

ECON 709 - PS 6

Alex von Hafften*

10/18/2020

1. Let X be distributed Bernoulli $P(X = 1) = p$ and $P(X = 0) = 1 - p$ for some unknown parameter $0 < p < 1$.

(a) Verify the probability mass function can be written as $f(x) = p^x(1 - p)^{(1-x)}$.

$$\begin{aligned}f(1) &= p^1(1 - p)^{(1-1)} = p = P(X = 1) \\f(0) &= p^0(1 - p)^{(1-0)} = 1 - p = P(X = 0)\end{aligned}$$

(b) Find the log-likelihood function $\ell_n(\theta)$.

$$\begin{aligned}\ell_n(\theta) &= \sum_{i=1}^n \ln(f(x_i|\theta)) \\&= \sum_{i=1}^n \ln(p^{x_i}(1 - p)^{(1-x_i)}) \\&= \sum_{i=1}^n [x_i \ln(p) + (1 - x_i) \ln(1 - p)] \\&= \ln(p) \sum_{i=1}^n x_i + \ln(1 - p) \left(n - \sum_{i=1}^n x_i \right)\end{aligned}$$

(c) Find the MLE \hat{p} for p .

$$\begin{aligned}\frac{\partial \ell_n}{\partial p} &= 0 \\ \frac{\partial}{\partial p} \left[\ln(p) \sum_{i=1}^n x_i + \ln(1 - p) \left(n - \sum_{i=1}^n x_i \right) \right] &= 0 \\ \frac{\sum_{i=1}^n x_i}{p} - \frac{\left(n - \sum_{i=1}^n x_i \right)}{1 - p} &= 0 \\ \sum_{i=1}^n x_i &= pn - p \sum_{i=1}^n x_i + p \sum_{i=1}^n x_i \\ \hat{p} &= \frac{1}{n} \sum_{i=1}^n x_i \\ \hat{p} &= \bar{X}_n\end{aligned}$$

*I worked on this problem set with a study group of Michael Nattinger, Andrew Smith, and Ryan Mather. I also discussed problems with Emily Case, Sarah Bass, and Danny Edgel.

2. Let X be distributed Pareto with density $f(x) = \frac{\alpha}{x^{1+\alpha}}$ for $x \geq 1$. The unknown parameter is $\alpha > 0$.
(a) Find the log-likelihood function $\ell_n(\alpha)$.

$$\begin{aligned}\ell_n(\alpha) &= \sum_{i=1}^n \ln(f(x_i|\alpha)) \\ &= \sum_{i=1}^n \ln\left(\frac{\alpha}{x_i^{1+\alpha}}\right) \\ &= \sum_{i=1}^n \ln \alpha - \sum_{i=1}^n \ln x_i^{1+\alpha} \\ &= n \ln \alpha - (1 + \alpha) \sum_{i=1}^n \ln x_i\end{aligned}$$

- (b) Find the MLE $\hat{\alpha}_n$ for α .

$$\frac{\partial \ell_n}{\partial \alpha} = 0 \implies \frac{n}{\hat{\alpha}_n} - \sum_{i=1}^n \ln x_i = 0 \implies \hat{\alpha}_n = \frac{n}{\sum_{i=1}^n \ln x_i}$$

3. Let X be distributed Cauchy with density $f(x) = \frac{1}{\pi(1+(x-\theta)^2)}$ for $x \in \mathbb{R}$. The unknown parameter is θ .
(a) Find the log-likelihood function $\ell_n(\theta)$.

$$\begin{aligned}\ell_n(\theta) &= \sum_{i=1}^n \ln(f(x_i|\theta)) \\ &= \sum_{i=1}^n \ln\left(\frac{1}{\pi(1+(x_i-\theta)^2)}\right) \\ &= -\sum_{i=1}^n \ln(\pi) - \sum_{i=1}^n \ln(1+(x_i-\theta)^2) \\ &= -n \ln(\pi) - \sum_{i=1}^n \ln(1+(x_i-\theta)^2)\end{aligned}$$

- (b) Find the first-order condition for the MLE $\hat{\theta}$ for θ . You will not be able to solve for $\hat{\theta}$.

$$\frac{\partial \ell_n}{\partial \theta} = 0 \implies 0 - \sum_{i=1}^n \frac{2(x_i - \theta)(-1)}{1 + (x_i - \theta)^2} \implies \sum_{i=1}^n \frac{2(x_i - \theta)}{1 + (x_i - \theta)^2}$$

4. Let X be distributed double exponential (or Laplace) with density $f(x) = \frac{1}{2} \exp(-|x - \theta|)$ for $x \in \mathbb{R}$. The unknown parameter is θ .

(a) Find the log-likelihood function $\ell_n(\theta)$.

$$\begin{aligned}\ell_n(\theta) &= \sum_{i=1}^n \ln(f(x_i|\theta)) \\ &= \sum_{i=1}^n \ln\left(\frac{1}{2} \exp(-|x_i - \theta|)\right) \\ &= -\sum_{i=1}^n \ln(2) + \sum_{i=1}^n \ln(\exp(-|x_i - \theta|)) \\ &= -n \ln(2) - \sum_{i=1}^n |x_i - \theta|\end{aligned}$$

(b) Extra challenge: Find the MLE $\hat{\theta}_n$ for θ . This is challenging as it is not simply solving the FOC due to the nondifferentiability of the density function.

$$\ell_n(\theta) = -n \ln(2) - \sum_{i=1}^n |x_i - \theta| = -n \ln(2) - \sum_{i=1}^n ((x_i - \theta)^2)^{1/2}$$

$\ell_n(\theta)$ is now differentiable.

$$\frac{\partial \ell_n}{\partial \theta} = -(1/2) \sum_{i=1}^n ((x_i - \theta)^2)^{-1/2} (2(x_i - \theta))(-1) = \sum_{i=1}^n \frac{x_i - \theta}{|x_i - \theta|}$$

If $x_i > \theta$, $\frac{x_i - \theta}{|x_i - \theta|} = 1$ and if $x_i < \theta$, $\frac{x_i - \theta}{|x_i - \theta|} = -1$.

...

5. Take the Pareto model $f(x) = \alpha x^{-1-\alpha}, x \geq 1$. Calculate the information for α using the second derivative.

The information for α is

$$\begin{aligned}
I_0 &= -E \left[\frac{\partial^2}{\partial^2 \alpha} \log(\alpha X^{-1-\alpha}) \Big|_{\alpha=\alpha_0} \right] \\
&= -E \left[\frac{\partial^2}{\partial^2 \alpha} (-1 - \alpha)(\log \alpha + \log X) \Big|_{\alpha=\alpha_0} \right] \\
&= -E \left[\frac{\partial^2}{\partial^2 \alpha} (-\log \alpha - \log X - \alpha \log \alpha - \alpha \log X) \Big|_{\alpha=\alpha_0} \right] \\
&= -E \left[\frac{\partial}{\partial \alpha} \left(-\frac{1}{\alpha} - \log \alpha - 1 - \log X \right) \Big|_{\alpha=\alpha_0} \right] \\
&= -E \left[\frac{1}{\alpha^2} - \frac{1}{\alpha} \Big|_{\alpha=\alpha_0} \right] \\
&= \frac{1}{\alpha_0} - \frac{1}{\alpha_0^2}
\end{aligned}$$

6. Take the model $f(x) = \theta \exp(-\theta x), x \geq 0, \theta > 0$.

(a) Find the Cramer-Rao lower bound for θ .

$$\begin{aligned}
I_0 &= -E \left[\frac{\partial^2}{\partial^2 \theta} \log(\theta \exp(-\theta X)) \Big|_{\theta=\theta_0} \right] \\
&= -E \left[\frac{\partial^2}{\partial^2 \theta} \log(\theta) - \theta X \Big|_{\theta=\theta_0} \right] \\
&= -E \left[\frac{\partial}{\partial \theta} \frac{1}{\theta} - \theta \Big|_{\theta=\theta_0} \right] \\
&= -E \left[-\frac{1}{\theta^2} \Big|_{\theta=\theta_0} \right] \\
&= \frac{1}{\theta_0^2}
\end{aligned}$$

Thus, the Cramer-Rao lower bound is $(nI_0)^{-1} = (n\theta_0^{-2})^{-1} = \theta_0^2/n$.

- (b) Find the MLE $\hat{\theta}_n$ for θ . Notice that this is a function of the sample mean. Use this formula and the delta method to find the asymptotic distribution for $\hat{\theta}_n$.

The log-likelihood function $\ell_n(\theta)$ is

$$\begin{aligned}\ell_n(\theta) &= \sum_{i=1}^n \ln(f(x_i|\theta)) \\ &= \sum_{i=1}^n \ln(\theta \exp(-\theta x_i)) \\ &= \sum_{i=1}^n (\ln(\theta) - \theta x_i) \\ &= n \ln(\theta) - \theta \sum_{i=1}^n x_i \\ &= n \ln(\theta) - n\theta \bar{X}_n\end{aligned}$$

Thus, $\hat{\theta}_n$ is

$$\frac{\partial \ell_n}{\partial \theta} = 0 \implies 0 = \frac{n}{\hat{\theta}_n} - n\bar{X}_n \implies \hat{\theta}_n = \frac{1}{\bar{X}_n}$$

By the delta method, $\sqrt{n}(\hat{\theta}_n - \theta_0) \rightarrow_d N(0, V)$ where $V = \left((-1)\left(\frac{1}{\theta_0}\right)^{-2}\right)^2 \sigma^2 = \sigma^2 \theta_0^4$ and $\sigma^2 = \text{Var}(X) = \frac{1}{\theta_0^2}$. Therefore, $\sqrt{n}(\hat{\theta}_n - \theta_0) \rightarrow_d N(0, \theta_0^2)$

- (c) Find the asymptotic distribution for $\hat{\theta}_n$ using the general formula for the asymptotic distribution of MLE introduced in Section 6. Do you find the same answer as in part (b)?

From Section 6, we have that

$$\sqrt{n}(\hat{\theta}_n - \theta_0) \rightarrow_d N(0, I_0^{-1})$$

The information of θ is

$$\begin{aligned}I_0 &= -E \left[\frac{\partial^2}{\partial^2 \theta} \log(\theta \exp(-\theta X)) \Big|_{\theta=\theta_0} \right] \\ &= -E \left[\frac{\partial^2}{\partial^2 \theta} (\log(\theta) - \theta X) \Big|_{\theta=\theta_0} \right] \\ &= -E \left[\frac{\partial}{\partial \theta} (\theta^{-1} - X) \Big|_{\theta=\theta_0} \right] \\ &= -E \left[-\theta^{-2} \Big|_{\theta=\theta_0} \right] \\ &= \theta_0^{-2}\end{aligned}$$

Therefore, we get the same asymptotic distribution:

$$\sqrt{n}(\hat{\theta}_n - \theta_0) \rightarrow_d N(0, \theta_0^2)$$

7. In the Bernoulli model, you found the asymptotic distribution of the MLE in Problem 1(c).

(a) Propose an estimator of V , the asymptotic variance.

In 1(c), we found that $\hat{p} = \bar{X}_n$. So, by the CLT, we know that $\sqrt{n}(\hat{p} - p) \rightarrow_d N(0, \sigma^2)$ where $\sigma^2 = \text{Var}(X)$. Thus, V should be an estimator for $\text{Var}(X)$. Since X is Bernoulli, consider $\bar{X}_n(1 - \bar{X}_n)$.

(b) Show that this estimator is consistent for V as $n \rightarrow \infty$.

By the WLLN, $\bar{X}_n \rightarrow_p p$. Define g as $g(x) = x(1 - x)$. By the continuous mapping theorem, $\bar{X}_n(1 - \bar{X}_n) = g(\bar{X}_n) \rightarrow_p g(p) = p(1 - p) = \text{Var}(X)$.

(c) Propose a standard error $s(\hat{p}_n)$ for the MLE \hat{p}_n .¹

Based on (a) and (b), consider $s(\hat{p}_n) = \frac{\sqrt{\bar{X}_n(1 - \bar{X}_n)}}{\sqrt{n}}$.

8. Consider the MLE for the upper bound of the uniform distribution in the Uniform Boundary example in Section 3. Assume that $\{X_1, \dots, X_n\}$ is a random sample from $\text{Uniform}[0, \theta]$. The general asymptotic distribution formula in Section 6 does not apply here because $\ell_n(\theta)$ is not differentiable at the MLE. But you can derive the asymptotic distribution using the definition of convergences in distribution. Do so by following the steps below.

(a) Let F_X denote the CDF of $\text{Uniform}[0, \theta]$. Calculate $F_X(c)$ for all $c \in \mathbb{R}$ based on the PDF of $\text{Uniform}[0, \theta]$.

$$F_X(c) = \int_{-\infty}^c f_X(x) dx = \begin{cases} 0, & c < 0 \\ c/\theta, & 0 \leq c < \theta \\ 1, & \theta \leq c \end{cases}$$

Because $\int_0^c \frac{1}{\theta} dx = \frac{c}{\theta}$.

(b) Show that the CDF of $n(\hat{\theta}_n - \theta) : F_{n(\hat{\theta}_n - \theta)}(x) = \Pr(\max_{i=1, \dots, n} (n(X_i - \theta)) \leq x) = (F_X(\theta + \frac{x}{n}))^n$.

In Section 3, we found that $\hat{\theta}_n = \max_{i=1, \dots, n} X_i$. Because $n(\hat{\theta}_n - \theta) = n(\max_{i=1, \dots, n} (X_i) - \theta) = \max_{i=1, \dots, n} (n(X_i - \theta))$. Thus, $F_{n(\hat{\theta}_n - \theta)}(x) = \Pr(\max_{i=1, \dots, n} (n(X_i - \theta)) \leq x)$. Furthermore,

$$\begin{aligned} \Pr\left(\max_{i=1, \dots, n} (n(X_i - \theta)) \leq x\right) &= \Pr(n(X_i - \theta) \leq x \forall i = 1, \dots, n) \\ &= \prod_{i=1}^n \Pr(n(X_i - \theta) \leq x) \\ &= \Pr(n(X_i - \theta) \leq x)^n \\ &= \Pr\left(X_i \leq \frac{x}{n} + \theta\right)^n \\ &= \left(F_X\left(\theta + \frac{x}{n}\right)\right)^n \end{aligned}$$

¹Recall that the standard error is supposed to approximate the variance of \hat{p}_n , not that of the variance of $\sqrt{n}(\hat{p}_n - p)$. What would be a reasonable approximation of the variance of \hat{p}_n once you have a reasonable approximation of the variance of $\sqrt{n}(\hat{p}_n - p)$ from part (b)?

(c) Recall that $\lim_{n \rightarrow \infty} (1 + \frac{y}{n})^n = e^y$ for any $y \in \mathbb{R}$. Derive the limit of $F_{n(\hat{\theta}_n - \theta)}(x)$ for all fixed $x \in \mathbb{R}$.² Fix $x \in \mathbb{R}$. If $x < 0$,

$$\begin{aligned} \lim_{n \rightarrow \infty} F_{n(\hat{\theta}_n - \theta)}(x) &= \lim_{n \rightarrow \infty} \left(F_X \left(\theta + \frac{x}{n} \right) \right)^n \\ &= \lim_{n \rightarrow \infty} \left(\theta^{-1} \left(\theta + \frac{x}{n} \right) \right)^n \\ &= \lim_{n \rightarrow \infty} \left(\theta^{-1} \left(\theta \left(1 + \frac{x/\theta}{n} \right) \right) \right)^n \\ &= \lim_{n \rightarrow \infty} \left(1 + \frac{x/\theta}{n} \right)^n \\ &= e^{x/\theta} \end{aligned}$$

If $x \geq 0$,

$$\begin{aligned} \lim_{n \rightarrow \infty} F_{n(\hat{\theta}_n - \theta)}(x) &= \lim_{n \rightarrow \infty} \left(F_X \left(\theta + \frac{x}{n} \right) \right)^n \\ &= \lim_{n \rightarrow \infty} (1)^n \\ &= 1 \end{aligned}$$

(d) Conclude that $n(\hat{\theta}_n - \theta) \rightarrow_d -Z$ for Z being an exponential distribution with parameter θ .

Since $F_{n(\hat{\theta}_n - \theta)}(x) \rightarrow e^{x/\theta}$, $f_{n(\hat{\theta}_n - \theta)}(x) = \frac{\partial}{\partial x} F_{n(\hat{\theta}_n - \theta)}(x) \rightarrow \frac{\partial}{\partial x} e^{x/\theta} = \frac{e^{x/\theta}}{\theta}$. Thus, $f_{n(\hat{\theta}_n - \theta)}(-x) = \frac{e^{-x/\theta}}{\theta}$, which is the density function of an exponential distribution with parameter θ . So $n(\hat{\theta}_n - \theta) \rightarrow_d -Z$ for Z being an exponential distribution with parameter θ .

9. Take the model $X \sim N(\mu, \sigma^2)$. Propose a test for $H_0 : \mu = 1$ against $H_1 : \mu \neq 1$.

Assuming that σ^2 is unknown, we can use a two-sided t-test by constructing the following t-statistic:

$$T = \frac{|\sqrt{n}(\bar{X}_n - 1)|}{S_X}$$

where $S_X^2 = \frac{1}{n-1} \sum (X_i - \bar{X}_n)^2$. Under the $H_0 : \mu = 1$, $T \sim |t_{n-1}|$. Therefore, $\phi_n(\alpha) = 1(T > t_{\alpha/2, n-1})$ where $t_{\alpha/2, n-1}$ is the $(1 - \alpha/2)$ quantile of t_{n-1} .

If σ^2 is known, we can use a z-test by replacing S_X with σ in the test statistic:

$$T = \frac{|\sqrt{n}(\bar{X}_n - 1)|}{\sigma}$$

Under the $H_0 : \mu = 1$, $T \sim |N(0, 1)|$. Therefore, $\phi_n(\alpha) = 1(T > z_{\alpha/2})$ where $z_{\alpha/2}$ is the $(1 - \alpha/2)$ quantile of a standard normal.

²Hint: consider the case where $x < 0$ and the case where $x \geq 0$ separately.

10. Take the model $X \sim N(\mu, 1)$. Consider testing $H_0 : \mu \in \{0, 1\}$ against $H_1 : \mu \notin \{0, 1\}$. Consider the test statistic $T = \min\{|\sqrt{n}\bar{X}_n|, |\sqrt{n}(\bar{X}_n - 1)|\}$. Let the critical value be the $1 - \alpha$ quantile of the random variable $\min\{|Z|, |Z - \sqrt{n}|\}$, where $Z \sim N(0, 1)$. Show that $\Pr(T > c | \mu = 1) = \alpha$. Conclude that the size of the test $\phi_n = 1(T > c)$ is α .³

$$\Pr(T > c | \mu = 1) = \Pr(\min\{|\sqrt{n}\bar{X}_n|, |\sqrt{n}(\bar{X}_n - 1)|\} > c | \mu = 1)$$

³Use the fact that Z and $-Z$ have the same distribution. This is an example where the null distribution is the same under different points in a composite null. The test $\phi_n = 1(T > c)$ is called a similar test because $\inf_{\theta_0 \in \Theta_0} \Pr(T > c | \theta = \theta_0) = \sup_{\theta_0 \in \Theta_0} \Pr(T > c | \theta = \theta_0)$.