ECON 340
Economics Research Methods

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Lecture 22: Regression Analysis in R

Housekeeping

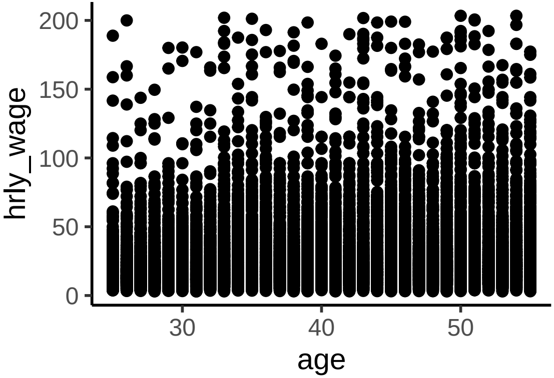
```
rm(list=ls())
library(tidyverse)
library(stargazer)
#setwd("~/Dropbox (CSU Fullerton)/Econ340_R")
data <- read.csv("acs2019.csv")
```

Preparing the data

```
# Select sample and variables
data <- data %>%
  filter(empstat==1) %>%
  select(-fertyr, -rent)

# Remove missing values
data <- na.omit(data)
```

Hourly wage and age

```
ggplot(data, aes(x=age, y=hrly_wage)) +
  geom_point() + theme_classic()
```

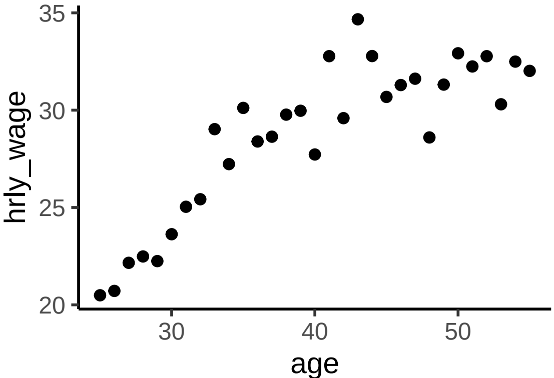


Hourly wage and age

- Too much data to make sense
- Better to plot average hourly wage at each wage
- use `stat_summary()` and specify `fun` as `mean`

Average wages by age

```
ggplot(data, aes(x=age, y=hrly_wage)) +
      stat_summary(fun = mean, geom = "point") +
      theme_classic()
```



Hourly wage and age

- To fit a quadratic model, generate age-squared term

```
data <- data %>%
  mutate(age.sq = age*age)
```

- Fit linear and quadratic model

```
mdl.lnr <- lm(hrly_wage ~ age, data)
mdl.qdr <- lm(hrly_wage ~ age + age.sq, data)
```

- Output using `stargazer()`

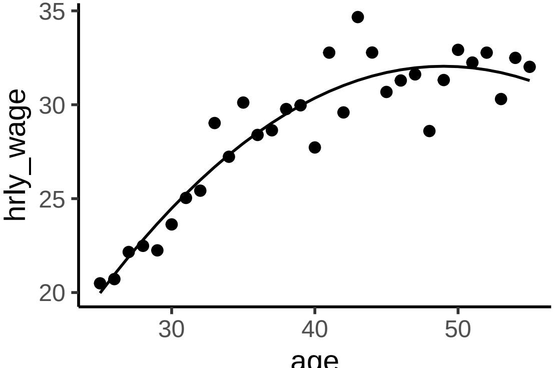
```
stargazer(mdl.lnr, mdl.qdr, type="text")
```

Hourly wage and age

	Dependent variable:	
	hrly_wage	
	(1)	(2)
age	0.375^{***}	2.056^{***}
	(0.020)	(0.198)
age.sq		-0.021^{***}
		(0.002)
Observations	17,109	17,109
Adjusted R^2	0.021	0.025
Note:	$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$	

Plotting the fitted curve

```
data$prd.qdr <- predict(mdl.qdr)
ggplot(data, aes(x=age, y=hrly_wage)) +
      stat_summary(fun = mean, geom = "point") +
      geom_line(aes(y=prd.qdr)) + theme_classic()
```



Dummy variables

```
data %>% group_by(female) %>%
  summarise(avg_wages=mean(hrly_wage))
```

```
# A tibble: 2 x 2
  female avg_wages
   <int>     <dbl>
1      0      31.3
2      1      25.8
```

Dummy variables

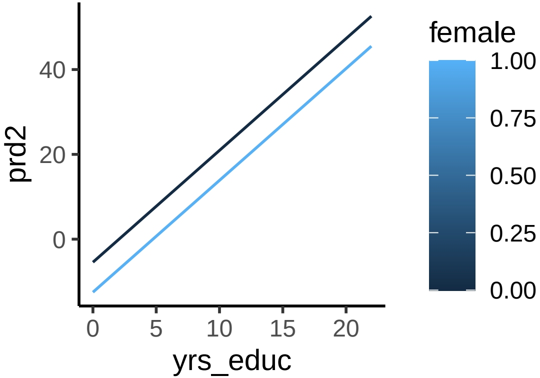
```
mdl1 <- lm(hrly_wage ~ female, data)
mdl2 <- lm(hrly_wage ~ female + yrs_educ, data)
mdl3 <- lm(hrly_wage ~ female*yrs_educ, data)

stargazer(mdl1, mdl2, mdl3, type="text")
```

Dummy variables

	Dependent variable:		
	hrly_wage		
	(1)	(2)	(3)
female	−5.512***	−7.067***	−0.963
	(0.354)	(0.334)	(1.611)
yrs_educ		2.637***	2.833***
		(0.055)	(0.075)
female:yrs_educ			−0.429***
			(0.111)
Observations	17,109	17,109	17,109
Adjusted R^2	0.014	0.180	0.181

Model 2

```
data$prd2 <- predict(mdl2)
ggplot(data, aes(x=yrs_educ, y=prd2, group=female)) +
  geom_line(aes(color=female)) + theme_classic()
```



Factor variables

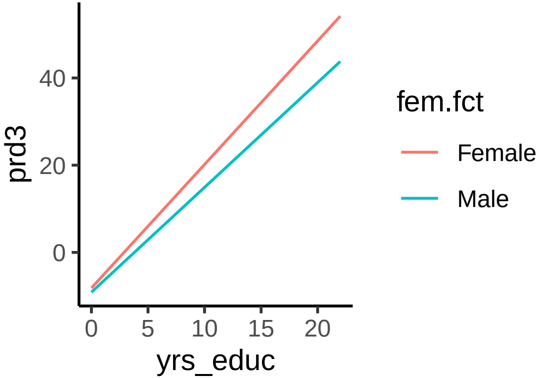
- R thinks of all variables as numeric unless you tell it otherwise
- To create a factor variable (specifying levels and labels is optional)

```
data$fem.fct <- factor(data$female, levels = c(0,1),
                       labels = c('Female', 'Male'))
table(data$fem.fct)
```

```
Female   Male
  8886   8223
```

Model 3

```r
data$prd3 <- predict(mdl3)
ggplot(data, aes(x=yrs_educ, y=prd3, group=fem.fct)) +
  geom_line(aes(color=fem.fct)) + theme_classic()
```



More Interaction Terms

```r
mdl.int1 <- lm(hrly_wage ~ female*married, data)
stargazer(mdl.int1, type="text")
```

	Dependent variable:
	hrly_wage
female	-1.738^{***}
	(0.548)
married	10.652^{***}
	(0.495)
female:married	-6.070^{***}
	(0.710)

More Interaction Terms

```
mdl.int2 <- lm(hrly_wage ~ black*female, data)
stargazer(mdl.int2, type="text")
```

	Dependent variable:
	hrly_wage
black	−7.645***
	(0.912)
female	−5.817***
	(0.370)
black:female	4.659***
	(1.249)

Variables with several categories

```
# Specify levels and labels
levs <- c(1, 2, 3, 4, 5)
labs <- c("Less than HS", "High School",
          "Some College", "College Degree",
          "More than College")

# Create factor variable
data$educ.fct <- factor(data$educ_cat,
                        levels=levs, labels=labs)
```

Variables with several categories

```
data %>% group_by(educ.fct) %>%
  summarise(m = mean(hrly_wage))
```

```
# A tibble: 5 x 2
  educ.fct                m
  <fct>               <dbl>
1 Less than HS         17.5
2 High School          20.6
3 Some College         23.7
4 College Degree       34.2
5 More than College    43.5
```

Variables with several categories

- Want to specify to R to treat education as a categorical variable
- Which of the following models is correct?

```
summary(lm(hrly_wage ~ educ_cat, data))
summary(lm(hrly_wage ~ as.factor(educ_cat), data))
summary(lm(hrly_wage ~ educ.fct, data))
```

- Coefficients capture mean differences from the baseline

Variables with several categories

	Dependent variable:
	hrly_wage
educ.fctHigh School	3.139***
	(0.820)
educ.fctSome College	6.180***
	(0.831)
educ.fctCollege Degree	16.715***
	(0.825)
educ.fctMore than College	26.035***
	(0.859)
Constant	17.497***
	(0.759)
Observations	17,109
Adjusted R^2	0.139
Note:	*p<0.1; **p<0.05; ***p<0.01

Log Transformations

- Create transformed variable

```
data$lwage <- log(data$hrly_wage)
```

- Fit the model and output results

```
mdl.lnr <- lm(hrly_wage ~ yrs_educ, data)
mdl.log <- lm(lwage ~ yrs_educ, data)
stargazer(mdl.lnr, mdl.log, type="text")
```

Log Transformations

	Dependent variable:	
	hrly_wage	lwage
	(1)	(2)
yrs_educ	2.524***	0.086***
	(0.056)	(0.002)
Constant	−7.223***	1.901***
	(0.807)	(0.023)
Observations	17,109	17,109
Adjusted R^2	0.107	0.147
Note:	*p<0.1; **p<0.05; ***p<0.01	

Log Transformations

How much does hourly wage change going from 10 to 11 years of education?

- Linear model: \$2.52
- Log-level model: $100 \times 0.086 = 8.6\%$ of \$18.87 = \$1.68

```
data %>% filter(yrs_educ==10) %>%
  summarise(m = mean(hrly_wage))
```

```
         m
1 18.87474
```

Log Transformations

- What about going from 13 to 14 years of education?
- Fitting a linear model between log wages and years of education $\rightarrow$ non-linear model between wages and years of education

```
# Predictions from the log-level model
data$lw.hat <- predict(mdl.log)

# Convert predictions back to levels
data$w.hat <- exp(data$lw.hat)
```

Log Transformations

```
ggplot(data, aes(x=yrs_educ, y=w.hat)) +
  geom_line() + theme_classic()
```