

(1) **Distribution of the maximum**

Let X_1, X_2, \dots be a sequence of i.i.d. with uniform $(0, 1)$ distribution and let $X_{(n)} = \max_{1 \leq i \leq n} X_i$.

Show that the sequence

$$Y_n = n(1 - X_{(n)}), \quad n \in \mathbb{N}$$

converges to an exponential $\exp(1)$ random variable as $n \rightarrow \infty$.

$$\bullet) F_n(x) := P(X_{(n)} \leq x) = P\left(\max_{1 \leq i \leq n} X_i \leq x\right) = P\left(\bigcap_{i=1}^n [X_i \leq x]\right) = \prod_{i=1}^n P(X_i \leq x) = \begin{cases} 0, & \text{if } x < 0 \\ x^n, & \text{if } 0 \leq x < 1 \\ 1, & \text{if } 1 \leq x \end{cases}$$

$$G_n(y) := P(Y_n \leq y) = P(n(1 - X_{(n)}) \leq y) = P(1 - X_{(n)} \leq \frac{y}{n}) = P(1 - \frac{y}{n} \leq X_{(n)})$$

$$= 1 - P(X_{(n)} < 1 - \frac{y}{n}) = \begin{cases} 0, & \text{if } y \leq 0 \\ 1 - (1 - \frac{y}{n})^n, & \text{if } 0 < y \leq n \\ 1, & \text{if } n < y \end{cases}$$

We know from Analysis, that $(1 + \frac{(-y)}{n})^n \xrightarrow{n \rightarrow \infty} e^{-y}$ pointwise in \mathbb{R} , hence

$$G_n(y) \xrightarrow{n \rightarrow \infty} \begin{cases} 0, & \text{if } y < 0 \\ 1 - e^{-y}, & \text{if } y \geq 0 \end{cases}, \quad \text{which is the distribution function}$$

of an $\exp(1)$ random variable, hence $Y_n \xrightarrow{d} Z \sim \exp(1)$

(2) **Coin throws**

An unfair coin is thrown 600 times. The probability of getting a tail in each throw is $\frac{1}{4}$.

- (a) Use a Binomial distribution to compute the probability that the number of heads obtained does not differ more than 10 from 450.
- (b) Use a Normal approximation without a continuity correction to calculate the probability in (a). How does the result change if the approximation is provided with a continuity correction?

a) Y ... number of tails after 600 tosses, $Y \sim \text{bin}(n, p)$, $n = 600$, $p = \frac{1}{4}$

$$P(|600 - Y| \leq 10) = P(|150 - Y| \leq 10) = P(140 \leq Y \leq 160) \stackrel{R}{\approx} 0,68$$

b) $Y \approx Z \sim \mathcal{N}(np, np(1-p))$

Symmetry of normal.

$$\begin{aligned} P(140 \leq Z \leq 160) &= 1 - P(Z < 140) - P(Z > 160) \stackrel{!}{=} 1 - P(Z < 140) - P(Z < 140) \\ &= 1 - 2P(Z < 140) \stackrel{R}{\approx} 0,65 \end{aligned}$$

$$np = \frac{600}{4} = 150; \quad np(1-p) = \frac{600}{4} \cdot \frac{3}{4} = \frac{3 \cdot 150}{4} = \frac{450}{4} = \frac{225}{2}$$

with continuity correction:

$$P(140 \leq Y \leq 160) \approx P(140 - \frac{1}{2} < Z < 160 + \frac{1}{2}) = 1 - 2P(Z < 140 - \frac{1}{2}) \stackrel{R}{\approx} 0,68$$

(3) Simulations

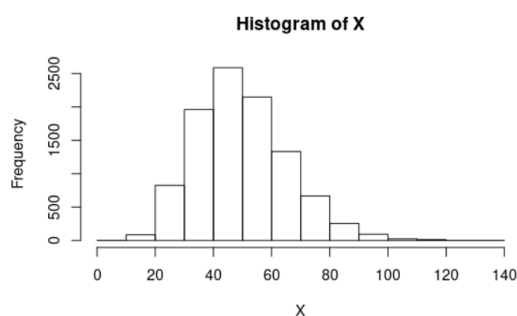
- (a) By applying the R-function `replicate()` generate a sample X_1, \dots, X_{10} of size 10 from an exponential distribution with a rate parameter 0.2 and sum up its elements. Do this sum 10 000 times and make a histogram of the simulation. Can you say something about the shape of distribution?
- (b) Use R to simulate 50 tosses of a fair coin (0 and 1). We call a *run* a sequence of all 1's or all 0's. Estimate the average length of the longest run in 10000 trials and report the result.

Hint: Use the commands `rbinom` and `rle`. The command `rle()` stands for run length encoding. For example,

```
rle(rbinom(5, 1, 0.5))$lengths
```

is a vector of the lengths of all the different runs in trial of 5 flips of a fair coin.

a) Defining $V := \sum_{i=1}^n X_i$, $n=10$, $\lambda := \frac{1}{5}$ we expect $V \sim \text{Gamma}(n, \lambda)$,
where $E(V) = \frac{n}{\lambda} = 5 \cdot 10 = 50$ and $\text{Var}(V) = \frac{n}{\lambda^2} = 10 \cdot 25 = 250$



b) Estimation: longest run is approximately 5,94

(4) Conditional variance

(a) Show that for any two random variables X and Y the conditional variance identity holds

$$\text{Var } Y = \mathbb{E}(\text{Var}(Y|X)) + \text{Var}(\mathbb{E}(Y|X)),$$

provided that the expectations exist. The law of total expectation (the tower property) $\mathbb{E}X = \mathbb{E}(\mathbb{E}(X|Y))$ should be applied.

(b) Suppose that the distribution of Y conditional on $X = x$ is $\mathcal{N}(x, x^2)$ and that the marginal distribution of X is uniform on $(0, 1)$. Compute $\mathbb{E}Y$, $\text{Var } Y$ and $\text{Cov}(X, Y)$.

$$\begin{aligned} a) \quad \mathbb{E}(\text{Var}(Y|X)) + \text{Var}(\mathbb{E}(Y|X)) &= \mathbb{E}(\mathbb{E}(Y^2|X) - (\mathbb{E}(Y|X))^2) + \mathbb{E}((\mathbb{E}(Y|X))^2) - (\mathbb{E}(\mathbb{E}(Y|X)))^2 \\ &= \mathbb{E}(\mathbb{E}(Y^2|X)) - \underbrace{\mathbb{E}((\mathbb{E}(Y|X))^2) + \mathbb{E}((\mathbb{E}(Y|X))^2) - (\mathbb{E}(\mathbb{E}(Y|X)))^2}_{=0} \\ &= \mathbb{E}(Y^2) - (\mathbb{E}(Y))^2 = \text{Var}(Y) \end{aligned}$$

$$b) \quad f(y|x) = \frac{f_{X,Y}(x,y)}{f_X(x)} \Leftrightarrow f_{X,Y}(x,y) = f_X(x) f(y|x) = \begin{cases} 0 & \text{if } x < 0 \\ \frac{1}{\sqrt{2\pi}x} \exp\left(-\frac{(y-x)^2}{2x^2}\right) & \text{if } 0 \leq x < 1 \\ 0 & \text{if } 1 \leq x \end{cases}$$

$$f_Y(y) = \int_0^1 f_{X,Y}(x,y) dx$$

$$Z \sim \mathcal{N}(x, x^2)$$

$$\mathbb{E}(Y) = \int_{\mathbb{R}} y f_Y(y) dy = \int_0^1 \int_{\mathbb{R}} y f_{X,Y}(x,y) dy dx \stackrel{\text{Fubini}}{=} \int_0^1 \mathbb{E}(Z_x) dx = \int_0^1 x dx = \boxed{\frac{1}{2}}$$

$f_{X,Y}(x,y)$ is normal distribution with expectation x

$$\mathbb{E}(Y^2) = \int_{\mathbb{R}} y^2 f_Y(y) dy = \int_0^1 \int_{\mathbb{R}} y^2 f_{X,Y}(x,y) dy dx \stackrel{\text{Fubini}}{=} \int_0^1 \mathbb{E}(Z_x^2) dx = \int_0^1 (x^2 + x^2) dx = \int_0^1 2x^2 dx = \frac{2}{3}$$

$\mathbb{E}(Z^2) = \text{Var}(Z) + (\mathbb{E}(Z))^2 = x^2$

$$\text{Var}(Y) = \mathbb{E}(Y^2) - (\mathbb{E}(Y))^2 = \frac{2}{3} - \frac{1}{4} = \frac{8-3}{12} = \boxed{\frac{5}{12}}$$

$$\mathbb{E}(XY) = \int_{\mathbb{R}^2} xy f_{X,Y}(x,y) dx dy = \int_0^1 x \int_{\mathbb{R}} y f_{X,Y}(x,y) dy dx = \int_0^1 x \mathbb{E}(Z_x) dx = \int_0^1 x^2 dx = \frac{1}{3}$$

$$\Rightarrow \text{Cov}(X, Y) = \mathbb{E}(XY) - \mathbb{E}(X)\mathbb{E}(Y) = \frac{1}{3} - \frac{1}{2} \cdot \frac{1}{2} = \frac{4-3}{12} = \boxed{\frac{1}{12}}$$

(5) (a) **Delta method**

Let X_1, \dots, X_n be i.i.d. from normal distribution with unknown mean μ and known variance σ^2 . Let $\bar{X} = \frac{1}{n} \sum_{i=1}^n X_i$. Find the limiting distribution of $\sqrt{n}(\bar{X}^3 - c)$ for an appropriate constant c .

(b) **Logit transformation**

Let $X_n \sim \text{bin}(n, p)$. Consider the logit transformation, defined by

$$\text{logit}(y) = \ln \frac{y}{1-y}, \quad 0 < y < 1.$$

Determine the approximate distribution of $\text{logit}\left(\frac{X_n}{n}\right)$.

a) By the CLT, $\frac{\sqrt{n}(\bar{X}_n - \mu)}{\sigma} \xrightarrow{d} Y \sim \mathcal{N}(0, 1)$

$Y_n := \frac{\bar{X}_n}{\sigma}, \quad \theta := \frac{\mu}{\sigma}, \text{ then } \sqrt{n}(Y_n - \theta) \xrightarrow{d} Y \sim \mathcal{N}(0, 1)$

$g: \mathbb{R} \rightarrow \mathbb{R}: y \mapsto (\sigma y)^3, \Rightarrow g'(y) = 3\sigma^3 y^2$, and by the delta method,

$\sqrt{n}(\bar{X}_n^3 - \mu^3) = \sqrt{n}((\sigma Y_n)^3 - (\sigma \theta)^3) = \sqrt{n}(g(Y_n) - g(\theta)) \xrightarrow{d} g'(\theta)Y = 3\sigma^3 \theta^2 Y$

and $3\sigma^3 \theta^2 Y = 3\sigma^3 \frac{\mu^2}{\sigma^2} Y = 3\sigma \mu^2 Y \sim \mathcal{N}(0, (3\sigma \mu^2)^2)$

b) let $Y_1, \dots, Y_n \sim \text{bin}(1, p)$; $X_n = \sum_{i=1}^n Y_i \sim \text{bin}(n, p)$, $\mathbb{E}(X_n) = np$, $\text{Var}(X_n) = np(1-p)$

$\mathbb{E}(Y_i) = p$, $\text{Var}(Y_i) = p(1-p)$

* For $p \in (0, 1)$

By CLT: $\sqrt{n} \frac{\frac{X_n}{n} - p}{\sqrt{p(1-p)}} = \frac{\sqrt{n}(X_n - np)}{n\sqrt{p(1-p)}} = \frac{X_n - np}{\sqrt{np(1-p)}} \xrightarrow{d} Z \sim \mathcal{N}(0, 1)$

We define $Z_n := \frac{X_n}{n\sqrt{p(1-p)}}$ and $\theta := \sqrt{\frac{p}{1-p}}$, then

$\sqrt{n}(Z_n - \theta) \xrightarrow{d} \mathcal{N}(0, 1)$, we define $g: (0, 1) \rightarrow \mathbb{R}: z \mapsto \text{logit}(\sqrt{p(1-p)} z)$, hence

$g'(z) = \frac{1 - \sqrt{p(1-p)} z}{z} \left(\frac{\sqrt{p(1-p)}}{1 - \sqrt{p(1-p)} z} + z \sqrt{p(1-p)} (1 - \sqrt{p(1-p)} z)^{-2} \sqrt{p(1-p)} \right)$
 $= \frac{1 - \sqrt{p(1-p)} z}{\sqrt{p(1-p)} z} \frac{\sqrt{p(1-p)} (1 - \sqrt{p(1-p)} z) + z p(1-p)}{(1 - \sqrt{p(1-p)} z)^2} = \frac{1}{z(1 - \sqrt{p(1-p)} z)}$ and $g(\theta) = \log\left(\frac{p}{1-p}\right)$

by application of the delta method we obtain and

$\sqrt{n}(\text{logit}\left(\frac{X_n}{n}\right) - \text{logit}(p)) = \sqrt{n}(g(Z_n) - g(\theta)) \xrightarrow{d} g'(\theta)Z = \frac{\sqrt{1-p}}{\sqrt{p}(1-p)} Z = \frac{1}{\sqrt{p(1-p)}} Z \sim \mathcal{N}\left(0, \frac{1}{p(1-p)}\right)$

hence, $\text{logit}\left(\frac{X_n}{n}\right) \approx \mathcal{N}\left(\text{logit}(p), \frac{1}{np(1-p)}\right)$