Generally, for a linear reg

$$\hat{Y} = \hat{\beta}_0 + \hat{\beta}_1 x,$$

We can use RSS to ~~be~~ be our cost function, $\sum_{i=1}^{n} (y-\hat{y})^2$.

- Lets say we are given a sample N to measure the population mean, our sample mean will be more or less $\approx$ population over an ∞ amount of samples, going towards a normal distribution.

- But for a small amount of samples, ~~we~~ ~~can~~ how much would we on average be off by?

$$S.E = \frac{\sigma}{\sqrt{n}} = \sqrt{\frac{\sigma^2}{n}}$$

So for β_1 and β_0, our standard error would be roughly

$$S.E(\beta_0) = \sigma^2\left(\frac{1}{n} + \frac{\bar{x}^2}{\sum_{i=1}^{n}(x-\bar{x})^2}\right)$$

$$S.E(\beta_1) = \sigma^2 \left(\frac{1}{\sum (x_i - \bar{x})^2} \right).$$

we are 95% confident
that our true β_0 & β_1
lies within
$[\hat{\beta}_1 - 2S.E(\beta_1), \hat{\beta}_1 + 2S.E(\beta_1)]$.

H_0 = null hypothesis.
H_a = alt hypo.
Our conclusion should
be based on observation and H_a.

p-value → the probability of
residual standard error.
Something based
RSE
on chance.

$$R^2 = 1 - \frac{RSS}{TSS}$$

unexplained. $\frac{RSS}{TSS}$ → total variance explained
by fitting regression.

$R^2 \simeq r$ (corr)

when

$$corr = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{s\,\sigma_x \sigma_y}.$$

$$var\ V_1 = \frac{\sum (x_i - \bar{x})}{n-1}.$$