Rise of the Machines in MC Integration for Rendering

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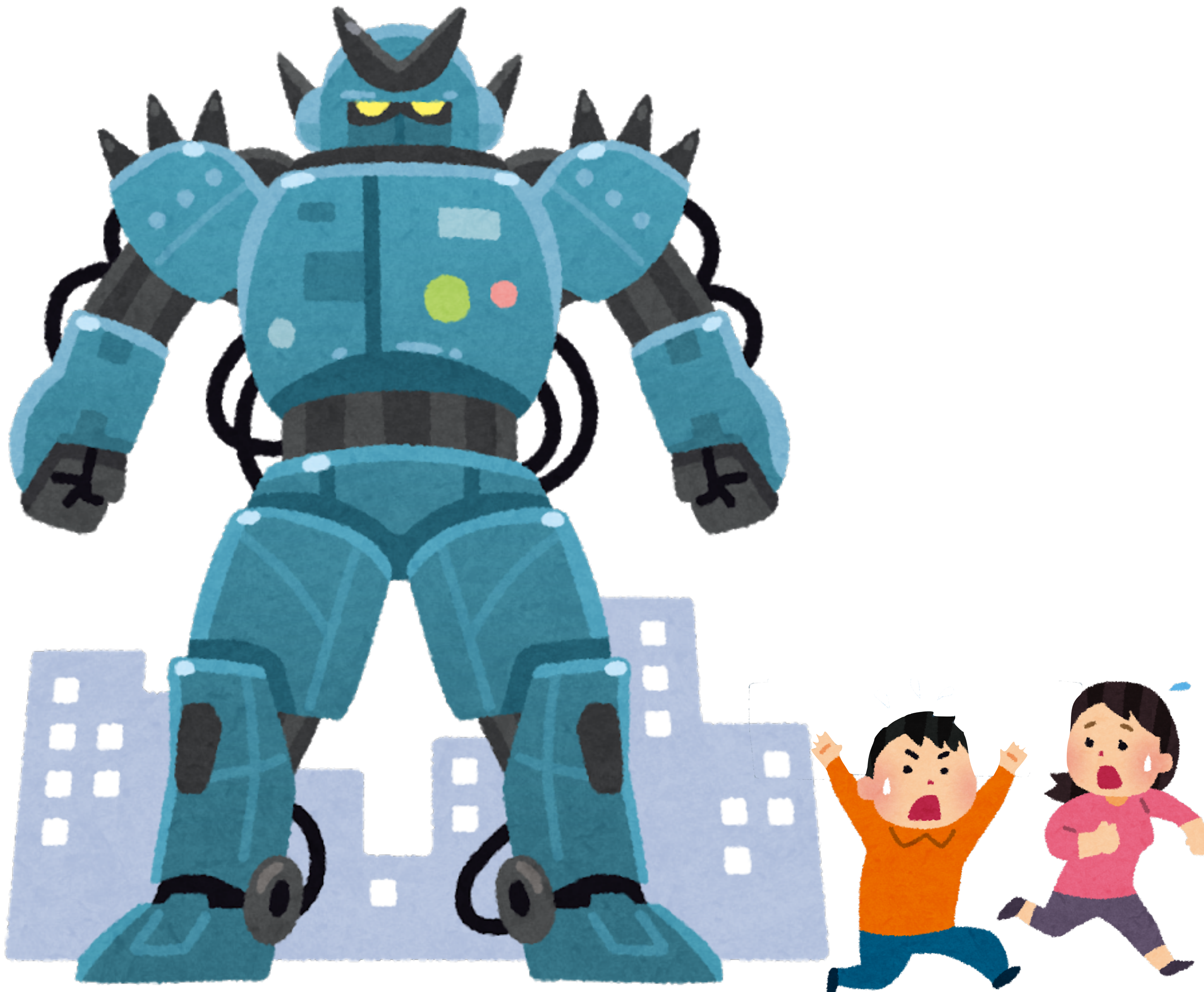
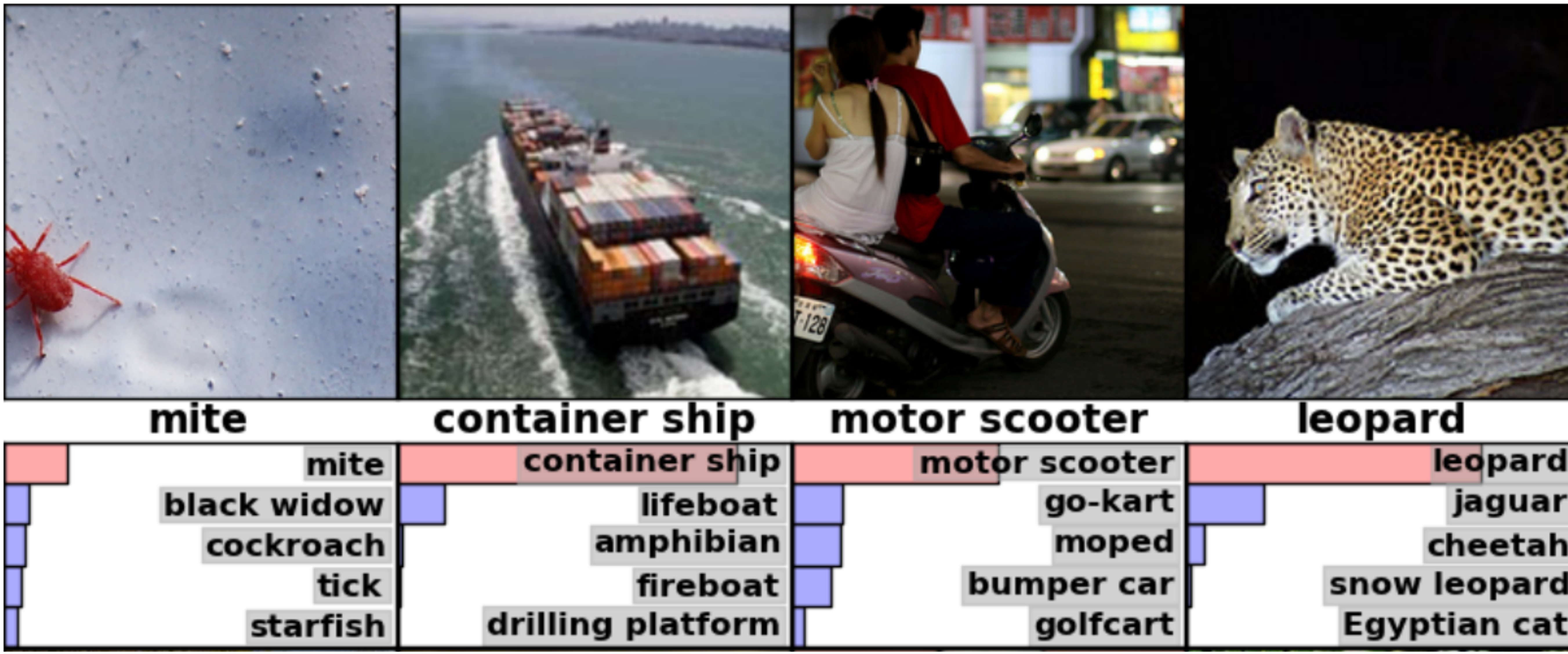
The University of Tokyo

This talk is NOT about



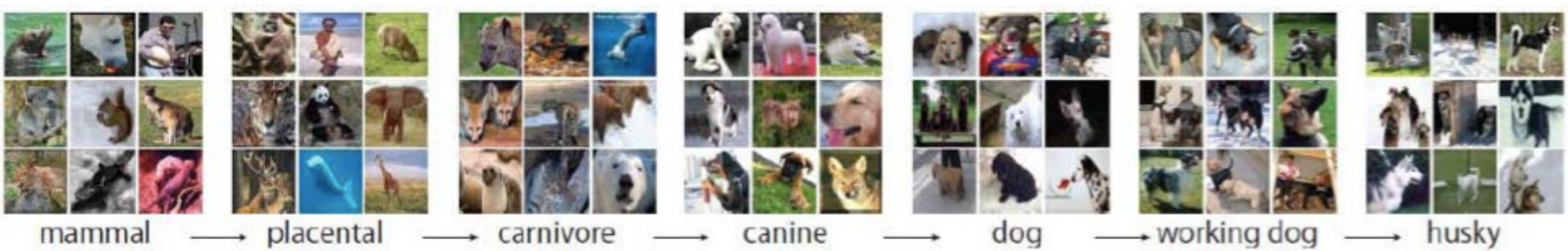
but about this



https://www.tensorflow.org/versions/r0.10/tutorials/image_recognition/index.html

Deep (learning) impact

- Significant step on classification tasks in 2012
- 10% improvement (where 1% was typical)
- Better than a “man-made” classifier

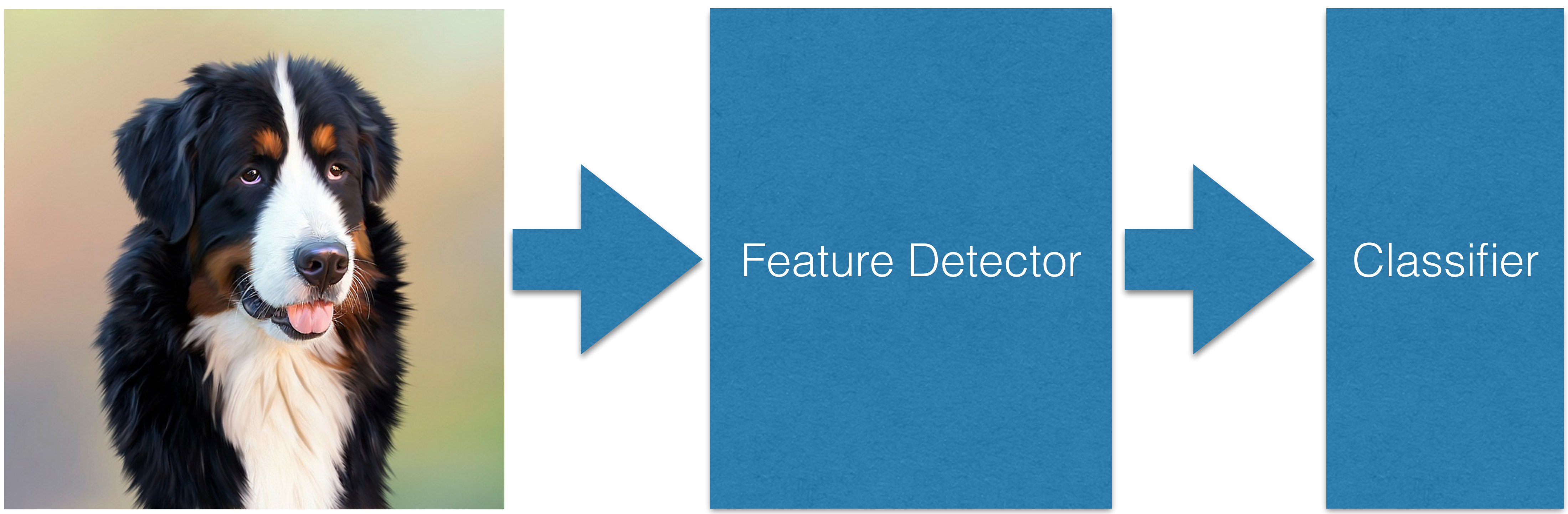


ImageNet [Deng et al.09]

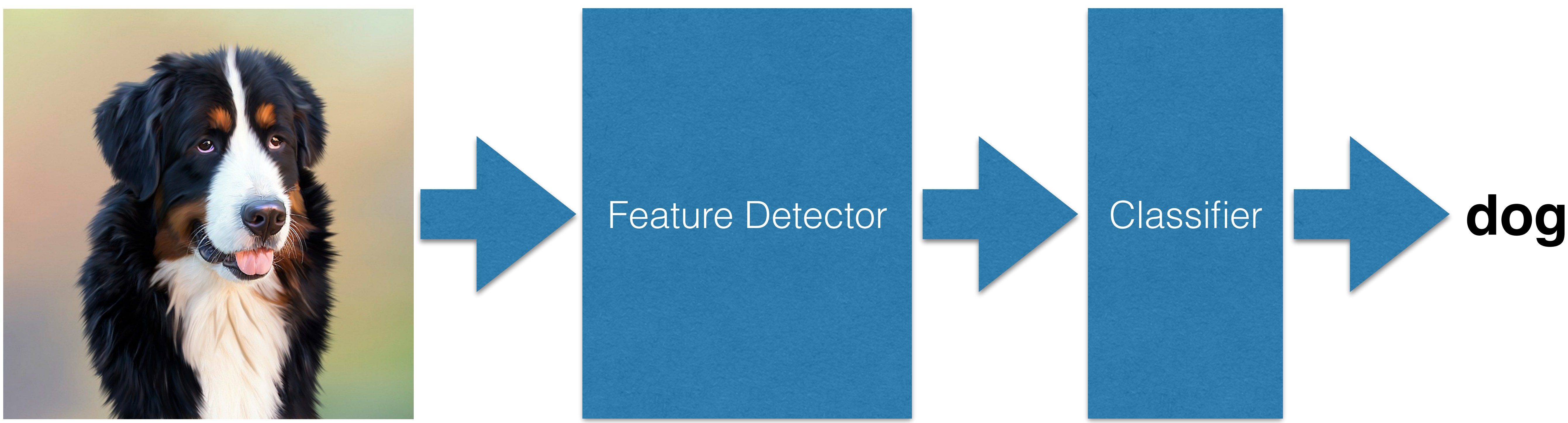
Before deep learning

Feature Detector

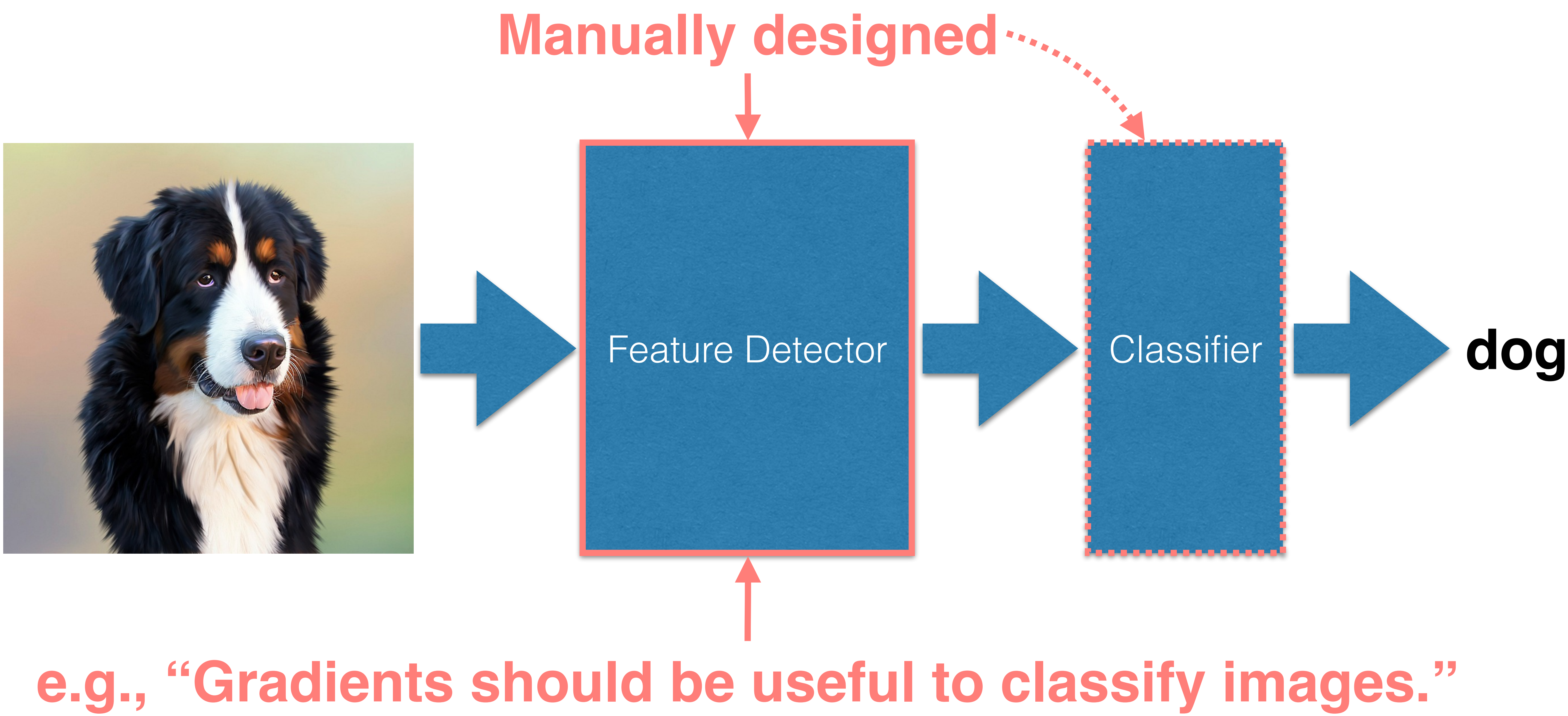
Before deep learning



Before deep learning

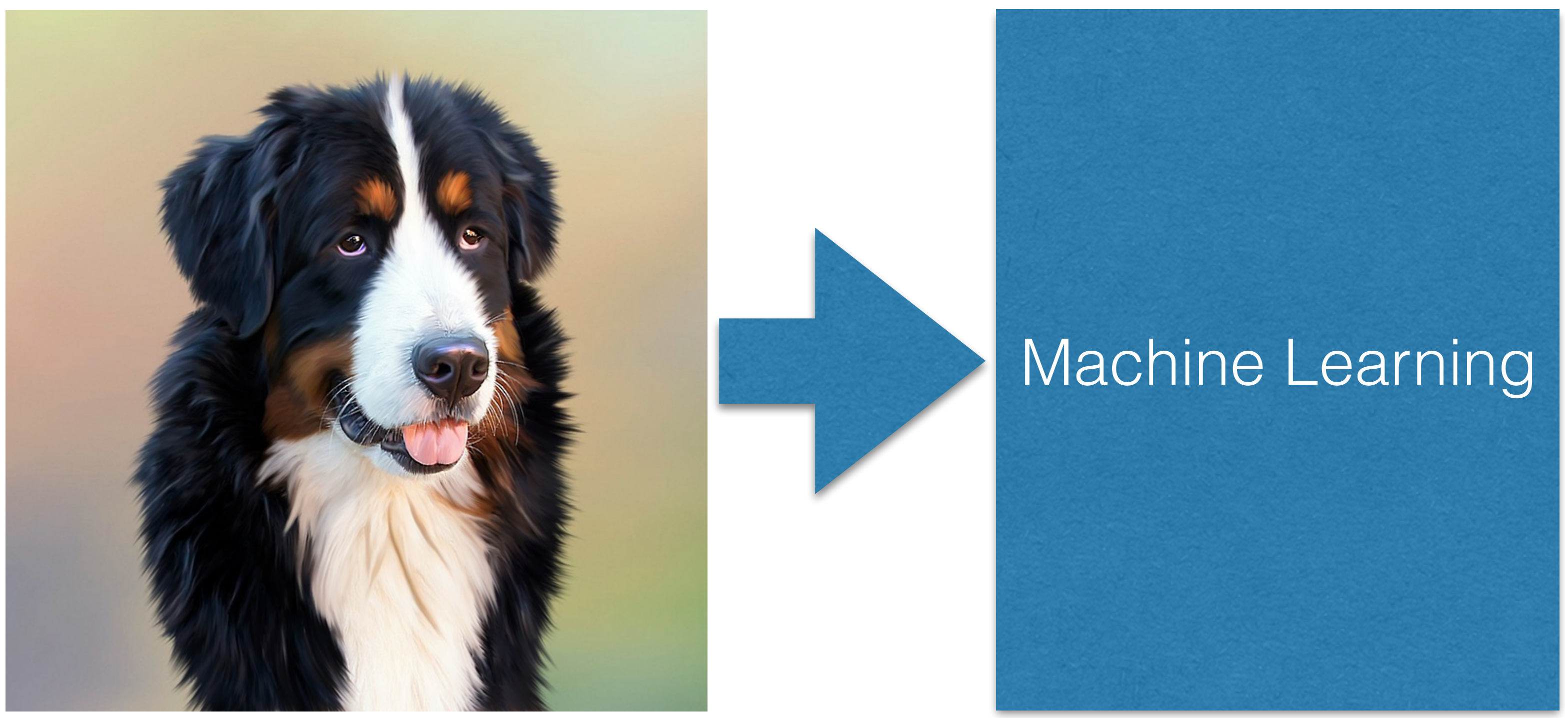


Before deep learning

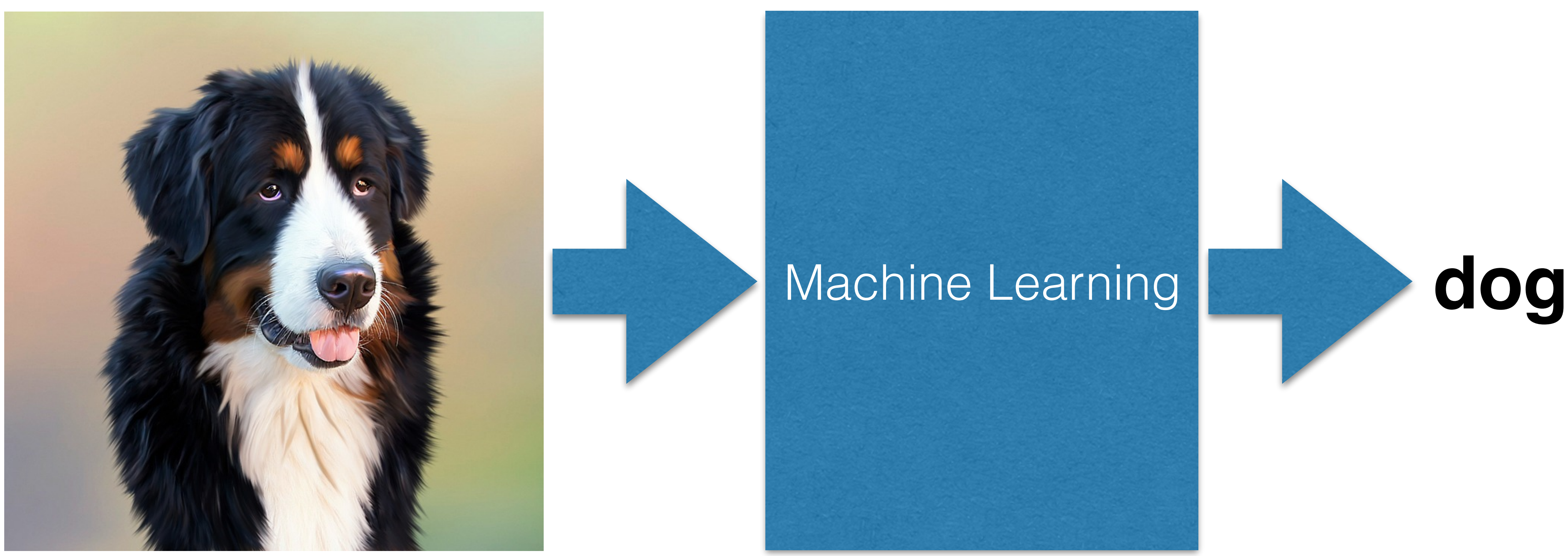


After deep learning

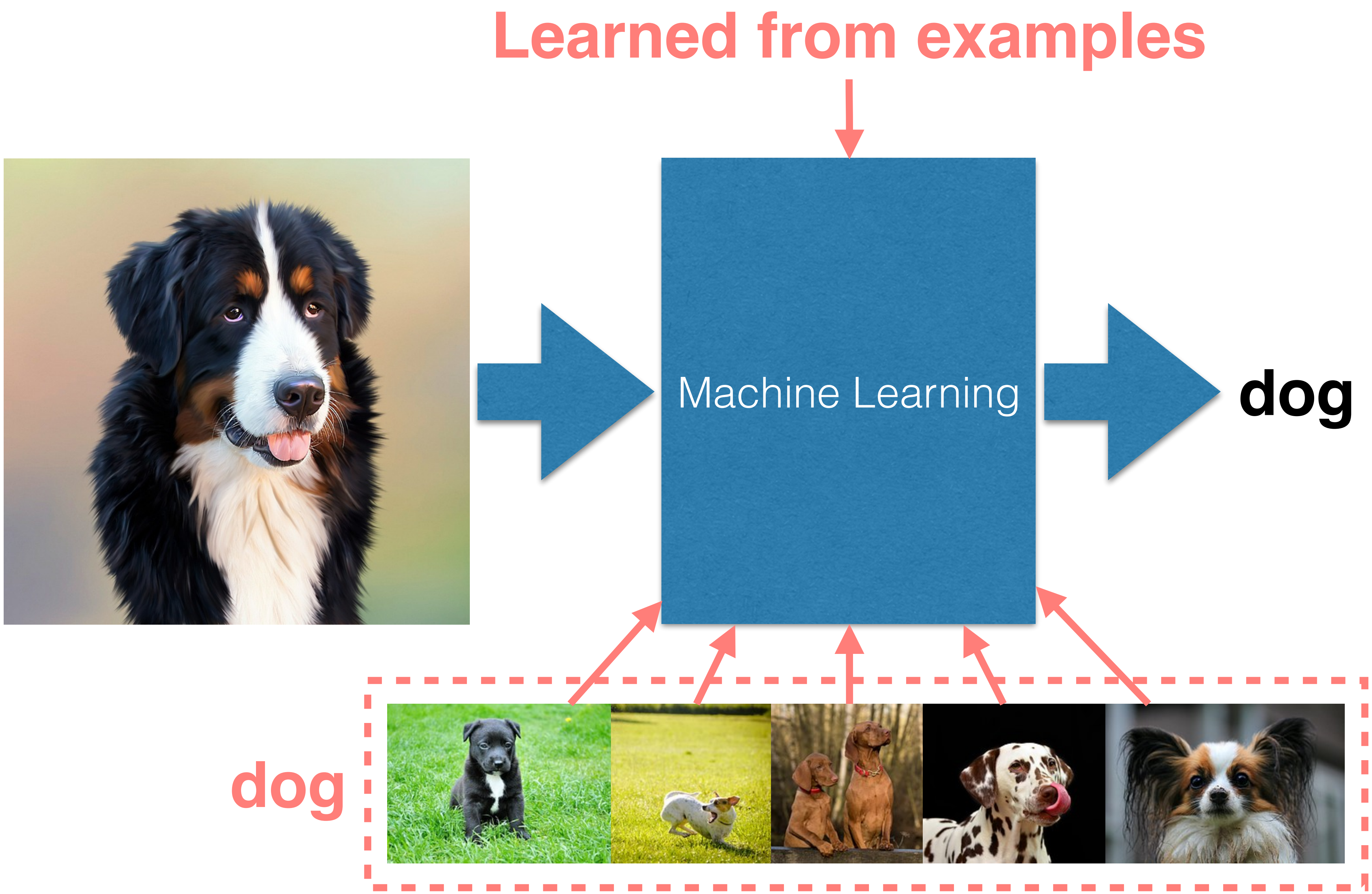
After deep learning



After deep learning



After deep learning

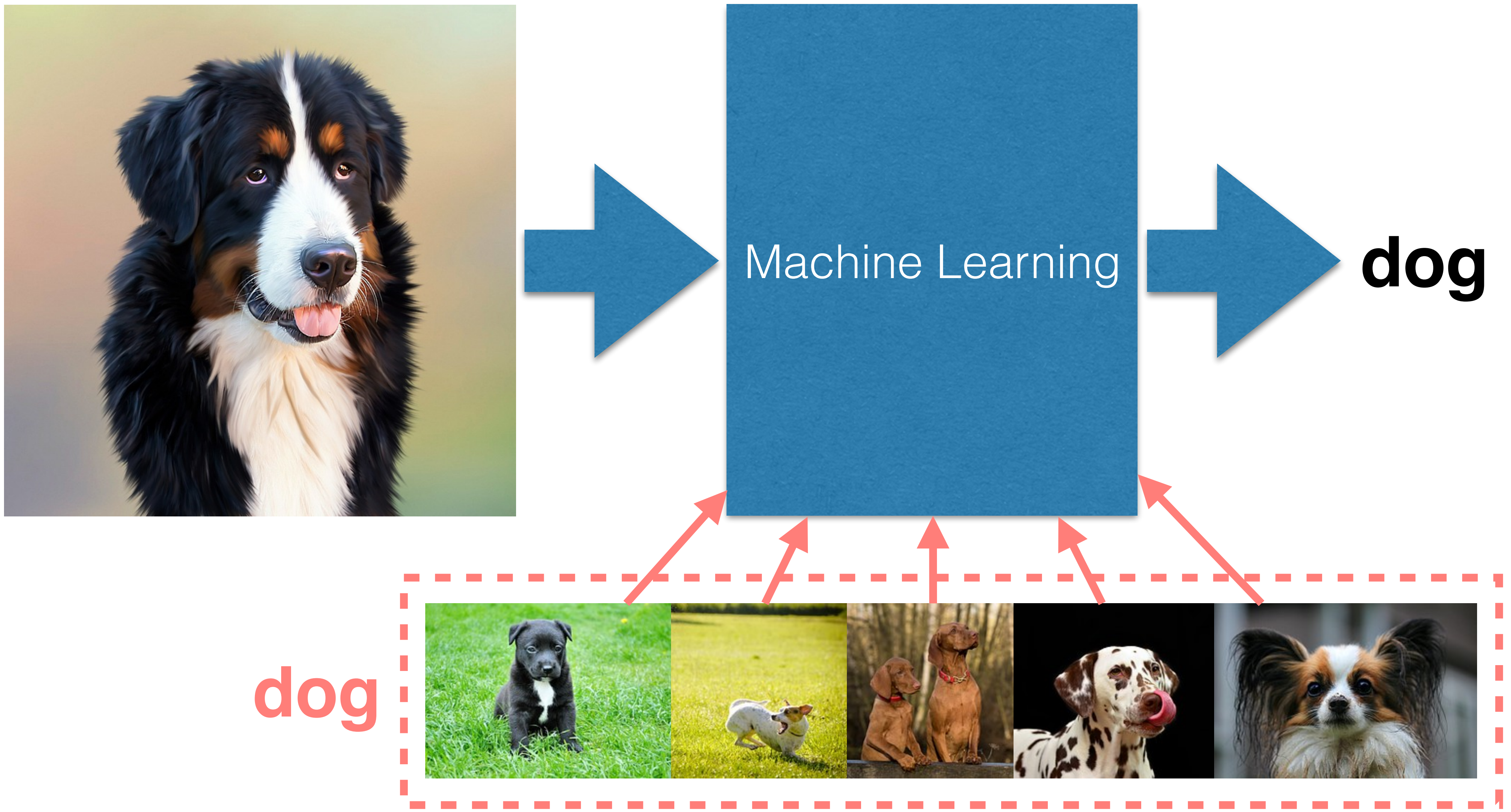


Successes of deep learning

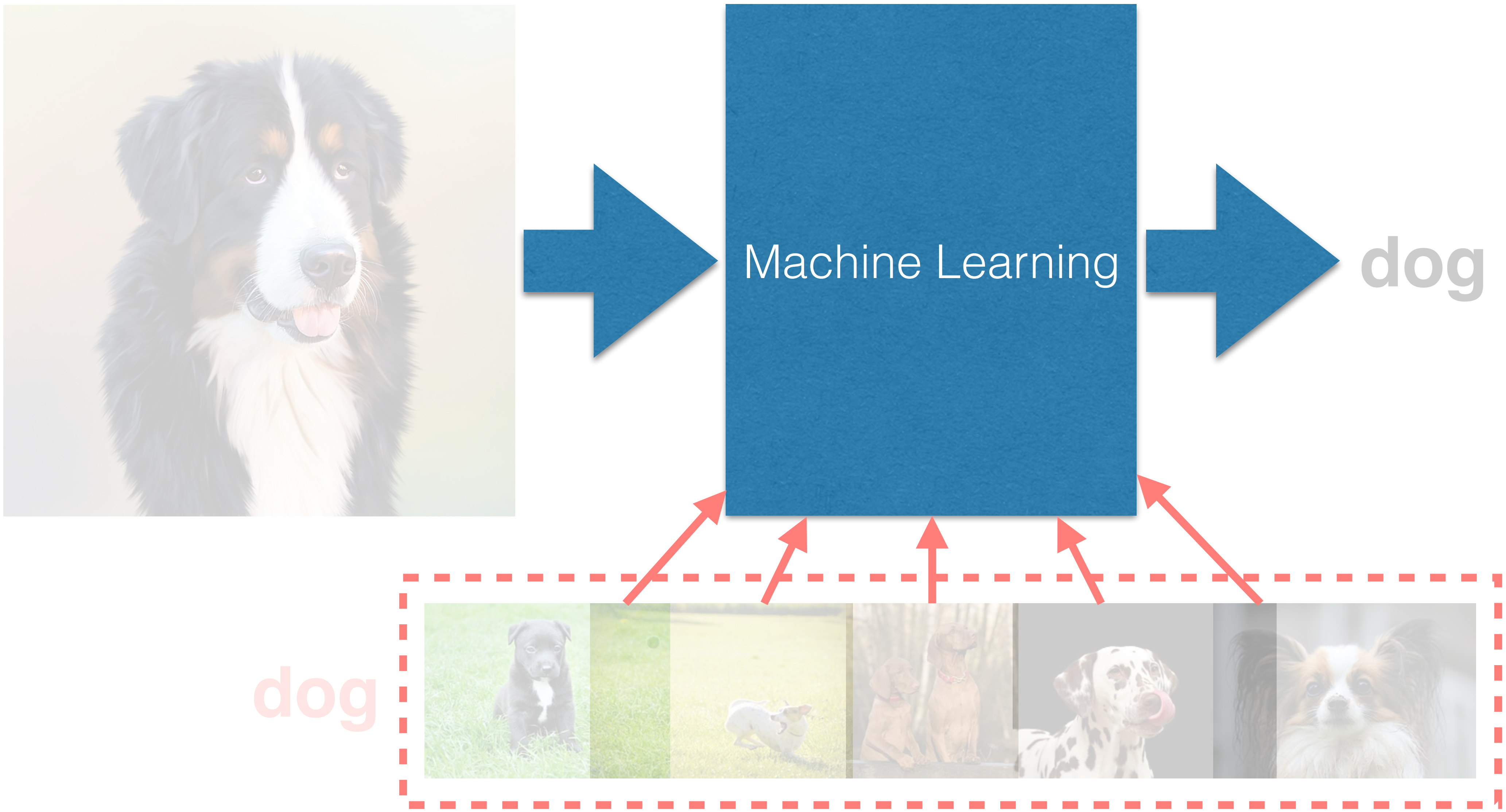
- Achieving significant results in many applications
  - Image segmentation [Long et al.14]
  - Image captioning (many groups in 2014)
  - Playing video games [Mnih et al.13]
  - Lip reading [Ngiam et al.11]
  - and more…

How can we utilize deep learning in MC?

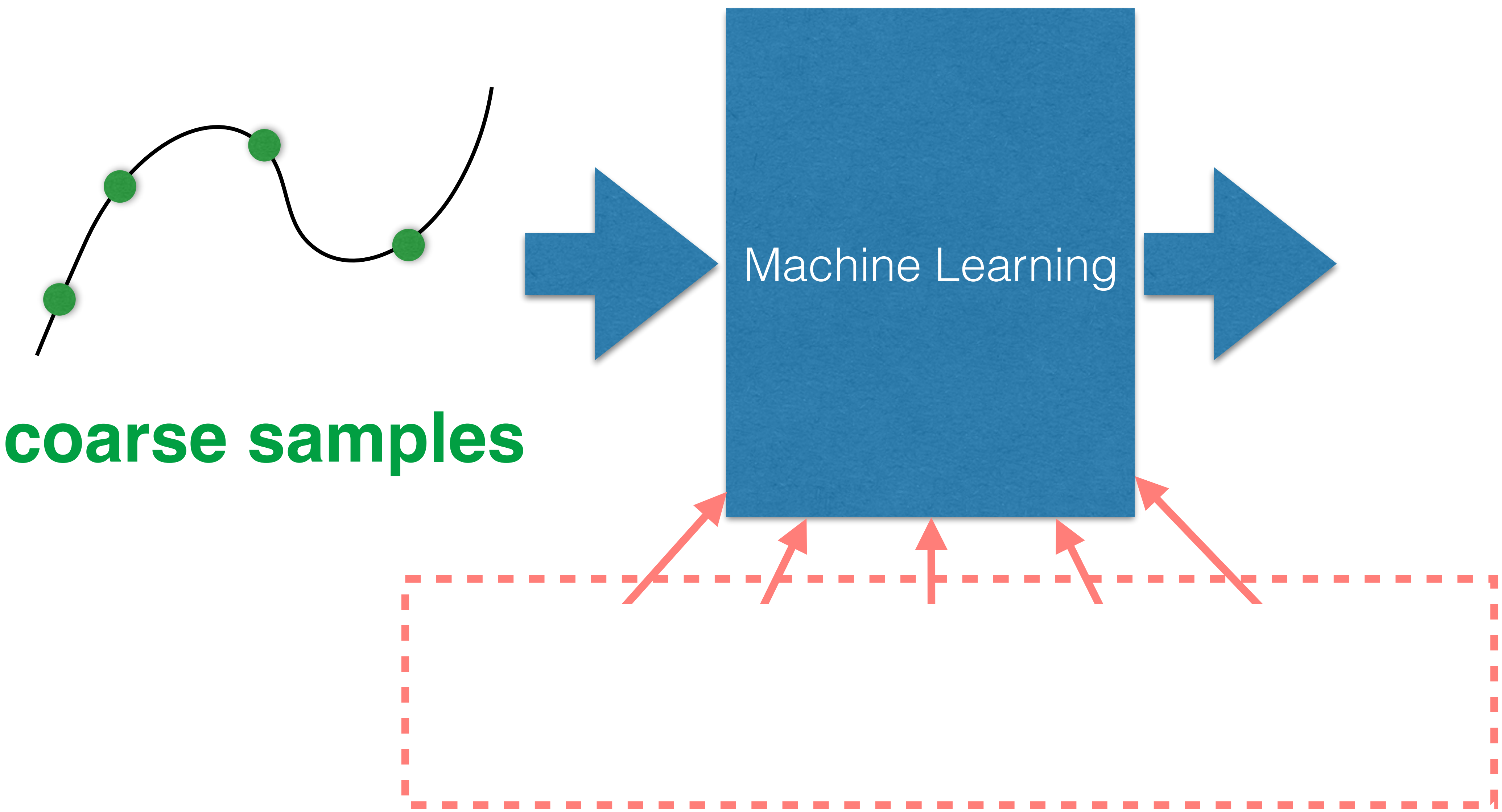
Deep learning in MC



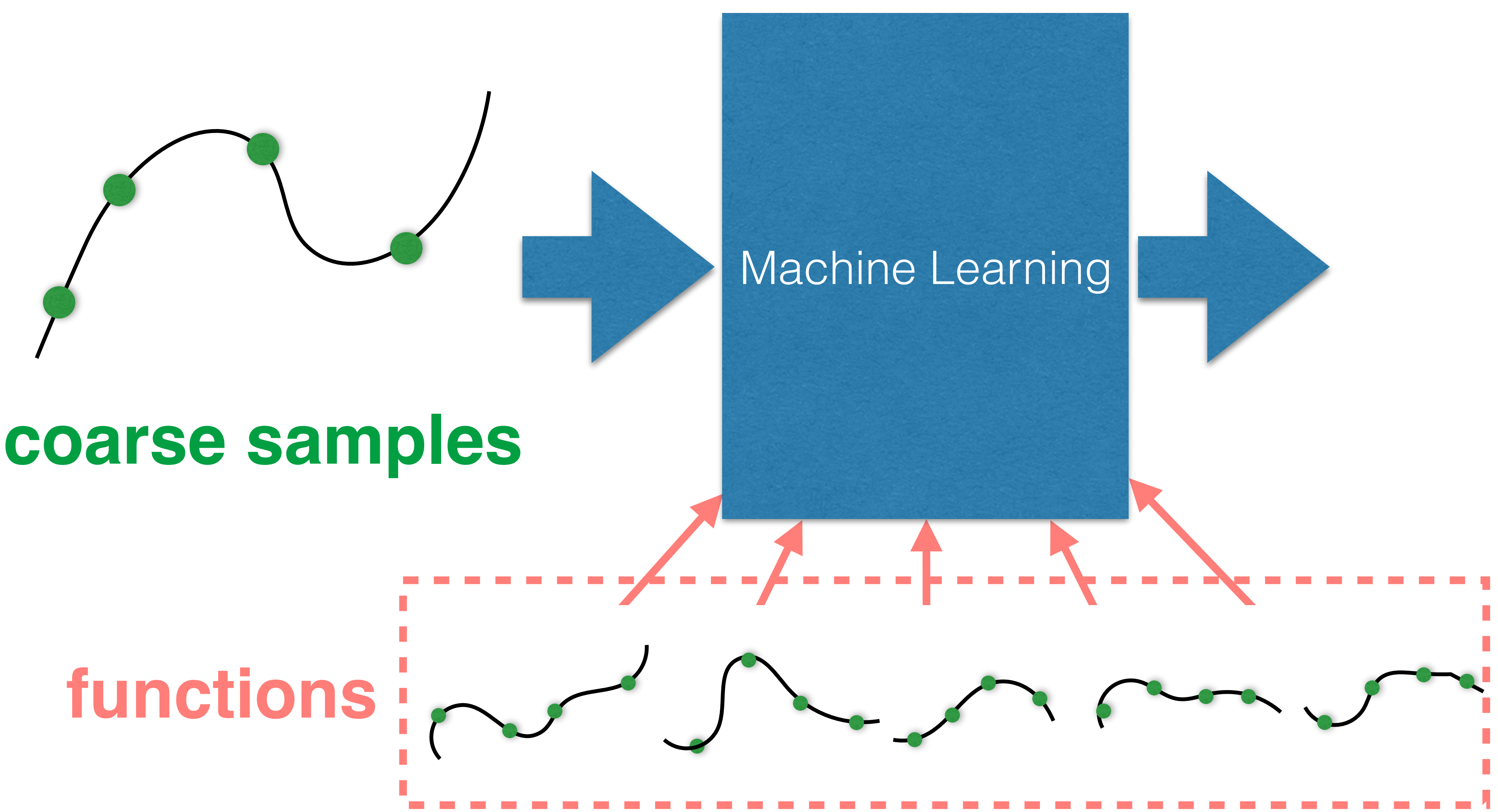
Deep learning in MC



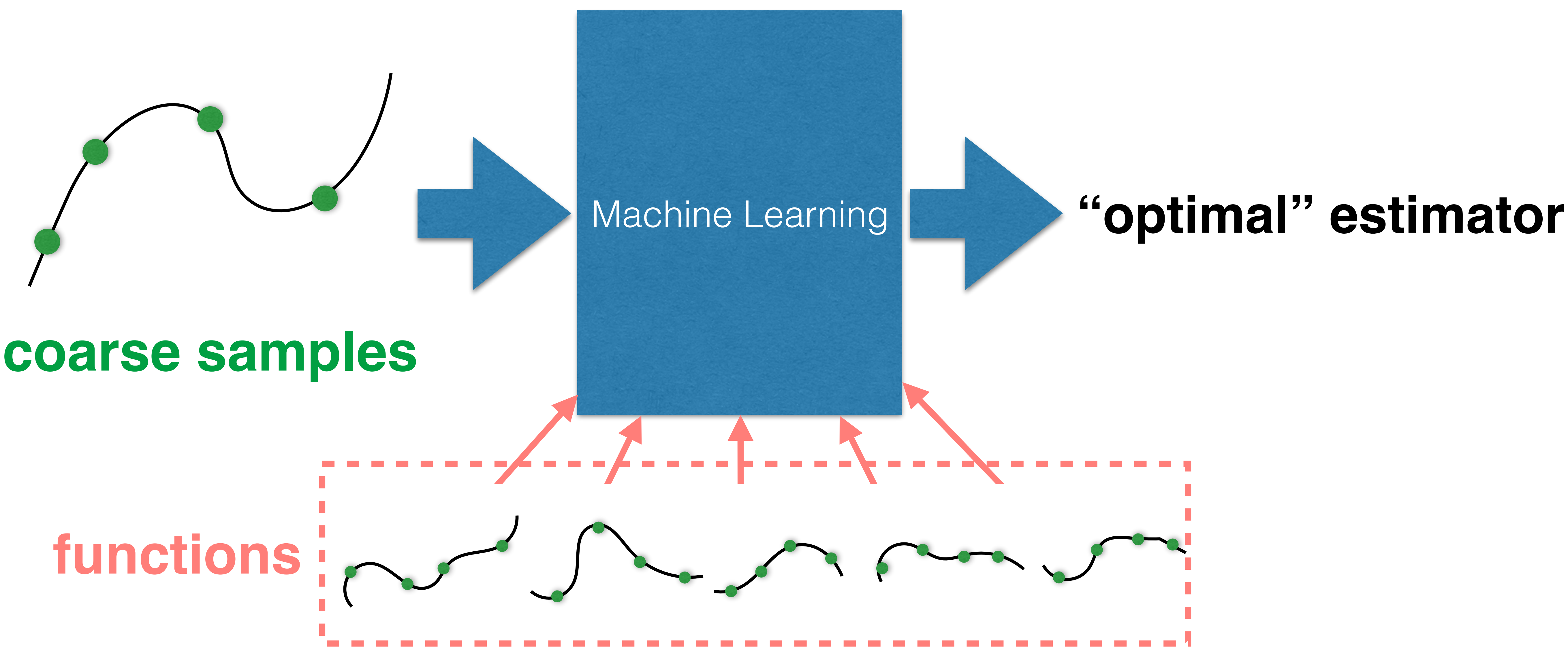
Deep learning in MC



Deep learning in MC



Deep learning in MC

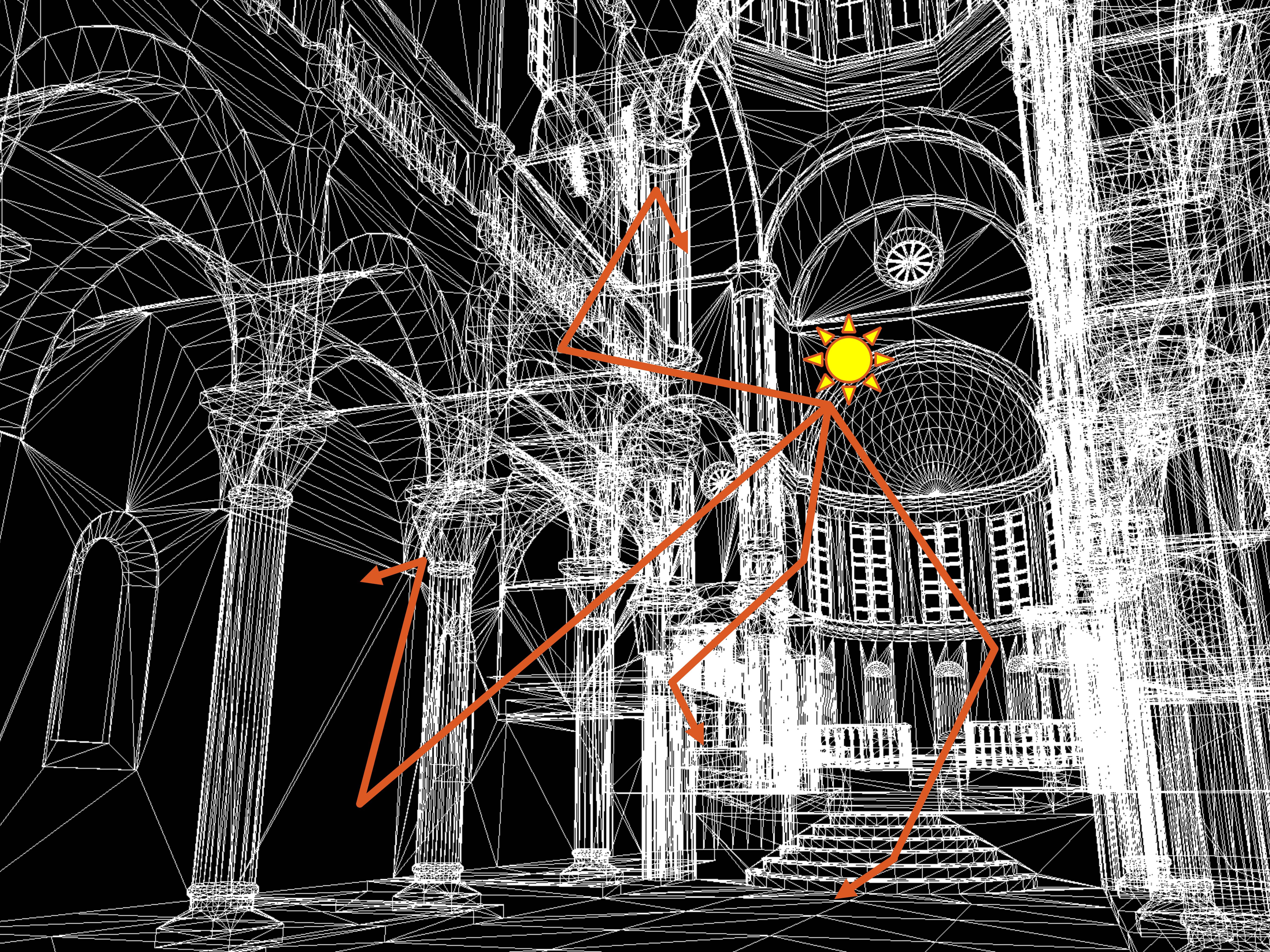


Rise of the Machines

- Learn the “optimal” estimator for a given function
  - Uses coarse samples as “images”
  - Assume a set of specific (non-arbitrary) functions
  - Automatically exploit “hidden” structures
  - Similar to adaptive Monte Carlo, but we use **machine learning to decide how to adapt**

Automatic Mixing of MC Integrators

joint work with S. Kinuwaki and H. Otsu (in submission)



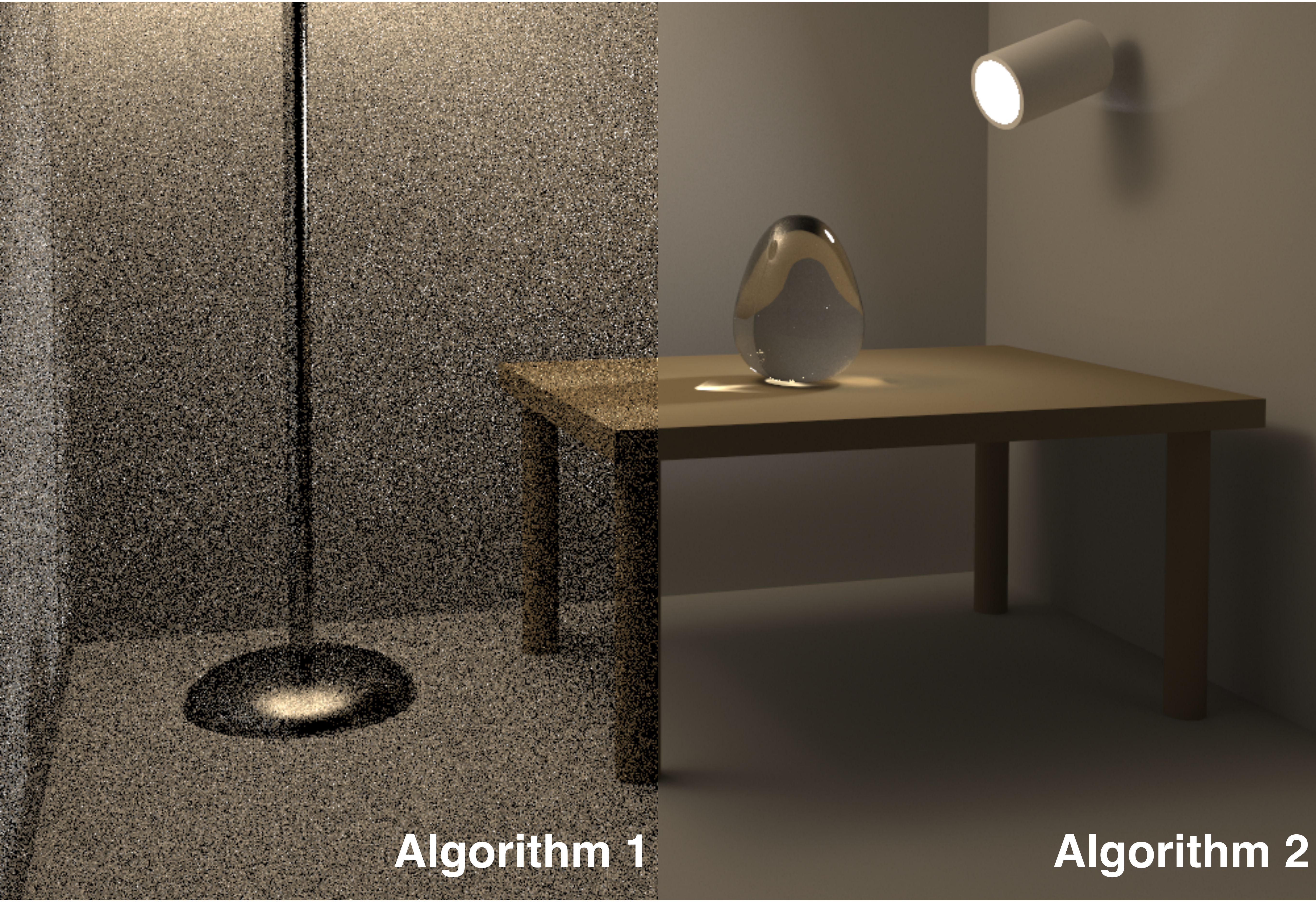
Light transport simulation

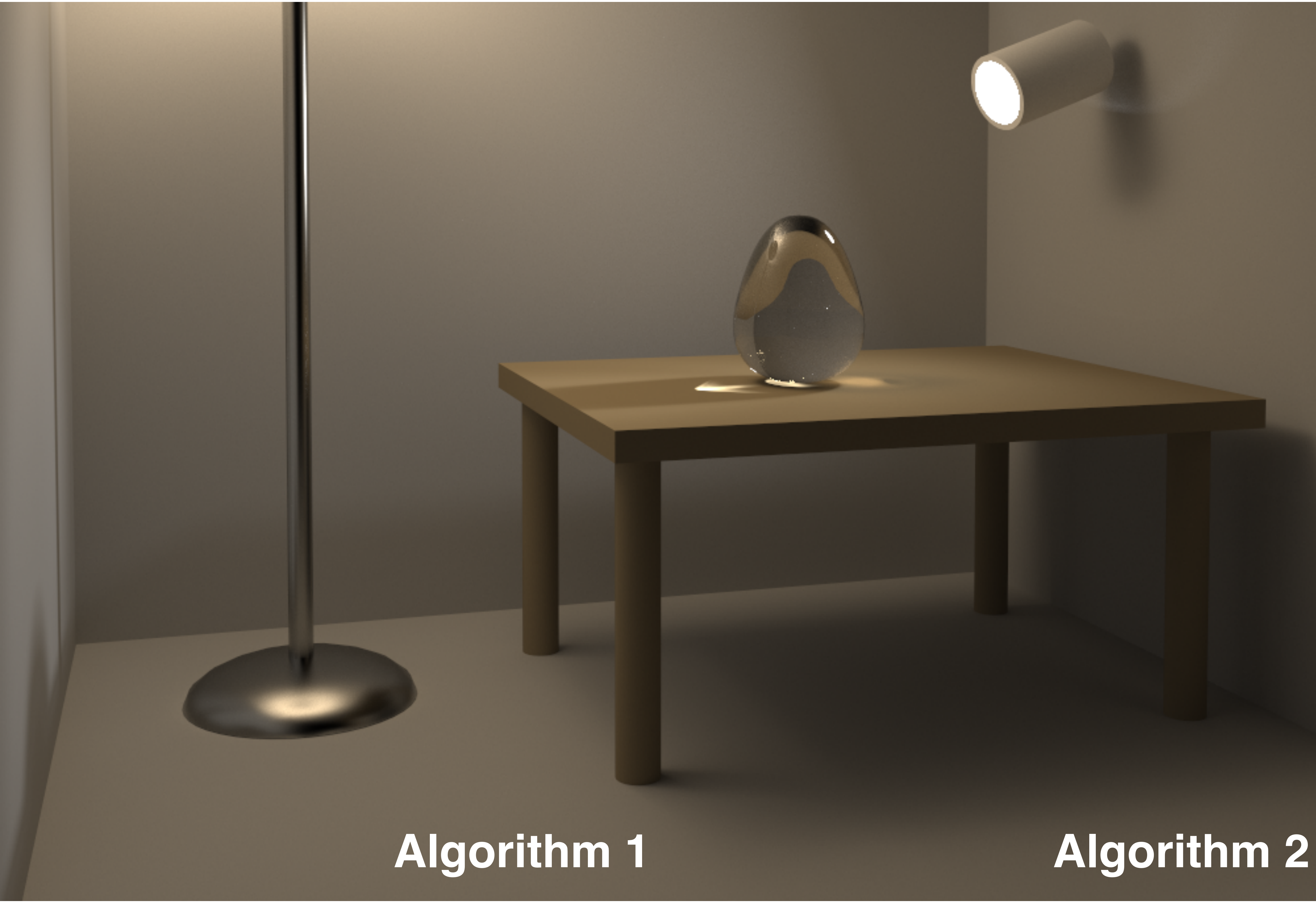
- Solution of the following governing equation

$$L(x,\vec{o}) = L_e(x,\vec{o}) + \int_\Omega f_r(x,\vec{\omega},\vec{o})L(x,\vec{\omega})(\vec{\omega}\cdot\vec{n})\mathrm{d}\vec{\omega}$$

  - Can be formulated as **a simple MC integration**

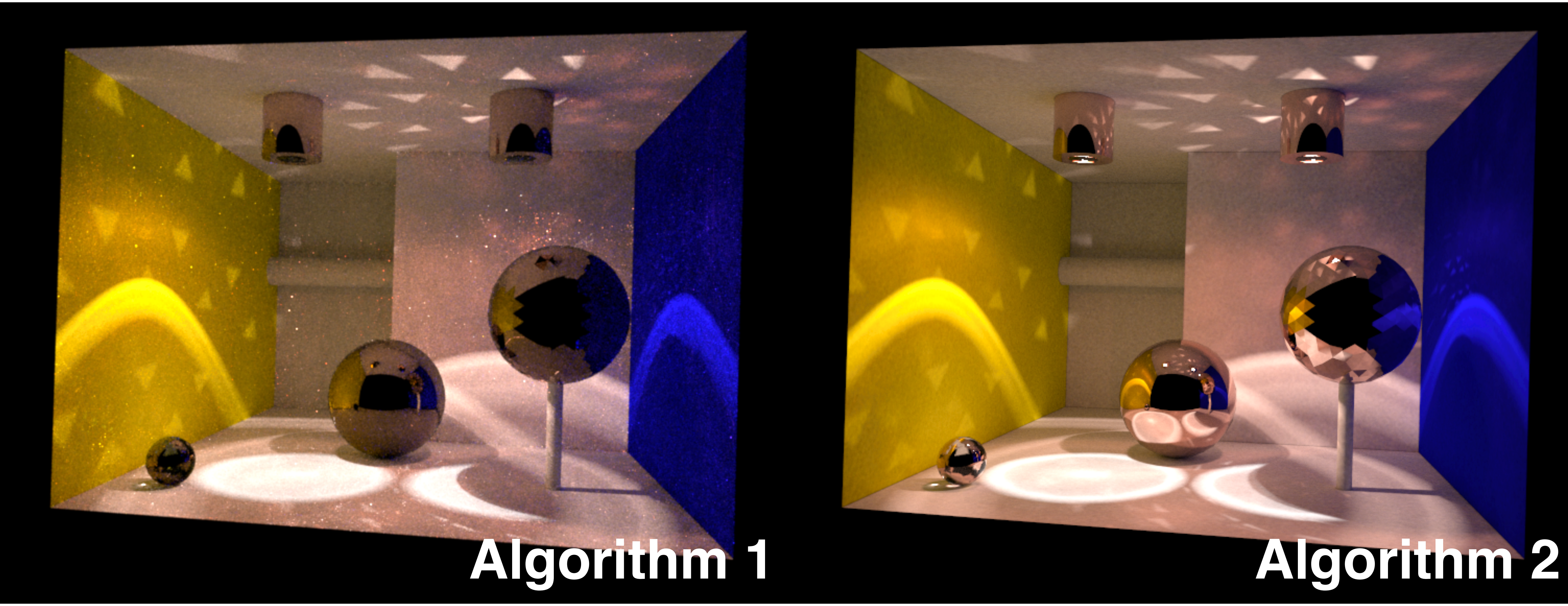
- Different algorithms coverage to the same results


Algorithm 1
Algorithm 2


Algorithm 1
Algorithm 2

Varying efficiency

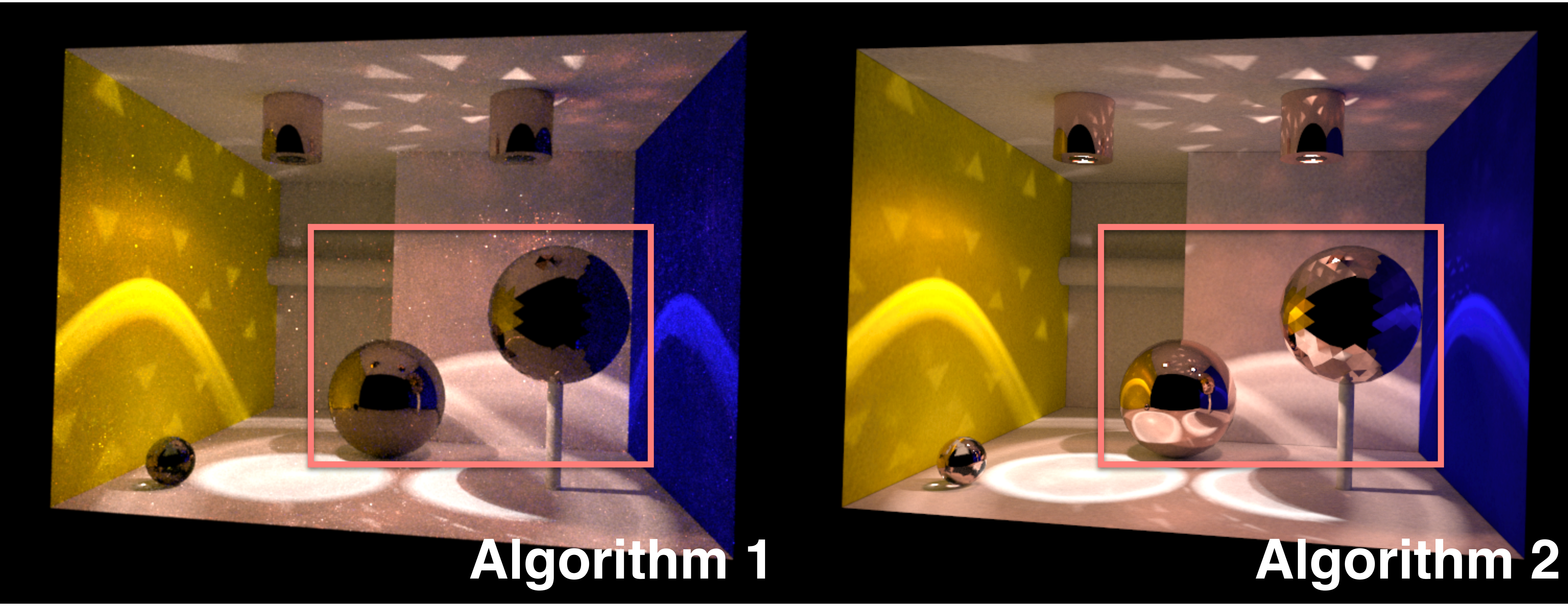
- Efficiency of each algorithm varies for different inputs



Varying efficiency

- Efficiency of each algorithm varies for different inputs

Algorithm 2 is more efficient



Varying efficiency

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Varying efficiency

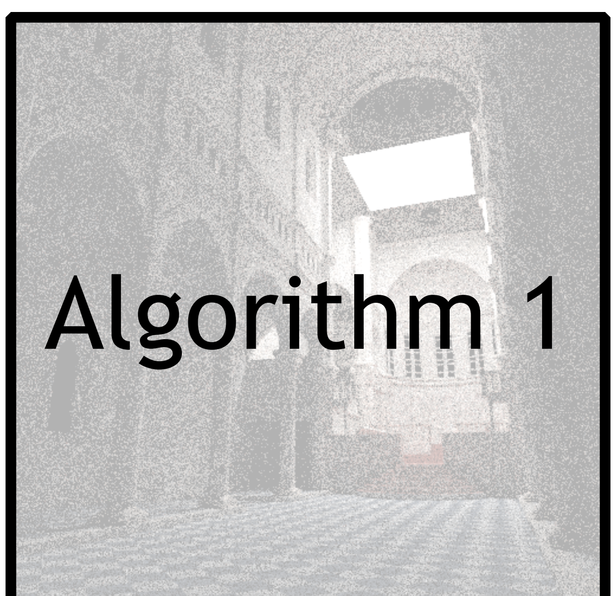
- Efficiency of each algorithm varies for different inputs

Algorithm 1 is more efficient

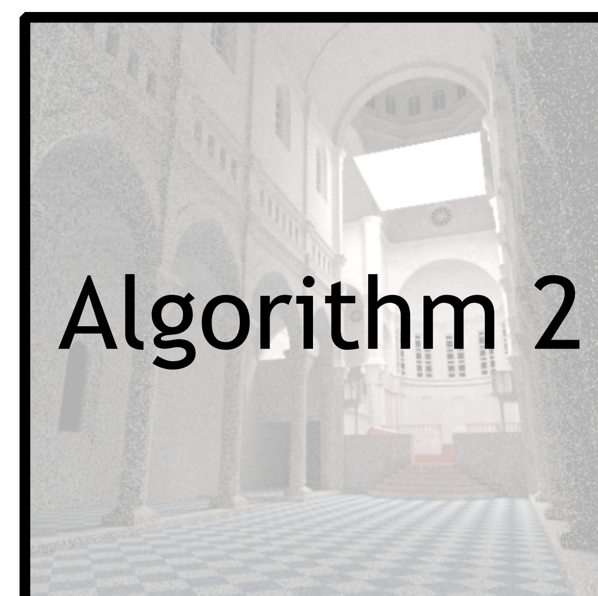
Mixing different algorithms

- Combine the results by a weighted sum
  - More efficient algorithm should have larger weight
  - Often called "blending" in graphics

$w \cdot$

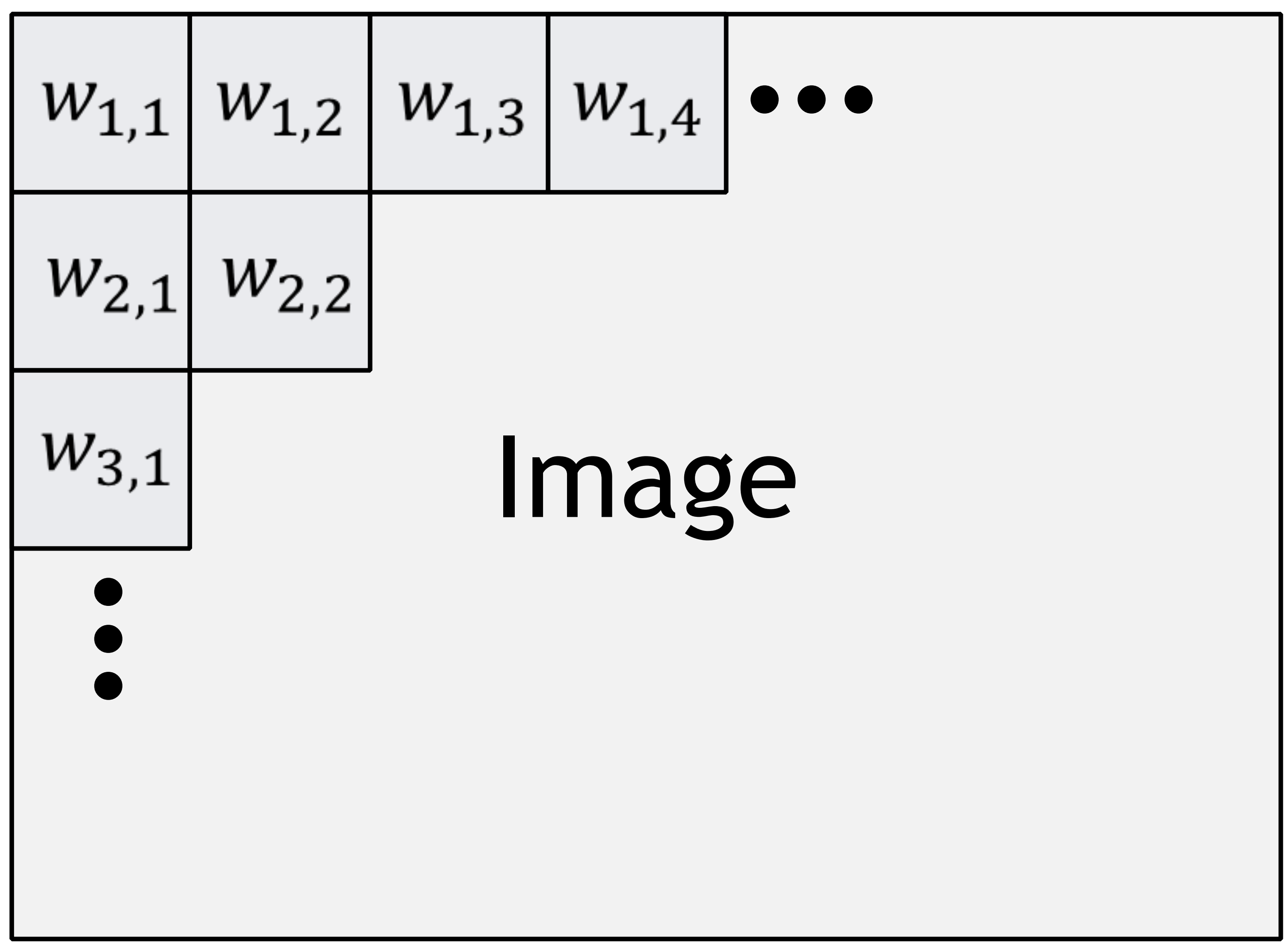


$+(1 - w) \cdot$

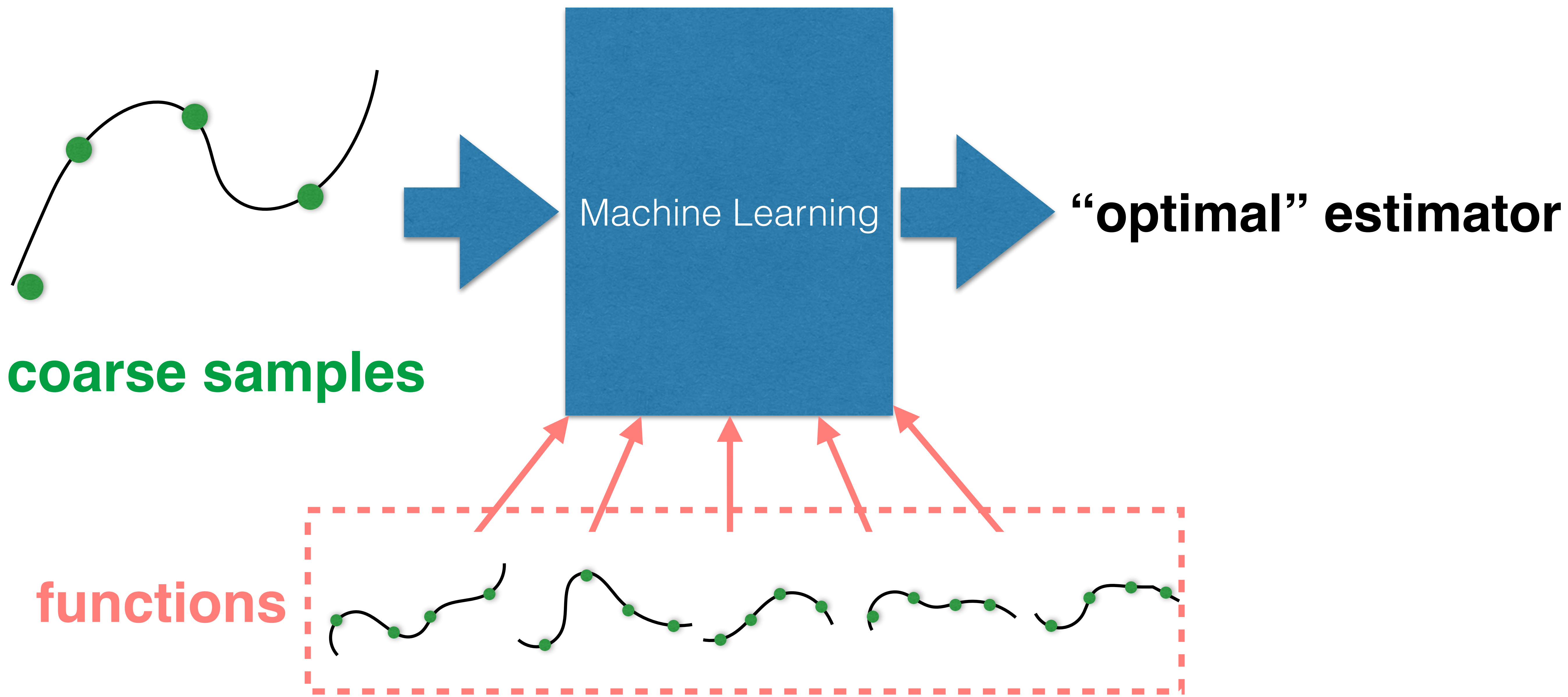


Pixel-wise blending

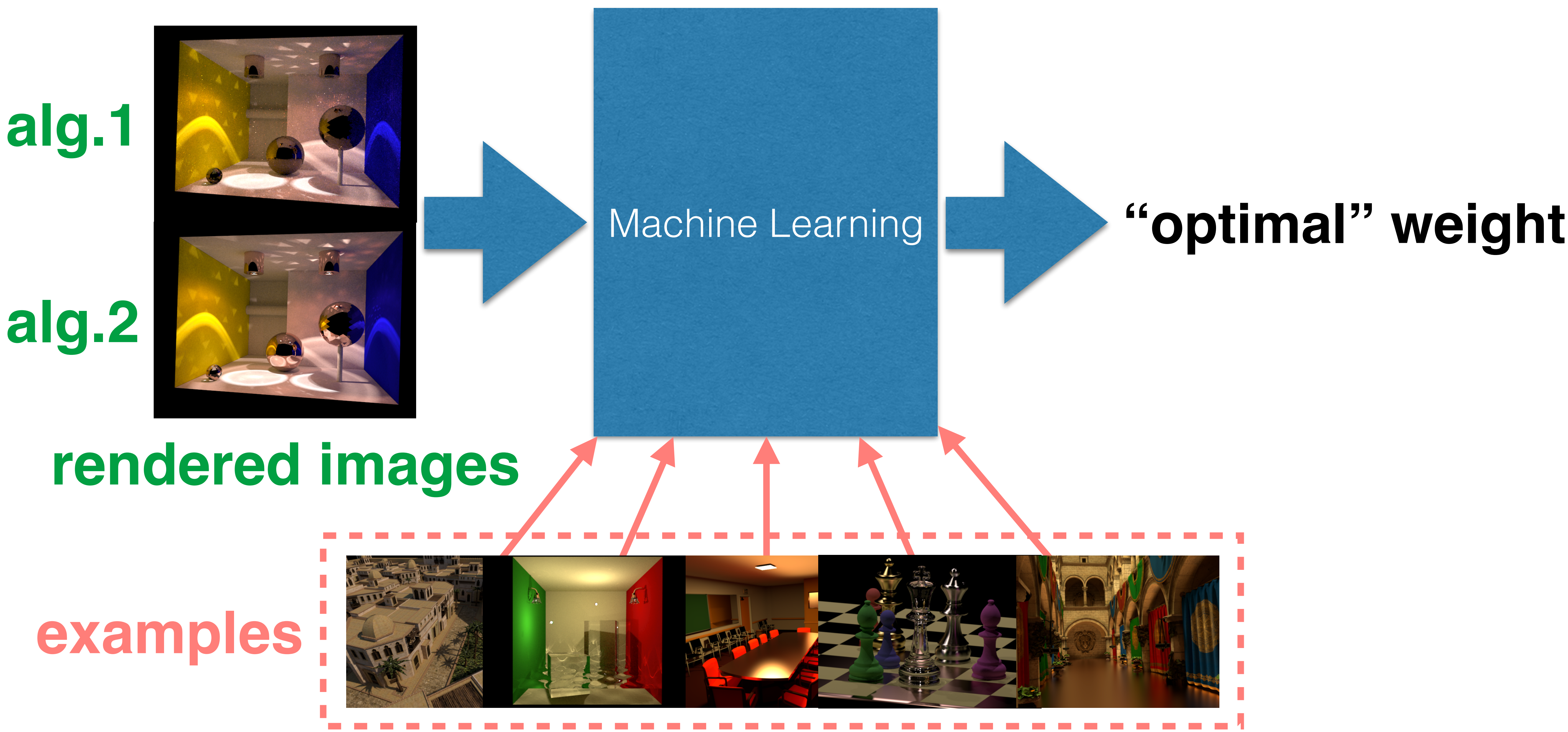
- Each pixel has its own blending weight



Key idea


coarse samples
Machine Learning
“optimal” estimator
functions

Key idea

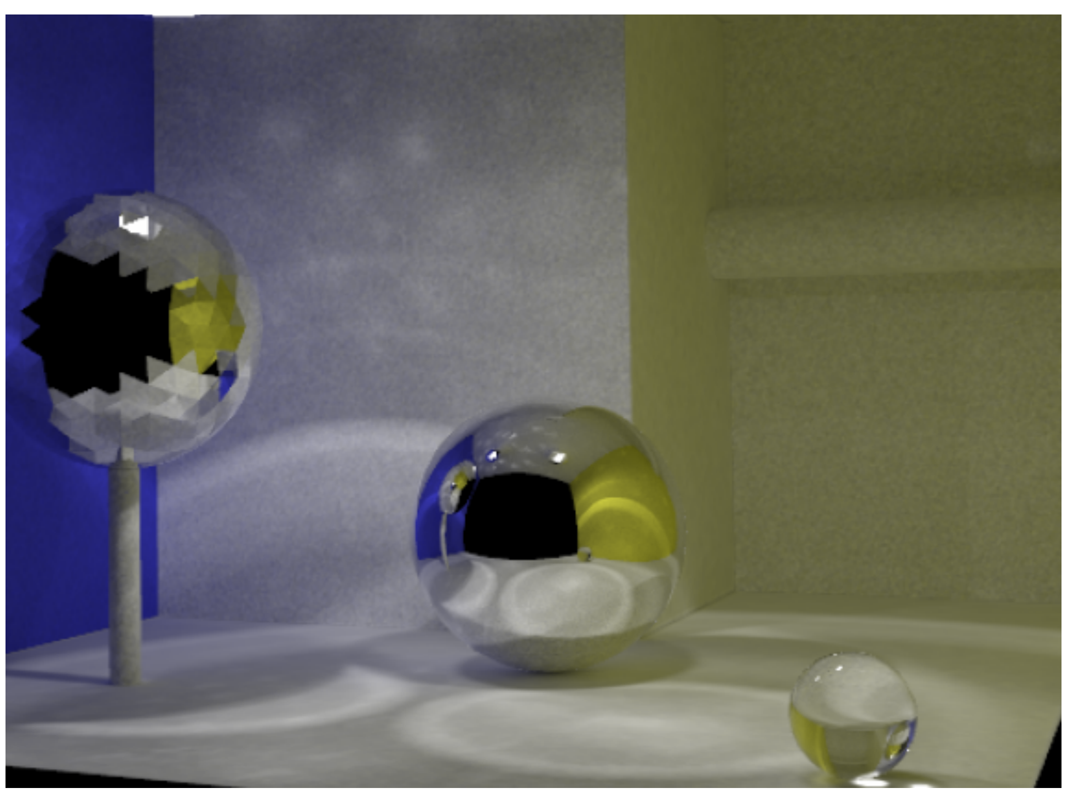

alg.1
alg.2
rendered images
Machine Learning
"optimal" weight
examples

Method

Two algorithms

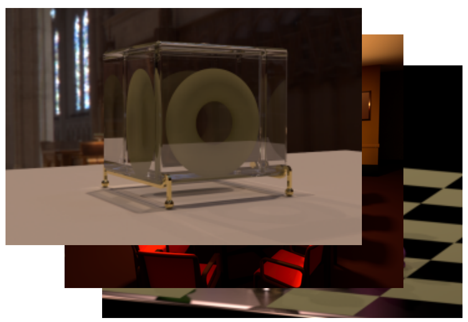
- Stochastic progressive photon mapping (**SPPM**)
  [Hachisuka & Jensen 2009]

- Manifold exploration (**MLT**)
  [Jacob & Marschner 2012]

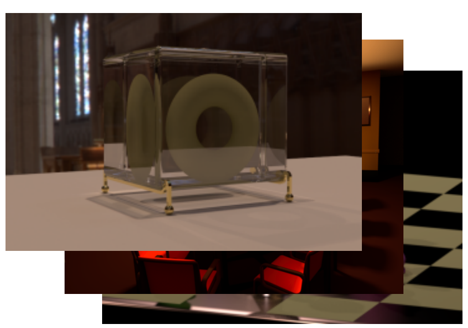


Learning

References

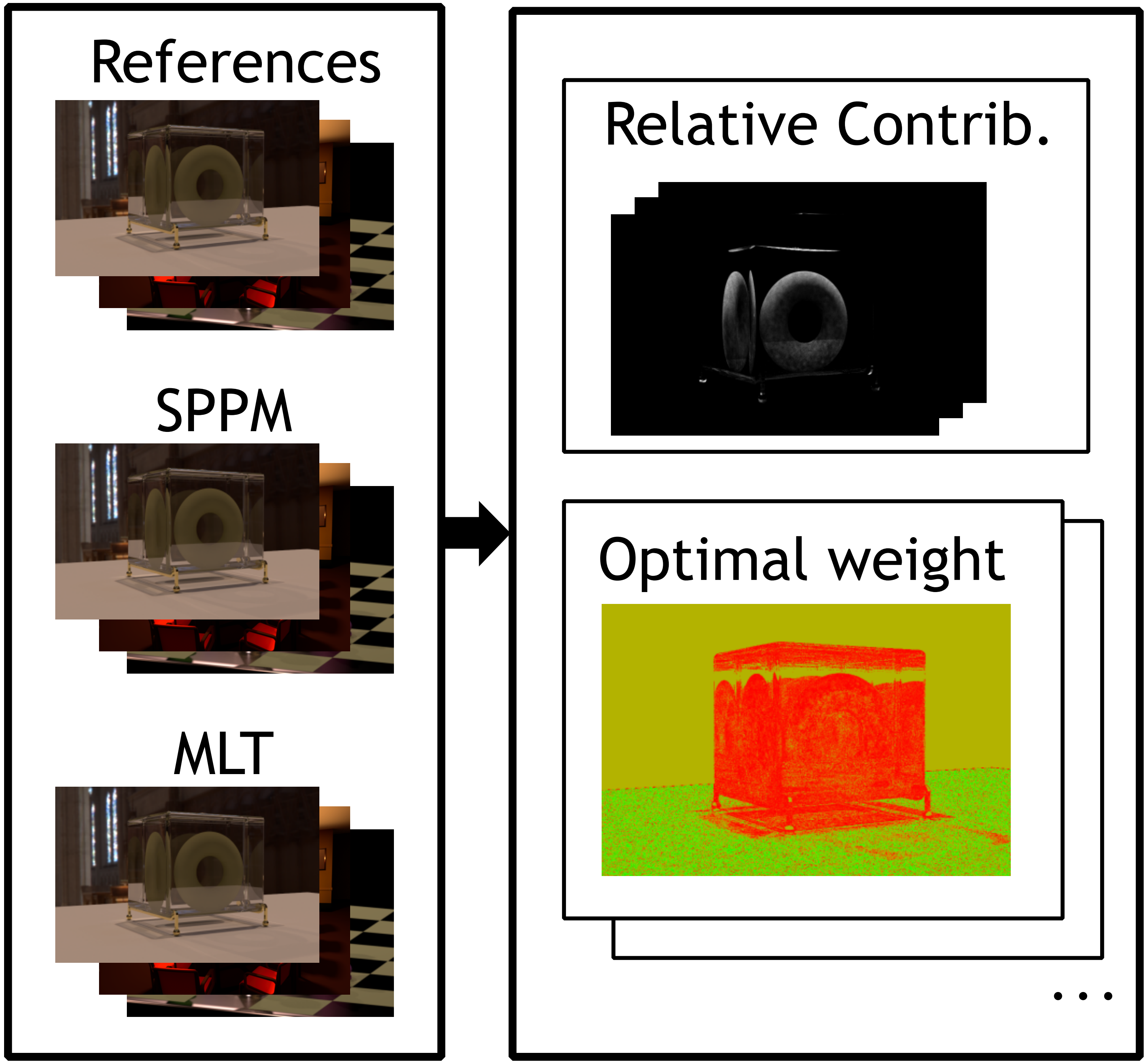


SPPM

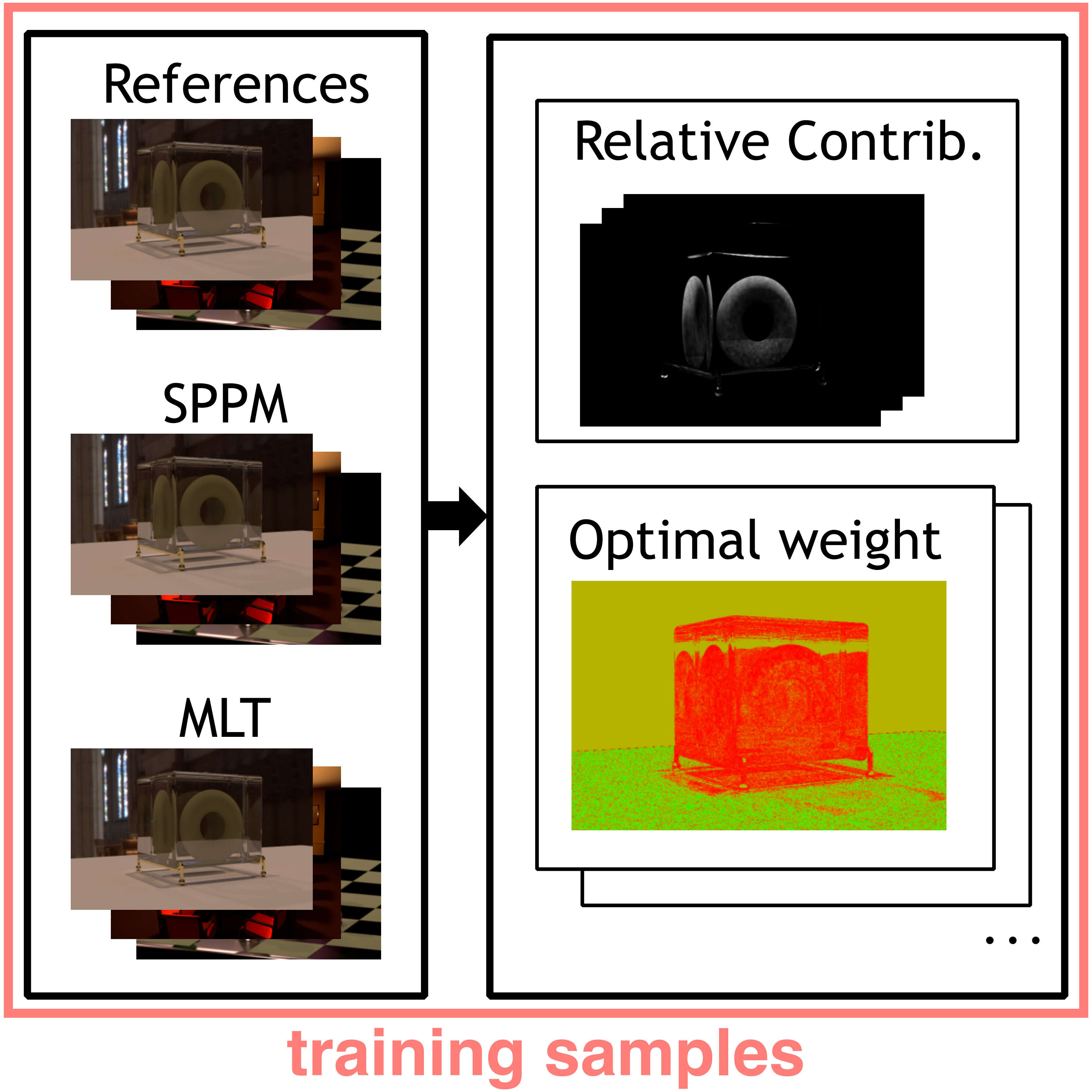


MLT

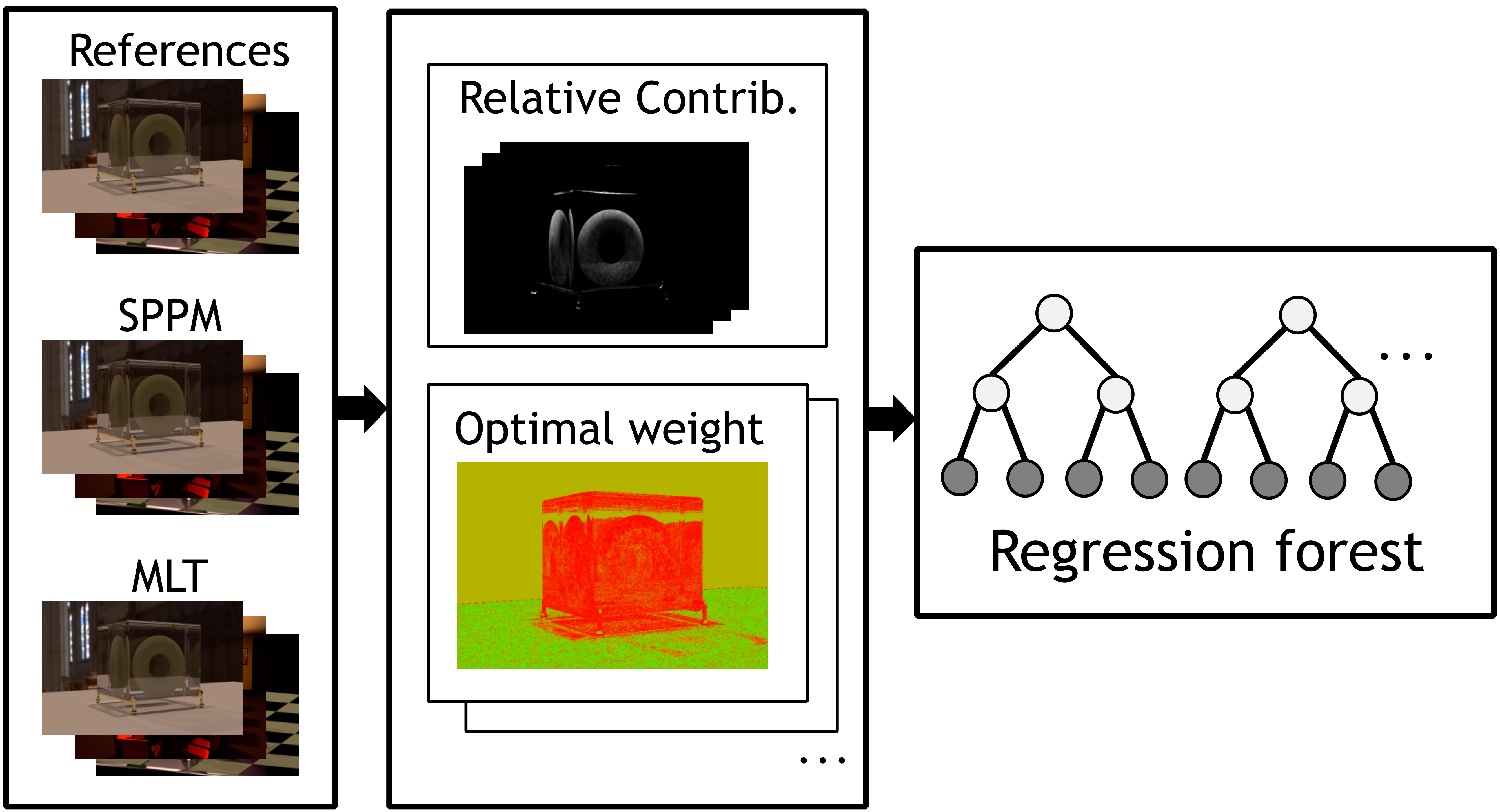
Learning



Learning

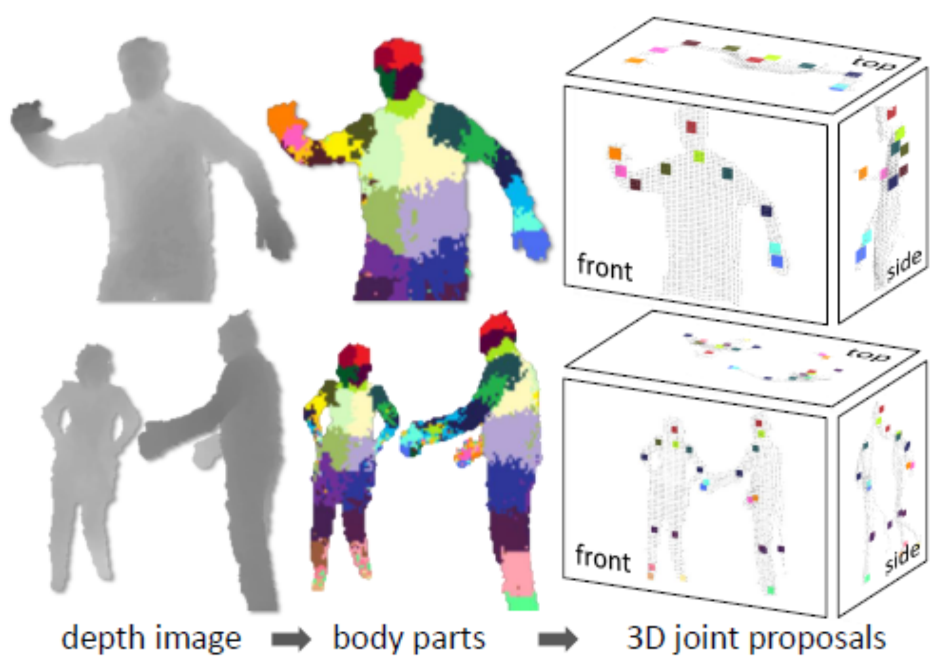

References
SPPM
MLT
Relative Contrib.
Optimal weight
...
training samples

Learning

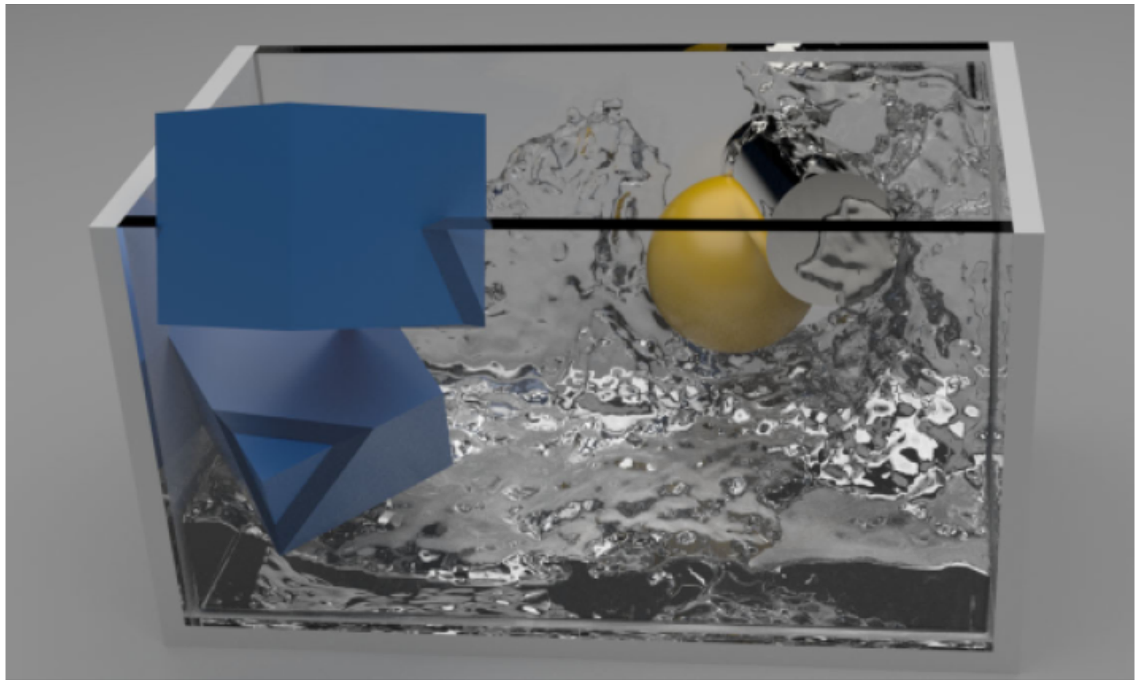

References
SPPM
MLT
Relative Contrib.
Optimal weight
...
...
Regression forest

Regression forests

- Machine learning technique which uses an ensemble of randomized regression trees

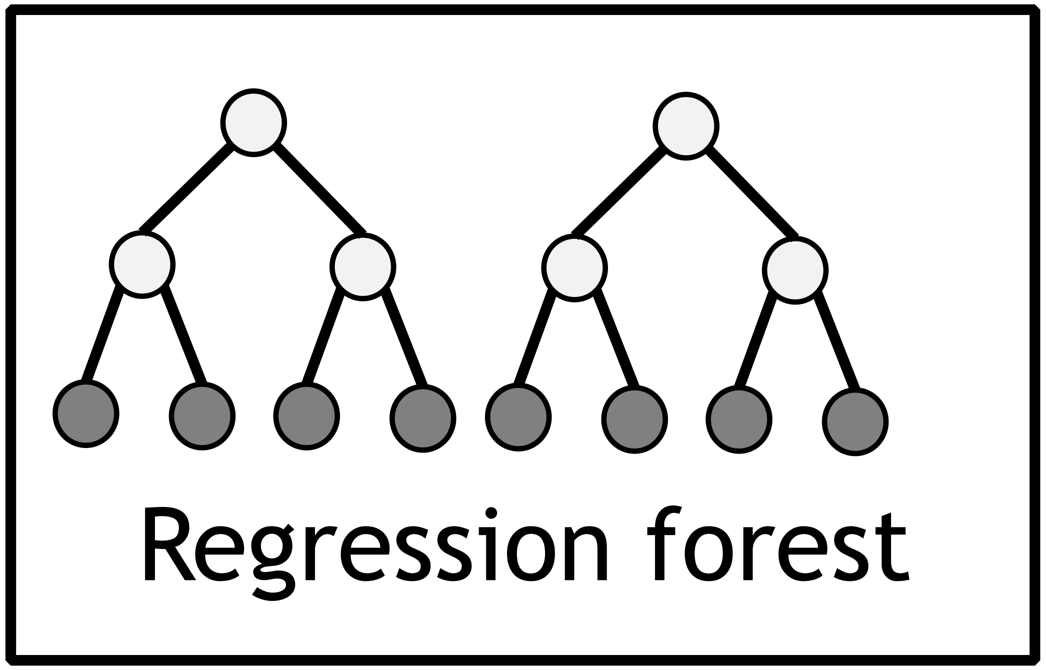


Body segmentation
[Shotton et al. 2011]



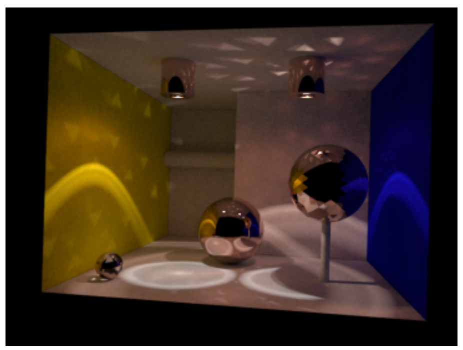
Fluid simulation
[Ladický et al. 2015]

Runtime

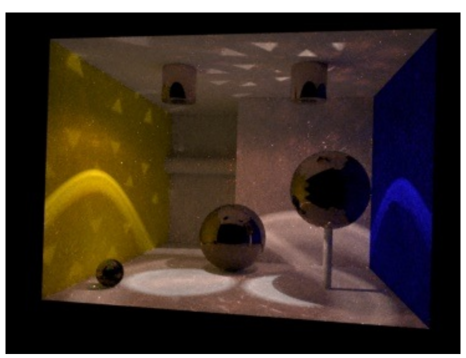


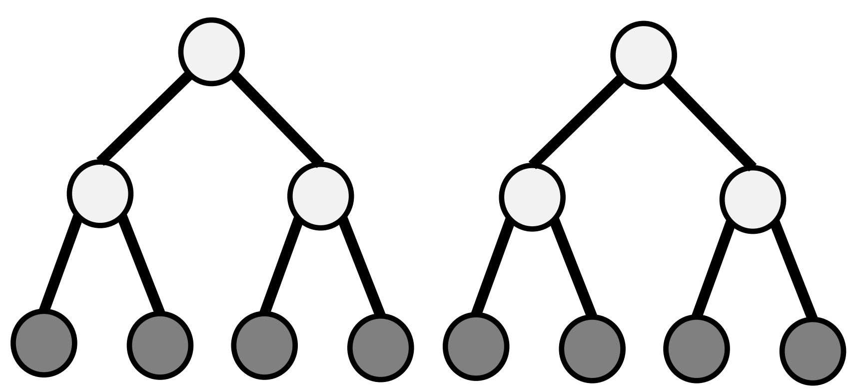
Runtime

SPPM



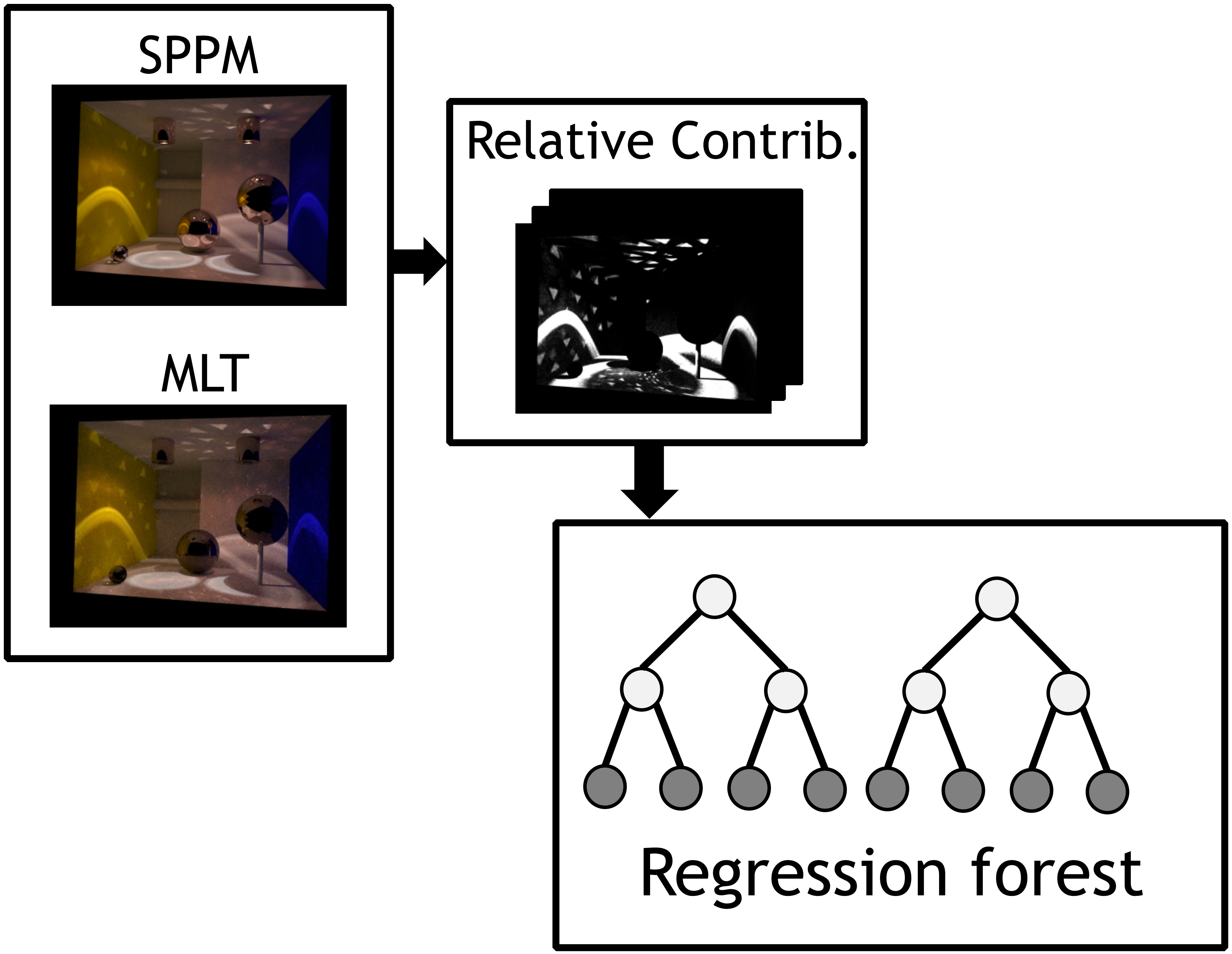
MLT



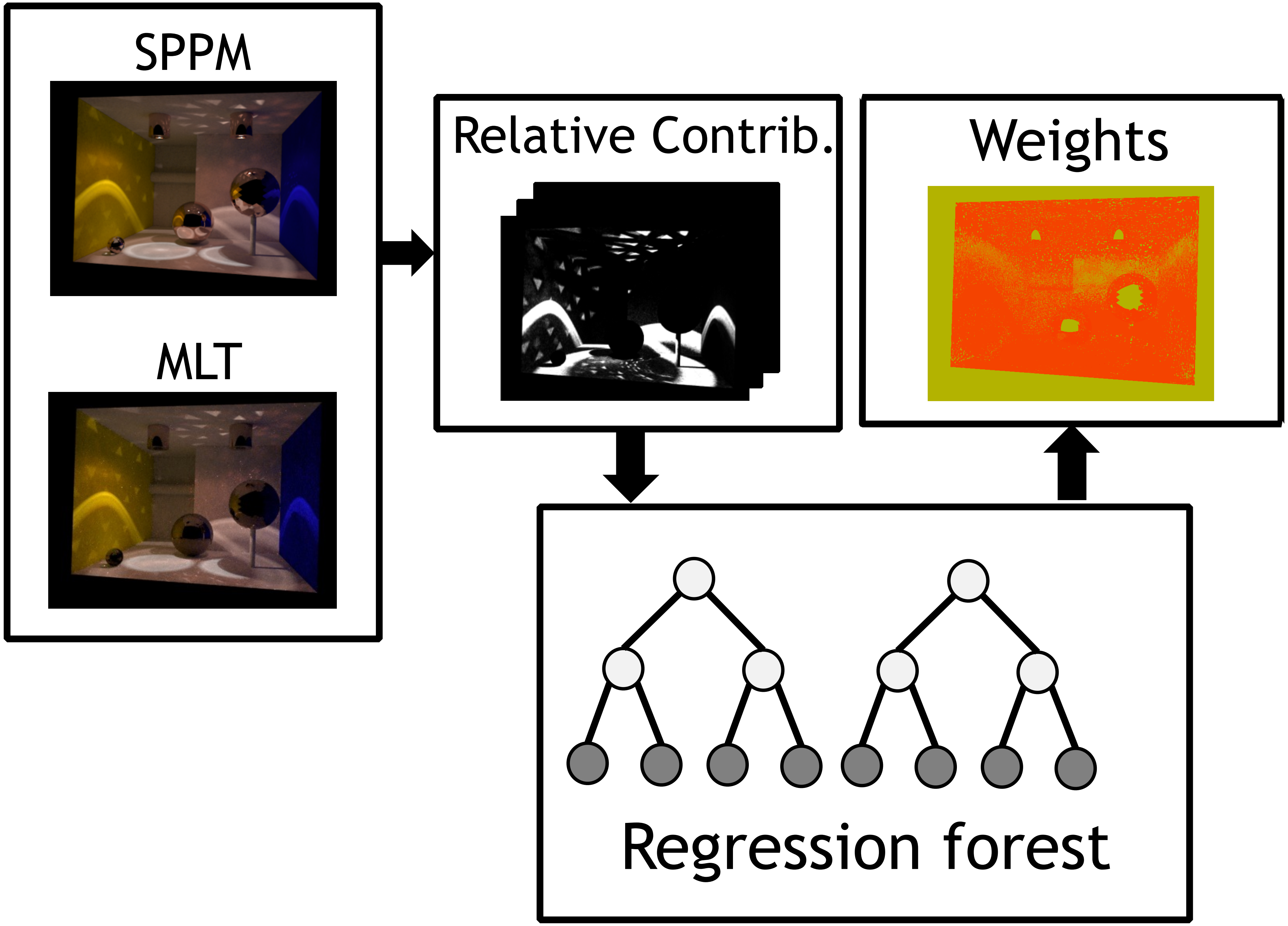


Regression forest

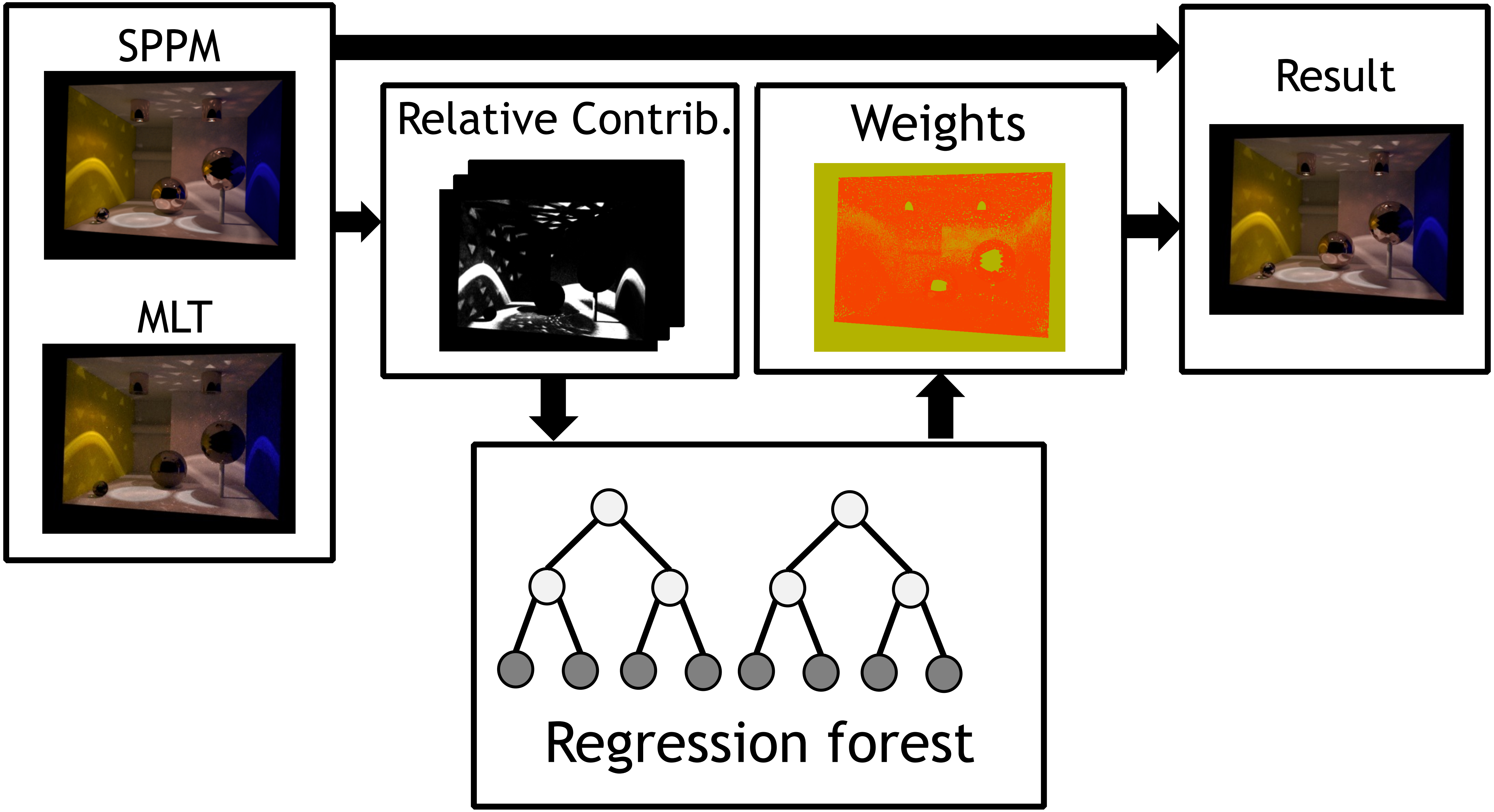
Runtime



Runtime

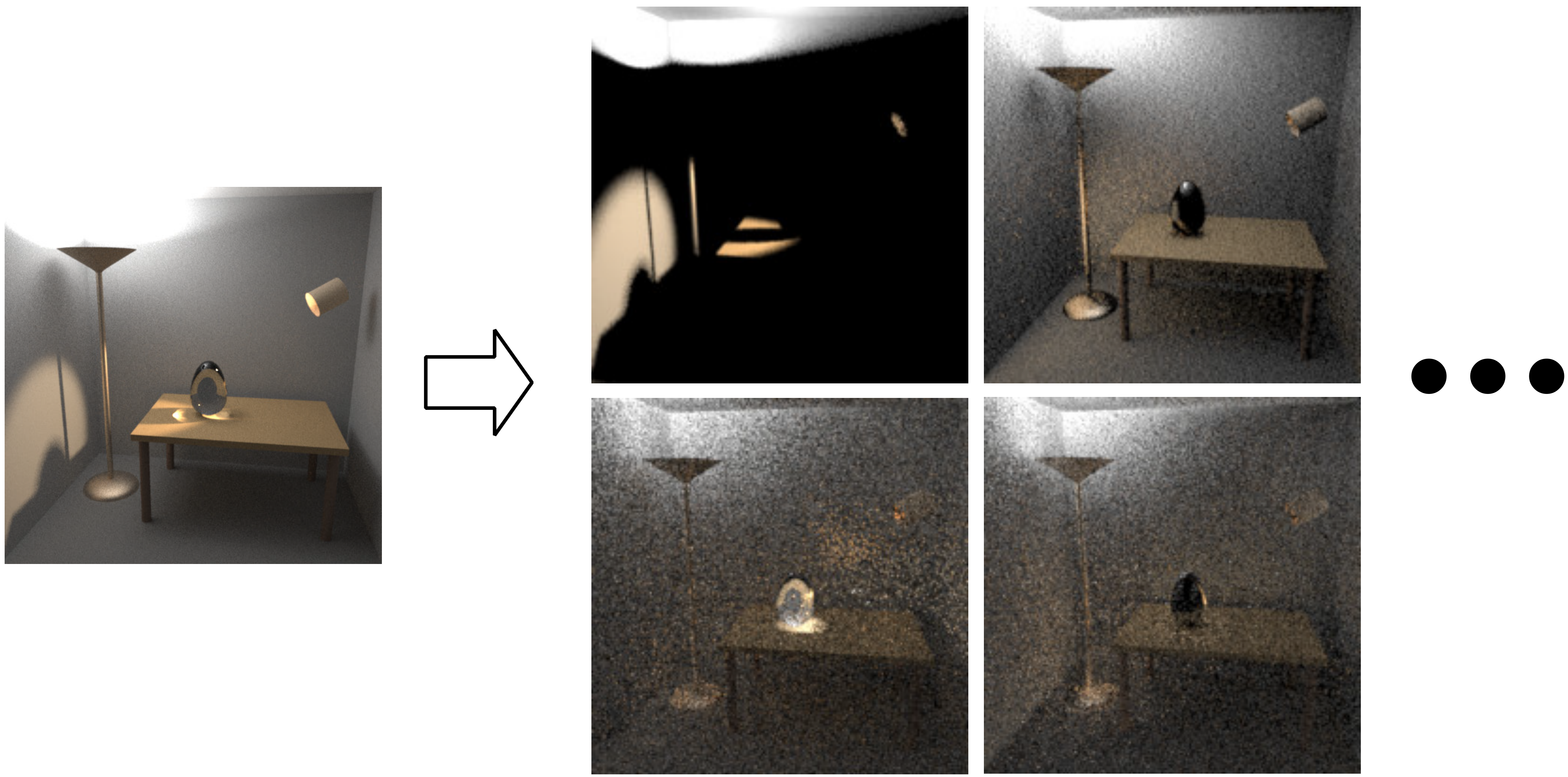


Runtime

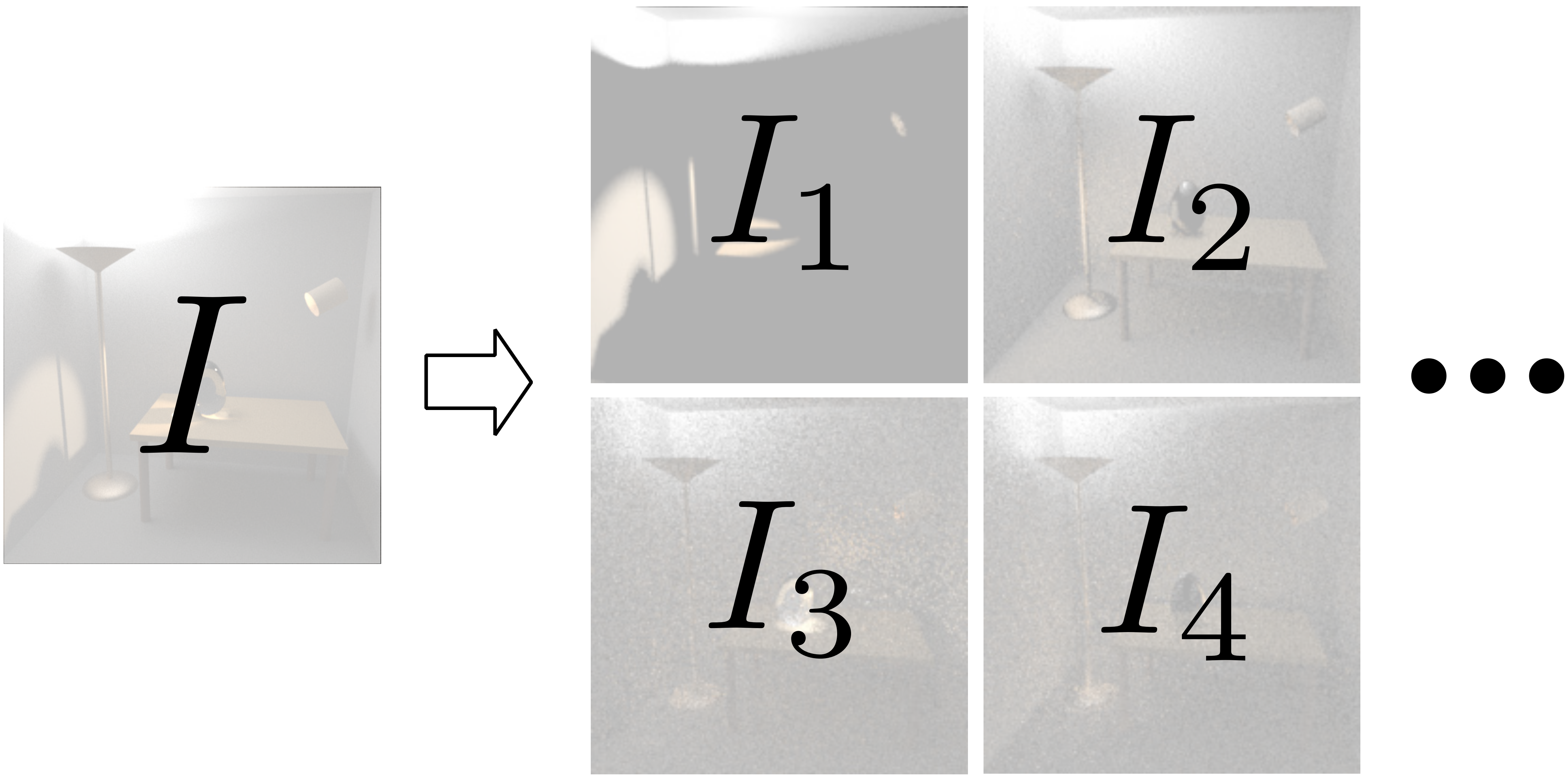


SPPM
MLT
Relative Contrib.
Weights
Result
Regression forest

Relative contributions



Relative contributions



$$I = I_1 + I_2 + I_3 + I_4 + \cdots$$

Relative contributions

- Vector of relative intensities of each integral

$$\vec{\phi}(I) = \frac{(I_1, I_2, I_3, I_4, \ldots)}{I}$$

- Similar to relative magnitudes of subsets of samples
  - Samples are clustered by some fixed rules

Optimal weights

- Given pixel intensities from two algorithm (α and β), the optimal weight (minimizes error) is defined as

$$w_{\text{opt}} = \arg\min_{w} \left| \left(w\hat{I}_{\alpha} + (1 - w)\hat{I}_{\beta} \right) - I \right|$$

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blended result **reference**

Optimal weights

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$$\boxed{w_{\text{opt}} \approx w_{\text{reg}}(\vec{\phi}(\hat{I}_\alpha), \vec{\phi}(\hat{I}_\alpha))}$$

what we learn

Optimal weights

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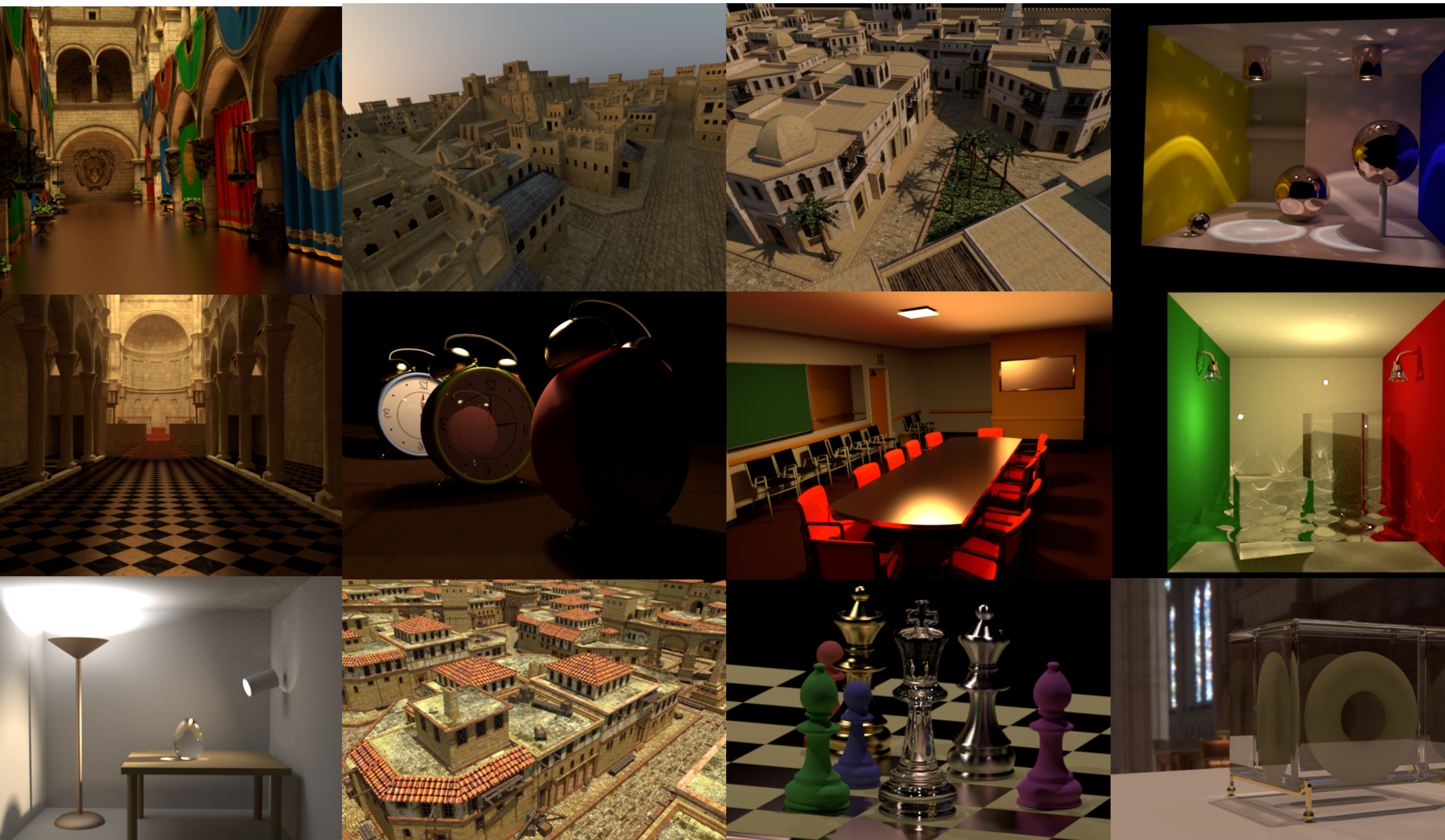
what we learn

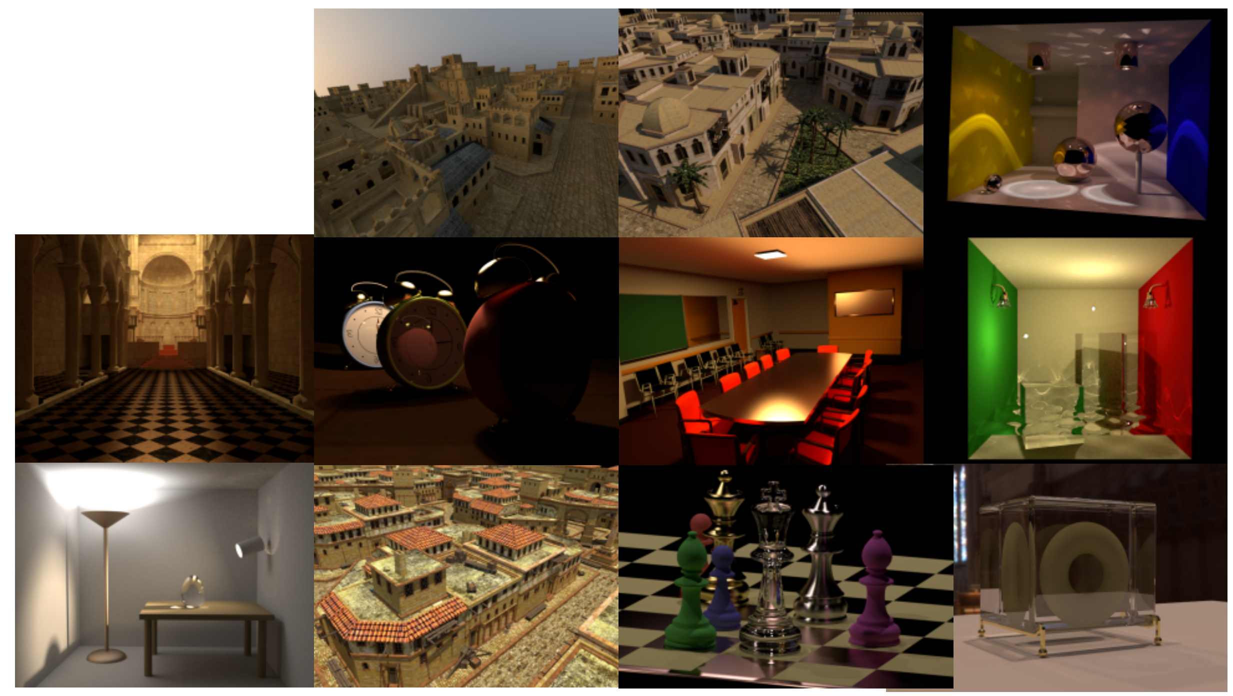
note: $w_{\text{opt}}(\hat{I}_\alpha, \hat{I}_\beta, I) \approx w_{\text{reg}}(\hat{I}_\alpha, \hat{I}_\beta)$ $\quad \lim \hat{I}_\alpha = \lim \hat{I}_\beta = I$

Results

Training scenes



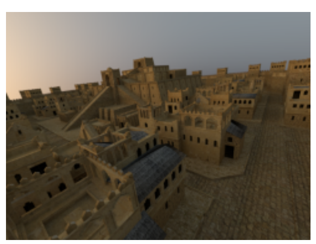
Evaluation



One scene for testing

Other scenes for training

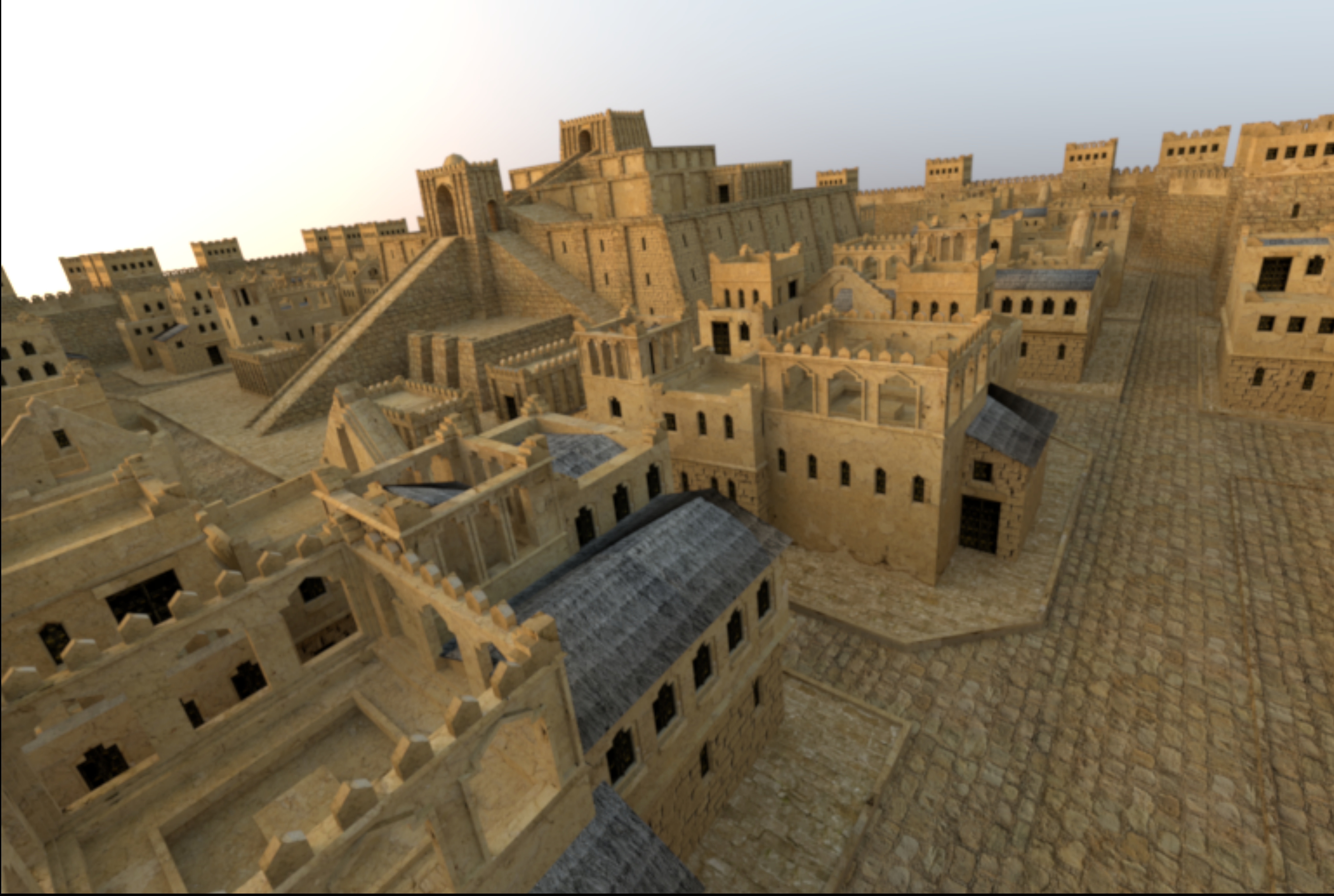
Evaluation



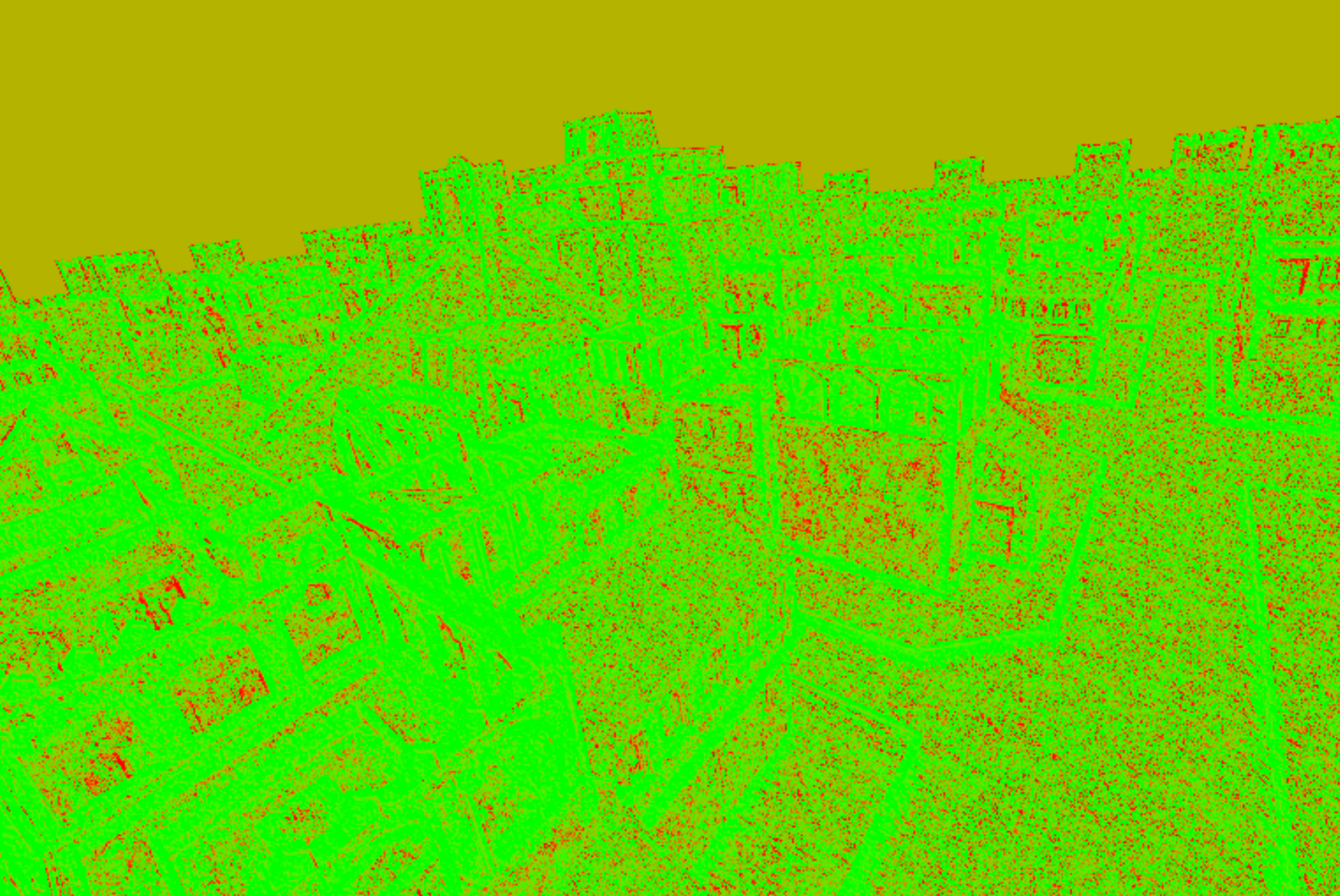
One scene for testing

Other scenes for training

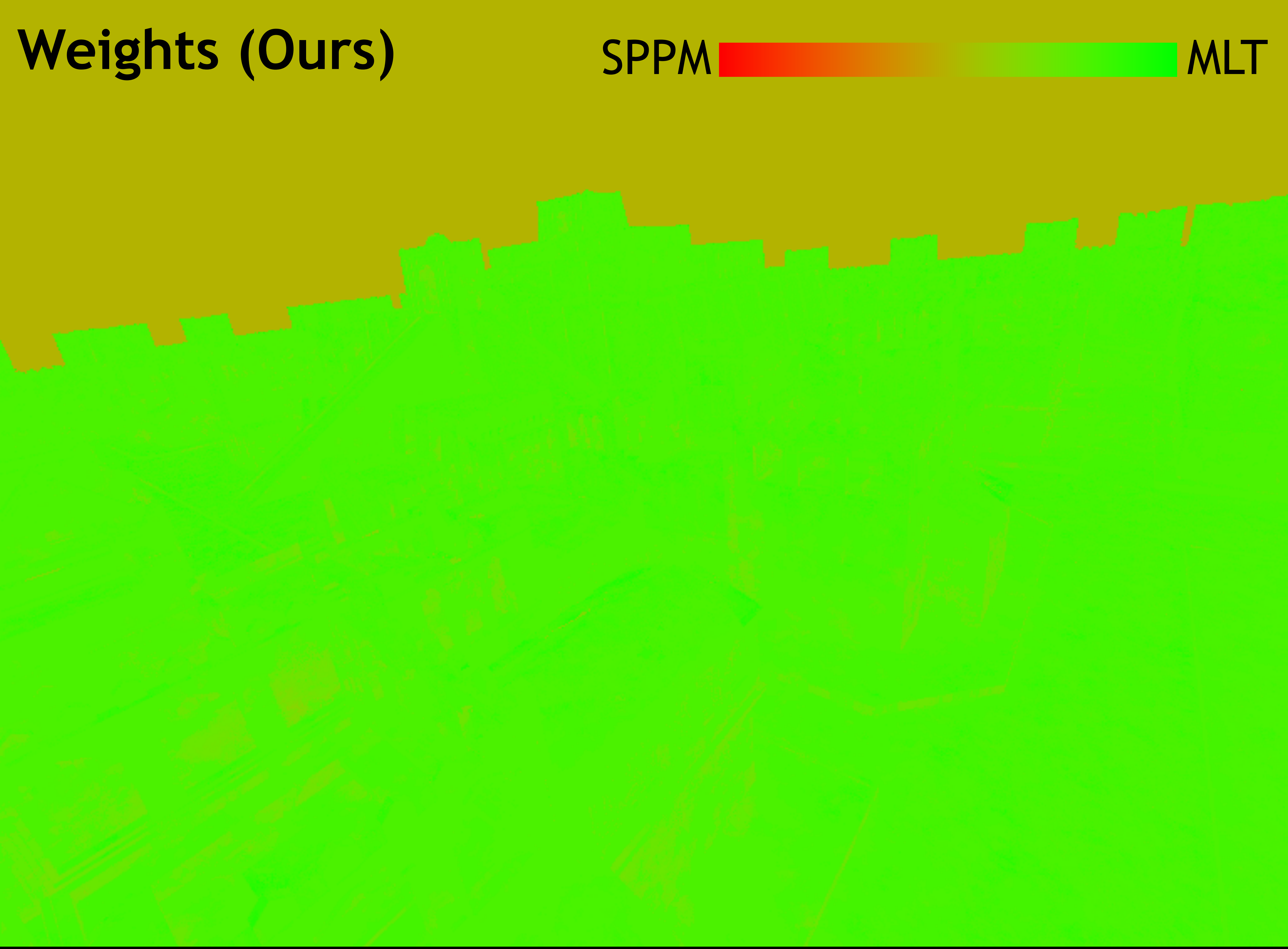
Scene: babylonian-city



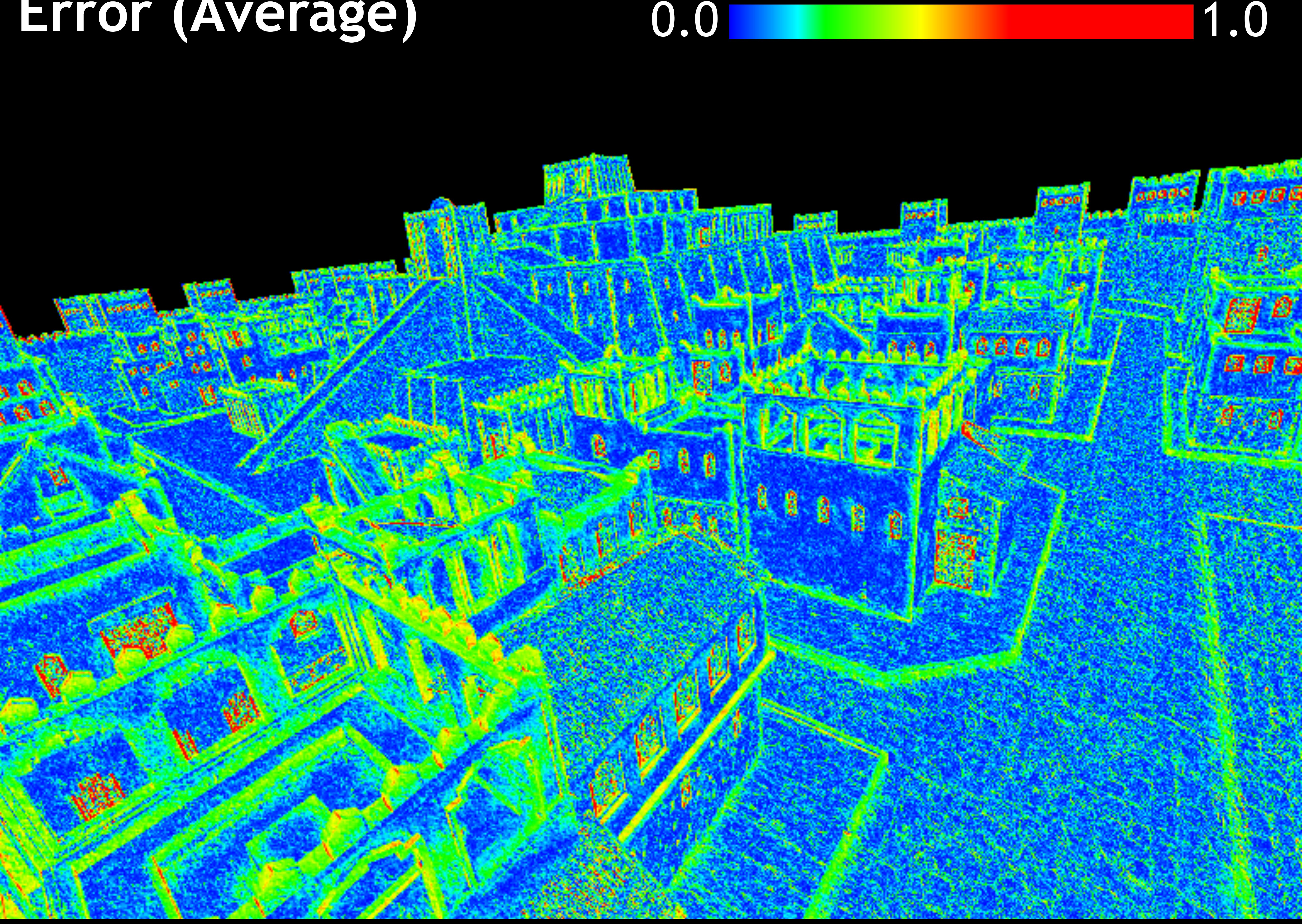
Weights (Optimal)



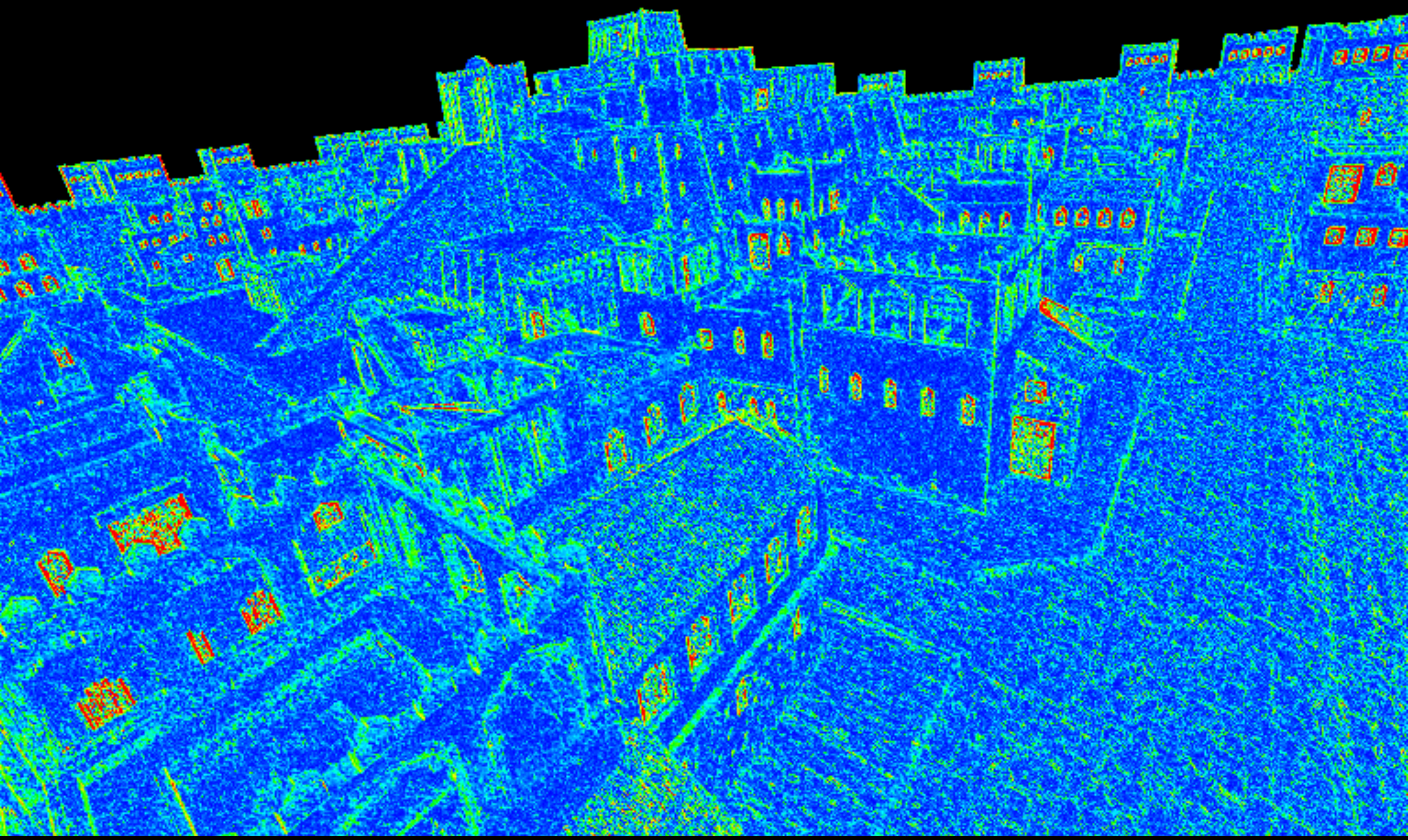
Weights (Ours)



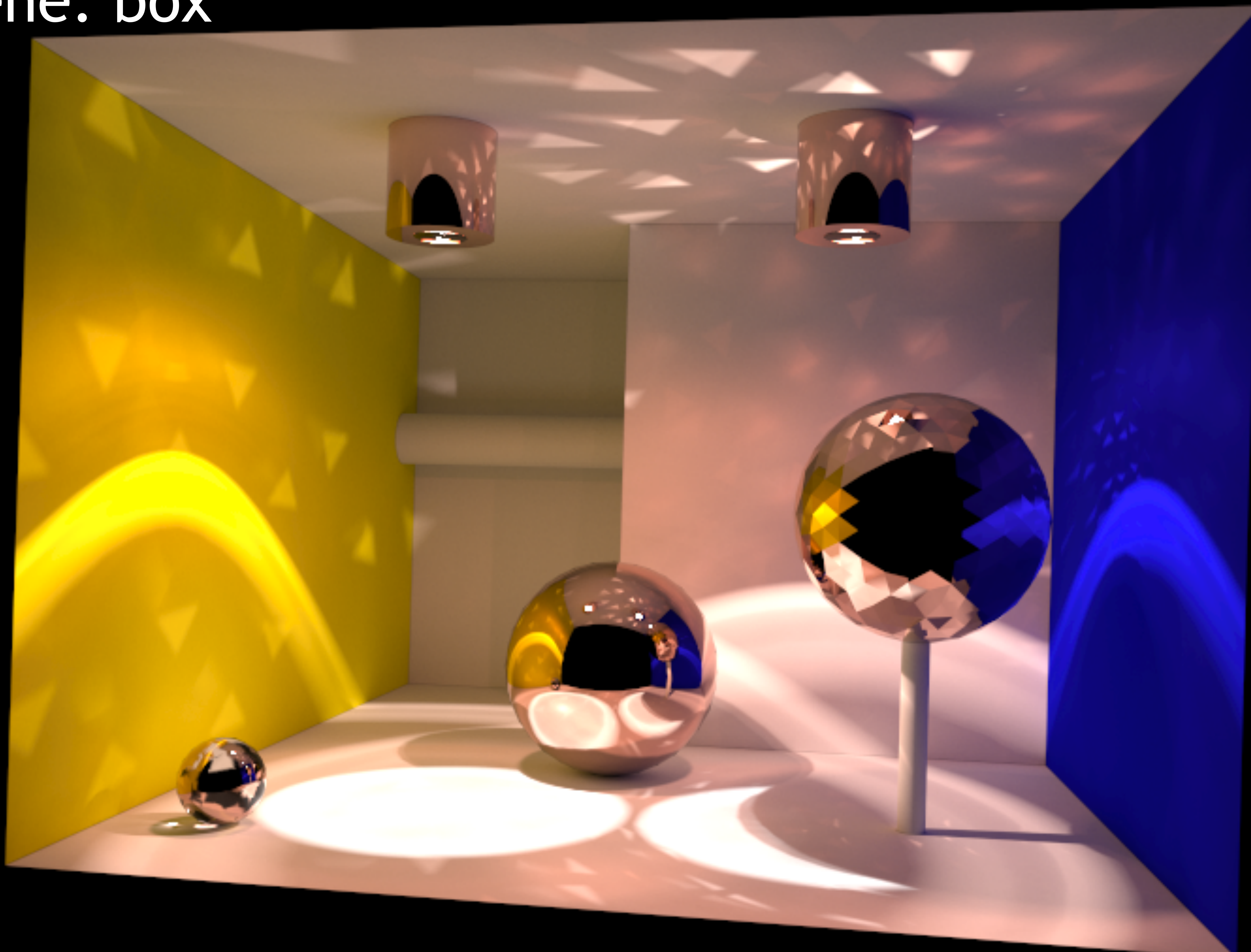
Error (Average)



Error (Ours)



Scene: box



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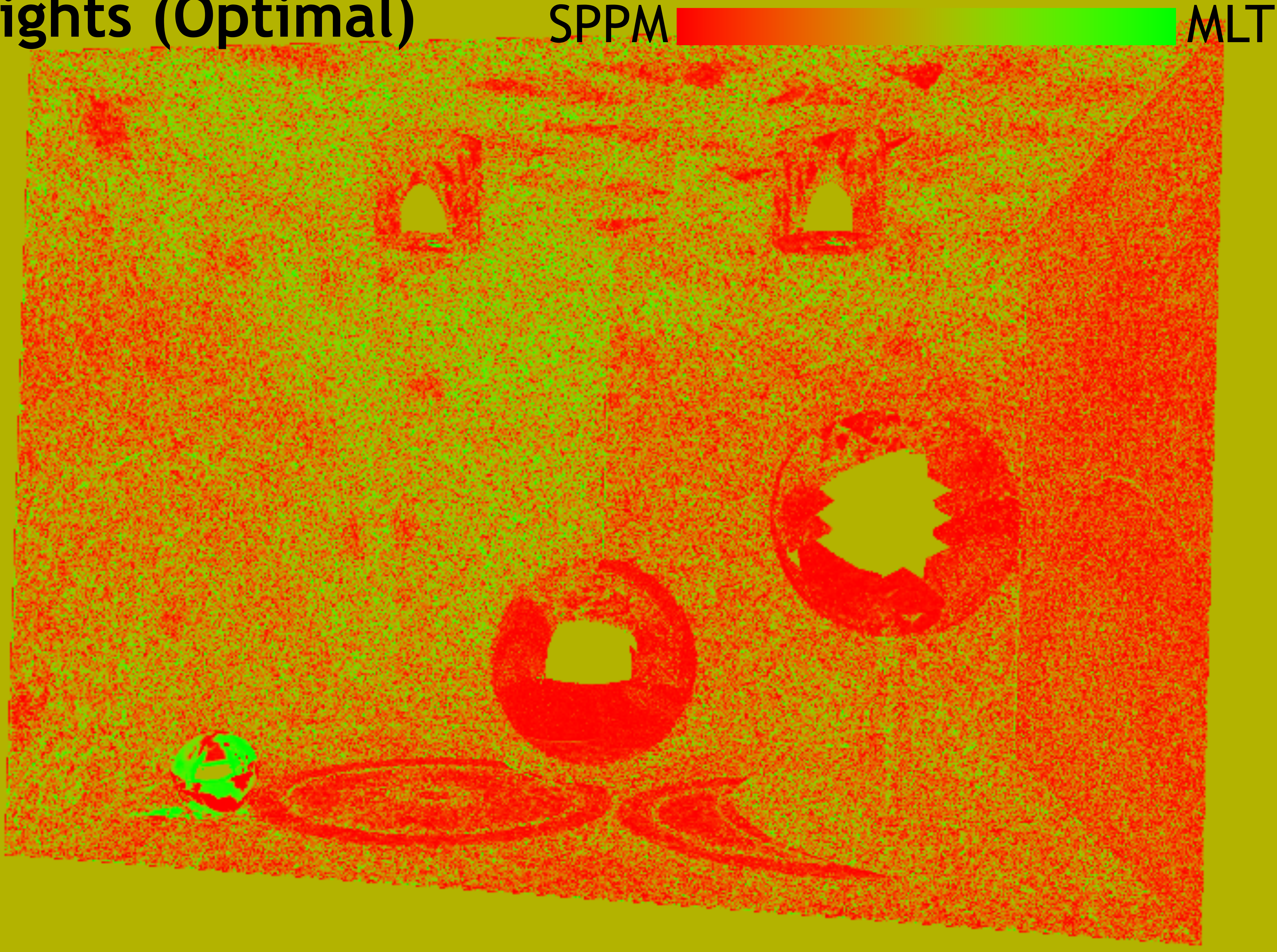

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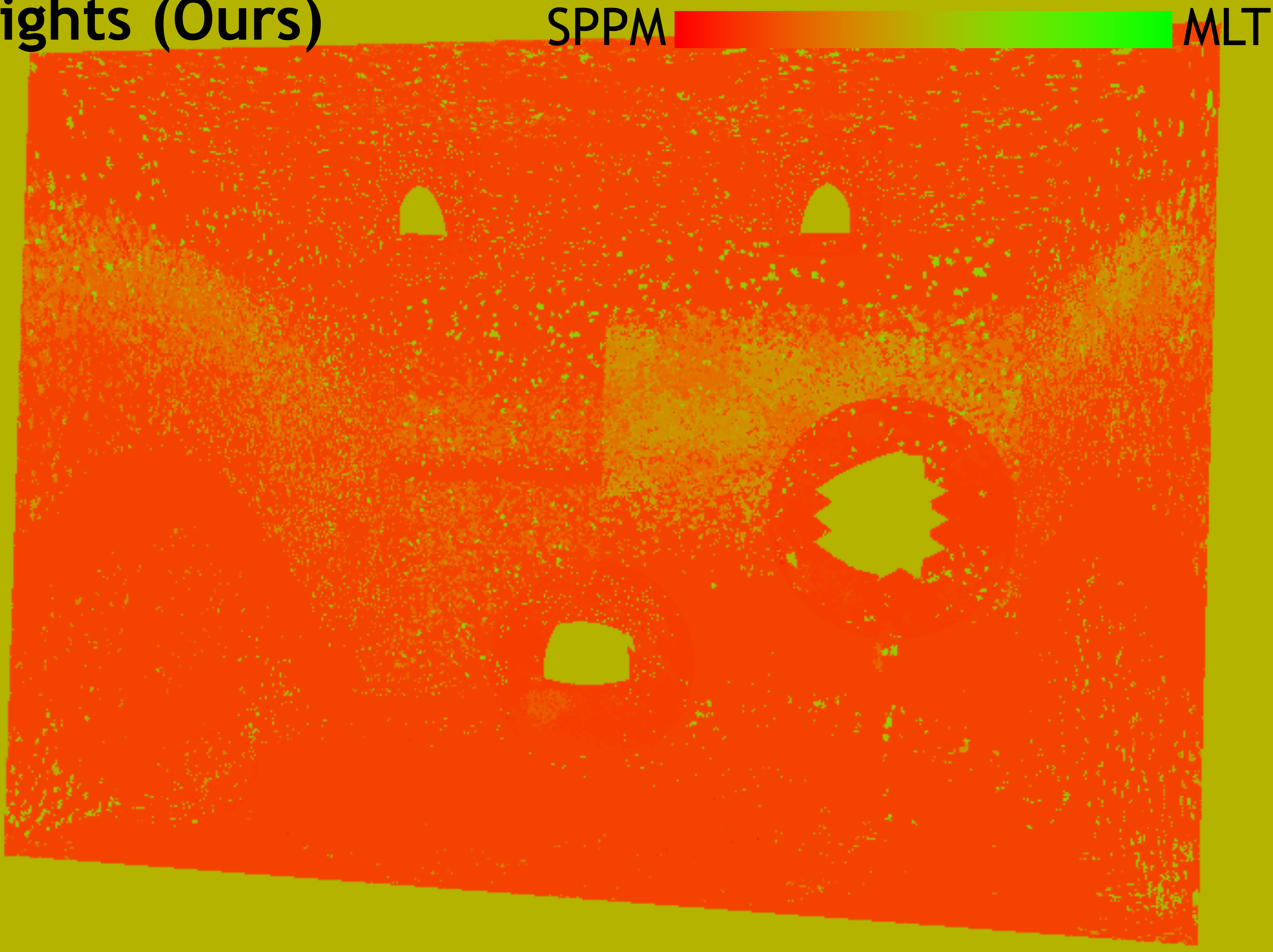
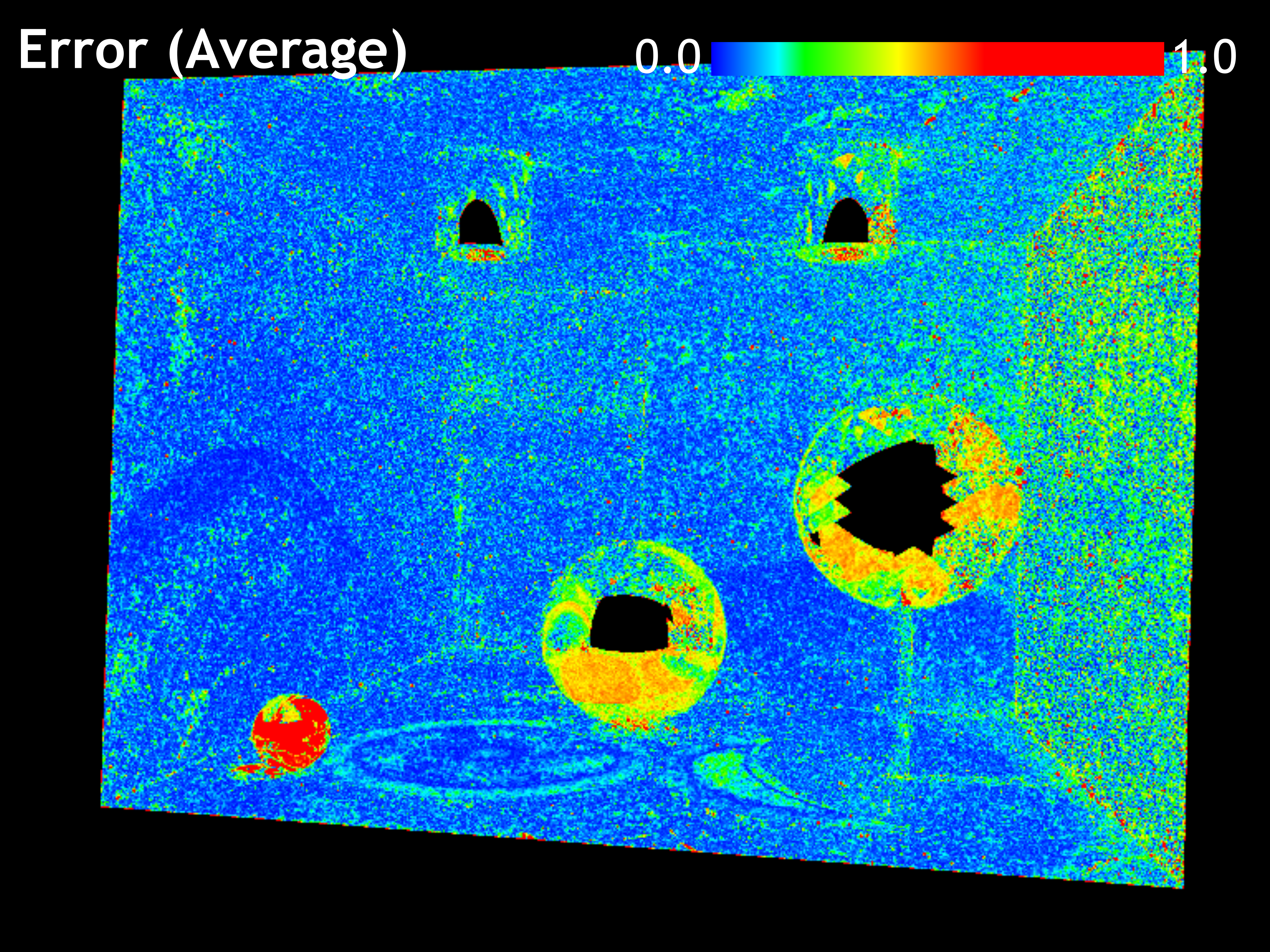
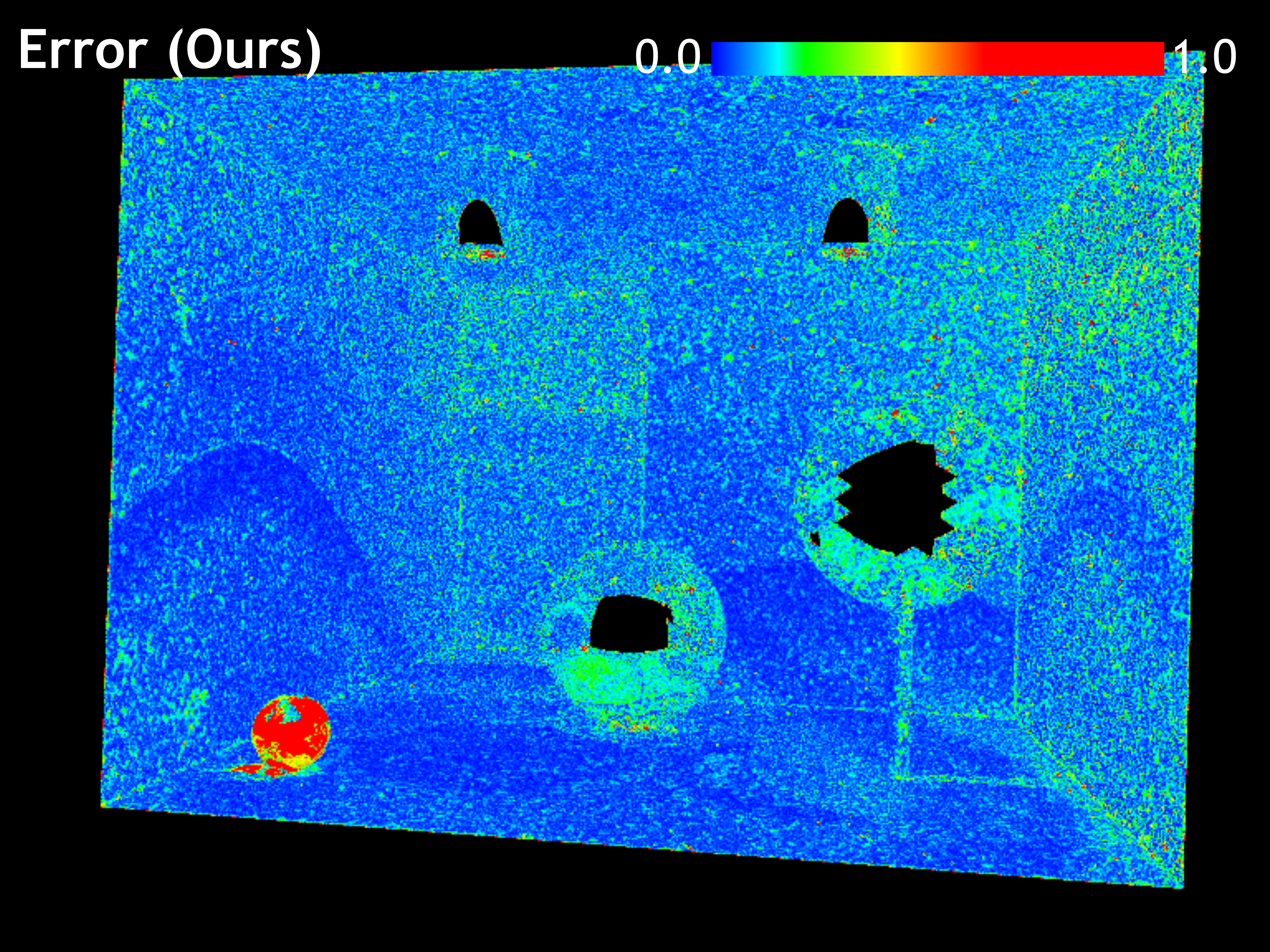
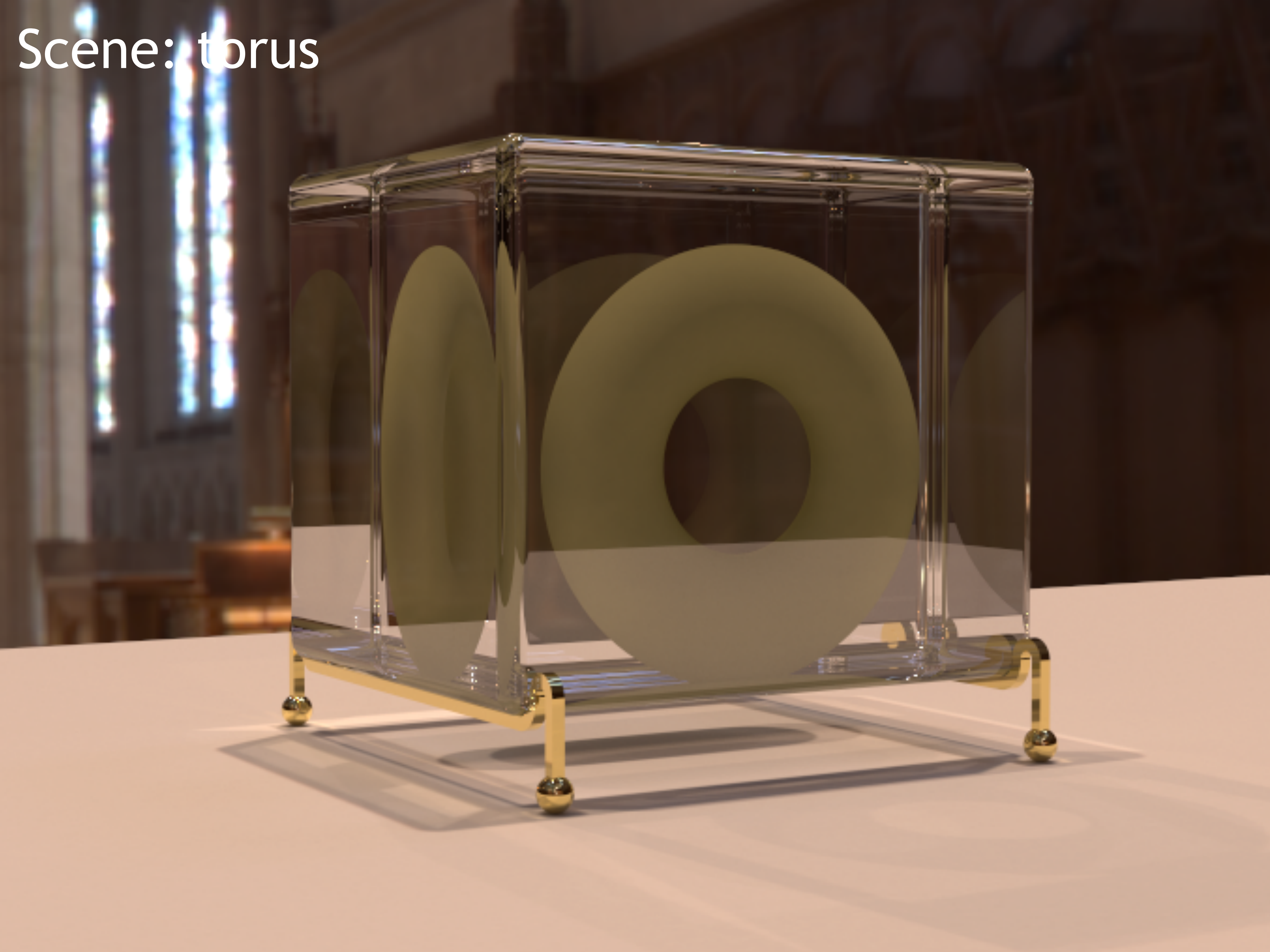
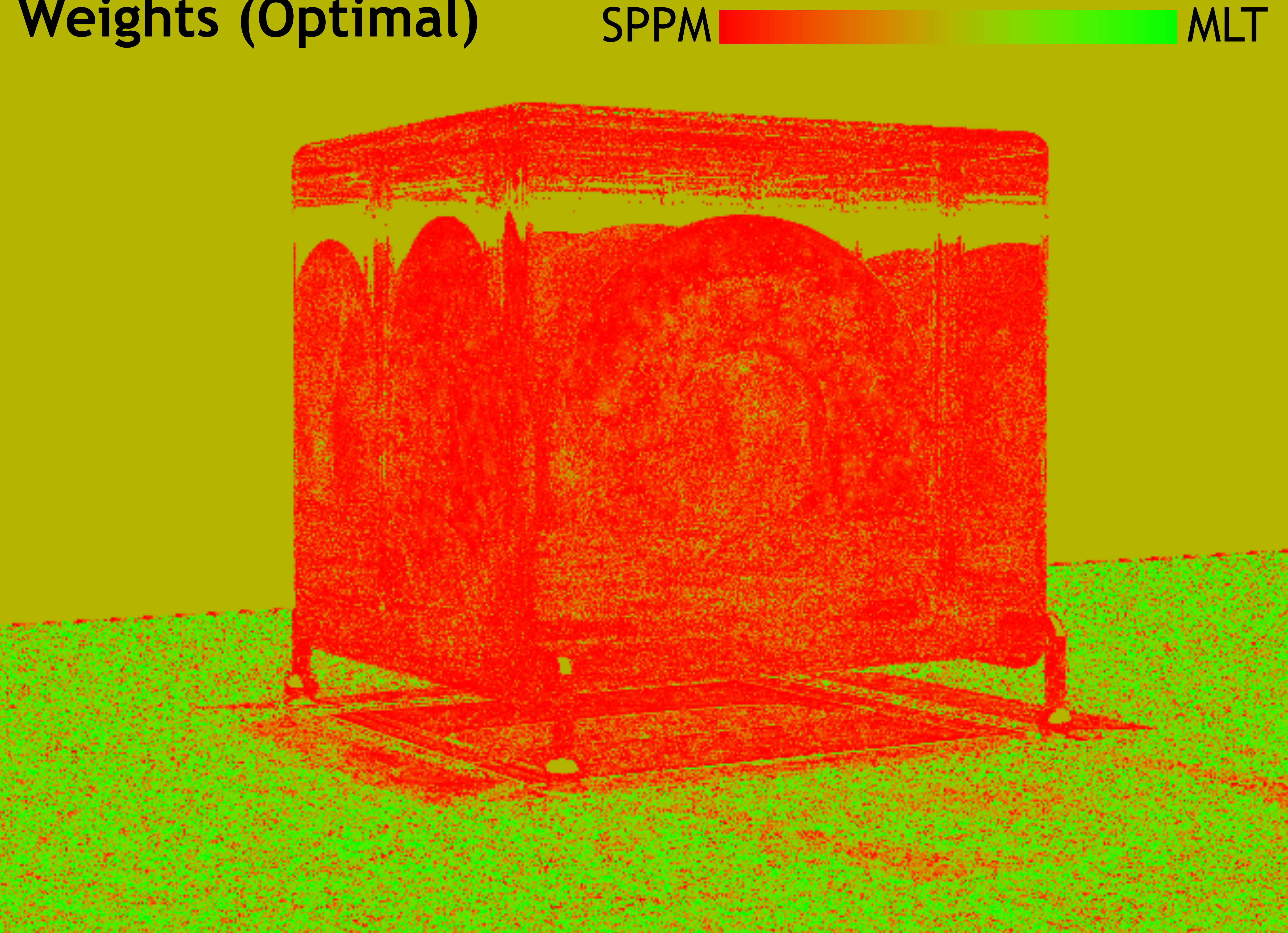


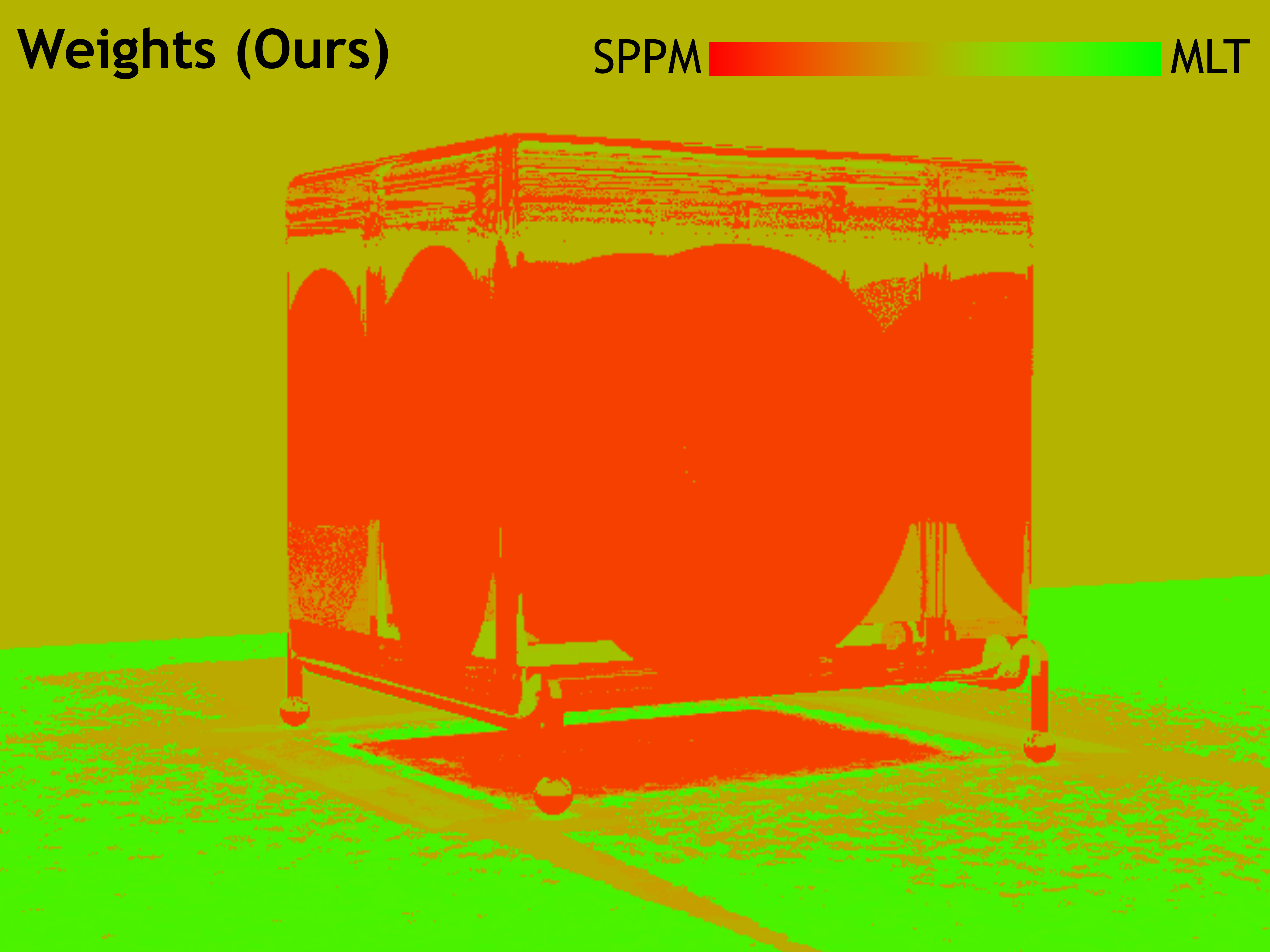

Error (Average)
0.0
1.0

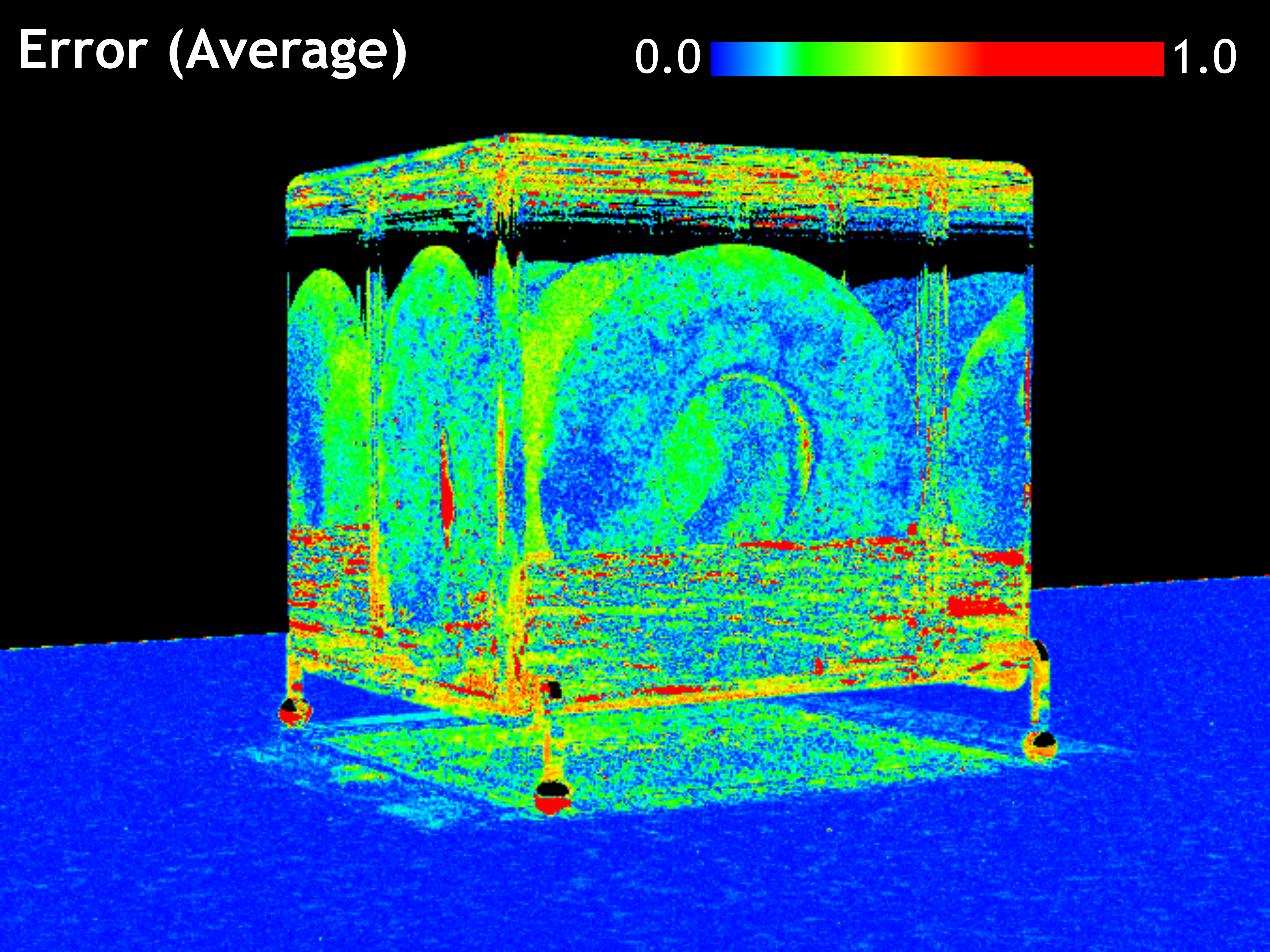

Error (Ours)
0.0
1.0

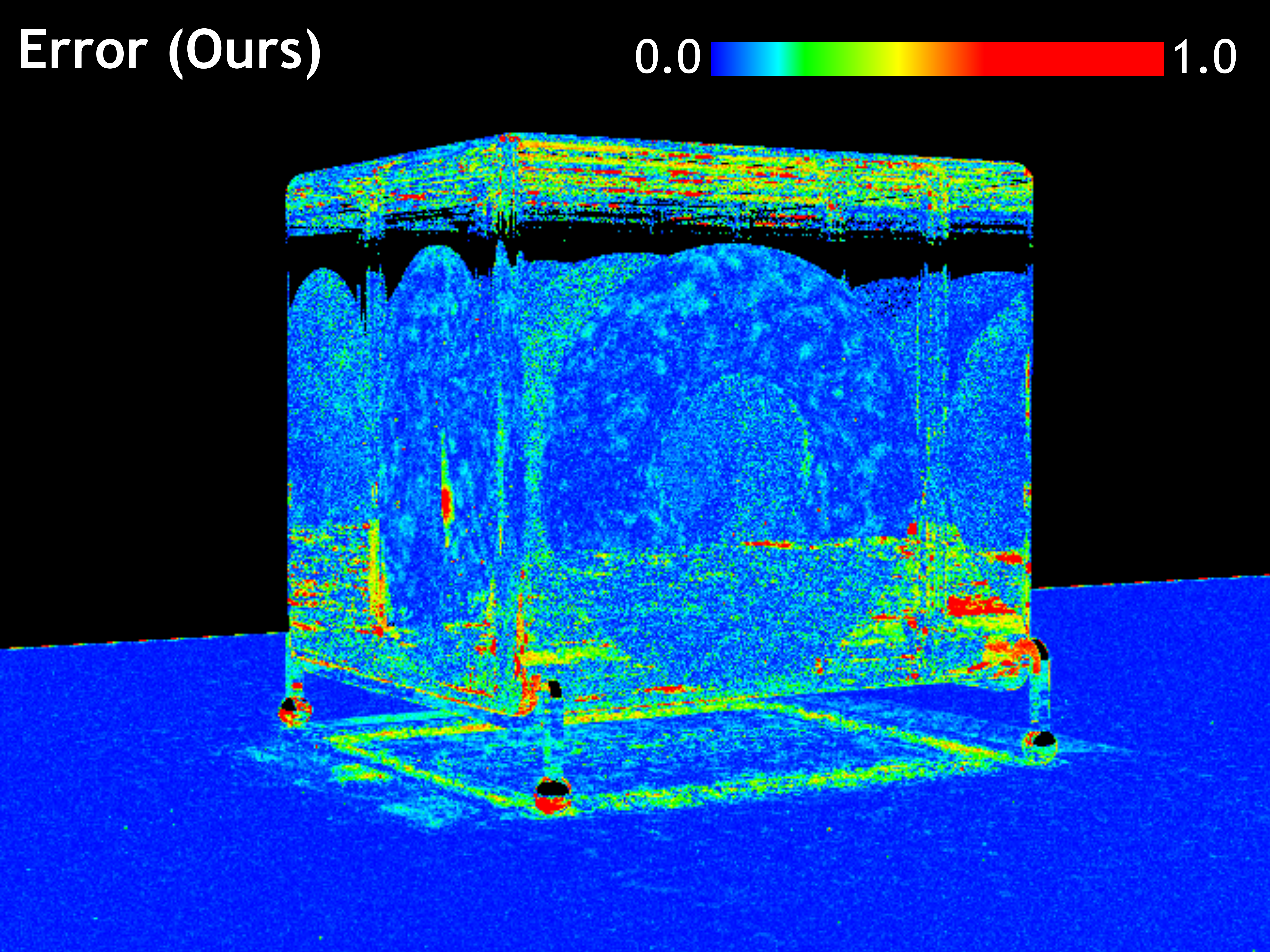

Scene: torus

Weights (Optimal)




Weights (Ours)
SPPM
MLT


Error (Average)
0.0
1.0


Error (Ours)
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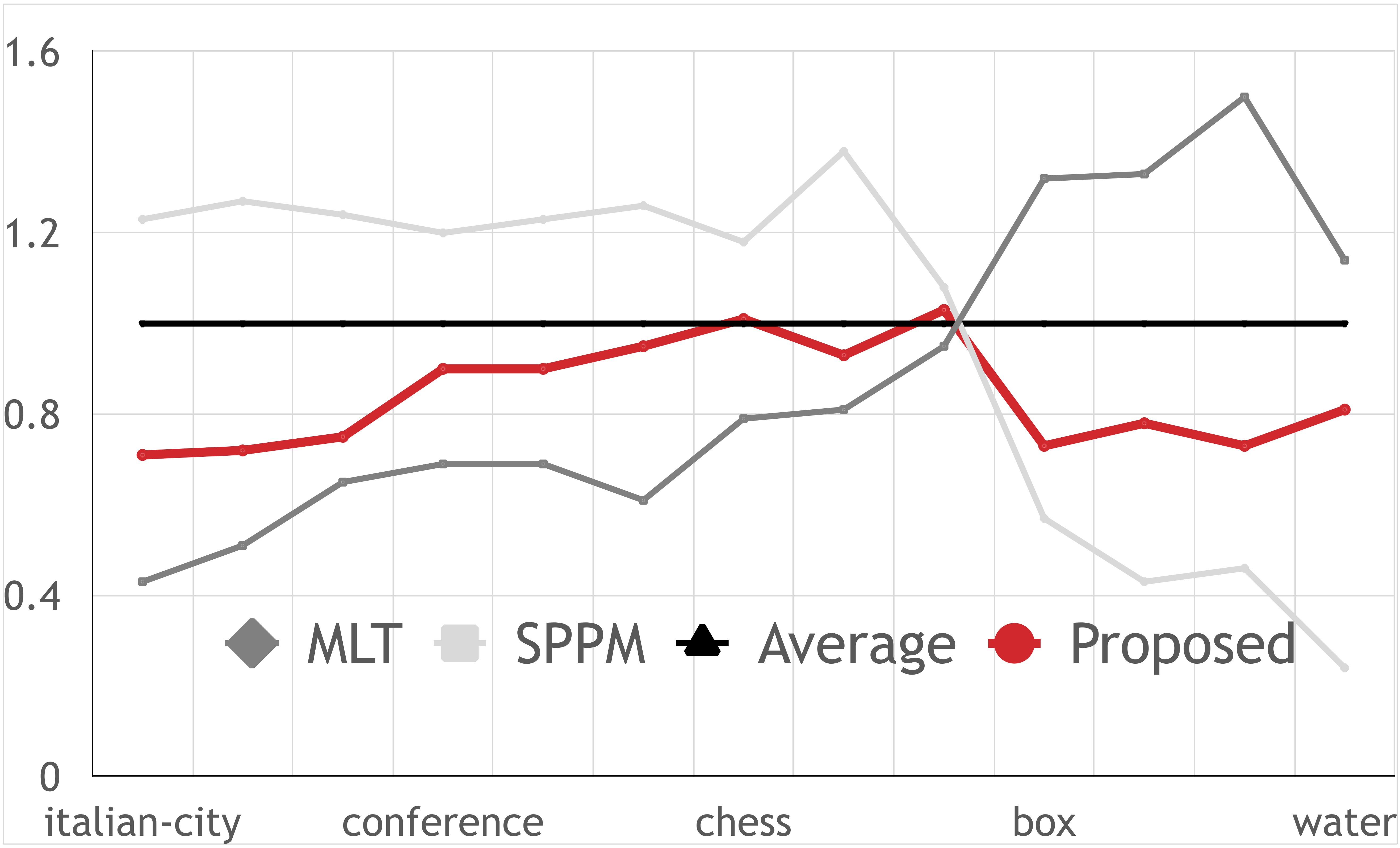
1.0



1.6
1.2
0.8
0.4
0
MLT
SPPM
Average
Proposed
italian-city
conference
chess
box
water

Automatic mixing of MC

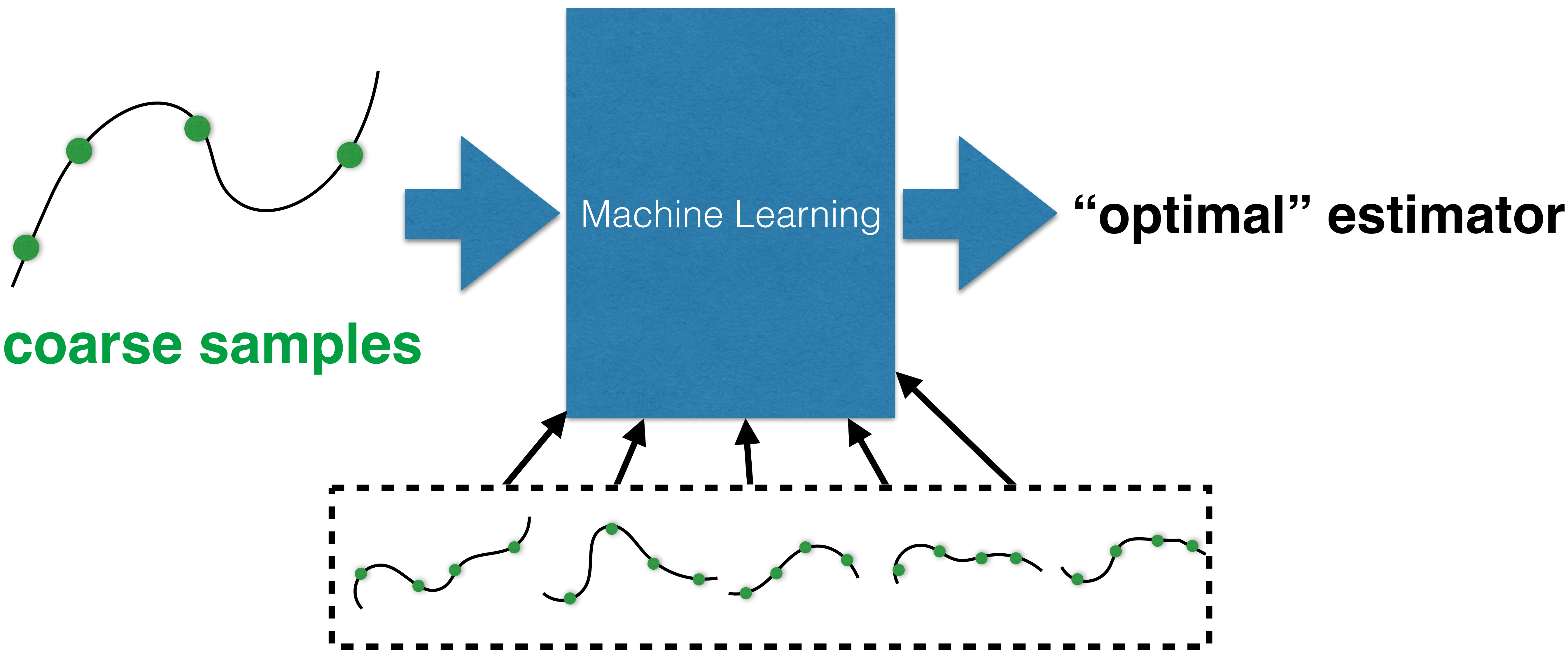
- Tries to optimally mix two Monte Carlo integrators
  - Learn optimal weights by examples
  - Better results than the baseline
- The same approach can be used for **any other** problems where we have **multiple MC integrators**
  - No modification to MC integrators themselves

Auto-adaptive MCMC

joint work with H. Otsu, M. Šik, and J. Křivánek (in progress)

Idea

- Adapt proposal distributions according to pre-trained data for various functions



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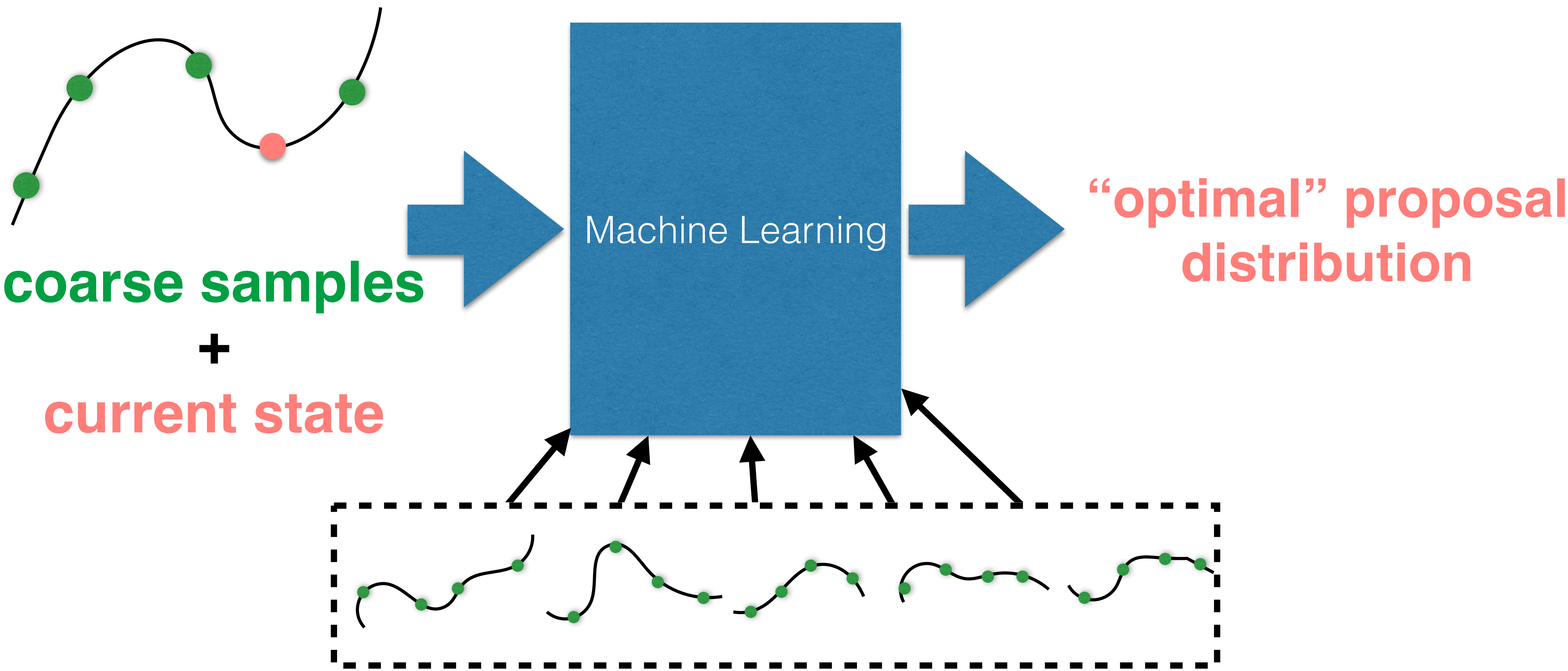

Auto-adaptive MCMC

- **Learning**
  - Given coarse samples + current state,
    maximize the expected jumping distance
  - Learn the relationship with the proposal distribution
- **Runtime**
  - Given coarse samples + current state,
    output the parameters of the proposal distribution

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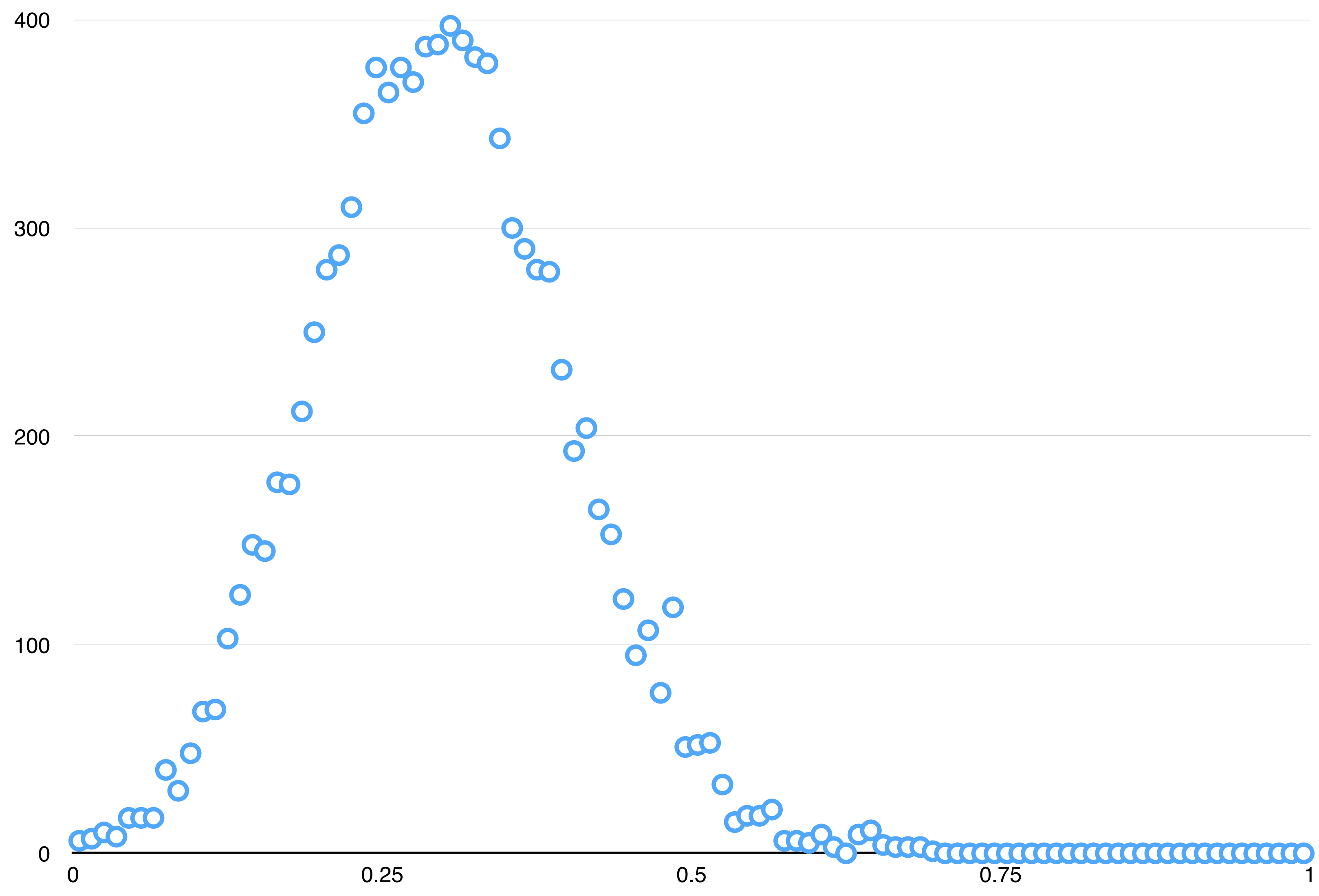
Adaptively maximize the expected jumping distance

Early experiments

- Samples from a mixture of two non-gaussians
- Radial basis functions for learning
- Instead of coarse samples, used parameters of a mixture distribution (still contains complex relations)

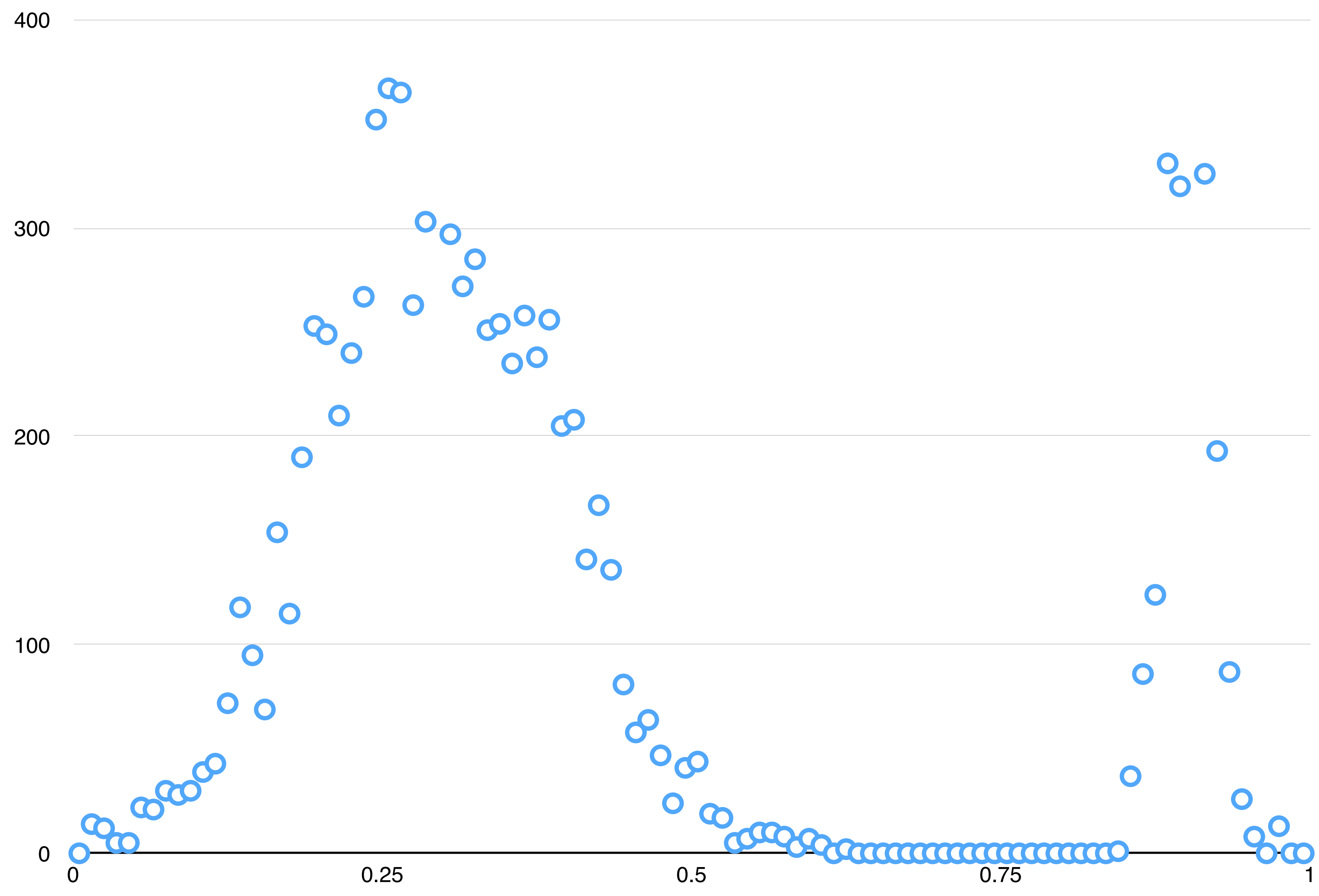
Histogram

- Baseline



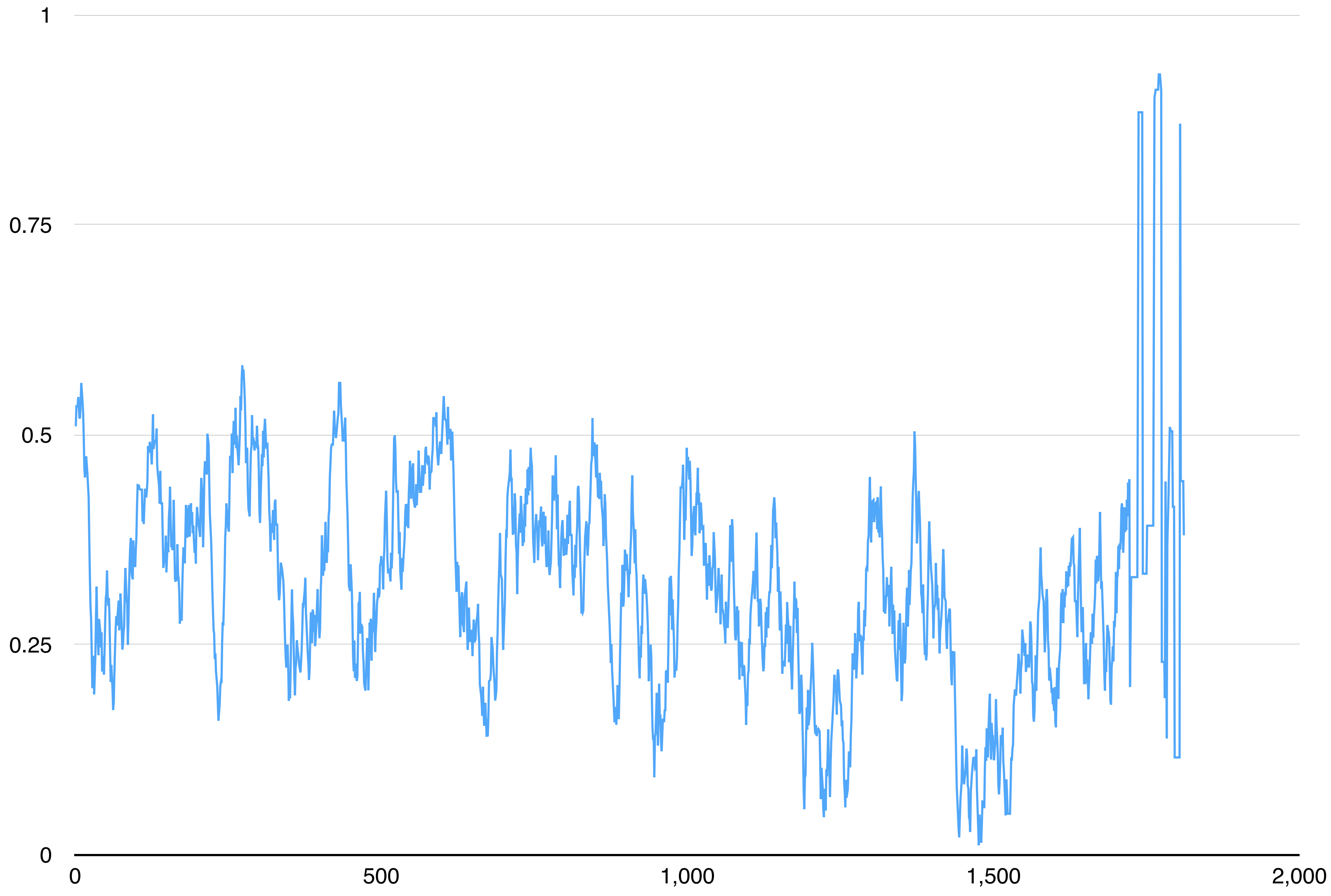
Histogram

- Our machine-learned MCMC



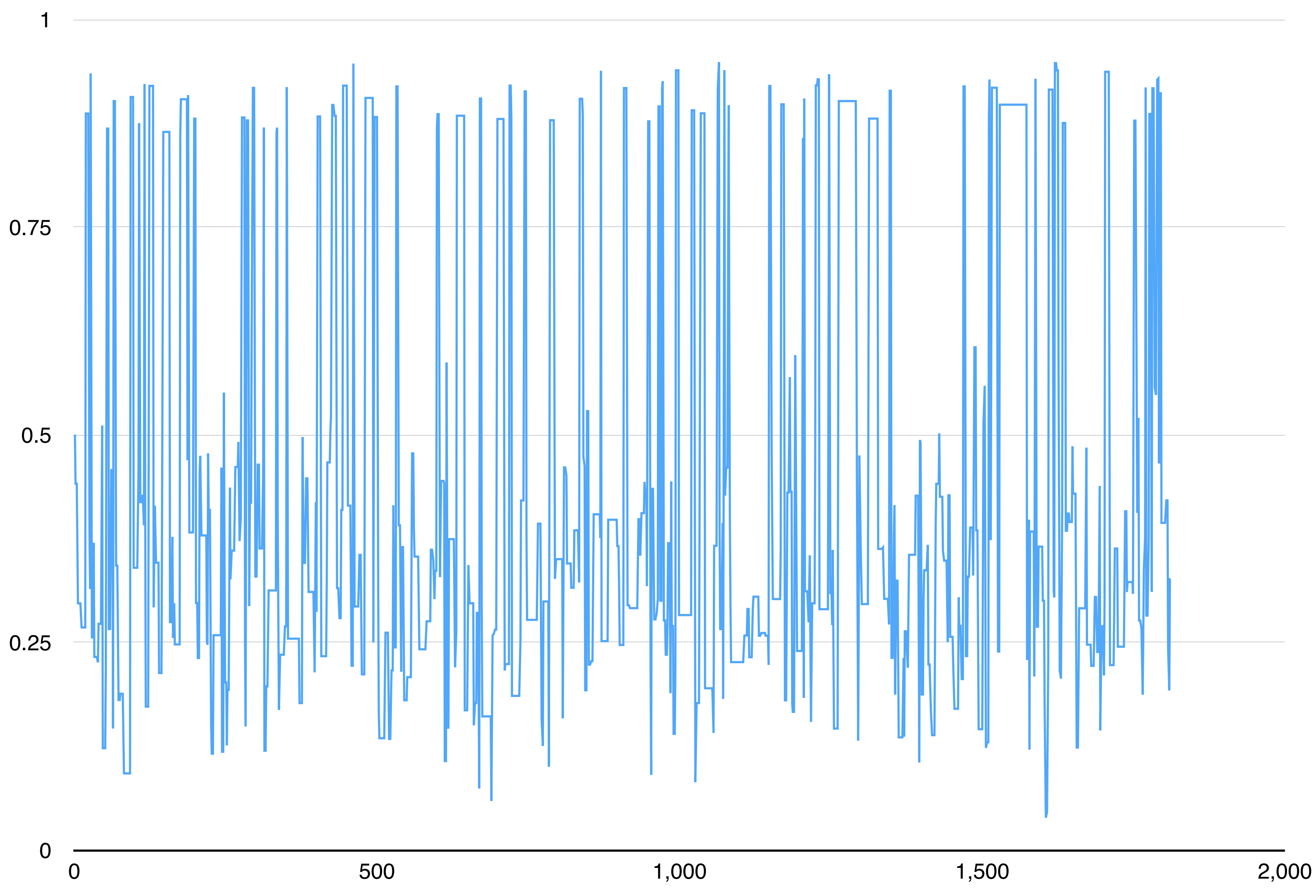
Trace plot

- Baseline



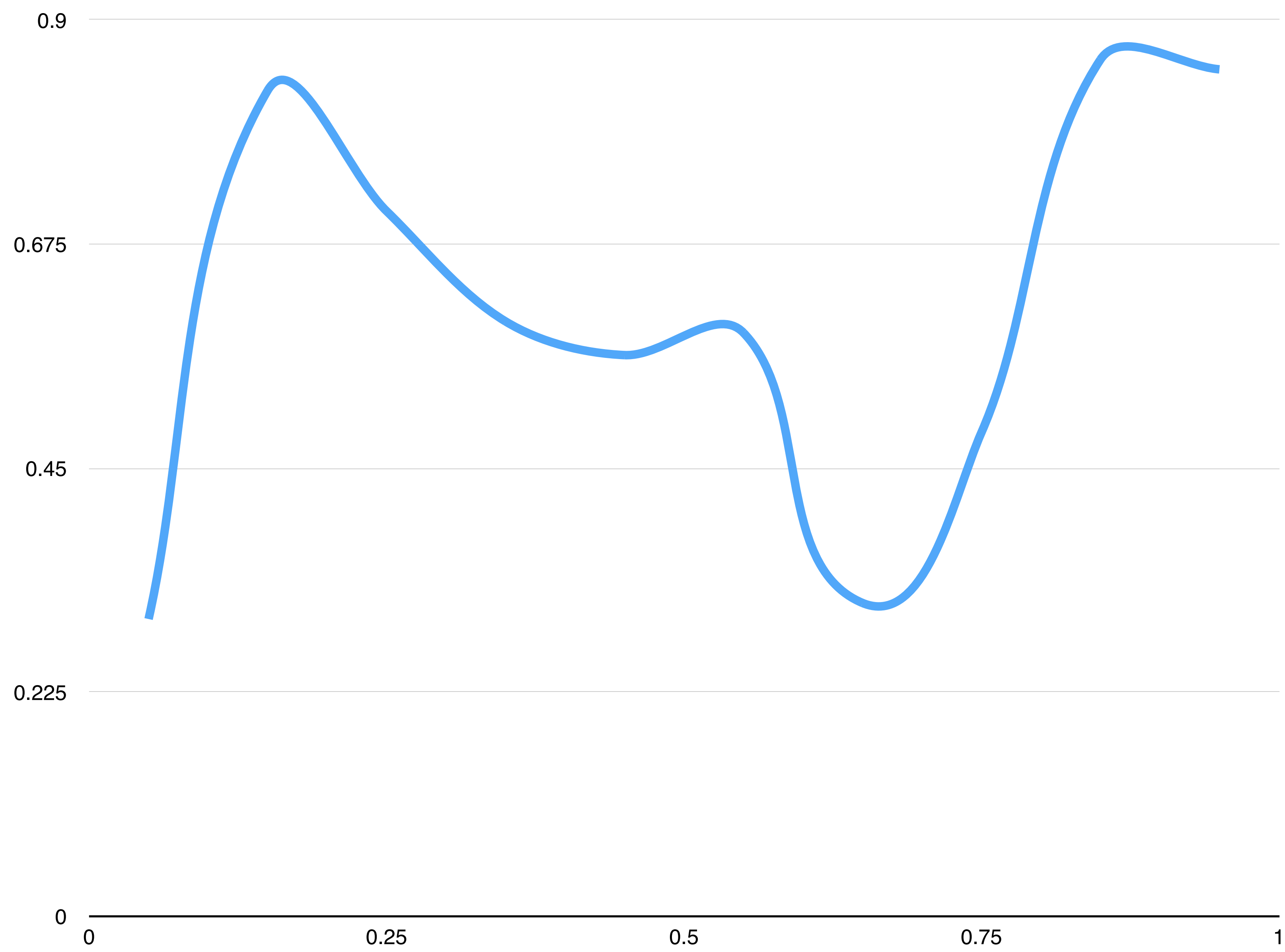
Trace plot

- Our machine-learned MCMC



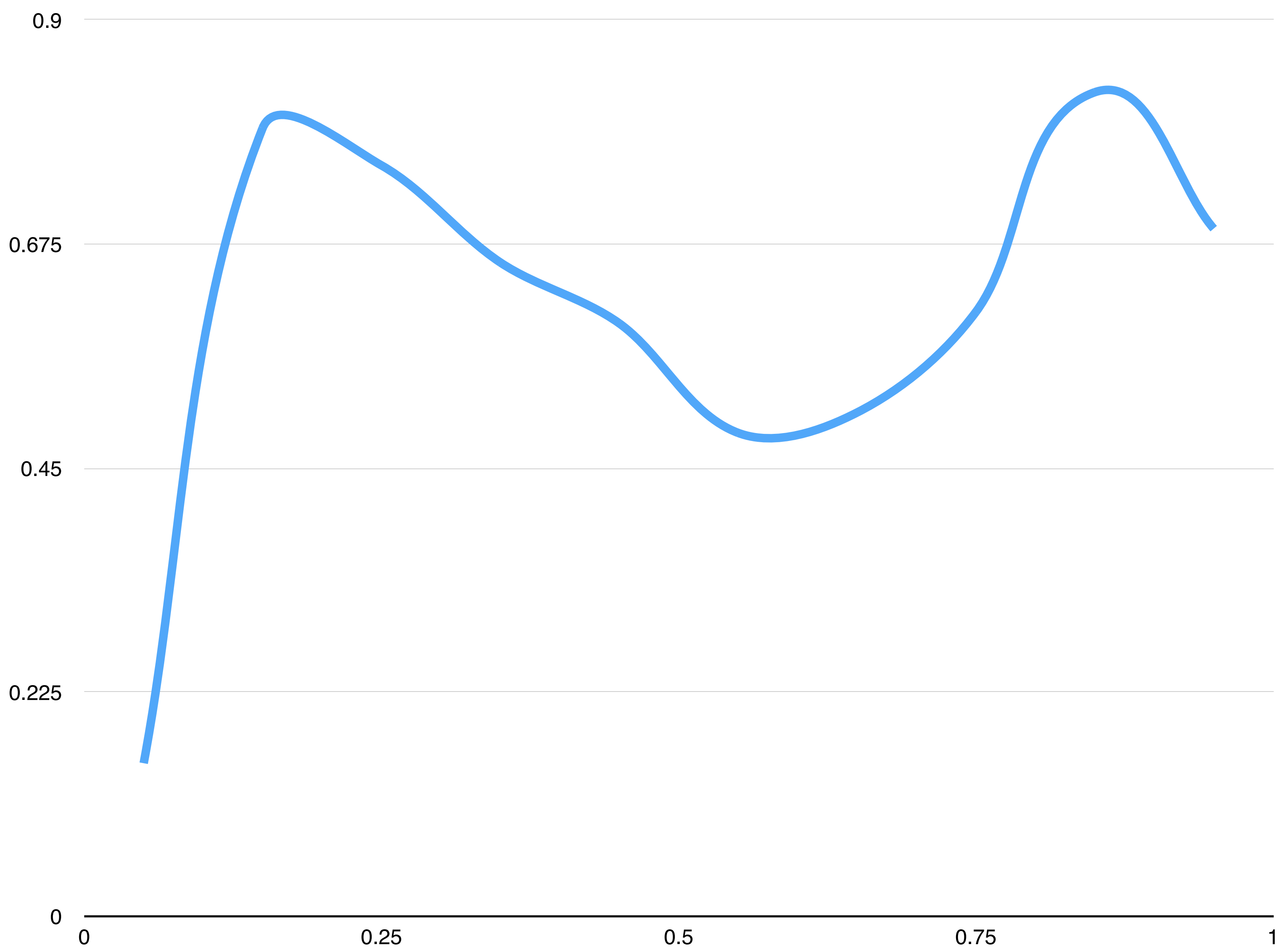
Expected jumping distance

- Numerically maximized at each point

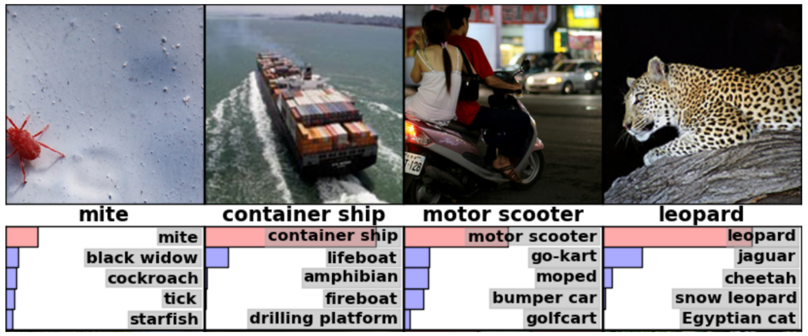


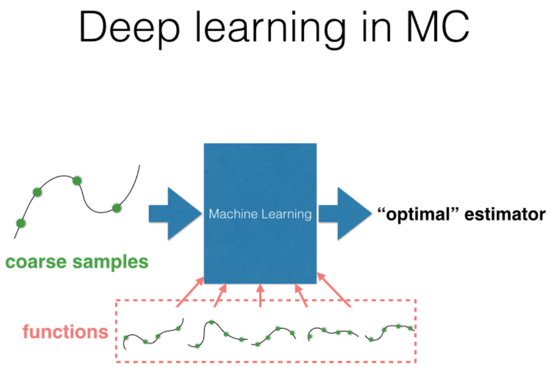
Expected jumping distance

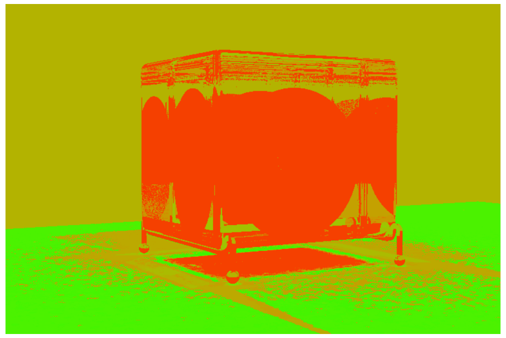
- Our machine-learned MCMC

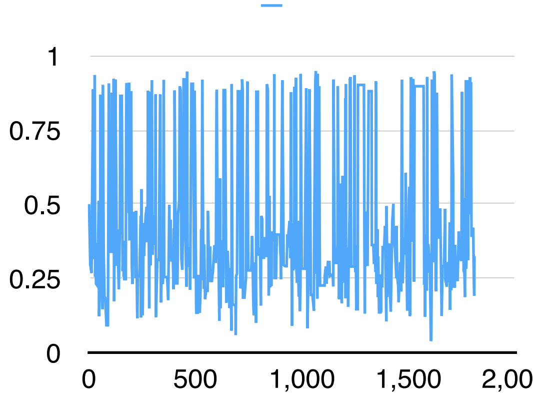


Conclusions









Conclusions

- Two general frameworks on how to utilize machine learning to improve MC/MCMC estimators
  - Auto-mixing MC
  - Auto-adaptive MCMC
- Same key idea
  - Consider samples as “images”, then learns the relationship between them and optimal estimators