(a) Suppose that the random variables X and Y are jointly distributed with probability density function

$$f(x,y) = \begin{cases} \frac{1}{3\log 2} \left(\frac{x}{y} + \frac{y}{x}\right) & 1 \le x \le 2, 1 \le y \le 2; \\ 0 & \text{otherwise} \end{cases}$$

i) Find the marginal probability density function of X;

[3]

PDT Chapter 3

2. If X and Y are continuous random variables with joint density function $f_{(X,Y)}(x,y)$, then

$$F_X(x) = \mathbb{P}(X \le x, -\infty < Y < \infty) = \int_{-\infty}^x \left(\int_{-\infty}^\infty f_{(X,Y)}(u,y) dy \right) du.$$

It follows that the marginal density function of X is

$$f_X(x) = \int_{-\infty}^{\infty} f_{(X,Y)}(x,y)dy.$$

(a) Suppose that the random variables X and Y are jointly distributed with probability density function

$$f(x,y) = \left\{ \begin{array}{ll} \frac{1}{3\log 2} (\frac{x}{y} + \frac{y}{x}) & 1 \leq x \leq 2, 1 \leq y \leq 2; \\ \\ 0 & \text{otherwise} \end{array} \right.$$

- i) Find the marginal probability density function of X;
- ii) Calculate E(XY); [3]

4 D > 4 P > 4 E > 4 E > 9 Q P

[3]

PDT Chapter 3

Lemma 3 Law of the unconscious statistician - 2 variables

If $g: \mathbb{R}^2 \longrightarrow \mathbb{R}$ is a sufficiently nice function then

$$\mathbb{E}[g(X,Y)] = \sum_{(x,y)} g(x,y) p_{(X,Y)}(x,y)$$

when X and Y are discrete and

$$\mathbb{E}[g(X,Y)] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} g(x,y) f_{(X,Y)}(x,y) dx dy$$

when X and Y are continuous.

1. (a) Suppose that the random variables X and Y are jointly distributed with probability density function

$$f(x,y) = \begin{cases} \frac{1}{3\log 2} \left(\frac{x}{y} + \frac{y}{x}\right) & 1 \le x \le 2, 1 \le y \le 2; \\ 0 & \text{otherwise} \end{cases}$$

- Find the marginal probability density function of X;
- ii) Calculate E(XY); [3]
- iii) Find the conditional probability density function f(y|x) for $1 \le x \le 2, 1 \le y \le 2$ and hence evaluate P(Y < 1.5|X = 1). [4]

[3]

PDT Chapter 3

Lemma 6 Conditional density function.

The conditional density function of Y given X is the function $f_{Y|X}$ given by

$$f_{Y|X}(y|x) = \frac{f_{(X,Y)}(x,y)}{f_{X}(x)}$$

for any x such that $f_X(x) > 0$.

Definition 9 Conditional distribution function.

Let X and Y be continuous random variables. The conditional distribution function of the random variable Y given X = x is the function $F_{Y|X}(\cdot|x)$ given by

$$F_{Y|X}(y|x) = \int_{-\infty}^{y} \frac{f_{(X,Y)}(x,v)}{f_{X}(x)} dv$$
 (2)

for any x such that $f_X(x) > 0$.

(b) Let X and Y be independent random variables with the probability distribution functions defined as

$$F_X(x) = P(X \le x)$$
 and $F_Y(y) = P(Y \le y)$.

i) Let $U = \min\{X, Y\}$ and $V = \max\{X, Y\}$. Show that

$$F_U(u) = 1 - \{1 - F_X(u)\}\{1 - F_Y(u)\}\$$

$$F_V(v) = F_X(v)F_Y(v)$$

[4]

PDT Chapter 3

Definition 4 Independence. X and Y are independent if $\{X \leq x\}$ and $\{Y \leq y\}$ are independent events for all $x, y \in \mathbb{R}$. In other words, X and Y are independent if

$$F_{(X,Y)}(x,y) = F_X(x)F_Y(y).$$

(b) Let X and Y be independent random variables with the probability distribution functions defined as

$$F_X(x) = P(X \le x)$$
 and $F_Y(y) = P(Y \le y)$.

i) Let $U = \min\{X, Y\}$ and $V = \max\{X, Y\}$. Show that

$$F_U(u) = 1 - \{1 - F_X(u)\}\{1 - F_Y(u)\}\$$

$$F_V(v) = F_X(v)F_Y(v)$$

[4]

Now let X and Y be the independent exponential random variables with density functions

$$f(x)=e^{-x}\quad (x\geq 0)\qquad and \qquad f(y)=e^{-y}\quad (y\geq 0).$$

ii) Find the distribution function of $V = \max\{X, Y\}$. [2]

(b) Let X and Y be independent random variables with the probability distribution functions defined as

$$F_X(x) = P(X \le x)$$
 and $F_Y(y) = P(Y \le y)$.

i) Let $U = \min\{X, Y\}$ and $V = \max\{X, Y\}$. Show that

$$\begin{array}{rcl} F_U(u) & = & 1 - \{1 - F_X(u)\}\{1 - F_Y(u)\} \\ F_V(v) & = & F_X(v)F_Y(v) \end{array}$$

[4]

Now let X and Y be the independent exponential random variables with density functions

$$f(x) = e^{-x}$$
 $(x \ge 0)$ and $f(y) = e^{-y}$ $(y \ge 0)$.

- ii) Find the distribution function of $V = \max\{X, Y\}$. [2]
- iii) Show that $Z = X + \frac{1}{2}Y$ has the same distribution function as V. [4]

PDT Chapter 4

Theorem 1 If X and Y have joint density function $f_{(X,Y)}(x,y)(\cdot,\cdot)$, then Z=X+Y has density function

$$f_Z(z) = \int_{-\infty}^{\infty} f_{(X,Y)}(x, z - x) dx.$$

Moreover, if they are independent we have

$$f_Z(z) = \int_{-\infty}^{\infty} f_X(x) f_Y(z - x) dx = \int_{-\infty}^{\infty} f_X(z - y) f_Y(y) dy$$

in which case, the function f_Z , also denoted by f_{X+Y} , is called the convolution of f_X and f_Y and is written as

$$f_{X+Y} = f_X * f_Y.$$

Proof.

$$F_Z(z) = \mathbb{P}(Z \le z) = \mathbb{P}(X + Y \le z) = \int \int_{x+y \le z} f_{(X,Y)}(x,y) dx dy$$

2. The random variable Z has the χ^2_k distribution (k is the degrees of freedom) which has the moment generating function (mgf)

$$M_Z(\theta) = (1 - 2\theta)^{-\frac{k}{2}} \quad \text{for} \quad \theta < \frac{1}{2}.$$

(a) Using the mgf, find the mean and variance of Z.

[4]

PDT Chapter 4, page 13 & Chapter 2, Lemma 5

where μ_k is the kth moment of X, i.e, $\mu_r = \mathbb{E}[X^r]$ for $r = 1, 2, \dots$ We recover the moments by the operation of differentiation, i.e,

$$\mu_k = \frac{\partial^k}{\partial \theta^k} M_X(\theta)|_{\theta=0}.$$

5.
$$var(X) = \mathbb{E}[(X - \mathbb{E}[X])^2] = \mathbb{E}[X^2] - (\mathbb{E}[X])^2$$
.

2. The random variable Z has the χ^2_k distribution (k is the degrees of freedom) which has the moment generating function (mgf)

$$M_Z(\theta) = (1 - 2\theta)^{-\frac{k}{2}}$$
 for $\theta < \frac{1}{2}$.

- (a) Using the mgf, find the mean and variance of Z.
- (b) Suppose X has standard normal distribution N(0,1). Using integration, show that $Y = X^2$ has the χ_1^2 distribution. [6]

[4]

PDT Chapter 4, pages 11 & 12

Remark: If X has the generating function $M_X(\theta)$, then the generating function of Y = g(X) can be found in the following way:

$$M_Y(\theta) = \mathbb{E}[e^{\theta Y}] = \mathbb{E}[e^{\theta g(X)}],$$

Uniqueness

If X and Y have the same moment generating function, then X and Y have the same distribution.

2. The random variable Z has the χ^2_k distribution (k is the degrees of freedom) which has the moment generating function (mgf)

$$M_Z(\theta) = (1 - 2\theta)^{-\frac{k}{2}}$$
 for $\theta < \frac{1}{2}$.

- (a) Using the mgf, find the mean and variance of Z.
- (b) Suppose X has standard normal distribution N(0,1). Using integration, show that $Y = X^2$ has the χ_1^2 distribution. [6]
- (c) Show that if Y_1, Y_2, \dots, Y_n are independent, each with a χ^2_1 distribution, then $V = \sum_{i=1}^n Y_i$ has a χ^2_n distribution. [2]

[4]

PDT Chapter 4, page 14

Independence

If X and Y are independent random variables then

$$M_{X+Y}(\theta) = M_X(\theta)M_Y(\theta)$$

for all θ for which both $M_X(\theta)$ and $M_Y(\theta)$ are defined.

2. The random variable Z has the χ_k^2 distribution (k is the degrees of freedom) which has the moment generating function (mgf)

$$M_Z(\theta) = (1 - 2\theta)^{-\frac{k}{2}}$$
 for $\theta < \frac{1}{2}$.

- (a) Using the mgf, find the mean and variance of Z.
- (b) Suppose X has standard normal distribution N(0,1). Using integration, show that $Y = X^2$ has the χ_1^2 distribution. [6]
- (c) Show that if Y_1, Y_2, \dots, Y_n are independent, each with a χ_1^2 distribution, then $V = \sum_{i=1}^n Y_i$ has a χ_n^2 distribution. [2]
- (d) Use the previous results and the central limit theorem to find the approximate probability that V < 310 when n = 300. [4]

[4]

PDT Chapter 5

Theorem 3 (central limit theorem). Let X_1, X_2, \ldots be a sequence of i.i.d. random variables with finite mean μ and finite non-zero variance σ^2 , and let $S_n = X_1 + \cdots + X_n$. Then

$$\frac{\frac{S_n}{n} - \mu}{\frac{\sigma}{\sqrt{n}}} = \frac{S_n - n\mu}{\sigma\sqrt{n}} \xrightarrow{D} N(0, 1) \quad \text{as } n \longrightarrow \infty.$$

(e) Suppose that X_1, \dots, X_n is a random sample drawn from a normal distribution $N(\mu, \sigma^2)$. Let

$$\overline{X} = \frac{1}{n} \sum_{i=1}^{n} X_i; \quad S^2 = \frac{1}{n-1} \sum_{i=1}^{n} (X_i - \overline{X})^2.$$

State without proof the distributions of the two statistics \overline{X} and

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

Further, find the distribution of

$$T = \frac{\sqrt{n}(\overline{X} - \mu)}{S}$$

by quoting a proper definition. Here S is the square root of S^2 . [Note: all the parameters in these distributions should be properly stated.] [4]

PDT Chapter 5, section 5.4

If X_1, X_2, \cdots are independent $N(\mu, \sigma^2)$ variables then

$$\overline{X} \sim N(\mu, \sigma^2/n),$$

Using (2), it can be shown that

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

If $Z \sim N(0,1)$ and $Y \sim \chi_r^2$ independently of each other then

$$T = \frac{Z}{(Y/r)^{1/2}}$$

is defined to have a t distribution with r degrees of freedom.

(a) Find the constant C.

3. For a productive pair from a particular species of bird, the number X of eggs laid per season has the probability mass function

$$P(X=k) = C \frac{e^{-\lambda} \lambda^k}{k!}$$
 for $k = 1, 2, 3, \cdots$

Suppose X_1, \dots, X_n is a random sample drawn from the population.

appose
$$n_1, \dots, n_n$$
 is a random sample drawn from the population.

[4]

3. For a productive pair from a particular species of bird, the number X of eggs laid per season has the probability mass function

$$P(X = k) = C \frac{e^{-\lambda} \lambda^k}{k!}$$
 for $k = 1, 2, 3, \dots$

Suppose X_1, \dots, X_n is a random sample drawn from the population.

(a) Find the constant C.

- [4]
- (b) Find an equation for determining $\tilde{\lambda}$, the estimator of λ by Method of Moments based on X_1, \dots, X_n . (Note: Do not attempt to solve the equation.) [4]

Inference Chapter 2, page 2

Let $\mathbf{X} \equiv (X_1, X_2, \dots, X_n)$ be a random sample of size n from some family of distributions depending upon the vector of q parameters, $\theta = (\theta_1, \theta_2, \dots, \theta_q)$. Assume that the first q moments μ_j , $j = 1, \dots, q$ of the distributions exist,

$$\mu_j(\theta_1, \theta_2, \dots, \theta_q) = E[X_i^j; \theta_1, \theta_2, \dots, \theta_q] \qquad j = 1, \dots, q.$$

Let m_j , j = 1, ..., q be the corresponding sample moments,

$$m_j = \frac{1}{n} \sum_{i=1}^n X_i^j$$
 $j = 1, \dots, q.$

According to the method of moments, we match the sample and population/distribution moments. We solve the following set of q simultaneous equations for the q unknown parameter values,

$$m_{1} = \mu_{1}(\hat{\theta}_{1}, \hat{\theta}_{2}, \dots, \hat{\theta}_{q})$$

$$m_{2} = \mu_{2}(\hat{\theta}_{1}, \hat{\theta}_{2}, \dots, \hat{\theta}_{q})$$

$$\vdots$$

$$m_{q} = \mu_{q}(\hat{\theta}_{1}, \hat{\theta}_{2}, \dots, \hat{\theta}_{q}),$$
(1)

to obtain the estimator $(\hat{\theta}_1, \hat{\theta}_2, \dots, \hat{\theta}_g)$.

3. For a productive pair from a particular species of bird, the number X of eggs laid per season has the probability mass function

$$P(X = k) = C \frac{e^{-\lambda} \lambda^k}{k!}$$
 for $k = 1, 2, 3, \cdots$

Suppose X_1, \dots, X_n is a random sample drawn from the population.

(a) Find the constant C.

[4]

- (b) Find an equation for determining λ , the estimator of λ by Method of Moments based on X_1, \dots, X_n . (Note: Do not attempt to solve the equation.) [4]
- (c) Show that the maximum likelihood estimator $\widehat{\lambda}$ of λ based on X_1, \dots, X_n is identical with the estimator of the method of moments. (Note: Do not attempt to solve the equation.)

Inference Chapter 2, pages 3 & 4

Definition

For each $\mathbf{x} \in \mathcal{X}$, let $\hat{\theta}(\mathbf{x})$ be such that, with \mathbf{x} held fixed, the likelihood function $\{L(\theta; \mathbf{x}) : \theta \in \Theta\}$ attains its maximum value as a function of θ at $\hat{\theta}(\mathbf{x})$. The estimator $\hat{\theta}(\mathbf{X})$ is then said to be a maximum likelihood estimator (MLE) of θ .

Assuming that the likelihood function $L(\theta; \mathbf{x})$ is a continuously differentiable function of θ , given $\mathbf{x} \in \mathcal{X}$, an interior stationary point of $\ln L(\theta; \mathbf{x})$ or of $L(\theta; \mathbf{x})$ is given by a solution of the *likelihood equations*,

$$\frac{\partial \ln L(\theta; \mathbf{x})}{\partial \theta_j} = 0, \qquad j = 1, \dots, q. \tag{4}$$

A solution of Equations (4) may or may not be unique, and may or may not give us a MLE. In many of the standard cases, solution of the Equations (4) does give us the MLE, but we cannot take this for granted.

3. For a productive pair from a particular species of bird, the number X of eggs laid per season has the probability mass function

$$P(X = k) = C \frac{e^{-\lambda} \lambda^k}{k!}$$
 for $k = 1, 2, 3, \dots$

Suppose X_1, \dots, X_n is a random sample drawn from the population.

- (a) Find the constant C. [4]
- (b) Find an equation for determining $\tilde{\lambda}$, the estimator of λ by Method of Moments based on X_1, \dots, X_n . (Note: Do not attempt to solve the equation.) [4]
- (c) Show that the maximum likelihood estimator $\hat{\lambda}$ of λ based on X_1, \dots, X_n is identical with the estimator of the method of moments. (Note: Do not attempt to solve the equation.)
- (d) Find the Fisher information of λ from the simple random sample X_1, \dots, X_n . [4]

Inference Chapter 3

where $I(\theta)$ is the Fisher information,

$$I(\theta) = E_{\theta} \left[\left(\frac{\partial \ln f(\mathbf{X}; \theta)}{\partial \theta} \right)^{2} \right] \qquad \theta \in \Theta.$$
 (2)

Theorem 3 Under appropriate regularity conditions,

$$I(\theta) = E_{\theta} \left[-\frac{\partial^2 \ln f(\mathbf{X}; \theta)}{\partial \theta^2} \right] \qquad \theta \in \Theta.$$

For a productive pair from a particular species of bird, the number X of eggs laid per season has the probability mass function

$$P(X = k) = C \frac{e^{-\lambda} \lambda^k}{k!}$$
 for $k = 1, 2, 3, \dots$

Suppose X_1, \dots, X_n is a random sample drawn from the population.

- (a) Find the constant C. [4]
- (b) Find an equation for determining $\tilde{\lambda}$, the estimator of λ by Method of Moments based on X_1, \dots, X_n . (Note: Do not attempt to solve the equation.) [4]
- (c) Show that the maximum likelihood estimator $\widehat{\lambda}$ of λ based on X_1, \dots, X_n is identical with the estimator of the method of moments. (Note: Do not attempt to solve the equation.)
- (d) Find the Fisher information of λ from the simple random sample X_1, \dots, X_n . [4]
- (e) Quoting any appropriate asymptotic properties of the maximum likelihood estimators, deduce the approximate distribution of $\hat{\lambda}$ for large n. [2]

Inference Chapter 3, page 8

It can be shown, using the Central Limit theorem, that MLEs are asymptotically normally distributed and asymptotically efficient, i.e., in the case of $\Theta \subseteq \mathbb{R}$, for all $\theta \in \Theta$

$$\sqrt{n}(\hat{\tau}_n - \tau(\theta)) \to N\left(0, \frac{\left(\frac{d\tau}{d\theta}\right)^2}{i(\theta)}\right).$$

Put less formally, for large n,

$$\hat{\tau}_n \sim N\left(\tau(\theta), \frac{\left(\frac{d\tau}{d\theta}\right)^2}{I(\theta)}\right)$$

- 4. (a) Let X_1, X_2, \dots, X_n be a random sample from $N(0, \sigma^2)$.
 - i) Find the most powerful test for the simple hypothesis $H_0: \sigma^2 = \sigma_0^2$ against $H_1: \sigma^2 = \sigma_1^2$ where $\sigma_1^2 > \sigma_0^2$. [3]

Inference Chapter 4

Theorem 1 (The Neyman-Pearson Lemma) Given the simple hypotheses H_0 and H_1 , let C be the critical region as specified in Equation (1) of a likelihood ratio test for some given k > 0. Let α be the significance level and β the power of this test. Any other test with significance level less than or equal to α has power less than or equal to β .

$$C = \{ \mathbf{x} \in \mathcal{X} : \frac{f_1(\mathbf{x})}{f_0(\mathbf{x})} \ge k \}$$
 (1)

for some positive constant k. This is known as a likelihood ratio test.

In the case of simple hypotheses, the significance level and power of a test with critical region \mathcal{C} may be defined particularly simply. The *significance level* α is given by

$$\alpha = \mathbb{P}(\mathbf{X} \in \mathcal{C}; \theta_0) = \mathbb{P}(H_0 \text{ is rejected}; H_0)$$

and the power β by

$$\beta = \mathbb{P}(\mathbf{X} \in \mathcal{C}; \theta_1) = \mathbb{P}(H_0 \text{ is rejected}; H_1).$$

- 4. (a) Let X_1, X_2, \cdots, X_n be a random sample from $N(0, \sigma^2)$.
 - i) Find the most powerful test for the simple hypothesis $H_0: \sigma^2 = \sigma_0^2$ against $H_1: \sigma^2 = \sigma_1^2$ where $\sigma_1^2 > \sigma_0^2$. [3]
 - ii) Find the uniformly most powerful test for the simple hypothesis $H_0: \sigma^2 = \sigma_0^2$ against the composite hypothesis $H_1: \sigma^2 > \sigma_0^2$. [3]

Inference Chapter 4, page 6

test is said to be a uniformly most powerful (UMP) test of significance level α if it has significance level less than or equal to α and $\beta(\theta) \geq \beta^*(\theta)$ for all $\theta \in \Theta_1$ for the power function $\beta^*(\theta)$ of every other test with significance level less than or equal to α .

The form of the likelihood ratio test is the same for all pairs of parameter values θ_0 and θ_1 with $\theta_1 > \theta_0$. It follows that a test with critical region of the form (6) is UMP for testing

$$H_0: \theta = \theta_0$$
 against $H_1: \theta > \theta_0$,

or, indeed, for testing

$$H_0: \theta \leq \theta_0$$
 against $H_1: \theta > \theta_0$.

- 4. (a) Let X_1, X_2, \dots, X_n be a random sample from $N(0, \sigma^2)$.
 - i) Find the most powerful test for the simple hypothesis $H_0: \sigma^2 = \sigma_0^2$ against $H_1: \sigma^2 = \sigma_1^2$ where $\sigma_1^2 > \sigma_0^2$. [3]
 - ii) Find the uniformly most powerful test for the simple hypothesis $H_0: \sigma^2 = \sigma_0^2$ against the composite hypothesis $H_1: \sigma^2 > \sigma_0^2$. [3]
 - iii) Let $\alpha = P(\sum_{i=1}^{n} X_i^2 > c | \sigma_0^2)$ where c is an unknown parameter to be determined. Given $\sigma_0^2 = 4$ and n = 15, find the value of c such that the significance level $\alpha = 0.05$. [3]

Statistical tables

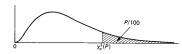
TABLE 8. PERCENTAGE POINTS OF THE x²-DISTRIBUTION

This table gives percentage points $\chi^2_{\nu}(P)$ defined by the equation

$$\frac{P}{100} = \frac{1}{2^{\nu/2} \Gamma(\frac{\nu}{5})} \int_{v_n^2(P)}^{\infty} x^{\frac{1}{5}\nu - 1} e^{-\frac{1}{5}x} dx.$$

If X is a variable distributed as χ^2 with ν degrees of freedom, P/100 is the probability that $X \geqslant \chi^2_{\nu}(P)$.

For $\nu > 100$, $\sqrt{2X}$ is approximately normally distributed with mean $\sqrt{2\nu - 1}$ and unit variance.



(The above shape applies for $\nu \geqslant 3$ only. When $\nu < 3$ the mode is at the origin.)

P	50	40	30	20	10	5	2.5	r	0.2	0.1	0.02	
$\nu = \mathbf{r}$	0.4549	0.7083	1.074	1.642	2.706	3.841	5.024	6.635	7.879	10.83	12.12	
2	1.386	1.833	2.408	3.219	4.605	5.991	7:378	9.210	10.60	13.82	15.30	
3	2.366	2.946	3.665	4.642	6.251	7.815	9.348	11.34	12.84	16.27	17.73	
4	3.357	4.045	4.878	5.989	7.779	9.488	11.14	13.28	14.86	18.47	20.00	
5	4.321	5.132	6.064	7.289	9.236	11.07	12.83	15.09	16.75	20.52	22.11	
6	5.348	6.211	7.231	8.558	10.64	12.59	14.45	16.81	18.55	22.46	24.10	
7	6.346	7.283	8.383	9.803	12.02	14.07	16.01	18.48	20.28	24.32	26.02	
8	7.344	8-351	9.524	11.03	13.36	15.51	17.53	20.09	21.95	26.12	27.87	
9	8.343	9.414	10.66	12.24	14.68	16.92	19.02	21.67	23.29	27.88	29.67	
10	9.342	10.47	11.78	13.44	15.99	18-31	20.48	23.21	25.19	29.59	31.42	
11	10.34	11.53	12.90	14.63	17.28	19.68	21.92	24.72	26.76	31.26	33.14	
12	11.34	12.58	14.01	15.81	18.55	21.03	23.34	26.22	28.30	32.91	34.82	
13	12.34	13.64	15.12	16.98	19.81	22.36	24.74	27.69	29.82	34.23	36.48	
14	13.34	14.69	16.22	18.12	21.06	23.68	26.13	29.14	31.32	36.12	38.11	
15	14.34	15.73	17.32	19.31	22.31	25.00	27:49	30.28	32.80	37.70	39.72	

- 4. (a) Let X_1, X_2, \dots, X_n be a random sample from $N(0, \sigma^2)$.
 - i) Find the most powerful test for the simple hypothesis $H_0: \sigma^2 = \sigma_0^2$ against $H_1: \sigma^2 = \sigma_1^2$ where $\sigma_1^2 > \sigma_0^2$. [3]
 - ii) Find the uniformly most powerful test for the simple hypothesis $H_0: \sigma^2 = \sigma_0^2$ against the composite hypothesis $H_1: \sigma^2 > \sigma_0^2$. [3]
 - iii) Let $\alpha = P(\sum_{i=1}^{n} X_i^2 > c | \sigma_0^2)$ where c is an unknown parameter to be determined. Given $\sigma_0^2 = 4$ and n = 15, find the value of c such that the significance level $\alpha = 0.05$.
 - iv) Given n=15 and c is the value found in part (iii), find the approximate value of $\beta=P(\sum_{i=1}^n X_i^2 < c|\sigma_1^2=16)$. [3]

Statistical tables

	TABLE 7. THE χ^2 -DISTRIBUTION FUNCTION									
ν =	15	16	17	18	19	20	21	22	23	
x = 3	0.0004	0.0003	0.0001							
4	.0023	.0011	.0002	0.0002	0.0001					
5	0.0079	0.0042	0.0022	0.0011	0.0006	0.0003	0.0001	0.0001		
5 6	.0203	.0119	.0068	.0038	·002I	.0011	.0006	.0003	0.0001	
7	.0424	.0267	·0165	.0099	.0028	.0033	.0019	.0010	.0002	
8	.0762	0511	.0335	.0214	.0133	.0081	.0049	.0028	.0016	
9	1225	∙0866	.0597	.0403	.0265	.0171	.0108	.0067	.0040	

(b) The probability density function of gamma distribution with parameters $\alpha>0$ and $\theta>0$ is given by

$$f(x) = \frac{x^{\alpha - 1}e^{-x/\theta}}{\Gamma(\alpha)\theta^{\alpha}} \quad \text{for} \quad x > 0.$$

Let X_1, X_2, \dots, X_n be a random sample from a gamma distribution with the parameter $\alpha = 1$ and the unknown parameter θ . Let $\tau = \log \theta$. Suppose that the prior density function of τ is an improper uniform prior, i.e,

$$\pi(\tau) \propto 1, \quad \tau \in (-\infty, \infty).$$

i) Find the prior density function of θ up to a constant of proportionality. [2]

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Note also that if the parameter space Θ is not bounded then there does not exist a uniform distribution on Θ . If we take $\pi(\theta) = k$ for some constant $k \ge 0$ then

$$\int_{\Theta} \pi(\theta) d\theta = \begin{cases} \infty & k > 0 \\ 0 & k = 0 \end{cases}$$

Thus it is not possible to make the integral take the value 1. However, in view of Equation (2), we only have to specify $\pi(\theta)$ up to a constant of proportionality. So we can proceed, using $\pi(\theta) = k$, despite the fact that $\pi(\theta)$ does not specify a proper distribution. In such a case, $\pi(\theta)$ is known as an *improper prior*.

Example 2 On many occasions we will be interested in calculating the distribution function of a random variable Y = g(X) where $g : \mathbb{R} \longrightarrow \mathbb{R}$ is a sufficiently nice function. Let X be a random variable with probability density function $f_X(\cdot)$.

So we have the following result: if g is a monotone function (increasing or decreasing), the density function of Y is

$$f_Y(y) = f_X(g^{-1}(y)) | (g^{-1}(y))' |.$$

(b) The probability density function of gamma distribution with parameters $\alpha>0$ and $\theta>0$ is given by

$$f(x) = \frac{x^{\alpha - 1}e^{-x/\theta}}{\Gamma(\alpha)\theta^{\alpha}}$$
 for $x > 0$.

Let X_1, X_2, \dots, X_n be a random sample from a gamma distribution with the parameter $\alpha = 1$ and the unknown parameter θ . Let $\tau = \log \theta$. Suppose that the prior density function of τ is an improper uniform prior, i.e,

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- i) Find the prior density function of θ up to a constant of proportionality. [2]
- ii) Find the posterior density function of θ up to a constant of proportionality. [2]

Inference Chapter 5

Given $\mathbf{x} \in \mathcal{X}$, the posterior density for θ is computed using Bayes' Theorem,

$$\pi(\theta|\mathbf{x}) = \frac{\pi(\theta)f(\mathbf{x}|\theta)}{m(\mathbf{x})} \qquad \theta \in \Theta, \tag{1}$$

where $m(\mathbf{x})$ is the marginal p.d.f. of \mathbf{X} ,

$$m(\mathbf{x}) = \int_{\Omega} \pi(\theta) f(\mathbf{x}|\theta) d\theta.$$

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Let X_1, X_2, \dots, X_n be a random sample from a gamma distribution with the parameter $\alpha = 1$ and the unknown parameter θ . Let $\tau = \log \theta$. Suppose that the prior density function of τ is an improper uniform prior, i.e,

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- i) Find the prior density function of θ up to a constant of proportionality. [2]
- ii) Find the posterior density function of θ up to a constant of proportionality. [2]
- iii) Let $z=1/\theta$ and show that the posterior distribution of Z is a gamma distribution with parameter $\alpha=n$ and $\theta=1/y$, where $y=\sum_{i=1}^n x_i$. [4]

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