# Part A Simulation and Statistical Programming HT19 

## Problem Sheet 2 - due Week 4 Thursday 10am

1. Suppose $X$ is a discrete random variable taking values $X \in\{1,2, \ldots, m\}$ with probability mass function (pmf) $p(i)=\operatorname{Pr}(X=i)$. Let $q(i)=1 / m$ be the pmf of the uniform distribution on $\{1,2, \ldots, m\}$. Give a rejection algorithm simulating $X \sim p$ using proposals $Y$ distributed according to $q$. Calculate the expected number of simulations $Y \sim q$ per returned value of $X$ if $p=(0.5,0.25,0.125,0.125)$.
2. Let $Y \sim q$ with probability density function (pdf) $q(x) \propto \exp (-|x|)$ for $x \in \mathbb{R}$. Let $X \sim \mathrm{~N}(0,1)$ be a standard normal random variable, with pdf $p(x) \propto \exp \left(-x^{2} / 2\right)$.
(a) Find $M$ to bound $p(x) / q(x)$ for all real $x$.
(b) Give a rejection algorithm simulating $X$ using $q$ as the proposal pdf.
(c) Can we simulate $Y \sim q$ by rejection using $p$ as the proposal pdf?
3. Consider a discrete random variable $X \in\{1,2, \ldots\}$ with probability mass function

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

where $s>1$.
(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 inversion algorithm as an R function. Your function should take as input an integer $n>0$ and return as output $n$ iid realisations of $Y \sim p(y ; 2)$. Say briefly how you checked your code.
(c) Give a rejection algorithm simulating $X$ with pmf $p(x ; s)$ for $s>$ 2, using the rejection algorithm and draws from $Y \sim q$ where the proposal is $q(y)=p(y ; 2)$. You will need to derive the upper bound $M^{\prime} \geq \tilde{p}(x ; s) / \tilde{q}(x)$ for all $x$.
(d) Compute the expected number of simulations of $Y \sim q$ for each simulated $X$ 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 $X$.
4. Suppose $X \sim N\left(0, \sigma^{2}\right)$ is a Gaussian random variable with mean 0 and variance $\sigma^{2}$. We want to estimate $\mu_{\phi}=\mathbb{E}(\phi(X))$ for some function $\phi$ :
$\mathbb{R} \rightarrow \mathbb{R}$ such that $\phi(X)$ has finite mean and variance. Suppose we have iid samples $Y_{1}, \ldots, Y_{n}$ with $Y_{i} \sim N(0,1), i=1,2, \ldots, n$. We consider the following two estimators for $\mu_{\phi}$ :

$$
\widehat{\theta}_{1, n}=\frac{1}{n} \sum_{i=1}^{n} \phi\left(\sigma Y_{i}\right)
$$

and

$$
\widehat{\theta}_{2, n}=\frac{1}{n \sigma} \sum_{i=1}^{n} \exp \left[-Y_{i}^{2}\left(\frac{1}{2 \sigma^{2}}-\frac{1}{2}\right)\right] \phi\left(Y_{i}\right)
$$

(a) Show that $\widehat{\theta}_{1, n}$ and $\widehat{\theta}_{2, n}$ are unbiased and give the expression of their variances.
(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 $\sigma \ll 1)$.

