Variance reduction by importance sampling

a

Suppose we want to compute $\alpha \equiv \mathrm{E}\left(g\left(W\right)\right)$ with g non-negative and $W \sim f_W$. Let X be a random variable $X \sim f_X$, then

$$\alpha = \mathrm{E}\left(g\left(X\right)\frac{f_W\left(X\right)}{f_X\left(X\right)}\right). \tag{1}$$

Proof:

$$\begin{aligned}\alpha =& \int_{\mathbb{R}} g\left(x\right) f_W\left(x\right) dx && (2)\\ =& \int_{\mathbb{R}} g\left(x\right)\frac{f_X\left(x\right)}{f_X\left(x\right)} f_W\left(x\right) dx && (3)\\ =& \int_{\mathbb{R}} g\left(x\right)\frac{f_W\left(x\right)}{f_X\left(x\right)} f_X\left(x\right) dx && (4)\\ =&\mathrm{E}\left(g\left(X\right)\frac{f_W\left(X\right)}{f_X\left(X\right)}\right). && (5)\end{aligned}$$

b,c

The above result allows solving α by Monte Carlo (MC) methods. When we sample from distribution f_X to estimate α, the mean square error (MSE) of the MC estimator

$$\mathrm{MSE} \propto \int_{\mathbb{R}} \left(\left(g\left(x\right)\frac{f_W}{f_X}\left(x\right)\right)^2 - \alpha^2\right) f_X\left(x\right) dx. \tag{6}$$

The integrand is zero by choosing $f_X\left(x\right) = f_X^*\left(x\right) = \frac{f_W(x)g(x)}{\alpha}$, and thus the variance of the MC estimator is minimised by choosing $f_X = f_X^*$. In practice, this result is of little significance, since if we knew the exact value of α, there would be no need for the MC estimator in the first place.

d

Suppose we wish to evaluate $\mathrm{P}\left(\mathcal{N}\left(0,1\right) > 3.75\right)$. The naive MC estimator would be given by $g\left(x\right) = \mathbf{1}_{x>\frac{15}{4}}\left(x\right)$ and $f_W\left(x\right) = \sqrt{2\pi}\exp\left(-\frac{x^2}{2}\right)$. Alternatively, using an affine change of variables, we may choose for any $\delta \in \mathbf{R}$: $g_\delta\left(x\right) = \mathbf{1}_{x>\frac{15}{4}+\delta}$ and $f_W = \sqrt{2\pi}\exp\left(-\frac{(x-\delta)^2}{2}\right)$ and obtain the correct result.

In order to use the MC estimate, we need to be able to sample numbers, from the distribution $\mathcal{N}\left(\delta,1\right)$. And evaluate g for each of those realisations. An example implementation of this is given in `https://github.com/`

M	$M=10^4$	$M=10^5$
Naive MC	$[0.000000, 0.000433]$ (116 %)	$[0.000055, 0.000165]$ (50 %)
Refined MC	$[0.000084, 0.000090]$ (3%)	$[0.000088, 0.000089]$ (1%)
Exponential	$[0.000086, 0.000103]$ (9%)	$[0.000085, 0.000091]$ (3%)

Table 1: Confidence intervals for the MC estimators and relative errors when sampling from $\mathcal{N}(0,1)$ and from $\mathcal{N}(5.75,1)$. Note that the reference value is $\Phi(5.75) = 0.000088$ so that there is almost 40% that none of the realisations of of a random sample of $M = 10^4$ exceed 5.75, leading to an estimate of zero, and vanishing variance.

`Virtakuono/SME_HW3_Example/blob/master/examples.py` The MC estimator is given by:

$$\overline{\alpha} = \sum_{m=1}^{M} \frac{g_\delta(X)}{M}, \tag{7}$$

with $X_m \sim N(\delta, 1)$ i.i.d. In the example we set $\delta = 2$. Since $\mathrm{E}(X_m) = \delta$, $\mathrm{E}(\overline{\alpha}) = \alpha$. Central limit theorem guarantees that $\overline{\alpha}$ is approximately normally distributed. To estimate the confidence interval, we compute the sample variance as

$$\overline{\sigma}^2 = \sum_{m=1}^{M} \frac{(g_\delta(x) - \overline{\alpha})}{M-1}. \tag{8}$$

Let

$$\Phi_{\mu,\sigma}(z) = \left(2\pi\sigma^2\right)^{-1} \int_{-\infty}^{z} \exp\left(\frac{(x-\mu)^2}{2\sigma^2}\right). \tag{9}$$

Then, there are ready implementations for the inverse of $\Phi_{\mu,\sigma}$, that allow us to compute z^* such that $\Phi_{0,1}(z^*) = 0.95$. Using this together with the fact that our MC estimator is approximately normally distributed, we set $\eta = z^* \sqrt{\frac{\overline{\sigma}^2}{M}}$ and obtain the confidence interval $[\overline{\alpha} - \eta, \overline{\alpha} + \eta]$. For the precise results, see table 1.

e

We may, of course, use an exponential density too. To ensure that half of the samples generated exceed 5.75, we may set

$$\lambda = \frac{\ln 2}{5.75}. \tag{10}$$

. Further improvements can naturally be made, optimising over λ as well as making affine transformation of the random variable.

Generate non-uniformly distributed random numbers given uniform

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a

A mean zero unit variance random variable X has a Laplace distribution if its pdf is $f(x) = \frac{1}{2}e^{-|x|}$.
Algorithm to generate such random variable:

- $u \sim U(0,1)$
- $X \sim F_U^{-1}(u)$, where

$$F_X(x) = \begin{cases} 1 - \frac{1}{2}e^{-x},\ x \geq 0 \\ \frac{1}{2}e^{-x},\ x < 0 \end{cases}$$

$$F_U^{-1}(u) = \begin{cases} \log(2u),\ 0 < u \leq \frac{1}{2} \\ -\log(2(1-u)),\ \frac{1}{2} \leq u < 1. \end{cases}$$

b

Algorithm to generate $Y \sim N(\mu, \sigma)$ random variables using the result above. Assume that there exists $\epsilon \in (0,1]$ such that $\epsilon \frac{f_Y(X_k)}{f_X(X_k)} \leq 1$. **Algorithm** (Acceptance-Rejection)

- Set k=1
- Sample two independent random variables X_k and $U_k \sim U(0,1)$
- If $U_k \leq \epsilon \frac{f_Y(X_k)}{f_X(X_k)}$, then accept $Y = X_k$ as sample from $N(\mu, \sigma)$. Otherwise, reject X_k, increment k by 1 and go back to previous step.

c

Let U and V be two independent standard Gaussian random variables. Prove that the ratio $\frac{U}{V}$ is a Cauchy random variable.
Proof Let $Z = \frac{U}{V}$ then cdf of Z is given by

$$\begin{aligned} F_Z(z) &= P(\frac{U}{V} \leq z), \\ &= P(U \leq zV|V > 0) + P(U \geq zv|V < 0), \\ &= \int_0^{\infty} \left(\int_{-\infty}^{zv} f_U(u) \right) f_V(v)dv + \int_{-\infty}^{0} \left(\int_{zv}^{-\infty} f_U(u) \right) f_V(v)dv. \end{aligned}$$

Then, the pdf of Z is given by

$$\begin{aligned} f_Z(z) &= \frac{dF_Z(z)}{dz}, \\ &= \int_0^\infty v f_U(zv) f_V(v) dv + \int_{-\infty}^0 v f_U(zv) f_V(v) dv, \\ &= 2\int_0^\infty v f_U(zv) f_V(v) dv = \frac{1}{\pi(1+z^2)} \end{aligned}$$

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Algorithm

- Generate samples from independent standard Gaussian random variables U and V.
- Compute the samples $Z = \frac{U}{V}$.

Kernel Density Estimator (KDE)

a

We propose to estimate a density function $\rho(y)$ based on a MC sample of realisations $y_i \in \mathbb{R}^d$ from the density ρ as follows

$$\hat{\rho}(y) = \frac{1}{Mh^{-d}} \sum_{m=1}^{M} K\left(\frac{y - y_i}{h}\right), \tag{11}$$

with

$$K(x) = 2^{-d} \mathbf{1}_{||x||_{L_2}}(x) \tag{12}$$

In this estimation, we commit two errors.

bias error

$$\rho(u) - \mathrm{E}(\hat{\rho}(y)) \tag{13}$$

$$= \rho(y) \int_{\mathbb{R}^d} h^{-d} K\left(\frac{y-z}{h}\right) \rho(z)\, dz \tag{14}$$

$$= \int_{\mathbb{R}^d} (\rho(y) - \rho(y - hz))\, K(z)\, dz \tag{15}$$

$$\approx \int_{\mathbb{R}^d} \left(\rho(y) - \left(\rho(y) - hz_i \partial_{y_i} \rho(y) + h^2 z_i z_j \partial^2_{z_i, z_j} \rho(y)\right)\right) K(z)\, dz \tag{16}$$

$$= \frac{h^2}{2} \partial_{y_i y_j} \rho(u) \int_{\mathbb{R}^d} z_i z_j K(z)\, dz \propto h^2 \tag{17}$$

statistical error

The variance is bounded by

$$\mathrm{V}\left(K\left(\frac{y-z}{h}\right)\right)\leq \mathrm{E}\left(K^2\left(\frac{y-z}{h}\right)\right) \tag{18}$$

and

$$\mathrm{E}\left(K^2\left(\frac{y-z}{h}\right)\right)\approx\int_{\mathbb{R}^d}K^2\left(z\right)h^d\left(\rho\left(y\right)-hz_i\partial_{y_i}\rho\left(y\right)+\frac{h^2}{2}z_iz_j\partial^2_{y_iy_j}\rho\left(y\right)\right)dz, \tag{19}$$

thus

$$\begin{aligned}\mathrm{V}\left(\hat{\rho}\left(y\right)\right)=&M^{-1}h^{-2d}\mathrm{V}\left(K\left(\frac{y-z}{h}\right)\right) &(20)\\ \geq&M^{-1}h^{-2d}h^d\rho\left(y\right)\int_{\mathbb{R}^d}K^2\left(z\right)dz\propto M^{-1}h^d &(21)\end{aligned}$$

Total error

With undefined constants A and B we have that the total error squared (TSE) is given as

$$\mathrm{TSE}\approx Ah^4+\frac{B}{Mh^d}. \tag{22}$$

The critical point of the total square error is thus given by

$$h^{4+d}\propto M^{-1}. \tag{23}$$

This choice implies that the bias and sampling errors are of the same order

$$\mathrm{TSE}=\mathcal{O}\left(M^{-\frac{2}{d+4}}\right) \tag{24}$$

With the above analysis, we produce the set of three images (1) for varying M for a one-dimensional KDE and an example of two-dimensional gaussian example (2).

KDE for conditional expectation

a

Consider the Nadaraya-Watson estimator $\hat{g}(x)$ for $E[Y|X=x]$ which is derived as follows:

$$g(x)=E[Y|X=x]=\frac{\int yf(y,x)dy}{f(x)},$$

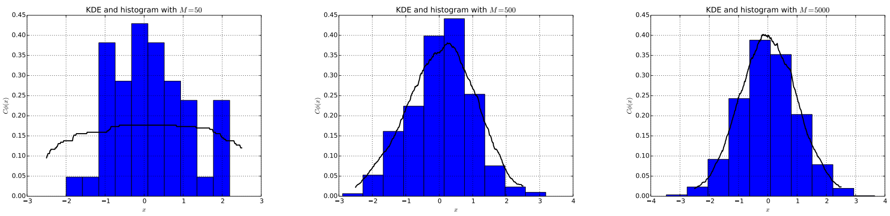

Figure 1: One-dimensional multivariate Gaussian and corresponding KDEs.

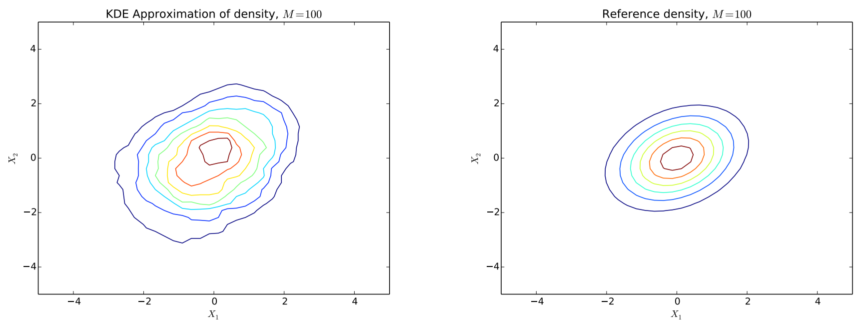

Figure 2: Two-dimensional multivariate Gaussian estimated (left) and exactly computed (right). $M = 100$ samples, $h = 0.5$

using the KDE for both $f(y,x)$ and $f(x)$

$$\begin{aligned}\hat{f}(y,x) &= \frac{1}{n}\sum_{i=1}^{n}\kappa_h(y-Y_i)\kappa_H(x-X_i),\\ \hat{f}(x) &= \frac{1}{n}\sum_{i=1}^{n}\kappa_H(x-X_i),\end{aligned}$$

and the fact that $\int z\kappa_h(z)dz = 0$, we obtain

$$\hat{g}(x) = \frac{\sum_{i=1}^{n}\kappa_H(x-X_i)Y_i}{\sum_{i=1}^{n}\kappa_H(x-X_i)}.$$

Optimal rate of convergence
Note we have

$$\begin{aligned}Y_i &= g(X_i)+\epsilon_i,\\ Y_i &= g(x)+(g(X_i)-g(x))+\epsilon_i,\end{aligned}$$

where $E(\epsilon_i|X_i)=0$ and $E(\epsilon_i^2|X_i=x)=\sigma^2(x)$.
Therefore, the estimator can be written as

$$\hat{g}(x) = g(x)+\frac{\hat{m}_1(x)}{\hat{f}_X(x)}+\frac{\hat{m}_2(x)}{\hat{f}(x)},$$

where

$$\begin{aligned}\hat{m}_1(x) &= \frac{1}{n}\sum_{i=1}^{n}\kappa_H(x-X_i)(g(X_i)-g(x)),\\ \hat{m}_1(x) &= \frac{1}{n}\sum_{i=1}^{n}\kappa_H(x-X_i)\epsilon_i.\end{aligned}$$

If $d=1$, we can show that

$$\begin{aligned}E(\hat{m}_1(x)) &= \frac{1}{h}\int k\left(\frac{x-u}{h}\right)(g(u)-g(x))f(u)du\\ &= \int k(z)(g(x+hz)-g(x))f(x+hz)dz\\ &\quad \text{(Taylor expansion)}\\ &= h^2B(x)f(x)\int k(z)z^2dz+o(h^2),\end{aligned}$$

where $B(x)=\frac{1}{2}g''(x)+\frac{g'(x)}{f(x)}f'(x)$.
Similarly, we can obtain $Var(\hat{m}_1(x)) = O(\frac{1}{nh})$.

$$
\begin{aligned}
E(\hat{m}_2(x)) &= 0, \\
Var(\hat{m}_2(x)) &= \frac{1}{nh^2}\int k\left(\frac{x-u}{h}\right)^2 \sigma^2(u) f(u) du \\
&= \frac{1}{nh}\int k(z)\sigma^2(x+hz) f(x+hz) dz \\
&\quad \text{(Taylor expansion)} \\
&= \frac{\sigma^2(x) f(x)}{nh}\int k(z)^2 dz + o(h^2),
\end{aligned}
$$

The asymptotic mean square error(AMSE) when $d = 1$ is

$$
\left(h^2 B(x)\right)^2 \left(\int k(z) z^2 dz\right)^2 + \frac{\sigma(x)^2 f_X(x)}{nh}\left(\int k(z)^2 dz\right).
$$

In General, the asymptotic mean square error(AMSE) is given by

$$
\left(\sum_{j=1}^{d} h_j^2 B_j(x)\right)^2 \left(\int k(z) z^2 dz\right)^2 + \frac{\sigma(x)^2 f_X(x)}{n|H|}\left(\int k(z)^2 dz\right)^d,
$$

where $B_j(x) = \frac{1}{2}\partial^2_{x_j} g(x) + f(x)^{-1}\partial_{x_j} g(x)\partial_{x_j} f(x)$ and the optimal value for h is proportional to $N^{-\frac{1}{d+4}}$.

Monte Carlo and Variance Reduction

The task at hand is to evaluate an option on an underlying that is an arithmetic mean of a log-normal random variable. No closed form solution exists. However, we do have a closed form expression for the arithmetic mean of normal variables. Based on a visual inspection (cf. fig 3), the distribution of the underlying is, however, somewhat close to a Gaussian and especially the relevant part, the right tail of the distribution could be approximated with a Gaussian with a decent fidelity. We have

$$
V_N = V_0 \prod_{n}^{N} R_n. \tag{25}
$$

Empirically, we see that the probability P_{otm} of V_N being out of the money is approximately 72 per cent. Define

$$
Q = \sum_{n=1}^{N} (50 - n)\left(\ln R_n - r\Delta t\right), \tag{26}
$$

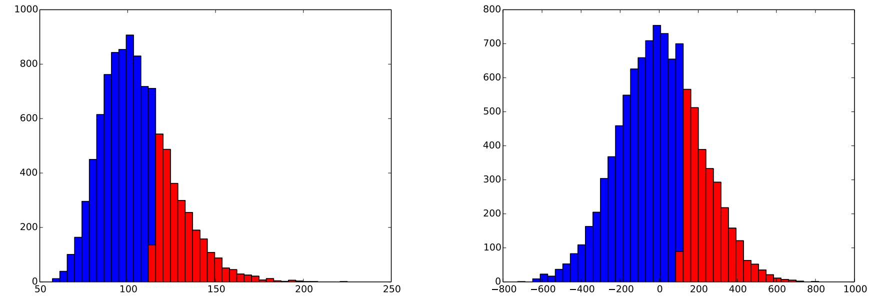

Figure 3: The distribution of the underlying of the Asian Option (left) and a control variate (right). The right tail of the distribution is coloured left to indicate realisations *in the money* with strikes K and $\tilde{K}$.

we note that both Q and V_N are increasing in all the random variables R_n. Furthermore, we know that Q entered and normally distributed with $\tilde{\sigma}^2 = \sum_{n=1}^{N} (50-n)^2$. With the inverse cumulative distribution Φ^{-1} we can define

$$\tilde{K} = \tilde{\sigma}\Phi^{-1}\left(P_{otm}\right). \tag{27}$$

Then our control variate is

$$G = \left(Q - \tilde{K}\right)^+. \tag{28}$$

We have

$$\int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{x^2}{2\tilde{\sigma}^2}\right)(x-k)^+ = \frac{\tilde{\sigma}}{\sqrt{2\pi}} \exp\left(-\frac{k^2}{2\tilde{\sigma}^2}\right) + k\left(\Phi\left(k\right)-1\right). \tag{29}$$

We have that the correlation coefficient ρ between G and $C = \left(\sum_{n=1}^{N} \frac{V_n}{K} - K, 0\right)^+$ exceeds 0.99, see fig 4.

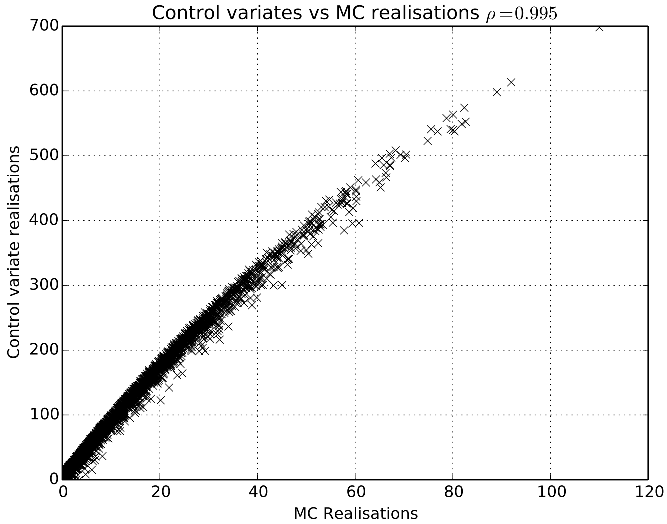

Figure 4: The MC realisations and corresponding control variates show a near-perfect correlation

We can form the estimators

$$\overline{C}_1 = \sum_{m=1}^{M} \frac{\left(\left(\sum_{n=1}^{N} V_0 \prod_{m=1}^{n} R_n\right) - K\right)^+}{M} \tag{30}$$

$$\overline{C}_2 = \sum_{m=1}^{2M} \frac{\left(\left(\sum_{n=1}^{N} V_0 \prod_{m=1}^{n} \tilde{R}_{n,m}\right) - K\right)^+}{M} + \sum_{m=1}^{2M} \frac{\left(\left(\sum_{n=1}^{N} V_0 \prod_{m=1}^{n} \tilde{R}_{n,m}\right) - K\right)^+}{M} \tag{31}$$

$$\overline{C}_3 = \sum_{m=1}^{M} \frac{\left(\left(\sum_{n=1}^{N} V_0 \prod_{m=1}^{n} R_n\right) - K\right)^+ + \beta\left(G_m - \mathrm{E}\left(Q\right)\right)}{M} \tag{32}$$

$$\overline{C}_4 = \sum_{m=1}^{2M} \frac{\left(\left(\sum_{n=1}^{N} V_0 \prod_{m=1}^{n} R_n\right) - K\right)^+ + \beta\left(G_m - \mathrm{E}\left(Q\right)\right)}{M}$$
$$\sum_{m=1}^{2M} \frac{\left(\left(\sum_{n=1}^{N} V_0 \prod_{m=1}^{n} R_n\right) - K\right)^+ + \beta\left(Q_m - \mathrm{E}\left(Q\right)\right)}{M}, \tag{33}$$

Plain vanilla	Antithetic	Control variate	Hybrid
0.15 %	0.10 %	0.012 %	0.0085 %

Table 2: Widths of 95 % confidence bands for different Monte Carlo estimators for $M = 1000$. Modified option price approximately 4.3.

for the plain vanilla, antithetic, control variate, and combination methods, respectively. The $R_{n,m}$ are understood to be independent realisations of the incrementation for nth time step for realisation m The antithetic variables are defined as

$$\tilde{R}_{n,m} = \exp\left(-\log R_{n,m} + \Delta t r\right) \tag{34}$$

and

$$\tilde{Q}_m = \sum_{n=1}^{N} (50 - n) \left(\ln \tilde{R}_{nm} - r\Delta t\right), \tag{35}$$

$$G_m = \left(Q_m - \tilde{K}\right)^+ \tag{36}$$

$$\tilde{G}_m = \left(\tilde{Q}_m - \tilde{K}\right)^+. \tag{37}$$

In order to minimise the variance of the estimators, we set $\beta = \rho\sqrt{\frac{\sigma_C^2}{\sigma_Q^2}}$ with σ_C^2 being the variance of the plain vanilla MC realisations and σ_Q^2 the variance of the control variate realisations. With $M = 10000$, we obtain the results in table 2: The exact computational cost of each estimator depends on how computationally costly it is to generate time steps compared to the cost of generating random numbers. For a rough approximation, we may state that the computational cost of the antithetic and control variate estimators are twice that of the plain vanilla and the hybrid method requires four-fold computational effort.

Confidence interval, Bootstrapping

In order to compute the expected shortfall we reuse the MC sample from the previous exercise. Let our MC estimator $\overline{C}$ be given as:

$$\overline{C} = \sum_{m=1}^{M} \frac{X_i}{M}. \tag{38}$$

Then let us draw $N \times M,\ N, M \in \mathbb{Z}$ random variables $k_i \in \{1, 2, 3, ...M\}$. Then define S_j such that

$$\#A_j = \#\left\{k_i : X_{k_i} > S_j, (j-1)\,M \leq i \leq jM - 1\right\} = \lfloor pM \rfloor \tag{39}$$

p	0.9	0.95	0.99
Confidence interval	$[28.28, 30.01]$	$[36.51, 38.80]$	$[52.34, 57.68]$

Table 3: Confidence intervals for the Expected Shortfall for problem 5 example for various quantiles. The width of the confidence interval tends to increase as a function of q.

for $j \in 1, 2, 3, 4, ..., N$. and

$$Q_j = \sum_{i \in A_j} \frac{X_i \mathbf{1}_{x > S_j}(X_i)}{\# A_j} \tag{40}$$

then the estimated confidence interval can be noted as $[Q^-, Q^+]$ as

$$\#\left\{j : Q_j < Q^-\right\} = \left\lfloor \frac{qN}{2} \right\rfloor \tag{41}$$

$$\#\left\{j : Q_j < Q^+\right\} = \left\lfloor \frac{qN}{2} \right\rfloor . \tag{42}$$

Setting $N = 1000$, we obtain the results in the table 3