

Lecture 28

Review for the Midterm Test

Chapter 1: Probability and Distributions

Chapter 2: Sampling Distribution

Chapter 3: Point Estimation

Chapter 4: CI Estimation

Appendix B



(i) Midterm Test 2018

- **Time and Date:** 10:00am – 12:00noon, May 27 (Sunday), 120 minutes
- **Venue:** The First Teaching Building, Room 111 (**Class I, 70 students**), Room 108 (**Class I, 40 students**), and Room 110 (**Class II, 90 students**)
- **Range:** Chapters 1–4, Appendix B
- **Assessment:** Midterm test (25%)

(ii) Distribution of Questions in the Midterm Test 2018

- There are **five** questions in the midterm test with **20 marks** per question.
- **Q1–Q2** are in Chapters 1 and 2;
- **Q3–Q4** are in Chapter 3;
- **Q5** is in Chapter 4.

(iii) Bring Your Calculator

- Please bring one **calculator** and check the battery.
- Please bring **two** pens/pencils in case one is not available.
- The Midterm test is the closed book test, i.e., you are not allowed to bring any material (including **iPhone/iPad**) to the test venue.

(iv) Remember Some Densities

- Please remember the pmf/pdf of **Bernoulli**(p), **Binomial**(n, p), **Uniform**(a, b), **Beta**(a, b), and $N(\mu, \sigma^2)$ distributions.
- Other pmfs or pdfs will be given.

0) Given conditional expectation/variance to find the expectation and variance

$$E(X) = E\{E(X|Y)\},$$

$$\text{Var}(X) = E\{\text{Var}(X|Y)\} + \text{Var}\{E(X|Y)\}.$$

全概率?

1) Given two conditional densities,
to find the marginal densities

$$f_X(x)f_{Y|X}(y|x) = f_Y(y)f_{X|Y}(x|y)$$

1. Continuous case

1.10

$$f_X(x) \propto \frac{f_{X|Y}(x|y_0)}{f_{Y|X}(y_0|x)}, \quad \text{任意 } y_0$$

$$f_X(x) = \left\{ \int \frac{f_{Y|X}(y|x)}{f_{X|Y}(x|y)} dy \right\}^{-1}.$$

$$\begin{aligned} & \Pr(X = x_i) \Pr(Y = y_j | X = x_i) \\ &= \Pr(Y = y_j) \Pr(X = x_i | Y = y_j) \end{aligned}$$

2. Discrete case

$$p_i = \Pr(X = x_i) \propto \frac{\Pr(X = x_i | Y = y_{j0})}{\Pr(Y = y_{j0} | X = x_i)} \hat{=} q_i,$$

$$p_i = \frac{q_i}{\sum_{i'} q_{i'}},$$

$$\Pr(X = x_i) = \left\{ \sum_j \frac{\Pr(Y = y_j | X = x_i)}{\Pr(X = x_i | Y = y_j)} \right\}^{-1}.$$

2) Three Methods to Find the Distribution of the Function of Random Variables (§2.1)

3. **Cumulative distribution function** technique (§2.1.1)

4. **Transformation** technique (§2.1.2)
(a) Monotone transformation

$$g(y) = f(x) \times |dx/dy|. \quad (2.1)$$

(b) Piecewise monotone transformation

$$g(y) = \sum_{i=1}^n f(h_i^{-1}(y)) \times \left| \frac{dh_i^{-1}(y)}{dy} \right|. \quad (2.2)$$

e.g., $X \sim N(0, 1)$, then $Y = X^2 \sim \chi^2(1)$.

(c) Bivariate transformation

绝对值

$$g(y_1, y_2) = f(x_1, x_2) \times \left| \frac{\partial(x_1, x_2)}{\partial(y_1, y_2)} \right|. \quad (2.3)$$

- Examples 2.8 and 2.9 (p.65–68)
- Another example: Let $X \sim \text{Beta}(a, b)$, $Y \sim U(0, 1)$, and $X \perp\!\!\!\perp Y$. Find the distribution of $Z = XY$.

(d) Multivariate transformation

$$g(y_1, \dots, y_n) = f(x_1, \dots, x_n) \times \left| \frac{\partial(x_1, \dots, x_n)}{\partial(y_1, \dots, y_n)} \right|.$$

5. Moment generating function technique (§2.1.3)

3) Order Statistics (§2.4, p.81)

6. The cdf and pdf of

$$X_{(1)} = \min\{X_1, \dots, X_n\}$$

$$G_1(x) = 1 - [1 - F(x)]^n,$$

$$g_1(x) = n[1 - F(x)]^{n-1}f(x).$$

7. The cdf and pdf of

$$X_{(n)} = \max\{X_1, \dots, X_n\}$$

$$G_n(x) = [F(x)]^n,$$

$$g_n(x) = n[F(x)]^{n-1}f(x).$$

8. The cdf and pdf of $X_{(r)}$

$$G_r(x) = \sum_{i=r}^n \binom{n}{i} F^i(x) [1 - F(x)]^{n-i}, \quad (2.21)$$

$$g_r(x) = \frac{n!}{(r-1)!(n-r)!} f(x) F^{r-1}(x) [1 - F(x)]^{n-r}. \quad (2.23)$$

9. The joint pdf of $X_{(1)}, \dots, X_{(n)}$ is

$$g_{X_{(1)}, \dots, X_{(n)}}(x_{(1)}, \dots, x_{(n)}) = n! f_X(x_{(1)}) \cdots f_X(x_{(n)}). \quad (2.27)$$

where $x_{(1)} \leq \dots \leq x_{(n)}$ and $f_X(\cdot)$ is the density function of the population random variable X , i.e., $X_1, \dots, X_n \stackrel{\text{iid}}{\sim} f_X(x)$.

4) Central Limit Theorem (§2.5.5, p.94)

10. **Theorem 2.9** Let $\{X_n\}_{n=1}^{\infty}$ be a sequence of i.i.d. r.v.'s with common mean μ and common variance $\sigma^2 > 0$. Let

$$\bar{X}_n = \sum_{i=1}^n X_i/n \quad \text{and} \quad Y_n = \sqrt{n}(\bar{X}_n - \mu)/\sigma,$$

then $Y_n \xrightarrow{L} Z$, where $Z \sim N(0, 1)$.



5) Point Estimation (Chapter 3)

11. Joint density and likelihood function (p.103)

$$L(\boldsymbol{\theta}) = f(\mathbf{x}; \boldsymbol{\theta}) = \prod_{i=1}^n f(x_i; \boldsymbol{\theta}), \quad \boldsymbol{\theta} \in \Theta.$$

– Example 3.3 (p.107):

$$f(\mathbf{x}; \theta) = \begin{cases} \frac{1}{\theta^n}, & \text{if } 0 < x_i \leq \theta, i = 1, \dots, n, \\ 0, & \text{elsewhere.} \end{cases}$$

$$L(\theta) = \begin{cases} \frac{1}{\theta^n}, & \text{if } \theta \geq x_{(n)} \hat{=} \max\{x_1, \dots, x_n\}, \\ 0, & \text{elsewhere.} \end{cases}$$

12. MLE and mle (p.104)

$$\hat{\theta} = \arg \max_{\theta \in \Theta} L(\theta) = \arg \max_{\theta \in \Theta} \ell(\theta),$$

then $\hat{\theta} = u(X_1, \dots, X_n)$ is called the MLE of θ and $u(x_1, \dots, x_n)$ is called a *maximum likelihood estimate* (mle) of θ .

13. Unrestricted MLE

Let

$$\frac{d\ell(\theta)}{d\theta} = 0,$$

we can obtain the unrestricted MLE.

- Example 3.1: **Bernoulli**(θ)
- Example 3.2: $N(\mu, \sigma^2)$

14. How to find MLEs of parameters in other distributions, e.g.

- $X_1, \dots, X_n \stackrel{\text{iid}}{\sim} \text{Poisson}(\lambda),$
- $X_i \stackrel{\text{ind}}{\sim} \text{Binomial}(n_i, \theta),$
- $X_1, \dots, X_n \stackrel{\text{iid}}{\sim} U[\theta_1, \theta_2],$
- $X_1, \dots, X_n \stackrel{\text{iid}}{\sim} \text{Exponential}(\beta),$
- $X_i \stackrel{\text{ind}}{\sim} \text{Gamma}(n_i, \beta).$
同样分布族，但参数不同

15. MLE with equality constraints

- Example 3.6: Multinomial distribution

16. MLE with inequality constraints

- Example 3.7: Normal distribution with constraints $a \leq \mu \leq b$.

17. Moment estimator

(§3.2): Replace MLE by Moment estimator in Item 14.

18. Bayesian estimator

(§3.3)

19. Efficiency (§3.4.2):

- 19.1 How to calculate the Fisher information (Theorem 3.4, p.131): If $E[S(\theta)] = 0$, then

$$I_n(\theta) = nI(\theta),$$

where

$$\begin{aligned} I(\theta) &= E \left[\left(\frac{d \log f(X; \theta)}{d\theta} \right)^2 \right] \\ &= E \left[-\frac{d^2 \log f(X; \theta)}{d\theta^2} \right]. \end{aligned}$$

– 19.2 How to calculate the efficiency of an unbiased estimator $\hat{\theta}$ for θ (p. 135):

$$\text{Eff}_{\hat{\theta}}(\theta) = \frac{1/I_n(\theta)}{\text{Var}(\hat{\theta})}. \quad (3.26)$$

20. Sufficiency (§3.4.3):

- 20.1 The definition of a sufficient statistic.
- 20.2 Use Theorem 3.5 (Factorization Theorem, p.140) to find a sufficient statistic $T(\mathbf{x})$ for θ :

$$f(x_1, \dots, x_n; \theta) = f(\mathbf{x}; \theta) = g(T(\mathbf{x}); \theta) \times h(\mathbf{x}), \quad (3.27)$$

– 20.3 Jointly sufficient statistics. For example, let $X_1, \dots, X_n \stackrel{\text{iid}}{\sim} \text{Gamma}(\alpha, \beta)$, the joint density is

$$f(x; \alpha, \beta) = \prod_{i=1}^n \frac{\beta^\alpha}{\Gamma(\alpha)} x_i^{\alpha-1} e^{-\beta x_i},$$

then

$$\prod_{i=1}^n X_i \quad \text{and} \quad \sum_{i=1}^n X_i$$

are jointly sufficient statistics of (α, β) . So the distribution of

$$(X_1, \dots, X_n) | (\prod_{i=1}^n X_i = t_1, \sum_{i=1}^n X_i = t_2)$$

does not depends on (α, β) .

– 20.4 Let $X_1, \dots, X_n \stackrel{\text{iid}}{\sim} N(\mu, 1)$, find the joint distribution of

$$(X_1, \dots, X_n) | (\sum_{i=1}^n X_i = t)$$

– 20.5 Let $X_1, \dots, X_n \stackrel{\text{iid}}{\sim} \text{Bernoulli}(\theta)$, find the joint distribution of

$$(X_1, \dots, X_n) | (\sum_{i=1}^n X_i = t)$$

– 20.6 Let $X_1, \dots, X_n \stackrel{\text{iid}}{\sim} \text{Poisson}(\lambda)$, find the joint distribution of

$$(X_1, \dots, X_n) | (\sum_{i=1}^n X_i = t)$$

21. Data reduction

- Let $X_1, \dots, X_n \stackrel{\text{iid}}{\sim} f(x; \theta)$. To estimate the parameter θ , first we need to find a sufficient statistic $T(X_1, \dots, X_n) = T(\mathbf{x}) = T$ for θ .
- Then the MLE, moment estimator, Bayesian estimator of θ are functions of T , say $g_1(T), g_2(T), g_3(T)$.
- A pivotal quantity is a function of both T and θ , i.e., $g_4(T, \theta)$.
- Finally, the lower limit and upper limit of the CI of θ are also functions of T , say $[g_5(T), g_6(T)]$.

22. Completeness (§3.4.4):

- 22.1 How to prove that a statistic $T(X_1, \dots, X_n)$ is complete for θ (Definition 3.9, p.146):

The statistic T is said to be *complete* if for any $h(t)$,

$$E[h(T)] = 0 \quad \text{for all } \theta \in \Theta$$

implies that $h(T) = 0$ with probability 1.

– 22.2 How to find the unique UMVUE for θ (Theorem 3.7, Lehmann-Scheffé Theorem, p.148):

Step 1: To prove that $T(\mathbf{x})$ is sufficient for θ ;

Step 2: To prove that $T(\mathbf{x})$ is complete for θ ;

Step 3: To find a function of T , say, $g(T)$, which is an unbiased estimator of $\tau(\theta)$.

Then $g(T)$ is the unique UMVUE for $\tau(\theta)$.

23. Limiting Properties of MLE (§3.5):

$$[nI(\theta)]^{1/2}(\hat{\theta}_n - \theta) \xrightarrow{L} Z \sim N(0, 1) \quad \text{as } n \rightarrow \infty. \quad (3.34)$$

– 23.1 Let $g(\cdot)$ is a function and its first derivative $g'(\cdot)$ exists. Then, using the first-order Taylor expansion, we have

$$\begin{aligned} g(\hat{\theta}_n) &\approx g(\theta) + (\hat{\theta}_n - \theta)g'(\theta) \\ &\sim N(g(\theta), [g'(\theta)]^2 \text{Var}(\hat{\theta}_n)), \end{aligned}$$

i.e.

$$\frac{\sqrt{nI(\theta)}[g(\hat{\theta}_n) - g(\theta)]}{g'(\theta)} \rightsquigarrow N(0, 1). \quad (3.35)$$

– 23.2 Let $X_1, \dots, X_n \stackrel{\text{iid}}{\sim} \text{Bernoulli}(\theta)$, then the MLE of θ is $\hat{\theta}_n = (1/n) \sum_{i=1}^n X_i$. Let $g(x) = \arcsin \sqrt{x}$, then $g'(x) = \frac{1}{2\sqrt{x(1-x)}}$. Note $\text{Var}(\hat{\theta}_n) = \text{Var}(\bar{X}) = \theta(1 - \theta)/n$ so that

$$[g'(\theta)]^2 \text{Var}(\hat{\theta}_n) = \frac{1}{4n}$$

当这个等式为常数时, CI 比较好

is a constant. From (3.35), we have

$$\frac{\arcsin \sqrt{\bar{X}} - \arcsin \sqrt{\theta}}{1/\sqrt{4n}} \rightsquigarrow N(0, 1),$$

which results in a CI for θ .

6) CI Estimation (Chapter 4)

24. Upper α -th quantile points:

上 α 分位点

$$\alpha = \Pr\{Z > z_\alpha\}, \quad Z \sim N(0, 1),$$

$$\alpha = \Pr\{t(n) > t(\alpha, n)\},$$

$$\alpha = \Pr\{\chi^2(n) > \chi^2(\alpha, n)\},$$

$$\alpha = \Pr\{F(n, m) > F(\alpha, n, m)\}.$$

25. Pivotal quantity (Definition 4.1, p.163)

26. The CI of normal mean (§4.2):

- 26.1 If σ_0^2 is known, use the pivotal quantity

$$\frac{\sqrt{n}(\bar{X} - \mu)}{\sigma_0} \sim N(0, 1)$$

to construct a $100(1 - \alpha)\%$ CI of μ as follows:

$$\left[\bar{X} - z_{\alpha/2} \frac{\sigma_0}{\sqrt{n}}, \bar{X} + z_{\alpha/2} \frac{\sigma_0}{\sqrt{n}} \right] \quad (4.4)$$

- 26.2 If σ^2 is unknown, use the pivotal quantity

$$T = \frac{\sqrt{n}(\bar{X} - \mu)}{S} \sim t(n - 1)$$

to construct a $100(1-\alpha)\%$ **CI** of μ as follows:

$$\left[\bar{X} - t(\alpha/2, n - 1) \frac{S}{\sqrt{n}}, \bar{X} + t(\alpha/2, n - 1) \frac{S}{\sqrt{n}} \right] \quad (4.6)$$

27. The CI of normal variance (§4.4):

- 27.1 If μ is known, use the pivotal quantity

$$\sum_{i=1}^n \frac{(X_i - \mu)^2}{\sigma^2} \sim \chi^2(n)$$

to construct a $100(1 - \alpha)\%$ CI of σ^2 as follows:

$$\left[\frac{\sum_{i=1}^n (X_i - \mu)^2}{\chi^2(\alpha/2, n)}, \frac{\sum_{i=1}^n (X_i - \mu)^2}{\chi^2(1 - \alpha/2, n)} \right], \quad (4.14)$$

– 27.2 If μ is unknown, use the pivotal quantity

$$\frac{(n-1)S^2}{\sigma^2} \sim \chi^2(n-1)$$

to construct a $100(1-\alpha)\%$ CI of σ^2 as follows:

$$\left[\frac{(n-1)S^2}{\chi^2(\alpha/2, n-1)}, \frac{(n-1)S^2}{\chi^2(1-\alpha/2, n-1)} \right], \quad (4.15)$$

28. Large-Sample Confidence Intervals (§4.6, three methods)

7) Appendix B

Please review B.1, B.2 and B.4

- 29. All questions in Assignments 1–4.
- 30. All questions in Tutorials.

End of Lecture 28



GOD Bless You! See You Next Time!