Business Location Explore in Toronto

This is Peer-graded Assignment for Course [Applied Data Science Capstone (https://www.coursera.org/learn/applied-data-science-capstone/home/welcome)](https://www.coursera.org/learn/applied-data-science-capstone/home/welcome), Week 4/5

Contents

1. Introduction

1.1 Business Requests

The location problem has been the challenge for many businesses starts for a long time. Many academic and industrial approaches focus on this problem. In this project we're trying to answer the question, where is the realistic location to start a new business based on existing data. We use Chinese restaurant as the business category to apply machine learning to help investors to make a better decision of location choice in downtown Toronto.

We assume that an investor wants to start a new business to serve Chinese food in downtown Toronto due to its density of population, higher average income, as well as the diversity of culture.

1.2 Analytic Approach

A good location should satisfy the two criteria at the same time:

(1) Sufficient demand
(2) Insufficient support

To address the first criteria, we could assume that if in some locations exists many restaurants business, there should have a good demand for foodservice in that location.

As per the second criteria, if we could hardly find a Chinese restaurant in the area, then we could say that the support is insufficient.

In summary, we need to gain the data of the food services venue information in the area, as well as their categories.

More specifically, we want to know how many restaurants in specific areas, how many of them provide Chinese food or Asian food. Based on this information we want to find out the most interesting area which has sufficient demand and insufficient support for Chinese food.

2. Data Collection

Majority we will use data provided by [FourSqare (https://foursquare.com/)](https://foursquare.com/) to perform our analysis.

FourSquare is a location technology platform to allow developers to fetch the location data, as well as venues information. With the free account one can make 100K calls per day to access their 105M+ points of interest data.

Aiming to the business request described above, we will collect all restrants information in downtown Toronto, and find out their distribution and rating, etc.

2.1 Scrape location info in Toronto

We use pandas function read_html to get postal code list in Toronto, as well as the neibourhoods.

In [3]:
```
import pandas as pd
import numpy as np
import requests
import pickle
import folium
import re
import uuid
```

Step(1) Fetch postal code in Toronto

We get the list of postal codes in Toronto from the Wiki page: [List_of_postal_codes_of_Canada (https://en.wikipedia.org/wiki/List_of_postal_codes_of_Canada:_M)](https://en.wikipedia.org/wiki/List_of_postal_codes_of_Canada:_M), and perform some simple data cleaning job.

In [2]:
```
url = 'https://en.wikipedia.org/wiki/List_of_postal_codes_of_Canada:_M'
dfs = pd.read_html(url)
for idx, df in enumerate(dfs):
    print('DataFrame[{}]:{}'.format(idx, df.shape))

dfs[0].head()
```

```
DataFrame[0]:(180, 3)
DataFrame[1]:(4, 18)
DataFrame[2]:(2, 18)
```

Out[2]:

	Postal code	Borough	Neighborhood
0	M1A	Not assigned	NaN
1	M2A	Not assigned	NaN
2	M3A	North York	Parkwoods
3	M4A	North York	Victoria Village
4	M5A	Downtown Toronto	Regent Park / Harbourfront

Oberviously the first data frame is what we need.

Lets remove those 'Not assigned' rows as per column Borough, and check the duplications for Postal Code.

Lets remove these 'Not assigned' rows as per column Borough, and check the duplications for Postal Code.

In [3]:
```
df = dfs[0]
df = df[df['Borough'] != 'Not assigned']
print(df.shape)
len(df['Postal code'].unique())
```

```
(103, 3)
```

Out[3]:
```
103
```

We are good there's no duplication in column Postal Code.

Chose Postal code as index.

In [4]:
```
df.set_index('Postal code', inplace=True)
df.head()
```

Out[4]:

	Borough	Neighborhood
Postal code		
M3A	North York	Parkwoods
M4A	North York	Victoria Village
M5A	Downtown Toronto	Regent Park / Harbourfront
M6A	North York	Lawrence Manor / Lawrence Heights
M7A	Downtown Toronto	Queen's Park / Ontario Provincial Government

Step(2) Attaching geo info for each postal code

We could get geospatial information for each postal code via the online csv file: [Geospatial_data (http://cocl.us/Geospatial_data)](http://cocl.us/Geospatial_data), then attach it to existing data set.

In [5]:
```
url = 'http://cocl.us/Geospatial_data'
geo_info = pd.read_csv(url)
geo_info.set_index('Postal Code', inplace=True)
print(geo_info.shape)
geo_info.head()
```

```
(103, 2)
```

Out[5]:

	Latitude	Longitude
Postal Code		
M1B	43.806686	-79.194353
M1C	43.784535	-79.160497
M1E	43.763573	-79.188711
M1G	43.770992	-79.216917
M1H	43.773136	-79.239476

Now we can merge these two data set into one.

In [6]:
```
df = df.merge( geo_info, left_index= True, right_index = True)

df.index.name='Postal Code'
df.head()
```

Out[6]:

Postal Code	Borough	Neighborhood	Latitude	Longitude
M3A	North York	Parkwoods	43.753259	-79.329656
M4A	North York	Victoria Village	43.725882	-79.315572
M5A	Downtown Toronto	Regent Park / Harbourfront	43.654260	-79.360636
M6A	North York	Lawrence Manor / Lawrence Heights	43.718518	-79.464763
M7A	Downtown Toronto	Queen's Park / Ontario Provincial Government	43.662301	-79.389494

Step (3) Visualization areas on map

We can have a general idea of the area by visulize these data on map.

First we get the center point of the map:

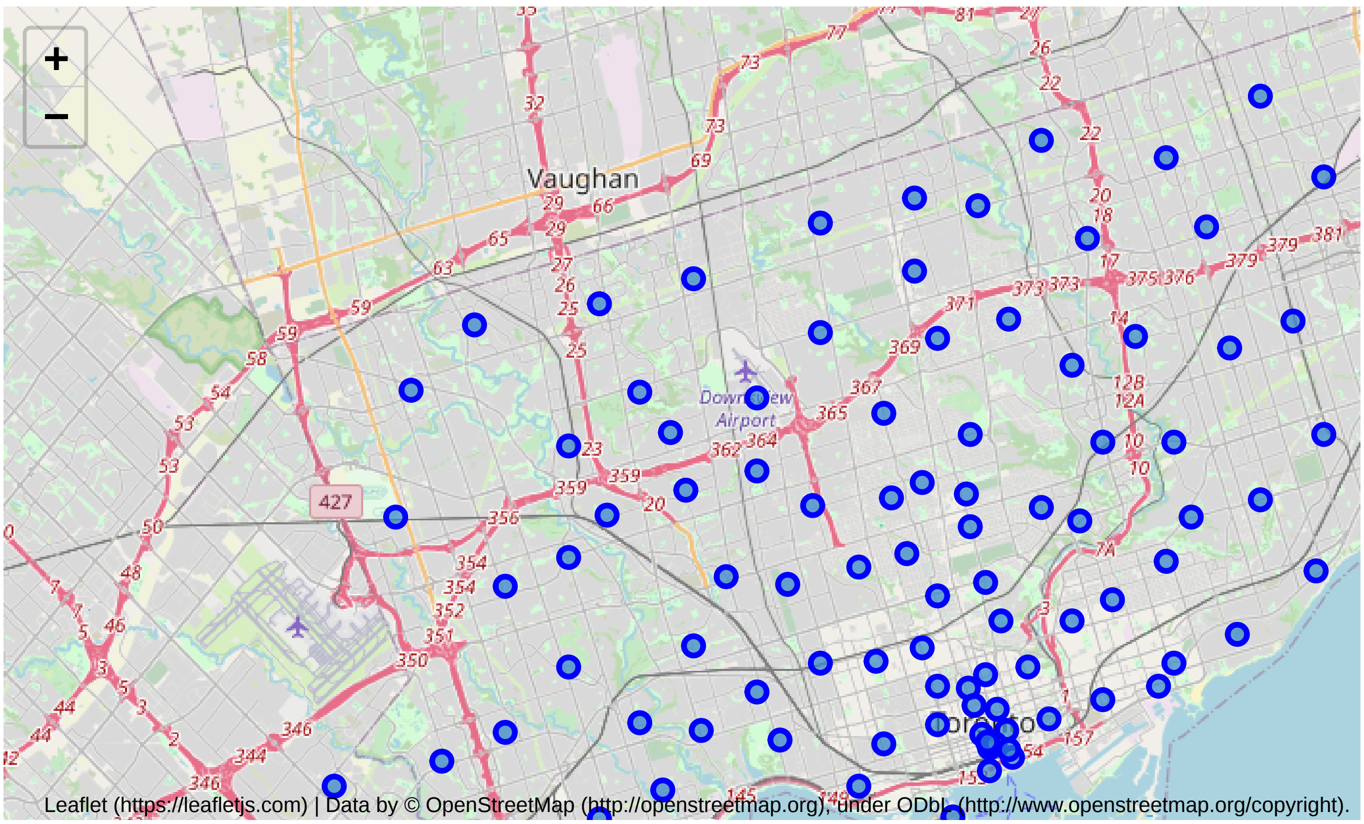
In [7]:
```
lat, lng = df[['Latitude','Longitude']].max() + df[['Latitude','Longitude']].min()

lat, lng  = lat /2, lng /2
lat, lng
```

Out[7]:
```
(43.71926920000001, -79.38815804999999)
```

Then we can illustrate them on the map:

In [8]:
```python
# create map of Toronto using latitude and longitude values
map_toronto = folium.Map(location=[lat, lng], zoom_start=11)

# add markers to map
for idx, r  in df.iterrows():
    lat, lng, bor, postalcode  =  r['Latitude'], r['Longitude'],r['Borough'], r.name
    label = '{}, {}'.format(bor, postalcode)
    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_toronto)

map_toronto
```

Out[8]:



This map clearly shows our research geo scope.

2.2 Fetch all 'FOOD' venues in Toronto

In this step we will employee FourSquare API to fetch all venues under category 'FOOD' in Toronto.

Step(1) First we set API credentials

In [62]:
```
#hide this cell while exporting#
api_credentials = {'CLIENT_ID':'Y5FK5TTSXY24B0DDCUJBGCWCL2B01DYMXZRFOXROSYNCSSYJ',
                    'CLIENT_SECRET':'Q4I1XUTLLTDWF1OWT5S0W2H0MZAS3QRJBM1XRA1OEH5E1GVW
                    'VERSION':'20180605'}
api_credentials
```

Out[62]:
```
{'CLIENT_ID': 'Y5FK5TTSXY24B0DDCUJBGCWCL2B01DYMXZRFOXROSYNCSSYJ',
 'CLIENT_SECRET': 'Q4I1XUTLLTDWF1OWT5S0W2H0MZAS3QRJBM1XRA1OEH5E1GVW',
 'VERSION': '20180605'}
```

Step(2) Fetch data via FourSquare API

From FourSquare API doc [Venue Categories (https://developer.foursquare.com/docs/build-with-foursquare/categories/)](https://developer.foursquare.com/docs/build-with-foursquare/categories/), we can tell the following Foursquare Venue Category Hierarchy, as well as their ID.

- Category: Food: 4d4b7105d754a06374d81259
  - Asian Restaurant: 4bf58dd8d48988d142941735
    - Chinese Restaurant: 4bf58dd8d48988d145941735

In [63]:
```
CATEGORYID = '4d4b7105d754a06374d81259'
```

Due to restriction of max API calls to FourSquares, we save data for future usage.

In [21]:
```
def dump2file( obj , name = None  ):
    if name is None:
        try:
            name = obj.__name__
        except:
            name = str(uuid.uuid4())

    valid_chars_in_filename = '-_.() abcdefghijklmnopqrstuvwxyzABCDEFGHIJKLMNOPQRSTU\
    fn = ''.join(x if x in valid_chars_in_filename else '_' for x in name )

    with open(fn, 'wb') as f:
        pickle.dump(obj, f)

def loadFromFile( name  ):

    valid_chars_in_filename = '-_.() abcdefghijklmnopqrstuvwxyzABCDEFGHIJKLMNOPQRSTU\
    fn = ''.join(x if x in valid_chars_in_filename else '_' for x in name )

    with open(fn, 'rb') as f:
        obj = pickle.load(f)

    return obj
```

In [220]:
```python
# search venues at specific location
# Fire API call only when it's not in local files

def venuesbyarea(df = df, radius = 1200 ):
    ret = pd.DataFrame()
    for  idx, area  in df.iterrows():

        area_id, name, lng, lat = area['AREA_ID'], area['NAME'], area['LONGITUDE'], a

        d = loadFromFile(name)

        if not d.empty:
            ret = ret.append( d, ignore_index=True)
            continue

        url = '{}{}{}{}'.format('https://api.foursquare.com/v2/venues/search?',
              '&client_id={id}&client_secret={pw}&v={v}'.format(id = api_credentials
                                                                pw = api_credentials
                                                                v  = api_credentials
                '&ll={},{}&radius={}'.format(lat, lng, radius),
                '&categoryId={}'.format(CATEGORYID)
                )
        print(url)
        try:
            results = requests.get(url).json()
            results = results['response']['venues']
        except Exception  as ex:
            print('Exception on ID:{},lat:{},lng:{}, name:{}, Err:{}'.format(area_id,
            print('>>>>results:\n{}\n<<<<<<'.format(results))
            continue

        d = pd.json_normalize(results)
        d['AREA_ID'] = area_id
        for idx, row in d.iterrows():
            for catidx, cat in enumerate(row['categories']):
                if cat['primary']:
                    d.loc[idx, 'PrimaryCategory'] = cat['name']
                else:
                    d.loc[idx, 'Category-{}'.format(catidx)] = cat['name']

        d.drop(['categories', 'referralId', 'hasPerk', 'location.cc', 'location.cross
                 'location.labeledLatLngs',
                 'location.city', 'location.state',
                'location.formattedAddress',
               ], axis =1, errors = 'ignore', inplace=True)

        dump2file(d, name)
        ret = ret.append( d, ignore_index=True)


    return ret
```

Removing duplicated venues by id

In [23]:
```
venues.drop_duplicates('id', inplace=True)

with open('Venues', 'wb') as f:
    pickle.dump(venues, f)
print(venues.shape)
```

(2073, 11)

Step(3) Review venues contains **Restaurant** in their Name

Lets' foucs on those Restaurants in the venues list, since the stackholder/investor's purpose is to open a restaurnat.

In [24]:
```
len(venues['PrimaryCategory'].unique())
```

Out[24]: 139

In [25]:
```
# Find the most frequency categories by Grouping by category and sorting by count des
categories_counts = venues[['id','PrimaryCategory']].groupby('PrimaryCategory').count
                                                    .sort_values(by='id', ascending=F

categories_counts.rename({'id':'count'}, axis =1, inplace=True)

categories_counts.head(10)
```

Out[25]:

PrimaryCategory	count
Coffee Shop	317
Pizza Place	130
Fast Food Restaurant	111
Bakery	97
Café	91
Restaurant	88
Chinese Restaurant	81
Grocery Store	65
Sandwich Place	60
Caribbean Restaurant	59

There are lots of categories under **FOOD**, most of them are caffee shop, Pizza Place, even many Grocery Stores are included in the search result.

Let's focust on those **real** Restaurants.

In [26]:
```
restaurants = venues[venues['PrimaryCategory'].str.contains('Restaurant')]
restaurants.shape
```

Out[26]: (884, 11)

Now lets see how many Asian/Chinese Restaurant here:

In [28]:
```
categories_counts.loc[['Restaurant','Asian Restaurant','Chinese Restaurant']]
```

Out[28]:

PrimaryCategory	count
Restaurant	88
Asian Restaurant	34
Chinese Restaurant	81

Seems like the category Hierarchy is not well defined.

In [29]:
```
restaurants_counts = restaurants.groupby('PrimaryCategory').count().sort_values('id',
restaurants_counts.rename({'id':'count'}, axis =1, inplace=True)
restaurants_counts.head(10)
```

Out[29]:

PrimaryCategory	count
Fast Food Restaurant	111
Restaurant	88
Chinese Restaurant	81
Caribbean Restaurant	59
Italian Restaurant	54
Middle Eastern Restaurant	41
Indian Restaurant	38
Asian Restaurant	34
Sushi Restaurant	34
Vietnamese Restaurant	32

By reviewing the whole list, we setup a mapping on top of the current category hierarchy. We will use the mapping for further analysis.

In [49]:
```
AsianRestaurants = ['Asian Restaurant','Burmese Restaurant','Sushi Restaurant', 'Viet
                    'Japanese Restaurant','Korean Restaurant','Thai Restaurant',
                    'Japanese Curry Restaurant', 'Indian Chinese Restaurant',
                   ]
ChineseRestaurants = ['Chinese Restaurant','Cantonese Restaurant','Hakka Restaurant',
                      'Tibetan Restaurant','Taiwanese Restaurant','Udon Restaurant',
                      'Hong Kong Restaurant','Hotpot Restaurant',
                     ]
```

2.3 Show venues on map

Step (1) Find the center of the map

In [31]:
```python
lat, lng = restaurants[['location.lat','location.lng']].max() + restaurants[['locatio
lat, lng  = lat /2, lng /2
lat, lng
```

Out[31]:
```
(43.706925113970044, -79.38951799620264)
```

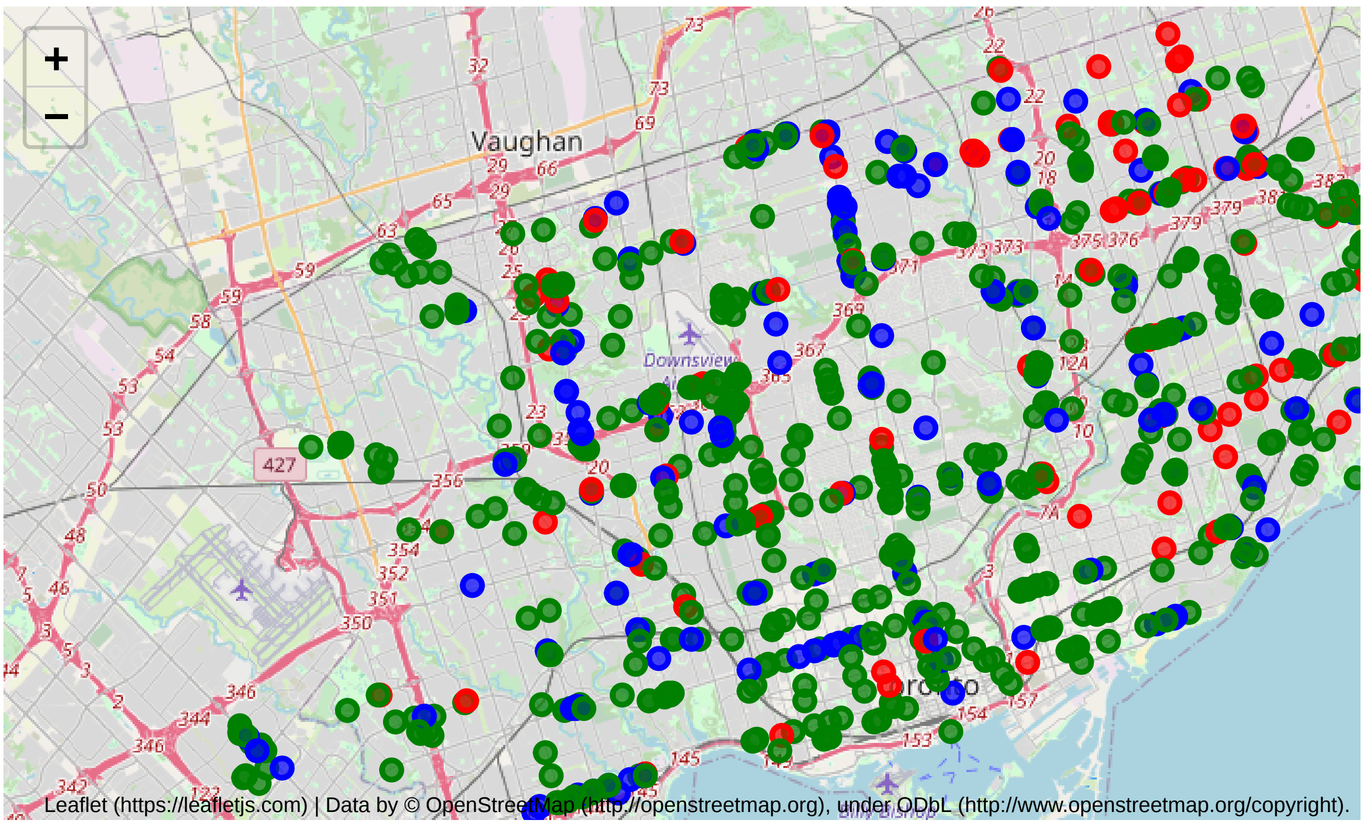
Step (2) Mark the venues on maps

We use three colors in the visulization:

- Red: Chinese Restaurants
- Blue: Asian Restaurants, excluding Chinese Restaurants
- Green: All other restaurants

In [32]:
```python
# create map of New York using latitude and longitude values
map_all_venues = folium.Map(location=[lat, lng], zoom_start=11)

# add markers to map
for idx, r  in restaurants.iterrows():
    lat, lng, name, category =  r['location.lat'], r['location.lng'],r['name'], r['P
    if category in ChineseRestaurants:
        color = 'red'
    elif category in AsianRestaurants:
        color = 'blue'
    else:
        color = 'green'

    label = '{}, {}'.format(name, category)
    label = folium.Popup(label, parse_html=True)

    folium.CircleMarker(
        [lat, lng],
        radius=5,
        popup=label,
        color=color,
        fill=True,
        fill_color= color, #'#3186cc',
        fill_opacity=0.7,
        parse_html=False).add_to(map_all_venues)

map_all_venues
```

Out[32]:



3. Methodology

In this part we will employee *** to analysis the data, to find out the area which satisfies:

(1) Sufficient demand
(2) Insufficient support

We define a 'Sufficient Demand' as a bigger average restaurant provider over the neighborhood area, and 'Insufficient Support' as a smaller average restaurant business over the area.

Since most business opportunities arise in system edge, like optimization value is always on the boundary of the scope, we employed **Anomaly** Detection model using **Isolation Forest** in Python library scikit-learn.

3.1 Definition of Sufficiency and InSufficiency

Step(1) Get Area info

From City of Toronto [Open Data Portol (https://www.toronto.ca/city-government/data-research-maps/open-data/)](https://www.toronto.ca/city-government/data-research-maps/open-data/) we can get all neibourhood boundary, area we can calculate the average food service provider over area.

In [68]:
```
url='https://ckan0.cf.opendata.inter.prod-toronto.ca/download_resource/a083c865-6d60-
r = requests.get(url).json()
pd.json_normalize(r['features']).head()

cols =  ['properties._id','properties.AREA_SHORT_CODE', 'properties.AREA_NAME', 'prop
        'properties.LATITUDE',    'properties.LONGITUDE',    ]
df = pd.json_normalize(r['features'])[cols]
df.columns = ['AREA_ID','CODE', 'NAME', 'AREA', 'LATITUDE', 'LONGITUDE'    ]
print(df.shape)
df.head()
```

```
(140, 6)
```

Out[68]:

	AREA_ID	CODE	NAME	AREA	LATITUDE	LONGITUDE
0	4621	94	Wychwood (94)	3.217960e+06	43.676919	-79.425515
1	4622	100	Yonge-Eglinton (100)	3.160334e+06	43.704689	-79.403590
2	4623	97	Yonge-St.Clair (97)	2.222464e+06	43.687859	-79.397871
3	4624	27	York University Heights (27)	2.541821e+07	43.765736	-79.488883
4	4625	31	Yorkdale-Glen Park (31)	1.156669e+07	43.714672	-79.457108

Step (2) Aggregation restaurants

Now we count the restaurants in each area, as per pre defined categories.

In [222]:
```
restaurnatsByArea = venuesByArea[ venuesByArea['PrimaryCategory'].str.contains('Resta
restaurnatsByArea.shape

AsianR_ExCN = restaurnatsByArea.apply(lambda x: 1 if x['PrimaryCategory'] in AsianRes
ChineseR = restaurnatsByArea.apply(lambda x: 1 if x['PrimaryCategory'] in ChineseRest
OtherR = restaurnatsByArea.apply(lambda x: 0 if x['PrimaryCategory'] in ChineseRestau
                                               x['PrimaryCategory'] in AsianRestaura

df_grp  = pd.DataFrame({'AREA_ID':restaurnatsByArea['AREA_ID'],
                        'ChineseR':ChineseR,
                        'AsianR_ExCN':AsianR_ExCN,
                        'OtherR':OtherR,
                        'AnyR': 1})
df_grp.shape

df_grp = df_grp.groupby('AREA_ID').sum().merge(df, left_index=True, right_on ='AREA_I
df_grp.fillna(0, inplace=True)
print(df_grp.shape)
df_grp.head()
```

(140, 10)

Out[222]:

	ChineseR	AsianR_ExCN	OtherR	AnyR	AREA_ID	CODE	NAME	AREA	LATITUDE	LONGITUDE
0	0.0	1.0	5.0	6.0	4621	94	Wychwood (94)	3.217960e+06	43.676919	-79.425515
1	0.0	0.0	3.0	3.0	4622	100	Yonge-Eglinton (100)	3.160334e+06	43.704689	-79.403590
2	0.0	1.0	11.0	12.0	4623	97	Yonge-St.Clair (97)	2.222464e+06	43.687859	-79.397871
3	1.0	3.0	7.0	11.0	4624	27	York University Heights (27)	2.541821e+07	43.765736	-79.488883
4	0.0	4.0	11.0	15.0	4625	31	Yorkdale-Glen Park (31)	1.156669e+07	43.714672	-79.457108

Step (3) Calculating the Average value

Now we have count of restaurants, and size of the area, we can calculate the density of existing business.

To enlarge the distribution, we apply log to the mean value.

In [223]:
```
Avg_AsianR = df_grp.apply(lambda x: np.log( 1 + x['AsianR_ExCN'] / (1 + x['AREA']) * 
Avg_ChineseR = df_grp.apply(lambda x: np.log( 1 + x['ChineseR'] / (1 + x['AREA']) * 1
Avg_OtherR = df_grp.apply(lambda x: np.log( 1 + x['OtherR'] / (1 + x['AREA']) * 1e7 )
Avg_AnyR = df_grp.apply(lambda x: np.log( 1 + x['AnyR'] / (1 + x['AREA']) * 1e7 ), ax


df_avg  = pd.DataFrame({'AREA_ID':df_grp['AREA_ID'],
                      'Avg_ChineseR':Avg_ChineseR,
                      'Avg_AsianR':Avg_AsianR,
                      'Avg_OtherR':Avg_OtherR,
                       'Avg_AnyR':Avg_AnyR })
print(df_avg.shape)

df_avg.head()
```

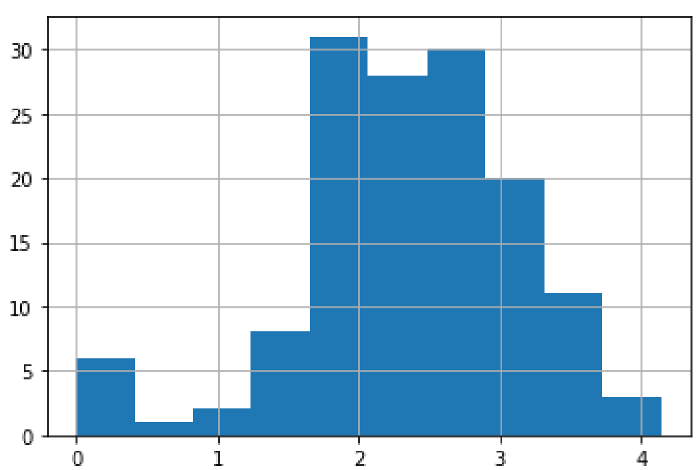
```
(140, 5)
```

Out[223]:

	AREA_ID	Avg_ChineseR	Avg_AsianR	Avg_OtherR	Avg_AnyR
0	4621	0.00000	1.412829	2.805648	2.977841
1	4622	0.00000	0.000000	2.350676	2.350676
2	4623	0.00000	1.704659	3.921866	4.007226
3	4624	0.33176	0.779442	1.322804	1.672902
4	4625	0.00000	1.494747	2.352334	2.636789

Step (4) distribution of the mean values

In [224]:
```
df_avg['Avg_AnyR'].hist();
```



3.2 Isolation Forest Anomaly Detection

As you might expect from the name, Isolation Forest instead works by isolating anomalies explicitly isolating anomalous points in the dataset.

Most business opportunities exist in those edge points, which drove us to apply the Isolation Forest Anomaly Detection model to find those specific opportunities.

Step (1) Define and Fit the model

We only consider the mean values in our model.

In [167]:
```
IF_cols = ['Avg_ChineseR','Avg_AsianR','Avg_OtherR','Avg_AnyR']
```

In [166]:
```
model=IsolationForest( n_estimators=50, max_samples='auto', contamination=float(0.1),
model.fit( df_avg[])
```

Out[166]:
```
IsolationForest(behaviour='deprecated', bootstrap=False, contamination=0.1,
                max_features=4, max_samples='auto', n_estimators=50,
                n_jobs=None, random_state=None, verbose=0, warm_start=False)
```

Now we have the model tained successfully.

Step (2) Attached Scores and Anomaly Column

Let's find the scores and anomaly status for each sample. We can get this information by calling **decision_function()** of the above model and passing the four mean values as parameters.

Also, we can get the values of anomaly status by calling the **predict()** function of the above model and using the four mean values as parameters.

In [179]:
```
result_cols = ['AREA_ID', 'scores','anomaly', 'NAME', 'LATITUDE','LONGITUDE' ]
df_avg['scores'] = model.decision_function(df_avg[IF_cols])
df_avg['anomaly']=model.predict(df_avg[IF_cols])
df_result = df_avg.merge( df )[result_cols]
df_result.sort_values('scores', inplace=True)
```

In [180]:
```
df_result
```

Out[180]:

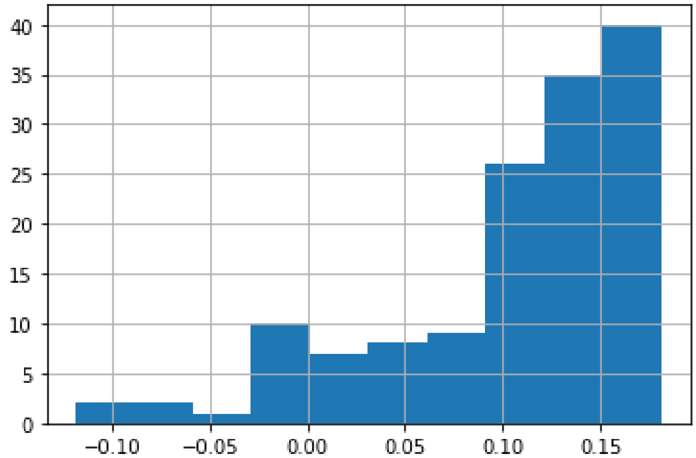
	AREA_ID	scores	anomaly	NAME	LATITUDE	LONGITUDE
27	4649	-0.118717	-1	North St.James Town (74)	43.669623	-79.375247
37	4660	-0.115751	-1	Regent Park (72)	43.659992	-79.360509
2	4623	-0.079746	-1	Yonge-St.Clair (97)	43.687859	-79.397871
42	4665	-0.065879	-1	Rouge (131)	43.821201	-79.186343
40	4663	-0.055065	-1	Roncesvalles (86)	43.646123	-79.442992
...	...	...	...	...	...	...
24	4646	0.173633	1	Newtonbrook West (36)	43.785830	-79.431422
113	4739	0.174701	1	Forest Hill South (101)	43.694526	-79.414318
39	4662	0.177534	1	Rockcliffe-Smythe (111)	43.674790	-79.494420
41	4664	0.180706	1	Rosedale-Moore Park (98)	43.682820	-79.379669
9	4630	0.181015	1	Leaside-Bennington (56)	43.703797	-79.366072

140 rows × 6 columns

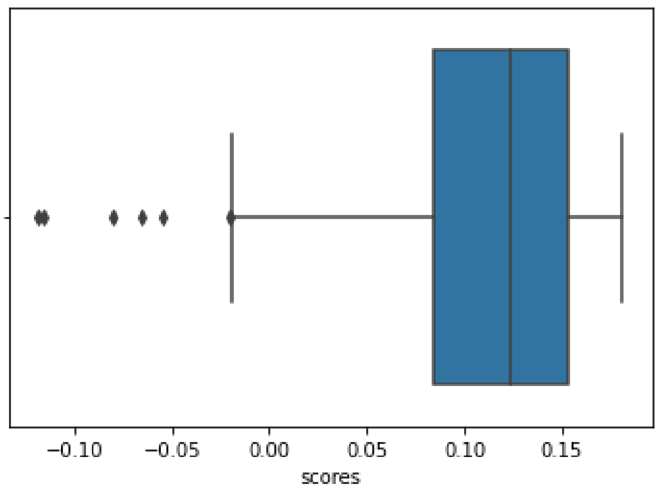
Step (3) Visulization the result

We can use the hist char to visulize the scores of model result.

In [225]:
```
df_result['scores'].hist();
```



In [236]:
```
sns.boxplot(df_result['scores']);
```



We can tell that the anomaly exists on the very left side.

Step (4) Visualization on map

For better impact, we put the model result on the map, which will give our stakeholders a better understanding of the **data-driven** approach.

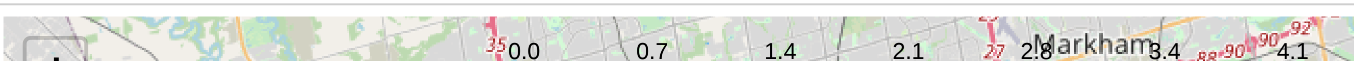
We added **Three** Layers on top of the geo map:

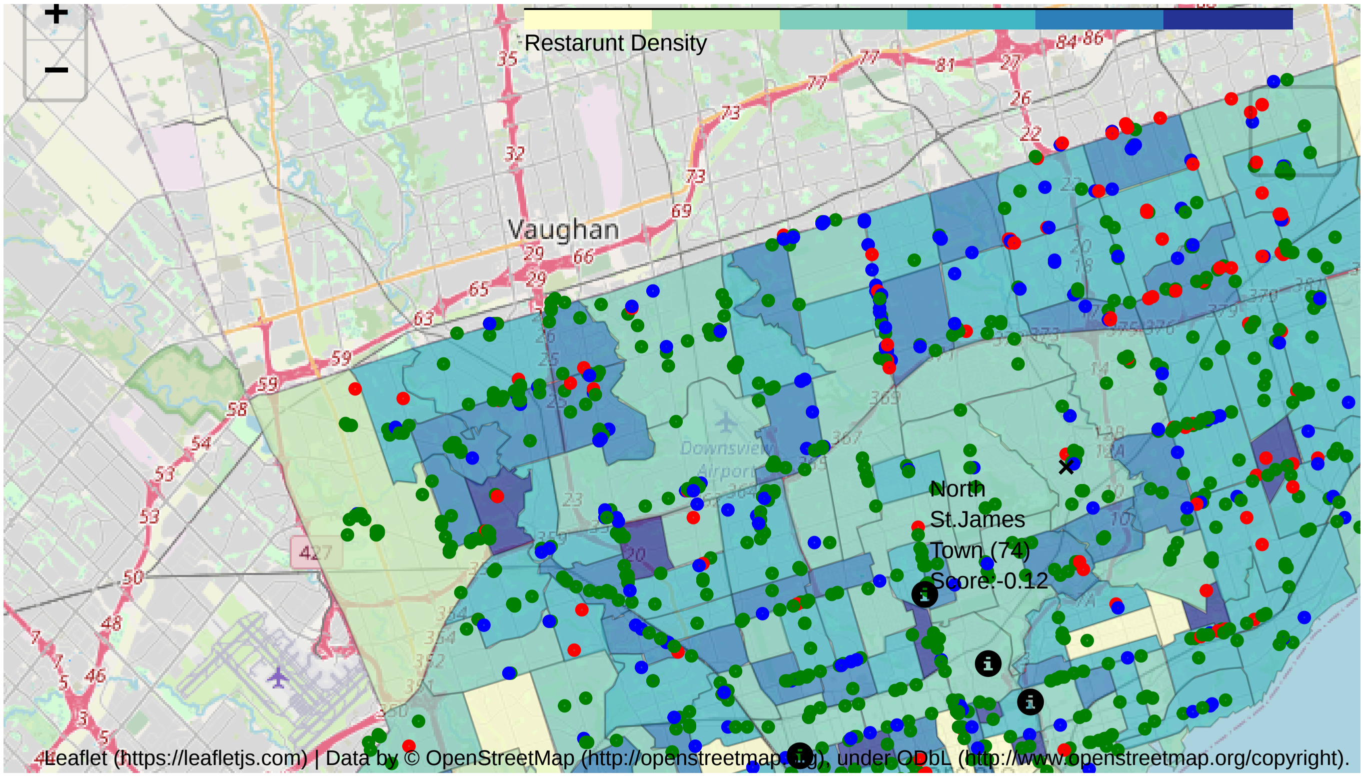
- Choropleth maps, to tell the density of restaurants
- Circle Markers, to plot all restaurants plus categories
- Leaflet Markers, to flag the two anomalies location

In [240]:

```
lat, lng = venuesByArea[['location.lat','location.lng']].min() + venuesByArea[['locat
lat, lng = lat/2, lng/2
m = folium.Map( location = [lat, lng], zoom_start = 11)

# Choropleth maps, to tell the density of resterauants
folium.Choropleth(
    geo_data = url,
    name='choropleth',
    data= df_avg,    columns=('AREA_ID', 'Avg_AnyR'),
    key_on='feature.properties._id',
    fill_color= 'YlGnBu', #'YlGn',
    fill_opacity=0.7,
    line_opacity=0.2,
    legend_name='Restarunt Density'
).add_to(m)

#Circle Markers, to plot all restaurants plus categories
for idx, r  in restaurnatsByArea.iterrows():
    lat, lng, name, category =  r['location.lat'], r['location.lng'],r['name'], r['Pr
    if category in ChineseRestaurants:
        color = 'red'
    elif category in AsianRestaurants:
        color = 'blue'
    else:
        color = 'green'

    label = '{}, {}'.format(name, category)
    label = folium.Popup(label, parse_html=True)

    folium.CircleMarker(
        [lat, lng],
        radius=2,
        popup=label,
        color=color,
        fill=True,
        fill_color= color,
        fill_opacity=0.7,
        parse_html=False).add_to(m)

# Leaflet Markers, to flag the two anomalies location
for idx, r  in df_result[df_result['scores'] <= -0.05].iterrows():
    lat, lng, name, score, =  r['LATITUDE'], r['LONGITUDE'],r['NAME'], r['scores']

    label = '{}\nScore:{:.2f}'.format(name, score)
    color = 'red' if score <= -0.1 else 'orange'

    folium.Marker(
        [lat, lng],
        radius=5,
        popup=label,
        icon=folium.Icon(color=color, icon='info-sign')
        ).add_to(m)



folium.LayerControl().add_to(m)

m
```

Out[240]:





4. Result

To open a new Chinese restaurant, we have two locations with potentially highest opportunites, marked as Red on above map:

- North St.James Town
- Regent Park

Plus the other three locations may also have moderate oppertunites, marked as Orange on above map:

- Yonge-St.Clair
- Rouge
- Roncesvalles

In [245]:
```
df_grp[df_grp['AREA_ID'].isin([4649,4660,4623, 4665, 4663])]\
         [['NAME','AREA','ChineseR','AsianR_ExCN','OtherR','AnyR']]
```

Out[245]:

	NAME	AREA	ChineseR	AsianR_ExCN	OtherR	AnyR
2	Yonge-St.Clair (97)	2.222464e+06	0.0	1.0	11.0	12.0
28	North St.James Town (74)	8.113039e+05	1.0	1.0	3.0	5.0
39	Regent Park (72)	1.243326e+06	1.0	0.0	6.0	7.0
42	Roncesvalles (86)	2.875399e+06	0.0	1.0	0.0	1.0
44	Rouge (131)	7.214402e+07	0.0	1.0	5.0	6.0

5. Discussion

We could add more features into the model, such as the rating of the venues, size of the business, etc.

Also, it would be better if we could fetch more data from different data sources, along with FourQuares, it may help us to build a more accurate model.

Plus, We could introduce other dimensional data like population, Demographics, income, etc., for this information also has an impact on the consuming market.

6. Conclusion

Since many believe that business opportunities most-likely happen in an abnormal scenario, we employed the Isolation Forest model to find outliers in the restaurant business, and find out location-based significantly different from those majority of the other locations.