

STAT 243 HW#4

1. We use the Monte Carlo method to evaluate each of the following integrals:

a.

$$\int_0^1 x^2 dx$$

Here, we let $f(x) = \frac{1}{1-0}$, a Uniform(0,1) distribution, and we let $h(x) = x^2$. We take 1,000,000 samples from a Uniform(0,1), and using the Monte Carlo method we obtain an estimate of the evaluated integral as .333328, or equivalently $\frac{1}{3}$.

b.

$$\int_0^1 \int_{-2}^2 x^2 \cos(xy) \, dx dy$$

c.

$$\int_0^\infty \frac{3}{4} e^{-\frac{x^3}{4}} dx$$

2. We let

$$I = \frac{1}{\sqrt{2\pi}} \int_1^2 e^{-\frac{x^3}{2}} dx$$

and estimate I using importance sampling. We take g to be $N(1.5, \nu^2)$ with $\nu = 0.1$ and 10.

3. We will approximate the following integral using both the simple Monte Carlo integration and the control variate method:

$$I = \int_0^1 \frac{1}{1+x} dx$$

a. We let $h(x) = \frac{1}{1+x}$ and U_1, \dots, U_n be iid Unif[0,1].

b.

c.

d.

4. We consider a common application in statistics: three different treatments are to be compared by applying them to a randomly selected experimental units. However; instead of the usual assumption associated with e_{ij} in the typical analysis of variance methods of comparison, we assume that the e_{ij} have independent and identical double exponential distributions centered on zero.

- a.
- b.

5. We consider the zero-inflated Poisson (ZIP) model, in which random data X_1, \dots, X_n are assumed to be of the form $X_i = R_i Y_i$, where Y_i 's have a $\text{Poisson}(\lambda)$ distribution and the R_i 's have a $\text{Bernoulli}(p)$ distribution, all independent of each other. Given an outcome $x = (x_1, \dots, x_n)$, the objective is to estimate both λ and p . We consider the following hierarchical Bayes model:

- $p \sim \text{Uniform}(0,1)$ (prior for p)
- $(\lambda|p) \sim \text{Gamma}(a, b)$ (prior for λ)
- $(r_i|p, \lambda) \sim \text{Bernoulli}(p)$ independently (from the model above)
- $(x_i|r, \lambda, p) \sim \text{Poisson}(\lambda r_i)$ independently (from the model above)

where a and b are known parameters, and $r = (r_1, \dots, r_n)$. It follows that:

$$f(x, r, \lambda, p) = \frac{b^a \lambda^{a-1} e^{-b\lambda}}{\Gamma(a)} \prod_{i=1}^n \frac{e^{-\lambda r_i} (\lambda r_i)^{x_i}}{x_i!} p^{r_i} (1-p)^{1-r_i}$$

We wish to sample from the posterior pdf $f(\lambda, p, r|x)$ using the Gibbs sampler.

- a.
- b.
- c.

6. The Independence - Metropolis - Hastings Algorithm is an importance-sampling version of MCMC. We draw the proposal from a fixed distribution g . Generally, g is chosen to be an approximation to f . The acceptance probability becomes:

$$r(x, y) = \min \left\{ \frac{f(y)}{f(x)} \cdot \frac{g(x)}{g(y)}, 1 \right\}$$

A random variable Z has an inverse Gaussian distribution if it has density

$$f(z) \propto z^{-3/2} \exp \left\{ -\theta_1 z - \frac{\theta_2}{z} + 2\sqrt{\theta_1 \theta_2} + \log \sqrt{2\theta_2} \right\}, \quad z > 0$$

where $\theta_1 > 0$ and $\theta_2 > 0$ are parameters. It can be shown that

$$E(Z) = \sqrt{\frac{\theta_2}{\theta_1}} \quad \text{and} \quad E\left(\frac{1}{Z}\right) = \sqrt{\frac{\theta_1}{\theta_2}} + \frac{1}{2\theta_2}$$

We let $\theta_1 = 1.5$ and $\theta_2 = 2$, and draw a sample of size 1,000 using the independence-Metropolis-Hastings algorithm. We use a Gamma distribution as the proposal density.