The purpose of this section is to estimate the returns to education using R. There is nothing valid about the results found in this section; but the empirical application gives us a chance to explore categorical dummies and the ggplot package. First, as always, we load the required libraries.

```
library(foreign)
library(ggplot2)
library(xtable)
```

We can then read the wage data directly from the online repository for the supplementary data sets for the Wooldridge (2002) text. You will need an internet connection. We only need the wage, educ, and age variables, and we omit all observations with missing observations.

```
f <- "http://fmwww.bc.edu/ec-p/data/wooldridge/wage2.dta"
data <- read.dta(f)
data <- data[ , c("wage", "educ", "age")]
data <- na.omit(data)</pre>
```

A quick visualization reveals the distribution of wages in the data set:

```
hist(data$wage, xlab = "wage", main = "", col = "grey", border = "white")
```

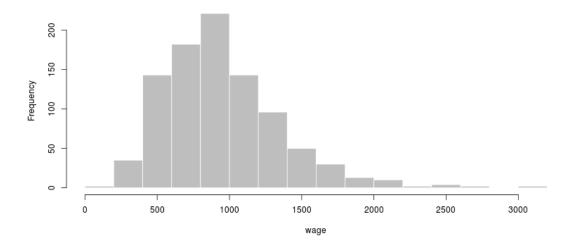


Figure 1: Wage histogram

Roughly following page 38 of the lecture notes, we create a rough measure of educational attainment from the educ variable.

```
e1 <- ifelse(data$educ %in% 1:12, 1, 0)
e2 <- ifelse(data$educ %in% 13:14, 1, 0)
e3 <- ifelse(data$educ %in% 15:16, 1, 0)
e4 <- ifelse(data$educ %in% 17:18, 1, 0)
```

The categorical education variables sum to one, and the lm() function will force-drop one of the variables. Note that the intercept in this regression reflects the mean wage of the e4 class. The other coefficients reflect the relative wages of the other three classes.

Suppose we want to estimate the premium on education, relative to the least educated class. We can then specify the following regression and print the output directly to LATEX using the xtable package¹:

```
xtable(m2 <- lm(wage ~1 + e2 + e3 + e4, data = data))
```

-	Estimate	Std. Error	t value	$\Pr(> t)$
(Intercept)	846.4948	17.4837	48.42	0.0000
e2	120.4929	34.8322	3.46	0.0006
e3	259.9565	32.5528	7.99	0.0000
e4	350.4640	42.6787	8.21	0.0000

None that the coefficients, now, indicate the premium over the base level of education for all subsequent levels. Consider, for example, the premium on the e4 class. The average wage for people in this class, the class with the highest educational attainment levels, is found by:

```
mean(data[e4 == 1, c("wage")])
[1] 1196.959
```

This is equivalent to adding the coefficient on e4 to the intercept from the well-specified regression above. Specifically:

```
b <- m2$coefficients
b[["(Intercept)"]] + b[["e4"]]
[1] 1196.959</pre>
```

This equality only holds because there are no other covariates in the regression. If we condition on age, for example, then the simple addition does not yield an average wage. For illustration, consider the previous regression with age and squared age as cofactors. Note also the manner by which the lm() function accepts a nested function to specify squared age within the line:

```
coef(summary(lm(wage ~1 + e2 + e3 + e4 + age + I(age^2), data = data)))
                Estimate Std. Error
                                         t value
                                                     Pr(>|t|)
 (Intercept) -148.0041478 1660.163718 -0.08915033 9.289817e-01
             142.0919504
                           34.603321 4.10630965 4.374401e-05
e3
             276.4462130
                           32.327306 8.55147690 4.954754e-17
e4
             329.3717601
                           42.427654
                                      7.76313861 2.181854e-14
              38.4978013
                          100.467589 0.38318628 7.016693e-01
age
I(age^2)
              -0.2572671
                            1.508597 -0.17053405 8.646273e-01
```

It looks like age has a positive but diminishing effect on wage. This makes sense, maybe, but the coefficients are not significantly different from zero. Why might this be the case? This is where some non-parametric graphing comes in handy.

```
(g <- ggplot(data, aes(x=age, y=wage)) + geom_smooth(method="loess", size=1.5))
```

We use the ggplot2 package instead of the base R plotting facilities. The plots reveal a reasonable relationship between wage and age, but there is a significant amount of variation in wage, relative to the short time frame of age.

```
g + geom_point()
```

¹Note that this is a little superfluous, but it's worth examining the different ways to export tables.

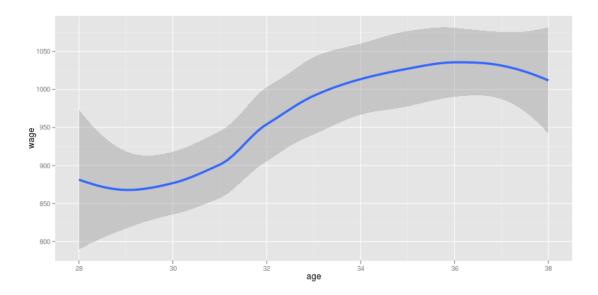


Figure 2: Smoothed line

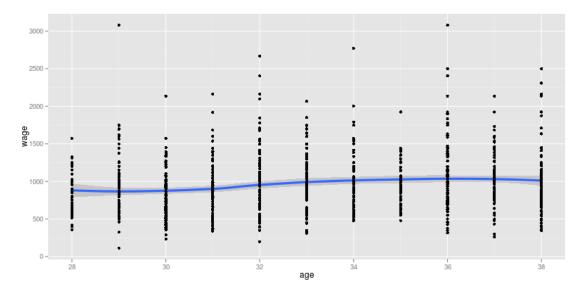


Figure 3: Smoothed line with points