

Data Mining & Machine Learning

Regularization Methods for Regression

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L2 Norm: Ridge

Motivation

Framework

Similarities

L1 Norm: Lasso

Similarities

Motivation

Framework

Regularization Methods

Important Facts

Empirical Example: Kaggle's Amazon Competition

Amazon Data: LASSO Model

Amazon Data: Ridge Model

Amazon Data: Performance

Some Resources

Ridge Regression

$$\hat{\beta}_{ridge} = \underset{\beta}{\operatorname{argmin}} \sum_{i=1}^n (y_i - \sum_{j=1}^p \beta_j x_{ij})^2 + \lambda \sum_{j=1}^p \beta_j^2 \quad (1)$$

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- ▶ Originally called Tikhonov regularization
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- ▶ Method to deal with non-invertible $(\mathbf{X}'\mathbf{X})$ matrices

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$$\hat{\beta}_{j,ridge} = \frac{\sum_{i=1}^n (x_{ij} - \bar{x}_j)(y_i - \bar{y})}{\sum_{i=1}^n (x_{ij} - \bar{x}_j)^2} \frac{1}{1 + \lambda} = \frac{\hat{\beta}_{j,ols}}{1 + \lambda} \quad (3)$$

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- ▶ Back to Ordinary Least-Squares solution!

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$$\hat{\beta}_{ridge} = \underset{\beta}{\operatorname{argmin}} (\mathbf{y} - \mathbf{x}^T \beta)^2 + \lambda \beta^2 \quad (5)$$

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- ▶ What happens when we change the norm? What about the L1 norm?

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- ▶ Difference is in the constraint of the minimization problem

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- ▶ Using LASSO results in models with less parameters (features)

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$$\hat{\beta}_{lasso}(\lambda) = S(\hat{\beta}, \lambda) \equiv \text{sign}(\hat{\beta})(|\hat{\beta}| - \lambda)_+ \quad (11)$$

$$S(\hat{\beta}, \lambda) = \begin{cases} \hat{\beta} - \lambda, & \text{if } \hat{\beta} > 0 \text{ and } \lambda < |\hat{\beta}| \\ \hat{\beta} + \lambda, & \text{if } \hat{\beta} < 0 \text{ and } \lambda < |\hat{\beta}| \\ 0, & \text{if } \lambda > |\hat{\beta}|. \end{cases}$$

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- ▶ LASSO does variable selection by setting select variables to 0!

LASSO and Ridge Regression

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- ▶ Both biased in the statistical sense but asymptotically unbiased and can be shown that they select the true features with probability $\rightarrow 1$

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- ▶ Useful in banking, tech, insurance, marketing, and other fields

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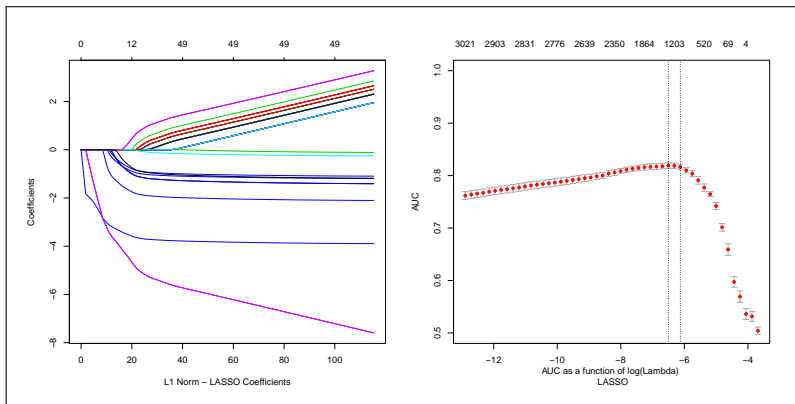
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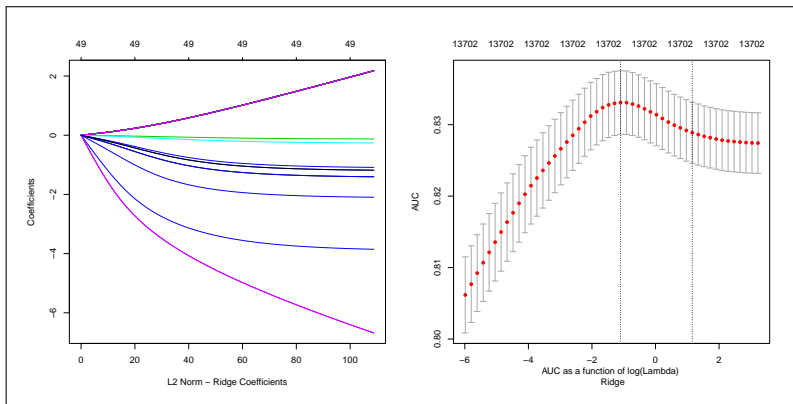
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- ▶ Binary representation of all 10 features leads to a very sparse (32,769 × 15,618) matrix

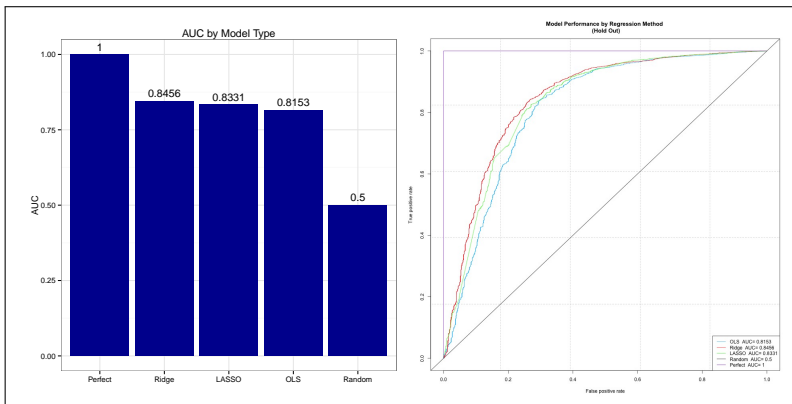
LASSO Model Performance



Ridge Model Performance



Comparison of Ridge, LASSO, and OLS



Useful Links below

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- ▶ Original LASSO Publication (REALLY Useful)

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- ▶ Sweet paper on asymptotic properties of Ridge and LASSO