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Advanced Statistical Inference II

Homework 1: Review of probability language and some concepts in statistics.

Due Date: March 2nd, 2017

- (Review operation of random variables) Let X and Y be independent Poisson random variables with mean μ and λ respectively. Find the distribution of $X + Y$ and conditional distribution of X given that $X + Y = n$.
- (Review change of variable and integration) Let X and Y be independent exponential random variables with rate α . Find the densities of the random variables X^3 , $|X - Y|$, and $\min(X, Y^3)$.
- (Review college level probability and statistics) In R^2 let the two coordinate axes be denoted by the x -axis and the y -axis. An isosceles triangle is formed by a unit vector in the (positive) x -direction and another unit vector in a random direction. Find the distribution of the length of the third side.
- (Key fact) Let F be a cumulative distribution function which is continuous and strictly increasing. Let $X \sim U[0, 1]$ and define $Y = F^{-1}(X)$. Compute the distribution function of Y .
- (Order statistics) Let $X_i, 1 \leq i \leq 3$ be IID $U[0, 1]$ and let the corresponding order statistics be $X_{(i)}$. Let $U_1 = X_{(1)}/X_{(2)}$ and $U_2 = X_{(2)}/X_{(3)}$. Show that U_1 and U_2 are independent. Your can refer to the note at

<http://www.math.ntu.edu.tw/~hchen/teaching/LargeSample/notes/noteorder.pdf>

- (Order statistics) It is assumed that the lifetimes of electric bulbs have an exponential distribution with an unknown expectation α^{-1} . To estimate α , a sample of n bulbs is taken but one only observes the lifetimes of these bulbs $X_{(1)} < X_{(2)} < \dots < X_{(r)}$. Let

$$U = \frac{n-r}{r} X_{(r)} + \frac{1}{r} \sum_{i=1}^r X_{(i)}$$

Show that $E(U) = \alpha^{-1}$ and $Var(U) = \alpha^{-2}/r$.

- Let X_1 and X_2 be independent and identically distributed. Show that

$$P(|X_1 - X_2| > t) \leq 2P(|X_1| > t/2)$$

- (Review MLE and asymptotic analysis) Let X_1, \dots, X_n be i.i.d. random variables with common density function

$$f_{\theta}(x) = \frac{\theta}{(1+x)^{\theta+1}}, \quad x > 0, \theta > 0.$$

- Find the maximum likelihood estimator of θ , denoted as $\hat{\theta}_n$.
- Find the asymptotic distribution of $\sqrt{n}(\hat{\theta}_n - \theta)$.
- Find a function g such that, regardless the value of θ , $\sqrt{n}(g(\hat{\theta}_n) - g(\theta)) \rightarrow N(0, 1)$ in distribution.

(7E) $Y_i \sim \text{Exp}(1) \sim \exp(-y)$

$$X_1 = \frac{Y_1}{Y_1 + \dots + Y_{n-1}}, \quad X_2 = \frac{Y_1 + Y_2}{Y_1 + \dots + Y_{n-1}}, \quad \dots, \quad X_n = \frac{Y_1 + \dots + Y_n}{Y_1 + \dots + Y_{n-1}} \quad 1$$

(X_1, \dots, X_n) vs $(U_1, U_2, \dots, U_{n-1})$ 的變換

(7F) $X_{n+1} = Y_1 + \dots + Y_n$, 查表查取

9. (Law of large numbers and importance sampling) The following algorithm has been proposed to find $P(Z > 5) = 1 - \Phi(5)$ where Z is a standard normal random variable.

Step 1. Sample x_1, x_2, \dots, x_m from $N(5, 1)$.

Step 2. Calculate

$$\hat{p}_{IS} = \frac{1}{m} \sum_{i=1}^m I(x_i \geq 5) \frac{\phi(x_i)}{\phi(x_i - 5)}$$

where $\phi(\cdot)$ is the density function of Z .

(a) Is \hat{p}_{IS} an unbiased estimator of $1 - \Phi(5)$? Justify your answer.

(b) Determine the variance of \hat{p}_{IS} .

10. (Over Dispersion and Mixture Distribution) The Conway-Maxwell-Poisson distribution has the probability function

$$P(Y = y) = \frac{\lambda^y}{(y!)^\nu Z(\lambda, \nu)}, \quad y = 0, 1, 2, \dots$$

where

$$Z(\lambda, \nu) = \sum_{i=1}^{\infty} \frac{\lambda^i}{(i!)^\nu}.$$

(a) Place this distribution in an exponential family form with respect to both parameters, and identify all the relevant components.

(b) Determine ν such that the Conway-Maxwell-Poisson distribution is reduced to the Poisson distribution.

(c) Explain why this distribution can be used to model overdispersion for count data.

To have a better understanding on the term *overdispersion*, please refer to

<http://data.princeton.edu/wws509/notes/c4a.pdf>

11. Long (1990, 1997) gave data on the number of publications by 915 doctoral candidates in biochemistry. The numbers of published papers during last three years of Ph.D. are 0, 1, 2, 3, \dots , 12, 16 and 19. The corresponding number of students from 275, 246, 178, 84, 67, 27, 17, 12, 1, 2, 1, 1, 2, 1, 1. When the number of publications can be modelled as a Poisson random variable with mean λ , can you be certain that they come from Poisson based on the fact that $E(X) = Var(X) = \lambda$.

12. The double-exponential distribution has pdf $f(x) = (\lambda/2) \exp(-\lambda|x|)$, for fixed $\lambda > 0$.

(a) Find the MGF $M_X(t)$ of a double exponential. For which t is it finite?

(b) Let U and V are independent and identically distributed random variables with exponential distribution with mean 1, and 0 find the MGF $M_Y(t)$ of $Y = U - V$. What is the distribution of Y ?

$$\frac{1}{4} \left(\frac{2}{\sqrt{\pi}} \int_0^{\sqrt{y}} e^{-v^2} dv \right)^2 = \left(\frac{1}{\sqrt{\pi}} \int_0^{\sqrt{y}} e^{-v^2} dv \right)^2$$

2y

(c) Find the mean and variance of a double exponential. If X_1, \dots, X_n are i.i.d. double exponentials, find the MGF $M_n(t)$ of the standardized mean,

$$W_n = \frac{\bar{X} - E[X_1]}{\sqrt{Var(X)/n}}$$

(d) What is the limit of $M_n(t)$ as $n \rightarrow \infty$? What distribution has this function for its MGF?

13. Let X_1, \dots, X_n be IID normal random variables with mean μ and variance 1. Here $\mu \geq 1$.

- (a) Find the MLE of μ which is denoted by $\hat{\mu}_{mle}$.
- (b) When the true $\mu > 0$, determine the distribution of $\sqrt{n}(\hat{\mu}_{mle} - \mu)$ when n is large.
- (c) When the true $\mu = 0$, determine the distribution of $\sqrt{n}(\hat{\mu}_{mle} - \mu)$ when n is large.

14. Suppose U and V are independent with exponential distribution with parameter λ . (A random variable T is exponentially distributed with parameter λ if its density is given by $f(t) = \lambda \exp(-\lambda t)$ with support $T > 0$.) Define $X = U + V$ and $Y = UV$.

- (a) Derive the joint density of (X, Y) .
- (b) Find the best linear predictor of Y given X .
- (c) Find the best predictor of Y given X .

15. Suppose that X and Y have a joint pdf given by

$$f_{X,Y}(x, y) = \begin{cases} 2 & 0 < x < y < 1 \\ 0 & \text{otherwise.} \end{cases}$$

- (a) Find $E[Y|X = x_0]$.
- (b) Plot the CEF (conditional expectation function) $E[Y|X = x]$. Can you explain heuristically why the function has this particular form?
- (c) Find $E[YX^3 + 1|X = x_0]$.
- (d) Find $V(Y|X = x_0)$. Does its dependence on x_0 make sense to you?

16. The Weibull cumulative distribution function is

$$F(x) = 1 - \exp \left[- \left(\frac{x}{\alpha} \right)^\beta \right], \quad x \geq 0, \alpha > 0, \beta > 0.$$

- (a) Find the density function.
- (b) Show that if W follows a Weibull distribution, then $X = (W/\alpha)^\beta$ follows an exponential distribution.
- (c) How could Weibull random variables be generated from a uniform random number generator?

17. Let $X_1, X_2 \sim \text{Uniform}(0, \theta)$ where $\theta > 0$.

(a) Find the distribution of (X_1, X_2) given T where $T = \max\{X_1, X_2\}$.

Handwritten notes for problem 17:

$X_i = t$

$\frac{1}{\theta} \exp(-t) \cdot \frac{1}{\theta}$

$\frac{1}{\theta^2}$

$\frac{1}{\theta} \exp(-t)$

$\frac{1}{\theta} \exp(-t)$

$\frac{1}{\theta} \exp(-t)$

- (b) Show that $X_1 + X_2$ is not sufficient.
18. Let $X_1, \dots, X_n \sim \text{Uniform}(-\theta, 2\theta)$ where $\theta > 0$. Find the likelihood function.
19. Consider four observations $-1, 0, 0.5,$ and 3 and evaluation at $x = 0, x = 0.5,$ and $x = 1$. Using a bandwidth of 1 , determine Gaussian kernel density estimate at $x = 0, x = 0.5,$ and $x = 1$. Note that the resulting estimate at $x = 0$ should be 0.249 .
20. You are given a kernel $K(\cdot)$ which satisfies $K(u) \geq 0, \int K(u)du = 1, \int uK(u)du = 0, \int u^2K(u)du = \sigma_K^2 < \infty$. You are also given a bandwidth $h > 0$, and a collection of n univariate observations x_1, x_2, \dots, x_n . Assume that the data are independent samples from some unknown density f .
- (a) Give the formula for \hat{f}_h , the kernel density estimate corresponding to these data, this bandwidth, and this kernel.
- (b) Find the expectation of a random variable whose density is \hat{f} , in terms of the sample moments, h , and the properties of the kernel function.
- (c) Find the variance of a random variable whose density is \hat{f}_h , in terms of the sample moments, h , and the properties of h the kernel function.
- (d) How must h change as n grows to ensure that the expectation and variance of \hat{f}_h will converge on the expectation and variance of f ?

21. Let X_1, \dots, X_n be a random sample from the density

$$f(x|\theta) = \theta x^{\theta-1} I_{(0,1)}(x).$$

The parameter space is $\Theta = (0, \infty)$.

- (a) Verify that $-\log X_1 = Y$ has an exponential distribution.
- (b) Find the Cramer Rao lower bound for unbiased estimators of $\tau(\theta) = 1/\theta$.
- (c) Show that $-\sum_{i=1}^n \log X_i/n$ is an UMVUE of $1/\theta$.
22. Let X_1, \dots, X_n be iid $U[0, \theta]$, and suppose that we want to estimate θ .
- (a) Show that $X_{(n)} = \max_{1 \leq i \leq n} X_i$ is sufficient for θ .
- (b) Let $\tilde{\theta} = 2X_1$, show that $\tilde{\theta}$ is an unbiased estimator for θ .
- (c) Find $E(\tilde{\theta}|X_{(n)})$ and show that it is a UNVUE of θ
23. Suppose X_1, \dots, X_n are iid Poisson(λ), and let $\theta = \exp(-\lambda)$ which is $P(X_1 = 0)$.
- (a) Show that $T = \sum_{i=1}^n X_i$ is sufficient for θ .
- (b) Consider an estimator $\tilde{\theta} = 1_{X_1=0}$. Show that $\tilde{\theta}$ is an unbiased estimator of θ .
- (c) Show that $E(\tilde{\theta}|T = t) = (1 - 1/n)^{\sum_i X_i}$.
24. Let $\mathbf{X} = (X_1, \dots, X_n)$ be a sample from an exponential distribution with individual densities

$$f(x; \theta) = \frac{1}{\theta} \exp\left(-\frac{x}{\theta}\right), \quad x > 0,$$

where $\theta > 0$ is unknown.

- (a) Show that $\tilde{\theta} = X_1^2/2$ is an unbiased estimator of $g(\theta) = \theta$. θ^2 ?
- (b) Show that $t(\mathbf{X}) = \sum_{i=1}^n X_i$ is sufficient for θ .
- (c) Rao-Blackwellize $\tilde{\theta}$ to find an improved unbiased estimator of $g(\theta)$ which is denoted by $\hat{\theta}_u$;
 Hint: You may use without proof that the distribution of $U = X_1/(\sum_{i=1}^n X_i)$ follows a Beta-distribution $\mathcal{B}(1, n-1)$, where $\mathcal{B}(\alpha, \beta)$ is the distribution with density

$$f(t; \alpha, \beta) = \frac{\Gamma(\alpha + \beta)}{\Gamma(\alpha)\Gamma(\beta)} t^{\alpha-1}(1-t)^{\beta-1}, \quad 0 < t < 1.$$

- (d) Find the MLE of θ^2 and denote it by $\hat{\theta}_{mle}$. Compare the mean square error of the two estimates.

25. Suppose $X \sim N(0, \sigma^2)$. Note that the density function of X can be parametrized by a single parameter σ and

$$f(x|\sigma) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{x^2}{2\sigma^2}\right) I(x \in R).$$

- (a) Specify $\eta(\sigma)$, $T(x)$, $\psi(\sigma) = \log \sigma$, $h(x) = (1/\sqrt{2\pi})I(x \in R)$ to represent the density in the form

$$f(x|\sigma) = \exp(\eta(\sigma)T(x) - \psi(\sigma))h(x),$$

for any $\sigma \in R^+$.

- (b) Suppose that we have an iid sample $X_1, X_2, \dots, X_n \sim N(0, \sigma^2)$. Then write the joint density of X_1, X_2, \dots, X_n in the same general form

$$f(x_1, x_2, \dots, x_n|\sigma) = \exp(\eta(\sigma)T(x_1, x_2, \dots, x_n) - \psi(\sigma))h(x_1, x_2, \dots, x_n).$$

Show that the sufficient statistic is $\sum_{i=1}^n X_i^2$.

- (c) Using the fact that the sum of squares of n independent standard normal variables is a chi square variable with n degrees of freedom, we have that the density of $T(X_1, X_2, \dots, X_n)$ is

$$f_T(t|\sigma) = \frac{\exp(-t/(2\sigma^2))t^{n/2-1}}{\sigma^n 2^{n/2} \Gamma(n/2)} I(t > 0).$$

Please identify $\eta(\sigma)$, $S(t)$, $\psi(\sigma)$ and $h(t)$.

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Advanced Statistical Inference II

Homework 2: Review of probability language, asymptotic analysis and some concepts in statistics.

Due Date: March 20th, 2017

- ✓ Suppose X is a *Binomial*(n, p) random variable, $0 < p < 1$.
- (a) Find the mle for $p(1 - p)$.
 - (b) Show that the mle is not unbiased for $p(1 - p)$.
 - (c) Construct an unbiased estimator for $p(1 - p)$ using this mle given in (a).
- ✓ (complete) Suppose X is a *Binomial*($2, p$) random variable where p can take only two values $1/2$ and $1/4$. Show that this family is not complete by constructing a non-zero function $g(X)$ whose expectation is zero for both $p = 1/2$ and $1/4$.
- ✓ (order statistic) Let X_1, X_2, X_3 be a random sample of size three from the uniform distribution $U(0, \theta)$, where $\theta > 0$ is an unknown parameter. Let $X_{(1)}, X_{(2)}, X_{(3)}$ be the corresponding order statistics.
- (a) Find the marginal pdf $X_{(1)}$ and show that $X_{(1)}/\theta$ is distributed as *Beta*($1, 3$).
 - (b) Compute $E[X_{(1)}]$. Construct an unbiased estimator for θ using $X_{(1)}$.
 - (c) Show that $X_{(3)}/X_{(1)}$ is independent of $X_{(3)}$.
- ④ (order restricted inference) Let X be a single observation from the $N(\theta, 1)$ distribution, $\theta > 0$. Notice that the unknown mean is assumed to be positive.
- ④ (a) Obtain the maximum likelihood estimator (MLE) of $\theta, \hat{\theta}$. (Be sure to consider the parameter space.)
- (b) Show that $E(\hat{\theta}) \neq \theta$.
- ✓ (Review change of variable and integration) Let X and Y be independent exponential random variables with rate α . Find the densities of the random variables $X^3, |X - Y|$, and $\min(X, Y^3)$.
- ④ (Order statistics) It is assumed that the lifetimes of electric bulbs have an exponential distribution with an unknown expectation α^{-1} . To estimate α , a sample of n bulbs is taken but one only observes the lifetimes of these bulbs $X_{(1)} < X_{(2)} < \dots < X_{(r)}$. Let

$$U = \frac{n-r}{r} X_{(r)} + \frac{1}{r} \sum_{i=1}^r X_{(i)}.$$

Show that $E(U) = \alpha^{-1}$ and $Var(U) = \alpha^{-2}/r$.

7. (Review MLE and asymptotic analysis) Let X_1, \dots, X_n be i.i.d. random variables with common density function

$$f_{\theta}(x) = \frac{\theta}{(1+x)^{\theta+1}}, \quad x > 0, \theta > 0.$$

- (a) Find the maximum likelihood estimator of θ , denoted as $\hat{\theta}_n$.
- (b) Find the asymptotic distribution of $\sqrt{n}(\hat{\theta}_n - \theta)$.

(c) Find a function g such that, regardless the value of θ , $\sqrt{n}(g(\hat{\theta}_n) - g(\theta)) \rightarrow N(0, 1)$ in distribution.

item (Law of large numbers and importance sampling) The following algorithm has been proposed to find $P(Z > 5) = 1 - \Phi(5)$ where Z is a standard normal random variable.

Step 1. Sample x_1, x_2, \dots, x_m from $N(5, 1)$.

Step 2. Calculate

$$\hat{p}_{IS} = \frac{1}{m} \sum_{i=1}^m I(x_i \geq 5) \frac{\phi(x_i)}{\phi(x_i - 5)}$$

where $\phi(\cdot)$ is the density function of Z .

(a) Is \hat{p}_{IS} an unbiased estimator of $1 - \Phi(5)$? Justify your answer.

(b) Determine the variance of \hat{p}_{IS} .

8. (Truncated random variables) Let X be a continuous random variable with pdf $f(x)$ and cdf $F(x)$. For a fixed number x_0 , define the function

$$g(x) = \begin{cases} f(x)/[1 - F(x_0)] & \text{if } x \geq x_0 \\ 0 & \text{if } x < x_0 \end{cases}$$

Prove that $g(x)$ is a pdf. (Assume that $F(x_0) < 1$.) Derive, via integration, the CDF (cumulative distribution function) corresponding to the pdf $g(x)$.

9. (Markov's inequality) Let X be a non-negative random variable and let g be an increasing non-negative function defined on $[0, \infty)$. Suppose that $E(g(X))$ is finite. Prove that, for any $\epsilon > 0$,

$$P(X \geq \epsilon) \leq E(g(X))/g(\epsilon).$$

10. (constrained optimization) Let X be a single observation from the $N(\theta, 1)$ distribution, $\theta > 0$. Notice that the unknown mean is assumed to be positive.

(4.) (a) Obtain the maximum likelihood estimator (MLE) of θ , $\hat{\theta}$. (Be sure to consider the parameter space.)

(b) Show that $E(\hat{\theta}) \neq \theta$.

11. It has been determined that the total food consumption for a particular ant species in a region is a random variable. T which, given the number of colonies N , has $Normal(N\mu, N\sigma^2)$ distribution. Suppose $N \sim Poisson(\lambda)$. Suppose iid data $(T_1, N_1), (T_2, N_2), \dots$ can be observed according to the above and let \bar{T} and \bar{N} be the corresponding means for samples of size n . Show that $\sqrt{n}(\bar{T} - \lambda\mu)$ and $\frac{\sqrt{n}}{\bar{N}}(\bar{T} - \lambda\mu)$ each converge in distribution, as $n \rightarrow \infty$, and describe the limits.

(72) 12. (Sample selection bias) Assume that ϵ and ν are random variables jointly normally distributed $N(0, 0, 1, 1, \rho)$, where $0 < \rho < 1$. Assume that a wage offer W are a random linear function of schooling S :

$$\begin{pmatrix} \epsilon \\ \nu \end{pmatrix} \sim N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix}\right) W = \alpha S + \epsilon.$$

Assume that wage offers are accepted (and therefore observed) only if the worker decides to enter the workplace. ν is a measure of *propensity to work*, and a worker enters the workplace only if $\nu > 0$. Derive an expression for the expected wage for the working population. Do not solve any complicated integrals.

13. Suppose U and V are independent with exponential distribution with parameter λ . (A random variable T is exponentially distributed with parameter λ if its density is given by $f(t) = \lambda \exp(-\lambda t)$ with support $T > 0$.) Define $X = U + V$ and $Y = UV$.

- (a) Derive the joint density of (X, Y) .
- (b) Find the best linear predictor of Y given X .
- (c) Find the best predictor of Y given X .

14. Adapted from *A Simple Population Estimate Based on Simulation for Capture-Recapture and Capture-Resight Data* by Minta and Mangel, Ecology 1989.

In the fall of 1984, North American badgers (*Taxidea taxus*) were snowtracked in a 15 km^2 area on the National Elk Refuge, Jackson, Wyoming. The size and shape of the target area were dictated by topographic and plant community features that created a relatively isolated area of high badger density. Fifteen of the badgers were radiotagged and known to be occupying or overlapping the area. During the 2-month tracking period there was no death or emigration of radiotagged badgers, and radiotagged badgers outside the target area did not immigrate. One badger emigrated near the end of the sampling period. During daylight and under suitable weather conditions, the target was searched for badger snowtracks. A total of 24 tracks could be followed to a terminal hole, where the badger would be inactive in an underground burrow. All telemetry frequencies were then scanned to determine whether the badger was *marked* or *unmarked*. Radiotelemetry revealed that 11 of the tracks were generated by marked badgers.

- (a) Let N be the (unknown) total badger population size. Explain why the hypergeometric distribution can be used to model this experiment. Identify the values of the parameters M and K .
- (b) For the values of the parameters given above, what is your best guess (estimate) of N .
- (c) For the value of N from part (b), draw the hypergeometric distribution. How likely is the observed value of x ?
- (d) For values of N near that of part (b), evaluate the probability of the observed value of x . What might you conclude about the population size?

Advanced Statistical Inference II

Homework 2: Review of probability language, asymptotic analysis and some concepts in statistics.

Due Date: ~~March 20th~~, 2017

1 (root-finding algorithm) Let X_1, X_2, X_3 be independent observations from the Cauchy distribution about θ , $f(x, \theta) = \pi^{-1}(1 + (x - \theta)^2)^{-1}$. Suppose $X_1 = 0, X_2 = 1, X_3 = a$. Show that for a sufficiently large the likelihood function has local maxima between 0 and 1 and θ and a . Deduce that depending on where bisection is started the sequence of iterates may converge to one or the other of the local maxima.

2 (convex function) Consider a convex function $f(x)$ where $x \in R$.

- Prove
- (a) If f is continuous, ~~then $f(x + y) \leq f(x) + f(y)$, for all $x, y \in R$.~~
 - (b) If f is continuously differentiable, $f(y) \geq f(x) + f'(x)(y - x)$, for all $x, y \in R$.
 - (c) If f is twice differentiable, $f''(x) \geq 0$, for all $x \in R$.

Definition of convex set:

A set $C \subset R^n$ is called convex set, iff for all $x, y \in C, tx + (1 - t)y \in C$ for $0 \leq t \leq 1$. That means for every pairs of points in the convex set C , every point falls on the straight line segment that joins the pair of points will also be in the set. A set that has such properties is super powerful, because you can get to any point in the set from a given point through a straight line without hitting the boundary. Hitting the boundary often means you might get stuck at a local minimum and never have the chance to find the global optimal solution.

Definition of convex function:

A function $f : R^p \rightarrow R$ is a convex function, if $dom(f)$ is a convex set, and $f(tx + (1 - t)y) \leq tf(x) + (1 - t)f(y)$ for $0 \leq t \leq 1$. The inequalities say that the line segment between two points on the function will always lies above the function. Function that has such property is very powerful when you are trying to find the minimum value on the function. Because for any randomly chosen two points, x, y , you can always find a point z that lies between x and y such that $f(z) = \min(f(x), f(y))$. So you will surely be able find the optimal value.

3. (mle) An exponential distribution with parameter λ follows a distribution $p(x) = \lambda \exp(-\lambda x)$. Given some i.i.d. data x_1, \dots, x_n from $EXP(\lambda)$, derive the maximum likelihood estimate $\hat{\lambda}_{mle}$.

- (a) Is this estimator biased?
- (b) Is it consistent?
- (c) Determine its asymptotic distribution.

4. (Non-closed Form Estimation) Given some data x_1, x_2, \dots, x_3 which is a random sample from $Gamma(\alpha, \beta)$, Use *gradient descent* to find the maximizer of the likelihood function and derive the steps to calculate the MLE estimators $(\hat{\alpha}_{mle}, \hat{\beta}_{mle})$. Please refer to the following webpage on *gradient descent*.

https://en.wikipedia.org/wiki/Gradient_descent

5. Let X have density function $f(x|\sigma) = (2\sigma)^{-1} \exp(-|x|/\sigma)$. We have a random sample of size n from $f(\cdot)$. Derive the estimate of σ by the method of moments (denoted by $\hat{\sigma}_{mm}$) and maximum likelihood estimate (denoted by $\hat{\sigma}_{mle}$). Derive their asymptotic distributions.

✓ (discrete random variable) Suppose we take one observation, X from a discrete random variable. X can take on five possible values on $-2, -1, 0, 1,$ and 2 with probability $(1 - \theta)/4, \theta/12, 1/2, (3 - \theta)/12, \theta/4,$ respectively. Here, $0 \leq \theta \leq 1.$

(a) Find an unbiased estimator of $\theta.$

(b) Obtain the maximum likelihood estimator (MLE) and show that it is not unique. Is any choice of MLE unbiased?

⑧ ✓ (order statistic) Let X_1, \dots, X_n be a random sample from the uniform distribution on the interval $(\theta - 1, \theta + 1),$ where $\theta \in R$ is unknown. Let $X_{(j)}$ be the j th order statistic.

(a) Show that $(X_{(1)} + X_{(n)})/2$ is strongly consistent for $\theta,$ i.e., that $\lim_{n \rightarrow \infty} (X_{(1)} + \dots + X_{(n)})/2 = \theta$ almost surely.

(b) Show that $\bar{X}_n = (X_{(1)} + \dots + X_{(n)})/n$ is L^2 consistent.

8. (exponential distribution) Let X be a random variable having probability density $f(x|\theta) = h(x) \exp[\eta(\theta)T(x) - A(\theta)],$ where η is an increasing and differentiable function of $\theta \in \Theta \subset R.$

(a) Show that $\log \ell(\hat{\theta}) - \log \ell(\theta_0)$ is increasing (or decreasing) in $X,$ when $\hat{\theta} > \theta_0$ (or $\hat{\theta} < \theta_0$). Here $\ell(\theta) = f(x|\theta), \theta$ is an MLE of θ and $\theta_0 \in \Theta.$

(b) Show that $A(\theta) = \log \int h(x) \exp(\theta T(x)) dx.$

✓ (number of unknown parameters is half of the sample size) Let $X_{ij}, i = 1, 2, \dots, n$ and $j = 1, 2, \dots, k$ be independent with $X_{ij} \sim N(\mu_i, \sigma^2).$ Note that this is basically a balanced one-way ANOVA design where we assume k is fixed and $n \rightarrow \infty.$ So the sample sizes of the groups are (probably) big, but the number of groups is bigger.

(a) Find the mle of μ_i and $\sigma^2.$

(b) Show that the MLE of $\sigma^2, \hat{\sigma}^2$ that is not consistent.

(c) Determine c such that $c\hat{\sigma}^2$ is a consistent estimate of $\sigma^2.$

✓ 10. Suppose X_1, \dots, X_n are p -vectors uniformly distributed in the ball $B_r = \{x : \|x\|_2 \leq r\};$ $r > 0$ is an unknown parameter. Find the MLE of r and its asymptotic distribution.

⑨ (qualitative information on unknown parameters) Suppose X_1, \dots, X_{m+n} are independent, with $X_1, \dots, X_m \sim N(\mu_1, \sigma^2), X_{m+1}, \dots, X_{m+n} \sim N(\mu_2, \sigma^2),$ where $\mu_1 \leq \mu_2$ and σ^2 are unknown.

(a) Find the MLE of $(\mu_1, \mu_2).$ $(\hat{\mu}_1, \hat{\mu}_2)$

(b) Derive its asymptotic distribution when $\mu_1 < \mu_2, \mu_1 = \mu_2.$

✓ 12. (survival function) Suppose X_1, \dots, X_n are iid $\text{Exp}(\lambda).$ Find the MLE of the expected residual life $E(X_1 - t | X_1 > t)$ and its asymptotic distribution.

$E(X_1 - t | X_1 > t) = E(X_1) - t = 1/\lambda - t$

Advanced Statistical Inference II

Homework 4: Review of probability language, asymptotic analysis and some concepts in statistics.

Due Date: April ?, 2017

1. Suppose we take one observation, X , from a discrete distribution. It takes on values $-2, -1, 0, 1, 2$ with probabilities $(1 - \theta)/4, \theta/12, 1/2, (3 - \theta)/12, \theta/4$, respectively. Here, $0 \leq \theta \leq 1$. Find an unbiased estimator of θ and obtain the maximum likelihood estimator (MLE) of θ and show that it is not unique. Is any choice of MLE unbiased?

2. Let X_1, \dots, X_n be a random sample of binary random variables with $P(X_1 = 1) = p$, where $p \in (0, 1)$ is unknown. Let $\hat{\theta}$ be the MLE of $\theta = p(1 - p)$.

(a) Show that $\hat{\theta}$ is asymptotically normal when $p \neq 1/2$.

(b) When $p = 1/2$, derive a nondegenerated asymptotic distribution of $\hat{\theta}$ with an appropriate normalization.

3. Let $(X_1, Y_1), \dots, (X_n, Y_n)$ be independent and identically distributed random 2-vectors taking values in the unit square $[0, 1] \times [0, 1]$, with joint CDF

$$F(x, y) = P(X_1 \leq x, Y_1 \leq y) = x \cdot y \cdot (x \wedge y)^\theta$$

for $0 \leq x \leq 1, 0 \leq y \leq 1$, where $\theta \geq 0$ is unknown.

(a) Obtain the likelihood function for θ .

(b) Obtain the MLE $\hat{\theta}_n((x_1, y_1), \dots, (x_n, y_n))$ of θ .

(c) Can you find the asymptotic distribution of $\hat{\theta}_n$? Hints: You can avoid the min by considering $x < y$ and $x \geq y$ separately; It is a little easier to work with the $\min U := (X \wedge Y)$ and $\max V := (X \vee Y)$. Note that $F(x, y)$ is twice differentiable (once w.r.t x , once w.r.t y) where $x \neq y$ but not on the diagonal where $x = y$ - in fact, $P(X = Y) > 0$, so you may want to consider observations with $X_i \neq Y_i$ and those with $X_i = Y_i$ separately. How can you find the p.d.f. for X when $X = Y$?

4. Let X be a random variable having probability density $f(x|\theta) = \exp\{\eta(\theta)Y(x) - B(\theta)\}h(x)$, where η is an increasing and differentiable function of $\theta \in \Theta \subset \mathbb{R}$. Show that $\log \ell(\hat{\theta}) - \log \ell(\theta_0)$ is increasing (resp., decreasing) in Y , when $\hat{\theta} > \theta_0$ (resp., $\hat{\theta} < \theta_0$), where $\ell(\theta) = f(x|\theta)$, $\hat{\theta}$ is an MLE of θ , and $\theta_0 \in \Theta$.

5. (Review MLE and asymptotic analysis) Let X_1, \dots, X_n be i.i.d. random variables with common density function

$$f_\theta(x) = \frac{\theta}{(1+x)^{\theta+1}}, \quad x > 0, \theta > 0.$$

(a) Find the maximum likelihood estimator of θ , denoted as $\hat{\theta}_n$.

(b) Find the asymptotic distribution of $\sqrt{n}(\hat{\theta}_n - \theta)$.

(c) Find a function g such that, regardless the value of θ , $\sqrt{n}(g(\hat{\theta}_n) - g(\theta)) \rightarrow N(0, 1)$ in distribution.

6. Long (1990, 1997) gave data on the number of publications by 915 doctoral candidates in biochemistry. The numbers of published papers during last three years of Ph.D. are 0, 1, 2, 3, ..., 12, 16 and 19. The corresponding number of students from 275, 246, 178, 84, 67, 27, 17, 12, 1, 2, 1, 1, 2, 1, 1. When the number of publications can be modelled as a Poisson random variable with mean λ , can you be certain that they come from Poisson based on the fact that $E(X) = Var(X) = \lambda$.

7. The double-exponential distribution has pdf $f(x) = (\lambda/2) \exp(-\lambda|x|)$, for fixed $\lambda > 0$.

- (a) Find the MGF $M_X(t)$ of a double exponential. For which t is it finite?
 (b) Let U and V are independent and identically distributed random variables with exponential distribution with mean 1, and 0 find the MGF $M_Y(t)$ of $Y = U - V$. What is the distribution of Y ?
 (c) Find the mean and variance of a double exponential. If X_1, \dots, X_n are i.i.d. double exponentials, find the MGF $M_n(t)$ of the standardized mean,

$$W_n = \frac{\bar{X} - E[X_1]}{\sqrt{Var(X)/n}}$$

- (d) What is the limit of $M_n(t)$ as $n \rightarrow \infty$? What distribution has this function for its MGF?

8. Let X_1, \dots, X_n be IID normal random variables with mean μ and variance 1. Here $\mu \geq 1$.

- (a) Find the MLE of μ which is denoted by $\hat{\mu}_{mle}$.
 (b) When the true $\mu > 0$, determine the distribution of $\sqrt{n}(\hat{\mu}_{mle} - \mu)$ when n is large.
 (c) When the true $\mu = 0$, determine the distribution of $\sqrt{n}(\hat{\mu}_{mle} - \mu)$ when n is large.

9. Let $X_1, X_2 \sim Uniform(0, \theta)$ where $\theta > 0$.

- (a) Find the distribution of (X_1, X_2) given T where $T = \max\{X_1, X_2\}$.
 (b) Show that $X_1 + X_2$ is not sufficient.

10. Let X_1, \dots, X_n be a random sample from the density

$$f(x|\theta) = \theta x^{\theta-1} I_{(0,1)}(x).$$

The parameter space is $\Theta = (0, \infty)$.

- (a) Verify that $-\log X_1 = Y$ has an exponential distribution.
 (b) Find the Cramer Rao lower bound for unbiased estimators of $\tau(\theta) = 1/\theta$.
 (c) Show that $-\sum_{i=1}^n \log X_i/n$ is an UMVUE of $1/\theta$.

(New)

Advanced Statistical Inference II

Homework 5: Hypothesis Testing

Due Date: June 6th, 2017 6/6

1. Let X_1, \dots, X_n be iid with probability density $f_\theta(x)$. Denote $\hat{\theta}$ as the MLE. Suppose we are interested in estimating some function of θ .

(a) If $\eta = g(\theta)$ and g is strictly increasing (or decreasing). Determine the MLE of η . (Justify your answer.)

(b) Usually, the MLE of η is defined to be $g(\hat{\theta})$. The reason is the following:
Let w_η be the set of θ -values for which $g(\theta) = \eta$ and let

$$M(\eta) = \sup_{\theta \in w_\eta} L(\theta),$$

where $L(\theta)$ is the likelihood function.

Then it claims that if $\hat{\theta}$ maximizes $L(\theta)$, $\hat{\eta}$ maximizes $M(\eta)$.

Justify the above claim. (If you are interested in this issue, read Zehna, Annals of Math. Stat., 1966.)

2. A random sample of five values, x_1, x_2, \dots, x_5 , is taken from a population whose density function is $f(x|\lambda) = x\lambda^2 \exp(-\lambda x)$ where $x > 0$.

(a) Use the Neyman Pearson Lemma to construct a test of

$$H_0 : \lambda = 2 \text{ against } H_1 : \lambda = 1$$

such that $\alpha = 0.05$ while it minimizes $3\alpha + \beta$. Here α and β are the Type I and Type II error probabilities respectively.

(b) Find the approximate power of the test in (a) and the approximate value of α for the test in (b). (The approximations should be as accurate as the chisquared tables allow.)

(c) If the alternative hypothesis had been $H_1 : \lambda < 1$ would the test be uniformly most powerful?

3. A new drug is being proposed for the treatment of migraine headaches. Unfortunately some users in early tests of the drug have reported mild nausea as a side effect. The FDA will reject the drug if it thinks that more than 15% (i.e., 0.15) of the population would suffer from this side effect. In an experiment to test this side effect, 400 people who suffer from migraine headaches receive the new drug and 80 of them report nausea as a side effect.

(a) Define the parameter of interest, giving appropriate notation and writing a sentence saying what it is.

(b) Carry out the five steps of a hypothesis test to determine if the FDA should reject the drug. (In Step 1, you need to specify the null and alternative hypotheses: Use notation, not words. In Step 2, compute the test statistic. (Show your work)

(c) Find the p -value.

(d) Decide whether the result is statistically significant (i.e. make a conclusion about the hypotheses); use $\alpha = 0.05$.

(e) Report the conclusion in context.

✓ The following data give the number of aying bomb hits recorded in each of 576 small areas of $0.25km^2$ in the south of London during World War II. The following Table gives the number of flying bomb hits on London

Number of hits in an area	0	1	2	3	4	5	≥ 6
Frequency	229	211	93	35	7	1	0

1 ~ 279
229 ~ 440
441 ~ 576
576 ~ 568

Propaganda broadcasts claimed that the weapon could be aimed accurately. If, however, this was not the case, the hits should be randomly distributed over the area and should therefore be Ottded by a Poisson distribution. Is this the case?

5. It is claimed that a new treatment is more effective than the standard treatment for prolonging the lives of terminal cancer patients. The standard treatment has been in use for a long time, and from records in medical journals the mean survival period has been 4.2 years with a standard deviation of 1.1 years. The new treatment is administered to 80 patients, and their average duration of survival is calculated to be 4.5 years. Is the claim supported by these results? In your answer, you should include H_0 versus H_a , p value, and your conclusion.

✓ The manager at Costello Drug Store assumes the companys employees are honest. However, there have been many shortages from the cash register lately. There is only one employee who could have taken money from the register during these periods. Realizing that the shortages might have resulted from the employee inadvertently giving incorrect change to customers, the employer does not know whether to forget the situation or accuse the employee of theft. In words, what are the null and alternative hypotheses? Explain your choices.

(a) What constitutes a Type I error in this problem?

(b) What is a Type II error? Which do you think is more serious? Explain.

✓ Let X_1, X_2, \dots be independent and identically distributed random variables with probability density function

$$f_{\theta}(x) = \theta \exp(-\theta x) \quad \text{for } x > 0.$$

The distribution is exponential with unknown, but fixed, scale $\theta > 0$. Define, for $\theta > 0$, the function

$$\phi_{\theta}(x) = \frac{1}{\theta} - x \quad \text{for } x > 0,$$

and consider the Z -estimator $\hat{\theta}_n$ defined as a zero of the function

$$\Phi_n(\theta) = P_n \phi_{\theta} = \frac{1}{n} \sum_{i=1}^n \phi_{\theta}(X_i).$$

(a) Using properties of the function Φ_n , show that $\hat{\theta}_n$ is well defined, i.e. Φ_n has exactly one point where it takes the value zero.

(b) Show that $\Phi_n(\theta)$ converges in probability, for fixed $\theta > 0$.

(c) Prove that $\hat{\theta}_n$ converges to θ in probability.

(d) The random variables $\sqrt{n}(\hat{\theta}_n - \theta)$ are asymptotically normally distributed. What parameters do you expect for this asymptotic normal distribution?

(e) Derive the maximum likelihood estimator for θ . How does it relate to $\hat{\theta}_n$? Based on this and (d), give the Fisher information I_θ .

8. Let X_1, \dots, X_n be i.i.d. from the Poisson distribution $P(\theta)$ with an unknown $\theta > 0$. Find the bias and mean squared error of $T_n = (1 - a/n)^{nX}$ as an estimator of $\exp(-a\theta)$, where $a \neq 0$ is a known constant.

9. Let X_1, \dots, X_n be a sample from the normal distribution with mean θ and variance θ .

(a) Find a variance stabilizing transformation for the sample mean and construct a confidence interval for based on this.

(b) Find the limit distribution of the sequence $\sqrt{n}(\cos(\bar{X}_n) - \cos(\theta))$. For which values of θ is this distribution degenerate?

10. Let $\Theta = \{-1, 0, 1\}$. Let f_θ be the pdf of a $N(\theta, 1)$ random variable. Consider the null hypothesis $\theta = 0$ and the alternate hypothesis $\theta \in \{1, -1\}$. Suppose we have one sample $X \sim N(\theta, 1)$ and we wish to test H_0 against H_a . Show that there is no uniformly most powerful test at level $\alpha \in (0, 1)$.

11. Let $\Theta = \{0, 1, 2\}$. Let f_θ be the pdf of a $N(\theta, 1)$ random variable. Consider the null hypothesis $\theta = 0$ and the alternate hypothesis $\theta \in \{1, 2\}$. Suppose we have one sample $X \sim N(\theta, 1)$ and we wish to test H_0 against H_a . Show that there is a uniformly most powerful test at level $\alpha \in (0, 1)$.

12. Let X be a random variable having probability density $f(x|\theta) = \exp\{\eta(\theta)Y(x) - \xi(\theta)\}h(x)$, where η is an increasing and differentiable function of $\theta \in \Theta \subset R$.

(a) Show that $\log \ell(\hat{\theta}) - \log \ell(\theta_0)$ is increasing (or decreasing) in Y , when $\hat{\theta} > \theta_0$ (or $\hat{\theta} < \theta_0$), where $\ell(\theta) = f(x|\theta)$, $\hat{\theta}$ is an MLE of θ , and $\theta_0 \in \Theta$.

(b) For testing $H_0 : \theta_1 \leq \theta \leq \theta_2$ versus $H_1 : \theta < \theta_1$ or $\theta > \theta_2$ or for testing $H_0 : \theta = \theta_0$ versus $H_1 : \theta \neq \theta_0$, show that there is a likelihood ratio test whose rejection region is equivalent to $Y(X) < c_1$ or $Y(x) > c_2$ for some constants c_1 and c_2 .

13. Let F and G be two known cumulative distribution functions (CDFs) on R and X be a single observation from the CDF $\theta F(x) + (1 - \theta)G(x)$, where $\theta \in [0, 1]$ is unknown.

(a) Find a UMP test of size α for testing $H_0 : \theta \leq \theta_0$ versus $H_1 : \theta > \theta_0$, where $\theta_0 \in [0, 1]$ is known.

(b) Show that the test $T(X) = \alpha$ is a UMP test of size α for testing $H_0 : \theta \leq \theta_1$ or $\theta \geq \theta_2$ versus $H_1 : \theta_1 < \theta < \theta_2$, where $\theta_j \in [0, 1]$ is known, $j = 1, 2$, and $\theta_1 < \theta_2$.

(c) Derive the likelihood ratio $\lambda(X)$ for $H_0 : \theta \leq \theta_1$ or $\theta \geq \theta_2$.

(. F. G. differentiable
 . θ to (a) ,
 (1) 作定 θ 的 $\lambda(X)$

$\frac{dY}{d\theta} \approx \frac{Y}{\theta}$

14. A family of probability density functions $f(x|\theta)$ on R , indexed by $\theta \in \Theta \subset R$, is said to have a *monotone likelihood ratio (MLR)* if, for each $\theta_0 \neq \theta_1$, the ratio $f(x|\theta_1)/f(x|\theta_0)$ is monotonic in x . Assume that $\partial^2 \log f(x|\theta)/\partial\theta\partial x$ exists.

(a) Show that a family of density functions $\{f(x|\theta) : \theta \in \Theta \subset R\}$ has MLR in x is equivalent to one of the following conditions:

(1) $\partial^2 \log f(x|\theta)/\partial\theta\partial x \geq 0$ for all x and θ ;

(2) $f(x|\theta) [\partial^2 \log f(x|\theta)/\partial\theta\partial x] \geq (\partial f(x|\theta)/\partial\theta)(\partial f(x|\theta)/\partial x)$ for all x and θ .

(b) Let $Z \sim N(\sqrt{\theta}, 1)$, then Z^2 has the non-central chi-square distribution $\chi_1^2(\theta)$. Show that $\{\chi_1^2(\theta)\}$ has MLR in x .

15. A family of probability distributions on R , indexed by $\theta \in \Theta \subset R$, is called *stochastically increasing* if their CDFs $\{F(x|\theta), \theta \in \Theta\}$ satisfy the following statement

$$\text{When } \theta_1 < \theta_2, \text{ we have } F(x|\theta_1) \geq F(x|\theta_2) \text{ for all } x \in R.$$

(Intuitively this says that larger values of the parameter θ are associated with larger values of the random variable X).

(a) Show that if a family of pdfs $\{f(x|\theta) : \theta \in \Theta\}$ has an MLR, then the corresponding family of CDFs is stochastically increasing in θ .

(b) Show that the converse of part (a) is false.

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□ $Z \stackrel{\text{def}}{=} X+Y$

$$\begin{aligned}
Pr(X=x, Z=z) &= Pr(X=x, Z-X=z-x) \\
&= Pr(X=x, Y=z-x) = Pr(X=x) \cdot Pr(Y=z-x) \\
&= e^{-\mu} \cdot \frac{\mu^x}{x!} \cdot e^{-\lambda} \cdot \frac{\lambda^{z-x}}{(z-x)!} \quad (x \geq 0, z-x \geq 0)
\end{aligned}$$

$$Pr(X=x | Z=z) = \frac{Pr(X=x, Z=z)}{Pr(Z=z)}$$

$$\left(\begin{aligned}
&\because X+Y=Z \sim Po(\lambda+\mu) \\
&Pr(Z=z) = e^{-(\lambda+\mu)} \cdot \frac{(\lambda+\mu)^z}{z!} \\
&= \frac{e^{-\mu} \cdot \frac{\mu^x}{x!} \cdot e^{-\lambda} \cdot \frac{\lambda^{z-x}}{(z-x)!}}{e^{-(\lambda+\mu)} \cdot \frac{(\lambda+\mu)^z}{z!}}
\end{aligned} \right)$$

$$= \frac{z!}{x!(z-x)!} \left(\frac{\mu}{\lambda+\mu}\right)^x \left(1 - \frac{\mu}{\lambda+\mu}\right)^{z-x}$$

由此可知 $X | X+Y=Z \sim Bn(z, \frac{\mu}{\lambda+\mu})$

$\therefore X | Z=n \sim Bn(n, \frac{\mu}{\lambda+\mu})$

$$\boxed{2} \quad X, Y \stackrel{iid}{\sim} e(\lambda)$$

$$\textcircled{1} \quad \Pr(X^3 \leq t) = 1 - \Pr(X^3 > t) = 1 - \Pr(X > t^{\frac{1}{3}})$$

$$\Pr(X > x) = \int_x^{\infty} \lambda \exp(-\lambda t) dt = [-\exp(-\lambda t)]_x^{\infty}$$

$$= \exp(-\lambda x)$$

$$\therefore \Pr(X > t^{\frac{1}{3}}) = \exp(-\lambda t^{\frac{1}{3}})$$

$$\therefore \Pr(X^3 \leq t) = 1 - \exp(-\lambda t^{\frac{1}{3}})$$

$$\frac{d}{dt} \Pr(X^3 \leq t) = \frac{\lambda t^{\frac{2}{3}}}{3} \exp(-\lambda t^{\frac{1}{3}})$$

$$\therefore f_{X^3}(x) = \frac{\lambda x^{\frac{2}{3}}}{3} \exp(-\lambda x^{\frac{1}{3}})$$

② $|X - Y| \dots$ sample range

将情况一般化：

$$X_1, X_2, \dots, X_n \stackrel{iid}{\sim} e(\lambda) \quad (n=2)$$

$$R = X_{(n)} - X_{(1)}$$

$$S = \frac{X_{(n)} + X_{(1)}}{2}$$

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$$\begin{aligned} & \Pr(X_{(1)} \leq x, X_{(n)} \leq y) \\ &= \Pr(X_{(n)} \leq y) - \Pr(x < X_{(1)}, X_{(n)} \leq y) \\ & \quad \parallel \qquad \qquad \parallel \\ & \Pr(X_1 \sim X_n \leq y) \quad \Pr(x < X_1 \sim X_n \leq y) \\ & \quad \parallel \qquad \qquad \parallel \\ & \left(\int_0^y \lambda \exp(-\lambda t) dt \right)^n \quad \left(\exp(-\lambda x) - \exp(-\lambda y) \right)^n \\ &= (1 - \exp(-\lambda y))^n \end{aligned}$$

$$\begin{aligned} \therefore \frac{\partial^2}{\partial x \partial y} \Pr(X_{(1)} \leq x, X_{(n)} \leq y) \\ &= n(n-1) (\exp(-\lambda x) - \exp(-\lambda y))^{n-2} \cdot \lambda \exp(-\lambda x) \cdot \lambda \exp(-\lambda y) \\ &= f_{X_{(1)}, X_{(n)}}(X_{(1)}=x, X_{(n)}=y) \end{aligned}$$

$$\begin{cases} r = y - x \\ s = \frac{y+x}{2} \end{cases} \quad \text{變數轉換} \quad \begin{pmatrix} X_{(1)} \\ X_{(n)} \end{pmatrix} \rightarrow \begin{pmatrix} r \\ s \end{pmatrix}$$

$$\Leftrightarrow \begin{cases} x = s - \frac{r}{2} \\ y = s + \frac{r}{2} \end{cases}$$

$$dx dy = dr ds$$

$$\begin{array}{ccc} X_{(1)} & & X_{(n)} \\ \parallel & & \parallel \\ 0 \leq S - \frac{r}{2} \leq S + \frac{r}{2} < \infty \end{array}$$

$$\Leftrightarrow \frac{r}{2} \leq S, \quad r \geq 0.$$

$$\begin{aligned} f_{RS}(r, s) &= n(n-1) \left\{ \exp(-\lambda(S - \frac{r}{2})) - \exp(-\lambda(S + \frac{r}{2})) \right\} \\ &\quad \cdot \lambda^2 \exp(-\lambda(2s)) \\ &= n(n-1) \exp(-\lambda s) \cdot \left\{ \exp(\frac{\lambda r}{2}) - \exp(-\frac{\lambda r}{2}) \right\} \\ &\quad \lambda^2 \exp(-2\lambda s) \\ &= n(n-1) \lambda^2 \exp(-\lambda h s) \left\{ \exp(\frac{\lambda r}{2}) - \exp(-\frac{\lambda r}{2}) \right\} \end{aligned}$$

$$f_R(r) =$$

$$\begin{aligned} \int_{S \geq \frac{r}{2}} f_{RS}(r, s) ds &= \int_{S \geq \frac{r}{2}} \lambda n \exp(-\lambda h s) ds \\ &\quad \cdot \lambda(n-1) \left\{ \exp(\frac{\lambda r}{2}) - \exp(-\frac{\lambda r}{2}) \right\} \\ &= \left[\exp(-\lambda h s) \right]_{\frac{r}{2}}^{\infty} \cdot \lambda(n-1) \left\{ \exp(\frac{\lambda r}{2}) - \exp(-\frac{\lambda r}{2}) \right\} \\ &= \exp(-\frac{\lambda h r}{2}) \cdot \lambda(n-1) \left\{ \exp(\frac{\lambda r}{2}) - \exp(-\frac{\lambda r}{2}) \right\} \\ &= f_R(r) \end{aligned}$$

$$n=2, \quad f_{R2}(r) = \lambda \exp(-\lambda r) \quad \therefore |X-Y| \sim \exp(\lambda) \\ (r \geq 0)$$

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$$\textcircled{3} \min\{X, Y^3\}$$

$$\Pr(\min\{X, Y^3\} \leq t) = 1 - \Pr(\min\{X, Y^3\} > t)$$

$$= 1 - \Pr(X > t) \Pr(Y^3 > t)$$

$$= 1 - \Pr(X > t) \Pr(Y > t^{\frac{1}{3}})$$

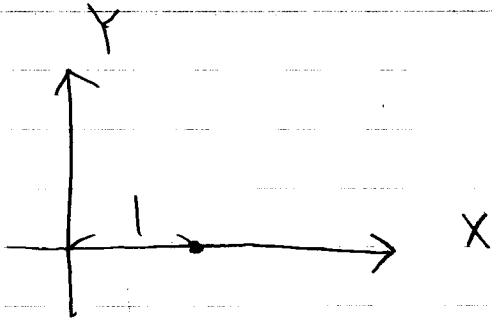
$$= 1 - \exp(-\lambda t) \exp(-\lambda t^{\frac{1}{3}})$$

$$= 1 - \exp(-\lambda(t + t^{\frac{1}{3}}))$$

$$\frac{d}{dt}(1 - \exp(-\lambda(t + t^{\frac{1}{3}}))) = \lambda(1 + \frac{1}{3}t^{\frac{-2}{3}}) \exp(-\lambda(t + t^{\frac{1}{3}}))$$

$$\therefore f_{\min\{X, Y^3\}}(t) = \lambda(1 + \frac{1}{3}t^{\frac{-2}{3}}) \exp(-\lambda(t + t^{\frac{1}{3}})) \quad (t \geq 0)$$

3



$$\theta \sim U(-\pi, \pi)$$

$$l = \| (\cos\theta, \sin\theta) - (1, 0) \|$$

$$= \sqrt{(1 - \cos\theta)^2 + \sin^2\theta} = \sqrt{2 - 2\cos\theta}$$

$$= \sqrt{2 - 2\cos\left(\frac{\theta}{2} + \frac{\theta}{2}\right)} = |2\sin\frac{\theta}{2}|$$

$\therefore \theta$ 之 概 率 密 度 函 數 .. $f(\theta) = \frac{1}{2\pi} \cdot I_{(-\pi, \pi)}(\theta)$

$$1 = \int_{-\pi}^{\pi} \frac{1}{2\pi} d\theta = \int_0^{\pi} \frac{1}{2\pi} d\theta + \int_{-\pi}^0 \frac{1}{2\pi} d\theta$$

$$\textcircled{1} \begin{array}{l} \theta: 0 \rightarrow \pi \\ l: 0 \rightarrow 2 \end{array} \quad \begin{array}{l} l = 2\sin\frac{\theta}{2} \\ \theta = 2\arcsin\left(\frac{l}{2}\right) \end{array}$$

$$\frac{d\theta}{dl} = \frac{1}{\sqrt{1 - \left(\frac{l}{2}\right)^2}}$$

$$\textcircled{2} \begin{array}{l} \theta: -\pi \rightarrow 0 \\ l: 2 \rightarrow 0 \end{array} \quad \begin{array}{l} l = -2\sin\frac{\theta}{2} \\ \theta = 2\arcsin\left(\frac{-l}{2}\right) \end{array}$$

$$\frac{d\theta}{dl} = \frac{(-1)}{\sqrt{1 - \left(\frac{-l}{2}\right)^2}}$$

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$$\int_0^{\pi} \frac{1}{2\pi} d\theta + \int_{-\pi}^0 \frac{1}{2\pi} d\theta$$
$$= \int_0^2 \frac{1}{2\pi} \cdot \frac{dl}{\sqrt{1-\frac{l^2}{4}}} + \int_2^0 \frac{1}{2\pi} \cdot \frac{-dl}{\sqrt{1-\frac{l^2}{4}}}$$
$$= \int_0^2 \frac{1}{\pi} \cdot \frac{dl}{\sqrt{1-\frac{l^2}{4}}}$$

$$\therefore f_L(l) = \frac{2}{\pi} \cdot \frac{1}{\sqrt{4-l^2}} \quad (0 < l < 2)$$

$$\boxed{4} \quad \Pr(Y \leq z) = \Pr(F^{-1}(X) \leq z)$$

$$(F: \text{遞增函數}) = \Pr(X \leq F(z)) = F(z)$$

由此可知, Y 之 cdf 亦為 F .

$$\therefore Y \sim F$$

$\boxed{5}$ 首先考慮 $W_1, W_2, W_3, W_4 \stackrel{\text{iid}}{\sim} \text{exp}(1)$

$$\left\{ \begin{array}{l} Y_1 \stackrel{\text{def}}{=} \frac{W_1}{W_1 + W_2 + W_3 + W_4} \\ Y_2 \stackrel{\text{def}}{=} \frac{W_1 + W_2}{W_1 + W_2 + W_3 + W_4} \\ Y_3 \stackrel{\text{def}}{=} \frac{W_1 + W_2 + W_3}{W_1 + W_2 + W_3 + W_4} \\ Y_4 \stackrel{\text{def}}{=} W_1 + W_2 + W_3 + W_4 \end{array} \right.$$

$$\Rightarrow \left\{ \begin{array}{l} W_1 = Y_1 Y_4 \\ W_2 = Y_2 Y_4 - Y_1 Y_4 \\ W_3 = Y_3 Y_4 - Y_2 Y_4 \\ W_4 = Y_4 - Y_3 Y_4 \end{array} \right.$$

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$$\frac{\partial}{\partial y_1} \begin{pmatrix} u_1 \\ u_2 \\ u_3 \\ u_4 \end{pmatrix} = \begin{pmatrix} y_4 \\ -y_4 \\ 0 \\ 0 \end{pmatrix}$$

$$\frac{\partial}{\partial y_2} \begin{pmatrix} u_1 \\ u_2 \\ u_3 \\ u_4 \end{pmatrix} = \begin{pmatrix} 0 \\ y_4 \\ -y_4 \\ 0 \end{pmatrix}$$

$$\frac{\partial}{\partial y_3} \begin{pmatrix} u_1 \\ u_2 \\ u_3 \\ u_4 \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \\ y_4 \\ -y_4 \end{pmatrix}$$

$$\frac{\partial}{\partial y_4} \begin{pmatrix} u_1 \\ u_2 \\ u_3 \\ u_4 \end{pmatrix} = \begin{pmatrix} y_1 \\ y_2 - y_1 \\ y_3 - y_2 \\ 1 - y_3 \end{pmatrix}$$

$$J = \begin{pmatrix} y_4 & 0 & 0 & y_1 \\ -y_4 & y_4 & 0 & y_2 - y_1 \\ 0 & -y_4 & y_4 & y_3 - y_2 \\ 0 & 0 & -y_4 & 1 - y_3 \end{pmatrix}$$

$$\det J = y_4^3 \cdot \det \begin{pmatrix} 1 & 0 & 0 & y_1 \\ -1 & 1 & 0 & y_2 - y_1 \\ 0 & -1 & 1 & y_3 - y_2 \\ 0 & 0 & -1 & 1 - y_3 \end{pmatrix}$$

$$= y_4^3 \cdot \det \begin{pmatrix} 1 & 0 & 0 & y_1 \\ 0 & 1 & 0 & y_2 \\ 0 & 0 & 1 & y_3 \\ 0 & 0 & 0 & 1 \end{pmatrix} = y_4^3$$

$$\therefore du_1 du_2 du_3 du_4 = y_4^3 dy_1 dy_2 dy_3 dy_4$$

$$\text{全標本} = 1 = \int_{\substack{u_1 > 0 \\ u_4 > 0}} \exp(-(u_1 + u_2 + u_3 + u_4)) du_1 \dots du_4$$

$$= \int_{\substack{0 < y_1 < y_2 < y_3 < y_4 \\ y_4 > 0}} y_4^3 \exp(-y_4) dy_4 dy_1 dy_2 dy_3$$

$$\begin{aligned}
 f_{Y_1, Y_2, Y_3}(y_1, y_2, y_3) &= \int_{y_1 > 0} y_1^3 e^{-y_1} dy_1 \\
 &= P(4) I(0 < y_1 < y_2 < y_3 < 1) \\
 &= 3! I(0 < y_1 < y_2 < y_3 < 1)
 \end{aligned}$$

由此可知, $X_1, X_2, X_3 \stackrel{iid}{\sim} U(0, 1)$

$$\Rightarrow \begin{pmatrix} X_{(1)} \\ X_{(2)} \\ X_{(3)} \end{pmatrix} \text{ 之分布等於 } \begin{pmatrix} Y_1 \\ Y_2 \\ Y_3 \end{pmatrix}$$

(順序統計量)

根據題意,

$$\begin{aligned}
 U_1 &= \frac{X_{(1)}}{X_{(2)}} = \frac{Y_1}{Y_2} = \frac{W_1}{W_1 + W_2} \\
 U_2 &= \frac{X_{(2)}}{X_{(3)}} = \frac{Y_2}{Y_3} = \frac{W_1 + W_2}{W_1 + W_2 + W_3}
 \end{aligned}$$

$$(W_1, W_2, W_3 \sim iid \text{ } e(1))$$

$$U_3 \stackrel{\text{def}}{=} W_1 + W_2 + W_3$$

$$\Rightarrow \begin{cases} W_1 = U_1 U_2 U_3 \\ W_2 = U_2 U_3 - U_1 U_2 U_3 \\ W_3 = U_3 - U_2 U_3 \end{cases}$$

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$$\frac{\partial}{\partial u_1} \begin{pmatrix} w_1 \\ w_2 \\ w_3 \end{pmatrix} = \begin{pmatrix} u_2 u_3 \\ -u_2 u_3 \\ 0 \end{pmatrix} \quad \frac{\partial}{\partial u_2} \begin{pmatrix} u_1 u_3 \\ u_3 - u_1 u_3 \\ -u_3 \end{pmatrix}$$

$$\frac{\partial}{\partial u_3} \begin{pmatrix} w_1 \\ w_2 \\ w_3 \end{pmatrix} = \begin{pmatrix} u_1 u_2 \\ u_2 - u_1 u_2 \\ 1 - u_2 \end{pmatrix}$$

$$\therefore J = \begin{pmatrix} u_2 u_3 & u_1 u_3 & u_1 u_2 \\ -u_2 u_3 & u_3 - u_1 u_3 & u_2 - u_1 u_2 \\ 0 & -u_3 & 1 - u_2 \end{pmatrix}$$

$$\det J = u_2 u_3^2 \cdot \det \begin{pmatrix} 1 & u_1 & u_1 u_2 \\ -1 & 1 - u_1 & u_2 - u_1 u_2 \\ 0 & 1 & 1 - u_2 \end{pmatrix}$$

$$= u_2 u_3^2 \det \begin{pmatrix} 1 & u_1 & u_1 u_2 \\ 0 & 1 & u_2 \\ 0 & 0 & 1 \end{pmatrix} = u_2 u_3^2$$

$$w_1 \geq 0, w_2 \geq 0, w_3 \geq 0$$

$$\therefore 0 \leq u_1 \leq 1, 0 \leq u_2 \leq 1, u_3 \geq 0$$

$$\text{全概率} = 1 = \int_{\substack{u_1 > 0 \\ u_2 > 0 \\ u_3 > 0}} \exp(-(u_1 + u_2 + u_3)) \, du_1 du_2 du_3$$

$$= \int_{\substack{0 \leq u_1 \leq 1 \\ 0 \leq u_2 \leq 1 \\ u_3 \geq 0}} \exp(-u_3) \cdot u_2 u_3^2 \, du_1 du_2 du_3$$

$$f_{U_1, U_2}(u_1, u_2) = \int_{u_3 \geq 0} u_2 \cdot u_3^2 \exp(-u_3) du_3$$

$$= \Gamma(3) \cdot u_2 = 2u_2$$

$$U_1 = \frac{W_1}{W_1 + W_2} \quad U_2 = \frac{W_1 + W_2}{W_1 + W_2 + W_3}$$

利用以下事實... $\begin{pmatrix} X \sim P(\alpha, \lambda) \\ Y \sim P(\beta, \lambda) \end{pmatrix}$, X, Y 獨立

$$\Rightarrow \frac{X}{X+Y} \sim \text{Be}(\alpha, \beta)$$

根據這個事實, $U_1 = \frac{W_1}{W_1 + W_2} \sim \text{Be}(1, 1) = \text{Uni}(0, 1)$

$$U_2 = \frac{W_1 + W_2}{W_1 + W_2 + W_3} \sim \text{Be}(2, 1)$$

$$\therefore f_{U_1}(u_1) = 1 \quad (0 \leq u_1 \leq 1)$$

$$f_{U_2}(u_2) = \frac{1}{\text{Be}(2, 1)} u_2^{2-1} (1-u_2)^{1-1} = 2u_2 \quad (0 \leq u_2 \leq 1)$$

由此可知, $f_{U_1, U_2}(u_1, u_2) = f_{U_1}(u_1) f_{U_2}(u_2)$

$\therefore U_1, U_2$ 為獨立.

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$$\boxed{6} \quad X_1, X_2, \dots, X_n \sim \exp(\lambda)$$

• 先求 $X_{(1)}, \dots, X_{(n)}$ 之聯合機率密度函數

$$f_{X_1, \dots, X_n}(x_1, \dots, x_n) = \lambda \exp(-\lambda x_1) \dots \lambda \exp(-\lambda x_n)$$

n 個順序統計量的聯合機率密度函數

$$f_{X_{(1)}, \dots, X_{(n)}}(x_1, \dots, x_n) = n! f_{X_1, \dots, X_n}(x_1, \dots, x_n) \\ (0 \leq x_1 \leq \dots \leq x_n)$$

• Step 1 \dots $X_{(1)}, \dots, X_{(n-1)}$ 之聯合分布

$$n! \int_{x_{(n)} > x_{(n-1)}} \lambda \exp(-\lambda x_1) \dots \lambda \exp(-\lambda x_n) dx_n$$

$$= n! \lambda \exp(-\lambda x_1) \dots \lambda \exp(-\lambda x_{n-1}) \cdot \exp(-\lambda x_{n-1})$$

$$= n! \lambda \exp(-\lambda x_1) \dots \lambda \exp(-\lambda x_{n-2}) \lambda \exp(-2\lambda x_{n-1})$$

• Step 2 \dots $X_{(1)}, \dots, X_{(n-2)}$ 之聯合分布

$$n! \int_{x_{(n-1)} > x_{(n-2)}} \lambda \exp(-\lambda x_1) \dots \lambda \exp(-\lambda x_{n-2}) \cdot \lambda \exp(-2\lambda x_{n-1}) dx_{n-1}$$

$$= \frac{n!}{2!} \cdot \lambda \exp(-\lambda x_1) \dots \lambda \exp(-\lambda x_{n-3}) \lambda \exp(-3\lambda x_{n-2})$$

⋮

• Step j... $X_{(1)} \dots X_{(n-j)}$ 是聯合分佈

$$= \frac{n!}{j!} \lambda \exp(-\lambda x_1) \dots \lambda \exp(-\lambda x_{n-j}) \lambda \exp(-(n-j+1)\lambda x_{n-j})$$

$j = n-r$ 得到 $X_{(1)} \dots X_{(r)}$ 是聯合分佈

$$= \frac{n!}{(n-r)!} \lambda \exp(-\lambda x_1) \dots \lambda \exp(-\lambda x_{r-1}) \lambda \exp(-(n-r+1)\lambda x_r)$$

($X_1 \leq X_2 \leq \dots \leq X_n$)

接下來考慮以下變數轉換.

$$\begin{cases} Y_1 = n X_{(1)} \\ Y_2 = (n-1)(X_{(2)} - X_{(1)}) \\ \vdots \\ Y_r = (n-r+1)(X_{(r)} - X_{(r-1)}) \end{cases}$$

$$\begin{pmatrix} Y_1 \\ \vdots \\ Y_r \end{pmatrix} = \begin{pmatrix} n & & & \\ -(n-1) & (n-1) & & \\ & -(n-2) & (n-2) & \\ & & \ddots & \ddots \\ & & & (n-r+1) \end{pmatrix} \begin{pmatrix} X_{(1)} \\ \vdots \\ X_{(r)} \end{pmatrix}$$

$$dy_1 \dots dy_r = \frac{n!}{(n-r)!} dx_1 \dots dx_r$$

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$$X(1) \leq X(2) \leq \dots \leq X(n)$$

$$\therefore Y_1 \geq 0, Y_2 \geq 0, \dots, Y_n \geq 0$$

Y_1, Y_2, \dots, Y_n 之聯合機率密度函數

$$\begin{aligned} \text{全機率} = 1 &= \int_{0 \leq x_1 \leq x_2 \leq \dots \leq x_n} \frac{n!}{(n-1)!} \lambda \exp(-\lambda x_1) \dots \lambda \exp(-\lambda x_n) \\ &\quad \lambda \cdot \exp(-(n-1)\lambda x_n) dx_1 \dots dx_n \end{aligned}$$

$$= \int_{y_i > 0} \lambda^n \exp(-\lambda(y_1 + \dots + y_n)) dy_1 \dots dy_n$$

$$f_{Y_1, \dots, Y_n}(y_1, \dots, y_n) = \lambda^n \exp(-\lambda(y_1 + \dots + y_n)) \quad (y_1, y_2, \dots > 0)$$

$$f_{Y_i} = \lambda \exp(-\lambda y_i)$$

$$f_{Y_1, \dots, Y_n}(y_1, \dots, y_n) = f_{Y_1}(y_1) \dots f_{Y_n}(y_n) \quad (Y_1 \sim Y_n \text{ 獨立})$$

由此可知, $Y_1, Y_2, \dots, Y_n \stackrel{i.i.d.}{\sim} \exp(\lambda)$

$$W = (n-1)X(n) + \sum_{i=1}^n X(i)$$

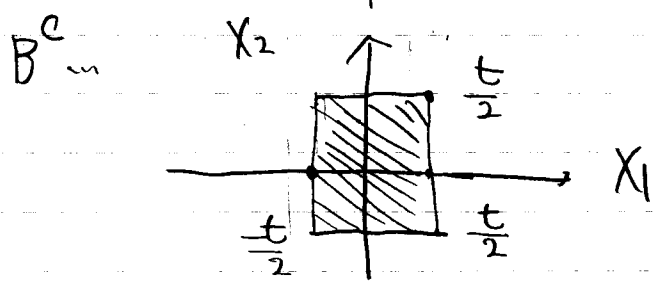
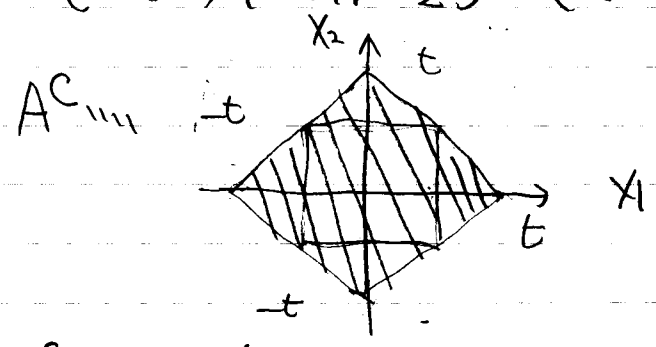
$$= Y_1 + Y_2 + \dots + Y_n \sim \Gamma(n, \lambda) \quad (\text{Gamma 分布})$$

$$\therefore E[W] = \frac{n}{\lambda} \quad \text{Var}[W] = \frac{n}{\lambda^2} \Rightarrow$$

$$\therefore E[U] = \frac{1}{\lambda} \quad \text{Var}[U] = \frac{1}{n\lambda^2}$$

$$\square A = \{(X_1, X_2) \mid |X_1 - X_2| > t\}$$

$$B = \{(X_1, X_2) \mid |X_1| > \frac{t}{2}\} \cup \{(X_1, X_2) \mid |X_2| > \frac{t}{2}\}$$



由此可知 $A^c \supset B^c$

$$\therefore A \subseteq B$$

$$\therefore P(A) \leq P(B)$$

$$\begin{aligned} & \parallel P(\{(X_1, X_2) \mid |X_1| > \frac{t}{2}\} \cup \{(X_1, X_2) \mid |X_2| > \frac{t}{2}\}) \\ & = 2P(|X_1| > \frac{t}{2}) \end{aligned}$$

C: $X_1, X_2 \sim iid$

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$$(a) f_{\theta}(x_1, \dots, x_n) = \frac{\theta}{(1+x_1)^{\theta+1}} \cdots \frac{\theta}{(1+x_n)^{\theta+1}}$$

$$\log f_{\theta}(x_1, \dots, x_n) = n \log \theta - (\theta+1) \sum_{j=1}^n \log(1+x_j)$$

$$\frac{\partial}{\partial \theta} \log f_{\theta}(x_1, \dots, x_n) = \frac{n}{\theta} - \sum_{j=1}^n \log(1+x_j)$$

$$\frac{\partial^2}{\partial \theta^2} \log f_{\theta}(x_1, \dots, x_n) = -\frac{n}{\theta^2} < 0$$

$$\frac{\partial}{\partial \theta} \log f_{\theta}(x_1, \dots, x_n) = 0$$

$$\Rightarrow \theta = \frac{n}{\sum_{j=1}^n \log(1+x_j)}$$

$$\therefore \hat{\theta}_{MLE} = \frac{n}{\sum_{j=1}^n \log(1+x_j)}$$

(b) 流程... 求 $\log(1+x_j)$ 之分布

↓
中央極限定理

↓
S-method

$$t = \log(1+\lambda) \quad (1+\lambda) = e^t \quad \begin{cases} \lambda: 0 \rightarrow \infty \\ t: 0 \rightarrow \infty \end{cases}$$

$$\frac{dt}{d\lambda} = \frac{1}{1+\lambda}$$

$$\begin{aligned} \text{全確率} = 1 &= \int_{\lambda > 0} \frac{\theta}{(1+\lambda)^{\theta+1}} d\lambda \\ &= \int_{t > 0} \theta \cdot e^{-\theta t} dt \end{aligned}$$

$$\therefore T = \log(1+X) \sim \text{exp}(\theta) \quad (E[T] = \frac{1}{\theta} \quad V[T] = \frac{1}{\theta^2})$$

$$E[T] < \infty \quad E[T^2] < \infty$$

根據中央極限定理,

$$\sqrt{n} \left(\frac{T_1 + \dots + T_n}{n} - \frac{1}{\theta} \right) \xrightarrow{d} N\left(0, \frac{1}{\theta^2}\right)$$

接下來利用 Δ -method

$$g(x) = x^{\frac{1}{\theta}}$$

$$\sqrt{n} \left(g\left(\frac{T_1 + \dots + T_n}{n}\right) - g\left(\frac{1}{\theta}\right) \right) \xrightarrow{d} N\left(0, \frac{1}{\theta^2} (g'\left(\frac{1}{\theta}\right))^2\right)$$

$$g(x) = \frac{1}{x^{\frac{1}{\theta}}} \quad g'\left(\frac{1}{\theta}\right) = -\theta^2 \quad (g'\left(\frac{1}{\theta}\right))^2 = \theta^4$$

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$$\therefore \sqrt{n} \left(g\left(\frac{X_1 + \dots + X_n}{n}\right) - g\left(\frac{1}{\theta}\right) \right) \xrightarrow{d} N(0, \theta^2)$$

$$\sqrt{n} (\hat{\theta}_{MLE} - \theta) \xrightarrow{d} N(0, \theta^2)$$

(c) 同樣利用 Δ -method

$$\sqrt{n} \left(g\left(\frac{X_1 + \dots + X_n}{n}\right) - g\left(\frac{1}{\theta}\right) \right) \xrightarrow{d} N\left(0, \frac{1}{\theta^2} \cdot (g'\left(\frac{1}{\theta}\right))^2\right)$$

$$\therefore g'\left(\frac{1}{\theta}\right) = \pm \theta$$

$$\therefore g'(\theta) = \pm \frac{1}{\theta}$$

$$g(\theta) = \pm \log \theta + c \quad (c=0)$$

在此採用 $g(\theta) = -\log \theta$

$$\sqrt{n} \left(-\log\left(\frac{X_1 + \dots + X_n}{n}\right) + \log\left(\frac{1}{\theta}\right) \right) \xrightarrow{d} N(0, 1)$$

$$\Leftrightarrow \sqrt{n} \left(\log \hat{\theta}_{MLE} - \log \theta \right) \xrightarrow{d} N(0, 1) \quad (\text{同樣道理 } \log \theta \text{ 亦可})$$

$$g(x) = \pm \log x + c \quad (c: \text{常數})$$

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$$\begin{aligned}
 \text{(a) } E[\hat{p}] &= E\left[\frac{1}{m} \sum_{i=1}^m I(X_i \geq 5) \cdot \frac{\phi(X_i)}{\phi(X_i - 5)}\right] \\
 &= \frac{1}{m} \sum_{i=1}^m E\left[I(X_i \geq 5) \cdot \frac{\phi(X_i)}{\phi(X_i - 5)}\right] \\
 &= \frac{1}{m} \sum_{i=1}^m \int_{x_i \in R} I(x_i \geq 5) \cdot \frac{\phi(x_i)}{\phi(x_i - 5)} \cdot \phi(x_i - 5) dx_i \\
 &= \frac{1}{m} \sum_{i=1}^m \int_{x_i \geq 5} \phi(x_i) dx_i \\
 &= \frac{1}{m} \sum_{i=1}^m (1 - \Phi(5)) = 1 - \Phi(5).
 \end{aligned}$$

$\therefore \hat{p}$ 為 $1 - \Phi(5)$ 之 不偏估計量

$$\text{(b) } V[\hat{p}] = V\left[\frac{1}{m} \sum_{i=1}^m I(X_i \geq 5) \cdot \frac{\phi(X_i)}{\phi(X_i - 5)}\right]$$

$$= \frac{1}{m} V\left[I(X_i \geq 5) \cdot \frac{\phi(X_i)}{\phi(X_i - 5)}\right]$$

$$\cdot E\left[\left(I(X_i \geq 5) \cdot \frac{\phi(X_i)}{\phi(X_i - 5)}\right)^2\right] = 1 - \Phi(5)$$

$$\cdot E\left[\left(I(X_i \geq 5) \cdot \frac{\phi(X_i)}{\phi(X_i - 5)}\right)^2\right] = \int_{x_i \geq 5} \frac{\phi(x_i)^2}{\phi(x_i - 5)^2} \cdot \phi(x_i - 5) dx_i$$

$$= \int_{x \geq 5} \frac{\phi(x)^2}{\phi(x - 5)} dx$$

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$$\int_{x \geq 5} \frac{\frac{1}{\sqrt{2\pi}} \exp(-x^2)}{\frac{1}{\sqrt{2\pi}} \exp(-\frac{1}{2}(x-5)^2)} dx$$

$$= \int_{x \geq 5} \frac{1}{\sqrt{2\pi}} \exp(-x^2 + \frac{1}{2}(x-5)^2) dx$$

$$= \int_{x \geq 5} \frac{1}{\sqrt{2\pi}} \exp\left(\frac{-x^2 - 10x + 25}{2}\right) dx$$

$$= \int_{x \geq 5} \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{1}{2}(x+5)^2 + \frac{50}{2}\right) dx$$

$$y = x+5$$

$$= \int_{y \geq 10} \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{y^2}{2}\right) \cdot \exp(25) dy$$

$$= \exp(25) \cdot (1 - \Phi(10))$$

$$\therefore V\left[I(X_i \geq 5) \cdot \frac{\phi(X_i)}{\phi(X_i-5)}\right]$$

$$= \exp(25) (1 - \Phi(10)) - (1 - \Phi(5))^2$$

$$\therefore V[\hat{p}] = \frac{1}{n} \left\{ \exp(25) (1 - \Phi(10)) - (1 - \Phi(5))^2 \right\}$$

$$\boxed{10} \quad Z(\lambda, \nu) \text{ 應為 } \sum_{i=0}^{\infty} \frac{\lambda^i}{(i!)^\nu} \quad (i=1 \rightarrow (\infty))$$

$$(a) \quad P(Y=y | \lambda, \nu) = \frac{\lambda^y}{(y!)^\nu} \cdot \frac{1}{Z(\lambda, \nu)}$$

$$= \exp\left(\log \frac{\lambda^y}{(y!)^\nu} - \log Z(\lambda, \nu)\right)$$

$$= \exp\left(y \log \lambda - \nu \log y! - \log Z(\lambda, \nu)\right)$$

$$= \exp\left(\sum_{j=1}^2 Q_j(\lambda, \nu) T_j(y) + d(\lambda, \nu)\right)$$

$$Q_1(\lambda, \nu) = \log \lambda, \quad T_1(y) = y, \quad d(\lambda, \nu) = -\log Z(\lambda, \nu)$$

$$Q_2(\lambda, \nu) = -\nu, \quad T_2(y) = y!$$

∴ 此分布為指數族。

$$(b) \quad \nu=1 \Rightarrow Z(\lambda, \nu) = \sum_{i=0}^{\infty} \frac{\lambda^i}{(i!)} = 1 + \lambda + \frac{\lambda^2}{2!} + \dots = e^\lambda$$

$$P(Y=y) = e^{-\lambda} \cdot \frac{\lambda^y}{y!}$$

$$\therefore Y \sim P(\lambda)$$

$$\therefore \nu=1 \text{ 時 } Y \sim \text{Poi}(\lambda)$$

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(C) Poisson 分布的期望值與變異數一致。

$$(E(X) = V(X) = \lambda)$$

但實際上觀測到的樣本平均與
樣本變異數可能有很大的差異。

在這種情況下，Poisson 分布不適合用來解釋
該筆資料的分布。

Comrey-Maxwell-Poisson 分布，根據 ν 之值，

除了 Poisson 分布之外，也可以表達幾何分布

Bernoulli 分布等的分布。

利用這因模型可以給更自然的解釋。

III 在此, 根據題意解釋為利用 χ^2 -test 檢定資料是否來自 Poisson 分布 (H₀: 資料來自 Poisson 分布)

$$\hat{\lambda} = \frac{1}{n} \sum_{j=1}^n X_j = 1.692 \dots \quad (n=915)$$

$$T = \sum_{j=0}^k \frac{(E_j - O_j)^2}{E_j} \quad (k=3, \text{ 將 } \geq 3 \text{ 整理在一起})$$

j	0	1	2	...	≥ 3
E _j	168.341	284.994	$2.881 \cdot 10^5$
O _j	275	246	2

$$T \sim \chi^2_{k-1} = \chi^2_2$$

(估計 1 個參數, 所以減一個自由度)

$$T = 160496.3 \gg \chi^2_2(0.95)$$

棄 H₀.

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12 $X \sim \text{Laplace}(\lambda, \mu=0)$

(a)

$$f(x) = \frac{\lambda}{2} \exp(-\lambda|x|)$$

$$M_X(t) = \int_{\mathbb{R}} e^{tx} \cdot \frac{\lambda}{2} \exp(-\lambda|x|) dx$$

$$= \int_{x \geq 0} e^{tx} \cdot \frac{\lambda}{2} \exp(-\lambda x) dx$$

$$+ \int_{x < 0} e^{tx} \cdot \frac{\lambda}{2} \exp(\lambda x) dx \quad (\dots (x \rightarrow -x))$$

$$= \frac{1}{2} \int_{x \geq 0} \lambda e^{tx} \cdot e^{-\lambda x} dx \quad (\lambda - t > 0)$$

$$+ \frac{1}{2} \int_{x \geq 0} \lambda e^{-tx} \cdot e^{-\lambda x} dx \quad (\lambda + t > 0)$$

$$Y \sim \exp(\lambda)$$

$$M_Y(t) = \int_{x \geq 0} \lambda e^{tx} \cdot e^{-\lambda x} dx \quad (\lambda - t > 0)$$

$$= \int_{x \geq 0} \lambda e^{-(\lambda - t)x} dx$$

$$= \left[\frac{-\lambda}{\lambda - t} e^{-(\lambda - t)x} \right]_{x=0}^{\infty}$$

$$= \frac{\lambda}{\lambda - t} = \left(1 - \frac{t}{\lambda}\right)^{-1}$$

$$\therefore M_X(t) = \frac{1}{2} (M_Y(t) + M_Y(-t)) = \frac{1}{2} \left(\left(1 - \frac{t}{\lambda}\right)^{-1} + \left(1 + \frac{t}{\lambda}\right)^{-1} \right) \quad (-\lambda < t < \lambda)$$

$$\frac{f}{g} + f \cdot \frac{g'}{g^2}$$

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$$\left(\frac{\#}{2} \lambda = 1 \dots M_X(t) = \frac{1}{2} \left(\frac{1}{1-t} + \frac{1}{1+t} \right) = \frac{1}{1-t^2} \right)$$

(b) $U, V \stackrel{iid}{\sim} \text{Exp}(1)$

$$E[e^{t(U-V)}] = E[e^{tU}] E[e^{-tV}]$$

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

由此可知, $U-V \sim \text{Laplace}(\lambda=1, \mu=0)$

(c) $X_1, \dots, X_n \stackrel{iid}{\sim} \text{Laplace}(\lambda)$

$$M_X(t) = \frac{1}{2} \left\{ \frac{1}{1-\frac{t}{\lambda}} + \frac{1}{1+\frac{t}{\lambda}} \right\} = \frac{1}{2} \cdot \frac{2}{1-\frac{t^2}{\lambda^2}} = \frac{\lambda^2}{\lambda^2 - t^2}$$

$$K_X(t) = \log M_X(t) = -\log(\lambda^2 - t^2)$$

$$\frac{\partial K}{\partial t} = \frac{2t}{\lambda^2 - t^2}$$

$$\frac{\partial^2 K}{\partial t^2} = \frac{2(\lambda^2 - t^2) + 4t^2}{(\lambda^2 - t^2)^2} = \frac{2\lambda^2 + 2t^2}{(\lambda^2 - t^2)^2}$$

$$\left. \frac{\partial K}{\partial t} \right|_{t=0} = 0, \quad \left. \frac{\partial^2 K}{\partial t^2} \right|_{t=0} = \frac{2\lambda^2}{\lambda^4} = \frac{2}{\lambda^2}$$

$$\therefore E[X_j] = 0 \quad V[X_j] = \frac{2}{\lambda^2}$$

$$\therefore W_n = \frac{\bar{X}}{\sqrt{\frac{1}{n} \cdot \frac{2}{\lambda^2}}} = \frac{X_1 + \dots + X_n}{\sqrt{\frac{2}{\lambda^2} \cdot n}}$$

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$$E[e^{tW_n}] = E\left[\exp\left(\frac{t\lambda}{\sqrt{2n}}(X_1 + \dots + X_n)\right)\right]$$

$$= E\left[\exp\left(\frac{t\lambda}{\sqrt{2n}}X_j\right)\right]^n$$

$$= \left(\frac{\lambda^2}{\lambda^2 - \frac{t^2\lambda^2}{2n}}\right)^n = \left(1 - \frac{t^2}{2n}\right)^{-n}$$

$$\therefore M_{W_n}(t) = \left(1 - \frac{t^2}{2n}\right)^{-n}$$

$$(d) \lim_{n \rightarrow \infty} M_{W_n}(t) = \lim_{n \rightarrow \infty} \left(1 - \frac{t^2}{2n}\right)^{-n}$$

$$= \lim_{n \rightarrow \infty} \left(1 - \frac{t^2}{2n}\right)^{\left(\frac{-2n}{t^2}\right) \cdot \frac{t^2}{2}}$$

$$= \exp\left(\frac{t^2}{2}\right)$$

根據 Levy 連續性定理

$$\therefore W_n \xrightarrow{d} N(0,1)$$

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$$(a) X_1, \dots, X_n \sim N(\mu, 1)$$

$$f(x) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{1}{2}(x-\mu)^2\right)$$

$$f(x_1, \dots, x_n | \mu) = \left(\frac{1}{\sqrt{2\pi}}\right)^n \exp\left(-\sum_{j=1}^n \frac{1}{2}(x_j - \mu)^2\right)$$

$$\log f(x_1, \dots, x_n | \mu) = -\left(\frac{n}{2}\right) \log(2\pi) - \frac{1}{2} \sum_{j=1}^n (x_j - \mu)^2$$

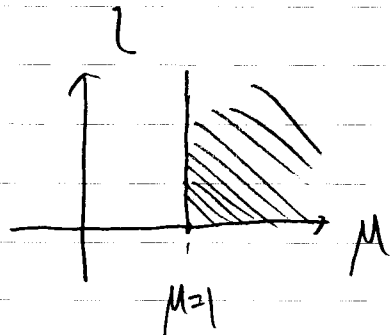
$$\frac{\partial}{\partial \mu} \log f(x_1, \dots, x_n | \mu) = \sum_{j=1}^n (x_j - \mu) = 0$$

$$\Rightarrow \mu = \bar{X}$$

$$L(\mu | X_1, \dots, X_n) = \frac{1}{2} \sum_{j=1}^n (x_j - \mu)^2 - \frac{n}{2} \log 2\pi$$

$$l(\mu) = \log L$$

μ		\bar{X}	
l	+		-
l	\rightarrow	MAX	\downarrow



if ... $\bar{X} < 1 \Rightarrow \mu = 1$ 使得 l 为最大
 else $\bar{X} \geq 1 \Rightarrow \mu = \bar{X}$ 使得 l 为最大

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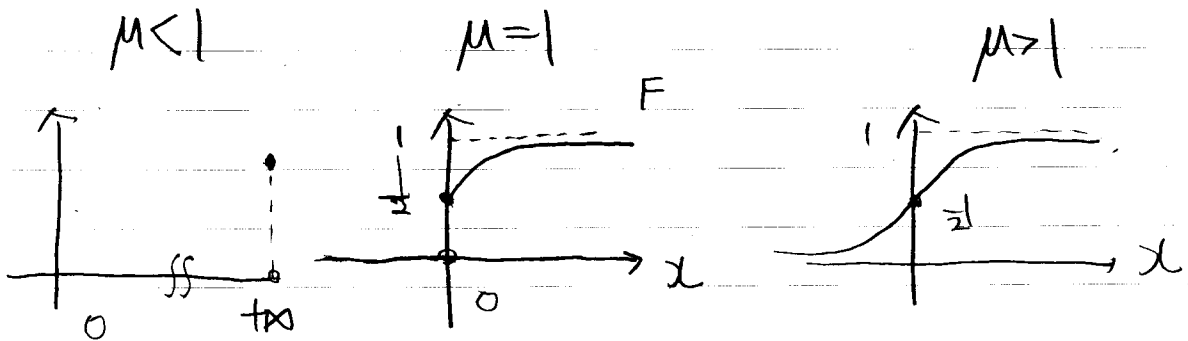
$$\therefore \hat{\mu}_{MUE} = \max\{1, \bar{X}\}$$

(b) (c) $\hat{\mu} = \max\{1, \bar{X}\}$ (題目是不是隱改為 $\underline{\mu=1}$?)

$$\begin{aligned} & \Pr(\sqrt{n}(\hat{\mu} - \mu) \leq \lambda) \\ &= \Pr(\hat{\mu} - \mu \leq \frac{\lambda}{\sqrt{n}}) \\ &= \Pr(\hat{\mu} \leq \frac{\lambda}{\sqrt{n}} + \mu) \\ &= \Pr(\max\{1, \bar{X}\} \leq \frac{\lambda}{\sqrt{n}} + \mu) \\ &= \Pr(1 \leq \frac{\lambda}{\sqrt{n}} + \mu) \cdot \Pr(\bar{X} \leq \frac{\lambda}{\sqrt{n}} + \mu) \\ &= \Pr(1 \leq \frac{\lambda}{\sqrt{n}} + \mu) \cdot \Pr(\sqrt{n}(\bar{X} - \mu) \leq \lambda) \\ &= \Pr(1 \leq \frac{\lambda}{\sqrt{n}} + \mu) \cdot \Phi(\lambda) \\ &= \Pr(\sqrt{n}(1 - \mu) \leq \lambda) \cdot \Phi(\lambda) \\ &= I(\lambda \geq \sqrt{n}(1 - \mu)) \Phi(\lambda) \quad (= I_{[\sqrt{n}(1 - \mu), \infty)}(\lambda) \cdot \Phi(\lambda)) \end{aligned}$$

• $\mu < 1 \dots \lim_{n \rightarrow \infty} \Pr(\sqrt{n}(\hat{\mu} - \mu) \leq \lambda) = 0$ (for all $-\infty < \lambda < \infty$)
($\therefore \lim_{n \rightarrow \infty} \Pr(\sqrt{n}(\hat{\mu} - \mu) = +\infty) = 1$)

- $\mu = 1 \dots \lim_{n \rightarrow \infty} \Pr(\sqrt{n}(\hat{\mu} - \mu) \leq x) = \begin{cases} \Phi(x) & (x \geq 0) \\ 0 & (x < 0) \end{cases}$
- $\mu > 1 \dots \lim_{n \rightarrow \infty} \Pr(\sqrt{n}(\hat{\mu} - \mu) \leq x) = \Phi(x) \quad (\text{for all } x)$



3)

$$\boxed{14} \quad U, V \sim \text{exp}(\lambda)$$

$$(a) \quad \begin{cases} X = U+V \\ Y = UV \end{cases}$$

考慮二次方程式

$$g(t) = (t-U)(t-V) = 0$$

$$\Leftrightarrow t^2 - (U+V)t + UV = 0$$

$$\Leftrightarrow t^2 - Xt + Y = 0$$

$$t = \frac{X \pm \sqrt{X^2 - 4Y}}{2}$$

$$\therefore \begin{pmatrix} U \\ V \end{pmatrix} = \begin{pmatrix} \frac{X + \sqrt{X^2 - 4Y}}{2} \\ \frac{X - \sqrt{X^2 - 4Y}}{2} \end{pmatrix} \text{ or } \begin{pmatrix} \frac{X - \sqrt{X^2 - 4Y}}{2} \\ \frac{X + \sqrt{X^2 - 4Y}}{2} \end{pmatrix}$$

$$J = \begin{pmatrix} \frac{\partial x}{\partial u} & \frac{\partial x}{\partial v} \\ \frac{\partial y}{\partial u} & \frac{\partial y}{\partial v} \end{pmatrix} = \begin{pmatrix} 1 & 1 \\ v & u \end{pmatrix}$$

$$|J| = |u-v| = \sqrt{X^2 - 4Y}$$

$$\frac{dxdy}{\sqrt{X^2 - 4Y}} = dudv$$

$$I = \int_{u,v \geq 0} f_{uv}(u,v) du dv = \int_{u,v \geq 0} \lambda \exp(-\lambda u) \lambda \exp(-\lambda v) du dv$$

$$= \int_{\substack{x^2-4y \geq 0 \\ x, y \geq 0}} \lambda^2 \exp(-\lambda x) \cdot \frac{dx dy}{\sqrt{x^2-4y}} \cdot \underbrace{x^2}_{\substack{\text{C: } \begin{pmatrix} u \\ v \end{pmatrix} = \begin{pmatrix} \frac{x+\sqrt{x^2-4y}}{2} \\ \frac{x-\sqrt{x^2-4y}}{2} \end{pmatrix} \text{ or } \\ \begin{pmatrix} \frac{x-\sqrt{x^2-4y}}{2} \\ \frac{x+\sqrt{x^2-4y}}{2} \end{pmatrix}}}$$

$$= \int_{\substack{x^2-4y \geq 0 \\ x, y > 0}} \frac{2\lambda^2}{\sqrt{x^2-4y}} \exp(-\lambda x) dx dy$$

↓

$g(t) = 0$ 有兩個正實數解

$g(0) > 0$, $\frac{1}{2x} > 0$, 判別式 ≥ 0

$$\therefore f_{XY}(\lambda, y) = \frac{2\lambda^2}{\sqrt{x^2-4y}} \exp(-\lambda x)$$

$$(\lambda > 0, y > 0, x^2-4y \geq 0)$$

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(b) 求 α, β 使得 $E[(Y - \alpha X - \beta)^2]$ 為最小

\parallel
 $S(\alpha, \beta)$

$$\begin{pmatrix} \alpha \\ \beta \end{pmatrix} = \underset{\begin{pmatrix} \alpha \\ \beta \end{pmatrix}}{\text{Arg min}} E[(Y - \alpha X - \beta)^2]$$

$$\frac{\partial S}{\partial \alpha} = 0 \quad \frac{\partial S}{\partial \beta} = 0$$

$$\begin{cases} \alpha = E[Y] - \frac{\text{cov}(X, Y)}{\text{var}(X)} E[X] \\ \beta = \frac{\text{cov}(X, Y)}{\text{var}(X)} \end{cases}$$

求 X 之邊際分佈...

$$\begin{aligned} & \int_{0 \leq y \leq \frac{x^2}{4}} \frac{2\lambda^2}{\sqrt{x^2 - 4y}} \exp(-\lambda y) dy \\ &= 2\lambda^2 \exp(-\lambda y) \cdot \left[-\frac{(x^2 - 4y)^{\frac{1}{2}}}{2} \right]_{y=0}^{y=\frac{x^2}{4}} \\ &= \lambda^2 x \exp(-\lambda x) \end{aligned}$$

$$E[X] = \int_0^{\infty} \lambda^2 x^2 \exp(-\lambda x) dx = \frac{2}{\lambda}$$

$$E[X^2] = \int_0^{\infty} \lambda^2 x^3 \exp(-\lambda x) dx = \frac{6}{\lambda^2}$$

$$\therefore \text{var}(X) = \frac{2}{\lambda^2}$$



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$$\begin{aligned}
 E[Y] &= \int_{x=0}^{x=\infty} \int_{y=0}^{y=\frac{x^2}{4}} 2\lambda^2 \exp(-\lambda x) \cdot \frac{y}{\sqrt{x^2 - 4y}} dy dx \\
 &= \int_{x=0}^{x=\infty} \int_{y=0}^{y=\frac{x^2}{4}} \lambda^2 \exp(-\lambda x) \frac{y}{\sqrt{\frac{x^2}{4} - y}} dy dx \\
 &= \int_{x=0}^{x=\infty} \int_{y=0}^{y=\frac{x^2}{4}} \lambda^2 \exp(-\lambda x) \frac{\left(y - \frac{x^2}{4}\right) + \left(\frac{x^2}{4}\right)}{\sqrt{\frac{x^2}{4} - y}} dy dx \\
 &= \int_{x=0}^{x=\infty} \int_{y=0}^{y=\frac{x^2}{4}} \lambda^2 \exp(-\lambda x) \left\{ \frac{\frac{x^2}{4}}{\sqrt{\frac{x^2}{4} - y}} - \sqrt{\frac{x^2}{4} - y} \right\} dy dx \\
 &\quad \underbrace{\hspace{10em}}_{\textcircled{1}} \quad \underbrace{\hspace{10em}}_{\textcircled{2}}
 \end{aligned}$$

$$\begin{aligned}
 \textcircled{1} &\dots \int_{x=0}^{x=\infty} \int_{y=0}^{y=\frac{x^2}{4}} 2\lambda^2 \exp(-\lambda x) \frac{1}{\sqrt{x^2 - 4y}} \cdot \frac{x^2}{4} dy dx \\
 &= E\left[\frac{x^2}{4}\right] = \frac{3}{2\lambda^2}
 \end{aligned}$$

$$\begin{aligned}
 \textcircled{2} &\dots \int_{x=0}^{x=\infty} \int_{y=0}^{y=\frac{x^2}{4}} \lambda^2 \exp(-\lambda x) \sqrt{\frac{x^2}{4} - y} dy dx \\
 &= \int_{x=0}^{x=\infty} \left[-\lambda^2 \exp(-\lambda x) \frac{2}{3} \left(\frac{x^2}{4} - y\right)^{\frac{3}{2}} \right]_{y=0}^{y=\frac{x^2}{4}} dx \\
 &= \int_{x=0}^{x=\infty} \frac{2\lambda^2}{3} \frac{x^3}{8} \exp(-\lambda x) dx = \frac{1}{12} E[X^3] = \frac{1}{2\lambda^2} \\
 &\therefore \textcircled{1} - \textcircled{2} = \frac{1}{\lambda^2} \quad \therefore E[Y] = \frac{1}{\lambda^2}
 \end{aligned}$$

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$$E[XY] = \int_{x=0}^{\infty} \int_{y=0}^{\frac{x^2}{4}} 2\lambda^2 \exp(-\lambda x) \cdot \frac{xy}{\sqrt{x^2-4y}} dy dx$$

$$2\lambda^2 \exp(-\lambda x) \left(\underbrace{\frac{x^3}{4}}_{\textcircled{1}} - \underbrace{x\sqrt{\frac{x^2}{4}y}}_{\textcircled{2}} \right)$$

$$\begin{aligned} \textcircled{1} \dots E\left[\frac{X^3}{4}\right] &= \frac{1}{4} \int_0^{\infty} x^2 x^2 \exp(-\lambda x) dx \\ &= \frac{1}{4} \int_{z=0}^{\infty} \frac{z^4}{\lambda^2} \exp(-z) \frac{dz}{\lambda} \\ &= \frac{\Gamma(5)}{4\lambda^3} = \frac{6}{\lambda^3} \end{aligned}$$

$$\textcircled{2} \dots E\left[\frac{X^3}{2}\right] = \frac{2}{\lambda^3} \quad (\because \text{出現跟 } E[X] \text{ 時一樣的算式})$$

$$\textcircled{1} - \textcircled{2} = \frac{4}{\lambda^3}$$

$$\text{cov}(X, Y) = E[XY] - E[X]E[Y] = \frac{4}{\lambda^3} - \frac{2}{\lambda} \cdot \frac{1}{\lambda^2} = \frac{2}{\lambda^3}$$

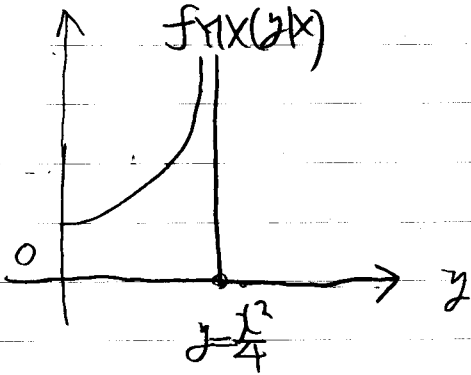
$$\alpha = E[Y] - \frac{\text{cov}(X, Y)}{V(X)} E[X] = \frac{1}{\lambda^2} - \frac{\left(\frac{2}{\lambda^3}\right)}{\left(\frac{2}{\lambda^2}\right)} \cdot \frac{2}{\lambda} = \frac{1}{\lambda^2} - \frac{2}{\lambda^2} = -\frac{1}{\lambda^2}$$

$$\beta = \frac{\text{cov}(X, Y)}{V(X)} = \frac{\left(\frac{2}{\lambda^3}\right)}{\left(\frac{2}{\lambda^2}\right)} = \frac{1}{\lambda}$$

c) 求 $Y|X=\lambda$ 之分布...

$$f_{Y|X}(y|\lambda) = \frac{f_{X,Y}(\lambda, y)}{f_X(\lambda)} = \frac{\frac{2\lambda^2}{\sqrt{\lambda^2 - 4y}} \exp(-\lambda y)}{\lambda^2 \exp(-\lambda \lambda)} = \frac{2}{\sqrt{\lambda^2 - 4y} \lambda}$$

$$0 \leq y < \frac{\lambda^2}{4}$$



又隨 λ^2 越近, 其機率密度越高。

因此 λ^2 為給定 λ 情況下的 Best Prediction

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(a) 求 $Y|X=\lambda$ 之分布

X 之邊際分布 $\int_{y=\lambda}^{y=1} 2 dy = 2 - 2\lambda \quad (0 < \lambda < 1)$

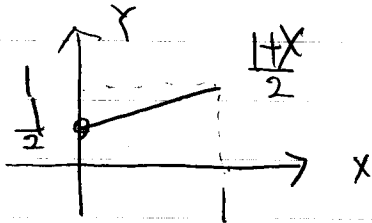
$f_X(x) = 2(1-x) \quad (\sim \text{Be}(1, 2))$

$f_{Y|X}(Y|X) = \frac{f_{X,Y}(x,y)}{f_X(x)} = \frac{1}{1-x} \quad (0 < x < y < 1)$

由此可知 $Y|X=\lambda \sim \text{Uni}(x, 1)$

$\therefore E[Y|X=\lambda_0] = \frac{1+\lambda_0}{2}$

(b) $E[Y|X=\lambda] = \frac{1+\lambda}{2}$



$Y|X=\lambda \sim \text{Uni}(x, 1)$

均勻分布的期望值為 $\frac{\alpha+\beta}{2}$
($\text{Uni}(\alpha, \beta)$)

因此可知 $E[Y|X=\lambda] = \frac{1+\lambda}{2}$

(c) 给定 $X=x_0$ 后, $YX^3+1 = x_0^3 Y+1$

$$E[Y | X=x_0] = \frac{1+x_0}{2}$$

$$E[x_0^3 Y+1 | X=x_0] = \frac{x_0^4 + x_0^3}{2} + 1$$

(d) 考虑 $Uni(0, \theta)$ 之 变数 $(W \sim U(0, \theta))$

$$E[W] = \frac{\theta}{2}$$

$$E[W^2] = \frac{\theta^2}{3}$$

$$\therefore V[W] = \frac{\theta^2}{12}$$

$Y | X=x_0 \sim Uni(x_0, 1)$

$V[Y | X=x_0]$ 相同於 $Uni(0, 1-x_0)$ 之 变数

$$\therefore \frac{1}{12} (1-x_0)^2 \quad (\because V[X-a] = V[X])$$

a: 常数

给定 $X=x_0$ 之后, Y 服从 $Uni(x_0, 1)$.

换言之, x_0 为 Y 之参数, 所以期望值, 变数都会受其影响.

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$$(a) \frac{dF}{dx} = \frac{\beta \lambda^\beta}{x^\beta} \exp\left(-\left(\frac{x}{\alpha}\right)^\beta\right) \quad (x \geq 0)$$

$$f(x) = \frac{\beta \lambda^\beta}{x^\beta} \exp\left(-\left(\frac{x}{\alpha}\right)^\beta\right) \quad (x \geq 0)$$

$$(b) \Pr(X \leq x) = \Pr\left(\left(\frac{W}{\alpha}\right)^\beta \leq x\right)$$

$$= \Pr\left(\frac{W}{\alpha} \leq x^{1/\beta}\right) = \Pr(W \leq \alpha x^{1/\beta})$$

$$= F(\alpha x^{1/\beta}) = 1 - \exp\left(-\left(\frac{\alpha x^{1/\beta}}{\alpha}\right)^\beta\right) = 1 - \exp(-x)$$

$$\therefore X \sim \exp(1)$$

$$(c) U_1, U_2, \dots, U_n \sim U(0,1)$$

$$X_n \stackrel{\text{def}}{=} n \cdot \min\{U_1, U_2, \dots, U_n\}$$

$$\Pr(X_n \leq x) = 1 - \Pr(X_n > x) = 1 - \Pr(\min\{U_1, \dots, U_n\} > \frac{x}{n})$$

$$= 1 - \Pr(\min\{U_1, \dots, U_n\} > \frac{x}{n})$$

$$= 1 - \left(1 - \frac{x}{n}\right)^n = 1 - \left(1 - \frac{x}{n}\right)^{\frac{n}{x} \cdot x}$$

$$\lim_{n \rightarrow \infty} \Pr(X_n \leq x) = 1 - e^{-x}$$

$$\therefore X_n \xrightarrow{d} \exp(1)$$

$$\therefore X_n = \left(\frac{W_n}{\alpha}\right)^\beta \quad (\text{利用(b)的结果})$$

$$W_n = \alpha X_n^{\frac{1}{\beta}}$$

$$W_n \stackrel{d}{\rightarrow} \text{Weibull}(\alpha, \beta) \quad \therefore W_n = \alpha \left(n \cdot \min\{X_1, \dots, X_n\}\right)^{\frac{1}{\beta}}$$

□ (a) $X_1, X_2 \sim \text{Unif}(0, \theta)$

$$\bullet f_{X_1, X_2}(x_1, x_2) = \frac{1}{\theta^2} I_{(0, \theta)}(x_1) I_{(0, \theta)}(x_2)$$

$$\bullet P(T \leq t) = P(X_1, X_2 \leq t) = \frac{t^2}{\theta^2}$$

$$\frac{d}{dt} P(T \leq t) = \frac{2t}{\theta^2} \quad (0 < t < \theta)$$

$$\bullet f_T(t) = 2t I_{(0, \theta)}(t) / \theta^2$$

$$\bullet f_{X_1, X_2, T}(x_1, x_2, t) = \begin{cases} \text{if } X_1 = t & \frac{1}{\theta^2} I_{(0, t)}(x_2) I_{(0, \theta)}(t) \\ \text{or } X_2 = t & \frac{1}{\theta^2} I_{(0, t)}(x_1) I_{(0, \theta)}(t) \end{cases}$$

$$= \frac{1}{\theta^2} \cdot I_{(0, t)}(x_2) I_{(0, \theta)}(t) I(t=x_1) +$$

$$\frac{1}{\theta^2} I_{(0, t)}(x_1) I_{(0, \theta)}(t) I(t=x_2)$$

$$\therefore \frac{f_{X_1, X_2, T}(x_1, x_2, t)}{f_T(t)} = \frac{1}{2t} \left\{ I_{(0, t)}(x_2) I(t=x_1) + I_{(0, t)}(x_1) I(t=x_2) \right\}$$

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(b) 求 θ 之最小充分統計量

$$\frac{f(Y_1=y_1, Y_2=y_2)}{f(X_1=x_1, X_2=x_2)} \text{ 與 } \theta \text{ 無關} \Rightarrow$$

$$\frac{\int_{\theta}^{\infty} I(0 < Y_{(1)}) I(Y_{(2)} < \theta)}{\int_{\theta}^{\infty} I(0 < X_{(1)}) I(X_{(2)} < \theta)} = \frac{I(0 < Y_{(1)})}{I(0 < X_{(1)})} \cdot \frac{I(Y_{(2)} < \theta)}{I(X_{(2)} < \theta)}$$

與 θ 無關 $\Rightarrow X_{(2)} = Y_{(2)}$ 為必要條件。

$$\text{若 } X_{(2)} = Y_{(2)} \Rightarrow \frac{f(Y_1=y_1, Y_2=y_2)}{f(X_1=x_1, X_2=x_2)} \text{ 與 } \theta \text{ 無關。}$$

$$\therefore \lceil X_{(2)} = Y_{(2)} \rceil \text{ 為 } \frac{f(Y_1=y_1, Y_2=y_2)}{f(X_1=x_1, X_2=x_2)} \text{ 與 } \theta \text{ 無關}$$

之必要充分條件。

故此, $X_{(2)} = \max\{X_1, X_2\}$ 為 θ 之最小充分統計量

我們無法由 $X_1 + X_2$ 得知 $\max\{X_1, X_2\}$ 之值。

$\therefore X_1 + X_2$ 並非 θ 之充分統計量。

$$\boxed{8.} \quad f(x|\theta) = \frac{1}{3\theta} I(-\theta < x < 2\theta)$$

$$f(x_1, \dots, x_n|\theta) = \left(\frac{1}{3\theta}\right)^n I(-\theta < x_1 < 2\theta) \dots I(-\theta < x_n < 2\theta)$$

$$= \left(\frac{1}{3\theta}\right)^n I(-\theta < x_{(1)}, x_{(n)} < 2\theta)$$

$$= \left(\frac{1}{3\theta}\right)^n I(-x_{(1)} < \theta \cap \frac{x_{(n)}}{2} < \theta)$$

$$= \left(\frac{1}{3\theta}\right)^n I(\theta > \max\{-x_{(1)}, \frac{x_{(n)}}{2}\})$$

$$= \left(\frac{1}{3\theta}\right)^n I(\max\{x_{(1)}, \frac{x_{(n)}}{2}, \infty\}(\theta))$$

$$\therefore L(\theta | x_1, \dots, x_n) = \left(\frac{1}{3\theta}\right)^n I(\max\{-x_{(1)}, \frac{x_{(n)}}{2}, \infty\}(\theta))$$

(由此可知, $\hat{\theta}_{MLE} = \max\{-x_{(1)}, \frac{x_{(n)}}{2}\}$)

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$$\hat{f}_h(x) = \frac{1}{nh} \sum_{j=1}^n k\left(\frac{x-x_j}{h}\right) \quad (\text{Kernel Density Estimation})$$

$$n=4, h=1 \quad \begin{pmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{pmatrix} = \begin{pmatrix} 1 \\ 0 \\ 0.5 \\ 3 \end{pmatrix}$$
$$k = \phi$$

$$\hat{f}_h(x) = \frac{1}{n} \sum_{j=1}^n \phi(x-x_j)$$

$$\textcircled{1} x=0 \dots \hat{f}_h(0) = \frac{1}{n} \sum_{j=1}^n \phi(-x_j) = \frac{1}{4} (\phi(1) + \phi(0) + \phi(0.5) + \phi(3))$$

$$\textcircled{2} x=0.5 \dots \hat{f}_h(0.5) = \frac{1}{n} \sum_{j=1}^n \phi(0.5-x_j) = \frac{1}{4} (\phi(1.5) + \phi(0.5) + \phi(0) + \phi(-2.5))$$

$$\textcircled{3} x=1 \dots \hat{f}_h(1) = \frac{1}{n} \sum_{j=1}^n \phi(1-x_j) = \frac{1}{4} (\phi(2) + \phi(1) + \phi(0.5) + \phi(-2))$$

$$\rightarrow \begin{cases} \textcircled{1} = 0.249353 \\ \textcircled{2} = 0.224513 \\ \textcircled{3} = 0.175504 \end{cases}$$



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$$(a) \hat{f}_n(x) | X_1, X_2, \dots, X_n = \frac{1}{nh} \sum_{j=1}^n K\left(\frac{x-x_j}{h}\right)$$

$$(b) X | X_1, \dots, X_n \sim \hat{f}_n(x)$$

$$E[X | X_1, \dots, X_n] = \int_{x \in \mathbb{R}} x \frac{1}{nh} \sum_{j=1}^n K\left(\frac{x-x_j}{h}\right) dx$$

$$= \frac{1}{nh} \sum_{j=1}^n \int_{x \in \mathbb{R}} x K\left(\frac{x-x_j}{h}\right) dx$$

$$y = \frac{x-x_j}{h} \quad \frac{dy}{dx} = \frac{1}{h}$$

$$= \frac{1}{nh} \sum_{j=1}^n \int_{y \in \mathbb{R}} (hy+x_j) K(y) h dy$$

$$= \frac{1}{nh} \sum_{j=1}^n h x_j = \frac{1}{n} \sum_{j=1}^n x_j = \frac{X_1 + \dots + X_n}{n} = \bar{X}$$

$$(c) E[X^2 | X_1, \dots, X_n] = \int_{x \in \mathbb{R}} x^2 \frac{1}{nh} \sum_{j=1}^n K\left(\frac{x-x_j}{h}\right) dx$$

$$= \frac{1}{nh} \sum_{j=1}^n \int_{x \in \mathbb{R}} (hy+x_j)^2 K(y) \cdot h dy$$

$$= \frac{1}{n} \sum_{j=1}^n \int_{x \in \mathbb{R}} (h^2 y^2 + 2hx_j y + x_j^2) K(y) dy$$

$$= \frac{1}{n} \sum_{j=1}^n (h^2 \sigma_K^2 + x_j^2) = h^2 \sigma_K^2 + \frac{1}{n} \sum_{j=1}^n x_j^2$$

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$$V[X | X_1, X_2, \dots, X_n] = h^2 \sigma_k^2 + \frac{1}{n} \sum_{j=1}^n x_j^2 - \bar{x}^2$$

$$= h^2 \sigma_k^2 + \frac{1}{n} \sum_{j=1}^n (x_j - \bar{x})^2$$

(d) $E[X | X_1=x_1, \dots, X_n=x_n] = \bar{x}$

$$V[X | X_1=x_1, \dots, X_n=x_n] = \frac{1}{n} \sum_{j=1}^n (x_j - \bar{x})^2 + h^2 \sigma_k^2$$

現在假設 X_1, X_2, \dots, X_n 存在 $E[X_j]$ 及 $E[X_j^2]$

(換言之 $|E[X_j]| < \infty, E[X_j^2] < \infty$)

根據弱大數法則, $\bar{x} \xrightarrow{P} \mu$ (X_j 之期望值)

(Khinchine 的弱大數法則) $\frac{1}{n} \sum_{j=1}^n (X_j - \bar{x})^2 \xrightarrow{P} \sigma^2$ (X_j 之變異數)

所以 $n \rightarrow \infty$ 時, $h^2 \sigma_k^2$ 需趨近於 0.

⊕ Khinchine 弱大數法則

$$X_1, X_2, \dots, X_n \text{ i.i.d. } |E[X_j]| < \infty \Rightarrow \frac{X_1 + \dots + X_n}{n} \xrightarrow{P} E[X] = \mu$$

$$M_X(t) = E[e^{tX}] = E\left[e^{\frac{t}{n} X_j}\right]^n = M_X\left(\frac{t}{n}\right)^n$$

泰勒展開 $M_X(t) = M(0) + M'(0)t + \frac{M''(0)}{2!}t^2 + \dots$

$$M_X\left(\frac{t}{n}\right) = 1 + \mu \frac{t}{n} + o\left(\frac{1}{n}\right)$$

$$n \rightarrow \infty \quad M_X\left(\frac{t}{n}\right)^n \rightarrow \lim_{n \rightarrow \infty} \left(1 + \frac{\mu t}{n}\right)^n = e^{\mu t} \quad ; \quad \bar{x} \xrightarrow{P} \mu$$

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 $(\theta > 0)$

$$(a) \Pr(Y \leq a) = \Pr(-\frac{1}{\theta} X \leq a) = \Pr(\exp(-\frac{1}{\theta} X) \leq e^{\theta a}) \\ = \Pr(\frac{1}{X} \leq e^{\theta a}) = \Pr(e^{-\theta a} \leq X) = 1 - \Pr(X < e^{-\theta a})$$

$$\left(\begin{aligned} \because \Pr(X \leq \lambda) \quad (0 < \lambda < 1) &= \int_0^\lambda \theta t^{\theta-1} dt \\ &= [t^\theta]_0^\lambda = \lambda^\theta \end{aligned} \right) \quad \downarrow$$

$$\therefore \Pr(Y \leq a) = 1 - \Pr(X < e^{-\theta a}) = 1 - (e^{-\theta a})^\theta = 1 - e^{-\theta^2 a}$$

由此可知, $Y \sim \exp(\theta)$ (mean $\frac{1}{\theta}$ 之指數分布)

(b) 假設 T 為 θ 之無偏估計量

$$V[T] \geq \frac{(\tau'(\theta))^2}{I_n(\theta)} = \frac{(\tau'(\theta))^2}{n I_1(\theta)}$$

$$\tau(\theta) = \frac{1}{\theta} \quad (\tau'(\theta))^2 = \frac{1}{\theta^4}$$

觀察到一個 X 時, 其 Fisher 資訊量 $I_1(\theta) = \frac{1}{\theta^2}$

$$\left(\begin{aligned} \because \frac{\partial}{\partial \theta} \log f(x; \theta) &= \frac{\partial}{\partial \theta} \left\{ (1-\theta) \log x + \log \theta \right\} = \log x + \frac{1}{\theta} \\ E \left[\left(\frac{\partial}{\partial \theta} \log f(x; \theta) \right)^2 \right] &= E \left[\left(\log x - \frac{1}{\theta} \right)^2 \right] = V[\log x] = \frac{1}{\theta^2} \end{aligned} \right)$$

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$$I(\theta) = \frac{1}{\theta^2} \quad \ln l(\theta) = \frac{n}{\theta}$$

$$\therefore \text{Var}[T] \geq \frac{(l'(\theta))^2}{I(\theta)} = \frac{\frac{1}{\theta^2}}{\left(\frac{n}{\theta^2}\right)} = \frac{1}{n\theta^2} \quad \text{Cramer}$$

故 Cramer Rao's Lower Bound = $\frac{1}{n\theta^2}$

(c) (方法 1) 證明 $\sum_{j=1}^n \frac{1}{n} X_j$ 為 θ 之有效估計量,

• $X_j \sim \text{exp}(\theta)$ (mean = θ , var = θ^2)

• $\sum_{j=1}^n X_j \sim \Gamma(n, \theta)$ (mean $\frac{n}{\theta}$, var $\frac{n}{\theta^2}$)

• $\frac{1}{n} \sum_{j=1}^n X_j$ 期望值 θ , 變異數 $\frac{1}{n\theta^2}$ (若足 Cramer Rao's Lower Bound)

由此可知, $\frac{1}{n} \sum_{j=1}^n X_j$ 為 θ 之 unbiased 估計量,

且達到 Cramer Rao's Lower Bound, 所以此估計量

為有效估計量, 有效估計量必是 UMVUE.



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$$\textcircled{\text{法2}} \quad f(x_1, x_2, \dots, x_n | \theta) = \theta^n (x_1 x_2 \dots x_n)^{\theta-1} I_{(0,1)}(x_1, \dots, x_n) \\ = \theta^n \cdot (x_1 x_2 \dots x_n)^{\theta-1} \cdot \exp\left(\theta \sum_{i=1}^n \log x_i\right)$$

此分布屬於指數族。

即內 $\sum_{i=1}^n \log x_i$ 之係數為 θ 。

$\{\theta | \theta \in \Theta\}$ (CR) 顯然包含內點 (interior point)

故此, $\sum_{i=1}^n \log x_i$ 為 θ 之完備充分統計量。

如法1所示, $-\sum_{i=1}^n \log x_i / n$ 為 θ 之 unbiased 估計量。

且完備統計量 $\sum_{i=1}^n \log x_i$ 之函數。

根據 Lehman-Scheffe 定理, $-\sum_{i=1}^n \frac{1}{n} \log x_i$ 為 θ 之 UMVUE。

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$$(a) f(x|\theta) = \frac{1}{\theta} I(0 < x < \theta)$$

$$f(x_1, \dots, x_n | \theta) = \frac{1}{\theta^n} I(0 < X_{(n)}, X_{(n)} < \theta)$$

$$= \underbrace{I(0, \infty)}_{h(x)}(X_{(n)}) \cdot \frac{1}{\theta^n} \underbrace{I(-\infty, \theta)}_{g(X_{(n)}|\theta)}(X_{(n)})$$

根據 Neyman-Fisher 的分解定理,

$X_{(n)}$ 為 θ 之充分統計量,

(a)' 為了方便起見, 在此證明 $X_{(n)}$ 為 θ 之充分統計量,

$$\Pr(X_{(n)} \leq t) = \Pr(X_1, X_2, \dots, X_n \leq t) = \left(\frac{t}{\theta}\right)^n \quad (0 < t \leq \theta)$$

$$\frac{d}{dt} \Pr(X_{(n)} \leq t) = \frac{n t^{n-1}}{\theta^n}$$

$$\therefore f_{X_{(n)}}(t) = \frac{n t^{n-1}}{\theta^n} \quad (0 < t \leq \theta) \quad \dots \quad X_{(n)} \text{ 之機率密度函數}$$

$$E[g(X_{(n)})] = \int_0^\theta g(t) \cdot \frac{n t^{n-1}}{\theta^n} dt = 0 \quad \left(\times \frac{\theta^n}{n} \right)$$

$$\Rightarrow \int_0^\theta g(t) t^{n-1} dt = 0$$

$$\Rightarrow \frac{d}{d\theta} \int_0^\theta g(t) t^{n-1} dt = g(\theta) \cdot \theta^{n-1} = 0$$

$$\Rightarrow g(\theta) = 0 \quad (\text{for all } \theta > 0)$$

$$\therefore E[g(X_{(n)})] = 0 \Rightarrow \Pr(g(X_{(n)}) = 0) = 1$$

由此可知 $X_{(n)}$ 為 θ 之完備充份統計量

$$(b) E[\hat{\theta}] = E[2X_{(n)}] = \int_0^\theta 2x \cdot \frac{1}{\theta} dx = \left[\frac{x^2}{\theta} \right]_0^\theta = \frac{\theta^2}{\theta} = \theta$$

$\therefore \hat{\theta}$ 為 θ 之無偏估計量

(c) $\hat{\theta}$ 為由 $\begin{pmatrix} X_1 \\ \vdots \\ X_n \end{pmatrix}$ 構成的統計量,

$X_{(n)}$ 為充份統計量,

$\hat{\theta} | X_{(n)}$ 的分佈與 θ 無關,

因此, $E[\hat{\theta} | X_{(n)} = t]$ 為 t 之函數,

如 (a)' 所述, $X_{(n)}$ 為 θ 之完備充份統計量

所以, $E[\hat{\theta} | X_{(n)} = t]$ 為完備充份統計量 $X_{(n)}$ 之函數

$$\text{而且, } E[E[\hat{\theta} | X_{(n)}]] = E[\hat{\theta}] = \theta,$$

所以 $E[\hat{\theta} | X_{(n)}]$ 為 θ 之無偏估計量

根據 Lehman-Scheffé 定理, $E[\hat{\theta} | X_{(n)}]$ 為 θ 之 UMVUE

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我們找出一個 $X(n)$ 之函數滿足 $E[g(X(n))] = \theta$

$$f_{X(n)}(t) = \frac{nt^{n-1}}{\theta^n} \quad (0 < t \leq \theta)$$

$$E[X(n)] = \int_0^\theta \frac{nt^n}{\theta^n} dt = \frac{n}{n+1} \left[\frac{t^{n+1}}{\theta^n} \right]_0^\theta = \frac{n}{n+1} \theta$$

$$\therefore E\left[\frac{n+1}{n} X(n)\right] = \theta$$

由此可知 $E[\hat{\theta} | X(n)] = \frac{n+1}{n} X(n)$ 為 θ 之 UMVUE. \downarrow

別的方法 ... 直接求 $E[\hat{\theta} | X(n)]$

\downarrow

先考慮 $X_1 | X(n) = t$ 之條件分佈

$$P(X_1 \leq u, X(n) \leq t)$$

$$= P(X_1 \leq u, X_1 \leq t, X_2 \leq t, \dots, X_n \leq t)$$

$$= P(X_1 \leq \min\{u, t\}, X_2 \sim X_n \leq t)$$

$$= \left(\frac{\min\{u, t\}}{\theta} \right) \cdot \frac{t^{n-1}}{\theta^{n-1}}$$

$$= \frac{\min\{u, t\}}{\theta} \cdot t^{n-1}$$

• case 1 in $x_1 \leq t$... $P(X_1 \leq x_1, X_{(n)} \leq t) = \frac{x_1 t^{n-1}}{\theta^n}$

$$\frac{\partial^2}{\partial x_1 \partial t} P(X_1 \leq x_1, X_{(n)} \leq t) = \frac{(n-1)t^{n-2}}{\theta^n}$$

• case 2 in $x_1 > t$... $P(X_1 \leq x_1, X_{(n)} \leq t) = \frac{t^n}{\theta^n}$

$$\frac{\partial^2}{\partial x_1 \partial t} P(X_1 \leq x_1, X_{(n)} \leq t) = 0$$

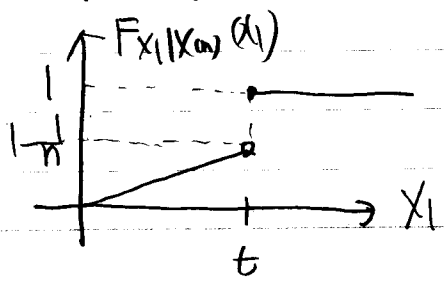
$$\therefore f_{X_1, X_{(n)}}(x_1, t) = \frac{(n-1)t^{n-2}}{\theta^n} \cdot I(x_1 < t)$$

$$f_{X_{(n)}}(t) = \frac{nt^{n-1}}{\theta^n}$$

$$\therefore f_{X_1 | X_{(n)}}(X_1 = x_1 | X_{(n)} = t) = \frac{\frac{(n-1)t^{n-2}}{\theta^n} I(x_1 < t)}{\left(\frac{nt^{n-1}}{\theta^n}\right)}$$

$$= \frac{n-1}{n} \cdot \frac{1}{t} \cdot I(x_1 < t)$$

由此可知 $X_1 | X_{(n)} = t$ 之条件累积分布函数如下:



$$F_{X_1 | X_{(n)}}(x_1) = \begin{cases} \frac{n-1}{n} \cdot \frac{x_1}{t} & (0 < x_1 < t) \\ 1 & (x_1 \geq t) \end{cases}$$

($P(X_1 = t) = \frac{1}{n}$)

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$$\therefore E[X_1 | X_{(n)}=t] = \int_0^t \frac{n-1}{n} \frac{x}{t} dx + t \cdot \underbrace{P(X_1=t)}_{\frac{1}{n}}$$

$$= (1 - \frac{1}{n}) \cdot \left[\frac{x^2}{2t} \right]_0^t + \frac{t}{n}$$

$$= (1 - \frac{1}{n}) \cdot \frac{t}{2} + \frac{t}{n}$$

$$= \left(\frac{1}{2} - \frac{1}{2n} + \frac{1}{n} \right) t = \left(\frac{1}{2} + \frac{1}{2n} \right) t$$

$$\therefore E[\hat{\theta} | X_{(n)}=t] = E[2X_1 | X_{(n)}=t]$$

$$= 2 \left(\frac{1}{2} + \frac{1}{2n} \right) t = \left(1 + \frac{1}{n} \right) t$$

$$\therefore E[\tilde{\theta} | X_{(n)}=t] = \left(\frac{n+1}{n} \right) t$$

$$\therefore \hat{\theta} \text{ 是 UMVUE 為 } \frac{n+1}{n} X_{(n)}$$

(得到跟第一個做法一樣的結論)

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$$(a) P(X_1 = x_1) = e^{-\lambda} \cdot \frac{\lambda^{x_1}}{x_1!}$$

$$P(X_1 = x_1, \dots, X_n = x_n) = e^{-n\lambda} \cdot \frac{\lambda^{(x_1 + \dots + x_n)}}{(x_1! \dots x_n!)}$$

$$= \frac{1}{x_1! \dots x_n!} \cdot e^{-n\lambda} \cdot \lambda^{(x_1 + \dots + x_n)}$$

$h(x)$ $g(x_1 + x_2 + \dots + x_n | \lambda)$

根據 Neyman-Fisher 的分解定理,

$X_1 + X_2 + \dots + X_n$ 為 θ 之充分統計量,

$$(b) P(\hat{\theta} = 1) = P(X_1 = 0) = e^{-\lambda} \cdot \frac{\lambda^0}{0!} = e^{-\lambda}$$

$$\therefore E[\hat{\theta}] = \sum_{a=0,1} a \cdot P(\hat{\theta} = a) = P(\hat{\theta} = 1) = e^{-\lambda}$$

$\therefore \hat{\theta}$ 為 $e^{-\lambda} = \theta$ 之 unbiased 估計量

$$(c) E[\hat{\theta} | T = t] = P(\hat{\theta} = 1 | T = t) = P(X_1 = 0, T = t)$$

$$= \frac{P(X_1 = 0, T = t)}{P(T = t)} = \frac{P(X_1 = 0, X_2 + \dots + X_n = t)}{P(T = t)}$$

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$$\frac{P_r(X_1=0, X_2+X_3+\dots+X_n=t)}{P_r(T=t)} = \frac{P_r(X_1=0) P_r(X_2+\dots+X_n=t)}{P_r(X_1+X_2+\dots+X_n=t)}$$

- $X_1+X_2+\dots+X_n \sim P_0(n\lambda)$
- $X_2+X_3+\dots+X_n \sim P_0((n-1)\lambda)$

$$= \frac{e^{-\lambda} \cdot e^{-(n-1)\lambda} \cdot \frac{((n-1)\lambda)^t}{t!}}{\left(e^{-n\lambda} \cdot \frac{(n\lambda)^t}{t!} \right)} = \frac{((n-1)\lambda)^t}{(n\lambda)^t} = \left(1 - \frac{1}{n}\right)^t$$

$$\therefore E[\hat{\theta} | T=t] = \left(1 - \frac{1}{n}\right)^t = \left(1 - \frac{1}{n}\right)^{(X_1+X_2+\dots+X_n)}$$

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$$(a) \int_0^{\infty} x^2 \frac{1}{\theta} \exp\left(-\frac{x}{\theta}\right) dx \quad y = \frac{x}{\theta} \quad \frac{dx}{d\theta} = \frac{1}{\theta}$$

$$= \int_0^{\infty} (\theta y)^2 \cdot \frac{1}{\theta} \exp(-y) \cdot \theta dy$$

$$= \int_0^{\infty} \theta^2 y^2 \exp(-y) dy = \theta^2 \Gamma(3) = 2\theta^2$$

$$\therefore E[X_1^2] = 2\theta^2$$

$$\therefore E\left[\frac{1}{2}X_1^2\right] = \theta^2$$

$\therefore \frac{1}{2}X_1^2$ 为 θ^2 之 不偏估计量

$$(b) f(x|\theta) = \frac{1}{\theta} \exp\left(-\frac{x}{\theta}\right)$$

$$f(x_1, \dots, x_n|\theta) = \frac{1}{\theta^n} \exp\left(-\frac{1}{\theta}(x_1 + x_2 + \dots + x_n)\right)$$

$$\left(\exists g \text{ st.}\right) = g(x_1 + x_2 + \dots + x_n|\theta)$$

\therefore 根据 Neyman-Fisher 的分解定理

$x_1 + x_2 + \dots + x_n$ 为 θ 之 充分统计量

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$$cc) f(x_1, x_2, \dots, x_n | \theta) = \frac{1}{\theta^n} \exp\left(-\frac{1}{\theta}(x_1 + x_2 + \dots + x_n)\right)$$

即內... $(X_1 + X_2 + \dots + X_n)$ 之係數為 $\frac{1}{\theta}$

$\left\{ \frac{1}{\theta} \mid \theta > 0 \right\}$ 可內含 \mathbb{R} 上之開集 G

$\therefore X_1 + X_2 + \dots + X_n$ 為 θ 之充分統計量

根據 Rao-Blackwell & Lehman-Scheffe 定理

$E\left[\frac{X_1^2}{2} \mid X_1 + X_2 + \dots + X_n = t\right]$ 為 θ^2 之 UMVUE

① 方法 1... 我們知道 $E\left[\frac{X_1^2}{2} \mid X_1 + X_2 + \dots + X_n = t\right]$ 為

T 之函數, 而且, θ^2 之 unbiased 估計量

$$T = X_1 + X_2 + \dots + X_n \sim \Gamma(n, \frac{1}{\theta})$$

$$E[T^2] = \int_0^{\infty} \frac{t^{n+1}}{\Gamma(n) \cdot \theta^n} \exp\left(-\frac{t}{\theta}\right) dt \quad \left(\begin{array}{l} u = \frac{t}{\theta} \\ \frac{dt}{d\theta} = \frac{1}{\theta} \end{array} \right)$$

$$= \int_0^{\infty} \frac{(\theta u)^{n+1}}{\Gamma(n) \theta^n} \exp(-u) \cdot \theta du$$

$$= \theta^2 \cdot \frac{\Gamma(n+1)}{\Gamma(n)} = \theta^2 \cdot \frac{(n+1)!}{(n-1)!} = \theta^2 \cdot n \cdot (n+1)$$

$$\therefore E\left[\frac{T^2}{n(n+1)}\right] = \theta^2$$

$\frac{T^2}{n(n+1)}$ 为完备统计量 T 之函数, 且满足 $E\left[\frac{T^2}{n(n+1)}\right] = \theta^2$

$\therefore \frac{T^2}{n(n+1)}$ 为 θ^2 之 UMWE, (C: Rao-Blackwell, & Lehman-Scheffe 定理)

$$\therefore E\left[\frac{X_1^2}{2} \mid X_1 + X_2 + \dots + X_n = T\right] \text{ 亦为 } \frac{T^2}{n(n+1)}$$

② 亦可直接求 $E\left[\frac{X_1^2}{2} \mid X_1 + X_2 + \dots + X_n = t\right]$

先考虑 $X_1 \mid X_1 + X_2 + \dots + X_n = t$ 之分布 (但先求 X_1, T 之联合分布)

$$\begin{cases} W = X_1 & \sim \text{exp}\left(\frac{1}{\theta}\right) \\ Z = X_2 + X_3 + \dots + X_n & \sim \Gamma(n-1, \frac{1}{\theta}) \end{cases}$$

W, Z : 独立, $f_{W,Z}(w,z) = \frac{1}{\theta} \exp\left(-\frac{w}{\theta}\right) \cdot \frac{z^{n-2}}{\Gamma(n-1) \cdot \theta^{n-1}} \exp\left(-\frac{z}{\theta}\right)$
($W \geq 0, Z \geq 0$)

$$\begin{cases} X_1 = W \\ T = W + Z \end{cases} \quad (\text{变数转换})$$

$$\frac{\partial}{\partial w}\begin{pmatrix} w \\ t \end{pmatrix} = \begin{pmatrix} 1 \\ 1 \end{pmatrix}, \quad \frac{\partial}{\partial z}\begin{pmatrix} w \\ t \end{pmatrix} = \begin{pmatrix} 0 \\ 1 \end{pmatrix}$$

$$\therefore J = \begin{pmatrix} 1 & 0 \\ 1 & 1 \end{pmatrix} \quad \det J = 1 \quad \underline{\underline{dw dt = dw dz}}$$

$$\left(\begin{matrix} W \geq 0 \\ Z \geq 0 \end{matrix} \right) \Rightarrow \begin{matrix} X_1 \geq 0 \\ T \geq X_1 \end{matrix}$$

$$\begin{aligned} \text{全機率} = 1 &= \iint_{w, z \geq 0} \frac{1}{\theta} \varphi\left(\frac{w}{\theta}\right) \cdot \frac{1}{\theta^{n-1}} \frac{z^{n-2}}{\Gamma(n)} \varphi\left(\frac{z}{\theta}\right) dw dz \\ &= \iint_{t \geq x_1 \geq 0} \frac{1}{\theta^n} \frac{1}{\Gamma(n)} (t-x_1)^{n-2} \varphi\left(\frac{t}{\theta}\right) \cdot dx_1 dt \end{aligned}$$

$$\therefore f_{X_1, T}(x_1, t) = \frac{1}{\theta^n} \frac{1}{\Gamma(n)} (t-x_1)^{n-2} \varphi\left(\frac{t}{\theta}\right) \quad (0 \leq x_1 \leq t)$$

(X_1, T) 之聯合分布

$$T \sim \Gamma(n, \theta) \quad \therefore f_T(t) = \frac{t^{n-1}}{\Gamma(n) \theta^n} \varphi\left(\frac{t}{\theta}\right) \quad (t > 0)$$

$$\text{故, } f_{X_1|T}(x_1|t) = \frac{\left\{ \frac{(t-x_1)^{n-2}}{\Gamma(n) \theta^n} \varphi\left(\frac{t}{\theta}\right) \right\}}{\left\{ \frac{t^{n-1}}{\Gamma(n) \theta^n} \varphi\left(\frac{t}{\theta}\right) \right\}} \quad \left(= \frac{f_{X_1, T}(x_1, t)}{f_T(t)} \right)$$

$$= (n-1) \cdot \frac{1}{t} \left(1 - \frac{x_1}{t}\right)^{n-2} \quad (0 \leq x_1 \leq t)$$

↓

$X_1|T=t$ 之條件分布

$$\therefore E\left[\frac{X_1^2}{2} \mid T=t\right] = \int_0^t \frac{X_1^2}{2} \cdot (n-1) \cdot \frac{1}{t} \cdot \left(1 - \frac{x_1}{t}\right)^{n-2} dx_1$$

$$= \frac{(n-1)}{2t} \int_0^t x_1^2 \left(1 - \frac{x_1}{t}\right)^{n-2} dx_1$$

$$\left(\begin{array}{l} \text{令} \\ \frac{x_1}{t} = y \quad \frac{dx_1}{dt} = \frac{1}{t} \end{array}\right)$$

$$= \frac{n-1}{2t} \int_0^1 (ty)^2 (1-y)^{n-2} t dy$$

$$= \left(\frac{n-1}{2}\right) \cdot t^2 \int_0^1 y^2 (1-y)^{n-2} dy$$

$$= \left(\frac{n-1}{2}\right) t^2 \cdot B(3, n-1)$$

$$= \left(\frac{n-1}{2}\right) t^2 \cdot \frac{\Gamma(3)\Gamma(n-1)}{\Gamma(n+2)} = \left(\frac{n-1}{2}\right) \cdot t^2 \cdot \frac{2! (n-2)!}{(n+1)!}$$

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

$$= \frac{t^2}{n(n+1)}$$

$$\therefore E\left[\frac{X_1^2}{2} \mid T=t\right] = \frac{t^2}{n(n+1)} \quad \therefore \frac{(X_1 + X_2 + \dots + X_n)^2}{n(n+1)} \text{ 为 } \theta^2 \text{ 的 UMVUE}$$

(得到跟办法①相同的结论)

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(d) 求 θ 之 MLE

$$f(\lambda_1, \lambda_2, \dots, \lambda_n | \theta) = \frac{1}{\theta^n} \exp\left(-\frac{1}{\theta}(\lambda_1 + \lambda_2 + \dots + \lambda_n)\right)$$

$$\log f(\lambda_1, \lambda_2, \dots, \lambda_n | \theta) = -n \log \theta - \frac{1}{\theta}(\lambda_1 + \lambda_2 + \dots + \lambda_n)$$

$$\frac{\partial}{\partial \theta} \log f(\lambda_1, \lambda_2, \dots, \lambda_n | \theta) = -\frac{n}{\theta} + \frac{1}{\theta^2}(\lambda_1 + \lambda_2 + \dots + \lambda_n)$$

$$= \frac{n\bar{X} - n\theta}{\theta^2} = \frac{n(\bar{X} - \theta)}{\theta^2}$$

θ	0	\bar{X}	
$\frac{\partial}{\partial \theta} \log f$	+	0	-
f	\nearrow	max	\searrow

$\therefore \theta = \bar{X}$ 使得 $L(\theta | \lambda_1, \dots, \lambda_n) = f(\lambda_1, \dots, \lambda_n | \theta)$

为最大 $\therefore \theta_{MLE} = \bar{X}$

根据 MLE 的不变性, θ^2 的 MLE 为 $(\hat{\theta})^2 = \bar{X}^2$

比较 $MSE\left(\frac{(\bar{X} + X_n)^2}{n(n+1)}\right)$ vs $MSE\left(\frac{(\bar{X} + X_n)^2}{n^2}\right)$

①

②

$$\begin{aligned} \textcircled{1} \text{MSE}\left(\frac{(X_1 + \dots + X_n)^2}{n(n+1)}\right) &= \text{MSE}\left(\frac{T^2}{n(n+1)}\right) \\ &= E\left[\left(\frac{T^2}{n(n+1)} - \theta^2\right)^2\right] = V\left[\frac{T^2}{n(n+1)}\right] \\ &= \frac{1}{n^2(n+1)^2} V[T^2] \end{aligned}$$

$$\begin{aligned} \textcircled{2} \text{MSE}\left(\frac{(X_1 + \dots + X_n)^2}{n^2}\right) &= \text{MSE}\left(\frac{T^2}{n^2}\right) \\ &= E\left[\left(\frac{T^2}{n^2} - \theta^2\right)^2\right] \quad \left(E\left[\frac{T^2}{n^2}\right] = \frac{n+1}{n}\theta^2\right) \\ &= E\left[\left(\frac{T^2}{n^2} - \frac{n+1}{n}\theta^2 + \frac{\theta^2}{n}\right)^2\right] \\ &= E\left[\left(\frac{T^2}{n^2} - \frac{n+1}{n}\theta^2\right)^2 + 2\left(\frac{T^2}{n^2} - \frac{n+1}{n}\theta^2\right) \cdot \frac{\theta^2}{n} + \frac{\theta^4}{n^2}\right] \\ &= V\left[\frac{T^2}{n^2}\right] + \frac{\theta^4}{n^2} = \frac{1}{n^4} V[T^2] + \frac{\theta^4}{n^4} \end{aligned}$$

$$\textcircled{1} \text{ vs } \textcircled{2} \dots \frac{1}{n^2(n+1)^2} V[T^2] < \frac{1}{n^4} V[T^2] + \frac{\theta^4}{n^4}$$

⓪
Ⓛ
Ⓜ

∴ ⓪ 的 MSE 比較小

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$$(a) f(x|s) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(\frac{-x^2}{2\sigma^2}\right) I(x \in R)$$

$$= \frac{1}{\sqrt{2\pi}} \cdot \frac{1}{\sigma} \exp\left(\frac{-x^2}{2\sigma^2}\right) I(x \in R)$$

$$= \frac{1}{\sqrt{2\pi}} \cdot I(x \in R) \cdot \exp\left(\frac{-x^2}{2\sigma^2}\right) \cdot \exp(-\log \sigma)$$

$$= \underbrace{\frac{1}{\sqrt{2\pi}}}_{h(x)} \cdot I(x \in R) \cdot \underbrace{\exp\left(\frac{-x^2}{2\sigma^2}\right)}_{T(x)} \cdot \underbrace{\exp(-\log \sigma)}_{\psi(s)}$$

$$\therefore h(x) = \frac{1}{\sqrt{2\pi}} I(x \in R)$$

$$T(x) = \frac{-x^2}{2\sigma^2}$$

$$T(x) = x^2$$

$$\psi(s) = -\log \sigma$$

$$(b) f(x_1, x_2, \dots, x_n | s) = \prod_{j=1}^n f(x_j | s)$$

$$= h(x_1) h(x_2) \dots h(x_n) \exp\left(\frac{-1}{2\sigma^2} \sum_{j=1}^n x_j^2 - n \log \sigma\right)$$

$$\begin{cases} \therefore h(\theta) = \left(\frac{1}{2\pi\sigma}\right)^n I((x_1, \dots, x_n) \in \mathbb{R}^n) \\ \eta(\sigma) = \frac{1}{2\sigma^2} \\ T_n(\mathbf{X}) = \sum_{j=1}^n x_j^2 \\ \psi(\sigma) = n \log \sigma \end{cases}$$

\therefore 根據 Neyman-Fisher 的分解定理,

$T_n(\mathbf{X}) = \sum_{j=1}^n x_j^2$ 為 σ^2 的充分統計量

(c) $\frac{x_j}{\sigma} \sim N(0,1)$ (iid)

根據 χ_n^2 的定義, $\sum_{j=1}^n \left(\frac{x_j}{\sigma}\right)^2 \sim \chi_n^2 = f\left(\frac{n}{2}, \frac{1}{2}\right)$

$$\therefore U \stackrel{\text{def}}{=} \sum_{j=1}^n \left(\frac{x_j}{\sigma}\right)^2 = \frac{T_n}{\sigma^2} \quad \frac{dU}{d\sigma} = \frac{1}{\sigma^3}$$

$$f_U(u) = \frac{u^{\frac{n}{2}-1}}{\Gamma\left(\frac{n}{2}\right) \cdot 2^{\frac{n}{2}}} \exp\left(-\frac{u}{2}\right)$$

$$\begin{aligned} \text{全確率} = 1 &= \int_{u=0}^{u=\infty} \frac{u^{\frac{n}{2}-1}}{\Gamma\left(\frac{n}{2}\right) 2^{\frac{n}{2}}} \exp\left(-\frac{u}{2}\right) du \quad (u \rightarrow t) \\ &= \int_{t=0}^{t=\infty} \frac{\left(\frac{t}{\sigma^2}\right)^{\frac{n}{2}-1}}{\Gamma\left(\frac{n}{2}\right) 2^{\frac{n}{2}}} \exp\left(-\frac{t}{2\sigma^2}\right) \cdot \frac{dt}{\sigma^2} \quad \checkmark \end{aligned}$$

$$\therefore f_T(t) = \frac{t^{\frac{n}{2}-1}}{\sigma^n \Gamma\left(\frac{n}{2}\right) \cdot 2^{\frac{n}{2}}} \exp\left(-\frac{t}{2\sigma^2}\right) \quad (t > 0)$$

$$\begin{aligned}
 f_T(t) &= \frac{t^{\frac{n}{2}-1}}{6^n \Gamma\left(\frac{n}{2}\right) 2^{\frac{n}{2}}} \exp\left(\frac{-t}{26^2}\right) \quad (t > 0) \\
 &= \underbrace{\frac{t^{\frac{n}{2}-1}}{\Gamma\left(\frac{n}{2}\right) \cdot 2^{\frac{n}{2}}}}_{h(t)} \cdot \exp\left(\underbrace{\frac{-1}{26^2}}_{\eta(s)} \cdot t - \underbrace{n \log 6}_{\psi(s)}\right) \\
 &\qquad\qquad\qquad \downarrow \\
 &\qquad\qquad\qquad s(t)
 \end{aligned}$$

作業 2 森元俊成

□ $X \sim \text{Bin}(n, p)$

(1) $P(X=x) = n C_x \cdot p^x (1-p)^{n-x} = L(p|x)$

$\log L(p|x) = (n-x) \log(1-p) + x \log p + \log n C_x$

$$\frac{\partial \log L(p|x)}{\partial p} = \frac{-1}{1-p} (n-x) + \frac{x}{p}$$

$$= \frac{x(1-p) - p(n-x)}{p(1-p)} = \frac{x - np}{p(1-p)} = 0$$

$\Rightarrow p = \frac{x}{n}$

		$\frac{x}{n}$	
L'	+	0	-
L	\nearrow		\searrow

$\therefore p = \frac{x}{n} \Rightarrow L: \text{MAX}$

$\therefore p_{\text{MLE}} = \frac{x}{n} \left(\frac{X}{n} \right)$

根據 MLE 的不變性, $p(1-p)$ 的 MLE 為 $\hat{p}(1-\hat{p})$

(2) $E[\hat{p}(1-\hat{p})] = E\left[\frac{X}{n} \left(1 - \frac{X}{n}\right)\right]$

$$E\left[\frac{X(n-X)}{n^2}\right] = \frac{1}{n^2} E[nX - X^2]$$

$$\left\{ \begin{aligned} V[X] &= E[X^2] - \underbrace{E[X]^2}_{(np)^2} = np(1-p) \\ \therefore E[X^2] &= (np)^2 + np(1-p) \\ E[nX] &= n^2p \end{aligned} \right.$$

$$\begin{aligned} \frac{1}{n^2} E[nX - X^2] &= \frac{1}{n^2} (n^2p - (np)^2 - np(1-p)) \\ &= \frac{1}{n^2} (n^2p(1-p) - np(1-p)) \\ &= \frac{1}{n^2} (n^2 - n) p(1-p) \\ &= \left(1 - \frac{1}{n}\right) p(1-p) \end{aligned}$$

$$\therefore E\left[\frac{1}{1-p} p(1-p)\right] = \underbrace{\left(1 - \frac{1}{n}\right)} p(1-p)$$

\therefore 並非 $p(1-p)$ 之不偏估計量

$$(7) \quad E\left[\frac{1}{1-p} p(1-p)\right] = p(1-p)$$

$$= \frac{n}{n-1} p(1-p)$$

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$$\boxed{2} \quad X \sim \text{Bin}(2, p)$$

若 X 為完備, $E[g(X)] = 0 \Rightarrow P(g(X) = 0) = 1$.

$$E[X] = 2p$$

$$V[X] = 2p(1-p)$$

$$\therefore E[X^2] = 2p(1-p) + (2p)^2 = 2p^2 + 2p$$

$$E[aX^2 + bX + c] = a(2p^2 + 2p) + 2bp + c$$

$$\begin{cases} E[aX^2 + bX + c \mid p = \frac{1}{2}] = \frac{3}{2}a + b + c = 0 \quad \dots \textcircled{1} \\ E[aX^2 + bX + c \mid p = \frac{1}{4}] = \frac{5}{8}a + \frac{b}{2} + c = 0 \quad \dots \textcircled{2} \end{cases}$$

$$\therefore \frac{7a}{8} + \frac{b}{2} = 0 \quad (\because \textcircled{1} - \textcircled{2})$$

$$\therefore b = -\frac{7a}{4}$$

$$\therefore a = 1 \Rightarrow b = -\frac{7}{4} \quad c = \frac{1}{4}$$

$$\therefore E\left[X^2 - \frac{7}{4}X + \frac{1}{4} \mid P\right] = 0 \quad (\text{for all } p = \frac{1}{2} \text{ or } \frac{1}{4})$$

$$g(X) = X^2 - \frac{7}{4}X + \frac{1}{4} \quad \begin{cases} \Pr(g(X) = 0) = 1 \\ E[g(X)] = 0 \end{cases}$$

$\therefore X$ 並非完備

3] $U_1 \stackrel{\text{def}}{=} \frac{X_1}{\theta}, U_2 \stackrel{\text{def}}{=} \frac{X_2}{\theta}, U_3 \stackrel{\text{def}}{=} \frac{X_3}{\theta}$
 $U_1, U_2, U_3 \sim U(0,1)$. 顯然: $U(x) = \frac{X(x)}{\theta}$.

(a) $P_r(X(x) \leq x) = 1 - P_r(X(x) > x) = 1 - P_r(X_1 \wedge X_2 > x)$
 $= 1 - \left(\frac{\theta - x}{\theta}\right)^3 = 1 - \left(1 - \frac{x}{\theta}\right)^3 \quad (0 \leq x \leq \theta)$

$\frac{d}{dx} P_r(X(x) \leq x) = -3\left(1 - \frac{x}{\theta}\right)^2 \cdot \left(-\frac{1}{\theta}\right) = \frac{3}{\theta} \left(1 - \frac{x}{\theta}\right)^2 \quad (0 \leq x \leq \theta)$
0 (otherwise)

$\therefore f_{X(x)}(x) = \frac{3}{\theta} \left(1 - \frac{x}{\theta}\right)^2 \cdot I_{(0,\theta)}(x)$

$U(x) = \frac{X(x)}{\theta} \quad (U_1 \wedge U_2 \sim U(0,1))$

$\therefore f_{X(x)}(x | \theta=1) = \frac{3}{1} \left(1-x\right)^2 = \frac{1}{\text{Be}(1,3)} \cdot x^{1-1} (1-x)^{3-1} \cdot I_{(0,1)}(x)$
1 $I_{(0,1)}(x)$

由此可知, $\frac{X(x)}{\theta} \sim \text{Be}(1,3)$

(b) $E[X(x)] = \theta \cdot E\left[\frac{X(x)}{\theta}\right] = \theta \cdot E[U(x)]$

$= \theta \cdot \int_{x=0}^{x=1} 3x(1-x)^2 dx = 3\theta \cdot \text{Be}(2,3)$

$= 3\theta \cdot \frac{\Gamma(2)\Gamma(3)}{\Gamma(5)} = 3\theta \cdot \frac{2!}{4!} = \frac{\theta}{4}$

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$$E[X(1)] = \frac{\theta}{4} \quad ; \quad E[4X(1)] = \theta$$

$$= \underline{\underline{4X(1)}}$$

(c) 將情況一般化:

$$X_1, X_2, \dots, X_n \sim \text{Uni}(0, \theta)$$

證明 $\frac{X^{(n)}}{X^{(1)}}$ 與 $X^{(1)}$ 相互獨立

① $X^{(n)}$ 為 θ 之完備充分統計量

$$\text{原因} \quad \frac{d}{d\lambda} P(X^{(n)} \leq \lambda) = \frac{d}{d\lambda} P(X_1, \dots, X_n \leq \lambda)$$

$$= \frac{d}{d\lambda} \left(\frac{\lambda}{\theta}\right)^n = \frac{n\lambda^{n-1}}{\theta^n} \quad (0 \leq \lambda \leq \theta)$$

$$0 \quad (\text{elsewhere})$$

$$f_{X^{(n)}}(\lambda) = \frac{n\lambda^{n-1}}{\theta^n} \cdot I_{(0, \theta)}(\lambda) \quad (\theta > 0)$$

$$E[g(X)] = 0 \Rightarrow \int_0^\theta g(x) \frac{n\lambda^{n-1}}{\theta^n} d\lambda = 0$$

$$\Rightarrow \int_0^\theta g(x) \cdot x^{n-1} d\lambda = 0 \Rightarrow \frac{d}{d\theta} \int_0^\theta g(x) x^{n-1} d\lambda = 0$$

$$\Rightarrow g(\theta) \cdot \theta^{n-1} = 0 \Rightarrow g(\theta) = 0 \quad (\text{for all } \theta \in \{\theta \mid \theta > 0\})$$

$$(\theta > 0)$$

$$\therefore P(g(X) = 0) = 1$$

$\therefore X(n)$ 為 θ 之 完備 充份 統計量

② $\frac{X(n)}{X(1)}$ 為 θ 之 輔助 統計量

$$\therefore \frac{V(n)}{X(n)} = \frac{\left(\frac{X(n)}{\theta}\right)}{\left(\frac{X(1)}{\theta}\right)} \quad \left(\frac{X(n)}{\theta}, \frac{X(1)}{\theta} \text{ 的分布與 } \theta \text{ 無關}\right)$$

↓
(跟 θ 無關)

③ BASU 定理... $\frac{X(n)}{X(1)}$ vs $X(n)$ 為 獨立
輔助 · 完備

証) $S = \frac{V(n)}{X(n)}, T = X(n)$

$S|T$ 的分布與 θ 無關 ($\because T =$ 充份統計量)

$P(S \in A | T) \dots$ 與 θ 無關, \dots T 的函數

$$E[P(S \in A | T)] = \int_T \underbrace{P(S \in A | T)}_1 \cdot f_T(t) dt$$
$$= \int_T \int_{S \in A} f_{S|T}(s, t) ds \cdot f_T(t) dt$$

$$= \int_T \int_{S \in A} \frac{f_{S|T}(s, t)}{f_T(t)} ds \cdot f_T(t) dt = \int_T \int_{S \in A} f_{S, T}(s, t) ds dt$$
$$= P(S \in A) \dots \text{常數}$$

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$$E[P(S \in A | T)] = P(S \in A)$$

$$E[\underbrace{P(S \in A | T) - P(S \in A)}_{=0}] = 0$$

||
T (是備用統計量) 的函數

根據備用統計量的定義,

$$P(P(S \in A | T) - P(S \in A) = 0) = 1$$

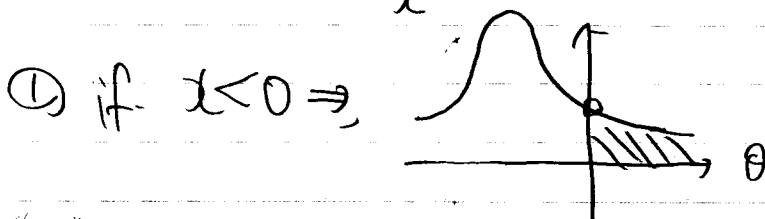
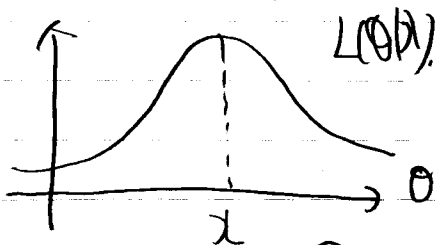
$$\therefore P(S \in A | T) = P(S \in A) \quad (a.s.) \quad (\text{for all } A)$$

\(\therefore\) 由此可知, S, T 為獨立

$$\boxed{4} \quad X \sim N(\theta, 1) \quad (\theta > 0)$$

$$(a) \quad f(x|\theta) = \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2\pi}(x-\theta)^2}$$

$$\therefore f(x|\theta) = f(\theta|x) \quad L(\theta|x) \stackrel{\text{def}}{=} f(x|\theta)$$



若允許 $\theta=0 \Rightarrow \theta=0$ 使得 $L(\theta|\lambda)$ 為最大
 (不允許 \Rightarrow MLE 不存在) $\hat{\theta}_{MLE}=0$

② $\lambda \geq 0, \theta = \lambda$ 使得 $L(\theta|\lambda)$ 為最大
 $\hat{\theta}_{MLE} = \lambda$

\therefore 允許 $\theta=0 \Rightarrow \hat{\theta}_{MLE} = \max\{\lambda, 0\}$
 (不允許 $\theta=0 \Rightarrow \hat{\theta}_{MLE} = \begin{cases} \lambda & (\lambda > 0) \\ \text{不存在} \end{cases}$)

(b) 假設 $\hat{\theta}_{MLE} = \max\{\lambda, 0\}$ (換言之允許 $\theta=0$)

$$F_{\hat{\theta}_{MLE}}(t) = P(\hat{\theta}_{MLE} \leq t) = P(X \leq t \cap 0 \leq t)$$

(cdf)

$$= P(X - \theta \leq t - \theta \cap 0 \leq t)$$

$$= P(X - \theta \leq t - \theta) \cdot I_{[0, \infty)}(t)$$

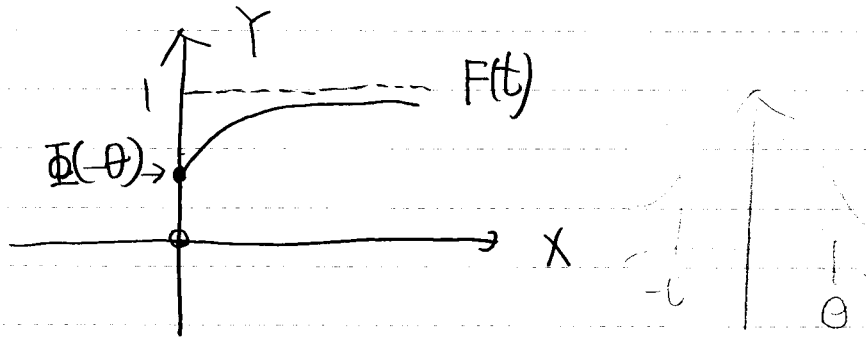
$$= \Phi(t - \theta) \cdot I_{[0, \infty)}(t)$$

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$$F_{\Theta_{MLE}}(t) = \Phi(t - \theta) \cdot I_{[0, \infty)}(t)$$



$\therefore \Theta_{MLE}$ 包含一个 atom. ($\Theta_{MLE}=0$)

① $Pr(\Theta_{MLE}=0) = \Phi(-\theta) = 1 - \Phi(\theta)$ (离散的部分)

② $\Theta_{MLE} > 0 \Rightarrow \frac{d}{dt} F_{\Theta_{MLE}}(t) = \phi(t - \theta)$ (连续的部分)

$$\therefore E[\Theta_{MLE}] = 0 \cdot Pr(\Theta_{MLE}=0) + \int_{t>0} t \phi(t - \theta) dt$$

$$= \int_{t>0} t \cdot \phi(t - \theta) dt \quad (u = t - \theta)$$

$$= \int_{-\theta}^{\infty} (u + \theta) \phi(u) du$$

$$= \int_{-\theta}^{\infty} u \phi(u) du + \theta \int_{-\theta}^{\infty} \phi(u) du$$

$$\left[-\frac{1}{\sqrt{2\pi}} \exp\left(-\frac{u^2}{2}\right) \right]_{-\theta}^{\infty} + \theta \left[\Phi(u) \right]_{-\theta}^{\infty} = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{\theta^2}{2}\right) + \theta (1 - \Phi(-\theta)) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{\theta^2}{2}\right) + \theta \Phi(\theta)$$

$$\int_t^{\infty} \lambda \exp(-\lambda t) dt = \left[-\exp(-\lambda t) \right]_t^{\infty} = \exp(-\lambda t)$$

$$\therefore E[\hat{\theta}_{MLE}] = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{\theta^2}{2}\right) + \theta \Phi(\theta)$$

$$\therefore E[\hat{\theta}_{MLE}] \neq \theta$$

5) $X \sim \text{exp}(\lambda)$ $Y \sim \text{exp}(\lambda)$ ($\alpha + \lambda$)
(independent)

① $Pr(X^3 \leq t) = Pr(X \leq t^{1/3}) = 1 - Pr(X > t^{1/3})$

$$\frac{d}{dt} Pr(X^3 \leq t) = \frac{d}{dt} \left(1 - \exp(-\lambda t^{1/3}) \right) \quad (t > 0)$$

$$= \lambda t^{-2/3} \exp(-\lambda t^{1/3}) \quad (t > 0)$$

$$\therefore f_{X^3}(t) = \lambda t^{-2/3} \exp(-\lambda t^{1/3}) \quad (t > 0)$$

② 將情況一般化...

$|X - Y| =$ 樣本範圍 (Sample Range)

$X_1, \dots, X_n \stackrel{i.i.d.}{\sim} \text{e}(\lambda)$

考慮 $X(n) - X(1)$ 之分布

$$\begin{cases} R = X(n) - X(1) \\ S = \frac{X(n) + X(1)}{2} \end{cases}$$

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$$Pr(A \cap B) = Pr(B)$$

$$Pr(X_{(1)} \leq a, X_{(n)} \leq b) = Pr(X_{(n)} \leq b) - Pr(a < X_{(1)}, X_{(n)} \leq b)$$

$$= Pr(X_{(1)} \wedge X_{(n)} \leq b) - Pr(a < X_{(1)} \wedge X_{(n)} \leq b)$$

$$(1 - \exp(-\lambda b))^n - (\exp(-\lambda a) - \exp(-\lambda b))^n$$

$$\frac{\partial^2}{\partial a \partial b} Pr(X_{(1)} \leq a, X_{(n)} \leq b) =$$

$$\frac{\partial}{\partial a} -n (\exp(-\lambda a) - \exp(-\lambda b))^{n-1} \cdot (-\lambda) \exp(-\lambda a) =$$

$$\frac{\partial}{\partial b} \{ n \lambda \exp(-\lambda a) (\exp(-\lambda a) - \exp(-\lambda b))^{n-1} \}$$

$$= n(n-1) \lambda^2 \exp(-\lambda a) \exp(-\lambda b) (\exp(-\lambda a) - \exp(-\lambda b))^{n-2} \quad (a \geq 0, b \geq 0)$$

$$\therefore f_{X_{(1)}, X_{(n)}}(a, b) = n(n-1) \lambda^2 \exp(-\lambda(a+b)) \{ \exp(-\lambda a) - \exp(-\lambda b) \}^{n-2}$$

(a ≥ 0, b ≥ 0)

$$X_{(n)} = S + \frac{h}{2} \quad (= b)$$

$$X_{(1)} = S - \frac{h}{2} \quad (= a)$$

$$\therefore 0 \leq S - \frac{h}{2} \leq S + \frac{h}{2} < \infty$$

$$\therefore 0 \leq \frac{h}{2} \leq S < \infty$$

$$\frac{\partial}{\partial s} \begin{pmatrix} X(s) \\ X(s) \end{pmatrix} = \begin{pmatrix} 1 \\ 1 \end{pmatrix} \quad \frac{\partial}{\partial r} \begin{pmatrix} X(s) \\ X(s) \end{pmatrix} = \begin{pmatrix} \frac{1}{2} \\ -\frac{1}{2} \end{pmatrix}$$

$$\therefore |J| = 1 \quad \therefore \underline{\underline{d(x,y)dx(s) = ds ds}}$$

$$\begin{aligned} \therefore \text{全概率} = 1 &= \iint_{0 \leq X(s) \leq X(r) < \infty} f_{X(s), X(r)}(x, y) dx dy \\ &= \iint_{0 \leq \frac{t}{2} \leq s < \infty} n(n-1) \lambda^2 \exp(-2\lambda s) \cdot \left\{ \exp(-\lambda s + \frac{\lambda r}{2}) - \exp(-\lambda s - \frac{\lambda r}{2}) \right\}^{n-2} ds dt \\ &= \iint_{0 \leq \frac{t}{2} \leq s < \infty} n(n-1) \lambda^2 \exp(-2\lambda s) \cdot \left\{ \exp(-\lambda s) \cdot \left(\exp(\frac{\lambda r}{2}) - \exp(-\frac{\lambda r}{2}) \right) \right\}^{n-2} ds dt \\ &= \iint_{(s)} n(n-1) \lambda^2 \exp(-2\lambda s) \exp(-\lambda(n-2)s) \left\{ \exp(\frac{\lambda r}{2}) - \exp(-\frac{\lambda r}{2}) \right\}^{n-2} ds dt \\ &= \int_{s \geq \frac{t}{2} \leq s < \infty} n(n-1) \lambda^2 \exp(-\lambda n s) \left\{ \exp(\frac{\lambda r}{2}) - \exp(-\frac{\lambda r}{2}) \right\}^{n-2} ds dt \end{aligned}$$

求R的累积分布 $\int_{s \geq \frac{t}{2}} \exp(-\lambda n s) ds$

$$= \left[\frac{-1}{\lambda n} \exp(-\lambda n s) \right]_{\frac{t}{2}}^{\infty} = \frac{1}{\lambda n} \exp\left(-\frac{n\lambda r}{2}\right)$$

$$\begin{aligned} \therefore f(r) &= n(n-1) \lambda^2 \cdot \frac{1}{\lambda n} \exp\left(-\frac{n\lambda r}{2}\right) \left\{ \exp(\frac{\lambda r}{2}) - \exp(-\frac{\lambda r}{2}) \right\}^{n-2} \quad (r \geq 0) \\ &= (n-1) \lambda \exp\left(-\frac{n\lambda r}{2}\right) \left\{ \exp(\frac{\lambda r}{2}) - \exp(-\frac{\lambda r}{2}) \right\}^{n-2} \quad (r \geq 0) \end{aligned}$$

$$\therefore \underline{\underline{n=2}} \implies \underline{\underline{f(r) = \lambda \exp(-\lambda r)}} \quad \therefore \underline{\underline{R \sim \exp(\lambda)}} \quad (\text{mean} = \frac{1}{\lambda})$$

⑬

$$\begin{aligned}
 \textcircled{2} \quad \Pr(\min\{X, Y^3\} \leq t) &= 1 - \Pr(\min\{X, Y^3\} > t) \\
 &= 1 - \Pr(X > t, Y^3 > t) = 1 - \Pr(X > t) \Pr(Y^3 > t) \\
 &= 1 - \Pr(X > t) \Pr(Y > t^{\frac{1}{3}}) \quad (t > 0) \\
 &= 1 - \exp(-\lambda t) \cdot \exp(-\lambda t^{\frac{1}{3}}) \\
 &= 1 - \exp(-\lambda(t + t^{\frac{1}{3}}))
 \end{aligned}$$

$$\begin{aligned}
 \frac{d}{dt} \Pr(\min\{X, Y^3\} \leq t) &= \frac{d}{dt} (1 - \exp(-\lambda(t + t^{\frac{1}{3}}))) \\
 &= -\frac{d}{dt} (-\lambda(t + t^{\frac{1}{3}})) \cdot \exp(-\lambda(t + t^{\frac{1}{3}})) \\
 &= \lambda(1 + \frac{1}{3}t^{-\frac{2}{3}}) \exp(-\lambda(t + t^{\frac{1}{3}})) \quad (t > 0)
 \end{aligned}$$

$$\therefore f_{\min\{X, Y^3\}}(t) = \begin{cases} \lambda(1 + \frac{1}{3}t^{-\frac{2}{3}}) \exp(-\lambda(t + t^{\frac{1}{3}})) & (t > 0) \\ 0 & (\text{else}) \end{cases}$$

⑥ 證明 $E[U] = \frac{1}{\alpha}$ $V[U] = \frac{1}{\alpha^2}$ 即可

先考慮 $X(1) \dots X(n)$ 的聯合分佈

$$f(X(1) \dots X(n)) = n! \alpha^n \exp(-\alpha X(1) - \alpha X(2) \dots - \alpha X(n))$$

$$(0 \leq X(1) \leq X(2) \dots \leq X(n))$$

①

$$\int_{X(n) \geq X(n-1)} f(X(1) \dots X(n)) dX(n)$$

$$= n! \alpha^{n-1} \exp(-\alpha X(1)) \dots \exp(-\alpha X(n-1)) \cdot \left[-\exp(-\alpha X(n)) \right]_{X(n-1)}^{\infty}$$

$$= n! \alpha^{n-1} \exp(-\alpha X(1)) \dots \exp(-\alpha X(n-1)) \cdot \exp(-2\alpha X(n-1))$$

(↑ $X(1) \sim X(n-1)$ 是聯合分佈)

$$\textcircled{2} \int_{X(n-1) \geq X(n-2)} f(X(1) \dots X(n-1)) dX(n-1)$$

$$= n! \alpha^{n-2} \exp(-\alpha X(1)) \dots \exp(-\alpha X(n-2)) \cdot \left[-\frac{1}{2} \exp(-2\alpha X(n-1)) \right]_{X(n-2)}^{\infty}$$

$$= \frac{n!}{2!} \alpha^{n-2} \exp(-\alpha X(1)) \dots \exp(-\alpha X(n-2)) \cdot \exp(-3\alpha X(n-2))$$

∫∫ (↑ $X(1) \sim X(n-2)$ 是聯合分佈)

$$\textcircled{3} \frac{n!}{j!} \alpha^{n-j} \exp(-\alpha X(1)) \dots \exp(-\alpha X(n-j-1)) \exp(-(j+1)\alpha X(n-j))$$

(↑ $X(1) \sim X(n-j)$ 是聯合分佈)

15

no.
Date.

∴ $j = n+1$ 即可得 $X(1) \sim X(n)$ 之聯合分布

$$\frac{n!}{(n+1)!} \alpha^n \exp(-\alpha X(1)) \dots \exp(-\alpha X(n-1)) \exp(-\alpha(n+1)X(n))$$

$$(0 \leq X(1) \leq \dots \leq X(n))$$

接下來考慮以下變數轉換

$$\begin{cases} Y_1 = nX(1) \\ Y_2 = (n-1)(X(2) - X(1)) \\ \vdots \\ Y_n = (n+1)(X(n) - X(n-1)) \end{cases}$$

$$\frac{Y_3}{n-2} = X(3) - X(2)$$

$$\begin{pmatrix} Y_1 \\ \vdots \\ Y_n \end{pmatrix} = \begin{pmatrix} n & & & & & \\ -(n-1) & (n-1) & & & & \\ & -(n-2) & (n-2) & & & \\ & & & \ddots & & \\ 0 & & & & -(n+1) & (n+1) \end{pmatrix} \begin{pmatrix} X(1) \\ \vdots \\ X(n) \end{pmatrix}$$

$$dy_1 \dots dy_n = |J| dx_1 \dots dx_n$$

$$= n(n-1) \dots (n+1) dx_1 \dots dx_n$$

$$= \frac{n!}{(n+1)!} dx_1 \dots dx_n$$

$$X(1) = \frac{Y_1}{n}, \quad X(2) = \frac{Y_1}{n} + \frac{Y_2}{n-1}, \quad X(3) = \frac{Y_1}{n} + \frac{Y_2}{n-1} + \frac{Y_3}{n-2} \dots$$

$$0 \leq X(1) \leq X(2) \leq \dots$$

$$\Leftrightarrow \underbrace{Y_1 \geq 0, Y_2 \geq 0, \dots, Y_n \geq 0}$$

全概率

$$1 = \int \dots \int_{0 \leq X(1) \leq \dots \leq X(r)} \frac{n!}{(n-r)!} \alpha^r \exp(-\alpha X(1)) \dots \exp(-\alpha(n-r+1) X(r)) dX(1) \dots dX(r)$$

$$\left(\text{另外 } Y_1 + Y_2 + \dots + Y_n = X(1) + X(2) + \dots + X(r) + (n-r+1) X(r) \right)$$

全概率

$$\therefore = \int \dots \int_{\substack{Y_1 \geq 0 \\ \vdots \\ Y_n \geq 0}} \frac{n!}{(n-r)!} \alpha^r \exp(-\alpha(Y_1 + Y_2 + \dots + Y_n)) \cdot \frac{(n-r)!}{n!} dY_1 \dots dY_n$$

$$= \int \dots \int_{\substack{Y_1 \geq 0 \\ \vdots \\ Y_n \geq 0}} \alpha \exp(-\alpha Y_1) \cdot \alpha \exp(-\alpha Y_2) \dots \alpha \exp(-\alpha Y_n) dY_1 \dots dY_n$$

由此可知 $Y_1 \sim Y_n \stackrel{iid}{\sim} \exp(\alpha)$ (mean: $\frac{1}{\alpha}$)

$$\therefore Y_1 + Y_2 + \dots + Y_n = X(1) + X(2) + \dots + X(r) + (n-r+1) X(r)$$

$$= UV \sim P(r, \alpha) \quad (\text{Gamma 分布})$$

$$\therefore E[UV] = \frac{r}{\alpha}, \quad V[UV] = \frac{r}{\alpha^2} \quad (\because \text{Gamma 分布}) \quad \therefore \underline{\underline{\text{证明完毕}}}$$

17. 在求的过程中还有一题, 所以[7]分成[7-1]和[7-2]

[7-1] $X_1 \sim X_n$: iid $f(x) = \frac{\theta}{(1+x)^{\theta+1}} \quad (x > 0)$

(a) $f(x_1, \dots, x_n | \theta) = \frac{\theta}{(1+x_1)^{\theta+1}} \dots \frac{\theta}{(1+x_n)^{\theta+1}} \quad (x_1, \dots, x_n > 0)$

$L(\theta | \mathcal{X}) = \log f(x_1, \dots, x_n | \theta) = \log \frac{\theta^n}{(1+x_1)^{\theta+1} \dots (1+x_n)^{\theta+1}}$

$= n \log \theta - (\theta+1) \sum_{j=1}^n \log(1+x_j)$

$\frac{\partial L(\theta | \mathcal{X})}{\partial \theta} = \frac{n}{\theta} - \sum_{j=1}^n \log(1+x_j) = 0$

$\therefore \frac{\theta}{n} = \frac{1}{\sum_{j=1}^n \log(1+x_j)}$

$\therefore \theta = \frac{n}{\sum_{j=1}^n \log(1+x_j)}$

θ	0		$\sum_{j=1}^n \log(1+x_j)$	
$L(\theta)$		+	0	-
$L(\theta)$		→	max	↓

$\therefore \hat{\theta}_{MLE} = \frac{n}{\sum_{j=1}^n \log(1+x_j)}$

- (b) ① 求 $g(X_i)$ 的分布
- ② $\frac{\sum g(X_i)}{n}$... 中央极限定理
- ③ $g(X) = x$ - δ -method.

$Y_i \stackrel{\text{def}}{=} g(X_i) \quad X_i = 0 \rightarrow \infty$
 $Y_i = 0 \rightarrow \infty$

$$\frac{dy_i}{dx_i} = \frac{1}{1+x_i} = e^{-y_i}$$

$$\begin{aligned} \text{全概率} = 1 &= \int_{x_i=0}^{x_i=\infty} \frac{\theta}{(1+x_i)^{\theta+1}} dx_i \\ &= \int_{y_i=0}^{y_i=\infty} \theta e^{-\theta y_i} \cdot e^{y_i} dy_i \\ &= \int_0^{\infty} \theta e^{-\theta y_i} dy_i \end{aligned}$$

由此可知 $Y_i \sim \text{exp}(\theta)$ (mean: $\frac{1}{\theta}$, var: $\frac{1}{\theta^2}$)

故 $E[Y_i] < \infty$ \therefore 根据中央极限定理,

$$\frac{Y_1 + \dots + Y_n}{n} \xrightarrow{d} N\left(\frac{1}{\theta}, \frac{1}{n\theta^2}\right)$$

(9)

$$\therefore \sqrt{n}(\bar{Y} - \theta) \xrightarrow{d} N(0, \frac{1}{\theta^2})$$

$$g(\theta) = \frac{1}{\lambda}$$

$$g(\bar{Y}) \approx g(\theta) + g'(\theta)(\bar{Y} - \theta)$$

$$\therefore g(\bar{Y}) - g(\theta) \approx g'(\theta)(\bar{Y} - \theta)$$

$$\sqrt{n}(g(\bar{Y}) - g(\theta)) \approx g'(\theta) \underbrace{\sqrt{n}(\bar{Y} - \theta)}_{\xrightarrow{d} N(0, \frac{1}{\theta^2})}$$

$$\xrightarrow{d} N(0, (g'(\theta))^2 \cdot \frac{1}{\theta^2})$$

$$g'(\lambda) = \frac{1}{\lambda^2} \quad g'(\theta) = -\theta^{-2}$$

$$= N(0, \theta^4 \cdot \frac{1}{\theta^2})$$

" "

$$N(0, \theta^2)$$

$$\therefore \sqrt{n}(g(\bar{Y}) - g(\theta)) \xrightarrow{d} N(0, \theta^2)$$

$$\frac{1}{\bar{Y}} = \frac{n}{\sum_{i=1}^n (Y_i X_i)} = \hat{\theta}_{MLE}$$

$$\therefore \sqrt{n}(\hat{\theta}_{MLE} - \theta) \xrightarrow{d} N(0, \sigma^2)$$

cc) 同樣利用 d -method

$$\begin{aligned} \sqrt{n}(g(\hat{\theta}_{MLE}) - g(\theta)) &\xrightarrow{d} N(0, (g'(\theta))^2 \cdot \sigma^2) \\ &= N(0, 1) \end{aligned}$$

$$\therefore g(\theta) = \frac{\pm 1}{\theta} + C$$

$$\therefore g(\theta) = \pm \frac{1}{\theta} + C$$

CC: 常數)

7和8之間有一題

7-2

$$(a) \hat{p}_{IS} = \frac{1}{m} \sum_{i=1}^m I(x_i \geq t) \cdot \frac{\phi(x_i)}{\phi(x_i - t)}$$

$$E[\hat{p}_{IS}] = E\left[\frac{1}{m} \sum_{i=1}^m I(x_i \geq t) \cdot \frac{\phi(x_i)}{\phi(x_i - t)}\right]$$

$$= \frac{1}{m} \sum_{i=1}^m E\left[I(x_i \geq t) \cdot \frac{\phi(x_i)}{\phi(x_i - t)}\right]$$

$$\int_{x_i \geq t} \frac{\phi(x_i)}{\phi(x_i - t)} \cdot \underbrace{\phi(x_i - t)}_{x_i \sim \text{pdf}} dx_i$$

$$= \int_{x_i \geq t} \phi(x_i) dx_i$$

$$= [\Phi(x_i)]_t^{\infty} = 1 - \Phi(t)$$

$$= \frac{1}{m} \sum_{i=1}^m (1 - \Phi(t)) = \underline{1 - \Phi(t)}$$

$\therefore \hat{p}_{IS} \dots 1 - \Phi(t)$ unbiased estimator

$$(b) V[\hat{p}_{IS}] = V\left[\frac{1}{m} \sum_{i=1}^m I(x_i \geq t) \frac{\phi(x_i)}{\phi(x_i - t)}\right]$$

$$= \frac{1}{m^2} \sum_{i=1}^m V\left[I(x_i \geq t) \frac{\phi(x_i)}{\phi(x_i - t)}\right]$$

$$= \frac{1}{m} V\left[I(x_i \geq t) \frac{\phi(x_i)}{\phi(x_i - t)}\right] \quad (-: \text{獨立})$$

$$E\left[I(X_1 \geq 5) \cdot \frac{\phi(X_1)}{\phi(X_1-5)} \right]^2$$

$$= \int_{x_1 \in \mathbb{R}} I(x_1 \geq 5) \cdot \frac{\phi(x_1)^2}{\phi(x_1-5)^2} \cdot \phi(x_1-5) dx_1$$

$$= \int_{x_1 \geq 5} \frac{\phi(x_1)^2}{\phi(x_1-5)} dx_1$$

$$\because \frac{\phi(x_1)^2}{\phi(x_1-5)} = \frac{1}{\sqrt{\pi}} e^{-x_1^2} \cdot \sqrt{2\pi} e^{-\frac{1}{2}(x_1-5)^2}$$

$$= \frac{1}{\sqrt{2\pi}} e^{-\left(x_1^2 + \frac{1}{2}(x_1^2 - 10x_1 + 25)\right)}$$

$$= \frac{1}{\sqrt{2\pi}} e^{-\left(\frac{3}{2}x_1^2 - 5x_1 + \frac{25}{2}\right)}$$

$$= \frac{1}{\sqrt{2\pi}} e^{-\left(\frac{3}{2}(x_1+5)^2 + \frac{50}{2}\right)}$$

$$= \frac{1}{\sqrt{2\pi}} e^{-\left(\frac{3}{2}(x_1+5)^2\right)} \cdot e^{-25}$$

$$= \int_{x_1 \geq 5} \frac{1}{\sqrt{2\pi}} e^{-\left(\frac{3}{2}(x_1+5)^2\right)} e^{-25} dx_1$$

$z = x_1 + 5 \quad dx_1 = dz$

$$= \int_{z \geq 10} \frac{1}{\sqrt{2\pi}} e^{-\left(\frac{3}{2}z^2\right)} e^{-25} dz$$

$$= e^{-25} (1 - \Phi(10))$$

22)

$$\therefore E\left[\left\{I(X_1 \geq 5) \cdot \frac{\phi(X_1)}{\phi(X_1-5)}\right\}^2\right] = \varphi(25)(1-\Phi(10))$$

$$\therefore V\left[I(X_1 \geq 5) \frac{\phi(X_1)}{\phi(X_1-5)}\right] = \varphi(25)(1-\Phi(10)) - (1-\Phi(5))^2$$

$$\therefore V[\hat{p}_{25}] = \frac{1}{m} \left\{ \varphi(25)(1-\Phi(10)) - (1-\Phi(5))^2 \right\}$$

$$\square \quad g(x) = \frac{f(x)}{1-F(x_0)} I_{[x_0, \infty)}(x)$$

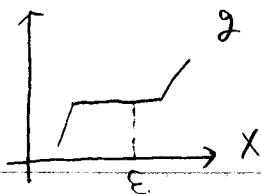
$$\textcircled{1} \quad g(x) \geq 0 \quad (\because f(x) > 0, 1-F(x_0) > 0)$$

$$\textcircled{2} \quad \int_{x \in \mathbb{R}} g(x) dx = \int_{x \geq x_0} \frac{f(x)}{1-F(x_0)} dx$$

$$= \frac{1}{1-F(x_0)} [F(x)]_{x_0}^{\infty} = \frac{1-F(x_0)}{1-F(x_0)} = 1$$

\therefore 由 $\textcircled{1}, \textcircled{2}$, $g(x)$ 為標準密度函數

$$\text{cdf: } G(x) = \int_{-\infty}^x g(t) dt = \begin{cases} \frac{F(x)-F(x_0)}{1-F(x_0)} & (x \geq x_0) \\ 0 & (x < x_0) \end{cases}$$



$$\{\omega | X(\omega) \geq \varepsilon\} \subseteq \{\omega | g(X) \geq g(\varepsilon)\} \quad (*)$$

[9] 由於 g 為遞增函數, $P(X \geq \varepsilon) \leq P(g(X) \geq g(\varepsilon))$ ↓

$$E[g(X)] = \int_{\omega \in \Omega} g(X) \cdot P(dX(\omega)) \quad \dots (*)$$

$$\geq \int_{\{\omega \in \Omega | g(X) \geq g(\varepsilon)\}} g(X) P(dX(\omega))$$

$$\begin{cases} \Omega \supseteq \{\omega \in \Omega | g(X) \geq g(\varepsilon)\} \\ g \text{ non-negative} \end{cases}$$

$$\geq \int_{\{\omega \in \Omega | g(X) \geq g(\varepsilon)\}} g(\varepsilon) P(dX(\omega))$$

$$= g(\varepsilon) \int_{\{\omega \in \Omega | g(X) \geq g(\varepsilon)\}} P(dX(\omega))$$

$$= g(\varepsilon) \cdot P(\{\omega \in \Omega | g(X) \geq g(\varepsilon)\}) \quad (\because *)$$

$$\geq g(\varepsilon) \cdot P(\{\omega \in \Omega | X \geq \varepsilon\})$$

$$= g(\varepsilon) P(X \geq \varepsilon)$$

$$\therefore P(X \geq \varepsilon) \leq \frac{E[g(X)]}{g(\varepsilon)}$$

∴ 證明完成

(25)

• 10 跟 4 一樣, 請參閱 4.

• 11 $T|N \sim N(N\mu, N\sigma^2)$ $N \sim \text{Po}(\lambda)$

① $\sqrt{n} \left(\frac{T_1 + \dots + T_n}{n} - \lambda\mu \right)$ 之極限分布...

求 T_j 的期望值與變異數 (T_1, T_2, \dots, T_n iid 某種分布)

• $E[T|N] = N\mu$

$$E[E[T|N]] = E[N\mu] = \mu E[N] = \mu\lambda$$

• $E[T^2|N] = N\sigma^2 + N^2\mu^2$

$$E[E[T^2|N]] = E[N\sigma^2 + N^2\mu^2] = \lambda\sigma^2 + (\lambda^2 + \lambda)\mu^2$$

$$\text{②} \quad E[N] = \lambda \quad E[N^2] = \lambda^2 + \lambda$$

$$\text{故 } E[T] = \mu\lambda \quad E[T^2] = \lambda\sigma^2 + (\lambda^2 + \lambda)\mu^2$$

$$\Rightarrow V[T] = \lambda\sigma^2 + (\lambda^2 + \lambda)\mu^2 - \mu^2\lambda^2$$

$$= \lambda\sigma^2 + \lambda\mu^2 = \lambda(\sigma^2 + \mu^2) \quad (\text{for all } T_j)_{j=1, \dots, n}$$

$\therefore E[T_j] < \infty, V[T_j] < \infty$ (\rightarrow 中央極限定理)

根據中央極限定理, $(T_1 \sim T_n: iid)$

$$\sqrt{n} \left(\frac{T_1 + T_2 + \dots + T_n}{n} - \lambda\mu \right) \xrightarrow{d} N(0, \lambda(\sigma^2 + \mu^2))$$

② $\frac{\sqrt{n}}{N}(\bar{T} - \lambda\mu)$ 之極限分布

利用 Slutsky 定理,
$$\begin{cases} X_n \xrightarrow{d} X \\ Y_n \xrightarrow{P} c \text{ (常數)} \end{cases} \Rightarrow X_n Y_n \xrightarrow{d} cX$$

我們已知 $\sqrt{n}(\bar{T} - \lambda\mu) \xrightarrow{d} N(0, \lambda(\sigma^2 + \mu^2))$

觀察 $\frac{1}{N} = \frac{n}{N_1 + N_2 + \dots + N_n}$ 是否機率收斂到常數.

根據 Khinchine 弱大數法則, $\frac{N_1 + \dots + N_n}{n} \xrightarrow{P} \lambda \quad (\because \sum_{k=1}^{\infty} \frac{1}{k^2} < \infty)$

由於 $g(x) = \frac{1}{x} \quad (x > 0)$ 為 \mathbb{R} 上的連續函數

因此 $g\left(\frac{N_1 + \dots + N_n}{n}\right) \xrightarrow{P} g(\lambda) \quad (\because \frac{1}{N} \xrightarrow{P} \frac{1}{\lambda})$

綜上所述事實, 得知 $\sqrt{n}(\bar{T} - \lambda\mu) \xrightarrow{d} N(0, \frac{1}{\lambda}(\sigma^2 + \mu^2))$

$$\boxed{12} \quad \begin{pmatrix} \varepsilon \\ v \end{pmatrix} \sim N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \underbrace{\begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix}}_{\Sigma}\right)$$

$$W = \alpha S + \varepsilon \quad (\text{報酬})$$

$$\therefore \begin{pmatrix} W \\ v \end{pmatrix} = \begin{pmatrix} \varepsilon \\ v \end{pmatrix} + \begin{pmatrix} \alpha S \\ 0 \end{pmatrix} \sim N\left(\begin{pmatrix} \alpha S \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix}\right)$$

• 將題意解釋為求 $E[W | v > 0]$.

• 先求 $W | v > 0$ 之分布

$$\Pr(W \leq w | v > 0) = \frac{\Pr(W \leq w, v > 0)}{\Pr(v > 0)}$$

$$(i) \Pr(v > 0) = \frac{1}{2} \quad (\because v \text{ 的邊際分布為 } N(0, 1))$$

$$(ii) \Pr(W \leq w, v > 0) = \Pr(W - \alpha S \leq w - \alpha S, v > 0) \\ = \Pr(\varepsilon \leq w - \alpha S, v > 0)$$

→ 需要求複雜的積分，因此先保留。

$$\left(\iint_{\left\{ \begin{pmatrix} \varepsilon \\ v \end{pmatrix} \mid \varepsilon \leq w - \alpha S, v > 0 \right\}} \frac{1}{2\pi |\Sigma|^{\frac{1}{2}}} \exp\left(-\frac{1}{2}(\varepsilon, v) \Sigma^{-1} \begin{pmatrix} \varepsilon \\ v \end{pmatrix}\right) d\varepsilon dv \right)$$

於是得到 $\Pr(W \leq w | V > 0)$

$$f_{W|V>0}(w) = \frac{d}{dw} \Pr(W \leq w | V > 0)$$

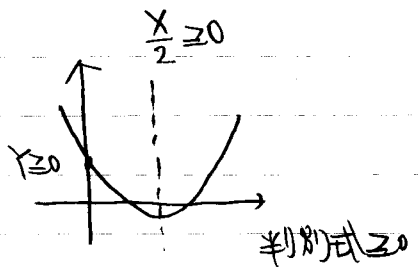
$$\therefore \text{求 } E[W | V > 0] = \int_{w \in R} w \cdot \frac{d}{dw} \Pr(W \leq w | V > 0) dw$$

$$= \int_{w \in R} w \cdot \frac{d}{dw} \left(\frac{\Pr(E \leq w - dS, V > 0)}{\Pr(V > 0)} \right) dw$$

(i.i.d)
[3] $U, V \sim e(\lambda)$

(a) 考慮二次方程式

$$(t-U)(t-V) = 0$$



$$\Leftrightarrow t^2 - (U+V)t + UV = 0 \quad (\because \text{方程式具有兩個非負根})$$

$$\Leftrightarrow t^2 - Xt + Y = 0$$

$$t = \frac{X \pm \sqrt{X^2 - 4Y}}{2} \quad (X^2 - 4Y \geq 0, X \geq 0, Y \geq 0)$$

$$\therefore \begin{pmatrix} U \\ V \end{pmatrix} = \begin{pmatrix} \frac{X + \sqrt{X^2 - 4Y}}{2} \\ \frac{X - \sqrt{X^2 - 4Y}}{2} \end{pmatrix} \text{ or } \begin{pmatrix} \frac{X - \sqrt{X^2 - 4Y}}{2} \\ \frac{X + \sqrt{X^2 - 4Y}}{2} \end{pmatrix}$$

$$\text{全機率} = 1 = \iint_{\substack{U \geq 0 \\ V \geq 0}} \lambda^2 \exp(-\lambda(U+V)) dU dV$$

將此積分改為 X, Y 的積分。

Case 1... $\begin{pmatrix} U \\ V \end{pmatrix} = \begin{pmatrix} \frac{X + \sqrt{X^2 - 4Y}}{2} \\ \frac{X - \sqrt{X^2 - 4Y}}{2} \end{pmatrix}$ ($U \geq V$ 的情況)

$$\frac{\partial}{\partial x} \begin{pmatrix} U \\ V \end{pmatrix} = \begin{pmatrix} \frac{1}{2} \left(1 + \frac{X}{\sqrt{X^2 - 4Y}} \right) \\ \frac{1}{2} \left(1 - \frac{X}{\sqrt{X^2 - 4Y}} \right) \end{pmatrix}$$

$$\frac{1}{2} \left(1 + \frac{x}{\sqrt{x^2 - 4y}} \right) \cdot \frac{1}{\sqrt{x^2 - 4y}} + \frac{1}{2} \left(1 - \frac{x}{\sqrt{x^2 - 4y}} \right) \cdot \frac{1}{\sqrt{x^2 - 4y}}$$

$$\frac{\partial}{\partial y} \begin{pmatrix} U \\ V \end{pmatrix} = \begin{pmatrix} -1/\sqrt{x^2 - 4y} \\ 1/\sqrt{x^2 - 4y} \end{pmatrix}$$

$$\begin{aligned} \therefore \det J &= \frac{1}{2} \left(1 + \frac{x}{\sqrt{x^2 - 4y}} \right) \cdot \frac{1}{\sqrt{x^2 - 4y}} + \frac{1}{2} \left(1 - \frac{x}{\sqrt{x^2 - 4y}} \right) \cdot \frac{1}{\sqrt{x^2 - 4y}} \\ &= (\sqrt{x^2 - 4y})^{-1} \end{aligned}$$

$$\therefore du dv = (\sqrt{x^2 - 4y})^{-1} dx dy$$

case 2 ... $\begin{pmatrix} U \\ V \end{pmatrix} = \begin{pmatrix} \frac{x - \sqrt{x^2 - 4y}}{2} \\ \frac{x + \sqrt{x^2 - 4y}}{2} \end{pmatrix}$ (U < V 的情况)

同樣 $du dv = (\sqrt{x^2 - 4y})^{-1} dx dy$

$$\therefore \text{全機率} = 1 = \int_{v \geq 0} \int_{u \geq 0} f(u, v) du dv$$

$$= \int_{\substack{u \geq v > 0 \\ \downarrow \\ \begin{cases} x^2 - 4y \geq 0 \\ x, y \geq 0 \end{cases} \\ \text{case 1} \\ \downarrow \\ \sqrt{x^2 - 4y}^{-1} dx dy}} f(u, v) du dv + \int_{\substack{v \geq u > 0 \\ \downarrow \\ \begin{cases} x^2 - 4y \geq 0 \\ x, y \geq 0 \end{cases} \\ \text{case 2} \\ \downarrow \\ \sqrt{x^2 - 4y}^{-1} dx dy}} f(u, v) du dv$$

$$= \int_{\substack{x^2 - 4y \geq 0 \\ x, y \geq 0}} \left(\frac{1}{2} \right) \lambda^2 \exp(-\lambda x) / \sqrt{x^2 - 4y} dx dy \times 2$$

$$\therefore f_{X,Y}(x, y) = \frac{2\lambda^2 \exp(-\lambda x)}{\sqrt{x^2 - 4y}} \quad \begin{matrix} (x, y \geq 0 \\ x^2 - 4y \geq 0) \end{matrix}$$

(b) 13 接下來求 Y 的 Best Linear Prediction.

$$\begin{pmatrix} \alpha \\ \beta \end{pmatrix} = \underset{(\beta)}{\operatorname{arg\,min}} \underbrace{E[(Y - \alpha X - \beta)^2]} = S \begin{pmatrix} \alpha \\ \beta \end{pmatrix}$$

$$S(\alpha, \beta) = E[Y^2 + \alpha^2 X^2 + \beta^2 - 2\alpha XY + 2\beta X - 2\beta Y]$$

$$\textcircled{1} \frac{\partial S(\alpha, \beta)}{\partial \alpha} = 2\alpha E[X^2] - 2E[XY] + 2\beta E[X] = 0$$

$$\textcircled{2} \frac{\partial S(\alpha, \beta)}{\partial \beta} = 2\beta + 2E[X] - 2E[Y] = 0$$

$$\bullet \textcircled{1} = \textcircled{2}, E[X] = 2\alpha E[X^2] - 2E[XY] + 2\beta E[X]$$

$$-2\beta E[X] - 2\alpha E[X]^2 + 2E[X]E[Y] = 0$$

$$\Rightarrow 2\alpha V[X] = 2 \operatorname{cov}[X, Y]$$

$$\Rightarrow \hat{\alpha} = \frac{\operatorname{cov}[X, Y]}{V[X]}$$

$$\bullet \textcircled{2} \Leftrightarrow \beta = E[Y] - \alpha E[X] = E[Y] - \frac{E[X]}{V[X]} \operatorname{cov}[X, Y]$$

$$\Rightarrow \hat{\beta} = E[Y] - \frac{E[X]}{V[X]} \operatorname{cov}[X, Y]$$

接著求 $E[X]$, $V[X]$, $E[Y]$, $\text{cov}[X, Y]$

$$(i) E[X] = \iint_{\substack{x \geq 0, y \geq 0 \\ x^2 - 4y \geq 0}} x \cdot \frac{2\lambda^2 \exp(-\lambda x)}{\sqrt{x^2 - 4y}} dx dy$$

先處理 y 的積分... $0 \leq y \leq \frac{x^2}{4}$

$$\int_{y=0}^{\frac{x^2}{4}} \lambda^2 x \exp(-\lambda x) \frac{1}{\sqrt{\frac{x^2}{4} - y}} dy$$

$$= \lambda^2 x \exp(-\lambda x) \cdot \left[(-2) \left(\frac{x^2}{4} - y \right)^{\frac{1}{2}} \right]_{y=0}^{\frac{x^2}{4}}$$

$$= \lambda^2 x \exp(-\lambda x) \cdot 2 \cdot \left(\frac{x}{2} \right)$$

$$= \lambda^2 x^2 \exp(-\lambda x)$$

接下來求 $E[X] = \int_{x=0}^{x=\infty} x \cdot \underbrace{\lambda^2 x \exp(-\lambda x)}_{\substack{\text{X 的邊際 pdf} \\ X \sim P(2, \lambda)}}$ dx

$$\therefore E[X] = \frac{2}{\lambda}$$

$$(ii) X \sim P(2, \lambda) \quad \therefore E[X^2] = \frac{6}{\lambda^2}$$

$$\left(\therefore V[X] = \frac{2}{\lambda^2} \right)$$

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$$(iii) E[Y] = \iint_{\substack{x \geq 0 \\ y \geq 0 \\ x^2 - 4y \geq 0}} y \cdot \frac{2\lambda^2 \exp(-\lambda x)}{\sqrt{x^2 - 4y}} dx dy$$

先處理 y 的積分

$$\lambda^2 \exp(-\lambda x) \int_{y=0}^{y=\frac{x^2}{4}} \frac{y}{\sqrt{\frac{x^2}{4} - y}} dy$$

$$\int_{y=0}^{y=\frac{x^2}{4}} \frac{\left(y - \frac{x^2}{4}\right) + \left(\frac{x^2}{4}\right)}{\sqrt{\frac{x^2}{4} - y}} dy$$

$$= \int_{y=0}^{y=\frac{x^2}{4}} \left\{ \frac{x^2}{4} \cdot \frac{1}{\sqrt{\frac{x^2}{4} - y}} - \sqrt{\frac{x^2}{4} - y} \right\} dy$$

$$= \left[-\frac{x^2}{4} \cdot 2 \cdot \left(\frac{x^2}{4} - y\right)^{\frac{1}{2}} + \frac{2}{3} \left(\frac{x^2}{4} - y\right)^{\frac{3}{2}} \right]_{y=0}^{y=\frac{x^2}{4}}$$

$$= \frac{x^2}{4} \cdot 2 \cdot \left(\frac{x^2}{4}\right) - \frac{2}{3} \cdot \left(\frac{x^2}{4}\right)^{\frac{3}{2}}$$

$$= \frac{\lambda^3}{4} - \frac{\lambda^3}{12} = \frac{\lambda^3}{6}$$

接著求 $\int_{x=0}^{x=\infty} \lambda^2 \exp(-\lambda x) \cdot \frac{\lambda^3}{6} dx$

$$z = \lambda x \quad \frac{dz}{dx} = \lambda \quad \int_{z=0}^{z=\infty} \lambda^2 \exp(-z) \cdot \frac{1}{6} \left(\frac{z}{\lambda}\right)^3 \cdot \frac{dz}{\lambda}$$

$$= \int_{z=0}^{z=\infty} \frac{1}{6} \cdot z^3 \cdot \frac{1}{\lambda^2} \exp(-z) dz$$

$$= \frac{1}{6\lambda^2} \Gamma(4) = \frac{1}{\lambda^2} \quad \therefore E(Y) = \frac{1}{\lambda^2}$$

(iv) $E[XY]$... 可以利用 (iii) 中間的結果

$$= \int_0^{\infty} \frac{\lambda^2}{6} x^4 \exp(-\lambda x) dx$$

(x 的指數 3 → 4)

$$z = \lambda x \quad \frac{dz}{dx} = \lambda \quad \int_0^{\infty} \frac{\lambda^2}{6} \left(\frac{z}{\lambda}\right)^4 \exp(-z) \cdot \frac{dz}{\lambda}$$

$$= \int_0^{\infty} \frac{1}{6} \frac{1}{\lambda^3} \cdot z^4 \exp(-z) dz$$

$$= \frac{\Gamma(5)}{6\lambda^3} = \frac{4}{\lambda^3}$$

$$\therefore E[XY] = \frac{4}{\lambda^3}$$

$$\text{由 (i) ~ (iv) } \text{cov}(X, Y) = \frac{4}{\lambda^3} - \frac{2}{\lambda} \cdot \frac{1}{\lambda^2} = \frac{2}{\lambda^3}$$

$$\left\{ \begin{aligned} \cdot \rho &= \text{cov}(X, Y) / \sqrt{V(X)} = \frac{2}{\lambda^3} / \frac{2}{\lambda^2} = \frac{1}{\lambda} \\ \cdot \beta &= \frac{E(Y) - E(X)}{V(X)} \text{cov}(X, Y) = \frac{1}{\lambda^2} - \frac{2}{\lambda} \cdot \frac{\lambda^2}{2} \cdot \frac{2}{\lambda^3} = \frac{-1}{\lambda^2} \end{aligned} \right.$$

$$\therefore \rho = \frac{1}{\lambda}, \beta = \frac{-1}{\lambda^2} \quad \left(\frac{X}{\lambda} - \frac{1}{\lambda^2} \right)$$

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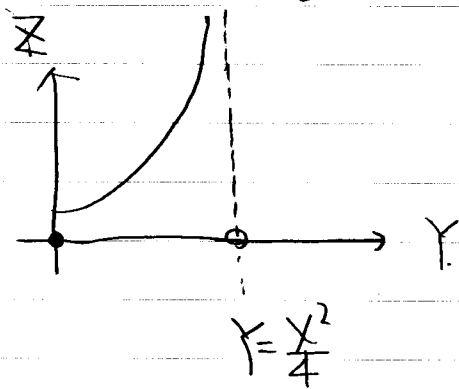
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CC) 求 Y 的 Best Prediction Given X

$$f_{Y|X}(y|x) = \frac{f_{XY}(x,y)}{f_X(x)} = \frac{2x^2 \exp(-1/x)}{\sqrt{x^2 - 4y}} \div x^2 \exp(-1/x)$$
$$= \frac{2}{x} \cdot \frac{1}{\sqrt{x^2 - 4y}} \quad (0 \leq y \leq \frac{x^2}{4})$$



$f_{Y|X}(y|x)$ 为 概率密度函数 随 $\frac{x^2}{4}$ 趋近, 越大

$\therefore Y = \frac{x^2}{4}$ 为 Best Prediction of Y Given X .

$$\boxed{\binom{N}{k} \binom{N-k}{n-k}}$$

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[4]

(a) 狗籠總數... N (這題該考慮有限母體)

$\left\{ \begin{array}{l} \cdot \text{其中有標記的個數} \dots k \\ \cdot \text{無標記的個數} \dots N-k \quad (=M?) \end{array} \right.$

抽出來的樣本個數... n

觀測到 x 個有標記的狗籠之機率

$$= P(X=x | N, k, n) = \frac{k C_x \cdot (N-k) C_{n-x}}{N C_n}$$

$$\therefore X \sim HG(N, k, n)$$

(b) 根據題意, $k=15, n=24, x=11$

$$L(N|x, k, n) = \frac{k C_x \cdot (N-k) C_{n-x}}{N C_n}$$

$$\hat{N}_{MLE} = \underset{N}{\operatorname{argmax}} L(N|x, k, n)$$

(用微分求 \hat{N}_{MLE} 應該相當困難, 所以考慮 $\frac{L(N)}{L(N-1)}$)

$$\bullet L(N|x, k, n) = \frac{k C_n \cdot (N-k) C_{n-1}}{N C_n}$$

$$\frac{L(N|x, k, n)}{L(N-1|x, k, n)} = \frac{k C_n \cdot (N-k) C_{n-1}}{N C_n} \cdot \frac{(N-1) C_n}{k C_n \cdot (N-k-1) C_{n-1}}$$

$$= \frac{(N-1) C_n}{N C_n} \cdot \frac{(N-k) C_{n-1}}{(N-k-1) C_{n-1}}$$

① ②

$$\textcircled{1} \dots \frac{(N-1)!}{(N-1-1)! \cdot 1!} \cdot \frac{(N-1)! \cdot N!}{N!} = \frac{N-1}{N}$$

$$\textcircled{2} \dots \frac{(N-k)!}{(n-1)! \cdot (N-k-n+1)!} \cdot \frac{(n-1)! \cdot (N-k-n+1)!}{(N-k-1)!}$$

$$= \frac{(N-k)}{(N-k-n+1)}$$

$$\therefore \frac{L(N|x, k, n)}{L(N-1|x, k, n)} = \textcircled{1} \times \textcircled{2} = \frac{N-1}{N} \cdot \frac{N-k}{N-k-n+1}$$

考慮 $\frac{L(N|x, k, n)}{L(N-1|x, k, n)} \geq 1$ 的範圍

$k=15 \quad n=24 \quad \lambda=1$

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(根據題意 $(N-k)-(h-\lambda) \geq 0$)

$$\therefore \frac{L(N|\lambda, k, h)}{L(N-1|\lambda, k, h)} \geq 1$$

$$\Leftrightarrow (N-h)(N-k) \geq N(N-k-h+\lambda)$$

$$N^2 - (h+k)N + hk \geq N^2 - (h+k)N + N\lambda$$

$$\therefore N\lambda \leq hk$$

$$\therefore N \leq \frac{hk}{\lambda}$$

• If $\dots \frac{hk}{\lambda} \in \text{integer} \dots$

$$\frac{L(2)}{L(1)} > 1, \frac{L(3)}{L(2)} > 1, \dots, \frac{L(\frac{hk}{\lambda})}{L(\frac{hk}{\lambda}-1)} = 1, \frac{L(\frac{hk}{\lambda}+1)}{L(\frac{hk}{\lambda})} < 1, \dots$$

$$\therefore L(1) < L(2) < \dots < \underbrace{L(\frac{hk}{\lambda}-1) = L(\frac{hk}{\lambda})} > \dots$$

$$N = \frac{hk}{\lambda} \text{ or } \frac{hk}{\lambda} - 1$$

• If $\dots \frac{hk}{\lambda} \notin \text{integer} \dots$

$$\frac{L(2)}{L(1)} > 1, \frac{L(3)}{L(2)} > 1, \dots, \frac{L(\lceil \frac{hk}{\lambda} \rceil)}{L(\lceil \frac{hk}{\lambda} \rceil - 1)} > 1, \frac{L(\lceil \frac{hk}{\lambda} \rceil + 1)}{L(\lceil \frac{hk}{\lambda} \rceil)} < 1, \dots$$

$$\therefore L(1) < L(2) < \dots < L\left(\left[\frac{nK}{\lambda}\right] - 1\right) < L\left(\left[\frac{nK}{\lambda}\right]\right) > L\left(\left[\frac{nK}{\lambda}\right] + 1\right) \dots$$

$$\therefore \hat{N}_{MLE} = \left[\frac{nK}{\lambda}\right]$$

$$\lambda = 1, \quad n = 24, \quad K = 15$$

$$\therefore \frac{nK}{\lambda} = \frac{360}{11} \notin \text{整數}$$

$$= \left[\frac{360}{11}\right] = 32$$

$$\therefore \hat{N}_{MLE} = 32$$

(c) HG ($N=32, K=15, n=24$)

$\left\{ \begin{array}{l} \text{tagged } 15 \\ \text{untagged } 17 \end{array} \right.$



$\left(\begin{array}{l} x=11 \text{ 使得機率最大 } (\because (b) \dots L(N|x, K, n) \\ = P(X|N, K, n)) \\ \frac{24 - 17}{n} \text{ untagged } \rightarrow \therefore 7 \leq X \leq 15 \end{array} \right)$

$$\Pr(X=11 | N=32, K=15, n=24)$$

$$= \frac{15C_{11} \cdot 17C_3}{32C_{24}}$$

(d) 根據 (b) 的討論, $N=32$ 使得 $L(N|X, K, n)$ 最大。

由於 $L(N|X, K, n) = \Pr(X|N, K, n)$, 因此

$N \neq 32$ 時 $\Pr(X|N, K, n)$ 會低於 (c): $\frac{15C_{11} \cdot 17C_3}{32C_{24}}$.

(總而言之, $N_{MLE}=32$ 是 Maximum Likelihood Estimator,

無論是機率, 還是概似函數, $N=32$ 時會最大)

①

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高等統計推論II 作業3. 森元俊成

$$\square f(x|\theta) = \frac{1}{\pi} \cdot \frac{1}{1+(x-\theta)^2} \quad (-\infty < x < \infty, \theta \in \mathbb{R})$$

$$f(x_1, x_2, x_3 | \theta) = \frac{1}{\pi^3} \cdot \frac{1}{1+(x_1-\theta)^2} \cdot \frac{1}{1+(x_2-\theta)^2} \cdot \frac{1}{1+(x_3-\theta)^2}$$

$$x_1=0, x_2=1, x_3=a$$

$$\therefore f(0, 1, a | \theta) = \frac{1}{\pi^3} \cdot \frac{1}{1+\theta^2} \cdot \frac{1}{1+(1-\theta)^2} \cdot \frac{1}{1+(a-\theta)^2}$$

$$\therefore L(\theta) \stackrel{\text{def}}{=} \frac{1}{\pi^3} \cdot \frac{1}{1+\theta^2} \cdot \frac{1}{1+(1-\theta)^2} \cdot \frac{1}{1+(a-\theta)^2} \quad (\theta \in \mathbb{R})$$

$$l(\theta) = \log L(\theta) = -3 \log \pi - \log(1+\theta^2) - \log(1+(1-\theta)^2) - \log(1+(a-\theta)^2)$$

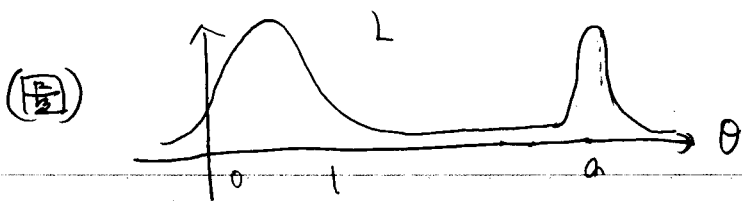
$$\frac{l'(\theta)}{\#} = \frac{-2\theta}{1+\theta^2} + \frac{2(1-\theta)}{1+(1-\theta)^2} + \frac{2(a-\theta)}{1+(a-\theta)^2}$$

$$\frac{\partial l(\theta)}{\partial \theta}$$

$$\cdot l'(0) = 2 + \frac{2a}{1+a^2} \approx 2 \quad (\because a \text{ 很大}, \therefore \frac{2a}{1+a^2} \approx 0)$$

$$\cdot l'(1) = -1 + \frac{2(a-1)}{1+(a-1)^2} \approx -1 \quad (\because a \text{ 很大}, \frac{2(a-1)}{1+(a-1)^2} \approx 0)$$

$$\cdot l'(a) = \frac{-2a}{1+a^2} + \frac{2(1-a)}{1+(1-a)^2} \approx 0 \quad (\text{但} < 0)$$



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① 由於 $f'(0) \approx 2 > 0$ 且 $f'(1) \approx -1 < 0$,
故 $(0,1)$ 之間一定存在 $f'(x)$ 從「正」變成「負」點

\therefore 區間 $(0,1)$ 之間發生極大值

② $f'(1) \approx -1$, $f'(a) \approx 0$, $f'(a) < 0$

但考慮很小的正數 ϵ - 例如... $\epsilon = \frac{100}{a}$ ($a = 100000 \dots$)

$$f'(a-\epsilon) = \frac{-2a}{1+(a-\epsilon)^2} + \frac{2(1-a+\epsilon)}{1+(1-a+\epsilon)^2} + \frac{2\epsilon}{1+\epsilon^2}$$

$$\downarrow \qquad \qquad \qquad \downarrow \qquad \qquad \qquad \downarrow$$

$$\approx \frac{2}{a} \qquad \qquad \qquad \approx \frac{-2}{a} \qquad \qquad \qquad \frac{\frac{200}{a}}{1 + \frac{10000}{a^2}} = \frac{200a}{10000 + a^2} \approx \frac{200}{a}$$

$$\therefore f'(a-\epsilon) \approx \frac{2}{a} - \frac{2}{a} + \frac{200}{a} = \frac{196}{a} > 0$$

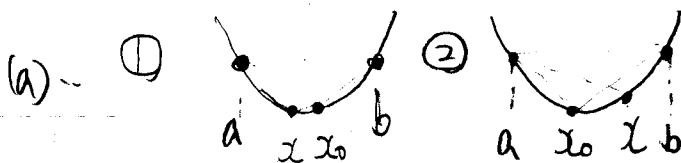
由此可知，比 a 稍微小一點的地方存在 $f'(x) > 0$
($x \approx a$, 但是 $x < a$)

故區間 $(a-\epsilon, a)$ 之間也存在 $f'(x)$ 從「正」變成「負」的地方。
 $\therefore (a-\epsilon, a) \subseteq (1, a)$ (\therefore 也可以說 $(1, a)$ 之間) 發生極大值 (實際上是離 a 很近的地方)

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2 $f(x) (x \in C \subseteq \mathbb{R})$

(a) 請參閱「後面 Note 2」

$$\uparrow \frac{f(y)-f(x)}{y-x} \leq \frac{f(z)-f(x)}{z-x} \leq \frac{f(z)-f(y)}{z-y} \quad (x \leq y \leq z)$$

考慮開區間 (a, b) 以及 $x, x_0 \in (a, b)$

$$\begin{aligned} \text{① } x < x_0 & \quad \frac{f(x)-f(a)}{x-a} \leq \frac{f(x_0)-f(a)}{x_0-a} \leq \frac{f(x_0)-f(x)}{x_0-x} \leq \frac{f(b)-f(x)}{b-x} \leq \frac{f(b)-f(x_0)}{b-x_0} \\ \text{or} & \\ \text{② } x_0 < x & \quad \frac{f(x_0)-f(a)}{x_0-a} \leq \frac{f(x)-f(a)}{x-a} \leq \frac{f(x)-f(x_0)}{x-x_0} \leq \frac{f(b)-f(x_0)}{b-x_0} \end{aligned}$$

~~無論~~ ① or ②, $\left| \frac{f(x)-f(x_0)}{x-x_0} \right| \leq \max \left\{ \left| \frac{f(b)-f(x_0)}{b-x_0} \right|, \left| \frac{f(x_0)-f(a)}{x_0-a} \right| \right\}$

$$\therefore |f(x)-f(x_0)| \leq |x-x_0| \max \left\{ \left| \frac{f(b)-f(x_0)}{b-x_0} \right|, \left| \frac{f(x_0)-f(a)}{x_0-a} \right| \right\}$$

$$\therefore x \rightarrow x_0 \Rightarrow |f(x)-f(x_0)| \rightarrow 0 \quad (\text{因 } a, b, x_0 \text{ 均 fixed})$$

$\therefore f$ 於 $\forall x_0 \in (a, b)$ 連續. \square

(b) Note 2 ① $\frac{f(y)-f(x)}{y-x} \leq \frac{f(z)-f(x)}{z-x} \quad (x \leq y \leq z)$

(i) $z \rightarrow x \Rightarrow$ 得 $f'(x) \leq \frac{f(z)-f(x)}{z-x}$

(\because 可微)

$(x \leq y \text{ or } x > y)$

$$(1) z > y \rightarrow \text{得 } f'(x) \leq \frac{f(y) - f(x)}{y - x} \quad \therefore f(x)(y - x) \leq f(y) - f(x)$$

同樣道理 ② $\frac{f(z) - f(x)}{z - x} \leq \frac{f(z) - f(y)}{z - y} \quad (x \leq y \leq z)$

$$z > y \rightarrow \text{得 } \frac{f(y) - f(x)}{y - x} \leq f'(y) \quad \therefore f(y) - f(x) \leq (y - x)f'(y) \quad (x \leq y)$$

$$\Rightarrow \text{替換 } x \text{ 與 } y \quad \lceil f(x) - f(y) \leq (x - y)f'(x) \quad (y \leq x) \rceil$$

$$\Leftrightarrow \lceil f(x)(y - x) \leq f(y) - f(x) \quad (y \leq x) \rceil$$

由此可知 無論 $x \leq y$ or $y \leq x$ 皆成立

(c) 利用 (b) 的結果...

$$① z > x \dots \lceil f'(x) \leq \frac{f(y) - f(x)}{y - x} \rceil \dots z > x \text{ 得 } \lceil f'(x) \leq f'(x + 0) \rceil$$

$$② z \leq x \dots \lceil \frac{f(x) - f(y)}{x - y} \leq f'(x) \rceil \dots z > x \text{ 得 } \lceil f'(x - 0) \leq f'(x) \rceil$$

$$\text{由 ① ② 得知 } f'(x - 0) \leq f'(x) \leq f'(x + 0)$$

$\therefore f'$ 為非減函數, $f'(x) \geq 0$

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$$f(x_1, x_2, \dots, x_n | \lambda) = \lambda^n \exp(-\lambda(\lambda + x_2 + \dots + x_n)) \quad (x_i \geq 0)$$

$$\log f(x_1, \dots, x_n | \lambda) = n \log \lambda - \lambda(x_1 + x_2 + \dots + x_n)$$

$$\frac{\partial}{\partial \lambda} \log f(x_1, \dots, x_n | \lambda) = \frac{n}{\lambda} - (x_1 + x_2 + \dots + x_n) = 0 \Rightarrow \lambda = \frac{n}{x_1 + x_2 + \dots + x_n}$$

$$\frac{\partial}{\partial \lambda} \log f(x_1, \dots, x_n | \lambda) = -\frac{n}{\lambda^2} < 0$$

$$\therefore L(\lambda | x_1, \dots, x_n) = f(x_1, \dots, x_n | \lambda)$$

$\lambda = \frac{1}{\bar{x}}$ 使得 $L(\lambda | x_1, \dots, x_n)$ 為最大

$$\hat{\lambda}_{MLE} = \frac{1}{\bar{x}}$$

$$(a) \quad T \stackrel{\text{def}}{=} x_1 + x_2 + \dots + x_n \sim \Gamma(n, \lambda)$$

$$E\left[\frac{1}{T}\right] (= E\left[\frac{1}{x_1 + x_2 + \dots + x_n}\right])$$

$$= \int_{T=0}^{T=\infty} \frac{\lambda^n}{\Gamma(n)} t^{n-2} \exp(-\lambda t) dt \quad x = \lambda t \quad \frac{dx}{dt} = \lambda$$

$$= \int_0^{\infty} \frac{\lambda^n}{\Gamma(n)} \left(\frac{t}{\lambda}\right)^{n-2} \exp(-x) \frac{dx}{\lambda} = \frac{\lambda}{\Gamma(n)}, \Gamma(n-1) = \frac{\lambda}{n-1}$$

$$\therefore E\left[\frac{n}{T}\right] = \frac{n}{n-1}\lambda$$

$$\therefore E\left[\frac{1}{\bar{X}}\right] = \frac{n}{n-1}\lambda \neq \lambda \quad \therefore \hat{\lambda}_{MLE} \text{ 並非不偏估計量}$$

$$(b) E[X_j] = \frac{1}{\lambda} \quad (j=1, \dots, n), \quad X_1 \sim X_n = \text{i.i.d.}$$

根據弱大數法則 (Khinchine),

$$\frac{X_1 + X_2 + \dots + X_n}{n} \xrightarrow{P} \frac{1}{\lambda}$$

$g(x) = \frac{1}{x}$ ($\lambda \neq 0$) 為連續函數

$$\therefore g\left(\frac{X_1 + X_2 + \dots + X_n}{n}\right) \xrightarrow{P} g\left(\frac{1}{\lambda}\right) = \lambda$$

$$\therefore \frac{1}{\bar{X}} \xrightarrow{P} \lambda \quad \therefore \hat{\lambda}_{MLE} \text{ 為一致估計量}$$

$$(c) V[X_j] = \frac{1}{\lambda^2} \quad (j=1, \dots, n), \quad X_1 \sim X_n = \text{i.i.d.}$$

根據中央極限定理, $\sqrt{n}\left(\frac{X_1 + X_2 + \dots + X_n}{n} - \frac{1}{\lambda}\right) \xrightarrow{d} N\left(0, \frac{1}{\lambda^2}\right)$.

利用 δ -method: $g(x) = \frac{1}{x}$, $g(\bar{x}) \approx g'\left(\frac{1}{\lambda}\right)(\bar{x} - \frac{1}{\lambda}) + g\left(\frac{1}{\lambda}\right)$

$$\therefore \sqrt{n}(g(\bar{x}) - g\left(\frac{1}{\lambda}\right)) \approx \underbrace{g'\left(\frac{1}{\lambda}\right)}_{(-\lambda^2)} \cdot \underbrace{\sqrt{n}\left(\bar{x} - \frac{1}{\lambda}\right)}_{N\left(0, \frac{1}{\lambda^2}\right)} \xrightarrow{d} N(0, \lambda^2)$$

$$\therefore \sqrt{n}(\hat{\lambda}_{MLE} - \lambda) \xrightarrow{d} N(0, \lambda^2)$$

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4 叙述利用 Gradient Descent 求 MLE 的方法

$$f(x_1, x_2, \dots, x_n | \alpha, \beta) = \frac{\beta^{n\alpha} (x_1 x_2 \dots x_n)^{\alpha-1} \exp(-\beta(x_1 + \dots + x_n))}{\Gamma(\alpha)^n} \quad (x_1, \dots, x_n \geq 0)$$

$$\theta = \begin{pmatrix} \alpha \\ \beta \end{pmatrix}$$

$$L(\theta) = L\left(\begin{pmatrix} \alpha \\ \beta \end{pmatrix}\right) \stackrel{\text{def}}{=} \frac{\beta^{n\alpha}}{\Gamma(\alpha)^n} (x_1 x_2 \dots x_n)^{\alpha-1} \exp(-\beta(x_1 + x_2 + \dots + x_n)) \quad (\alpha > 0, \beta > 0)$$

「将 $L(\theta)$ 最大化」等於「将 $\log L(\theta)$ 最大化」

在此考慮 $\log L(\theta | x)$ 之最大化。

$$\log L(\theta | x) = n\alpha \log \beta - n \log \Gamma(\alpha) + (\alpha-1) \sum_{k=1}^n \log x_k - \beta \sum_{k=1}^n x_k$$

$$l(\theta) (= l\left(\begin{pmatrix} \alpha \\ \beta \end{pmatrix}\right)) \stackrel{\text{def}}{=} \log L(\theta | x)$$

$$\frac{\partial l}{\partial \theta} = \begin{pmatrix} \frac{\partial l}{\partial \alpha} \\ \frac{\partial l}{\partial \beta} \end{pmatrix} = \begin{pmatrix} n \log \beta - \frac{\partial}{\partial \alpha} n \log \Gamma(\alpha) + \sum_{k=1}^n \log x_k \\ \frac{n\alpha}{\beta} - \sum_{k=1}^n x_k \end{pmatrix}$$

⑤ $\Gamma(\alpha)$ 之 α 不一定為整數，故其微分直接寫成

$$\frac{\partial \Gamma(\alpha)}{\partial \alpha} = \frac{\partial}{\partial \alpha} \int_0^{\infty} x^{\alpha-1} \exp(-x) dx$$

• step 0... 設定初始值 $\hat{\theta}_0 = \begin{pmatrix} \alpha_0 \\ \beta_0 \end{pmatrix}$ ($\alpha_0, \beta_0 > 0$)

• step j... 依照以下公式更新 $\hat{\theta}_{j-1} \rightarrow \hat{\theta}_j$ ($j \geq 1$)

$$\hat{\theta}_j \stackrel{\text{update}}{=} \hat{\theta}_{j-1} - c \cdot \frac{\partial l}{\partial \theta} \Big|_{\theta = \begin{pmatrix} \alpha \\ \beta \end{pmatrix} = \hat{\theta}_{j-1}}$$

$$\text{where } \hat{\theta} = \begin{pmatrix} \hat{\alpha} \\ \hat{\beta} \end{pmatrix}, \frac{\partial l}{\partial \theta} = \begin{pmatrix} n \log \beta - \frac{\partial}{\partial \alpha} n \log P(\alpha) + \sum_{k=1}^n y_k x_k \\ \frac{n\alpha}{\beta} - \sum_{k=1}^n x_k \end{pmatrix}$$

c ... 常數

• $\hat{\theta}$ 收斂時 ($\hat{\theta} - \hat{\theta}_{j-1} \approx 0$ 時) 停止計算。

並將 $\hat{\theta}$ 作為 $\theta_{MLE} = \begin{pmatrix} \alpha_{MLE} \\ \beta_{MLE} \end{pmatrix}$

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5 $\theta \xrightarrow{\text{改用}} \beta$ $f(x|\beta) = \frac{1}{2\beta} \exp\left(-\frac{|x|}{\beta}\right)$

① Method of Moment Estimator 與其一致性:

$$E[X] = 0,$$

$$E[X^2] = \int_{-\infty}^{\infty} \frac{x^2}{2\beta} \cdot \exp\left(-\frac{|x|}{\beta}\right) dx = \int_0^{\infty} \frac{x^2}{\beta} \exp\left(-\frac{x}{\beta}\right) dx$$

$$\left(z = \frac{x}{\beta} \quad \frac{dz}{dx} = \frac{1}{\beta} \right) = \int_0^{\infty} \beta z^2 \exp(-z) \cdot \beta dz$$

$$= \int_0^{\infty} \beta^2 z^2 \exp(-z) dz = \beta^2 \cdot \Gamma(3) = \underline{2\beta^2} < \infty$$

根據弱大數法則, $\frac{X_1^2 + \dots + X_n^2}{n} \xrightarrow{P} 2\beta^2$

$g(x) = \sqrt{\frac{x}{2}}$ ($x > 0$) 為連續函數,

$$\xrightarrow{P} g\left(\frac{X_1^2 + X_2^2 + \dots + X_n^2}{n}\right) \xrightarrow{P} g(2\beta^2) = \beta \quad (\because \beta > 0)$$

$$\hat{\beta}_{MME} = \sqrt{\frac{X_1^2 + X_2^2 + \dots + X_n^2}{2n}} \quad (\hat{\beta}_{MME} \xrightarrow{P} \beta)$$

接下來考慮 $\hat{\beta}_{MME}$ 之極限分布, $(\sqrt{n}(\hat{\beta}_{MME} - \beta))$ 之極限分布

$$W_j \stackrel{\text{def}}{=} \frac{X_j^2}{2} \quad (j=1, \dots, n) \quad \left(\hat{\beta}_{MME} = \sqrt{\frac{W_1 + W_2 + \dots + W_n}{n}} \right)$$

$$\begin{aligned}
 E[W_j] &= \beta^2 & E[W_j^2] &= E\left[\frac{X_j^4}{4}\right] = \int_{-\infty}^{\infty} \frac{x^4}{4} \cdot \frac{1}{2\beta} \exp\left(-\frac{1}{\beta}|x|\right) dx \\
 &= \int_0^{\infty} \frac{x^4}{4} \cdot \frac{1}{\beta} \exp\left(-\frac{1}{\beta}x\right) dx & z &= \frac{1}{\beta}x & \frac{dz}{dx} &= \frac{1}{\beta} \\
 &= \int_0^{\infty} \frac{1}{4} \cdot (\beta z)^4 \cdot \frac{1}{\beta} \cdot \exp(-z) \beta dz \\
 &= \int_0^{\infty} \frac{\beta^4}{4} z^4 \exp(-z) dz = \frac{\beta^4}{4} \cdot \Gamma(5) = 6\beta^4
 \end{aligned}$$

$$\therefore V[W_j] = E[W_j^2] - E[W_j]^2 = 5\beta^4 < \infty$$

根據中央極限定理, $\sqrt{n} \left(\frac{W_1 + W_2 + \dots + W_n}{n} - \beta^2 \right) \xrightarrow{d} N(0, 5\beta^4)$

利用 δ -method. $g(x) \stackrel{\text{def}}{=} \sqrt{x}$ $g'(x) = \frac{1}{2\sqrt{x}}$

$$\sqrt{n} \left(g\left(\frac{W_1 + W_2 + \dots + W_n}{n}\right) - g(\beta^2) \right) \xrightarrow{d} N\left(0, (g'(\beta^2))^2 \cdot 5\beta^4\right)$$

\parallel
 β_{MLE}

$$= N\left(0, \frac{5}{4}\beta^2\right)$$

$$\therefore \sqrt{n} (\hat{\beta}_{MLE} - \beta) \xrightarrow{d} N\left(0, \frac{5}{4}\beta^2\right)$$

①

[5] - part 2

② MLE 與其致性...

$$f(x_1, \dots, x_n | \beta) = \left(\frac{1}{2\beta}\right)^n \exp\left(-\frac{1}{\beta}(|x_1| + \dots + |x_n|)\right) \quad (\beta > 0)$$

$$\log f(x_1, \dots, x_n | \beta) = -n \log(2\beta) - \frac{1}{\beta} \{ |x_1| + |x_2| + \dots + |x_n| \}$$

$$\frac{\partial \log f(x_1, \dots, x_n | \beta)}{\partial \beta} = -\frac{n}{\beta} + \frac{1}{\beta^2} \{ |x_1| + \dots + |x_n| \} = \frac{|x_1| + \dots + |x_n| - n\beta}{\beta^2}$$

$$\Rightarrow \beta = \frac{1}{n} (|x_1| + \dots + |x_n|)$$

β	0		$\frac{1}{n}(x_1 + \dots + x_n)$	
$\frac{\partial \log f}{\partial \beta}$		+	0	-
$\log f$		\uparrow	max	\downarrow

$$\therefore \hat{\beta}_{MLE} = \frac{1}{n} \sum_{j=1}^n |x_j|$$

求 $|x_j|$ 之分布... $Z = |X|$

$$\text{全概率} = 1 = \int_{-\infty}^{\infty} \left(\frac{1}{2\beta}\right) \exp\left(-\frac{1}{\beta}|x|\right) dx$$

$$= \int_0^{\infty} \frac{1}{2\beta} \exp\left(-\frac{1}{\beta}|x|\right) dx + \int_{-\infty}^0 \frac{1}{2\beta} \exp\left(-\frac{1}{\beta}|x|\right) dx$$

$\downarrow \quad \downarrow \quad \downarrow \quad \downarrow \quad \downarrow$
 $0 \rightarrow \infty \quad z \quad dz \quad \infty \rightarrow 0 \quad z \quad dz$

$$= \int_0^{\infty} \frac{1}{2\beta} e^{-\frac{1}{\beta} z} dz + \int_{-\infty}^0 \frac{1}{2\beta} e^{-\frac{1}{\beta} z} (-dz)$$

$$= \int_0^{\infty} \frac{1}{\beta} e^{-\frac{1}{\beta} z} dz \quad z = |X| \sim e^{-\frac{1}{\beta}}$$

$$\hat{\beta}_{MLE} = \frac{1}{n} (z_1 + z_2 + \dots + z_n) \quad (z_j \sim e^{-\frac{1}{\beta}})$$

$$V(z) = \beta^2 < \infty$$

(由根據弱大數法則, $\hat{\beta}_{MLE} \xrightarrow{P} \beta$)

$$\therefore \text{根據中央極限定理, } \sqrt{n} \left(\frac{z_1 + z_2 + \dots + z_n}{n} - \beta \right) \xrightarrow{d} N(0, \beta^2)$$

$$\therefore \sqrt{n} (\hat{\beta}_{MLE} - \beta) \xrightarrow{d} N(0, \beta^2)$$

(B)

X	Pr
-2	$\frac{1-\theta}{4}$
-1	$\frac{\theta}{12}$
0	$\frac{1}{2}$
1	$\frac{3-\theta}{12}$
2	$\frac{\theta}{4}$

(a)

$$E[X] = (-2) \cdot \frac{1-\theta}{4} + (-1) \cdot \frac{\theta}{12} + 0 \cdot \left(\frac{1}{2}\right)$$

$$+ (1) \cdot \frac{3-\theta}{12} + (2) \cdot \left(\frac{\theta}{4}\right)$$

$$= \frac{0-1}{2} - \frac{\theta}{12} + \frac{3-\theta}{12} + \frac{\theta}{2}$$

$$= \frac{6\theta - 6 - \theta + 3 - \theta + 6\theta}{12} = \frac{10\theta - 3}{12}$$

$$E\left[\frac{12X}{10}\right] = \theta - 0.3 \quad \therefore E[1.2X + 0.3] = \theta$$

$\therefore 1.2X + 0.3$ 為 θ 之 不偏估計量

(b)

$$Pr(X|\theta) = \left(\frac{1-\theta}{4}\right)^{I(X=-2)} \cdot \left(\frac{\theta}{12}\right)^{I(X=-1)} \cdot \left(\frac{1}{2}\right)^{I(X=0)}$$

$$\cdot \left(\frac{3-\theta}{12}\right)^{I(X=1)} \cdot \left(\frac{\theta}{4}\right)^{I(X=2)}$$

$$\therefore L(\theta|X=\lambda) = \left(\frac{1-\theta}{4}\right)^{I(X=-2)} \cdot \left(\frac{\theta}{12}\right)^{I(X=-1)} \cdot \left(\frac{1}{2}\right)^{I(X=0)} \cdot \left(\frac{3-\theta}{12}\right)^{I(X=1)} \cdot \left(\frac{\theta}{4}\right)^{I(X=2)}$$

$$(0 \leq \theta \leq 1)$$

考慮 θ 使得 $L(\theta|x)$ 為最大.

$$L(\theta|x=-2) = \frac{1-\theta}{4} \quad \dots \quad \theta=0 \text{ 時最大} \quad \hat{\theta}_{MLE} = 0$$

$$L(\theta|x=+1) = \frac{\theta}{12} \quad \dots \quad \theta=1 \text{ 時最大} \quad \hat{\theta}_{MLE} = 1$$

$$L(\theta|x=0) = \frac{1}{2} \quad \dots \quad \forall c \in [0,1) \quad \hat{\theta}_{MLE} = c$$

$$L(\theta|x=-1) = \frac{3-\theta}{12} \quad \dots \quad \theta=0 \text{ 時最大} \quad \hat{\theta}_{MLE} = 0$$

$$L(\theta|x=2) = \frac{\theta}{4} \quad \dots \quad \theta=1 \text{ 時最大} \quad \hat{\theta}_{MLE} = 1$$

由此可知, $\hat{\theta}_{MLE}$ 並不唯一 (觀測到 $X=0$ 時)

$$E[\hat{\theta}_{MLE}] = \sum_{x \in \{-2, -1, 0, 1, 2\}} P_r(X=x) \cdot \hat{\theta}_{MLE|x}$$

$$= \frac{1-\theta}{4} \cdot 0 + \frac{\theta}{12} \cdot 1 + \frac{1}{2} \cdot c + \frac{3-\theta}{12} \cdot 0 + \frac{\theta}{4} \cdot 1$$

$$= \frac{\theta}{12} + \frac{c}{2} + \frac{\theta}{4} = \frac{\theta}{3} + \frac{c}{2}$$

無論 $c \in [0,1)$ 為多少, 由於 c 與 θ 無關,

故無法使得 $E[\hat{\theta}_{MLE}] = \theta$

$\therefore \hat{\theta}_{MLE}$ 並非無偏估計量

(5)

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(a) 先求 $X_{(1)}$ 與 $X_{(n)}$ 之聯合分布

$$\begin{aligned} P(X_{(1)} \leq \lambda, X_{(n)} \leq y) &= P(X_{(n)} \leq y) - P(\lambda < X_{(1)}, X_{(n)} \leq y) \\ &= \left(\frac{y-\theta+1}{2}\right)^n - \left(\frac{y-\lambda}{2}\right)^n \quad ((\lambda, y) \subseteq (\theta+1, \theta+1)) \end{aligned}$$

$$\frac{\partial^2}{\partial \lambda \partial y} P(X_{(1)} \leq \lambda, X_{(n)} \leq y) = \frac{n(n-1)(y-\lambda)^{n-2}}{2^n}$$

$$\therefore f_{X_{(1)}, X_{(n)}}(\lambda, y) = \frac{n(n-1)}{2^n} (y-\lambda)^{n-2} \quad (\theta+1 \leq \lambda \leq y \leq \theta+1)$$

$$\begin{cases} r = y - \lambda \\ s = \frac{y + \lambda}{2} \end{cases} \Leftrightarrow \begin{cases} \lambda = s - \frac{r}{2} \\ y = s + \frac{r}{2} \end{cases}$$

$$(dr ds = d\lambda dy)$$

$$\theta+1 \leq s - \frac{r}{2} \leq s + \frac{r}{2} \leq \theta+1$$

$$\therefore 0 \leq \frac{r}{2} \leq \min\{s - \theta+1, \theta+1 - s\}$$

$$I = \iint_{\theta+1 \leq \lambda \leq y \leq \theta+1} \frac{n(n-1)}{2^n} (y-\lambda)^{n-2} d\lambda dy$$

$$= \iint_{\theta+1 \leq s - \frac{r}{2} \leq s + \frac{r}{2} \leq \theta+1} \frac{n(n-1)}{2^n} r^{n-2} dr ds$$

$$\begin{aligned}
 f_S(s) &= \int_0^{2\min\{s-\theta, \theta-s\}} \frac{h(h)}{2^n} r^{n-2} dh \\
 &= \frac{n}{2^n} [r^{n-1}]_0^{2\min\{s-\theta, \theta-s\}} \\
 &= \frac{n}{2} \min\{s-\theta, \theta-s\}^{n-1}
 \end{aligned}$$

$$\left\{ \begin{array}{l}
 \bullet \theta \leq s \leq \theta \dots f_S(s) = \frac{n}{2} (s-\theta)^{n-1} \dots \left(\frac{X_U + X_L}{2}\right) \text{ pdf} \\
 \bullet \theta < s \leq \theta \dots f_S(s) = \frac{n}{2} (\theta-s)^{n-1}
 \end{array} \right.$$

• 接著證明 $S_n \xrightarrow{d} \theta$

$$\begin{aligned}
 \textcircled{*} \text{ 為了方便, 先求 } P(|S_n - \theta| < \epsilon) &= \int_{\theta-\epsilon}^{\theta} f_S(s) ds + \int_{\theta}^{\theta+\epsilon} f_S(s) ds \\
 &= \int_{\theta-\epsilon}^{\theta} \frac{n}{2} (s-\theta)^{n-1} ds + \int_{\theta}^{\theta+\epsilon} \frac{n}{2} (\theta-s)^{n-1} ds \\
 &= \left[\frac{1}{2} (s-\theta)^n \right]_{\theta-\epsilon}^{\theta} + \left[-\frac{1}{2} (\theta-s)^n \right]_{\theta}^{\theta+\epsilon} \\
 &= \frac{1 - (1-\epsilon)^n}{2} + \frac{1 - (1-\epsilon)^n}{2} = \underline{1 - (1-\epsilon)^n}
 \end{aligned}$$

$$\begin{cases}
 = P(|S_n - \theta| < \epsilon) = 1 - (1-\epsilon)^n \\
 = P(|S_n - \theta| \geq \epsilon) = (1-\epsilon)^n
 \end{cases}$$

(17)

[17] - part 2.

$$\otimes S_n \xrightarrow{a.s.} \theta \Leftrightarrow \Pr\left(\lim_{n \rightarrow \infty} S_n = \theta\right) = 1$$

$$\Leftrightarrow \Pr\left(\limsup_n |S_n - \theta| \geq \varepsilon\right) = 0$$

$$\Leftrightarrow \Pr\left(\lim_n \sup_{m \geq n} |S_m - \theta| \geq \varepsilon\right) = 0 = \Pr\left(\bigcap_{n=1}^{\infty} \left\{ \sup_{m \geq n} |S_m - \theta| \geq \varepsilon \right\}\right)$$

$$\Leftrightarrow \lim_{n \rightarrow \infty} \Pr(A_n) = 0 \quad \left(\because \Pr(A_i) < \infty \right) \quad \underbrace{\qquad\qquad}_{A_n}$$

$$\Leftrightarrow \lim_{n \rightarrow \infty} \Pr\left(\bigcup_{m \geq n} \{|S_m - \theta| \geq \varepsilon\}\right) = 0$$

$$\oplus \left(\because A_n \supseteq A_{n+1}, \quad \Pr(A_i) < \infty \right)$$

$$\left(\therefore \lim_{n \rightarrow \infty} \Pr(A_n) = \Pr\left(\bigcap_{n=1}^{\infty} A_n\right) \right)$$

因此, 证明:

$$\lim_{n \rightarrow \infty} \Pr\left(\bigcup_{m \geq n} \{|S_m - \theta| \geq \varepsilon\}\right) = 0$$

$$0 \leq \Pr\left(\bigcup_{m \geq n} \{|S_m - \theta| \geq \varepsilon\}\right) \leq \sum_{m \geq n} \Pr(|S_m - \theta| \geq \varepsilon)$$

$$= \sum_{m \geq n} (1 - \varepsilon)^m = (1 - \varepsilon)^n \cdot \frac{1}{\varepsilon}$$

(测度之 sub-additivity)

$$0 \leq \lim_{n \rightarrow \infty} \Pr\left(\bigcup_{m \geq n} \{|S_m - \theta| \geq \varepsilon\}\right) \leq \lim_{n \rightarrow \infty} \frac{1}{\varepsilon} (1 - \varepsilon)^n = 0$$

(for all $\varepsilon \in (0, 1)$)

\therefore 因此 $S_n \xrightarrow{a.s.} \theta$

$$(b) \text{ 證明 } \lim_{n \rightarrow \infty} E[|\bar{X}_n - \theta|^2] = 0$$

$$\text{由於 } E[\bar{X}_n] = \theta \quad (\because E[\frac{X_{(1)} + \dots + X_{(n)}}{n}] = E[\frac{X_1 + X_2 + \dots + X_n}{n}] = \theta)$$

$$\text{故 } E[(\bar{X}_n - \theta)^2] = V[\bar{X}_n] = V[\frac{X_1 + X_2 + \dots + X_n}{n}]$$

$$= \frac{1}{n^2} V[X_1 + X_2 + \dots + X_n] = \frac{1}{n} V[X_1] \quad (\because X_1 \sim X_n = \text{i.i.d.})$$

$$= \frac{1}{n} \frac{1}{2} \sigma^2 = \frac{1}{3n}$$

$$\therefore \lim_{n \rightarrow \infty} E[(\bar{X}_n - \theta)^2] = \lim_{n \rightarrow \infty} \frac{1}{n} V(X_1) = \lim_{n \rightarrow \infty} \frac{1}{3n} = 0$$

$$\therefore \bar{X}_n \xrightarrow{L_2} \theta$$

$$\text{註：題目中 } X_{(1)} + X_{(2)} + \dots + X_{(n)} = X_1 + X_2 + \dots + X_n$$

(不需考慮順序統計量)

$$\square (a) \log f(x|\theta) = \log h(x) + \eta(\theta)T(x) - A(\theta)$$

$$\frac{\partial}{\partial \theta} \log f(x|\theta) = \eta'(\theta)T(x) - A'(\theta) = 0$$

$$\circledast \therefore \hat{\theta} = \text{滿足 } \eta'(\hat{\theta})T(x) - A'(\hat{\theta}) = 0 \quad (\hat{\theta} \text{ 為 MLE})$$

$$\log l(\hat{\theta}) = \log h(x) + \eta(\hat{\theta})T(x) - A(\hat{\theta})$$

$$\log l(\theta_0) = \log h(x) + \eta(\theta_0)T(x) - A(\theta_0)$$

$$\log l(\hat{\theta}) - \log l(\theta_0) = (\eta(\hat{\theta}) - \eta(\theta_0))T(x) - A(\hat{\theta}) + A(\theta_0)$$

$$\frac{\partial}{\partial \alpha} (\log l(\hat{\theta}) - \log l(\theta_0)) = \eta'(\hat{\theta})\hat{\theta}'(x)T(x) + (\eta(\hat{\theta}) - \eta(\theta_0))T'(x)$$

$$= \hat{\theta}'(x) (\underbrace{\eta'(\hat{\theta})T(x) - A'(\hat{\theta})}_0) + (\eta(\hat{\theta}) - \eta(\theta_0))T'(x)$$

$$= (\eta(\hat{\theta}) - \eta(\theta_0))T'(x)$$

這題應該需要假設
 $\hat{\theta}(x) \geq \theta_0 \Rightarrow T'(x) \geq 0$

$$\left\{ \begin{array}{l} \eta: \text{遞增} \\ \therefore \hat{\theta} > \theta_0 \Rightarrow \eta(\hat{\theta}) - \eta(\theta_0) > 0 \end{array} \right.$$

若此假設成立
 $\Rightarrow \log l(\hat{\theta}) - \log l(\theta_0) \geq 0$

\therefore 證明完成

(b) 題目應為「 $A(\theta) = \log \int h(x) \exp(\eta(\theta)T(x)) dx$ 」

由於 $f(x|\theta)$ 為 pdf, 故 $\int_{x \in R} h(x) \exp(\eta(\theta)T(x) - A(\theta)) dx = 1$.

$$\begin{aligned} \therefore e^{A(\theta)} \int_{x \in R} h(x) \exp(\eta(\theta)T(x) - A(\theta)) dx &= e^{A(\theta)} \\ &= \int_{x \in R} h(x) \exp(\eta(\theta)T(x)) dx = e^{A(\theta)} \end{aligned}$$

取兩邊的 $\log \rightarrow \log \int_{x \in R} h(x) \exp(\eta(\theta)T(x)) dx = A(\theta)$

\therefore 證明完成

②

$$\square f(x_{ij} | \mu_i, \sigma^2) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{1}{2\sigma^2}(x_{ij} - \mu_i)^2\right)$$

$$f(x_{11} \sim x_{1k}, \dots, x_{n1} \sim x_{nk} | \mu_1 \sim \mu_k, \sigma^2)$$

$$= \prod_{i=1}^n \prod_{j=1}^k \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{1}{2\sigma^2}(x_{ij} - \mu_i)^2\right)$$

$$\therefore L(\mu_1 \sim \mu_k, \sigma^2 | x_{ij}) = \prod_{i=1}^n \prod_{j=1}^k \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{1}{2\sigma^2}(x_{ij} - \mu_i)^2\right)$$

$$\log L(\mu_1 \sim \mu_k, \sigma^2 | x_{ij}) = \sum_{i=1}^n \sum_{j=1}^k \left\{ -\frac{1}{2} \log(2\pi\sigma^2) - \frac{1}{2\sigma^2}(x_{ij} - \mu_i)^2 \right\}$$

$$(1) \frac{\partial \log L}{\partial \sigma^2} = \sum_{i=1}^n \sum_{j=1}^k \left(\frac{1}{2\sigma^4}(x_{ij} - \mu_i)^2 - \frac{1}{2\sigma^2} \right) = 0$$

$$\therefore \sum_{i=1}^n \sum_{j=1}^k (x_{ij} - \mu_i)^2 = nk\sigma^2 \quad \therefore \hat{\sigma}_{MLE}^2 = \frac{1}{nk} \sum_{i=1}^n \sum_{j=1}^k (x_{ij} - \hat{\mu}_i)^2$$

$$\frac{\partial \log L}{\partial \mu_i} = \sum_{j=1}^k -\frac{1}{\sigma^2}(x_{ij} - \mu_i) = 0 \Rightarrow \hat{\mu}_{MLE} = \bar{x}_{i\cdot} = \frac{x_{i1} + \dots + x_{ik}}{k}$$

$$\text{(同樣道理)} \quad \hat{\mu}_{MLE} = \bar{x}_{\cdot} = \frac{x_{11} + x_{12} + \dots + x_{1k}}{k}$$

$$\therefore \hat{\sigma}_{MLE}^2 = \frac{1}{nk} \sum_{i=1}^n \sum_{j=1}^k (x_{ij} - \bar{x}_{i\cdot})^2; \quad \hat{\mu}_{MLE} = \bar{x}_{\cdot} = \frac{x_{11} + \dots + x_{1k}}{k}$$

(2) 證明 $\hat{\sigma}_{MLE}^2$ 並非 σ^2 的一致估計量
我們注意 x_{ij} 為獨立 而且 $\sum_{j=1}^k \frac{(x_{ij} - \bar{x}_{i\cdot})^2}{\sigma^2} \sim \chi_{k-1}^2$

$$\therefore \sum_{i=1}^n \sum_{j=1}^k \frac{(X_{ij} - \bar{X}_{i\cdot})^2}{\sigma^2} \sim \chi^2_{nk-n}$$

$$\therefore E \left[\sum_{i=1}^n \sum_{j=1}^k \frac{(X_{ij} - \bar{X}_{i\cdot})^2}{\sigma^2} \right] = nk - n = n(k-1)$$

$$\therefore E \left[\sum_{i=1}^n \sum_{j=1}^k (X_{ij} - \bar{X}_{i\cdot})^2 \right] = n(k-1)\sigma^2$$

$$\therefore E \left[\hat{\sigma}_{MSE}^2 \right] = \frac{n(k-1)\sigma^2}{nk} = \frac{k-1}{k} \sigma^2 \quad "$$

$$\therefore V \left[\sum_{i=1}^n \sum_{j=1}^k \frac{(X_{ij} - \bar{X}_{i\cdot})^2}{\sigma^2} \right] = 2n(k-1)$$

$$\therefore V \left[\sum_{i=1}^n \sum_{j=1}^k (X_{ij} - \bar{X}_{i\cdot})^2 \right] = 2n(k-1)\sigma^4$$

$$V \left[\underbrace{\frac{1}{nk} \sum_{i=1}^n \sum_{j=1}^k (X_{ij} - \bar{X}_{i\cdot})^2}_{\hat{\sigma}_{MSE}^2} \right] = \frac{2(k-1)\sigma^4}{nk^2}$$

$$\therefore \lim_{n \rightarrow \infty} V[\hat{\sigma}_{MSE}^2] = 0 \quad \therefore \hat{\sigma}_{MSE}^2 \xrightarrow{P} \frac{k-1}{k} \sigma^2 \quad (\because \text{無效})$$

在此 k 是個固定的常數 (跟 n 無關)

$\therefore \hat{\sigma}_{MSE}^2$ 為 $\frac{k-1}{k} \sigma^2$ 的一致估計量, 而並非 σ^2 的一致估計量

$$(3) \text{ 根據 (2) 的討論 } \frac{k}{k-1} (\hat{\sigma}_{MSE}^2) \xrightarrow{P} \sigma^2$$

$$(\because X_n \xrightarrow{P} c \quad aX_n \xrightarrow{P} ac)$$

$$\therefore C = \frac{k}{k-1}$$

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$$\textcircled{\oplus} V_p(r) = \frac{\pi^{\frac{p}{2}}}{\Gamma(\frac{p}{2}+1)} r^p$$

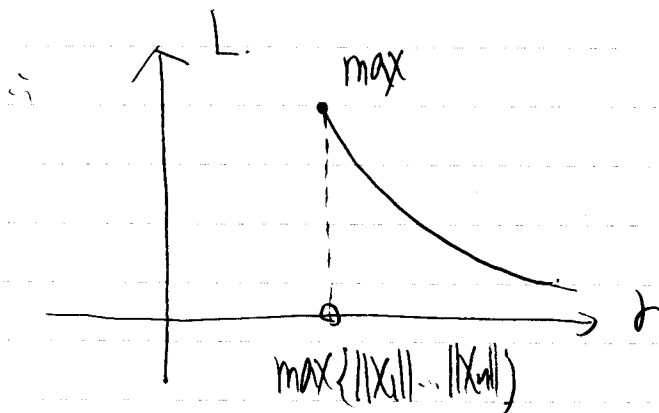
10 $V_p(r) \stackrel{\text{def}}{=} p$ 維空間之球的體積 (半徑 = r)

$$f(x|r) = \frac{1}{V_p(r)} \cdot I_{[0,r]}(\|x\|)$$

$$\therefore f(x_1, \dots, x_n | r) = \left\{ \frac{1}{V_p(r)} \right\}^n \cdot I_{[0,r]}(\|x_1\|) \cdot I_{[0,r]}(\|x_2\|) \dots I_{[0,r]}(\|x_n\|)$$

$$= \left\{ \frac{1}{V_p(r)} \right\}^n \cdot I_{[0,r]}(\max\{\|x_1\|, \dots, \|x_n\|\})$$

$$L(r | x_1, \dots, x_n) \stackrel{\text{def}}{=} \left\{ \frac{1}{V_p(r)} \right\}^n \cdot I_{[\max\{\|x_1\|, \dots, \|x_n\|\}, \infty)}(r)$$



$$\therefore r_{\text{MS}} = \max\{\|x_1\|, \dots, \|x_n\|\}$$

$$\textcircled{\oplus} \|x\| = \left(\sum_{j=1}^p x_j^2 \right)^{\frac{1}{2}} \quad \vec{x} = \begin{pmatrix} x_1 \\ \vdots \\ x_p \end{pmatrix}$$

接著考慮 \hat{r}_{MLE} 極限分布

$$\Pr(\hat{r}_{MLE} \leq t) = \Pr(\|X_1\| \leq t, \|X_2\| \leq t, \dots, \|X_n\| \leq t)$$

$$F_A(t) = \begin{cases} \left(\frac{V_p(t)}{V_p(r)} \right)^n = \left(\frac{t}{r} \right)^{np} & (0 \leq t \leq r) \\ 1 & (t > r) \end{cases}$$

$$\lim_{n \rightarrow \infty} \Pr(\hat{r}_{MLE} \leq r - \frac{t}{n}) = \lim_{n \rightarrow \infty} \left(1 - \frac{t}{rn} \right)^{np} = \lim_{n \rightarrow \infty} \left(1 - \frac{t}{rn} \right)^{\frac{pt}{r}} = e^{-\frac{pt}{r}}$$

$$\therefore \lim_{n \rightarrow \infty} \Pr(\hat{r}_{MLE} > r - \frac{t}{n}) = \lim_{n \rightarrow \infty} \Pr\left(\frac{t}{n} > r - \hat{r}_{MLE}\right) = 1 - e^{-\frac{pt}{r}}$$

$$\Leftrightarrow \lim_{n \rightarrow \infty} \Pr(n(r - \hat{r}_{MLE}) < t) = 1 - e^{-\frac{pt}{r}}$$

由此可知 $n(r - \hat{r}_{MLE}) \xrightarrow{d} \exp\left(\frac{p}{r}\right)$

(25)

III 為了避免混淆, $X_{m+1} \sim X_{m+n}$ 寫成 $Y_1 \sim Y_n$
 $\stackrel{\text{iid}}{=} X_1 \sim X_m \sim N(\mu_1, \sigma^2)$ $\stackrel{\text{iid}}{=} Y_1 \sim Y_n \sim N(\mu_2, \sigma^2)$
 $(\mu_1 \leq \mu_2)$

$$(a) f(x_1 \sim x_m, y_1 \sim y_n | \mu_1, \mu_2, \sigma^2) \\ = \left\{ \prod_{j=1}^m \left(\frac{1}{\sqrt{2\pi\sigma^2}} \right) \exp\left(-\frac{1}{2\sigma^2} (x_j - \mu_1)^2 \right) \right\} \left\{ \prod_{j=1}^n \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{1}{2\sigma^2} (y_j - \mu_2)^2 \right) \right\}$$

$$\log f(x_1 \sim x_m, y_1 \sim y_n | \mu_1, \mu_2, \sigma^2) = \frac{1}{2} (m+n) \log(2\pi\sigma^2) - \sum_{j=1}^m \frac{1}{2\sigma^2} (x_j - \mu_1)^2 \\ - \sum_{j=1}^n \frac{1}{2\sigma^2} (y_j - \mu_2)^2$$

$$L(\mu_1, \mu_2, \sigma^2) \stackrel{\text{def}}{=} \frac{1}{2} (m+n) \log(2\pi\sigma^2) - \sum_{j=1}^m \frac{1}{2\sigma^2} (x_j - \mu_1)^2 - \sum_{j=1}^n \frac{1}{2\sigma^2} (y_j - \mu_2)^2$$

(這是我們只對 μ_1 和 μ_2 的 MLE 有興趣, 而且 μ_1, μ_2

的 MLE 跟 σ^2 無關, 所以以下將 σ^2 當一個固定常數)

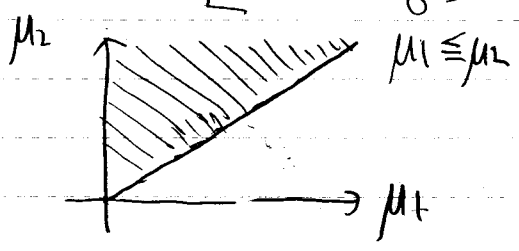
$$\frac{\partial L}{\partial \mu_1} = \sum_{j=1}^m \frac{(x_j - \mu_1)}{\sigma^2} = 0 \Rightarrow \mu_1 = \bar{x}$$

$$\frac{\partial L}{\partial \mu_2} = \frac{-n}{\sigma^2}$$

$$\text{同樣道理, } \frac{\partial L}{\partial \mu_2} = 0 \Rightarrow \mu_2 = \bar{y} \quad \frac{\partial L}{\partial \mu_2} = \frac{-n}{\sigma^2}$$

$$\text{另外 } \frac{\partial L}{\partial \mu_1 \partial \mu_2} = 0$$

∴ Hessian $\begin{bmatrix} \frac{n}{\sigma^2} & 0 \\ 0 & \frac{m}{\sigma^2} \end{bmatrix}$... 顯然為負定矩陣.



↓
接下來考慮 L 的最大值

• case I ... 若 $\bar{X} \leq \bar{Y}$... $\begin{cases} \hat{\mu}_{MLE} = \bar{X} \\ \hat{\mu}_{MLE} = \bar{Y} \end{cases}$ 使得 L 最大

• case II ... 若 $\bar{X} > \bar{Y}$... 最大值發生於 $\mu_1 = \mu_2$ 上

⇒ 我們應利用 Lagrange 乘數法

⇒ 但在此直接 $\mu = \mu_1 = \mu_2$ 比較快.

re-def
$$L(\mu) = \frac{1}{2}(m+n) \log(2\pi\sigma^2) - \sum_{j=1}^m \frac{1}{2\sigma^2} (x_j - \mu)^2 - \sum_{j=1}^n \frac{1}{2\sigma^2} (y_j - \mu)^2$$

$$\frac{\partial L}{\partial \mu} = \sum_{j=1}^m \frac{1}{\sigma^2} (x_j - \mu) + \sum_{j=1}^n \frac{1}{\sigma^2} (y_j - \mu) = 0$$

$$\Leftrightarrow (m+n)\mu = m\bar{X} + n\bar{Y} \quad \therefore \mu = \frac{m\bar{X} + n\bar{Y}}{m+n}$$

綜合 case I, II ... $\begin{cases} \text{if } \bar{X} \leq \bar{Y} \Rightarrow \hat{\mu}_{MLE} = \bar{X} & \hat{\mu}_{MLE} = \bar{Y} \\ \text{if } \bar{X} > \bar{Y} \Rightarrow \hat{\mu}_1 = \hat{\mu}_2 = \frac{m\bar{X} + n\bar{Y}}{m+n} \end{cases}$

(27)

(PS) 老師後來把「asymptotic distribution」改為「distribution」

但 Case I 應該考慮 $m \rightarrow \infty, n \rightarrow \infty$ 的情況。

故此，依照原來的題目作答。（Case I 應該不用考慮 asymptotic）

III - part 2

(b) 接下來考慮 $(\hat{\mu}_1, \hat{\mu}_2)$ 之極限分佈... (考慮聯合分佈)

$$\Pr(\hat{\mu}_1 \leq a, \hat{\mu}_2 \leq b) = \overset{\textcircled{1}}{\Pr(\hat{\mu}_1 \leq a, \hat{\mu}_2 \leq b, \bar{X} \leq \bar{Y})} + \overset{\textcircled{2}}{\Pr(\hat{\mu}_1 \leq a, \hat{\mu}_2 \leq b, \bar{X} > \bar{Y})}$$

$$= \overset{\textcircled{1}}{\Pr(\bar{X} \leq a, \bar{Y} \leq b, \bar{X} \leq \bar{Y})} + \overset{\textcircled{2}}{\Pr\left(\frac{m\bar{X} + n\bar{Y}}{m+n} \leq \min\{a, b\}, \bar{X} > \bar{Y}\right)}$$

Case I $\mu_1 < \mu_2 \dots$

$$\textcircled{1} = \Pr(\bar{X} \leq a, \bar{Y} \leq b, \bar{X} \leq \bar{Y}) = \Pr(\bar{X} \leq a, \bar{Y} \leq b) - \Pr(\bar{X} \leq a, \bar{Y} \geq b, \bar{X} > \bar{Y})$$

$$\geq \Pr(\bar{X} \leq a, \bar{Y} \leq b) - \Pr(\bar{X} > \bar{Y})$$

$$\Pr(\bar{X} \leq a, \bar{Y} \leq b) - \Pr(\bar{X} > \bar{Y}) \leq \textcircled{1} \leq \Pr(\bar{X} \leq a, \bar{Y} \leq b)$$

$$\Pr(\bar{X} > \bar{Y}) = \Pr(W > 0) \text{ where } W = \bar{X} - \bar{Y}$$

$$W \sim N(\mu_1 - \mu_2, \left(\frac{1}{m} + \frac{1}{n}\right) \sigma^2)$$

$$\text{且 } m \rightarrow \infty, n \rightarrow \infty \text{ 時 } \dots \left(\frac{1}{m} + \frac{1}{n}\right) \sigma^2 \rightarrow 0$$

$$\therefore W \xrightarrow{P} \mu_1 - \mu_2 < 0$$

$$\therefore \Pr(\bar{X} > \bar{Y}) \rightarrow 0$$

$$\therefore m \rightarrow \infty, n \rightarrow \infty \Rightarrow \textcircled{1} \rightarrow \Pr(\bar{X} \leq a, \bar{Y} \leq b)$$

$$\textcircled{2} \dots \textcircled{2} \leq \Pr(\bar{X} > \bar{Y}) \text{ 同樣道理, } \Pr(\bar{X} > \bar{Y}) \rightarrow 0$$

$$\therefore \textcircled{2} \rightarrow 0$$

$$\bar{X} \sim N(\mu_1, \frac{\sigma^2}{m}) \quad \bar{Y} \sim N(\mu_2, \frac{\sigma^2}{n})$$

$$\left(\frac{m\bar{X} + n\bar{Y}}{m+n} \sim N(\mu_1, \frac{\sigma^2}{m+n}) \text{ if } \mu_1 = \mu_2 \right)$$

No.
Date

$\therefore \mu_1 < \mu_2$ 時, $m, n \rightarrow \infty$ $\Pr(\hat{\mu}_1 \leq a, \hat{\mu}_2 \leq b) \rightarrow \Pr(\bar{X} \leq a, \bar{Y} \leq b)$

$$\Pr(\hat{\mu}_1 \leq a) \rightarrow \Pr(\bar{X} \leq a), \Pr(\hat{\mu}_2 \leq b) \rightarrow \Pr(\bar{Y} \leq b)$$

故, $\hat{\mu}_1$ 與 $\hat{\mu}_2$ 之極限分佈與 \bar{X} 與 \bar{Y} 之分佈一致,

$$\hat{\mu}_1 \xrightarrow{d} N(\mu_1, \frac{\sigma^2}{m}), \hat{\mu}_2 \xrightarrow{d} N(\mu_2, \frac{\sigma^2}{n})$$

Case II $\mu_1 = \mu_2 \dots$ (if $\bar{X} \leq \bar{Y} \dots \hat{\mu}_{1MLE} = \bar{X}, \hat{\mu}_{2MLE} = \bar{Y}$
if $\bar{X} > \bar{Y} \dots \hat{\mu}_{1MLE} = \hat{\mu}_{2MLE} = \frac{m\bar{X} + n\bar{Y}}{m+n}$)

我們應該先考慮 $\Pr(\bar{X} \leq \bar{Y})$ 與 $\Pr(\bar{X} > \bar{Y})$ 之機率。

$$W \stackrel{\text{def}}{=} \bar{X} - \bar{Y} \quad W \sim N(0, (\frac{1}{m} + \frac{1}{n})\sigma^2) \quad (\because \mu_1 = \mu_2)$$

$$\Pr(W < 0) = \frac{1}{2}, \Pr(W \geq 0) = \frac{1}{2} \quad (\forall m, n \in \mathbb{Z})$$

$$\hat{\mu}_{1MLE} = \begin{cases} \bar{X} & (\frac{1}{2}) \\ \frac{m\bar{X} + n\bar{Y}}{m+n} & (\frac{1}{2}) \end{cases} \quad \hat{\mu}_{2MLE} = \begin{cases} \bar{Y} & (\frac{1}{2}) \\ \frac{m\bar{X} + n\bar{Y}}{m+n} & (\frac{1}{2}) \end{cases}$$

由此可知, $\hat{\mu}_{1MLE}$ 和 $\hat{\mu}_{2MLE}$ 為 Mixture Normal Distribution.

(但跟 case I 不同的是, $\Pr(\bar{X} \leq \bar{Y}) = \Pr(\bar{X} > \bar{Y}) = \frac{1}{2}$ for all $m, n \in \mathbb{Z}$
所以不用考慮 asymptotic distribution.)

$$\left. \begin{aligned} & \hat{\mu}_{1MLE} \sim \frac{1}{2} N(\mu_1, \frac{\sigma^2}{m}) \& \frac{1}{2} N(\mu_1, \frac{\sigma^2}{m+n}) \quad \left(\frac{1}{2}, \frac{1}{2} \right) \text{ 之混合常態分佈} \\ & \hat{\mu}_{2MLE} \sim \frac{1}{2} N(\mu_1, \frac{\sigma^2}{n}) \& \frac{1}{2} N(\mu_1, \frac{\sigma^2}{m+n}) \quad \left(\frac{1}{2}, \frac{1}{2} \right) \text{ 之混合常態分佈} \end{aligned} \right\}$$

(29)

12 先求 $E[X_1 - t | X_1 > t]$

考慮 $X_1 - t | X_1 > t$ 之分布.

$$\begin{aligned} \Pr(X_1 - t < \alpha | X_1 > t) &= \frac{\Pr(t < X_1 < t + \alpha)}{\Pr(X_1 > t)} \\ &= \frac{\int_t^{t+\alpha} \lambda e^{-\lambda x} dx}{\int_t^{\infty} \lambda e^{-\lambda x} dx} = \frac{\lambda(e^{-\lambda t} - e^{-\lambda(t+\alpha)})}{\lambda e^{-\lambda t}} \\ &= (1 - e^{-\lambda \alpha}) \end{aligned}$$

$$\therefore \frac{d}{d\alpha} \Pr(X_1 - t < \alpha | X_1 > t) = \lambda e^{-\lambda \alpha}$$

由此可知 $X_1 - t | X_1 > t \sim \text{exp}(\lambda)$

$$\therefore E[X_1 - t | X_1 > t] = \frac{1}{\lambda}$$

\therefore 求 λ 之 MLE. 根據 MLE 之不變性 (invariant property)

$$\lambda \text{ 之 MLE} = \frac{1}{\bar{X}}$$

X_1, X_2 之聯合密度函數 $f(x_1, x_2 | \lambda) = \lambda^n \exp(-\lambda(x_1 + x_2))$
($x_1, x_2 \geq 0$)

$$L(\lambda) = \lambda^n \exp(-\lambda(x_1 + x_2)) \quad \frac{d}{d\lambda} \log L(\lambda) = \frac{n}{\lambda} - (x_1 + x_2)$$

$$\frac{d|g|}{d\lambda} = 0 \Rightarrow \lambda = \frac{1}{\bar{X}}$$

λ	0	$\frac{1}{\bar{X}}$	
$\frac{d g }{d\lambda}$		+	-
L		↗	↘
		max	

$$\hat{\lambda}_{MLE} = \frac{1}{\bar{X}}$$

$$\hat{\lambda}_{MLE} = \frac{1}{\bar{X}} = \frac{1}{\frac{X_1 + X_2 + \dots + X_n}{n}}$$

$E[\hat{X}] = \frac{1}{\lambda} < \infty$ ∴ 根據 Khinchine 弱大數法則

$$\frac{X_1 + X_2 + \dots + X_n}{n} \xrightarrow{P} \frac{1}{\lambda} \quad (\because X_1, X_2, \dots, X_n \text{ i.i.d. } |E[X_i]| < \infty)$$

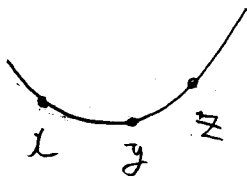
$$\hat{\lambda} = \frac{1}{\bar{X}} = \frac{X_1 + \dots + X_n}{n} \xrightarrow{P} \frac{1}{\lambda} \quad (\text{退化})$$

或者 $V[X_i] = \frac{1}{\lambda^2} < \infty$ ∴ 根據中央極限定理,

$$\sqrt{n} \left(\frac{X_1 + \dots + X_n}{n} - \frac{1}{\lambda} \right) \xrightarrow{d} N\left(0, \frac{1}{\lambda^2}\right)$$

$$\hat{\lambda} = \frac{1}{\bar{X}} \Rightarrow \sqrt{n} \left(\frac{1}{\hat{X}} - \frac{1}{\lambda} \right) \xrightarrow{d} N\left(0, \frac{1}{\lambda^2}\right)$$

NOTE of 2



NOTE 2 $x \leq z$

$$\textcircled{1} f((1-t)x + tz) \leq (1-t)f(x) + tf(z)$$

$$\Leftrightarrow f((1-t)x + tz) - f(x) \leq t(f(z) - f(x))$$

$$\Leftrightarrow \frac{f((1-t)x + tz) - f(x)}{t(z-x)} \leq \frac{f(z) - f(x)}{z-x}$$

$$y \stackrel{\text{pt}}{=} x + t(z-x)$$

$$\Leftrightarrow \frac{f(y) - f(x)}{y-x} \leq \frac{f(z) - f(x)}{z-x} \quad (x \leq y \leq z)$$

$$\textcircled{2} f((1-t)x + tz) \leq (1-t)f(x) + tf(z)$$

$$\Leftrightarrow f((1-t)x + tz) - f(z) \leq (1-t)(f(x) - f(z))$$

$$\Leftrightarrow f((1-t)x + tz) - f(z) \geq (1-t)(f(z) - f(x))$$

$$\Leftrightarrow \frac{f((1-t)x + tz) - f(z)}{(1-t)(z-x)} \geq \frac{f(z) - f(x)}{z-x}$$

$$y \stackrel{\text{pt}}{=} (1-t)x + tz$$

$$\Leftrightarrow \frac{f(z) - f(y)}{z-y} \geq \frac{f(z) - f(x)}{z-x} \quad (x \leq y \leq z)$$

綜合①,② : $x \leq y \leq z \Rightarrow \frac{f(y)-f(x)}{y-x} \leq \frac{f(z)-f(x)}{z-x} \leq \frac{f(z)-f(y)}{z-y}$

□

求MLE (θ 使得 $L(\theta)$ 最大 $\theta \in [0, 1]$)

$$X = -2 \dots L(\theta) = \frac{1-\theta}{4} \quad \arg \max_{\theta} L(\theta) = 0$$

$$X = -1 \dots L(\theta) = \frac{\theta}{12} \quad \arg \max_{\theta} L(\theta) = 1$$

$$X = 0 \dots L(\theta) = \frac{1}{2} \quad \arg \max_{\theta} L(\theta) = \forall c \in [0, 1]$$

$$X = 1 \dots L(\theta) = \frac{3-\theta}{12} \quad \arg \max_{\theta} L(\theta) = 0$$

$$X = 2 \dots L(\theta) = \frac{\theta}{4} \quad \arg \max_{\theta} L(\theta) = 1$$

$$\hat{\theta}_{MLE} = \begin{cases} 0 & (X = -2) \\ 1 & (X = -1) \\ \forall c \in [0, 1] & (X = 0) \\ 0 & (X = 1) \\ 1 & (X = 2) \end{cases} \quad \dots \hat{\theta}_{MLE} \text{ 並不唯一.}$$

求 θ 的不偏估計量

$$E[X] = \frac{1-\theta}{4} \cdot (-2) + \frac{\theta}{12} \cdot (-1) + \frac{1}{2} \cdot (0) + \frac{3-\theta}{12} \cdot 1 + \frac{\theta}{4} \cdot (2)$$

$$= \frac{\theta-1}{2} - \frac{\theta}{12} + \frac{3-\theta}{12} + \frac{\theta}{2}$$

$$= \frac{6\theta - 6 - \theta + 3 - \theta + 6\theta}{12}$$

$$= \frac{10\theta - 3}{12} \quad \therefore E\left[\frac{6X}{5} + \frac{3}{10}\right] = \theta$$

$\therefore \frac{6}{5}X + \frac{3}{10}$ 為 θ 的不偏估計量,

$$\begin{aligned} E[\hat{\theta}_{MLE}] &= \frac{1}{4}\theta + \frac{\theta}{12} + \frac{1}{2}C + \frac{3\theta}{12} + \frac{\theta}{4} \\ &= \frac{\theta}{12} + \frac{C}{2} + \frac{\theta}{4} = \frac{\theta}{3} + \frac{C}{2} \end{aligned}$$

C 為與 θ 無關的常數, $\forall C$ 無法使得

$E[\hat{\theta}_{MLE}] = \theta$. $\hat{\theta}_{MLE}$ 不可能為 θ 的不偏估計量.

$$\boxed{2} \quad X_1, X_2, \dots, X_n \sim \text{bernoulli}(p)$$

$$\begin{aligned} (a) \quad & \Pr(X_1=x_1, \dots, X_n=x_n | p) \\ &= p^{(x_1+x_2+\dots+x_n)} (1-p)^{(n-x_1-x_2-\dots-x_n)} \end{aligned}$$

$$l(p) = \ln \Pr(X_1=x_1, \dots, X_n=x_n)$$

$$= (x_1+x_2+\dots+x_n) \ln p + (n-x_1-x_2-\dots-x_n) \ln(1-p)$$

$$l'(p) = \frac{1}{p} (x_1+x_2+\dots+x_n) - \frac{1}{1-p} (n-x_1-x_2-\dots-x_n) = 0$$

$$\Leftrightarrow (1-p)(x_1+x_2+\dots+x_n) - p(n-x_1-x_2-\dots-x_n) = 0$$

$$\Leftrightarrow p = \bar{X}$$

$$l''(p) = -\frac{1}{p^2} (x_1+\dots+x_n) - \frac{1}{(1-p)^2} (n-x_1-x_2-\dots-x_n) < 0$$

$$\therefore \hat{p}_{MLE} = \bar{X}$$

根據中央極限定理,

$$\sqrt{n} \left(\frac{X_1+X_2+\dots+X_n}{n} - p \right) \xrightarrow{d} N(0, p(1-p))$$

$$[E[X_i]] = p \quad V[X_i] = p(1-p)$$

$\hat{\theta}_{MLE} = \hat{p}_{MLE} (1 - \hat{p}_{MLE})$ (\because MLE 不變性 \Rightarrow 第5次作業 11)

$$g(p) = p(1-p) \quad g'(p) = 1-2p$$

利用 Δ -method

$$\sqrt{n}(g(\hat{p}) - g(p)) \xrightarrow{d} N(0, p(1-p) \cdot \{g'(p)\}^2)$$

$$\therefore \sqrt{n}(\hat{\theta}_{MLE} - \theta) \xrightarrow{d} N(0, p(1-p)(1-2p)^2) \quad (p \neq \frac{1}{2})$$

(b) 自己重新定義: $h(p)$ ($h(\frac{1}{2}) = g(\frac{1}{2}) = \frac{1}{4}$)

例如: 取 $h(x) = x^2$. $h'(x) = 2x$

$$\therefore \sqrt{n}(\underbrace{h(\hat{p})}_{\hat{\theta}_{MLE}} - \underbrace{h(p)}_{\theta_2}) \xrightarrow{d} N(0, p(1-p) \cdot \{h'(p)\}^2)$$
$$N(0, p(1-p) \cdot 4)$$

$$p = \frac{1}{2} \quad \sqrt{n}(\hat{\theta}_{MLE} - \theta_2) \xrightarrow{d} N(0, 1)$$

$$\boxed{3} \quad F(x, y) = x \cdot y \cdot (\min\{x, y\})^\theta$$

$$\bullet \quad x > y \implies F(x, y) = x \cdot y^{\theta+1}$$

$$\bullet \quad x < y \implies F(x, y) = x^{\theta+1} \cdot y$$

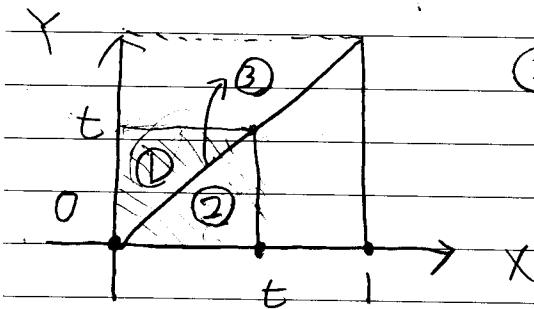
$$\frac{\partial^2 F}{\partial x \partial y} = \begin{cases} (\theta+1) y^\theta & (x > y) \\ (\theta+1) x^\theta & (x < y) \end{cases}$$

$$= (\theta+1) \cdot (\min\{x, y\})^\theta$$

這個分佈其實是兩種連續分佈的混合分佈

($X=Y$ 的部分與 $X \neq Y$ 的部分)

接著求 $X=Y$ 的分佈:



③. $X=Y$ 的直線上

① 的機率 ($0 < X < Y < t$)

$$= \int_0^t \int_0^y (\theta+1) x^\theta dx dy$$

$$= \int_0^t \left[x^{\theta+1} \right]_0^y dy$$

$$= \int_0^t z^{\theta+1} dz = \frac{t^{\theta+2}}{\theta+2}$$

② 的機率 ($0 < Y < X < t$)

同理, $= \frac{t^{\theta+2}}{\theta+2}$

①+②+③ 的機率 ($X, Y \leq t$)

$$F(t, t) = t^{\theta+2}$$

\therefore ③ (= $P(X=Y \leq t)$) 的機率

$$= (\text{①+②+③}) - (\text{①+②})$$

$$= t^{\theta+2} - \frac{2t^{\theta+2}}{\theta+2} = \frac{\theta}{\theta+2} t^{\theta+2}$$

另外, 代入 $t=1$ 得知

$$\begin{cases} P(X=Y) = \frac{\theta}{\theta+2} \\ P(X \neq Y) = \frac{2}{\theta+2} \end{cases}$$

• $X \neq Y$ 下的機率密度... $\left(\frac{\theta+2}{2}\right) \cdot (\theta+1) (\min(x, y))^{\theta}$

• $X=Y$ 下的機率密度... $P(X=Y \leq x | X=Y)$
 $= x^{\theta+2}$

$$\therefore \frac{d}{dx} x^{\theta+2} = (\theta+2)x^{\theta+1} \quad \therefore \text{Beta}(\theta+2, 1)$$

總而言之,

$$\left\{ \begin{array}{l} \bullet (X, Y) \mid X \neq Y \sim f_{X \neq Y}(x, y) = \left(\frac{\theta+2}{2}\right) (\theta+1) (\min\{x, y\})^{\theta} \\ \quad \Pr(X \neq Y) = \frac{2}{\theta+2} \\ \bullet (X, Y) \mid X = Y \sim f_{X=Y}(x) = (\theta+2)x^{\theta+1} \\ \quad \Pr(X = Y) = \frac{\theta}{\theta+2} \end{array} \right.$$

(但 $0 < x < 1, 0 < y < 1$)

(a) 根據以上的討論, 完整的機率密度函數為

$$\begin{aligned} f(x, y) &= f_{X \neq Y}(x, y) \cdot \Pr(X \neq Y) + f_{X=Y}(x) \cdot \Pr(X=Y) \\ &= (\theta+1) (\min\{x, y\})^{\theta} \underset{1 - I(X=Y)}{I(X \neq Y)} + \theta x^{\theta+1} \underset{I(X=Y)}{I(X=Y)} \\ &= \left\{ (\theta+1) \min\{x, y\}^{\theta} \right\} \cdot \left\{ \theta x^{\theta+1} \right\} \end{aligned}$$

故似然比函數為

$$L(\theta) = \prod_{j=1}^n \left\{ (\theta+1) \min\{x_j, y_j\}^{\theta} \right\} \cdot \left(\theta x_j^{\theta+1} \right)^{I(X_j=Y_j)}$$

(b) 接著考慮 θ_{MLE} (但應該不漂亮)

為了簡單, $I_j \stackrel{\text{def}}{=} I(X_j = Y_j)$

$$l(\theta) = \ln L(\theta) = \sum_{j=1}^n \left\{ (1-I_j) \ln(\theta+1) + (1-I_j) \cdot \theta \cdot \ln \min\{X_j, Y_j\} \right. \\ \left. + I_j \ln \theta + I_j \cdot (\theta+1) \ln X_j \right\}$$

$$l'(\theta) = \sum_{j=1}^n \left(\frac{1-I_j}{\theta+1} + (1-I_j) \ln \min\{X_j, Y_j\} + \frac{I_j}{\theta} + I_j \ln X_j \right)$$

$$l''(\theta) = \frac{-1}{(\theta+1)^2} \sum_{j=1}^n (1-I_j) - \frac{1}{\theta^2} \sum_{j=1}^n I_j < 0$$

$$l'(\theta) = 0 \Rightarrow \theta(\theta+1)l'(\theta) = 0$$

$$\Rightarrow \sum_{j=1}^n \left\{ \underbrace{\theta(1-I_j) + (\theta+1)I_j}_{\rightarrow \theta+I_j} + \theta(\theta+1) \left\{ (1-I_j) \ln \min\{X_j, Y_j\} \right. \right. \\ \left. \left. + I_j \ln X_j \right\} \right\}$$

$$= \sum_{j=1}^n \left\{ \theta^2 \left((1-I_j) \ln \min\{X_j, Y_j\} + I_j \ln X_j \right) \right. \\ \left. + \theta \left((1-I_j) \ln \min\{X_j, Y_j\} + I_j \ln X_j + 1 \right) \right. \\ \left. + I_j \right\} = 0 \Leftrightarrow a\theta^2 + b\theta + c = 0$$

where

$$\begin{cases} a = \sum_{j=1}^n \left\{ (1-I_j) \ln \min\{X_j, Y_j\} + I_j \ln X_j \right\} \\ b = \sum_{j=1}^n \left\{ (1-I_j) \ln \min\{X_j, Y_j\} + I_j \ln X_j + 1 \right\} \\ c = \sum_{j=1}^n I_j \end{cases}$$

$\hat{\theta}_{MLE}$ 為 $a\theta^2 + b\theta + c = 0$ 之根。

$$\begin{cases} \cdot a = \sum_{j=1}^n (1 - I_j) \ln \min\{X_j, Y_j\} + \sum_{j=1}^n I_j \ln X_j \\ \cdot b = n + \sum_{j=1}^n (1 - I_j) \ln \min\{X_j, Y_j\} + \sum_{j=1}^n I_j \ln X_j \\ \cdot c = \sum_{j=1}^n I_j \quad (I_j = I(X_j = Y_j)) \end{cases}$$

(C) $\hat{\theta}_{MLE}$ 之漸近分佈

我們假設 Regularity Condition 成立：

$$l''(\theta) = \frac{-1}{(\theta+1)^2} \sum_{j=1}^n (1 - I_j) - \frac{1}{\theta^2} \sum_{j=1}^n I_j$$

$$E[I_j] = \Pr(I_j = 1) = \Pr(X_j = Y_j) = \frac{\theta}{\theta+2}$$

$$-E[l'(\theta)] = E\left[\frac{1}{(\theta+1)^2} \sum_{j=1}^n (1 - I_j) + \frac{1}{\theta^2} \sum_{j=1}^n I_j \right]$$

$$= \left\{ \frac{1}{(\theta+1)^2} \cdot \left(\frac{2}{\theta+2} \right) + \frac{1}{\theta^2} \cdot \frac{\theta}{\theta+2} \right\} \cdot n$$

$$= n \cdot \left(\frac{2}{(\theta+1)^2(\theta+2)} + \frac{1}{\theta(\theta+2)} \right)$$

$$\therefore \hat{\theta}_{MLE} - \theta \xrightarrow{d} N\left(0, -E[l'(\theta)]^{-1}\right)$$

$$\text{故 } \sqrt{n}(\hat{\theta}_{MLE} - \theta) \xrightarrow{d} N\left(0, \left\{ \frac{2}{(\cos\theta)^2(\sin\theta)} + \frac{1}{\sin^3\theta} \right\}^{-1}\right)$$

$$\boxed{4} \quad L(\theta|x) \stackrel{\text{def}}{=} \exp(\eta(\theta)Y(x) - B(\theta))h(x)$$

$$l(\theta) \stackrel{\text{def}}{=} \ln L(\theta|x) = \eta(\theta)Y(x) - B(\theta) + \ln h(x)$$

$$\bullet \quad \frac{\partial l(\theta)}{\partial \theta} = \eta'(\theta)Y(x) - B'(\theta) = 0$$

$$\therefore \hat{\theta}_{MLE}(x) \text{ 满足 } \eta'(\hat{\theta})Y(x) - B'(\hat{\theta}) = 0 \quad \text{--- } \otimes$$

$$l(\hat{\theta}) - l(\theta_0) = \eta(\hat{\theta})Y(x) - B(\hat{\theta}) + \ln h(x) \\ - \eta(\theta_0)Y(x) + B(\theta_0) - \ln h(x)$$

$$= \eta(\hat{\theta})Y(x) - \eta(\theta_0)Y(x) - B(\hat{\theta}) + B(\theta_0)$$

$$\frac{d}{d\eta} (l(\hat{\theta}) - l(\theta_0)) = \frac{d\eta}{d\eta} \frac{d}{d\eta} (\eta(\hat{\theta})Y(x) - \eta(\theta_0)Y(x) - B(\hat{\theta}) + B(\theta_0))$$

$$= \frac{d\eta}{d\eta} \cdot \left\{ \eta'(\hat{\theta})\hat{\theta}'(x)Y(x) + \eta(\hat{\theta})Y'(x) - \eta(\theta_0)Y'(x) - B'(\hat{\theta})\hat{\theta}'(x) \right\}$$

$$= \hat{\theta}'(x) \left\{ \eta'(\hat{\theta})Y(x) - B'(\hat{\theta}) \right\} + Y'(x) (\eta(\hat{\theta}) - \eta(\theta_0))$$

$$= Y'(x) (\eta(\hat{\theta}) - \eta(\theta_0)) \quad (\because \otimes \text{ 的條件})$$

$$= \frac{d\eta}{d\eta} \cdot Y'(x) (\eta(\hat{\theta}) - \eta(\theta_0))$$

$$= \eta(\hat{\theta}) - \eta(\theta_0) \geq 0 \quad (\text{when } \hat{\theta} \geq \theta_0)$$

$$\therefore \frac{d}{dx} (\ell(\hat{\theta}(x)) - \ell(\theta_0)) = \eta(\hat{\theta}_{MLE}(x)) - \eta(\theta_0) \geq 0$$

when $\hat{\theta}_{MLE} \geq \theta_0$

($\because \eta$ 為 遞增函數)

5

$$(a) L(\theta | x_1, \dots, x_n) = \prod_{j=1}^n \frac{\theta}{(1+x_j)^{\theta+1}}$$

$$\ell(\theta | x_1, \dots, x_n) = \ln L(\theta | x_1, x_2, \dots, x_n)$$

$$= \sum_{j=1}^n (\ln \theta - (\theta+1) \ln(1+x_j))$$

$$= n \ln \theta - (\theta+1) \sum_{j=1}^n \ln(1+x_j)$$

$$\frac{\partial \ell(\theta | x_1, \dots, x_n)}{\partial \theta} = \frac{n}{\theta} - \sum_{j=1}^n \ln(1+x_j) = 0$$

$$\frac{\partial^2 \ell(\theta | x_1, \dots, x_n)}{\partial \theta^2} = -\frac{n}{\theta^2} < 0$$

$$\hat{\theta}_{MLE} = \frac{n}{\sum_{j=1}^n \ln(1+x_j)}$$

$$(b) Y \stackrel{\text{def}}{=} \ln(1+X)$$

$$\frac{dY}{dX} = \frac{1}{1+X} = \exp(-Y)$$

$$f = \int_{x=0}^{x=\infty} \frac{\theta}{(1+x)^{\theta+1}} dx$$

$$= \int_{y=0}^{y=\infty} \theta \cdot e^{-(\theta+1)y} \cdot e^y dy$$

$$= \int_0^{\infty} \theta e^{-\theta y} dy \quad \therefore Y = \ln(1+X) \sim \exp(\theta) \quad (\text{mean } \frac{1}{\theta})$$

根據中央極限定理,

$$\sqrt{n} \left(\frac{Y_1 + Y_2 + \dots + Y_n}{n} - \frac{1}{\theta} \right) \xrightarrow{d} N(0, \frac{1}{\theta^2})$$

利用 Δ -method $g(x) = \frac{1}{x}$ ($x > 0$) $g'(x) = -\frac{1}{x^2}$

$$\sqrt{n} \left(g\left(\frac{Y_1 + \dots + Y_n}{n}\right) - g\left(\frac{1}{\theta}\right) \right) \xrightarrow{d} N\left(0, \frac{1}{\theta^2} g'\left(\frac{1}{\theta}\right)^2\right)$$

$$\Leftrightarrow \sqrt{n}(\hat{\theta}_{MLE} - \theta) \xrightarrow{d} N(0, \theta^2)$$

$$\therefore \underline{N(0, \theta^2)}$$

$$(c) \sqrt{n}(g(\hat{\theta}_{MLE}) - g(\theta)) \xrightarrow{d} N(0, \theta^2 \cdot g'(\theta)^2)$$

$$\therefore g'(\theta) = \pm \frac{1}{\theta} \quad (\Delta\text{-method})$$

$$\therefore g(\theta) = \pm \ln \theta + C \quad (C = \text{常數})$$

6 利用 χ^2 -test : $H_0: \sim \text{Poisson}$; $H_1: \text{not Poisson}$

k	0	1	2	3	4	5	6	7	8	9	10	11	...
O_k	275	246	178	84	67	27	17	12	1	2	1	1	...

k	12	16	19
O_k	2	1	1

$$\bullet n = \sum_{k=0}^{19} O_k = 915.$$

$$\bullet \hat{\lambda} = \sum_{k=0}^{19} k \cdot O_k / n = 1.6929$$

$$E_k = n \cdot e^{-\hat{\lambda}} \cdot \frac{(\hat{\lambda})^k}{k!} \quad (k=0 \sim 12)$$

$$E_3 = n \cdot \left(1 - \sum_{k=0}^{12} e^{-\hat{\lambda}} \cdot \frac{(\hat{\lambda})^k}{k!} \right)$$

($k \geq 3$ 的部分合在一起)

k	0	1	...	13	5
E_k	168.3477	284.9942	...	2.8811	10^{-5}

• 檢定統計量

$$T = \sum_{k=0}^{13} \frac{(E_k - O_k)^2}{E_k} = 1.605 \cdot 10^5$$

T 的分佈 ($H_0: T$)

$$T \sim \chi^2_{k-1} = \chi^2_{12} \quad \chi^2_{12}(0.95) = 21.0261$$

$$T \gg 21.0261$$

\therefore 棄 H_0 . (並不服從 Poisson.)

7

$$(a) E[e^{tX}] = \int_{x=-\infty}^{x=\infty} e^{tX} \cdot f(x) dx$$

$$= \int_{-\infty}^{\infty} e^{tX} \frac{\lambda}{2} \exp(-\lambda|X|) dx$$

$$= \int_0^{\infty} e^{tX} \frac{\lambda}{2} \exp(-\lambda X) dx + \int_{-\infty}^0 e^{tX} \frac{\lambda}{2} \exp(\lambda X) dx$$

$$= \int_0^{\infty} \frac{\lambda}{2} \exp(-(\lambda-t)X) dx + \int_{-\infty}^0 \frac{\lambda}{2} \exp((\lambda+t)X) dx$$

$$\frac{\lambda}{2} \cdot \frac{1}{\lambda-t} \int_0^{\infty} (\lambda-t) \exp(-(\lambda-t)X) dx \quad \int_0^0 \frac{-\lambda}{2} \exp(-(\lambda+t)X) dx$$

$$\int_0^{\infty} \frac{\lambda}{2} \exp(-(\lambda+t)X) dx$$

$$\frac{\lambda}{2} \cdot \frac{1}{\lambda+t}$$

$$= \frac{\lambda}{2} \left(\frac{1}{\lambda-t} + \frac{1}{\lambda+t} \right) = \frac{\lambda}{2} \cdot \frac{2\lambda}{\lambda^2 - t^2} = \frac{\lambda^2}{\lambda^2 - t^2} = M_X(t)$$

$$(b) U, V \stackrel{i.i.d.}{\sim} \exp(1)$$

$$E[e^{t(U-V)}] = E[e^{tU}] \cdot E[e^{(-t)V}]$$

$$E[e^{tU}] = \int_{u=0}^{u=\infty} e^{tu} \cdot e^{-u} du = \int_{u=0}^{u=\infty} e^{-(1-t)u} du$$

$$= \frac{1}{1-t}$$

$$\therefore E[e^{(t)N}] = \frac{1}{1-t} \quad (c: c'd)$$

$$\therefore E[e^{t(U-V)}] = \frac{1}{1-t} \cdot \frac{1}{1+t} = \frac{1}{1-t^2} = \frac{1^2}{1-t^2} \quad (\lambda=1)$$

由(a)可知, $X|\lambda=1$ 與 $Y(=U-V)$ 之分布相同.

(Lévy 連續性定理)

$$\therefore Y \sim \text{Double-Exp}(1) (= \text{Laplace}(1))$$

(c) 若 $U, V \stackrel{iid}{\sim} \text{exp}(\lambda)$ (mean $\frac{1}{\lambda}$)

$U-V \sim \text{Laplace}(\lambda)$ (Double-Exp(λ))

$\therefore X_j \stackrel{\text{def}}{=} U_j - V_j (\sim \text{Laplace}(\lambda))$

$$E[X_j] = 0, \quad V[X_j] = V[U_j] + V[V_j] = \frac{1}{\lambda^2} + \frac{1}{\lambda^2} = \frac{2}{\lambda^2}$$

\therefore 期望值 = 0

$$\text{變異數} = \frac{2}{\lambda^2} \quad ; \quad \sigma^2 \stackrel{\text{def}}{=} \frac{2}{\lambda^2}$$

$$M_{W_n}(t) = E[e^{tW_n}] = E\left[\exp\left(t \frac{\sqrt{n}}{\sigma} \frac{1}{n} (X_1 + \dots + X_n)\right)\right]$$

$$= E\left[\exp\left(\frac{t}{\sigma\sqrt{n}} (X_1 + X_2 + \dots + X_n)\right)\right]$$

$$= E\left[\exp\left(\frac{t}{\sigma\sqrt{n}} X_1\right)\right]^n$$

$$M_{nn}(t) = E \left[\exp \left(\frac{t}{\sigma\sqrt{n}} X_1 \right) \right]^n$$

$$= \left(M_X \left(\frac{t}{\sigma\sqrt{n}} \right) \right)^n$$

$$= \left(\frac{\lambda^2}{\lambda^2 - \left(\frac{t}{\sigma\sqrt{n}} \right)^2} \right)^n = \left(\frac{\lambda^2}{\lambda^2 - \frac{t^2}{n\sigma^2}} \right)^n \quad \left(\sigma^2 = \frac{2}{\lambda^2} \right)$$

$$= \left(\frac{\lambda^2}{\lambda^2 - \frac{\lambda^2 t^2}{2n}} \right)^n = \left(1 - \frac{t^2}{2n} \right)^n$$

$$\therefore M_{nn}(t) = \left(1 - \frac{t^2}{2n} \right)^n$$

$$(d) \lim_{n \rightarrow \infty} M_{nn}(t) = \lim_{n \rightarrow \infty} \left(1 - \frac{t^2}{2n} \right)^n$$

$$= \lim_{n \rightarrow \infty} \left(1 - \frac{t^2}{2n} \right)^{\frac{2n}{\frac{t^2}{2}}} \left(\frac{t^2}{2} \right)$$

$\rightarrow e$

$$= \exp \left(-\frac{t^2}{2} \right) \quad \text{... } N(0,1) \text{ 的 Moment Generating Function}$$

根據 Levy 的連續性定理,

$$\lim_n M_{nn}(t) = \exp \left(-\frac{t^2}{2} \right) \Rightarrow W_n \xrightarrow{d} N(0,1)$$

$$\textcircled{1} \quad \sqrt{V[X_i]} < \infty$$

利用中央極限定理, $\sqrt{n} \left(\frac{X_1 + \dots + X_n}{n} \right) \xrightarrow{d} N(0, \frac{\sigma^2}{n})$

$\Rightarrow \sqrt{n} \left(\frac{\bar{X}}{\sqrt{V[X_i]}} \right) \xrightarrow{d} N(0, 1)$ (得到相同的結論)

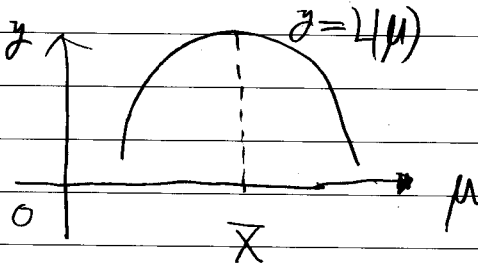
$$\textcircled{8} X_1, X_2, \dots, X_n \overset{\text{i.i.d.}}{\sim} N(\mu, 1)$$

$$(a) \prod_{j=1}^n f(x_j | \mu) = \prod_{j=1}^n \left(\frac{1}{\sqrt{2\pi}} \right) \cdot \exp\left(-\frac{1}{2}(x_j - \mu)^2\right)$$

$$\ell(\mu) = \ln \prod_{j=1}^n f(x_j | \mu) = \sum_{j=1}^n \frac{1}{2} \ln(2\pi) - \frac{1}{2} \sum_{j=1}^n (x_j - \mu)^2$$

$$\ell'(\mu) = \sum_{j=1}^n (x_j - \mu) = n(\bar{x} - \mu)$$

$$\ell''(\mu) = -n < 0$$



$$\begin{cases} \textcircled{1} \text{ if } \bar{x} \leq 1 & \hat{\mu}_{MLE} = \bar{x} \\ \textcircled{2} \text{ if } \bar{x} > 1 & \hat{\mu}_{MLE} = 1 \end{cases}$$

$$\therefore \hat{\mu}_{MLE} = \max\{\bar{x}, 1\}$$

(b) 考慮 $\sqrt{n}(\hat{\mu}_{MLE} - \mu)$ 之累積分布函數

$$Pr(\sqrt{n}(\hat{\mu}_{MLE} - \mu) \leq \lambda)$$

$$= Pr(\hat{\mu}_{MLE} \leq \mu + \frac{\lambda}{\sqrt{n}})$$

$$= Pr(\bar{x}, 1 \leq \mu + \frac{\lambda}{\sqrt{n}})$$

$$\Pr(\sqrt{n}(\bar{X} - \mu) \leq \lambda) \cdot I(1 \leq \mu + \frac{\lambda}{\sqrt{n}})$$

$$= \Phi(x) \cdot I[\sqrt{n}(\mu - 1), \infty)(x)$$

題目有錯, " $\mu > 0$ " 應為 " $\mu > 1$ "

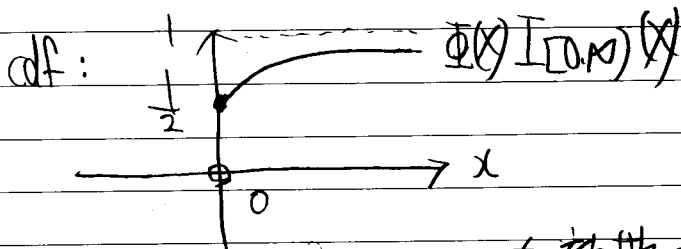
$$\mu > 1, n \rightarrow \infty \quad \sqrt{n}(\mu - 1) \rightarrow -\infty$$

$$\begin{aligned} \lim_{n \rightarrow \infty} \Pr(\sqrt{n}(\hat{\mu}_{MLE} - \mu) \leq \lambda) &= \lim_{n \rightarrow \infty} \Phi(x) I[\sqrt{n}(\mu - 1), \infty)(x) \\ &= \Phi(x) I(-\infty, \infty)(x) = \Phi(x) \end{aligned}$$

$$\therefore \mu > 1 \dots \sqrt{n}(\hat{\mu}_{MLE} - \mu) \xrightarrow{d} N(0, 1)$$

(c) 題目有錯, " $\mu = 0$ " 應為 " $\mu = 1$ "

$$\Pr(\sqrt{n}(\hat{\mu}_{MLE} - \mu) \leq \lambda) = \Phi(x) \cdot I[0, \infty)(x) \quad (\text{for all } n)$$



... 有離散的部分

$$\begin{cases} \Pr(\sqrt{n}(\hat{\mu}_{MLE} - \mu) = 0) = \frac{1}{2} \\ \Pr(\sqrt{n}(\hat{\mu}_{MLE} - \mu) \leq \lambda) = \Phi(x) \quad (x > 0) \end{cases} \quad (\text{for all } n \geq 1)$$

9

$$(a) \Pr(T \leq t) = \begin{cases} 0 & t < 0 \\ \left(\frac{t}{\theta}\right)^2 & 0 < t < \theta \\ 1 & t \geq \theta \end{cases}$$

$$\frac{d}{dt} \Pr(T \leq t) = \frac{2t}{\theta^2} \cdot I_{(0, \theta)}(t)$$

$$\therefore f_T(t) = \frac{2t}{\theta^2} I_{(0, \theta)}(t)$$

$$f_{X_1, X_2, T}(x_1, x_2, t) = \frac{1}{\theta^2} \cdot I_{(0, t)}(x_2) \cdot I_{(t, \theta)}(x_1) \\ + \frac{1}{\theta^2} I_{(0, t)}(x_1) I_{(t, \theta)}(x_2)$$

$$\therefore f_{X_1, X_2 | T}(x_1, x_2 | T=t) = \frac{f_{X_1, X_2, T}(x_1, x_2, t)}{f_T(t)}$$

$$= \frac{\frac{1}{\theta^2} \left\{ I_{(0, t)}(x_2) I_{(t, \theta)}(x_1) + I_{(0, t)}(x_1) I_{(t, \theta)}(x_2) \right\}}{\frac{2t}{\theta^2} I_{(0, \theta)}(t)}$$

($0 < t < \theta$ 滿足)

$$= \frac{1}{2t} \left\{ I_{(0, t)}(x_2) I_{(t, \theta)}(x_1) + I_{(0, t)}(x_1) I_{(t, \theta)}(x_2) \right\}$$

(b) 求 θ 之最小充份統計量

$(X_1, X_2) \neq (Y_1, Y_2)$ 之下

$$\frac{f_{X_1, X_2}(X_1, X_2)}{f_{Y_1, Y_2}(Y_1, Y_2)} \text{ 與 } \theta \text{ 無關} \Rightarrow \frac{\frac{1}{\theta^2} \cdot I(0, \theta)(\max\{X_1, X_2\})}{\frac{1}{\theta^2} \cdot I(0, \theta)(\max\{Y_1, Y_2\})}$$

$$= \frac{I(0, \theta)(\max\{X_1, X_2\})}{I(0, \theta)(\max\{Y_1, Y_2\})} \text{ 與 } \theta \text{ 無關}$$

$\Rightarrow \max\{X_1, X_2\} = \max\{Y_1, Y_2\}$ 為必要條件。

相反地, $\max\{X_1, X_2\} = \max\{Y_1, Y_2\} \Rightarrow \frac{f_{X_1, X_2}(X_1, X_2)}{f_{Y_1, Y_2}(Y_1, Y_2)} \text{ 與 } \theta \text{ 無關}$

$\therefore \max\{X_1, X_2\}$ 為 θ 之最小充份統計量。

我們無法由 $X_1 + X_2$ 得到 $\max\{X_1, X_2\}$ 。

$\therefore X_1 + X_2$ 並非充份統計量。

10 $X_1, X_2, \dots, X_n \sim f(x|\theta) = \theta x^{\theta-1} I_{(0,1)}(x)$

(a) $\int_0^1 \theta x^{\theta-1} dx = 1 = \int_{-\infty}^0 \theta (e^{-y})^{\theta-1} \cdot (-e^{-y}) dy$

$$\begin{cases} y = -\ln x \Leftrightarrow x = e^{-y} \\ \frac{dx}{dy} = -e^{-y} \end{cases}$$

$$= \int_0^{\infty} \theta e^{-\theta y} \cdot e^{-y} dy = \int_0^{\infty} \theta e^{-\theta y} dy$$

由此可知, $Y \sim \exp(\theta)$ (mean: $\frac{1}{\theta}$)

(b) $VLT \geq \frac{(\tau'(\theta))^2}{I_n(\theta)}$ Cramer Rao's Lower Bound

(τ 為 $\tau(\theta)$ 之 unbiased 估計量)

$$I_n(\theta) = E \left[\left(\frac{\partial}{\partial \theta} \ln f(X|\theta) \right)^2 \right]$$

$$= -E \left[\frac{\partial}{\partial \theta} \ln f(X|\theta) \right] = -E \left[\frac{\partial}{\partial \theta} ((\theta-1)\ln X + \ln \theta) \right]$$

$$= -E \left[\frac{1}{\theta^2} \right] = \frac{1}{\theta^2}$$

$$\therefore I_n(\theta) = \frac{n}{\theta^2} \quad \therefore VLT \geq \frac{\theta^2 \cdot (\tau'(\theta))^2}{n}$$

Cramer-Rao's Lower Bound

$$= \frac{\sigma^2 \cdot (t'(\theta))^2}{n} \quad t'(\theta) = \frac{1}{\theta} \Rightarrow \frac{1}{n\theta^2}$$

(c) $Y_i = -\ln X_i \sim \text{exp}(\theta)$ (mean $\frac{1}{\theta}$; var $\frac{1}{\theta^2}$)

$$\Rightarrow E\left[\frac{Y_1 + Y_2 + \dots + Y_n}{n}\right] = \frac{1}{\theta} \quad \dots \text{不偏估計量}$$

$$V\left[\frac{Y_1 + Y_2 + \dots + Y_n}{n}\right] = \frac{1}{n\theta^2} \quad (\because V[X_i] = \frac{1}{\theta^2})$$

↳ 達到 Cramer Rao's Lower Bound.

$\therefore \sum_{j=1}^n \frac{-\ln X_j}{n}$ 為 $\frac{1}{\theta}$ 之有效估計量

\Rightarrow UMVUE

□ MLE 的不變性:

$$(a) L(\theta) = \prod_{j=1}^n f_{\theta}(x_j)$$

$$\hat{\theta}_{MLE} = \underset{\theta \in \Theta}{\operatorname{argmax}} L(\theta) \quad \dots \textcircled{*}$$

($\theta \in \Theta$ 使得 $L(\theta)$ 最大)

$g(\theta)$ 為嚴格遞增函數, g : 一對一函數

$$\therefore \eta = g(\theta) \Leftrightarrow \theta = g^{-1}(\eta)$$

$$\begin{aligned} \hat{\eta}_{MLE} &= \underset{\eta}{\operatorname{argmax}} L \\ &= \underset{\eta \in g(\Theta)}{\operatorname{argmax}} L(g^{-1}(\eta)) \end{aligned} \quad \textcircled{**} \quad \{g(\theta) = \{g(\theta) \mid \theta \in \Theta\}\}$$

根據 $\textcircled{*}$, $g^{-1}(\eta) = \hat{\theta}_{MLE}$ 使得 $L(g^{-1}(\eta))$ 最大

$$\therefore g^{-1}(\eta) = \hat{\theta}_{MLE} \Leftrightarrow \underset{\eta}{g \circ g^{-1}(\eta)} = g(\hat{\theta}_{MLE})$$

$$\therefore \hat{\eta}_{MLE} = g(\hat{\theta}_{MLE})$$

(b) 接著考慮 g 不定為一對一函數的狀況。

$$\hat{\eta}_{MLE} = \underset{\eta}{\operatorname{argmax}} L(\theta) = \underset{\eta}{\operatorname{argmax}} L(\beta)$$

$(\cdot \eta = g(\theta))$ $\left\{ \begin{array}{l} \cdot \eta \in g(\Theta) \\ \cdot \beta \in g^{-1}(\eta) \cap \Theta = \Theta \end{array} \right.$

$\beta = \hat{\theta}_{MLE}$ 使得 L 最大。 ($\beta \in \Theta$ 。 \therefore 至少存在一個 $\hat{\theta}_{MLE}$)

假設 $\hat{\theta}_{MLE1}$ 和 $\hat{\theta}_{MLE2}$ 皆使得 L 最大。

$$\{\hat{\theta}_{MLE1}, \hat{\theta}_{MLE2}\} \subseteq g^{-1}(\hat{\eta}_{MLE})$$

$$\hat{\theta}_{MLE1}, \hat{\theta}_{MLE2} \text{ 皆 } g(\hat{\theta}_{MLE1}) = g(\hat{\theta}_{MLE2})。$$

$$\therefore \hat{\eta}_{MLE} = g(\hat{\theta}_{MLE1}) = g(\hat{\theta}_{MLE2})$$

\therefore 我們不妨將 $g(\hat{\theta}_{MLE})$ 視為 $g(\theta)$ 之 MLE。

$$\boxed{2} \quad n=5$$

(a) 求最強檢定 \Rightarrow 檢定力最大 \Rightarrow 犯下型 II 錯誤

之機率最低 $\Rightarrow \alpha + \beta$ 最小 ($\alpha=0.05$ 固定的情況下)

\therefore 利用 Neyman-Pearson's lemma

$$\Lambda = \frac{f(x_1, \dots, x_n | \lambda=1)}{f(x_1, \dots, x_n | \lambda=2)} = \frac{x_1 \exp(-x_1) \cdot x_2 \exp(-x_2) \cdots x_n \exp(-x_n)}{4^n \exp(-2x_1) \cdots \exp(-2x_n)}$$

$$= \left(\frac{1}{4}\right)^n \exp(-(x_1 + \dots + x_n)) \geq k$$

充分統計量 $X_{1+n} + X_n$ 增加 $\Rightarrow \Lambda$: 增加

檢定函數: $\phi(X) = \begin{cases} 1 & \text{if } X_{1+n} + X_n \geq c: \text{ 常數} \\ 0 & \text{else} \end{cases}$

$$E[\phi(X) | \lambda=2] = 0.05 \quad (\because \text{Type I error})$$

$$\lambda=2 \Rightarrow X_i \sim \Gamma(2, \frac{1}{2}) \quad (\text{mean: } 1)$$

$$X_{1+n}, X_n \sim \Gamma(2n, \frac{1}{2})$$

$$4(X_{1+n} + X_n) \sim \Gamma(2n, 2) = \chi^2(4n)$$

$$P_r(X_{1+n} + X_n \geq c | \lambda=2)$$

$$= P_r(W \geq 4c) = 0.05$$

$$4C = \sqrt[4]{4n} (0.95) \quad \sqrt[4]{4n} \dots \sqrt[4]{4n} \bar{x} \text{ cdf.}$$

$$\therefore C = \frac{1}{4} \sqrt[4]{4n} (0.95)$$

$$\therefore \phi(x) = \begin{cases} 1 & : X_1 + X_2 + \dots + X_n \geq \frac{1}{4} \sqrt[4]{4n} (0.95) \\ 0 & : \text{otherwise} \end{cases}$$

$$(b) \text{ 檢定力} = E[\phi(x) | \lambda=1]$$

$$= P(X_1 + X_2 + \dots + X_n \geq \frac{1}{4} \sqrt[4]{4n} (0.95) | \lambda=1)$$

利用中央極限定理: $\lambda=1$ 下, $X_1 \sim X_n \sim P(2,1)$

$$E[X_i] = 2 \quad V[X_i] = 2 < \infty$$

$$\sqrt{n} \left(\frac{\bar{X} - 2}{\sqrt{2}} \right) \xrightarrow{d} N(0,1)$$

$$P(X_1 + \dots + X_n \geq C | \lambda=1)$$

$$= P(\bar{X} \geq \frac{C}{n} | \lambda=1) = P(\bar{X} - 2 \geq \frac{C}{n} - 2 | \lambda=1)$$

$$= P\left(\frac{\sqrt{n}}{\sqrt{2}} (\bar{X} - 2) \geq \frac{\sqrt{n}}{\sqrt{2}} \left(\frac{C}{n} - 2 \right) | \lambda=1 \right)$$

$$= 1 - \Phi\left(\frac{\sqrt{n}}{\sqrt{2}} \left(\frac{C}{n} - 2 \right) \right) \quad \text{where } C = \frac{1}{4} \sqrt[4]{4n} (0.95)$$

⊕ (a), (b)

$$n=5 \dots C = \frac{1}{4} \sqrt{20} (0.95) = \frac{1}{4} \cdot (31.4104) = 7.8526$$

$$\therefore \text{MP-test} = \phi(X) = \begin{cases} 1 & \dots X_1 + X_2 + \dots + X_n \geq 7.8526 \\ 0 & \dots \text{else} \end{cases}$$

$$n=5 \dots 1 - \Phi\left(\frac{\sqrt{n}}{\sqrt{2}}\left(\frac{C}{n} - 2\right)\right) = 1 - \Phi\left(\sqrt{2.5}\left(\frac{7.8526}{5} - 2\right)\right)$$

$$= 1 - \Phi(-0.6791) = \Phi(0.6791) \approx \Phi(0.68)$$

$$\approx 0.7517 \dots \quad \bullet \text{ power} \approx 0.7517$$

cc) YES.

考慮 $H_0: \lambda = 2$ vs $H_1: \lambda = \lambda_1$

($\lambda_1 < 2$)

$$\Lambda = \frac{\lambda_1^2 x_1 \exp(-\lambda_1 x_1) \dots \lambda_1^2 x_n \exp(-\lambda_1 x_n)}{4 x_1 \exp(-2x_1) \dots 4 x_n \exp(-2x_n)}$$

$$= \left(\frac{\lambda_1^2}{4}\right)^n \exp\left(\underbrace{(2-\lambda_1)}_{>0} (x_1 + \dots + x_n)\right)$$

\therefore 充分統計量 $X_1 + X_2 + \dots + X_n$: 增加 $\Rightarrow \Lambda$: 增加

$$\alpha = 0.05 \text{ 天下}$$

跟 (a) 同理, \checkmark MP 檢定 $\phi(X) = \begin{cases} 1 & : X_1 + X_2 + \dots + X_n \geq c \\ 0 & : \text{else} \end{cases}$

$$c = \frac{1}{n} \chi_{4n}^2(0.95)$$

由此可知 $\forall \lambda < 2$, $\phi(X)$ 均為最強檢定.

$$\{\lambda \mid \lambda < 1\} \subseteq \{\lambda \mid \lambda < 2\}$$

故此, 對於 $H_0: \lambda = 2$ vs $H_1: \lambda < 1$, $\phi(X)$ 為
均勻最強檢定. (UMP-test)

3

(a) p : 發生副作用之機率

(b) 我們欲得到的結論為 $p < 0.15$.

(\therefore 我們希望新藥可以通過測試, 所以
想要否定 $p \geq 0.15$)

故此, $H_0: p \geq 0.15$ vs $H_1: p < 0.15$.

我們先考慮對 $H_0: p = p_0$ vs $H_1: p = p_1$ ($p_0 > p_1$)

之最強力檢定. (利用 Neyman-Pearson's Lemma)

$X_j = \begin{cases} 1 & \dots \text{第 } j \text{ 個人發生副作用} \\ 0 & \dots \text{未發生} \end{cases}$

($j=1, \dots, n$) ($n=400$)

$$\Lambda = \frac{P(X_1=x_1, \dots, X_n=x_n | p_1)}{P(X_1=x_1, \dots, X_n=x_n | p_0)}$$

$$= \frac{p_1^{(x_1+\dots+x_n)} (1-p_1)^{n-(x_1+\dots+x_n)}}{p_0^{(x_1+\dots+x_n)} (1-p_0)^{n-(x_1+\dots+x_n)}}$$

$$= \frac{p_1^{(x_1+\dots+x_n)} (1-p_1)^{n-(x_1+\dots+x_n)}}{p_0^{(x_1+\dots+x_n)} (1-p_0)^{n-(x_1+\dots+x_n)}}$$

$$= \left(\frac{1-p_1}{1-p_0} \right)^n \cdot \left(\frac{\left(\frac{p_1}{1-p_1} \right)^{(x_1+\dots+x_n)}}{\left(\frac{p_0}{1-p_0} \right)^{(x_1+\dots+x_n)}} \right)$$

$$g(p) \stackrel{\text{def}}{=} \frac{p}{1-p} \quad (0 < p < 1) \dots \text{遞增函數}$$

$$g(p_0) > g(p_1) \quad \Rightarrow \quad \frac{g(p_1)}{g(p_0)} < 1$$

$$\Lambda = \left(\frac{1-p_1}{1-p_0} \right)^n \underbrace{\left(\frac{g(p_1)}{g(p_0)} \right)^{(X_1+X_2+\dots+X_n)}}_{< 1} > k \Rightarrow \text{棄却}$$

\therefore 充分統計量 $X_1+X_2+\dots+X_n$: 增加 $p_0 \Rightarrow \Lambda$: 減少

$$\therefore \text{最強檢定 } \varphi(X) = \begin{cases} 1 & : X_1+\dots+X_n < C \\ r & : X_1+\dots+X_n = C \quad (\text{隨機化}) \\ 0 & : X_1+\dots+X_n > C \end{cases}$$

$$(E[\varphi(X) | p_0] = \alpha)$$

接著考慮隨機化檢定 $\varphi^* = \begin{cases} 1 & \text{(with probability } \alpha) \\ 0 & \text{(1-}\alpha) \end{cases}$

由於 $\varphi(X)$ 為最強檢定，故滿足：

$$E[\varphi(X) | p_1] \geq E[\varphi^*(X) | p_1] = \alpha = E[\varphi(X) | p_0]$$

由此可知， $\forall p_0, p_1$
($p_0 < p_1$) $\beta_{\varphi}(p_0) \leq \beta_{\varphi}(p_1) \dots \otimes$

根據先前的討論, 對於 $H_0: p = p_0 = 0.15$

vs $H_1: p = p_1 (< 0.15)$ 顯著水準 α 下的

最強檢定亦為 對於 $H_0: p \geq 0.15$

vs $H_1: p < 0.15$ 顯著水準 α 下的 均勻最強檢定.

• $\beta_\phi(p)$ 為遞減函數, 故 $\sup_{p \geq 0.15} \beta_\phi(p) = \beta_\phi(0.15)$

\Rightarrow 顯著水準不變.

• $\forall p_1 > p_0 = 0.15$ 滿足 $\beta_\phi(p_1) \geq \beta_{\phi^*}(p_1)$

(β_{ϕ^*} 為任意顯著水準 α 的檢定 π 檢定)

(\therefore 對立假設變成 $H_0: p < 0.15$, ϕ 依然為最強 (for all $p < 0.15$))

接著求 C 使得 $E[\phi(X) | p = 0.15] = \alpha$

$$= P(X_1 + X_2 + \dots + X_n \leq C | p = 0.15) = \alpha$$

利用中央極限定理. ($n = 400, p = 0.15$)

$$\frac{X_1 + X_2 + \dots + X_n}{n} \xrightarrow{d} N(p, \frac{p(1-p)}{n})$$

$$Z \stackrel{\text{def}}{=} \frac{\sqrt{400}(\bar{X} - 0.15)}{\sqrt{0.85}\sqrt{0.15}} \quad P(Z \leq \frac{\sqrt{400}(\frac{c}{n} - 0.15)}{\sqrt{0.85}\sqrt{0.15}}) = \alpha$$

(n=400)

$$\therefore C = 60 + 20\sqrt{0.85}\sqrt{0.15} \cdot \Phi^{-1}(\alpha)$$

$$\therefore \varphi(X) = \begin{cases} 1 & \dots \text{ if } X_1 + X_2 + \dots + X_{400} \leq 60 + 20\sqrt{0.85}\sqrt{0.15} \cdot \Phi^{-1}(\alpha) \\ 0 & \dots \text{ otherwise.} \end{cases}$$

為對 $H_0: p \geq 0.15$ vs $H_1: p < 0.15$ 之 UMP 檢定.

$$(c) P(X_1 + X_2 + \dots + X_{400} \leq 80 \mid p = 0.15) = P(Z \leq \frac{1}{\sqrt{0.85}\sqrt{0.15}})$$

$$\therefore \text{p值} = \Phi\left(\frac{1}{\sqrt{0.85}\sqrt{0.15}}\right)$$

(d) $\alpha = 0.05$ 時...

$$\varphi(X) = \begin{cases} 1 & \text{if } X_1 + X_2 + \dots + X_{400} \leq 71.74 \\ 0 & \text{else} \end{cases}$$

$$X_1 + X_2 + \dots + X_{400} = 80 \Rightarrow \varphi(X) = 0$$

\therefore 不棄卻 H_0 :

4 利用 χ^2 -test.

H_0 : 資料服從 Poisson 分佈

H_1 : 資料不服從 Poisson 分佈

$$\text{檢定統計量} = \sum_{i=0}^k \frac{(E_i - O_i)^2}{E_i}$$

H_0 下的分佈... χ^2_{k-1}

$$(\because \text{自由度} = (k - 0 + 1) - 1)$$

估計的參數的個數
(X)

① 求 λ 的 MLE

$$\begin{aligned} \hat{\lambda}_{MLE} = \bar{X} &= \frac{0.229 + 1.211 + 2.93 + 3.35 + 4.7 + 5.1}{576} \\ &= \frac{211 + 186 + 105 + 28 + 5}{576} \\ &= \frac{535}{576} = 0.9288 \end{aligned}$$

$$\textcircled{2} E_i = 576 \cdot P(X_i = i) \quad (i=0 \sim 4)$$

$$E_i = 576 \cdot P(X_i \geq i) \quad (i=5)$$

$$(\because k=5)$$

$$E_0 = 227.5314$$

$$E_1 = 211.3356$$

$$E_2 = 98.1463$$

$$E_3 = 30.3867$$

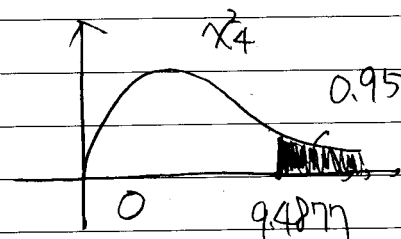
$$E_4 = 7.0559$$

$$E_5 = 1.5441$$

$$\textcircled{3} \text{ 檢定統計量 } T = \sum_{i=0}^k \frac{(E_i - O_i)^2}{E_i}$$

$$= 0.9807$$

$T \sim \chi^2_4$



$$0.9807 \ll 9.4877$$

∴ 不棄卻 H_0

(無法否定資料服從 Poisson 分佈)

5 假設資料服從常態分佈且舊的壽命與新的壽命之變異數是共同的。

$$\therefore X_1 \sim X_n \sim N(\mu, 1.1^2) \quad (\text{新的壽命之資料})$$

我們欲檢定 $H_0: \mu = 4.2$ vs $H_1: \mu > 4.2$

我們先利用 Neyman-Pearson's lemma 來求

對於 $H_0: \mu = \mu_0 = 4.2$ vs $H_1: \mu = \mu_1$ ($\mu_1 > \mu_0$)

之最強檢定。

$$\Lambda(X) \stackrel{\text{def}}{=} \frac{f(X|\mu_1)}{f(X|\mu_0)} = \frac{\left(\frac{1}{\sqrt{2\pi}}\right)^n \exp\left(-\frac{1}{2\sigma^2} \sum_{i=1}^n (X_i - \mu_1)^2\right)}{\left(\frac{1}{\sqrt{2\pi}}\right)^n \exp\left(-\frac{1}{2\sigma^2} \sum_{i=1}^n (X_i - \mu_0)^2\right)}$$

(註: $\sigma^2 = 1.1^2$; $n = 80$)

$$= \exp\left(\frac{1}{\sigma^2} \underbrace{(\mu_1 - \mu_0)}_{> 0} (X_1 + X_2 + \dots + X_n) - \frac{n\mu_1^2}{2\sigma^2} + \frac{n\mu_0^2}{2\sigma^2}\right)$$

$X_1 + X_2 + \dots + X_n \dots$ μ 之充分統計量

$X_1 + X_2 + \dots + X_n$: 增加 $\Leftrightarrow \Lambda$: 增加

$$\therefore \phi(X) = \begin{cases} 1 & \text{if } X_1 + X_2 + \dots + X_n \geq c \\ 0 & \text{else} \end{cases}$$

設顯著水準為 α , $E[\varphi(X) | \mu = \mu_0] = \alpha$

$$\mu = \mu_0 \Rightarrow \sqrt{n} \left(\frac{\bar{X} - \mu_0}{\sigma} \right) \sim N(0,1)$$

$$Pr \left(\frac{\sqrt{n}(\bar{X} - \mu_0)}{\sigma} \geq \frac{\sqrt{n}(c/n - \mu_0)}{\sigma} \right) = 1 - \Phi \left(\frac{\sqrt{n}(c/n - \mu_0)}{\sigma} \right) = \alpha$$

$$\Rightarrow \frac{\sqrt{n}}{\sigma} \left(\frac{c}{n} - \mu_0 \right) = \Phi^{-1}(1 - \alpha)$$

$$\Rightarrow \frac{c}{n} - \mu_0 = \frac{\sigma}{\sqrt{n}} \Phi^{-1}(1 - \alpha) \quad \therefore c = n\mu_0 + \sigma\sqrt{n} \Phi^{-1}(1 - \alpha)$$

$$\therefore \varphi(X) = \begin{cases} 1 & : \text{if } \bar{X} \geq \mu_0 + \frac{\sigma}{\sqrt{n}} \Phi^{-1}(1 - \alpha) \\ 0 & : \text{else} \end{cases}$$

$\forall \mu > \mu_0$, $\varphi(X)$ 均為顯著水準 α 下的最強檢定

對於 $H_0: \mu = \mu_0 = 4.2$ vs $H_1: \mu > \mu_0$,

$\varphi(X)$ 為顯著水準 α 下的均勻最強檢定

$$C_\alpha = \left\{ (X_1, \dots, X_n) \mid \bar{X} \geq \mu_0 + \frac{\sigma}{\sqrt{n}} \Phi^{-1}(1 - \alpha) \right\}$$

$$p\text{-value} = \inf_{\alpha} (X_1, \dots, X_n) \mid \bar{X} = 4.5 \in C_\alpha$$

$$4.5 = 4.2 + \frac{1.1}{\sqrt{20}} \Phi^{-1}(1 - \alpha) \Rightarrow \Phi^{-1}(1 - \alpha) = 2.44$$

$$\Rightarrow 1 - \alpha = 0.9921 \Rightarrow \alpha = 0.0079 \quad \therefore p\text{-value} = 0.0079$$

由於 $p\text{-value}$ 很小, 故棄 H_0 .

6

{ 虛無假設... 試者推翻的假設
 { 對立假設... 試者證明的假設
 (具顛倒性的假設)

在信任員工的情況下, 「某某侵占公款」
 被視為比「某某並未侵占公款」(=無辜)
 更具顛倒性的消息。

故此, $\begin{cases} H_0: \text{○○無辜的} \\ H_1: \text{○○是兇手} \end{cases}$

(a) 型 I 錯誤

雖然 H_0 為真, 卻棄卻 H_0 的錯誤

⊆ 冤枉無辜店員的錯誤

(b) 型II錯誤

雖然 H_0 為真, 卻未察知 H_0 之錯誤

↳ 放過兇手的錯誤.

* 犯下型I錯誤通常比較嚴重.

• 照這個案例來說, 在信任自己員工的情況下, 你會覺得冤枉無辜的員工是一個很嚴重的錯誤。(比放過兇手更嚴重)

• 相反地, 如果你不信任自己員工的話,

H_0 跟 H_1 會顛倒. (H_0 : OO 是兇手; H_1 : OO 無辜)

在這種情況下, 保護公司資產比員工名譽

更重要, 所以你會認為放過兇手 (= 型I錯誤)

比較嚴重.

⇒ 無論 H_0, H_1 為何, 犯下型I錯誤比較嚴重.

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$$(a) \Phi_n(\theta) = \frac{1}{\theta} - \bar{X} = 0 \Leftrightarrow \theta = \frac{1}{\bar{X}} \quad (X_i > 0)$$

$$(b) X_i \sim \text{exp}(\theta) \quad (\text{mean } \frac{1}{\theta})$$

$$Y_i \stackrel{\text{def}}{=} \frac{1}{\theta} - X_i \dots \quad (\text{mean } 0)$$

$$\text{根據弱大數法則} \quad \frac{Y_1 + Y_2 + \dots + Y_n}{n} \xrightarrow{P} 0$$

$$\therefore \frac{1}{\theta} - \bar{X} \xrightarrow{P} 0$$

$$\therefore \Phi_n(\theta) \xrightarrow{P} 0$$

$$(c) \hat{\theta}_n = \frac{1}{\bar{X}}$$

$$g(t) = \frac{1}{t} \quad (t > 0) \text{ 為連續函數}$$

$$\text{根據弱大數法則, } \bar{X} \xrightarrow{P} \theta.$$

$$g(\bar{X}) \xrightarrow{P} g(\theta) \quad \therefore \frac{1}{\bar{X}} \xrightarrow{P} \frac{1}{\theta}$$

(d) 根據中央極限定理,

$$\sqrt{n}(\bar{X} - \frac{1}{\theta}) \xrightarrow{d} N(0, \frac{1}{\theta^2})$$

利用 Δ -method...

$$\sqrt{n}(g(\bar{X}) - g(\frac{1}{\theta})) \xrightarrow{d} N(0, \frac{1}{\theta^2} (g'(\frac{1}{\theta}))^2)$$

$$\approx \sqrt{n} \left(\frac{1}{\bar{x}} - \theta \right) \stackrel{d}{\rightarrow} N(0, \theta^2) \quad (\theta > 0)$$

$$(e) \quad L(\theta | X) = \prod_{j=1}^n f(x_j | \theta) = \theta^n \exp(-\theta(x_1 + x_2 + \dots + x_n))$$

$$\log L(\theta | X) = n \log \theta - \theta(x_1 + x_2 + \dots + x_n) = 0$$

$$\frac{\partial}{\partial \theta} \log L(\theta | X) = \frac{n}{\theta} - (x_1 + \dots + x_n) = 0 \quad \therefore \hat{\theta}_{MLE} = \frac{1}{\bar{x}}$$

($\hat{\theta}_{MLE}$ 使得 L 最大)

$$\hat{\theta}_{MLE} = \hat{\theta}_n$$

$$\text{根據 (d)} \quad \sqrt{n}(\hat{\theta}_{MLE} - \theta) \stackrel{d}{\rightarrow} N(0, \theta^2) = N(0, I(\theta)^{-1})$$

$$\therefore I(\theta) = \frac{1}{\theta^2} \quad (\text{觀測到一個樣本時得到的 Fisher 資訊量})$$

$$\boxed{8} \quad X_1, X_2, \dots, X_n \sim P_0(\theta) \quad (\theta > 0)$$

$$n\bar{X} = X_1 + X_2 + \dots + X_n \sim P_0(n\theta)$$

$$Y \stackrel{\text{def}}{=} X_1 + X_2 + \dots + X_n$$

$$E\left[\left(1 - \frac{a}{n}\right)^Y\right] = \sum_{y=0}^{\infty} \left(1 - \frac{a}{n}\right)^y \cdot e^{-n\theta} \cdot \frac{(n\theta)^y}{y!}$$

$$= e^{-n\theta} \sum_{y=0}^{\infty} \frac{(n\theta - a\theta)^y}{y!} = e^{-n\theta} \sum_{y=0}^{\infty} \frac{(\theta(n-a))^y}{y!}$$

$$= e^{-n\theta} \exp(\theta(n-a)) = \exp(-a\theta)$$

由此可知 $\left(1 - \frac{a}{n}\right)^Y$ 為 $\exp(-a\theta)$ 之 unbiased 估計量

$$\therefore \text{MSE}\left(\left(1 - \frac{a}{n}\right)^Y; \exp(-a\theta)\right) = V\left[\left(1 - \frac{a}{n}\right)^Y\right]$$

$$= E\left[\left(1 - \frac{a}{n}\right)^{2Y}\right] - \underbrace{E\left[\left(1 - \frac{a}{n}\right)^Y\right]^2}_{\exp(-2a\theta)}$$

$$\sum_{y=0}^{\infty} \left(1 - \frac{a}{n}\right)^{2y} \cdot e^{-n\theta} \cdot \frac{(n\theta)^y}{y!}$$

$$= e^{-n\theta} \sum_{y=0}^{\infty} \left(1 - \frac{2a}{n} + \frac{a^2}{n^2}\right)^y \cdot (n\theta)^y \cdot \frac{1}{y!}$$

$$= e^{-n\theta} \sum_{y=0}^{\infty} \left\{ \left(n - 2a + \frac{a^2}{n}\right) \theta \right\}^y \cdot \frac{1}{y!}$$

$$= e^{-n\theta} \cdot \exp\left(n\theta - 2n\theta + \frac{a^2\theta}{n}\right) = \exp\left(-2n\theta + \frac{a^2\theta}{n}\right)$$

$$\left\{ \begin{array}{l} \therefore \text{Var}\left[\left(1 - \frac{a}{n}\right)^X\right] = \exp\left(-2n\theta + \frac{a^2\theta}{n}\right) - \exp(-2n\theta) \\ \text{(MSE)} \\ \text{bias} = 0 \end{array} \right.$$

$$\boxed{9} \quad X_1, X_2, \dots, X_n \sim N(\theta, \theta)$$

$$(1) \quad X_1 + X_2 + \dots + X_n \sim N(n\theta, n\theta)$$

$$\bar{X} \sim N\left(\theta, \frac{\theta}{n}\right) \Rightarrow \frac{\sqrt{n}}{\sqrt{\theta}}(\bar{X} - \theta) \sim N(0, 1)$$

(2) 利用 d -method:

$$g(x) \stackrel{\text{def}}{=} \cos x$$

$$\frac{\sqrt{n}}{\sqrt{\theta}}(g(\bar{X}) - g(\theta)) \stackrel{d}{\rightarrow} N\left(0, \{g'(\theta)\}^2\right)$$

$$g'(x) = -\sin x \quad \{g'(x)\}^2 = \sin^2 x$$

$$\therefore \frac{\sqrt{n}}{\sqrt{\theta}}(\cos \bar{X} - \cos \theta) \stackrel{d}{\rightarrow} N(0, \sin^2 \theta)$$

$$\therefore \sqrt{n}(\cos \bar{X} - \cos \theta) \stackrel{d}{\rightarrow} N(0, \theta \sin^2 \theta)$$

若 $\theta = k\pi$ ($k=1, 2, 3, \dots$) 時, $\sqrt{n}(\cos \bar{X} - \cos \theta)$

之變異數為 0. \Rightarrow 退化.

$$\boxed{10} \quad X \sim N(\theta, 1)$$

$$H_0: \theta \in \Theta_0 = \{0\} \text{ vs } H_1: \theta \in \Theta_1 = \{1, -1\}$$

證明不存在UMP檢定

$$\text{先考慮 } \textcircled{1} \quad H_0: \theta = 0 \text{ vs } H_1: \theta = 1$$

$$\textcircled{2} \quad H_0: \theta = 0 \text{ vs } H_1: \theta = -1$$

① 利用 Neyman-Pearson's lemma:

$$\Lambda(X) = \frac{\prod_{j=1}^n f(x_j | \theta=1)}{\prod_{j=1}^n f(x_j | \theta=0)} = \frac{\left(\frac{1}{\sqrt{2\pi}}\right)^n \exp\left(-\frac{1}{2} \sum_{j=1}^n (x_j - 1)^2\right)}{\left(\frac{1}{\sqrt{2\pi}}\right)^n \exp\left(-\frac{1}{2} \sum_{j=1}^n (x_j)^2\right)}$$

$$= \exp\left(\sum_{j=1}^n x_j - \frac{n}{2}\right) \geq k_1 \Leftrightarrow \sum_{j=1}^n x_j \geq c_1$$

($\sum_{j=1}^n x_j$ 為 θ 之充分統計量)

$$\varphi_1(X) = \begin{cases} 1 & \dots \sum_{j=1}^n x_j \geq c_1 \\ 0 & \dots \text{elsewhere} \end{cases}$$

$$\text{顯著水準: } E[\varphi_1(X) | \theta=0] = \alpha$$

$$= 1 - \Phi\left(\frac{c_1}{\sqrt{n}}\right) \quad \therefore c_1 = \sqrt{n} \Phi^{-1}(1-\alpha)$$

$$\therefore \varphi_1(X) = \begin{cases} 1 & \dots \sum_{j=1}^n x_j \geq \sqrt{n} \Phi^{-1}(1-\alpha) \\ 0 & \dots \text{otherwise} \end{cases}$$

對

為 $H_0: \theta = 0$ vs $H_1: \theta = 1$ 之 MP 檢定.

$$\textcircled{2} H_0: \theta = 0 \text{ vs } H_1: \theta = 1$$

$$\text{同樣道理, } \varphi_2(X) = \begin{cases} 1 & \dots \sum_{j=1}^n X_j \leq \sqrt{n} \varphi_2^*(\alpha) \\ 0 & \dots \text{otherwise} \end{cases}$$

為 MP 檢定

$$\textcircled{3} \text{ 接著考慮對於 } H_0: \theta = 0 \text{ vs } H_1: \theta \in \{1, -1\} \text{ 之}$$

$$\text{UMP 檢定 } \varphi. \quad \left(\begin{array}{l} \beta_1(\theta) \stackrel{\text{def}}{=} E[\varphi_1 | \theta], \quad \beta_2(\theta) \stackrel{\text{def}}{=} E[\varphi_2 | \theta] \\ \beta(\theta) = E[\varphi | \theta] \end{array} \right)$$

$$\beta(\theta) = \max\{\beta_1(\theta), \beta_2(\theta)\} \quad (\forall \theta \in \{1, -1\})$$

$$\theta = 1 \text{ 時 } \beta(1) = \beta_1(1) \quad \therefore \varphi = \varphi_1$$

$$\theta = -1 \text{ 時 } \beta(-1) = \beta_2(-1) \quad \therefore \varphi = \varphi_2$$

\therefore 若存在 UMP 檢定, 則需滿足 $\varphi = \varphi_2$ (a.s.).

\therefore 但 $\varphi_1 \neq \varphi_2 \quad \therefore$ 不存在 UMP 檢定.



① 先考慮對 $H_0: \theta=0$ vs $H_1: \theta=1$ 之最強檢定
(顯著水準 α)

利用 Neyman Pearson's lemma:

$$\Lambda(X) = \frac{\prod_{j=1}^n f(x_j | \theta=1)}{\prod_{j=1}^n f(x_j | \theta=0)} = \exp\left((X_1 + X_2 + \dots + X_n) - \frac{n}{2}\right) \geq k_1$$

$$\phi_1(X) = \begin{cases} 1 & \dots \text{ if } X_1 + X_2 + \dots + X_n \geq C_1 \\ 0 & \dots \text{ else} \end{cases}$$

$$E[\phi_1(X) | \theta=0] = \alpha$$

||

$$1 - \Phi\left(\frac{C_1}{\sqrt{n}}\right) = \alpha \quad \therefore C_1 = \sqrt{n} \Phi^{-1}(1-\alpha)$$

$$\therefore \phi_1(X) = \begin{cases} 1 & X_1 + X_2 + \dots + X_n \geq \sqrt{n} \Phi^{-1}(1-\alpha) \\ 0 & \text{elsewhere} \end{cases}$$

② 接著考慮 $H_0: \theta=0$ vs $H_1: \theta=2$ 之情形。

$$\Lambda(X) = \frac{\prod_{j=1}^n f(x_j | \theta=2)}{\prod_{j=1}^n f(x_j | \theta=0)} \geq k_2$$

||

$$\exp\left(2(X_1 + X_2 + \dots + X_n) - 2n\right)$$

$$\therefore \phi_2(X) = \begin{cases} 1 & \text{if } X_1 + X_2 + \dots + X_n \geq C_2 \\ 0 & \text{else} \end{cases}$$

$$E[\phi_2(X) | \theta=0] = \alpha$$

$$\therefore C_2 = \sqrt{n} \Phi^{-1}(1-\alpha)$$

$$\phi_2(X) = \begin{cases} 1 & \text{if } X_1 + X_2 + \dots + X_n \geq \sqrt{n} \Phi^{-1}(1-\alpha) \\ 0 & \text{elsewhere} \end{cases}$$

由此可知 $\phi_1(X) = \phi_2(X)$.

故此無論 $\theta=1$ 還是 $\theta=2$, $\phi_1(X)$ ($\phi_2(X)$) 均擁有最大的檢定力。

$\therefore \phi_1(X)$ ($=\phi_2(X)$) 為對於 $H_0: \theta=0$ vs $H_1: \theta \in \{1, 2\}$ 顯著水準 α 下的均勻最強檢定。

(a) 題目應為 $l(\theta) - l(\theta_0)$ is increasing or decreasing

$$\boxed{12} \quad L \stackrel{\text{def}}{=} f(x|\theta) \quad l \stackrel{\text{def}}{=} \log L \quad (l = \ln f)$$

$$(a) \quad \log f(x|\theta) = \eta(\theta) Y(x) - \xi(\theta) + \log h(x) = l(\theta)$$

$$\frac{\partial}{\partial \theta} \log f(x|\theta) = \frac{\partial l}{\partial \theta} = \eta'(\theta) Y(x) - \xi'(\theta) = 0$$

$$\hat{\theta}_{MLE} (= \hat{\theta}(x)) \quad \text{滿足} \quad \eta(\hat{\theta}) Y(x) - \xi(\hat{\theta}) = 0.$$

$$\frac{d}{dY} (l(\hat{\theta}) - l(\theta_0)) = \frac{dY}{dY} \cdot \frac{d}{dY} (l(\hat{\theta}) - l(\theta_0))$$

$$\downarrow$$

$$(\eta(\hat{\theta}) Y(x) - \xi(\hat{\theta})) \quad \eta(\theta_0) Y(x) + \xi(\theta_0)$$

$$= \left(\frac{dY}{dY} \right)^T \cdot \left\{ \eta'(\hat{\theta}) \cdot \hat{\theta}(x) Y(x) + \eta(\hat{\theta}) Y'(x) - \xi'(\hat{\theta}) \cdot \hat{\theta}'(x) - \eta(\theta_0) Y'(x) \right\}$$

$$= \left(\frac{1}{Y'(x)} \right) \cdot \left\{ \hat{\theta}'(x) \underbrace{(\eta(\hat{\theta}) Y(x) - \xi(\hat{\theta}))}_0 + Y'(x) (\eta(\hat{\theta}) - \eta(\theta_0)) \right\}$$

$$= \eta(\hat{\theta}) - \eta(\theta_0)$$

由於 η 為遞增函數, 故 $\eta(\hat{\theta}) - \eta(\theta_0) \geq 0$ ($\hat{\theta} \geq \theta_0$)

$$\therefore \frac{d}{dY} (l(\hat{\theta}) - l(\theta_0)) \geq 0$$

由此可知 $l(\hat{\theta}) - l(\theta)$ is increasing in Y ($\hat{\theta} \geq \theta$)

\therefore 證明完成

(b) 在討論概似比檢定前, 我們有必要

證明 $\frac{d\theta}{d\eta} \geq 0$. (假設 $\frac{d\theta}{d\eta}$ 與 \int 可替換)

• 全機率 = 1 $\therefore \int_{\mathcal{R}} f(x|\theta) dx = 1$

$$\Rightarrow \int_{\mathcal{R}} \frac{d}{d\theta} f(x|\theta) dx = 0$$

$$\Rightarrow \int_{\mathcal{R}} (\eta'(\theta) Y(x) - \xi'(\theta)) f(x|\theta) dx = 0$$

由此可知 $E[Y(x)] = \frac{\xi'(\theta)}{\eta'(\theta)}$

• 同樣道理, $\int_{\mathcal{R}} \{ \eta''(\theta) Y(x) - \xi''(\theta) \} f(x|\theta) dx$

$$+ \int_{\mathcal{R}} (\eta'(\theta) Y(x) - \xi'(\theta))^2 f(x|\theta) dx = 0$$

$$\Rightarrow \eta''(\theta) \cdot \frac{\xi'(\theta)}{\eta'(\theta)} - \xi''(\theta) + \eta'(\theta)^2 E[Y(x)^2] - 2\eta'(\theta)\xi'(\theta) \frac{\xi'(\theta)}{\eta'(\theta)} + (\xi'(\theta))^2 = 0$$

$$\Leftrightarrow \eta''(\theta) \cdot \frac{\xi'(\theta)}{\eta'(\theta)} - \xi''(\theta) + \eta'(\theta)^2 E[Y^2] - (\xi'(\theta))^2 = 0$$

$$\Leftrightarrow \eta'(\theta)^2 E[Y^2] = \xi''(\theta) + (\xi'(\theta))^2 - \eta''(\theta) \cdot \frac{\xi'(\theta)}{\eta'(\theta)}$$

$$\therefore E[Y^2] = \frac{\xi''(\theta)}{\eta'(\theta)^2} + \underbrace{\left(\frac{\xi'(\theta)}{\eta'(\theta)} \right)^2}_{E[Y]^2} - \eta''(\theta) \cdot \frac{\xi'(\theta)}{\eta'(\theta)^3}$$

$$\begin{aligned} \therefore v[\tau] &= \frac{\zeta''(\theta)}{(\eta'(\theta))^2} - \eta''(\theta) \frac{\zeta'(\theta)}{\eta'(\theta)^3} \\ &= \frac{\zeta''(\theta)\eta'(\theta) - \eta''(\theta)\zeta'(\theta)}{(\eta'(\theta))^3} > 0 \end{aligned}$$

$\eta'(\theta) \geq 0$ ($\because \eta(\theta)$ 為 廣增函數)

$$\therefore \zeta''(\theta)\eta'(\theta) - \eta''(\theta)\zeta'(\theta) > 0 \quad \text{--- } \otimes$$

• $\hat{\theta}_{MLE}$ 定理... $\eta'(\hat{\theta}) \tau(x) - \zeta'(\hat{\theta}) = 0$

$$\therefore \tau(x) = \frac{\zeta'(\hat{\theta})}{\eta'(\hat{\theta})}$$

$$\therefore \frac{d\tau}{d\theta} = \frac{\zeta'(\theta)\eta'(\theta) - \zeta(\theta)\eta''(\theta)}{(\eta'(\theta))^2} > 0 \quad (\because \otimes)$$

$$\left(\frac{d\theta}{d\tau} > 0 \right) \quad \therefore \tau: \text{增加} \Leftrightarrow \theta: \text{增加}$$

接著考慮概似比檢定 ($H_0: \theta = \theta_0$ vs $H_1: \theta \neq \theta_0$)

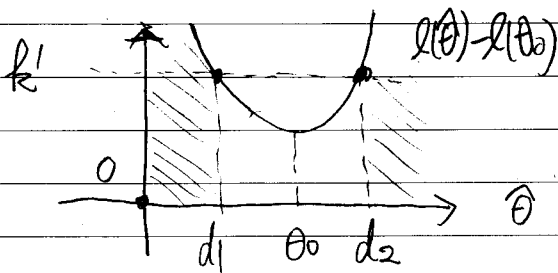
$$\Lambda(x) = \frac{\sup_{\theta = \theta_0} f(x|\theta)}{\sup_{\theta \in \Theta} f(x|\theta)} = \frac{f(x|\theta_0)}{\sup_{\theta \in \Theta} f(x|\theta)} < k \Rightarrow \text{棄卻}$$

$$-\ln \Lambda(x) = \ell(\hat{\theta}) - \ell(\theta_0) > k' \Rightarrow \text{棄卻}$$

$$(\oplus) \ell = \ln f$$

$\therefore \hat{\theta} > \theta_0$ 時... $\hat{\theta}$: 增加, $l(\hat{\theta}) - l(\theta_0)$: 增加

$\hat{\theta} < \theta_0$ 時... $\hat{\theta}$: 增加, $l(\hat{\theta}) - l(\theta_0)$: 減少



\therefore 棄卻域: $\{\theta \mid \theta < d_1 \text{ or } \theta > d_2\}$

$\Leftrightarrow \{Y \mid Y < C_1 \text{ or } Y > C_2\}$

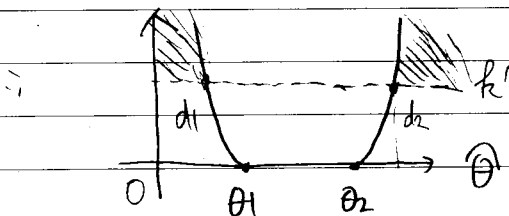
$(\because \frac{dY}{d\theta} > 0)$

\therefore 證明完成. ■

Ⓢ $H_0: \theta \in [\theta_1, \theta_2]$ vs $H_1: \theta \notin [\theta_1, \theta_2]$ 的 case.

$$\sup_{\theta \in [\theta_1, \theta_2]} \ln f(X|\theta) = \begin{cases} l(\theta_1) & (\hat{\theta} < \theta_1) \\ l(\hat{\theta}) & (\theta_1 \leq \hat{\theta} \leq \theta_2) \\ l(\theta_2) & (\hat{\theta} > \theta_2) \end{cases}$$

$$\therefore -\ln \lambda = \begin{cases} l(\hat{\theta}) - l(\theta_1) & (\hat{\theta} < \theta_1) & \dots & \text{(減少函數)} \\ 0 & (\theta_1 \leq \hat{\theta} \leq \theta_2) & \dots & (0) \\ l(\hat{\theta}) - l(\theta_2) & (\hat{\theta} > \theta_2) & \dots & \text{(增加函數)} \end{cases}$$



$\therefore \hat{\theta} < d_1 \text{ or } \hat{\theta} > d_2$

$\Leftrightarrow Y < C_1 \text{ or } Y > C_2$

\therefore 證明完成. ■

13 假設 F, G 為可微函數

$$(1) \text{ 令 } h(x) = \frac{d}{dx} (\theta F(x) + (1-\theta) G(x)) = \theta f(x) + (1-\theta) g(x)$$

先考慮對 $H_0: \theta = \theta_0$ vs $H_1: \theta = \theta_1$ ($\theta_0 < \theta_1$)

元最強檢定, (令其顯著水準 = α)

$$\Lambda(x) = \frac{h(x|\theta_1)}{h(x|\theta_0)} = \frac{\theta_1 f(x) + (1-\theta_1) g(x)}{\theta_0 f(x) + (1-\theta_0) g(x)} \geq k$$

$$\Leftrightarrow \frac{\theta_1 \frac{f(x)}{g(x)} + (1-\theta_1)}{\theta_0 \frac{f(x)}{g(x)} + (1-\theta_0)} \geq k$$

$$u(x) \stackrel{\text{def}}{=} \frac{f(x)}{g(x)}$$

$$\Lambda(x) = \frac{\theta_1 u(x) + (1-\theta_1)}{\theta_0 u(x) + (1-\theta_0)} = \frac{\theta_1}{\theta_0} + \frac{(1-\frac{\theta_1}{\theta_0})}{\theta_0 u(x) + (1-\theta_0)}$$

$$= \frac{\theta_1}{\theta_0} - \frac{(\frac{\theta_1}{\theta_0} - 1)}{\theta_0 u(x) + (1-\theta_0)} \geq k$$

$$\Leftrightarrow \left(\frac{\theta_1}{\theta_0} - k \right) \geq \frac{(\frac{\theta_1}{\theta_0} - 1)}{\theta_0 u(x) + (1-\theta_0)} \quad \left(\frac{\theta_1}{\theta_0} - 1 > 0 \right)$$

$$u: \text{增加} \Rightarrow \frac{\frac{\theta_1}{\theta_0} - 1}{\theta_0 u(x) + (1-\theta_0)} \text{ 減少}$$

$$\varphi(x) \stackrel{\text{def}}{=} \begin{cases} 1 & X \in C \\ 0 & X \notin C \end{cases} \quad C \stackrel{\text{def}}{=} \{x \mid U(x) \geq c_\alpha\}$$

$$E[\varphi(X) \mid \theta_0] = \alpha$$

$\varphi(x)$ 為對 $H_0: \theta = \theta_0$ vs $H_1: \theta = \theta_1$, 顯著水準 α 下的最強力檢定。

我們另外考慮 $\varphi^*(x) = \begin{cases} 1 & (\text{with probability } \alpha) \\ 0 & (= 1 - \alpha) \end{cases}$

(隨機化檢定)

$$\beta(\theta) \stackrel{\text{def}}{=} E[\varphi(X) \mid \theta], \quad \beta^*(\theta) \stackrel{\text{def}}{=} E[\varphi^*(X) \mid \theta] = \alpha \Rightarrow$$

$$\beta(\theta_1) \geq \beta^*(\theta_1) = \alpha = \beta(\theta_0) \quad \therefore \forall \theta_1, \theta_0, \beta(\theta_1) \geq \beta(\theta_0)$$

由此可知, $\beta(\theta)$ 為遞增函數. $\therefore \sup_{\theta \leq \theta_0} \beta(\theta) = \alpha$

另外, $\forall \theta > \theta_0$, $\varphi(x)$ 均擁有最強力。

\therefore 對於 $H_0: \theta \leq \theta_0$ vs $H_1: \theta > \theta_0$,

$\varphi(x)$ 為顯著水準 α 下的均勻最強力檢定。

(= Karlin Rubin 定理)

(2) 令 $T(X)$ 為顯著水準 α 下對 $H_0: \theta \in \Theta_0$

vs $H_1: \theta \in \Theta_1$ 之 UMP 檢定.

$$\begin{cases} \Theta_0 = [0, \theta_1] \cup [\theta_2, 1] \\ \Theta_1 = (\theta_1, \theta_2) \end{cases}$$

$$\beta_T(\theta) = E[\varphi(X) | \theta]$$

(1) T 為非隨機化檢定之 case

$$T(X) = \begin{cases} 1 & X \in C \\ 0 & X \notin C \end{cases}$$

$$\beta_T(\theta) = \int_{C_C} (\theta f(x) + (1-\theta)g(x)) dx$$

$$= \int_{C_C} g(x) dx + \theta \int_{C_C} (f-g) dx$$

由於 T 為 UMP 檢定, 故應滿足:

$$\sup_{\theta \in \Theta_0} \beta(\theta) = \alpha \leq \beta(\theta) \quad (\theta \in \Theta_1)$$

↳ 由此可知 θ 之係數又定為 0.

$$\begin{cases} \therefore \int_{C_C} (f-g) dx = 0 \\ \Rightarrow \int_{C_C} g(x) dx = \alpha \end{cases}$$

$$\therefore \beta(\theta) = \alpha \quad (\text{for all } \theta)$$

由此可知, UMP 檢定的檢定力, 無論 θ 均為相同.

但是無法保證隨時都存在 C_c 使得

$$\int_{C_c} g(x) dx = \int_{C_c} f(x) dx = \alpha.$$

但 τ 元檢定力與顯著水準 α 下的隨機化檢定

相同. \therefore 我們直接考慮隨機化檢定即可. (\Rightarrow ②)

② τ 為隨機化檢定的 case

$$\tau(x) = \begin{cases} 1 & (\text{with probability } \alpha) \\ 0 & (\text{with probability } 1-\alpha) \end{cases} = T(x)$$

根據①的討論, $\tau(x)$ ($= T(x)$) 為顯著水準 α 下的 UMP 檢定.

(3) 對於 $H_0: \theta \leq \theta_1$ or $\theta \geq \theta_2$ vs $H_1: \theta_1 < \theta < \theta_2$

之 概似似比檢定.

$$\Lambda(x) = \frac{\sup_{\theta \leq \theta_1 \text{ or } \theta \geq \theta_2} f(x|\theta)}{\sup_{\theta \in [0,1]} f(x|\theta)} < \lambda$$

$$\frac{\partial f(x|\theta)}{\partial \theta} = f(x) - g(x) \quad (\text{與 } \theta \text{ 無關})$$

① $f(x) - g(x) \geq 0$ 的 case...

$L(\theta|x) = f(x|\theta)$ 為 θ 之 遞增函數.

$\therefore \theta = 1$ 使得 $L(\theta|x) = f(x|\theta)$ 最大.

② $f(x) - g(x) < 0$ 的 case

$L(\theta|x) = f(x|\theta)$ 為 θ 之 遞減函數.

$\theta = 0$ 使得 $L(\theta|x) = f(x|\theta)$ 最大.

無論 ① 或 ②,

$$\frac{\sup_{\substack{\theta \leq \theta_1 \text{ or} \\ \theta \geq \theta_2}} f(x|\theta)}{\sup_{\theta \in [0,1]} f(x|\theta)} = 1$$

$$\therefore \Lambda(X) = 1 \quad (\text{for all } X)$$

∴ 利用隨機化檢定

$$\varphi_{\Lambda}(X) = \begin{cases} 1 & (\text{with probability } \alpha) \\ 0 & (\text{with probability } 1-\alpha) \end{cases}$$

例 (1) $\theta_1 > \theta_0$

我們希望證明 $\frac{f(x|\theta_1)}{f(x|\theta_0)}$ 為遞增函數。

$$\Leftrightarrow \frac{\partial}{\partial x} \left(\frac{f(x|\theta_1)}{f(x|\theta_0)} \right) = \frac{f_x(x|\theta_1)f(x|\theta_0) - f(x|\theta_1)f_x(x|\theta_0)}{\{f(x|\theta_0)\}^2} \geq 0$$

$$\Leftrightarrow f_x(x|\theta_1)f(x|\theta_0) \geq f(x|\theta_1)f_x(x|\theta_0)$$

$$\Leftrightarrow \frac{f_x(x|\theta_1)}{f(x|\theta_1)} \geq \frac{f_x(x|\theta_0)}{f(x|\theta_0)} \quad (\text{因 } f_x = \frac{\partial f}{\partial x}, f_\theta = \frac{\partial f}{\partial \theta}, f_{\theta\theta} = \frac{\partial^2 f}{\partial x \partial \theta})$$

$\Leftrightarrow \frac{f_x(x|\theta)}{f(x|\theta)}$ 為 θ 之遞增函數。(x 固定的情況下)

$$\frac{\partial}{\partial \theta} \frac{f_x(x|\theta)}{f(x|\theta)} = \frac{f_{x\theta}(x|\theta)f(x|\theta) - f_x(x|\theta)f_\theta(x|\theta)}{\{f(x|\theta)\}^2} \geq 0$$

$$\Leftrightarrow f_{x\theta}(x|\theta)f(x|\theta) \geq f_x(x|\theta)f_\theta(x|\theta) \quad \dots \text{以下證明 } \textcircled{1} \Leftrightarrow \textcircled{2}$$

以及 $\textcircled{2} \Leftrightarrow \textcircled{1}$

$$\textcircled{1} \text{ 若 } \frac{\partial^2}{\partial \theta \partial x} \log f(x|\theta) \geq 0 \quad (\forall x, \theta)$$

$$\Leftrightarrow \frac{\partial}{\partial \theta} \frac{f_x(x|\theta)}{f(x|\theta)} = \frac{f_{x\theta}(x|\theta)f(x|\theta) - f_x(x|\theta)f_\theta(x|\theta)}{\{f(x|\theta)\}^2} \geq 0$$

$$\Leftrightarrow f_{x\theta}(x|\theta)f(x|\theta) \geq f_x(x|\theta)f_\theta(x|\theta)$$

$\Leftrightarrow \textcircled{1} \quad \therefore$ 證明完成

② 題目應該有錯：

$$f(x|0) \frac{\partial}{\partial \theta} \left(\frac{\partial}{\partial x} \log f(x|0) \right) \geq \frac{\partial f(x|0)}{\partial \theta} \frac{\partial f(x|0)}{\partial x}$$

$$\Leftrightarrow f(x|0) \left\{ \frac{f_{x0}(x|0) f'(x|0) - f_x(x|0) f_{\theta}(x|0)}{(f(x|0))^2} \right\} \geq f_{\theta}(x|0) f_x(x|0)$$

$$\Leftrightarrow f_{x0}(x|0) f'(x|0) - f_x(x|0) f_{\theta}(x|0) \geq f_{\theta}(x|0) f_x(x|0) / f(x|0)$$

這跟 ⊛ 並非等價。

題目應改為 $f(x|0) \cdot \frac{\partial^2 f(x|0)}{\partial \theta \partial x} \geq \frac{\partial f(x|0)}{\partial \theta} \frac{\partial f(x|0)}{\partial x}$
(去掉 \log)

$$\Leftrightarrow f_{x0}(x|0) f'(x|0) \geq f_x(x|0) f_{\theta}(x|0)$$

$$\Leftrightarrow \text{⊛}$$

(2) 先求 Z 之機率密度函數

$$P(Z \leq x) = P(-\sqrt{x} \leq Z \leq \sqrt{x}) = P(-\sqrt{x} - \sqrt{\theta} \leq Z - \sqrt{\theta} \leq \sqrt{x} - \sqrt{\theta})$$

$$= \Phi(\sqrt{x} - \sqrt{\theta}) - \Phi(-\sqrt{x} - \sqrt{\theta})$$

$$\frac{d}{dx} P(Z \leq x) = \frac{1}{2\sqrt{x}} \phi(\sqrt{x} - \sqrt{\theta}) + \frac{1}{2\sqrt{x}} \phi(-\sqrt{x} - \sqrt{\theta})$$

$$= \frac{1}{2\sqrt{x} \sqrt{2\pi}} \exp\left(-\frac{x - \theta}{2}\right) \left\{ \exp(\sqrt{\theta x}) + \exp(-\sqrt{\theta x}) \right\} \quad (x > 0)$$

$$\therefore f(x|\theta) = \frac{1}{2\sqrt{x} \sqrt{2\pi}} \exp\left(-\frac{x - \theta}{2}\right) \left\{ \exp(\sqrt{\theta x}) + \exp(-\sqrt{\theta x}) \right\} \quad (x > 0)$$

$$\frac{f(x|\theta_1)}{f(x|\theta_0)} = \exp\left(\frac{-\theta_1 + \theta_0}{2}\right) \cdot \frac{\exp(\sqrt{\theta_1 x}) + \exp(-\sqrt{\theta_1 x})}{\exp(\sqrt{\theta_0 x}) + \exp(-\sqrt{\theta_0 x})} \quad (x > 0)$$

$$a_1 \stackrel{\text{def}}{=} \sqrt{\theta_1} \quad a_0 \stackrel{\text{def}}{=} \sqrt{\theta_0} \quad z \stackrel{\text{def}}{=} \sqrt{x}$$

$$\lambda = \frac{f(x|\theta_1)}{f(x|\theta_0)} = \exp\left(\frac{-a_1 + a_0}{2}\right) \cdot \frac{\cosh(a_1 z)}{\cosh(a_0 z)}$$

我們先證明 λ 與 z 間有遞增或遞減的關係

$$\lambda'(z) \stackrel{\text{def}}{=} \frac{\cosh(a_1 z)}{\cosh(a_0 z)}$$

$$\lambda'(z) = \frac{a_1 \sinh(a_1 z) \cosh(a_0 z) - a_0 \cosh(a_1 z) \sinh(a_0 z)}{(\cosh(a_0 z))^2}$$

$$g(y) \stackrel{\text{def}}{=} a_1 \sinh(a_2 y) \cosh(a_2 y) - a_0 \cosh(a_2 y) \sinh(a_2 y) \quad (y > 0)$$

$$g'(y) = a_1^2 \cosh(a_2 y) \cosh(a_2 y) + a_0 a_1 \sinh(a_2 y) \sinh(a_2 y) \\ - a_0^2 \cosh(a_2 y) \cosh(a_2 y) - a_0 a_1 \sinh(a_2 y) \sinh(a_2 y)$$

$$= (a_1^2 - a_0^2) \cosh(a_2 y) \cosh(a_2 y) > 0 \quad (y > 0) \quad (\text{if } \theta_1 > \theta_0)$$

$g(y)$ 為遞增函數, $g(0) = 0$. $\therefore g(y) > 0$

$\Rightarrow \lambda'(y) > 0 \Rightarrow \lambda(y)$ 為遞增函數

$\therefore y$: 增加 $\Leftrightarrow \lambda$: 增加

\Updownarrow
 λ : 增加

\therefore 證明完成.

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(1) 考慮對於 $H_0: \theta = \theta_0$ vs $H_1: \theta = \theta_1$ 之最強力
檢定. ^{假設} ($\theta_0 < \theta_1$)

利用 Neyman-Pearson's lemma:

$C = \{x \mid \frac{f(x|\theta_1)}{f(x|\theta_0)} > k\}$ 為 MP 檢定的棄卻域.

由於 $f(x)$ 具有單調概似比,

x 增加 $\Leftrightarrow \frac{f(x|\theta_1)}{f(x|\theta_0)}$ 增加

$\therefore C = \{x \mid x > x_0\}$

$\varphi_C(x) = \begin{cases} 1 & x \in C \\ 0 & x \notin C \end{cases}$ 為最強力檢定.

但 $E[\varphi_C(x) \mid \theta = \theta_0] = \alpha$ (顯著水準)

另外, 考慮隨機化檢定.

$\varphi_C^*(x) = \begin{cases} 1 & (\text{機率 } \alpha) \\ 0 & (1 - \alpha) \end{cases}$

$\varphi_C^*(x)$ 亦為顯著水準 α 之檢定

φ_c 之模定 $\rho \geq \varphi_c^*$ 之模定 ρ

$$\therefore E[\varphi_c(x)|\theta_1] \geq E[\varphi_c^*(x)|\theta_1] = \alpha = E[\varphi_c(x)|\theta_0]$$

$$\text{故此 } E[\varphi_c(x)|\theta_1] \geq E[\varphi_c(x)|\theta_0]$$

$$\Leftrightarrow \int_{x > x_0} f(x|\theta_1) dx \geq \int_{x > x_0} f(x|\theta_0) dx$$

$$\Leftrightarrow 1 - F(x_0|\theta_1) \geq 1 - F(x_0|\theta_0)$$

$$\Leftrightarrow F(x_0|\theta_0) \geq F(x_0|\theta_1)$$

\therefore stochastically increasing

(根據 x_0 , 我們可以選擇不同的 α)

(2) 證明存在 stochastically increasing

卻不具 MLR 的分佈.

考慮以下分佈: ($\theta_0 < \theta_1$)

X	0	1	2
$P(X \theta_0)$	$\frac{1}{3}$	$\frac{1}{3}$	$\frac{1}{3}$
$P(X \theta_1)$	$\frac{1}{3}$	$\frac{1}{6}$	$\frac{2}{3}$

$$P(X \leq 0 | \theta_0) = \frac{1}{3} \cong P(X \leq 0 | \theta_1) = \frac{1}{3}$$

$$P(X \leq 1 | \theta_0) = \frac{2}{3} \cong P(X \leq 1 | \theta_1) = \frac{1}{2}$$

$$P(X \leq 2 | \theta_0) = 1 \cong P(X \leq 2 | \theta_1) = 1$$

由此可知, X is stochastically increasing.

$$\frac{P(X=0|\theta_1)}{P(X=0|\theta_0)} = 1, \quad \frac{P(X=1|\theta_1)}{P(X=1|\theta_0)} = 0.5, \quad \frac{P(X=2|\theta_1)}{P(X=2|\theta_0)} = 1.5$$

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由此可知, X 並不具 MLR.

∴ 證明完成.