Model Search Methods

Forward Stepwise Selection

1. Let M_0 denote null model which contains no predictors.
2. For $k = 1,2,\ldots,p-1$
   - Consider all $p-k$ models that augment the predictors in M_k with one additional predictor
   - Choose the best among these $p-k$ models and call it M_{k+1}.
     Here, *best* is defined as having the smallest RSS or largest R^2
3. Select a single best model from among $M_0, M_1, \ldots, M_p$ using cross validated prediction error, C_p (AIC), BIC, or Adjusted-R^2

requires training $1 + \dfrac{p(p+1)}{2}$ models

Example

$p = 3$

M_0 : intercept only (null)

C_1: X_1 X_2 X_3

$\downarrow$

lowest training RSS within C_1

$\Longrightarrow M_1$

C_2: X_1, X_2 X_2, X_3

$\downarrow$

lowest training RSS within C_2

$\Longrightarrow M_2$

M_3 : full model with

X_1 X_2 X_3

Model Search Methods

Backward Stepwise Selection

1. Let M_p denote full model which all predictors.
2. For $k = p,\ p-1,\ p-2, \ldots, 1$
   - Consider all k models that contain all but one of the predictors in M_k , for a total of $k-1$ predictors
   - Choose the best among these k models and call it M_{k-1}.
     Here, *best* is defined as having the smallest RSS or largest R^2
3. Select a single best model from among $M_0, M_1, \ldots, M_p$ using cross validated prediction error, C_p (AIC), BIC, or Adjusted-R^2

requires training $1 + \dfrac{p(p+1)}{2}$ models

Example

$p = 3$

M_3 : full mode X_1 X_2 X_3

C_2: X_1, X_2 X_1, X_3 X_2, X_3

lowest training RSS within C_1

$\Longrightarrow M_2$

C_1: X_1 X_2

lowest training RSS within C_2

$\Longrightarrow M_1$

M_0 : intercept only (null)