

Monte Carlo Techniques

Monte Carlo:

The use of statistical methods to solve math problems that may or may not (initially) involve probability

Monte Carlo Algorithm:

- 1) Devise a random variable whose mean is the solution
- 2) Devise a way to generate samples
- 3) Collect statistics

Why Use Monte Carlo?

Advantages:

- 1) Usually easy to formulate (independent of problem)
- 2) Scales well (easy in any dimension)

Disadvantages:

- 1) Solutions are imprecise or “noisy”
- 2) Can be very slow

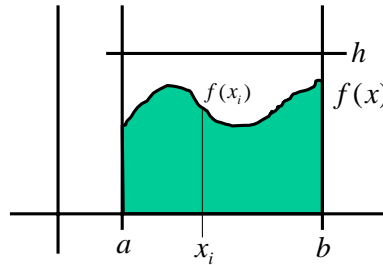
Basic Monte Carlo

Sample with uniformly distributed random points

$$\alpha = \int_a^b f(x) dx$$

x_i is a uniformly distributed random variable on $[a, b]$

$$\alpha \approx \frac{b-a}{N} \sum_{i=1}^N f(x_i)$$



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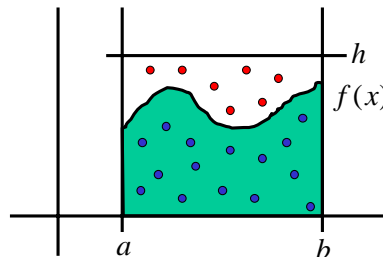
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Rejection Method

Compute the integral as a percent of an area

$$\alpha = \int_a^b f(x) dx$$

$$= \lim_{N \rightarrow \infty} \frac{N^*}{N} h(b-a)$$



N^* is the # of samples below $f(x)$

N is the total # of samples

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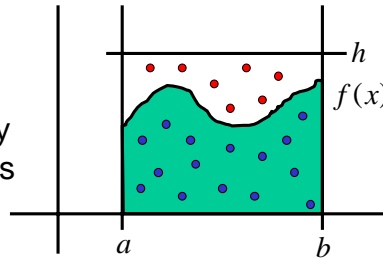
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Rejection Method

Compute the integral as a percent of an area

$$\alpha \approx \frac{N^*}{N} h(b-a)$$

Sample points are uniformly distributed random variables on $[a, b] \times [0, h]$



$$\begin{aligned} \xi &\sim [0,1] \\ (x, y) &= (a + (b-a)\xi_1, h\xi_2) \\ \text{if } y &\leq f(x) \text{ then } N^*++ \end{aligned}$$

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Why is Monte Carlo Good Here?

Why not use quadrature?

- 1) Integrand may be discontinuous
- 2) Quadrature is useless in high dimensions

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Probability Density Function

Probability Density Function (PDF):

is a function from $[a,b]$ to R such that:

$$1) f(x) \geq 0 \quad \forall x \in [a, b]$$

$$2) \int_a^b f(x) dx = 1$$

$$3) P(x_1 \leq x < x_2) = \int_{x_1}^{x_2} f(x) dx$$

Theorem

If g is a PDF on $[a, b]$, then

$$\begin{aligned} \int_a^b h(x)g(x) dx &= \int_a^b h(x) (g(x) dx) \\ &= E[h(X)] \end{aligned}$$

where X is distributed (\sim) according to g

Primary Estimators

Using a uniform PDF

$$\begin{aligned}\alpha &= \int_a^b f(x) dx \\ &= \int_a^b [f(x)(b-a)] \frac{1}{(b-a)} dx \\ &= E[f(X)(b-a)] \quad X \sim \frac{1}{b-a} \\ &\approx f(x_i)(b-a)\end{aligned}$$

where x_i is drawn from X

One sample is usually not enough

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Average Estimator

Take an average of multiple samples

$$\alpha \approx \frac{b-a}{N} \sum_{i=1}^N f(x_i)$$

where x_i are drawn from X

This is what we called basic monte carlo

Why can't we use a nonuniform PDF?

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NonUniform PDFs

We can rewrite any integral with a PDF

$$\begin{aligned}\alpha &= \int_a^b f(x) dx \\ &= \int_a^b \frac{f(x)}{g(x)} (g(x) dx) \\ &\approx \frac{1}{N} \sum_{i=1}^N \frac{f(x_i)}{g(x_i)} \quad x_i \sim \frac{1}{b-a}\end{aligned}$$

But what is the best PDF to choose?

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Variance Reduction

Variance $\sigma^2(Z) = \langle Z^2 \rangle - \langle Z \rangle^2$

If $Z = \frac{f(X)}{g(X)}$ with $X \sim g$

then $\sigma^2(Z) = \int_a^b \frac{f^2(x)}{g(x)} dx - \alpha^2$

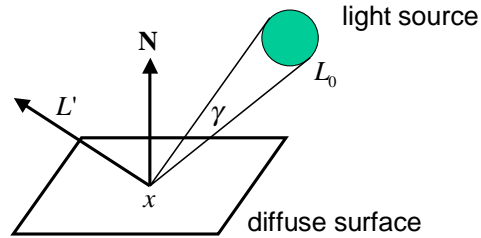
$g(x) = \frac{f(x)}{\int_a^b f(x) dx}$ will give zero variance

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This is known as importance sampling

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Monte Carlo in Image Synthesis



$$\begin{aligned} L' &= \frac{\rho}{\pi} \int_{\Omega} L(\omega) \cos \theta \, d\omega \\ &= \frac{\rho L_0}{\pi} \int_{\gamma} \cos \theta \, d\omega \end{aligned}$$

How to sample the source?

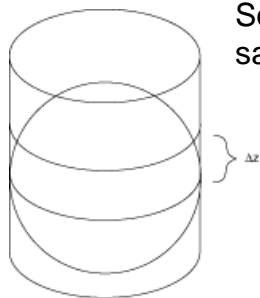
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Uniform Sampling

Archimedes Theorem

Given a sphere inscribed within a cylinder,
for any Δz , both surfaces have equal area



So we can generate uniform samples by
sampling the cylinder and projecting inwards

$$z = 1 - 2\xi_1$$

$$\theta = 2\pi\xi_2$$

$$x = \cos \theta \sqrt{1 - z^2}$$

$$y = \sin \theta \sqrt{1 - z^2}$$

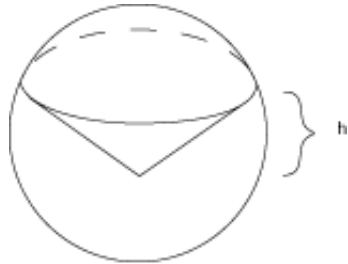
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Uniform Sampling

Sampling the top of the sphere

Sample the cylinder and project inwards



$$z = 1 - (1 - h)\xi_1$$

$$\theta = 2\pi\xi_2$$

$$x = \cos\theta\sqrt{1-z^2}$$

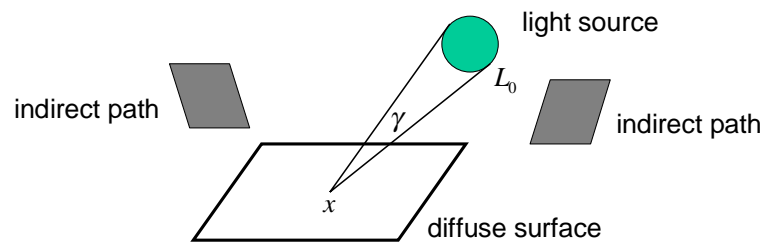
$$y = \sin\theta\sqrt{1-z^2}$$

This is useful for sampling the light sources

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Incorporating Indirect Lighting



$$L' = \frac{\rho}{\pi} \int_{\Omega} L(\omega) \cos\theta \, d\omega$$

$$= \frac{\rho}{\pi} \int_{\Omega-\gamma} L(\omega) \cos\theta \, d\omega + \frac{\rho L_0}{\pi} \int_{\gamma} \cos\theta \, d\omega$$

This is known as stratification

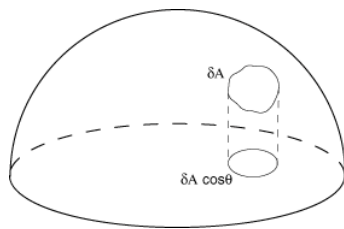
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Weighted Sampling

Sampling the hemisphere with a $\cos\theta$ distribution

Sample the base and project upwards



x, y = uniform sampling of the disk

$$z = \sqrt{1 - x^2 - y^2}$$

But how do we sample the disk?

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Weighted Sampling

Sampling the disk

If $\xi \in [0,1]$ is uniformly distributed, then $X = F^{-1}(\xi)$, where F is the CDF of g , is distributed according to g

Proof

$$\begin{aligned} P(X \leq x) &= P(F^{-1}(\xi) \leq x) \\ &= P(\xi \leq F(x)) \\ &= F(x) \end{aligned}$$

Disk sampling is thus:

$$r = \sqrt{\xi_1}$$

$$\theta = 2\pi\xi_2$$

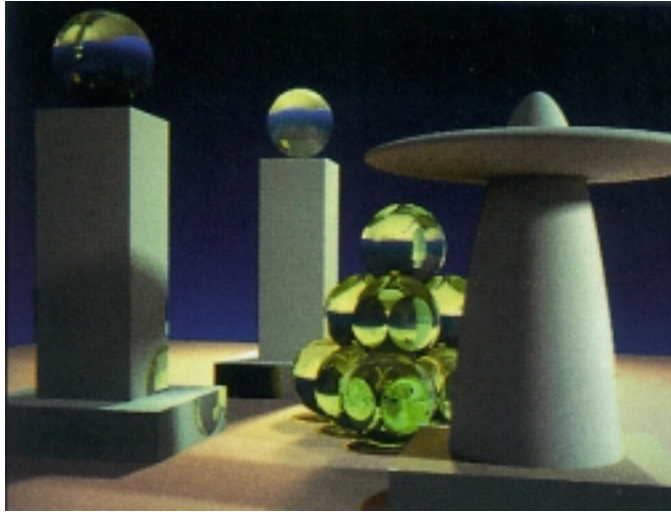
$$x = r \cos\theta$$

$$y = r \sin\theta$$

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Monte Carlo Rendering



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