

Political Methodology III: Model Based Inference

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Statistical Inference

- Model based inference:
- **Assume**: data generated via distributional process
- Defines a likelihood function: parameter values \rightarrow likelihood of parameters, given data
- Derive estimators that identify values that **maximize** likelihood

General Likelihood Theory \rightarrow Example \rightarrow General Theory \rightarrow Example

Likelihood Inference, the Basics

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We're going to be interested in making an inference about θ_0 using the observed data.

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- $L(\theta|\mathbf{y}) : \underbrace{\Theta}_{\text{parameter space}} \rightarrow \mathbb{R}$
- Idea: values of $\theta \in \Theta$ will be **more likely** if they make the observed data a higher probability

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We also are only able to infer most likely value **given modeling assumptions**

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- $y_i = 1$ or $y_i = 0$

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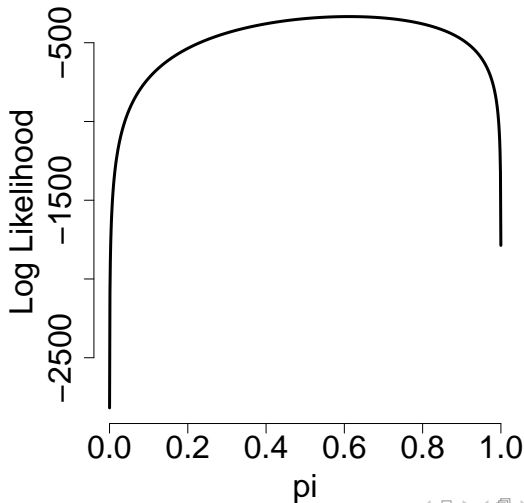
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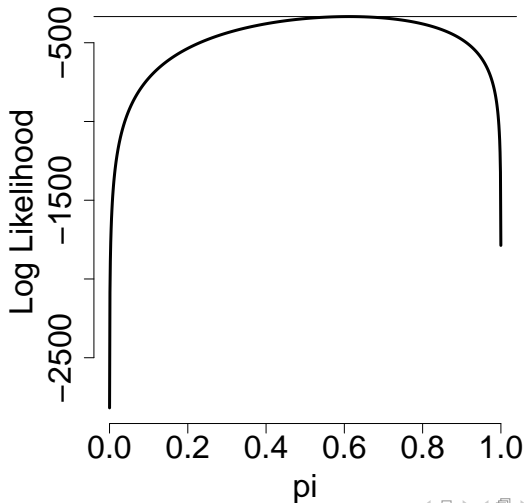
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For a fixed set of observations, what does this look like?

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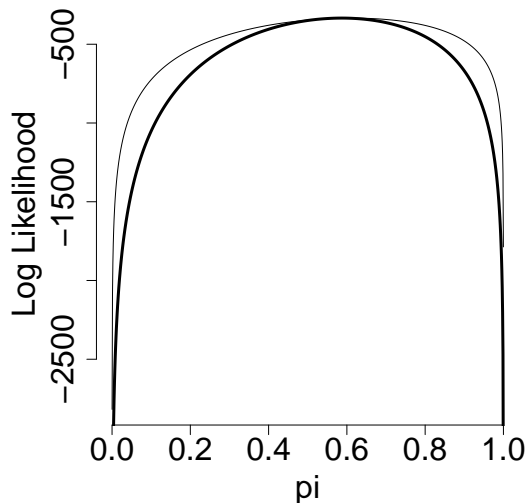
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Uncertainty About Mode

$\pi^* = \bar{y}$ maximizes $L(\pi|\mathbf{y})$.

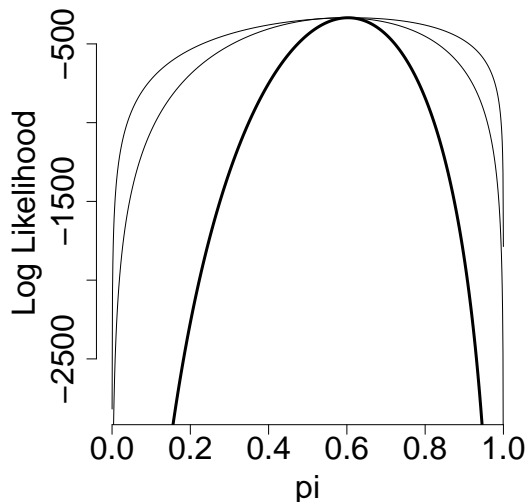
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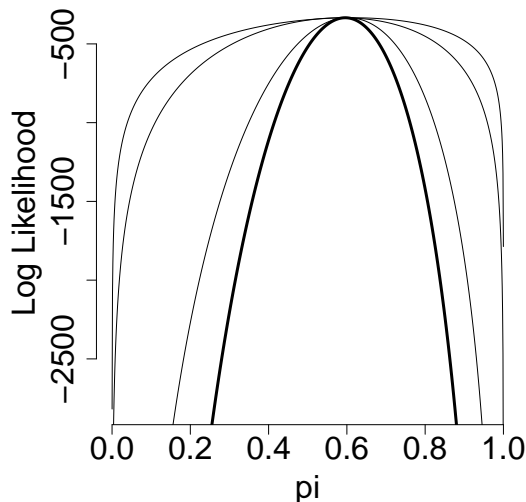
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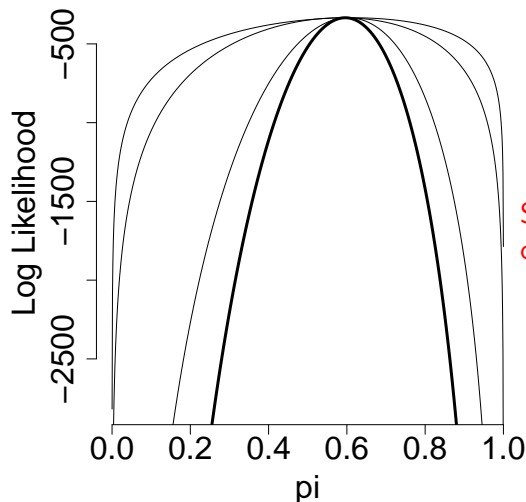
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Second derivative captures this curvature

The **Fisher Information** measures the information that \mathbf{y} conveys about the parameter θ . Define it using the two equivalent definitions:

Definition

The **Fisher Information** for a log-likelihood $l(\theta|\mathbf{Y})$ is

$$\begin{aligned} I(\theta) &= E \left[\left(\frac{\partial l(\theta|\mathbf{Y})}{\partial \theta} \right)^2 \middle| \theta \right] \\ &= -E \left[\left(\frac{\partial^2 l(\theta|\mathbf{Y})}{\partial \theta \partial \theta} \right) \middle| \theta \right] \end{aligned}$$

The **observed Fisher information** for a sample of n observations is given by

$$I_n(\theta) = -\frac{\partial^2}{\partial \theta^2} l(\theta|\mathbf{y})$$

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Inverting the information provides the asymptotic variance for the maximum likelihood estimator (under some regulatory conditions we will discuss later)

$$\text{Variance}(\theta^*) = \frac{1}{nI_1(\theta^*)}$$

$$\text{Standard Error}(\theta^*) = \sqrt{\frac{1}{nI_1(\theta^*)}}$$

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- **Curvature** determines sampling distribution of maximum likelihood estimator

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- 1) The MLE gets as “close” as possible to the true answer

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Definition

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Proposition

MLE is consistent: Assume y_1, y_2, \dots, y_n are simple random samples from $p(y|\theta_0)$. Define θ_n^* as the mle estimator with sample size n . Then, as $n \rightarrow \infty$, $\theta_n^* \rightarrow \theta_0$ (in probability)

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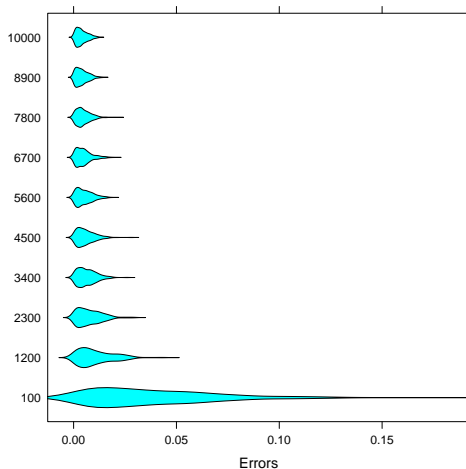
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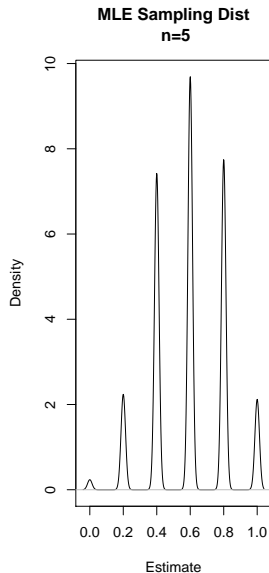
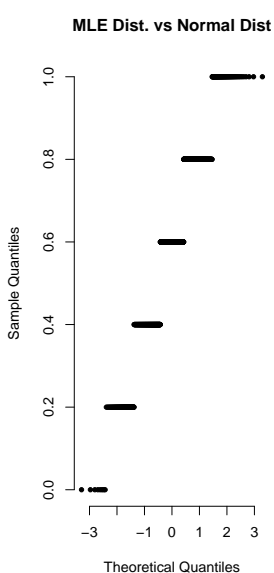
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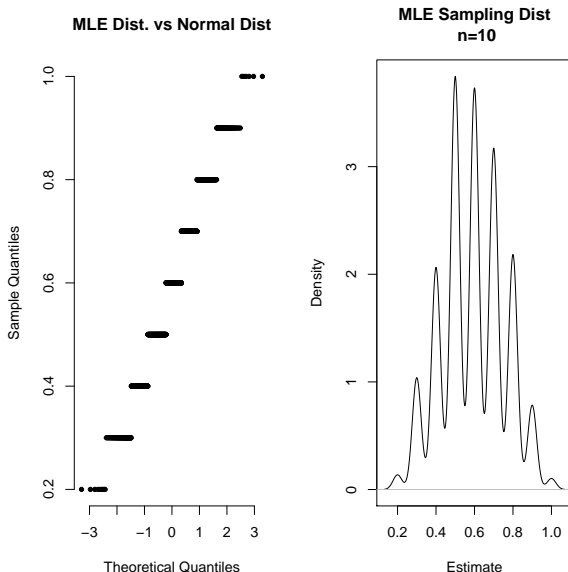
- MLE central limit theorem
- As we have more observations, the MLE converges, **in distribution** to a normal distribution

Central Limit Theorem for Maximum Likelihood Estimators



Example:
 $\pi = 0.6$
Increasing n

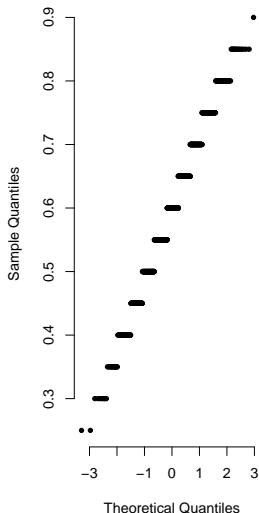
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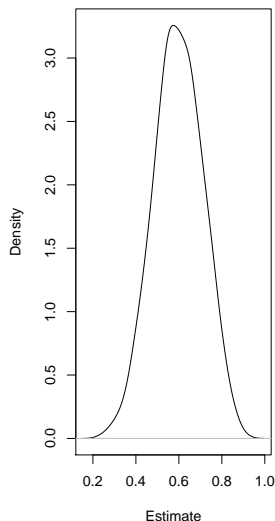
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Central Limit Theorem for Maximum Likelihood Estimators

MLE Dist. vs Normal Dist



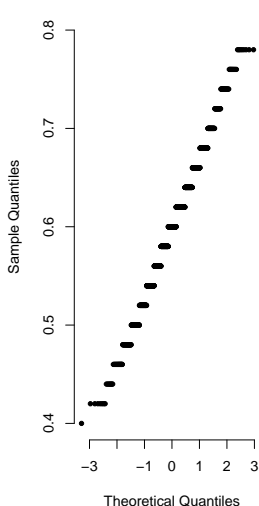
MLE Sampling Dist
n=20



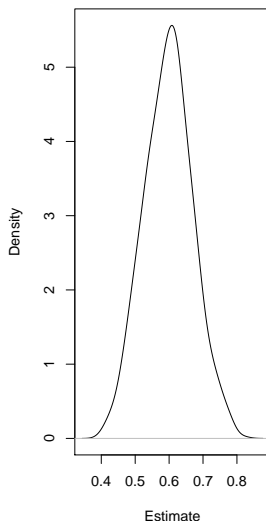
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Central Limit Theorem for Maximum Likelihood Estimators

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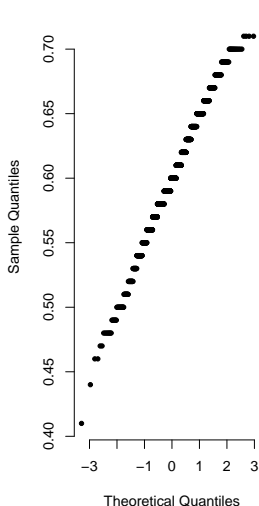
MLE Sampling Dist
n=50



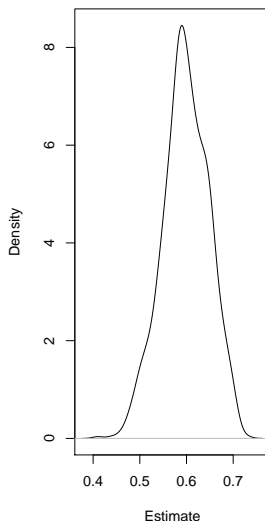
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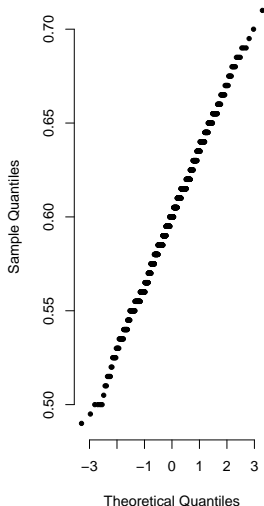
MLE Sampling Dist
 $n=100$



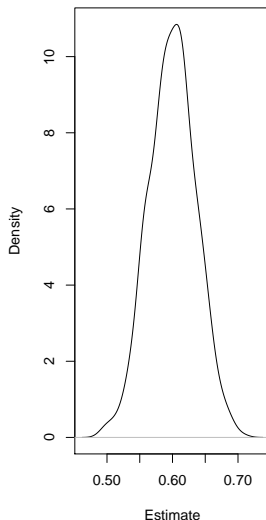
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Central Limit Theorem for Maximum Likelihood Estimators

MLE Dist. vs Normal Dist



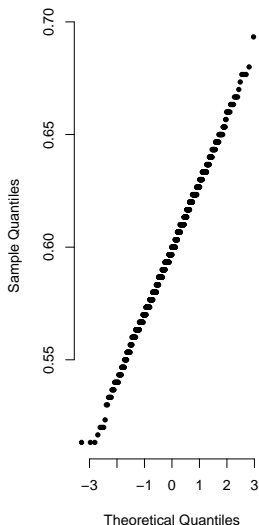
MLE Sampling Dist
n=200



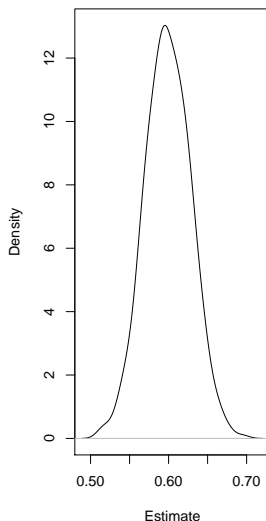
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Central Limit Theorem for Maximum Likelihood Estimators

MLE Dist. vs Normal Dist

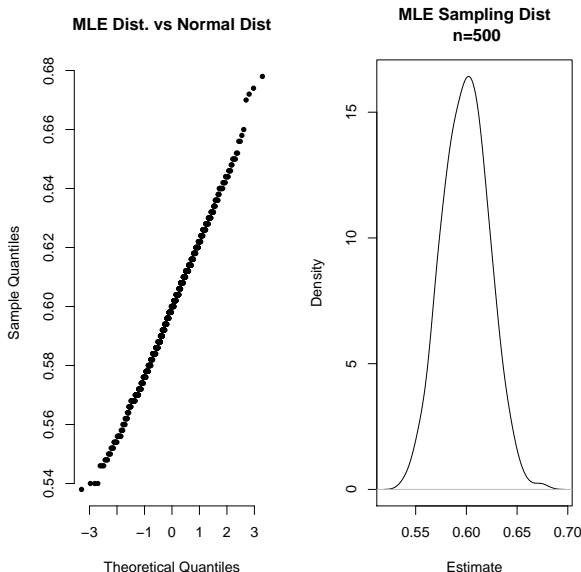


MLE Sampling Dist
n=300



Example:
 $\pi = 0.6$
Increasing n

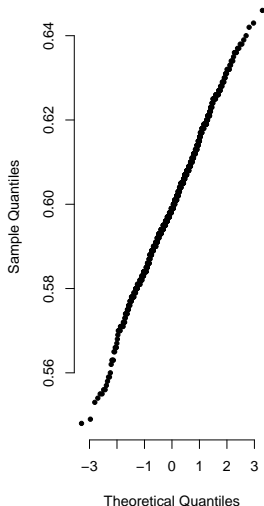
Central Limit Theorem for Maximum Likelihood Estimators



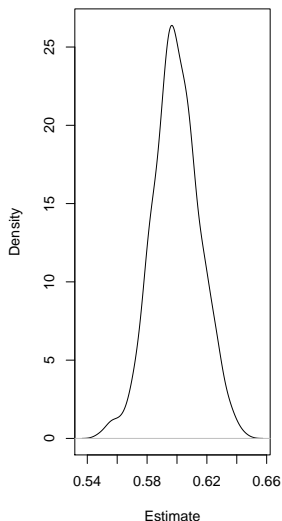
Example:
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Increasing n

Central Limit Theorem for Maximum Likelihood Estimators

MLE Dist. vs Normal Dist

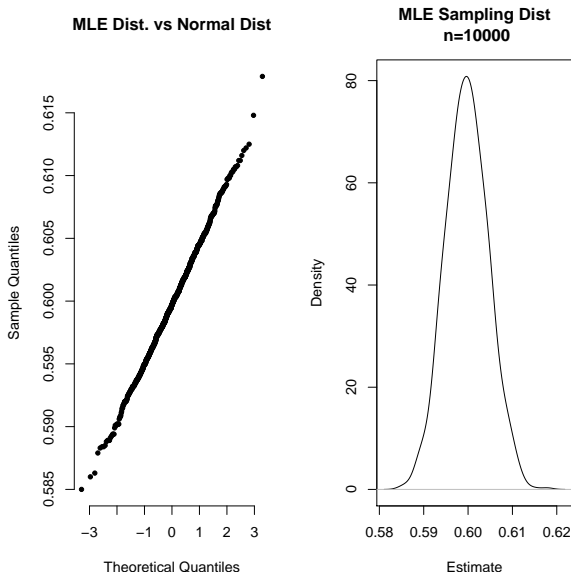


MLE Sampling Dist
n=1000



Example:
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Central Limit Theorem for Maximum Likelihood Estimators



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Returning to Our Examples

Summary: θ^* is an MLE and θ_0 is the true value and we know the right distributional family

1) As $n \rightarrow \infty$, $\theta_n^* \rightarrow \theta_0$

2) As $n \rightarrow \infty$, $\sqrt{n}(\theta_n^* - \theta_0) \rightarrow \text{Normal}(0, \frac{1}{I(\theta_0)})$

where $I(\theta_0) = -\frac{\partial^2}{\partial \pi^2} l(\theta_0|y)$ or curvature of log-likelihood at true value of θ_0

Two-parameter MLE

Multivariate Normal Distribution

Suppose that we have a vector of random variables,

$$\mathbf{X} = (X_1, X_2, \dots, X_k)$$

Then we'll say that $X \sim \text{Multivariate Normal}(\boldsymbol{\mu}, \boldsymbol{\Sigma})$ where,

$$\boldsymbol{\mu} = (\mu_1, \mu_2, \dots, \mu_k)$$

$$\boldsymbol{\Sigma} = \begin{pmatrix} \sigma_1^2 & \text{Cov}(X_1, X_2) & \text{Cov}(X_1, X_3) & \dots & \text{Cov}(X_1, X_n) \\ \text{Cov}(X_1, X_2) & \sigma_2^2 & \text{Cov}(X_2, X_3) & \dots & \text{Cov}(X_2, X_n) \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \text{Cov}(X_1, X_k) & \text{Cov}(X_2, X_k) & \text{Cov}(X_3, X_k) & \dots & \sigma_k^2 \end{pmatrix}$$

Multivariate Normal Distribution

$$f(\mathbf{x}) = \frac{1}{(2\pi)^{k/2} |\boldsymbol{\Sigma}|^{1/2}} \exp \left(-\frac{1}{2} (\mathbf{x} - \boldsymbol{\mu})' \boldsymbol{\Sigma}^{-1} (\mathbf{x} - \boldsymbol{\mu}) \right)$$

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Inverting the Fisher-information matrix provides **Variance-Covariance Matrix**

Maximum Likelihood Estimation, Normal Distribution

Example 2:

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- Obtain likelihood (summary estimator)
- Derive maximum likelihood estimators for μ and σ^2
- Characterize sampling distribution

Maximum Likelihood Estimation, Normal Distribution

Maximum Likelihood Estimation, Normal Distribution

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Maximum Likelihood Estimation, Normal Distribution

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$$l(\mu, \sigma^2 | \mathbf{y}) = -\sum_{i=1}^n \frac{(y_i - \mu)^2}{2\sigma^2} - \frac{n}{2} \log(2\pi) - \frac{n}{2} \log(\sigma^2)$$

Maximum Likelihood Estimation, Normal Distribution

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Maximum Likelihood Estimation, Normal Distribution

Let's find μ^* and $(\sigma^2)^*$ that maximizes log-likelihood.

$$l(\mu, \sigma^2 | \mathbf{y}) = - \sum_{i=1}^n \frac{(y_i - \mu)^2}{2\sigma^2} - \frac{n}{2} \log(\sigma^2) + \textcolor{red}{c}$$

$$\frac{\partial l(\mu, \sigma^2) | \mathbf{y}}{\partial \mu} = - \sum_{i=1}^n \frac{2(y_i - \mu)}{2\sigma^2}$$

$$\frac{\partial l(\mu, \sigma^2) | \mathbf{y}}{\partial \sigma^2} = - \frac{n}{2\sigma^2} + \frac{1}{2\sigma^4} \sum_{i=1}^n (Y_i - \mu)^2$$

Maximum Likelihood Estimation, Normal Distribution

$$0 = -\sum_{i=1}^n \frac{2(y_i - \mu^*)}{2\sigma^2}$$

$$0 = -\frac{n}{2\sigma^2} + \frac{1}{2\sigma^4} \sum_{i=1}^n (y_i - \mu^*)^2$$

Solving for μ and σ^2 yields,

$$\mu^* = \frac{\sum_{i=1}^n y_i}{n}$$

$$\sigma^2 = \frac{1}{n} \sum_{i=1}^n (y_i - \bar{y})^2$$

Maximum Likelihood Estimation, Normal Distribution

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Taking derivatives and evaluating at MLE's yields

$$I_n(\mu^*, \hat{\sigma}^2) = \begin{pmatrix} \frac{n}{\hat{\sigma}^2} & 0 \\ 0 & \frac{n}{(\hat{\sigma}^2)^2} \end{pmatrix}$$

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$$p(\mu, \sigma^2) \rightarrow^d \text{Multivariate Normal} \left(\left(\bar{y}, \frac{1}{n} \sum_{i=1}^n (y_i - \bar{y})^2 \right), \begin{pmatrix} \frac{\hat{\sigma}^2}{n} & 0 \\ 0 & \frac{(\hat{\sigma}^2)^2}{n} \end{pmatrix} \right)$$

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Therefore, as $n \rightarrow \infty$, we have that

$$p(\mu, \sigma^2) \rightarrow^d \text{Multivariate Normal} \left(\left(\bar{y}, \frac{1}{n} \sum_{i=1}^n (y_i - \bar{y})^2 \right), \begin{pmatrix} \frac{\hat{\sigma}^2}{n} & 0 \\ 0 & \frac{(\hat{\sigma}^2)^2}{n} \end{pmatrix} \right)$$

Because normal distribution \Rightarrow that mle of μ and σ^2 are **independent**!

Maximum Likelihood Estimation, Normal Distribution

Multivariate analogy: observed Fisher information **matrix** (Negative Hessian) (Negative matrix of second derivatives)

$$I_n(\mu^*, \hat{\sigma}^2) = - \begin{pmatrix} \frac{\partial^2 l(\mu, \sigma^2 | \mathbf{y})}{\partial \mu^2} & \frac{\partial^2 l(\mu, \sigma^2 | \mathbf{y})}{\partial \sigma^2 \partial \mu} \\ \frac{\partial^2 l(\mu, \sigma^2 | \mathbf{y})}{\partial \sigma^2 \partial \mu} & \frac{\partial^2 l(\mu, \sigma^2 | \mathbf{y})}{\partial^2 \sigma^2} \end{pmatrix}$$

Taking derivatives and evaluating at MLE's yields

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Because normal distribution \Rightarrow that mle of μ and σ^2 are **independent**!

This is an asymptotic result: results will vary with small sample sizes

Up next:

- 1) Linear regression in maximum likelihood
- 2) Logit/Probit
- 3) Numerical optimization