Selection and estimation for varying-coefficients regression

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March 8, 2013

Outline

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Varying-coefficients regression

- What if the effect of my variable is not constant?
  - Agriculture more valuable in regions with richer soil
  - Mining more valuable in regions with greater mineral deposits
- Consider coefficients as functions of location: $\beta(s)$
- How to estimate $\beta(s)$?

Estimating coefficient functions

- Estimate model locally at each model point
  - Give weight to each observation based on distance from model point
  - Multiply design matrix by weight matrix
  - Use the adaptive Lasso for selection/estimation

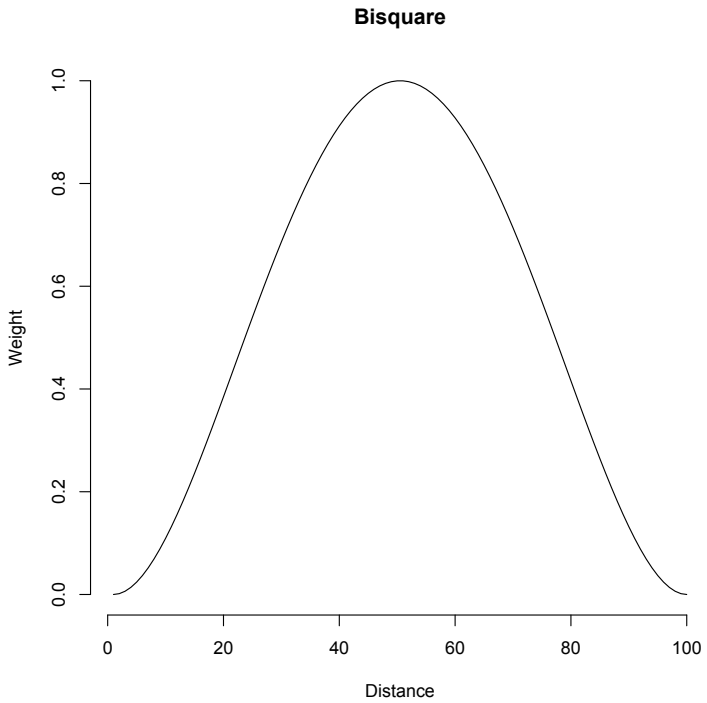

Figure: The bisquare kernel.

Model parameter selection

Estimate model parameters using the AIC

- Each model point has a Lasso tuning parameter
  - Use local AIC
- Bandwidth for the kernel function
  - Use total AIC

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Simulation study

- Five covariates simulated on a 30×30 grid with a GRF
- True coefficient surfaces: β_1 below, β_2 - $\beta_5 \equiv 0$ everywhere
- Random error simulated from a GRF
  - ρ : between-covariates correlation $(0, 0.5, 0.8)$
  - τ_x : spatial autocorrelation of the covariates $(0.03, 0.1)$
  - τ_σ : spatial autocorrelation of the random errors $(0, 0.03, 0.1)$

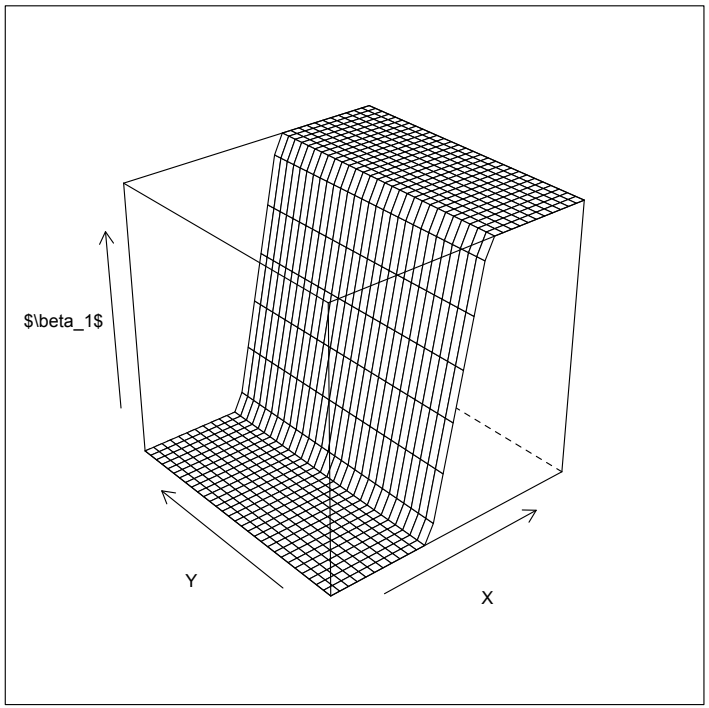
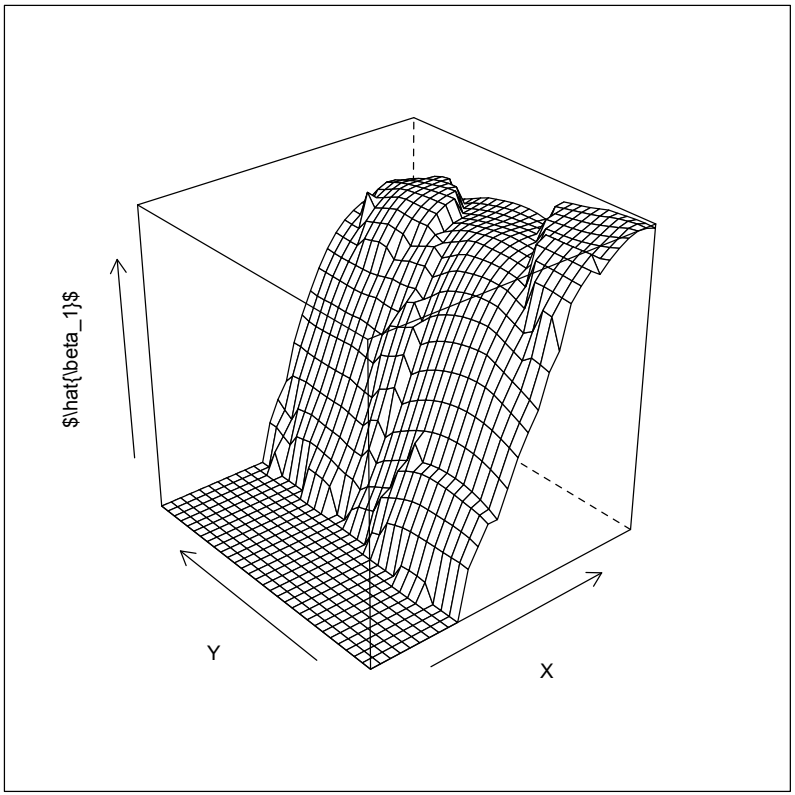


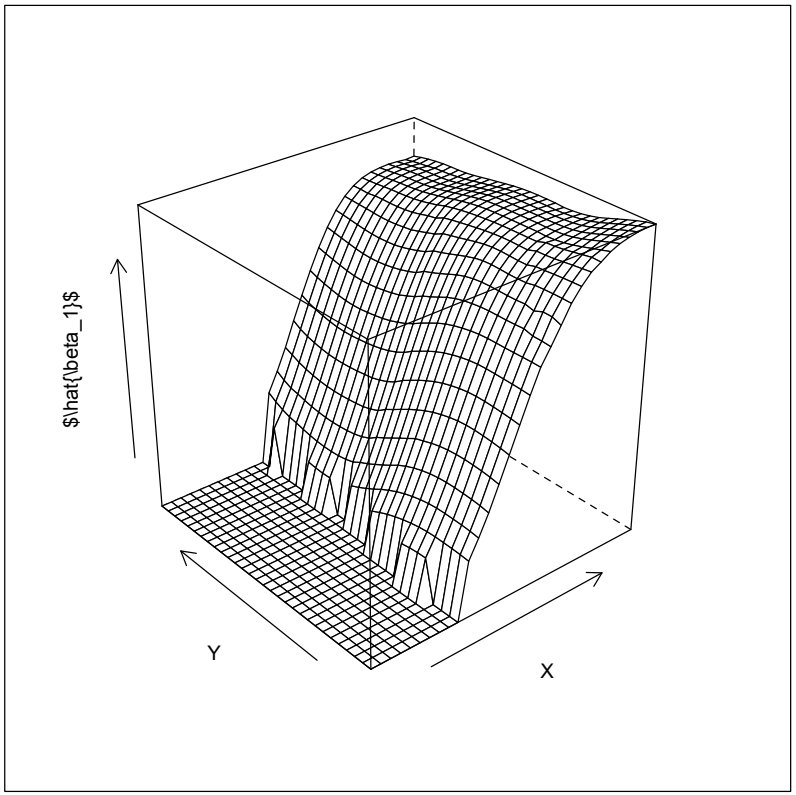
Figure: The true coefficient surface for β_1.

Simulation result - estimate of β_1

- Simulation setting: $\rho = 0$, $\tau_x = 0.03$, $\tau_\sigma = 0$



(a)

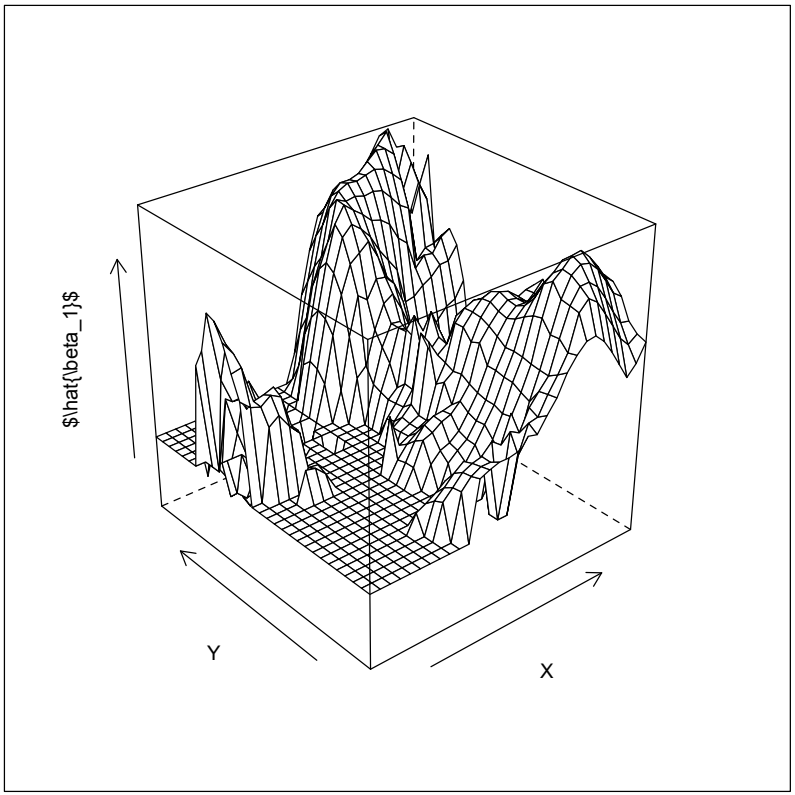


(b)

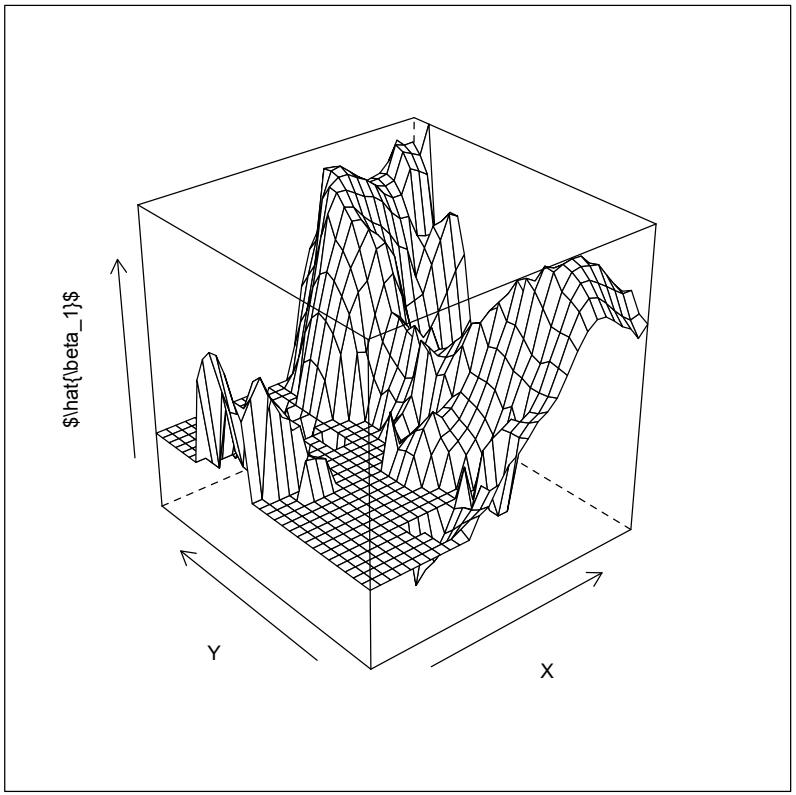
Figure: Left: estimated using GWL for selection and estimation; Right: GWL for selection, least squares for estimation.

Simulation result - estimate of β_1

- Simulation setting: $\rho = 0.8$, $\tau_x = 0.1$, $\tau_\sigma = 0.1$



(a)



(b)

Figure: Left: estimated using GWL for selection and estimation; Right: GWL for selection, least squares for estimation.

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Census data: model of poverty rate

Images are separate