Statistics 452: Statistical Learning and Prediction

Chapter 7, Part 1: Simple Extensions of the Linear Model

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2017-10-24

Polynomial Regression

- ▶ We have used polynomial regression before.
- ▶ This was the standard way to extend the linear model.
- ▶ The text recommends against a degree of more than 4.
- To avoid collinearity we can use the covariates returned by the poly() function (more on these functions in the next set of notes).

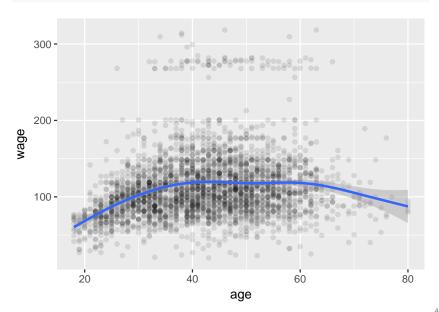
Example: Wage Data

Predict wages as a function of age.

```
library(ISLR)
data(Wage)
head(Wage,n=3)
```

```
##
                                              education
         year age
                          maritl
                                    race
## 231655 2006 18 1. Never Married 1. White
                                           1. < HS Grad
## 86582 2004 24 1. Never Married 1. White 4. College Grad
## 161300 2003 45
                      2. Married 1. White 3. Some College
                                jobclass
                                               health health ins
##
                    region
## 231655 2. Middle Atlantic 1. Industrial 1. <=Good 2. No
## 86582 2. Middle Atlantic 2. Information 2. >=Very Good 2. No
## 161300 2. Middle Atlantic 1. Industrial 1. <=Good 1. Yes
##
          logwage
                     wage
## 231655 4.318063 75.04315
## 86582 4.255273 70.47602
## 161300 4.875061 130.98218
```

```
library(ggplot2)
ggplot(Wage,aes(x=age,y=wage)) + geom_point(alpha=0.1) +
  geom_smooth(formula=formula(wage ~ poly(age,4)))
```

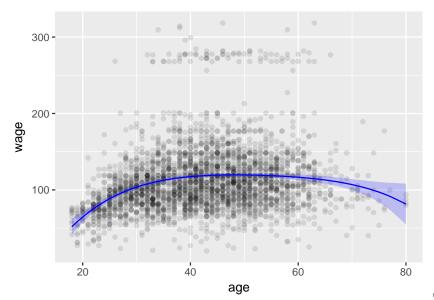


DIY Confidence Bands

- Use predict() to get the predictions and plot CI bands with geom_ribbon()
- First the predictions and point-wise Cls.

```
wfit <- lm(wage ~ poly(age,4),data=Wage)
newWage <- data.frame(age = sort(unique(Wage$age)))
wpred <- data.frame(newWage,predict(wfit,newdata=newWage,interval="confidence")
head(wpred,n=3)</pre>
```

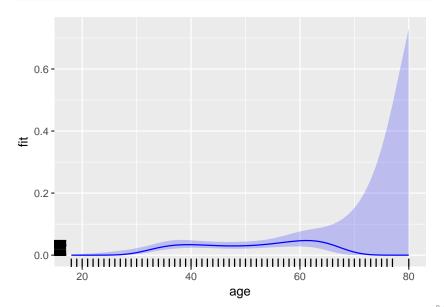
```
## age fit lwr upr
## 1 18 51.93145 41.54284 62.32006
## 2 19 58.49674 49.92674 67.06674
## 3 20 64.57188 57.52864 71.61511
```



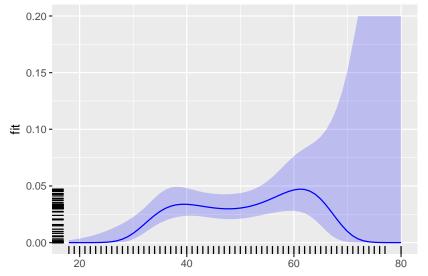
Classification Example: Wage > 250K

```
## age fit se.fit residual.scale lwr upr
## 1 18 9.826427e-09 6.140231 1 4.560982e-14 0.002112586
## 2 19 7.577844e-08 5.254561 1 2.067720e-12 0.002769461
## 3 20 4.746699e-07 4.464911 1 6.283757e-11 0.003572811
```

```
ggplot(wpred,aes(x=age,y=fit)) + geom_rug() +
  geom_ribbon(aes(ymin=lwr,ymax=upr),fill="blue",alpha=.2,limits=c(0,.2)) +
  geom_line(aes(y=fit),data=wpred,color="blue")
```



```
wpred <- mutate(wpred,upr = pmin(upr,0.2))
ggplot(wpred,aes(x=age,y=fit)) + geom_rug() +
   geom_ribbon(aes(ymin=lwr,ymax=upr),fill="blue",alpha=.2,limits=c(0,.2)) +
   geom_line(aes(y=fit),data=wpred,color="blue")</pre>
```

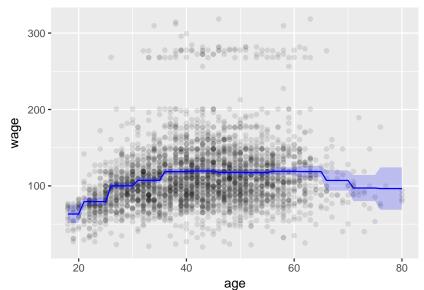


Step Functions

- In Epidemiology it is common to discretize age and treat as a categorical variable.
 - Categorical variables are coded as dummy variables for regression.
- ► The regression will fit a separate mean for each category, which is more flexible than, say, linear in age.

```
with(Wage,range(age))
## [1] 18 80

agebreaks <- c(15,20,25,30,35,40,45,50,55,60,65,70,75,80)
wfit <- lm(wage ~ cut(age,breaks=agebreaks),data=Wage)
newWage <- data.frame(age = sort(unique(Wage$age)))
wpred <- data.frame(newWage,predict(wfit,newdata=newWage,interval="confidence")
head(wpred,n=3)</pre>
```



Classification Example: Wage > 250K

```
## age fit se.fit residual.scale lwr upr
## 1 18 3.181005e-09 1603.114 1 0 NaN
## 2 19 3.181005e-09 1603.114 1 0 NaN
## 3 20 3.181005e-09 1603.114 1 0 NaN
```

```
ggplot(wpred,aes(x=age,y=fit)) + geom_rug() +
  geom_ribbon(aes(ymin=lwr,ymax=upr),fill="blue",alpha=.2,limits=c(0,.2)) +
  geom_line(aes(y=fit),data=wpred,color="blue")
```

