① In our lecture, we ran OLS for

$\underline{y}$ $\underline{x}$

- One output, one input.

$$\hat{\sigma}_{\hat{y}_i} = \underbrace{\hat{\sigma}_\epsilon}_{= \left[\frac{\sum (y_i - \hat{y}_i)^2}{(N-2)}\right]^{1/2}} \cdot \left[\frac{1}{N} + \frac{\overset{30}{(x_i - \bar{x})^2}}{\sum_{i=1}^{n} (x_i - \bar{x})^2}\right]^{1/2}$$

- Now, we have

$\underline{y}$ $\boxed{\underline{x} \quad \underline{x^2} \quad \underline{x^3}} \rightarrow X$

- We need an expression for $\hat{\sigma}_{\hat{y}_i}$ that works for multidimensional $\underline{X}$.

① Fit regression. Get ε_i (residuals)

② Compute degrees of freedom $N - \underbrace{p}_{\text{dimensionality of } \underline{X}} - \underbrace{1}_{\text{intercept}}$

③ Calculate $(X^T X)^{-1}$

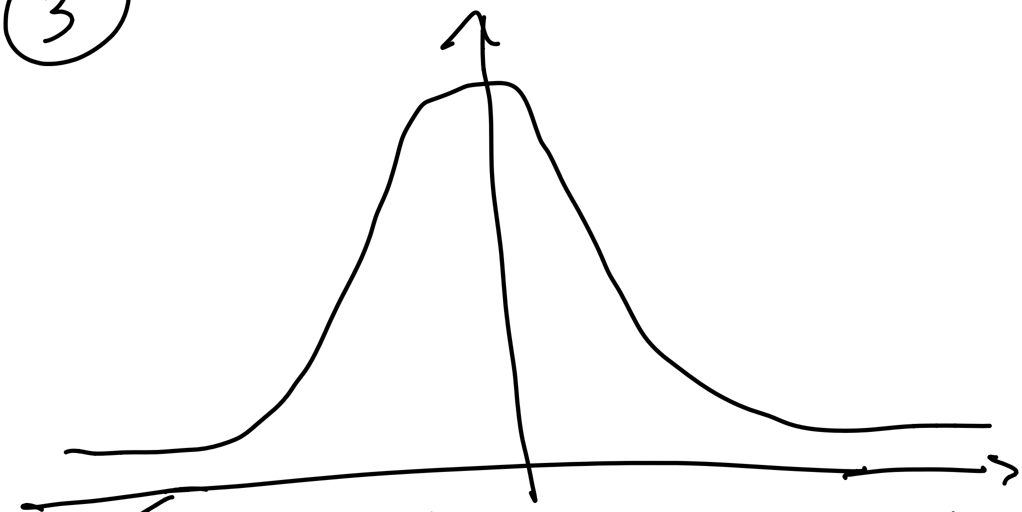
④ $\hat{\sigma}_{\hat{y}_i} = \hat{\sigma}_\varepsilon \cdot \sqrt{x \, (X^T X)^{-1} \, x}$

$$\left[\frac{\sum_{i=1}^{n} \varepsilon_i^2}{N-p-1}\right]^{1/2}$$

3

$\boxed{\text{t-student w/ 70 dof.}}$

– Recall we have 7128 genes.

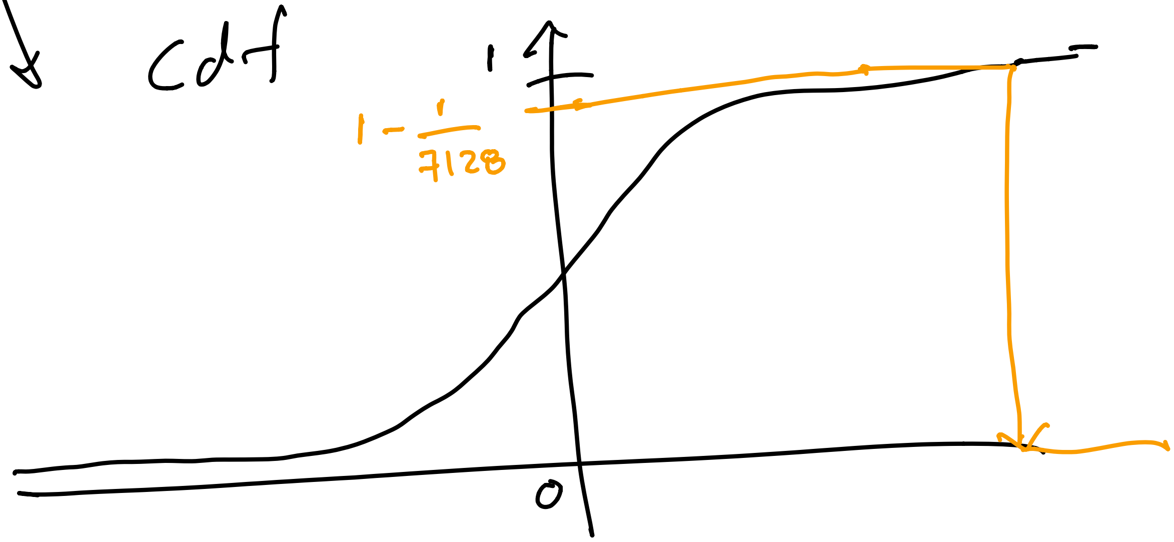


pdf

$$t = \frac{\bar{x}_{AML} - \bar{x}_{ALL}}{\hat{se}}$$

- If there is truly no difference between AML and ALL, then the largest value happened just by chance! The prob. that a random value is the largest would be $\frac{1}{7128}$

cdf



Look for $(1 - \frac{1}{7128})$ in the inverse cdf of a t_{70} distribution $\rightarrow$ 3.826.

CH 2

① $E(\hat{\theta}) = \dfrac{n\theta + 1}{n+2}$

Bias: $E(\hat{\theta}) - \theta$

$$: \frac{n\theta}{n+2} + \underbrace{\frac{1}{n+2}} - \theta = \theta\left[\frac{\cancel{n}}{n+2} - \frac{\cancel{n+2}}{n+2}\right] + \frac{1}{n+2}$$

$$= \frac{1 - 2\theta}{n+2}$$

Bias of $\hat{\theta}$

Variance: $V(\hat{\theta}) = V\left(\dfrac{S+1}{n+2}\right) = \dfrac{1}{(n+2)^2} V(S+1)$

$$= \frac{V(S)}{(n+2)^2} = \frac{n\theta(1-\theta)}{(n+2)^2}$$

b) $se(\hat{\theta})$ is just $\sqrt{V(\hat{\theta})}$, thus

True parameter value.

$$se(\hat{\theta}) = \frac{[n\theta . (1-\theta)]^{1/2}}{n+2}$$

. Since we don't know θ, we use our estimator $\hat{\theta} = \frac{S+1}{}$ instead of θ.

$n+2$

This is the plug-in principle. we get...

$$\hat{se}(\hat{\theta}) = \frac{\left[n \cdot \left(\frac{s+1}{n+2}\right) \cdot \left(1 - \frac{s+1}{n+2}\right)\right]^{1/2}}{n+2}$$

yay!