GSERM 2017

Regression III Linear Regression Review

June 19, 2017 (morning session)

"Regression III"

- "Regression" course
- Texts: Weisberg (2013) and others
- Course materials at the github repo: https://github.com/PrisonRodeo/GSERM-2017-git
- Software: R > Stata
- "Introduction to R and RStudio" today after the break...
- Grading: Two homework assignments plus a final examination

Regression

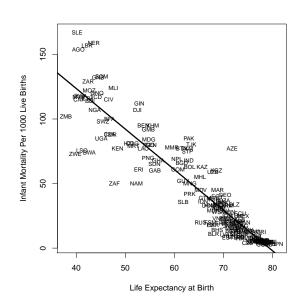
"Regression," conceptually:

$$Pr(Y|\mathbf{X}) = f(\mathbf{X})$$

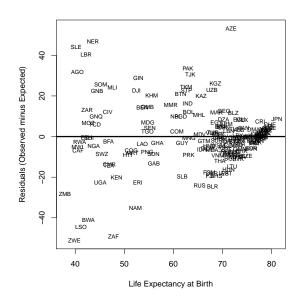
Two important things:

- The distribution of Y is conditional on all variables in X, and
- The conditional distribution of *Y* is conditional on the *joint* distribution of the elements of **X**.
- \rightarrow Regression is <u>hard</u>...

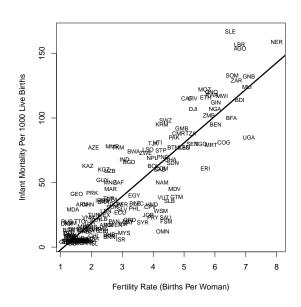
Infant Mortality and Life Expectancy



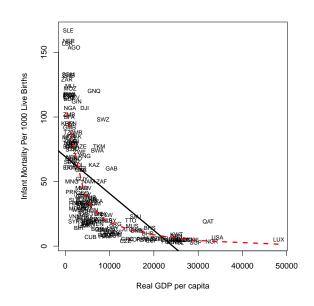
Infant Mortality and Life Expectancy: "Residuals"



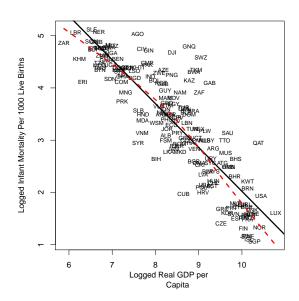
Infant Mortality and Fertility



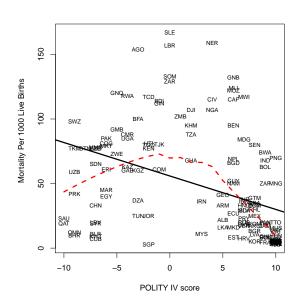
Infant Mortality and Wealth



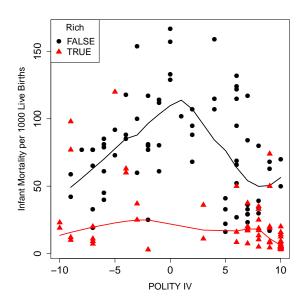
(Logged) Infant Mortality and (Logged) Wealth



Infant Mortality and Democracy



Infant Mortality, (Dichotomized) Wealth, and Democracy



Wherefore Regression?

	Description	Explanation	Prediction
Task	Summarize data	Correlation/causation	Forecast OOS /
			future data
Emphasis	Data	Theory / Hypotheses	Outcomes
Focus	Univariate	Multivariate	Multivariate
Typical Application	Summarize /	Discuss marginal	Optimize out-of-
	"reduce" data	associations between	sample predictive
		predictors and an	power / minimize
		outcome of interest	prediction error

Linear Regression

$$Y_i = \mu + u_i \tag{1}$$

$$\mu_i = \beta_0 + \beta_1 X_i$$

so:

$$Y_i = \beta_0 + \beta_1 X_i + u_i \tag{2}$$

Goals:

- Estimate $\hat{\beta}_0$ and $\hat{\beta}_1$
- ullet Estimate the *variability* \hat{eta}_0 and \hat{eta}_1

Linear Regression (continued)

If we have $\hat{\beta}_0$ and $\hat{\beta}_1$, then:

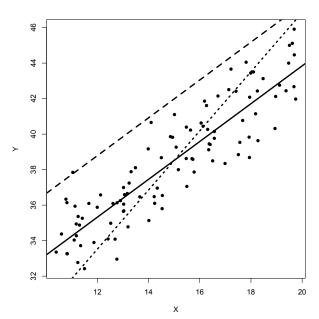
$$\hat{Y}_i = \hat{\beta}_0 + \hat{\beta}_1 X_i \tag{3}$$

and

$$\hat{u}_i = Y_i - \hat{Y}_i
= Y_i - \hat{\beta}_0 - \hat{\beta}_1 X_i$$
(4)

Q: How to estimate $\hat{\beta}_0$ and $\hat{\beta}_1$?

Scatterplot: X and Y (with regression lines)



Ordinary Least Squares

Choose $\hat{\beta}_0$ and $\hat{\beta}_1$ to minimize $\hat{S} = \sum_{i=1}^N \hat{u}_i^2$.

$$\hat{S} = \sum_{i=1}^{N} (Y_i - \hat{Y}_i)^2$$

$$= \sum_{i=1}^{N} (Y_i - \hat{\beta}_0 - \hat{\beta}_1 X_i)^2$$

$$= \sum_{i=1}^{N} (Y_i^2 - 2Y_i \hat{\beta}_0 - 2Y_i \hat{\beta}_1 X_i + \hat{\beta}_0^2 + 2\hat{\beta}_0 \hat{\beta}_1 X_i + \hat{\beta}_1^2 X_i^2)$$

OLS (continued)

Differentiate:

$$\frac{\partial \hat{S}}{\partial \hat{\beta}_0} = \sum_{i=1}^{N} (-2Y_i + 2\hat{\beta}_0 + 2\hat{\beta}_1 X_i)$$

$$= -2\sum_{i=1}^{N} (Y_i - \hat{\beta}_0 - \hat{\beta}_1 X_i)$$

$$= -2\sum_{i=1}^{N} \hat{u}_i$$

$$\frac{\partial \hat{S}}{\partial \hat{\beta}_1} = \sum_{i=1}^N (-2Y_i X_i + 2\hat{\beta}_0 X_i + 2\hat{\beta}_1 X_i^2)$$

$$= -2\sum_{i=1}^N (Y_i - \hat{\beta}_0 - \hat{\beta}_1 X_i) X_i$$

$$= -2\sum_{i=1}^N \hat{u}_i X_i$$

OLS (continued)

Yields:

$$\sum_{i=1}^{N} Y_{i} = N\hat{\beta}_{0} + \hat{\beta}_{1} \sum_{i=1}^{N} X_{i}$$

$$\sum_{i=1}^{N} Y_i X_i = \hat{\beta}_0 \sum_{i=1}^{N} X_i + \hat{\beta}_1 \sum_{i=1}^{N} X_i^2$$

OLS (continued)

Solving yields:

$$\hat{\beta}_{1} = \frac{\sum_{i=1}^{N} (X_{i} - \bar{X})(Y_{i} - \bar{Y})}{\sum_{i=1}^{N} (X_{i} - \bar{X})^{2}}$$

$$= \frac{\text{Covariance of } X \text{ and } Y}{\text{Variance of } X}$$
(5)

$$\hat{\beta}_0 = \bar{Y} - \hat{\beta}_1 \bar{X} \tag{6}$$

$$u_i \sim \text{i.i.d. } N(0, \sigma^2)$$

meaning:

$$Var(Y|X,\beta) = \sigma^2$$

so:

$$\operatorname{Var}(\hat{\beta}_{1}) = \operatorname{Var}\left[\frac{\sum_{i=1}^{N}(X_{i}-\bar{X})Y_{i}}{\sum_{i=1}^{N}(X_{i}-\bar{X})^{2}}\right]$$

$$= \left[\frac{1}{\sum(X_{i}-\bar{X})^{2}}\right]^{2}\sum(X_{i}-\bar{X})^{2}\operatorname{Var}(Y)$$

$$= \left[\frac{1}{\sum(X_{i}-\bar{X})^{2}}\right]^{2}\sum(X_{i}-\bar{X})^{2}\sigma^{2}$$

$$= \frac{\sigma^{2}}{\sum(X_{i}-\bar{X})^{2}}.$$

$Var(\hat{eta}_0)$ and $Cov(\hat{eta}_0,\hat{eta}_1)$

Similarly:

$$Var(\hat{\beta}_0) = \frac{\sum X_i^2}{N \sum (X_i - \bar{X})^2} \sigma^2$$

and:

$$\mathsf{Cov}(\hat{eta}_0,\hat{eta}_1) = rac{-ar{X}}{\sum (X_i - ar{X})^2} \sigma^2$$

Important Things

- $Var(\hat{\beta}_0)$ and $Var(\hat{\beta}_1) \propto \sigma^2$
- $\mathsf{Var}(\hat{eta}_0)$ and $\mathsf{Var}(\hat{eta}_1) \propto -\sum (X_i \bar{X})$
- $Var(\hat{\beta}_0)$ and $Var(\hat{\beta}_1) \propto -N$
- $\operatorname{sign}[\operatorname{Cov}(\hat{\beta}_0, \hat{\beta}_1)] = \operatorname{sign}(\bar{X})$

If $u_i \sim N(0, \sigma^2)$, then:

$$\hat{\beta}_0 \sim N[\beta_0, Var(\hat{\beta}_0)]$$

and

$$\hat{\beta}_1 \sim N[\beta_1, Var(\hat{\beta}_1)]$$

Means:

$$z_{\hat{\beta}_1} = \frac{(\hat{\beta}_1 - \beta_1)}{\sqrt{\mathsf{Var}(\hat{\beta}_1)}}$$
$$= \frac{(\hat{\beta}_1 - \beta_1)}{\mathsf{s.e.}(\hat{\beta}_1)}$$
$$= \sim N(0, 1)$$

A Small Problem...

$$\sigma^2 = ???$$

Solution: use

$$\hat{\sigma}^2 = \frac{\sum \hat{u}_i^2}{N - k}$$

Gives:

$$\widehat{\mathsf{Var}(\hat{eta}_1)} = rac{\hat{\sigma}^2}{\sum (X_i - \bar{X})^2},$$

$$\widehat{\mathsf{Var}(\hat{\beta}_0)} = \frac{\sum X_i^2}{N \sum (X_i - \bar{X})^2} \hat{\sigma}^2$$

Inference (continued)

$$\widehat{\text{s.e.}(\hat{\beta}_1)} = \sqrt{\widehat{\text{Var}(\hat{\beta}_1)}}$$

$$= \sqrt{\frac{\hat{\sigma}^2}{\sum (X_i - \bar{X})^2}}$$

$$= \frac{\hat{\sigma}}{\sqrt{\sum (X_i - \bar{X})^2}}$$

implies:

$$t_{\hat{\beta}_{1}} \equiv \frac{(\hat{\beta}_{1} - \beta_{1})}{\widehat{s.e.}(\hat{\beta}_{1})} = \frac{(\hat{\beta}_{1} - \beta_{1})}{\frac{\hat{\sigma}}{\sqrt{\sum (X_{i} - \bar{X}})^{2}}}$$
$$= \frac{(\hat{\beta}_{1} - \beta_{1})\sqrt{\sum (X_{i} - \bar{X}})^{2}}{\hat{\sigma}}$$
$$\sim t_{N-k}$$

Predictions and Variance

Point prediction:

$$\hat{Y}_k = \hat{\beta}_0 + \hat{\beta}_1 X_k$$

 Y_k is unbiased:

$$E(\hat{Y}_k) = E(\hat{\beta}_0 + \hat{\beta}_1 X_k)$$

$$= E(\hat{\beta}_0) + X_k E(\hat{\beta}_1)$$

$$= \beta_0 + \beta_1 X_k$$

$$= E(Y_k)$$

Variability:

$$\begin{aligned} \operatorname{Var}(\hat{Y}_k) &= \operatorname{Var}(\hat{\beta}_0 + \hat{\beta}_1 X_k) \\ &= \frac{\sum X_i^2}{N \sum (X_i - \bar{X})^2} \sigma^2 + \left[\frac{\sigma^2}{\sum (X_i - \bar{X})^2} \right] X_k^2 + 2 \left[\frac{-\bar{X}}{\sum (X_i - \bar{X})^2} \sigma^2 \right] X_k \\ &= \sigma^2 \left[\frac{1}{N} + \frac{(X_k - \bar{X})^2}{\sum (X_i - \bar{X})^2} \right] \end{aligned}$$

Variability of Predictions

$$\mathsf{Var}(\hat{Y}_k) = \sigma^2 \left[\frac{1}{N} + \frac{(X_k - \bar{X})^2}{\sum (X_i - \bar{X})^2} \right]$$

means that $Var(\hat{Y}_k)$:

- Decreases in N
- Decreases in Var(X)
- Increases in $|X \bar{X}|$

Predictions and Inference

Standard error of the prediction:

$$\widehat{\text{s.e.}(\hat{Y}_k)} = \sqrt{\sigma^2 \left[\frac{1}{N} + \frac{(X_k - \bar{X})^2}{\sum (X_i - \bar{X})^2} \right]}$$

 \rightarrow (e.g.) confidence intervals:

95% c.i.
$$(\hat{Y}_k) = \hat{Y}_k \pm [1.96 \times \widehat{\text{s.e.}(\hat{Y}_k)}]$$

Variation in Y

$$Var(Y) = Var(\hat{Y} + \hat{u})$$

$$= Var(\hat{Y}) + Var(\hat{u}) + 2 Cov(\hat{Y}, \hat{u})$$

$$= Var(\hat{Y}) + Var(\hat{u})$$

$$\begin{array}{lll} \textbf{TSS} & = & \textbf{MSS} & + & \textbf{RSS} \\ \text{("Total")} & & \text{("Estimated," or "Model")} & & \text{("Residual")} \end{array}$$

Model Fit: R^2

$$R^{2} = \frac{\text{MSS}}{\text{TSS}}$$

$$= \frac{\sum (\hat{Y}_{i} - \bar{Y})^{2}}{\sum (Y_{i} - \bar{Y})^{2}}$$

$$= 1 - \frac{\text{RSS}}{\text{TSS}}$$

$$= 1 - \frac{\sum \hat{u}_{i}^{2}}{\sum (Y_{i} - \bar{Y})^{2}}$$

R-squared:

- is "the proportion of variance explained"
- $\bullet \in [0,1]$
 - $\cdot R^2 = 1.0 \equiv a$ "perfect (linear) fit"
 - $\cdot R^2 = 0 \equiv \text{no (linear)} X Y \text{ association}$

For a single X,

$$R^{2} = \hat{\beta}_{1}^{2} \frac{\sum (X_{i} - \bar{X})^{2}}{\sum (Y_{i} - \bar{Y})^{2}}$$
$$= r_{XY}^{2}$$

Adjusted R^2

$$R_{adj.}^2 = 1 - \frac{(1 - R^2)(N - c)}{(N - k)}$$

where c=1 if there is a constant in the model and c=0 otherwise.

 $R_{adj.}^2$:

- $R_{adi.}^2 \to R^2$ as $N \to \infty$
- $R_{adi.}^2$ can be > 1, or < 0...
- $R_{adi.}^2$ increases with model "fit," but
- The extent of that increase is discounted by a factor proportional to the number of covariates.

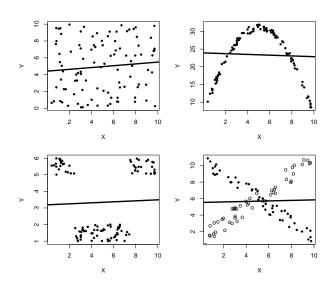
R^2 Alternatives

• Standard Error of the Estimate:

$$\mathsf{SEE} = \sqrt{\frac{\mathsf{RSS}}{N - k}}$$

- *F*-tests
- ROC / AUC
- Graphical methods

Caution: Different Ways to get $R^2 = 0$



Linear Regression: *k* Predictors

$$Y = X\beta + u$$

$$Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + ... + \beta_K X_{Ki} + u_i$$

$$\begin{bmatrix} Y_1 \\ Y_2 \\ \vdots \\ Y_N \end{bmatrix} = \begin{bmatrix} 1 & X_{11} & X_{21} & \cdots & X_{K1} \\ 1 & X_{12} & X_{22} & \cdots & X_{K2} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & X_{1N} & X_{2N} & \cdots & X_{KN} \end{bmatrix} \begin{bmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_K \end{bmatrix} + \begin{bmatrix} u_1 \\ u_2 \\ \vdots \\ u_N \end{bmatrix}.$$

Residuals:

$$\mathbf{u} = \mathbf{Y} - \mathbf{X}\boldsymbol{\beta}$$

The inner product of **u**:

$$\mathbf{u}'\mathbf{u} = \begin{bmatrix} u_1 & u_2 & \cdots & u_N \end{bmatrix} \begin{bmatrix} u_1 \\ u_2 \\ \vdots \\ u_N \end{bmatrix}$$
$$= u_1^2 + u_2^2 + \dots + u_N^2$$
$$= \sum_{i=1}^N u_i^2$$

Estimating β

$$\mathbf{u}'\mathbf{u} = (\mathbf{Y} - \mathbf{X}\beta)'(\mathbf{Y} - \mathbf{X}\beta)$$
$$= \mathbf{Y}'\mathbf{Y} - 2\beta'\mathbf{X}'\mathbf{Y}' + \beta'\mathbf{X}'\mathbf{X}\beta$$

Now get:

$$\frac{\partial \mathbf{u}' \mathbf{u}}{\partial \boldsymbol{\beta}} = -2\mathbf{X}'\mathbf{Y} + 2\mathbf{X}'\mathbf{X}\boldsymbol{\beta}$$

Solve:

$$-2\mathbf{X}'\mathbf{Y} + 2\mathbf{X}'\mathbf{X}\boldsymbol{\beta} = 0$$

$$-\mathbf{X}'\mathbf{Y} + \mathbf{X}'\mathbf{X}\boldsymbol{\beta} = 0$$

$$\mathbf{X}'\mathbf{X}\boldsymbol{\beta} = \mathbf{X}'\mathbf{Y}$$

$$(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{X}\boldsymbol{\beta} = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{Y}$$

$$\boldsymbol{\beta} = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{Y}$$

The Importance of $\mathbf{V}(\hat{\boldsymbol{\beta}})$

$$\mathbf{V}(\hat{\boldsymbol{\beta}}) = \mathsf{E}[\hat{\boldsymbol{\beta}} - \mathsf{E}(\hat{\boldsymbol{\beta}})]^2$$
$$= \mathsf{E}\{[\hat{\boldsymbol{\beta}} - \mathsf{E}(\hat{\boldsymbol{\beta}})][\hat{\boldsymbol{\beta}} - \mathsf{E}(\hat{\boldsymbol{\beta}})]'\}$$

Rewrite:

$$V(\hat{\beta}) = E(\hat{\beta} - \beta)(\hat{\beta} - \beta)'$$

$$= E\{[(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{u}][(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{u}]'\}$$

$$= E[(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{u}\mathbf{u}'\mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}]$$

The Importance of $\mathbf{V}(\hat{\beta})$

Taking expectations:

$$\begin{aligned} \mathbf{V}(\hat{\boldsymbol{\beta}}) &= & (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathsf{E}(\mathbf{u}\mathbf{u}')\mathbf{X}(\mathbf{X}'\mathbf{X})^{-1} \\ &= & (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\sigma^2\mathbf{I}\mathbf{X}(\mathbf{X}'\mathbf{X})^{-1} \\ &= & \sigma^2(\mathbf{X}'\mathbf{X})^{-1} \end{aligned}$$

Estimating $\mathbf{V}(\hat{\boldsymbol{\beta}})$

Empirical estimate:

$$\hat{\sigma}^2 = \frac{\hat{\mathbf{u}}'\hat{\mathbf{u}}}{N - K}$$

Yields:

$$\widehat{\mathbf{V}(\hat{\boldsymbol{\beta}})} = \hat{\sigma}^2 (\mathbf{X}'\mathbf{X})^{-1}$$

OLS Assumptions

1. Zero Expectation Disturbances

$$\mathsf{E}(u) = 0$$

OLS Assumptions

2. Homoscedasticity / No Error Correlation

$$\mathbf{u}\mathbf{u}' = \begin{bmatrix} u_1 \\ u_2 \\ \vdots \\ u_N \end{bmatrix} \begin{bmatrix} u_1 & u_2 & \cdots & u_N \end{bmatrix}$$

$$= \begin{bmatrix} u_1^2 & u_1 u_2 & \cdots & u_1 u_N \\ u_2 u_1 & u_2^2 & \cdots & u_2 u_N \\ \vdots & \vdots & \ddots & \vdots \\ u_N u_1 & u_N u_2 & \cdots & u_N^2 \end{bmatrix}$$

Expectation must be:

$$\mathsf{E}(\mathbf{u}\mathbf{u}') = \begin{bmatrix} \sigma^2 & 0 & \cdots & 0 \\ 0 & \sigma^2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \sigma^2 \end{bmatrix}$$

OLS Assumptions

3. "Fixed" X...

- No measurement error in the Xs, and
- Cov(X, u) = 0.

4. X is full column rank.

Means:

- no exact linear relationship among X, and
- K < N.

5. Normal Disturbances

$$\mathbf{u} \sim \mathbf{N}(\mathbf{0}, \sigma^2 \mathbf{I})$$

OLS: Properties

Under these assumptions, the OLS estimate of $\hat{\beta}$ is:

- Unbiased
- Fully Efficient

```
(i.e., "BLUE")
```

BREAK

Software

• Preferred: R + RStudio

Also viable: Stata

Highly discouraged: SAS, SPSS/PSPP, etc.



R version 3.3.1 (2016-06-21) -- "Bug in Your Hair" Copyright (C) 2016 The R Foundation for Statistical Computing Platform: x86.64-aople-darwin13.4.0 (64-bit)

R is free software and comes with ABSOLUTELY NO WARRANTY.
You are welcome to redistribute it under certain conditions.
Type 'license()' or 'licence()' for distribution details.

Natural language support but running in an English locale

R is a collaborative project with many contributors. Type 'contributors()' for more information and 'citation()' on how to cite R or R packages in publications.

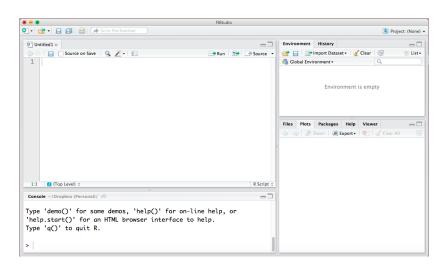
Type 'demo()' for some demos, 'help()' for on-line help, or 'help.start()' for an HTML browser interface to help.
Type 'q()' to quit R.

[R.app GUI 1.68 (7238) x86_64-apple-darwin13.4.0]

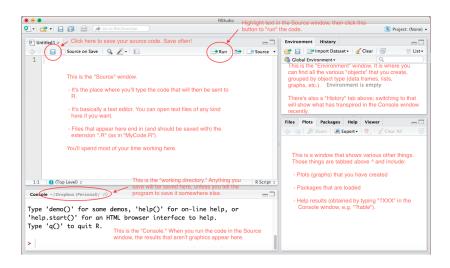
[Workspace restored from /Users/cuz10lcl/.RData] [History restored from /Users/cuz10lcl/.Rapp.history]

>

RStudio



RStudio (annotated)



Inside the Source Window

This:

> table(df\$X)

... means "Type the phrase 'table(dfX)' on the command line," or – equivalently – "Type the phrase 'table(dfX)' into your Source code, and then run it."

Inside the Source Window

More often, you'll see:

```
with(df, plot(Y~X,pch=19,col="red")) # draw a scatterplot
abline(h=0,lty=2) # add a horizontal line at zero
abline(v=0,lty=2) # add a vertical line at zero
text(df$X,df$Y,labels=df$names,pos=1) # add labels
```

... which means "Put this block of text into your Source code, and then run it."

Note:

- R / RStudio ignores line breaks
- Anything to the right of a "#" is a comment

Very basic R examples... (see GSERM-2017-R-Intro.R)

Help For Learning R(Studio)

In rough order of preference:

- Quick-R (http://www.statmethods.net/)
- The "Level-Zero" R Tutorial (doesn't integrate RStudio, but is otherwise very good)
- Statistics with R
- The Do It Yourself Introduction to R
- Also be sure to consult the Regression III "Useful R Resources" guide (on GitHub).

Example Data: Infant Mortality

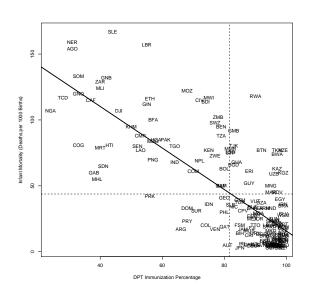
```
> url <- getURL("https://raw.githubusercontent.com/PrisonRodeo/
   GSERM-2017-git/master/Data/CountryData2000.csv")
> Data <- read.csv(text = url) # read the "votes" data
> rm(url)
> # Summary statistics
> # install.packages("psych") <- Install psych package, if necessary
> library(psych)
> with(Data, describe(infantmortalityperK))
                   sd median trimmed mad min max range skew kurtosis
 vars
        n mean
                                                                         se
    1 179 43.83 40.39
                          29
                               38.38 34.26 2.9 167 164.1
                                                                 0.06 3.02
> with(Data, describe(DPTpct))
                   sd median trimmed mad min max range skew kurtosis
    1 181 81.71 19.77
                          90 85.23 11.86 24 99
                                                      75 -1.31
                                                                  0.57 1.47
```

OLS Regression

```
> IMDPT<-lm(infantmortalityperK~DPTpct,data=Data,na.action=na.exclude)
> summarv.lm(IMDPT)
Call:
lm(formula = infantmortalityperK ~ DPTpct, data = Data)
Residuals:
   Min
           10 Median 30
                                  Max
-56.801 -16.328 -5.105 11.777 86.590
Coefficients:
           Estimate Std. Error t value Pr(>|t|)
(Intercept) 173.2771 8.4893 20.41 <2e-16 ***
DPTpct -1.5763 0.1009 -15.62 <2e-16 ***
Signif. codes: 0 *** 0.001 ** 0.01 * 0.05 . 0.1 1
Residual standard error: 26.19 on 175 degrees of freedom
  (14 observations deleted due to missingness)
Multiple R-squared: 0.5824, Adjusted R-squared: 0.58
F-statistic: 244.1 on 1 and 175 DF, p-value: < 2.2e-16
```

Analysis of Variance

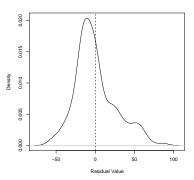
Regression of Infant Mortality on DPT Immunization Rates



Fitted Values, Residuals, etc.

```
> # Residuals (u):
> Data$IMDPTres <- with(Data, residuals(IMDPT))
> describe(Data$IMDPTres)
```

var n mean sd median mad min max range skew kurtosis se 1 1 177 0 26.12 -5.1 19.42 -56.8 86.59 143.4 0.75 0.44 1.96

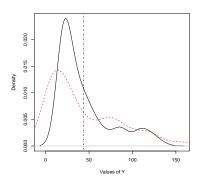


Fitted Values

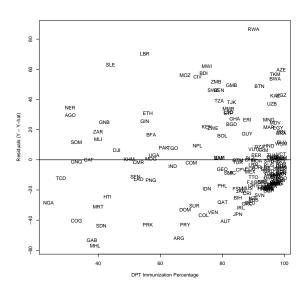
- > # Fitted Values:
- > Data\$IMDPThat<-fitted.values(IMDPT)
- > describe(Data\$IMDPThat)

var n mean sd median mad min max range skew kurtosis se 1 1 177 44.26 30.84 31.41 18.7 17.22 135.4 118.2 1.3 0.59 2.32

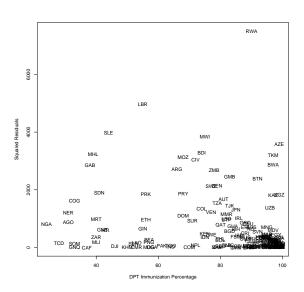
Density Plot: Actual (Y) and Fitted Values (\hat{Y})



Regression Residuals (\hat{u}) vs. DPT Percentage



Squared Residuals vs. DPT Percentage



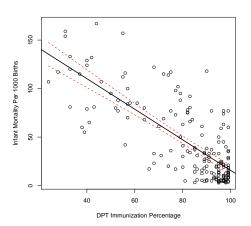
Inference

```
Var(\hat{\beta}):
> vcov(IMDPT)
            (Intercept) DPTpct
(Intercept) 72.0677 -0.83317
DPTpct
            -0.8332 0.01018
95 percent c.i.s:
> confint(IMDPT)
              2.5 % 97.5 %
(Intercept) 156.523 190.032
DPTpct -1.775 -1.377
```

Predictions

A Plot, With Cls

Scatterplot of Infant Mortality and DPT Immunizations, along with Least-Squares Line and 95% Prediction Confidence Intervals



Multivariate Example: Africa Data

- > library(RCurl)
- > temp<-getURL("https://raw.githubusercontent.com/PrisonRodeo/GSERM-2017-git/master/Data/africa2001.csv")
- > Data<-read.csv(text=temp, header=TRUE)
- > Data<-with(Data, data.frame(adrate,polity,
- + subsaharan=as.numeric(subsaharan),muslperc,literacy))

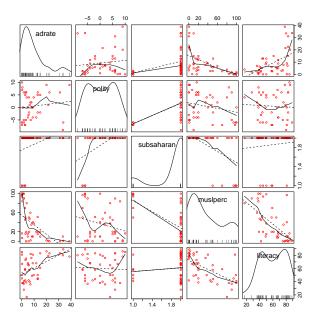
> summary(Data)

, building (baca)				
adrate	polity	subsaharan	muslperc	literacy
Min. : 0.100	Min. :-9.0000	Min. :1.00	Min. : 0.00	Min. :17.00
1st Qu.: 2.700	1st Qu.:-4.5000	1st Qu.:2.00	1st Qu.: 10.00	1st Qu.:43.00
Median : 6.000	Median : 0.0000	Median :2.00	Median : 20.00	Median :61.00
Mean : 9.365	Mean : 0.5116	Mean :1.86	Mean : 35.96	Mean :60.07
3rd Qu.:12.900	3rd Qu.: 5.5000	3rd Qu.:2.00	3rd Qu.: 55.50	3rd Qu.:78.50
Max. :38.800	Max. :10.0000	Max. :2.00	Max. :100.00	Max. :89.00

> cor(Data)

	adrate	polity	subsaharan	muslperc	literacy
adrate	1.0000000	0.11794182	0.33129420	-0.5709233	0.51489444
polity	0.1179418	1.00000000	0.52819844	-0.2391715	-0.05079354
subsaharan	0.3312942	0.52819844	1.00000000	-0.5772513	0.09472968
muslperc	-0.5709233	-0.23917151	-0.57725134	1.0000000	-0.61960385
literacv	0.5148944	-0.05079354	0.09472968	-0.6196039	1.00000000

Africa Data



A Regression

```
> model<-lm(adrate~polity+subsaharan+muslperc+literacy,data=Data)
> summary(model)
Call:
lm(formula = adrate ~ polity + subsaharan + muslperc + literacy,
   data = Data)
Residuals:
             10 Median
    Min
                               30
                                      Max
-15.4681 -4.3947 -0.5251 3.4246 22.9358
Coefficients:
           Estimate Std. Error t value Pr(>|t|)
(Intercept) -4.39843 14.94744 -0.294 0.7702
polity
         -0.01390 0.27969 -0.050 0.9606
subsaharan 3.72969 5.43093 0.687 0.4964
muslperc -0.08689 0.06282 -1.383 0.1747
literacy 0.16575 0.09433 1.757 0.0869 .
---
Signif. codes: 0 *** 0.001 ** 0.01 * 0.05 . 0.1 1
Residual standard error: 8.264 on 38 degrees of freedom
Multiple R-squared: 0.3771, Adjusted R-squared: 0.3115
F-statistic: 5.751 on 4 and 38 DF, p-value: 0.001013
```

Variance-Covariance Matrix of $\hat{oldsymbol{eta}}$

- > options(digits=4)
- > vcov(model)

	(Intercept)	polity	subsaharan	muslperc	literacy
(Intercept)	223.4259	1.088030	-72.2628	-0.771309	-1.002421
polity	1.0880	0.078229	-0.6642	-0.000293	0.001968
subsaharan	-72.2628	-0.664212	29.4950	0.206067	0.171765
muslperc	-0.7713	-0.000293	0.2061	0.003946	0.004098
literacy	-1.0024	0.001968	0.1718	0.004098	0.008898

Inference: Tests...

```
Test H_0: \beta_{\mathrm{polity}} = \beta_{\mathrm{subsaharan}} = 0:

> library(lmtest)
> modelsmall<-lm(adrate~muslperc+literacy,data=Data)
> waldtest(model,modelsmall)

Wald test

Model 1: adrate ~ polity + subsaharan + muslperc + literacy
Model 2: adrate ~ muslperc + literacy
Res. Df Df F Pr(>F)

1 38
2 40 -2 0.27 0.76
```

More tests...

```
Test H_0: \beta_{\text{muslperc}} = 0.1:
> library(car)
> linearHypothesis(model, "muslperc=0.1")
Linear hypothesis test
Hypothesis:
muslperc = 0.1
Model 1: restricted model
Model 2: adrate ~ polity + subsaharan + muslperc + literacy
  Res.Df RSS Df Sum of Sq F Pr(>F)
      39 3200
  38 2595 1 605 8.85 0.0051 **
Signif. codes: 0 *** 0.001 ** 0.01 * 0.05 . 0.1 1
```

More tests...

```
Test H_0: \beta_{literacy} = \beta_{muslperc}:
> linearHypothesis(model,"literacy=muslperc")
Linear hypothesis test
Hypothesis:
- muslperc + literacy = 0
Model 1: restricted model
Model 2: adrate ~ polity + subsaharan + muslperc + literacy
  Res.Df RSS Df Sum of Sq F Pr(>F)
     39 3534
2 38 2595 1 938 13.7 0.00067 ***
Signif. codes: 0 *** 0.001 ** 0.01 * 0.05 . 0.1 1
```