

Progressive Photon Mapping Extensions

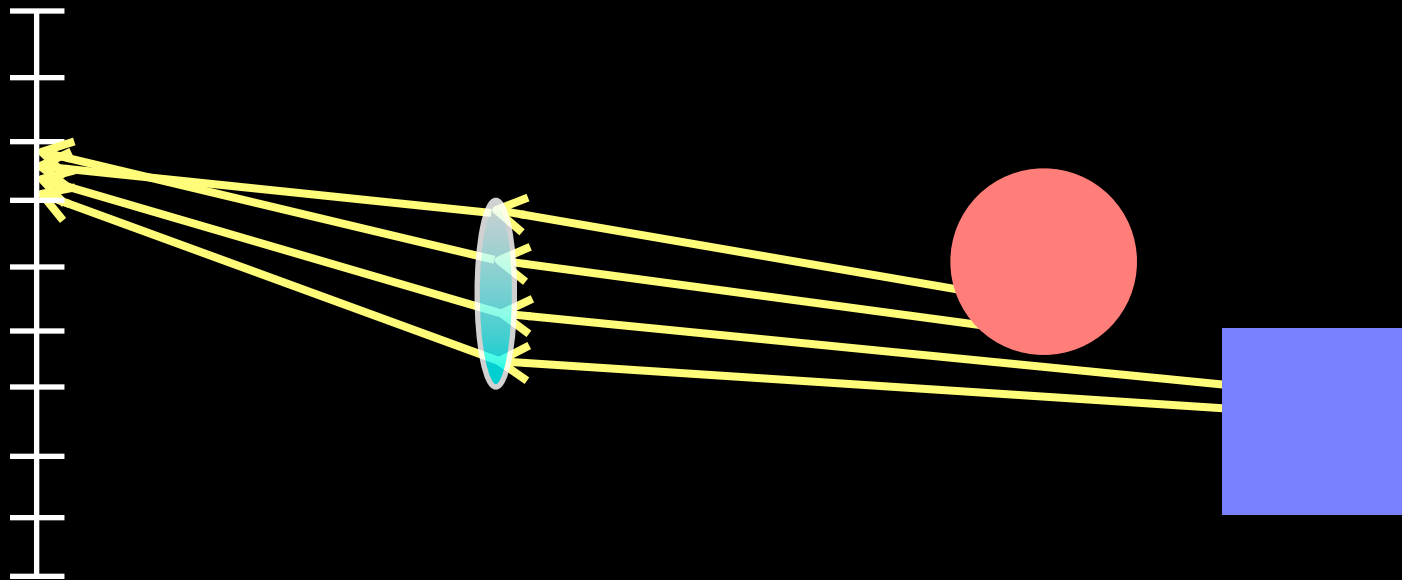
Toshiya Hachisuka
Aarhus University

State of the Art in Photon Density Estimation

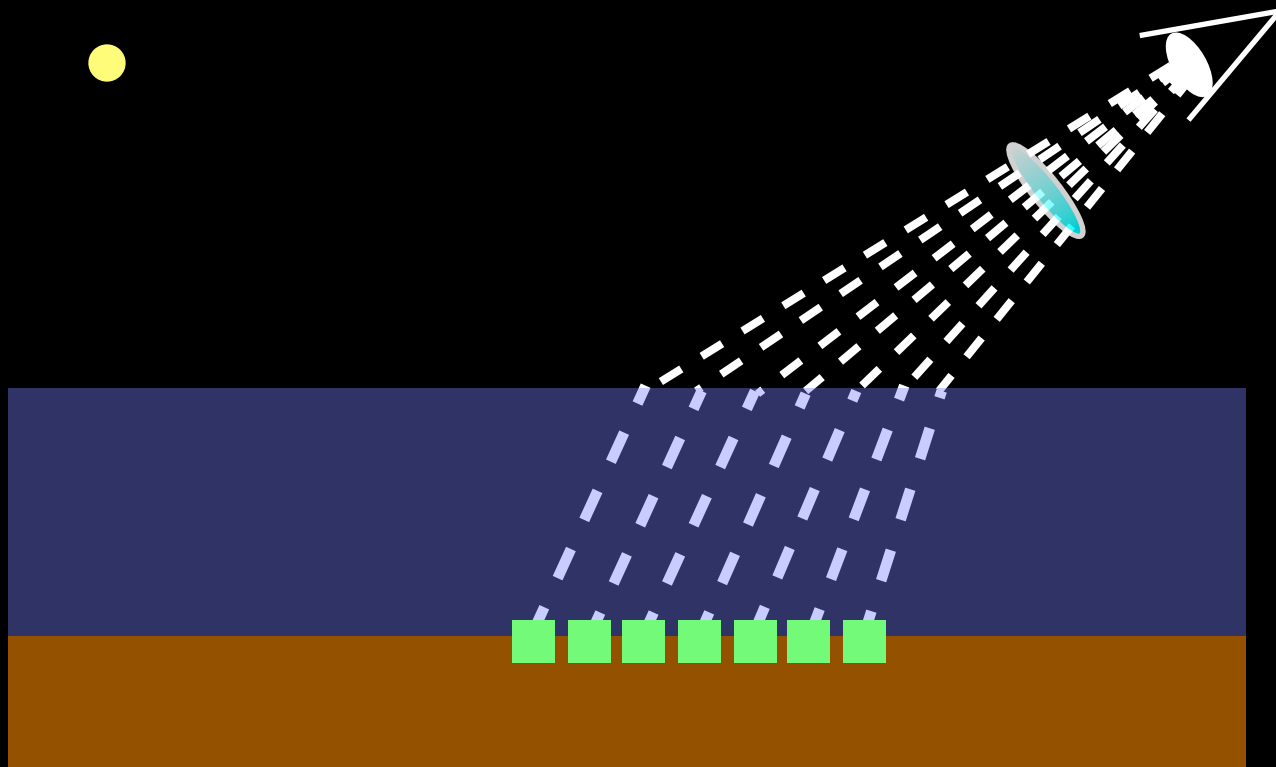




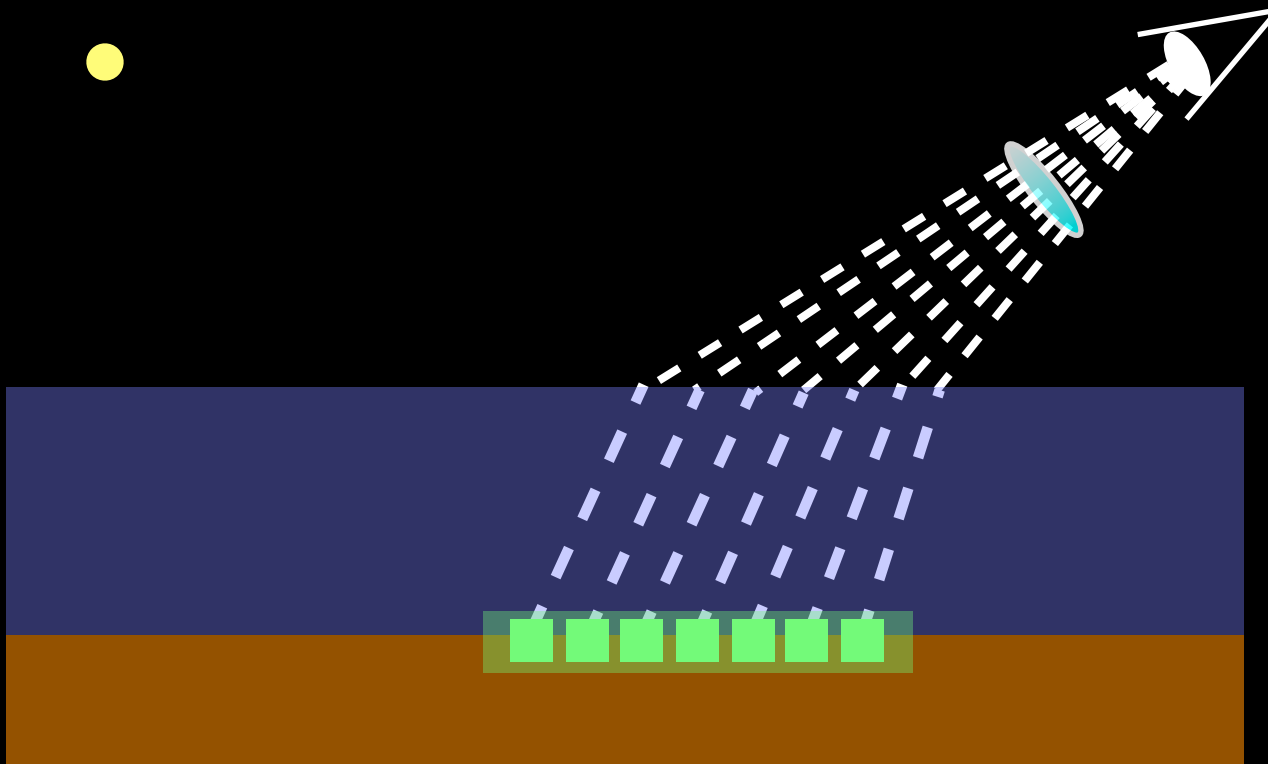
- Computes average illumination [Cook et al. 84]



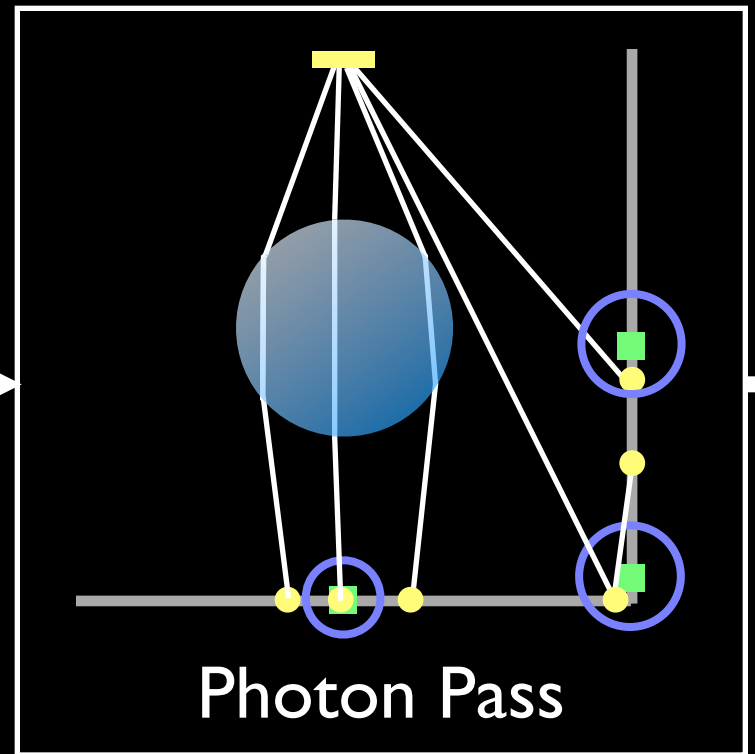
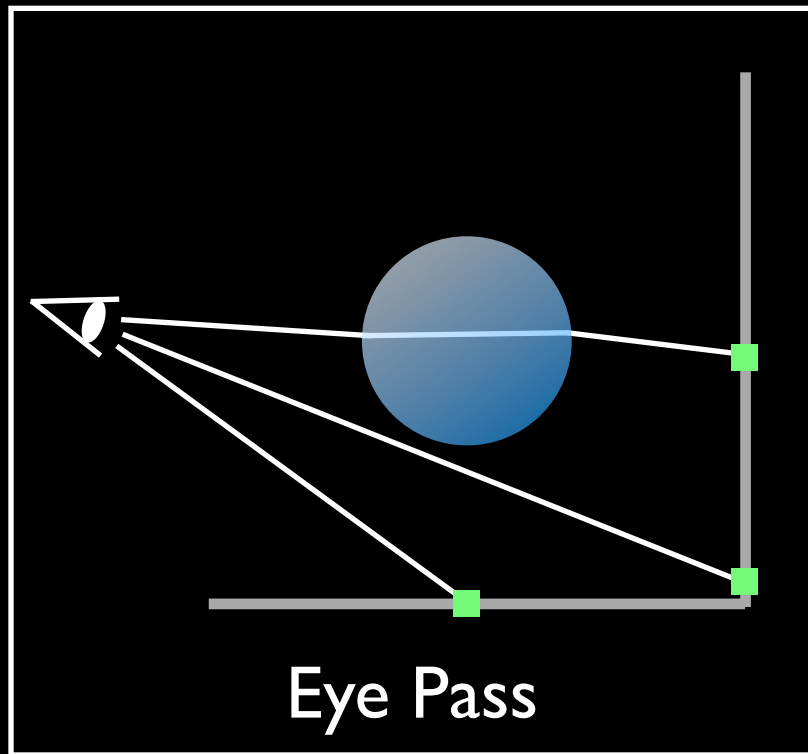
Lens Simulation with PPM



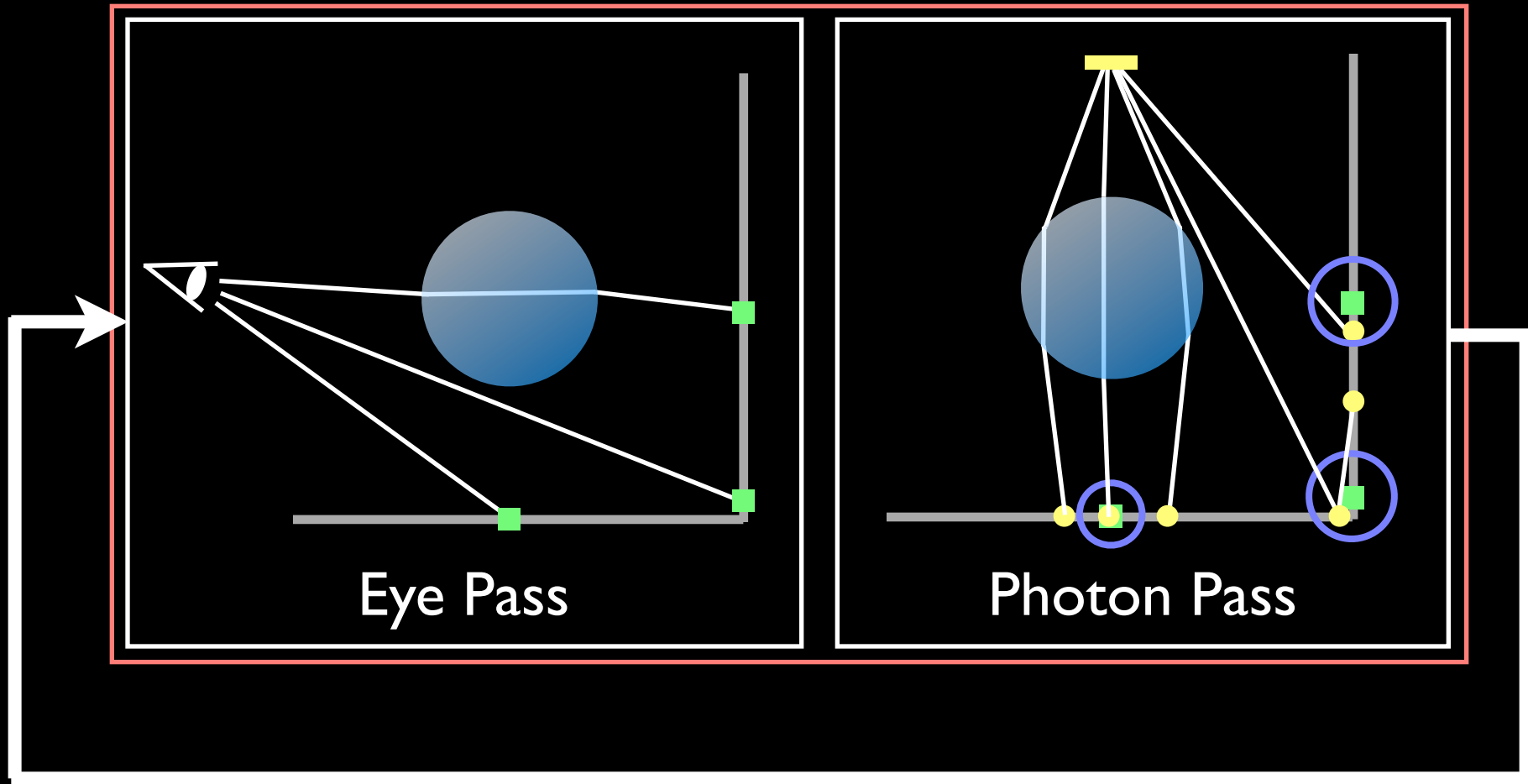
Lens Simulation with PPM



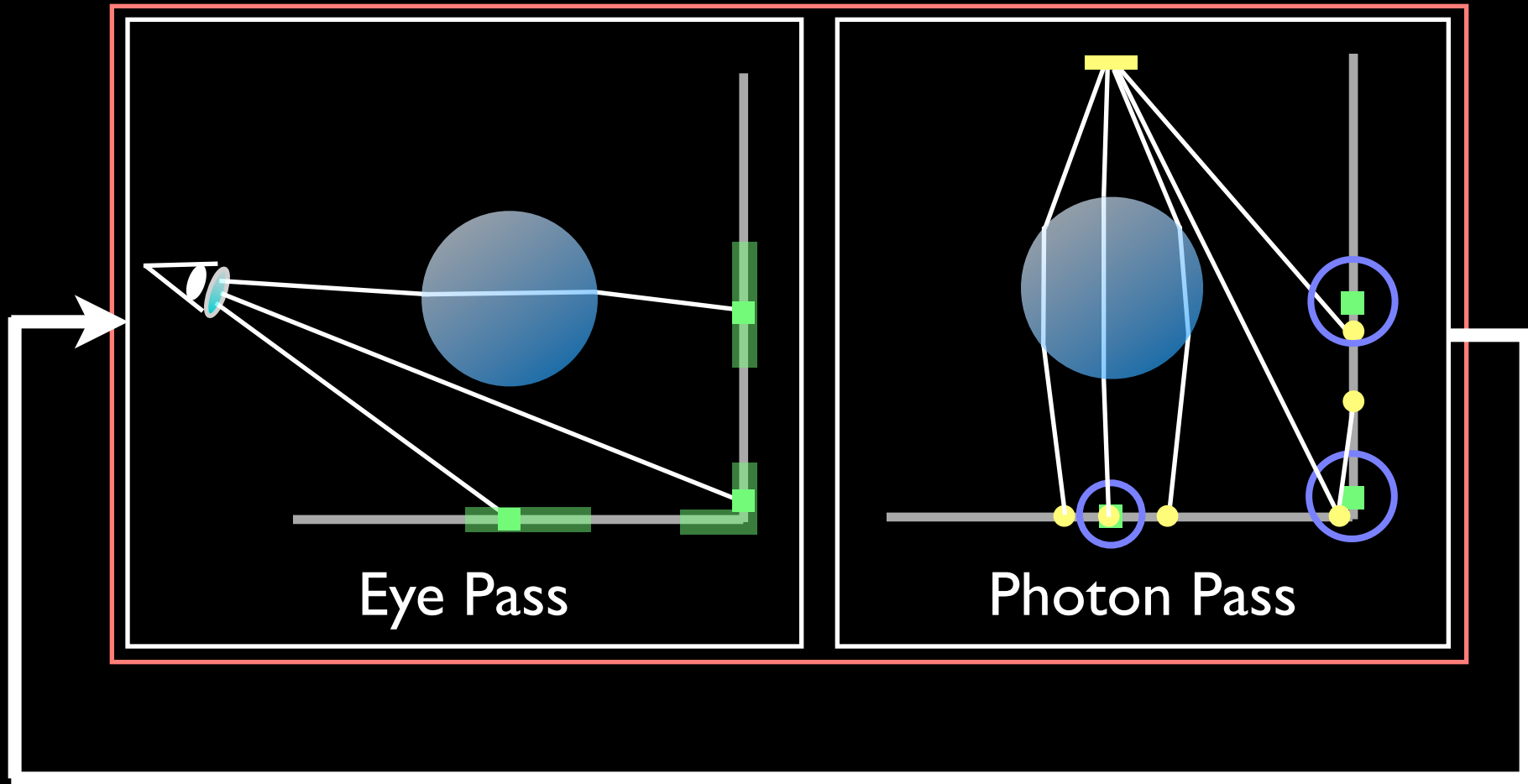
Infinite number of measurement points



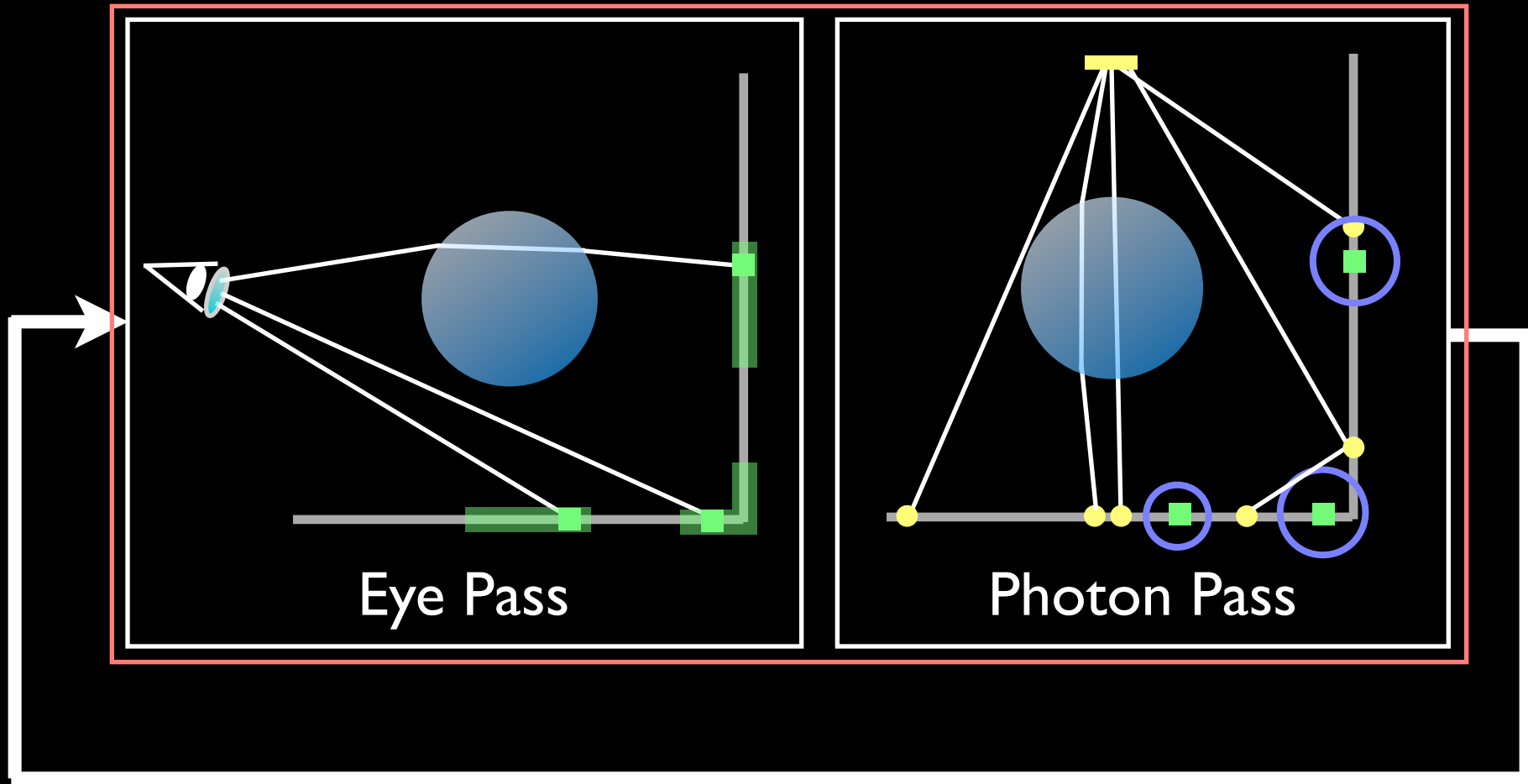
Stochastic PPM



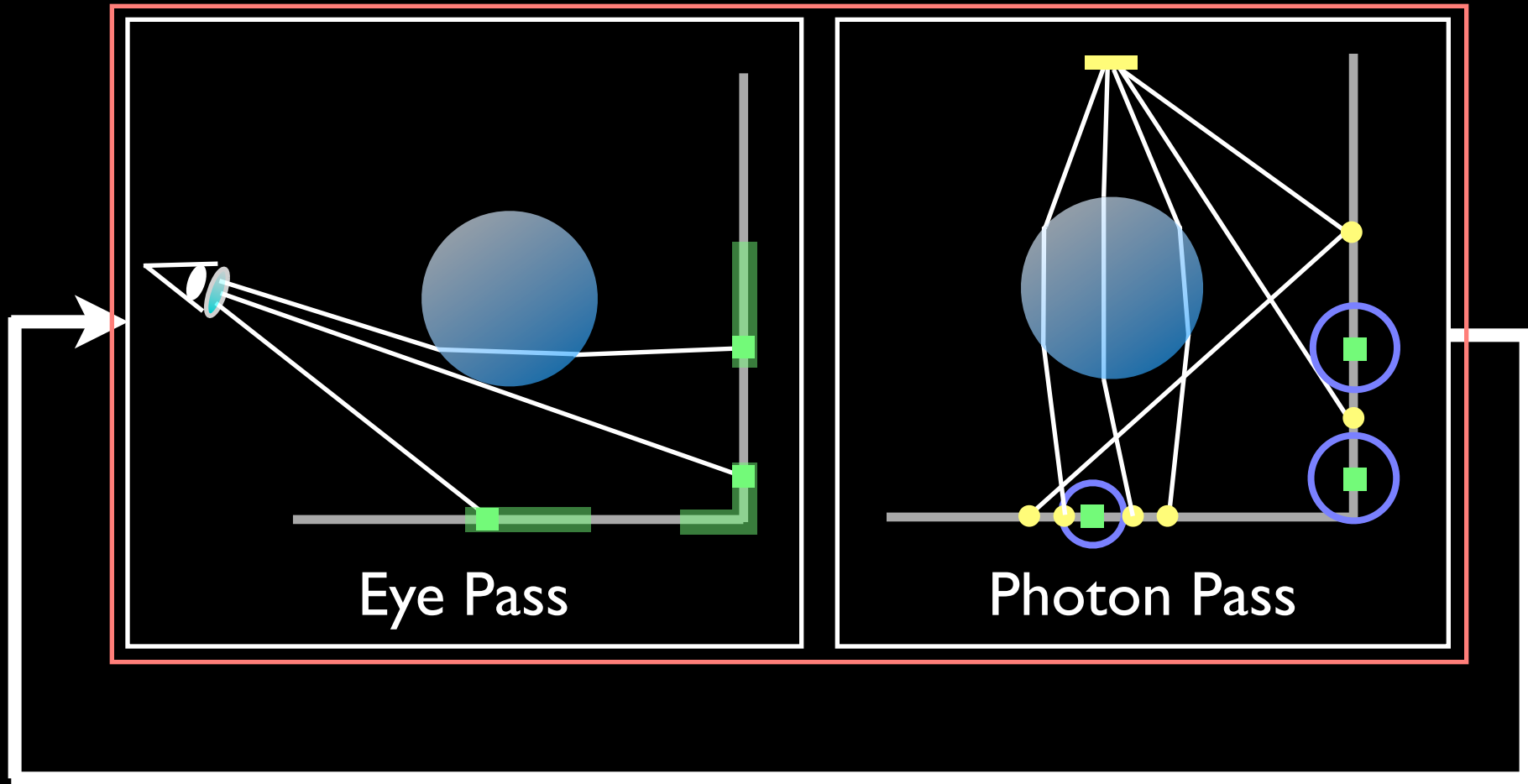
Stochastic PPM



Stochastic PPM



Stochastic PPM



$$L_i(S, \vec{\omega}) = \frac{\tau_i(S, \vec{\omega})}{\pi R_i(S)^2 N_e(i)}$$

$$\lim_{i \rightarrow \infty} L_i(S, \vec{\omega}) = L(S, \vec{\omega})$$

Provable convergence to
average photon density over a region S

Bidirectional Path Tracing



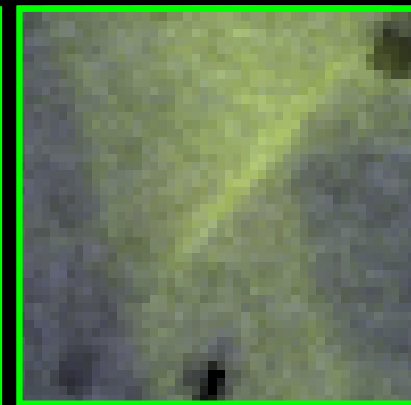
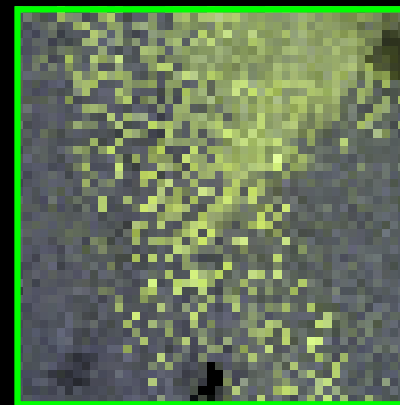
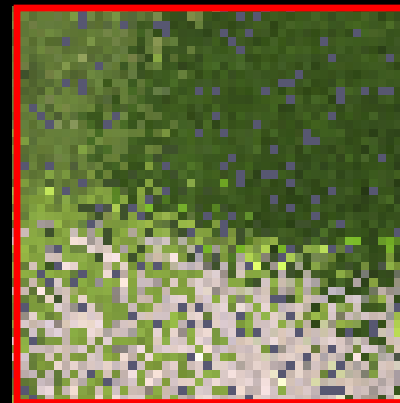
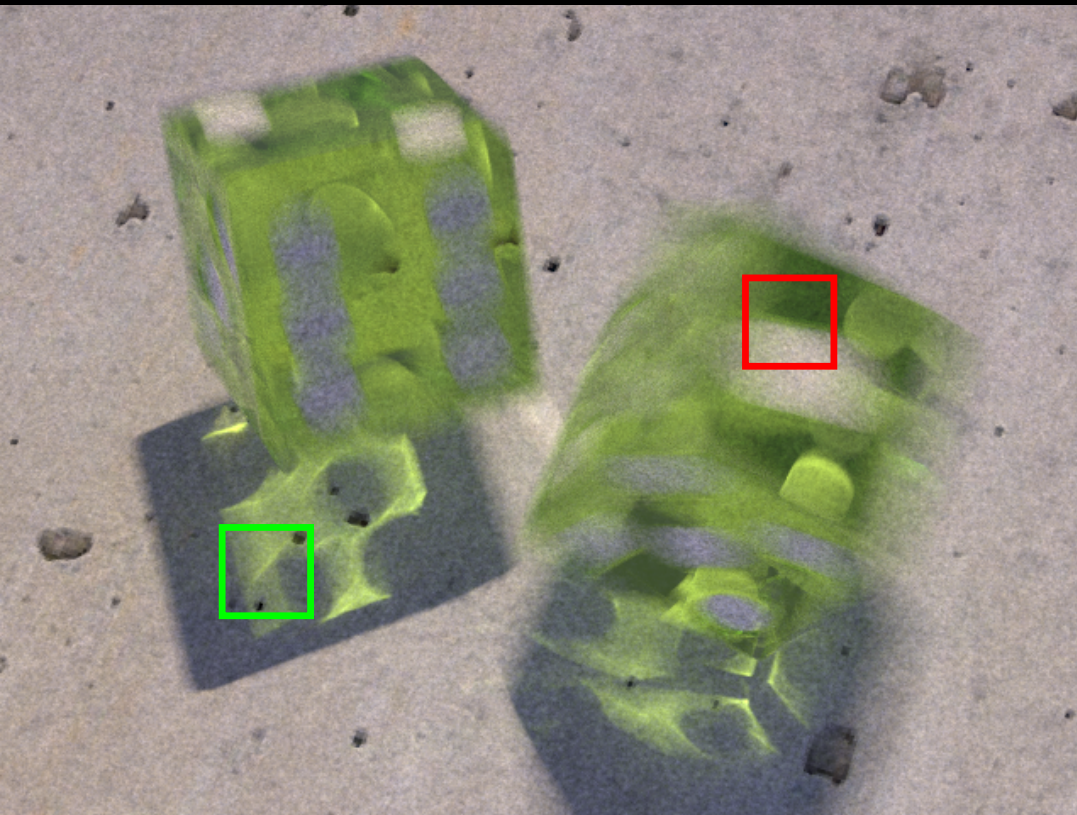
Original PPM



Stochastic PPM



Motion Blur

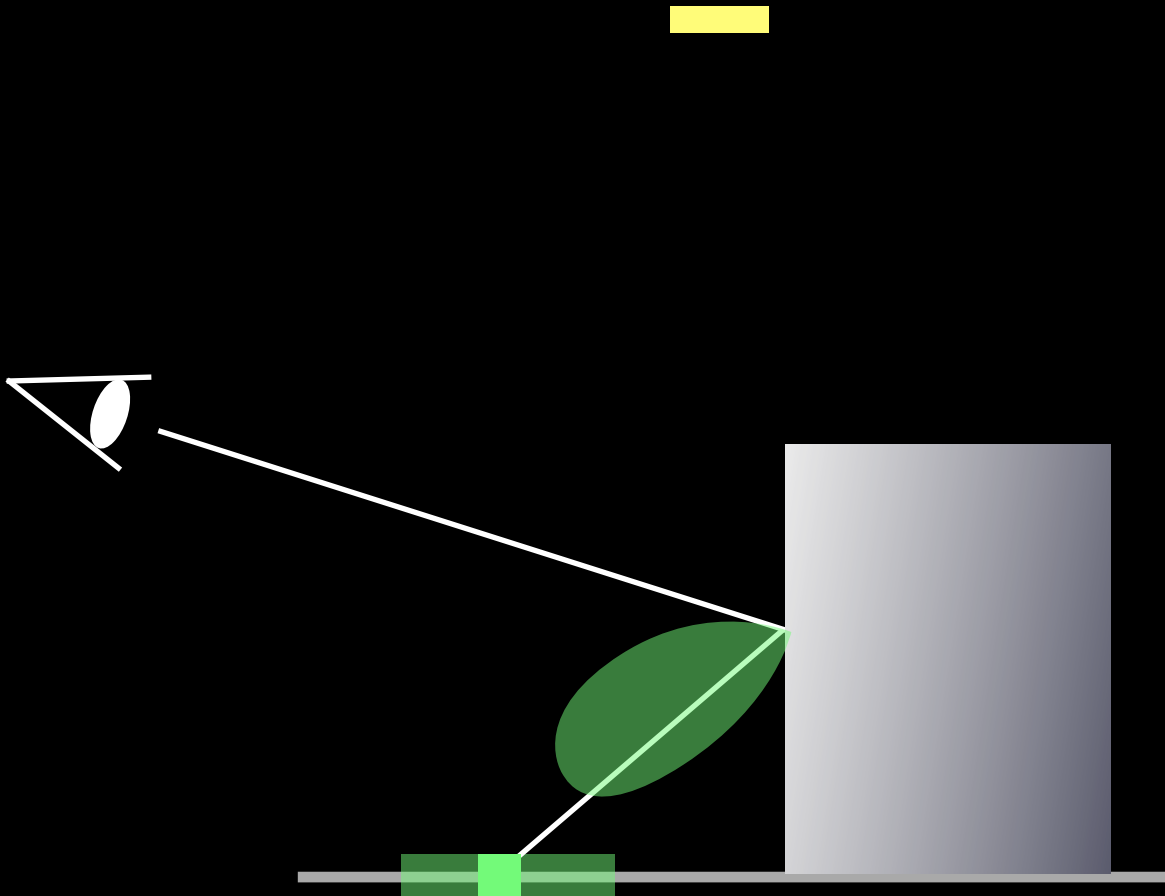


Equal time, Equal memory

PPM

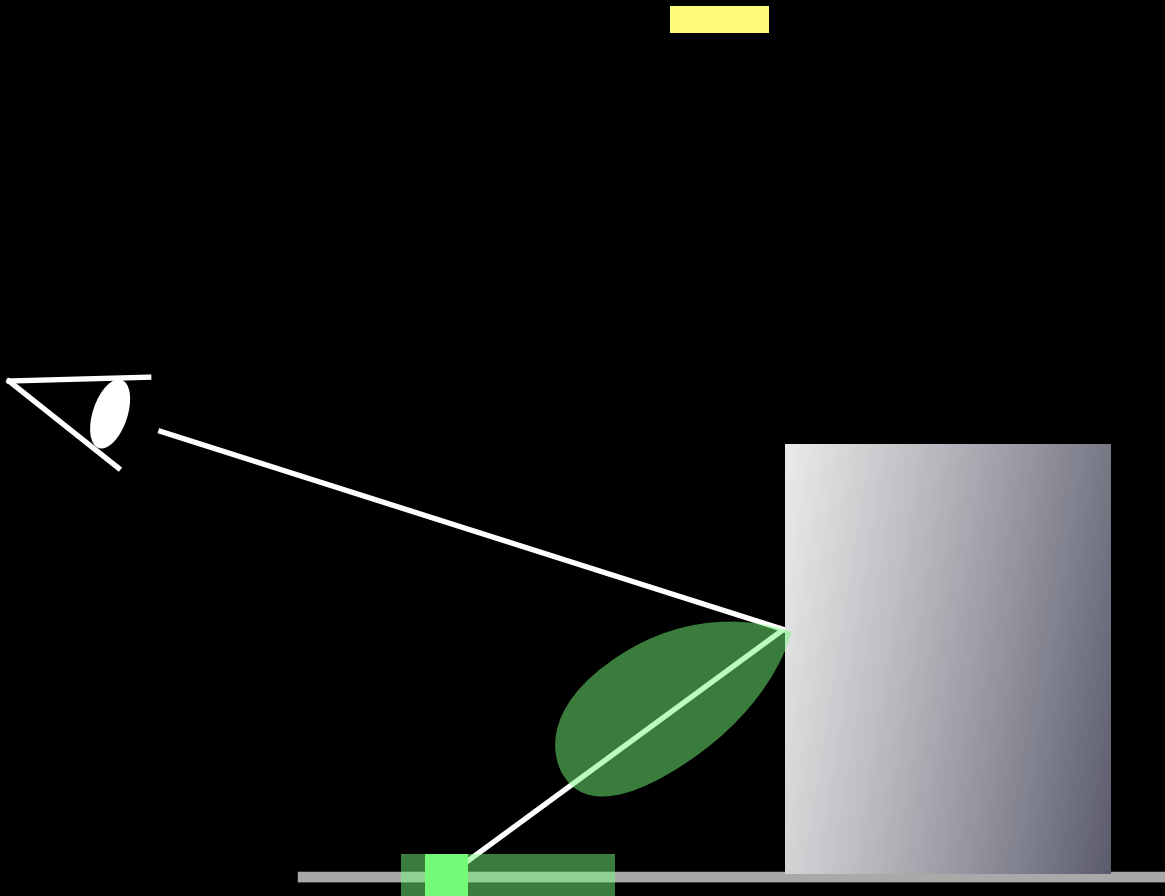
SPPM

Glossy Materials with SPPM



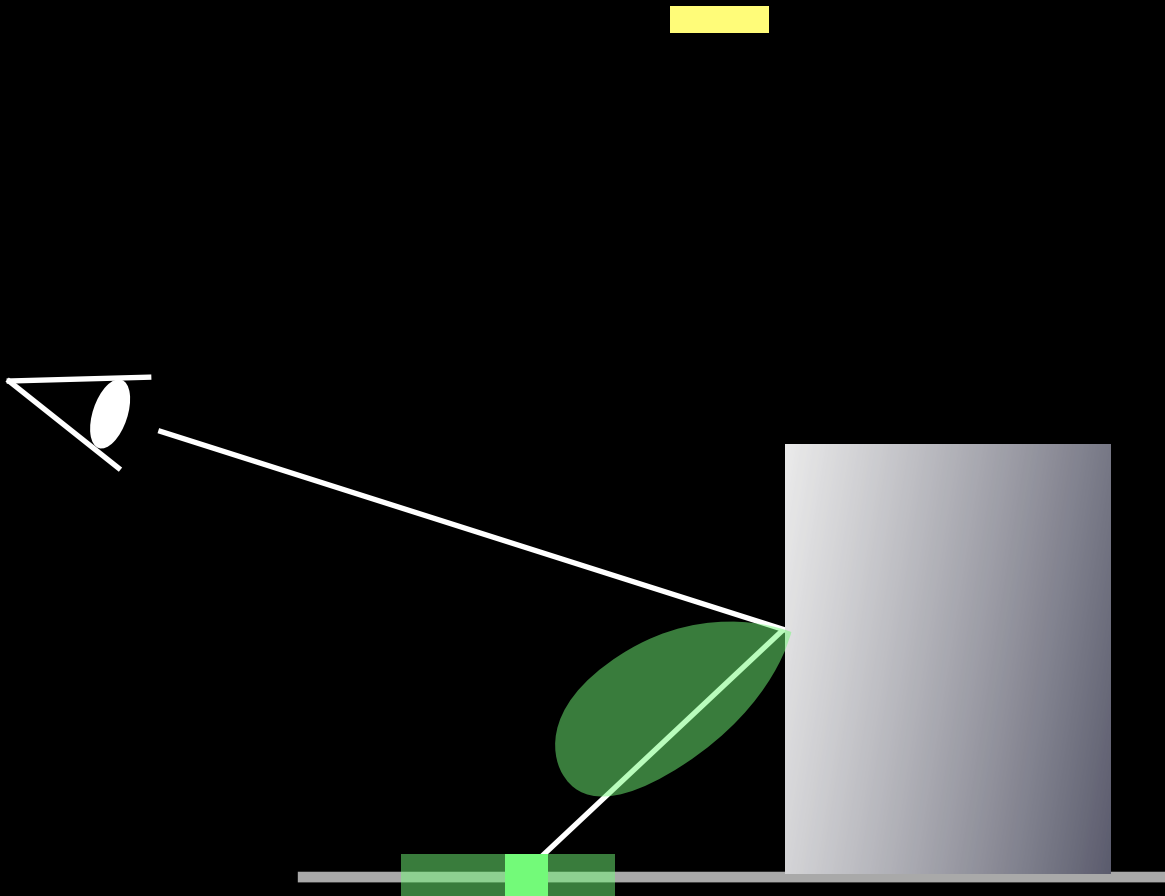
Trace one bounce rays

Glossy Materials with SPPM



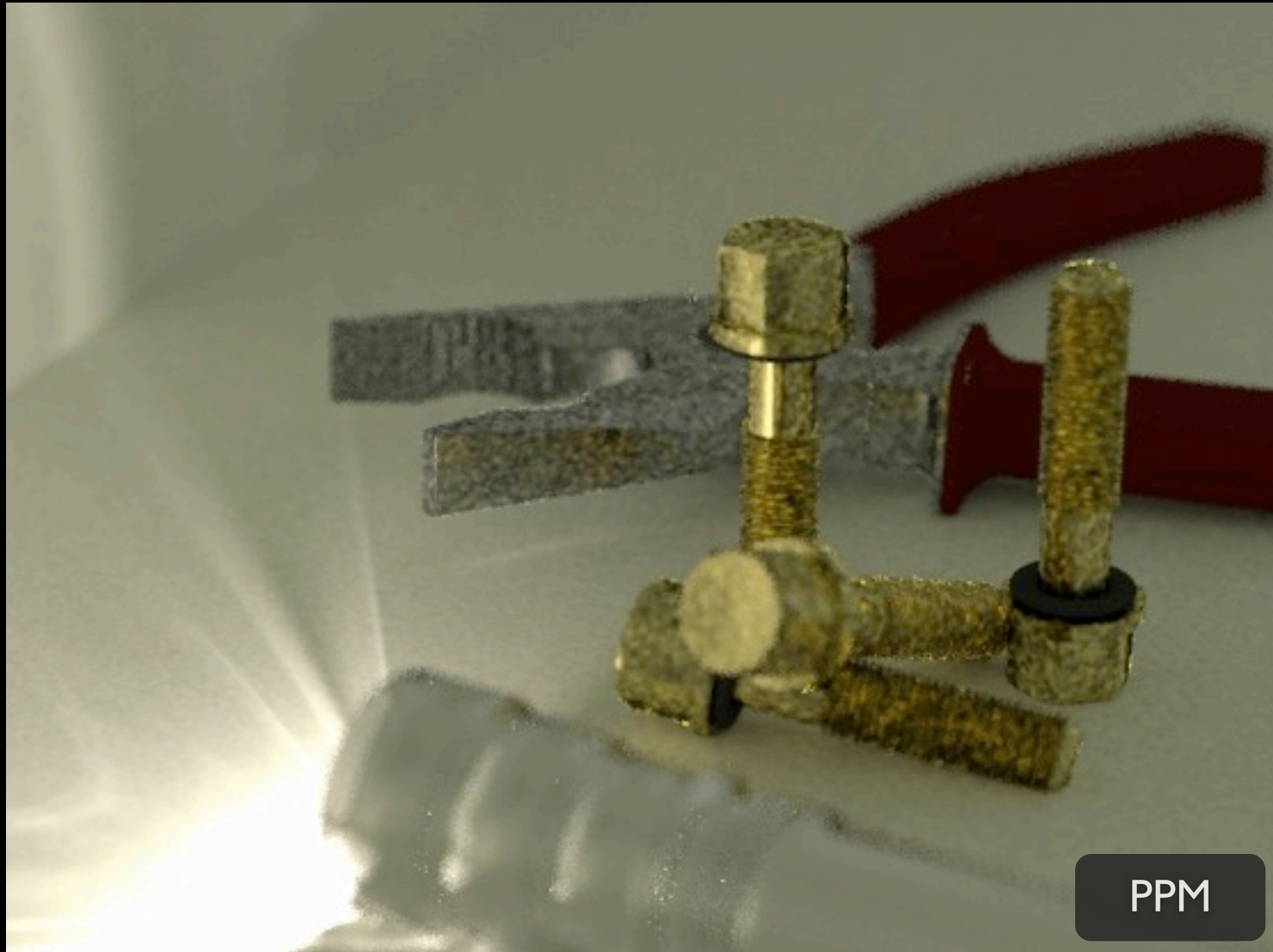
Trace one bounce rays

Glossy Materials with SPPM

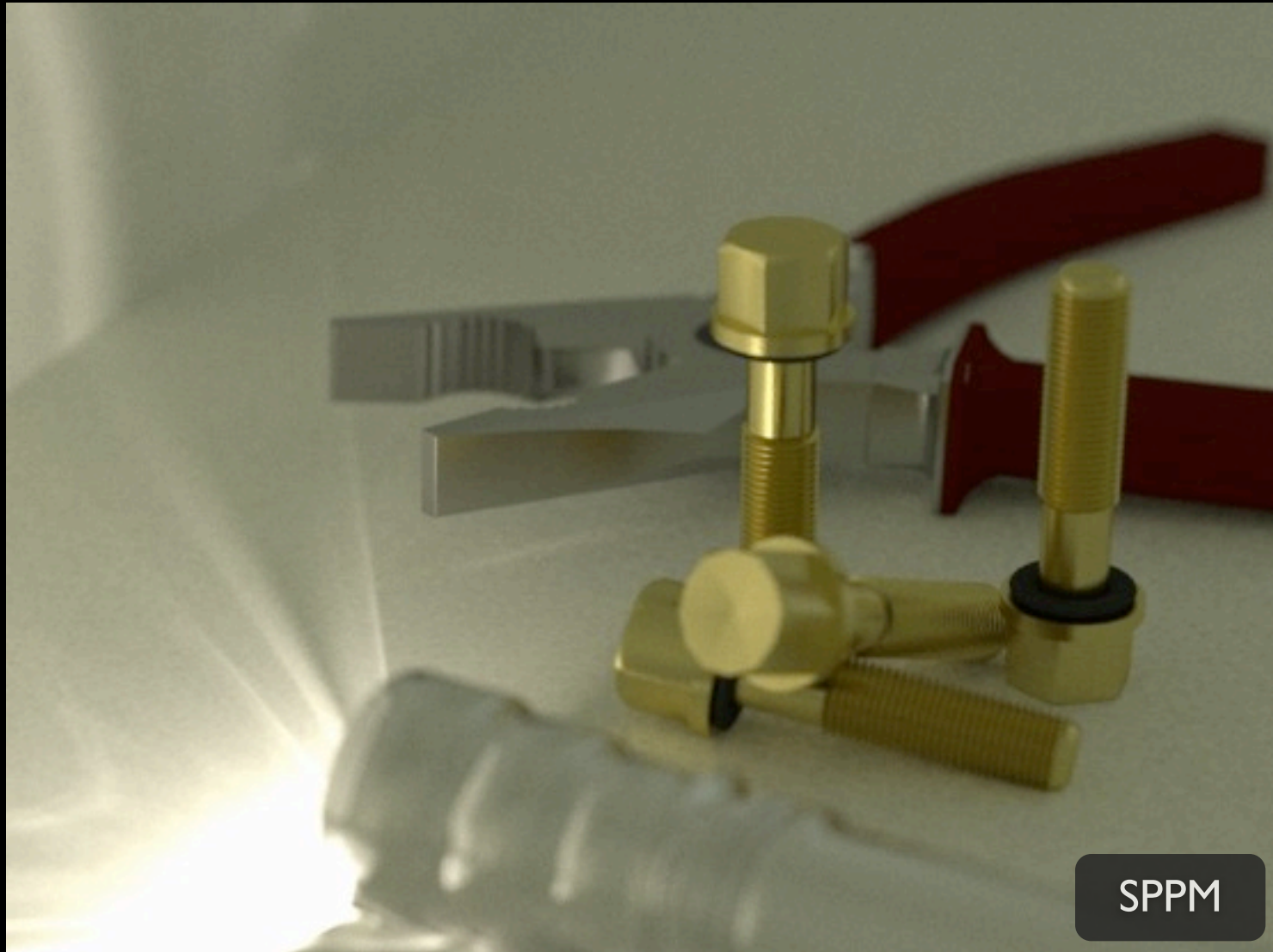


Trace one bounce rays

DOF + Glossy Reflection + Caustics

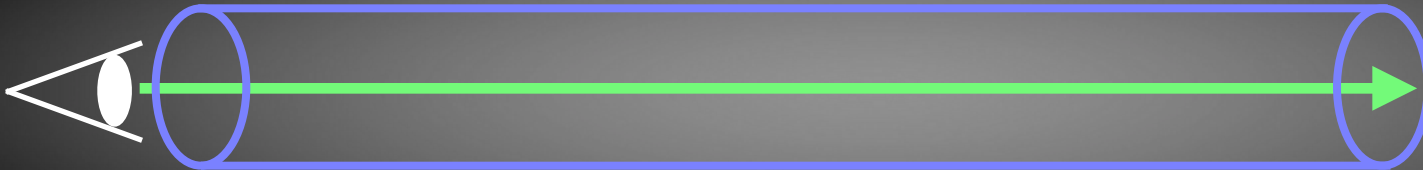


DOF + Glossy Reflection + Caustics



SPPM

- ▶ Two basic approaches
 - ▶ Progressive beam radiance estimate (PPM)
 - ▶ Stochastically sample a point along eye ray (SPPM)



PPM style: cylinder progressive estimate

- ▶ Two basic approaches
 - ▶ Progressive beam radiance estimate (PPM)
 - ▶ Stochastically sample a point along eye ray (SPPM)



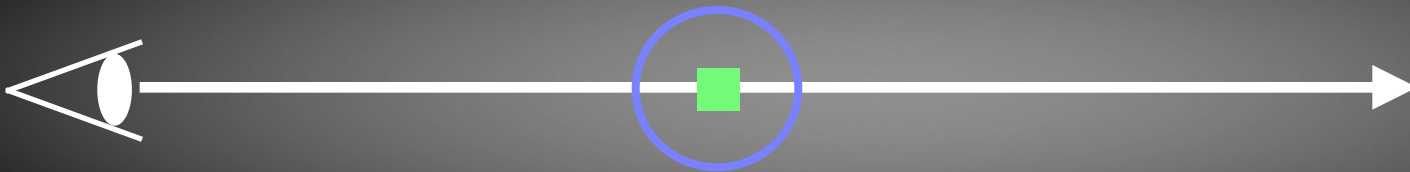
SPPM style: stochastic sampling along a ray

- ▶ Two basic approaches
 - ▶ Progressive beam radiance estimate (PPM)
 - ▶ Stochastically sample a point along eye ray (SPPM)



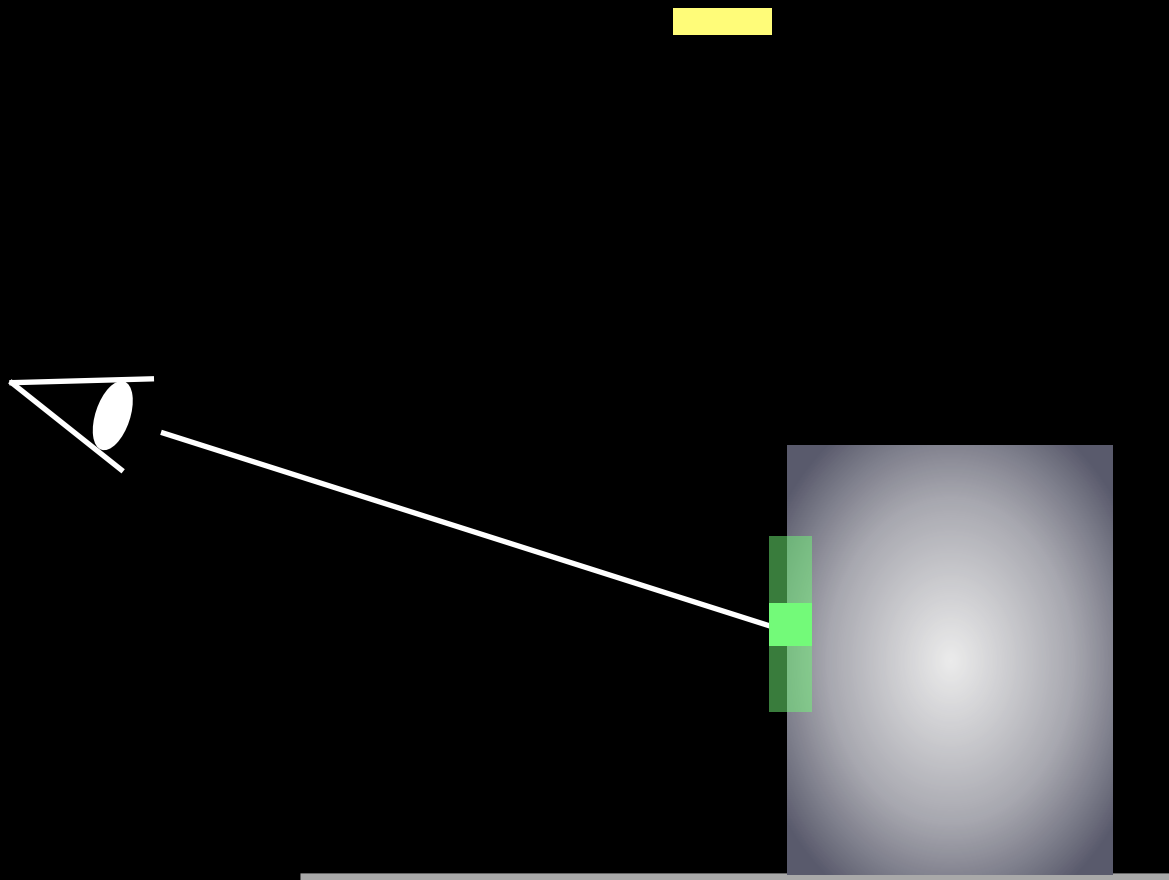
SPPM style: stochastic sampling along a ray

- ▶ Two basic approaches
 - ▶ Progressive beam radiance estimate (PPM)
 - ▶ Stochastically sample a point along eye ray (SPPM)

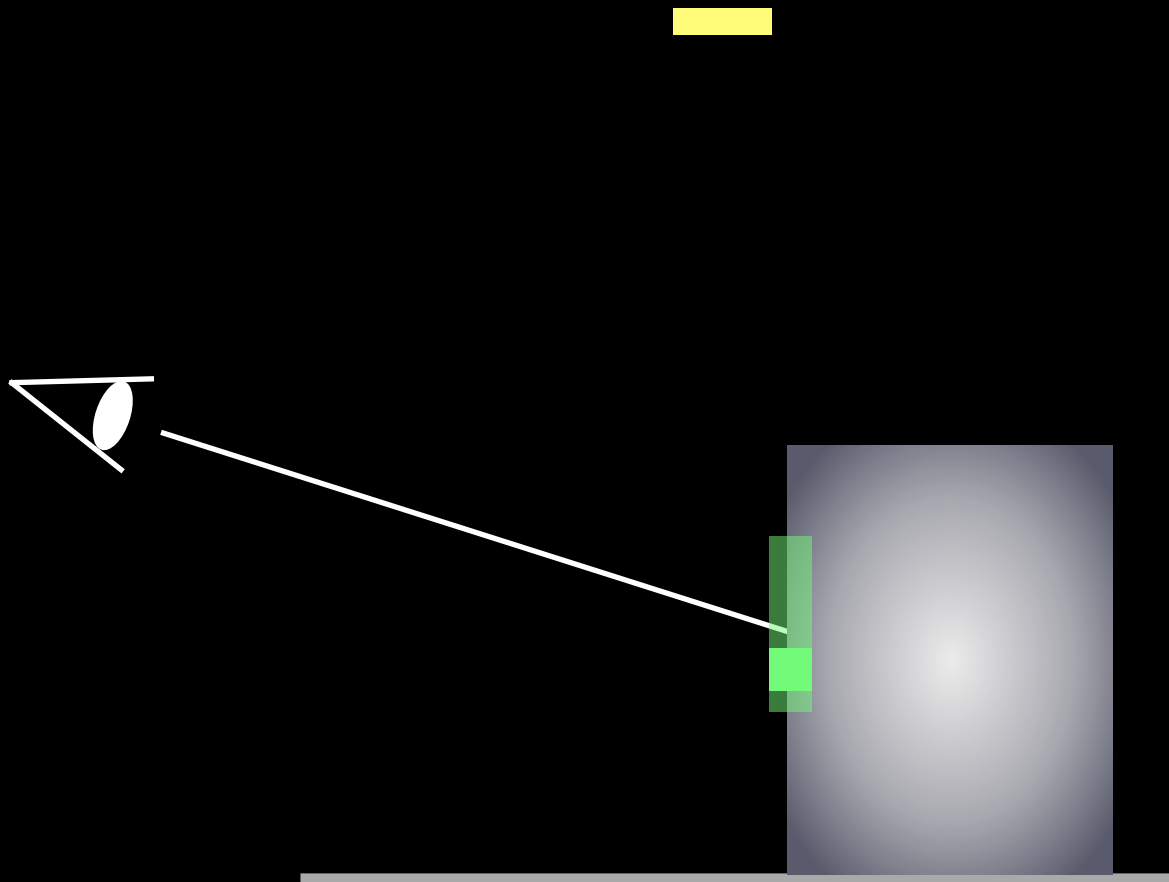


SPPM style: stochastic sampling along a ray

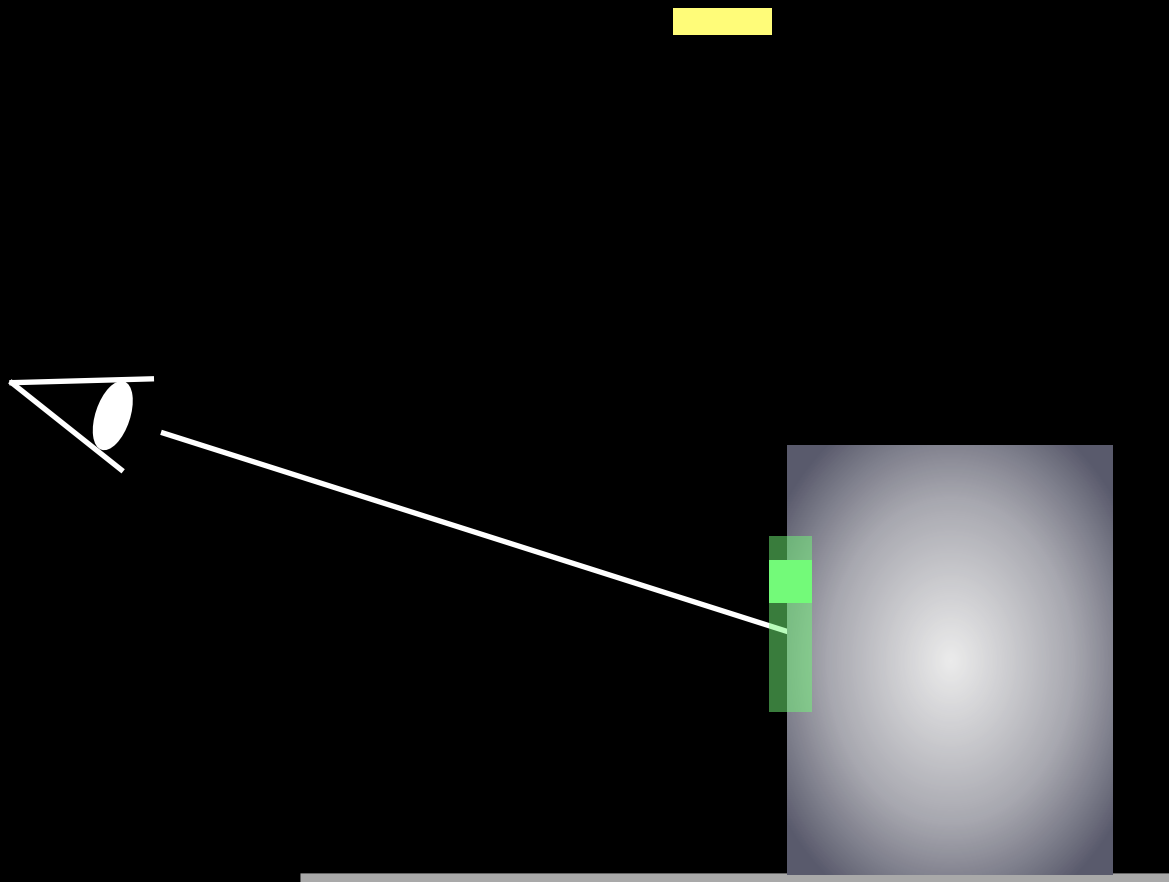
- ▶ Stochastically sample a disc around the original location
 - ▶ e.g., BSSRDF Importance Sampling [King et al. 2013]



- ▶ Stochastically sample a disc around the original location
 - ▶ e.g., BSSRDF Importance Sampling [King et al. 2013]



- ▶ Stochastically sample a disc around the original location
 - ▶ e.g., BSSRDF Importance Sampling [King et al. 2013]

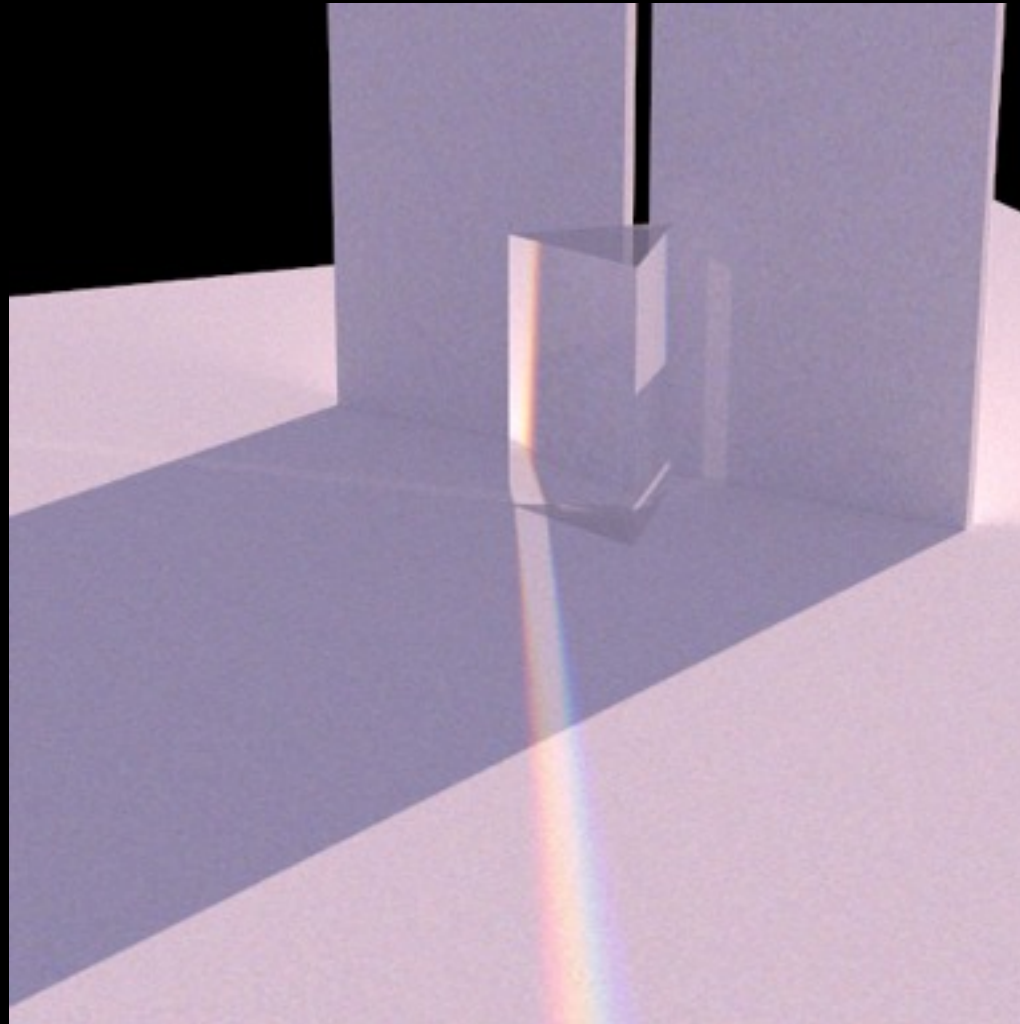


- ▶ Stochastically sample a disc around the original location
 - ▶ e.g., BSSRDF Importance Sampling [King et al. 2013]

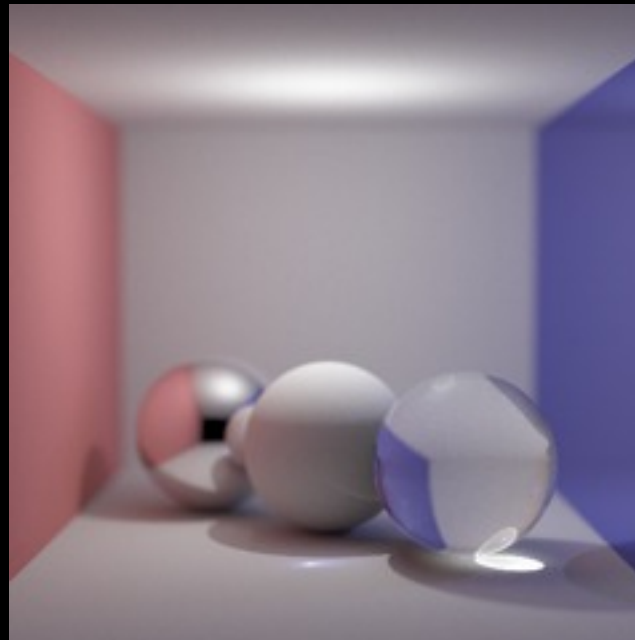


Full Spectrum Rendering

- Pick one random wavelength per iteration



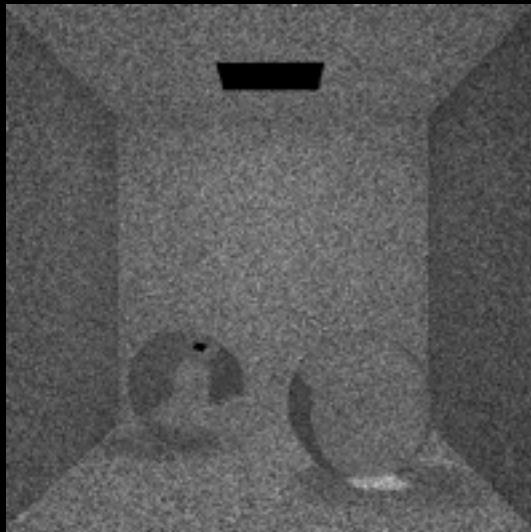
- ▶ SPPM implementation using GLSL
 - ▶ Based on smallppm
 - ▶ DOF, motion blur, glossy reflection, full spectrum
 - ▶ Stochastic hashing for accel. data structure
- “Parallel Progressive Photon Mapping on GPUs”, 2010



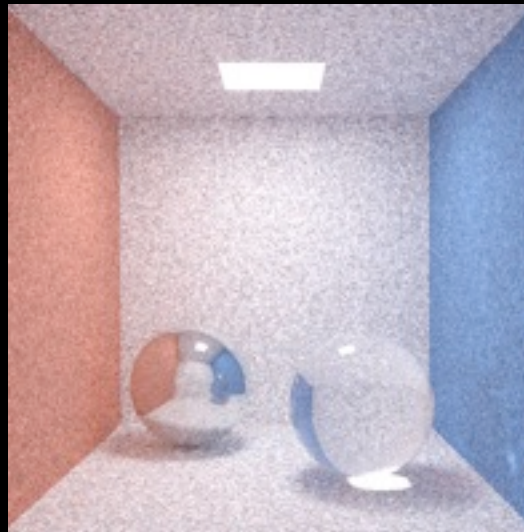
How much computation is enough?

- Difference between computed and exact

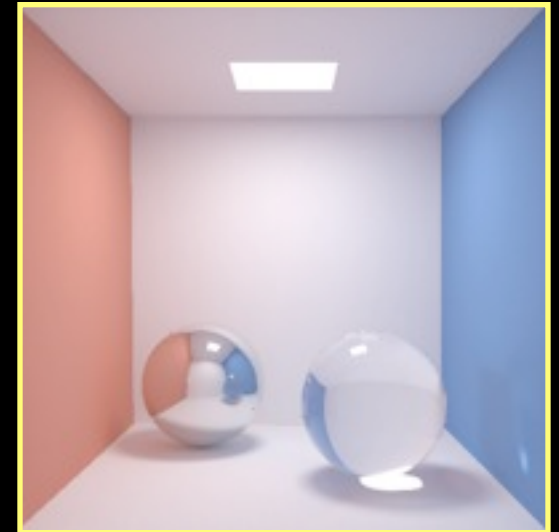
$$E_i = L_i - \boxed{L} \text{ Unknown}$$



=

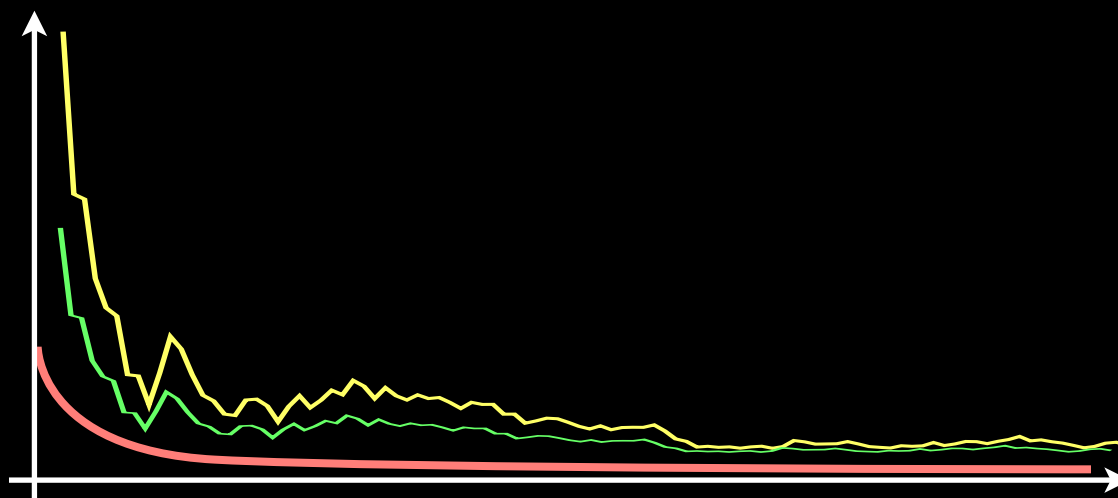


-



► Bias-Noise decomposition

$$E_i = L_i - L = B_i + N_i$$



$$E_i = L_i - L = B_i + N_i$$

Stochastic error bound

User-defined
Probability

$$P(|E_i| \leq E_{b,i}) \leq 1 - \beta$$

$$E_{b,i} = C_{i,1-\frac{\beta}{2}} \sqrt{\frac{\text{Variance}}{i}} + |B_i|$$

$$E_i = L_i - L = B_i + N_i$$

$$P(|E_i| \leq E_{b,i}) \leq 1 - \beta$$

$$E_{b,i} = \boxed{C_{i,1-\frac{\beta}{2}} \sqrt{\frac{\text{Variance}}{i}}} + |B_i|$$

Error due to Noise

$$E_i = L_i - L = B_i + N_i$$

$$P(|E_i| \leq E_{b,i}) \leq 1 - \beta$$

$$E_{b,i} = C_{i,1-\frac{\beta}{2}} \sqrt{\frac{\text{Variance}}{i}} + \boxed{|B_i|}$$

Error due to Bias

- ▶ Bias can be approximated by Laplacian
- ▶ Progressive estimation of Laplacian (and any derivatives)

$$B_i \approx k_2 R_i^2 \Delta L$$

k_2 constant

R_i search radius

ΔL Laplacian of radiance

Kernel

$$L_i(x) = \frac{\sum \boxed{K(x_p - x)} f_r(x, \omega, \omega_p) \Phi(x_p, x)}{\pi R_i^2}$$

- ▶ Bias can be approximated by Laplacian
- ▶ Progressive estimation of Laplacian (and any derivatives)

$$B_i \approx k_2 R_i^2 \Delta L$$

k_2 constant

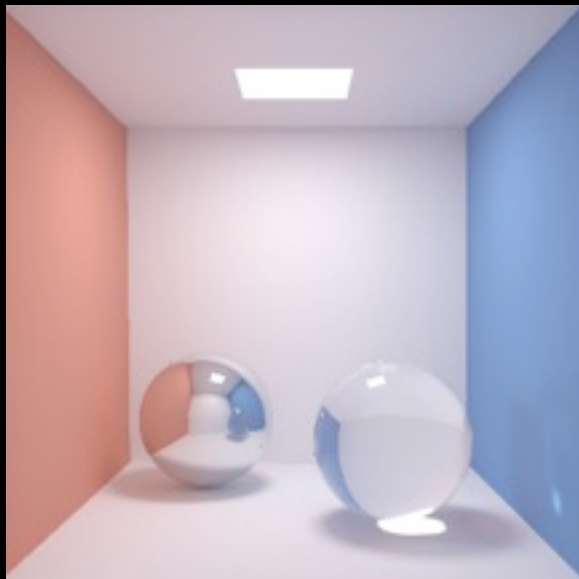
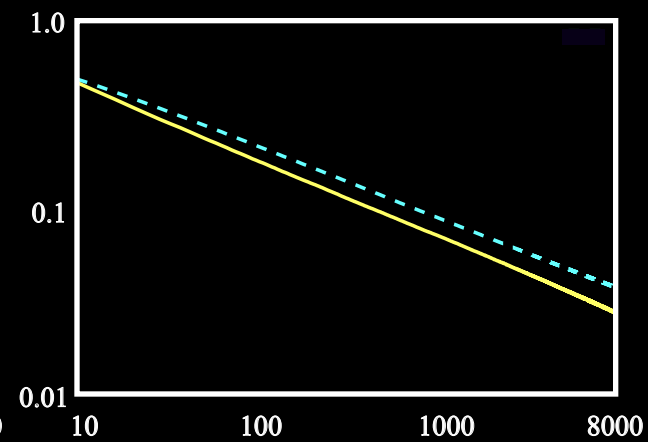
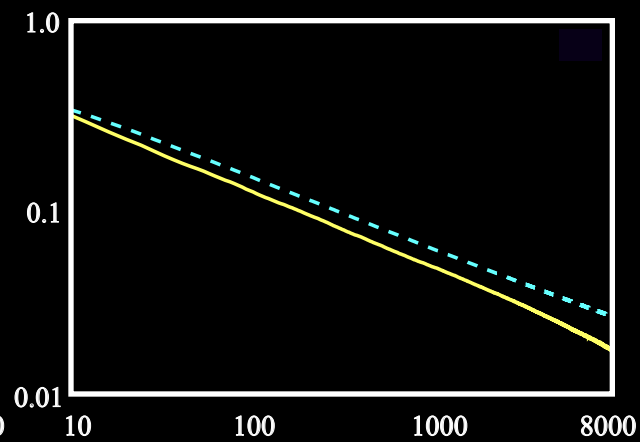
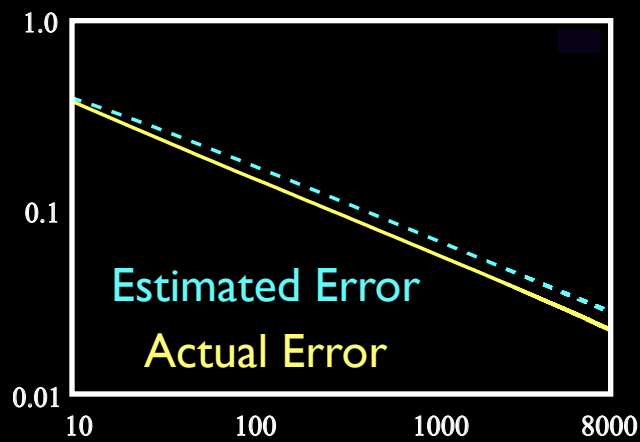
R_i search radius

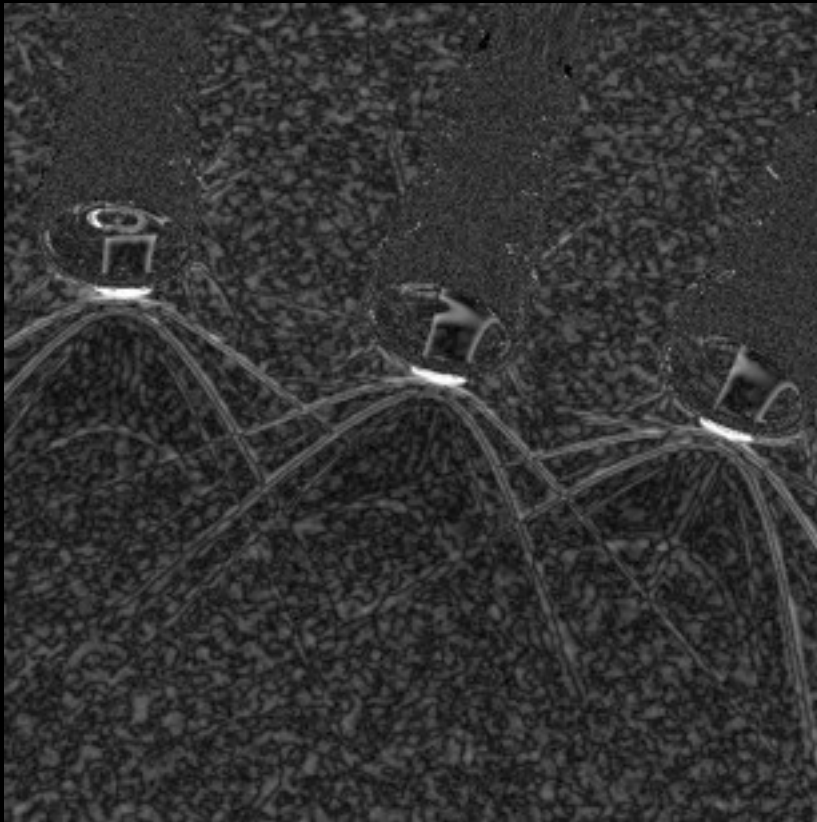
ΔL Laplacian of radiance

Laplacian of the kernel

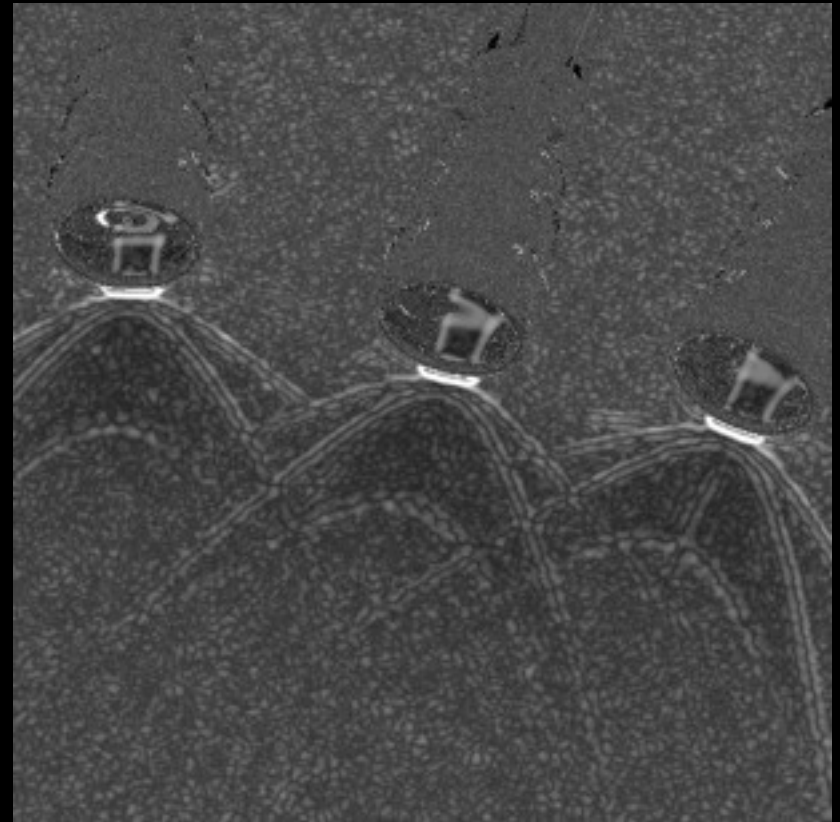
$$\Delta L_i(x) = \frac{\sum \boxed{\Delta K(x_p - x)} f_r(x, \omega, \omega_p) \Phi(x_p, x)}{\pi R_i^2}$$

Error Estimation



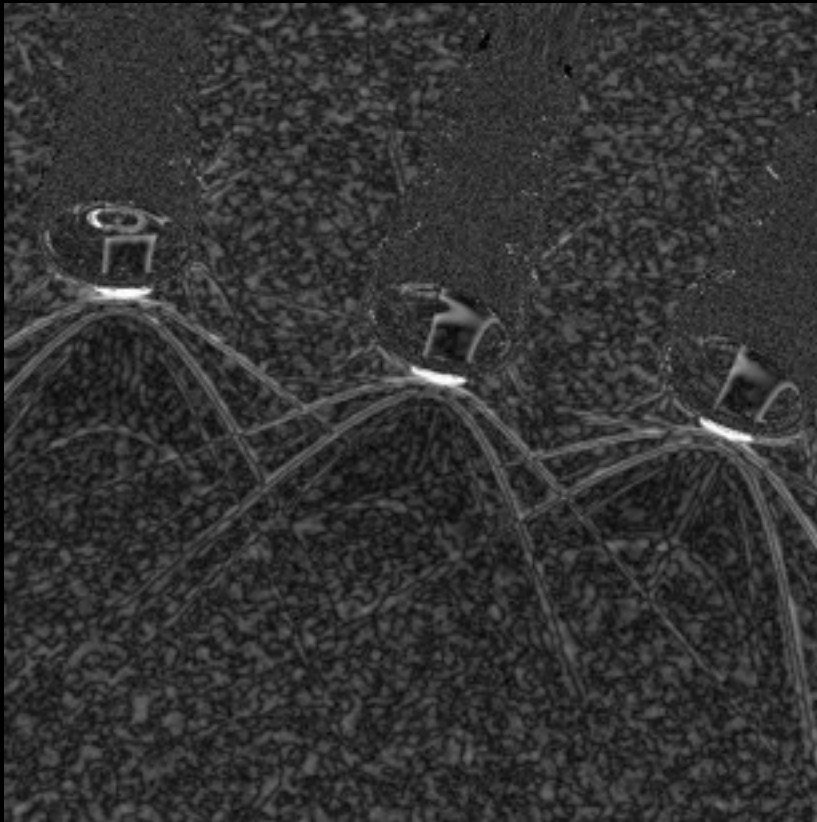


Actual Error

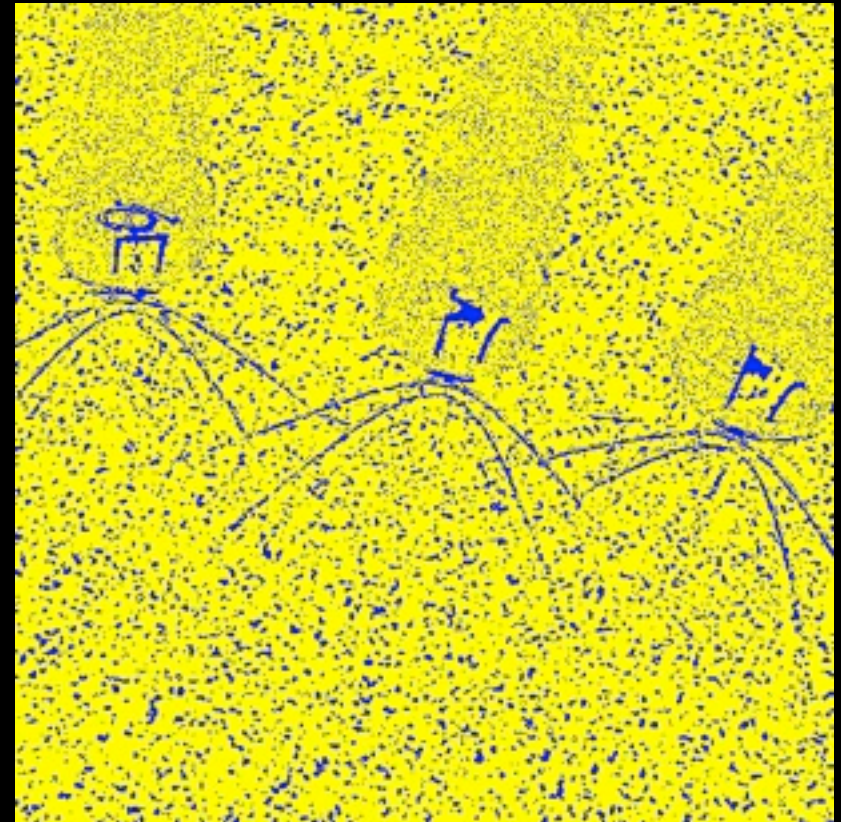


Estimated Error Bound

Error Estimation

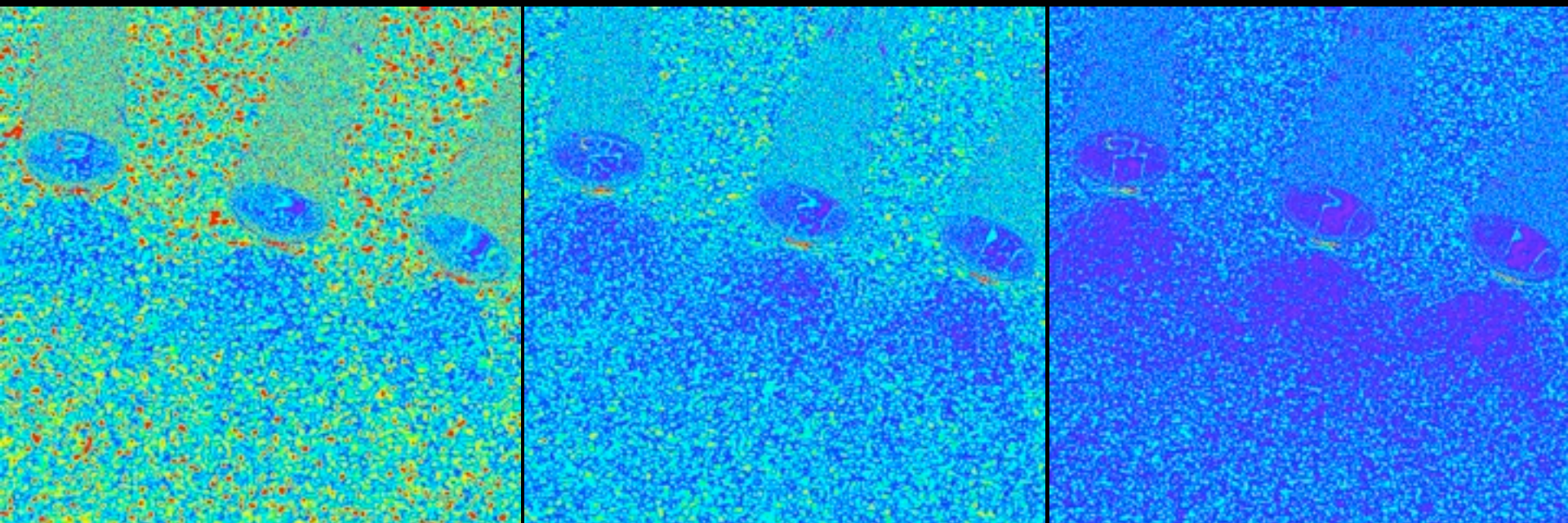


Actual Error



Bounded/Not bounded

Automatic Rendering Termination



specified: 0.25

actual: 0.1916

specified: 0.125

actual: 0.09294

specified: 0.0625

actual: 0.04482

1.3 times overestimation on average

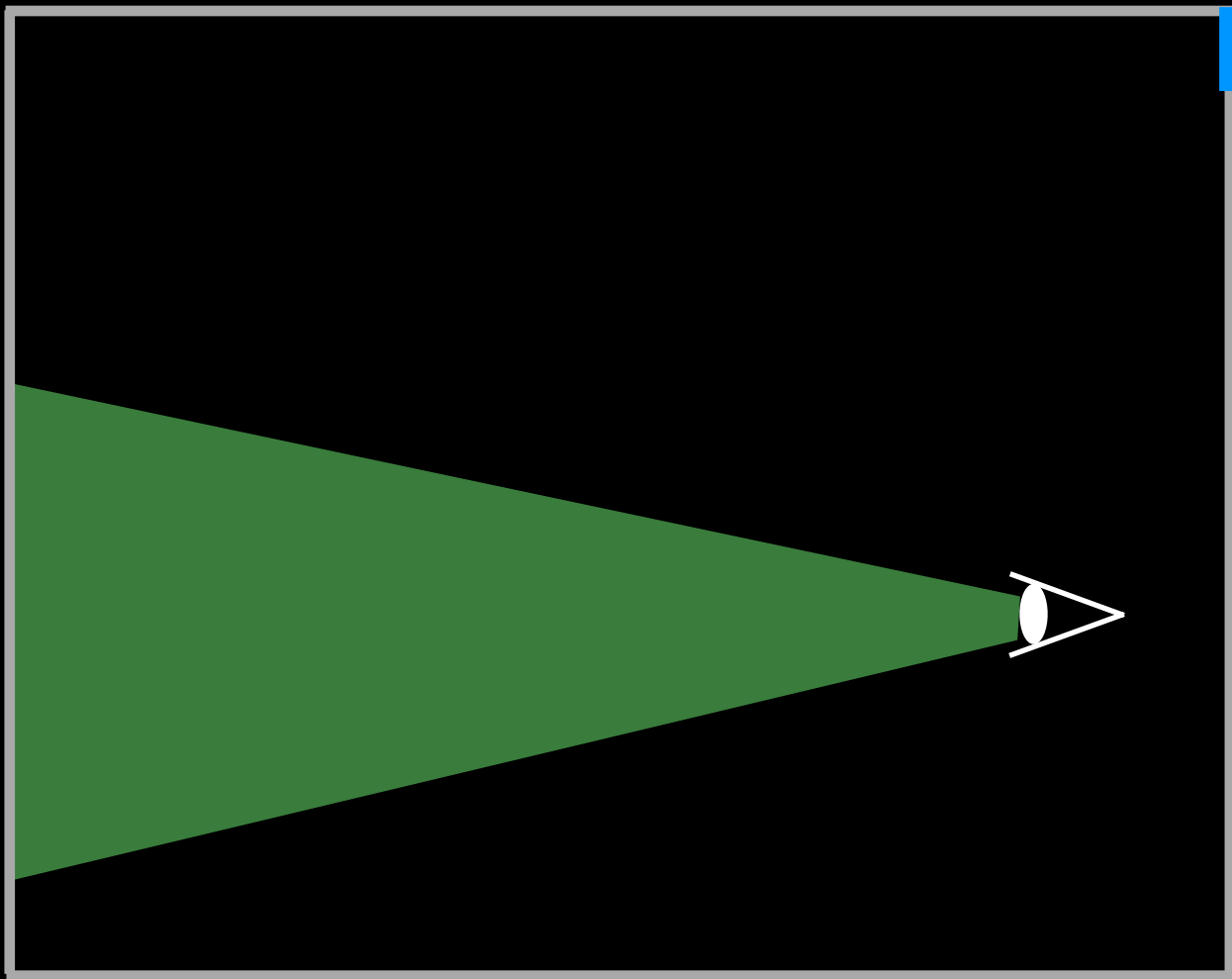


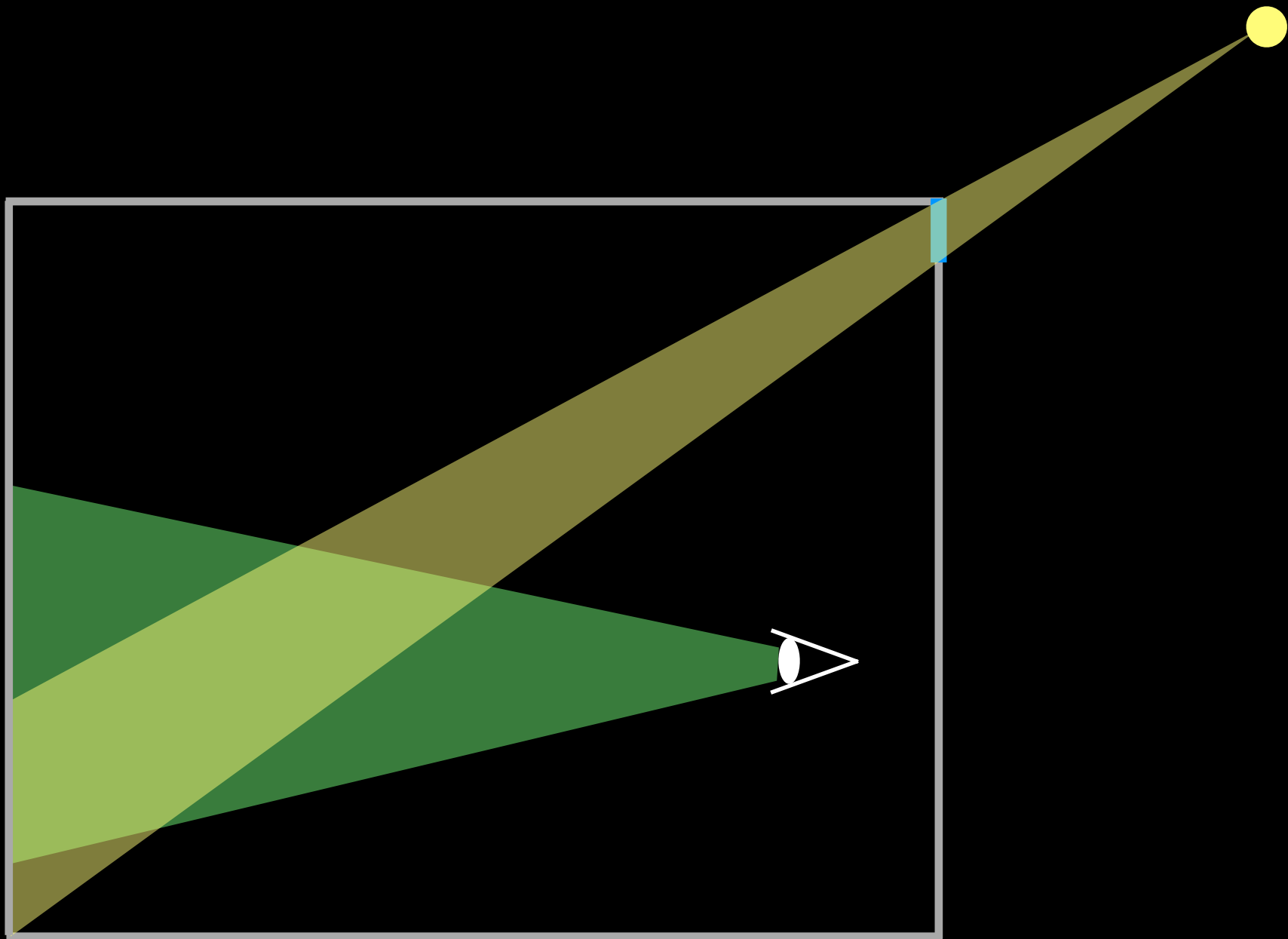
Light source ●

Window

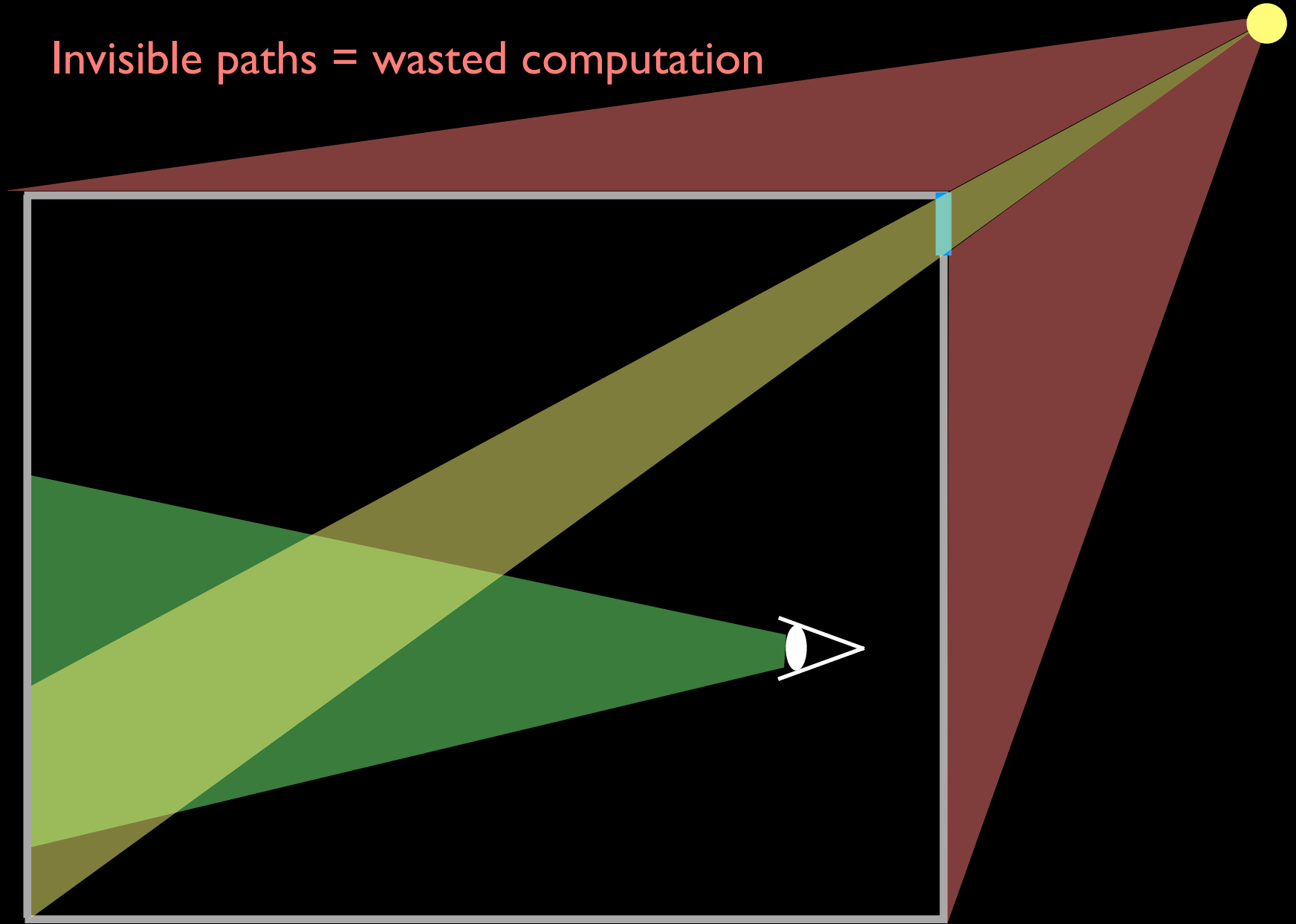


Eye





Invisible paths = wasted computation



Metropolis Light Transport

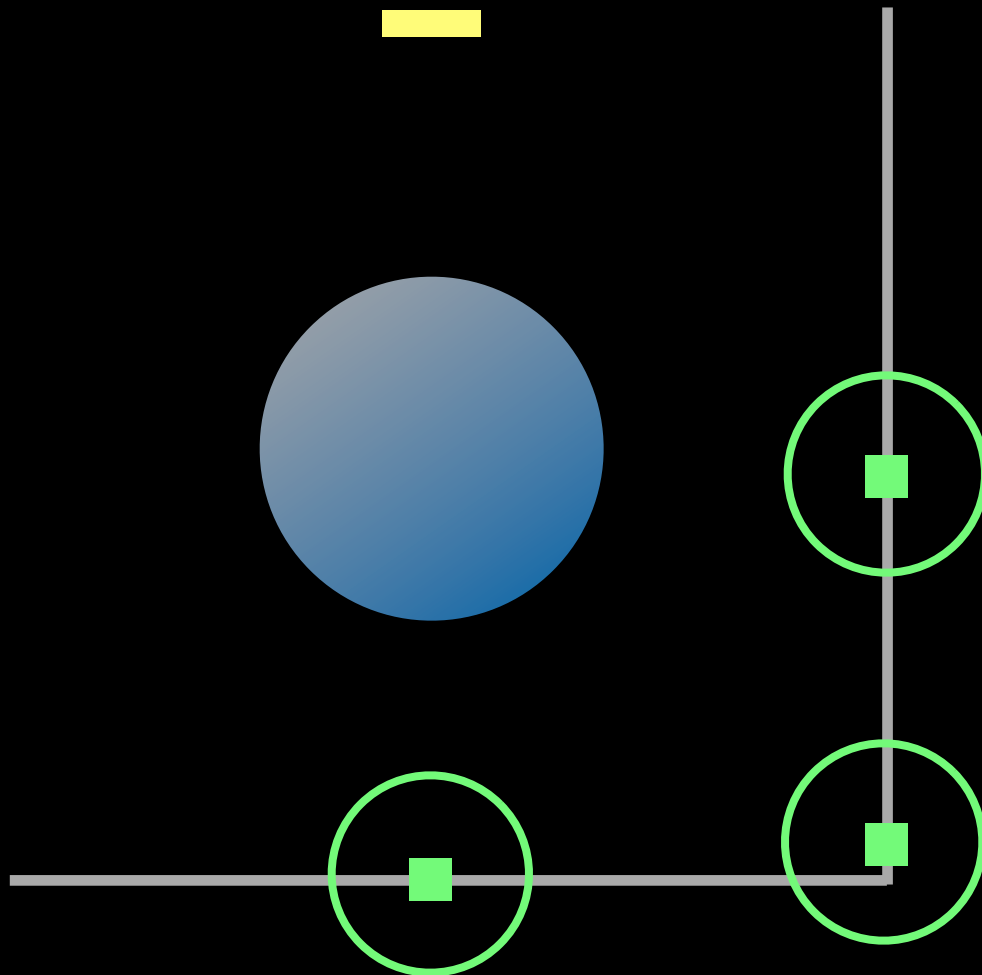
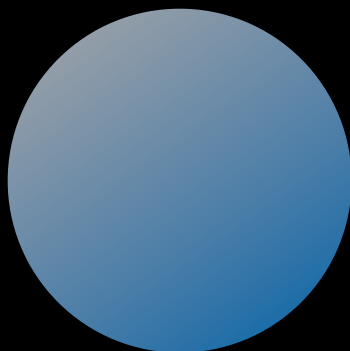


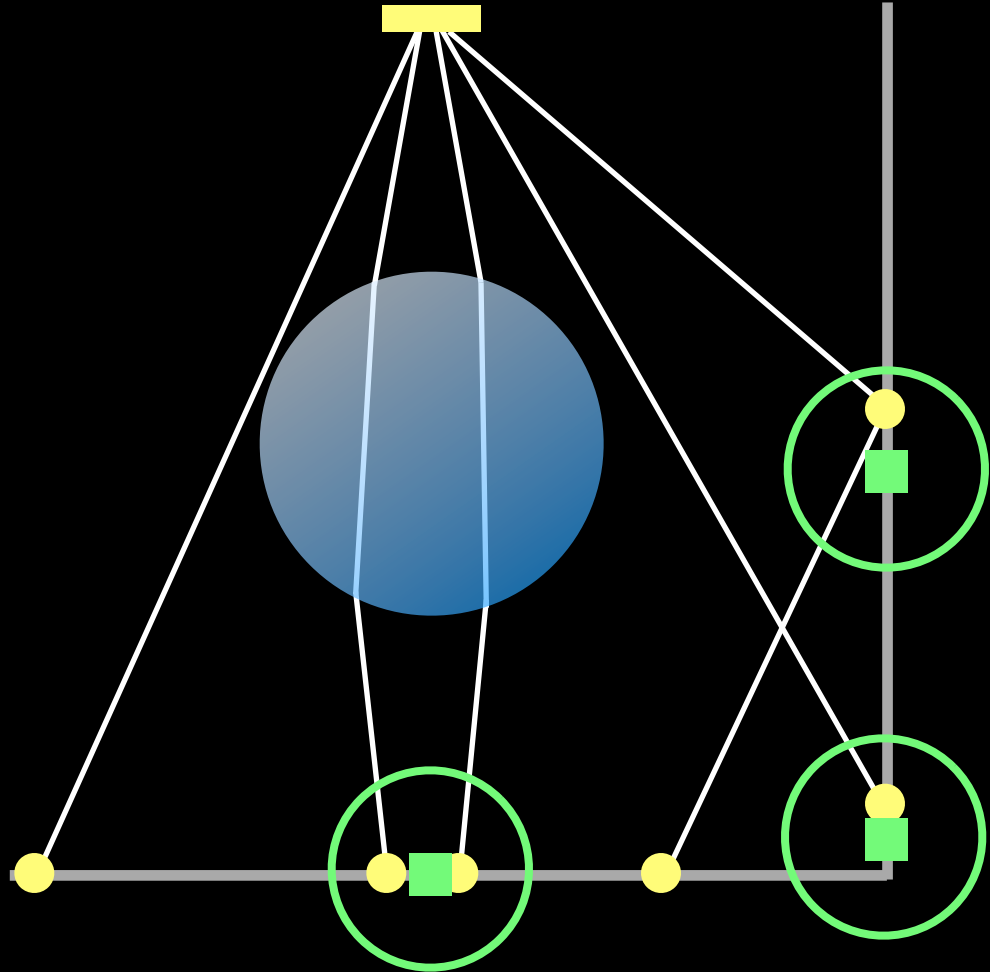
- ▶ Can we combine these two algorithms?
 - ▶ **MLT**: Efficient for difficult lighting scenarios
 - ▶ **PPM**: Robust to complex types of light paths

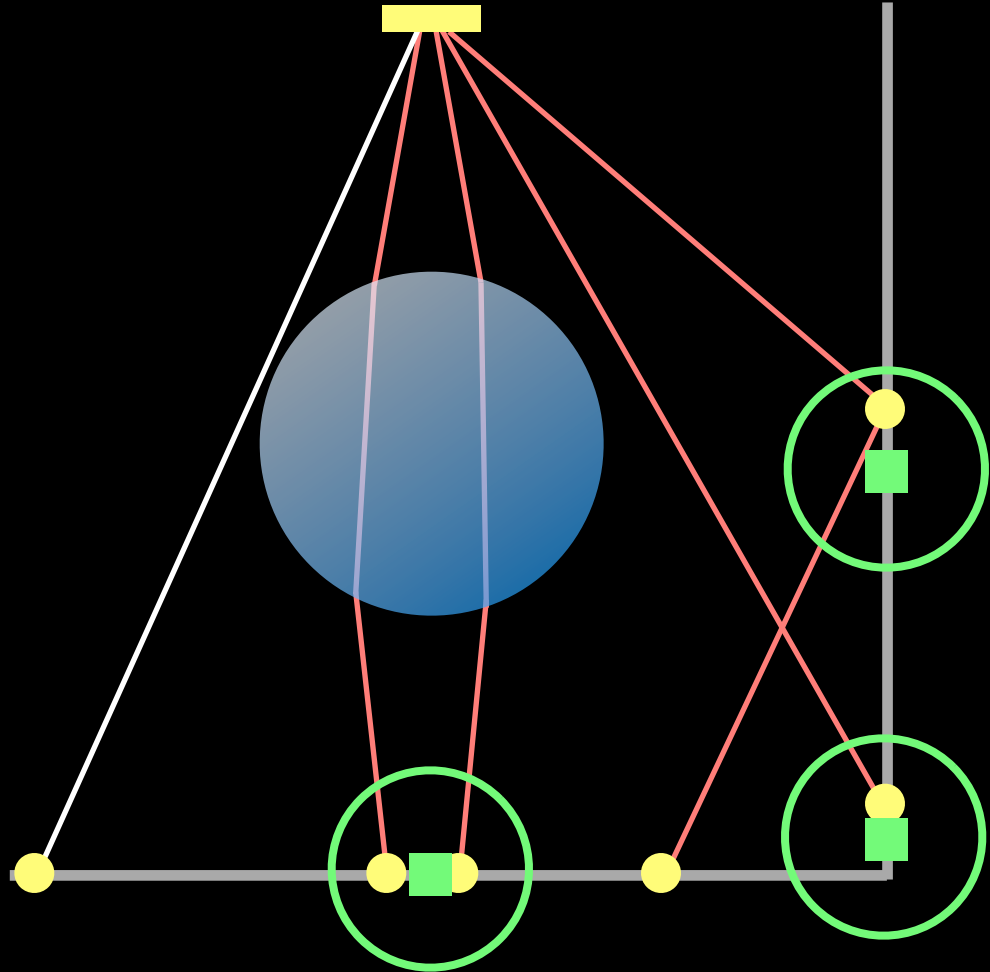
- ▶ Can we combine these two algorithms?
 - ▶ **MLT**: Efficient for difficult lighting scenarios
 - ▶ **PPM**: Robust to complex types of light paths

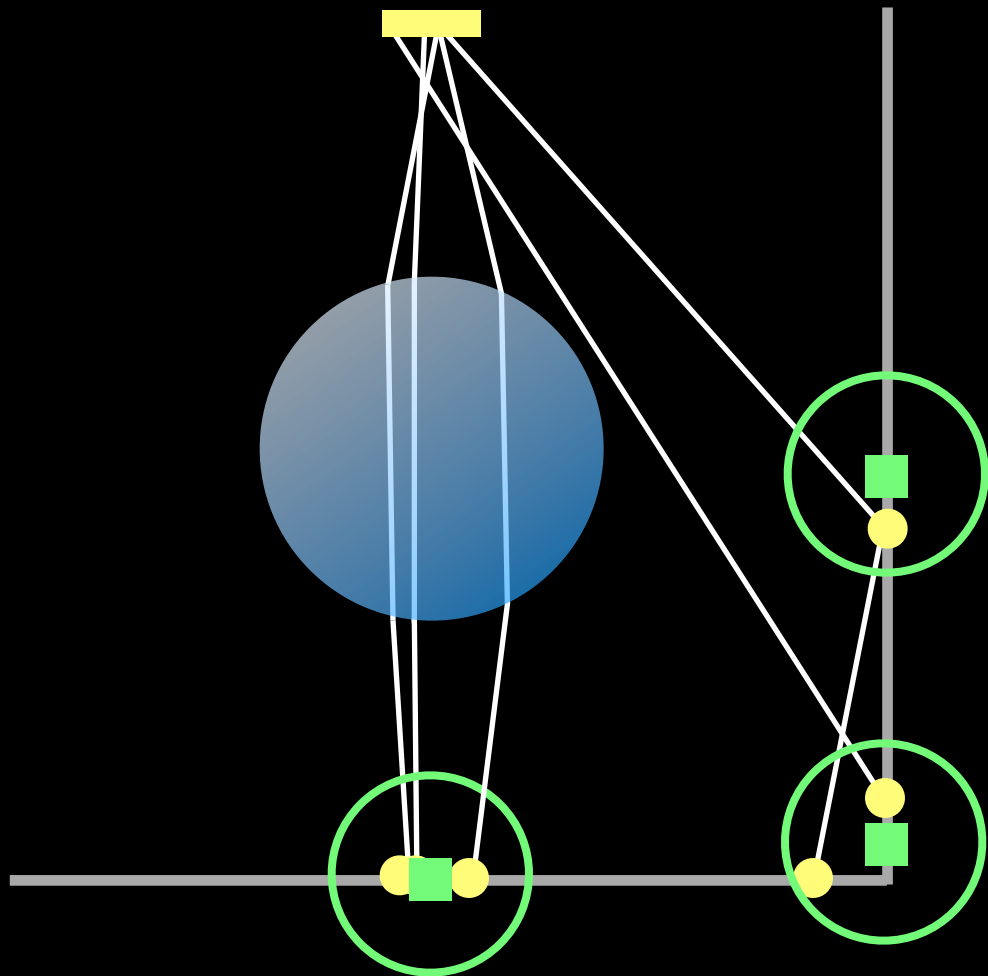
MLT + PPM

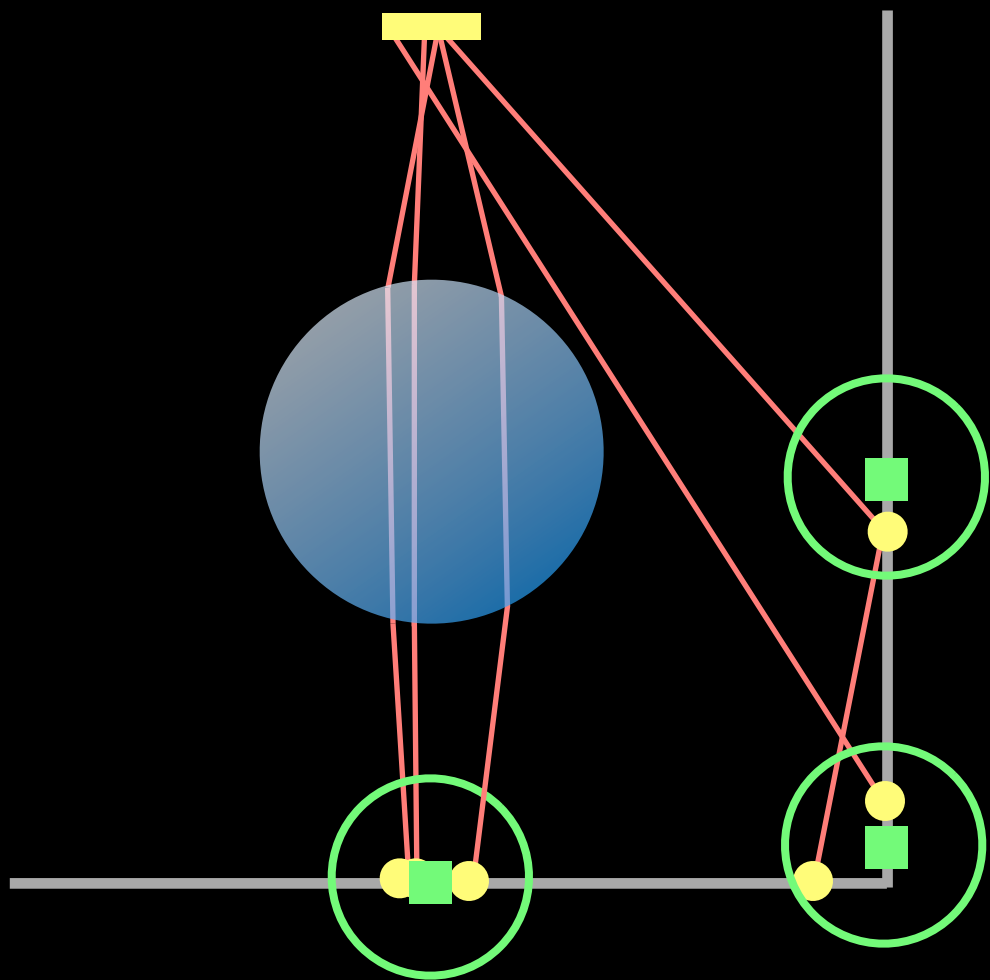
- ▶ We can determine whether a photon path is visible or not
 - ▶ Because PPM stores visible points from the eye
 - ▶ Contributed to at least one visible point = visible



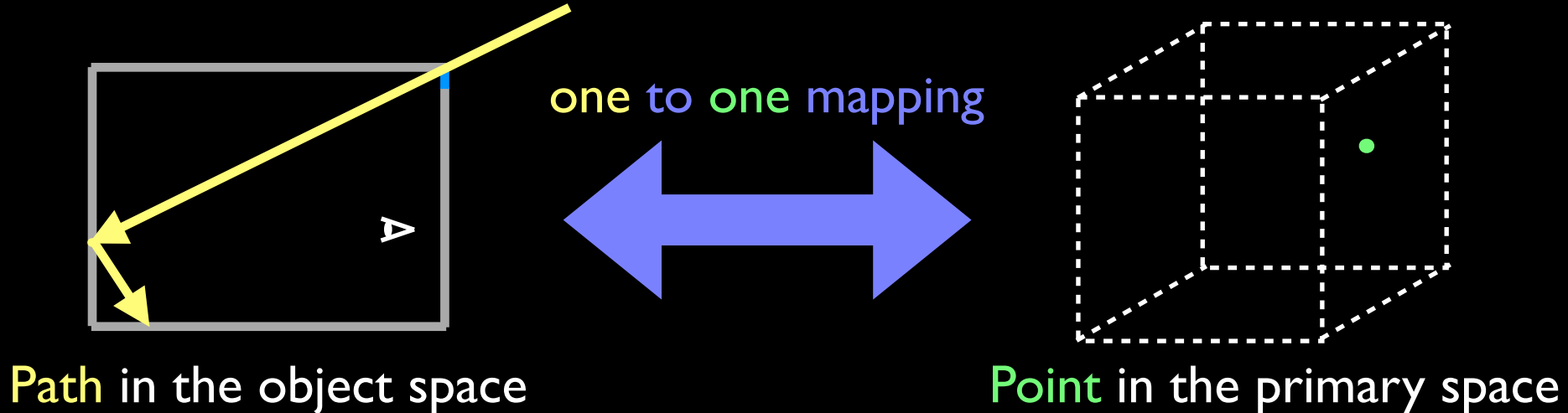








- ▶ Mapping a path to a point [Kelemen et al. 2002]
- ▶ Path = vector of random numbers $\vec{u} = (\xi_1, \dots, \xi_N) \in (0, 1)^N$



- ▶ Consider space of random numbers
- ▶ Photon path visibility function

If the photon is not visible:

$$V(\vec{u}) = 0$$

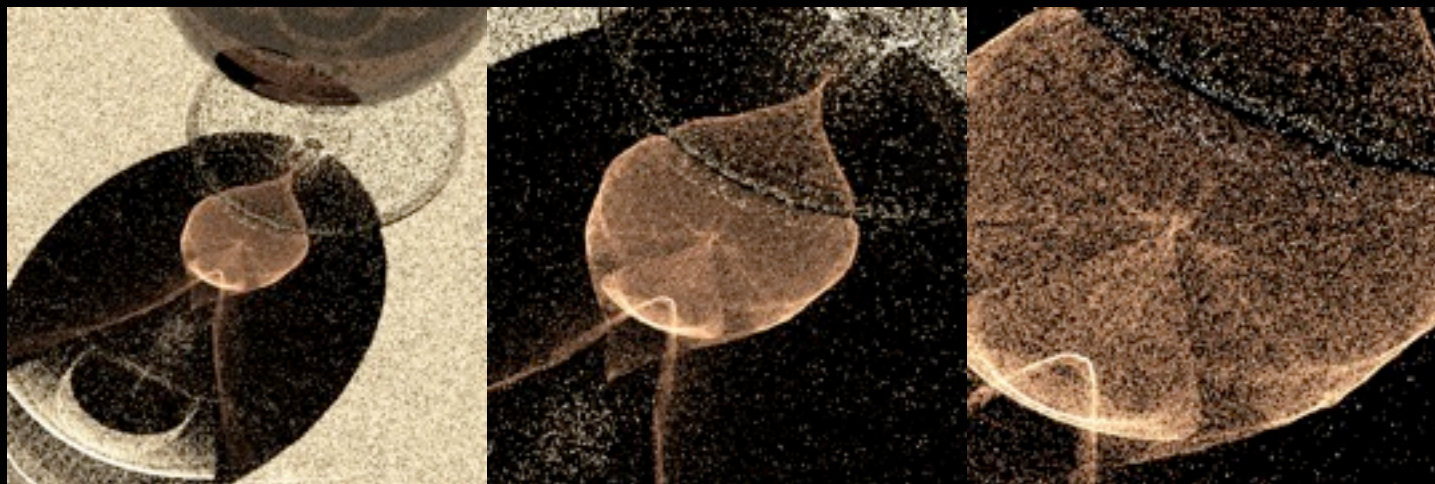
If the photon is visible:

$$V(\vec{u}) = 1$$

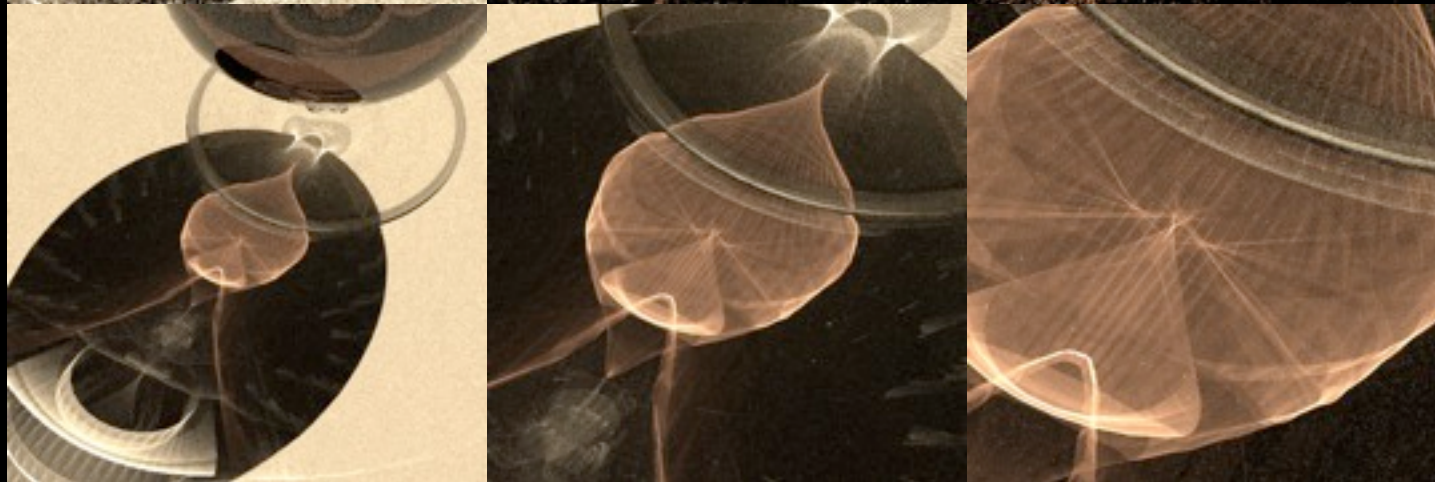
Sample $V(\vec{u})$ using Markov chain Monte Carlo Methods

Small-scale Lighting Details

Uniform



Adaptive



Automatic Parameter Tuning



Value is too small

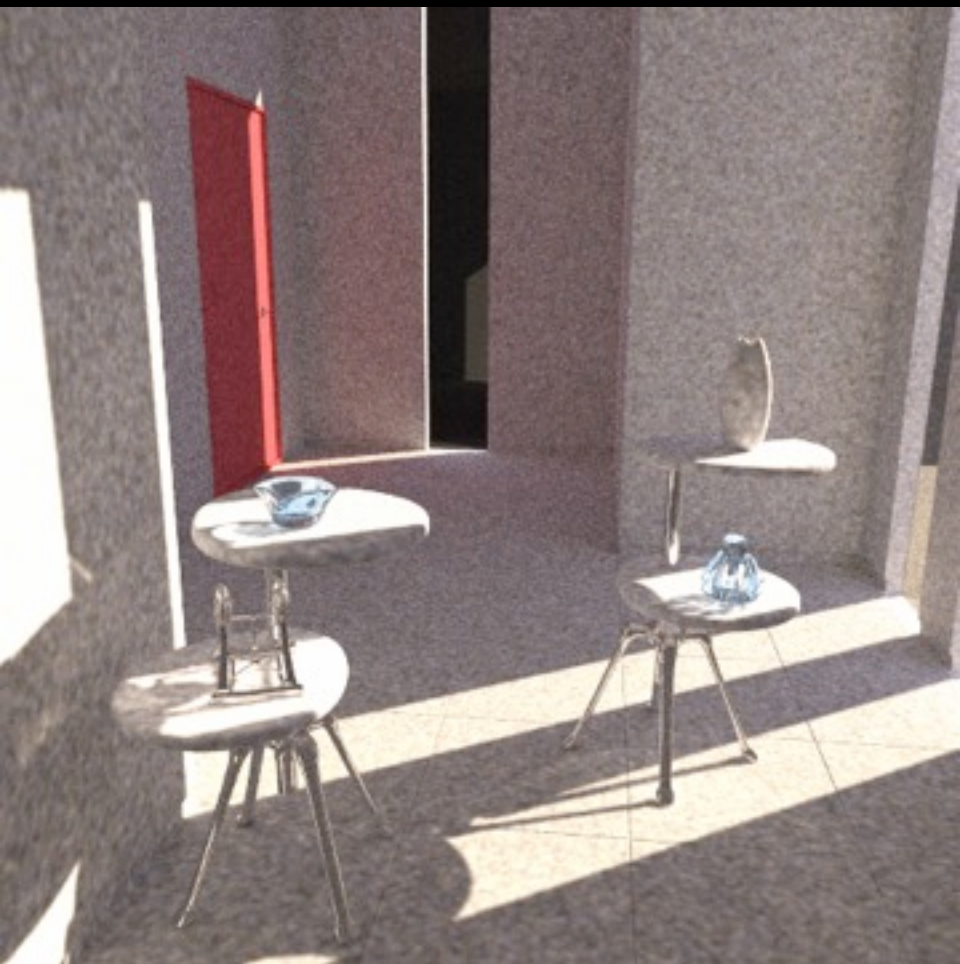


Automatic

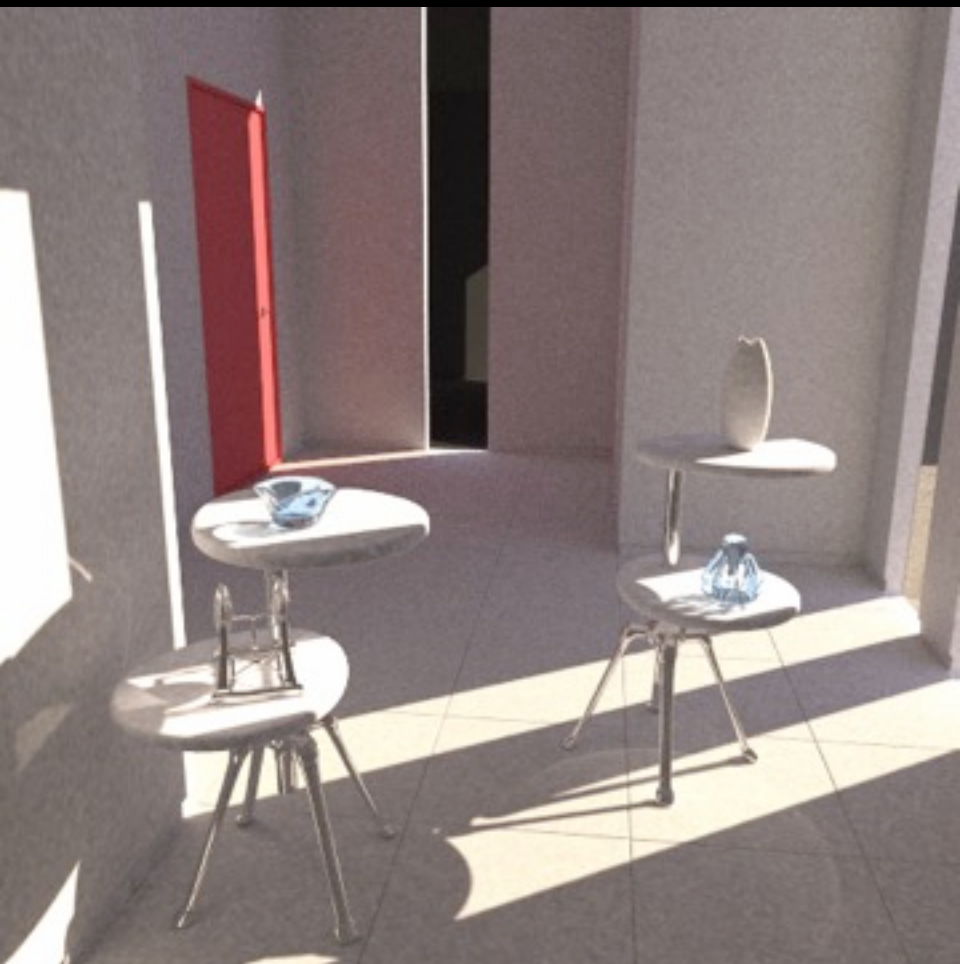


Value is too large

Sunlit Room



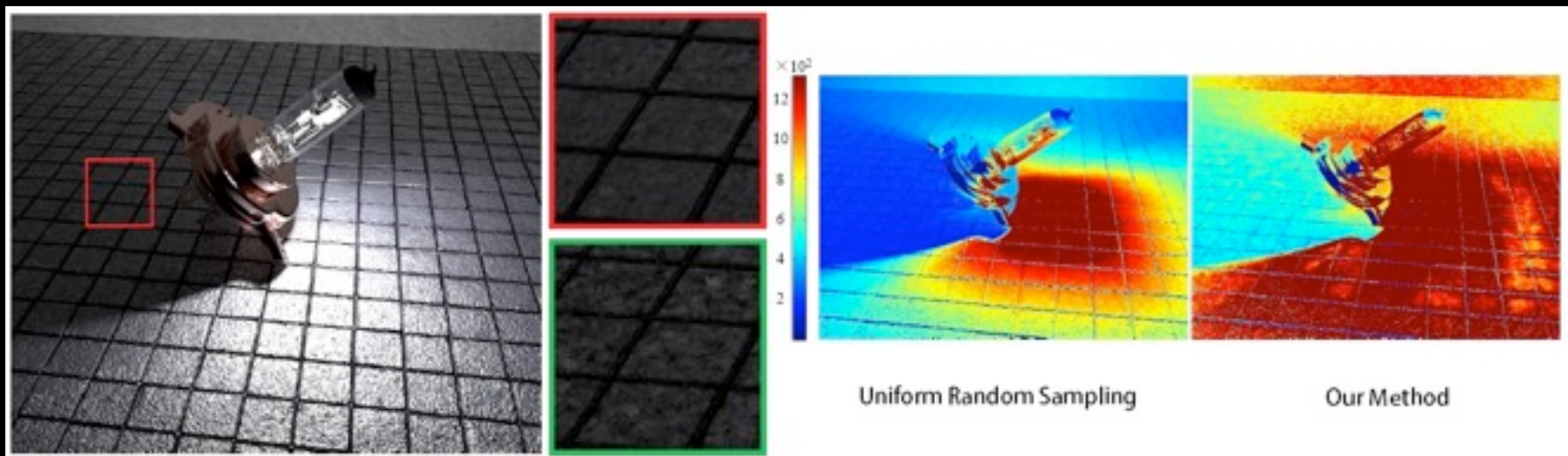
Uniform



Adaptive

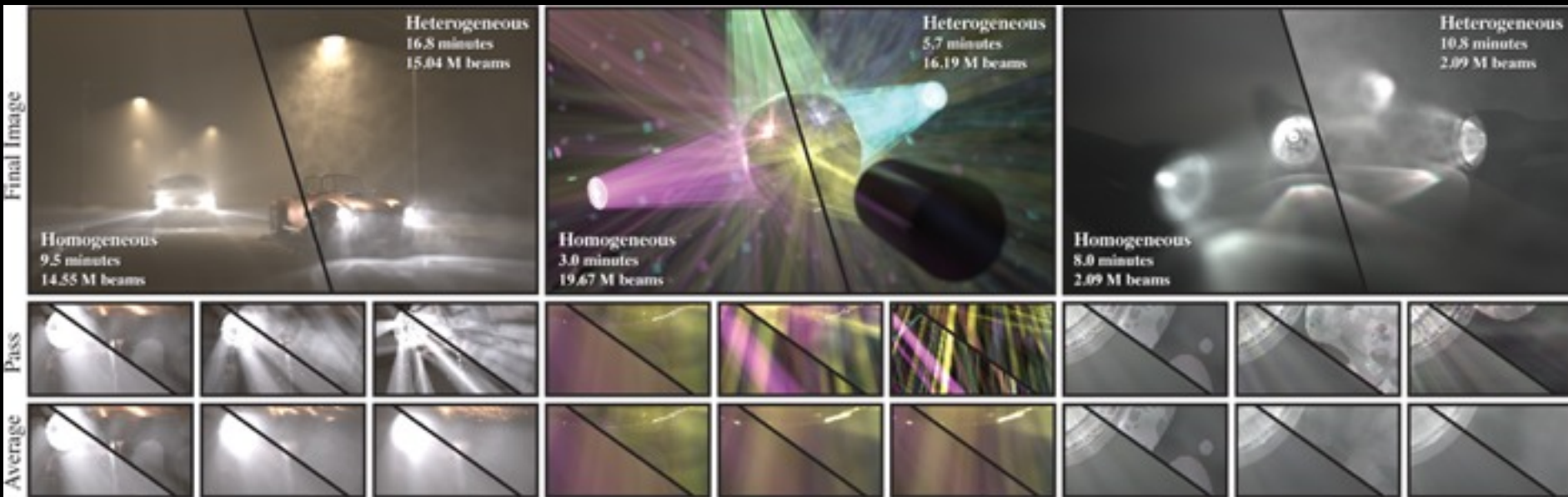
Some Related Work

- Adaptive photon tracing based on photon density on the image [Chen et al. 2011]



Some Related Work

- ▶ Progressive photon beams [Jarosz et al. 2011]
- ▶ Wojciech will talk more about it



Some Related Work

- Efficient rendering of dynamic scenes
[Weiss and Grosch 2012]



Some Related Work

- ▶ Combine density estimation and MC integration
[Hachisuka et al. 2012, Georgiev et al. 2012]
- ▶ Iliyan will talk more about it



► Q: Is PPM unbiased?

- ▶ Q: Is PPM unbiased?
- ▶ A: It is biased and consistent, but does not matter in practice.

$$E[X] = \lim_{\boxed{N \rightarrow \infty}} \sum_{i=1}^N x_i$$

BOTH unbiased and consistent methods need inf. samples!

- ▶ Q: Is PPM unbiased?
- ▶ A: It is biased and consistent, but does not matter in practice.

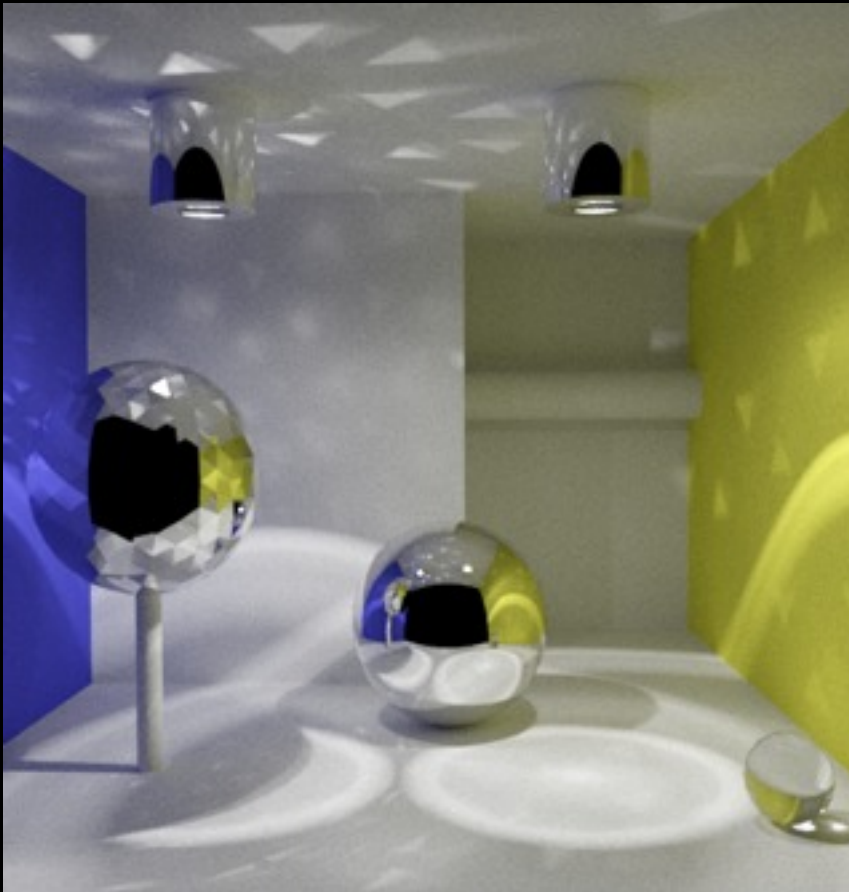
$$E[X] = \lim_{\boxed{N \rightarrow \infty}} \sum_{i=1}^N x_i$$

BOTH unbiased and consistent methods need inf. samples!

“Five Common Misconceptions about Bias in Light Transport Simulation”
cs.au.dk/~toshiya/misc.pdf

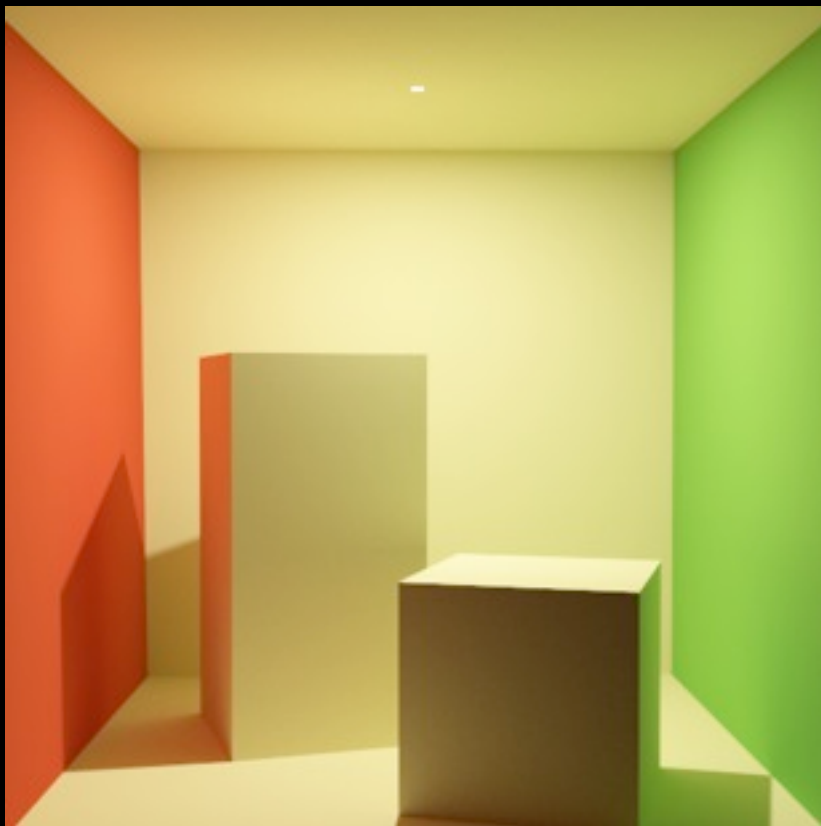
- ▶ Q: Do we still use global + caustics separation?

- ▶ Q: Do we still use global + caustics separation?
- ▶ A: No. Just render everything as one.

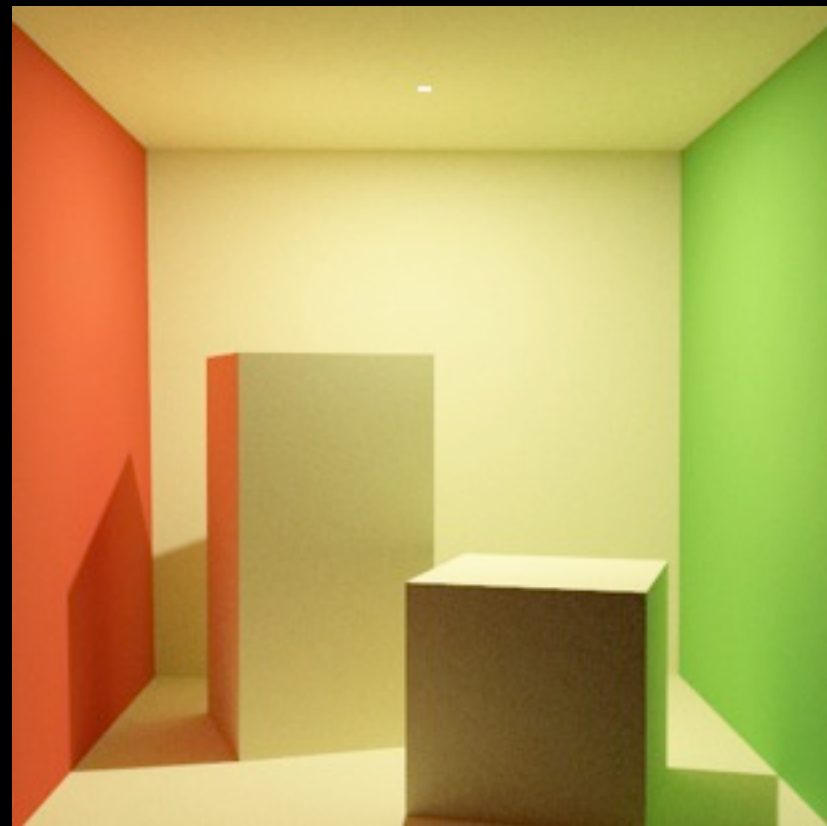


- ▶ Q: Is PPM slower for diffuse scenes than other methods?

- ▶ Q: Is PPM slower for diffuse scenes than other methods?
- ▶ A: True, but not much, and you can do more.

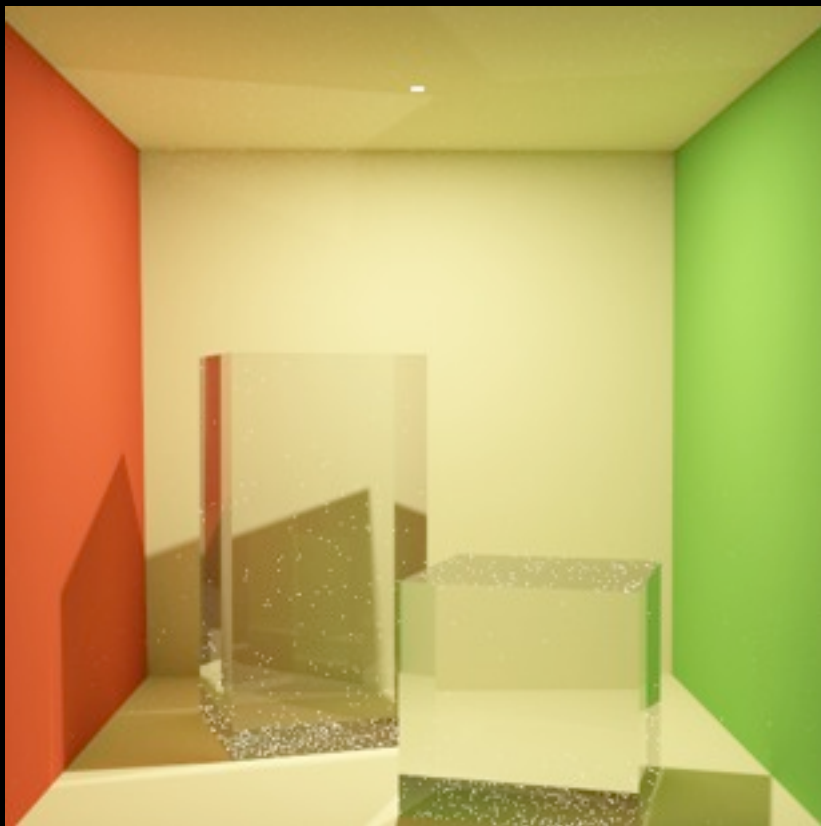


Bidirectional PT

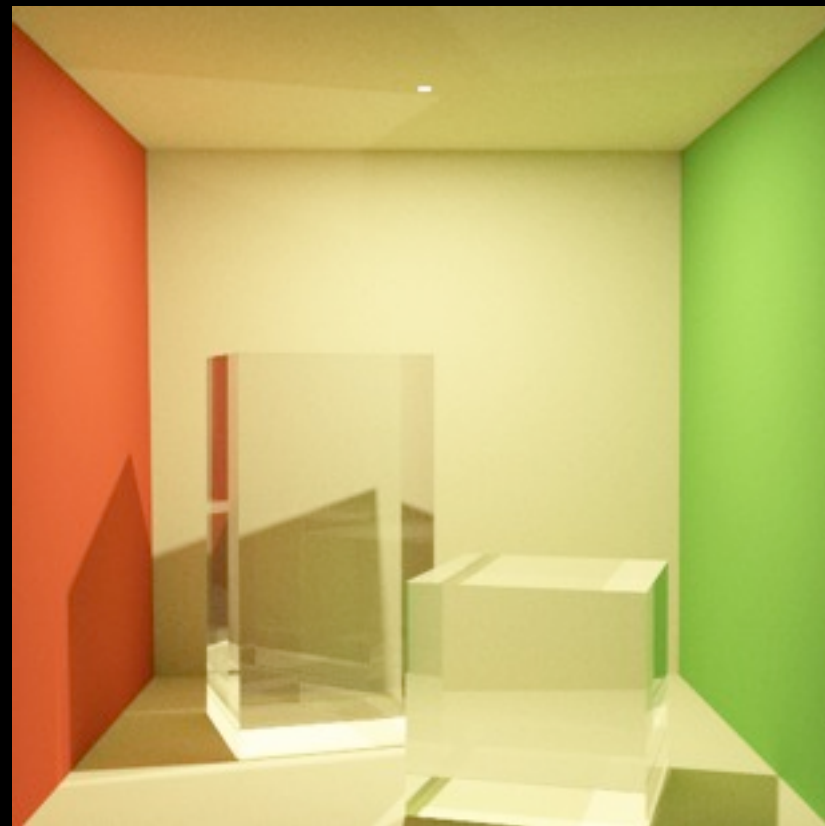


PPM

- ▶ Q: Is PPM slower for diffuse scenes than other methods?
- ▶ A: True, but not much, and you can do more.



Bidirectional PT



PPM

- ▶ SPPM = PPM + Distributed Ray Tracing
- ▶ Error estimation is available
- ▶ Adaptive photon tracing based on visibility
- ▶ Lots of useful extensions

- ▶ My opinion: (S)PPM + extensions is very hard to “break”
 - ▶ Just works fine in really many cases

More details

► cs.au.dk/~toshiya



- ▶ More advanced and efficient radius reduction