

Agenda:

- 1 p-values
2. classical linear model
3. method of moments

Recap:

Linear model w/ Gaussian normal errors

$$\underbrace{y \mid X}_{n \times 1 \quad n \times p} \sim N(X\beta^*, \sigma^2 I_n) \text{ for some vector of "true" regression coeff's } \beta^* \in \mathbb{R}^p$$

Under the lin. model w/ Gaussian errors: $\hat{\beta} = (X^T X)^{-1} X^T y$

$$\hat{\beta} - \beta^* \mid X \sim N(0, \sigma^2 (X^T X)^{-1})$$

Hypothesis testing under normality:

want to test $H_0: \beta_j^* = 0$

'reject H_0 if $\left| \frac{\hat{\beta}_j - \beta_j^*}{SE(\hat{\beta}_j)} \right| > t_\alpha$ (rejection statement)
(for hypothesis test)

Type I error rate: t is chosen so that

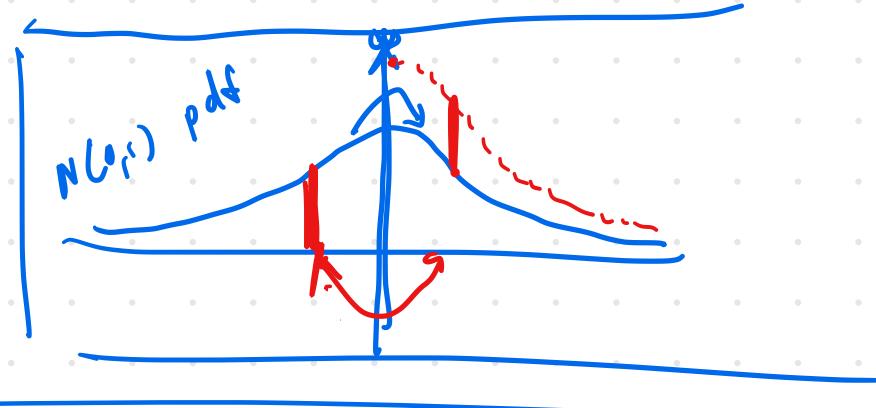
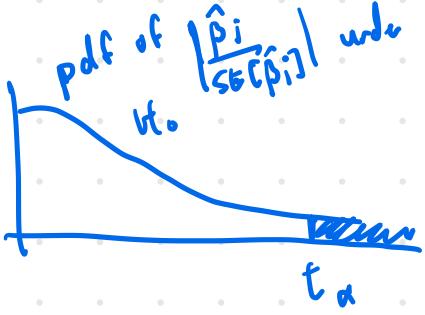
$$P_0 \left(\left| \frac{\hat{\beta}_j - \beta_j^*}{SE(\hat{\beta}_j)} \right| > t_\alpha \right) \leq \boxed{\alpha} \quad \text{usually } 0.05 \quad \left(t \text{ is the } (-\alpha) \text{ quantile of } \left| \frac{\hat{\beta}_j}{SE(\hat{\beta}_j)} \right| \text{ under } H_0 \right)$$

The correct value of t_α is about 2 (for $\alpha \approx 0.05$).

The rejection statement is equivalent to

reject if $\underbrace{\left| \frac{\hat{\beta}_j}{SE(\hat{\beta}_j)} \right|}_{\text{p-value}} \leq \alpha$, where F is the CDF of $a \left| \frac{\hat{\beta}_j}{SE(\hat{\beta}_j)} \right|$ under H_0 .

In the z-test F is the CDF of $|z|$, where $z \sim N(0, 1)$



Classical linear model:

$$\text{Condition (linearity): } y = X\beta^* + \epsilon \quad (\text{nx1 approx px1 nx1})$$

$$\text{"definition of error terms as } \epsilon = y - X\beta^* \text{"}$$

$$\text{exogeneity : } E[\epsilon | X] = 0$$

$$\text{spherical error variance : } E[\epsilon \epsilon^T | X] = \sigma^2 I_n \quad \left. \begin{array}{l} \text{comparable} \\ \text{to Gaussian} \\ \text{err terms condition} \end{array} \right\}$$

Aside: covariance of random vector

$$\text{If } x \in \mathbb{R}^n,$$

$$\text{then } \text{var}[x] \stackrel{\text{def}}{=} E[(x - \mu)^2]$$

$$\mu \stackrel{\text{def}}{=} E[x]$$

If $x \in \mathbb{R}^n$ is random vector

$$\text{then } \text{Var}[x] = E[(x - \mu)(x - \mu)^T]$$

$$\mu = E[x]$$

$$[\text{Var}[x]] = E[(x_i - \mu_i)(x_j - \mu_j)]$$

$$E[\epsilon \epsilon^T | X] = \sigma^2 I_n \quad \left. \begin{array}{l} \text{homoskedasticity: } E[\epsilon_i^2 | X] = \sigma^2 \text{ for all } i: \text{long} \\ \text{no serial correlation: } E[\epsilon_i \epsilon_j | X] = 0 \text{ for } i \neq j \end{array} \right\}$$

method of moments:

$$E[x_i \epsilon_i] = E[x_i(y_i - x_i^T \beta^*)]$$

$$= E[E[x_i \epsilon_i | X]]$$

$$= E[X_i E[\epsilon_i | X]]$$

(tower property
law of total expectations)

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