

# ncaa\_region\_optimizer

April 6, 2020

## 1 Genetic Algorithms for Region Partitioning

We will be using some Python modules installed by pip rather than Anaconda, so I must adjust the import path.

```
[1]: import sys
      sys.path.insert( 1, '/usr/local/lib/python3.7/site-packages' )
```

Import other packages.

```
[2]: import pandas
      from geopy.distance import great_circle
      import random
      import statistics
      from plotly_for_usa_points import usa_map # this works only if you've done
      ↪ conda install plotly
      # also one needs all the extensions mentioned here:
      # https://github.com/plotly/plotly.py#jupyterlab-support-python-35
      from tqdm.notebook import tqdm
      from ga_for_partitions import optimize_partition, set_seed
      import math
      from matplotlib import pyplot as plt
```

```
[3]: %matplotlib inline
```

---

### 1.1 Import the data

```
[4]: data_filename = 'wrestling-schools-data.csv'
      df = pandas.read_csv( data_filename )
      len( df )
```

```
[4]: 106
```

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

```
[5]: UniqueID      College/University Name      Street \
0         1          Adrian College          10 S Madison St
1         2  Alfred State College (add 2018)  10 Upper College Drive
2         3          Alma College          614 W Superior St
3         4          Augsburg          2211 Riverside Ave
4         5      Augustana (IL)          639 38th St

      City State  Latitude Longitude Power-1 Power-2 NCAA Asgt \
0      Adrian  MI  41.899337 -84.044547  2.4514  2.927      3
1      Alfred  NY  42.254334 -77.789646  0.0000  0.000      0
2      Alma    MI  43.380011 -84.655654  5.1091  5.941      3
3  Minneapolis  MN  44.963541 -93.267835  9.6340  8.890      2
4  Rock Island  IL  41.470591 -90.583733  0.0000  0.301      1

      ND Asgt  ND Asgt2  ND Asgt3
0         2.0      1.0      5.0
1         NaN      NaN      NaN
2         6.0      1.0      5.0
3         6.0      5.0      3.0
4         2.0      4.0      3.0
```

### 1.1.1 Drop schools we don't want in this analysis

Some schools were dropped for various domain-specific reasons. See paper.

```
[6]: df = df.drop( [ 31, 61, 85 ] )
      num_schools = len( df )
      num_schools
```

[6]: 103

### 1.1.2 Make it easy to fetch desired rows/columns

```
[7]: def school ( key ):
      column = 'UniqueID' if type( key ) == int else 'College/University Name'
      return df[df[column] == key].iloc[0]
      ( SCH_ID, SCH_NAME, SCH_ADDR, SCH_CITY, SCH_STATE, SCH_LAT, SCH_LNG, SCH_POW1,
      ↪SCH_POW2,
      SCH_NCAA, SCH_ND1, SCH_ND2, SCH_ND3 ) = list( df.columns.values )
      def all_ids ():
          return list( df['UniqueID'] )
      def index_to_id ( index ):
          return all_ids()[index]
      # print( school( 2 )[SCH_NAME] )
      # print( school( 'Augsburg' )[SCH_ID] )
      # print( school( 50 )[SCH_LAT], get_school( 50 )[SCH_LNG] )
```

---

## 1.2 Map distance tools

Define measure for computing distance on the (curved) surface of the earth.

```
[8]: def school_latlng ( school ):  
      return ( school[SCH_LAT], school[SCH_LNG] )
```

Now pre-compute the distance between any two pair of schools and cache it in a matrix, because we'll be asking these distance questions a million times below, and this cache will speed it up a lot.

```
[9]: school_locations = [ school_latlng( school( index_to_id( i ) ) )  
                          for i in range( num_schools ) ]  
distance_matrix = [ [ great_circle( school_locations[i], school_locations[j] ).  
                      ↪miles  
                      for i in range( num_schools ) ] for j in range(↪  
                      ↪num_schools ) ]  
def distance_lookup ( school_index1, school_index2 ):  
    return distance_matrix[school_index1][school_index2]
```

---

## 1.3 Utilities for partitions

```
[10]: num_parts_in_partition = 6  
def indices_for_part_in_partition ( part_index, partition ):  
    return [ i for i in range( len( partition ) ) if partition[i] == part_index↪  
            ↪]  
def schools_in_part_in_partition ( part_index, partition ):  
    return [ school( index_to_id( i ) )  
            for i in indices_for_part_in_partition( part_index, partition ) ]  
def size_of_part_in_partition ( part_index, partition ):  
    return len( indices_for_part_in_partition( part_index, partition ) )  
def random_partition ():  
    return [ random.randint( 0, num_parts_in_partition ) for i in range(↪  
            ↪num_schools ) ]
```

```
[11]: def print_partition ( partition ):  
    for part_index in range( num_parts_in_partition ):  
        schools = schools_in_part_in_partition( part_index, partition )  
        powers = [ school[SCH_POW2] for school in schools ]  
        print( 'Region {:1d}, {:2d} schools, mean power {:.75f} (stdev {:.75f}):  
            ↪'.format(  
                part_index + 1, size_of_part_in_partition( part_index, partition ),  
                statistics.mean( powers ), statistics.stdev( powers ) ) )  
        print( '-----' )  
        centroid = (
```

```

        statistics.mean( [ school[SCH_LAT] for school in schools ] ),
        statistics.mean( [ school[SCH_LNG] for school in schools ] ),
    )
    print( '    Centroid: {:.3f} lat, {:.3f} lon'.format(
        centroid[0], centroid[1] ) )
    latlngs = [ school_latlng( school ) for school in schools ]
    print( '    Mean distance to centroid: {:.3f} miles'.format(
        statistics.mean( [ great_circle( centroid, latlng ).miles for
↪latlng in latlngs ] )
    ) )
    for s in schools:
        print( '        {:.30s} {:.30s} {:.>7.1f} miles'.format(
            s[SCH_NAME],
            '{}', '{}', '{}'.format( s[SCH_ADDR], s[SCH_CITY], s[SCH_STATE] ),
            great_circle( school_latlng( s ), centroid ).miles
        ) )
    print()
# print_partition( random_partition() )

```

## 1.4 Test map-drawing tools

```

[12]: usa_map( { 'black' : [ school_latlng( school( id ) ) for id in all_ids() ] },
↪    'All Schools' )

```

All Schools



```

[13]: def partition_map ( schools_partition, title = 'Partition of All Schools' ):

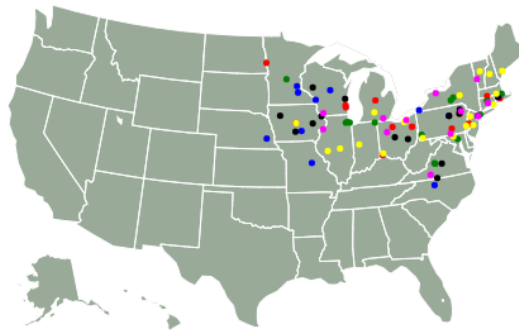
```

```

    colors = [ 'red', 'blue', 'green', 'black', 'yellow', 'magenta', 'cyan',
↪ 'white', 'gray', 'orange' ]
    def points_in_part ( part_index ):
        return [ school_latlng( s )
                for s in schools_in_part_in_partition( part_index,
↪ schools_partition ) ]
    return usa_map( {
        colors[i] : points_in_part( i ) for i in range( max( schools_partition
↪ ) )
    }, title )
partition_map( random_partition(), 'Plotting a random parition as an example' )

```

Plotting a random partition as an example



## 1.5 Components of the Objective Function

First, we will want to experiment with the range of the various components of the objective function, to see how we should rescale them to match each other.

```

[14]: def range_experiment ( func, num_tries=100 ):
        data = [ func( random_partition() ) for i in range( num_tries ) ]
        return min( data ), max( data )

```

### 1.5.1 Component 1: Variance of size of parts in the partition

```

[15]: def part_size_variance ( partition ):
        return statistics.variance( [
            size_of_part_in_partition( part, partition )

```

```

        for part in range( num_parts_in_partition )
    ] )
# print( range_experiment( part_size_variance ) ) # gives a max in the 50s
# plus we want size variance to be bad, so we need a -1 multiplier, so:
def obj_fn_component_1 ( partition ):
    return part_size_variance( partition ) * -1.0 / 50

```

### 1.5.2 Component 2: Total distance between schools in each part of the partition

```

[16]: def total_distance_in_one_part ( part_index, partition ):
        indices = indices_for_part_in_partition( part_index, partition )
        return sum( [ distance_lookup( i, j )
                        for i in indices for j in indices if i < j ] )
def total_distance_of_all_parts ( partition ):
    return sum( [ total_distance_in_one_part( index, partition )
                  for index in range( num_parts_in_partition ) ] )
# print( range_experiment( total_distance_of_all_parts ) ) # gives a max in to
↪50000s
# plus we want travel distance to be bad, so we need a -1 multiplier, so:
def obj_fn_component_2 ( partition ):
    return total_distance_of_all_parts( partition ) * -1.0 / 50000

```

### 1.5.3 Component 3: Variance of mean powers of each part in partition

```

[17]: def mean_power_of_part ( part_index, partition ):
        powers = [ s[SCH_POW2] for s in schools_in_part_in_partition( part_index,
↪partition ) ]
        if len( powers ) > 0:
            return statistics.mean( powers )
        else:
            return 0
def part_power_variance ( partition ):
    return statistics.variance( [
        mean_power_of_part( part, partition )
        for part in range( num_parts_in_partition )
    ] )
# print( range_experiment( part_power_variance ) ) # gives a max around 5
# plus we want power variance to be bad, so we need a -1 multiplier, so:
def obj_fn_component_3 ( partition ):
    return part_power_variance( partition ) * -1.0 / 5

```

### 1.5.4 Objective function: sum of 3 components

```
[18]: def objective_function ( partition ):  
      return obj_fn_component_1( partition ) \  
          + obj_fn_component_2( partition ) \  
          + obj_fn_component_3( partition )
```

## 1.6 Solving the problem with Genetic Algorithms

```
[19]: num_generations = 10000  
def progress_bar ( name="Progress", size=num_generations ):  
    bar = tqdm( range( size ), desc=name )  
    def step ( *args ):  
        bar.update( 1 )  
        bar.display()  
    return step  
best, fitness_curve = optimize_partition(  
    objective_function = objective_function,  
    initial_pool = [ random_partition() for i in range( num_parts_in_partition_  
→ ) ],  
    size_of_partition = num_parts_in_partition,  
    probab_mutate = 0.1,  
    num_generations = num_generations,  
    progress_callback = progress_bar()  
)
```

HBox(children=(FloatProgress(value=0.0, description='Progress', max=10000.0, style=ProgressStyle...))

After 10000 generations: max score = -1.4149 100% done, 11:11/11:11 (00:00)

```
[20]: print_partition( best )
```

Region 1, 11 schools, mean power 2.36036 (stdev 3.62114):

```
-----  
Centroid:  41.834 lat, -92.081 lon  
Mean distance to centroid:  141.262 miles  
miles      Buena Vista      610 W 4th St, Storm Lake, IA      169.0  
miles      Central College    812 University St, Pella , IA      52.4  
miles      Coe                1220 First Avenue NE, Cedar Ra      22.7  
miles      Loras              450 Alta Vista St,, Dubuque, I      85.3  
miles      Luther             700 College Dr, Decorah, IA      102.6
```

miles	MacMurray College	447 E College Ave, Jacksonvill	174.7
miles	Nebraska Wesleyan University	5000 St Paul Ave, Lincoln, NE	246.6
miles	North Central (IL)	30 North Brainard Street, Nape	202.0
miles	St. Olaf	1520 St Olaf Ave, Northfield,	189.3
miles	Westminster (add 2017)	501 Westminster Ave, Fulton, M	206.3
miles	Wisconsin-Platteville	1 University Plaza, Plattville	103.1
miles			

Region 2, 11 schools, mean power 2.47845 (stdev 6.81742):

-----

Centroid: 41.031 lat, -77.598 lon  
Mean distance to centroid: 217.364 miles

	Hunter	695 Park Ave, New York, NY	190.6
miles	Keystone College	1 College Rd, La Plume, PA	102.2
miles	Rochester Institute of Technol	Lomb Memorial Dr, Rochester, N	158.5
miles	Scranton	800 Linden St, Scranton, PA	103.7
miles	Southern Virginia University	1 University Hill Dr, Buena Vi	246.6
miles	SUNY-Oneonta	08 Ravine Pkwy, Oneonta, NY	158.5
miles	SUNY-Oswego	7060 New York 104, Oswego, NY	158.5
miles	The College of New Jersey	2000 Pennington Rd, Ewing Town	164.3
miles	Wartburg	100 Wartburg Blvd, Waverly, IA	773.0
miles	Washington and Lee	204 W Washington St,, Lexingto	245.1
miles	Wilkes	84 W South St, Wilkes-Barre, P	90.1
miles			

Region 3, 12 schools, mean power 2.78942 (stdev 3.08961):

-----

Centroid: 43.969 lat, -90.151 lon  
Mean distance to centroid: 113.287 miles

	Augsburg	2211 Riverside Ave, Minneapoli	168.3
miles	Concordia (WI)	12800 N Lake Shore Dr, Mequon,	119.8



miles	Dubuque	2000 University Ave, Dubuque,	105.2
miles	Elmhurst	190 S Prospect Ave, Elmhurst,	181.5
miles	Lakeland	W3718 South Dr, Plymouth, WI	110.0
miles	Milwaukee School of Engineerin	1025 N Broadway, Milwaukee, WI	126.0
miles	St. Johns (MN)	2850 Abbey Plaza, Collegeville	237.1
miles	Wisconsin-Eau Claire	105 Garfield Ave, Eau Claire,	88.7
miles	Wisconsin-La Crosse	1725 State St, La Crosse , WI	54.5
miles	Wisconsin-Oshkosh	800 Algoma Blvd, Oshkosh, WI	59.9
miles	Wisconsin-Stevens Point	100 Main St, Stevens Point, WI	48.5
miles	Wisconsin-Whitewater	800 W Main St, Whitewater, WI	59.9

Region 4, 12 schools, mean power 2.12350 (stdev 2.02969):

-----

Centroid: 40.015 lat, -76.674 lon

Mean distance to centroid: 116.517 miles

miles	Averett University (add 2017)	420 W Main St, Danville, VA	279.7
miles	Centenary (NJ)	400 Jefferson St, Hackettstown	113.2
miles	College of Mount Saint Vincent	6301 Riverdale Ave, Bronx , NY	159.1
miles	Delaware Valley	700 E Butler Ave, Doylestown,	84.2
miles	Elizabethtown	1 Alpha Dr, Elizabethtown, PA	10.3
miles	Ferrum College	215 Ferrum Mountain Rd, Ferrum	279.4
miles	Gettysburg	300 N Washington St, Gettysbur	32.3
miles	Ithaca	953 Danby Rd, Ithaca, NY	166.5
miles	Lycoming	700 College Pl, Williamsport,	87.1
miles	McDaniel	2 College Hill, Westminster, M	34.9
miles	Pennsylvania College (add 2017	1 College Ave, Williamsport, P	86.2

Ursinus	01 E Main St, Collegeville, PA	65.3
---------	--------------------------------	------

miles

Region 5, 12 schools, mean power 2.04617 (stdev 1.89098):

-----

Centroid: 41.297 lat, -82.304 lon  
Mean distance to centroid: 92.856 miles

Adrian College	10 S Madison St, Adrian, MI	99.1
----------------	-----------------------------	------

miles

Alma College	614 W Superior St, Alma, MI	187.4
--------------	-----------------------------	-------

miles

Baldwin Wallace	275 Eastland Rd, Berea, OH	23.4
-----------------	----------------------------	------

miles

Case Western Reserve	10900 Euclid Ave, Cleveland, O	38.8
----------------------	--------------------------------	------

miles

Heidelberg	310 E Market St, Tiffin, OH	47.2
------------	-----------------------------	------

miles

John Carroll	1 John Carroll Boulevard, Univ	42.2
--------------	--------------------------------	------

miles

Mount Union	1972 Clark Ave, Alliance, OH	67.2
-------------	------------------------------	------

miles

Ohio Northern	525 S Main St, Ada, OH	87.3
---------------	------------------------	------

miles

Thiel	College Ave, Greenville, PA	99.9
-------	-----------------------------	------

miles

Trine University	1 University Ave, Angola, IN	141.8
------------------	------------------------------	-------

miles

Washington and Jefferson	60 S Lincoln St, Washington, P	132.7
--------------------------	--------------------------------	-------

miles

Waynesburg	51 W College S, Waynesburg, PA	147.3
------------	--------------------------------	-------

miles

Region 6, 12 schools, mean power 1.87958 (stdev 2.50535):

-----

Centroid: 42.255 lat, -72.538 lon  
Mean distance to centroid: 96.471 miles

Bridgewater State University	131 Summer Street, Bridgewater	82.3
------------------------------	--------------------------------	------

miles

Castleton University	62 Alumni Dr,, Castleton, VT	98.9
----------------------	------------------------------	------

miles

Coast Guard	31 Mohegan Ave Pkwy, New Londo	67.7
-------------	--------------------------------	------

miles

Merchant Marine	300 Steamboat Rd, Kings Point,	117.2
-----------------	--------------------------------	-------

miles

New England College	98 Bridge St,, Henniker, NH	73.7
---------------------	-----------------------------	------

miles

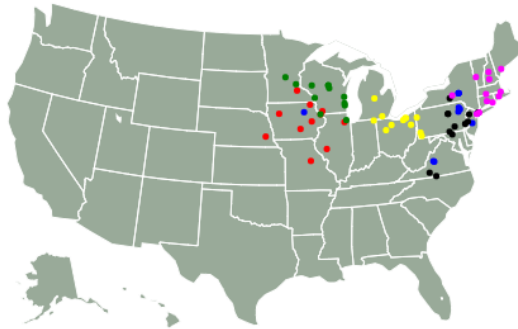
Plymouth State	17 High St, Plymouth, NH	111.2
----------------	--------------------------	-------

miles

	Roger Williams	1 Old Ferry Road, Bristol, RI	76.3
miles			
	Southern Maine	96 Falmouth St, Portland, ME	153.6
miles			
	Springfield	263 Alden Street, Springfield,	10.6
miles			
	Stevens Institute Of Technolog	1 Castle Point Terrace, Hoboke	129.7
miles			
	SUNY-Cortland	2 Graham Ave, Cortland, NY	187.2
miles			
	Wesleyan (CT)	45 Wyllys Ave, Middletown, CT	49.3
miles			

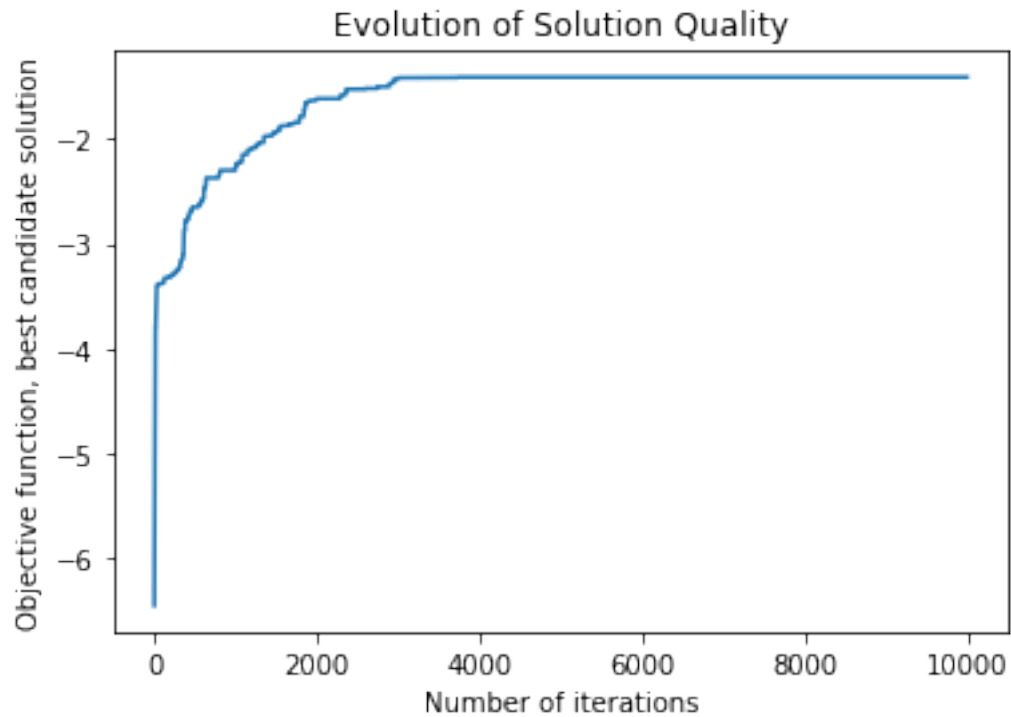
```
[21]: partition_map( best )
```

Partition of All Schools



```
[22]: plt.plot( range( len( fitness_curve ) ), fitness_curve )
plt.xlabel( 'Number of iterations' )
plt.ylabel( 'Objective function, best candidate solution' )
plt.title( 'Evolution of Solution Quality' )
```

```
[22]: Text(0.5, 1.0, 'Evolution of Solution Quality')
```



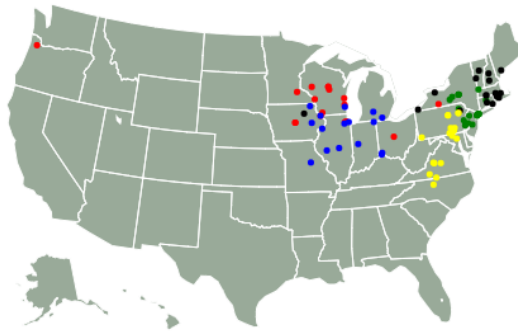
```
[23]: objective_function( best )
```

```
[23]: -1.4148877257165877
```

## 1.7 Viewing Other Solutions

```
[24]: partition = [ int( n ) - 1 if not math.isnan( n ) else 0 for n in df[ SCH_ND1 ] ]  
partition_map( partition )
```

### Partition of All Schools

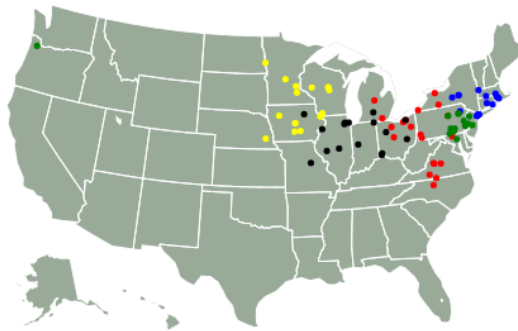


```
[25]: objective_function( partition )
```

```
[25]: -4.486573875023253
```

```
[26]: partition = [ int( n ) - 1 if not math.isnan( n ) else 0 for n in df[ SCH_ND2 ] ]  
partition_map( partition )
```

### Partition of All Schools

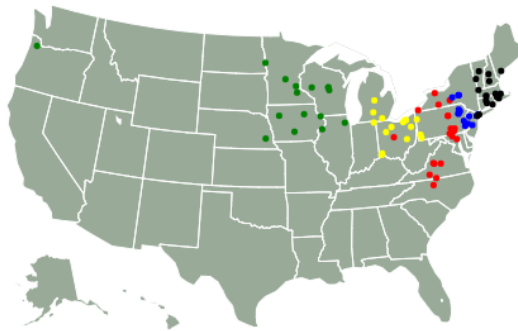


```
[27]: objective_function( partition )
```

```
[27]: -4.940869315953698
```

```
[28]: partition = [ int( n ) - 1 if not math.isnan( n ) else 0 for n in df[SCH_ND3] ]  
partition_map( partition )
```

Partition of All Schools



```
[29]: objective_function( partition )
```

```
[29]: -3.3577779150908267
```

```
[ ]:
```