['Latitude'], df 2['Longitude'], df 2['Neighborh
ood']):
    label = '{}'.format(nei)
    label = folium.Popup(label, parse html=True)
    folium.CircleMarker(
        [lat, lng],
       radius=5,
        popup=label,
        color='blue',
        fill=True,
        fill color='#3186cc',
        fill opacity=0.7,
        parse html=False).add to(map Scarborough)
map Scarborough
                                                                       Out[19]:
Make this Notebook Trusted to load map: File -> Trust Notebook
                                                                       In [20]:
address = 'Scarborough, Toronto'
geolocator = Nominatim(user agent="http")
location = geolocator.geocode(address)
latitude n1 = location.latitude
longitude n1 = location.longitude
print('The Geograpical Co-ordinate of Neighborhood 1 are {}, {}.'.format(lati
tude x, longitude y))
The Geograpical Co-ordinate of Neighborhood 1 are 43.7729744, -79.2576479.
                                                                       In [21]:
# @hiddel cell
CLIENT ID = 'DPBYY4JUY3DU20ALPSUV4ONY2K1GOJJKJ1NIHBB32XEMOVYY' # my Foursquar
CLIENT SECRET = '1MV443TYEP4HU00WDUW5NQ5W10L2Y4G05NWG11WIR3NUGC5B' # my Fours
quare Secret
VERSION = '20180604'
LIMIT = 30
print('Your credentails:')
print('CLIENT ID: '+CLIENT ID)
print('CLIENT SECRET: '+CLIENT SECRET)
Your credentails:
CLIENT ID: DPBYY4JUY3DU20ALPSUV4ONY2K1GOJJKJ1NIHBB32XEMOVYY
CLIENT SECRET: 1MV443TYEP4HUO0WDUW5NQ5W10L2Y4G05NWG11WIR3NUGC5B
                                                                       In [22]:
```

```
radius = 700
LIMIT = 100
url = 'https://api.foursquare.com/v2/venues/explore?&client id={}&client secr
et={}&v={}&ll={},{}&radius={}&limit={}'.format(
    CLIENT ID,
   CLIENT_SECRET,
   VERSION,
   latitude n1,
  longitude n1,
   radius,
   LIMIT)
results = requests.get(url).json()
                                                                       In [23]:
venues=results['response']['groups'][0]['items']
nearby venues = json normalize(venues)
nearby venues.columns
                                                                       Out[23]:
Index(['referralId', 'reasons.count', 'reasons.items', 'venue.id',
       'venue.name', 'venue.location.address', 'venue.location.crossStreet',
       'venue.location.lat', 'venue.location.lng',
       'venue.location.labeledLatLngs', 'venue.location.distance',
       'venue.location.postalCode', 'venue.location.cc', 'venue.location.city
       'venue.location.state', 'venue.location.country',
       'venue.location.formattedAddress', 'venue.categories',
       'venue.photos.count', 'venue.photos.groups',
       'venue.location.neighborhood', 'venue.venuePage.id'],
      dtype='object')
                                                                       In [24]:
def get category type(row):
    try:
        categories list = row['categories']
    except:
        categories list = row['venue.categories']
    if len(categories list) == 0:
        return None
        return categories_list[0]['name']
4. Nearby Venues/Locations
                                                                       In [25]:
filtered columns = ['venue.name', 'venue.categories', 'venue.location.lat', '
venue.location.lng']
```

				Out[25]:
	v e n u e n a m e	venu e.cat egori es	v e n u e . l o c a t i o n . l a t	v e n u e . l o c a t i o n . l n g
0	D i s n e y S t o r e	[{'id' : '4bf5 8dd8 d489 88d1 f394 1735 ', 'nam e': 'T	4 3 7 7 5 5 5 3 7	7 9 2 5 6 8 3 3
1	S E P H O	[{'id' : '4bf5 8dd8 d489 88d1 0c95	4 3 7 7 5 0	- 7 9 2 5 8

	v e n u e · n a m e	venu e.cat egori es	v e n u e . l o c a t i o n . l a t	v e n u e . l o c a t i o n . l n g
	R A	1735 ', 'nam e': 'C	1 7	1 0 9
2	C o l i s e u m S c a r b o r o u g	[{'id' : '4bf5 8dd8 d489 88d1 7f94 1735 ', 'nam e': 'M	4 3 7 7 5 9 9 9	7 9 2 5 5 6 4

	v e n u e n a m e	venu e.cat egori es	v e n u e . l o c a t i o n . l a t	v e n u e . l o c a t i o n . l
	h C i n e m a s			
3	T o m m y H i l f r	[{'id' : '4bf5 8dd8 d489 88d1 0395 1735 ', 'nam e': 'C	4 3 7 7 6 0 1 5	7 9 2 5 7 3 6

	v e n u e n a m e	venu e.cat egori es	v e n u e . l o c a t i o n	v e n u e . l o c a t i o n . l
4	S h o p p e r s D r u g M a r t	[{'id' : '4bf5 8dd8 d489 88d1 0f95 1735 ', 'nam e': 'P	a t 4 3 . 7 7 3 3 0 5	n g

5. Categories of Nearby Venues/Locations

```
In [26]:
nearby_venues['venue.categories'] = nearby_venues.apply(get_category_type, ax
is=1)

# clean columns
nearby_venues.columns = [col.split(".")[-1] for col in nearby_venues.columns]
```

				Out[26]:
	n a m e	c a t e g o r i e s	l a t	l n g
0	D i s n e y S t o r e	T o y / G a m e S t o r e	4 3 7 7 5 5 5 3 7	7 9 2 5 6 8 3 3
1	S E P H O R A	C o s m e t i c s S h o	4 3 7 7 5 0 1	- 7 9 2 5 8 1 0

	n a m e	c a t e g o r i e s	l a t	l n g
2	C o l i s e u m S c a r b o r o u g h C i n e m a s	M o v i e T h e a t e r	4 3 7 7 5 9 9 5	- 7 9 2 5 5 6 4 9
3	T o m m y	C l o t h	4 3 7 7	- 7 9 2

	n a m e	c a t e g o r i e s	l a t	l n g
	H i l f i g e	i n g S t o r e	6 0 1 5	5 7 3 6 9
4	S h o p p e r s D r u g M a r t	P h a r m a c	4 3 7 7 3 3 0 5	- 7 9 2 5 1 6 6 2

In [27]:

Top 10 Categories

a=pd.Series(nearby_venues.categories) a.value_counts()[:10]

Out[27]:

```
5
Restaurant
Coffee Shop
Sandwich Place
Furniture / Home Store
                         2
Gas Station
                          2
Intersection
Department Store
                         2
Pharmacy
                          1
Grocery Store
Name: categories, dtype: int64
                                                                      In [28]:
def getNearbyVenues(names, latitudes, longitudes, radius=700):
    venues list=[]
    for name, lat, lng in zip(names, latitudes, longitudes):
       print(name)
        url = 'https://api.foursquare.com/v2/venues/explore?&client id={}&cli
ent secret={}&v={}&ll={},{}&radius={}&limit={}'.format(
            CLIENT ID,
            CLIENT SECRET,
            VERSION,
            lat,
            lng,
            radius,
            LIMIT)
        # making GET request
        venue results = requests.get(url).json()["response"]['groups'][0]['it
ems']
        # return only relevant information for each nearby venue
        venues list.append([(
            name,
            lat,
            lnq,
            v['venue']['name'],
            v['venue']['location']['lat'],
            v['venue']['location']['lng'],
            v['venue']['categories'][0]['name']) for v in venue 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)
                                                                      In [29]:
# Nearby Venues
Scarborough venues = getNearbyVenues(names=df 2['Neighborhood'],
                                   latitudes=df 2['Latitude'],
                                   longitudes=df 2['Longitude']
Not assigned
Malvern, Rouge
Rouge Hill, Port Union, Highland Creek
Guildwood, Morningside, West Hill
Woburn
Cedarbrae
Scarborough Village
Kennedy Park, Ionview, East Birchmount Park
Golden Mile, Clairlea, Oakridge
Cliffside, Cliffcrest, Scarborough Village West
Birch Cliff, Cliffside West
Dorset Park, Wexford Heights, Scarborough Town Centre
Wexford, Maryvale
Agincourt
Clarks Corners, Tam O'Shanter, Sullivan
Milliken, Agincourt North, Steeles East, L'Amoreaux East
Steeles West, L'Amoreaux West
Upper Rouge
Not assigned
Hillcrest Village
Fairview, Henry Farm, Oriole
```

Bayview Village York Mills, Silver Hills Willowdale, Newtonbrook Willowdale, Willowdale East York Mills West Willowdale, Willowdale West Not assigned

Not assigned

Not assigned

Not assigned Not assigned

Not assigned

Not assigned

Parkwoods Don Mills Don Mills Not assigned

Not assigned

Bathurst Manor, Wilson Heights, Downsview North Northwood Park, York University Downsview

Downsview Downsview Downsview Not assigned

Not assigned Victoria Village Parkview Hill, Woodbine Gardens Woodbine Heights The Beaches Leaside Thorncliffe Park
East Toronto, Broadview North (Old East York)
The Danforth West, Riverdale
India Bazaar, The Beaches West
Studio District
Lawrence Park
Davisville North
North Toronto West, Lawrence Park
Davisville
Moore Park, Summerhill East
Summerhill West, Rathnelly, South Hill, Forest Hill SE, Deer Park
Rosedale
St. James Town, Cabbagetown
Church and Wellesley
Not assigned

Regent Park, Harbourfront Garden District, Ryerson St. James Town Berczy Park Central Bay Street Richmond, Adelaide, King Harbourfront East, Union Station, Toronto Islands Toronto Dominion Centre, Design Exchange Commerce Court, Victoria Hotel Bedford Park, Lawrence Manor East Roselawn Forest Hill North & West, Forest Hill Road Park The Annex, North Midtown, Yorkville University of Toronto, Harbord Kensington Market, Chinatown, Grange Park CN Tower, King and Spadina, Railway Lands, Harbourfront West, Bathurst Qua y, South Niagara, Island airport Stn A PO Boxes First Canadian Place, Underground city Not assigned

Not assigned

Lawrence Manor, Lawrence Heights
Glencairn
Humewood-Cedarvale
Caledonia-Fairbanks
Christie
Dufferin, Dovercourt Village
Little Portugal, Trinity
Brockton, Parkdale Village, Exhibition Place
North Park, Maple Leaf Park, Upwood Park
Del Ray, Mount Dennis, Keelsdale and Silverthorn
Runnymede, The Junction North
High Park, The Junction South
Parkdale, Roncesvalles
Runnymede, Swansea
Not assigned

```
Not assigned
Not assigned
Not assigned
Not assigned
Not assigned
Queen's Park, Ontario Provincial Government
Not assigned
Canada Post Gateway Processing Centre
Not assigned
Not assigned
Not assigned
Not assigned
Not assigned
Business reply mail Processing Centre, South Central Letter Processing Pla
nt Toronto
Not assigned
Not assigned
Not assigned
Not assigned
Not assigned
```

Not assigned

New Toronto, Mimico South, Humber Bay Shores

Alderwood, Long Branch

The Kingsway, Montgomery Road, Old Mill North

Old Mill South, King's Mill Park, Sunnylea, Humber Bay, Mimico NE, The Que ensway East, Royal York South East, Kingsway Park South East

Mimico NW, The Queensway West, South of Bloor, Kingsway Park South West, R oyal York South West

Islington Avenue, Humber Valley Village

West Deane Park, Princess Gardens, Martin Grove, Islington, Cloverdale Eringate, Bloordale Gardens, Old Burnhamthorpe, Markland Wood

Not assigned

Not assigned

Not assigned

Not assigned

Not assigned

Humber Summit Humberlea, Emery

Weston

Westmount

Kingsview Village, St. Phillips, Martin Grove Gardens, Richview Gardens Not assigned

Not assigned

South Steeles, Silverstone, Humbergate, Jamestown, Mount Olive, Beaumond H eights, Thistletown, Albion Gardens

```
Northwest, West Humber - Clairville
Not assigned

Not assigned

In [30]:
print('There are {} Uniques Categories.'.format(len(Scarborough_venues['Venue Category'].unique())))
Scarborough_venues.groupby('Neighborhood').count().head()
There are 307 Uniques Categories.

Out[30]:
```

	N e i g h b o r h o d L a t i t u d e	N e i g h b o r h o d L o n g i t u d e	V e n u e	L a t	V e n u e L o n g i t u d e	V e n u e C a t e g o r y
N e i g h b o r h o d						
A g i n c o u	2 0	2 0	2 0	2 0	2 0	2 0

	N e i g h b o r h o d L a t i t u d e	Nei ghborrhood Longitude	V e n u e	a t	V e n u e L o n g i t u d e	V e n u e C a t e g o r y
N e i g h b o r h o d						
r t						
A l d e	7	7	7	7	7	7

	Neighborhood Latitude	N e i g h b o r h o d L o n g i t u d e	V e n u e	t	V e n u e L o n g i t u d e	V e n u e C a t e g o r y
N e i g h b o r h o d						
r w o o d d , L						

	N e i ghborhood Latitude	N e i g h b o r h o d L o n g i t u d e	V e n u e	t	V e n u e L o n g i t u d e	V e n u e C a t e g o r y
N e i g h b o r h o d n g B r a n c h						

	N e i g h b o r h o d L a t i t u d e	N e i g h b o r h o d L o n g i t u d e	V e n u e	a t	V e n u e L o n g i t u d e	V e n u e C a t e g o r y
N e i g h b o r h o d						
B a t h u r s t	1 3	1 3	1 3	1 3	1 3	1 3

	N e i g h o r h o d L a t i t u d e	N e i g h b o r h o d L o n g i t u d e	V e n u e	a t	V e n u e L o n g i t u d e	V e n u e C a t e g o r y
N e i g h b o r h o d						
M a n o r W i						

	N e i g h o r h o d L a t i t u d e	N e i g h b o r h o d L o n g i t u d e	V e n u e	a t	V e n u e L o n g i t u d e	V e n u e C a t e g o r y
N e i g h b o r h o o d						
l s o n H e i						

	Neighborhood Latitude	N e i g h b o r h o d L o n g i t u d e	V e n u e	t	V e n u e L o n g i t u d e	V e n u e C a t e g o r y
N e i g h b o r h o o d						
h t s D o w n						

	N e i g h b o r h o d L a t i t u d e	N e i g h b o r h o d L o n g i t u d e	V e n u e	L a t	V e n u e L o n g i t u d e	V e n u e C a t e g o r y
N e i g h b o r h o d						
s v i e w N o r						

	N e i g h o r h o o d L a t i t u d e	Neighborhood Longitude	V e n u	a t	V e n u e L o n g i t u d e	V e n u e C a t e g o r y
N e i g h o r h o d						
t h B a y	6	6	6	6	6	6

	N e i g h b o r h o d L a t i t u d e	N e i g h b o r h o d L o n g i t u d e	V e n u e	a t	V e n u e L o n g i t u d e	V e n u e C a t e g o r y
N e i g h b o r h o d						
i e W V i l						

	N e i g h b o r h o d L a t i t u d e	N e i g h b o r h o d L o n g i t u d e	V e n u e	L a t	V e n u e L o n g i t u d e	V e n u e C a t e g o r y
N e i g h b o r h o d						
g e						
B e d f	2 4	2 4	2 4	2 4	2 4	2 4

	Neighborhood Latitude	N e i g h b o r h o d L o n g i t u d e	V e n u e	t	V e n u e L o n g i t u d e	V e n u e C a t e g o r y
N e i g h b o r h o o d						
o r d P a r k						

	Neighborhood Latitude	N e i g h b o r h o d L o n g i t u d e	V e n u e	t	V e n u e L o n g i t u d e	V e n u e C a t e g o r y
N e i g h b o r h o d						
L a w r e n c						

	N e i ghborhood Latitude	N e i g h b o r h o d L o n g i t u d e	V e n u e	L a t	V e n u e L o n g i t u d e	V e n u e C a t e g o r y
N e i g h b o r h o o d						
a n o r E a						

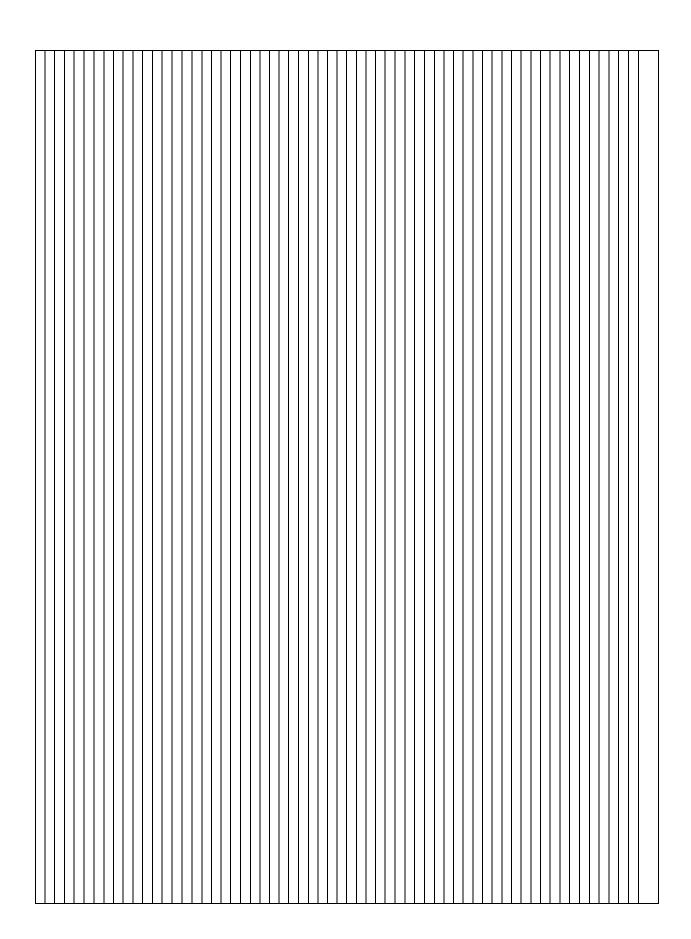
	N e i g h b o r h o d L a t i t u d e	N e i g h b o r h o o d L o n g i t u d e	V e n u e	t	V e n u e L o n g i t u d e	V e n u e C a t e g o r y
N e i g h b o r h o o d						
s t						

One Hot Encoding of Features

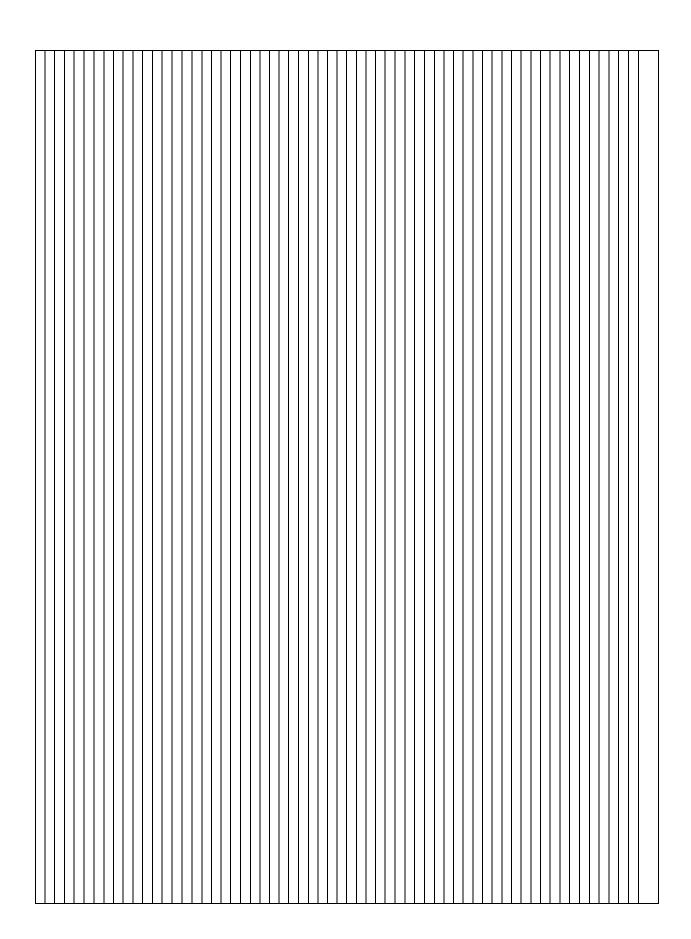
```
In [31]:
# one hot encoding
Scarborough_onehot = pd.get_dummies(Scarborough_venues[['Venue Category']], p
refix="", prefix_sep="")
```

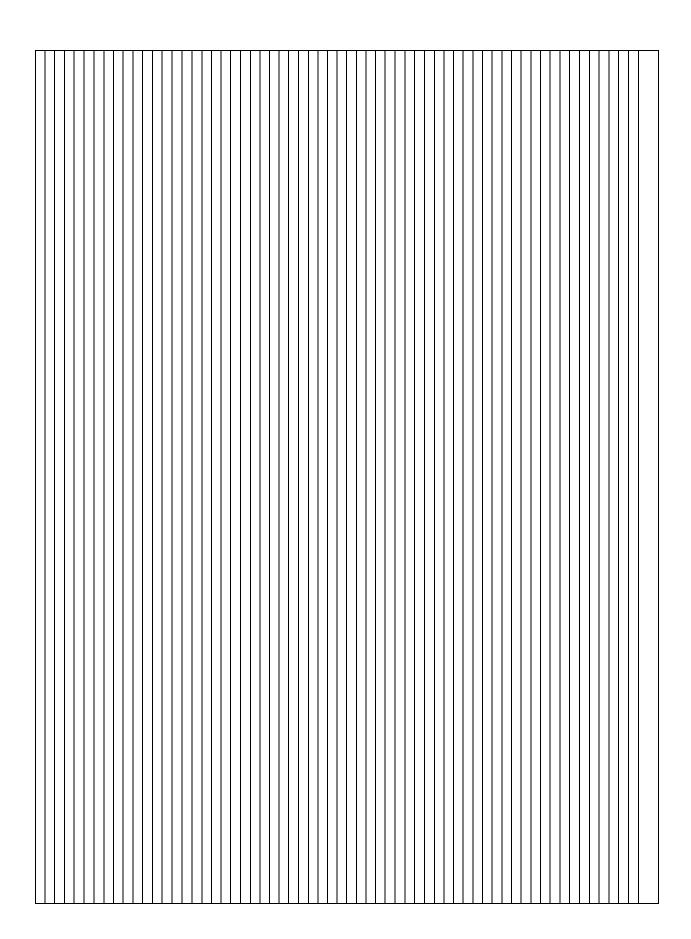
```
# add neighborhood column back to dataframe
Scarborough_onehot['Neighborhood'] = Scarborough_venues['Neighborhood']

# move neighborhood column to the first column
fixed_columns = [Scarborough_onehot.columns[-1]] + list(Scarborough_onehot.columns[:-1])
Scarborough_onehot = Scarborough_onehot[fixed_columns]
Scarborough_grouped = Scarborough_onehot.groupby('Neighborhood').mean().reset __index()
Scarborough_onehot.head(5)
Out[31]:
```

















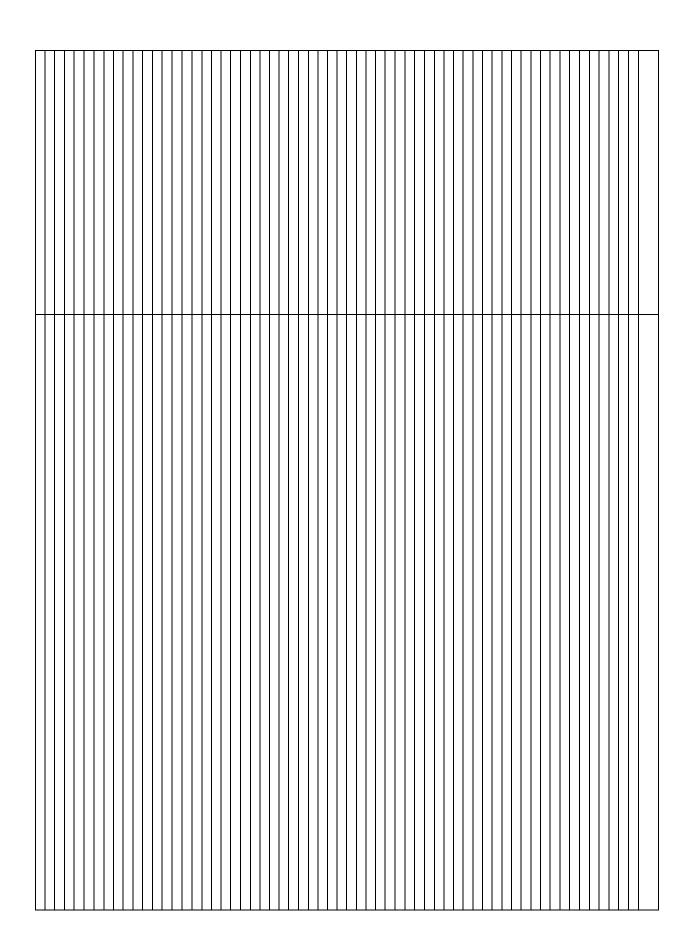










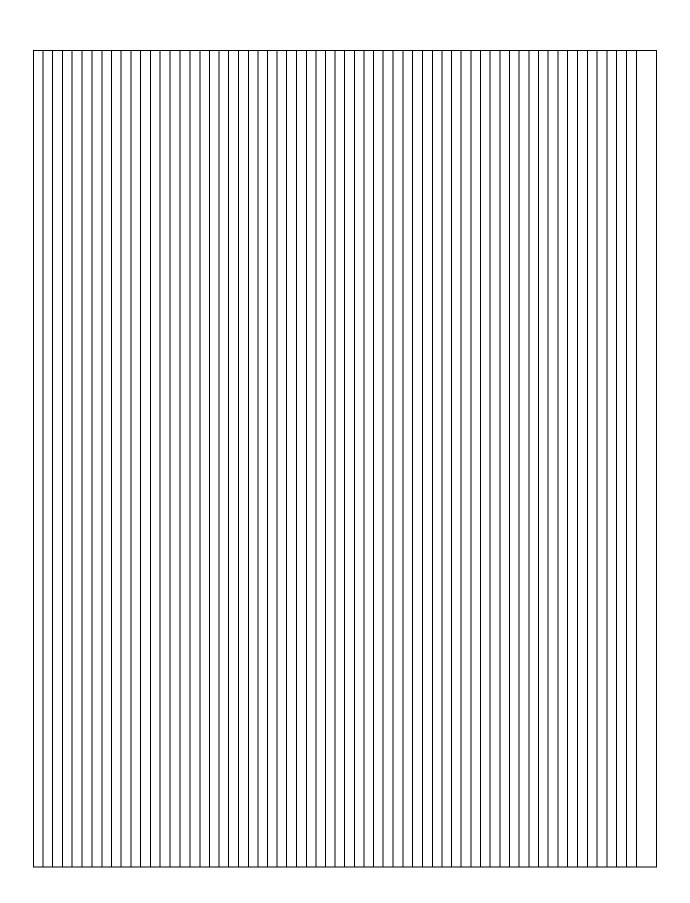


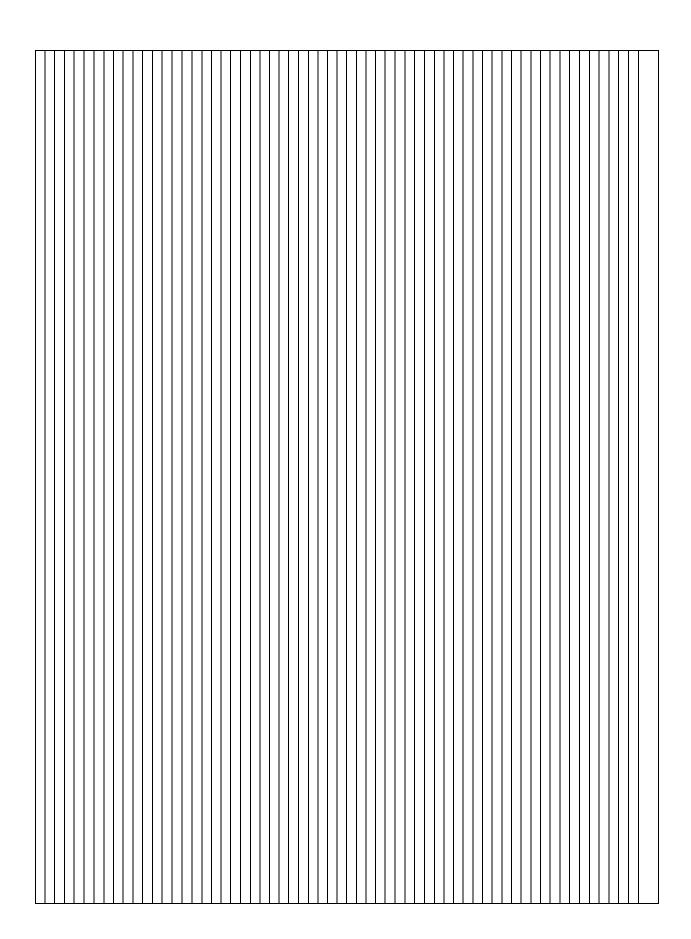






























```
In [32]:
num top venues = 5
for hood in Scarborough grouped['Neighborhood']:
   print("---- "+hood+" ----")
    temp =Scarborough grouped[Scarborough grouped['Neighborhood'] == hood].T.
reset index()
    temp.columns = ['venue','freq']
    temp = temp.iloc[1:]
    temp['freq'] = temp['freq'].astype(float)
   temp = temp.round({'freq': 2})
   print(temp.sort values('freq', ascending=False).reset index(drop=True).he
ad(num top venues))
   print('\n')
---- Agincourt ----
               venue freq
       Shopping Mall 0.10
1
       Breakfast Spot 0.05
2 Chinese Restaurant 0.05
3
         Skating Rink 0.05
                Park 0.05
4
---- Alderwood, Long Branch ----
        venue freq
          Pub 0.14
\cap
1 Pizza Place 0.14
          Gym 0.14
3 Gas Station 0.14
4 Pharmacy 0.14
---- Bathurst Manor, Wilson Heights, Downsview North ----
                     venue freq
                Coffee Shop 0.15
1 Mediterranean Restaurant 0.08
               Men's Store 0.08
3
                      Park 0.08
          Sushi Restaurant 0.08
---- Bayview Village ----
             venue freq
              Park 0.17
0
1 Asian Restaurant 0.17
2 Flower Shop 0.17
3
             Trail 0.17
            Dog Run 0.17
4
---- Bedford Park, Lawrence Manor East ----
               venue freq
0
       Sandwich Place 0.08
          Coffee Shop 0.08
1
```

```
Pet Store 0.08
3 Italian Restaurant 0.08
   Thai Restaurant 0.04
---- Berczy Park ----
                venue freq
          Coffee Shop 0.09
1 Japanese Restaurant 0.05
                Hotel 0.05
3
                 Café 0.04
4
           Restaurant 0.03
---- Birch Cliff, Cliffside West ----
                  venue freq
                   Park 0.17
0
                   Café 0.17
1
2
                    Gym 0.17
3 General Entertainment 0.17
           Skating Rink 0.17
---- Brockton, Parkdale Village, Exhibition Place ----
        venue freq
         Café 0.07
1 Coffee Shop 0.07
          Bar 0.06
3
       Bakery 0.05
4 Restaurant 0.05
---- Business reply mail Processing Centre, South Central Letter Processin
q Plant Toronto ----
                venue freq
          Coffee Shop 0.11
0
1
                 Café 0.07
2
                Hotel 0.07
3
           Restaurant 0.04
4 Japanese Restaurant 0.03
---- CN Tower, King and Spadina, Railway Lands, Harbourfront West, Bathurs
t Quay, South Niagara, Island airport ----
          venue freq
0
    Coffee Shop 0.09
            Gym 0.07
1
           Café 0.06
2
3 Grocery Store 0.05
           Park 0.05
---- Caledonia-Fairbanks ----
               venue freq
                Park 0.33
0
1
              Bakery 0.17
```

```
Women's Store 0.17
3 Mexican Restaurant 0.17
        Pizza Place 0.17
---- Canada Post Gateway Processing Centre ----
                venue freq
          Coffee Shop 0.11
1
                Café 0.07
2
                Hotel 0.07
3
           Restaurant 0.04
4 Japanese Restaurant 0.03
---- Cedarbrae ----
             venue freq
            Bakery 0.12
       Gas Station 0.12
  Thai Restaurant 0.12
3 Hakka Restaurant 0.12
           Lounge 0.12
---- Central Bay Street ----
           venue freq
    Coffee Shop 0.14
1 Clothing Store 0.06
            Café 0.03
3
     Art Gallery 0.03
          Diner 0.02
---- Christie ----
              venue freq
  Korean Restaurant 0.16
1
       Grocery Store 0.10
        Pizza Place 0.04
3 Mexican Restaurant 0.04
               Café 0.04
---- Church and Wellesley ----
                venue freq
          Coffee Shop 0.09
1 Japanese Restaurant 0.06
2
  Sushi Restaurant 0.04
3
           Restaurant 0.04
                 Café 0.03
---- Clarks Corners, Tam O'Shanter, Sullivan ----
                  venue freq
  Fast Food Restaurant 0.09
1
               Pharmacy 0.06
2 Vietnamese Restaurant 0.06
           Pizza Place 0.06
           Liquor Store 0.03
---- Cliffside, Cliffcrest, Scarborough Village West ----
```

```
venue freq
0 Ice Cream Shop 0.17
1 Hardware Store 0.08
          Bistro 0.08
3
            Bank 0.08
4
        Pharmacy 0.08
---- Commerce Court, Victoria Hotel ----
               venue freq
         Coffee Shop 0.10
0
1
                Café 0.06
2
           Gastropub 0.04
3 Seafood Restaurant 0.04
                 Gym 0.03
---- Davisville ----
           venue freq
     Pizza Place 0.09
1 Sandwich Place 0.07
   Dessert Shop 0.07
3
    Coffee Shop 0.07
            Café 0.05
---- Davisville North ----
              venue freq
        Pizza Place 0.08
1
  Department Store 0.04
  Sandwich Place 0.04
3 Food & Drink Shop 0.04
               Café 0.04
---- Del Ray, Mount Dennis, Keelsdale and Silverthorn ----
                      venue freq
                Home Service 0.33
        Fast Food Restaurant 0.17
1
2 Construction & Landscaping 0.17
3
                 Playground 0.17
                 Coffee Shop 0.17
---- Don Mills ----
                venue freq
          Coffee Shop 0.08
           Restaurant 0.06
1
2 Japanese Restaurant 0.06
3
       Sandwich Place 0.04
4
                  Gym 0.04
---- Dorset Park, Wexford Heights, Scarborough Town Centre ----
           venue freq
         Brewery 0.2
```

```
1 Rental Service 0.2
2 Coffee Shop 0.2
3
          Bakery 0.2
4
           Park 0.2
---- Downsview ----
                 venue freq
           Coffee Shop 0.09
          Grocery Store 0.06
1
2
           Pizza Place 0.06
         Discount Store 0.05
4 Vietnamese Restaurant 0.05
---- Dufferin, Dovercourt Village ----
         venue freq
           Bar 0.10
    Coffee Shop 0.10
1
         Bakery 0.08
2
3
           Park 0.04
4 Grocery Store 0.04
---- East Toronto, Broadview North (Old East York) ----
               venue freq
      Farmers Market 0.17
1
            Bus Line 0.17
         Coffee Shop 0.17
3 Italian Restaurant 0.17
               Park 0.17
---- Eringate, Bloordale Gardens, Old Burnhamthorpe, Markland Wood ----
              venue freq
              Park 0.18
0
1 Convenience Store 0.09
       Pizza Place 0.09
     Shopping Mall 0.09
3
     Baseball Field 0.09
---- Fairview, Henry Farm, Oriole ----
                venue freq
        Clothing Store 0.11
          Coffee Shop 0.08
2 Fast Food Restaurant 0.05
3
            Restaurant 0.03
    Convenience Store 0.03
---- First Canadian Place, Underground city ----
             venue freq
0
             Hotel 0.10
1
       Coffee Shop 0.08
             Café 0.06
2
        Restaurant 0.05
4 Asian Restaurant 0.03
```

```
---- Forest Hill North & West, Forest Hill Road Park ----
                     venue freq
0
                      Bank 0.15
        Salon / Barbershop 0.08
1
2
                      Café 0.08
3
                 Bookstore 0.08
4 Mediterranean Restaurant 0.08
---- Garden District, Ryerson ----
                venue freq
          Coffee Shop 0.10
1
       Clothing Store 0.04
            Gastropub 0.03
3 Japanese Restaurant 0.03
4 Italian Restaurant 0.03
---- Glencairn ----
          venue freq
0
   Grocery Store 0.15
1
     Pizza Place 0.10
2 Ice Cream Shop 0.05
3 Photography Lab 0.05
      Fish Market 0.05
---- Golden Mile, Clairlea, Oakridge ----
         venue freq
        Bakery 0.14
1 Intersection 0.14
         Diner 0.07
3
     Bus Line 0.07
4 Bus Station 0.07
---- Guildwood, Morningside, West Hill ----
                          venue freq
                           Park 0.4
0
           Gym / Fitness Center 0.2
1
2
                 Gymnastics Gym 0.2
             Athletics & Sports 0.2
4 Paper / Office Supplies Store
                                 0.0
---- Harbourfront East, Union Station, Toronto Islands ----
                venue freq
0
          Coffee Shop 0.11
1
                 Café 0.06
                Hotel 0.06
2
3 Japanese Restaurant 0.03
           Restaurant 0.03
```

```
venue freq
O Convenience Store 0.10
               Bar 0.08
1
2
    Thai Restaurant 0.06
3
     Pizza Place 0.04
             Bakery 0.04
---- Hillcrest Village ----
                                   venue freq
                                   Park 0.29
1 Residential Building (Apartment / Condo) 0.14
2
                                Pharmacy 0.14
3
                                  Bakery 0.14
                       Chinese Restaurant 0.14
---- Humber Summit ----
      venue freq
0 Home Service 0.33
   Hobby Shop 0.33
1
2 Music Store 0.33
3 Zoo Exhibit 0.00
   Nightclub 0.00
---- Humberlea, Emery ----
                     venue freq
               Coffee Shop 0.29
1 Latin American Restaurant 0.14
                Nightclub 0.14
3
             Discount Store 0.14
                     Café 0.14
4
---- Humewood-Cedarvale ----
             venue freq
     Grocery Store 0.22
1 Convenience Store 0.11
     Hockey Arena 0.11
2
3
    Soccer Stadium 0.11
             Field 0.11
---- Hillcrest Village ----
                                   venue freq
                                    Park 0.29
1 Residential Building (Apartment / Condo) 0.14
                                 Pharmacy 0.14
3
                                  Bakery 0.14
                       Chinese Restaurant 0.14
---- Humber Summit ----
         venue freq
```

---- High Park, The Junction South ----

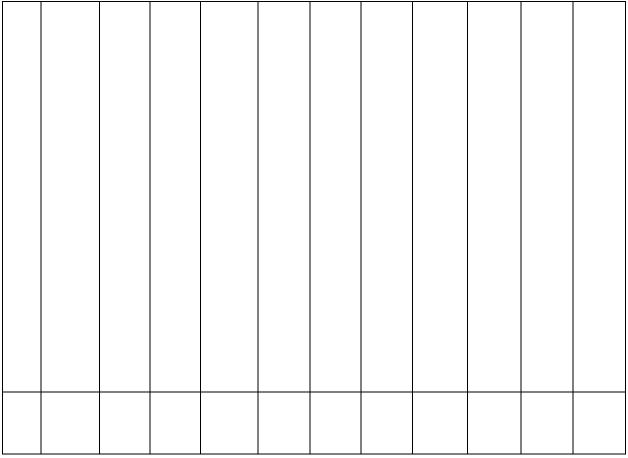
```
0 Home Service 0.33
1
   Hobby Shop 0.33
2
  Music Store 0.33
3
  Zoo Exhibit 0.00
    Nightclub 0.00
4
---- Humberlea, Emery ----
                      venue freq
                Coffee Shop 0.29
1 Latin American Restaurant 0.14
2
                 Nightclub 0.14
3
             Discount Store 0.14
4
                       Café 0.14
---- Humewood-Cedarvale ----
              venue freq
      Grocery Store 0.22
1 Convenience Store 0.11
2
      Hockey Arena 0.11
     Soccer Stadium 0.11
3
              Field 0.11
---- India Bazaar, The Beaches West ----
                 venue freq
0 Fast Food Restaurant 0.09
1
            Restaurant 0.09
2
               Bakery 0.06
               Brewery 0.06
3
4
           Coffee Shop 0.06
---- Islington Avenue, Humber Valley Village ----
                venue freq
0
             Pharmacy 0.18
    Convenience Store 0.09
1
2 Japanese Restaurant 0.09
3
                 Café 0.09
4
         Skating Rink 0.09
---- Kennedy Park, Ionview, East Birchmount Park ----
               venue freq
      Discount Store 0.33
1 Chinese Restaurant 0.17
2
   Department Store 0.17
3
         Bus Station 0.17
         Coffee Shop 0.17
---- Kensington Market, Chinatown, Grange Park ----
                          venue freq
                           Café 0.08
0
1
                    Coffee Shop 0.06
```

```
2 Vegetarian / Vegan Restaurant 0.06
                           Bar 0.04
                    Yoga Studio 0.03
---- Kingsview Village, St. Phillips, Martin Grove Gardens, Richview Garde
                venue freq
   Mobile Phone Shop 0.14
1 American Restaurant 0.14
             Bus Line 0.14
3
             Pharmacy 0.14
4 Business Service 0.14
---- Lawrence Manor, Lawrence Heights ----
            venue freq
   Clothing Store 0.17
      Dessert Shop 0.05
Restaurant 0.05
1
3 Greek Restaurant 0.03
        Bookstore 0.03
---- Lawrence Park ----
                venue freq
           Coffee Shop 0.14
1 Gym / Fitness Center 0.14
            Bus Line 0.14
3
           Restaurant 0.14
4
            Bookstore 0.14
---- Leaside ----
               venue freq
          Coffee Shop 0.08
1 Sporting Goods Shop 0.06
          Restaurant 0.04
     Department Store 0.04
3
       Shopping Mall 0.04
---- York Mills West ----
          venue freq
0
     Restaurant 0.19
1
     Coffee Shop 0.14
           Gym 0.10
3 Sandwich Place 0.05
4 Metro Station 0.05
---- York Mills, Silver Hills ----
           venue freq
  Concert Hall 0.5
0
            Park 0.5
```

```
2
     Zoo Exhibit 0.0
     Noodle House 0.0
4 Paintball Field 0.0
                                                                      In [33]:
def return most common venues(row, num top venues):
   row categories = row.iloc[1:]
    row_categories_sorted = row_categories.sort_values(ascending=False)
    return row categories sorted.index.values[0:num top venues]
Most Common venues near neighborhood
                                                                      In [34]:
import numpy as np
num top venues = 10
indicators = ['st', 'nd', 'rd']
columns = ['Neighborhood']
for ind in np.arange(num_top_venues):
       columns.append('{}{} Most Common Venue'.format(ind+1, indicators[ind]
) )
    except:
        columns.append('{}th Most Common Venue'.format(ind+1))
neighborhoods venues sorted = pd.DataFrame(columns=columns)
neighborhoods venues sorted['Neighborhood'] = Scarborough grouped['Neighborho
od'1
for ind in np.arange(Scarborough grouped.shape[0]):
    neighborhoods venues sorted.iloc[ind, 1:] = return most common venues(Sca
rborough grouped.iloc[ind, :], num top venues)
neighborhoods venues sorted.head()
```

Out[34]:

					\Box



K-Means Clustering Approach

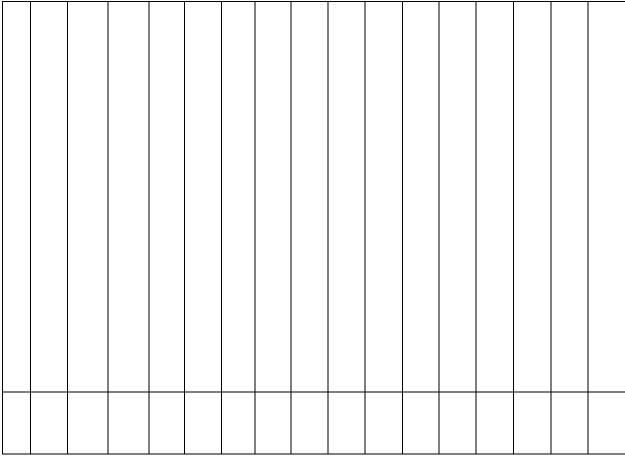
neighborhood

```
In [35]:
# Using K-Means to cluster neighborhood into 3 clusters
Scarborough_grouped_clustering = Scarborough_grouped.drop('Neighborhood', 1)
kmeans = KMeans(n clusters=3, random state=0).fit(Scarborough grouped cluster
ing)
kmeans.labels
                                                         Out[35]:
0, 2, 0, 0, 0, 2, 0, 0, 0, 0, 0, 0, 2, 0, 0, 2, 1, 0, 2, 0, 0,
     0, 0, 0, 0, 0, 0, 0, 0, 0, 2, 2, 1, 0, 0, 0, 0, 0, 0, 0, 2, 0, 0,
     2, 0, 0, 0, 0, 0, 2, 2, 0, 0, 2], dtype=int32)
                                                         In [36]:
neighborhoods_venues_sorted.insert(0, 'Cluster Labels', kmeans.labels_)
Scarborough_merged =df_2.iloc[:16,:]
# merge toronto grouped with toronto data to add latitude/longitude for each
```

Scarborough_merged = Scarborough_merged.join(neighborhoods_venues_sorted.set_ index('Neighborhood'), on='Neighborhood')

Scarborough_merged.head() # check the last columns!

,							Out	[36]:



Map of Clusters

```
In [37]:
kclusters = 10
                                                                      In [38]:
# create map
map_clusters = folium.Map(location=[latitude_x, longitude_y], zoom_start=11)
# set color scheme for the clusters
x = np.arange(kclusters)
colors_array = cm.rainbow(np.linspace(0, 1, kclusters))
rainbow = [colors.rgb2hex(i) for i in colors_array]
print(rainbow)
# add markers to the map
markers_colors = []
for lat, lon, nei , cluster in zip(Scarborough_merged['Latitude'],
                                   Scarborough_merged['Longitude'],
                                   Scarborough_merged['Neighborhood'],
                                   Scarborough merged['Cluster Labels']):
```

```
label = folium.Popup(str(nei) + ' Cluster ' + str(cluster), parse html=Tr
ue)
    folium.CircleMarker(
        [lat, lon],
        radius=5,
        popup=label,
        color=rainbow[cluster-1],
        fill=True,
        fill color=rainbow[cluster-1],
        fill opacity=0.7).add to(map clusters)
map clusters
['#8000ff', '#4856fb', '#10a2f0', '#2adddd', '#62fbc4', '#9cfba4', '#d4dd80',
'#ffa256', '#ff562c', '#ff0000']
                                                                       Out[38]:
Make this Notebook Trusted to load map: File -> Trust Notebook
                                                                       In [39]:
df1=Scarborough merged.loc[Scarborough merged['Cluster Labels'] == 0,Scarboro
ugh merged.columns[[2] + list(range(5, Scarborough merged.shape[1]))]]
df2=Scarborough merged.loc[Scarborough merged['Cluster Labels'] == 1,Scarboro
ugh merged.columns[[2] + list(range(5, Scarborough merged.shape[1]))]]
df3=Scarborough merged.loc[Scarborough merged['Cluster Labels'] == 2,Scarboro
ugh merged.columns[[2] + list(range(5, Scarborough merged.shape[1]))]]
                                                                       In [46]:
Scarborough Avg HousingPrice=pd.DataFrame({"Neighborhood":df 2["Neighborhood"
],
                                       "Average Housing Price":[335000.0,28660
0.0,175000.0,225900.0,219400.0,
                                                                573900.0,22500
0.0,370500.0,370500.0,433500.0,279200.0,
                                                                279200.0,22500
0.0,370500.,255400.0,433500.0,433500.0,
                                                                435000.0,28950
0.0,265000.0,285900.0,239400.0,
                                                                589900.0,29500
0.0,380500.0,378500.0,438500.0,229200.0,
                                                                229200.0,36500
0.0,388500.,285400.0,493500.0,477500.0,378000.0,316600.0,195000.0,225900.0,21
9400.0,
                                                                573900.0,36700
0.0,370500.0,370500.0,363500.0,279200.0,
                                                                279200.0,27100
0.0, 370500., 255400.0, 383500.0, 433500.0, 335000.0, 286600.0, 185000.0, 225900.0, 21
9400.0,
```

```
573900.0,32900
0.0,370500.0,370500.0,533500.0,279200.0,
                                                                 279200.0,37500
0.0, 370500., 255400.0, 493500.0, 433500.0, 335000.0, 286600.0, 165000.0, 225900.0, 21
9400.0,
                                                                 573900.0,42500
0.0,370500.0,370500.0,433500.0,279200.0,
                                                                 279200.0,19500
0.0, 370500., 255400.0, 403500.0, 433500.0, 335000.0, 286600.0, 187000.0, 225900.0, 21
9400.0,
                                                                 573900.0,32500
0.0,370500.0,370500.0,333500.0,279200.0,
                                                                 279200.0,28900
0.0,370500.,255400.0,413500.0,433500.0,254800.0,
                                                                 573900.0,32900
0.0,370500.0,370500.0,533500.0,279200.0,
                                                                 279200.0,37500
0.0,370500.,255400.0,493500.0,433500.0,335000.0,286600.0,165
000.0,225900.0,219400.0,
                                                                 573900.0,32900
0.0,370500.0,370500.0,533500.0,279200.0,
                                                                 279200.0,37500
0.0, 370500., 255400.0, 493500.0, 433500.0, 335000.0, 286600.0, 165000.0, 225900.0, 21
9400.0,
                                                                 573900.0,32900
0.0,370500.0,370500.0,533500.0,279200.0,
                                                                 279200.0,37500
0.0, 370500., 255400.0, 493500.0, 433500.0, 335000.0, 286600.0, 165000.0, 225900.0, 21
9400.0,
                                                                 573900.0,32900
0.0,370500.0,370500.0,533500.0,279200.0,
                                                                 279200.0,37500
0.0,370500.,255400.0,493500.0,433500.0,335000.0,286600.0,165000.0,225900.0,21
9400.0,
                                                                 573900.0,32900
0.0,370500.0,370500.0,533500.0,279200.0,
                                                                 279200.0,37500
0.0,370500.
```

Scarborough Avg HousingPrice.set index('Neighborhood', inplace=True, drop=True)

] })

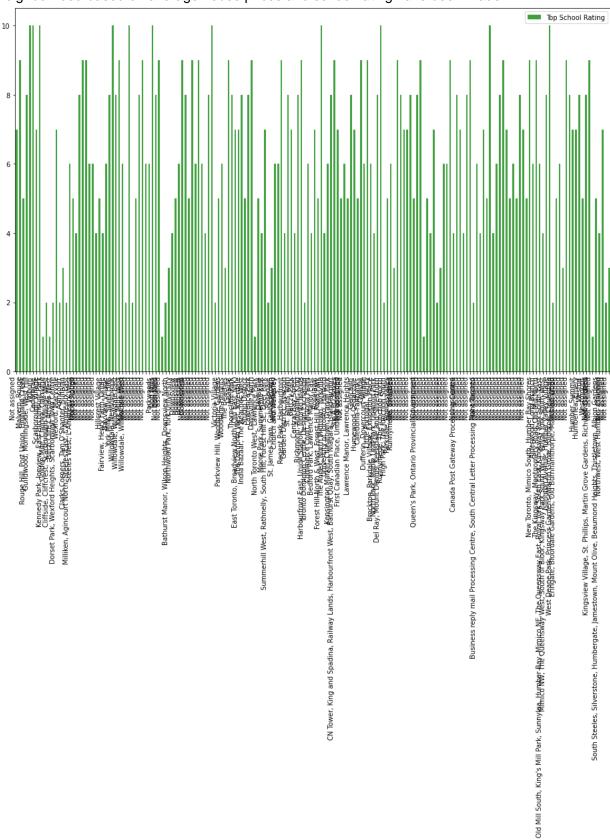
In [47]:

In [48]: Scarborough Avg HousingPrice.plot(kind='bar', figsize=(24,18),alpha=0.75) Out[48]: <matplotlib.axes._subplots.AxesSubplot at 0x7fb7580dee80> Average_Housing_Price Rouge Jillings Huming Services of Children Services Clarks Comers, Tam O'Shante Milliken, Agincourt North Steeles Fast, L'Amor Kennedy Park, Jonyiew, East Bloch Cilffside, Cliffcrest, Searbologis V. K., Wexford Heights, Scarbologis V. Old Mill South, King's Mill Park, Sunnyfilm, CONNY, The Voluenssay Wes, South Will Sark, Royal Monday, The Vigo Mest Deane Park, Princess Card West Deane Park, Princess Card

```
In [49]:
clusters=pd.DataFrame({"Cluster1":df1["Neighborhood"],
                       "Cluster2":df2["Neighborhood"],
                       "Cluster4":df3["Neighborhood"]})
clusters = clusters.replace(np.nan, '', regex=True)
                                                                        In [54]:
new Scarborough=Scarborough merged.set index("Neighborhood",drop=True)
#Source:https://www.greatschools.org
Scarborough school ratings=pd.DataFrame({"Neighborhood":df["Neighborhood"],
                                       "Top School Rating": [7,9,5,8,10,10,7,10
,1,2,1,2,7,2,3,2,6,
                                                             5, 4, 8, 9, 9, 6, 6, 4, 5,
4,6,8,10,8,9,6,2,
                                                             10,2,5,8,9,6,6,10,
8,9,1,2,3,4,5,6,9,
                                                             8,5,9,6,9,6,4,8,10
,2,5,6,3,9,8,7,
                                                             7,8,5,8,9,1,5,4,7,
2,3,6,6,9,4,8,7,
                                                             4,8,9,2,6,4,7,5,10
,4,6,8,9,7,5,6,5,8,7,
                                                             5,9,6,9,6,4,8,10,2
,5,6,3,9,8,7,
                                                             7,8,5,8,9,1,5,4,7,
2,3,6,6,9,4,8,7,
                                                             4,8,9,2,6,4,7,5,10
,4,6,8,9,7,5,6,5,8,7,
                                                             5, 9, 6, 9, 6, 4, 8, 10, 2
,5,6,3,9,8,7,
                                                             7,8,5,8,9,1,5,4,7,
2,3
                                                             ] } )
                                                                        In [55]:
Scarborough school ratings.set index('Neighborhood',inplace=True,drop=True)
Scarborough school ratings.plot(kind='bar',figsize=(16,10),color='green',alph
a=0.75);
```

Conclusion: In this project, using k-means cluster algorithm I separated the neighborhood into 10(Ten) different clusters and for 103 different lattitude and logitude from dataset, which have very-similar neighborhoods around them. Using the charts above results presented to a particular

neighborhood based on average house prices and school rating have been made.



Conclusion: In this project, using k-means cluster algorithm I separated the neighborhood into 10(Ten) different clusters and for 103 different lattitude and logitude from dataset, which have very-similar neighborhoods around them. Using the charts above results presented to a particular neighborhood based on average house prices and school rating have been made.