

2. $X_i \sim \text{Bern}(p=0.2)$

$$S_n = \sum_{i=1}^n X_i \quad \Theta = P(S_n > a), \quad n=40, \quad a=16$$

By Cramer's we get that $\frac{1}{n} \log P(S_n > a) = -I(a)$

$$\text{where } I(a) = \sup_{\theta} (\theta a - \psi(\theta))$$

so we pick θ^* s.t. $a = \psi'(\theta^*)$

From example 9u we know that for $E[\theta]$ and S_n that

$$\psi(\theta) = \sum_{i=1}^n p_i e^{\theta} + 1 - p_i$$

$$= (p e^{\theta} + 1 - p)^n \quad \text{when } p_i = p \quad \forall i$$

$$\text{so } \psi(\theta) = n \log(p e^{\theta} + 1 - p)$$

$$\text{and } \psi'(\theta) = \frac{n p e^{\theta}}{p e^{\theta} + 1 - p}$$

$$\text{so we pick } \theta^* \text{ s.t. } a = \frac{n p e^{\theta^*}}{p e^{\theta^*} + 1 - p}$$

$$\text{so } \theta^* = \ln\left(\frac{a(1-p)}{p(n-a)}\right)$$

rather than simulate $I(S_n > a)$ directly by generating $X_i \sim \text{Bern}(p)$

we instead simulate $I(S_n > a) \psi(\theta^*) e^{-\theta^* S_n}$ where $X_i \sim \text{Bern}(e^{\theta^*})$

$$\text{in our problem } \theta^* = \ln\left(\frac{8}{3}\right), \quad \psi(\theta^*) = (2e^{\theta^*} + 0.8)^{40}, \quad e^{-\theta^* S_n} = \left(\frac{3}{8}\right)^{S_n}$$

$$= \left(\frac{4}{3}\right)^{40}$$

Raw E: 0.002887. Tilted E: 0.002943

Raw Var: 2.9e-05. Tilted Var: 0.0

3.

By Siegmund we choose θ^* s.t. $\psi(\theta^*) = 0$, $\psi(\theta^*) = 1$

For the normal dist. $\psi(\theta) = \theta\mu + \frac{1}{2}\sigma^2\theta^2$

$$\text{so } \theta^*\mu + \frac{1}{2}\theta^2\sigma^2 = 0$$

$$\theta^* = \frac{-2\mu}{\sigma^2}$$

Thus to find $P(\tau(x) < \infty)$, $\tau(x) = \inf\{n: S_n > x\}$, $S_n = \sum_{i=1}^n X_i$, ~~$X_i \sim N(\mu, \sigma^2)$~~

where $X_i \sim N(\mu, \sigma^2)$ we can generate the X_i with

$X_i \sim N(\mu + \theta^*\sigma^2, \sigma^2)$ and find

$$P(\tau(x) < \infty) = \frac{1}{n} \sum_{i=1}^n e^{-\theta^* X} e^{-\theta^* B^{(i)}(x)}$$

where $B(x) = S_{\tau(x)} - x$

The following algorithm suffices to simulate $P(\tau(x) < \infty) = P$

$E = []$ $X = 10$ $\theta^* = .4$

$B = []$ $\mu = -.1$ $\sigma^2 = .5$

$N \in \mathbb{R}$

for i in range(N)

$S_{\tau(x)} = \alpha \sim N(\mu + \theta^*\sigma^2, \sigma^2)$

while $S_{\tau(x)} \leq x$

$S_{\tau(x)} += \alpha \sim N(\mu + \theta^*\sigma^2, \sigma^2)$

$B[i] = S_{\tau(x)} - x$

$E.append(e^{-\theta^* X} \frac{1}{|B|} \sum_{k=1}^{|B|} e^{-\theta^* B[k]})$

return $\frac{P}{|E|}$ $mean(E)$, $var(E)$

E: 0.015574615063278889, Var: 1.1624724272507568e-09

95% CI: (0.015574612068376651, 0.015574618058181127)

4.

Let $\Delta_n = S_n - T_{n+1}$, then $E[\Delta] < 0$ and $D_n = (D_{n-1} + \Delta_{n-1})^+$ follow

$$D_n \triangleq \max_{k \leq n} \sum_{i=1}^k \Delta_i = M_n, \text{ so } P(D_n \geq d) \triangleq P(D > d) \text{ in steady state}$$

$$\text{and } P(D > d) = P(M > d) = P(\tau(d) < \infty), \tau(d) = \inf\{n: R_n > d\}$$

$$\text{where } R_n = \sum_{i=1}^n \Delta_i, \text{ so}$$

$$P(D > d) = e^{-\theta^* d} E_{\theta^*} [e^{-\theta^* B(d)}], B(d) = \sum_{i=1}^{\tau(d)} \Delta_i - d$$

$$\text{thus we pick a } \theta^* \text{ s.t. } E[e^{\theta^* \Delta}] = 1$$

$$\begin{aligned} \text{b/c } E[e^{\theta^* \Delta}] &= E[e^{\theta^* (S-T)}] \\ &= E[e^{\theta^* S}] E[e^{-\theta^* T}] \end{aligned}$$

$$\text{since } T \sim \exp(\lambda), E[e^{-\theta^* T}] = \frac{\lambda}{\lambda + \theta^*}$$

Since S is erlang- k

$$\psi(\theta) = \int_0^{\infty} e^{-\theta t} \frac{\mu^k t^{k-1} e^{-\mu t}}{(k-1)!} dt = I_k$$

$$\text{so } I_1 = \mu \int_0^{\infty} e^{-(\theta+\mu)t} dt = (\mu) \left(-\frac{e^{-(\theta+\mu)t}}{\theta+\mu} \Big|_0^{\infty} \right) = \frac{\mu}{\theta+\mu}$$

$$\text{and } I_{k+1} = \frac{\mu^{k+1}}{k!} \left(t^k e^{-(\theta+\mu)t} \Big|_0^{\infty} + \frac{\mu}{\theta+\mu} \int_0^{\infty} t^k e^{-(\theta+\mu)t} dt \right)$$

$$= \frac{\mu}{\theta+\mu} \int_0^{\infty} e^{-\theta t} \frac{\mu^k t^{k-1} e^{-\mu t}}{(k-1)!} dt$$

$$= \frac{\mu}{\theta+\mu} I_k$$

$$\text{so } \psi(\theta) = \left(\frac{\mu}{\mu+\theta} \right)^k \text{ for erlang dist.}$$

4. cont.

So then

$$E[e^{\theta^* \Delta}] = \left(\frac{\lambda}{\lambda - \theta^*} \right) \left(\frac{\mu}{\mu + \theta^*} \right)^k = 1, \quad k=2$$

since $\mu=3$, $\lambda=1$ we get

$$\left(\frac{1}{1 - \theta^*} \right) \left(\frac{3}{3 + \theta^*} \right)^2 = 1$$

$$\text{and } 3 = (3 + \theta^*) \sqrt{1 - \theta^*} \Rightarrow \theta^* = .697224$$

We can simulate $P(D > d) = e^{-\theta^* d} E_{\theta^*} [e^{-\theta^* B(d)}]$, $B(d) = \sum_{i=1}^{T(d)} \Delta_i - d$

by using $T_i \sim \exp(\lambda - \theta^*)$, $S_i \sim \text{erlang-2}(\mu - \theta^*)$

with the following algorithm

$E = []$ $d = 10$ $\theta^* = .697224$

$B = \{\}$ $\mu = 3$ $\lambda = 1$ $N \in \mathbb{R}$

for k in range(N)

gen $S_i \sim \text{erlang-2}(\mu - \theta^*)$, $T_i \sim \exp(\lambda - \theta^*)$

set $\Delta = 0$

while $\Delta \leq d$

$\Delta \pm S_i - T_i$

$B[i] = \Delta - d$

$E.append(e^{-\theta^* d} \frac{1}{|B|} \sum_{i=1}^{|B|} e^{-\theta^* B[i]})$

return mean(E)

E: 0.005086344730696122