

Goals of Lecture 3

1. Motivate extensions of OLS
2. Matrix decompositions
3. Ridge regression
4. Subset selection : greedy methods

Recall linear regression

$$\hat{\mathbf{y}} = \mathbf{X} \hat{\boldsymbol{\beta}} \quad \hat{\boldsymbol{\beta}} = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{y}$$

$n \quad n \times p \quad p$

$$\hat{\mathbf{y}} = \underbrace{\mathbf{X} (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T}_{\mathbf{H}} \mathbf{y}$$

\mathbf{H} : hat matrix

$$\text{Fit: solve } \mathbf{X}^T \mathbf{X} \hat{\boldsymbol{\beta}} = \mathbf{X}^T \mathbf{y}$$

Algorithm 3.1 Regression by Successive Orthogonalization.

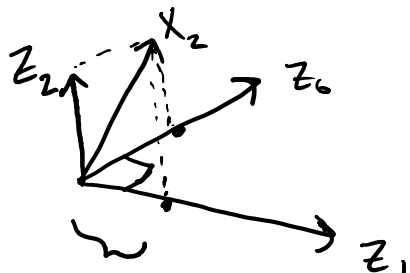
1. Initialize $\mathbf{z}_0 = \mathbf{x}_0 = \mathbf{1}$.

ESL pg. 54

2. For $j = 1, 2, \dots, p$

Regress \mathbf{x}_j on $\mathbf{z}_0, \mathbf{z}_1, \dots, \mathbf{z}_{j-1}$ to produce coefficients $\hat{\gamma}_{\ell j} = \langle \mathbf{z}_\ell, \mathbf{x}_j \rangle / \langle \mathbf{z}_\ell, \mathbf{z}_\ell \rangle$, $\ell = 0, \dots, j-1$ and residual vector $\mathbf{z}_j = \mathbf{x}_j - \sum_{k=0}^{j-1} \hat{\gamma}_{kj} \mathbf{z}_k$.

3. Regress \mathbf{y} on the residual \mathbf{z}_p to give the estimate $\hat{\beta}_p$.


$$\frac{\langle \mathbf{z}_1, \mathbf{x}_2 \rangle}{\langle \mathbf{z}_1, \mathbf{z}_1 \rangle} = \hat{\gamma}_{12}$$

\mathbf{x}_i - n dim column of \mathbf{X}

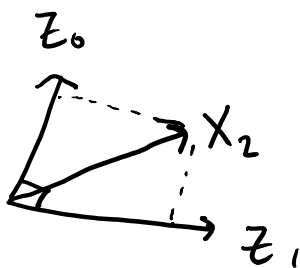
$$\hat{\beta}_p = \frac{\langle \mathbf{z}_p, \mathbf{y} \rangle}{\langle \mathbf{z}_p, \mathbf{z}_p \rangle}$$



Unstable if $\langle \mathbf{z}_p, \mathbf{z}_p \rangle$ is small



Impossible if $\langle \mathbf{z}_p, \mathbf{z}_p \rangle = 0$



$$\Rightarrow \mathbf{z}_2 = \mathbf{0}$$

linear dependence (always happens if $p > n$)