

Linear Regression

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_n X_n$$

for a given dataset (x_i, y_i)
Closed form solution using Ordinary Least Squares (OLS)
 At minimum RSS (residual sum of squares)
 $\sum_{i=1}^n (y_i - \hat{y}_i)^2$
 Susceptible to Outliers $\frac{\partial \text{RSS}}{\partial \beta_j} = 0 \rightarrow \hat{\beta} = (X^T X)^{-1} X^T Y = (X^T X)^{-1} X^T \hat{y}$

$$\text{Evaluations} \rightarrow \text{RMSE} = \sqrt{\frac{\sum (y_i - \hat{y}_i)^2}{n}}$$

$$\text{Residual Standard Error (RSE)} \rightarrow \sqrt{\frac{\sum (y_i - \hat{y}_i)^2}{n-p-1}}$$

$\{P = \# \text{ of } X_i\}$
 dot

$$\rightarrow R^2 \text{ statistics: how much of variation explained by model}$$

$$(0-1) \rightarrow 1 - \frac{\text{RSS}}{\text{TS}} \quad \{ \text{TS} = \sum (y_i - \bar{y})^2 \}$$

$$\text{(adjusted } R^2 \text{)} \rightarrow 1 - \frac{(P-1)\text{RSS}}{(n-p-1)}$$

$$\rightarrow t\text{-statistics of Coefficients: } t_{bi} = \frac{b_i}{\text{Standard Error (SE)}} \rightarrow \text{higher } |t_{bi}| \rightarrow \text{higher significance}$$

\rightarrow and $p\text{-value}$
 \rightarrow higher $|t_{bi}| \rightarrow$ higher significance
 X_i can be used in feature selection

Regression-I

Factor Variables {Categoricals}

One hot Encoding: category with multiple individual cat's $\{A, B, C, \dots\}$
 (due to multicollinearity)

FV with multiple levels: Subgroup similar categories $\{$ may acc to another var $\}$
 Ordered FV: can use single column with #s

To penalize adding more X_i
 $AIC = 2P + n \log(\text{RSS}/n)$

Albeitics Information Criteria $\{$ see also, BIC, AICc, Mallows Q $\}$

Feature Selection

Forward Selection: Add X_i which has highest bump to RSS
 STOP: the t in RSS is no more stat sig

Backward Selection: start: all features
 Next: drop the X_i with least t until all t_{bi} (pval) are stat significant

Penalized Regression: Ridge and Lasso regression

Confounding Variables: \rightarrow omission bias
 Goodness eff on P. or SE from LR equation

Main effect: relationship b/w y and X_i independent of other X_j
 assumption that main effects are independent of each other

IF NOT
Interaction Effect

Inter-dependence of y, X_i and X_j
 add interaction term $X_i X_j$ to LR eqn

Confidence Interval: in the estimation of β_i
Prediction Interval: for the predicted \hat{y}
 prediction interval usually much wider than confidence interval

Bootstrap method:
 ① get a bootstrap sample
 ② fit a LM
 ③ record $\hat{\beta}_i$
 N times
 ④ record residue of some random sample $(\hat{y}_i - \hat{y})$