

Midterm 2 Review

Fall 2017

1. Two-Population Sampling

We are conducting a public opinion poll to determine the fraction p of people who will vote for Mr. Whatshisname as the next president. We ask N_1 college-educated and N_2 non-college-educated people, where N_1 and N_2 are positive integers. We assume that the votes in each of the two groups are i.i.d. Bernoulli(p_1) and Bernoulli(p_2), respectively in favor of Whatshisname. In the general population, the percentage of college-educated people is known to be q .

- (a) What is a 95% confidence interval for p , using an upper bound for the variance?
- (b) How do we choose N_1 and N_2 subject to $N_1 + N_2 = N$ to minimize the width of that interval? (You may ignore the constraint that N_1 and N_2 must be integers.)

Solution:

- (a) If we let \hat{p}_1 and \hat{p}_2 denote the fraction of people who vote for Mr. Whatshisname in the two groups respectively, then an unbiased estimator for p is $\hat{p} := q\hat{p}_1 + (1 - q)\hat{p}_2$. The variance of \hat{p} is

$$\text{var } \hat{p} = \frac{q^2 p_1 (1 - p_1)}{N_1} + \frac{(1 - q)^2 p_2 (1 - p_2)}{N_2} \leq \frac{1}{4} \left(\frac{q^2}{N_1} + \frac{(1 - q)^2}{N_2} \right).$$

So, an approximate 95% confidence interval for p , using the CLT, is $\hat{p} \pm \sqrt{q^2/N_1 + (1 - q)^2/N_2}$.

- (b) Minimizing the width of the interval is equivalent to minimizing the variance. We can explicitly enforce the constraint by writing $N_2 = N - N_1$, and then we have:

$$\frac{d}{dN_1} \left(\frac{q^2}{N_1} + \frac{(1 - q)^2}{N - N_1} \right) = -\frac{q^2}{N_1^2} + \frac{(1 - q)^2}{(N - N_1)^2}.$$

The second derivative is positive so the function is convex, and so the first-order condition tells us the minimizer. Setting the derivative to 0, we find that $q/N_1 = (1 - q)/(N - N_1)$. Therefore, the minimizer is $N_1 = qN$, $N_2 = (1 - q)N$.

2. Minimum and Maximum of Exponentials

Let $\lambda_1, \lambda_2 > 0$, and $X_1 \sim \text{Exponential}(\lambda_1)$, $X_2 \sim \text{Exponential}(\lambda_2)$ are independent. Also, define $U := \min(X_1, X_2)$ and $V := \max(X_1, X_2)$. Show that U and $V - U$ are independent.

Solution:

For $u, w > 0$,

$$\begin{aligned} \mathbb{P}(U \leq u, V - U \leq w, X_1 < X_2) &= \mathbb{P}(X_1 \leq u, X_1 < X_2 \leq X_1 + w) \\ &= \int_0^u \int_{x_1}^{x_1+w} \lambda_2 \exp(-\lambda_2 x_2) dx_2 \lambda_1 \exp(-\lambda_1 x_1) dx_1 \\ &= \int_0^u \{\exp(-\lambda_2 x_1) - \exp(-\lambda_2(x_1 + w))\} \lambda_1 \exp(-\lambda_1 x_1) dx_1 \\ &= (1 - \exp(-\lambda_2 w)) \int_0^u \lambda_1 \exp(-(\lambda_1 + \lambda_2)x_1) dx_1 \\ &= \frac{\lambda_1}{\lambda_1 + \lambda_2} (1 - \exp\{-(\lambda_1 + \lambda_2)u\}) (1 - \exp(-\lambda_2 w)). \end{aligned}$$

By symmetry, interchanging the roles of 1 and 2 yields

$$\begin{aligned} \mathbb{P}(U \leq u, V - U \leq w, X_2 < X_1) \\ &= \frac{\lambda_2}{\lambda_1 + \lambda_2} (1 - \exp\{-(\lambda_1 + \lambda_2)u\}) (1 - \exp(-\lambda_1 w)). \end{aligned}$$

Adding these two expressions yields

$$\begin{aligned} \mathbb{P}(U \leq u, V - U \leq w) &= (1 - \exp\{-(\lambda_1 + \lambda_2)u\}) p_w, \quad \text{where} \\ p_w &:= \frac{\lambda_1}{\lambda_1 + \lambda_2} (1 - \exp(-\lambda_2 w)) + \frac{\lambda_2}{\lambda_1 + \lambda_2} (1 - \exp(-\lambda_1 w)). \end{aligned}$$

The joint CDF splits into a product of factors $\mathbb{P}(U \leq u)\mathbb{P}(V - U \leq w)$ which proves independence. To interpret the second term, observe that $\lambda_1/(\lambda_1 + \lambda_2)$ is the probability of the event $\{X_1 < X_2\}$; and conditioned on this event, $V - U \sim \text{Exponential}(\lambda_2)$ by the memoryless property.

3. Integrated Shot Noise

A noise impulse occurs at time $t = 0$, and later impulses occur at Poisson process times with mean rate $\lambda > 0$. Each impulse instantaneously charges a capacitor to 1 volt, and the voltage then decreases exponentially as e^{-t} until the next impulse occurs. Let V_t denote the voltage at time t . Let

$$Z_n = \int_0^{T_n} V_t dt$$

be the integrated voltage up to the time of the n^{th} impulse occurring after $t = 0$, for each positive integer n .

Find $\mathbb{E}[Z_n]$ and $\text{var } Z_n$.

Solution:

At T_n , there have been n impulses, and the interarrival times are i.i.d. and exponentially distributed. Thus,

$$\begin{aligned}\mathbb{E}[Z_n] &= \mathbb{E}\left[\int_0^{T_n} V_t dt\right] = \sum_{i=1}^n \mathbb{E}\left[\int_{T_{i-1}}^{T_i} V_t dt\right] \\ &= n \int_0^\infty \int_0^s \exp(-t) \lambda \exp(-\lambda s) dt ds \\ &= n \int_0^\infty (1 - \exp(-s)) \lambda \exp(-\lambda s) ds = n \left(1 - \frac{\lambda}{1 + \lambda}\right) = \frac{n}{1 + \lambda}\end{aligned}$$

and

$$\begin{aligned}\text{var } Z_n &= \sum_{i=1}^n \text{var} \int_{T_{i-1}}^{T_i} V_t dt \\ &= n \left\{ \int_0^\infty \left(\int_0^s \exp(-t) dt \right)^2 \lambda \exp(-\lambda s) ds - \frac{1}{(1 + \lambda)^2} \right\} \\ &= n \left(\int_0^\infty (1 - \exp(-s))^2 \lambda \exp(-\lambda s) ds - \frac{1}{(1 + \lambda)^2} \right) \\ &= n \left(1 - \frac{2\lambda}{1 + \lambda} + \frac{\lambda}{2 + \lambda} - \frac{1}{(1 + \lambda)^2} \right) = \frac{n\lambda}{(1 + \lambda)^2(2 + \lambda)}.\end{aligned}$$

4. Doubly Stochastic Matrix

A matrix is called **doubly stochastic** if all of its entries are non-negative and each row and each column sums to 1. Find the stationary distribution for a doubly stochastic irreducible matrix.

Solution:

The stationary distribution is uniform over the state space \mathcal{X} . Indeed, if we define $\pi(x) := |\mathcal{X}|^{-1}$ for each $x \in \mathcal{X}$, then

$$\sum_{y \in \mathcal{X}} \pi(y) P(y, x) = |\mathcal{X}|^{-1} \sum_{y \in \mathcal{X}} P(y, x) = |\mathcal{X}|^{-1} = \pi(x).$$

5. Flea on a Triangle

A flea hops about at random on the vertices of a triangle, with all jumps equally likely. Find the probability that after n ($n \in \mathbb{N}$) hops the flea is back where it started.

Solution:

Let x be the flea's starting state. When $n = 0$, $p^{(0)}(x, x) = 1$, and when $n = 1$, $p^{(1)}(x, x) = 0$. Otherwise, for $n \in \mathbb{Z}_{\geq 2}$, in order for the flea to return to its original state after n hops, it must have *not* returned to its original state after $n - 1$ hops, and then return to its original state. So, we have the recurrence $p^{(n)}(x, x) = (1 - p^{(n-1)}(x, x))/2$. Iterating this recurrence, we find that

$$p^{(n)}(x, x) = \frac{1 - p^{(n-1)}(x, x)}{2} = \frac{1}{2} \sum_{k=0}^{n-2} \left(-\frac{1}{2}\right)^k + \frac{(-1)^{n-1}}{2^n} + \frac{(-1)^n}{2^n} p^{(0)}(x, x)$$

$$= \frac{1}{2} \sum_{k=0}^{n-2} \left(-\frac{1}{2}\right)^k = \frac{(1/2)(1 - (-1/2)^{n-1})}{3/2} = \frac{1 - (-1/2)^{n-1}}{3}.$$