

# Simulation-Based Learning: Theory and Applications

H2 MVA 2014-15.

## Homework 1.

### Exercise 1:

(a)  $X$  is the number of time you have to run the algorithm. ( $X \in \mathbb{N}$ -valued)

Let us find  $P(X=k)$  for  $k \geq 1$ .

$$P(X=k) = P\left(\sum_{i=1}^{k-1} p(i) < v \leq \sum_{i=1}^k p(i)\right)$$

$$= F_v\left(\sum_{i=1}^k p(i)\right) - F_v\left(\sum_{i=1}^{k-1} p(i)\right) = \sum_{i=1}^k p(i) - \sum_{i=1}^{k-1} p(i) = p(k).$$

(b) The average number of loops is:

$$E[X] = \sum_{i=1}^{+\infty} i \cdot p(i) \text{ with } p(i) = \frac{6}{\pi^2 i^2}$$

$$= \sum_{i=1}^{+\infty} \frac{6}{\pi^2 i^2} + i = \frac{6}{\pi^2} \sum_{i=1}^{+\infty} \frac{1}{i^2} \text{ with divergence.}$$

Rg: It's due to the construction of  $X$ . for  $p(i) = \frac{6}{\pi^2 i^2}$ . In fact if  $v=0, 99\dots$  then it will take a infinite time (never reach) the stop condition.

(a) Distribution of  $[1/v]$ .

$$P([1/v]=k) = P(k \leq \frac{1}{v} < k+1) = P\left(\frac{1}{k+1} \leq v \leq \frac{1}{k}\right) = F_v\left(\frac{1}{k}\right) - F_v\left(\frac{1}{k+1}\right)$$

$$= \frac{1}{k} - \frac{1}{k+1} = \frac{1}{k(k+1)}.$$

(b) + (c): Because the samples are independent, the algorithm terminates at first success in a sequence of independent trials with same probability of success:

$$P = P(V \leq (X+1)/2X)$$

$$= \mathbb{E}[\mathbb{E}[1_{\{V \leq (X+1)/2X\}} | X]]$$

$$= \mathbb{E}\left[P\left(V \leq \frac{X+1}{2X}\right)\right] = \mathbb{E}\left[\frac{X+1}{2X}\right] = \sum_{k=1}^{+\infty} \frac{k+1}{2k} \times \frac{1}{(k+1)k}$$

$$= \frac{1}{2} \sum_{k \geq 1} \frac{1}{k^2} = \frac{\pi^2}{12}$$

The average time is thus  $\frac{1}{P} = \frac{12}{\pi^2}$ .

The algorithm draws a r.v.  $X$  with distribution  $q$ , and then a r.v.  $V$  uniformly distributed on  $[0,1]$ . until:

$$Vq(X) \leq p(x) \text{ with } q(x) = \frac{1}{k(k+1)} \text{ for } X=k.$$

Following the arguments that we have shown in lecture 1, we can show that the pair  $(X, Vq(X))$  is uniformly distributed under the curve  $\{(x,y) : 0 \leq y \leq q(x)\}$ ; Then that the element  $X$  is distributed according to  $p$ .

$$\{(x,y) : 0 \leq y \leq q(x)\} = \{(x, \frac{1}{k(k+1)}) : 0 \leq x \leq k\} = \{(x, \frac{1}{k(k+1)}) : x \in \mathbb{Z}\}$$

### Exercise 2:

1) At the end of the loop, line 4:

$$P(E \leq x | E^2 \leq \frac{2E'}{x}) = \frac{P(E \leq x, E^2 \leq \frac{2E'}{x})}{P(E^2 \leq \frac{2E'}{x})} \quad (*)$$

$$(*) P(E \leq x, E^2 \leq \frac{2E'}{x}) = E \left[ \mathbb{E} [ \mathbb{1}_{\{E \leq x\}} \mathbb{1}_{\{E^2 \leq \frac{2E'}{x}\}} | E] \right]$$

$$= E \left[ \mathbb{1}_{\{E \leq x\}} P(E^2 \leq \frac{2E'}{x}) \right]$$

$$= E \left[ \mathbb{1}_{\{E \leq x\}} P(E' \geq \frac{t}{2} E^2) \right]; \quad P(E' \geq \frac{t}{2} E^2) = 1 - 1 + e^{-\frac{tE^2}{2}} = e^{-\frac{tE^2}{2}}.$$

$$= E \left[ \mathbb{1}_{\{E \leq x\}} e^{-\frac{tE^2}{2}} \right] = \int_0^{+\infty} \mathbb{1}_{\{y \leq x\}} e^{-\frac{ty^2}{2}} e^{-y} dy.$$

$$= \begin{cases} \int_0^x e^{-\frac{t(\sqrt{y} + \frac{1}{\sqrt{t}})^2 + 1}{2t}} dy = e^{\frac{1}{2t}} \int_0^x e^{-\frac{1}{2t} (\sqrt{ty} + \frac{1}{\sqrt{t}})^2} dy & \text{if } x \geq 0 \\ 0 & \text{otherwise} \end{cases}$$

$$= \begin{cases} \frac{e^{-1/2t}}{\sqrt{t}} - e^{-1/2t} \int_{1/\sqrt{t}}^{\sqrt{tx} + 1/\sqrt{t}} e^{-\frac{1}{2} u^2} du = \frac{e^{-1/2t}}{\sqrt{t}} \left( \Phi(\sqrt{tx} + \frac{1}{\sqrt{t}}) - \Phi(\frac{1}{\sqrt{t}}) \right) & \text{if } x \geq 0 \\ 0 & \text{otherwise} \end{cases}$$

with  $\Phi$  the c.d.f. of  $N(0,1)$

$$\text{and } P(E^2 \leq 2E'/t) = \frac{e^{-1/2t}}{\sqrt{t}} \left( 1 - \Phi(\frac{1}{\sqrt{t}}) \right) \text{ if } x \geq 0$$

$$\text{so } P(E \leq x | E^2 \leq \frac{2E'}{t}) = \frac{\Phi(\sqrt{tx} + \frac{1}{\sqrt{t}}) - \Phi(\frac{1}{\sqrt{t}})}{1 - \Phi(\frac{1}{\sqrt{t}})} \mathbb{1}_{x \geq 0}$$

$$2) X = \frac{t}{(1+tE)^2}$$

$$\begin{aligned} P(X \leq y) &= P\left(\frac{t}{(1+tE)^2} \leq y\right) = P\left(\frac{t}{y} \leq (1+tE)^2\right) = 1 - P((1+tE)^2 \leq t/y) \\ &= 1 - P\left(-\frac{1}{tEy} - 1 \leq E \leq \frac{1}{tEy} - 1\right) \\ &= 1 - \left(F_E\left(\frac{1}{tEy} - 1\right) - F_E\left(-\frac{1}{tEy} - 1\right)\right) \end{aligned}$$

$$F_E\left(\frac{1}{tEy} - 1\right) = \frac{\Phi\left(\frac{1}{\sqrt{y}}\right) - \Phi\left(\frac{1}{\sqrt{E}}\right)}{1 - \Phi\left(\frac{1}{\sqrt{E}}\right)}$$

$$\text{So } P(X \leq y) = 1 - \frac{2\Phi\left(\frac{1}{\sqrt{y}}\right) - 1}{1 - \Phi\left(\frac{1}{\sqrt{E}}\right)} \quad M_{dy \geq 0}.$$

density de X:  $\frac{dF_X(y)}{dy}$

$$\begin{aligned} \frac{d\Phi\left(\frac{1}{\sqrt{y}}\right)}{dy} &= -\frac{1}{2} y^{-3/2} \varphi\left(\frac{1}{\sqrt{y}}\right) \text{ with } \varphi \text{ the density of } \mathcal{N}(0,1), \\ &= -\frac{1}{2} y^{-3/2} \frac{1}{\sqrt{2\pi}} e^{-1/2y^{-1}} = -\frac{1}{2} \left(\frac{1}{2\pi y^3}\right)^{1/2} e^{-1/2y^{-1}} \end{aligned}$$

$$\text{So } \frac{dF_X(y)}{dy} = \frac{1}{1 - \Phi\left(\frac{1}{\sqrt{E}}\right)} \left(\frac{1}{2\pi y^3}\right)^{1/2} e^{-1/2y^{-1}} \quad M_{dy \geq 0}.$$

$$3) P(X \leq w | U \leq \alpha) = \frac{P(X \leq w, U \leq \alpha) (*)}{P(U \leq \alpha)}$$

$$(*) P(X \leq w, U \leq \alpha) = \mathbb{E}[\mathbb{E}[1_{\{X \leq w\}} 1_{\{U \leq \alpha\}} | X]]$$

$$= \mathbb{E}[1_{\{X \leq w\}} \underbrace{P(U \leq \alpha)}_{\alpha}] = \mathbb{E}[1_{\{X \leq w\}} \exp(-\frac{1}{2\alpha^2} X)]$$

$$= \int_{\{x \leq w\}} \exp(-\frac{1}{2\gamma^2}x) \times \frac{1}{1 - \Phi(\frac{1}{\sqrt{\gamma}})} \left(\frac{1}{2\pi\gamma^3}\right)^{1/2} e^{-\frac{1}{2\gamma^2}x^2} \mathbb{1}_{\{x \geq 0\}} dx.$$

$$= \frac{1}{1 - \Phi(\frac{1}{\sqrt{\gamma}})} \times \int_{\{x \leq w\}} \left(\frac{1}{2\pi\gamma^3}\right)^{1/2} \underbrace{\exp\left(-\frac{1}{2\gamma^2}x^2 - \frac{1}{2\gamma^2}w^2\right)}_{= \exp\left(-\frac{1}{2\gamma^2}[(x-\mu)^2 + 2\gamma^2w]\right)} \mathbb{1}_{\{x \leq 0\}}$$

$$\begin{cases} = \frac{\exp(-1/2\gamma)}{1 - \Phi(\frac{1}{\sqrt{\gamma}})} \int_{-\infty}^w \left(\frac{1}{2\pi\gamma^3}\right)^{1/2} \exp\left(-\frac{1}{2\gamma^2}x^2 - \frac{1}{2\gamma^2}(w-\mu)^2\right) \mathbb{1}_{\{x \geq 0\}} & \text{if } w \geq 0 \\ 0 & \text{otherwise} \end{cases}$$

Same as previously,  $P(N \leq \omega) = P(X < \infty, U \leq \omega)$

$$= \frac{\exp(-1/2\gamma)}{1 - \Phi(\frac{1}{\sqrt{\gamma}})} \int_{\mathbb{R}} \left(\frac{1}{2\pi\gamma^3}\right)^{1/2} \exp\left(-\frac{(x-\mu)^2}{2\gamma^2}\right) \mathbb{1}_{\{x \geq 0\}}$$

$= 1$   
(inverse gaussian distribution  
with parameters  $(\gamma, 1)$ )

$$\text{So } P(X \leq w | U \leq \omega) = \int_{-\infty}^w \left(\frac{1}{2\pi\gamma^3}\right)^{1/2} \exp\left(-\frac{1}{2\gamma^2} \frac{(x-\mu)^2}{x}\right) \mathbb{1}_{\{x \geq 0\}}$$

$$= F_{IG}(\omega) \text{ with parameters } (\gamma, 1).$$

### Exercise 3

1. (a).

Let  $f$  be a measurable function:

$$\mathbb{E}[f(Y)] = \mathbb{E}[f(\Psi(X))] = \int_{\Omega} f(\Psi_1(u)) g(u) du = \int_{\Omega_1} f(\Psi_1(u)) g(u) du + \int_{\Omega_2} f(\Psi_2(u)) g(u) du$$

$$\mathbb{E}[f(Y)] = \int_{\Delta} f(y) |\Psi_1^{-1}(y)| g(\Psi_1^{-1}(y)) dy + \int_{\Delta} f(y) |\Psi_2^{-1}(y)| g(\Psi_2^{-1}(y)) dy$$

$$\mathbb{E}[f(Y)] = \int_{\Delta} f(y) [|\Psi_1^{-1}(y)| g(\Psi_1^{-1}(y)) + |\Psi_2^{-1}(y)| g(\Psi_2^{-1}(y))] dy$$

This works for every  $f$  measurable:

$\Rightarrow$

$$\forall y \in \Delta, h(y) = |\Psi_1^{-1}(y)| \cdot g(\Psi_1^{-1}(y)) + |\Psi_2^{-1}(y)| \cdot g(\Psi_2^{-1}(y))$$

1. (b).

Let  $f$  be a measurable function and  $X$  the random variable obtained by Algorithm 2.

$$\mathbb{E}[f(X)] = \mathbb{E}[f(X), X \in \Omega_1] + \mathbb{E}[f(X), X \in \Omega_2]$$

$$= \mathbb{E}[f(X), X = \Psi_1^{-1}(y)] + \mathbb{E}[f(X), X = \Psi_2^{-1}(y)]$$

$$= \int_{\Delta} f(\Psi_1^{-1}(y)) h(y) dy \frac{|\Psi_1^{-1}(y)| g(\Psi_1^{-1}(y))}{h(y)} + \int_{\Delta} f(\Psi_2^{-1}(y)) h(y) dy \frac{|\Psi_2^{-1}(y)| g(\Psi_2^{-1}(y))}{h(y)}$$

$$= \int_{\Delta} f(\Psi_1^{-1}(y)) |\Psi_1^{-1}(y)| g(\Psi_1^{-1}(y)) dy + \int_{\Delta} f(\Psi_2^{-1}(y)) |\Psi_2^{-1}(y)| g(\Psi_2^{-1}(y)) dy$$

$$= \int_{\Omega_1} f(u) g(u) du + \int_{\Omega_2} f(u) g(u) du$$

$$\mathbb{E}[f(X)] = \int f(u) g(u) du$$

so  $X$ 's distribution is  $g$ .

$$2.(a) \frac{(u-n)^2}{n^2 u} = y \Leftrightarrow u^2 - 2u n + n^2 - n^2 u y = 0$$

$$\Leftrightarrow u^2 - u(2n + n^2 y) + n^2 = 0$$

There are two solutions for this second order equation:  $u_1$  and  $u_2$ :

$$u_1 u_2 = n^2$$

and:

$$u_i = \frac{1}{2} n (2 + ny) \pm \frac{1}{2} \sqrt{n^2 (2 + ny)^2 - 4n^2}, \quad i=1,2$$

If we study the variations of  $\Psi(u)$ ,  $u \in \mathbb{R}_+$

$$\frac{d}{du} \Psi(u) = \frac{2u(u-n) - (u-n)^2}{n^2 u^2} = \frac{(u+n)}{n^2 u^2} (u-n)$$

so

$$\Psi(0_1) = R_+ \text{ and } \Psi(0_2) = R_+$$

and knowing that  $u_1 < u_2$

We get

$$\psi_1^{-1}(y) = n + \frac{1}{2} n^2 y - \frac{1}{2} n \sqrt{4ny + (ny)^2} \in [0, \infty]$$

$$\text{and } \psi_2^{-1}(y) = \frac{n^2}{\psi_1^{-1}(y)} \in ]n, +\infty[$$

2.(b) if  $Y \sim N(0,1)$  what is the distribution of  $Y^2 \sim h_2(y) dy$

$$\text{we define: } \phi: \mathbb{R} \rightarrow \mathbb{R}_+$$

$$u \mapsto u^2$$

$$\phi_+: \mathbb{R}_+ \rightarrow \mathbb{R}_+$$

$$u \mapsto u^2$$

$$\phi_-: \mathbb{R}_- \rightarrow \mathbb{R}_+$$

$$u \mapsto u^2$$

$\phi_+$  is a  $C^1$ -diffeomorphism so is  $\phi_-$ .

$$\phi_+^{-1}: \mathbb{R}_+ \rightarrow \mathbb{R}_+ \quad \text{and} \quad \phi_-^{-1}: \mathbb{R}_+ \rightarrow \mathbb{R}_- \\ n \mapsto \sqrt{n} \qquad \qquad \qquad n \mapsto -\sqrt{n}$$

$$(\phi_+^{-1})'(n) = \frac{1}{2\sqrt{n}} = -(\phi_-^{-1})'(n)$$

We applye then the result of question 1.(a)

$$\forall y \in \mathbb{R}_+, h_2(y) = \frac{1}{2\sqrt{n}} \left( \frac{1}{\sqrt{2\pi}} \exp(-\frac{1}{2}y) + \frac{1}{2\sqrt{n}} \frac{1}{\sqrt{2\pi}} \exp(-\frac{1}{2}y) \right)$$

$$h_2(y) = \frac{1}{\sqrt{2\pi n}} \exp(-\frac{1}{2}y)$$

We now have to prove that steps 2 to 8 are equivalent to Algorithm 2:

Actually:

$$\psi_2^{-1}(y) \psi_1^+(y) = n^2 \Rightarrow \psi_2'^{-1}(y) \psi_1^+(y) + \psi_2^{-1}(y) (\psi_1^+)'(y) = 0$$

$$\Rightarrow \frac{[\psi_2^{-1}]'(y)}{[\psi_1^+]'(y)} = - \frac{\psi_2^{-1}(y)}{\psi_1^+(y)}$$

$$\Rightarrow \left| \frac{[\psi_2^{-1}]'(y)}{[\psi_1^+]'(y)} \right| = \frac{n^2}{|\psi_1^+(y)|^2} = \frac{n^2}{X^2}$$

$$g(\psi_2^{-1}(y)) = \left( \frac{\lambda}{2\pi} \right)^{\frac{1}{2}} \left( \frac{1}{\psi_2^{-1}(y)} \right)^{\frac{3}{2}} \exp \left( - \lambda \psi(\psi_2^{-1}(y)) \right)$$

$$= \left( \frac{\lambda}{2\pi} \right)^{\frac{1}{2}} \left( \frac{1}{\psi_2^{-1}(y)} \right)^{\frac{3}{2}} \exp(-\lambda Y)$$

$$\text{so: } \frac{g(\psi_2^{-1}(y))}{g(\psi_1^+(y))} = \left( \frac{\psi_1^+(y)}{\psi_2^{-1}(y)} \right)^{\frac{3}{2}} = \frac{X^3}{N^3}$$

This means that

$$\left[ 1 + \left| \frac{[\Psi_2^{-1}]'(x)}{[\Psi_1^{-1}]'(y)} \right| \frac{g(\Psi_2^{-1}(y))}{g(\Psi_1^{-1}(y))} \right]^{-1} = \left( 1 + \frac{x}{y} \right)^{-1} = \frac{y}{x+y}$$

This means that steps 2 to 8 yields:  $X \sim \text{IG}(1, N)$

Algorithm 3 repeats these steps until  $X$  is inferior to  $t$

This means that Algorithm 3 yields an inverted gamma with parameters:  $(1, N)$

and truncated in  $[0, t]$ .

## 4 Problem

### 4.1 Rejection Method

1.  $\Leftarrow$  This one is easy:

$$\begin{cases} \exists q \geq 0 \text{ s.t. } u \leq S_{2q+1}(n) \\ S_{2q+1}(n) < f_x(u) \end{cases} \Rightarrow u \leq f_x(u)$$

$\Rightarrow$  To prove this we need to prove, first, that  $S_n(n)$  converges

Set  $n \in \mathbb{N}_+^*$ :  $\forall n \geq 0$

$$n^2 a_n(n) \underset{\cancel{\text{if } n \text{ even}}}{\cancel{\rightarrow}} (n + \frac{1}{2}) n^2 \left[ \exp \left( - \frac{2(n+1)\gamma_2^2}{n} \right) \right] \underset{n \rightarrow \infty}{\rightarrow} \exp \left[ - \frac{(n+1)^2 \pi^2}{2} \right]$$

$$\Rightarrow n^2 a_n(n) = O \left[ n^3 \exp \left( - \text{const. } n^2 \right) \right], \dots$$

$$\Rightarrow n^2 a_n(n) \xrightarrow[n \rightarrow \infty]{} 0$$

$$\text{and thus } S_n(n) \xrightarrow[n \rightarrow \infty]{} S(n)$$

Let's suppose now that

$$\exists u > 0 \text{ s.t.}$$

$$u < f_\alpha(u) \text{ and } \forall q \geq 0 : S_{2q+1}(u) < u$$

$$\Rightarrow S_{2q+1} \xrightarrow[q \rightarrow \infty]{} S^{(1)}(u) < u < f_\alpha(u) \leq \lim_{q \rightarrow \infty} S_{2q}(u)$$

$$\Rightarrow \limsup_{n \rightarrow \infty} S_n(u) \neq \liminf_{n \rightarrow \infty} S_n(u) (= S^{(1)}(u))$$

which is absurd

Q.

$$\text{Set: } V = \frac{U}{S_0(u)} \in [0, 1] \text{ s.t. } V \sim U([0, 1])$$

We know that  $\exists K > 0$  s.t.  $g(x) = K S_0(x)$ ,  $\forall x$

when we stop at  $n$  odd (i.e.  $n = 2q+1$ ): we have:

$$U \leq S_{2q+1}(X) \Rightarrow \frac{U}{g(X)} = \frac{U}{K S_0(u)} \leq \frac{S_{2q+1}(X)}{g(X)}.$$

$$\Rightarrow \frac{U}{K} \leq \frac{S_{2q+1}(X)}{g(X)}$$

This means that:

$$V \leq \frac{S_{2q+1}(X)}{g(X)} K \leq K \frac{f_\alpha(X)}{g(X)}$$

Algorithm 4 is then a readaptation of the rejection algorithm to

sample  $X \sim f_\alpha$  d.u

## 4.2 Sampling the proposal distribution:

1. Back to the definition:  $\forall u \in \mathbb{R}_+^*$

$$S_0(u) = \cosh(3) \exp(-\frac{u^2 3^2}{2}) \cdot \frac{\pi}{2} \begin{cases} (\frac{2}{\pi u})^{\frac{3}{2}} \exp(-\frac{1}{2u}), & u \in [0, t] \\ \exp(-\frac{\pi^2 u}{8}), & u > t \end{cases}$$

$$S(u) = \frac{\pi}{2} \cosh(3) \left(\frac{2}{\pi u}\right)^{\frac{3}{2}} \exp\left(-\frac{u^2 3^2 + 1}{2u}\right) \mathbb{1}_{[u \in [0, t]]} + \frac{\pi}{2} \cosh(3) \exp\left(-\left(\frac{3^2 + \pi^2}{8}\right)u\right) \mathbb{1}_{[u \in [t, \infty))}$$

$$g_0(u) = \frac{\pi}{2} \cosh(3) \left(\frac{2}{\pi u}\right)^{\frac{3}{2}} \exp\left(-\frac{(u^2 - 1)^2}{2u} - 3\right) \mathbb{1}_{[u \in [0, t]]} + \frac{\pi}{2} \cosh(3) \exp\left(-\left(\frac{3^2 + \pi^2}{8}\right)u\right) \mathbb{1}_{[u \in [t, \infty))}$$

$$g_0(u) = \frac{\pi}{2} \cosh(3) \exp(-3) \left(\frac{2}{\pi u}\right)^{\frac{3}{2}} \exp\left(-\frac{(u^2 - 1)^2}{2u \left(\frac{1}{K}\right)^2}\right) \mathbb{1}_{[u \in [0, t]]} + \frac{\pi}{2} \cosh(3) \exp(Ku) \mathbb{1}_{[u \in [t, \infty))}$$

$$\text{where } K = \frac{3^2 + \pi^2}{8}$$

We define:  $g_1(u) \stackrel{d}{=} g_0(u) \sim \text{IG}(\lambda, \nu)$

$$g_2(u) \stackrel{d}{=} g_0(u) \sim \mathcal{E}(K)$$

$$\text{with } \lambda = 1$$

$$\nu = \frac{1}{3}$$

$$K = \frac{3^2 + \pi^2}{8}$$

Then clearly:  $g(u) = (1-\alpha) g_1(u) \mathbb{1}_{[0, t]}(u) + \alpha g_2(u) \mathbb{1}_{[t, \infty)}(u)$

$$1 = \int_{\mathbb{R}_+} g(u) du = ((st)^{-1} \int_{\mathbb{R}_+} S_0(u) du)$$

$$\int_{\mathbb{R}_+} S_0(u) du = \left[ \int_{[0, t]} \exp(-3) \left(\frac{2}{\pi u}\right)^{\frac{3}{2}} \sqrt{2\pi} g_1(u) du + \int_t^{+\infty} \frac{1}{K} \exp(Ku) \frac{\pi}{2} \cosh(3) du \right]$$

$$cst = \frac{\pi}{2} \cosh(3) \left[ \frac{4}{\pi} \exp(-3) F_{\text{IG}}(t) + K^{-1} \exp(-Kt) \right]$$

$$\alpha = \int_t^{+\infty} g(u) du = \int_t^{+\infty} ((st)^{-1} S_0(u)) du = \frac{\frac{\pi}{2} \cosh(3) K^{-1} \exp(-Kt)}{[K^{-1} \exp(-Kh) + F_{\text{IG}}(t)] 4\pi^{-1} \exp(-3) \frac{\pi}{2} \cosh(3)}$$

20 Let  $Y = t + X$  and  $X \sim E(\lambda)$ , Set  $f$  measurable function:

$$\mathbb{E}[f(Y)] = \int_{\mathbb{R}} f(t+u) \lambda \exp(-\lambda u) \mathbb{I}_{u \in \mathbb{R}_+} du$$

$$= \int_{\mathbb{R}} f(y) \lambda \exp(-\lambda y) \exp(\lambda t) \mathbb{I}_{y \in [t, +\infty)} dy$$

We can observe that

$$e^{-\lambda t} = \left[ \int_t^{+\infty} \lambda e^{-\lambda u} du \right]^{-1}$$

So  $t + X$  is just the truncated exponential with parameter  $\lambda$  and in the interval  $[t, +\infty]$ .

### Algorithm 5: Sample G2

1. Draw  $U \sim U[0,1]$

2.  $G2 \leftarrow -\frac{\log(U)}{\lambda}$

3.  $G2 \leftarrow G2 + t$

4. Return  $G2$

### Algorithm 6: Sample G1

1. If  $t < \frac{1}{3}$

2.  $G1 \leftarrow$  Algorithm 1

3. else

4.  $G1 \leftarrow$  Algorithm 3

5. end.

6. Return  $G1$

$$F_{G_1}(u) = \begin{cases} (1-\alpha) \bar{F}_{IG}(u), & u \leq t \\ (1-\alpha) \bar{F}_{IG}(t) + \alpha \bar{F}_{G_2}(u), & u > t \end{cases} \Rightarrow F_{G_1}^{-1}(u) = \begin{cases} \bar{F}_{IG}^{-1}\left(\frac{u}{1-\alpha}\right), & u \leq (1-\alpha) \bar{F}_{IG}(t) \\ \bar{F}_{G_2}^{-1}\left(\frac{u - (1-\alpha) \bar{F}_{IG}(t)}{\alpha}\right), & u > (1-\alpha) \bar{F}_{IG}(t) \end{cases}$$

### Algorithm 7: Sample G

1. Draw  $U \sim U[0,1]$
2. If  $U < 1-\alpha$
3.      $X \leftarrow \text{sample G1}$
4. else
5.      $X \leftarrow \text{sample G2}$
6. end
7. return  $X$

In fact, let  $f$  be a measurable function

$$\begin{aligned} E[f(X)] &= E[f(X), U < 1-\alpha] + E[f(X), U > 1-\alpha] \\ &= \int f(u) \cdot g_1(u) \mathbb{1}_{u \in [0, 1-\alpha]}(1-\alpha) du + \int f(u) \cdot g_2(u) \mathbb{1}_{u \in [1-\alpha, 1]}(1-(1-\alpha)) du \\ &= \int_{\mathbb{R}_+} f(u) g(u) du \end{aligned}$$

### 4.3 Implementation

#### Algorithm 8: HomeWork1

1. repeat
2.      $n \leftarrow 3$ ;
3.      $X \leftarrow \text{sample G};$
4.     Draw  $U \sim U[0, S_0(X)]$ ;
5.     Iteratively calculate  $S_n(X)$ , starting at  $S_1(X)$  and until  
 $U \leq S_n(X)$  for an odd  $n$  or  $U > S_n(X)$  for an even  $n$ ;
6. until  $n$  is odd
7. return  $X$

(i) c.f Figure 1

(ii)

$$z = 3000, \quad \mathbb{E}[T_{1/4}] = 2,7561 \cdot 10^5$$

$$z = 2000, \quad \mathbb{E}[T_{1/4}] = 1,1924 \cdot 10^5$$

$$z = 1000, \quad \mathbb{E}[T_{1/4}] = 3,155 \cdot 10^4$$

