# Physics takes a gamble! The science behind Monte Carlo methods

# A chance-driven computation

Given: a bounded function  $f(x) = f(x_1, ..., x_D)$  on the unit cube  $[0, 1]^D$  with  $|f(x)| \le 1$ 

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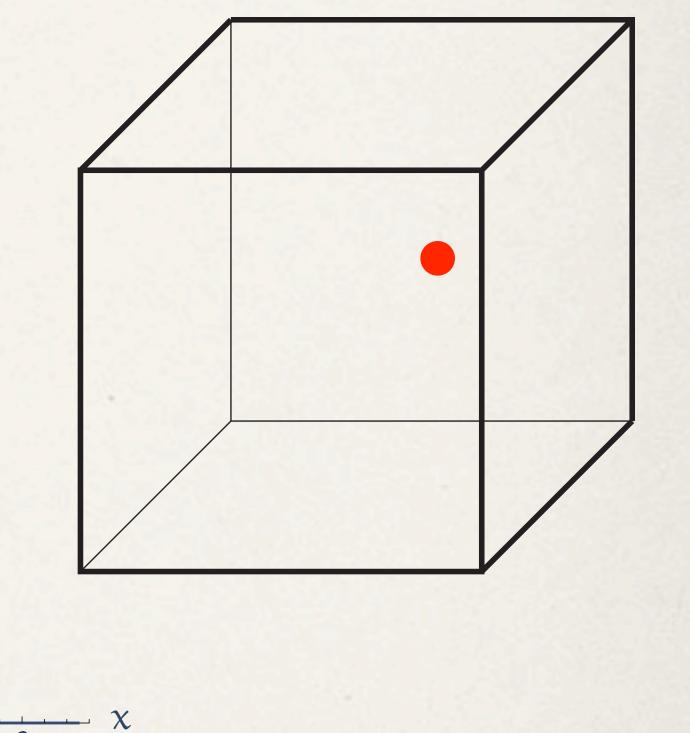
Compute: 
$$J = \int \cdots \int_{[0,1]^D} f(x) dx$$

Select  $X = (X_1, ..., X_D)$  at random from the D-dimensional cube  $[0, 1]^D$ 

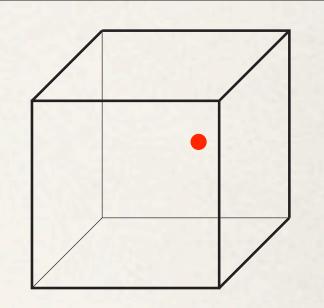
This means:  $X_1$ , ...,  $X_D$  are independent and are each uniformly distributed in the unit interval.

$$\mathbf{X} \sim \mathbf{p}(\mathbf{x}) = \mathbf{u}(\mathbf{x}_1) \times \cdots \times \mathbf{u}(\mathbf{x}_D) = \begin{cases} 1 & \text{if } \mathbf{x} \in [0, 1]^D \\ 0 & \text{otherwise} \end{cases}$$

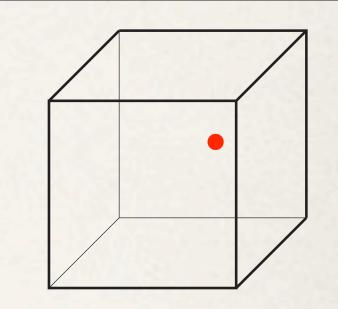
Evaluate Y = f(X)



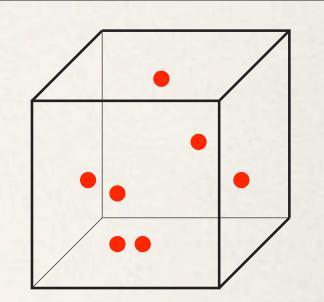
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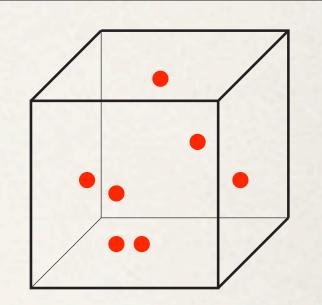
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  $\mathbf{E}(\mathbf{f}(\mathbf{X})) = \mathbf{J}$   $\mathbf{Var}(\mathbf{f}(\mathbf{X})) \leq 1$ 



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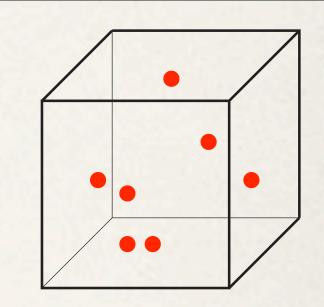


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Evaluate: 
$$Y_1 = f(X^{(1)}), Y_2 = f(X^{(2)}), \dots, Y_n = f(X^{(n)})$$

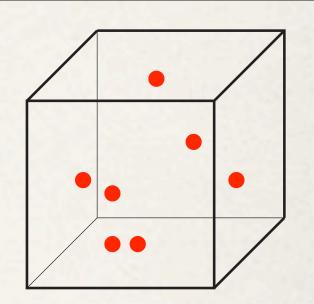
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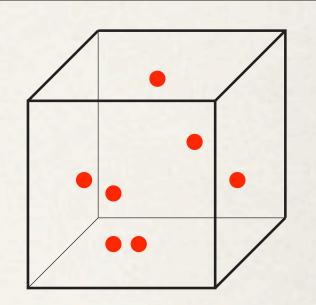


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#### What do we know about these values?

The induced sample  $Y_1, ..., Y_n$  constitutes a sequence of repeated independent trials with common expectation J and variance bounded above by 1.

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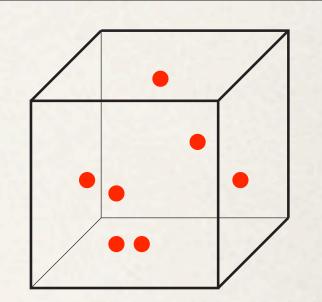


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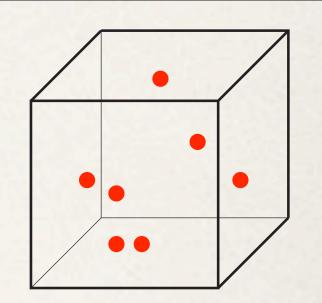
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Form: 
$$S_n = Y_1 + \cdots + Y_n = f(X^{(1)}) + \cdots + f(X^{(n)})$$

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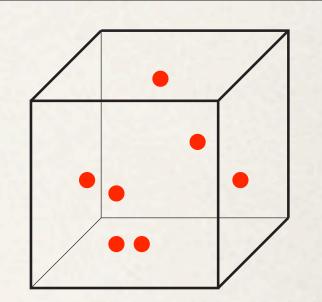
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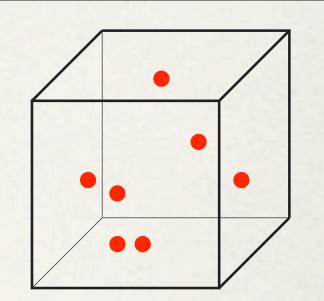
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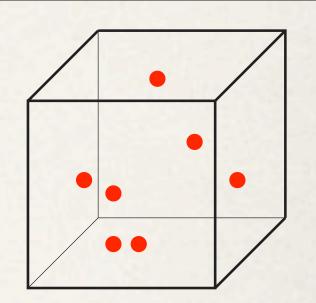
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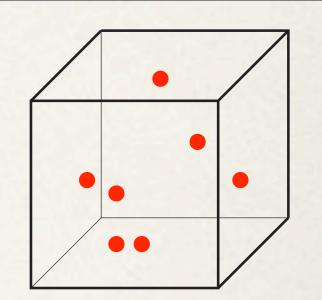
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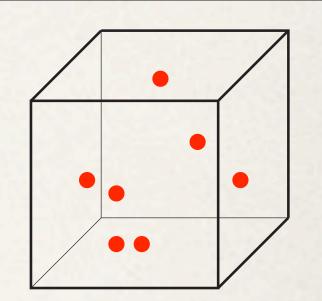
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# The law of large numbers beckons!

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Estimate the unknown J by the sample mean  $S_n/n$ 

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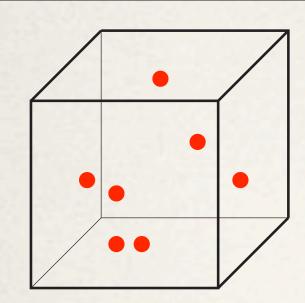
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Monte Carlo method

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$$\begin{split} S_n &= Y_1 + \dots + Y_n = f\big(X^{(1)}\big) + \dots + f\big(X^{(n)}\big) \\ E(S_n) &= nJ \\ Var(S_n) &\leq n \end{split}$$

$$\mathbf{P}\left\{\left|\frac{S_n}{n}-J\right|>\epsilon\right\}$$

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The sample mean  $S_n/n$  estimate the unknown integral J with an absolute error of no more than  $\epsilon$  and a confidence of at least  $1 - \delta$  if the sample size n satisfies

$$\frac{1}{n\epsilon^2} \le \delta \qquad -or - \qquad n \ge \frac{1}{\epsilon^2 \delta}$$

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To illustrate: if  $n = 10^6$  then the estimate error will be less than 1% ( $\varepsilon = 0.01$ ) and the confidence in excess of 99% ( $\delta = 0.01$ )!