

THE FINAL STRETCH

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THE NEW
STUFF

ESTIMATION

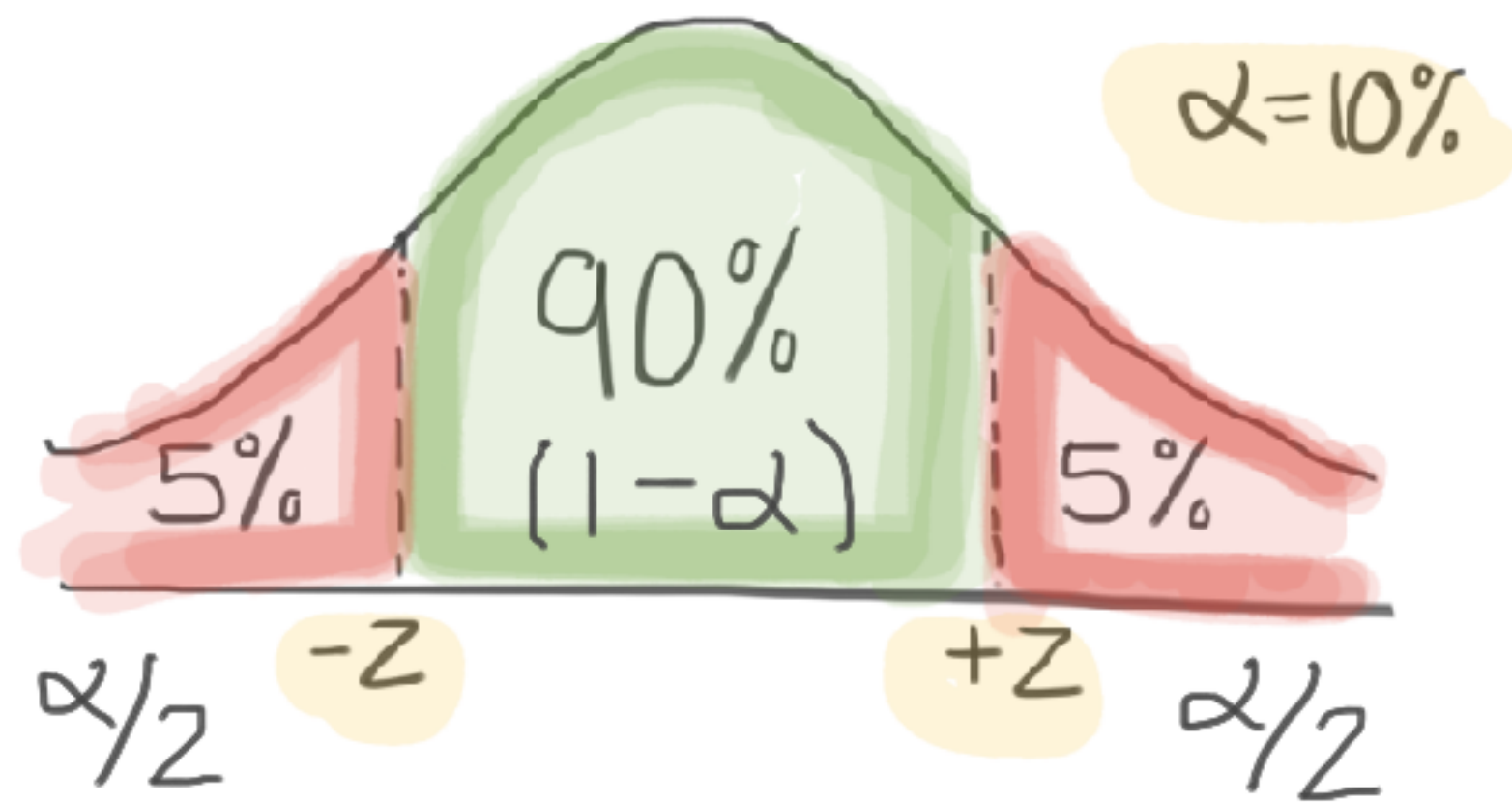


⇒ depending on how we calculate $\hat{\theta}$, how accurate can we get to θ ???

⇒ **BIAS** $\text{bias}(\hat{\theta}) = E[\hat{\theta}] - \theta$

⇒ **MEAN SQUARE ERROR** $\text{MSE}(\hat{\theta}) = E[(\hat{\theta} - \theta)^2] = \text{var}[\hat{\theta}] + (\text{bias}(\hat{\theta}))^2$

CONFIDENCE INTERVALS



$$\Rightarrow \frac{\hat{\mu} - \mu}{\sigma/\sqrt{n}} \sim N(0,1)$$

$$\begin{aligned} \Rightarrow P(-z < \frac{\hat{\mu} - \mu}{\sigma/\sqrt{n}} < z) &= 90\% \quad \text{rearrange} \\ &= P(-z(\frac{\sigma}{\sqrt{n}}) - \hat{\mu} < -\mu < z(\frac{\sigma}{\sqrt{n}}) - \hat{\mu}) = 90\% \quad \times -1 \\ &= P(z(\frac{\sigma}{\sqrt{n}}) + \hat{\mu} > \mu > \hat{\mu} - z(\frac{\sigma}{\sqrt{n}})) = 90\% \end{aligned}$$

$$\Rightarrow \text{if sample data: } s^2 = \frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x})^2$$

if $n \leq 30$

\Rightarrow if n is "small"

\Rightarrow use t-dist

\hookrightarrow different value table from Z_s

EFFICIENT

An unbiased estimator is said to be the **most efficient** if it has the **smallest variance** among all possible unbiased estimators

CONSISTENT

$$\lim_{n \rightarrow \infty} P(|\hat{\theta} - \theta| > \epsilon) = 0 \rightsquigarrow \lim_{n \rightarrow \infty} \hat{\theta} = \theta$$

$$\hookrightarrow \text{WLLN: } \lim_{n \rightarrow \infty} \frac{1}{n} \sum_{i=1}^n \beta_i^k = E[B^k]$$

$$\hookrightarrow \lim_{n \rightarrow \infty} \frac{s^2}{n} = 0$$

SUFFICIENT

$P(X_1 = x_1, \dots, X_n = x_n | \hat{\theta}(x_1, \dots, x_n) = u)$ does not depend on θ

$$\hookrightarrow L(\theta) = L(x_1, \dots, x_n | \theta) = g(u, \theta) \cdot h(x_1, \dots, x_n)$$

METHOD OF MOMENTS

⇒ relating sample and theoretical moments

① figure out $E[X]$, $E[X^2]$, etc.
(however many equations you need)

↳ use what you know about distribution

↳ variance

↳ integrate given PDF

② Solve system of equations for parameters you're looking for

THEORETICAL

$$E[X]$$

→

SAMPLE

$$\frac{1}{n} \sum_{i=1}^n X_i$$

$$E[X^2]$$

↔

$$\frac{1}{n} \sum_{i=1}^n X_i^2$$

$$E[X^k]$$

↔

$$\frac{1}{n} \sum_{i=1}^n X_i^k$$

often in terms of parameters

Maximum Likelihood Estimator

⇒ take the derivative of some expression

→ not to be confused w/ MSE

① usually given $X_1 \dots X_n$ where $f(x|\star) = \dots$

② $L(\star) = P(X_1 = x_1, \dots, X_n = x_n | \star)$ ← "joint probability in terms of \star "

③ $L(\star) \Rightarrow \prod_{i=1}^n f(x_i | \star)$ because X_i s are IID

④ note: $\ln(AB) = \ln(A) + \ln(B)$

⑤ take derivative $\frac{d}{d\star} \Rightarrow \text{set} = 0 \Rightarrow \text{solve for } \star$

INVARIANCE PROPERTY

\Rightarrow if $t(\theta)$ is a one-to-one function of θ and if $\hat{\theta}$ is the MLE for θ , then the MLE of $t(\theta)$ is given by

$$\widehat{t(\theta)} = t(\hat{\theta})$$

\hookrightarrow plug in $\hat{\theta}$ into t function

OTHER USEFUL THINGS

$$\Rightarrow \ln(AB) = \ln(A) + \ln(B)$$

\Rightarrow expected values and variances of common distributions

\Rightarrow t-dist = normal + small n

$$\Rightarrow E[f(x)] = \int f(x) \cdot \text{pdf}(x) dx \text{ OR } \sum f(x) \cdot \text{pdf}(x)$$

Ex: let $X = (X_1, \dots, X_n)$ be a random sample of size n w/ mean μ and variance σ^2

\Rightarrow let $\hat{s}^2(X) = \frac{1}{n} \sum_{i=1}^n (X_i - \frac{1}{n} \sum_{i=1}^n X_i)^2$ AND suppose $E[X_i^4] < \infty$

\Rightarrow show \hat{s}^2 is consistent

Ex: let $X \sim \text{Gamma}(\alpha, \beta) \Rightarrow E[X] = \alpha\beta$ and $\text{Var}[X] = \alpha\beta^2$

\Rightarrow find **MME** for α and β

Ex: let $Y \sim \text{geometric}(\theta)$ where $f(y|\theta) = \theta(1-\theta)^{y-1}$ for $y=1,2,3,\dots$

\Rightarrow find **MLE** for θ