

# NBA 4920/6921 Lecture 11

## Linear Model Stepwise Selection

Murat Unal

Johnson Graduate School of Management

10/05/2021

# Agenda

Quiz 9

Best subset selection

Stepwise selection

- Forward stepwise selection

- Backward stepwise selection

Application in R

# Model selection

## **Best subset selection:**

The idea is to estimate a model for every possible subset of variables; then compare their performances

# Model selection

## Best subset selection:

1. Let  $M_0$  denote the null model, which contains no predictors.
2. For  $k$  in 1 to  $p$ :
  - ▶ Fit every possible model with  $k$  variables
  - ▶ Let  $M_k$  denote the **best** model with  $k$  variables
  - ▶ Here best is defined as having the smallest  $RSS$ , or equivalently largest  $R^2$
3. Select the **best** model from  $M_0, \dots, M_p$  using cross-validated prediction error
4. Train the chosen model on the full dataset

# Model selection

**Best subset selection:**

Problem?

# Model selection

## Best subset selection:

### Problem?

- ▶  $p = 10 \rightsquigarrow$  fitting 1,024 models
- ▶  $p = 25 \rightsquigarrow$  fitting  $\approx 33.5$  mil models

# Stepwise selection

**Stepwise selection:** reduces the computational burden of best subset selection

The main idea is:

1. Start by fitting an arbitrary model
2. Improve the model by adding/removing variables one-at-a-time
3. Select the best fitting model

# Model selection

Two main strategies for stepwise selection are:

1. **Forward**: start with only intercept model  $M_0$ , and add variables one-at-a-time
2. **Backward**: start with all variables model  $M_p$ , and remove variables one-at-a-time



# Forward stepwise selection

## **Forward stepwise selection:**

Start with the null model, and add predictors one-at-a-time, until all  $p$  variables are in the model

At each step the variable that give the greatest improvement in model fit is added

# Forward stepwise selection

## Forward stepwise selection:

1. Let  $M_0$  denote the null model, which contains no predictors.
2. For  $k$  in 0 to  $p - 1$ :
  - ▶ Consider all  $p - k$  models that augment the variables 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 equivalently largest  $R^2$
3. Select the **best** model from  $M_0, \dots, M_p$  using cross-validated prediction error
4. Train the chosen model on the full dataset

# Forward stepwise selection

## Forward stepwise selection:

Problem? It is not guaranteed to find the best possible model out of all  $2^p$  models containing subsets of the  $p$  predictors

# Model selection

Best subset and forward stepwise selection for Credit dataset

# Variables	Best subset	Forward stepwise
One	<code>rating</code>	<code>rating</code>
Two	<code>rating, income</code>	<code>rating, income</code>
Three	<code>rating, income, student</code>	<code>rating, income, student</code>
Four	<code>cards, income, student, limit</code>	<code>rating, income, student, limit</code>

Source: ISL

# Backward stepwise selection

## **Backward stepwise selection:**

Start with the full model containing all  $p$  predictors, and then remove the least useful predictor one-at-a-time

# Backward stepwise selection

## Backward stepwise selection:

1. Let  $M_p$  denote the full model, which contains all predictors.
2. For  $k$  in  $p$  to 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 equivalently largest  $R^2$
3. Select the **best** model from  $M_0, \dots, M_p$  using cross-validated prediction error
4. Train the chosen model on the full dataset

# Backward stepwise selection

## Backward stepwise selection:

Problem? It is not guaranteed to find the best possible model out of all  $2^p$  models containing subsets of the  $p$  predictors

# References



Gareth James, Daniela Witten, Trevor Hastie, Robert Tibshirani (2017)

An Introduction to Statistical Learning

*Springer.*

<https://www.statlearning.com/>



Ed Rubin (2020)

Economics 524 (424): Prediction and Machine-Learning in Econometrics

*Univ, of Oregon.*