

Geospatial Voronoi Analysis with Python

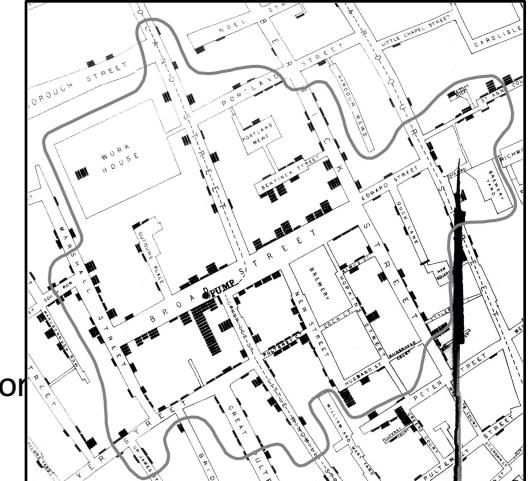
Dan Finkel PhD
Service Management Group (SMG)
Boston Python Meetup
December 20 2016

1854 Broad Street Cholera Outbreak

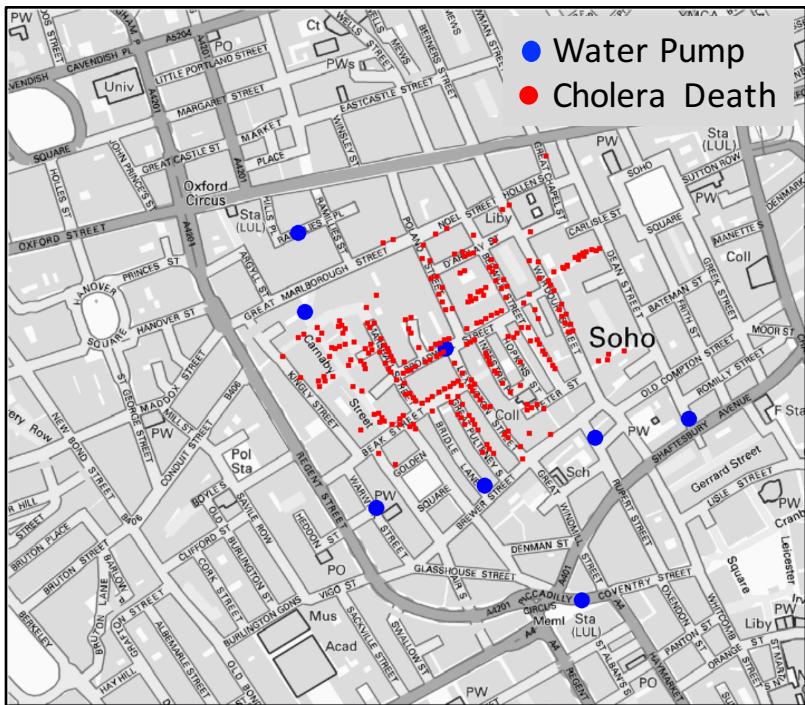
- A major cholera outbreak killed over 600 London Soho residents and caused 75% of residents to flee the area
- A local physician, John Snow, connected the outbreak to filth polluting the water
 - Conclusions were based on graph and pattern analysis
 - Regarded as the founding event of epidemiology
- In the absence of hard biological evidence Snow relied on graph and pattern analysis
- Postscript
 - Snow's evidence caused Broad St well to be disabled
 - After the disease subsided Snow's theory was rejected and air pollution was blamed
 - "To accept Snow's theory of oral-foecal transmission of disease was too unpleasant for most of the public to contemplate"



John Snow Memorial

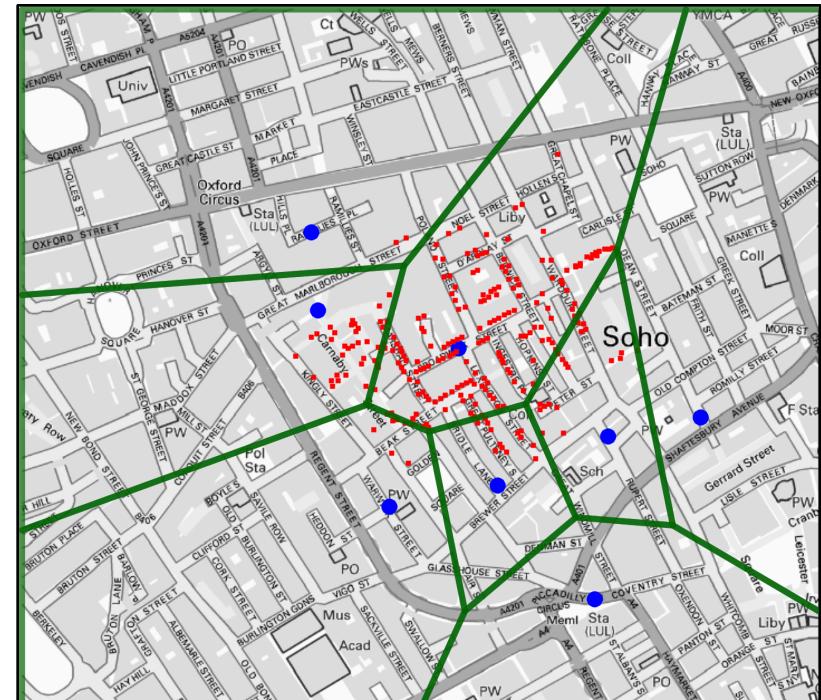
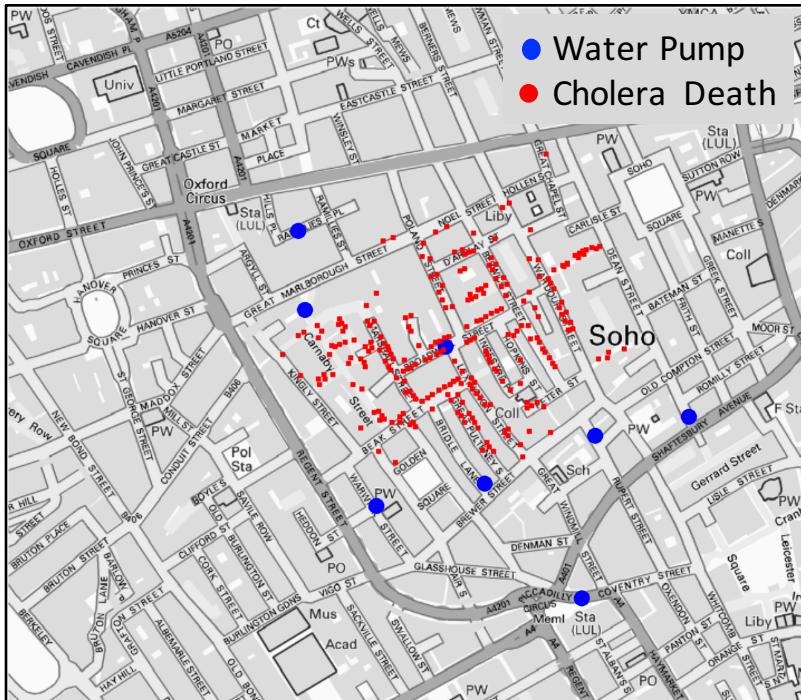


Visualizing the Cholera Outbreak by Water Pump Region



Data obtained from <http://blog.rtwilson.com/john-snows-famous-cholera-analysis-data-in-modern-gis-formats/>

Visualizing the Cholera Outbreak by Water Pump Region



Planar partitions by pump proximity helped Snow argue outbreak was due to polluted water

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Voronoi Diagram Overview



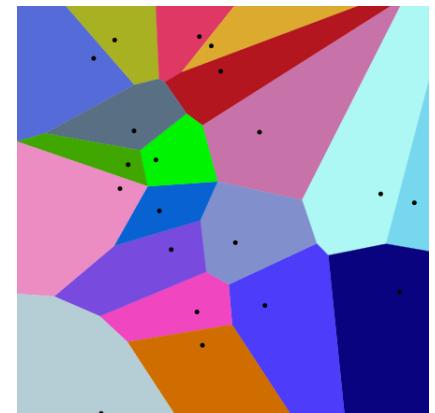
Georgy Voronoy
1868 - 1908

Wikipedia

- A Voronoi diagram is a planar partition based on distance to a set of points (“seeds”) within the plane
- Each seed defines a partition as those points in the plane closer to that seed than any other

$$R_k = \{x \in X \mid d(x, P_k) \leq d(x, P_j) \text{ for all } j \neq k\}$$

- Algorithms / implementations
 - Typically $O(n \log n)$
 - Can scale to multiple dimensions
 - Python implementation in `scipy`
 - Utilizes Qhull library
 - Computes via its dual (Delaunay triangulation)



Voronoi Diagram Example (Wikipedia)

Constructing Voronoi Polygons in Python

Simple Functionality

1. Import the library

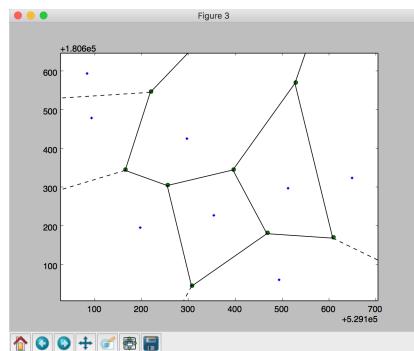
```
> from scipy.spatial import Voronoi, voronoi_plot_2d
```

2. Instantiate

```
> vor = Voronoi(pumps_xy)
```

3. Plot / Visualize

```
> voronoi_plot_2d(vor)
```



Constructing Voronoi Polygons in Python

Simple Functionality

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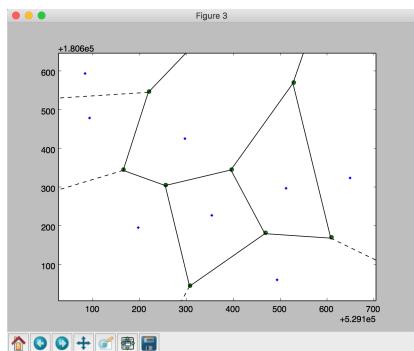
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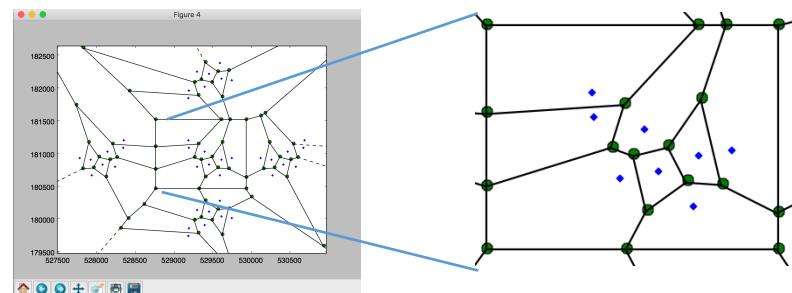
3. Plot / Visualize

```
> voronoi_plot_2d(v)
```



Additional Modifications

Mirror pumps and build Voronoi off expanded set
(to create hard boundaries)



Convert Voronoi regions into polygons

```
def build_vor_polys(vor, soho_poly, pumps_xy):
    polys = []

    # Build all lines in the voronoi region set
    lines = [shapely.geometry.LineString(vor.vertices[line])
             for line in vor.ridge_vertices
             if -1 not in line]

    # polygonize the lines and check if
    # they are original or copies
    for poly in shapely.ops.polygonize(lines):
        if is_in(poly, pumps_xy):
            poly = poly.intersection(soho_poly)
            x, y = poly.exterior.xy
            polys.append(poly)

    return polys
```

- Shapely Geospatial functions
- Compute area
- Intersect, overlap with other polygons
- Join / union with other objects

All code available on <http://github.com/danfinkel/python>

MLB Stadium Market Research Example



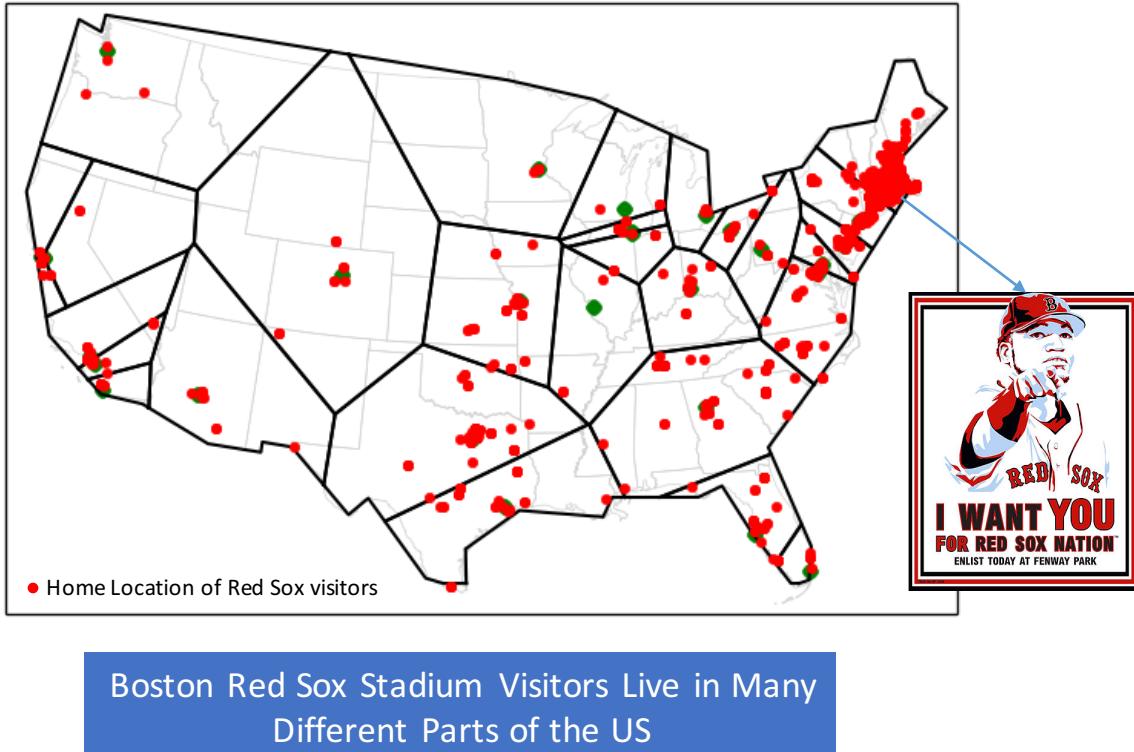
- SMG maintains a large panel of individuals who report behavior and customer experiences
- During 2016 MLB season we monitored stadium visits to identify geospatial patterns and preferences



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Behavioral Analysis

Red Sox Nation

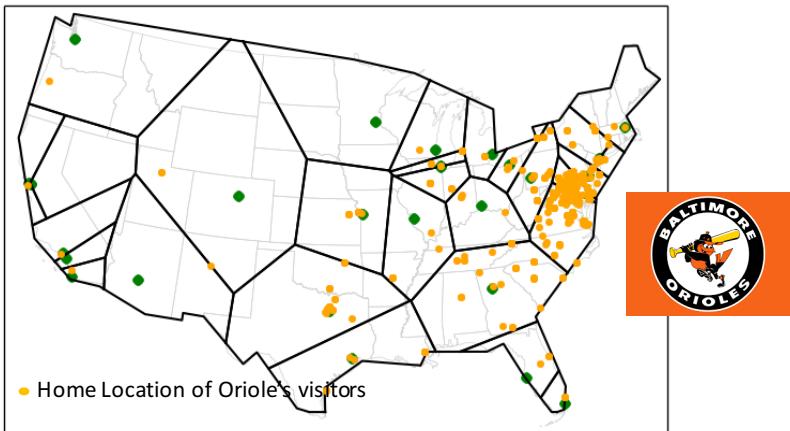
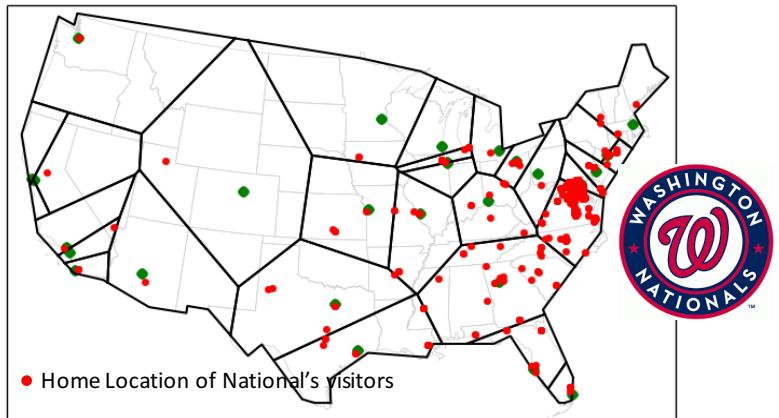


SMG Panelists Visit to Voronoi "Home" Team (2016)

Stadium	Home Ratio	Away Ratio	Rival Ratio
Nationals Park	80.56%	15.10%	4.34%
Citizens Bank Park	83.74%	16.26%	0.00%
Citi Field	63.02%	18.63%	18.35%
Safeco Field	79.41%	20.59%	0.00%
AT&T Park	20.98%	33.26%	45.76%
Tropicana Field	82.35%	17.65%	0.00%
PETCO Park	62.79%	37.21%	0.00%
Great American Ball Park	88.94%	11.06%	0.00%
U.S. Cellular Field	59.51%	13.59%	26.90%
Comerica Park	84.26%	15.74%	0.00%
Chase Field	85.46%	14.54%	0.00%
Fenway Park	62.82%	37.18%	0.00%
Progressive Field	82.36%	17.64%	0.00%
Busch Stadium	79.67%	20.33%	0.00%
Minute Maid Park	88.64%	11.36%	0.00%
Globe Life Park in Arlington	94.28%	5.72%	0.00%
Camden Yards	56.89%	20.38%	22.72%
Angel Stadium of Anaheim	69.47%	15.09%	15.44%
PNC Park	83.82%	16.18%	0.00%
Target Field	90.75%	9.25%	0.00%
Turner Field	90.70%	9.30%	0.00%
Wrigley Field	35.34%	29.33%	35.34%
Kauffman Stadium	93.11%	6.89%	0.00%
Yankee Stadium	64.24%	16.19%	19.57%
O.co Coliseum	60.10%	30.39%	9.51%
Miller Park	81.01%	18.99%	0.00%
Coors Field	82.99%	17.01%	0.00%
Marlins Park	0.97%	99.03%	0.0 Mapping Error
Dodger Stadium	66.47%	12.60%	20.93%

Behavioral Analysis

Rivals Compete for Guests



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Asymmetry an opportunity for Nationals?

Mapping Error

Thanks!

Dan Finkel

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<http://github.com/danfinkel/python>