

## Chapter 11

### More Results

#### 11.1 Hints and Solutions to Selected Problems

**2.1.** c) The histograms should become more like a normal distribution as  $n$  increases from 1 to 200. In particular, when  $n = 1$  the histogram should be right skewed while for  $n = 200$  the histogram should be nearly symmetric. Also the scale on the horizontal axis should decrease as  $n$  increases.

d) Now  $\bar{Y} \sim N(0, 1/n)$ . Hence the histograms should all be roughly symmetric, but the scale on the horizontal axis should be from about  $-3/\sqrt{n}$  to  $3/\sqrt{n}$ .

**2.3.** a)  $E(X) = \frac{3\theta}{\theta+1}$ , thus  $\sqrt{n}(\bar{X} - E(X)) \xrightarrow{D} N(0, V(X))$ , where  $V(X) = \frac{9\theta}{(\theta+2)(\theta+1)^2}$ . Let  $g(y) = \frac{y}{3-y}$ , thus  $g'(y) = \frac{3}{(3-y)^2}$ . Using the delta method,  $\sqrt{n}(T_n - \theta) \xrightarrow{D} N(0, \frac{\theta(\theta+1)^2}{\theta+2})$ .

b) It is asymptotically efficient if  $\sqrt{n}(T_n - \theta) \xrightarrow{D} N(0, \nu(\theta))$ , where

$$\nu(\theta) = \frac{\frac{d}{d\theta}(\theta)}{-E(\frac{d^2}{d\theta^2} \ln f(x|\theta))}.$$

But,  $E(\frac{d^2}{d\theta^2} \ln f(x|\theta)) = \frac{1}{\theta^2}$ . Thus  $\nu(\theta) = \theta^2 \neq \frac{\theta(\theta+1)^2}{\theta+2}$ .

c)  $\bar{X} \rightarrow \frac{3\theta}{\theta+1}$  in probability. Thus  $T_n \rightarrow \theta$  in probability.

**2.5.** See Example 2.9.

**2.7.** a) See Example 2.8.

**2.12.** a)  $Y_n \stackrel{D}{=} \sum_{i=1}^n X_i$  where the  $X_i$  are iid  $\chi_1^2$ . Hence  $E(X_i) = 1$  and  $\text{Var}(X_i) = 2$ . Thus by the CLT,

$$\sqrt{n} \left( \frac{Y_n}{n} - 1 \right) \stackrel{D}{=} \sqrt{n} \left( \frac{\sum_{i=1}^n X_i}{n} - 1 \right) \stackrel{D}{\rightarrow} N(0, 2).$$

b) Let  $g(\theta) = \theta^3$ . Then  $g'(\theta) = 3\theta^2$ ,  $g'(1) = 3$ , and by the delta method,

$$\sqrt{n} \left[ \left( \frac{Y_n}{n} \right)^3 - 1 \right] \stackrel{D}{\rightarrow} N(0, 2(g'(1))^2) = N(0, 18).$$

**2.22.** See the proof of Theorem 1.33.

**2.26.** a) See Example 2.1b.

b) See Example 2.3.

c) See Example 2.6.

**2.27.** a) By the CLT,  $\sqrt{n}(\bar{X} - \lambda)/\sqrt{\lambda} \stackrel{D}{\rightarrow} N(0, 1)$ . Hence  $\sqrt{n}(\bar{X} - \lambda) \stackrel{D}{\rightarrow} N(0, \lambda)$ .

b) Let  $g(\lambda) = \lambda^3$  so that  $g'(\lambda) = 3\lambda^2$  then  $\sqrt{n}[(\bar{X})^3 - (\lambda)^3] \stackrel{D}{\rightarrow} N(0, \lambda[g'(\lambda)]^2) = N(0, 9\lambda^5)$ .

**2.28.** a)  $\bar{X}$  is a complete sufficient statistic. Also, we have  $\frac{(n-1)S^2}{\sigma^2}$  has a chi square distribution with  $df = n - 1$ , thus since  $\sigma^2$  is known the distribution of  $S^2$  does not depend on  $\mu$ , so  $S^2$  is ancillary. Thus, by Basu's Theorem  $\bar{X}$  and  $S^2$  are independent.

b) by CLT ( $n$  is large)  $\sqrt{n}(\bar{X} - \mu)$  has approximately normal distribution with mean 0 and variance  $\sigma^2$ . Let  $g(x) = x^3$ , thus,  $g'(x) = 3x^2$ . Using delta method  $\sqrt{n}(g(\bar{X}) - g(\mu))$  goes in distribution to  $N(0, \sigma^2(g'(\mu))^2)$  or  $\sqrt{n}(\bar{X}^3 - \mu^3)$  goes in distribution to  $N(0, \sigma^2(3\mu^2)^2)$ .

**2.29.** a) According to the standard theorem,  $\sqrt{n}(\hat{\theta}_n - \theta) \rightarrow N(0, 3)$ .

b)  $E(Y) = \theta$ ,  $Var(Y) = \frac{\pi^2}{3}$ , according to CLT we have  $\sqrt{n}(\bar{Y}_n - \theta) \rightarrow N(0, \frac{\pi^2}{3})$ .

c)  $MED(Y) = \theta$ , then  $\sqrt{n}(MED(n) - \theta) \rightarrow N(0, \frac{1}{4f^2(MED(Y))})$  and  $f(MED(Y)) = \frac{\exp(-(\theta-\theta))}{[1+\exp(-(\theta-\theta))]^2} = \frac{1}{4}$ . Thus  $\sqrt{n}(MED(n) - \theta) \rightarrow N(0, \frac{1}{4 \cdot \frac{1}{16}}) \rightarrow \sqrt{n}(MED(n) - \theta) \rightarrow N(0, 4)$ .

d) All three estimators are consistent, but  $3 < \frac{\pi^2}{3} < 4$ , therefore the estimator  $\hat{\theta}_n$  is the best, and the estimator  $MED(n)$  is the worst.

**2.31.** a)  $F_n(y) = 0.5 + 0.5y/n$  for  $-n < y < n$ , so  $F(y) \equiv 0.5$ .

b) No, since  $F(y)$  is not a cdf.

**2.32.** a)  $F_n(y) = y/n$  for  $0 < y < n$ , so  $F(y) \equiv 0$ .

b) No, since  $F(y)$  is not a cdf.

**2.33.** a)

$$\sqrt{n} \left( \bar{Y} - \frac{1-\rho}{\rho} \right) \xrightarrow{D} N \left( 0, \frac{1-\rho}{\rho^2} \right)$$

by the CLT.

c) The method of moments estimator of  $\rho$  is  $\hat{\rho} = \frac{\bar{Y}}{1+\bar{Y}}$ .

d) Let  $g(\theta) = 1 + \theta$  so  $g'(\theta) = 1$ . Then by the delta method,

$$\sqrt{n} \left( g(\bar{Y}) - g\left(\frac{1-\rho}{\rho}\right) \right) \xrightarrow{D} N \left( 0, \frac{1-\rho}{\rho^2} 1^2 \right)$$

or

$$\sqrt{n} \left( (1 + \bar{Y}) - \frac{1}{\rho} \right) \xrightarrow{D} N \left( 0, \frac{1-\rho}{\rho^2} \right).$$

This result could also be found with algebra since  $1 + \bar{Y} - \frac{1}{\rho} = \bar{Y} + 1 - \frac{1}{\rho} = \bar{Y} + \frac{\rho-1}{\rho} = \bar{Y} - \frac{1-\rho}{\rho}$ .

e)  $\bar{Y}$  is the method of moments estimator of  $E(Y) = (1-\rho)/\rho$ , so  $1 + \bar{Y}$  is the method of moments estimator of  $1 + E(Y) = 1/\rho$ .

**2.34.** a)  $\sqrt{n}(\bar{X} - \mu)$  is approximately  $N(0, \sigma^2)$ . Define  $g(x) = \frac{1}{x}$ ,  $g'(x) = -\frac{1}{x^2}$ . Using delta method,  $\sqrt{n}\left(\frac{1}{\bar{X}} - \frac{1}{\mu}\right)$  is approximately  $N\left(0, \frac{\sigma^2}{\mu^4}\right)$ . Thus  $1/\bar{X}$  is approximately  $N\left(\frac{1}{\mu}, \frac{\sigma^2}{n\mu^4}\right)$ , provided  $\mu \neq 0$ .

b) Using part a)

$\frac{1}{\bar{X}}$  is asymptotically efficient for  $\frac{1}{\mu}$  if

$$\begin{aligned} \frac{\sigma^2}{\mu^4} &= \left[ \frac{(\tau'(\mu))^2}{E_{\mu} \left( \frac{\partial}{\partial \mu} \ln f(X/\mu) \right)^2} \right] \\ \tau(\mu) &= \frac{1}{\mu} \\ \tau'(\mu) &= \frac{-1}{\mu^2} \\ \ln f(x|\mu) &= \frac{-1}{2} \ln 2\pi\sigma^2 - \frac{(x-\mu)^2}{2\sigma^2} \\ E \left[ \frac{\partial}{\partial \mu} \ln f(X/\mu) \right]^2 &= \frac{E(X-\mu)^2}{\sigma^4} \\ &= \frac{1}{\sigma^2} \end{aligned}$$

Thus

$$\frac{(\tau'(\mu))^2}{E_\mu \left[ \frac{\partial}{\partial \mu} \ln f(X/\mu) \right]^2} = \frac{\sigma^2}{\mu^4}.$$

**2.35.** a)  $E(Y^k) = 2\theta^k/(k+2)$  so  $E(Y) = 2\theta/3$ ,  $E(Y^2) = \theta^2/2$  and  $V(Y) = \theta^2/18$ . So  $\sqrt{n} \left( \bar{Y} - \frac{2\theta}{3} \right) \xrightarrow{D} N \left( 0, \frac{\theta^2}{18} \right)$  by the CLT.

b) Let  $g(\tau) = \log(\tau)$  so  $[g'(\tau)]^2 = 1/\tau^2$  where  $\tau = 2\theta/3$ . Then by the delta method,

$$\sqrt{n} \left( \log(\bar{Y}) - \log \left( \frac{2\theta}{3} \right) \right) \xrightarrow{D} N \left( 0, \frac{1}{8} \right).$$

c)  $\hat{\theta}^k = \frac{k+2}{2n} \sum Y_i^k$ .

**2.36.** a)  $\sqrt{n} \left( \bar{Y} - \frac{r(1-\rho)}{\rho} \right) \xrightarrow{D} N \left( 0, \frac{r(1-\rho)}{\rho^2} \right)$  by the CLT.

b) Let  $\theta = r(1-\rho)/\rho$ . Then

$$g(\theta) = \frac{r}{r + \frac{r(1-\rho)}{\rho}} = \frac{r\rho}{r\rho + r(1-\rho)} = \rho = c.$$

Now

$$g'(\theta) = \frac{-r}{(r+\theta)^2} = \frac{-r}{\left(r + \frac{r(1-\rho)}{\rho}\right)^2} = \frac{-r\rho^2}{r^2}.$$

So

$$[g'(\theta)]^2 = \frac{r^2\rho^4}{r^4} = \frac{\rho^4}{r^2}.$$

Hence by the delta method

$$\sqrt{n} (g(\bar{Y}) - \rho) \xrightarrow{D} N \left( 0, \frac{r(1-\rho)\rho^4}{\rho^2 r^2} \right) = N \left( 0, \frac{\rho^2(1-\rho)}{r} \right).$$

c)  $\bar{Y} \stackrel{\text{set}}{=} r(1-\rho)/\rho$  or  $\rho\bar{Y} = r - r\rho$  or  $\rho\bar{Y} + r\rho = r$  or  $\hat{\rho} = r/(r + \bar{Y})$ .

**2.37.** a) By the CLT,

$$\sqrt{n} \left( \bar{X} - \frac{\theta}{2} \right) \xrightarrow{D} N \left( 0, \frac{\theta^2}{12} \right).$$

b) Let  $g(y) = y^2$ . Then  $g'(y) = 2y$  and by the delta method,

$$\sqrt{n} \left( \bar{X}^2 - \left(\frac{\theta}{2}\right)^2 \right) = \sqrt{n} \left( \bar{X}^2 - \frac{\theta^2}{4} \right) = \sqrt{n} \left( g(\bar{X}) - g\left(\frac{\theta}{2}\right) \right) \xrightarrow{D}$$

$$N \left( 0, \frac{\theta^2}{12} [g'(\frac{\theta}{2})]^2 \right) = N \left( 0, \frac{\theta^2}{12} \frac{4\theta^2}{4} \right) = N \left( 0, \frac{\theta^4}{12} \right).$$

**2.38.** a)  $E(X_i) = \beta/(\beta + \beta) = 1/2$  and  $V(X_i) = \frac{\beta^2}{(2\beta)^2(2\beta + 1)} = \frac{1}{4(2\beta + 1)} = \frac{1}{8\beta + 4}$ . So

$$\sqrt{n} \left( \bar{X}_n - \frac{1}{2} \right) \xrightarrow{D} N \left( 0, \frac{1}{8\beta + 4} \right)$$

by the CLT.

b) Let  $g(x) = \log(x)$ . So  $d = g(1/2) = \log(1/2)$ . Now  $g'(x) = 1/x$  and  $(g'(x))^2 = 1/x^2$ . So  $(g'(1/2))^2 = 4$ . So

$$\sqrt{n}(\log(\bar{X}_n) - \log(1/2)) \xrightarrow{D} N \left( 0, \frac{1}{8\beta + 4} \cdot 4 \right) = N \left( 0, \frac{1}{2\beta + 1} \right)$$

by the delta method.

## 11.2 Tables

Tabled values are  $F(0.95, k, d)$  where  $P(F < F(0.95, k, d)) = 0.95$ .

00 stands for  $\infty$ . Entries produced with the `qf(.95, k, d)` command in *R*.

The numerator degrees of freedom are  $k$  while the denominator degrees of freedom are  $d$ .

k	1	2	3	4	5	6	7	8	9	00
d										
1	161	200	216	225	230	234	237	239	241	254
2	18.5	19.0	19.2	19.3	19.3	19.3	19.4	19.4	19.4	19.5
3	10.1	9.55	9.28	9.12	9.01	8.94	8.89	8.85	8.81	8.53
4	7.71	6.94	6.59	6.39	6.26	6.16	6.09	6.04	6.00	5.63
5	6.61	5.79	5.41	5.19	5.05	4.95	4.88	4.82	4.77	4.37
6	5.99	5.14	4.76	4.53	4.39	4.28	4.21	4.15	4.10	3.67
7	5.59	4.74	4.35	4.12	3.97	3.87	3.79	3.73	3.68	3.23
8	5.32	4.46	4.07	3.84	3.69	3.58	3.50	3.44	3.39	2.93
9	5.12	4.26	3.86	3.63	3.48	3.37	3.29	3.23	3.18	2.71
10	4.96	4.10	3.71	3.48	3.33	3.22	3.14	3.07	3.02	2.54
11	4.84	3.98	3.59	3.36	3.20	3.09	3.01	2.95	2.90	2.41
12	4.75	3.89	3.49	3.26	3.11	3.00	2.91	2.85	2.80	2.30
13	4.67	3.81	3.41	3.18	3.03	2.92	2.83	2.77	2.71	2.21
14	4.60	3.74	3.34	3.11	2.96	2.85	2.76	2.70	2.65	2.13
15	4.54	3.68	3.29	3.06	2.90	2.79	2.71	2.64	2.59	2.07
16	4.49	3.63	3.24	3.01	2.85	2.74	2.66	2.59	2.54	2.01
17	4.45	3.59	3.20	2.96	2.81	2.70	2.61	2.55	2.49	1.96
18	4.41	3.55	3.16	2.93	2.77	2.66	2.58	2.51	2.46	1.92
19	4.38	3.52	3.13	2.90	2.74	2.63	2.54	2.48	2.42	1.88
20	4.35	3.49	3.10	2.87	2.71	2.60	2.51	2.45	2.39	1.84
25	4.24	3.39	2.99	2.76	2.60	2.49	2.40	2.34	2.28	1.71
30	4.17	3.32	2.92	2.69	2.53	2.42	2.33	2.27	2.21	1.62
00	3.84	3.00	2.61	2.37	2.21	2.10	2.01	1.94	1.88	1.00

Tabled values are  $t_{\alpha,d}$  where  $P(t < t_{\alpha,d}) = \alpha$  where  $t$  has a  $t$  distribution with  $d$  degrees of freedom. If  $d > 29$  use the  $N(0, 1)$  cutoffs  $d = Z = \infty$ .

d	alpha									pvalue
	0.005	0.01	0.025	0.05	0.5	0.95	0.975	0.99	0.995	left tail
1	-63.66	-31.82	-12.71	-6.314	0	6.314	12.71	31.82	63.66	
2	-9.925	-6.965	-4.303	-2.920	0	2.920	4.303	6.965	9.925	
3	-5.841	-4.541	-3.182	-2.353	0	2.353	3.182	4.541	5.841	
4	-4.604	-3.747	-2.776	-2.132	0	2.132	2.776	3.747	4.604	
5	-4.032	-3.365	-2.571	-2.015	0	2.015	2.571	3.365	4.032	
6	-3.707	-3.143	-2.447	-1.943	0	1.943	2.447	3.143	3.707	
7	-3.499	-2.998	-2.365	-1.895	0	1.895	2.365	2.998	3.499	
8	-3.355	-2.896	-2.306	-1.860	0	1.860	2.306	2.896	3.355	
9	-3.250	-2.821	-2.262	-1.833	0	1.833	2.262	2.821	3.250	
10	-3.169	-2.764	-2.228	-1.812	0	1.812	2.228	2.764	3.169	
11	-3.106	-2.718	-2.201	-1.796	0	1.796	2.201	2.718	3.106	
12	-3.055	-2.681	-2.179	-1.782	0	1.782	2.179	2.681	3.055	
13	-3.012	-2.650	-2.160	-1.771	0	1.771	2.160	2.650	3.012	
14	-2.977	-2.624	-2.145	-1.761	0	1.761	2.145	2.624	2.977	
15	-2.947	-2.602	-2.131	-1.753	0	1.753	2.131	2.602	2.947	
16	-2.921	-2.583	-2.120	-1.746	0	1.746	2.120	2.583	2.921	
17	-2.898	-2.567	-2.110	-1.740	0	1.740	2.110	2.567	2.898	
18	-2.878	-2.552	-2.101	-1.734	0	1.734	2.101	2.552	2.878	
19	-2.861	-2.539	-2.093	-1.729	0	1.729	2.093	2.539	2.861	
20	-2.845	-2.528	-2.086	-1.725	0	1.725	2.086	2.528	2.845	
21	-2.831	-2.518	-2.080	-1.721	0	1.721	2.080	2.518	2.831	
22	-2.819	-2.508	-2.074	-1.717	0	1.717	2.074	2.508	2.819	
23	-2.807	-2.500	-2.069	-1.714	0	1.714	2.069	2.500	2.807	
24	-2.797	-2.492	-2.064	-1.711	0	1.711	2.064	2.492	2.797	
25	-2.787	-2.485	-2.060	-1.708	0	1.708	2.060	2.485	2.787	
26	-2.779	-2.479	-2.056	-1.706	0	1.706	2.056	2.479	2.779	
27	-2.771	-2.473	-2.052	-1.703	0	1.703	2.052	2.473	2.771	
28	-2.763	-2.467	-2.048	-1.701	0	1.701	2.048	2.467	2.763	
29	-2.756	-2.462	-2.045	-1.699	0	1.699	2.045	2.462	2.756	
Z	-2.576	-2.326	-1.960	-1.645	0	1.645	1.960	2.326	2.576	
CI						90%	95%		99%	
	0.995	0.99	0.975	0.95	0.5	0.05	0.025	0.01	0.005	right tail
	0.01	0.02	0.05	0.10	1	0.10	0.05	0.02	0.01	two tail