

Monte Carlo Rendering

Last Time?

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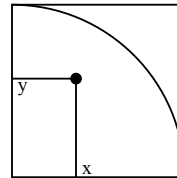
Today

- **Monte-Carlo Integration**
- Probabilities and Variance
- Analysis of Monte-Carlo Integration
- Monte-Carlo in Graphics
- Stratified Sampling
- Importance Sampling
- Advanced Monte-Carlo Rendering

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Monte-Carlo computation of π

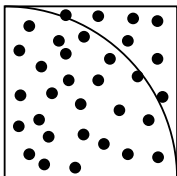
- Take a square
- Take a random point (x,y) in the square
- Test if it is inside the $\frac{1}{4}$ disc ($x^2+y^2 < 1$)
- The probability is $\pi/4$



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Monte-Carlo computation of π

- The probability is $\pi/4$
- Count the inside ratio $n = \# \text{ inside} / \text{total} \# \text{ trials}$
- $\pi \approx n * 4$
- The error depends on the number of trials



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Convergence & Error

- Let's compute 0.5 by flipping a coin:
 - 1 flip: 0 or 1
→ average error = 0.5
 - 2 flips: 0, 0.5, 0.5 or 1
→ average error = 0.25
 - 4 flips: 0 (*1), 0.25 (*4), 0.5 (*6), 0.75(*4), 1(*1)
→ average error = 0.1875
- Does not converge very fast
- Doubling the number of samples does not double accuracy

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Questions?

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Review of Probability (discrete)

- Random variable can take discrete values x_i
- Probability p_i for each x_i
 $0 < p_i < 1, \sum p_i = 1$
- Expected value $E(x) = \sum_{i=1}^n p_i x_i$
- Expected value of function of random variable
– $f(x_i)$ is also a random variable

$$E[f(x)] = \sum_{i=1}^n p_i f(x_i)$$

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Variance & Standard Deviation

- Variance σ^2 : deviation from expected value
- Expected value of square difference

$$\sigma^2 = E[(x - E[x])^2] = \sum_i (x_i - E[x])^2 p_i$$

- Also

$$\sigma^2 = E[x^2] - (E[x])^2$$

- Standard deviation σ :
square root of variance (notion of error, RMS)

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Monte Carlo Integration

- Consider N random samples over domain with probability $p(x)$
- Define estimator:

$$\langle I \rangle = \frac{1}{N} \sum_{i=1}^N \frac{f(x_i)}{p(x_i)}$$

- Probability p allows us to sample the domain more intelligently

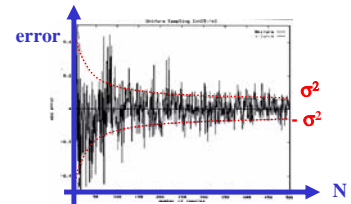
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Example

$$I = \int_0^1 5x^4 dx$$

- We know it should be 1.0

- In practice with uniform samples:



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Monte Carlo Analysis

- We want to compute the average of a function
- We can pick a random value of this function and hope to fall in the middle
 - chances are slim
 - but on average we'll be right
- For N tries,
 - the expectation stays the same
 - but the variance decreases by N
 - the standard deviation (error) decreases by \sqrt{N}
i.e. quadrupling the number of sampled points will halve the error, regardless of the number of dimensions

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Advantages of MC Integration

- Few restrictions on the integrand
 - Doesn't need to be continuous, smooth, ...
 - Only need to be able to evaluate at a point
- Extends to high-dimensional problems
 - Same convergence
- Conceptually straightforward
- Efficient for solving at just a few points

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Disadvantages of MC

- Noisy
- Slow convergence
- Good implementation is hard
 - Debugging code
 - Debugging math
 - Choosing appropriate techniques
- Punctual technique, no notion of smoothness of function

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Monte Carlo Recap

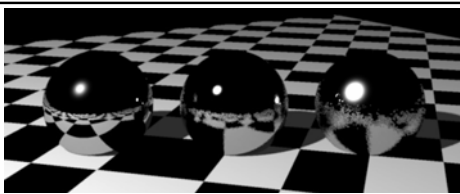
- Turn integral into finite sum
- Use random samples
- Convergence $\frac{1}{\sqrt{n}}$
- Independent of dimension
- Very flexible

- Tweak sampling/probabilities for optimal result
- A lot of integration and probability theory to get things right

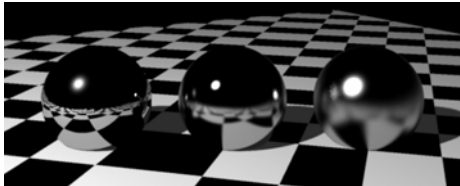
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Questions?

1 glossy
sample
per pixel



256 glossy
samples
per pixel



Today

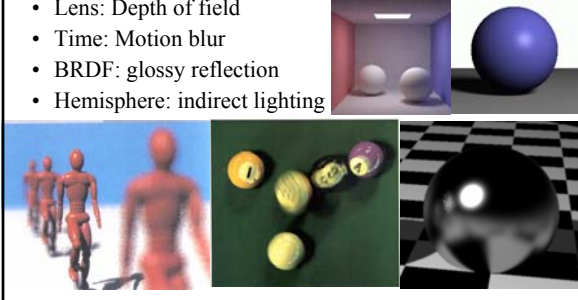
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What can we integrate?

- Pixel: antialiasing
- Light sources: Soft shadows
- Lens: Depth of field
- Time: Motion blur
- BRDF: glossy reflection
- Hemisphere: indirect lighting

$$\iiint\iiint L(x, y, t, u, v) dx dy dt du dv$$



Domains of integration

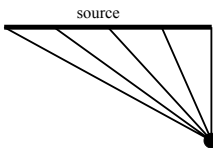
- Pixel, lens (Euclidean 2D domain)
- Time (1D)
- Hemisphere
 - Work needed to ensure uniform probability
- Light source
 - Same thing: make sure that the probabilities and the measures are right.

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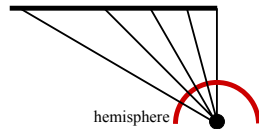
Example: Light source

- Integrate over surface or over angle
- Be careful to get probabilities and integration measure right!

Sampling the source uniformly



Sampling the hemisphere uniformly



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Questions?

- Images from the ARNOLD Renderer by Marcos Fajardo



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Important issues in MC rendering

Reduce variance!

- Choose a smart probability distribution
- Choose smart sampling patterns

And of course, cheat to make it faster without being noticed

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Stratified sampling

- With uniform sampling, we can get unlucky
 - E.g. all samples in a corner
- To prevent it, subdivide domain Ω into non-overlapping regions Ω_i
 - Each region is called a stratum
- Take one random samples per Ω_i



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Example

- Borrowed from Henrik Wann Jensen

$f(x) = e^{\sin(3x^2)}$		$f(x) = e^{\sin(3x^2)}$	
N	I	N	I
1	2.75039	1	2.70457
10	1.9893	10	1.72858
100	1.79139	100	1.77925
1000	1.75146	1000	1.77606
10000	1.77313	10000	1.77610
100000	1.77862	100000	1.77610

Unstratified
 $O(1/\sqrt{N})$

Stratified
 $O(1/N)$

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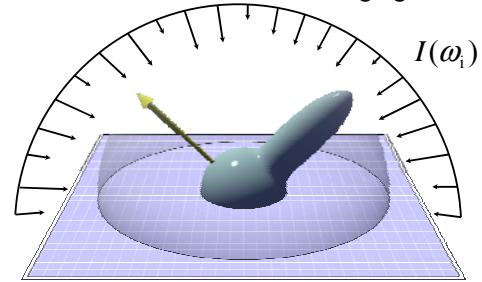
Stratified Sampling Recap

- Cheap and effective
- Typical example: jittering for antialiasing
 - Signal processing perspective: better than uniform because less aliasing (spatial patterns)
 - Monte-Carlo perspective: better than random because lower variance (error for a given pixel)

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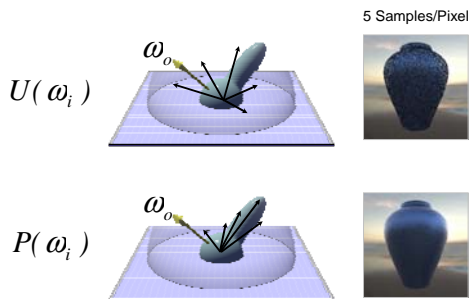
Glossy Rendering

- Integrate over hemisphere
- BRDF times cosine times incoming light



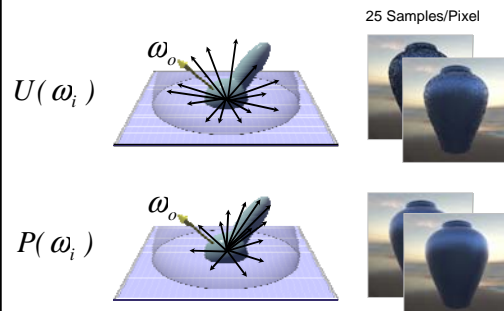
Slide from Jason Lawrence

Sampling a BRDF



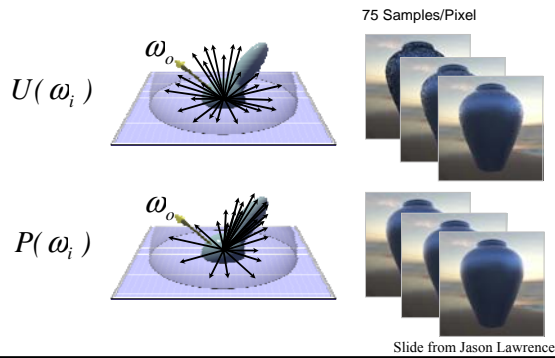
Slide from Jason Lawrence

Sampling a BRDF



Slide from Jason Lawrence

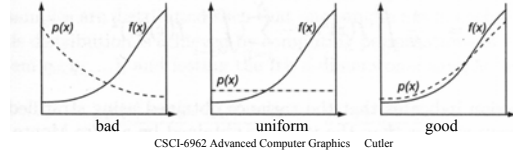
Sampling a BRDF



Importance sampling

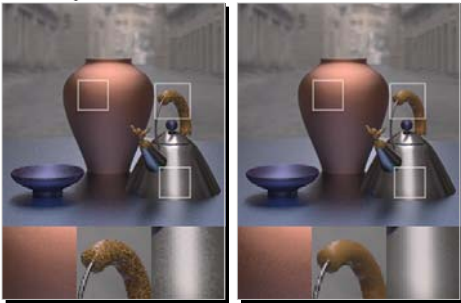
$$\langle I \rangle = \frac{1}{N} \sum_{i=1}^N \frac{f(x_i)}{p(x_i)}$$

- Choose p wisely to reduce variance
 - p that resembles f
 - Does not change convergence rate (still sqrt)
 - But decreases the constant



Results

1200 Samples/Pixel



Traditional importance function

Better importance by Lawrence et al.

Questions?

- Images by Veach and Guibas



Naïve sampling strategy

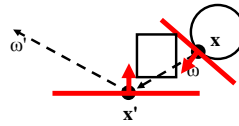
Optimal sampling strategy

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The Rendering Equation



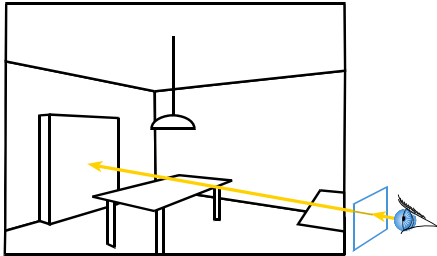
$$L(x', \omega') = E(x', \omega') + \int \rho_r(\omega, \omega') L(x, \omega) G(x, x') V(x, x') dA$$

emission BRDF Incoming light Geometric term visibility

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Ray Casting

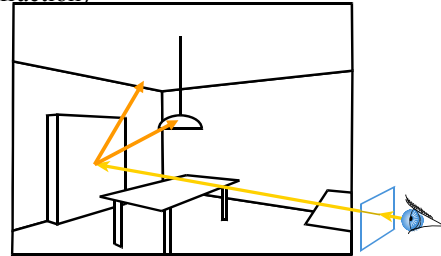
- Cast a ray from the eye through each pixel



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Ray Tracing

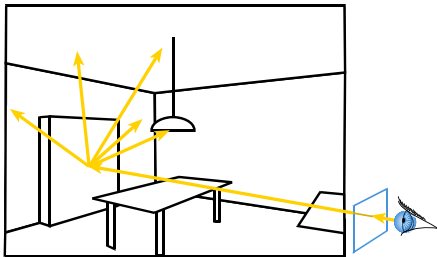
- Cast a ray from the eye through each pixel
- Trace secondary rays (light, reflection, refraction)



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Monte-Carlo Ray Tracing

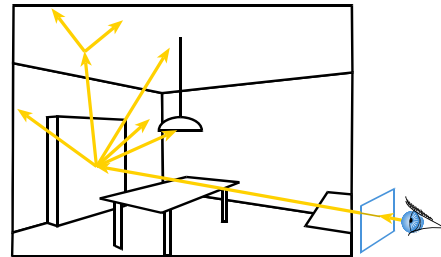
- Cast a ray from the eye through each pixel
- Cast random rays from the visible point
 - Accumulate radiance contribution



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Monte-Carlo Ray Tracing

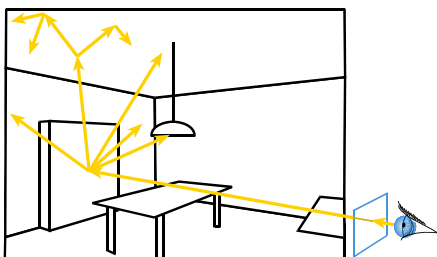
- Cast a ray from the eye through each pixel
- Cast random rays from the visible point
- Recurse



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Monte-Carlo

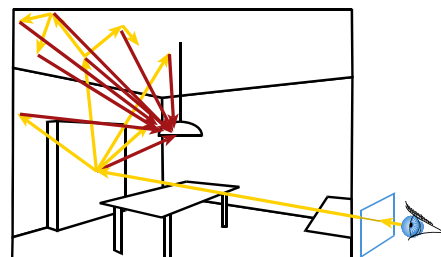
- Cast a ray from the eye through each pixel
- Cast random rays from the visible point
- Recurse



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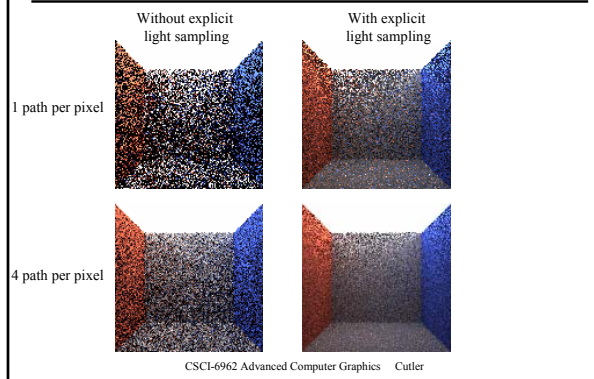
Monte-Carlo

- Systematically sample primary light



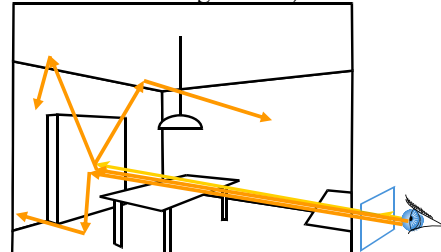
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Importance of sampling the light

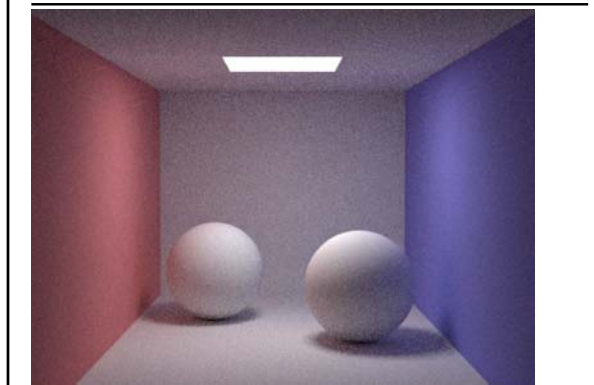


Monte Carlo Path Tracing

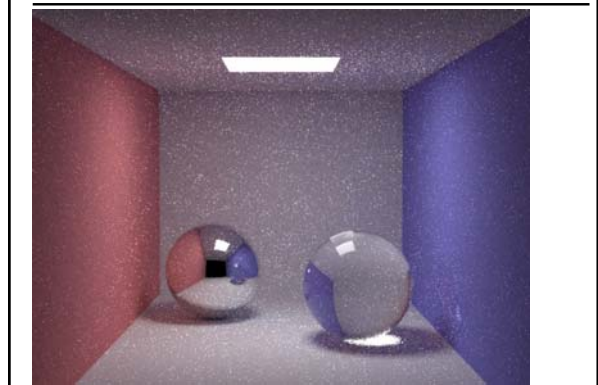
- Trace only one secondary ray per recursion
- But send many primary rays per pixel
- (performs antialiasing as well)



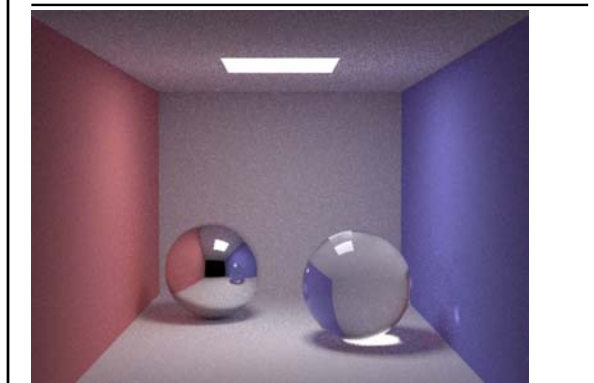
Results: 10 paths/pixel



Results: 10 paths/pixel, glossy



Results: 100 paths/pixel, glossy



Questions?