SERGIO REY

GPH 483/598
Geographic Information Analysis
School of Geographical Sciences and Urban Planning
Arizona State University
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Outline

Concepts and Issues

Null and Alternative Hypotheses

Spatial Autocorrelation Tests



There is no question with respect to emergent geospatial science. The important harbingers were Geary's article on spatial autocorrelation, Dacey's paper about two- and K-color maps, and that of Bachi on geographic series.

- Berry, Griifth, Tiefelsdorf (2008)

Working Concept

- what happens at one place depends on events in nearby places
- all things are related but nearby things are more related than distant things (Tobler)

- impossible world
- impossible to describe
- impossible to live in
- hell is a place with no spatial dependence

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Categorizing

- Type: Substantive versus nuisance
- Direction: Positive versus negative

Issues

- Time versus space
- Inference

Process Based

- Part of the process under study
- Leaving it out

Incomplete understanding Riased inferences

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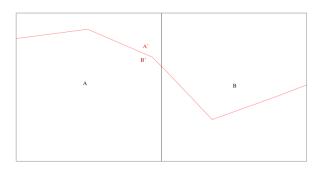
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Boundary



Boundary Mismatch



- Even if A and B are independent
- A' and B' will be dependent

Nusiance vs. Substantive Dependence

Issues

- Not always easy to differentiate from substantive
- Different implications for each type
- Specification strategies (Econometrics)
- Both can be operating jointly

Space versus Time

Temporal Dependence

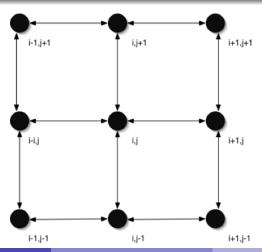
- Past influences the future
- Recursive
- One dimension



Space versus Time

Spatial Dependence

- Multi-directional
- Simultaneous



Terminology

Related Concepts

- Spatial Dependence
- Spatial Autocorrelation
- Spatial Association

Distributional Characteristic

- Multivariate density function
- difficult/impossible to verify empirically

Dependent Distribution

does not factor in marginal densities

Spatial Autocorrelation

- Auto = same variable
- Correlation = scaled covariance
- Spatial geographic pattern to the correlation

Spatial Autocorrelation

Measurement of Moment of Distribution

- off-diagonal elements of variance-covariance matrix
- autocovariance
- $C[y_i, y_j] \neq 0 \ \forall i \neq j$
- can be estimated

Spatial Autocorrelation Coefficient

significance test on coefficient = 0



Spatial Autocorrelation

Joint multivariate distribution function

$$f(y) = \frac{\exp\left[-\frac{1}{2}(y-\mu)'\Sigma^{-1}(y-\mu)\right]}{\sqrt{(2\pi)^n|\Sigma|}} \tag{1}$$



Variance-Covariance Matrix

$$\Sigma = \begin{bmatrix} \sigma_{1,1} & \sigma_{1,2} & \dots & \sigma_{1,n} \\ \sigma_{2,1} & \sigma_{2,2} & \dots & \sigma_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{n,1} & \sigma_{n,2} & \dots & \sigma_{n,n} \end{bmatrix}$$
(2)

- covariance: $\sigma_{i,j} = E[(y_i \mu_i)(y_j \mu_j)]$
- symmetry: $\sigma_{i,j} = \sigma_{i,j}$
- variance: $\sigma_{i,i} = E[(y_i \mu_i)(y_i \mu_i)]$



Correlation

$$\rho_{ij} = \frac{\sigma_{ij}}{\sqrt{\sigma_i^2} \sqrt{\sigma_j^2}}$$

$$-1.0 \le \rho_{ij} \le 1.0$$
(3)

$$-1.0 \le \rho_{ij} \le 1.0 \tag{4}$$



Data Types and Autocorrelation

Point Data

- focus on geometric pattern
- random vs. nonrandom
- clustered vs. uniform

Geostatistics

- 2-D modeling of spatial covariance (pairs of observations in function of distance)
- kriging, spatial prediction

Data Types and Autocorrelation

Lattice Data

- areal units: states, counties, census tracts, watersheds
- points: centroids of areal units
- focus on the spatial nonrandomness of attribute values

Spatial Association

Not a Rigorously Defined Term

- Usually the same as spatial autocorrelation
- often used in non-technical discussion
- avoid unless meaning is clear

Spatial Dependence

Good News (for geographers)

- Space matters
- Suggestive of underlying process

Bad news

- invalidates random sampling assumption
- necessitates new methods = spatial statistics and spatial econometrics

Spatial Dependence: Implications

The specific process we are simulating is as follows:

$$y = X\beta + \epsilon$$

$$\epsilon = \lambda W\epsilon + \nu$$
(5)

where $\nu^{\sim}N(0,\sigma^2I)$, λ is a spatial autocorrelation parameter (scalar) and W is a spatial weights matrix. We will shortly explain these new entities, but for now we simply note that they allow us to simulate a process whereby the ϵ 's, and therefore the y's are spatially autocorrelated. If $\lambda=0$ then the i.i.d. assumption holds, otherwise there is spatial dependence.

$$\beta = 40, \ \sigma^2 = 16, \ x = [1, 1, ...]$$

 $\lambda = [0.0, 0.25, 0.50, 0.75], \ n = 25$

Spatial Dependence: Implications

For each D.G.P. we are going to generate 500 samples of size n=25 for our map. You can think of this as generating 500 maps using the same D.G.P.. For each sample we will then do the following:

- Estimate μ with \bar{y}
- 2 Test the hypothesis that $\mu = 40$

Implications

Table: Monte Carlo Results

λ	0.00	0.25	0.50	0.75
$\hat{\mu}$	39.947	39.931	39.901	39.814
$\sigma_{ar{\textit{X}}}$	0.816	1.090	1.641	3.304
р	0.056	0.148	0.278	0.492

Spatial Randomness

Null Hypothesis

- observed spatial pattern of values is equally likely as any other spatial pattern
- values at one location do no depend on values at other (neighboring) locations
- under spatial randomness, the location of values may be altered without affecting the information content of the data

Spatial Autocorrelation on a Grid

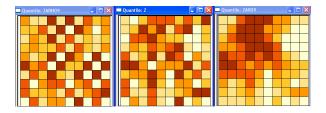


Figure: Negative, Random, Positive

Positive Spatial Autocorrelation

Clustering

• like values tend to be in similar locations

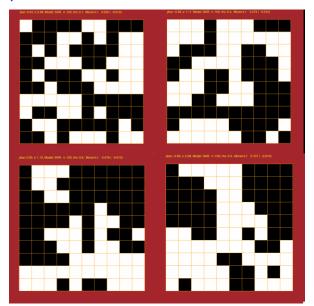
Neighbor similarity

more alike than they would be under spatial randomness

Compatible with Diffusion

• but not necessarily caused by diffusion

Positive Spatial Autocorrelation



Negative Spatial Autocorrelation

Checkerboard pattern

anti-clustering

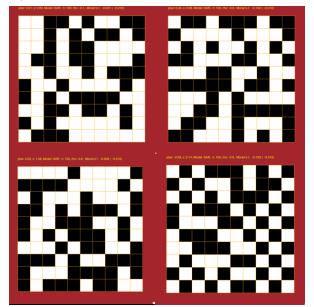
Neighbor dissimilarity

more dissimilar than they would be under spatial randomness

Compatible with Competition

but not necessarily caused by competition

Negative Spatial Autocorrelation



Autocorrelation and Diffusion

One does not necessarily imply the other

- diffusion tends to yield positive spatial autocorrelation but the reverse is not necessary
- positive spatial correlation may be due to structural factors, without contagion or diffusion

True vs. Apparent Contagion

What is the Cause behind the clustering?

- True contagion
 - result of a contagious process, social interaction, dynamic process
- Apparent contagion
 - spatial heterogeneity
 - stratification
- Cannot be distinguished in a pure cross section
- Equifinality or Identification Problem

Clustering

Global characeristic

- property of overall pattern = all observations
- are like values more grouped in space than random
- test by means of a global spatial autocorrelation statistic
- no location of the clusters determined

Clusters

Local characeristic

- where are the like values more grouped in space than random?
- property of local pattern = location-specific
- test by means of a local spatial autocorrelation statistic
- local clusters may be compatible with global spatial randomness

Spatial Autocorrelation Statistic

Structure

- Formal Test of Match between Value Similarity and Locational Similarity
- Statistic Summarizes Both Aspects
- Significance
 - how likely is it (p-value) that the computed statistic would take this (extreme) value in a spatially random pattern

Attribute Similarity

- Summary of the similarity or dissimilarity of a variable at different locations
 - variable y at locations i, j with $i \neq j$
- Measures of similarity
 - cross product: y_iy_i
- Measures of dissimilarity
 - squared differences: $(y_i y_i)^2$
 - ▶ absolute differences: $|y_i y_j|$

Locational Similarity

- Formalizing the notion of Neighbor
 - when two spatial units a-priori are likely to interact
- Spatial Weights
 - not necessarility geographical
 - many approaches

Summary

Spatial Dependence

- Core of Lattice Analysis
- Spatial Autocorrelation More Complex than Temporal Autocorrelation
- Combine Value and Locational Similarities