

# Residuals, Outliers, and Diagnostics

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## Some Definitions

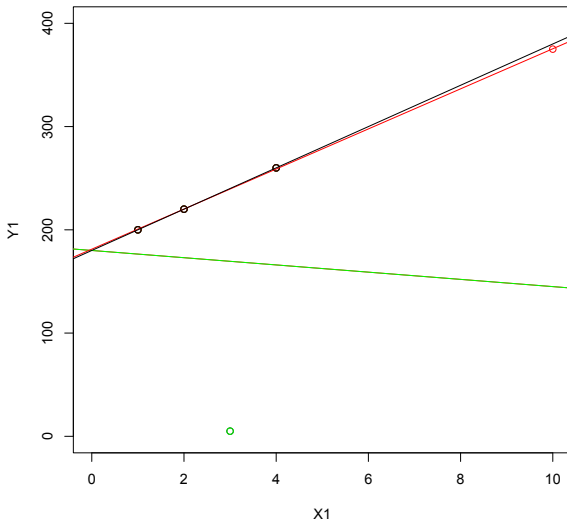
**Leverage:** the degree of influence an observation **CAN**—but not necessarily does—have on coefficient estimates

**Discrepancy:** the degree to which an observation is different from the rest of the data

**Influence:** Leverage \* Discrepancy. What is the effect of an observations values for  $Y$  and  $\mathbf{X}$  have on the coefficient estimates

**Outlier:** An observation with an unusual value for  $Y$  given its values for  $\mathbf{X}$

## An Illustration



## Leverage

$$\begin{aligned}\hat{\mathbf{Y}} &= \mathbf{X}\hat{\boldsymbol{\beta}} \\ &= \mathbf{X}[(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{Y}] \\ &= \mathbf{H}\mathbf{Y}\end{aligned}$$

where

$$\mathbf{H} = \mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'.$$

$$h_i = \mathbf{X}_i(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}_i'$$

## Residuals

Variation:

$$\widehat{\text{Var}}(\hat{u}_i) = \hat{\sigma}^2 [1 - \mathbf{x}_i(\mathbf{X}'\mathbf{X})^{-1}\mathbf{x}_i']$$

$$\begin{aligned}\widehat{\text{s.e.}}(\hat{u}_i) &= \hat{\sigma} \sqrt{[1 - \mathbf{x}_i(\mathbf{X}'\mathbf{X})^{-1}\mathbf{x}_i']} \\ &= \hat{\sigma} \sqrt{1 - h_i}\end{aligned}$$

“Standardized” Residuals:

$$\tilde{u}_i = \frac{\hat{u}_i}{\hat{\sigma} \sqrt{1 - h_i}}$$

## Residuals

“Studentized” Residuals:

$$\begin{aligned}\hat{\sigma}_{-i}^2 &= \text{Variance for the } N - 1 \text{ observations } \neq i \\ &= \frac{\hat{\sigma}^2(N - K)}{N - K - 1} - \frac{\hat{u}_i^2}{(N - K - 1)(1 - h_i)}.\end{aligned}$$

Then:

$$\hat{u}'_i = \frac{\hat{u}_i}{\hat{\sigma}_{-i}\sqrt{1 - h_i}}$$

## Why Does this Matter?

- The  $\hat{u}_i'$  follow a  $t$  distribution with  $N - K - 1$  degrees of freedom
- This means that approximately 95% fall on the interval  $[-2, 2]$
- This allows for hypothesis testing

## Influence

- If influence is effective a measure of how unusual an observation is (discrepancy) combined with where it is located (leverage), then how can we measure this?
- DFBETA and DFBETAS (the “S” is for standardized) do this
  - Where positive values correspond with observations that *decrease* the value of  $\hat{\beta}_k$
  - And negative values correspond with observations that *increase* the value of  $\hat{\beta}_k$
- Plots of DFBETAs and DFBETASs generally reveal when specific observations are highly influential



# Influence

“DFBETA”:

$$D_{ki} = \hat{\beta}_k - \hat{\beta}_{k(-i)}$$

“DFBETAS” (the “S” is for “standardized”):

$$D_{ki}^* = \frac{D_{ki}}{\widehat{\text{s.e.}}(\hat{\beta}_{k(-i)})}$$

## Influence

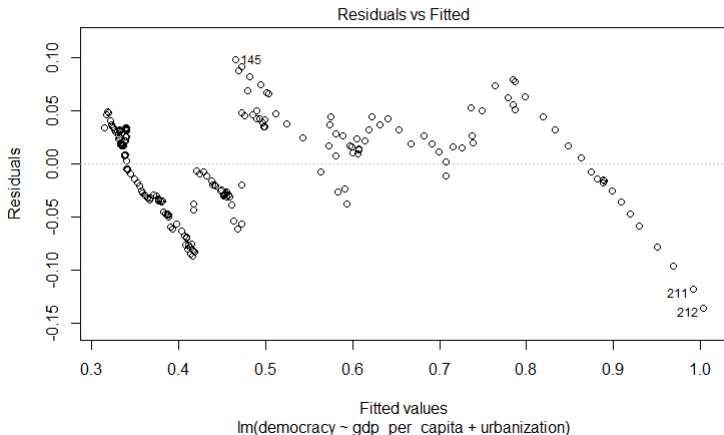
- Cook's  $D$  is a summary statistic calculated from DFBETAs to measure each observations influence on the overall regression model

$$\begin{aligned} D_i &= \frac{\tilde{u}_i^2}{K} \times \frac{h_i}{1 - h_i} \\ &= \frac{h_i \hat{u}_i^2}{K \hat{\sigma}^2 (1 - h_i)^2} \end{aligned}$$

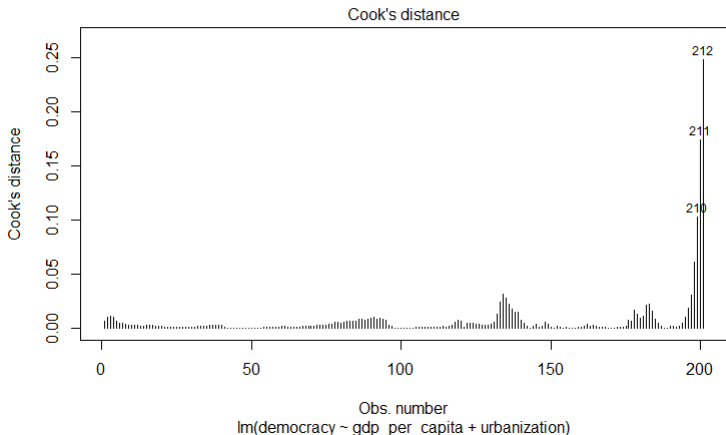
# Toy Model

```
Predictors of democracy in the US
=====
Dependent variable:
-----
democracy
-----
gdp_per_capita      0.013
                    (0.0003)
                    t = 38.604
                    p = 0.000***
urbanization        0.253
                    (0.056)
                    t = 4.562
                    p = 0.00001***
Constant            0.264
                    (0.010)
                    t = 25.127
                    p = 0.000***
-----
Observations        201
R2                  0.942
Adjusted R2         0.942
Residual Std. Error 0.044 (df = 198)
F Statistic         1,615.404*** (df = 2; 198)
=====
Note:                *p<0.1; **p<0.05; ***p<0.01
> |
```

*plot(my\_model)*



`plot(my_model)`

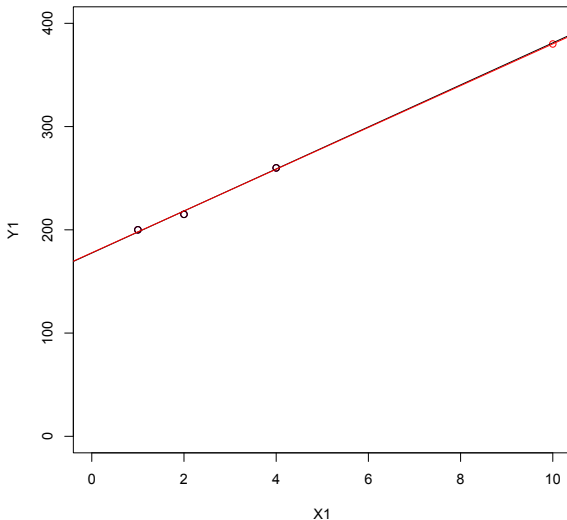


## Or, do everything manually?

```
# Or, you can manually find observations ----  
# Get cook's D  
cooksD <- cooks.distance(my_model)  
# any values greater than 3x the mean  
cooksD[(cooksD > (3 * mean(cooksD, na.rm = TRUE)))]  
  
# Get DFBETA for gdp_per_capita  
# I decided that 2/sqrt(n) is my threshold for suspicious dfbetas  
my_data[which(abs(dfbetas(my_model)[,'gdp_per_capita']) > 0.15),]
```

```
> cooksD[(cooksD > (3 * mean(cooksD, na.rm = TRUE)))]  
144      145      146      147      193      194      208      209      210      211      212  
0.02368734 0.03163166 0.02753306 0.02200472 0.02124732 0.02206320 0.03023971 0.06099106 0.10293906 0.17365460 0.24792651  
>  
> # Get DFBETA for gdp_per_capita  
> # I decided that 2/sqrt(n) is my threshold for suspicious dfbetas  
> my_data[which(abs(dfbetas(my_model)[,'gdp_per_capita']) > 0.15),]  
  year democracy gdp_per_capita urbanization  
133 1921      0.520      10.155      0.281  
134 1922      0.522      10.459      0.282  
135 1923      0.531      11.076      0.284  
136 1924      0.532      11.382      0.285  
178 1966      0.708      25.415      0.298  
182 1970      0.709      27.314      0.296  
183 1971      0.731      27.914      0.296  
184 1972      0.741      28.732      0.295  
195 1983      0.862      34.138      0.293  
196 1984      0.863      35.674      0.292  
197 1985      0.865      36.750      0.292  
198 1986      0.865      37.846      0.292  
199 1987      0.868      38.917      0.292  
200 1988      0.868      39.853      0.292  
201 1989      0.870      40.848      0.291
```

## Our Earlier Illustration



## Regression: Black Line

```
> summary(lm(Y1~X1))
```

Call:

```
lm(formula = Y1 ~ X1)
```

Residuals:

```
      1      2      3  
2.143 -3.214  1.071
```

Coefficients:

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	177.500	4.910	36.15	0.0176 *
X1	20.357	1.856	10.97	0.0579 .

---

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 4.009 on 1 degrees of freedom

Multiple R-squared: 0.9918, Adjusted R-squared: 0.9835

F-statistic: 120.3 on 1 and 1 DF, p-value: 0.05787



## Regression: Red Line

```
> summary(lm(Y3~X3))
```

Call:

```
lm(formula = Y3 ~ X3)
```

Residuals:

1	2	3	4
2.00000	-3.23077	1.30769	-0.07692

Coefficients:

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	177.769	2.239	79.41	0.000159 ***
X3	20.231	0.407	49.70	0.000405 ***

---

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 2.842 on 2 degrees of freedom

Multiple R-squared: 0.9992, Adjusted R-squared: 0.9988

F-statistic: 2470 on 1 and 2 DF, p-value: 0.0004046

## A Variance-Based Statistic

- “COVRATIO” is a statistic that provides an estimate of whether a particular observation has a large effect on the variance-covariance estimates of our parameters

$$\text{COVRATIO}_i = \left[ (1 - h_i) \left( \frac{N - K - 1 + \hat{u}_i'^2}{N - K} \right)^K \right]^{-1}$$

- Observations with  $\text{COVRATIO}_i > 1$  *increase* the precision of our estimates (decrease S.E. estimates)
- Observations with  $\text{COVRATIO}_i < 1$  *decrease* the precision of our estimates (increase S.E. estimates)

# COVRATIO statistics in R

```
> influence.measures(my_model)
Influence measures of
lm(formula = democracy ~ gdp_per_capita + urbanization, data = my_data) :

      dfb.1 dfb.gd__ dfb.urbn   dffit cov.r   cook.d    hat inf
12  1.36e-01  0.04288 -0.11563  0.13742 1.036  6.31e-03  0.02939
13  1.77e-01  0.05262 -0.14814  0.17881 1.026  1.07e-02  0.02728
14  1.81e-01  0.05045 -0.14962  0.18390 1.021  1.13e-02  0.02528
15  1.69e-01  0.04426 -0.13840  0.17310 1.021  9.98e-03  0.02369
16  1.38e-01  0.03340 -0.11101  0.14156 1.024  6.68e-03  0.02218
17  1.18e-01  0.02619 -0.09346  0.12178 1.026  4.95e-03  0.02075
18  1.08e-01  0.02171 -0.08428  0.11250 1.025  4.23e-03  0.01940
19  1.02e-01  0.01840 -0.07829  0.10696 1.025  3.82e-03  0.01837
20  9.15e-02  0.01401 -0.06886  0.09720 1.025  3.16e-03  0.01715
21  8.37e-02  0.01113 -0.06196  0.08979 1.024  2.69e-03  0.01625
22  7.89e-02  0.00878 -0.05735  0.08558 1.024  2.45e-03  0.01539
23  7.91e-02  0.00845 -0.05721  0.08593 1.023  2.47e-03  0.01519
24  7.07e-02  0.00667 -0.05063  0.07736 1.024  2.00e-03  0.01479
25  6.11e-02  0.00543 -0.04355  0.06709 1.026  1.51e-03  0.01459
26  7.94e-02  0.00660 -0.05627  0.08740 1.022  2.55e-03  0.01440
27  7.90e-02  0.00543 -0.05530  0.08762 1.021  2.56e-03  0.01401
28  7.63e-02  0.00446 -0.05301  0.08510 1.021  2.42e-03  0.01382
29  7.35e-02  0.00355 -0.05062  0.08233 1.022  2.27e-03  0.01363
30  7.45e-02  0.00300 -0.05101  0.08391 1.021  2.35e-03  0.01345
31  7.30e-02  0.00239 -0.04959  0.08249 1.021  2.27e-03  0.01328
32  5.71e-02  0.00148 -0.03859  0.06487 1.024  1.41e-03  0.01311
```

## So What Do We Do with Outliers?

- Two relevant questions here:
  1. Is the outlier due to a coding error or mistake of some sort?
  2. Is the outlier correctly coded but a true outlier (i.e. weird)?

## Dealing with Outliers: Coding Errors

- Here the answer is simple, just fix the error and your problem is solved
- If you cannot fix the issue, drop the observation
  - Can assume the observation is “missing at random”
  - Could also use imputation approaches for solving missing data issues

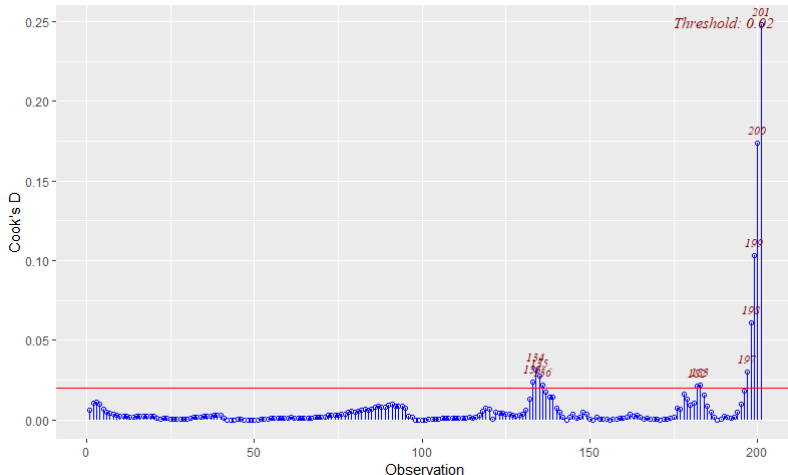
## Dealing with Outliers: True Outliers

- If there some reason why that observation is very different:
  - AND that reason is theoretically important, then this is now a *theoretical* issue and you may need to revisit your theory or model selection to account for it
  - AND that reason is NOT theoretically important, then you can probably safely drop it
- If there is no reason why that observation is very different:
  - There isn't an easy answer: look at that data point more deeply and make a judgement call
  - Whether you keep or drop, you probably need to run the alternative specification as a robustness check and footnote it

## Cook's Distance (using *olsrr* package)

```
# Bar Plot of Cook's distance to detect observations that strongly influence
# fitted values of the model.
ols_plot_cooksd_bar(my_model)
ols_plot_cooksd_chart(my_model)
```

Cook's D Chart



## Let's check these observations

```
> my_data[197:201, ]  
  year democracy gdp_per_capita urbanization  
197 1985      0.865         36.750        0.292  
198 1986      0.865         37.846        0.292  
199 1987      0.868         38.917        0.292  
200 1988      0.868         39.853        0.292  
201 1989      0.870         40.848        0.291  
> # maybe after-effect of oil crisis? Or, Reagan defeated Carter? More conservative economy?
```

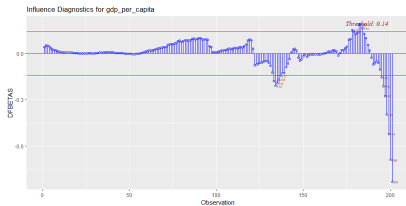
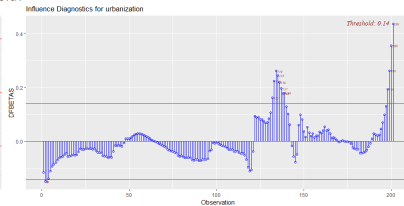
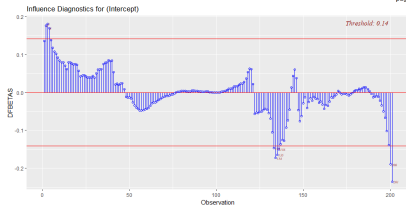


## DFBETAs (using *olsrr* package)

```
## DEBETAs ----  
# DFBETA measures the difference in each parameter estimate with and without the influential point.  
ols_plot_dfbetas(my_model)  
# Let's check these observations
```

# DFBETAs (using *olsrr* package)

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## Let's check these observations

```
> my_data[134:136, ]
  year democracy gdp_per_capita urbanization
134 1922      0.522        10.459         0.282
135 1923      0.531        11.076         0.284
136 1924      0.532        11.382         0.285
> # Supreme Court rejected women's right to vote? US occupies Haiti?
```

# What happens if we drop influential points and outliers?

Dependent variable:		
	full sample (1)	democracy influential/outliers removed (2)
gdp_per_capita	0.013 (0.0003) t = 38.604 p = 0.000***	0.014 (0.0004) t = 35.791 p = 0.000***
urbanization	0.253 (0.056) t = 4.562 p = 0.00001***	0.240 (0.057) t = 4.193 p = 0.00005***
Constant	0.264 (0.010) t = 25.127 p = 0.000***	0.265 (0.011) t = 24.884 p = 0.000***
Observations	201	193
R2	0.942	0.937
Adjusted R2	0.942	0.936
Residual Std. Error	0.044 (df = 198)	0.044 (df = 190)
F Statistic	1,615.404*** (df = 2; 198)	1,402.193*** (df = 2; 190)
Note:		
*p<0.1; **p<0.05; ***p<0.01		