Bayesian Learning for Guided Direct Illumination Sampling

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- Guiding needs **radiance approximations**
- How to learn them **reliably**?
- Our proposition:

(Online, Bayesian) **Machine learning**

[*Vorba et al. 2014, Vévoda et al. 2018*]

Take home message

Machine Learning | Bayesian modeling

=

Excellent framework for guided/adaptive Monte Carlo

Bayesian online regression
for
adaptive direct illumination sampling

Petr Vévoda, Ivo Kondapaneni, and Jaroslav Křivánek

Chaos Czech a.s.
Charles University, Prague

corona

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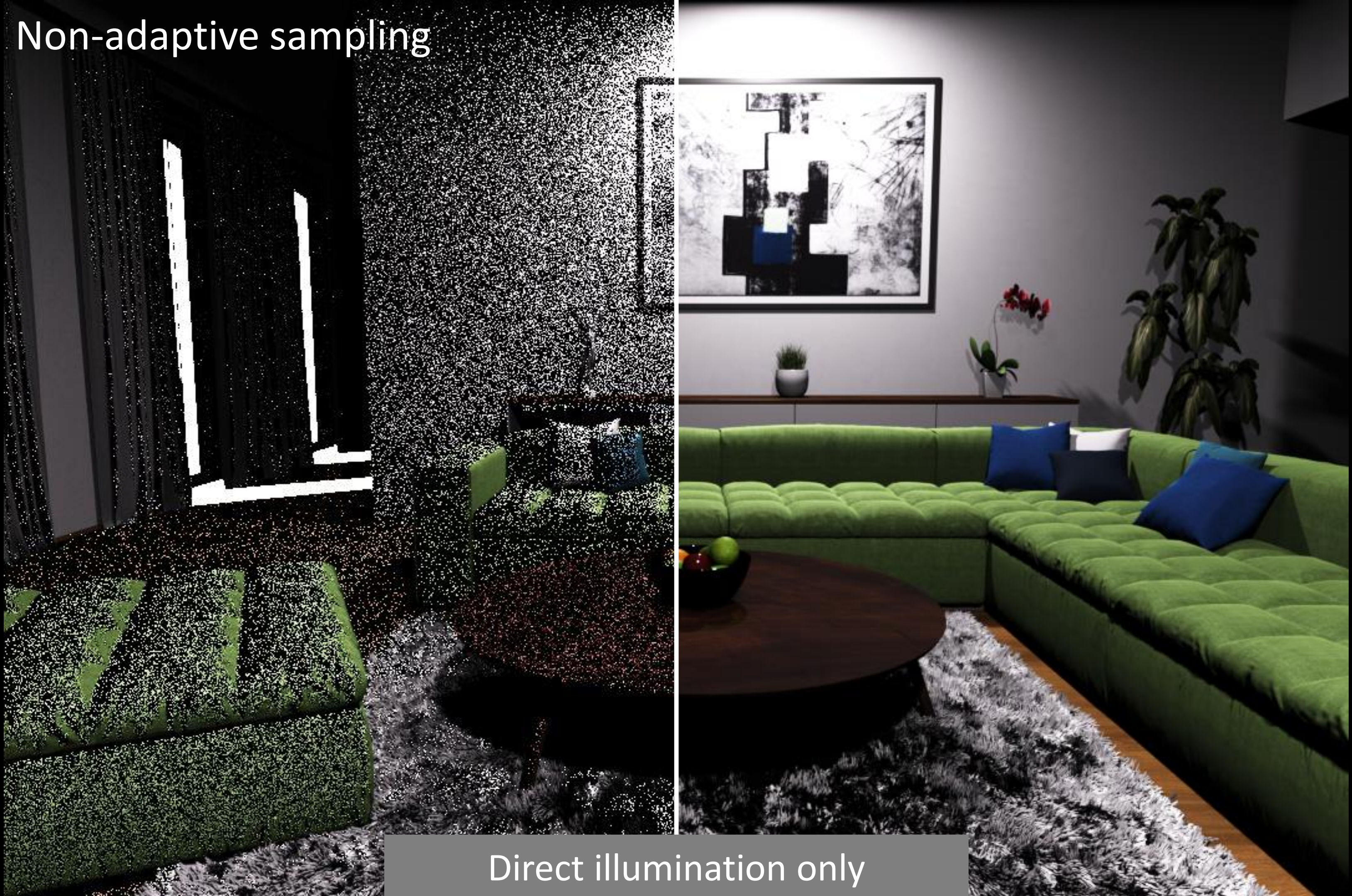
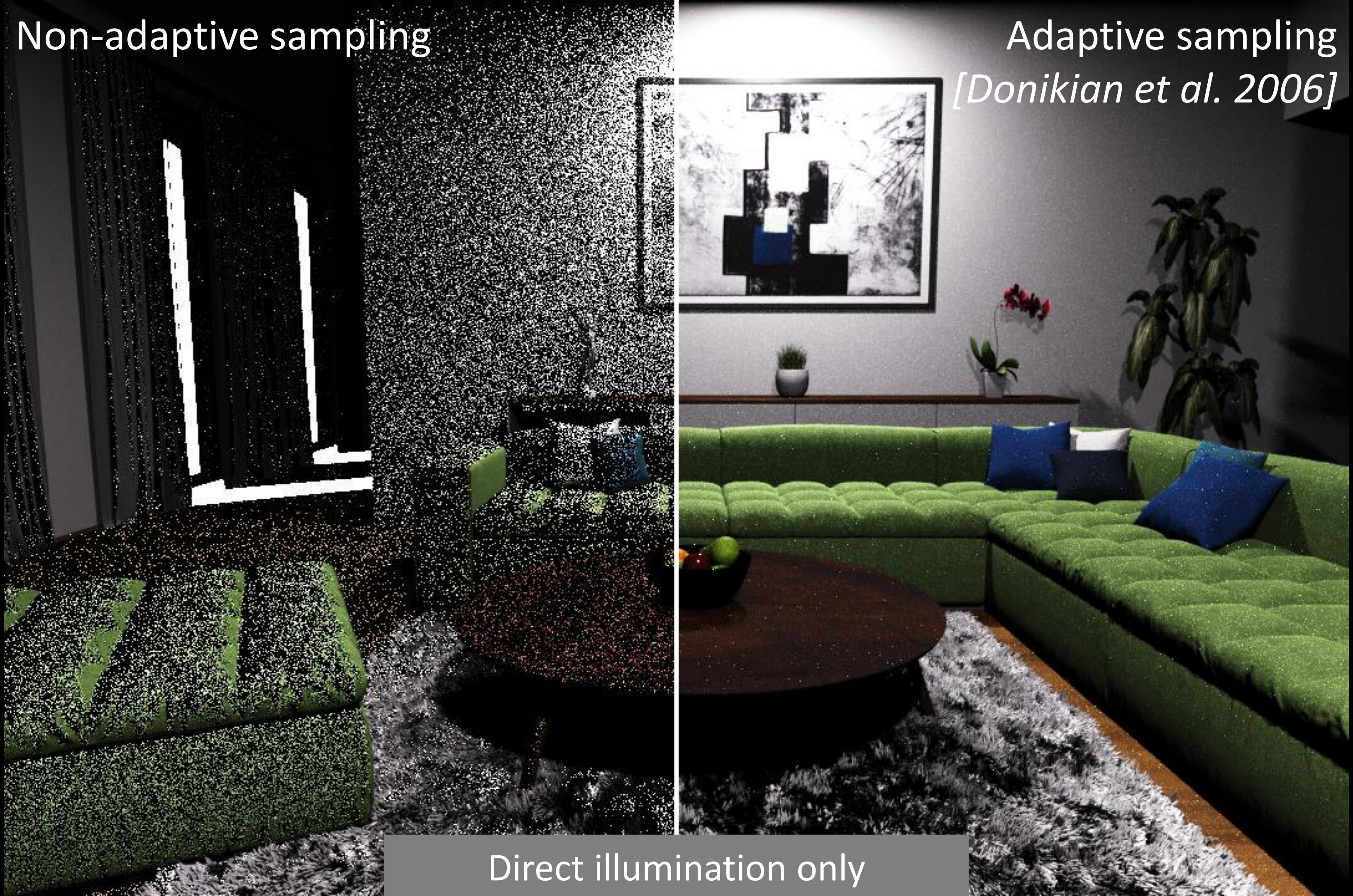
Direct + indirect illumination

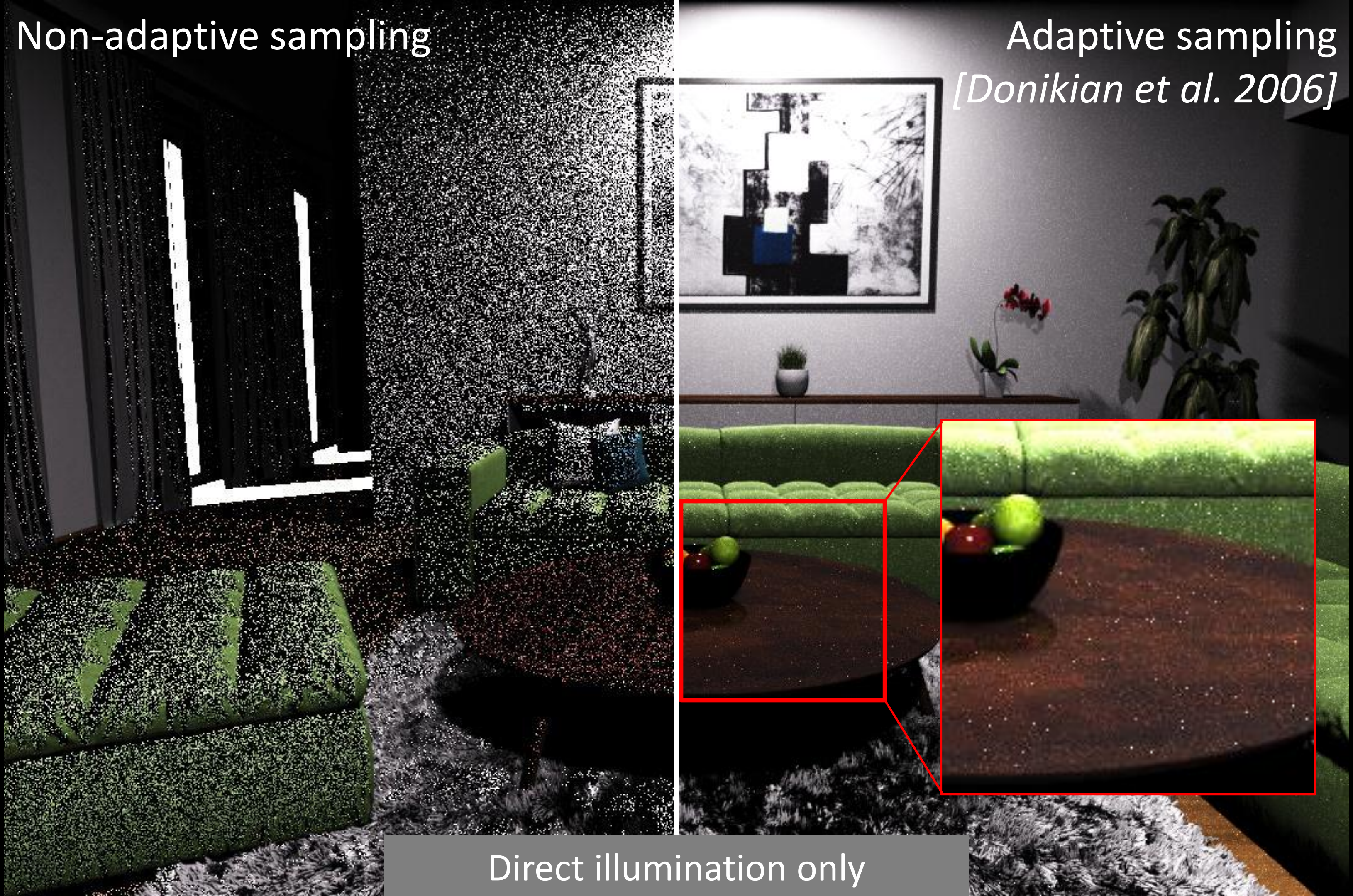
Direct + indirect illumination

Non-adaptive sampling

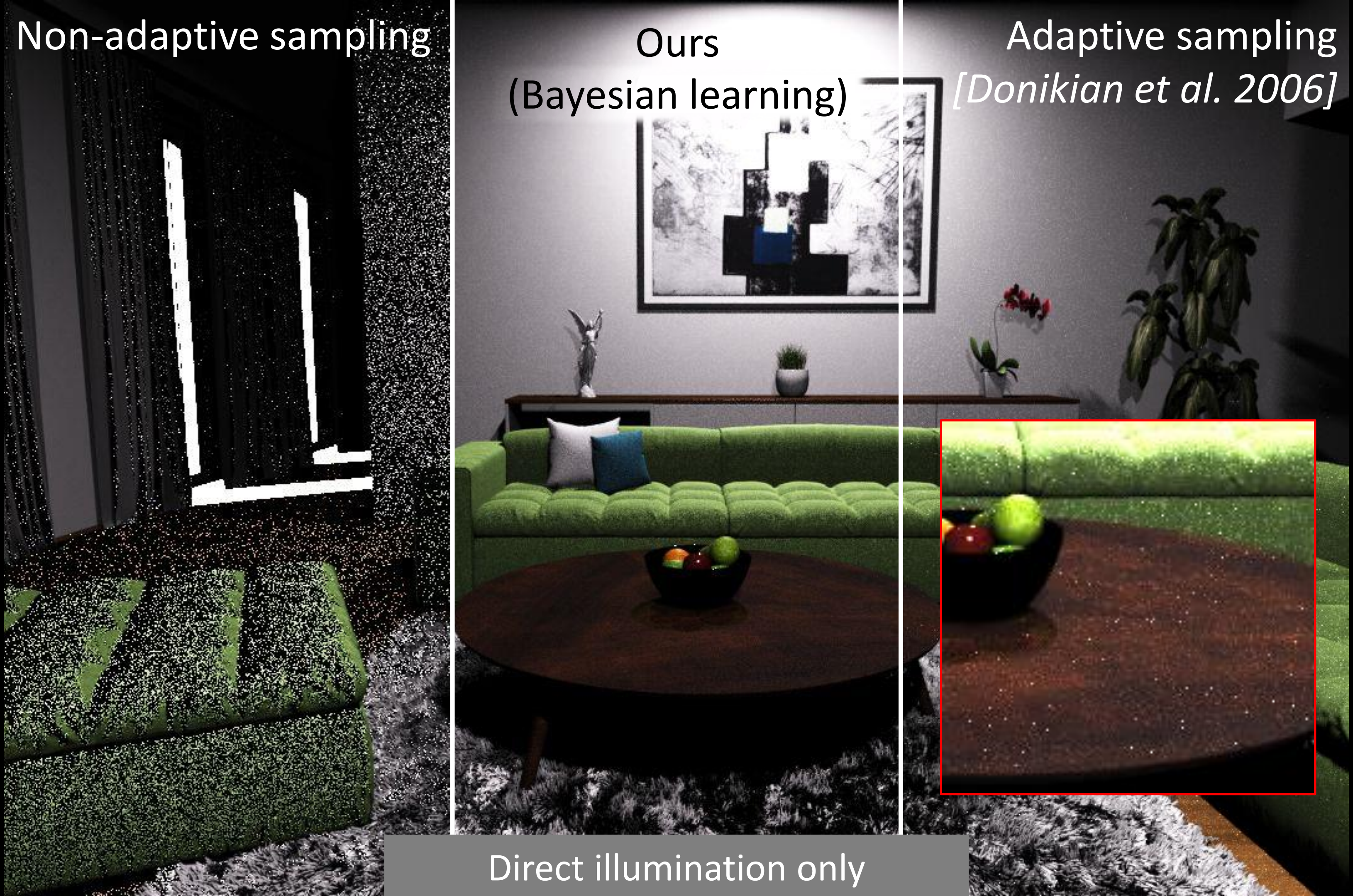


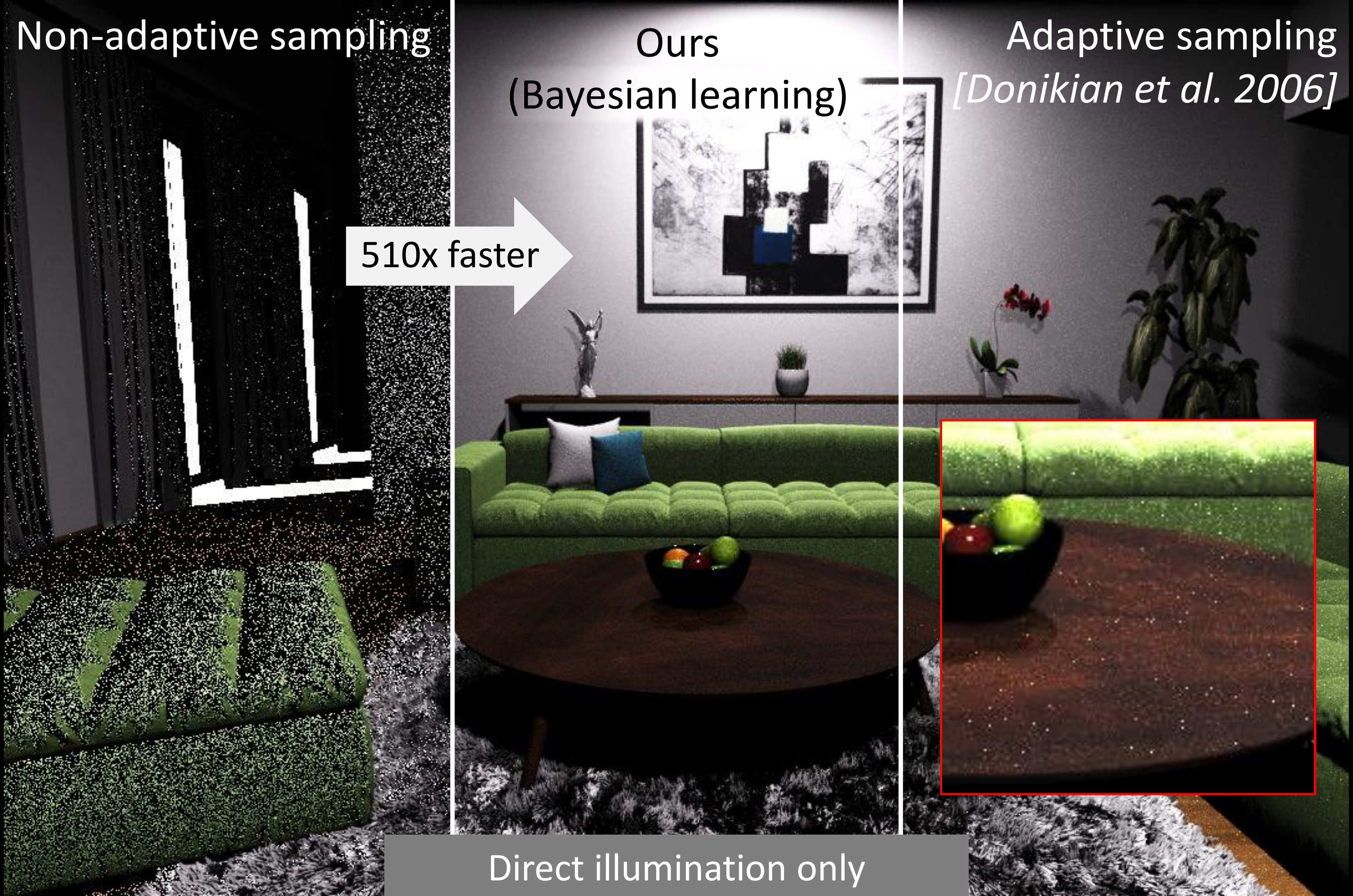
Direct illumination only

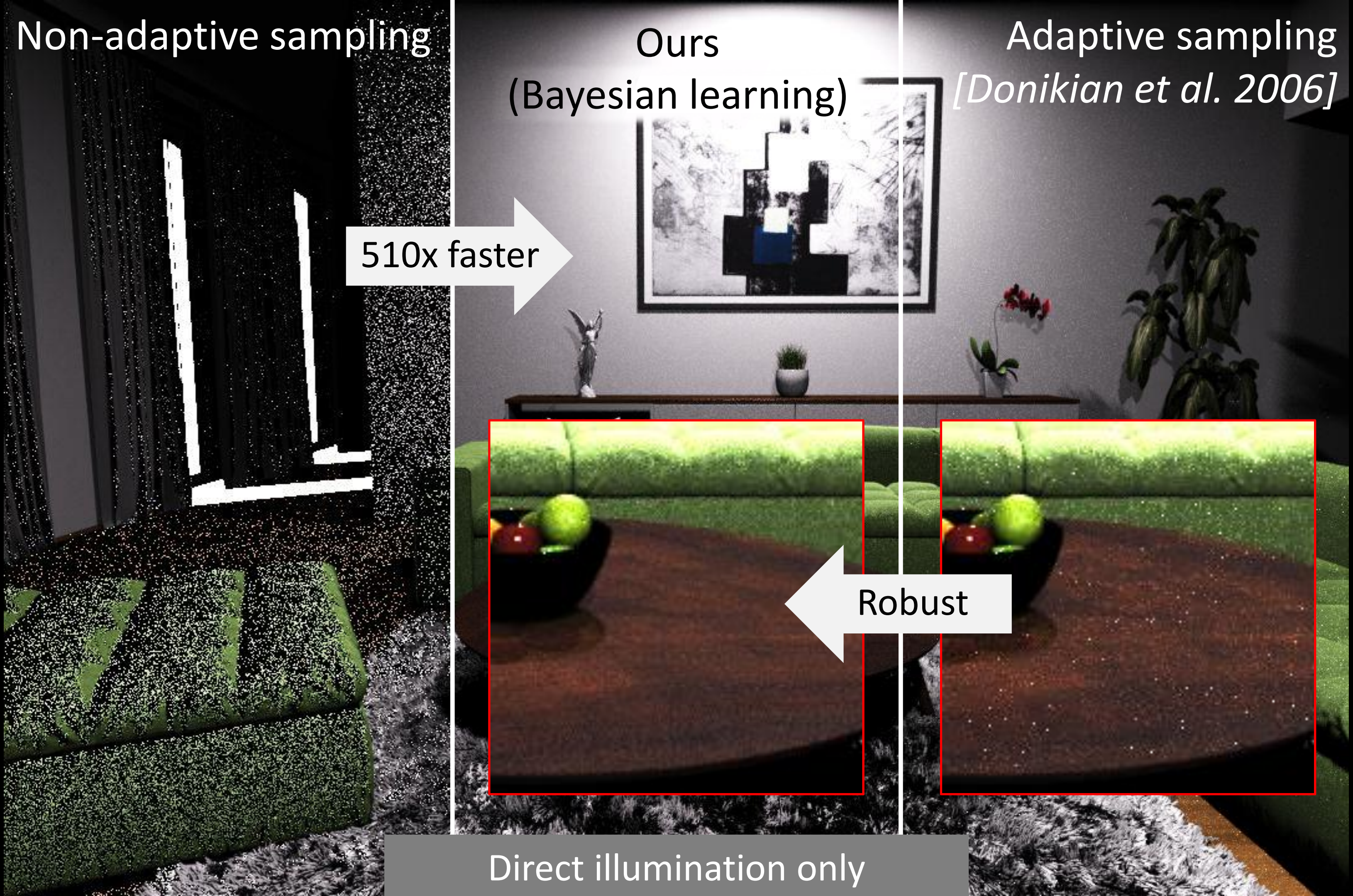

Non-adaptive sampling
Adaptive sampling
[Donikian et al. 2006]
Direct illumination only



Direct illumination only


Non-adaptive sampling
Ours
(Bayesian learning)
Adaptive sampling
[Donikian et al. 2006]
Direct illumination only


Non-adaptive sampling
Ours
(Bayesian learning)
Adaptive sampling
[Donikian et al. 2006]
510x faster
Direct illumination only


Non-adaptive sampling
Ours
(Bayesian learning)
Adaptive sampling
[Donikian et al. 2006]
510x faster
Robust
Direct illumination only

Previous work

Adaptive sampling

- General Monte Carlo
  - Vegas algorithm
    - [*Lepage 1980*]
  - Population MC
    - [*Cappé et al. 2004, ...*]
- Rendering
  - Image sampling
    - [*Mitchell 1987, ...*]
  - Indirect illumination (path guiding)
    - [*Dutre and Willems 1995*, *Jensen 1995*, *Lafortune et al. 1995, ...*]
    - [*Vorba et al. 2014, Muller et al. 2017*]
  - Direct illumination
    - [*Shirley et al. 1996, Donikian et al. 2006, Wang et al. 2009*]

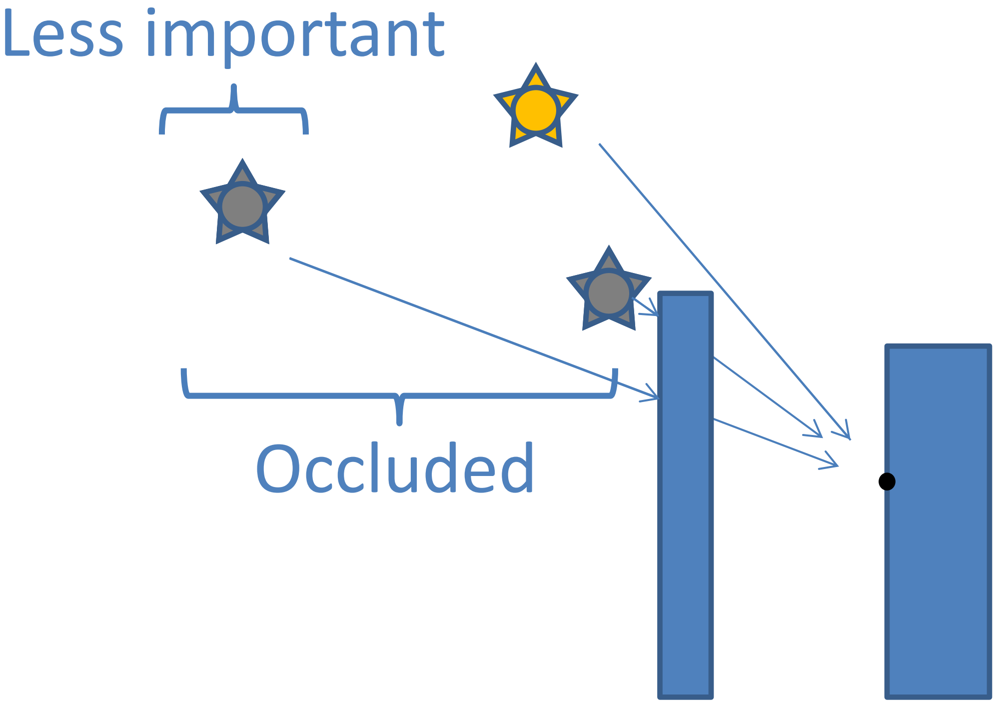
Bayesian methods in rendering

- Filtering
  - NonLocal Bayes [*Boughida and Boubekeur 2017*]

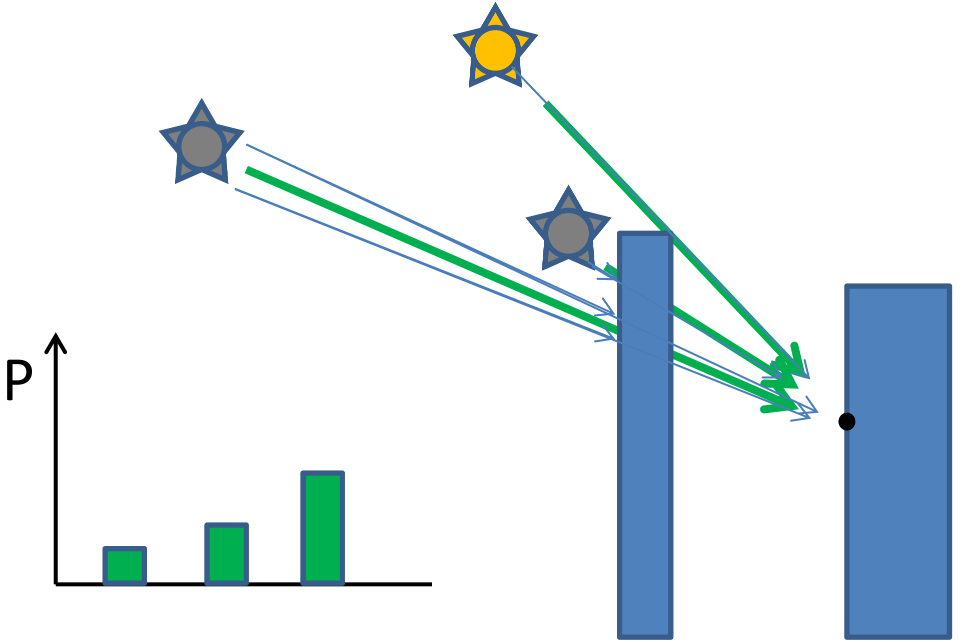
- Global illumination
  - Bayesian Monte Carlo [*Brouilat et al. 2009, Marques et al. 2013*]
  - Path guiding [*Vorba et al. 2014*]

Background

Direct illumination problem

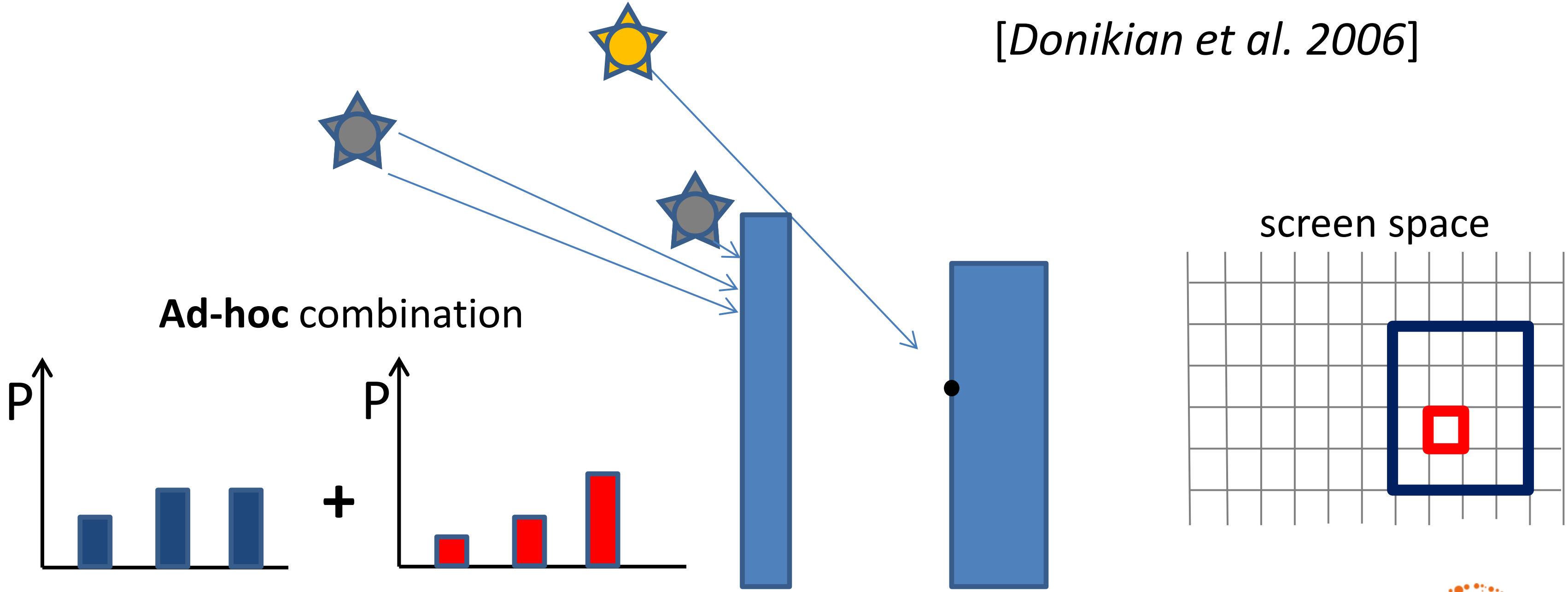


Non-adaptive, un-occluded light sampling

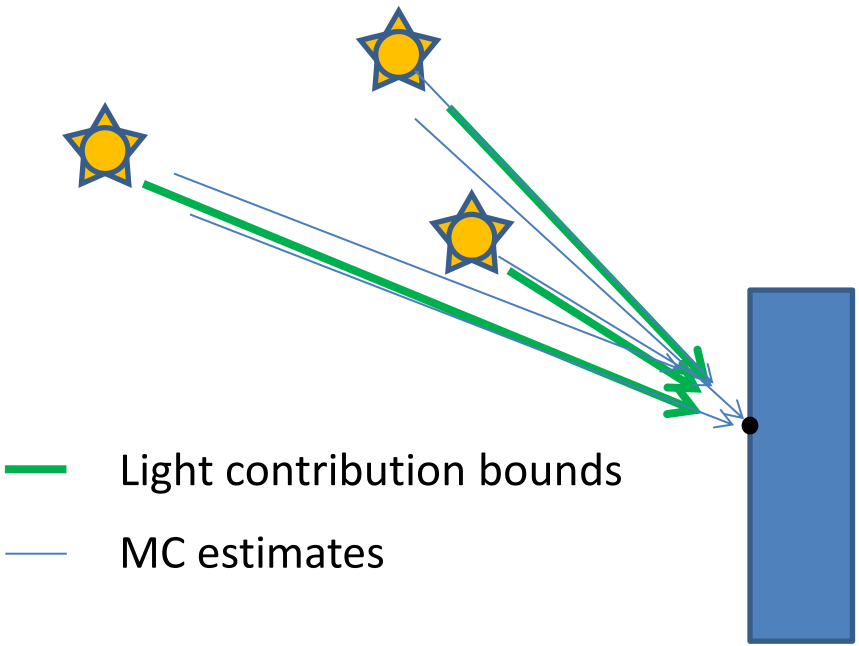


Adaptive light sampling

[*Donikian et al. 2006*]



Problem summary



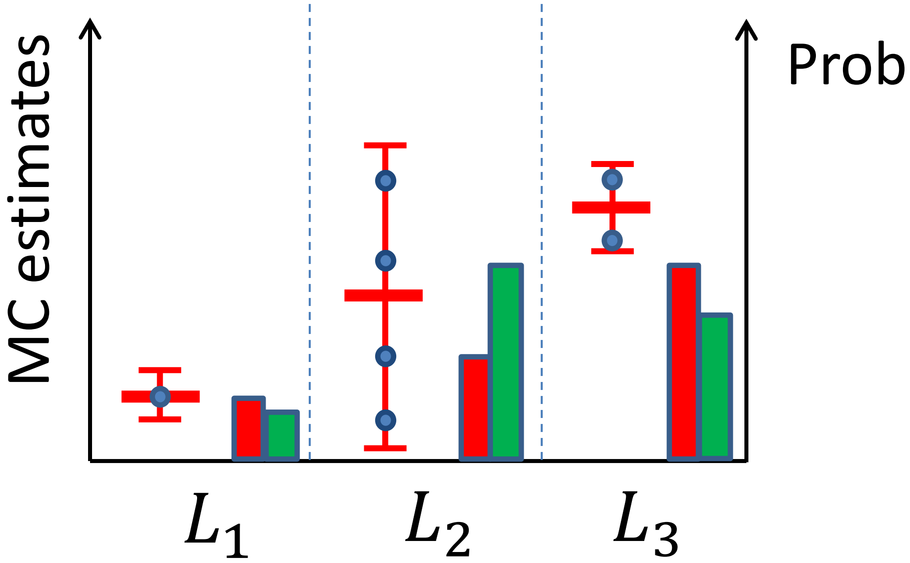
Our approach

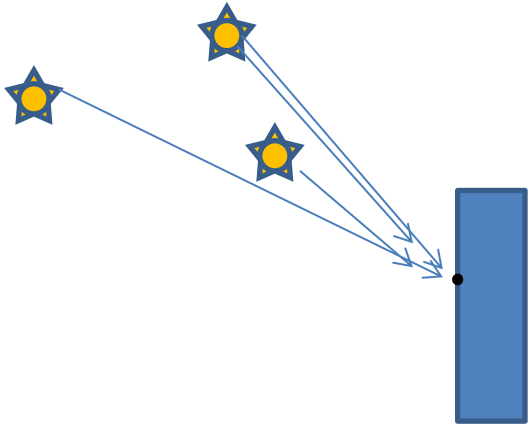
Contributions

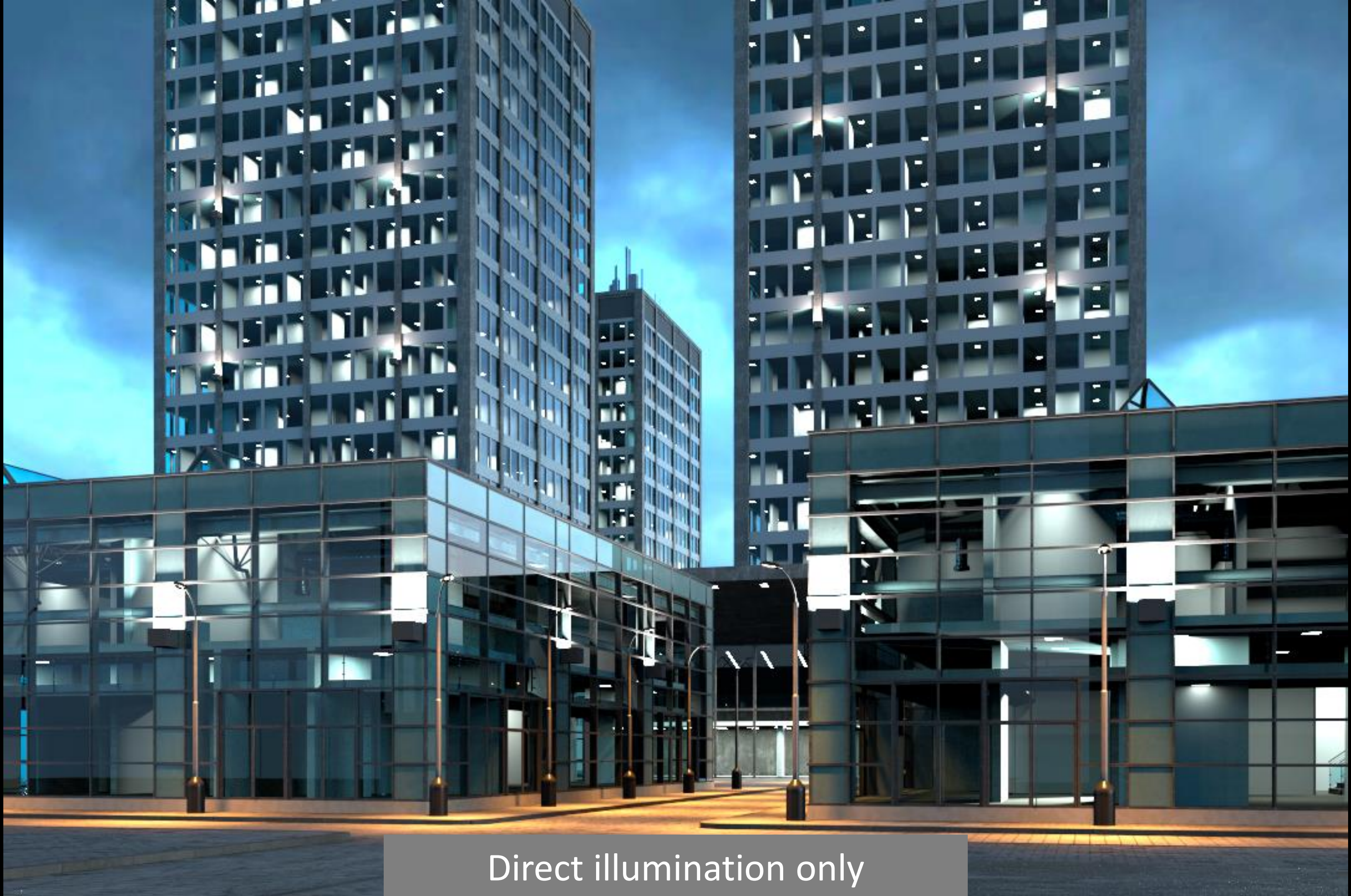
- What distribution should we learn?
- Learning the distribution through Bayesian inference

Optimal light sampling distribution

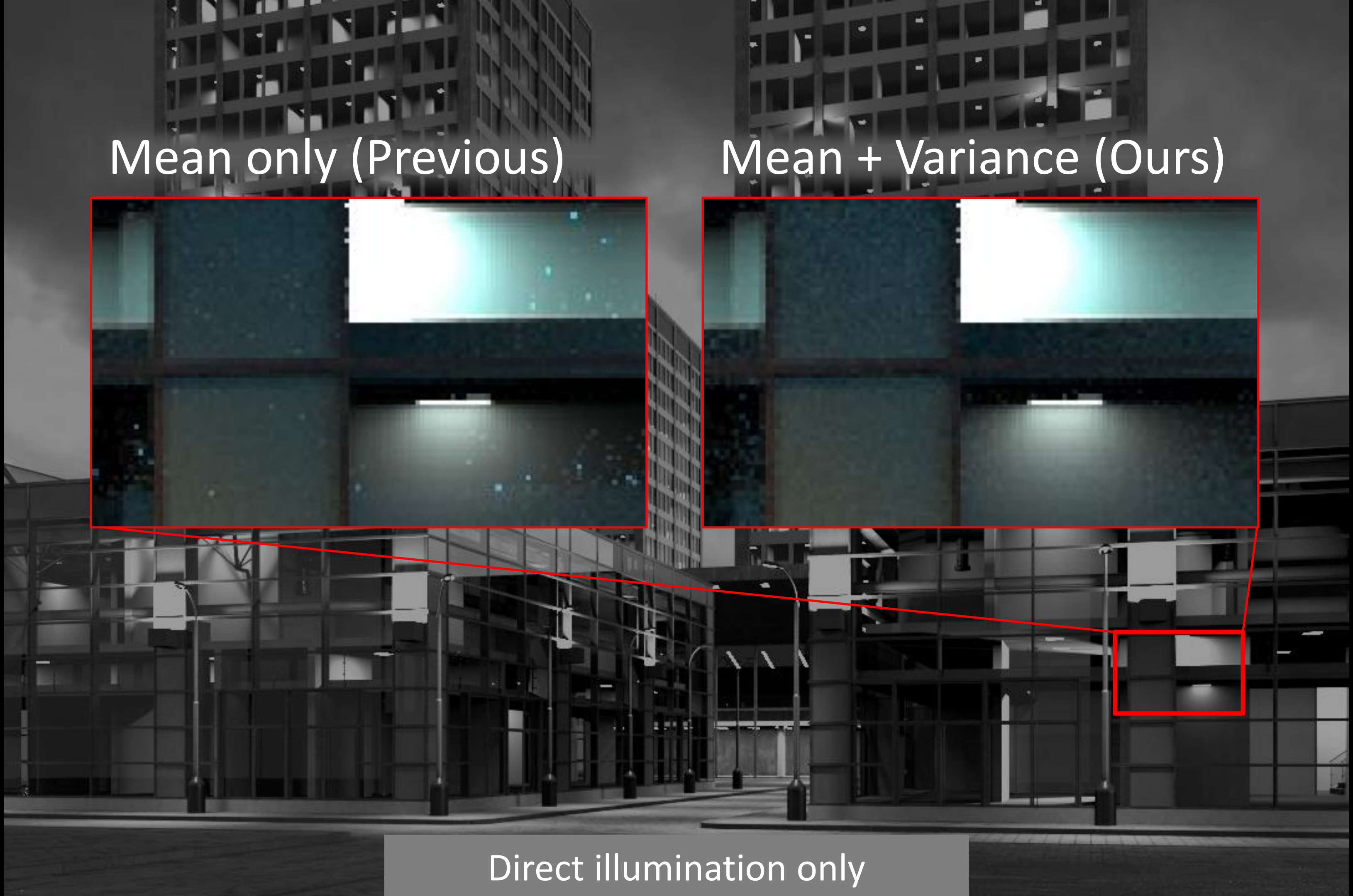
$$P(L) \propto \sqrt{\text{mean}^2 + \text{variance}}$$







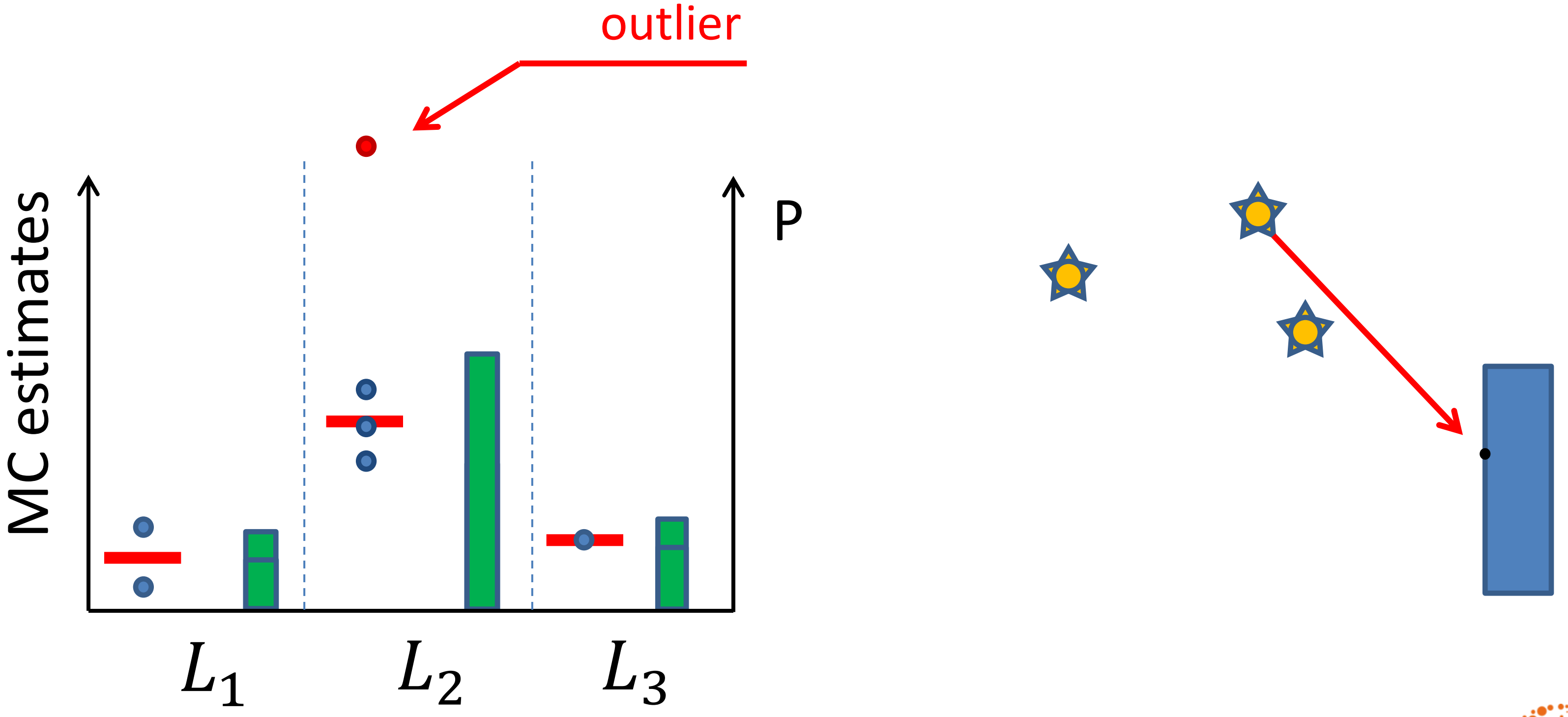
Direct illumination only


Mean only (Previous)
Mean + Variance (Ours)
Direct illumination only

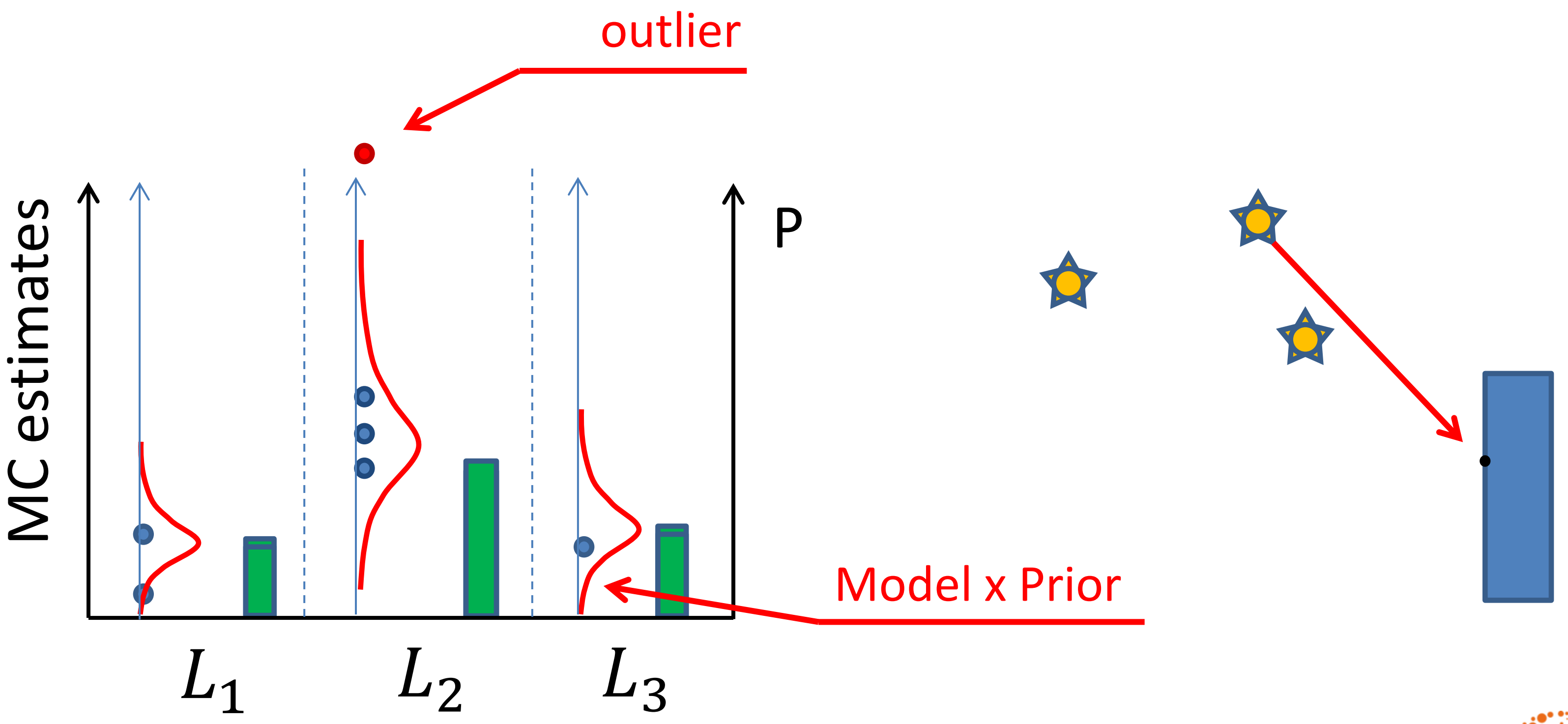
Contributions

- Optimal sampling distribution
- Learning the distribution through Bayesian inference

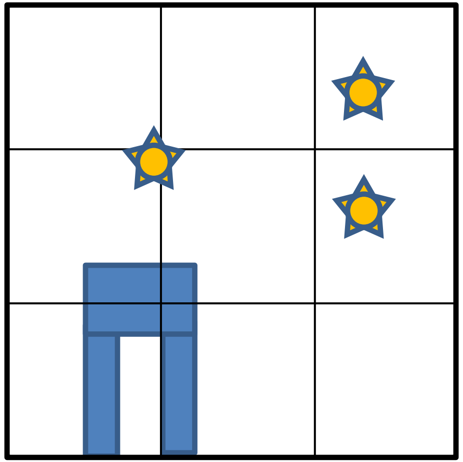
Naive adaptive light sampling



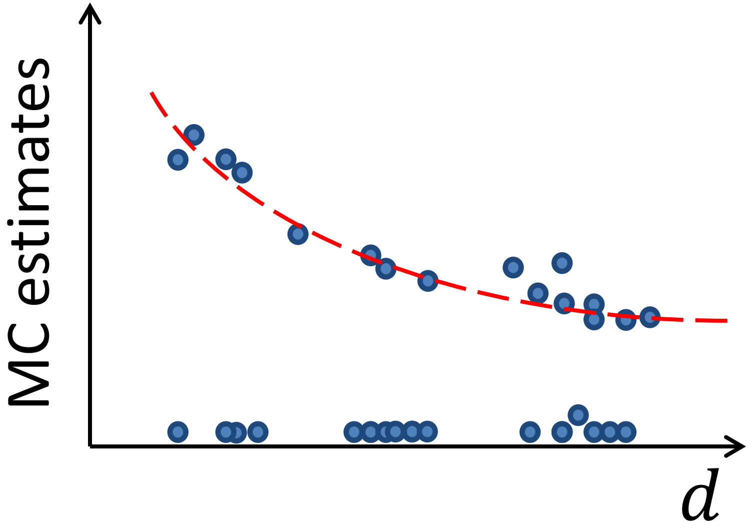
Bayesian adaptive light sampling

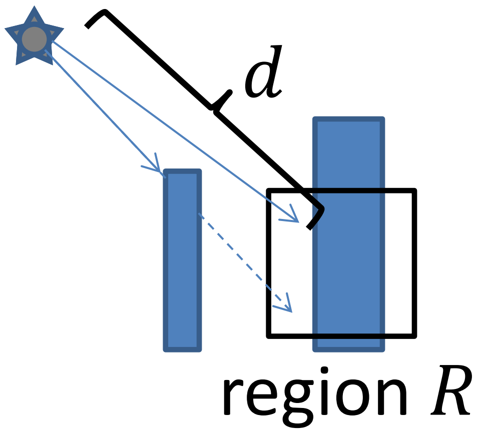


Scene subdivided in regions



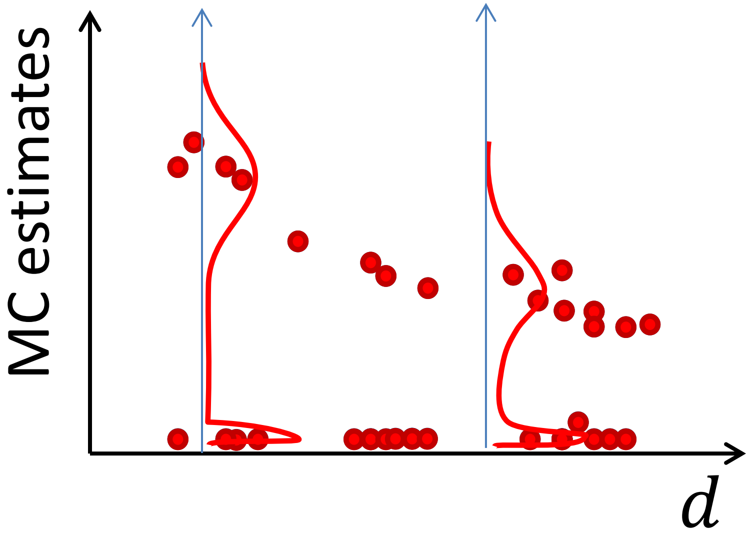
Light-region statistics





Regression data model

Light-region data



Parameters:

- k, h - normal distr. parameters
- p_0 - probability of occlusion

$$(1 - p_0) \times N(\text{est.} \,|\, \frac{k}{d^2}, \frac{h}{d^4})$$

$$p_0 \times \delta(\text{est.})$$

Conjugate prior

$$\textbf{posterior} \propto \text{likelihood} \times \textbf{prior}$$

Same functional form

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Our (conjugate) priors

$$p_0 \sim \mathrm{Beta}(p_0 | \underbrace{\ldots}_{})$$

$$k, h \sim \text{Normal inverse gamma}(k, h | \underbrace{\mu_0}_{}, \underbrace{\ldots}_{})$$

Hyperparameters

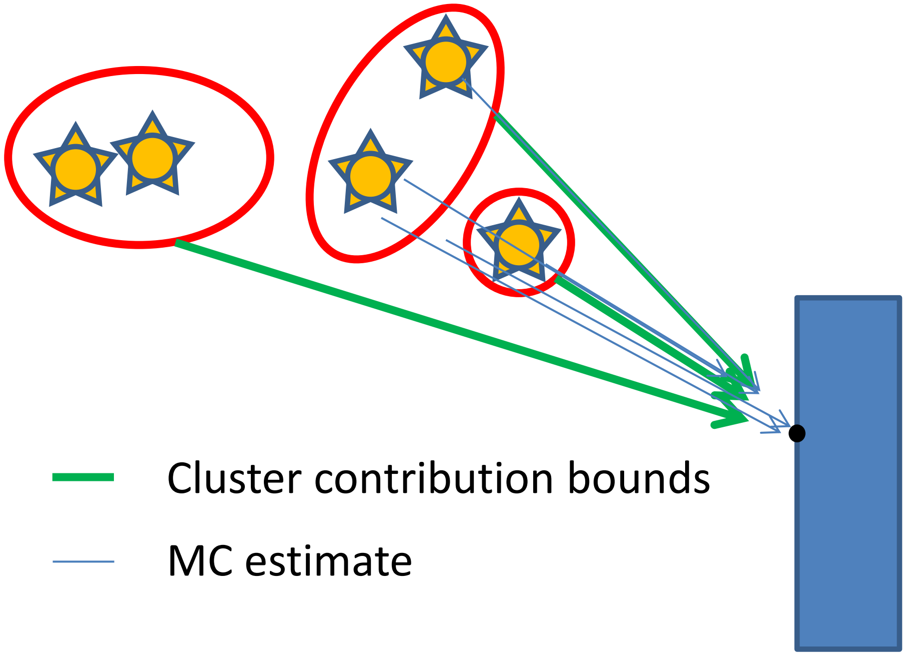
Light contrib. estimate

Algorithmic summary

- During each Next event estimation (in a region)
  - Compute data distributions for each light (mean, variance).
  - Build sampling PMF over lights
  - Choose lights form the PMF & samples on lights at random
  - Update light-region stats

Scalability – Light clustering

Technical detail – not essential for our take-home message



Cluster contribution bounds

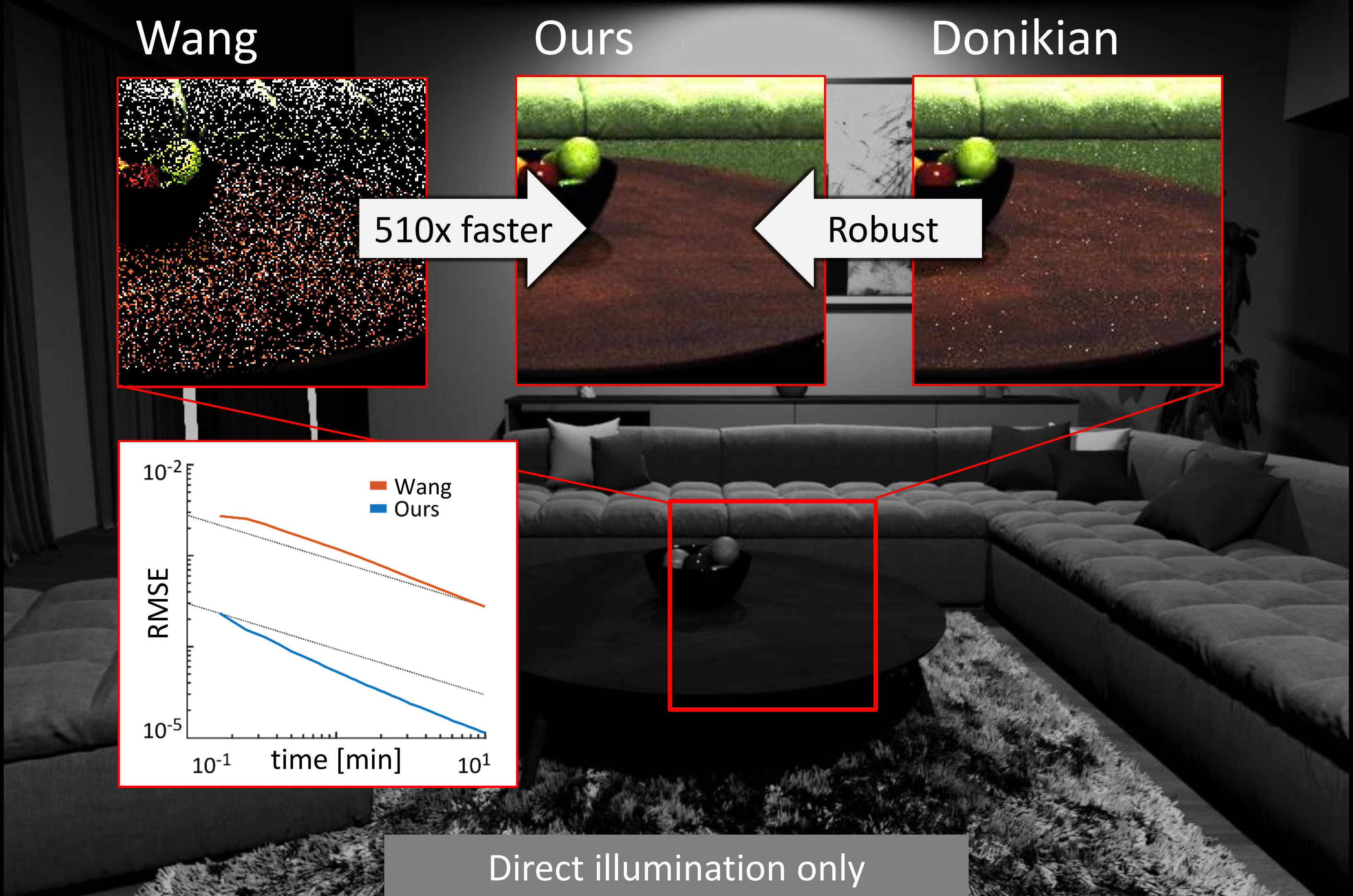
MC estimate

Results

Tests

	Direct only	Direct + indirect
Simple occlusion		
Complex occlusion		

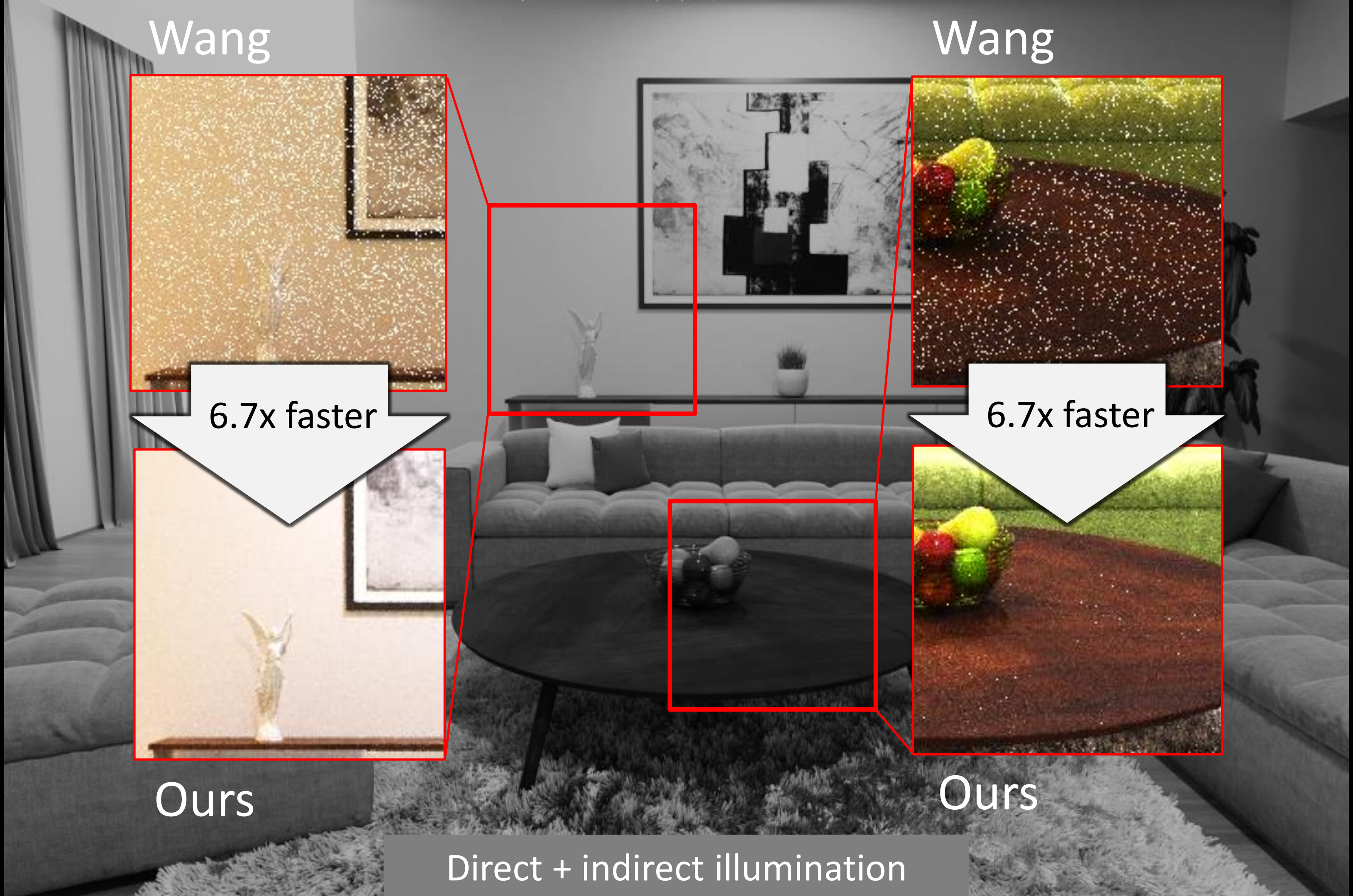
Direct illumination only


Wang
Ours
Donikian
510x faster
Robust
10^{-2}
10^{-5}
RMSE
Wang
Ours
10^{-1}
time [min]
10^{1}
Direct illumination only

Tests

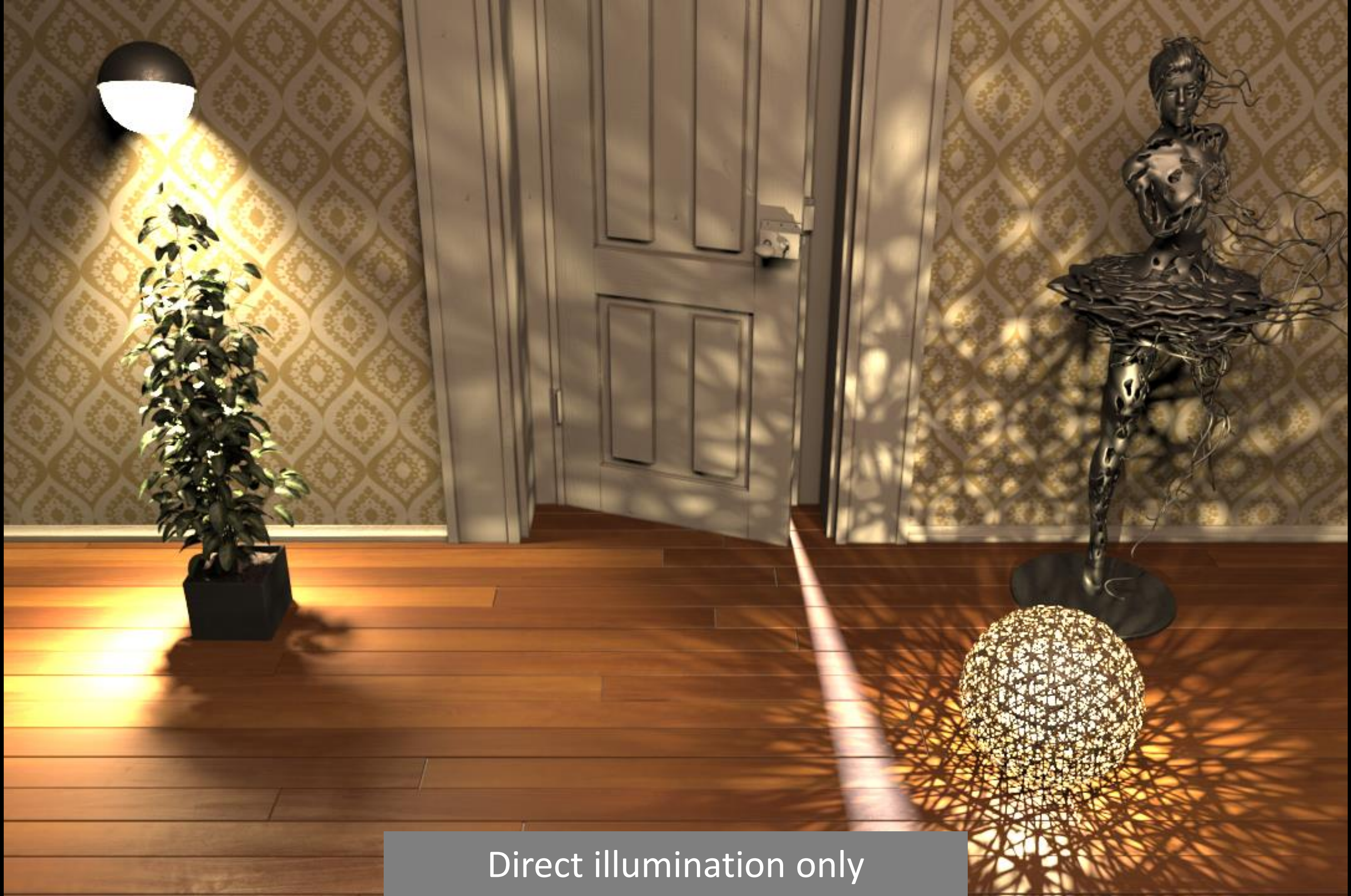
	Direct only	Direct + indirect
Simple occlusion	✓	
Complex occlusion		

Direct + indirect illumination

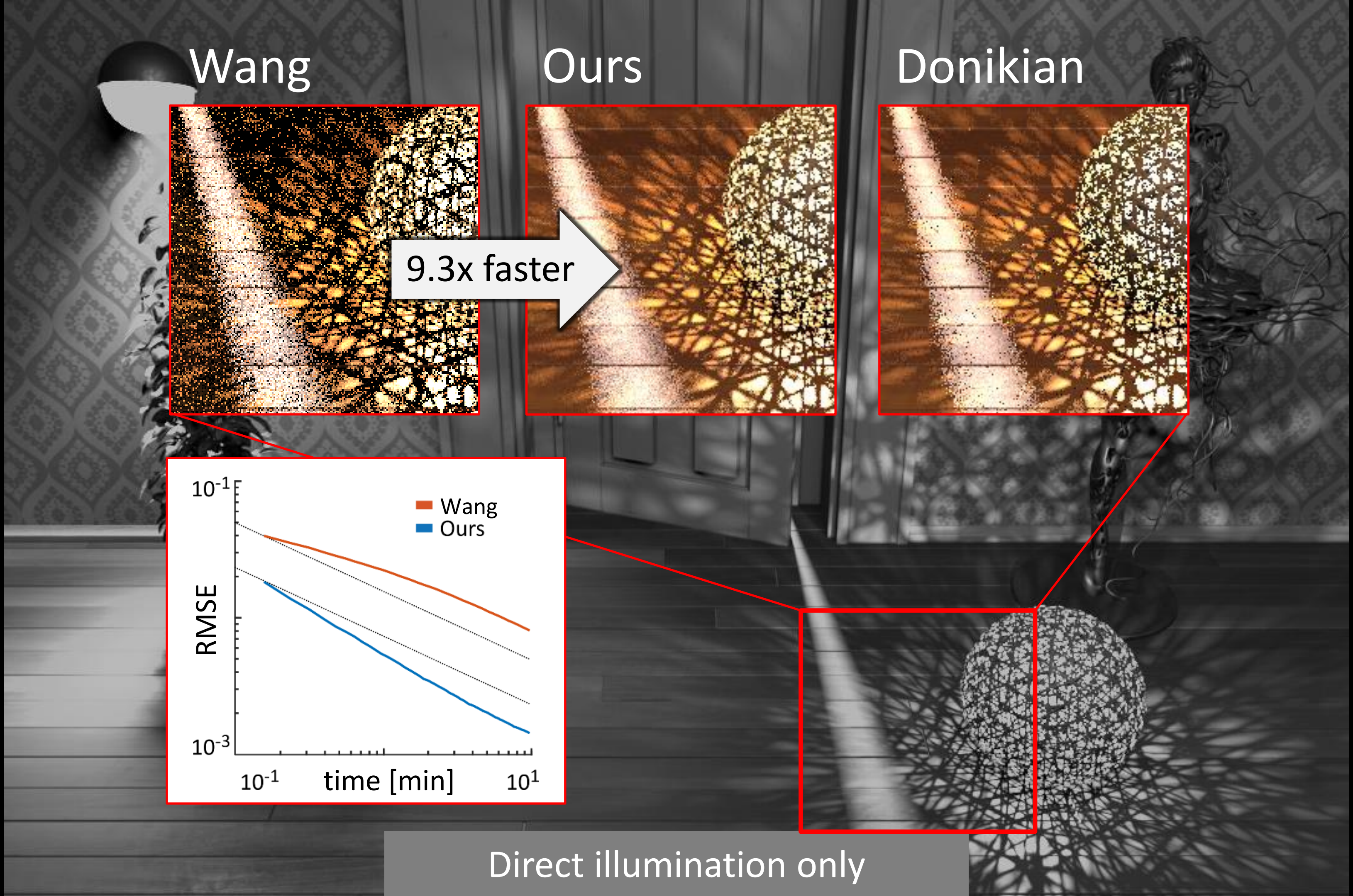

Wang
Wang
6.7x faster
6.7x faster
Ours
Ours
Direct + indirect illumination

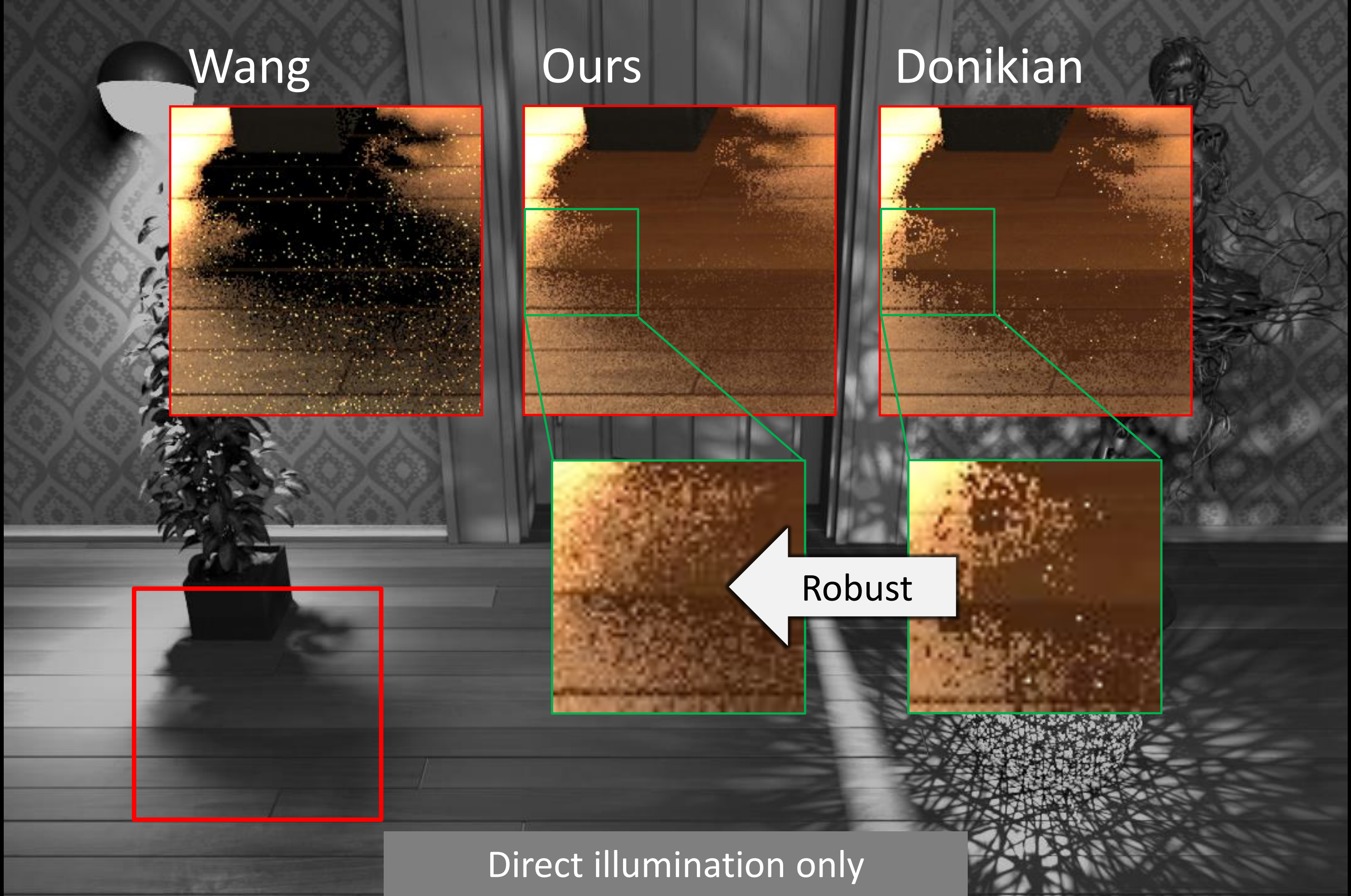
Tests

	Direct only	Direct + indirect
Simple occlusion	✓	✓
Complex occlusion		



Direct illumination only

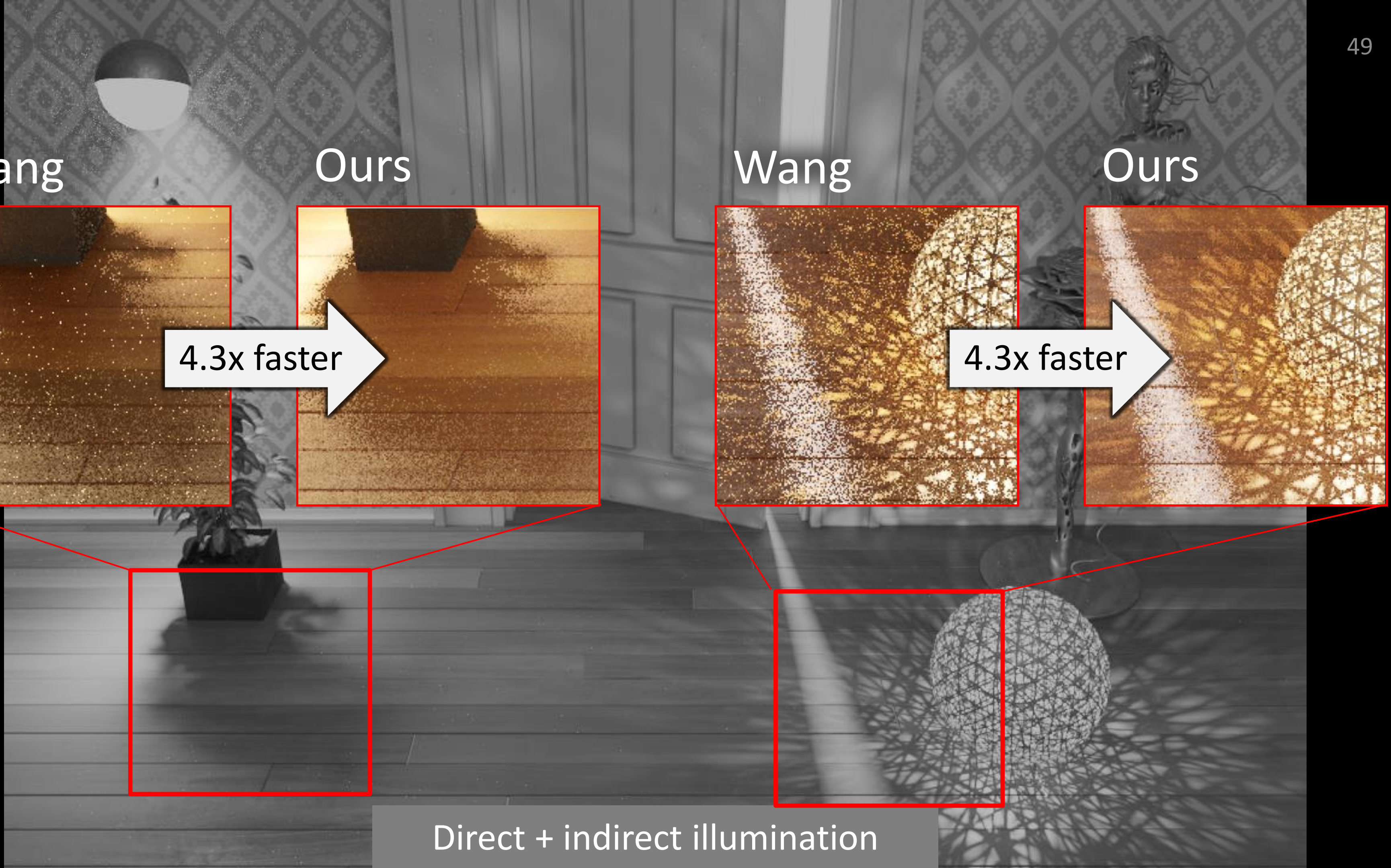

Wang
Ours
Donikian
9.3x faster
10^{-1}
10^{-3}
RMSE
Wang
Ours
10^{-1}
time [min]
10^{1}
Direct illumination only

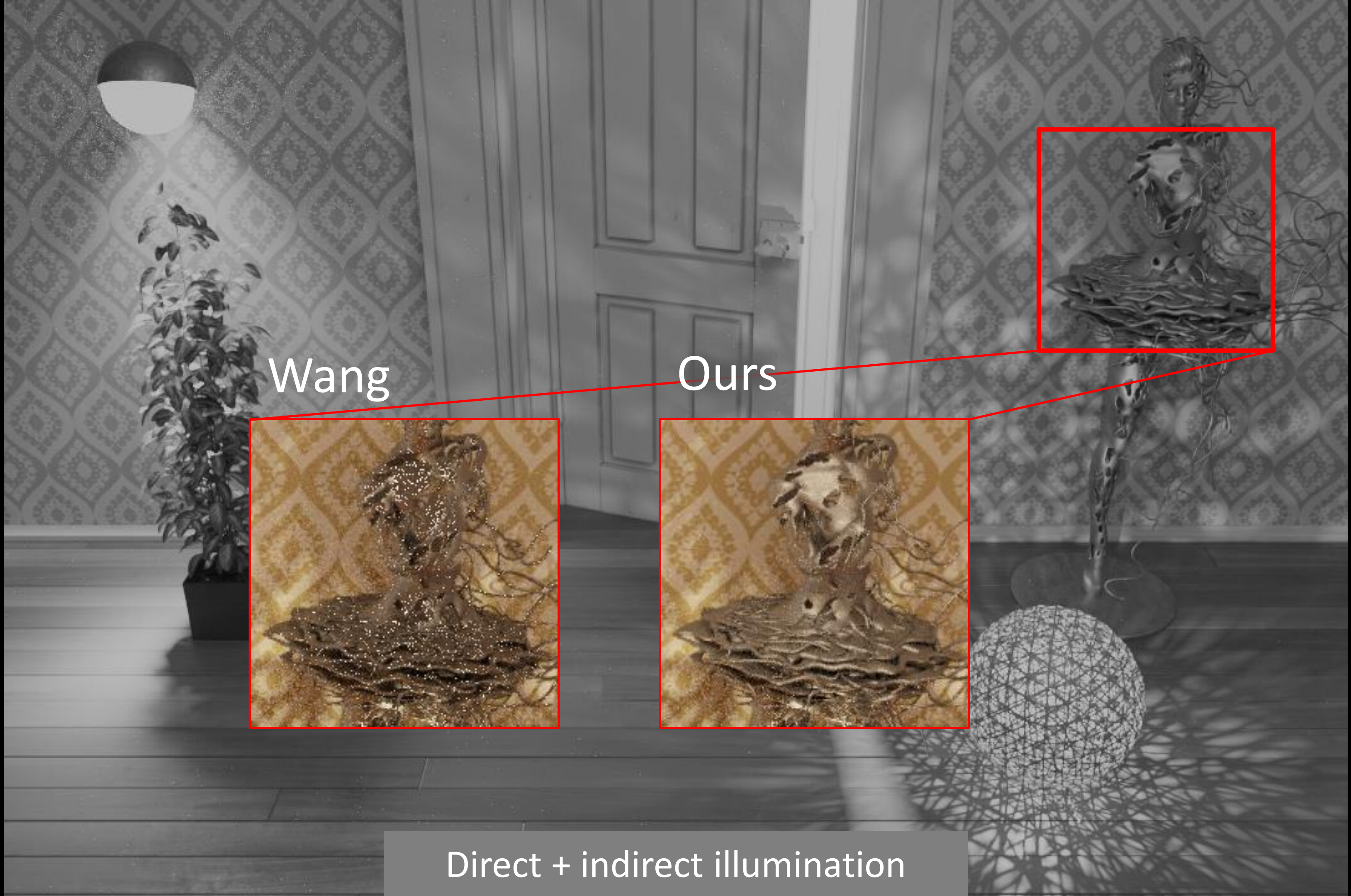

Wang
Ours
Donikian
Robust
Direct illumination only

Tests

	Direct only	Direct + indirect
Simple occlusion	✓	✓
Complex occlusion	✓	

Direct + indirect illumination

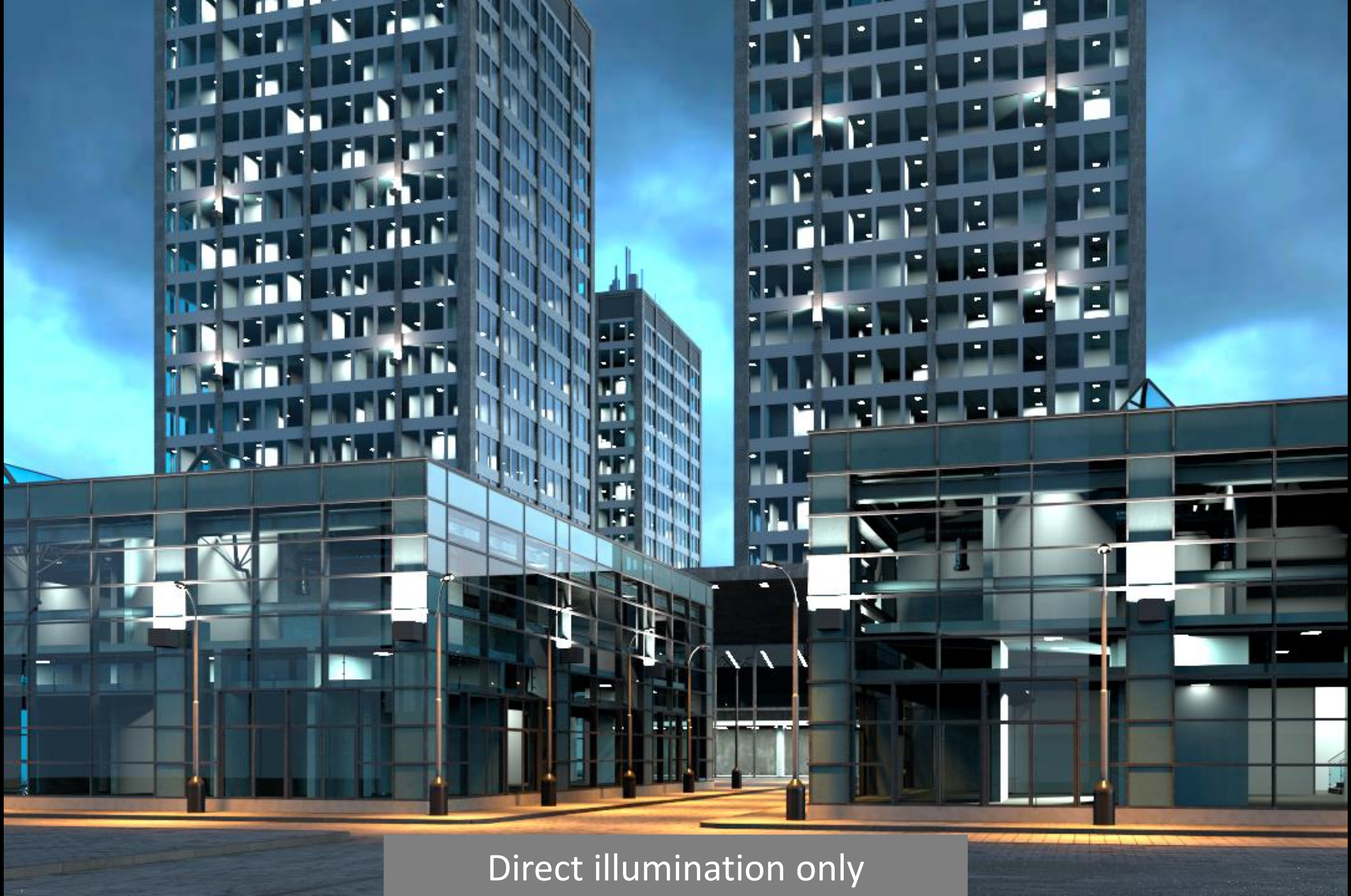

Wang
Ours
4.3x faster
Wang
Ours
4.3x faster
Direct + indirect illumination


Wang
Ours
Direct + indirect illumination

Tests

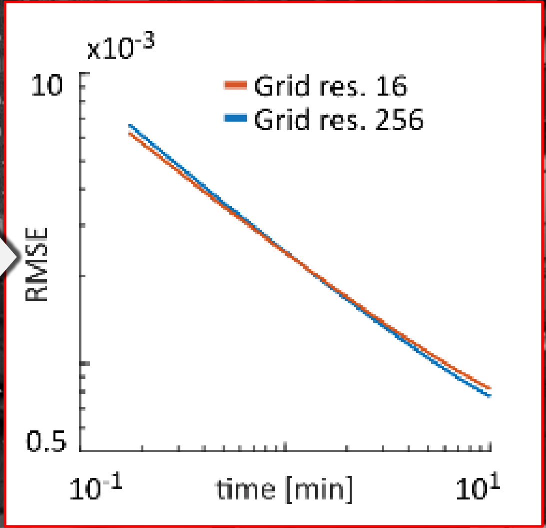
	Direct only	Direct + indirect
Simple occlusion	✓	✓
Complex occlusion	✓	✓

- Grid resolution



Direct illumination only

$$(1-p_0)\times N\left(\text{est.}\middle|\frac{k}{d^2},\frac{h}{d^4}\right)$$
$$p_0 \times \delta(\text{est.})$$



Direct illumination only

Tests

	Direct only	Direct + indirect
Simple occlusion	✓	✓
Complex occlusion	✓	✓

- Grid resolution ✓
- Temporal coherence


Ours
Wang
Direct illumination only

Contribution

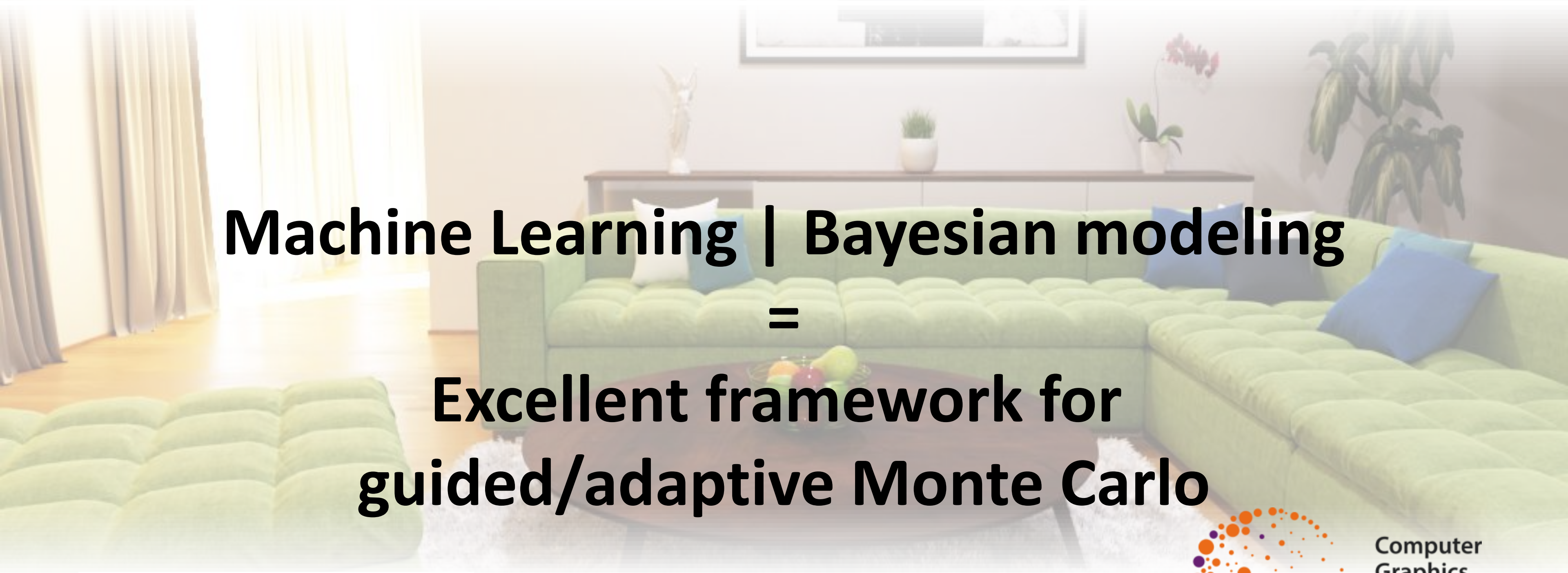
- **Bayesian framework for robust adaptivity/guiding**
- Optimal sampling distribution
- Algorithm for direct illumination
  - Unbiased, adaptive, robust
  - Easy to integrate

Acknowledgments

- Ludvík Koutný (a.k.a. rawalanche)

- Funding
  - Charles University: GAUK 1172416, SVV-2017-260452
  - Czech Science Foundation: 16-18964S, 19-07626S.

Take home message



Machine Learning | Bayesian modeling

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Excellent framework for
guided/adaptive Monte Carlo

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