Week 1. Peer-graded Assignment - Capstone Project Notebook

▼ Instructions

Start a Jupyter Notebook using any platform that you are comfortable with and do the following:

1. Write some markdown to explain that this notebook will be mainly used for the capstone project.

This Jupyter Notebook is going to be used mainly for the developement of the Capstone Project.

- 2. Import the pandas library as pd.
- **3.** Import the Numpy library as np.
- 1 import pandas as pd
- 2 import numpy as np
- 4. Print the following the statement: Hello Capstone Project Course!
- 1 print('Hello Capstone Project Course!')



Hello Capstone Project Course!

Push the Notebook to your Github repository and submit a link to the notebook on your Github repository.

Week 3. Peer-graded Assignment: Segmenting and Clustering Neighb

Instructions

For this assignment, you will be required to explore and cluster the neighborhoods in Toronto.

- 1. Start by creating a new Notebook for this assignment.
- 2. Use the Notebook to build the code to scrape the following Wikipedia page,

https://en.wikipedia.org/wiki/List_of_postal_codes_of_Canada:_M, in order to obtain the data that is in the table transform the data into a pandas dataframe like the one shown below:

- 1 # We import the required packages for the Peer-graded Assigment
- 2 import pandas as pd
- 3 import numpy as np

```
1 # We set the display options of pandas, so we can display the whole table when we are done.
2 pd.options.display.max_rows = 999

1 # We use the pandas' read_html function to read the wikitable
2 df1 = pd.read_html('http://en.wikipedia.org/wiki/List_of_postal_codes_of_Canada:_M', match='Postal codes_of_Canada:_M', match='Po
```

3. To create the above dataframe:

2 df1

- The dataframe will consist of three columns: PostalCode, Borough, and Neighborhood
- Only process the cells that have an assigned borough. Ignore cells with a borough that is Not assigned.
- More than one neighborhood can exist in one postal code area. For example, in the table on the Wikipedia
 is listed twice and has two neighborhoods: Harbourfront and Regent Park. These two rows will be combine
 neighborhoods separated with a comma as shown in row 11 in the above table.
- If a cell has a borough but a Not assigned neighborhood, then the neighborhood will be the same as the bo
- Clean your Notebook and add Markdown cells to explain your work and any assumptions you are making.
- In the last cell of your notebook, use the .shape method to print the number of rows of your dataframe.

```
1 # We get the index of those registers whose Boroughs are not assigned
2 indexNames = df1[df1.Borough=='Not assigned'].index

1 # We drop the rows in which the Borough is not assigned
2 df1.drop(indexNames,inplace=True)

1 # We reset the index of the DataFrame
2 df1.reset_index(drop=True, inplace=True)

1 # We replace the '/' with ',' for every Neighborhood
2 df1['Neighborhood'] = df1['Neighborhood'].apply(lambda x: x.replace(' /',','))

1 # We now check there are no Neighborhoods with 'Not assigned' values
2 if sum(df1['Neighborhood']=='Not assigned')==0:
3    print('All Neighborhood values are Ok.')

All Neighborhood values are Ok.
```

1 # We finally display the complete table of the List_of_postal_codes_of_Canada:_M

	Postal code	Borough	Neighborhood
0	МЗА	North York	Parkwoods
1	M4A	North York	Victoria Village
2	M5A	Downtown Toronto	Regent Park, Harbourfront
3	M6A	North York	Lawrence Manor, Lawrence Heights
4	M7A	Downtown Toronto	Queen's Park, Ontario Provincial Government
5	M9A	Etobicoke	Islington Avenue
6	M1B	Scarborough	Malvern, Rouge
7	МЗВ	North York	Don Mills
8	M4B	East York	Parkview Hill, Woodbine Gardens
9	M5B	Downtown Toronto	Garden District, Ryerson
10	M6B	North York	Glencairn
11	M9B	Etobicoke	West Deane Park, Princess Gardens, Martin Grov
12	M1C	Scarborough	Rouge Hill, Port Union, Highland Creek
13	МЗС	North York	Don Mills
14	M4C	East York	Woodbine Heights
15	M5C	Downtown Toronto	St. James Town
16	M6C	York	Humewood-Cedarvale
17	M9C	Etobicoke	Eringate, Bloordale Gardens, Old Burnhamthorpe
18	M1E	Scarborough	Guildwood, Morningside, West Hill
19	M4E	East Toronto	The Beaches
20	M5E	Downtown Toronto	Berczy Park
21	M6E	York	Caledonia-Fairbanks
22	M1G	Scarborough	Woburn
23	M4G	East York	Leaside
24	M5G	Downtown Toronto	Central Bay Street
25	M6G	Downtown Toronto	Christie
26	M1H	Scarborough	Cedarbrae
27	M2H	North York	Hillcrest Village
28	МЗН	North York	Bathurst Manor, Wilson Heights, Downsview North
29	M4H	East York	Thorncliffe Park
30	M5H	Downtown Toronto	Richmond, Adelaide, King
31	M6H	West Toronto	Dufferin Dovercourt Village

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32	M1J	Scarborough	Scarborough Village	
33	M2J	North York	Fairview, Henry Farm, Oriole	
34	МЗЈ	North York	Northwood Park, York University	
35	M4J	East York	East Toronto	
36	M5J	Downtown Toronto	Harbourfront East, Union Station, Toronto Islands	
37	M6J	West Toronto	Little Portugal, Trinity	
38	M1K	Scarborough	Kennedy Park, Ionview, East Birchmount Park	
39	M2K	North York	Bayview Village	
40	МЗК	North York	Downsview	
41	M4K	East Toronto	The Danforth West, Riverdale	
42	M5K	Downtown Toronto	Toronto Dominion Centre, Design Exchange	
43	M6K	West Toronto	Brockton, Parkdale Village, Exhibition Place	
44	M1L	Scarborough	Golden Mile, Clairlea, Oakridge	
45	M2L	North York	York Mills, Silver Hills	
46	M3L	North York	Downsview	
47	M4L	East Toronto	India Bazaar, The Beaches West	
48	M5L	Downtown Toronto	Commerce Court, Victoria Hotel	
49	M6L	North York	North Park, Maple Leaf Park, Upwood Park	
50	M9L	North York	Humber Summit	
51	M1M	Scarborough	Cliffside, Cliffcrest, Scarborough Village West	
52	M2M	North York	Willowdale, Newtonbrook	
53	МЗМ	North York	Downsview	
54	M4M	East Toronto	Studio District	
55	M5M	North York	Bedford Park, Lawrence Manor East	
56	M6M	York	Del Ray, Mount Dennis, Keelsdale and Silverthorn	
57	M9M	North York	Humberlea, Emery	
58	M1N	Scarborough	Birch Cliff, Cliffside West	
59	M2N	North York	Willowdale	
60	M3N	North York	Downsview	
61	M4N	Central Toronto	Lawrence Park	
62	M5N	Central Toronto	Roselawn	
62				
63	M6N	York	Runnymede, The Junction North	

64	IVI9IV	үогк	vveston	
65	M1P	Scarborough	Dorset Park, Wexford Heights, Scarborough Town	
66	M2P	North York	York Mills West	
67	M4P	Central Toronto	Davisville North	
68	M5P	Central Toronto	Forest Hill North & West	
69	M6P	West Toronto	High Park, The Junction South	
70	M9P	Etobicoke	Westmount	
71	M1R	Scarborough	Wexford, Maryvale	
72	M2R	North York	Willowdale	
73	M4R	Central Toronto	North Toronto West	
74	M5R	Central Toronto	The Annex, North Midtown, Yorkville	
75	M6R	West Toronto	Parkdale, Roncesvalles	
76	M7R	Mississauga	Canada Post Gateway Processing Centre	
77	M9R	Etobicoke	Kingsview Village, St. Phillips, Martin Grove	
78	M1S	Scarborough	Agincourt	
79	M4S	Central Toronto	Davisville	
80	M5S	Downtown Toronto	University of Toronto, Harbord	
81	M6S	West Toronto	Runnymede, Swansea	
82	M1T	Scarborough	Clarks Corners, Tam O'Shanter, Sullivan	
83	M4T	Central Toronto	Moore Park, Summerhill East	
84	M5T	Downtown Toronto	Kensington Market, Chinatown, Grange Park	
85	M1V	Scarborough	Milliken, Agincourt North, Steeles East, L'Amo	
86	M4V	Central Toronto	Summerhill West, Rathnelly, South Hill, Forest	
87	M5V	Downtown Toronto	CN Tower, King and Spadina, Railway Lands, Har	
88	M8V	Etobicoke	New Toronto, Mimico South, Humber Bay Shores	
89	M9V	Etobicoke	South Steeles, Silverstone, Humbergate, Jamest	
90	M1W	Scarborough	Steeles West, L'Amoreaux West	
91	M4W	Downtown Toronto	Rosedale	
92	M5W	Downtown Toronto	Stn A PO Boxes	
93	M8W	Etobicoke	Alderwood, Long Branch	
94	M9W	Etobicoke	Northwest	
95	M1X	Scarborough	Upper Rouge	
96	M4X	Downtown Toronto	St. James Town, Cabbagetown	

M5X	Downtown Toronto	First Canadian Place, Underground city
M8X	Etobicoke	The Kingsway, Montgomery Road, Old Mill North
M4Y	Downtown Toronto	Church and Wellesley
M7Y	East Toronto	Business reply mail Processing CentrE
M8Y	Etobicoke	Old Mill South, King's Mill Park, Sunnylea, Hu
M8Z	Etobicoke	Mimico NW, The Queensway West, South of Bloor,
	M8X M4Y M7Y M8Y	M8X Etobicoke M4Y Downtown Toronto M7Y East Toronto M8Y Etobicoke

4. Submit a link to your Notebook on your Github repository. (10 marks)

Note: There are different website scraping libraries and packages in Python. For scraping the above table, you can the table into a pandas dataframe.

Here is a link to a csv file that has the geographical coordinates of each postal code:

<u>http://cocl.us/Geospatial_data/Geospatial_Coordinates.csv</u>
. Use the csv file to create the following dataframe:

```
1 df2 = pd.read_csv(r'http://cocl.us/Geospatial_data/Geospatial_Coordinates.csv')
2 # df2.head()

1 # We now merge both DataFrames
2 df = df1.merge(df2[['Latitude','Longitude']], how = 'left', left_on=df1['Postal code'],right_on=df2[
3 df
```



key_0Postal codeBoroughNeighborho0M3AM3ANorth YorkParkwood1M4AM4ANorth YorkVictoria Villa2M5AM5ADowntown TorontoRegent Park, Harbourfro3M6AM6ANorth YorkLawrence Manor, Lawrence Height4M7AM7ADowntown TorontoQueen's Park, Ontario Provincial Government5M9AM9AEtobicokeIslington Aven6M1BM1BScarboroughMalvern, Rou7M3BM3BNorth YorkDon M8M4BEast YorkParkview Hill, Woodbine Garde9M5BM5BDowntown TorontoGarden District, Ryers10M6BM6BNorth YorkGlenca11M9BM9BEtobicokeWest Deane Park, Princess Gardens, Martin Grown12M1CM1CScarboroughRouge Hill, Port Union, Highland Crewn13M3CM3CNorth YorkDon M14M4CM4CEast YorkWoodbine Height15M5CM5CDowntown TorontoSt. James Town16M6CM6CYorkHumewood-Cedary	od Latitude
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10M6BM6BNorth YorkGlenca11M9BM9BEtobicokeWest Deane Park, Princess Gardens, Martin Grown12M1CM1CScarboroughRouge Hill, Port Union, Highland Crewn13M3CM3CNorth YorkDon M14M4CM4CEast YorkWoodbine Height15M5CM5CDowntown TorontoSt. James Toronto	ns 43.706397
11M9BM9BEtobicokeWest Deane Park, Princess Gardens, Martin Grown12M1CM1CScarboroughRouge Hill, Port Union, Highland Crewn13M3CM3CNorth YorkDon M14M4CM4CEast YorkWoodbine Height15M5CM5CDowntown TorontoSt. James Toronto	on 43.657162
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13M3CM3CNorth YorkDon M14M4CM4CEast YorkWoodbine Height15M5CM5CDowntown TorontoSt. James Toronto	43.650943
14 M4C M4C East York Woodbine Height 15 M5C M5C Downtown Toronto St. James Toronto	ek 43.784535
15 M5C M5C Downtown Toronto St. James Toronto	ls 43.725900
	ts 43.695344
16 M6C M6C York Humewood-Cedary:	n 43.651494
10 moo Tork Trainewood-Octaive	le 43.693781
17 M9C M9C Etobicoke Eringate, Bloordale Gardens, Old Burnhamthorpe	43.643515
18 M1E M1E Scarborough Guildwood, Morningside, West I	ill 43.763573
19 M4E M4E East Toronto The Beach	es 43.676357
20 M5E M5E Downtown Toronto Berczy Pa	rk 43.644771
21 M6E M6E York Caledonia-Fairbar	ks 43.689026
22 M1G M1G Scarborough Wobu	rn 43.770992
23 M4G M4G East York Leasi	de 43.709060
24 M5G M5G Downtown Toronto Central Bay Stre	et 43.657952
25 M6G M6G Downtown Toronto Chris	ie 43.669542
26 M1H M1H Scarborough Cedarbr	ae 43.773136
27 M2H M2H North York Hillcrest Villa	ge 43.803762
28 M3H M3H North York Bathurst Manor, Wilson Heights, Downsview No	th 43.754328
29 M4H M4H East York Thorncliffe Pa	rk 43.705369
30 M5H M5H Downtown Toronto Richmond, Adelaide, Ki	ng 43.650571
31 M6H M6H West Toronto Dufferin Dovercourt Villa	ne 43 669005

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32	M1J	M1J	Scarborough	Scarborough Village	43.744734 -
33	M2J	M2J	North York	Fairview, Henry Farm, Oriole	43.778517 -
34	M3J	M3J	North York	Northwood Park, York University	43.767980 -
35	M4J	M4J	East York	East Toronto	43.685347 -
36	M5J	M5J	Downtown Toronto	Harbourfront East, Union Station, Toronto Islands	43.640816 -
37	M6J	M6J	West Toronto	Little Portugal, Trinity	43.647927 -
38	M1K	M1K	Scarborough	Kennedy Park, Ionview, East Birchmount Park	43.727929 -
39	M2K	M2K	North York	Bayview Village	43.786947 -
40	МЗК	МЗК	North York	Downsview	43.737473 -
41	M4K	M4K	East Toronto	The Danforth West, Riverdale	43.679557 -
42	M5K	M5K	Downtown Toronto	Toronto Dominion Centre, Design Exchange	43.647177 -
43	M6K	M6K	West Toronto	Brockton, Parkdale Village, Exhibition Place	43.636847 -
44	M1L	M1L	Scarborough	Golden Mile, Clairlea, Oakridge	43.711112 -
45	M2L	M2L	North York	York Mills, Silver Hills	43.757490 -
46	M3L	M3L	North York	Downsview	43.739015 -
47	M4L	M4L	East Toronto	India Bazaar, The Beaches West	43.668999 -
48	M5L	M5L	Downtown Toronto	Commerce Court, Victoria Hotel	43.648198 -
49	M6L	M6L	North York	North Park, Maple Leaf Park, Upwood Park	43.713756 -
50	M9L	M9L	North York	Humber Summit	43.756303 -
51	M1M	M1M	Scarborough	Cliffside, Cliffcrest, Scarborough Village West	43.716316 -
52	M2M	M2M	North York	Willowdale, Newtonbrook	43.789053 -
53	МЗМ	M3M	North York	Downsview	43.728496 -
54	M4M	M4M	East Toronto	Studio District	43.659526 -
55	M5M	M5M	North York	Bedford Park, Lawrence Manor East	43.733283 -
56	M6M	M6M	York	Del Ray, Mount Dennis, Keelsdale and Silverthorn	43.691116 -
57	M9M	M9M	North York	Humberlea, Emery	43.724766 -
58	M1N	M1N	Scarborough	Birch Cliff, Cliffside West	43.692657 -
59	M2N	M2N	North York	Willowdale	43.770120 -
60	M3N	M3N	North York	Downsview	43.761631 -
61	M4N	M4N	Central Toronto	Lawrence Park	43.728020 -
62	M5N	M5N	Central Toronto	Roselawn	43.711695 -
63	M6N	M6N	York	Runnymede, The Junction North	43.673185 -
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64	IVI9IN	IVI9IV	үогк	vveston	43./008/0	
65	M1P	M1P	Scarborough	Dorset Park, Wexford Heights, Scarborough Town	43.757410	
66	M2P	M2P	North York	York Mills West	43.752758	
67	M4P	M4P	Central Toronto	Davisville North	43.712751	
68	M5P	M5P	Central Toronto	Forest Hill North & West	43.696948	
69	M6P	M6P	West Toronto	High Park, The Junction South	43.661608	,
70	M9P	M9P	Etobicoke	Westmount	43.696319	
71	M1R	M1R	Scarborough	Wexford, Maryvale	43.750072	
72	M2R	M2R	North York	Willowdale	43.782736	
73	M4R	M4R	Central Toronto	North Toronto West	43.715383	
74	M5R	M5R	Central Toronto	The Annex, North Midtown, Yorkville	43.672710	
75	M6R	M6R	West Toronto	Parkdale, Roncesvalles	43.648960	
76	M7R	M7R	Mississauga	Canada Post Gateway Processing Centre	43.636966	
77	M9R	M9R	Etobicoke	Kingsview Village, St. Phillips, Martin Grove	43.688905	
78	M1S	M1S	Scarborough	Agincourt	43.794200	
79	M4S	M4S	Central Toronto	Davisville	43.704324	
80	M5S	M5S	Downtown Toronto	University of Toronto, Harbord	43.662696	
81	M6S	M6S	West Toronto	Runnymede, Swansea	43.651571	
82	M1T	M1T	Scarborough	Clarks Corners, Tam O'Shanter, Sullivan	43.781638	
83	M4T	M4T	Central Toronto	Moore Park, Summerhill East	43.689574	
84	M5T	M5T	Downtown Toronto	Kensington Market, Chinatown, Grange Park	43.653206	
85	M1V	M1V	Scarborough	Milliken, Agincourt North, Steeles East, L'Amo	43.815252	
86	M4V	M4V	Central Toronto	Summerhill West, Rathnelly, South Hill, Forest	43.686412	
87	M5V	M5V	Downtown Toronto	CN Tower, King and Spadina, Railway Lands, Har	43.628947	
88	M8V	M8V	Etobicoke	New Toronto, Mimico South, Humber Bay Shores	43.605647	
89	M9V	M9V	Etobicoke	South Steeles, Silverstone, Humbergate, Jamest	43.739416	
90	M1W	M1W	Scarborough	Steeles West, L'Amoreaux West	43.799525	
91	M4W	M4W	Downtown Toronto	Rosedale	43.679563	
92	M5W	M5W	Downtown Toronto	Stn A PO Boxes	43.646435	
93	W8W	M8W	Etobicoke	Alderwood, Long Branch	43.602414	
94	M9W	M9W	Etobicoke	Northwest	43.706748	
95	M1X	M1X	Scarborough	Upper Rouge	43.836125	
96	M4X	M4X	Downtown Toronto	St. James Town, Cabbagetown	43.667967	

97	M5X	M5X	Downtown Toronto	First Canadian Place, Underground city	43.648429 -
98	M8X	M8X	Etobicoke	The Kingsway, Montgomery Road, Old Mill North	43.653654 -
99	M4Y	M4Y	Downtown Toronto	Church and Wellesley	43.665860 -
100	M7Y	M7Y	East Toronto	Business reply mail Processing CentrE	43.662744 -
101	M8Y	M8Y	Etobicoke	Old Mill South, King's Mill Park, Sunnylea, Hu	43.636258 -
102	M8Z	M8Z	Etobicoke	Mimico NW, The Queensway West, South of Bloor,	43.628841 -

5. Explore and cluster the neighborhoods in Toronto. You can decide to work with only boroughs that contain the replicate the same analysis we did to the New York City data. It is up to you.

Just make sure:

- 1. to add enough Markdown cells to explain what you decided to do and to report any observations you make
- 2. to generate maps to visualize your neighborhoods and how they cluster together.

Once you are happy with your analysis, submit a link to the new Notebook on your Github repository. (3 marks)

▼ 1. Download and Explore Dataset

```
1 # To simplify the analysis, we have decided to work only with Boroughs that contain the word Toronto
```

2 downtown_data = df[df['Borough'] == 'Downtown Toronto'].reset_index(drop=True)

M5E Downtown Toronto

3 downtown_data.head()

M₅E

4



Berczy Park 43.644771 -79.37330

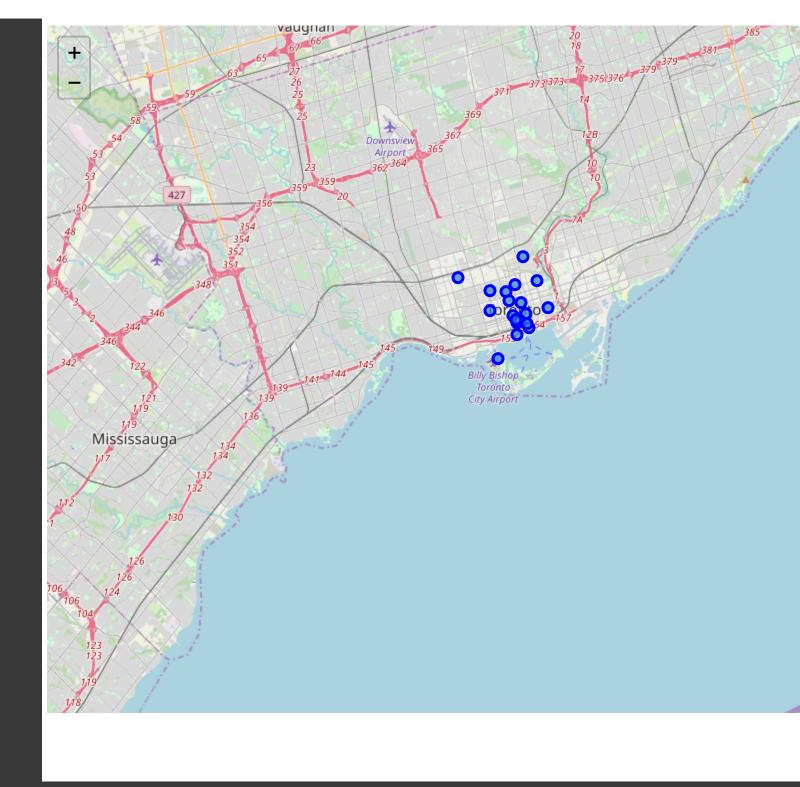
```
1 from geopy.geocoders import Nominatim # convert an address into latitude and longitude values
2
3 # Let's get the geographic coordinates of Toronto's Downtown
4
5 address = 'Downtown Toronto'
6
7 geolocator = Nominatim(user_agent="toronto_explorer")
8 location = geolocator.geocode(address)
9 latitude = location.latitude
10 longitude = location.longitude
11 print('The geograpical coordinate of Manhattan are {}, {}.'.format(latitude, longitude))
```



Let's visualize Toronto and the neighborhoods in it.

```
1 # Create map of Downtown Toronto using latitude and longitude values
 3 import folium # map rendering library
 4 # Matplotlib and associated plotting modules
 5 import matplotlib.cm as cm
 6 import matplotlib.colors as colors
 7
 8 map_downtown = folium.Map(location=[latitude, longitude], zoom_start=11)
 9
10 # add markers to map
11 for lat, lng, label in zip(downtown_data['Latitude'], downtown_data['Longitude'], downtown_data['Nei
       label = folium.Popup(label, parse_html=True)
       folium.CircleMarker(
13
14
           [lat, lng],
           radius=5,
15
16
           popup=label,
17
           color='blue',
18
           fill=True,
19
           fill_color='#3186cc',
           fill_opacity=0.7,
20
           parse_html=False).add_to(map_downtown)
21
22
23 map_downtown
```





Next, we are going to start utilizing the Foursquare API to explore the neighborhoods and segment them.

Define Foursquare Credentials and Version

```
1 CLIENT_ID = 'xxx' # your Foursquare ID
2 CLIENT_SECRET = 'xxx' # your Foursquare Secret
3 VERSION = '20180605' # Foursquare API version
4
5 print('Your credentails:')
6 print('CLIENT_ID: ' + CLIENT_ID)
```

```
7 print('CLIENT_SECRET:' + CLIENT_SECRET)
```

```
Your credentails:
CLIENT_ID: xxx
CLIENT_SECRET:xxx
```

▼ 2. Explore Neighborhoods in Manhattan

```
1 import json # library to handle JSON files
 2 import requests # library to handle requests
 3 from pandas.io.json import json_normalize # tranform JSON file into a pandas dataframe
 1 # Let's create a function to get the top 100 venues that are in a radius of 500
 2 # meters for all the neighborhoods in Downtown Toronto
 4 LIMIT = 100 # limit of number of venues returned by Foursquare API
 5
 6 def getNearbyVenues(names, latitudes, longitudes, radius=500):
 7
 8
       venues_list=[]
 9
       for name, lat, lng in zip(names, latitudes, longitudes):
           print(name)
10
11
12
           # create the API request URL
13
           url = 'https://api.foursquare.com/v2/venues/explore?&client_id={}&client_secret={}&v={}&ll={
               CLIENT_ID,
14
15
               CLIENT_SECRET,
               VERSION,
16
17
               lat,
18
               lng,
19
               radius,
20
               LIMIT)
21
22
           # make the GET request
           results = requests.get(url).json()["response"]['groups'][0]['items']
23
24
25
           # return only relevant information for each nearby venue
           venues list.append([(
26
27
               name,
28
               lat,
29
               lng,
               v['venue']['name'],
30
               v['venue']['location']['lat'],
31
               v['venue']['location']['lng'],
32
               v['venue']['categories'][0]['name']) for v in results])
33
34
35
       nearby venues = pd.DataFrame([item for venue list in venues list for item in venue list])
       nearby_venues.columns = ['Neighborhood',
36
37
                     'Neighborhood Latitude',
                     'Neighborhood Longitude',
38
                     'Venue',
39
```

```
41
                     'Venue Longitude',
42
                     'Venue Category']
43
44
      return(nearby_venues)
 1 downtown_venues = getNearbyVenues(names=downtown_data['Neighborhood'],
 2
                                      latitudes=downtown_data['Latitude'],
 3
                                      longitudes=downtown_data['Longitude']
 4
     Regent Park, Harbourfront
     Queen's Park, Ontario Provincial Government
     Garden District, Ryerson
     St. James Town
     Berczy Park
     Central Bay Street
     Christie
     Richmond, Adelaide, King
     Harbourfront East, Union Station, Toronto Islands
     Toronto Dominion Centre, Design Exchange
     Commerce Court, Victoria Hotel
     University of Toronto, Harbord
     Kensington Market, Chinatown, Grange Park
     CN Tower, King and Spadina, Railway Lands, Harbourfront West, Bathurst Quay, South Niagara, Islan
     Rosedale
     Stn A PO Boxes
     St. James Town, Cabbagetown
     First Canadian Place, Underground city
     Church and Wellesley
 1 # Let's check the size of the resulting dataframe
 2 print(downtown_venues.shape)
```

3 downtown venues.head()



(1259, 7)

	Neighborhood	Neighborhood Latitude	Neighborhood Longitude	Venue V
0	Regent Park, Harbourfront	43.65426	-79.360636	Roselle Desserts
1	Regent Park, Harbourfront	43.65426	-79.360636	Tandem Coffee
2	Regent Park, Harbourfront	43.65426	-79.360636	Cooper Koo Family YMCA
3	Regent Park, Harbourfront	43.65426	-79.360636	Body Blitz Spa East
4	Regent Park, Harbourfront	43.65426	-79.360636	Morning Glory Cafe

Let's check how many venues were returned for each neighborhood

venue Latituue ,

1 downtown_venues.groupby('Neighborhood').count()



Neighborhood

Berczy Park	56
CN Tower, King and Spadina, Railway Lands, Harbourfront West, Bathurst Quay, South Niagara, Island airport	16
Central Bay Street	73
Christie	18
Church and Wellesley	77
Commerce Court, Victoria Hotel	100
First Canadian Place, Underground city	100
Garden District, Ryerson	100
Harbourfront East, Union Station, Toronto Islands	100
Kensington Market, Chinatown, Grange Park	66
Queen's Park, Ontario Provincial Government	34
Regent Park, Harbourfront	45
Richmond, Adelaide, King	100
Rosedale	4
St. James Town	91
St. James Town, Cabbagetown	46
Stn A PO Boxes	97
Toronto Dominion Centre, Design Exchange	100
University of Toronto, Harbord	36

Let's find out how many unique categories can be curated from all the returned venues

```
1 print('There are {} uniques categories.'.format(len(downtown_venues['Venue Category'].unique())))
```



There are 207 uniques categories.

▼ 3. Analyze Each Neighborhood

```
1 # one hot encoding
2 downtown_onehot = pd.get_dummies(downtown_venues[['Venue Category']], prefix="", prefix_sep="")
3
```

^{4 #} add neighborhood column back to dataframe

```
5 downtown_onehot['Neighborhood'] = downtown_venues['Neighborhood']
6
7 # move neighborhood column to the first column
8 fixed_columns = [downtown_onehot.columns[-1]] + list(downtown_onehot.columns[:-1])
9 downtown_onehot = downtown_onehot[fixed_columns]
10
11 downtown_onehot.head()
```



	Yoga Studio	Afghan Restaurant	Airport	Airport Food Court	Airport Gate	Airport Lounge		Airport Terminal		Antique Shop
0	0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0

5 rows × 207 columns

And let's examine the new dataframe size.

1 downtown_onehot.shape



(1259, 207)

Next, let's group rows by neighborhood and by taking the mean of the frequency of occurrence of each category

- 1 downtown_grouped = downtown_onehot.groupby('Neighborhood').mean().reset_index()
- 2 downtown_grouped



_	Neighborhood	Yoga Studio	Afghan Restaurant	Airport	Airport Food Court	Airport Gate	Airport Lounge	Airport Service	Airport Terminal	Am Rest
0	Berczy Park	0.000000	0.000000	0.0000	0.0000	0.0000	0.000	0.000	0.0000	0.
1	CN Tower, King and Spadina, Railway Lands, Har	0.000000	0.000000	0.0625	0.0625	0.0625	0.125	0.125	0.0625	0.
2	Central Bay Street	0.013699	0.000000	0.0000	0.0000	0.0000	0.000	0.000	0.0000	0.
3	Christie	0.000000	0.000000	0.0000	0.0000	0.0000	0.000	0.000	0.0000	0.
4	Church and Wellesley	0.025974	0.012987	0.0000	0.0000	0.0000	0.000	0.000	0.0000	0.
5	Commerce Court, Victoria Hotel	0.000000	0.000000	0.0000	0.0000	0.0000	0.000	0.000	0.0000	0.
6	First Canadian Place, Underground city	0.000000	0.000000	0.0000	0.0000	0.0000	0.000	0.000	0.0000	0.
7	Garden District, Ryerson	0.000000	0.000000	0.0000	0.0000	0.0000	0.000	0.000	0.0000	0.
8	Harbourfront East, Union Station, Toronto Islands	0.000000	0.000000	0.0000	0.0000	0.0000	0.000	0.000	0.0000	0.
9	Kensington Market, Chinatown, Grange Park	0.000000	0.000000	0.0000	0.0000	0.0000	0.000	0.000	0.0000	0.
10	Queen's Park, Ontario Provincial Government	0.029412	0.000000	0.0000	0.0000	0.0000	0.000	0.000	0.0000	0.
11	Regent Park, Harbourfront	0.022222	0.000000	0.0000	0.0000	0.0000	0.000	0.000	0.0000	0.
12	Richmond, Adelaide, King	0.000000	0.000000	0.0000	0.0000	0.0000	0.000	0.000	0.0000	0.
13	Rosedale	0.000000	0.000000	0.0000	0.0000	0.0000	0.000	0.000	0.0000	0.
14	St. James Town	0.000000	0.000000	0.0000	0.0000	0.0000	0.000	0.000	0.0000	0.
15	St. James Town,	0.000000	0.000000	0.0000	0.0000	0.0000	0.000	0.000	0.0000	0.

	Cabbagetown									
16	Stn A PO Boxes	0.000000	0.000000	0.0000	0.0000	0.0000	0.000	0.000	0.0000	0.
17	Toronto Dominion Centre, Design Exchange	0.000000	0.000000	0.0000	0.0000	0.0000	0.000	0.000	0.0000	0.
18	University of Toronto, Harbord	0.027778	0.000000	0.0000	0.0000	0.0000	0.000	0.000	0.0000	0.
19 rov	vs × 207 column	S								

Let's confirm the new size

Let's print each neighborhood along with the top 5 most common venues

```
1 num_top_venues = 5
 2
 3 for hood in downtown_grouped['Neighborhood']:
       print("----"+hood+"----")
 4
      temp = downtown_grouped[downtown_grouped['Neighborhood'] == hood].T.reset_index()
 5
      temp.columns = ['venue','freq']
 6
      temp = temp.iloc[1:]
      temp['freq'] = temp['freq'].astype(float)
 8
 9
      temp = temp.round({'freq': 2})
      print(temp.sort_values('freq', ascending=False).reset_index(drop=True).head(num_top_venues))
10
      print('\n')
11
```



```
----Berczy Park----
               venue freq
         Coffee Shop 0.05
          Restaurant 0.04
1
2 Italian Restaurant 0.04
3
                Café 0.04
4 Seafood Restaurant 0.04
----CN Tower, King and Spadina, Railway Lands, Harbourfront West, Bathurst Quay, South Niagara, I
               venue freq
      Airport Lounge 0.12
1
     Airport Service 0.12
2
         Coffee Shop 0.06
3
             Airport 0.06
  Airport Food Court 0.06
----Central Bay Street----
                venue freq
          Coffee Shop 0.16
1
   Italian Restaurant 0.05
2
                 Café 0.05
3
       Sandwich Place 0.04
  Japanese Restaurant 0.04
----Christie----
          venue freq
  Grocery Store 0.22
1
           Café 0.17
2
           Park 0.11
      Nightclub 0.06
3
    Gas Station 0.06
----Church and Wellesley----
                venue freq
0
          Coffee Shop 0.06
1
              Gay Bar 0.05
  Japanese Restaurant 0.05
3
    Sushi Restaurant 0.04
4
           Restaurant 0.04
----Commerce Court, Victoria Hotel----
        venue freq
  Coffee Shop 0.10
1
   Restaurant 0.07
2
         Café 0.07
3
        Hotel 0.06
4
          Gym 0.04
----First Canadian Place, Underground city----
        venue freq
  Coffee Shop 0.12
1
         Café 0.07
2
    Restaurant 0.06
```

Cum a as

```
----Garden District, Ryerson----
                venue freq
       Clothing Store 0.09
0
          Coffee Shop 0.09
1
2
      Bubble Tea Shop 0.03
3
   Italian Restaurant 0.03
  Japanese Restaurant 0.03
----Harbourfront East, Union Station, Toronto Islands----
               venue freq
          Coffee Shop 0.12
            Aquarium 0.05
1
2
               Hotel 0.04
3
          Restaurant 0.04
4 Italian Restaurant 0.04
----Kensington Market, Chinatown, Grange Park----
                  venue freq
0
            Coffee Shop 0.06
1
                   Café 0.06
  Vietnamese Restaurant 0.06
3
     Mexican Restaurant 0.05
4
                    Bar 0.05
----Queen's Park, Ontario Provincial Government----
                venue freq
          Coffee Shop 0.24
1
                Diner 0.06
          Yoga Studio 0.03
2
  Distribution Center 0.03
3
          Burger Joint 0.03
----Regent Park, Harbourfront----
           venue freq
     Coffee Shop 0.16
0
1
            Park 0.07
2
          Bakery 0.07
3
             Pub 0.07
4 Breakfast Spot 0.04
----Richmond, Adelaide, King----
        venue freq
  Coffee Shop 0.09
         Café 0.05
1
2
          Gym 0.04
3
   Restaurant 0.04
       Bakery 0.03
----Rosedale----
                venue freq
```

Hotel 0.03

```
Ø
                 Park 0.50
1
           Playground 0.25
2
                Trail 0.25
3 Moroccan Restaurant 0.00
4
              Market 0.00
----St. James Town----
         venue freq
          Café 0.05
1
   Coffee Shop 0.05
2
  Cocktail Bar 0.04
3
    Beer Bar 0.03
  Restaurant 0.03
----St. James Town, Cabbagetown----
        venue freq
  Coffee Shop 0.09
  Restaurant 0.07
1
2
        Park 0.07
3
      Bakery 0.04
4
        Café 0.04
----Stn A PO Boxes----
               venue freq
         Coffee Shop 0.11
1 Italian Restaurant 0.04
2 Seafood Restaurant 0.04
3
                Café 0.04
          Restaurant 0.04
4
----Toronto Dominion Centre, Design Exchange----
               venue freq
         Coffee Shop 0.13
1
               Hotel 0.08
2
                Café 0.07
3
          Restaurant 0.05
 Seafood Restaurant 0.03
----University of Toronto, Harbord----
               venue freq
0
               Café 0.14
1
           Bookstore 0.08
2
              Bakery 0.06
          Restaurant 0.06
4 Italian Restaurant 0.06
```

Let's put that into a pandas dataframe¶

```
row_categories = row.iloc[1:]
       row_categories_sorted = row_categories.sort_values(ascending=False)
 4
 5
 6
       return row_categories_sorted.index.values[0:num_top_venues]
 7
 8 # Now let's create the new dataframe and display the top 10 venues for each neighborhood.
 9 num_top_venues = 10
10
11 indicators = ['st', 'nd', 'rd']
12
13 # create columns according to number of top venues
14 columns = ['Neighborhood']
15 for ind in np.arange(num_top_venues):
16
       try:
17
           columns.append('{}{} Most Common Venue'.format(ind+1, indicators[ind]))
18
       except:
19
           columns.append('{}th Most Common Venue'.format(ind+1))
20
21 # create a new dataframe
22 neighborhoods_venues_sorted = pd.DataFrame(columns=columns)
23 neighborhoods_venues_sorted['Neighborhood'] = downtown_grouped['Neighborhood']
24
25 for ind in np.arange(downtown_grouped.shape[0]):
26
       neighborhoods_venues_sorted.iloc[ind, 1:] = return_most_common_venues(downtown_grouped.iloc[ind,
27
28 neighborhoods_venues_sorted.head()
```

	Neighborhood	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue	6th (
0	Berczy Park	Coffee Shop	Seafood Restaurant	Cocktail Bar	Café	Cheese Shop	Res
1	CN Tower, King and Spadina, Railway Lands, Har	Airport Lounge	Airport Service	Harbor / Marina	Boat or Ferry	Plane	Ren Lo
2	Central Bay Street	Coffee Shop	Café	Italian Restaurant	Sandwich Place	Middle Eastern Restaurant	Jar Res
3	Christie	Grocery Store	Café	Park	Baby Store	Nightclub	Coffe
4	Church and Wellesley	Coffee Shop	Gay Bar	Japanese Restaurant	Sushi Restaurant	Restaurant	Pizza

4. Cluster Neighborhoods

```
1 # import k-means from clustering stage
2 from sklearn.cluster import KMeans
3
4 # Run k-means to cluster the neighborhood into 5 clusters
```

```
5 # set number of clusters
6 kclusters = 5
7
8 downtown_grouped_clustering = downtown_grouped.drop('Neighborhood', 1)
9
10 # run k-means clustering
11 kmeans = KMeans(n_clusters=kclusters, random_state=0).fit(downtown_grouped_clustering)
12
13 # check cluster labels generated for each row in the dataframe
14 kmeans.labels_[0:10]
```

array([2, 3, 2, 4, 2, 2, 2, 2, 2], dtype=int32)

Let's create a new dataframe that includes the cluster as well as the top 10 venues for each neighborhood.

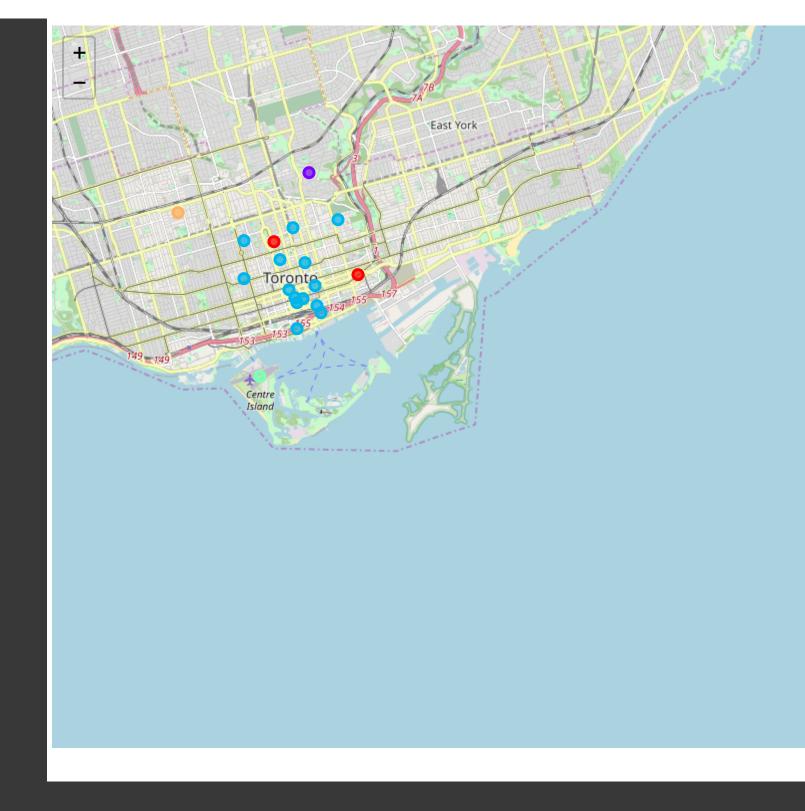


	key_0	Postal code	Borough	Neighborhood	Latitude	Longitude	Cluster Labels	1st Most Common Venue	2nd Most Common Venue	3rd M Com Ve
0	M5A	M5A	Downtown Toronto	Regent Park, Harbourfront	43.654260	-79.360636	0	Coffee Shop	Pub	F
1	M7A	М7А	Downtown Toronto	Queen's Park, Ontario Provincial Government	43.662301	-79.389494	0	Coffee Shop	Diner	Y Sti
2	M5B	M5B	Downtown Toronto	Garden District, Ryerson	43.657162	-79.378937	2	Coffee Shop	Clothing Store	Mid Eas Restau
3	M5C	M5C	Downtown Toronto	St. James Town	43.651494	-79.375418	2	Café	Coffee Shop	Coc
4	M5E	M5E	Downtown Toronto	Berczy Park	43.644771	-79.373306	2	Coffee Shop	Seafood Restaurant	Coc

Finally, let's visualize the resulting clusters

```
1 # create map
2 map_clusters = folium.Map(location=[latitude, longitude], zoom_start=11)
3
```

```
4 # set color scheme for the clusters
 5 x = np.arange(kclusters)
 6 ys = [i + x + (i*x)**2 \text{ for } i \text{ in range(kclusters)}]
 7 colors_array = cm.rainbow(np.linspace(0, 1, len(ys)))
 8 rainbow = [colors.rgb2hex(i) for i in colors_array]
9
10 # add markers to the map
11 markers_colors = []
12 for lat, lon, poi, cluster in zip(downtown_merged['Latitude'], downtown_merged['Longitude'], downtown
       label = folium.Popup(str(poi) + ' Cluster ' + str(cluster), parse_html=True)
13
14
       folium.CircleMarker(
15
           [lat, lon],
16
           radius=5,
17
           popup=label,
           color=rainbow[cluster-1],
18
19
           fill=True,
20
           fill_color=rainbow[cluster-1],
21
           fill_opacity=0.7).add_to(map_clusters)
22
23 map_clusters
```



→ 5. Examine Clusters

Now, you can examine each cluster and determine the discriminating venue categories that distinguish each clucategories, you can then assign a name to each cluster.

→ Cluster 1

1 downtown manged lacidowntown manged['Cluston Labels'] -- 0 downtown manged columns[[1] + list(nand

I u	JWIIC	.own_iller g	eu. Toc [down	icowii_iiiei g	eul Clustei	Laueis] 0,	down cown_iiie	i geu.coruiiiis	[[1] + 1130()	alige
		Postal code	Longitude	Cluster Labels	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue	6.
	0	M5A	-79.360636	0	Coffee Shop	Pub	Park	Bakery	Café	В
	1	M7A	-79.389494	0	Coffee Shop	Diner	Yoga Studio	Beer Bar	Distribution Center	ı

→ Cluster 2

1 downtown_merged.loc[downtown_merged['Cluster Labels'] == 1, downtown_merged.columns[[1] + list(range

	Postal code	Longitude	Cluster Labels	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue	6
14	M4W	-79.377529	1	Park	Playground	Trail	Dance Studio	Dumpling Restaurant	Doi

→ Cluster 3

1 downtown_merged.loc[downtown_merged['Cluster Labels'] == 2, downtown_merged.columns[[1] + list(range



	Postal code	Longitude	Cluster Labels	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue	
2	M5B	-79.378937	2	Coffee Shop	Clothing Store	Middle Eastern Restaurant	Bubble Tea Shop	Café	
3	M5C	-79.375418	2	Café	Coffee Shop	Cocktail Bar	Italian Restaurant	Beer Bar	F
4	M5E	-79.373306	2	Coffee Shop	Seafood Restaurant	Cocktail Bar	Café	Cheese Shop	F
5	M5G	-79.387383	2	Coffee Shop	Café	Italian Restaurant	Sandwich Place	Middle Eastern Restaurant	F
7	М5Н	-79.384568	2	Coffee Shop	Café	Restaurant	Gym	Thai Restaurant	
8	M5J	-79.381752	2	Coffee Shop	Aquarium	Restaurant	Café	Hotel	F
9	M5K	-79.381576	2	Coffee Shop	Hotel	Café	Restaurant	Bar	(
10	M5L	-79.379817	2	Coffee Shop	Café	Restaurant	Hotel	Gym	F
11	M5S	-79.400049	2	Café	Bookstore	Japanese Restaurant	Bar	Italian Restaurant	
12	M5T	-79.400049	2	Café	Vietnamese Restaurant	Coffee Shop	Bar	Vegetarian / Vegan Restaurant	F
15	M5W	-79.374846	2	Coffee Shop	Restaurant	Seafood Restaurant	Café	Italian Restaurant	
16	M4X	-79.367675	2	Coffee Shop	Restaurant	Park	Pub	Italian Restaurant	Р
17	M5X	-79.382280	2	Coffee Shop	Café	Restaurant	Gym	Seafood Restaurant	F
18	M4Y	-79.383160	2	Coffee Shop	Gay Bar	Japanese Restaurant	Sushi Restaurant	Restaurant	Р

→ Cluster 4

1 downtown_merged.loc[downtown_merged['Cluster Labels'] == 3, downtown_merged.columns[[1] + list(range



	Postal code	Longitude	Cluster Labels	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue	6
13	M5V	-79.39442	3	Airport Lounge	Airport Service	Harbor / Marina	Boat or Ferry	Plane	R

→ Cluster 5

1 downtown_merged.loc[downtown_merged['Cluster Labels'] == 4, downtown_merged.columns[[1] + list(range

Postal code	Longitude	Cluster Labels	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue	6
6 M6G	-79.422564	4	Grocery Store	Café	Park	Baby Store	Nightclub	Coff

1