

# Math 244 Lecture Notes

## CHAPTER 25 DAY ONE: LINEAR REGRESSION DAY 2

**Overview:** Linear Regression is used for examining the relationship between two variables—an **explanatory variable**,  $x$ , and a **response variable**,  $y$ .

When done correctly, it allows us to make predictions about what should happen given a limited amount of information. Here's what we know so far.

- Our approximation for the line of best fit is  $\hat{y} = b_1(x) + b_0$  where  $b_1$  is our slope and  $b_0$  is our  $y$ -intercept.
- We calculate the slope using the formula  $b_1 = r \frac{s_y}{s_x}$ .
- We found the slope by plugging in the point  $(\bar{x}, \bar{y})$  and solving for  $b_0$ .
- $r$  and  $R^2$  were both calculated using technology. Recall that  $R^2$  is the percentage of variation accounted for by our model.
- Residuals are the error in our predictions. We find these by  $e = y - \hat{y} = \text{data value} - \text{line value}$ .

Much to our surprise, we found that under ideal situations the residuals followed a t-distribution

$$e \approx t_{k-2}(0, s_e)$$

where  $s_e^2 = \frac{\sum (e-0)^2}{k-2}$ .

Unfortunately, error is unavoidable. We are making two big predictions that cause this. We predict a value for the slope  $b_1$  when the actual slope is  $\beta_1$ . We predict a value for the starting value  $b_0$  when the actual starting value is  $\beta_0$ . As a result, we “lost” two degrees of freedom due to the unknown factors. This gave us  $df = k - 2$ . Both of these predictions are affected by our residual distribution, so both of these unknowns can be analyzed with the t-distribution. The assumptions for these tests include...

- The usual: Random, Independence.
- Linearity: The data should look linear when plotted. Of course.
- Equal Spread: Much like ANOVA. This means that the data stays clumped near the line.
- Normal Population for Errors: We want the errors to look normal. Everything else is based off this. We can either do a histogram of the errors to check for nearly normal OR do a normality plot.

Let's do one final experiment for the term! I want to know if the drop height of a ball in centimeters affects the bounce height of a ball.

Drop Height	Bounce Height
10	
15	
20	
25	
30	
35	
40	
45	
50	
55	
60	
65	
70	
75	
80	
85	

- (a) State the Explanatory and Response Variable.
- (b) Determine the line of best fit. Using technology is okay.
- (c) Calculate  $R^2$ . How good is the fit?
- (d) **Test for Linearity** Using technology, perform the test for linearity! Recall that this refers to  $\beta_1$ .
- (e) Assumption Check:
  - (a) The usual:
  - (b) Linearity:
  - (c) Equal Spread:
  - (d) Normal Population for Errors:

We will use a printout from CrunchIt <[http://crunchit2.bfwpub.com/crunchit2/ips5e/?section\\_id=>](http://crunchit2.bfwpub.com/crunchit2/ips5e/?section_id=>) for the last two components. Fill in the table first. You may be expected to read such tables for the final.

Estimates	t-Stat	P-Value	CI Low	CI High
(Intercept)				
Drop Height				

- (f) **Test for  $y$ -intercept,  $\beta_0$ .** Using the printout, perform a test for a  $y$ -intercept. State your hypotheses, degrees of freedom, model, P-value, and conclusion.

- (g) State the 95% CI for the slope,  $\beta_1$ .

- (h) State the 95% CI for the  $y$ -intercept.

- (i) Create the 95% CI for predicted bounce height if we drop the ball from 100 cm.