

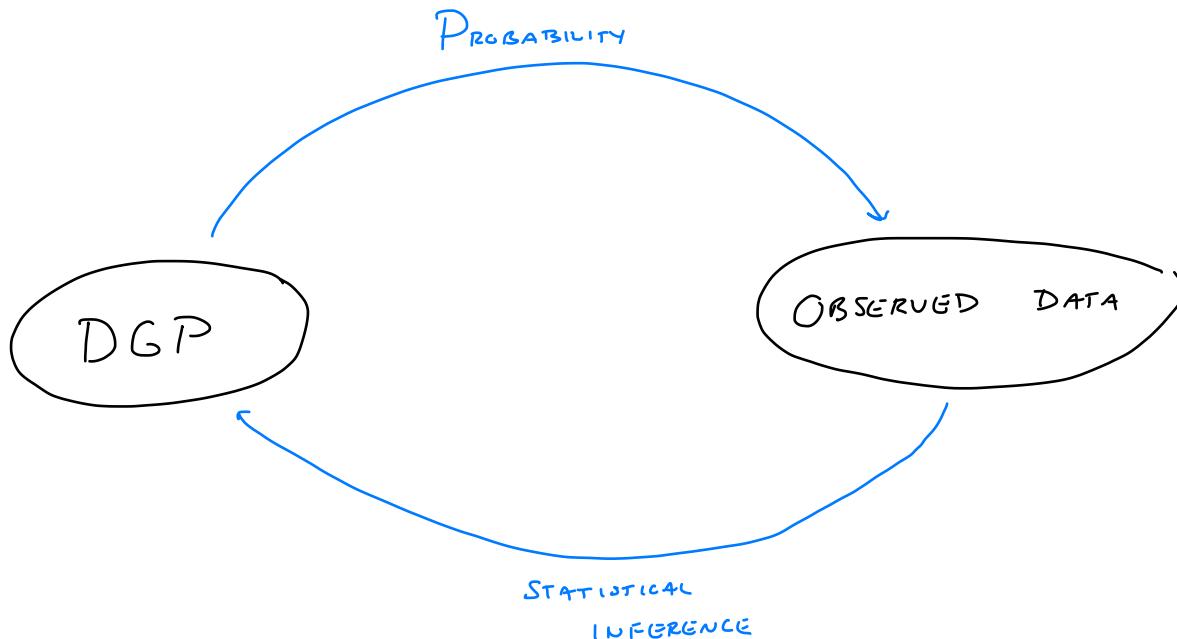
# STATISTICAL INFERENCE

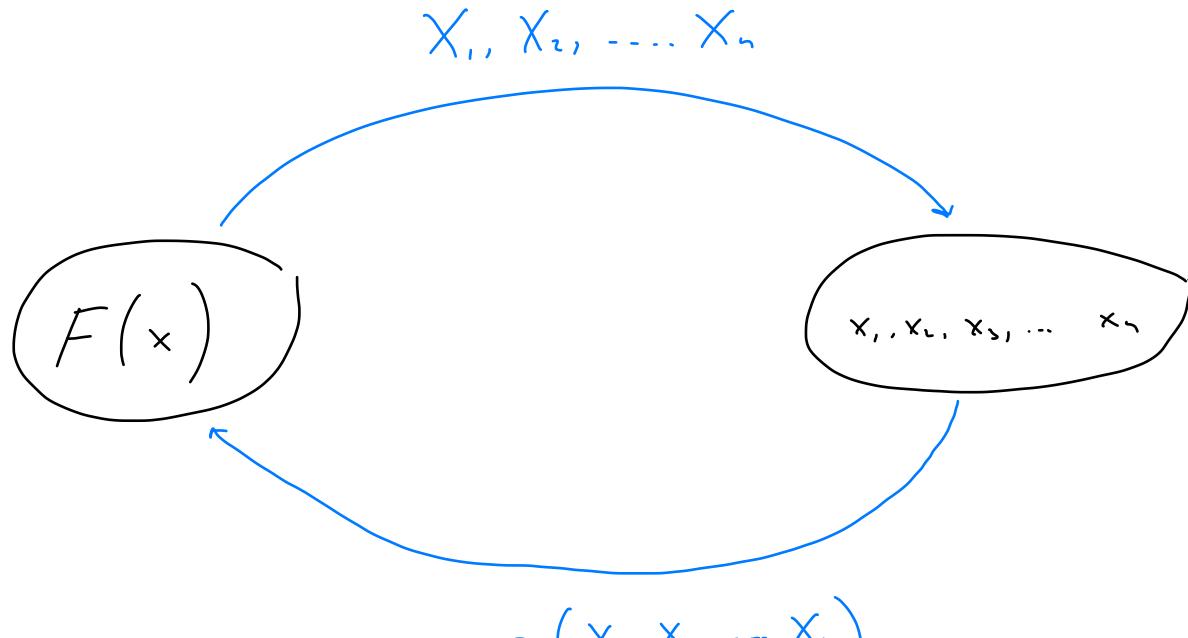
STAT 510

$$X_1, X_2, X_3, \dots, X_n \sim F$$

How do we "infer"  $F$ ?







STATISTIC

↳ A FUNCTION OF DATA

↳ CAN BE A RANDOM VARIABLE

$$X_1, X_2, \dots, X_n \sim F$$

• How to estimate  $F$ ? STATISTICAL MODEL

• PARAMETRIC ESTIMATION

• NONPARAMETRIC ESTIMATION

$$X_1, X_2, \dots, X_n \sim F$$

PARAMETRIC  
STATISTICAL  
Model

$$\mathcal{F} = \left\{ f(x; \theta) : \theta \in \Theta \right\}$$

DENSITY      PARAMETER THAT DETERMINES DENSITY      PARAMETER SPACE

$X_1, X_2, \dots, X_n \sim F$

Assume  $f \in \mathcal{F}$  where

$$\mathcal{F} = \left\{ f(x; p) = p^x (1-p)^{x-1}, \quad 0 < p < 1 \right\}$$

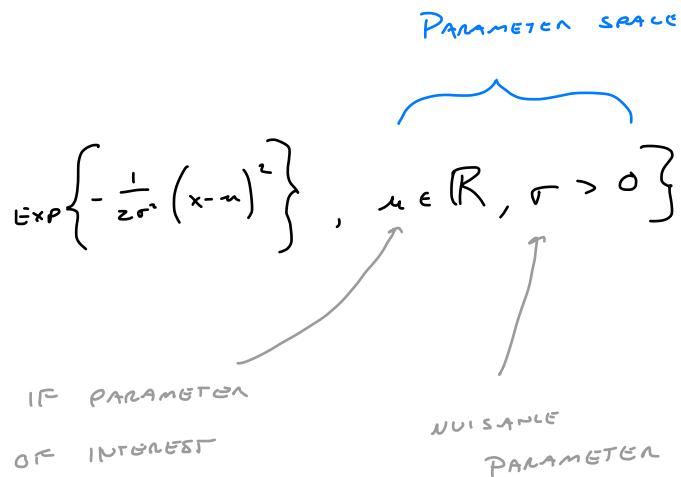
$X_1, X_2, \dots, X_n \sim \text{Bernoulli}(p)$

Problem reduced to estimating  $p$

$$X_1, X_2, \dots, X_n \sim \text{Normal}(\mu, \sigma^2)$$

Assume  $f \in \mathcal{F}$  where

$$\mathcal{F} = \left\{ f(x; \mu, \sigma^2) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left\{-\frac{1}{2\sigma^2}(x-\mu)^2\right\}, \mu \in \mathbb{R}, \sigma > 0 \right\}$$



$$X_1, X_2, \dots, X_n \sim N(\mu, \sigma^2)$$

$$X_1, X_2, \dots, X_n \sim F$$

Assume  $F \in \mathcal{F}_{\text{ALL}} = \{\text{ALL CDFs}\}$

NON PARAMETRIC



A

NOTE ABOUT



FREQUENTIST

INFERENCE

VS

BAYESIAN

INFERENCE

# INFERENCE CONCEPTS

- POINT ESTIMATION
- INTERVAL ESTIMATION
- HYPOTHESIS TESTING

## POINT ESTIMATION

USE  $\hat{\theta}$  AS "BEST GUESS" FOR  $\theta$ .

PARAMETER OF INTEREST  
↓  
FIXED, UNKNOWN  
↑

Given  $X_1, X_2, \dots, X_n \sim F$

Point estimator  $\longrightarrow \hat{\theta}_n = g(X_1, X_2, \dots, X_n)$

Random VARIABLE  $\uparrow$  Function  $\downarrow$  DATA

SAMPLING DISTRIBUTION...

## DEFN

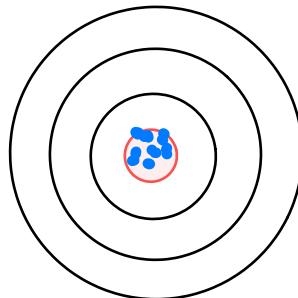
$$\text{BIAS}[\hat{\theta}] = \mathbb{E}[\hat{\theta}] - \theta$$

$$\text{VAR}[\hat{\theta}] = \mathbb{E}\left[(\hat{\theta} - \mathbb{E}[\hat{\theta}])^2\right]$$

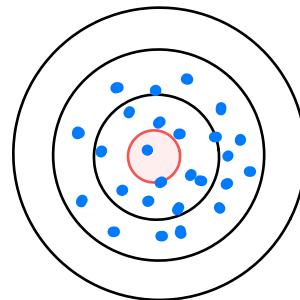
$$\text{MSE}[\hat{\theta}] = \mathbb{E}\left[(\hat{\theta} - \theta)^2\right] = (\text{BIAS}[\hat{\theta}])^2 + \text{VAR}[\hat{\theta}]$$

Low  
BIAS

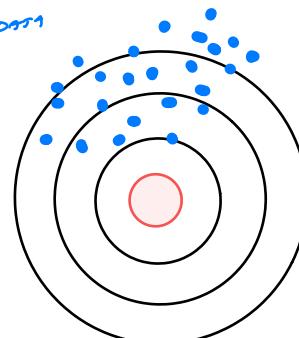
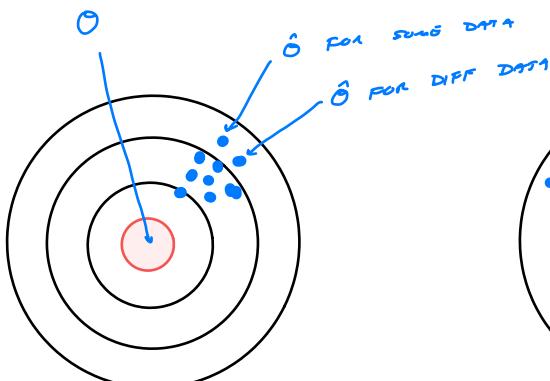
Low  
VARIANCE



High  
VARIANCE



HIGH  
BIAS



## DEFN

A POINT ESTIMATOR  $\hat{\theta}_n$  OF A PARAMETER  $\theta$

IS CONSISTENT IF

$$\hat{\theta}_n \xrightarrow{P} \theta$$

ESTIMATOR GETS "BETTER" WITH MORE DATA!

Theorem

IF BIAS  $\rightarrow 0$   
AND VAR  $\rightarrow 0$  AS  $n \rightarrow \infty$

THEN  $\hat{\theta}_n$  IS CONSISTENT.

Proof

IF BIAS AND VARIANCE GO TO ZERO, THEN  
 $MSE \rightarrow 0$

THUS  $\hat{\theta}_n \xrightarrow{q^n} \theta$ , SO  $\hat{\theta}_n \xrightarrow{P} \theta$ . ✓

# A NOTE ABOUT "STANDARD ERROR"

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$$se = se(\hat{\theta}_n) = \sqrt{V[\hat{\theta}_n]} = sd(\hat{\theta}_n)$$

$$\hat{se} = \hat{se}(\hat{\theta}_n) = \sqrt{\hat{V}[\hat{\theta}_n]} = \hat{sd}(\hat{\theta}_n)$$

Example

$X_1, X_2, \dots, X_n \sim \text{BERNOULLI}(p)$

$$\hat{p} = \frac{1}{n} \sum X_i$$

$$\mathbb{E}[\hat{p}] = \frac{1}{n} \sum_{i=1}^n \mathbb{E}[X_i] = p \Rightarrow \hat{p} \text{ UNBIASED}$$

$$\mathbb{V}[\hat{p}] = \frac{p(1-p)}{n} \quad \hat{\sigma}(\hat{p}) = \sqrt{\frac{\hat{p}(1-\hat{p})}{n}}$$

ESTIMATED STANDARD ERROR

SINCE  $\hat{p}$  UNBIASED AND

$\mathbb{V}[\hat{p}] \rightarrow 0$  THEN  $\hat{p}$  IS CONSISTENT.

AS  $n \rightarrow \infty$

## DEFN

An estimator is

Asymptotically normal

IF

$$\frac{\hat{\theta} - \theta}{\text{sd}(\hat{\theta})} \xrightarrow{d} N(0, 1)$$

## CONFIDENCE INTERVALS

$1 - \alpha$  CI for  $\theta$  is an interval

NOT RANDOM

$$C_n = (a, b)$$

Random!  $\rightarrow a = a(x_1, x_2, \dots, x_n)$

Random!  $\rightarrow b = b(x_1, x_2, \dots, x_n)$

Such that

$$P[a < \theta < b] = P[\theta \in C_n] \geq 1 - \alpha \quad \text{for all } \theta \in \Theta$$

COVERAGE

## INTERPRETATION

$$\hat{p} \pm z_{\alpha/2} \sqrt{\frac{\hat{p}(1-\hat{p})}{n}}$$

CAN MAKE PROB STATEMENTS

RANDOM DEPENDENCE  
ON DATA

$$(0.48 - 0.07, 0.48 + 0.07)$$

NOTHING RANDOM

DO NOT MAKE PROBABILITY STATEMENTS!!

Example

BERGER AND WOLPERT

 $X_1, X_2$  IND

$$P[X_i = 1] = P[X_i = -1] = 0.5$$

$X_1$	$X_2$	
-1	-1	x
-1	1	
1	-1	✓
1	1	✓

DEFINE  $Y_i = \theta + X_i$  OBSERVE  $Y_1, Y_2$ 

DEFINE "INTERVAL"

$$C = \begin{cases} Y_1 - 1 & \text{if } Y_1 = Y_2 \\ (Y_1 + Y_2)/2 & \text{if } Y_1 \neq Y_2 \end{cases}$$

$$P[\theta \in C] = 3/4 \quad \text{FOR ANY } \theta \Rightarrow 75\% \text{ CI}$$

$$\begin{aligned} Y_1 = 15 \\ Y_2 = 17 \end{aligned} \Rightarrow \theta = 16$$

$$P[\theta \in C | Y_1 = Y_2] = 1$$

BAYESIAN....

Normal Based CIs

Given  $\hat{\theta}_n \approx N(\theta, \hat{s}_{\theta}^2)$   $\hat{s}_{\theta} = \hat{s}_{\theta}(\hat{\theta}_n)$

$$P[Z > z_{\alpha/2}] = \alpha/2$$

DEFINE  $C_n = (\hat{\theta}_n - z_{\alpha/2} \cdot \hat{s}_{\theta}, \hat{\theta}_n + z_{\alpha/2} \cdot \hat{s}_{\theta})$

THEN  $P(\theta \in C_n) \rightarrow 1 - \alpha$

$\alpha = 0.05 \Rightarrow z_{\alpha/2} = 1.96 \text{ ``=`` } Z$   $\hat{\theta} \pm Z \cdot \hat{s}_{\theta}$

$$Z_n = \frac{\hat{\theta} - \theta}{\hat{s_e}}$$

WE ASSUME  $Z_n \xrightarrow{d} Z$   
 $Z \sim N(0, 1)$

$$\begin{aligned} P(\theta \in C_n) &= P\left(\hat{\theta} - z_{\alpha/2} \hat{s_e} < \theta < \hat{\theta} + z_{\alpha/2} \hat{s_e}\right) \\ &= P\left(-z_{\alpha/2} < \frac{\hat{\theta} - \theta}{\hat{s_e}} < z_{\alpha/2}\right) \\ &\approx P(-z_{\alpha/2} < Z < z_{\alpha/2}) \\ &= 1 - \alpha \end{aligned}$$

# HYPOTHESIS TESTING

Assume  $X_1, X_2, \dots, X_n \sim \text{BERNOULLI}(\rho)$

NULL  $\rightarrow H_0: p = \frac{1}{2}$

ALTERNATIVE  $\rightarrow H_1: p \neq \frac{1}{2}$

DEFINE  $T = |\hat{p} - \frac{1}{2}|$

“Reject  $H_0$ ” when  $T$  is “large”

How large?