

Math 541 A - Spring 2025  
Midterm 2  
April 9, 2025  
11:00-11:50 AM

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- There are 3 problems in total. Make sure your exam contains all these questions.
- You are allowed to use one page of double-sided **hand-written** 8.5 by 11 inch notes.
- You must show your work on all problems. The correct answer with no supporting work may result in no credit.
- If you need more room, use the backs of the pages and indicate to the grader that you have done so.

Problem 1	20	
Problem 2	20	
Problem 3	20	
Total	60	

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1. (20 pts) Let  $X_1, \dots, X_n \sim N(\mu, 1)$  be i.i.d. samples. Recall the PDF for  $N(\mu, 1)$  is

$$f(x|\mu) = \frac{1}{\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2}}.$$

(a) (7 pts) For one random variable  $X \sim N(\mu, 1)$ , compute its Fisher information

$$I_X(\mu) = \mathbb{E} \left( \frac{d}{d\mu} \log f(X|\mu) \right)^2.$$

(b) (6 pts) Find the the Cramé-Rao lower bound for any unbiased estimator (as a function of  $X_1, \dots, X_n$ ) of  $\mu$ .

(c) (7 pts) Assume  $X_1, \dots, X_n \sim N(0, 1)$  be i.i.d. random variables. Show the following convergence in distribution holds:

$$\frac{\sum_{i=1}^n (X_i^2 - 1)}{\sqrt{2n}} \xrightarrow{d} N(0, 1).$$

$$a) \quad \frac{d}{d\mu} \log f(x|\mu) = \frac{d}{d\mu} \left[ \log \frac{1}{\sqrt{2\pi}} - \frac{(x-\mu)^2}{2} \right] = \frac{-2(x-\mu)}{2} \cdot \frac{1}{\sqrt{2\pi}} = -(x-\mu)$$

$$\mathbb{E}_X \left[ \left( \frac{d}{d\mu} \log f(x|\mu) \right)^2 \right] = \mathbb{E}_X \left[ (X-\mu)^2 \right] = \text{Var}(X) = 1$$

$$b) \quad \text{C.R. lower bound} = \frac{1}{n I_X(\mu)} = \frac{1}{n \cdot 1} = \frac{1}{n}$$

c) By CLT

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$$p^2 \cdot \frac{1-p}{1-p} + (1-p)^2 \cdot \frac{p}{1-p} = p^2 + (1-p)^2$$

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2. (20 pts) Let  $X_1, \dots, X_n$  be i.i.d.  $\text{Ber}(p)$ .

(a) (5 pts) Show that the following convergence in probability holds:

$$\frac{1}{n^2}(X_1 + \dots + X_n)^2 \xrightarrow{p} p^2.$$

(b) (5 pts) Consider a risk function for any estimator  $\delta(\mathbf{X})$  of  $p$  given by

$$R(p, \delta(\mathbf{X})) = \mathbb{E}_p |\delta(\mathbf{X}) - p|.$$

Let  $\delta(\mathbf{X}) = X_1$  be the estimator, and  $\pi(p) = \text{Uniform}(0, 1)$  be the prior distribution on  $p$ . Find the Bayes risk

$$\int_0^1 R(p, \delta(\mathbf{X})) \pi(p) dp.$$

(c) (10 pts) Show that  $\phi(\mathbf{X}) = X_1 X_2$  is an unbiased estimator of  $p^2$ . Based on  $\phi(\mathbf{X})$  and the Lehmann-Scheffé Theorem, find the best unbiased estimator  $W = W(X_1, \dots, X_n)$  of  $p^2$  with an explicit form.

$$\begin{aligned} \text{a) } E\left[\frac{1}{n^2}(X_1 + \dots + X_n)^2\right] &= \text{Var}\left(\frac{1}{n}(X_1 + \dots + X_n)\right) + E\left[\frac{1}{n}(X_1 + \dots + X_n)\right]^2 \\ &= \frac{1}{n} p(1-p) + p^2 = p^2 + \frac{p(1-p)}{n}. \end{aligned}$$

Also  $\text{var}\left(\frac{1}{n^2}(X_1 + \dots + X_n)^2\right) < \infty$ .  $\therefore$  by WLL,  $\frac{1}{n^2}(X_1 + \dots + X_n)^2 \xrightarrow{p} p^2$ .

$$\pi(p|\mathbf{x}) = \frac{L(\mathbf{x}|p) \cdot \pi(p)}{\int_{p \in (0,1)} L(\mathbf{x}|p) \cdot \pi(p) dp} = \frac{p^{x_1} (1-p)^{1-x_1} \cdot 1}{\int_0^1 p^{x_1} (1-p)^{1-x_1} dp} = \frac{p^{x_1} (1-p)^{1-x_1}}{\frac{1}{x_1+1-x_1+1}} = (x_1+1) p^{x_1} (1-p)^{1-x_1}$$

Bayes risk for absolute error loss is median of posterior.

~~Bayes risk~~

$$\text{b) } \pi(p|\mathbf{x}) = L(\mathbf{x}|p) \cdot \pi(p) = p^{x_1} (1-p)^{1-x_1} \cdot 1_{[0,1]}(p)$$

The minimizer is the median of posterior.

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(c)  $\phi(X) = X_1 X_2$  is unbiased estimator for  $p^2$ .

~~$f(\vec{x}|p) = p^2 x_1 (1-p)^{x_1-1} \sum_{k=0}^{\infty} \binom{x_2}{k} p^k (1-p)^{x_2-k}$~~

We ~~know that~~ need to find a complete sufficient statistic  $T$  of  $p^2$  & by L. Schotté.

$W = E[\phi(X) | T]$  is the UMVUE

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3. (20 pts) Let  $X_1, \dots, X_n$  be i.i.d.  $\text{Exp}(\lambda)$  with pdf  $f(x; \lambda) = \lambda e^{-\lambda x}$  for  $x > 0$ . For each  $i = 1, \dots, n$ , define the indicator  $Y_i = 1\{X_i > 1\}$ .

- (a) (7 pts) Compute the log-likelihood function

$$\log L(\lambda) = \log f(X_1, \dots, X_n | \lambda).$$

- (b) (7 pts) Consider the  $t$ -th iteration of an EM algorithm for approximating the MLE of  $\lambda$ . For the E-step, expected log-likelihood satisfies

$$Q(\lambda | \lambda^{(t)}) = n \log \lambda - \lambda \sum_{i=1}^n \mathbb{E}[X_i | Y_i, \lambda^{(t)}]. \quad \leftarrow \text{given.} \quad (1)$$

Given Equation (1), find the explicit solution for  $\lambda^{(t+1)}$  in the M-step:

$$\lambda^{(t+1)} = \arg \max_{\lambda} Q(\lambda | \lambda^{(t)}).$$

Your answer should be a function of  $\mathbb{E}[X_i | Y_i, \lambda^{(t)}]$ .

- (c) (6 pts) Compute  $\mathbb{P}(Y_1 = 1 | \lambda)$  and  $\mathbb{E}[X_1 | Y_1 = 1, \lambda]$ .

a)  $\log L(\lambda) = \log f(x_1, \dots, x_n | \lambda) = \log \prod_{i=1}^n \lambda e^{-\lambda x_i} = \sum_{i=1}^n \log \lambda e^{-\lambda x_i}$

$$= n \log \lambda - \lambda \sum_{i=1}^n x_i$$

b)  $\frac{d}{d\lambda} Q(\lambda | \lambda^{(t)}) = \frac{n}{\lambda} - \sum \mathbb{E}[X_i | Y_i, \lambda^{(t)}]$

c)  $\mathbb{P}(Y_1 = 1 | \lambda) = \mathbb{P}(X_1 > 1 | \lambda) = \int_1^{\infty} \lambda e^{-\lambda x} dx = \lambda \int_1^{\infty} e^{-\lambda x} dx$

$$= \lambda \left[ \frac{e^{-\lambda x}}{-\lambda} \right]_1^{\infty} = e^{-\lambda}$$

$$\mathbb{E}[X_1 | Y_1 = 1, \lambda] = \int x f_x(x | Y_1 = 1, \lambda) dx = \int x f_x(x | x > 1, \lambda) dx$$

$$f_x(x | x > 1) = \frac{\lambda e^{-\lambda x}}{e^{-\lambda}} = \lambda e^{-\lambda(x-1)}$$

$$\int_1^{\infty} x \lambda e^{-\lambda(x-1)} dx$$

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$$\begin{aligned} &= \lambda \int_1^{\infty} x e^{-\lambda(x-1)} dx = \lambda \left[ x \int e^{-\lambda(x-1)} dx - \int \int e^{-\lambda(x-1)} dx \right] \\ &= \lambda \left[ x \frac{e^{-\lambda(x-1)}}{-\lambda} \right]_1^{\infty} - \int_1^{\infty} \frac{e^{-\lambda(x-1)}}{-\lambda} dx \\ &= \cancel{\lambda} \left[ \frac{1}{\cancel{\lambda}} + \frac{1}{\cancel{\lambda}} \int_1^{\infty} e^{-\lambda(x-1)} dx \right] \\ &= \left[ 1 + \int_1^{\infty} e^{-\lambda(x-1)} dx \right] \\ &= 1 + \left[ \frac{e^{-\lambda(x-1)}}{-\lambda} \right]_1^{\infty} = 1 - \frac{e^{-\lambda(x-1)}}{\lambda} \Big|_1^{\infty} \\ &= 1 - \left( 0 - \frac{1}{\lambda} \right) = 1 + \frac{1}{\lambda} \end{aligned}$$

