High Schools in Baton Rouge Neighborhoods

IBM Data Science Course Capstone Project
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Introduction

East Baton Rouge Parish is the most populous parish in the U.S. state of Louisiana. The parish seat is Baton Rouge, Louisiana's state capital. Baton Rouge is the capital city of the state of Louisiana. Baton Rouge is the center of Greater Baton Rouge, the second-largest metropolitan area in Louisiana, with a population of 834,159 as of 2017, up from 802,484 in 2010 and 829,719 in 2015.[1]

East Baton Rouge Parish Public School System (EBRPSS) operates primary and secondary schools serving the city. The East Baton Rouge Parish School System is the second-largest public school system in the state with more than 40,000 students. The system has 90 schools with 56 elementary schools, 16 middle schools, and 18 high schools.[2]

Discussion

Baton Rouge's population has been growing. There has been a discussion among the Baton Rouge Community about the need of a new high school in the south side of the city. The EBRPSS is looking for building another facility to meet the need.[3]

In this project, I would like to explore schools in Baton Rouge using Foursquare location data, and try to figure out where to open a new high school in Baton Rouge.

Data Description

Baton Rouge has many neighborhoods both inside and outside the city limits. City of Baton Rouge and Parish of East Baton Rouge use GIS(Geographic Information Systems) technology. The City-Parish has a publicly available EBR GIS platform which can be used for exploring and downloading open data, discovering maps and apps, and engaging your local government to solve important community issues. Through this platform, the City-Parish shares a vast amount of geospatial data with everyone.[4]

EBRGIS platforms has a data set available which provides information about the population of neighborhoods in Baton Rouge. The figure below shows the attributes of the data set:

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[1] https://en.wikipedia.org/wiki/Baton_Rouge,_Louisiana
[2] https://en.wikipedia.org/wiki/Baton_Rouge,_Louisiana#Education
[3] https://www.theadvocate.com/baton_rouge/news/education/article_1cb93a98-120b-11e8-bd0d-6f3e02c44af7.html
[4] https://web-ebrgis.opendata.arcgis.com/

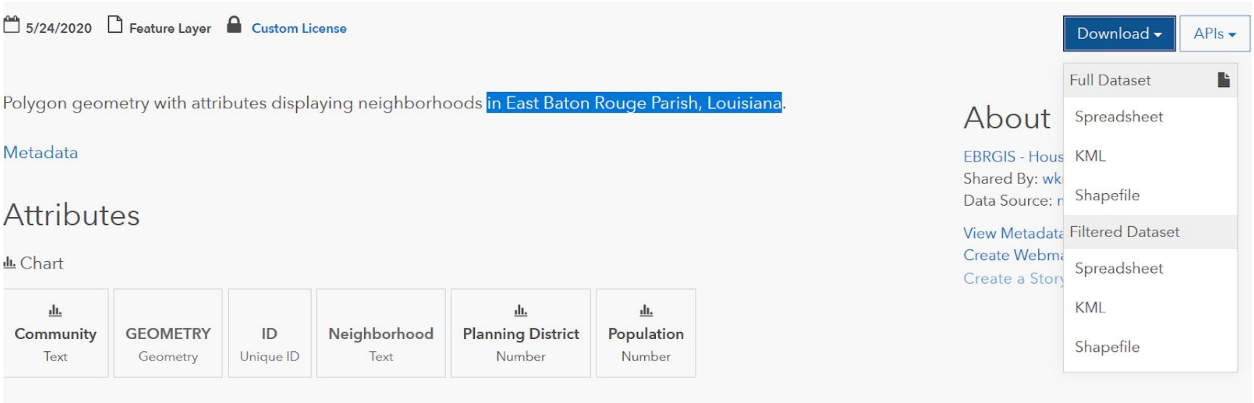


Figure I - GIS Data displaying neighborhoods

The data set is available to download as an KML file. Keyhole Markup Language (KML) is an XML notation for expressing geographic annotation and visualization within two-dimensional maps and three-dimensional Earth browsers. KML was developed for use with Google Earth, which was originally named Keyhole Earth Viewer. It was created by Keyhole, Inc, which was acquired by Google in 2004.[5]

I would like to explore the number of high schools around each neighborhood in Baton Rouge compared to their latest population data. The goal would be to figure out which neighborhood has the least number of high schools. Based on findings, I will recommend top neighborhood choices to open a new high school in the city.

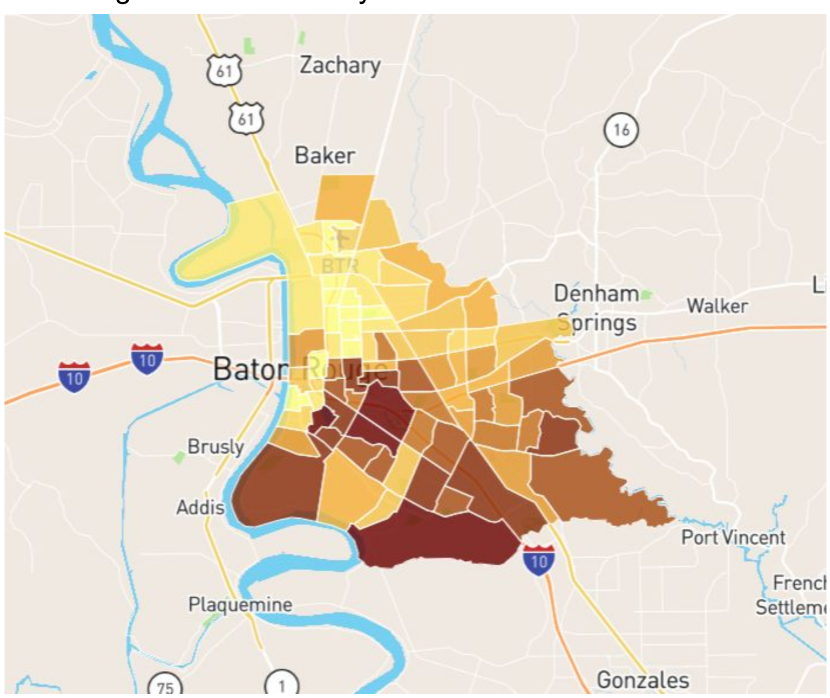


Figure II - Neighborhoods in Baton Rouge[6]

[5] https://en.wikipedia.org/wiki/Keyhole_Markup_Language
[6] https://www.neighborhoodscout.com/la/baton-rouge

Methodology

Creating Baton Rouge City Map with Neighborhoods

First of all, download the neighborhoods data from EBRGIS platform. In order to use the Folium library in Python, the data needs to be in geojson format. Convert KML file download into a geojson file at this website: https://mygeodata.cloud/converter/kmz-to-json

Second, add a marker for each neighborhood with its name. I have the following map.

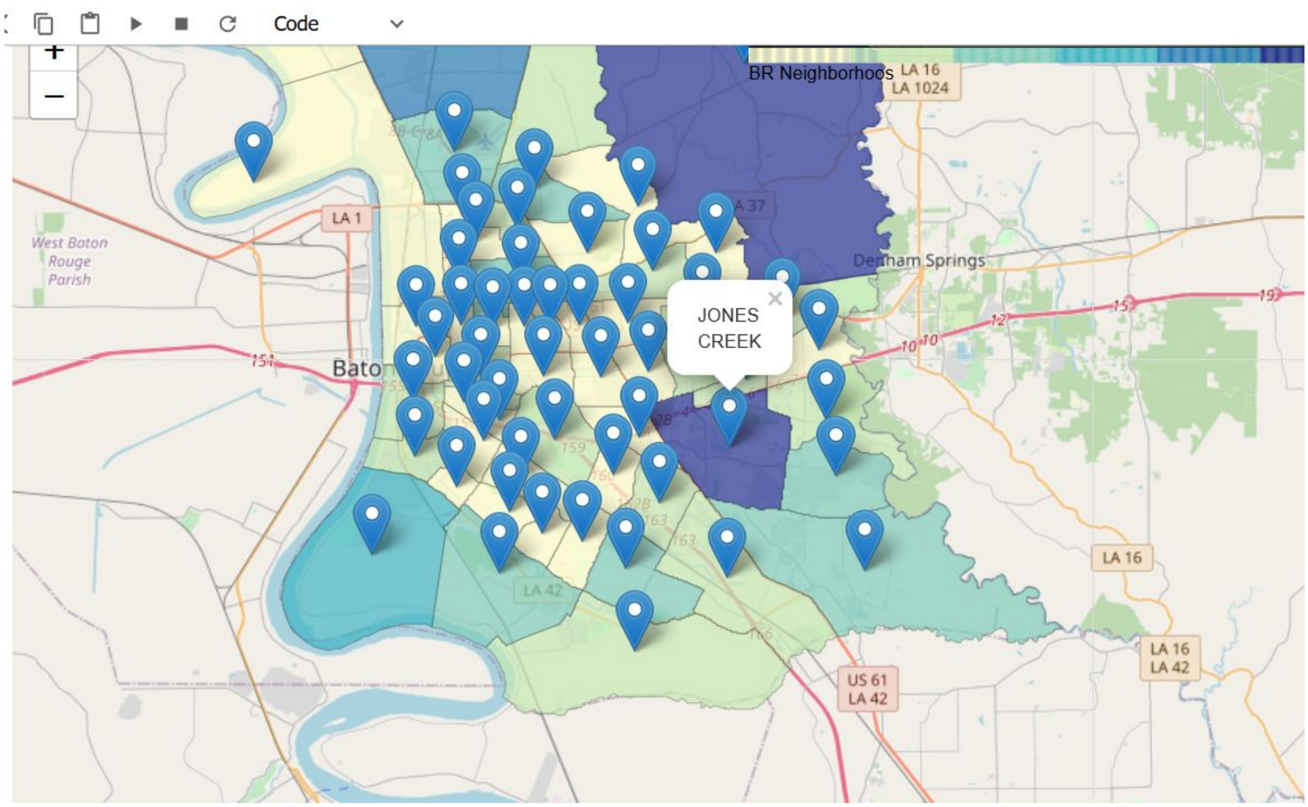


Figure III - Baton Rouge Neighborhoods Map

Finding High Schools in the City

Foursquare API has a category attribute where you can search only certain venues[7]. Search for “high school” category in Baton Rouge returns the following data set:

[7] https://developer.foursquare.com/docs/build-with-foursquare/categories/

	id	name	categories	referralId	hasPerk	location.lat	location.lng	location.labeledLatLngs
0	5203e478498e04c9796f1442	Lee High - Bawell Street Temporary Campus	[{'id': '4bf58dd8d48988d13d941735', 'name': 'H...	v-1590579428	False	30.425901	-91.146662	[{'label': 'display', 'lat': 30.42590096338909...
1	4ca49a717f84224b82a5ce58	Lee Magnet High School	[{'id': '4bf58dd8d48988d13d941735', 'name': 'H...	v-1590579428	False	30.406771	-91.152079	[{'label': 'display', 'lat': 30.40677064307260...
2	50441763e4b06a6d9f792997	Xcution	[{'id': '4bf58dd8d48988d13d941735', 'name': 'H...	v-1590579428	False	30.448140	-90.863403	[{'label': 'display', 'lat': 30.44814, 'lng': ...
3	4c9d3a9554c8a1cdb4d0814b	Baker high	[{'id': '4bf58dd8d48988d13d941735', 'name': 'H...	v-1590579428	False	30.587010	-91.164385	[{'label': 'display', 'lat': 30.58701001619391...
4	4c116cae416620a11e16d9e4	East Ascension High School	[{'id': '4bf58dd8d48988d13d941735', 'name': 'H...	v-1590579428	False	30.226997	-90.914984	[{'label': 'display', 'lat': 30.22699687253794...
5	4ec1759eb803bca7defaadf1	St. Joseph Hall	[{'id': '4bf58dd8d48988d13d941735', 'name': 'H...	v-1590579428	False	30.440395	-91.150993	[{'label': 'display', 'lat': 30.4403949, 'lng'...
6	4bc38016920eb713f28b1d2c	Baton Rouge Magnet High School	[{'id': '4bf58dd8d48988d13d941735', 'name': 'H...	v-1590579428	False	30.446467	-91.159913	[{'label': 'display', 'lat': 30.44646663135539...
7	4e9a1596d3e3697fbfb3934d	FCA (Family Christian Academy)	[{'id': '4bf58dd8d48988d13d941735', 'name': 'H...	v-1590579428	False	30.384570	-91.093918	[{'label': 'display', 'lat': 30.38457, 'lng': ...
8	4b70a56ef964a52058272de3	Denham Springs High School	[{'id': '4bf58dd8d48988d13d941735', 'name': 'H...	v-1590579428	False	30.496739	-90.953312	[{'label': 'display', 'lat': 30.49673873443869...
9	4bfe6fe2f61dc9b65566a0de	Family Christian Academy	[{'id': '4bf58dd8d48988d13d941735', 'name': 'H...	v-1590579428	False	30.384297	-91.091724	[{'label': 'display', 'lat': 30.38429702368381...

	location.distance	location.cc	location.city	location.state	location.country	location.formattedAddress	location.address	location.postalCode	location.crossStr
0	764	US	Baton Rouge	LA	United States	[Baton Rouge, LA, United States]	NaN	NaN	N
1	1545	US	Baton Rouge	LA	United States	[1105 Lee Dr, Baton Rouge, LA 70808, United St...	1105 Lee Dr	70808	N
2	27209	US	Denham Springs	LA	United States	[Denham Springs, LA 70726, United States]	NaN	70726	N
3	18773	US	Baker	LA	United States	[Baker, LA 70714, United States]	NaN	70714	N
4	30754	US	Gonzales	LA	United States	[Gonzales, LA 70737, United States]	NaN	70737	N
5	2430	US	Baton Rouge	LA	United States	[Broussard St, Baton Rouge, LA 70808, Baton Ro...	Broussard St, Baton Rouge, LA 70808	70808	N
6	3359	US	Baton Rouge	LA	United States	[2820 Government Street, Baton Rouge, LA 70806...	2820 Government Street	70806	N
7	6230	US	Baton Rouge	LA	United States	[Baton Rouge, LA, United States]	NaN	NaN	N
8	20309	US	Denham Springs	LA	United States	[S. Range, Denham Springs, LA 70726, United St...	S. Range	70726	N
9	6415	US	Baton Rouge	LA	United States	[8919 World Ministry Ave, Baton Rouge, LA 7081...	8919 World Ministry Ave	70810	N

Figure IV - High School Data Set returned by Foursquare API

Data set return has repeating high school values. For example, the first two rows are both for Lee High School where the first row represents a temporary campus building. Also, these types of duplicate entries have a NaN value for postal code data. In order to get clear data, all rows with a NaN value in postal code will be dropped.

After data is cleared, there are 30 unique high schools in the city. The following figure shows neighborhoods in the city with high schools marked.

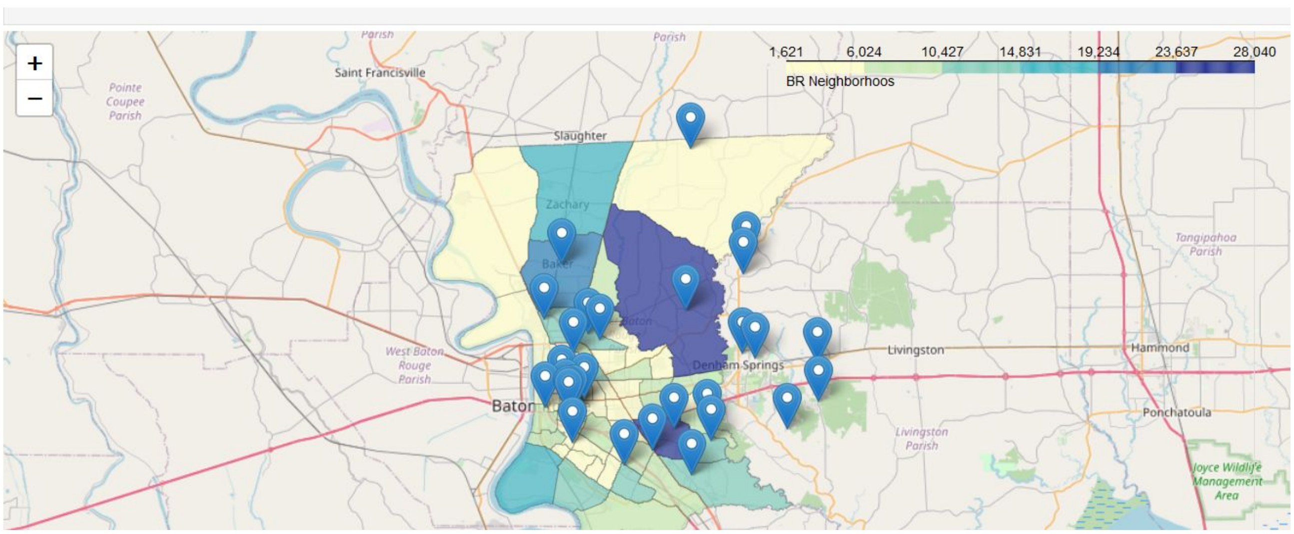


Figure V - High Schools in the City with neighborhoods and population

High Schools vs Neighborhoods

In order to figure out in which neighborhood there is a bigger need for a high school, the following methodology will be used:

- Count how many high schools there are within about 1 miles of the neighborhood. Add this data as a new column - 2000 (A)

- Count how many high schools there are within about 2.5 miles of the neighborhood. Add this data as a new column - 4000 (B)
- Count how many high schools there are within about 4 miles of the neighborhood. Add this data as a new column - 6000 (C)
- Calculate a final proximity score of high schools' density using the following formula
  - 3 X A + 2 X B + 3 X C
- Calculate final proximity score (# of high school options) per 1000 population

After all these steps, the following dataset is obtained:

	X	Y	gid	community	id	neighborhood	planning_district	population	2000	4000	6000	ProScore	ProScore_per_1K
0	-91.076035	30.482581	1	EAST	57	PARK FOREST/OAKCREST	6	6857	1.0	3.0	10.0	19.0	2.770891
1	-91.034190	30.440869	2	EAST	58	FAIRWOOD	12	6439	1.0	6.0	11.0	26.0	4.037894
2	-91.133658	30.460864	3	MID CITY	1	EAST FAIRFIELDS/MELROSE PLACE	10	3281	3.0	16.0	25.0	66.0	20.115818
3	-91.121647	30.461267	4	MID CITY	2	SMILEY HEIGHTS/MELROSE EAST	10	4430	1.0	13.0	26.0	55.0	12.415350
4	-91.254457	30.515923	5	NORTH	3	THE AVENUES/SOUTHERN UNIV	4	4758	0.0	0.0	1.0	1.0	0.210172
5	-91.164122	30.399546	6	SOUTH	4	COLLEGE TOWN	13	3732	7.0	14.0	19.0	68.0	18.220793
6	-91.139954	30.389799	7	SOUTH	5	UNIVERSITY ACRES/WOODSTONE	14	4673	6.0	8.0	20.0	54.0	11.555746
7	-91.084463	30.336785	8	SOUTHWEST	6	SOUTH BLUEBONNET/NICHOLSON	16	6775	0.0	0.0	4.0	4.0	0.590406
8	-91.125106	30.381854	9	SOUTH	7	KENILWORTH	14	3203	0.0	9.0	13.0	31.0	9.678426
9	-91.134790	30.402801	10	SOUTH	8	POLLARD/WOODCHASE	14	3916	6.0	14.0	25.0	71.0	18.130746

Figure VI - Final Dataset

Using the data set above, create two visualizations using Python

- Draw a choropleth & buble map: Choropleth represents Proximity Score whereas bubbles represent Proximity Score per 1K population
- Draw a horizontal bar graph with sorted values on Proximity Score per 1K population

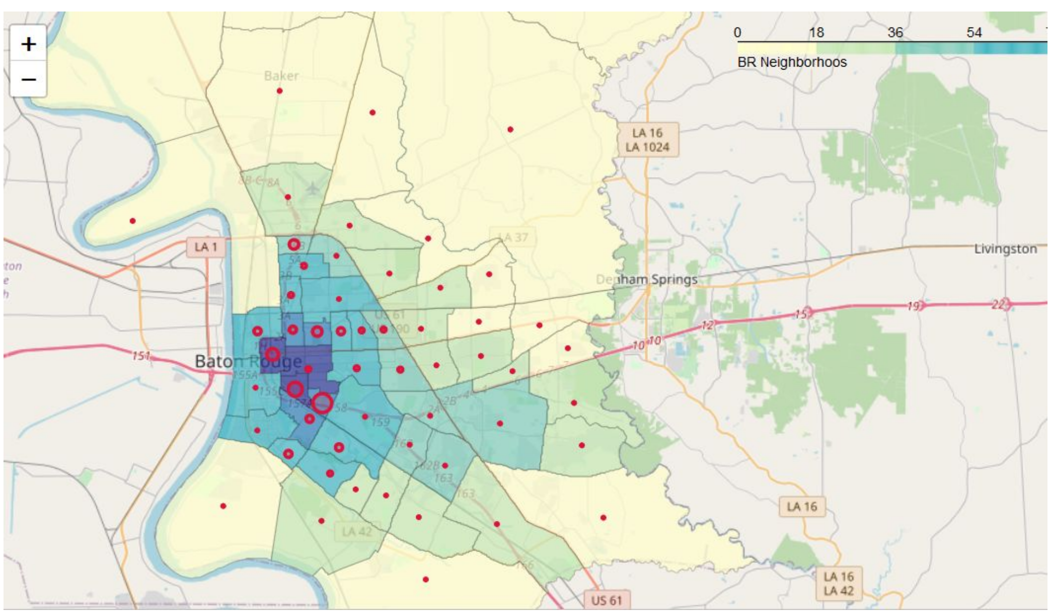


Figure VII - Choropleth and Bubbles Map representing High School density

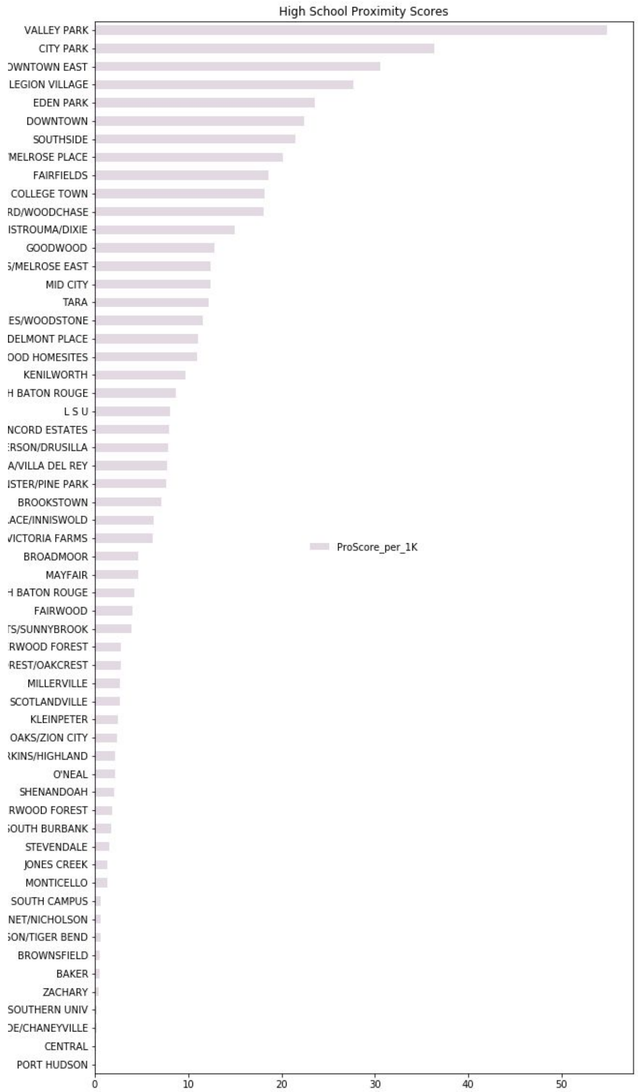


Figure VIII - Horizontal Bar Graph representing roximity Score per 1K population for each neighborhood

Results & Discussion

Based on the results, the following ten neighborhoods have the least number of high schools (less than 1) within the 6000 meters proximity per 1000 people.

	X	Y	gid	community	id	neighborhood	planning_district	population	2000	4000	6000	ProScore	ProScore_per_1K
54	-91.243177	30.630251	55	NORTHWEST	52	PORT HUDSON	1	4536	0.0	0.0	0.0	0.0	0.000000
49	-91.035427	30.561565	50	NORTHEAST	46	CENTRAL	2	28040	0.0	1.0	1.0	3.0	0.106990
29	-91.007689	30.653422	30	NORTHEAST	27	PRIDE/CHANEYVILLE	2	5610	0.0	0.0	1.0	1.0	0.178253
4	-91.254457	30.515923	5	NORTH	3	THE AVENUES/SOUTHERN UNIV	4	4758	0.0	0.0	1.0	1.0	0.210172
50	-91.146981	30.660436	51	NORTHWEST	47	ZACHARY	1	15350	1.0	1.0	1.0	6.0	0.390879
48	-91.169210	30.580816	49	NORTHWEST	45	BAKER	3	19295	1.0	1.0	4.0	9.0	0.466442
47	-91.115305	30.569997	48	NORTHWEST	44	BROWNSFIELD	2	7759	0.0	0.0	4.0	4.0	0.515530
34	-90.981452	30.367685	35	SOUTHEAST	32	JEFFERSON/TIGER BEND	16	13772	0.0	2.0	4.0	8.0	0.580889
7	-91.084463	30.336785	8	SOUTHWEST	6	SOUTH BLUEBONNET/NICHOLSON	16	6775	0.0	0.0	4.0	4.0	0.590406
39	-91.201932	30.373520	40	SOUTHWEST	36	SOUTH CAMPUS	13	15957	0.0	1.0	8.0	10.0	0.626684

Figure IX - Top 10 neighborhoods in need of a near high school

There are more than one school districts in East Baton Rouge Parish. Zachary, Baker and Central City districts were separated in the past as a separate school system[8]. The first seven neighborhoods in the above list are NOT managed by East Baton Rouge Parish School Board.

The top three neighborhoods under East Baton Rouge Parish which are in need of a high school are Jefferson/Tiger Bend, South Bluebonnet/Nicholson, and South Campus.

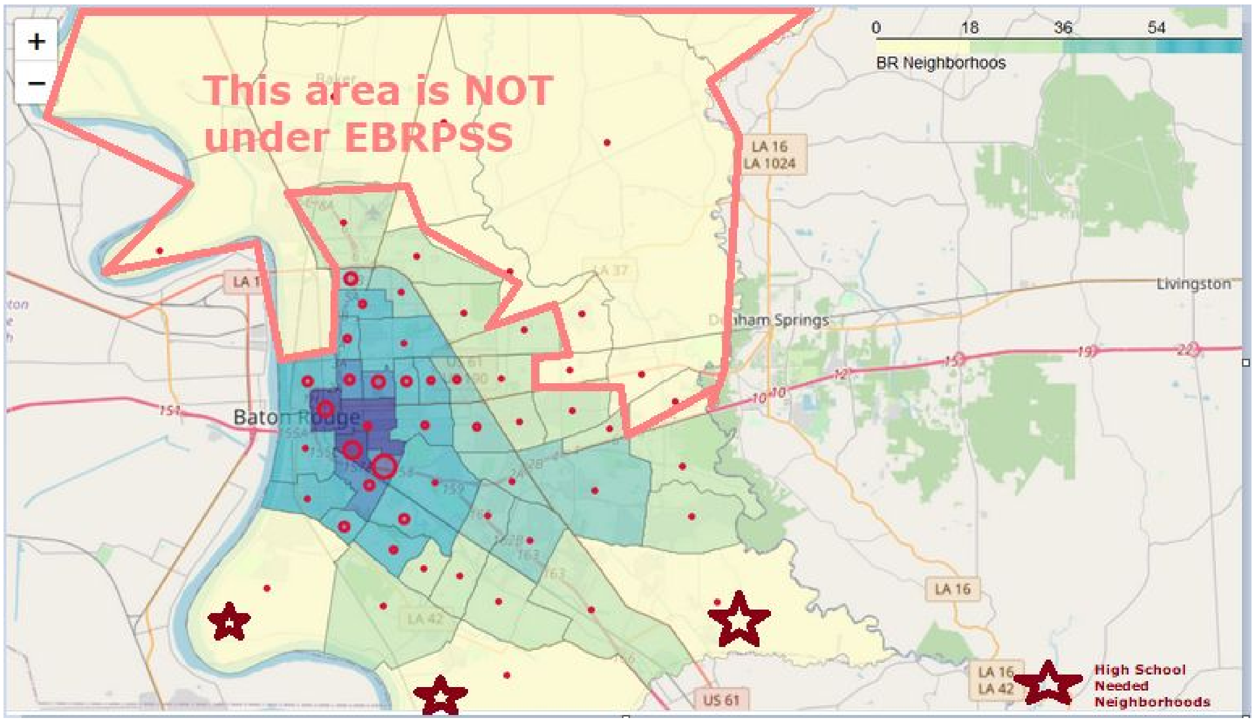


Figure X - Neighborhoods in need of a near high school within EBRPSS

Conclusion

In this project, I tried to figure out where a new high school would benefit the city of Baton Rouge. Based on the population of neighborhoods , and number of high schools around, there are three top neighborhoods in the city who need a high school the most.

As a further study, the following points should be considered:

- Not only the population but also the number of high school age people in each neighborhood should be considered.
- Differentiate between private, public and charter schools.
- Capacity of current high schools

[8] https://gisdata.brla.gov/datasets/school-district

APPENDIX - Codes

In [1]:
```
#install and import necessary libraries for the project
!conda install -c conda-forge folium=0.11.0 --yes # folium new version
import numpy as np  # useful for many scientific computing in Python
import pandas as pd # primary data structure library
import folium
import json # library to handle JSON files
import requests # library to handle requests
from pandas.io.json import json_normalize # tranform JSON file into a pandas datafr
ame

print('Libraries are installed and imported!')
```

```
Collecting package metadata (current_repodata.json): done
Solving environment: done

## Package Plan ##

  environment location: /home/jupyterlab/conda/envs/python

  added / updated specs:
    - folium=0.11.0


The following packages will be downloaded:

    package                    |            build
    ---------------------------|-----------------
    branca-0.4.1               |             py_0          26 KB  conda-forge
    brotlipy-0.7.0             |py36h8c4c3a4_1000         346 KB  conda-forge
    chardet-3.0.4              |py36h9f0ad1d_1006         188 KB  conda-forge
    cryptography-2.9.2         |   py36h45558ae_0         613 KB  conda-forge
    folium-0.11.0              |             py_0          61 KB  conda-forge
    pysocks-1.7.1              |   py36h9f0ad1d_1          27 KB  conda-forge
    ------------------------------------------------------------
                                           Total:         1.2 MB

The following NEW packages will be INSTALLED:

  branca             conda-forge/noarch::branca-0.4.1-py_0
  brotlipy           conda-forge/linux-64::brotlipy-0.7.0-py36h8c4c3a4_1000
  chardet            conda-forge/linux-64::chardet-3.0.4-py36h9f0ad1d_1006
  cryptography       conda-forge/linux-64::cryptography-2.9.2-py36h45558ae_0
  folium             conda-forge/noarch::folium-0.11.0-py_0
  idna               conda-forge/noarch::idna-2.9-py_1
  jinja2             conda-forge/noarch::jinja2-2.11.2-pyh9f0ad1d_0
  markupsafe         conda-forge/linux-64::markupsafe-1.1.1-py36h8c4c3a4_1
  pyopenssl          conda-forge/noarch::pyopenssl-19.1.0-py_1
  pysocks            conda-forge/linux-64::pysocks-1.7.1-py36h9f0ad1d_1
  requests           conda-forge/noarch::requests-2.23.0-pyh8c360ce_2
  urllib3            conda-forge/noarch::urllib3-1.25.9-py_0



Downloading and Extracting Packages
chardet-3.0.4        | 188 KB    | ##################################### | 100%
branca-0.4.1         | 26 KB     | ##################################### | 100%
cryptography-2.9.2   | 613 KB    | ##################################### | 100%
brotlipy-0.7.0       | 346 KB    | ##################################### | 100%
pysocks-1.7.1        | 27 KB     | ##################################### | 100%
folium-0.11.0        | 61 KB     | ##################################### | 100%
Preparing transaction: done
Verifying transaction: done
Executing transaction: done
Libraries are installed and imported!
```

In [2]:
```
#Baton Rouge lat and lon information
br_lat = 30.4192
br_lon = -91.1449

# create a plain city map
br_map = folium.Map(location=[br_lat, br_lon], zoom_start=10)
br_map
```

Out[2]:

In [3]:
```
#Read geojson file into a data frame
br_geo = r'Neighborhood.geojson' # geojson file

#Read neighborhood information into a data frame
df_br = pd.read_csv('Neighborhood.csv')
df_br.head()
```

Out[3]:

	X	Y	gid	Name	description	community	id	neighborhood	planning_district	po
0	-91.076035	30.482581	1	NaN	NaN	EAST	57	PARK FOREST/OAKCREST	6	
1	-91.034190	30.440869	2	NaN	NaN	EAST	58	FAIRWOOD	12	
2	-91.133658	30.460864	3	NaN	NaN	MID CITY	1	EAST FAIRFIELDS/MELROSE PLACE	10	
3	-91.121647	30.461267	4	NaN	NaN	MID CITY	2	SMILEY HEIGHTS/MELROSE EAST	10	
4	-91.254457	30.515923	5	NaN	NaN	NORTH	3	THE AVENUES/SOUTHERN UNIV	4	

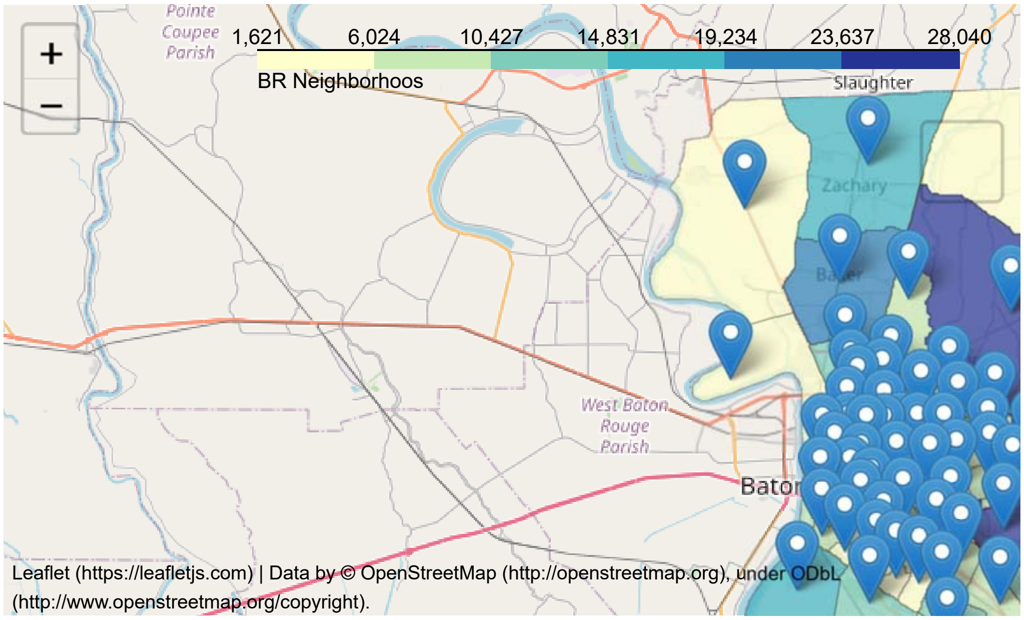
In [15]:
```
#delete non-used columns
del df_br['Name']
del df_br['description']
```

In [4]:
```
# add tile layers to the map
tiles = ['stamenwatercolor', 'cartodbpositron', 'openstreetmap', 'stamenterrain']
for tile in tiles:
    folium.TileLayer(tile).add_to(br_map)

# generate choropleth map using the total population of each neighborhood
folium.Choropleth(
    geo_data=br_geo,
    data=df_br,
    columns=['neighborhood','population'],
    key_on='feature.properties.neighborhood',
    fill_color='YlGnBu',
    fill_opacity=0.7,
    line_opacity=0.2,
    legend_name='BR Neighborhoos',
    smooth_factor=0,
    highlight=True,
    line_color='black'
).add_to(br_map)

# create a layer control
folium.LayerControl().add_to(br_map)
```

Out[4]:
```
<folium.map.LayerControl at 0x7f0ffe898e80>
```

In [5]:
```
# add a marker to each neigborhood
for index,row in df_br.iterrows():
    lat = row['Y']
    lng = row['X']
    folium.Marker(
        [lat, lng],
        radius=5,
        color='green',
        popup=row['neighborhood'],
        fill = True,
        fill_color='green',
        fill_opacity=0.6
    ).add_to(br_map)

# display map
br_map
```

Out[5]:



In [6]:
```
CLIENT_ID = 'VBXSTWM51FOOBV2MZLUMQT5UITMYSXIILAVW04KORPQLP42S' # your Foursquare ID
CLIENT_SECRET = 'C4LB20JG5AJVL3SNEYVOJ4PN5ANB5QIM3D1QOTY15AWAXELA' # your Foursquar
e Secret
VERSION = '20180604'

print('My credentails:')
print('CLIENT_ID: ' + CLIENT_ID)
print('CLIENT_SECRET:' + CLIENT_SECRET)
```

```
My credentails:
CLIENT_ID: VBXSTWM51FOOBV2MZLUMQT5UITMYSXIILAVW04KORPQLP42S
CLIENT_SECRET:C4LB20JG5AJVL3SNEYVOJ4PN5ANB5QIM3D1QOTY15AWAXELA
```

In [8]:
```
LIMIT = 100 # limit of number of venues returned by Foursquare API

# https://developer.foursquare.com/docs/build-with-foursquare/categories/
categoryId = "4bf58dd8d48988d13d941735" #category to high school

url = 'https://api.foursquare.com/v2/venues/search?&client_id={}&client_secret={}&v
={}&categoryId={}&ll={},{}&limit={}'.format(
    CLIENT_ID,
    CLIENT_SECRET,
    VERSION,
    categoryId,
    br_lat,
    br_lon,
    LIMIT)

results = requests.get(url).json()
schools = results['response']['venues']
nearby_venues = pd.json_normalize(schools) # flatten JSON
nearby_venues.dropna(subset=['location.postalCode'],inplace=True)
```

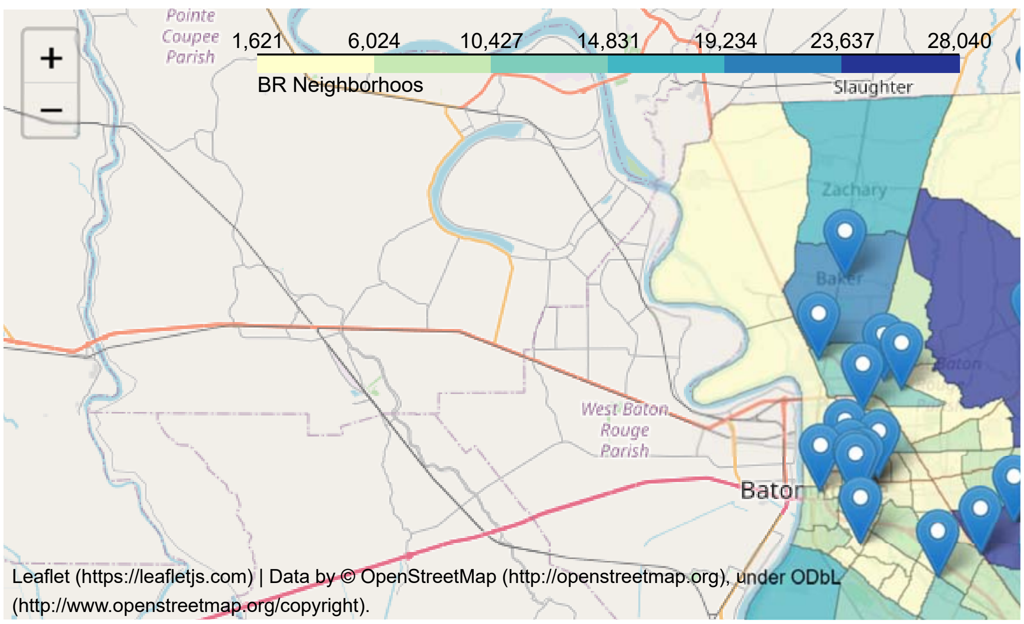
In [9]:
```
nearby_venues.reset_index(inplace=True, drop=True)
nearby_venues
```

Out[9]:

	id	name	categories	referralId	hasPerk	location.lat
0	4ca49a717f84224b82a5ce58	Lee Magnet High School	[{'id': '4bf58dd8d48988d13d941735', 'name': 'H...	v-1590599523	False	30.406771
1	50441763e4b06a6d9f792997	Xcution	[{'id': '4bf58dd8d48988d13d941735', 'name': 'H...	v-1590599523	False	30.448140
2	4bc38016920eb713f28b1d2c	Baton Rouge Magnet High School	[{'id': '4bf58dd8d48988d13d941735', 'name': 'H...	v-1590599523	False	30.446467
3	4c116cae416620a11e16d9e4	East Ascension High School	[{'id': '4bf58dd8d48988d13d941735', 'name': 'H...	v-1590599523	False	30.226997
4	4ec1759eb803bca7defaadf1	St. Joseph Hall	[{'id': '4bf58dd8d48988d13d941735', 'name': 'H...	v-1590599523	False	30.440395
5	4c9d3a9554c8a1cdb4d0814b	Baker high	[{'id': '4bf58dd8d48988d13d941735', 'name': 'H...	v-1590599523	False	30.587010
6	4bfe6fe2f61dc9b65566a0de	Family Christian Academy	[{'id': '4bf58dd8d48988d13d941735', 'name': 'H...	v-1590599523	False	30.384297
7	4f881451e4b0089de79523cf	Northdale North Academy	[{'id': '4bf58dd8d48988d13d941735', 'name': 'H...	v-1590599523	False	30.517751
8	4cc718643d7fa1cd3732bb5f	Capitol High School	[{'id': '4bf58dd8d48988d13d941735', 'name': 'H...	v-1590599523	False	30.458965
9	4e5f795b149582866d4103c8	SJA Medaille Hall	[{'id': '4bf58dd8d48988d13d941735', 'name': 'H...	v-1590599523	False	30.436595
10	4b70a56ef964a52058272de3	Denham Springs High School	[{'id': '4bf58dd8d48988d13d941735', 'name': 'H...	v-1590599523	False	30.496739
11	4fa26f4fe4b0887595842959	Juban Parc Jr High	[{'id': '4bf58dd8d48988d13d941735', 'name': 'H...	v-1590599523	False	30.421042
12	4c9d8266542b224bdf35eb9f	Glen Oaks High School	[{'id': '4bf58dd8d48988d13d941735', 'name': 'H...	v-1590599523	False	30.511307
13	505713e1e4b0de8bef634ec7	The New Live Oak High	[{'id': '4bf58dd8d48988d13d941735', 'name': 'H...	v-1590599523	False	30.594319
14	4bacbc98f964a52000083be3	The Runnels School	[{'id': '4bf58dd8d48988d13d941735', 'name': 'H...	v-1590599523	False	30.424586
15	4c4aeeef5609c9b694996690	Central High School	[{'id': '4bf58dd8d48988d13d941735', 'name': 'H...	v-1590599523	False	30.540716
16	4e56619c1495eb38e2070c57	Northeast High School	[{'id': '4bf58dd8d48988d13d941735', 'name': 'H...	v-1590599523	False	30.703389
17	4bbc74363de8c9b6a0f19aad	Dutchtown High School	[{'id': '4bf58dd8d48988d13d941735', 'name': 'H...	v-1590599523	False	30.259458
18	4c67480b9cb82d7f9f6693d2	St Michael High School	[{'id': '4bf58dd8d48988d13d941735', 'name': 'H...	v-1590599523	False	30.409343
[illegible]	[illegible]	Woodlawn	[{'id': [illegible]	[illegible]	[illegible]	[illegible]

In [10]:
```
br_map2 = folium.Map(location=[br_lat, br_lon], zoom_start=10)
# generate choropleth map using the total population of each neighborhood
folium.Choropleth(
    geo_data=br_geo,
    data=df_br,
    columns=['neighborhood','population'],
    key_on='feature.properties.neighborhood',
    fill_color='YlGnBu',
    fill_opacity=0.7,
    line_opacity=0.2,
    legend_name='BR Neighborhoos',
    smooth_factor=0,
    highlight=True,
    line_color='black'
).add_to(br_map2)

# add a marker for each high schools
for index,row in nearby_venues.iterrows():
    lat = row['location.lat']
    lng = row['location.lng']
    folium.Marker(
        [lat, lng],
        radius=5,
        color='green',
        popup=row['name'],
        fill = True,
        fill_color='red',
        fill_opacity=0.6
    ).add_to(br_map2)

# display map
br_map2
```

Out[10]:



In [11]:
```
#define a function to creae specific url to make a search for each neighborhood
def set_url(xlat,ylon,radius):

    url = 'https://api.foursquare.com/v2/venues/search?&client_id={}&client_secret=
{}&v={}&categoryId={}&ll={},{}&radius={}&limit={}'.format(
    CLIENT_ID,
    CLIENT_SECRET,
    VERSION,
    categoryId,
    xlat,
    ylon,
    radius,
    LIMIT)

    return url
```

In [12]:
```
LIMIT = 100 # limit of number of venues returned by Foursquare API
# query = "high school" #search for high schools closed to neighborhood
# https://developer.foursquare.com/docs/build-with-foursquare/categories/
categoryId = "4bf58dd8d48988d13d941735" #category ID for high school
```

In [14]:
```
#search for number of high schools in each neighborhood within 2000, 4000, 6000 met
ers 1.2, 2.5, 3.7 miles
radius = [2000, 4000, 6000]
for r in radius:
    for index,row in df_br.iterrows():
        lat = row['Y']
        lon = row['X']
        url = set_url(lat,lon,r)
        results = requests.get(url).json()
        schools = results['response']['venues']
        nearby_venues = pd.json_normalize(schools) # flatten JSON
        #nearby_venues.dropna(subset=['location.postalCode'],inplace=True)
        df_br.loc[index, str(r)] = int(len(nearby_venues))
```

In [16]:
```
df_br
```

Out[16]:

	X	Y	gid	community	id	neighborhood	planning_district	population	200
0	-91.076035	30.482581	1	EAST	57	PARK FOREST/OAKCREST	6	6857	1.
1	-91.034190	30.440869	2	EAST	58	FAIRWOOD	12	6439	1.
2	-91.133658	30.460864	3	MID CITY	1	EAST FAIRFIELDS/MELROSE PLACE	10	3281	3.
3	-91.121647	30.461267	4	MID CITY	2	SMILEY HEIGHTS/MELROSE EAST	10	4430	1.
4	-91.254457	30.515923	5	NORTH	3	THE AVENUES/SOUTHERN UNIV	4	4758	0.
5	-91.164122	30.399546	6	SOUTH	4	COLLEGE TOWN	13	3732	7.
6	-91.139954	30.389799	7	SOUTH	5	UNIVERSITY ACRES/WOODSTONE	14	4673	6.
7	-91.084463	30.336785	8	SOUTHWEST	6	SOUTH BLUEBONNET/NICHOLSON	16	6775	0.
8	-91.125106	30.381854	9	SOUTH	7	KENILWORTH	14	3203	0.
9	-91.134790	30.402801	10	SOUTH	8	POLLARD/WOODCHASE	14	3916	6.
10	-91.107502	30.378797	11	SOUTH	9	MAYFAIR	14	6005	3.
11	-91.093806	30.404161	12	SOUTH	10	WESTMINSTER/PINE PARK	14	4808	0.
12	-91.173279	30.449235	13	MID CITY	11	DOWNTOWN EAST	8	3076	11.
13	-91.182043	30.460871	14	DOWNTOWN	12	DOWNTOWN	8	2944	5.
14	-91.151839	30.417065	15	SOUTH	13	SOUTHSIDE	13	3822	8.
15	-91.160226	30.431837	16	SOUTH	14	CITY PARK	9	2776	10.
16	-91.144504	30.424939	17	SOUTH	15	VALLEY PARK	9	1621	9.
17	-91.147401	30.460664	18	MID CITY	18	EDEN PARK	9	3527	6.
18	-91.119676	30.418127	19	SOUTH	16	BOCAGE/CITIPLACE /CONCORD ESTATES	14	7574	0.
19	-91.161528	30.461610	20	MID CITY	17	FAIRFIELDS	9	4239	7.
20	-91.162631	30.478913	21	NORTH	19	ISTROUMA/DIXIE	7	4152	5.
21	-91.160910	30.504182	22	NORTH	20	LEGION VILLAGE	7	1624	1.
22	-91.081942	30.418618	23	SOUTH	21	JEFFERSON/DRUSILLA	14	5361	1.
23	-91.099221	30.441679	24	EAST	22	TARA	10	3435	1.
24	-91.108931	30.461663	25	EAST	23	GOODWOOD HOMESITES	10	3388	0.
25	-91.002082	30.452373	26	EAST	24	MILLERVILLE	12	5877	0.
26	-91.018491	30.463813	27	EAST	25	STEVENDALE	12	6525	0.
27	-91.087203	30.462037	28	EAST	48	CORTANA/VILLA DEL REY	11	3483	2.
28	-90.998483	30.425023	29	SOUTHEAST	26	O'NEAL	15	9578	2.
29	-91.007689	30.653422	30	NORTHEAST	27	PRIDE/CHANEYVILLE	2	5610	0.
30	-91.088546	30.367936	31	SOUTH	28	PERKINS/HIGHLAND	16	13069	3.
31	-91.182173	30.411274	32	SOUTH	29	L S U	13	7582	1.
32	-91.183183	30.432674	33	SOUTH	30	OLD SOUTH BATON ROUGE	8	7920	3.
33	-91.041383	30.414746	34	SOUTHEAST	31	JONES CREEK	15	26626	3.
34	-90.981452	30.367685	35	SOUTHEAST	32	JEFFERSON/TIGER BEND	16	13772	0.
35	-91.136281	30.498500	36	NORTH	49	BROOKSTOWN	5	6750	3.

In [18]:
```
#calculate high school proximity score and  ProScore per 1000 people
df_br['ProScore'] = df_br['2000']*3 + df_br['4000']*2 + df_br['6000']
df_br['ProScore_per_1K'] = df_br['ProScore'] * 1000 / df_br['population']
df_br
```

Out[18]:

	X	Y	gid	community	id	neighborhood	planning_district	population	200
0	-91.076035	30.482581	1	EAST	57	PARK FOREST/OAKCREST	6	6857	1.
1	-91.034190	30.440869	2	EAST	58	FAIRWOOD	12	6439	1.
2	-91.133658	30.460864	3	MID CITY	1	EAST FAIRFIELDS/MELROSE PLACE	10	3281	3.
3	-91.121647	30.461267	4	MID CITY	2	SMILEY HEIGHTS/MELROSE EAST	10	4430	1.
4	-91.254457	30.515923	5	NORTH	3	THE AVENUES/SOUTHERN UNIV	4	4758	0.
5	-91.164122	30.399546	6	SOUTH	4	COLLEGE TOWN	13	3732	7.
6	-91.139954	30.389799	7	SOUTH	5	UNIVERSITY ACRES/WOODSTONE	14	4673	6.
7	-91.084463	30.336785	8	SOUTHWEST	6	SOUTH BLUEBONNET/NICHOLSON	16	6775	0.
8	-91.125106	30.381854	9	SOUTH	7	KENILWORTH	14	3203	0.
9	-91.134790	30.402801	10	SOUTH	8	POLLARD/WOODCHASE	14	3916	6.
10	-91.107502	30.378797	11	SOUTH	9	MAYFAIR	14	6005	3.
11	-91.093806	30.404161	12	SOUTH	10	WESTMINSTER/PINE PARK	14	4808	0.
12	-91.173279	30.449235	13	MID CITY	11	DOWNTOWN EAST	8	3076	11.
13	-91.182043	30.460871	14	DOWNTOWN	12	DOWNTOWN	8	2944	5.
14	-91.151839	30.417065	15	SOUTH	13	SOUTHSIDE	13	3822	8.
15	-91.160226	30.431837	16	SOUTH	14	CITY PARK	9	2776	10.
16	-91.144504	30.424939	17	SOUTH	15	VALLEY PARK	9	1621	9.
17	-91.147401	30.460664	18	MID CITY	18	EDEN PARK	9	3527	6.
18	-91.119676	30.418127	19	SOUTH	16	BOCAGE/CITIPLACE /CONCORD ESTATES	14	7574	0.
19	-91.161528	30.461610	20	MID CITY	17	FAIRFIELDS	9	4239	7.
20	-91.162631	30.478913	21	NORTH	19	ISTROUMA/DIXIE	7	4152	5.
21	-91.160910	30.504182	22	NORTH	20	LEGION VILLAGE	7	1624	1.
22	-91.081942	30.418618	23	SOUTH	21	JEFFERSON/DRUSILLA	14	5361	1.
23	-91.099221	30.441679	24	EAST	22	TARA	10	3435	1.
24	-91.108931	30.461663	25	EAST	23	GOODWOOD HOMESITES	10	3388	0.
25	-91.002082	30.452373	26	EAST	24	MILLERVILLE	12	5877	0.
26	-91.018491	30.463813	27	EAST	25	STEVENDALE	12	6525	0.
27	-91.087203	30.462037	28	EAST	48	CORTANA/VILLA DEL REY	11	3483	2.
28	-90.998483	30.425023	29	SOUTHEAST	26	O'NEAL	15	9578	2.
29	-91.007689	30.653422	30	NORTHEAST	27	PRIDE/CHANEYVILLE	2	5610	0.
30	-91.088546	30.367936	31	SOUTH	28	PERKINS/HIGHLAND	16	13069	3.
31	-91.182173	30.411274	32	SOUTH	29	L S U	13	7582	1.
32	-91.183183	30.432674	33	SOUTH	30	OLD SOUTH BATON ROUGE	8	7920	3.
33	-91.041383	30.414746	34	SOUTHEAST	31	JONES CREEK	15	26626	3.
34	-90.981452	30.367685	35	SOUTHEAST	32	JEFFERSON/TIGER BEND	16	13772	0.
35	-91.136281	30.498500	36	NORTH	49	BROOKSTOWN	5	6750	3.

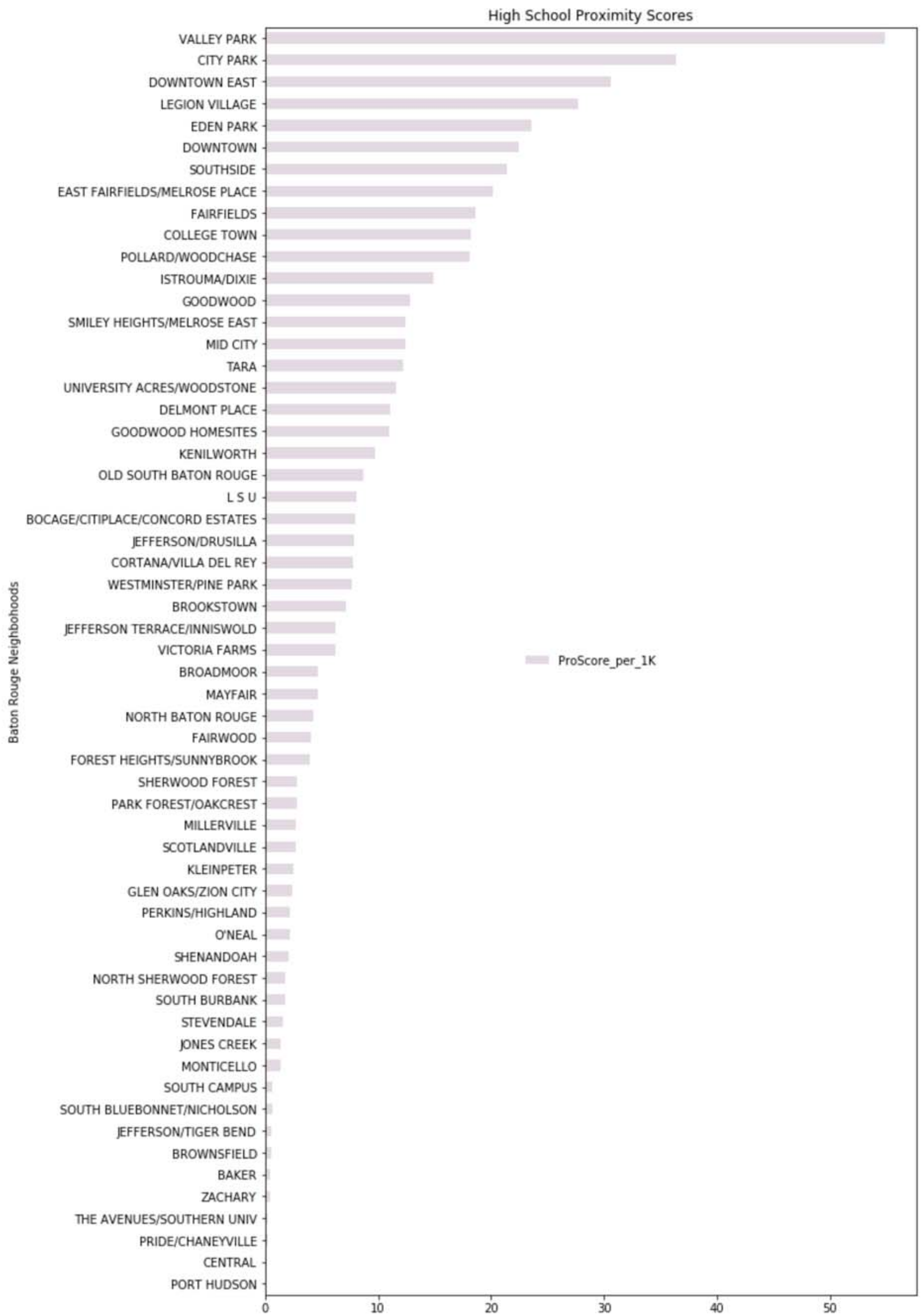
In [59]:
```
# use the inline backend to generate the plots within the browser
%matplotlib inline

import matplotlib as mpl
import matplotlib.pyplot as plt

mpl.style.use('ggplot') # optional: for ggplot-like style
```

In [58]:
```
df_br.sort_values(['ProScore_per_1K'], ascending=True, axis=0, inplace=True)
df_br
```

Out[58]:

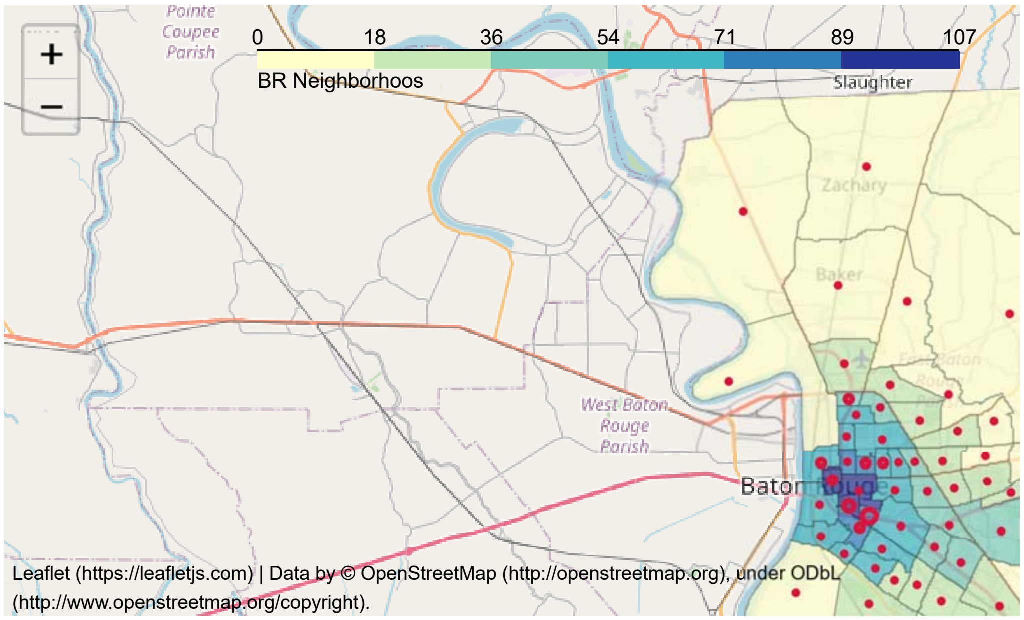
	X	Y	gid	community	id	neighborhood	planning_district	population	200
54	-91.243177	30.630251	55	NORTHWEST	52	PORT HUDSON	1	4536	0.
49	-91.035427	30.561565	50	NORTHEAST	46	CENTRAL	2	28040	0.
29	-91.007689	30.653422	30	NORTHEAST	27	PRIDE/CHANEYVILLE	2	5610	0.
4	-91.254457	30.515923	5	NORTH	3	THE AVENUES/SOUTHERN UNIV	4	4758	0.
50	-91.146981	30.660436	51	NORTHWEST	47	ZACHARY	1	15350	1.
48	-91.169210	30.580816	49	NORTHWEST	45	BAKER	3	19295	1.
47	-91.115305	30.569997	48	NORTHWEST	44	BROWNSFIELD	2	7759	0.
34	-90.981452	30.367685	35	SOUTHEAST	32	JEFFERSON/TIGER BEND	16	13772	0.
7	-91.084463	30.336785	8	SOUTHWEST	6	SOUTH BLUEBONNET/NICHOLSON	16	6775	0.
39	-91.201932	30.373520	40	SOUTHWEST	36	SOUTH CAMPUS	13	15957	0.
57	-91.047655	30.489311	58	EAST	56	MONTICELLO	6	5314	0.
33	-91.041383	30.414746	34	SOUTHEAST	31	JONES CREEK	15	26626	3.
26	-91.018491	30.463813	27	EAST	25	STEVENDALE	12	6525	0.
40	-91.144918	30.366074	41	SOUTHWEST	37	SOUTH BURBANK	16	13205	0.
45	-91.053728	30.465585	46	EAST	42	NORTH SHERWOOD FOREST	12	9402	2.
36	-90.993921	30.403841	37	SOUTHEAST	33	SHENANDOAH	15	12730	3.
28	-90.998483	30.425023	29	SOUTHEAST	26	O'NEAL	15	9578	2.
30	-91.088546	30.367936	31	SOUTH	28	PERKINS/HIGHLAND	16	13069	3.
44	-91.128651	30.513603	45	NORTH	41	GLEN OAKS/ZION CITY	5	12845	3.
55	-91.043162	30.364495	56	SOUTH	54	KLEINPETER	16	8470	0.
46	-91.164394	30.527823	47	NORTH	43	SCOTLANDVILLE	4	12548	3.
25	-91.002082	30.452373	26	EAST	24	MILLERVILLE	12	5877	0.
0	-91.076035	30.482581	1	EAST	57	PARK FOREST/OAKCREST	6	6857	1.
37	-91.052498	30.448479	38	EAST	34	SHERWOOD FOREST	12	9645	2.
53	-91.083079	30.507172	54	NORTH	51	FOREST HEIGHTS/SUNNYBROOK	5	3060	0.
1	-91.034190	30.440869	2	EAST	58	FAIRWOOD	12	6439	1.
42	-91.134863	30.476916	43	NORTH	39	NORTH BATON ROUGE	5	13947	3.
10	-91.107502	30.378797	11	SOUTH	9	MAYFAIR	14	6005	3.
56	-91.078315	30.443810	57	EAST	55	BROADMOOR	11	5966	3.
51	-91.105524	30.489660	52	NORTH	50	VICTORIA FARMS	5	4176	0.
52	-91.073262	30.393702	53	SOUTH	53	JEFFERSON TERRACE/INNISWOLD	16	6715	4.
35	-91.136281	30.498500	36	NORTH	49	BROOKSTOWN	5	6750	3.
11	-91.093806	30.404161	12	SOUTH	10	WESTMINSTER/PINE PARK	14	4808	0.
27	-91.087203	30.462037	28	EAST	48	CORTANA/VILLA DEL REY	11	3483	2.
22	-91.081942	30.418618	23	SOUTH	21	JEFFERSON/DRUSILLA	14	5361	1.
18	-91.119676	30.418127	19	SOUTH	16	BOCAGE/CITIPLACE /CONCORD ESTATES	14	7574	0.
31	-91.182173	30.411274	32	SOUTH	29	L S U	13	7582	1.

In [55]:
```
from matplotlib import pyplot as plt

df_br.plot.barh(x="neighborhood", y="ProScore_per_1K", title="High School Proximity Scores", figsize=(10,20), colormap='twilight')
plt.ylabel('Baton Rouge Neighbohoods')
plt.legend(loc='center', frameon=False)
plt.savefig('bargraph.png')
```


High School Proximity Scores
Baton Rouge Neighbohoods
ProScore_per_1K
VALLEY PARK
CITY PARK
DOWNTOWN EAST
LEGION VILLAGE
EDEN PARK
DOWNTOWN
SOUTHSIDE
EAST FAIRFIELDS/MELROSE PLACE
FAIRFIELDS
COLLEGE TOWN
POLLARD/WOODCHASE
ISTROUMA/DIXIE
GOODWOOD
SMILEY HEIGHTS/MELROSE EAST
MID CITY
TARA
UNIVERSITY ACRES/WOODSTONE
DELMONT PLACE
GOODWOOD HOMESITES
KENILWORTH
OLD SOUTH BATON ROUGE
L S U
BOCAGE/CITIPLACE/CONCORD ESTATES
JEFFERSON/DRUSILLA
CORTANA/VILLA DEL REY
WESTMINSTER/PINE PARK
BROOKSTOWN
JEFFERSON TERRACE/INNISWOLD
VICTORIA FARMS
BROADMOOR
MAYFAIR
NORTH BATON ROUGE
FAIRWOOD
FOREST HEIGHTS/SUNNYBROOK
SHERWOOD FOREST
PARK FOREST/OAKCREST
MILLERVILLE
SCOTLANDVILLE
KLEINPETER
GLEN OAKS/ZION CITY
PERKINS/HIGHLAND
O'NEAL
SHENANDOAH
NORTH SHERWOOD FOREST
SOUTH BURBANK
STEVENDALE
JONES CREEK
MONTICELLO
SOUTH CAMPUS
SOUTH BLUEBONNET/NICHOLSON
JEFFERSON/TIGER BEND
BROWNSFIELD
BAKER
ZACHARY
THE AVENUES/SOUTHERN UNIV
PRIDE/CHANEYVILLE
CENTRAL
PORT HUDSON
0
10
20
30
40
50

In [38]:
```
br_map3 = folium.Map(location=[br_lat, br_lon], zoom_start=10)
# generate choropleth map using proximity score
folium.Choropleth(
    geo_data=br_geo,
    data=df_br,
    columns=['neighborhood','ProScore'],
    key_on='feature.properties.neighborhood',
    fill_color='YlGnBu',
    fill_opacity=0.7,
    line_opacity=0.2,
    legend_name='BR Neighborhoos',
    smooth_factor=0,
    highlight=True,
    line_color='black'
).add_to(br_map3)

for i,row in df_br.iterrows():
    lat = row['Y']
    lon = row['X']
    folium.Circle(
        location=[lat,lon],
        popup = row['neighborhood'],
        radius= row['ProScore_per_1K']*10,
        color='crimson',
        fill=False,
        fill_color='crimson'
    ).add_to(br_map3)

br_map3
```

Out[38]:



In [ ]: