p8106_hw2_jsg2145

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```
collegedf = read_csv("./data/College.csv") %>%
  janitor::clean_names() %>%
  mutate(college = factor(college)) %>%
  select(outstate, everything())
```

```
## Parsed with column specification:
## cols(
##   College = col_character(),
##   Apps = col_double(),
##   Accept = col_double(),
##   Enroll = col_double(),
##   Top10perc = col_double(),
##   Top25perc = col_double(),
##   F.Undergrad = col_double(),
##   P.Undergrad = col_double(),
##   Outstate = col_double(),
##   Room.Board = col_double(),
##   Books = col_double(),
##   Personal = col_double(),
##   PhD = col_double(),
##   Terminal = col_double(),
##   S.F.Ratio = col_double(),
##   perc.alumni = col_double(),
##   Expend = col_double(),
##   Grad.Rate = col_double()
## )
```

```
college.train = collegedf %>%
  filter(college != "Columbia University")
```

```
x.train = model.matrix(outstate ~ apps + accept + enroll + top10perc + top25perc + f_undergrad + p_unde

y.train = pull(college.train, outstate)

ctrl1 = trainControl(method = "cv", number = 5)
```

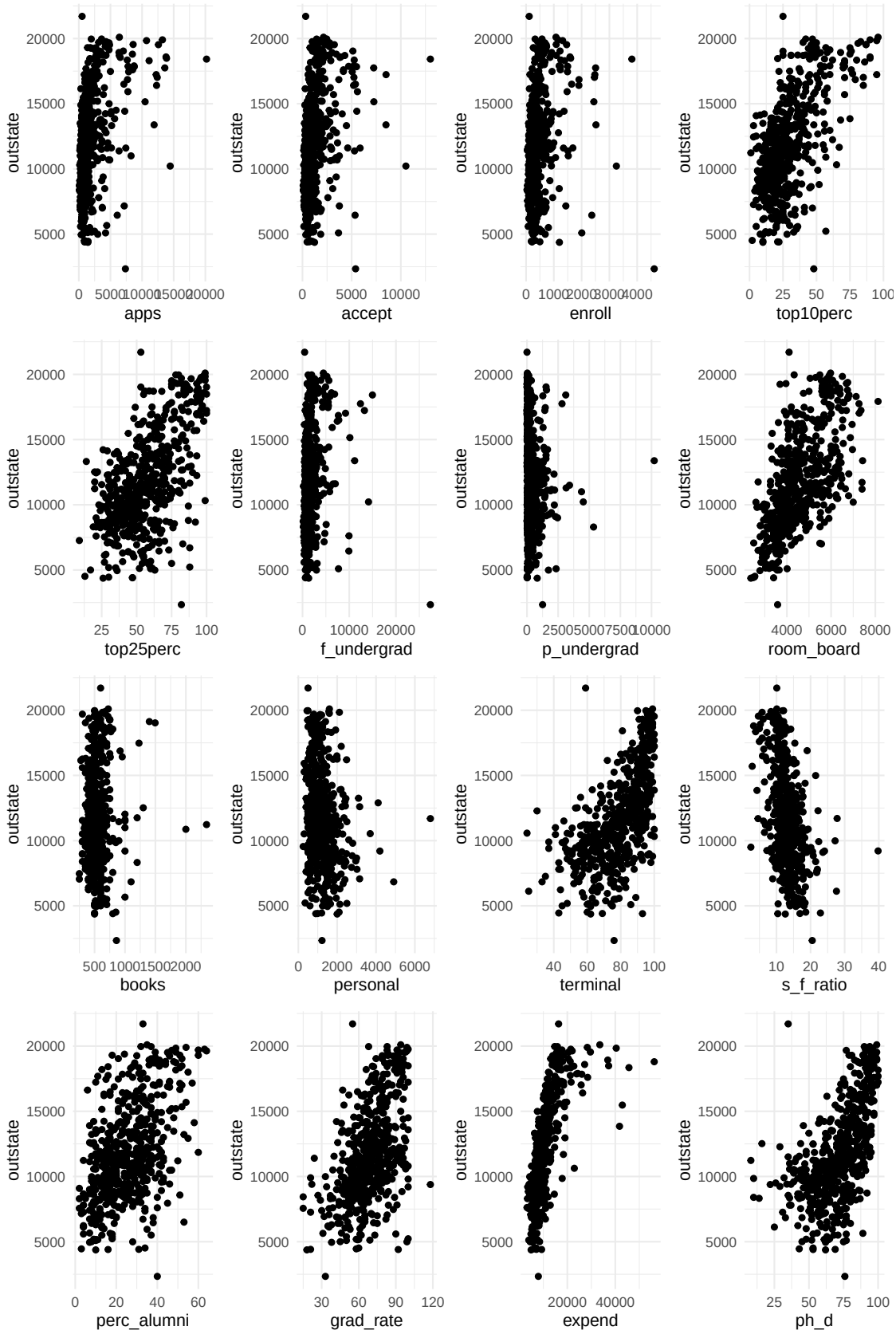
```
p1 = college.train %>%
  ggplot(aes(x = apps, y = outstate)) +
  geom_point()

p2 = college.train %>%
  ggplot(aes(x = accept, y = outstate)) +
  geom_point()

p3 = college.train %>%
  ggplot(aes(x = enroll, y = outstate)) +
```

```
  geom_point()

p4 = college.train %>%
  ggplot(aes(x = top10perc, y = outstate)) +
  geom_point()

p5 = college.train %>%
  ggplot(aes(x = top25perc, y = outstate)) +
  geom_point()

p6 = college.train %>%
  ggplot(aes(x = f_undergrad, y = outstate)) +
  geom_point()

p7 = college.train %>%
  ggplot(aes(x = p_undergrad, y = outstate)) +
  geom_point()

p8 = college.train %>%
  ggplot(aes(x = room_board, y = outstate)) +
  geom_point()

p9 = college.train %>%
  ggplot(aes(x = books, y = outstate)) +
  geom_point()

p16 = college.train %>%
  ggplot(aes(x = ph_d, y = outstate)) +
  geom_point()

p10 = college.train %>%
  ggplot(aes(x = personal, y = outstate)) +
  geom_point()

p11 = college.train %>%
  ggplot(aes(x = terminal, y = outstate)) +
  geom_point()

p12 = college.train %>%
  ggplot(aes(x = s_f_ratio, y = outstate)) +
  geom_point()

p13 = college.train %>%
  ggplot(aes(x = perc_alumni, y = outstate)) +
  geom_point()

p14 = college.train %>%
  ggplot(aes(x = grad_rate, y = outstate)) +
  geom_point()

p15 = college.train %>%
  ggplot(aes(x = expend, y = outstate)) +
  geom_point() +
```

```
  scale_x_continuous(breaks = c(0, 20000, 40000, 65000))
```

Part a

```
plots = list(p1, p2, p3, p4, p5, p6, p7, p8, p9, p10, p11, p12, p13, p14, p15, p16)

wrap_plots(plots, ncol = 4)
```

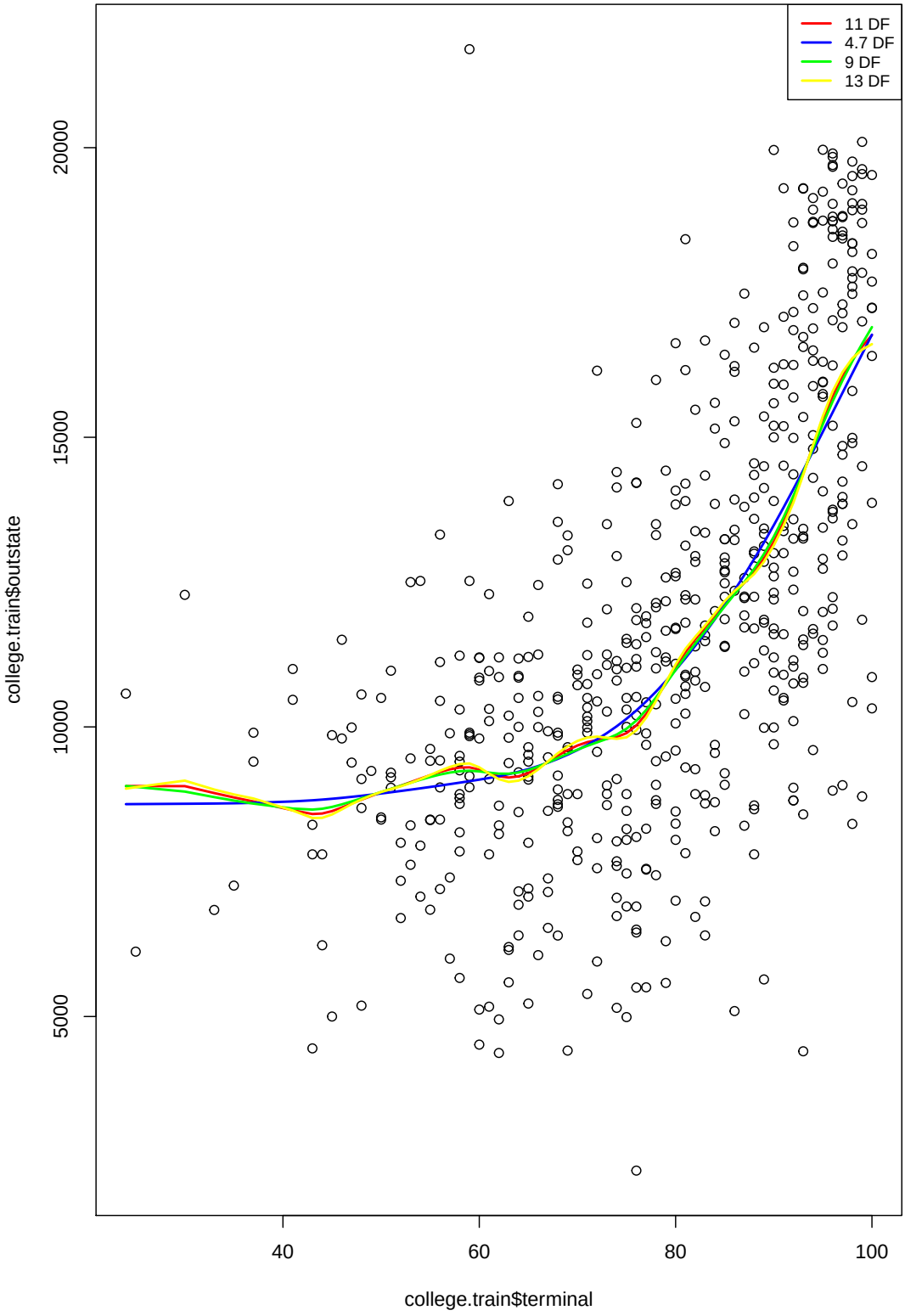

outstate
apps
accept
enroll
top10perc
top25perc
f_undergrad
p_undergrad
room_board
books
personal
terminal
s_f_ratio
perc_alumni
grad_rate
expend
ph_d

Part b

```
spline.term9 = smooth.spline(pull(college.train, terminal), pull(college.train, outstate), df = 9)
spline.term10 = smooth.spline(pull(college.train, terminal), pull(college.train, outstate), df = 10)
spline.term11 = smooth.spline(pull(college.train, terminal), pull(college.train, outstate), df = 11)
spline.term12 = smooth.spline(pull(college.train, terminal), pull(college.train, outstate), df = 12)
spline.term13 = smooth.spline(pull(college.train, terminal), pull(college.train, outstate), df = 13)
spline.termA = smooth.spline(pull(college.train, terminal), pull(college.train, outstate), cv = TRUE)
spline.termA$df
```

```
## [1] 4.686019
```

```
plot(college.train$terminal, college.train$outstate)
points(x.train, cex = .5,
       col = "darkgrey")
lines(spline.term11, col = "red ", lwd = 2)
lines(spline.termA, col = "blue", lwd = 2)
lines(spline.term9, col = "green", lwd = 2)
lines(spline.term13, col = "yellow", lwd = 2)
legend("topright", legend = c("11 DF", "4.7 DF", "9 DF", "13 DF"),
       col = c("red", "blue", "green", "yellow"), lty = 1, lwd = 2, cex = .8)
```

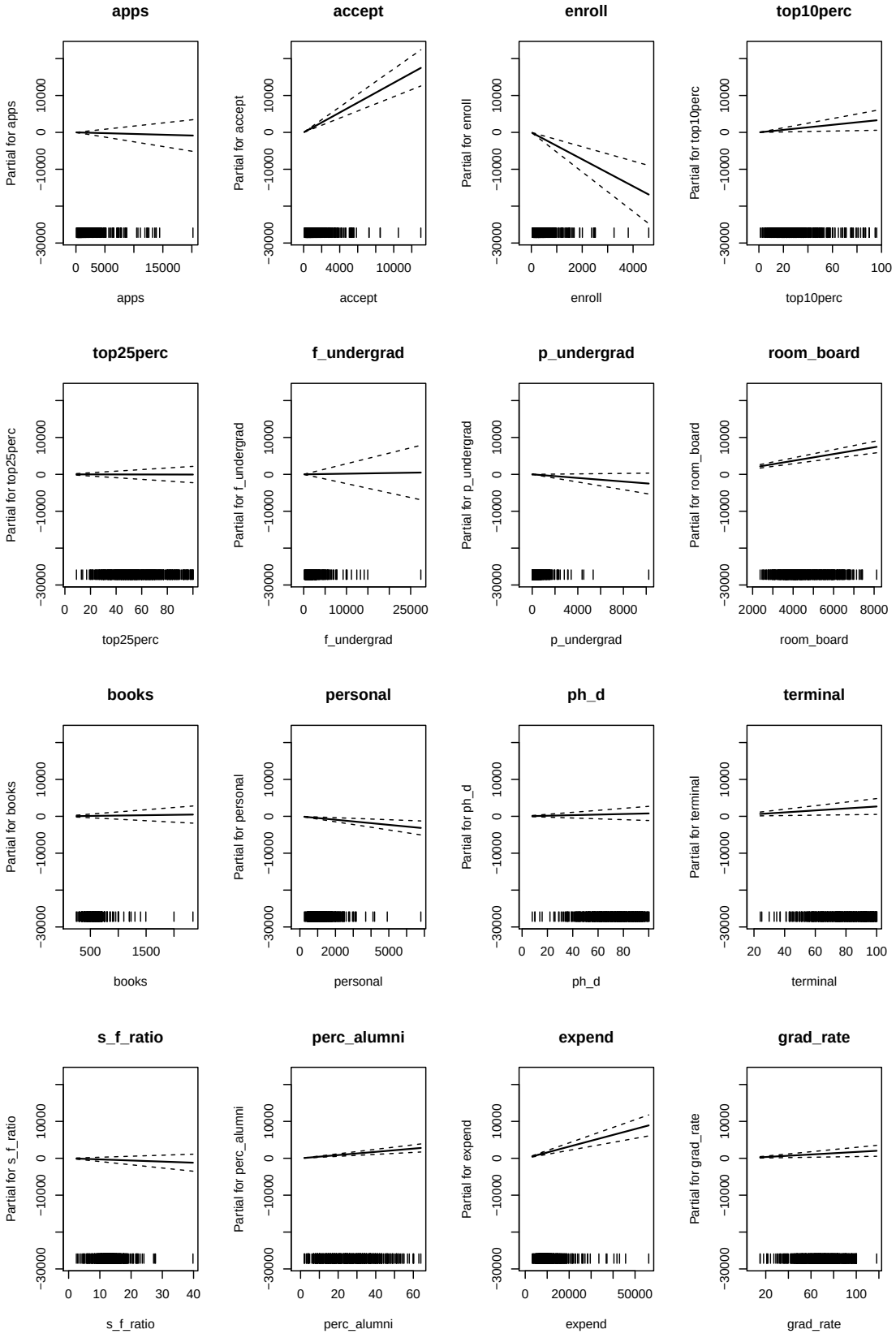

11 DF
4.7 DF
9 DF
13 DF
5000
10000
15000
20000
college.train$outstate
40
60
80
100
college.train$terminal

This graph shows a smoothing spline using cross validation to choose degrees of freedom compared with various other degrees of freedom.

Part c

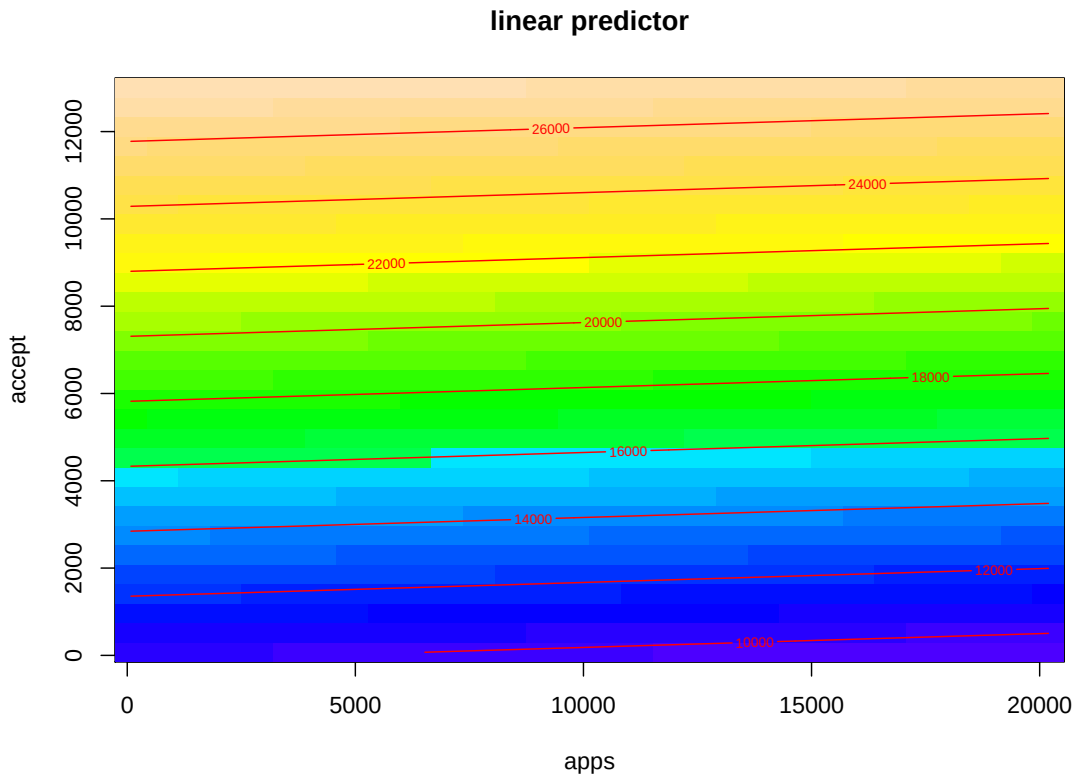
```
gam1 = gam(outstate ~ apps + accept + enroll + top10perc + top25perc + f_undergrad + p_undergrad + room
```

```
par(mfrow = c(4,4))
plot(gam1, pages=1,residuals=TRUE,all.terms=TRUE,shade=TRUE,shade.col=2)
```


apps
accept
enroll
top10perc
top25perc
f_undergrad
p_undergrad
room_board
books
personal
ph_d
terminal
s_f_ratio
perc_alumni
expend
grad_rate
Partial for apps
Partial for accept
Partial for enroll
Partial for top10perc
Partial for top25perc
Partial for f_undergrad
Partial for p_undergrad
Partial for room_board
Partial for books
Partial for personal
Partial for ph_d
Partial for terminal
Partial for s_f_ratio
Partial for perc_alumni
Partial for expend
Partial for grad_rate
−30000
−10000
0
10000
0 5000 15000
0 4000 10000
0 2000 4000
0 20 60 100
0 20 40 60 80
0 10000 25000
0 4000 8000
2000 4000 6000 8000
500 1500
0 2000 5000
0 20 40 60 80
20 40 60 80 100
0 10 20 30 40
0 20 40 60
0 20000 50000
20 60 100

The above graph shows a plot of the partial dependence of each predictor in relation to the tuition.

```
vis.gam(gam1, view = c("apps", "accept"),
        plot.type = "contour", color = "topo")
```



This plot shows a contour of the dependence of two predictors on each other.

```
set.seed(22)
college.gam = train(x.train, y.train,
                    method = "gam",
                    tuneGrid = data.frame(method = "GCV.Cp",
                                          select = c(TRUE,FALSE)),
                    trControl = ctrl1)

college.gam$bestTune
```

```
##   select method
## 1  FALSE GCV.Cp
```

```
college.gam$finalModel
```

```
##
## Family: gaussian
## Link function: identity
##
```

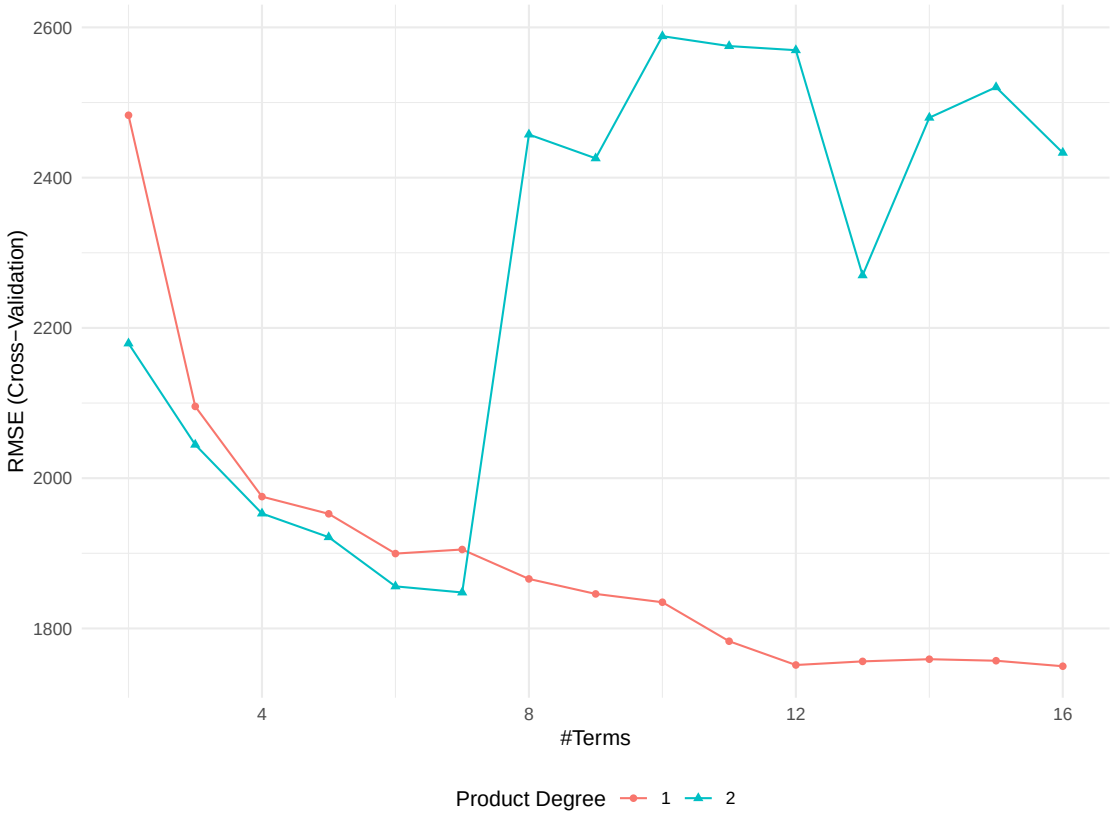
```
## Formula:
## .outcome ~ s(perc_alumni) + s(terminal) + s(top10perc) + s(ph_d) +
##     s(grad_rate) + s(books) + s(top25perc) + s(s_f_ratio) + s(personal) +
##     s(p_undergrad) + s(enroll) + s(room_board) + s(accept) +
##     s(f_undergrad) + s(apps) + s(expend)
##
## Estimated degrees of freedom:
## 1.90 5.14 3.64 6.32 4.27 2.35 1.00
## 4.33 1.00 1.00 1.00 2.13 3.58 6.28
## 4.59 6.45  total = 55.98
##
## GCV score: 2761951
```

Part d

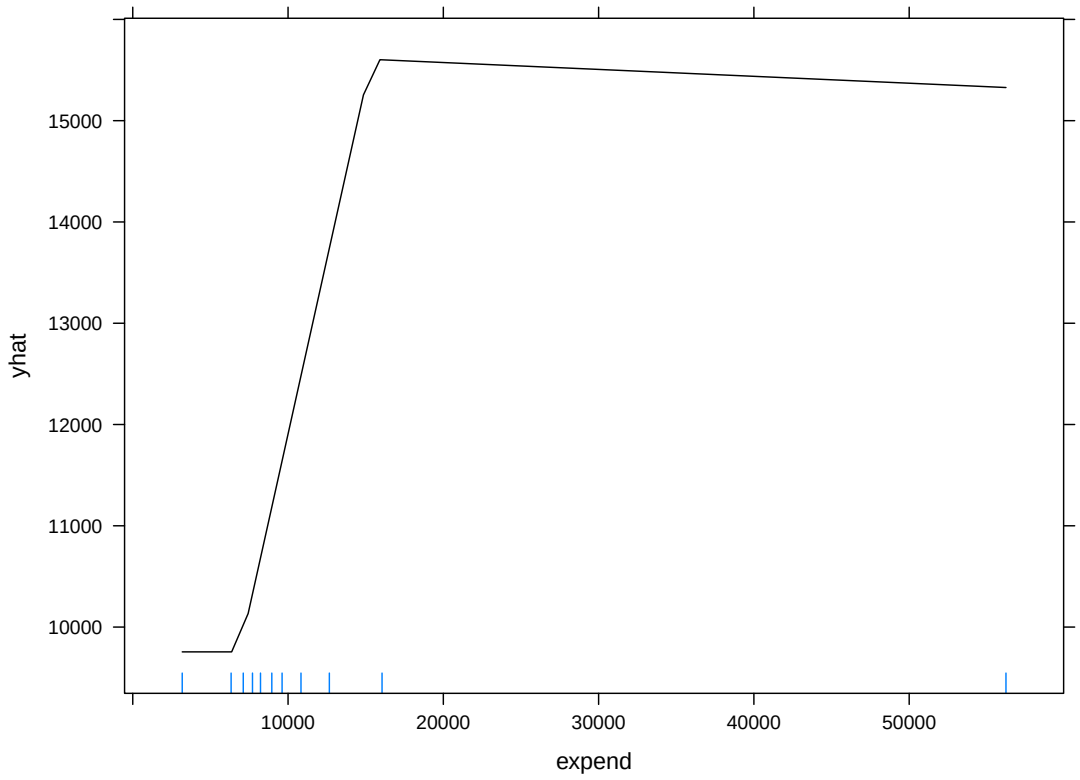
```
mars_grid <- expand.grid(degree = 1:2,
                         nprune = 2:16)

college.earth = train(x.train, y.train,
                      method = "earth", tuneGrid = mars_grid, trControl = ctrl1)
```

```
## Loading required package: earth

## Loading required package: Formula

## Loading required package: plotmo

## Loading required package: plotrix

## Loading required package: TeachingDemos
```

```
ggplot(college.earth)
```




```
partial(college.earth, pred.var = "expend", plot = TRUE, rug = TRUE)
```




```
college.earth$bestTune
```

```
##    nprune degree
## 15     16      1
```

```
coef(college.earth$finalModel)
```

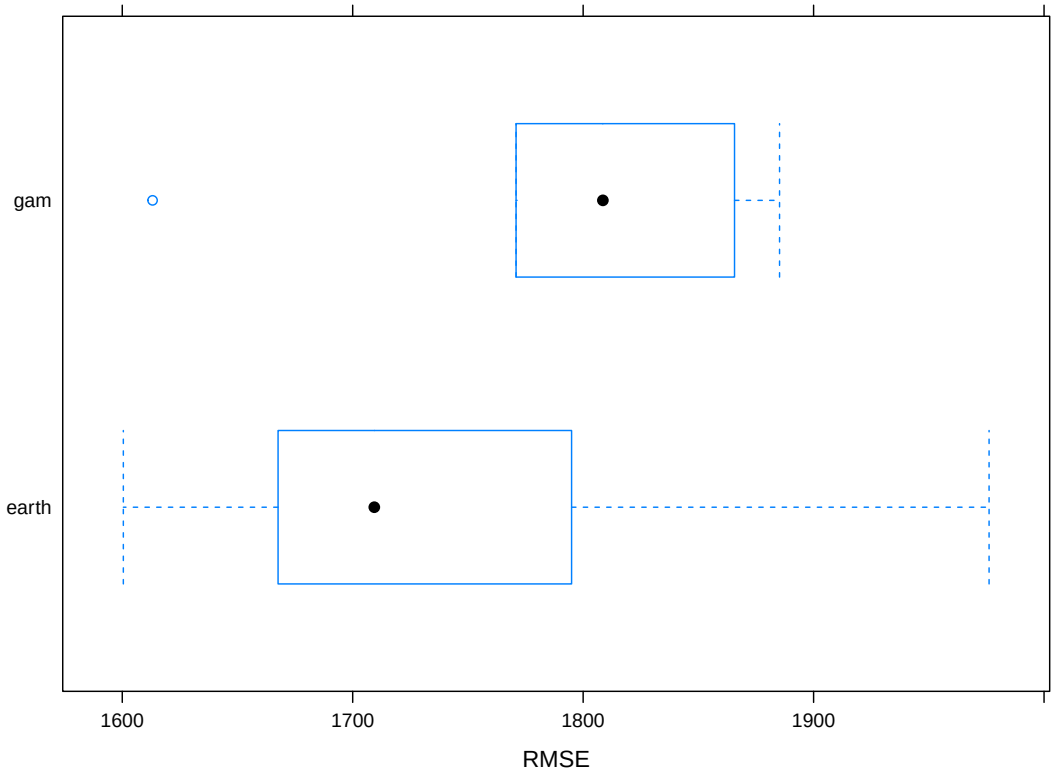
```
##          (Intercept)     h(expend-15365)  h(4450-room_board)
##        11157.3323100          -0.6964270          -1.2721516
##     h(grad_rate-97)     h(97-grad_rate) h(f_undergrad-1355)
##         -242.9852028         -24.1380627          -0.3567241
## h(1355-f_undergrad)   h(22-perc_alumni)        h(apps-3712)
##           -1.7564383         -77.0359905           7.0815293
##    h(1300-personal)       h(913-enroll)      h(2193-accept)
##            1.0492662           5.2944664          -1.9951560
##      h(expend-6881)        h(apps-3877)   h(s_f_ratio-10.1)
##            0.6896165          -6.7393719         -97.7224105
##   h(s_f_ratio-17.8)
##          222.5913868
```

Using multivariate adaptive regression spline (MARS), a final model is -0.745*"expend"* - *1.294*"room_board" - 21.71*"grad_rate"* - *0.337*"f_undergrad" - 1.442*"f_undergrad"* - *79.612*"perc_alumni" + 0.417*"apps"* + *0.947*"personal" + 4.572*"enroll"* - *1.922*"accept" + 0.745*"expend."

```r
resamp <- resamples(list(earth = college.earth,
                         gam = college.gam))

summary(resamp)
```

```
##
## Call:
## summary.resamples(object = resamp)
##
## Models: earth, gam
## Number of resamples: 5
##
## MAE
##           Min.  1st Qu.   Median     Mean  3rd Qu.     Max. NA's
## earth 1304.020 1308.502 1351.310 1359.150 1367.087 1464.831    0
## gam   1305.207 1369.317 1376.875 1384.362 1393.167 1477.245    0
##
## RMSE
##           Min.  1st Qu.   Median     Mean  3rd Qu.     Max. NA's
## earth 1600.466 1667.612 1709.368 1749.716 1794.982 1976.150    0
## gam   1613.150 1770.887 1808.560 1788.702 1865.690 1885.225    0
##
## Rsquared
##            Min.   1st Qu.    Median      Mean   3rd Qu.      Max. NA's
## earth 0.7487180 0.7546039 0.7868256 0.7838266 0.8063247 0.8226606    0
## gam   0.7228419 0.7489326 0.7796175 0.7721217 0.7929478 0.8162689    0
```

```r
bwplot(resamp, metric = "RMSE")
```



Part e

```
columbia = collegedf %>%
  filter(college == "Columbia University")

pred.earth = predict(college.earth, newdata = columbia)

pred.gam = predict(gam1, newdata = columbia)
```

The MARS model predicts a tuition of 1.8521×10^4 dollars and the GAM model predicts a tuition of 1.944176×10^4 dollars. Because the MARS model has a lower RMSE it is appropriate to accept this model and predict a tuition of 1.8521×10^4 dollars.