

Homework 2

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Question 1

Suppose that $Y \sim \text{Bin}(100, p)$, and we want to make an inference about the value of p . We test $H_0 : p = 0.08$ against $H_A : p < 0.08$, and our test δ will reject H_0 if and only if $Y = 6$.

- (a) The significance α is the probability of making a Type I error,

$$\alpha(\delta) = \Pr(Y = 6 | p = 0.08) = \binom{100}{6} (0.08)^6 (0.92)^{94} = 0.123.$$

- (b) Suppose that $p = 0.04$. The probability of a Type II error, β , is

$$\beta(\delta) = \Pr(Y \neq 6 | p = 0.04) = 1 - \Pr(Y = 6 | p = 0.04) = 1 - \binom{100}{6} (0.04)^6 (0.96)^{94} = 0.895.$$

Question 2

For a random variable $Y \sim \text{Binom}(n, p)$, if n is large enough we can approximate it using a normal distribution with the same mean and variance, i.e. $Y \sim N(np, np(1-p))$. Then the sample proportion, $\hat{p} = Y/n$, is also normally distributed as $\hat{p} \sim N(p, p(1-p)/n)$, and standardizing \hat{p} gives us $(\hat{p} - p)/\sqrt{p(1-p)/n} \sim N(0, 1)$. It can then be shown that a $100\gamma\%$ confidence interval for \hat{p} is given by

$$\mathcal{I} = \left(\frac{\hat{p} + z_\gamma^2/2n}{1 + z_\gamma^2/2n} - z_\gamma \cdot \frac{\sqrt{\hat{p}(1-\hat{p})/n + z_\gamma^2/4n^2}}{1 + z_\gamma^2/n}, \frac{\hat{p} + z_\gamma^2/2n}{1 + z_\gamma^2/2n} + z_\gamma \cdot \frac{\sqrt{\hat{p}(1-\hat{p})/n + z_\gamma^2/4n^2}}{1 + z_\gamma^2/n} \right),$$

where $z_\gamma = \Phi^{-1}((1+\gamma)/2)$. For this example, we have $n = 300$ and $\hat{p} = 75/300 = 1/4$, and to get a 90% confidence interval, we have $z_\gamma = 1.645$. Therefore, a 90% confidence interval for p is $(0.212, 0.294)$.

Question 3

Suppose we have a random sample $\mathbf{X} \stackrel{\text{iid}}{\sim} \text{Gamma}(4, \beta)$, so $\mathbb{E}[X_i] = 4\beta$ and $\text{Var}[X_i] = 4\beta^2$. The expected value and variance of the sample mean \bar{X} is then given by $\mathbb{E}[\bar{X}] = 4\beta$ and $\text{Var}[\bar{X}] = 4\beta^2/n$, and from the CLT we have $\sqrt{n}(\bar{X} - 4\beta)/2\beta = \sqrt{n}(\bar{X}/2\beta - 2) \sim N(0, 1)$. If $z_\gamma = \Phi^{-1}((1+\gamma)/2)$, then we have $\gamma = \Pr(-z_\gamma \leq \sqrt{n}(\bar{X}/2\beta - 2) \leq z_\gamma)$. Rearranging to get β in the middle gives us

$$\mathcal{I} = \left(\frac{2\bar{X}}{2 + z_\gamma/\sqrt{n}}, \frac{2\bar{X}}{2 - z_\gamma/\sqrt{n}} \right).$$

For this random sample, $n = 25$, and because we want a 95.4% confidence interval (oddly specific), we have $z_\gamma = 2$, so the confidence interval is given by $\mathcal{I} = (5\bar{X}/6, 5\bar{X}/4)$.

Question 4

Suppose that $X \sim \text{Binom}(100, p)$, where $p \in (1/4, 1/2)$ is unknown. We test $H_0 : 1/2$ against $H_A : p = 1/4$ using δ : reject H_0 if $X \leq 3$. That is, our rejection region is $\mathcal{S}_X = \{0, 1, 2, 3\}$, and so the power function for this test is

$$\pi(p | \delta) = \Pr(X \in \mathcal{S}_X | p) = \sum_{k=0}^3 \binom{100}{k} p^k (1-p)^{100-k}.$$

Question 5

Suppose $X_1, X_2 \stackrel{\text{iid}}{\sim} \text{Exp}(1/\theta)$, where $\theta > 0$, which means $\mathbb{E}[X_i] = \theta$ and $\text{Var}[X_i] = \theta^2$. The joint density is

$$f_{\mathbf{X}}(\mathbf{x}) = \frac{e^{-x_1/\theta}}{\theta} \cdot \frac{e^{-x_2/\theta}}{\theta} = \frac{e^{-(x_1+x_2)/\theta}}{\theta^2}$$

Consider the transformation $Y_1 = X_1 + X_2$ and $Y_2 = X_2$, which implies $Y_1 \sim \text{Gamma}(2, 1/\theta)$ and $Y_2 \sim \text{Exp}(1/\theta)$. We note that because $f_{\mathbf{X}}(\mathbf{x})$, which is also the likelihood function of the random sample, is a function of y_1 and θ , so it is a sufficient statistic. In vector notation, the transformation is given by $\mathbf{Y} = \mathbf{A}\mathbf{X}$, where $\mathbf{A} = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix}$, and so $\mathbf{X} = \mathbf{A}^{-1}\mathbf{Y}$, where $\mathbf{A}^{-1} = \begin{bmatrix} 1 & -1 \\ 0 & 1 \end{bmatrix}$. Therefore, the joint density of Y_1 and Y_2 is

$$g_{\mathbf{Y}}(\mathbf{y}) = f_{\mathbf{X}}(\mathbf{x}) \cdot \left| \det \left(\frac{\partial \mathbf{A}\mathbf{x}}{\partial \mathbf{y}} \right) \right| = f_{\mathbf{X}}(\mathbf{A}^{-1}\mathbf{y}) \cdot |\det(\mathbf{A})| = \frac{e^{-(y_1-y_2+y_2)/\theta}}{\theta^2} \cdot 1 = \frac{e^{-y_1/\theta}}{\theta^2},$$

for $0 < y_2 < y_1$. Because $Y_2 \sim \text{Exp}(1/\theta)$, we have $\mathbb{E}[Y_2] = \theta$, and so Y_2 is an unbiased estimator for θ . The conditional density of Y_2 given Y_1 is

$$g_{Y_2|Y_1}(y_2 | y_1) = \frac{g_{\mathbf{Y}}(\mathbf{y})}{g_{Y_1}(y_1)} = \frac{e^{-y_1/\theta}/\theta^2}{y_1 e^{-y_1/\theta}} = \frac{1}{y_1},$$

and so the conditional expectation of Y_2 given Y_1 is

$$\mathbb{E}[Y_2 | y_1] = \int y_2 \cdot g_{Y_2|Y_1}(y_2 | y_1) \partial y_2 = \int_0^{y_1} \frac{y_2}{y_1} \partial y_2 = \frac{y_2^2}{2y_1} \Big|_0^{y_1} = \frac{y_1}{2} := \varphi(y_1).$$

As is standard, we can define the random variable $\varphi(Y_1)$, and immediately see that $\mathbb{E}[\varphi(Y_1)] = \mathbb{E}[Y_2] = \theta$. In addition, we have

$$\mathbb{E}[\varphi(Y_1)^2] = \int \varphi(y_1)^2 \cdot g_{Y_1}(y_1) \partial y_1 = \int_0^\infty \frac{y_1^2}{4} \cdot \frac{y_1 e^{-y_1/\theta}}{\theta^2} = \frac{3\theta^2}{2} \int_0^\infty \frac{y_1^{4-1} \cdot e^{-y_1/\theta}}{\theta^4 \Gamma(4)} \partial y_1 = \frac{3\theta^2}{2},$$

and so $\text{Var}[\varphi(Y_1)] = \mathbb{E}[\varphi(Y_1)^2] - \mathbb{E}[\varphi(Y_1)]^2 = \theta^2/2$.

Question 6

Suppose that $\mathbf{X} \stackrel{\text{iid}}{\sim} \text{Poisson}(\theta)$. We test $H_0 : \theta = 1/2$ against $H_A : \theta < 1/2$ using our procedure δ : reject H_0 if the test statistic $Y = \mathbf{1}^T \mathbf{X} = \sum X_i \leq 2$. Since it is a sum of independent Poisson random variables, our test statistic is also a Poisson random variable, namely $Y \sim \text{Poisson}(n\theta)$, and the rejection region for Y is $\mathcal{S}_Y = \{0, 1, 2\}$. Therefore, for $\theta \in (0, 1/2]$, the power function of δ is given by

$$\pi(\theta | \delta) = \Pr(Y \in \mathcal{S}_Y | \theta) = \sum_{k=0}^2 \frac{(n\theta)^k e^{-n\theta}}{k!}.$$

A graph of $\pi(\theta | \delta)$ can be found in the left panel of Figure 1 for when $n = 12$. The values of $\pi(\theta | \delta)$ when $\theta = \{1/2, 1/3, 1/4, 1/6, 1/12\}$ are given by 0.062, 0.238, 0.423, 0.677, 0.920, respectively, and have also been marked on Figure 1. The significance of this test is given by $\alpha(\delta) = \pi(1/2 | \delta) = 0.062$.

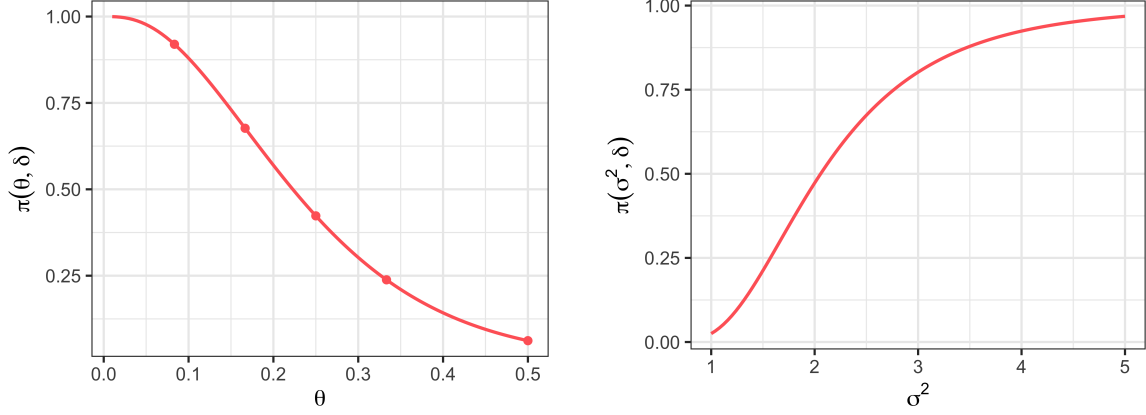


Figure 1: The power functions $\pi(\theta | \delta)$ (question 6) and $\pi(\sigma^2 | \delta)$ (question 8).

Question 7

Let $X_1, \dots, X_n \stackrel{\text{iid}}{\sim} \text{Unif}(0, \theta)$, where θ is unknown, and let Y_1, \dots, Y_n be the n order statistics of the random sample. We are testing $H_0 : \theta = 1$ against $H_A : \theta > 1$ with procedure δ : reject H_0 if $Y_n \geq c$, where c is an unknown constant that will be determined by the significance of δ . If Y_n is the n th order statistic of \mathbf{X} , its cdf and density are respectively given by $F_{Y_n}(y_n) = (y_n/\theta)^n$ and $f_{Y_n}(y_n) = ny_n^{n-1}/\theta^n$ for $y_n \in [0, \theta]$.

(b) The rejection region of Y_n is $\mathcal{S}_{Y_n} = [c, \theta]$, and so the power function is given by

$$\pi(\theta | \delta) = \Pr(Y_n \in \mathcal{S}_{Y_n} | \theta) = F_{Y_n}(\theta) - F_{Y_n}(c) = 1 - \frac{c^n}{\theta^n}.$$

(a) To have a significance level of $\alpha = 0.05$, we must have $\alpha(\delta) = \pi(1 | \delta) = 1 - c^n \stackrel{\text{set}}{=} 0.05$, and solving for c gives us $c = \sqrt[4]{0.95}$, and the power function with this level of significance is $\pi(\theta | \delta) = 1 - 0.95/\theta^4$. The question specifically asks for $n = 4$, in which case $c = \sqrt[4]{0.95}$ and $\pi(\theta | \delta) = 1 - 0.95/\theta^4$. More generally, for any specified significance level α_* , we will have $c = \sqrt[n]{1 - \alpha_*}$ and $\pi(\theta | \delta) = 1 - (1 - \alpha_*)/\theta^n$.

Question 8

Let $\mathbf{X} \stackrel{\text{iid}}{\sim} N(\mu, \sigma^2)$, where both μ and σ^2 are unknown. We want to test $H_0 : \sigma^2 = \sigma_0^2$ against $H_A : \sigma^2 > \sigma_0^2$ using procedure δ : reject H_0 if $nS^2/\sigma_0^2 \geq c$, where c will be determined by the significance of the test. Our test statistic is based off of $S^2 = \frac{1}{n} \sum_{i=1}^n (X_i - \bar{X})^2$, and we know that $T(\mathbf{X}) := nS^2/\sigma_0^2 \sim \chi^2(n-1)$. The rejection region for our test statistic is $\mathcal{S}_{T(\mathbf{X})} = [c, \infty)$, and we would like to find a value of c such that the significance is $\alpha = 0.025$.

$$\alpha(\delta) = \pi(\sigma_0^2 | \delta) = \Pr(T(\mathbf{X}) \in \mathcal{S}_{T(\mathbf{X})} | \sigma_0^2) = \int_c^\infty \frac{t^{(n-3)/2} \cdot e^{-t/2}}{2^{(n-1)/2} \Gamma((n-1)/2)} dt \stackrel{\text{set}}{=} 0.025.$$

There is no way to derive a closed form relationship between c and α like we did in question 7, but using R we can write a function to find the value of c for a given significance value α . When $n = 13$ and $\alpha = 0.025$, we have $c = 23.337$. To find a general formula of $\pi(\sigma^2 | \delta)$, we notice that if $T(\mathbf{X}) \geq c$, then $S^2 \geq c\sigma_0^2/n$, which serves as a rejection region for S^2 . Since $nS^2/\sigma^2 \sim \chi^2(n-1)$ for any value of σ^2 , it can be shown that $S^2 \sim \text{Gamma}((n-1)/2, n/2\sigma^2)$. Therefore, the power function is given by

$$\pi(\sigma^2 | \delta) = \Pr(S^2 \geq c\sigma_0^2/n | \sigma^2) = \int_{c\sigma_0^2/n}^\infty \frac{x^{(n-3)/2} \cdot e^{-nx/2\sigma^2}}{(n/2\sigma^2)^{(n-1)/2} \Gamma((n-1)/2)} dx,$$

where c is chosen to make $\alpha(\delta) = 0.025$ (or any specified value, for that matter). Again, there is no closed form solution to this function, but using **R** we can find its values, and given a specified value of σ_0^2 , we will always have $\pi(\sigma_0^2 | \delta) = \alpha$ as desired. A plot of $\pi(\sigma^2 | \delta)$ can be found in the right panel of Figure 1.

Question 9

If $\mathbf{X} \stackrel{\text{iid}}{\sim} N(\mu, \sigma^2)$ with unknown μ and σ^2 , then a 100 $\gamma\%$ confidence interval for μ is given by

$$\mathcal{I} = \left(\bar{X} - t_\gamma(n) \cdot S/\sqrt{n}, \bar{X} + t_\gamma(n) \cdot S/\sqrt{n} \right),$$

where $t_\gamma(n) = T_{n-1}^{-1}((1 + \gamma)/2)$ is the $(1 + \gamma)/2$ th quantile of the t distribution with $\text{df} = n - 1$ and S is the sample standard deviation. The length of this confidence interval is given by

$$\Delta = \max(\mathcal{I}) - \min(\mathcal{I}) = \left(\bar{X} + t_\gamma(n) \cdot S/\sqrt{n} \right) - \left(\bar{X} - t_\gamma(n) \cdot S/\sqrt{n} \right) = 2t_\gamma(n) \cdot S/\sqrt{n}.$$

The squared length is then given by $\Delta^2 = 4t_\gamma^2(n) \cdot S^2/n$. Because the sample variance is an unbiased estimator for σ^2 , we have $\mathbb{E}[\Delta^2] = \mathbb{E}[4t_\gamma^2(n) \cdot S^2/n] = 4t_\gamma^2(n) \cdot \sigma^2/n$. We now set $\mathbb{E}[\Delta^2] < \sigma^2/2$, and after some cancellations, we see that we need $t_\gamma^2(n)/n < 1/8$. There is no way to find a closed-form expression for this, so we will have to check the value of $t_\gamma^2(n)/n$ for increasing values of n . I set up a **while** loop in **R** to solve for it, and when $\gamma = 0.9$, we find that $n = 24$ is the smallest value of n such that $\mathbb{E}[\Delta^2] < \sigma^2/2$.

Question 10

Let $\mathbf{X} \stackrel{\text{iid}}{\sim} N(\theta, \sigma^2)$, where θ is unknown and σ^2 is known, and we assume prior that $\theta \sim N(\mu, \nu^2)$, where both μ and ν^2 are known.

- (a) Since normal distributions are conjugate to normal sampling, it follows that $\theta | \mathbf{x} \sim N(\tilde{\mu}, \tilde{\sigma}^2)$, where

$$\tilde{\mu} = \frac{\sigma^2\mu + n\nu^2\bar{x}}{\sigma^2 + n\nu^2} \quad \text{and} \quad \tilde{\sigma}^2 = \frac{\sigma^2\nu^2}{\sigma^2 + n\nu^2}.$$

We also know that $(\theta | \mathbf{x} - \tilde{\mu})/\tilde{\sigma} \sim N(0, 1)$, and so a 95% confidence interval for $\theta | \mathbf{x}$ is given by

$$\mathcal{I} = \left(\tilde{\mu} - \Phi^{-1}(0.975) \cdot \tilde{\sigma}, \tilde{\mu} + \Phi^{-1}(0.975) \cdot \tilde{\sigma} \right).$$

- (b) We can think of our interval \mathcal{I} as a function of ν^2 . To examine what happens to $\mathcal{I}(\nu^2)$ as $\nu^2 \rightarrow \infty$, we will first look at $\tilde{\mu}$ and $\tilde{\sigma}$. Using L'Hopital's rule, we have

$$\begin{aligned} \lim_{\nu^2 \rightarrow \infty} \tilde{\mu} &= \lim_{\nu^2 \rightarrow \infty} \frac{\sigma^2\mu + n\nu^2\bar{x}}{\sigma^2 + n\nu^2} = \lim_{\nu^2 \rightarrow \infty} \frac{n\bar{x}}{n} = \bar{x}, \\ \lim_{\nu^2 \rightarrow \infty} \tilde{\sigma} &= \lim_{\nu^2 \rightarrow \infty} \sqrt{\frac{\sigma^2\nu^2}{\sigma^2 + n\nu^2}} = \sqrt{\lim_{\nu^2 \rightarrow \infty} \frac{\sigma^2\nu^2}{\sigma^2 + n\nu^2}} = \sqrt{\lim_{\nu^2 \rightarrow \infty} \frac{\sigma^2}{n}} = \frac{\sigma}{\sqrt{n}}, \end{aligned}$$

and so $\mathcal{I}(\nu^2) \rightarrow (\bar{x} - \Phi^{-1}(0.975) \cdot \sigma/\sqrt{n}, \bar{x} + \Phi^{-1}(0.975) \cdot \sigma/\sqrt{n})$, which is a 95% confidence interval for θ .

Question 11

Let $\mathbf{X} \stackrel{\text{iid}}{\sim} \text{Unif}(0, \theta)$, where θ is unknown, and let $Y = X_{(n)}$ be the n th order statistic.

- (a) Let $F_i(x) = \Pr(X_i \leq x) = x/\theta$ for all $i \in \{1, \dots, n\}$. Then the cdf of Y is $G(y) = \prod_{i=1}^n F_i(y) = (y/\theta)^n$, since all of the X_i 's are independent. The density of Y is then given by $g(y) = ny^{n-1}/\theta^n$ for $y \in [0, \theta]$. By letting $W = Y/\theta$, we have $Y = \theta W$ and $\partial Y/\partial W = \theta$, so the density of Y/θ is given by $h(w) = g(y(w)) \cdot \theta = nw^{n-1}$ for $w \in [0, 1]$. The cdf is then seen to be $H(w) = w^n$, and so the quantile is given by $H^{-1}(w) = \sqrt[n]{w}$.

(b) Since we must have $y \leq \theta$, it is natural that Y will underestimate θ , and is therefore biased. We have

$$\mathbb{E}[Y] = \int_0^\theta y \cdot \frac{ny^{n-1}}{\theta^n} \partial y = \frac{n}{\theta^n} \int_0^\theta y^n \partial y = \frac{n}{\theta^n} \cdot \frac{y^{n+1}}{n+1} \Big|_0^\theta = \frac{n}{\theta^n} \cdot \frac{\theta^{n+1}}{n+1} = \frac{n\theta}{n+1},$$

and so the bias is $\text{bias}(Y) = \mathbb{E}[Y] - \theta = -\theta/(n+1)$.

(d) Using the cdf of Y/θ , for any interval involving Y/θ , we have $\Pr(a \leq Y/\theta \leq b) = b^n - a^n$, where $a, b \in (0, 1]$. Rearranging the terms inside the interval gives us $\Pr(Y/b \leq \theta \leq Y/a) = b^n - a^n \stackrel{\text{set}}{=} \gamma$. That is, as long as we impose the constraint that $b^n - a^n = \gamma$, any interval $(Y/b, Y/a)$ is a 100% confidence interval for θ .

Question 12

Suppose that $X \sim P$, where P is an unknown distribution, and we want to test $H_0 : P = \text{Unif}(0, 1)$ against $H_A : P = N(0, 1)$. The densities of both distributions (within their support) are given by $f(x | P_0) = 1$ for $x \in [0, 1]$ and $f(x | P_A) = (2\pi)^{-1/2} \exp(-x^2/2)$ for $x \in \mathbb{R}$, respectively, and so the likelihood ratio is given by

$$\ell(x) = \frac{f(x | P_A)}{f(x | P_0)} = \begin{cases} \phi(x) & \text{if } x \in [0, 1] \\ \infty & \text{if } x \notin [0, 1], \end{cases}$$

where $\phi(x)$ is the standard normal density. As a result, we will reject H_0 if $\ell(X) \geq k$, and so the power function is given by $\pi(P | \delta) = \Pr(\ell(X) \geq k | P)$. We note that if H_0 is true, then we will always have $x \in [0, 1]$, since we would be sampling from $\text{Unif}(0, 1)$, so in this case $\ell(x) = \phi(x)$. We also note that $\phi(x)$ is a decreasing function on this interval. As a result, the significance of this test is

$$\alpha(\delta) = \pi(P_0 | \delta) = \Pr(\ell(X) \geq k | P_0) = \Pr(\phi(X) \geq k) = \Pr(X \leq c) = F_0(c) \stackrel{\text{set}}{=} 0.01$$

where $c = \phi^{-1}(k)$ and $F_0(c)$ is the cdf of $\text{Unif}(0, 1)$. As a result, $c = 0.01$ gives us a test with significance 0.01. More generally, since $\phi(X) > k$ for any value of k (and thus any level of significance), we will always reject H_0 when $X \notin [0, 1]$, which makes the power function

$$\begin{aligned} \pi(P | \delta) &= \Pr(\phi(X) \geq \phi(0.01) | P) \\ &= \Pr(X < 0 \cup X \leq 0.01 \cup X > 1 | P) = \Pr(X \leq 0.01 | P) + \Pr(X > 1 | P) \end{aligned}$$

Therefore, when H_A is true, the power of δ is

$$\pi(P_A | \delta) = \Pr(X \leq 0.01 | P_A) + \Pr(X > 1 | P_A) = \Phi(0.01) + 1 - \Phi(1) = 0.663.$$

Question 13

Suppose that $\mathbf{X} \stackrel{\text{iid}}{\sim} N(\theta, 1)$, where $\theta > 1$ is unknown, and we wish to test $H_0 : \theta \leq \theta_*$ against $H_A : \theta > \theta_*$ using some UMP test δ^* . More specifically, we want our UMP test to have some pre-determined power π_* at a given mean φ , i.e. $\pi(\varphi | \delta^*) = \pi_*$. Since we are sampling from a normal distribution, the joint distribution of \mathbf{X} has increasing monotone likelihood ratio in the test statistic \bar{X} , where $\bar{X} \sim N(\theta, 1/n)$, so our UMP test is given by $\delta^* : \text{reject } H_0 \text{ if } \bar{X} \geq c$. We also notice that $\sqrt{n}(\bar{X} - \theta) := Z_\theta \sim N(0, 1)$. The rejection region for $\bar{X} = \mathcal{S}_{\bar{X}} = [c, \infty)$, so to find c we have

$$\pi(\varphi | \delta^*) = \Pr(\bar{X} \geq c | \theta = \varphi) = \Pr(Z_\varphi \geq \sqrt{n}(c - \varphi)) = 1 - \Phi(\sqrt{n}(c - \varphi)) \stackrel{\text{set}}{=} \pi_*.$$

From here, we have $\sqrt{n}(c - \varphi) = \Phi^{-1}(1 - \pi_*) := z_{\pi_*}$, and so $c = \varphi + z_{\pi_*}/\sqrt{n}$. With the value of c determined, the power function is then given by

$$\pi(\theta | \delta^*) = \Pr(\bar{X} \geq \varphi + z_{\pi_*}/\sqrt{n} | \theta) = \Pr(Z_\theta \geq \sqrt{n}(\varphi - \theta) + z_{\pi_*}) = 1 - \Phi(\sqrt{n}(\varphi - \theta) + z_{\pi_*}).$$

Since $\pi(\theta | \delta^*)$ is a monotone increasing function of θ , it will be maximized at the largest possible value over an interval. Therefore, the significance of this test is

$$\alpha(\delta^*) = \sup_{\theta \leq \theta_*} \pi(\theta | \delta^*) = \pi(\theta_* | \delta^*) = 1 - \Phi(\sqrt{n}(\varphi - \theta_*) + z_{\pi_*}).$$

The question specifically asks for c and α when $\theta_* = 0$, $\varphi = 1$, $\pi_* = 0.95$, and $n = 16$. In this case, we have $z_{\pi_*} = \Phi^{-1}(0.05) \approx -1.64$, which means $c = 1 - 1.64/4 = 0.589$ and $\alpha = 1 - \Phi(4 - 1.64) = 0.00926$. Put more formally, if we have a random sample $\mathbf{X} \stackrel{\text{iid}}{\sim} N(\theta, 1)$, and want to test $H_0 : \theta \leq 0$ against $H_A : \theta > 0$ using a UMP test with a power of 0.95 at $\theta = 1$, then our test is given by $\delta^* : \text{reject } H_0 \text{ if } \bar{X} \geq 0.589$. With 16 observations, the size of this test is $\alpha = 0.00926$.

Question 14

Suppose X_1, \dots, X_8 are randomly sampled from a random variable with density $f(x | \theta) = \theta x^{\theta-1}$, supported for all $x \in (0, 1)$, and we would like to test $H_0 : \theta \leq 1$ against $H_A : \theta > 1$ using a UMP test δ^* . For two values θ_1, θ_2 such that $\theta_1 < \theta_2$, the ratio of the joint densities (which are also the likelihood functions) is

$$\frac{f(\mathbf{x} | \theta_2)}{f(\mathbf{x} | \theta_1)} = \frac{\prod_{i=1}^8 \theta_2 x_i^{\theta_2-1}}{\prod_{i=1}^8 \theta_1 x_i^{\theta_1-1}} = \frac{\theta_2^8 \left(\prod_{i=1}^8 x_i \right)^{\theta_2-1}}{\theta_1^8 \left(\prod_{i=1}^8 x_i \right)^{\theta_1-1}} = \left(\frac{\theta_2}{\theta_1} \right)^8 \cdot \left(\prod_{i=1}^8 x_i \right)^{\theta_2-\theta_1}.$$

which is a function of the test statistic $\prod_{i=1}^8 x_i$. Because $\theta_2 > \theta_1$, we have $\theta_2/\theta_1 > 1$ and $\theta_2 - \theta_1 > 0$, so the likelihood ratio is monotone and increasing in the parameter $\prod_{i=1}^8 x_i$. As a result, the UMP test is $\delta^* : \text{reject } H_0 \text{ if } \prod_{i=1}^8 x_i \geq c$ for some value of c . For this test, we specify the level of significance as $\alpha_* = 0.05$, and since $\pi(\theta | \delta^*)$ is a monotone increasing function, we have

$$\alpha_* = \sup_{\theta \leq 1} \pi(\theta | \delta^*) = \pi(1 | \delta^*) \stackrel{\text{set}}{=} 0.05.$$

When $\theta = 1$, we can see from the density function that $X \sim \text{Unif}(0, 1)$, with its cdf given by $F(X) = X$. It can be shown, then, that $-2 \sum_{i=1}^8 \log F(X_i) \sim \chi^2(16)$. Therefore,

$$\pi(1 | \delta^*) = \Pr \left(\prod_{i=1}^8 x_i \geq c | \theta = 1 \right) = \Pr \left(-2 \sum_{i=1}^8 \log X_i \leq -2 \log c \right) = C_{16}(-2 \log c) = 0.05$$

where $C_{16}(x)$ is the cdf of $\chi^2(16)$. If $k := -2 \log c$, it follows that $k = C_{16}^{-1}(0.05) = 7.962$, and as a result, $\sum_{i=1}^8 \log X_i \geq -k/2 = 3.981$.

Question 15

Suppose that $\mathbf{X} \stackrel{\text{iid}}{\sim} \chi^2(\theta)$, where $\theta \in \mathbb{N}$ is unknown. We would like to test $H_0 : \theta \leq 8$ against $H_A : \theta > 8$, using a UMP test δ^* with a specified significance $\alpha_* \in (0, 1)$. The joint density of \mathbf{X} is given by

$$f(\mathbf{x} | \theta) = \prod_{i=1}^n \frac{x_i^{\theta/2-1} e^{-x_i/2}}{2^{\theta/2} \Gamma(\theta/2)} = 2^{-n\theta/2} \cdot \Gamma^{-n}(\theta/2) \cdot \left(\prod_{i=1}^n x_i \right)^{n(\theta/2-1)} \cdot \exp \left(-\frac{1}{2} \sum_{i=1}^n x_i \right)$$

To determine δ^* , we will look at the likelihood ratio. If we have two values θ_1, θ_2 such that $\theta_1 < \theta_2$, then then likelihood ratio is

$$\begin{aligned} \frac{f(\mathbf{x} | \theta_2)}{f(\mathbf{x} | \theta_1)} &= \frac{2^{-n\theta_1/2} \cdot \Gamma^{-n}(\theta_2/2) \cdot \left(\prod_i x_i \right)^{n(\theta_2/2-1)} \cdot \exp \left(-\frac{1}{2} \sum_i x_i \right)}{2^{-n\theta_1/2} \cdot \Gamma^{-n}(\theta_1/2) \cdot \left(\prod_i x_i \right)^{n(\theta_1/2-1)} \cdot \exp \left(-\frac{1}{2} \sum_i x_i \right)} \\ &= 2^{n(\theta_1-\theta_2)/2} \left(\frac{\Gamma(\theta_1/2)}{\Gamma(\theta_2/2)} \right)^n \left(\prod_{i=1}^n x_i \right)^{n(\theta_2-\theta_1)/2}, \end{aligned}$$

which is a monotone increasing function of the test statistic $\prod_{i=1}^n x_i$. Therefore, the UMP test is δ^* : reject H_0 if $\prod_{i=1}^n X_i \geq c_*$, where c_* is chosen such that the test has a significance level α_* . Taking the log of both sides gives us $\sum_{i=1}^n \log X_i \geq \log c_* := k$.