

# MTH210: Lab 6

## Importance Sampling

### 1. Moments of Gamma Distribution using Importance Sampling:

We will estimate moments of  $\text{Gamma}(\alpha, \beta)$  distribution, so that we are interested in  $h(x) = x^k$  for some  $k \geq 1$ . Let  $X \sim \text{Gamma}(\alpha, \beta)$ , where  $\alpha$  is the shape and  $\beta$  is the rate parameter.

The Simple Monte Carlo estimator of  $E_F[X^k]$  can be found by sampling from Gamma and taking sample means. Suppose  $\alpha = 2$  and  $\beta = 5$ . I will obtain 1e3 samples from this Gamma and suppose  $k = 2$  (second moment). Luckily for this problem, I know the true values of the second moment, and can compare the results with this value

$$\frac{\alpha}{\beta^2} + \left(\frac{\alpha}{\beta}\right)^2$$

```
k <- 2
N <- 1e3
alpha <- 2
beta <- 5

(truth <- (alpha / beta^2) + (alpha/beta)^2) # true second moment
#[1] 0.24

samples <- rgamma(N, shape = alpha, rate = beta)
# simple Monte Carlo
mean(samples^k)
```

When you run the above, you get an estimator of the required expectation. We can also do this using importance sampling. Suppose the choice of importance distribution is  $\text{Exp}(\lambda)$ , which has density  $g(x)$ . Then recall that for  $Z_1, Z_2, \dots, Z_t \sim G$  the importance sampling estimator for this  $g$  is

$$\hat{\theta}_g = \frac{1}{N} \sum_{t=1}^N Z_t^k \frac{f(Z_t)}{g(Z_t)}$$

We can now obtain the importance sampling estimator with  $\lambda = 3$  say.

```

set.seed(1)
lambda <- 3 #proposal

N <- 1e4
samp <- rexp(N, rate = lambda) # importance samples

#evaluate inside the sum
funcs <- samp^k * dgamma(samp, shape = alpha, rate = beta) / dexp(samp, rate = lambda)

# take the average gives me the Importance Sampling estimator
mean(funcs)

# Estimate of sigma^2_g: Sample variance of h(Z)f(Z)/g(Z)
var(funcs)

```

We obtain the estimate  $\hat{\theta}_g$  in `mean(funcs)`, and in `var(funcs)` we obtain an estimate of  $\sigma_g^2$

$$\sigma_g^2 = \text{Var}_G \left( \underbrace{h(Z) \frac{f(Z)}{g(Z)}}_{s(Z)} \right).$$

In order to estimate  $\sigma_g^2$ , we obtain all the  $s(Z_t)$  and take the sample variance of the  $s(Z_t)$ . This is what `var(funcs)` does.

- Repeat the above experiment for different values of  $\lambda$ . Which  $\lambda$  value returns the smallest estimate of  $\sigma_g^2$ ?
- Repeat the above experiment for a different proposal  $\text{Gamma}(3, 3)$ .
- Repeat the above experiment for  $\alpha = 4, \beta = 10, k = 3$  and the importance distribution  $\text{Gamma}(7, 10)$ . What are the values in `funcs`? What is `var(funcs)` in this case? Why?

## 2. Law of Large Numbers:

We would like to “verify” the claim of convergence in probability of the importance sampling estimator. We know theoretically that as  $N \rightarrow \infty$ ,

$$\hat{\theta}_g \xrightarrow{p} \theta,$$

where, recall  $\theta = E_F[h(X)]$ . In order to visualize this result, we will generate large number of samples from  $G$  ( $N$  is large) and plot the average  $\hat{\theta}_g$  of the samples as  $N$  increases.

```

## Checking convergence
N <- 1e5 # very large N

```

```

samp <- rexp(N, rate = lambda) # importance samples

func <- samp^k * dgamma(samp, shape = alpha, rate = beta) / dexp(samp, rate = lambda)

x.axis <- 1:N # sample size on the x-axis
y.axis <- cumsum(func)/(1:N) # IS estimator for each N

# Plotting the running average
plot(x.axis, y.axis , type = 'l', xlab = "N", ylab = "Running average")
abline(h = truth, col = "red")

```

### 3. Implement Problem 3 from Exercises of Section 5 in R.

Note, you may choose a grid of values for  $t$ :

```

# choosing 50 values of t between (-5, 5)
t <- seq(-5, 5, length = 50)

```