Gov 50: 11. Linear Regression

Matthew Blackwell

Harvard University

Fall 2018

1/ Today's agenda

Logistics

- Mid-semester evaluation out—please respond!

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- DataCamp 4 due Thursday.

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- Matt’s OH moved to Fri, 10:30am-12:00pm this week only.

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- Big technical tool: **linear regression**
  - Now: how to fit, get predictions

2/ Prediction using a second variable

Predicting my weight

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Name	Description
`date`	date of measurements
`active.calories`	calories burned
`steps`	number of steps taken (in 1,000s)
`weight`	weight (lbs)
`steps.lag`	steps on day before (in 1,000s)
`calories.lag`	calories burned on day before

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  - **Dependent/outcome variable**: the variable we want to predict (weight).

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  - what's our best guess about my weight this morning if I know how many steps I took yesterday?
- Terminology:
  - **Dependent/outcome variable**: the variable we want to predict (weight).
  - **Independent/explanatory variable**: the variable we're using to predict (steps).

- Load the data:

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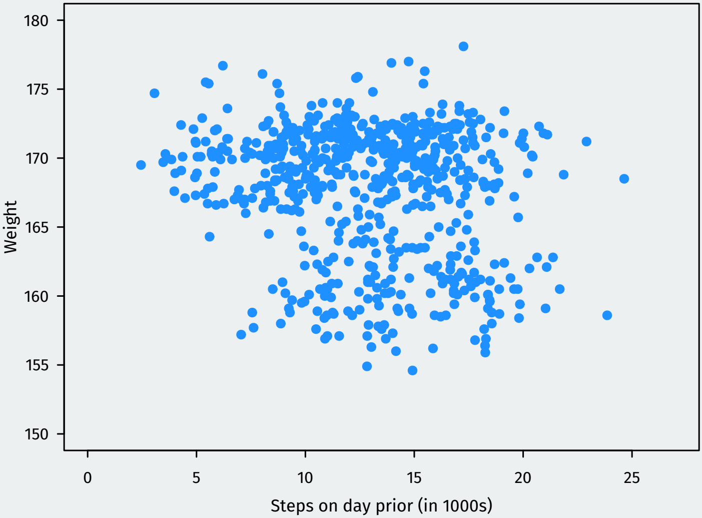
```
plot(health$steps.lag, health$weight, pch = 19,
     col =  "dodgerblue",
     xlim = c(0, 27), ylim = c(150, 180),
     xlab = "Steps on day prior (in 1000s)",
     ylab = "Weight",
     main = "Weight and Steps")
```

Weight and Steps



Correlation and scatterplots

- Recall the definition of correlation:

$$\frac{1}{n-1}\sum_{i=1}^{n}\left[(\text{z-score for } x_i) \times (\text{z-score for } y_i)\right]$$

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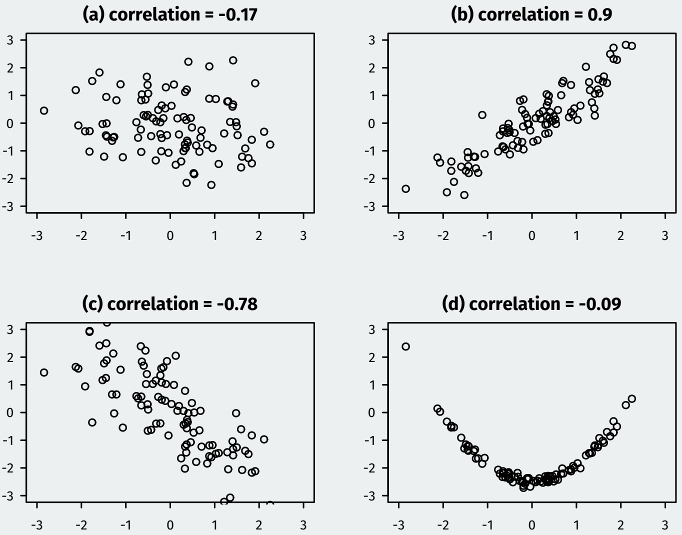
    4. correlation cannot capture nonlinear relationship.


(a) correlation = -0.17
(b) correlation = 0.9
(c) correlation = -0.78
(d) correlation = -0.09
3
2
1
0
-1
-2
-3
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3/ Linear regression

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    - Some weights will be above the line, some below.
    - Need a way to account for **chance variation** away from the line.

Linear regression model

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    - Chance errors are 0 on average.

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- But we don't know α or β. How can we estimate them?

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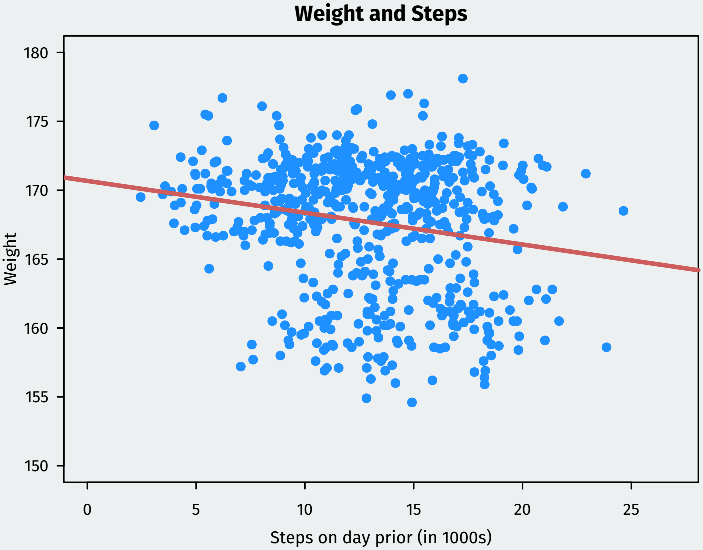
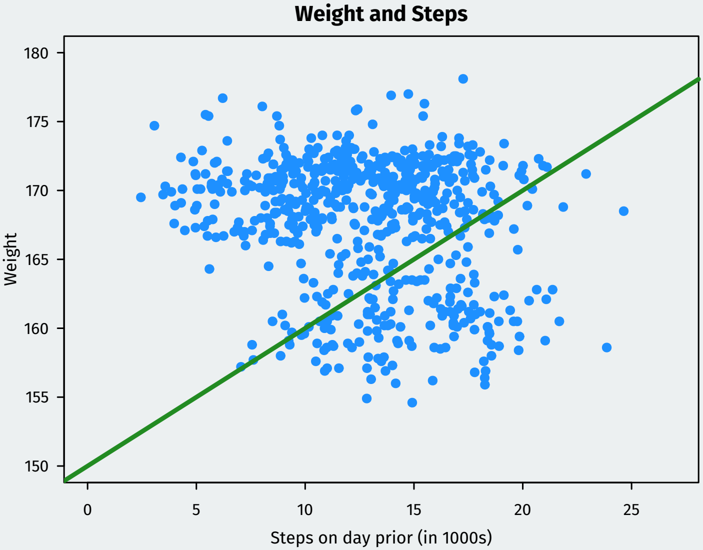
  - Represents the best guess or **predicted value** of the outcome at x.

Line of best fit



Why not this line?



4/ Ordinary least squares

Least squares

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- This finds the line that minimizes the magnitude of the prediction errors!

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- Interpretation?

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```
##   2   3   4   5   6   7
## 167 166 166 168 166 169
```

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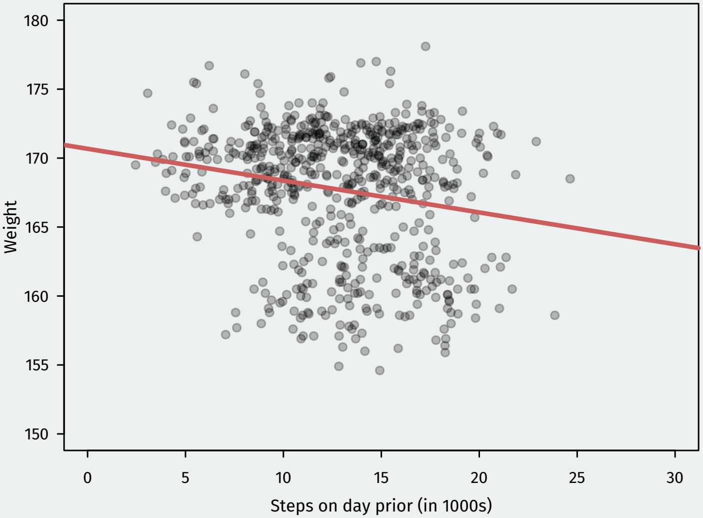
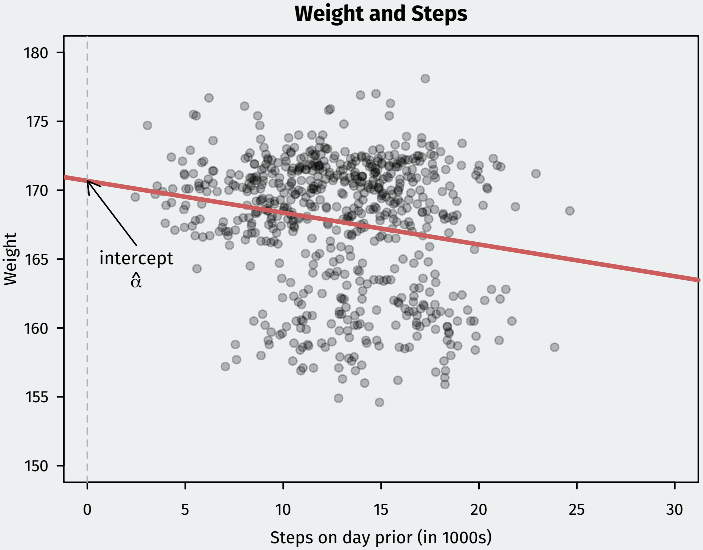
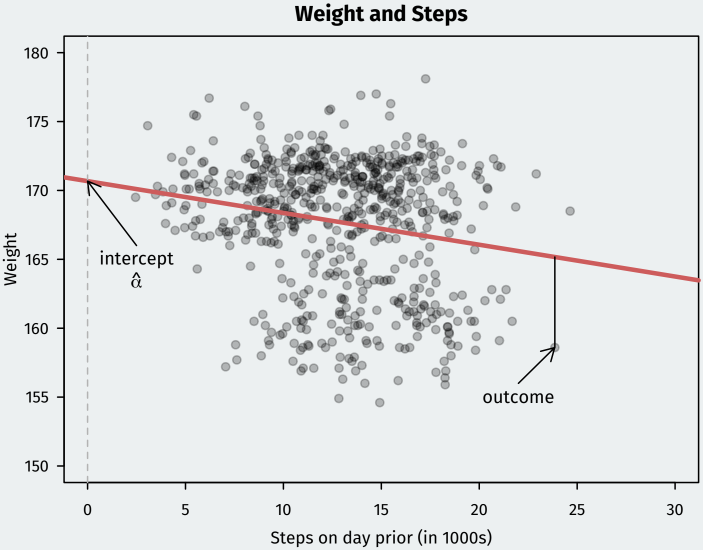
- Mean of residuals is always 0.

Weight and Steps




Weight and Steps
180
175
170
165
160
155
150
Weight
intercept
$\hat{\alpha}$
0
5
10
15
20
25
30
Steps on day prior (in 1000s)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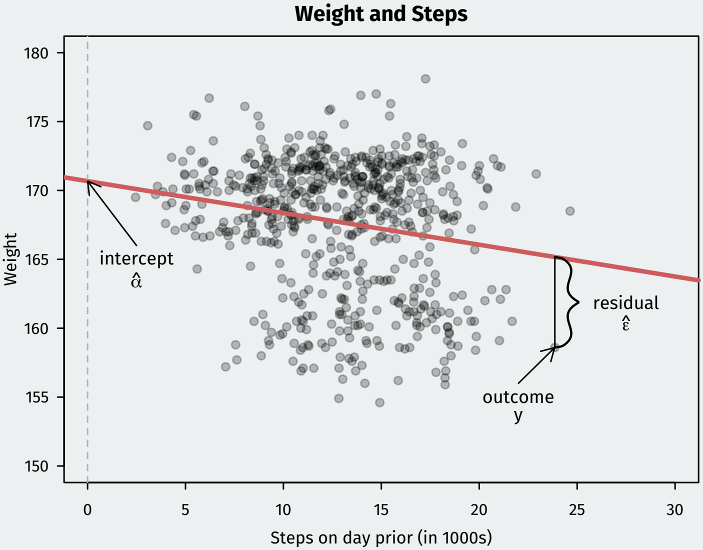
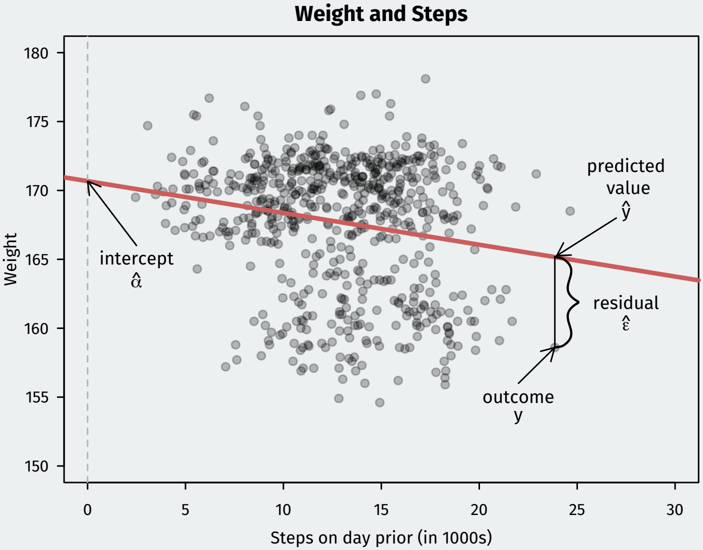
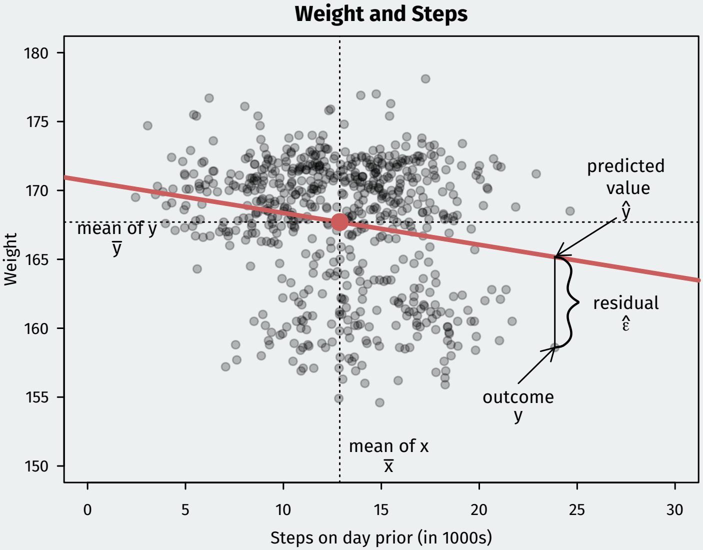
30
Steps on day prior (in 1000s)


Weight and Steps
180
175
170
165
160
155
150
Weight
intercept
α̂
residual
ε̂
outcome
y
0
5
10
15
20
25
30
Steps on day prior (in 1000s)


Weight and Steps
Weight
180
175
170
165
160
155
150
0
5
10
15
20
25
30
Steps on day prior (in 1000s)
intercept
α̂
predicted
value
ŷ
residual
ε̂
outcome
y


Weight and Steps
180
175
170
165
160
155
150
Weight
0
5
10
15
20
25
30
Steps on day prior (in 1000s)
mean of y
$\bar{y}$
mean of x
$\bar{x}$
predicted
value
$\hat{y}$
residual
$\hat{\varepsilon}$
outcome
y

5/ Prediction midterm elections

Presidential popularity and the midterms

- How does the popularity of a president predict how well their party will do in the midterm elections?

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- Small dataset with information on approval and midterm election outcomes:

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Name	Description
`year`	midterm election year
`president`	name of president
`party`	Democrat or Republican
`approval`	Gallup approval rating at midterms
`seat.change`	change in the number of House seat's for the president's party

Loading the data

```r
midterms <- read.csv("data/midterms.csv")
head(midterms)
```

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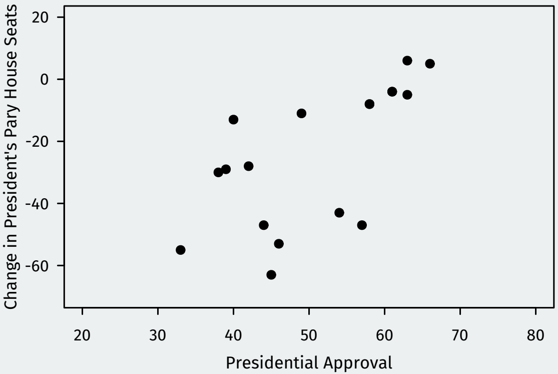
```
##   year  president party approval seat.change
## 1 1946     Truman     D       33         -55
## 2 1950     Truman     D       39         -29
## 3 1954 Eisenhower     R       61          -4
## 4 1958 Eisenhower     R       57         -47
## 5 1962    Kennedy     D       61          -4
## 6 1966    Johnson     D       44         -47
```

Scatterplot

```
plot(midterms$approval, midterms$seat.change, xlim = c(20, 80),
     ylim = c(-70, 20), pch = 19, xlab = "Presidential Approval",
     ylab = "Change in President's Pary House Seats")
```



Running a regression

- Run the regression with `seat.change` as dependent variable and `approval` as independent variable:

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```
##
## Call:
## lm(formula = seat.change ~ approval, data = midterms)
##
## Coefficients:
## (Intercept)     approval
##      -96.84         1.42
```

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- Intercept: predicted seat change when presidential approval is 0.

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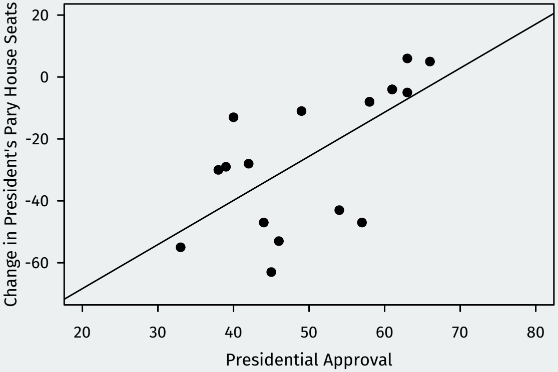
```

- Intercept: predicted seat change when presidential approval is 0.
- Slope: a one-percentage point increase in approval ≈ 1.42 increase in House seats

Scatterplot

```
plot(midterms$approval, midterms$seat.change, xlim = c(20, 80),
     ylim = c(-70, 20), pch = 19, xlab = "Presidential Approval",
     ylab = "Change in President's Pary House Seats")

abline(appseats)  ## appseats is call to lm() from above
```



Predicting the next midterm

- Can we get a prediction for Republicans in 2018?

Predicting the next midterm

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```
tail(midterms)
```

Predicting the next midterm

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```

```
##    year president party approval seat.change
## 14 1998   Clinton     D       66           5
## 15 2002   W. Bush     R       63           6
## 16 2006   W. Bush     R       38         -30
## 17 2010     Obama     D       45         -63
## 18 2014     Obama     D       40         -13
## 19 2018     Trump     R       38          NA
```

Predicting 2018

- We can use the `coef()` function to access the estimated slope and intercept:

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```
a.hat <- coef(appseats)[1] ## estimated intercept
b.hat <- coef(appseats)[2] ## estimated slope
```

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```
pred2018 <- a.hat + b.hat * 38
pred2018
```

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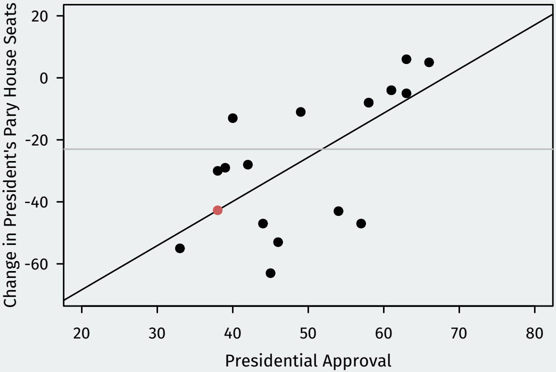
- Use these to create prediction, $\widehat{Y} = \widehat{\alpha} + \widehat{\beta} \cdot x$:

```
pred2018 <- a.hat + b.hat * 38
pred2018
```

```
## (Intercept)
##       -42.7
```

Scatterplot

```
plot(midterms$approval, midterms$seat.change, xlim = c(20, 80),
     ylim = c(-70, 20), pch = 19, xlab = "Presidential Approval",
     ylab = "Change in President's Pary House Seats")
abline(appseats)  ## appseats is call to lm() from above
points(x = 38, y = pred2018, col = "indianred", pch = 19)
abline(h = -23, col = "grey") ## flips the House
```



Regressions on subsets

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```

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```

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regR <- lm(seat.change ~ approval, data = midterms, subset = party == "R")
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```

```
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```

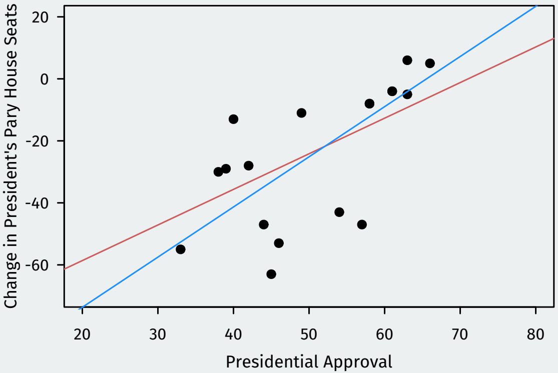
```
regD <- lm(seat.change ~ approval, data = midterms, subset = party == "D")
coef(regD)
```

```
## (Intercept)    approval
##     -106.03        1.62
```

Scatterplot

```
plot(midterms$approval, midterms$seat.change, xlim = c(20, 80),
     ylim = c(-70, 20), pch = 19, xlab = "Presidential Approval",
     ylab = "Change in President's Pary House Seats")

abline(regR, col = "indianred")
abline(regD, col = "dodgerblue")
```



On deck

- Mid-semester evaluation: please respond!

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- Mid-semester evaluation: please respond!
- DataCamp assignment 4: due this Thursday.
- Homework 3: Out today, due next Thursday.
- Start thinking about groups for final project.