

# Estimation, Bias and Variance

CS 3130 / ECE 3530: Probability and Statistics for Engineers

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# Parameters of a Distribution

All distributions we've discussed have parameters that fully describe their pdf or pmf.

- Normal:  $X \sim N(\mu, \sigma^2)$  with parameters  $\mu$  and  $\sigma^2$
- Exponential:  $X \sim \text{Exp}(\lambda)$  with rate  $\lambda$
- Bernoulli:  $X \sim \text{Ber}(p)$  with probability  $p$

These parameters are *constants*.

# Generic Notation

**Notation:** When making general statements, we use the Greek letter  $\theta$  to denote a parameter.

# Estimation of Distribution Parameters

If we assume our data follows a certain distribution (e.g., Normal via CLT), we need to estimate its parameters.

- Example: For Normal, estimate  $\mu$  and  $\sigma^2$
- Use sample mean  $\bar{x}_n$  and variance  $s_n^2$  as estimators

# Definition: Estimator

Let  $X_1, \dots, X_n$  be iid from a distribution with parameter  $\theta$ .

**Estimator:**  $\hat{\theta} = T(X_1, \dots, X_n)$

- “Hat” notation indicates estimation
- E.g., estimate mean  $\mu$  with  $\hat{\mu}$

# Definition: Unbiased Estimator

An estimator  $\hat{\theta}$  is **unbiased** if:

$$E[\hat{\theta}] = \theta$$

**Bias:**

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

## Example: Estimating $\mu$ of a Normal

If  $\hat{\mu} = \bar{X}_n$ , then:

$$E[\bar{X}_n] = E[X_i] = \mu$$

Thus,  $\bar{X}_n$  is an unbiased estimator of  $\mu$ .

# Example: Estimating $\sigma^2$ of a Normal

Estimator:  $\hat{\sigma}^2 = S_n^2$

We use:

$$\text{Var}(X) = E[X^2] - E[X]^2$$

And compute:

$$E[X_i^2] = \sigma^2 + \mu^2$$

$$E[\bar{X}_n^2] = \frac{\sigma^2}{n} + \mu^2$$

$$E[X_i \bar{X}_n] = \frac{\sigma^2}{n} + \mu^2$$



# Putting It Together: Expected Sample Variance

$$E[S_n^2] = \sigma^2$$

If we used  $n$  instead of  $n - 1$ , we would get a biased estimator:

$$E\left[\frac{1}{n} \sum (X_i - \bar{X}_n)^2\right] = \frac{n-1}{n} \sigma^2$$

## Example: Estimating $p$ for Bernoulli

Let  $X_i \sim \text{Ber}(p)$ . Then:

$$E[X_i] = p \Rightarrow E[\bar{X}_n] = p$$

**Conclusion:**  $\bar{X}_n$  is an unbiased estimator for  $p$ .

# Estimator Efficiency

Suppose  $\hat{\theta}_1$  and  $\hat{\theta}_2$  are both unbiased.

**Efficiency:**  $\hat{\theta}_1$  is more efficient than  $\hat{\theta}_2$  if:

$$\text{Var}(\hat{\theta}_1) < \text{Var}(\hat{\theta}_2)$$