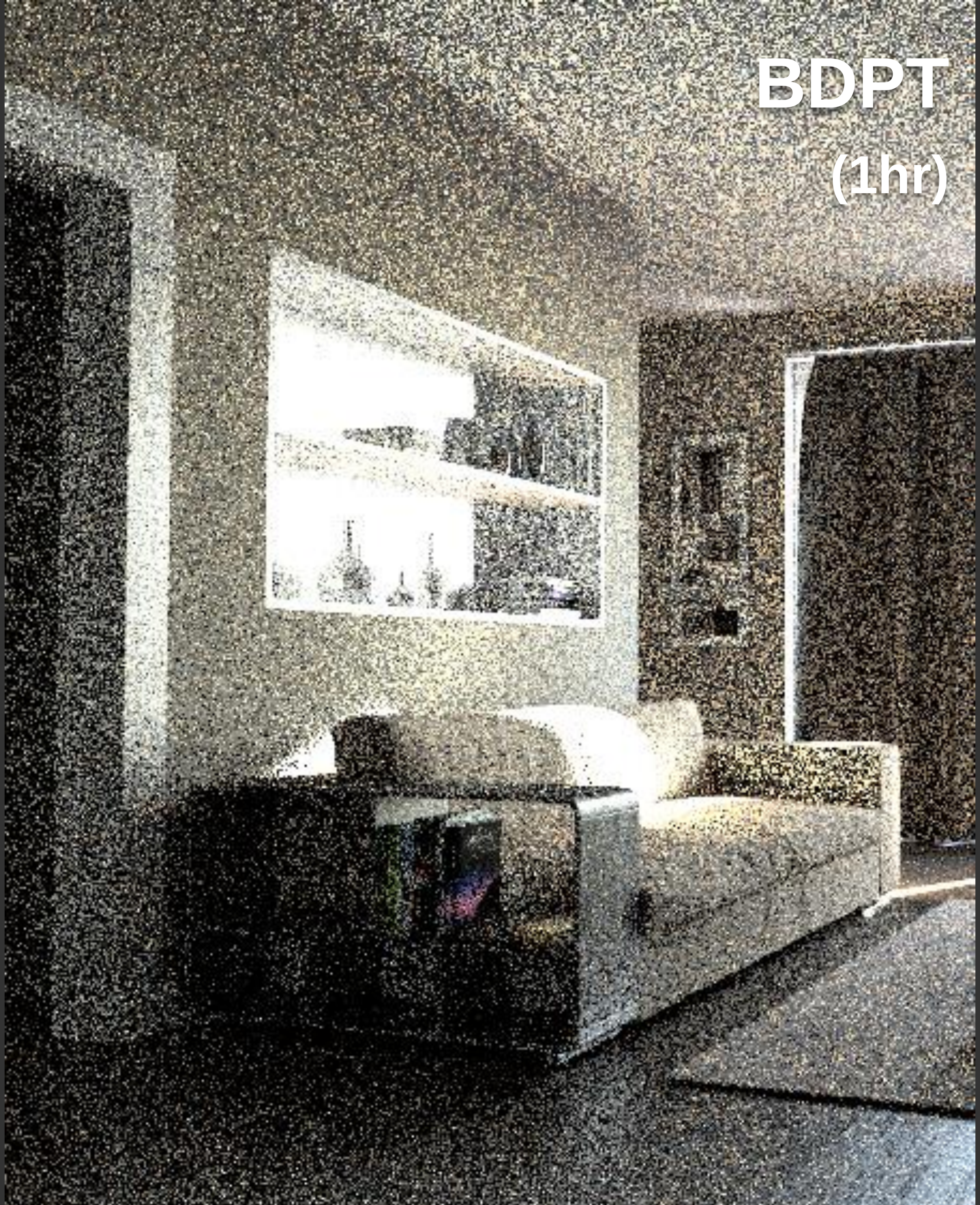
Product Importance Sampling for Light Transport Path Guiding

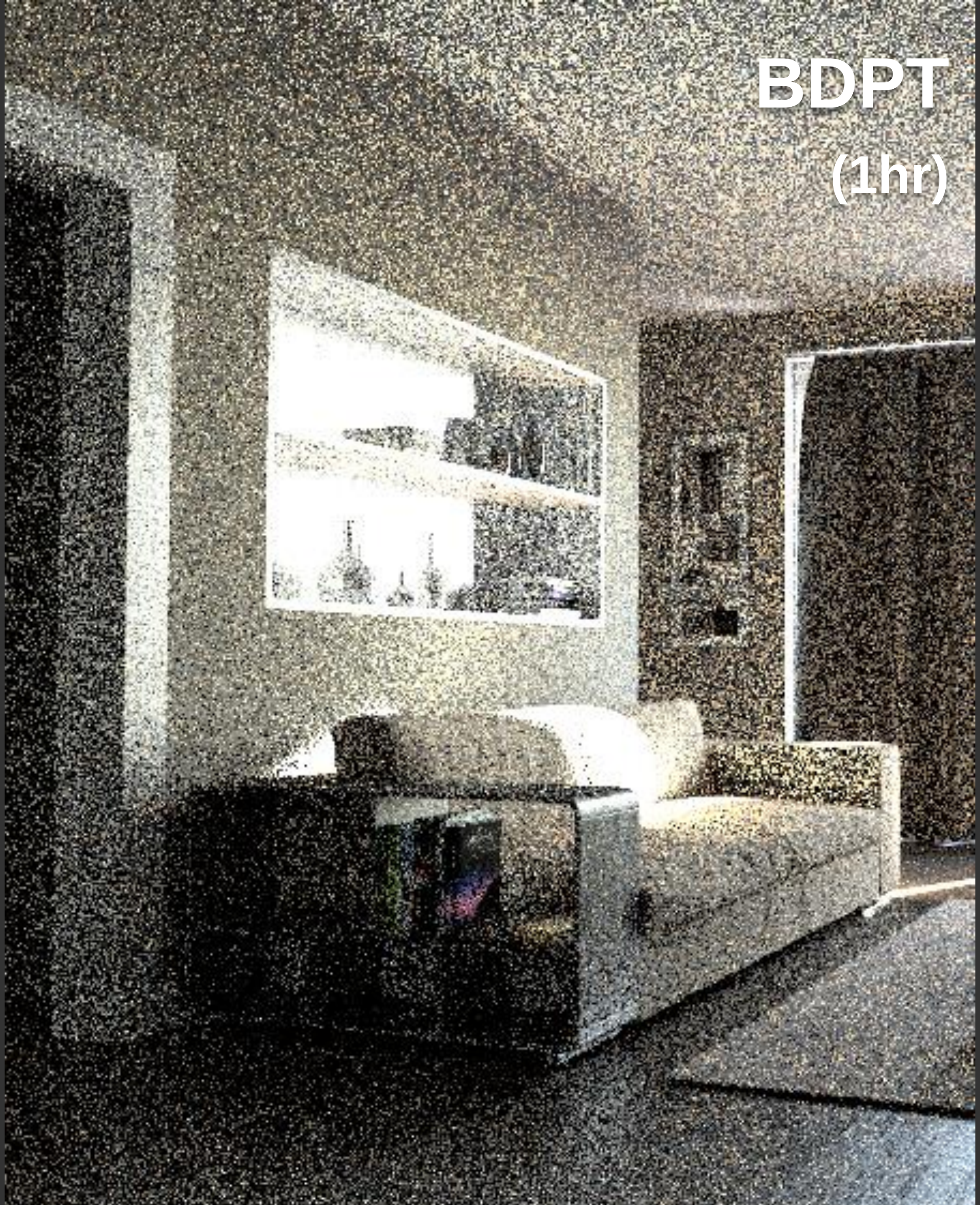
Sebastian Herholz[1] Oskar Elek[2] Jiří Vorba[2,3]
Hendrik Lensch[1] Jaroslav Křivánek[2]

[1]University Tübingen [2]Charles University Prague [3]Weta Digital

Motivation


Reference
(4 weeks)

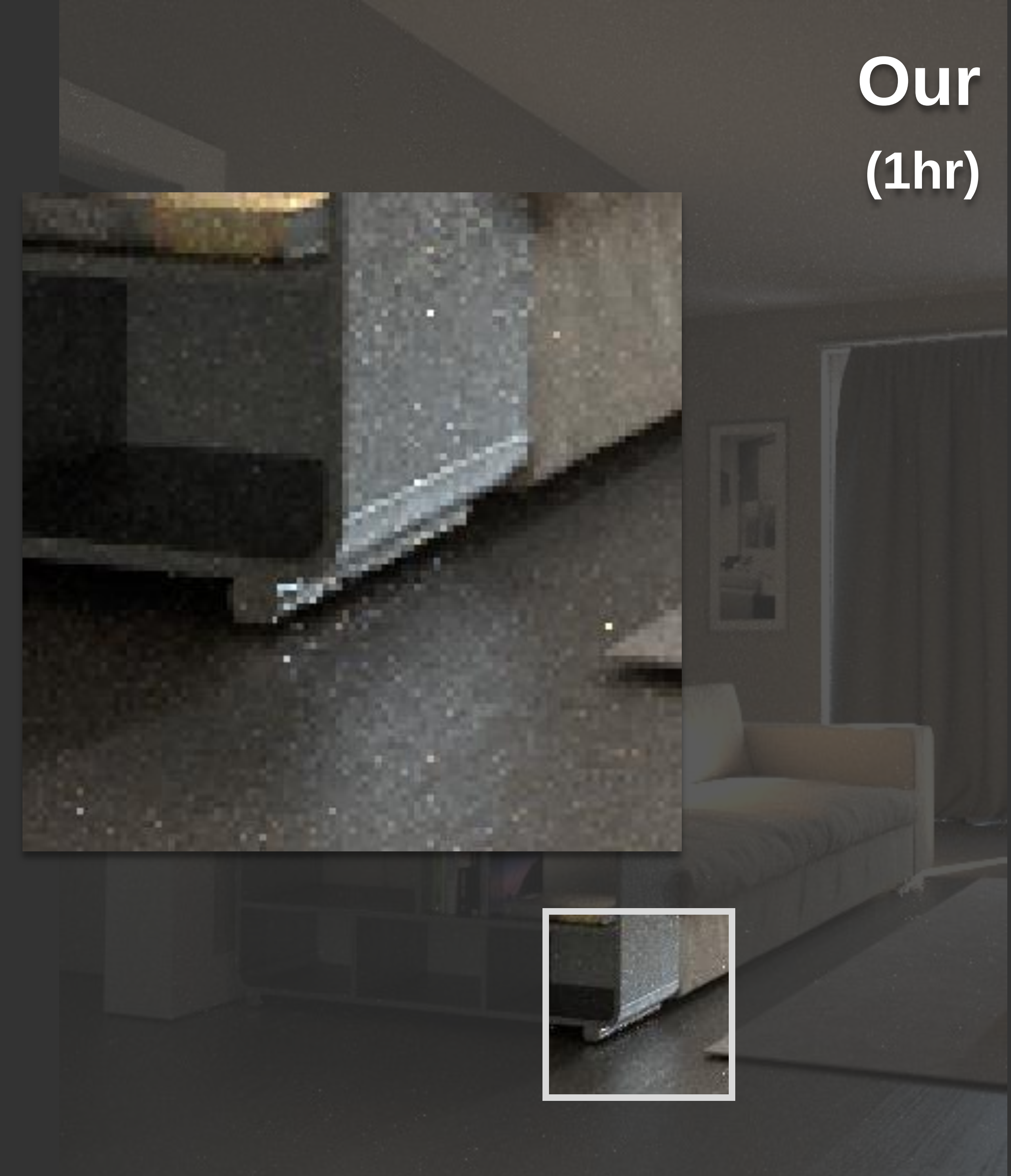

BDPT
(1hr)


BDPT
(1hr)

Vorba2014
(1hr)


Our
(1hr)

Vorba2014
(1hr)

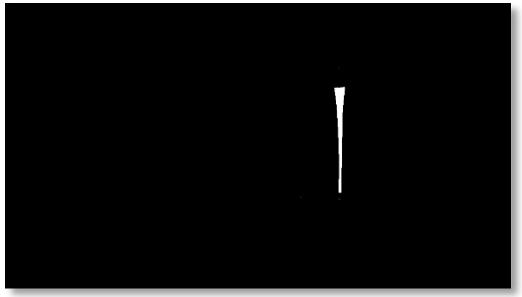

Our
(1hr)


Vorba2014
(1hr)

Light Transport: Rendering Equation

$$L_o = L_e + \underbrace{\int_{\Omega} f_r \cdot L_i \cdot cos\theta \cdot d\vec{\omega}_i}_{L_R}$$

emission



direct

indirect

combined

Light Transport: Rendering Equation

$$L_o = L_e + \underbrace{\int_{\Omega} f_r \cdot L_i \cdot cos\theta \cdot d\vec{\omega}_i}_{L_R}$$

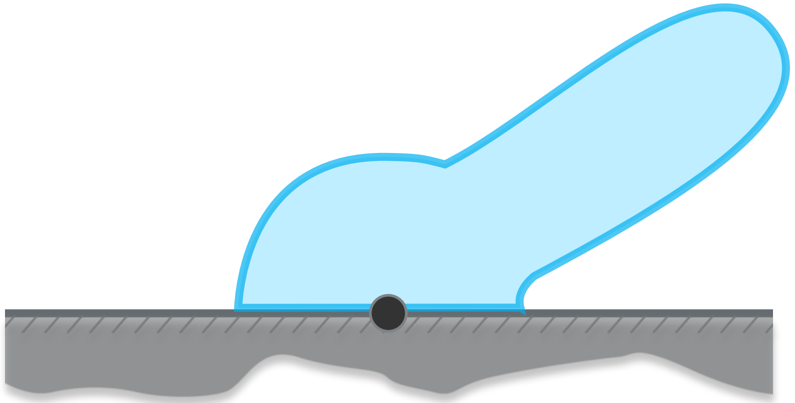
emission

direct

indirect

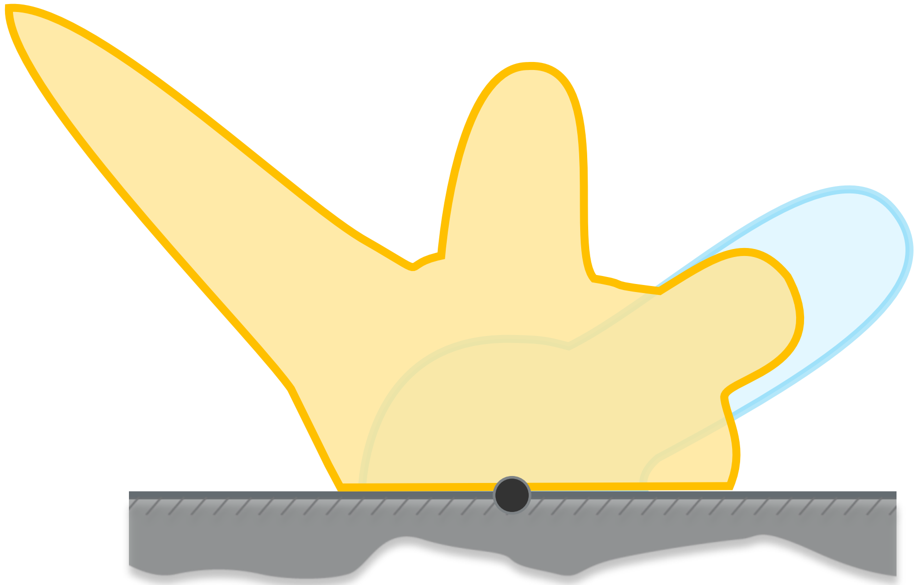
combined

Bidirectional Reflectance Distribution Function (BRDF)



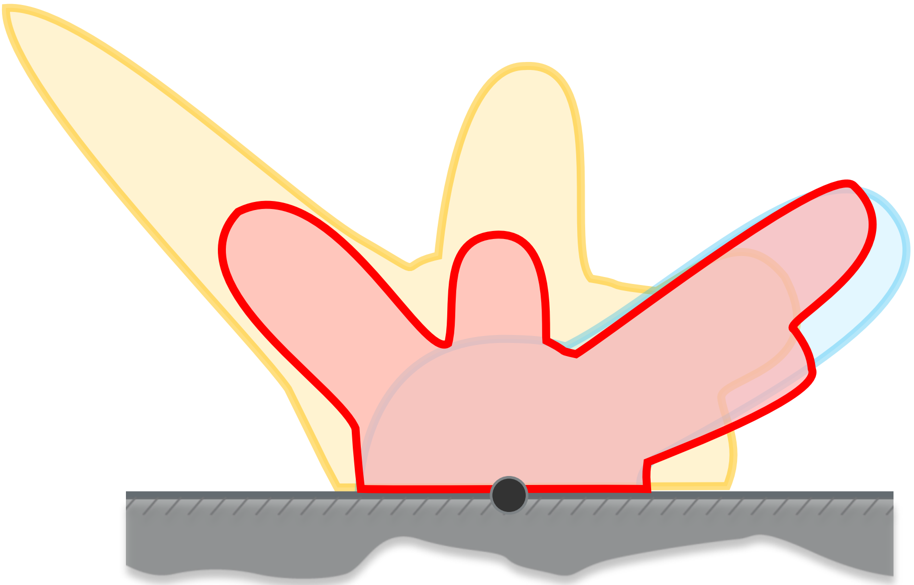
$$L_R = \int_\Omega \boxed{f_r} \cdot L_i \cdot cos\theta \cdot d\vec{\omega}_i$$

Incomming Illumination



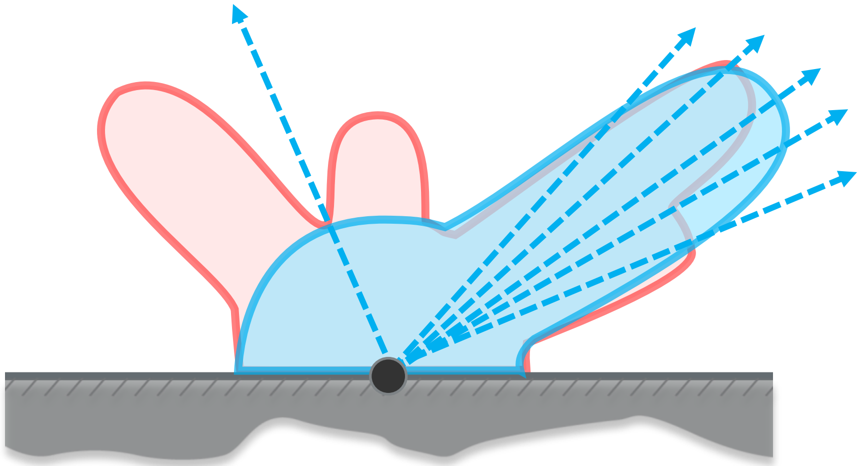
$$L_R = \int_{\Omega} f_r \cdot \boxed{L_i \cdot cos\theta} \cdot d\vec{\omega}_i$$

Reflectance Integral



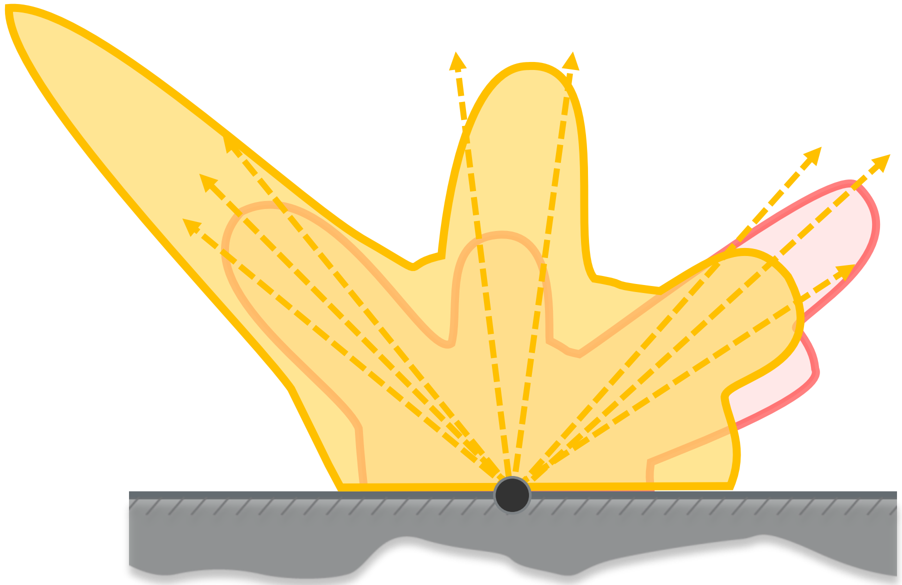
$$L_R = \int_{\Omega} \boxed{f_r \cdot L_i \cdot cos\theta} \cdot d\vec{\omega}_i$$

BRDF-based Sampling



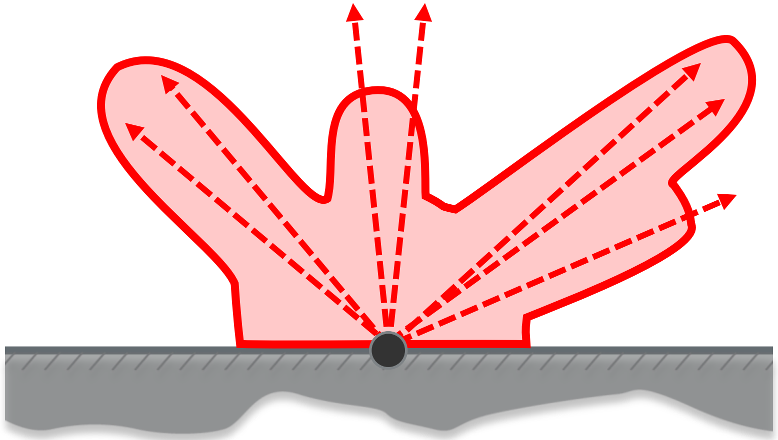
$$p_{f_r}(\omega_i|\omega_o, x) \propto f_r(x, \vec{\omega}_o, \vec{\omega}_i)$$

Guided Illumination Sampling



$$p_L(\omega_i|\omega_o, x) \propto L_i(x, \vec{\omega}_i) \cdot cos\theta$$

Optimal (Product) Sampling



$$p_{opt}(\omega_i|\omega_o, x) \propto f_r(x, \vec{\omega}_o, \vec{\omega}_i)L_i(x, \vec{\omega}_i) \cdot cos\theta$$

Related Work

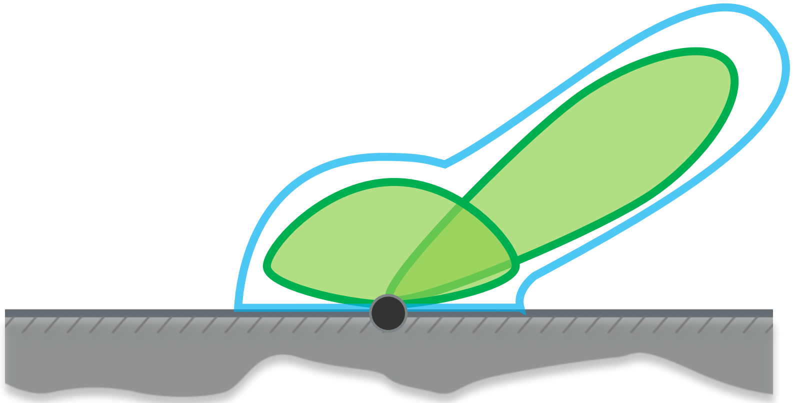
[CAM08]: Practical product importance sampling for direct illumination

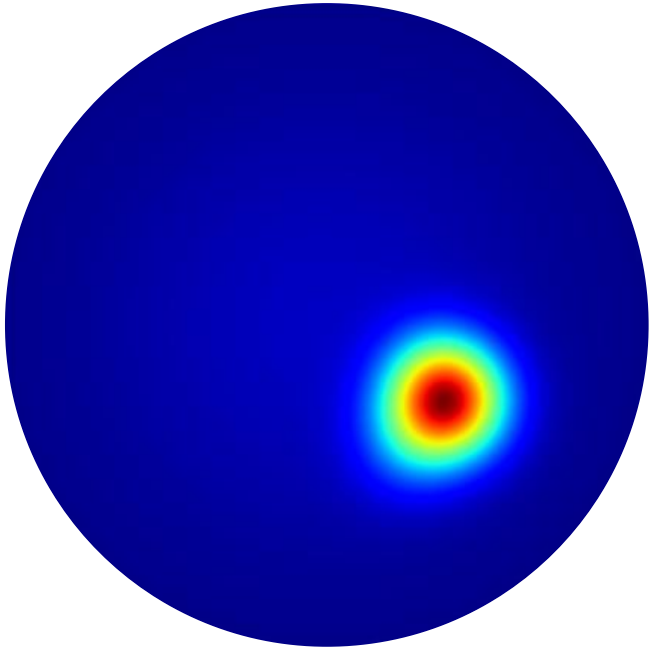
[TCE05]: Importance resampling for global illumination

[CJAMJ05]: Wavelet importance sampling: efficiently evaluating products of complex functions
[JCJ09]: Importance sampling spherical harmonics

Product Importance Sampling

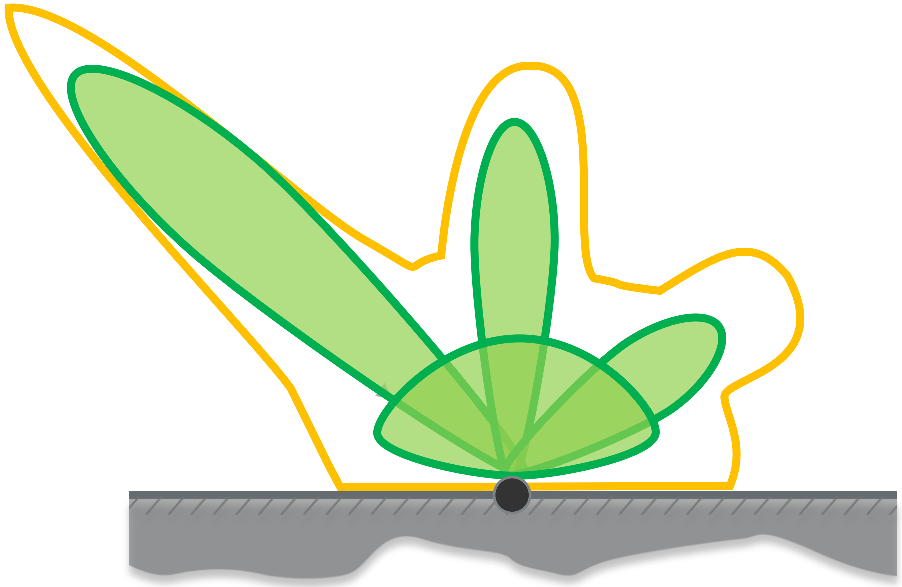
BRDF GMM Representation

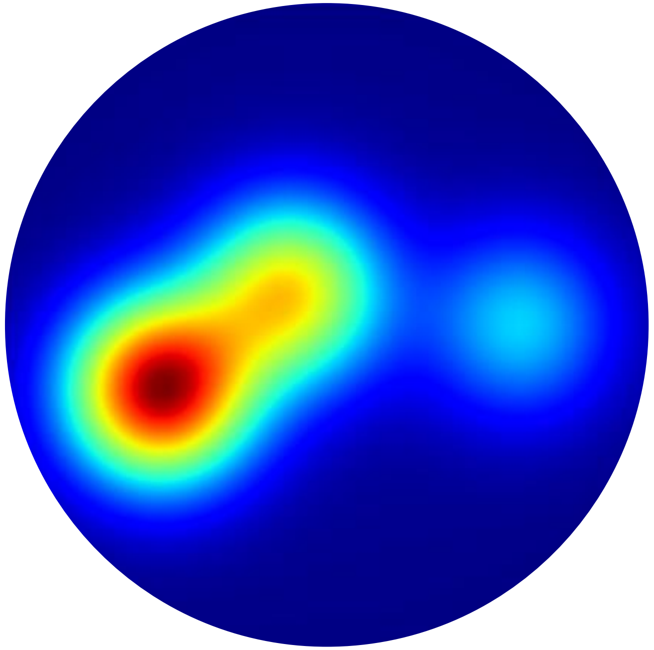




$$p_{f_r}(\omega_i|\omega_o, x) \approx G_{f_r}(y, \Theta)$$

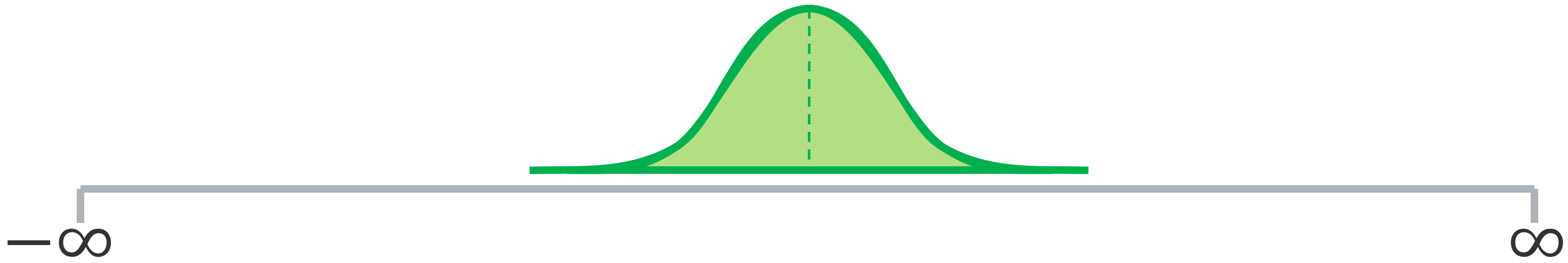
Illumination GMM Representation





$$p_L(\omega_i|\omega_o, x) \approx G_L(y, \Theta)$$

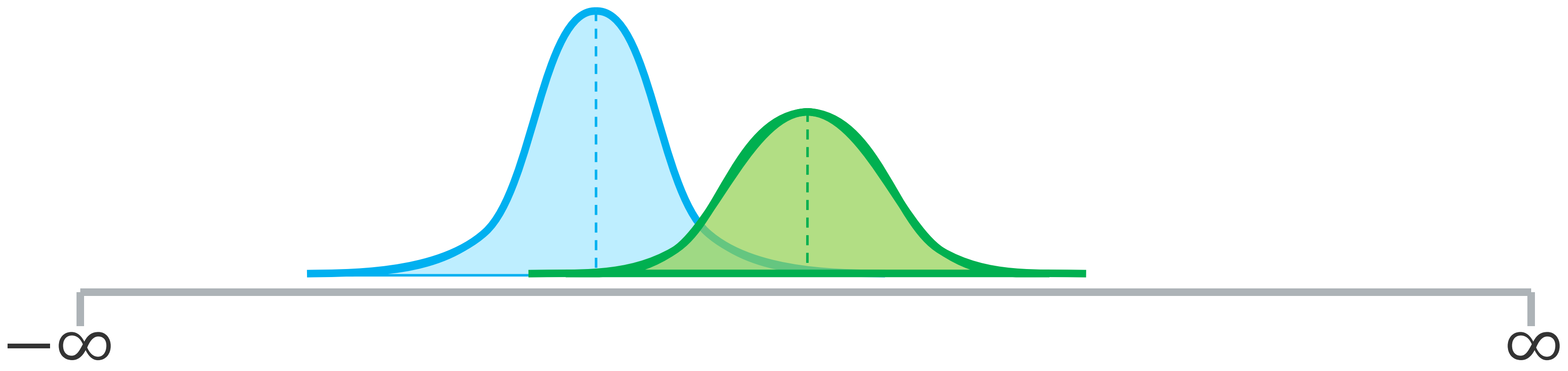
Gaussian Mixture Model (GMM)



$$G(y, \Theta) = \sum^{K} \pi_i N(y, \mu_i, \Sigma_i)$$

$$\Theta = \{\pi_0 \ldots, \mu_0 \ldots, \Sigma_0 \ldots\}$$

Gaussian Mixture Model (GMM)



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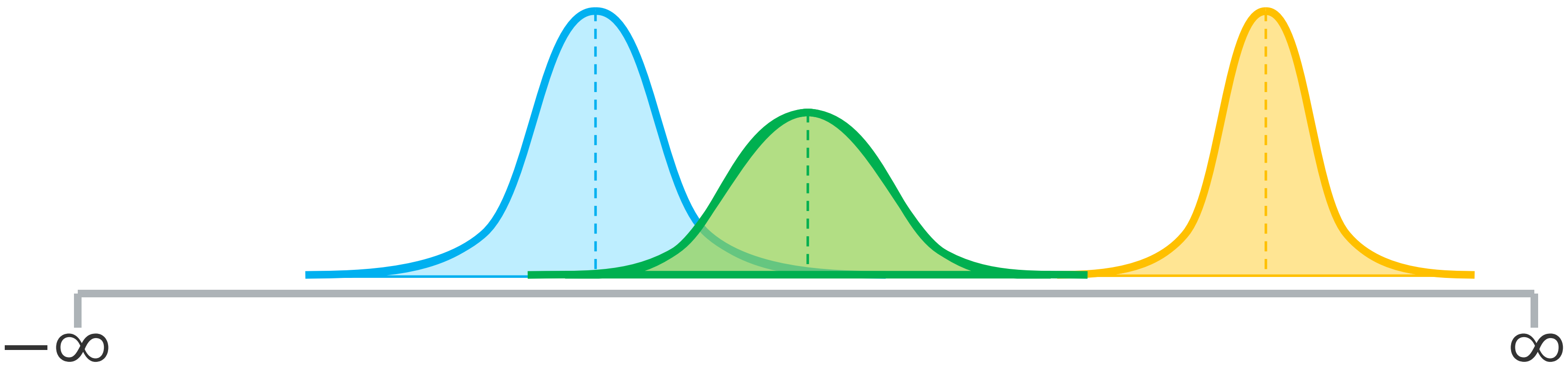

$$G(y, \Theta) = \sum^{K} \pi_i N(y, \mu_i, \Sigma_i)$$

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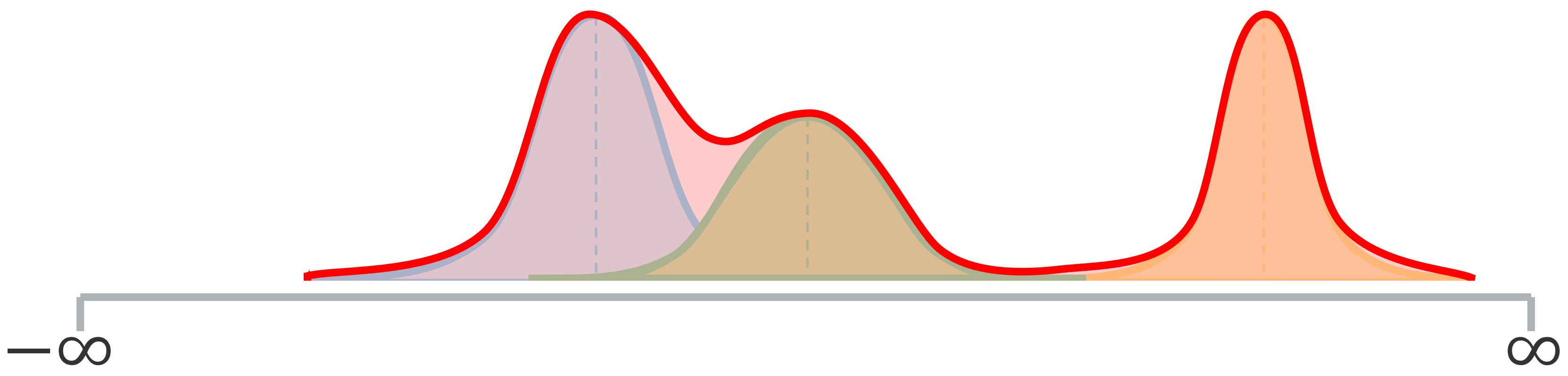
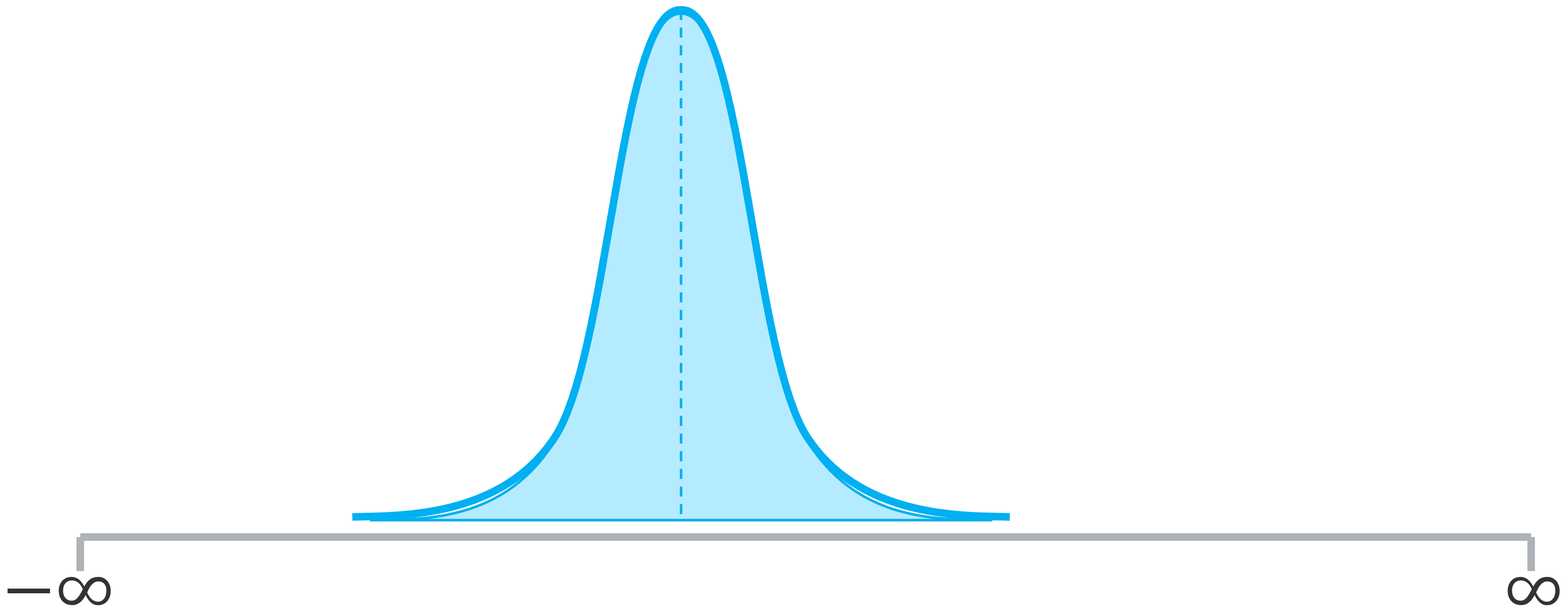


$$G(y,\Theta) = \sum^{K} \pi_i N(y,\mu_i,\Sigma_i)$$

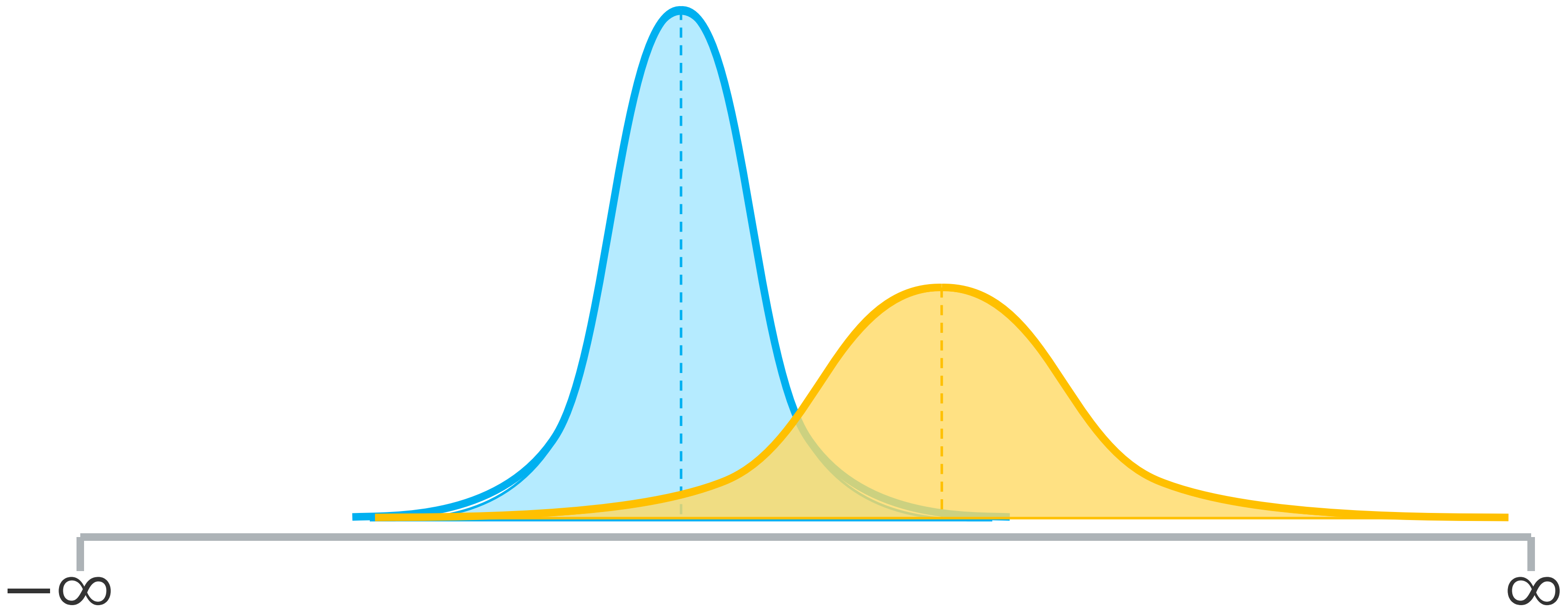
$$\Theta = \{\pi_0 \dots, \mu_0 \dots, \Sigma_0 \dots\}$$

Product of two Gaussians is a Gaussian



$$\boxed{\pi_i N(y, \mu_i, \Sigma_i)} \cdot \pi_j N\left(y, \mu_j, \Sigma_j\right) = \pi_{ij} N(y, \mu_{ij}, \Sigma_{ij})$$

Product of two Gaussians is a Gaussian



$$\boxed{\pi_i N(y, \mu_i, \Sigma_i)} \cdot \boxed{\pi_j N(y, \mu_j, \Sigma_j)} = \pi_{ij} N(y, \mu_{ij}, \Sigma_{ij})$$

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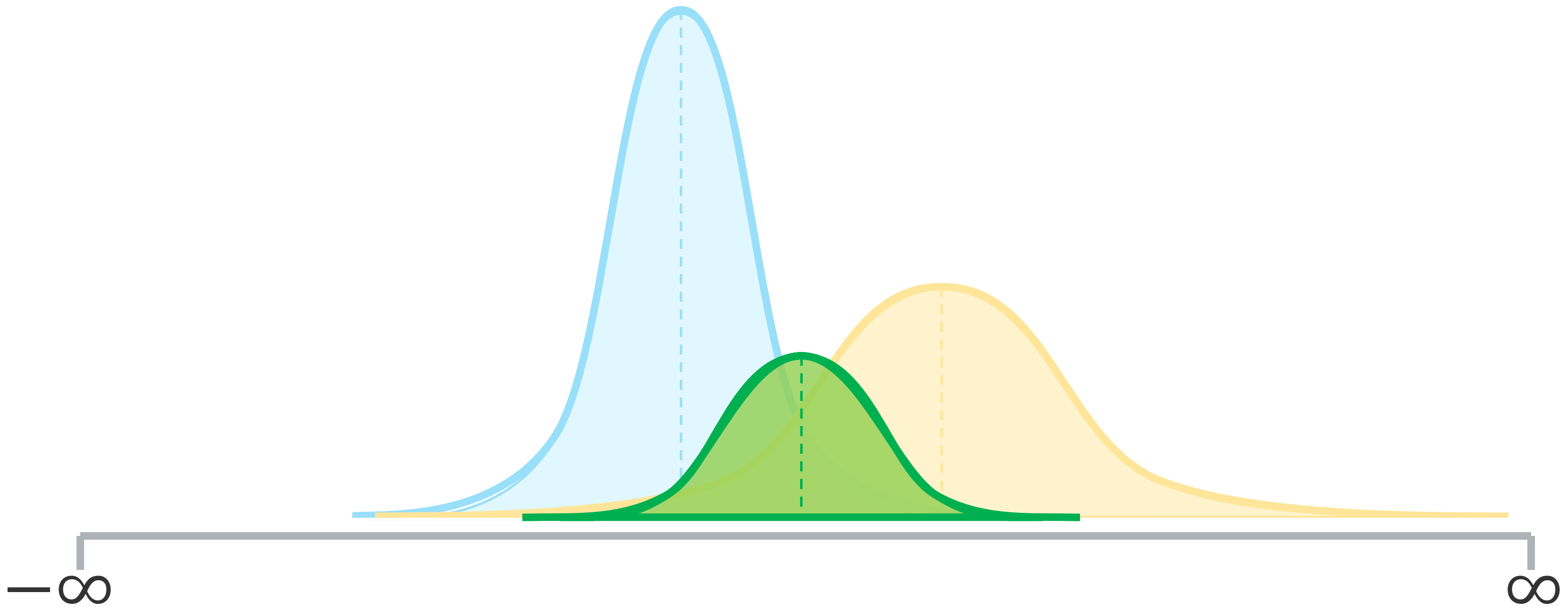
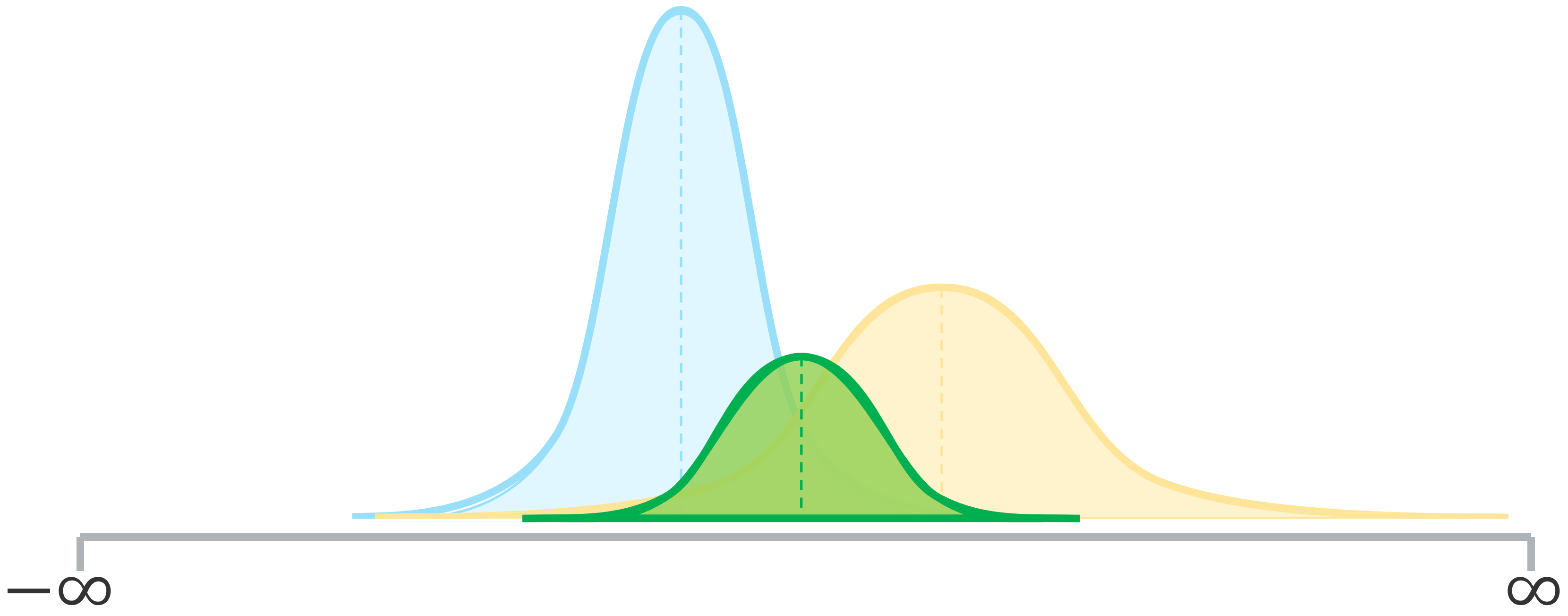


$$\boxed{\pi_i N(y, \mu_i, \Sigma_i)} \cdot \boxed{\pi_j N(y, \mu_j, \Sigma_j)} = \boxed{\pi_{ij} N(y, \mu_{ij}, \Sigma_{ij})}$$

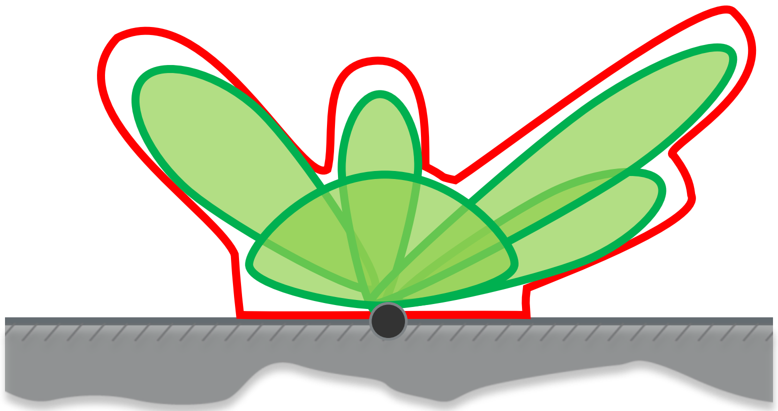
Product of two Gaussians is a Gaussian

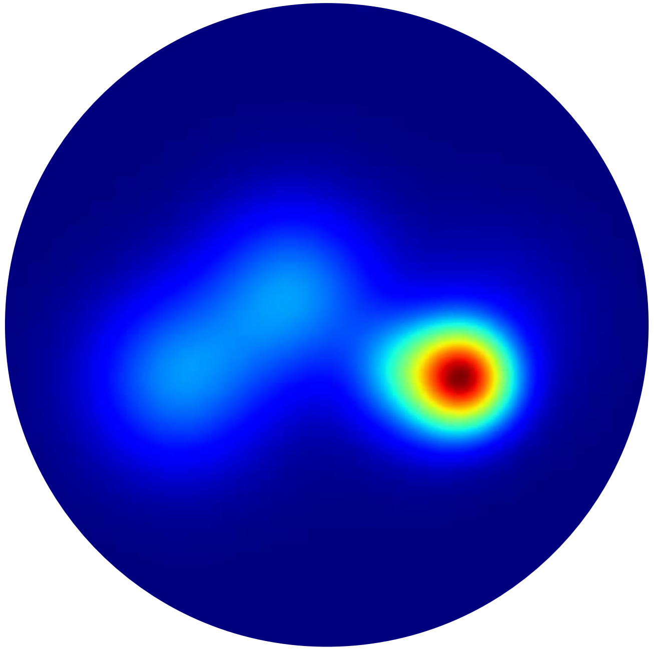


$$\boxed{\pi_i N(y, \mu_i, \Sigma_i)} \cdot \boxed{\pi_j N(y, \mu_j, \Sigma_j)} = \boxed{\pi_{ij} N(y, \mu_{ij}, \Sigma_{ij})}$$

- Full GMM product contains K^2 components

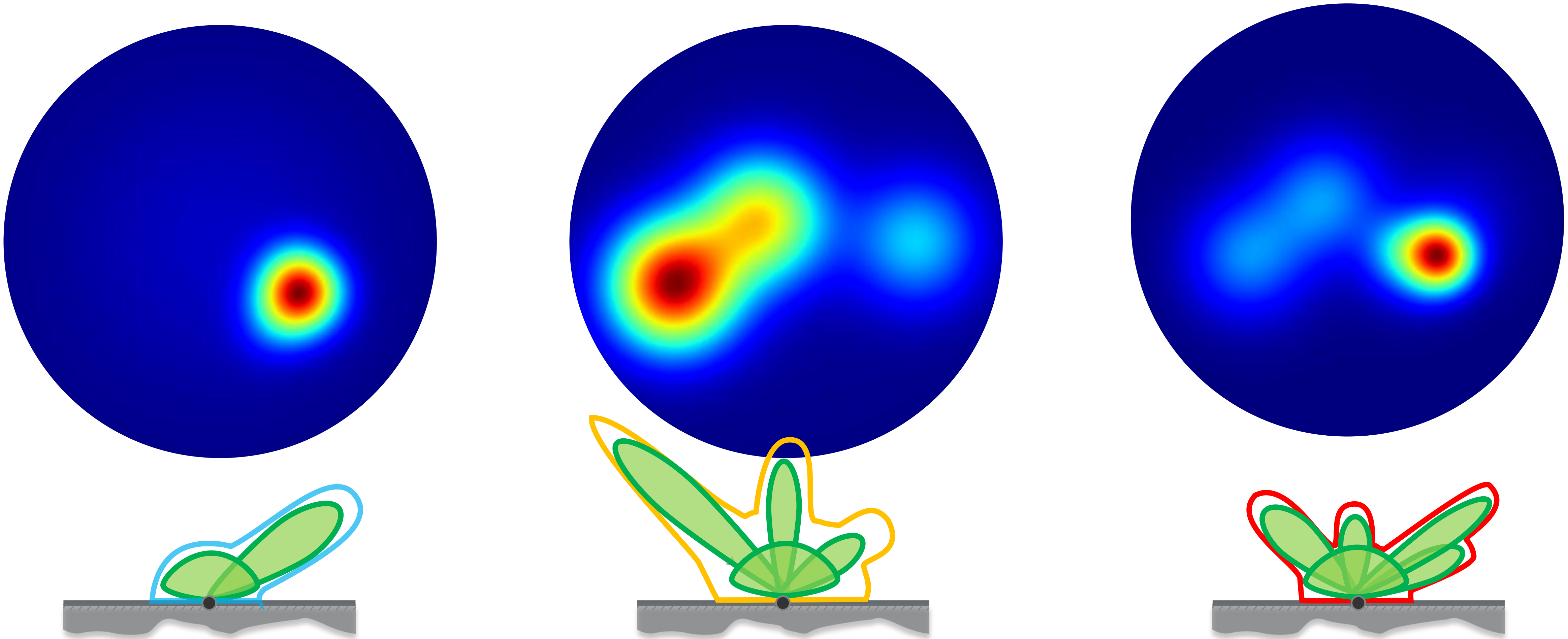
Product GMM Representation





$$p_{f_r} \otimes p_L \approx G_{f_r} \otimes G_L = G_{\otimes}(y, \Theta)$$

Product GMM Representation

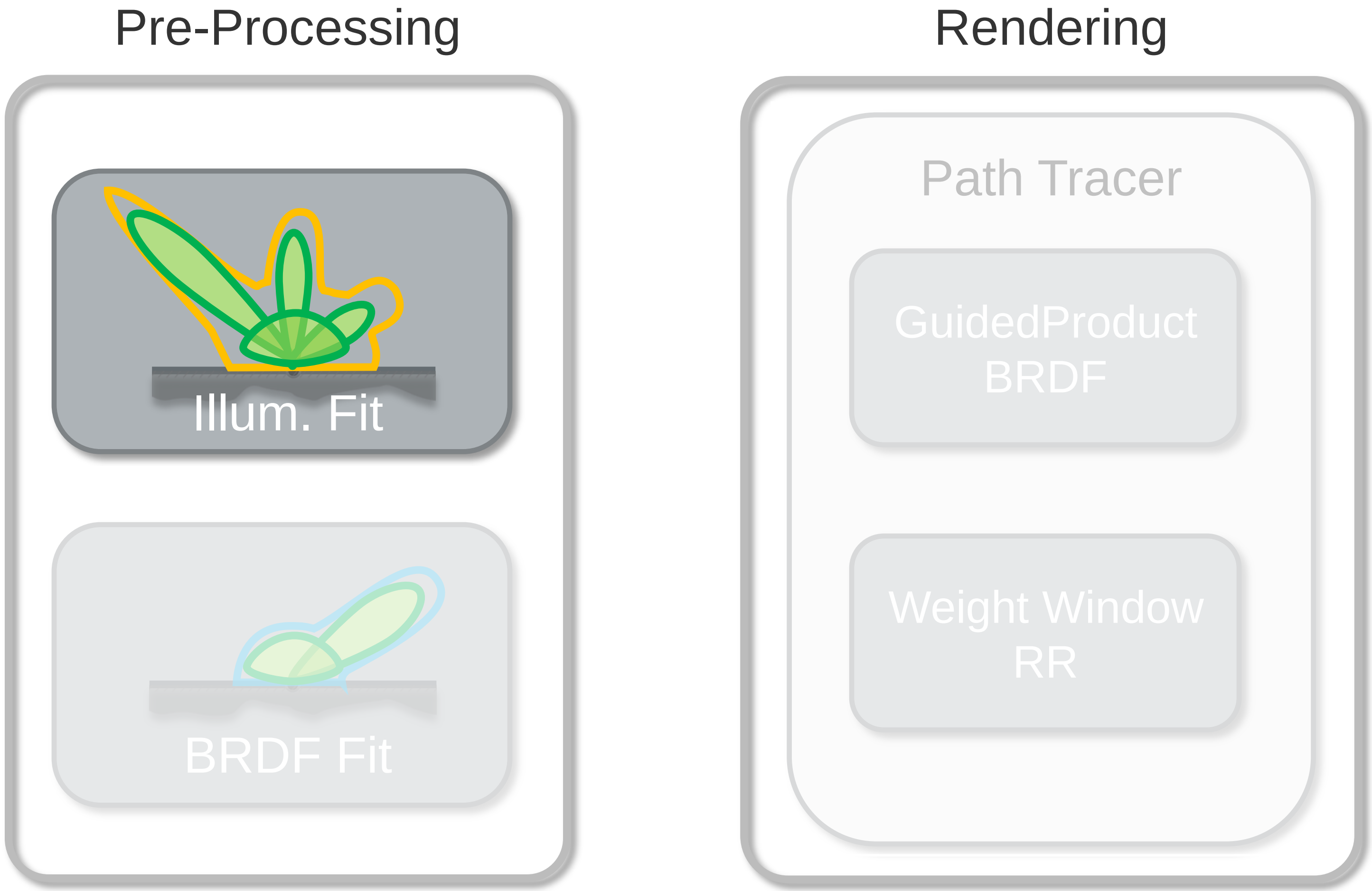


Pipeline

Pre-Processing

Rendering

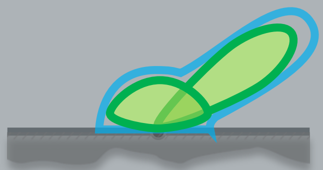
Pipeline


Pre-Processing
Illum. Fit
BRDF Fit
Rendering
Path Tracer
GuidedProduct
BRDF
Weight Window
RR

Pipeline

Pre-Processing

Illum. Fit



BRDF Fit

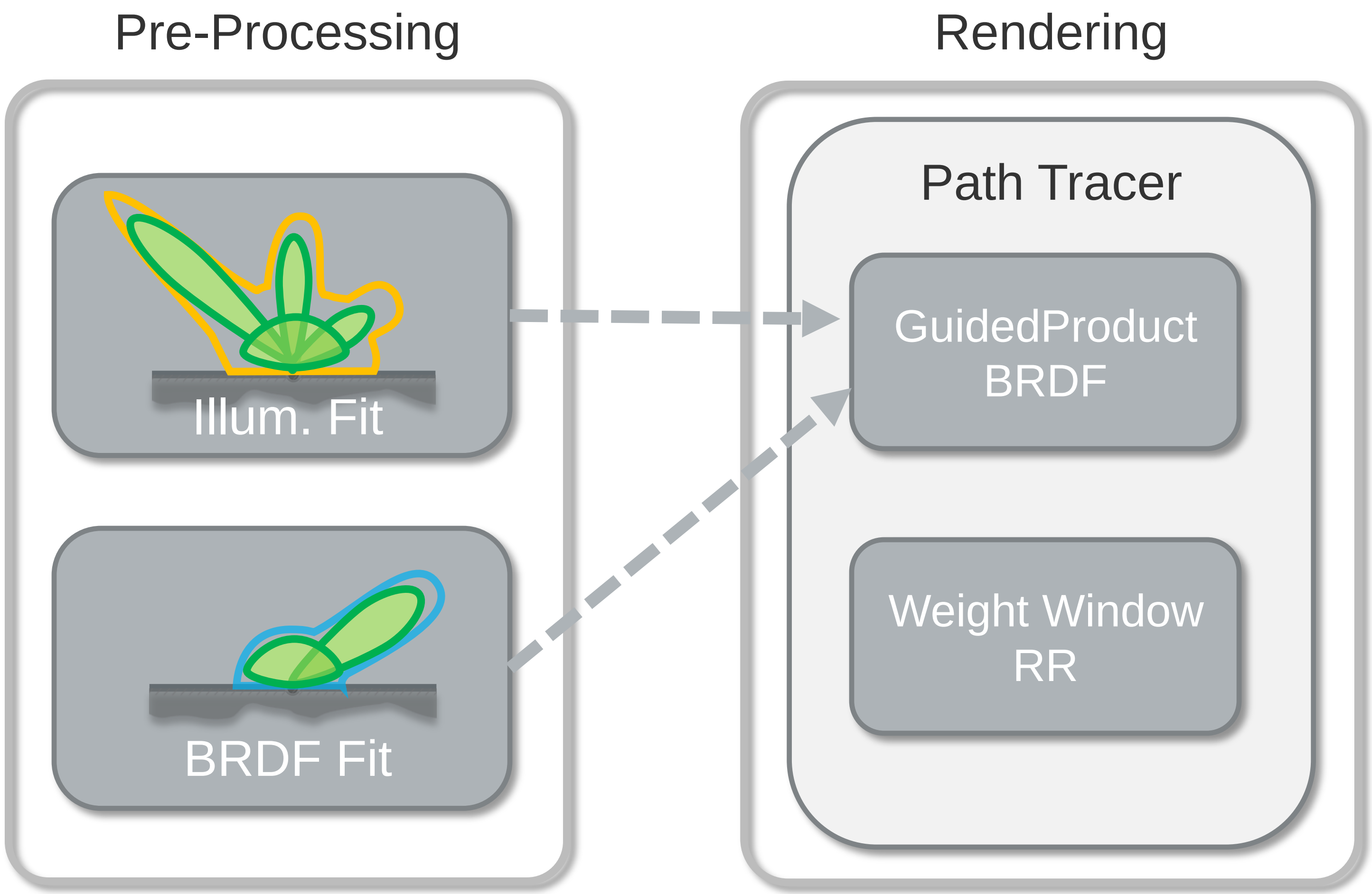
Rendering

Path Tracer

GuidedProduct
BRDF

Weight Window
RR

Pipeline



Pre-Processing
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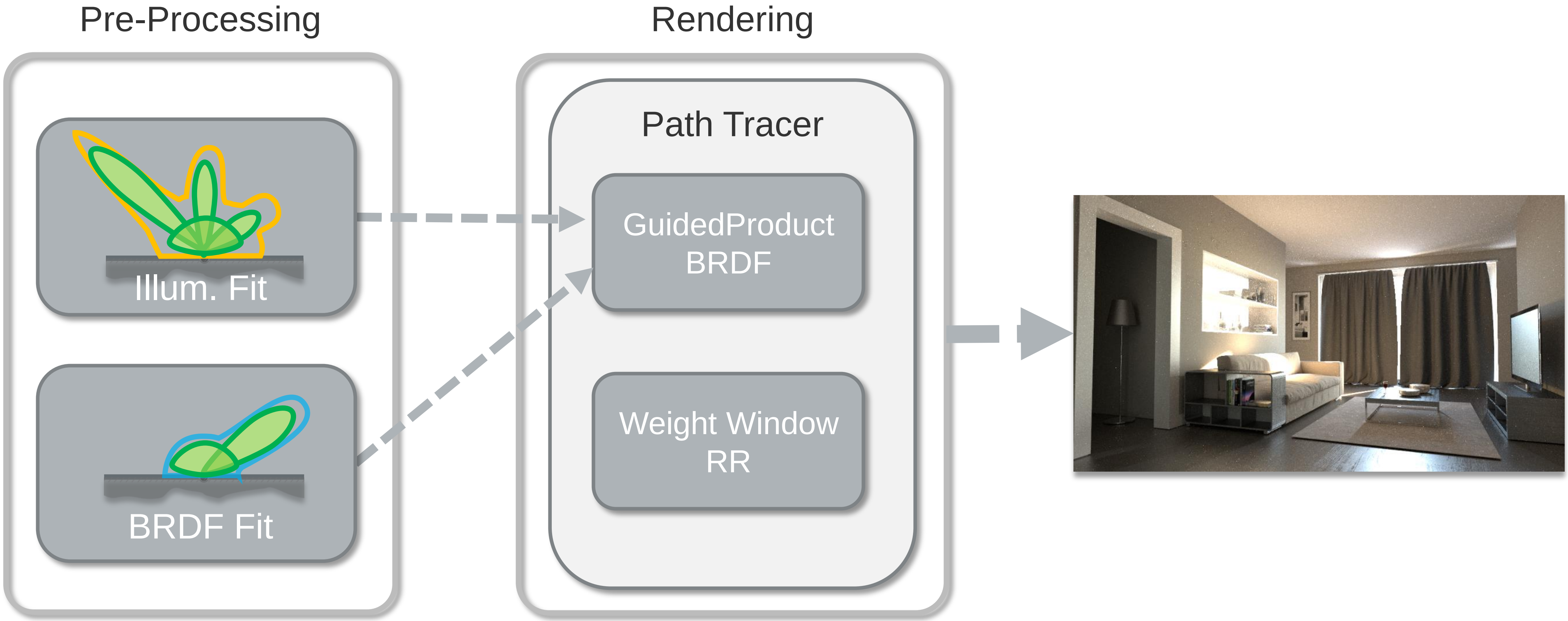

Pre-Processing
Rendering
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BRDF Fit
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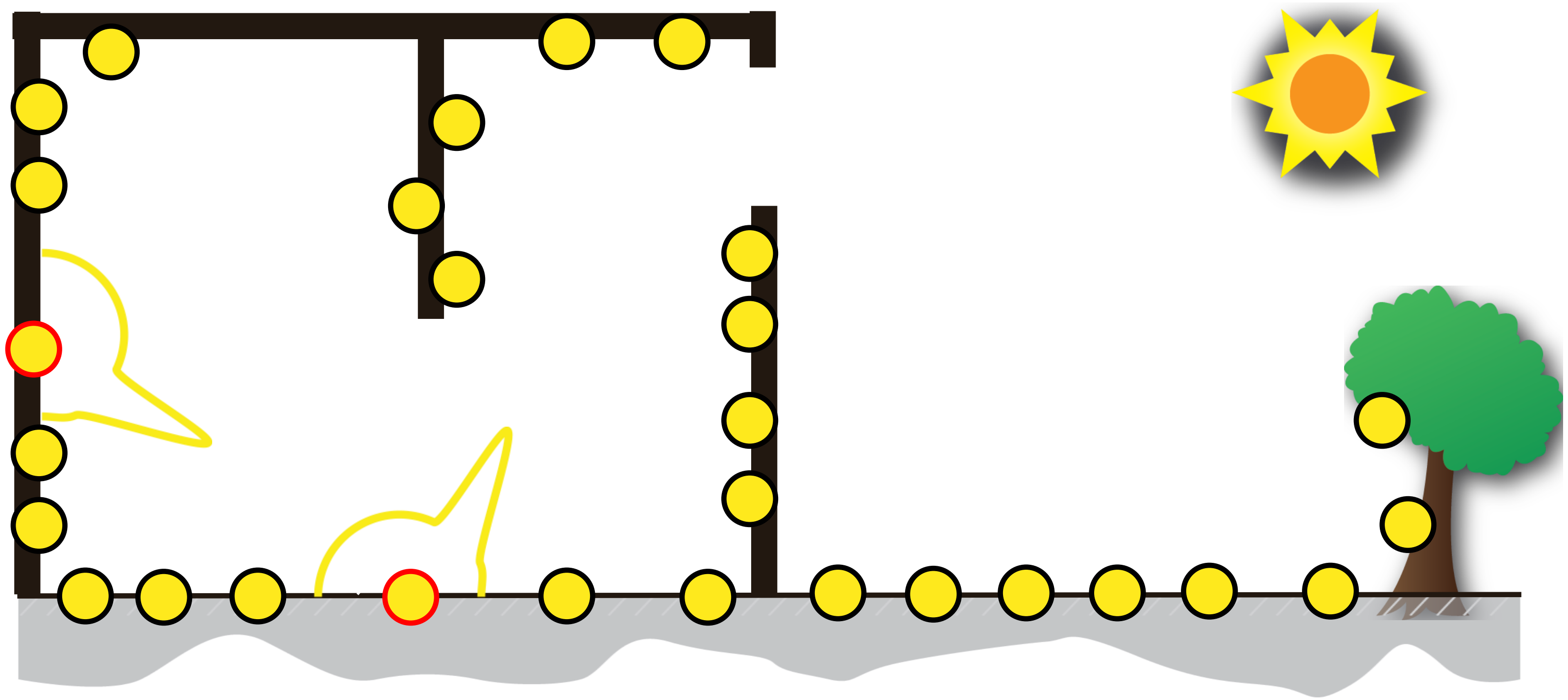
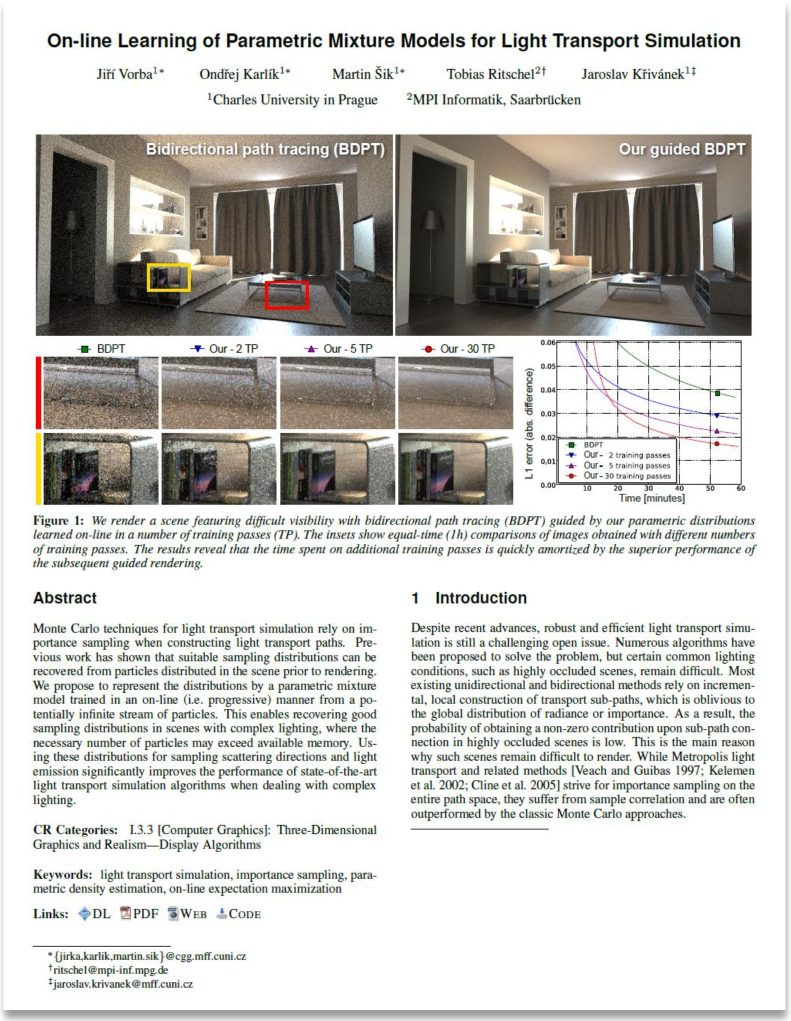
GuidedProduct BRDF
Weight Window RR

Illumination Fit: [Vorba2014]

GMM Illumination caches



[Vorba2014]



On-line Learning of Parametric Mixture Models for Light Transport Simulation

Jiří Vorba[1*] Ondřej Karlík[1*] Martin Šik[1*] Tobias Ritschel[2†] Jaroslav Křivánek[1‡]

[1]Charles University in Prague [2]MPI Informatik, Saarbrücken

Figure 1: *We render a scene featuring difficult visibility with bidirectional path tracing (BDPT) guided by our parametric distributions learned on-line in a number of training passes (TP). The insets show equal-time (1h) comparisons of images obtained with different numbers of training passes. The results reveal that the time spent on additional training passes is quickly amortized by the superior performance of the subsequent guided rendering.*

Abstract

Monte Carlo techniques for light transport simulation rely on importance sampling when constructing light transport paths. Previous work has shown that suitable sampling distributions can be recovered from particles distributed in the scene prior to rendering. We propose to represent the distributions by a parametric mixture model trained in an on-line (i.e. progressive) manner from a potentially infinite stream of particles. This enables recovering good sampling distributions in scenes with complex lighting, where the necessary number of particles may exceed available memory. Using these distributions for sampling scattering directions and light emission significantly improves the performance of state-of-the-art light transport simulation algorithms when dealing with complex lighting.

CR Categories: I.3.3 [Computer Graphics]: Three-Dimensional Graphics and Realism—Display Algorithms

Keywords: light transport simulation, importance sampling, parametric density estimation, on-line expectation maximization

Links: DL PDF WEB CODE

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1 Introduction

Despite recent advances, robust and efficient light transport simulation is still a challenging open issue. Numerous algorithms have been proposed to solve the problem, but certain common lighting conditions, such as highly occluded scenes, remain difficult. Most existing unidirectional and bidirectional methods rely on incremental, local construction of transport sub-paths, which is oblivious to the global distribution of radiance or importance. As a result, the probability of obtaining a non-zero contribution upon sub-path connection in highly occluded scenes is low. This is the main reason why such scenes remain difficult to render. While Metropolis light transport and related methods [Veach and Guibas 1997; Kelemen et al. 2002; Cline et al. 2005] strive for importance sampling on the entire path space, they suffer from sample correlation and are often outperformed by the classic Monte Carlo approaches.

BRDF Fitting and Caching

Fitting BRDF GMM

Weighted EM

- Weighted MAP EM [Vorba2014]
- Sample BRDF (N=512)
- $w_i = \dfrac{f_r(x,\omega_i,\omega_o)}{p(\omega_o)}$
- Init components using K BRDF samples (QMC sampler)

CERES

- Non-linear optimization
- Init with weighted EM
- Objective function:

$$\sum_{i}^{N}\left[1 - \frac{\widehat{f_r}(\omega_i)}{G(y|\Theta)}\right]^2$$

Fitting BRDF GMM

Weighted EM

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CERES

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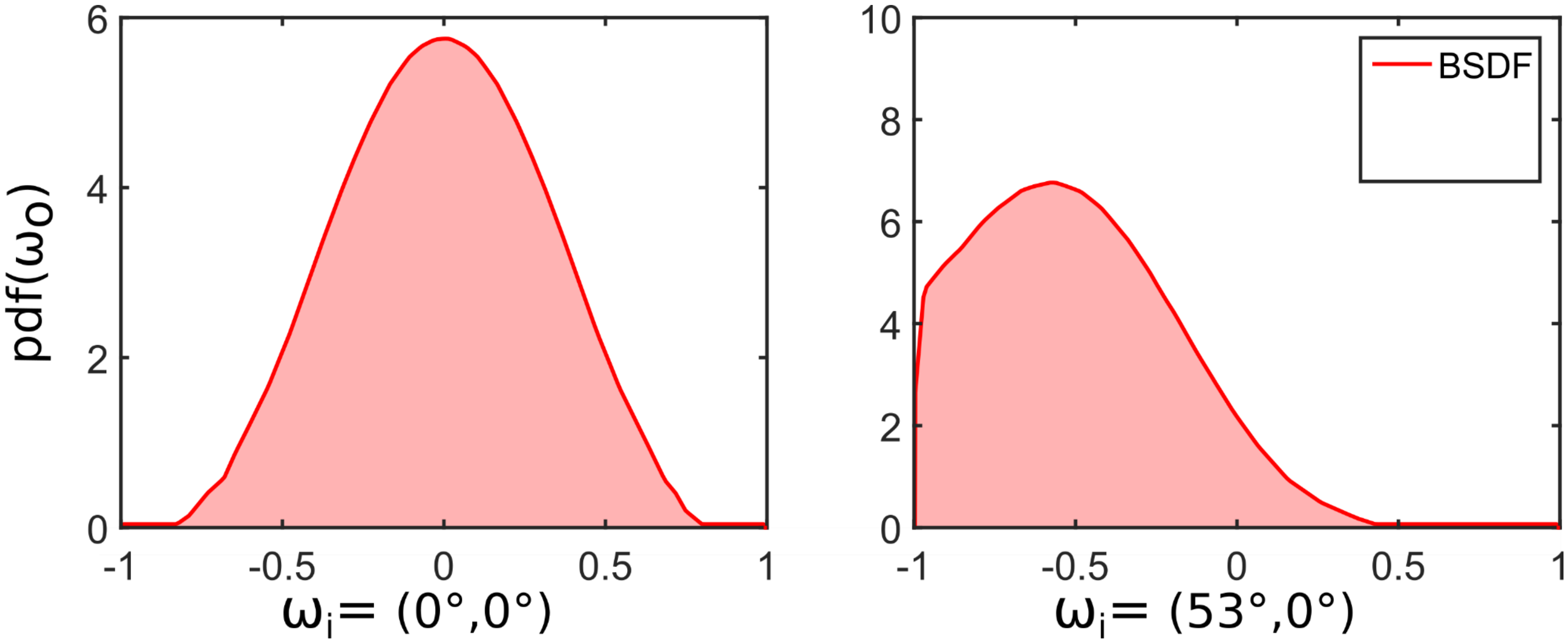
$$\sum_{i}^{N}\left[1-\frac{\widehat{f_r}(\omega_i)}{G(y|\Theta)}\right]^2$$

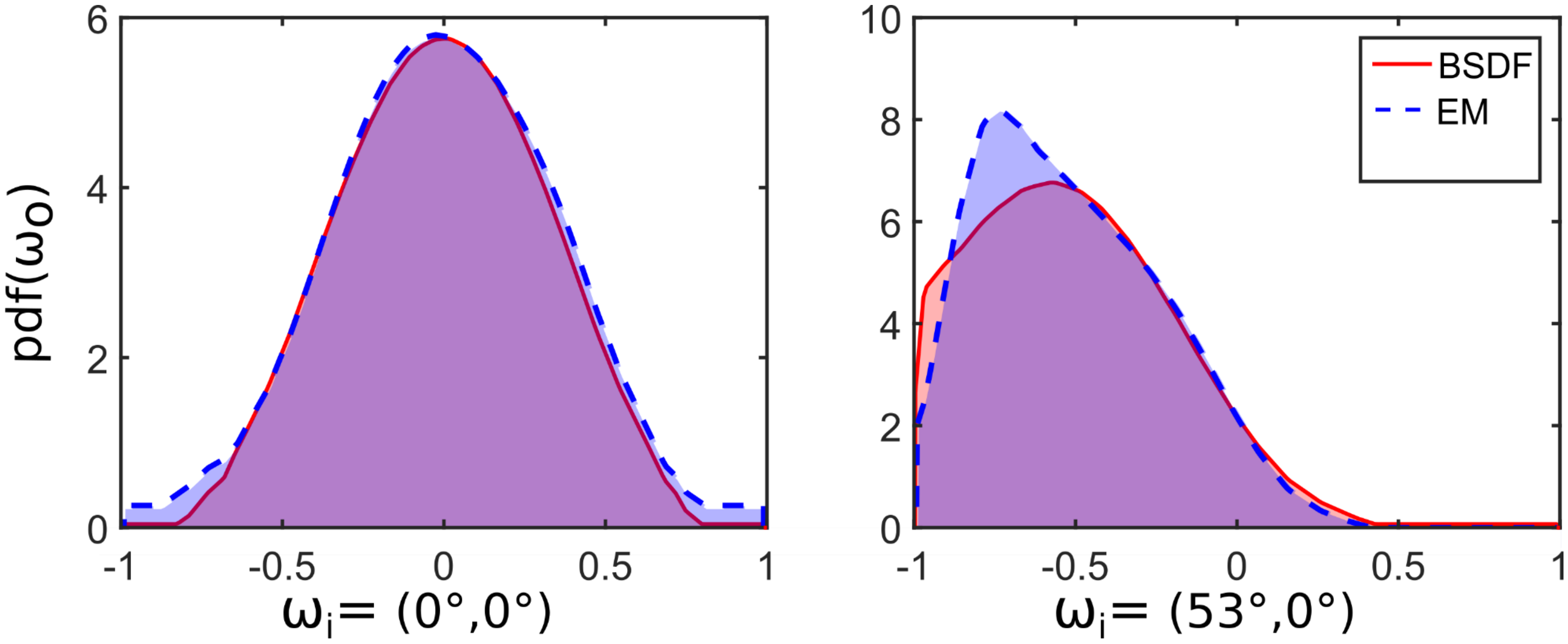
wEM vs CERES



rough conductor $\alpha = 0.3$

$K = 8$

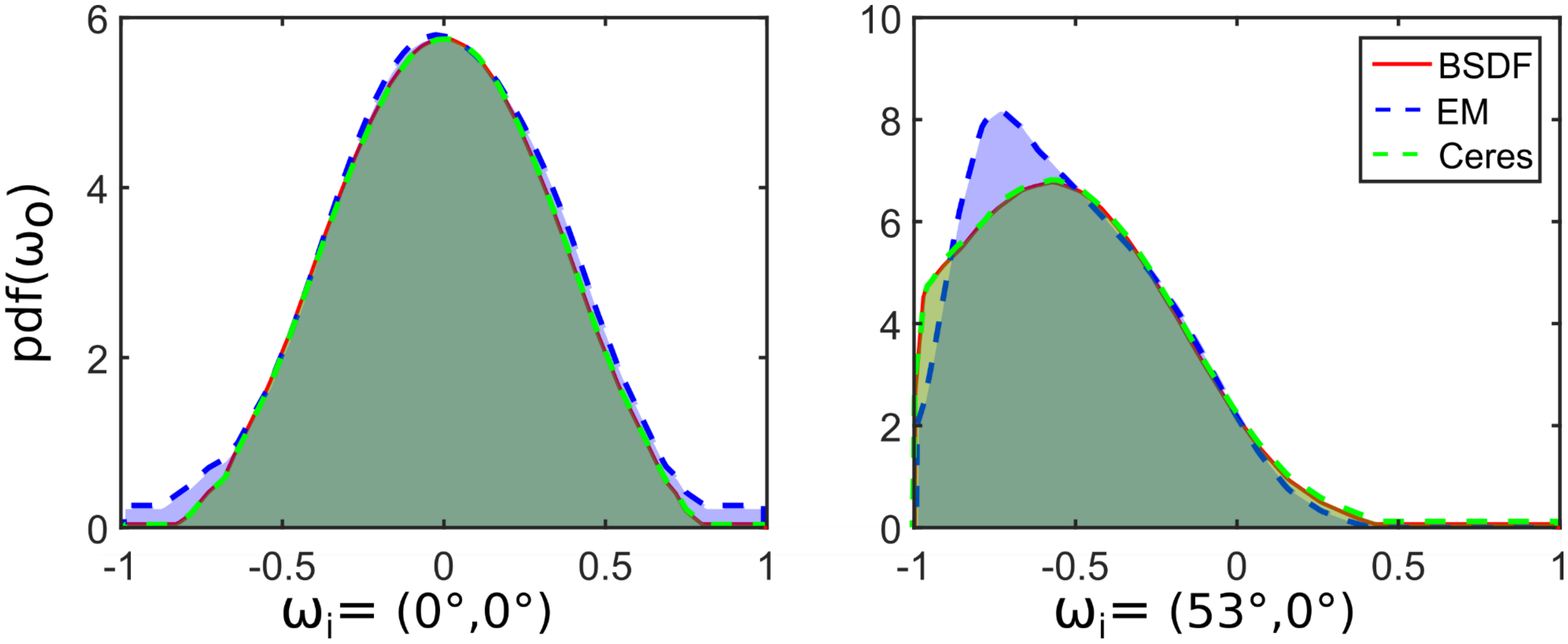
wEM vs CERES



rough conductor $\alpha = 0.3$

$K = 8$

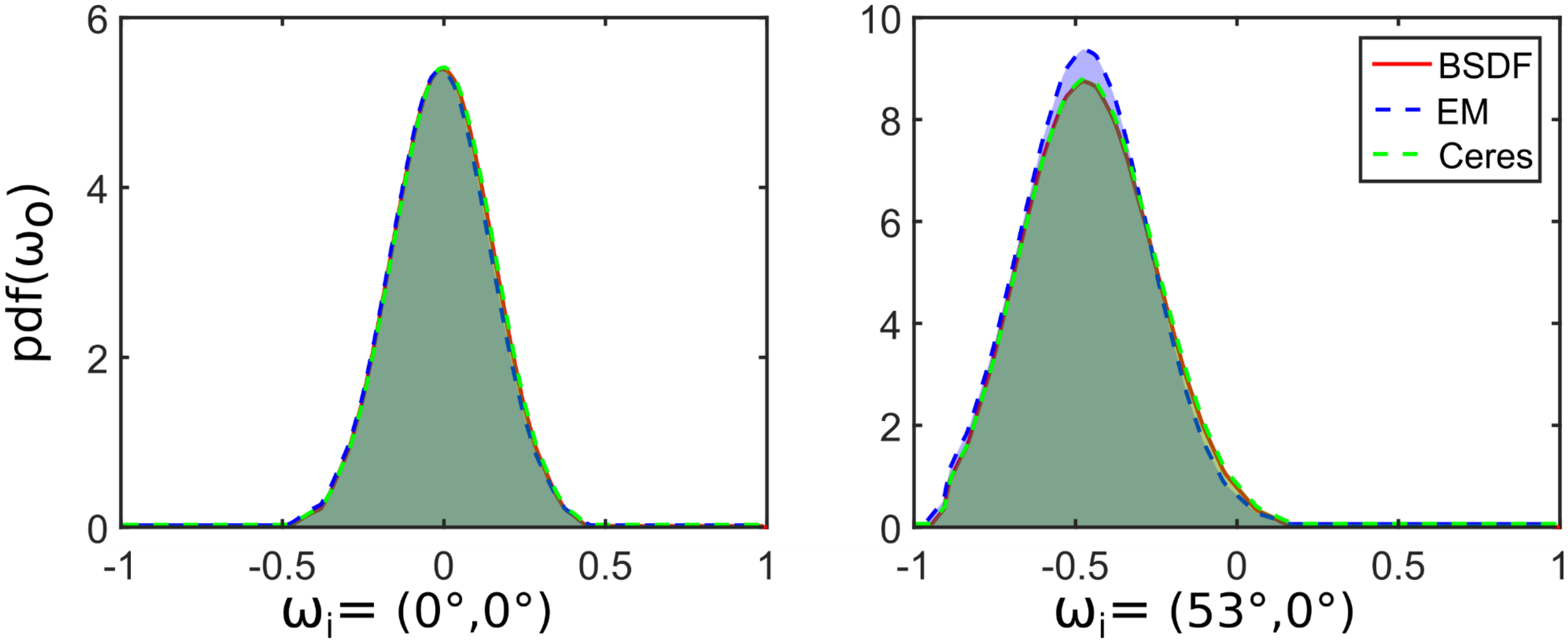
wEM vs CERES



rough conductor $\alpha = 0.3$

$K = 8$

wEM vs CERES

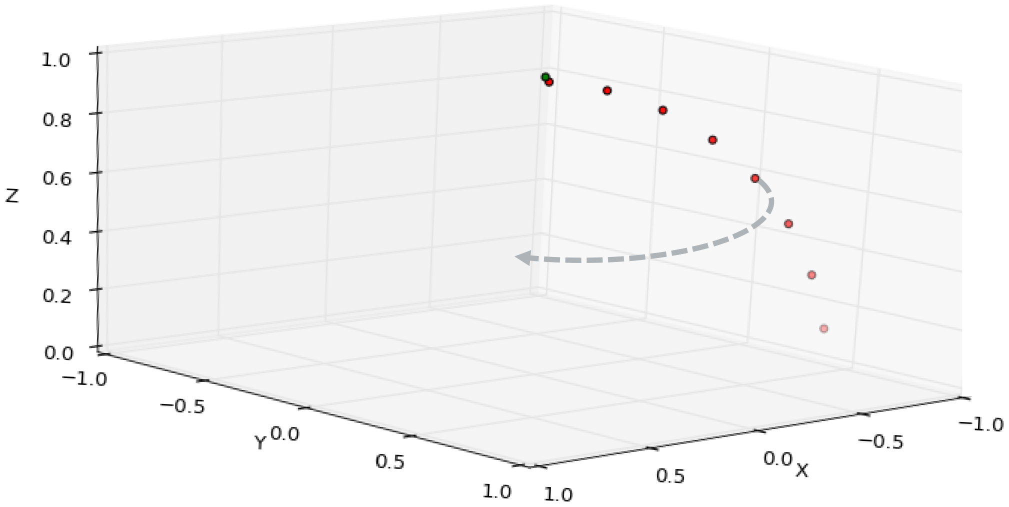


rough conductor $\alpha = 0.15$

$K = 8$

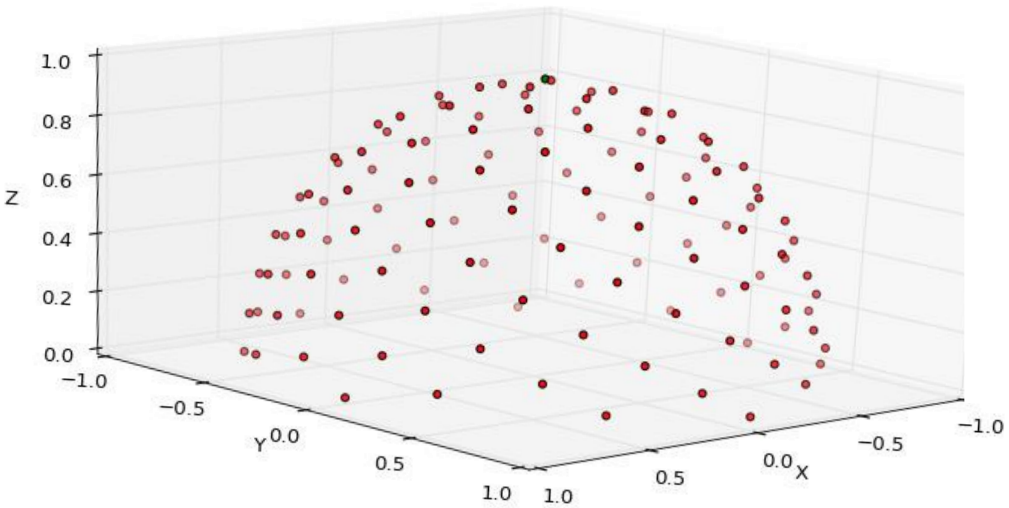
Caching

- Isotropic



- 512 different elevation angles

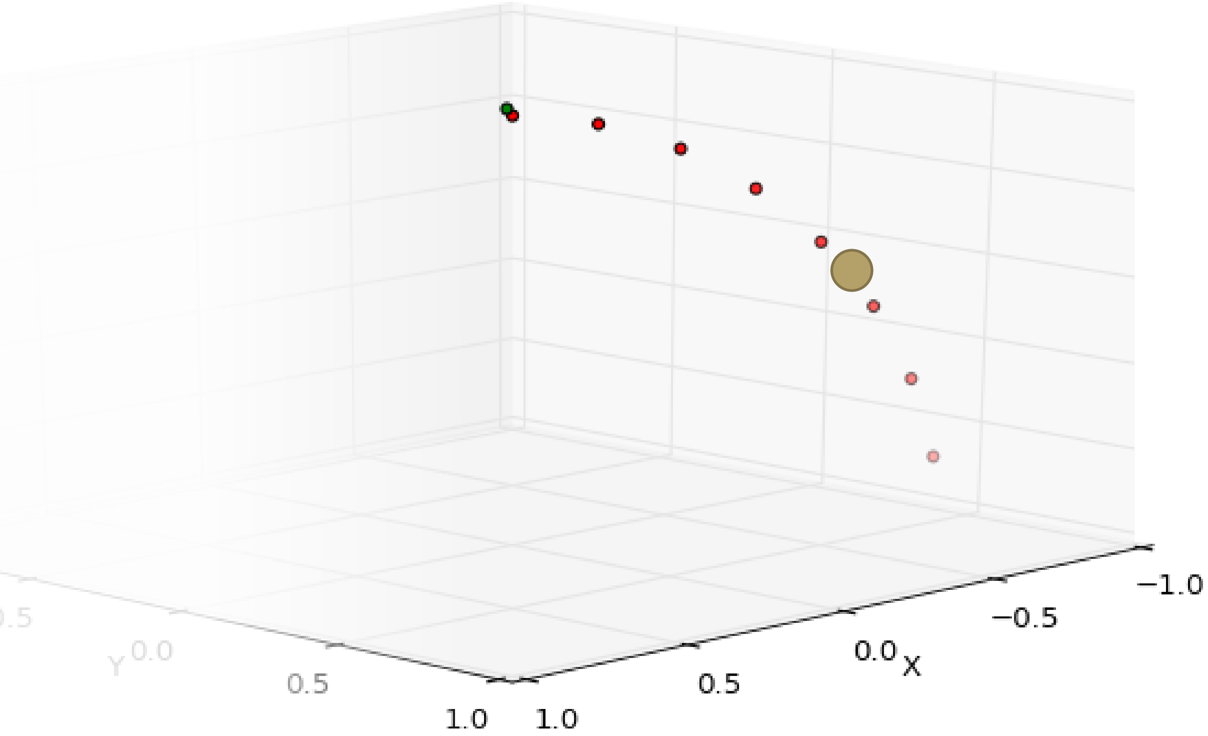
- Anisotropic

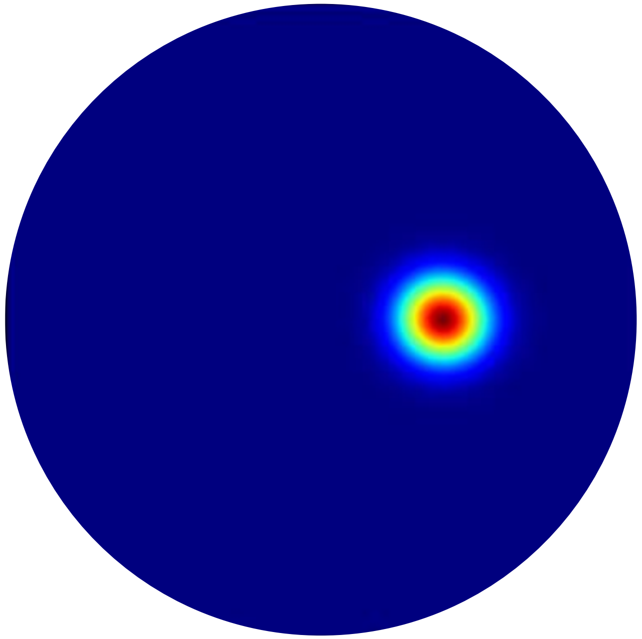


- 4096 spherical Fibonacci points [KISS15]

Caching

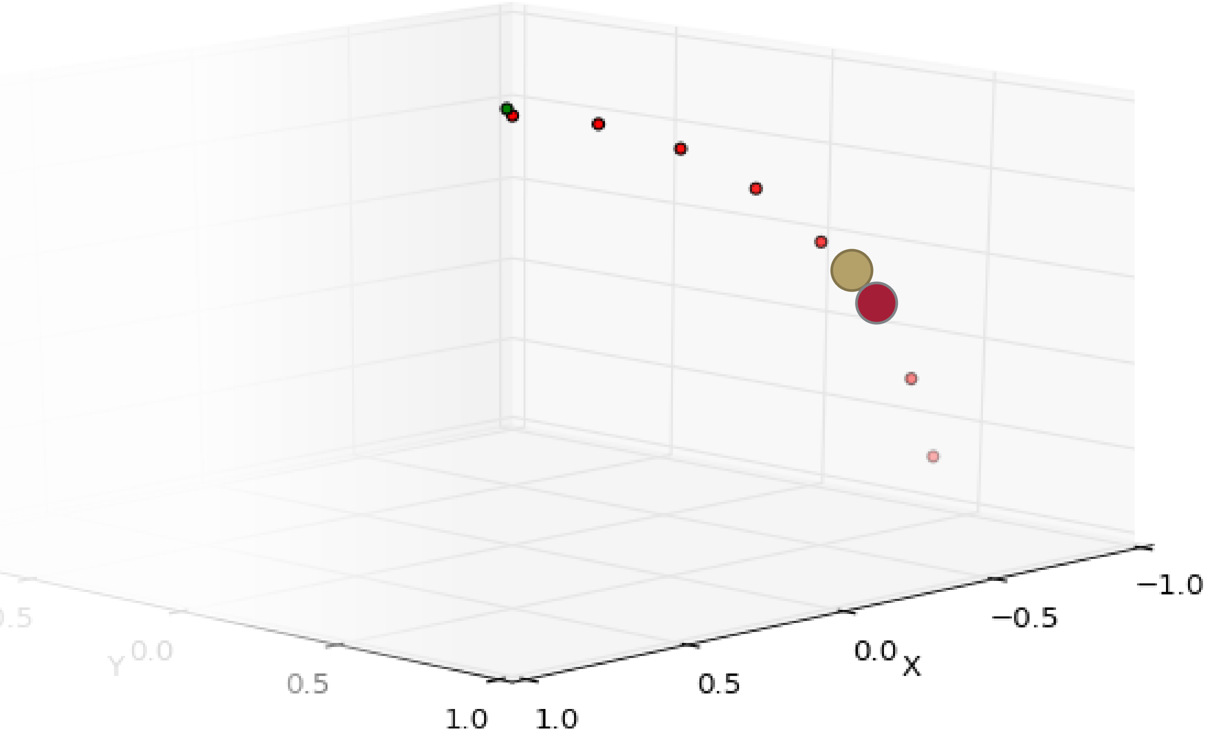
- Isotropic

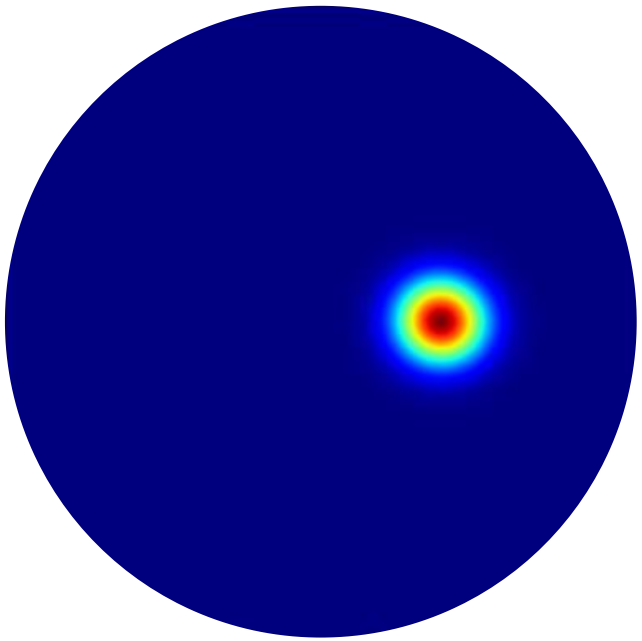




Caching

- Isotropic





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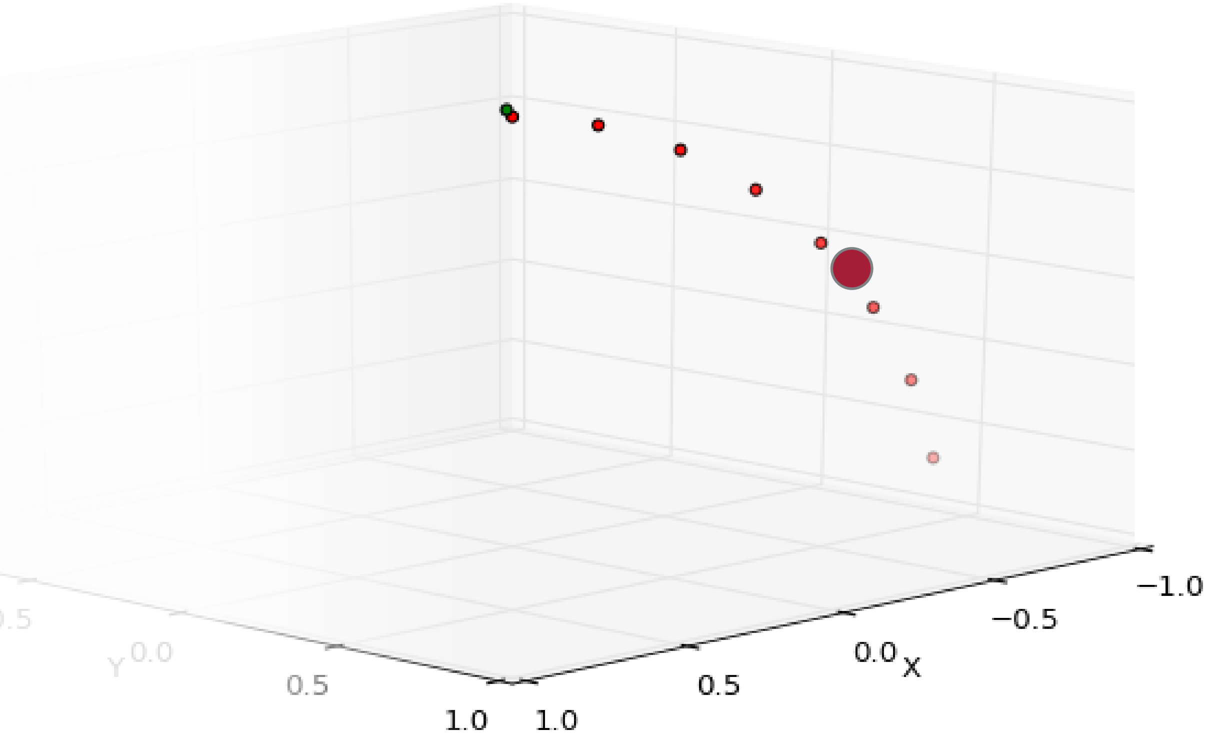

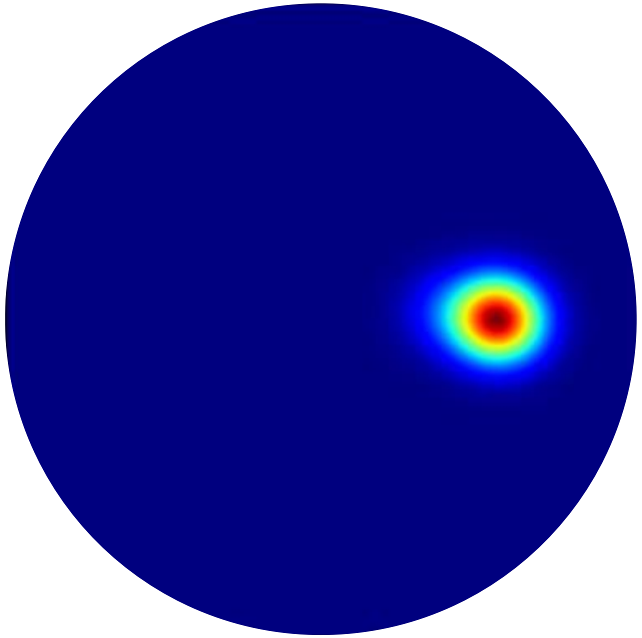

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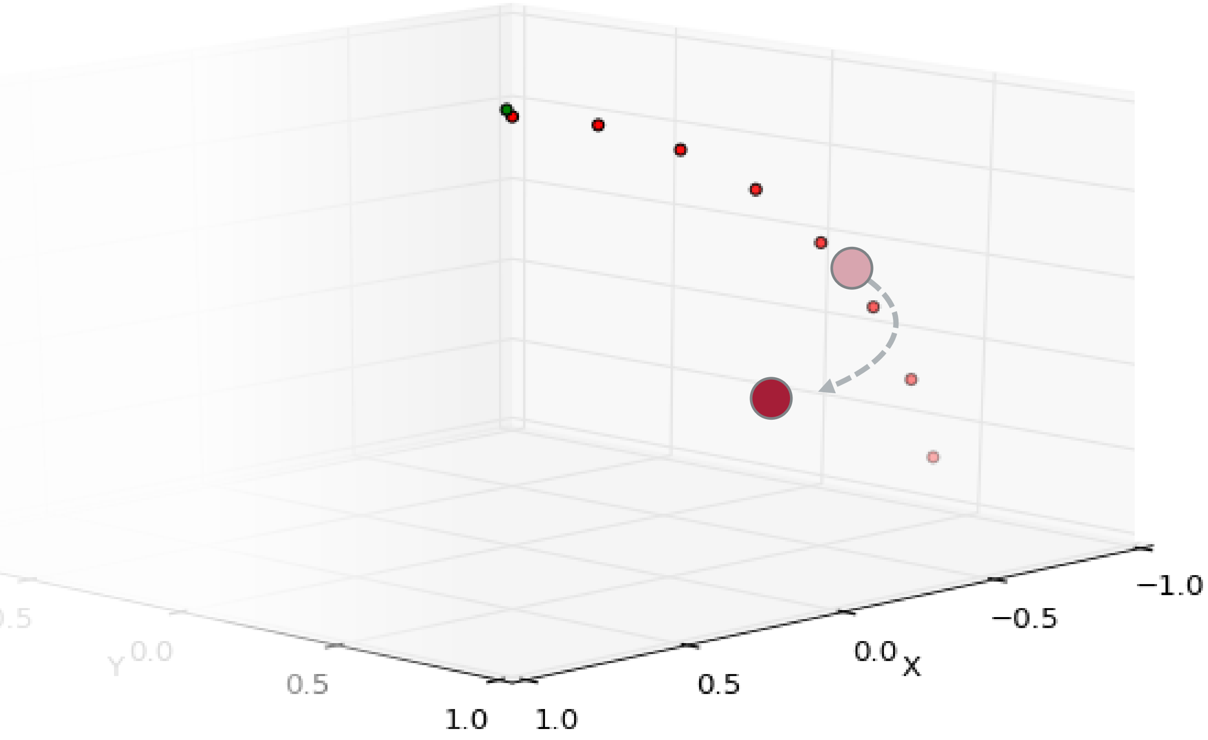
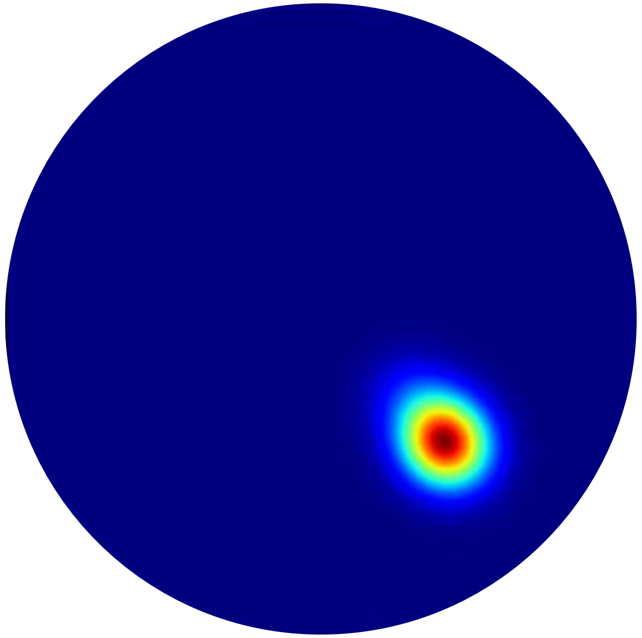
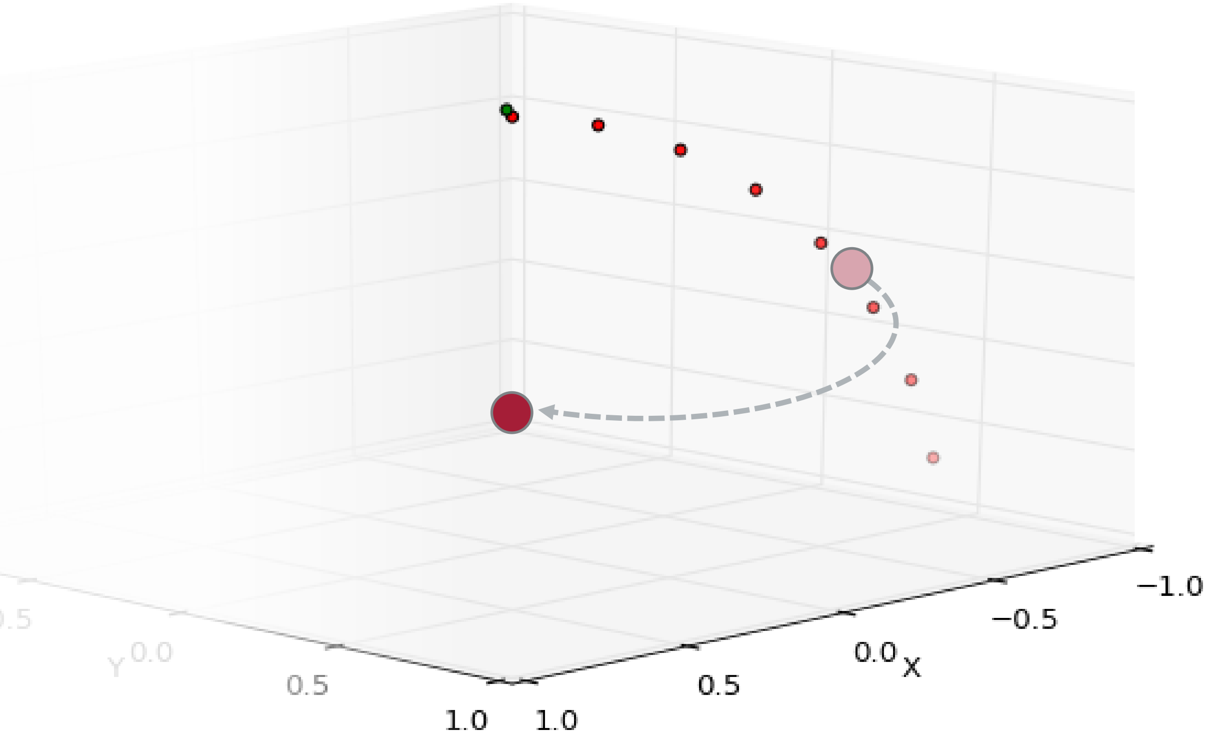
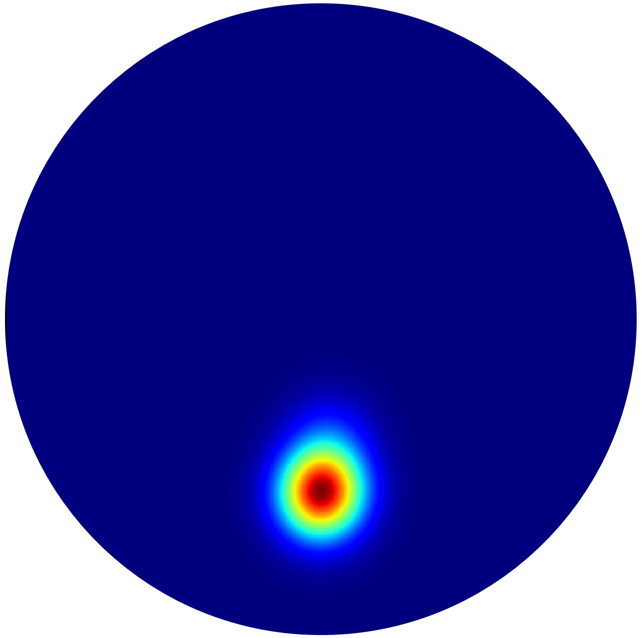




Caching

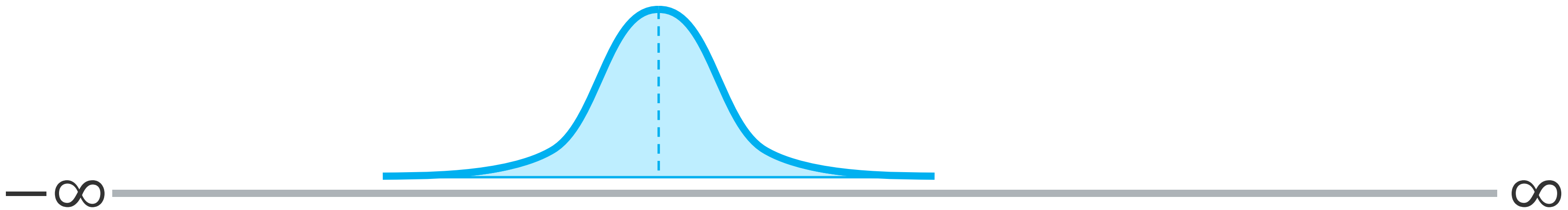
- Isotropic





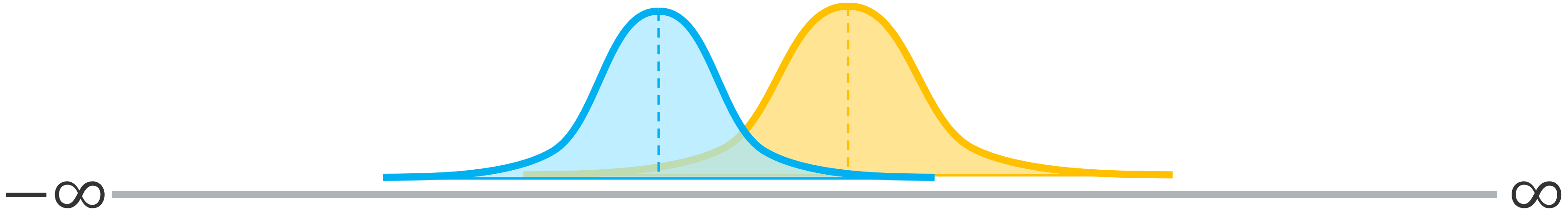
GMM Component Reduction

Component Reduction



$$c_{i,j} = d_{KL}(\{\boxed{(\pi_i, \mu_i, \Sigma_i)}, (\pi_j, \mu_j, \Sigma_j)\}, (\pi_{ij}, \mu_{ij}, \Sigma_{ij}))$$

Component Reduction



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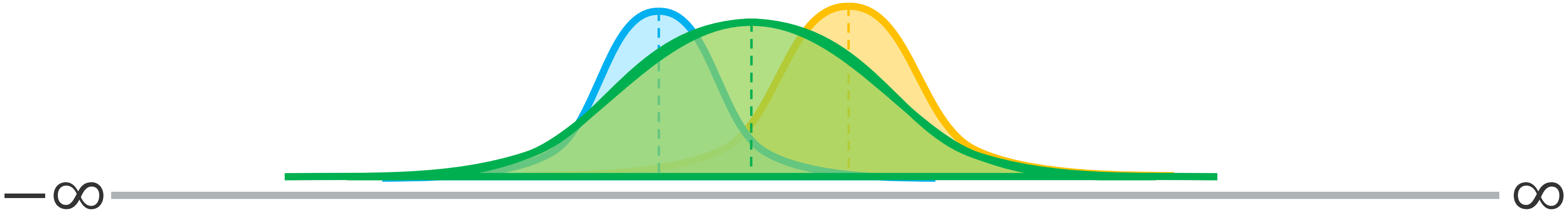
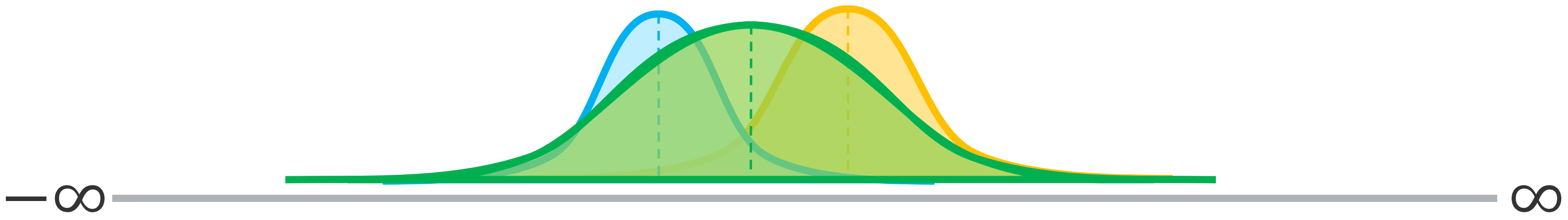


$$c_{i,j} = d_{KL}\left(\left\{\boxed{(\pi_i, \mu_i, \Sigma_i)}, \boxed{(\pi_j, \mu_j, \Sigma_j)}\right\}, \boxed{(\pi_{ij}, \mu_{ij}, \Sigma_{ij})}\right)$$

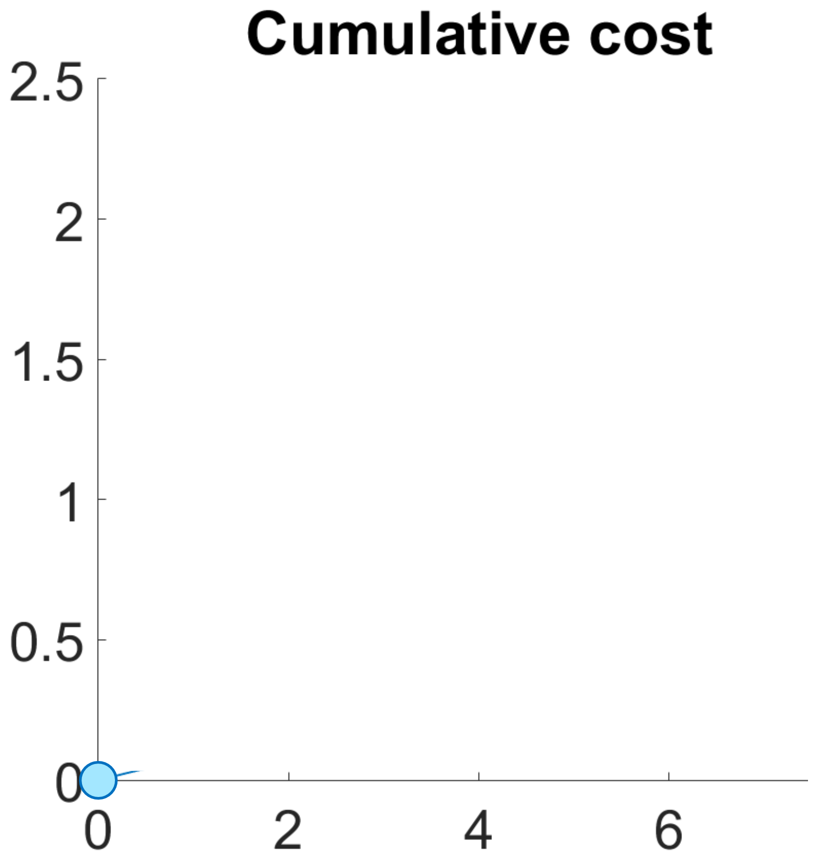
Component Reduction

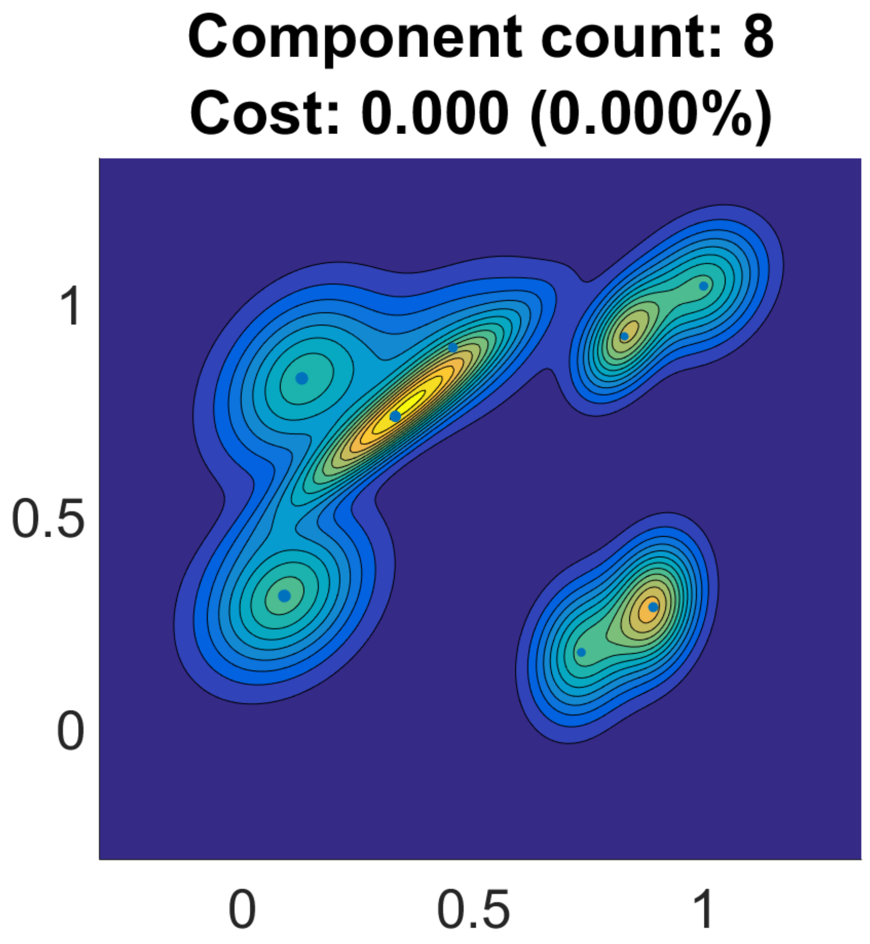


$$c_{i,j} = d_{KL}(\{\boxed{(\pi_i, \mu_i, \Sigma_i)}, \boxed{(\pi_j, \mu_j, \Sigma_j)}\}, \boxed{(\pi_{ij}, \mu_{ij}, \Sigma_{ij})})$$

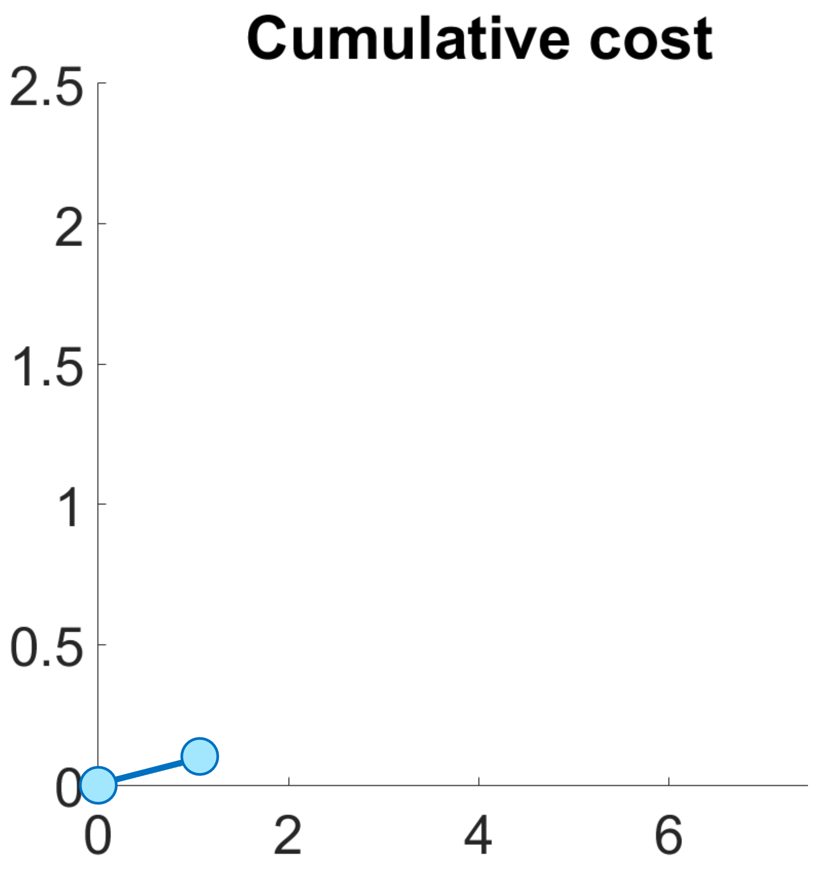
- Adapted from [Runnals2007], used also in [Jacob2011]
- Kullback-Leibler discrimination: d_{KL}

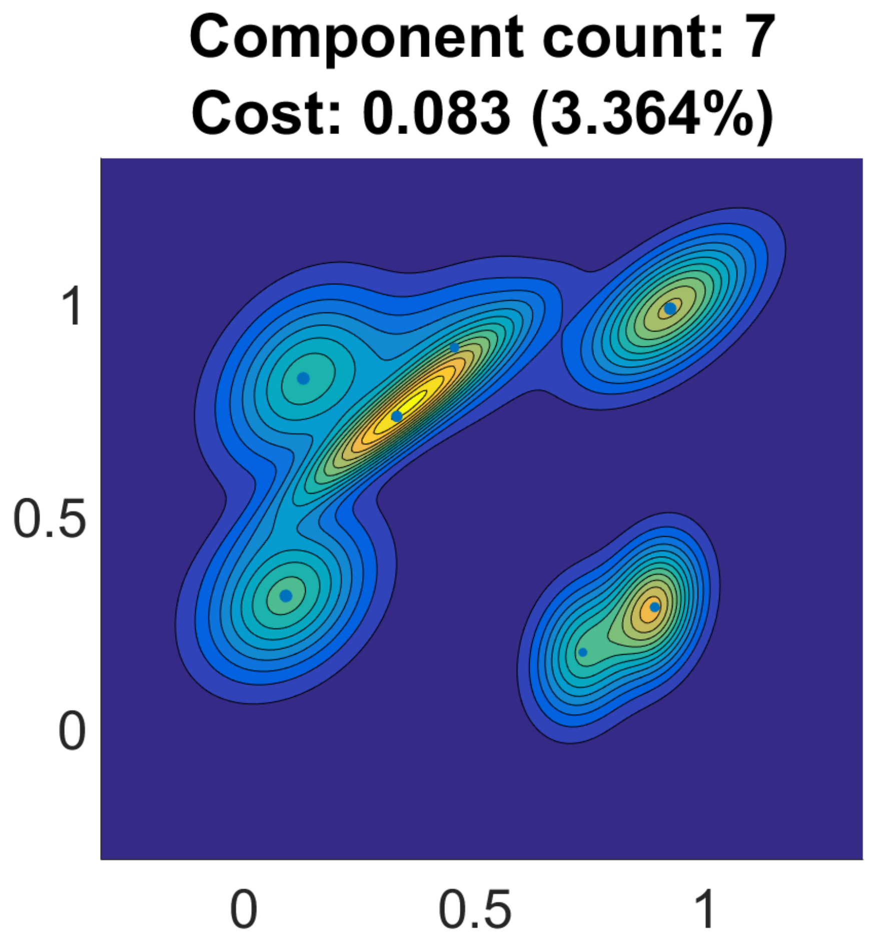
Component Reduction



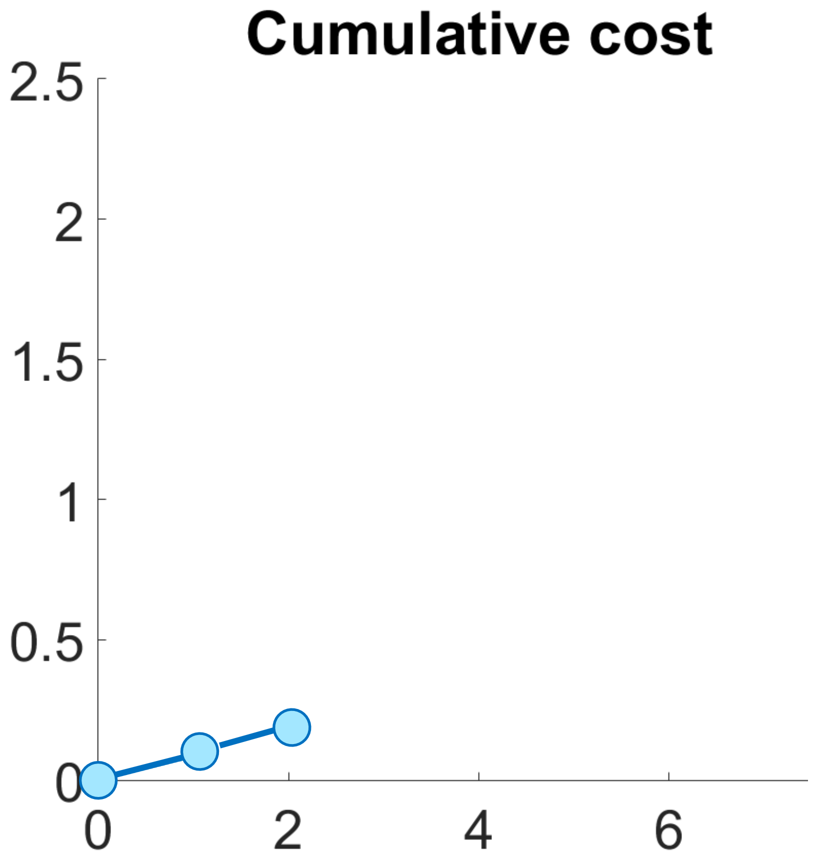


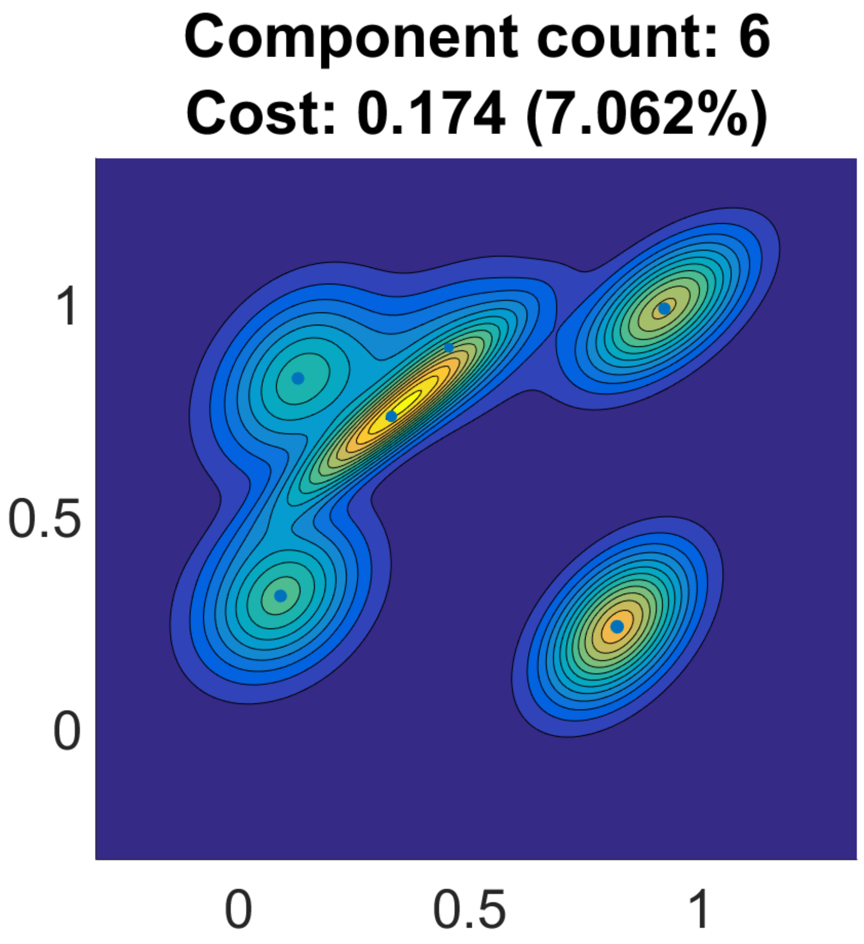
Component Reduction



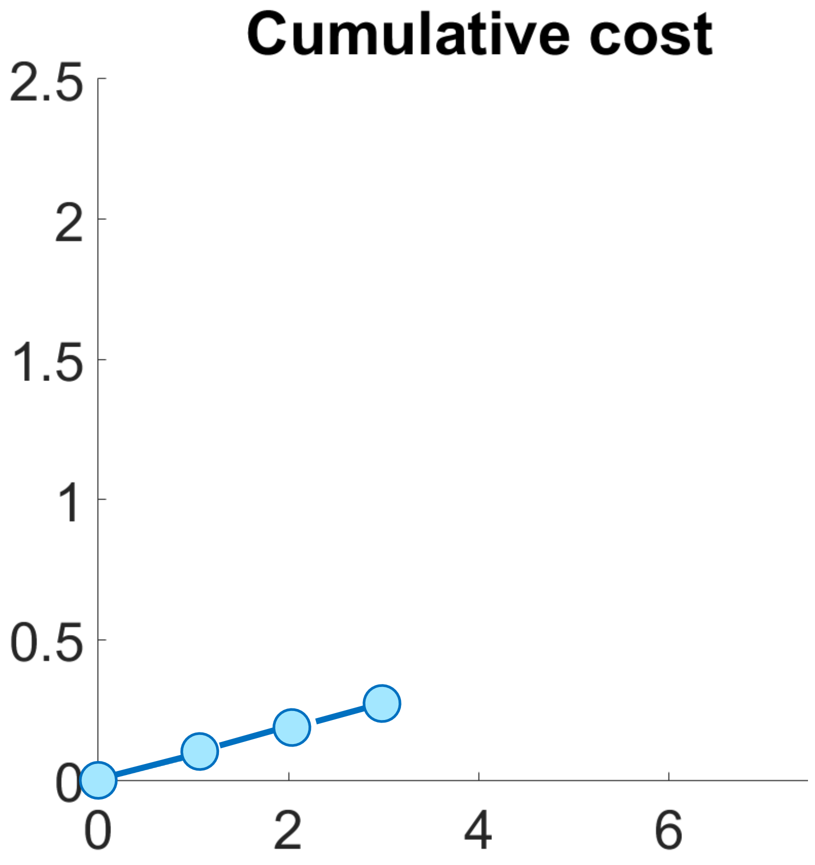


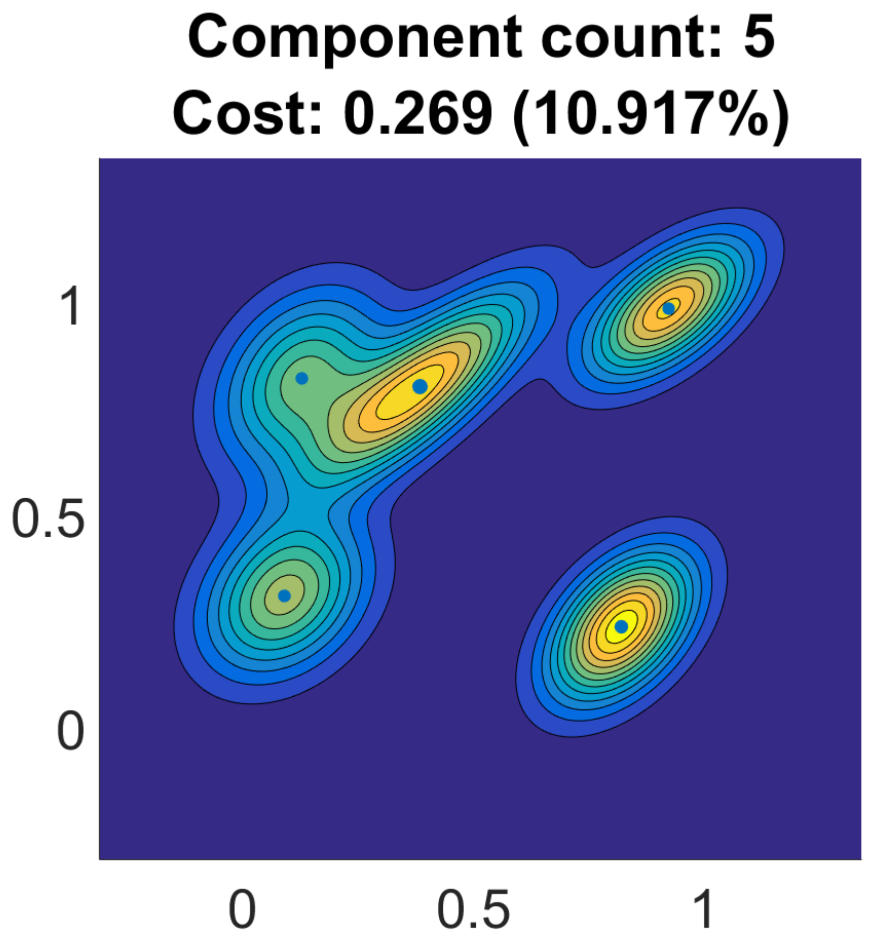
Component Reduction





Component Reduction





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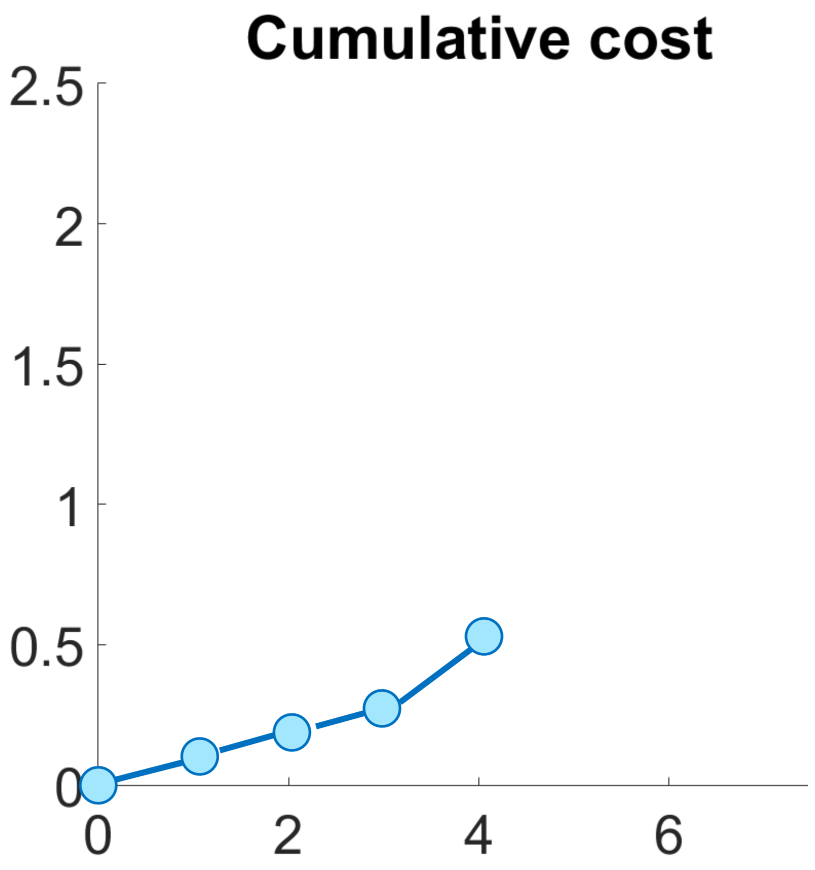

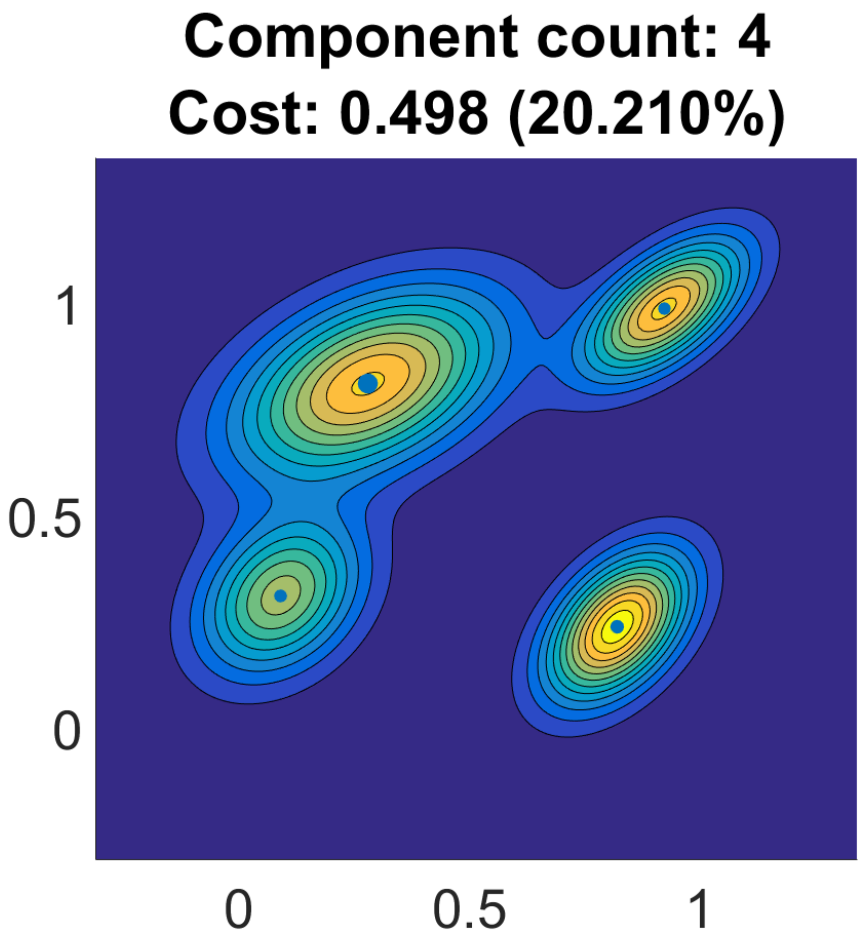

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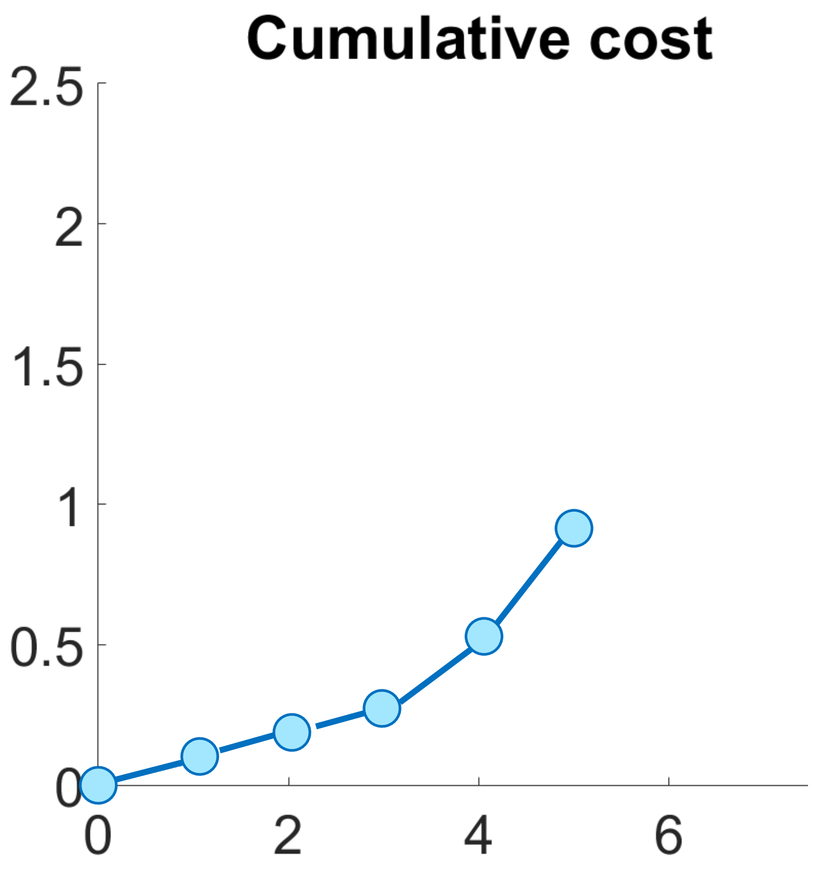

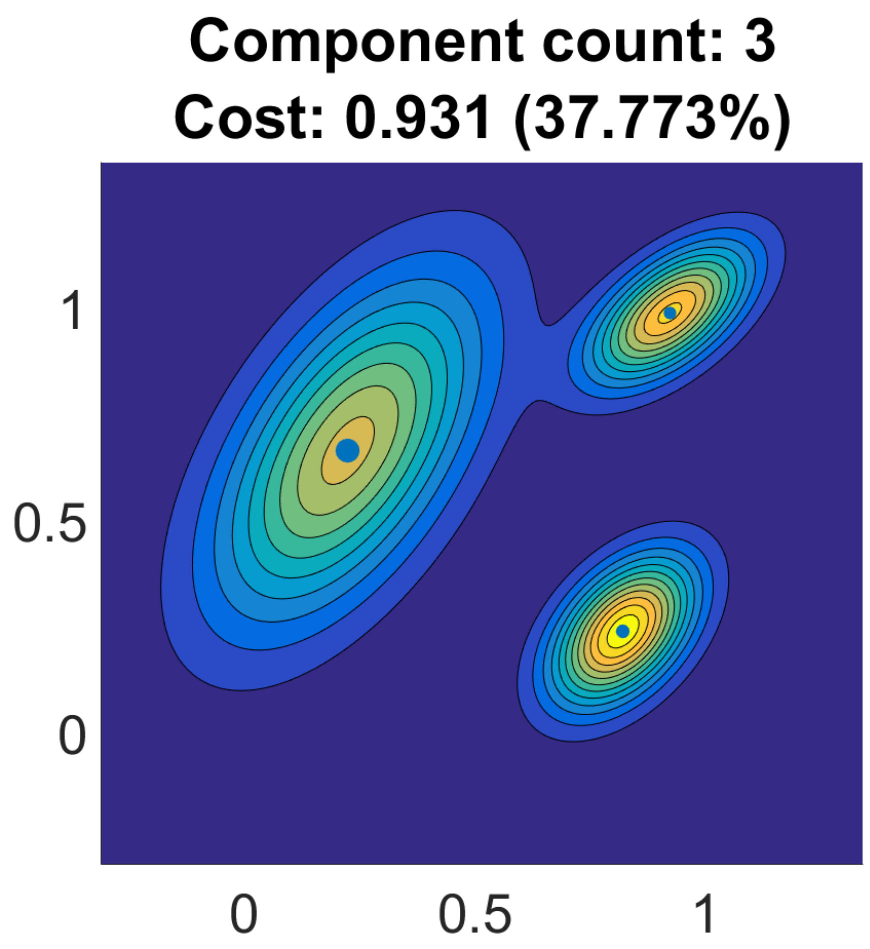

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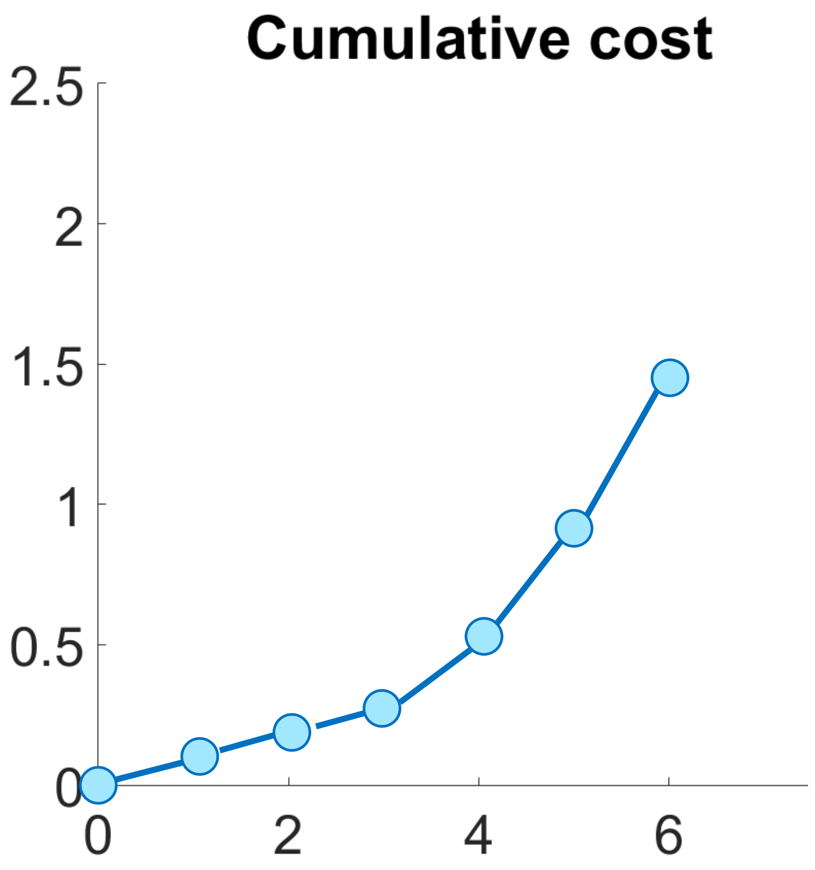
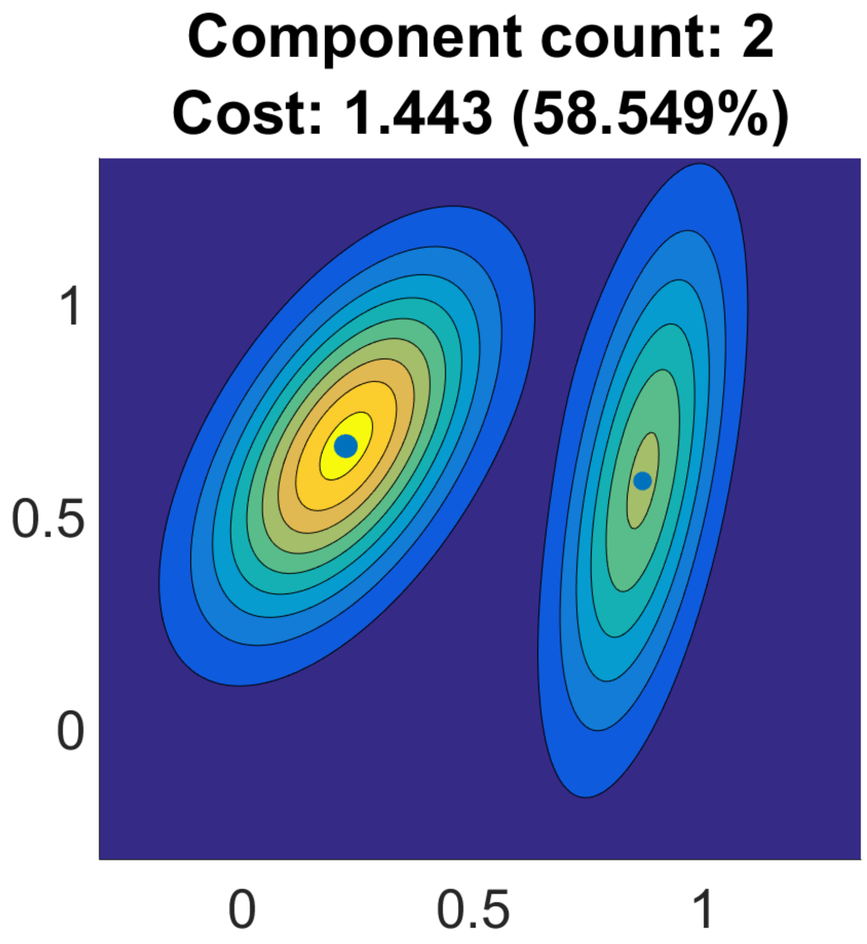
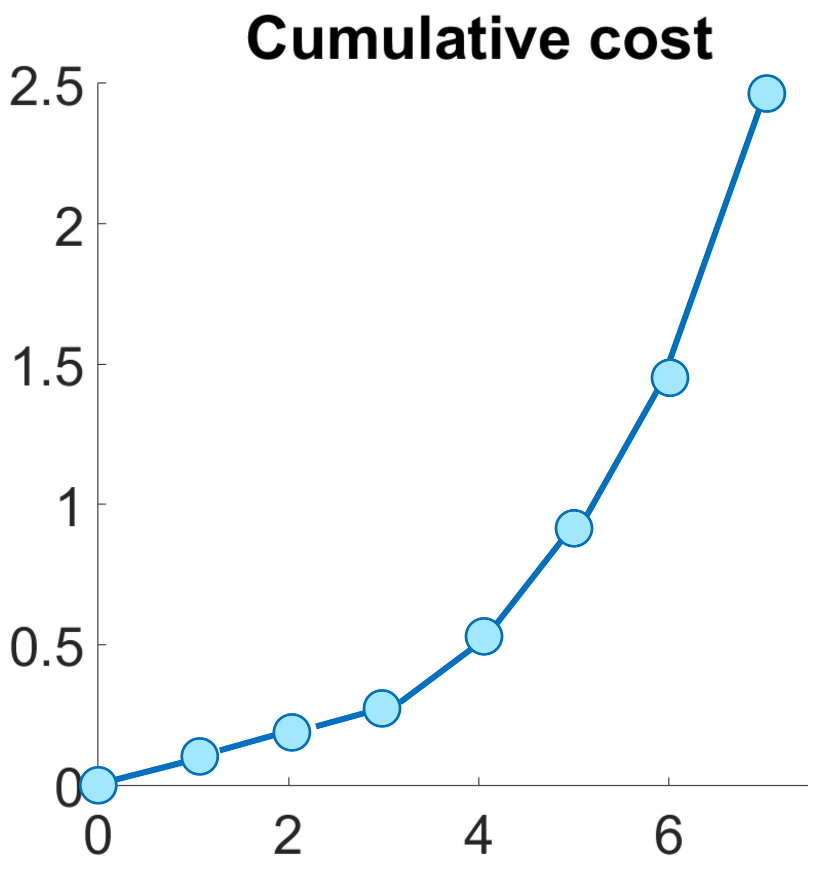
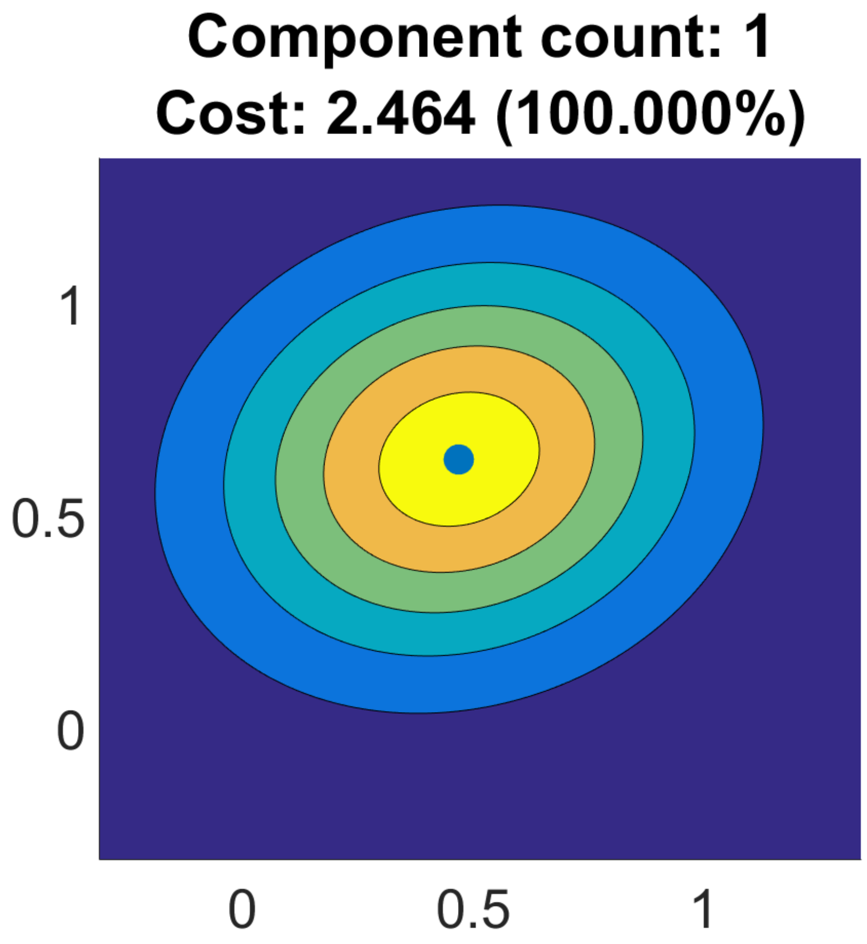


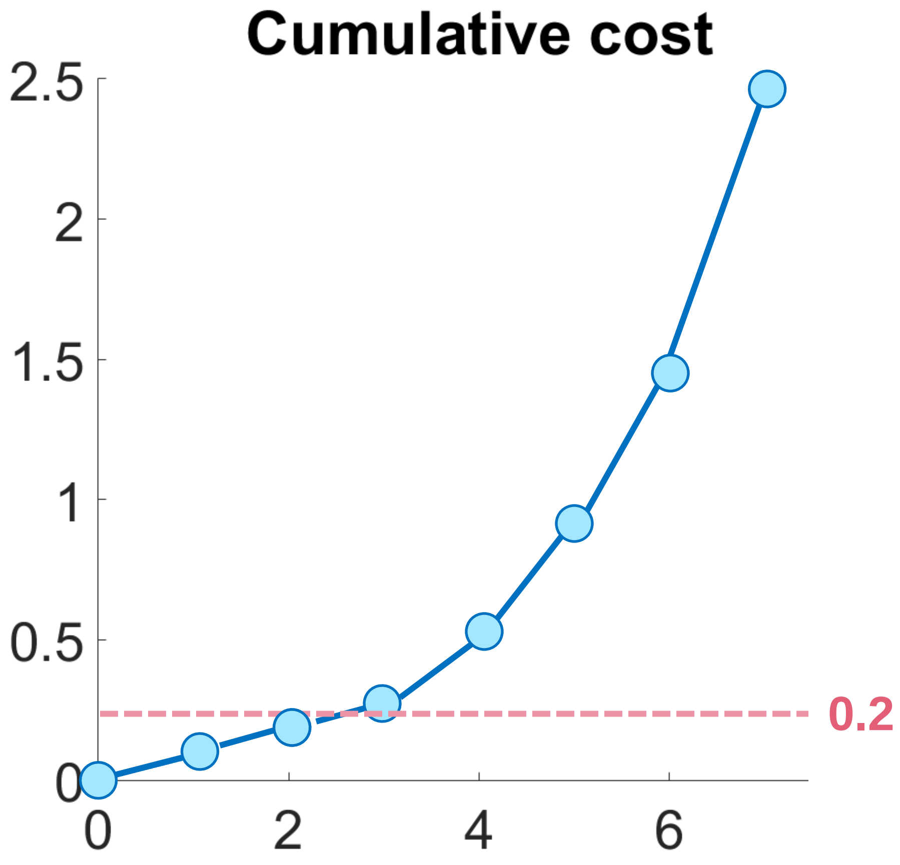


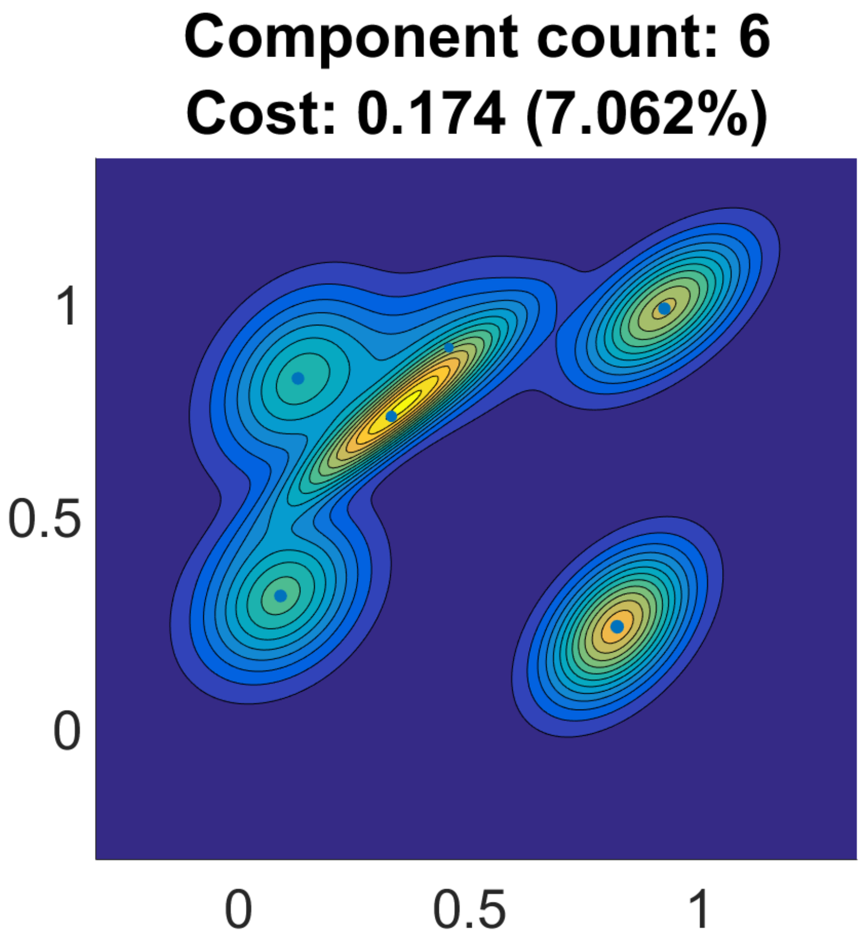
Component Reduction



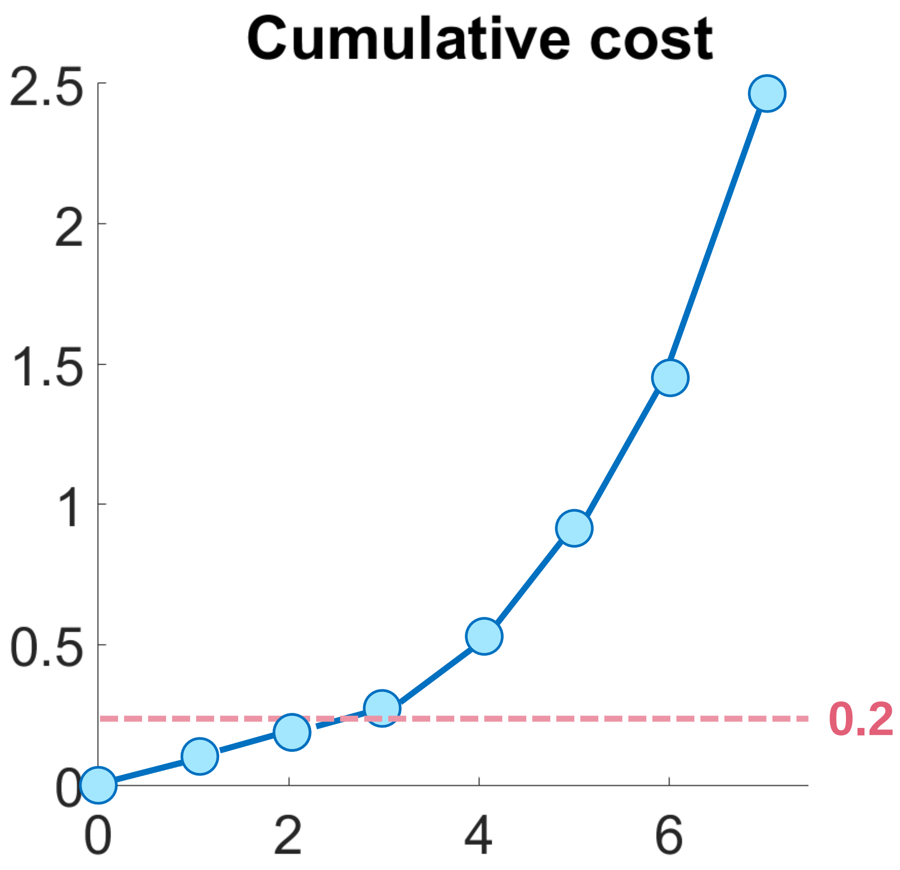


Component Reduction





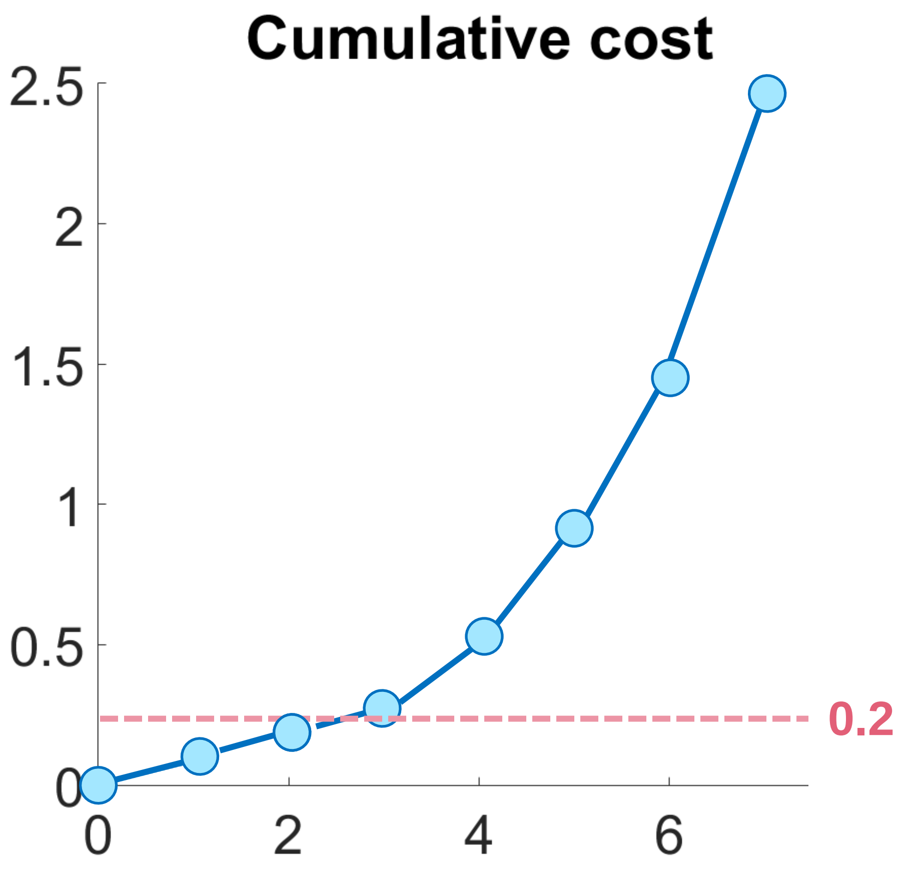
Component Reduction



Reduction

- BRDF:
  - Full $K = 8$
- Illumination
  - Full $K = 8$
- Product GMM:
  - Avg. $K_{ij} = 64$

Component Reduction



Reduction

- BRDF:
  - Full $K = 8$
  - **Red. avg. $K = 2$**
- Illumination
  - Full $K = 8$
  - **Red. 50% to 4 comp.**
- Product GMM:
  - Avg. $K_{ij} = 64$
  - **Red. avg. $K_{ij} = 12$**

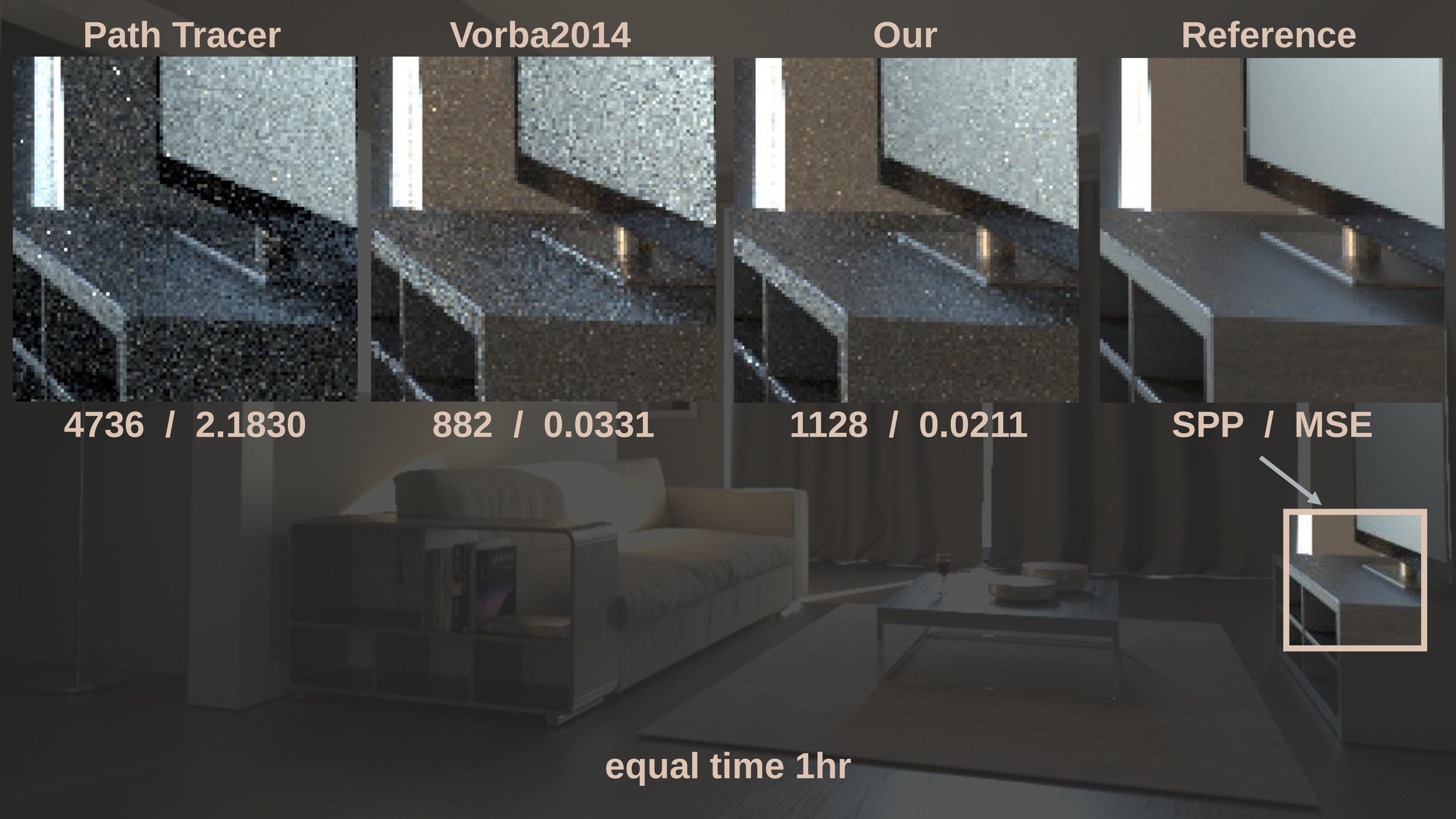
Results

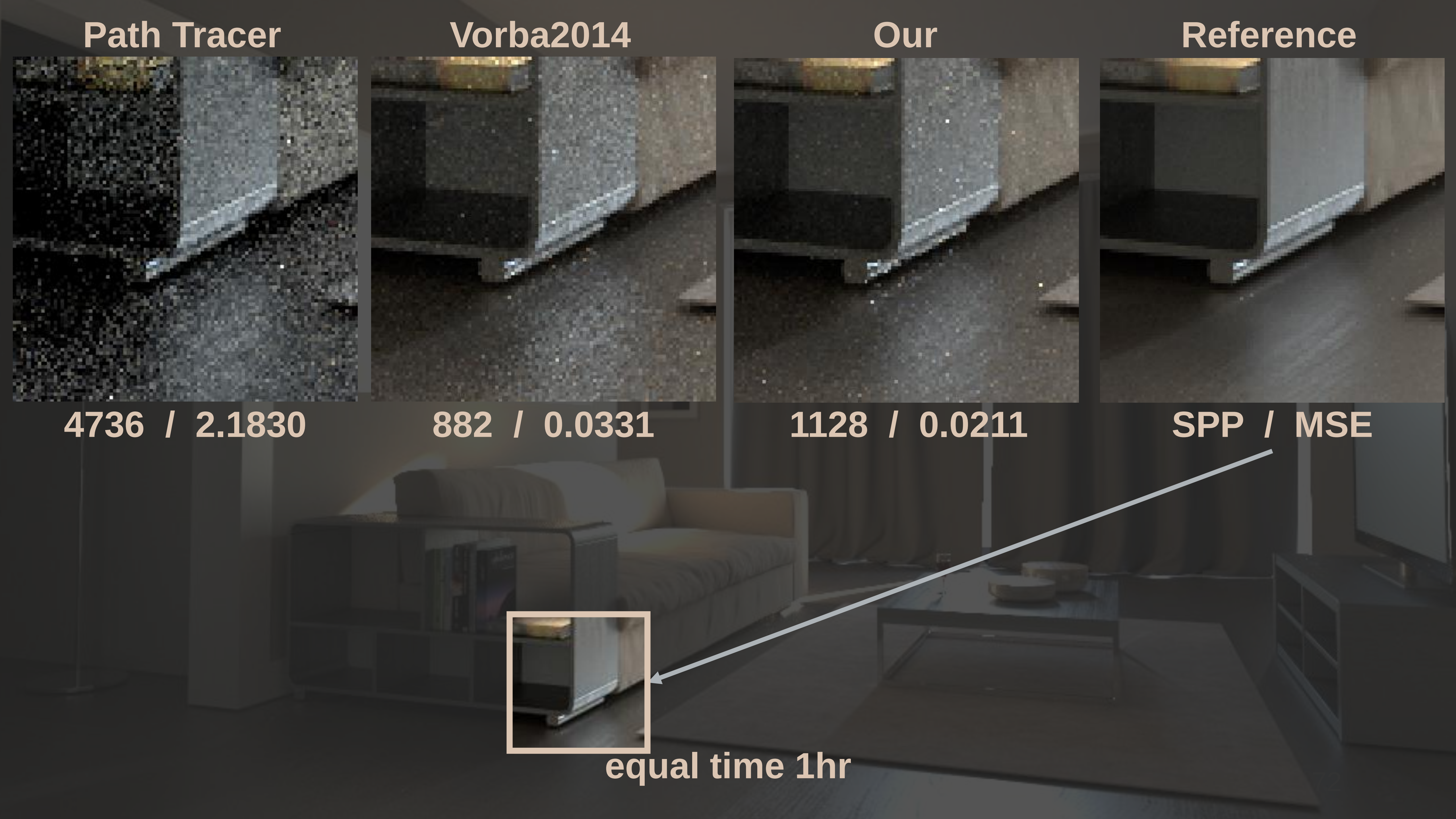
Reference


Reference
SPP / MSE
equal time 1hr

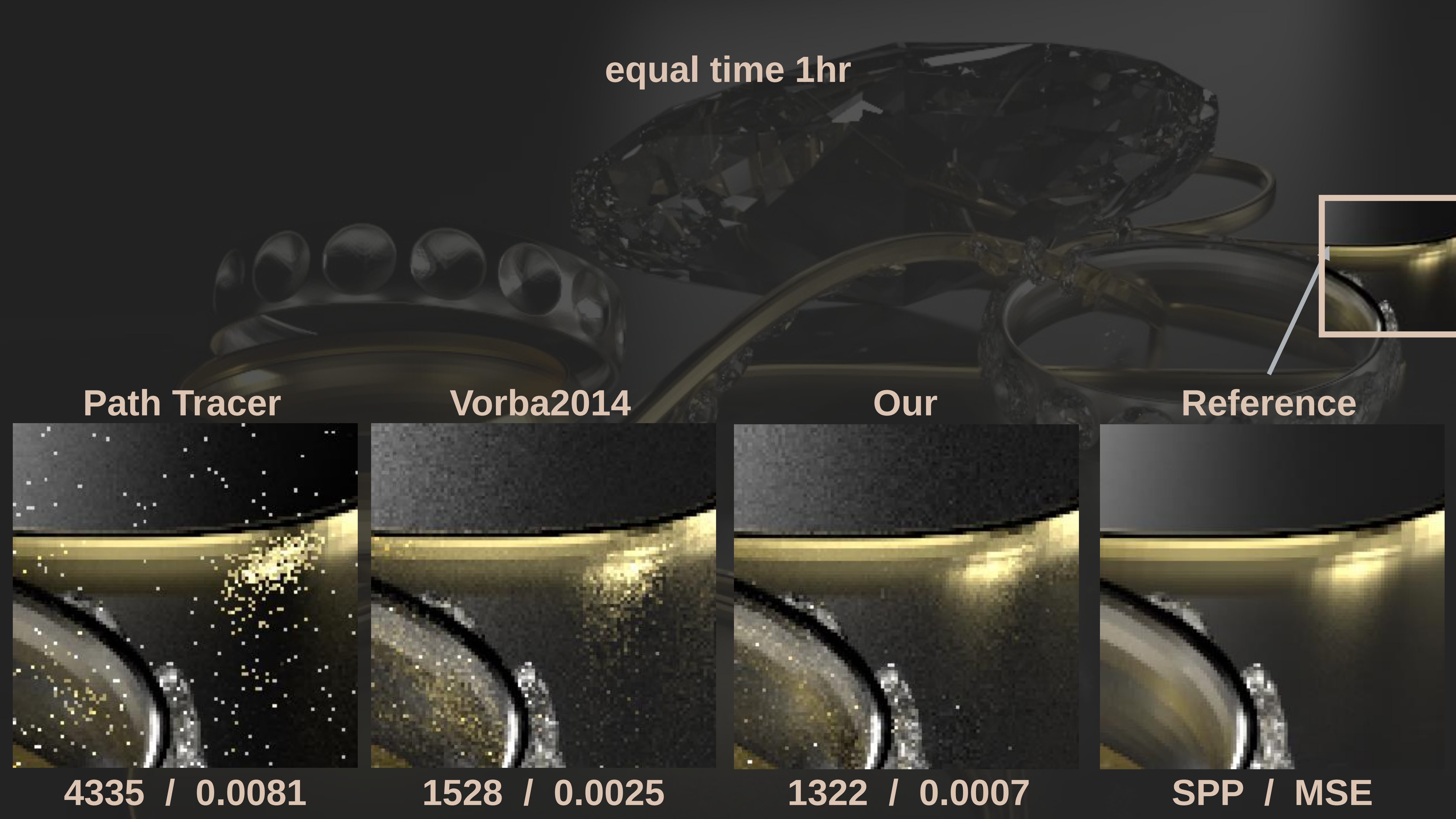

Path Tracer
Reference
4736 / 2.1830
SPP / MSE
equal time 1hr

Path Tracer
Vorba2014
Reference
4736 / 2.1830
882 / 0.0331
SPP / MSE
equal time 1hr


Path Tracer
Vorba2014
Our
Reference
4736 / 2.1830
882 / 0.0331
1128 / 0.0211
SPP / MSE
equal time 1hr


Path Tracer
Vorba2014
Our
Reference
4736 / 2.1830
882 / 0.0331
1128 / 0.0211
SPP / MSE
equal time 1hr

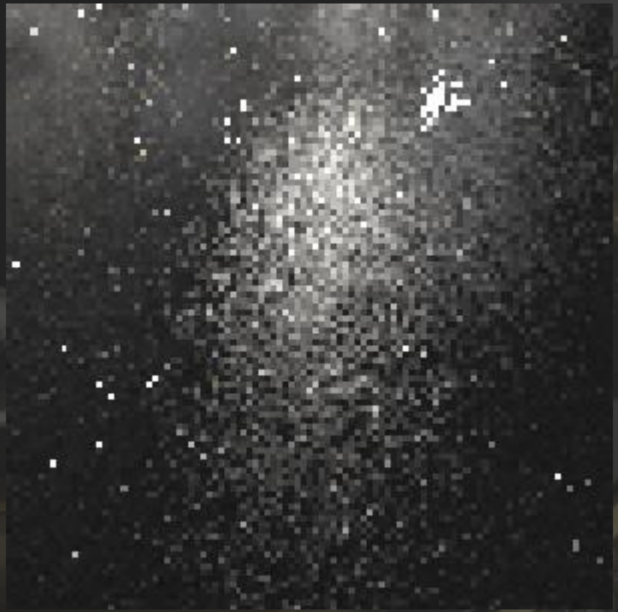
Reference


equal time 1hr
Path Tracer
Vorba2014
Our
Reference
4335 / 0.0081
1528 / 0.0025
1322 / 0.0007
SPP / MSE

Path Tracer

4335 / 0.0081

Vorba2014



1528 / 0.0025

Our

1322 / 0.0007

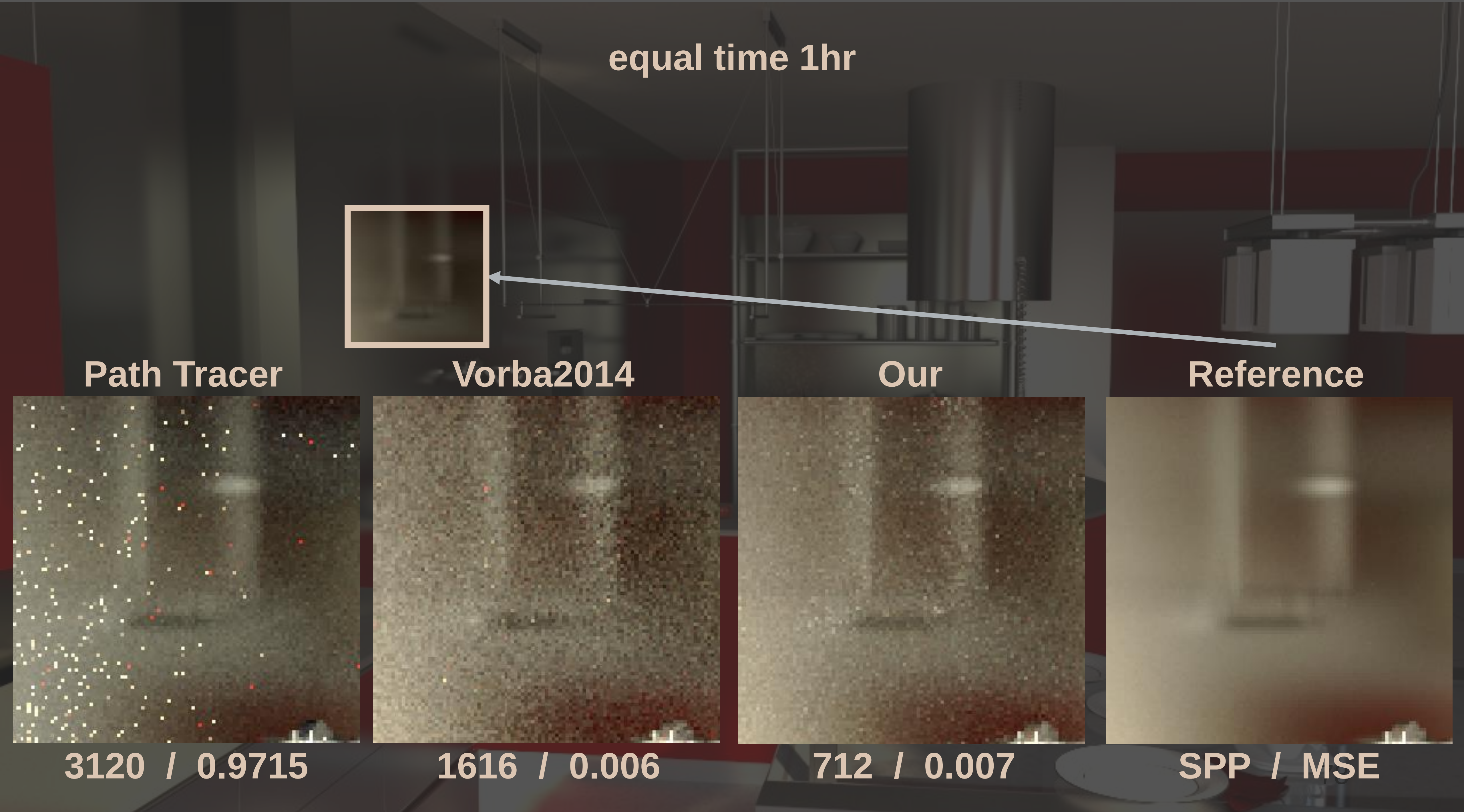
Reference

SPP / MSE

equal time 1hr


Reference

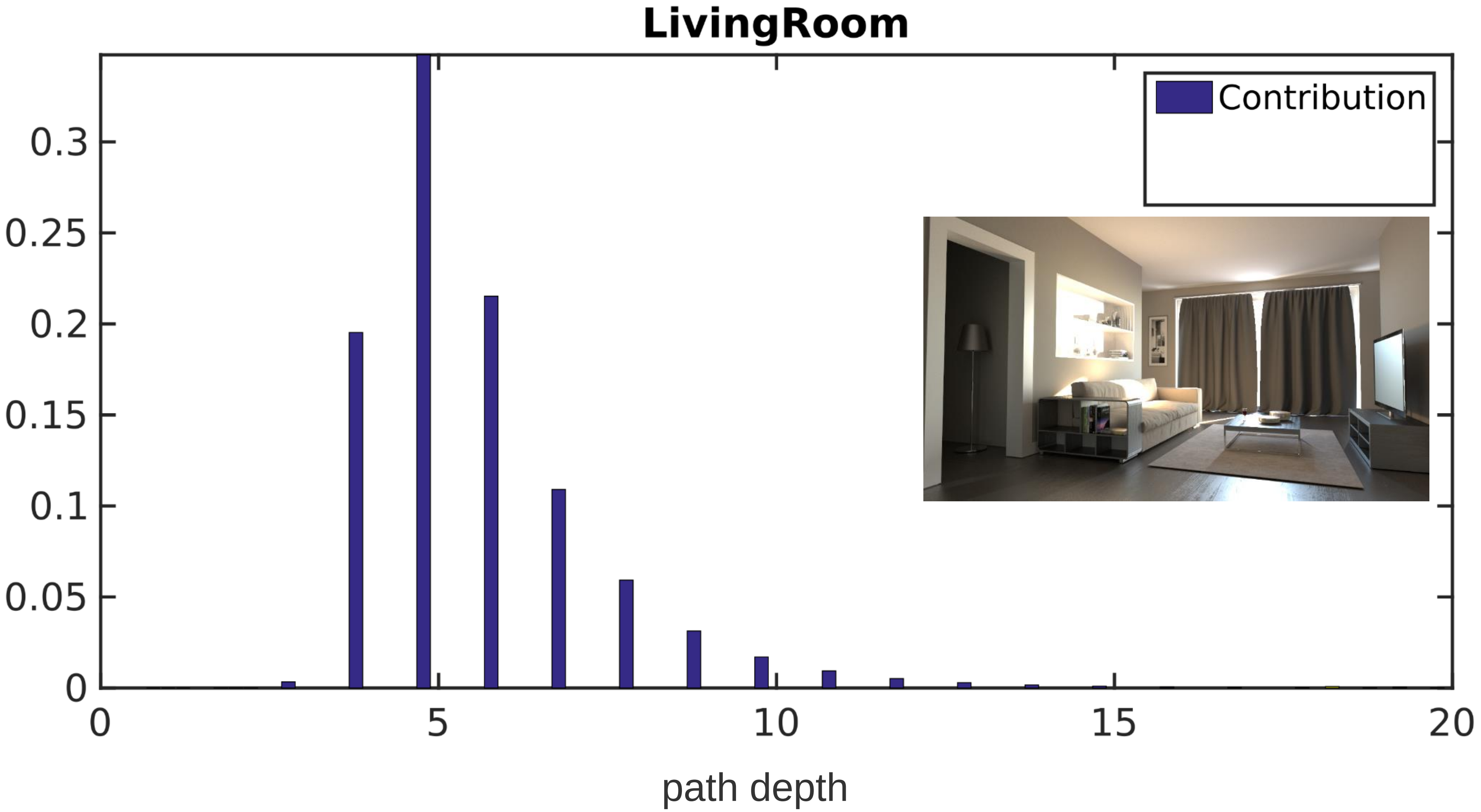

Path Tracer
Vorba2014
Our
Reference
3120 / 0.9715
1616 / 0.006
712 / 0.007
SPP / MSE
equal time 1hr


equal time 1hr
Path Tracer
Vorba2014
Our
Reference
3120 / 0.9715
1616 / 0.006
712 / 0.007
SPP / MSE

Average Path Lenghts

Vorba: 9.8 Ours: 4.9

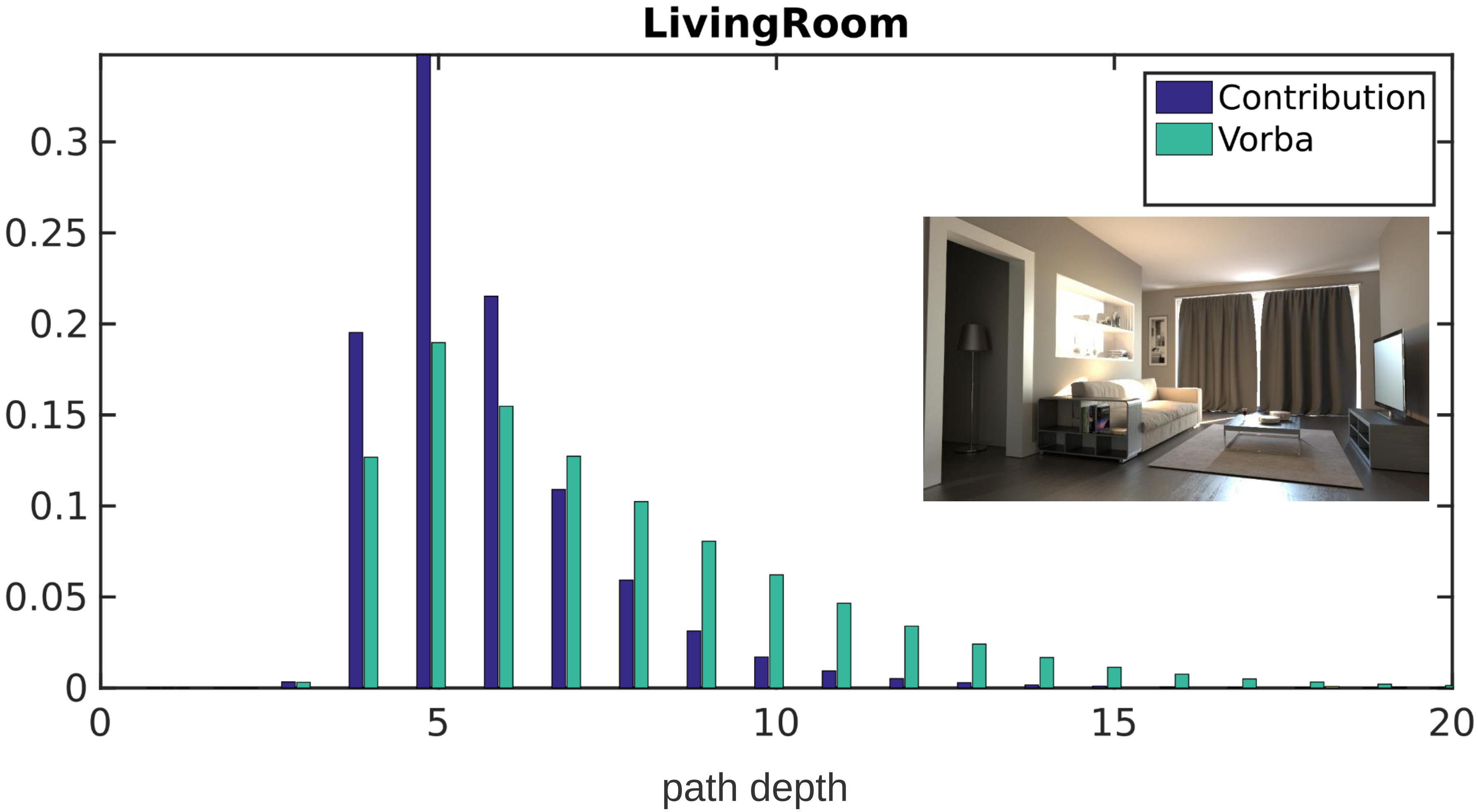
normalized per-path segment contribution



Average Path Lenghts

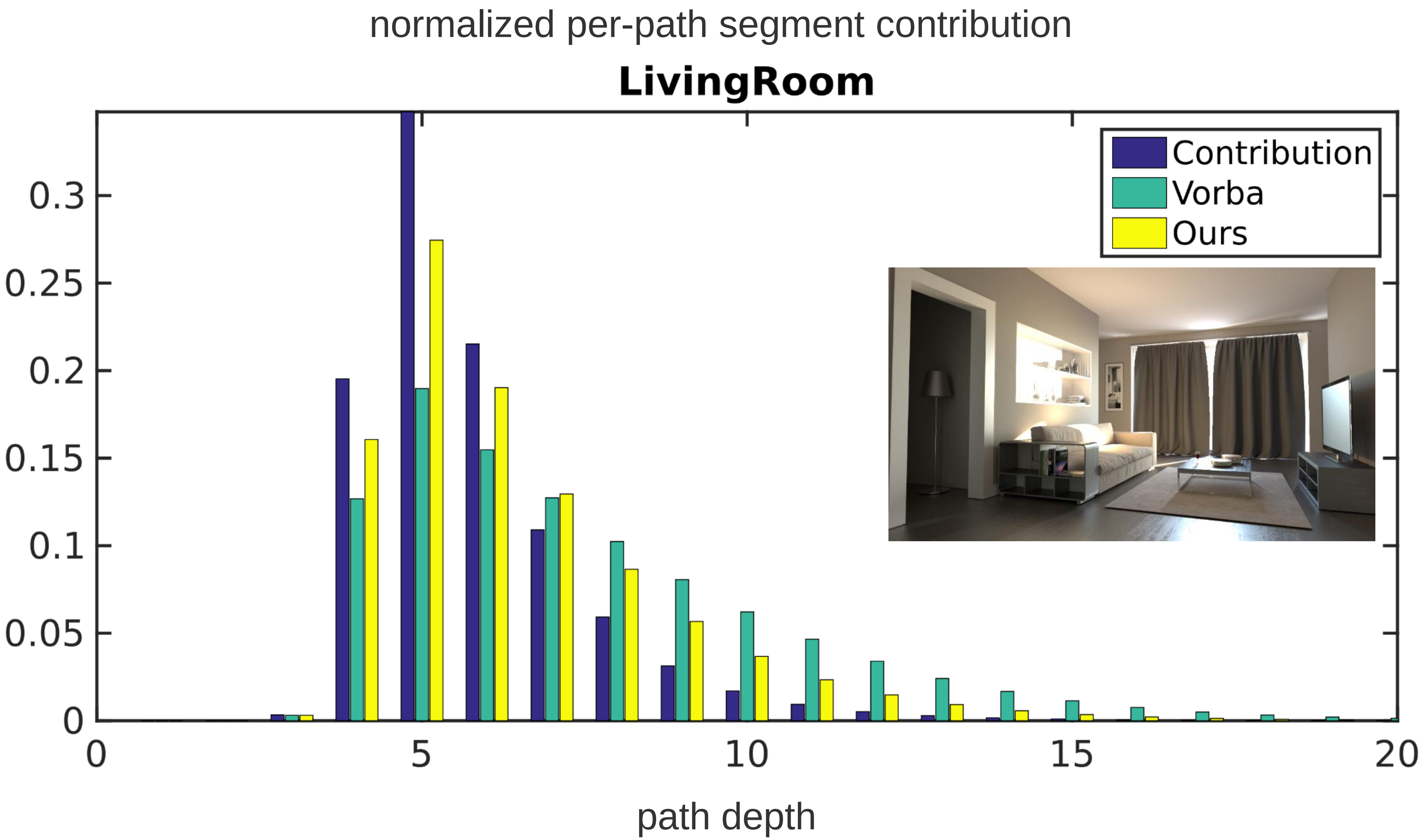
Vorba: 9.8 Ours: 4.9

normalized per-path segment contribution



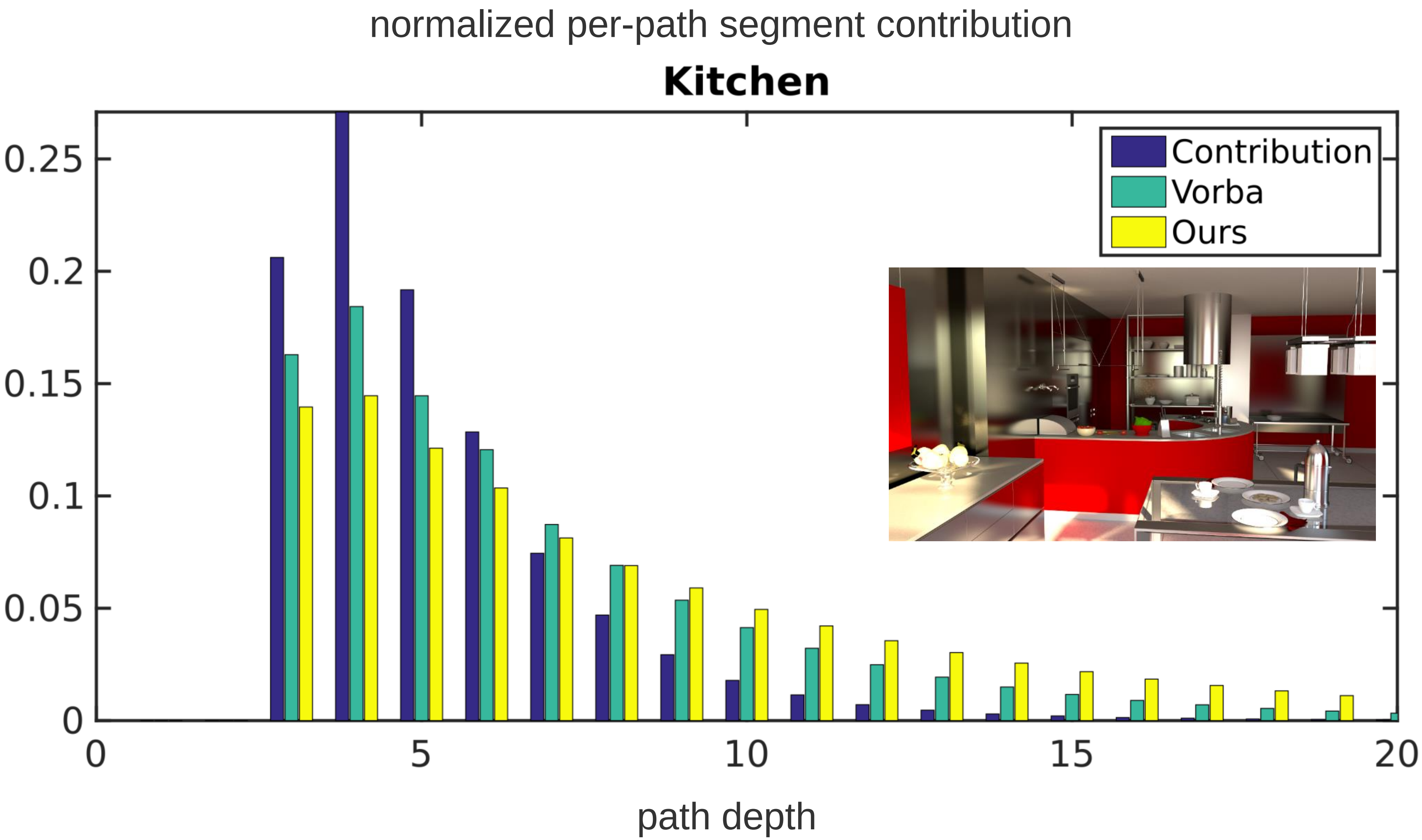
Average Path Lenghts

Vorba: 9.8 **Ours: 4.9**



Average Path Lenghts

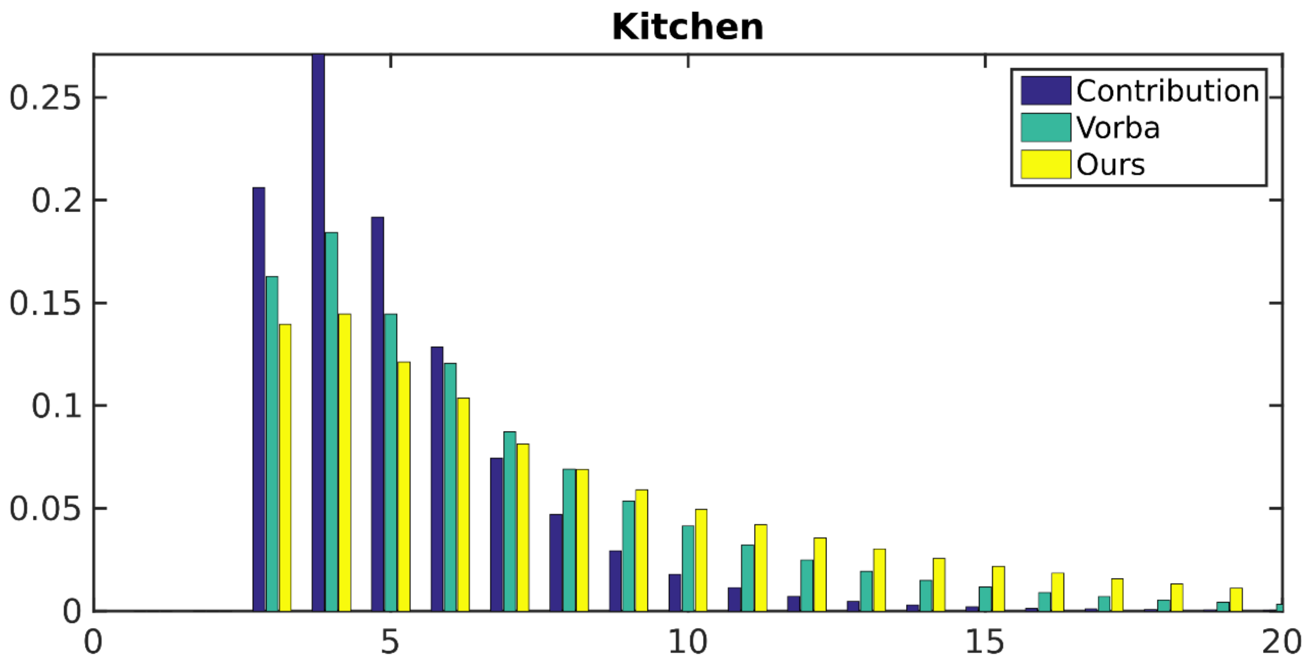
Vorba: 6.5 Ours: 9.0



Discussion / Future work

Discussion / Future Work

- Path Length and Russian Roulette
  - Adjoint-driven RR and Splitting [Vorba2016]



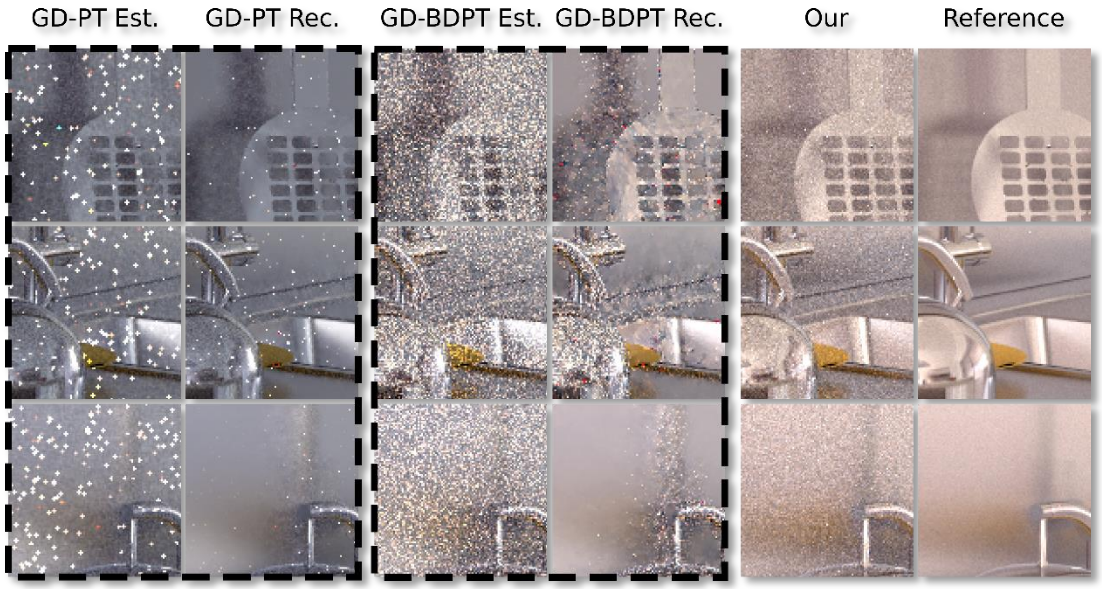
Discussion / Future Work

- SVBRDFs
  - Enlarge BRDF caches
  - Direct function transform BRDF->GMM

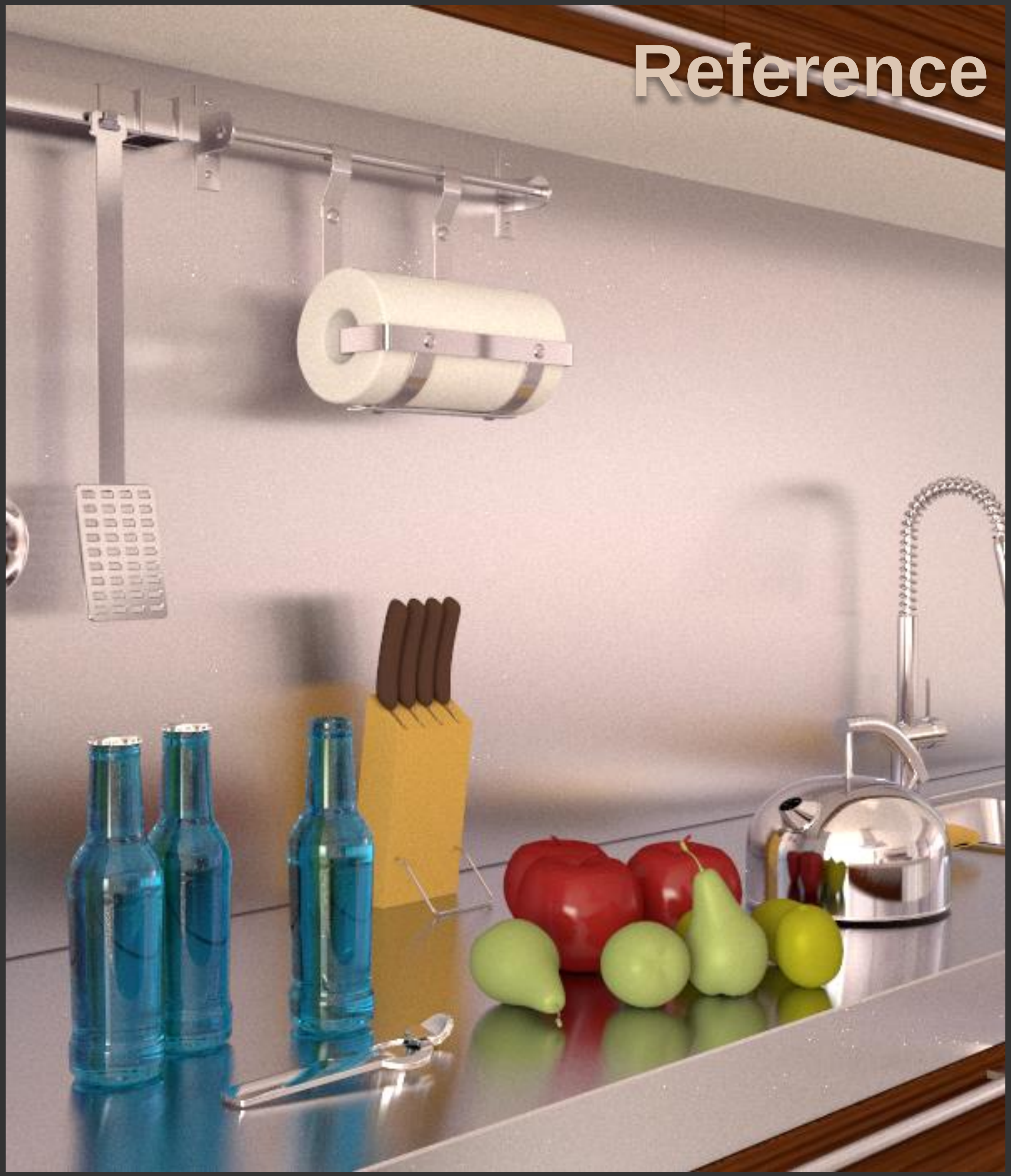
Scene	BRDF caching			
	# BRDFs	# Caches	Avg. # comp.	Mem.
LIVINGROOM	41	15k	2.5	7.7 MB
KITCHEN	72	2.5k	1.8	10 MB
JEWELRY	6	1.5k	1.44	0.7 MB

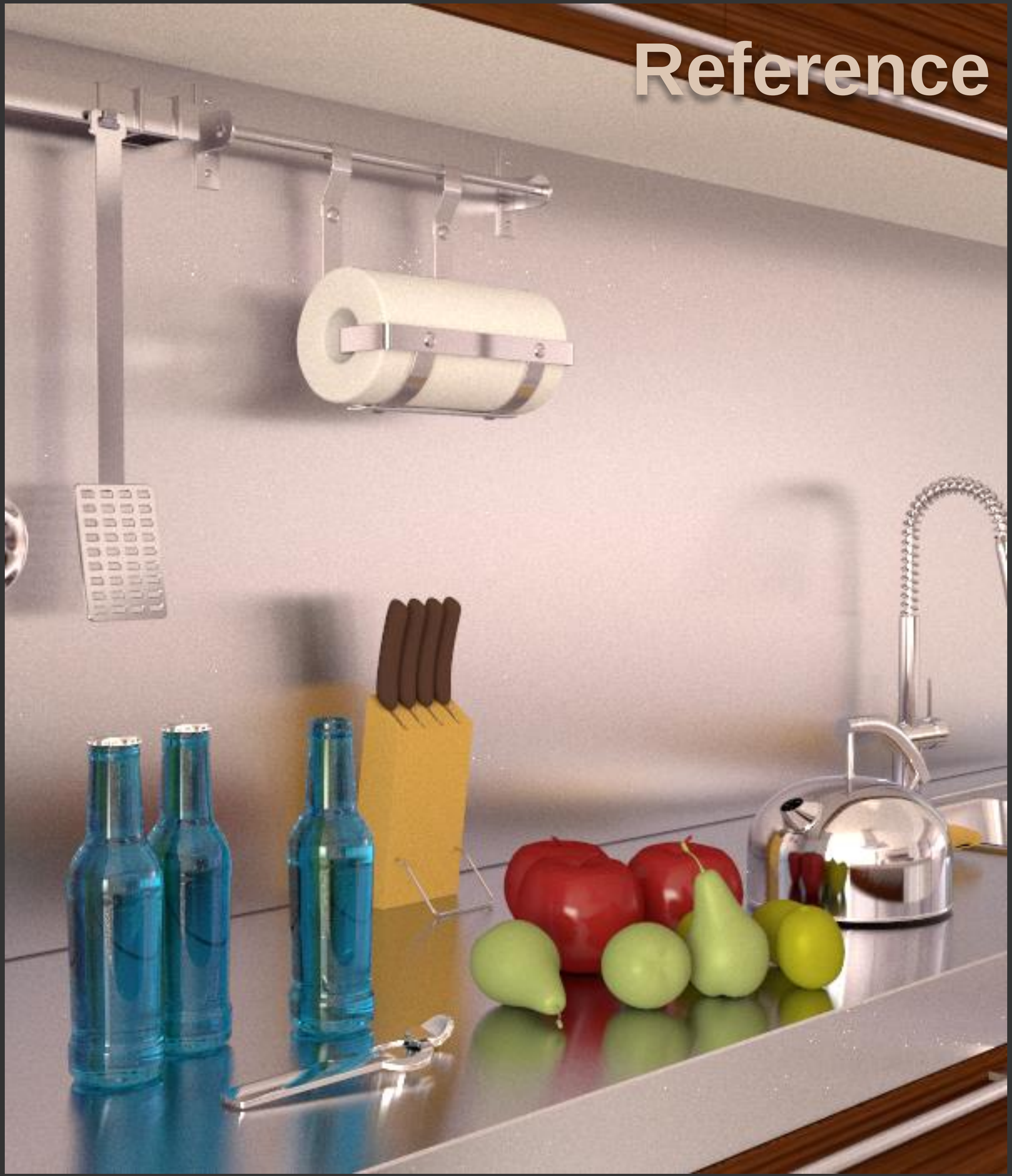
Discussion / Future Work

- Extension to other MC-algorithms
  - BDPT
  - MCMC
  - Gradient domain

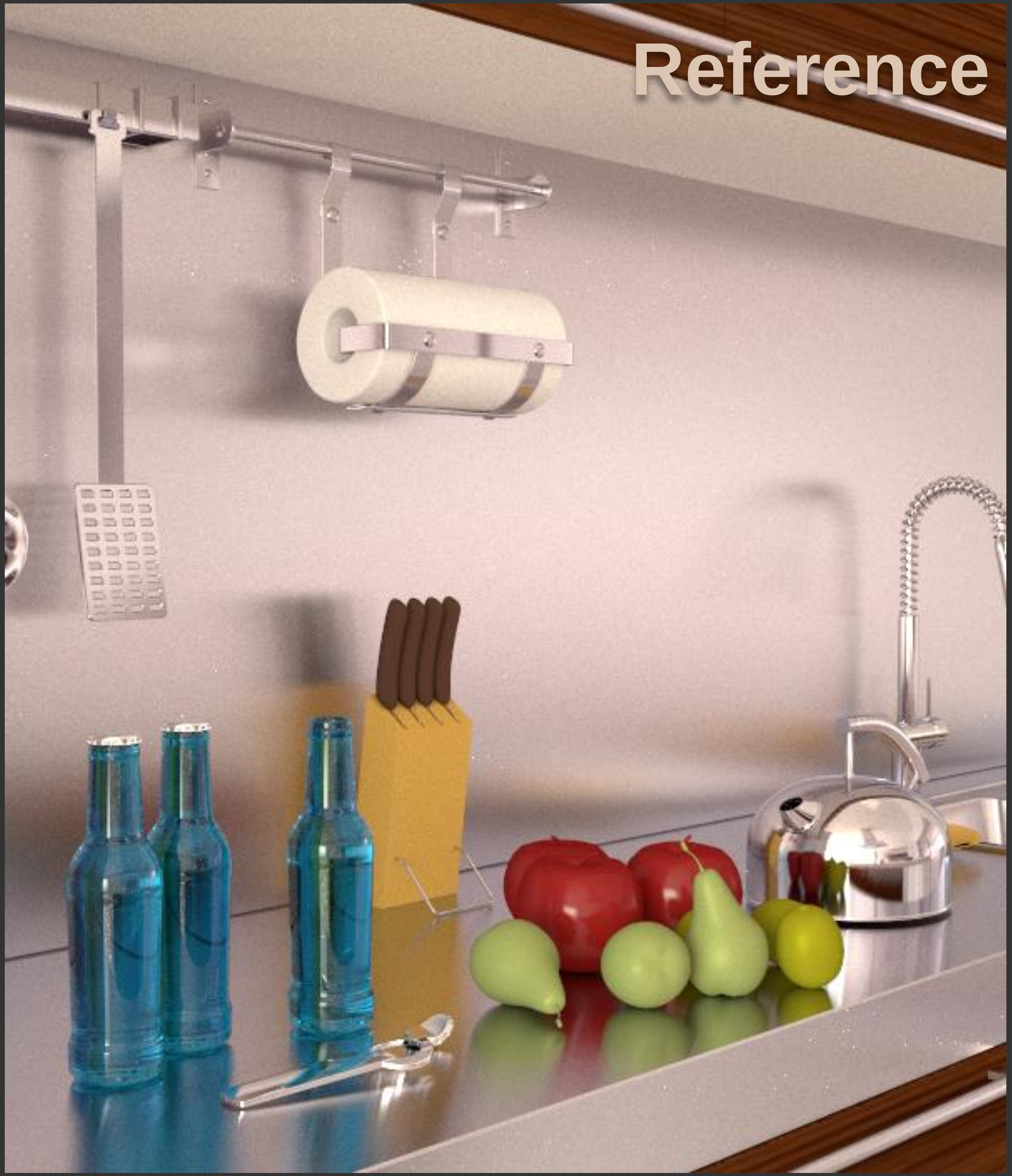



GD-PT
(full)
GD-BDPT
(full)


Reference


GD-PT
(estimate)
GD-BDPT
(estimate)

Reference


Our


Reference

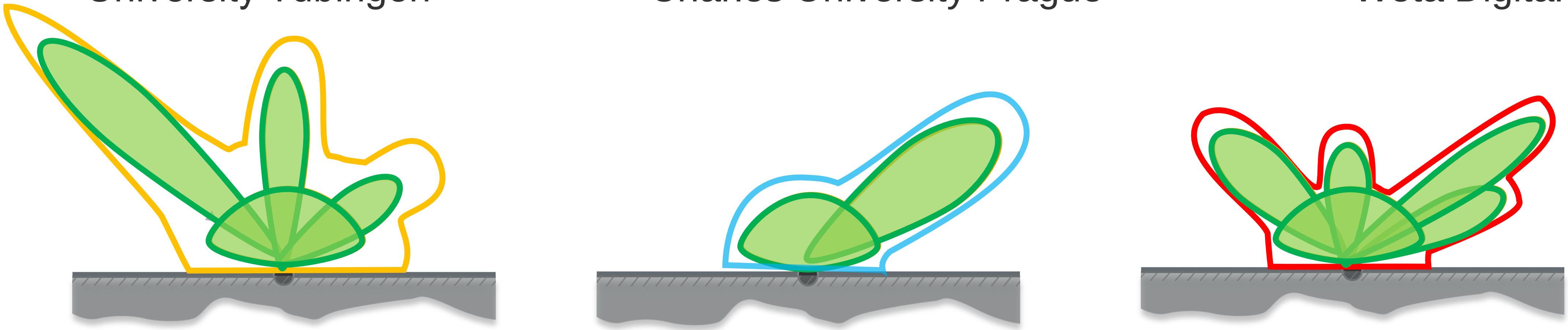
Discussion/Future Work

- Optimizing Illumination caches
  - Poorly fitted illumination caches cause inconsistent convergence rates

Product Importance Sampling for Light Transport Path Guiding

Sebastian Herholz[1] Oskar Elek[2] Jiří Vorba[2,3]
Hendrik Lensch[1] Jaroslav Křivánek[2]

[1]University Tübingen [2]Charles University Prague [3]Weta Digital

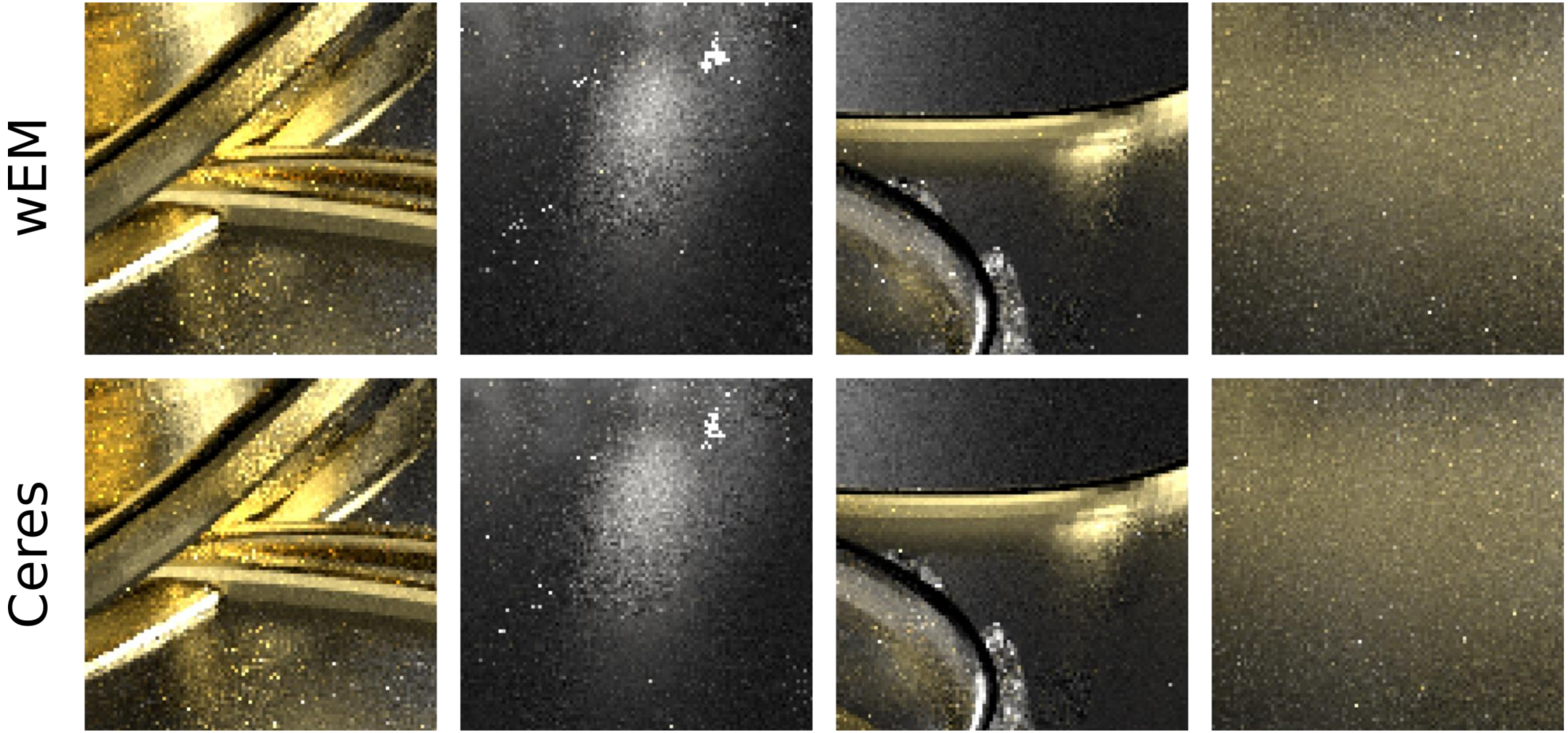


Thanks to:

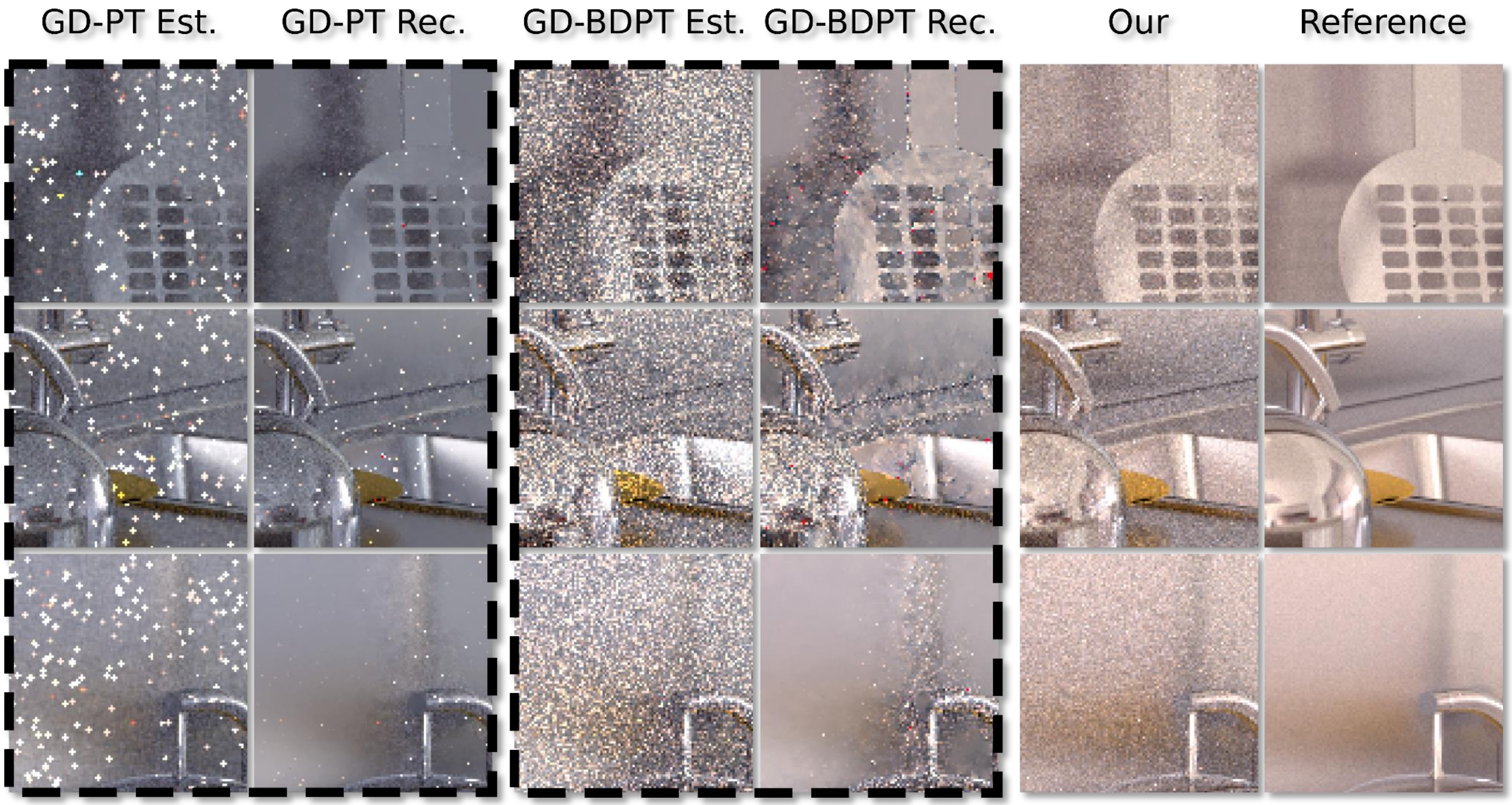
- Martin Šik, Ivo Kondapaneni, Ludvík Koutný, Anton Kaplanyan, Johannes Hanika
- Anonymous reviewers
- You!

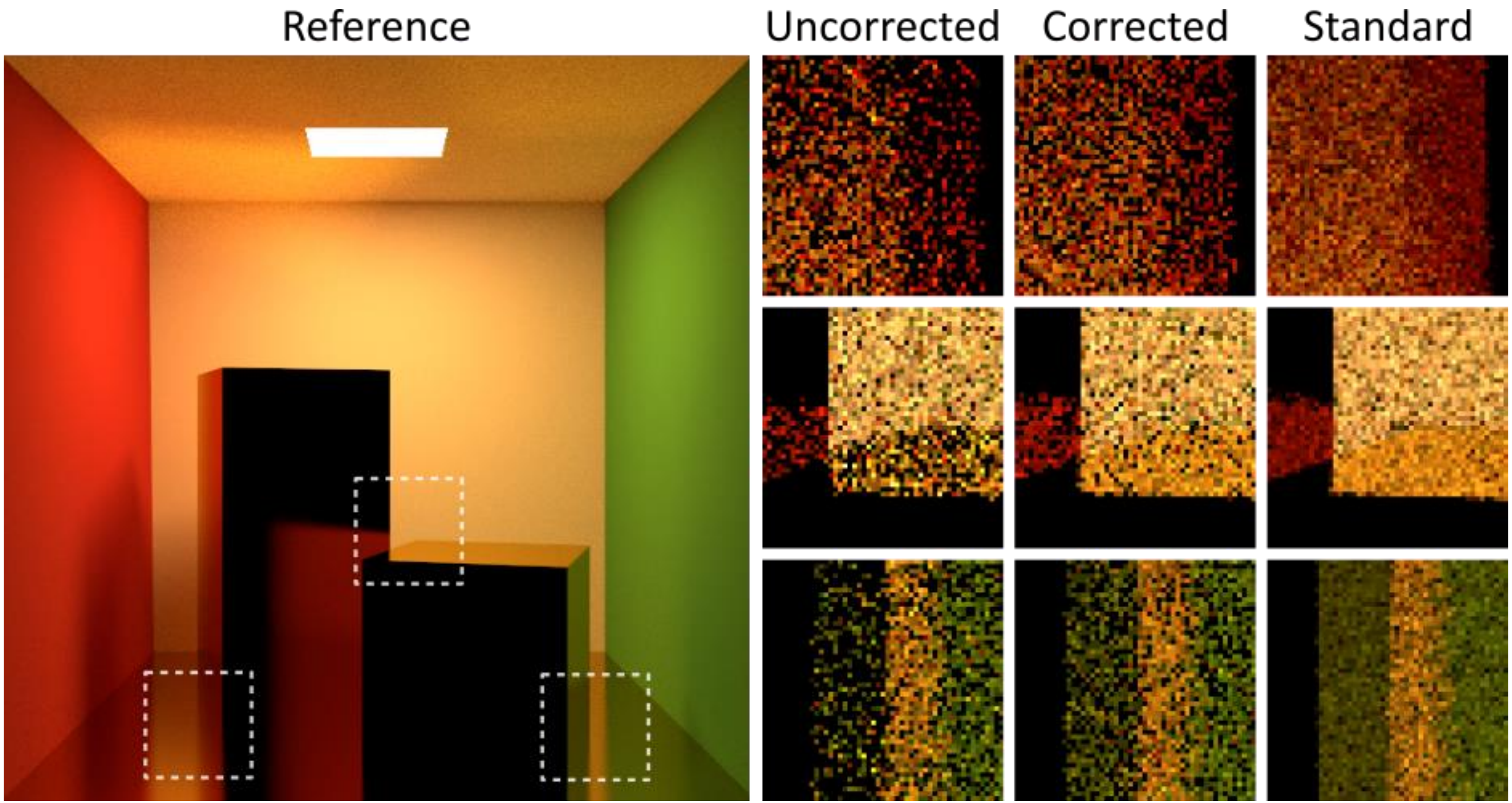
Backup

wEM vs CERES



Gradient Domain




Reference
Uncorrected
Corrected
Standard

Preporcessing times:

Table 1: *Timings for the cache fitting stages (in minutes).*

Scene	Illumination	BRDF	
		wEM	Ceres
LIVINGROOM	14.0	0.31	25.5
KITCHEN	20.1	0.44	42.3
JEWELRY	6.1	0.04	6.3

Statistics:

ble 2: Left *and* middle*: BRDF and illumination caching statistics for the scenes in Fig. 8.* Right*: Overhead of the product sampling rel*
llumination-only sampling, without ('naïve') and with the reduction of the BRDF and illumination mixtures.

Scene	BRDF caching				Illumination caching			Sampling overhead [%]	
	# BRDFs	# Caches	Avg. # comp.	Mem.	# Caches	# Reduced	Mem.	Naïve	Reduced
LIVINGROOM	41	15k	2.5	7.7 MB	82k	57 %	192.9 MB	10.8	7.1
KITCHEN	72	2.5k	1.8	10 MB	107k	62 %	236.9 MB	26.7	9.9
JEWELRY	6	1.5k	1.44	0.7 MB	16k	33 %	19.5 MB	16.5	−1.1

END