capstone_project_w2

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1 Capstone Project - The Battle of the Neighborhoods (Week 2)

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1.0.1 Table of contents

1.1 Introduction: Business Problem

Over the last years cycling has becoming increasingly popular as a transport method all over the world, and my city Porto Alegre, Brazil, is no exception. While it is still mainly used for recreational purposes due to city shy advance in infrastructure it just keeps growing and so are the business oportunities. The goal is to show that there is plenty of room for new business, but also this map could help guide for building new bike lanes or emergency units for this specificity.

1.2 Data

A list of Porto Alegre's neighborhood and some statistical information from wikipedia: https://pt.wikipedia.org/wiki/Lista_de_bairros_de_Porto_Alegre

A dataset from the city administration, it is avaliable at http://datapoa.com.br/dataset/acidentes-de-transito-acidentes in a csv file. The website is in Portuguese. It is actually a record of many types of traffic accidents, I filtered only the ones with bycicle (more than one thousand!) and from that I did the cycling flux map.

[1]:
```
# import libraries

import pandas as pd
import numpy as np
import matplotlib.cm as cm
import matplotlib.colors as colors
import matplotlib.pyplot as plt
from bs4 import BeautifulSoup
```

```
import requests
import geocoder
from geopy.geocoders import Nominatim
from IPython.display import Image
from IPython.core.display import HTML
from pandas.io.json import json_normalize
import folium

from sklearn.cluster import KMeans
from sklearn import preprocessing

print('Libraries imported.')
```

```
Libraries imported.
```

[2]:
```
# get the response in the form of html

wikiurl="https://pt.wikipedia.org/wiki/Lista_de_bairros_de_Porto_Alegre"
response=requests.get(wikiurl)
print(response.status_code, '...means ok!')
```

```
200 ...means ok!
```

[3]:
```
#use BeautifulSoup to turn wikipage into a dataframe

soup = BeautifulSoup(response.text, 'html.parser')
can_postal_table = soup.find('table', {'class':"wikitable"})
df = pd.read_html(str(can_postal_table))
df = pd.DataFrame(df[0])
df.head()
```

[3]:

	Bairro	Data de Criação	Área	População2010	\
0	Aberta dos Morros	21 dez 2015	NaN	NaN	
1	Agronomia	21 set 1976	1241 ha	12222.0	
2	Anchieta	7 dez 1959	84 ha	203.0	
3	Arquipélago	7 dez 1959	4718 ha	5061.0	
4	Auxiliadora	7 dez 1959	82 ha	9985.0	

	Tx Cresc Pop 91-00	Densidade	Renda média por domicílio	Nota
0	NaN	NaN	NaN	NaN
1	19,24% a.a.	8,6 hab/ha	3,98 SM/mês	(1)
2	0,51% a.a.	2,4 hab/ha	8,41 SM/mês	NaN
3	9,32% a.a.	1,1 hab/ha	2,96 SM/mês	NaN
4	-0,25% a.a.	121,8 hab/ha	19,57 SM/mês	NaN

[4]:
```
# Shape the dataframe with only the necessary information

```

```
df.rename(columns={'Bairro':'Neighborhood', 'População2010':'Population',␣
 ↪'Renda média por domicílio':'Monthly Avg Income'}, inplace=True)
df.drop(['Data de Criação', 'Tx Cresc Pop 91-00', 'Densidade', 'Nota', 'Área'],␣
 ↪axis=1, inplace=True)
df['Monthly Avg Income'] = df['Monthly Avg Income'].astype('str')
df['Monthly Avg Income'] = df['Monthly Avg Income'].apply(lambda x: x[:4])
df['Monthly Avg Income'] = (df['Monthly Avg Income'].str.split()).apply(lambda␣
 ↪x: float(x[0].replace(',', '.')))
df = df[~df.Neighborhood.str.contains('TOTAL')]
df = df[df['Population'].notna()]
df = df[df['Monthly Avg Income'].notna()]
df.reset_index()
```

[4]:

	index	Neighborhood	Population	Monthly Avg Income
0	1	Agronomia	12222.0	3.98
1	2	Anchieta	203.0	8.41
2	3	Arquipélago	5061.0	2.96
3	4	Auxiliadora	9985.0	19.50
4	5	Azenha	13449.0	10.70
..	…	…	…	…
74	90	Vila Conceição	1467.0	11.90
75	91	Vila Ipiranga	20951.0	8.99
76	92	Vila Jardim	14251.0	5.30
77	93	Vila João Pessoa	10522.0	5.58
78	94	Vila Nova	33145.0	5.35

[79 rows x 4 columns]

[5]:
```
df.head()
```

[5]:

	Neighborhood	Population	Monthly Avg Income
1	Agronomia	12222.0	3.98
2	Anchieta	203.0	8.41
3	Arquipélago	5061.0	2.96
4	Auxiliadora	9985.0	19.50
5	Azenha	13449.0	10.70

[6]:
```
# Get the neighborhoods coordinates

neighborhoods = df['Neighborhood'].to_list()

longitude = []
latitude = []

for neighborhood in neighborhoods:

    # initialize the variable to None
```

```
    lat_lng_coords = None

    # loop until getting the coordinates
    while(lat_lng_coords is None):
        g = geocoder.arcgis('{}, Porto Alegre, Rio Grande do Sul'.
 ↪format(neighborhood))
        lat_lng_coords = g.latlng


    # Append the data to the lists
    latitude.append(lat_lng_coords[0])
    longitude.append(lat_lng_coords[1])
```

[7]:
```
poa_coord = pd.DataFrame({'Neighborhood': neighborhoods, 'Latitude': latitude,␣
 ↪'Longitude': longitude})
poa_coord.head()
```

[7]:
```
   Neighborhood  Latitude  Longitude
0    Agronomia -30.09137  -51.12186
1     Anchieta -29.98371  -51.16616
2  Arquipélago -29.99078  -51.23045
3  Auxiliadora -30.01978  -51.18847
4       Azenha -30.04896  -51.21540
```

[8]:
```
# This the second data, for the bicycle flux in the city

df_traff = pd.read_csv('https://dadosabertos.poa.br/dataset/
 ↪d6cfbe48-ee1f-450f-87f5-9426f6a09328/resource/
 ↪b56f8123-716a-4893-9348-23945f1ea1b9/download/cat_acidentes.csvData', sep=';
 ↪')
df_traff.head()
```

[8]:
```
          data_extracao  idacidente  longitude   latitude  \
0  2020-12-01 01:33:39      190816        NaN        NaN
1  2020-12-01 01:33:39      601004 -51.146812 -30.151813
2  2020-12-01 01:33:39      601028 -51.232759 -30.037344
3  2020-12-01 01:33:39      601080 -51.214493 -30.026976
4  2020-12-01 01:33:39      601111 -51.185210 -30.036497

                            log1              log2  predial1     tipo_acid  \
0              R MARCOS MOREIRA  R GASTON ENGLERT         0  ABALROAMENTO
1  R ENG OSCAR DE OLIVEIRA RAMOS               NaN      4141  ABALROAMENTO
2                            NaN               NaN         0      EVENTUAL
3               R SANTO ANTONIO               NaN       215       COLISÃO
4                   R CARAZINHO               NaN       741  ABALROAMENTO

   queda_arr                 data  … caminhao moto  carroca  bicicleta  \
```

```
0          0  2020-10-17 00:00:00  …        0    1        0          0
1          0  2015-01-02 00:00:00  …        0    0        0          0
2          0  2015-01-02 00:00:00  …        0    0        0          0
3          0  2015-01-05 00:00:00  …        0    0        0          0
4          0  2015-01-04 00:00:00  …        0    1        0          0

   outro  noite_dia               regiao  cont_vit  ups  consorcio
0      0      NOITE  NORTE                      1    5        NaN
1      1      NOITE  SUL                        1    5        NaN
2      0        DIA  CENTRO                     0    1        NaN
3      0        DIA  CENTRO                     0    1        NaN
4      0        DIA  NORTE                      1    5        NaN

[5 rows x 33 columns]
```

[9]:
```
df_bike = df_traff[df_traff.bicicleta != 0]
df_bike.reset_index(drop=True, inplace=True)
df_bike.head()
```

[9]:
```
         data_extracao  idacidente  longitude   latitude  \
0  2020-12-01 01:33:39      601251 -51.227888 -30.048904
1  2020-12-01 01:33:39      601236 -51.148988 -30.067380
2  2020-12-01 01:33:39      601112 -51.256198 -30.109581
3  2020-12-01 01:33:39      601014 -51.233611 -30.105825
4  2020-12-01 01:33:39      601215 -51.184114 -30.113348

                              log1         log2  predial1     tipo_acid  \
0                AV PRAIA DE BELAS          NaN      1181  ABALROAMENTO
1                AV BENTO GONCALVES          NaN      6741  ABALROAMENTO
2  R SARGENTO NICOLAU DIAS DE FARIAS          NaN       486  ABALROAMENTO
3                R DR PEREIRA NETO  R JOAO MORA         0  ABALROAMENTO
4                  R VENTURA PINTO          NaN       185  ABALROAMENTO

   queda_arr                 data  … caminhao moto  carroca  bicicleta  \
0          0  2015-01-11 00:00:00  …        0    0        0          1
1          0  2015-01-09 00:00:00  …        0    1        0          1
2          0  2015-01-05 00:00:00  …        0    0        0          1
3          0  2015-01-04 00:00:00  …        0    1        0          1
4          0  2015-01-07 00:00:00  …        0    0        0          1

   outro  noite_dia               regiao  cont_vit  ups  consorcio
0      0      NOITE  CENTRO                     1    5        NaN
1      0      NOITE  LESTE                      1    5        NaN
2      0      NOITE  SUL                        1    5        NaN
3      0        DIA  SUL                        1    5        NaN
4      0        DIA  SUL                        1    5        NaN
```

```
[5 rows x 33 columns]
```

[10]:
```
df_bike.drop(['cont_vit', 'ups', 'consorcio', 'data_extracao', 'log1', 'log2',␣
↪'predial1', 'outro', 'noite_dia',
              'queda_arr', 'data', 'dia_sem', 'hora', 'feridos', 'feridos_gr',␣
↪'mortes', 'morte_post', 'fatais',
               'auto', 'taxi', 'lotacao', 'onibus_urb', 'onibus_met',␣
↪'onibus_int', 'caminhao','moto', 'carroca', 'tipo_acid', 'bicicleta'],
             axis=1, inplace=True)
df_bike = df_bike[df_bike['longitude'].notna()]
df_bike = df_bike[df_bike['latitude'].notna()]
df_bike.reset_index(drop=True, inplace=True)
```

```
C:\Users\ceb_p\anaconda3\lib\site-packages\pandas\core\frame.py:4174:
SettingWithCopyWarning:
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_guide/indexing.html#returning-a-view-versus-a-copy
  errors=errors,
```

[11]:
```
# reducing its size a bit

df_bike = df_bike[0:300]
df_bike.reset_index(drop=True, inplace=True)
df_bike.rename(columns={'idacidente':'id', 'regiao':'borough'}, inplace=True)
```

[12]:
```
# translating the column names
# the data has a good proportion

df_bike['borough'] = df_bike['borough'].str.replace('NORTE','North')
df_bike['borough'] = df_bike['borough'].str.replace('SUL','South')
df_bike['borough'] = df_bike['borough'].str.replace('LESTE','East')
df_bike['borough'] = df_bike['borough'].str.replace('CENTRO','Centre')
df_bike.groupby('borough').count()
```

[12]:

borough	id	longitude	latitude
Centre	53	53	53
East	71	71	71
North	87	87	87
South	89	89	89

[13]:
```
df_bike.head()
```

[13]:

	id	longitude	latitude	borough
0	601251	-51.227888	-30.048904	Centre
1	601236	-51.148988	-30.067380	East

```
2  601112 -51.256198 -30.109581  South
3  601014 -51.233611 -30.105825  South
4  601215 -51.184114 -30.113348  South
```

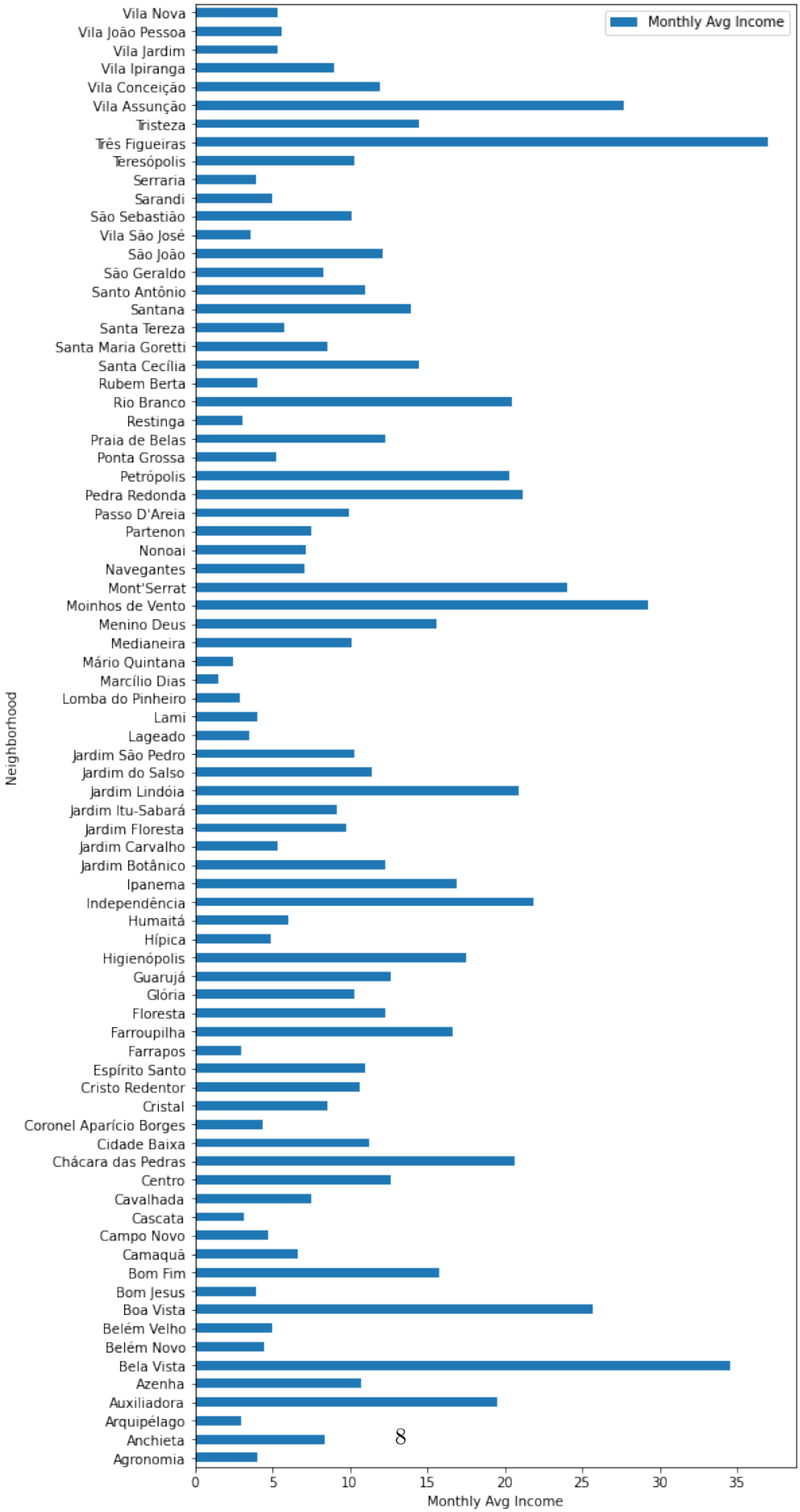
1.3 Methodology

For this project I will look to areas of Porto Alegre with low bycicle shop density, if possible near to bike lanes, and try to align it with economic and populational density aspects. We will look to all neighboors we had the proper data.

So I took a look at general aspects of the neighborhoods, mainly its population and average income. Then with FourSquare API made a list of all bycicle shops in Porto Alegre. With that information I latter applied KClusters algorithm to map bycicle shops and neighborhood in one indicator (the clusters) and contrasted that with the map of bycicle flux and the map of actual bycle lanes.

1.3.1 Data exploration

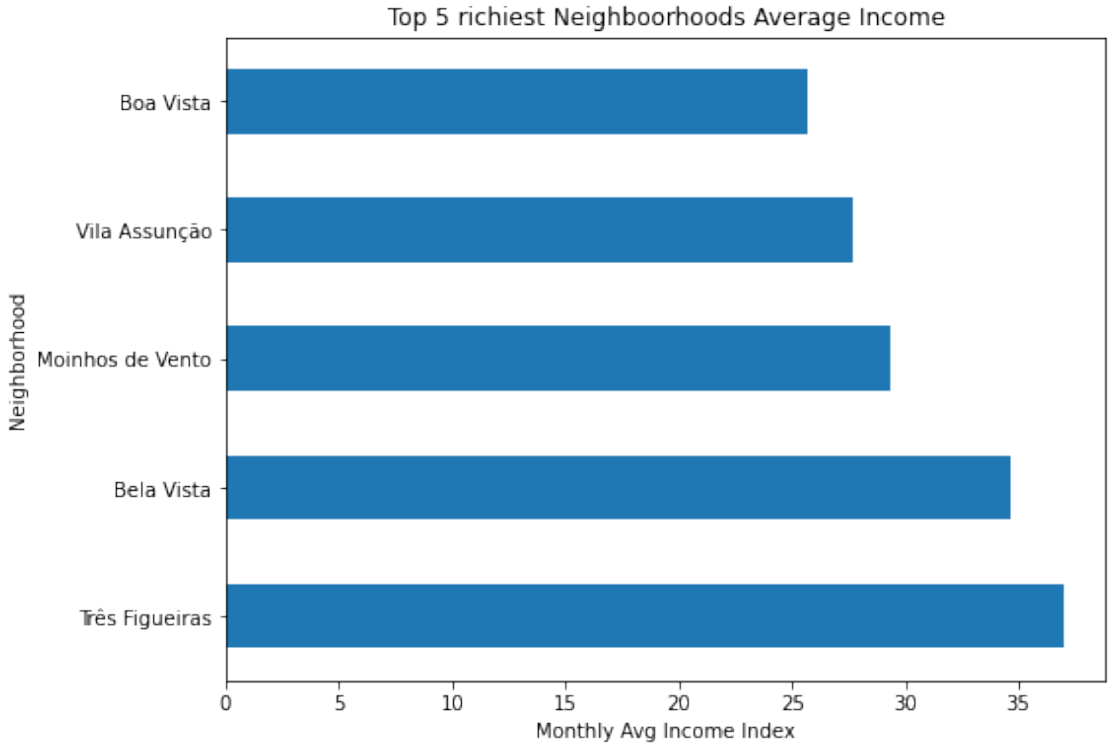
[14]:
```
# Take the neighborhood dataframe to look at it's income average.
# It's income index is the minimum wage per month in Reais(R$), each unit is␣
 ↪approximately U$ 204.00

df.plot(x='Neighborhood', y='Monthly Avg Income', kind='barh', figsize=(8,20))

plt.xlabel('Monthly Avg Income')
plt.ylabel('Neighborhood')

plt.show()
```


Monthly Avg Income
Vila Nova
Vila João Pessoa
Vila Jardim
Vila Ipiranga
Vila Conceição
Vila Assunção
Tristeza
Três Figueiras
Teresópolis
Serraria
Sarandi
São Sebastião
Vila São José
São João
São Geraldo
Santo Antônio
Santana
Santa Tereza
Santa Maria Goretti
Santa Cecília
Rubem Berta
Rio Branco
Restinga
Praia de Belas
Ponta Grossa
Petrópolis
Pedra Redonda
Passo D'Areia
Partenon
Nonoai
Navegantes
Mont'Serrat
Moinhos de Vento
Menino Deus
Medianeira
Mário Quintana
Marcílio Dias
Lomba do Pinheiro
Lami
Lageado
Jardim São Pedro
Jardim do Salso
Jardim Lindóia
Jardim Itu-Sabará
Jardim Floresta
Jardim Carvalho
Jardim Botânico
Ipanema
Independência
Humaitá
Hípica
Higienópolis
Guarujá
Glória
Floresta
Farroupilha
Farrapos
Espírito Santo
Cristo Redentor
Cristal
Coronel Aparício Borges
Cidade Baixa
Chácara das Pedras
Centro
Cavalhada
Cascata
Campo Novo
Camaquã
Bom Fim
Bom Jesus
Boa Vista
Belém Velho
Belém Novo
Bela Vista
Azenha
Auxiliadora
Arquipélago
Anchieta
Agronomia
Neighborhood
0
5
10
15
20
25
30
35
Monthly Avg Income

[15]:
```
N5 = df['Monthly Avg Income'].groupby(df['Neighborhood']).sum().
 ↪sort_values(ascending=False).head()
N5
```

[15]:
```
Neighborhood
Três Figueiras      37.0
Bela Vista          34.6
Moinhos de Vento    29.3
Vila Assunção       27.7
Boa Vista           25.7
Name: Monthly Avg Income, dtype: float64
```

[16]:
```
N5.plot(kind='barh', figsize=(8,6))

plt.title('Top 5 richiest Neighboorhoods Average Income')
plt.xlabel('Monthly Avg Income Index')
plt.ylabel('Neighborhood')

plt.show()
```



[17]:
```
# Foursquare Credentials

CLIENT_ID = '1ZOPOCBN35HTOOUZRDHULNLIQWUMOORVEOEQ4CLQW52VGBDF' # your␣
↪Foursquare ID
CLIENT_SECRET = 'DCNLFUDB3OCNK5LRP3RMXRVGKPTGZEVMA3QGTLI5DQKDUIVY' # your␣
↪Foursquare Secret
ACCESS_TOKEN = '3IYJYOFCZTDCDNYUCTHX5MFHBGOKIDPOJVGKDBLGZQACEVQD' # your␣
↪FourSquare Access Token
VERSION = '20180605'
```

[18]:
```
# Get the bikeshops list by neighborhood

def getNearbyVenues(names, latitudes, longitudes, radius=1500, LIMIT=300,␣
↪categoryId='4bf58dd8d48988d115951735'):

    venues_list=[]
    for name, lat, lng in zip(names, latitudes, longitudes):
        print(name)

        # create the API request URL
        url = 'https://api.foursquare.com/v2/venues/explore?
↪&client_id={}&client_secret={}&v={}&ll={},{}&radius={}&limit={}&categoryId={}'.
↪format(
            CLIENT_ID,
            CLIENT_SECRET,
            VERSION,
            lat,
            lng,
            radius,
            LIMIT,
            categoryId)

        # 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)

venues = getNearbyVenues(names=poa_coord['Neighborhood'],
                                    latitudes=poa_coord['Latitude'],
                                    longitudes=poa_coord['Longitude']
                                   )
```

```
Agronomia
Anchieta
Arquipélago
Auxiliadora
Azenha
Bela Vista
Belém Novo
Belém Velho
Boa Vista
Bom Jesus
Bom Fim
Camaquã
Campo Novo
Cascata
Cavalhada
Centro
Chácara das Pedras
Cidade Baixa
Coronel Aparício Borges
Cristal
Cristo Redentor
Espírito Santo
Farrapos
Farroupilha
Floresta
Glória
Guarujá
Higienópolis
Hípica
Humaitá
Independência
Ipanema
Jardim Botânico
```

Jardim Carvalho
Jardim Floresta
Jardim Itu-Sabará
Jardim Lindóia
Jardim do Salso
Jardim São Pedro
Lageado
Lami
Lomba do Pinheiro
Marcílio Dias
Mário Quintana
Medianeira
Menino Deus
Moinhos de Vento
Mont'Serrat
Navegantes
Nonoai
Partenon
Passo D'Areia
Pedra Redonda
Petrópolis
Ponta Grossa
Praia de Belas
Restinga
Rio Branco
Rubem Berta
Santa Cecília
Santa Maria Goretti
Santa Tereza
Santana
Santo Antônio
São Geraldo
São João
Vila São José
São Sebastião
Sarandi
Serraria
Teresópolis
Três Figueiras
Tristeza
Vila Assunção
Vila Conceição
Vila Ipiranga
Vila Jardim
Vila João Pessoa
Vila Nova

[19]:
```
# Removing motorbike shops

venues = venues[~venues.Venue.str.contains("Ducati", 'Bs Motos')]
venues = venues[~venues.Venue.str.contains('mototech')]
venues.reset_index(drop=True, inplace=True)
venues.head()
```

[19]:

	Neighborhood	Neighborhood Latitude	Neighborhood Longitude	Venue	Venue Latitude	Venue Longitude	Venue Category
0	Auxiliadora	-30.01978	-51.18847	Espaço do Ciclista	-30.010239	-51.188943	Bike Shop
1	Auxiliadora	-30.01978	-51.18847	Gaúcha Bike ZN	-30.007717	-51.193079	Bike Shop
2	Auxiliadora	-30.01978	-51.18847	Velocity	-30.021953	-51.194049	Bike Shop
3	Auxiliadora	-30.01978	-51.18847	Biketech	-30.023465	-51.197879	Bike Shop
4	Auxiliadora	-30.01978	-51.18847	M. Bike	-30.015607	-51.196491	Bike Shop

[20]:
```
venues.shape
```

[20]:
```
(209, 7)
```

Pre-processing

[21]:
```
df.head(2)
```

[21]:

	Neighborhood	Population	Monthly Avg Income
1	Agronomia	12222.0	3.98
2	Anchieta	203.0	8.41

[22]:
```
# Removing non numerical data

df_2 = df.drop('Neighborhood', axis=1)
df_2.head(2)
```

[22]:

	Population	Monthly Avg Income
1	12222.0	3.98
2	203.0	8.41

[23]:
```
# Pre-processing

from sklearn.preprocessing import StandardScaler

X = df_2.values
X = np.nan_to_num(X)
```

```
cluster_dataset = StandardScaler().fit_transform(X)
cluster_dataset[:5]
```

[23]:
```
array([[-0.25485461, -0.9364534 ],
       [-1.09340799, -0.34890146],
       [-0.75447028, -1.07173624],
       [-0.41092782,  1.12196784],
       [-0.16924807, -0.04517822]])
```

Modeling

[24]:
```
# Initialize the Cluster Algorithm

num_clusters = 6

k_means = KMeans(init="k-means++", n_clusters=num_clusters, n_init=12)
k_means.fit(cluster_dataset)
labels = k_means.labels_

print(labels)
```

```
[5 5 5 0 4 0 5 5 0 1 4 1 5 1 1 2 0 4 1 1 4 4 1 4 4 4 4 4 5 5 0 4 4 1 4 1 0
 4 4 5 5 1 5 1 4 2 0 0 5 1 3 1 0 2 5 4 3 0 3 4 5 3 2 4 5 4 1 4 3 5 4 0 4 0
 4 1 5 5 1]
```

[25]:
```
# Take the label so we can identify the cluster on the map

df['Labels'] = labels
df.head()
```

[25]:

	Neighborhood	Population	Monthly Avg Income	Labels
1	Agronomia	12222.0	3.98	5
2	Anchieta	203.0	8.41	5
3	Arquipélago	5061.0	2.96	5
4	Auxiliadora	9985.0	19.50	0
5	Azenha	13449.0	10.70	4

[26]:
```
# Merge the dataframes to have all the needed information more easily

venues_merged = df.join(venues.set_index('Neighborhood'), on='Neighborhood')
venues_merged.head()
```

[26]:

	Neighborhood	Population	Monthly Avg Income	Labels	Neighborhood Latitude	\
1	Agronomia	12222.0	3.98	5	NaN	
2	Anchieta	203.0	8.41	5	NaN	
3	Arquipélago	5061.0	2.96	5	NaN	
4	Auxiliadora	9985.0	19.50	0	-30.01978	
4	Auxiliadora	9985.0	19.50	0	-30.01978	

```
   Neighborhood Longitude                Venue  Venue Latitude  \
1                     NaN                  NaN             NaN
2                     NaN                  NaN             NaN
3                     NaN                  NaN             NaN
4               -51.18847  Espaço do Ciclista      -30.010239
4               -51.18847      Gaúcha Bike ZN      -30.007717

   Venue Longitude Venue Category
1              NaN            NaN
2              NaN            NaN
3              NaN            NaN
4       -51.188943      Bike Shop
4       -51.193079      Bike Shop
```

[27]:
```
venues_merged = venues_merged[venues_merged['Neighborhood Latitude'].notna()]
venues_merged = venues_merged[venues_merged['Neighborhood Longitude'].notna()]
venues_merged = venues_merged[venues_merged['Venue'].notna()]
venues_merged = venues_merged[venues_merged['Venue Latitude'].notna()]
venues_merged = venues_merged[venues_merged['Venue Longitude'].notna()]
venues_merged = venues_merged[venues_merged['Venue Category'].notna()]
venues_merged = venues_merged[venues_merged['Labels'].notna()]
```

[28]:
```
venues_merged['Labels'] = venues_merged['Labels'].apply(lambda x: int(x))
venues_merged.reset_index(drop=True)
```

[28]:
```
          Neighborhood  Population  Monthly Avg Income  Labels  \
0          Auxiliadora      9985.0               19.50       0
1          Auxiliadora      9985.0               19.50       0
2          Auxiliadora      9985.0               19.50       0
3          Auxiliadora      9985.0               19.50       0
4          Auxiliadora      9985.0               19.50       0
..                 …         …                   …      …
204        Vila Jardim     14251.0                5.30       5
205        Vila Jardim     14251.0                5.30       5
206        Vila Jardim     14251.0                5.30       5
207  Vila João Pessoa     10522.0                5.58       5
208  Vila João Pessoa     10522.0                5.58       5

     Neighborhood Latitude  Neighborhood Longitude  \
0                -30.01978               -51.18847
1                -30.01978               -51.18847
2                -30.01978               -51.18847
3                -30.01978               -51.18847
4                -30.01978               -51.18847
..                     …                       …
204              -30.03298               -51.14992
205              -30.03298               -51.14992
```

```
206              -30.03298               -51.14992
207              -30.06967               -51.17551
208              -30.06967               -51.17551

                                    Venue  Venue Latitude  Venue Longitude  \
0                       Espaço do Ciclista      -30.010239       -51.188943
1                           Gaúcha Bike ZN      -30.007717       -51.193079
2                                 Velocity      -30.021953       -51.194049
3                                 Biketech      -30.023465       -51.197879
4                                  M. Bike      -30.015607       -51.196491
..                                     …             …               …
204                   Casa das Bicicletas      -30.040904       -51.158022
205                         Studio Motos      -30.040527       -51.160467
206                      Cia do Ciclista      -30.044287       -51.141983
207                              Bs Motos      -30.064282       -51.179932
208  Cycle Sport - Bicicletas e Mobiletes      -30.062381       -51.174917

    Venue Category
0        Bike Shop
1        Bike Shop
2        Bike Shop
3        Bike Shop
4        Bike Shop
..             …
204      Bike Shop
205      Bike Shop
206      Bike Shop
207      Bike Shop
208      Bike Shop

[209 rows x 10 columns]
```

[29]:
```
venues_merged.head()
```

[29]:
```
  Neighborhood  Population  Monthly Avg Income  Labels  Neighborhood Latitude  \
4  Auxiliadora      9985.0                19.5       0              -30.01978
4  Auxiliadora      9985.0                19.5       0              -30.01978
4  Auxiliadora      9985.0                19.5       0              -30.01978
4  Auxiliadora      9985.0                19.5       0              -30.01978
4  Auxiliadora      9985.0                19.5       0              -30.01978

   Neighborhood Longitude              Venue  Venue Latitude  \
4               -51.18847  Espaço do Ciclista      -30.010239
4               -51.18847      Gaúcha Bike ZN      -30.007717
4               -51.18847            Velocity      -30.021953
4               -51.18847            Biketech      -30.023465
4               -51.18847             M. Bike      -30.015607
```

```
   Venue Longitude Venue Category
4       -51.188943      Bike Shop
4       -51.193079      Bike Shop
4       -51.194049      Bike Shop
4       -51.197879      Bike Shop
4       -51.196491      Bike Shop
```

[30]:
```
# Get the coordinates

address = 'Porto Alegre, RS'

geolocator = Nominatim(user_agent="poa_agent")
location = geolocator.geocode(address)
latitude = location.latitude
longitude = location.longitude
print(latitude, longitude)
```

```
-30.0324999 -51.2303767
```

[31]:
```
# Creating the map of bikeshop/neighborhood clusters

map_clusters = folium.Map(location=[latitude, longitude], zoom_start=12)

# set color scheme for the clusters
x = np.arange(num_clusters)
ys = [i + x + (i*x)**2 for i in range(num_clusters)]
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(venues_merged['Venue Latitude'],␣
 ↪venues_merged['Venue Longitude'], venues_merged['Neighborhood'],␣
 ↪venues_merged['Labels']):
    label = folium.Popup(str(poi) + ' Cluster ' + str(cluster), parse_html=True)
    folium.CircleMarker(
        [lat, lon],
        radius=5,
        popup=label,
        color=rainbow[cluster-1],
        fill=True,
        fill_color=rainbow[cluster-1],
        fill_opacity=0.7).add_to(map_clusters)

map_clusters
```

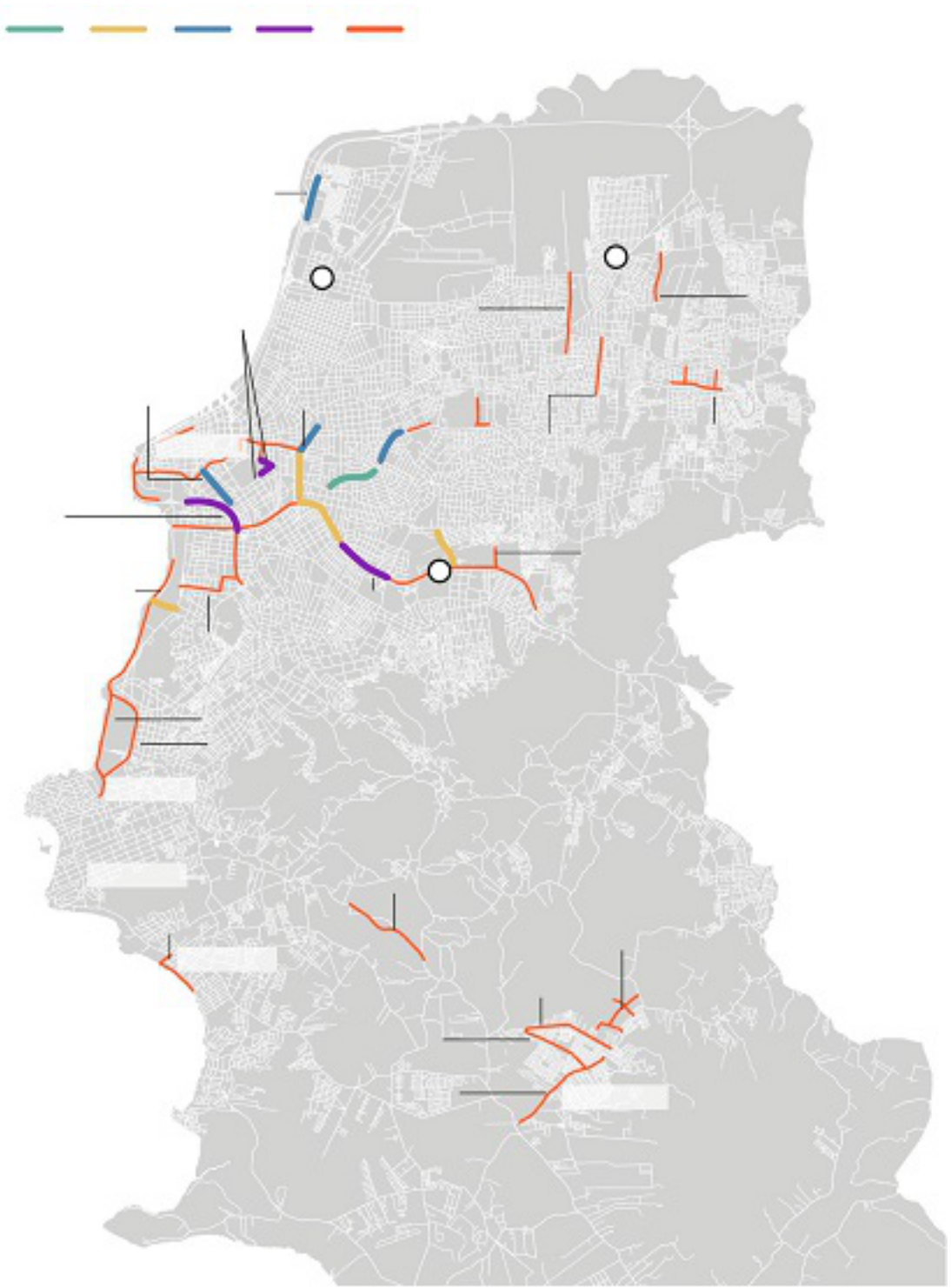
[31]:
```
<folium.folium.Map at 0x1d58d4a8b88>
```

[32]:
```
# Now contrasting it with the bicycle flux of the city

map_clusters_flux = folium.Map(location=[latitude, longitude], zoom_start=12)

# set color scheme for the clusters
x = np.arange(num_clusters)
ys = [i + x + (i*x)**2 for i in range(num_clusters)]
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(venues_merged['Venue Latitude'],␣
 ↪venues_merged['Venue Longitude'], venues_merged['Neighborhood'],␣
 ↪venues_merged['Labels']):
    label = folium.Popup(str(poi) + ' Cluster ' + str(cluster), parse_html=True)
    folium.CircleMarker(
        [lat, lon],
        radius=5,
        popup=label,
        color=rainbow[cluster-1],
        fill=True,
        fill_color=rainbow[cluster-1],
        fill_opacity=0.7).add_to(map_clusters_flux)

for lat, lng, borough in zip(df_bike['latitude'], df_bike['longitude'],␣
 ↪df_bike['borough']):
    label = '{}'.format(borough)
    label = folium.Popup(label, parse_html=True)
    folium.CircleMarker(
        [lat, lng],
        radius=0.8,
        popup=label,
        color='black',
        fill=True,
        fill_color='#3186cc',
        fill_opacity=0.7,
        parse_html=False).add_to(map_clusters_flux)

map_clusters_flux
```

[32]:
```
<folium.folium.Map at 0x1d58cb8a988>
```

1.4 Results and Discussion

[33]:
```
from IPython.display import display
from PIL import Image

path="ciclovias-Artboard_1.jpg"
display(Image.open(path))
print('Map of current bycicle lanes in Porto Alegre, Brazil')
```



Map of current bycicle lanes in Porto Alegre, Brazil

There is a clear alignment between the cyclist flux and the location of bikeshops in the city, specially in the zone between North and South of city, but is also clear that there are spaces with potencial for new busines that happen with economic and social dinamics, like São Geraldo and Floresta which were almost abandoned neighborhoods and now are trend, with new places, buildings, young people and also with a better terrain for cycling. Also the bay area of the city is getting refreshed by new spaces, getting increasingly higher number of visitors, tourists, and spaces to buy or rent bikes.

The clusters show that neighborhoods of contrasting income profile and population density are very near each other, so finding the perfect spot for a new business can be quite a challenge, specially if you consider the dinamics of the changes in the city.

When opening new business and solutions there are many complex aspects to consider, so I made quite a simplification just to show how the tools of Data Science with Python can help achieve sharper solutions; with that in mind I made 3 sugetions of places where it can be done.

[34]:
```
# Making a black circle around the suggested areas and removing the flux dots␣
↪for cleaner visual.

map_final = folium.Map(location=[latitude, longitude], zoom_start=13)

folium.CircleMarker(
    [-30.018086745728123, -51.20769468412793],
    radius=15,
    color='black',
    popup='Suggestion 1',
    fill = True,
    fill_color = 'white',
    fill_opacity = 0.5
    ).add_to(map_final)

folium.CircleMarker(
    [-30.033272133840505, -51.18851022142575],
    radius=15,
    color='black',
    popup='Suggestion 3',
    fill = True,
    fill_color = 'white',
    fill_opacity = 0.5
    ).add_to(map_final)

folium.CircleMarker(
    [-30.006534151285326, -51.17552502154391],
    radius=15,
```

```
    color='black',
    popup='Suggestion 2',
    fill = True,
    fill_color = 'white',
    fill_opacity = 0.6
    ).add_to(map_final)

# set color scheme for the clusters
x = np.arange(num_clusters)
ys = [i + x + (i*x)**2 for i in range(num_clusters)]
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(venues_merged['Venue Latitude'],␣
 ↪venues_merged['Venue Longitude'], venues_merged['Neighborhood'],␣
 ↪venues_merged['Labels']):
    label = folium.Popup(str(poi) + ' Cluster ' + str(cluster), parse_html=True)
    folium.CircleMarker(
        [lat, lon],
        radius=5,
        popup=label,
        color=rainbow[cluster-1],
        fill=True,
        fill_color=rainbow[cluster-1],
        fill_opacity=0.7).add_to(map_final)

map_final
```

[34]: <folium.folium.Map at 0x1d58e585188>

Selecionar tres areas para sugestão

Suggestion 1: Floresta A revigorated neighborhood, near one of the richiest neighborhood (Moinhos de Vento), has a high flux of cyclists, also it is near the bay area which is the postal card of the city.

Suggestion 2: Santa Maria Goretti It is better suited to a more midrange profile, but the north of the city is highly populated, has most of the city industries and flat streets, with plenty of potential for bycicle lanes.

Suggestion 1: Bela Vista This area is like a cluster of rich neighborhoods. Though a high part of town, it has room for high profile shops. The bikelanes are still shy, but people there would love more.

1.5 Conclusion

Purpose of this project was to identify Porto Alegre areas with low number of bikeshops and with high potential for cycling, in order to aid stakeholders in narrowing down the search for optimal location for a new shop. Clustering of those locations was then performed in order to create major zones of interest (containing greatest number of potential locations) and addresses of those zone centers were created to be used as starting points for final exploration by stakeholders.

Final decission on optimal bikeshop location will be made by stakeholders based on specific characteristics of neighborhoods and locations in every recommended zone, taking into consideration additional factors like attractiveness of each location (proximity to park or water), levels of noise / proximity to major roads, real estate availability, prices, social and economic dynamics of every neighborhood etc.