

# Models

## Statistical Model

A set of probability distributions (typically a strict subset of all probability distributions)

This can be specified as either a pdf, cdf, or a group of known models (i.e. normal distributions)

- We will refer to a general model as  $P_\theta$  where  $\theta \in \Theta$ 
  - $\Theta$  is the parameter space

## Parametric vs Nonparametric Models

A **parametric** model has a parameter space with finite dimension while a **nonparametric** model does not

Examples of parametric:

- Normal distributions
- Polynomials of degree at most  $d$

Examples of nonparametric:

- Any polynomial

# Point Estimation

## Point Estimate

A **point estimate**  $\hat{\theta}$  is a single best guess for a parameter  $\theta$

The notation  $\theta \rightsquigarrow \hat{\theta}$  is used to denote that  $\theta$  is estimated by  $\hat{\theta}$

This can be written with as  $\hat{\theta}_n$  to indicate the dependence on  $n$  datapoints

# Properties of Estimators

## Bias

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

- The expectation is taken over all possible  $\theta$
- An estimator is **unbiased** if the bias is 0
- It is **asymptotically unbiased** if the bias approaches 0 as  $n \rightarrow \infty$

## Standard Error

$$\text{se}(\hat{\theta}) = \sqrt{\text{Var}[\hat{\theta}]}$$

## Mean Squared Error

$$\text{MSE}(\hat{\theta}) = \mathbb{E}[(\hat{\theta} - \theta)^2] = \text{bias}(\hat{\theta})^2 + \text{se}(\hat{\theta})^2$$

- The second half can be derived by subtracting and adding  $\mathbb{E}[\hat{\theta}]$  inside the parentheses, rewriting in terms of bias, and then expanding
- Crucially,  $\mathbb{E}[\hat{\theta} - \mathbb{E}[\hat{\theta}]] = 0$

## Consistency

An estimator  $\hat{\theta}$  is **consistent** if  $\hat{\theta} \xrightarrow{\mathbb{P}} \theta$  as  $n \rightarrow \infty$

- The LLN is one way of showing consistency
  - i.e. that the sample mean is a consistent estimator of  $\mu$
- Continuous mapping theorem also helps
  - Shows that  $\overline{X_n^2}$  is a consistent estimator of  $\mu^2$

## Showing Consistency with MSE

If MSE approaches 0 as  $n \rightarrow \infty$ , then the estimator is consistent

# Asymptotically Normal

## Asymptotically Normal

An estimator  $\hat{\theta}$  is **asymptotically normal** if there is an **asymptotic variance**  $\sigma^2$  such that:

$$\sqrt{n}(\hat{\theta} - \mu) \rightsquigarrow \mathcal{N}(0, \sigma^2)$$

- Can then think of  $\hat{\theta}$  as:
  - $\hat{\theta} = \theta + \frac{\sigma}{\sqrt{n}}Z$
  - $Z$  is standard normal
- CLT can be used to prove sample means are asymptotically normal with variance equal to the variance of the original distribution
- Delta method can be used to show functions of the sample mean are also asymptotically normal
  - Tells us that the asymptotic variance is equal to the variance of the underlying distribution multiplied by  $g'(\mu)^2$

# Alternative Definition

## Alt Def for Asymptotically Normal

An estimator is **asymptotically normal** if

$$\hat{\theta} - \theta \rightsquigarrow \mathcal{N}(0, \text{se}(\hat{\theta}))$$

It is often difficult to compute the standard error of our estimator exactly than to derive the asymptotic variance

- As a result, we prefer our previous definition

# Confidence Intervals

## Confidence Interval

A  $1 - \alpha$  confidence interval for  $\theta$  is a random interval of the form  $C_n = (A_n, B_n)$  such that:

$$P(\theta \in (A_n, B_n)) \geq 1 - \alpha$$

$1 - \alpha$  is the coverage of

- This means that with  $\alpha = 0.05$ , we expect that 95% of the time we construct our confidence interval, it contains the true value of  $\theta$
- Confidence intervals typically look like  $\hat{\theta} \pm c_\alpha$

# Constructing

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- If  $\hat{\theta}$  is asymptotically normal, then we can construct an interval using the normal distribution
  - We set  $c_\alpha = \frac{\sigma}{\sqrt{n}} = z_{\alpha/2}$
  - $P(Z \geq z_{\alpha/2}) = \alpha/2$
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- However,  $\sigma$  typically depends on  $\theta$ , which we don't know!
- We can use the asymptotic variance of the estimator instead
- This means our confidence interval only works asymptotically (as  $n$  increases)
- Formally, this means that the confidence interval we construct only has an **asymptotic coverage**