

# STA 674

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Regression Analysis And Design Of Experiments  
Fitting Simple Linear Regression Models – Lecture 3



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## Fitting Simple Linear Regression Models

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- Last time: introduced to LSE—least squares estimation.
- This time we will talk about where that estimation comes from and why it is useful.

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### Some Notation

- **Population parameters:** Population parameters are denoted with Greek letters— $\beta_0$  and  $\beta_1$  are the true intercept and slope—and are numbers that describe the population.
- **Parameter estimates:** Least squares estimates are denoted with Latin letters— $b_0$  and  $b_1$  are the least squares estimates of the intercept and slope—and are numbers calculated from the sample (statistics).



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### Some Notation

- **Fitted values:** Given estimates  $b_0$  and  $b_1$ , the fitted value for observation  $i$  is:

$$\hat{y}_i = b_0 + b_1 x_i$$

- **Residual:** the residual:

$$\hat{e}_i = y_i - \hat{y}_i$$

is an estimate of the error for observation  $i$ .

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### Least Squares Estimation – why?

BLUE - best linear unbiased estimate

- **Unique:** LS estimates,  $b_0$  and  $b_1$ , for a given set of data are unique.
- (Could be) **Computed by hand:**

$$b_1 = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^n (x_i - \bar{x})^2}$$
$$b_0 = \bar{y} - b_1 \bar{x}$$

- **Optimal:** provided we assume the distribution of the errors is normal

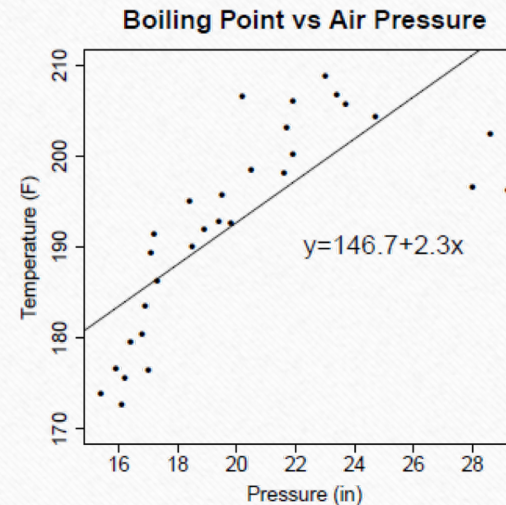
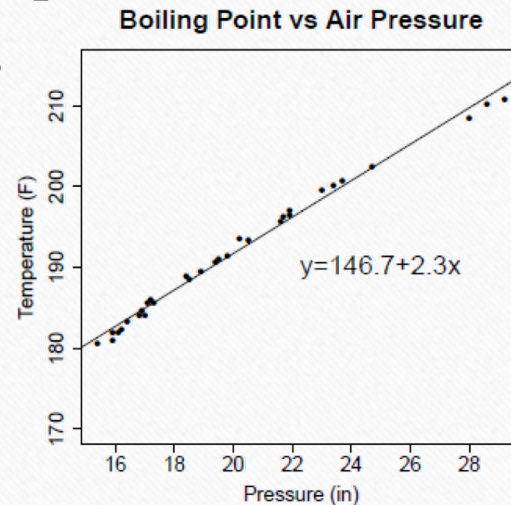


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### Least Squares Estimation – one more thing ...

- Look at the two plots—the estimates,  $b_0$  and  $b_1$ , for both are the same (146.7 and 2.3, respectively.)
- What's different?



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### Least squares estimation – the **error variance**

The full model of  $y_i$  is:

$$y_i = \hat{y}_i + e_i$$

$\hat{y}_i$ ...estimate of linear model

all variability is in  $e_i$

The (usually, but not here) implicit assumptions in linear regression are that:

1. the expected value of the  $e_1, e_2, \dots, e_n$  is 0.
2. the variance of the  $e_1, e_2, \dots, e_n$  is  $\sigma_e^2$
3.  $e_1, e_2, \dots, e_n$  are normally distributed
4.  $e_1, e_2, \dots, e_n$  are independent



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### Least squares estimation – the **error variance**

The least squares estimate (LSE) of  $\sigma_e^2$  is:

$$s_e^2 = \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{(n - 2)}$$

Interpret the slope, intercept of the LS line.

What would be your estimate of the boiling temperature at 22 inches of air pressure?

$s_e = \sqrt{s_e^2} \approx 0.8^\circ\text{F}$ . What would that tell you about your estimate?

