## Problem 1

Using the central limit theorem  $\bar{X_1}$  and  $\bar{X_2}$  are approximately normally distributed

$$egin{aligned} ar{X_1} &\sim N(\mu,\sigma^2/n) \\ ar{X_2} &\sim N(\mu,\sigma^2/n) \end{aligned}$$
 Since  $ar{X_1}$  and  $ar{X_2}$  are independent:  $ar{X_1} - ar{X_2} &\sim N(\mu_1 - \mu_2,\sigma_1^2 + \sigma_2^2) \\ ar{X_1} - ar{X_2} &\sim N(0,2\sigma^2/n) \end{aligned}$  Let  $Z = \dfrac{[ar{X_1} - ar{X_2}]\sqrt{n}}{\sqrt{2}\sigma} \\ Z &\sim N(0,1)$ 

We want to find n such that:

$$P(|\bar{X}_1 - \bar{X}_2| < \sigma/5) \approx .99$$

$$P(|\bar{X}_1 - \bar{X}_2| < \sigma/5) = P(-\sigma/5 < \bar{X}_1 - \bar{X}_2 < \sigma/5)$$

$$= P(\frac{-\sqrt{n}\sigma}{5\sqrt{2}\sigma} < Z < \frac{\sqrt{n}\sigma}{5\sqrt{2}\sigma})$$

$$= P(\frac{-\sqrt{n}}{5\sqrt{2}} < Z < \frac{\sqrt{n}}{5\sqrt{2}})$$

$$.99 \approx P(\frac{-\sqrt{n}}{5\sqrt{2}} < Z < \frac{\sqrt{n}}{5\sqrt{2}})$$

$$.99 \approx P(Z < \frac{\sqrt{n}}{5\sqrt{2}}) - P(Z > -\frac{\sqrt{n}}{5\sqrt{2}})$$

$$.99 \approx P(Z < \frac{\sqrt{n}}{5\sqrt{2}}) - (1 - P(Z < \frac{\sqrt{n}}{5\sqrt{2}}))$$

$$.99 \approx 2P(Z < \frac{\sqrt{n}}{5\sqrt{2}}) - 1$$

$$P(Z < \frac{\sqrt{n}}{5\sqrt{2}}) \approx .995$$

$$qnorm(.995) = 2.575829 \quad \text{(using R)}$$

$$2.575829 = \frac{\sqrt{n}}{5\sqrt{2}}$$

$$n = [2.575829(5\sqrt{2})]^2 = 50 * 2.575829^2 = 331.7448$$

$$n = 332$$

### Problem 2

(a)

Given 
$$X_n \stackrel{\mathcal{P}}{\to} a$$

$$\forall \; \epsilon > 0 \quad \lim_{n \to \infty} P[|X_n - a| > \epsilon] = 0$$

$$\text{WTS: } Y_i = \sqrt{X_i} \; \text{converges in probability}$$

$$\text{That is: } \lim_{n \to \infty} P(|\sqrt{X_n} - \sqrt{a} > \epsilon) = 0$$

$$P(|\sqrt{X_n} - \sqrt{a} > \epsilon) = P(|\sqrt{X_n} - \sqrt{a}||\sqrt{X_n} + \sqrt{a}| > \epsilon|\sqrt{X_n} + \sqrt{a}|)$$

$$= P(|X_n - a| > \epsilon|\sqrt{X_n} + \sqrt{a}|)$$

$$\leq P(|X_n - a| > \epsilon\sqrt{a})$$

$$P(|\sqrt{X_n} - \sqrt{a} > \epsilon) \leq P(|X_n - a| > \epsilon\sqrt{a})$$

$$\text{Since } \forall \; \epsilon > 0 \quad \lim_{n \to \infty} P[|X_n - a| > \epsilon] = 0$$

$$\text{and } \; \epsilon \leq \sqrt{a}\epsilon$$

$$\text{We have } \lim_{n \to \infty} P(|X_n - a| > \epsilon\sqrt{a}) = 0$$

$$\text{Which means } \lim_{n \to \infty} P(|\sqrt{X_n} - \sqrt{a} > \epsilon) \leq \lim_{n \to \infty} P(|X_n - a| > \epsilon\sqrt{a}) = 0$$

$$\text{Thus } \lim_{n \to \infty} P(|\sqrt{X_n} - \sqrt{a} > \epsilon) = 0$$

$$\text{Therefore } \sqrt{X_n} \stackrel{\mathcal{P}}{\to} \sqrt{a}$$

WTS: 
$$Y_i^{'} = a/X_i$$
 converges in probability

That is:  $\lim_{n \to \infty} P(|a/X_n - 1| \le \epsilon) = 1$ 

$$P(|a/X_n - 1| \le \epsilon) = P(-\epsilon \le a/X_n - 1 \le \epsilon)$$

$$= P\left(\frac{1 - \epsilon}{a} \le 1/X_n \le \frac{1 + \epsilon}{a}\right)$$

$$= P\left(\frac{a}{1 + \epsilon} \le X_n \le \frac{a}{1 - \epsilon}\right)$$

$$= P\left(\frac{a + a\epsilon - a\epsilon}{1 + \epsilon} \le X_n \le \frac{a - a\epsilon + a\epsilon}{1 - \epsilon}\right)$$

$$= P\left(\frac{a(1 + \epsilon) - a\epsilon}{1 + \epsilon} \le X_n \le \frac{a(1 - \epsilon) + a\epsilon}{1 - \epsilon}\right)$$

$$= P\left(a - \frac{a\epsilon}{1 + \epsilon} \le X_n \le a + \frac{a\epsilon}{1 - \epsilon}\right)$$

$$\geq P\left(a - \frac{a\epsilon}{1+\epsilon} \leq X_n \leq a + \frac{a\epsilon}{1+\epsilon}\right) \text{ Since } a + \frac{a\epsilon}{1+\epsilon} < a + \frac{a\epsilon}{1-\epsilon}$$

$$= P\left(-\frac{a\epsilon}{1+\epsilon} \leq X_n - a \leq \frac{a\epsilon}{1+\epsilon}\right)$$

$$= P\left(|X_n - a| \leq \frac{a\epsilon}{1+\epsilon}\right)$$

$$P(|a/X_n - 1| \leq \epsilon) \geq P\left(|X_n - a| \leq \frac{a\epsilon}{1+\epsilon}\right)$$
Since  $\lim_{n \to \infty} P\left(|X_n - a| \leq \epsilon\right) = 1$ 
We have  $\lim_{n \to \infty} P\left(|X_n - a| \leq \frac{a\epsilon}{1+\epsilon}\right) = 1$ 
Therefore  $\lim_{n \to \infty} P(|a/X_n - 1| \leq \epsilon) = 1$ 
Thus  $a/X_n \stackrel{p}{\to} 1$ 

(b)

WTS: 
$$\frac{\sigma}{S_n} \stackrel{p}{\to} 1$$

Using the result from the first part of a:

$$X_n \stackrel{p}{\to} a$$
 means that  $\sqrt{X_n} \stackrel{p}{\to} \sqrt{a}$  
$$S_n = \sqrt{S_n^2} \\ \sqrt{S_n^2} \stackrel{p}{\to} \sqrt{\sigma^2} \\ S_n \stackrel{p}{\to} \sigma$$

Using the result from the second part of a:

$$X_n \stackrel{p}{\to} a$$
 means that  $a/X_n \stackrel{p}{\to} 1$   
Since  $S_n \stackrel{p}{\to} \sigma$   
$$\frac{\sigma}{S_n} \stackrel{p}{\to} 1$$

## Problem 3

$$\begin{split} f_Y(y) &= \theta \gamma^\theta y^{-(\theta+1)} \quad 0 < \gamma < y < \infty, \ 2 < \theta < \infty \\ F_Y(y) &= 1 - \left(\frac{\gamma}{y}\right)^\theta \\ f_{Y_{(1)}}(y) &= n(\theta \gamma^\theta y^{-(\theta+1)}) \left[1 - \left(1 - \left(\frac{\gamma}{y}\right)^\theta\right)\right]^{n-1} \\ f_{Y_{(1)}}(y) &= n\theta \gamma^{\theta n} y^{-(\theta n+1)} \quad 0 < \gamma < y < \infty, \ 2 < \theta < \infty \\ EY_{(1)} &= \int_{\gamma}^{\infty} y(n\theta \gamma^{\theta n} y^{-(\theta n+1)}) \ dy \\ &= n\theta \gamma^{\theta n} \int_{\gamma}^{\infty} y^{-\theta n} \ dy \\ &= n\theta \gamma^{\theta n} \left[ \int_{\gamma}^{\infty} \frac{1}{-\theta n+1} y^{-\theta n+1} \right] \\ &= \frac{n\theta \gamma^{\theta n}}{-\theta n+1} (0 - \gamma^{-\theta n+1}) \\ EY_{(1)} &= \frac{-n\theta \gamma}{-\theta n+1} \\ &= \lim_{n \to \infty} \frac{-\eta \gamma}{-\theta n+1} \\ &= \lim_{n \to \infty} \frac{-\theta \gamma}{-\theta n+1} \\ &= \lim_{n \to \infty} \frac{-\theta \gamma}{-\theta n+1} \\ &= \frac{-\theta \gamma}{-\theta + 0} = \gamma \\ &\lim_{n \to \infty} EY_{(1)} &= \gamma \\ Var(Y_{(1)}) &= E(Y_{(1)}^2) - (EY_{(1)})^2 \\ E(Y_{(1)}^2) &= \int_{\gamma}^{\infty} y^2 (n\theta \gamma^{\theta n} y^{-(\theta n+1)}) \ dy \\ &= n\theta \gamma^{\theta n} \int_{\gamma}^{\infty} y^{-\theta n+1} \ dy \\ &= n\theta \gamma^{\theta n} \left[ \int_{\gamma}^{\infty} \frac{1}{-\theta n+2} y^{-\theta n+2} \right] \\ &= \frac{n\theta \gamma^{\theta n}}{-\theta n+2} (0 - \gamma^{-\theta n+2}) \\ &= \frac{-n\theta \gamma^{\theta n}}{-\theta n+2} \\ &= \frac{-n\theta \gamma^{\theta n}}{-\theta n+2} \end{aligned}$$

$$\lim_{n \to \infty} Var(Y_{(1)}) = \lim_{n \to \infty} E(Y_{(1)}^2) - \lim_{n \to \infty} (EY_{(1)})^2$$

$$\lim_{n \to \infty} E(Y_{(1)}^2) = \lim_{n \to \infty} \frac{-n\theta\gamma^2}{-\theta n + 2}$$

$$= \lim_{n \to \infty} \frac{-\theta\gamma^2}{-\theta + (2/n)}$$

$$= \frac{-\theta\gamma^2}{-\theta + 0} = \gamma^2$$

$$\lim_{n \to \infty} E(Y_{(1)}^2) = \gamma^2$$

$$\lim_{n \to \infty} E(Y_{(1)}^2)^2 = \lim_{n \to \infty} \left(\frac{-n\theta\gamma}{-\theta n + 1}\right)^2$$

$$= \lim_{n \to \infty} \frac{n^2\theta^2\gamma^2}{\theta^2n^2 - 2\theta^2n + 1}$$

$$= \lim_{n \to \infty} \frac{\theta^2\gamma^2}{\theta^2 - 2\theta^2(1/n) + 1/n^2}$$

$$= \frac{\theta^2\gamma^2}{\theta^2 - 0 + 0} = \gamma^2$$

$$\lim_{n \to \infty} E(Y_{(1)})^2 = \gamma^2$$

$$\lim_{n \to \infty} Var(Y_{(1)}) = \gamma^2 - \gamma^2 = 0$$

Thus  $Y_{(1)}$  is a consistent estimator of  $\gamma$ 

$$Y_{(1)} \stackrel{p}{\to} \gamma$$

# Problem 4

(a)

 $X_1, \ldots, X_n$  are iid random variables  $\sim Pois(\mu)$   $\mu > 0$ 

$$E(X_i) = \mu$$

$$\bar{X}_n = n^{-1} \sum_{i=1}^n X_i$$

$$\sqrt{n}(\bar{X}_n - EX_1) \stackrel{d}{\to} N(0, \sigma^2)$$

Since the mean and the variance of poisson rv are equal:

$$\sigma^2 = \mu \quad \sigma = \sqrt{\mu}$$

Since we have iid random variables, a finite mean and variance:

$$\frac{\sqrt{n}(\bar{X_n} - \mu)}{\sqrt{\mu}} \xrightarrow{d} N(0, 1)$$

(b)

$$T_n = \sqrt{n}(\bar{X}_n - \mu)$$

$$T_n \stackrel{d}{\to} N(0, \mu)$$
asymptotic variance  $= \mu$ 

Want to find  $h(\bar{X}_n)$  such that  $h(\bar{X}_n)T_n \stackrel{d}{\to} N(0,1)$ 

(c)

$$T_{n} = \sqrt{n}(\bar{X}_{n} - \mu) \xrightarrow{d} N(0, \mu)$$

$$\frac{\sqrt{n}(\bar{X}_{n} - \mu)}{\sqrt{\mu}} \xrightarrow{d} N(0, 1) \text{ (CLT)}$$
Since Xs are iid,  $EX_{i} = \mu$ , variance is finite:
$$\bar{X}_{n} \xrightarrow{p} \mu \text{ (WLLN)}$$

$$\frac{\sqrt{\mu}}{\sqrt{\bar{X}_{n}}} \xrightarrow{p} 1$$

$$\frac{\sqrt{\mu}}{\sqrt{\bar{X}_{n}}} \frac{\sqrt{n}(\bar{X}_{n} - \mu)}{\sqrt{\mu}} \xrightarrow{d} N(0, 1) \text{ (Slutsky's Thm)}$$

$$\frac{\sqrt{n}(\bar{X}_{n} - \mu)}{\sqrt{\bar{X}_{n}}} \xrightarrow{d} N(0, 1)$$

$$g(\bar{X}_{n}) \xrightarrow{p} g(\mu)$$

$$g(x) = \frac{1}{\sqrt{x}}$$

$$h(\bar{X}_{n}) = \frac{1}{\sqrt{\bar{X}_{n}}}$$

(d)

95% CI for 
$$\mu$$
 : Since  $\frac{\bar{X} - \mu}{\sqrt{\bar{X_n}}} \xrightarrow{d} N(0, 1)$ 

$$.95 \approx P\left(-1.96 < \frac{\sqrt{n}(\bar{X} - \mu)}{\sqrt{\bar{X_n}}} < 1.96\right)$$

$$= P\left(\bar{X} + \frac{1.96\sqrt{\bar{X_n}}}{\sqrt{n}} > \mu > \bar{X} - \frac{1.96\sqrt{\bar{X_n}}}{\sqrt{n}}\right)$$

$$= P\left(\bar{X} - \frac{1.96\sqrt{\bar{X_n}}}{\sqrt{n}} < \mu < \bar{X} + \frac{1.96\sqrt{\bar{X_n}}}{\sqrt{n}}\right)$$
Since  $\frac{\bar{X} - \mu}{\sqrt{\mu}} \xrightarrow{d} N(0, 1)$ 

$$\approx P\left(-1.96 < \frac{\bar{X} - \mu}{\sqrt{\mu}} < 1.96\right)$$

(e)

$$\sqrt{n}(g(\bar{X}_n) - g(\mu)) \stackrel{d}{\to} N(0, 1)$$

$$\sqrt{n}(g(\bar{X}_n) - g(\mu)) \stackrel{d}{\to} N(0, [g'(\mu)]^2 \mu)$$

$$[g'(\mu)]^2 \mu = 1$$

$$[g'(\mu)]^2 = \frac{1}{\mu}$$

$$g'(\mu) = \frac{1}{\sqrt{\mu}} = \mu^{-1/2}$$

$$g(\mu) = 2\mu^{1/2}$$

## Problem 5

(a)

$$X_1, \dots, X_n \sim N(\mu, 1)$$
$$U_n = \frac{1}{\sqrt{n}} \sum_{i=1}^n (X_i - \mu)$$

Want to find limiting distribution for  $U_n$ 

$$\sqrt{n}(\bar{X}_n - \mu) \xrightarrow{d} N(0, 1) \text{ (CLT)}$$
$$= \sqrt{n} \left( \left[ 1/n \sum_{i=1}^n X_i \right] - \mu \right)$$

$$= \frac{1}{\sqrt{n}} \left( \sum_{i=1}^{n} X_i \right) - \sqrt{n}\mu$$

$$= \frac{1}{\sqrt{n}} \left( \sum_{i=1}^{n} (X_i - \mu) \right) = U_n$$
Thus  $U_n \stackrel{d}{\to} N(0, 1)$ 

(b)

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

$$Var(X_i) = 1$$

$$V_n = \frac{1}{n} \sum_{i=1}^n (X_i - \mu)^2$$

$$\text{WTS: } V_n \stackrel{p}{\rightarrow} 1$$

$$\frac{1}{n} \sum_{i=1}^n X_i \stackrel{p}{\rightarrow} E(X_1) \text{ (WLLN)}$$

$$\frac{1}{n} \sum_{i=1}^n X_i^2 \stackrel{p}{\rightarrow} E(X_i^2)$$

$$\text{If } Y_i = X_i^2 \text{ then } \frac{1}{n} \sum_{i=1}^n Y_i \stackrel{p}{\rightarrow} E(Y_i) = E(X_i^2)$$

$$\text{Let } Y_i = X_i - \mu$$

$$V_n = \frac{1}{n} \sum_{i=1}^n (X_i - \mu)^2 = \frac{1}{n} \sum_{i=1}^n Y_i^2 \stackrel{p}{\rightarrow} E(Y_i^2) = E[(X_1 - \mu)^2] = Var(X_i) = 1$$

$$V_n \stackrel{p}{\rightarrow} 1$$

(c)

$$W_n=U_n/V_n$$
 
$$U_n\stackrel{d}{\to} N(0,1)$$
 
$$V_n\stackrel{p}{\to} 1$$
 
$$U_n/V_n\stackrel{d}{\to} N(0,1)/1=N(0,1) \text{ (Slutsky's Thm)}$$

(d)

$$\sqrt{n}(\bar{X}^2 - \mu^2) \xrightarrow{d} ?$$

$$\bar{X} = n^{-1} \sum_{i=1}^{n} X_i$$

$$\sqrt{n}(\bar{X} - \mu) \xrightarrow{d} N(0, 1)$$

$$\sqrt{n}(g(\bar{X}_n) - g(\mu)) \xrightarrow{d} N(0, [g'(\mu)]^2 \sigma^2)$$

$$g(\mu) = \mu^2$$

$$g'(\mu) = 2\mu$$

$$N(0, [g'(\mu)]^2 \sigma^2) = N(0, [2\mu]^2 (1)) = N(0, 4\mu^2)$$

$$\sqrt{n}(\bar{X}^2 - \mu^2) \xrightarrow{d} N(0, 4\mu^2)$$

(e)

$$X_{1}, \dots, X_{n} \sim N(\mu, 1)$$

$$\bar{X} \sim N(\mu, 1/n)$$
Exact 95% CI
$$.95 = P\left(-1.96 \le \frac{\bar{X} - \mu}{\sqrt{1/n}} \le 1.96\right)$$

$$= P\left(\bar{X} - 1.96 \frac{1}{\sqrt{n}} \le \mu \le \bar{X} + 1.96 \frac{1}{\sqrt{n}}\right)$$

$$.95 = P\left(L^{2} \le \mu^{2} \le U^{2}\right)$$

$$= P\left(\left[\bar{X} - 1.96 \frac{1}{\sqrt{n}}\right]^{2} \le \mu^{2} \le \left[\bar{X} + 1.96 \frac{1}{\sqrt{n}}\right]^{2}\right)$$