

$$\begin{aligned}\hat{\beta}_1 &= \frac{\sum_{i=1}^n x_i (y_i - \bar{y})}{\sum_{i=1}^n x_i (x_i - \bar{x})} = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^n (x_i - \bar{x})^2} \\ &= \frac{\frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x})^2} \\ &= \frac{\text{Cov}(x, y)}{\text{Var}(x)} \\ &= \frac{\text{Corr}(X, Y) \times \text{SD}(Y)}{\text{SD}(X)}\end{aligned}$$

$$* \text{Corr}(X, Y) = \frac{\text{Cov}(X, Y)}{\text{SD}(X) \text{SD}(Y)}$$

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

$$\rightarrow \hat{\mu} = \hat{\beta}_0 + \hat{\beta}_1 x \quad \leftarrow \text{Eqn of line of best fit.}$$

What about an estimate of σ ?

• Recall $\sigma = \text{SD}(\varepsilon_i)$

• We can't observe the $\varepsilon_i = y_i - \mu_i$, but we can observe $e_i = y_i - \hat{\mu}_i$, which we call a residual. We estimate σ by quantifying dispersion in the residuals:

$$\hat{\sigma} = \sqrt{\frac{\sum_{i=1}^n (e_i - \bar{e})^2}{n-2}} \quad \begin{array}{l} \bar{e} = 0 \\ \text{"residual error"} \end{array} = \sqrt{\frac{\sum_{i=1}^n e_i^2}{n-2}} \quad \begin{array}{l} \text{"sum of squared residuals"} \\ = \sqrt{\frac{\sum_{i=1}^n (y_i - \hat{\beta}_0 - \hat{\beta}_1 x_i)^2}{n-2}} \end{array}$$

PGA Example:

$$\hat{\beta}_1 = -0.39175$$

$$\hat{\beta}_0 = 176.5841$$

$$\hat{\sigma} = 4.215$$

How do we interpret this?



$$E[y] = \mu = \beta_0 + \beta_1 x$$

• If $x=0 \rightarrow E[y|x=0] = \beta_0 =$ expected response when $x=0$

$$E[y|x=a+1] - E[y|x=a] = [\beta_0 + \beta_1(a+1)] - [\beta_0 + \beta_1 a] = \beta_1$$

= expected change in y for a unit increase in x

• σ is loosely interpreted as the average deviation between an observed response and our predicted value for it.