Sample-based Monte Carlo Denoising using a Kernel-Splatting Network

Michaël Gharbi[1,2], Tzu-Mao Li[2], Miika Aittala[2], Jaakko Lehtinen[3,4], Frédo Durand[2]

Adobe

MIT CSAIL

Aalto-yliopisto

NVIDIA

Monte Carlo rendering

Monte Carlo integration

$$I = \int f(x, y, \ldots, u, v, t) dx dy \ldots du dv dt$$

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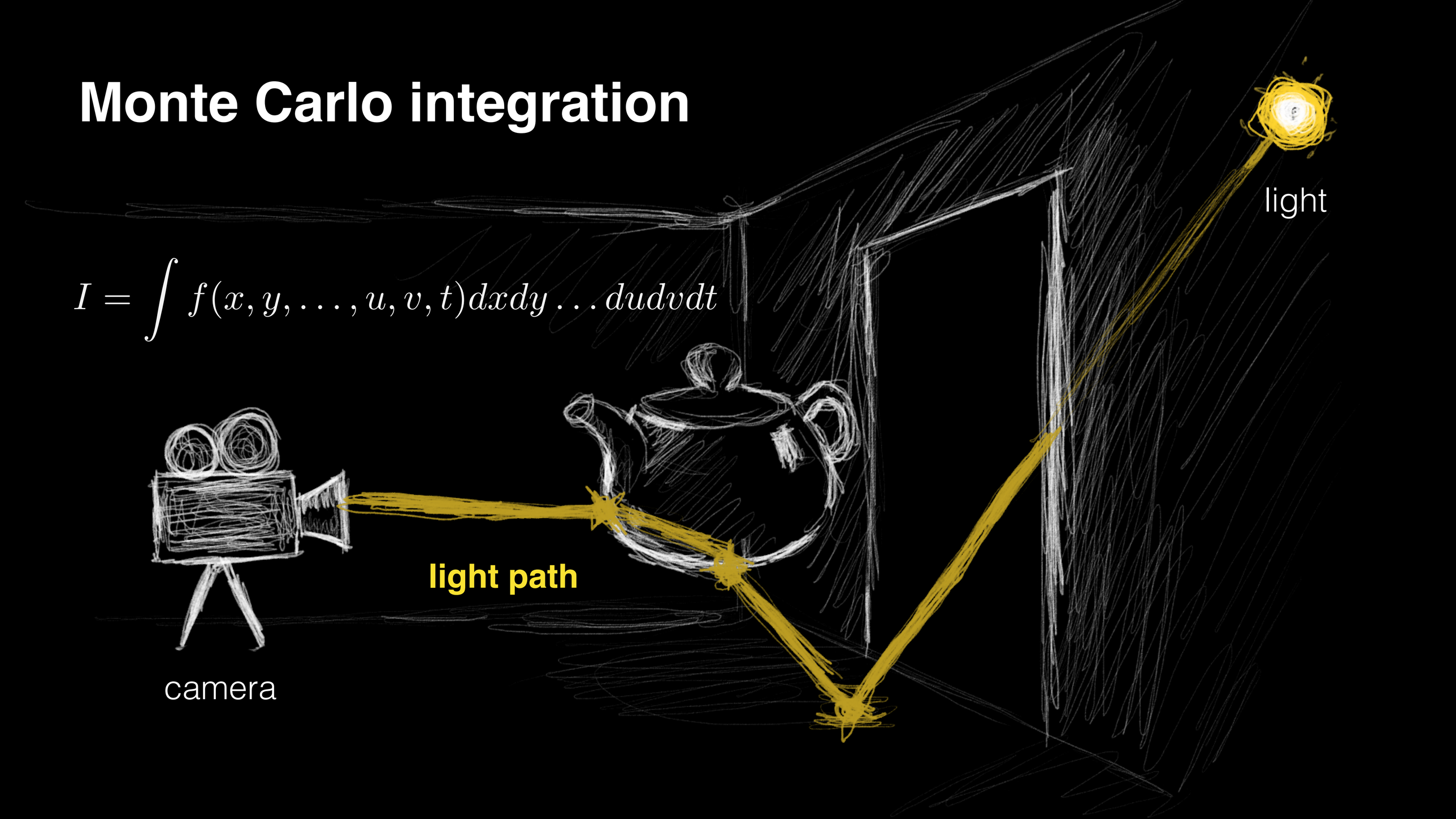

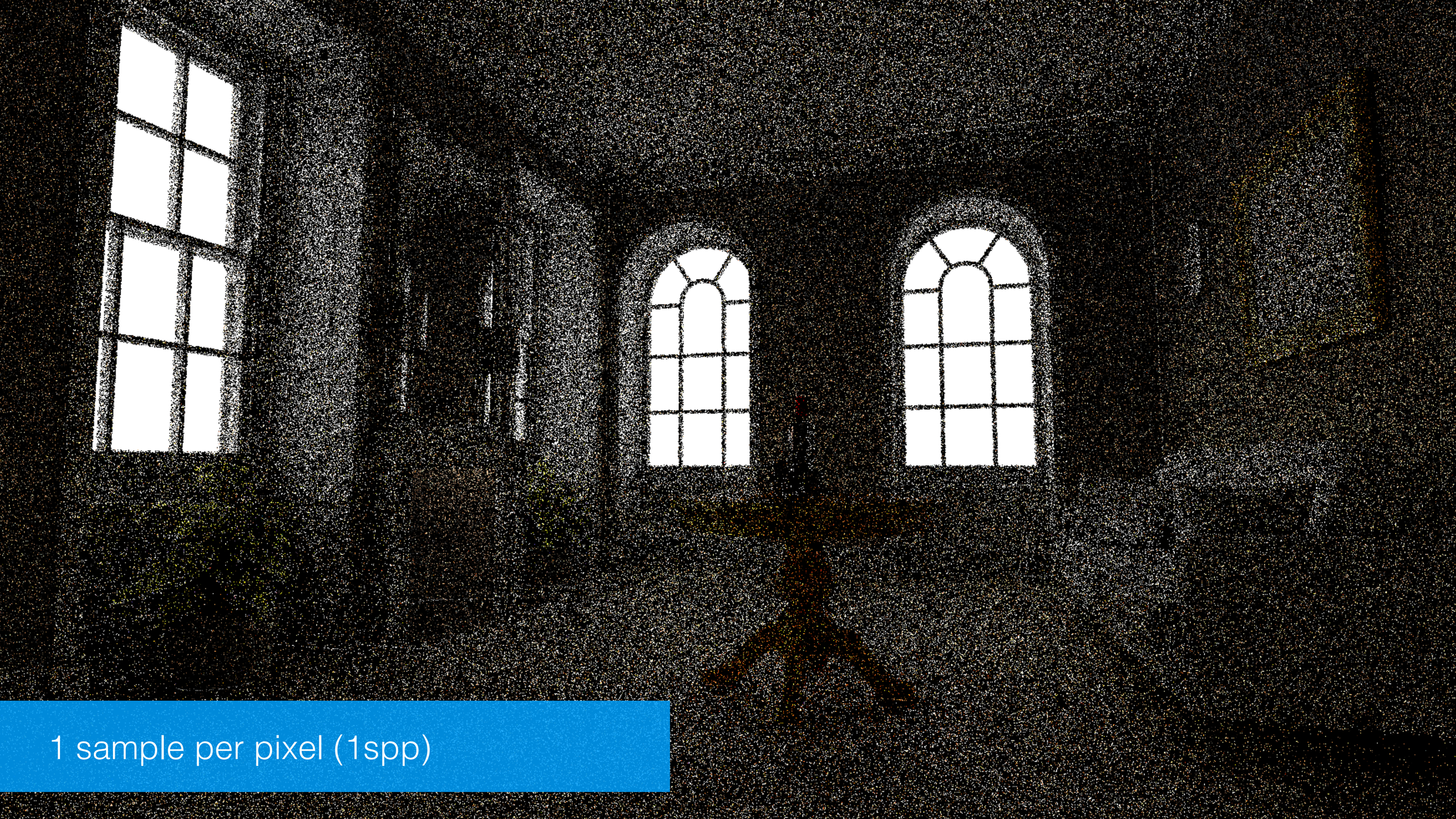

1 sample per pixel (1spp)


32spp


our result | 32spp


input | 32spp

Goal: faster rendering, fewer samples

- Produce high-quality renderings

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  - variance decreases only linearly with sample count

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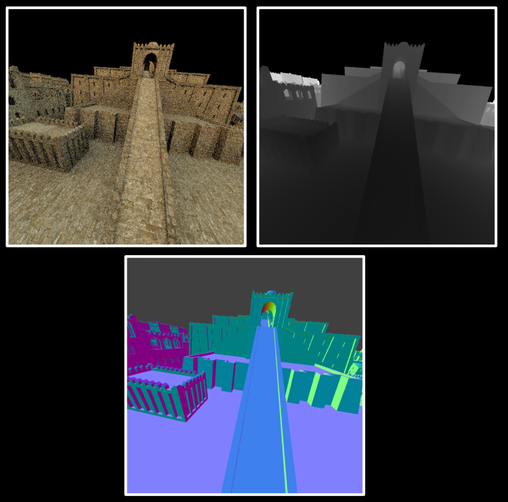
  - variance decreases only linearly with sample count
- General transport effects
  - depth of field, motion blur, etc

Previous work: Monte Carlo denoising

- Image-space adaptive sampling and reconstruction
  - often guided by aux. features (normals, depth, albedo)
  - Overbeck [2009], Dammertz [2010], Rouselle [2011], Li [2012], Sen & Darabi [2012], Bitterli [2016]



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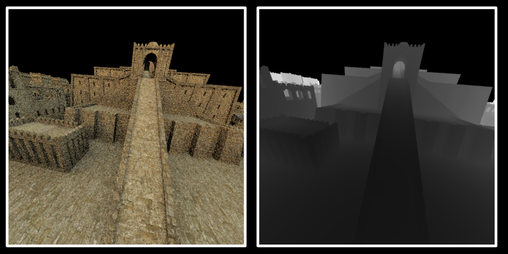
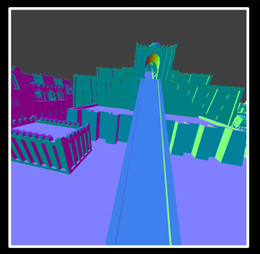
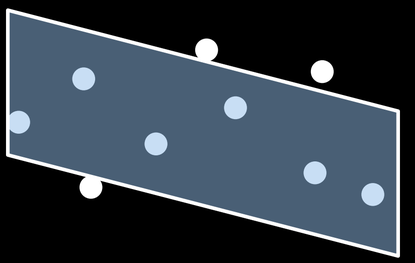


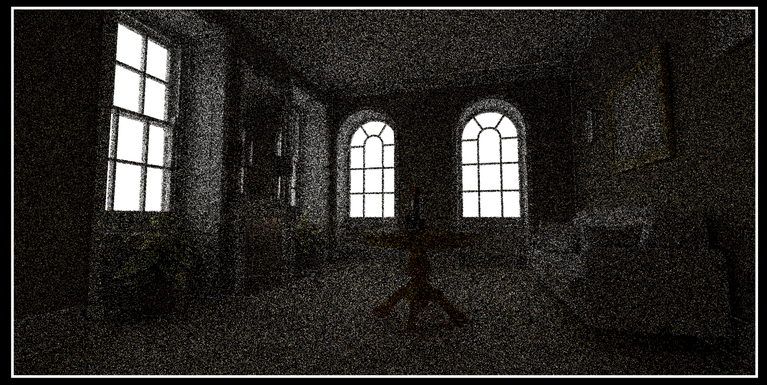


- High-dimensional filtering
  - nearest neighbor filter [Hashisuka 2008]
  - sample re-projection [Lehtinen 2011; Lehtinen 2012]
  - sheared filters [Egan 2009; Egan 2011; Yan 2015; Wu 2017]

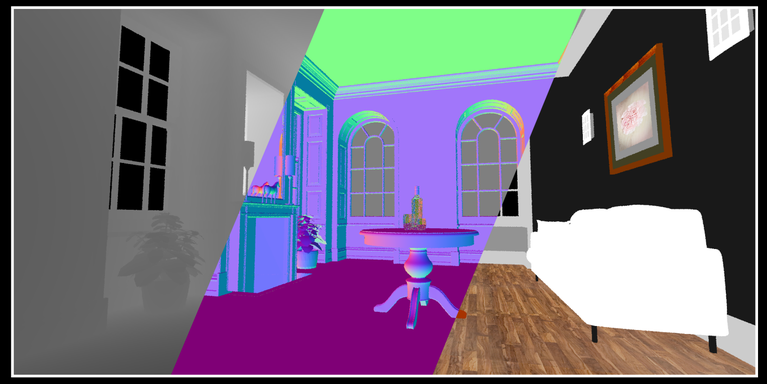


Deep-learning-based denoising

[Bako 2017; Chaitanya 2017; Vogels 2018]



noisy image



averaged auxiliary buffers
depth, normals, albedo

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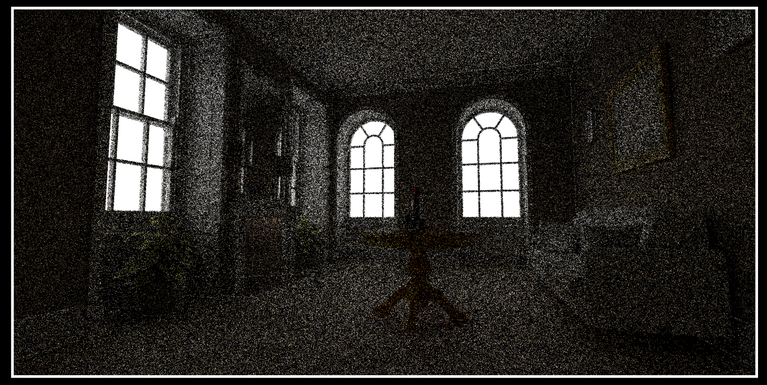

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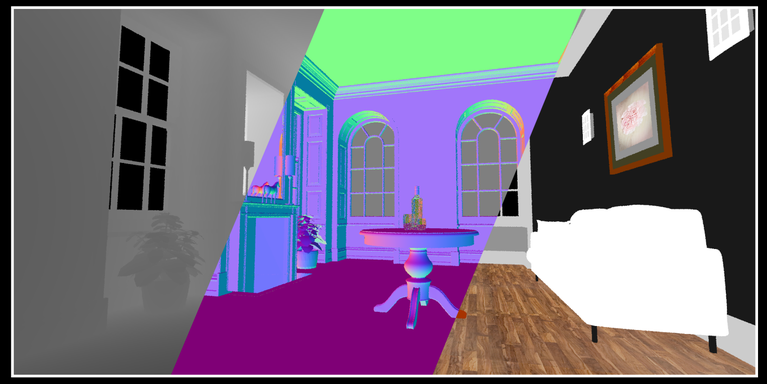

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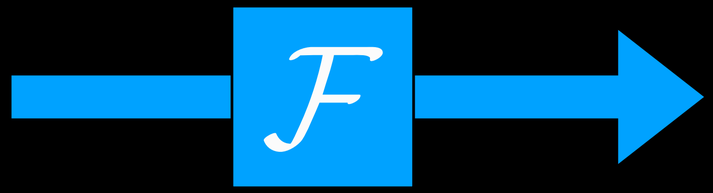

neural network

Deep-learning-based denoising

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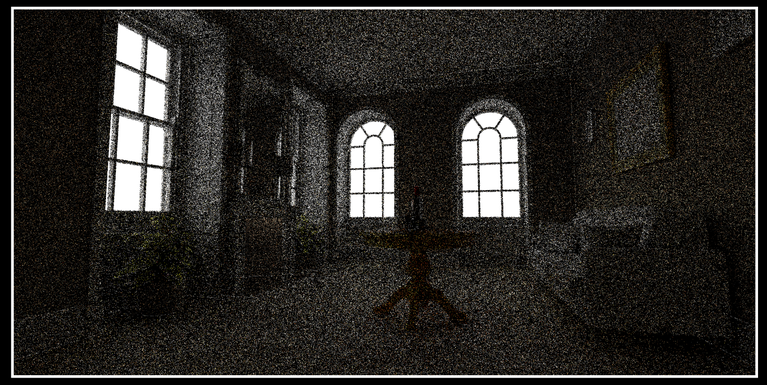

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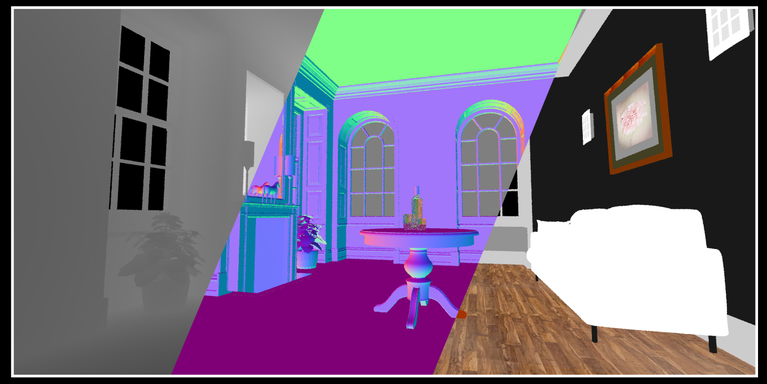

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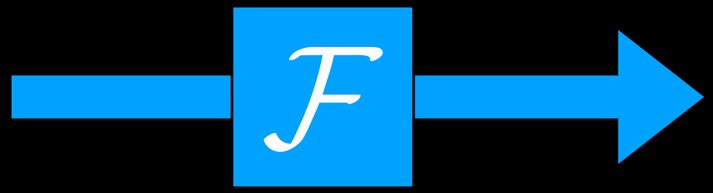
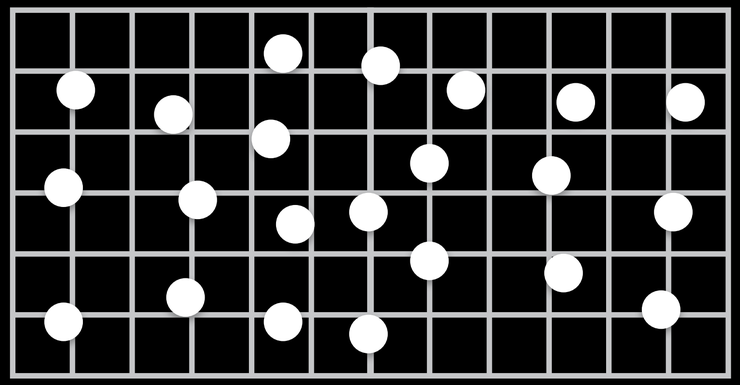


neural network

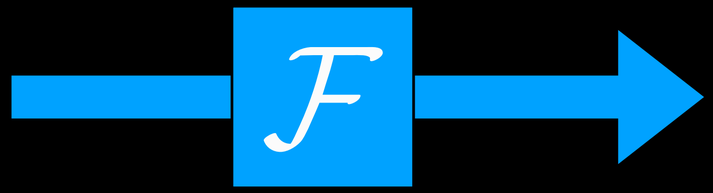
denoised image

Our approach

Learning to denoise, from the samples



input samples
(radiance + auxiliary features)

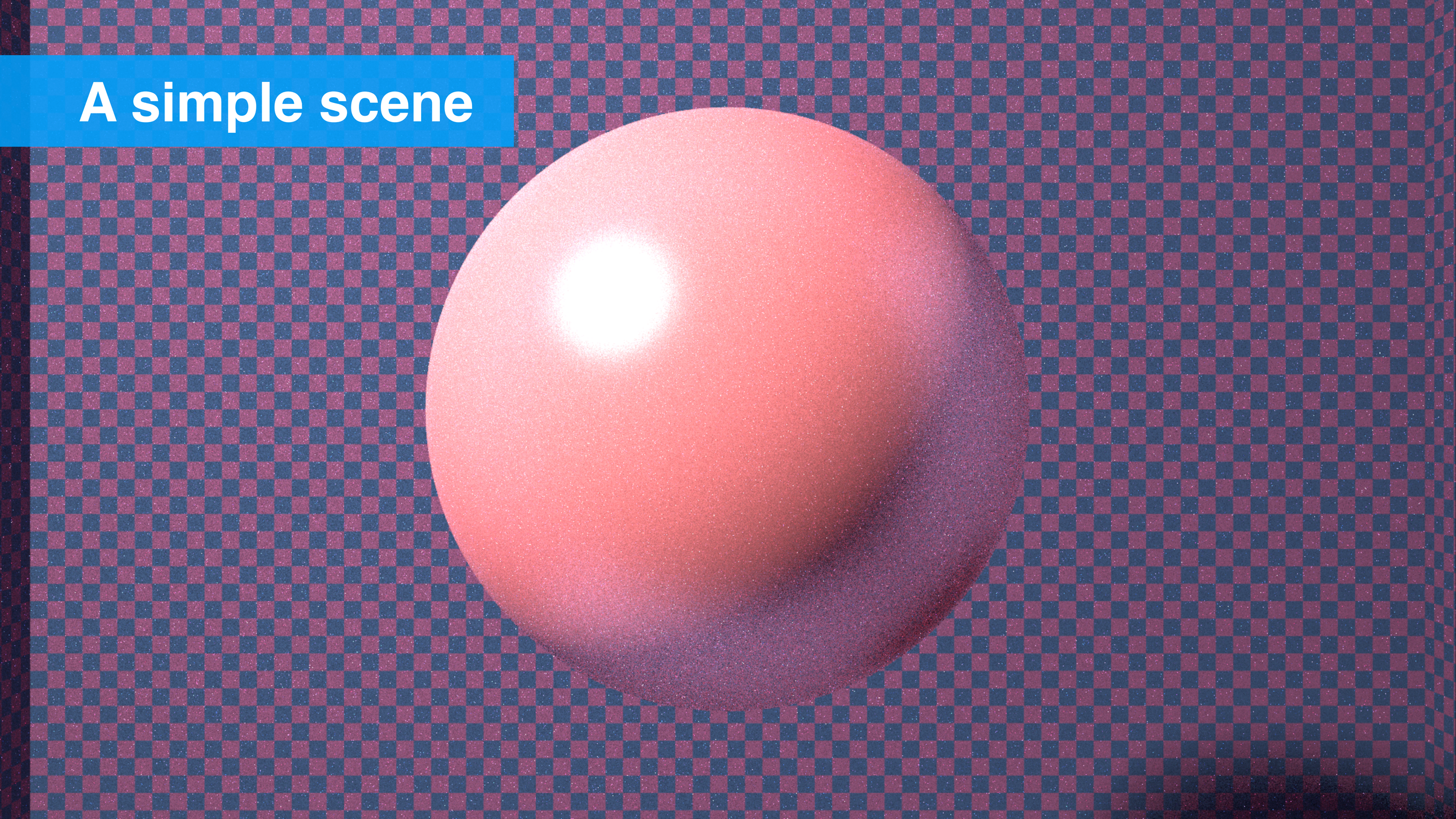


neural network

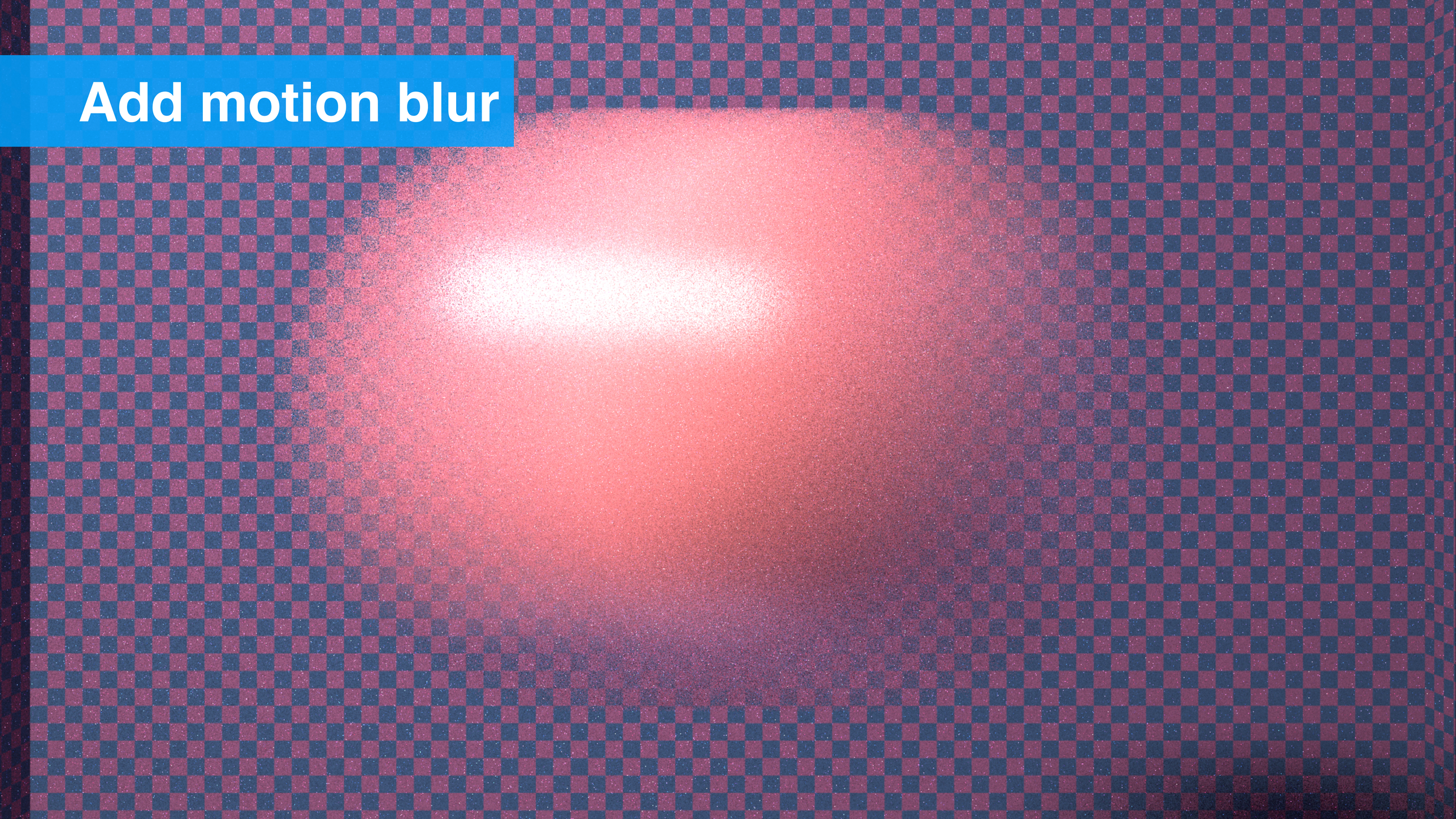
denoised image

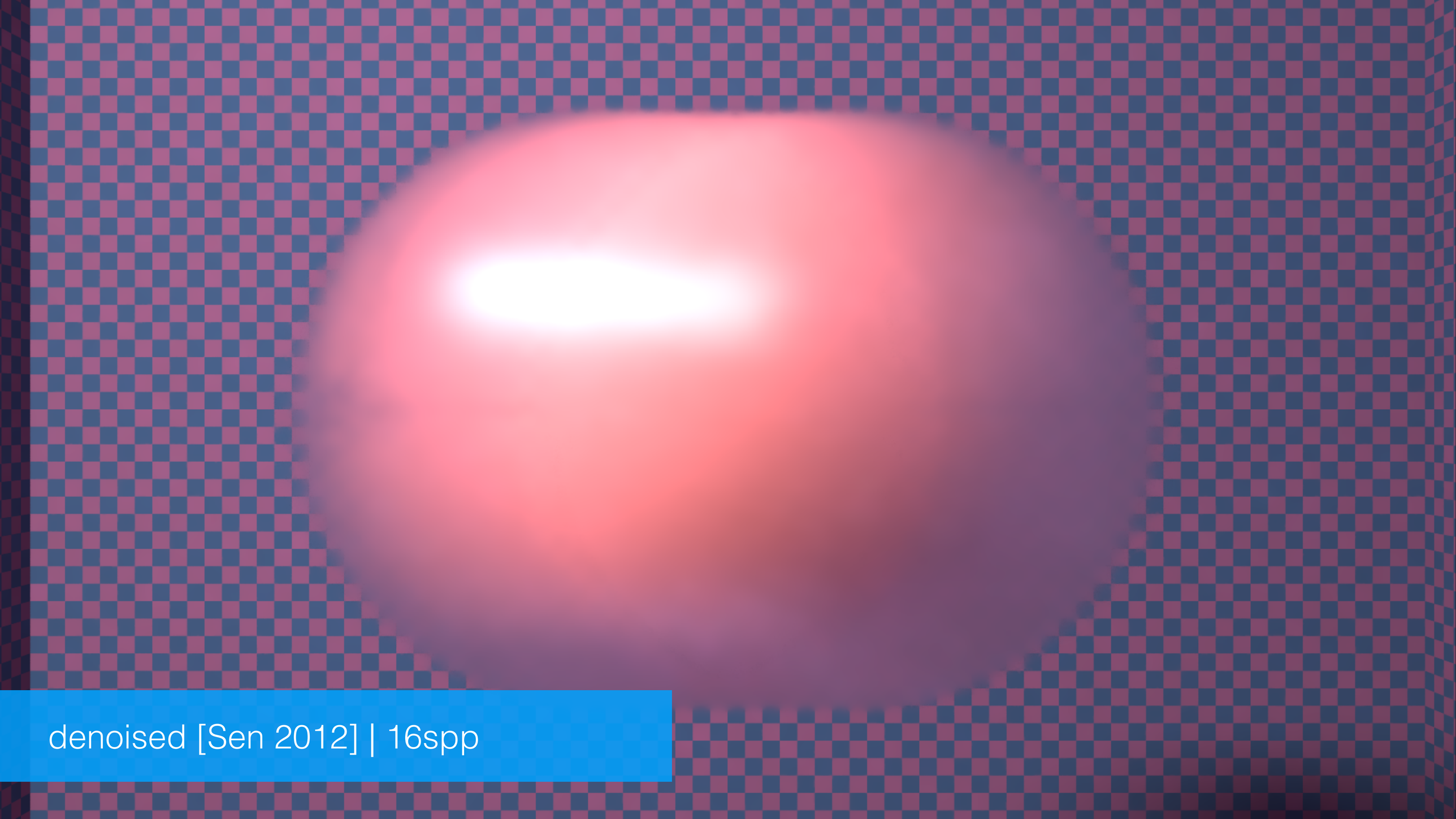
Why care about individual samples?

A simple scene

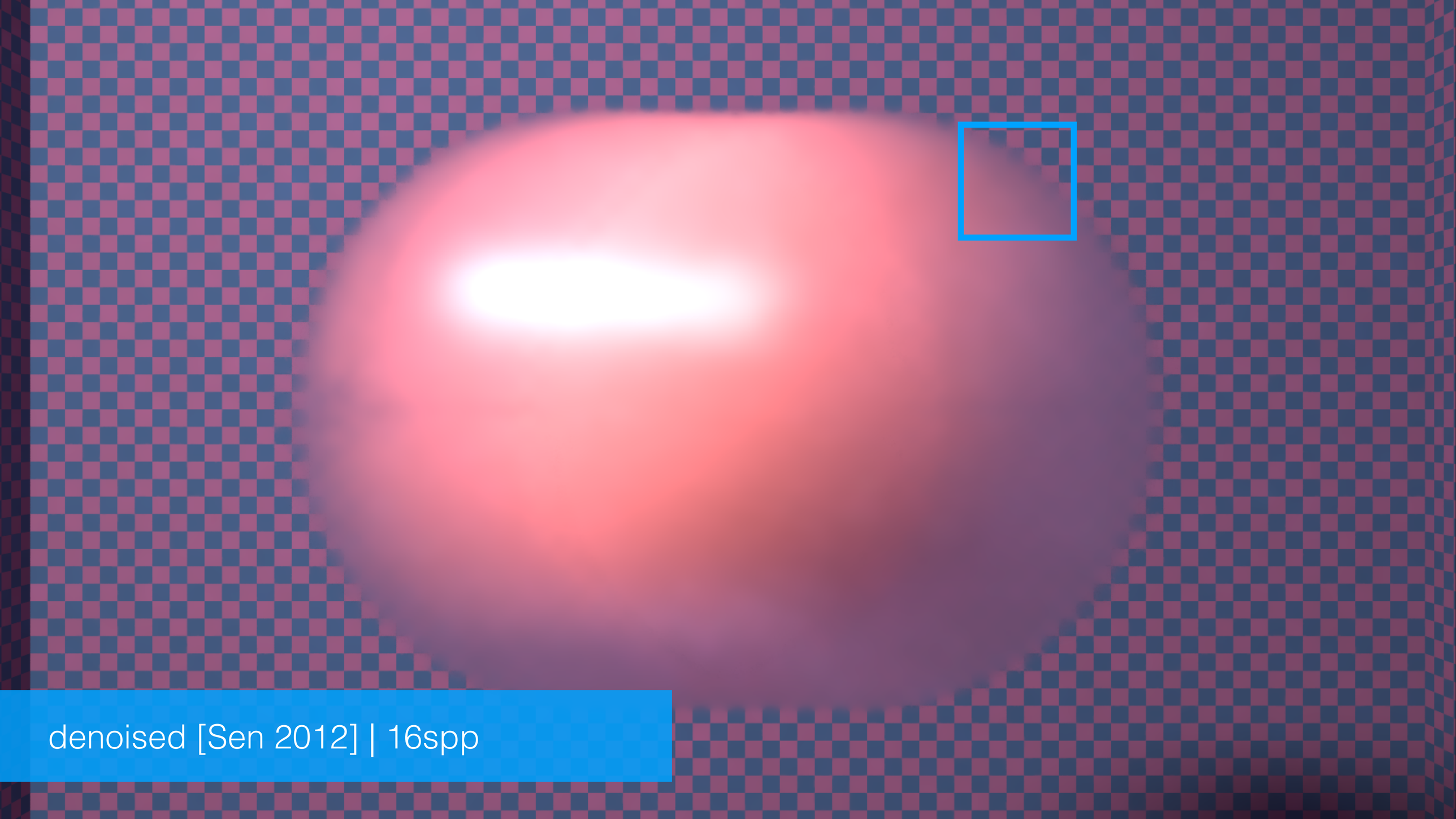


Add motion blur





denoised [Sen 2012] | 16spp



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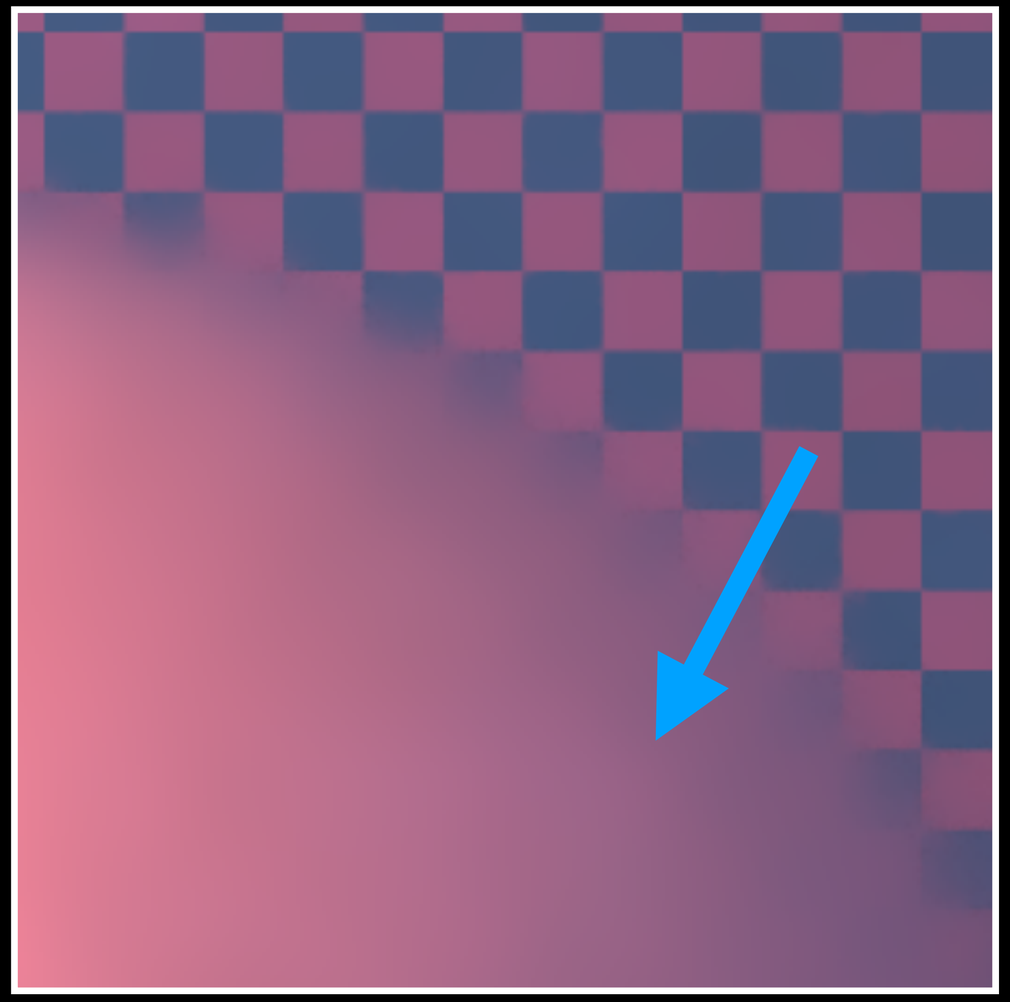

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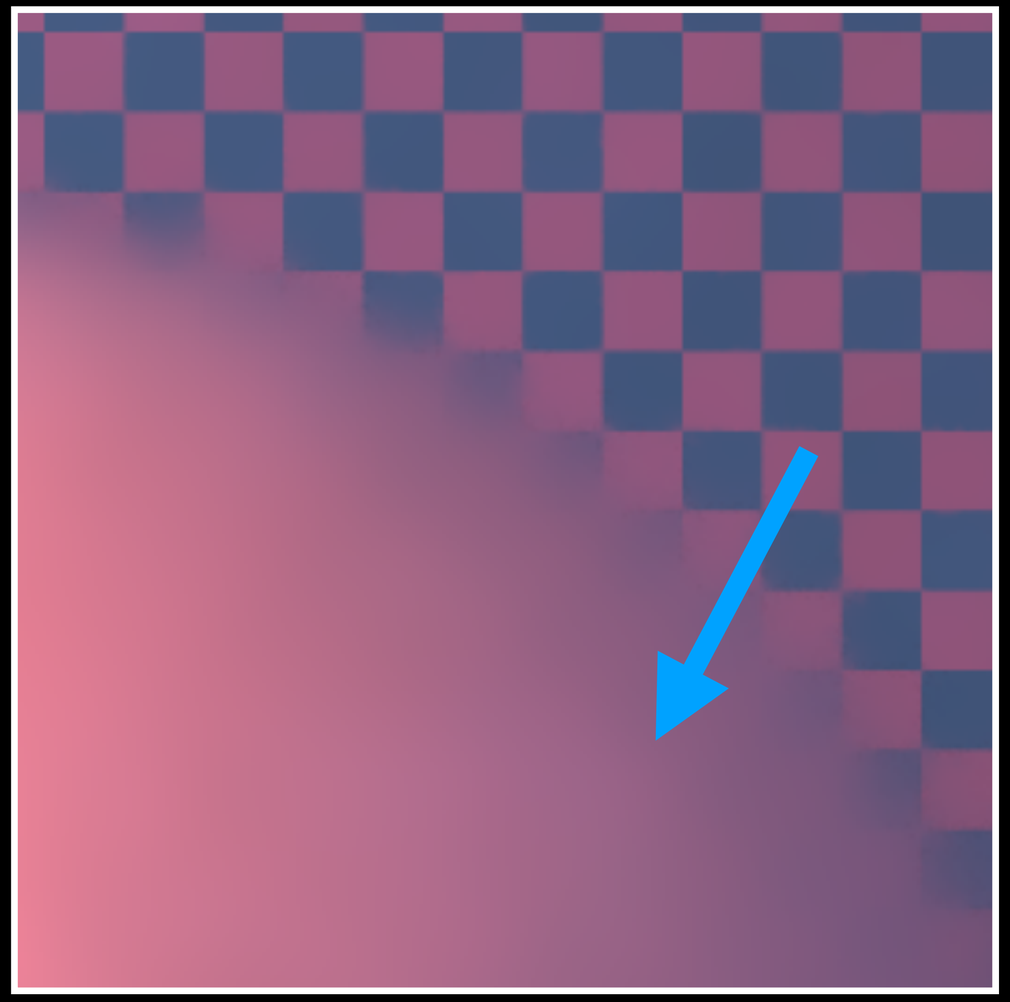

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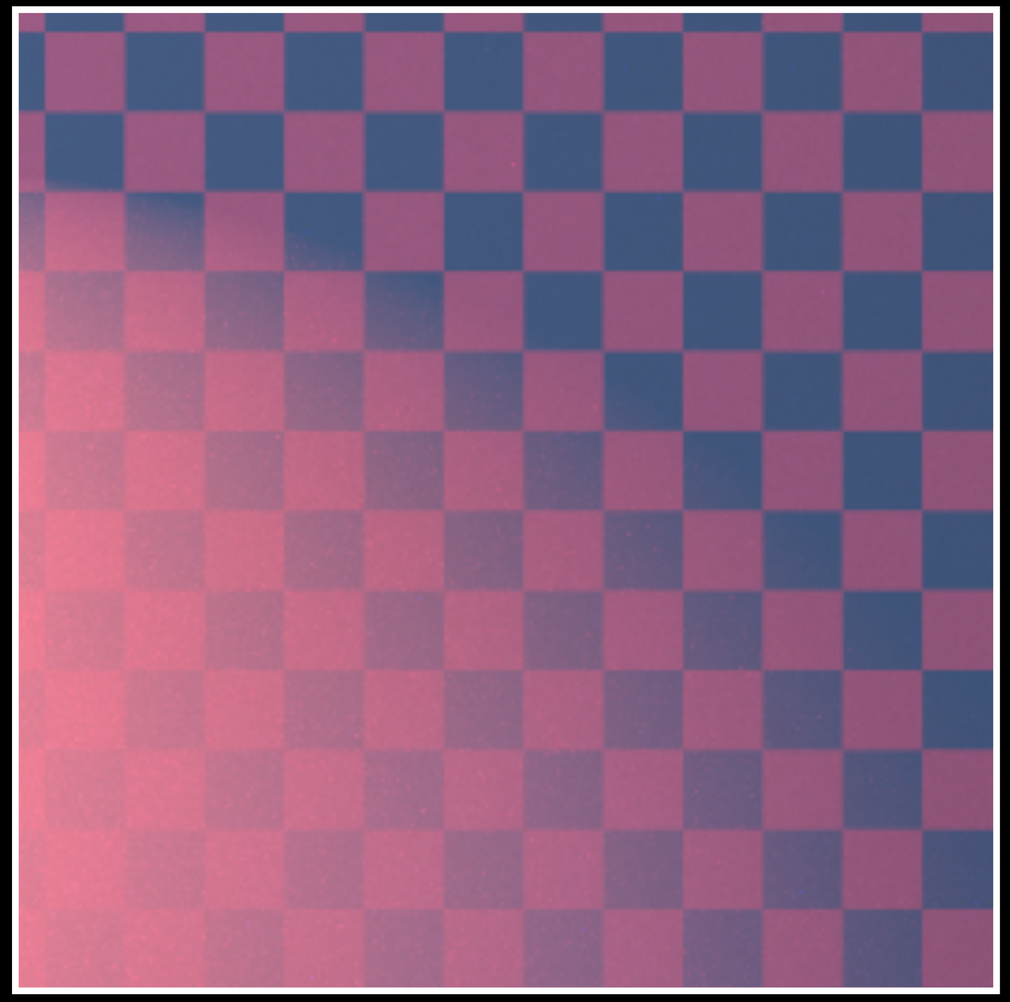
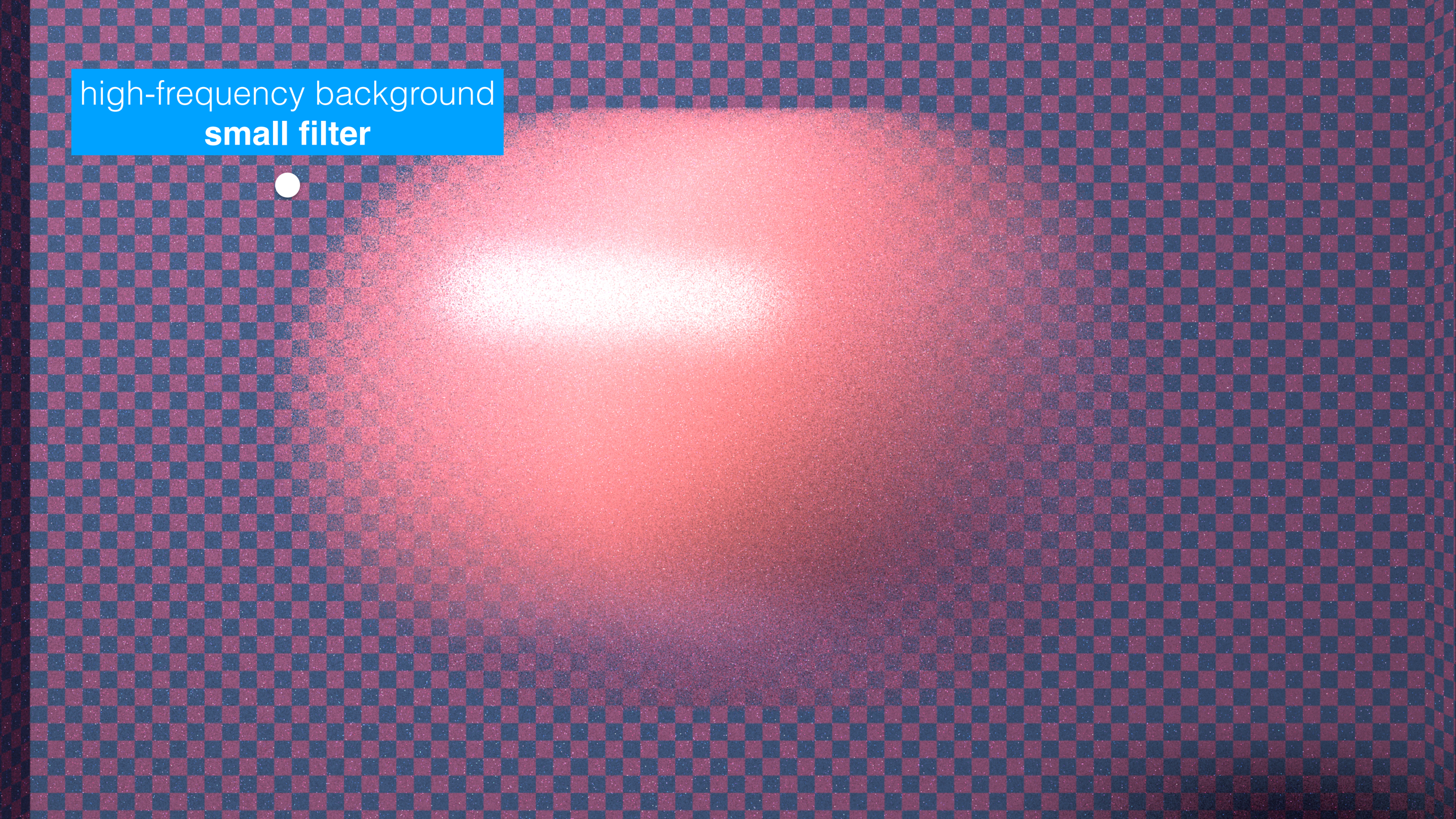
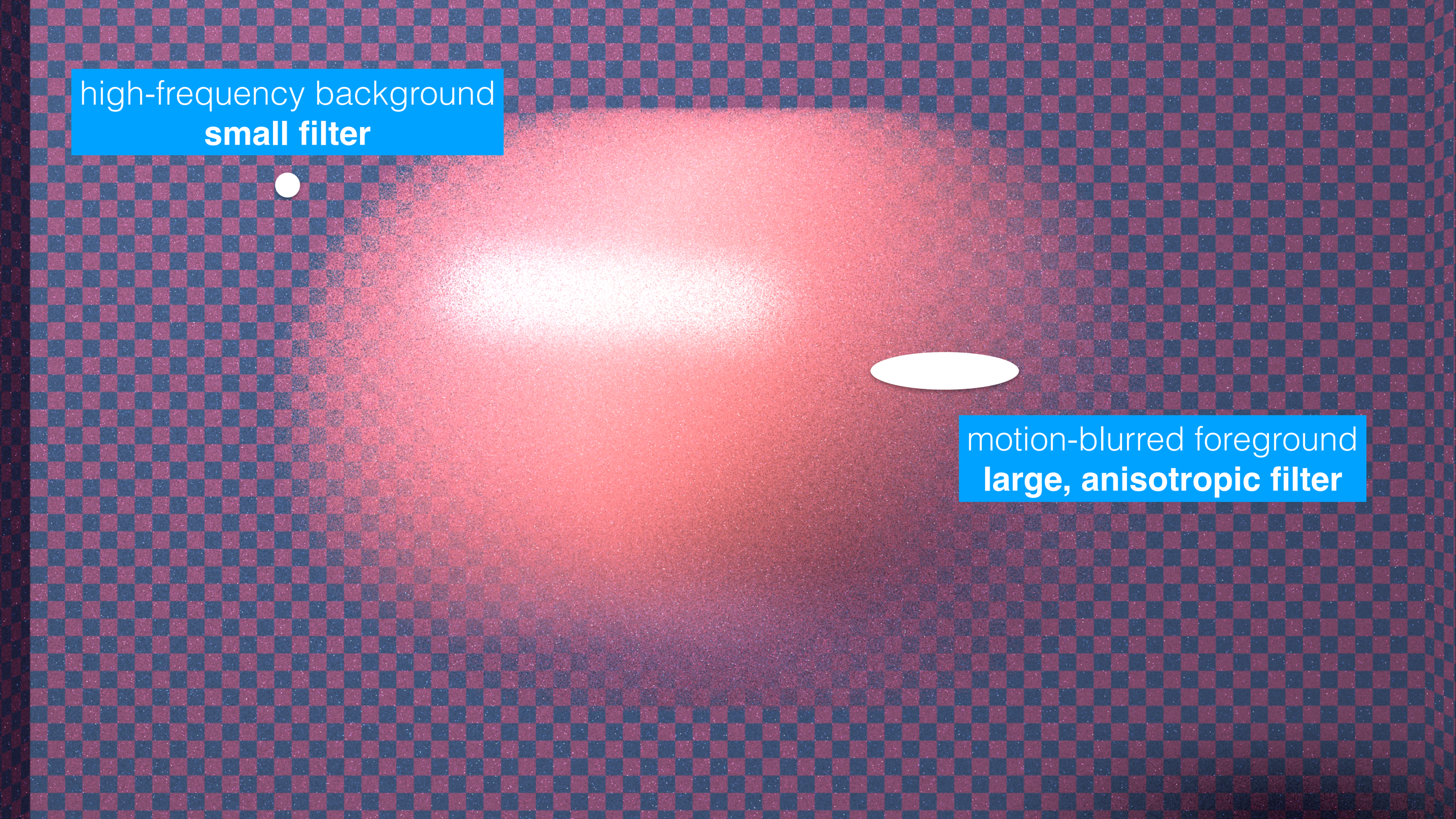
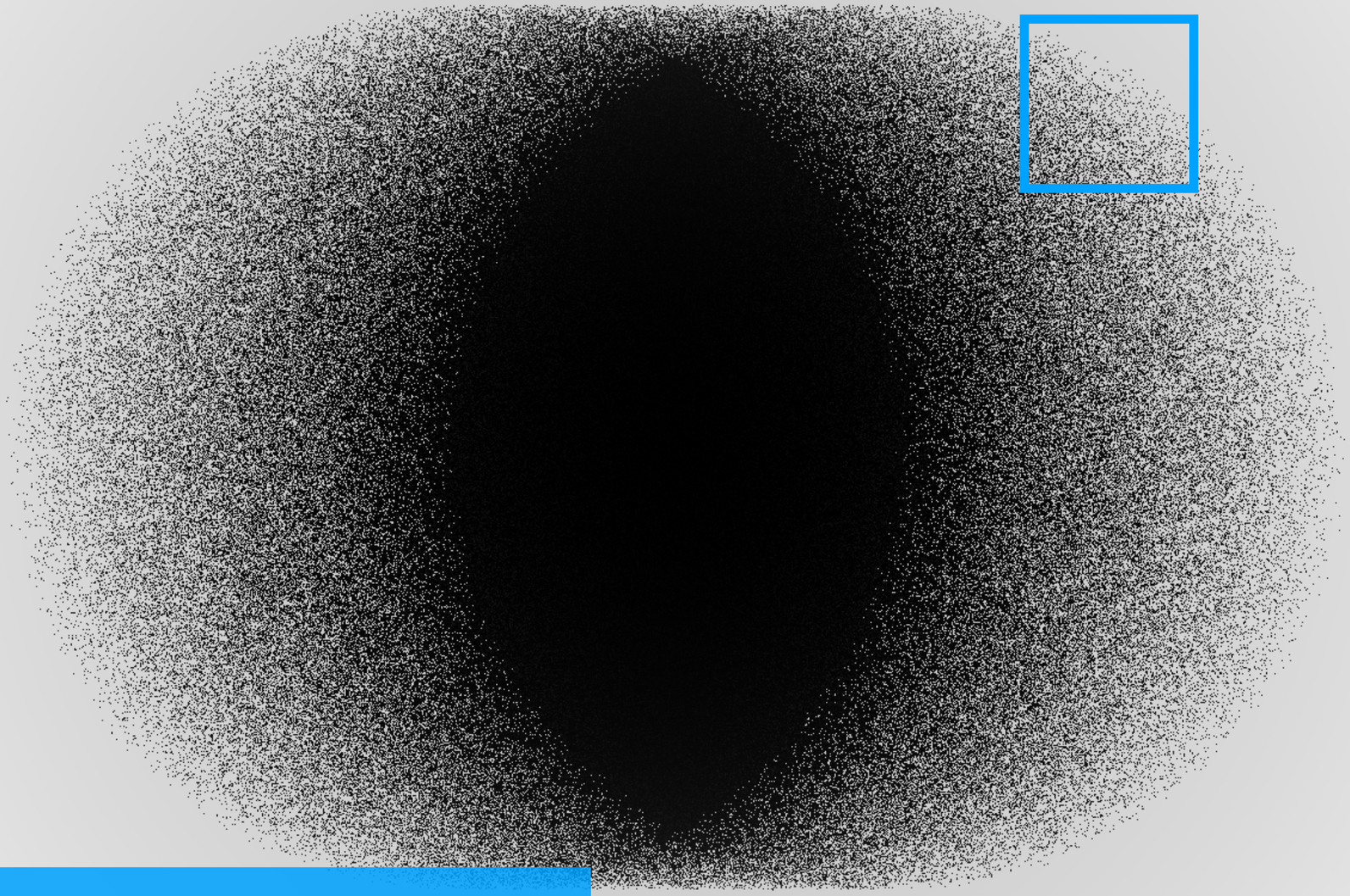


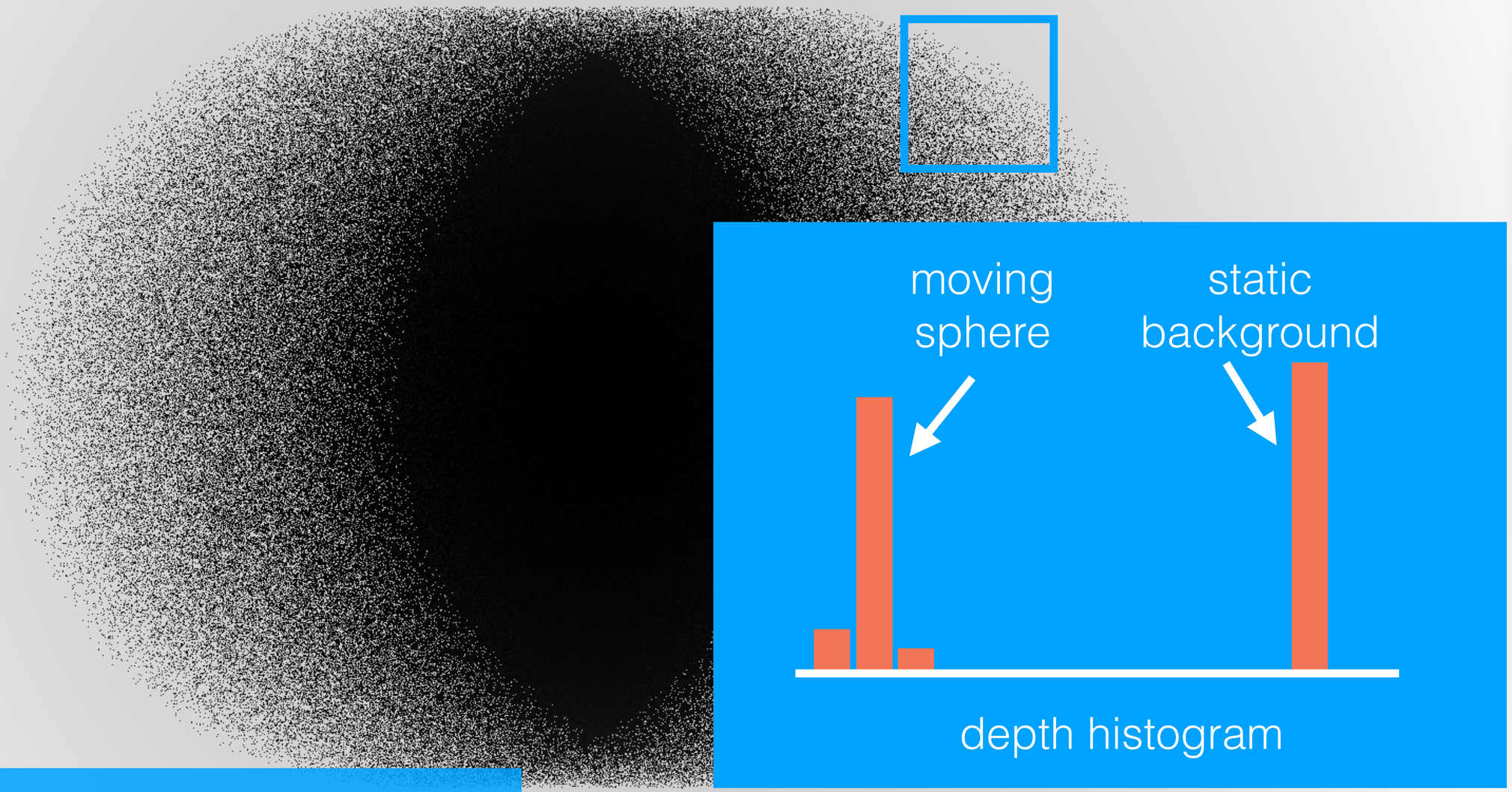
ground truth | 8192spp


high-frequency background
small filter


high-frequency background
small filter
motion-blurred foreground
large, anisotropic filter



auxiliary depth buffer



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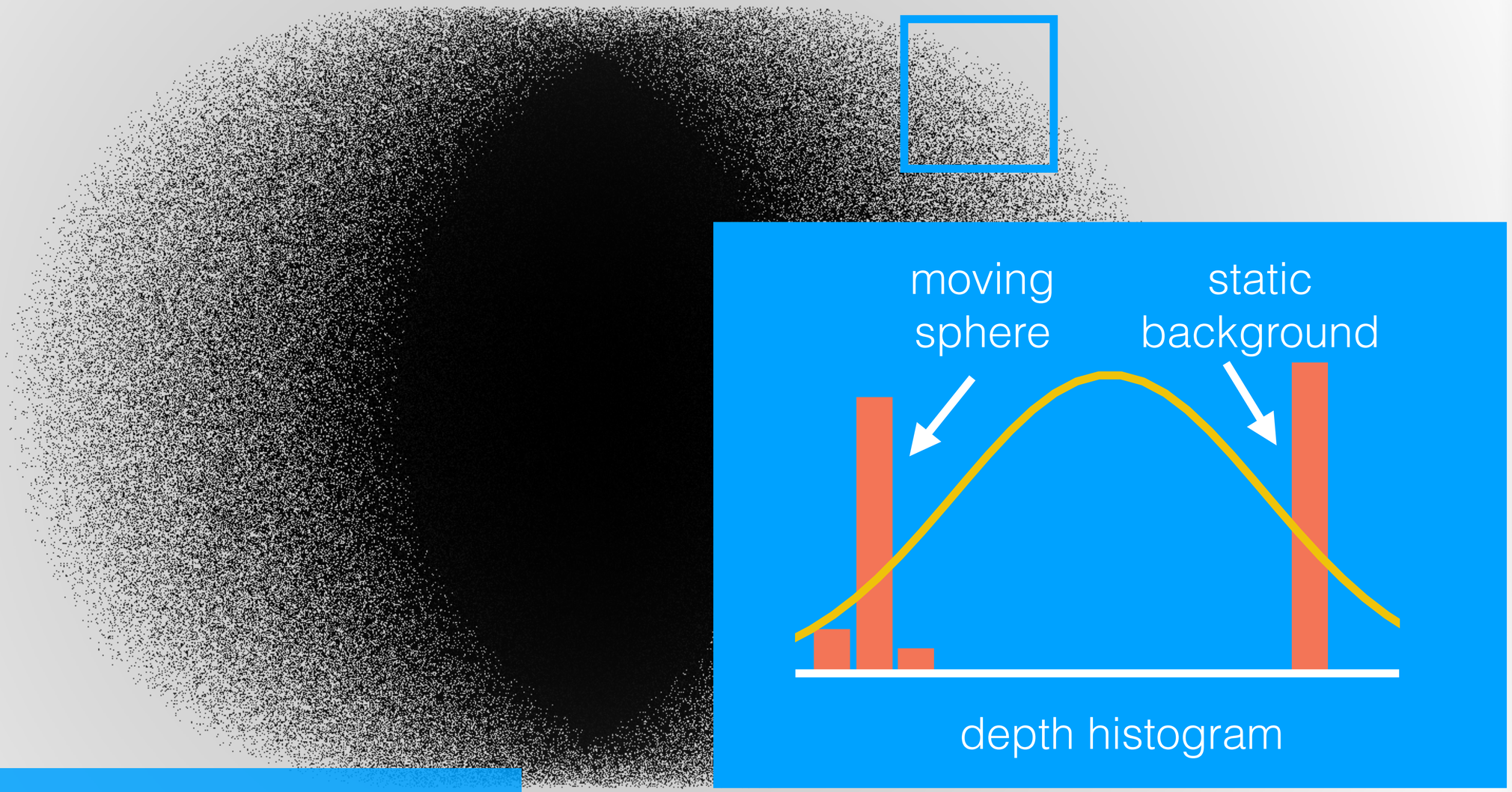

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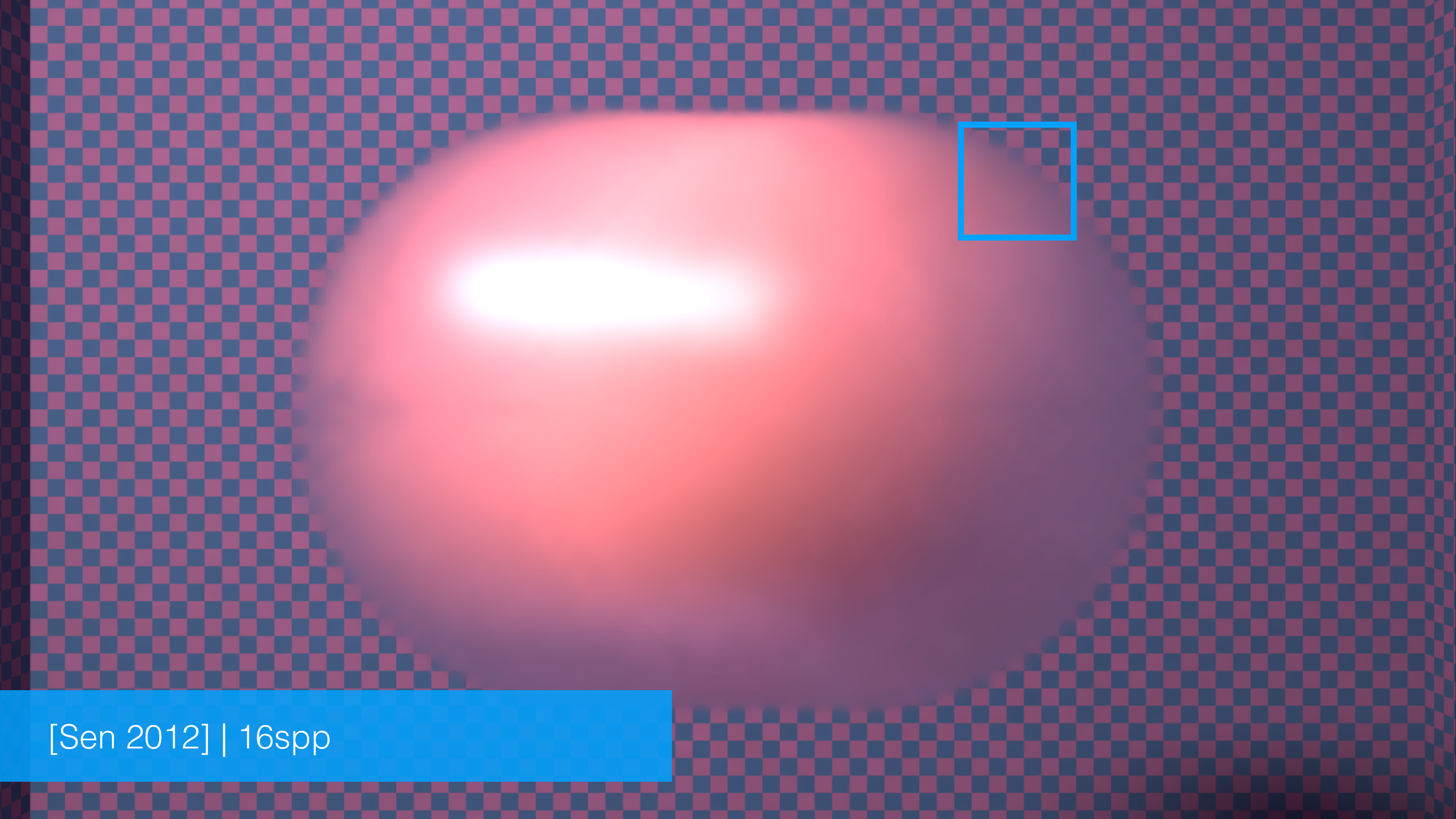
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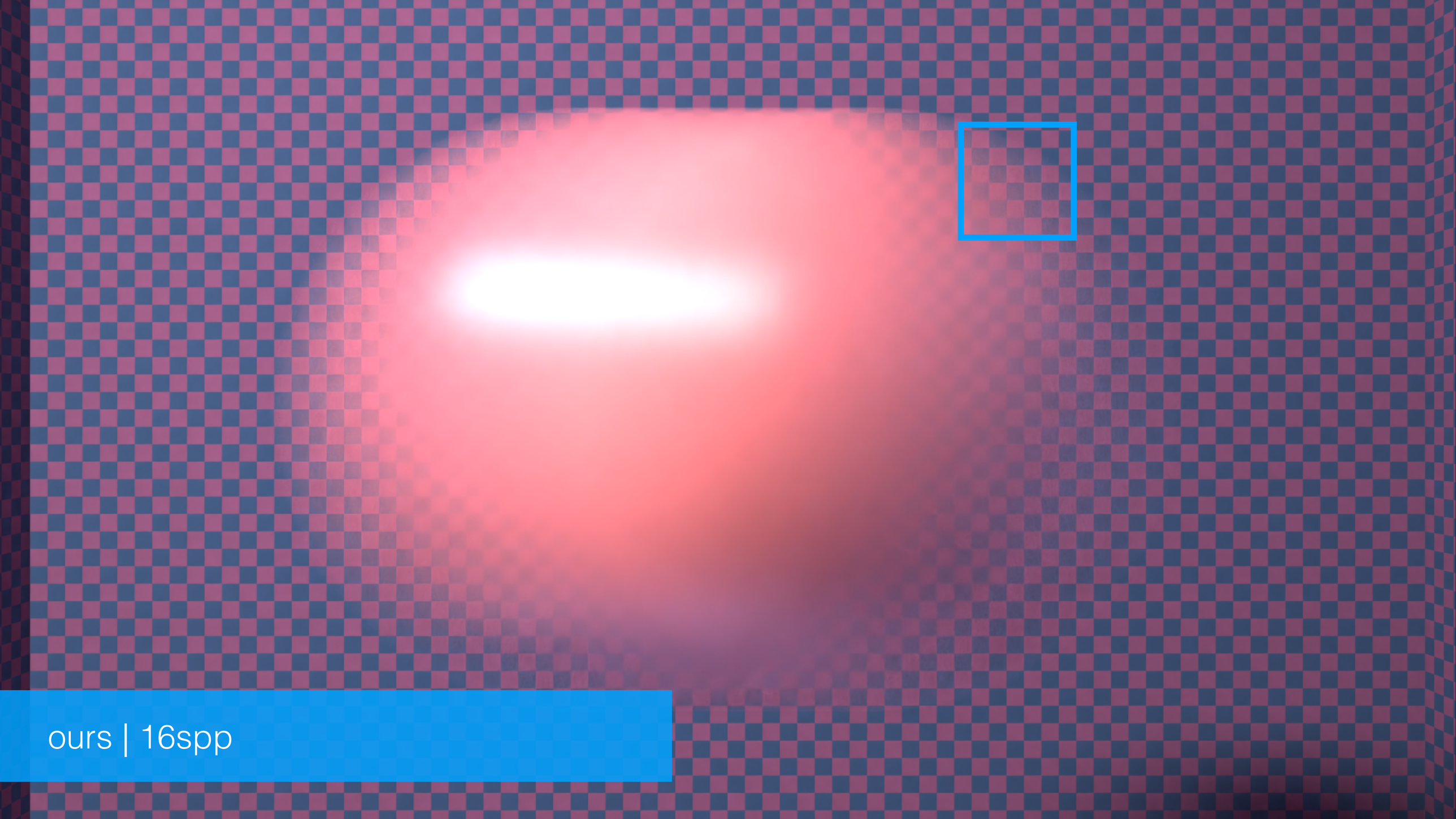
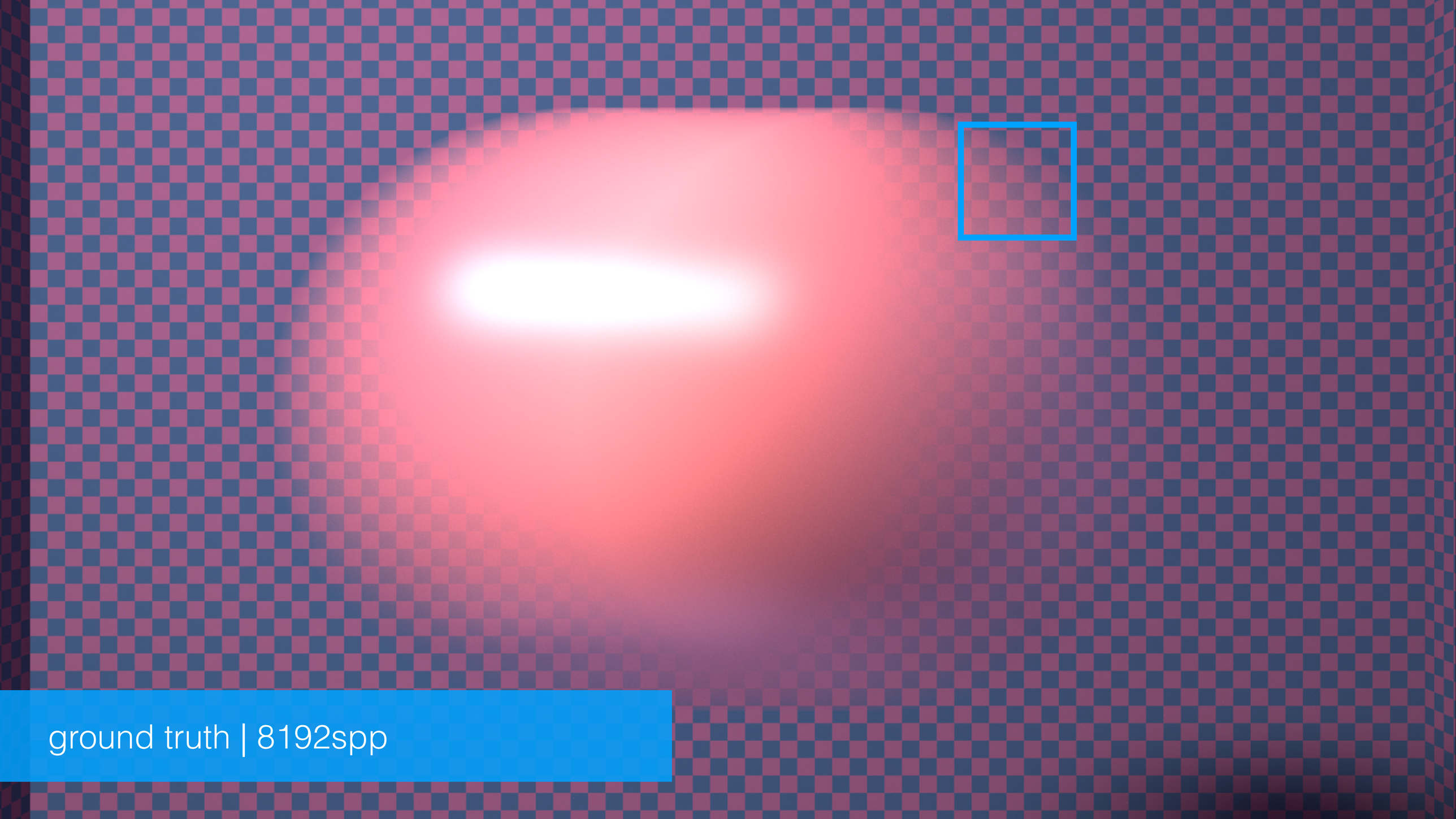
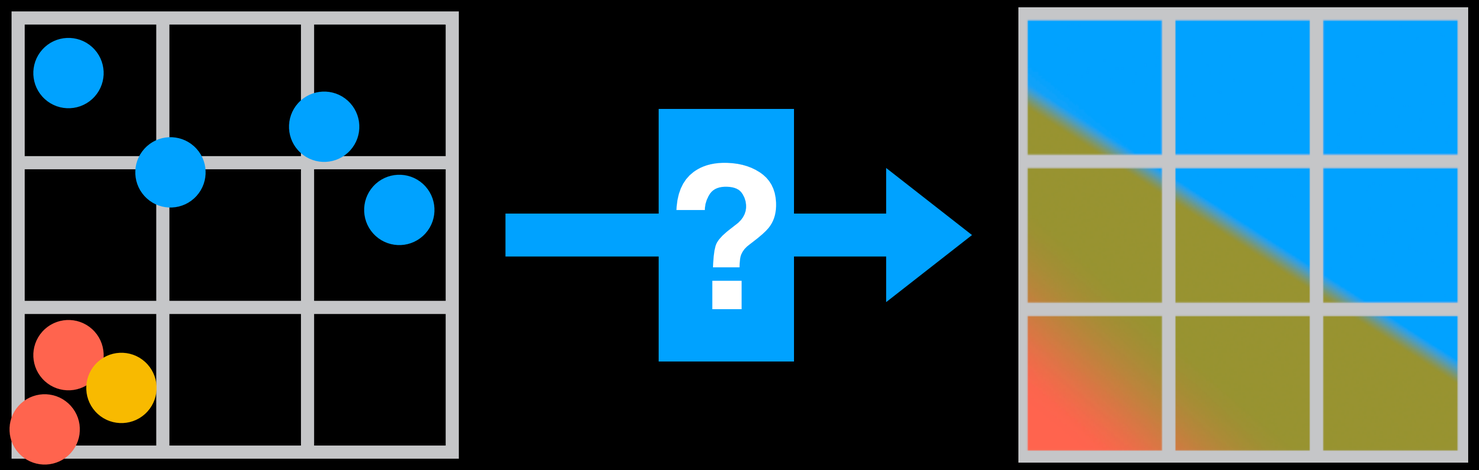

ours | 16spp

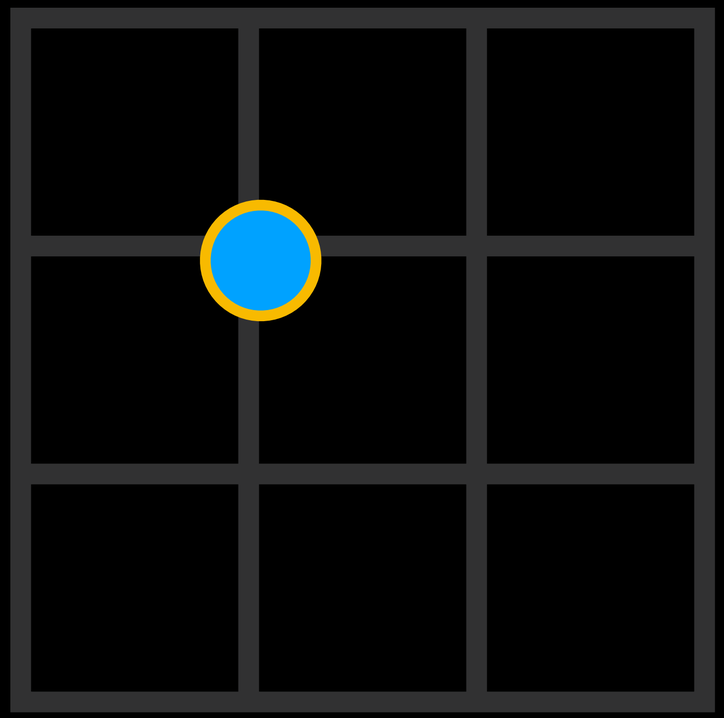


ground truth | 8192spp

Mapping samples to pixels: challenges



Samples need to know their surroundings



unordered samples

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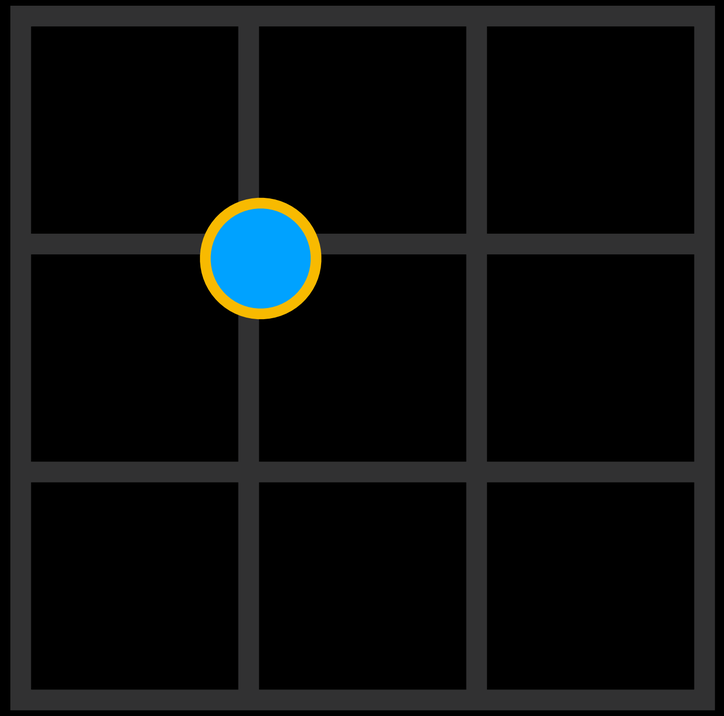

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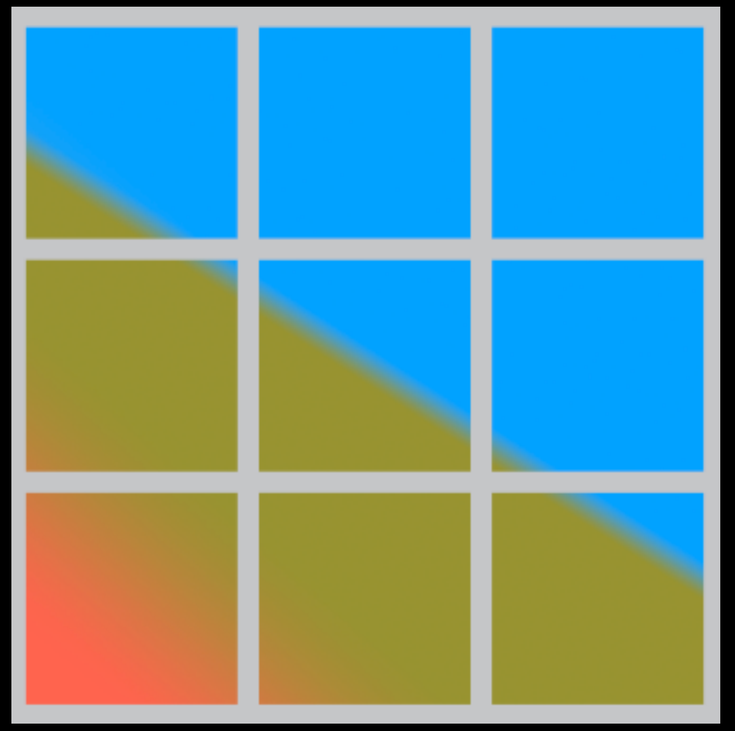

target reconstruction

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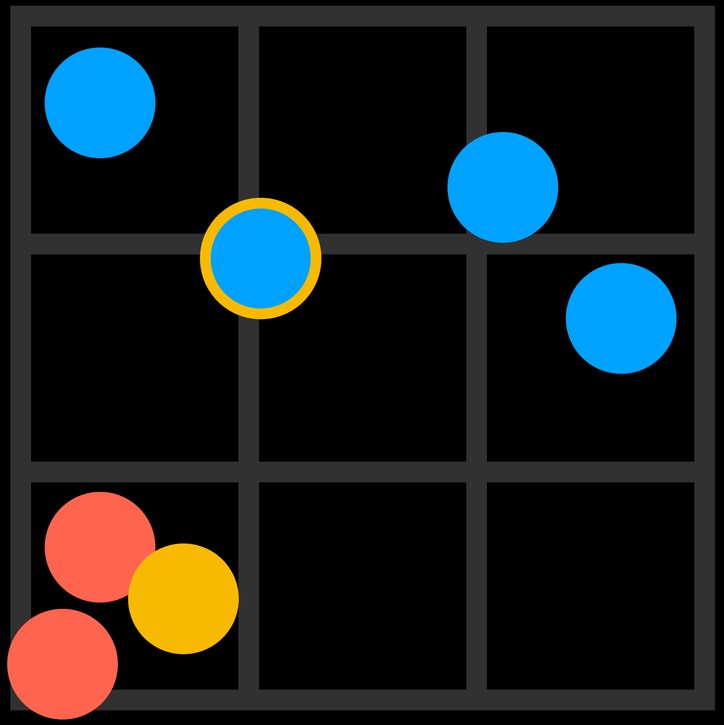

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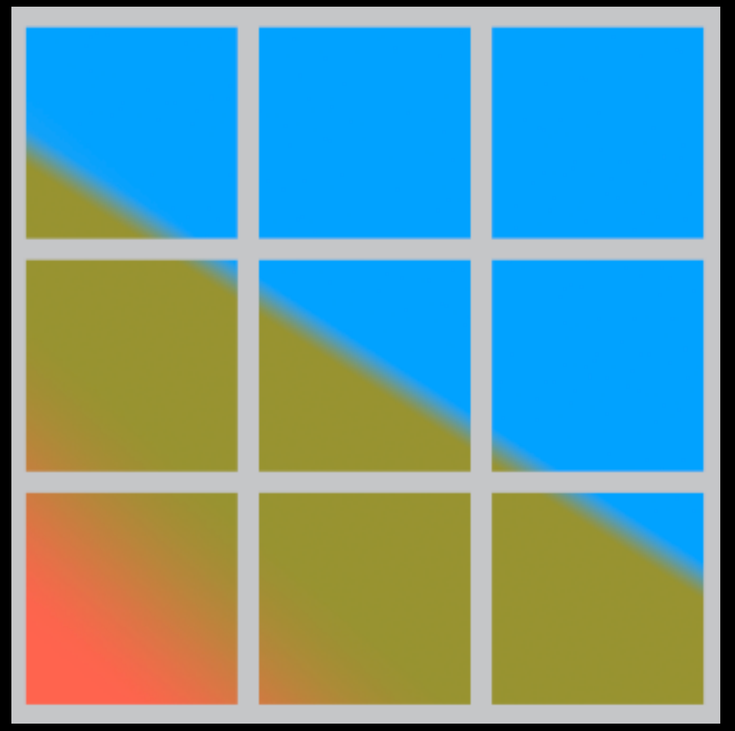
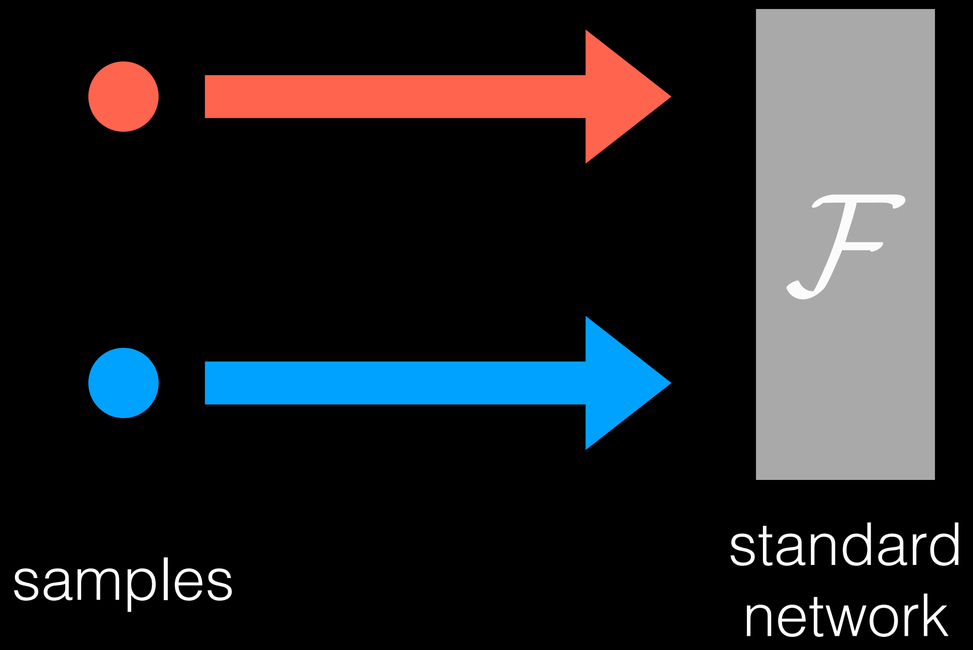


target reconstruction

Standard networks have implicit ordering

and cannot track samples



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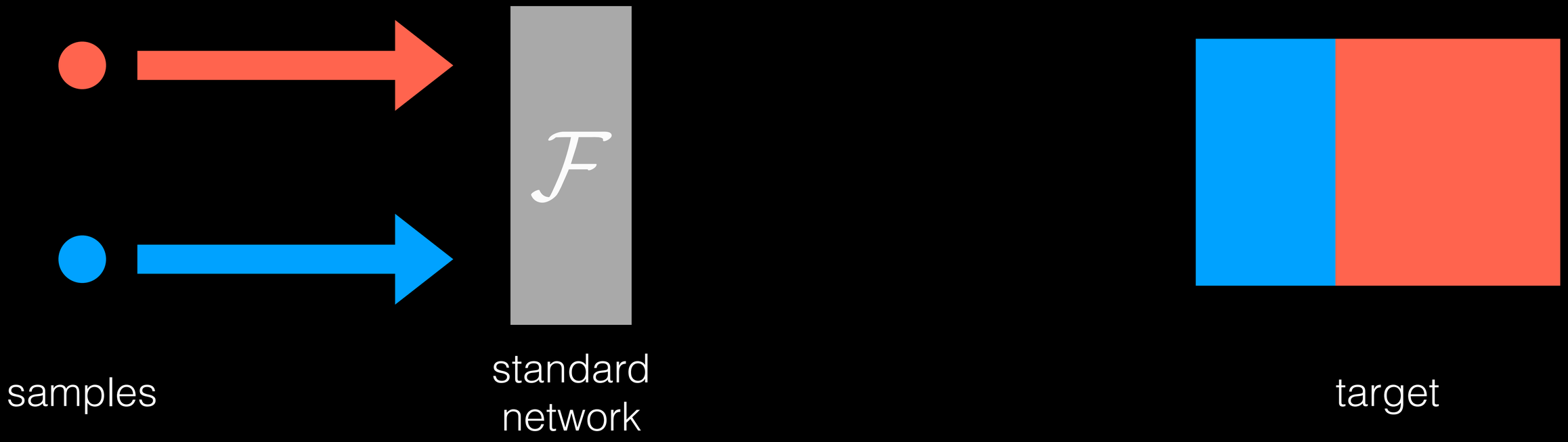

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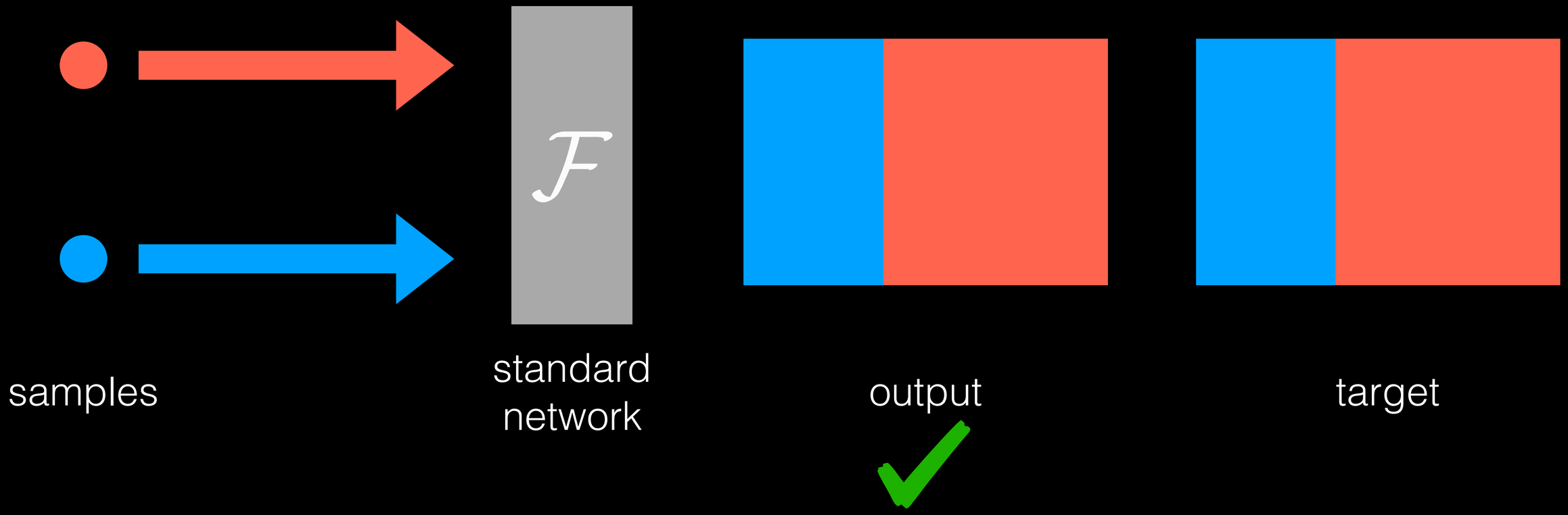

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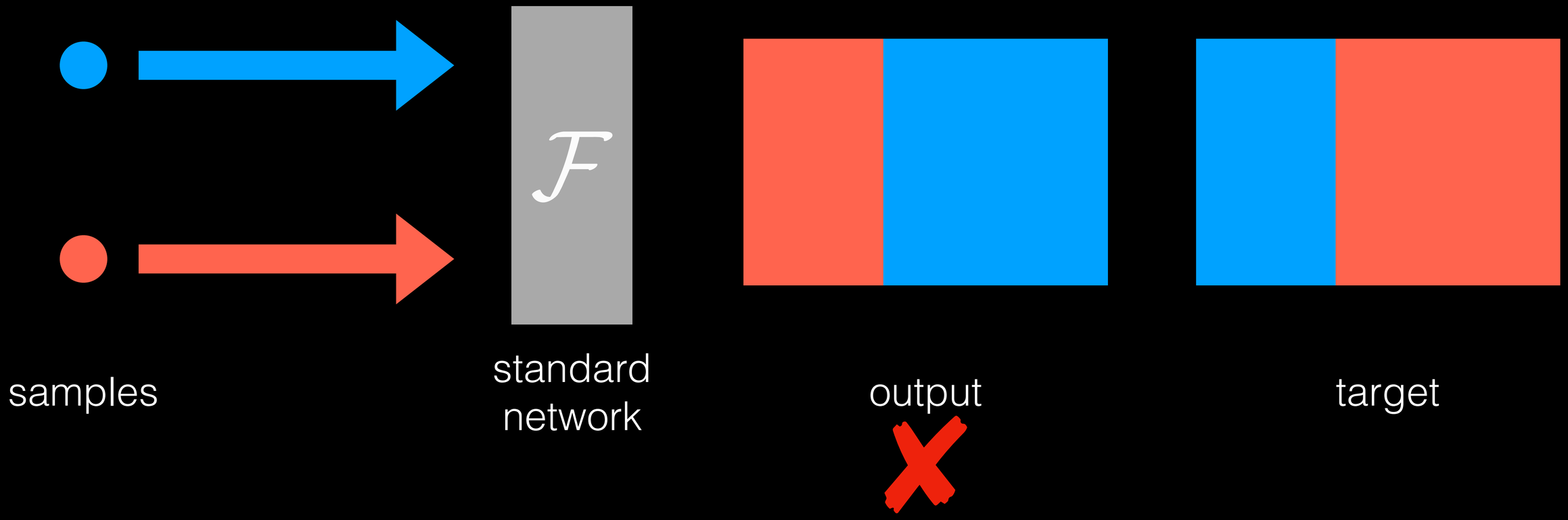

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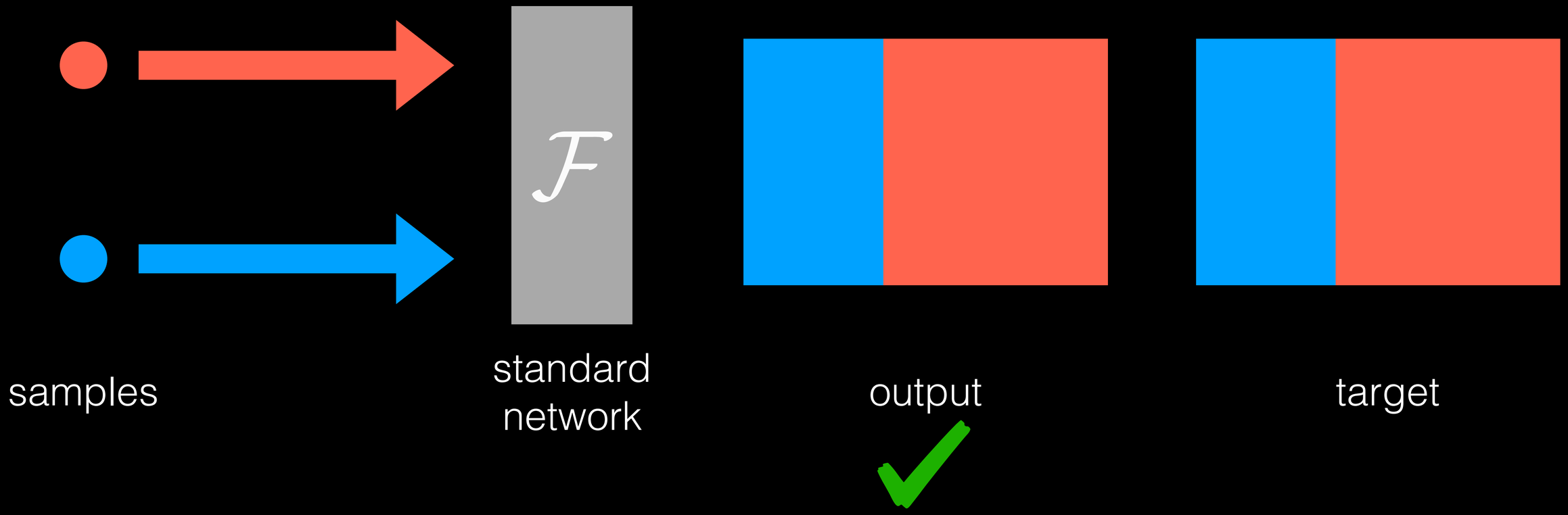
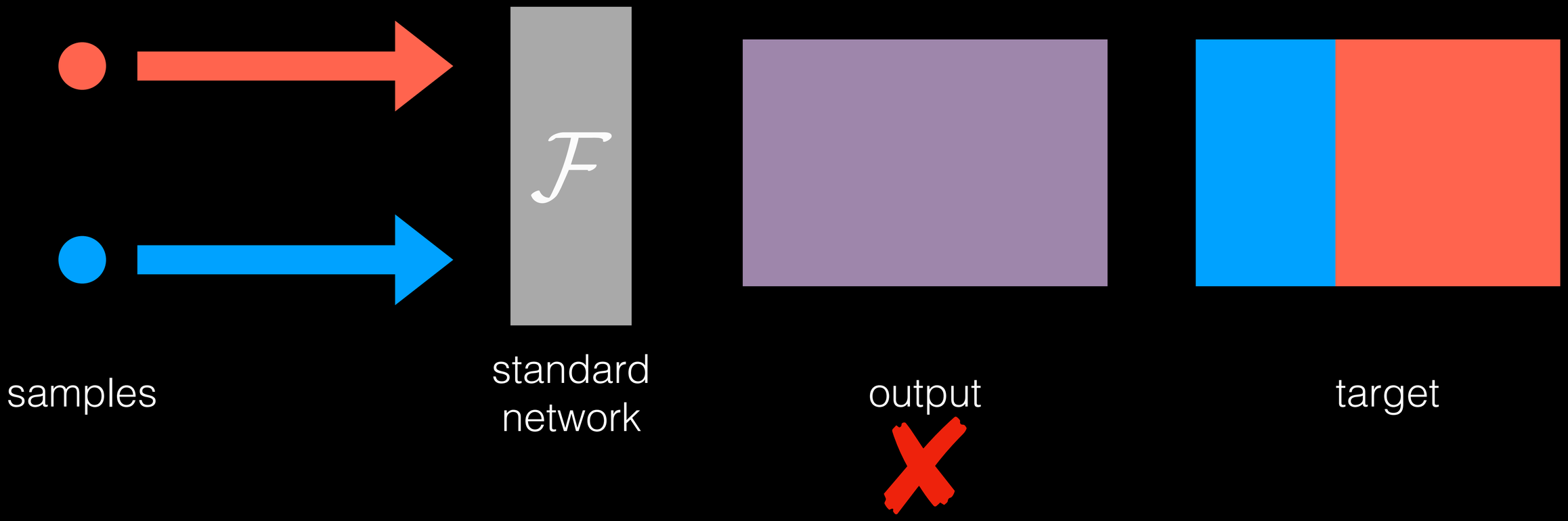


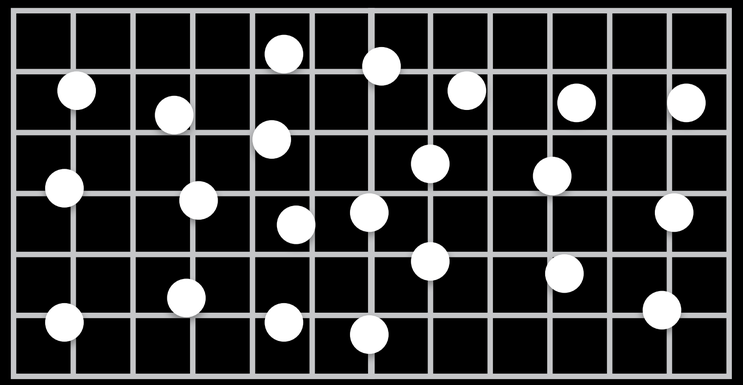
No better than averaging samples

and cannot track samples



Method: map unordered samples to pixels

using splatting kernels



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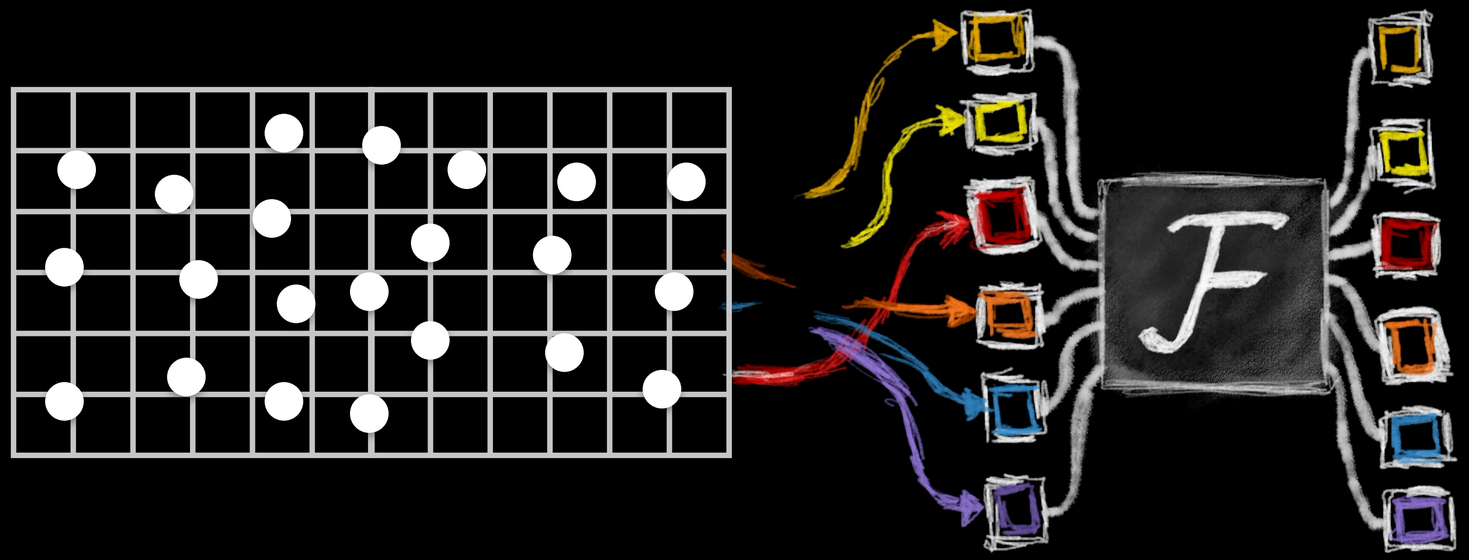

unordered samples

permutation-invariant neural network

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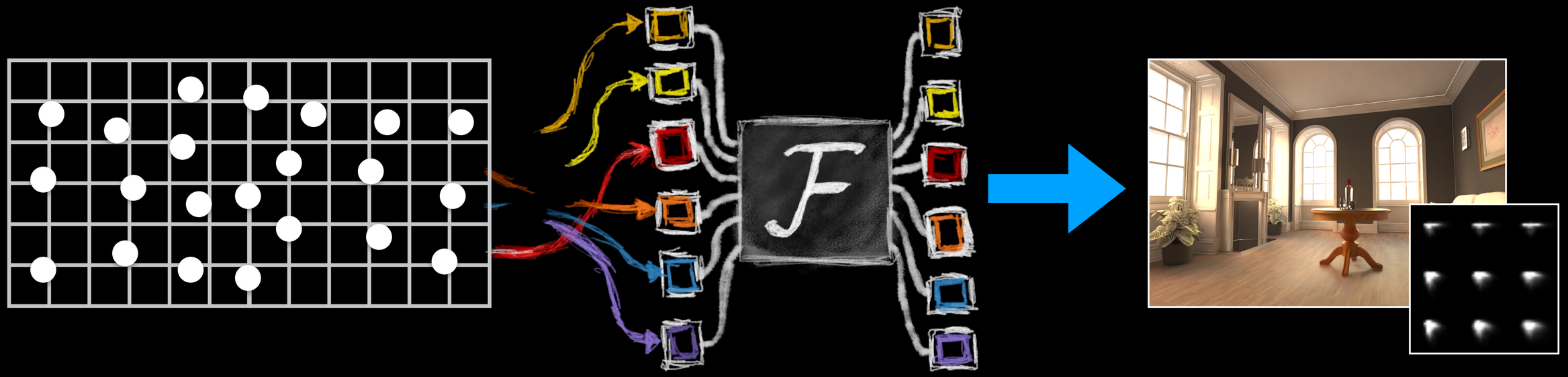
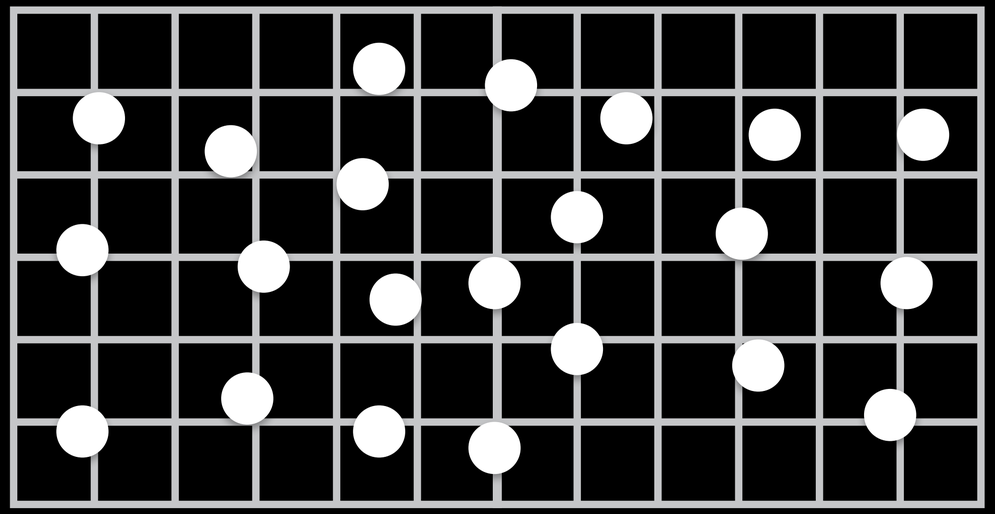


unordered samples

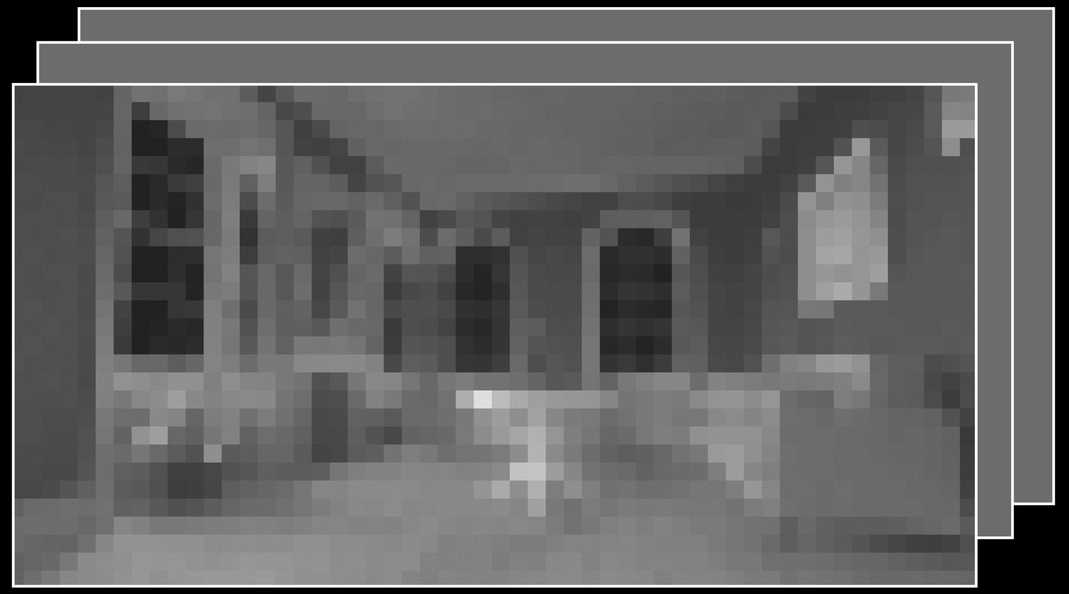
permutation-invariant neural network

splatting kernels reconstruction

Two representations: samples/pixels

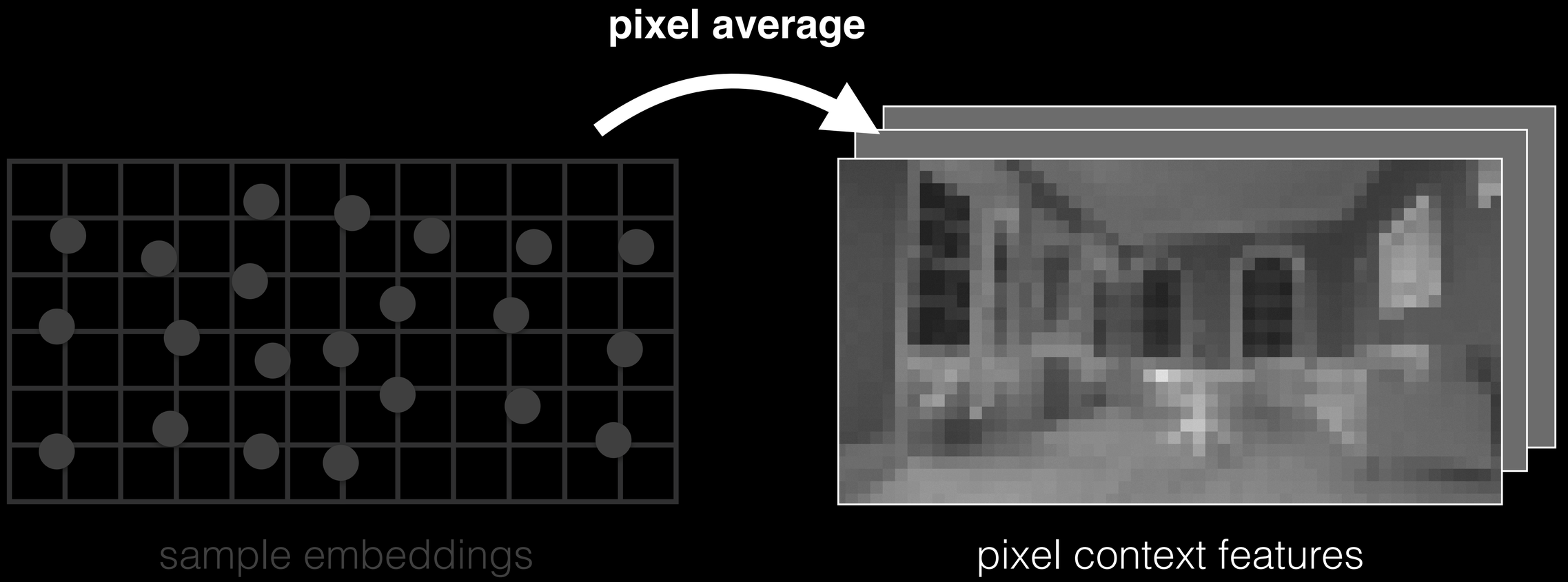


sample embeddings



pixel context features

Two representations: samples/pixels



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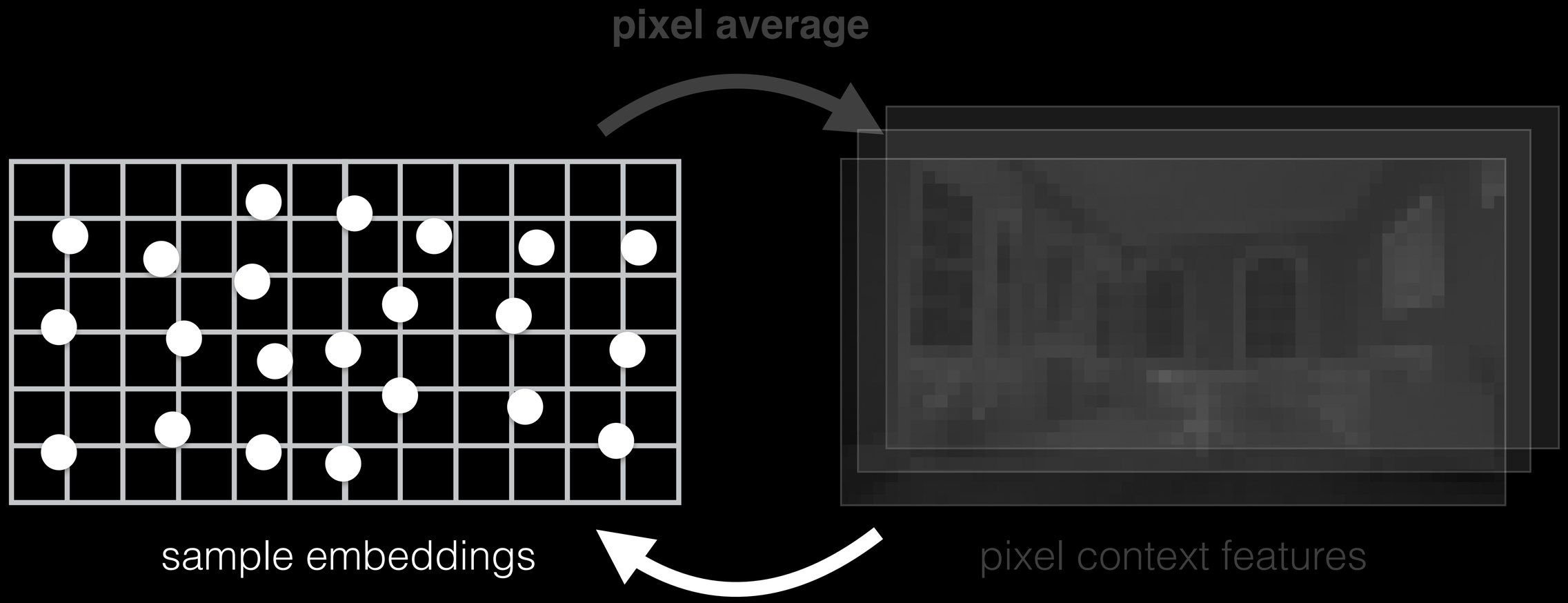
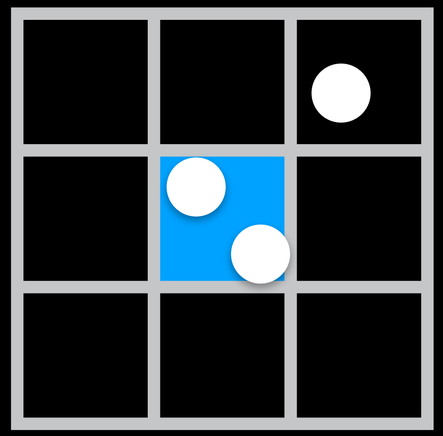
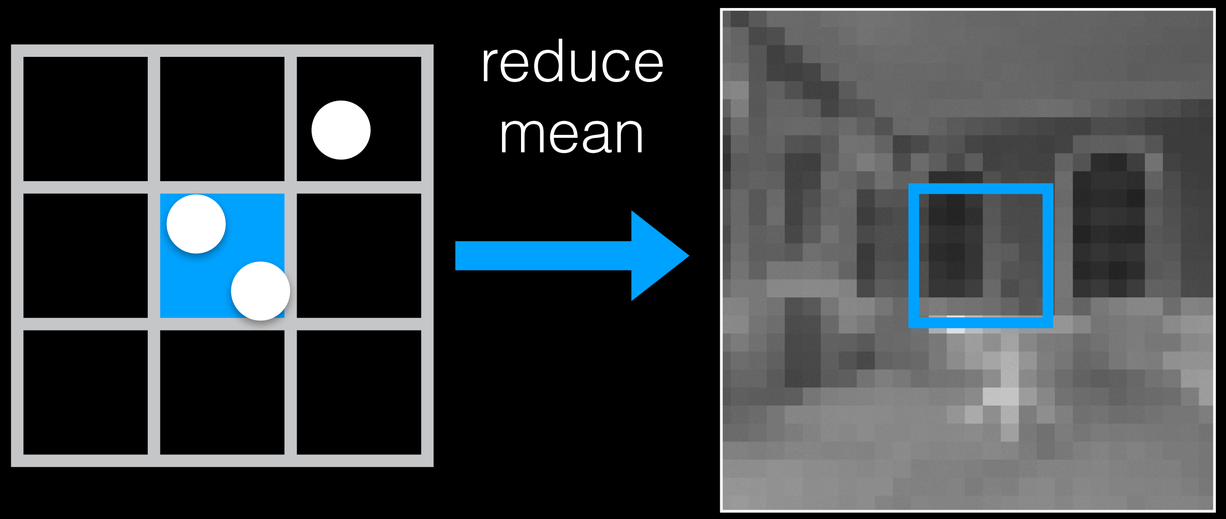


Update pixel context



sample
features

Update pixel context



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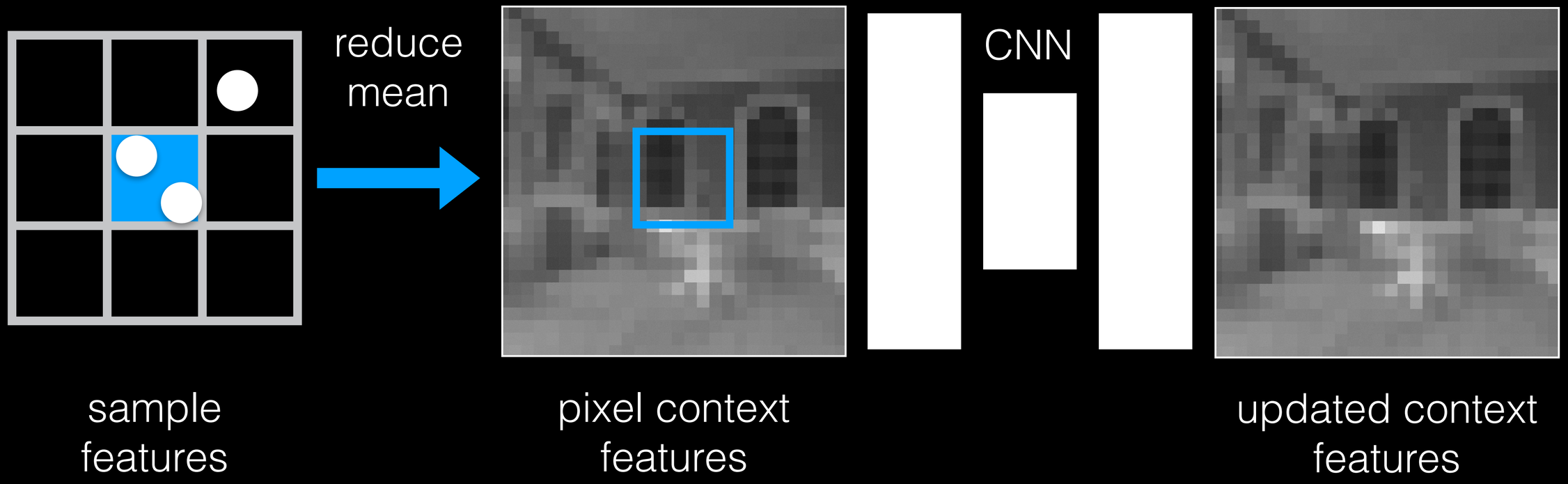
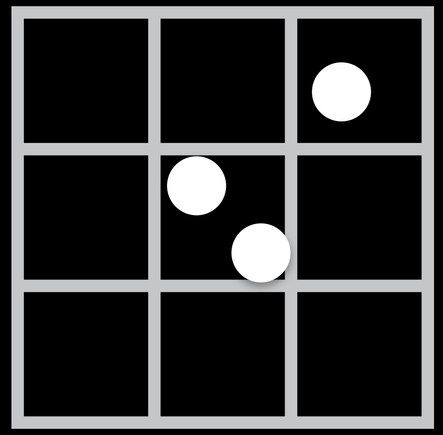


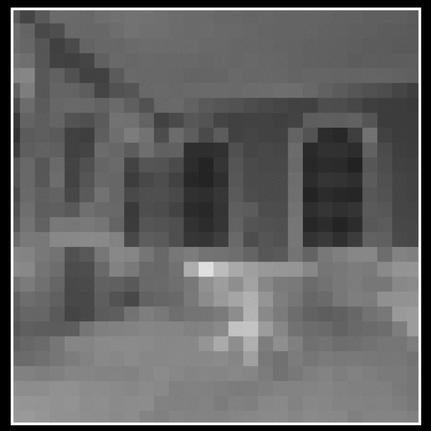
Independently process samples

conditioned on pixel context

input
sample features

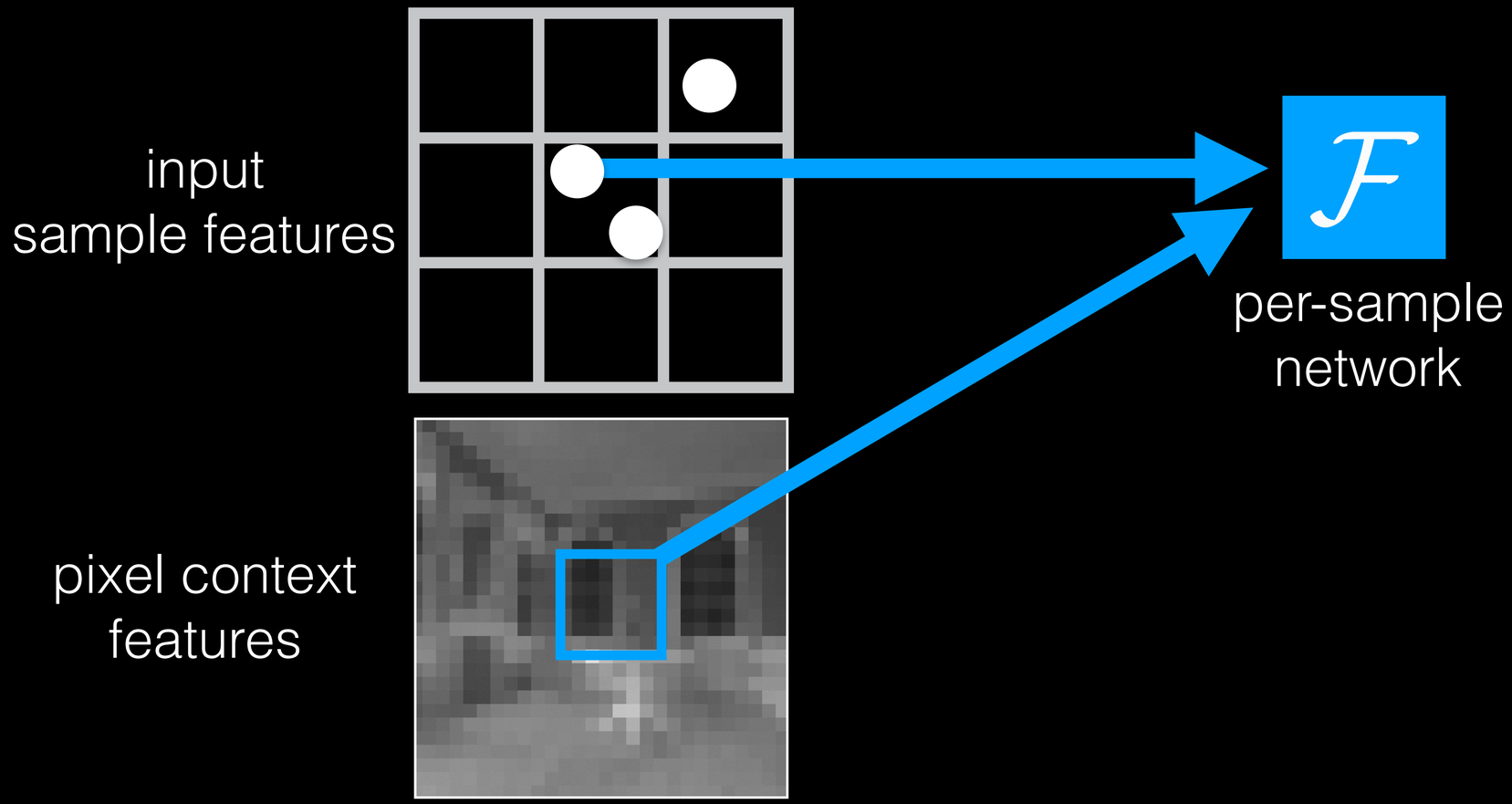


pixel context
features



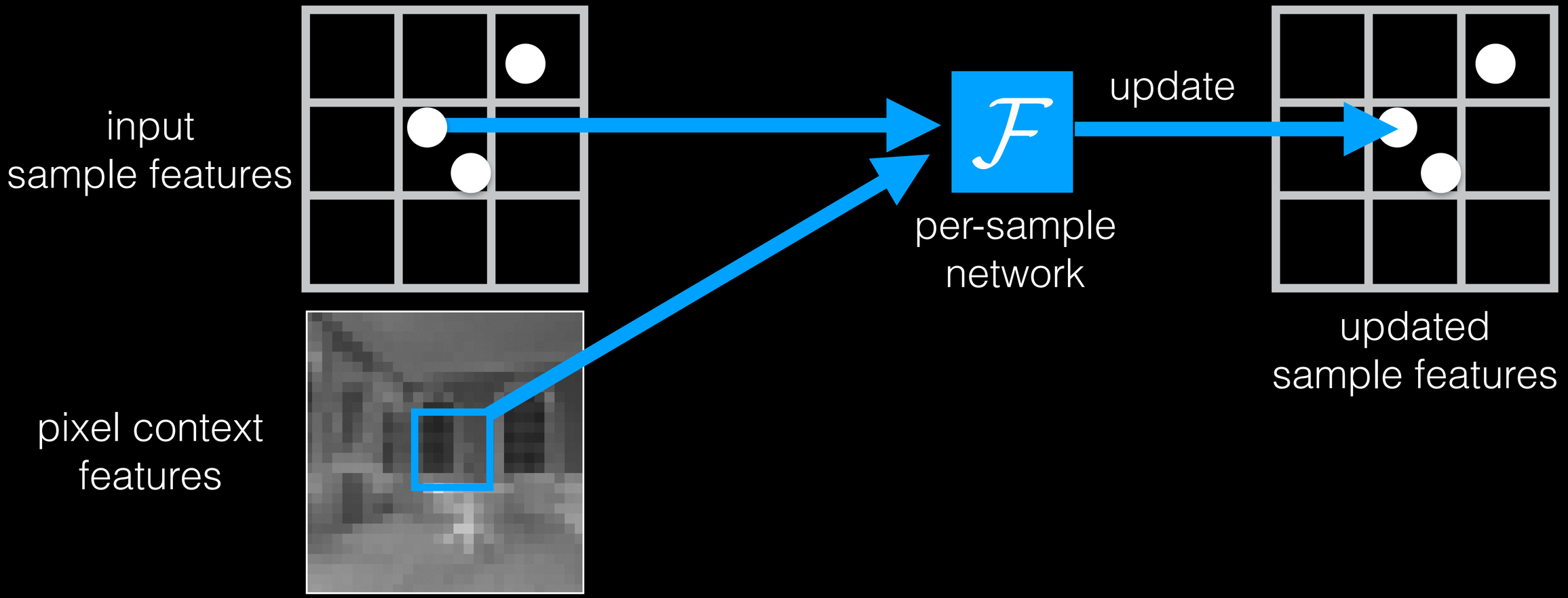
Independently process samples

conditioned on pixel context

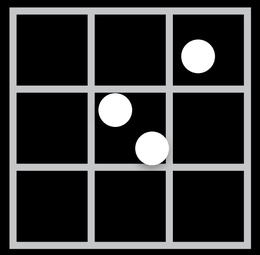


Independently process samples

conditioned on pixel context

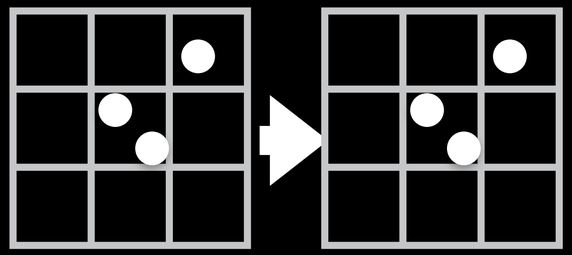


Permutation-invariant network



input
samples

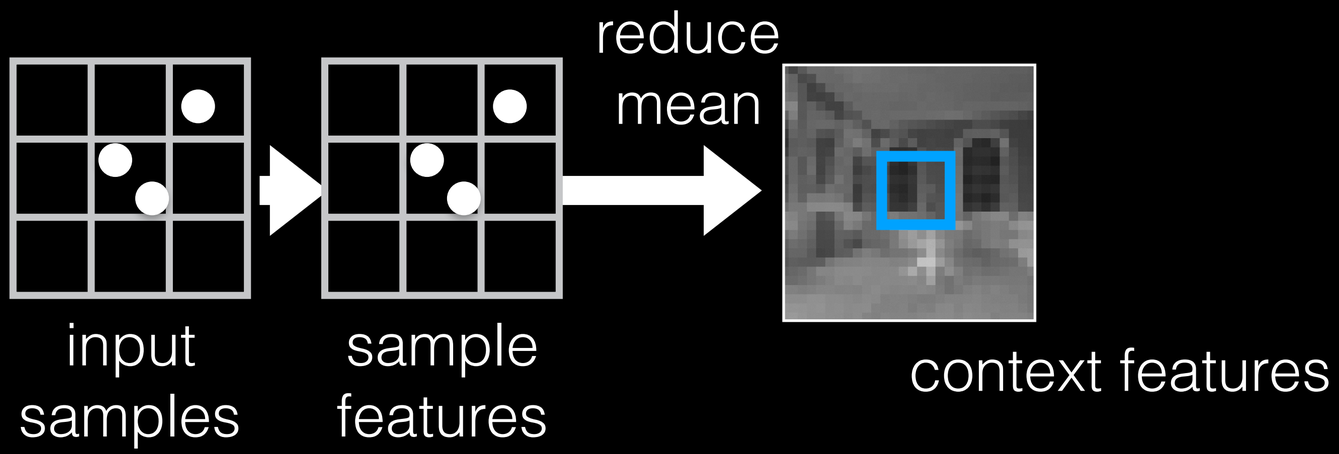
Permutation-invariant network



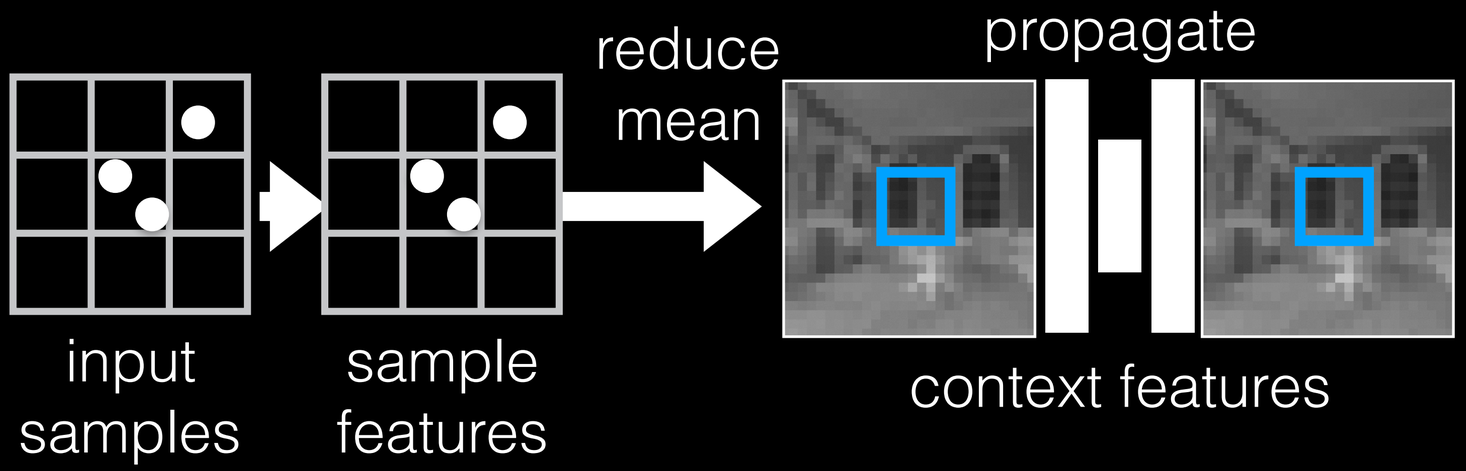
input samples

sample features

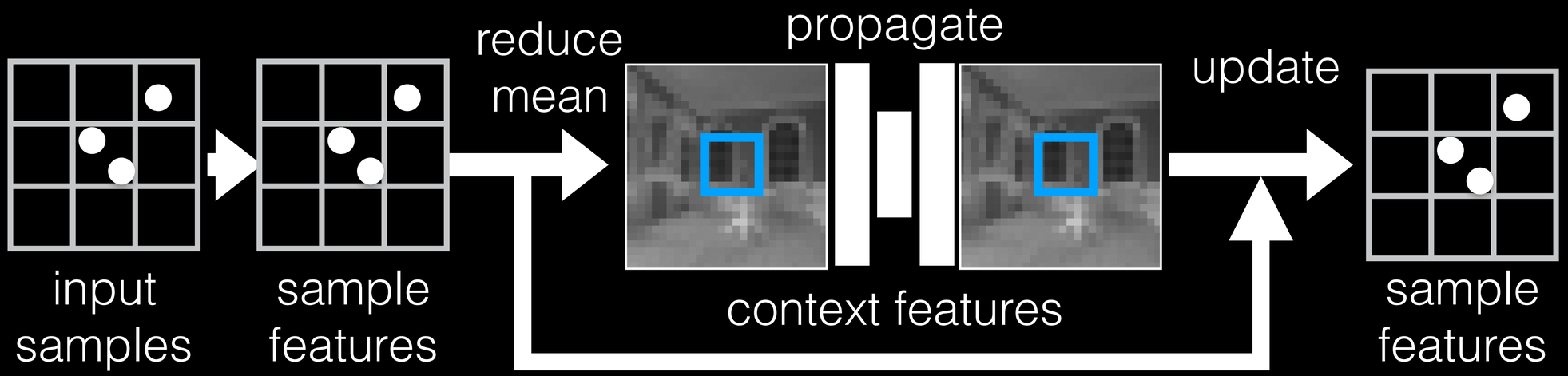
Permutation-invariant network



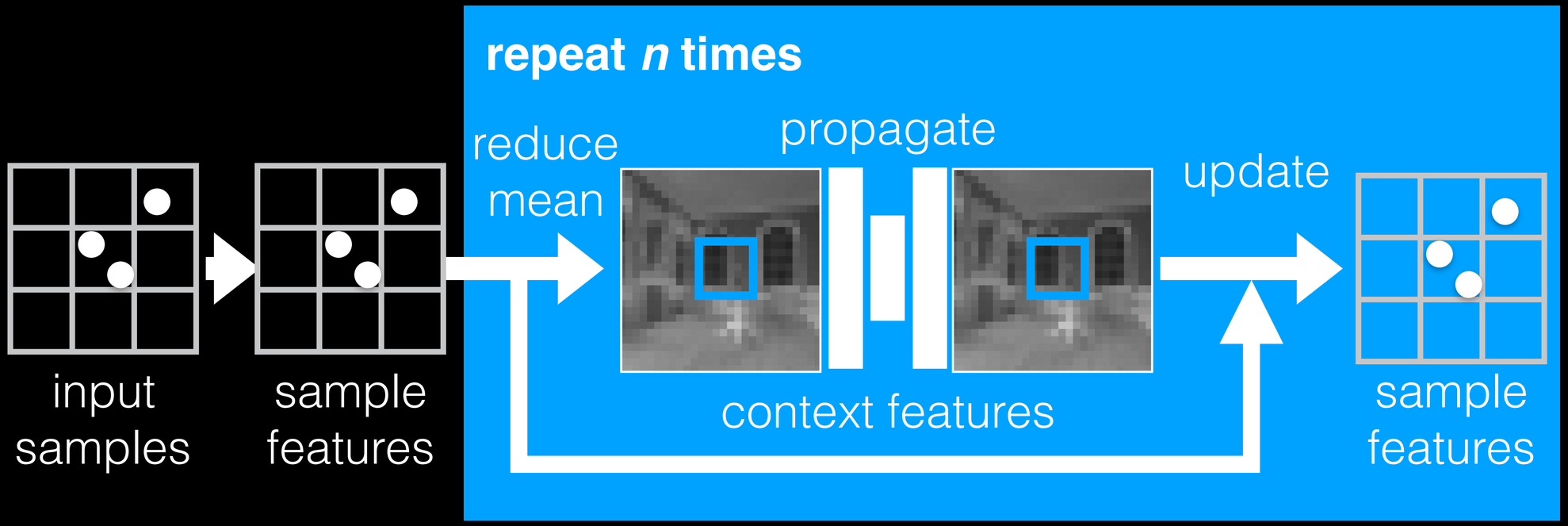
Permutation-invariant network



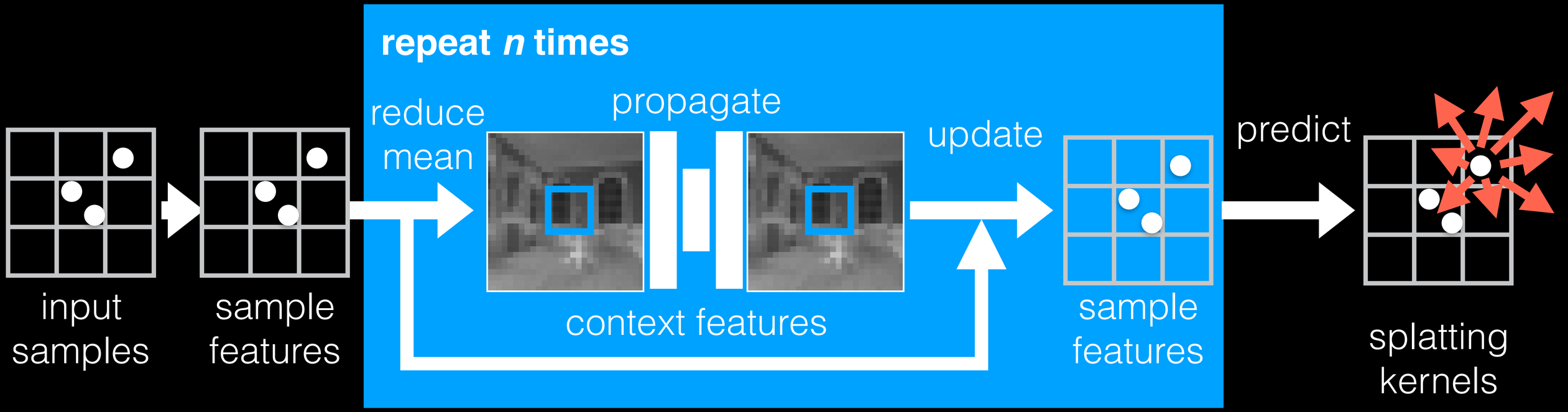
Permutation-invariant network



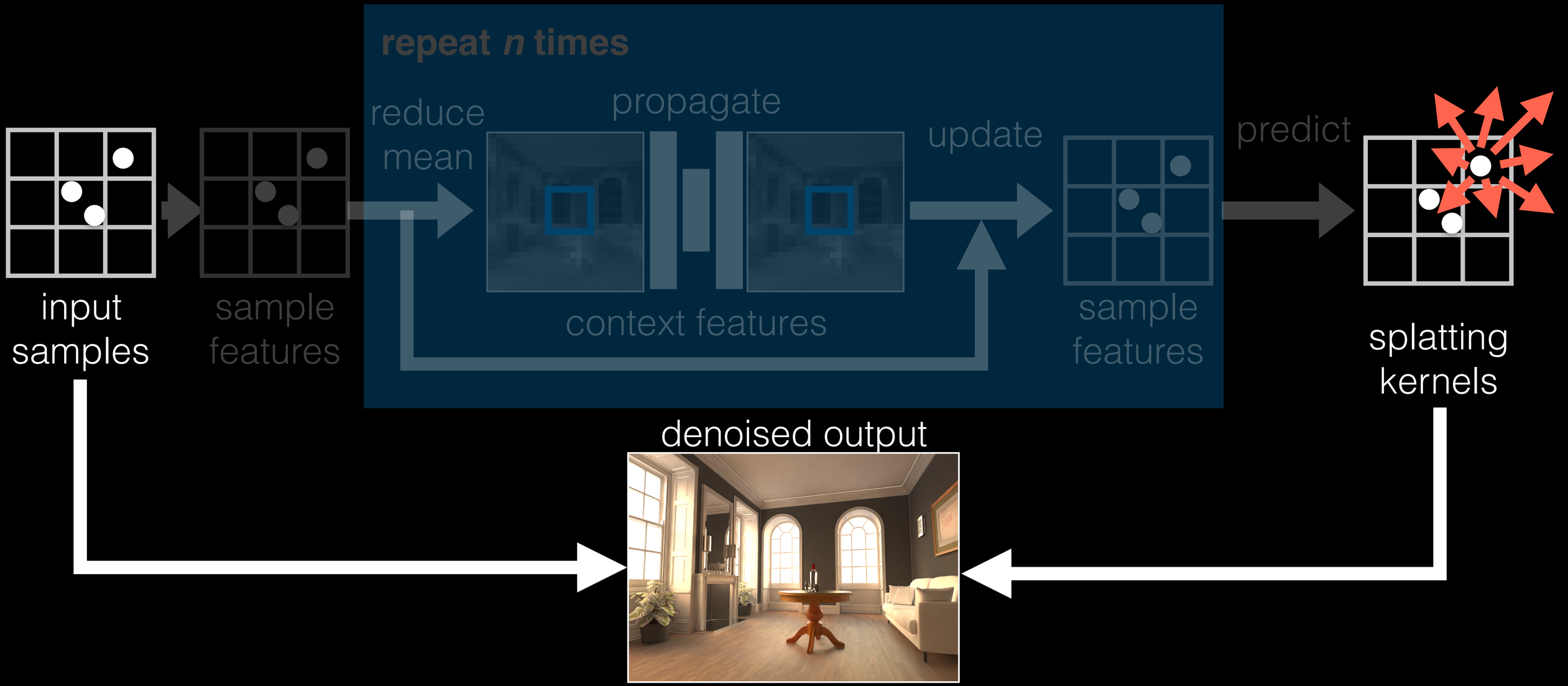
Permutation-invariant network



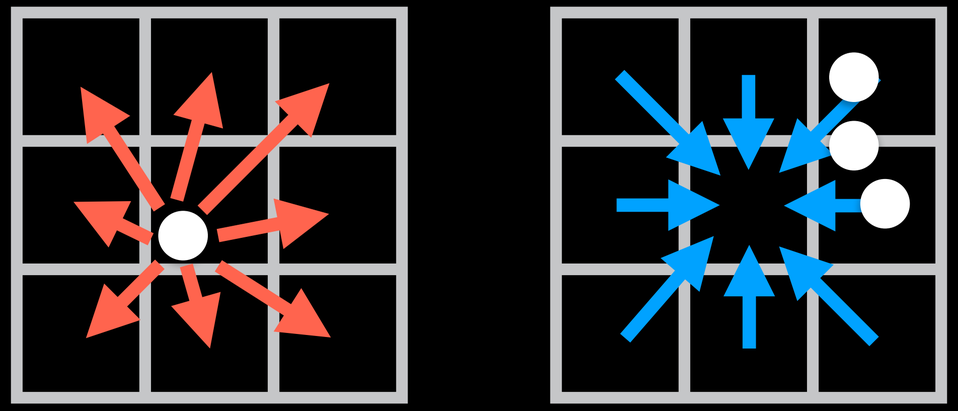
Permutation-invariant network



Permutation-invariant network

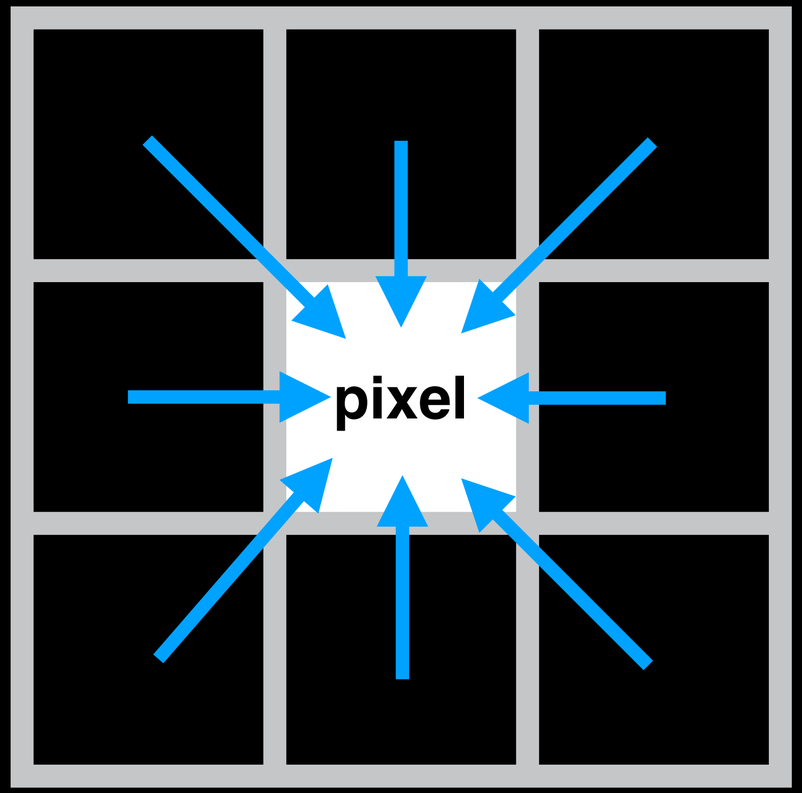


Why splatting kernels?



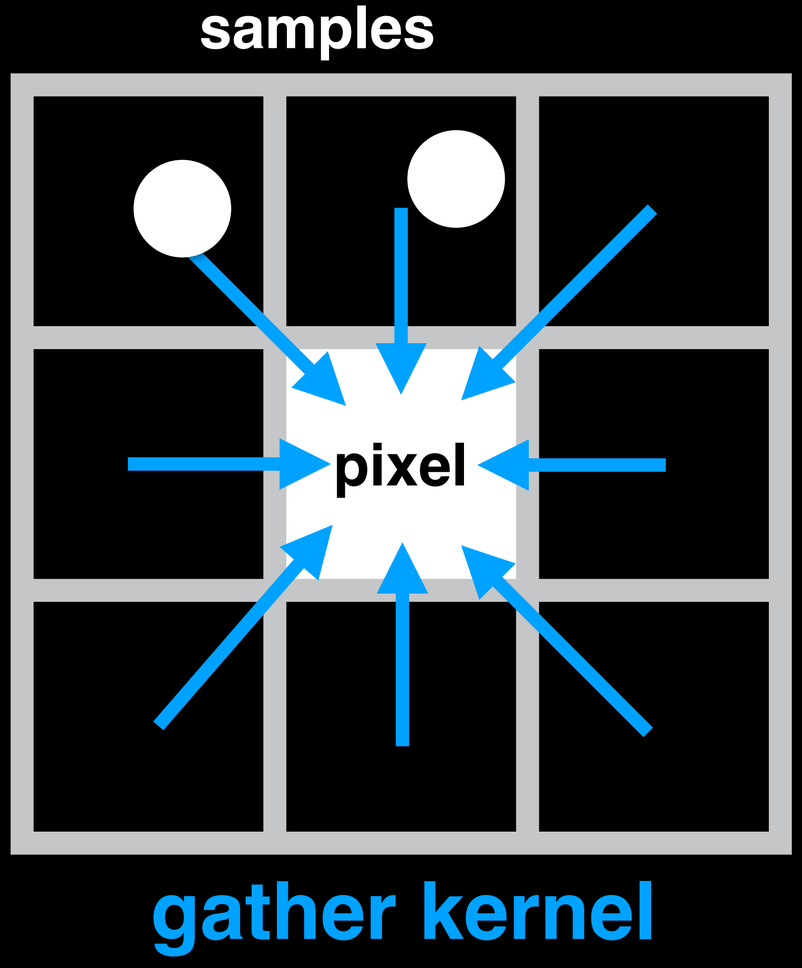
Why not *gather* kernels?

[Bako 2017; Vogels 2018] predict a kernel per pixel



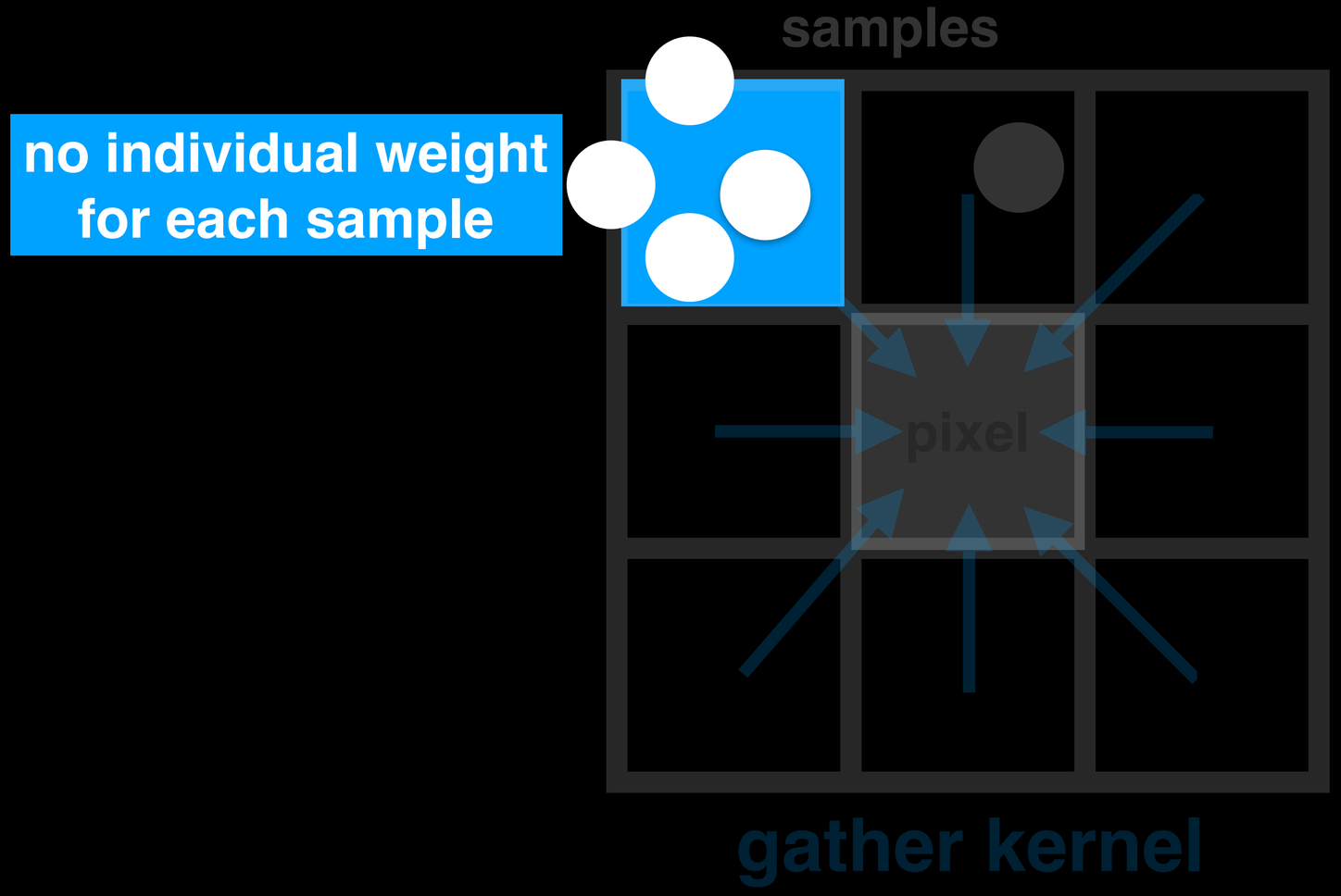
Why not *gather* kernels?

[Bako 2017; Vogels 2018] predict a kernel per pixel



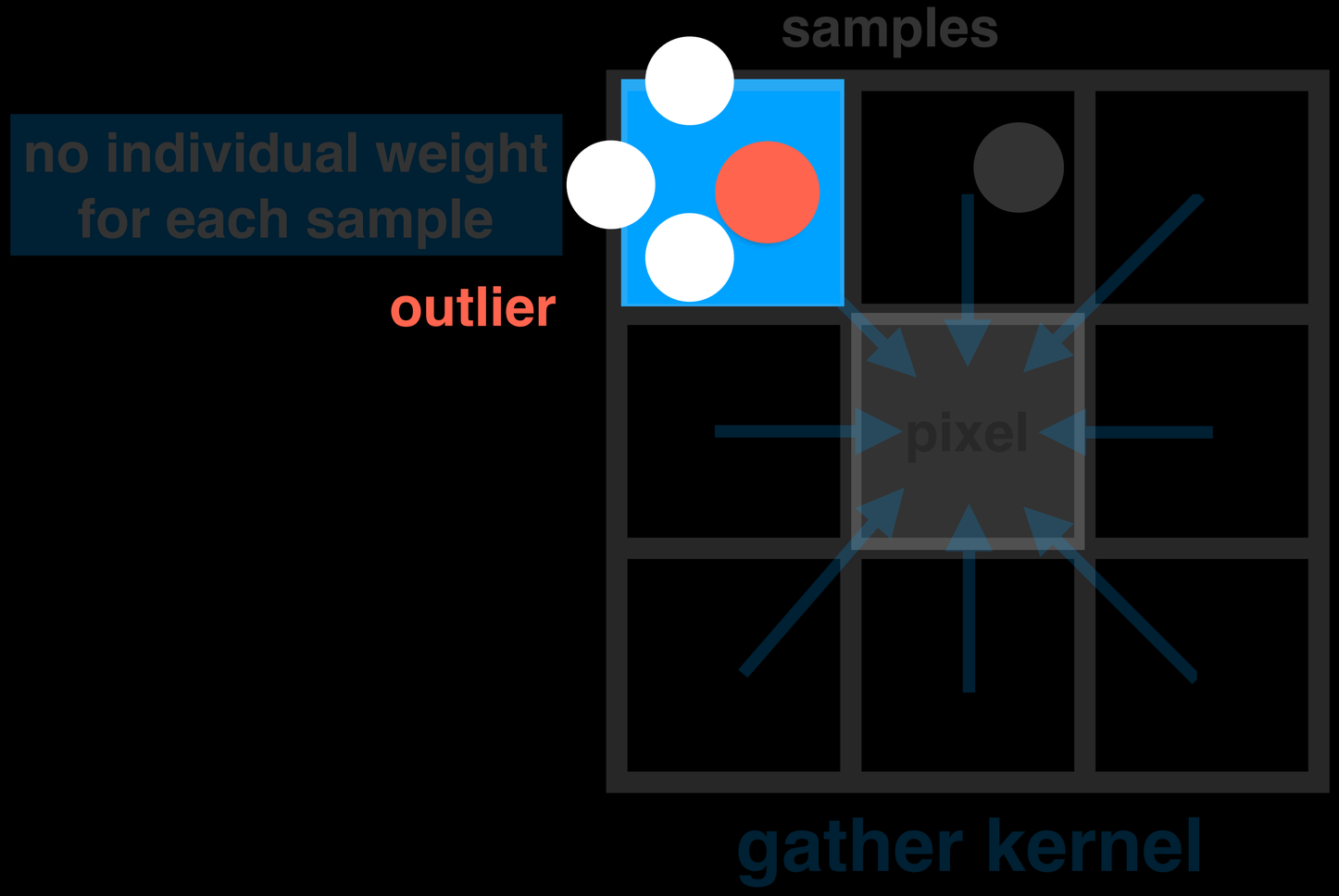
Why not *gather* kernels?

[Bako 2017; Vogels 2018] predict a kernel per pixel

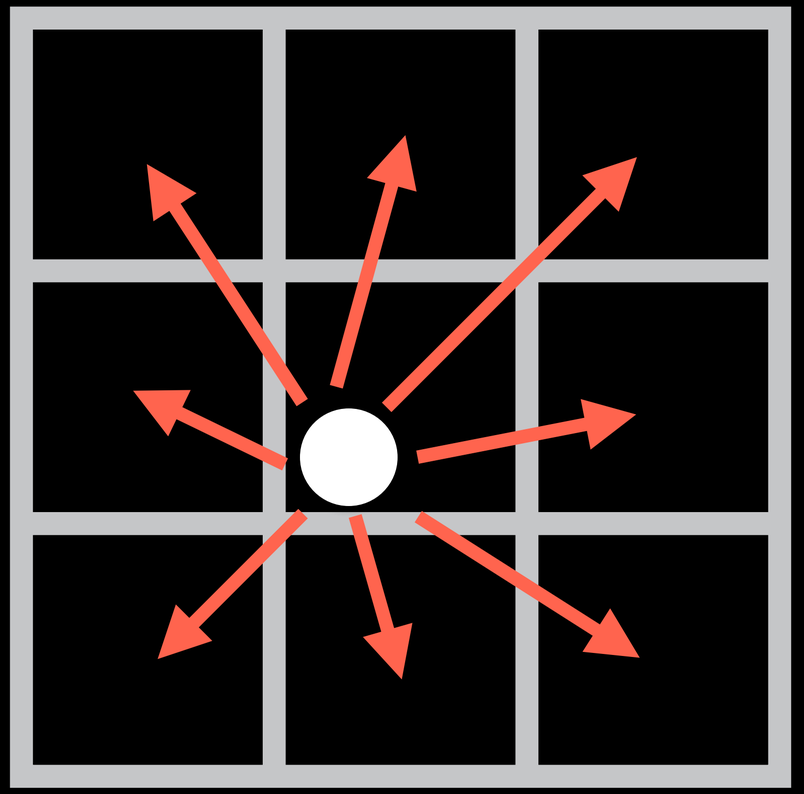


Why not *gather* kernels?

[Bako 2017; Vogels 2018] predict a kernel per pixel

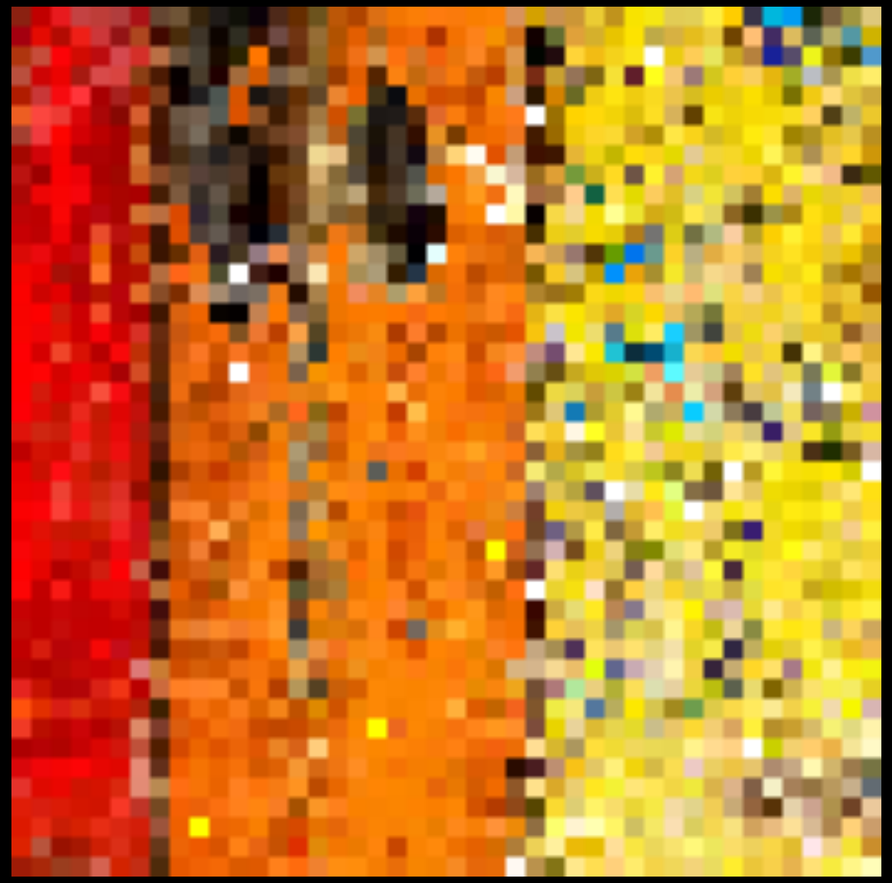


Splatting kernels: more natural for samples



splatting kernel

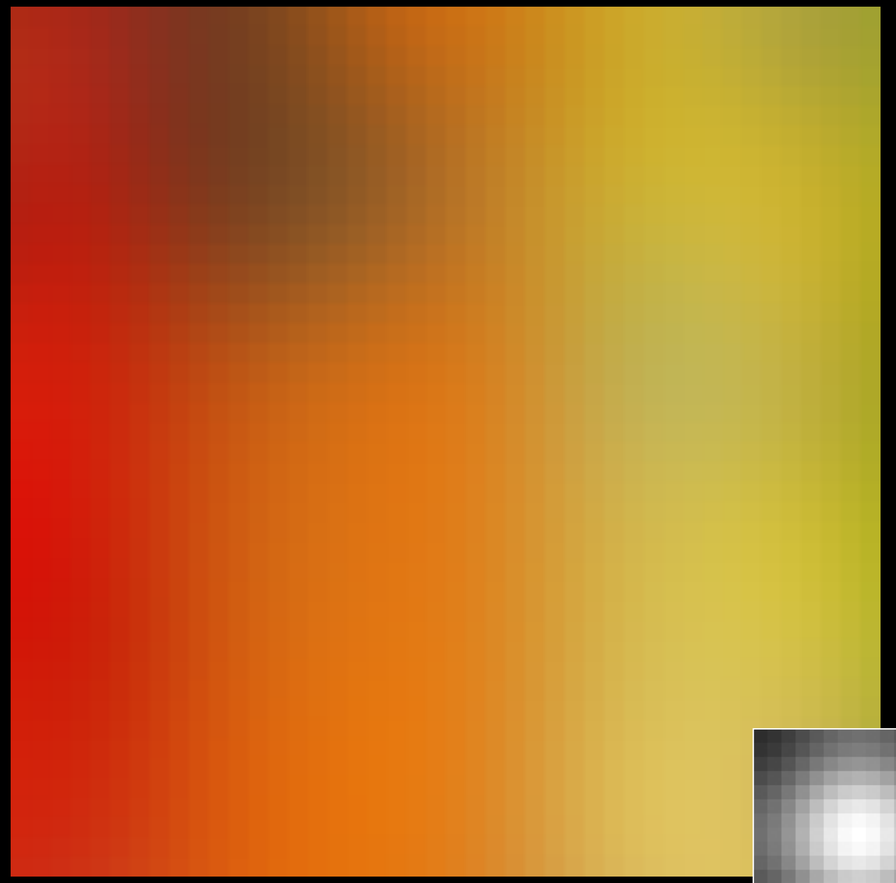
Toy example: learn Gaussian blur



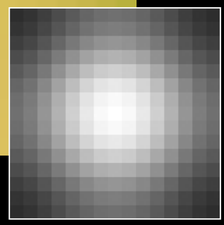
input

kernel-predicting network

$\mathcal{F}$

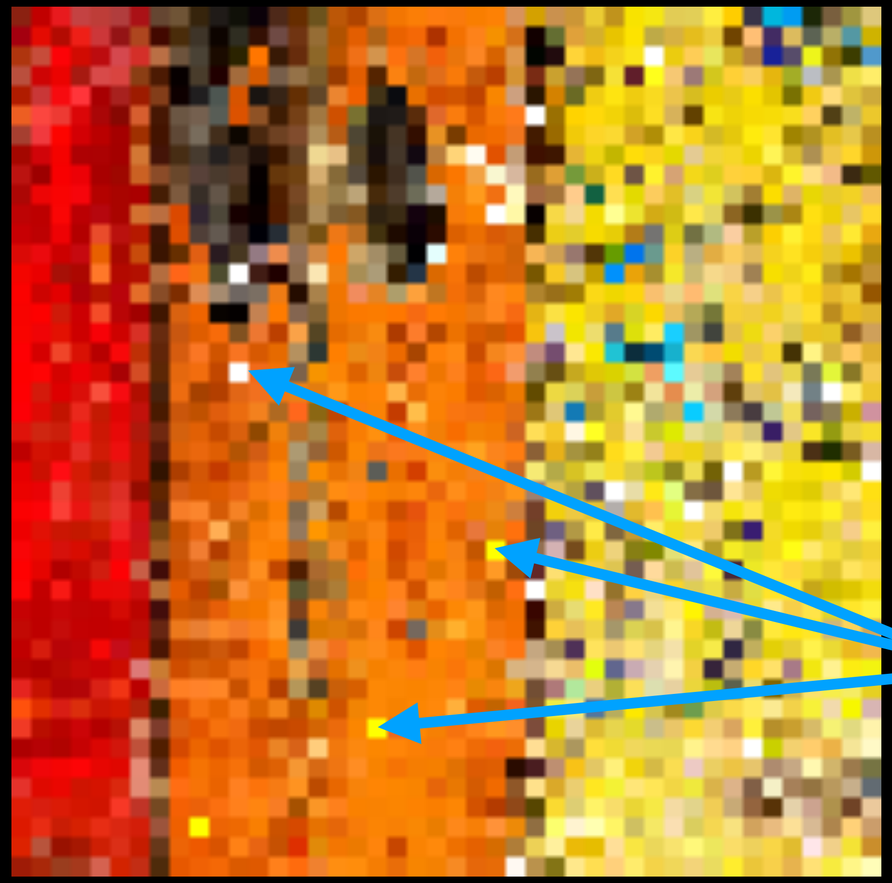


target: Gaussian blur



Toy example: learn Gaussian blur

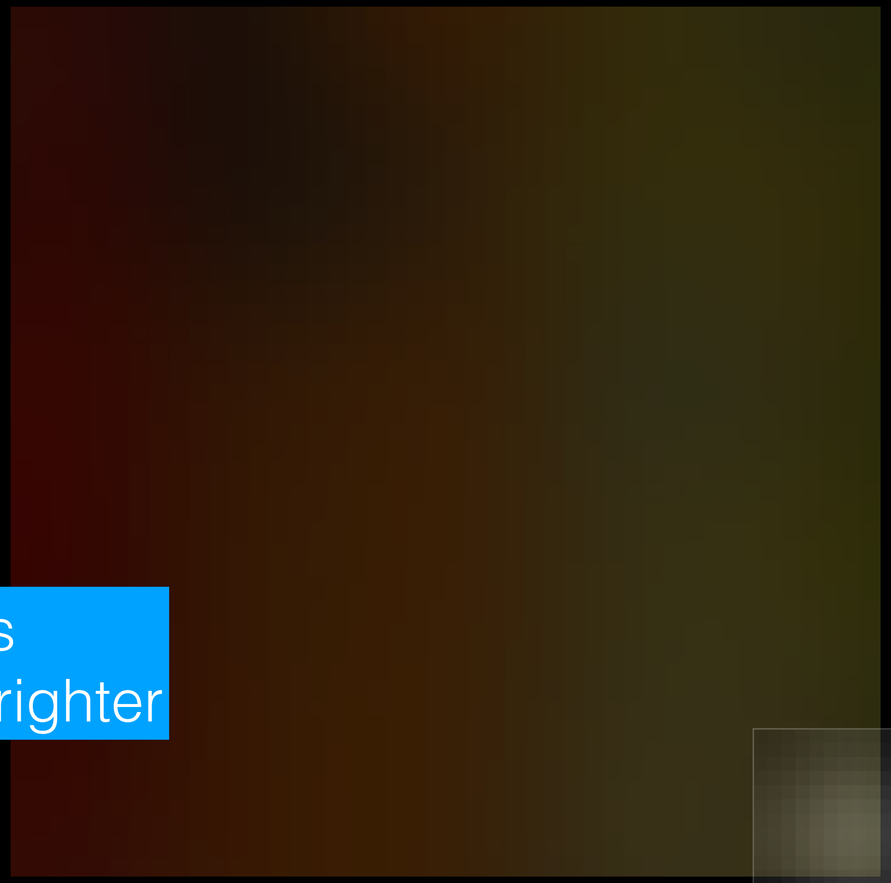
with outliers



kernel-predicting network

$\mathcal{F}$

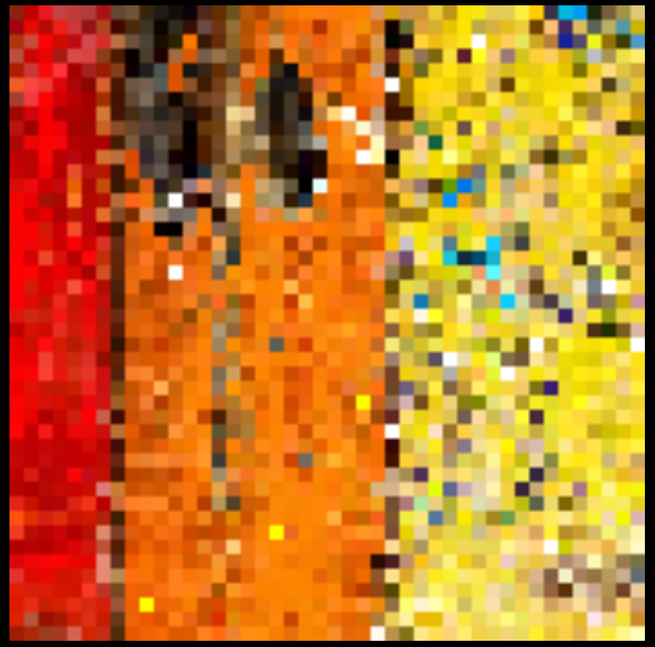
1 % outliers
100x — 1000x brighter



input

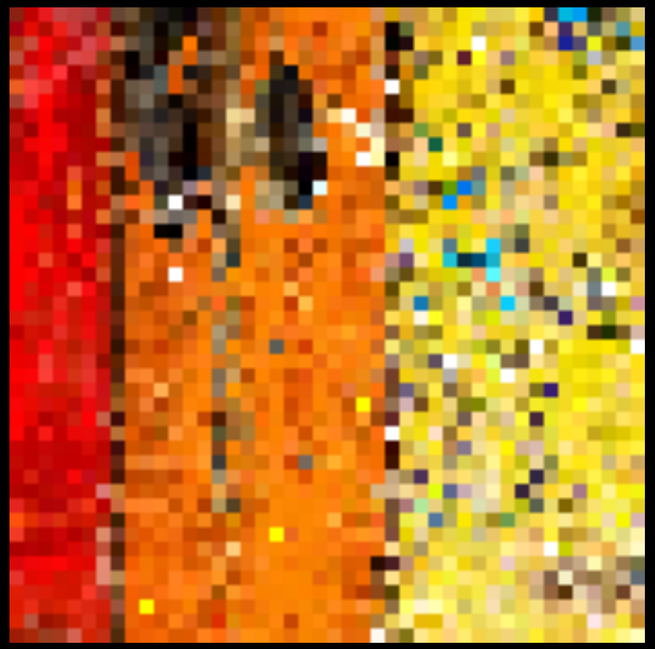
target: Gaussian blur

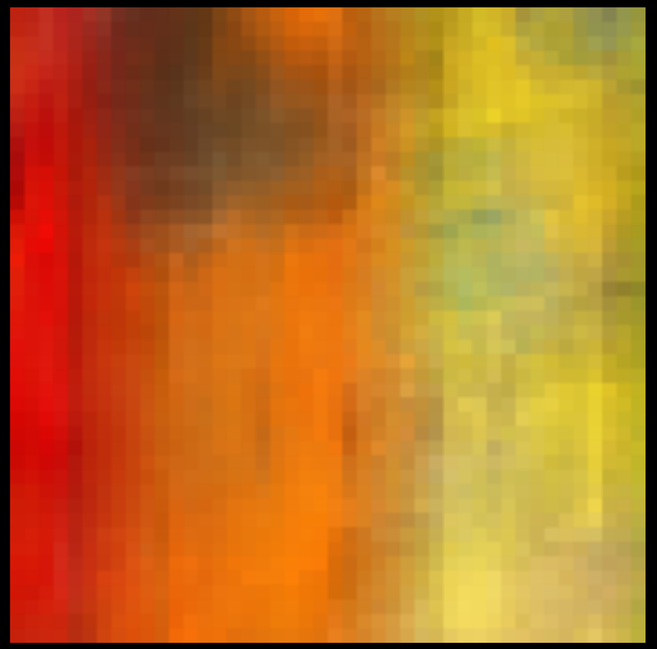
input



target

input

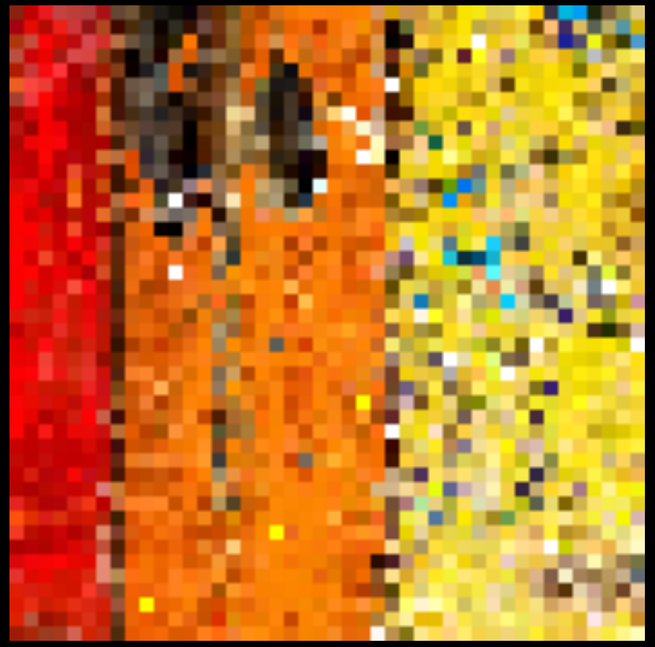


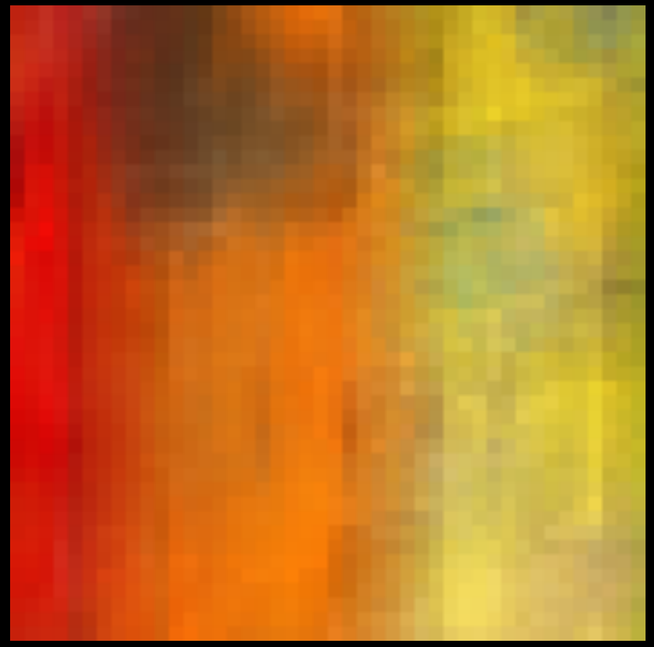


network with
gather kernels
~[Bako 2017]

target

input



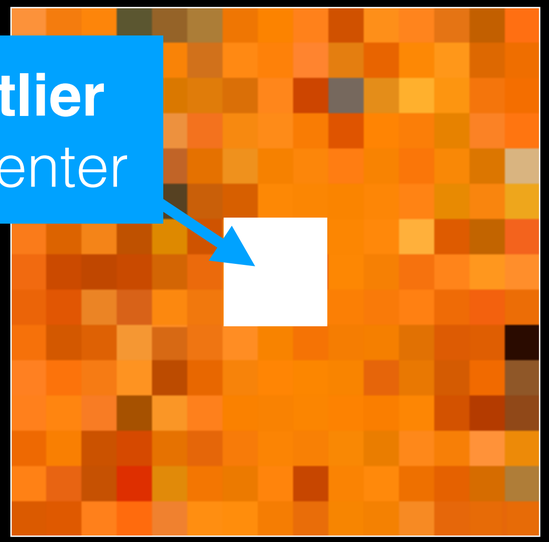


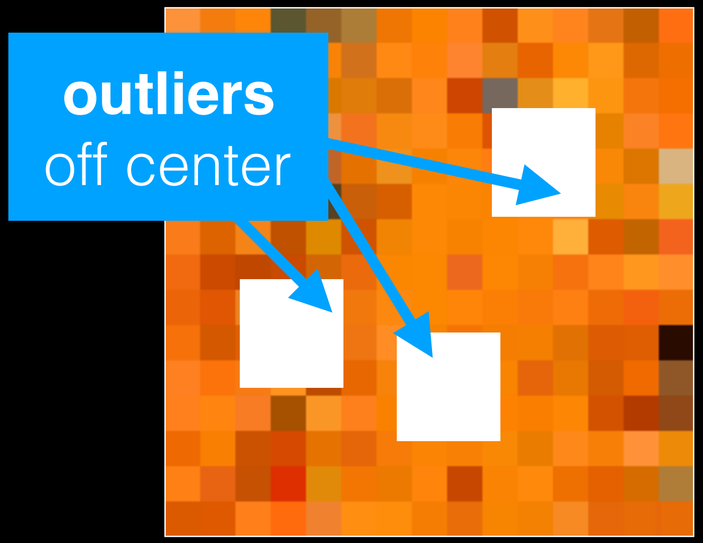
network with
gather kernels
~[Bako 2017]

target

network with
splatting kernels
(ours)

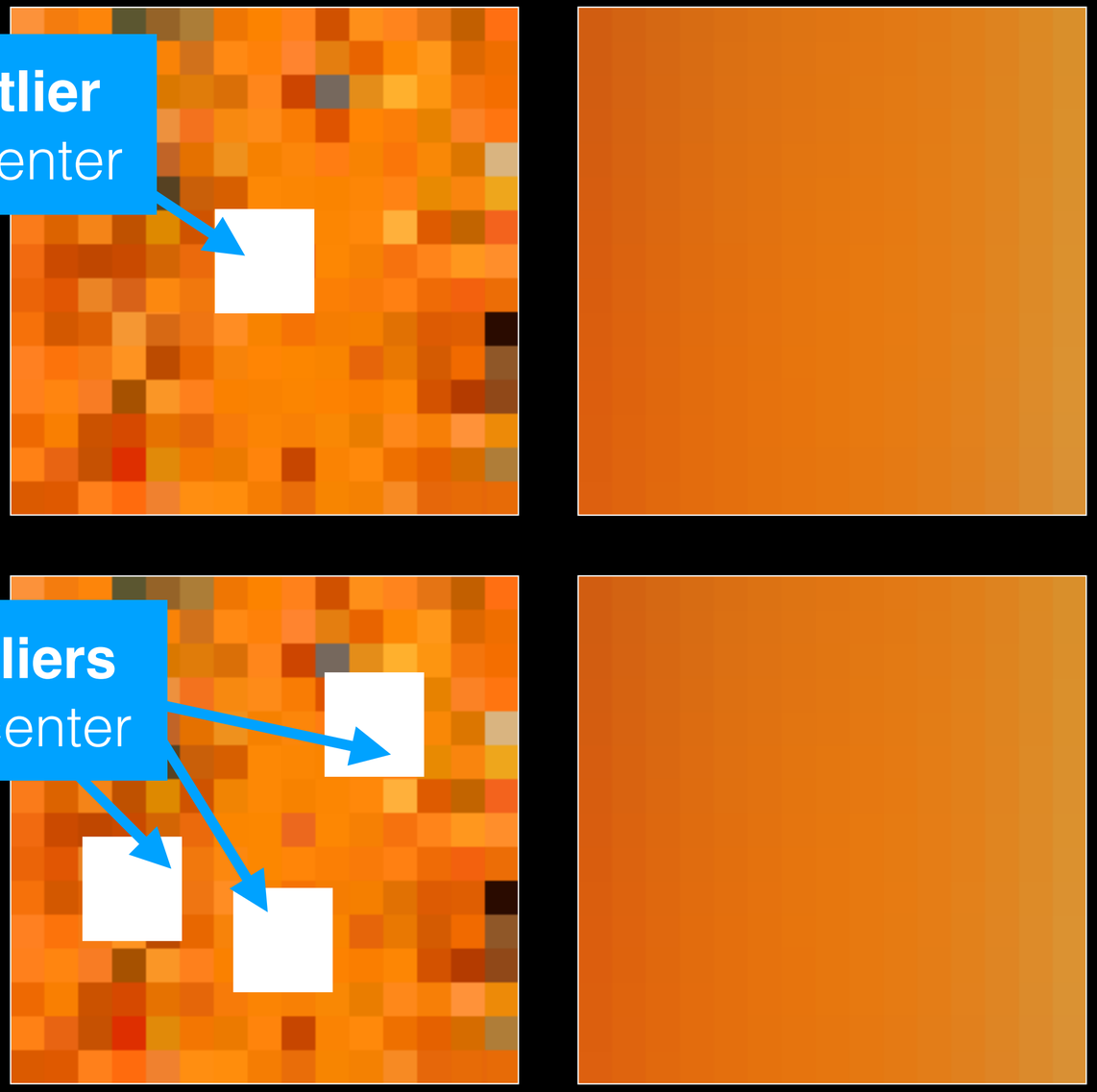
input





input

target

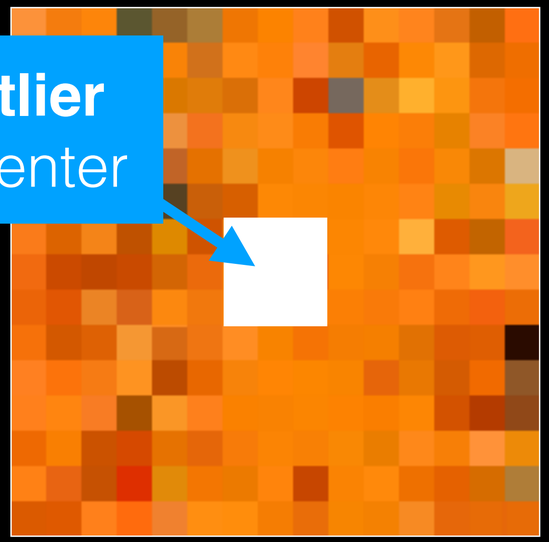


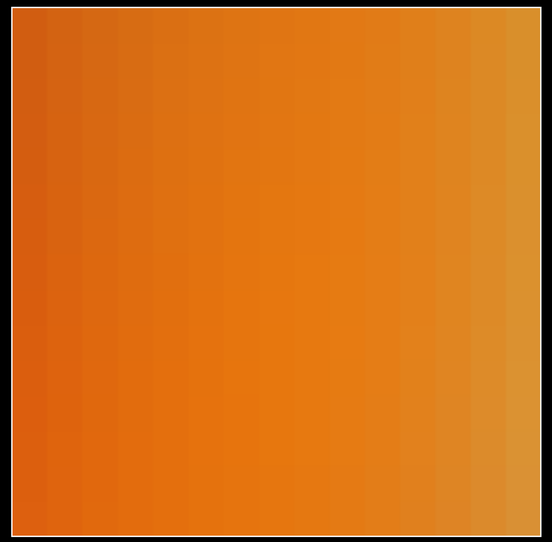
input

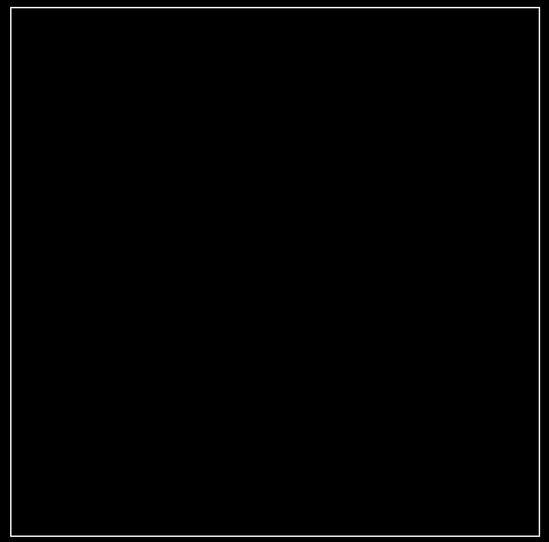
target

expected
splatting kernel

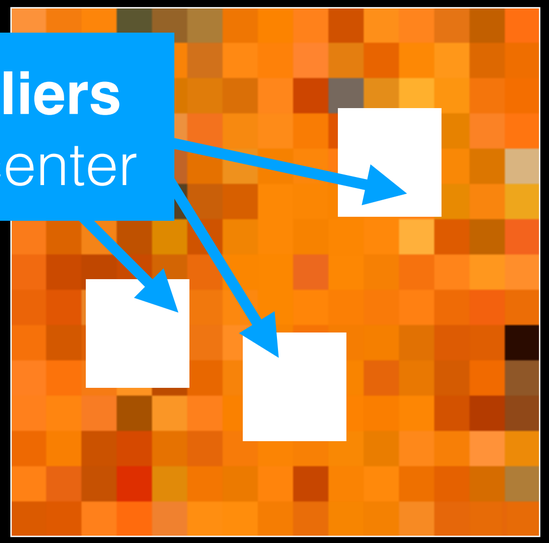
outlier
in center

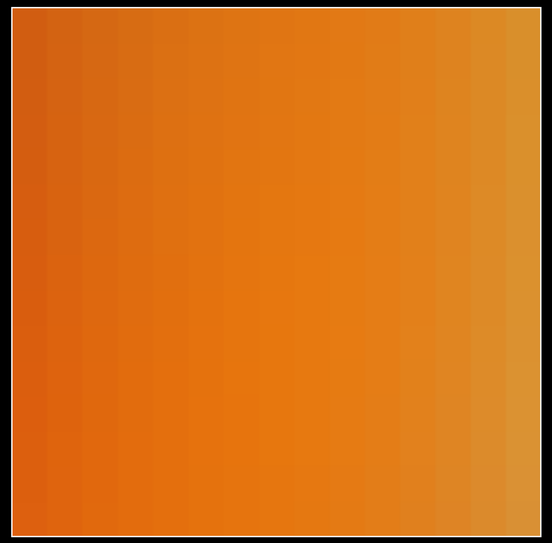






outliers
off center



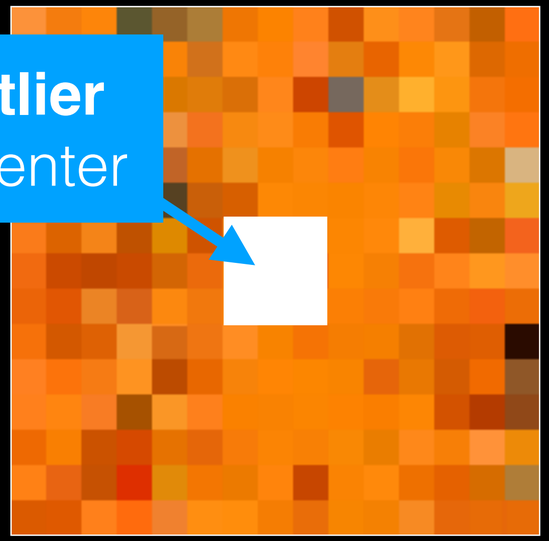


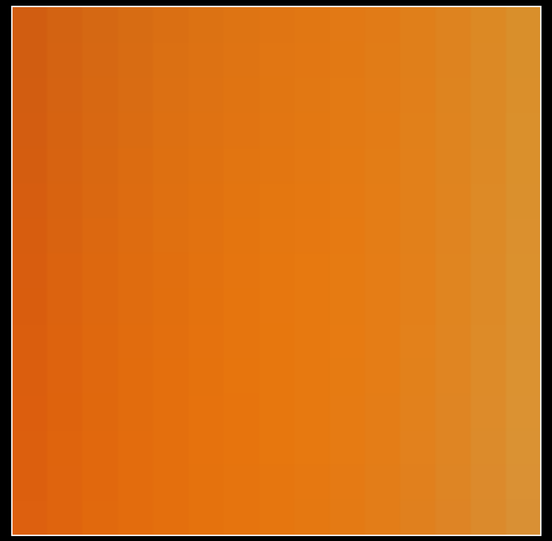
input

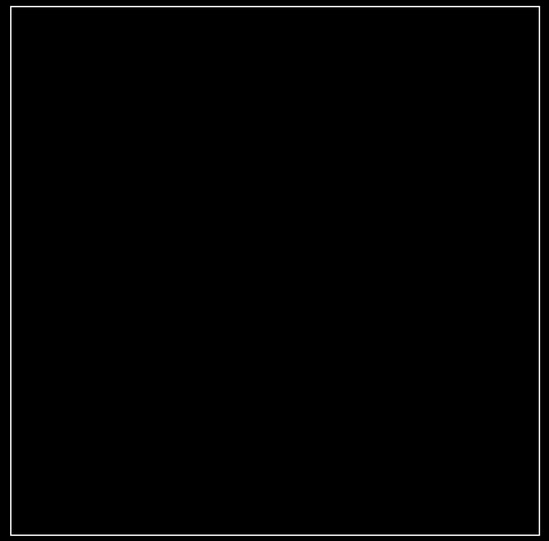
target

expected
splatting kernel

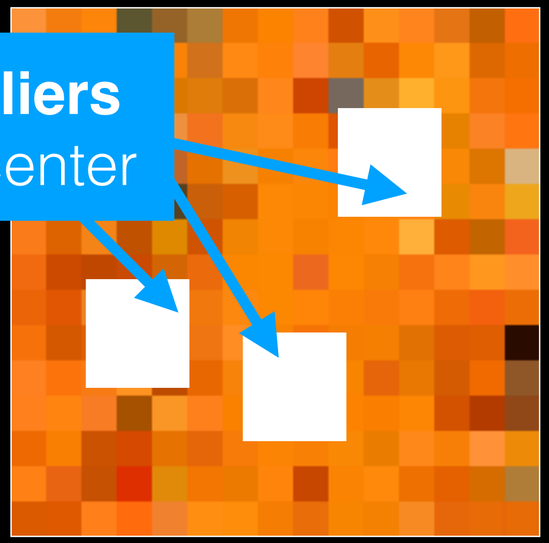
outlier
in center

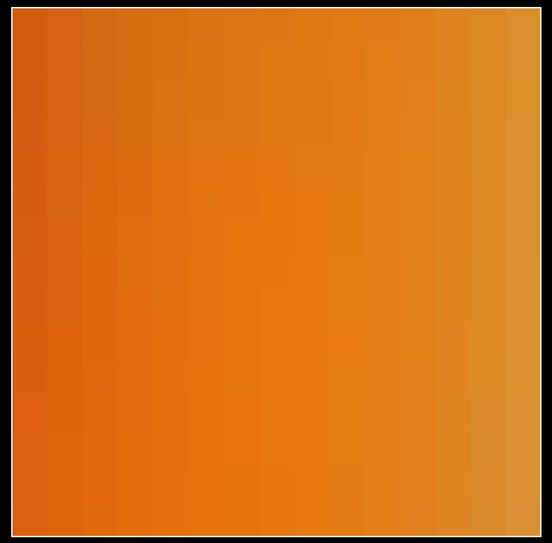


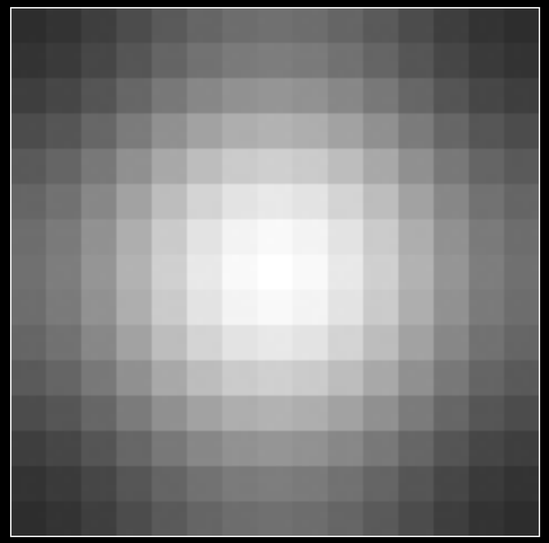




outliers
off center







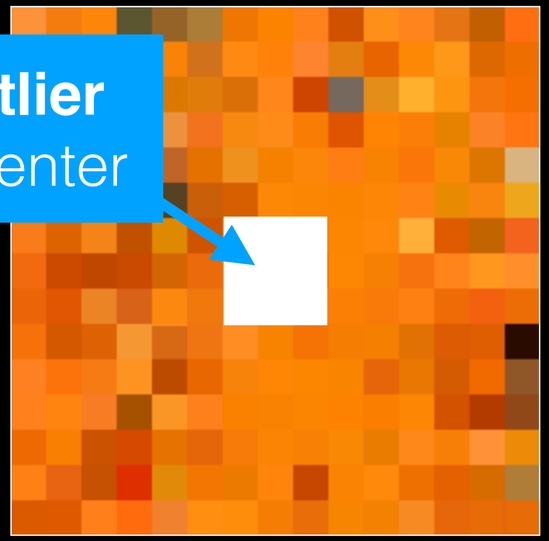
input

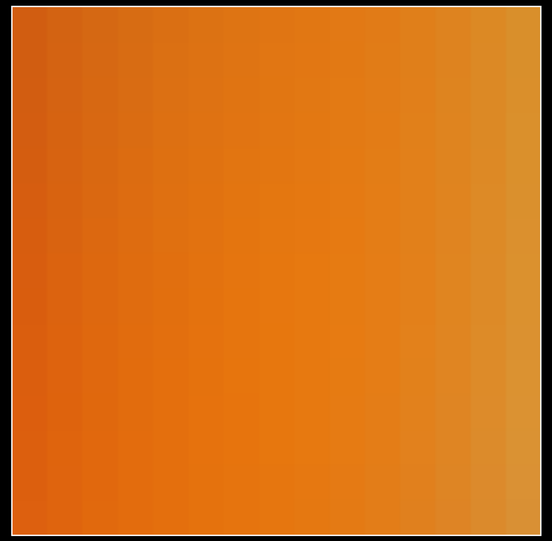
target

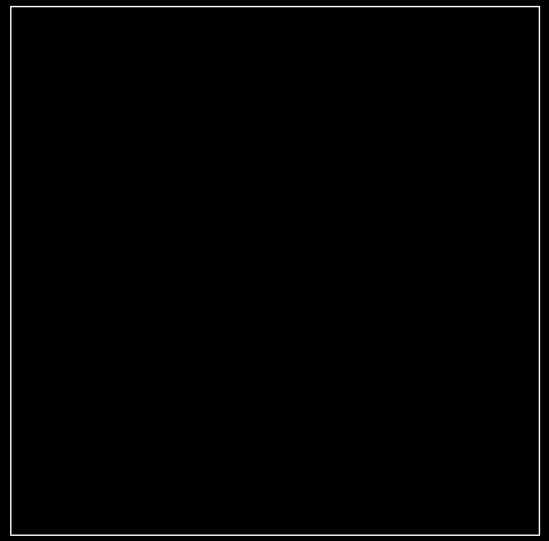
expected
splatting kernel

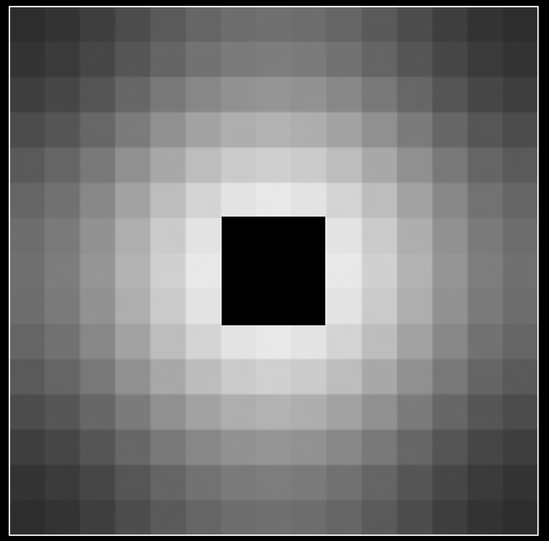
expected
gather kernel

outlier
in center

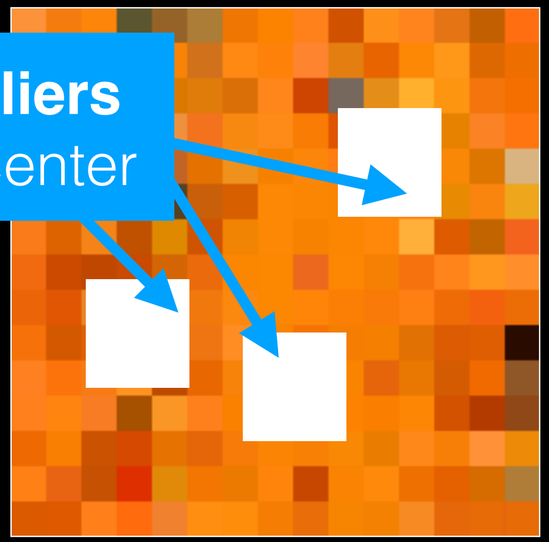


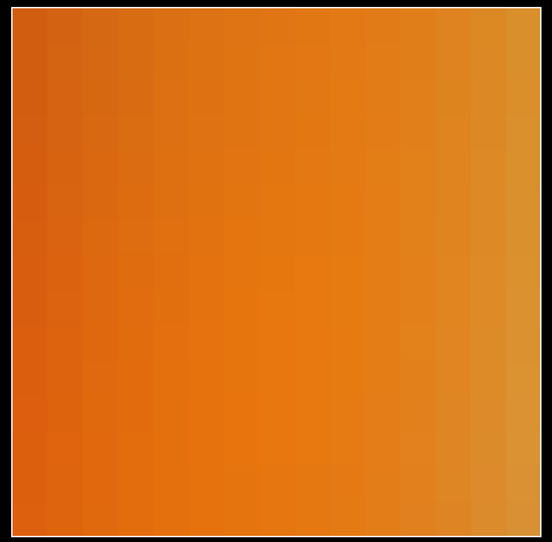


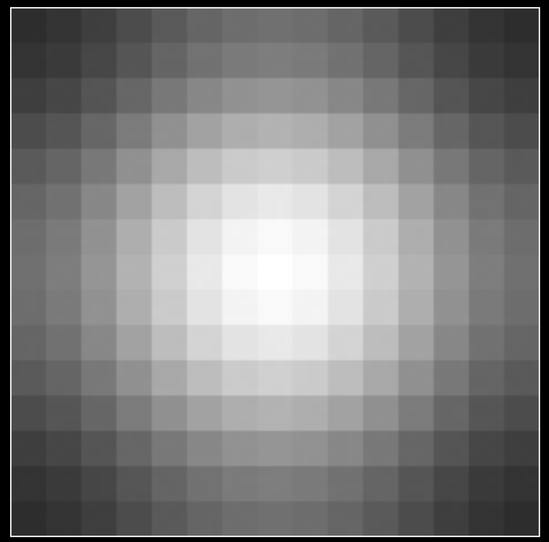




outliers
off center







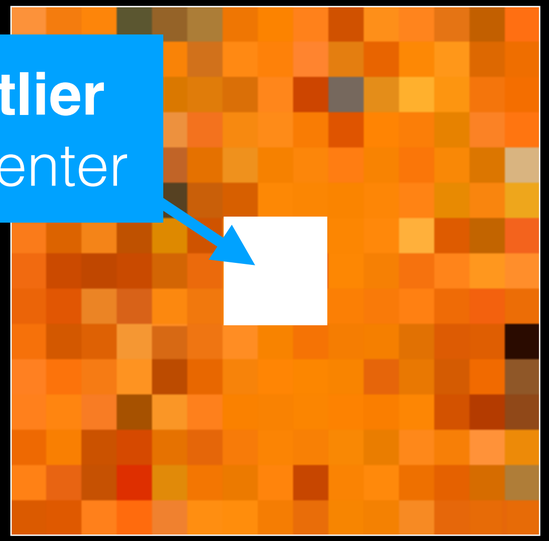
input

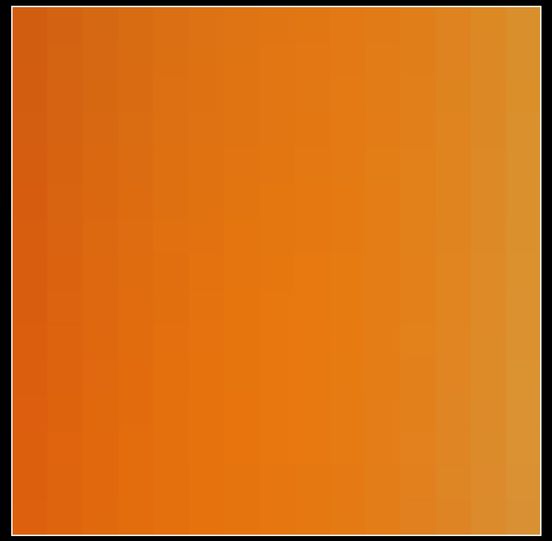
target

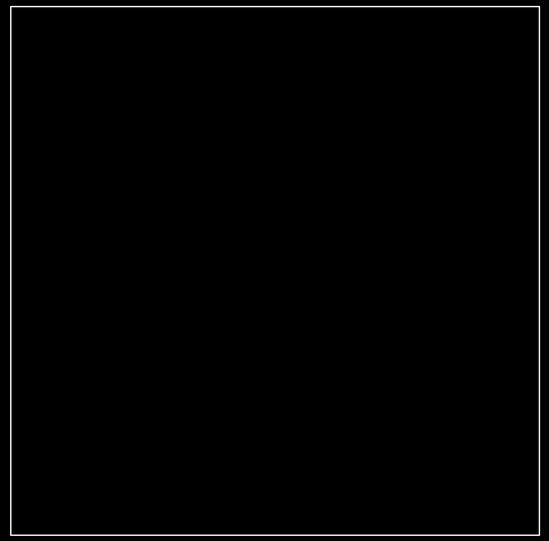
expected
splatting kernel

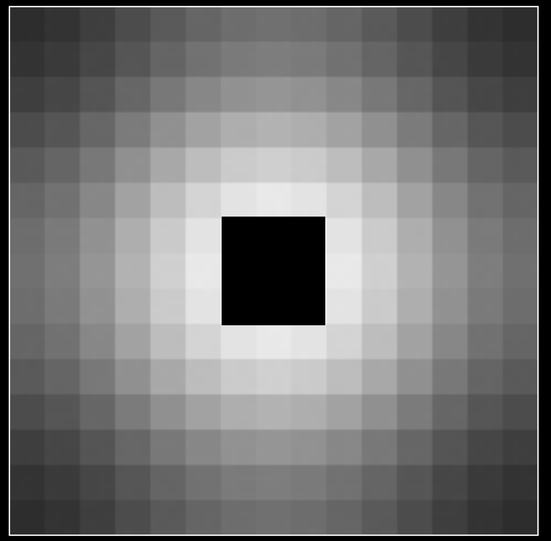
expected
gather kernel

outlier
in center

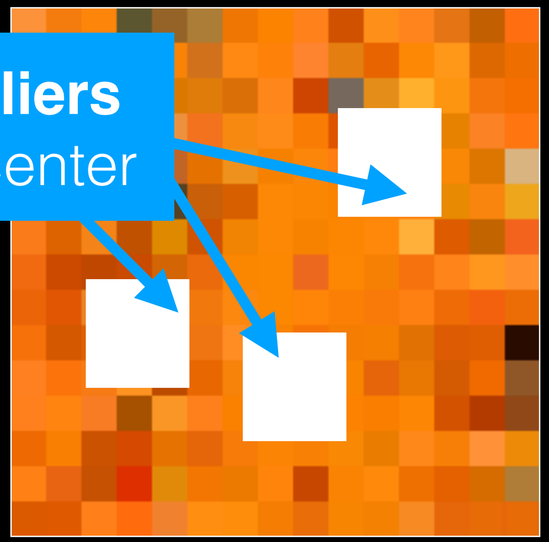


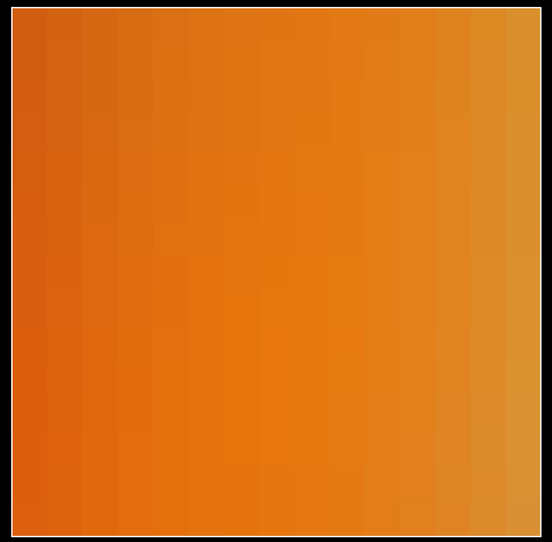


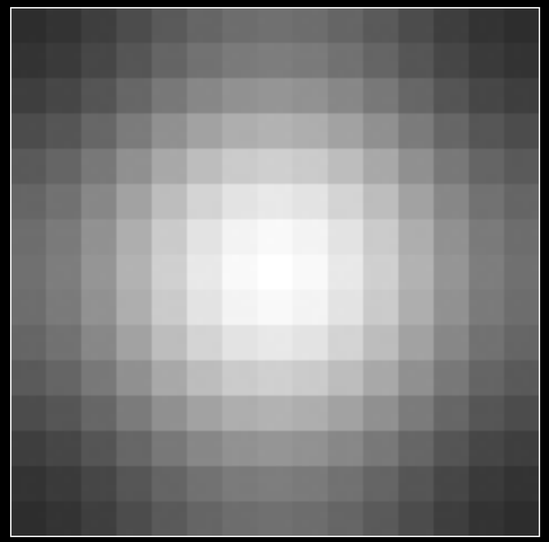


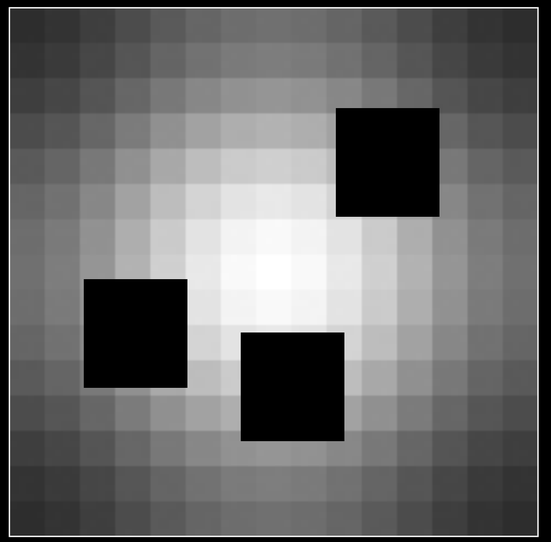


outliers
off center









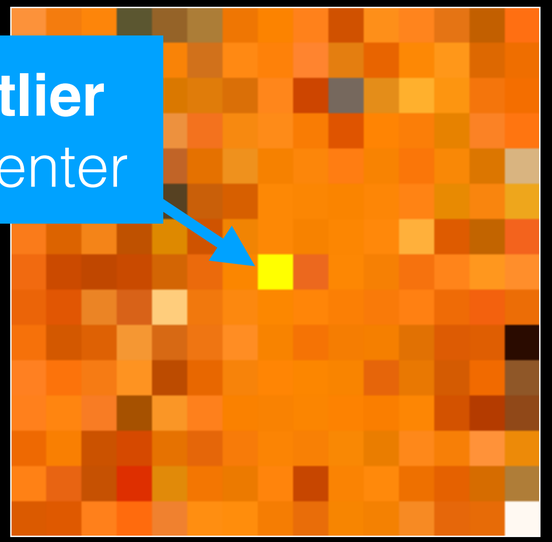
input

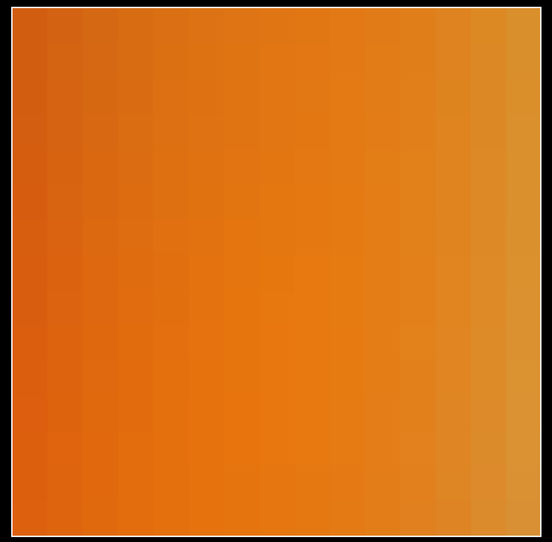
target

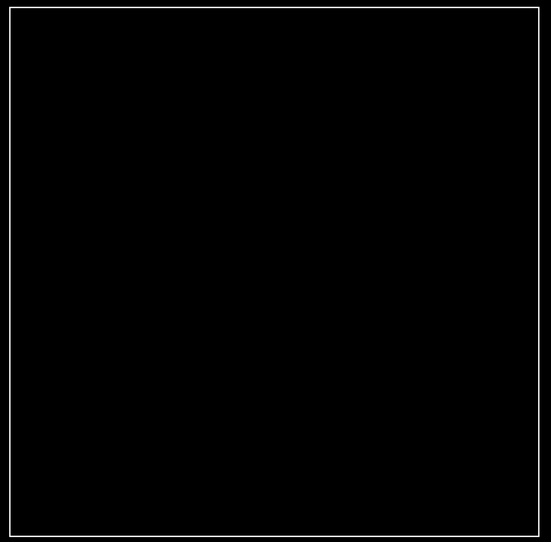
splatting kernel

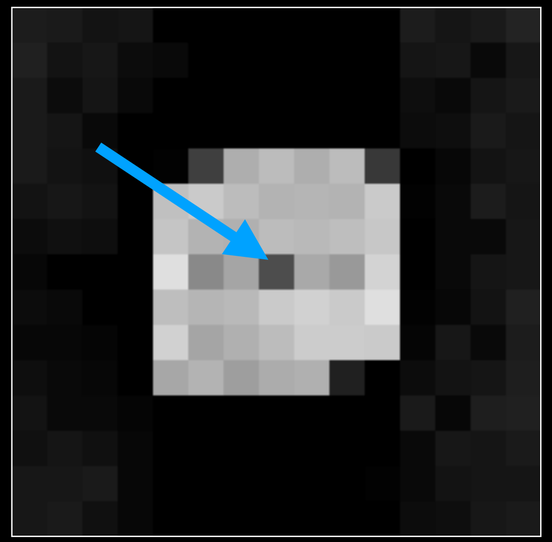
gather kernel

outlier
in center

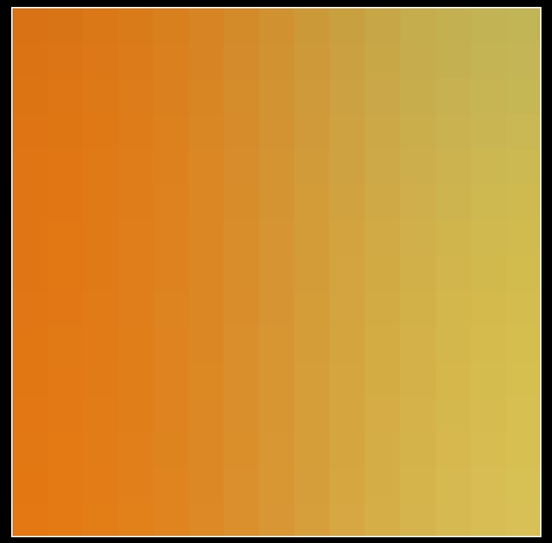


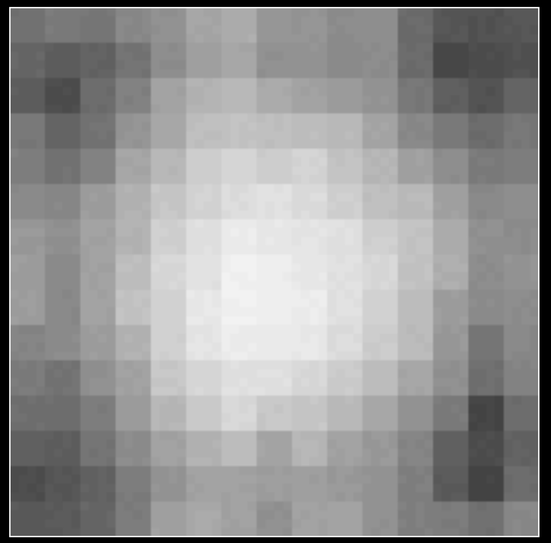


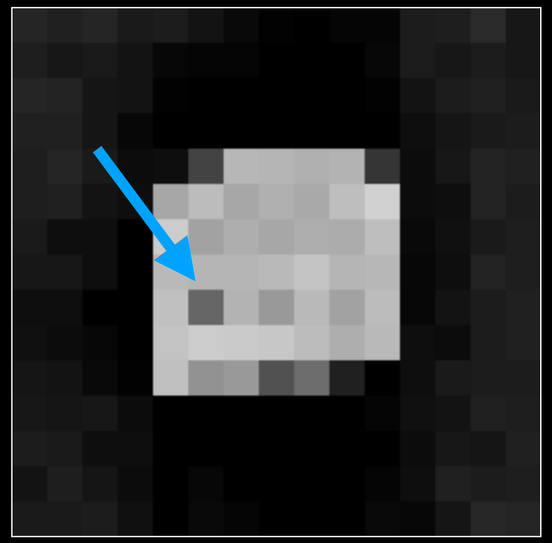




outliers
off center





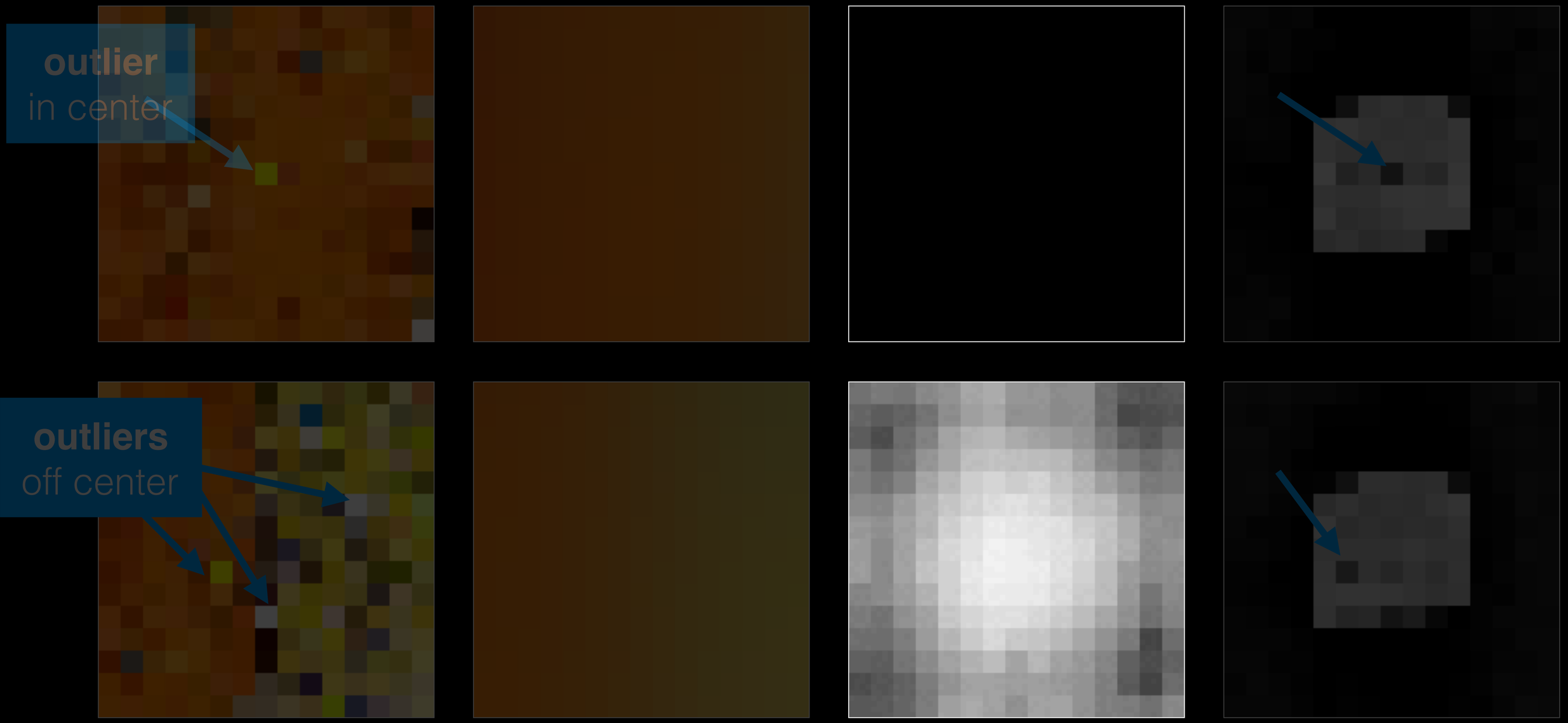


input

target

splatting kernel

gather kernel



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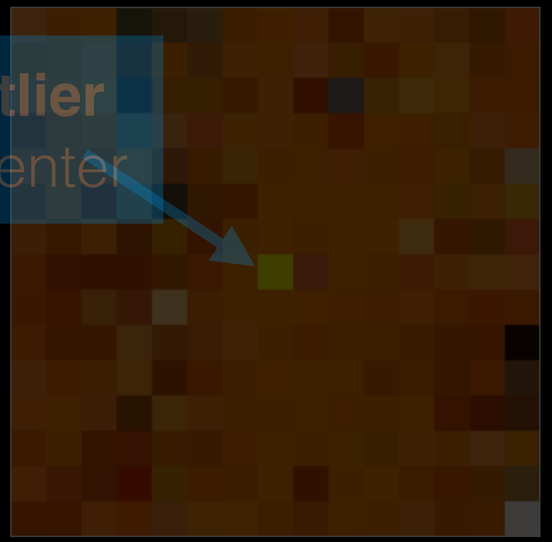
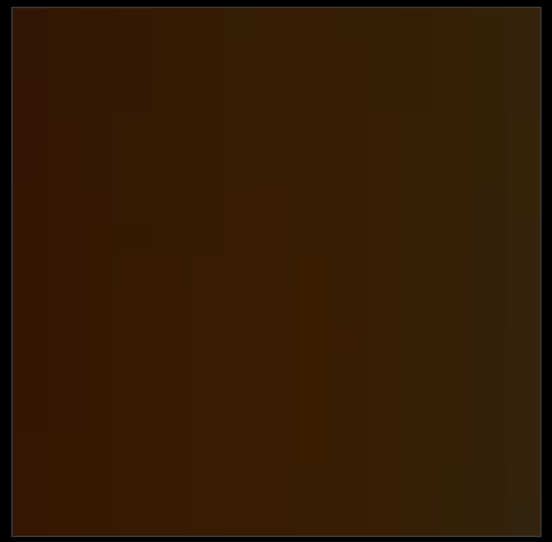
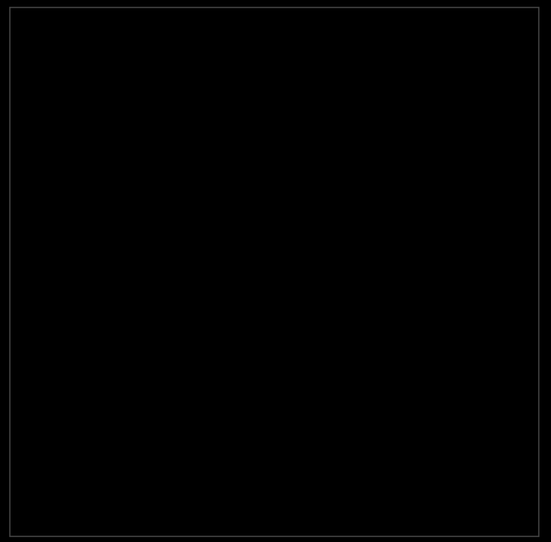
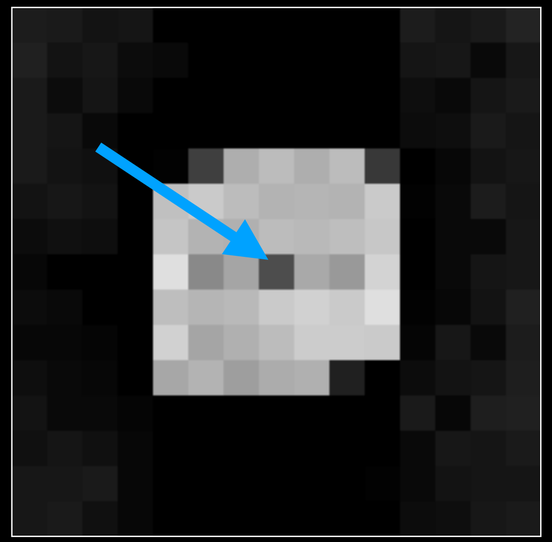
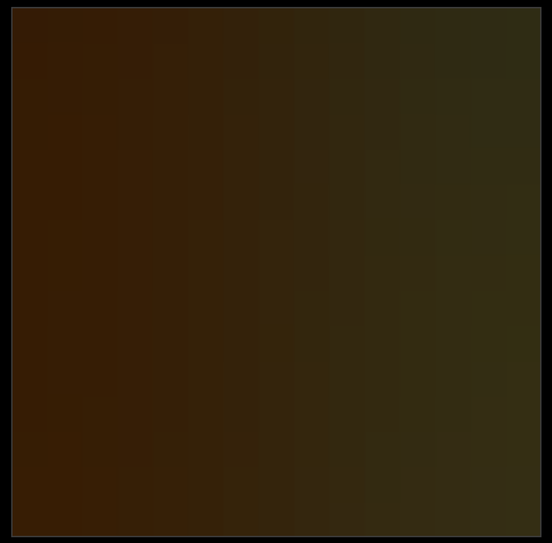


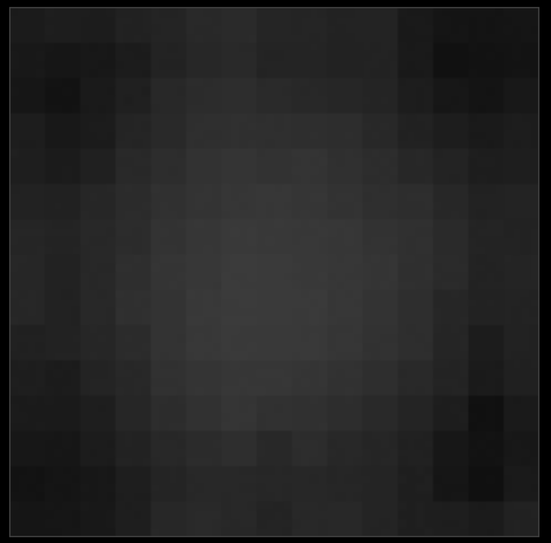


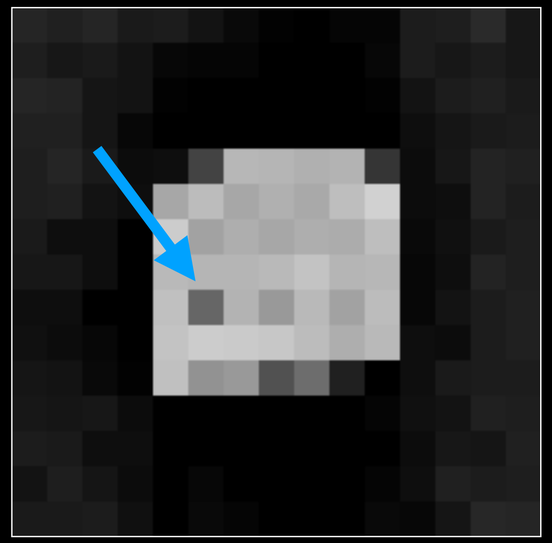


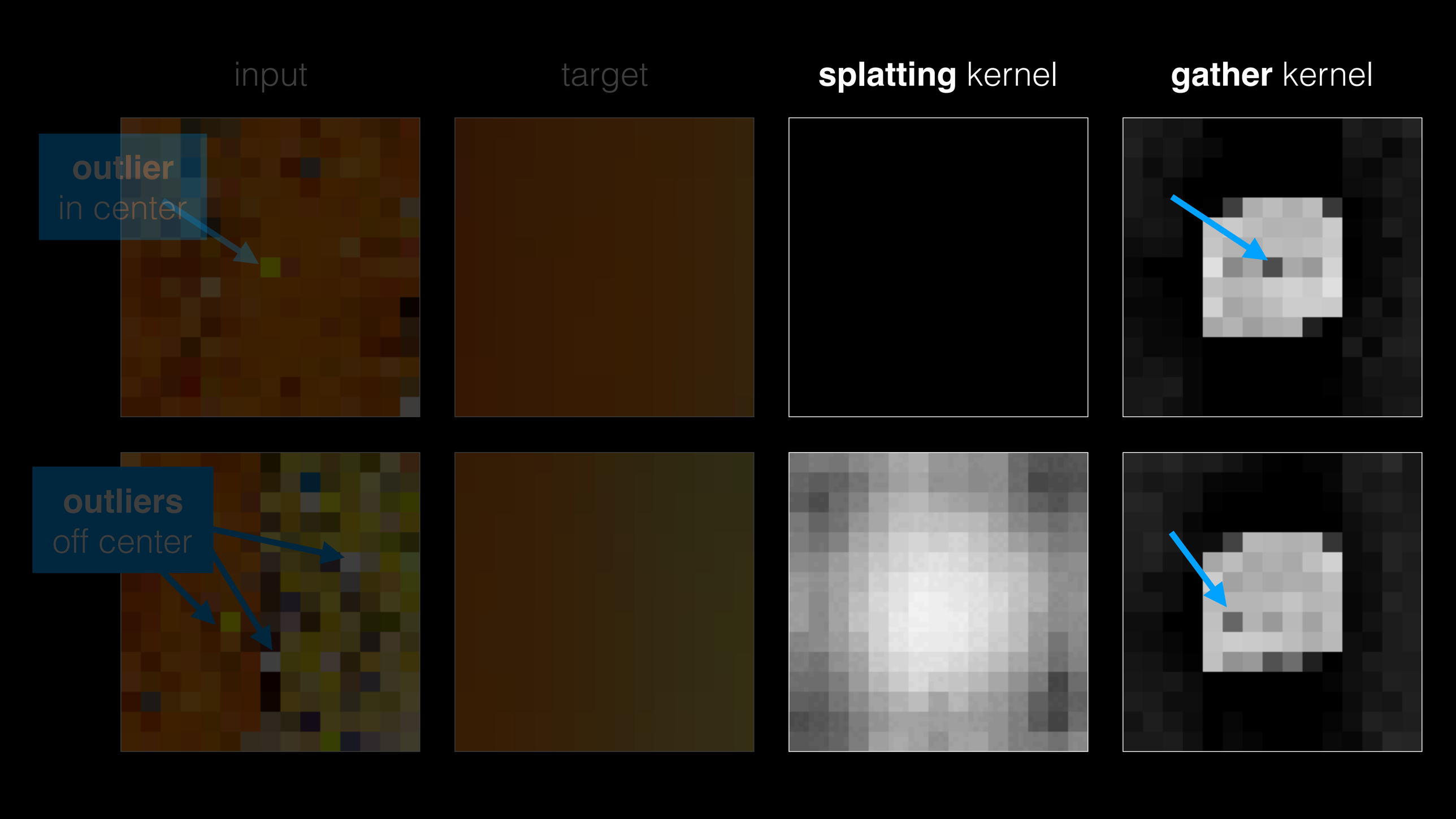


outliers
off center

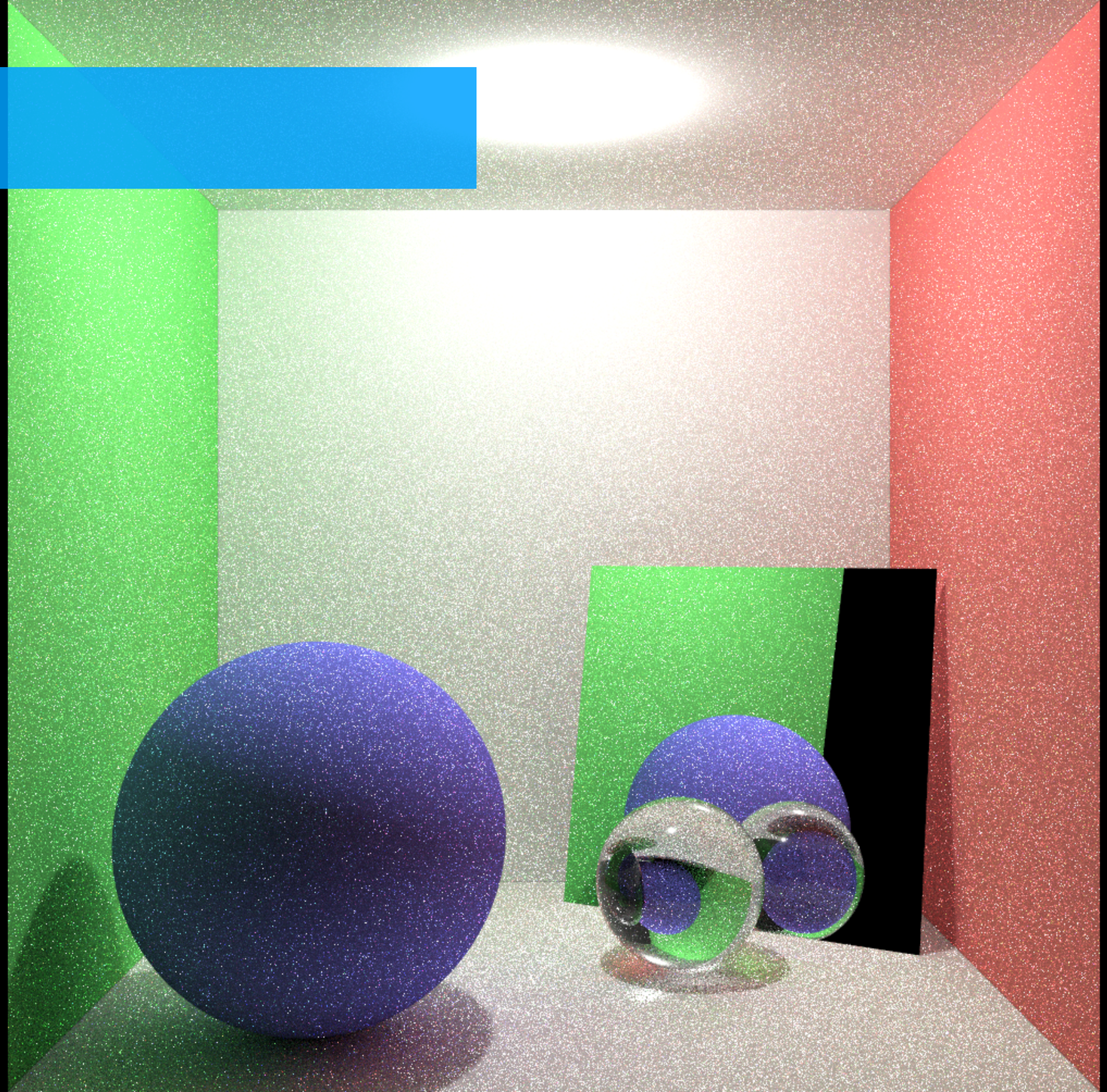


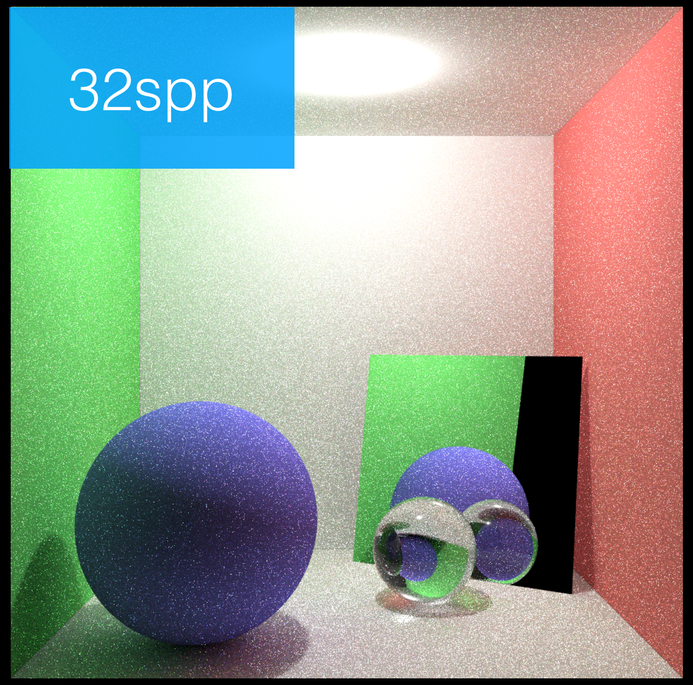





input
target
splatting kernel
gather kernel
outlier
in center
outliers
off center

input | 32spp

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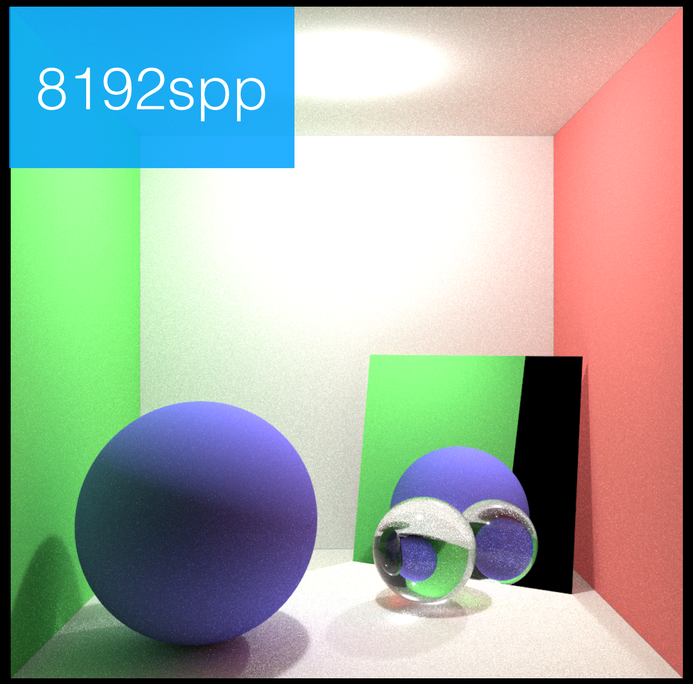
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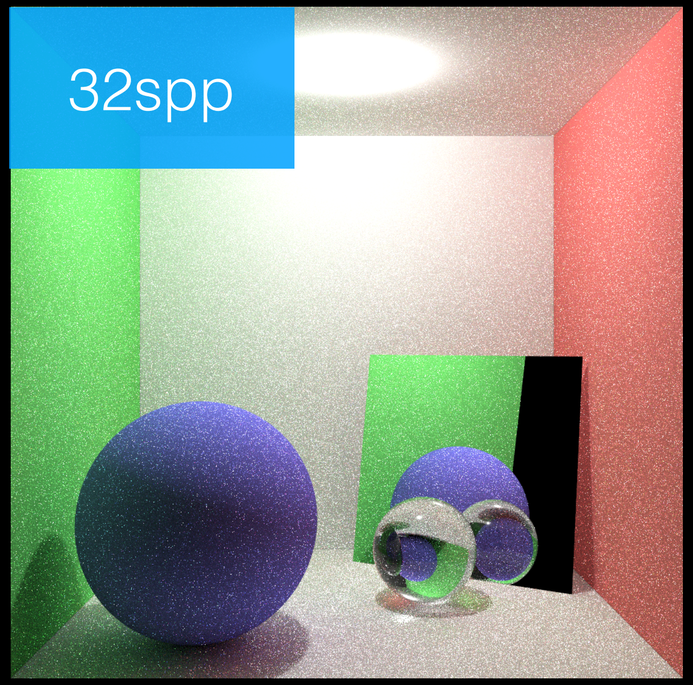
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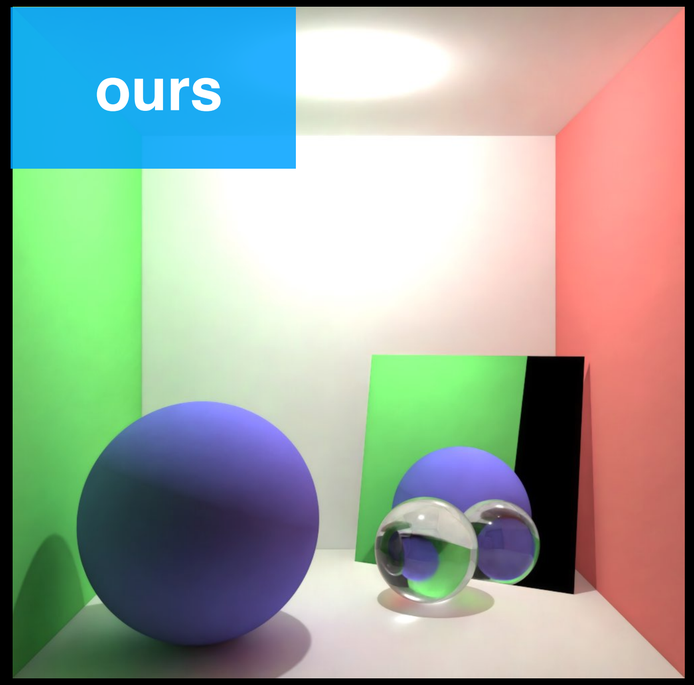
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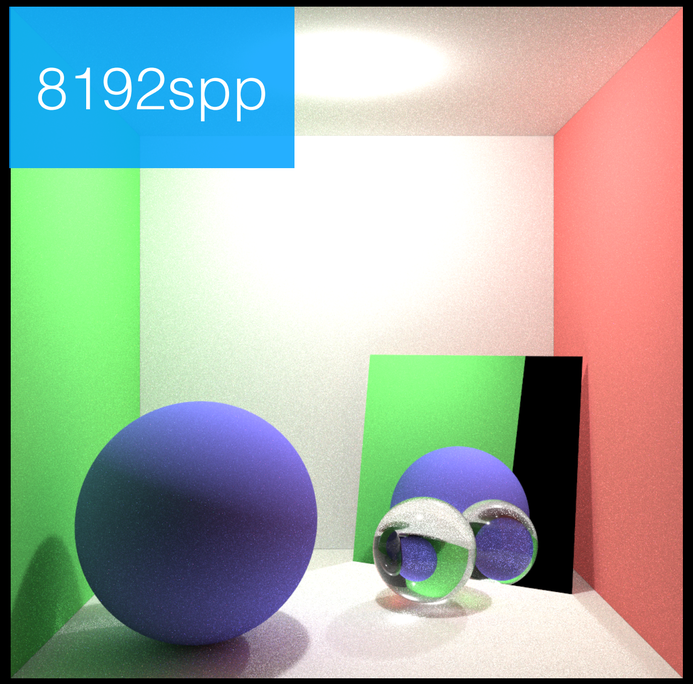
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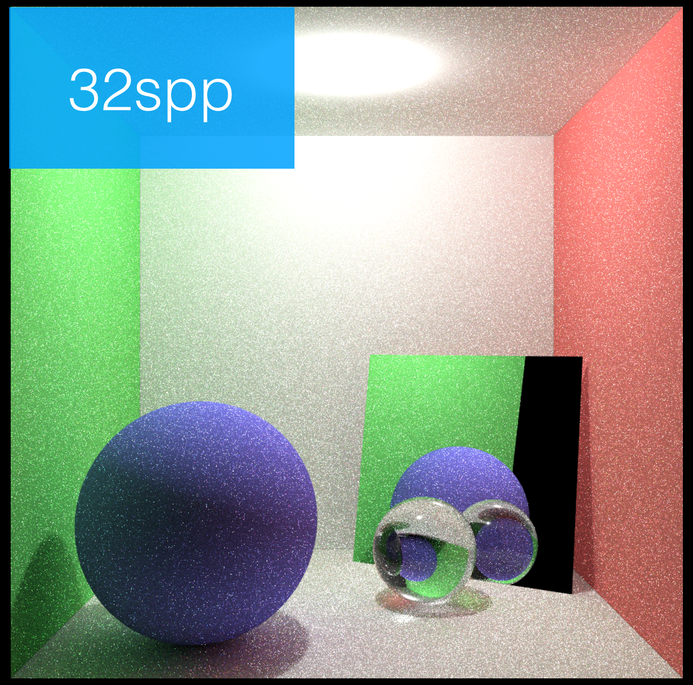

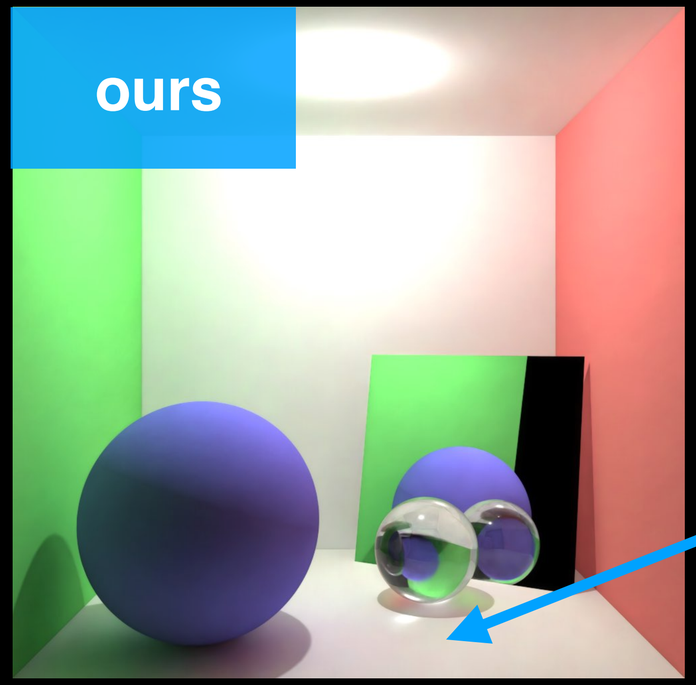

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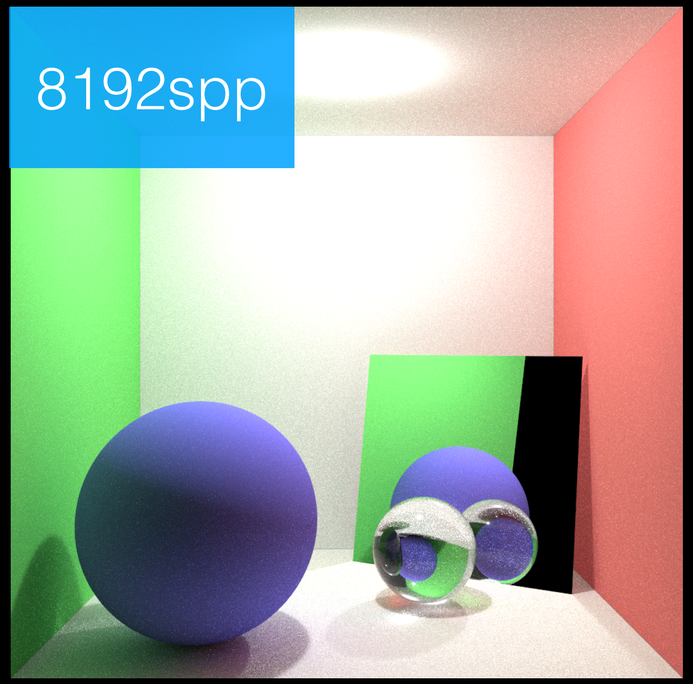
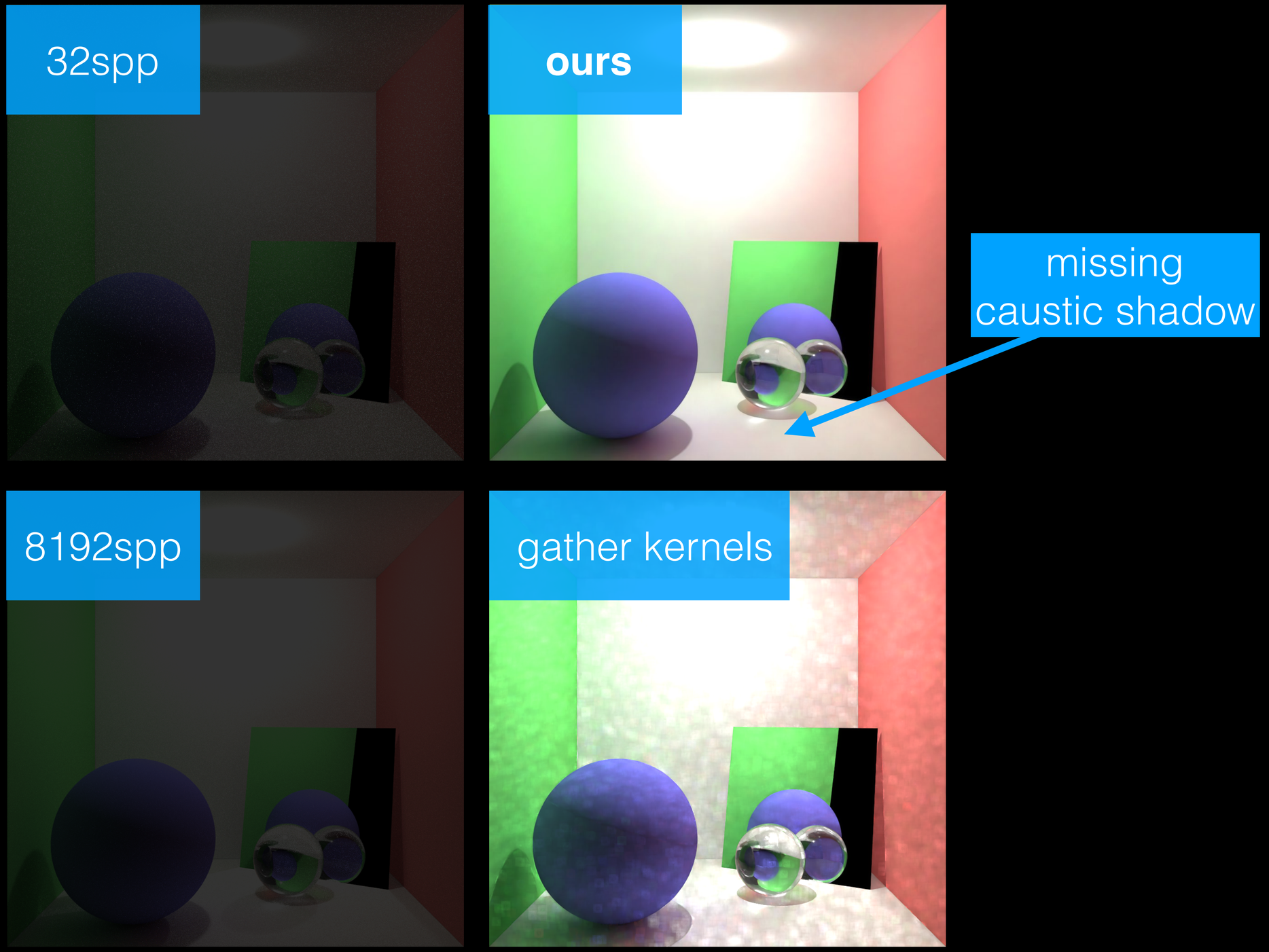
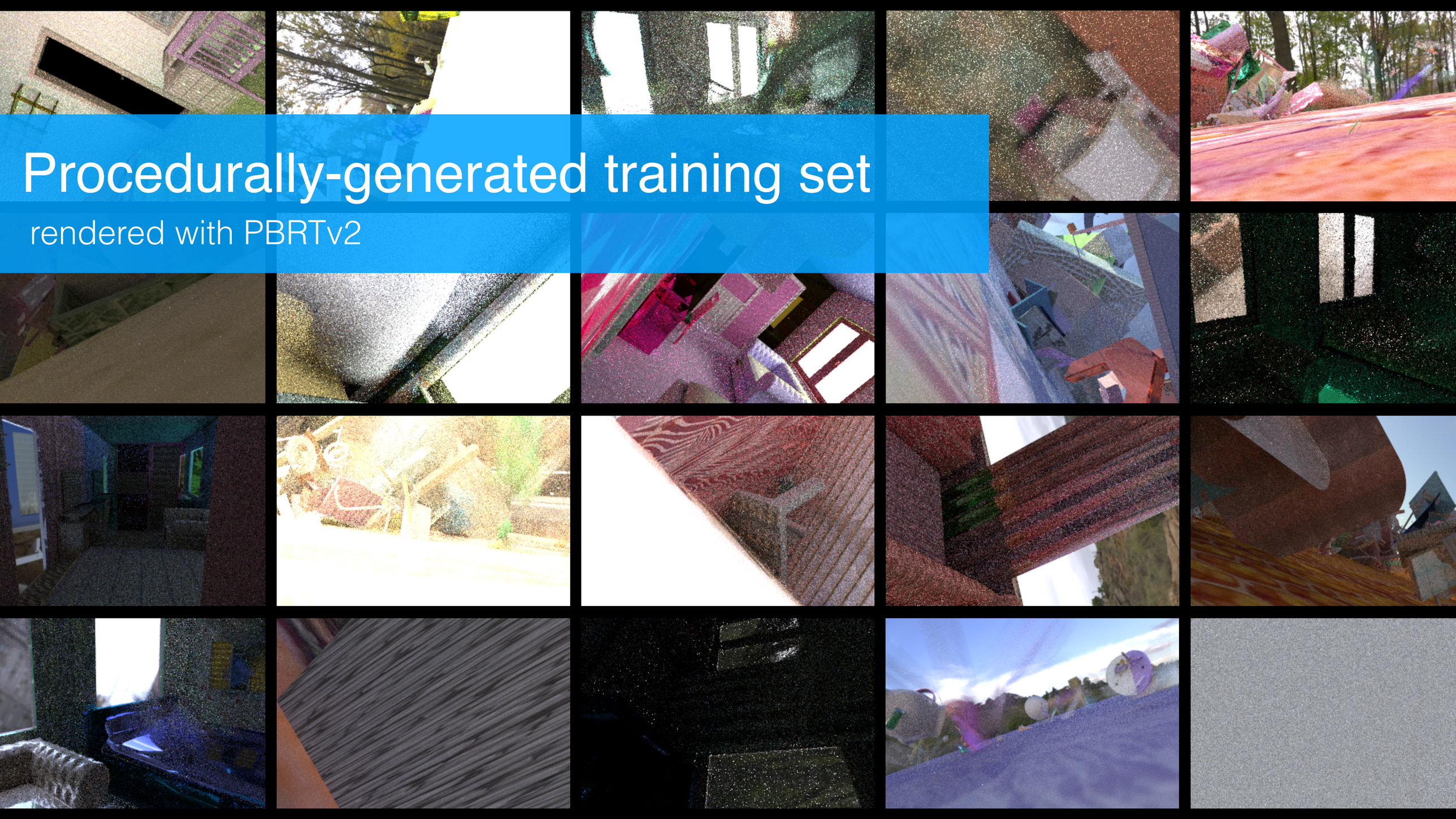
caustic shadow




32spp
ours
missing
caustic shadow
8192spp
gather kernels


Procedurally-generated training set
rendered with PBRTv2

Results

Evaluation

- 55 test scenes

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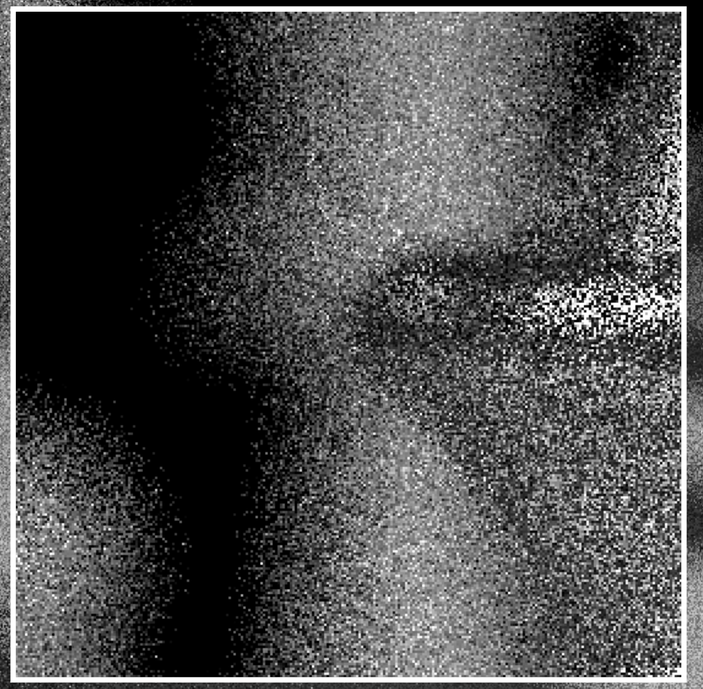
- 55 test scenes
- 5 reference denoisers
  - algorithmic and learning-based

Evaluation

- 55 test scenes
- 5 reference denoisers
  - algorithmic and learning-based
- Ablation study
  - splatting vs. gather kernels
  - per-sample vs. per-pixel
  - constant number of network parameters

input | 4spp



Bako et al. [2017] | 4spp

ours | 4spp

reference | 8192spp

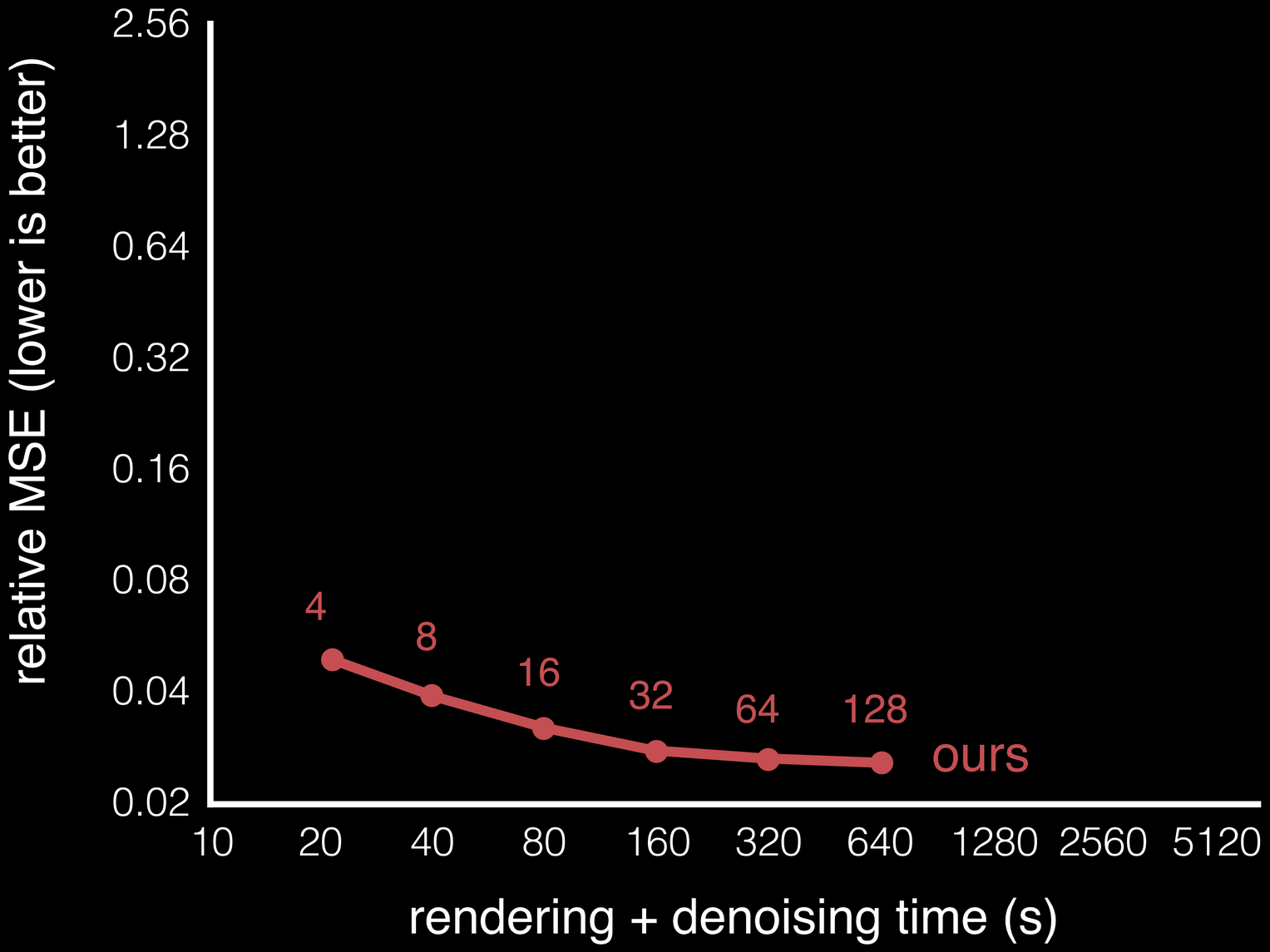
input | 4spp

Bako et al. [2017] | 4spp

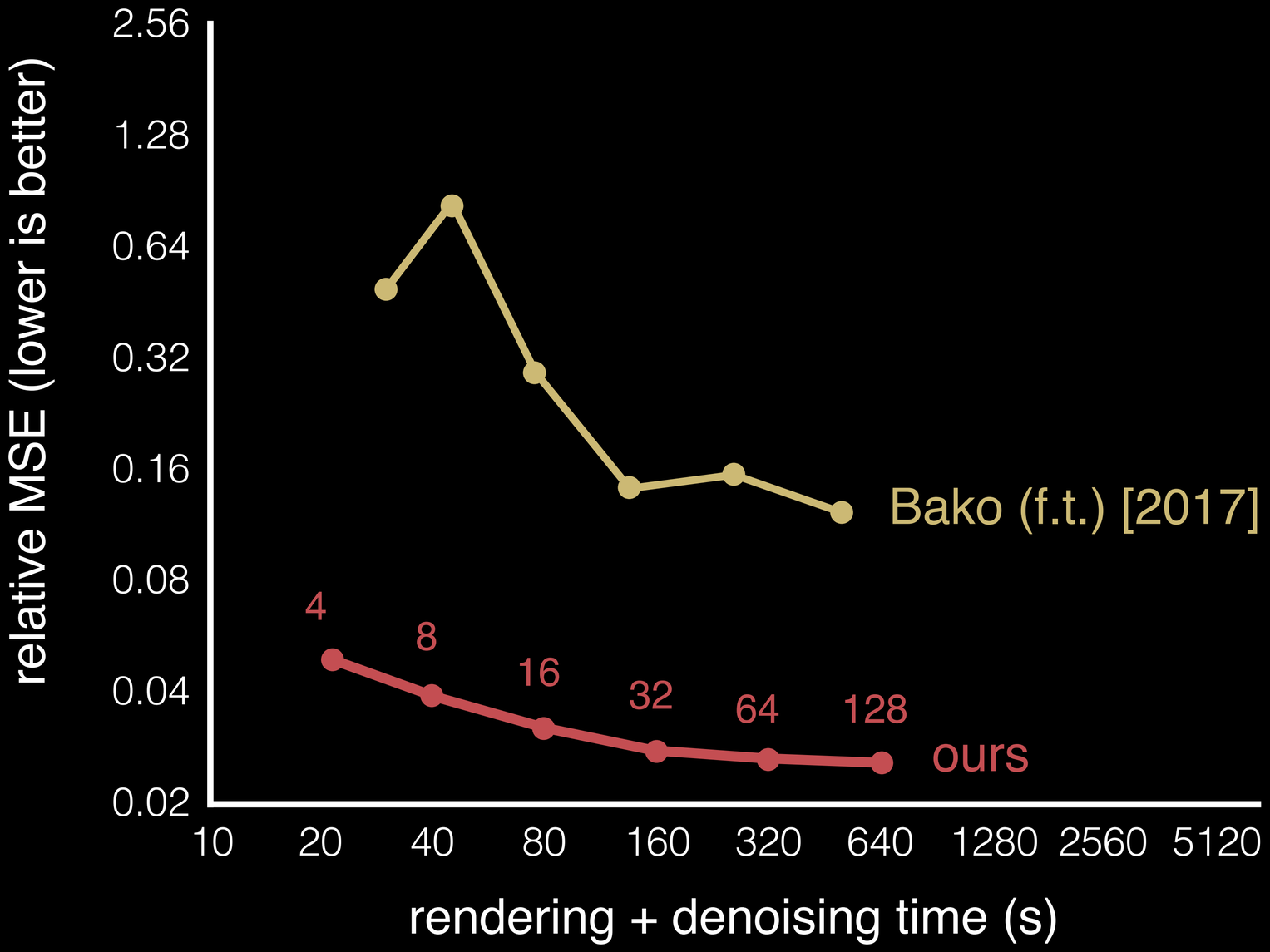
ours | 4spp

reference | 8192spp

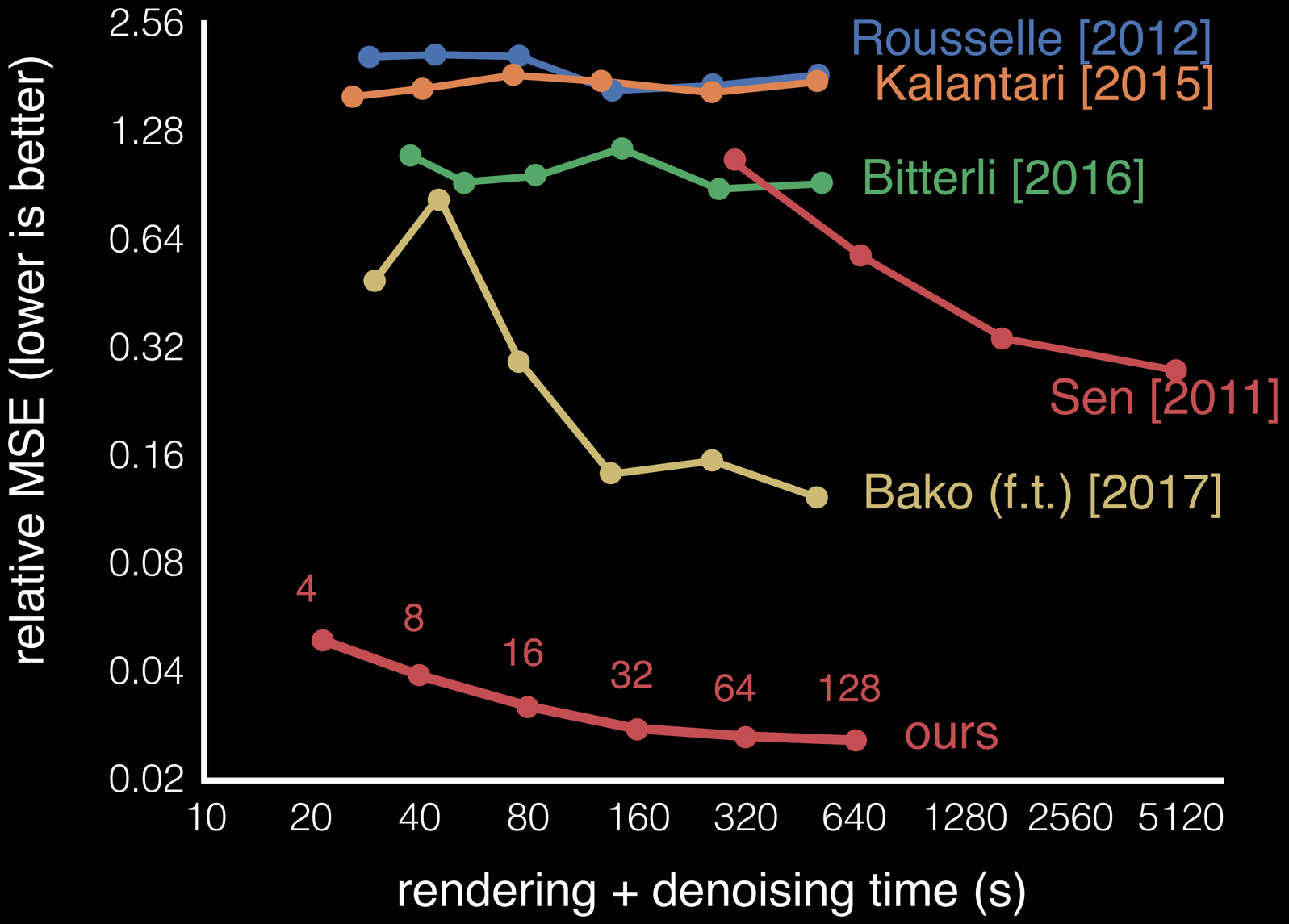
rMSE vs. running time (rendering + denoising)



rMSE vs. running time (rendering + denoising)



rMSE vs. running time (rendering + denoising)



Discussion

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  - More applicable to few sample regime (4—32spp)
- Samples sum radiance over complete light path

Conclusion

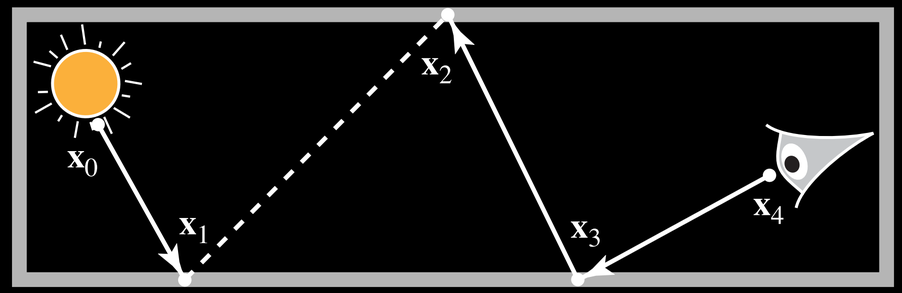
- Samples provide richer information
  - compared to per-pixel statistics
- Splatting kernels
  - high-quality output, simpler prediction
  - robust to severe noise
- Permutation-invariant network
  - map from arbitrary number of samples to pixels

Michaël GHARBI mgharbi@adobe.com
code/models/data - www.mgharbi.com

Extras

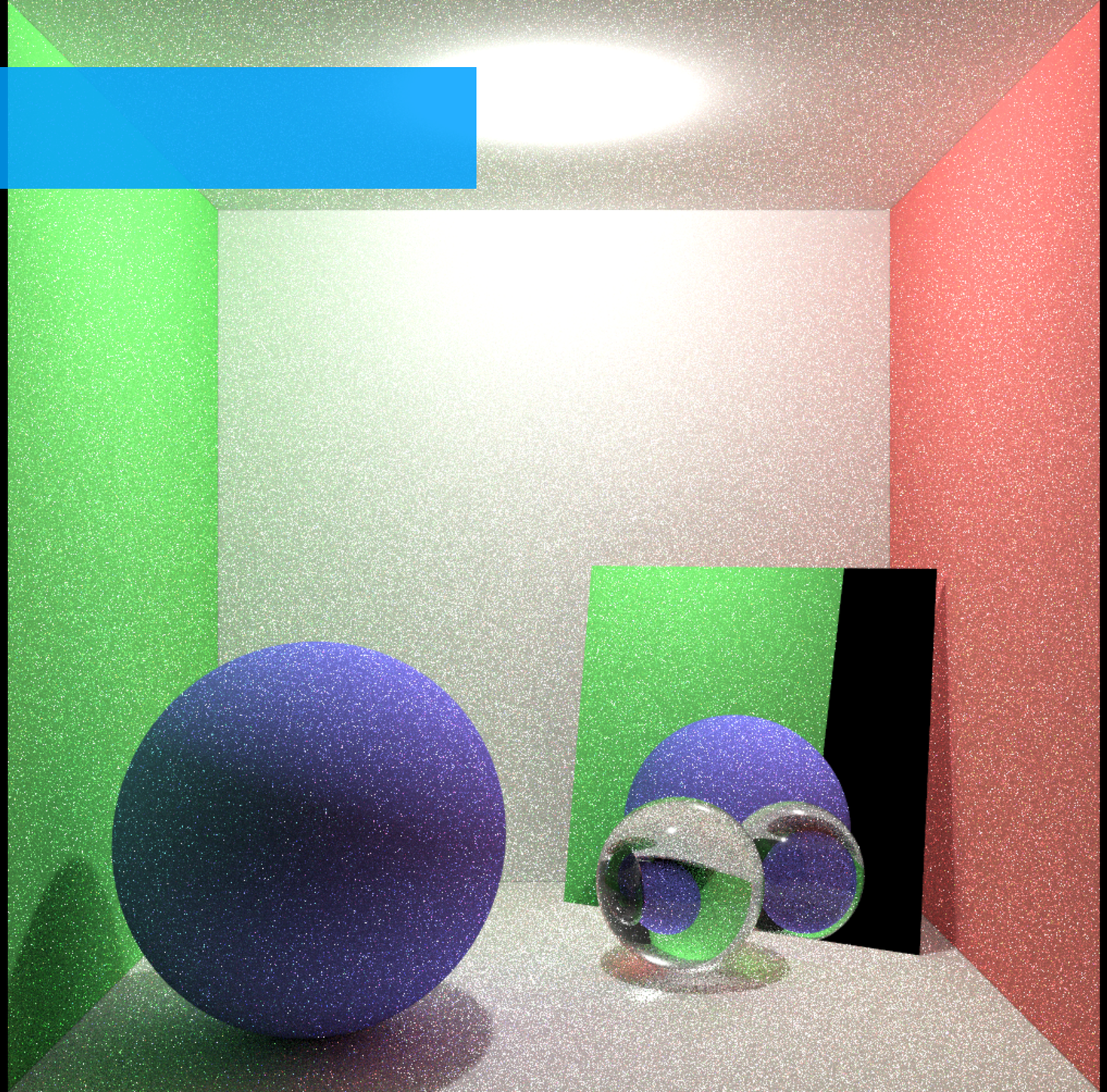
Data generation

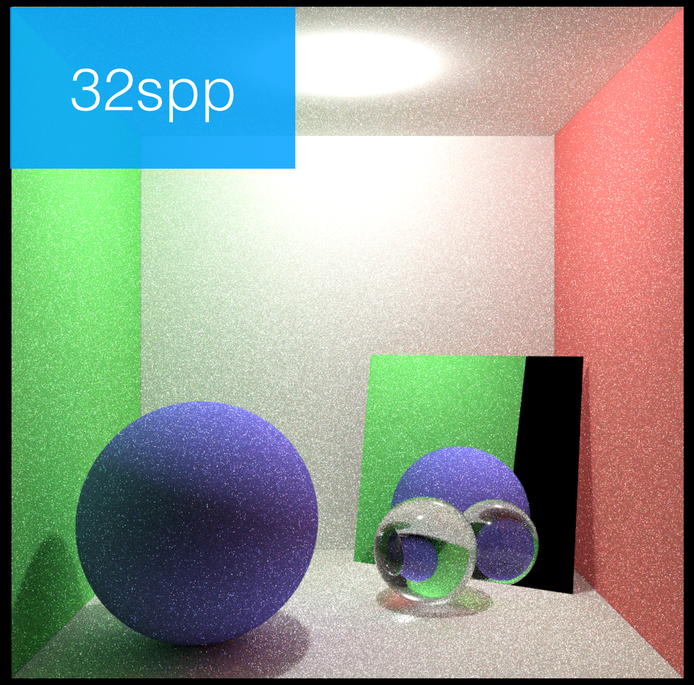
- Custom scene generator
  - geometry from SunCG [Song 2017] and ShapeNet [Chang 2015]
  - textures from Cimpoi et al. [2014]
  - randomized materials, cameras, lights
- Path tracing with fixed path length
  - PBRTv2 [Pharr 2004]
- Store samples and path information
  - radiance at multiple bounces along the path
  - depth, normals, albedo, x, y, t, lens position, etc



Model ablations

input | 32spp

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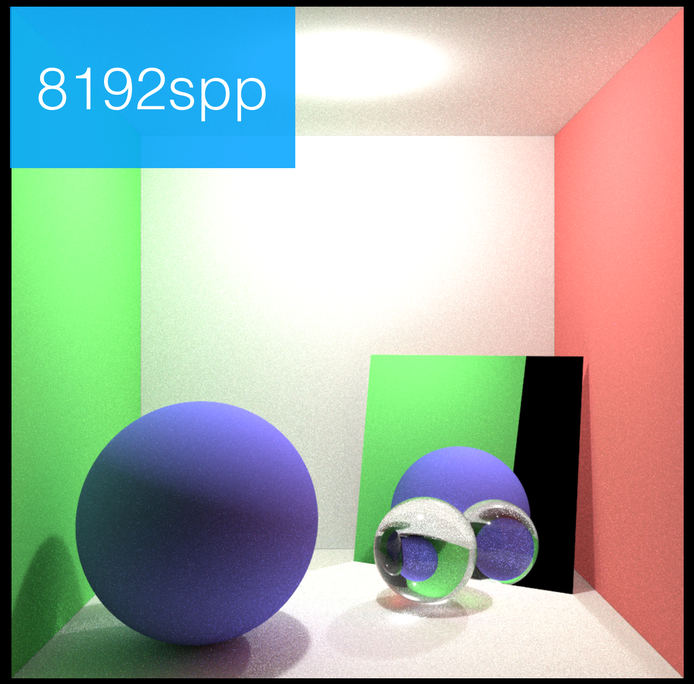
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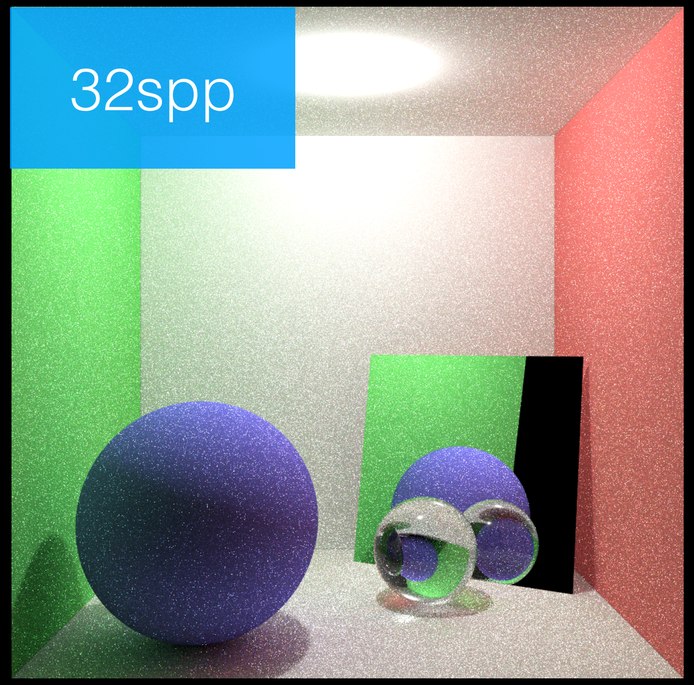
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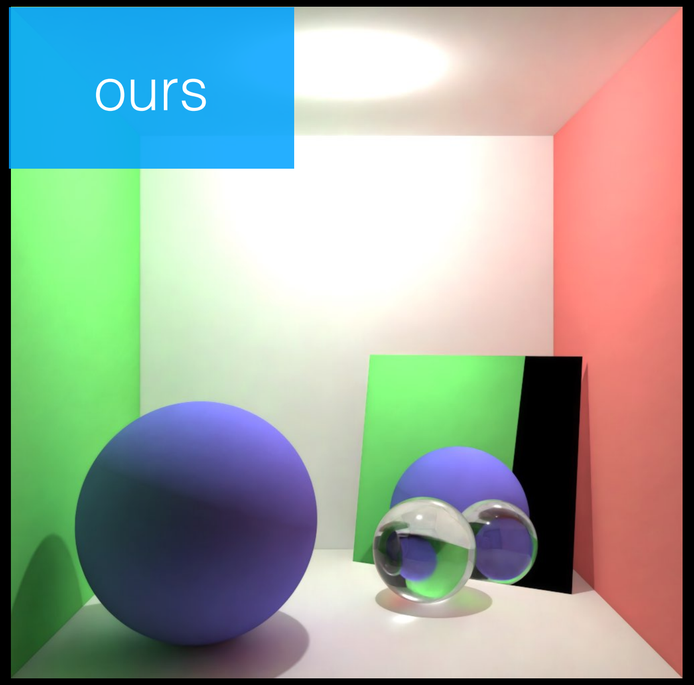
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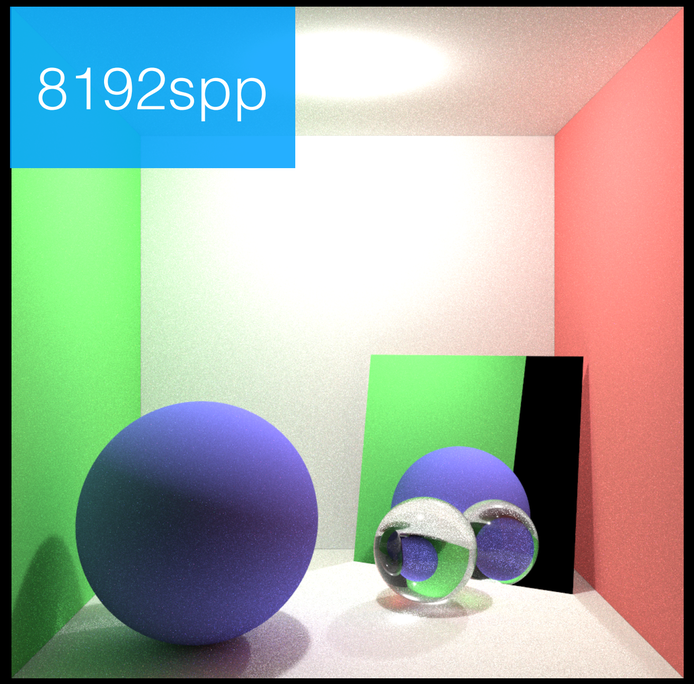
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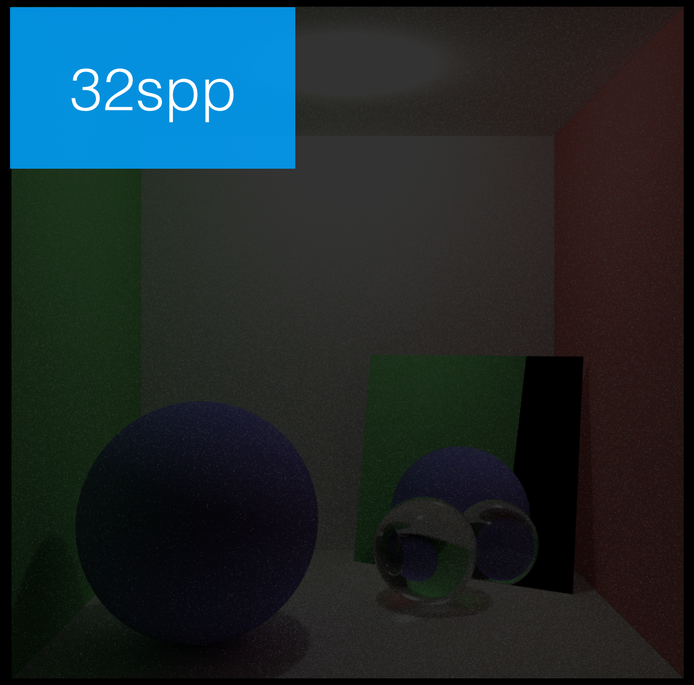
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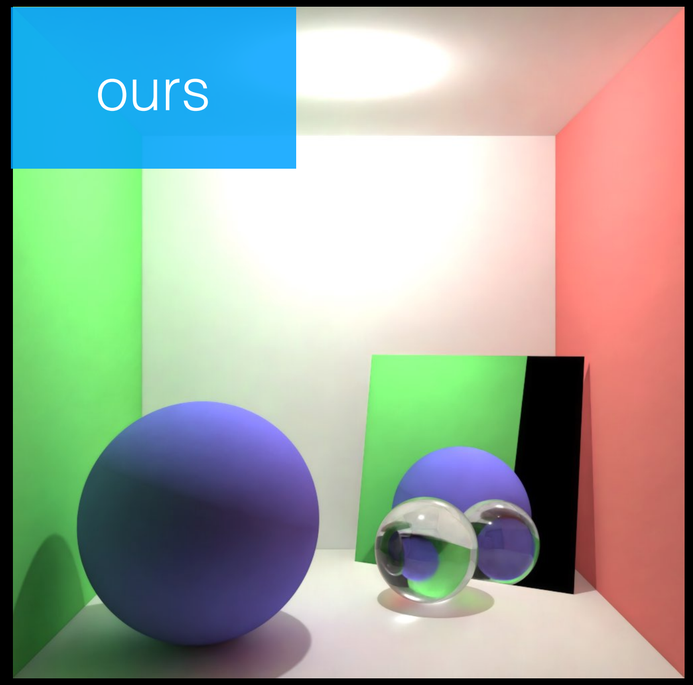
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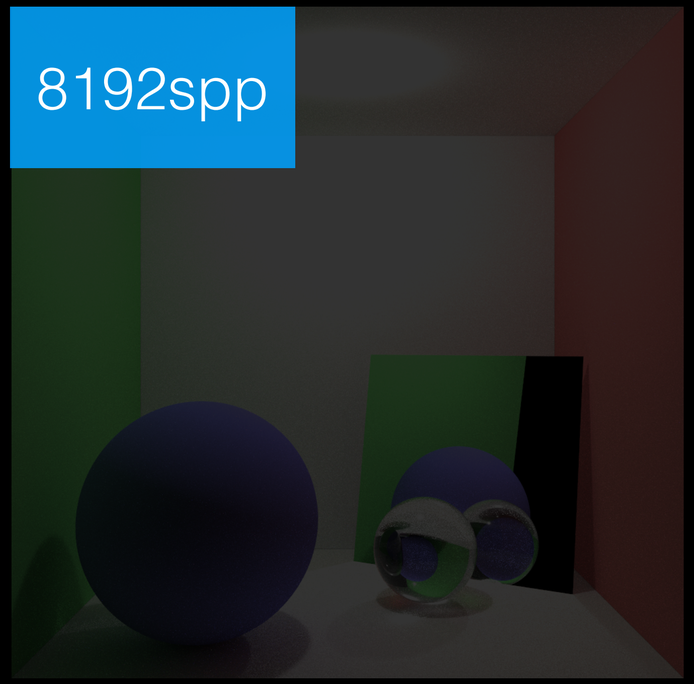
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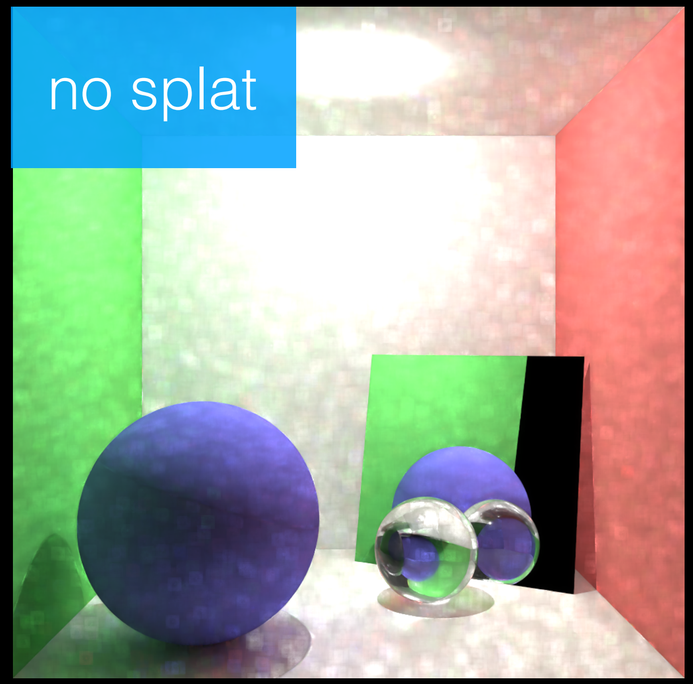
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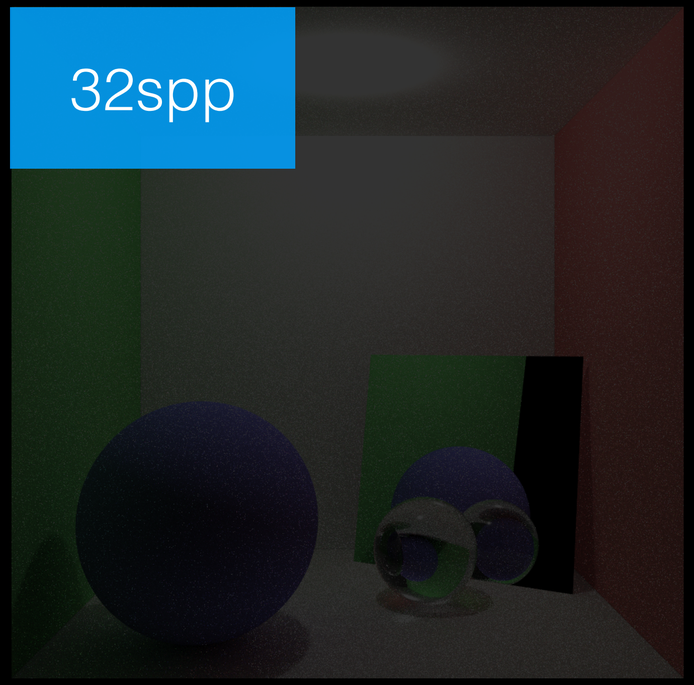
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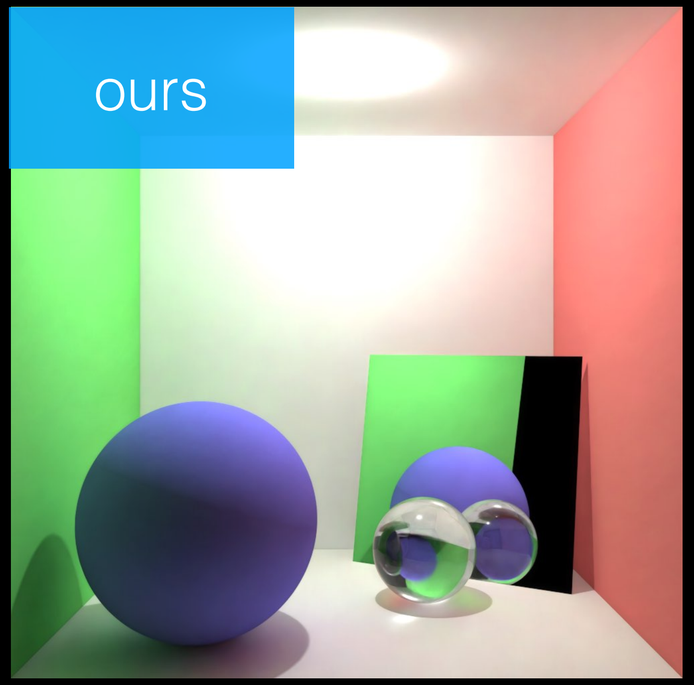
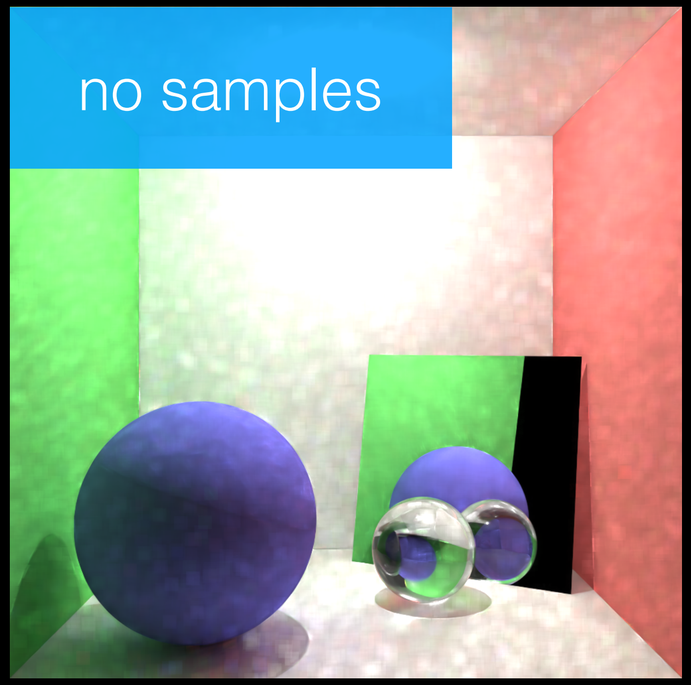

ours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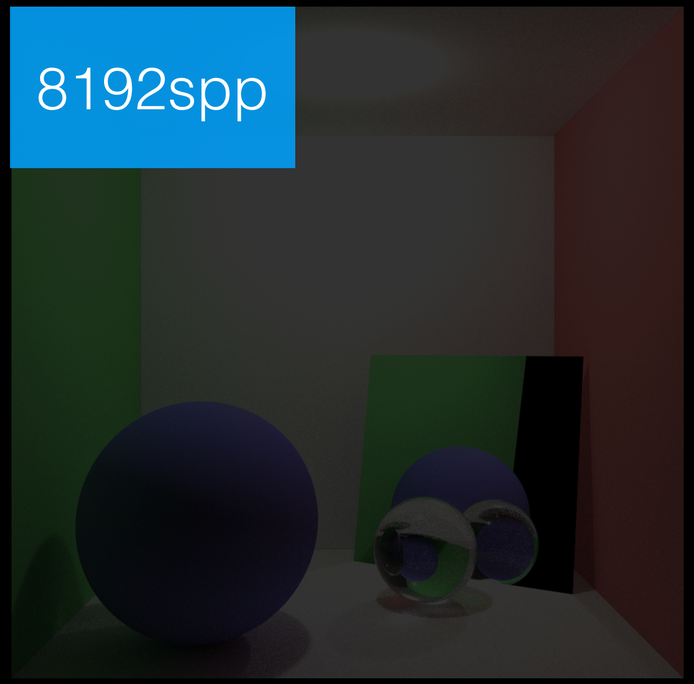
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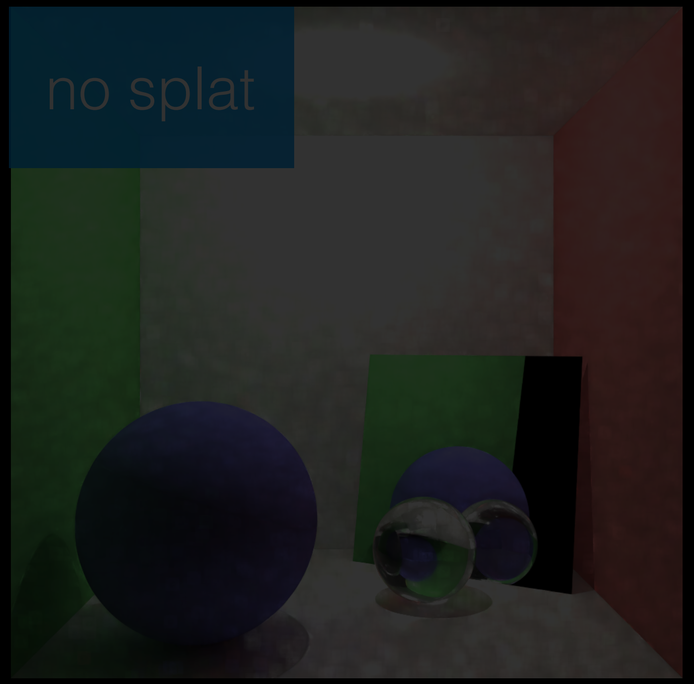
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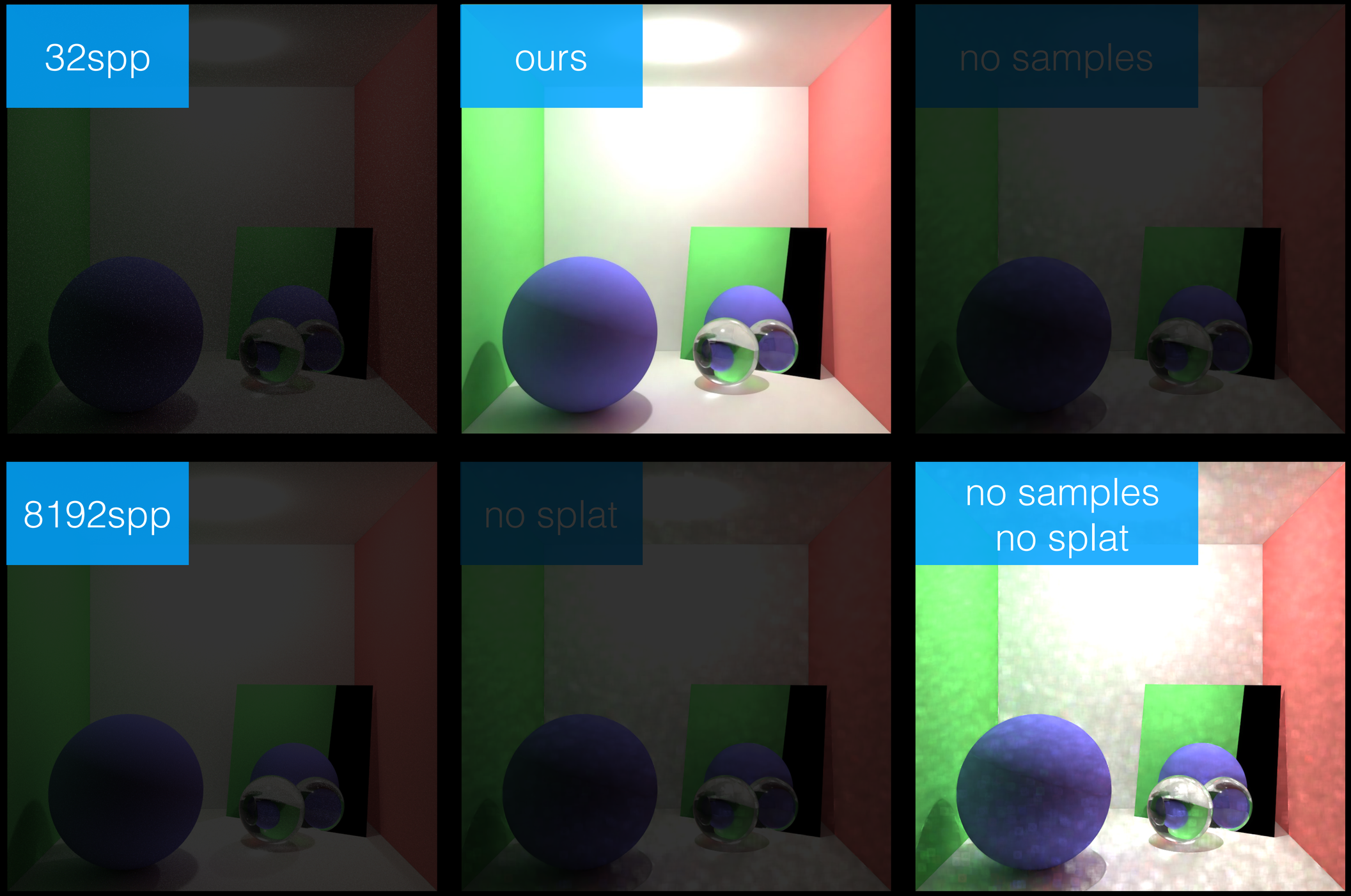
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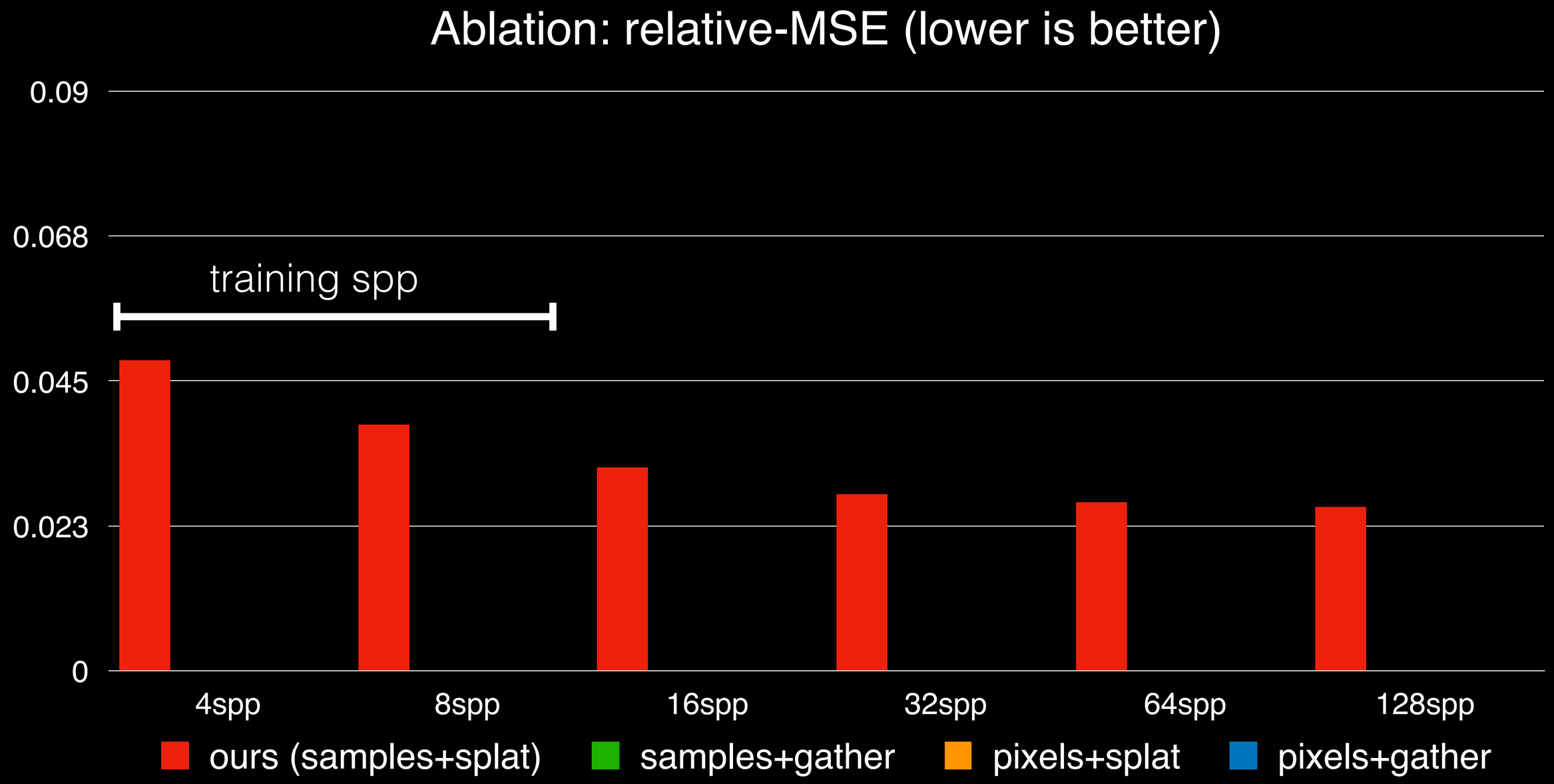
Ablation: relative-MSE (lower is better)
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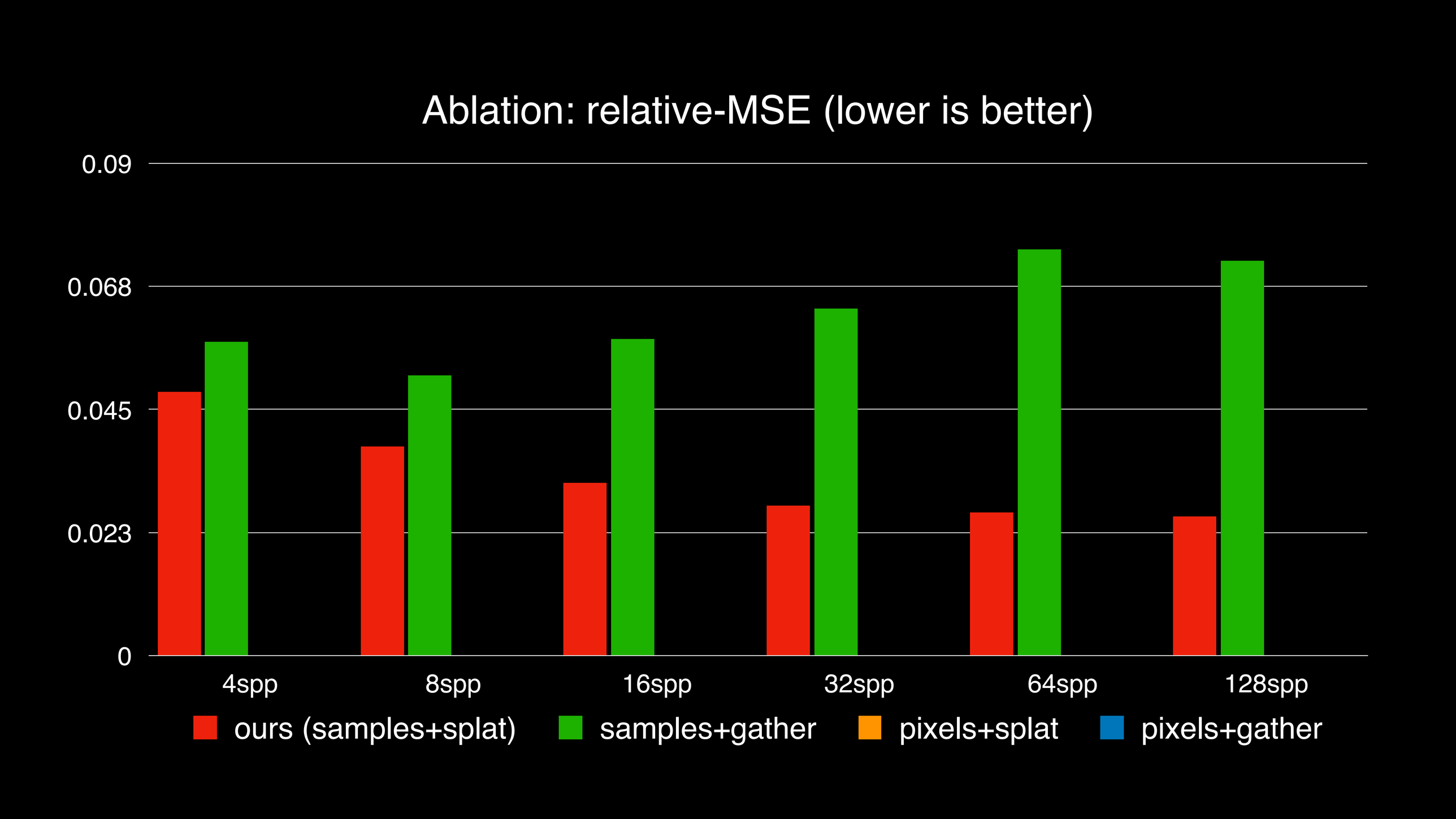
ours (samples+splat)
samples+gather
pixels+splat
pixels+gather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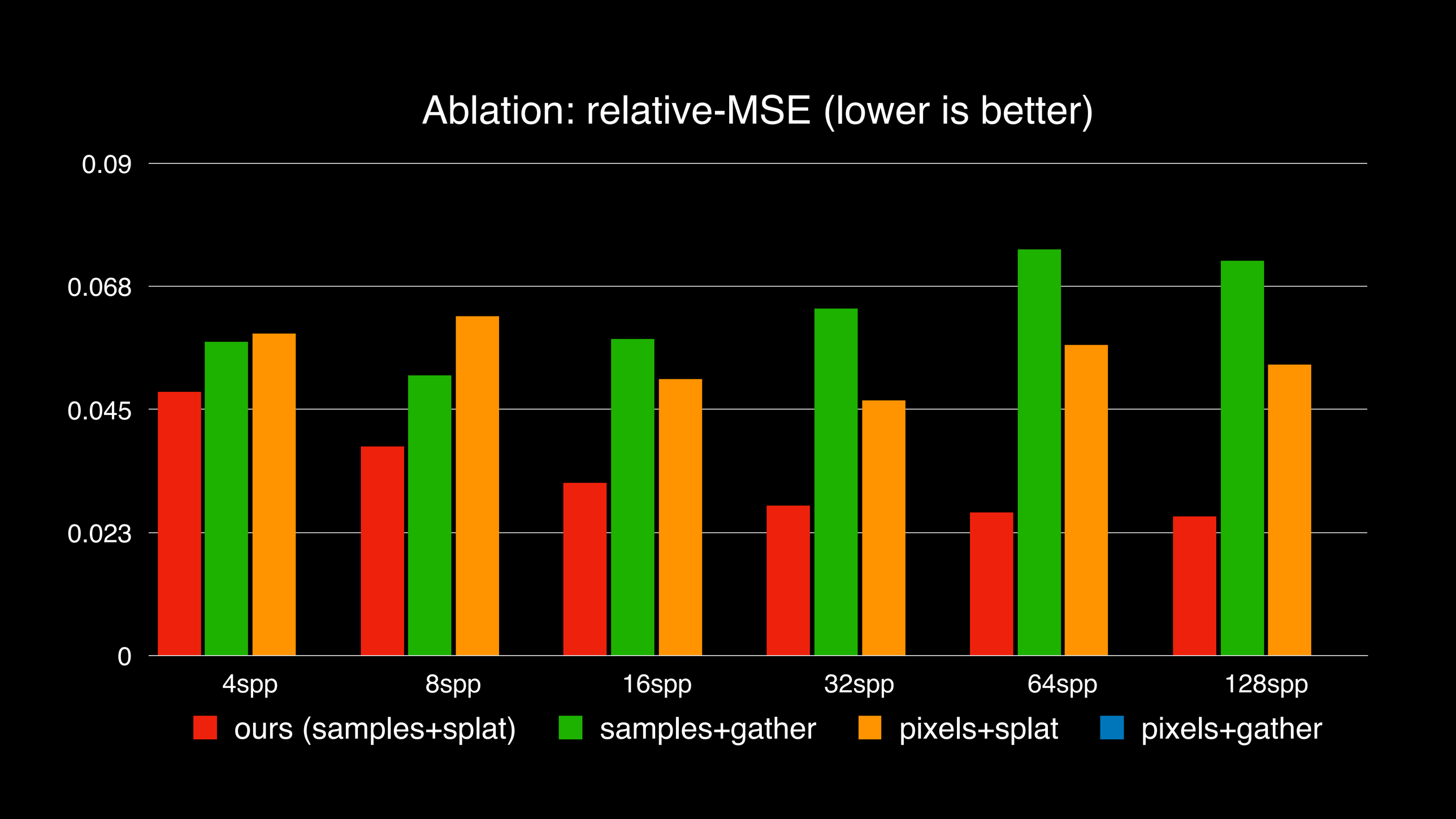
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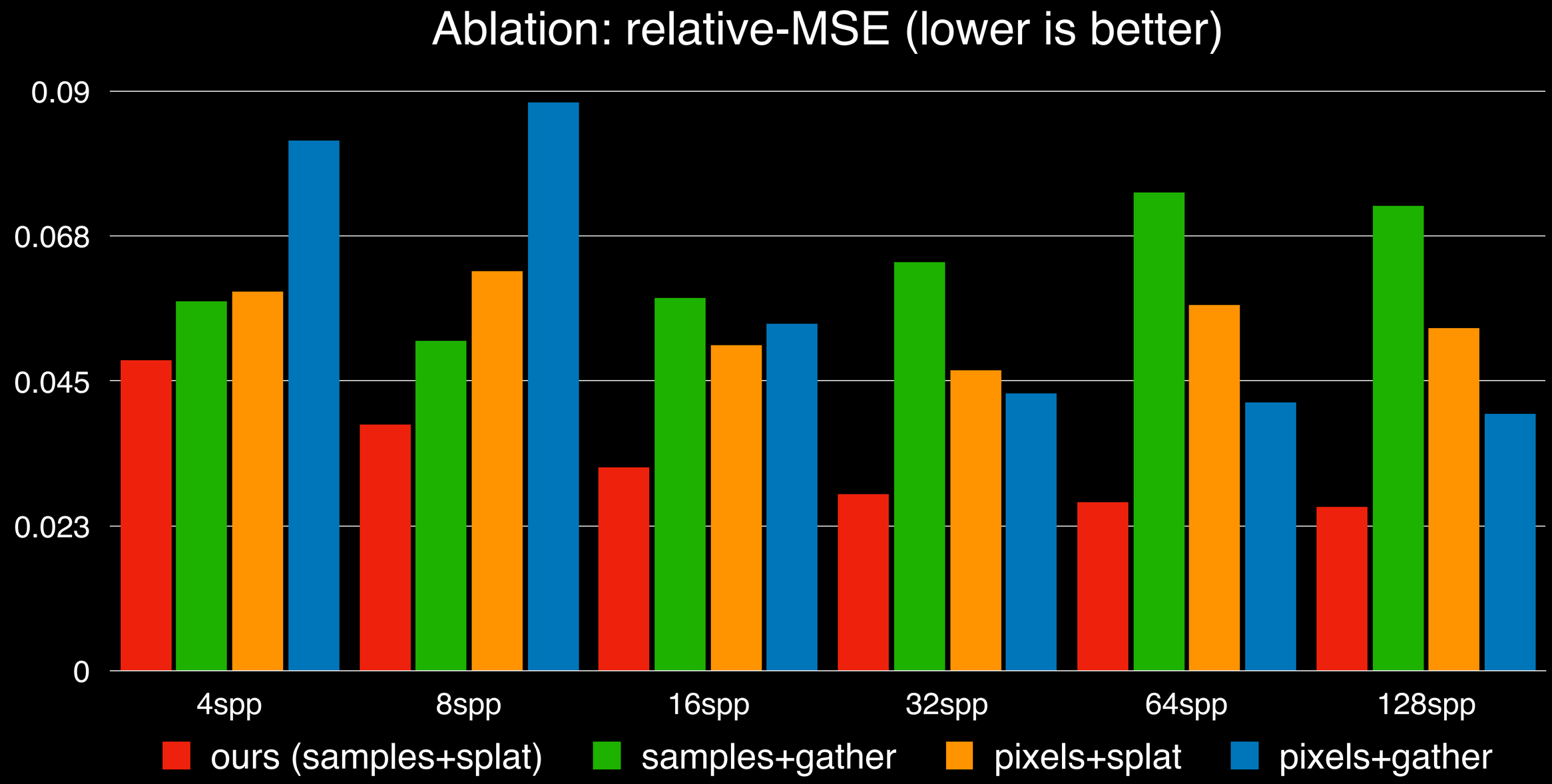
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8spp
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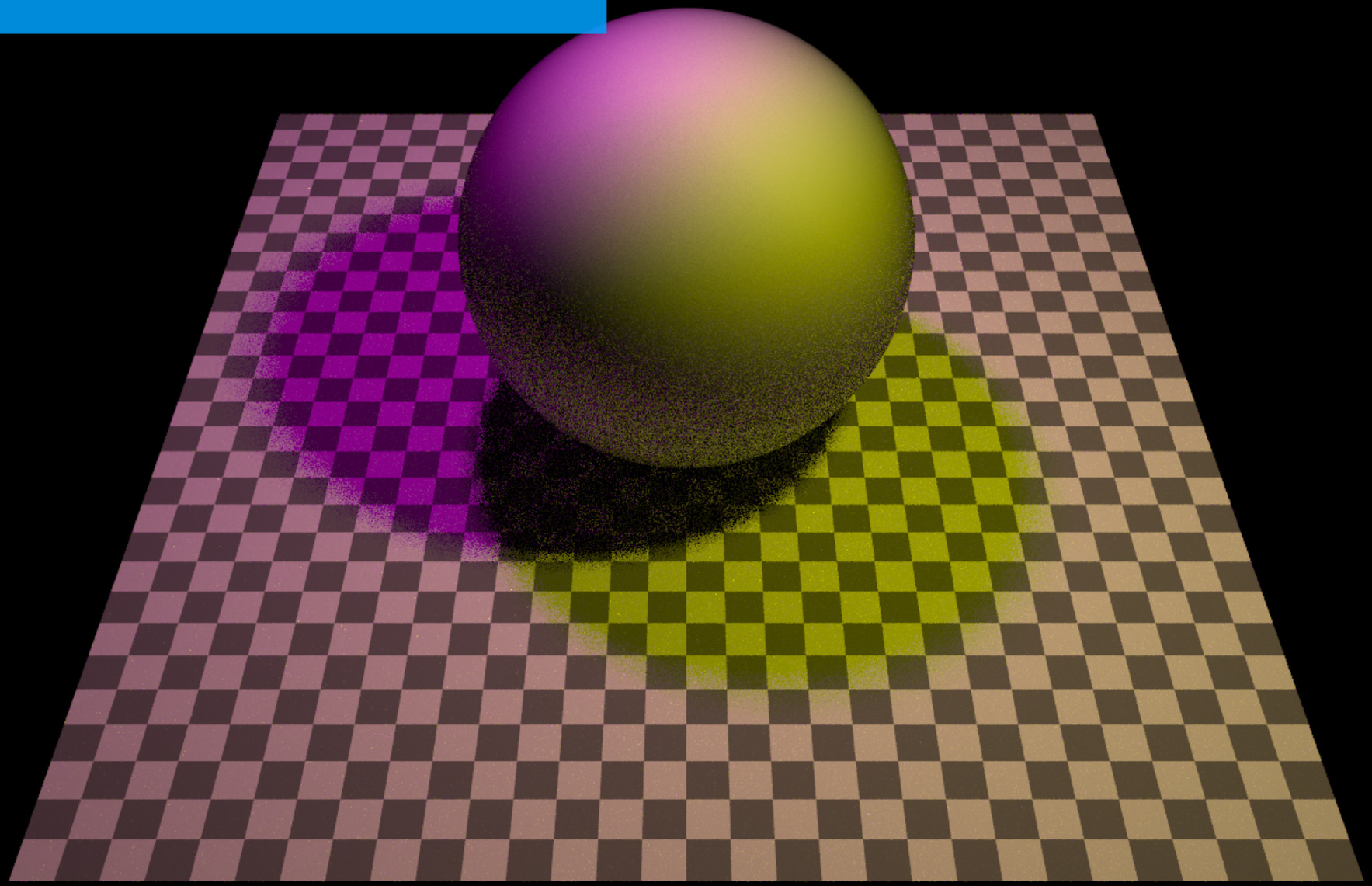
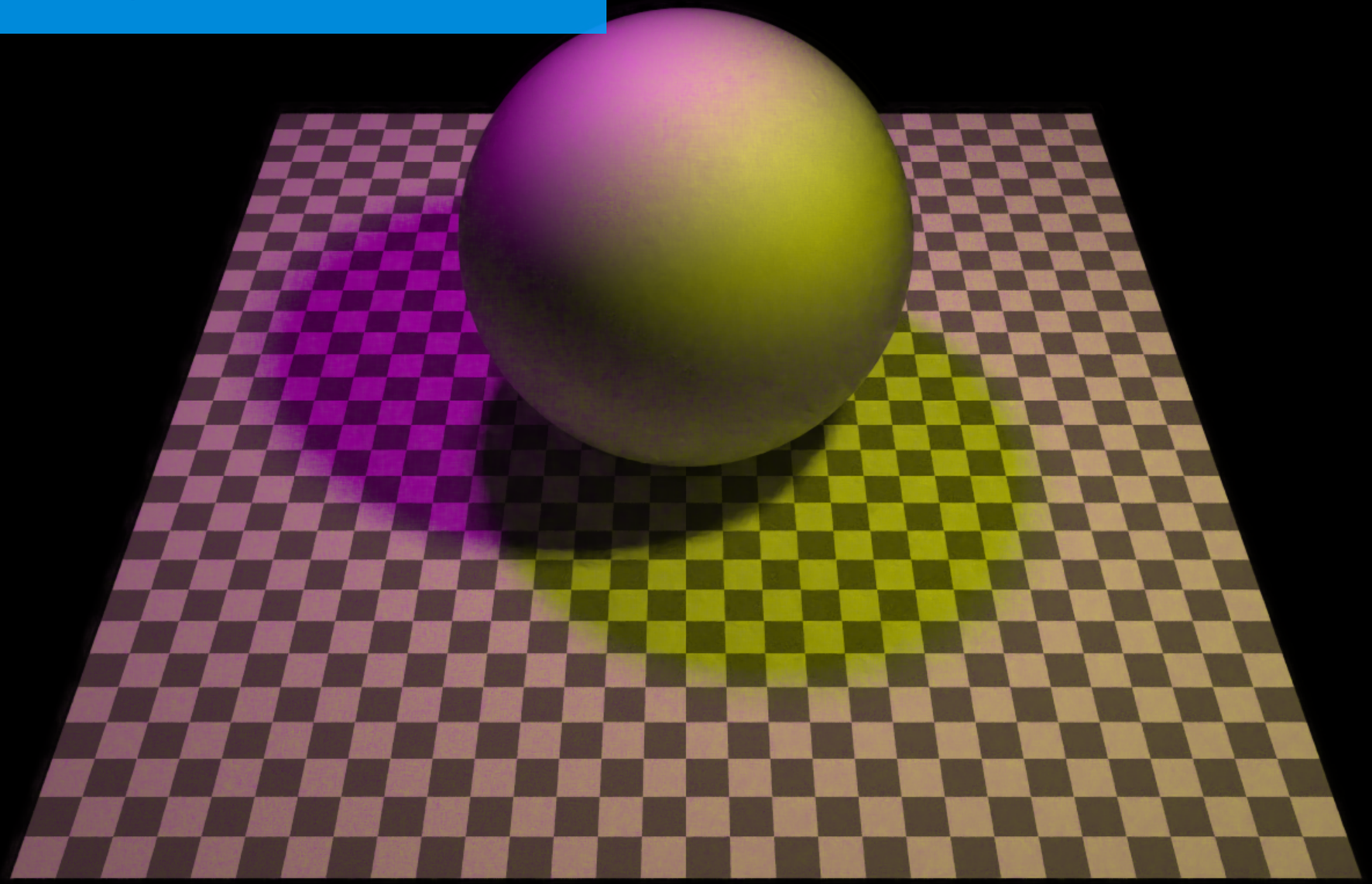
128spp
ours (samples+splat)
samples+gather
pixels+splat
pixels+gather

Extra results

input | 8spp



Bako et al. [2017] | 8spp



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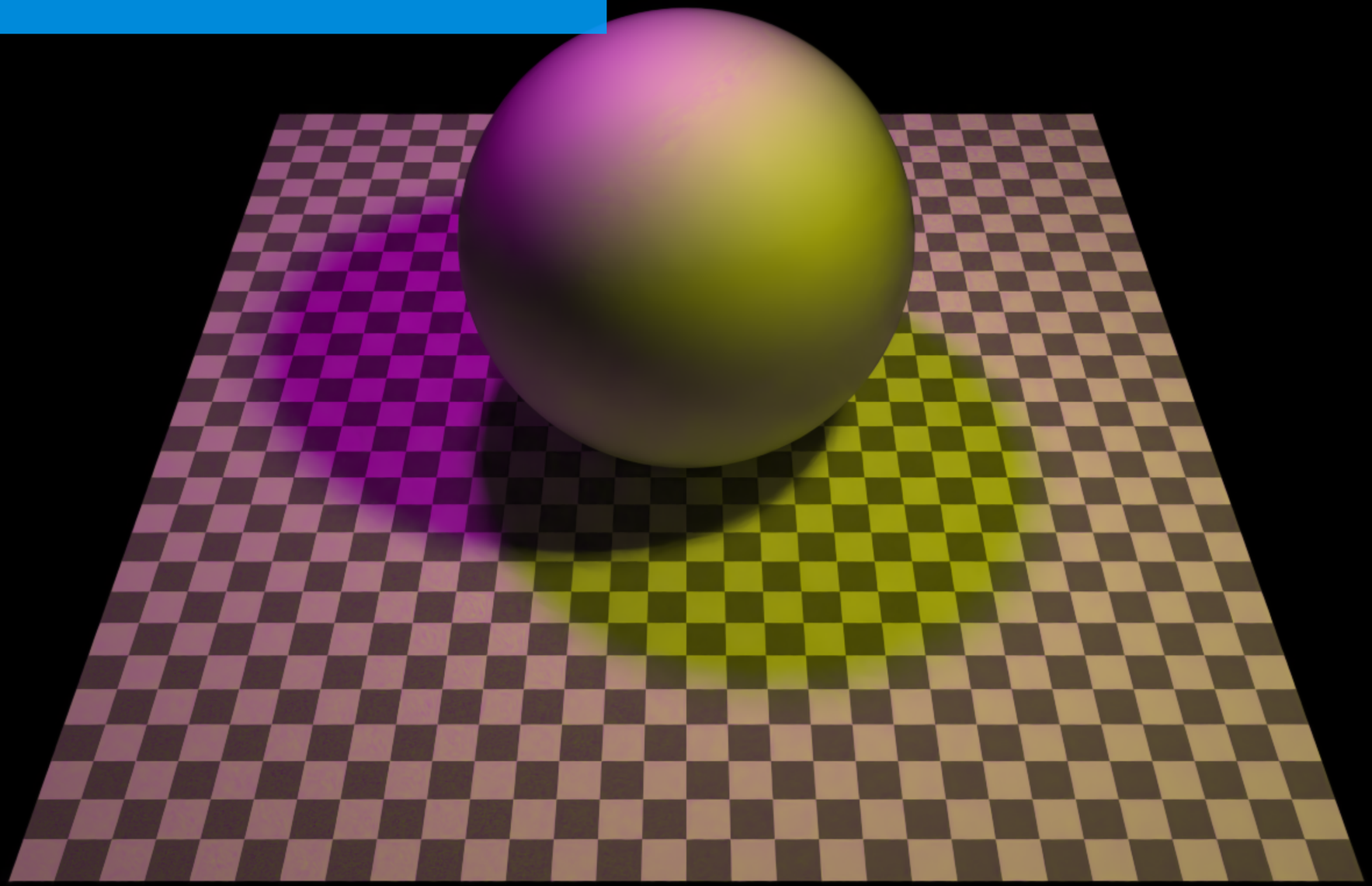

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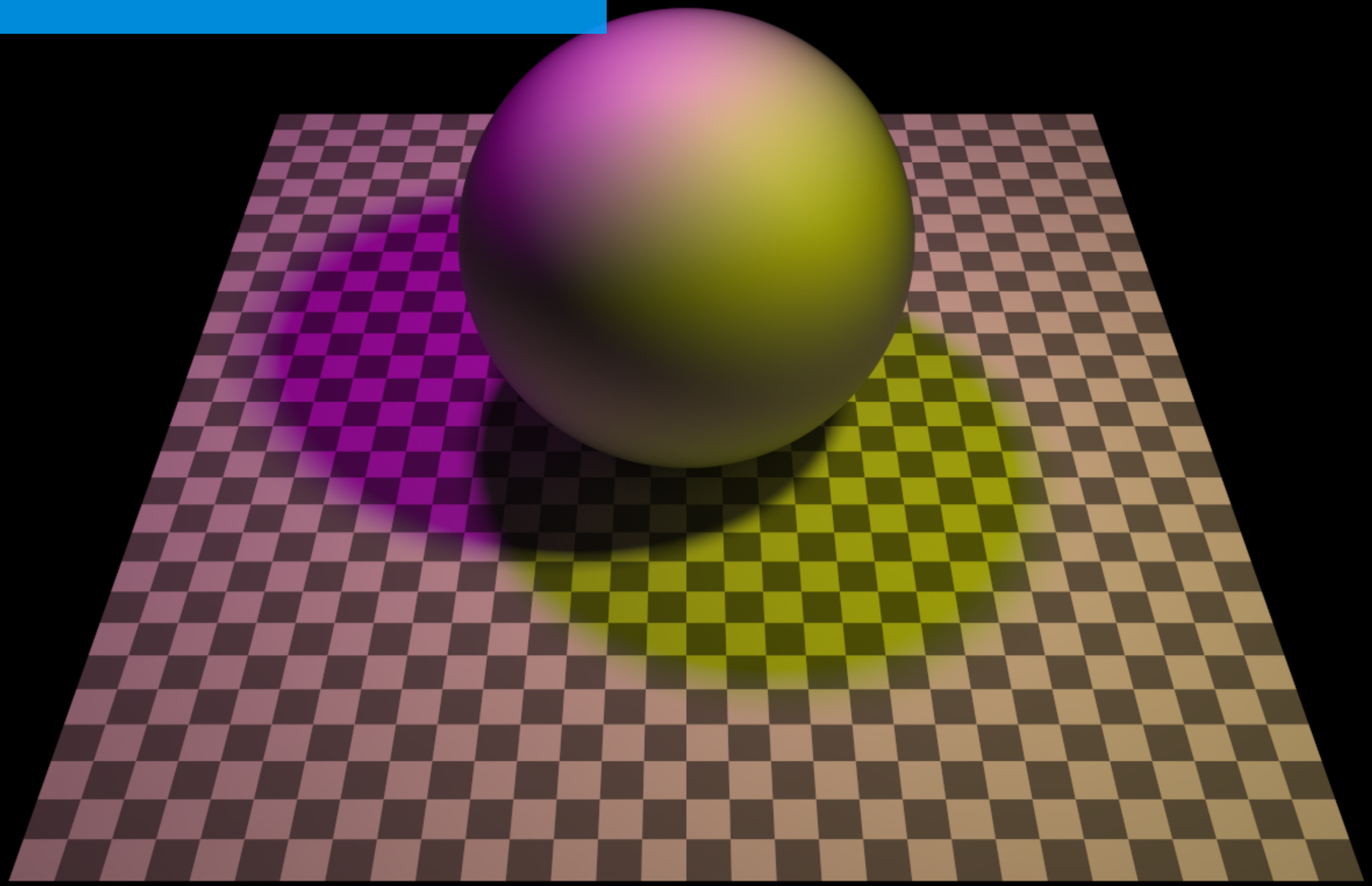

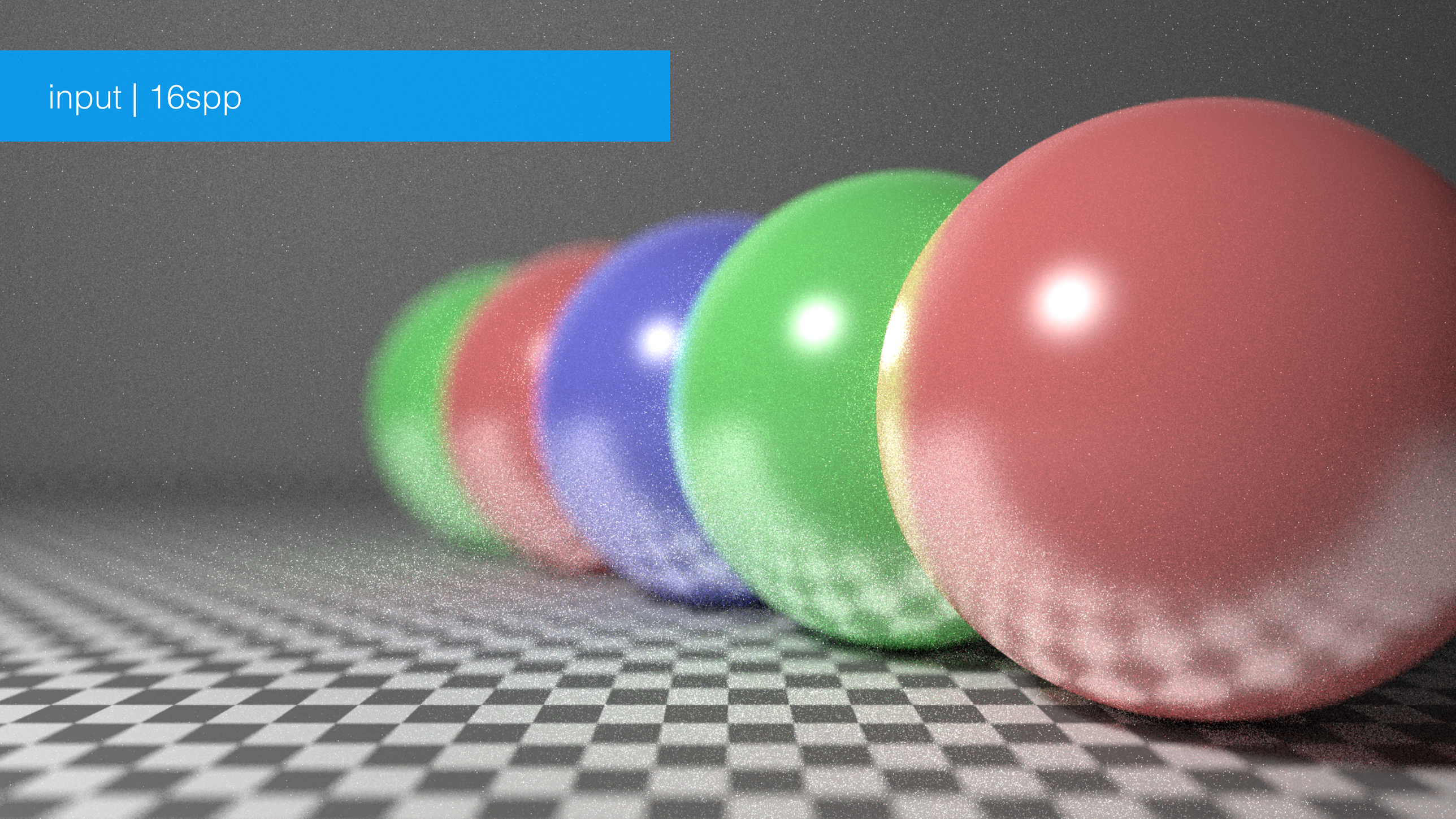
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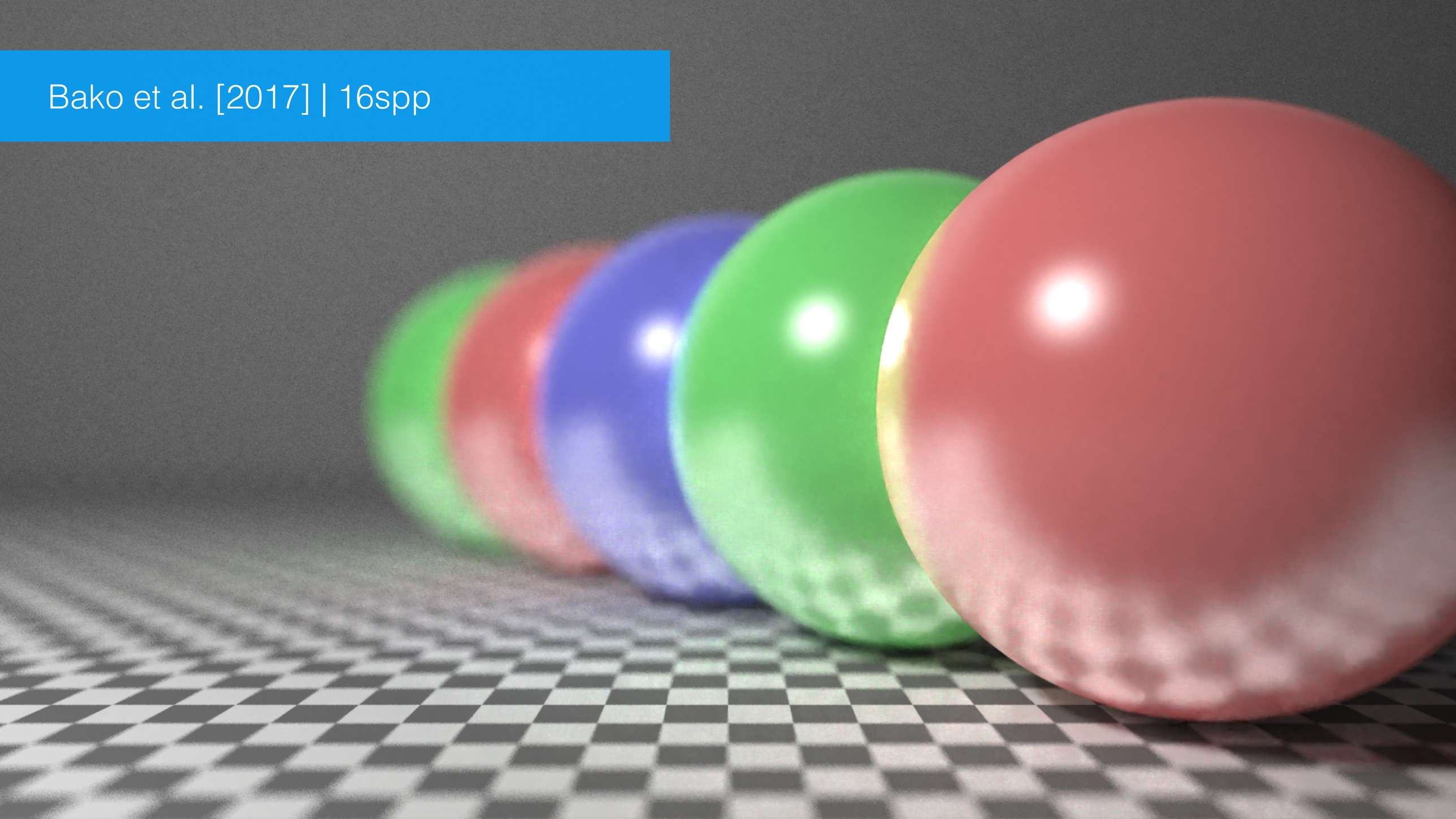
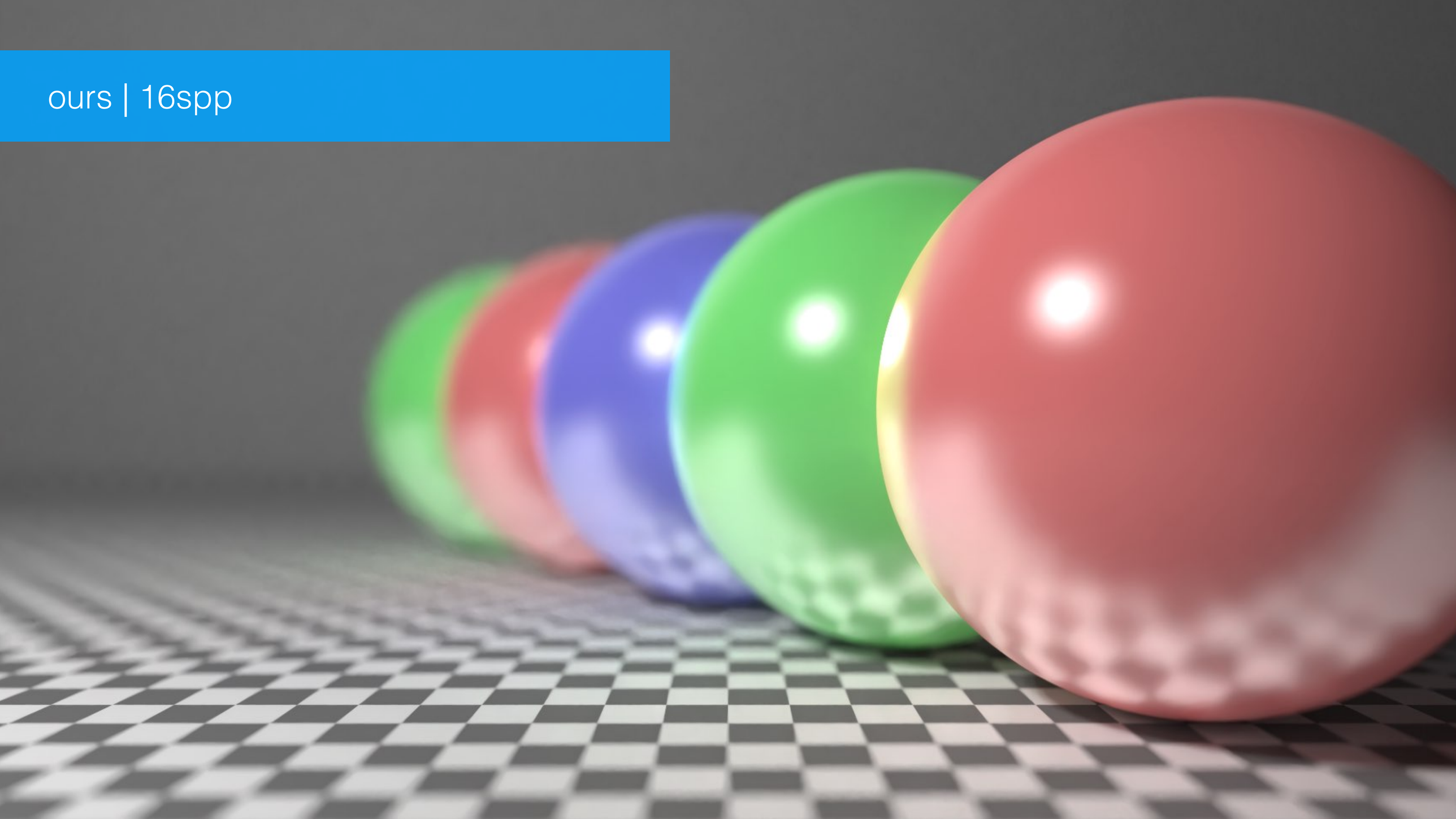

Bako et al. [2017] | 16spp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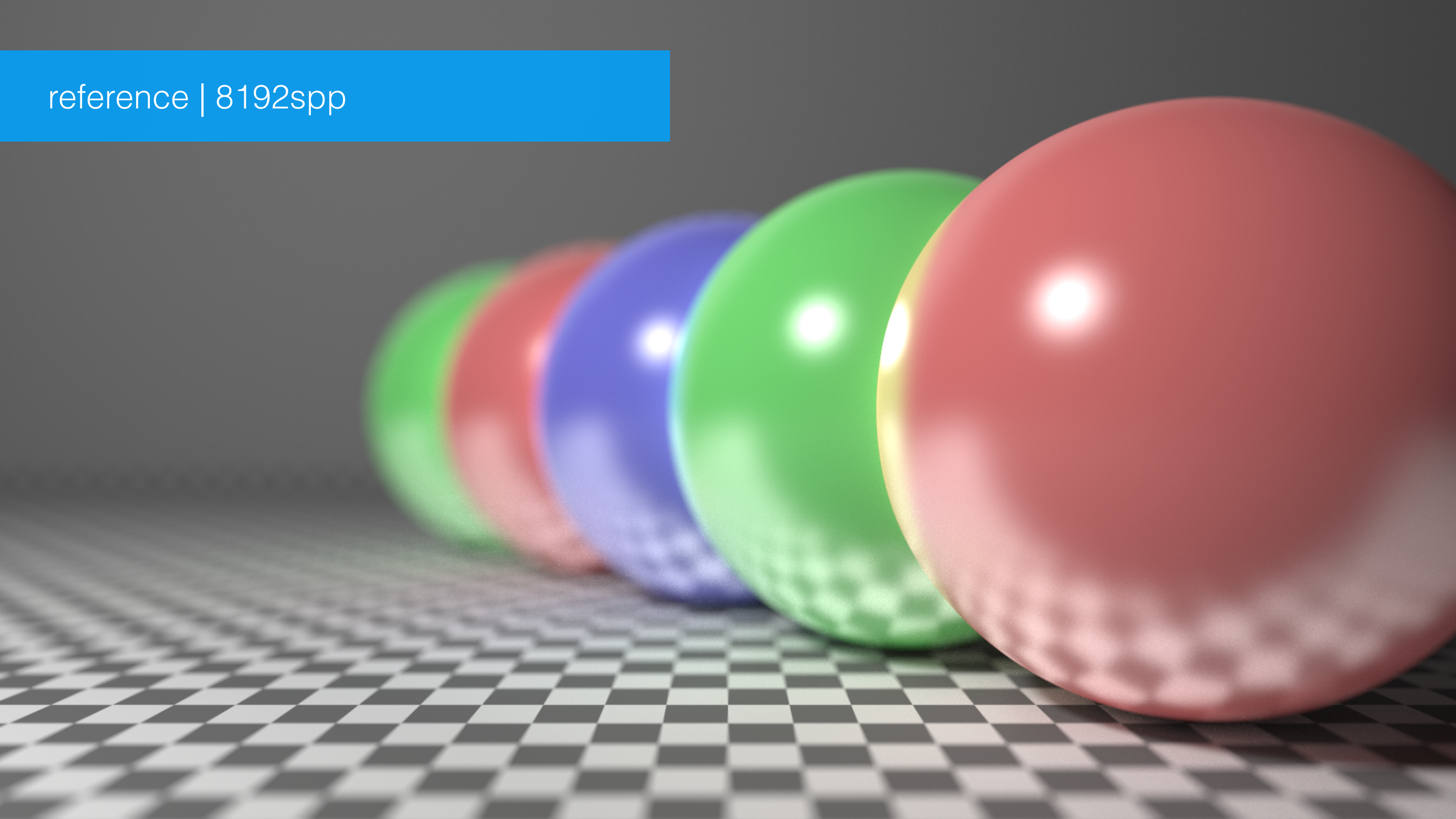
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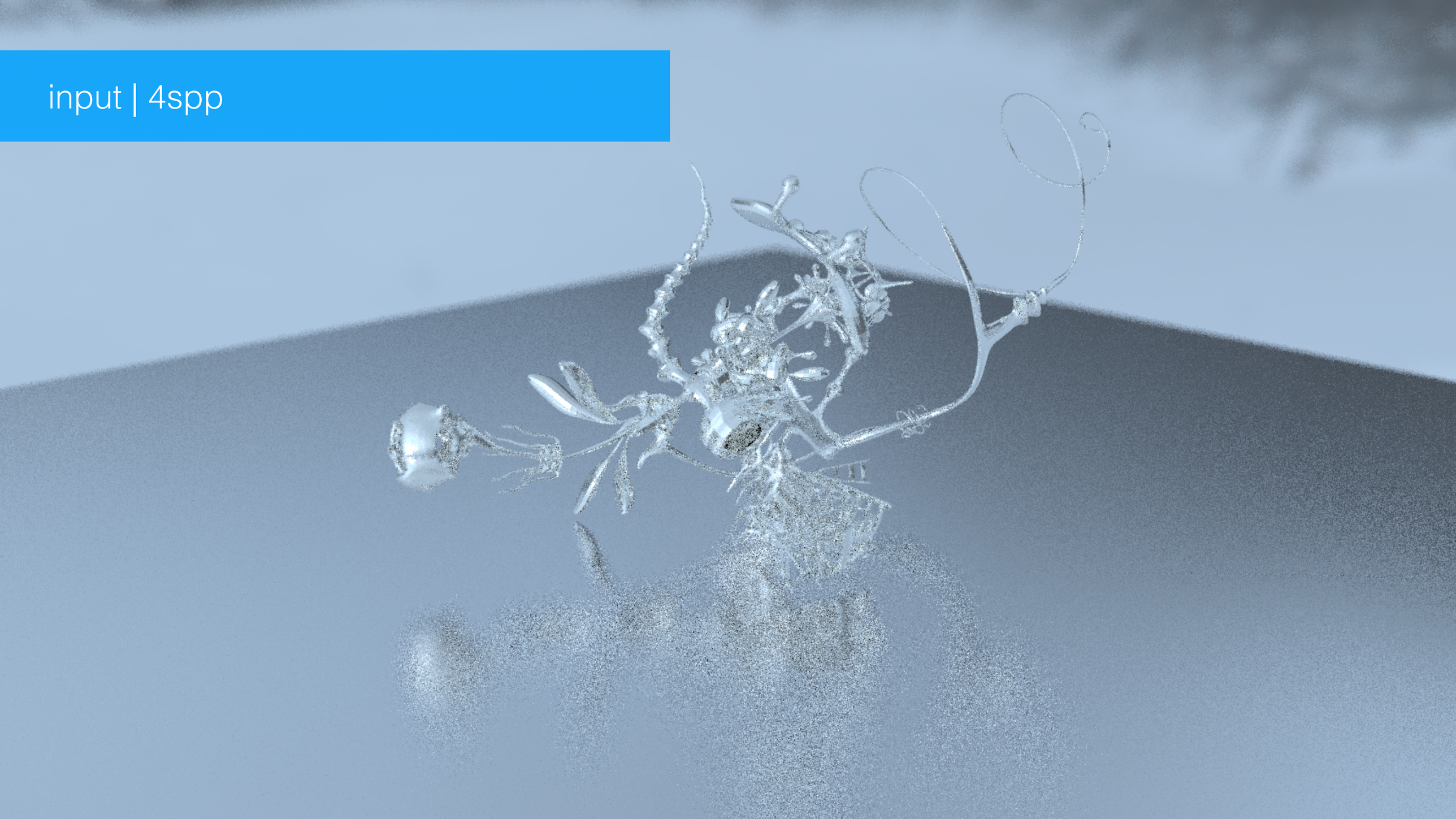
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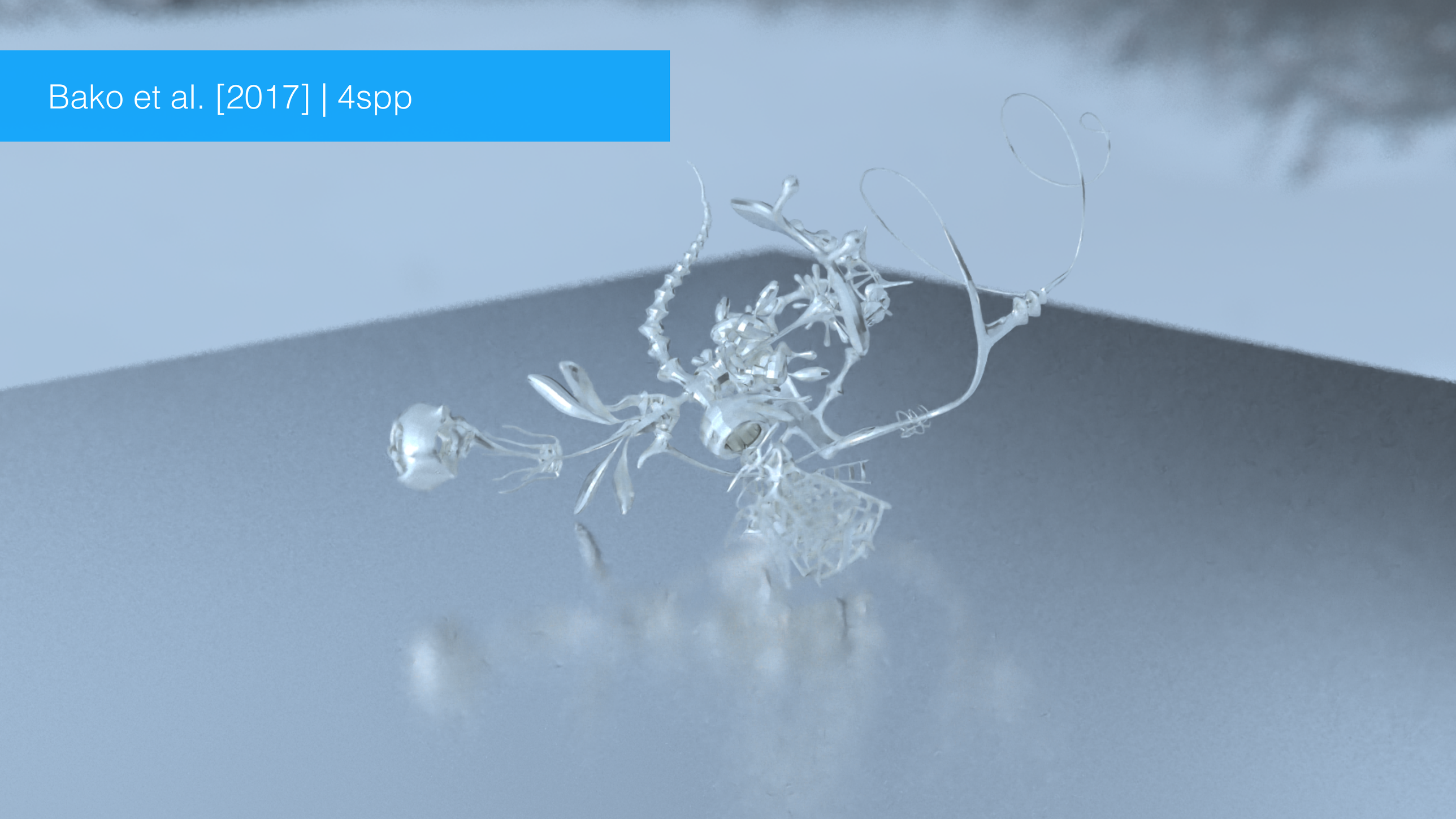
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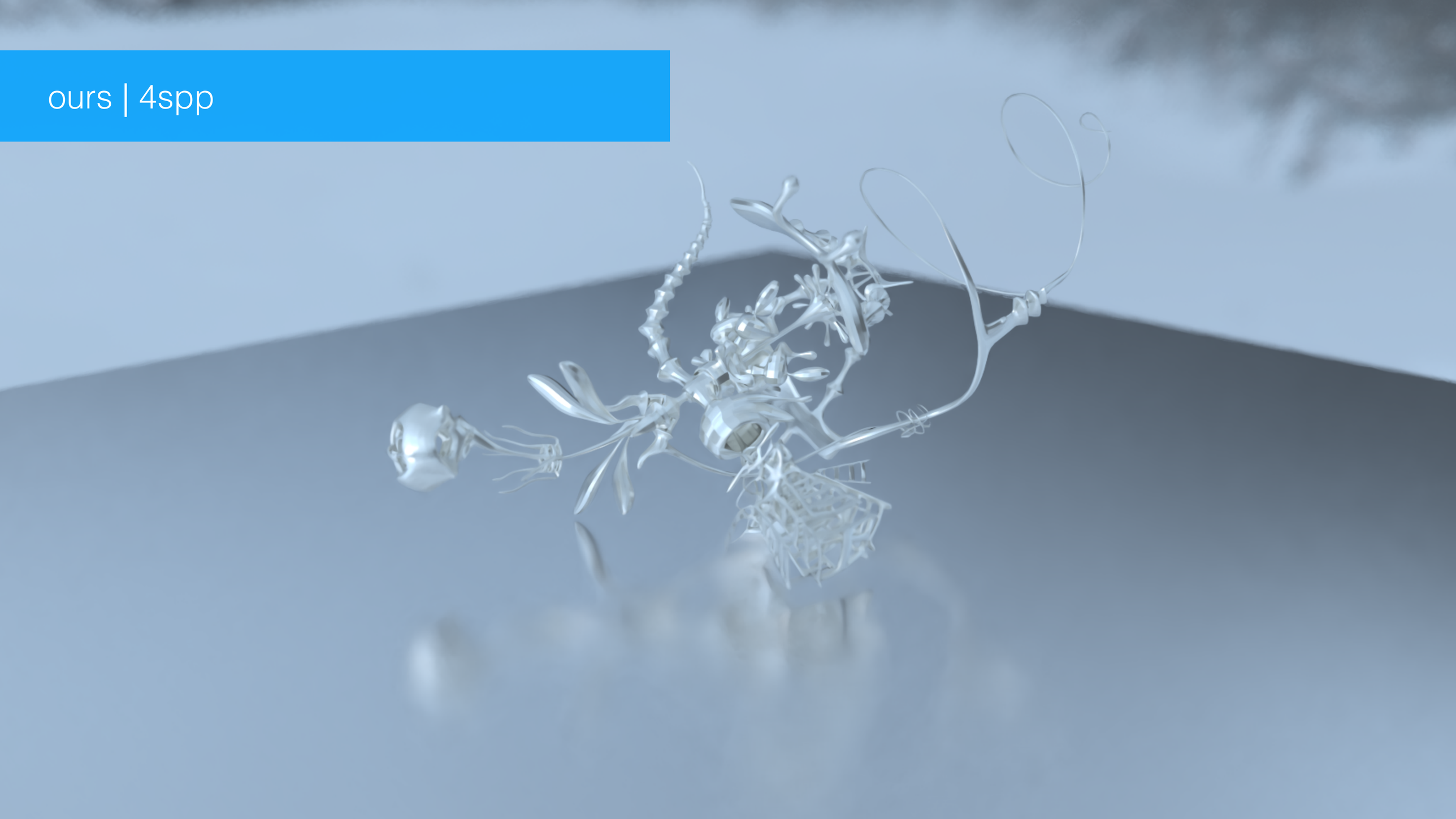
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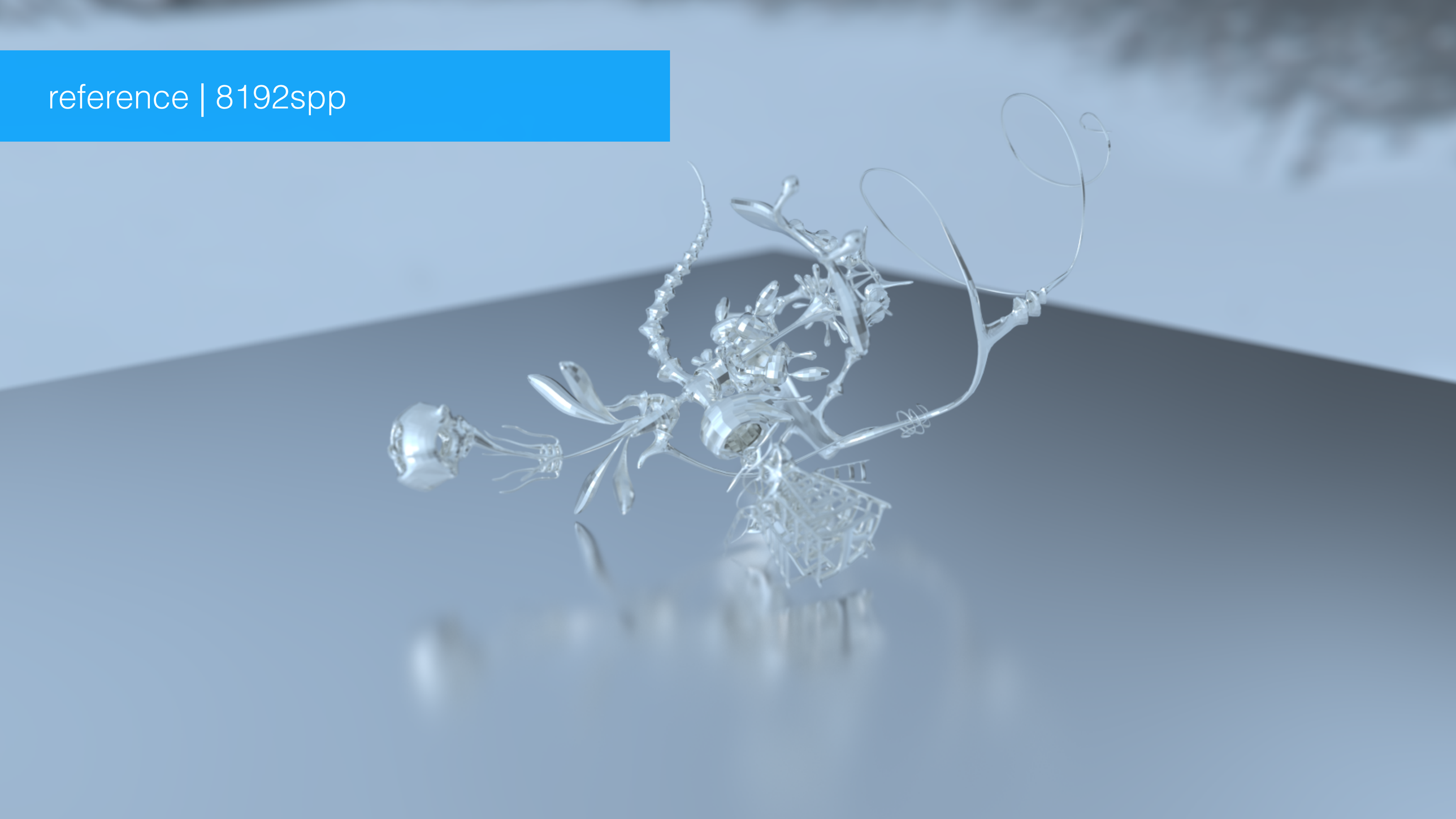
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