

몬테카를로 방사선해석 (Monte Carlo Radiation Analysis)

Variance Reduction: Techniques

Estimation Mean and Variance

- To estimate the integral

$$I = \int_0^5 \frac{1}{1+x^2} dx, \quad (1)$$

- Define the function

$$f(x) = \begin{cases} 1/5, & 0 \leq x \leq 5 \\ 0, & \text{otherwise} \end{cases} \quad (2) \quad \text{so that} \quad \int_{-\infty}^{\infty} f(x) dx = 1.$$

- Now define the random variable $V(x)$ as

$$V(x) = \frac{5}{1+x^2} \quad \text{so that} \quad \int_0^5 V(x) \cdot f(x) dx = \int_0^5 \frac{1}{1+x^2} dx.$$

Estimation Mean and Variance (cont.)

- The expected value of V is then

$$E(V) = \int_{-\infty}^{\infty} V(x) f(x) dx = \int_0^5 \frac{1}{1+x^2} dx, \quad (3)$$

which gives $E(V) = \tan^{-1}(5) - \tan^{-1}(0) \doteq 1.373400$.

- The mean value of V^2 is, on the other hand,

$$E(V^2) = \int_{-\infty}^{\infty} V^2(x) f(x) dx = \int_0^5 \left(\frac{5}{1+x^2} \right)^2 \frac{dx}{5} \approx 3.914270.$$

Estimation Mean and Variance (cont.)

- The variance of the random variable V is then

$$\text{var}(V) = E(V^2) - [E(V)]^2 \doteq 2.028042, \text{ and}$$

the standard deviation is, therefore,

$$\sigma(V) \approx \sqrt{2.028042} \approx 1.424093.$$

$$\text{Note } \text{var}(\bar{V}) = \frac{1}{n} \text{var}(V) = \frac{1}{n} \sigma^2(V)$$

$$\text{ex. } \text{var}(\bar{V}) = 2.028042 \times 10^{-4} \text{ with } n = 10000$$

Improvement of Certainty in Estimate

- The purpose of MC calculation is usually to obtain an estimate of the expected value of a random variable.
- The usual measure of the certainty of the result is the standard deviation of the estimate obtained.
- The improvement in the certainty of an estimate of the mean can be made by increasing the number of samples:

$$\text{var}(\bar{S}) = \frac{1}{n} \text{var}(X) = \frac{\sigma^2(X)}{n}. \quad (18)$$

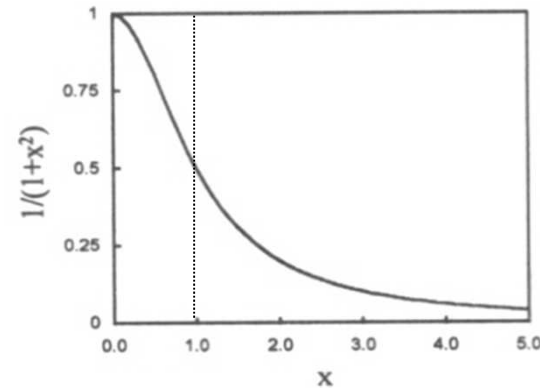
which might cost too much time.

- Other methods for improvement in certainty?

Stratified Sampling

- The range over which the independent variable is sampled is divided into strata and each stratum is sampled separately.
- Exercise
 - Estimate the integral of

$$I = \int_{x=0}^5 \frac{1}{1+x^2} dx \quad (1)$$



Stratified Sampling: exercise

- Step 1. Define the pdf $f_1(x)$ for the first stratum

$$f_1(x) = \begin{cases} 1, & 0 \leq x \leq 1 \\ 0, & \text{elsewhere} \end{cases} \quad (4)$$

and the pdf $f_2(x)$ for the second stratum

$$f_2(x) = \begin{cases} 0.25, & 1 \leq x \leq 5 \\ 0, & \text{elsewhere} \end{cases} \quad (5)$$

Stratified Sampling: exercise (cont.)

- Step 2. Define the corresponding random variables as

$$V_1(x) = \frac{1}{1+x^2} \quad (6) \quad \text{and} \quad V_2(x) = \frac{4}{1+x^2} \quad (7)$$

so that

$$\int_0^1 V_1(x) f_1(x) dx = \int_0^1 \frac{1}{1+x^2} dx; \quad \text{and} \quad \int_1^5 V_2(x) f_2(x) dx = \int_1^5 \frac{1}{1+x^2} dx, \quad (8)$$

which leads to

$$\int_0^1 V_1(x) f_1(x) dx + \int_1^5 V_2(x) f_2(x) dx = \int_0^1 \frac{1}{1+x^2} dx + \int_1^5 \frac{1}{1+x^2} dx = \int_0^5 \frac{1}{1+x^2} dx$$

$$\text{or } 1 = E(V_1) + E(V_2). \quad (9)$$

Stratified Sampling: exercise (cont.)

- Step 3. Calculate the expected value $E(V_1)$ in the first stratum and $E(V_2)$ in the second stratum:

$$E(V_1) = \int_{x=0}^1 V_1(x) f_1(x) dx = \int_{x=0}^1 \frac{1}{1+x^2} dx \approx 0.7853982 \quad (10)'$$

$$E(V_2) = \int_{x=1}^5 V_2(x) f_2(x) dx = \int_{x=1}^5 \frac{4}{1+x^2} \frac{dx}{4} \approx 0.5880026 \quad (10)''$$

Stratified Sampling: exercise (cont.)

- Step 4. Calculate the variances V_1 for the first stratum and V_2 for the second stratum:

$$E(V_1^2) = \int_{x=0}^1 \left(\frac{1}{1+x^2} \right)^2 dx \approx 0.6426991 \quad (11)'$$

$$E(V_2^2) = \int_{x=1}^5 \left(\frac{4}{1+x^2} \right)^2 \frac{dx}{4} \approx 0.5606200 \quad (11)''$$

Hence,

$$\text{var}(V_1) = E(V_1^2) - [E(V_1)]^2 \approx 0.0258488 \quad (12)'$$

$$\text{var}(V_2) = E(V_2^2) - [E(V_2)]^2 \approx 0.2148729 \quad (12)''$$

Stratified Sampling: exercise (cont.)

- Step 5. The value of the original integral is

$$I = \int_0^5 \frac{1}{1+x^2} dx = E(V_1) + E(V_2) \approx 1.373400.$$

- Step 6. Compare the mean and the variance

$$E(V_1) + E(V_2) \doteq 1.373400 \quad \text{as (3)}$$

$$\begin{aligned} \text{var}[E(V_1)+E(V_2)] \\ &= \text{var}[E(V_1)] + \text{var}[E(V_2)] \\ &= \text{var}(V_1)/n_1 + \text{var}(V_2)/n_2 \quad \text{and} \end{aligned}$$

the standard deviation is $\sigma(\bar{V}_1 + \bar{V}_2) = \sqrt{\text{var}(\bar{V}_1 + \bar{V}_2)}$.

- $\text{ex. var}[E(V_1)+E(V_2)] \doteq 4.8144 \times 10^{-5}$ with $n_1=5000$ and $n_2=5000$

$$\text{ex. var}(\bar{V}) = 2.028042 \times 10^{-4} \quad \text{with } n=10000$$

Demonstration of the Stratification Property: nomenclature

- *Conditional probability $P\{X=x \mid B\}$
 \equiv the probability of $X=x$ given condition B .*
- *$E(V \mid A) \equiv$ the expected value of random variable $V(x)$
over the set A of x 's.*
- *“ \sim ” indicates the subtraction of one set from another.*

Demonstration of the Stratification Property

- Theorem

Given a variable function $V(x)$ for x in a set R of real numbers such that $E(V | A)$ in a subset A and $E(V | R)$ and $\text{var}(V | R)$ in the set R exist and are finite, if $E(V | A)$ does not equal $E(V | R)$ then the variance of the estimate of $E(V | R)$ using the strata defined by A and $R \sim A$ is less than the variance of the estimate without stratification.

Demonstration of the Stratification Property : Proof

- Let $f(x)$ be the pdf of x for $V(x)$ and let

$$a = \int_A f(x)dx. \quad \text{Then } 1-a = \int_{R \sim A} f(x)dx.$$

- Define

$$f_1(x) = \begin{cases} \frac{f(x)}{a}, & \text{for } x \text{ in } A \\ 0, & \text{otherwise} \end{cases} \quad \text{and} \quad f_2(x) = \begin{cases} \frac{f(x)}{1-a}, & \text{for } x \text{ not in } A \\ 0, & \text{otherwise} \end{cases}$$

Demonstration of the Stratification Property : Proof (cont.)

- Then

$$E(V | A) = \bar{V}_1 = \int_A V(x)f_1(x)dx = \frac{1}{a} \int_A V(x)f(x)dx \quad \text{and}$$

$$E(V | R \sim A) = \bar{V}_2 = \int_{R \sim A} V(x)f_2(x)dx = \frac{1}{1-a} \int_{R \sim A} V(x)f(x)dx$$

whereas $E(V | R) = \bar{V} = \int_R V(x)f(x)dx$.

And thus,

$$E(V | R) = a \cdot E(V | A) + (1-a) \cdot E(V | R \sim A) \quad \text{or} \quad \bar{V} = a\bar{V}_1 + (1-a)\bar{V}_2.$$

- Since $E(V | A) \neq E(V | R)$, defining $\delta = E(V | A) - E(V | R)$ gives

$$E(V | R \sim A) = E(V | R) - \frac{a}{1-a} \delta.$$

Therefore, if $\delta > 0$, $E(V | A) > E(V | R)$ then $E(V | R \sim A) < E(V | R)$
and vice versa.

Demonstration of the Stratification Property : Proof (cont.)

- The variance of V is given by

$$\begin{aligned} \text{var}(V) &= \int_R [V(x) - E(V)]^2 f(x) dx \\ &= \int_A [V(x) - E(V)]^2 f(x) dx + \int_{R-A} [V(x) - E(V)]^2 f(x) dx . \end{aligned}$$

- The variance of the estimate of the mean of V or \bar{V} , based on n samples is then $[\text{var}(V)]/n$, or

$$\text{var}(\bar{V}) = \frac{1}{n} \int_A [V(x) - E(V)]^2 f(x) dx + \frac{1}{n} \int_{R-A} [V(x) - E(V)]^2 f(x) dx \quad (13)$$

Demonstration of the Stratification Property : Proof (cont.)

- In an unbiased sampling scheme with total n samples for these two strata, $nP(A)$ or na samples are used for stratum A and $nP(R\sim A)$ or $n(1-a)$ are used for stratum $R\sim A$. Therefore, the variance of $[a\bar{V}_1 + (1-a)\bar{V}_2]$ is

$$\begin{aligned} \text{var}[a\bar{V}_1 + (1-a)\bar{V}_2] &= a^2 \cdot \text{var}(\bar{V}_1) + (1-a)^2 \cdot \text{var}(\bar{V}_2) \\ &= \frac{a^2}{na} \cdot \text{var}(V_1) + \frac{(1-a)^2}{n(1-a)} \cdot \text{var}(V_2) \\ &= \frac{a}{n} \int_A [V(x) - \bar{V}_1]^2 f_1(x) dx + \frac{(1-a)}{n} \int_{R\sim A} [V(x) - \bar{V}_2]^2 f_2(x) dx \\ &= \frac{1}{n} \int_A [V(x) - \bar{V}_1]^2 f(x) dx + \frac{1}{n} \int_{R\sim A} [V(x) - \bar{V}_2]^2 f(x) dx \quad (14) \end{aligned}$$

Demonstration of the Stratification Property : Proof (cont.)

- By comparing (13) and (14), $\text{var}[\bar{V}] = \text{var}[a\bar{V}_1 + (1-a)\bar{V}_2]$
if $\bar{V} = \bar{V}_1 = \bar{V}_2$.

$$\text{var}[\bar{V}] = \frac{1}{n} \int_A [V(x) - \bar{V}]^2 f(x) dx + \frac{1}{n} \int_{R \sim A} [V(x) - \bar{V}]^2 f(x) dx \quad (13)$$

$$\text{var}[a\bar{V}_1 + (1-a)\bar{V}_2]$$

$$= \frac{1}{n} \int_A [V(x) - \bar{V}_1]^2 f(x) dx + \frac{1}{n} \int_{R \sim A} [V(x) - \bar{V}_2]^2 f(x) dx \quad (14)$$

Demonstration of the Stratification Property : Proof (cont.)

- When $E(V | A) \neq E(V | R)$, which is the assumption of the theorem, consider a function $h(v)$ defined by

$$h(v) = \int_A [V(x) - v]^2 f(x) dx .$$

- Taking the derivative of $h(v)$ with respect to v gives

$$\begin{aligned} \frac{dh(v)}{dv} &= -2 \int_A [V(x) - v] f(x) dx \\ &= -2 \int_A V(x) f(x) dx + 2 \int_A v \cdot f(x) dx \\ &= -2a\bar{V}_1 + 2av = 2a(v - \bar{V}_1) \end{aligned}$$

and $dh(v)/dv = 0$ implies $v = \bar{V}_1$.

Demonstration of the Stratification Property : Proof (cont.)

- Note that the second derivative of $h(v)$ with respect to v is $2a > 0$. Then, $v = \bar{V}_1$ as the minimum value for $h(v)$, which means that if $E(V | A) \neq E(V | R)$ then*

$$\int_A [V(x) - \bar{V}_1]^2 f(x) dx < \int_A [V(x) - \bar{V}]^2 f(x) dx.$$

Similarly, if $E(V | R \sim A) \neq E(V | R)$ then

$$\int_{R \sim A} [V(x) - \bar{V}_2]^2 f(x) dx < \int_{R \sim A} [V(x) - \bar{V}]^2 f(x) dx.$$

- Therefore, $\text{var}[a\bar{V}_1 + (1-a)\bar{V}_2] < \text{var}[\bar{V}]$.*

Optimal Choice of the Number of Samples

- Let w denote the variance of the mean of the stratified sample, i.e.,

$$w = \text{var}[a\bar{V}_1 + (1-a)\bar{V}_2].$$

made with total n samples, with m samples for the first stratum and $n-m$ samples for the second stratum.

This gives

$$w(m) = \frac{a^2}{m} \text{var}(V_1) + \frac{(1-a)^2}{n-m} \text{var}(V_2).$$

- By setting $dw(m)/dm = 0$, the optimum value m is

$$m = \frac{n}{1 + \sqrt{k}} \quad \text{where} \quad k = \frac{(1-a)^2 \text{var}(V_2)}{a^2 \cdot \text{var}(V_1)}.$$

Biased Sampling Scheme

- In the general case of biased sampling, the samples are picked from a modified pdf.
- Consider the random variable $V(x)$ with pdf $f(x)$. The expected value of V is then given by

$$E(V) = \int_{\mathcal{R}} V(x) f(x) dx. \quad (1)$$

- Given a different pdf $g(x)$, such that $g(x) > 0$ everywhere that $V(x)f(x) > 0$, one has

$$E(V) = \int_{\mathcal{R}} \frac{V(x) f(x)}{g(x)} \cdot g(x) dx. \quad (2)$$

Biased Sampling Scheme (cont.)

- The random variable V' associated with the pdf $g(x)$ is

$$V'(x) = V(x) \cdot f(x) / g(x) \quad \text{and} \quad E(V') = E(V).$$

- The proper selection of $g(x)$ can result in the variance being significantly reduced.
 - Select $g(x)$ such that

$$\underline{V'(x) = V(x) \cdot f(x) / g(x) = c \equiv \text{Constant.}} \quad (3)$$

Then,

$$E(V) = \underline{E(V')} = \int_R \frac{V(x) f(x)}{g(x)} \cdot g(x) dx = \int_R c \cdot g(x) dx = c.$$

and

$$\text{var}(V') = \int_R [(V'(x) - E(V'))]^2 g(x) dx = 0.$$

Biased Sampling Scheme (cont.)

- *Therefore, in theory, it is possible to choose a modified pdf such that the sampling process gives an answer with zero variance if one can find $g(x)$ that has the same shape as $V(x)f(x)$ to satisfy (3).*

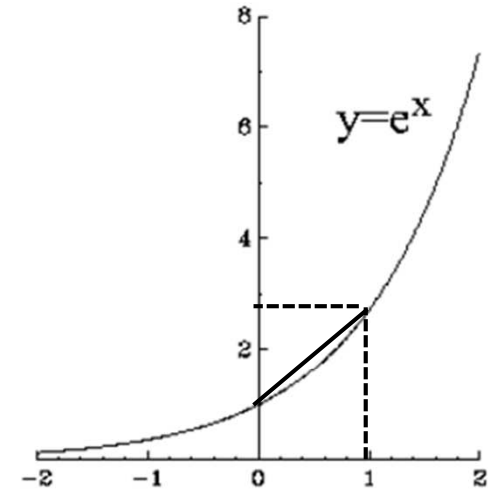
Biased Sampling Scheme: example

- Consider the variable $V(x) = e^x$ and the pdf

$$f(x) = \begin{cases} 1, & \text{for } 0 \leq x \leq 1 \\ 0, & \text{elsewhere} \end{cases} \quad (4)$$

- Then

$$E(V) = \int_0^1 V(x) f(x) dx = \int_0^1 e^x dx \approx 1.71828.$$



- The MC estimates with 10^6 samples without biasing are
 - the integral estimate, $\bar{V}(x) = 1.71825757$
 - standard deviation of random variable values $V(x_i)$'s $= 0.49168896$
 - standard deviation of the integral estimate $\bar{V}(x) = \underline{0.00049169}$

(5)

Biased Sampling Scheme: example (cont.)

- Select a pdf for biasing
 - Considering a straight line from (0,1) to (1,2.718) is somewhat the same shape as $V(x)f(x)$, define a modified pdf as

$$g(x) = \frac{1+1.718x}{1.859}. \quad (6)$$

- The MC results by the biased sampling are
 - the integral value = 1.71823566
 - standard deviation of random variable = 0.06507303
 - standard deviation of the integral estimate = 0.00006507
- (7)

→ The result obtained by biased sampling is more reliable.

Biased Sampling/ weighting factor

- A new random variable V' is defined for a modified pdf $g(x)$ as*

$$V'(x) = V(x) \cdot f(x)/g(x) \text{ to give } E(V') = E(V).$$

- The original random variable $V(x)$ is weighted by*

$$V'(x)/V(x) = f(x)/g(x) \equiv \text{weighting factor}$$

to compensate the modification of pdf from $f(x)$ to $g(x)$.

Homework #3