

## Lecture 13

### Confidence intervals

Relate true value with  
value of estimate.

$f(D)$  true value

$X = g(D)$  estimate.

want to make a statement that  
holds when  $f(D)$  is w.p. to  $X$

An interval  $[A, B]$  is called  
 $(1-\delta)$  conf interval if  
 $f(D) \in [A, B]$  with  
probability at least  $1-\delta$

$\delta$  - small  $\Rightarrow$  good confidenc.

$\delta = 0.05 \Rightarrow 95\%$  conf  
interval.

$X \rightarrow [X_L, X_U] \rightarrow \delta$

$$\begin{aligned} P\{f(D) \in [X_L, X_U]\} &\geq 1-\delta \\ &\equiv P\{f(D) \notin [X_L, X_U]\} < \delta \\ &= P\{f(D) < X_L \vee f(D) > X_U\} < \delta \end{aligned}$$

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$$P\{f(D) > X_L \vee f(D) < X_U\} > 1-\delta$$

## Useful Inequalities

1° Markov inequality. For given  $\lambda > 0$

$$\forall \lambda > 0, P[|X| \geq \lambda] \leq \frac{E[|X|]}{\lambda}$$

$$X \Rightarrow E[X] = 1 \quad \text{Take } X > 0$$

$$\lambda \rightarrow 100$$

$$P[|X| \geq 100] < \frac{1}{100}$$

2° Chebyshev inequality:

$$\text{For } \lambda > 0 \text{ and } \text{Var}(X) = \sigma^2 < \infty$$

$$P[|X - E[X]| \geq \lambda] \leq \frac{\text{Var}(X)}{\lambda^2}$$

$$\text{pick } \lambda = \sigma \cdot \sqrt{\text{Var}(X)} \\ = \sigma \cdot \text{Std}(X)$$

$$P\{|X - E[X]| \geq \sigma \cdot \sqrt{\text{Var}(X)}\} \leq \\ \frac{\text{Var}(X)}{\sigma^2 \text{Var}(X)} = \frac{1}{\sigma^2}$$

if we pick  $\sigma = 10$

$$P\{X \text{ is off by } 100 \text{ or from } f(\theta)\} \leq \frac{1}{100}$$

Recipe for Conf. Interval:

- make  $x$  an unbiased estimate  $f(\theta) = E[X]$

• compute  $\sigma = \sqrt{\text{Var}(X)}$

$$\left( X - \sigma \cdot \frac{1}{\sigma}, X + \sigma \cdot \frac{1}{\sigma} \right) \text{ with conf. } 1 - \frac{1}{\sigma^2}$$

How can we make this better?

- determine and use the distribution of  $X$ 
  - cumulative distrib. fct of  $X$

$$F(x) = P[X \leq x]$$

$$F^{-1}(x)$$

- symmetric conf. interval

$$E[X] = f(\theta)$$

$$\text{find } x_c \text{ s.t. } F(x_c) = \frac{\delta}{2}$$

$$x_n \text{ s.t. } 1 - F(x_n) = \frac{\delta}{2}$$

## Central limit theorem

For any  $X_1, X_2, \dots, X_n$  iid  
st  $\text{var}(X_i) < \infty$

$$\mu = E(X)$$

$$\frac{\sum_{i=1}^n X_i}{\sigma \sqrt{n}} \xrightarrow{d} N(0, 1)$$

$$\frac{\sum_{i=1}^n X_i}{n} \xrightarrow{d} N\left(\mu, \frac{\sigma^2}{n}\right)$$

$n > 100$

Has for Hellenstein

c.l.t for saying  
with explained.

Normal

