Lab8

Setup

```
Loading required package: lattice

Loading required package: KernSmooth

KernSmooth 2.23 loaded
Copyright M. P. Wand 1997-2009

Loading required package: randomForest

randomForest 4.7-1.2

Type rfNews() to see new features/changes/bug fixes.

library(MASS)  # For stepwise selection

Attaching package: 'MASS'

The following object is masked from 'package:MPV':
    cement
```

```
library(leaps)  # For subset selection
library(car)  # For PRESS statistic calculation
```

Loading required package: carData

```
library(stats) # For AIC and BIC calculation
```

Problem 1

P 1. Consider the Hald Cement data set given in Table 10.1 of Montgomery Book.

Load the Dataset

```
data(cement)
data <- cement</pre>
```

Define the full model

```
# Full model with all predictors
full_model <- lm(y ~ x1 + x2 + x3 + x4, data=data)</pre>
```

Part (i): Subset Models Selection Based on Different Criteria

- (i) Find at least two subset models based on:
 - (a) R^2
 - (b) R_p^2
 - (c) Mallow C_p statistics
 - (d) Forward selection
 - (e) Backward elimination
 - (f) Step wise selection

 $(a)R^2$

```
# (a) & (b): R-squared and Adjusted R-squared based models using regsubsets
subset_models <- regsubsets(y ~ x1 + x2 + x3 + x4, data=data, nbest=1)</pre>
subset_summary <- summary(subset_models)</pre>
# Select models based on R^{2} and Adjusted R^{2}
best_r2_model <- which.max(subset_summary$rsq)</pre>
best_r2_formula <- paste("y ~", paste(names(coef(subset_models, best_r2_model))[-1], collapse</pre>
best_r2_formula
[1] "y \sim x1 + x2 + x3 + x4"
(b)R_p^2
best_adj_r2_model <- which.max(subset_summary$adjr2)</pre>
best_adj_r2_formula <- paste("y ~", paste(names(coef(subset_models, best_adj_r2_model))[-1],
best_adj_r2_formula
[1] "y \sim x1 + x2 + x4"
 (c) Mallow C_p Statistics
# (c): Mallow's Cp statistic
best_cp_model <- which.min(subset_summary$cp)</pre>
best_cp_formula <- paste("y ~", paste(names(coef(subset_models, best_cp_model))[-1], collapse</pre>
best_cp_formula
[1] "y \sim x1 + x2"
(d) Forward selection
null_model <- lm(y ~ 1, data=data)</pre>
# Forward Selection
forward_model <- step(null_model, direction="forward", scope=formula(full_model), trace=FALS</pre>
forward_model
```

```
Call:
```

 $lm(formula = y \sim x4 + x1 + x2, data = data)$

Coefficients:

(Intercept) x4 x1 x2 71.6483 -0.2365 1.4519 0.4161

(e) Backward Elimination

```
# Backward Elimination
backward_model <- step(full_model, direction="backward", trace=FALSE)
backward_model</pre>
```

Call:

 $lm(formula = y \sim x1 + x2 + x4, data = data)$

Coefficients:

(Intercept) x1 x2 x4 71.6483 1.4519 0.4161 -0.2365

(f) Stepwise Selection

```
# Stepwise Selection
stepwise_model <- step(null_model, direction="both", scope=formula(full_model), trace=FALSE)
stepwise_model</pre>
```

Call:

 $lm(formula = y \sim x4 + x1 + x2, data = data)$

Coefficients:

(Intercept) x4 x1 x2 71.6483 -0.2365 1.4519 0.4161

Part (ii): Compute PRESS, AIC, and BIC for selected subset models

- (ii) For the selected subset models, find
 - (a) Value of the PRESS statistics
 - (b) AIC
 - (c) BIC
- (a) PRESS Statistics

```
# Define function for PRESS statistic
PRESS <- function(model) {
    pr <- residuals(model)/(1 - lm.influence(model)$hat)
    sum(pr^2)
}

# Fit the selected models
model_r2 <- lm(best_r2_formula, data=data)
model_adj_r2 <- lm(best_adj_r2_formula, data=data)
model_cp <- lm(best_cp_formula, data=data)

# PRESS statistic
press_r2 <- PRESS(model_r2)
press_adj_r2 <- PRESS(model_adj_r2)
press_cp <- PRESS(model_cp)</pre>
```

(b) AIC

```
aic_r2 <- AIC(model_r2)
aic_adj_r2 <- AIC(model_adj_r2)
aic_cp <- AIC(model_cp)</pre>
```

(c) BIC

```
bic_r2 <- BIC(model_r2)
bic_adj_r2 <- BIC(model_adj_r2)
bic_cp <- BIC(model_cp)</pre>
```

Ouput the Results

```
cat("Model based on R-squared:\n")
Model based on R-squared:
cat("Formula:", best_r2_formula, "\n")
Formula: y \sim x1 + x2 + x3 + x4
cat("PRESS:", press_r2, "\n")
PRESS: 110.3466
cat("AIC:", aic_r2, "\n")
AIC: 65.83669
cat("BIC:", bic_r2, "\n\")
BIC: 69.22639
cat("Model based on Adjusted R-squared:\n")
Model based on Adjusted R-squared:
cat("Formula:", best_adj_r2_formula, "\n")
Formula: y \sim x1 + x2 + x4
cat("PRESS:", press_adj_r2, "\n")
PRESS: 85.35112
cat("AIC:", aic_adj_r2, "\n")
```

AIC: 63.86629

```
cat("BIC:", bic_adj_r2, "\n\n")
BIC: 66.69103
cat("Model based on Mallow's Cp:\n")
Model based on Mallow's Cp:
cat("Formula:", best_cp_formula, "\n")
Formula: y \sim x1 + x2
cat("PRESS:", press_cp, "\n")
PRESS: 93.88255
cat("AIC:", aic_cp, "\n")
AIC: 64.31239
cat("BIC:", bic_cp, "\n\n")
BIC: 66.57219
cat("Forward Selection Model:\n")
Forward Selection Model:
cat("Formula:", as.character(forward_model$call$formula), "\n")
Formula: \sim y x4 + x1 + x2
cat("PRESS:", PRESS(forward_model), "\n")
```

PRESS: 85.35112

```
cat("AIC:", AIC(forward_model), "\n")
AIC: 63.86629
cat("BIC:", BIC(forward_model), "\n\n")
BIC: 66.69103
cat("Backward Elimination Model:\n")
Backward Elimination Model:
cat("Formula:", as.character(backward_model$call$formula), "\n")
Formula: \sim y \times 1 + x^2 + x^4
cat("PRESS:", PRESS(backward_model), "\n")
PRESS: 85.35112
cat("AIC:", AIC(backward_model), "\n")
AIC: 63.86629
cat("BIC:", BIC(backward_model), "\n\n")
BIC: 66.69103
cat("Stepwise Selection Model:\n")
Stepwise Selection Model:
cat("Formula:", as.character(stepwise_model$call$formula), "\n")
Formula: \sim y x4 + x1 + x2
```

```
cat("PRESS:", PRESS(stepwise_model), "\n")
```

PRESS: 85.35112

```
cat("AIC:", AIC(stepwise_model), "\n")
```

AIC: 63.86629

```
cat("BIC:", BIC(stepwise_model), "\n")
```

BIC: 66.69103