

# Lecture 8: The Monte Carlo method for estimating expectations

Professor Ilias Bilonis

## The uncertainty propagation problem

# The uncertainty propagation problem

- You are given a function  $g(x)$  representing a physical model.  
*x: input, g(x): output*
- The inputs of the model are uncertain.
- You represent this uncertainty with a random variable:

$$X \sim p(x)$$

- You would like to quantify your uncertainty about the model output:

$$Y = g(X)$$

# The uncertainty propagation problem

- We would like to estimate the expected value of the output:

$$\mathbb{E}[Y] = \mathbb{E}[g(X)] = \int g(x) p(x) dx$$

# The uncertainty propagation problem

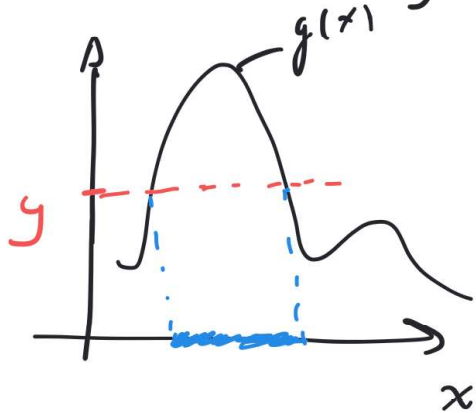
- We would like to estimate the variance of the output:

$$\begin{aligned}\mathbb{V}[Y] &= \int (g(x) - \mathbb{E}[Y])^2 p(x) dx \\ &= \mathbb{E} [ [g(x)]^2 ] - \left( \mathbb{E} [ g(x) ] \right)^2 \\ \mathbb{E} [ [g(x)]^2 ] &= \int g^2(x) p(x) dx\end{aligned}$$

# The uncertainty propagation problem

- Or maybe the probability that the output exceeds a threshold:

$$p(Y \geq y) = \int \mathbb{1}_{[y, \infty)}(g(x)) p(x) dx = \mathbb{E}[\mathbb{1}_{[y, \infty)}(g(X))] = \mathbb{P}[\mathbb{1}_{[y, \infty)}(Y)]$$



$$\mathbb{1}_{[y, \infty)}(g(x)) = \begin{cases} 1, & \text{if } g(x) \geq y \\ 0, & \text{otherwise} \end{cases}$$

↘ The indicator function of the set  $[y, \infty)$

# The uncertainty propagation problem

- Notice that all these statistics are essentially expectations of functions of  $X$ .
- We must learn how to do such integrals!

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## The curse of dimensionality

# The curse of dimensionality

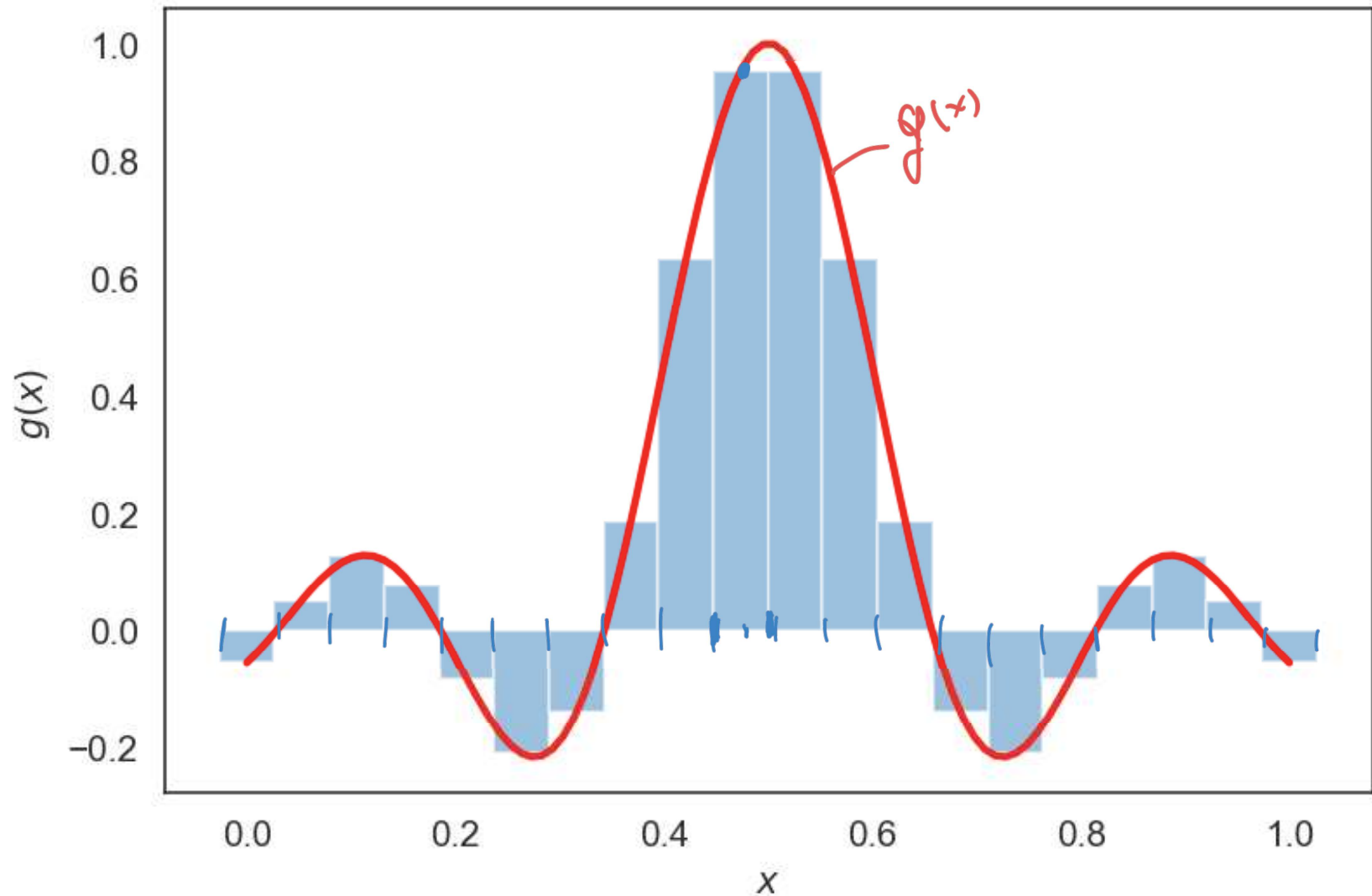
$$\underline{X} = (X_1, \dots, X_d), \quad X_i \sim U([0, 1]) \text{ independent}$$
$$p(\underline{x}) = \prod_{i=1}^d p(x_i) = \prod_{i=1}^d \mathbb{1}_{[0,1]}(x_i) = \mathbb{1}_{[0,1]^d}(\underline{x})$$

- Take the d-dimensional uniform:  $X \sim U([0,1]^d)$ .
- Take a function  $g(x)$ .
- We would like to estimate:

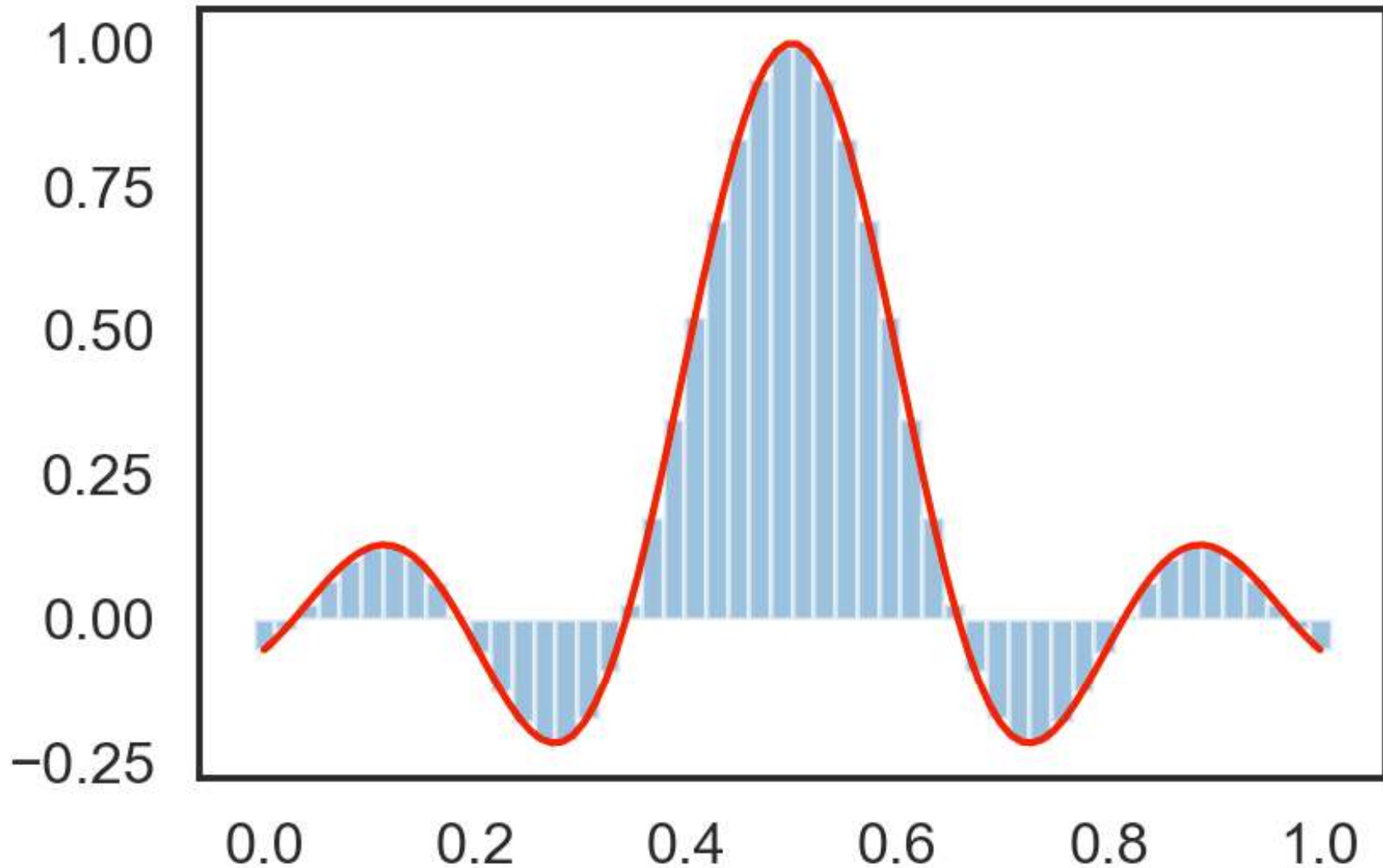
$$\mathbb{E}[g(X)] = \int g(x) \underline{p}(x) dx$$



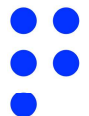
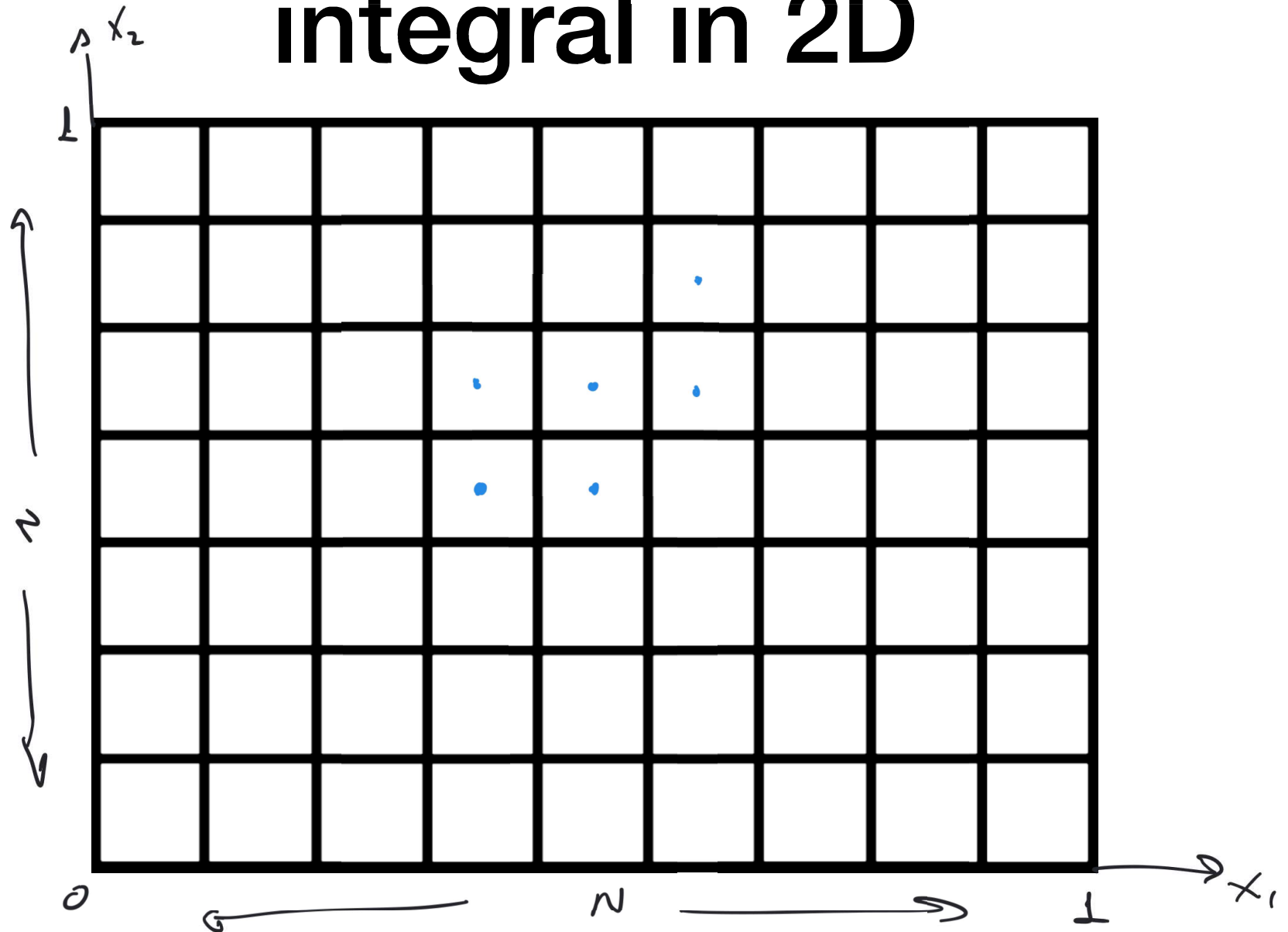
# Example: Evaluating integral in 1D



# Example: Evaluating integral in 1D



# Example: Evaluating integral in 2D



# The curse of dimensionality

- Use  $n$  equidistant points per dimension.
- You will have  $n^d$  boxes each with volume  $n^{-d}$ .
- You can evaluate the integral by:

$$\mathbb{E}[g(X)] \approx n^{-d} \sum_{j=1}^{n^d} g(x_{c,j})$$

# The Curse of dimensionality

- Assume it takes a millisecond to evaluate the function.
- Take  $n = 10$  points per dimension.
- $d=2$ , needs 0.1 seconds.
- $d=3$ , needs 1 second.
- $d=5$ , needs 100 seconds.
- $d=6$ , needs, 1000 seconds or 16 minutes.
- $d=10$ , needs 115 days...
- $d=20$ , needs 3.17 billion years

$g(x)$

$n^d$

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## The law of large numbers

# The strong law of large numbers

- Take an infinite series of independent random variables  $X_1, X_2, \dots$  with the same distribution (it doesn't matter what distribution).

- The *sample average*:

$$\frac{X_1 + \dots + X_N}{N} \longrightarrow \mu$$

$$\bar{X}_N = \frac{1}{N} \sum_{i=1}^N X_i \rightarrow \mu \text{ a.s.}$$

almost surely  
(measure theory)

where  $\mu = \mathbb{E}[X_i]$  (as  $N \rightarrow \infty$ ).

# The Monte Carlo method for estimating integrals

- Take a random variable  $X \sim p(x)$  and some function  $g(x)$ .

- We want to estimate the expectation:

$$I = \mathbb{E}[g(X)] = \int g(x)p(x)dx$$

- Make independent identical copies of  $X$ :  $X_1, X_2, \dots \sim p(x)$

- Consider the also the independent iden. dist.:

$$Y_1 = g(X_1), Y_2 = g(X_2), \dots$$

- By the strong law of large numbers:

$$I_N = \frac{Y_1 + \dots + Y_N}{N} \longrightarrow \mathbb{E}[Y_i] = \mathbb{E}[g(X_i)] = I \text{ a.s.}$$



# Example: 1D expectation

(This is Example 3.4 of Robert & Casella (2004))

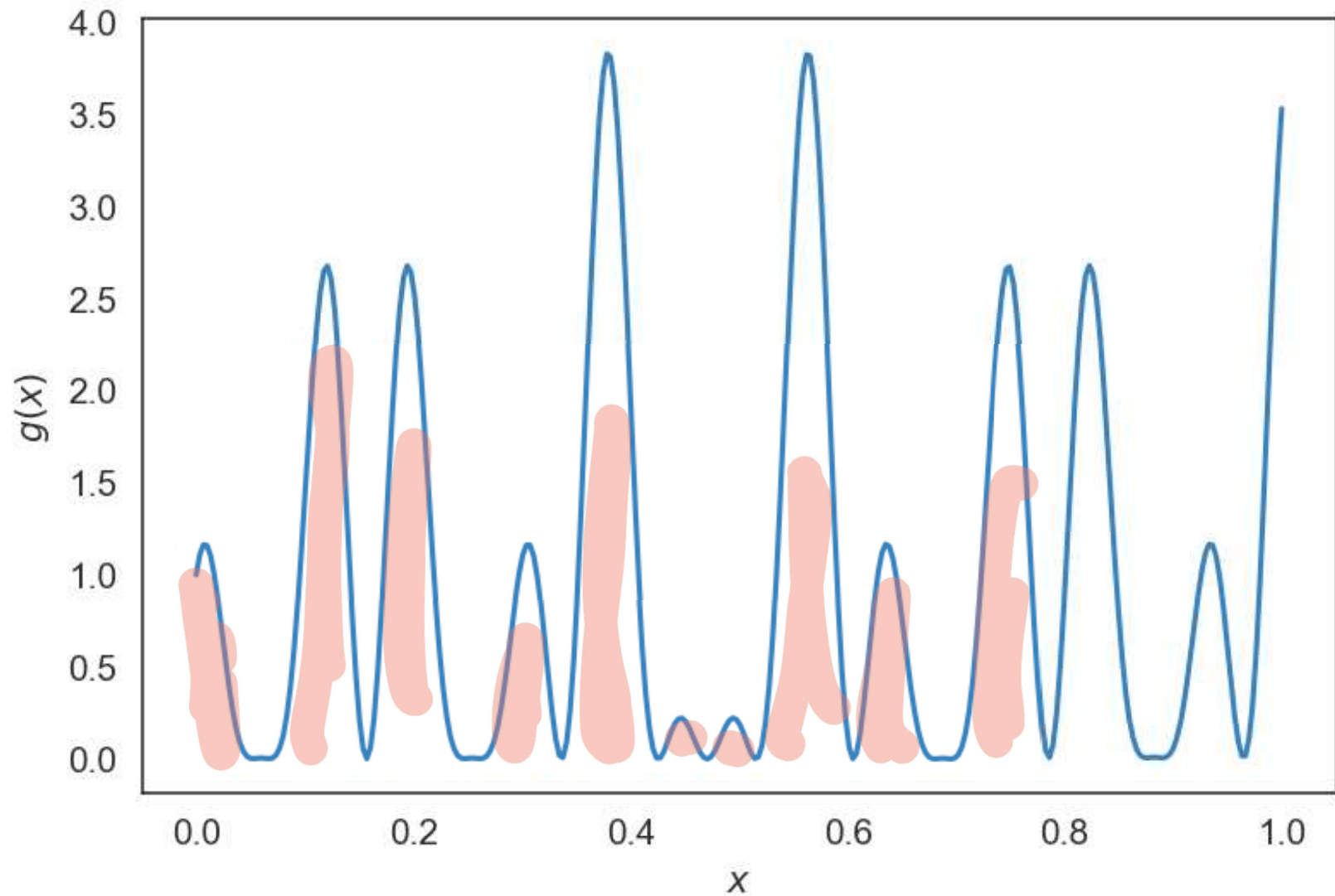
$$X \sim \mathcal{U}([0, 1])$$

$$g(x) = (\cos(50x) + \sin(20x))^2$$

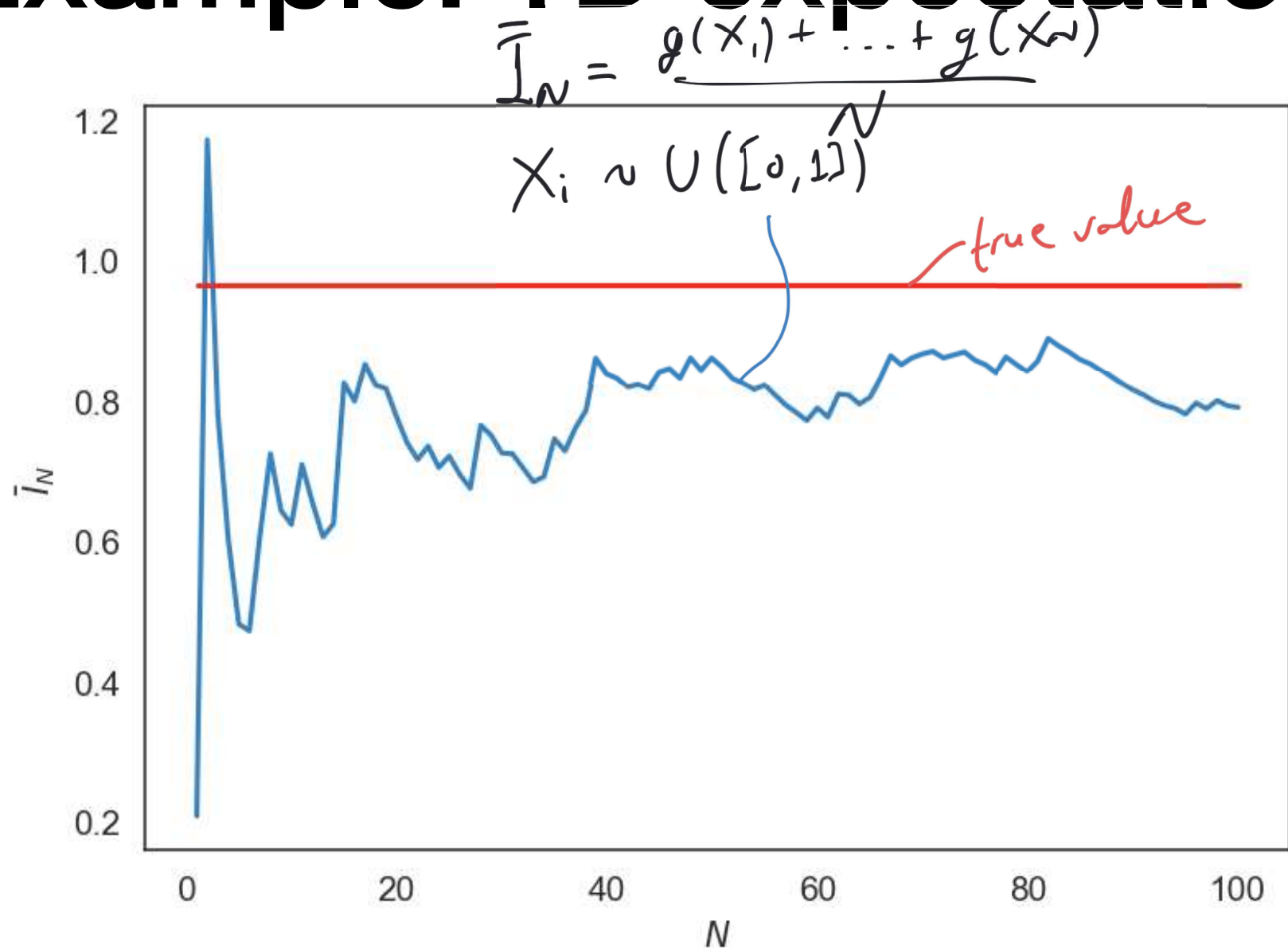
The correct value for the integral is:

$$\mathbb{E}[g(X)] = 0.965$$

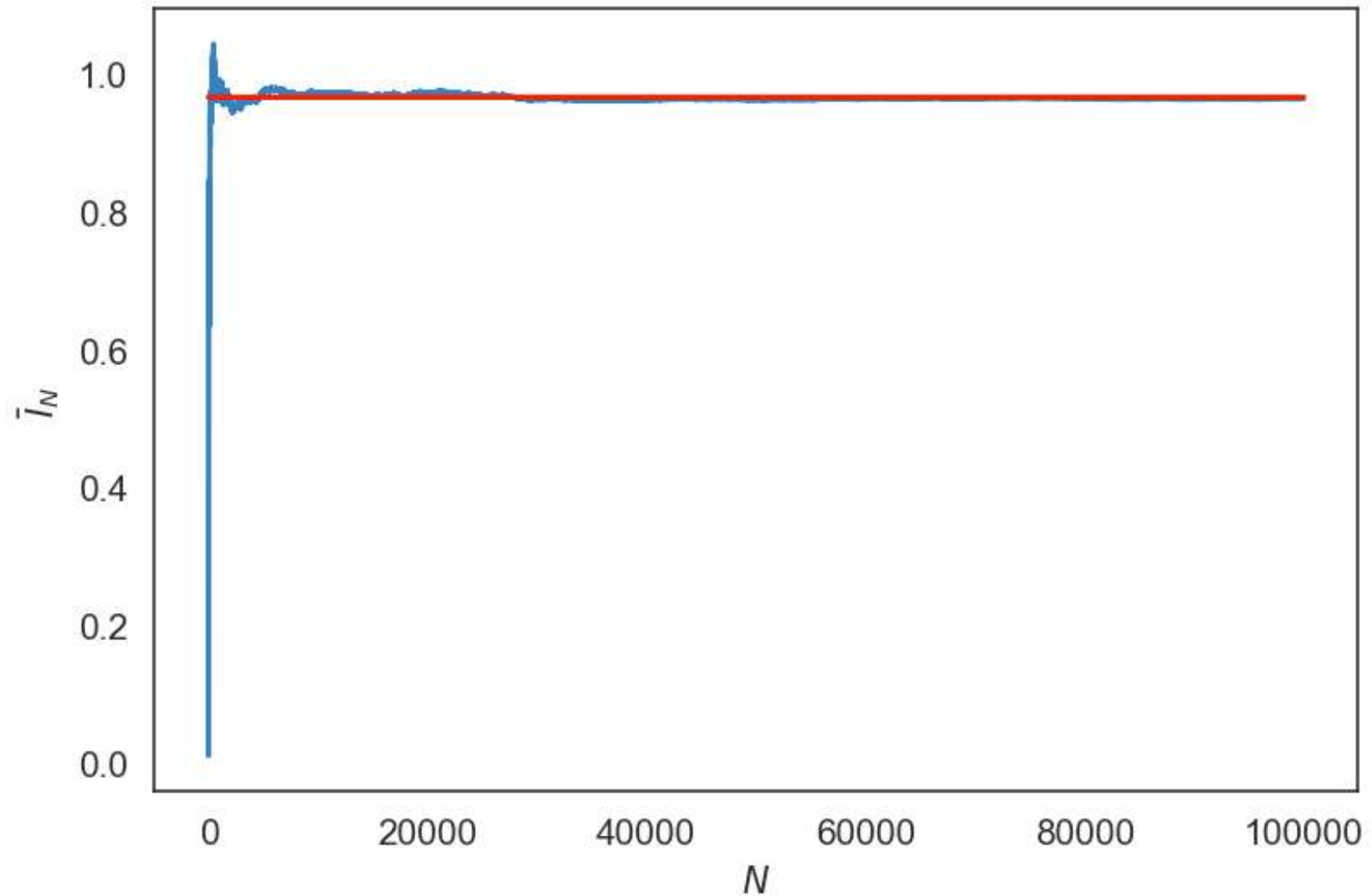
# Example: 1D expectation



# Example: 1D expectation



# Example: 1D expectation



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## Estimating the variance

# Estimating the variance

- Take a random variable  $X \sim p(x)$  and some function  $g(x)$ .
- We would like to estimate the variance:

$$V = \mathbb{V}[g(X)] = \mathbb{E} \left[ \left( g(X) - \mathbb{E}[g(X)] \right)^2 \right] = \mathbb{E} \left[ \left( g(X) - \underline{I} \right)^2 \right]$$

- Note that:

$$V = \mathbb{V}[g(X)] = \underline{\mathbb{E} [g^2(X)]} - \underline{I}^2$$

# Estimating the variance

- Take  $X_1, X_2, \dots$  independent identical copies of  $X$ .
- Estimate the mean using a sample average:

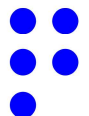
$$\bar{I}_N = \frac{1}{N} \sum_{i=1}^N g(X_i)$$

$$E[g^2(X)]$$

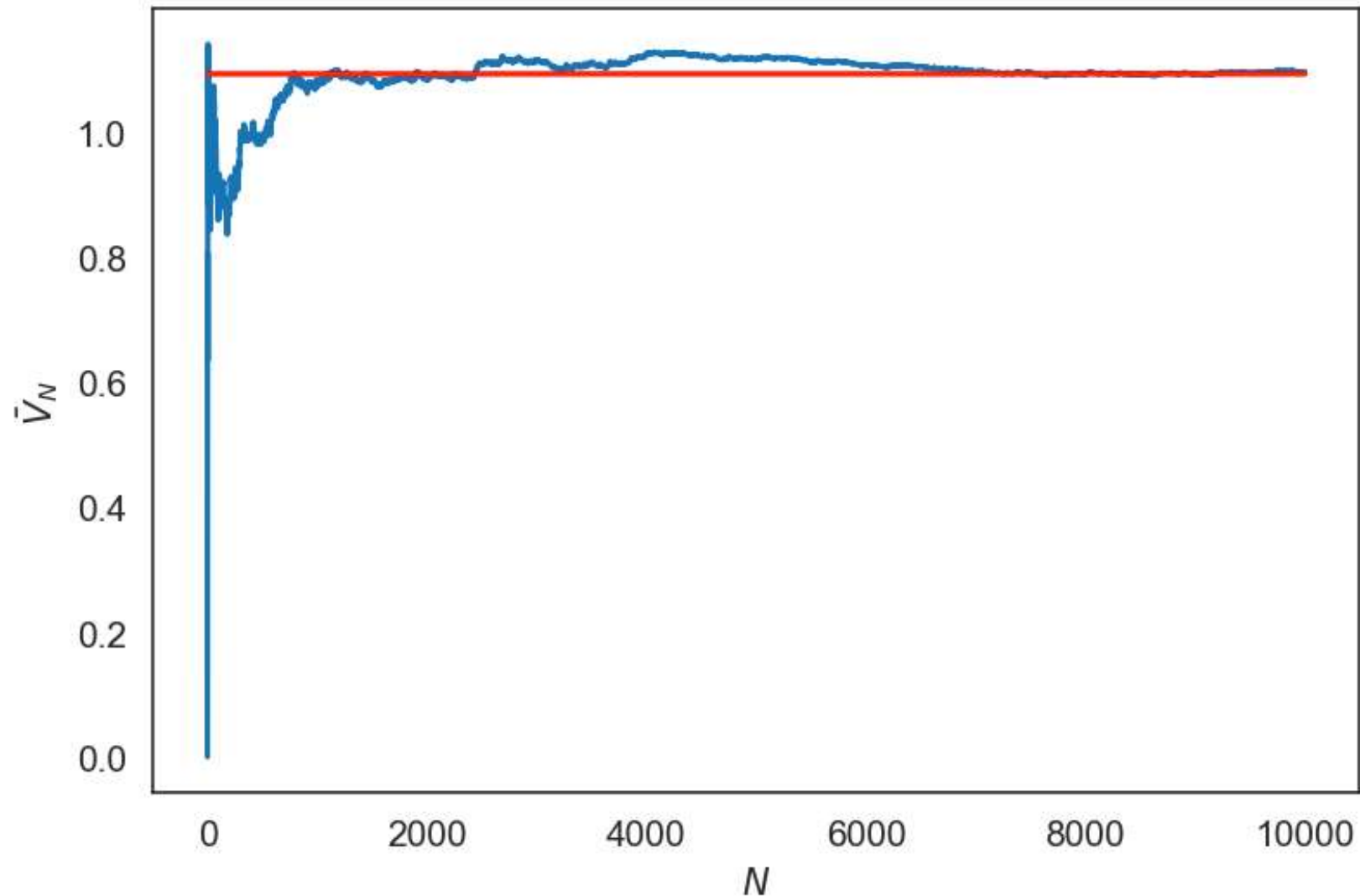
- Estimate the variance by:

$$\bar{V}_N = \frac{1}{N} \sum_{i=1}^N g^2(X_i) - \bar{I}_N^2$$

estimate



# Example: 1D variance





# Example: 1D variance

