

# Monte Carlo Path Tracing

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## Today

- Path tracing
- Random walks and Markov chains
- Eye vs. light ray tracing
- Bidirectional ray tracing

## Next

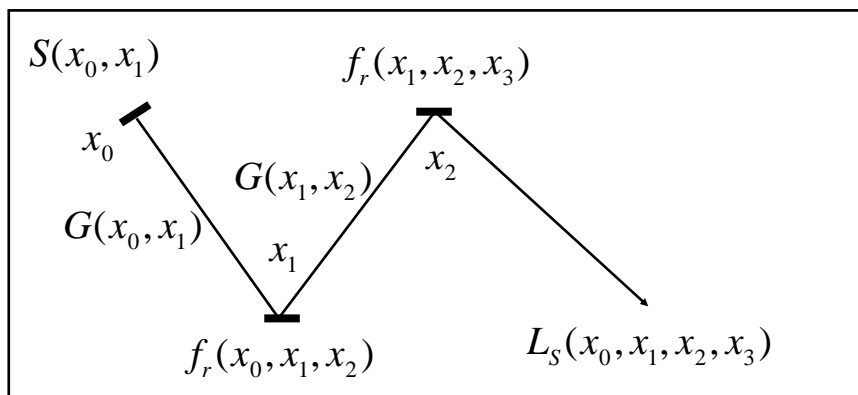
- Irradiance caching
- Photon mapping

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# Light Path

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$$L_S(x_0, x_1, x_2, x_3) = S(x_0, x_1)G(x_0, x_1)f_r(x_0, x_1, x_2)G(x_1, x_2)f_r(x_1, x_2, x_3)$$

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# Light Transport

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**Integrate over all paths**

$$L(x_{k-1}, x_k) \\ = \sum_{k=1}^{\infty} \int_{M^2} \cdots \int_{M^2} L_S(x_0, \dots, x_{k-2}, x_{k-1}, x_k) dA(x_0) \cdots dA(x_{k-2})$$

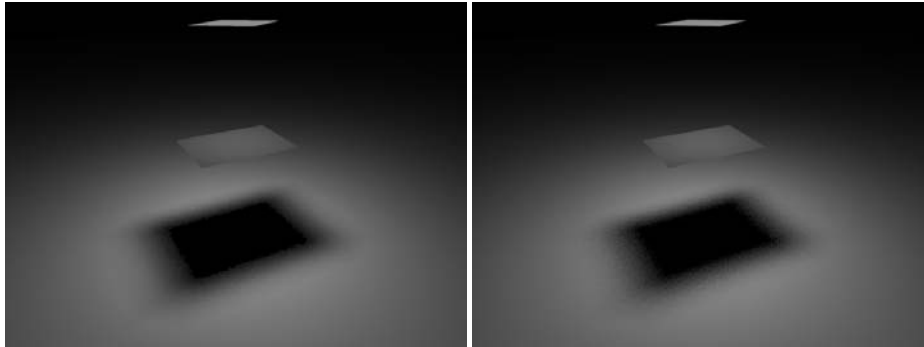
**Questions**

- **How to sample space of paths**

# Path Tracing

## Penumbra: Trees vs. Paths

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4 eye rays per pixel  
16 shadow rays per eye ray

64 eye rays per pixel  
1 shadow ray per eye ray

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## Path Tracing: From Camera

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Step 1. Choose a camera ray  $r$  given the  
( $x, y, u, v, t$ ) sample

```
weight = 1;
```

Step 2. Find ray-surface intersection

Step 3.

```
if light
```

```
return weight * Le();
```

```
else
```

```
weight *= reflectance(r)
```

```
Choose new ray  $r' \sim \text{BRDF pdf}(r)$ 
```

```
Go to Step 2.
```

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# M. Fajardo Arnold Path Tracer

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**ARNOLD** - GLOBAL ILLUMINATION RENDERER -

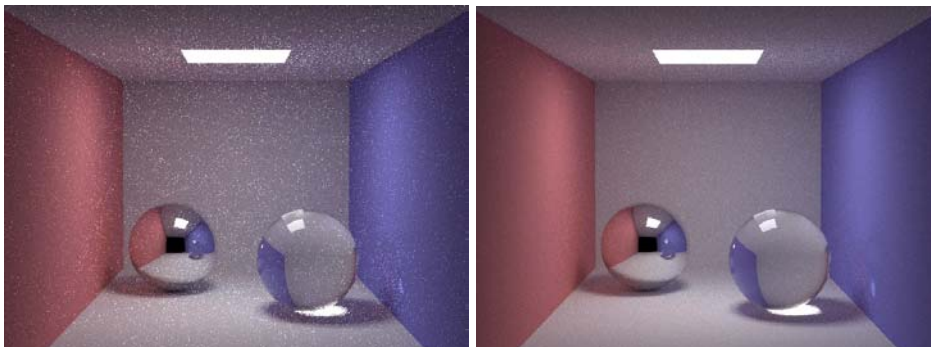


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# Cornell Box: Path Tracing

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**10 rays per pixel**

**100 rays per pixel**

**From Jensen, Realistic Image Synthesis Using Photon Maps**

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## Path Tracing: Include Direct Lighting

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Step 1. Choose a camera ray  $r$  given the  
( $x, y, u, v, t$ ) sample

weight = 1;

Step 2. Find ray-surface intersection

Step 3.

weight +=  $L_r(\text{light sources})$

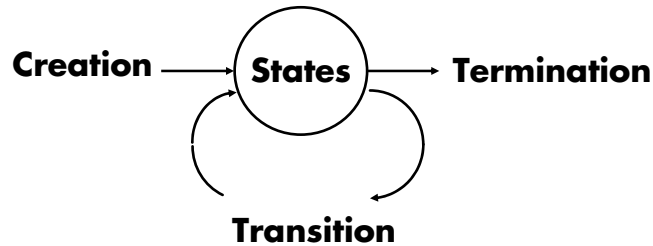
Choose new ray  $r' \sim \text{BRDF pdf}(r)$

Go to Step 2.

## Discrete Random Walk

## Discrete Random Process

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**Assign probabilities to each process**

$p_i^0$  : probability of creation in state  $i$

$p_{i,j}$  : probability of transition from state  $i \rightarrow j$

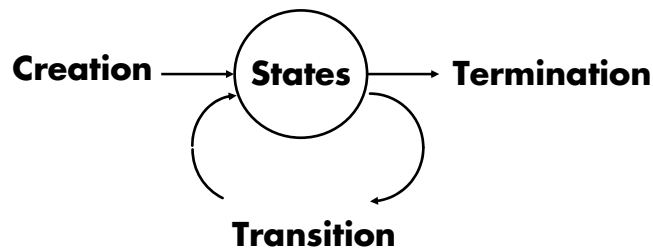
$p_i^*$  : probability of termination in state  $i$      $p_i^* = 1 - \sum_j p_{i,j}$

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## Discrete Random Process

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**Equilibrium number of particles in each state**

$$P_i = \sum_j p_{i,j} P_j + p_i^0 \quad M_{i,j} = p_{i,j}$$

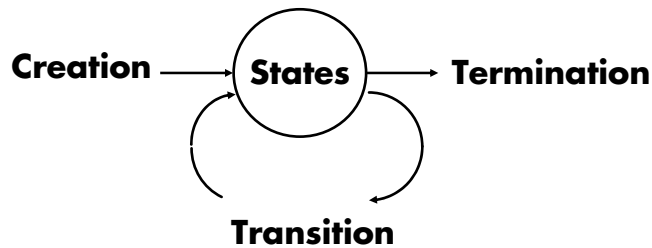
$$P = MP + p^0$$

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# Discrete Random Walk

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1. Generate random particles from sources.
2. Undertake a discrete random walk.
3. Count how many terminate in state  $i$

[von Neumann and Ulam; Forsythe and Leibler; 1950s]

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# Monte Carlo Algorithm

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Define a random variable on the space of paths

**Path:**  $\alpha_k = (i_1, i_2, \dots, i_k)$

**Probability:**  $P(\alpha_k)$

**Estimator:**  $W(\alpha_k)$

**Expectation:**

$$E[W] = \sum_{k=1}^{\infty} \sum_{\alpha_k} P(\alpha_k) W(\alpha_k)$$

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# Monte Carlo Algorithm

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Define a random variable on the space of paths

**Probability:**  $P(\alpha_k) = p_{i_1}^0 \times p_{i_1, i_2} \cdots p_{i_{k-1}, i_k} \times p_{i_k}^*$

**Estimator:**  $W_j(\alpha_k) = \frac{\delta_{i_k, j}}{p_{i_k}^*}$

## Estimator

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Count the number of particles terminating in state  $j$

$$\begin{aligned} E[W_j] &= \sum_{k=1}^{\infty} \sum_{i_k} \cdots \sum_{i_1} (p_{i_1}^0 p_{i_1, i_2} \cdots p_{i_{k-1}, i_k} p_{i_k}^*) \frac{\delta_{i_k, j}}{p_{i_k}^*} \\ &= [p^0]_j + [Mp^0]_j + [M^2 p^0]_j \cdots \end{aligned}$$



## **Equilibrium Distribution of States**

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**Total probability of being in states  $P$**

$$P = (I + M + M^2 + \dots) p^0$$

**Note that this is the solution of the equation**

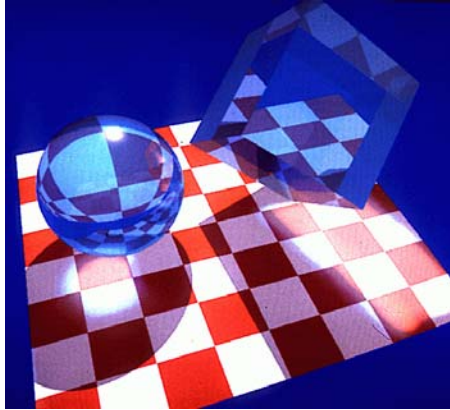
$$(I - M)P = p^0$$

**Thus, the discrete random walk is an unbiased estimate of the equilibrium number of particles in each state**

## **Light Ray Tracing**

## Examples

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Backward ray tracing, Arvo 1986

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## Path Tracing: From Lights

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Step 1. Choose a light ray

Choose a light source according to the light source power distribution function.

Choose a ray from the light source radiance (area) or intensity (point) distribution function

$w = 1;$

Step 2. Trace ray to find surface intersect

Step 3. Interaction

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## Path Tracing: From Lights

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Step 1. Choose a light ray

Step 2. Find ray-surface intersection

Step 3. Interaction

```
u = rand()
```

```
if u < reflectance
```

```
    Choose new ray  $r \sim \text{BRDF}$ 
```

```
    goto Step 2
```

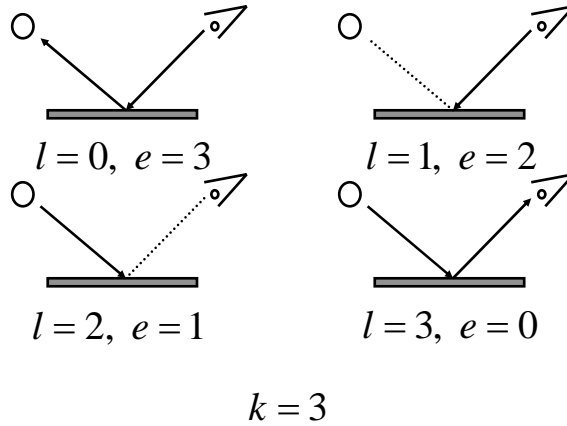
```
else
```

```
    terminate on surface; deposit energy
```

## Bidirectional Path Tracing

# Bidirectional Ray Tracing

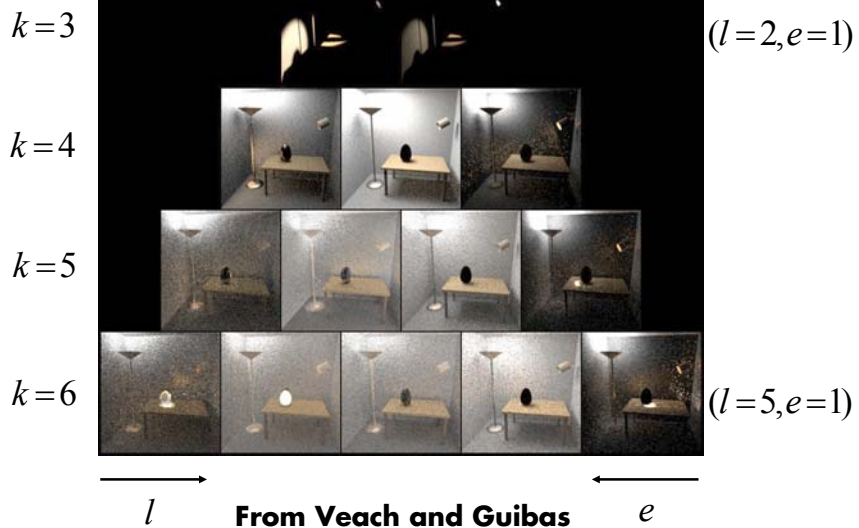
$$k = l + e$$



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# Path Pyramid



From Veach and Guibas

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# Comparison



Bidirectional path tracing



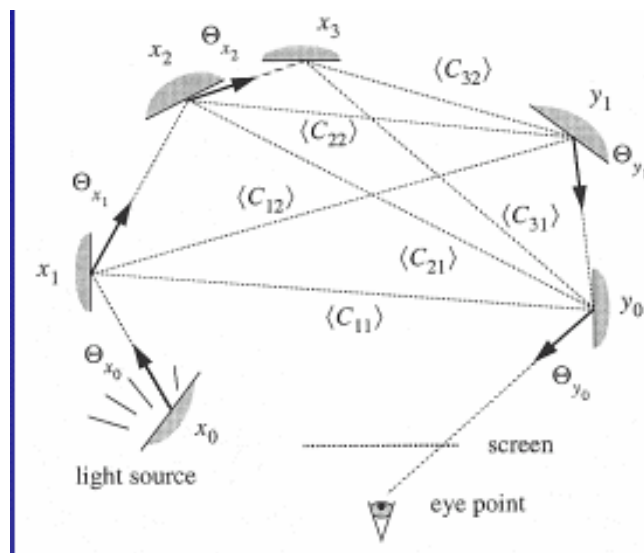
Path tracing

From Veach and Guibas

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# Generating All Paths

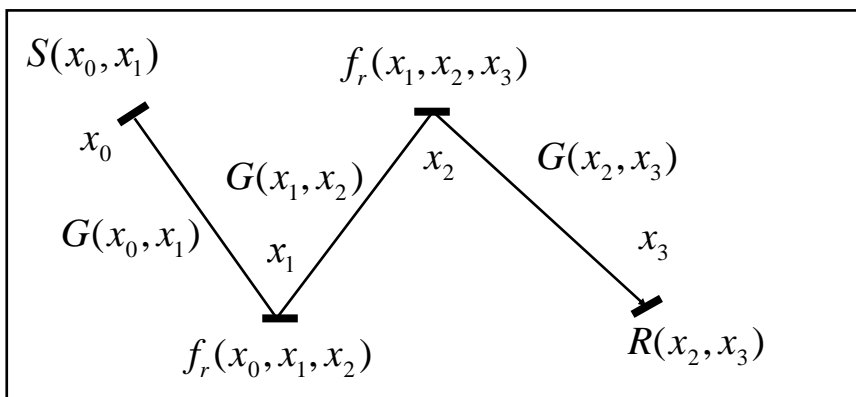


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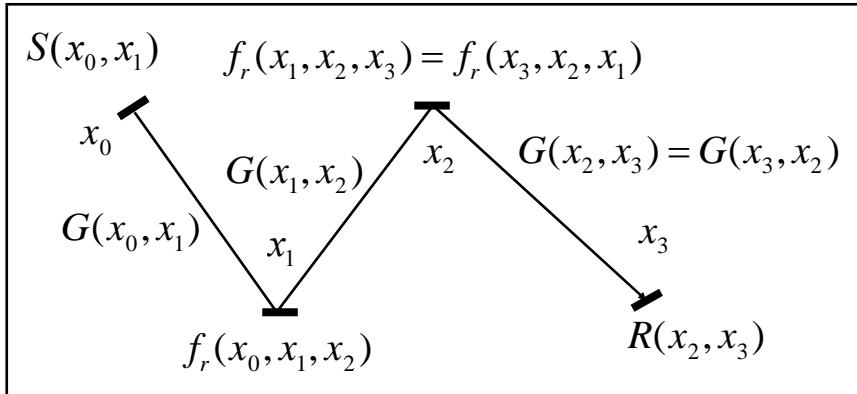
# Adjoint Formulation

## Symmetric Light Path



$$M = S(x_0, x_1)G(x_0, x_1)f_r(x_0, x_1, x_2)G(x_1, x_2)f_r(x_1, x_2, x_3)G(x_2, x_3)R(x_2, x_3)$$

## Symmetric Light Path

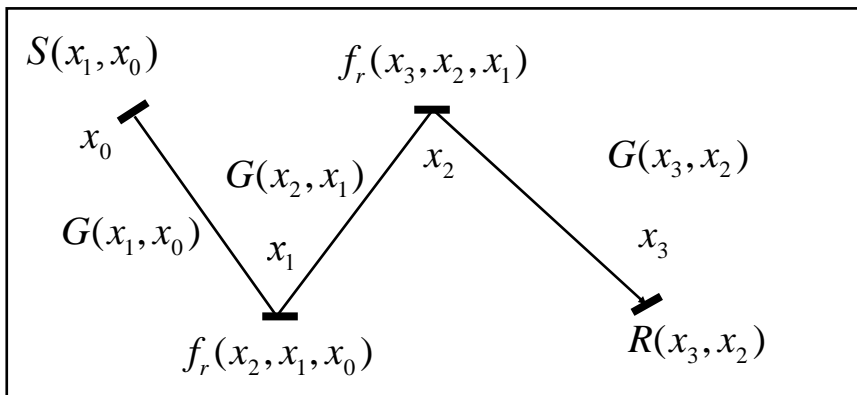


$$M = S(x_0, x_1)G(x_0, x_1)f_r(x_0, x_1, x_2)G(x_1, x_2)f_r(x_1, x_2, x_3)G(x_2, x_3)R(x_2, x_3)$$

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## Symmetric Light Path



$$M = R(x_3, x_2)G(x_3, x_2)f_r(x_3, x_2, x_1)G(x_2, x_1)f_r(x_2, x_1, x_0)G(x_1, x_0)S(x_1, x_0)$$

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## Three Consequences

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1. **Forward estimate equal backward estimate**
  - May use forward or backward ray tracing
2. **Adjoint solution**
  - Importance sampling paths
3. **Solve for small subset of the answer**

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## Example: Linear Equations

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**Solve a linear system**  $Mx = b$

**Solve for a single  $x_i$ ?**

**Solve the adjoint equation**

**Source**  $x_i$

**Estimator**  $\langle (x_i + Mx_i + M^2x_i + \dots), b \rangle$

**More efficient than solving for all the unknowns**  
**[von Neumann and Ulam]**

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