

Introduction to spatial statistics

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- Introduction – types of spatial data, exploratory data analysis
- Modeling univariate point referenced data – Gaussian Processes (GP), spatial regression, estimation, spatial prediction (kriging)
- Bayesian modeling – Metropolis Hastings, Gibbs sampler
- Large data – computing challenges, efficient alternatives
- Areal data – disease mapping

More about the course

- Materials available on <https://github.com/abhirupdatta/spatial-statistics-2018>
- Texts for reference:
 - (Main) Banerjee, S., Carlin, B. P., and Gelfand, A. E. (2014), Hierarchical Modeling and Analysis for Spatial Data, Boca Raton, FL: Chapman and Hall/CRC, 2nd ed (BCG)
 - Cressie, N. A. C. and Wikle, C. K. (2011), Statistics for spatio-temporal data, Hoboken, NJ: Wiley, Wiley Series in Probability and Statistics

What is spatial data?

- Any data with some geographical information

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 - have many important predictors and response variables
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- Any data with some geographical information
- Common sources of spatial data: climatology, forestry, ecology, environmental health, disease epidemiology, real estate marketing etc
 - have many important predictors and response variables
 - are often presented as maps
- Other examples where spatial need not refer to space on earth:
 - Neuroimaging (data for each voxel in the brain)
 - Genetics (position along a chromosome)

Types of spatial data

- Three broad categories

Types of spatial data

- Point-referenced data
 - Each observation is associated with a location (point)
 - Data represents a sample from a continuous spatial domain
 - Also referred to as *geocoded* or *geostatistical* data

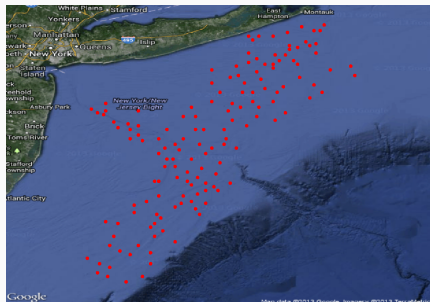


Figure: Locations of scallops abundance data

Types of spatial data

- Areal data
 - Each observation is associated with a region like state, county etc.
 - Usually a result of aggregating point level data

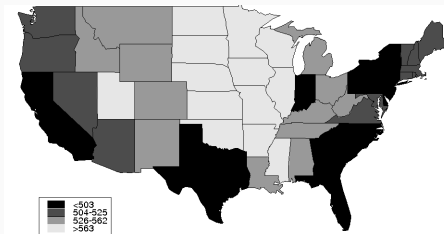


Figure: SAT scores across the 48 contiguous states in the US

Types of spatial data

- Point pattern data
 - The locations are viewed as “random”
 - Need not have variables at locations, just the pattern of points
 - Interest in the pattern of occurrences of an event like disease incidence, species distribution, crimes etc.

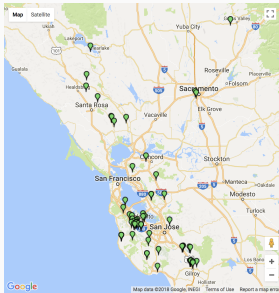


Figure: Locations of confirmed mountain lion sightings in the Bay area since 2004

Geostatistics – Analysis of point-referenced spatial data

- Each observation is associated with a location (point)
- Data represents a sample from a continuous spatial domain
- Also referred to as **geocoded** or **geostatistical** data

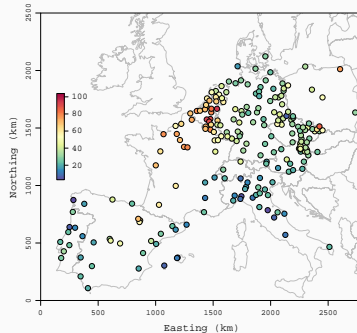


Figure: Pollutant levels in Europe in March, 2009

Point level modeling

- **Point-level modeling** refers to modeling of point-referenced data collected at locations referenced by **coordinates** (e.g., lat-long, Easting-Northing).
Euclidean space.
- **Example:** Data about pollution levels $Y(s_1), Y(s_2), \dots, Y(s_n)$ at sites s_1, s_2, \dots, s_n
- **Conceptually:** Pollutant level exists at all possible sites
- We can learn about $Y(s)$ for any s in the region based on this data !
- Key to achieve this is exploiting **structured dependence**

Exploratory data analysis (EDA): Plotting the data

- At each s_i we observe the response $y(s_i)$ and a $p \times 1$ vector of covariates $x(s_i)'$
- **Goals:** Identify **association** between y and x , **predict** $y(s)$ at any arbitrary s

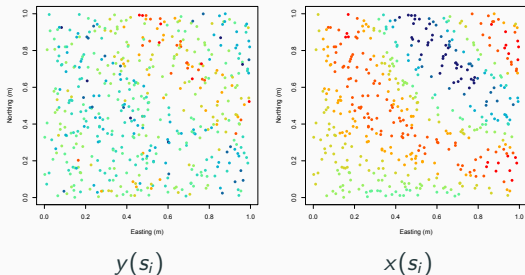


Figure: Response and covariate data for Dataset 1

Exploratory data analysis (EDA): Plotting the data

- At each s_i we observe the response $y(s_i)$ and a $p \times 1$ vector of covariates $x(s_i)'$
- **Goals:** Identify **association** between y and x , **predict** $y(s)$ at any arbitrary s
- **Surface plots** of the data often helps to better understand spatial patterns

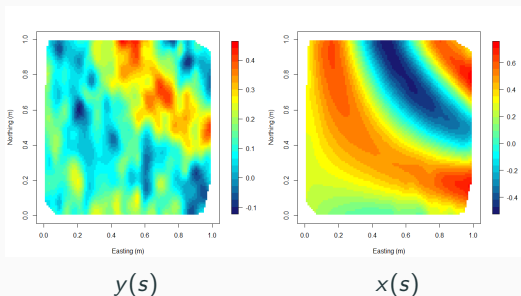


Figure: Response and covariate surface plots for Dataset 1

What's so special about spatial?

- Linear regression model: $y(s_i) = x(s_i)' \beta + \epsilon(s_i)$
- $\epsilon(s_i)$ are iid $N(0, \tau^2)$ errors
- $y = (y(s_1), y(s_2), \dots, y(s_n))'$; $X = (x(s_1)', x(s_2)', \dots, x(s_n'))'$
- Inference: $\hat{\beta} = (X'X)^{-1}X'Y \sim N(\beta, \tau^2(X'X)^{-1})$
- Prediction at new location s_0 : $\widehat{y(s_0)} = x(s_0)' \hat{\beta}$
- Although the data is spatial, this is an **ordinary linear regression** model

Residual plots

- Surface plots of the residuals ($y(s) - \widehat{y(s)}$) help to identify any spatial patterns left unexplained by the covariates

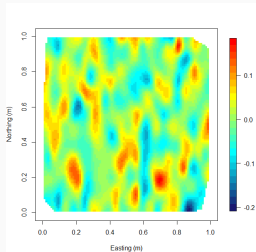


Figure: Residual plot for Dataset 1 after linear regression on $x(s)$

Residual plots

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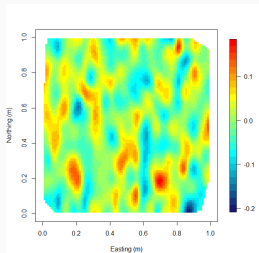
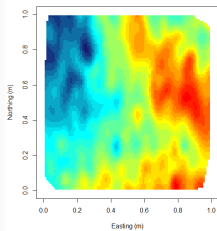


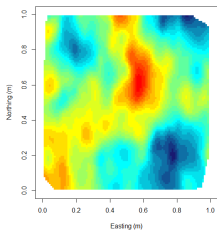
Figure: Residual plot for Dataset 1 after linear regression on $x(s)$

- No evident spatial pattern in plot of the residuals
- The covariate $x(s)$ seem to explain all spatial variation in $y(s)$
- Does a non-spatial regression model always suffice?

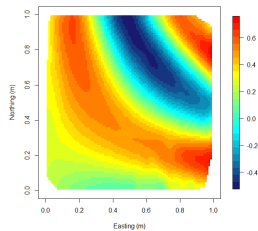
Two more datasets



Dataset 2: $y(s)$



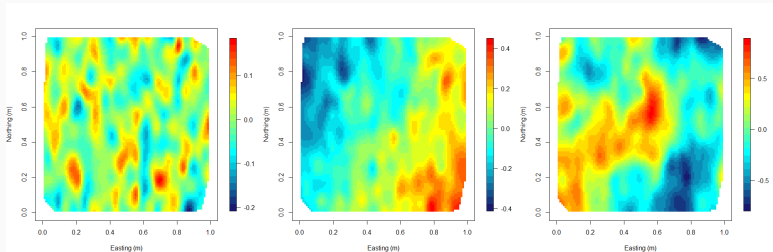
Dataset 3: $y(s)$



Same $x(s)$

Residual plots

- Linear regression: $y(\mathbf{s}_i) = \beta_0 + x(\mathbf{s}_i)\beta_1 + \epsilon(\mathbf{s}_i)$



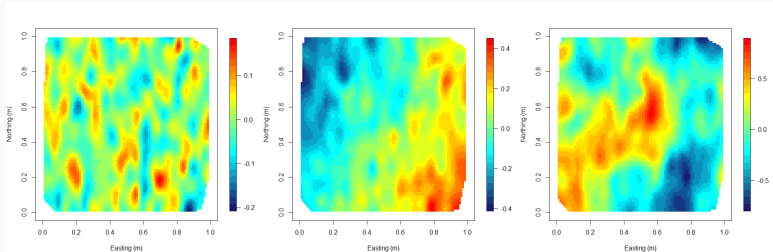
Dataset 1: $y(s)$

Dataset 2: $y(s)$

Dataset 3: $y(s)$

Residual plots

- Linear regression: $y(\mathbf{s}_i) = \beta_0 + x(\mathbf{s}_i)\beta_1 + \epsilon(\mathbf{s}_i)$



- Strong residual **spatial pattern** in datasets 2 and 3
- The covariate $x(\mathbf{s})$ does not explain all spatial variation in $y(\mathbf{s})$

- Besides eyeballing residual surfaces, how to do more formal EDA to identify spatial pattern ?

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First law of geography

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First law of geography

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- In general pairwise squared differences of the data should have higher values if the locations are far apart
- In other words: $(Y(s+h) - Y(s))^2$ should be roughly increasing with $||h||$ will imply a spatial correlation
- Can this be formalized to identify spatial pattern?

Empirical semivariogram

- **Binning:** Make intervals $I_1 = (0, m_1)$, $I_2 = (m_1, m_2)$, and so forth, up to $I_K = (m_{K-1}, m_K)$. Representing each interval by its midpoint t_k , we define:

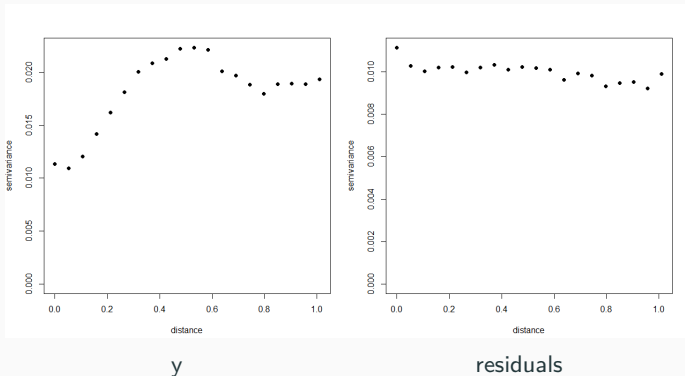
$$N(t_k) = \{(s_i, s_j) : \|s_i - s_j\| \in I_k\}, k = 1, \dots, K.$$

- **Empirical semivariogram:**

$$\gamma(t_k) = \frac{1}{2|N(t_k)|} \sum_{s_i, s_j \in N(t_k)} (Y(s_i) - Y(s_j))^2$$

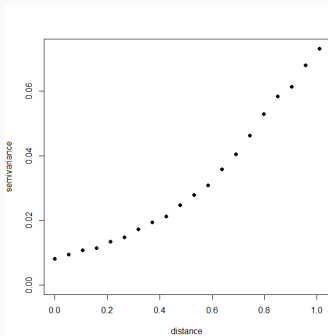
- For spatial data, the $\gamma(t_k)$ is expected to roughly increase with t_k
- A flat semivariogram would suggest little spatial variation

Empirical semivariogram: Data 1

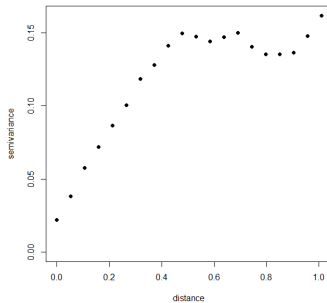


- *variog* command in the *geoR* package in R calculates empirical semivariograms
- Residuals display little spatial variation

Empirical semivariograms: Data 2 and 3



Data 2: residuals



Data 3: residuals

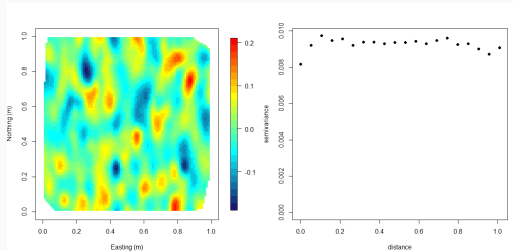
- Semivariograms of the residuals point to spatial variation

Using the locations

- When covariates does not explain all variation, one needs to leverage the information from the locations

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- When covariates does not explain all variation, one needs to leverage the information from the locations
- Linear regression with the **co-ordinates** added as regressors:
$$y(\mathbf{s}_i) = \beta_0 + x(\mathbf{s}_i)\beta_1 + s_{ix}\beta_2 + s_{iy}\beta_3 + \epsilon(\mathbf{s}_i)$$

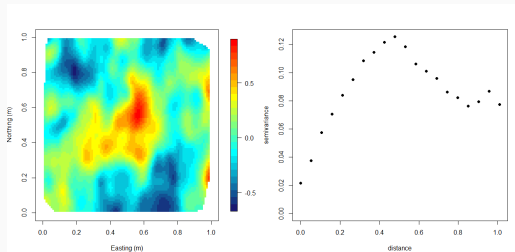


New residuals for data 2 Empirical semivariogram

- The linear model for the co-ordinates explains most of the spatial variation in dataset 2

Using the locations

- Linear regression with the co-ordinates added as regressors:
$$y(\mathbf{s}_i) = \beta_0 + x(\mathbf{s}_i)\beta_1 + s_{ix}\beta_2 + s_{iy}\beta_3 + \epsilon(\mathbf{s}_i)$$



Residuals for data 3 Empirical semivariogram

- Dataset 3 still exhibits strong spatial correlation

Modeling with the locations

- When purely covariate based models does not suffice, one needs to leverage the information from locations
- General model using the locations:
$$y(s) = x(s)' \beta + w(s) + \epsilon(s) \text{ for all } s \in D$$
- How to choose the function $w(\cdot)$?
- Since we want to predict at any location over the entire domain D , this choice will amount to choosing a **surface** $w(s)$
- How to do this ?

Gaussian Processes (GPs)

- One popular approach to **model** $w(s)$ is via Gaussian Processes (GP)
- The collection of random variables $\{w(s) \mid s \in D\}$ is a GP if
 - it is a **valid** stochastic process
 - all finite dimensional densities $\{w(s_1), \dots, w(s_n)\}$ follow multivariate Gaussian distribution
- A GP is completely characterized by a mean function $m(s)$ and a covariance function $C(\cdot, \cdot)$
- **Advantage:** **Likelihood** based inference.
 $w = (w(s_1), \dots, w(s_n))' \sim N(m, C)$ where
 $m = (m(s_1), \dots, m(s_n))'$ and $C = C(s_i, s_j)$

Valid covariance functions and isotropy

- $C(\cdot, \cdot)$ needs to be **valid**. For all n and all $\{s_1, s_2, \dots, s_n\}$, the resulting covariance matrix $C(s_i, s_j)$ for $(w(s_1), w(s_2), \dots, w(s_n))$ must be positive definite
- So, $C(\cdot, \cdot)$ needs to be a **positive definite** function
- Simplifying assumptions:
 - **Stationarity**: $C(s_1, s_2)$ only depends on $h = s_1 - s_2$ (and is denoted by $C(h)$)
 - **Isotropic**: $C(h) = C(\|h\|)$
 - **Anisotropic**: Stationary but not isotropic
- Isotropic models are popular because of their **simplicity**, **interpretability**, and because a number of relatively **simple parametric forms** are available as candidates for C .

Some common isotropic covariance functions

Model	Covariance function, $C(t) = C(h)$
Spherical	$C(t) = \begin{cases} 0 & \text{if } t \geq 1/\phi \\ \sigma^2 \left[1 - \frac{3}{2}\phi t + \frac{1}{2}(\phi t)^3 \right] & \text{if } 0 < t \leq 1/\phi \\ \tau^2 + \sigma^2 & \text{otherwise} \end{cases}$
Exponential	$C(t) = \begin{cases} \sigma^2 \exp(-\phi t) & \text{if } t > 0 \\ \tau^2 + \sigma^2 & \text{otherwise} \end{cases}$
Powered exponential	$C(t) = \begin{cases} \sigma^2 \exp(- \phi t ^p) & \text{if } t > 0 \\ \tau^2 + \sigma^2 & \text{otherwise} \end{cases}$
Matérn at $\nu = 3/2$	$C(t) = \begin{cases} \sigma^2 (1 + \phi t) \exp(-\phi t) & \text{if } t > 0 \\ \tau^2 + \sigma^2 & \text{otherwise} \end{cases}$

Notes on exponential model

$$C(t) = \begin{cases} \tau^2 + \sigma^2 & \text{if } t = 0 \\ \sigma^2 \exp(-\phi t) & \text{if } t > 0 \end{cases}.$$

- We define the **effective range**, t_0 , as the distance at which this correlation has dropped to only 0.05. Setting $\exp(-\phi t_0)$ equal to this value we obtain $t_0 \approx 3/\phi$, since $\log(0.05) \approx -3$.
- The **nugget** τ^2 is often viewed as a “**nonspatial effect variance**,”
- The **partial sill** (σ^2) is viewed as a “**spatial effect variance**.”
- $\sigma^2 + \tau^2$ gives the maximum total variance often referred to as the **sill**
- Note **discontinuity** at 0 due to the nugget. **Intentional!** To account for measurement error or micro-scale variability.

Covariance functions and semivariograms

- **Recall:** Empirical semivariogram:

$$\gamma(t_k) = \frac{1}{2|N(t_k)|} \sum_{s_i, s_j \in N(t_k)} (Y(s_i) - Y(s_j))^2$$

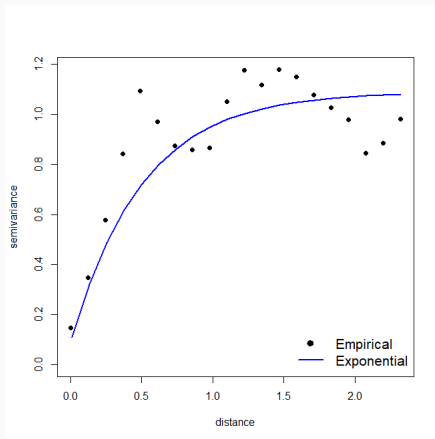
- For any stationary GP,

$$E(Y(s+h) - Y(s))^2/2 = C(0) - C(h) = \gamma(h)$$

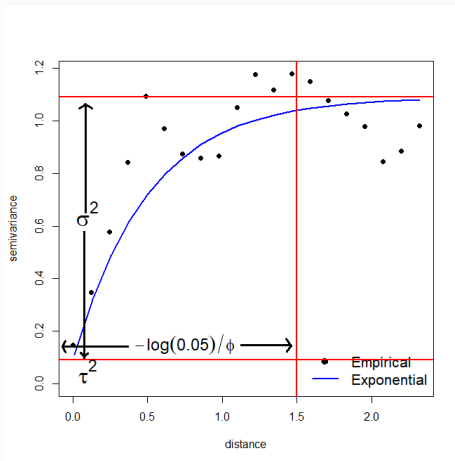
- $\gamma(h)$ is the **semivariogram** corresponding to the covariance function $C(h)$
- **Example:** For exponential GP,

$$\gamma(t) = \begin{cases} \tau^2 + \sigma^2(1 - \exp(-\phi t)) & \text{if } t > 0 \\ 0 & \text{if } t = 0 \end{cases}, \text{ where } t = \|h\|$$

Covariance functions and semivariograms



Covariance functions and semivariograms



Summary

- Geostatistics – Analysis of point-referenced spatial data
- Surface plots of data and residuals
- EDA with empirical semivariograms
- Modeling unknown surfaces with Gaussian Processes
- Relationship between covariance functions and variograms