





$$\begin{aligned}
 \hat{\beta}_1 &= \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sum (x_i - \bar{x})^2} = \frac{1}{SS_x} \sum [(x_i - \bar{x})y_i - (x_i - \bar{x})\bar{y}] \\
 &= \frac{1}{SS_x} \left[ \sum (x_i - \bar{x})y_i - \bar{y} \sum (x_i - \bar{x}) \right] \\
 &= \frac{1}{SS_x} \sum (x_i - \bar{x})y_i
 \end{aligned}$$

$$\begin{aligned}
 & x_1 - \bar{x} + x_2 - \bar{x} + x_3 - \bar{x} \\
 & \underbrace{x_1 + x_2 + x_3}_{\text{sum of } x_i} - \underbrace{\frac{1}{n}(x_1 + x_2 + x_3)}_{\bar{x}}
 \end{aligned}$$

$$\text{Var}(\hat{\beta}_1) = \frac{1}{(SS_x)^2} \sum \text{Var}[(x_i - \bar{x})y_i]$$

$$= \frac{1}{(SS_x)^2} \sum (x_i - \bar{x})^2 \text{Var}(y_i)$$

$$= \frac{\sigma^2}{SS_x}$$

$$\cancel{\text{Var}(\beta_1)} =$$

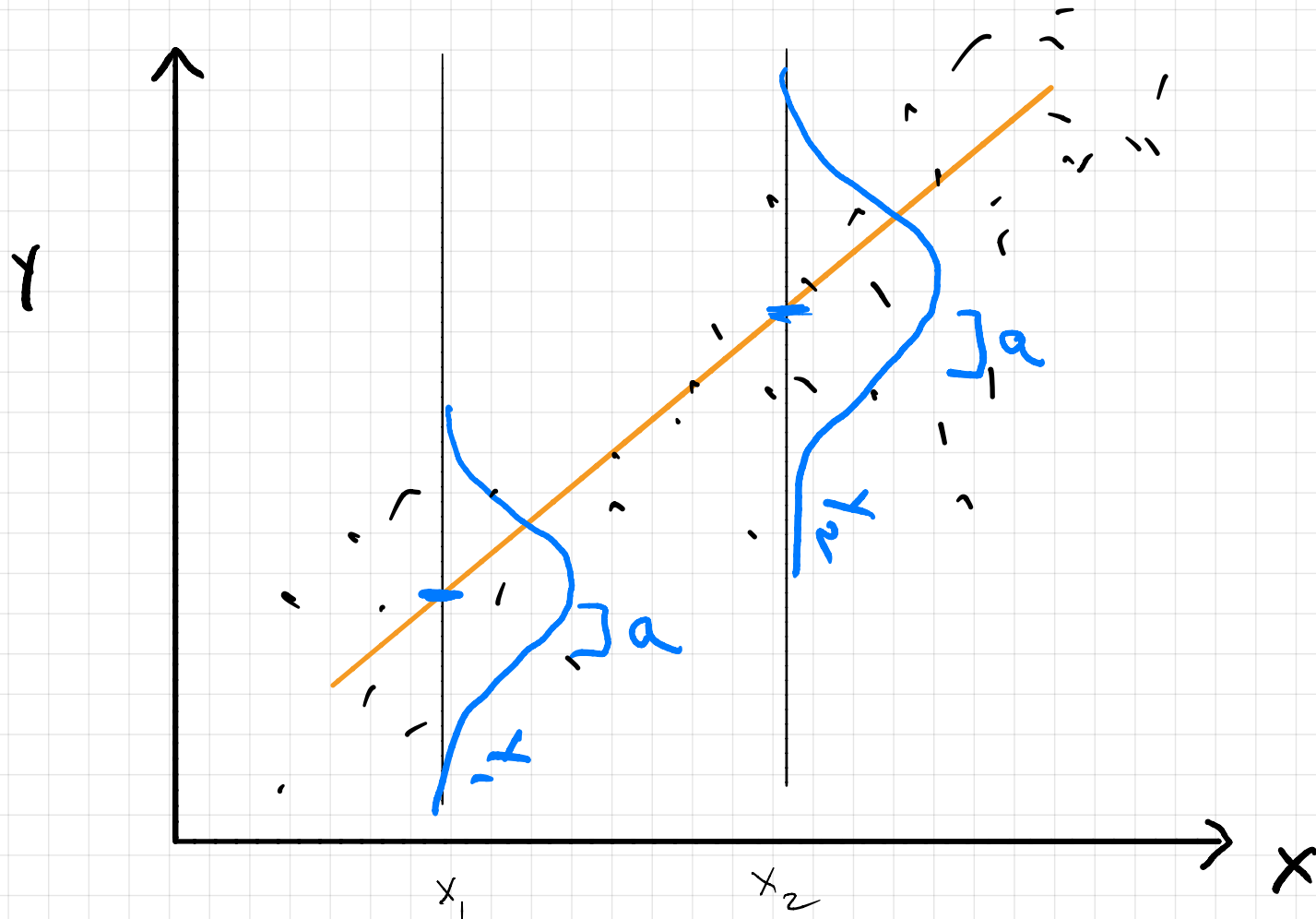
$$\text{Var}(\hat{\beta}_1)$$

# Inference for the Simple Linear Model

The Simple Linear Model:  $Y_i = \beta_0 + \beta_1 x_i + \varepsilon_i; \varepsilon \sim N(0, \sigma^2)$

OR

$$[Y_i | X = x_i] \sim N(\mu = \beta_0 + \beta_1 x_i, \sigma^2 = \sigma^2)$$



## Some Inferential results

$$\textcircled{A} \hat{\beta}_1 \sim N\left(\beta, \frac{\sigma^2}{ss_x}\right)$$

$\textcircled{B}$  If  $\sigma^2$  is unknown, estimate w/

$$s^2 = \frac{1}{n-2} \sum_{i=1}^n (y_i - \hat{y}_i)^2$$

$$\cdot E(s^2) = \sigma^2$$

$$\cdot s^2 \sim \chi^2\text{-ish}$$

$$\textcircled{C} \frac{\hat{\beta}_1 - \beta}{\sqrt{s^2/ss_x}} \sim t_{df=n-2}$$

$$\frac{\bar{x} - \mu}{\sqrt{s^2/n}} \leftarrow Z$$
$$\leftarrow \chi^2$$

# Classic Inference on $\hat{\beta}_1$

## H-test on $\hat{\beta}_1$

$$H_0: \beta_1 = 0$$

$$H_1: \beta_1 \neq 0$$

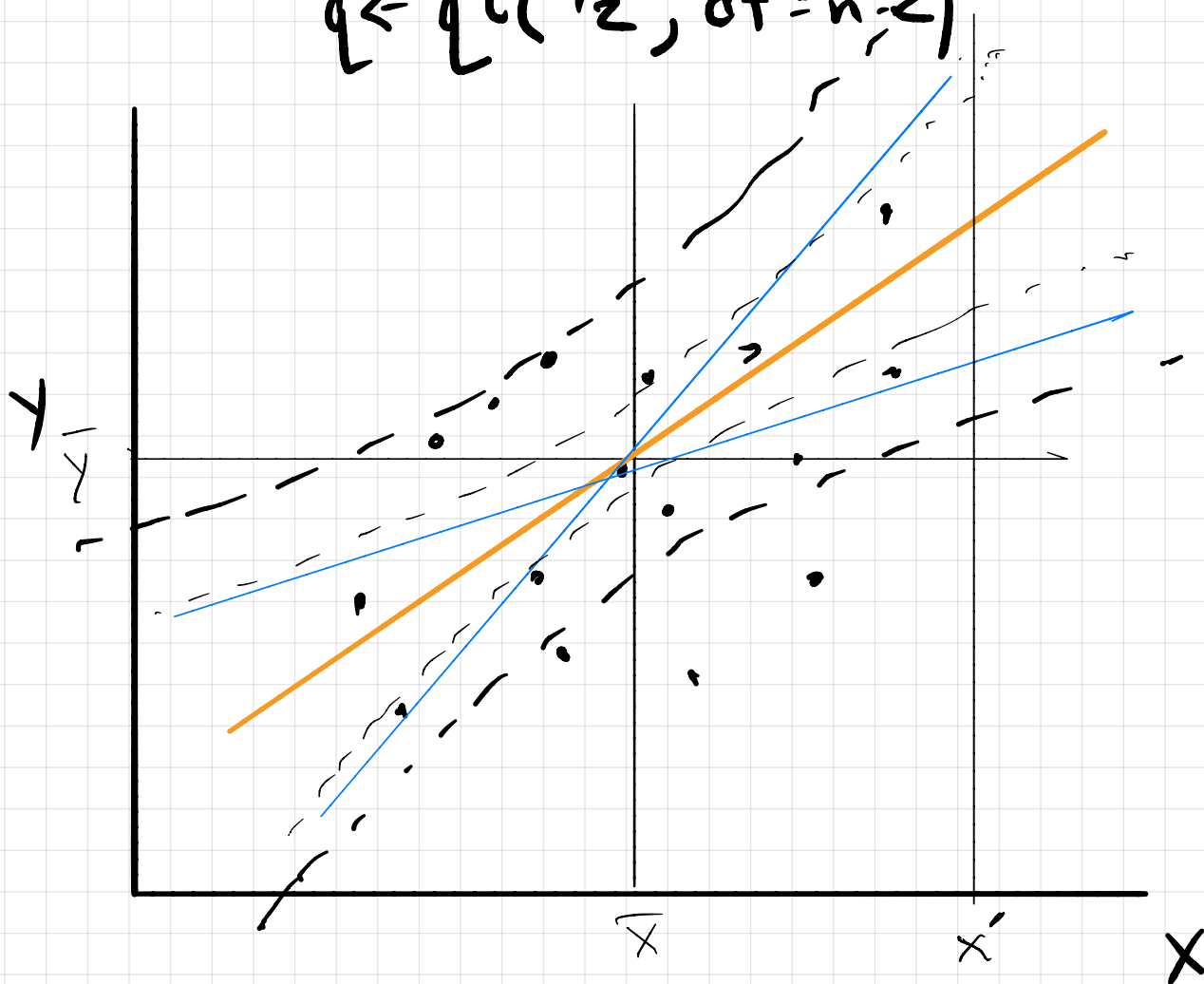
$$\frac{\hat{\beta}_1}{s/\sqrt{SS_x}} \sim t_{n-2}$$

test statistic

## $1-\alpha$ CI for $\beta_1$

$$\hat{\beta}_1 \pm q_{s/\sqrt{SS_x}}$$

$$q \leftarrow q_{t(\alpha/2, df=n-2)}$$



## I. Assessing Uncertainty in a Prediction

We want to form a confidence interval for  $\hat{y} = E(y|x=x')$

$$\begin{aligned} E(\hat{E}(y|x=x')) &= E(\hat{\beta}_0 + \hat{\beta}_1 x') \\ &= E(\hat{\beta}_0) + x' E(\hat{\beta}_1) \\ &= \beta_0 + \beta_1 x' \end{aligned}$$

if we try the same approach w/ var we'd need  $\hat{\beta}_0 \perp \hat{\beta}_1$  (it's not).  
We do know  $\hat{\beta}_0 = \bar{y} - \hat{\beta}_1 \bar{x}$ , and  $\hat{\beta}_1 \perp \bar{y}$

$$\begin{aligned} V(\hat{E}(y|x=x')) &= \text{Var}(\hat{\beta}_0 + \hat{\beta}_1 x') \\ &= \text{Var}(\bar{y} - \hat{\beta}_1 \bar{x} + \hat{\beta}_1 x') \\ &= \text{Var}(\bar{y} + \hat{\beta}_1 (x' - \bar{x})) \\ &= \frac{\sigma^2}{n} + (x' - \bar{x})^2 \text{Var}(\hat{\beta}_1) \\ &= \frac{\sigma^2}{n} + (x' - \bar{x})^2 \frac{\sigma^2}{SS_x} \end{aligned}$$

## II. Assessing Uncertainty in a new value

We want to form a CI for  $[Y|X=x'] \leftarrow$  "Prediction Interval",

$$\begin{aligned} E(Y|X=x') &= E(\hat{\beta}_0 + \hat{\beta}_1 x' + \varepsilon) \\ &= E(\hat{\beta}_0) + x' E(\hat{\beta}_1) + E(\varepsilon) \\ &= \beta_0 + \beta_1 x' \end{aligned}$$

$$\begin{aligned} V(Y|X=x') &= V(\hat{\beta}_0 + \hat{\beta}_1 x' + \varepsilon) \\ &= \frac{\sigma^2}{n} + (x' - \bar{x})^2 \frac{\sigma^2}{SS_x} + \sigma^2 \\ &= \sigma^2 \left( \frac{1}{n} + \frac{(x' - \bar{x})^2}{SS_x} + 1 \right) \end{aligned}$$



Find  $\text{Cov}(\hat{\beta}_0, \hat{\beta}_1)$

$$\begin{aligned}\text{Cov}(\hat{\beta}_0, \hat{\beta}_1) &= \text{Cov}(\bar{y} - \hat{\beta}_1 \bar{x}, \hat{\beta}_1) \\ &= 0 - \text{Cov}(\hat{\beta}_1 \bar{x}, \hat{\beta}_1) \\ &= 0 - \bar{x} \text{Cov}(\hat{\beta}_1, \hat{\beta}_1) \\ &= 0 - \bar{x} \text{Var}(\hat{\beta}_1) \\ &= -\bar{x} \frac{\sigma^2}{SS_x}\end{aligned}$$

$$-\bar{x} \frac{\sigma^2}{SS_x}$$

$$\begin{aligned}\bullet \text{Cov}(A-B, C) &= \\ \text{Cov}(A, C) - \text{Cov}(B, C)\end{aligned}$$

$$\bullet \hat{\beta}_1 \perp \bar{y}$$

$$\text{Cov}(X, Y) = \underline{E((X - E(X))(Y - E(Y)))}$$

