

# 1 Abstract

You will learn

- taking definite integral by ordinary Monte Carlo (OMC)
- exact sampling with python provided random number generators

## 2 Problem

Our goal is to compute, using OMC by exact sampling

$$\alpha = \int_0^1 h(x)dx$$

where

$$h(x) = 100 \cdot I_{(0,1/100]}(x) + 1 \cdot I_{(1/100,1)}(x).$$

The exact value shall be

$$\alpha = 1.98.$$

## 3 Analysis

### 3.1 OMC by exact sampling

To estimate

$$\alpha = \mathbb{E}[X], \quad X \sim p(x)$$

one can use random number generator by computer (if possible)

$$\{iid \ X_i \sim p(x) : i = 1, 2, \dots, n, \}.$$

Then, one can compute the approximation of  $\alpha$  by

$$\hat{\alpha}_n = \frac{1}{n} \sum_{i=1}^n X_i.$$

We say  $\hat{\alpha}_n$  as OMC by exact sampling, since the sample  $X_i$  produced by random generator has the same distribution as true distribution  $X$ , i.e.

$$X_i \sim X, \quad \forall i.$$

The properties of the OMC by exact sampling are listed below:

- $X_1$  its self can be treated as an unbiased MC, because

$$\mathbb{E}[X_1] = \alpha.$$

However, MSE is big, ie.

$$MSE(X_1) = Var(X) = \int x^2 p(x) dx.$$

- $\hat{\alpha}_n$  is consistent almost surely due by LLN, i.e.

$$\hat{\alpha}_n \rightarrow \alpha, \text{ almost surely as } n \rightarrow \infty.$$

Moreover,  $\hat{\alpha}_n$  is unbiased too, and

$$MSE(\hat{\alpha}_n) = Var(\hat{\alpha}_n) = \frac{1}{n} Var(X) \rightarrow 0.$$

### 3.2 Evaluation of integral

Back to our example, we write

$$\alpha = \mathbb{E}[X] = \mathbb{E}[h(Y)],$$

where  $X = h(Y)$  and  $Y \sim U(0, 1)$ . In other words, although  $X$ -sampling is not directly available in python, one can use  $U(0, 1)$  random generator (see `numpy.random.uniform`) to produce  $Y_i$ , then compute  $h(Y_i)$  for the sample  $X_i$ .

Pseudocode for `omc_integral(n)`:

- Generate  $n$  iid samples

$$\{iid Y_i \sim U(0, 1) : i = 1, 2, \dots, n\};$$

- Compute  $n$   $X$  samples by

$$\{X_i = h(Y_i) : i = 1, 2, \dots, n\};$$

- Take average of  $X_i$ 's

## 4 Others

### 4.1 Homework

For the problem setup given above,

- Find its convergence rate by the following procedure:  
Compute RMSE (root MSE) for  $\hat{\alpha}_n$  in terms of  $Cn^{-\alpha}$ . We say  $\alpha$  as the convergence rate.
- Implement `omc_integral(n = 64)`.
- Demonstrate convergence rate numerically by doing the following:
  - Fix a batch number  $m = 100$ ;
  - For  $i$  in `range(5, 10)`:
    - \* run  $m$  times of `omc_integral(n = 2i)`, store it into  $\{\alpha_{ij} : j = 1, \dots, m\}$ .
    - \* compute standard deviation (`numpy.std`) of  $\{\alpha_{ij} : j = 1, \dots, m\}$ , save it to  $\sigma_i$ .
  - plot and find slope (`scipy.stats.linregress`) for the data

$$\{(i, -\log_2 \sigma_i) : i = 5, \dots, 10\}.$$