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# Spatial Weights

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# Outline

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- Connectivity in Space
- Spatial Weights
- Practical Issues
- Spatial Lag Operator

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# Spatial Connectivity

# Why Spatial Weights?

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- Spatial Correlation
  - $\text{Cov}[y_i, y_h] \neq 0$ , for  $i \neq h$
- Structure of Correlation
  - which  $i, h$  interact?
  - $N$  observations to estimate  $N(N-1)/2$  interactions
  - impose **structure** in terms of what are the “**neighbors**” for each location

# Spatial Arrangement

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- Need to Impose **Structure** on the Extent of Spatial Interaction
- Neighborhood View
  - define **neighborhood set**  $N(i)$  for each location  $i$
  - **spatial weights matrix**
- Pairs View
  - order pairs of locations  $i-j$  in function of separating distance
  - **semivariogram** (geostatistics)

# Neighborhood Set

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- Geographic-Cartographic Contiguity (GIS)
  - common boundary = contiguity
    - » common border, common vertex
  - distance band = isotropy
  - interaction border length and distance
- Spatial Interaction
  - distance decay, gravity, entropy
  - scale dependent, identification problems

# Neighborhood Set (continued)

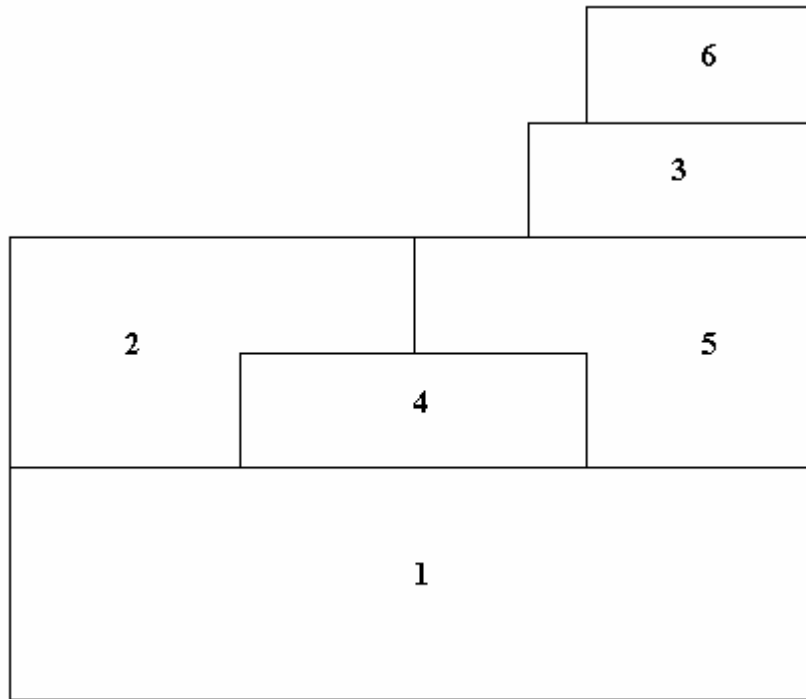
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## ➤ Socio-Economic Distance

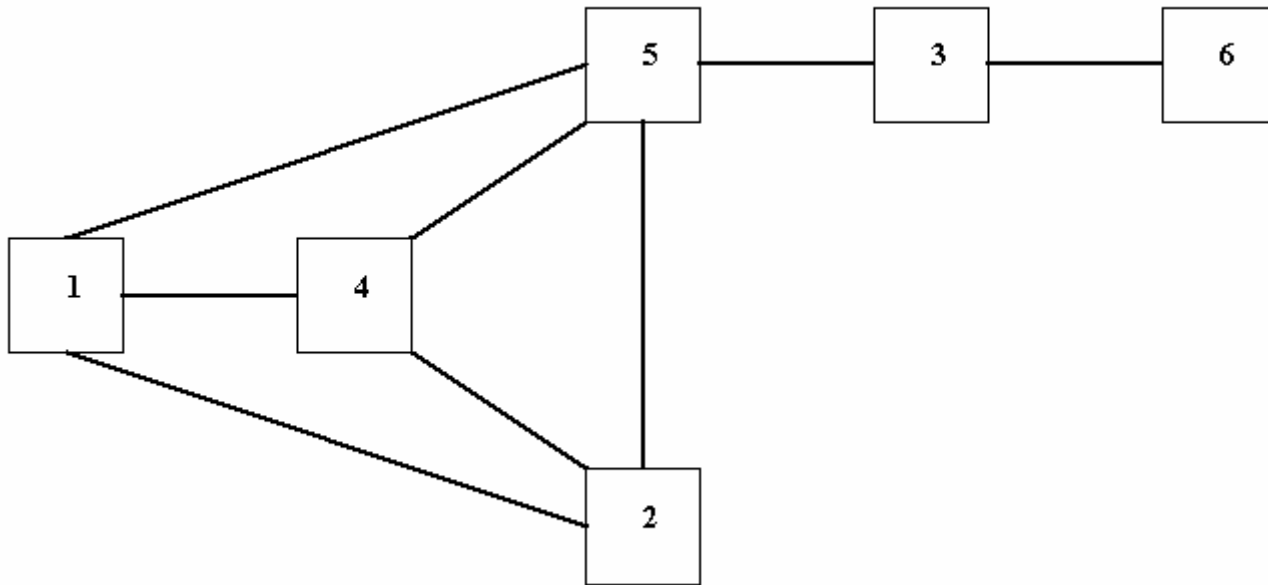
- multidimensional distance based on socio-economic indicators
  - » Euclidean, Mahalanobis
  - » example: income, ethnicity, industrial structure, trade flows, migration flows
- problem with endogeneity
  - » variables for distance same as in model
- zero distances
  - »  $1/(z_i - z_j)$  when  $z_i = z_j$

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# Spatial Weights



Example:  $N=6$   
contiguity = common boundary



contiguity as a graph  
link between nodes = contiguity

|   |   |   |   |   |   |
|---|---|---|---|---|---|
| 0 | 1 | 0 | 1 | 1 | 0 |
| 1 | 0 | 0 | 1 | 1 | 0 |
| 0 | 0 | 0 | 0 | 1 | 1 |
| 1 | 1 | 0 | 0 | 1 | 0 |
| 1 | 1 | 1 | 1 | 0 | 0 |
| 0 | 0 | 1 | 0 | 0 | 0 |

First Order Contiguity Matrix

# Spatial Weights Matrix

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## ➤ Definition

- N by N **positive** matrix  $W$ , with elements  $w_{ij}$

## ➤ Simplest Form: Binary Contiguity

»  $w_{ij} = 1$  for  $i$  and  $j$  “neighbors”  
(e.g.  $d_{ij} < \text{critical distance}$ )

»  $w_{ij} = 0$  otherwise,

»  $w_{ii} = 0$  by convention

# How to Define Weights

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- Contiguity
  - common boundary
- Distance
  - distance band
  - k-nearest neighbors
- General
  - social distance
  - complex distance decay functions

# Contiguity – Regular Grid

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## ➤ Regular Grid

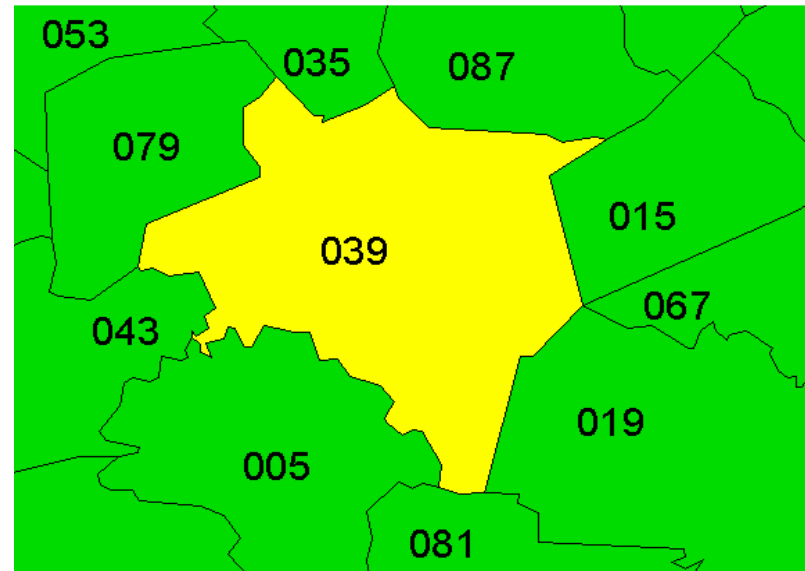
- rook
  - » 2, 4, 6, 8
- bishop
  - » 1, 3, 7, 9
- queen
  - » both

|   |   |   |
|---|---|---|
| 1 | 2 | 3 |
| 4 | 5 | 6 |
| 7 | 8 | 9 |

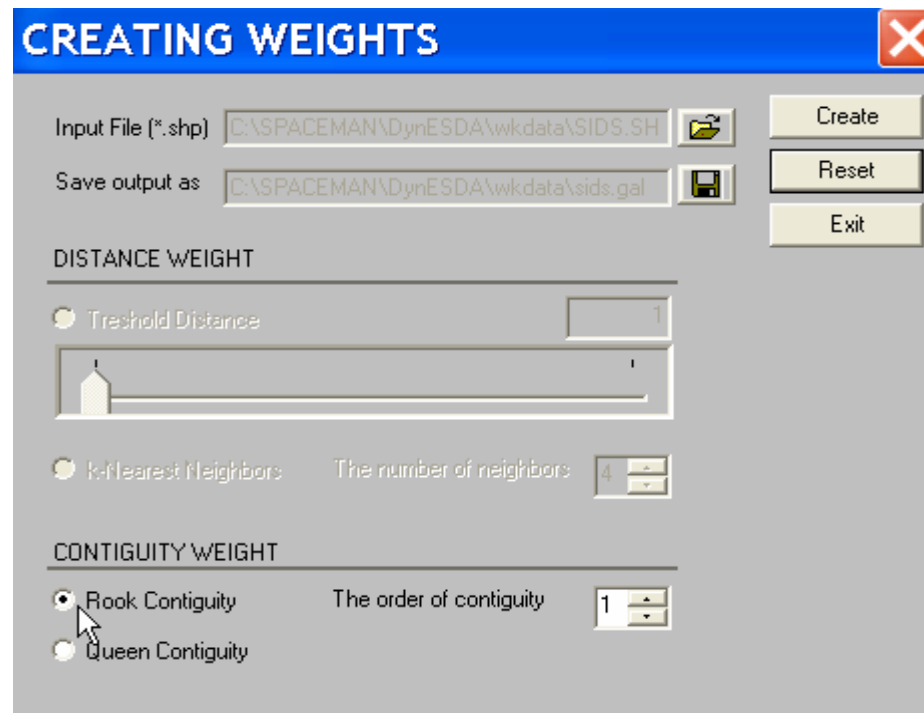
# Contiguity – Irregular Units

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- Irregular Units
  - common border
    - » rook
  - common vertex
    - » 039 and 067
    - » queen

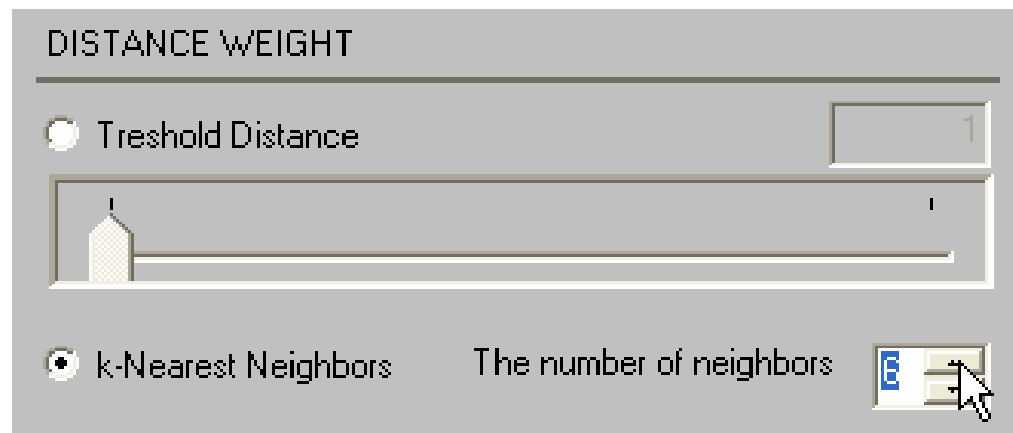
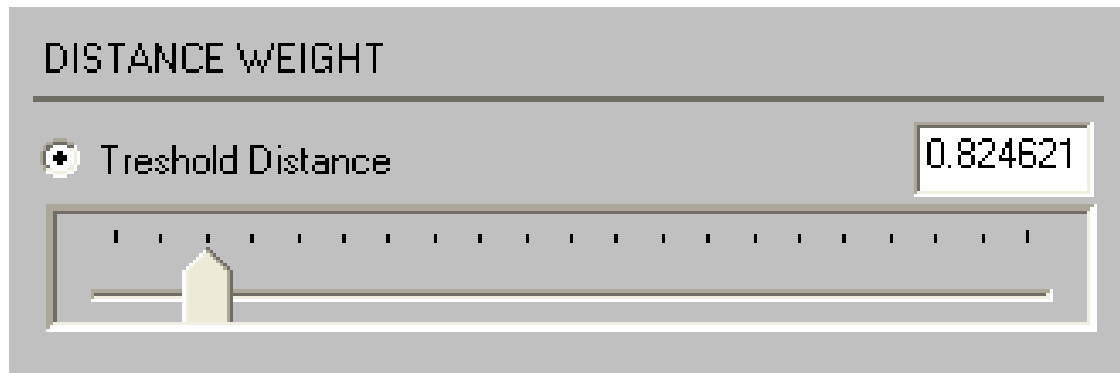


# Contiguity Weights in DynESDA2



# Distance Based Weights

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# General Spatial Weights

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## ➤ Cliff-Ord Weights

- $w_{ij}$  to reflect potential spatial interaction between  $i$  and  $j$

- $w_{ij} = [d_{ij}]^{-a} \cdot [b_{ij}]^b$

» with

$d_{ij}$  as distance between  $i$  and  $j$

$b_{ij}$  as share of common boundary between  $i$  and  $j$  in perimeter of  $i$

# General Spatial Weights

(continued)

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- Weights May Contain Parameters
  - inverse distance weights
    - »  $w_{ij} = 1 / d_{ij}^{\alpha}$
  - estimated from data or chosen a priori
    - » in practice: second power (gravity model)
  - identification problems in nonlinear weights
    - » interaction is multiplicative:  $\rho \cdot w_{ij} = \rho (1 / d_{ij}^{\alpha})$
    - » parameters  $\rho$  and  $\alpha$  not separately identified

# General Spatial Weights

(continued)

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- K-Nearest Neighbor Weights
  - k neighbors, irrespective of actual distance
  - “warps” space
- Economic Weights (Case)
  - block structure, state effect
    - »  $w_{ij} = 1$  for all  $i, j$  in “block”
  - economic distance  $|r_i - r_j|$ , weight =  $1/|r_i - r_j|$ 
    - » e.g.,  $r$  = total employment

# Row-Standardized Spatial Weights

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## ➤ Motivation

- averaging of neighboring values  
= form of **spatial smoothing**
- spatial parameters comparable

➤  $w_{ij}^s = w_{ij} / \sum_j w_{ij}$

➤  $\sum_j w_{ij}^s = 1$

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# Practical Issues

# Characteristics of Spatial Weights

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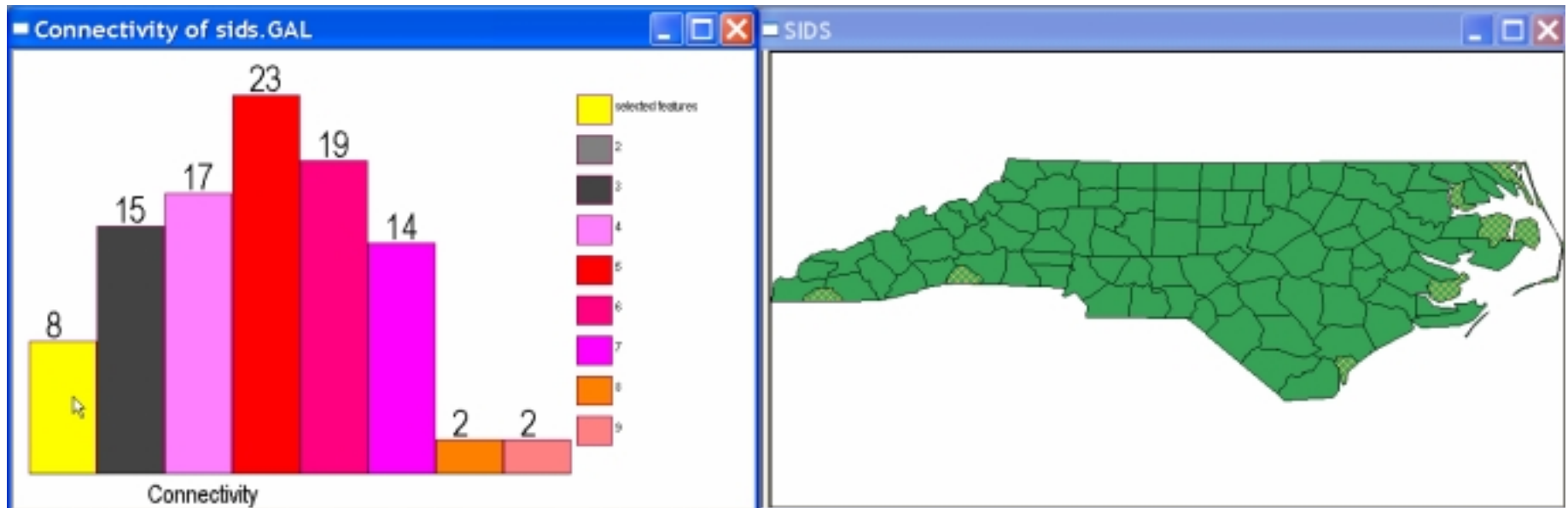
- Measures of Overall Connectedness
  - percent nonzero weights (sparseness)
  - average weight
  - average number of links
  - principal eigenvalue
- Location-Specific Measures
  - most/least connected observations
  - unconnected observations = **islands**

```
Connectivity characteristics of weights matrix wvhouse
Weights matrix stored in GAL format
Weights are row-standardized
Dimension:                55
# nonzero links:          248
% nonzero weights:        8.35017
Average weight:           0.221774
Average # links:          4.50909
With observations referred to by indicator variable FIPSNO
1 most connected observation(s) - with 8 link(s):
54039
2 least connected observation(s) - with 1 link(s):
54029 54037
```

```
Frequency Count for Weights File wvhouse
Connections      Frequency
```

|   |    |
|---|----|
| 1 | 2  |
| 2 | 6  |
| 3 | 7  |
| 4 | 10 |
| 5 | 14 |
| 6 | 10 |
| 7 | 5  |
| 8 | 1  |

# Weights Characteristics in DynESDA2



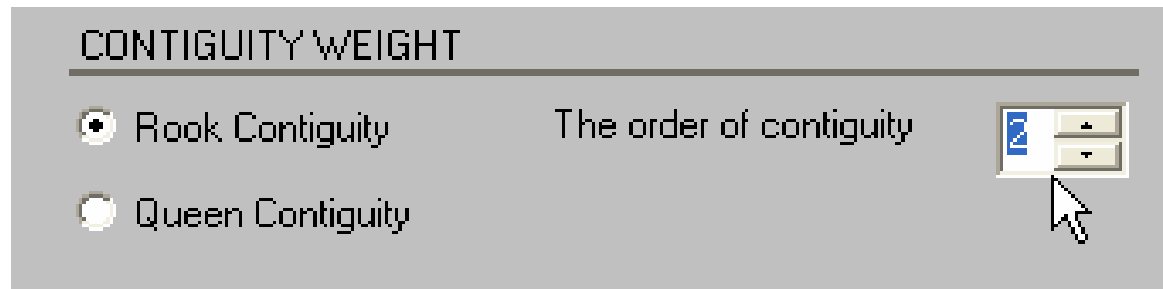
# Higher Order Contiguity

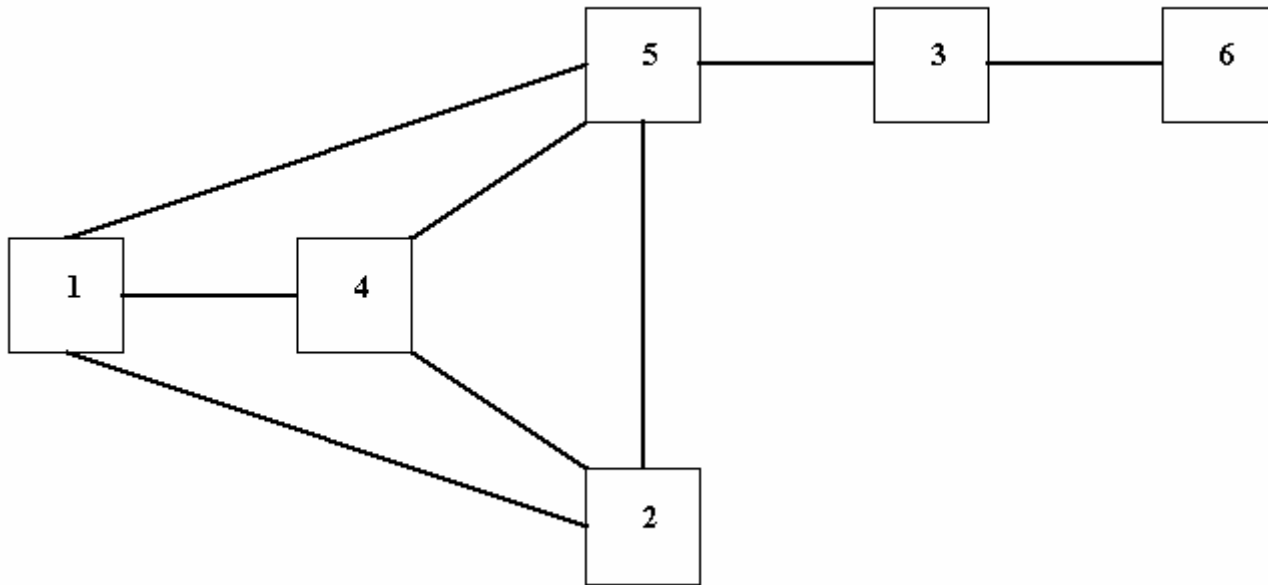
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## ➤ Recursive Definition

- contiguous of order  $k$  is **first order** contiguous to order  $k-1$ 
  - » 2<sup>nd</sup> is first order contiguous to first

## ➤ Remove Circularity and Redundancy





contiguity as a graph  
link between nodes = contiguity

# Circularity and Redundancy in Higher Order Weights

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- Powering of the Weights Matrix
  - standard approach invalid for contiguity
- Removing Circularity and Redundancy
  - sparse network representation of weights
  - modified Dijkstra algorithm to identify number of steps between nearest neighbors (Anselin and Smirnov)
  - number of steps = order of contiguity

|   |   |   |   |   |   |
|---|---|---|---|---|---|
| 0 | 1 | 0 | 1 | 1 | 0 |
| 1 | 0 | 0 | 1 | 1 | 0 |
| 0 | 0 | 0 | 0 | 1 | 1 |
| 1 | 1 | 0 | 0 | 1 | 0 |
| 1 | 1 | 1 | 1 | 0 | 0 |
| 0 | 0 | 1 | 0 | 0 | 0 |

First Order Contiguity Matrix

|   |   |   |   |   |   |
|---|---|---|---|---|---|
| 3 | 2 | 1 | 2 | 2 | 0 |
| 2 | 3 | 1 | 2 | 2 | 0 |
| 1 | 1 | 2 | 1 | 0 | 0 |
| 2 | 2 | 1 | 3 | 2 | 0 |
| 2 | 2 | 0 | 2 | 4 | 1 |
| 0 | 0 | 0 | 0 | 1 | 1 |

Second Power of First Order Contiguity

|   |   |   |   |   |   |
|---|---|---|---|---|---|
| 0 | 0 | 1 | 0 | 0 | 0 |
| 0 | 0 | 1 | 0 | 0 | 0 |
| 1 | 1 | 0 | 1 | 0 | 0 |
| 0 | 0 | 1 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 1 |
| 0 | 0 | 0 | 0 | 1 | 0 |

Correct Second Order Contiguity Matrix

|    |    |    |    |    |    |
|----|----|----|----|----|----|
| -1 | 1  | 2  | 1  | 1  | 3  |
| 1  | -1 | 2  | 1  | 1  | 3  |
| 2  | 2  | -1 | 2  | 1  | 1  |
| 1  | 1  | 2  | -1 | 1  | 3  |
| 1  | 1  | 1  | 1  | -1 | 2  |
| 3  | 3  | 1  | 3  | 2  | -1 |

Matrix Constructed by Bottom-Up Algorithm

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# Spatial Lag Operator

# Spatial Shift

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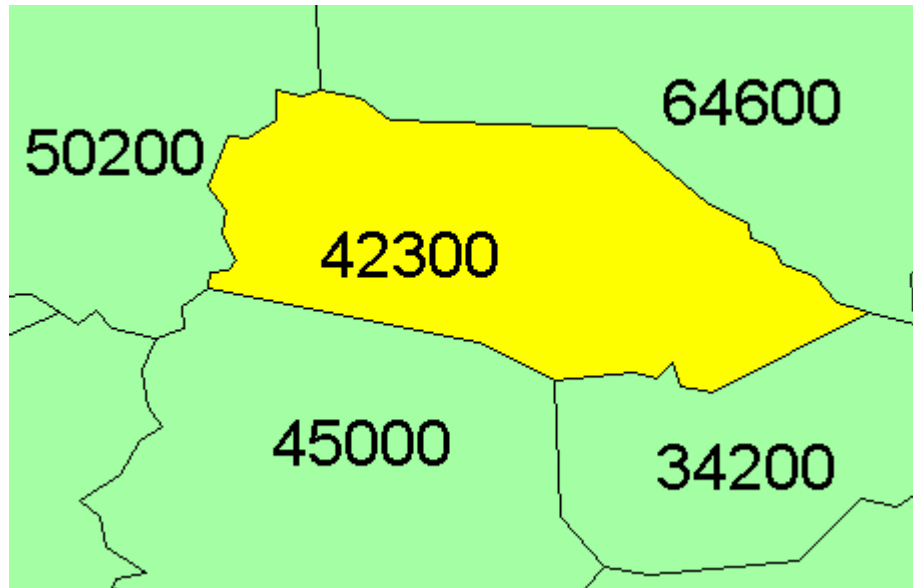
- No Direct Counterpart to Time Series Shift Operator
  - time series:  $L_k = y_{t-k}$
  - spatial series: which h are shifted by “k” from location i?
    - » on regular lattice: east, west, north, south
    - »  $(i - 1, j)$   $(i + 1, j)$   $(i, j - 1)$   $(i, j + 1)$
  - arbitrary for irregular lattice
    - » different number of neighbors by observation

# Spatial Lag Operator

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## ➤ Distributed Lag

- row-standardized weights  $\sum_j w_{ij} = 1$
- spatial lag is weighted average of neighboring values
  - »  $\sum_j w_{ij} \cdot y_j$ , for each  $i$
  - » vector  $Wy$
  - » spatial lag does not contain  $y_i$
- spatial lag is a smoother
  - » **not** a window average



value  $y_i = \$42,300$

4 neighbors

values for neighbors: \$50,200,  
\$64,600, \$45,000, \$34,200

spatial lag =  $(1/4)\$50,200 +$   
 $(1/4)\$64,600 + (1/4)\$45,000 +$   
 $(1/4)\$34,200 = \$48,500$

# Interpretation of Spatial Lag

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- **Linear Association = Spatial Autocorrelation**
  - comparison of value of  $y$  at  $i$  to average of values at neighboring locations
    - »  $y_i$  and  $(Wy)_i$  similar = **positive** spatial autocorrelation (**high-high, low-low**)
    - »  $y_i$  and  $(Wy)_i$  dissimilar = **negative** spatial autocorrelation (**low-high, high-low**)