

Regression Part II: Model Fit and Variable type/quantity

PSC7475: Week 6

Prof. Weldzius

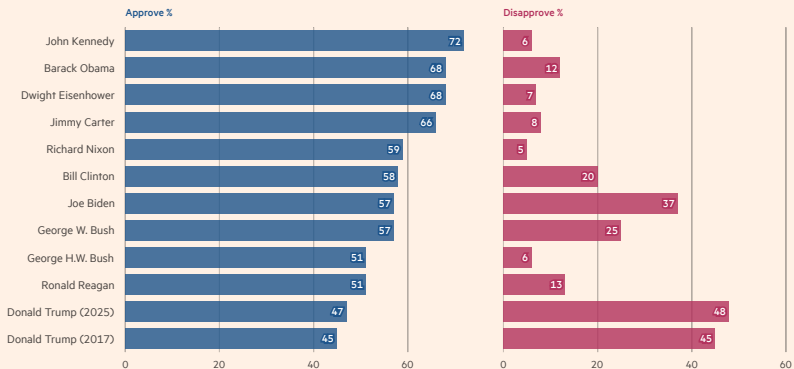
Villanova University

Slides Updated: 2025-02-26

Presidential Popularity and the Midterms

Trump's inaugural approval ratings are the lowest out of any president since the 50s

Per cent of polled respondents who approve and disapprove of each president after their first-term* inauguration



Source: Gallup • *Donald Trump's second-term inauguration is included.

FINANCIAL TIMES

Presidential Popularity and the Midterms

- Does popularity of the president or recent changes in the economy better predict midterm election outcomes?

Name	Description
year	midterm election year
president	name of president
party	Democrat or Republican
approval	Gallup approval rating at midterms
rdi.change	change in real disposable income over the year before midterms
seat.change	change in the number of House seats for the president's party

Loading the data:

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

	##	year	president	party	approval	seat.change	rdi.change
## 1	1946	Truman	D	33	-55	NA	
## 2	1950	Truman	D	39	-29	8.2	
## 3	1954	Eisenhower	R	61	-4	1.0	
## 4	1958	Eisenhower	R	57	-47	1.1	
## 5	1962	Kennedy	D	61	-4	5.0	
## 6	1966	Johnson	D	44	-47	5.3	

Fitting the Approval Model

```
fit.app <- lm(seat.change ~ approval, data = midterms)
fit.app
```

```
##
## Call:
## lm(formula = seat.change ~ approval, data = midterms)
##
## Coefficients:
## (Intercept)      approval
##      -96.845         1.424
```

Fitting the Income Model

```
fit.rdi <- lm(seat.change ~ rdi.change, data = midterms)
fit.rdi
```

```
##
```

```
## Call:
```

```
## lm(formula = seat.change ~ rdi.change, data = midterms)
```

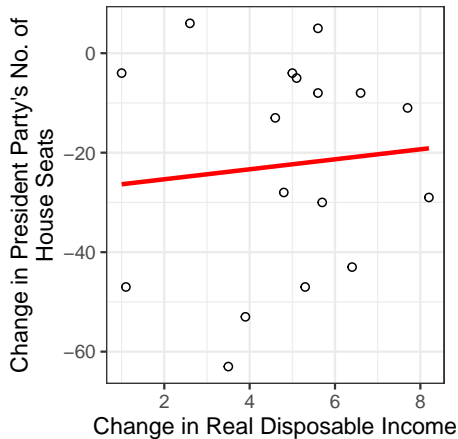
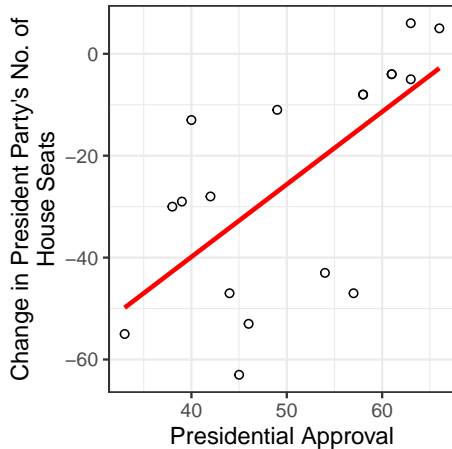
```
##
```

```
## Coefficients:
```

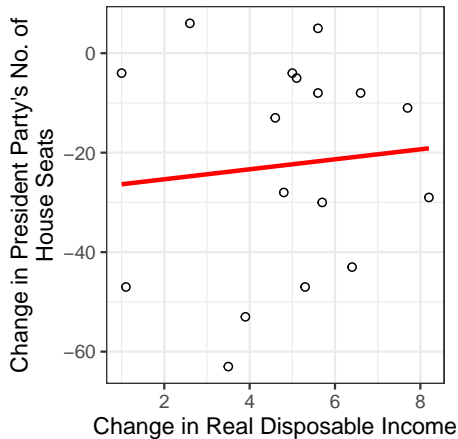
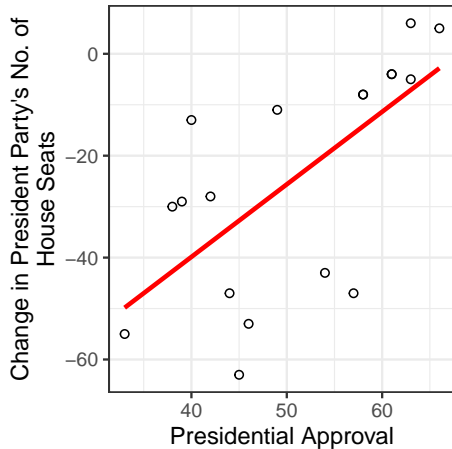
```
## (Intercept)    rdi.change
```

```
##      -27.354         1.004
```

Comparing Models

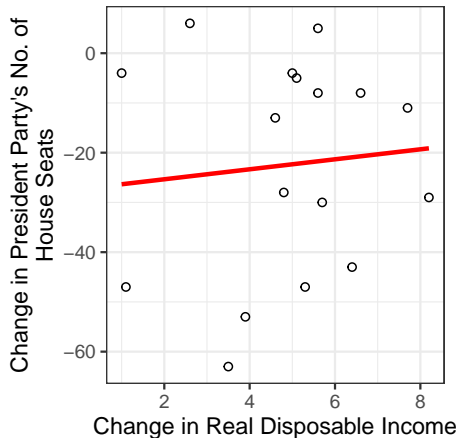
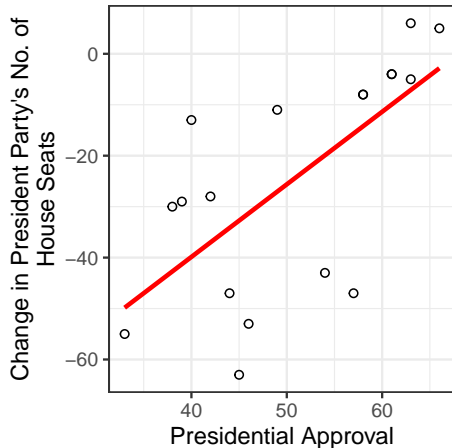


Comparing Models



- How well do the models “fit the data”?

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 - How well does the model predict the outcome variable in the data?

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- R^2 is this reduction in error divided by the baseline error:

$$R^2 = \frac{TSS - SSR}{TSS}$$

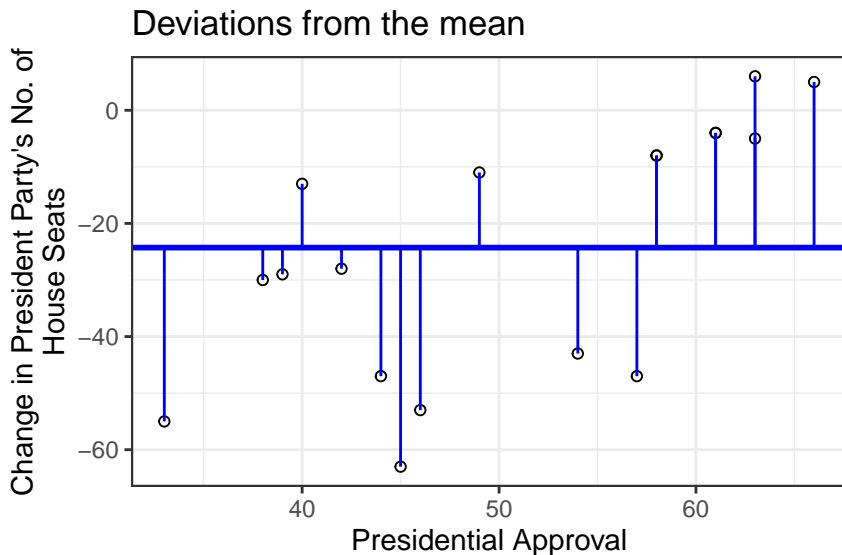
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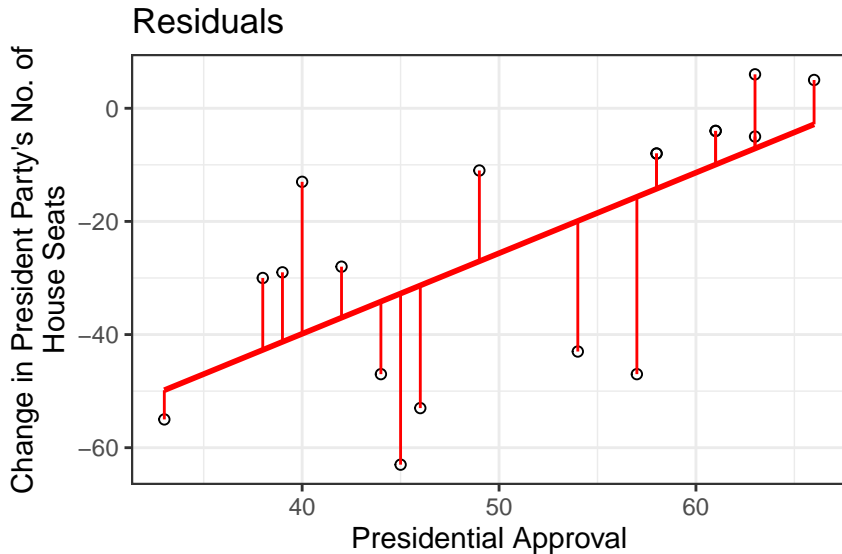
$$R^2 = \frac{TSS - SSR}{TSS}$$

- Roughly: proportion of the variation in Y_i “explained by” X_i

Total sum of squares vs. Sum of squared residuals



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Model Fit in R

- To access R^2 from the `lm()` output, use the `summary()` function:

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fit.app.sum <- summary(fit.app)
fit.app.sum$r.squared
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- Compare to fit using change in income:

```
fit.rdi.sum <- summary(fit.rdi)
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- Which does a better job predicting midterm election outcomes?

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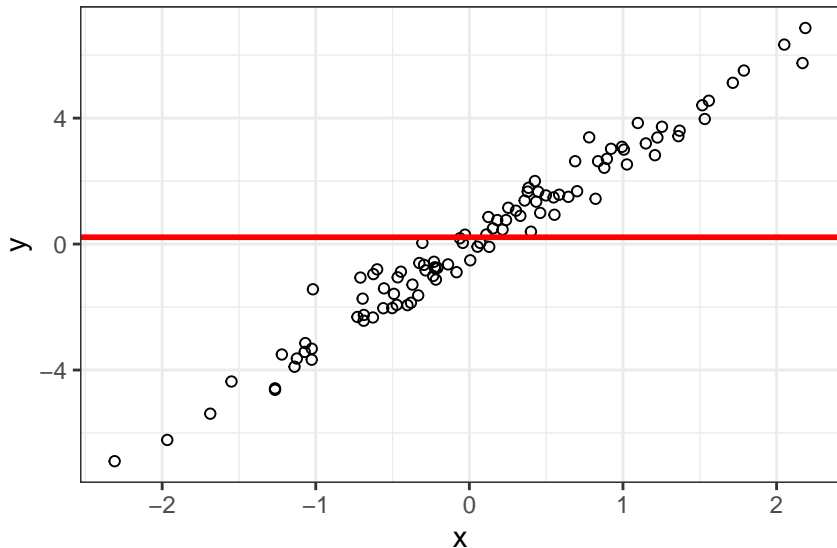
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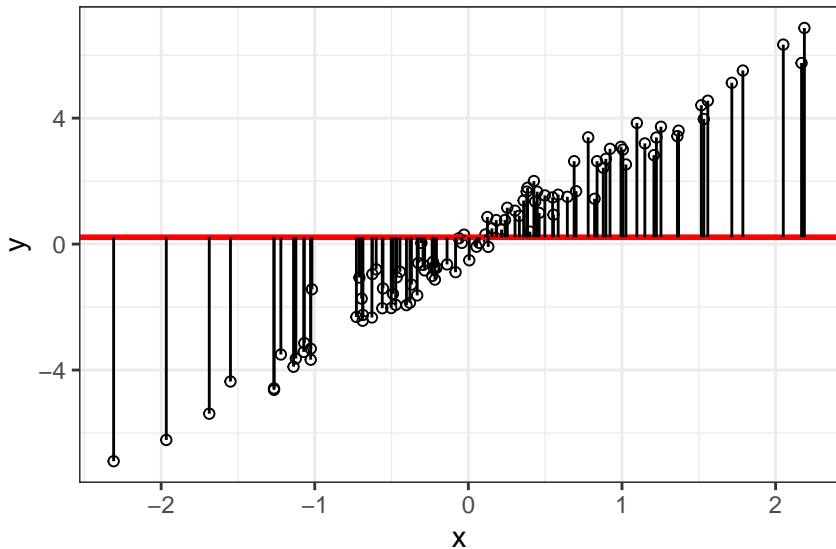
```
fit.x <- lm(y ~ x)
```

- Very good model fit: $R^2 \approx 0.95$

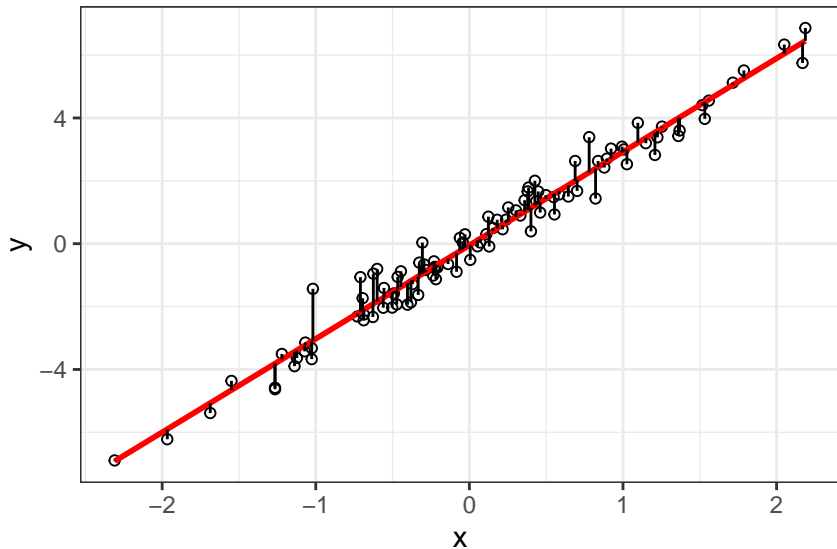
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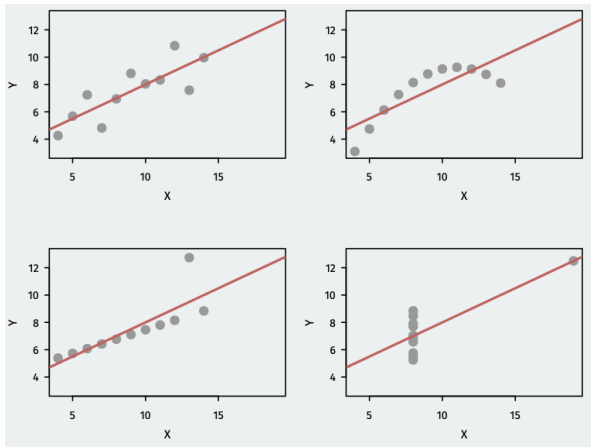


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Is R-squared useful?

- Can be very misleading. Each of these samples have the same R^2 even though they are vastly different:



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 - Example: predicting winner of Democratic presidential primary with gender of the candidate.
 - Until 2016, gender was a **perfect** predictor of who wins the primary.
 - Prediction for 2016 based on this: Bernie Sanders as Dem. nominee.
 - Bad out-of-sample prediction due to overfitting!

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 - Better interpretation as ceteris paribus relationships:
 - β_1 is the relationship between `approval` and `seat.change` holding `rdi.change` constant.

Multiple regression in R

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```
mult.fit <- lm(seat.change ~ approval + rdi.change, data = midterms)
mult.fit
```

```
##
```

```
## Call:
```

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```
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## Coefficients:
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## (Intercept)      approval      rdi.change
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```
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- $\hat{\beta}_1 = 1.57$: average increase in seat change for additional percentage point of approval, **holding RDI change fixed**
- $\hat{\beta}_1 = 3.334$: average increase in seat change for each additional percentage point increase of RDI, **holding approval fixed**

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$$\hat{\epsilon}_i = \text{seat.change}_i - \hat{\alpha} - \hat{\beta}_1 \text{approval}_i - \hat{\beta}_2 \text{rdi.change}_i$$

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- Find the coefficients that minimizes the **sum of the squared residuals**:

$$\text{SSR} = \sum_{i=1}^n \hat{\epsilon}_i^2 = (Y_i - \hat{\alpha} - \hat{\beta}_1 X_{i1} - \hat{\beta}_2 X_{i2})^2$$

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 - But this could be overfitting!!
- Solution: penalize regression models with more variables.
 - Occam's razor: **simpler models are preferred**
- Adjusted R^2 : lowers regular R^2 for each additional covariate.
 - If the added covariates don't help predict, adjusted R^2 goes down!

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```
summary(mult.fit)$adj.r.squared
```

```
## [1] 0.3655299
```

Binary and Categorical Predictors



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 - Do these programs have political effects?
 - Program had support from most parties.
 - Was implemented in a nonpartisan fashion.
 - Would the incumbent presidential party be rewarded?

The Data

- Randomized roll-out of the CCT program:
 - treatment: receive CCT 21 months before 2000 election
 - control: receive CCT 6 months before 2000 election
 - Does having CCT longer mobilize voters for incumbent PRI party?

Name	Description
treatment	early Progresa (1) or late Progresa (0)
pri2000s	PRI votes in the 2000 election as a share of adults in precinct
t2000	turnout in the 2000 election as share of adults in precinct

```
cct <- read.csv("../data/progres.csv")
```

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- Does CCT affect turnout?

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```
cct.turn.ate <- cct %>% group_by(treatment) %>%  
  summarize(t2000_mean = mean(t2000)) %>%  
  pivot_wider(names_from = treatment, values_from = t2000_mean) %>%  
  mutate(turnout_ate = `1` - `0`)  
cct.turn.ate$turnout_ate
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```
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- If there are other independent variables, this becomes the difference-in-means controlling for those covariates.

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```
lm(pri2000s ~ treatment, data = cct)
```

```
##  
## Call:  
## lm(formula = pri2000s ~ treatment, data = cct)  
##  
## Coefficients:  
## (Intercept)      treatment  
##      34.489         3.622
```

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3	Independent	0	0	1
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⋮	⋮	⋮	⋮	⋮

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- Then include all but one of these binary variables:

$$turnout_i = \alpha + \beta_1 \text{Republican}_i + \beta_2 \text{Independent}_i + \epsilon_i$$

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- $\hat{\beta}$ coefficients: average difference between each group and the baseline.
 - $\hat{\beta}_1$: average difference in turnout between Republicans and Democrats
 - $\hat{\beta}_2$: average difference in turnout between Independents and Democrats