

Math 342W Lecture 23

If you see correlation, there will be causation somewhere

Spurious Correlation: Concluding x and y are correlated when they're not

If $\hat{y} = b_0 + b_1 x_1 + \dots + b_p x_p$, how can we interpret b_j ,

Wrong: Holding the rest of the features constant, a change of 1 in x_j results in b_j change in y 's mean.

Correct: When comparing two mutually observed observation (A) and (B) are sampled in the same way as observations in the training set where (A) has a x_j value one unit larger than the x_j of (B), and share some values x_2, \dots, x_p then (A) is predicted to have a response y that differs by b_j units on average from response of (B), assuming linear model is true.

$$X = \begin{matrix} & \overset{p}{\text{---}} \\ \underset{n}{\text{---}} & \boxed{} \end{matrix}, p > n$$

$X^T X$ not invertible now,
 \vec{b}_{OLS} DNE...

$$\Rightarrow X^T X \quad \begin{matrix} \boxed{} \\ \text{0} \quad \text{0} \quad \text{0} \quad \text{0} \quad \text{0} \quad \text{0} \quad \text{0} \quad \text{0} \quad \text{0} \quad \text{0} \end{matrix}$$

$$\Rightarrow \vec{b}_{\text{ridge}} = (X^T X + \lambda I)^{-1} X^T \vec{y}$$

Essentially Cauchy's Diagonalization plus a little "shift" to add more λ .

Diagonalization: $X^T X = V D V^{-1}$

$(p+1) \times (p+1)$

Cols are $p+1$
Eigen vectors
 $\text{rank}[V] = p+1$

$$\begin{bmatrix} \lambda_1 & & 0 \\ & \ddots & \\ 0 & & \lambda_{p+1} \end{bmatrix}$$

Diagonal with
Eigen values

Ridge Regression
 $\&$
 Lasso Regression

$$\vec{b}_{\text{ridge}} = (X^T X + 2I)^{-1} X^T \vec{y}$$

$$(V D V^{-1} + 2I)^{-1} = (V D V^{-1} + 2I V V^{-1})^{-1} = (V D V^{-1} + V(2I)V^{-1})^{-1}$$

$$= (V(D + 2I)V^{-1})^{-1} = V(D + 2I)^{-1} V^{-1} \Rightarrow$$

Now we have shifted λ 's up to $\lambda + 2$
on the diagonal! and got λ 's up to $p+1$
so now we are full rank.

$$\begin{bmatrix} \lambda_1 + 2 & & & \\ & \lambda_2 + 2 & & \\ & & \ddots & \\ 0 & & & \lambda_{p+1} + 2 \end{bmatrix}$$

Consider $\mathcal{R}: \vec{b}_{\text{ridge}} = \arg\min \{ \text{SSE} + 2 \|\vec{w}\|_2^2 \}$

Consider $\mathcal{R}: \vec{b}_{\text{lasso}} = \arg\min \{ \text{SSE} + 2 \|\vec{w}\|_1 \}$

$\lambda \in \mathbb{R} > 0$

Regularization
($\vec{b} \rightarrow \vec{0}$)

Roughly speaking, Ridge is used for prediction and Lasso is used for feature selection.

Consider $\mathcal{R}: \vec{b}_{\text{elastic}} = \arg\min \{ \text{SSE} + \lambda (\alpha \|\vec{w}\|_1 + (1-\alpha) \|\vec{w}\|_2^2) \}$