

Variance Bias in Monte Carlo Eigenvalue Calculations

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Sample Variance

- In the Monte Carlo eigenvalue calculations, the sample variance of the mean value of a tally denoted by Q can be calculated by

$$\sigma_s^2[\bar{Q}] = \frac{1}{N(N-1)} \sum_{i=1}^N (Q^i - \bar{Q})^2, \quad \bar{Q} = \frac{1}{N} \sum_{i=1}^N Q^i, \quad \dots\dots\dots (1)$$

where

Q = tally variable

Q^i = value estimated by the MC calculations at i -th cycle

\bar{Q} = mean value of Q

N = total number of stationary cycles

Central Limit Theorem

- Let $X_1, X_2, X_3, \dots, X_n$ be a sequence of **n independent and identically distributed (i.i.d)** random variables each having finite values of expectation μ and variance $\sigma^2 > 0$.
- The central limit theorem states that as the sample size n increases, the distribution of the sample average of these random variables approaches the normal distribution with a mean μ and variance σ^2 / n irrespective of the shape of the original distribution.

Central Limit Theorem (Contd.)

- Telescopes and sampling errors
 - The mathematician Gauss (1777-1855) was also a keen astronomer. He acquired a new telescope, and decided to use it to produce a more accurate calculation of the diameter of the moon.
 - To his surprise, he discovered that every time he took a measurement, his answer was slightly different.
 - He plotted the results and found that they formed a bell shaped curve, with most results close to the central average but the occasional one quite inaccurate.
- Gauss quickly realized that any measurement he took was a ‘sample’ prone to error but which could be used as an estimate of the correct answer. The more readings he took, the closer the average would be to the correct reading.
- He established that errors in readings belonged to a famous **bell curve** (or **normal distribution** or **Gaussian distribution**).

Bias of Sample Variance (1/2)

- The sample variance of Q can be calculated by

$$\sigma_s^2[Q] = \frac{1}{N-1} \sum_{i=1}^N (Q_i - \bar{Q})^2, \quad \bar{Q} = \frac{1}{N} \sum_{i=1}^N Q_i \quad \text{..... (A.1)}$$

- The expected value of $\sum_{i=1}^N (Q_i - \bar{Q})^2$ can be written as

$$\begin{aligned} E \left[\sum_{i=1}^n (Q_i - \bar{Q})^2 \right] &= E \left[\sum_{i=1}^n Q_i^2 - n\bar{Q}^2 \right] \\ &= \sum_{i=1}^n E[Q_i^2] - nE[\bar{Q}^2] \\ &= nE[Q_i^2] - nE[\bar{Q}^2] \\ &= n \left\{ \sigma^2[Q] + \cancel{(E[Q])^2} \right\} - n \left\{ \sigma^2[\bar{Q}] + \cancel{(E[\bar{Q}])^2} \right\} \\ &= n\sigma^2[Q] - n \left(\frac{\sigma^2[Q]}{n} \right) \\ &= (n-1)\sigma^2[Q] \quad \text{..... (A.2)} \end{aligned}$$

Bias of Sample Variance (2/2)

- The variance of \bar{Q} , $\sigma^2[\bar{Q}]$ can be written as

$$\begin{aligned}
 \sigma^2[\bar{Q}] &= \frac{1}{n^2} \sigma^2[Q_1 + Q_2 + \dots + Q_n] \\
 &= \frac{1}{n^2} \left\{ E[(Q_1 + Q_2 + \dots + Q_n)^2] - n^2 (E[Q])^2 \right\} \\
 &= \frac{1}{n^2} \left\{ nE[Q_i^2] - n(E[Q])^2 \right\} + \frac{1}{n^2} \sum_i \sum_{i \neq j} \left\{ E[Q_i Q_j] - (E[Q])^2 \right\} \\
 &= \frac{1}{n} \sigma^2[Q] + \frac{1}{n^2} \sum_i \sum_{i \neq j} \left\{ \text{cov}[Q_i, Q_j] \right\} \quad \text{----- (A.3)}
 \end{aligned}$$

- Then the sample are independent each other ($\text{cov}[Q_i, Q_j] = 0$), $\sigma^2[\bar{Q}]$ becomes

$$\sigma^2[\bar{Q}] = \frac{1}{n} \sigma^2[Q] \quad (\text{if } \text{cov}[Q_i, Q_j] = 0) \quad \text{----- (A.4)}$$

Derivation of Variance Bias (1/4)

- The real or true variance of \bar{Q} can be written as

$$\begin{aligned}
 \sigma_R^2[\bar{Q}] &= E[\bar{Q}^2] - E[\bar{Q}]^2 \\
 &= E\left[\left(\frac{1}{NM} \sum_{i=1}^N \sum_{j=1}^M Q_j^i\right)^2\right] - E\left[\frac{1}{NM} \sum_{i=1}^N \sum_{j=1}^M Q_j^i\right]^2 \\
 &= \frac{NM}{(NM)^2} E[(Q_j^i)^2] + \frac{1}{(NM)^2} \sum_{i,j} \sum_{i',j' \neq i,j} E[Q_j^i Q_{j'}^{i'}] \\
 &\quad - \frac{NM}{(NM)^2} E[Q_j^i]^2 - \frac{1}{(NM)^2} \sum_{i,j} \sum_{i',j' \neq i,j} E[Q_j^i] E[Q_{j'}^{i'}] \\
 &= \frac{1}{NM} \sigma^2[Q_j^i] + \frac{1}{(NM)^2} \sum_{i,j} \sum_{i',j' \neq i,j} \text{cov}[Q_j^i, Q_{j'}^{i'}] \quad \dots\dots\dots (B.1)
 \end{aligned}$$

- On the other hand, the apparent variance of Q is defined as the expected value of the sample variance

$$\sigma_A^2[\bar{Q}] = E[\sigma_S^2[\bar{Q}]] \quad \dots\dots\dots (B.2)$$

Derivation of Variance Bias (2/4)

- In the same way that Ueki et al [1] formulated the variance bias for the multiplication factor k_{eff} from its apparent variance, $\sigma_A^2[\bar{Q}]$ can be expressed as

$$\begin{aligned}\sigma_A^2[\bar{Q}] &= E\left[\frac{1}{NM(NM-1)}\sum_{i=1}^N\sum_{j=1}^M(Q_j^i - \bar{Q})^2\right] = \frac{1}{NM-1}\left(E[(Q_j^i)^2] - E[\bar{Q}^2]\right) \\ &= \frac{1}{NM-1}\left(\sigma^2[Q_j^i] + E[Q_j^i]^2 - E[\bar{Q}^2]\right) \quad \text{----- (B.3)}\end{aligned}$$

[1] T. Ueki, T. Mori, and M. Nakagawa, "Error Estimation and their Biases in Monte Carlo Eigenvalue Calculations," *Nucl. Sci. Eng.*, 125, 1-11 (1997).

- And $E[\bar{Q}^2]$ in Eq. (B.3) can be expressed as

$$\begin{aligned}E[\bar{Q}^2] &= E\left[\left(\frac{1}{NM}\sum_{i=1}^N\sum_{j=1}^MQ_j^i\right)^2\right] = \frac{NM}{(NM)^2}E[(Q_j^i)^2] + \frac{1}{(NM)^2}\sum_{i,j}\sum_{i',j'\neq i,j}E[Q_j^iQ_{j'}^{i'}] \\ &= \frac{1}{NM}E[(Q_j^i)^2] + \frac{NM-1}{NM}E[Q_j^i]^2 + \frac{1}{(NM)^2}\sum_{i,j}\sum_{i',j'\neq i,j}\left(E[Q_j^iQ_{j'}^{i'}] - E[Q_j^i]^2\right) \\ &= \frac{1}{NM}\sigma^2[Q_j^i] + E[Q_j^i]^2 + \frac{1}{(NM)^2}\sum_{i,j}\sum_{i',j'\neq i,j}\text{cov}[Q_j^i, Q_{j'}^{i'}]. \quad \text{----- (B.4)}\end{aligned}$$

Derivation of Variance Bias (3/4)

- Insertion of Eq. (B.4) into Eq. (B.3) leads to

$$\begin{aligned}
 \sigma_A^2[\bar{Q}] &= \frac{1}{NM-1} \left\{ \sigma^2[Q_j^i] + \cancel{E[Q_j^i]^2} - \frac{1}{NM} \sigma^2[Q_j^i] - \cancel{E[Q_j^i]^2} - \frac{1}{(NM)^2} \sum_{i,j} \sum_{i',j' \neq i,j} \text{cov}[Q_j^i, Q_{j'}^{i'}] \right\} \\
 &= \frac{1}{NM-1} \cdot \frac{NM-1}{NM} \sigma^2[Q_j^i] - \frac{1}{NM-1} \cdot \frac{1}{(NM)^2} \sum_{i,j} \sum_{i',j' \neq i,j} \text{cov}[Q_j^i, Q_{j'}^{i'}] \\
 &= \frac{1}{NM} \sigma^2[Q_j^i] - \frac{1}{NM-1} \cdot \frac{1}{(NM)^2} \sum_{i,j} \sum_{i',j' \neq i,j} \text{cov}[Q_j^i, Q_{j'}^{i'}]. \quad \text{----- (B.5)}
 \end{aligned}$$

- From Eqs. (B.1) and (B.5), the variance bias defined by the difference between the real and apparent variance can be written as

$$\begin{aligned}
 \sigma_R^2[\bar{Q}] - \sigma_A^2[\bar{Q}] &= \frac{1}{NM} \cancel{\sigma^2[Q_j^i]} + \frac{1}{(NM)^2} \sum_{i,j} \sum_{i',j' \neq i,j} \text{cov}[Q_j^i, Q_{j'}^{i'}] \\
 &\quad - \frac{1}{NM} \cancel{\sigma^2[Q_j^i]} + \frac{1}{NM-1} \cdot \frac{1}{(NM)^2} \sum_{i,j} \sum_{i',j' \neq i,j} \text{cov}[Q_j^i, Q_{j'}^{i'}] \\
 &= \frac{1}{NM(NM-1)} \sum_{i,j} \sum_{i',j' \neq i,j} \text{cov}[Q_j^i, Q_{j'}^{i'}]. \quad \text{----- (B.6)}
 \end{aligned}$$

Derivation of Variance Bias (4/4)

- Because there is no inter-cycle correlation between the histories except when $j' \neq j$, the following condition is satisfied

$$\text{cov}[Q_j^i, Q_{j'}^{i'}] = 0 \quad (j \neq j') \quad \text{----- (B.7)}$$

- Using Eq. (B.7), the variance bias of Eq. (B.6) can be expressed as

$$\sigma_R^2[\bar{Q}] - \sigma_A^2[\bar{Q}] = \frac{1}{N(NM-1)} \sum_i \sum_{i' \neq i} \text{cov}[Q_j^i, Q_j^{i'}] \quad \text{----- (B.8)}$$

- Because $\text{cov}[Q_j^i, Q_j^{i'}] = \frac{1}{M} \text{cov}[Q^i, Q^{i'}]$, Eq. (B.8) can be written as

$$\sigma_R^2[\bar{Q}] - \sigma_A^2[\bar{Q}] = \frac{1}{N(N-1/M)} \sum_i \sum_{i' \neq i} \text{cov}[Q^i, Q^{i'}] \quad \text{----- (B.9)}$$

- Assuming that $\text{cov}[Q^i, Q^{i'}]$ depends only on the cycle difference from the equilibrium property, the variance bias of Eq. (B.9) can be expressed as

$$\sigma_R^2[\bar{Q}] - \sigma_A^2[\bar{Q}] = \frac{2}{N(N-1/M)} \sum_{l=1}^{N-1} (N-l) \cdot \text{cov}[Q^i, Q^{i+l}] \quad \text{----- (B.10)}$$

$$\sigma_R^2[\bar{k}] - \sigma_A^2[\bar{k}] = \frac{2}{N(N-1)} \sum_{l=1}^{N-1} (N-l) \cdot \text{cov}[k^i, k^{i+l}]$$

Bias of the Sample Variance in MC Eigenvalue Calculations

- As Ueki et al derived^[1] the relation between the real variance, σ_R^2 and the expected value of the sample variance, $E[\sigma_S^2]$ of the eigenvalue k , the bias of the sample variance of Q can be expressed by

$$\sigma_R^2[\bar{Q}] - E[\sigma_S^2[\bar{Q}]] = \frac{1}{N(N-1)} \sum_{i=1}^N \sum_{\substack{j=1 \\ j \neq i}}^N \text{cov}[Q^i, Q^j]. \quad \dots\dots\dots (2)$$

Correlation betw. Samples

- If Q^i and Q^j ($i \neq j$) are uncorrelated ($\text{cov}[Q^i, Q^j] = 0$), the sample variance becomes unbiased.

$$E\left[\sigma_S^2[\bar{Q}]\right] = \sigma_R^2[\bar{Q}]$$

- If Q^i and Q^j ($i \neq j$) are correlated ($\text{cov}[Q^i, Q^j] \neq 0$), the sample variance is biased as much

as
$$\frac{1}{N(N-1)} \sum_{i=1}^N \sum_{\substack{j=1 \\ j \neq i}}^N \text{cov}[Q^i, Q^j].$$

- **Why are Q^i and Q^j ($i \neq j$) correlated in the MC eigenvalue calculations?**

Correlation betw. Fission Source Distributions

- In the Monte Carlo power method, the fission source distribution (FSD) at cycle t is calculated from the FSD of the previous cycle by

$$S^t(\mathbf{r}) = \frac{1}{k^{t-1}} \int H(\mathbf{r}' \rightarrow \mathbf{r}) S^{t-1}(\mathbf{r}) d\mathbf{r} + \varepsilon^t(\mathbf{r}), \quad \text{..... (3)}$$

where

$S^t(\mathbf{r})$ = fission source distribution at cycle t ,

k^t = eigenvalue estimated at cycle t ,

$H(\mathbf{r}' \rightarrow \mathbf{r})$ = expected number of first-generation fission neutrons born per unit volume about \mathbf{r} , due to a parent neutron born at \mathbf{r}' ,

ε^t = stochastic error generated at cycle t .

- **The FSD at t -th cycle gets correlated with the FSDs of the previous cycles by Eq. (3).**

Relation betw. FSD and Tally

- The tally Q is defined by a detector response in the MC simulation as follows:

$$\begin{aligned}
 Q &= \int_{\chi} dP g(P) \Psi(P) \\
 &= \sum_{j=0}^{\infty} \int_{\chi} dP g(P) \int dP' K_j(P' \rightarrow P) \int dP'' T(P'' \rightarrow P') S(P''), \quad \dots (4)
 \end{aligned}$$

where

$$P \equiv (\mathbf{r}, E, \boldsymbol{\Omega}),$$

$\Psi(P)$ = collision density,

$g(P)$ = response function for the tally Q at P ,

$$K_0(P' \rightarrow P) = \delta(P' - P),$$

$$K_j(P' \rightarrow P) = \int dP_1 \dots \int dP_{j-1} K(P_{j-1} \rightarrow P) \dots K(P' \rightarrow P_1),$$

$K(P' \rightarrow P) \equiv C(\mathbf{r}'; E', \boldsymbol{\Omega}' \rightarrow E, \boldsymbol{\Omega}) T(E, \boldsymbol{\Omega}; \mathbf{r}' \rightarrow \mathbf{r})$ = transport kernel

$S(P)$ = fission source distribution.

- The tally Q is related to the FSD by Eq. (4).

Mechanism of Variance Bias in MC Eigenvalue Cal.

Correlation betw. FSDs by the MC power method:

$$S^t(\mathbf{r}) = \frac{1}{k^{t-1}} \int H(\mathbf{r}' \rightarrow \mathbf{r}) S^{t-1}(\mathbf{r}') d\mathbf{r}' + \varepsilon^t(\mathbf{r}) \quad \text{..... (3)}$$

$$\downarrow \text{cov}[S^t, S^{t'}] \neq 0, (t \neq t')$$

Relation betw. tally and FSD:

$$Q = \sum_{j=0}^{\infty} \int_{\chi} dP g(P) \int dP' K_j(P' \rightarrow P) \int dP'' T(P'' \rightarrow P') S(P'') \quad \text{..... (4)}$$

$$\downarrow \text{cov}[Q^i, Q^j] \neq 0, (i \neq j)$$

Bias of the sample variance:

$$\sigma_R^2[\bar{Q}] - E[\sigma_S^2[\bar{Q}]] = \frac{1}{N(N-1)} \sum_{i=1}^N \sum_{\substack{j=1 \\ j \neq i}}^N \text{cov}[Q^i, Q^j]$$