Problem1:

The log likelihood function of β is

$$l(\beta|X_1, \dots, X_n, \alpha) = log L(\beta|X_1, \dots, X_n, \alpha)$$

$$= \sum_{i=1}^n log f(X_i|\alpha, \beta)$$

$$= \sum_{i=1}^n log \left[\frac{\beta^{\alpha}}{\Gamma(\alpha)} X_i^{\alpha-1} e^{-\beta X_i}\right]$$

As MLE of β maximizes $l(\beta|X_1,\ldots,X_n,\alpha)$, we use the first order and second order conditions and get

$$\frac{\partial}{\partial \beta} l(\beta | X_1, \dots, X_n, \alpha) |_{\beta = \hat{\beta}} = 0$$

$$\sum_{i=1}^n \left(\frac{\alpha}{\hat{\beta}} - X_i \right) = 0$$

$$\hat{\beta} = \frac{1}{n\alpha} \sum_{i=1}^n X_i,$$

and,

$$\frac{\partial^2}{\partial \beta^2} l(\beta | X_1, \dots, X_n, \alpha) |_{\beta = \hat{\beta}}$$

$$= \sum_{i=1}^n -\frac{\alpha}{\hat{\beta}^2} < 0.$$

Thus, the MLE of β is $\hat{\beta} = \frac{1}{n\alpha} \sum_{i=1}^{n} X_i$.

Problem2:

(a) The joint density of X_1, \ldots, X_n is

$$f(x_1, \dots, x_n | \theta) = \theta^n \prod_{i=1}^n x_i^{-2} I[x_1 \ge \theta, \dots, x_n \ge \theta] = \theta^n \prod_{i=1}^n x_i^{-2} I[\min_{1 \le i \le n} x_i \ge \theta],$$

where $I(\cdot)$ is indicator function. By factorization theorem, we know $\min_{1 \le i \le n} x_i$ is sufficient statistic for θ .

(b) The MLE of θ maximizes $f(x_1, \ldots, x_n | \theta)$, so, $\hat{\beta} = \min_{1 \le i \le n} x_i$. (c) Since $E[X_i] = \infty$, let us consider $E[\frac{1}{X_i}] = \frac{1}{2\theta}$. Replace $E[\frac{1}{X_i}]$ with $\frac{1}{n} \sum_{i=1}^n \frac{1}{X_i}$, then we get a moment estimator of θ : $\hat{\theta} = \frac{n}{2\sum_{i=1}^{n} \frac{1}{X_{i}}}$.

Problem3:

(b) The p.d.f. of X_i is $f(x|\alpha,\beta) = \frac{\alpha}{\beta}(\frac{x}{\beta})^{\alpha-1}, 0 \le x \le \beta$. The likelihood function of (α,β) is the joint density of X_1,\ldots,X_n . So the likelihood function is

$$L(\alpha, \beta | x_1, \dots, x_n) = \prod_{i=1}^n \frac{\alpha}{\beta} (\frac{x}{\beta})^{\alpha - 1} I[0 \le x_i \le \beta]$$
$$= \left[\prod_{i=1}^n \frac{\alpha}{\beta} (\frac{x}{\beta})^{\alpha - 1} \right] I[\min_{1 \le i \le n} x_i \ge 0] I[\max_{1 \le i \le n} x_i \le \beta].$$

To minimize likelihood function, we should choose β as small as possible. But as $\max_{1 \le i \le n} x_i \le \beta$, $\hat{\beta} = \max_{1 \le i \le n} X_i$. Take the fist order condition of log likelihood function,

$$\frac{\partial}{\partial \alpha} l(\alpha, \beta | x_1, \dots, x_n)|_{\alpha = \hat{\alpha}} = 0$$

$$\frac{n}{\hat{\alpha}} + \sum_{i=1}^n \log(\frac{X_i}{\hat{\beta}}) = 0$$

$$\hat{\alpha} = \frac{n}{\sum_{i=1}^n \log(\frac{\hat{\beta}}{X_i})}.$$

(c)
$$\hat{\beta} = \max_{1 \le i \le n} X_i = 25. \ \hat{\alpha} = \frac{n}{\sum_{i=1}^n \log(\frac{\hat{\beta}}{X_i})} = 12.59487.$$

Problem5:

MLE of θ makes $f(x|\theta)$ attain its maximum for any x, thus

$$\hat{\theta} = \begin{cases} 1 & x = 0 \text{ or } 1, \\ 2 \text{ or } 3 & x = 2, \\ 3 & x = 3 \text{ or } 4. \end{cases}$$

Problem6:

 $L(\theta|\mathbf{x}) = \prod_i \frac{1}{2} e^{-\frac{1}{2}|x_i - \theta|} = \frac{1}{2^n} e^{-\frac{1}{2}\Sigma_i|x_i - \theta|}$, so the MLE minimizes $\sum_i |x_i - \theta| = \sum_i |x_{(i)} - \theta|$, where $x_{(1)}, \ldots, x_{(n)}$ are the order statistics. For $x_{(j)} \leq \theta \leq x_{(j+1)}$,

$$\sum_{i=1}^{n} |x_{(i)} - \theta| = \sum_{i=1}^{j} (\theta - x_{(i)}) + \sum_{i=j+1}^{n} (x_{(i)} - \theta) = (2j - n)\theta - \sum_{i=1}^{j} x_{(i)} + \sum_{i=j+1}^{n} x_{(i)}.$$

This is a linear function of θ that decreases for j < n/2 and increases for j > n/2. If n is even, 2j - n = 0 if j = n/2. So the likelihood is constant between $x_{(n/2)}$ and $x_{((n/2)+1)}$, and any value in this interval is the MLE. Usually the midpoint of this interval is taken as the MLE. If n is odd, the likelihood is minimized at $\hat{\theta} = x_{((n+1)/2)}$.