

Numerical methods: efficient Monte Carlo simulation

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1 Basic Monte Carlo simulation

- From random numbers to Monte Carlo simulation
- Central Limit theorem, Law of Iterated Logarithm
- Confidence intervals
- Back to the simulation of Gaussian random vectors

2 Variance reduction techniques

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- Typical examples: Parity equations and option pricing
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3 From the hedge side

4 Quasi-Monte Carlo methods

- Monte Carlo revisited
- Uniformly distributed sequences
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Introduction: the Monte Carlo method

▷ **Aim:** Let $X : (\Omega, \mathcal{A}, \mathbb{P}) \rightarrow \mathbb{R}$ be an integrable random variable i.e. satisfying $\mathbb{E} |X| < +\infty$. Then the *expectation of X* exists

$$m_X = \mathbb{E} X = \int_{\Omega} X(\omega) \mathbb{P}(d\omega) \in \mathbb{R}.$$

Basic question: How to compute m_X ?

▷ **Method 1: transfer principle.** Switch – or not – from the scenario space to the state space:

$$X : \underbrace{(\Omega, \mathcal{A}, \mathbb{P})}_{\text{Scenarios space}} \longrightarrow \underbrace{\mathbb{R}}_{\text{state space}}$$

▷ Distribution

$$\forall B \text{ Borel set of } \mathbb{R} \quad \mathbb{P}_X(B) = \mathbb{P}(\{\omega \in \Omega : X(\omega) \in B\}).$$

- $\mathbb{P}$ is a probability on $(\Omega, \mathcal{A})$ and $\mathbb{P}_X$ is a probability (exercise!) on the state space $\mathbb{R}$.
- X random variable means: if B is a Borel set (say an interval) then $\{\omega \in \Omega : X(\omega) \in B\} \in \mathcal{A}$
- Notation : $\{X \in B\} := X^{-1}(B) := \{\omega \in \Omega : X(\omega) \in B\}$.

▷ Integration theory.

If $X = \sum_{i \in I} \alpha_i \mathbf{1}_{A_i}$ where $(A_i)_{i \in I}$ is a finite measurable partition of Ω

$$\mathbb{E} X = \sum_{i \in I} \alpha_i \mathbb{P}(A_i)$$

[It is Blaise Pascal's idea to multiply the value by its probability to define *expectation*]. We note that

$$A_i = \{\omega \in \Omega : X(\omega) = \alpha_i\} = X^{-1}(\{\alpha_i\}) = \{X = \alpha_i\}.$$

- Then

$$\begin{aligned}\mathbb{E} X &= \sum_{i \in I} \alpha_i \mathbb{P}(\{\omega \in \Omega : X(\omega) = \alpha_i\}) \\ &= \sum_{i \in I} \alpha_i \mathbb{P}_X(\{\alpha_i\}) \\ &= \int_{\mathbb{R}} \xi \mathbb{P}_X(d\xi).\end{aligned}$$

- In particular: if $X = \mathbf{1}_A$ i.e $X(\omega) = 1$ if $\omega \in A$ and $X(\omega) = 0$ if $\omega \notin A$. Then
$$\begin{aligned}\mathbb{E} X &= 1 \times \mathbb{P}(A) + 0 \times \mathbb{P}(A^c) \\ &= \mathbb{P}(A) = \mathbb{P}(\{X = 1\}) = \mathbb{P}_X(\{1\}) = 1 \times \mathbb{P}_X(\{1\}) + 0 \times \mathbb{P}_X(\{0\}) = \int_{\mathbb{R}} \xi \mathbb{P}_X(d\xi).\end{aligned}$$

- Extends to more general random variables: one has the transfert property

$$\mathbb{E} X = \int_{\mathbb{R}} \xi \mathbb{P}_X(d\xi)$$

with $\mathbb{P}_X = \mathbb{P} \circ X^{-1}$ distribution of X on $\mathbb{R}$.

- Both are integrals, one on Ω , the other on $\mathbb{R}$.

Examples I

X takes finitely or countably many values. Staying on the scenario space is possible

- Heads & Tails (once): $X \stackrel{d}{=} \text{Bernoulli}(\{0, 1\}, p)$ with $\mathbb{P}(\text{"Head"}) = p \in [0, 1]$.

$$\mathbb{E} X = 1 \times \mathbb{P}(\text{Head}) + 0 \times \mathbb{P}(\text{Tail}) = p \cdot 1 + 0 \cdot (1 - p) = p$$

- Head & Tails (n times): $\text{Binomial}(n, p)$,

$$\mathbb{E} X = n \cdot p$$

since $X = X_1 + \dots + X_n$ using [linearity of expectation](#)... One also has

$$\mathbb{P}(X = k) = \binom{n}{k} p^k (1 - p)^{n-k}.$$

Then, as $\binom{n}{k} = \frac{n}{k} \binom{n-1}{k-1}$

$$\begin{aligned} \mathbb{E} X &= \sum_{k=0}^n k \mathbb{P}(X = k) = \sum_{k=1}^n k \binom{n}{k} p^k (1 - p)^{n-k} \\ &= np \sum_{k=1}^n \binom{n-1}{k-1} p^{k-1} (1 - p)^{(n-1)-(k-1)} = np \cdot 1 \quad \text{by Newton's binomial formula.} \end{aligned}$$

- First succes: $\text{Geometric}^*(p)$,

$$\begin{aligned}
 \mathbb{E} X &= \sum_{k \geq 1} k p (1-p)^{k-1} \\
 &= p \sum_{k \geq 1} k (1-p)^{k-1} = p \left(\sum_{k \geq 0} x^k \right)' \Big|_{x=1-p} \\
 &= p \left(\frac{1}{1-x} \right)' = p \frac{1}{(1-(1-p))^2} = p \frac{1}{p^2} = \frac{1}{p}
 \end{aligned}$$

by geometric formula. Here no smart trick like for the binomial distribution.

- More generally $\mathbb{P}(X = x_i) = p_i$, $i \in I$, I finite or countable

$$\mathbb{E} X = \sum_{i \in I} p_i x_i$$

More difficult with Head & Tails

- Let $S_n = X_1 + \dots + X_n$ with X_k independent (...) identically distributed (i.i.d.) Bernoulli distributed with values ± 1 .

$$\mathbb{P}(X_1 = 1) = p \in [0, 1] \quad \mathbb{P}(X_1 = -1) = 1 - p \in [0, 1].$$

so that $\mathbb{E} X = 1/p - 1 \cdot (1 - p) = 2p - 1$.

- Assume $p = \frac{1}{2}$. Then $\mathbb{E} X_k = 0$, $\mathbb{E} S_n = 0$ and (...) $\mathbb{E} S_n^2 = n$. Let

$$a \in \mathbb{N}, \quad b \in \mathbb{Z}, \quad \tau_b = \min \{k : S_k = b\}, \quad S_{\tau_b \wedge \tau_a}$$

- One has $\mathbb{E} S_{\tau_b \wedge \tau_a} = 0$ (stopped martingale) but, as $S_n^2 - n$ is also a martingale

$$\mathbb{E} \tau_b \wedge \tau_a = \mathbb{E} S_{\tau_b \wedge \tau_a}^2 = a^2 \mathbb{P}(\tau_a < \tau_b) + b^2 \mathbb{P}(\tau_b < \tau_a).$$

- Why not use (repeated) simulation?

Examples II

▷ What happens if the law of X takes **infinitely many values** and $\mathbb{P}_X$ is **absolutely continuous to the Lebesgue measure** i.e.

$$\mathbb{P}_X(d\xi) = f_X(\xi)d\xi$$

▷ One has to do some work on the state space. If the *density* f_X is **explicit** then closed form/quadrature formula.

- Closed form: $f_X(\xi) = \lambda e^{-\lambda\xi} \mathbf{1}_{\{x \geq 0\}}$, $\lambda > 0$, then $\mathbb{E} X = 1/\lambda$,

$$\mathbb{E} X = \int_0^{+\infty} \xi \lambda e^{-\lambda\xi} d\xi = \dots = \frac{1}{\lambda}$$

- Gaussian law: $f_X(\xi) = \exp(-\frac{\xi^2}{2})/\sqrt{2\pi}$, $\mathbb{E} X = 0$.

$$\mathbb{E} X = \int_{-\infty}^{+\infty} \xi \exp(-\frac{\xi^2}{2})/\sqrt{2\pi} d\xi = 0.$$

- Symmetry argument: f_X even, then $\mathbb{E} X = 0$, if $f_X(L - \xi) = f_X(\xi)$ then $\mathbb{E} X = L/2$, etc.

- Quadrature: If $X = \varphi(U)$, $U \stackrel{d}{=} \mathcal{U}([0, 1])$,

$$\mathbb{E} X = \mathbb{E} \varphi(U) = \int_0^1 \varphi(u) du = \lim_n \frac{1}{n} \sum_{k=1}^n \varphi\left(\frac{2k-1}{2n}\right).$$

among others “quadrature methods” to compute such integrals.

- What about this $\mathbb{E} \varphi(U)$?

Function of a random variable

- **Discrete world:** $X : (\Omega, \mathcal{A}, \mathbb{P}) \rightarrow \{x_i, i \in I\}$ ($\subset \mathbb{N}$ or $\mathbb{R}^d$ or ...) with $\mathbb{P}(X = x_i) = p_i, i \in I$ ($I = \{1, \dots, N\}$ or $I = \mathbb{N}$, etc, at most countable).

Let $g : \mathbb{R}$ or $\mathbb{R}^d \rightarrow \mathbb{R}$

$$\mathbb{E} g(X) = \sum_{i \in I} p_i g(x_i).$$

- **Absolutely continuous world:** $X : (\Omega, \mathcal{A}, \mathbb{P}) \rightarrow \mathbb{R}$ (or $\mathbb{R}^d$ or any vector space...) with density $f : \mathbb{R} \rightarrow \mathbb{R}$.

Let $\varphi : \mathbb{R}$ or $\mathbb{R}^d \rightarrow \mathbb{R}$. Then

$$\mathbb{E} \varphi(X) = \int_{\mathbb{R}} \varphi(\xi) \underbrace{f(\xi) d\xi}_{=\mathbb{P}_X(d\xi)}.$$

Independence of random vectors: discrete world

- **Discrete world:** $X : (\Omega, \mathcal{A}, \mathbb{P}) \rightarrow \{x_i, i \in I\}$ and $Y : (\Omega, \mathcal{A}, \mathbb{P}) \rightarrow \{y_j, j \in J\}$ (or $\subset \mathbb{R}$ or $\mathbb{R}^d$) are **independent** if

$$\forall i \in I, j \in J, \quad \mathbb{P}(\{X = x_i\} \cap \{Y = y_j\}) = \mathbb{P}(\{X = x_i\}) \cdot \mathbb{P}(\{Y = y_j\})$$

or, equivalently, for every $\varphi, \psi : \mathbb{R}^d \rightarrow \mathbb{R}$ (for which the quantities below exist),

$$\mathbb{E} \varphi(X) \psi(Y) = \mathbb{E} \varphi(X) \cdot \mathbb{E} \psi(Y).$$

- **Example. Roll of two dice.** Let

$$\Omega = \{1, 2, 3, 4, 5, 6\}^2 = \{(i, j) : 1 \leq i, j \leq 6\} \quad \omega = (\omega_1, \omega_2)$$

$$X(\omega) = \omega_1 \quad Y(\omega) = \omega_2$$

are independent since

$$\mathbb{P}(X = i, Y = j) = \frac{1}{36} = \frac{1}{6} \cdot \frac{1}{6} = \mathbb{P}(X = i) \cdot \mathbb{P}(Y = j), \quad \forall i, j.$$

Independence of random vectors: Interpretation

- The identity

$$\forall i \in I, j \in J, \quad \mathbb{P}(\{X = x_i\} \cap \{Y = y_j\}) = \mathbb{P}(\{X = x_i\}) \cdot \mathbb{P}(\{Y = y_j\})$$

also reads

$$\forall i \in I, j \in J, \quad \underbrace{\mathbb{P}(\{X = x_i\} | \{Y = y_j\})}_{\text{conditional prob.}} := \frac{\mathbb{P}(\{X = x_i\} \cap \{Y = y_j\})}{\mathbb{P}(\{Y = y_j\})} \\ = \mathbb{P}(\{X = x_i\}).$$

Independence of random vectors: continuous world

- **Absolutely continuous world:** $X : (\Omega, \mathcal{A}, \mathbb{P}) \rightarrow \mathbb{R}$ (or $\mathbb{R}^d$ or any vector space. . .) with density $f : \mathbb{R} \rightarrow \mathbb{R}$ and $Y : (\Omega, \mathcal{A}, \mathbb{P}) \rightarrow \mathbb{R}$ (or $\mathbb{R}^d$ or any vector space. . .) with density g are **independent** if (X, Y) has a density such that

$$\underbrace{\mathbb{P}_{(X,Y)}(dx, dy)}_{\text{law of } (X, Y)} = f(x)g(y)dxdy$$

or, equivalently, for every $\varphi, \psi : \mathbb{R}^d \rightarrow \mathbb{R}$ (for which such quantities exist),

$$\mathbb{E} \varphi(X) \psi(Y) = \mathbb{E} \varphi(X) \cdot \mathbb{E} \psi(Y).$$

Independence of random vectors: Example

▷ Normal distribution $\mathcal{N}(0, I_d)$ on $\mathbb{R}^d$. Let

$X = (X_1, \dots, X_d) : (\Omega, \mathcal{A}, \mathbb{P}) \rightarrow \mathbb{R}^d$ with density

$$\begin{aligned} \mathbb{P}_X(dx) &= \underbrace{\mathbb{P}(X \in dx)}_{\text{alternative notation}} = e^{-\frac{|x|^2}{2}} \frac{dx}{(2\pi)^{d/2}} \\ &= e^{-\frac{x_1^2 + \dots + x_d^2}{2}} \frac{dx_1 \cdots dx_d}{\sqrt{2\pi} \cdots \sqrt{2\pi}} \\ &= \prod_{k=1}^d \underbrace{\frac{e^{-\frac{x_k^2}{2}}}{\sqrt{2\pi}}}_{\mathcal{N}(0;1) \text{ density}} dx_1 \cdots dx_d \end{aligned}$$

- However, if $\mathbb{P}_X(dx) = f(x_1, \dots, x_d) dx_1 \cdots dx_d$, how to compute in general

$$\mathbb{E} \psi(X) = \int_{\mathbb{R}^d} \psi(x) f(x_1, \dots, x_d) dx_1 \cdots dx_d.$$

even if ψ and the density f are explicit, e.g. if $d \geq 3$ or 4 ?