DS-6030 Homework Module 6

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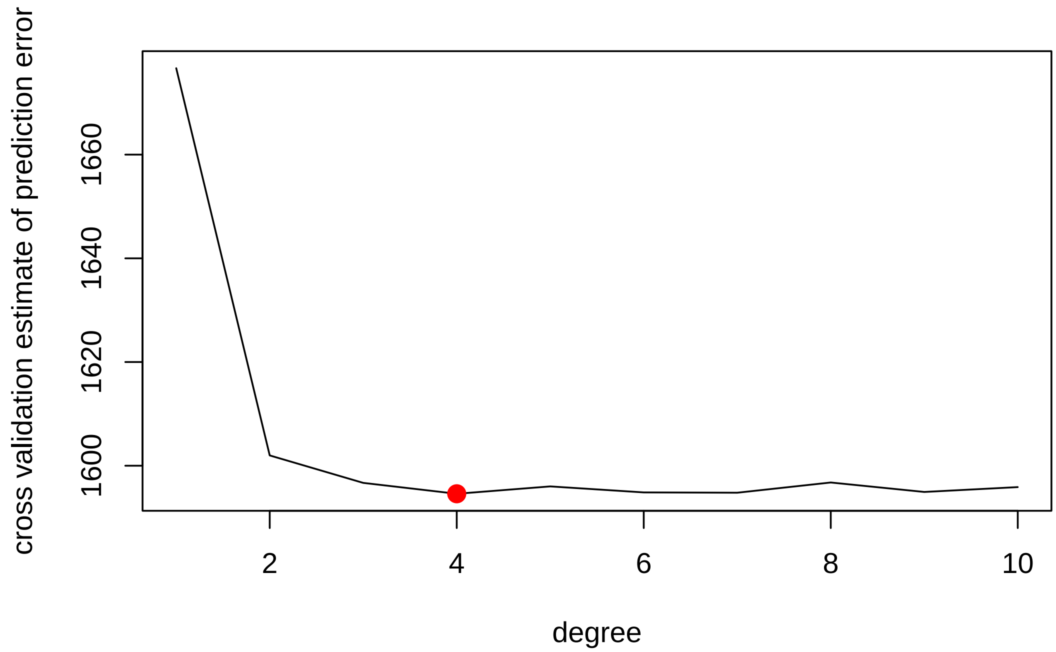
6. In this exercise, you will further analyze the `Wage` data set considered throughout this chapter.

   (a) Perform polynomial regression to predict wage using age. Use cross-validation to select the optimal degree d for the polynomial. What degree was chosen, and how does this compare to the results of hypothesis testing using ANOVA? Make a plot of the resulting polynomial fit to the data.

   The optimal degree for a polynomial regression to predict wage vs. age is $d = 4$. According to the documentation for `anova`, "When given a sequence of objects, `anova` tests the models against one another in the order specified... It produces a table which tests whether the model terms [for a given model] are significant [in the context of the previous model]." Examining the column of p values in below table, a term of degree 1 is significant in the context of an intercept-only model, a term of degree 2 is significant in the context of a polynomial of degree 2, a term of degree 3 is significant in the context of a polynomial of degree 2, a term of degree 4 is approximately significant in the context of a polynomial of degree 4, but a term of degree 5 is insignificant in the context of a polynomial of degree 4. This interpretation accords with using cross-validation to select the optimal degree for the polynomial.

```r
library(ISLR2)
set.seed(4)
range_of_degrees <- 1:10
number_of_degrees <- length(range_of_degrees)
cross_validation_estimates_of_prediction_errors <- rep(NA, number_of_degrees)
for (degree in range_of_degrees) {
    the_glm <- glm(wage ~ poly(age, degree), data = Wage)
    cross_validation_estimates_of_prediction_errors[degree] <-
        boot::cv.glm(Wage, the_glm, K = 10)$delta[1]
}
plot(
    x = range_of_degrees,
    y = cross_validation_estimates_of_prediction_errors,
    xlab = "degree",
    ylab = "cross validation estimate of prediction error",
    type = "l"
)
optimal_degree <-
    which.min(cross_validation_estimates_of_prediction_errors)
points(
    x = optimal_degree,
    y = cross_validation_estimates_of_prediction_errors[optimal_degree],
    col = "red",
    cex = 2,
```

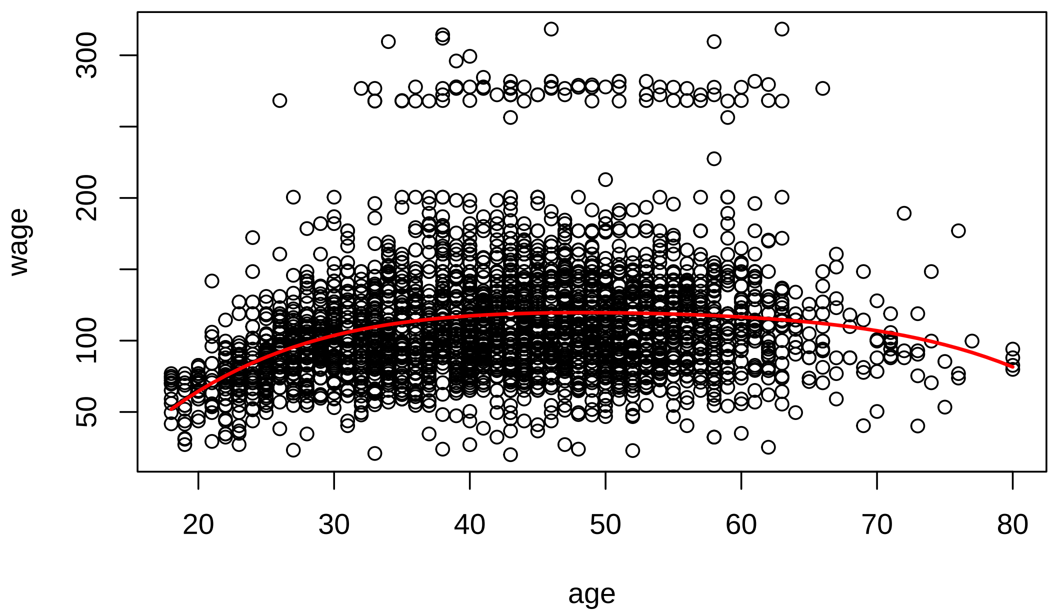
```
    pch = 20
)
```




```
lm_0 <- lm(wage ~ 1, data = Wage)
lm_1 <- lm(wage ~ age, data = Wage)
lm_2 <- lm(wage ~ poly(age, 2), data = Wage)
lm_3 <- lm(wage ~ poly(age, 3), data = Wage)
lm_4 <- lm(wage ~ poly(age, 4), data = Wage)
lm_5 <- lm(wage ~ poly(age, 5), data = Wage)
anova(lm_0, lm_1, lm_2, lm_3, lm_4, lm_5)
```

```
# Analysis of Variance Table
#
# Model 1: wage ~ 1
# Model 2: wage ~ age
# Model 3: wage ~ poly(age, 2)
# Model 4: wage ~ poly(age, 3)
# Model 5: wage ~ poly(age, 4)
# Model 6: wage ~ poly(age, 5)
#   Res.Df     RSS Df Sum of Sq        F    Pr(>F)
# 1   2999 5222086
# 2   2998 5022216  1    199870 125.4443 < 2.2e-16 ***
# 3   2997 4793430  1    228786 143.5931 < 2.2e-16 ***
# 4   2996 4777674  1     15756   9.8888  0.001679 **
# 5   2995 4771604  1      6070   3.8098  0.051046 .
# 6   2994 4770322  1      1283   0.8050  0.369682
# ---
# Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

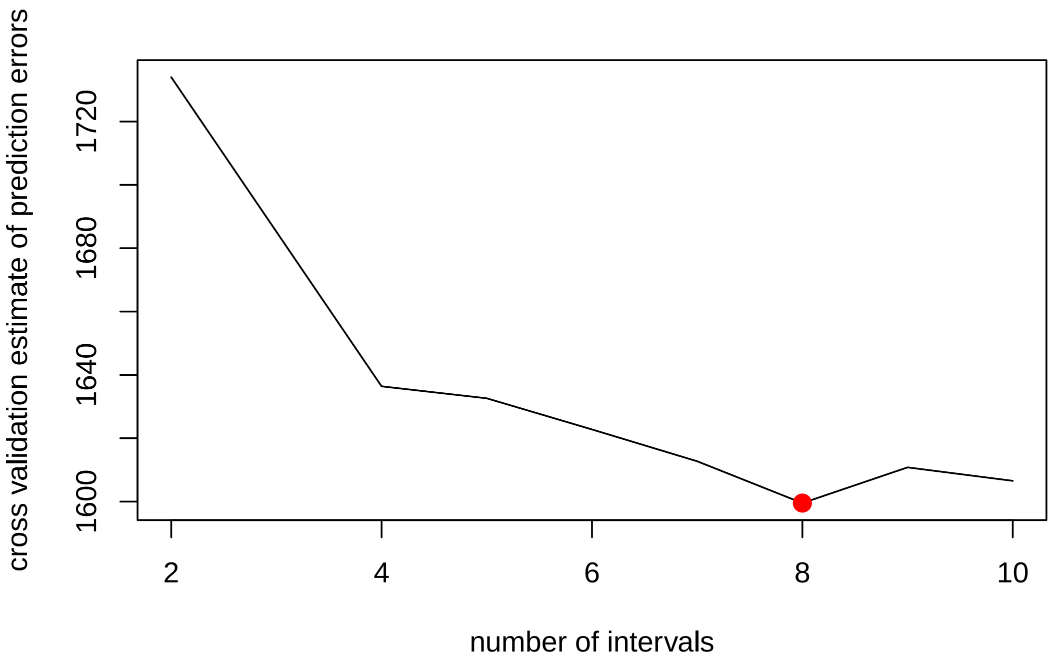
```
plot(wage ~ age, data = Wage)
minimum_age <- min(Wage$age)
maximum_age <- max(Wage$age)
sequence_of_ages <- seq(from = minimum_age, to = maximum_age)
list_with_age <- list(age = sequence_of_ages)
vector_of_predicted_wages <- predict(object = lm_4, newdata = list_with_age)
lines(sequence_of_ages, vector_of_predicted_wages, col = "red", lwd = 2)
```



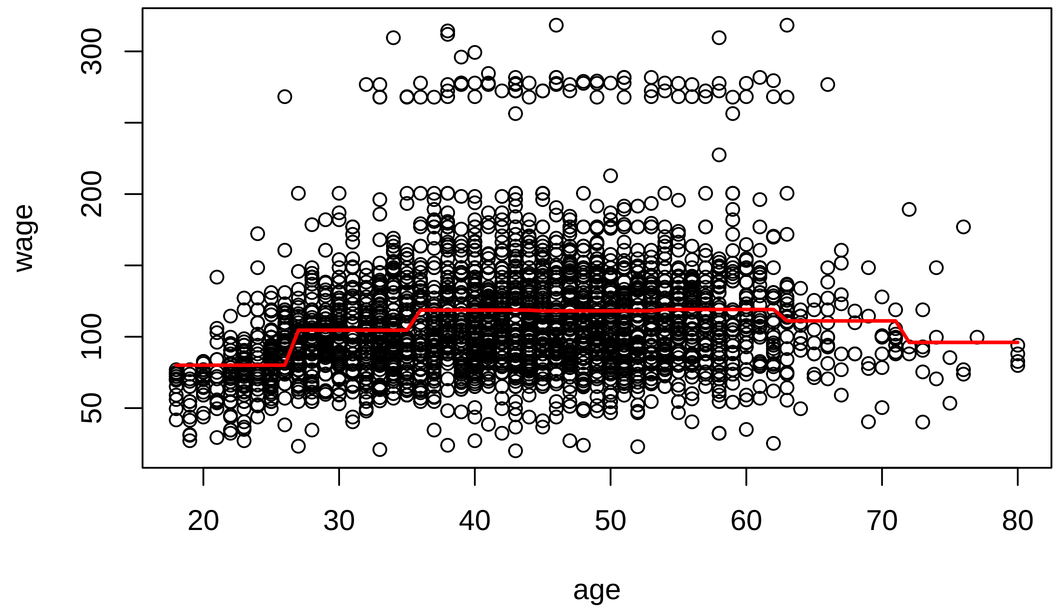
(b) Fit a step function to predict wage using age, and perform cross-validation to choose the optimal number of cuts. Make a plot of the fit obtained.
A cross-validated estimate of prediction error is minimum for 8 intervals.

```
range_of_numbers_of_intervals <- 2:10
number_of_numbers_of_intervals <- length(range_of_numbers_of_intervals)
cross_validation_estimates_of_prediction_errors <-
    rep(NA, number_of_numbers_of_intervals)
for (number_of_intervals in range_of_numbers_of_intervals) {
    Wage$interval <- cut(Wage$age, number_of_intervals)
    the_glm <- glm(wage ~ interval, data = Wage)
    cross_validation_estimates_of_prediction_errors[number_of_intervals - 1] <-
       boot::cv.glm(Wage, the_glm, K = 10)$delta[1]
}
plot(
    x = range_of_numbers_of_intervals,
    y = cross_validation_estimates_of_prediction_errors,
    xlab = "number of intervals",
    ylab = "cross validation estimate of prediction errors",
    type = "l"
)
```

```r
optimal_number_of_intervals <-
    which.min(cross_validation_estimates_of_prediction_errors)
points(
    x = optimal_number_of_intervals + 1,
    y = cross_validation_estimates_of_prediction_errors[
        optimal_number_of_intervals
    ],
    col = "red",
    cex = 2,
    pch = 20
)
```




```r
the_glm <- glm(wage ~ cut(age, optimal_number_of_intervals), data = Wage)
plot(wage ~ age, data = Wage)
vector_of_predicted_wages <- predict(object = the_glm, newdata = list_with_age)
lines(sequence_of_ages, vector_of_predicted_wages, col = "red", lwd = 2)
```



7. This question uses the variables `dis` (the weighted mean of distances to five Boston employment centers) and `nox` (nitrogen oxides concentration in parts per 10 million) from the Boston data. We will treat `dis` as the predictor and nox as the response.

   (a) Use the `poly()` function to fit a cubic polynomial regression to predict `nox` using `dis`. Report the regression output, and plot the resulting data and polynomial fits.
   Per the regression output, all coefficients are significant in the context of the multiple linear model.

```
library(ggplot2)
library(MASS)
```

```
#
# Attaching package: 'MASS'

# The following object is masked from 'package:ISLR2':
#
#     Boston
```

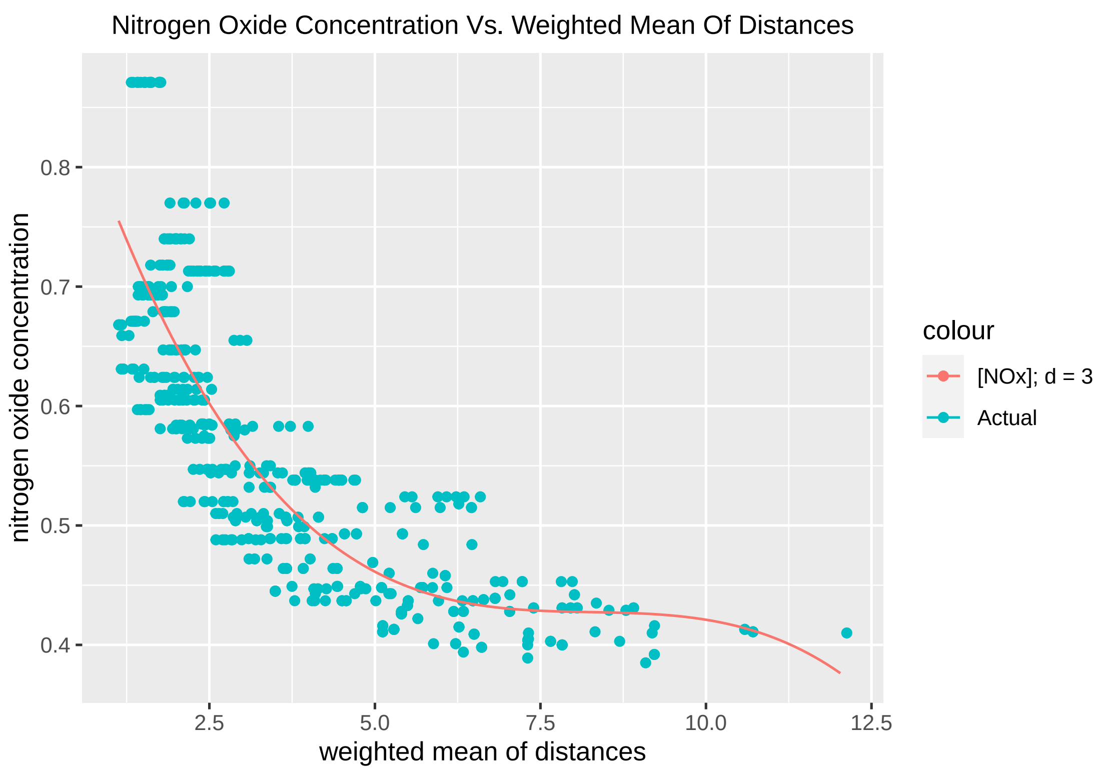
```
set.seed(1)
lm_3 <- lm(nox ~ poly(dis, 3), data = Boston)
summary(lm_3)
```

```
#
# Call:
# lm(formula = nox ~ poly(dis, 3), data = Boston)
#
# Residuals:
#       Min        1Q    Median        3Q       Max
# -0.121130 -0.040619 -0.009738  0.023385  0.194904
#
```

```
# Coefficients:
#                Estimate Std. Error t value Pr(>|t|)
# (Intercept)    0.554695   0.002759 201.021  < 2e-16 ***
# poly(dis, 3)1 -2.003096   0.062071 -32.271  < 2e-16 ***
# poly(dis, 3)2  0.856330   0.062071  13.796  < 2e-16 ***
# poly(dis, 3)3 -0.318049   0.062071  -5.124 4.27e-07 ***
# ---
# Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# Residual standard error: 0.06207 on 502 degrees of freedom
# Multiple R-squared:  0.7148,  Adjusted R-squared:  0.7131
# F-statistic: 419.3 on 3 and 502 DF,  p-value: < 2.2e-16
```

```r
minimum_weighted_mean_of_distances <- min(Boston$dis)
maximum_weighted_mean_of_distances <- max(Boston$dis)
sequence_of_weighted_means_of_distances <- seq(
    from = minimum_weighted_mean_of_distances,
    to = maximum_weighted_mean_of_distances,
    by = 0.1
)
list_with_dis <- list(dis = sequence_of_weighted_means_of_distances)
data_frame_of_weighted_means_of_distances_and_predicted_NOx_concentrations <-
    data.frame(
        weighted_mean_of_distances =
            sequence_of_weighted_means_of_distances
    )
for (degree in range_of_degrees) {
    the_lm <- lm(nox ~ poly(dis, degree), data = Boston)
    vector_of_predicted_nitrogen_oxide_concentrations <- predict(
        object = the_lm,
        list_with_dis
    )
    column_label <- paste(
        "NOx_concentration_predicted_by_polynomial_of_degree_",
        degree,
        sep = ""
    )
    data_frame_of_weighted_means_of_distances_and_predicted_NOx_concentrations[
        ,
        column_label
    ] <- vector_of_predicted_nitrogen_oxide_concentrations
}
ggplot() +
 geom_point(
     data = Boston,
     mapping = aes(
         x = dis,
         y = nox,
         color = "Actual"
     )
 ) +
 geom_line(
     data = data_frame_of_weighted_means_of_distances_and_predicted_NOx_concentrations,
     mapping = aes(
```

```
        x = weighted_mean_of_distances,
        y = NOx_concentration_predicted_by_polynomial_of_degree_3,
        color = "[NOx]; d = 3"
    )
) +
labs(
    x = "weighted mean of distances",
    y = "nitrogen oxide concentration",
    title = "Nitrogen Oxide Concentration Vs. Weighted Mean Of Distances"
) +
theme(
 plot.title = element_text(hjust = 0.5, size = 11),
)
```

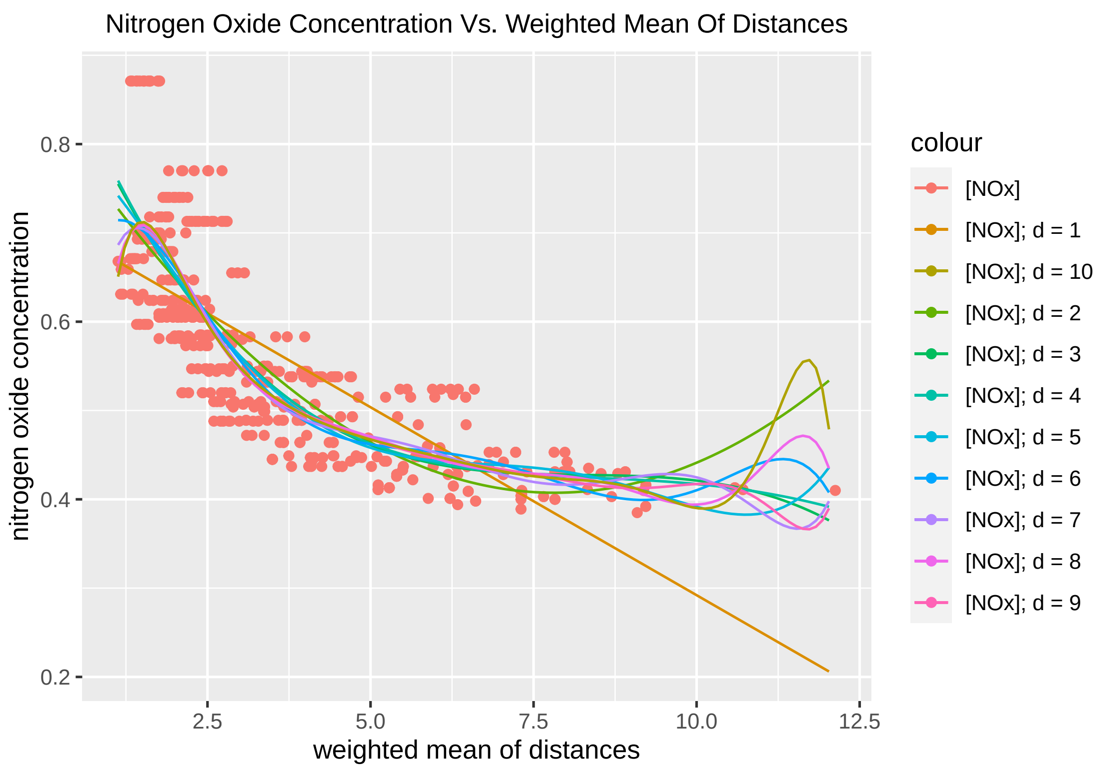


(b) Plot the polynomial fits for a range of different polynomial degrees (say, from 1 to 10), and report the associated residual sum of squares.

```
ggplot() +
 geom_point(
     data = Boston,
     mapping = aes(
         x = dis,
         y = nox,
         color = "[NOx]"
     )
 ) +
 geom_line(
     data = data_frame_of_weighted_means_of_distances_and_predicted_NOx_concentrations,
     mapping = aes(
```

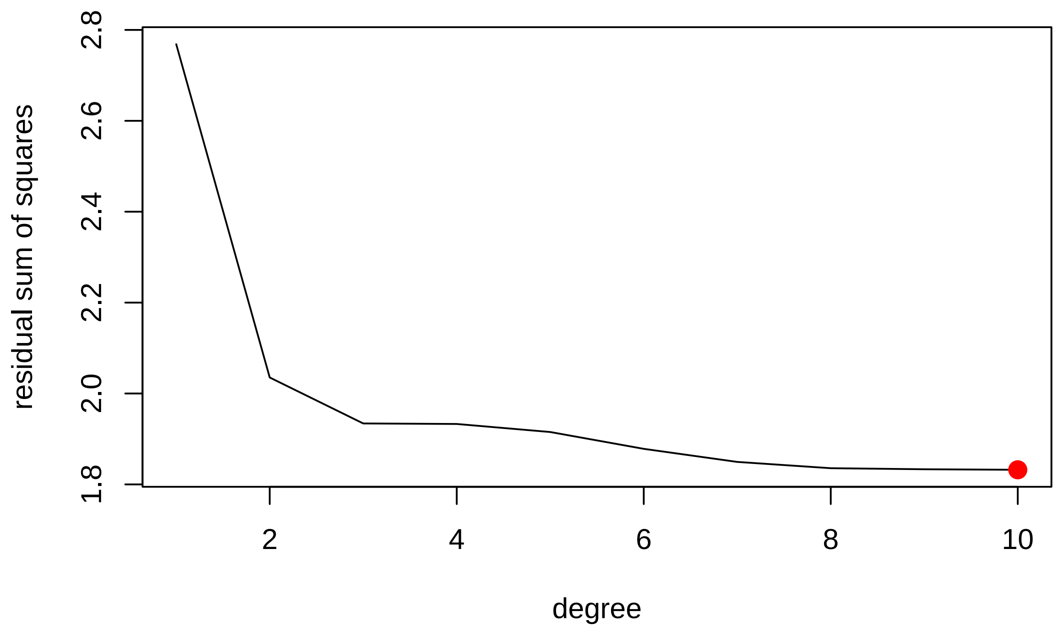
```
        x = weighted_mean_of_distances,
        y = NOx_concentration_predicted_by_polynomial_of_degree_1,
        color = "[NOx]; d = 1"
    )
) +
geom_line(
    data = data_frame_of_weighted_means_of_distances_and_predicted_NOx_concentrations,
    mapping = aes(
        x = weighted_mean_of_distances,
        y = NOx_concentration_predicted_by_polynomial_of_degree_2,
        color = "[NOx]; d = 2"
    )
) +
geom_line(
    data = data_frame_of_weighted_means_of_distances_and_predicted_NOx_concentrations,
    mapping = aes(
        x = weighted_mean_of_distances,
        y = NOx_concentration_predicted_by_polynomial_of_degree_3,
        color = "[NOx]; d = 3"
    )
) +
geom_line(
    data = data_frame_of_weighted_means_of_distances_and_predicted_NOx_concentrations,
    mapping = aes(
        x = weighted_mean_of_distances,
        y = NOx_concentration_predicted_by_polynomial_of_degree_4,
        color = "[NOx]; d = 4"
    )
) +
geom_line(
    data = data_frame_of_weighted_means_of_distances_and_predicted_NOx_concentrations,
    mapping = aes(
        x = weighted_mean_of_distances,
        y = NOx_concentration_predicted_by_polynomial_of_degree_5,
        color = "[NOx]; d = 5"
    )
) +
geom_line(
    data = data_frame_of_weighted_means_of_distances_and_predicted_NOx_concentrations,
    mapping = aes(
        x = weighted_mean_of_distances,
        y = NOx_concentration_predicted_by_polynomial_of_degree_6,
        color = "[NOx]; d = 6"
    )
) +
geom_line(
    data = data_frame_of_weighted_means_of_distances_and_predicted_NOx_concentrations,
    mapping = aes(
        x = weighted_mean_of_distances,
        y = NOx_concentration_predicted_by_polynomial_of_degree_7,
        color = "[NOx]; d = 7"
    )
) +
```

```r
geom_line(
    data = data_frame_of_weighted_means_of_distances_and_predicted_NOx_concentrations,
    mapping = aes(
        x = weighted_mean_of_distances,
        y = NOx_concentration_predicted_by_polynomial_of_degree_8,
        color = "[NOx]; d = 8"
    )
) +
geom_line(
    data = data_frame_of_weighted_means_of_distances_and_predicted_NOx_concentrations,
    mapping = aes(
        x = weighted_mean_of_distances,
        y = NOx_concentration_predicted_by_polynomial_of_degree_9,
        color = "[NOx]; d = 9"
    )
) +
geom_line(
    data = data_frame_of_weighted_means_of_distances_and_predicted_NOx_concentrations,
    mapping = aes(
        x = weighted_mean_of_distances,
        y = NOx_concentration_predicted_by_polynomial_of_degree_10,
        color = "[NOx]; d = 10"
    )
) +
labs(
    x = "weighted mean of distances",
    y = "nitrogen oxide concentration",
    title = "Nitrogen Oxide Concentration Vs. Weighted Mean Of Distances"
) +
theme(
 plot.title = element_text(hjust = 0.5, size = 11),
)
```



Per a plot of residual sum of squares vs. degree of polynomial, residual sum of squares decreases with degree of polynomial to a minimum for degree 10.

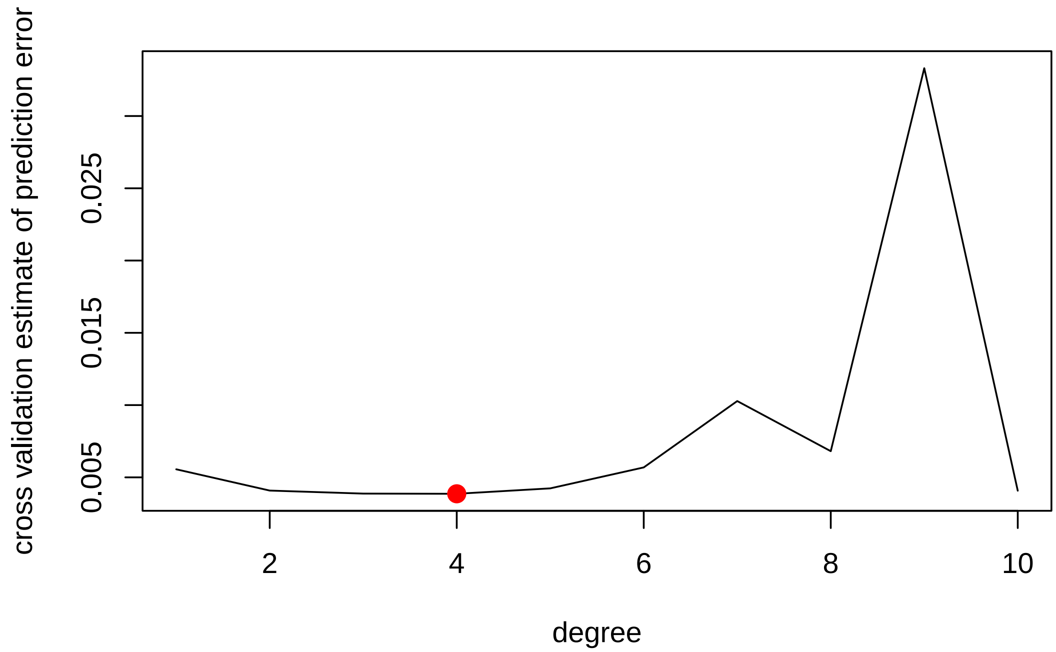
```
range_of_degrees <- 1:10
number_of_degrees <- length(range_of_degrees)
vector_of_residual_sums_of_squares <- rep(NA, number_of_degrees)
for (degree in range_of_degrees) {
    the_lm <- lm(nox ~ poly(dis, degree), data = Boston)
    vector_of_residual_sums_of_squares[degree] <- sum(the_lm$residuals^2)
}
plot(
    x = range_of_degrees,
    y = vector_of_residual_sums_of_squares,
    xlab = "degree",
    ylab = "residual sum of squares",
    type = "l"
)
optimal_degree <-
    which.min(vector_of_residual_sums_of_squares)
points(
    x = optimal_degree,
    y = vector_of_residual_sums_of_squares[optimal_degree],
    col = "red",
    cex = 2,
    pch = 20
)
```



(c) Perform cross-validation or another approach to select the optimal degree for the polynomial, and explain your results.

The minimum cross-validation estimate of prediction error occurs for degree 4.

```
cross_validation_estimates_of_prediction_errors <- rep(NA, number_of_degrees)
for (degree in range_of_degrees) {
    the_glm <- glm(nox ~ poly(dis, degree), data = Boston)
    cross_validation_estimates_of_prediction_errors[degree] <-
        boot::cv.glm(Boston, the_glm, K = 10)$delta[1]
}
plot(
    range_of_degrees,
    cross_validation_estimates_of_prediction_errors,
    xlab = "degree",
    ylab = "cross validation estimate of prediction error",
    type = "l"
)
optimal_degree <- which.min(cross_validation_estimates_of_prediction_errors)
points(
    x = optimal_degree,
    y = cross_validation_estimates_of_prediction_errors[optimal_degree],
    col = "red",
    cex = 2,
    pch = 20
)
```



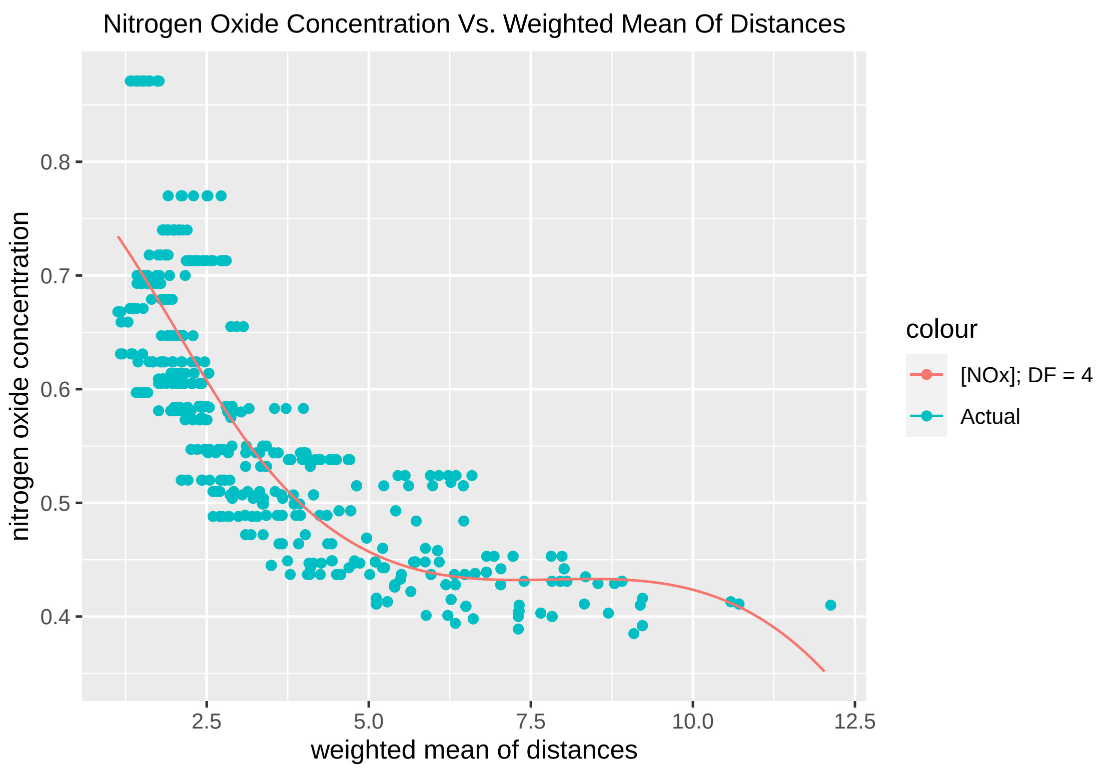
(d) Use the `bs()` function to fit a regression spline to predict `nox` using `dis`. Report the output for the fit using four degrees of freedom. How did you choose the knots? Plot the resulting fit.
The R interpreter determines knots automatically.

```
library(ggplot2)
library(MASS)
lm_4 <- lm(nox ~ splines::bs(dis, df = 4), data = Boston)
summary(lm_4)
```

```
#
# Call:
# lm(formula = nox ~ splines::bs(dis, df = 4), data = Boston)
#
# Residuals:
#       Min        1Q    Median        3Q       Max
# -0.124622 -0.039259 -0.008514  0.020850  0.193891
#
# Coefficients:
#                            Estimate Std. Error t value Pr(>|t|)
# (Intercept)                 0.73447    0.01460  50.306  < 2e-16 ***
# splines::bs(dis, df = 4)1 -0.05810    0.02186  -2.658  0.00812 **
# splines::bs(dis, df = 4)2 -0.46356    0.02366 -19.596  < 2e-16 ***
# splines::bs(dis, df = 4)3 -0.19979    0.04311  -4.634 4.58e-06 ***
# splines::bs(dis, df = 4)4 -0.38881    0.04551  -8.544  < 2e-16 ***
# ---
# Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# Residual standard error: 0.06195 on 501 degrees of freedom
# Multiple R-squared:  0.7164,  Adjusted R-squared:  0.7142
```

```
# F-statistic: 316.5 on 4 and 501 DF,  p-value: < 2.2e-16
```

```
data_frame_of_weighted_means_of_distances_and_predicted_NOx_concentrations <-
    data.frame(
        weighted_mean_of_distances =
            sequence_of_weighted_means_of_distances
    )
numbers_of_degrees_of_freedom <- 3:10
for (number_of_degrees_of_freedom in numbers_of_degrees_of_freedom) {
    the_lm <- lm(
        nox ~ splines::bs(dis, df = number_of_degrees_of_freedom),
        data = Boston
    )
    vector_of_predicted_nitrogen_oxide_concentrations <- predict(
        object = the_lm,
        list_with_dis
    )
    column_label <- paste(
        "NOx_concentration_predicted_by_B_spline_with_DF_",
        number_of_degrees_of_freedom,
        sep = ""
    )
    data_frame_of_weighted_means_of_distances_and_predicted_NOx_concentrations[
        ,
        column_label
    ] <- vector_of_predicted_nitrogen_oxide_concentrations
}
ggplot() +
 geom_point(
     data = Boston,
     mapping = aes(
         x = dis,
         y = nox,
         color = "Actual"
     )
 ) +
 geom_line(
     data = data_frame_of_weighted_means_of_distances_and_predicted_NOx_concentrations,
     mapping = aes(
         x = weighted_mean_of_distances,
         y = NOx_concentration_predicted_by_B_spline_with_DF_4,
         color = "[NOx]; DF = 4"
     )
 ) +
 labs(
     x = "weighted mean of distances",
     y = "nitrogen oxide concentration",
     title = "Nitrogen Oxide Concentration Vs. Weighted Mean Of Distances"
 ) +
 theme(
  plot.title = element_text(hjust = 0.5, size = 11),
 )
```

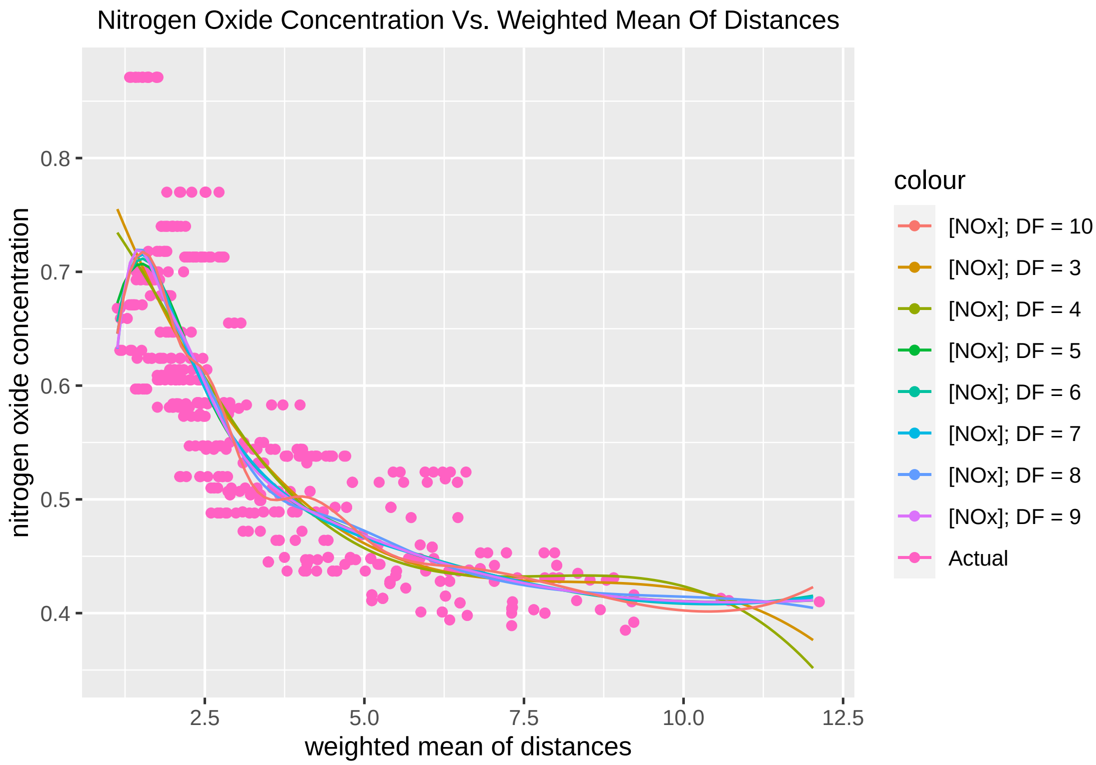


(e) Now fit a regression spline for a range of degrees of freedom, and plot the resulting fits and report the resulting RSS. Describe the results obtained.

```
ggplot() +
 geom_point(
     data = Boston,
     mapping = aes(
         x = dis,
         y = nox,
         color = "Actual"
     )
 ) +
 geom_line(
     data = data_frame_of_weighted_means_of_distances_and_predicted_NOx_concentrations,
     mapping = aes(
         x = weighted_mean_of_distances,
         y = NOx_concentration_predicted_by_B_spline_with_DF_3,
         color = "[NOx]; DF = 3"
     )
 ) +
 geom_line(
     data = data_frame_of_weighted_means_of_distances_and_predicted_NOx_concentrations,
     mapping = aes(
         x = weighted_mean_of_distances,
         y = NOx_concentration_predicted_by_B_spline_with_DF_4,
         color = "[NOx]; DF = 4"
     )
 ) +
 geom_line(
```

```
    data = data_frame_of_weighted_means_of_distances_and_predicted_NOx_concentrations,
    mapping = aes(
        x = weighted_mean_of_distances,
        y = NOx_concentration_predicted_by_B_spline_with_DF_5,
        color = "[NOx]; DF = 5"
    )
) +
geom_line(
    data = data_frame_of_weighted_means_of_distances_and_predicted_NOx_concentrations,
    mapping = aes(
        x = weighted_mean_of_distances,
        y = NOx_concentration_predicted_by_B_spline_with_DF_6,
        color = "[NOx]; DF = 6"
    )
) +
geom_line(
    data = data_frame_of_weighted_means_of_distances_and_predicted_NOx_concentrations,
    mapping = aes(
        x = weighted_mean_of_distances,
        y = NOx_concentration_predicted_by_B_spline_with_DF_7,
        color = "[NOx]; DF = 7"
    )
) +
geom_line(
    data = data_frame_of_weighted_means_of_distances_and_predicted_NOx_concentrations,
    mapping = aes(
        x = weighted_mean_of_distances,
        y = NOx_concentration_predicted_by_B_spline_with_DF_8,
        color = "[NOx]; DF = 8"
    )
) +
geom_line(
    data = data_frame_of_weighted_means_of_distances_and_predicted_NOx_concentrations,
    mapping = aes(
        x = weighted_mean_of_distances,
        y = NOx_concentration_predicted_by_B_spline_with_DF_9,
        color = "[NOx]; DF = 9"
    )
) +
geom_line(
    data = data_frame_of_weighted_means_of_distances_and_predicted_NOx_concentrations,
    mapping = aes(
        x = weighted_mean_of_distances,
        y = NOx_concentration_predicted_by_B_spline_with_DF_10,
        color = "[NOx]; DF = 10"
    )
) +
labs(
    x = "weighted mean of distances",
    y = "nitrogen oxide concentration",
    title = "Nitrogen Oxide Concentration Vs. Weighted Mean Of Distances"
) +
theme(
```

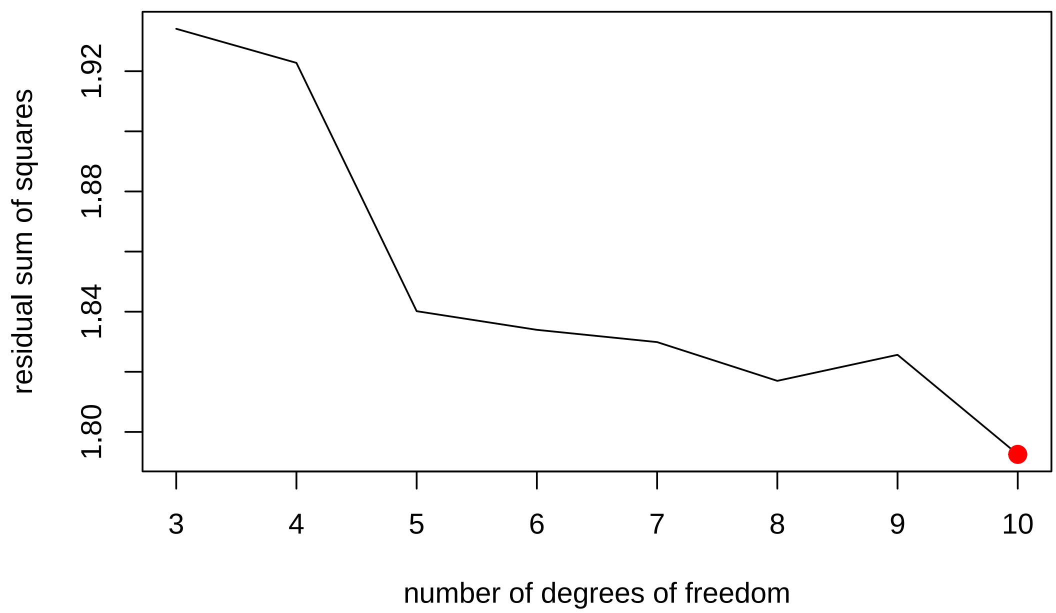
```
  plot.title = element_text(hjust = 0.5, size = 11),
 )
```



Per a plot of residual sum of squares vs. number of degrees of freedom of B-spline, residual sum of squares decreases with number of degrees of freedom of B-spline to a minimum for number of degrees of freedom 10.

```
numbers_of_degrees_of_freedom <- 3:10
number_of_numbers_of_degrees_of_freedom <- length(numbers_of_degrees_of_freedom)
vector_of_residual_sums_of_squares <-
    rep(NA, number_of_numbers_of_degrees_of_freedom)
for (number_of_degrees_of_freedom in numbers_of_degrees_of_freedom) {
    the_lm <- lm(
        nox ~ splines::bs(dis, df = number_of_degrees_of_freedom),
        data = Boston
    )
    vector_of_residual_sums_of_squares[number_of_degrees_of_freedom - 2] <-
        sum(the_lm$residuals^2)
}
plot(
    x = numbers_of_degrees_of_freedom,
    y = vector_of_residual_sums_of_squares,
    xlab = "number of degrees of freedom",
    ylab = "residual sum of squares",
    type = "l"
)
optimal_number_of_degrees_of_freedom <-
    which.min(vector_of_residual_sums_of_squares)
points(
```

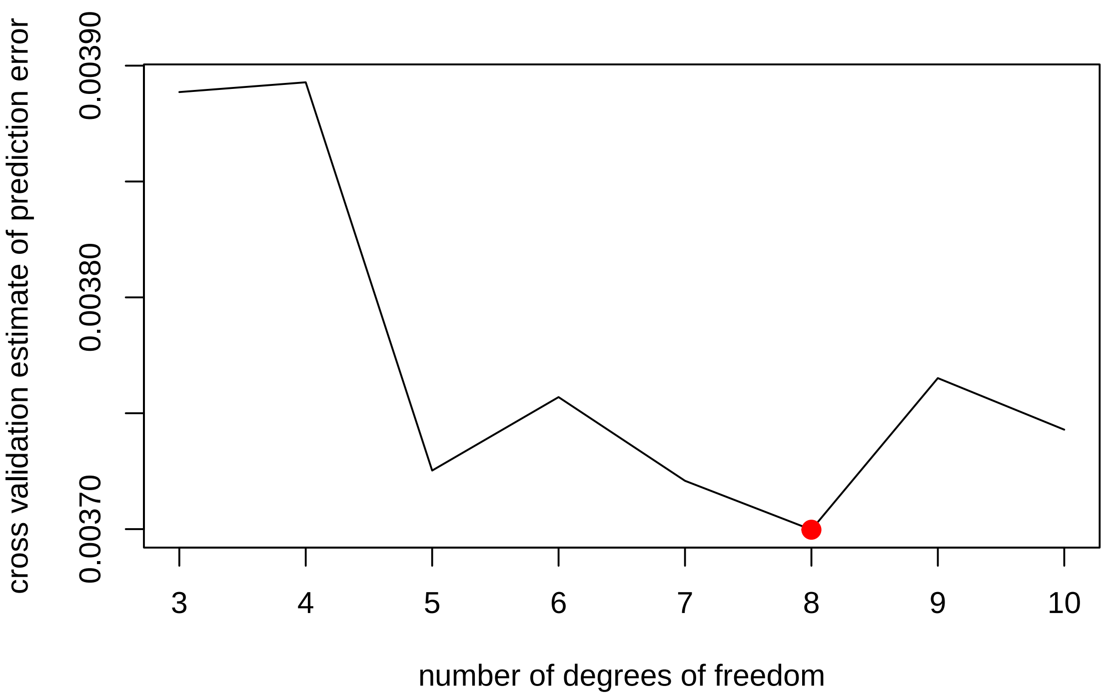
```
    x = optimal_number_of_degrees_of_freedom + 2,
    y = vector_of_residual_sums_of_squares[
        optimal_number_of_degrees_of_freedom
    ],
    col = "red",
    cex = 2,
    pch = 20
)
```



(f) Perform cross-validation or another approach in order to select the best degrees of freedom for a regression spline on this data. Describe your results.

```
cross_validation_estimates_of_prediction_errors <-
    rep(NA, number_of_numbers_of_degrees_of_freedom)
for (number_of_degrees_of_freedom in numbers_of_degrees_of_freedom) {
    the_glm <- glm(
        nox ~ splines::bs(dis, df = number_of_degrees_of_freedom),
        data = Boston
    )
    cross_validation_estimates_of_prediction_errors[
        number_of_degrees_of_freedom - 2
    ] <- boot::cv.glm(Boston, the_glm, K = 10)$delta[1]
}
plot(
    numbers_of_degrees_of_freedom,
    cross_validation_estimates_of_prediction_errors,
    xlab = "number of degrees of freedom",
    ylab = "cross validation estimate of prediction error",
```

```
    type = "l"
)
optimal_degree <- which.min(cross_validation_estimates_of_prediction_errors)
points(
    x = optimal_degree + 2,
    y = cross_validation_estimates_of_prediction_errors[optimal_degree],
    col = "red",
    cex = 2,
    pch = 20
)
```



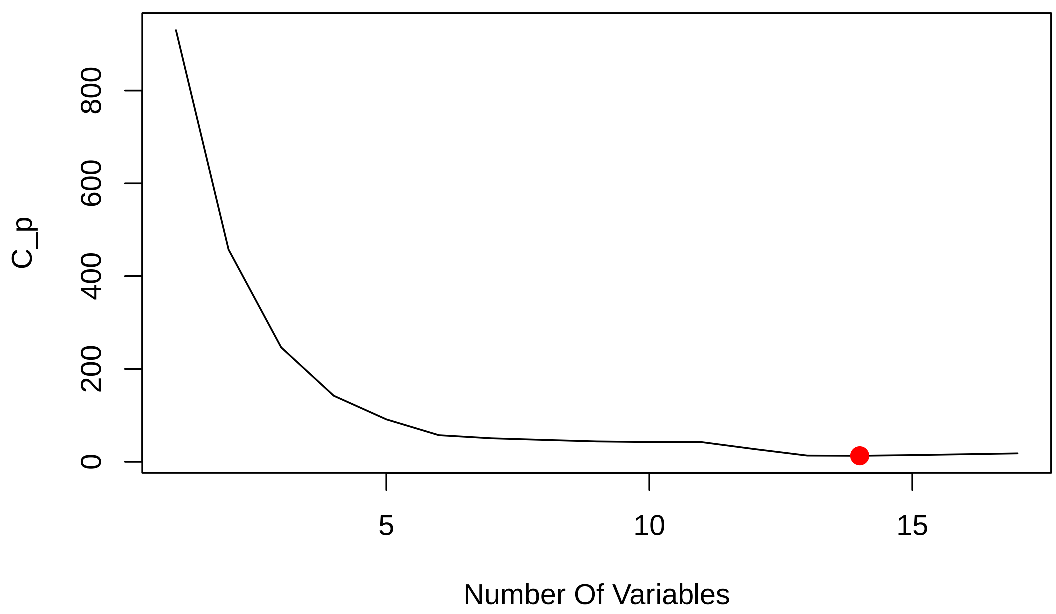
10. This question relates to the College data set.

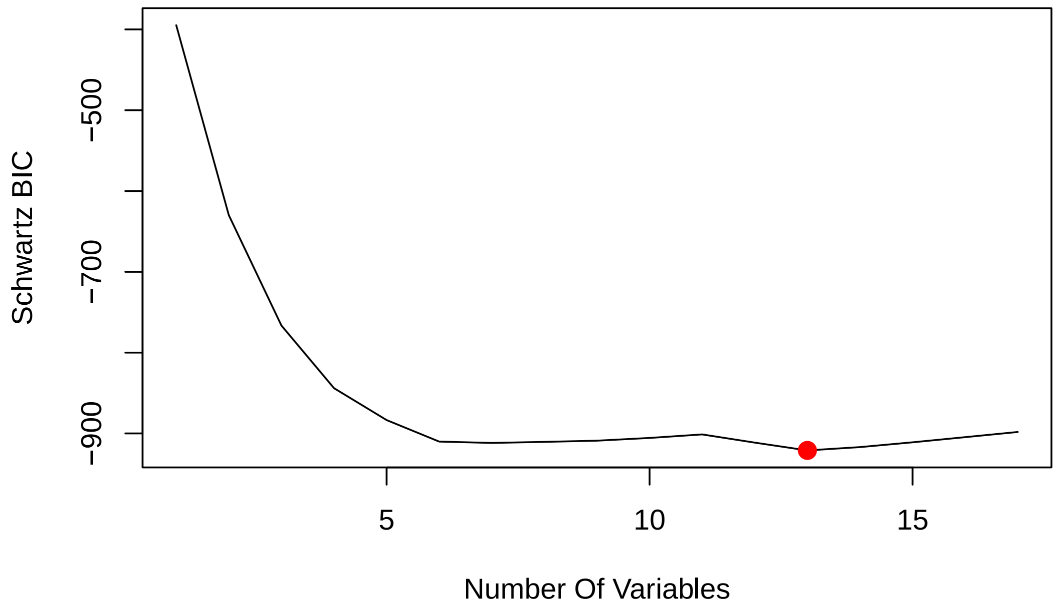
    (a) Split the data into a training set and a test set. Using out-of-state tuition as the response and the other variables as the predictors, perform forward stepwise selection on the training set in order to identify a satisfactory model that uses just a subset of the predictors.

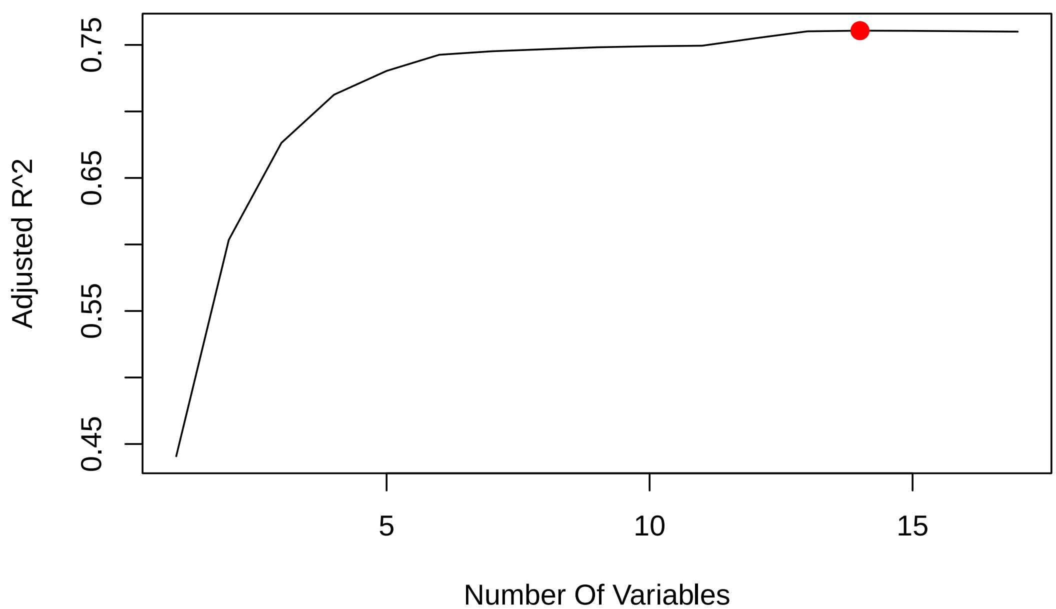
        According to Mallow's C_p, adjusted R^2, and Schwartz Bayesian Information Criterion approximately, the best model by forward selection on the training set is a model that uses 14 predictors.

```
library(leaps)
colleges <- College
list_of_training_and_testing_data <-
    TomLeversRPackage::split_data_set_into_training_and_testing_data(
        data_frame = colleges,
        proportion_of_training_data = 0.9
    )
training_data <- list_of_training_and_testing_data$training_data
```

```r
testing_data <- list_of_training_and_testing_data$testing_data
subset_selection_object <- regsubsets(
    Outstate ~ .,
    data = training_data,
    nvmax = 17,
    method = "forward"
)
TomLeversRPackage::analyze_subset_selection_object(subset_selection_object)
```








```
# $coefficients_by_Mallows_Cp
#   (Intercept)    PrivateYes          Apps        Accept        Enroll
# -1.675751e+03  2.190844e+03 -2.922056e-01  7.816260e-01 -5.591633e-01
#     Top10perc   F.Undergrad    Room.Board      Personal           PhD
```

```
#  2.544466e+01 -8.696432e-02  8.412901e-01 -2.799464e-01  1.473434e+01
#      Terminal      S.F.Ratio   perc.alumni        Expend     Grad.Rate
#  2.135001e+01 -5.027035e+01  4.148921e+01  1.894437e-01  2.599650e+01
#
# $coefficients_by_Schwartz_BIC
#   (Intercept)    PrivateYes          Apps        Accept     Top10perc
# -1760.7876572  2203.6868443    -0.2745499     0.6941289    24.1023505
#   F.Undergrad    Room.Board      Personal           PhD      Terminal
#    -0.1629121     0.8580574    -0.2835728    14.7886440    22.1407883
#     S.F.Ratio   perc.alumni        Expend     Grad.Rate
#   -50.0931302    40.3891913     0.1877100    25.7705077
#
# $coefficients_by_adjusted_R2
#   (Intercept)    PrivateYes          Apps        Accept        Enroll
# -1.675751e+03  2.190844e+03 -2.922056e-01  7.816260e-01 -5.591633e-01
#     Top10perc   F.Undergrad    Room.Board      Personal           PhD
#  2.544466e+01 -8.696432e-02  8.412901e-01 -2.799464e-01  1.473434e+01
#      Terminal     S.F.Ratio   perc.alumni        Expend     Grad.Rate
#  2.135001e+01 -5.027035e+01  4.148921e+01  1.894437e-01  2.599650e+01
```

The names of the 14 predictors of the best 14-predictor model according to forward selection are *Private*, *Apps*, *Accept*, *Enroll*, *Top10perc*, *F.Undergrad*, *Room.Board*, *Personal*, *PhD*, *Terminal*, *S.F.Ratio*, *perc.alumni*, *Expend*, and *Grad.Rate*.

(b) Fit a GAM on the training data, using out-of-state tuition as the response and the features selected in the previous step as the predictors. Plot the results, and explain your findings.

According to the documentation for `gam::s`, `s` is a "symbolic wrapper to indicate a smooth term in a formala argument to gam."

Below is a plot of a Generalized Additive Model (GAM) with subplots of `s(x = x, df = 4)` vs. x, where x represents one of our 14 predictors. In these plots, the function of *Room.Board* looks relatively linear. We can perform a series of ANOVA tests in order to determine which of these three models is best: a GAM that excludes *Room.Board* (M1), a GAM that uses a linear function of *Room.Board* (M2), or a GAM that uses a spline function of *Room.Board* (M3).

```r
library(gam)
```

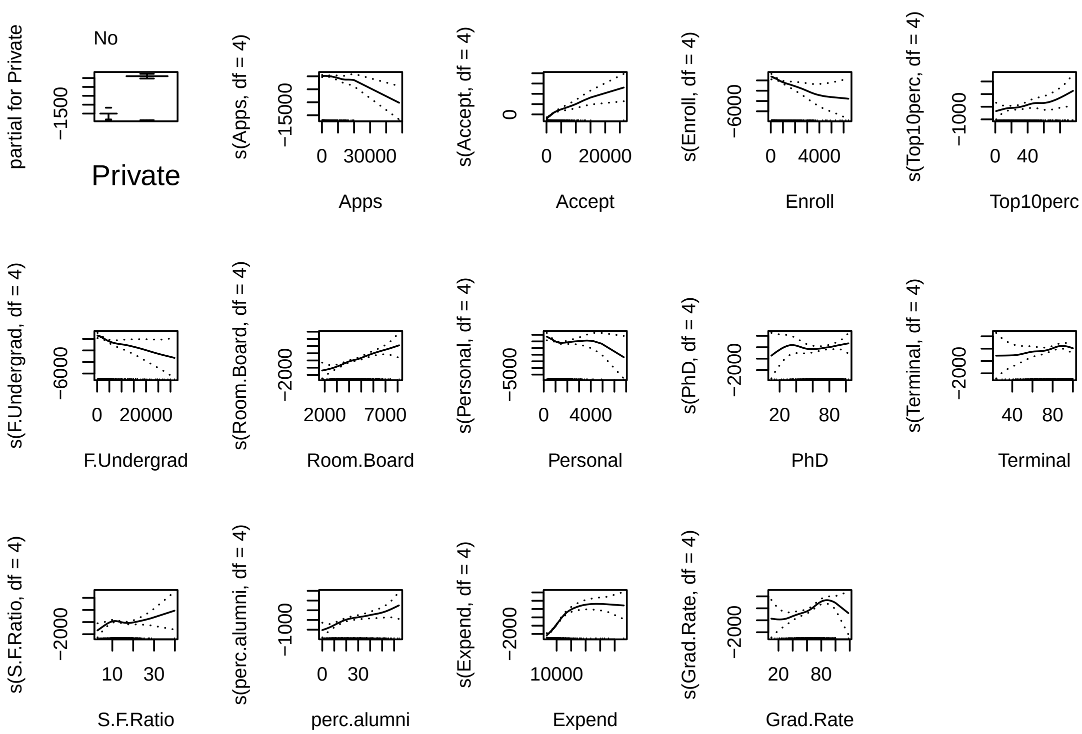
```
# Loading required package: splines

# Loading required package: foreach

# Loaded gam 1.22-2
```

```r
the_gam <- gam(
    Outstate ~
        Private +
        s(Apps, df = 4) +
        s(Accept, df = 4) +
        s(Enroll, df = 4) +
        s(Top10perc, df = 4) +
        s(F.Undergrad, df = 4) +
        s(Room.Board, df = 4) +
        s(Personal, df = 4) +
        s(PhD, df = 4) +
        s(Terminal, df = 4) +
        s(S.F.Ratio, df = 4) +
        s(perc.alumni, df = 4) +
```

```r
        s(Expend, df = 4) +
        s(Grad.Rate, df = 4),
    data = training_data
)
par(mfrow = c(3, 5))
plot(the_gam, se = TRUE)
the_gam_without_Room_And_Board <- gam(
    Outstate ~
        Private +
        s(Apps, df = 4) +
        s(Accept, df = 4) +
        s(Enroll, df = 4) +
        s(Top10perc, df = 4) +
        s(F.Undergrad, df = 4) +
        s(Personal, df = 4) +
        s(PhD, df = 4) +
        s(Terminal, df = 4) +
        s(S.F.Ratio, df = 4) +
        s(perc.alumni, df = 4) +
        s(Expend, df = 4) +
        s(Grad.Rate, df = 4),
    data = training_data
)
the_gam_with_linear_Room_And_Board <- gam(
    Outstate ~
        Private +
        s(Apps, df = 4) +
        s(Accept, df = 4) +
        s(Enroll, df = 4) +
        s(Top10perc, df = 4) +
        s(F.Undergrad, df = 4) +
        Room.Board +
        s(Personal, df = 4) +
        s(PhD, df = 4) +
        s(Terminal, df = 4) +
        s(S.F.Ratio, df = 4) +
        s(perc.alumni, df = 4) +
        s(Expend, df = 4) +
        s(Grad.Rate, df = 4),
    data = training_data
)
anova(
    the_gam_without_Room_And_Board,
    the_gam_with_linear_Room_And_Board,
    the_gam
)
```

```
# Analysis of Deviance Table
#
# Model 1: Outstate ~ Private + s(Apps, df = 4) + s(Accept, df = 4) + s(Enroll,
#     df = 4) + s(Top10perc, df = 4) + s(F.Undergrad, df = 4) +
#     s(Personal, df = 4) + s(PhD, df = 4) + s(Terminal, df = 4) +
#     s(S.F.Ratio, df = 4) + s(perc.alumni, df = 4) + s(Expend,
#     df = 4) + s(Grad.Rate, df = 4)
```

```
# Model 2: Outstate ~ Private + s(Apps, df = 4) + s(Accept, df = 4) + s(Enroll,
#     df = 4) + s(Top10perc, df = 4) + s(F.Undergrad, df = 4) +
#     Room.Board + s(Personal, df = 4) + s(PhD, df = 4) + s(Terminal,
#     df = 4) + s(S.F.Ratio, df = 4) + s(perc.alumni, df = 4) +
#     s(Expend, df = 4) + s(Grad.Rate, df = 4)
# Model 3: Outstate ~ Private + s(Apps, df = 4) + s(Accept, df = 4) + s(Enroll,
#     df = 4) + s(Top10perc, df = 4) + s(F.Undergrad, df = 4) +
#     s(Room.Board, df = 4) + s(Personal, df = 4) + s(PhD, df = 4) +
#     s(Terminal, df = 4) + s(S.F.Ratio, df = 4) + s(perc.alumni,
#     df = 4) + s(Expend, df = 4) + s(Grad.Rate, df = 4)
#   Resid. Df Resid. Dev Df  Deviance  Pr(>Chi)
# 1       650 2162407730
# 2       649 2030070388  1 132337342 8.037e-11 ***
# 3       646 2023484554  3   6585833    0.5514
# ---
# Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```



We find that there is compelling evidence that a GAM with a linear function of *Room.Board* is better than a GAM that does not include *Room.Board* at all. However, there is no evidence that a non-linear function of *Room.Board* is needed. In other words, based on the results of this ANOVA, M2 is preferred.

(c) Evaluate the model obtained on the test set, and explain the results obtained.

```r
vector_of_predicted_out_of_state_tuitions <- predict(the_gam, testing_data)
vector_of_residuals <-
    testing_data$Outstate - vector_of_predicted_out_of_state_tuitions
residual_sum_of_squares <- t(vector_of_residuals) %*% vector_of_residuals
residual_sum_of_squares <- residual_sum_of_squares[1, 1]
number_of_observations <- nrow(testing_data)
```

```
number_of_variables <- 14
residual_mean_square <-
    residual_sum_of_squares / (number_of_observations - number_of_variables)
response_values <- testing_data$Outstate
sum_of_response_values <- sum(response_values)
square_of_sum_of_response_values <- sum_of_response_values^2
total_sum_of_squares <-
    (t(response_values) %*% response_values) -
    (square_of_sum_of_response_values / number_of_observations)
total_mean_square <- total_sum_of_squares / (number_of_observations - 1)
adjusted_coefficient_of_determination_R2 <-
    1 - (residual_mean_square / total_mean_square)
adjusted_coefficient_of_determination_R2
```

```
#            [,1]
# [1,] 0.7858769
```

Our GAM with 14 predictors has an adjusted coefficient of determination R^2 of 0.785, which indicates that our GAM predicts out of state tuition decently.

(d) For which variables, if any, is there evidence of a non-linear relationship with the response?

The "Anova for Parametric Effects" p-values demonstrate that predictors with low p values are all highly statistically significant, even when only assuming a linear relationship. Alternatively, the "Anova for Nonparametric Effects" p values age correspond to a null hypothesis of a linear relationship versus the alternative of a non-linear relationship.

There is evidence of a nonlinear relationship for *Apps*, *Accept*, *Personal*, *S.F.Ratio*, *Expend*, and *Grad.Rate*.

```
summary(the_gam)
```

```
#
# Call: gam(formula = Outstate ~ Private + s(Apps, df = 4) + s(Accept,
#     df = 4) + s(Enroll, df = 4) + s(Top10perc, df = 4) + s(F.Undergrad,
#     df = 4) + s(Room.Board, df = 4) + s(Personal, df = 4) + s(PhD,
#     df = 4) + s(Terminal, df = 4) + s(S.F.Ratio, df = 4) + s(perc.alumni,
#     df = 4) + s(Expend, df = 4) + s(Grad.Rate, df = 4), data = training_data)
# Deviance Residuals:
#      Min       1Q   Median       3Q      Max
# -6424.89 -1044.53    64.88  1127.10  7641.42
#
# (Dispersion Parameter for gaussian family taken to be 3132326)
#
#     Null Deviance: 11294049290 on 699 degrees of freedom
# Residual Deviance: 2023484554 on 646.0006 degrees of freedom
# AIC: 12510.42
#
# Number of Local Scoring Iterations: NA
#
# Anova for Parametric Effects
#                         Df     Sum Sq    Mean Sq   F value    Pr(>F)
# Private                  1 3266642255 3266642255 1042.8807 < 2.2e-16 ***
# s(Apps, df = 4)          1 1085460731 1085460731  346.5350 < 2.2e-16 ***
# s(Accept, df = 4)        1  155135905  155135905   49.5274 5.008e-12 ***
# s(Enroll, df = 4)        1  194365305  194365305   62.0514 1.422e-14 ***
# s(Top10perc, df = 4)     1 1254583773 1254583773  400.5278 < 2.2e-16 ***
```

```
# s(F.Undergrad, df = 4)   1   61629047   61629047   19.6752 1.079e-05 ***
# s(Room.Board, df = 4)    1  696650839  696650839  222.4069 < 2.2e-16 ***
# s(Personal, df = 4)      1   35358560   35358560   11.2883 0.0008259 ***
# s(PhD, df = 4)           1  120621779  120621779   38.5087 9.742e-10 ***
# s(Terminal, df = 4)      1   30530298   30530298    9.7468 0.0018765 **
# s(S.F.Ratio, df = 4)     1  135063601  135063601   43.1193 1.059e-10 ***
# s(perc.alumni, df = 4)   1  151746512  151746512   48.4453 8.363e-12 ***
# s(Expend, df = 4)        1  522755364  522755364  166.8905 < 2.2e-16 ***
# s(Grad.Rate, df = 4)     1   77736593   77736593   24.8175 8.100e-07 ***
# Residuals              646 2023484554    3132326
# ---
# Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# Anova for Nonparametric Effects
#                        Npar Df  Npar F     Pr(F)
# (Intercept)
# Private
# s(Apps, df = 4)              3  4.3103  0.005059 **
# s(Accept, df = 4)            3 11.2535 3.326e-07 ***
# s(Enroll, df = 4)            3  2.0592  0.104410
# s(Top10perc, df = 4)         3  0.8199  0.483104
# s(F.Undergrad, df = 4)       3  2.1723  0.090090 .
# s(Room.Board, df = 4)        3  0.7618  0.515734
# s(Personal, df = 4)          3  4.2825  0.005255 **
# s(PhD, df = 4)               3  1.8972  0.128763
# s(Terminal, df = 4)          3  1.2857  0.278286
# s(S.F.Ratio, df = 4)         3  5.1175  0.001666 **
# s(perc.alumni, df = 4)       3  1.2863  0.278085
# s(Expend, df = 4)            3 24.6601 3.997e-15 ***
# s(Grad.Rate, df = 4)         3  3.5216  0.014847 *
# ---
# Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```