## Part A Simulation and Statistical Programming Hilary 2014 Problem Sheet 2, due Wednesday 5pm Week 5 at SPR1

1. The random variable $X$ has probability mass function

$$
p(x ; s)=\frac{1}{\zeta(s)} \frac{1}{x^{s}}, \quad \text { for } x=1,2,3, \ldots
$$

(a) The normalising constant $\zeta(s)$ is hard to calculate, However, when $s=2$ we do have $\zeta(2)=\pi^{2} / 6$. Give an algorithm to simulate $Y \sim p(y ; 2)$ by inversion.
(b) Implement your algorithm as an R function. Your function should take as input an integer $n>0$ and return a vector of $n$ iid realisations of $Y \sim p(y ; 2)$. State briefly how you checked your code.
(c) Give a rejection algorithm simulating $X \sim p(x)=p(x ; s)$ for $s>2$ using draws from $Y \sim q(y)$ with $q(y)=p(y ; 2)$.
(d) Compute the expected number of simulations of $Y \sim q$ for each simulated $X \sim p$ in the previous part question, giving your answer in terms of $\zeta(s)$.
(e) Implement your algorithm as an R function. Your function should take as input $s$ and return as output $X \sim p(x ; s)$ and the number of trials $N$ it took to simulate $X$.
2. Suppose $X \sim N\left(0, \sigma^{2}\right)$ and we want to estimate $\mu_{\phi}=\mathbb{E}(\phi(X))$ for some function $\phi(x)$ known to have finite mean and variance. Suppose we have samples $Y=\left(Y_{1}, \ldots, Y_{n}\right)$ with $Y_{i} \sim N(0,1), i=1,2, \ldots, n$ iid. Here are two estimators for $\mu_{\phi}$ given in terms of $Y$ :

$$
\widehat{\theta}_{1, n}=\frac{1}{n} \sum_{i=1}^{n} \phi\left(\sigma Y_{i}\right) \quad \widehat{\theta}_{2, n}=\frac{1}{n \sigma} \sum_{i=1}^{n} e^{-Y_{i}^{2}\left(1 / 2 \sigma^{2}-1 / 2\right)} \phi\left(Y_{i}\right) .
$$

(a) Show that $\widehat{\theta}_{1, n}$ and $\widehat{\theta}_{2, n}$ are unbiased and give their variances in terms of expectations of $\phi$ etc.
(b) What range of values must $\sigma$ be in for $\widehat{\theta}_{2, n}$ to have finite variance? Can you give a weaker condition if it is known that $\int_{-\infty}^{\infty} \phi^{2}(x) d x<\infty$ ?
(c) Why might we prefer $\widehat{\theta}_{2, n}$ to $\widehat{\theta}_{1, n}$, for some values of $\sigma^{2}$ and functions $\phi$ ? (Hint: consider estimating $\mathbb{P}(X>1)$ with $\sigma \ll 1)$.
3. We are interested in performing inference for the parameters of internet traffic model.
(a) The arrival rate $\Lambda$ for packets at an internet switch has a log-normal distribution $\operatorname{LogNormal}(\mu, \sigma)$ with parameters $\mu$ and $\sigma$. The $\operatorname{LogNormal}(\mu, \sigma)$ probability density is

$$
p_{\Lambda}(\lambda ; \mu, \sigma)=\frac{1}{\lambda \sqrt{2 \pi \sigma^{2}}} \exp \left(-(\log (\lambda)-\mu)^{2} / 2 \sigma^{2}\right)
$$

Show that if $V \sim N\left(\mu, \sigma^{2}\right)$ and we set $W=\exp (V)$ then $W \sim \operatorname{LogNormal}(\mu, \sigma)$.
(b) Given an arrival rate $\Lambda=\lambda$, the number $N$ of packets which actually arrive has a Poisson distribution, $N \sim \operatorname{Poisson}(\lambda)$. Suppose we observe $N=n$. Show that the likelihood $L(\mu, \sigma ; n)$ for $\mu$ and $\sigma$ is

$$
L(\mu, \sigma ; n) \propto \mathbb{E}\left(\Lambda^{n} \exp (-\Lambda) \mid \mu, \sigma\right) .
$$

(c) Give an algorithm simulating $\Lambda \sim \operatorname{LogNormal}(\mu, \sigma)$ using $Y \sim N(0,1)$ as a base distribution, and explain how you could use simulated $\Lambda$-values to estimate $L(\mu, \sigma ; n)$ by simulating values for $\Lambda$.
(d) Suppose now we have $m$ iid samples

$$
\Lambda^{(j)} \sim \log \operatorname{Normal}(\mu, \sigma), j=1,2, \ldots, m
$$

for one pair of $(\mu, \sigma)$-values. Give an importance sampling estimator for $L\left(\mu^{\prime}, \sigma^{\prime} ; n\right)$ at new parameter values $\left(\mu^{\prime}, \sigma^{\prime}\right) \neq(\mu, \sigma)$, in terms of the $\Lambda^{(j)}$ 's.
(e) For what range of $\mu^{\prime}, \sigma^{\prime}$ values can the $\Lambda^{(j)}$-realisation be safely 'recycled' in this way?

