## ST425 - Computer session 5

## Q 4.5 - Monte-Carlo Methods

To compute

$$J = \int_{-\infty}^{\infty} g(x)dx = \int_{-\infty}^{\infty} \exp\left(\sin(x) - (x-2)^2\right)dx$$

we can find a density function f(x) of which support is  $(-\infty, \infty)$ , then rewrite J as

$$J = \int_{-\infty}^{\infty} g(x)dx = \int_{-\infty}^{\infty} h(x)f(x)dx$$

where h(x) = g(x)/f(x). Generally, if f(x) is a valid density function  $(f(x) \ge 0 \forall x, \int f(x) dx = 1)$ ,  $\mathbb{E}[h(X)] = \int h(x)f(x)dx$ . So to approximate J, we can (1) sample n independent  $X_1, \ldots X_n$  from  $f(\cdot)$ , (2) compute  $h(X_i)$  for  $i = 1, \ldots, n$  and (3) take the average, i.e.,

$$\hat{J} = \frac{1}{n} \sum_{i=1}^{n} h(\mathbf{X}_i)$$

For Q 4.5(c), by looking at the integral, we notice that one of the natural choices for f(x) is N(2, 1/2) (See the document for R workshop week 5 on Moodle). Then

$$J = \int_{-\infty}^{\infty} h(x)f(x)dx = \int_{-\infty}^{\infty} \sqrt{\pi} \exp\left(\sin(x)\right) \times \frac{1}{\sqrt{\pi}} \exp(-(x-2)^2)dx$$

To implement these 3 steps in R,

```
reps<-1000
X <- rnorm(reps, mean=2, sd = sqrt(1/2))
h <- sqrt(pi)*exp(sin(X))
mean(h); sd(h)/sqrt(reps)</pre>
```

## [1] 3.736936

## [1] 0.03198649

However, there are a number of ways to choose f(x). For example, you can rewrite g(x) as

$$g(x) = \sqrt{\pi} \exp\left(\sin(x) + 4x - 4\right) \times \frac{1}{\sqrt{\pi}} \exp\left(-x^2\right)$$

Then J is approximated by  $\frac{1}{n} \sum_{i=1}^{n} \sqrt{\pi} \exp\left(\sin(X_i) + 4X_i - 4\right)$  where  $X_i \sim N(0, \frac{1}{2})$ . We can program this as follows.

```
X <- rnorm(reps, mean=0, sd = sqrt(1/2))
h <- sqrt(pi)*exp(sin(X)+4*X-4)
mean(h); sd(h)/sqrt(reps)</pre>
```

## [1] 14.92984

## [1] 12.73765

You can also sample from N(0,1), or any  $N(\mu, \sigma^2)$  and find appropriate h(x) that corresponds to each f(x). To generalise this in R, noting that h(x) = g(x)/f(x), we can write

 $g \leftarrow function(x) \{exp(sin(x)-(x-2)^2)\}$ 

```
MCresult4.5c <- function(mu=0,sigma=1,reps){</pre>
  x <- rnorm(reps, mean=mu, sd = sigma)
  h \leftarrow g(x)/(dnorm(x,mean=mu,sd = sigma))
  return(list(mean(h), sd(h)/sqrt(reps)))
}
By running a few examples, we see that \hat{J} and its S.E. vary depending on the choice of f(x).
MCresult4.5c(mu=2, sigma=sqrt(.5), reps = reps)
## [[1]]
## [1] 3.754169
## [[2]]
## [1] 0.03188613
MCresult4.5c(mu=0, sigma=sqrt(.5), reps = reps)
## [[1]]
## [1] 3.23813
##
## [[2]]
## [1] 0.957977
MCresult4.5c(mu=0, sigma=1, reps = reps)
## [[1]]
## [1] 3.84127
##
## [[2]]
## [1] 0.3769763
MCresult4.5c(mu=6, sigma=1, reps = reps)
## [[1]]
## [1] 1.474246
##
## [[2]]
## [1] 0.9006234
```

How do we know which one gives the best performance? As discussed in the seminar, we use the one that is naturally given by the problem, i.e.  $N(2, \frac{1}{2})$  in this case. We can also see that by plotting g(x) and candidates for f(x).

