# STAT 401A - Statistical Methods for Research Workers Simple linear regression

Jarad Niemi (Dr. J)

Iowa State University

last updated: October 11, 2014

## Simple Linear Regression

Recall the One-way ANOVA model:

$$Y_{ij} \stackrel{ind}{\sim} N(\mu_i, \sigma^2)$$

where  $Y_{ij}$  is the observation for individual j in group i.

The simple linear regression model is

$$Y_i \stackrel{ind}{\sim} N(\beta_0 + \beta_1 X_i, \sigma^2)$$

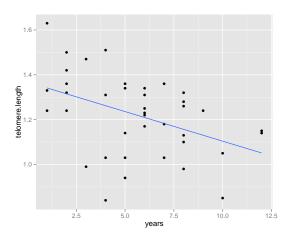
where  $Y_i$  and  $X_i$  are the response and explanatory variable, respectively, for individual i.

Terminology (all of these are equivalent):

response	
outcome	
dependent	
endogenous	

explanatory covariate independent exogenous

```
Warning: package 'abd' was built under R version 3.1.1
Warning: package 'mosaic' was built under R version 3.1.1
Warning: package 'car' was built under R version 3.1.1
```



## Interpretation

$$E[Y_i|X_i=x] = \beta_0 + \beta_1 x \qquad V[Y_i|X_i=x] = \sigma^2$$

- If  $X_i = 0$ , then  $E[Y_i|X_i = 0] = \beta_0$ .  $\beta_0$  is the expected response when the explanatory variable is zero.
- If  $X_i$  increases from x to x + 1, then

$$E[Y_i|X_i = x + 1] = \beta_0 + \beta_1 x + \beta_1$$

$$-E[Y_i|X_i = x] = \beta_0 + \beta_1 x$$

$$= \beta_1$$

 $\beta_1$  is the expected increase in the response for each unit increase in the explanatory variable.

 $\bullet$   $\sigma$  is the standard deviation of the response for a fixed value of the explanatory variable.

Remove the mean:

$$Y_i = \beta_0 + \beta_1 X_i + e_i$$
  $e_i \stackrel{iid}{\sim} N(0, \sigma^2)$ 

So

$$e_i = Y_i - (\beta_0 + \beta_1 X_i)$$

which we approximate by the residual

$$r_i = \hat{\mathbf{e}}_i = Y_i - (\hat{\beta}_0 + \hat{\beta}_1 X_i)$$

The least squares, maximum likelihood, and Bayesian estimators are

$$\hat{\beta}_{1} = \frac{SXY}{SXX}$$

$$\hat{\beta}_{0} = \overline{Y} - \hat{\beta}_{1}\overline{X}$$

$$\hat{\sigma}^{2} = \frac{SSE}{(n-2)} \quad \text{d.f.} = n-2$$

$$SXY = \sum_{i=1}^{n} (X_{i} - \overline{X})(Y_{i} - \overline{Y})$$

$$SXX = \sum_{i=1}^{n} (X_{i} - \overline{X})(X_{i} - \overline{X}) = \sum_{i=1}^{n} (X_{i} - \overline{X})^{2}$$

$$SSE = \sum_{i=1}^{n} r_{i}^{2}$$

$$\overline{X} = \frac{1}{n} \sum_{i=1}^{n} X_{i}$$

$$\overline{Y} = \frac{1}{n} \sum_{i=1}^{n} X_{i}$$

$$\overline{Y} = \frac{1}{n} \sum_{i=1}^{n} X_{i}$$

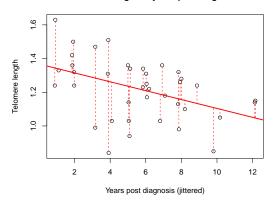
How certain are we about  $\hat{\beta}_0$  and  $\hat{\beta}_1$  being equal to  $\beta_0$  and  $\beta_1$ ?

We quantify this uncertainty using their standard errors:

$$\begin{split} SE(\beta_0) &= \hat{\sigma} \sqrt{\frac{1}{n} + \frac{\overline{X}^2}{(n-1)s_X^2}} & d.f. = n-2 \\ SE(\beta_1) &= \hat{\sigma} \sqrt{\frac{1}{(n-1)s_X^2}} & d.f. = n-2 \\ s_X^2 &= \frac{SXX}{(n-1)} \\ s_Y^2 &= \frac{SYY}{(n-1)} \\ SYY &= \sum_{i=1}^n (Y_i - \overline{Y})^2 \\ r_{XY} &= \frac{\frac{SXY}{(n-1)}}{s_X s_Y} & \text{correlation coefficient} \\ R^2 &= r_{XY}^2 &= \frac{SYY}{(n-1)} \\ SST &= SYY = \sum_{i=1}^n (Y_i - \overline{Y})^2 \end{split}$$

The coefficient of determination is the percentage of the total response variation explained by the explanatory variable(s).

### Telomere length vs years post diagnosis



## Pvalues and confidence interval

We can compute two-sided pvalues via

$$2P\left(t_{n-2} > \left| \frac{\hat{\beta_0}}{SE(\beta_0)} \right| \right) \qquad \text{and} \qquad 2P\left(t_{n-2} > \left| \frac{\hat{\beta_1}}{SE(\beta_1)} \right| \right)$$

These test the null hypothesis that the corresponding parameter is zero.

We can construct  $100(1-\alpha)\%$  confidence intervals via

$$\hat{eta}_0 \pm t_{n-2}(1-lpha/2)SE(eta_0)$$
 and  $\hat{eta}_1 \pm t_{n-2}(1-lpha/2)SE(eta_1)$ 

These provide ranges of the parameter consistent with the data.

```
DATA t:
```

INFILE 'telomeres.csv' DSD FIRSTOBS=2; INPUT years length;

PROC REG DATA=t;

MODEL length = years; RUN:

The REG Procedure Model: MODEL1 Dependent Variable: length

Number of Observations Read 39 Number of Observations Used 39

#### Analysis of Variance

			Sum of	Mean		
	Source	DF	Squares	Square	F Value	Pr > F
	Model	1	0.22777	0.22777	8.42	0.0062
	Error	37	1.00033	0.02704		
	Corrected Total	38	1.22810			
Root MSE		0.16443	R-Square	0.1855		
	Depen Coeff	dent Mean Var	1.22026 13.47473	Adj R-Sq	0.1634	

#### Parameter Estimates Standard

Variable	DF	Estimate	Error	t Value	Pr >  t	95% Confiden	ce Limits
Intercept	1	1.36768	0.05721	23.91	<.0001	1.25176	1.48360
years	1	-0.02637	0.00909	-2.90	0.0062	-0.04479	-0.00796

Daramotor

# Summary

• The simple linear regression model is

$$Y_i \stackrel{ind}{\sim} N(\beta_0 + \beta_1 X_i, \sigma^2)$$

where  $Y_i$  and  $X_i$  are the response and explanatory variable, respectively, for individual i.

- Know how to use SAS/R to obtain  $\hat{\beta}_0$ ,  $\hat{\beta}_1$ ,  $\hat{\sigma}^2$ ,  $R^2$ , pvalues, CIs, etc.
- Interpret SAS output
  - At a value of zero for the explanatory variable  $(X_i = 0)$ ,  $\beta_0$  is the expected value for the response  $(Y_i)$ .
  - For each unit increase in the explanatory variable value,  $\beta_1$  is the expected increase in the response.
  - At a constant value of the explanatory variable,  $\sigma^2$  is the variance of the responses.
  - The coefficient of determination  $(R^2)$  is the percentage of the total response variation explained by the explanatory variable(s).