Topics in statistics III/IV (MATH3361/4071)	Michaelmas term, 2020-2021

Exercises: Likelihood methods

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1 Handout 1: Basic probability tools in asymptotics

This is out of the scope

Exercise 1. ($\star\star$) From Fatou-Lesbeque Lemma, prove Monotone Convergence theorem. (Hint: Use $Y \equiv 0$, use $\limsup_{n\to\infty} f_n$and $\liminf_{n\to\infty} f_n$)

Solution. Since $0 < X_1 \leq ... \leq \lim_{n\to\infty} X_n = X$ a.s.. Then $\mathrm{E}X_n \leq \mathrm{E}X$ or $\limsup_{n\to\infty} \mathrm{E}X_n \leq \mathrm{E}X$.

From Fatou-Lesbeque Lemma, it is $\liminf_{n\to\infty} \mathrm{E}X_n \geq \mathrm{E}X$. Also the limit $\lim \mathrm{E}X_n$ exists. Then, it is $\lim \mathrm{E}X_n = \mathrm{E}X$

This is out of the scope

Exercise 2. ($\star\star$) From Fatou-Lesbeque Lemma, prove Lesbeque Dominant Convergence theorem. (Hint: Use that $-Y \leq -X_n$ and $-Y \leq X_n$, use $\limsup_{n\to\infty} f_n$and $\liminf_{n\to\infty} f_n$)

Solution.

Since $|X_n| \leq Y$, it is $-Y \leq -X_n$, and because $X_n \xrightarrow{a.s.} X$ it is $\liminf_{n\to\infty} \mathrm{E}(-X_n) \geq \mathrm{E}(-Y) \Longleftrightarrow \limsup_{n\to\infty} \mathrm{E}(X_n) \leq \mathrm{E}(Y)$

Since $|X_n| \leq Y$, it is $-Y \leq X_n$ and because $X_n \xrightarrow{a.s.} X$ it is $\liminf_{n\to\infty} \mathrm{E}(X_n) \geq \mathrm{E}(Y)$

So $\lim_{n\to\infty} \mathrm{E}(X_n) = \mathrm{E}(Y)$

Exercise 3. ($\star\star$) Let μ be a constant. Show that $X_n \xrightarrow{\text{qm}} \mu$ if and only if $\mathrm{E}X_n \to \mu$ and $\mathrm{Var}(X_n) \to 0$, both in uni-variate and multivariate case.

Solution. It is $\mathrm{E}(X_n - \mu)^2 = \mathrm{Var}(X_n) + (\mathrm{E}X_n - \mu)^2$. Hence, $\mathrm{E}(X_n - \mu)^2 \to 0$. In the multivariate case, it is $\mathrm{E}(X_n - \mu)^T(X_n - \mu) = \mathrm{E}\sum_{i=1}^{d}(X_{n,i} - \mu_i)^2 \to 0$ by treating each element separately.

Exercise 4. ($\star\star$) Consider a sequence of discrete r.v. $\{X_n\}$ with probability $P(X_n = k) = \frac{1}{n}$, for $k = 1/n, 2/n, ..., n/n$. Show that $X_n \xrightarrow{D} X$ where $X \sim \mathrm{U}(0, 1)$. (Hint: Just use the definition.)

Solution. The probability function is $P(X_n \leq x) = k/n$ for $k/n \leq x \leq (k+1)/n$.

Then because $|k/n - x| < 1/n$, we have $\lim_{n\to\infty} P(X_n \leq x) = x$.

Note that $P(X \leq x) = x$ is the distribution function of the Uniform random variable $X \sim \mathrm{U}(0, 1)$. So $X_n \xrightarrow{D} \mathrm{U}(0, 1)$.

Exercise 5. ($\star$)

1. Show that
$$\mathrm{E}_\pi(X - \theta)^T(X - \theta) = \mathrm{Var}_\pi(X) + (\mathrm{E}_\pi(X) - \theta)^T(\mathrm{E}_\pi(X) - \theta)$$
, where is a constant point, and X is a random variable $X \sim \mathrm{d}\pi(\cdot)$.

2. Show that
$$\mathrm{E}_\pi|X - \theta|^2 = \mathrm{Var}_\pi(X) + |\mathrm{E}_\pi(X) - \theta|^2$$
, where is a constant point, X is a random variable $X \sim \mathrm{d}\pi(\cdot)$, and $|X| = \sqrt{X_1^2 + ...X_d^2}$ is the Euclidean norm.

Solution.

(a) It is
$$\begin{aligned}\mathrm{E}_\pi(X - \theta)^T(X - \theta) &= \mathrm{E}_\pi([X - \mathrm{E}_\pi(X)] + [\mathrm{E}_\pi(X) - \theta])^T([X - \mathrm{E}_\pi(X)] + [\mathrm{E}_\pi(X) - \theta]) = ... \\ &= \mathrm{E}_\pi(X - \theta)^T(X - \theta) + (\mathrm{E}_\pi(X) - \theta)^T(\mathrm{E}_\pi(X) - \theta) \\ &= \mathrm{Var}_\pi(X) + (\mathrm{E}_\pi(X) - \theta)^T(\mathrm{E}_\pi(X) - \theta)\end{aligned}$$

(b) It is
$$\begin{aligned}\mathrm{E}_\pi|X - \theta|^2 &= \mathrm{E}_\pi(X - \theta)^T(X - \theta) \\ |\mathrm{E}_\pi(X) - \theta|^2 &= (\mathrm{E}_\pi(X) - \theta)^T(\mathrm{E}_\pi(X) - \theta)\end{aligned}$$
from the definition of the is the Euclidean norm $|X| = \sqrt{X_1^2 + ...X_d^2}$. So the result follows from then previous task.

Exercise 6. Show that
$$\log(1 + x) = x + o(x), \text{ as } x \to 0.$$

Solution. Let $f(x) = \log(1+x)$. Then $\dot{f}(x) = \frac{1}{1+x}$. The 1st order Taylor expansion of $f(x)$ around 0 is

$$f(x) = f(0) + \frac{1}{1!}\dot{f}(0)(x-0) + o(x), \text{ as }, \text{ as } x \to 0$$

where $h = x - 0$.
So

$$\log(1+x) = x + o(x), \text{ as } x \to 0.$$

Exercise 7. Show that

$$\lim_{n\to\infty}(1 + \frac{1}{n}a_n)^n = \exp(\lim_{n\to\infty} a_n)$$

provided that $\frac{1}{n}a_n \to 0$, as $n \to \infty$.

Hint: From Taylor expansion, it is

$$\log(1+x) = x + o(x), \text{ as } x \to 0.$$

Solution.

- It is

$$\begin{aligned}(1 + \frac{1}{n}a_n)^n &= \exp(n\log(1 + \frac{1}{n}a_n)) \\ &= \exp(n(\frac{1}{n}a_n + o(\frac{1}{n}a_n))) \\ &= \exp(a_n(1 + o(1)))\end{aligned}$$

- Then provided that a_n increases slower than n, aka $\frac{1}{n}a_n \to 0$ it is

$$\lim_{n\to\infty}(1 + \frac{1}{n}a_n)^n = \exp(\lim_{n\to\infty} a_n)$$

Exercise 8. It is $X_n \xrightarrow{a.s.} X$ if and only if

$$\text{for every } \epsilon > 0, \quad P(|X_k - X| < \epsilon\,, \forall k \geq n) \to 1, \qquad \text{as } n \to \infty,$$

Solution. Let $A_{n,\epsilon} = \{|X_k - X| < \epsilon\,, \forall k \geq n\}$. Then

$$P(\lim_{n\to\infty} X_n = X) = P\{\forall \epsilon > 0,\ \exists n > 0, \text{ s.t. } |X_k - X| < \epsilon, \forall k \geq n\} = P\{\cap_{\epsilon>0} \cup_{\forall n} A_{n,\epsilon}\}$$

So $X_n \xrightarrow{a.s.} X$ is equivalent to $P\{\cap_{\epsilon>0} \cup_{\forall n} A_{n,\epsilon}\} = 1$. Because sets $\cup_{\forall n} A_{n,\epsilon}$ decrease to $\cap_{\epsilon>0} \cup_{\forall n} A_{n,\epsilon}$ as $\epsilon \to 0$, it is

$$P\{\cap_{\epsilon>0} \cup_{\forall n} A_{n,\epsilon}\} = 1 \Longleftrightarrow P\{\cup_{\forall n} A_{n,\epsilon}\} = 1, \ \forall \epsilon > 0$$

Because $A_{n,\epsilon}$ increases to $\cup_{\forall n} A_{n,\epsilon}$ as $n \to \infty$, it is

$$P\{\cup_{\forall n} A_{n,\epsilon}\} = 1 \Longleftrightarrow P\{A_{n,\epsilon}\} = 1, \text{ as } n \to \infty, \ \forall \epsilon > 0$$

Exercise 9. Prove the following relations betweeng different modes of convergence

1. $X_n \xrightarrow{a.s.} X \implies X_n \xrightarrow{P} X$
2. $X_n \xrightarrow{r} X$, for some $r > 0 \implies X_n \xrightarrow{P} X$
3. $(\star\star\star) X_n \xrightarrow{P} X \implies X_n \xrightarrow{D} X$

Solution.

1. For any $\epsilon > 0$, then

$$P(|X_n - X| > \epsilon) \geq P(|X_k - X| < \epsilon\,, \forall k \geq n) \to 1, \text{ as, } n \to \infty$$

from Lemma 6 in the Handout.

2. It is

$$E|X_n - X|^r \geq E(|X_k - X|^r 1(|X_n - X| \geq \epsilon)) \geq \epsilon^r P(|X_n - X| \geq \epsilon) \to 0, \text{ as, } n \to \infty$$

This is Markov inequality (Prob. I)

3. This is difficult and it can be skipped.

For any $\epsilon > 0$, $\{X > z + 1\epsilon\}$ and $|X_n - X| < \epsilon$ imply $\{X_n > z\}$. Hence, $\{X_n > z\} \supseteq \{X > z + \epsilon\} \cap \{|X_n - X| < \epsilon\}$. By taking complements, we get $\{X_n \leq z\} \subseteq \{X \leq z + 1\epsilon\} \cup \{|X_n - X| > \epsilon\}$. So I get $P(X_n \leq z) \leq P(X \leq z + \epsilon) + P(|X_n - X| > \epsilon)$.

In a similar way (by interchanging X and X_n), I get $P(X_n \leq z) \geq P(X \leq z - \epsilon) + P(|X_n - X| > \epsilon)$. [1]

[1] It is:

(a) $\limsup_{n\to\infty} f_n := \lim_{n\to\infty}(\sup_{\forall m \geq n} f_m)$ and $\liminf_{n\to\infty} f_n := \lim_{n\to\infty}(\inf_{\forall m \geq n} f_m)$

(b) It is $\liminf_{n\to\infty} f_n \leq \limsup_{n\to\infty} f_n$ if both exist.

(c) It is $\lim_{n\to\infty} f_n = \liminf_{n\to\infty} f_n = \limsup_{n\to\infty} f_n$ if $\lim_{n\to\infty} f_n$ exists

So as $n \to \infty$

$$P(X \leq z - 1\epsilon) \leq \lim \inf_{n\to\infty} P(X_n \leq z) \leq \lim \sup_{n\to\infty} P(X_n \leq z) \leq P(X \leq z + 1\epsilon)$$

As $F_X(x) = P(X \leq x)$ is continuous at z, the two ends should converge to $F_X(z) = P(X \leq z)$ as $\epsilon \to 0$, which implies that $\lim_{n\to\infty} F_{X_n}(z) = F_X(z)$

Exercise 10. ($\star\star$) Prove that:

1. if $Z \sim \mathrm{N}(0, I)$ then $\varphi_Z(t) = \exp(-\frac{1}{2}t^T t)$, where $Z \in \mathbb{R}^d$
2. if $X \sim \mathrm{N}(\mu, \Sigma)$ then $\varphi_X(t) = \exp(it^T\mu - \frac{1}{2}t^T\Sigma t)$, where $X \in \mathbb{R}^d$

Hint: Assume as known that if $Z \sim \mathrm{N}(0, 1)$ then $\varphi_Z(t) = \exp(-\frac{1}{2}t^2)$, where $Z \in \mathbb{R}$

Solution.

1. It is

$$\begin{aligned}\varphi_Z(t) &= \mathrm{E}(\exp(it^T Z)) = \mathrm{E}(\exp(i\sum_{j=1}^{d}(t_j Z_j))) = \mathrm{E}(\prod_{j=1}^{d}\exp(it_j Z_j)) = \prod_{j=1}^{d}\mathrm{E}(\exp(it_j Z_j))\\ &= \prod_{j=1}^{d}\varphi_{Z_j}(t) = \prod_{j=1}^{d}\exp(-\frac{1}{2}t_j^2) = \exp(-\frac{1}{2}\sum_{j=1}^{d}t_j^2) = \exp(-\frac{1}{2}t^T t)\end{aligned}$$

2. Assume a matrix L such as $\Sigma = LL^T$. It is $X = \mu + LZ$. Then

$$\begin{aligned}\varphi_X(t) &= \varphi_{\mu+LZ}(t) = e^{it^T\mu}\varphi_Z(L^T t) = e^{it^T\mu}\exp(-\frac{1}{2}(L^T t)^T L^T t)\\ &= e^{it^T\mu}\exp(-\frac{1}{2}t^T LL^T t) = \exp(it^T\mu - \frac{1}{2}t^T\Sigma t)\end{aligned}$$

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2 Handout 2: Basic tools for asymptotics in statistics

Exercise 11. Let $X, X_1, X_2, ...$ be i.i.d. random vectors, and let

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

then

1. (Weak law) If $E|X| < \infty$, then $\bar{X}_n \xrightarrow{P} \mathrm{E}(X)$

2. (Strong law) $E|X| < \infty$, iff $\bar{X}_n \xrightarrow{as} \mathrm{E}(X)$

3. (in qm) $E|X|^2 < \infty$, iff $\bar{X}_n \xrightarrow{\mathrm{qm}} \mathrm{E}(X)$

4. Let $\varphi_X(t) = \mathrm{E}(e^{it^T X})$, and $\mu = \mathrm{E}(X)$.

Solution.

1. It is

$$\begin{aligned}\varphi_{\bar{X}_n}(t) =&\varphi_{X_1+\ldots+X_n}(\frac{t}{n}) = \prod_{i=1}^{n} \varphi_{X_j}(\frac{t}{n}) = \left(\varphi_X(\frac{t}{n})\right)^n \\ =& \left(\varphi_X(0) + \left(\int_0^1 \dot{\varphi}_X(u\frac{t}{n})\mathrm{d}u\right)\frac{t}{n}\right)^n\end{aligned}$$

since by the Mean-Value theorem

$$\varphi_X(\frac{t}{n}) = \varphi_X(0) + \left(\int_0^1 \dot{\varphi}_X(u\frac{t}{n})\mathrm{d}u\right)\frac{t}{n}.$$

Because $\varphi_X(0) = 1$, and $\lim_{\epsilon\to 0}\dot{\varphi}_X(\epsilon) = \dot{\varphi}_X(0) = i\mu^T$ it is

$$\lim_{n\to\infty}\varphi_{\bar{X}_n}(t) = \exp\left(\lim_{n\to\infty}\left(\int_0^1 \dot{\varphi}_X(u\frac{t}{n})\mathrm{d}u\right)t\right) = \exp(i\mu^T t) \tag{1}$$

Here I used that $\lim_{n\to\infty}(1+a_n)^n = \exp(\lim_{n\to\infty} na_n)$ if $\lim_{n\to\infty} na_n$ exists (Exercise #7).

So (1) says that the characteristic function of $\bar{X}_n$ converges to a characteristic function of the degenerate random variable μ

$$\varphi_{\bar{X}_n}(t) \to \varphi_\mu(t)$$

From the continuity Theorem 24 it is $\bar{X}_n \xrightarrow{D} \mu$. Then from Theorem 7(3) it is $\bar{X}_n \xrightarrow{P} \mu$ because $\mu = \mathrm{E}(X)$ is just a constant point.

(a) Proof is out of the scope; for more details see in[**?**].

(b) It is

$$\begin{aligned}
\mathrm{E}|\bar{X}_n-\mu|^2 =& \mathrm{E}(\bar{X}_n-\mu)^T(\bar{X}_n-\mu)\\
=&\frac{1}{n^2}\sum_i\sum_j \mathrm{E}(X_i-\mu)^T(X_j-\mu)\\
\overset{\text{simplify}}{=}&\frac{1}{n^2}\sum_i \mathrm{E}(X_i-\mu)^T(X_i-\mu) \overset{\text{iid}}{=} \frac{1}{n^2}n\mathrm{E}(X-\mu)^T(X-\mu)\\
=&\frac{1}{n}\mathrm{Var}(X)\rightarrow 0
\end{aligned}$$

as the 2nd mode is finite.

Exercise 12. Show

$$\text{If}\quad h_n\rightarrow 0,\quad \text{and}\quad X_n=O_P(h_n)\quad \text{then}\quad X_n=o_P(1).$$

Solution.

- Deterministic: If $x_n = O(h_n)$ and $h_n \rightarrow 0$, then $x_n = o(1)$, because we sandwich $|x_n| \leq Kh_n \rightarrow 0$.
- Stochastic: If $x_n = O_P(h_n)$ and $h_n \rightarrow 0$, then $x_n = o_P(1)$. Because $h_n \rightarrow 0$, for sufficiently large $n > 0$ $Kh_n \leq \delta$. Also as $x_n = O_P(h_n)$ for any $\epsilon > 0$ I can find a $K > 0$ such that $P(|x_n| \leq Kh_n) \geq 1-\epsilon$. Putting both together, for any $\epsilon > 0$ and any $\delta > 0$, I can get K such that, for sufficiently large $n > 0$, I can get

$$P(|x_n|\leq\delta)\geq P(|x_n|\leq Kh_n)\geq 1-\epsilon$$

Exercise 13. Let $X_1, X_2, ...$ IID random vectors $X_i \in \mathbb{R}^d$ with mean $\mathrm{E}(X_i) = \mu$ and finite covariance matrix $\mathrm{Var}(X_i) < \infty$ for all $i = 1, ...,$ Then

$$\sqrt{n}(\bar{X}_n-\mu)\xrightarrow{D}\mathrm{N}(0,\Sigma)$$

Solution. We 'll gonna use again the characteristic function, and its property with the IID variables. It is

$$\sqrt{n}(\bar{X}_n-\mu)=\frac{1}{\sqrt{n}}\sum_{j=1}^{n}(X_j-\mu)$$

Hence, for any $t \in \mathbb{R}^d$

$$\begin{aligned}
\varphi_{\sqrt{n}(\bar{X}_n-\mu)}(t) &= \varphi_{\frac{1}{\sqrt{n}}\sum_{j=1}^{n}(X_j-\mu)}(t) = \varphi_{\sum_{j=1}^{n}(X_j-\mu)}(\frac{t}{\sqrt{n}}) \\
&= \prod_{j=1}^{n} \varphi_{(X_j-\mu)}(\frac{t}{\sqrt{n}}) \\
&= \left(\varphi_{(X_j-\mu)}(\frac{t}{\sqrt{n}})\right)^n = \left(\varphi_{(X-\mu)}(\frac{t}{\sqrt{n}})\right)^n
\end{aligned}$$

Here, let $\varphi(t) := \varphi_{(X_j-\mu)}(t)$ for notation convenience, as $X_1, X_2, ...$ are IID and hence have the same moments. We use Taylor expansion around 0 as

$$\varphi_{(X-\mu)}(\frac{t}{\sqrt{n}}) = \cancelto{1}{\varphi_{(X-\mu)}(0)} + \cancelto{0}{\dot{\varphi}_{(X-\mu)}(0)}\frac{t}{\sqrt{n}} + t^T\left(\int_0^1\int_0^1 v\ddot{\varphi}_{(X-\mu)}(0+vu\frac{t}{n})\mathrm{d}u\mathrm{d}v\right)\frac{t}{n}$$

because $\ddot{\varphi}_X(t)$ is obviously continuous. So

$$\begin{aligned}
\varphi_{\sqrt{n}(\bar{X}_n-\mu)}(t) &= \left(\varphi_{(X-\mu)}(\frac{t}{\sqrt{n}})\right)^n \\
&= \left(1 + t^T\left(\int_0^1\int_0^1 v\ddot{\varphi}_{(X-\mu)}(vu\frac{t}{n})\mathrm{d}u\mathrm{d}v\right)\frac{t}{n}\right)^n
\end{aligned}$$

Because $\lim_{n\to\infty}(1+a_n)^n = \exp(\lim_{n\to\infty} na_n)$ if $\lim_{n\to\infty} na_n$ exists (Exercise #7), it is

$$\begin{aligned}
\lim_{n\to\infty}\varphi_{\sqrt{n}(\bar{X}_n-\mu)}(t) &= \lim_{n\to\infty}\left(1 + t^T\left(\int_0^1\int_0^1 v\ddot{\varphi}_{(X-\mu)}(vu\frac{t}{n})\mathrm{d}u\mathrm{d}v\right)\frac{t}{n}\right)^n \\
&= \exp\left(\lim_{n\to\infty} t^T\left(\int_0^1\int_0^1 v\ddot{\varphi}_{(X-\mu)}(vu\frac{t}{n})\mathrm{d}u\mathrm{d}v\right)t\right) \qquad (2)\\
&= \exp\left(t^T\left(\int_0^1\int_0^1 v(-\Sigma)\mathrm{d}u\mathrm{d}v\right)t\right) \\
&= \exp(-\frac{1}{2}t^T\Sigma\, t)
\end{aligned}$$

This is because $\ddot{\varphi}_{(X-\mu)}(\cdot)$ is continuous so $\lim_{n\to\infty}\ddot{\varphi}_{(X-\mu)}(u\frac{t}{n}) = \ddot{\varphi}_{(X-\mu)}(0) = -\mathrm{E}((X-\mu)^T(X-\mu)) = -\Sigma$.

Since $\lim_{n\to\infty}\varphi_{\sqrt{n}(\bar{X}_n-\mu)}(t) = \exp(-\frac{1}{2}t^T\Sigma\, t)$, aka $\varphi_{\sqrt{n}(\bar{X}_n-\mu)}(t) \to \varphi_Z(t)$ where $Z \sim \mathrm{N}(0,\Sigma)$, it is $\sqrt{n}(\bar{X}_n-\mu) \xrightarrow{D} \mathrm{N}(0,\Sigma)$.

Exercise 14. ($\star\star$) Consider that $\sqrt{n}(X_n-\mu) \underset{D}{\to} Z$, where $Z \sim \mathrm{N}(0,\Sigma)$ for $\Sigma > 0$ (positive definite). Show that $X_n \xrightarrow{P} \mu$. (Hint: Use the concept 'bounded in probability)'

Solution. I show this result by using 2 ways.

First way: It is $\sqrt{n}(X_n-\mu)\underset{D}{\to}Z$, so

$$\sqrt{n}(X_n-\mu)=O_P(1)\implies(X_n-\mu)=O_P(1)O_P(1/\sqrt{n})=O_P(1)o_P(1)=o_P(1)$$

So $X_n\xrightarrow{P}\mu$.

Second way: I observe that

$$(X_n-\mu)=\underbrace{\frac{1}{\sqrt{n}}}_{=A_n}\underbrace{\sqrt{n}(X_n-\mu)}_{=B_n}$$

It is $A_n=\sqrt{n}(X_n-\mu)\underset{D}{\to}Z$, and $B_n=\frac{1}{\sqrt{n}}\to 0$. By Slutsky theorem it is

$$(X_n-\mu)=A_nB_n\underset{D}{\to}0Z=0$$

So

$$(X_n-\mu)\underset{D}{\to}0$$

which implies

$$X_n\xrightarrow{P}\mu$$

Exercise 15. ($\star\star$)

1. If $X_1,X_2,...$ are IID in $\mathbb{R}^2$ with distribution giving probability

$$\mathrm{P}(X=x)=\begin{cases}\theta_1 & ,\text{if } x=\begin{bmatrix}1\\0\end{bmatrix}\\ \theta_2 & ,\text{if } x=\begin{bmatrix}0\\1\end{bmatrix}\\ \theta_1+\theta_2 & ,\text{if } x=\begin{bmatrix}0\\0\end{bmatrix}\end{cases}$$

there $\theta_1+\theta_2\leq 1$.. What is the asymptotic distribution of $\bar{X}_n$ given the CLT?

2. If $X_1,X_2,...$ are IID from a Poisson distribution $\mathrm{Poi}(\theta)$ distribution as

$$\mathrm{P}(x|\theta)=\frac{e^{-\theta}\theta^x}{x!}1(x\in\{0,1,2,...\})$$

Let Z_n be the proportion of zeros observed $Z_n=\frac{1}{n}\sum_{j=1}^{n}1(X_j=0)$. What is the joint asymptotic distribution of $(\bar{X}_n,Z_n)$

Solution.

1. It is $\mu = \mathrm{E}(X) = \begin{bmatrix} \theta_1 \\ \theta_2 \end{bmatrix}$, $\mathrm{E}(X^T X) = \begin{bmatrix} \theta_1 & 0 \\ 0 & \theta_2 \end{bmatrix}$, so $\mathrm{Var}(X) = \mathrm{E}(X - \mathrm{E}(X))^T (X - \mathrm{E}(X)) = \mathrm{E}(X^T X) - \mu^T \mu = \begin{bmatrix} \theta_1(1-\theta_1) & -\theta_1\theta_2 \\ -\theta_1\theta_2 & \theta_2(1-\theta_2) \end{bmatrix}$ The CLT says $\sqrt{n}(\bar{X}_n - \mu) \xrightarrow{D} \mathrm{N}(0, \Sigma)$

2. It is $E(X) = \theta$, $E(1(X=0)) = \exp(\theta)$, $\mathrm{Var}(X) = \theta$, $\mathrm{Var}(1(X=0)) = \exp(-\theta)(1-\exp(-\theta))$ and $E(X1(X=0)) = 0$, so $\mathrm{cov}(X, 1(X=0)) = -\theta\exp(-\theta)$. So $\Sigma = \begin{bmatrix} \theta & -\theta\exp(-\theta) \\ -\theta\exp(-\theta) & \exp(-\theta)(1-\exp(-\theta)) \end{bmatrix}$. The CLT says $\sqrt{n}(\bar{X}_n - \mu) \xrightarrow{D} \mathrm{N}(0, \Sigma)$

Exercise 16. (⋆⋆⋆⋆Super difficult) (The autoregressive model) Consider that $\{\epsilon_n\}$ are IID, with mean $\mathrm{E}(\epsilon_n) = \mu$, and variance $\mathrm{Var}(\epsilon_n) = \sigma^2$, $\forall n$. A time series $\{X_n\}_{n\geq 1}$ is modeled as $X_n \sim \mathrm{AR}(\beta)$ where $\beta \in (-1, 1)$ if

$$\begin{aligned} X_n =& \beta X_{n-1} + \epsilon_n; \text{ for } n \geq 2 \\ X_1 =& \epsilon_1 \end{aligned}$$

Show that $\bar{X}_n \xrightarrow{\text{qm}} \mu/(1-\beta)$

1. Show that $\bar{X}_n = \frac{1}{n}\sum_{i=1}^{n} \epsilon_j (1 - \beta^{n-j+1})/(1-\beta)$
2. Find $\lim_{n\to\infty} \mathrm{E}(\bar{X}_n) =?$
3. Show that $\lim_{n\to\infty} \mathrm{Var}(\bar{X}_n) = 0$
4. Show that $\bar{X}_n \xrightarrow{\text{qm}} \mu/(1-\beta)$

[Hint] (1.) Show that $\bar{X}_n = \frac{1}{n}\sum_{i=1}^{n} \epsilon_j (1 - \beta^{n-j+1})/(1-\beta)$ (2) Find $\lim_{n\to\infty} \mathrm{E}(\bar{X}_n) = \mu/(1-\beta)$; (3) Show that $\lim_{n\to\infty} \mathrm{Var}(\bar{X}_n) = 0$, (4.) ...

Solution.

1. It is $X_i = \sum_{j=1}^{i} \epsilon_j \beta^{n-j}$. So

$$\bar{X}_n = \frac{1}{n}\frac{\mu}{1-\beta}\sum_{i=1}^{n}\sum_{j=1}^{i} \epsilon_j \beta^{n-j} = \frac{1}{n}\sum_{j=1}^{n} \epsilon_j \frac{1-\beta^{n-j+1}}{1-\beta}$$

2. It is

$$\begin{aligned}
\mathrm{E}\bar{X}_n &= \frac{1}{n}\sum_{i=1}^{n}\mathrm{E}(\epsilon_j)\frac{1-\beta^{n-j+1}}{1-\beta} = \frac{1}{n}\frac{\mu}{1-\beta}\sum_{j=1}^{n}(1-\beta^{n-j+1}) \\
&= \frac{1}{n}\frac{\mu}{1-\beta}\sum_{j=1}^{n}(1-\beta^{j}) \\
&= \frac{1}{n}\frac{\mu}{1-\beta}(n-\frac{\beta(1-\beta^n)}{1-\beta}) \\
&= \frac{\mu}{1-\beta}-\frac{\beta\mu}{n}\frac{(1-\beta^n)}{(1-\beta)^2}
\end{aligned}$$

So $\lim \mathrm{E}\bar{X}_n = \frac{\mu}{1-\beta}$

3. It is

$$\begin{aligned}
\mathrm{Var}(\bar{X}_n) &= \sum_{i=1}^{n}\mathrm{Var}(\epsilon_j)(\frac{1}{n}\frac{1-\beta^{n-j+1}}{1-\beta})^2 = \sigma^2\frac{1}{n^2}\sum_{i=1}^{n}\frac{(1-\beta^{n-j+1})^2}{(1-\beta)^2} \\
&\le \sigma^2\frac{1}{n^2}\sum_{j=1}^{n}\frac{1}{(1-\beta)^2} \le \sigma^2\frac{1}{n}
\end{aligned}$$

as $\beta \in (0,1)$. So $\lim \mathrm{Var}(\bar{X}_n) = 0$

4. It is

$$\begin{aligned}
\lim(\mathrm{E}\bar{X}_n\text{-}\frac{\mu}{1-\beta})^2 &= \lim(\mathrm{Var}(\bar{X}_n) + (\mathrm{E}\bar{X}_n - \frac{\mu}{1-\beta})^2) \\
&= \lim\mathrm{Var}(\bar{X}_n) + (\lim\mathrm{E}\bar{X}_n - \frac{\mu}{1-\beta})^2 \\
&= 0
\end{aligned}$$

So $\bar{X}_n \xrightarrow{\text{qm}} \mu/(1-\beta)$

Exercise 17. ($\star\star$) Let $X_i \overset{\text{IID}}{\sim} F_X$ for $i = 1, ..., n$, and $F_X = P(X \le x)$. Show that the empirical distribution function $\hat{F}_X(x) = \frac{1}{n}\sum_{i=1}^{n} 1(x \in [x_i, \infty))$ is a strongly consistent estimator of F_X.

Solution. It is $\mathrm{E}(\hat{F}_X(x)) = \frac{1}{n}\sum_{i=1}^{n}\mathrm{E}(1(x \in (-\infty, x_i])) = \frac{1}{n}\sum_{i=1}^{n}\mathrm{P}(x \in (-\infty, x_i]) \le \frac{1}{n}\sum_{i=1}^{n} 1 < \infty$ So the strong LLN applies.

Exercise 18. ($\star\star$) Assume X_1,X_2,X_3 independent from Uniform distribution $\mathrm{U}(0,1)$. Compare the exact, Normal approximation, and Edgeworth approximation.

Hint: The exact result is $P(X_1 + X_2 + x_3 \leq 2) = 0.8333$

Solution.

It is $\mu = 1/2$, $\sigma^2 = 1/12$, $\kappa_3 = 0$. Also, $\mathrm{E}(X - 1/2)^4 = \int_0^1 (x - 1/2)^4 \mathrm{d}x = 1/80$. So $\kappa_4 = \mathrm{E}(X - 1/2)^4/\sigma^4 - 3 = -1.2$.

So

Normal approx. $P(X_1 + X_2 + x_3 \leq 2) = P(\sqrt{3}(\bar{X}_3 - \mu)^2/\sigma \leq (\frac{2}{3} - \frac{1}{2})\sqrt{12}\sqrt{3}) \approx \Phi(1) = 0.8413$

Edgeworth Expansion. $P(X_1 + X_2 + x_3 \leq 2) \approx \Phi(1) + 0 - 1.2(1-3)/(24 \times 3)\phi(1) = 0.8332$

The next exercise is from Problem Class 2

3 Handout 3: Asymptotics after transformations

Exercise 19. Consider random variables $X, X_1, X_2, ...$, where $\mu_n = \mathrm{E}(X - \mu)^n$, and $\mu = \mathrm{E}(X)$

1. Show that,

$$\sqrt{n}(\begin{bmatrix} \bar{X} \\ s_x^2 \end{bmatrix} - \begin{bmatrix} \mu \\ \sigma^2 \end{bmatrix}) \xrightarrow{D} \mathrm{N}(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma^2 & \mu_3 \\ \mu_3 & \mu_4 - \sigma^4 \end{bmatrix})$$

2. Show that the asymptotic distribution of the coefficient of variation $\mathrm{cv} = \frac{s_x}{\bar{X}}$, is

$$\sqrt{n}(\frac{s_x}{\bar{X}} - \frac{\sigma}{\mu}) \xrightarrow{D} \mathrm{N}(0, \frac{\mu_4 - \sigma^4}{4\mu^2\sigma^2} - \frac{\mu_3}{\mu^3} + \frac{\sigma^4}{\mu^4})$$

3. Show that the asymptotic distribution of the 3rd central moment $m_3 = \frac{1}{n}\sum_{i=1}^n (X_j - \bar{X})^3$ is

$$\sqrt{n}(m_3 - \mu_3) \xrightarrow{D} \mathrm{N}(0, \mu_6 - \mu_3^2 - 6\sigma^2\mu_4 + 9\sigma^6)$$

Solution.

1.

- I observe that

$$\begin{aligned}
\begin{bmatrix} \bar{X} \\ s_x^2 \end{bmatrix} - \begin{bmatrix} \mu \\ \sigma^2 \end{bmatrix} &= \begin{bmatrix} \bar{X} - \mu \\ \frac{1}{n}\sum_{i=1}^n (x_i - \mu)^2 - (\bar{X} - \mu)^2 \end{bmatrix} - \begin{bmatrix} 0 \\ \sigma^2 \end{bmatrix} \\
&= \begin{bmatrix} \frac{1}{n}\sum_{i=1}^n (X_i - \mu) \\ \frac{1}{n}\sum_{i=1}^n (X_i - \mu)^2 - (\frac{1}{n}\sum_{i=1}^n (X_i - \mu))^2 \end{bmatrix} - \begin{bmatrix} 0 \\ \sigma^2 \end{bmatrix} \\
&= \begin{bmatrix} m_1' \\ m_2' - (m_1')^2 \end{bmatrix} - \begin{bmatrix} 0 \\ \sigma^2 \end{bmatrix}
\end{aligned}$$

where $m'_1 = \frac{1}{n}\sum_{i=1}^{n}(X_i-\mu)$ and $m'_2 = \frac{1}{n}\sum_{i=1}^{n}(X_i-\mu)^2$.

- I will try to find the joint asymptotic distribution of $(m'_1, m'_2)^T$ by CLT, and then the asymptotic distribution of $(\bar{X}, s_x^2)^T$ by Delta method.
- Let

$$\xi_i = \begin{bmatrix} X_i-\mu \\ (X_i-\mu)^2 \end{bmatrix}$$

IID random vectors. It is

$$\mu_\xi = \mathrm{E}(\xi_i) = \begin{bmatrix} \mathrm{E}(X_i-\mu) \\ \mathrm{E}(X_i-\mu)^2 \end{bmatrix} = \begin{bmatrix} 0 \\ \sigma^2 \end{bmatrix}$$

and

$$\begin{aligned} \Sigma_\xi = \mathrm{Var}(\xi_i) &= \begin{bmatrix} \mathrm{Var}(X_i-\mu) & \mathrm{Cov}((X_i-\mu),(X_i-\mu)^2) \\ \mathrm{Cov}((X_i-\mu),(X_i-\mu)^2) & \mathrm{Var}(X_i-\mu)^2 \end{bmatrix} \\ &= \begin{bmatrix} \sigma^2 & \mu_3 \\ \mu_3 & \mu_4-\sigma^4 \end{bmatrix} \end{aligned}$$

since

$$\begin{aligned} \mathrm{Cov}((X_i-\mu),(X_i-\mu)^2) &= \mathrm{E}(((X_i-\mu)-\mathrm{E}(X_i-\mu))((X_i-\mu)^2-\mathrm{E}(X_i-\mu)^2)) \\ &= \mathrm{E}(((X_i-\mu)-\mu_1)((X_i-\mu)^2-\mu_2)) \\ &= \mathrm{E}(\,(X_i-\mu)^3-(X_i-\mu)\mu_2-\mu_1(X_i-\mu)^2+\mu_1\mu_2\,) \\ &= \mathrm{E}(X_i-\mu)^3 - \cancelto{0}{\mathrm{E}(X_i-\mu)}\mu_2 - \mu_1\cancelto{\mu_2}{\mathrm{E}(X_i-\mu)^2} + \mu_1\mu_2 \\ &= \mathrm{E}(X_i-\mu)^3 = \mu_3 \end{aligned}$$

It is

$$\bar{\xi} = \begin{bmatrix} m'_1 \\ m'_2 \end{bmatrix}$$

So by CLT, I have,

$$\sqrt{n}(\begin{bmatrix} m'_1 \\ m'_2 \end{bmatrix} - \begin{bmatrix} 0 \\ \sigma^2 \end{bmatrix}) \xrightarrow{D} \mathrm{N}(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma^2 & \mu_3 \\ \mu_3 & \mu_4-\sigma^4 \end{bmatrix})$$

- Now, I will calculate the asymptotic distribution of $(\bar{X}, s_x^2)^T$ by Delta method.
Let,

$$g(x,y) = \begin{bmatrix} x \\ y-x^2 \end{bmatrix}$$

with

$$\dot{g}(x,y) = \frac{\mathrm{d}g(x,y)}{\mathrm{d}(x,y)} = \begin{bmatrix} -1 & 0 \\ -2x & 1 \end{bmatrix}$$

So

$$g(\underbrace{m_1', m_2'}_{=\bar{\xi}}) = \begin{bmatrix} m_1' \\ m_2' - (m_1')^2 \end{bmatrix} = \begin{bmatrix} \bar{X} - \mu \\ s_x^2 \end{bmatrix}; \qquad g(\underbrace{0, \sigma^2}_{=\mu_\xi}) = \begin{bmatrix} 0 \\ \sigma^2 \end{bmatrix}$$

$$\dot{g}(\underbrace{0, \sigma^2}_{=\mu_\xi}) = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}; \qquad \Sigma_g = \dot{g}(\underbrace{0, \sigma^2}_{=\mu_\xi})\Sigma_\xi \dot{g}(\underbrace{0, \sigma^2}_{=\mu_\xi})^T = \begin{bmatrix} \sigma^2 & \mu_3 \\ \mu_3 & \mu_4 - \sigma^4 \end{bmatrix}$$

Then, according to Delta theorem

$$\sqrt{n}(g(\bar{\xi}) - g(\mu_\xi)) \xrightarrow{D} \mathrm{N}(0, \dot{g}(\mu_\xi)\Sigma_\xi \dot{g}(\mu_\xi)^T)$$
$$\sqrt{n}(\begin{bmatrix} \bar{X} \\ s_x^2 \end{bmatrix} - \begin{bmatrix} \mu \\ \sigma^2 \end{bmatrix}) \xrightarrow{D} \mathrm{N}(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma^2 & \mu_3 \\ \mu_3 & \mu_4 - \sigma^4 \end{bmatrix})$$

2. Since I have the asymptotic distribution of $(\bar{X}, s_x^2)^T$, I can use the Delta method.

- Let $h(a,b) = \sqrt{b}/a$, with $\dot{h}(a,b) = (-\frac{\sqrt{b}}{a^2}, \frac{1}{2a\sqrt{b}})$.
- Then

$$h(\bar{X}, s_x^2) = \frac{s_x}{\bar{X}}; \qquad h(\mu, \sigma^2) = \frac{\sigma}{\mu}$$
$$\dot{h}(\mu, \sigma^2) = \begin{bmatrix} -\frac{\sigma}{\mu^2}, & \frac{1}{2\mu\sigma} \end{bmatrix};$$

$$\Sigma_h = \dot{h}(\mu, \sigma^2)\Sigma_g \dot{h}(\mu, \sigma^2)^T$$
$$= \frac{\mu_4 - \sigma^4}{4\mu^2\sigma^2} - \frac{\mu_3}{\mu^3} + \frac{\sigma^4}{\mu^4}$$

- Then, according to Delta theorem

$$\sqrt{n}(h(\bar{X}, s_x^2) - h(\mu, \sigma^2)) \xrightarrow{D} \mathrm{N}(0, \dot{h}(\mu, \sigma^2)\Sigma_g \dot{h}(\mu, \sigma^2)^T)$$
$$\sqrt{n}(\frac{s_x}{\bar{X}} - \frac{\sigma}{\mu}) \xrightarrow{D} \mathrm{N}(0, \frac{\mu_4 - \sigma^4}{4\mu^2\sigma^2} - \frac{\mu_3}{\mu^3} + \frac{\sigma^4}{\mu^4})$$

3. I observe that

$$
\begin{aligned}
m_3 &= \frac{1}{n}\sum_{i=1}^{n}((\underbrace{X_i-\mu}_{=Z_i}) - (\underbrace{\bar{X}-\mu}_{=\bar{Z}}))^3 = \\
&= \frac{1}{n}\sum_{i=1}^{n} Z_i^3 - 3\frac{1}{n}\sum_{i=1}^{n} Z_i^2 \bar{Z} + 2\bar{Z} \\
&= m_3' - 3m_2' m_1' + 2(m_1')^2
\end{aligned}
$$

where $m_j' = \frac{1}{n}\sum_{i=1}^{n} Z_i^j = \frac{1}{n}\sum_{i=1}^{n}(X_i-\mu)^j$, since $Z_i = X_i - \mu$.

- I will use the CLT to calculate the joint asymptotic distribution of $(m_1', m_2', m_3')^T$ and then I will use Delta method to calculate that of m_3.

  I specify

$$
\psi_i = \begin{bmatrix} Z_i \\ Z_i^2 \\ Z_i^3 \end{bmatrix} = \begin{bmatrix} X_i-\mu \\ (X_i-\mu)^2 \\ (X_i-\mu)^3 \end{bmatrix};
$$

  which are IID, with

$$
\bar{\psi} = \frac{1}{n}\sum_{i=1}^{n}\psi_i = \begin{bmatrix} m_1' \\ m_2' \\ m_3' \end{bmatrix}
$$

$$
\mu_\psi = \mathrm{E}(\psi_i) = \begin{bmatrix} \mathrm{E}(X_i-\mu) \\ \mathrm{E}(X_i-\mu)^2 \\ \mathrm{E}(X_i-\mu)^3 \end{bmatrix} = \begin{bmatrix} \mu \\ \sigma^2 \\ \mu_3 \end{bmatrix};
$$

$$
\begin{aligned}
\Sigma_\psi = \mathrm{Var}(\psi_i) &= \begin{bmatrix} \mathrm{Var}(X_i-\mu) & \mathrm{Cov}((X_i-\mu),(X_i-\mu)^2) & \mathrm{Cov}((X_i-\mu),(X_i-\mu)^3) \\ \mathrm{Cov}((X_i-\mu),(X_i-\mu)^2) & \mathrm{Var}((X_i-\mu)^2) & \mathrm{Cov}((X_i-\mu)^2,(X_i-\mu)^3) \\ \mathrm{Cov}((X_i-\mu),(X_i-\mu)^3) & \mathrm{Cov}((X_i-\mu)^2,(X_i-\mu)^3) & \mathrm{Var}((X_i-\mu)^3) \end{bmatrix}; \\
&= \text{...calculations...} = \begin{bmatrix} \sigma^2 & \mu_3 & \mu_4 \\ \mu_3 & \mu_4-\sigma^2 & \mu_5-\sigma^2\mu_3 \\ \mu_4 & \mu_5-\sigma^2\mu_3 & \mu_6-\sigma^2\mu_3 \end{bmatrix}
\end{aligned}
$$

For instance, you can compute the covariance terms as

$$\begin{aligned}
\mathrm{Cov}((X_i-\mu)^2,(X_i-\mu)^3) &= \mathrm{E}(\,((X_i-\mu)^2-\mathrm{E}(X_i-\mu)^2)\,((X_i-\mu)^3-\mathrm{E}(X_i-\mu)^3)\,) \\
&= \mathrm{E}(\,((X_i-\mu)^2-\mu_2)\,((X_i-\mu)^3-\mu_3)\,) \\
&= \mathrm{E}(\,(X_i-\mu)^5-\mathrm{E}(X_i-\mu)^2\mu_3-\mu_2(X_i-\mu)^3+\mu_2\mu_3\,) \\
&= \mu_5-\mu_2\mu_3
\end{aligned}$$

So by CLT

$$\sqrt{n}(\underbrace{\begin{bmatrix} m_1' \\ m_2' \\ m_3' \end{bmatrix}}_{=\bar{\psi}} - \underbrace{\begin{bmatrix} \mu \\ \sigma^2 \\ \mu_3 \end{bmatrix}}_{=\mu_\psi}) \xrightarrow{D} \mathrm{N}(0\underbrace{\begin{bmatrix} \sigma^2 & \mu_3 & \mu_4 \\ \mu_3 & \mu_4-\sigma^2 & \mu_5-\sigma^2\mu_3 \\ \mu_4 & \mu_5-\sigma^2\mu_3 & \mu_6-\sigma^2\mu_3 \end{bmatrix}}_{=\Sigma_\psi})$$

- Now, in order to find the asymptotic distribution of $m_3 = m_3' - 3m_2'm_1' + 2(m_1')^2$, I will use Delta method

  Let

  $$q(a,b,c) = c - 3ab + 2a^3$$

  then

  $$\dot{q}(a,b,c) = \frac{\mathrm{d}}{\mathrm{d}(a,b,c)}q(a,b,c) = \begin{bmatrix} -3b+6a^2, & -3a, & 1 \end{bmatrix}$$

  So

  $$q(m_1',m_2',m_3') = m_3' - 3m_2'm_1' + 2(m_1')^2$$

  $$q(\mu_1',\mu_2',\mu_3') = \mu_3' - 3\mu_2'\mu_1' + 2(\mu_1')^2 = \mu_3$$

  and

  $$\dot{q}(\mu,\sigma^2,\mu_3) = \begin{bmatrix} -3\sigma^2, & \mu, & 1 \end{bmatrix}$$

  and

  $$\begin{aligned}
  \dot{q}(\mu_\psi)\Sigma_\psi\dot{q}(\mu_\psi)^T &= \begin{bmatrix} -3\sigma^2, & \mu, & 1 \end{bmatrix} \begin{bmatrix} \sigma^2 & \mu_3 & \mu_4 \\ \mu_3 & \mu_4-\sigma^2 & \mu_5-\sigma^2\mu_3 \\ \mu_4 & \mu_5-\sigma^2\mu_3 & \mu_6-\sigma^2\mu_3 \end{bmatrix} \begin{bmatrix} -3\sigma^2, & \mu, & 1 \end{bmatrix}^T \\
  &= \mu_6 - \mu_3^2 - 6\sigma^2\mu_4 + 9\sigma^6
  \end{aligned}$$

So the asymptotic distribution of m_3 is such that

$$\sqrt{n}(q(\bar{\psi}) - q(\mu_\psi)) \xrightarrow{D} \mathrm{N}(0, \dot{q}(\mu_\psi)\Sigma_\psi \dot{q}(\mu_\psi)^T)$$
$$\sqrt{n}(m_3 - \mu_3) \xrightarrow{D} \mathrm{N}(0, \mu_6 - \mu_3^2 - 6\sigma^2\mu_4 + 9\sigma^6)$$

Exercise 20. ($\star\star\star$) Consider an M-way contingency table and consider the quantities obs. cell counts, cell probabilities, cell proportions in their vectorised forms as

$$\underset{\sim}{n} = (n_1, ..., n_N)^T \; ; \qquad \underset{\sim}{\pi} = (\pi_1, ..., \pi_N)^T \; ; \qquad \underset{\sim}{p} = (p_1, ..., p_N)^T$$

where $n = \sum_{j=1}^N n_j$, and $p_j = n_j/n$.

1. Consider a constant matrix $C \in \mathbb{R}^{k\times N}$, and show that

$$\sqrt{n}(C\log(\underset{\sim}{p}) - C\log(\underset{\sim}{\pi})) \xrightarrow{D} \mathrm{N}(0, C\mathrm{diag}(\pi)^{-1}C^T - C11^TC^T) \tag{3}$$

2. Consider a 3×3 contingency table with probabilities $(\pi_{i,j})$. Find the joint asymptotic distribution of the vector of different log odd ratios

$$\log(\underset{\sim}{\theta}^C) = \begin{bmatrix} \log(\frac{\pi_{11}\pi_{22}}{\pi_{21}\pi_{12}}) \\ \log(\frac{\pi_{22}\pi_{33}}{\pi_{23}\pi_{32}}) \end{bmatrix}$$

Solution.

1. By using CLT (same as in Example in the CLT section in the Handouts), we get

$$\sqrt{n}(p - \pi) \xrightarrow{D} \mathrm{N}(0, \mathrm{diag}(\pi) - \pi\pi^T)$$

Recall from the example:
Denote the i-th observation by $\xi_i = (\xi_{i,1}, ..., \xi_{i,N})^T$, where

$$\xi_{i,j} = \begin{cases} 1 & \text{, if observation } i \text{ falls in cell } j \\ 0 & \text{, if observation } i \text{ does not fall in cell } j \end{cases}$$

Since its observation falls in only one cell, $\sum_j \xi_{i,j} = 1$ and $\xi_{i,j}\xi_{i,k} = 0$ when $j \neq k$.
Therefore p can be considered as the arithmetic mean of $\{\xi_{i,j}\}_{i=1}^n$ IID variables as

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

The moments of $\{\xi_i\}$, are equal to

$$\mathrm{E}(\xi_i) = \pi$$
$$\mathrm{Var}(\xi_i) = \Sigma$$

where

$$\begin{aligned} [\Sigma]_{j,j} =& \mathrm{var}(\xi_{i,j}) = \mathrm{E}(\xi_{i,j}^2) - (\mathrm{E}(\xi_{i,j}))^2 = \pi_j(1-\pi_j) \\ [\Sigma]_{j,k} =& \mathrm{cov}(\xi_{i,j}, \xi_{i,k}) = \mathrm{E}(\xi_{i,j}\xi_{i,k}) - \mathrm{E}(\xi_{i,j})\mathrm{E}(\xi_{i,k}) = -\pi_j\pi_k \end{aligned}$$

because

$$\begin{aligned} \mathrm{E}(\xi_{i,j}) =& \mathrm{P}(\xi_{i,j} = 1) = \pi_j \\ \mathrm{E}(\xi_{i,j}^2) =& \mathrm{P}(\xi_{i,j} = 1) = \pi_j \\ \mathrm{E}(\xi_{i,j}\xi_{i,k}) =& 0, \text{ if } j \neq k \end{aligned}$$

Hence

$$\Sigma = \mathrm{diag}(\pi) - \pi\pi^T$$

Therefore, according to the CLT

$$\sqrt{n}(p - \pi) \xrightarrow{D} \mathrm{N}(0, \mathrm{diag}(\pi) - \pi\pi^T) \tag{4}$$

Consider a function

$$g(x) = C\log(x) = C\begin{bmatrix} x_1 \\ \vdots \\ x_N \end{bmatrix}$$

Calculate

$$\dot{g}(x) = C\text{diag}(\pi)^{-1} = C \begin{bmatrix} 1/\pi_1 & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & 1/\pi_N \end{bmatrix}$$

and notice that it is continuous. So Delta method can be used.

Calculate

$$\begin{aligned} \dot{g}(\mu)\left(\text{diag}(\pi) - \pi\pi^T\right)\dot{g}(\mu)^T &= \dot{g}(\mu)\text{diag}(\pi)\,\dot{g}(\mu)^T - \dot{g}(\mu)\pi\pi^T\dot{g}(\mu)^T \\ &= C\cancelto{I}{\text{diag}(\pi)^{-1}\text{diag}(\pi)}\text{diag}(\pi)^{-1}C^T - C\cancelto{1}{\text{diag}(\pi)^{-1}\pi}\cancelto{1^T}{\pi^T\text{diag}(\pi)^{-1}}C^T \\ &= C\text{diag}(\pi)^{-1}C^T - C11^TC^T \end{aligned}$$

Hence from Delta method we get

$$\sqrt{n}(C\log(\underset{\sim}{p}) - C\log(\underset{\sim}{\pi})) \xrightarrow{D} \text{N}(0, C\text{diag}(\pi)^{-1}C^T - C11^TC^T)$$

(a) Let $\underset{\sim}{\pi} = \begin{bmatrix} \pi_{11} & \pi_{21} & \pi_{31} & \pi_{12} & \pi_{22} & \pi_{32} & \pi_{13} & \pi_{23} & \pi_{33} \end{bmatrix}^T$. In fact, the vector of different log odd ratios

$$\log(\underset{\sim}{\theta}^C) = \begin{bmatrix} \log(\frac{\pi_{11}\pi_{22}}{\pi_{21}\pi_{12}}) \\ \log(\frac{\pi_{22}\pi_{33}}{\pi_{23}\pi_{32}}) \end{bmatrix}$$

can be expressed as $\log(\underset{\sim}{\theta}^C) = C\log(\underset{\sim}{\pi})$ with

$$\begin{aligned} \log(\underset{\sim}{\theta}^C) &= \begin{bmatrix} \log(\pi_{11}) - \log(\pi_{12}) - \log(\pi_{21}) + \log(\pi_{22}) \\ \log(\pi_{22}) + \log(\pi_{33}) - \log(\pi_{23}) - \log(\pi_{32}) \end{bmatrix} \\ C &= \begin{bmatrix} 1 & -1 & 0 & -1 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & -1 & 0 & -1 & 1 \end{bmatrix} \\ \log(\underset{\sim}{\pi}) &= \begin{bmatrix} \log\pi_{11} & \log\pi_{21} & \log\pi_{31} & \log\pi_{12} & \log\pi_{22} & \log\pi_{32} & \log\pi_{13} & \log\pi_{23} & \log\pi_{33} \end{bmatrix}^T \end{aligned}$$

so

$$\sqrt{n}(\log(\hat{\underset{\sim}{\theta}}^C) - \log(\underset{\sim}{\theta}^C)) \xrightarrow{D} \text{N}(0, \Sigma)$$

where

$$\begin{aligned} \Sigma &= C\text{diag}(\pi)^{-1}C^T - C11^TC^T = ... = \\ &= \begin{bmatrix} \frac{1}{\pi_{11}} + \frac{1}{\pi_{12}} + \frac{1}{\pi_{21}} + \frac{1}{\pi_{22}} & \frac{1}{\pi_{22}} \\ \frac{1}{\pi_{22}} & \frac{1}{\pi_{22}} + \frac{1}{\pi_{32}} + \frac{1}{\pi_{23}} + \frac{1}{\pi_{33}} \end{bmatrix} \end{aligned}$$

Exercise 21. ($\star\star\star$) Consider a random sample $X, X_1, X_2, ...$ an IID sample with finite moments $E(X) = 0$, and $\mathrm{E}(X^4) < \infty$.

1. Show that if $m_1 = \frac{1}{n}\sum_{i=1}^n X_i$ and $m_2 = \frac{1}{n}\sum_{i=1}^n X_i^2$ then

$$\sqrt{n}(\begin{bmatrix} m_1 \\ m_2 \end{bmatrix} - \begin{bmatrix} 0 \\ \sigma^2 \end{bmatrix}) \xrightarrow{D} \mathrm{N}(0, \Sigma)$$

where $\Sigma = \begin{bmatrix} Var(X) & Cov(X^2, X) \\ Cov(X^2, X) & Var(X^2) \end{bmatrix}$

2. Find an $(1 - a)\%$ asymptotic confidence interval for S_n^2.

Solution.

1. Consider $\xi_i = \begin{bmatrix} X_i \\ X_i^2 \end{bmatrix}$, and $\bar{\xi} = \frac{1}{n}\sum_{i=1}^n \xi_i$ then $\bar{\xi} = (m_1, m_2)^T$. So from the CLT, we get

$$\sqrt{n}(\bar{\xi} - E\begin{bmatrix} X_i \\ X_i^2 \end{bmatrix}) \xrightarrow{D} \mathrm{N}(0, \begin{bmatrix} Var(X) & Cov(X^2, X) \\ Cov(X^2, X) & Var(X^2) \end{bmatrix})$$

which is what I want to show

2. I will try to compute the asymptotic distribution of S_n^2 with the Delta Method, and then I ll compute the asymptotic confidence interval.

- Because $S_n^2 = m_2 - (m_1)^2$, I consider $g((x, y)) = y - x^2$.
- Because $\frac{\mathrm{d}}{\mathrm{d}(x,y)}g((x, y)) = (-2x, 1)$ and continuous, then the assumptions of Delta method are satisfied, with

$$\begin{aligned} \dot{g}((0, \sigma^2))\Sigma\dot{g}((0, \sigma^2))^T =& Var(X^2) = E((X^2)^2) - (E(X^2))^2 \\ =& EX^4 - (E(X^2) - (\overset{0}{\cancel{EX}})^2)^2 \\ =& EX^4 - (Var(X))^2 = EX^4 - \sigma^4 \end{aligned}$$

- So

$$\sqrt{n}(S_n^2 - \sigma^2) \xrightarrow{D} \mathrm{N}(0, EX^4 - \sigma^4)$$

or

$$\sqrt{n}\frac{S_n^2 - \sigma^2}{\sqrt{EX^4 - \sigma^4}} \xrightarrow{D} \mathrm{N}(0, 1)$$

- By using slusky theorem it is $\frac{EX^4 - \sigma^4}{\overline{X^4} - S^4} \xrightarrow{D} 1$

- and again by using slusky theorem it is

$$\sqrt{n}\frac{S_n^2-\sigma^2}{\sqrt{\overline{X^4}-S^4}} \xrightarrow{D} \mathrm{N}(0,1)$$

- Hence

$$\{S_n^2 \pm z_{1-\frac{a}{2}}\sqrt{\frac{\overline{X^4}-S^4}{n}}\}$$

The next exercise is from Homework 3

Exercise 22. ($\star\star\star$) Consider an IID sample $X, X_1, X_2, ...$ with $EX = 0$, $EX^4 < \infty$. Consider that

$$\sqrt{n}\frac{S_n^2-\sigma^2}{\sqrt{EX^4-\sigma^4}} \xrightarrow{D} \mathrm{N}(0,1) \tag{5}$$

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

1. Find the asymptotic distribution of $\log(S_n^2)$.
2. Produce the $1-a$ asymptotic confidence interval for $\log(\sigma^2)$; by performing suitable calculations, so that the boundaries of the confidence interval do not depend on any unknown moments of the real distribution.

Solution.

Exercise 23. ($\star\star\star$) Let function $g : \mathbb{R} \to \mathbb{R}$ such that $\dot{g}(x)$ and $\ddot{g}(x)$ are continuous in a neighborhood of $\mu \in \mathbb{R}$, and $\dot{g}(\mu) = 0$. Prove the following statement:

- If $X_n \in \mathbb{R}$ is a sequence of random vectors such that $\sqrt{n}(X_n - \mu) \xrightarrow{D} \mathrm{N}(0, \sigma^2)$ then

$$n(g(X_n) - g(\mu)) \xrightarrow{D} \frac{\sigma^2 \ddot{g}(\mu)}{2}\chi_1^2$$

Hint-1. Use Taylor expansion of 2nd order.

Hint-2. The Taylor expansion of function $f : \mathbb{R} \to \mathbb{R}$ around point x_0 is:

$$f(x) = \sum_{k=0}^{n} \frac{1}{k!}(x-x_0)f^{(k)}(x_0) + R_n(x)$$

where $R_n(x) = \frac{1}{n!}\int_{x_0}^{x}(x-t)^n f^{(n)}(x_0) = o((x-x_0)^n)$ as $x \to x_0$, provided that the n-th derivative $f^{(n)}(x)$ exists in some interval containing x_0.

Solution.

We expand $g(X_n)$ by Taylor (2nd degree) around μ. So

$$\begin{aligned} g(x) =& g(\mu) + \cancelto{0}{\dot{g}(\mu)}(x-\mu) + \frac{\ddot{g}(\mu)}{2}(x-\mu)^2 + o((x-\mu)^2) \\ =& g(\mu) + \frac{\ddot{g}(\mu)}{2}(x-\mu)^2 + o((x-\mu)^2) \end{aligned}$$

So

$$n(g(X_n) - g(\mu)) \approx \frac{\sigma^2 \ddot{g}(\mu)}{2}(\sqrt{n}\frac{X_n-\mu}{\sigma})^2 + o\left((\sqrt{n}(X_n-\mu))^2\right)$$

For the first term, because $\sqrt{n}(X_n-\mu) \xrightarrow{D} \mathrm{N}(0,\sigma^2)$, it is $\sqrt{n}\frac{X_n-\mu}{\sigma} \xrightarrow{D} \mathrm{N}(0,1)$.

For the second term, because $\sqrt{n}(X_n-\mu) \xrightarrow{D} \mathrm{N}(0,\sigma^2)$ then $\sqrt{n}(X_n-\mu) = O_p(1)$, then $(\sqrt{n}(X_n-\mu))^2 = O_p(1)$. Hence $o\left((\sqrt{n}(X_n-\mu))^2\right) = o(O_p(1)) = o_p(1)$.

Hence by Slutsky rules:

$$n(g(X_n) - g(\mu)) \xrightarrow{D} \frac{\sigma^2 \ddot{g}(\mu)}{2}\chi^2_1$$

The next exercise is from Homework 3

Exercise 24. ($\star\star\star$) Consider random sample $X, X_1, X_2, ...$ IID from a Bernoulli distribution with probability of success p. Find the variance stabilization transformation for the estimator average $\hat{p}_n = \frac{1}{n}\sum_{i=1}^n X_i$.

Solution.

---

4 Handout 4: Estimation by the method of Maximum Likelihood

Exercise 25. Consider random sample $x_1, ..., x_n \overset{IID}{\sim} \mathrm{G}(a,b)$, $a>0$, $b>0$ with PDF

$$f(x|a,b) = \frac{1}{\Gamma(a)b^a}x^a e^{-x\frac{1}{b}}1(x>0)$$

1. Find the moment estimator $\tilde{\theta}$ of $\theta = (a,b)^T$ by using the first raw moment and the first central moment
2. Is the moment estimator $\tilde{\theta}$ consistent and asymptotically Normal?
3. Find the one step estimator by Fisher scoring algorithm.

Hint-1 Digamma function $\psi(x) = \frac{\mathrm{d}}{\mathrm{d}x} \log \Gamma(x)$

Hint-2 Trigamma function $\psi_1(x) = \frac{\mathrm{d}^2}{\mathrm{d}x^2} \log \Gamma(x)$

Hint-3 $\begin{bmatrix} a & b \\ c & d \end{bmatrix}^{-1} = \frac{1}{\det(A)} \begin{bmatrix} d & -b \\ -c & a \end{bmatrix} = \frac{1}{\det(A)} \begin{bmatrix} d & -b \\ -c & a \end{bmatrix}$

Solution.

1. The first raw moment is the expected value/mean, and the first central moment is the variance.

   The first raw moment is

$$\mathrm{E}(x) = \int_0^1 x \frac{1}{\Gamma(a) b^a} x^{a-1} e^{-x/b} \mathrm{d}x = \int_0^1 \frac{1}{\frac{1}{a}\Gamma(a+1)\frac{1}{b} b^{a+1}} x^{(a+1)-1} e^{-x/b} \mathrm{d}x = ab$$

   and the sample one

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

   The first central moment is

$$\mathrm{var}(x) = \mathrm{E}(x^2) - (\mathrm{E}(x))^2$$

   So

$$\mathrm{E}(x^2) = \int_0^1 x^2 \frac{1}{\Gamma(a) b^a} x^{a-1} e^{-x/b} \mathrm{d}x = \int_0^1 \frac{1}{\frac{1}{a(a+1)}\Gamma(a+2)\frac{1}{b^2} b^{a+2}} x^{(a+2)-1} e^{-x/b} \mathrm{d}x = a(a+1)b^2$$

   and hence

$$\mathrm{var}(x) = \mathrm{E}(x^2) - (\mathrm{E}(x))^2 = ab^2$$

   The sample first central moment is

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

   From the method of moments I get

$$\begin{cases} \mathrm{E}(x|\tilde{a}, \tilde{b}) = & \bar{x} \\ \mathrm{var}(x|\tilde{a}, \tilde{b}) = & s^2 \end{cases} \Longrightarrow \begin{cases} \tilde{a} = & \frac{\bar{x}^2}{s^2} \\ \tilde{b} = & \frac{\bar{x}^2}{s^2} \end{cases} \Longrightarrow \begin{cases} \tilde{a} = & \frac{(\mathrm{E}(x))^2}{\mathrm{var}(x)} = \frac{\bar{x}^2}{s^2} \\ \tilde{b} = & \frac{\mathrm{var}(x)}{\mathrm{E}(x)} = \frac{\bar{x}^2}{s^2} \end{cases}$$

   So the moment estimator is

$$\tilde{\theta} = \begin{bmatrix} \tilde{a} \\ \tilde{b} \end{bmatrix} = \begin{bmatrix} \frac{\bar{x}^2}{s^2} \\ \frac{s^2}{\bar{x}} \end{bmatrix} \tag{6}$$

2. It is consistent because $\tilde{\theta} \xrightarrow{as} \theta$. This is because of the following.

It is

$$\begin{cases} \mathrm{E}(x) = & ab \\ \mathrm{var}(x) = & ab^2 \end{cases} \implies \begin{cases} a = & \frac{(\mathrm{E}(x))^2}{\mathrm{var}(x)} \\ b = & \frac{\mathrm{var}(x)}{\mathrm{E}(x)} \end{cases} \implies \begin{cases} a = & \frac{(\mathrm{E}(x))^2}{\mathrm{var}(x)} \\ b = & \frac{\mathrm{var}(x)}{\mathrm{E}(x)} \end{cases}$$

From SLLN, $\bar{x} \xrightarrow{as} \mathrm{E}(x)$. From SLLN, $\overline{x^2} \xrightarrow{as} \mathrm{E}(x^2)$. From Slutsky Theorem, $s^2 = \overline{x^2} - (\overline{x})^2 \xrightarrow{as} \mathrm{E}(x^2) - \mathrm{E}(x)^2 = \mathrm{var}(x)$

So From Slutsky theorem

$$\tilde{\theta} = \begin{bmatrix} \frac{\bar{x}^2}{s^2} \\ \frac{s^2}{\bar{x}} \end{bmatrix} \xrightarrow{as} \begin{bmatrix} \frac{(\mathrm{E}(x))^2}{\mathrm{var}(x)} \\ \frac{\mathrm{var}(x)}{\mathrm{E}(x)} \end{bmatrix} = \theta$$

It is asymptotically Normal because of the following.

$\bar{x}$ and s^2 are asymptotically Normal by the CLT, as averages of IID quantities. Hence, by Delta method, (16) is asymptotically Normal.

3. Recall the the one-step estimators

$$\text{Newton alg.} \qquad \breve{\theta}_n = \tilde{\theta}_n - \ddot{\ell}_n(\tilde{\theta}_n)^{-1} \dot{\ell}_n(\tilde{\theta}_n) \tag{7}$$

$$\text{Fisher scoring alg.} \qquad \breve{\theta}_n = \tilde{\theta}_n + \frac{1}{n} \mathcal{I}(\tilde{\theta}_n)^{-1} \dot{\ell}_n(\tilde{\theta}_n) \tag{8}$$

For the Fisher algorithm, I need to find $\mathcal{I}(\theta)^{-1}$. It is

$$\begin{aligned}
\log f(x|\theta) &= -\log \Gamma(a) - a \log(b) - \frac{1}{b} x + (a-1)\log(x) \\
\frac{\mathrm{d}}{\mathrm{d}\theta} \log f(x|\theta) &= \begin{bmatrix} -\psi(a) - \log(b) + \log(x) \\ -\frac{a}{b} + \frac{1}{b^2} x \end{bmatrix} \\
\frac{\mathrm{d}^2}{\mathrm{d}\theta^2} \log f(x|\theta) &= \begin{bmatrix} -\psi_1(a) & -\frac{1}{b} \\ -\frac{1}{b} & -\frac{2x - ab}{b^3} \end{bmatrix} \\
\mathcal{I}(\theta) &= \begin{bmatrix} \psi_1(a) & \frac{1}{b} \\ \frac{1}{b} & \frac{a}{b^2} \end{bmatrix} \\
\mathcal{I}(\theta)^{-1} &= \frac{1}{a\psi_1(a) - 1} \begin{bmatrix} a & -b \\ -b & b^2 \psi_1(a) \end{bmatrix}
\end{aligned}$$

$$\begin{aligned}
\ell_n(\theta) &= -n \log \Gamma(a) - na \log(b) - \frac{1}{b} \sum_{i=1}^n x_i + (a-1) \sum_{i=1}^n \log(x_i) \\
\dot{\ell}_n(\theta) &= \begin{bmatrix} -n\psi(a) - n\log(b) + \sum_{i=1}^n \log(x_i) \\ -n\frac{a}{b} + n\frac{1}{b^2} \end{bmatrix}
\end{aligned}$$

The Fisher recursion is

$$
\begin{aligned}
\breve{\theta}_n &= \tilde{\theta}_n + \frac{1}{n}\mathcal{I}(\tilde{\theta}_n)^{-1}\dot{\ell}_n(\tilde{\theta}_n)\\
\breve{\theta}_n &= \begin{bmatrix}\tilde{a}\\ \tilde{b}\end{bmatrix} + \frac{1}{n}\frac{1}{\tilde{a}\psi_1(\tilde{a})-1}\begin{bmatrix}\tilde{a} & -\tilde{b}\\ -\tilde{b} & \tilde{b}^2\psi_1(\tilde{a})\end{bmatrix}\begin{bmatrix}-n\psi(\tilde{a}) - n\log(\tilde{b}) + \sum_{i=1}^n \log(x_i)\\ -n\frac{\tilde{a}}{\tilde{b}} + n\frac{1}{\tilde{b}^2}\end{bmatrix}\\
&= \begin{bmatrix}\tilde{a}\\ \tilde{b}\end{bmatrix} + \frac{1}{\tilde{a}\psi_1(\tilde{a})-1}\begin{bmatrix}\tilde{a} & -\tilde{b}\\ -\tilde{b} & \tilde{b}^2\psi_1(\tilde{a})\end{bmatrix}\begin{bmatrix}-\psi(\tilde{a}) - \log(\tilde{b}) + \frac{1}{n}\sum_{i=1}^n \log(x_i)\\ -\frac{\tilde{a}}{\tilde{b}} + \frac{1}{\tilde{b}^2}\end{bmatrix}\\
&= \begin{bmatrix}\tilde{a}\\ \tilde{b}\end{bmatrix} + \frac{1}{\tilde{a}\psi_1(\tilde{a})-1}\begin{bmatrix}-\tilde{a}\psi(\tilde{a}) - \frac{1}{\tilde{b}}(\bar{x}-\tilde{a}\tilde{b}) - \tilde{a}\log(\tilde{b}) + \frac{\tilde{a}}{n}\sum_{i=1}^n \log(x_i)\\ \tilde{b}\psi(\tilde{a}) - \psi_1(\tilde{a})(\bar{x}-\tilde{a}) + \tilde{b}\log(\tilde{b}) - \frac{\tilde{b}}{n}\sum_{i=1}^n \log(x_i)\end{bmatrix}
\end{aligned}
$$

So bu substituting

$$
\breve{\theta}_n = \begin{bmatrix}\frac{\bar{x}^2}{s^2}\\ \frac{s^2}{\bar{x}}\end{bmatrix} + \frac{1}{\frac{\bar{x}^2}{s^2}\psi_1(\frac{\bar{x}^2}{s^2})-1}\begin{bmatrix}-\frac{\bar{x}^2}{s^2}\psi(\frac{\bar{x}^2}{s^2}) - \frac{\bar{x}^2}{s^2}\log(\frac{s^2}{\bar{x}}) + \frac{1}{n}\frac{\bar{x}^2}{s^2}\sum_{i=1}^n \log(x_i)\\ \frac{s^2}{\bar{x}}\psi(\frac{\bar{x}^2}{s^2}) - \psi_1(\frac{\bar{x}^2}{s^2})(\bar{x}-\frac{\bar{x}^2}{s^2}) + \frac{s^2}{\bar{x}}\log(\frac{s^2}{\bar{x}}) - \frac{\tilde{b}}{n}\sum_{i=1}^n \log(x_i)\end{bmatrix}
$$

Additionally for the Newton recursion I need

$$
\begin{aligned}
\ddot{\ell}_n(\theta) &= -n\begin{bmatrix}\psi_1(a) & \frac{1}{b}\\ \frac{1}{b} & \frac{2\bar{x}-ab}{b^3}\end{bmatrix}\\
(\ddot{\ell}_n(\theta))^{-1} &= -\frac{1}{n}\frac{1}{\psi_1(a)\frac{2\bar{x}-ab}{b}-1}\begin{bmatrix}\frac{2\bar{x}-ab}{b} & -b\\ -b & b^2\psi_1(a)\end{bmatrix}
\end{aligned}
$$

The Newton recursion is

$$
\begin{aligned}
\breve{\theta}_n &= \tilde{\theta}_n - (\ddot{\ell}_n(\theta))^{-1}\dot{\ell}_n(\tilde{\theta}_n)\\
\breve{\theta}_n &= \begin{bmatrix}\tilde{a}\\ \tilde{b}\end{bmatrix} + \frac{1}{n}\frac{1}{\psi_1(\tilde{a})\frac{2\bar{x}-\tilde{a}\tilde{b}}{\tilde{b}}-1}\begin{bmatrix}2\bar{x}-\tilde{a}\tilde{b} & \tilde{b}\\ \tilde{b} & \tilde{b}^2\psi_1(\tilde{a})\end{bmatrix}\begin{bmatrix}-n\psi(\tilde{a}) - n\log(\tilde{b}) + \sum_{i=1}^n \log(x_i)\\ -n\frac{\tilde{a}}{\tilde{b}} + n\frac{1}{\tilde{b}^2}\end{bmatrix}\\
&= \begin{bmatrix}\tilde{a}\\ \tilde{b}\end{bmatrix} + \frac{1}{\psi_1(\tilde{a})\frac{2\bar{x}-\tilde{a}\tilde{b}}{\tilde{b}}-1}\begin{bmatrix}2\bar{x}-\tilde{a}\tilde{b} & \tilde{b}\\ \tilde{b} & \tilde{b}^2\psi_1(\tilde{b})\end{bmatrix}\begin{bmatrix}-\psi(\tilde{a}) - \log(\tilde{b}) + \frac{1}{n}\sum_{i=1}^n \log(x_i)\\ -\frac{\tilde{a}}{\tilde{b}} + \frac{1}{\tilde{b}^2}\end{bmatrix}\\
&= \text{...calculations}
\end{aligned}
$$

Exercise 26. Prove the Information inequality theorem:

Let $x \in \mathbb{R}^d$ random vector following distribution $\mathrm{d}f_\theta(\cdot)$ labeled by an parameter $\theta \in \Theta \subset \mathbb{R}^r$ and admitting PDF $f(\cdot|\theta)$. Consider an estimator $\hat{\theta}_n := \hat{\theta}_n(x) \in \Theta \subset \mathbb{R}^r$ such that $g(\theta) = \mathrm{E}_{f_\theta}(\hat{\theta}_n)$ exists on Θ. Assume that, $\frac{\mathrm{d}}{\mathrm{d}\theta}f(x|\theta)$ exists ; $\frac{\mathrm{d}}{\mathrm{d}\theta}$ can pass under the integral sign in $\int f(x|\theta)\mathrm{d}x$ and

$\int \hat{\theta}_n(x) f(x|\theta)\mathrm{d}x$. Then

$$\mathrm{var}_{f_\theta}(\hat{\theta}_n(x)) \geq \frac{1}{n}\dot{g}(\theta)\mathcal{I}(\theta)^{-1}\dot{g}(\theta)^T \tag{9}$$

where $\mathcal{I}(\theta)$ is the Fisher's information matrix.

- The quantity $\frac{1}{n}\dot{g}(\theta)\mathcal{I}(\theta)^{-1}\dot{g}(\theta)^T$ is called Cramer-Rao lower bound (CRLB).

Hint-1: Use $0 \leq \mathrm{var}_{f_\theta}(\hat{\theta}_n - \dot{g}(\theta)\mathcal{I}(\theta)^{-1}\Psi(x,\theta)) = ...$

Hint-2: Use $\mathrm{var}_{f_\theta}(A + B) = \mathrm{var}_{f_\theta}(A) + \mathrm{var}_{f_\theta}(B) + 2\mathrm{cov}_{f_\theta}(A, B)$

Solution. Let $\Psi(x,\theta) = (\frac{\mathrm{d}}{\mathrm{d}\theta}\log f(x|\theta))^T$.
It is

$$\begin{aligned}
\mathrm{E}_{f_\theta}\Psi(X,\theta) =& 0 \quad \text{(you have proved it before)}\\
\dot{g}_n(\theta) =& \frac{\mathrm{d}}{\mathrm{d}\theta}\int \hat{\theta}_n(x) f(x|\theta)\mathrm{d}x = \int \hat{\theta}_n(x)\frac{\frac{\mathrm{d}}{\mathrm{d}\theta}f(x|\theta)}{f(x|\theta)}f(x|\theta)\mathrm{d}x\\
=& \int \hat{\theta}_n(x)\frac{\mathrm{d}}{\mathrm{d}\theta}\log f(x|\theta) f(x|\theta)\mathrm{d}x = \mathrm{E}_{f_\theta}(\hat{\theta}_n(x)(\Psi(x,\theta) - \cancelto{= 0}{\mathrm{E}_\theta\Psi(X,\theta)}))\\
=& \mathrm{cov}_{f_\theta}(\hat{\theta}_n(x), \Psi(x,\theta))
\end{aligned} \tag{10}$$

So

$$\begin{aligned}
0 \leq& \mathrm{var}_{f_\theta}(\hat{\theta}_n - \dot{g}(\theta)\mathcal{I}(\theta)^{-1}\Psi(x,\theta))\\
=& \mathrm{var}_{f_\theta}(\hat{\theta}_n) - 2\mathrm{cov}_{f_\theta}(\hat{\theta}_n, \dot{g}(\theta)\mathcal{I}(\theta)^{-1}\Psi(x,\theta)) + \mathrm{var}_{f_\theta}(\dot{g}(\theta)\mathcal{I}(\theta)^{-1}\Psi(x,\theta))\\
=& \mathrm{var}_{f_\theta}(\hat{\theta}_n) - 2\frac{1}{n}\dot{g}(\theta)\mathcal{I}(\theta)^{-1}\dot{g}(\theta)^T + \frac{1}{n}\dot{g}(\theta)\mathcal{I}(\theta)^{-1}\mathcal{I}(\theta)\mathcal{I}(\theta)^{-1}\dot{g}(\theta)^T\\
=& \mathrm{var}_{f_\theta}(\hat{\theta}_n) - \frac{1}{n}\dot{g}(\theta)\mathcal{I}(\theta)^{-1}\dot{g}(\theta)^T
\end{aligned}$$

and the proof is done

Exercise 27. Prove the following statement: Given that the assumptions of Cramer Theorem (for the Normality of MLE) are satisfied, and that $\mathcal{I}(\theta)$ and $\mathcal{J}_n(\theta)$ are continuous on θ, then

$$\sqrt{n}\mathcal{I}(\theta_0)^{1/2}(\hat{\theta}_n - \theta_0) \xrightarrow{D} \mathrm{N}(0, I) \tag{11}$$

$$\sqrt{n}\mathcal{I}(\hat{\theta}_n)^{1/2}(\hat{\theta}_n - \theta_0) \xrightarrow{D} \mathrm{N}(0, I) \tag{12}$$

$$\mathcal{J}_n(\hat{\theta}_n)^{1/2}(\hat{\theta}_n - \theta_0) \xrightarrow{D} \mathrm{N}(0, I) \tag{13}$$

where $\hat{\theta}_n$ denotes the MLE, θ_0 denotes the true value of θ, and $A^{1/2}$ denotes the lower triangular matrix of the Cholesky decomposition of A; i.e., $A = A^{1/2}(A^{1/2})^T$.

Solution.

- Eq 11 results from Cramer Theorem, and the properties of covariance matrix.
  - Eq. 12 results by using Cramer Theorem and Slutsly theorems. Precisely, because $\hat{\theta}_n \xrightarrow{a.s.} \theta_0$, Slutsky implies $\mathcal{I}(\hat{\theta}_n) \xrightarrow{a.s.} \mathcal{I}(\theta_0)$ which implies $\mathcal{I}(\hat{\theta}_n)^{1/2}\mathcal{I}(\theta_0)^{-1/2} \xrightarrow{a.s.} I$. Therefore, by Slutsky

$$\underbrace{\mathcal{I}(\hat{\theta}_n)^{1/2}\mathcal{I}(\theta_0)^{-1/2}\sqrt{n}\mathcal{I}(\theta_0)^{1/2}(\hat{\theta}_n - \theta_0)}_{=\sqrt{n}\mathcal{I}(\hat{\theta}_n)^{1/2}(\hat{\theta}_n-\theta_0)} \xrightarrow{D} \underbrace{I \times \mathrm{N}(0, I)}_{=\mathrm{N}(0,I)}$$

  - Eq. 13 results by using the USLLN and Slutsly theorems. So I just need to show that

$$\frac{1}{n}\mathcal{J}_n(\hat{\theta}_n) \xrightarrow{a.s.} \mathcal{I}(\theta_0)$$

    Set $U(x,\theta) = -\frac{\mathrm{d}^2}{\mathrm{d}\theta^2}\log(f(x|\theta))$, and $\mathcal{I}(\theta) = \mathrm{E}(U(x,\theta))$. Then

$$|\frac{1}{n}\sum_{i=1}^{n}\underbrace{\left(-\frac{\mathrm{d}^2}{\mathrm{d}\theta^2}\log(f(x_i|\hat{\theta}_n))\right)}_{U(x_i,\hat{\theta}_n)} - \mathcal{I}(\theta_0)| \le |\frac{1}{n}\sum_{i=1}^{n}U(x_i,\hat{\theta}_n) - \mathcal{I}(\hat{\theta}_n)| + |\mathcal{I}(\hat{\theta}_n) - \mathcal{I}(\theta_0)| \tag{14}$$

$$\le \sup_{|\hat{\theta}_n-\theta_0|\le\delta} |\frac{1}{n}\sum_{i=1}^{n}U(x_i,\theta) - \mathcal{I}(\theta)| + |\mathcal{I}(\hat{\theta}_n) - \mathcal{I}(\theta_0)| \tag{15}$$

    The first term converges to zero because the assumptions of the USLLN are satisfied. The second term converges to zero because $\hat{\theta}_n \xrightarrow{a.s.} \theta_0$ and hence $\mathcal{I}(\hat{\theta}_n) \xrightarrow{a.s.} \mathcal{I}(\theta_0)$ by using Slutsky theorem.
    So by Slutsy $(\frac{1}{n}\mathcal{J}_n(\hat{\theta}_n))^{1/2}\mathcal{I}(\theta_0)^{-1/2} \xrightarrow{a.s.} I$, and by Slutsky again

$$\underbrace{(\frac{1}{n}\mathcal{J}_n(\hat{\theta}_n))^{1/2}\mathcal{I}(\theta_0)^{-1/2}I(\theta_0)^{1/2}(\hat{\theta}_n - \theta_0)}_{=\mathcal{J}_n(\hat{\theta}_n)^{1/2}(\hat{\theta}_n-\theta_0)} \xrightarrow{D} \underbrace{I \times \mathrm{N}(0, I)}_{=\mathrm{N}(0,I)}$$

Exercise 28. ($\star\star$) (Shannon-Kolmogorov Information Inequality) Prove the Shannon-Kolmogorov Information Inequality. Let f_0 and f_1 (like $f_0(\cdot) = f(\cdot|\theta_0)$ and $f_1(\cdot) = f(\cdot|\theta_1)$) be PDFs of corresponding distributions with respect to x. Then

$$\mathrm{KL}(f_0,f_1)=\mathrm{E}_0\log\frac{f_0(X)}{f_1(X)}=\int\log\frac{f_0(X)}{f_1(X)}f_0(X)\mathrm{d}X\geq 0$$

with the equality iff $f_0(x)=f_1(x)$ a.s.

Solution. Function $\log(\cdot)$ is convex, then Jensen's inequality[2] implies

$$-K(f_0,f_1)=\mathrm{E}_0\log\frac{f_1(X)}{f_0(X)} :: \begin{cases} <\log\mathrm{E}_0\frac{f_1(X)}{f_0(X)} & ,\text{if } f_1(x)\neq f_0(x)\\ =\log\mathrm{E}_0\frac{f_1(X)}{f_0(X)} & ,\text{if } f_1(x)=f_0(x)\end{cases}$$

But

$$\mathrm{E}_0\frac{f_1(x)}{f_0(x)}=\int\frac{f_1(x)}{f_0(x)}f_0(x)\mathrm{d}x=\int_{S_0}f_1(x)\mathrm{d}x\leq 1$$

at $S_0=\{x:f_0(x)>0\}$. Hence,

$$\mathrm{KL}(f_0,f_1):\begin{cases}>0 & ,\text{if } f_1(x)\neq f_0(x)\\ =0 & ,\text{if } f_1(x)=f_0(x)\end{cases}$$

---

5 Handout 5: Improving sub-efficient estimators

Exercise 29. Consider random sample $x_1,...,x_n\overset{IID}{\sim}\mathrm{G}(a,b)$, $a>0$, $b>0$ with PDF

$$f(x|a,b)=\frac{1}{\Gamma(a)b^a}x^ae^{-x\frac{1}{b}}1(x>0)$$

1. Find the moment estimator $\tilde{\theta}$ of $\theta=(a,b)^T$ by using the first raw moment and the first central moment

2. Is the moment estimator $\tilde{\theta}$ consistent and asymptotically Normal?

3. Find the one step estimator by Fisher scoring algorithm.

Hint-1 Digamma function $\psi(x)=\frac{\mathrm{d}}{\mathrm{d}x}\log\Gamma(x)$

[2]Jensen's inequality: Consider a function φ, it is

- $\mathrm{E}(\varphi(x))\leq\varphi(\mathrm{E}(x))$ if $\varphi(\cdot)$ is convex
- $\mathrm{E}(\varphi(x))\geq\varphi(\mathrm{E}(x))$ if $\varphi(\cdot)$ is concave
- The equality holds if x is constant a.s.

Hint-2 Trigamma function $\psi_1(x) = \frac{\mathrm{d}^2}{\mathrm{d}x^2} \log \Gamma(x)$

Hint-3 $\begin{bmatrix} a & b \\ c & d \end{bmatrix}^{-1} = \frac{1}{\det(A)} \begin{bmatrix} d & -b \\ -c & a \end{bmatrix} = \frac{1}{\det(A)} \begin{bmatrix} d & -b \\ -c & a \end{bmatrix}$

Solution.

1. The first raw moment is the expected value/mean, and the first central moment is the variance.

   The first raw moment is

$$\mathrm{E}(x) = \int_0^1 x \frac{1}{\Gamma(a) b^a} x^{a-1} e^{-x/b} \mathrm{d}x = \int_0^1 \frac{1}{\frac{1}{a}\Gamma(a+1)\frac{1}{b} b^{a+1}} x^{(a+1)-1} e^{-x/b} \mathrm{d}x = ab$$

   and the sample one

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

   The first central moment is

$$\mathrm{var}(x) = \mathrm{E}(x^2) - (\mathrm{E}(x))^2$$

   So

$$\mathrm{E}(x^2) = \int_0^1 x^2 \frac{1}{\Gamma(a) b^a} x^{a-1} e^{-x/b} \mathrm{d}x = \int_0^1 \frac{1}{\frac{1}{a(a+1)}\Gamma(a+2)\frac{1}{b^2} b^{a+2}} x^{(a+2)-1} e^{-x/b} \mathrm{d}x = a(a+1)b^2$$

   and hence

$$\mathrm{var}(x) = \mathrm{E}(x^2) - (\mathrm{E}(x))^2 = ab^2$$

   The sample first central moment is

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

   From the method of moments I get

$$\begin{cases} \mathrm{E}(x|\tilde{a}, \tilde{b}) = & \bar{x} \\ \mathrm{var}(x|\tilde{a}, \tilde{b}) = & s^2 \end{cases} \implies \begin{cases} \tilde{a} = & \frac{\bar{x}^2}{s^2} \\ \tilde{b} = & \frac{\bar{x}^2}{s^2} \end{cases} \implies \begin{cases} \tilde{a} = & \frac{(\mathrm{E}(x))^2}{\mathrm{var}(x)} = \frac{\bar{x}^2}{s^2} \\ \tilde{b} = & \frac{\mathrm{var}(x)}{\mathrm{E}(x)} = \frac{\bar{x}^2}{s^2} \end{cases}$$

   So the moment estimator is

$$\tilde{\theta} = \begin{bmatrix} \tilde{a} \\ \tilde{b} \end{bmatrix} = \begin{bmatrix} \frac{\bar{x}^2}{s^2} \\ \frac{s^2}{\bar{x}} \end{bmatrix} \tag{16}$$

2. It is consistent because $\tilde{\theta} \xrightarrow{as} \theta$. This is because of the following.

It is

$$\begin{cases} \mathrm{E}(x) = & ab \\ \mathrm{var}(x) = & ab^2 \end{cases} \Longrightarrow \qquad \begin{cases} a = & \frac{(\mathrm{E}(x))^2}{\mathrm{var}(x)} \\ b = & \frac{\mathrm{var}(x)}{\mathrm{E}(x)} \end{cases} \Longrightarrow \qquad \begin{cases} a = & \frac{(\mathrm{E}(x))^2}{\mathrm{var}(x)} \\ b = & \frac{\mathrm{var}(x)}{\mathrm{E}(x)} \end{cases}$$

From SLLN, $\bar{x} \xrightarrow{as} \mathrm{E}(x)$. From SLLN, $\overline{x^2} \xrightarrow{as} \mathrm{E}(x^2)$. From Slutsky Theorem, $s^2 = \overline{x^2} - (\overline{x})^2 \xrightarrow{as} \mathrm{E}(x^2) - \mathrm{E}(x)^2 = \mathrm{var}(x)$

So From Slutsky theorem

$$\tilde{\theta} = \begin{bmatrix} \frac{\bar{x}^2}{s^2} \\ \frac{s^2}{\bar{x}} \end{bmatrix} \xrightarrow{as} \begin{bmatrix} \frac{(\mathrm{E}(x))^2}{\mathrm{var}(x)} \\ \frac{\mathrm{var}(x)}{\mathrm{E}(x)} \end{bmatrix} = \theta$$

It is asymptotically Normal because of the following.

$\bar{x}$ and s^2 are asymptotically Normal by the CLT, as averages of IID quantities. Hence, by Delta method, (16) is asymptotically Normal.

3. Recall the the one-step estimators

$$\text{Newton alg.} \qquad \breve{\theta}_n = \tilde{\theta}_n - \ddot{\ell}_n(\tilde{\theta}_n)^{-1}\dot{\ell}_n(\tilde{\theta}_n) \tag{17}$$

$$\text{Fisher scoring alg.} \qquad \breve{\theta}_n = \tilde{\theta}_n + \frac{1}{n}\mathcal{I}(\tilde{\theta}_n)^{-1}\dot{\ell}_n(\tilde{\theta}_n) \tag{18}$$

For the Fisher algorithm, I need to find $\mathcal{I}(\theta)^{-1}$. It is

$$\begin{aligned}
\log f(x|\theta) &= -\log\Gamma(a) - a\log(b) - \frac{1}{b}x + (a-1)\log(x) \\
\frac{\mathrm{d}}{\mathrm{d}\theta}\log f(x|\theta) &= \begin{bmatrix} -\psi(a) - \log(b) + \log(x) \\ -\frac{a}{b} + \frac{1}{b^2}x \end{bmatrix} \\
\frac{\mathrm{d}^2}{\mathrm{d}\theta^2}\log f(x|\theta) &= \begin{bmatrix} -\psi_1(a) & -\frac{1}{b} \\ -\frac{1}{b} & -\frac{2x-ab}{b^3} \end{bmatrix} \\
\mathcal{I}(\theta) &= \begin{bmatrix} \psi_1(a) & \frac{1}{b} \\ \frac{1}{b} & \frac{a}{b^2} \end{bmatrix} \\
\mathcal{I}(\theta)^{-1} &= \frac{1}{a\psi_1(a) - 1}\begin{bmatrix} a & -b \\ -b & b^2\psi_1(a) \end{bmatrix}
\end{aligned}$$

$$\begin{aligned}
\ell_n(\theta) &= -n\log\Gamma(a) - na\log(b) - \frac{1}{b}\sum_{i=1}^n x_i + (a-1)\sum_{i=1}^n \log(x_i) \\
\dot{\ell}_n(\theta) &= \begin{bmatrix} -n\psi(a) - n\log(b) + \sum_{i=1}^n \log(x_i) \\ -n\frac{a}{b} + n\frac{1}{b^2} \end{bmatrix}
\end{aligned}$$

The Fisher recursion is

$$\breve{\theta}_n = \tilde{\theta}_n + \frac{1}{n}\mathcal{I}(\tilde{\theta}_n)^{-1}\dot{\ell}_n(\tilde{\theta}_n)$$

$$\breve{\theta}_n = \begin{bmatrix}\tilde{a}\\ \tilde{b}\end{bmatrix} + \frac{1}{n}\frac{1}{\tilde{a}\psi_1(\tilde{a})-1}\begin{bmatrix}\tilde{a} & -\tilde{b}\\ -\tilde{b} & \tilde{b}^2\psi_1(\tilde{a})\end{bmatrix}\begin{bmatrix}-n\psi(\tilde{a}) - n\log(\tilde{b}) + \sum_{i=1}^n \log(x_i)\\ -n\frac{\tilde{a}}{\tilde{b}} + n\frac{1}{\tilde{b}^2}\end{bmatrix}$$

$$= \begin{bmatrix}\tilde{a}\\ \tilde{b}\end{bmatrix} + \frac{1}{\tilde{a}\psi_1(\tilde{a})-1}\begin{bmatrix}\tilde{a} & -\tilde{b}\\ -\tilde{b} & \tilde{b}^2\psi_1(\tilde{a})\end{bmatrix}\begin{bmatrix}-\psi(\tilde{a}) - \log(\tilde{b}) + \frac{1}{n}\sum_{i=1}^n \log(x_i)\\ -\frac{\tilde{a}}{\tilde{b}} + \frac{1}{\tilde{b}^2}\end{bmatrix}$$

$$= \begin{bmatrix}\tilde{a}\\ \tilde{b}\end{bmatrix} + \frac{1}{\tilde{a}\psi_1(\tilde{a})-1}\begin{bmatrix}-\tilde{a}\psi(\tilde{a}) - \frac{1}{\tilde{b}}(\bar{x}-\tilde{a}\tilde{b}) - \tilde{a}\log(\tilde{b}) + \frac{\tilde{a}}{n}\sum_{i=1}^n \log(x_i)\\ \tilde{b}\psi(\tilde{a}) - \psi_1(\tilde{a})(\bar{x}-\tilde{a}) + \tilde{b}\log(\tilde{b}) - \frac{\tilde{b}}{n}\sum_{i=1}^n \log(x_i)\end{bmatrix}$$

So bu substituting

$$\breve{\theta}_n = \begin{bmatrix}\frac{\bar{x}^2}{s^2}\\ \frac{s^2}{\bar{x}}\end{bmatrix} + \frac{1}{\frac{\bar{x}^2}{s^2}\psi_1(\frac{\bar{x}^2}{s^2})-1}\begin{bmatrix}-\frac{\bar{x}^2}{s^2}\psi(\frac{\bar{x}^2}{s^2}) - \frac{\bar{x}^2}{s^2}\log(\frac{s^2}{\bar{x}}) + \frac{1}{n}\frac{\bar{x}^2}{s^2}\sum_{i=1}^n \log(x_i)\\ \frac{s^2}{\bar{x}}\psi(\frac{\bar{x}^2}{s^2}) - \psi_1(\frac{\bar{x}^2}{s^2})(\bar{x}-\frac{\bar{x}^2}{s^2}) + \frac{s^2}{\bar{x}}\log(\frac{s^2}{\bar{x}}) - \frac{\tilde{b}}{n}\sum_{i=1}^n \log(x_i)\end{bmatrix}$$

Additionally for the Newton recursion I need

$$\ddot{\ell}_n(\theta) = -n\begin{bmatrix}\psi_1(a) & \frac{1}{b}\\ \frac{1}{b} & \frac{2\bar{x}-ab}{b^3}\end{bmatrix}$$

$$(\ddot{\ell}_n(\theta))^{-1} = -\frac{1}{n}\frac{1}{\psi_1(a)\frac{2\bar{x}-ab}{b}-1}\begin{bmatrix}\frac{2\bar{x}-ab}{b} & -b\\ -b & b^2\psi_1(a)\end{bmatrix}$$

The Newton recursion is

$$\breve{\theta}_n = \tilde{\theta}_n - (\ddot{\ell}_n(\theta))^{-1}\dot{\ell}_n(\tilde{\theta}_n)$$

$$\breve{\theta}_n = \begin{bmatrix}\tilde{a}\\ \tilde{b}\end{bmatrix} + \frac{1}{n}\frac{1}{\psi_1(\tilde{a})\frac{2\bar{x}-\tilde{a}\tilde{b}}{\tilde{b}}-1}\begin{bmatrix}2\bar{x}-\tilde{a}\tilde{b} & \tilde{b}\\ \tilde{b} & \tilde{b}^2\psi_1(\tilde{a})\end{bmatrix}\begin{bmatrix}-n\psi(\tilde{a}) - n\log(\tilde{b}) + \sum_{i=1}^n \log(x_i)\\ -n\frac{\tilde{a}}{\tilde{b}} + n\frac{1}{\tilde{b}^2}\end{bmatrix}$$

$$= \begin{bmatrix}\tilde{a}\\ \tilde{b}\end{bmatrix} + \frac{1}{\psi_1(\tilde{a})\frac{2\bar{x}-\tilde{a}\tilde{b}}{\tilde{b}}-1}\begin{bmatrix}2\bar{x}-\tilde{a}\tilde{b} & \tilde{b}\\ \tilde{b} & \tilde{b}^2\psi_1(\tilde{b})\end{bmatrix}\begin{bmatrix}-\psi(\tilde{a}) - \log(\tilde{b}) + \frac{1}{n}\sum_{i=1}^n \log(x_i)\\ -\frac{\tilde{a}}{\tilde{b}} + \frac{1}{\tilde{b}^2}\end{bmatrix}$$

$$= \text{...calculations}$$

The next exercise is from Homework 4

Exercise 30. Let $x_1, ..., x_n \overset{IID}{\sim} f_\theta$ with unknown parameter $\theta \in (0, \infty)$ and PDF

$$f(x|\theta) = \begin{cases}\theta\exp(-x) + (1-\theta)x\exp(-x) & , x \geq 0\\ 0 & , x < 0\end{cases}$$

1. Calculate the moment estimator $\tilde{\theta}_n$ of θ, (I give you a bit of freedom here)
2. Calculate the asymptotic distribution of the $\tilde{\theta}_n$
3. Find the 1-step estimator $\breve{\theta}_n$ of θ such that it can be asymptotically efficient.

   Hint: Recall that $\Gamma(a) = \int_0^\infty x^{a-1} e^{-x} \mathrm{d}x$, and $\Gamma(a) = (a-1)\Gamma(a-1)$

   Solution.

---

6 Handout 6: Confidence intervals and hypothesis tests

Exercise 31. (Log likelihood ratio statistic)

1. Let $x_1, x_2, ..., x_n$ be IID random variables generated from a distribution f_θ labeled by a d-dimensional parameter $\theta \in \Theta \subset \mathbb{R}^d$, and admitting PDF $f(\cdot|\theta)$. Assume the conditions from the Cramér Theorem are satisfied, and that θ_0 is the true value. Prove that

$$W_{\mathrm{LR}}(\theta_0) = -2(\ell_n(\theta_0) - \ell_n(\hat{\theta}_n)) \xrightarrow{D} \chi^2_d$$

   it is where $\hat{\theta}_n$ is the MLE of θ.

   Hint-1 Expand $\ell_n(\theta_0)$ around $\hat{\theta}_n$ by Taylor expansion

   Hint-2 Prove that $W_{\mathrm{LR}}(\theta_0) \xrightarrow{a.s} n(\theta_0 - \hat{\theta}_n)^T \mathcal{I}(\theta_0)(\theta_0 - \hat{\theta}_n)$

   Hint-3 Prove that $W_{\mathrm{LR}}(\theta_0) \xrightarrow{D} \chi^2_d$

2. Calculate the asymptotic distribution of the statistic

$$\tilde{W}_{\mathrm{LR}}(\theta_0) = -2(\ell_n(\theta_0) - \ell_n(\breve{\theta}_n))$$

   where $\breve{\theta}_n$ is the one step estimator produced from the Fisher iterative method using the method of moments estimator as initial step.

Solution.

1. Right, let's expand it,

$$\begin{aligned}
\ell_n(\theta_0) &= \ell_n(\hat{\theta}_n) + \dot{\ell}_n(\hat{\theta}_n)(\theta_0 - \hat{\theta}_n) + (\theta_0 - \hat{\theta}_n)^T \int_0^1 \int_0^1 u \, \ddot{\ell}_n(\hat{\theta}_n + uv(\theta_0 - \hat{\theta}_n)) \mathrm{d}u \mathrm{d}v \; (\theta_0 - \hat{\theta}_n) \\
&= \ell_n(\hat{\theta}_n) + \dot{\ell}_n(\hat{\theta}_n)(\theta_0 - \hat{\theta}_n) + (\theta_0 - \hat{\theta}_n)^T \; n \int_0^1 \int_0^1 u \, \frac{1}{n} \ddot{\ell}_n(\hat{\theta}_n + uv(\theta_0 - \hat{\theta}_n)) \mathrm{d}u \mathrm{d}v \; (\theta_0 - \hat{\theta}_n)
\end{aligned}$$

So by rearranging the terms

$$-2(\ell_n(\theta_0)-\ell_n(\hat{\theta}_n)) = -\underbrace{\dot{\ell}_n(\hat{\theta}_n)}_{=0}(\theta_0-\hat{\theta}_n)-n(\theta_0-\hat{\theta}_n)^T \underbrace{\int_0^1\int_0^1 u\,\frac{1}{n}\ddot{\ell}_n(\hat{\theta}_n+uv(\theta_0-\hat{\theta}_n))\mathrm{d}u\mathrm{d}v}_{\xrightarrow{a.s}-\frac{1}{2}\mathcal{I}(\theta_0)}(\theta_0-\hat{\theta}_n)$$

It is

$$\dot{\ell}_n(\hat{\theta}_n)=0$$

because $\hat{\theta}_n$ is an MLE.

From Cramer' Theorem $\hat{\theta}_n \xrightarrow{a.s} \theta_0$. Then by Slutsky's theorem, $\hat{\theta}_n+uv(\theta_0-\hat{\theta}_n) \xrightarrow{a.s} \theta_0$. Then

$$\int_0^1\int_0^1 u\,\frac{1}{n}\ddot{\ell}_n(\theta_0)\mathrm{d}u\mathrm{d}v \xrightarrow{a.s} \int_0^1\int_0^1 u\,\frac{1}{n}\ddot{\ell}_n(\theta_0)\mathrm{d}u\mathrm{d}v = \frac{1}{2}\frac{1}{n}\ddot{\ell}_n(\theta_0)$$

But $\frac{1}{2}\frac{1}{n}\ddot{\ell}_n(\theta_0) \xrightarrow{a.s} -\frac{1}{2}\mathcal{I}(\theta_0)$.

So to sum up

$$-2(\ell_n(\theta_0)-\ell_n(\hat{\theta}_n)) \xrightarrow{a.s} n(\theta_0-\hat{\theta}_n)^T\mathcal{I}(\theta_0)(\theta_0-\hat{\theta}_n) \tag{19}$$

From Cramer' Theorem I know that

$$\begin{aligned}
\sqrt{n}(\hat{\theta}_n-\theta_0) &\xrightarrow{D} \mathrm{N}(0,\mathcal{I}(\theta_0)^{-1})\\
\implies \sqrt{n}\mathcal{I}(\theta_0)^{1/2}(\hat{\theta}_n-\theta_0) &\xrightarrow{D} \mathrm{N}(0,I)\\
\implies n(\hat{\theta}_n-\theta_0)^T\mathcal{I}(\theta_0)(\hat{\theta}_n-\theta_0) &\xrightarrow{D} \chi^2_d
\end{aligned}$$

But $-2(\ell_n(\theta_0)-\ell_n(\hat{\theta}_n))$ is asymptotic equivalent to $n(\hat{\theta}_n-\theta_0)^T\mathcal{I}(\theta_0)(\hat{\theta}_n-\theta_0)$ from (19). So by the Slutsky's theorem

$$-2(\ell_n(\theta_0)-\ell_n(\hat{\theta}_n)) \xrightarrow{D} \chi^2_d$$

2. It is

$$\tilde{W}_{\mathrm{LR}}(\theta_0) = -2(\ell_n(\theta_0)-\ell_n(\breve{\theta}_n)) \xrightarrow{D} \chi^2_d$$

because $\breve{\theta}_n$ and $\hat{\theta}_n$ are asymptotic equivalent.

The next exercise is from Homework 4

Exercise 32. Let

$$y_i \overset{\text{ind}}{\sim} \mathrm{Bin}(n,\pi_i)$$

where $i = 1, ..., N$. Consider that the probability of success is modeled such as

$$\text{logit}(\pi_i) = x_i^T \theta \tag{20}$$

where $\text{logit}(\pi_i) = \log(\frac{\pi_i}{1-\pi_i})$. Here $x_i = (x_{i,1}, ..., x_{i,d})^T$ are known vertors containing the values of the d regessions at the i-th observation, and $\theta \in \mathbb{R}^d$.

1. Show that

$$\pi_i = \frac{e^{x_i^T \theta}}{1 + e^{x_i^T \theta}}$$

2. Assume that the MLE $\hat{\theta}$ of θ is known/calculated. Show that the $(1 - a)$ Wald confidence interval for the unknown parameter θ, by using the observed information matrix, is

$$\text{C.I.} : \{ \theta \in \mathbb{R}^d \ : \ (\hat{\theta}_n - \theta)^T X^T (\text{diag}_{\forall i}(n\hat{\pi}_i(1 - \hat{\pi}_i)))X(\hat{\theta}_n - \theta) \le \chi^2_{d,1-a} \ \}$$

where

$$\hat{\pi}_i = \frac{e^{x_i^T \hat{\theta}}}{1 + e^{x_i^T \hat{\theta}}}$$

X is the so called design matrix from the regression

$$\begin{bmatrix} \text{logit}(\pi_1) \\ \vdots \\ \text{logit}(\pi_N) \end{bmatrix} = \underbrace{\begin{bmatrix} \longleftarrow x_1^T \longrightarrow \\ \vdots \\ \longleftarrow x_N^T \longrightarrow \end{bmatrix}}_{=X} \theta$$

and $\text{diag}_{\forall i}(\heartsuit_i) = \begin{bmatrix} \heartsuit_1 & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & \heartsuit_N \end{bmatrix}$.

3. Find the score statistic rejection area for the hypothesis test $\text{H}_0 : \theta = \theta_*$ versus $H_1 : \theta \neq \theta_*$.

   Solution.

Exercise 33. For $i = 1, ..., k$, let $x_{i,1}, ..., x_{i,n} \overset{\text{IID}}{\sim} \text{Poi}(\theta_i)$. Find the asymptotic likelihood ratio rejection area for teasting the hypothesis

$$\text{H}_0 : \theta_1 = ... = \theta_k$$

Hint: It is

$$f(x|\theta) = \frac{\theta^x e^{-\theta}}{x!} 1(x \in \mathbb{N})$$

Solution. Under H_1, the log-likelihood is

$$\begin{aligned}\ell_1(\theta) &= \sum_{i=1}^{k}\sum_{j=1}^{n}(-\theta_i + x_{i,j}\log(\theta_i) - \log(x_{i,j}!)) \\ &\propto -n\sum_{i=1}^{k}\theta_i + \sum_{i=1}^{k}\log(\theta_i)\sum_{j=1}^{n}x_{i,j}\end{aligned}$$

The MLE is

$$\begin{aligned}0 = \frac{\mathrm{d}}{\mathrm{d}\theta_i}\ell_1(\theta)|_{\theta=\hat{\theta}^{(1)}} &= -n + \frac{1}{\hat{\theta}_i^{(1)}}\sum_{j=1}^{n}x_{i,j} \\ \Longrightarrow\ \hat{\theta}_i^{(1)} &= \frac{1}{n}\sum_{j=1}^{n}x_{i,j} \\ \Longrightarrow\ \hat{\theta}^{(1)} &= (\bar{x}_{1,\bullet}, ..., \bar{x}_{k,\bullet})^T\end{aligned}$$

and there are $d_1 = k$ free parameters for estimation.

Under H_0, it is the log-likelihood is $\theta_1 = ... = \theta_k = \theta$

$$\begin{aligned}\ell_0(\theta) &= \sum_{i=1}^{k}\sum_{j=1}^{n}(-\theta + x_{i,j}\log(\theta) - \log(x_{i,j}!)) \\ &\propto -nk\theta + \log(\theta)\sum_{i=1}^{k}\sum_{j=1}^{n}x_{i,j}\end{aligned}$$

The MLE is

$$\begin{aligned}0 = \frac{\mathrm{d}}{\mathrm{d}\theta}\ell_0(\theta)|_{\theta=\hat{\theta}^{(0)}} &= -nk + \frac{1}{\hat{\theta}^{(0)}}\sum_{i=1}^{k}\sum_{j=1}^{n}x_{i,j} \\ \Longrightarrow\ \hat{\theta}^{(0)} &= \frac{1}{nk}\sum_{i=1}^{k}\sum_{j=1}^{n}x_{i,j} \\ \hat{\theta}^{(0)} &= \bar{x}_{\bullet,\bullet}\end{aligned}$$

and there is $d_0 = 1$ free parameter for estimation.

So

$$-2(\ell_n(\hat{\theta}^{(0)}) - \ell_n(\hat{\theta}^{(1)})) \xrightarrow{D} \chi^2_{k-1}$$

where

$$
\begin{aligned}
-2(\ell_n(\hat{\theta}^{(0)}) - \ell_n(\hat{\theta}^{(1)})) =& -2(-nk\hat{\theta}^{(0)} + \log(\hat{\theta}^{(0)}) \sum_{i=1}^{k}\sum_{j=1}^{n} x_{i,j} \\
& - n\sum_{i=1}^{k}\hat{\theta}_i^{(1)} + \sum_{i=1}^{k}\log(\hat{\theta}_i^{(1)})\sum_{j=1}^{n} x_{i,j}) \\
=& -2(\cancel{-nk\bar{x}_{\bullet,\bullet}} + \log(\bar{x}_{\bullet,\bullet})\sum_{i=1}^{k}\sum_{j=1}^{n} x_{i,j} \\
& \cancel{+n\sum_{i=1}^{k}\bar{x}_{i,\bullet}} - \sum_{i=1}^{k}\log(\bar{x}_{i,\bullet})\sum_{j=1}^{n} x_{i,j}) \\
=& 2n\sum_{i=1}^{k}\log(\bar{x}_{i,\bullet})\bar{x}_{i,\bullet} - 2nk\log(\bar{x}_{\bullet,\bullet})\bar{x}_{\bullet,\bullet}
\end{aligned}
$$

So the rejection area is

$$
\mathrm{RA} = \{2n\sum_{i=1}^{k}\log(\bar{x}_{i,\bullet})\bar{x}_{i,\bullet} - 2nk\log(\bar{x}_{\bullet,\bullet})\bar{x}_{\bullet,\bullet} \geq \chi^2_{k-1,1-a}\}
$$

Exercise 34. Let $x = (x_1, ..., x_c) \sim \mathrm{Mult}(\pi_1, ..., \pi_c)$, with $\pi_i \in (0, \infty)$ and $\sum_{i=1}^{c}\pi_i = 1$. Find the asymptotic likelihood ratio rejection area for teasting the hypothesis

$$
\mathrm{H}_0 : \pi_1 = ... = \pi_c = \frac{1}{c}
$$

Hint: It is

$$
f(x|\theta) = \binom{n}{x_1 ... x_c}\prod_{i=1}^{c}\pi_i^{x_i}
$$

Solution. It is

$$
\ell_n(\pi) = \log\binom{n}{x_1 ... x_c} + \sum_{i=1}^{k} x_i \log(\pi_i)
$$

Lagrandge function is

$$
\mathcal{L}(\pi, \theta) = \log\binom{n}{x_1 ... x_c} + \sum_{i=1}^{k} x_i\log(\pi_i) - \theta(\sum_{i=1}^{c}\pi_i - 1)
$$

Under H_1, the MLE is

$$\begin{aligned}
0 = \frac{\mathrm{d}}{\mathrm{d}\pi_i}\mathcal{L}(\pi,\theta)|_{\pi=\hat{\pi},\,\theta=\hat{\theta}} &\implies \hat{\pi}_i = \frac{x_i}{\theta} \\
0 = \frac{\mathrm{d}}{\mathrm{d}\theta}\mathcal{L}(\pi,\theta)|_{\pi=\hat{\pi},\,\theta=\hat{\theta}} &\implies \sum_{i=1}^{c}\pi_i = 1 \\
&\implies \hat{\pi}_i = \frac{x_i}{n} \\
&\implies \hat{\pi}^{(1)} = (\frac{x_1}{n},...,\frac{x_c}{n})^T
\end{aligned}$$

So

$$\ell(\hat{\pi}^{(1)}) = \log\binom{n}{x_1...x_c} + \sum_{i=1}^{k} x_i \log(\frac{x_i}{n})$$

with $d_1 = c-1$ free parameters.

Under H_0,

$$\hat{\pi}^{(0)} = (\frac{1}{c},...,\frac{1}{c})^T$$

So

$$\ell(\hat{\pi}^{(0)}) = \log\binom{n}{x_1...x_c} + n\bar{x}\log(\frac{1}{c})$$

with $d_0 = 0$ free parameters.

So

$$-2(\ell_n(\hat{\pi}^{(0)}) - \ell_n(\hat{\pi}^{(1)})) \xrightarrow{D} \chi^2_{c-1}$$

where

$$\begin{aligned}
-2(\ell_n(\hat{\pi}^{(0)}) - \ell_n(\hat{\pi}^{(1)})) =& -2(n\bar{x}\log(\frac{1}{c}) - \sum_{i=1}^{k} x_i \log(\frac{x_i}{n})) \\
=& 2\sum_{i=1}^{c} x_i \log(\frac{c x_i}{n})
\end{aligned}$$

So the rejection area is

$$\mathrm{RA} = \{2\sum_{i=1}^{c} x_i \log(\frac{c x_i}{n}) \geq \chi^2_{c-1,1-a}\}$$

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7 Handout 7: The Profile likelihood (MLE under the presence of nuisance parameters)

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8 Others

Exercise 35. (Very difficult) Consider a contigency table with N cells. Consider a Multimomial sampling scheme was used to collect n observations. Let $y = (y_1, ..., y_N)^T$ be the observed counts, and $\pi = (\pi_1, ..., \pi_N)^T$ be the expected probabilities in N cells of a contingency table. Let the total number of observations be $n = \sum_{i=1}^{N} y_i$. Assume that

$$y \sim \text{Mult}(n, \pi) \tag{21}$$

where

$$f(y|n, \pi) = \binom{n}{y_1 ... y_N} \prod_{i=1}^{n} \pi_i^{y_i}$$

Consider a log-linear model

$$\pi_i = \pi_i(\theta) = \frac{\exp(x_i^T \theta)}{\sum_{\forall k} \exp(x_i^T \theta)} \tag{22}$$

$\theta \in \Theta$ is a d-dimensional vector of unknown coefficients, and $x_i = (x_{i,1}, ..., x_{i,d})^T$ are the values of d regressors.

In a matrix form

$$\pi = \frac{\exp(X\theta)}{1_d^T \exp(X\theta)}$$

where

$$X = \begin{bmatrix} \longleftarrow & x_1^T & \longrightarrow \\ & \vdots & \\ \longleftarrow & x_N^T & \longrightarrow \end{bmatrix}$$

Assume that Cramer's Theorem conditions are satisfied. Consider that the MLE $\hat{\theta}_n$ of θ is computed/calculated, and that θ_0 is the unknown true value of θ. Then

1. Show that

$$\frac{\mathrm{d}\pi}{\mathrm{d}\theta} = (\text{diag}(\pi) - \pi\pi^T)X$$

2. Show that the likelihood equations to find the MLE $\hat{\theta}$ of θ are such as

$$X^T y = n X^T \pi(\hat{\theta}_n)$$

   Does it ring a bell?

3. Consider the j-th single observation $\xi_j = (\xi_{j,1}, ..., \xi_{j,N})^T$ where $\xi_{j,i} = 1$ if it falls in cell i and $\xi_{j,i} = 0$ if it does not fall in cell i. Write the probability distribution $f(\xi_i|...) =?$ in the form of the Multinomial distribution.

4. Calculate the asymptotic distribution of the MLE $\hat{\theta}$ of θ.

   Hint: Use the fact that a single observation falls in only one cell, and use its probability.

5. Calculate the asymptotic distribution of cell probability estimators $\hat{\pi}$ of π.

6. Calculate the Wald's $(1-a)$ CI for θ, that results as an ellipsoid easy to compute or plot in 2D on 3D.

Solution.

1. It is

$$
\begin{aligned}
[\frac{\mathrm{d}\pi}{\mathrm{d}\theta}]_{i,j} = \frac{\mathrm{d}\pi_i}{\mathrm{d}\theta_j} =& \frac{\mathrm{d}}{\mathrm{d}\theta_j}\frac{\exp(x_i^T\theta)}{\sum_{\forall k}\exp(x_k^T\theta)} \\
=& \frac{\exp(x_i^T\theta)x_{i,j}\sum_{\forall k}\exp(x_i^T\theta) - \exp(x_i^T\theta)\sum_{\forall k}\exp(x_k^T\theta)x_{k,j}}{[\sum_{\forall k}\exp(x_k^T\theta)]^2} \\
=& \frac{\exp(x_i^T\theta)}{\sum_{\forall k}\exp(x_k^T\theta)}\frac{x_{i,j}\sum_{\forall k}\exp(x_k^T\theta) - \sum_{\forall k}\exp(x_k^T\theta)x_{k,j}}{[\sum_{\forall k}\exp(x_k^T\theta)]^2} \\
=& \frac{\exp(x_i^T\theta)}{\sum_{\forall k}\exp(x_k^T\theta)}\left(x_{i,j}\frac{\sum_{\forall k}\exp(x_k^T\theta)}{\sum_{\forall k}\exp(x_k^T\theta)} - \sum_{\forall k}\frac{\exp(x_k^T\theta)}{\sum_{\forall k}\exp(x_k^T\theta)}x_{k,j}\right) \\
=& \pi_i\left(x_{i,j} - \sum_{\forall k}\pi_k x_{k,j}\right) = \pi_i x_{i,j} - \pi_i\sum_{\forall k}\pi_k x_{k,j}
\end{aligned}
$$

   So if I write it in a matrix form

$$
\begin{aligned}
\frac{\mathrm{d}\pi}{\mathrm{d}\theta} &= \mathrm{diag}(\pi)X - \pi\pi^T X \\
&= (\mathrm{diag}(\pi) - \pi\pi^T)X
\end{aligned}
$$

2. Well,

$$
\ell_n(\theta) = \log(\binom{n}{y_1 \ldots y_N}) + \sum_{i=1}^{N} y_i \log(\pi_i(\theta))
$$

It is

$$\begin{aligned}
\frac{\mathrm{d}}{\mathrm{d}\theta_j}\ell_n(\theta) &= \frac{\mathrm{d}}{\mathrm{d}\theta_j}\sum_{i=1}^{N} y_i \log(\pi_i(\theta)) \\
&= \sum_{i=1}^{N} y_i \frac{1}{\pi_i(\theta)} \frac{\mathrm{d}}{\mathrm{d}\theta_j}\pi_i(\theta) \\
&= \sum_{i=1}^{N} y_i \frac{1}{\pi_i(\theta)} \left(\pi_i(\theta)x_{i,j} - \pi_i(\theta)\sum_{\forall k}\pi_k(\theta)x_{k,j}\right) \\
&= \sum_{i=1}^{N} y_i x_{i,j} - \underbrace{\sum_{i=1}^{N} y_i}_{=n} \sum_{\forall k}\pi_k(\theta)x_{k,j} \\
&= \sum_{i=1}^{N} y_i x_{i,j} - n\sum_{\forall k}\pi_k(\theta)x_{k,j}
\end{aligned}$$

So

$$\dot{\ell}_n(\theta) = X^T y - nX^T\pi(\theta)$$

Hence

$$0 = \ell_n(\theta)|_{\theta=\hat{\theta}} \quad \Longrightarrow \quad X^T y = nX^T\pi(\hat{\theta})$$

It is the same equation as the one for the log-linear model under the Piosson samp[ling scheme, when $\mu(\theta) = n\pi(\theta)$.

3. Based on the Multinomial sampling scheme, each observation can fall in one only cell. Observation ξ_j can fall in i-cell with probability π_i. So

$$\xi_j \stackrel{\text{IID}}{\sim} \text{Mult}(1, \pi)$$

with

$$f(\xi_j|\pi) = \prod_{i=1}^{N} \pi_i^{\xi_{j,i}}$$

where $\xi_{j,i} \in \{0,1\}^d$ and $\sum_i \xi_{j,i} = 1$.

4. Since Cramer's Theorem conditions are satisfied, I will use Cramer's Theorem. Namely,

$$\sqrt{n}(\hat{\theta}_n - \theta_0) \xrightarrow{D} \text{N}(0, \mathcal{I}(\theta_0)^{-1})$$

where $\mathcal{I}(\theta)$ is the Fisher's information matrix, aka the information matrix for 1 observation, Let's say observation ξ. Therefor, I just need to find $\mathcal{I}(\theta)$ with

$$[\mathcal{I}(\theta)]_{j,k} = \mathrm{E}(\frac{\mathrm{d}}{\mathrm{d}\theta_j}\log(f(\xi|\pi))\frac{\mathrm{d}}{\mathrm{d}\theta_k}\log(f(\xi|\pi)))$$

.

It is

$$\log(f(\xi|\pi)) = \sum_{i=1}^{N}\xi_i\log(\pi_i)$$

It is

$$\frac{\mathrm{d}}{\mathrm{d}\theta_j}\log(f(\xi|\pi)) = \sum_{i=1}^{N}\xi_i\frac{1}{\pi_i}\frac{\mathrm{d}\pi_i}{\mathrm{d}\theta_j}$$

and

$$\frac{\mathrm{d}}{\mathrm{d}\theta_k}\log(f(\xi|\pi)) = \sum_{i=1}^{N}\xi_i\frac{1}{\pi_i}\frac{\mathrm{d}\pi_i}{\mathrm{d}\theta_k}$$

So

$$
\begin{aligned}
[\mathcal{I}(\theta)]_{j,k} =& \mathrm{E}\left(\left(\sum_{i=1}^{N}\xi_i \frac{\mathrm{d}\pi_i}{\mathrm{d}\theta_j}\right)\left(\sum_{i'=1}^{N}\xi_{i'}\frac{\mathrm{d}\pi_{i'}}{\mathrm{d}\theta_k}\right)\right)\\
=& \mathrm{E}\left(\sum_{i=1}^{N}\sum_{i'=1}^{N}\xi_i\xi_{i'}\frac{\mathrm{d}\pi_i}{\mathrm{d}\theta_j}\frac{\mathrm{d}\pi_{i'}}{\mathrm{d}\theta_k}\right)\\
=& \sum_{i=1}^{N}\sum_{i'=1}^{N}\frac{\mathrm{d}\pi_i}{\mathrm{d}\theta_j}\frac{\mathrm{d}\pi_{i'}}{\mathrm{d}\theta_k}\mathrm{E}\left(\xi_i\xi_{i'}\right) \quad = \begin{cases}\mathrm{E}\left(\xi_i^2\right) = 1^2\pi_i + 0^2(1-\pi_i) = \pi_i & ,i=i'\\ 0 & ,i\neq i'\end{cases}\\
=& \{\text{so we care for those where } \xi_i = \xi_{i'} = 1\}\\
=& \sum_{i=1}^{N}\pi_i\frac{1}{\pi_i}\frac{\mathrm{d}\pi_i}{\mathrm{d}\theta_j}\frac{1}{\pi_i}\frac{\mathrm{d}\pi_i}{\mathrm{d}\theta_k}\\
=& \sum_{i=1}^{N}\frac{\mathrm{d}\pi_i}{\mathrm{d}\theta_j}\frac{1}{\pi_i}\frac{\mathrm{d}\pi_i}{\mathrm{d}\theta_k}\\
=& \sum_{i=1}^{N}\left(\pi_i x_{i,j} - \pi_i\sum_{\forall s}\pi_s x_{s,j}\right)\left(\pi_i x_{i,k} - -\pi_i\sum_{\forall s}\pi_s x_{s,k}\right)\frac{1}{\pi_i}\\
=& \sum_{i=1}^{N}\left(x_{i,j} - (\pi^T X_{:,j})\right)\left(\pi_i x_{i,k} - \pi_i(\pi^T X_{:,k})\right)\\
=& \sum_{i=1}^{N}x_{i,j}\pi_i x_{i,k} - (\sum_{i=1}^{N}x_{i,j}\pi_i)(\pi^T X_{:,k}) - \underbrace{\sum_{i=1}^{N}(\pi^T X_{:,j})(\pi_i x_{i,k}) + (\pi^T X_{:,j})\overbrace{\sum_{i=1}^{N}\pi_i}^{=1}(\pi^T X_{:,k})}_{=0}\\
=& \sum_{i=1}^{N}x_{i,j}\pi_i x_{i,k} - \sum_{i=1}^{N}x_{i,j}\pi_i(\pi^T X_{:,k})\\
=& X_{:,j}^T\mathrm{diag}(\pi)X_{:,k} - (\pi^T X_{:,j})^T(\pi^T X_{:,k})
\end{aligned}
$$

So in a matrix form, it is

$$
\begin{aligned}
\mathcal{I}(\theta) &= X^T\mathrm{diag}(\pi)X - X^T\pi\pi^T X\\
&= X^T(\mathrm{diag}(\pi) - \pi\pi^T)X
\end{aligned}
$$

So

$$
\sqrt{n}(\hat{\theta}_n - \theta_0) \xrightarrow{D} \mathrm{N}\left(0, \left(X^T(\mathrm{diag}(\pi_0) - \pi_0\pi_0^T)X\right)^{-1}\right) \tag{23}
$$

where $\pi_0 = \pi(\theta_0)$.

5. Because $\hat{\pi}$ is a continuous function of θ's and because I know that (23), I can use Delta method in order to find the asymptotic distribution of $\hat{\pi}$.

   According to Delta method, it is

$$\sqrt{n}(\hat{\pi} - \pi_0) \xrightarrow{D} \mathrm{N}\left(0, \Sigma_{\pi_0}\right)$$

   where $\pi_0 = \pi(\theta_0)$, and

$$\begin{aligned}\Sigma_{\pi_0} =& \frac{\mathrm{d}\pi}{\mathrm{d}\theta}|_{\theta=\theta_0} \left(X^T(\mathrm{diag}(\pi_0) - \pi_0\pi_0^T)X\right)^{-1} (\frac{\mathrm{d}\pi}{\mathrm{d}\theta}|_{\theta=\theta_0})^T \\ =&(\mathrm{diag}(\pi_0) - \pi_0\pi_0^T)X \left(X^T(\mathrm{diag}(\pi_0) - \pi_0\pi_0^T)X\right)^{-1} X^T(\mathrm{diag}(\pi_0) - \pi_0\pi_0^T)\end{aligned}$$

6. Well, the $(1-a)100\%$ confidence interval for θ which is touch to invert is

$$\begin{aligned}\mathrm{CI}(\theta) =& \left\{\theta \in \mathbb{R}^d :\ \sqrt{n}(\hat{\theta} - \theta)\mathcal{I}(\theta)(\hat{\theta} - \theta)^T \leq \chi^2_{d,1-a}\right\} \\ =& \left\{\theta \in \mathbb{R}^d :\ \sqrt{n}(\hat{\theta} - \theta) \left(X^T(\mathrm{diag}(\pi(\theta)) - \pi(\theta)\pi(\theta)^T)X\right)(\hat{\theta} - \theta)^T \leq \chi^2_{d,1-a}\right\}\end{aligned}$$

   So probably I would go with the asymptotic equivalent one

$$\begin{aligned}\mathrm{CI}(\theta) =& \left\{\theta \in \mathbb{R}^d :\ \sqrt{n}(\hat{\theta} - \theta)\mathcal{I}(\hat{\theta})(\hat{\theta} - \theta)^T \leq \chi^2_{d,1-a}\right\} \\ =& \left\{\theta \in \mathbb{R}^d :\ \sqrt{n}(\hat{\theta} - \theta) \left(X^T(\mathrm{diag}(\hat{\pi}) - \hat{\pi}\hat{\pi}^T)X\right)(\hat{\theta} - \theta)^T \leq \chi^2_{d,1-a}\right\}\end{aligned}$$

   where $\hat{\pi} = \pi(\hat{\theta})$.

   The degrees of freedom of the critical values in the CI are d because there are d free parameters in θ.
