

# STAT 515 Lec 18 slides

## Simple linear regression

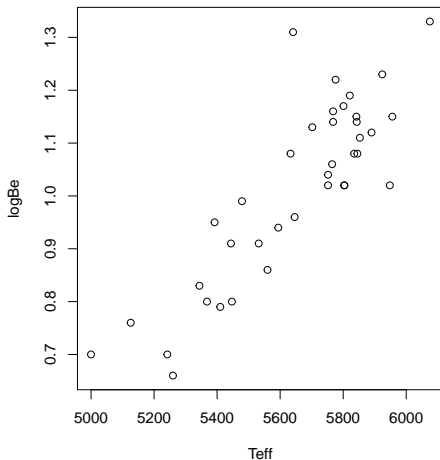
Karl Gregory

University of South Carolina

These slides are an instructional aid; their sole purpose is to display, during the lecture, definitions, plots, results, etc. which take too much time to write by hand on the blackboard. They are not intended to explain or expound on any material.

Study relationship between two variables with data  $(x_1, Y_1), \dots, (x_n, Y_n)$ .

**Example:** Log of beryllium abundance versus temperature of 38 stars (see [1]).



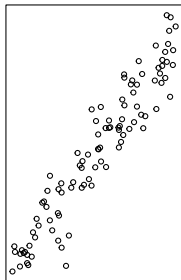
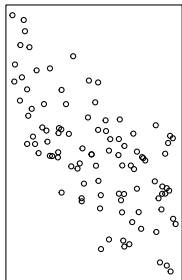
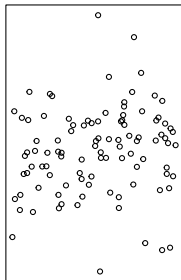
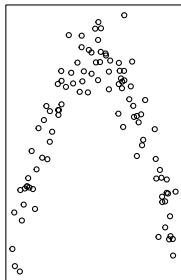
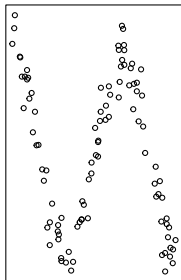
## Pearson's correlation coefficient

For data pairs  $(x_1, Y_1), \dots, (x_n, Y_n)$ , the Pearson correlation coefficient is

$$r_{xY} = \frac{\sum_{i=1}^n (x_i - \bar{x}_n)(Y_i - \bar{Y}_n)}{\sqrt{\sum_{i=1}^n (x_i - \bar{x}_n)^2 \sum_{i=1}^n (Y_i - \bar{Y}_n)^2}}.$$

- We have  $r_{xY} \in [-1, 1]$ .
- Values close to zero indicate weak linear relationship.
- Can use `cor()` function in R.



$r_{XY} = 0.95$  $r_{XY} = -0.67$  $r_{XY} = 0.13$  $r_{XY} = -0.01$  $r_{XY} = -0.20$ 

**Exercise:** Compute Pearson's correlation coefficient on the [beryllium data](#).

# Simple linear regression model

For data pairs  $(Y_1, x_1), \dots, (Y_n, x_n)$ , suppose

$$Y_i = \beta_0 + \beta_1 x_i + \varepsilon_i$$

for  $i = 1, \dots, n$ , where

- $x_1, \dots, x_n$  are fixed real numbers
- $Y_1, \dots, Y_n$  are independent random variables
- $\beta_0$  and  $\beta_1$  are unknown constants
- $\varepsilon_1, \dots, \varepsilon_n$  are iid errors with
  - ▶  $\mathbb{E}\varepsilon_i = 0$
  - ▶  $\text{Var}\varepsilon_i = \sigma^2$

for  $i = 1, \dots, n$ .

**Goal:** Estimate the unknown constants  $\beta_0$  and  $\beta_1$  and the error variance  $\sigma^2$ .

## Least-squares estimators of simple linear regression coefficients

Provided  $\sum_{i=1}^n (x_i - \bar{x}_n)^2 > 0$ , the function

$$Q_n(b_0, b_1) := \sum_{i=1}^n [Y_i - (b_0 + b_1 x_i)]^2$$

is (uniquely) minimized at

$$\hat{\beta}_0 = \bar{Y}_n - \hat{\beta}_1 \bar{x}_n$$

$$\hat{\beta}_1 = \frac{\sum_{i=1}^n (x_i - \bar{x}_n)(Y_i - \bar{Y}_n)}{\sum_{i=1}^n (x_i - \bar{x}_n)^2} = r_{xY} \cdot \frac{s_Y}{s_X}.$$

In above  $s_Y^2 = (n-1)^{-1} \sum_{i=1}^n (Y_i - \bar{Y}_n)^2$  and  $s_X^2 = (n-1)^{-1} \sum_{i=1}^n (x_i - \bar{x}_n)^2$ .

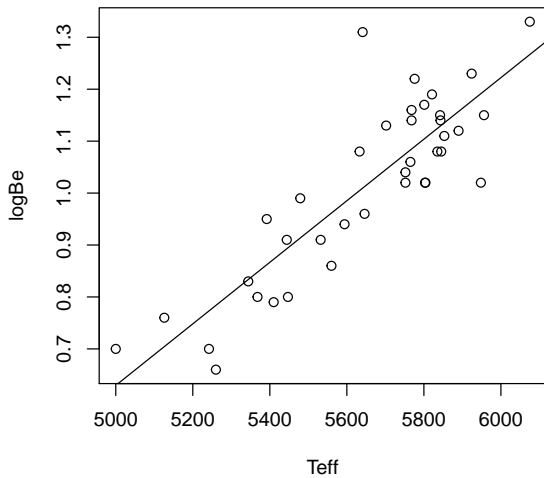
**Exercise:** Compute  $\hat{\beta}_0$  and  $\hat{\beta}_1$  for the beryllium data and plot the LS line.

```
# load the data
load(url("https://people.stat.sc.edu/gregorkb/data/beryllium.Rdata"))

# pull x and Y from the beryllium data frame
x <- beryllium$Teff
Y <- beryllium$logN_Be

# compute the least-squares regression coefficients
x_bar <- mean(x)
b1 <- cor(x,Y) * sd(Y) / sd(x)
b0 <- mean(Y) - b1*x_bar

# make a scatterplot with the least-squares line overlaid
plot(Y ~ x , xlab="Teff", ylab = "logBe")
abline(b0,b1)
```



- The *fitted values* are

$$\hat{Y}_i = \hat{\beta}_0 + \hat{\beta}_1 x_i \quad \text{for } i = 1, \dots, n.$$

- The *residuals* are

$$\hat{\varepsilon}_i = Y_i - \hat{Y}_i \quad \text{for } i = 1, \dots, n.$$

Our estimator of  $\sigma^2$  will be  $\hat{\sigma}^2 = \frac{1}{n-2} \sum_{i=1}^n \hat{\varepsilon}_i^2$ .

**Draw pictures:** Illustrate what the residuals and fitted values are.

Sampling distribution of  $\hat{\beta}_1$ 

Provided  $\varepsilon_1, \dots, \varepsilon_n \stackrel{\text{ind}}{\sim} \text{Normal}(0, \sigma^2)$ , we have

$$\hat{\beta}_1 \sim \text{Normal}(\beta_1, \sigma^2/S_{xx}) \quad \text{and} \quad (n-2)\hat{\sigma}^2/\sigma^2 \sim \chi_{n-2}^2$$

from which follows

$$\frac{\hat{\beta}_1 - \beta_1}{\hat{\sigma}/\sqrt{S_{xx}}} \sim t_{n-2}.$$

In the above  $S_{xx} = \sum_{i=1}^n (x_i - \bar{x}_n)^2$ .

A  $(1 - \alpha)100\%$  CI for  $\beta_1$  is given by

$$\hat{\beta}_1 \pm t_{n-2, \alpha/2} \hat{\sigma} / \sqrt{S_{xx}}.$$

**Exercise:** Build a 95% CI for  $\beta_1$  for the beryllium data.

```
n <- length(Y)
Sxx <- sum((x - x_bar)^2)
sigma_hat <- sqrt( sum(e_hat^2)/(n-2))

lo <- b1 - qt(.975,n-2) * sigma_hat / sqrt(Sxx)
up <- b1 + qt(.975,n-2) * sigma_hat / sqrt(Sxx)

# easy way:
confint(lm(Y ~ x))
```

Let  $Y_i = \beta_0 + \beta_1 x_i + \varepsilon_i$  for  $i = 1, \dots, n$ , where  $\varepsilon_1, \dots, \varepsilon_n \stackrel{\text{ind}}{\sim} \text{Normal}(0, \sigma^2)$ .

## Tests about $\beta_1$

Define the test statistic

$$T_{\text{test}} = \frac{\hat{\beta}_1}{\hat{\sigma} / \sqrt{S_{xx}}}.$$

Then the following tests have  $P(\text{Type I error}) \leq \alpha$ .

$$H_0: \beta_1 \geq 0$$

$$H_1: \beta_1 < 0$$

Reject  $H_0$  if

$$T_{\text{test}} < -t_{n-2, \alpha}$$

$$p\text{-val} = P(T < T_{\text{test}})$$

$$H_0: \beta_1 = 0$$

$$H_1: \beta_1 \neq 0$$

Reject  $H_0$  if

$$|T_{\text{test}}| > t_{n-2, \alpha/2}$$

$$p\text{-val} = 2 \cdot P(T > |T_{\text{test}}|)$$

$$H_0: \beta_1 \leq 0$$

$$H_1: \beta_1 > 0$$

Reject  $H_0$  if

$$T_{\text{test}} > t_{n-2, \alpha}$$

$$p\text{-val} = P(T > T_{\text{test}})$$

**Discuss:** Draw pictures of how to get the  $p$ -values.

**Exercise:** Get the  $p$ -value for testing  $H_0: \beta_1 = 0$  for the beryllium data.

**Exercise:** Use the `lm()`, `summary()`, the `confint()` functions in R to obtain

- 1 the least-squares estimators
- 2 the  $p$ -value for testing  $H_0: \beta_1 = 0$  vs  $H_1: \beta_1 \neq 0$
- 3 confidence intervals for  $\beta_0$  and  $\beta_1$

for the beryllium data.

```
lm_out <- lm(Y ~ x) # lm() is for "linear model"  
summary(lm_out)
```

Call:

```
lm(formula = Y ~ x)
```

Residuals:

Min	1Q	Median	3Q	Max
-0.1715	-0.0520	-0.0241	0.0651	0.3005

Coefficients:

	Estimate	Std. Error	t value	Pr(> t )	
(Intercept)	-2.333325	0.327886	-7.12	2.3e-08	***
x	0.000593	0.000058	10.22	3.5e-12	***

---

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

Residual standard error: 0.0882 on 36 degrees of freedom

Multiple R-squared: 0.744, Adjusted R-squared: 0.736

F-statistic: 104 on 1 and 36 DF, p-value: 3.48e-12

```
confint(lm_out,level=0.95)
```

```
                2.5 %   97.5 %  
(Intercept) -2.998309 -1.66834  
x              0.000475  0.00071
```

Consider the assumptions of the model

$$Y_i = \beta_0 + \beta_1 x_i + \varepsilon_i, \quad i = 1, \dots, n.$$

where  $\varepsilon_1, \dots, \varepsilon_n \stackrel{\text{ind}}{\sim} \text{Normal}(0, \sigma^2)$ .

(A.1) The responses are Normally distributed around the regression line.

To check: Look at a QQ plot of the residuals.

(A.2) The responses have the same variance for all values of the covariate.

To check: Look at the residuals versus fitted values plot.

(A.3) The covariate and the response are linearly related.

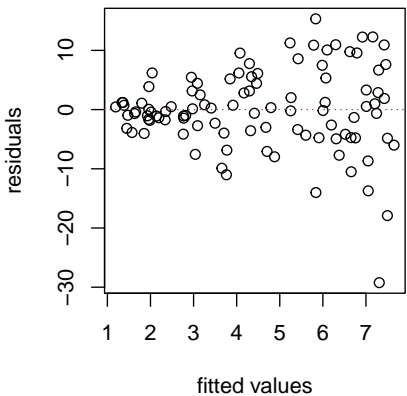
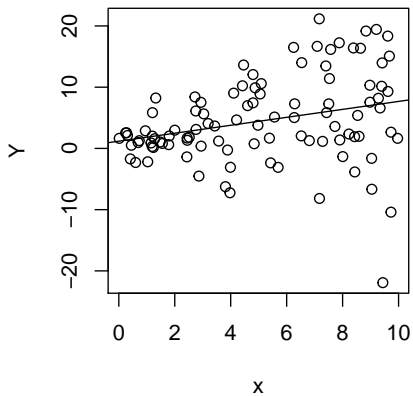
To check: Look at the residuals versus fitted values plot.

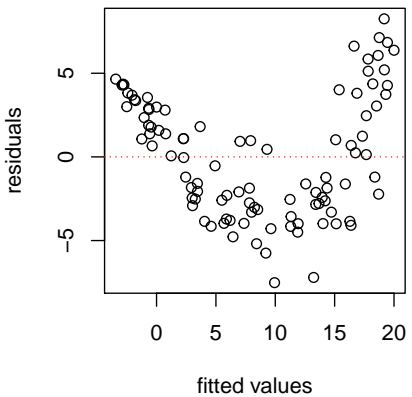
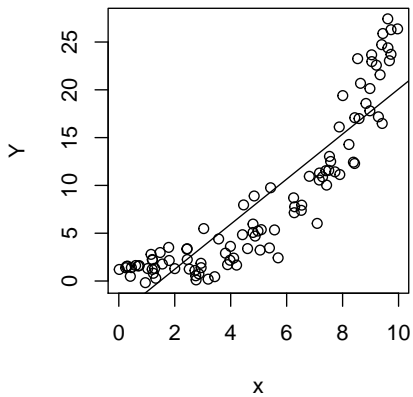
(A.4) The responses are independent from each other.

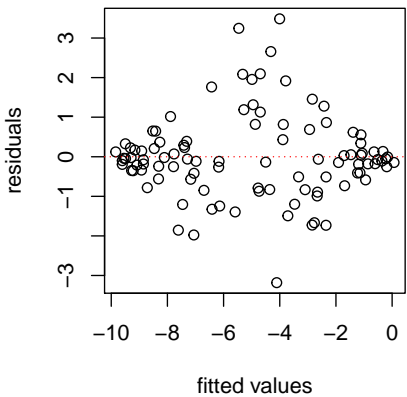
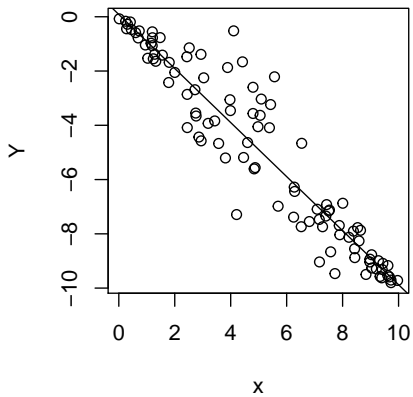
Cannot check: Trust the experimental design/beyond scope of course.

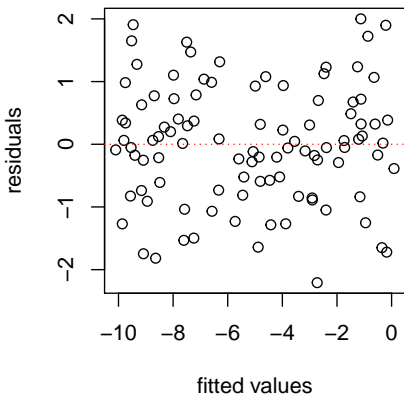
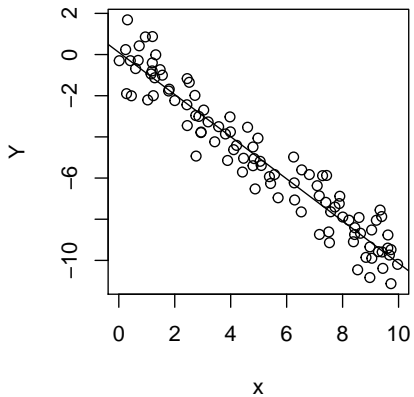
Use `plot()` on the output of `lm()`.

**Exercise:** Check the diagnostic plots for the beryllium data.









## Coefficient of determination

The *coefficient of determination* for a linear regression model is defined as

$$R^2 = \frac{SS_{\text{Regression}}}{SS_{\text{Total}}}$$

In the above

$$SS_{\text{Regression}} = \sum_{i=1}^n (\hat{Y}_i - \bar{Y}_n)^2 \quad \text{and} \quad SS_{\text{Total}} = \sum_{i=1}^n (Y_i - \bar{Y}_n)^2.$$

- $R^2 \in [0, 1]$ .
- $R^2$  is the proportion of variability in the response “explained” by the covariate.

Predicting the value of  $Y_{\text{new}}$  of the pair  $(Y_{\text{new}}, X_{\text{new}})$ .

- A  $(1 - \alpha)100\%$  confidence interval for  $\beta_0 + \beta_1 x_{\text{new}}$  is given by

$$\hat{\beta}_0 + \hat{\beta}_1 x_{\text{new}} \pm t_{n-1, \alpha/2} \hat{\sigma} \sqrt{\frac{1}{n} + \frac{(x_{\text{new}} - \bar{x}_n)^2}{S_{xx}}}.$$

- A  $(1 - \alpha)100\%$  *prediction interval* for  $Y_{\text{new}}$  at  $x_{\text{new}}$  is given by

$$\hat{\beta}_0 + \hat{\beta}_1 x_{\text{new}} \pm t_{n-1, \alpha/2} \hat{\sigma} \sqrt{1 + \frac{1}{n} + \frac{(x_{\text{new}} - \bar{x}_n)^2}{S_{xx}}}.$$

**Exercise:** Use `predict()` function on the `lm()` output to build a

- 1 CI for the mean `logBE` of stars with `Teff` equal to 5700.
- 2 PI for the `logBE` of a star with `Teff` equal to 5700.

```
# built-in way to obtain confidence or prediction intervals
lm.out <- lm(Y~x)
predict(lm.out, newdata = data.frame(x = 5700), interval = "confidence")
predict(lm.out, newdata = data.frame(x = 5700), interval = "prediction")
```

```

plot(Y ~ x , xlab="Teff",ylab = "logBe")
abline(beta0.hat,beta1.hat)

alpha <- .05
tval <- qt(1-alpha/2,n-2)

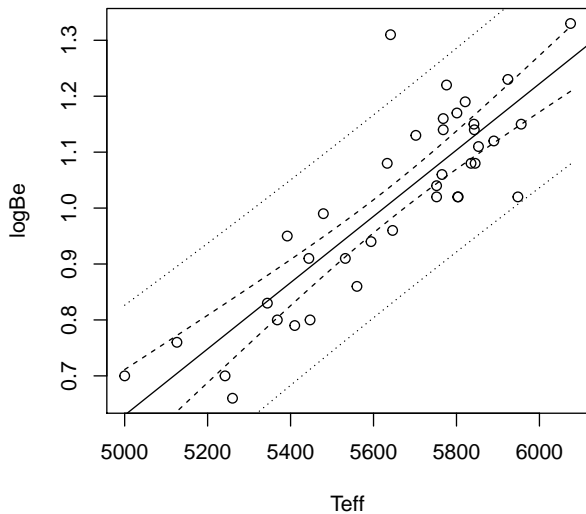
x.seq <- seq(min(x),max(x),length=99)
se.Y.hat.new <- sigma.hat * sqrt( 1/n + (x.seq - x.bar)^2/Sxx)
loconf <- beta0.hat+beta1.hat*x.seq - tval * se.Y.hat.new
upconf <- beta0.hat+beta1.hat*x.seq + tval * se.Y.hat.new

lines(loconf~x.seq,lty=2)
lines(upconf~x.seq,lty=2)

sd.e.hat.new <- sigma.hat *sqrt(1 + 1/n + (x.seq - x.bar)^2/Sxx)
lopred <- beta0.hat + beta1.hat * x.seq - tval * sd.e.hat.new
uppred <- beta0.hat + beta1.hat * x.seq + tval * sd.e.hat.new

lines(lopred~x.seq,lty=3)
lines(uppred~x.seq,lty=3)

```



Consider the effects of outliers on the estimated regression function.

Points can be outlying in  $x$  or  $Y$  direction.

## Leverage

The *leverage* of a point  $(Y_i, x_i)$  among  $(Y_1, x_1), \dots, (Y_n, x_n)$  is

$$\text{lev}_i = \frac{1}{n} + \frac{(x_i - \bar{x}_n)^2}{S_{xx}}$$

Points with high leverage have a large influence on the fitted regression line.

Consider fact: Least-squares line passes through the point  $(\bar{x}_n, \bar{Y}_n)$ .

**Draw pictures.**

*Extrapolation* is making predictions beyond the range of the observed data.

Specifically, if  $x_{\text{new}}$  is outside the range of observed  $x_1, \dots, x_n$ , it is extrapolation to build a CI for the expected value of  $Y_{\text{new}}$  or a PI for the realized value of  $Y_{\text{new}}$ .

A linear relationship may not continue beyond the range of observed  $x_1, \dots, x_n$ .



Nuno C Santos, G Israelian, RJ García López, M Mayor, R Rebolo, S Randich, A Ecuivillon, and C Domínguez Cerdeña.

Are beryllium abundances anomalous in stars with giant planets?

*Astronomy & Astrophysics*, 427(3):1085–1096, 2004.