

#### **Linear Regression Models**

Segment 1 – Simple Linear Regression Model

Topic 4 – Accuracy of the Coefficient Estimates

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#### **Topics**



- 1. Accuracy of the Coefficient Estimates: Standard Errors
- 2. Accuracy of the Coefficient Estimates: Confidence Intervals
- 3. Accuracy of the Coefficient Estimates: Hypothesis Tests
- 4. Summary

## Accuracy of the Coefficient Estimates: Standard Errors

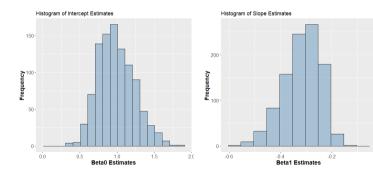


## Accuracy of the Coefficient Estimates: Standard Errors



How can we assess the accuracy of the SLRM coefficient estimates

$$\hat{eta}_0 = ar{y}_n - \hat{eta}_1 ar{x}_n$$
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- How to interpret this? Each dataset gives us one such CI; approximately 95% of those intervals will contain the true population parameter  $\beta_0$ .
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- For calculating CI as above, additional assumption on the random error term  $\varepsilon^{(i)}$  that it is normally distributed is needed.





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- Assuming that the null hypothesis is true,  $T = \frac{\hat{\beta_1} E[\hat{\beta_1}]}{SE(\hat{\beta_1})} = \frac{\hat{\beta_1} \underbrace{\beta_1}}{SE(\hat{\beta_1})}$



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- Assuming that the null hypothesis is true,  $T = \frac{\hat{\beta_1} E[\hat{\beta_1}]}{SE(\hat{\beta_1})} = \frac{1}{SE(\hat{\beta_1})}$  follows a t-distribution with n-2 degrees of freedom.





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- Rejecting the null hypothesis is equivalent to accepting the alternative hypothesis that  $\beta_1 \neq 0$ , and therefore mpg and hp are indeed related.
- If the p-value is greater than the threshold, we fail to reject the null hypothesis; this means that there possibly is no relationship between mpg and hp.

#### **Summary**







Different ways to assess the accuracy of coefficient estimates using standard errors, confidence intervals, and hypothesis tests.