Local variable selection and parameter estimation for spatially varying coefficient models

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January 16, 2014

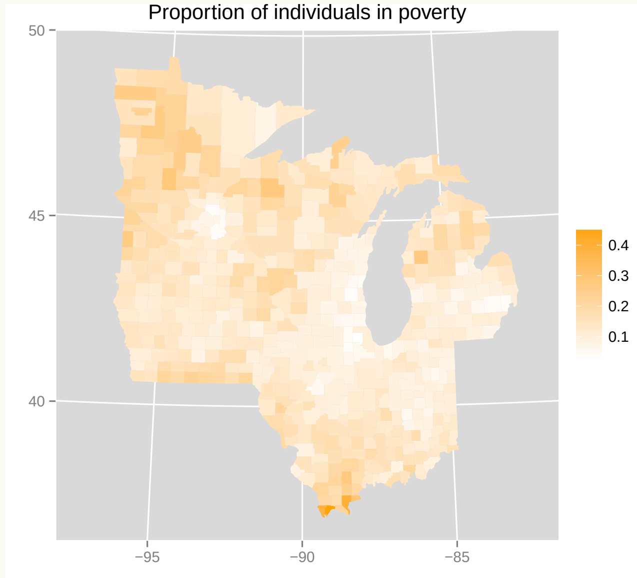
These slides were prepared for a practice version of my preliminary exam to advance to Ph.D candidacy in statistics at the University of Wisconsin–Madison.

Motivation

New Section

Motivation

Response variable

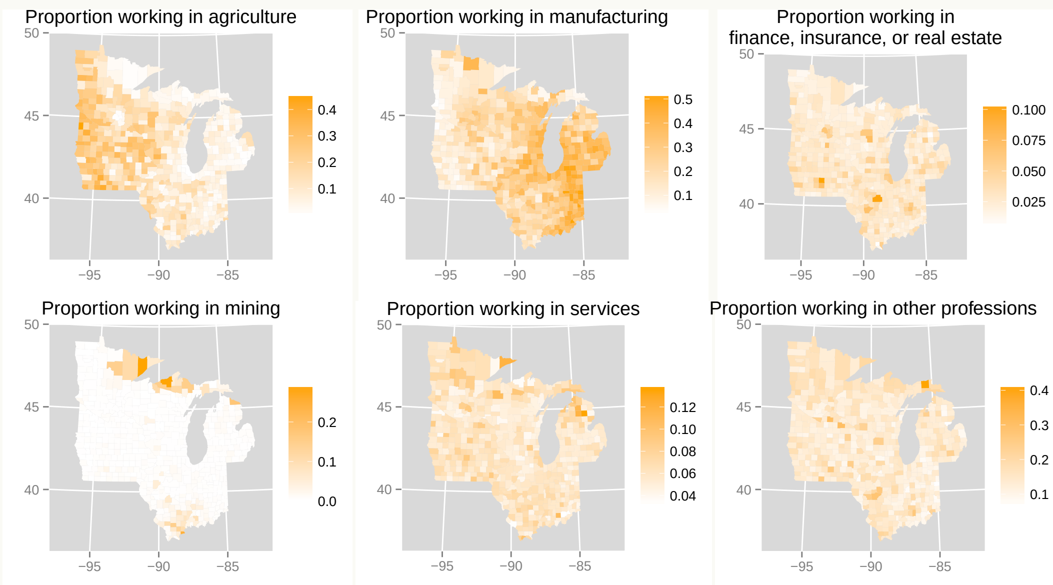


This is the county-level poverty rate in the upper midwestern states from the US census in 1970

and...

Motivation

Covariates



Here we have the proportion of people in each county who worked in agriculture, manufacturing, finance, mining, services, and other professions in 1970.

We want to understand how the poverty rate is related to these variables that describe the economic structure.

Motivation

Scientific questions

- Which of the economic-structure variables is associated with poverty rate?
- What are the sign and magnitude of that association?
- Is poverty rate associated with the same economic-structure variables across the entire region?
- How do the sign and magnitude of the associations vary across the region?

These are some sensible questions to ask about the county-level poverty rate. The work I'm presenting today attempts to answer these questions.

Which of the economic-structure variables is associated with poverty rate?

What are the sign and magnitude of that association?

Is poverty rate associated with the same economic-structure variables across the entire region?

How do the sign and magnitude of the associations vary across the region?

There are several other methods to answer at least some of these questions, which we'll cover next.

Introduction

New Section

Introduction

An overview

- Spatial regression
- Varying coefficient regression
  - Splines
  - Kernels
  - Wavelets
- Model selection via regularization

The existing methods to address the questions draw from these areas. Behind the methodology that I'm discussing is a wide range of literature.

Introduction

Definitions

- Univariate spatial response process $\{Y(\boldsymbol{s}) : \boldsymbol{s} \in \mathcal{D}\}$
- Multivariate spatial covariate process $\{\boldsymbol{X}(\boldsymbol{s}) : \boldsymbol{s} \in \mathcal{D}\}$
- $n =$ number of observations
- $p =$ number of covariates
- Location (2-dimensional) $\boldsymbol{s}$
- Spatial domain $\mathcal{D}$

We'll use these variables throughout.

Introduction

Spatial linear regression (Cressie, 1993)

- A typical spatial linear regression model

$$Y(\boldsymbol{s}) = \boldsymbol{X}(\boldsymbol{s})'\boldsymbol{\beta} + W(\boldsymbol{s}) + \varepsilon(\boldsymbol{s})$$

- $W(\boldsymbol{s})$ is a spatial random effect that accounts for autocorrelation in the response variable
- $\varepsilon(\boldsymbol{s})$ is iid random noise
- The coefficients $\boldsymbol{\beta} = (1, \beta_1, \ldots, \beta_p)$ are constant
- Requires *a priori* global variable selection

Here we have the usual spatial regression as described by Noel Cressie in his 1993 book.

This model assumes that the model coefficients are constant across the spatial domain and that the residuals can be separated into:

- The spatial random effect W that captures autocorrelation of the response, and

- epsilon, which is iid white noise

This model relies on a priori global variable selection.

Introduction

Spatially varying coefficient model (Gelfand *et al.*, 2003)

- A more flexible model: coefficients in a spatial regression model can vary

$$Y(\boldsymbol{s}) = \boldsymbol{X}(\boldsymbol{s})'\boldsymbol{\beta}(\boldsymbol{s}) + \varepsilon(\boldsymbol{s})$$

- $\{\beta_0(\boldsymbol{s}) : \boldsymbol{s} \in \mathcal{D}\}, \ldots, \{\beta_p(\boldsymbol{s}) : \boldsymbol{s} \in \mathcal{D}\}$ are stationary spatial processes
- Requires *a priori* global variable selection

The spatial regression model can be made more flexible by representing the coefficients as stationary spatial processes, rather than constants. The method was introduced by Gelfand in 2003.

The random effect W from the previous slide is now incorporated in the spatially varying intercept process.

This model also relies on a priori global variable selection.

Introduction

Varying coefficients regression (VCR) (Hastie and Tibshirani, 1993)

$$Y(\boldsymbol{s}) = \boldsymbol{X}(\boldsymbol{s})'\boldsymbol{\beta}(\boldsymbol{s}) + \varepsilon(\boldsymbol{s})$$

- Assume an effect modifying variable $\boldsymbol{s}$
- Coefficients are functions of $\boldsymbol{s}$

The varying coefficient regression model was described by Hastie and Tibshirani in 1993. The form of this model looks like the spatially varying coefficient process, but this model is more general because the coefficients are not necessarily spatial processes in this model.

In fact, the effect-modifying variable s does not necessarily need to represent spatial location.

Introduction

Spline-based VCR models (Wood, 2006)

- Splines are a way to parameterize smooth functions
- Estimate the varying coefficients via splines:

$$E\{Y(\boldsymbol{s})\} = \beta_1(\boldsymbol{s})X_1(\boldsymbol{s}) + \cdots + \beta_p(\boldsymbol{s})X_p(\boldsymbol{s})$$

Splines are a method of parameterizing smooth functions and it is possible to use splines to represent the coefficients in a varying coefficient regression model. There is a good overview of this topic in in Simon Wood's 2006 book.

Introduction

Global selection in spline-based VCR models

Regularization methods for global variable selection in VCR models:

- The $\mathcal{L}_2$ norm of a function (e.g. $\int \{f(t)\}^2 dt$) is zero if and only if the function is zero everywhere.
- Use regularization to encourage coefficient functions to be zero
  - SCAD penalty (Wang *et al.*, 2008a)
  - Non-negative garrote penalty (Antoniadis *et al.*, 2012b)

There are at least two references that describe how to select the covariates for a spline-based VCR model. Both use a similar regularization technique.

The regularization penalizes the smooth coefficient function for being non-zero. Antoniadis et al. used a non-negative garrote penalty and Wang et al. used a SCAD penalty.

These selection methods are global - that is, they select variables for the entire domain simultaneously.

Introduction

Wavelet methods for VCR models

- Wavelet methods: decompose coefficient function into local frequency components
- Selection of nonzero local frequency components with nonzero coefficients:
  - Bayesian variable selection (Shang, 2011)
  - Lasso (Zhang and Clayton, 2011)
- Sparsity in the local frequency components; not in the local covariates

Another way to fit a VCR model is to use a wavelet decomposition, which decomposes the coefficient function into its local frequency components. Model selection is then used to identify which local frequency components to use in the model.

Murray Clayton's students Zuofeng Shang and Jun Zhang used Bayesian variable selection and the Lasso, respectively, to select the local frequency components.

However, these methods achieve sparsity in the wavelet coefficients, which does not imply sparsity in the covariates. So these methods don't achieve local variable selection.

Now let's take a look at geographically weighted regression.

Geographically weighted regression

New Section

Geographically weighted regression

Brundson *et al.* (1998), Fotheringham *et al.* (2002)

- Consider observations at sampling locations $\boldsymbol{s}_1, \ldots, \boldsymbol{s}_n$
- $y(\boldsymbol{s}_i) = y_i$ the univariate response at location $\boldsymbol{s}_i$
- $\boldsymbol{x}(\boldsymbol{s}_i) = \boldsymbol{x}_i$ the $(p+1)$-variate vector of covariates at location $\boldsymbol{s}_i$
- Assume $y_i = \boldsymbol{x}_i' \boldsymbol{\beta}_i + \varepsilon_i$ where $\varepsilon_i \overset{iid}{\sim} \mathcal{N}(0, \sigma^2)$

Geographically weighted regression is the method of using local regression to estimate the coefficients in a spatially varying coefficient regression model.

Our sampling locations are called s, the response is y and the covariates (which number p) are called x.

Assume that the errors are iid normal.

The notation β_i is used to indicate that he coefficients are specific to location i.

Geographically weighted regression

Brundson *et al.* (1998), Fotheringham *et al.* (2002)

- The total log likelihood is

$$\ell(\boldsymbol{\beta}) = -(1/2)\left\{ n \log\left(2\pi\sigma^2\right) + \sigma^{-2}\sum_{i=1}^{n}\left(y_i - \boldsymbol{x}_i'\boldsymbol{\beta}_i\right)^2 \right\}$$

- With n observations and $np+1$ parameters, the model is not identifiable.
- Idea: to estimate parameters by borrowing strength from nearby observations

We have here the total log likelihood of the observed data.

Because each β_i is a p-vector of local coefficients, this model has n observations and np+1 parameters, so the model is not identifiable.

We will estimate the parameters by borrowing strength from nearby observations

Geographically weighted regression

Local regression (Loader, 1999)

Local regression uses a kernel function at each sampling location to weight observations based on their distance from the sampling location.

$$\mathcal{L}_i = \prod_{i'=1}^{n} \left(\mathcal{L}_{i'}\right)^{w_{ii'}}$$

$$\ell_i = \sum_{i'=1}^{n} w_{ii'} \left\{ \log\left(\sigma^2\right) + \sigma^{-2}\left(y_{i'} - \boldsymbol{x}'_{i'}\boldsymbol{\beta}_i\right)^2 \right\}$$

Given the weights, a local model is fit at each sampling location using the local likelihood

Local regression uses a kernel function at each sampling location to weight the observations. For a GWR model, the kernel weights are based on an observation's distance from the sampling location.

Here we have the likelihood at one sampling location. Note that each observation is given a weight $w_{ii'}$

Given the weights, a local model is fit at each sampling location using the local likelihood

Maximizing the local likelihood for a model of Gaussian data with iid errors can be done by weighted least squares.

Geographically weighted regression

Local likelihood (Loader, 1999)

Weights are calculated via a kernel, e.g. the bisquare kernel:

$$w_{ii'} = \begin{cases} \left\{1 - \left(\phi^{-1}\delta_{ii'}\right)^2\right\}^2 & \text{if } \delta_{ii'} < \phi, \\ 0 & \text{if } \delta_{ii'} \geq \phi \end{cases} \tag{1}$$

where

- ϕ is a bandwidth parameter
- $\delta_{ii'} = \delta(\boldsymbol{s}_i, \boldsymbol{s}_{i'}) = \|\boldsymbol{s}_i - \boldsymbol{s}_{i'}\|_2$ is the Euclidean distance between sampling locations $\boldsymbol{s}_i$ and $\boldsymbol{s}_{i'}$.

The local weights $w_{ii'}$ from the previous slide are calculated from a kernel.

This is the form of the bisquare kernel, which is what I've used in this work.

ϕ is a bandwidth parameter and $\delta_{ii'}$ is the distance between points i and i'.

Geographically weighted regression

Bandwidth estimation via the AIC_c (Hurvich *et al.*, 1998)

- Smaller bandwidth: less bias, more flexible coefficient surface
- Large bandwidth: less variance, less flexible coefficient surface
- Choose the bandwidth parameter to optimize the bias-variance tradeoff

To estimate a GWR model, it is necessary to estimate the bandwidth parameter, which involves a bias-variance tradeoff.

When the bandwidth is small, the coefficient surface is flexible and should have less bias but greater variance.

When the bandwidth is large, the coefficient surface is less flexible so it has less variance but potentially more bias.

Geographically weighted regression

Bandwidth estimation via the AIC$_c$ (Hurvich *et al.*, 1998)

- The corrected AIC for bandwidth selection is:

$$\text{AIC}_c = 2n \log \sigma + n \left\{ \frac{n + \nu}{n - 2 - \nu} \right\}$$

  - $\hat{\boldsymbol{y}} = \boldsymbol{H}\boldsymbol{y}$
  - $\nu = \text{tr}(\boldsymbol{H})$
  - $\boldsymbol{H}_j = \left\{ \boldsymbol{W}\boldsymbol{X}(\boldsymbol{X}'\boldsymbol{W}\boldsymbol{X})^{-1}\boldsymbol{X} \right\}_j$
  - Where subscript j indicates the jth row of the matrix

One way to estimate the GWR bandwidth is via the corrected AIC of Hurvich et al..

Geographically weighted regression

Bandwidth estimation via GCV (Wahba, 1990)

- The GCV criterion for bandwidth selection is:

$$\text{GCV} = \frac{\sum_{i=1}^{n} \left(y_i - \hat{y}_i\right)^2}{(n-\nu)^2}$$

  - $\hat{\boldsymbol{y}} = \boldsymbol{H}\boldsymbol{y}$
  - $\nu = \text{tr}(\boldsymbol{H})$
  - $\boldsymbol{H}_j = \left\{\boldsymbol{W}\boldsymbol{X}(\boldsymbol{X}'\boldsymbol{W}\boldsymbol{X})^{-1}\boldsymbol{X}\right\}_j$
  - Where subscript j indicates the jth row of the matrix

Another way to estimate the GWR bandwidth is via Generalized Cross Validation as described in Wahba, 1990.

Local variable selection and parameter estimation

New Section

Geographically weighted Lasso

Geographically weighted Lasso (Wheeler, 2009)

Within a GWR model, using the Lasso for local variable selection is called the geographically weighted Lasso (GWL).

- The GWL requires estimating a Lasso tuning parameter for each local model
- Wheeler (2009) estimates the local Lasso tuning parameter at location s_i by minimizing a jacknife criterion: $|y_i - \hat{y}_i^{(i)}|$
- The jacknife criterion can only be calculated where data are observed, making it impossible to use the GWL to impute missing data or to estimate the value of the coefficient surface at new locations
- Also, the Lasso is known to be biased in variable selection and suboptimal for coefficient estimation

For local variable selection in a GWR model, Wheeler proposed the geographically weighted lasso (GWL) in 2009.

At each model location, the Lasso is used to select the locally-relevant predictors

The GWL uses a jacknife criterion to select the local lasso tuning parameters, which means the GWL cannot be used at model locations other than sample locations.

That means the GWL cannot be used for interpolating the coefficient surface or for imputing missing values of the response variable.

Local variable selection and parameter estimation

Geographically weighted adaptive elastic net (GWEN)

- Local variable selection in a GWR model using the adaptive elastic net (AEN) (Zou and Zhang, 2009)

$$\begin{aligned}\mathcal{S}(\boldsymbol{\beta}_i) &= -2\ell_i(\boldsymbol{\beta}_i) + \mathcal{J}_2(\boldsymbol{\beta}_i)\\ &= \sum_{i'=1}^{n} w_{ii'} \left\{\log \sigma_i^2 + \left(\sigma_i^2\right)^{-1} \left(y_{i'} - \boldsymbol{x}_{i'}'\boldsymbol{\beta}_i\right)^2\right\}\\ &+ \alpha_i \lambda_i^* \sum_{j=1}^{p} |\beta_{ij}|/\gamma_{ij}\\ &+ (1-\alpha_i)\lambda_i^* \sum_{j=1}^{p} \left(\beta_{ij}/\gamma_{ij}\right)^2\end{aligned}$$

The geographically weighted adaptive elastic net (GWEN) overcomes these shortcomings of the GWL.

The adaptive elastic net consists of applying a different penalty to each covariate based on the adaptive weights, which are derived from traditional GWR's weighted least squares coefficients.

S here is the penalized likelihood for a local GWEN model

The adaptive weights $\boldsymbol{\gamma}_i = (\gamma_{i1}, \ldots, \gamma_{ip})'$ are defined in the same way as for the AL, and the elastic net parameter $\alpha_i \in [0, 1]$ controls the balance between ℓ_1 penalty $\lambda_i^* \sum_{j=1}^{p} |\beta_{ij}|/\gamma_{ij}$ and ℓ_2 penalty $\lambda_i^* \sum_{j=1}^{p} \left(\beta_{ij}/\gamma_{ij}\right)^2$.

Local variable selection and parameter estimation

Geographically weighted adaptive elastic net (GWEN)

- The AEN penalty function is

$$\mathcal{J}_2(\boldsymbol{\beta}_i) = \alpha_i \lambda_i^* \sum_{j=1}^{p} |\beta_{ij}|/\gamma_{ij} + (1-\alpha_i)\lambda_i^* \sum_{j=1}^{p} \left(\beta_{ij}/\gamma_{ij}\right)^2$$

- Under suitable conditions, the AEN has an oracle property for selection in linear regression

The GWEN uses the adaptive elastic net for variable selection, which has an oracle property under suitable conditions.

The adaptive elastic net consists of adding an L2 penalty to the regularization in addition to the L1 penalty of the adaptive lasso.

The geographically weighted adaptive lasso (GWAL) is a particular case of the GWEN, with no ℓ_2 penalty it uses the adaptive lasso for variable selection, which also has an oracle property under suitable conditions.

Local variable selection and parameter estimation

Tuning parameter estimation

To estimate an AEN tuning parameter for each local model, use a local BIC that allows fitting a local model at any location within the spatial domain

$$\begin{aligned}\mathsf{BIC}_i &= -2\sum_{i'=1}^{n} \ell_{ii'} + \log\left(\sum_{i'=1}^{n} w_{ii'}\right)\mathsf{df}_i \\ &= \sum_{i'=1}^{n} w_{ii'}\left\{\log(2\pi) + \log\left(\hat{\sigma}_i^2\right) + \hat{\sigma}_i^{-2}\left(y_{i'} - \boldsymbol{x}'_{i'}\hat{\boldsymbol{\beta}}_{i'}\right)^2\right\} \\ &+ \log\left(\sum_{i'=1}^{n} w_{ii'}\right)\mathsf{df}_i\end{aligned}$$

Variable selection via the adaptive elastic net requires selecting the tuning parameter λ. For the GWEN, λ is selected by the BIC.

We treat the sum of the weights around the sampling location as the number of observations for the local BIC.

This BIC can be computed for a model at any location within the domain, allowing the GWEN to be used for imputing missing data or interpolating a model between observation locations.

Local variable selection and parameter estimation

Bandwidth parameter estimation

- Traditional GWR:
  - $\hat{\boldsymbol{y}} = \boldsymbol{H}\boldsymbol{y}$
  - So traditional GWR is a linear smoother
  - $\nu = \text{tr}(\boldsymbol{H})$ is the degrees of freedom for the model
- GWEN:
  - $\hat{\boldsymbol{y}} = \boldsymbol{H}^*\boldsymbol{y} + \boldsymbol{T}^*\gamma$
- GWEN is not a linear smoother
  - There is no projection matrix for GWEN so the degrees of freedom cannot be estimated by the trace of the projection matrix.
- Solution: use GWEN for selection then fit local model for the selected variables via traditional GWR
  - Now df $= \nu = \text{tr}(\boldsymbol{H})$

As in the case of traditional GWR, it is necessary to estimate the bandwidth parameter for a GWEN model.

We for traditional GWR we can use the corrected AIC or generalized cross validation. Both methods use the the trace of the projection matrix as the degrees of freedom for the model.

Because it incorporates an $\mathcal{L}_1$ penalty, the adaptive elastic net is not a linear smoother and so there is no projection matrix for a GWEN model.

For this reason, the GWEN is used for local variable selection and the coefficients of the resulting local model are fit using weighted least squares, as in traditional GWR.

Local variable selection and parameter estimation

Locally linear coefficient estimation

- GWR, GWEN, GWAL: coefficients locally constant
  - as in Nadaraya-Watson kernel smoother
  - Leads to bias where there is a gradient at the boundary
- Solution: local polynomial modeling
  - First-order polynomial: locally linear coefficients
- Augment with covariate-by-location interactions
  - Two-dimensional
  - Augment with selected covariates only

The traditional GWR fits models with locally constant coefficients, and can be thought of as a Nadaraya-Watson kernel smoother for the regression coefficients. Such a smoother is known to exhibit a "boundary effect", meaning that the smoother produces estimates that are biased near the boundary of the domain, especially when there is a gradient at the boundary.

To reduce the boundary effect, the GWEN and GWAL can be fit with coefficient estimates that are locally linear, rather than locally constant. This is done after variable selection by augmenting the selected covariates with covariate-by-coordinate interactions.

The interactions are on both the x and y coordinates, so each covariate that is selected for the model will appear three times in the model.

Simulation study

New Section

Simulation study

Simulating covariates

- 30×30 grid on $[0,1] \times [0,1]$
- Five covariates $\tilde{X}_1, \ldots, \tilde{X}_5$
- Gaussian random fields:

$$\tilde{X}_j \sim N(0, \mathbf{\Sigma}) \text{ for } j = 1, \ldots, 5$$
$$\{\Sigma\}_{i,i'} = \exp\{-\tau^{-1}\delta_{ii'}\} \text{ for } i, i' = 1, \ldots, n$$

- Colinearity: ρ
  - none ($\rho = 0$)
  - moderate ($\rho = 0.5$)

In order to assess the utility of the GWEN for variable selection and coefficient estimation in a varying coefficients model, I performed a simulation study.

Spatial data were simulated on a 30 by 30 grid covering the domain [0,1]x[0,1]. Five covariates were simulated using Gaussian random fields with an exponential covariance function.

The marginal variance of the covariates was one, and the range of the covariance function was 0.1.

The covariates were simulated at two levels of collinearity: none, and moderate, for which the correlation was set to 0.5

Simulation study

Simulating the response

- $Y(\boldsymbol{s}) = \boldsymbol{X}(\boldsymbol{s})'\boldsymbol{\beta}(\boldsymbol{s}) = \sum_{j=1}^{5} \beta_j(\boldsymbol{s}) X_j(\boldsymbol{s}) + \varepsilon(\boldsymbol{s})$
- $\beta_1(\boldsymbol{s})$, the coefficient function for X_1, is nonzero in part of the domain.
- Coefficients for $X_2, \ldots, X_5$ are zero everywhere
- $\varepsilon(\boldsymbol{s}) \sim \ iid \ \ N(0, \sigma^2)$
  - Low noise: $\sigma = 0.5$
  - High noise: $\sigma = 1$

With the covariates in hand, the response variable was generated via a linear model.

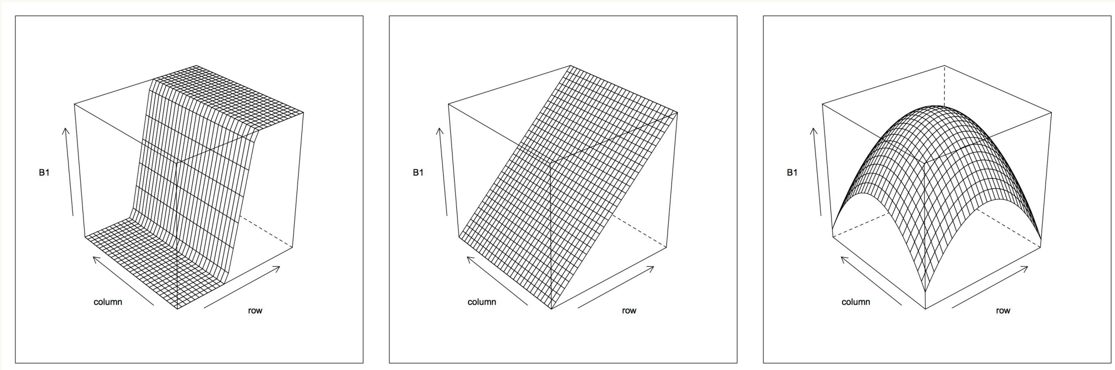
There are five covariates; four of them (β_2 through β_5) have a coefficient of zero everywhere on the domain.

For all the simulation settings, the coefficient of β_1 ranges within the domain from a minimum of zero to a maximum of one.

The random noise added to the linear model was iid Gaussian noise at two different settings for the variance. The low-noise setting was $\sigma = 0.5$ and the high-noise setting was $\sigma = 1$.

Simulation study

Coefficient functions: step, gradient, and parabola



The response variable was simulated for three different types of coefficient surface β_1.

First is a step function where the "step" is on a slope rather than a discontinuity.

Second is a constant gradient.

Third is a parabola centered at the center of the domain.

Simulation study

Simulation settings

Each setting simulated 100 times:

Setting	function	ρ	σ^2
1	step	0	0.25
2	step	0	1
3	step	0.5	0.25
4	step	0.5	1
5	gradient	0	0.25
6	gradient	0	1
7	gradient	0.5	0.25
8	gradient	0.5	1
9	parabola	0	0.25
10	parabola	0	1
11	parabola	0.5	0.25
12	parabola	0.5	1

The table lists the twelve settings for the simulation study, where once again the parameters being varied across the settings are the coefficient surface β_1, the amount of colinearity in the covariates, and the variance of the random noise.

Each setting was simulated 100 times and each time, each of the following models was used to estimate the varying coefficient regression model:

traditional GWR

oracular GWR (with locally linear estimation of the coefficients)

the GWEN with locally constant coefficients

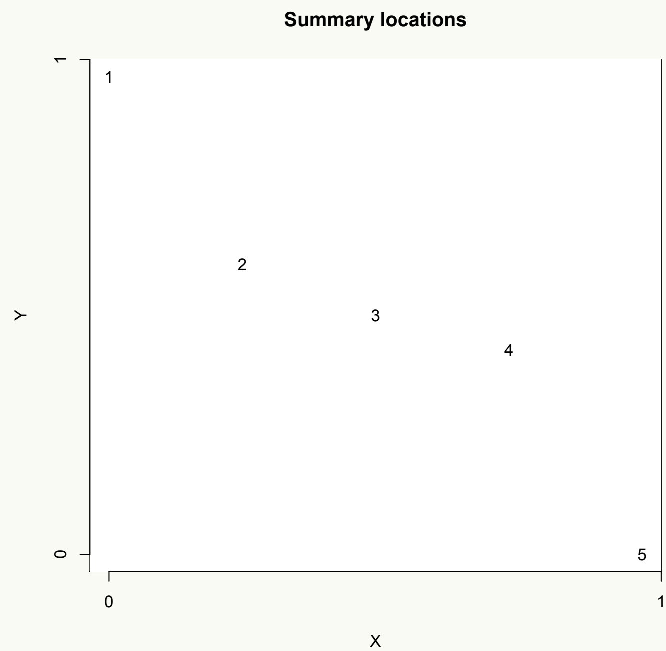
the GWAL with locally constant coefficients

the GWEN with locally linear coefficients

the GWAL with locally linear coefficients.

Simulation results

Summary locations



The results of the simulation were summarized at these five locations.

Locations two and four are at the ”corners” of the step function.

The correct result of selection is ambiguous at some locations where the summary location is at the spot where the true coefficient surface β_4 changes from zero to nonzero.

In particular, selection is ambiguous at location four for the step function, at location five for the gradient, and at locations one and five for the parabola.

We’ll ignore selection accuracy of β_1 where that is ambiguous

First we will consider the variable selection results of the simulation.

Simulation results

Selection performance

- GWEN selection (60 cases):
  - 21 with no false positives (3 came when $\sigma = 1$, 8 when $\rho = 0.5$)
  - 30 with no false negatives
  - 13 with neither
- GWAL selection (60 cases):
  - 27 with no false positives
  - 26 with no false negatives
  - 17 with neither
- Incerased noise variance led to worse selection performance
- Increased colinearity in the covariates led to worse selection performance
- No consistent difference between GWEN and GWAL

note

Simulation results

Estimation performance

- Oracular selection
  - best MSE($\hat{\beta}_1$) in 38 of the 60 cases
- Generally small difference between GWR, oracular, GWEN-LLE, and GWAL-LLE
- Incerased noise variance led to worse estimation accuracy
- Increased colinearity in the covariates led to worse estimation accuracy
- Fitting $\hat{y}$: MSE nearest σ^2 split between GWAL-LLE, oracle, and GWR

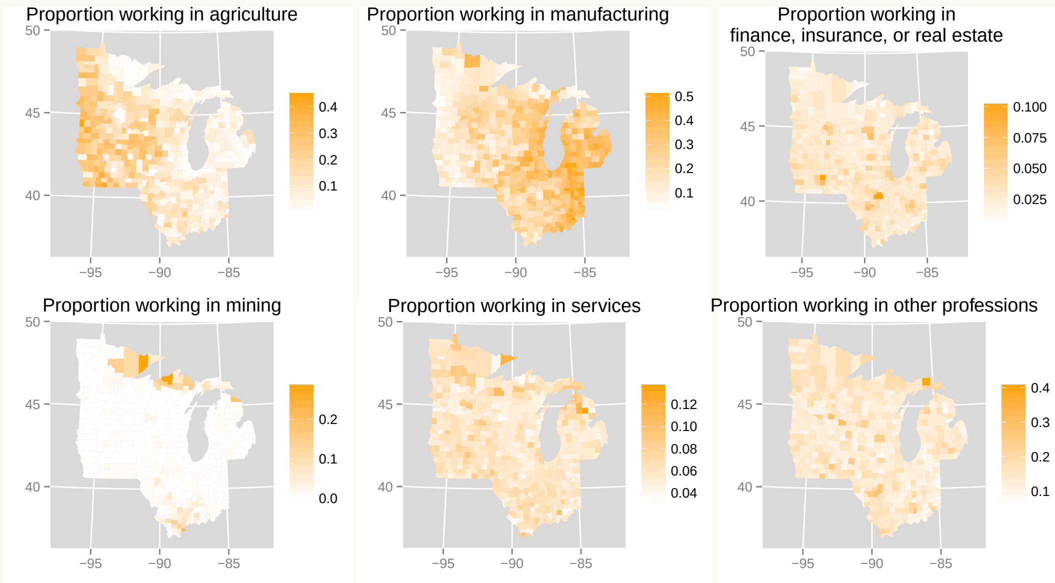
note

Data example: poverty rate in the upper midwest

New Section

Data example: poverty rate in the upper midwest

Revisiting the motivating example



We return to the data example that was introduced at the beginning of the talk.

Again, these are the covariates for a model of the county-level poverty rate.

Data example: poverty rate in the upper midwest

Data description

- Response: logit-transformed poverty rate in the Upper Midwest states of the U.S.
  - Minnesota, Iowa, Wisconsin, Illinois, Indiana, Michigan
- Covariates: employment structure (raw proportion employed in:)
  - agriculture
  - finance, insurance, and real estate
  - manufacturing
  - mining
  - services
  - other professions
- Data source: U.S. Census Bureau's decennial census of 1970

The covariates are the proportion of the county's population working in the economic sectors of agriculture, finance, manufacturing, mining, services, and other professions.

The response variable in this model is the logit-transformed county-level poverty rate from the 1970 US census.

The model's domain is the upper midwest states of Minnesota, Iowa, Wisconsin, Illinois, Indiana, and Michigan.

Data example: poverty rate in the upper midwest

Data description

- Data aggregated to the county level
  - counties are areal units
- county centroid treated as sampling location

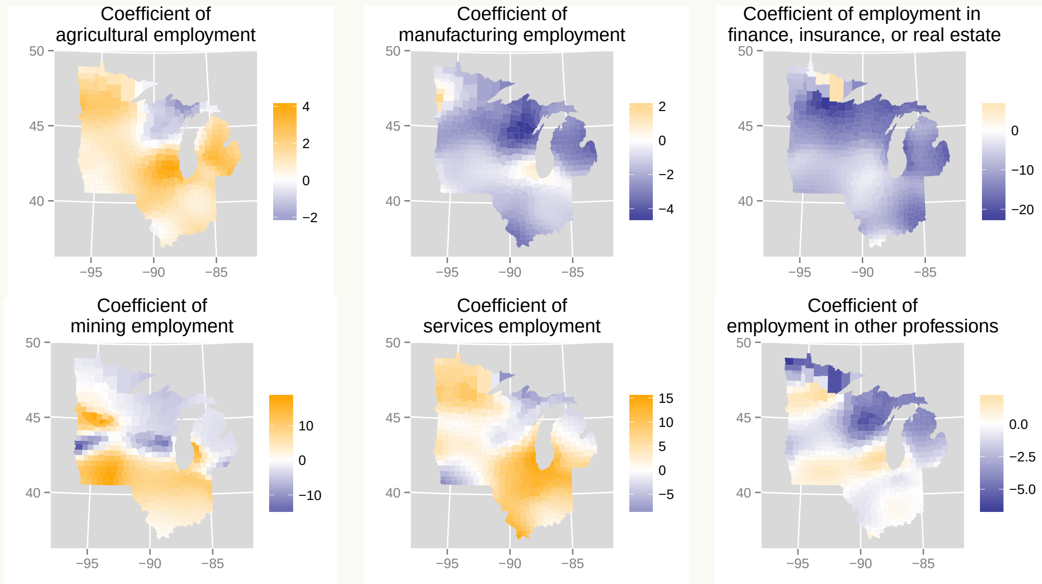
Since data is aggregated on counties and the counties exactly divide the domain, this is actually areal data.

We'll treat is as geostatistical data by assuming each counties data is sampled at the county's centroid.

The data is modeled using both traditional GWR and the GWEN with locally linear coefficient estimates.

Data example: poverty rate in the upper midwest

Results from traditional GWR



Here are plots of the coefficient estimates from the model fit by traditional GWR.

Data example: poverty rate in the upper midwest

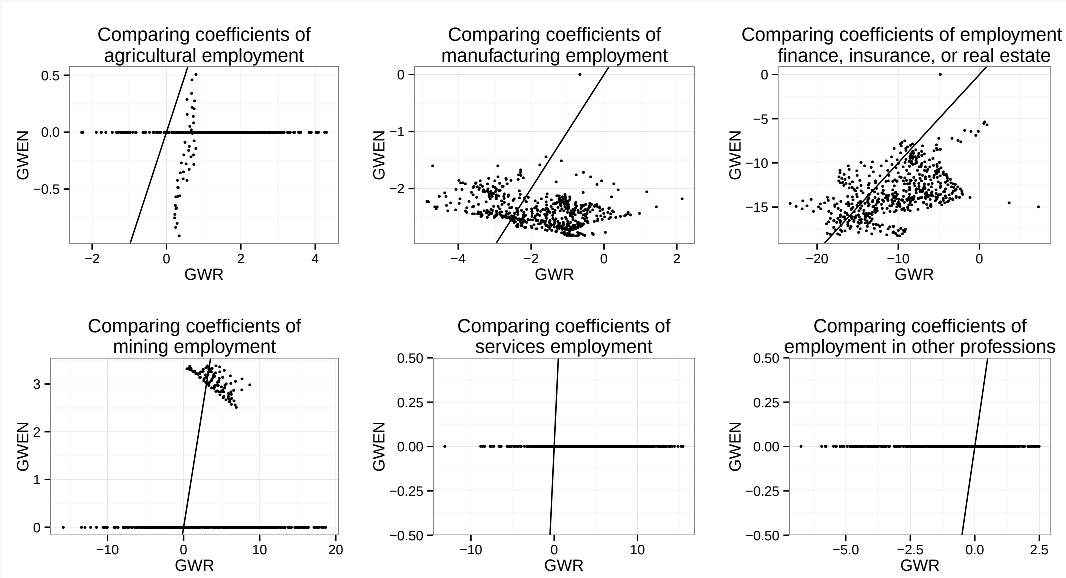
Results from GWEN

These are plots of the coefficients estimates from the model fit by the GWEN with locally linear coefficients.

It is obvious by glancing at the plots that the GWEN has selected just a few covariates as being important predictors of the county level poverty rate.

Data example: poverty rate in the upper midwest

Comparing the coefficients from GWR and the GWEN



note

Data example: poverty rate in the upper midwest

Results from GWEN-LLE

- Relatively constant compared to GWR
- Services, "other professions" do not affect the poverty rate
- Manufacturing: negative coefficient everywhere
- Finance, insurance, and real estate negative coefficient everywhere
  - Largest magnitude (min: -20, next-largest: -3)
  - GWR comparable to GWEN-LLE
- Manufacturing: negative coefficient everywhere
  - GWR: coefficient greater than zero near Chicago and in NW Minnesota
- Agriculture: nonzero in western Iowa
  - North-south gradient to coefficient
  - ranges positive to negative
- Mining: nonzero in parts south
  - Associated with increased poverty rate
  - Comparable to GWR within far southern range

Some observations about the models produced by traditional GWR and the GWEN-LLE:

The GWEN resulted in coefficient estimates that are less variable than traditional GWR. Employment in services and the ”other professions” sectors did not affect the poverty rate anywhere, according to the GWEN.

Employment in manufacturing and finance were both associated with a decreased poverty rate across the entire domain. This was not dissimilar to the relationship estimated by traditional GWR.

Agricultural employment was a selected as a meaningful predictor of the poverty rate only in western Iowa. Within that region there was a north-south gradient to the coefficient.

Future work

New Section

Future work

- Apply the GWEN to models for non-Gaussian response variable
- Incorporate spatial autocorrelation in the model
- PalEON project: modeling and mapping tree biomass in the upper midwest

note

Acknowledgements