

Statistics 354 (Fall 2018)  
Summary of Least Squares Estimation

Suppose that we observe data  $(x_i, y_i)$ ,  $i = 1, \dots, n$ , and postulate that a simple linear regression model

$$y = \beta_0 + \beta_1 x + \epsilon$$

is appropriate to describe the relationship between  $x$  and  $y$ . In particular, this assumes that

$$y_i = \beta_0 + \beta_1 x_i + \epsilon_i, \quad i = 1, \dots, n,$$

where  $\beta_0, \beta_1$  are parameters and  $\epsilon_1, \dots, \epsilon_n$  are independent with common mean  $\mathbb{E}(\epsilon_i) = 0$  and common variance  $\text{Var}(\epsilon_i) = \sigma^2$ .

**Note.** We call  $x_i$  the explanatory variable and  $y_i$  the response variable. We view the explanatory variable as deterministic (i.e., non-random), and we follow the standard statistical practice of viewing  $y_i$  as either a random variable or the realization of a random variable (i.e., observed data) depending on the context.

By minimizing

$$S(\beta_0, \beta_1) = \sum_{i=1}^n \epsilon_i^2 = \sum_{i=1}^n (y_i - \beta_0 - \beta_1 x_i)^2$$

with respect to  $\beta_0, \beta_1$ , we determine that the least squares estimators  $\hat{\beta}_0, \hat{\beta}_1$  of the parameters  $\beta_0, \beta_1$ , respectively, are given by

$$\hat{\beta}_1 = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sum (x_i - \bar{x})^2} = \frac{s_{xy}}{s_{xx}}$$

and

$$\hat{\beta}_0 = \bar{y} - \hat{\beta}_1 \bar{x}.$$

The simple linear regression line is

$$\hat{\mu} = \hat{\beta}_0 + \hat{\beta}_1 x.$$

If  $\hat{\mu}_i = \hat{\beta}_0 + \hat{\beta}_1 x_i$  denotes the  $i$ th fitted value, then the  $i$ th residual is given by

$$e_i = y_i - \hat{\mu}_i,$$

and we call

$$\sum_{i=1}^n e_i^2$$

the residual sum of squares. It can be shown that  $\mathbb{E}(\hat{\beta}_0) = \beta_0$  and  $\mathbb{E}(\hat{\beta}_1) = \beta_1$  implying that  $\hat{\beta}_0$  and  $\hat{\beta}_1$  are unbiased estimators of  $\beta_0, \beta_1$ , respectively, with variances

$$\text{Var}(\hat{\beta}_0) = \sigma^2 \left( \frac{1}{n} + \frac{\bar{x}^2}{s_{xx}} \right) \quad \text{and} \quad \text{Var}(\hat{\beta}_1) = \frac{\sigma^2}{s_{xx}}.$$