

PLSC 503 – Spring 2024

Introduction + Bivariate Regression Review

January 8, 2024

“Multivariate Analysis for Political Research”

- “Regression” course
- Texts: Weisberg (2014) / Gelman-Hill-Vehtari (2020)
- Class materials: <https://github.com/PrisonRodeo/PLSC503-2024-git>
- Preceptor: [Nathan Morse](#)
- Software: $R > \text{Stata} > \text{others}$
- Grading: Ten homework assignments (@ 50 points), plus a final project (500 points)

Things We Will And Won't Do

Will: "Regression":

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

Won't: Multivariate regression:

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

Won't: Measurement (e.g. PCA, factor analysis, etc.):

$$\mathbf{Y} = \mathbf{W}^T \mathbf{X}$$

Won't: Classification:

- Cluster Analysis
- Classification and Regression Trees \rightarrow Random Forests, etc.
- Pattern Recognition
- Machine Learning, Support Vector Machines, etc.

“Regression,” conceptually:

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

Two important things:

- The distribution of Y is *conditional on all variables in \mathbf{X}* , and
- The conditional distribution of Y is conditional on the *joint distribution* of the elements of \mathbf{X} .

→ Regression is hard...

Why 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 / "reduce" data	Discuss marginal associations between predictors and an outcome of interest	Optimize out-of-sample predictive power / minimize prediction error

$$Y_i = \mu + u_i \quad (1)$$

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

so:

$$Y_i = \beta_0 + \beta_1 X_i + u_i \quad (2)$$

Goals:

- Estimate $\hat{\beta}_0$ and $\hat{\beta}_1$
- Estimate the *variability* $\hat{\beta}_0$ and $\hat{\beta}_1$
- Assess *model fit*

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

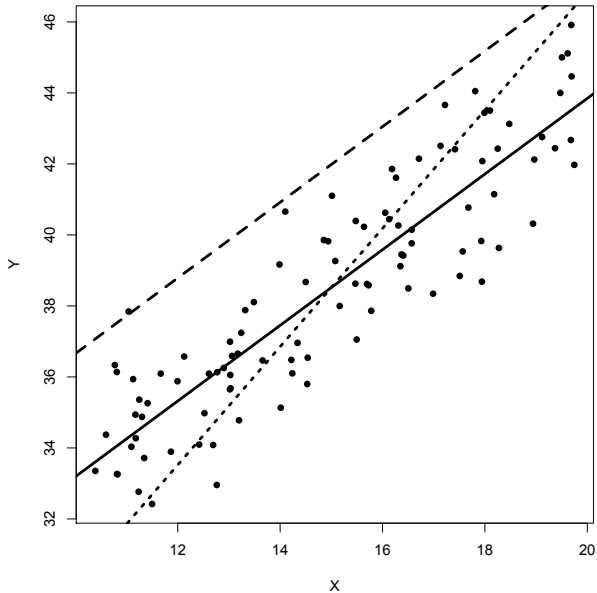
$$\hat{Y}_i = \hat{\beta}_0 + \hat{\beta}_1 X_i \quad (3)$$

and

$$\begin{aligned} \hat{u}_i &= Y_i - \hat{Y}_i \\ &= Y_i - \hat{\beta}_0 - \hat{\beta}_1 X_i \end{aligned} \quad (4)$$

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

$$\begin{aligned}\hat{S} &= \sum_{i=1}^N (Y_i - \hat{Y}_i)^2 \\ &= \sum_{i=1}^N (Y_i - \hat{\beta}_0 - \hat{\beta}_1 X_i)^2 \\ &= \sum_{i=1}^N (Y_i^2 - 2Y_i\hat{\beta}_0 - 2Y_i\hat{\beta}_1 X_i + \hat{\beta}_0^2 + 2\hat{\beta}_0\hat{\beta}_1 X_i + \hat{\beta}_1^2 X_i^2)\end{aligned}$$

Differentiate:

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

and

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

Yields:

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

and

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

Solving yields:

$$\begin{aligned}\hat{\beta}_1 &= \frac{\sum_{i=1}^N (X_i - \bar{X})(Y_i - \bar{Y})}{\sum_{i=1}^N (X_i - \bar{X})^2} \\ &= \frac{\text{Covariance of } X \text{ and } Y}{\text{Variance of } X}\end{aligned}\tag{5}$$

and

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

$$\begin{aligned}\text{Var}(Y) &= \text{Var}(\hat{Y} + \hat{u}) \\ &= \text{Var}(\hat{Y}) + \text{Var}(\hat{u}) + 2 \text{Cov}(\hat{Y}, \hat{u}) \\ &= \underset{\text{"Systematic"}}{\text{Var}(\hat{Y})} + \underset{\text{"Stochastic"}}{\text{Var}(\hat{u})}\end{aligned}$$

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

Running Example: Infant Mortality

```
> url <- getURL("https://raw.githubusercontent.com/PrisonRodeo/
  PLSC503-2024-git/master/Data/CountryData2000.csv")
> Data <- read.csv(text = url) # read the "countries" data
> rm(url)
>
> # Summary statistics
>
> # install.packages("psych") <- Install psych package, if necessary
> library(psych)

> with(Data, describe(infantmortalityperK))
  vars    n mean    sd median trimmed  mad min max range skew kurtosis   se
1     1 179 43.83 40.39     29   38.38 34.26 2.9 167 164.1    1    0.06 3.02

> with(Data, describe(DPTpct))
  vars    n mean    sd median trimmed  mad min max range skew kurtosis   se
1     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)
> summary.lm(IMDPT)
```

Call:

```
lm(formula = infantmortalityperK ~ DPTpct, data = Data)
```

Residuals:

	Min	1Q	Median	3Q	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 ***

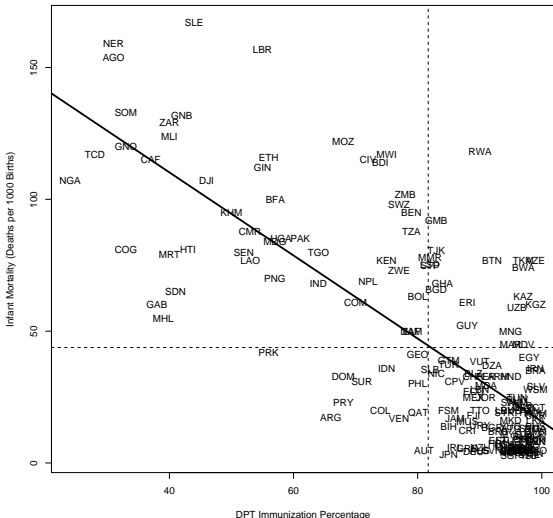
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

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

Scatterplot: Infant Mortality and DPT Immunization Rates



Analysis of Variance

```
> anova(IMDPT)
```

Analysis of Variance Table

Response: infantmortalityperK

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
DPTpct	1	167423	167423	244.09	< 2.2e-16 ***
Residuals	175	120033	686		

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

Moving Parts

$$\begin{aligned}TSS &= \text{total variability in } Y \text{ around its mean} \\&= \sum (Y_i - \bar{Y})^2 \\&= 167423 + 120033 \\&= \mathbf{287456}\end{aligned}$$

$$\begin{aligned}MSS(\equiv \text{DPTpct}) &= \text{model ("explained" or "regression") sum of squares} \\&= \sum (\hat{Y}_i - \bar{Y})^2 \\&= \mathbf{167423}\end{aligned}$$

$$\begin{aligned}RSS(\equiv \text{Residuals}) &= \text{residual ("unexplained" or "error") sum of squares} \\&= \sum \hat{u}_i^2 \\&= \mathbf{120033}\end{aligned}$$

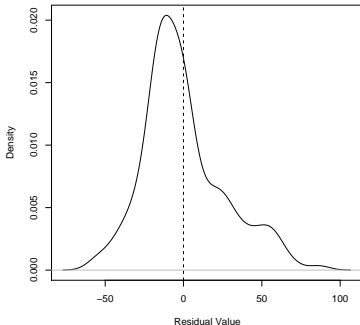
$$\begin{aligned}\hat{\sigma}^2 &= \frac{RSS}{N - k} \\&= \frac{\sum \hat{u}_i^2}{N - 2} \\&= \frac{120033}{175} \\&= \mathbf{686}\end{aligned}$$

$$\begin{aligned}\hat{\sigma} &= \text{"SEE" (the standard error of the estimate, or Residual standard error)} \\&= \sqrt{\hat{\sigma}^2} \\&= \sqrt{686} \\&= \mathbf{26.2}\end{aligned}$$

Fitted Values, Residuals, etc.

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

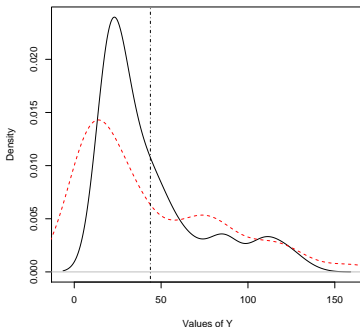
	var	n	mean	sd	median	mad	min	max	range	skew	kurtosis	se
1	1	177	0	26.12	-5.1	19.42	-56.8	86.59	143.4	0.75	0.44	1.96



```
> # Fitted Values:
> 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

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



Some Correlations

Corr(Y, X):

```
> with(Data, cor(infantmortalityperK,DPTpct,use="complete.obs"))  
[1] -0.7632
```

Corr(\hat{u}, Y):

```
> with(Data, cor(IMDPTres,infantmortalityperK,use="complete.obs"))  
[1] 0.6462
```

Corr(\hat{u}, X):

```
> with(Data, cor(IMDPTres,DPTpct,use="complete.obs"))  
[1] 9.573e-17
```

Corr(\hat{Y}, Y):

```
> with(Data, cor(IMDPThat,infantmortalityperK,use="complete.obs"))  
[1] 0.7632
```

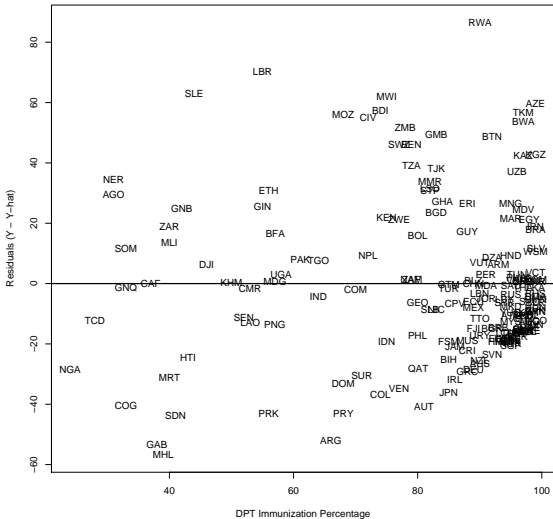
Corr(\hat{Y}, X):

```
> with(Data, cor(IMDPThat,DPTpct,use="complete.obs"))  
[1] -1
```

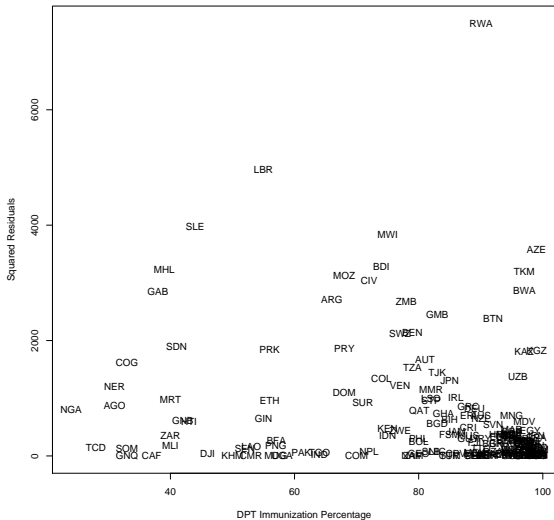
Corr(\hat{u}, \hat{Y}):

```
> with(Data, cor(IMDPTres,IMDPThat,use="complete.obs"))  
[1] 5.302e-17
```

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



Squared Residuals vs. DPT Percentage



Inference and Model Fit

The key point:

The estimators $\hat{\beta}_0$ and $\hat{\beta}_1$ are random variables.

Due to (*inter alia*):

- **Sampling variability:** Random samples from a population \rightarrow slightly different $\hat{\beta}_0$ s and $\hat{\beta}_1$ s.
- **Random variability in X :** In cases where X is also a random variable...
- **Intrinsic variability in Y :** Because $Y_i = \mu + u_i$.

$$\text{Var}(\hat{\beta}_1)$$

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

meaning:

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

so:

$$\begin{aligned} \text{Var}(\hat{\beta}_1) &= \text{Var} \left[\frac{\sum_{i=1}^N (X_i - \bar{X}) Y_i}{\sum_{i=1}^N (X_i - \bar{X})^2} \right] \\ &= \left[\frac{1}{\sum (X_i - \bar{X})^2} \right]^2 \sum (X_i - \bar{X})^2 \text{Var}(Y) \\ &= \left[\frac{1}{\sum (X_i - \bar{X})^2} \right]^2 \sum (X_i - \bar{X})^2 \sigma^2 \\ &= \frac{\sigma^2}{\sum (X_i - \bar{X})^2}. \end{aligned}$$

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

Similarly:

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

and :

$$\text{Cov}(\hat{\beta}_0, \hat{\beta}_1) = \frac{-\bar{X}}{\sum (X_i - \bar{X})^2} \sigma^2$$

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

For:

$$\hat{\beta}_1 = \frac{\sum (X_i - \bar{X})(Y_i - \bar{Y})}{\sum (X_i - \bar{X})^2}$$

Rewrite:

$$\hat{\beta}_1 = \frac{\sum_{i=1}^N (X_i - \bar{X}) Y_i}{\sum_{i=1}^N (X_i - \bar{X})^2} = \left[\frac{\sum_{i=1}^N (X_i - \bar{X})}{\sum_{i=1}^N (X_i - \bar{X})^2} \right] Y_i.$$

Define “weights” k :

$$\hat{\beta}_1 = \sum k_i Y_i$$

with $k_i = \frac{X_i - \bar{X}}{\sum (X_i - \bar{X})^2}.$

Alternative (non-LS) estimator:

$$\tilde{\beta}_1 = \sum w_i Y_i$$

Unbiasedness requires:

$$\begin{aligned} E(\tilde{\beta}_1) &= \sum w_i E(Y_i) \\ &= \sum w_i (\beta_0 + \beta_1 X_i) \\ &= \beta_0 \sum w_i + \beta_1 \sum w_i X_i \end{aligned}$$

Variance:

$$\begin{aligned}\text{Var}(\tilde{\beta}_1) &= \text{Var}\left(\sum w_i Y_i\right) \\&= \sigma^2 \sum w_i^2 \\&= \sigma^2 \sum \left[w_i - \frac{X_i - \bar{X}}{\sum (X_i - \bar{X})^2} + \frac{X_i - \bar{X}}{\sum (X_i - \bar{X})^2} \right]^2 \\&= \sigma^2 \sum \left[w_i - \frac{X_i - \bar{X}}{\sum (X_i - \bar{X})^2} \right]^2 + \sigma^2 \left[\frac{1}{\sum (X_i - \bar{X})^2} \right]\end{aligned}$$

Gauss-Markov (continued)

Because $\sigma^2 \left[\frac{1}{\sum (X_i - \bar{X})^2} \right]$ is a constant, $\min[\text{Var}(\tilde{\beta}_1)]$ minimizes

$$\sum \left[w_i - \frac{X_i - \bar{X}}{\sum (X_i - \bar{X})^2} \right]^2.$$

Minimized at:

$$w_i = \frac{X_i - \bar{X}}{\sum (X_i - \bar{X})^2}.$$

implying:

$$\begin{aligned} \text{Var}(\tilde{\beta}_1) &= \frac{\sigma^2}{\sum (X_i - \bar{X})^2} \\ &= \text{Var}(\hat{\beta}_1) \end{aligned}$$

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

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

and

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

Which means:

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

A Small Problem...

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

Solution: use

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

Yields:

$$\widehat{\text{Var}(\hat{\beta}_1)} = \frac{\hat{\sigma}^2}{\sum (X_i - \bar{X})^2},$$

and

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

$$\begin{aligned}
 \widehat{\text{s.e.}}(\hat{\beta}_1) &= \sqrt{\widehat{\text{Var}}(\hat{\beta}_1)} \\
 &= \sqrt{\frac{\hat{\sigma}^2}{\sum (X_i - \bar{X})^2}} \\
 &= \frac{\hat{\sigma}}{\sqrt{\sum (X_i - \bar{X})^2}}
 \end{aligned}$$

implies:

$$\begin{aligned}
 t_{\hat{\beta}_1} &\equiv \frac{(\hat{\beta}_1 - \beta_1)}{\widehat{\text{s.e.}}(\hat{\beta}_1)} = \frac{(\hat{\beta}_1 - \beta_1)}{\frac{\hat{\sigma}}{\sqrt{\sum (X_i - \bar{X})^2}}} \\
 &= \frac{(\hat{\beta}_1 - \beta_1) \sqrt{\sum (X_i - \bar{X})^2}}{\hat{\sigma}} \\
 &\sim t_{N-k}
 \end{aligned}$$

Predictions and Variance

Point prediction:

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

\hat{Y}_k is an unbiased estimate of Y_k :

$$\begin{aligned} E(\hat{Y}_k) &= E(\hat{\beta}_0 + \hat{\beta}_1 X_k) \\ &= E(\hat{\beta}_0) + X_k E(\hat{\beta}_1) \\ &= \beta_0 + \beta_1 X_k \\ &= E(Y_k) \end{aligned}$$

Variability:

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

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

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

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

Estimated standard error of the prediction:

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

→ (e.g.) confidence intervals:

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

Back to the Example

```
> summary(IMDPT)
```

Call:

```
lm(formula = infantmortalityperK ~ DPTpct, data = IMdata)
```

Residuals:

Min	1Q	Median	3Q	Max
-56.8	-16.3	-5.1	11.8	86.6

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	173.277	8.489	20.4	<2e-16 ***
DPTpct	-1.576	0.101	-15.6	<2e-16 ***

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

Residual standard error: 26.2 on 175 degrees of freedom

Multiple R-Squared: 0.582, Adjusted R-squared: 0.58

F-statistic: 244 on 1 and 175 DF, p-value: <2e-16

$\text{Var}(\hat{\beta})$:

```
> vcov(IMDPT)
```

	(Intercept)	DPTpct
(Intercept)	72.0677	-0.83317
DPTpct	-0.8332	0.01018

95 percent c.i.s:

```
> confint(IMDPT)
```

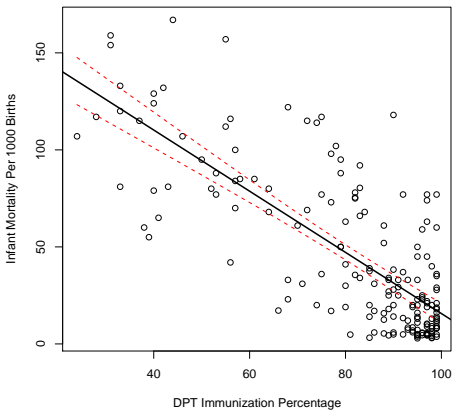
	2.5 %	97.5 %
(Intercept)	156.523	190.032
DPTpct	-1.775	-1.377


```
> SEs<-predict(IMDPT,interval="confidence")
> SEs
```

	fit	lwr	upr
1	25.10	20.53	29.68
3	17.22	12.05	22.40
4	23.53	18.84	28.21
.			
.			
<rows omitted>			
.			
.			
189	21.95	17.15	26.75
190	39.29	35.36	43.23
191	17.22	12.05	22.40

A Plot, With Confidence Intervals

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



General ideas:

- The closeness of the mapping between model-based values of Y and actual values of Y ...
- Can be *in-sample* or *out-of-sample* (\rightarrow “overfitting”)
- Is (in part) a function of *model specification* (choice of predictors, functional form, interactions, etc.)
- Related (but not identical) to prediction / predictive ability

$$\begin{aligned} R^2 &= \frac{\text{MSS}}{\text{TSS}} \\ &= \frac{\sum(\hat{Y}_i - \bar{Y})^2}{\sum(Y_i - \bar{Y})^2} \\ &= 1 - \frac{\text{RSS}}{\text{TSS}} \\ &= 1 - \frac{\sum \hat{u}_i^2}{\sum(Y_i - \bar{Y})^2} \end{aligned}$$

R-squared:

- is “the proportion of variance explained”
- $\in [0, 1]$
 - $R^2 = 1.0 \equiv$ a “perfect (linear) fit”
 - $R^2 = 0 \equiv$ no (linear) $X - Y$ association

For a single X ,

$$\begin{aligned} R^2 &= \hat{\beta}_1^2 \frac{\sum (X_i - \bar{X})^2}{\sum (Y_i - \bar{Y})^2} \\ &= r_{XY}^2 \end{aligned}$$

A (Simulated) Example

```
seed <- 7222009
set.seed(seed)
> X<-rnorm(250)
> Y1<-5+2*X+rnorm(250,mean=0,sd=sqrt(0.2))
> Y2<-5+2*X+rnorm(250,mean=0,sd=sqrt(20))
> fit<-lm(Y1~X)
> summary(fit)
```

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	4.97712	0.02846	174.86	<2e-16 ***
X	2.02529	0.02785	72.73	<2e-16 ***

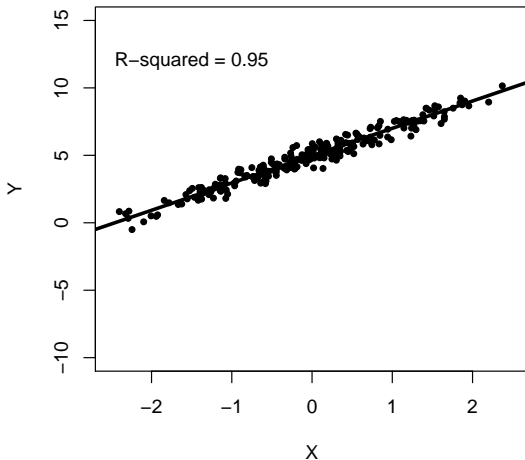
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.4491 on 248 degrees of freedom

Multiple R-squared: 0.9552, Adjusted R-squared: 0.955

F-statistic: 5290 on 1 and 248 DF, p-value: < 2.2e-16

Regression of $Y_i = 5 + 2X_i + u_i$ ($R^2 = 0.95$)



Same Slope/Intercept, Different R^2

```
> fit2<-lm(Y2~X)
> summary(fit2)
```

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	5.0048	0.2757	18.151	< 2e-16 ***
X	2.1402	0.2697	7.934	7.29e-14 ***

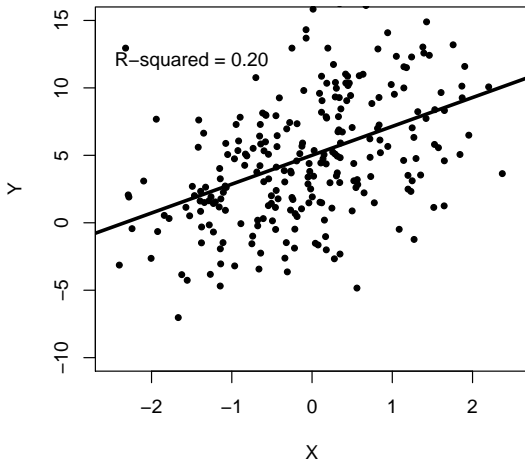
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 4.351 on 248 degrees of freedom

Multiple R-squared: 0.2024, Adjusted R-squared: 0.1992

F-statistic: 62.95 on 1 and 248 DF, p-value: 7.288e-14

Regression of $Y_i = 5 + 2X_i + u_i$ ($R^2 = 0.20$)



R^2 is Also an *Estimate*...

Luskin: Population analogue " P^2 ":

$$P^2 = 1 - \frac{\sigma^2}{\sigma_Y^2}$$

Then $\hat{P}^2 = R^2$ has variance:

$$\widehat{\text{Var}}(R^2) = \frac{4R^2(1 - R^2)^2(N - k)^2}{(N^2 - 1)(N + 3)}$$

and standard error:

$$\widehat{\text{s.e.}}(R^2) = \sqrt{\frac{4R^2(1 - R^2)^2(N - k)^2}{(N^2 - 1)(N + 3)}}.$$

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

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

$R_{adj.}^2$:

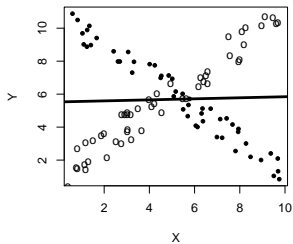
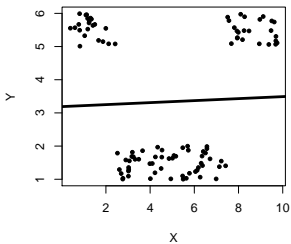
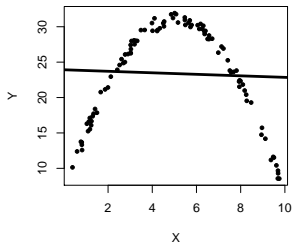
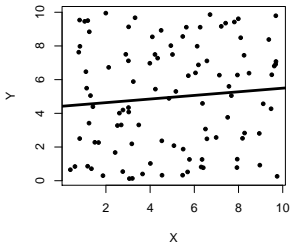
- $R_{adj.}^2 \rightarrow R^2$ as $N \rightarrow \infty$
- $R_{adj.}^2$ can be > 1 , or < 0 ...
- $R_{adj.}^2$ increases with model “fit,” but
- The extent of that increase is discounted by a factor proportional to the number of covariates.

- Standard Error of the Estimate:

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

- F -tests (later...)
- ROC / AUC
- Graphical methods

Caution: Different Ways to get $R^2 \approx 0$



The results:

```
> summary.lm(IMDPT)
```

Call:

```
lm(formula = infantmortalityperK ~ DPTpct, data = Data)
```

Residuals:

Min	1Q	Median	3Q	Max
-56.8	-16.3	-5.1	11.8	86.6

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	173.277	8.489	20.4	<2e-16 ***
DPTpct	-1.576	0.101	-15.6	<2e-16 ***

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

Residual standard error: 26.2 on 175 degrees of freedom

(14 observations deleted due to missingness)

Multiple R-squared: 0.582, Adjusted R-squared: 0.58

F-statistic: 244 on 1 and 175 DF, p-value: <2e-16

A Better Table (using default-y stargazer)

Table: OLS Regression Model of Infant Mortality Rates, 2000

	Model I
(Constant)	173.30*** (8.49)
DPT Immunization Rate	-1.58*** (0.10)
Observations	177
R ²	0.58
Adjusted R ²	0.58
Residual Std. Error	26.19 (df = 175)
F Statistic	244.10*** (df = 1; 175)

Note:

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Some Guidelines (“Rules”?)

Tables:

- *Use column headings descriptively.*
- *Use multiple rows / columns rather than multiple tables.*
- *Learn about significant digits, and don't report more than 4-5 of them.*
- *Use a figure to replace a table when you can.*
- *Be aware of norms about *s.*

Figures:

- *Report the scale of axes, and label them.*
- *Use as much “space” as you need, but no more.*
- *Use color sparingly.*