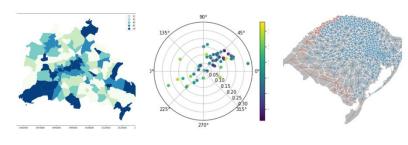


#### Capturing neighborhoods

- Spatial statistics between geographic tables
  - Often requires expensive computation, e.g. what's nearby?
    - Brute force = Pairwise distance calculation
  - Spatial weight matrices capture "topology" so that computation is cheaper

#### **PySAL: Python Spatial Analysis Library**

PySAL is an open source cross-platform library for geospatial data science with an emphasis on geospatial vector data written in Python.



Housing Prices Berlin

Rose diagram (directional LISAs)

Visualizing Non Planar Neighbours

PySAL supports the development of high level applications for spatial analysis, such as

- · detection of spatial clusters, hot-spots, and outliers
- · construction of graphs from spatial data
- · spatial regression and statistical modeling on geographically embedded networks
- · spatial econometrics
- · exploratory spatio-temporal data analysis



#### PySAL components

- **explore** modules to conduct exploratory analysis of spatial and spatio-temporal data, including statistical testing on points, networks, and polygonal lattices. Also includes methods for spatial inequality, distributional dynamics, and segregation.
- viz visualize patterns in spatial data to detect clusters, outliers, and hot-spots.
- model model spatial relationships in data with a variety of linear, generalized-linear, generalized-additive, and nonlinear models.
- lib solve a wide variety of computational geometry problems:
  - graph construction from polygonal lattices, lines, and points.
  - construction and interactive editing of spatial weights matrices & graphs
  - computation of alpha shapes, spatial indices, and spatial-topological relationships
  - reading and writing of sparse graph data, as well as pure python readers of spatial vector data.

## Tobler's First Law of Geography:

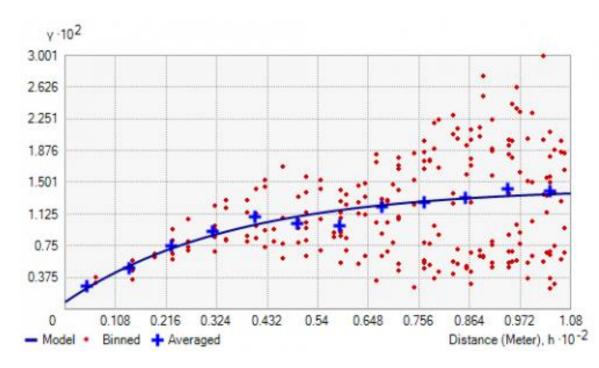
"Everything is related to everything else, but near things are more related than distant things."

Tobler, W. (1970) "A computer movie simulating urban growth in the Detroit region". Economic Geography, 46(2): 234-240.

#### Examples



Economic activity for shops nearby



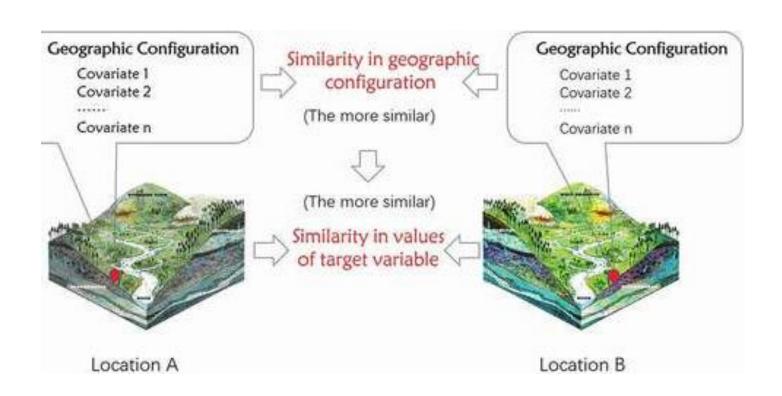
Terrain variability from a central point

## The second law of geography

the phenomenon external to a geographic area of interest affects what goes on inside.



## Third Law of Geography



# How to weigh your neighbors?

## Continuity/Adjacency relations

Distance based relations

Hybrid weights

# Continuity weights

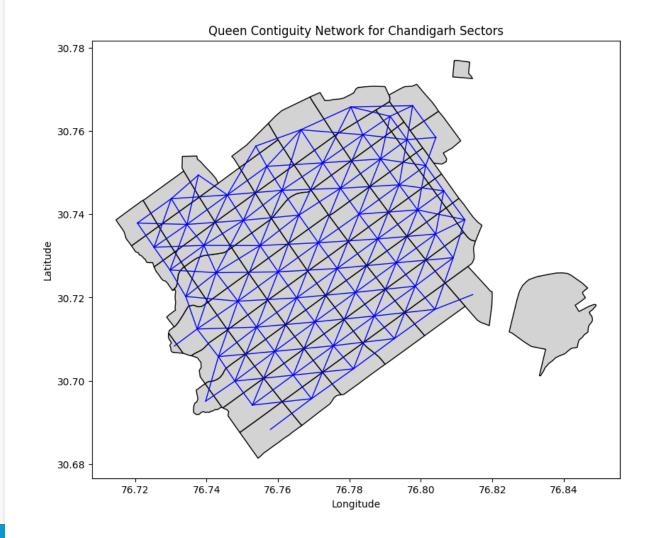
### Rook Contiguity Network for Chandigarh Sectors 76.72 76.74 76.76 76.78 76.80 76.82 Longitude

### Rook Neighbors

- 4 islands
- Connections amongst sectors that share an edge
- See code example on notebook.
- Note, weights.full() gives matrix representation
- Useful for modeling more rigid phenomenon, e.g.,
  - Roads, zoning, water flows, etc.

#### Queen Contiguity

- Neighbors share an edge or a vertex
  - Diagonal movement is allowed
- Allows for a more flexible definition of neighborhood
  - Useful for modeling more 'free' phenomenon, e.g., trade, ecology, etc.



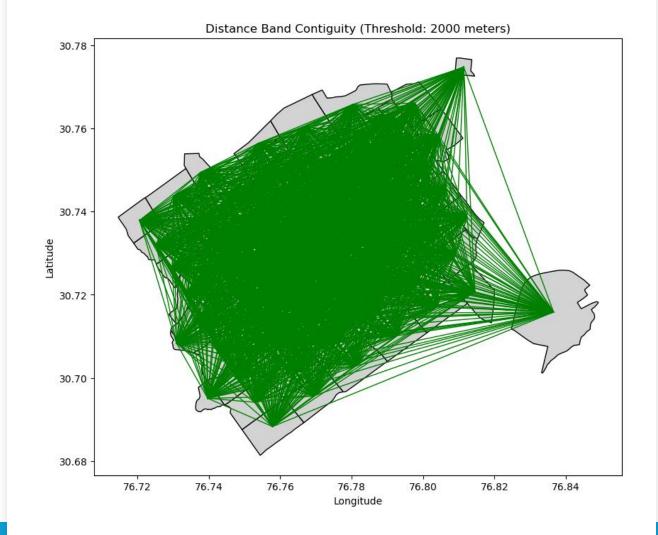
#### A note on islands

- Islands can create a problem in spatial statistics algorithms. It is thus preferred to add a single neighbor at least for further analysis.
  - Can be added by using sets (covered later) or
  - Can be added through manual editing of contiguity dictionary

# Distance based relations

### Define neighbors through a distance threshold

- Take all neighbors within a threshold distance
  - For example, blinkit deliveries
- Or just a few nearest neighbors,
  - E.g. kNN neighbors
  - Uses inter-centroid distances
- Shall we just use kernels?
  - Shape, e.g., gaussian, triangular,
  - Bandwidth, e.g., 500m. After this the weights are decayed.



#### Different kernel functions

 $z_{i,j}=d_{i,j}/h_i$ 

triangular

$$K(z)=(1-|z|)\ if|z|\leq 1$$

uniform

$$K(z)=1/2\ if|z|\leq 1$$

quadratic

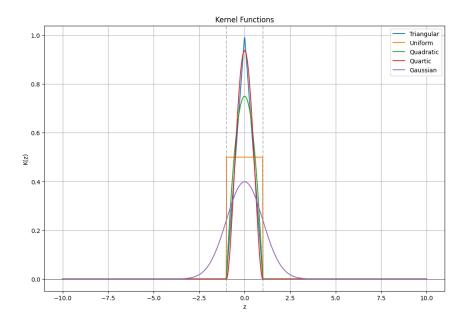
$$K(z) = (3/4)(1-z^2) \ if|z| \le 1$$

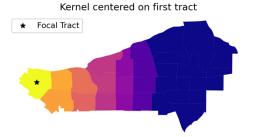
quartic

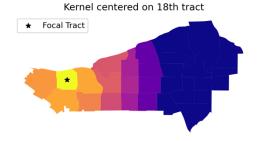
$$K(z) = (15/16)(1-z^2)^2 \ if|z| \leq 1$$

gaussian

$$K(z)=(2\pi)^{(-1/2)}exp(-z^2/2)$$







#### Summary

Spatial Weights Type	Best When	Pros	Cons
Rook Contiguity	Influence spreads via <b>shared borders</b> (e.g., political units)	Simple, interpretable	Ignores diagonal connections
Queen Contiguity	Influence spreads via borders & corners	More inclusive than Rook	Still ignores distance
Distance Band	You have a <b>fixed range of influence</b> (e.g., air pollution, traffic impact)	Ensures all close units are neighbors	Sharp cutoff—no gradual influence
Inverse Distance	Influence <b>decays with distance</b> (e.g., economic interactions)	Accounts for gradual influence loss	Needs careful choice of power
K-Nearest Neighbors (KNN)	You need a fixed number of neighbors per unit	Ensures every unit has neighbors	No distance-based weighting
Kernel Weights	Influence spreads smoothly over distance	Most flexible, smooth decay	Harder to interpret

# Hybrid

#### Hybrid weights

- Decaying distance within a threshold
  - w\_bdb = weights.distance.DistanceBand.from\_dataframe(gdf, 1.5, binary=True)
  - DistanceBand uses inverse distance relationship

#### Incorporating earth's curvature

```
# ignore curvature of the earth
knn4_bad = weights.distance.KNN.from_shapefile(
    "../data/texas/texas.shp", k=4
)
```

```
radius = geometry.sphere.RADIUS_EARTH_MILES
radius

knn4 = weights.distance.KNN.from_shapefile(
    "../data/texas/texas.shp", k=4, radius=radius
)
```

# Block Weights

#### Block weights

• Use a list as proxy for near-ness, e.g., all sectors with a waste treatment plant

#### Combining block and distance?

- Define neighbors as all schools in a ward within a distance of 2 km
  - Use **Sets** 
    - Sets allow you to do set operations union, intersection, etc. of neighbors from different weight matrices

```
w_fixed_sets = weights.set_operations.w_union(w_rook, wk1)
```

#### In Research

Jia, Yuhao, Zile Wu, Shengao Yi, and Yifei Sun. "GeoTransformer: Enhancing Urban Forecasting with Geospatial Attention Mechanisms." *arXiv* preprint arXiv:2408.08852 (2024).

https://arxiv.org/abs/2408.08852

Zhu, Di, Yu Liu, Xin Yao, and Manfred M. Fischer. "Spatial regression graph convolutional neural networks: A deep learning paradigm for spatial multivariate distributions." *GeoInformatica* 26, no. 4 (2022): 645-676.

https://link.springer.com/article/10. 1007/s10707-021-00454-x Liu, Pengyuan, and Filip Biljecki. "A review of spatially-explicit GeoAl applications in Urban Geography." *International Journal of Applied Earth Observation and Geoinformation* 112 (2022): 102936.

https://www.sciencedirect.com/science/article/pii/S1569843222001339

Zhao, Tianhong, Xiucheng Liang, Wei Tu, Zhengdong Huang, and Filip Biljecki. "Sensing urban soundscapes from street view imagery." *Computers, Environment and Urban Systems* 99 (2023): 101915.