

Math 152 Midterm Exam

6.

$$N_1 = 100,000$$

$$N_2 = 10,000,000$$

$$\text{Var}(\bar{X}) = \frac{\sigma^2}{25} \left(1 - \frac{24}{N_i - 1} \right)$$

so the difference is not significant

10.

Fabre. A large sample histogram will tend to reflect the distribution of ~~the value being sampled throughout the population~~ throughout the population of the variable (or value) being sampled.

e.g. times to swim 4 miles sampled

from a whole population may have a very skewed ~~distribution~~ ^{histogram} which looks like a Gamma distribution

12.

Sampling with replacement. [let σ^2 denote the population variance]

a)

$$s^2 = \frac{1}{n-1} \sum_{i=1}^n (X_i - \bar{X})^2$$

$$E(s^2) = \frac{1}{n-1} \sum_{i=1}^n E(X_i^2) - 2E(X_i \bar{X}) + E(\bar{X}^2)$$

$$= \frac{1}{n-1} \left(n(\sigma^2 + \mu^2) - 2nE(\bar{X}^2) + nE(\bar{X}^2) \right)$$

$$= \frac{n}{n-1} \left(\sigma^2 + \mu^2 - E(\bar{X}^2) \right)$$

Now

$$\bar{X}^2 = \frac{1}{n^2} \sum_{i=1}^n \sum_{j=1}^n X_i X_j$$

$$\begin{aligned} \text{So } E(\bar{X}^2) &= \frac{1}{n^2} \left(\sum_{i=1}^n E(X_i^2) + \sum_{i \neq j} E(X_i X_j) \right) \\ &= \frac{1}{n^2} \left(n(\sigma^2 + \mu^2) + (n^2 - n)\mu^2 \right) \end{aligned}$$

$$\begin{aligned} \text{So } E(S^2) &= \frac{n}{n-1} \left(\sigma^2 + \mu^2 - \frac{1}{n}(\sigma^2 + \mu^2) - (1 - \frac{1}{n})\mu^2 \right) \\ &= \frac{n}{n-1} \left((1 - \frac{1}{n})\sigma^2 \right) = \sigma^2. \end{aligned}$$

b) S will not be an unbiased estimator of σ

and

$$E(\sqrt{Y}) \neq \sqrt{E(Y)}$$

c)

Erl.

$$\sigma_{\bar{X}}^2 = E(\bar{X}^2) - E(\bar{X})^2.$$

$$= \text{Var}(\bar{X}).$$

$$= \frac{1}{n^2} \sum_{i=1}^n \text{Var}(X_i) = \frac{\sigma^2}{n^2}.$$

and $E\left(\frac{S^2}{n}\right) = \frac{\sigma^2}{n^2}$ by a)

so $\frac{S^2}{n}$ is an unbiased estimate for $\sigma_{\bar{X}}^2$

d). $E\left(\frac{N^2}{n} S^2\right) = \frac{\sigma^2 N^2}{n}.$

$$\sigma_T^2 = \text{Var}\left(\sum_{i=1}^n X_i\right)$$

$$T = N \bar{X}$$

$$\sigma_T^2 = N^2 \text{Var}(\bar{X}) = \frac{\sigma^2}{n^2} N^2.$$

$$e) \quad \frac{\hat{p}^1 (1 - \hat{p}^1)}{n-1}$$

$$\hat{p}^1 = \frac{1}{n} \sum_{i=1}^n X_i$$

$X_i = 0$ or 1 .
with prob p $X_i = 1$.

$$\begin{aligned} \text{Var}(\hat{p}^1) &= \frac{1}{n^2} \sum_{i=1}^n \text{Var}(X_i) = \frac{n p (1-p)}{n^2} \\ &= \frac{p(1-p)}{n}. \end{aligned}$$

$$\begin{aligned} E(\hat{p}^1 - \hat{p}^{12}) &= p - E(\hat{p}^{12}) \\ &= p - \left(\sigma_{\hat{p}}^2 + p^2 \right) \\ &= p - \left(\frac{p(1-p)}{n} + p^2 \right) \\ &= p(1-p) \left(1 - \frac{1}{n} \right) \\ &= \frac{n-1}{n} p(1-p). \end{aligned}$$

$$\begin{aligned} E\left(\frac{\hat{p}^1 (1 - \hat{p}^1)}{n-1}\right) &= \frac{1}{n} p(1-p) = \text{Var}(\hat{p}^1) \\ &= \frac{p(1-p)}{n} \end{aligned}$$

16. a) true.

b). false

c) false

d) false.

18. neither, with prob. $(.10)^2 = .01$

both, with prob $(.9)^2 = .81$

48.

a) $\frac{100}{3.2} = 31.25$

b) $S_R^2 = \frac{1}{100} \left(1 - \frac{99}{999,999} \right) \left(\frac{1}{3.2} \right)^2 \cdot$

$\cdot \left((31.25)^2 (S_x^2) + S_y^2 - 2(31.25)S_{xy} \right)$

$S_x^2 = \frac{1}{n} \left(\frac{1}{n} \sum_{i=1}^n x_i^2 - \bar{x}^2 \right)$

$\hat{\approx} 12.50 - (3.2)^2 = 2.26.$

$S_y^2 \hat{\approx} 110,000 - 10,000 = 1000.$

S_{xy}

$\hat{\approx} 360 - 3.2(100)$
 $= 40,$

$$s_{\bar{y}}^2 \hat{\approx} \frac{1}{100} \left(\frac{1}{3.2}\right)^2$$

$$\left(31.25^2 (2.26) + 1000 - 2(31.25)(40) \right)$$

$$\approx .69$$

$$s_{\bar{y}} \hat{\approx} .83$$

$$\left(31.25 - (1.96)(.83) , 31.25 + (1.96)(.83) \right)$$

c) $100,000 \bar{y} = 10,000,000$

~~Var~~

$$s_{\bar{y}}^2 \hat{\approx} \frac{1}{100} s_y^2 \approx 10$$

$$\sqrt{100,000^2 \cdot 10} \hat{\approx} \sqrt{10} (100,000)$$

$$10^7 \pm (1.64)(\sqrt{10}) \cdot 10^5$$

$$\hat{\approx} 10^7 \pm 5.19 \times 10^5$$

67a)

from 1 sample

i) $.184$

ii) $.968$

iii) $.204$

iv) $42,780.29$

$$.184 \pm \frac{\sqrt{.184(1-.184)}}{\sqrt{500}} \cdot 1.96 \approx .184 \pm (.017)(1.96) \\ (.154, .217)$$

$$.968 \pm \frac{(1.15)}{\sqrt{500}} \cdot 1.96 \approx .968 \pm (.051)(1.96) \\ (.868, 1.068)$$

$$.204 \pm \frac{\sqrt{.204(1-.204)}}{\sqrt{500}} \cdot 1.96 \approx .204 \pm (.018)(1.96) \\ (.1687, .2392)$$

$$42,780.29 \pm (1500.72) \cdot 1.96$$

$$= (39839, 45722)$$

8.4.

$$P(X=0) = \frac{2}{3}\theta$$

$$P(X=1) = \frac{1}{3}\theta$$

$$P(X=2) = \frac{2}{3}(1-\theta)$$

$$P(X=3) = \frac{1}{3}(1-\theta)$$

$$0 \leq \theta \leq 1.$$

$$X_i = (3, 0, 2, 1, 3, 2, 1, 0, 2, 1)$$

$$a) E(X) = \frac{1}{3}\theta + \frac{4}{3}(1-\theta) + (1-\theta)$$

$$= \frac{7}{3} - \frac{2}{3}\theta$$

$$\bar{X} = 1.5$$

$$\frac{7}{3} - \frac{2}{3}\theta = \frac{3}{2}$$

$$2 \cdot \frac{2}{3}\theta = \frac{7}{3} - \frac{3}{2} = \frac{5}{6}$$

$$\theta = \frac{5}{6} \cdot \frac{3}{4} = \frac{5}{8}$$

$$\theta = \frac{\frac{7}{3} - E(X)}{2} = \frac{7}{6} - \frac{1}{2} E(X).$$

$$\hat{\theta} = \frac{2}{6} - \frac{1}{2} \bar{X}$$

$$\text{Var}(\hat{\theta}) = \frac{1}{4} \text{Var}(\bar{X}).$$

$$\approx \frac{1}{4} \cdot \frac{1}{10} (s^2)$$

$$\text{where } s^2 = \frac{1}{n-1} \sum_{i=1}^n (X_i - \bar{X})^2.$$

$$= \frac{1}{9} \sum_{i=1}^9 (X_i - 1.5)^2.$$

$$\approx 1.16667.$$

$$\text{s.e.}(\hat{\theta}) \approx \frac{1}{\sqrt{40}} \sqrt{1.16667} \approx 0.171$$

c)

$$\begin{aligned} \text{LLK}(\theta) &= \left(\frac{2}{3}\theta\right)^2 \cdot \left(\frac{1}{3}\theta\right)^3 \cdot \left(\frac{2}{3}(1-\theta)\right)^3 \cdot \left(\frac{1}{3}(1-\theta)\right)^2 \\ &= C \theta^5 (1-\theta)^5 \end{aligned}$$

which is maximized at $\theta = 1/2$.

d)

$$\begin{aligned} \ell(\theta) &= \log C + 5 \log \theta + 5 \log(1-\theta) \\ \ell'(\theta) &= \frac{5}{\theta} - \frac{5}{1-\theta} \quad \ell''(\theta) = -\frac{5}{\theta^2} - \frac{5}{(1-\theta)^2} \end{aligned}$$

$$l''\left(\frac{1}{2}\right) = -\frac{5}{1/4} - \frac{5}{1/4} = -40.$$

So the ~~conjugate~~ ^{'large' sample} variational approximation is $+\frac{1}{40}$

and the approx standard error is

$$\sqrt{\frac{1}{40}} \approx .158$$

e). posterior is proportional to (likelihood) \cdot (prior).

So the posterior is.

$c \theta^5 (1-\theta)^5$ if the prior is uniform.

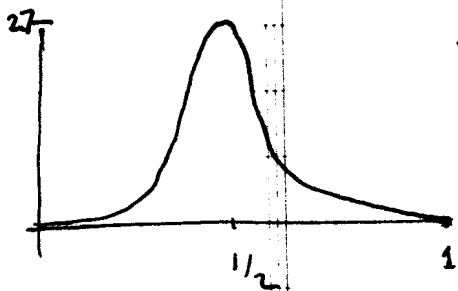
This is a Beta $\beta(6,6)$,

$$\text{so } c = \frac{\Gamma(12)}{\Gamma(6)\Gamma(6)} = \frac{11!}{5!5!} = 2772$$

So the posterior density is

$$2772 \theta^5 (1-\theta)^5$$

and the posterior mode is just the m.l.e. $\theta = 1/2$.



9. "You have not been paying attention in class and you have not been reading your text." (sigh) "I'm worried about your grade."

16.

$$f(x|\sigma) = \frac{1}{2\sigma} e^{-\left(\frac{|x|}{\sigma}\right)}$$

a) $E(X) = \int_{-\infty}^{\infty} \frac{1}{2\sigma} x e^{-\left(\frac{|x|}{\sigma}\right)} dx = 0.$

$$E(X^2) = \int_{-\infty}^{\infty} \frac{1}{2\sigma} x^2 e^{-\left(\frac{|x|}{\sigma}\right)} dx$$

$$= \frac{1}{\sigma} \int_0^{\infty} x^2 e^{-x/\sigma} dx.$$

$$u = x/\sigma \quad du = \frac{dx}{\sigma}.$$

$$x = \sigma u$$

$$= \sigma^2 \int_0^{\infty} u^2 e^{-u} du. = 2\sigma^2.$$

$$\int_0^{\infty} x^2 e^{-x} dx$$

~~$$u = e^{-x} \quad dv = x^2 dx \quad u = x^2 \quad dv = e^{-x} dx$$~~
~~$$du = -e^{-x} dx \quad v = -x^2 e^{-x}/\sigma + 2 \int_0^{\infty} x e^{-x} dx$$~~

$$du = -e^{-x} dx \quad v = -x^2 e^{-x}/\sigma + 2 \int_0^{\infty} x e^{-x} dx$$

$$\int_0^{\infty} x e^{-x} dx$$

$$u = x \quad dv = e^{-x} dx$$

$$du = dx \quad v = -e^{-x} dx$$

$$-x e^{-x} \Big|_0^{\infty} + \int_0^{\infty} e^{-x} dx = 1.$$

So the method of moments estimate of σ is $\hat{\sigma} = \sqrt{\frac{\hat{\mu}_2}{2}} = \sqrt{\frac{\sum x_i^2}{2n}}$

$$b) \text{lik}(\sigma) = \prod_{i=1}^n \frac{1}{2\sigma} e^{-|x_i|/\sigma}$$

$$l(\sigma) = n \log\left(\frac{1}{2}\right) + n \log\left(\frac{1}{\sigma}\right) - \sum \frac{|x_i|}{\sigma}$$

$$l'(\sigma) = -\frac{n}{\sigma} + \frac{1}{\sigma^2} \sum |x_i|$$

$$\hat{\sigma} \text{ satisfies } l'(\hat{\sigma}) = 0.$$

or

$$\frac{1}{\sigma^2} \sum |x_i| = \frac{n}{\sigma}$$

$$\frac{1}{n} \sum |x_i| = \hat{\sigma}$$

$$c) l''(\sigma) = \frac{n}{\sigma^2} - \frac{2}{\sigma^3} \sum_{i=1}^n |x_i|$$

c) cont $E(|X_i|) = \frac{1}{2\sigma} \int_{-\infty}^{\infty} |x| e^{-|x|/\sigma} dx$

$$= \frac{1}{\sigma} \int_0^{\infty} x e^{-x/\sigma} dx$$

$$u = x/\sigma \quad du = \frac{dx}{\sigma}$$

$$x = \sigma u.$$

$$= \sigma \int_0^{\infty} u e^{-u} du = \sigma.$$

So $E(l''(\sigma)) = \frac{n}{\sigma^2} - \frac{2n\sigma}{\sigma^3} = -\frac{n}{\sigma^2}$

and $-\frac{1}{E(l''(\sigma))} = \frac{\sigma^2}{n}$.

is the asymptotic variance of the m.l.e.

d).

$$f(x_1, \dots, x_n | \sigma) = \prod_{i=1}^n \frac{1}{2\sigma} e^{-|x_i|/\sigma}$$

$$= \frac{1}{(2\sigma)^n} e^{-\frac{1}{\sigma} \sum |x_i|}$$

$$= g(T, \sigma)$$

with $T = \sum_{i=1}^n |x_i|$

and $g(T, \sigma) = \frac{1}{(2\sigma)^n} e^{-T/\sigma}$

So T is sufficient.

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43.

(see the handout file).

- a) The histogram is skewed to the left, so a gamma distribution is a plausible model.

b). (moments) $\hat{\lambda} = \frac{\bar{X}}{\hat{\sigma}^2}$ where $\hat{\sigma}^2 = \frac{1}{n} \sum_{i=1}^n (X_i - \bar{X})^2$

$$\hat{\alpha} = \frac{\bar{X}^2}{\hat{\sigma}^2}$$

(from example C pg 263).

For these data: $\bar{X} = 79.935$

~~data~~

$$\hat{\sigma}^2 = 6311.676$$

$$\hat{\lambda} \approx .01206$$

$$\hat{\alpha} \approx 1.0124$$

(m.l.e.)

$$\hat{\lambda} = \frac{\hat{\alpha}}{\bar{X}}$$

$$n \log \hat{\alpha} - n \log \bar{X} + \sum_{i=1}^n \log X_i - n \frac{\Gamma'(\hat{\alpha})}{\Gamma(\hat{\alpha})} = 0$$

or

$$\log \hat{\alpha} - \log \bar{X} + \frac{1}{n} \sum_{i=1}^n \log X_i - \frac{P'(\hat{\alpha})}{P(\hat{\alpha})} = 0.$$

and solving numerically for $\hat{\alpha}$ gives

$$\hat{\alpha} \approx 1.026$$

$$\hat{\lambda} \approx 0.01284$$

c). When plotting the distributions with these parameters we see there is little difference and that the fit is good.

d). m.l.e.: .02024 s.e. ($\hat{\alpha}$)
 .000328 s.e. ($\hat{\lambda}$).

moments: .03140 s.e. ($\hat{\alpha}$)
 .000441 s.e. ($\hat{\lambda}$)

e) approximate 95% confidence intervals
m.l.e. $\hat{\lambda}$: (.012279, .013359)
 $\hat{\alpha}$: (~~.97716, 1.04337~~)
 (.99114; 1.05735)

e) cont.

moments: $\hat{\lambda}$: (.01193209, .01343938)

$\hat{\alpha}$: (.9771597, 1.0433721)

f): These data are consistent with a Poisson process model for the arrival times.

In such a model, the interarrival times are exponentially distributed

$$\alpha = 1$$

$$\hat{\lambda} = \frac{1}{\bar{X}} \approx .012510$$

66.

a) posterior \propto (likelihood) (Prior)

Since the prior is uniform and the likelihood is θ^2

the posterior is $f_{post}(\theta) = 3\theta^2$
 $0 \leq \theta \leq 1$

b) The posterior mode is at $\theta = 1$
which seems unreasonable

The posterior mean is
 $\int_0^1 \theta^3 d\theta = 3/4$.

67. See the file Glauxbt/example.txt.

For the Glaux martine, the Poisson model has a Chi-square p -value of $\approx .06$.

With the negative binomial model the p value is .18.

For the Potals Blatte data, the Poisson model is completely implausible (p value ≈ 0.0).

The negative binomial model gives a p -value of $\approx .33$.

Chptr 8 4, 9, 16, 43, 66, 67

Chptr 9 4, 10, 14.

9.4 a)
$$\frac{P(x_i | H_0)}{P(x_i | H_A)} = (2, \frac{3}{4}, 3, \frac{1}{2})$$
 $i=1, 2, 3, 4$ in order

least likely to most likely (under H_0)
vs H_A .

x_4, x_2, x_1, x_3

b) Under H_0 prob $\{x_4\} = .2$
prob $\{x_4, x_2\} = .5$
prob $\{x_4, x_2, x_1, x_3\} = .7$

at level $\alpha = .2$ we reject H_0 if $X = x_4$

at level $\alpha = .5$ we reject H_0 if $X = x_4$ or x_2 .

c). On the Bayesian framework we accept H_0 if

$$\frac{P(H_0 | x)}{P(H_1 | x)} = \frac{P(H_0) P(x | H_0)}{P(H_1) P(x | H_1)} > 1$$

if the priors are equal then

x_1 and x_3 favor H_0 .

and this corresponds to the decision rule
for $\alpha = 0.4$

At $\alpha = 0.2$ we have $\frac{P(x_2/H_0)}{P(x_2/H_1)} = \frac{3}{4}$

and any priors such that

$$\frac{P(H_0)}{P(H_1)} > \frac{4}{3}$$

will ~~allow~~ allow acceptance of x_2
on the other hand

$$\frac{P(x_4/H_0)}{P(x_2/H_1)} = \frac{1}{2}$$

so to reject for x_4 we need

$$\frac{P(H_0)}{P(H_1)} < 2$$

\therefore and priors with $\frac{4}{3} < \frac{P(H_0)}{P(H_1)} < 2$

e.g. $P(H_0) = \frac{5}{8}$, $P(H_1) = \frac{3}{8}$ will correspond to the decision rule at $\alpha = 0.2$.

9.10.

$$f(x_1, \dots, x_n | \theta)$$

$$= \prod_{j=1}^n f(x_j | \theta) = g(T(x_1, \dots, x_n), \theta) h(x_1, \dots, x_n)$$

The likelihood ratio for $H_0: \theta = \theta_0$
vs $H_A: \theta = \theta_1$

is therefore

$$q(T) \equiv \frac{g(T(x_1, \dots, x_n), \theta_0)}{g(T(x_1, \dots, x_n), \theta_1)}$$

and we reject H_0 when this function
 $q(T)$ is small.

If we know the null dist of T
we can find c s.t.

$$P \{ q(T) < c \} = \alpha$$

$$9.14 \quad H_0: X \sim N(0, \sigma^2)$$

$$H_1: X \sim N(1, \sigma^2)$$

Priors:

$$P(H_0) = 2 P(H_1).$$

$$\frac{P(H_0|x)}{P(H_1|x)} = \frac{P(H_0)}{P(H_1)} \frac{P(x|H_0)}{P(x|H_1)}$$

$$= \frac{2 \cdot \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{1}{2}\left(\frac{x}{\sigma}\right)^2}}{\frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{1}{2}\left(\frac{x-1}{\sigma}\right)^2}}$$

and we accept H_0 when this is larger than 1.

i.e.

$$\text{When } e^{-\left[\frac{1}{2}\left(\frac{x}{\sigma}\right)^2 - \frac{1}{2}\left(\frac{x-1}{\sigma}\right)^2\right]} > \frac{1}{2}.$$

$$\Leftrightarrow -\frac{1}{2}\left(\frac{x}{\sigma}\right)^2 + \frac{1}{2}\left(\frac{x-1}{\sigma}\right)^2 > \ln\left(\frac{1}{2}\right).$$

$$\Leftrightarrow \left(\frac{x}{\sigma}\right)^2 - \left(\frac{x-1}{\sigma}\right)^2 < +2 \ln 2.$$

$$x^2 - (x-1)^2 < + 2\sigma^2 \ln 2.$$

$$x^2 - (x^2 - 2x + 1) < + 2\sigma^2 \ln 2.$$

$$2x < 1 + 2\sigma^2 \ln 2.$$

$$x < \frac{1 + 2\sigma^2 \ln 2}{2} = \frac{1}{2} + \sigma^2 \ln 2.$$

$$x < (.57, .85, 1.19, 3.97).$$

b). with $c = (.57, .85, 1.19, 3.97)$

$$\text{Prob} \{ X < c \mid H_0 \} = P(H_0) + P(X < c \mid H_1) P(H_1)$$

$$\downarrow$$

$$\text{For } H_0: P(X < c) = \text{Prob} \left\{ \frac{X}{\sigma} < \frac{c}{\sigma} \right\}$$

$$\text{For } H_1: P(X < c) = \text{Prob} \left\{ \frac{X-1}{\sigma} < \frac{c-1}{\sigma} \right\}$$

So we have

$$\Phi\left(\frac{c}{\sigma}\right) \cdot \frac{2}{3} + \Phi\left(\frac{c-1}{\sigma}\right) \cdot \frac{1}{3}$$

$$= \Phi(0.672, 0.729, 0.780, 0.944)$$