

This document contains solution's to Exercises 5.29 to 5.36 from Chapter 5, of Statistical inference by Casella and Berger , focusing on Convergence of random variables, WLLN, SLLN and CLT.

Some problem's are still in progress , and the document will be updated with their solution's soon.

S-29

x_1, x_2, \dots, x_{100} i.i.d x

$$E[x] = 1$$

$$sd(x) = 0.05 = \sigma$$

$$P(x_1 + x_2 + \dots + x_{100} > 100.4) ?$$

soln

we can use central limit theorem

where we are approximating

$$P\left[\frac{\sum (x_i - \mu)}{\sigma} < c\right] < P[Z < c]$$

$$\forall c, \text{ and } Z \sim N(0, 1)$$

These form

$$P(x_1 + x_2 + \dots + x_{100} > 100.4)$$

$$= \text{IP} \left(\bar{x}_n > \frac{100.4}{100} \right)$$

$$= \text{IP} \left(\bar{x}_{n-1} > \frac{100.4}{100} - 1 \right)$$

$$= \text{IP} \left(\frac{\bar{x}_{n-1}}{0.05} > \frac{0.4}{100 \cdot 0.05} \right)$$

$$= \text{IP} \left(\frac{\bar{x}_{n-1}}{0.05} > \frac{0.4}{S} \right)$$

$$= \text{IP} \left(\sqrt{100} \left(\frac{\bar{x}_{n-1}}{0.05} \right) > \frac{4}{S} \right)$$

$$= 1 - \text{IP} \left(\sqrt{100} \left(\frac{\bar{x}_{n-1}}{0.05} \right) \leq \frac{4}{S} \right)$$

for large n

$$\approx 1 - \text{IP} \left(Z \leq \frac{4}{S} \right)$$

$$\approx 1 - 0.7881 = 0.2219$$

$\Rightarrow \text{IP}(100 \text{ booklets weigh more than } 100.4 \text{ ounce})$

$$\approx 0.2219$$

5.30

if \bar{x}_1 & \bar{x}_2 are the mean's of two independent samples of size n from a population with variance σ^2 . find a value of n so that

$$P(|\bar{x}_1 - \bar{x}_2| < \frac{\sigma}{n}) \approx 0.99.$$

Justify your calculation's.

Soln

Assume $x_1, x_2, \dots, x_n \sim x$

$$\text{Var}(x) = \sigma^2 \quad E(x) = \mu$$

$$\bar{x} = \frac{x_1 + x_2 + \dots + x_n}{n} \Rightarrow \text{Var}(\bar{x}) = \frac{\sigma^2}{n}$$

$$E(\bar{x}) = \mu$$

\bar{x}_1 & \bar{x}_2 are two samples from \bar{x}

using CLT for large n

$$\bar{x}_1 \sim N\left(\mu, \frac{\sigma^2}{n}\right)$$

$$\bar{x}_2 \sim N\left(\mu, \frac{\sigma^2}{n}\right)$$

$$\Rightarrow \bar{x}_1 - \bar{x}_2 \sim N(0, 2\frac{\sigma^2}{n})$$

$$\Rightarrow |\bar{x}_1 - \bar{x}_2| < \frac{\sigma}{\sqrt{n}}$$

$$\Rightarrow -\frac{\sigma}{\sqrt{n}} < \bar{x}_1 - \bar{x}_2 < \frac{\sigma}{\sqrt{n}}$$

$$\Rightarrow P\left(-\frac{\sigma}{\sqrt{n}} < \bar{x}_1 - \bar{x}_2 < \frac{\sigma}{\sqrt{n}}\right)$$

$$\Rightarrow P\left(-\frac{1}{S\sqrt{\frac{n}{2}}} < \frac{\bar{x}_1 - \bar{x}_2}{S\sqrt{\frac{n}{2}}} < \frac{1}{S\sqrt{\frac{n}{2}}}\right)$$

$$\Rightarrow P\left(-\frac{1}{S\sqrt{\frac{n}{2}}} < Z < \frac{1}{S\sqrt{\frac{n}{2}}}\right)$$

$$0.99 \approx P\left(-\frac{1}{S\sqrt{\frac{n}{2}}} < Z < +\frac{1}{S\sqrt{\frac{n}{2}}}\right)$$

$$0.99 \approx P(Z < \frac{1}{S\sqrt{\frac{n}{2}}}) - P(Z < -\frac{1}{S\sqrt{\frac{n}{2}}})$$

$$0.99 \approx 1 - 2P(Z < -\frac{1}{S\sqrt{\frac{n}{2}}})$$

$$P\left(Z < -\frac{1}{5} \sqrt{\frac{n}{2}}\right) \approx 0.005$$

$$-\frac{1}{5} \sqrt{\frac{n}{2}} = -2.576$$

$$\Rightarrow \sqrt{\frac{n}{2}} = 2.576 \times 5$$

$$\Rightarrow n = (2.576 \times 5)^2 \times 2$$

$$\Rightarrow n \approx 331.78 = 332$$

$$n = 332$$

5.31.

x_1, x_2, \dots, x_{100} is X

$$E[X] = \mu \quad \text{Var}(X) = \sigma^2$$

Find the limits below which \bar{X}_{-n} will lie with probability at least 0.90. Use both Chebychev's inequality and the CLT, and comment on each.

soⁿ

$$E[\bar{x} - \mu] = 0$$

$$\text{var}(\bar{x} - \mu) = \frac{\sigma^2}{100} = \frac{9}{100}$$

using Chebychev's inequality

$$P((\bar{x} - \mu)^2 \geq \alpha^2) \leq \frac{E((\bar{x} - \mu)^2)}{\alpha^2}$$

$$\Rightarrow P(|\bar{x} - \mu| \geq \alpha) \leq \frac{\text{var}(\bar{x} - \mu)}{\alpha^2}$$

$$\Rightarrow P(|\bar{x} - \mu| \geq \alpha) \leq \frac{9}{100 \alpha^2}$$

$$\Rightarrow 1 - P(|\bar{x} - \mu| \geq \alpha) \geq 1 - \frac{9}{100 \alpha^2}$$

$$= P(|\bar{x} - \mu| < \alpha) \geq 1 - \frac{9}{100 \alpha^2}$$

$$\Rightarrow P(-\alpha < \bar{x} - \mu < \alpha) \geq 1 - \frac{9}{100 \alpha^2}$$

$$\alpha = c\sigma = c \cdot \frac{3}{10}$$

$$\Rightarrow \text{IP} \left(-\frac{3c}{10} < \bar{x} - \mu < \frac{3c}{10} \right) \geq 1 - \frac{1}{c^2}$$

$$\geq 0.9$$

$$\Rightarrow 1 - \frac{1}{c^2} = 0.9$$

$$\Rightarrow \frac{1}{c^2} = 0.1$$

$$\Rightarrow c^2 = 10 \Rightarrow c = 3.1622$$

$$\text{IP}(-0.9486 < \bar{x} - \mu < 0.9486) \geq 0.9$$

using CLT

$$\bar{x} - \mu \sim N(0, \frac{9}{100})$$

$$\Rightarrow \frac{\bar{x} - \mu}{\sqrt{10}} \sim N(0, 1)$$

$$\Rightarrow \frac{(\bar{x} - \mu)}{\sqrt{10}} \sim N(0, 1)$$

$$0.9 = \text{IP} \left(-c < \frac{\bar{x} - \mu}{\sqrt{10}} < c \right)$$

$$c = 1.645$$

$$\Rightarrow \text{IP}\left(-1.645 \cdot \frac{3}{\sqrt{10}} < \bar{x} - \mu < 1.645 \cdot \frac{3}{\sqrt{10}}\right)$$

$$\Rightarrow \text{IP}\left(-0.4935 < \bar{x} - \mu < 0.4935\right)$$

Bounds of Chebychev's inequality

are high compared to CLT

\Rightarrow CLT is better in finding bounds than Chebychev's if n is large

5.32

X_1, X_2, \dots be a seq of random variables that converges in Prob to a constant a . Assume that $\text{IP}(X_i > 0) = 1$

A_i

@ Verify that the seqⁿ defined by

$y_i = \sum x_i$ and $x'_i = \frac{a}{x_i}$ converge

in Probability.

Soln the seq $x_1, x_2, \dots, x_n, x_{n+1}, \dots$

converges in Probability to constant a

$$\Rightarrow \forall \epsilon \lim_{n \rightarrow \infty} P(|x_n - a| > \epsilon) = 0$$

we want to prove $\forall \epsilon > 0$

$$\lim_{n \rightarrow \infty} P(|\sum x_n - \sum a| > \epsilon) = 0$$

$$P(|\sum x_n - \sum a| > \epsilon)$$

$$= P(|\sum x_n - \sum a| + |\sum x_{n+1} - \sum a| > \epsilon + |\sum x_{n+1} - \sum a|)$$

$$= P(|x_n - a| + |\sum x_{n+1} - \sum a| > \epsilon + |\sum x_{n+1} - \sum a|)$$

$\underbrace{\qquad\qquad\qquad}_{=0 \text{ as } n \rightarrow \infty}$

$$\Rightarrow \text{IP}(|S_n - \sigma| > \varepsilon) = 0$$

as $n \rightarrow$

⑥

use the result in Part(a) to prove
the fact used in Example S.S.18, that

$\frac{\sigma}{S_n}$ converges in prob to 1

Soln

we know that

$$S_n^2 = \frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x}_n)^2$$

$$\text{IP}(|S_n^2 - \sigma^2| \geq \varepsilon) \leq \frac{\text{var}(S_n^2)}{\varepsilon^2}$$

$$\Rightarrow S_n^2 \xrightarrow{\text{in probability}} \sigma^2$$

$$\Rightarrow S_n \xrightarrow{\text{in probability}} \sigma$$

$$\forall \varepsilon > 0 \quad \lim_{n \rightarrow \infty} \text{IP}(|S_n - \sigma| < \varepsilon) = 1$$

Let $\Sigma > 0$

$$\text{IP}\left(\left|\frac{\sigma}{S_n} - 1\right| < \varepsilon\right)$$

$$\Rightarrow \text{IP}\left(1 - \varepsilon < \frac{\sigma}{S_n} < 1 + \varepsilon\right)$$

$$\Rightarrow \text{IP}\left(\frac{1 - \varepsilon}{\sigma} < \frac{1}{S_n} < \frac{1 + \varepsilon}{\sigma}\right)$$

$$\Rightarrow \text{IP}\left(\frac{\sigma}{1 + \varepsilon} < S_n < \frac{\sigma}{1 - \varepsilon}\right)$$

$$\Rightarrow \text{IP}\left(\frac{\sigma}{1 + \varepsilon} - \sigma < S_n - \sigma < \frac{\sigma}{1 - \varepsilon} - \sigma\right)$$

$$\Rightarrow \text{IP}\left(-\frac{\sigma\varepsilon}{1 + \varepsilon} < S_n - \sigma < \frac{\sigma\varepsilon}{1 - \varepsilon}\right)$$

$$\Rightarrow \mathbb{P}\left(|S_n - \sigma| < \frac{\sigma\varepsilon}{1+\varepsilon}\right)$$

as $n \rightarrow \infty$

$\Rightarrow 1$

$\Rightarrow \forall \varepsilon > 0$ we have

$$\lim_{n \rightarrow \infty} \mathbb{P}\left(\left|\frac{\sigma}{S_n} - 1\right| < \varepsilon\right) = 1$$

$$\Rightarrow \frac{\sigma}{S_n} \xrightarrow{i.p} 1$$

5.23

Let X_n be a seq of r.v's that converges in distribution to a random variable X . Let Y_n be a seq of r.v's with the property that for any finite number c ,

$$\lim_{n \rightarrow \infty} \mathbb{P}(Y_n > c) = 1$$

Show that for any finite number c ,

$$\lim_{n \rightarrow \infty} \text{IP}(X_n + Y_n > c) = 1$$

Solⁿ

We have

$$\lim_{n \rightarrow \infty} F_{X_n}(x) = F_x(x)$$

$$\Rightarrow \lim_{n \rightarrow \infty} \text{IP}(X_n \leq x) = \text{IP}(X_n \leq x)$$

$$\Rightarrow 1 - \lim_{n \rightarrow \infty} \text{IP}(X_n \leq x) = 1 - \text{IP}(X_n \leq x)$$

$$\Rightarrow \lim_{n \rightarrow \infty} \text{IP}(X_n > x) = \text{IP}(X > x)$$

Q we have

$$\lim_{n \rightarrow \infty} \text{IP}(Y_n > c) = 1$$

5.34

Let x_1, x_2, \dots be a random sample from a population with mean μ and variance σ^2 .

Show that

$$\mathbb{E}\left[\sqrt{n} \left(\frac{\bar{x}_n - \mu}{\sigma} \right) \right] = 0$$

$$2 \quad \text{Var}\left(\sqrt{n} \left(\frac{\bar{x}_n - \mu}{\sigma} \right) \right) = 1$$

Sol'n $\mathbb{E}[\bar{x}] = \mu$ $\text{Var}(\bar{x}) = \frac{\sigma^2}{n}$

$$\mathbb{E}\left[\sqrt{n} \left(\frac{\bar{x} - \mu}{\sigma} \right) \right]$$

$$= \frac{\sqrt{n}}{\sigma} \left[\mathbb{E}[\bar{x}] - \mathbb{E}[\mu] \right]$$

$$= \frac{\sqrt{n}}{\sigma} [\mu - \mu] = 0$$

$$\text{Var}\left(\frac{\sum_n}{n} (\bar{x} - \mu)\right)$$

$$\Rightarrow \frac{n}{\sigma^2} \text{Var}(\bar{x} - \mu)$$

$$\Rightarrow \frac{n}{\sigma^2} \text{Var}(\bar{x}) = \frac{n}{\sigma^2} \cdot \frac{\sigma^2}{n} = 1$$

5.35

Stirling's formula

$$n! \approx \sqrt{2\pi n} n^{n+\frac{1}{2}} \cdot e^{-n}$$

a) Argue that, if $x_i \sim \exp(i)$, $i=1,2,\dots$
all independent. Then for every x ,

$$P\left(\frac{\bar{x}_n - 1}{1/\sqrt{n}} \leq x\right) \rightarrow P(Z \leq x)$$

$$Z \sim N(0,1)$$

Soln

$$x \sim \exp(i)$$

$$f_x(x) = e^{-x} \quad x > 0$$

$$E[x] = 1$$

$$\text{var}(x) = 1$$

then $\bar{x} = \frac{x_1 + x_2 + \dots + x_n}{n}$

$$E[\bar{x}] = 1 \quad \text{var}(\bar{x}) = \frac{1}{n}$$

Using CLT we know

$$P\left(\frac{\bar{x}_n - 1}{\sqrt{n}} < x\right) \approx P(Z < x)$$

b)

Show that differentiating both sides
of the approximation in part (a)
suggests.

so 1^m

$$P\left(\frac{\bar{x} - 1}{\sqrt{n}} < x\right)$$

$$\Rightarrow P\left(\bar{x} < \frac{x}{\sqrt{n}} + 1\right)$$

$$\Rightarrow P\left(\sum x_i < x\sqrt{n} + n\right)$$

we know that

$$x_i \sim \text{gamma}(1, 1)$$

$$x_1 + x_2 + \dots + x_n \sim \text{gamma}(n, 1)$$

$$\Rightarrow f_{x_1 + x_2 + \dots + x_n}(x) = \frac{1}{\Gamma(n)} x^{n-1} e^{-x}$$

$$\frac{d}{dx} F_{x_1 + x_2 + \dots + x_n}(x\sqrt{n} + n)$$

$$= f_{x_1 + \dots + x_n}(x\sqrt{n} + n) \cdot \sqrt{n}$$

$$= \frac{1}{\Gamma(n)} (x\sqrt{n} + n)^{n-1} \cdot e^{-(x\sqrt{n} + n)} \cdot \sqrt{n}$$

$$\frac{d}{dx} F_Z(x) = f_Z(x) = \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}}$$

$$\Rightarrow \frac{1}{\Gamma(n)} (x\sqrt{n} + n)^{n-1} \cdot e^{-(x\sqrt{n} + n)} \cdot \sqrt{n} \approx \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}}$$

as $n \rightarrow \infty$

Put $x=0$

$$\Rightarrow \frac{1}{\Gamma(n)} n^{n-1} \cdot e^{-n} \cdot \sqrt{n} \approx \frac{1}{\sqrt{2\pi}}$$

$$\Rightarrow \frac{n^n}{n \cdot (n-1)!} \cdot e^{-n} \sqrt{n} \approx \frac{1}{\sqrt{2\pi}}$$

$$\Rightarrow n! \approx \sqrt{2\pi} \cdot n^{n+\frac{1}{2}} \cdot e^{-n}$$

$$\Rightarrow n! \approx \sqrt{2\pi n} \left(\frac{n}{e}\right)^n$$

5.36

Given that $N=n$, the conditional distribution of Y is χ^2_{2n} .

The unconditional distribution of $N \sim \text{Poisson}(\theta)$

a) calculate $E[Y]$ and $\text{Var}(Y)$

Solⁿ

$N \sim \text{Poisson}(\theta)$

$$\text{IP}(N=n) = \frac{e^{-\theta} \cdot \theta^n}{n!} \quad n=0,1,2,\dots$$

Given

$$\text{IP}(Y|N=n) \sim \chi^2_{2n}$$

$$\Rightarrow Y|N=n \sim \chi^2_{2n}$$

$$Y|N=n \sim \text{gamma}(n, 2)$$

$$N \sim \text{Poisson}(\theta)$$

Using Theorem 4.4.3

$$\mathbb{E}[Y] = \mathbb{E}[\mathbb{E}[Y|N]]$$

$$= \mathbb{E}[2N]$$

$$\mathbb{E}[Y] = 2\Theta$$

Using Theorem 4.4.7

$$\text{var}(Y) = \mathbb{E}[\text{var}(Y|N)]$$

$$+ \text{var}(\mathbb{E}[Y|N])$$

$$= \mathbb{E}[4N]$$

$$+ \text{var}(2N)$$

$$= 4\Theta + 2\Theta = 6\Theta$$

$$\text{var}(Y) = 6\Theta$$

b) Show that as $\theta \rightarrow \infty$

$$\frac{(Y - E[Y])}{\sqrt{\text{Var}(Y)}} \xrightarrow{\text{D}} N(0, 1)$$

Sol'n $Y|N \sim \chi^2_{2N}$

$$= Y|N \sim \underbrace{\chi^2_1 + \chi^2_1 + \dots + \chi^2_1}_{2N \text{ term's.}}$$

$$P(Y=y) = \sum_{n=0}^{\infty} P(Y=y, N=n)$$

$$= \sum_{n=0}^{\infty} P(Y=y | N=n) P(N=n)$$

$$= \sum_{n=0}^{\infty} \frac{1}{\Gamma(n)} 2^n y^{n-1} \cdot e^{-\frac{y}{2}} \cdot \frac{e^{-\theta} \cdot \theta^n}{n!}$$

$$= \frac{1}{y} \cdot e^{-\theta} \cdot e^{-\frac{y}{2}} \sum_{n=0}^{\infty} \frac{1}{\Gamma(n)} \cdot y^n \cdot \frac{\theta^n}{n!}$$

$$= \frac{e^{-(\theta + \frac{\sigma^2}{2})}}{y} \sum_{n=0}^{\infty} \left(\frac{y\theta}{2}\right)^n \cdot \frac{1}{[n]n!}$$

(this method is not working)

$$\frac{Y - E[Y]}{\text{Var}(Y)} = \frac{Y - 20}{50}$$

5.44

Let x_i 's, $i = 1, 2, \dots$ be independent

Bernoulli (p) random variable and let

$$Y_n = \frac{1}{n} \sum_{i=1}^n x_i$$

(a) Show that $\sqrt{n}(Y_n - p) \xrightarrow{\text{dist}} N(0, p(1-p))$

Solⁿ using CLT

$$E[Y_n] = E[x] = np$$

$$\text{Var}(Y_n) = \frac{\text{Var}(x)}{n} = \frac{np(1-p)}{n}$$
$$= p(1-p)$$

\Rightarrow By CLT

$$\sqrt{n}\left(\frac{Y_n - np}{\sqrt{p(1-p)}}\right) \xrightarrow{\text{dist}} N(0, 1)$$

$$\Rightarrow \sqrt{n}(Y_n - np) \xrightarrow{\text{dist}} \sqrt{p(1-p)} N(0, 1)$$

$$\rightarrow N(0, p(1-p))$$