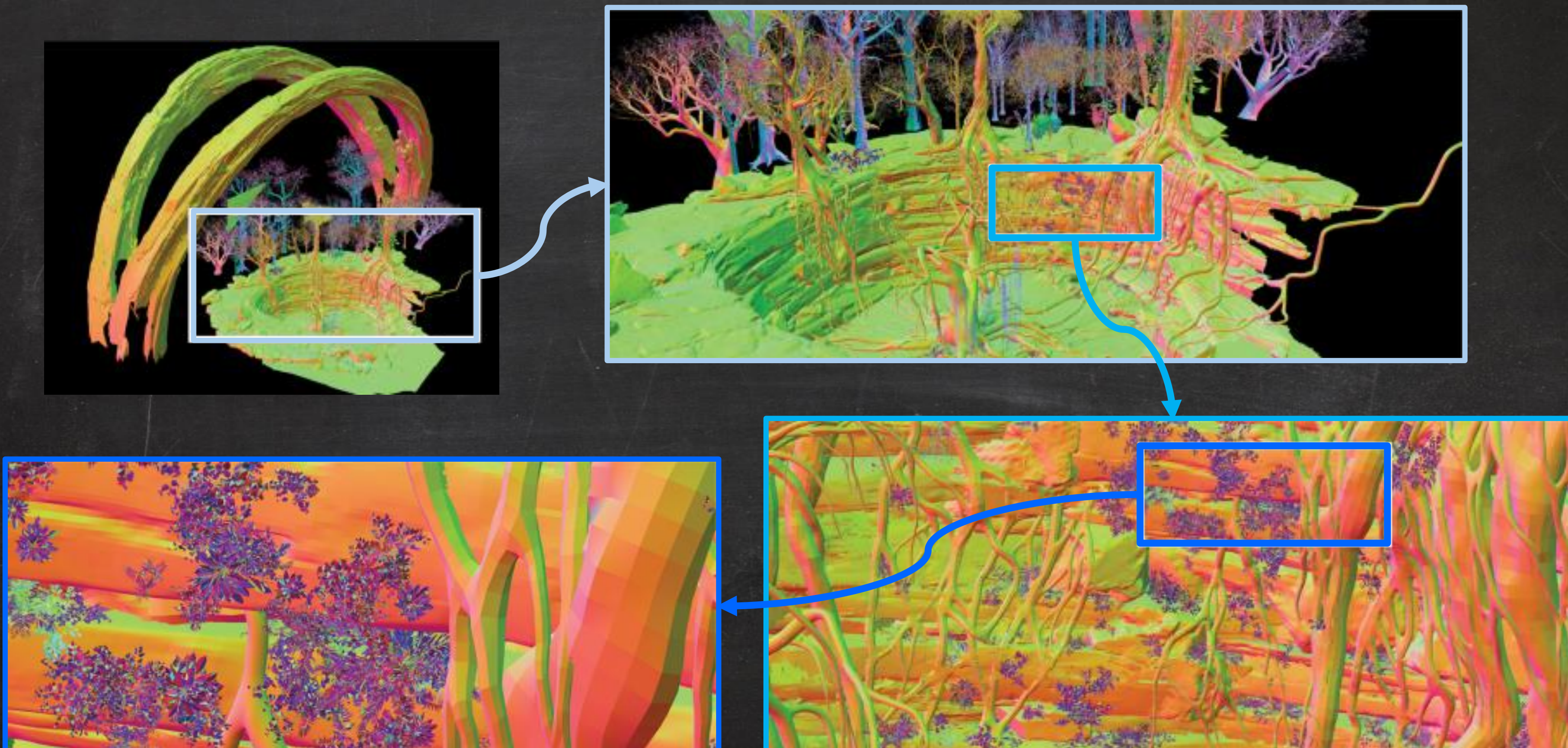
Global Illumination II

Shih-Chin Weng
shihchin.weng@gmail.com

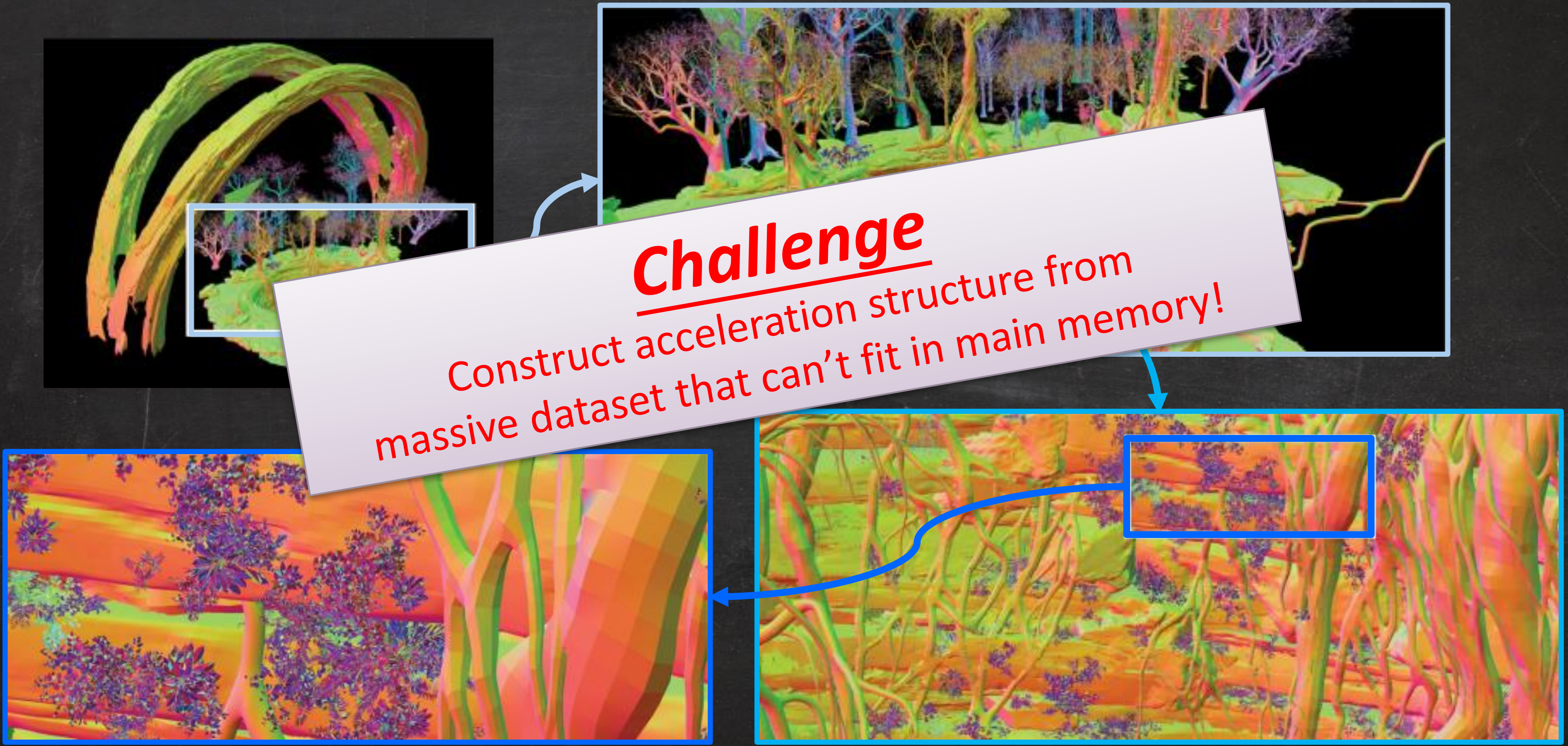
Case Study

PantaRay from NVidia & Weta

Scenario of PantaRay



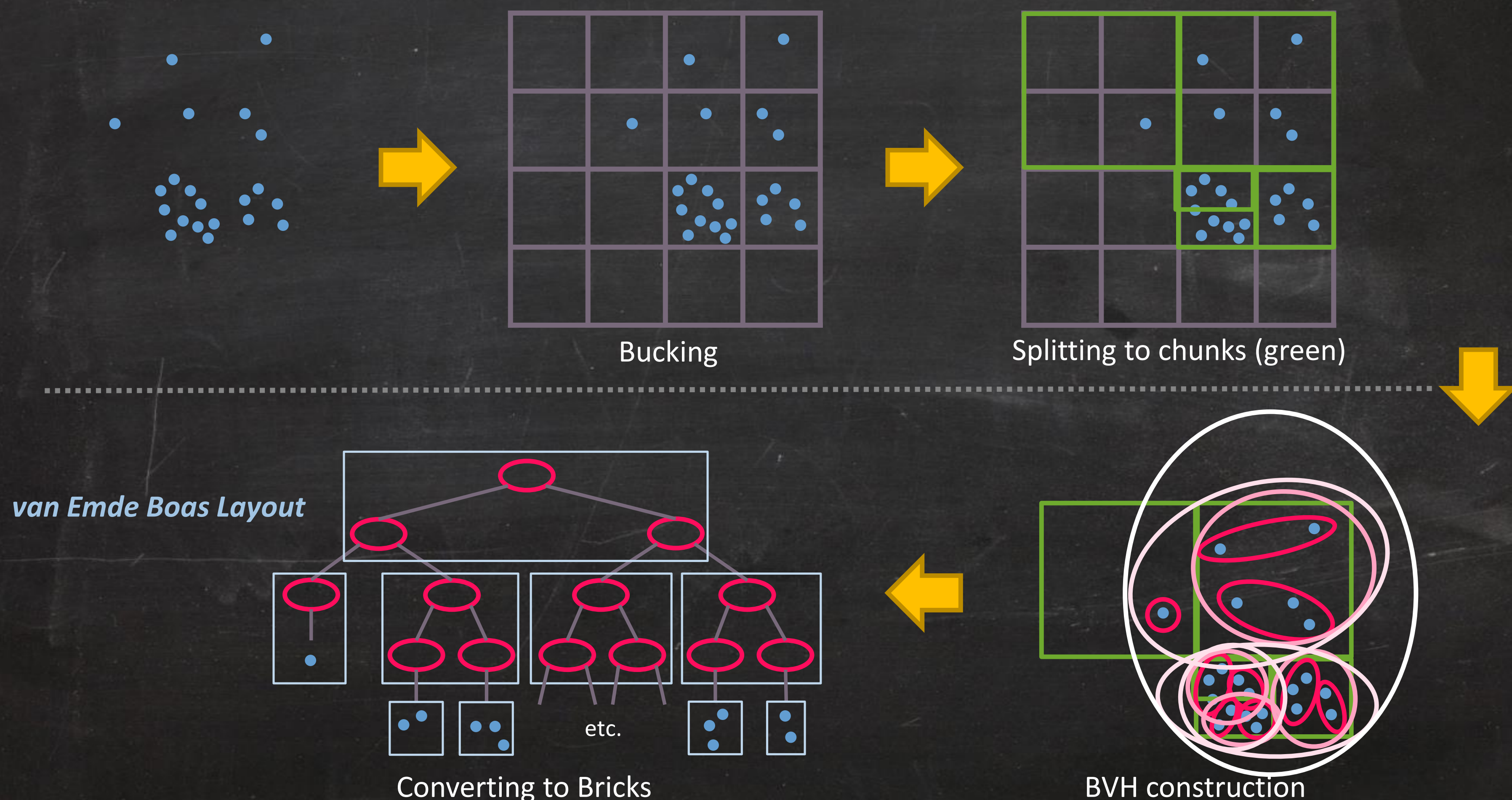
Scenario of PantaRay



Challenge

Construct acceleration structure from massive dataset that can't fit in main memory!

Case Study: PantaRay



Case Study

Hyperion from Disney Animation

Concerns of Production Renderers

- Computation bound or I/O bound?
- Challenges
  - Massive geometry data set
    - Buildings, forest, hair, fur, etc.
  - Large amount of high-resolution textures
- Goals
  - Reduce I/O costs
  - Improve memory access patterns

The Beauty of San Fransokyo

[Video courtesy of Disney Animation.]

City View of San Fransokyo

[Video courtesy of Disney Animation.]

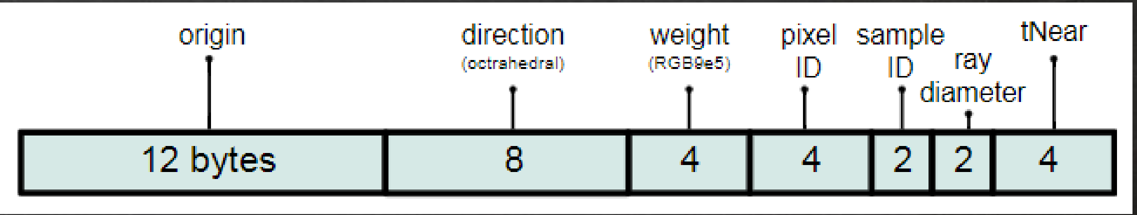
Introduction of Hyperion in Big Hero 6

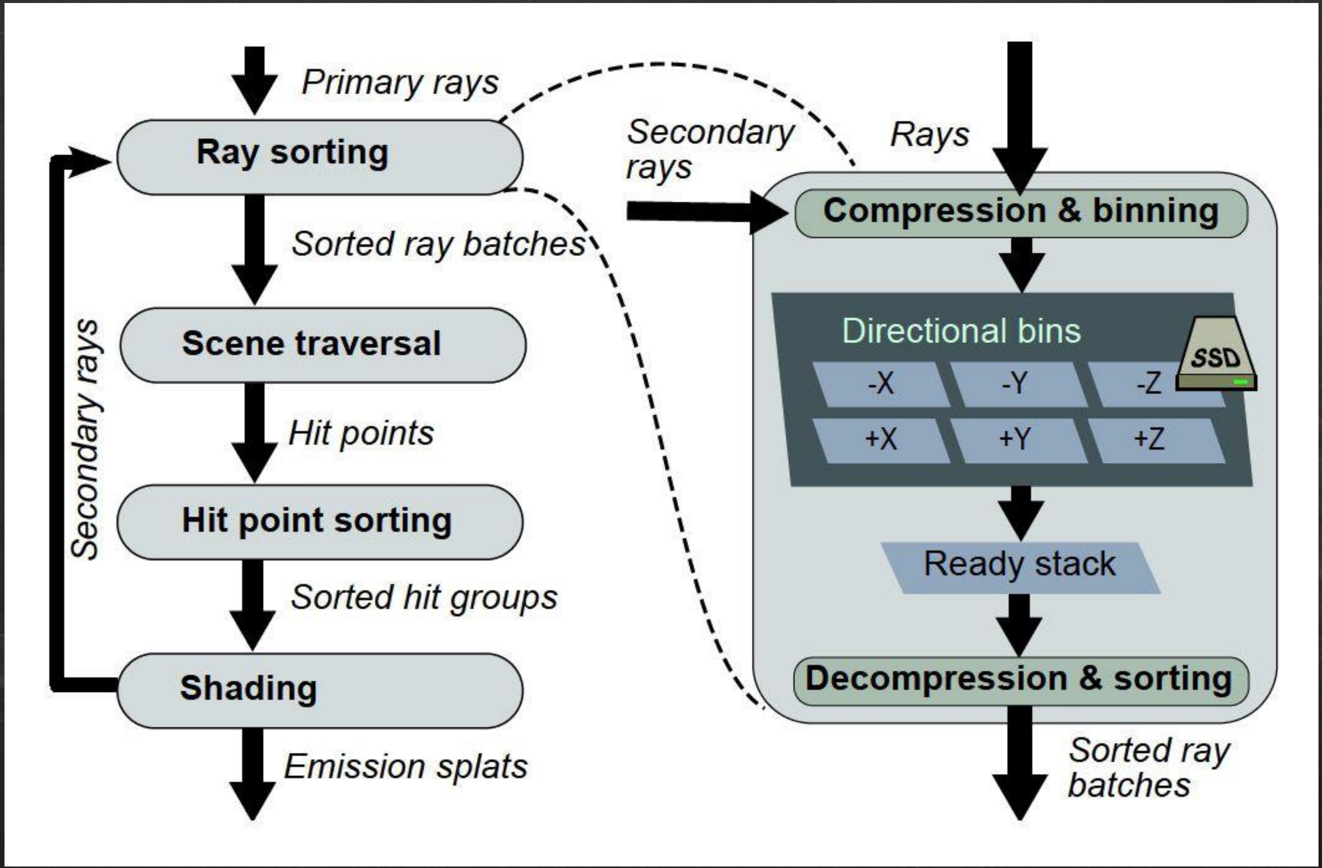
- Features
  - Uni-directional path tracer (w/o intermediate caches)
  - Physically based rendering
  - Support volumetric rendering and mesh lights, etc.
- Data complexity
  - 83,000 buildings
  - 216,000 street lights

Core Ideas To Ensure Coherence

- Sort potentially out-of-core ray batches to extract ray groups from a complex scene
  - There are 30~60M rays per batch
  - Perform scene traversal per ray batch at a time
- Sort ray hits for deferred shading w.r.t. shading context (mesh ID + face ID)
  - Hit points are grouped by mesh ID, then sorted by face ID
    - Achieve sequential texture reads with PTex

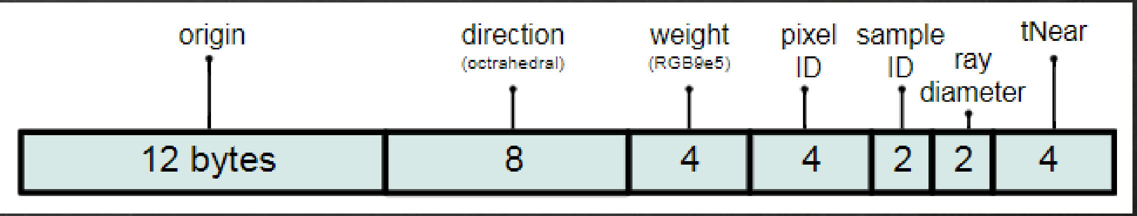
Tracing Pipeline

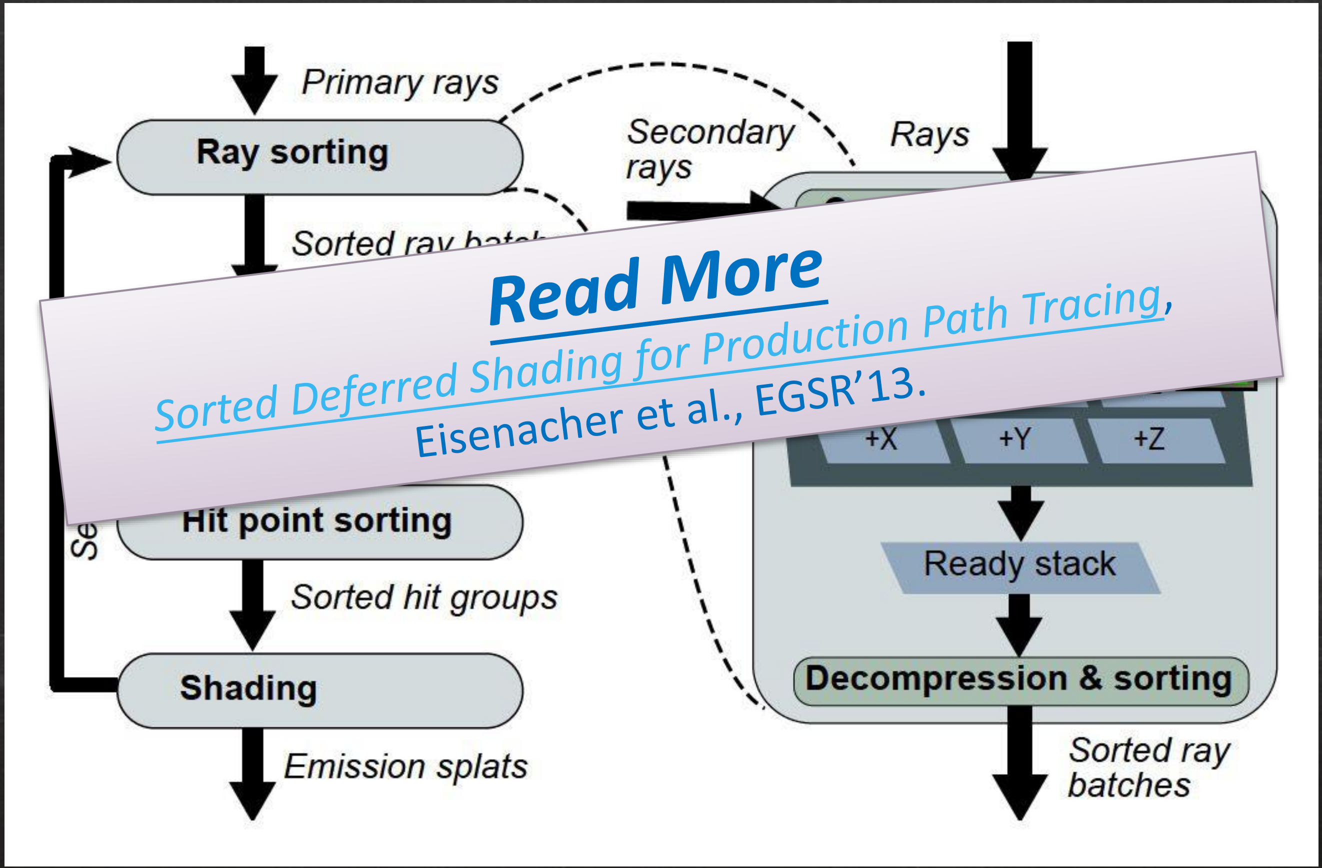




[Eisenacher et al., EGSR'13]

Tracing Pipeline





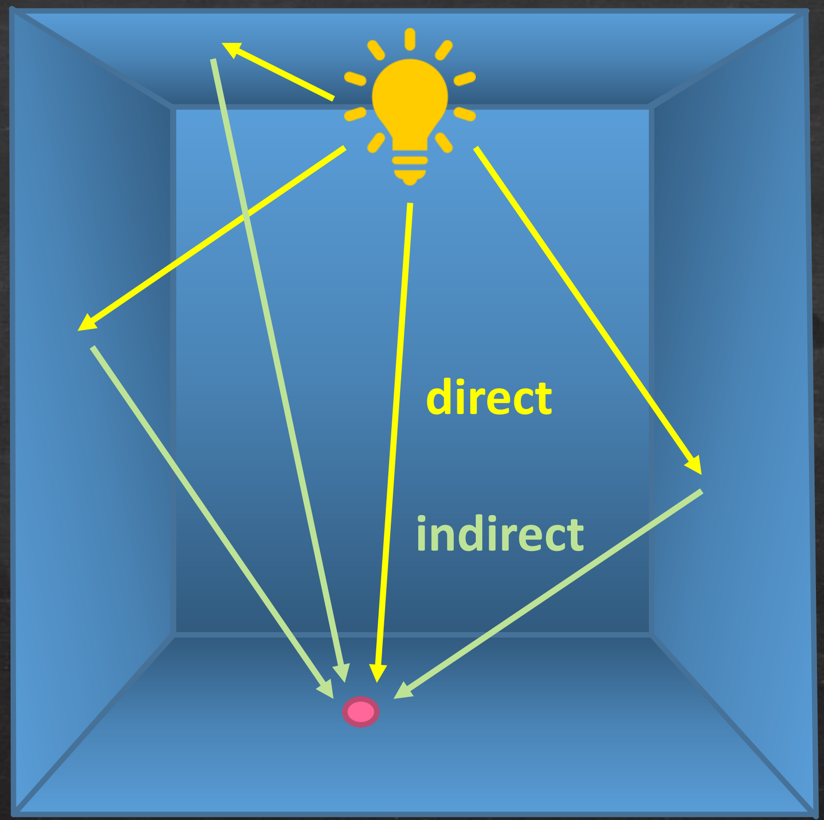
Read More

Sorted Deferred Shading for Production Path Tracing, Eisenacher et al., EGSR'13.

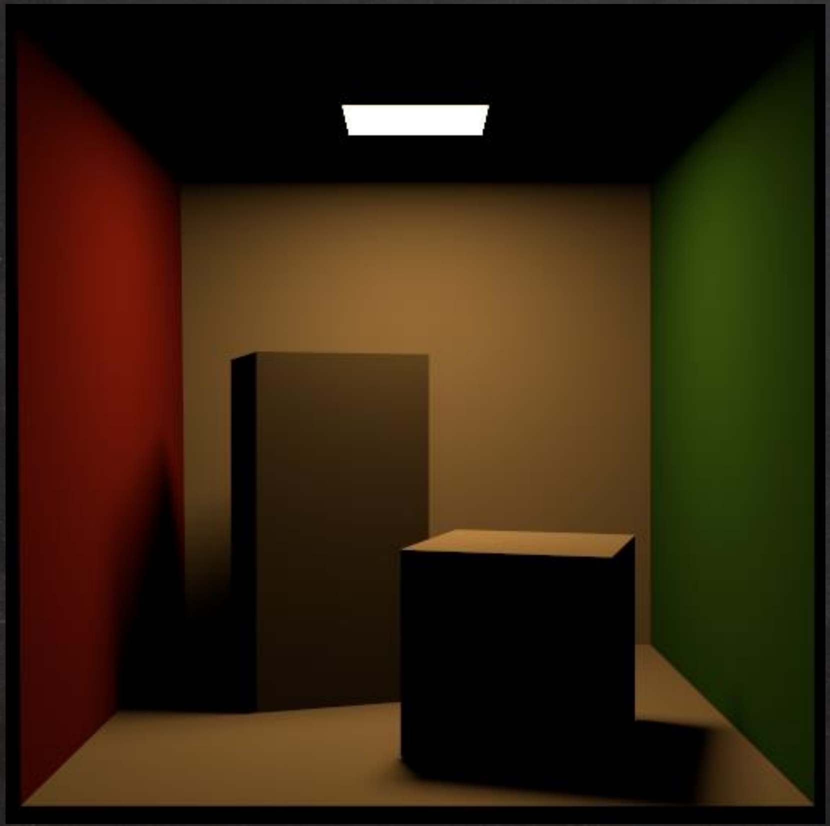
[Eisenacher et al., EGSR'13]

Render Equation

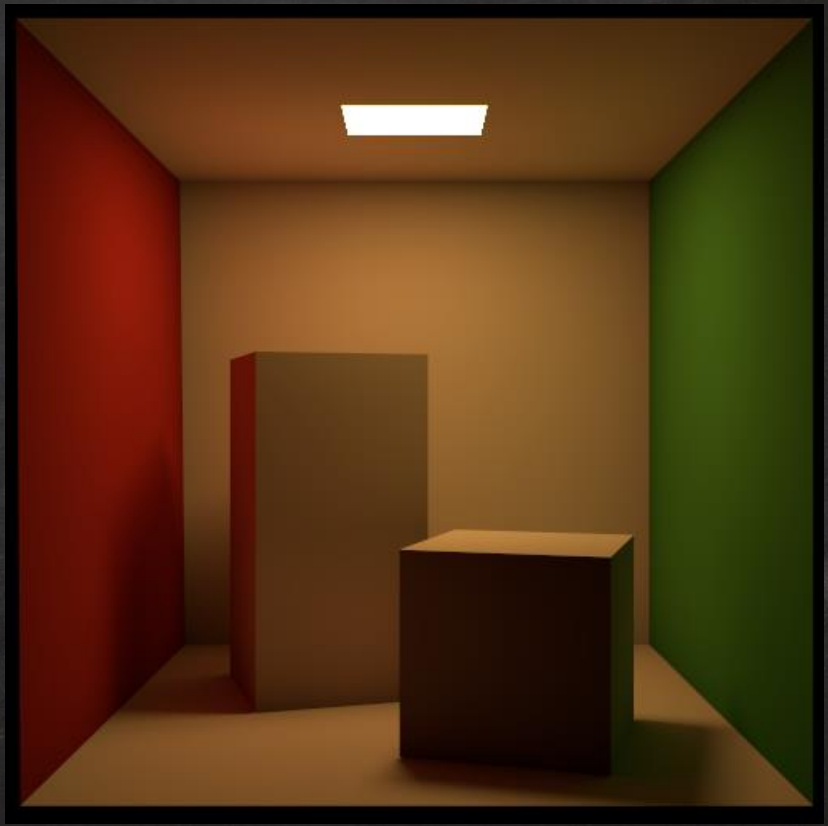
Where Does Light Come From?



Global = Direct + Indirect Lighting

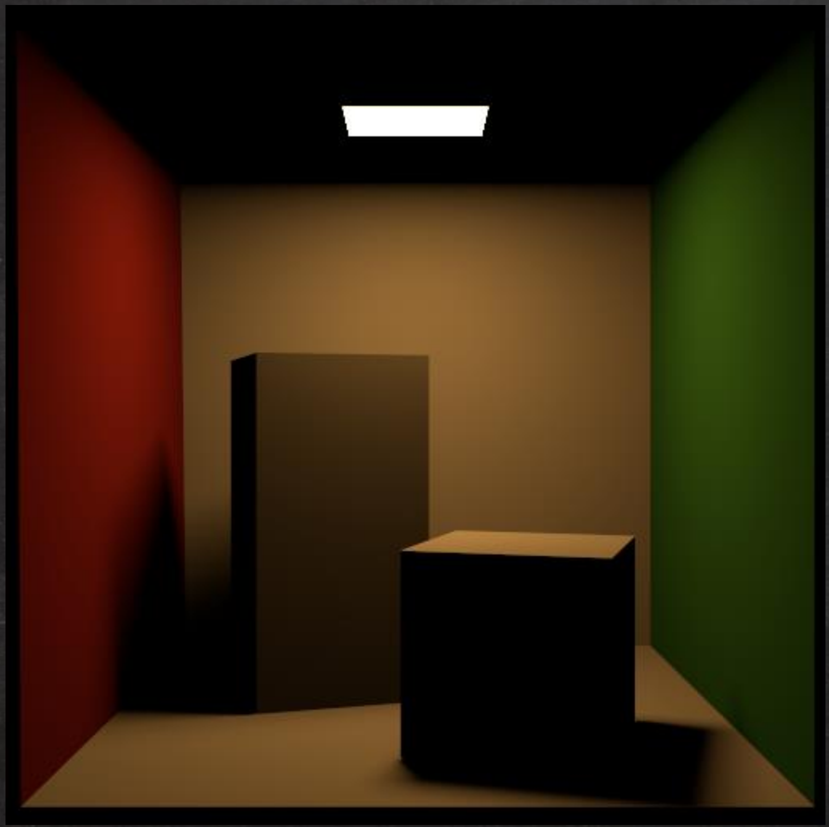


Direct Illumination

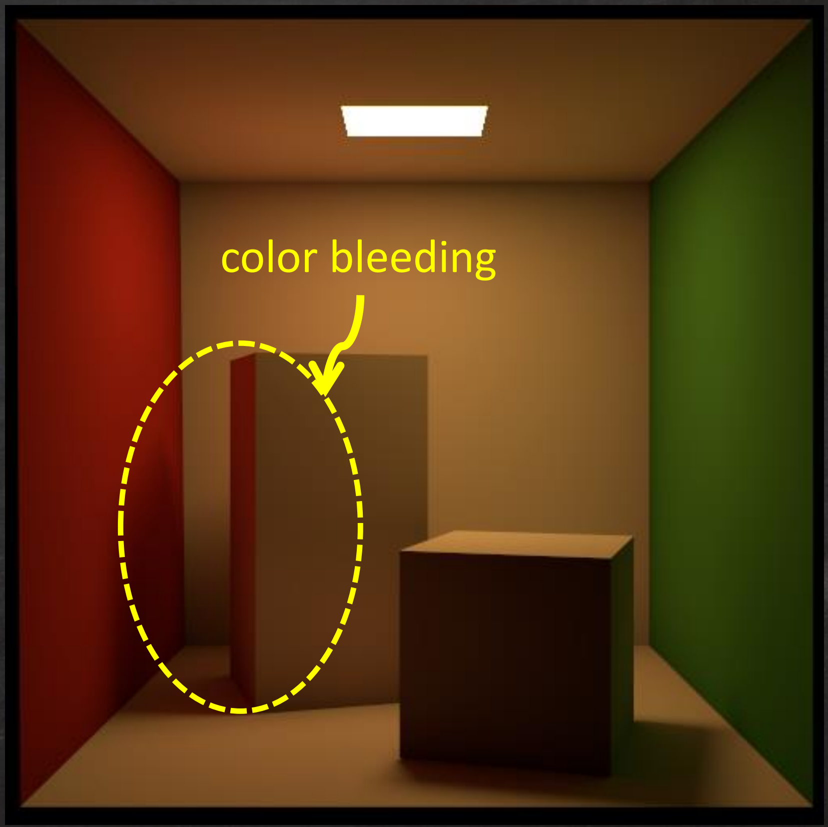


Global Illumination

Global = Direct + Indirect Lighting



Direct Illumination



Global Illumination

★Render Equation

Unknown!!

$$L(x,\vec{\omega}_o) = L_e(x,\vec{\omega}_o) + \int_\Omega L(x,\vec{\omega}_i) f(\vec{\omega}_i,\vec{\omega}_o)(\vec{\omega}_i \cdot \vec{n}) d\vec{\omega}_i$$

★Render Equation

Unknown!!

$$L(x, \vec{\omega}_o) = L_e(x, \vec{\omega}_o) + \int_{\Omega} L(x, \vec{\omega}_i) f(\vec{\omega}_i, \vec{\omega}_o)(\vec{\omega}_i \cdot \vec{n}) d\vec{\omega}_i$$

How do we solve this kind of equation??

★Render Equation

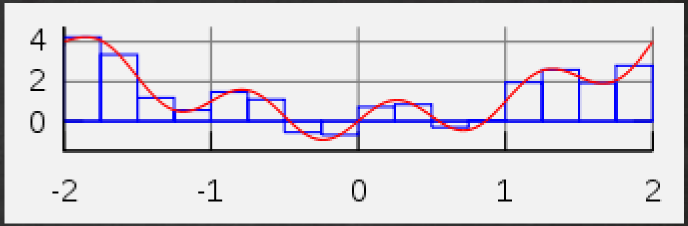
Unknown!!

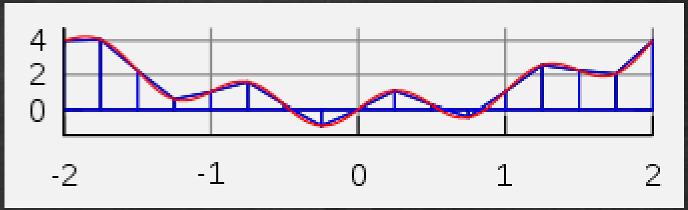
$$L(x,\vec{\omega}_o) = L_e(x,\vec{\omega}_o) + \int_\Omega L(x,\vec{\omega}_i) f(\vec{\omega}_i,\vec{\omega}_o)(\vec{\omega}_i \cdot \vec{n})\, d\vec{\omega}_i$$

How do we solve this kind of equation??

Quadrature

- 1D example
  - Rectangle/trapezoid
  - Gaussian quadrature

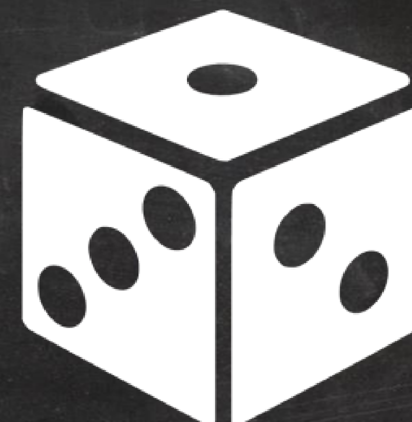




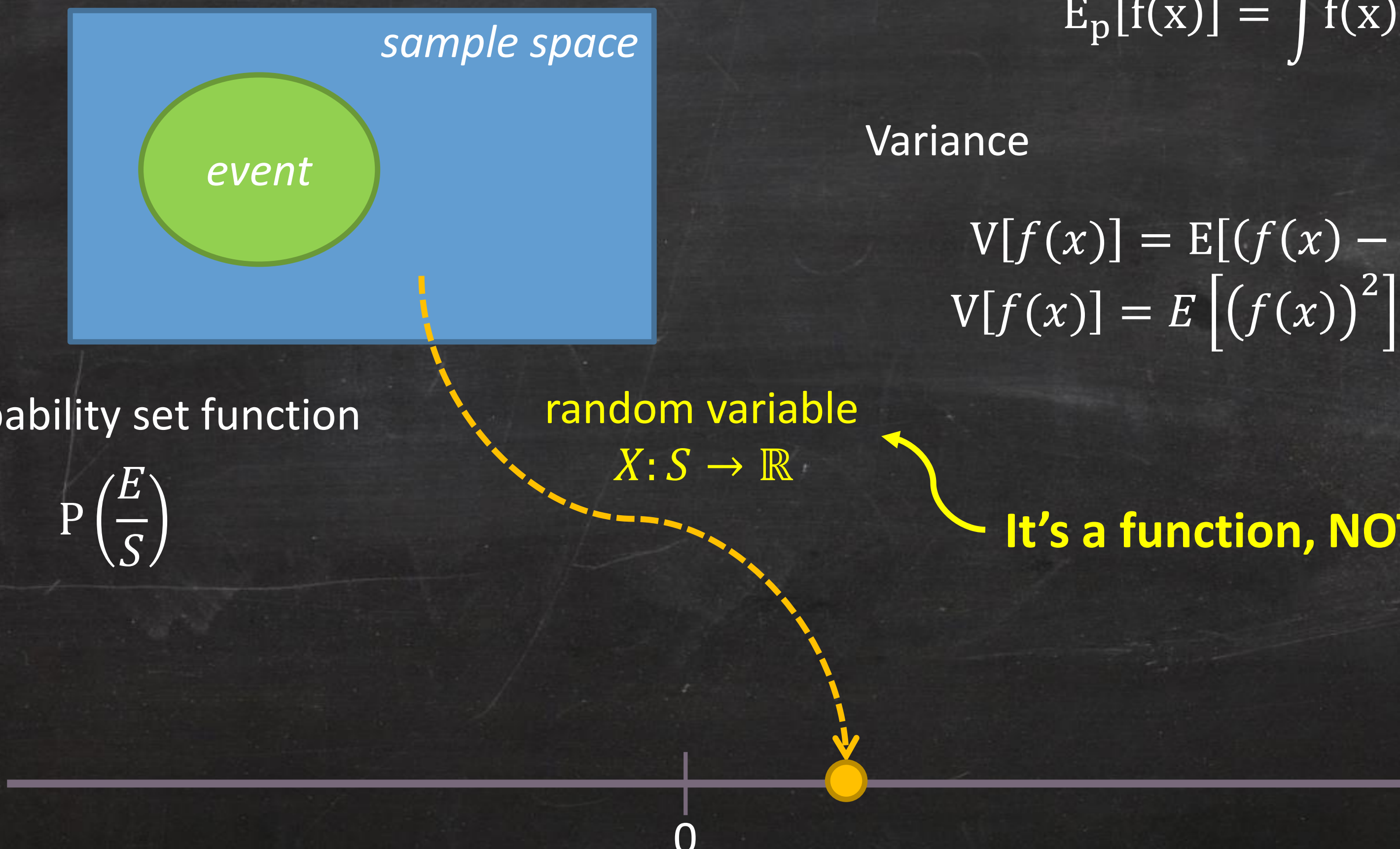
- Curse of dimensionality
  - The dimension of render equation is infinity!!
  - That’s why we need Monte Carlo

https://en.wikipedia.org/wiki/Numerical_integration

Monte Carlo Integration



Probability Review



probability set function

$$P\left(\frac{E}{S}\right)$$

Excepted value of a random variable

$$E_p[f(x)] = \int f(x)p(x)dx$$

Variance

$$V[f(x)] = E[(f(x) - E[f(x)])^2]$$
$$V[f(x)] = E\left[\left(f(x)\right)^2\right] - E[f(x)]^2$$

It's a function, NOT a variable!!

Concepts

- Use random numbers to approximate integrals
- It only estimates the values of integrals
  - i.e. gives the right answer **on average**
- It only requires to be able to evaluate the integrand at arbitrary points
  - Nice property for multi-dimensional integrand such as radiance in render equation

Monte Carlo Sampling

✓ Easy to implement

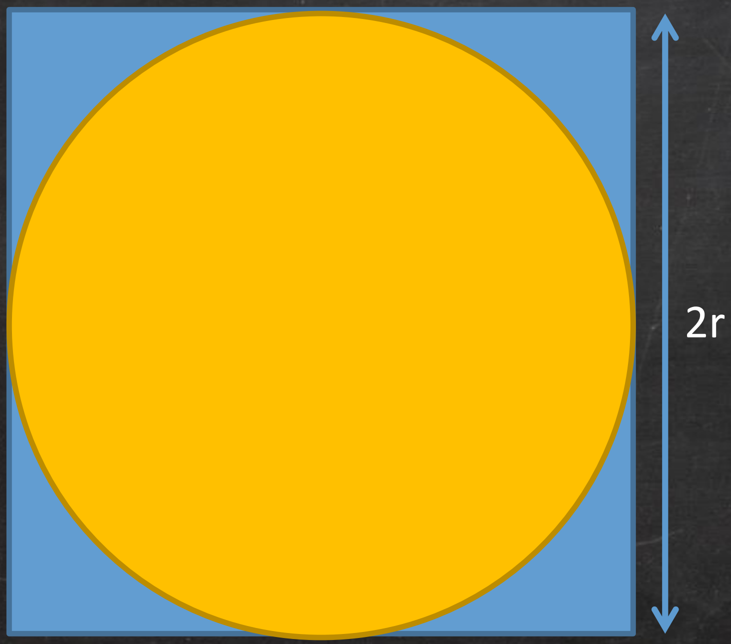
✓ Efficient for high dimensional integrals

✗ Noise (variance)

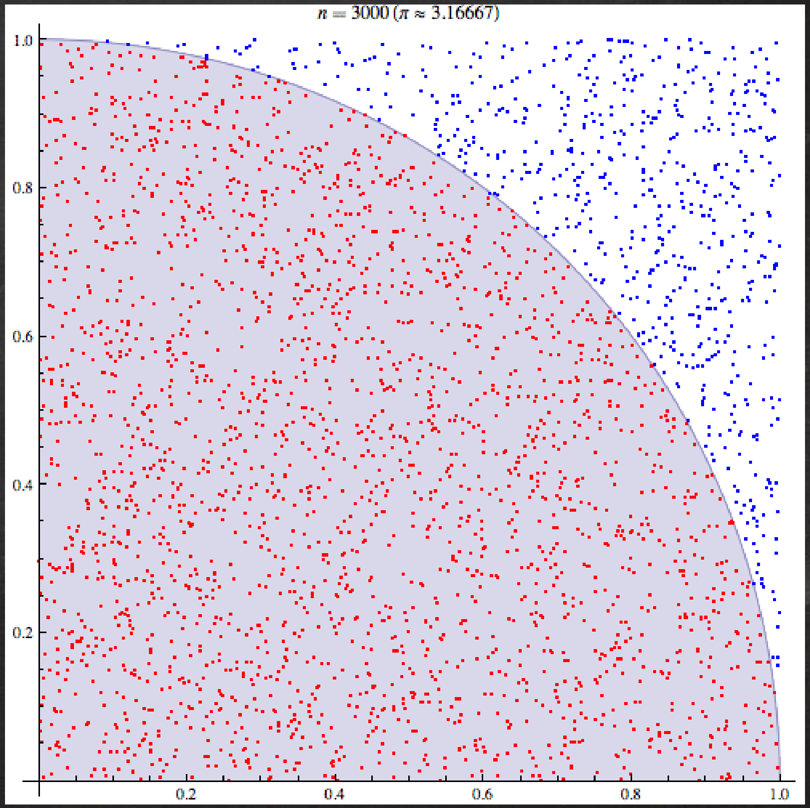
✗ Low convergence rate $(1/\sqrt{n})$

- But we don't have many other choices in high dimensional space!

Estimate π with Monte Carlo Sampling



$$P(PointsInCircle) = \frac{\pi r^2}{4r^2} \Rightarrow \pi = 4P$$



https://en.wikipedia.org/wiki/Monte_Carlo_method#/media/File:Pi_30K.gif

Probability Density Function (PDF)

$$\Pr(\mathrm{x} \in [\mathrm{a}, \mathrm{b}]) = \int_{\mathrm{a}}^{b} p(x)\, dx$$

The relative probability of a random variable taking on a particular value

- $p(x) = \frac{dPr(x)}{dx} \geq 0$
- $\int_{-\infty}^{\infty} p(x) dx = 1, \Pr(x \in \mathbb{R}) = 1$

Cumulative Distribution Function (CDF)

$$P(x) = Pr\{X \leq x\}$$

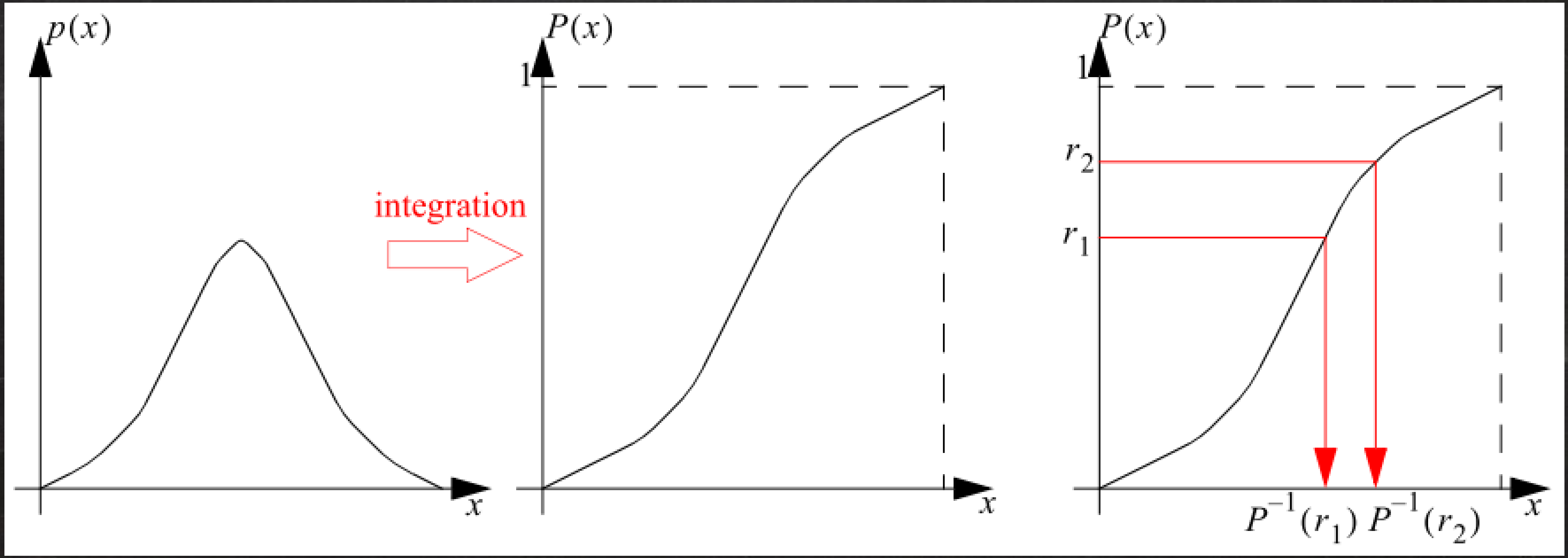


Figure from *"Global Illumination Compendium"*, Philip Dutré

Properties of Estimators

- Suppose Q is the unknown quantity
- Unbiased: $\mathrm{E}[F_N] = Q$
  - Bias $\beta[\mathrm{F_N}] = \mathrm{E}[F_N] - Q$
  - The expected value is independent of sample size N
- Consistent
  - $\lim_{N \to \infty} \beta[F_N] = 0$
  - $\lim_{N \to \infty} E[F_N] = Q$

Law of Large Numbers

$$\Pr\left[\mathrm{E}(\mathrm{x}) = \lim_{\mathrm{N}\to\infty} \frac{1}{N}\sum_{i=1}^{N} x_i\right] = 1$$

$$\mathrm{E}[f(x)] \approx \frac{1}{N}\sum_{i=1}^{N} f(x_i)$$

Law of Large Numbers

N → ∞

$$\Pr\left[\mathrm{E} \ldots \underset{N\to\ldots}{\ldots} \frac{1}{\ldots} \sum^{N} \ldots \right] \ldots = 1$$

$$\mathrm{E}[f \ldots \frac{\ldots}{N} \sum_{i=1} f(\ldots$$

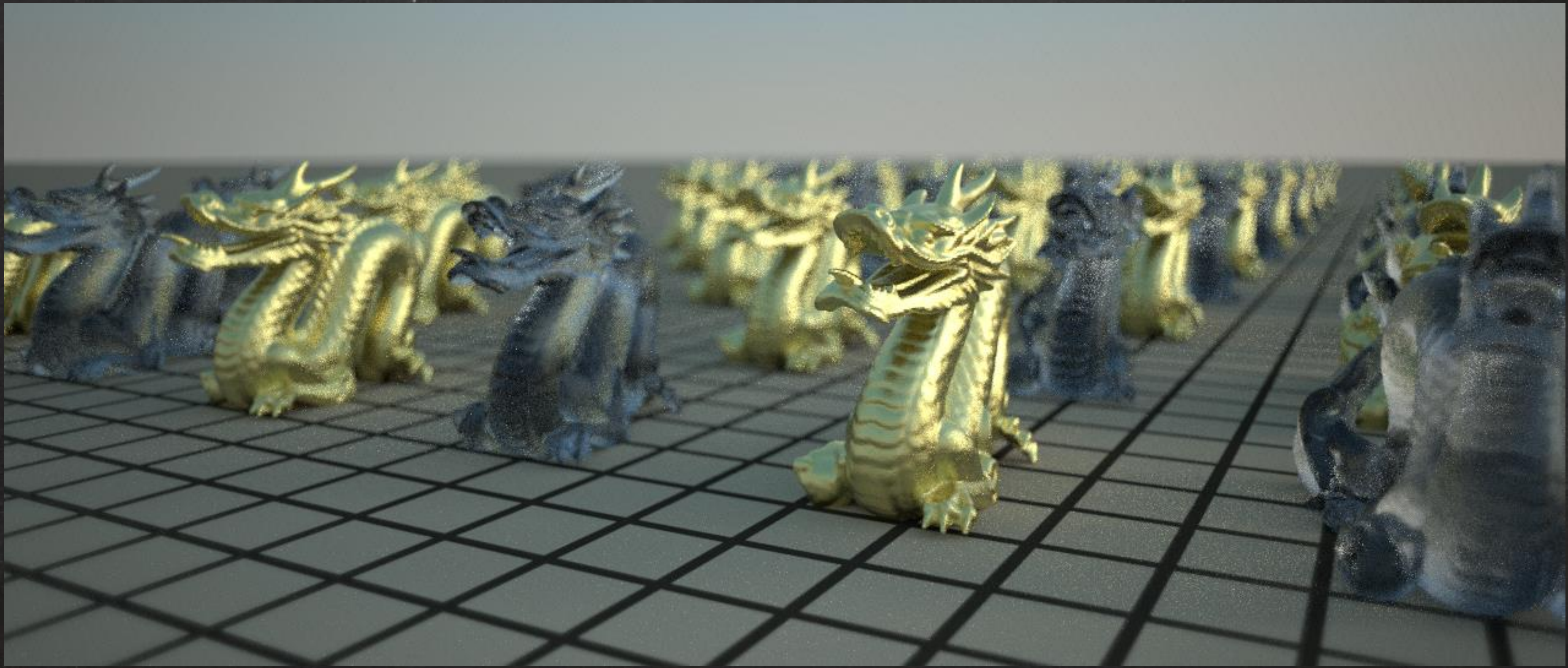
Law of Large Numbers

$$\Pr\left[\mathrm{E} \;\ldots\; \mathrm{N}\!\rightarrow \;\ldots\; \frac{1}{\ldots}\sum^{N} \;\ldots\; \right] = 1$$

N → ∞

$$\mathrm{E}[f(\ldots \;\ldots\; \frac{\ldots}{N}\sum_{i=1} f(\ldots$$

Insufficient Samples = High Variance = Noise



[Rendered with pbrt.v3]

Monte Carlo Estimation

estimator

$$\int f(x)\,dx = \int \frac{f(x)}{p(x)} p(x) dx = E\left[\frac{f(x)}{p(x)}\right] \approx \frac{1}{N}\sum_{i=1}^{N} \frac{f(x)}{p(x)}$$

$$\int_{\Omega} L_i(x, \vec{\omega}_i) f(\vec{\omega}_i, \vec{\omega}_o)(\vec{\omega}_i \cdot \vec{n}) d\vec{\omega}_i$$

$$\approx$$

$$\frac{1}{N}\sum_{i=1}^{N} \frac{L_i(x, \vec{\omega}_i) f(\vec{\omega}_i, \vec{\omega}_o)(\vec{\omega}_i \cdot \vec{n})}{p(\vec{\omega}_i)}$$

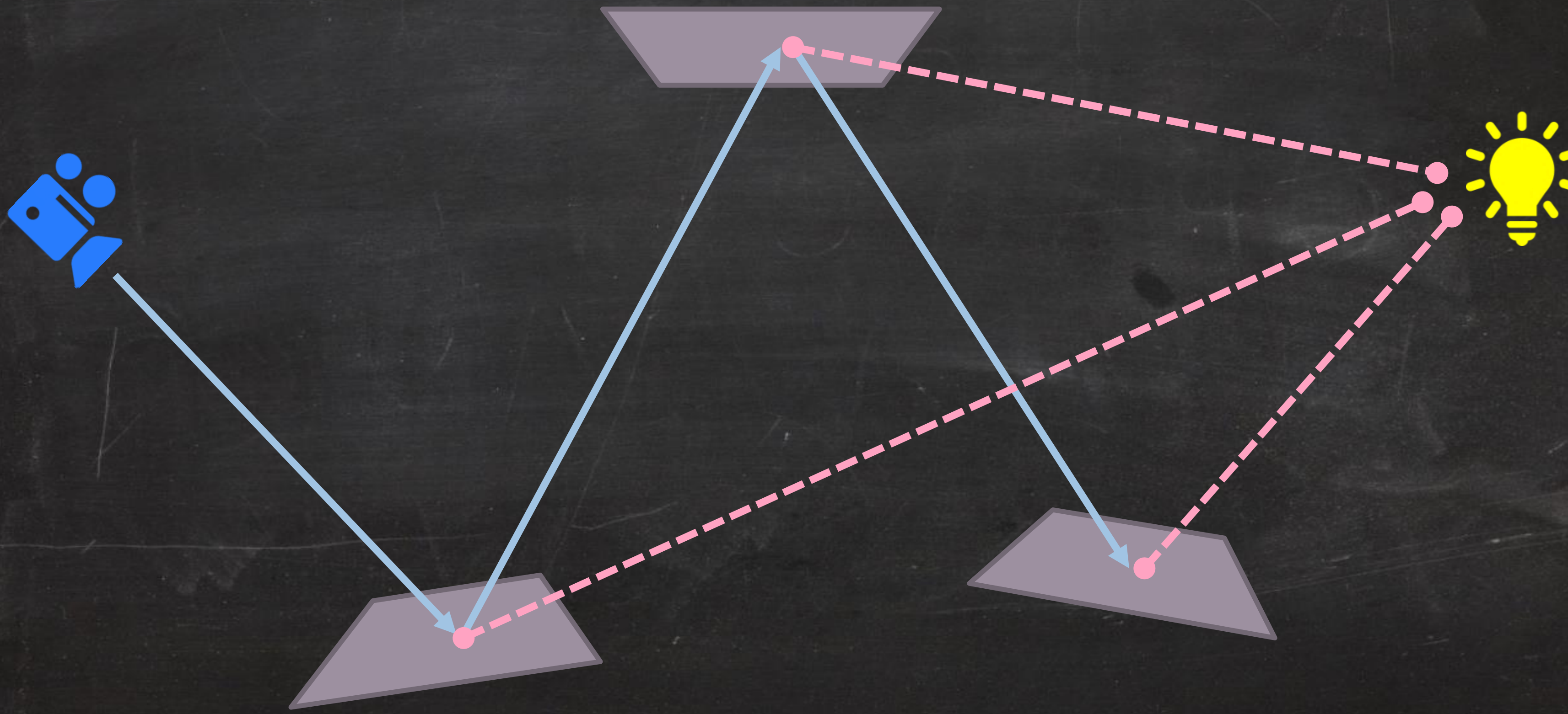
Tricky Part!!

Light Transport Algorithms

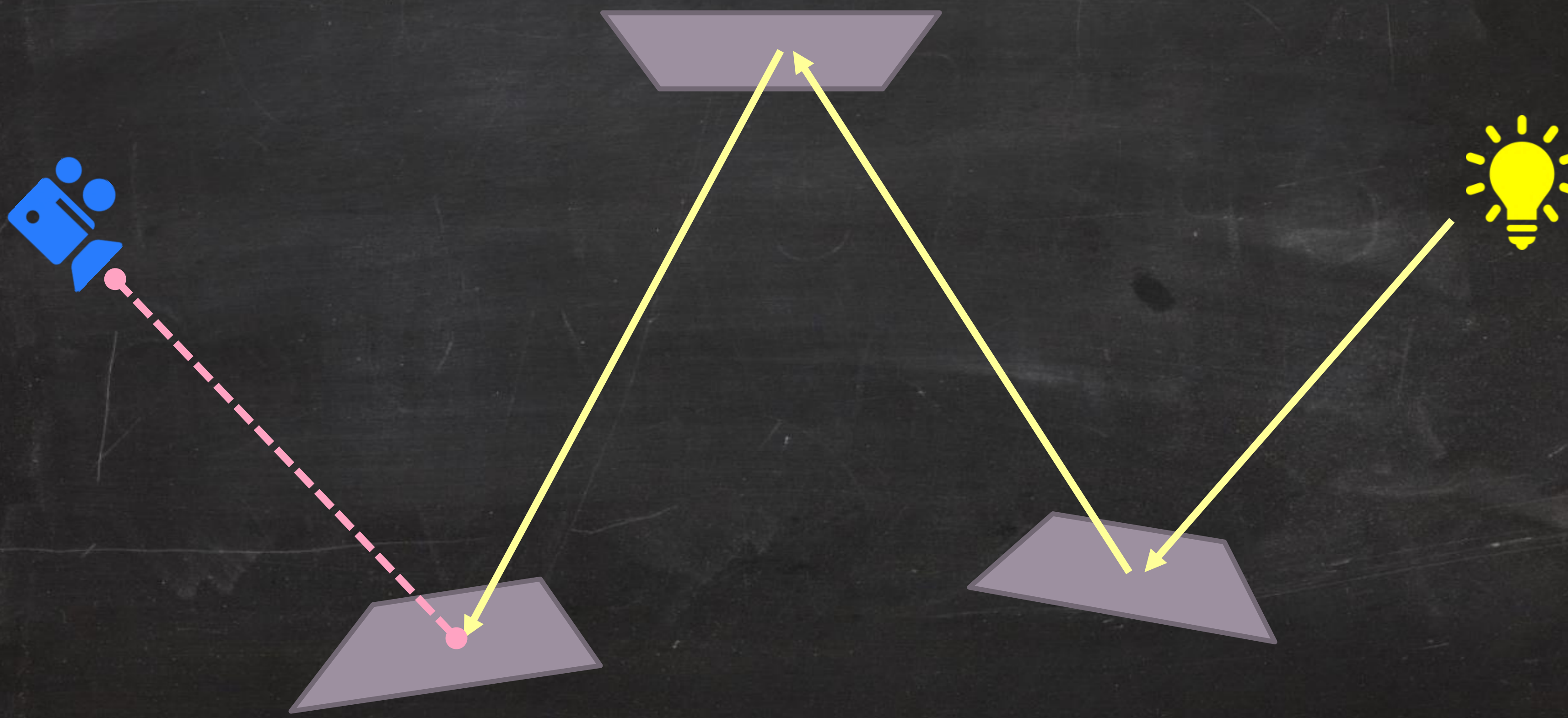
Light Transport Algorithms

- Path tracing
- Light tracing
- Bidirectional path tracing
- Photon mapping
- and many more…

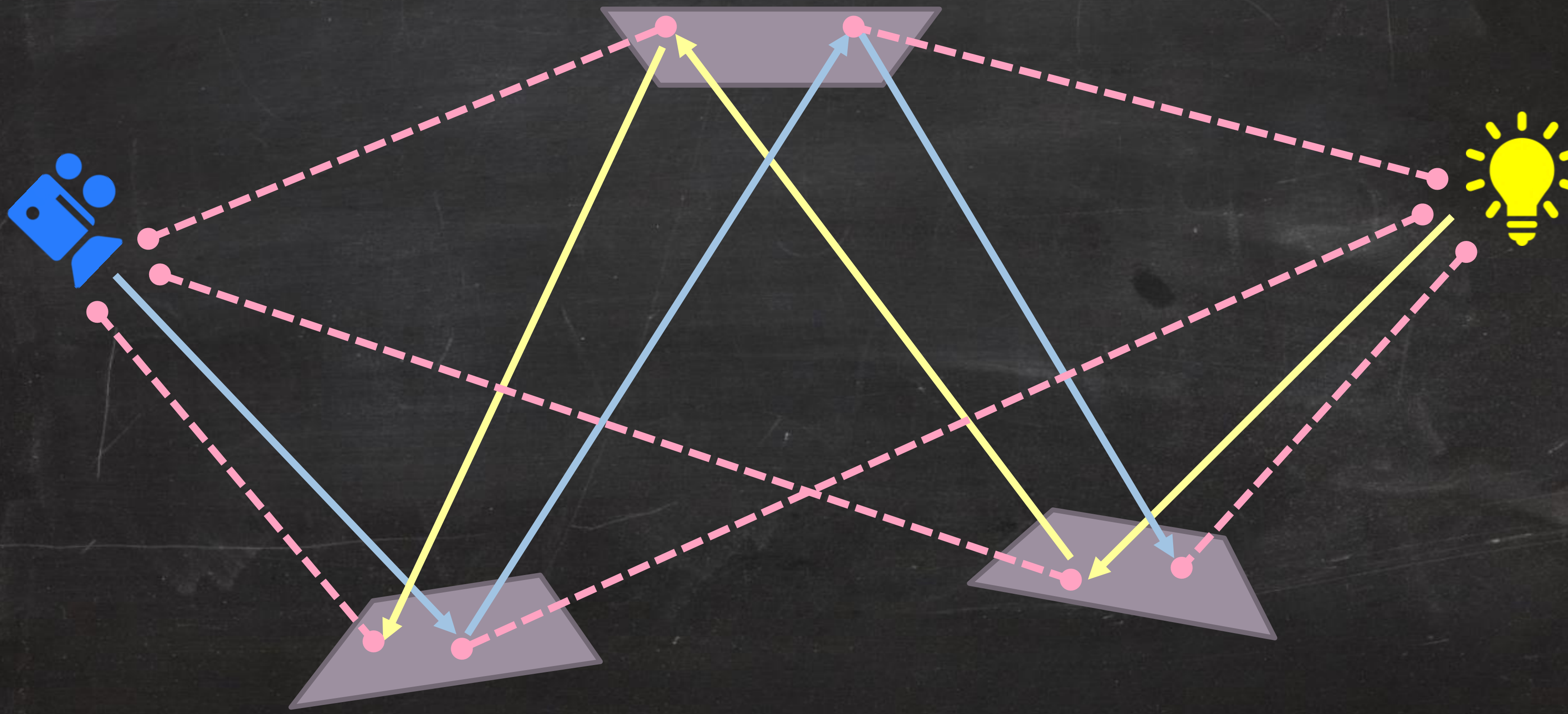
Path Tracing



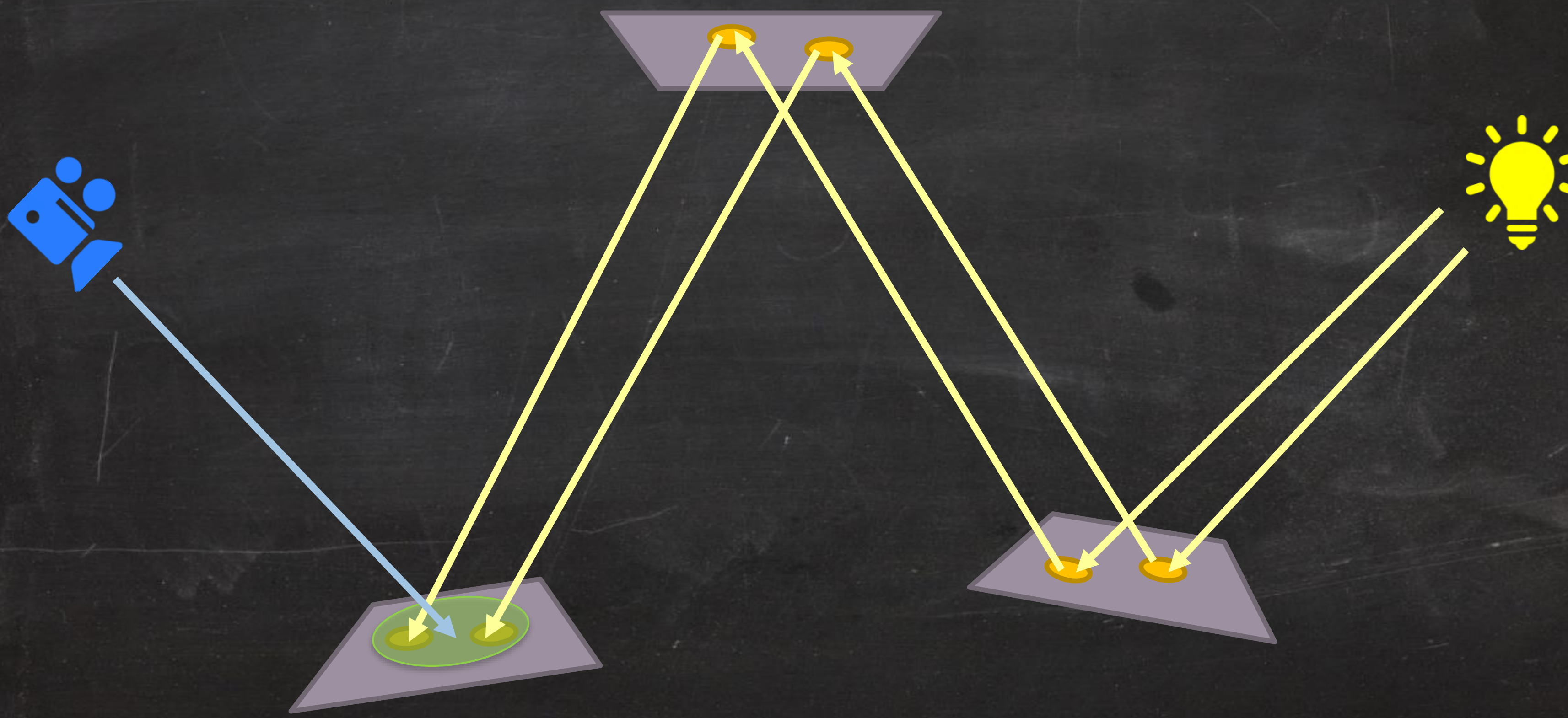
Light Tracing



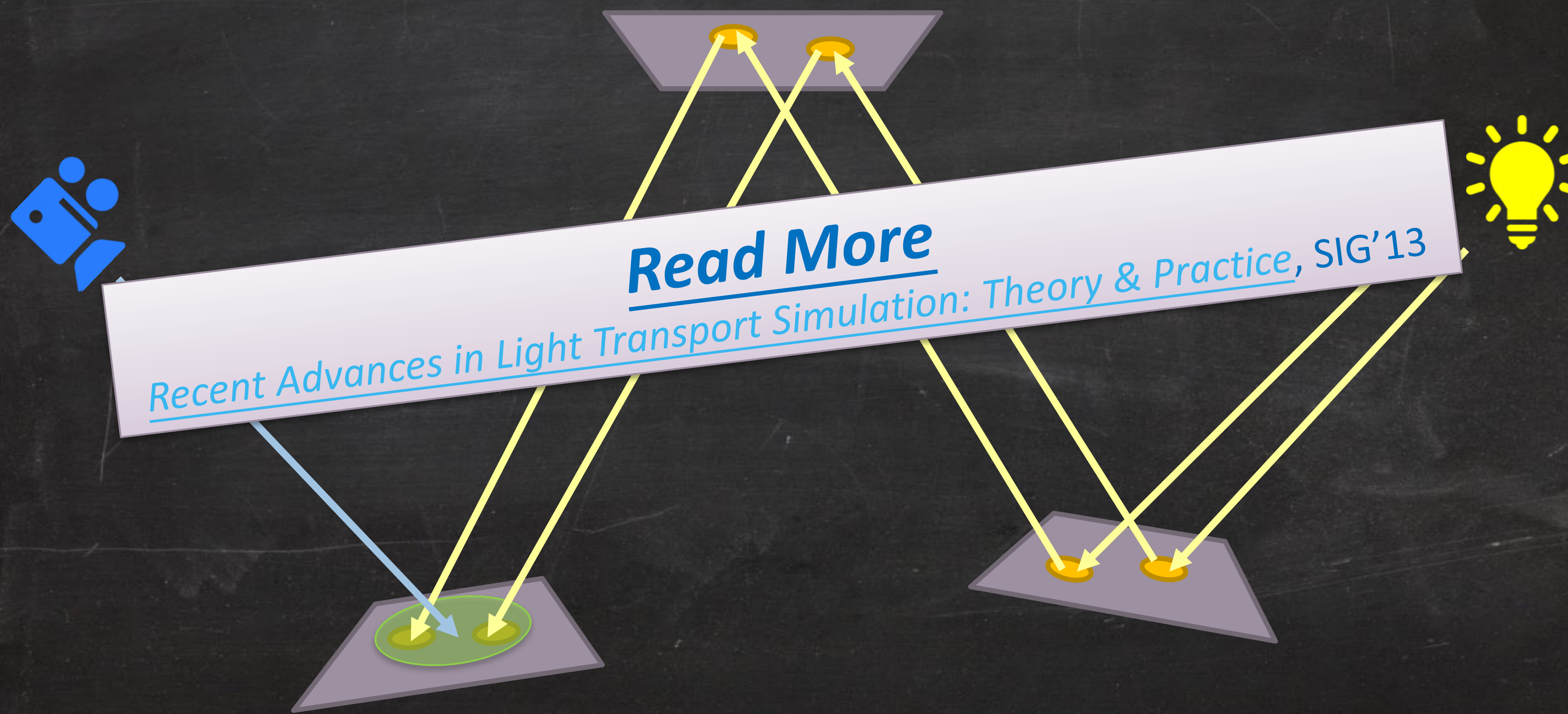
Bidirectional Path Tracing



Photon Tracing



Photon Tracing



Read More

Recent Advances in Light Transport Simulation: Theory & Practice, SIG'13

http://iliyan.com/publications/VertexMerging/comparison/

Path Tracing

Bidirectional Path Tracing

Progressive Photon Mapping

VCM

http://iliyan.com/publications/VertexMerging/comparison/

Importance Sampling

Direct Illumination

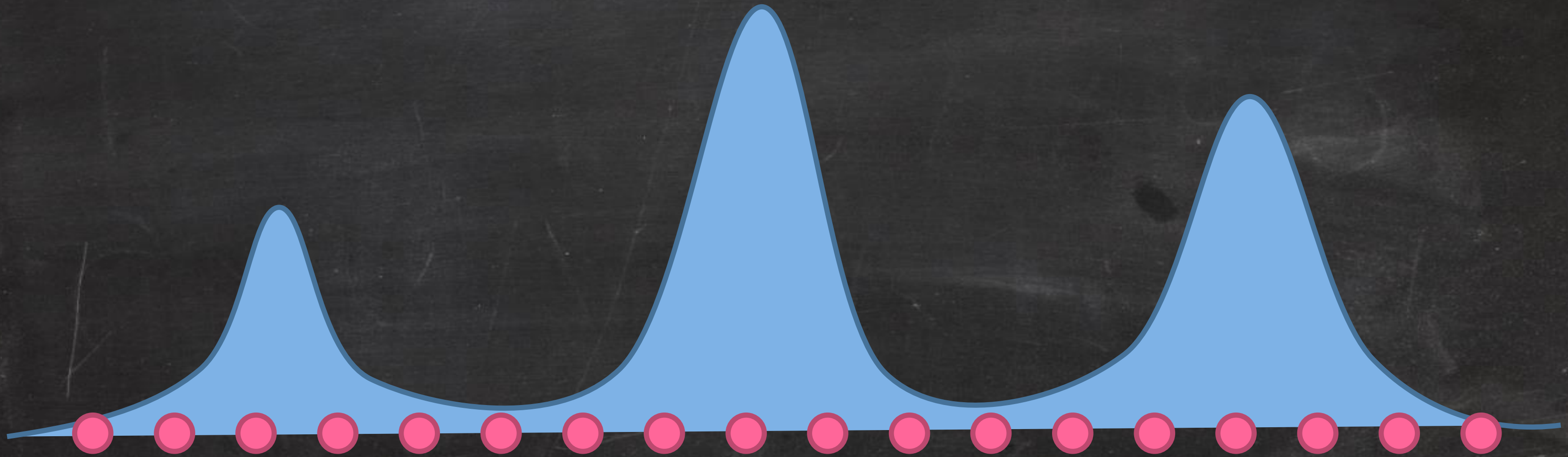
$$L_r(x, \vec{\omega}_o) = \int_{\Omega} L(x, \vec{\omega}_i) f(\vec{\omega}_i, \vec{\omega}_o)(\vec{\omega}_i \cdot \vec{n}) d\vec{\omega}_i$$

$$\approx$$

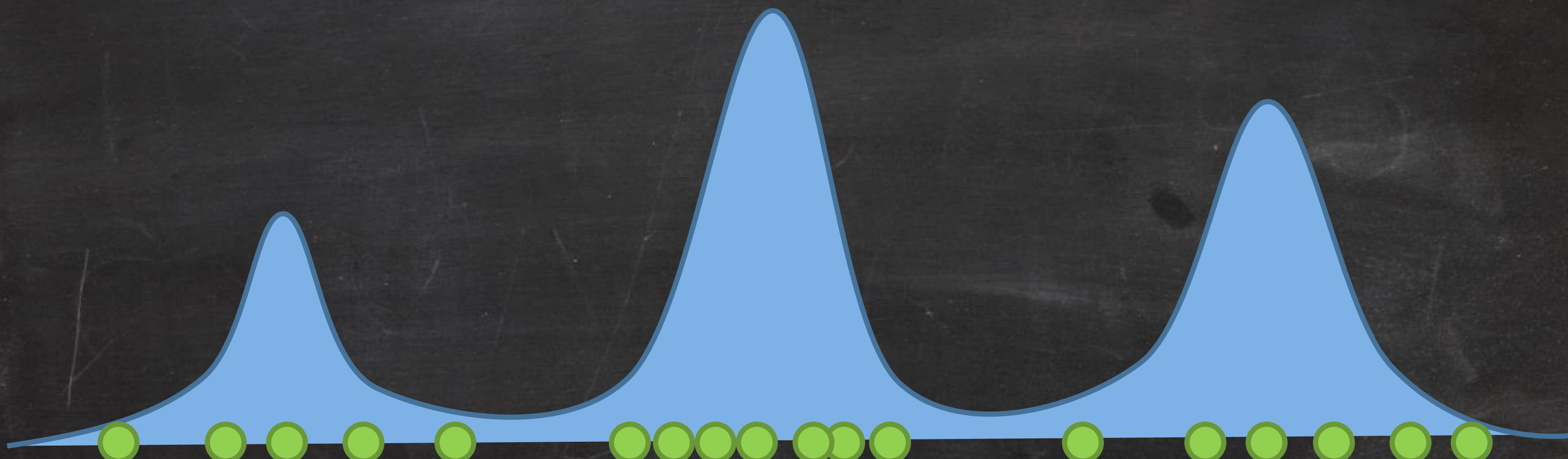
$$\frac{1}{N} \sum_{i=1}^{N} \frac{L_i(x, \vec{\omega}_i) f(\vec{\omega}_i, \vec{\omega}_o)(\vec{\omega}_i \cdot \vec{n})}{p(\vec{\omega}_i)}$$

1. $p(\vec{\omega}_i) \propto L_i(x, \vec{\omega}_i) f(\vec{\omega}_i, \vec{\omega}_o)(\vec{\omega}_i \cdot \vec{n})$?
2. $p(\vec{\omega}_i) \propto L_i(x, \vec{\omega}_i)$?
3. $p(\vec{\omega}_i) \propto f(\vec{\omega}_i, \vec{\omega}_o)(\vec{\omega}_i \cdot \vec{n})$?

Uniform Sampling



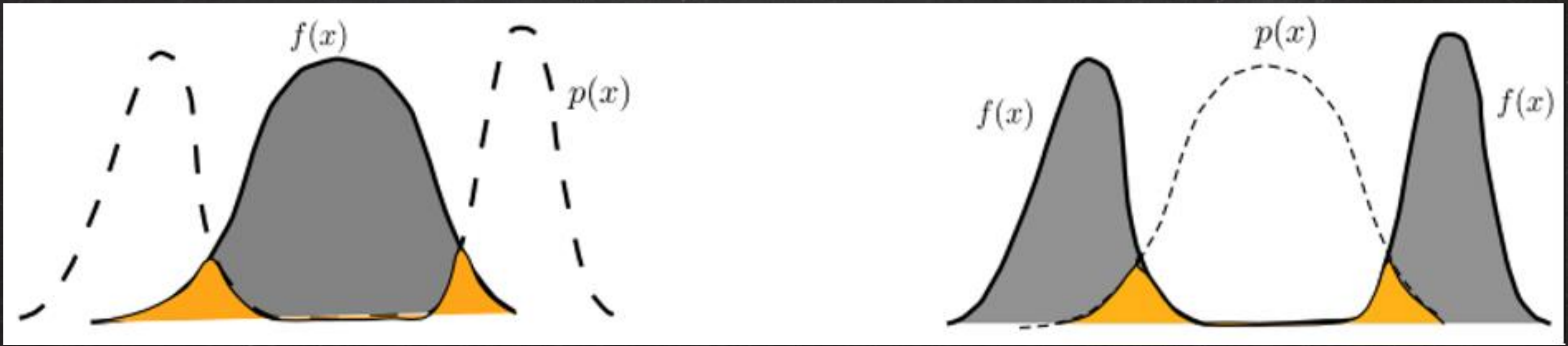
Importance Sampling



Importance Sampling (Cont'd)

Unknown!!

$$F_N = \frac{1}{N}\sum \frac{f(X_i)}{p(X_i)}, \qquad where\ p(X_i) \propto f(X_i)$$

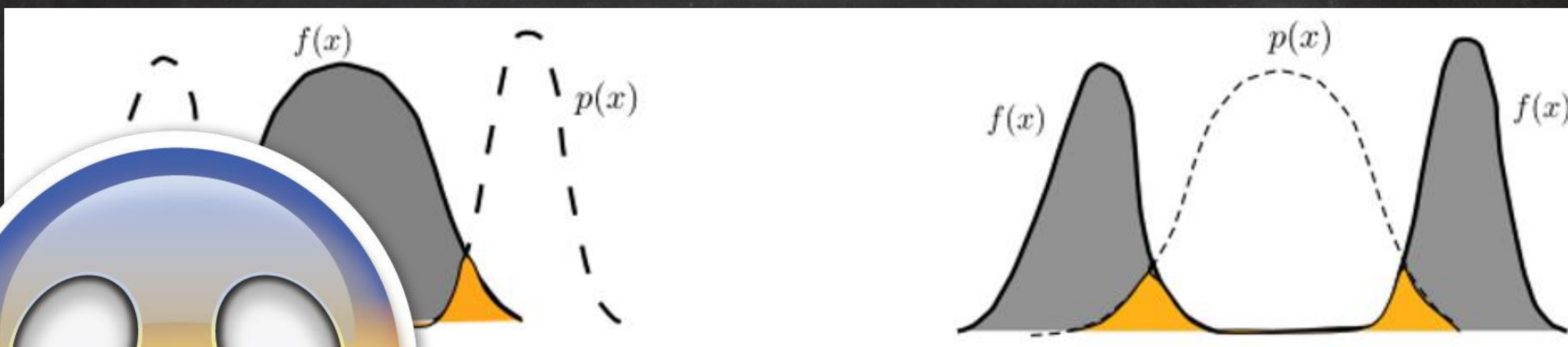


[Premože'10]

Importance Sampling (Cont'd)

Unknown!!

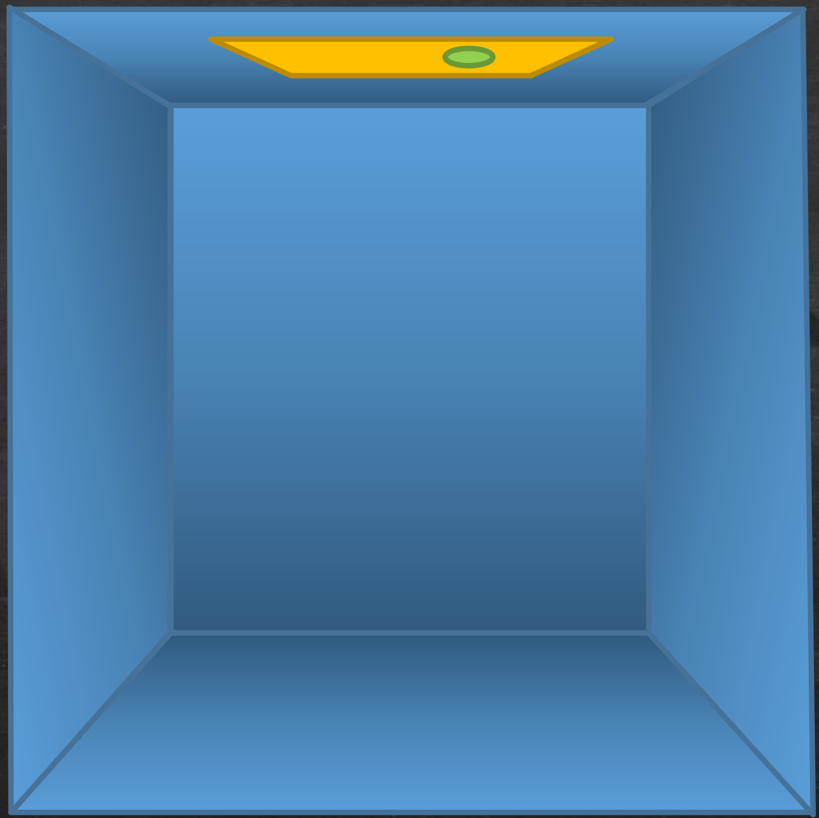
$$F_N = \frac{1}{N}\sum \frac{f(X_i)}{p(X_i)}, \qquad where\ p(X_i) \propto f(X_i)$$



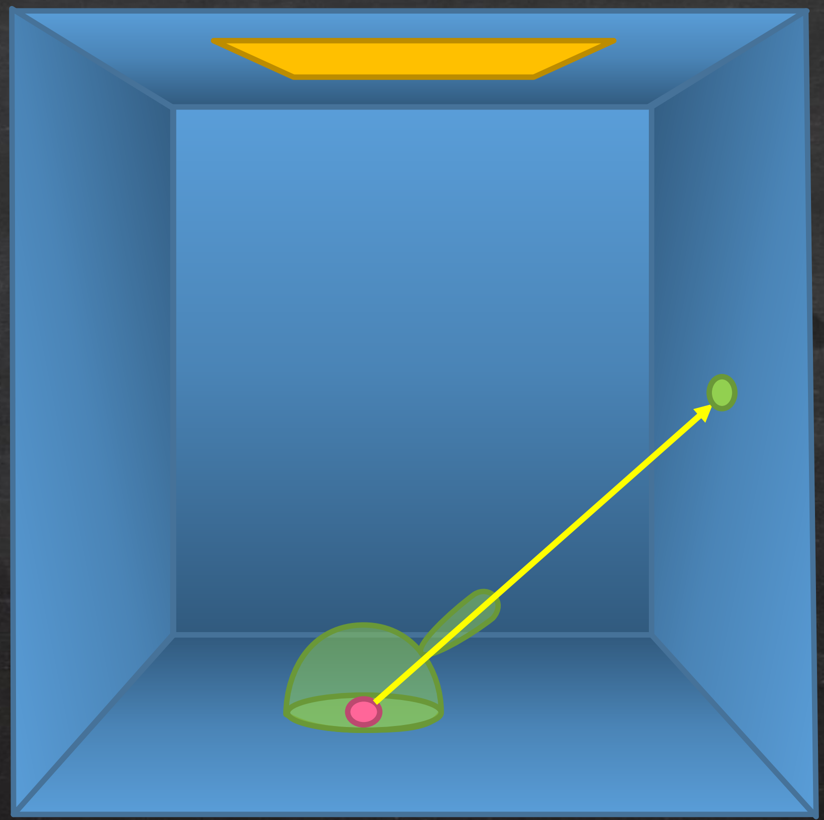
[Premože'10]

Bad choice of density function would increase the variance (to infinity)!!

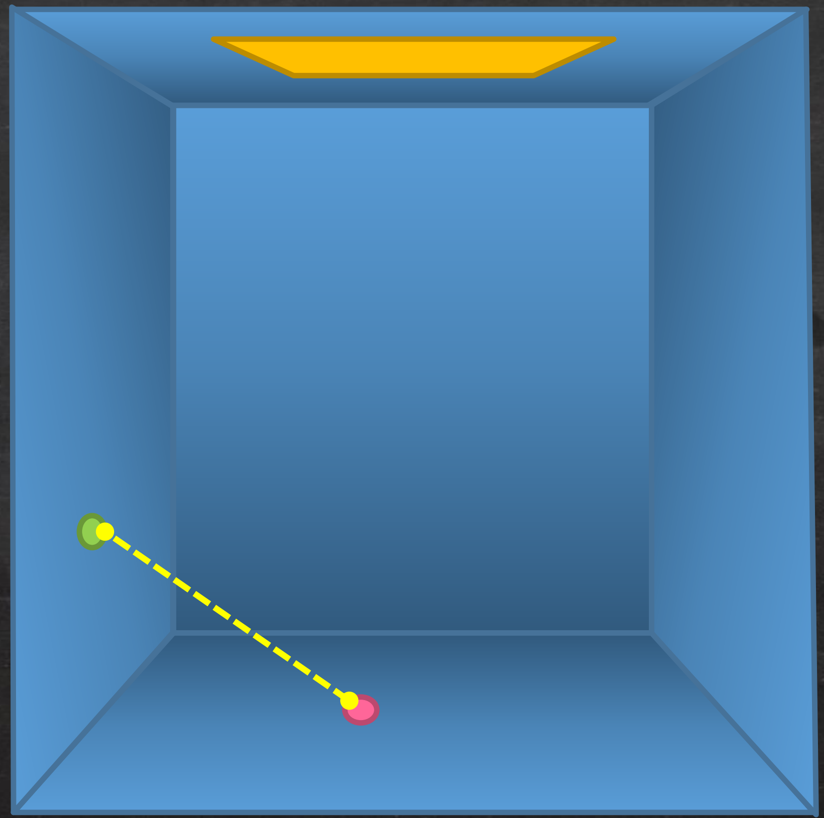
Emission Sampling



BRDF Sampling



High Throughput Connection

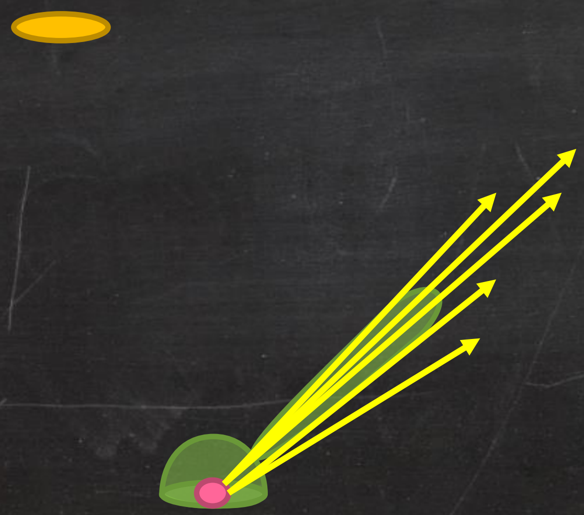


Challenges

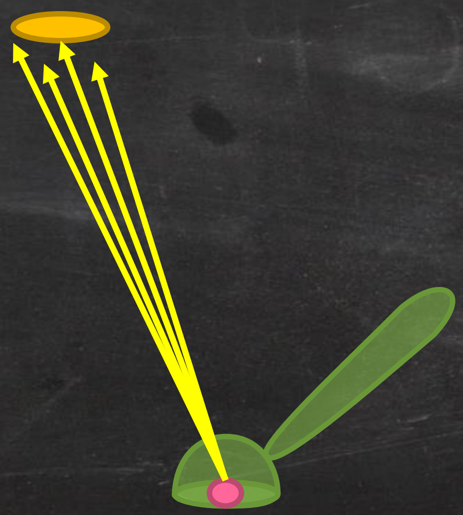
- It's hard to get the PDF of the convolution of
  - Incoming radiance $L(x, \vec{\omega}_i)$ and
  - BRDF $f(\vec{\omega}_i, \vec{\omega}_o)$
- There's an implicit visibility term within $L(x, \vec{\omega}_i)$
  - Visibility term can't be derived before tracing
    - Using machine learning to adapt sampling distribution?
- Dilemma
  - Highly specular BRDFs with point light sources

Highly Specular BRDF & Point Light

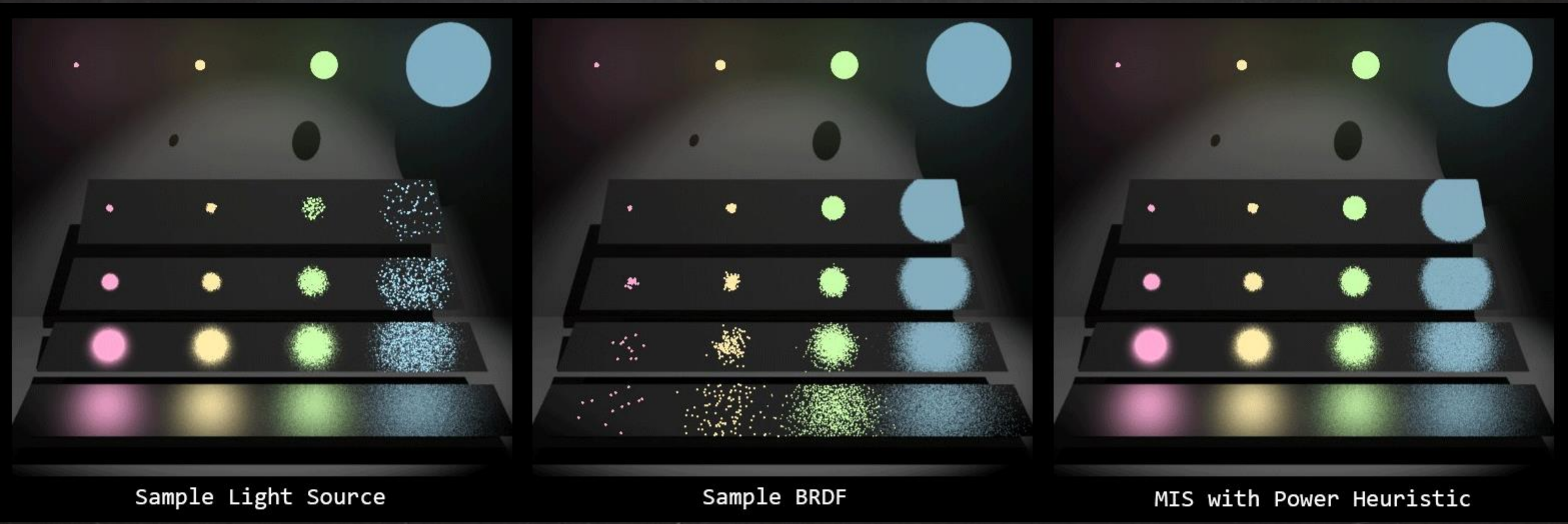
BRDF Sampling



Light Sampling



Multiple Importance Sampling



[Veach'95]

Multiple Importance Sampling (Cont'd)

$$\frac{1}{n_f}\sum_{i=1}^{n_f}\frac{f(X_i)g(X_i)w_f(X_i)}{p_f(X_i)}+\frac{1}{n_g}\sum_{j=1}^{n_g}\frac{f(Y_j)g(Y_j)w_g(Y_j)}{p_g(Y_j)}$$

- n_k is the number of samples taken from the p_k
- the weighting functions w_k take all of the different ways that a sample X_i *or* Y_i could have been generated

$$\mathrm{w_s(x)} = \frac{\mathrm{n_s p_s(x)}}{\sum_i n_i p_i(x)}$$

$$\mathrm{w_s(x)} = \frac{\left(\mathrm{n_s p_s(x)}\right)^{\beta}}{\sum_i \left(n_i p_i(x)\right)^{\beta}}$$

Multiple Importance Sampling (Cont'd)

$$\frac{1}{n_f}\sum^{n_f} \frac{f(X_i)g(X_i)w_f(X_i)}{\ldots} + \frac{1}{\ldots}\sum^{n_g} \frac{f(Y_j)g(Y_j)\ldots(Y_j)}{\ldots}$$

Read More

1. Robust Monte Carlo Methods for Light Transport Simulation, Ch 2 & 9. Veach'97.
2. IS for Production Rendering, SIG'10

... p_k

... functions w_k take all of the different ways that a sample X_i *or* Y_i could have been generated

$$\mathrm{w_s(x)} = \frac{\mathrm{n_s p_s(x)}}{\sum_i n_i p_i(x)} \qquad \mathrm{w_s(x)} = \frac{\left(\mathrm{n_s p_s(x)}\right)^\beta}{\sum_i \left(n_i p_i(x)\right)^\beta}$$