# **Algorithms and Data Structures**

# **Quadrature Monte Carlo Integration**

X X X



#### **Learning goals**

- Simple Monte Carlo
- Hit-or-Miss approach

# **SIMPLE MONTE CARLO**

**Goal:** Calculate  $I(f) = \int_{a}^{b} f(x) dx$ 

• We define

$$
I(f) = (b-a)\int_a^b f(x) \cdot \frac{1}{b-a} dx = (b-a) \cdot \mathbb{E}[f(x)]
$$

with  $x \sim U(a, b)$ 

With *x<sup>i</sup> iid*∼ *U*(*a*, *b*), *i* = 1, ..., *n* the Monte Carlo estimation is given by

$$
Q_{MC}(f)=\frac{b-a}{n}\sum_{i=1}^n f(x_i)
$$

 $\bullet$  By "sampling" *n* independent random numbers from  $U(a, b)$  an estimate for the integral can be calculated.



# **SIMPLE MONTE CARLO / 2**

Monte Carlo is a **non-deterministic** approach. The estimation for the integral  $\int_{a}^{b} f(x) dx$  is subject to randomness:

- $\bullet$  The strong law of large numbers states that  $Q_{MC}(f)$  converges almost certainly towards  $I(f) = \mathbb{E}[f(x)]$  for  $n \to \infty$
- $\bullet$  We can derive the variance from  $Q_{MC}(f)$ :

$$
\begin{array}{rcl}\n\text{Var}\left(Q_{MC}(f)\right) & = & \text{Var}\left(\frac{b-a}{n}\sum_{i=1}^{n}f(x_i)\right) \\
& \stackrel{\text{iid}}{=} & \frac{(b-a)^2}{n^2} \cdot n \cdot \text{Var}(f(x)) = \frac{(b-a)^2}{n}\sigma^2\n\end{array}
$$

where  $\sigma^2 = \textsf{Var}(f(x))$  denotes the variance of the random variable *f*(*x*) with *x* ∼ *U*(*a*, *b*) which can be empirically estimated by  $\hat{\sigma}^2 = \frac{1}{n-1} \sum_{i=1}^n$  $\left(f(x_i) - \frac{1}{n} \sum_{i=1}^n f(x_i)\right)^2, x_i \stackrel{iid}{\sim} U(a, b).$ 



# **SIMPLE MONTE CARLO / 3**

- If  $\sigma^2 < \infty$  the variance of the estimate (and thus also the worst case error of the procedure) approaches 0 for  $n \to \infty$
- Monte Carlo also works well in multidimensional settings:
	- The Monte Carlo integration can simply be generalized to multidimensional integrals  $\int_{\Omega} f(\textbf{\textit{x}}) \ d\textbf{\textit{x}}$  with  $\Omega \subset \mathbb{R}^{d}$  by drawing the random variables uniformly distributed in the *d*-dimensional space Ω.
	- **•** The variance is then

$$
\text{Var}\left(Q_{MC}(f)\right) = \frac{V^2}{n}\sigma^2, \quad V = \int_{\Omega} d\mathbf{x}
$$

In particular, the speed of convergence for the variance **does not** depend on the dimension of the function to be integrated.

#### **Idea:**

We draw *n* independently uniformly distributed data points from a rectangle enclosing our function:



X  $\times\overline{\times}$ 

#### **"Hit-or-Miss" Approach:**

 $\ddot{\mathbf{c}}$ 

 $\circ$  $0.0$ 

 $0.2$ 

We still consider the integral  $\int_{a}^{b} f(x) dx$ . We assume that  $0 \le f(x) \le c$ . If we count the number of hits (the points underneath the curve), we obtain the integral by:

$$
I(f) \approx \frac{\text{Hits}}{n} \cdot \text{area of the rectangle} = \frac{\sum_{i=1}^{n} \mathbf{1}_{y_i \leq f(x_i)}}{n} \cdot c \cdot (b - a)
$$

 $0.4$ 

×

$$
\begin{array}{c}\n\bigcirc \\
\times \\
\hline\n\end{array}
$$



 $1.0$ 

 $0.8$ 

 $0.6$ 

m\$estimate # Estimation of area ## [1] 2.288 m\$hits # Number of points underneath the curve ## [1] 286

$$
I(f) \approx \frac{286}{500} \cdot 1 \cdot 4 = 2.288
$$

This naive method works well for simple examples, but error rates are high for more complex applications.

 $\boldsymbol{\mathsf{X}}$  $\overline{x}$ 

#### **Advantages:**

- Monte Carlo integration does not require continuity for *f*
- Error does not depend on the dimension (in contrast to deterministic quadrature formulas), but only on the variance of the function *f* and the number of simulations *n*
	- $\bullet \rightarrow$  Improve precision through high number of simulations
	- $\bullet \rightarrow$  Improve precision by reducing variance

### **Disadvantages:**

• Relatively slow convergence rates

set.seed(333)

```
T = 10000; shape = 2; rate = 1 / 2
theta = rgamma(T, shape = shape, rate = rate)
```

```
hist(theta, freq = FALSE, ylim = c(0, 0.2), main = "")
lines(density(theta))
```
X  $\times\overline{\times}$ 



```
(Etheta = mean(theta)) # MC estimator
## [1] 4.007281
(se.Etheta = sqrt(var(theta) / T)) # variance
## [1] 0.02841768
shape * 1 / rate # Theoretical expectation
## [1] 4
(Ptheta = mean(theta > 5)) # MC Estimator
## [1] 0.2863
(se.Ptheta = sqrt(var(theta > 5) / T)) # variance
## [1] 0.004520539
1 - pgamma(5, shape = shape, rate = rate) # theo value
## [1] 0.2872975
f = function(x) {dgamma(x, shape = shape, rate = rate)}
integrate(f, 5, Inf) # Numerical integration in R
## 0.2872975 with absolute error < 9.3e-05
```
 $\times\overline{\times}$