Coursera Capstone Project

The Battle of Neighborhoods (Week 2)

Contents

Introduction

Yangon is the capital of Myanmar where local migrant workers are residing to work in various industries, and foreign investors are having their eye on new opportunities.

In [475]:

```
#library to convert an address to latitude and longitude values
from geopy.geocoders import Nominatim

# map rendering library
import folium

#converting the address of Yangon City to geocodes
address = 'Yangon City, MM'
geolocator = Nominatim(user_agent='mm_explorer')
location = geolocator.geocode(address)
latitude = location.latitude
longitude = location.longitude

#creating map
title_html = '''
    <h3 align="center" style="font-size:20px"><b>The Map of Yangon</b></h3>
    '''
map_yangon = folium.Map(location=[latitude, longitude], zoom_start=10)
map_yangon.get_root().html.add_child(folium.Element(title_html))
```

Out[475]:

```
<branca.element.Element at 0x2d6b097c888>
```

Recently, a local investor is looking for a place to run a burmese restaurant in a certain neighborhood of Yangon. The area of interest will be in the following criteria:

1. near to offices, hotels, and public attractions such as supermarket, shopping malls and cinemas
2. fewer competitors in the vicinity
3. ample space for parking

Data

To analyse the each neighborhoods, the coordinates of each neighborhoods in Yangon city will be required and can be found at the website, www.themimu.info.

In [476]:

```
#library to perform HTTP requests
import requests as rq

#library for handling Zip files
from zipfile import ZipFile as zf
from io import BytesIO as bi

#library to analyse the data
import pandas as pd

url = "http://themimu.info/sites/themimu.info/files/documents/Myanmar_PCodes_Release_9.3_Jan2021_Yangon.zip"
zipObj = rq.get(url)

#extract the Zip file
content = zf(bi(zipObj.content))

#we know that there is only one file
file = content.extract(content.namelist()[0])
```

Navigating to required data set.

In [477]:

```
#examine the available sheet names of extracted Excel file
print(pd.ExcelFile(file).sheet_names)
```

```
['01_SR', '02_District', '03_Township', '04_Town', '_05_Ward', '06-VillageTract', '_07_Village', 'Metadata']
```

In [478]:

```python
#the sheet we need is '04_Town'
data = pd.read_excel(file, '04_Town')
data.head()
```

Out[478]:

	SR_Pcode	SR_Name_Eng	District/SAZ_Pcode	District/SAZ_Name_Eng	Tsp_Pcode	Township
0	MMR013	Yangon	MMR013D004	Yangon (West)	MMR013037	
1	MMR013	Yangon	MMR013D004	Yangon (West)	MMR013044	
2	MMR013	Yangon	MMR013D002	Yangon (East)	MMR013017	
3	MMR013	Yangon	MMR013D003	Yangon (South)	MMR013032	
4	MMR013	Yangon	MMR013D004	Yangon (West)	MMR013043	

5 rows × 21 columns

The column names of the original data set will be changed to user friendly names as follows:

In [479]:

```python
#required column names
column_names = ['District/SAZ_Name_Eng', 'Township_Name_Eng', 'Longitude', 'Latitude']

#new column names
new_column_names = ['Borough','Neighborhood','Longitude','Latitude']

data = data[column_names]
data.columns = new_column_names
data.dropna(subset=['Longitude'], inplace=True)
data = data.reset_index()
data.head()
```

Out[479]:

	index	Borough	Neighborhood	Longitude	Latitude
0	0	Yangon (West)	Ahlone	96.127863	16.782398
1	1	Yangon (West)	Bahan	96.156112	16.815427
2	2	Yangon (East)	Botahtaung	96.169709	16.771967
3	3	Yangon (South)	Cocokyun	93.368213	14.134431
4	4	Yangon (West)	Dagon	96.146900	16.794952

In [480]:

```
old_names = ['Kamaryut','Mingalartaungnyunt']
new_names = ['Kamayut','Mingala Taungnyunt']
indexes = []

for old, new in zip(old_names,new_names):
    data.iloc[data[data['Neighborhood']==old].index[0],2] = new
    indexes.append(data[data['Neighborhood']==new].index[0])

data.iloc[indexes,2]
```

Out[480]:

```
17              Kamayut
31    Mingala Taungnyunt
Name: Neighborhood, dtype: object
```

In [481]:

```
#the shape of data
data = data.groupby(['Borough','Neighborhood']).head(1)
print('The data has {} rows and {} columns'.format(data.shape[0],data.shape[1]))
```

```
The data has 45 rows and 5 columns
```

With this data, we will be working to find the best place to run a burmese restaurant considering the criteria.

Methodology

We will find the neighborhoods of Yangon where:

1) low restaurants exists,
2) populated with public areas, offices, hotels, supermarkets, cinemas, etc.,
3) and population density is higher than average;

which will be:

a) good for customer acquisition with less competition,
b) and lower rental cost for spacious areas in return.

Firstly, for the requirements: population, neighborhood areas, we will need to **scrape from Wikipedia** and **explore venues using Foursquare API** based on coordinates of neighborhoods.

Secondly, as a exploratory analysis, we will find out **restaurant density, population density and existance of public and office areas** at every neighborhoods.

Finally, we will focus on areas with highest potential and highlight the selective areas for final decision on the map along with clusters of all neighborhoods using K-Means algorithm for further investigation at ground level.

1. Analysis

According to the data, there are 45 neighborhoods in the region.

In [482]:
```
townships = data['Neighborhood'].values
print('Total neighborhoods: {}'.format(len(townships)))
townships
```

```
Total neighborhoods: 45
```

Out[482]:
```
array(['Ahlone', 'Bahan', 'Botahtaung', 'Cocokyun', 'Dagon',
       'Dagon Myothit (East)', 'Dagon Myothit (North)',
       'Dagon Myothit (Seikkan)', 'Dagon Myothit (South)', 'Dala',
       'Dawbon', 'Hlaing', 'Hlaingtharya', 'Hlegu', 'Hmawbi', 'Htantabin',
       'Insein', 'Kamayut', 'Kawhmu', 'Kayan', 'Kungyangon', 'Kyauktada',
       'Kyauktan', 'Kyeemyindaing', 'Lanmadaw', 'Latha', 'Mayangone',
       'Mingaladon', 'Mingala Taungnyunt', 'North Okkalapa', 'Pabedan',
       'Pazundaung', 'Sanchaung', 'Seikgyikanaungto', 'Seikkan',
       'Shwepyithar', 'South Okkalapa', 'Taikkyi', 'Tamwe', 'Thaketa',
       'Thanlyin', 'Thingangyun', 'Thongwa', 'Twantay', 'Yankin'],
      dtype=object)
```

Let's plot the locations on the map.

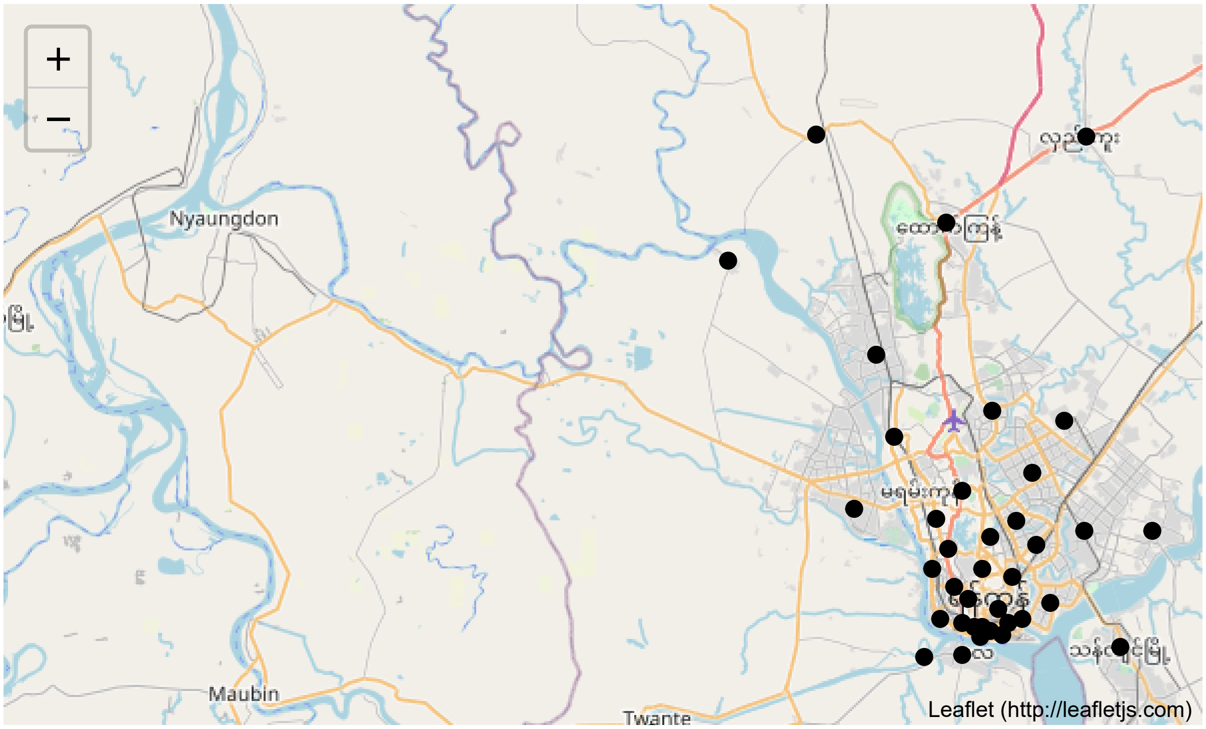
In [483]:
```
# getting coordinates of yangon
address = 'Yangon City, MM'

geolocator = Nominatim(user_agent="mm_explorer")
location = geolocator.geocode(address)
latitude = location.latitude
longitude = location.longitude
print('The geograpical coordinate of Yangon City are {}, {}.'.format(latitude, longitude))
```

```
The geograpical coordinate of Yangon City are 16.7967129, 96.1609916.
```

In [484]:

```
# create map of Yangon using latitude and longitude values
map_yangon = folium.Map(location=[latitude, longitude], zoom_start=10)

neighborhoods = data

# add markers to map
for lat, lng, borough, neighborhood in zip(neighborhoods['Latitude'], neighborhoods['Longitu
de'], neighborhoods['Borough'], neighborhoods['Neighborhood']):
    label = '{}, {}'.format(neighborhood, borough)
    label = folium.Popup(label, parse_html=True)
    folium.CircleMarker(
        [lat, lng],
        radius=3,
        popup=label,
        color='black',
        fill=True,
        fill_color='#000000',
        fill_opacity=1,
        parse_html=False).add_to(map_yangon)

map_yangon
```

Out[484]:



First, we need to select a few areas that are popular for business location because of infrastructure availability and population with higher income.

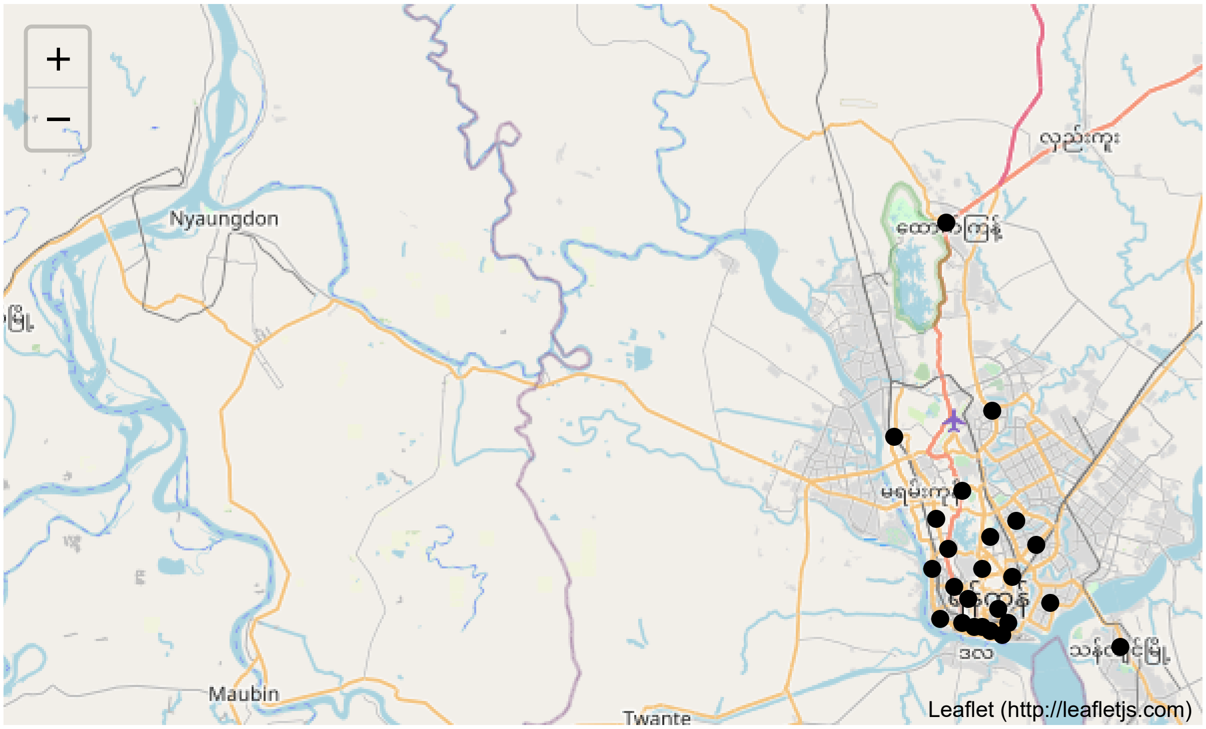
In [485]:

```
# selective areas for potential locations
townships = ['Ahlone', 'Bahan', 'Botahtaung', 'Dagon', 'Hlaing', 'Insein', 'Kamayut', 'Kyauktada', 'Kyeemyindaing', 'Lanmadaw', 'Latha', 'Mayangone', 'Mingaladon', 'Mingala Taungnyunt', 'North Okkalapa', 'Pabedan', 'Pazundaung', 'Sanchaung', 'South Okkalapa', 'Tamwe', 'Thaketa', 'Thanlyin', 'Thingangyun', 'Yankin']
```

In [486]:

```
# create map of Yangon with selective neighborhoods
map_yangon = folium.Map(location=[latitude, longitude], zoom_start=10)

neighborhoods = data[data['Neighborhood'].isin(townships)]

# add markers to map
for lat, lng, borough, neighborhood in zip(neighborhoods['Latitude'], neighborhoods['Longitude'], neighborhoods['Borough'], neighborhoods['Neighborhood']):
    label = '{}, {}'.format(neighborhood, borough)
    label = folium.Popup(label, parse_html=True)
    folium.CircleMarker(
        [lat, lng],
        radius=3,
        popup=label,
        color='black',
        fill=True,
        fill_color='#000000',
        fill_opacity=1,
        parse_html=False).add_to(map_yangon)

map_yangon
```

Out[486]:



Based on the filtered areas, required data such population and areas of neighborhoods will be scraped from www.wikipedia.org.

In [487]:

```
# loading necessary libraries for web scraping
import re
import numpy as np
import requests
from bs4 import BeautifulSoup
```

Let's define a function to scrape from Wikipedia.

In [488]:

```
def get_wiki_data(townships):
    wiki_table = pd.DataFrame(columns=['Neighborhood','Area','Population','Population Density'])
    print('=== Scrapping info of {} townships ==='.format(len(townships)))
    for i, township in zip(range(len(townships)),townships):
        print('        Index {}/{}: {}'.format(i,len(townships)-1,township))
        wiki_url = 'https://en.wikipedia.org/wiki/{}_Township'.format(township)
        wiki_data = requests.get(wiki_url).text
        soup = BeautifulSoup(wiki_data,'html5lib')
        tables = soup.find('table')
        cnt = 0
        tsp=[]
        area=[]
        population=[]
        pop_density =[]

        for row in tables.find_all('tr'):
            if (row.find('th',text=re.compile('.*Township'))):
                    tsp = row.find('td').text
            else:
                    tsp = township
        for row in tables.find_all('tr'):
            if (row.find('th',text=re.compile('.*Total'))):
                    if cnt == 0:
                        area = row.find('td').text
                    else:
                        population = row.find('td').text
                    cnt += 1

        for row in tables.find_all('tr'):
            if (row.find('th',text=re.compile('.*Density'))):
                    pop_density = row.find('td').text

        wiki_table = wiki_table.append({'Neighborhood':tsp,'Area':area,'Population':population,'Population Density':pop_density}, ignore_index=True)
    return wiki_table
```

With the function, store the data to variable "wiki_table".

In [489]:

```
wiki_table = get_wiki_data(townships)
```

```
=== Scrapping info of 24 townships ===
        Index 0/23: Ahlone
        Index 1/23: Bahan
        Index 2/23: Botahtaung
        Index 3/23: Dagon
        Index 4/23: Hlaing
        Index 5/23: Insein
        Index 6/23: Kamayut
        Index 7/23: Kyauktada
        Index 8/23: Kyeemyindaing
        Index 9/23: Lanmadaw
        Index 10/23: Latha
        Index 11/23: Mayangone
        Index 12/23: Mingaladon
        Index 13/23: Mingala Taungnyunt
        Index 14/23: North Okkalapa
        Index 15/23: Pabedan
        Index 16/23: Pazundaung
        Index 17/23: Sanchaung
        Index 18/23: South Okkalapa
        Index 19/23: Tamwe
        Index 20/23: Thaketa
        Index 21/23: Thanlyin
        Index 22/23: Thingangyun
        Index 23/23: Yankin
```

In [490]:

```
# copy the data for reproducibility
df_appended = wiki_table.copy()
df_appended.head()
```

Out[490]:

	Neighborhood	Area	Population	Population Density
0	Ahlone	4 km2 (1.4 sq mi)	41,200	11,000/km2 (29,000/sq mi)
1	Bahan	8.84 km2 (3.413 sq mi)	81,000	9,200/km2 (24,000/sq mi)
2	Botahtaung	2.4 km2 (0.92 sq mi)	42,000	18,000/km2 (46,000/sq mi)
3	Dagon	4.7 km2 (1.8 sq mi)	25,082	5,300/km2 (14,000/sq mi)
4	Hlaing	13.7 km2 (5.29 sq mi)	125,000	9,100/km2 (24,000/sq mi)

The data contains the required data but in formatted text, so, we will clean texts and characters from the data first.

In [491]:
```
# cleaning to have desired format

df_appended['Population']=df_appended['Population'].str.replace(',','').fillna('').astype('int')
df_appended['Area_sqkm']=df_appended['Area'].str.split('(', expand=True)[0].str.replace('km2', '').fillna('').astype('float')
df_appended['Area_sqm']=df_appended['Area_sqkm']*1000000
df_appended['Radius_m'] = np.sqrt(df_appended['Area_sqm']).astype('int')
df_appended['Population_density_per_sqkm']=df_appended['Population Density'].str.split('(', expand=True)[0]
df_appended['Population_density_per_sqkm']=df_appended['Population_density_per_sqkm'].str.replace('/km2','').fillna('').str.replace(',','').fillna('').astype('int')
new_data_columns = ['Neighborhood','Population','Area_sqkm','Radius_m','Population_density_per_sqkm']
new_data =df_appended[new_data_columns].copy()
new_data.head()
```

Out[491]:

	Neighborhood	Population	Area_sqkm	Radius_m	Population_density_per_sqkm
0	Ahlone	41200	4.00	2000	11000
1	Bahan	81000	8.84	2973	9200
2	Botahtaung	42000	2.40	1549	18000
3	Dagon	25082	4.70	2167	5300
4	Hlaing	125000	13.70	3701	9100

We will join to existing data with additional features derived from Wikipedia, and store as **new_data**.

In [492]:
```
new_data = pd.merge(data,new_data, how = 'inner', left_on = 'Neighborhood',right_on = "Neighborhood").drop('index', axis=1)
new_data.head()
```

Out[492]:

	Borough	Neighborhood	Longitude	Latitude	Population	Area_sqkm	Radius_m	Population_
0	Yangon (West)	Ahlone	96.127863	16.782398	41200	4.00	2000	
1	Yangon (West)	Bahan	96.156112	16.815427	81000	8.84	2973	
2	Yangon (East)	Botahtaung	96.169709	16.771967	42000	2.40	1549	
3	Yangon (West)	Dagon	96.146900	16.794952	25082	4.70	2167	
4	Yangon (West)	Hlaing	96.125227	16.847934	125000	13.70	3701	

Using the new_data, we will explore the venues of each townships by Foursquare.

In [493]:

```
# loading libraries required
from pandas.io.json import json_normalize # tranform JSON file into a pandas dataframe

# Matplotlib and associated plotting modules
import matplotlib.cm as cm
import matplotlib.colors as colors

# import k-means from clustering stage
from sklearn.cluster import KMeans
```

In [494]:

```
# setting up credentials for venue exploring
import os
from dotenv import load_dotenv
load_dotenv()

CLIENT_ID = os.getenv('CLIENT_ID')
CLIENT_SECRET = os.getenv('CLIENT_SECRET')
VERSION = '20180605' # Foursquare API version
LIMIT = 100 # foursquare maximum explore limit
```

Let's define a function to get nearby venues upon provided coordinates.

In [495]:

```
def getNearbyVenues(names, latitudes, longitudes, radius):
    print('=== Getting Nearby Venues ===')
    venues_list=[]
    cnt = 1
    for name, lat, lng, rds in zip(names, latitudes, longitudes, radius):
        print('        {}/{}: {}'.format(cnt, len(names), name))
        cnt += 1
        # create the API request URL
        url = 'https://api.foursquare.com/v2/venues/explore?&client_id={}&client_secret={}&v={}
&ll={},{}&radius={}&limit={}'.format(
            CLIENT_ID,
            CLIENT_SECRET,
            VERSION,
            lat,
            lng,
            rds,
            LIMIT)

        # make the GET request
        results = requests.get(url).json()["response"]['groups'][0]['items']

        # return only relevant information for each nearby venue
        venues_list.append([(
            name,
            lat,
            lng,
            v['venue']['name'],
            v['venue']['location']['lat'],
            v['venue']['location']['lng'],
            v['venue']['categories'][0]['name']) for v in 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)
```

Using the function, we will store venues of selective neighborhoods to **yangon_venues**.

In [496]:

```
nms = new_data['Neighborhood']
lats = new_data['Latitude']
lngs = new_data['Longitude']
rds = new_data['Radius_m']
yangon_venues = getNearbyVenues(nms,lats,lngs,rds)
```

```
=== Getting Nearby Venues ===
        1/24: Ahlone
        2/24: Bahan
        3/24: Botahtaung
        4/24: Dagon
        5/24: Hlaing
        6/24: Insein
        7/24: Kamayut
        8/24: Kyauktada
        9/24: Kyeemyindaing
        10/24: Lanmadaw
        11/24: Latha
        12/24: Mayangone
        13/24: Mingaladon
        14/24: Mingala Taungnyunt
        15/24: North Okkalapa
        16/24: Pabedan
        17/24: Pazundaung
        18/24: Sanchaung
        19/24: South Okkalapa
        20/24: Tamwe
        21/24: Thaketa
        22/24: Thanlyin
        23/24: Thingangyun
        24/24: Yankin
```

Let's check the size of the data and format.

In [499]:

```
print(yangon_venues.shape)
yangon_venues.head()
```

```
(1551, 7)
```

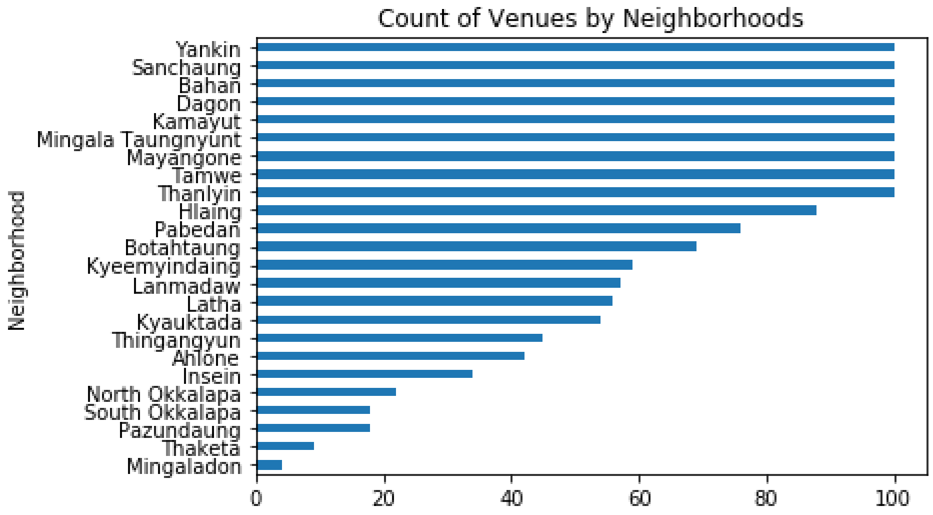
Out[499]:

	Neighborhood	Neighborhood Latitude	Neighborhood Longitude	Venue	Venue Latitude	Venue Longitude	Venue Category
0	Ahlone	16.782398	96.127863	Kou Fu Restaurant	16.787631	96.133878	Chinese Restaurant
1	Ahlone	16.782398	96.127863	Belmond Governor's Residence	16.788131	96.139003	Hotel
2	Ahlone	16.782398	96.127863	Shan Yoe Yar Fine Dining Restaurant	16.780792	96.139372	Burmese Restaurant
3	Ahlone	16.782398	96.127863	Lucky Seven Tea Shop	16.783131	96.133287	Café
4	Ahlone	16.782398	96.127863	Mahlzeit	16.797777	96.130063	German Restaurant

Let's see the venues count by neighborhood.

In [513]:

```
yangon_venues.groupby('Neighborhood').size().sort_values( ascending=True).plot.barh()
plt.title('Count of Venues by Neighborhoods')
plt.show()
```



We can see clearly that top 9 neighborhoods end up with 100 venues because of limit in Foursquare API.

In [516]:

```
# neighborhoods with limited venues
venue_counts = yangon_venues.groupby('Neighborhood').count()
neigh_to_adjust = venue_counts[venue_counts['Venue']==100]
print('Total neighborhoods with limited venues: {}'.format(neigh_to_adjust.shape[0]))
neigh_to_adjust.head()
```

```
Total neighborhoods with limited venues: 9
```

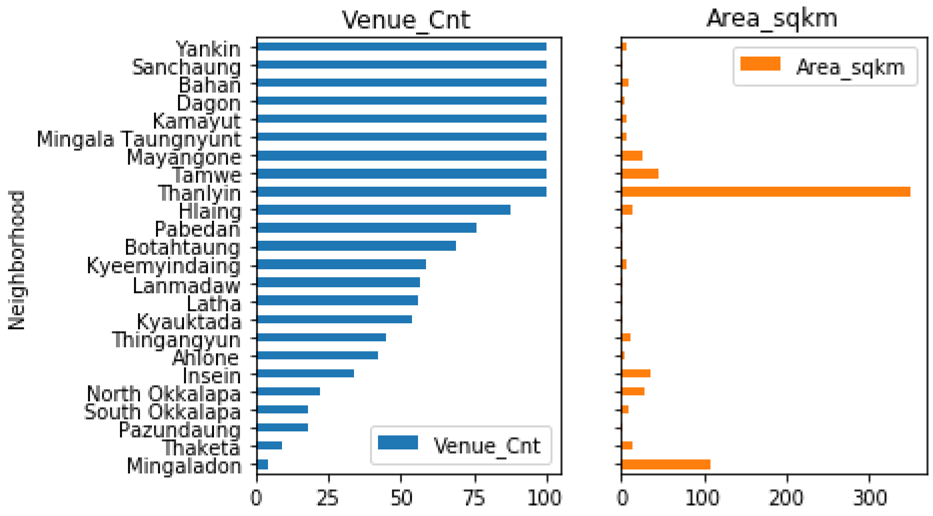
Out[516]:

	Neighborhood Latitude	Neighborhood Longitude	Venue	Venue Latitude	Venue Longitude	Venue Category
Neighborhood						
Bahan	100	100	100	100	100	100
Dagon	100	100	100	100	100	100
Kamayut	100	100	100	100	100	100
Mayangone	100	100	100	100	100	100
Mingala Taungnyunt	100	100	100	100	100	100

Let's create a table of those 9 neighorhoods with offseted coordinates in 4 areas of each neighborhoods. We will need to explore the venues with related radius of each neighborhoods since the areas of those are not the same as in below figure.

In [534]:
```
#plotting comparison

yangon_venues.groupby('Neighborhood').size().to_frame()\
        .rename(columns={0:'Venue_Cnt'})\
.merge(new_data[['Neighborhood','Area_sqkm']],\
        how='inner', left_on='Neighborhood', right_on='Neighborhood')\
.set_index('Neighborhood')\
.sort_values('Venue_Cnt', ascending=True)\
.plot(kind='barh',subplots=True, sharey=True, sharex=False, layout=(1,2))
```

Out[534]:
```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x000002D6B3207648>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000002D6B321C908>]],
      dtype=object)
```



In [535]:
```
# neighborhoods to adjust with venue exploration

neigh_to_adj_names = neigh_to_adjust.index.values.tolist()
neigh_to_adj = new_data[new_data['Neighborhood'].isin(neigh_to_adj_names)]
```

Let's define a function to offset the coordinates.

In [537]:

```
#function to offset each coordinates of each neighborhoods into 4 sub-areas
#accroding to their area

def offset_LatLng(neighs, lats, lngs, rds):
    offset_list = []
    for neigh, lat, lng, rd in zip(neighs, lats, lngs, rds):
        offset_list.append([
        neigh,
        lng + float(rd) / 2 / 111111 * np.cos(lat),
        lat + float(rd) / 2 / 111111,
        int(rd / 2)])

        offset_list.append([
        neigh,
        lng + float(rd) / 2 / 111111 * np.cos(lat),
        lat - float(rd) / 2 / 111111,
        int(rd / 2)])

        offset_list.append([
        neigh,
        lng - float(rd) / 2 / 111111 * np.cos(lat),
        lat - float(rd) / 2 / 111111,
        int(rd / 2)])

        offset_list.append([
        neigh,
        lng - float(rd) / 2 / 111111 * np.cos(lat),
        lat + float(rd) / 2 / 111111,
        int(rd / 2)])


    adjusted_coordinates = pd.DataFrame([lst for lst in offset_list])
    adjusted_coordinates.columns = ['Neighborhood', 'Longitude','Latitude','Radius_m']
    return adjusted_coordinates
```

Below is the sample of offset coordinates with updated radius for exploration.

In [538]:

```
new_data_adj = offset_LatLng(neigh_to_adj['Neighborhood'],neigh_to_adj['Latitude'],neigh_to_adj['Longitude'],neigh_to_adj['Radius_m'])
new_data_adj.head()
```

Out[538]:

	Neighborhood	Longitude	Latitude	Radius_m
0	Bahan	96.150133	16.828806	1486
1	Bahan	96.150133	16.802048	1486
2	Bahan	96.162091	16.802048	1486
3	Bahan	96.162091	16.828806	1486
4	Dagon	96.142364	16.804704	1083

Let's explore again with those coordinates and save to **yangon_venue_adj**.

In [539]:

```
nms = new_data_adj['Neighborhood']
lats = new_data_adj['Latitude']
lngs = new_data_adj['Longitude']
rds = new_data_adj['Radius_m']
yangon_venues_adj = getNearbyVenues(nms,lats,lngs,rds)
```

```
=== Getting Nearby Venues ===
        1/36: Bahan
        2/36: Bahan
        3/36: Bahan
        4/36: Bahan
        5/36: Dagon
        6/36: Dagon
        7/36: Dagon
        8/36: Dagon
        9/36: Kamayut
        10/36: Kamayut
        11/36: Kamayut
        12/36: Kamayut
        13/36: Mayangone
        14/36: Mayangone
        15/36: Mayangone
        16/36: Mayangone
        17/36: Mingala Taungnyunt
        18/36: Mingala Taungnyunt
        19/36: Mingala Taungnyunt
        20/36: Mingala Taungnyunt
        21/36: Sanchaung
        22/36: Sanchaung
        23/36: Sanchaung
        24/36: Sanchaung
        25/36: Tamwe
        26/36: Tamwe
        27/36: Tamwe
        28/36: Tamwe
        29/36: Thanlyin
        30/36: Thanlyin
        31/36: Thanlyin
        32/36: Thanlyin
        33/36: Yankin
        34/36: Yankin
        35/36: Yankin
        36/36: Yankin
```

Below is the data frame with updated venues.

In [540]:

```
print(yangon_venues_adj.shape)
yangon_venues_adj.head()
```

```
(1774, 7)
```

Out[540]:

	Neighborhood	Neighborhood Latitude	Neighborhood Longitude	Venue	Venue Latitude	Venue Longitude	Venue Category
0	Bahan	16.828806	96.150133	Le Planteur	16.826547	96.147652	French Restaurant
1	Bahan	16.828806	96.150133	Meliá Yangon	16.826573	96.154913	Hotel
2	Bahan	16.828806	96.150133	Sedona Hotel	16.829299	96.155425	Hotel
3	Bahan	16.828806	96.150133	The Market	16.826890	96.154479	Buffet
4	Bahan	16.828806	96.150133	Sabai at DMZ	16.830945	96.151925	Thai Restaurant

Adding actual coordinates back to the data frame.

In [541]:

```
yangon_venues_adj.drop(['Neighborhood Longitude','Neighborhood Latitude'], axis=1, inplace=True)
yangon_venues_adj = pd.merge(yangon_venues_adj,data, how='left', left_on='Neighborhood', right_on='Neighborhood')
```

Renaming the columns to keep as the same as original data.

In [542]:

```
yangon_venues_adj.rename(columns={'Longitude':'Neighborhood Longitude', 'Latitude':'Neighborhood Latitude'}, inplace=True)
yangon_venues_adj.drop(['index','Borough'],axis=1, inplace=True)
```

Reordering the columns.

In [543]:

```
fixed_columns = [yangon_venues_adj.columns[0]]+[yangon_venues_adj.columns[5]]+[yangon_venues_adj.columns[6]] + list(yangon_venues_adj.columns[1:-2])
yangon_venues_adj = yangon_venues_adj[fixed_columns]
```

Merging the data back to **yangon_venues**.

In [545]:

```
yangon_venues.drop(yangon_venues[yangon_venues['Neighborhood'].isin(neigh_to_adj_names)].index,axis=0, inplace=True)
yangon_venues = yangon_venues.append(yangon_venues_adj)
yangon_venues.shape
```

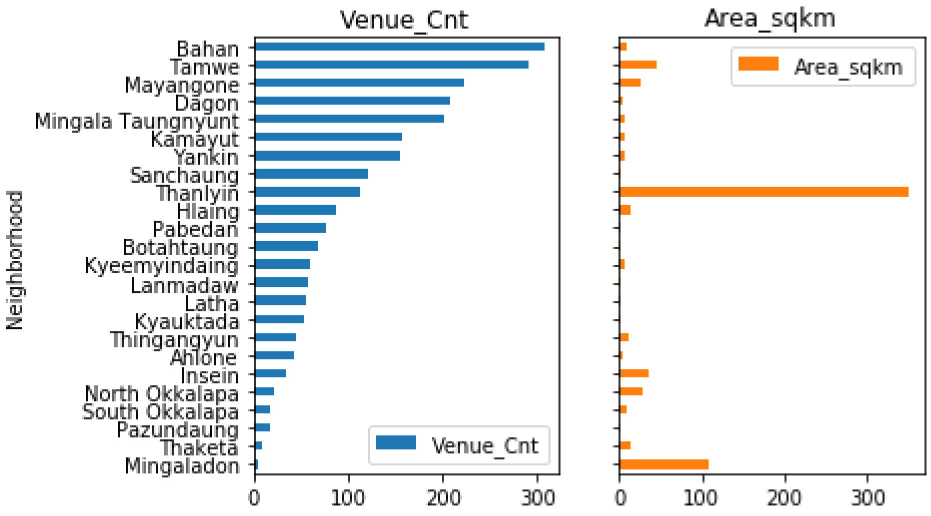
Out[545]:

```
(2425, 7)
```

Now, we can see the venues are more realistic.

In [547]:
```
#plotting comparison

yangon_venues.groupby('Neighborhood').size().to_frame()\
        .rename(columns={0:'Venue_Cnt'})\
.merge(new_data[['Neighborhood','Area_sqkm']],\
        how='inner', left_on='Neighborhood', right_on='Neighborhood')\
.set_index('Neighborhood')\
.sort_values('Venue_Cnt', ascending=True)\
.plot(kind='barh',subplots=True, sharey=True, sharex=False, layout=(1,2))
```

Out[547]:
```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x000002D6B4B2E688>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000002D6B4B3DE88>]],
      dtype=object)
```



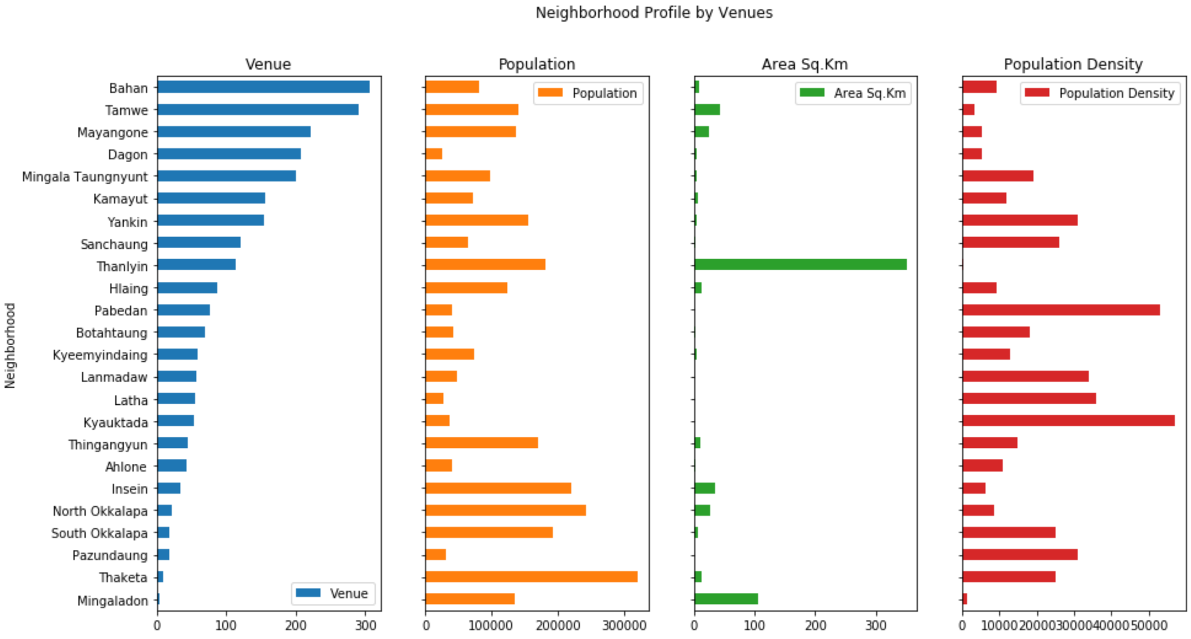
In [548]:
```
neigh_venu = yangon_venues.groupby('Neighborhood').count()[['Venue']]
neigh_info = new_data[['Neighborhood','Population','Area_sqkm','Population_density_per_sqk
m']]
neigh_info.rename(columns={'Population_density_per_sqkm':'Population Density', 'Area_sqkm':
'Area Sq.Km'}, inplace=True)
```

```
C:\Users\ThinkPad\anaconda3\lib\site-packages\pandas\core\frame.py:4133: SettingWithCopy
Warning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_gu
ide/indexing.html#returning-a-view-versus-a-copy
  errors=errors,
```

With the availables features to explore, we can quickly see in the below figures that venues are populated in some neighborhoods **regardless of population, area and population density**.

This is because those areas are populated with peoples in high income or include retails & wholesales supermarkets and shopping malls.

In [551]:
```
fig_df = pd.merge(neigh_venu,neigh_info,\
            how='inner',left_on='Neighborhood',right_on='Neighborhood')
fig_df.index=fig_df['Neighborhood']
axes = fig_df.sort_values(by=['Venue'],\
                 ascending=True).plot(kind='barh',\
                                figsize=(15,8), \
                         subplots=True, \
                         layout=(1,4), \
                         sharex=False, \
                         sharey=True, \
                         title='Neighborhood Profile by Venues')
```



Let's prepare data for K-Means clustering in order to find out how the neighborhoods are similar to each other.

In [552]:

```
# one hot encoding to convert categorical values to binary
yangon_onehot = pd.get_dummies(yangon_venues[['Venue Category']], prefix='', prefix_sep=''
)

# remove Neighborhood category value which is similar to Neighborhood name
yangon_onehot.drop('Neighborhood',axis=1,inplace=True)

# add Neighborhood column back
yangon_onehot['Neighborhood'] = yangon_venues['Neighborhood']

# move Neighborhood column to be first
fixed_columns = [yangon_onehot.columns[-1]]+list(yangon_onehot.columns[:-1])
yangon_onehot = yangon_onehot[fixed_columns]

yangon_onehot.head()
```

Out[552]:

	Neighborhood	Airport	Airport Food Court	Airport Lounge	Airport Service	Airport Terminal	American Restaurant	Arcade	Art Museum	Res
0	Ahlone	0	0	0	0	0	0	0	0	
1	Ahlone	0	0	0	0	0	0	0	0	
2	Ahlone	0	0	0	0	0	0	0	0	
3	Ahlone	0	0	0	0	0	0	0	0	
4	Ahlone	0	0	0	0	0	0	0	0	

5 rows × 139 columns

We can see in the above table that there are 139 venues (features) in total representing the whole region.

But, we will not require those detail venues to identify the poetntial area and we will group into the categories that we need for considering as potential.

In [553]:

```
# adding Main Category column grouping similar areas
venues =yangon_venues[['Venue Category']]
venues['Main Category'] = np.where(venues['Venue Category'].str.contains('Restaurant'),'Resta
urant',\
                    np.where(venues['Venue Category'].str.contains('BBQ'),'Restaurant',\
                    np.where(venues['Venue Category'].str.contains(re.compile('cafe', re.IGNOR
ECASE)), 'Coffee Shop',\
                    np.where(venues['Venue Category'].str.contains(re.compile('café', re.IGNOR
ECASE)),'Coffee Shop',\
                    np.where(venues['Venue Category'].str.contains('Breakfast'),'Restaurant',\
                    np.where(venues['Venue Category'].str.contains('Hotel'),'Accommodation',\
                    np.where(venues['Venue Category'].str.contains('Supermarket'),'Shopping
 Mall',\
                    np.where(venues['Venue Category'].str.contains('Karaoke'),'Entertainment',
\
                    np.where(venues['Venue Category'].str.contains('Bar'),'Entertainment',\
                    np.where(venues['Venue Category'].str.contains('Bakery'),'Coffee Shop',\
                    np.where(venues['Venue Category'].str.contains('Shopping'),'Shopping Mal
l',\
                    np.where(venues['Venue Category'].str.contains('Joint'),'Restaurant',\
                    np.where(venues['Venue Category'].str.contains('Multiplex'),'Shopping Mal
l',\
                    np.where(venues['Venue Category'].str.contains('Hostel'),'Accommodation',
\
                    np.where(venues['Venue Category'].str.contains(re.compile('store', re.IGNO
RECASE)),'Store',\
                    np.where(venues['Venue Category'].str.contains('Food'),'Coffee Shop',\
                    np.where(venues['Venue Category'].str.contains('Tea'),'Coffee Shop',\
                    np.where(venues['Venue Category'].str.contains('Gift'),'Store',\
                    np.where(venues['Venue Category'].str.contains('Ice Cream'),'Coffee Shop',
\
                    np.where(venues['Venue Category'].str.contains(re.compile('.*cake', re.IGN
ORECASE)),'Coffee Shop',\
                    np.where(venues['Venue Category'].str.contains(re.compile('.*noodle', re.IG
NORECASE)),'Restaurant',\
                    np.where(venues['Venue Category'].str.contains(re.compile('.*gym', re.IGN
ORECASE)),'Fitness Center',\
                    np.where(venues['Venue Category'].str.contains(re.compile('.*park', re.IGN
ORECASE)),'Public Space',\
                    np.where(venues['Venue Category'].str.contains(re.compile('.*lounge', re.IG
NORECASE)),'Accommodation',\
                    np.where(venues['Venue Category'].str.contains(re.compile('motel', re.IGN
ORECASE)),'Accommodation',\
                    np.where(venues['Venue Category'].str.contains(re.compile('.*ship', re.IGN
ORECASE)),'Transportation',\
                    np.where(venues['Venue Category'].str.contains(re.compile('.*boat', re.IGN
ORECASE)),'Transportation',\
                    np.where(venues['Venue Category'].str.contains(re.compile('^pub$', re.IGN
ORECASE)),'Entertainment',\
                    np.where(venues['Venue Category'].str.contains(re.compile('.*pizza', re.IGN
ORECASE)),'Restaurant',\
                    np.where(venues['Venue Category'].str.contains(re.compile('lake', re.IGNOR
ECASE)),'Public Space',\
                    np.where(venues['Venue Category'].str.contains(re.compile('.*golf', re.IGNO
RECASE)),'Sport Center',\
                    np.where(venues['Venue Category'].str.contains(re.compile('garden', re.IGNORECASE)),'Public Space',\
                    np.where(venues['Venue Category'].str.contains(re.compile('.*outdoor', re.IGNORECASE)),'Entertainment',\
                    np.where(venues['Venue Category'].str.contains(re.compile('coffee', re.IGNORECASE)),'Coffee Shop',\
                    np.where(venues['Venue Category'].str.contains(re.compile('.*entertainment', re.IGNORECASE)),'Entertainment',\
                    np.where(venues['Venue Category'].str.contains(re.compile('art', re.IGNORECASE)),'Store',\
                    np.where(venues['Venue Category'].str.contains(re.compile('.*airport', re.IGNORECASE)),'Transportation',\
                    np.where(venues['Venue Category'].str.contains(re.compile('soccer', re.IGNORECASE)),'Sport Center',\
                    np.where(venues['Venue Category'].str.contains(re.compile('dessert', re.IGNORECASE)),'Coffee Shop',\
                    np.where(venues['Venue Category'].str.contains(re.compile('train', re.IGNORECASE)),'Transportation',\
                    np.where(venues['Venue Category'].str.contains(re.compile('market', re.IGNORECASE)),'Market',\
                    np.where(venues['Venue Category'].str.contains(re.compile('sport', re.IGNORECASE)),'Sport Center',\
                    np.where(venues['Venue Category'].str.contains(re.compile('spa', re.IGNORECASE)),'Clinic',\
                    np.where(venues['Venue Category'].str.contains(re.compile('bodega', re.IGNORECASE)),'Store',\
                    np.where(venues['Venue Category'].str.contains(re.compile('buffet', re.IGNORECASE)),'Restaurant',\
                    np.where(venues['Venue Category'].str.contains(re.compile('steak', re.IGNORECASE)),'Restaurant',\
                    np.where(venues['Venue Category'].str.contains(re.compile('night club', re.IGNORECASE)),'Entertainment',\
                    np.where(venues['Venue Category'].str.contains(re.compile('nightclub', re.IGNORECASE)),'Entertainment',\
                    np.where(venues['Venue Category'].str.contains(re.compile('harbor', re.IGNORECASE)),'Transportation',\
                    np.where(venues['Venue Category'].str.contains(re.compile('bus', re.IGNORECASE)),'Transportation',\
                    np.where(venues['Venue Category'].str.contains(re.compile('donut', re.IGNORECASE)),'Coffee Shop',\
                    np.where(venues['Venue Category'].str.contains(re.compile('bistro', re.IGNORECASE)),'Restaurant',\
                    np.where(venues['Venue Category'].str.contains(re.compile('snack', re.IGNORECASE)),'Coffee Shop',\
                    np.where(venues['Venue Category'].str.contains(re.compile('movie', re.IGNORECASE)),'Cinema',\
                    np.where(venues['Venue Category'].str.contains(re.compile('soup', re.IGNORECASE)),'Restaurant',\
                    np.where(venues['Venue Category'].str.contains(re.compile('urrito', re.IGNORECASE)),'Restaurant',\
                    np.where(venues['Venue Category'].str.contains(re.compile('construction', re.IGNORECASE)),'Office',\
                    np.where(venues['Venue Category'].str.contains(re.compile('flower', re.IGNORECASE)),'Store',\
                    np.where(venues['Venue Category'].str.contains(re.compile('boarding', re.IGNORECASE)),'Accommodation',\
                    np.where(venues['Venue Category'].str.contains(re.compile('salad', re.IGNO
RECASE)),'Restaurant',\
                    np.where(venues['Venue Category'].str.contains(re.compile('Sandwich', re.I
GNORECASE)),'Restaurant',\
                    np.where(venues['Venue Category'].str.contains(re.compile('diner', re.IGNO
RECASE)),'Restaurant',\
                    np.where(venues['Venue Category'].str.contains(re.compile('museum', re.IG
NORECASE)),'Public Space',\
                    np.where(venues['Venue Category'].str.contains(re.compile('massage', re.IG
NORECASE)),'Clinic',\
                    np.where(venues['Venue Category'].str.contains(re.compile('zoo', re.IGNOR
ECASE)),'Public Space',\
                    np.where(venues['Venue Category'].str.contains(re.compile('rail', re.IGNOR
ECASE)),'Transportation',\
                    np.where(venues['Venue Category'].str.contains(re.compile('stadium', re.IG
NORECASE)),'Public Space',\
                    np.where(venues['Venue Category'].str.contains(re.compile('living', re.IGNO
RECASE)),'Accommodation',\
                    np.where(venues['Venue Category'].str.contains(re.compile('government', r
e.IGNORECASE)),'Office',\
                    np.where(venues['Venue Category'].str.contains(re.compile('bagel', re.IGN
ORECASE)),'Coffee Shop',\
                    np.where(venues['Venue Category'].str.contains(re.compile('boutique', re.I
GNORECASE)),'Store',\
                    np.where(venues['Venue Category'].str.contains(re.compile('yogurt', re.IGN
ORECASE)),'Coffee Shop',\
                    np.where(venues['Venue Category'].str.contains(re.compile('playground', re
.IGNORECASE)),'Sport Center',\
                    np.where(venues['Venue Category'].str.contains(re.compile('resort', re.IGN
ORECASE)),'Accommodation',\
                    np.where(venues['Venue Category'].str.contains(re.compile('bowling', re.IG
NORECASE)),'Sport Center'\
                     ,'General'))))))))))))))))))))))))))))))))))))))))))))))))))))))))))))))))))))))))))))))

venues.drop_duplicates(inplace=True)
```

```
C:\Users\ThinkPad\anaconda3\lib\site-packages\ipykernel_launcher.py:78: SettingWithCopyW
arning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_gu
ide/indexing.html#returning-a-view-versus-a-copy
C:\Users\ThinkPad\anaconda3\lib\site-packages\ipykernel_launcher.py:80: SettingWithCopyW
arning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_gu
ide/indexing.html#returning-a-view-versus-a-copy
```

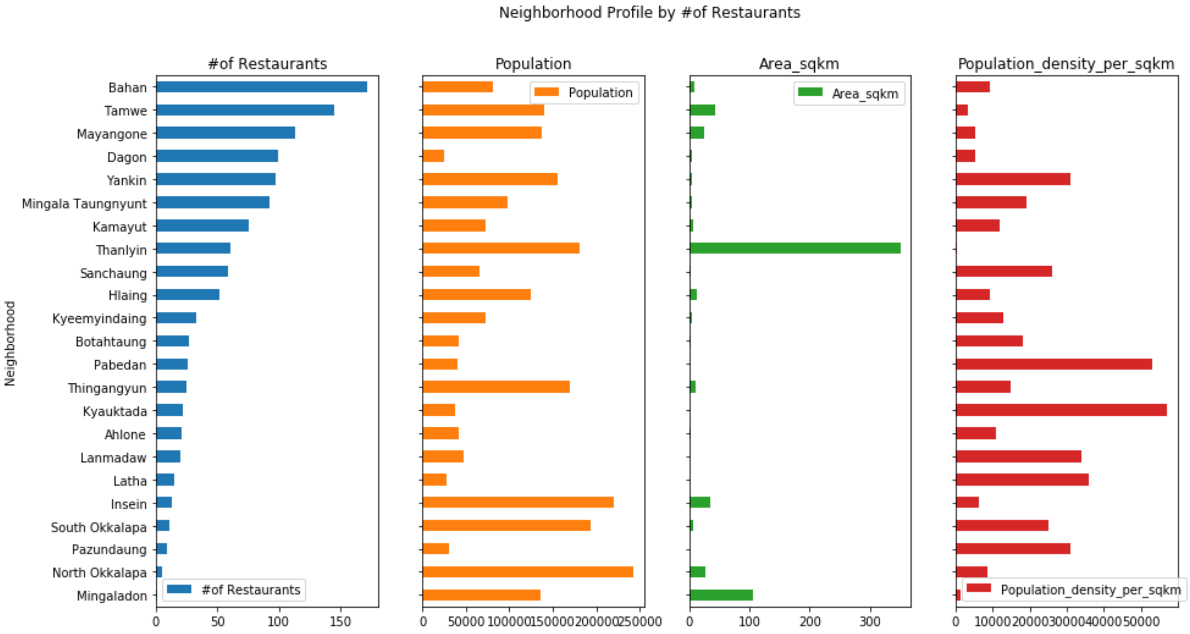
In [554]:

```
yangon_venues = pd.merge(yangon_venues,venues,how='inner',\
                left_on='Venue Category', \
                right_on='Venue Category')
```

Surprisingly, in the figure below, majority of restaurants are located in areas with high population but with low density. Which means, our assumption for having "ample space" is a good measurement.

```
In [587]: yangon_venues[yangon_venues['Main Category'].isin(['Restaurant'])]\
          [['Neighborhood','Main Category']].groupby('Neighborhood').size()\
          .to_frame().rename(columns={0:'#of Restaurants'})\
          .merge(new_data, how='left', left_index=True, right_on='Neighborhood')\
          .set_index('Neighborhood')[['#of Restaurants','Population','Area_sqkm',\
                              'Population_density_per_sqkm']].sort_values('#of Restaurants',\
                                                              ascending=True)\
          .plot(kind='barh',figsize=(15,8),subplots=True, layout=(1,4), sharex=False, \
               sharey=True, title='Neighborhood Profile by #of Restaurants')
```

```
Out[587]: array([[<matplotlib.axes._subplots.AxesSubplot object at 0x000002D6B5F49688>,
                  <matplotlib.axes._subplots.AxesSubplot object at 0x000002D6B61AF208>,
                  <matplotlib.axes._subplots.AxesSubplot object at 0x000002D6B5F49EC8>,
                  <matplotlib.axes._subplots.AxesSubplot object at 0x000002D6B5CCFE88>]],
                dtype=object)
```



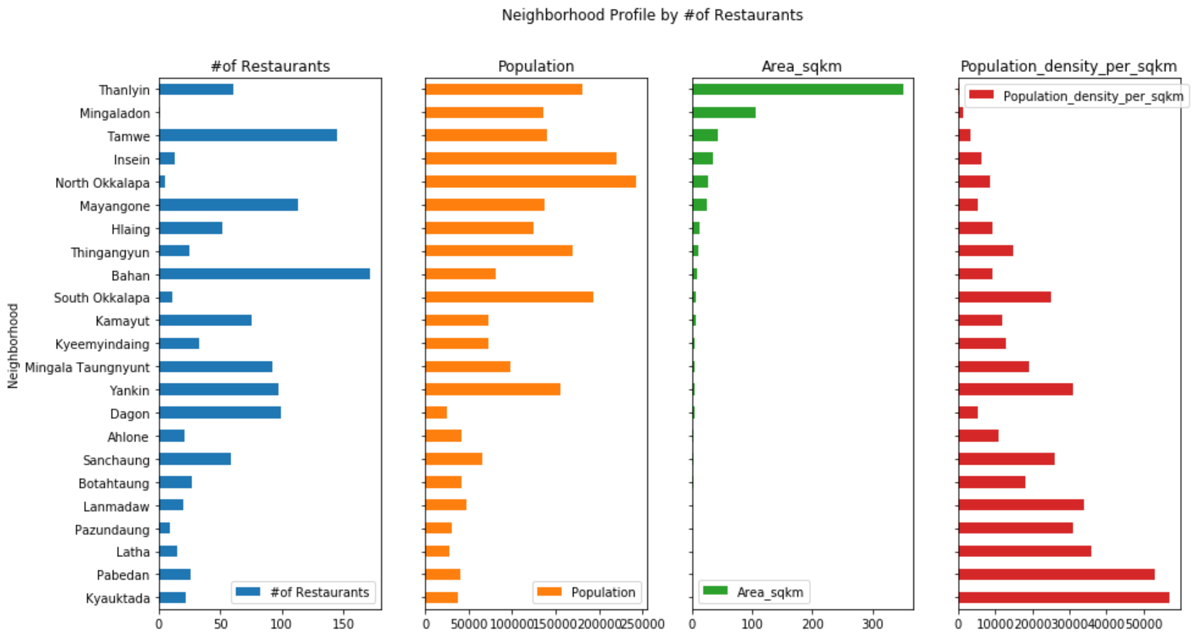
Let's review this comparison by sorting **Area_sqkm** to confirm our assumption again.

In [588]:

```
yangon_venues[yangon_venues['Main Category'].isin(['Restaurant'])]\
[['Neighborhood','Main Category']].groupby('Neighborhood').size()\
.to_frame().rename(columns={0:'#of Restaurants'})\
.merge(new_data, how='left', left_index=True, right_on='Neighborhood')\
.set_index('Neighborhood')[['#of Restaurants','Population','Area_sqkm',\
                    'Population_density_per_sqkm']].sort_values('Area_sqkm',\
                                                ascending=True)\
.plot(kind='barh',figsize=(15,8),subplots=True, layout=(1,4), sharex=False, \
    sharey=True, title='Neighborhood Profile by #of Restaurants')
```

Out[588]:

```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x000002D6B6507288>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000002D6AEB246C8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000002D6B6507AC8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000002D6B5855F48>]],
      dtype=object)
```



Accroding to above comparison, top 3 neighborhoods populated with restaurants have corelation to big areas with low population density while the existance of offices and income of the population are considered as top reasons.

With that details, we can estimate, the second neighborhood **Mingaladon** is the best option following **Insein** and **North Okkalapa**.

Let's focus on those 3 areas and plot them on to clusters of neighborhoods usings K-Means algorithm below.

In [589]:

```
# prepare data table for K-Means clustering
yangon_onehot = pd.get_dummies(yangon_venues['Main Category'], prefix='', prefix_sep='')
yangon_onehot['Neighborhood']=yangon_venues['Neighborhood']
fixed_columns = [yangon_onehot.columns.values[-1]]+list(yangon_onehot.columns.values[0:-1])
yangon_grouped = yangon_onehot[fixed_columns].groupby('Neighborhood').mean().reset_index()
yangon_grouped.head()
```

Out[589]:

	Neighborhood	Accommodation	Cinema	Clinic	Coffee Shop	Entertainment	Fitness Center	Gene
0	Ahlone	0.119048	0.000000	0.000000	0.166667	0.119048	0.000000	0.0000
1	Bahan	0.078176	0.000000	0.026059	0.127036	0.058632	0.009772	0.0130
2	Botahtaung	0.188406	0.000000	0.000000	0.101449	0.144928	0.014493	0.0000
3	Dagon	0.144928	0.009662	0.028986	0.173913	0.048309	0.004831	0.0048
4	Hlaing	0.068182	0.000000	0.011364	0.125000	0.022727	0.022727	0.0000

In [590]:

```
#define function to order the main categories accroding to occurance of them

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]
```

Let's create data frame of neighborhood along with common venues in order.

In [591]:

```
# limit top venues
num_top_venues = 10

indicators = ['st', 'nd', 'rd']

# create columns according to number of top venues
columns = ['Neighborhood']
for ind in np.arange(num_top_venues):
    try:
        columns.append('{}{} Most Common Venue'.format(ind+1, indicators[ind]))
    except:
        columns.append('{}th Most Common Venue'.format(ind+1))

# create a new dataframe
neighborhoods_venues_sorted = pd.DataFrame(columns=columns)
neighborhoods_venues_sorted['Neighborhood'] = yangon_grouped['Neighborhood']

for ind in np.arange(yangon_grouped.shape[0]):
    neighborhoods_venues_sorted.iloc[ind, 1:] = return_most_common_venues(yangon_grouped.iloc[ind, :], num_top_venues)

neighborhoods_venues_sorted.head()
```

Out[591]:

	Neighborhood	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue	6th M Comm Ve
0	Ahlone	Restaurant	Coffee Shop	Entertainment	Accommodation	Shopping Mall	S
1	Bahan	Restaurant	Coffee Shop	Accommodation	Entertainment	Public Space	S
2	Botahtaung	Restaurant	Accommodation	Entertainment	Coffee Shop	Shopping Mall	S
3	Dagon	Restaurant	Coffee Shop	Accommodation	Shopping Mall	Entertainment	C
4	Hlaing	Restaurant	Coffee Shop	Shopping Mall	Accommodation	Sport Center	Pu Sp

With that, we will run K-Means to create clusters.

In [592]:

```
# set number of clusters
kclusters = 5

yangon_grouped_clustering = yangon_grouped.drop('Neighborhood', 1)

# run k-means clustering
kmeans = KMeans(n_clusters=kclusters, random_state=0).fit(yangon_grouped_clustering)

# check cluster labels generated for each row in the dataframe

kmeans.labels_[0:10]
```

Out[592]:

```
array([3, 3, 1, 3, 3, 4, 3, 1, 3, 1])
```

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

In [593]:

```
# add clustering labels
neighborhoods_venues_sorted.insert(0, 'Cluster Labels', kmeans.labels_)

yangon_merged = new_data

# merge yangon_grouped with new_data to add latitude/longitude for each neighborhood
yangon_merged = yangon_merged.join(neighborhoods_venues_sorted.set_index('Neighborho
od'), on='Neighborhood')

yangon_merged.head()
```

Out[593]:

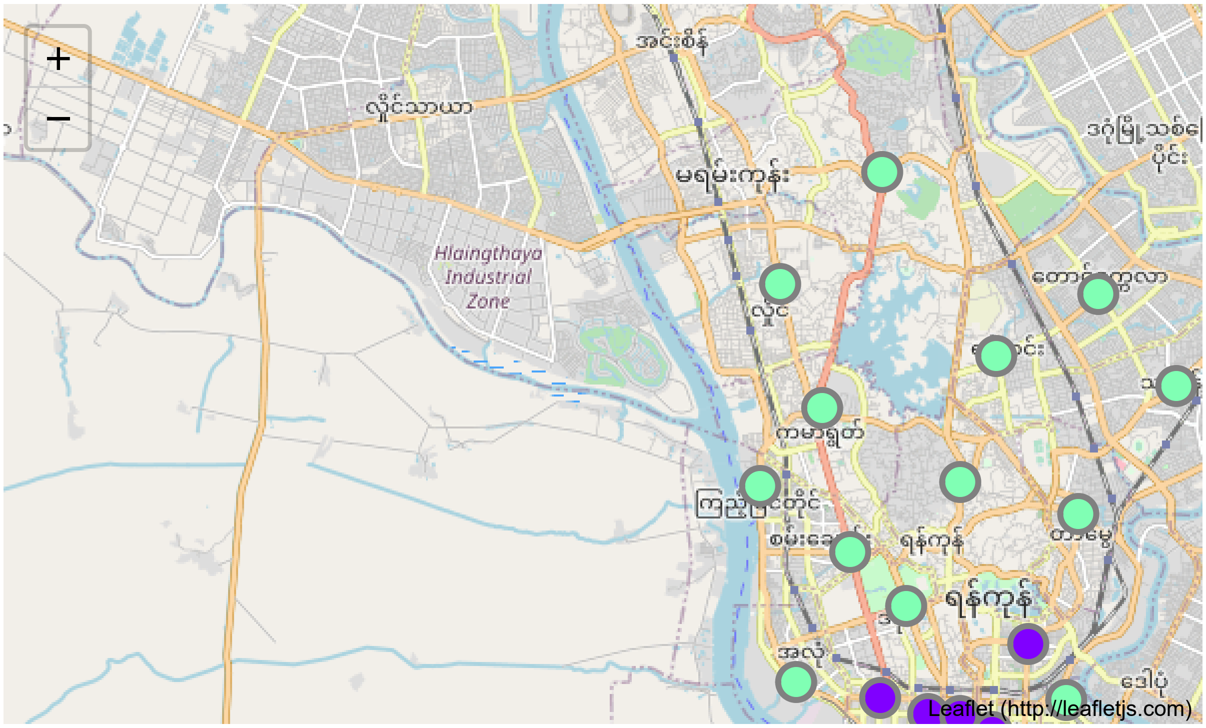
	Borough	Neighborhood	Longitude	Latitude	Population	Area_sqkm	Radius_m	Population_
0	Yangon (West)	Ahlone	96.127863	16.782398	41200	4.00	2000	
1	Yangon (West)	Bahan	96.156112	16.815427	81000	8.84	2973	
2	Yangon (East)	Botahtaung	96.169709	16.771967	42000	2.40	1549	
3	Yangon (West)	Dagon	96.146900	16.794952	25082	4.70	2167	
4	Yangon (West)	Hlaing	96.125227	16.847934	125000	13.70	3701	

Let's see how the clusters are formed on the map.

In [596]:

```
# create map
map_clusters = folium.Map(location=[latitude, longitude], zoom_start=12)

# set color scheme for the clusters
x = np.arange(kclusters)
ys = [i + x + (i*x)**2 for i in range(kclusters)]
colors_array = cm.rainbow(np.linspace(0, 1, len(ys)))
rainbow = [colors.rgb2hex(i) for i in colors_array]

# add markers to the map
markers_colors = []
for lat, lon, poi, cluster in zip(yangon_merged['Latitude'], yangon_merged['Longitude'], yangon_merged['Neighborhood'], yangon_merged['Cluster Labels']):
    label = folium.Popup(str(poi) + ' Cluster ' + str(cluster), parse_html=True)
    folium.CircleMarker(
        [lat, lon],
        radius=9,
        popup=label,
        color='grey',#rainbow[cluster-1],
        fill=True,
        fill_color=rainbow[cluster-1],
        fill_opacity=1).add_to(map_clusters)

temp = new_data[new_data['Neighborhood'].isin(['Mingaladon','Insein','North Okkalapa'])]
for i in range(len(temp)):
    folium.Marker(
        location=[temp.iloc[i]['Latitude'], temp.iloc[i]['Longitude']],
        popup=data.iloc[i]['Neighborhood']).add_to(map_clusters)

map_clusters
```

Out[596]:



Obviously, the 3 areas are located away from the downtown area but have potentials too.

Let's look at the info of those below.

In [336]:
```
yangon_merged.loc[yangon_merged['Cluster Labels'] == 0, yangon_merged.columns[[1] + list(
range(5, yangon_merged.shape[1]))]]
```

Out[336]:

	Neighborhood	Area_sqkm	Radius_m	Population_density_per_sqkm	Cluster Labels	1st Most Common Venue
12	Mingaladon	106.6	10324	1300	0	Restaurant

In [597]:
```
yangon_merged.loc[yangon_merged['Cluster Labels'] == 4, yangon_merged.columns[[1] + list(
range(5, yangon_merged.shape[1]))]]
```

Out[597]:

	Neighborhood	Area_sqkm	Radius_m	Population_density_per_sqkm	Cluster Labels	1st Most Common Venue
5	Insein	35.0	5916	6300	4	Restaurant
14	North Okkalapa	28.3	5319	8600	4	Transportation

Results

As we can see, both of the clusters where our top 3 prioritized areas have top popular venues in **Transportation**, **Public Space** and **Market**.

The existance of the competitors are also low and the areas have lesser population density comparing to other parts of the region which is the opportunity for acquiring new customers and the location with ample space at lower cost.

Besides, the areas are located near to the exist ways of Yangon; Pyay road and international airport of Yangon, to other parts of Myanmar and foreign countries. That will be an advangeous for attracting travellers in the holiday seasons as well.

So, we recommend to keep our priority in finding the location in those areas.

Discussion

We have explored the venues and examined the features to oversee the potential areas. But there are still limitations that:

1) exploring nearby venues from the center of neighborhood can not get venues within the area correctly since neighborhood boundaries are not in circular shape

2) venues obtained from Foursquare is limited and may not include new venues that are not registered on the web

But, with this solid information, we can start exploring at the ground level for futher project development works.

Conclusion

Eventhough the recommendation is for kicking off the project, we can improve our report on giving more time on:

1) using **SVM** that enables explored venues to be clustered into neighborhoods with better accuracy,

2) improving K-Means by finding best cluster size with **elbow method**

As a result, the recommendation will be more reliable