Lab 7.8

Jacob Thielemier

20 March 2024

7.8.1

```
library(ISLR2)
attach(Wage)

fit <- lm(wage ~ poly(age , 4), data = Wage)
coef(summary(fit))
```

```
##                 Estimate Std. Error    t value     Pr(>|t|)
## (Intercept)    111.70361  0.7287409 153.283015 0.000000e+00
## poly(age, 4)1  447.06785 39.9147851  11.200558 1.484604e-28
## poly(age, 4)2 -478.31581 39.9147851 -11.983424 2.355831e-32
## poly(age, 4)3  125.52169 39.9147851   3.144742 1.678622e-03
## poly(age, 4)4  -77.91118 39.9147851  -1.951938 5.103865e-02
```

```
fit2 <- lm(wage ~ poly(age , 4, raw = T), data = Wage)
coef(summary(fit2))
```

```
##                             Estimate   Std. Error   t value     Pr(>|t|)
## (Intercept)            -1.841542e+02 6.004038e+01 -3.067172 0.0021802539
## poly(age, 4, raw = T)1  2.124552e+01 5.886748e+00  3.609042 0.0003123618
## poly(age, 4, raw = T)2 -5.638593e-01 2.061083e-01 -2.735743 0.0062606446
## poly(age, 4, raw = T)3  6.810688e-03 3.065931e-03  2.221409 0.0263977518
## poly(age, 4, raw = T)4 -3.203830e-05 1.641359e-05 -1.951938 0.0510386498
```

```
fit2a <- lm(wage ~ age + I(age^2) + I(age^3) + I(age^4), data = Wage)
coef(fit2a)
```

```
##   (Intercept)           age      I(age^2)      I(age^3)      I(age^4)
## -1.841542e+02  2.124552e+01 -5.638593e-01  6.810688e-03 -3.203830e-05
```

```
fit2b <- lm(wage ~ cbind(age , age^2, age^3, age^4), data = Wage)

agelims <- range(age)
age.grid <- seq(from = agelims[1], to = agelims[2])
preds <- predict(fit , newdata = list(age = age.grid), se = TRUE)
se.bands <- cbind(preds$fit + 2 * preds$se.fit , preds$fit - 2 * preds$se.fit)
```

```
par(mfrow = c(1, 2), mar = c(4.5, 4.5, 1, 1), oma = c(0, 0, 4, 0))
plot(age , wage , xlim = agelims , cex = .5, col = "darkgrey")
title("Degree -4 Polynomial", outer = T)
lines(age.grid, preds$fit, lwd = 2, col = "blue")
matlines(age.grid , se.bands, lwd = 1, col = "blue", lty = 3)

preds2 <- predict(fit2 , newdata = list(age = age.grid), se = TRUE)
max(abs(preds$fit - preds2$fit))
```

```
## [1] 6.842527e-11
```

```
fit.1 <- lm(wage ~ age , data = Wage)
fit.2 <- lm(wage ~ poly(age , 2), data = Wage)
fit.3 <- lm(wage ~ poly(age , 3), data = Wage)
fit.4 <- lm(wage ~ poly(age , 4), data = Wage)
fit.5 <- lm(wage ~ poly(age , 5), data = Wage)
anova(fit.1, fit.2, fit.3, fit.4, fit.5)
```

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

```
coef(summary(fit.5))
```

```
##                Estimate Std. Error     t value     Pr(>|t|)
## (Intercept)    111.70361  0.7287647 153.2780243 0.000000e+00
## poly(age, 5)1  447.06785 39.9160847  11.2001930 1.491111e-28
## poly(age, 5)2 -478.31581 39.9160847 -11.9830341 2.367734e-32
## poly(age, 5)3  125.52169 39.9160847   3.1446392 1.679213e-03
## poly(age, 5)4  -77.91118 39.9160847  -1.9518743 5.104623e-02
## poly(age, 5)5  -35.81289 39.9160847  -0.8972045 3.696820e-01
```

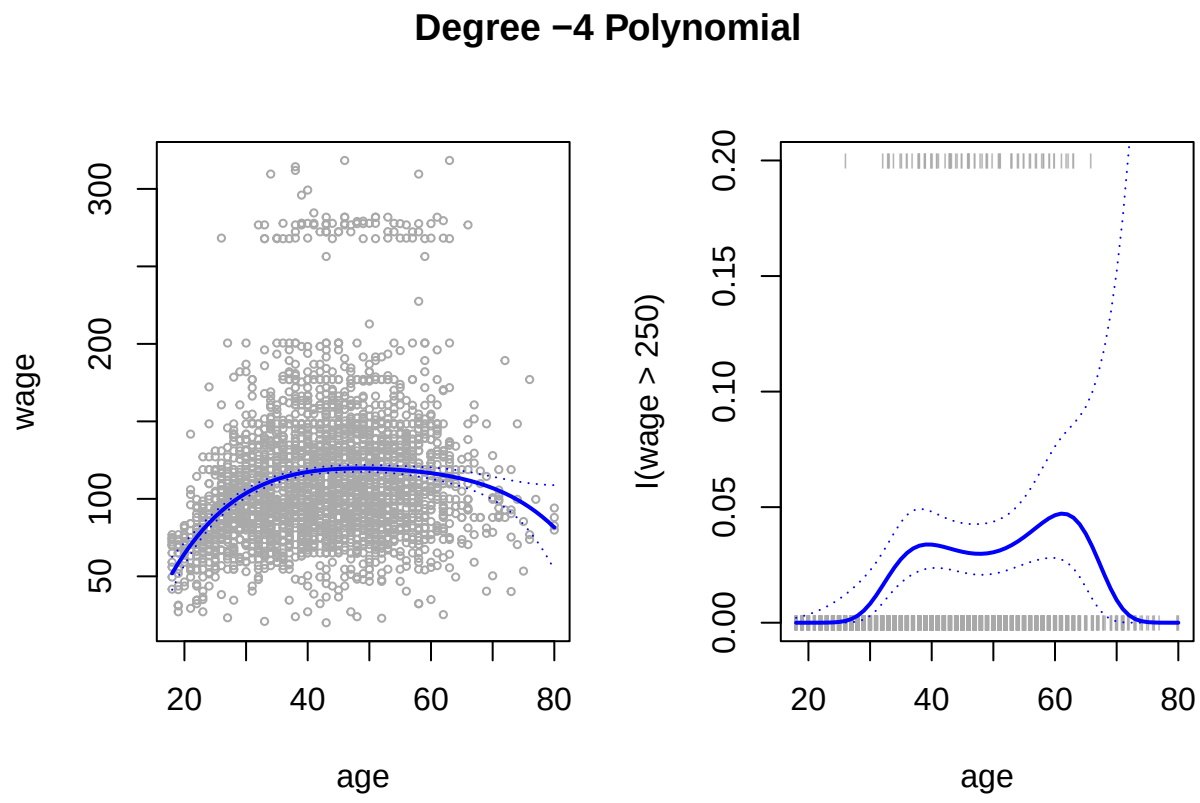
```
(-11.983)^2
```

```
## [1] 143.5923
```

```
fit.1 <- lm(wage ~ education + age , data = Wage)
fit.2 <- lm(wage ~ education + poly(age , 2), data = Wage)
fit.3 <- lm(wage ~ education + poly(age , 3), data = Wage)
anova(fit.1, fit.2, fit.3)
```

```
## Analysis of Variance Table
##
## Model 1: wage ~ education + age
## Model 2: wage ~ education + poly(age, 2)
## Model 3: wage ~ education + poly(age, 3)
##   Res.Df     RSS Df Sum of Sq        F Pr(>F)
## 1   2994 3867992
## 2   2993 3725395  1    142597 114.6969 <2e-16 ***
## 3   2992 3719809  1      5587   4.4936 0.0341 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
fit <- glm(I(wage > 250) ~ poly(age , 4), data = Wage , family = binomial)

preds <- predict(fit , newdata = list(age = age.grid), se = T)

pfit <- exp(preds$fit) / (1 + exp(preds$fit))
se.bands.logit <- cbind(preds$fit + 2 * preds$se.fit , preds$fit - 2 * preds$se.fit)
se.bands <- exp(se.bands.logit) / (1 + exp(se.bands.logit))

preds <- predict(fit , newdata = list(age = age.grid), type = "response", se = T)

plot(age , I(wage > 250), xlim = agelims , type = "n", ylim = c(0, .2))
points(jitter(age), I((wage > 250) / 5), cex = .5, pch = "|", col = "darkgrey")
lines(age.grid, pfit, lwd = 2, col = "blue")
matlines(age.grid , se.bands , lwd = 1, col = "blue", lty = 3)
```



```
table(cut(age , 4))
```

```
##
## (17.9,33.5]   (33.5,49]   (49,64.5] (64.5,80.1]
##         750        1399         779          72
```

```
fit <- lm(wage ~ cut(age , 4), data = Wage)
coef(summary(fit))
```

```
##                         Estimate Std. Error   t value     Pr(>|t|)
## (Intercept)            94.158392   1.476069 63.789970 0.000000e+00
## cut(age, 4)(33.5,49]   24.053491   1.829431 13.148074 1.982315e-38
## cut(age, 4)(49,64.5]   23.664559   2.067958 11.443444 1.040750e-29
## cut(age, 4)(64.5,80.1]  7.640592   4.987424  1.531972 1.256350e-01
```

7.8.2

```
library(splines)
fit <- lm(wage ~ bs(age , knots = c(25, 40, 60)), data = Wage)
pred <- predict(fit , newdata = list(age = age.grid), se = T)
plot(age , wage , col = "gray")
lines(age.grid, pred$fit, lwd = 2)
lines(age.grid , pred$fit + 2 * pred$se, lty = "dashed")
lines(age.grid , pred$fit - 2 * pred$se, lty = "dashed")

dim(bs(age , knots = c(25, 40, 60)))
```

```
## [1] 3000    6
```

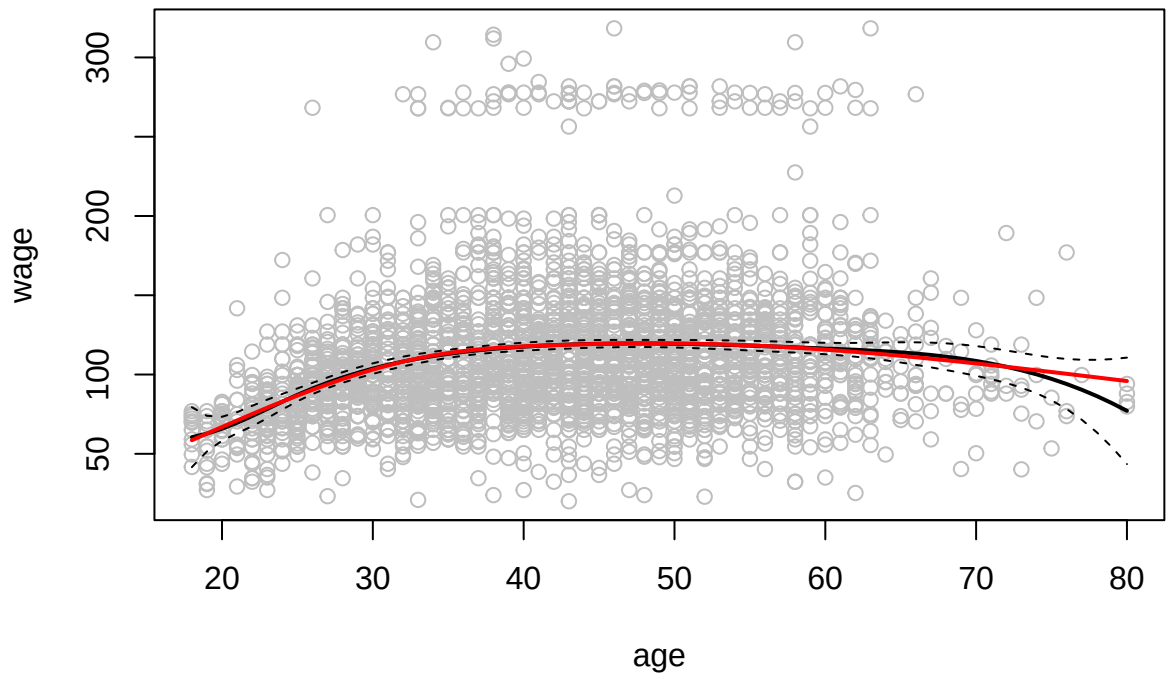
```
dim(bs(age , df = 6))
```

```
## [1] 3000    6
```

```
attr(bs(age , df = 6), "knots")
```

```
## [1] 33.75 42.00 51.00
```

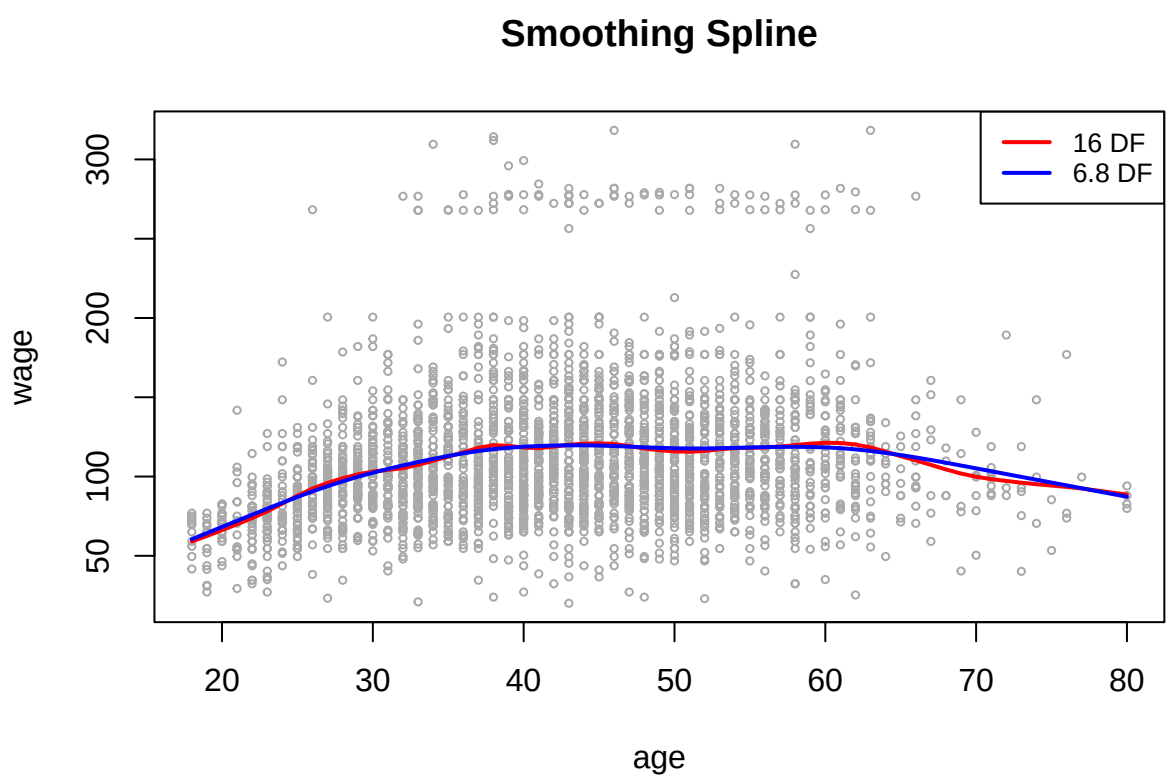
```
fit2 <- lm(wage ~ ns(age , df = 4), data = Wage)
pred2 <- predict(fit2 , newdata = list(age = age.grid), se = T)
lines(age.grid , pred2$fit , col = "red", lwd = 2)
```



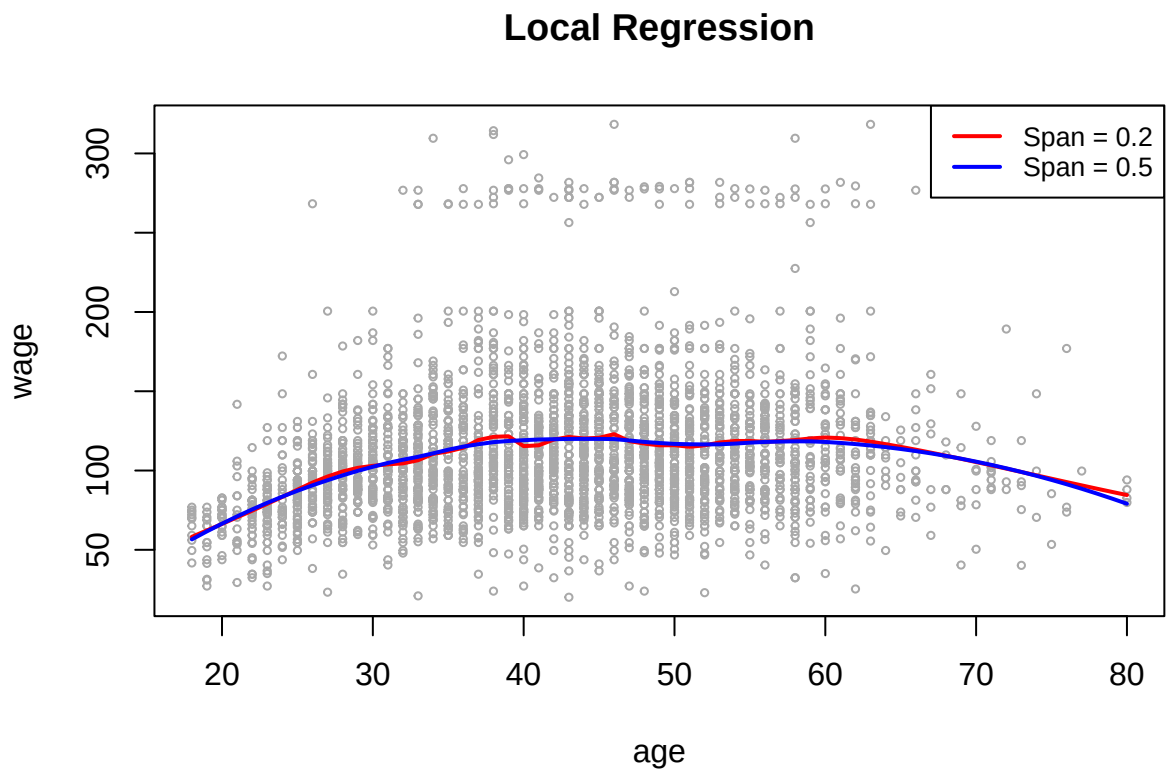

```
plot(age , wage , xlim = agelims , cex = .5, col = "darkgrey")
title("Smoothing Spline")
fit <- smooth.spline(age , wage , df = 16)
fit2 <- smooth.spline(age , wage , cv = TRUE)
fit2$df
```

```
## [1] 6.794596
```

```
lines(fit , col = "red", lwd = 2)
lines(fit2 , col = "blue", lwd = 2)
legend("topright", legend = c("16 DF", "6.8 DF"),
  col = c("red", "blue"), lty = 1, lwd = 2, cex = .8)
```




```
plot(age , wage , xlim = agelims , cex = .5, col = "darkgrey")
title("Local Regression")
fit <- loess(wage ~ age , span = .2, data = Wage)
fit2 <- loess(wage ~ age , span = .5, data = Wage)
lines(age.grid, predict(fit , data.frame(age = age.grid)),
  col = "red", lwd = 2)
lines(age.grid, predict(fit2 , data.frame(age = age.grid)),
  col = "blue", lwd = 2)
legend("topright", legend = c("Span = 0.2", "Span = 0.5"),
  col = c("red", "blue"), lty = 1, lwd = 2, cex = .8)
```

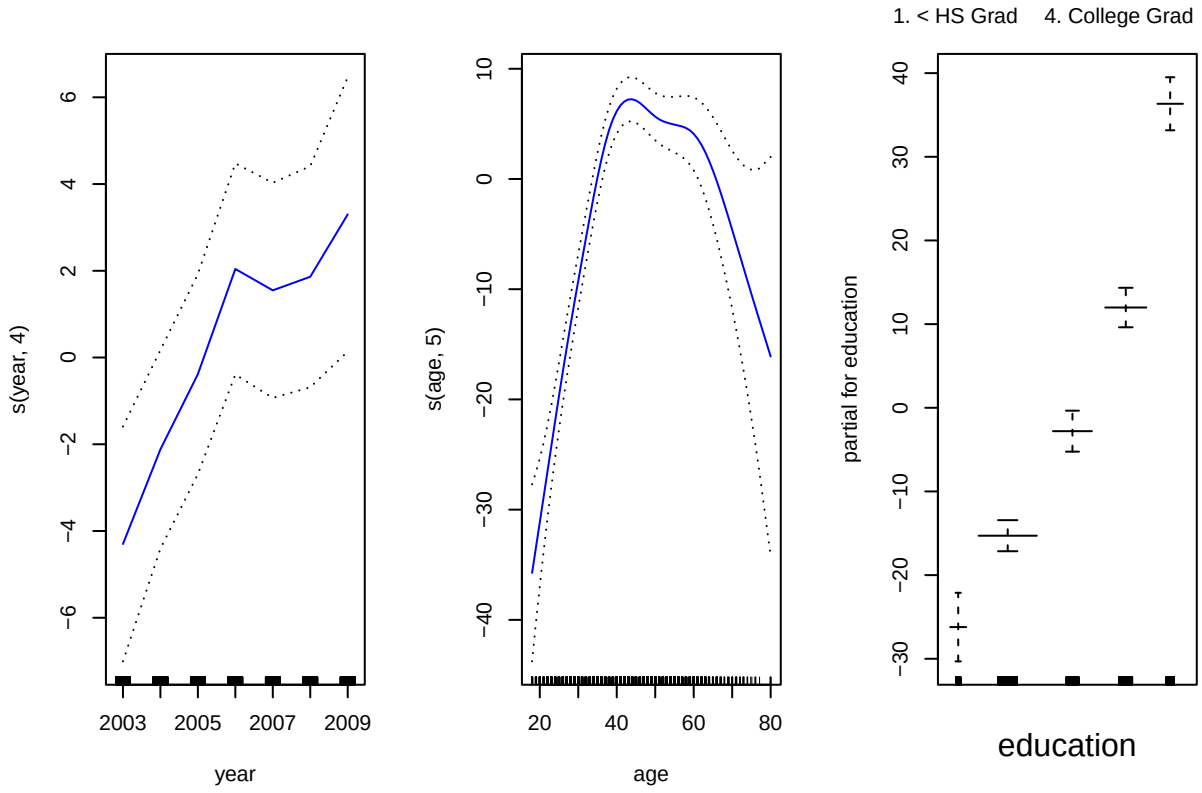


7.8.3

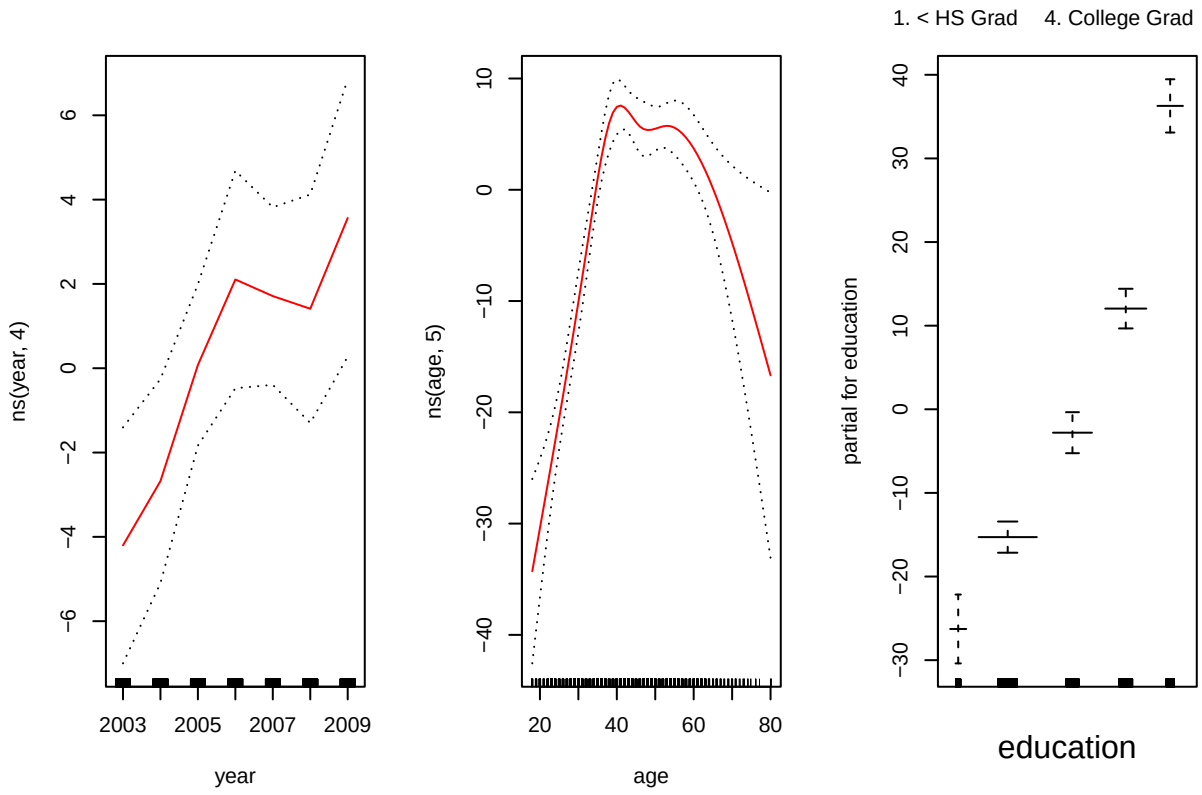
```
gam1 <- lm(wage ~ ns(year , 4) + ns(age , 5) + education , data = Wage)

library(gam)
```

```
## Loading required package: foreach

## Loaded gam 1.22-3
```

```
gam.m3 <- gam(wage ~ s(year , 4) + s(age , 5) + education , data = Wage)

par(mfrow = c(1, 3))
plot(gam.m3, se = TRUE, col = "blue")
```




```
plot.Gam(gam1 , se = TRUE, col = "red")
```




```
gam.m1 <- gam(wage ~ s(age , 5) + education , data = Wage)
gam.m2 <- gam(wage ~ year + s(age , 5) + education , data = Wage)
anova(gam.m1, gam.m2, gam.m3, test = "F")
```

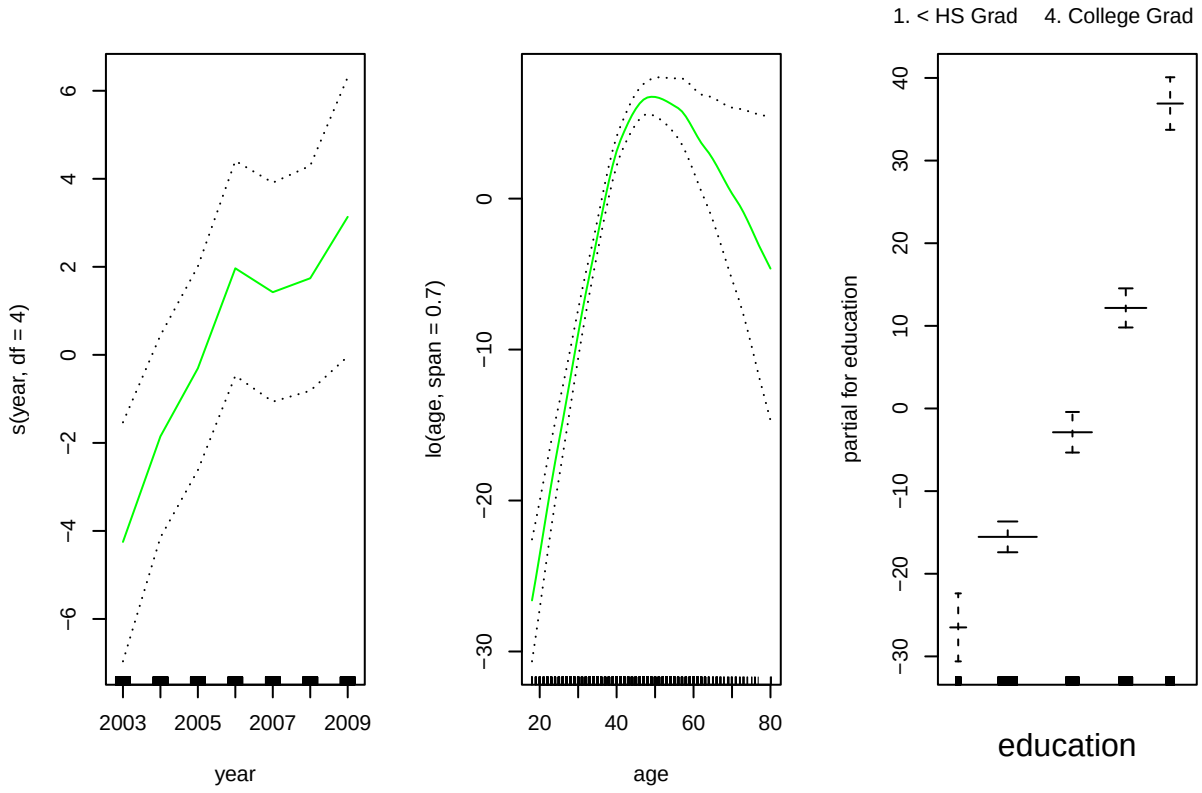
```
## Analysis of Deviance Table
##
## Model 1: wage ~ s(age, 5) + education
## Model 2: wage ~ year + s(age, 5) + education
## Model 3: wage ~ s(year, 4) + s(age, 5) + education
##   Resid. Df Resid. Dev Df Deviance       F    Pr(>F)
## 1      2990    3711731
## 2      2989    3693842  1  17889.2 14.4771 0.0001447 ***
## 3      2986    3689770  3   4071.1  1.0982 0.3485661
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
summary(gam.m3)
```

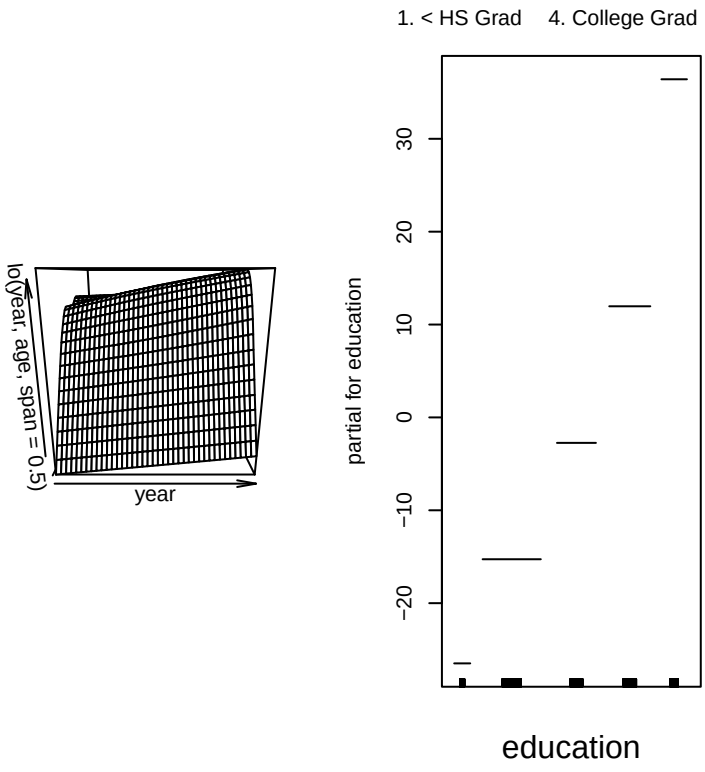
```
##
## Call: gam(formula = wage ~ s(year, 4) + s(age, 5) + education, data = Wage)
## Deviance Residuals:
##     Min      1Q  Median      3Q     Max
## -119.43  -19.70   -3.33   14.17  213.48
##
```

```
## (Dispersion Parameter for gaussian family taken to be 1235.69)
##
##     Null Deviance: 5222086 on 2999 degrees of freedom
## Residual Deviance: 3689770 on 2986 degrees of freedom
## AIC: 29887.75
##
## Number of Local Scoring Iterations: NA
##
## Anova for Parametric Effects
##              Df  Sum Sq Mean Sq F value    Pr(>F)
## s(year, 4)    1   27162   27162  21.981 2.877e-06 ***
## s(age, 5)     1  195338  195338 158.081 < 2.2e-16 ***
## education     4 1069726  267432 216.423 < 2.2e-16 ***
## Residuals  2986 3689770    1236
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Anova for Nonparametric Effects
##             Npar Df Npar F  Pr(F)
## (Intercept)
## s(year, 4)        3  1.086 0.3537
## s(age, 5)         4 32.380 <2e-16 ***
## education
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

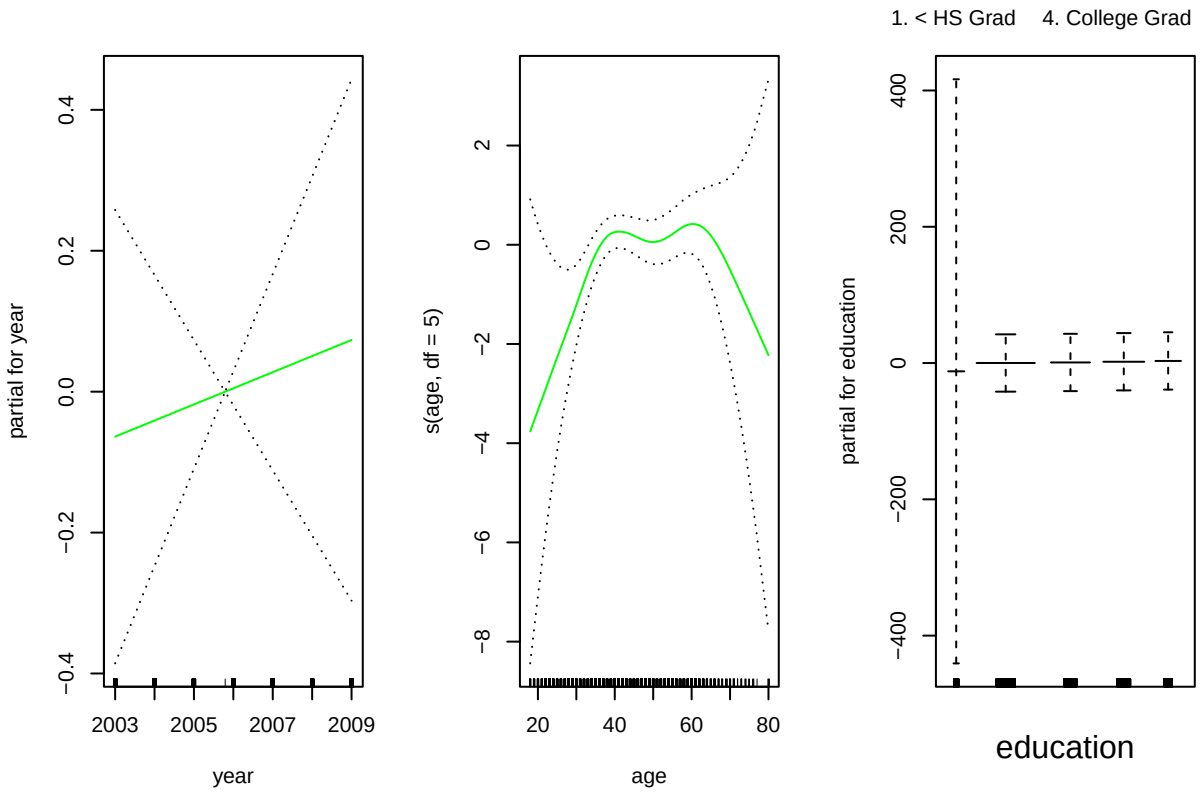
```r
preds <- predict(gam.m2, newdata = Wage)

gam.lo <- gam(
  wage ~ s(year , df = 4) + lo(age , span = 0.7) + education , data = Wage
  )
plot(gam.lo, se = TRUE, col = "green")

gam.lo.i <- gam(wage ~ lo(year , age , span = 0.5) + education , data = Wage)

library(akima)
```




```
plot(gam.lo.i)

gam.lr <- gam(
  I(wage > 250) ~ year + s(age , df = 5) + education ,
  family = binomial, data = Wage
  )
par(mfrow = c(1, 3))
```



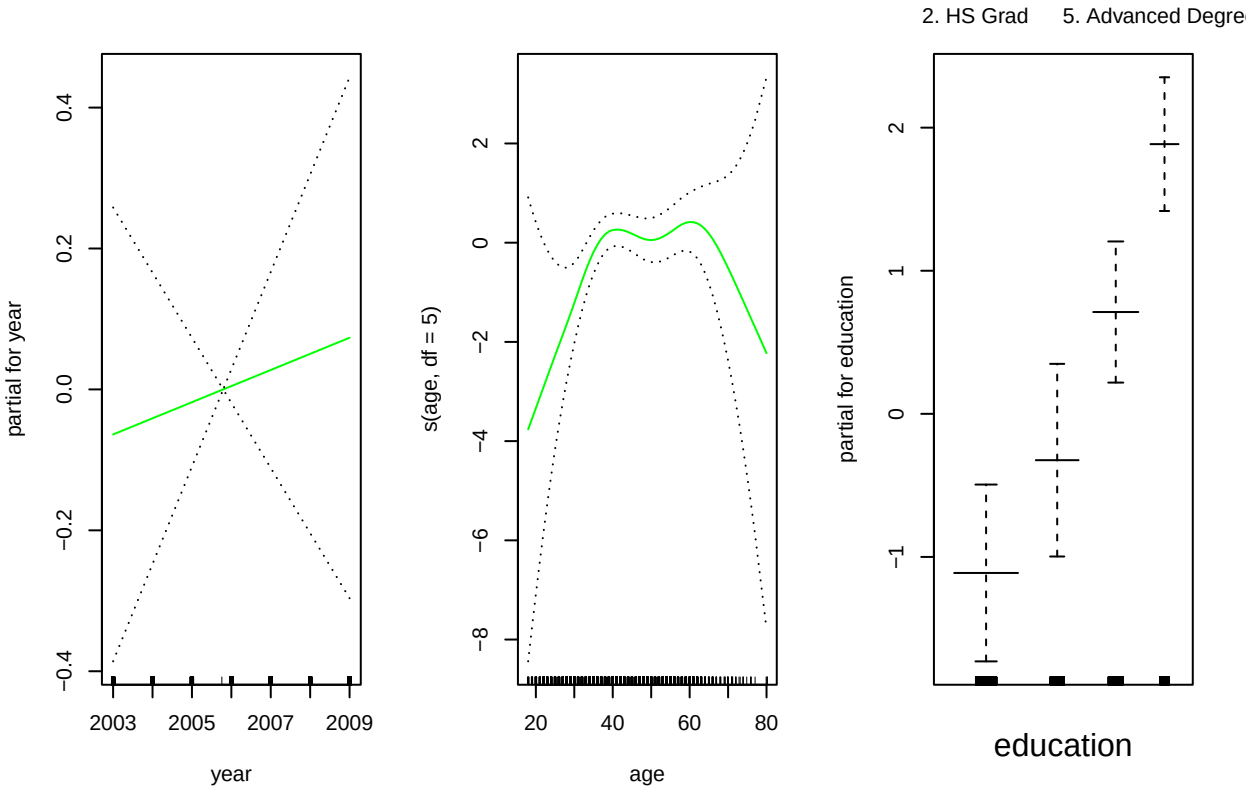

```
plot(gam.lr, se = T, col = "green")
```




```
table(education , I(wage > 250))
```

```
##
## education             FALSE TRUE
##   1. < HS Grad          268    0
##   2. HS Grad            966    5
##   3. Some College       643    7
##   4. College Grad       663   22
##   5. Advanced Degree    381   45
```

```
gam.lr.s <- gam(
  I(wage > 250) ~ year + s(age , df = 5) + education ,
  family = binomial , data = Wage ,
  subset = (education != "1. < HS Grad")
  )
plot(gam.lr.s, se = T, col = "green")
```


partial for year
0.4
0.2
0.0
−0.2
−0.4
2003
2005
2007
2009
year
s(age, df = 5)
2
0
−2
−4
−6
−8
20
40
60
80
age
2. HS Grad
5. Advanced Degre
partial for education
2
1
0
−1
education