```
#p1
#(a)
library(ISLR)
data(Default)
names (Default)
summary(Default)
set.seed(1)
LG.fit = glm(default~income+balance, family=binomial)
summary(LG.fit)
\#(b)
train set = sample(dim(Default)[1],dim(Default)[1]/1.5)
#i. Split the sample set into a training set and a validation set.
NLG.fit = glm(default ~ income + balance, data = Default, family =
"binomial", subset = train set)
#ii. Fit a logistic regression model using only the training data set.
probs = predict(NLG.fit, newdata = Default[-train set, ], type =
"response")
pred.glm = rep("No", length(probs))
pred.glm[probs > 0.5] = "Yes"
#iii. Obtain a prediction of default status for each individual in the
validation set using a threshold of 0.5.
mean(pred.glm != Default[-train set, ]$default)
# (C)
train set = sample(dim(Default)[1],dim(Default)[1]/1.5)
NLG.fit = glm(default ~ income + balance, data = Default, family =
"binomial", subset = train set)
probs = predict(NLG.fit, newdata = Default[-train set, ], type =
"response")
pred.glm = rep("No", length(probs))
pred.glm[probs > 0.5] = "Yes"
mean(pred.glm != Default[-train set, ]$default)
train set = sample(dim(Default)[1],dim(Default)[1]/1.5)
NLG.fit = glm(default ~ income + balance, data = Default, family =
"binomial", subset = train set)
probs = predict(NLG.fit, newdata = Default[-train set, ], type =
"response")
pred.glm = rep("No", length(probs))
pred.glm[probs > 0.5] = "Yes"
mean(pred.glm != Default[-train set, ]$default)
train set = sample(dim(Default)[1],dim(Default)[1]/1.5)
NLG.fit = glm(default ~ income + balance, data = Default, family =
"binomial", subset = train set)
probs = predict(NLG.fit, newdata = Default[-train set, ], type =
"response")
pred.glm = rep("No", length(probs))
pred.glm[probs > 0.5] = "Yes"
mean(pred.glm != Default[-train set, ]$default)
#(d)adding one student variable, check the test error
train set <- sample(dim(Default)[1], dim(Default)[1] / 1.5)</pre>
LG.glm <- glm(default ~ income + balance + student, data = Default,
family = "binomial", subset = train set)
pred.glm <- rep("No", length(probs))</pre>
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probs <- predict(LG.glm, newdata = Default[-train set, ], type =</pre>
"response")
pred.glm[probs > 0.5] <- "Yes"</pre>
mean(pred.glm != Default[-train_set, ]$default)
#p2
#(a) Generate a simulated data set as follows:
x=rnorm(200)
y=x-2*x^2+rnorm(200)
\#(b)
plot(x, y)
# (C)
library(boot)
Data = data.frame(x, y)
set.seed(1)
LG.fit = glm(y~x)
cv.glm(Data, LG.fit)$delta
LG2.fit = glm(y\sim poly(x,2))
cv.glm(Data, LG2.fit)$delta
LG3.fit = glm(y\sim poly(x,3))
cv.glm(Data, LG3.fit)$delta
LG4.fit = glm(y\sim poly(x,4))
cv.glm(Data, LG4.fit)$delta
\#(d)
set.seed(3)
LG.fit = glm(y~x)
cv.glm(Data, LG.fit)$delta
LG.fit = glm(y\sim poly(x, 2))
cv.glm(Data, LG.fit)$delta
LG.fit = glm(y\sim poly(x,3))
cv.glm(Data, LG.fit)$delta
LG.fit = glm(y\sim poly(x,4))
cv.glm(Data, LG.fit)$delta
#(f)
# Generate simulated data set
set.seed(1)
x <- rnorm(200)
y < -x - 2*x^2 + rnorm(200)
# Define the four models
model1 < -lm(y \sim x)
model2 <-lim(y \sim x + I(x^2))
model3 < -lm(y \sim x + I(x^2) + I(x^3))
model4 < -lm(y \sim x + I(x^2) + I(x^3) + I(x^4))
# Create a function to perform 5-fold cross-validation and return the
cross-validation error
cv <- function(model) {</pre>
  cv.error <- rep(NA, 5)
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folds \leftarrow cut(seq along(x), breaks = 5, labels = FALSE)
  for (i in 1:5) {
    test.index <- which(folds == i)</pre>
    train.index <- which(folds != i)</pre>
    cv.error[i] <- mean((y[test.index] - predict(model, newdata =</pre>
data.frame(x = x[test.index]))^2
  }
  mean(cv.error)
}
# Compute the cross-validation errors for the four models
cv.error1 <- cv(model1)</pre>
cv.error2 <- cv(model2)
cv.error3 <- cv(model3)
cv.error4 <- cv(model4)
# Print the cross-validation errors
cat("CV error for model 1:", cv.error1, "\n")
cat("CV error for model 2:", cv.error2, "\n")
cat("CV error for model 3:", cv.error3, "\n")
cat("CV error for model 4:", cv.error4, "\n")
\#(g)
set.seed(3)
x <- rnorm(200)
y < -x - 2*x^2 + rnorm(200)
# Define the four models
model1 10 <- lm(y \sim x)
model2 10 <- lm(y \sim x + I(x^2))
model3 10 <- lm(y \sim x + I(x^2) + I(x^3))
model4 10 <- lm(y \sim x + I(x^2) + I(x^3) + I(x^4))
# Create a function to perform 10-fold cross-validation and return the
cross-validation error
cv <- function(model) {
  cv.error <- rep(NA, 10)
  folds \leftarrow cut(seq along(x), breaks = 10, labels = FALSE)
  for (i in 1:10) {
    test.index <- which(folds == i)</pre>
    train.index <- which(folds != i)</pre>
    cv.error[i] <- mean((y[test.index] - predict(model, newdata =</pre>
data.frame(x = x[test.index]))^2
  mean (cv.error)
# Compute the cross-validation errors for the four models
cv.error1 10 <- cv(model1 10)</pre>
cv.error2 10 <- cv(model2 10)
cv.error3 10 <- cv(model3 10)</pre>
cv.error4 10 <- cv(model4 10)
# Print the cross-validation errors
cat("CV error for model 1:", cv.error1 10, "\n")
cat("CV error for model 2:", cv.error2 10, "\n")
cat("CV error for model 3:", cv.error3 10, "\n")
cat("CV error for model 4:", cv.error4 10, "\n")
```