

Of course, the linear model makes no sense unless the **Linearity Assumption** is satisfied. We check the **Straight Enough Condition** and **Outlier Condition** with a scatterplot, as we did for correlation, and also with a plot of residuals against either the  $x$  or the predicted values. For the standard deviation of the residuals to make sense as a summary, we have to make the **Equal Variance Assumption**. We check it by looking at both the original scatterplot and the residual plot for the **Does the Plot Thicken? Condition**.

## TERMS

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|---|---|
| <b>Model</b>                                  | An equation or formula that simplifies and represents reality. (p. 173)   |
| <b>Linear model</b>                           | A linear model is an equation of a line. To interpret a linear model, we need to know the variables (along with their W's) and their units. (p. 173)  |
| <b>Predicted value</b>                        | The value of $\hat{y}$ found for a given $x$ -value in the data. A predicted value is found by substituting the $x$ -value in the regression equation. The predicted values are the values on the fitted line; the points $(x, \hat{y})$ all lie exactly on the fitted line. (p. 173) |
| <b>Residuals</b>                              | Residuals are the differences between data values and the corresponding values predicted by the regression model—or, more generally, values predicted by any model. (p. 173)<br>$\text{Residual} = \text{Observed value} - \text{predicted value} = e = y - \hat{y}$                  |
| <b>Least squares</b>                          | The least squares criterion specifies the unique line that minimizes the variance of the residuals or, equivalently, the sum of the squared residuals. (p. 174)   |
| <b>Regression to the mean</b>                 | Because the correlation is always less than 1.0 in magnitude, each predicted $\hat{y}$ tends to be fewer standard deviations from its mean than its corresponding $x$ was from its mean. This is called regression to the mean. (p. 175)  |
| <b>Regression line<br/>(Line of best fit)</b> | The particular linear equation<br>$\hat{y} = b_0 + b_1x$<br>that satisfies the least squares criterion is called the least squares regression line (LSRL). Casually, we often just call it the regression line, or the line of best fit. (p. 175)                                     |
| <b>Slope</b>                                  | The slope, $b_1$ , gives a value in "y-units per x-unit." Changes of one unit in $x$ are associated with changes of $b_1$ units in predicted values of $y$ . The slope can be found by<br>$b_1 = \frac{rs_y}{s_x}. \text{ (p. 176)}$  |
| <b>Intercept</b>                              | The intercept, $b_0$ , gives a starting value in y-units. It's the $\hat{y}$ -value when $x$ is 0. You can find it from $b_0 = \bar{y} - b_1\bar{x}$ . (p. 177)   |
| <b>Standard error (<math>S_e</math>)</b>      | The standard deviation of the residuals is found by $s_e = \sqrt{\frac{\sum e^2}{n-2}}$ . When the assumptions and conditions are met, the residuals can be well described by using this standard deviation and the 68–95–99.7 Rule. (p. 182)   |
| <b><math>R^2</math></b>                       | $R^2$ (the square of the correlation between $y$ and $x$ ) gives the fraction of the variability of $y$ accounted for by the least squares linear regression model. (p. 185)  |
| <b>Does the Plot Thicken?<br/>Condition</b>   | The scatterplot or residuals plot should show consistent (vertical) spread in $y$ -values. (p. 187)   |

