

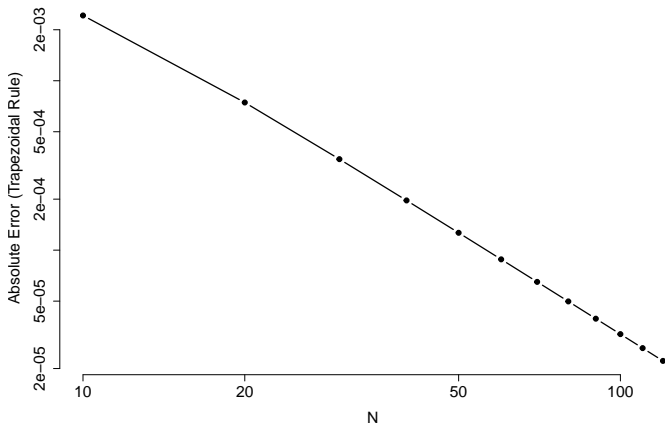
# Monte Carlo Integration 2

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# Why use Monte Carlo integration at all?

Apply Trapezoidal Rule to  $I = \frac{1}{\sqrt{2\pi}} \int_3^{\infty} e^{-x^2/2} dx$ :



- Trapezoidal Rule: Absolute error of  $\sim 1 \times 10^{-5}$  with only about 100 points.
- Gaussian Quadrature: far better approximation in far fewer # of points!

Then why use Monte Carlo integration at all?

# Error behaviour: Numerical integration in 1 dimension

Consider approximating integral of a function  $f$  of a *single* variable  $x$ :

$$I = \int_a^b g(x) dx$$

Error in the numerical approximation:

$$\epsilon \propto \delta^k,$$

where the grid spacing

$$\delta = (b - a)/n$$

and  $k$  (*order* of the integration method) is 2 for trapezoidal, 3 or 4 for Simpson, etc.

Because

$$\delta \propto n^{-1},$$

we have

$$\epsilon \propto n^{-k}.$$

## Error behaviour: Numerical integration in $d$ dimensions

Consider approximating integral of a function  $f$  of  $d$  variables  $x_1, \dots, x_d$ :

$$I = \int \dots \int g(x_1, \dots, x_d) dx_1, \dots, dx_d$$

Error in the numerical approximation (trapezoidal, Simpson, etc.)

$$\epsilon \propto \delta^k.$$

Now, the grid size along any dimension is

$$\delta^d \propto n^{-1}, \text{ that is, } \delta \propto n^{-1/d}.$$

Hence

$$\epsilon \propto n^{-k/d}.$$

Larger the  $d$ , slower the convergence!

Curse of Dimensionality

# Monte Carlo integration in $d$ dimensions

Multi-dimensional integral

$$\begin{aligned} I &= \int \dots \int g(x_1, \dots, x_d) dx_1, \dots, dx_d \\ &= \int \dots \int h(x_1, \dots, x_d) f(x_1, \dots, x_d) dx_1, \dots, dx_d \end{aligned}$$

with

$$\begin{aligned} f(x_1, \dots, x_d) &\geq 0 \\ \int \dots \int f(x_1, \dots, x_d) dx_1, \dots, dx_d &= 1 \\ h(x_1, \dots, x_d) f(x_1, \dots, x_d) &= g(x_1, \dots, x_d) \end{aligned}$$

for each  $(x_1, \dots, x_d)$ .

# Monte Carlo integration in $d$ dimensions

## Algorithm

- 1 Generate  $(X_1^{(1)}, X_2^{(1)}, \dots, X_d^{(1)}), \dots, (X_1^{(n)}, X_2^{(n)}, \dots, X_d^{(n)}) \sim f$
- 2 Estimator  $I$  as  $\hat{I}_n = \frac{1}{n} \sum_{i=1}^n h(X_1^{(i)}, \dots, X_d^{(i)})$
- 3  $\widehat{\text{Var}}(\hat{I}_n) = \frac{1}{n} \times \frac{1}{n-1} \sum_{i=1}^n \left( h(X_1^{(i)}, \dots, X_d^{(i)}) - \hat{I}_n \right)^2$
- 4 Etc.

## Error behaviour: Monte Carlo integration in $d$ dimensions

Because we *estimate* the value of  $I$   
the error in the estimate is expected to be

$$O(n^{-1/2})$$

independent of the # of dimensions!



# Error behaviour: Monte Carlo integration in $d$ dimensions

For any  $k$  (i.e., order of the numerical integration method), for sufficiently large number  $d$  of dimensions, we will have

$$k/d < 1/2.$$

This means that, beyond this value of  $d$ ; i.e., for

$$d > 2k,$$

the error in numerical approximation will be more than that in the Monte Carlo estimate.

more pointers here

Monte Carlo integration is therefore particularly useful when dealing with high-dimensional integrals. High-dimensional integrals often occur in statistical physics, Bayesian inference, etc.

# Toy example

Estimating / approximating  
volume of  $d$ -dimensional unit hypersphere

# Statutory Warning

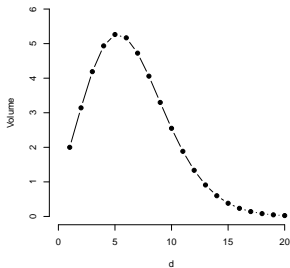
High-dimensional spaces and objects  
can be  
strange  
and  
injurious to intuition from 3 dimensions

# Hyperspheres and hypercubes in $d$ dimensions

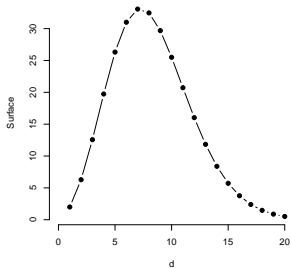
	Volume	Surface
Hypercube	$L^d$	$2dL^{d-1}$
Hypersphere	$\frac{\pi^{\frac{d}{2}}}{\Gamma(1 + \frac{d}{2})} R^d$	$\frac{\pi^{\frac{d}{2}}}{\Gamma(1 + \frac{d}{2})} dR^{d-1}$

# Hyperspheres and hypercubes in $d$ dimensions

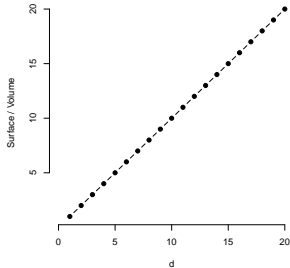
Unit hypersphere in  $d$  dimensions



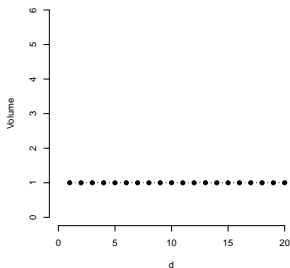
Unit hypersphere in  $d$  dimensions



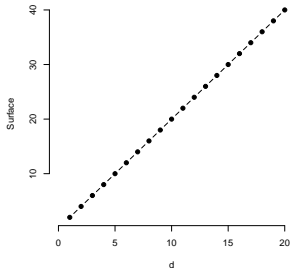
Unit hypersphere in  $d$  dimensions



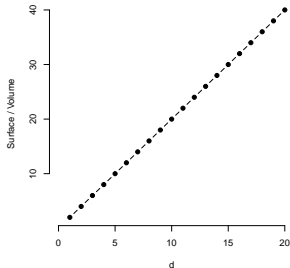
Unit hypercube in  $d$  dimensions



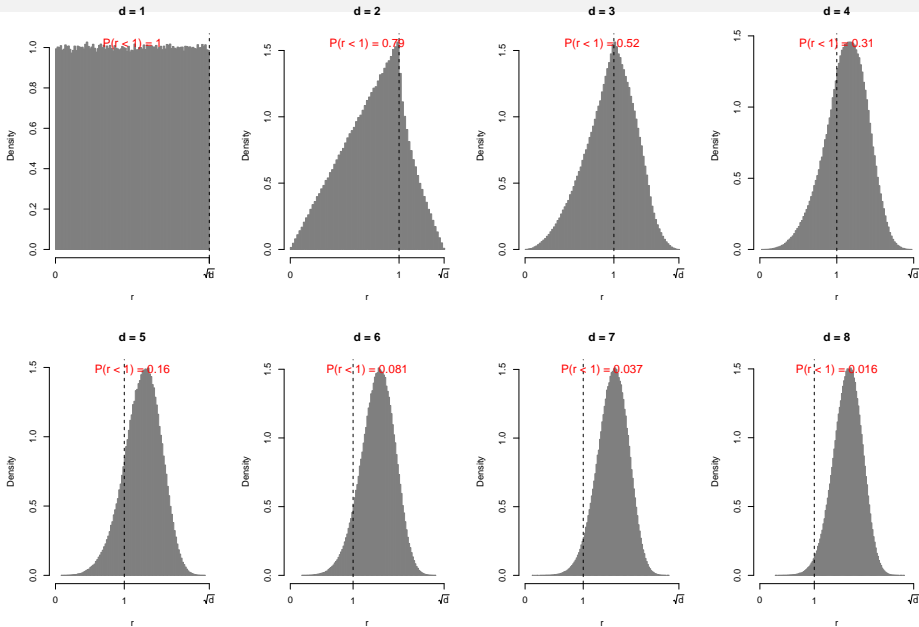
Unit hypercube in  $d$  dimensions



Unit hypercube in  $d$  dimensions

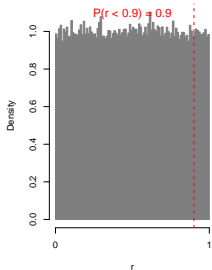


# Distance distribution inside unit $d$ -hypercubes

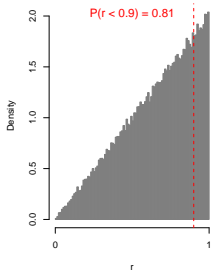


# Distance distribution inside unit $d$ -hyperspheres

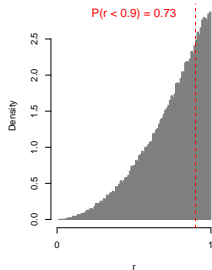
$d = 1$



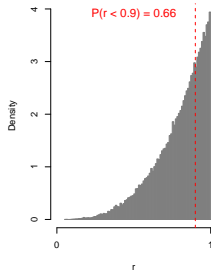
$d = 2$



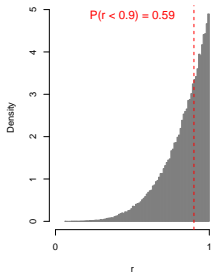
$d = 3$



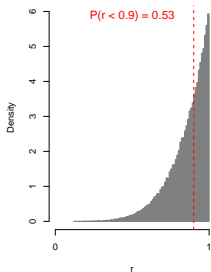
$d = 4$



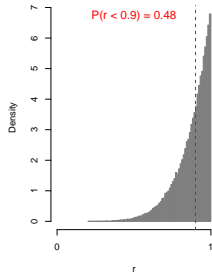
$d = 5$



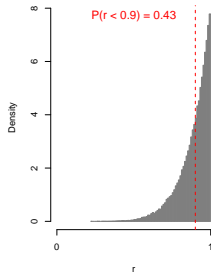
$d = 6$



$d = 7$



$d = 8$



**5.14. A property of the  $n$ -dimensional volume.** It consists in the fact that for very large  $n$  the “*volume of an  $n$ -dimensional figure is concentrated near its surface.*” For example, the volume of the spherical ring between spheres of radius 1 and  $1 - \epsilon$  equals  $b_n[1 - (1 - \epsilon)^n]$ , which, for fixed arbitrarily small  $\epsilon$ , but increasing  $n$  approaches  $b_n$ . A 20-dimensional watermelon with a radius of 20 cm. and a skin with a thickness of 1 cm. is nearly two-thirds skin:

$$1 - \left(1 - \frac{1}{20}\right)^{20} \approx 1 - e^{-1}.$$

p.124

Kostrikin & Manin

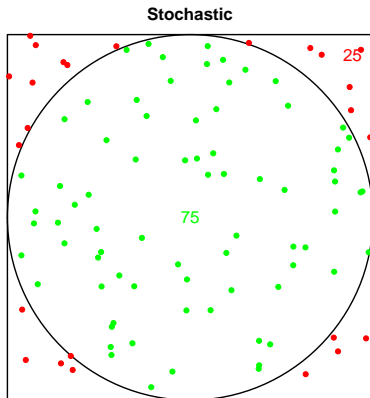
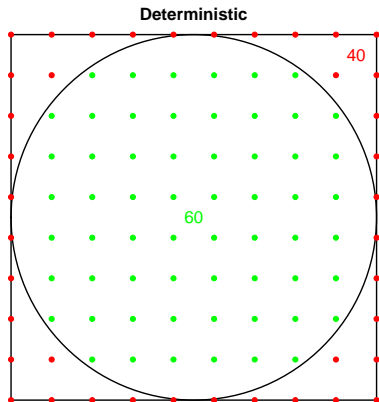
Linear Algebra & Geometry

Gordon & Breach Science Publishers (1989?)

Courtesy: Prof. Anil Gangal



# Estimating volume: deterministic & stochastic dartboards



$$\text{Area approximation or estimate} = 4 \times \frac{\# \text{ of points inside } \bigcirc}{\# \text{ of points inside } \square}.$$

# Volume of $d$ -dimensional unit hypersphere: MCI

Formally,

$$\begin{aligned}V(d) &= 2^d \int_0^1 \dots \int_0^1 h(x_1, \dots, x_d) dx_1 \dots dx_d \\ &= 2^d \int \dots \int h(x_1, \dots, x_d) f(x_1, \dots, x_d) dx_1 \dots dx_d,\end{aligned}$$

where

$$\begin{aligned}h(x_1, \dots, x_d) &= \begin{cases} 1 & \sum_{i=1}^d x_i^2 \leq 1 \\ 0 & \text{otherwise} \end{cases} \\ f(x_1, \dots, x_d) &= \begin{cases} 1 & 0 \leq x_1, \dots, x_d \leq 1 \\ 0 & \text{otherwise} \end{cases} .\end{aligned}$$

$f(x_1, \dots, x_d) ::$  uniform PDF over  $d$ -dimensional unit hypercube

# Volume of $d$ -dimensional unit hypersphere: MCI

## Algorithm

- 1 Generate  $(X_1^{(1)}, X_2^{(1)}, \dots, X_d^{(1)}), \dots, (X_1^{(n)}, X_2^{(n)}, \dots, X_d^{(n)}) \sim f$
- 2 Estimator  $V(d)$  as  $\hat{V}_n(d) = \frac{1}{n} \sum_{i=1}^n h(X_1^{(i)}, \dots, X_d^{(i)})$
- 3  $\widehat{\text{Var}}(\hat{V}_n(d)) = \frac{1}{n} \times \frac{1}{n-1} \sum_{i=1}^n \left( h(X_1^{(i)}, \dots, X_d^{(i)}) - \hat{V}_n(d) \right)^2$
- 4 Etc.

Effectively, step 2 yields

$$\hat{V}_n(d) = 2^d \times \frac{\# \text{ of points inside } \bigcirc}{\# \text{ of points inside } \square}.$$

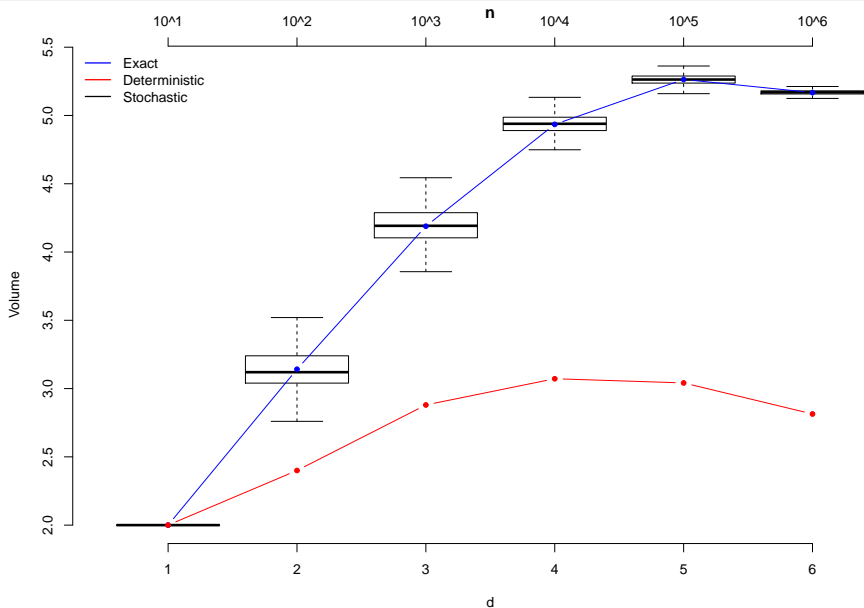
Let us now

- apply this MCI estimator to the deterministic and stochastic grids;
- compare results the exact volume volume of a  $d$ -dimensional unit hypersphere:

$$V(d) = \frac{\pi^{\frac{d}{2}}}{\Gamma\left(1 + \frac{d}{2}\right)};$$

- compare stochastic and deterministic results for the same  $n$  and  $d$ .

# Deterministic vs. stochastic dartboard comparison



# Hypersphere volume estimation using MCI: A surprise

$n = 1e+05$

$\widehat{SE}(\widehat{V}_n(d)) \approx d^2 ::$  not constant :: not clear why

