

Importance Sampling for Failure Recovery Probabilities in Computing and Data Transmission

Søren Asmussen

Aarhus University, Denmark

<http://home.imf.au.dk/asmus>

Efficient Monte Carlo:
From Variance Reduction to
Combinatorial Optimization

A Conference on the Occasion of
R.Y. Rubinstein's 70th Birthday

Sandbjerg, July 14, 2008

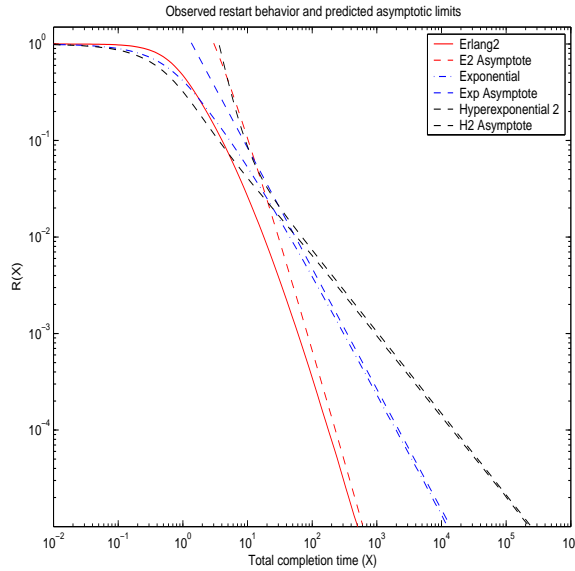
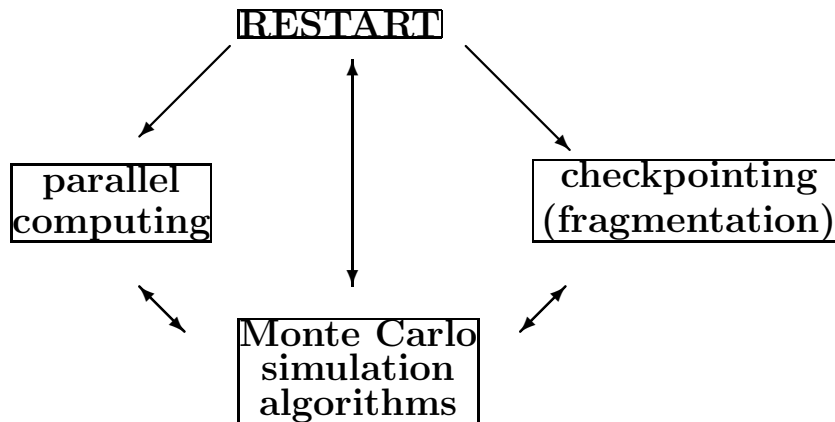


Figure 1: Sheahan, Lipsky, Fiorini 05

Power tails?

SA, Fiorini, Lipsky, Rolski, Sheahan
 Asymptotic total task times for tasks
 that must restart after a failure occurs
Mathematics of Operations Research 08/09
 (related work of Jelenkovic & Tan)



Lars Nørvang Andersen, SA+ 2-3 working papers

1. RESTART asymptotics
2. IS when $T \equiv t$
3. IS when T gamma-like
4. Role of rootfinding
5. IS when T reg. var.
6. Running time issues

RESTART

T ideal job time $\sim F$
(program time; file length;
call center time)

U failure time $\sim G$
(often exponential)

X total time $\sim H$

$$\frac{T}{\frac{U_1}{\frac{U_2}{\frac{U_N}{U_{N+1}}}}} \quad X = T + U_1 + \dots + U_N$$

Target: tail $\bar{H}(x) = \mathbb{P}(X > x)$

T bounded $\Rightarrow \bar{H}(x) \approx e^{-\gamma x}$

T unbd $\Rightarrow H$ heavy-tailed

4 examples of each of F, G :

LT Weibull
 exponential
 HT Weibull
 power

$\cdot \frac{\bar{F}(t)}{\bar{G}(u)}$	e^{-t^2}	e^{-t}	$e^{-t^{1/2}}$	$\frac{1}{t^\alpha}$
e^{-u^2}	$\frac{1}{x}$	$e^{-\log^{1/2} x}$	$e^{-\log^{1/4} x}$	$\frac{1}{\log^{\alpha/2} x}$
e^{-u}	$e^{-\log^2 x}$	$\frac{1}{x}$	$e^{-\log^{1/2} x}$	$\frac{1}{\log^\alpha x}$
$e^{-u^{1/2}}$	$e^{-\log^4 x}$	$e^{-\log^2 x}$	$\frac{1}{x}$	$\frac{1}{\log^{2\alpha} x}$
$\frac{1}{u^\alpha}$	$e^{-x^{\frac{2}{2+\alpha}}}$	$e^{-x^{\frac{1}{1+\alpha}}}$	$e^{-x^{\frac{1/2}{1/2+\alpha}}}$	$\frac{1}{x}$

Constants omitted $e^{-c \log^{1/2} x}$; $\frac{1}{x} = e^{-\log x}$

In some corners even $\log \log$ asymptotics

Omitted case: T bounded (later)

Also: cases of exact asymptotics
 (close-to-diagonal)

RESTART with $T \equiv t$,
 G exponential(μ)

$$\begin{array}{r} t \\ \hline U_1 \\ \hline U_2 \\ \hline U_N \\ \hline U_{N+1} \\ \hline \end{array} \quad X = t + U_1 + \cdots + U_N$$

Geometric sum

Geometric Sums and Renewal Theory

$$S_N = V_1 + \cdots + V_N$$

$$V_n \sim F, N \text{ geom}(\rho)$$

$$Z(x) = \mathbb{P}(S_N > x) \text{ solves}$$

$$Z(x) = \rho \bar{F}(x) + \int_0^x Z(x-y) \rho F(dy) \quad (1)$$

Defective renewal equation

Solution exponentially decaying

Lundberg inequality

$\rho F(dy)$ has mass $\rho < 1$

Choose γ as solution of

$$\int_0^\infty e^{\gamma x} \rho F(dx) = 1$$

(assumes light tails)

Let $F^*(dx) = e^{\gamma x} \rho F(dx)$

$\dots Z^*(x) = e^{\gamma x} Z(x)$

$$\dots z^*(x) = e^{\gamma x} \rho \bar{F}(x)$$

Multiply (1) by $e^{\gamma x}$

$$Z(x) \sim Ce^{-\gamma x}$$

Cramér-Lundberg approximation

Geometric Sums and Change of Measure

$$\rho \int_0^{\infty} e^{\gamma x} F(dx) = 1$$

$$\tilde{F}(dx) = \rho e^{\gamma x} F(dx)$$

$$\tau(x) = \inf\{n : S_n > x\}$$

$$\begin{aligned} \mathbb{P}(S_N > x) &= \mathbb{P}(N \geq \tau(x)) \\ &= \tilde{\mathbb{E}}[\mathbf{LR}; N \geq \tau(x)] \\ &= \tilde{\mathbb{E}}[\rho^{-\tau(x)} e^{-\gamma S_{\tau(x)}} \rho^{\tau(x)}] \\ &= \tilde{\mathbb{E}} e^{-\gamma S_{\tau(x)}} \end{aligned}$$

IS estimator $Z(x) = e^{-\gamma S_{\tau(x)}}$

Bounded relative error

$$\limsup \text{Var} Z(x) / \mathbb{P}(S_N > x)^2 < \infty$$

SA, Glynn p. 172; typos!!

Blanchet et al.

RESTART with $T \equiv t$,
 G exponential(μ)

$$\begin{array}{r} t \\ \hline U_1 \\ \hline U_2 \\ \hline U_N \\ \hline U_{N+1} \\ \hline \end{array} \quad X = t + U_1 + \cdots + U_N$$

$$\begin{aligned} 1 &= \int_0^t e^{-\gamma(t)y} \mu e^{-\mu y} dy \\ &= \frac{\mu}{\mu - \gamma(t)} (1 - e^{-(\mu - \gamma(t))t}) \end{aligned}$$

Algorithm 0

Simulate U 's

as exponential($\mu - \gamma(t)$)
truncated to $[0, t]$

Return $Z_0(x) = e^{-\gamma(t)} S_{\tau(x-t)}$

Random T

$$\begin{aligned}\overline{H}(x) &= \mathbb{P}(X > x) \\ &= \int_0^\infty \mathbb{P}(X > x \mid T = t) f(t) dt \\ &\sim \int_0^\infty C(t) e^{-\gamma(t)x} f(t) dt \\ &\sim \int_{t_0}^\infty C(t) e^{-\gamma(t)x} f(t) dt \\ &\sim \int_{t_0}^\infty 1 \cdot e^{-\mu \overline{G}(t)x} f(t) dt\end{aligned}$$

Close-to-diagonal:

assume F, G are connected

s.t. $y = \overline{G}(t)$ leads to

integral of Abelian/Tauberian type.

$$f(t) = g(t) \overline{G}(t)^{\beta-1} L_0(\overline{G}(t))$$

F Gamma-like: $\bar{F}(x) \sim cx^{\alpha-1}e^{-\lambda x}$
 $g(t) = \mu e^{-\mu t}$

$$\beta = \lambda/\mu$$

$$\bar{H}(x) \sim \frac{c\Gamma(\beta)}{\mu^{\alpha+\beta}} \frac{\log^{\alpha-1} x}{x^\beta}$$

General principle for IS:

conditional distributions

RESTART:

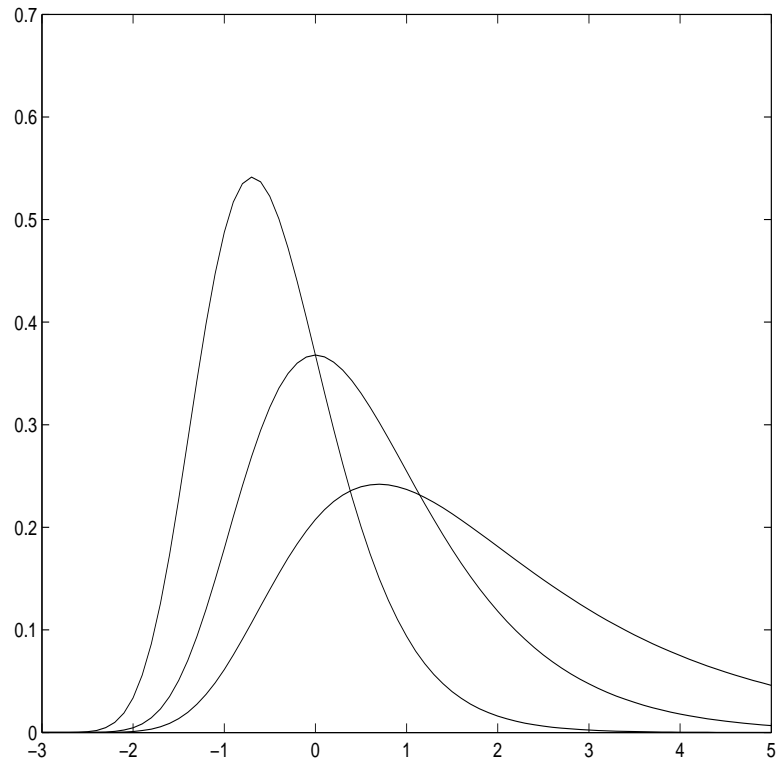
T given $X > x$?

$$Y = \mu T - \log x - \log \mu \rightarrow Q_\beta$$

$$q_\beta(y) = \exp\{-e^{-y} - \beta y\}/\Gamma(\beta)$$

$\beta = 1$: Gumbel (Fisher-Tippett)

$\beta \neq 1$: exponential tilting



Algorithm 1:

- 1) Simulate $Y = -\log \Gamma(\beta)$
from Q_β
- 2) Let $T = (Y + \log x + \log \mu) / \mu$
- 3) Given $T = t$, use CMC
for failures in $[0, x - t]$
- 4) Compute LR corrected
estimator

Worse than CMC

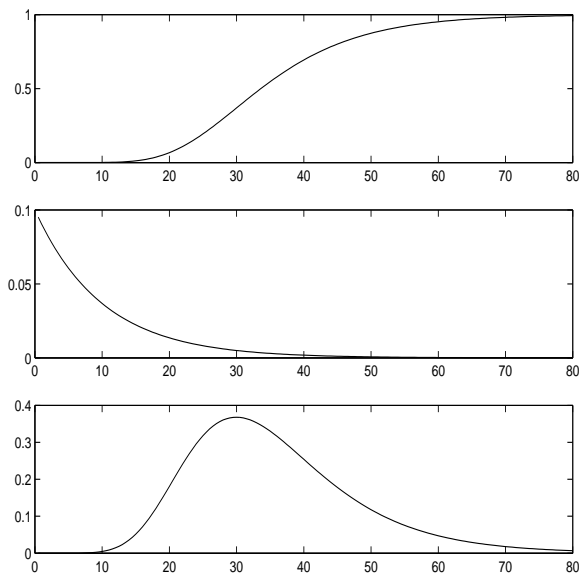


Figure 2:

Algorithm 1':

- 1) Simulate $Y = -\log \Gamma(\beta)$
from Q_β
- 2) Let $T = (Y + \log x + \log \mu) / \mu$
- 3') Given $T = t$, use
Algorithm 0 ($\gamma(t)$)
for failures in $[0, x - t]$
- 4) Compute LR corrected
estimator

Bounded relative error

The Role of Rootfinding

$$1 = \int_0^t e^{\gamma(t)y} g(y) dy$$

Algorithm 0

1) Simulate U 's from

$$e^{\gamma(t)y} g(y), 0 < y < t$$

2) Return $Z(x) = e^{-\gamma(t)S_{\tau(x-t)}}$

Set-up when $T \equiv t$

Each time if T random

Algorithm 0[#]

1) Simulate U 's from

$$g(y)/G(t), 0 < y < t$$

2) Return $Z_0^{\#} = G(t)^{\tau(x-t)}$

$$\text{Var} Z_0^{\#} \sim \exp\{-(\gamma(t) + \xi(t))x\}$$

$$1 = G(t) \int_0^t e^{(\gamma(t)+\xi(t))y} g(y) dy$$

$\xi(t) < \gamma(t) \Rightarrow$ not bd. rel. err.

But $\xi(t) \sim \gamma(t)$ as $t \rightarrow \infty$

F Gamma-like: $\bar{F}(x) \sim cx^{\alpha-1}e^{-\lambda x}$

$g(t) = \mu e^{-\mu t}$

Algorithm 3#:

1) Simulate $Y = -\log \Gamma(\beta)$
from Q_β

2) Let $T = (Y + \log x + \log \mu) / \mu$

3#) Given $T = t$, use
Algorithm 0#
for failures in $[0, x - t]$

4) Compute LR corrected
estimator

Bounded relative error

Sheahan's exp-exp example

Algorithm 3[#], 10^3 replications
Runs in 50 seconds

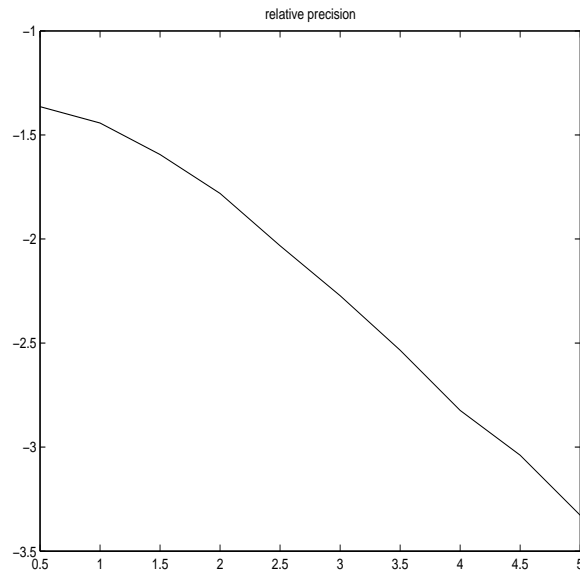


Figure 3:

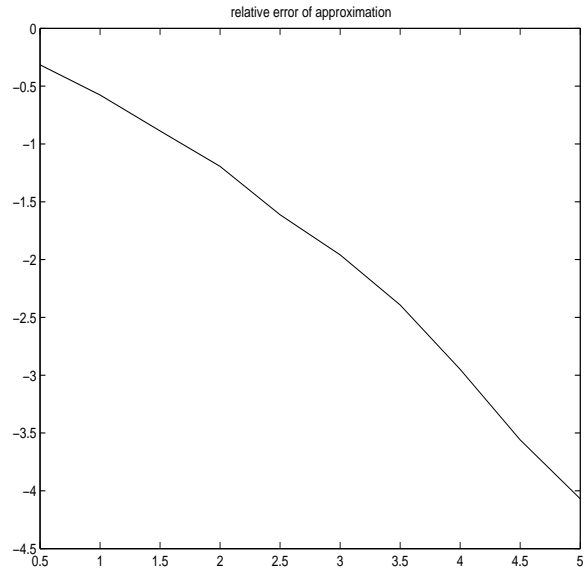


Figure 4:

T reg. varying

$$f(t) = L(t)/t^{\alpha+1}$$

$$\bar{H}(x) \sim \frac{L(\log x)\mu^\alpha}{\alpha \log^\alpha x}$$

Bare-hand calculations ...

$\mu T / \log x - 1$ has Pareto limit

Algorithm 2':

1) Simulate Y

from $\alpha/(1+y)^{\alpha+1}$

2) Let $T = \log x/\mu + \log x Y/\mu$

3') Given $T = t$, use

CMC, Alg. 0 or 0[#]

for failures in $[0, x - t]$

4) Compute LR corrected estimator

Absolute continuity fails

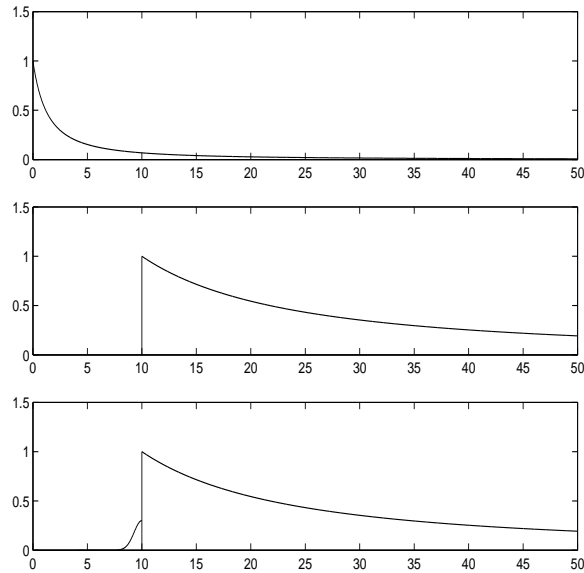


Figure 5:

Alg. 2' only gives

$$\mathbb{P}(X > x, T < \log x / \mu)$$

$\mathbb{P}(X > x, T < \log x / \mu)$?

Separate simulation

$\log x - \mu T \mid X > x, T < \log x / \mu$

has limit with density

$$e^{-e^z} / E_1(1)$$

Algorithm 2'':

- 1) Simulate Y
from $e^{-e^z} / E_1(1)$
- 2) Let $T = \log x / \mu - Y / \mu$
- 3') Given $T = t$, use
Alg. 0 or 0[#]
for failures in $[0, x - t]$
- 4) Compute LR corrected
estimator

Overall estimator: $Z'_2(x) + Z''_2(x)$

Bounded relative error

Running Time Issues

Variance σ^2 /replication
or rel. sq. error $\sigma^2/\mathbb{P}(X > x)^2$
too limited a criterion

Must consider also

$\mathbb{E}(\text{CPU time}) \tau$

Rel. sq. error / unit CPU time:

$$\frac{\tau \sigma^2}{\mathbb{P}(X > x)^2}$$

Present algorithms: $\tau \approx x$
(X is generated
as sum of failures)

Present algorithms: $\tau \approx x$
(X is generated
as sum of failures)

Comparison with CMC

Generate X , return $1(X > x)$

sometimes $\tau = \infty$

(Robert Sheahan's problem?)

always improved efficiency

But: Could stop when sum $\geq x$

Then $\tau \leq x$

Picture less clear