

Mini-course Machine Learning in Empirical Economic Research

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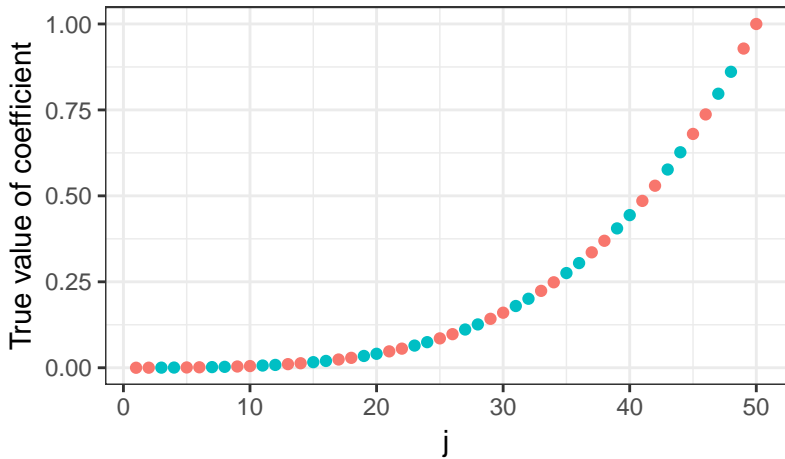


Figure: True values of coefficients

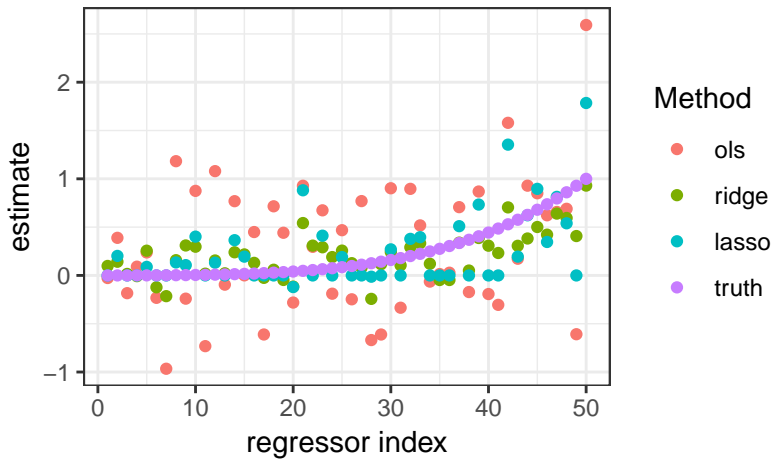


Figure: Estimation results

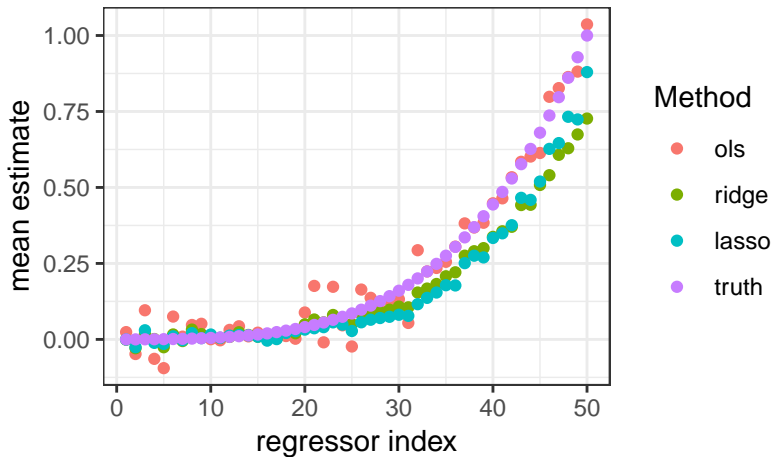


Figure: Expected estimates (average over 200 simulations)

OLS is terrible for prediction

	method	mse
1	ols	27.91
2	ridge	2.73
3	lasso	2.76

Table: Mean-squared-error $MSE(f)$

$$\begin{aligned}MSE(f) &= \mathbb{E} \int_x \left(\hat{f}(x) - f(x) \right)^2 dF(x) \\&= \int_x \left(\mathbb{E} \hat{f}(x) - f(x) \right)^2 dF(x) + \int_x \mathbb{E} \left(\hat{f}(x) - \mathbb{E} \hat{f}(x) \right)^2 dF(x) \\&= \int_x \text{bias}^2(f(x)) dF(x) + \int_x \text{var}(\hat{f}(x)) dF(x).\end{aligned}$$

Under Gauss-Markov assumptions OLS is unbiased

$$\begin{aligned}\int_x \text{bias}^2(f(x)) dF(x) &= \int_x (\mathbb{E}(\hat{\beta}'x) - \beta'x) dF(x) \\ &= \int_x (\underbrace{\mathbb{E}[\hat{\beta} - \beta]}_{=0})'x dF(x) = 0\end{aligned}$$

- For prediction unbiasedness is not a desirable property.
- Not surprising that Ridge performs best (James-Stein estimator, Empirical Bayes theory)

Lasso selects variables

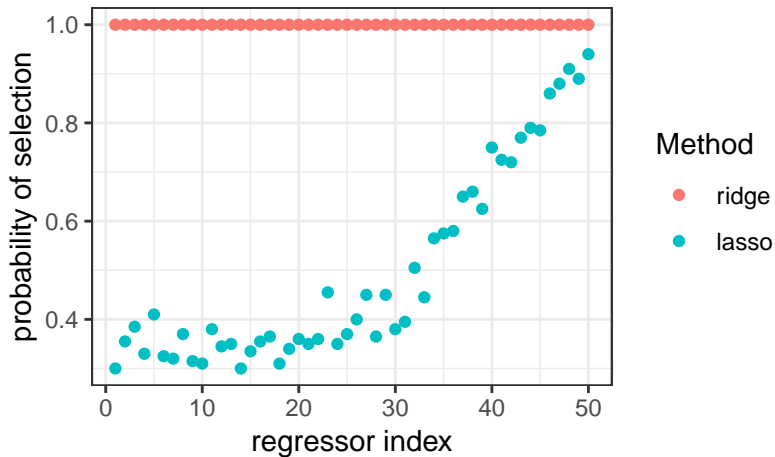


Figure: Probability of including variables (average over 200 simulations)

A sparse design

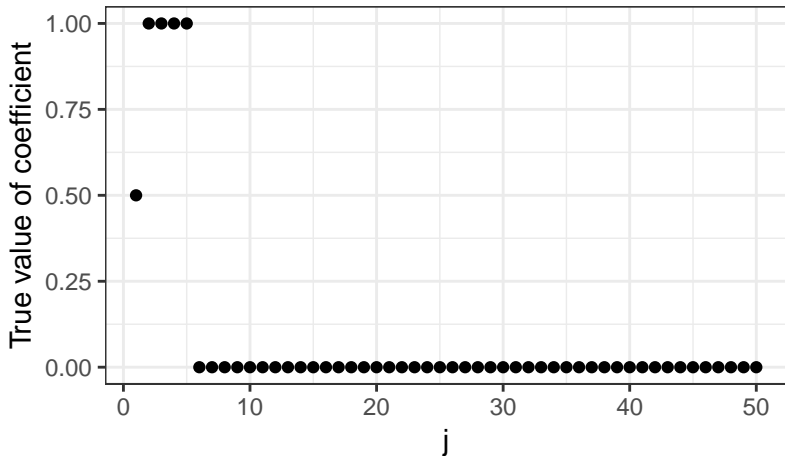


Figure: True values of coefficients

Lasso detects many of the zero coefficients

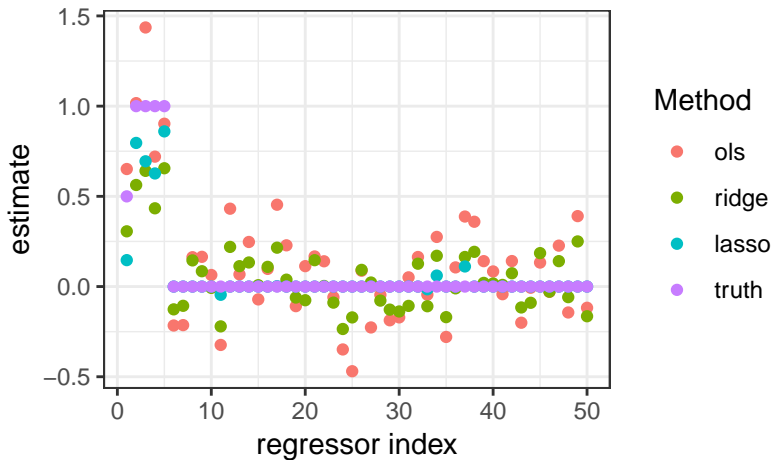


Figure: Estimation results

Lasso is good at selecting the true model

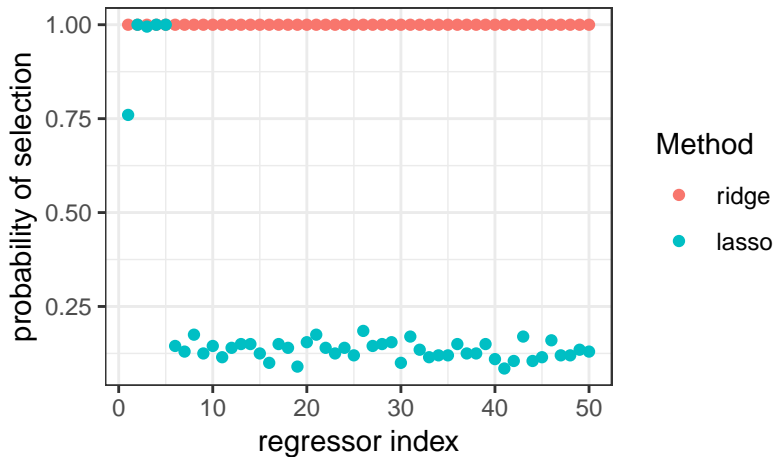


Figure: Probability of including variables (average over 200 simulations)

But still shrinkage

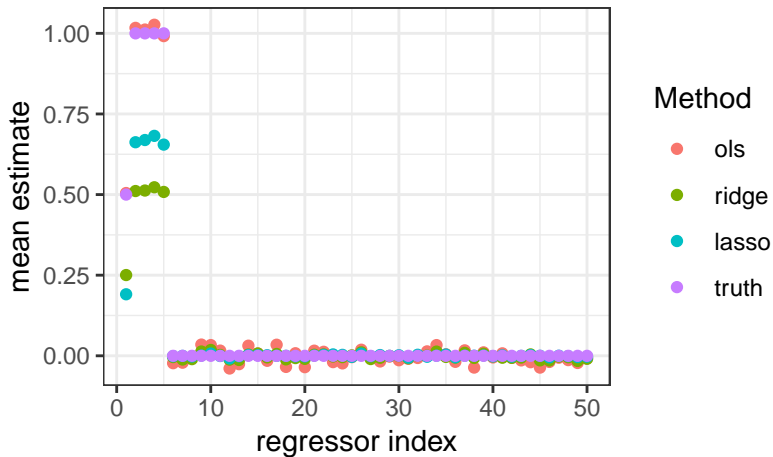


Figure: Expected estimates (average over 200 simulations)