Homework 1

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Question 1

When rolling two dice, there are six possible ways for their total to sum up to seven: $(1,6)$, $(2,5)$, $(3,4)$, $(4,3)$, $(5,2)$, and $(6,1)$, so the probability of the sum being seven is $6/36 = 1/6$. If X is the number of trials where the total of both rolls is seven, then we can think of $X \sim \mathrm{Bin}(120, 1/6)$, and so $\mathbb{E}X = 20$ and $\mathrm{Var}X = 50/3$. Using the Central Limit Theorem, we then have

$$\Pr\big(|X-20| \le k\big) = \Pr\left(\left|\frac{X-20}{\sqrt{50/3}}\right| \le k\sqrt{\frac{3}{50}}\right) = 2\Phi\left(k\sqrt{\frac{3}{50}}\right) - 1 \overset{\text{set}}{=} 0.95 \implies \Phi\left(k\sqrt{\frac{3}{50}}\right) = 0.975.$$

Using a table of values for $\Phi(z)$, we can see that $k\sqrt{3/50} = 1.96$, and so $k = 1.96\sqrt{50/3} \approx 8$.

Question 2

Let $X \sim \mathrm{Pois}(10)$, and so $\mathbb{E}X = \mathrm{Var}X = 10$. Using the CLT without any continuity correction, we have $(X-10)/\sqrt{10} \approx \mathrm{N}(0,1)$, and so

$$\Pr(8 \le X \le 12) = \Pr\left(\frac{8-10}{\sqrt{10}} \le Z \le \frac{12-10}{\sqrt{10}}\right) = \Pr\big(|Z| \le \sqrt{2/5}\big) \approx 2\Phi\big(\sqrt{2/5}\big) - 1 = 0.4714.$$

If we do use continuity correction, then we have

$$\begin{aligned}\Pr(8 \le X \le 12) &\approx \Pr(7.5 \le X \le 12.5)\\ &= \Pr\left(\frac{7.5-10}{\sqrt{10}} \le Z \le \frac{12.5-10}{\sqrt{10}}\right) = \Pr\big(|Z| \le 2.5/\sqrt{10}\big) \approx 2\Phi\big(2.5/\sqrt{10}\big) - 1 = 0.5704.\end{aligned}$$

Question 3

We are assuming that when a program is run, an execution error will occur with probability $\theta \in [0,1]$. If X is whether or not an execution error occurs, we have $X \sim \mathrm{Ber}(\theta)$, and $f(x\,|\,\theta) = \theta^x(1-\theta)^{1-x}$ for $x = \{0,1\}$. We also believe that $\theta \sim \mathrm{Unif}(0,1)$, and so $\xi(\theta) = 1$ for $0 \le \theta \le 1$.

(a) After 25 runs of the program we have 10 erros, so $f(\mathbf{x}\,|\,\theta) = \theta^{10}(1-\theta)^{15}$. The marginal distribution of $\boldsymbol{X}$ is given by

$$g_{\boldsymbol{X}}(\mathbf{x}) = \int_\Theta f(\mathbf{x}\,|\,\theta)\cdot\xi(\theta)\,\mathrm{d}\theta = \int_0^1 \theta^{10}(1-\theta)^{15}\cdot 1\,\mathrm{d}\theta = \int_0^1 \theta^{11-1}(1-\theta)^{16-1}\,\mathrm{d}\theta = \mathrm{B}(11,16),$$

and so the posterior pdf of θ is

$$\xi(\theta\,|\,\mathbf{x}) = \frac{f(\mathbf{x}\,|\,\theta)\cdot\xi(\theta)}{g_{\boldsymbol{X}}(\mathbf{x})} = \frac{\theta^{10}(1-\theta)^{15}\cdot 1}{\mathrm{B}(11,16)} = \frac{\theta^{11-1}(1-\theta)^{16-1}}{\mathrm{B}(11,16)}.$$

That is, $\theta\,|\,\mathbf{x} \sim \mathrm{Beta}(11,16)$.

(b) If we are using squared error loss, then our Bayes' estimate is $\delta^*(\mathbf{x}) = \mathbb{E}(\theta\,|\,\mathbf{x}) = 11/27$.

Question 4

We believe that $\theta \sim \text{Beta}(3, 4)$, where $\theta \in [0, 1]$ is the proportion of bad apples in the lot. Choosing apples from the lot is essentially sampling from a Bernoulli distribution with parameter θ, and we know that Beta distributions are closed under sampling from a Bernoulli distribution. After choosing 10 apples, we find that three of them are bad, so our posterior distribution becomes $\theta \,|\, \mathbf{x} \sim \text{Beta}(3 + 3, 4 + 7) = \text{Beta}(6, 11)$. If we use squared error loss, our Bayes' estimate is then $\delta^*(\mathbf{x}) = \mathbb{E}(\theta \,|\, \mathbf{x}) = 6/17$.

Question 5

Let $\boldsymbol{X} = (X_1, \ldots, X_n)^T$ be a random sample from $X \sim \text{Unif}(\theta, 2\theta)$, where $\theta > 0$. The likelihood function is then given by $f(\mathbf{x} \,|\, \theta) = 1/\theta^n$ when $\theta \leq x_i \leq 2\theta$ for $i \in \{1, \ldots, n\}$. We can re-frame the boundaries of the likelihood function using order statistics. Since we need every observation $x_i \in [\theta, 2\theta]$, it follows that $\theta \leq x_{(1)} \leq \cdots \leq x_{(n)} \leq 2\theta$, where $x_{(j)}$ is the jth order statistics; namely, we have $\theta \leq x_{(1)}$ and $x_{(n)} \leq 2\theta$. From the second inequality, we have $x_{(n)}/2 \leq \theta$, and so the possible values of θ are $x_{(n)}/2 \leq \theta \leq x_{(1)}$. In other words, even though we had the original parameter space $\Theta = (0, \infty)$, because the bounds of the density functions depended on θ, we were able to restrict θ to a new parameter space $\tilde{\Theta} = [x_{(n)}/2, x_{(1)}]$. We can see that our likelihood function is monotone decreasing, and so it will be maximized by the smallest possible value of θ. Therefore, the MLE of θ is $\hat{\theta}(\boldsymbol{X}) = X_{(n)}/2$.

Question 6

Suppose that $\boldsymbol{X} = (X_1, X_2, X_3)^T$ are each exponentially distributed with $\mathbb{E}X_i = i\theta$, where $\theta > 0$. This implies that $X_i \sim \text{Exp}(1/i\theta)$, and so $f(x_i \,|\, \theta) = \mathrm{e}^{-x_i/i\theta}/i\theta$.

(a) The likelihood function is given by

$$f(\mathbf{x} \,|\, \theta) = \prod_{i=1}^{3} f(x_i \,|\, \theta) = \prod_{i=1}^{3} \frac{\mathrm{e}^{-x_i/i\theta}}{i\theta} = \frac{1}{6\theta^3} \exp\left(-\frac{1}{\theta} \sum_{i=1}^{3} \frac{x_i}{i}\right),$$

and the corresponding log-likelihood function is given by $\ell(\mathbf{x} \,|\, \theta) = -3\log(6\theta) - \frac{1}{\theta}\sum_{i=1}^{3} x_i/i$. Differentiating $\ell(\mathbf{x} \,|\, \theta)$ with respect to θ, setting to 0, and solving for θ gives us the MLE:

$$\frac{\partial \ell}{\partial \theta} = -\frac{3}{\theta} + \frac{1}{\theta^2} \sum_{i=1}^{3} \frac{x_i}{i} \stackrel{\text{set}}{=} 0 \implies \hat{\theta}(\boldsymbol{X}) = \frac{1}{3} \sum_{i=1}^{3} \frac{X_i}{i}$$

(b) Let $\psi = 1/\theta$, and we believe that $\psi \sim \text{Gamma}(\alpha, \beta)$, i.e. $\xi(\psi) = \frac{\beta^\alpha}{\Gamma(\alpha)} \psi^\alpha \mathrm{e}^{-\beta\psi}$ for $\psi > 0$. For notational ease, let $\varphi(\mathbf{x}) = \sum_{i=1}^{3} x_i/i$; the likelihood function of ψ is then given by $f(\mathbf{x} \,|\, \psi) = \psi^3 \mathrm{e}^{-\varphi(\mathbf{x})\psi}/6$. We have

$$\xi(\psi \,|\, \mathbf{x}) \propto f(\mathbf{x} \,|\, \psi) \cdot \xi(\psi) = \frac{1}{6} \psi^3 \mathrm{e}^{-\varphi(\mathbf{x})\psi} \cdot \frac{\beta^\alpha}{\Gamma(\alpha)} \psi^{\alpha-1} \mathrm{e}^{-\beta\psi} \propto \psi^{\alpha+3-1} \mathrm{e}^{-(\beta+\varphi(\mathbf{x}))\psi}.$$

This is very similar to a Gamma distribution with parameters $\tilde{\alpha} = \alpha + 3$ and $\tilde{\beta} = \beta + \varphi(\mathbf{x})$, and adding in the normalizing constants would make it so. Therefore, we conclude that $\psi \,|\, \mathbf{x} \sim \text{Gamma}\big(\alpha+3, \beta+\varphi(\mathbf{x})\big)$.

Question 7

We assume that our parameter θ has a prior density $\xi(\theta) = \theta\mathrm{e}^{-\theta}$ for $\theta > 0$. Let $X \sim \text{Unif}(0, \theta)$, and so $f(x \,|\, \theta) = 1/\theta$ for $0 \leq x \leq \theta$. We note that while the original parameter space was $\Theta = (0, \infty)$, sampling from a uniform distribution who's bound depended on θ resulted in a new parameter space $\tilde{\Theta} = [x, \infty)$. The marginal distribution of X is given by

$$g_X(x) = \int_{\tilde{\Theta}} f(x \,|\, \theta) \cdot \xi(\theta) \, \mathrm{d}\theta = \int_x^\infty \frac{1}{\theta} \cdot \theta\mathrm{e}^{-\theta} \, \mathrm{d}\theta = \int_x^\infty \mathrm{e}^{-\theta} \, \mathrm{d}\theta = \Big[-\mathrm{e}^{-\theta}\Big]_x^\infty = \mathrm{e}^{-x},$$

and so our posterior density for θ is given by

$$\xi(\theta \,|\, x) = \frac{f(x \,|\, \theta) \cdot \xi(\theta)}{g_X(x)} = \frac{1}{\theta} \cdot \theta \mathrm{e}^{-\theta} \cdot \frac{1}{\mathrm{e}^{-x}} = \mathrm{e}^{-(\theta - x)}.$$

This denisty corresponds to a "shifted" exponential distribution with $\lambda = 1$; instead of starting at zero, we are starting at x.

(a) Using squared error loss, our Bayes' estimate is the mean of the posterior distribution:

$$\delta^*(x) = \mathbb{E}(\theta \,|\, x) = \int_x^\infty \theta \cdot \mathrm{e}^{-(\theta - x)} \, \mathrm{d}\theta = \Big[-\theta \mathrm{e}^{-(\theta - x)} \Big]_x^\infty + \int_x^\infty \mathrm{e}^{-(\theta - x)} \, \mathrm{d}\theta = x + 1.$$

(b) Using absolute error loss, our Bayes' estimate is the median of the posterior distribution. The posterior cdf is easily seen to be $\Xi(\theta \,|\, x) = 1 - \mathrm{e}^{-(\theta - x)}$. To get the median, we need $\Xi\big(\delta^*(x)\big) = 1 - \mathrm{e}^{-(\delta^*(x) - x)} = 1/2$, and solving for $\delta^*(x)$ gives us $\delta^*(x) = x + \log 2$.

Question 8

Because $0 \leq \beta \leq 1$, we have $1/3 \leq \theta \leq 2/3$. If we are sampling from $X \sim \mathrm{Ber}(\theta)$, then the likelihood and log-likelihood functions are given by $f(\mathbf{x} \,|\, \theta) = \theta^{n\bar{x}}(1 - \theta)^{n(1 - \bar{x})}$ and $\ell(\mathbf{x} \,|\, \theta) = n\bar{x} \log \theta + n(1 - \bar{x}) \log(1 - \theta)$. Differentiating $\ell(\mathbf{x} \,|\, \theta)$, setting equal to zero, and solving for θ gives the MLE as

$$\frac{\partial \ell(\mathbf{x} \,|\, \theta)}{\partial \theta} = \frac{n\bar{x}}{\theta} - \frac{n(1 - \bar{x})}{1 - \theta} = n \left(\frac{\bar{x} - \theta}{\theta(1 - \theta)} \right) \overset{\text{set}}{=} 0 \implies \hat{\theta} = \bar{x}.$$

We must be cautious; because each $x_i \in \{0, 1\}$, we can have $\bar{x} \in [0, 1]$, and so the maximum of $\ell(\mathbf{x} \,|\, \theta)$ can occur at $\hat{\theta} \in [0, 1]$. However, because of the contraints placed on θ by β, this maximum can potentially fall outside the range of possible values. To remedy this, we will consider two cases:

1. $\bar{x} < 1/3$: for all values $\theta \in [1/3, 2/3]$, we have $\partial \ell / \partial \theta < 0$, so $\ell(\mathbf{x} \,|\, \theta)$ is a decreasing function. Then the maximum value of $\ell(\mathbf{x} \,|\, \theta)$ is obtained when $\theta = 1/3$.
2. $\bar{x} > 2/3$: for all values $\theta \in [1/3, 2/3]$, we have $\partial \ell / \partial \theta > 0$, so $\ell(\mathbf{x} \,|\, \theta)$ is an increasing function. Then the maximum value of $\ell(\mathbf{x} \,|\, \theta)$ is obtained when $\theta = 2/3$.

Therefore, the MLEs for both θ and β are given by

$$\hat{\theta} = \begin{cases} \bar{X} & \text{if } 1/3 \leq \bar{X} \leq 2/3, \\ 1/3 & \text{if } \bar{X} < 1/3, \\ 2/3 & \text{if } \bar{X} > 2/3. \end{cases} \quad \text{and} \quad \hat{\beta} = 3\hat{\theta} - 1 = \begin{cases} 3\bar{X} - 1 & \text{if } 1/3 \leq \bar{X} \leq 2/3, \\ 0 & \text{if } \bar{X} < 1/3, \\ 1 & \text{if } \bar{X} > 2/3. \end{cases}$$

This is because $\beta = 3\theta - 1$, which means the MLE of β is given by $\hat{\beta} = 3\hat{\theta} - 1$.

Question 9

We are sampling from a "shifted" exponential distribution, i.e. its density is given by $f(x \,|\, \beta, \theta) = \beta \mathrm{e}^{-\beta(x - \theta)}$ for $x \geq \theta$. The likelihood function is then given by $f(\mathbf{x} \,|\, \beta, \theta) = \beta^n \mathrm{e}^{-n\beta(\bar{x} - \theta)}$ when $x_i \geq \theta$ for $i \in \{1, \ldots, n\}$. If every observation $x_i \geq \theta$, then it is also true that the lowest value for each observation is as well, so $x_{(1)} \geq \theta$. We can incorporate this condition into the likelihood function using an indicator function:

$$f(\mathbf{x} \,|\, \beta, \theta) = \beta^n \mathrm{e}^{-n\beta(\bar{x} - \theta)} \cdot \mathbb{I}_{[\theta, \infty)}(x_{(1)}).$$

By the Factorization Theorem, $\bar{X}$ and $X_{(1)}$ are a pair of jointly sufficient statistics for β and θ.

Question 10

Let $X_1, \ldots, X_n \overset{\text{iid}}{\sim} \text{Pareto}(\alpha, x_0)$, where $\alpha > 0$ is known and $x_0 > 0$ is unknown. The likelihood function is given by

$$f(\mathbf{x} \,|\, \alpha, x_0) = \prod_{i=1}^{n} \frac{\alpha x_0^{\alpha}}{x_i^{\alpha+1}} = \alpha^n x_0^{\alpha n} \left(\prod_{i=1}^{n} \frac{1}{x_i} \right)^{\alpha+1} = C(\mathbf{x}, \alpha) \cdot x_0^{\alpha n}, \quad \text{where} \quad C(\mathbf{x}, \alpha) = \alpha^n \left(\prod_{i=1}^{n} \frac{1}{x_i} \right)^{\alpha+1},$$

when $x_i \geq x_0$ for $i \in \{1, \ldots, n\}$. This is the same as saying $x_{(1)} \geq x_0$, where $x_{(1)}$ is the first order statistic, and so our new parameter space for x_0 is $(0, x_{(1)}]$ (it was originally $(0, \infty)$). In the likelihood function, $C(\mathbf{x}, \alpha)$ is a constant (with respect to x_0) that depends on $\mathbf{x}$ and α. We can see that for $x_0 \in (0, x_{(1)}]$, $f(\mathbf{x} \,|\, \alpha, x_0)$ is an increasing function, so its maximum will be obtained at the largest possible value, $x_{(1)}$. Therefore, our MLE is $\hat{x}_0 = X_{(1)}$.

Question 11

From the previous question, by incorporating indicator functions, our likelihood function can be written as

$$f(\mathbf{x} \,|\, \alpha, x_0) = C(\mathbf{x}, \alpha) \cdot x_0^{\alpha n} \cdot \mathbb{I}_{[x_0, \infty)}(x_{(1)}).$$

By the Factorization Theorem, where $u(\mathbf{x}) = C(\mathbf{x}, \alpha)$ and $v(x_{(1)}, x_0) = x_0^{\alpha n} \cdot \mathbb{I}_{[x_0, \infty)}(x_{(1)})$, the first order statistic $X_{(1)}$ is a sufficient statistic. Since it is also the MLE of x_0, is follows that $X_{(1)}$ is a minimal sufficient statistic.

Question 12

From question 10, we already know that $\hat{x}_0 = X_{(1)}$, the first order statistic; our likelihood function is already maximized with respect to x_0. We have already derived the likelihood function in question 10, and the log-likelihood function is given by

$$\ell(\mathbf{x} \,|\, \alpha, x_0 \overset{\text{set}}{=} x_{(1)}) = n \log \alpha + \alpha n \log x_{(1)} - (\alpha + 1) \sum_{i=1}^{n} \log x_i.$$

Differentiating with respect to α and setting equal to zero gives us the MLE as

$$\frac{\partial \ell}{\partial \alpha} = \frac{n}{\alpha} + n \log x_{(1)} - \sum_{i=1}^{n} \log x_i = \frac{n}{\alpha} - \sum_{i=1}^{n} \log \left(\frac{x_i}{x_{(1)}} \right) \overset{\text{set}}{=} 0 \implies \hat{\alpha} = \frac{n}{\sum_{i=1}^{n} \log(X_i / X_{(1)})}.$$

Question 13

Looking at our likelihood function, and incorporating indicator functions, we see that

$$f(\mathbf{x} \,|\, \alpha, x_0) = \alpha^n x_0^{\alpha n} \left(\prod_{i=1}^{n} \frac{1}{x_i} \right)^{\alpha+1} \cdot \mathbb{I}_{[x_0, \infty)}(x_{(1)}) = \alpha^n x_0^{\alpha n} \Big(r_2(\mathbf{x}) \Big)^{\alpha+1} \cdot \mathbb{I}_{[x_0, \infty)} \Big(r_1(\mathbf{x}) \Big),$$

where $r_1(\mathbf{x}) = x_{(1)}$ and $r_2(\mathbf{x}) = \prod_{i=1}^{n} 1/x_i$. By the Factorization Theorem, $r_1(\mathbf{x})$ and $r_2(\mathbf{x})$ are jointly sufficient statistics, and we immediately see that $\hat{x}_0 = x_{(1)}$ is a sufficient statistic. When looking at $\hat{\alpha}$, we see that it can be written as

$$\hat{\alpha} = \frac{n}{\sum_{i=1}^{n} \log(x_i / x_{(1)})} = -\frac{n}{\sum_{i=1}^{n} \log(x_{(1)} / x_i)} = -\frac{n}{\log \left(\prod_{i=1}^{n} x_{(1)} / x_i \right)} = -\frac{n}{\log \Big(x_{(1)}^n r_2(\mathbf{x}) \Big)}.$$

This means $\hat{\alpha}$ is an injective transformation of $r_2(\mathbf{x})$, and so it is a sufficient statistic, and $\hat{\alpha}$ and $\hat{x}_0$ form a pair of jointy sufficient statistics. Because the are the MLEs, then they are minimal jointly sufficient statistics.