Probability, Computation and Simulation Homework 3



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Problem 1

Suppose we wanted to estimate θ , where

$$\theta = \int_0^1 e^{x^2} \, dx.$$

Show that generating a random number U and then using the estimator

$$Y = e^{U^2} \left(\frac{1 + e^{1 - 2U}}{2} \right)$$

is better than generating two random numbers ${\cal U}_1$ and ${\cal U}_2$ and using

$$Z = \frac{e^{U_1^2} + e^{U_2^2}}{2}.$$

We aim to compare the variances of the two estimators Y and Z for estimating

$$\theta = \int_0^1 e^{x^2} \, dx.$$

Since U_1, U_2 are independent and uniformly distributed on ([0,1]), the variance of Z is

$$\operatorname{Var}(Z) = \operatorname{Var}\left(\frac{e^{U_1^2} + e^{U_2^2}}{2}\right) = \frac{1}{4}\left(\operatorname{Var}(e^{U_1^2}) + \operatorname{Var}(e^{U_2^2})\right) = \frac{1}{2}\operatorname{Var}(e^{U^2}),$$

where $U \sim \text{Uniform}(0,1)$.

Let $U \sim \text{Uniform}(0,1)$ and set V = 1 - U. Then U and V are dependent but satisfy U + V = 1. The estimator Y becomes

$$Y = \frac{e^{U^2} + e^{V^2}}{2}.$$

The variance of Y is

$$Var(Y) = Var\left(\frac{e^{U^2} + e^{V^2}}{2}\right) = \frac{1}{4}\left(Var(e^{U^2}) + Var(e^{V^2}) + 2\operatorname{Cov}(e^{U^2}, e^{V^2})\right).$$



Since U and V are symmetrically distributed over ([0,1]), e^{U^2} and e^{V^2} have the same variance:

$$Var(e^{U^2}) = Var(e^{V^2}).$$

Thus,

$$\mathrm{Var}(Y) = \frac{1}{2}\,\mathrm{Var}(e^{U^2}) + \frac{1}{2}\,\mathrm{Cov}(e^{U^2},e^{V^2}). \label{eq:Var}$$

Because U and V are negatively correlated (V=1-U), and e^{x^2} is an increasing function on ([0,1]), e^{U^2} and e^{V^2} are negatively correlated. Therefore,

$$\operatorname{Cov}(e^{U^2}, e^{V^2}) < 0.$$

This implies

$$\mathrm{Var}(Y) < \frac{1}{2}\,\mathrm{Var}(e^{U^2}).$$

From earlier,

$$\mathrm{Var}(Z) = \frac{1}{2}\,\mathrm{Var}(e^{U^2}).$$

Thus,

$$Var(Y) < Var(Z)$$
.

Therefore, the variance of Y is less than that of Z, the estimator Y is better for estimating θ due to its lower variance.



Let $X_i, i = 1, \dots, 5$, be independent exponential random variables each with mean 1, and consider the quantity

$$\theta = P\left(\sum_{i=1}^{5} iX_i \ge 21.6\right).$$

Part A

Now, we can estimate θ using Monte Carlo simulation by

- 1. Generating samples of X_i from an exponential distribution with mean 1. 2. Compute the weighted sum $S=\sum_{i=1}^5 iX_i$.
- 3. Then, we repeat this process many times to estimate the probability θ by calculating the proportion of times $S \ge 21.6$.



Let X_i , $i=1,\ldots,5$, be independent exponential random variables each with mean 1, and consider the quantity

$$\theta = P\left(\sum_{i=1}^5 iX_i \ge 21.6\right).$$

Part B

To use antithetic variables,

- 1. Generate uniform random variables $U_i \sim \text{Uniform}(0, 1)$.

- 2. Compute $X_i = -\ln(U_i)$ and $X_i' = -\ln(1 U_i)$. 3. Calculate $S = \sum_{i=1}^5 i X_i$ and $S' = \sum_{i=1}^5 i X_i'$. 4. Use the average indicator function $\frac{I(S \ge 21.6) + I(S' \ge 21.6)}{2}$ as the estimator.



Let X_i , i = 1, ..., 5, be independent exponential random variables each with mean 1, and consider the quantity

$$\theta = P\left(\sum_{i=1}^{5} iX_i \ge 21.6\right).$$

Part C

To determine efficiency, we compare the variances of the standard estimator, Var(S), and the antithetic estimator, Var(A). If the antithetic estimator has a lower variance, it is more efficient.

Putting it into Practice

```
set.seed(202425)
N <- 100000
# Standard estimator
standardResults <- replicate(N, {</pre>
  X \leftarrow \text{rexp}(5); S \leftarrow \text{sum}((1:5) * X); S >= 21.6
})
thetaS <- mean(standardResults)</pre>
varS <- var(standardResults)</pre>
# Antithetic estimator
antitheticResults <- replicate(N / 2, {</pre>
 U <- runif(5); X <- -log(U); X_prime <- -log(1 - U)
  S \leftarrow sum((1:5) * X); S_prime \leftarrow sum((1:5) * X_prime)
  c(S \ge 21.6, S_prime \ge 21.6)
})
# Compute the mean of each pair (average of S and S')
antitheticMeans <- rowMeans(matrix(antitheticResults, ncol = 2))</pre>
thetaA <- mean(antitheticMeans)</pre>
varA <- var(antitheticMeans)</pre>
print(paste0("Variance of standard estimator:", varS))
```

[1] "Variance of standard estimator: 0.142069459794319"

```
print(paste0("Variance of antithetic estimator:", varA))
```

[1] "Variance of antithetic estimator:0.0700363111261794"



If ${\rm Var}(S) < {\rm Var}(A)$, then the antithetic variables method is more efficient. Based on the simulation, the antithetic estimator shows reduced variance, indicating increased efficiency. To emphasis, 'varA

In certain situations, a random variable X, whose mean is known, is simulated to obtain an estimate of $P\{X \leq a\}$ for a given constant a. The raw simulation estimator from a single run is I, where

$$I = \begin{cases} 1 & \text{if } X \le a, \\ 0 & \text{if } X > a. \end{cases}$$

Because I and X are negatively correlated, a natural attempt to reduce the variance is to use X as a control variable and use an estimator of the form

$$I + c(X - \mathbb{E}[X]).$$

Part A

For $X \sim \text{Uniform}(0,1)$, we know the following,

- $\mathbb{E}[X] = 0.5$
- $Var(X) = \frac{1}{12}$
- $P(X \le a) = a$
- Var(I) = a(1-a)

Using this, we can compute the covariance between I and X by,

$$\mathrm{Cov}(I,X) = \mathbb{E}[IX] - \mathbb{E}[I]\mathbb{E}[X] = \frac{a^2}{2} - a \times 0.5 = \frac{a(a-1)}{2}$$

The optimal c^* is calculated by,

$$c^* = -\frac{\mathrm{Cov}(I,X)}{\mathrm{Var}(X)} = -\frac{\frac{a(a-1)}{2}}{\frac{1}{12}} = -6a(a-1)$$

Now, the variance reduction,

$$\operatorname{Var}(I) - \frac{\operatorname{Cov}(I,X)^2}{\operatorname{Var}(X)}$$

$$\text{Percentage Reduction} = \frac{\text{Cov}(I,X)^2}{\text{Var}(I)\,\text{Var}(X)} \times 100\% = 3a(1-a) \times 100\%$$



In certain situations, a random variable X, whose mean is known, is simulated to obtain an estimate of $P\{X \leq a\}$ for a given constant a. The raw simulation estimator from a single run is I, where

$$I = \begin{cases} 1 & \text{if } X \le a, \\ 0 & \text{if } X > a. \end{cases}$$

Because I and X are negatively correlated, a natural attempt to reduce the variance is to use X as a control variable and use an estimator of the form

$$I + c(X - \mathbb{E}[X]).$$

Part B

For $X \sim \text{Exponential}(1)$, we know the following attributes,

- $\mathbb{E}[X] = 1$
- Var(X) = 1
- $P(X \le a) = 1 e^{-a}$
- $Var(I) = (1 e^{-a})e^{-a}$

Next, compute Cov(I, X),

$$\mathrm{Cov}(I,X) = \mathbb{E}[IX] - \mathbb{E}[I]\mathbb{E}[X] = (-ae^{-a} + 1 - e^{-a}) - (1 - e^{-a})(1) = -ae^{-a}$$

To find the optimal c^* , do the following,

$$c^* = -\frac{\mathrm{Cov}(I,X)}{\mathrm{Var}(X)} = ae^{-a}$$

Here is the variance reduction,

$$\text{Percentage Reduction} = \frac{(\text{Cov}(I, X))^2}{\text{Var}(I) \, \text{Var}(X)} \times 100\% = \frac{a^2 e^{-2a}}{(1 - e^{-a}) e^{-a}} \times 100\% = \frac{a^2 e^{-a}}{1 - e^{-a}} \times 100\%$$



In certain situations, a random variable X, whose mean is known, is simulated to obtain an estimate of $P\{X \leq a\}$ for a given constant a. The raw simulation estimator from a single run is I, where

$$I = \begin{cases} 1 & \text{if } X \le a, \\ 0 & \text{if } X > a. \end{cases}$$

Because I and X are negatively correlated, a natural attempt to reduce the variance is to use X as a control variable and use an estimator of the form

$$I + c(X - \mathbb{E}[X]).$$

Part C

The indicator I is 1 when $X \leq a$ and 0 otherwise. Larger values of X (greater than a) correspond to I = 0. Therefore, as X increases, I tends to decrease, indicating a negative correlation between I and X.







In Exercise 1, $\theta = \int_0^1 e^{x^2} dx$. We can use e^x as a control variable since its expected value $\mathbb{E}[e^X]$ is known for $X \sim \text{Uniform}(0,1)$. The control variate estimator is:

$$Y = e^{U^2} + c(e^U - \mathbb{E}[e^U])$$

where c is chosen to minimize the variance (calculated in part b).

Part B

Putting it into Practice

```
set.seed(202425)
N <- 100
U <- runif(N)
eU2 <- exp(U^2)
eU <- exp(U)
E_eU <- (exp(1) - 1)
cov_eU2_eU <- cov(eU2, eU)
var_eU <- var(eU)
cStar <- -cov_eU2_eU / var_eU
# Control variate estimator
YControl <- eU2 + cStar * (eU - E_eU)
varControl <- var(YControl)
print(pasteO("Optimal c*: ", cStar))</pre>
```

[1] "Optimal c*: -0.988045042115672"

```
print(paste0("Variance of control variate estimator:", varControl))
```

[1] "Variance of control variate estimator:0.0134246377049571"



Part C

```
Oregon State
University
```

```
e_U2_antithetic <- exp(U^2) + exp((1 - U)^2)
YAntithetic <- e_U2_antithetic / 2
varAntithetic <- var(YAntithetic)
print(paste0("Variance of antithetic estimator:", varAntithetic))</pre>
```

[1] "Variance of antithetic estimator:0.0303702833131082"



By comparing $\mathrm{Var}(C)$ and $\mathrm{Var}(A)$, we determine which method provided greater variance reduction. In our simulation, it appears that $\mathrm{Var}(C) < \mathrm{Var}(A)$, so the control variate estimator is more efficient.



Show that in estimating

$$\theta = \mathbb{E}\left[\sqrt{1 - U^2}\right]$$

it is better to use U^2 rather than U as the control variate. Use simulation to approximate the necessary covariances.

We compare the effectiveness of using U and U^2 as control variates by doing a mini-simulation example,

Putting it into Practice

```
set.seed(202425)
N <- 10000
U <- runif(N)</pre>
Y <- sqrt(1 - U^2)
# Using U as control variate
C1 <- U
EC1 <- 0.5
covYC1 <- cov(Y, C1)
varC1 <- var(C1)</pre>
c1_star <- -covYC1 / varC1</pre>
Y1 <- Y + c1_star * (C1 - EC1)
var_Y1 <- var(Y1)</pre>
# Using U^2 as control variate
C2 <- U^2
EC2 <- 1/3
cov_Y_C2 \leftarrow cov(Y, C2)
varC2 <- var(C2)</pre>
c2_star <- -cov_Y_C2 / varC2</pre>
Y2 \leftarrow Y + c2_star * (C2 - EC2)
varY2 <- var(Y2)</pre>
print(paste0("Variance using U as control variate:", var_Y1))
```

[1] "Variance using U as control variate:0.00759764689972037"

```
print(paste0("Variance using U^2 as control variate:", varY2))
```

[1] "Variance using U^2 as control variate:0.00163425781626914"

The variance when using U^2 as the control variate, $Var(Y_2)$, is smaller than when using U, $Var(Y_1)$. Thus, U^2 is a better control variate for estimating θ in this scenario.

