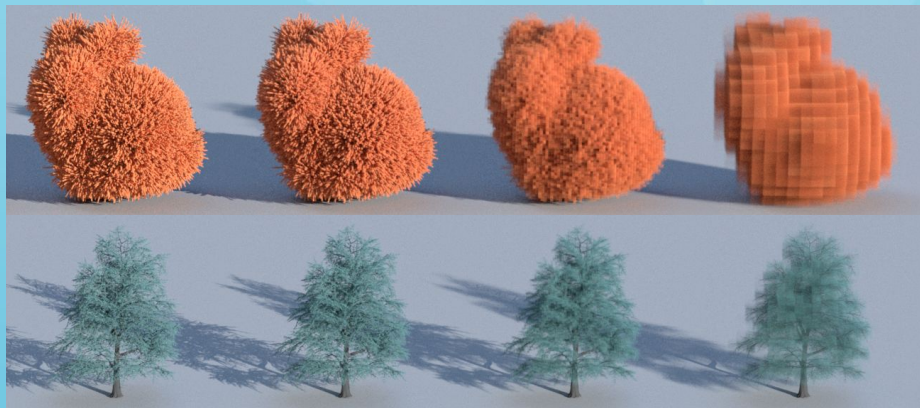


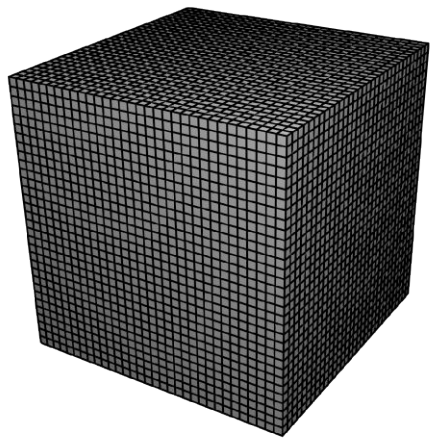
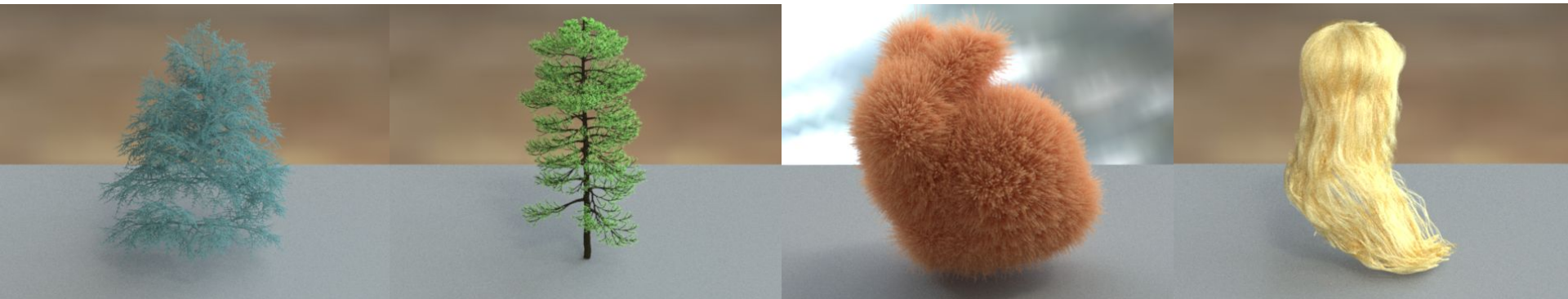
A new microflake model with microscopic self-shadowing for accurate volume downsampling

Guillaume Loubet, Fabrice Neyret

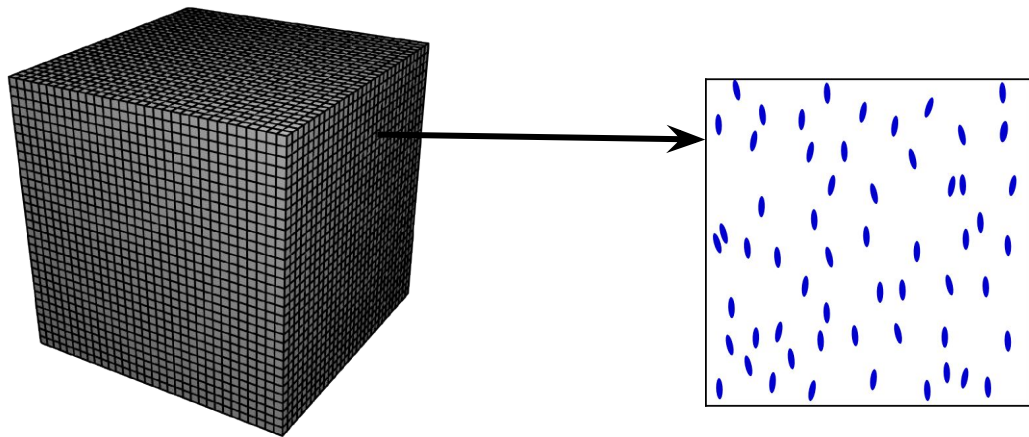
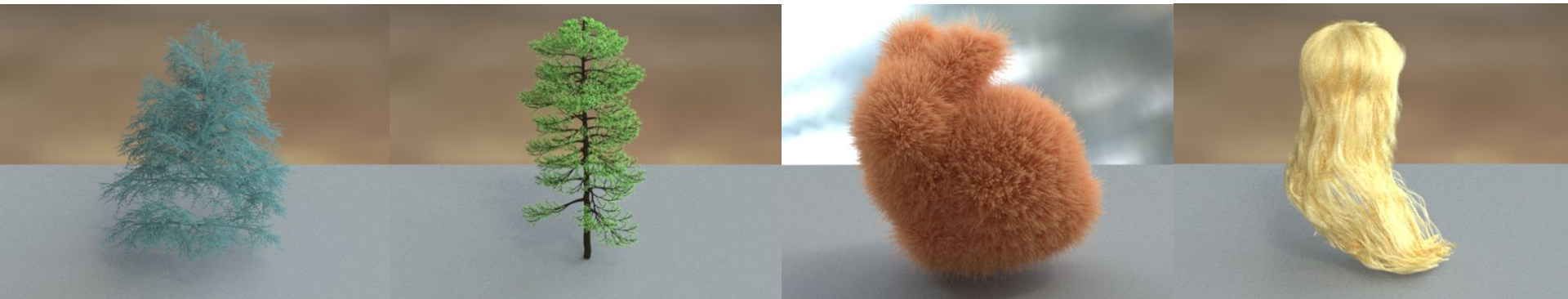
Univ. Grenoble Alpes, France



Path tracing high-resolution volumes



Path tracing high-resolution volumes



Microflake model [Jakob et al. 2010]

Parameters per voxel: **10 values**

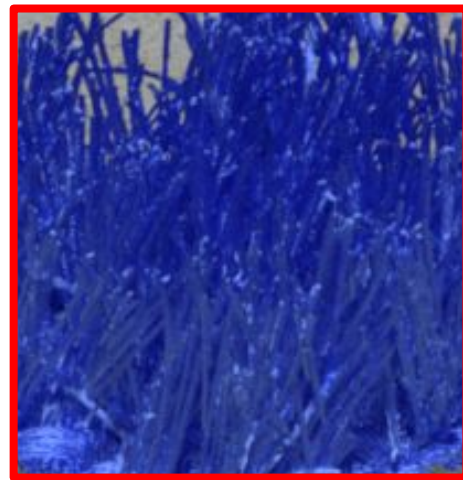
- **Density** of microflakes
- Microflake **normal distribution**
- Microflake **albedo**

Path tracing high-resolution volumes



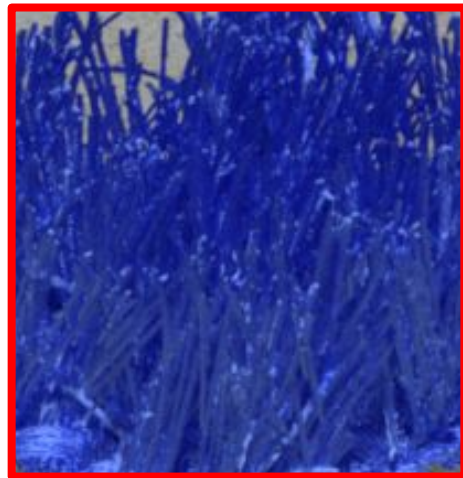
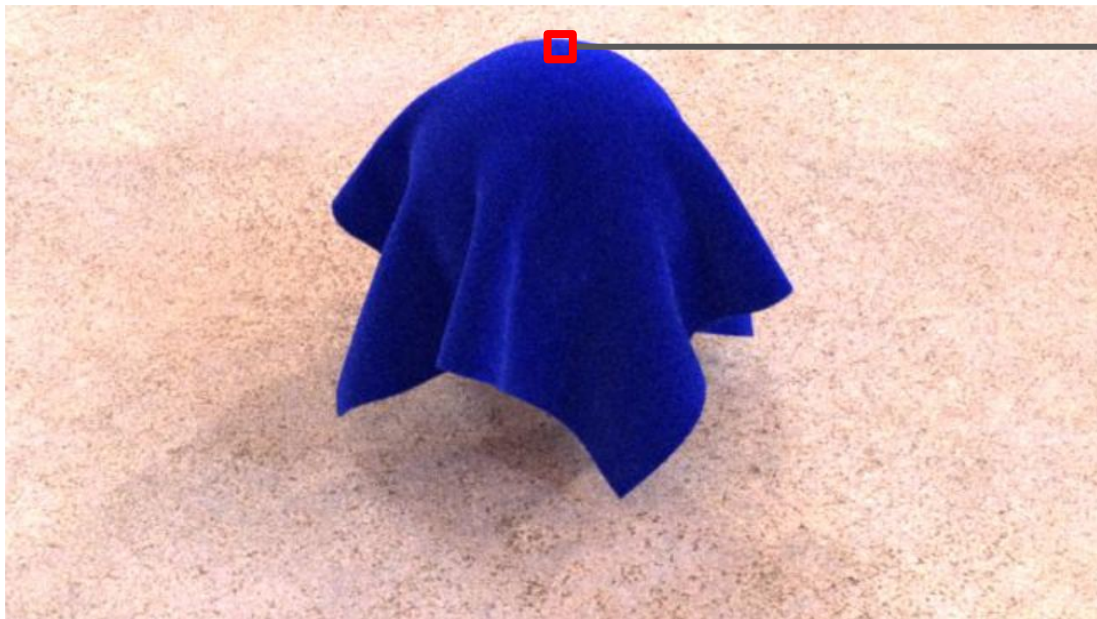
[Zhao, Wu et al. 2016]

Path tracing high-resolution volumes



[Zhao, Wu et al. 2016]

Path tracing high-resolution volumes

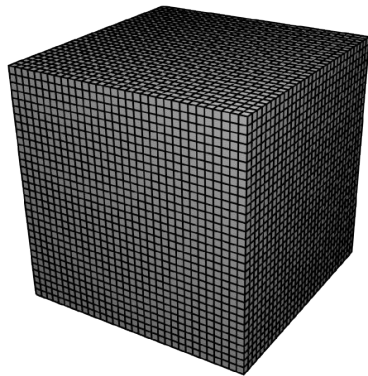


[Zhao, Wu et al. 2016]

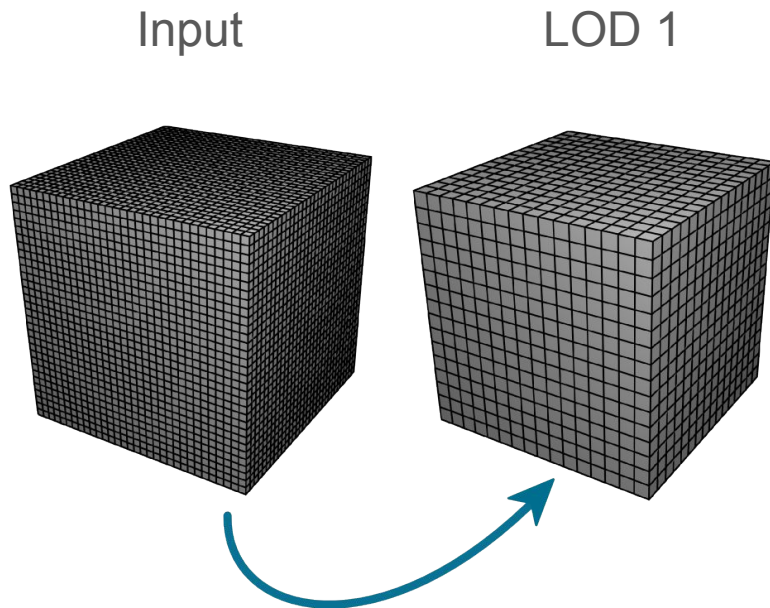
- Very realistic
- Rendering is long (minutes, hours)

Solution: volume downsampling, prefiltering

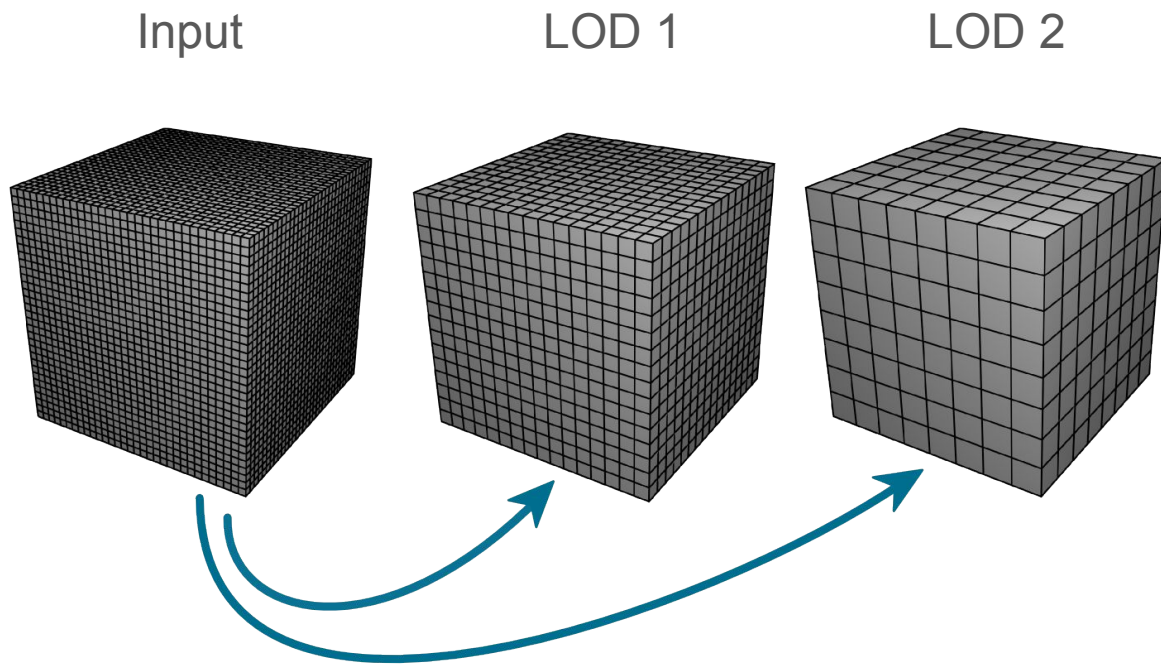
Input



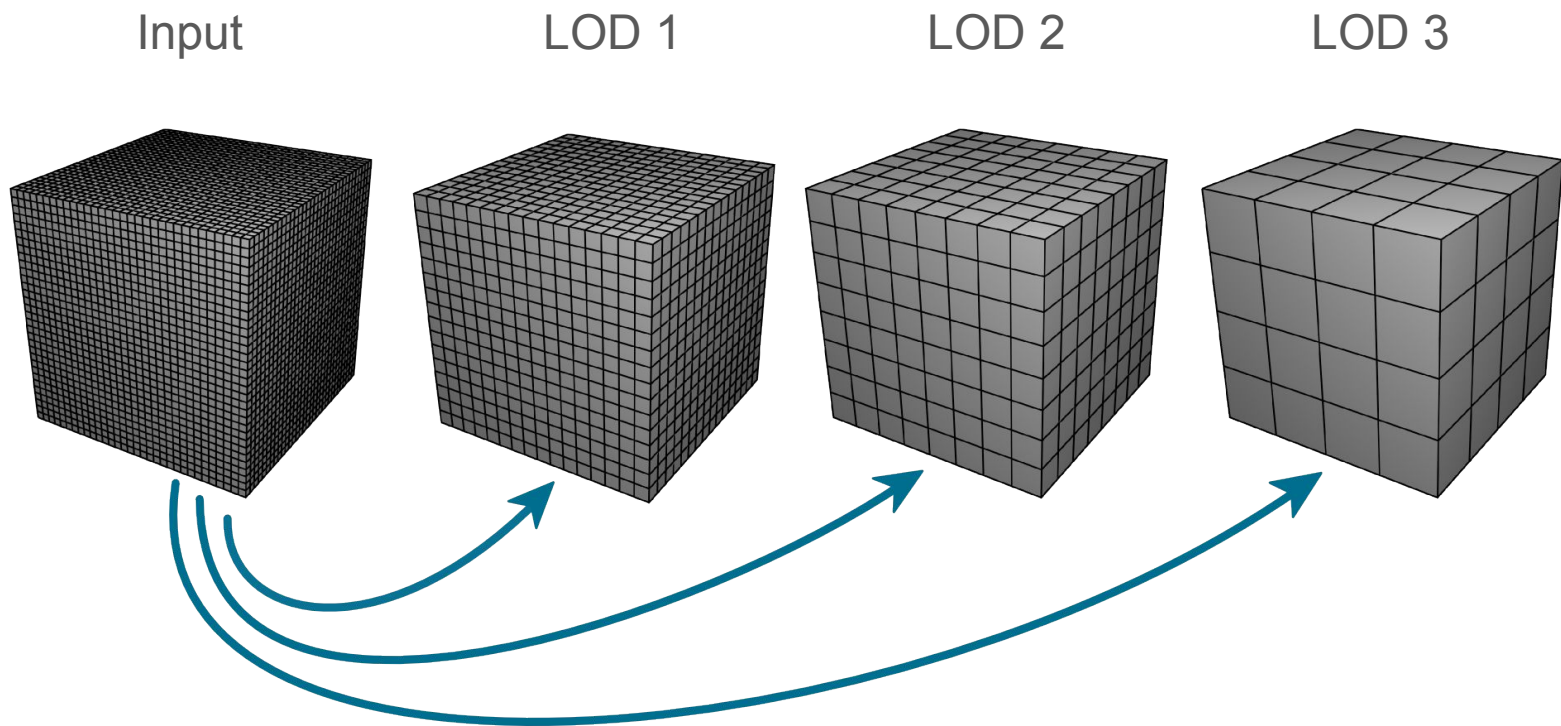
Solution: volume downsampling, prefiltering



Solution: volume downsampling, prefiltering



Solution: volume downsampling, prefiltering



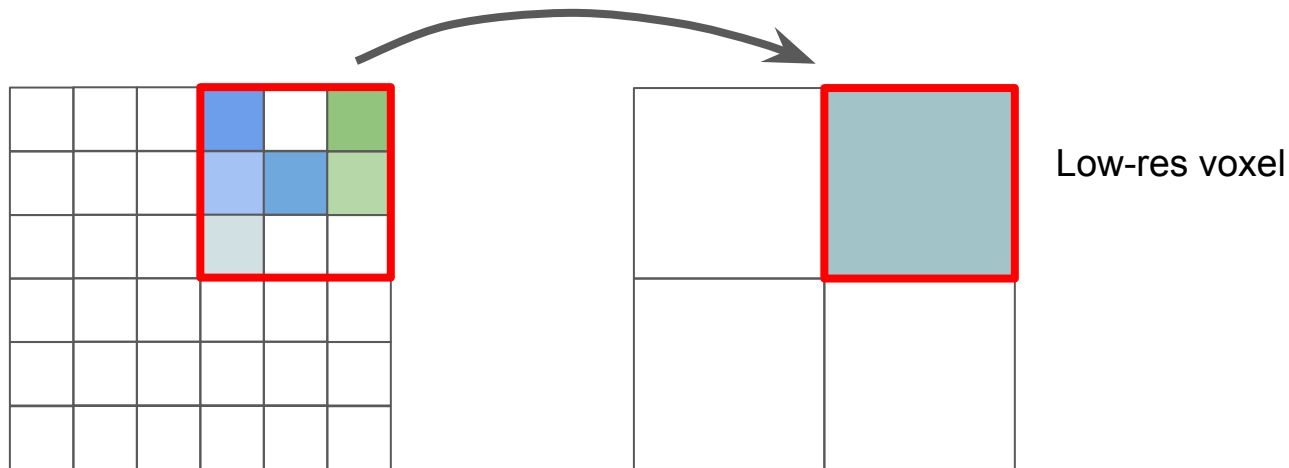
Benefits of volume downsampling



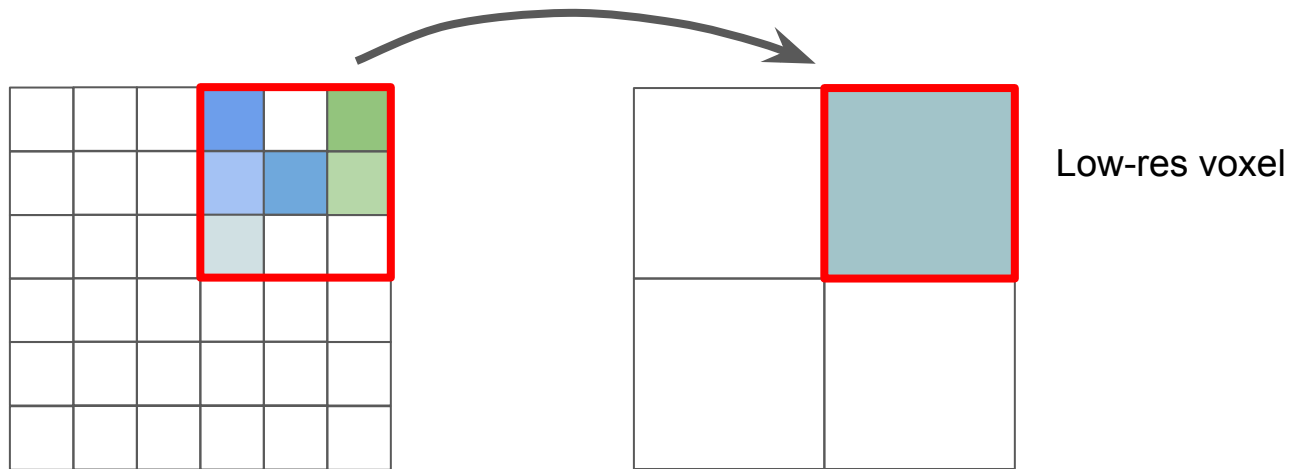
Input high-res volume
2.1 GB

LOD from [Zhao, Wu et al. 2016]
55.3 KB
Fast, less noise

Linear downsampling

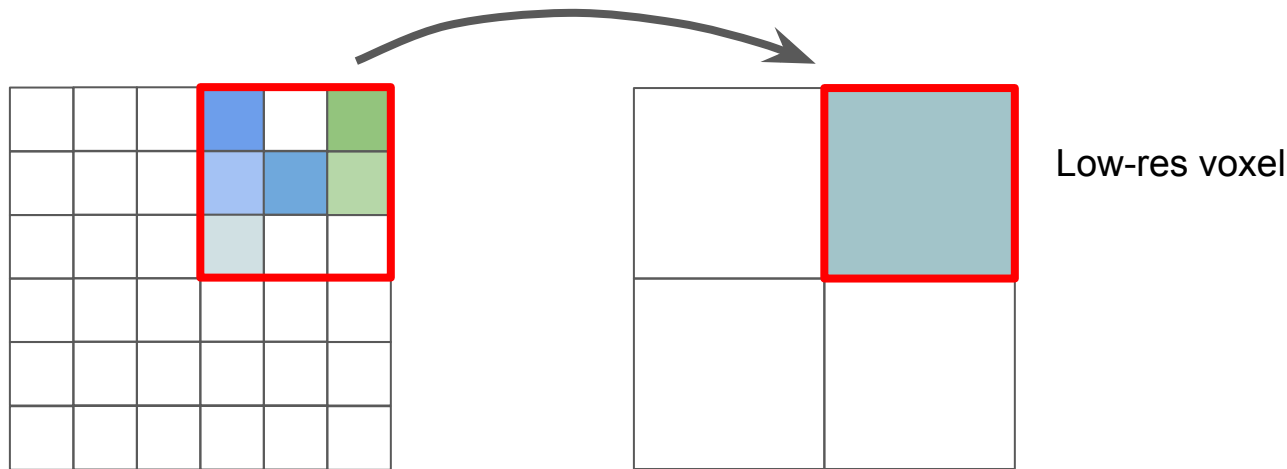


Linear downsampling



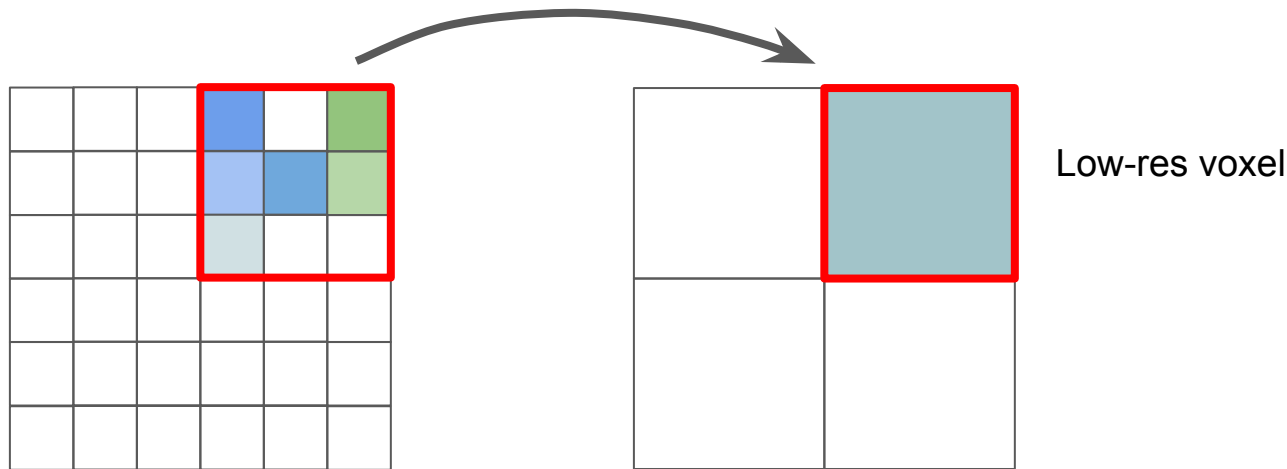
Density: $\frac{1}{N} \sum \rho_i$

Linear downsampling



$$\text{Density: } \frac{1}{N} \sum \rho_i \quad \text{Albedos: } \frac{\sum \rho_i \alpha_i}{\sum \rho_i}$$

Linear downsampling



Density: $\frac{1}{N} \sum \rho_i$ *Albedos:* $\frac{\sum \rho_i \alpha_i}{\sum \rho_i}$

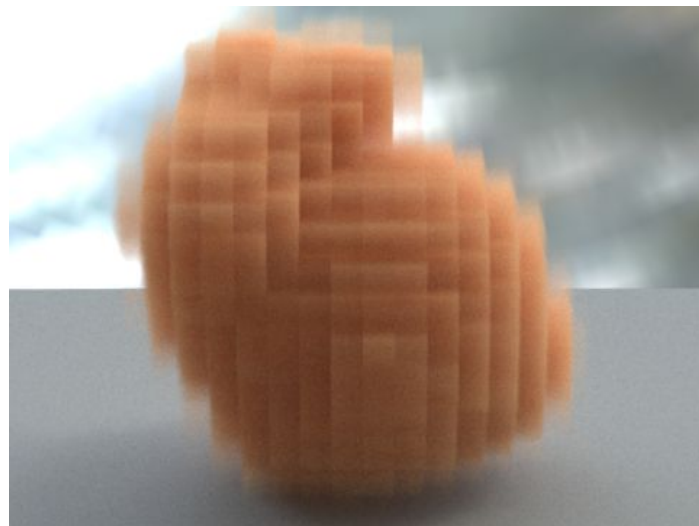
Normal distributions: [Heitz et al. 2015]
[Zhao, Wu et al. 2016]

Linear downsampling



500^3 voxels

Linear
downsampling



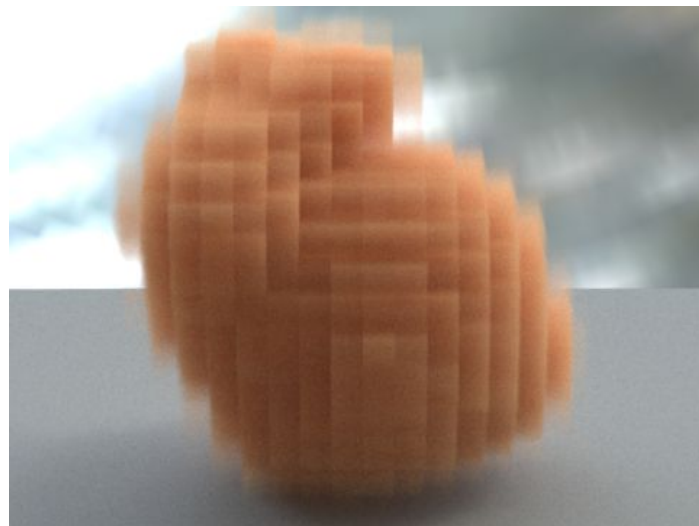
16^3 voxels ($< 1\%$)

Linear downsampling



500^3 voxels

Linear
downsampling



16^3 voxels ($< 1\%$)

Comparison: 

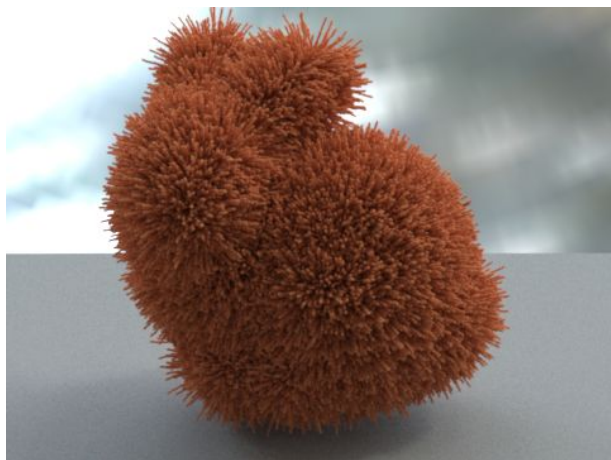
The problem with linear downsampling

Input



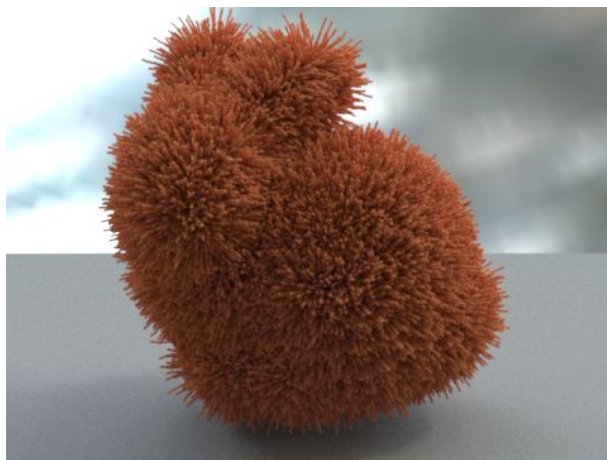
The problem with linear downsampling

Input (density x20)

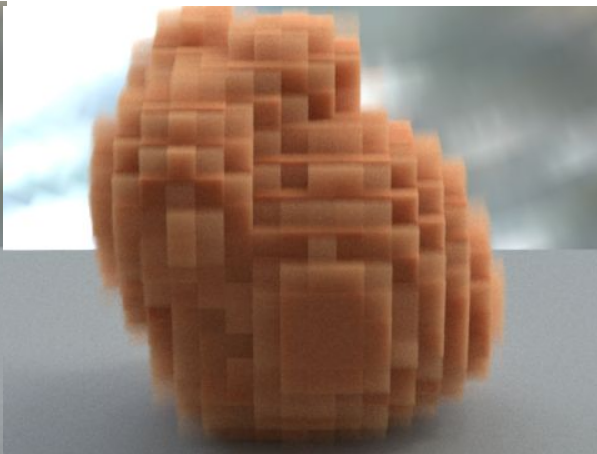


The problem with linear downsampling

Input (density x20)

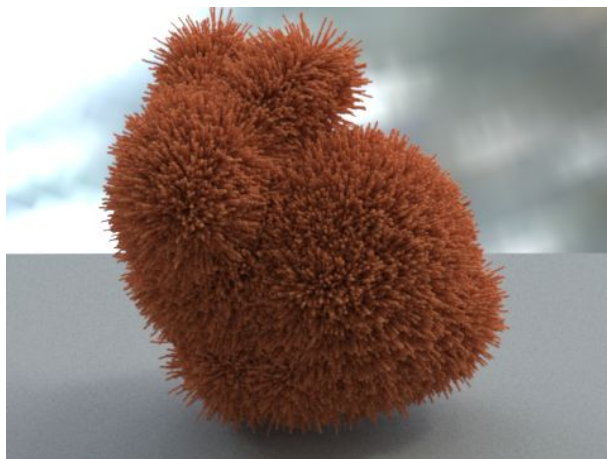


Linear downsampling

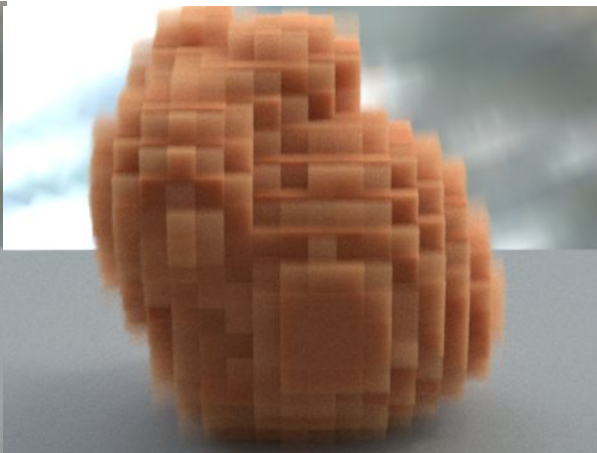


The problem with linear downsampling

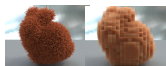
Input (density x20)



Linear downsampling

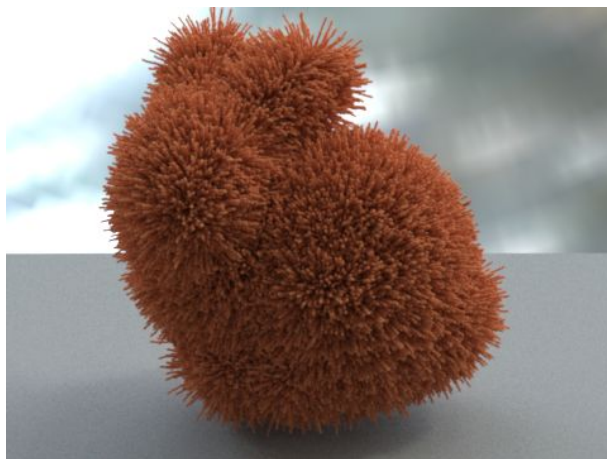


Comparison:

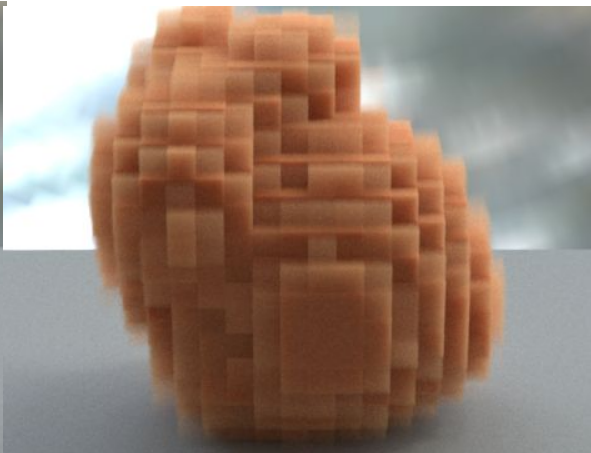


The problem with linear downsampling

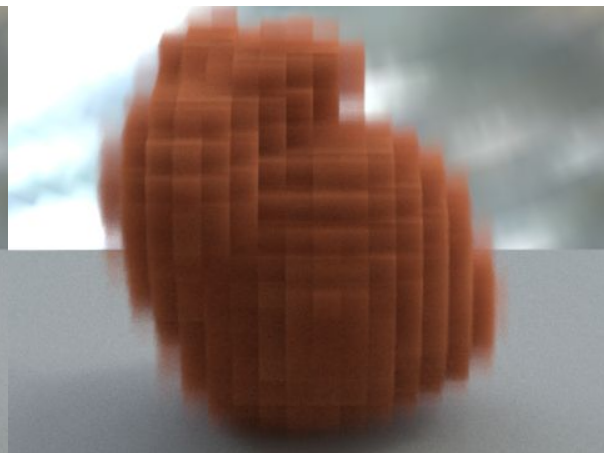
Input (density x20)



Linear downsampling



Goal



Comparison:

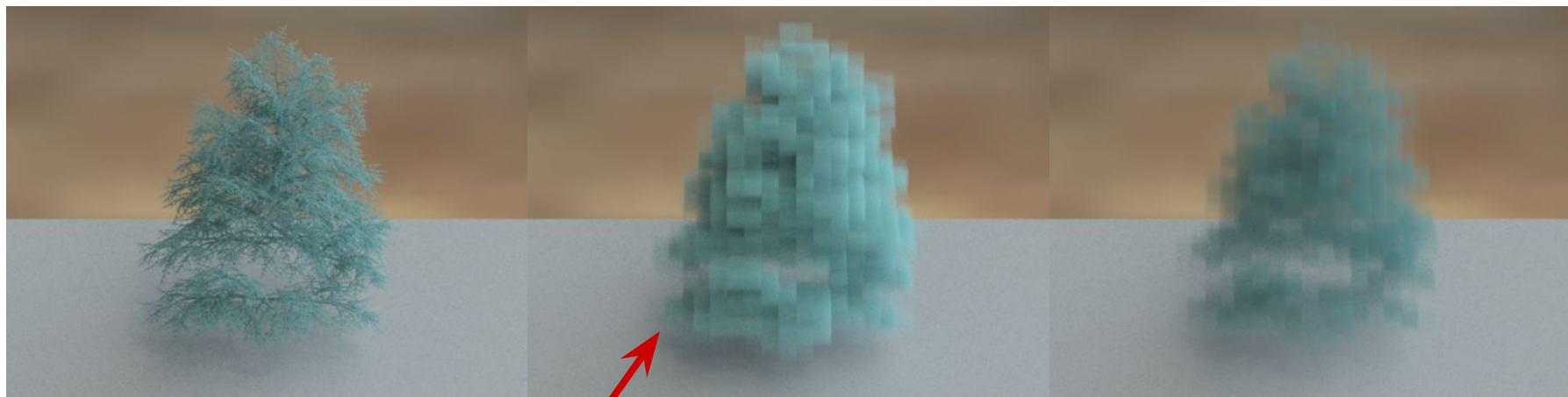


Problem with linear downsampling

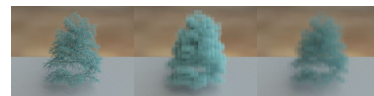
Input

Linear downsampling

Goal



Incorrect transparency & incorrect colors



Problem with linear downsampling?

Problem with linear downsampling?

#1: Transparency

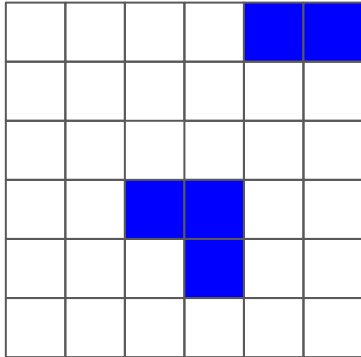
#2: Local shadowing

Problem with linear downsampling?

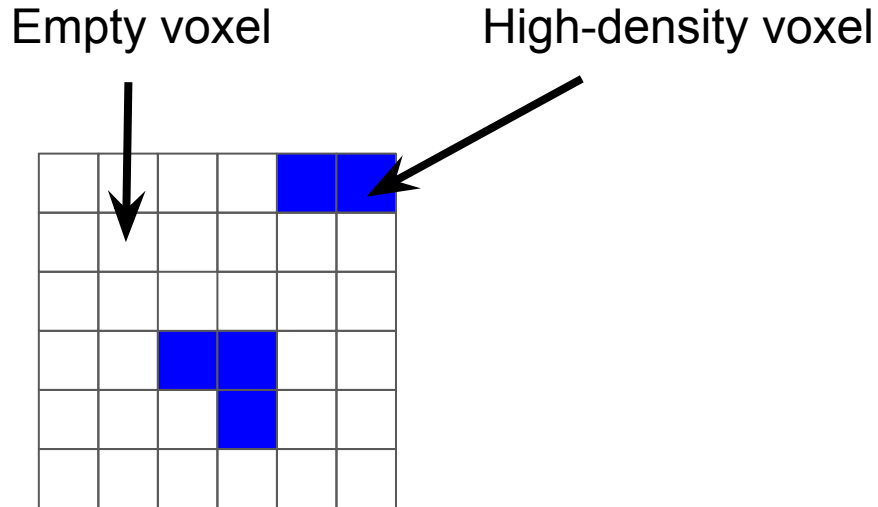
#1: Transparency

#2: Local shadowing

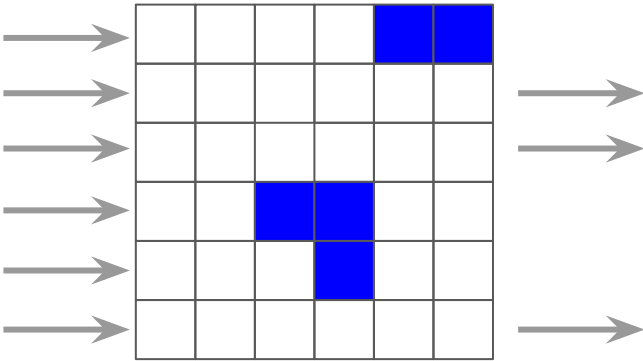
Problem #1: transparency



Problem #1: transparency

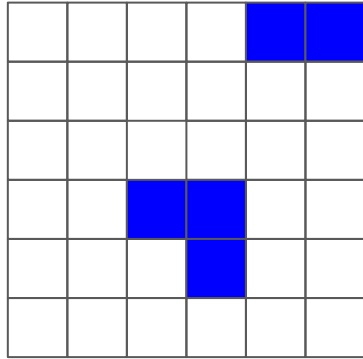


Problem #1: transparency



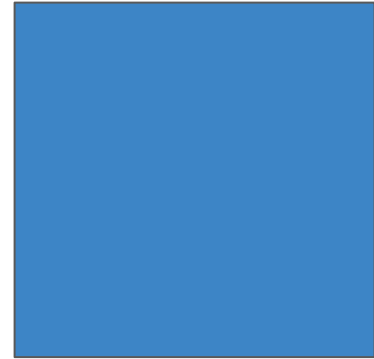
Transparency: 50%

Problem #1: transparency

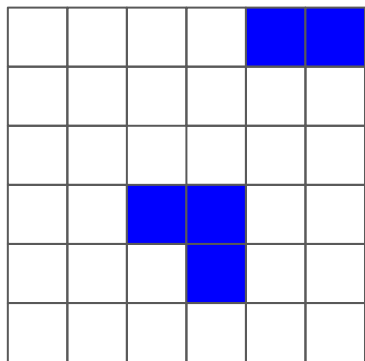


Transparency: 50%

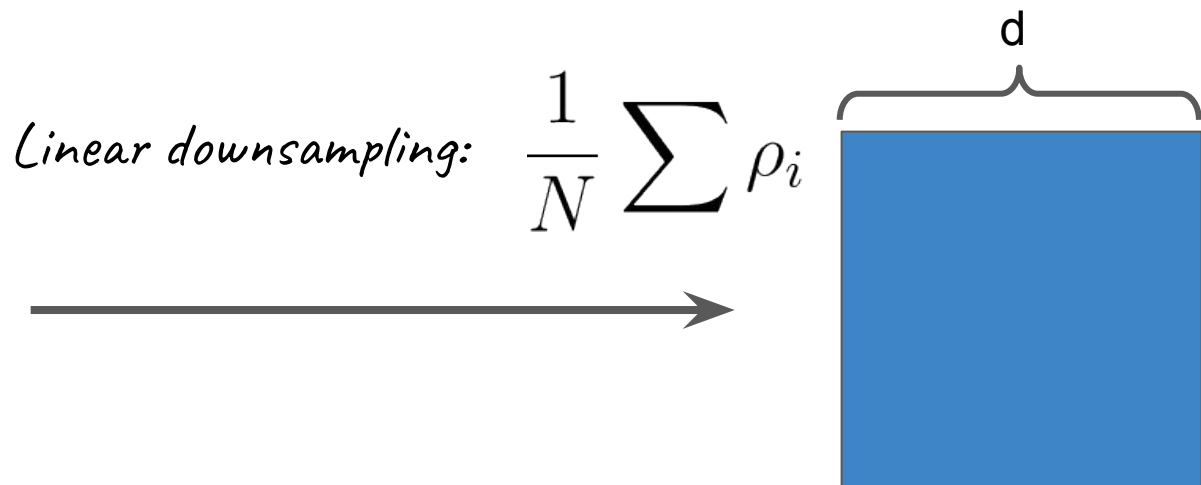
Linear downsampling: $\frac{1}{N} \sum \rho_i$



Problem #1: transparency

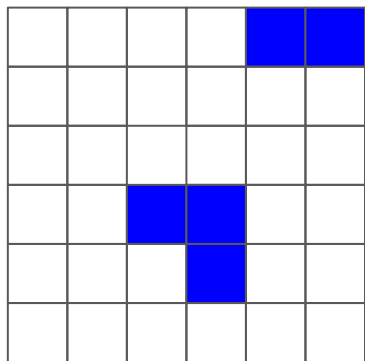


Transparency: 50%



Transparency: $e^{-d\rho} < 50\%$

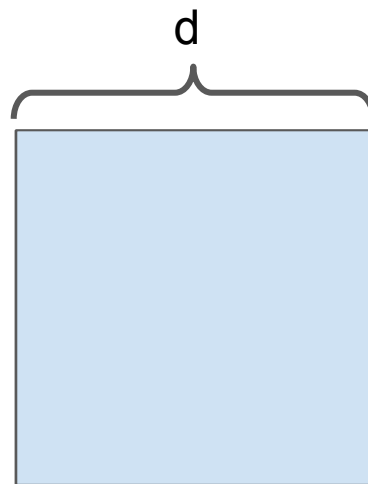
Problem #1: transparency



Transparency: 50%

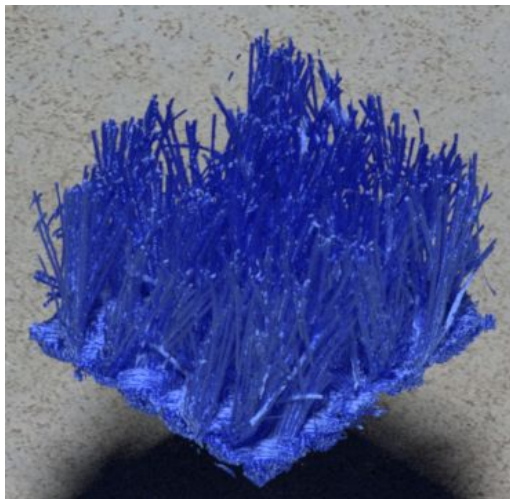
Non-linear downsampling

$$\rho = \frac{-\log(0.5)}{d}$$

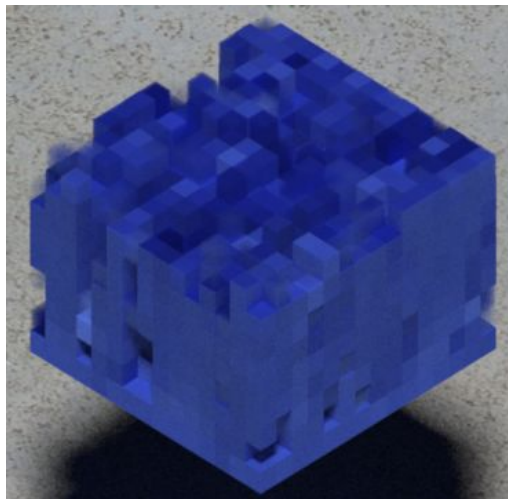


Transparency: 50%

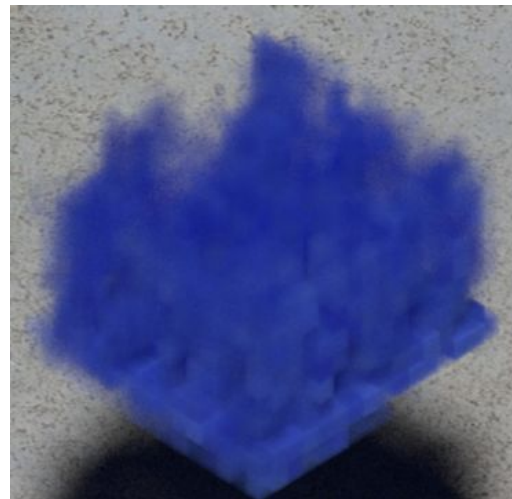
Problem #1: transparency



Input



Linear downsampling of density
[Zhao et al. 2016]



Correct transparency

Problem with linear downsampling?

#1: Transparency

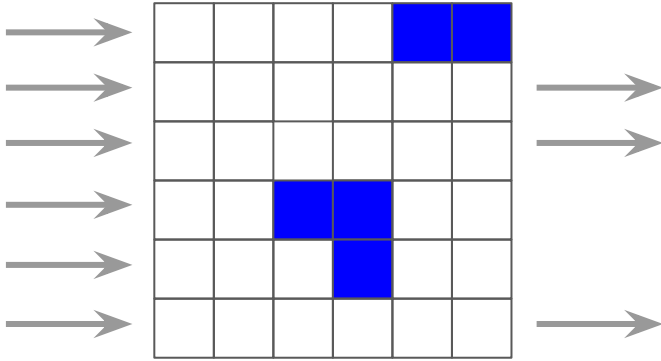
#2: Local shadowing

Problem with linear downsampling?

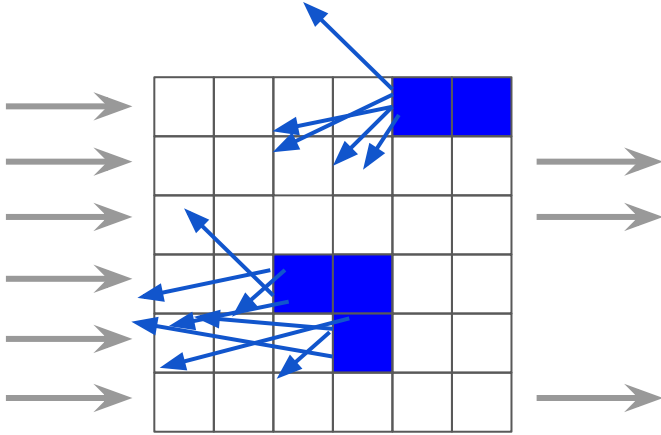
#1: Transparency

#2: Local shadowing

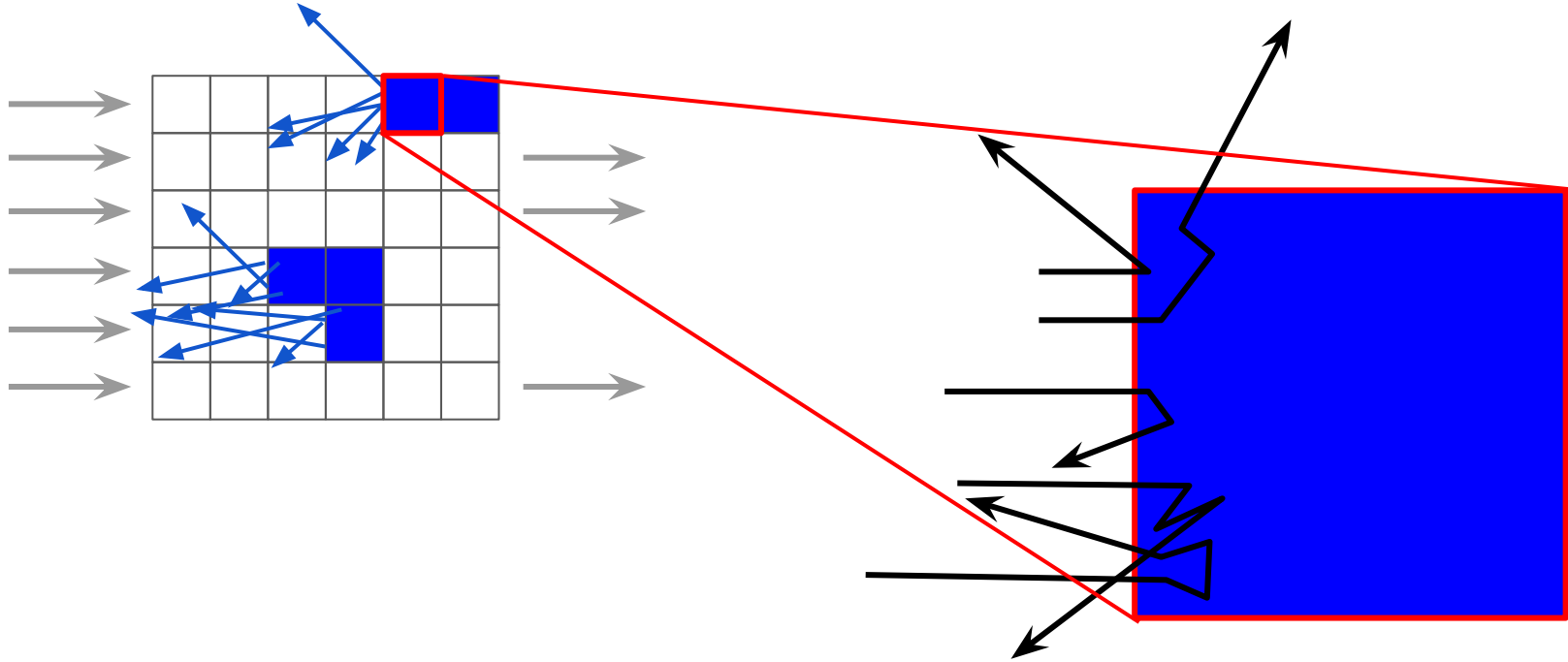
Problem #2: local shadowing



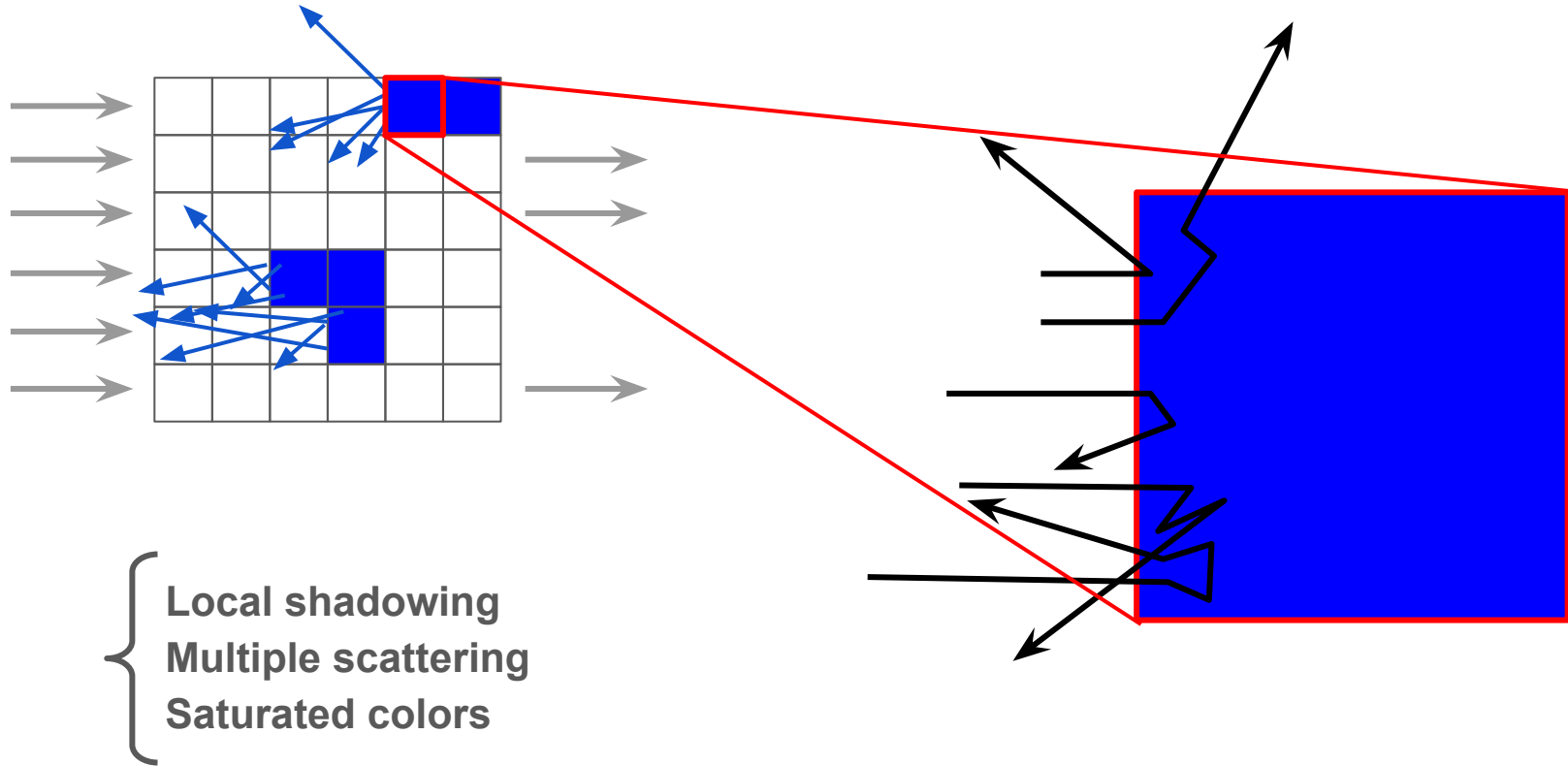
Problem #2: local shadowing



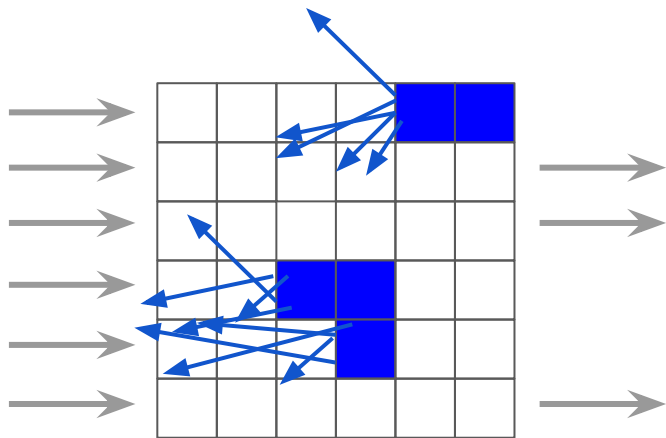
Problem #2: local shadowing



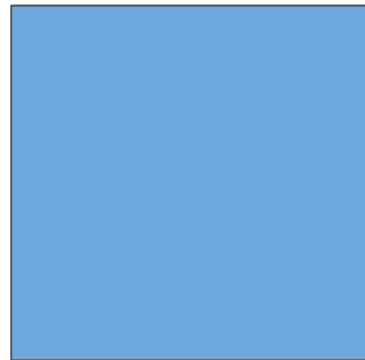
Problem #2: local shadowing



Problem #2: local shadowing

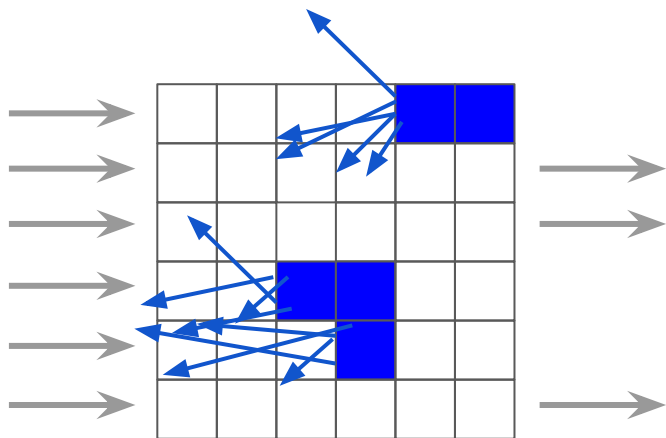


{
Local shadowing
Multiple scattering
Saturated colors

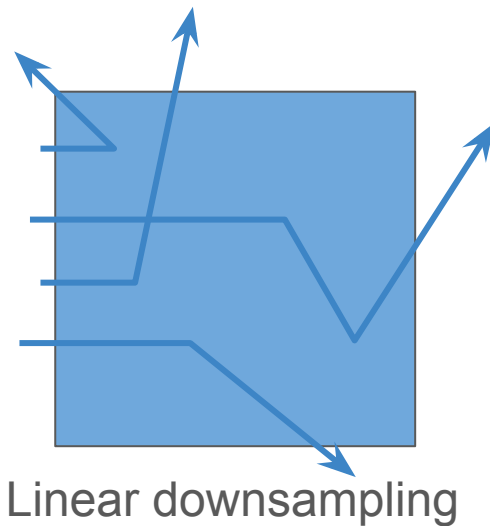


Linear downsampling

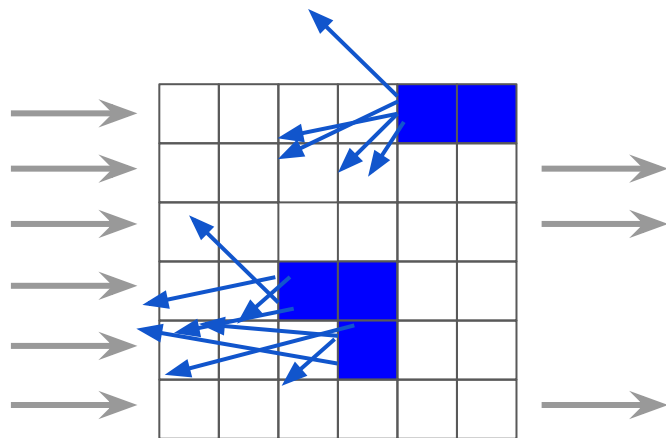
Problem #2: local shadowing



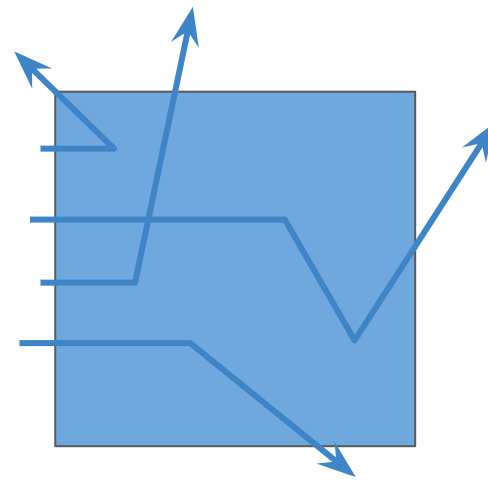
{
Local shadowing
Multiple scattering
Saturated colors



Problem #2: local shadowing



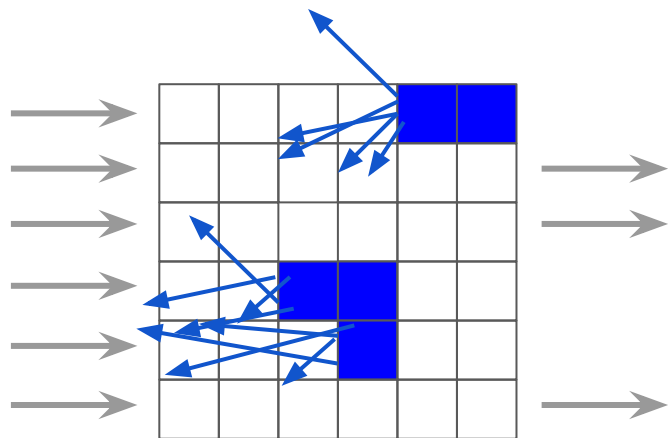
{
Local shadowing
Multiple scattering
Saturated colors



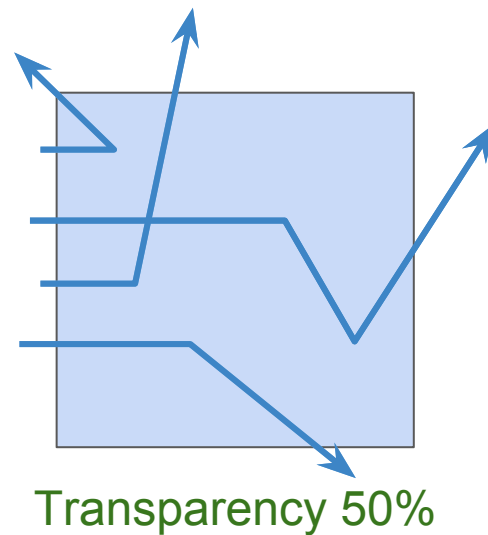
Linear downsampling

{
Less local shadowing
More single scattering
Light colors

Problem #2: local shadowing

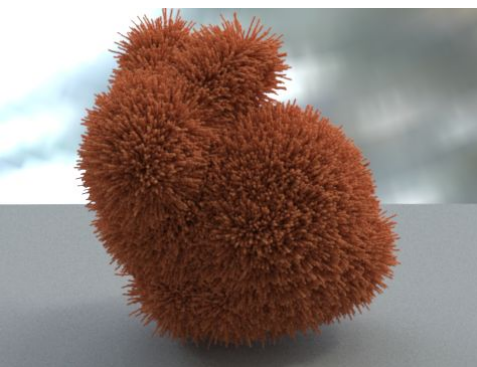


{
Local shadowing
Multiple scattering
Saturated colors

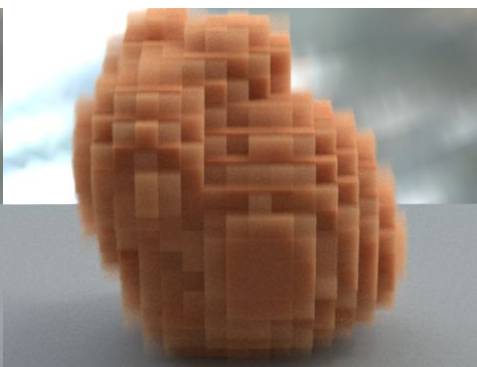


{
Less local shadowing
More single scattering
Light colors

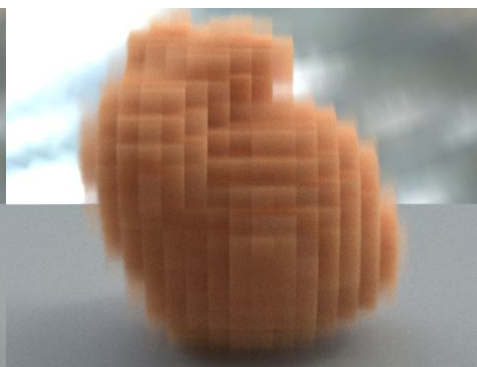
Problem #2: local shadowing



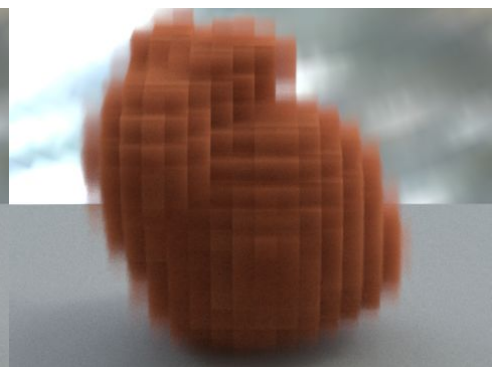
Input



Naïve (linear)

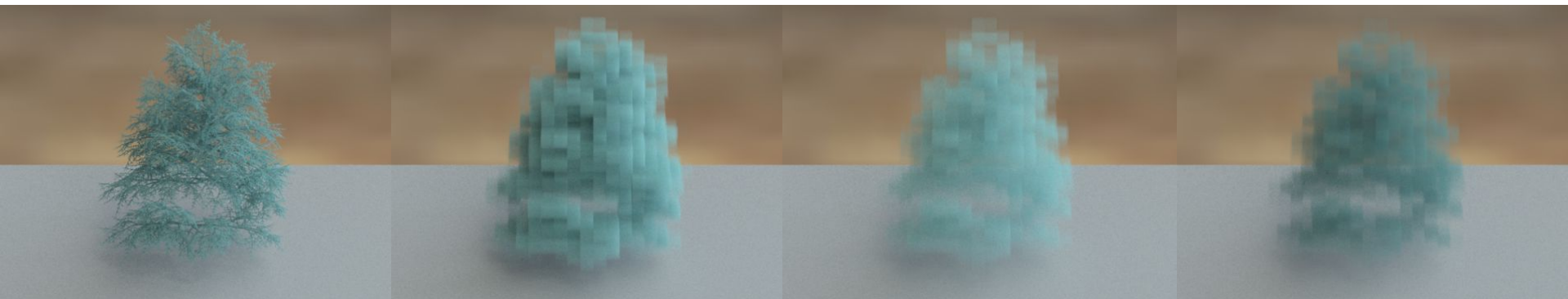


Naïve (correct transp.)



Goal

Problem #2: local shadowing



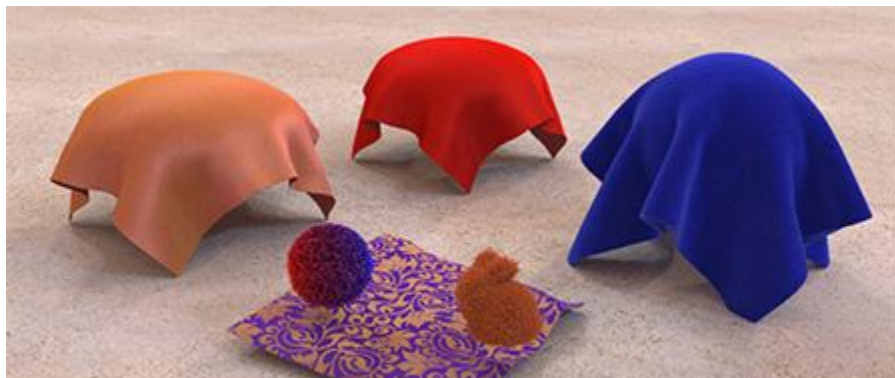
Input

Naïve (linear)

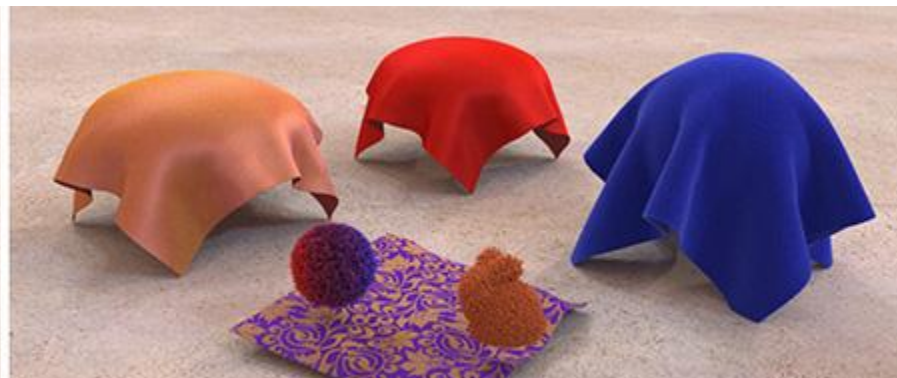
Naïve (correct transp.)

Goal

Previous work: [Zhao, Wu et al. 2016]



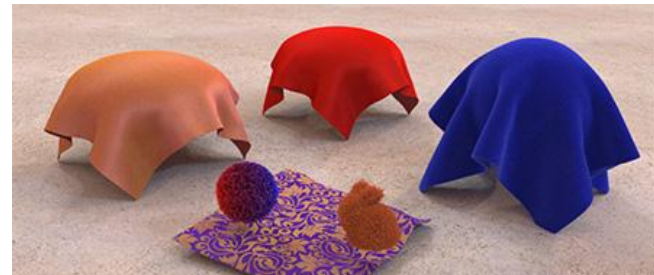
Reference, 25.4 GB



LODs, 45.6 MB

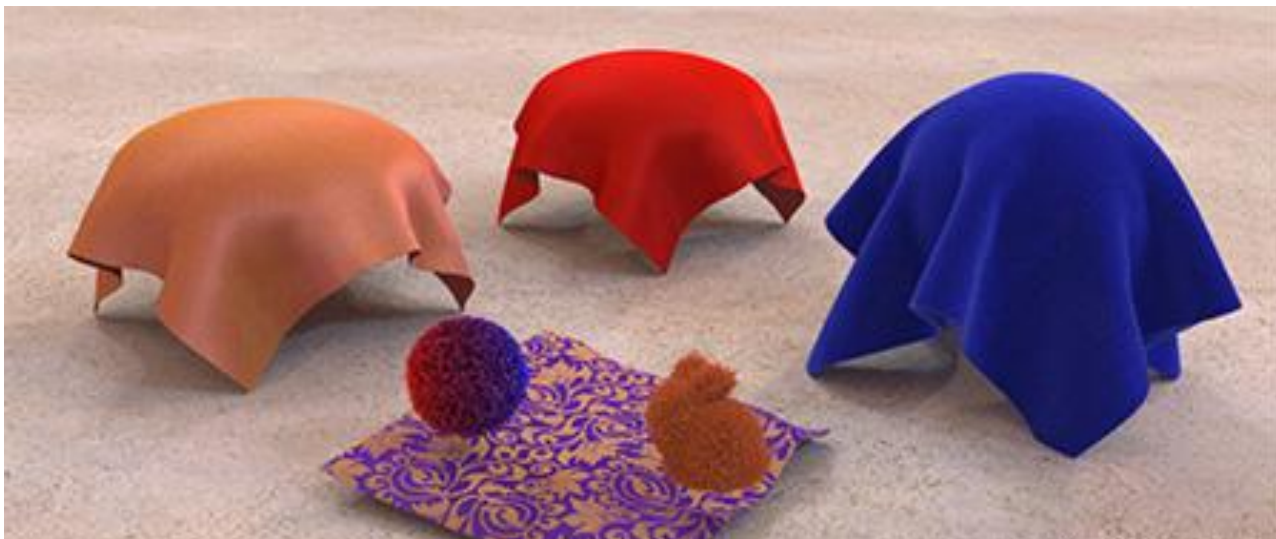
Much more accurate than naïve methods

Previous work: [Zhao, Wu et al. 2016]

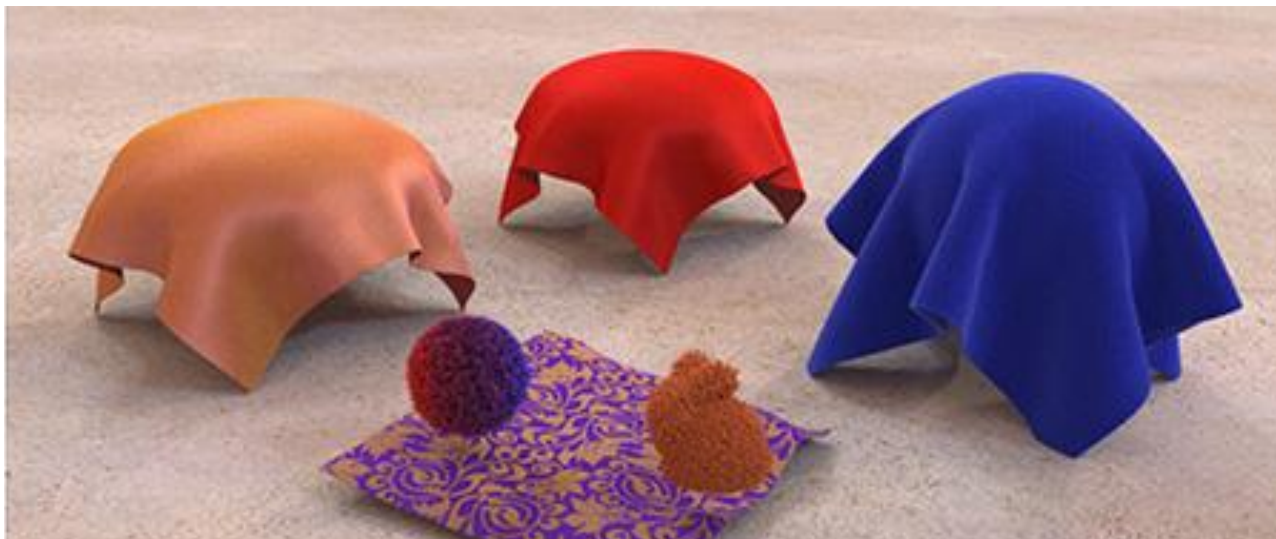


Algorithm:

- 1) Downsample linearly
- 2) Iterative **optimization**:
 - Render input and current LOD (several views & lights)
 - Obtain pixel **derivatives for each parameter**, view & light

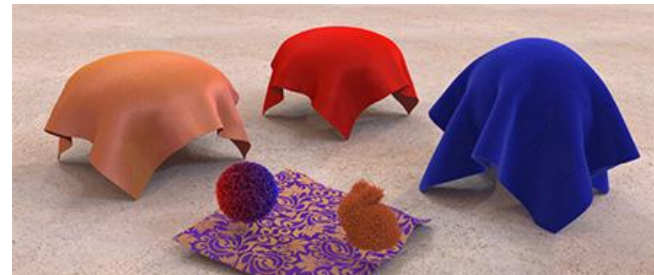


Reference, 25.4 GB



LODs, 45.6 MB

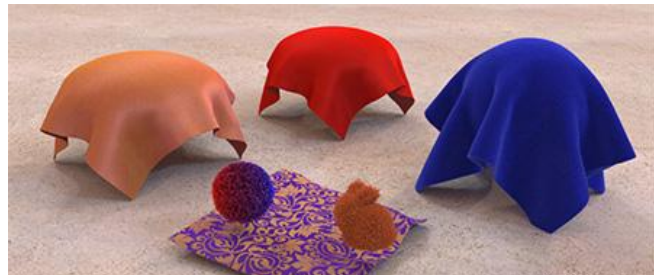
Previous work: [Zhao, Wu et al. 2016]



Algorithm:

- 1) Downsample linearly
- 2) Iterative **optimization**:
 - Render input and current LOD (several views & lights)
 - Obtain pixel **derivatives for each parameter**, view & light

Previous work: [Zhao, Wu et al. 2016]



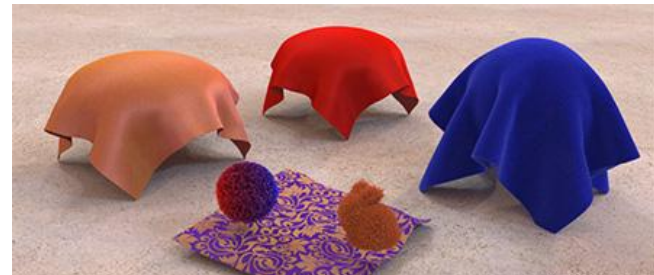
Algorithm:

- 1) Downsample linearly
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 - Render input and current LOD (several views & lights)
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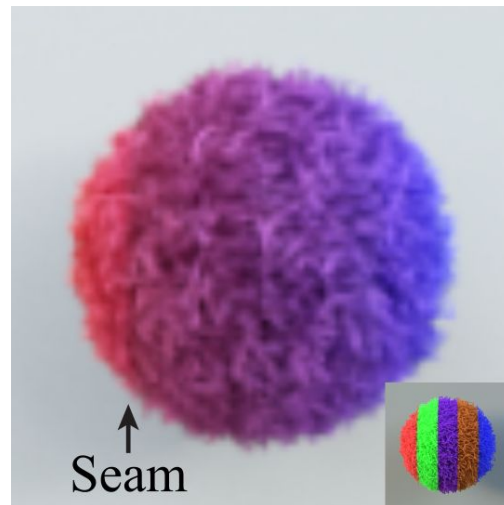


Too costly if too many parameters: clusters

Previous work: [Zhao, Wu et al. 2016]



Input

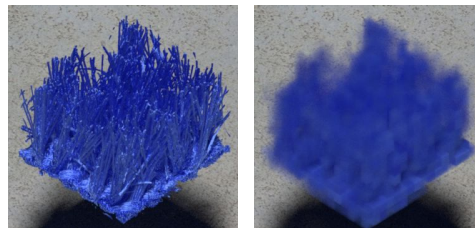


LOD

Not general, prone to artifacts

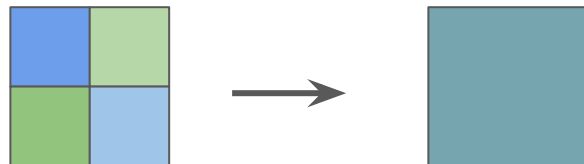
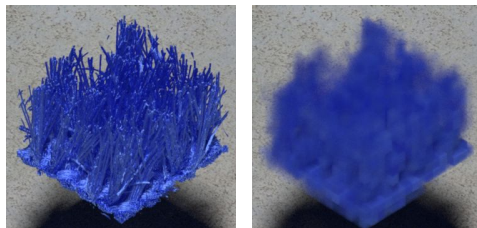
Our approach

- **Correct transparency (non-linear)**



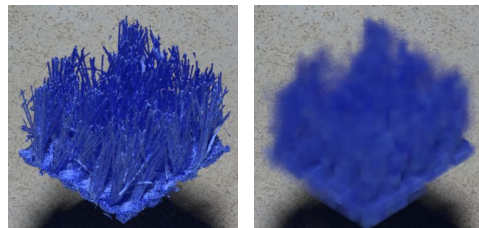
Our approach

- **Correct transparency (non-linear)**
- **Local estimation of parameters**
No training rendering, no clusters
About x10 faster than [Zhao, Wu et al. 2016]



Our approach

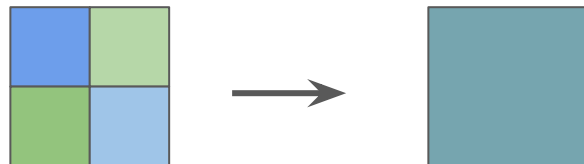
- **Correct transparency (non-linear)**



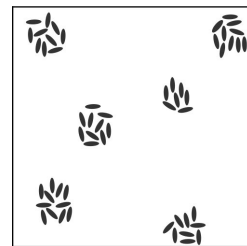
- **Local estimation of parameters**

No training rendering, no clusters

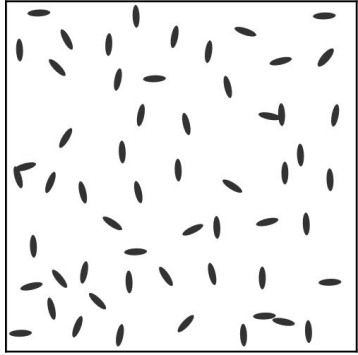
About x10 faster than [Zhao, Wu et al. 2016]



- **New microflake model for correct local shadowing**

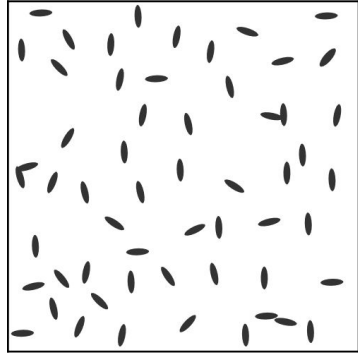


Our new model: microscopic self-shadowing

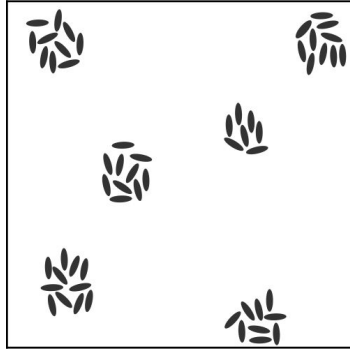


Standard model

Our new model: microscopic self-shadowing

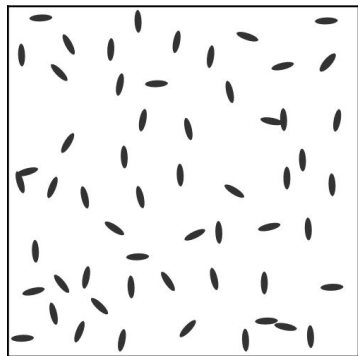


Standard model

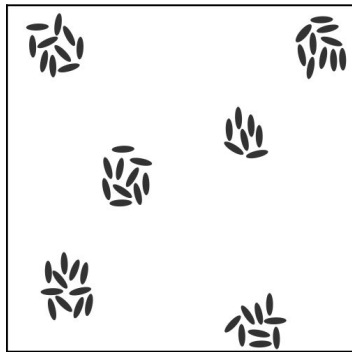


Our model
Isotropic shadowing

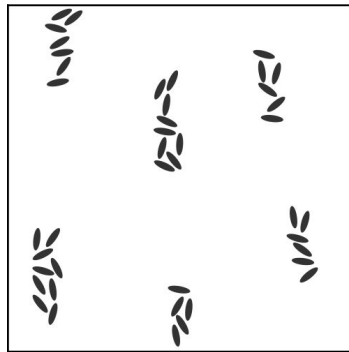
Our new model: microscopic self-shadowing



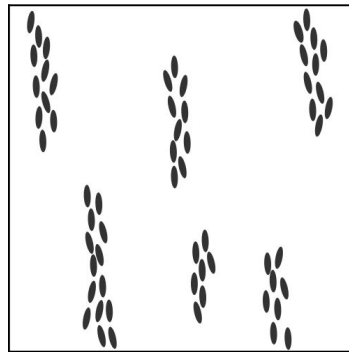
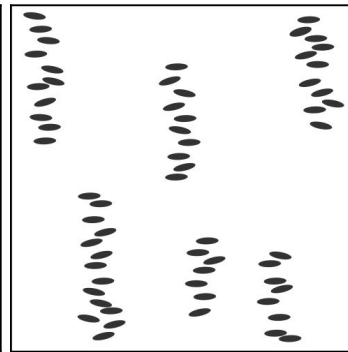
Standard model



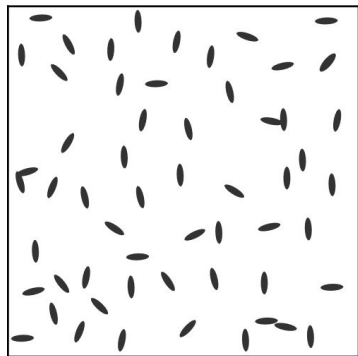
Our model
Isotropic shadowing



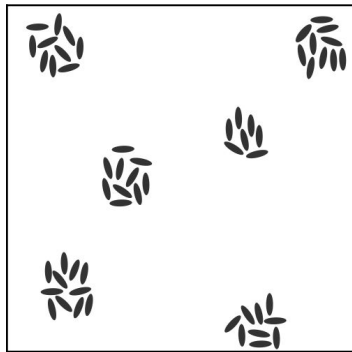
Our model
Anisotropic shadowing



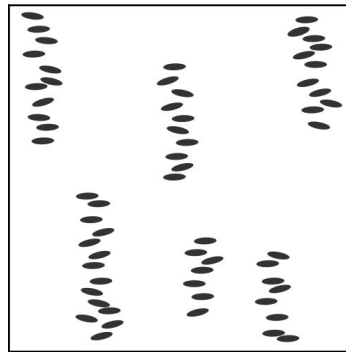
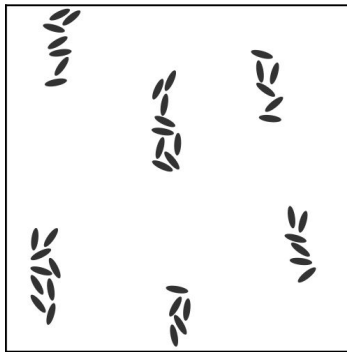
Our new model: microscopic self-shadowing



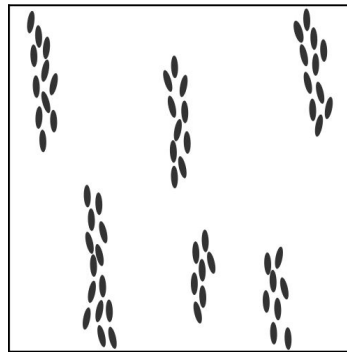
Standard model



Our model
Isotropic shadowing

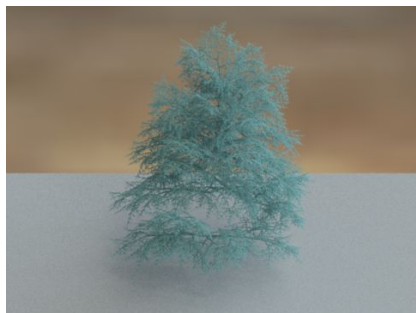
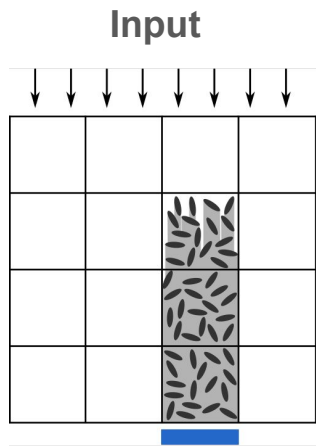


Our model
Anisotropic shadowing

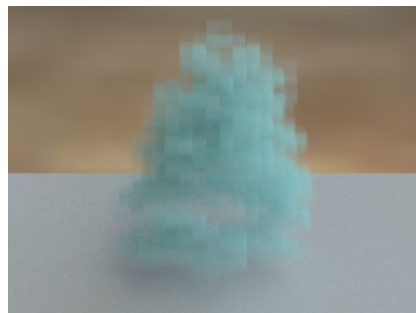
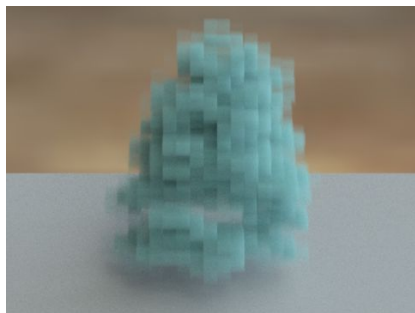
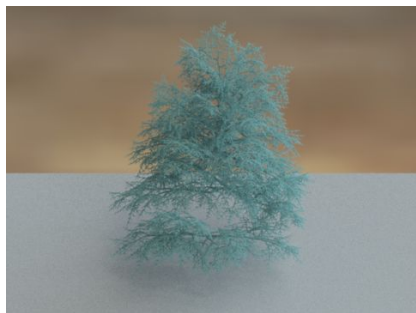
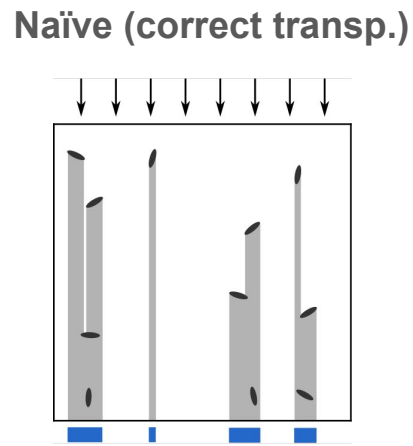
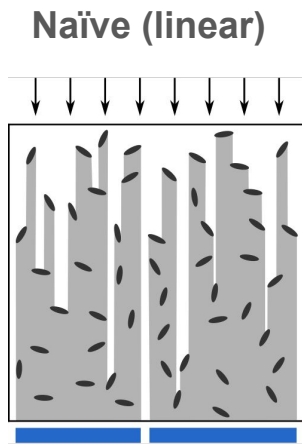
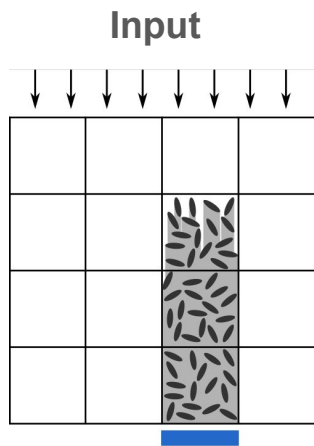


Model of **transparent media** with **multiple scattering** at micro-scales

Our new model: microscopic self-shadowing

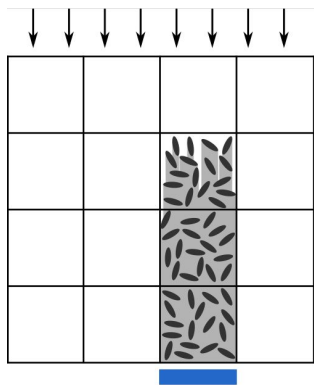


Our new model: microscopic self-shadowing

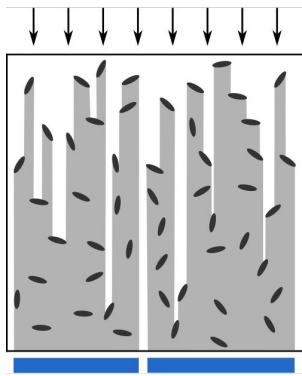


Our new model: microscopic self-shadowing

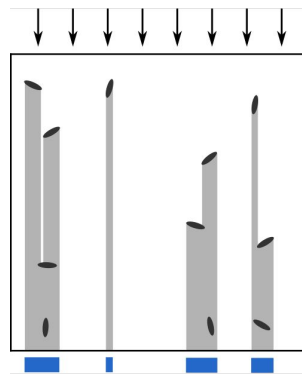
Input



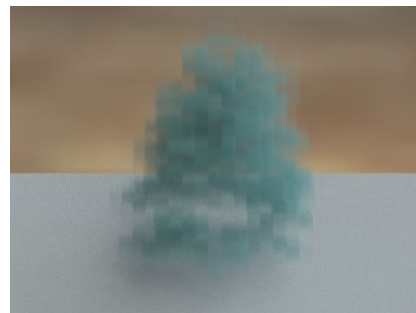
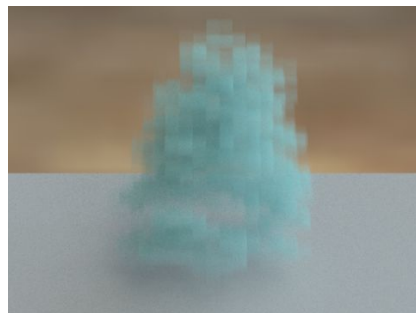
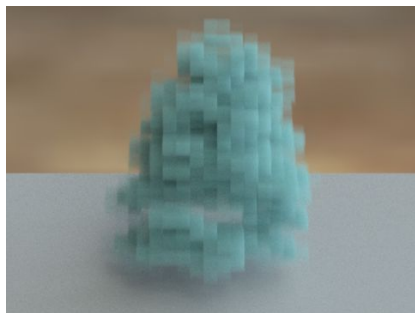
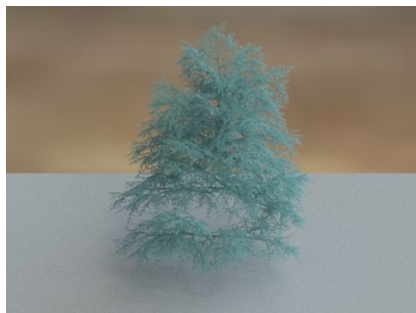
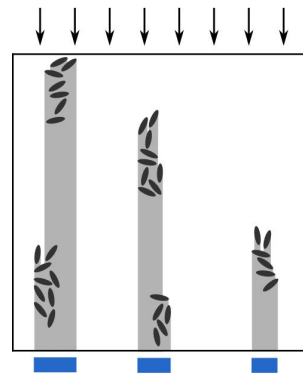
Naïve (linear)



Naïve (correct transp.)



Our model




Our new model: microscopic self-shadowing

$$\sigma_t(\omega) = A(\omega)\rho \int_{S^2} D(\omega_m) \langle \omega \cdot \omega_m \rangle \, d\omega$$


Our new model: microscopic self-shadowing

Local shadowing (1 or 6 parameters)


$$\sigma_t(\omega) = A(\omega)\rho \int_{S^2} D(\omega_m) \langle \omega \cdot \omega_m \rangle d\omega$$

Our new model: microscopic self-shadowing


Local shadowing (1 or 6 parameters)


$$\sigma_t(\omega) = A(\omega)\rho \int_{S^2} D(\omega_m) \langle \omega \cdot \omega_m \rangle d\omega$$

$$\sigma_{ss}(\omega) = \alpha_{ss}(\lambda) A(\omega)\rho \int_{S^2} A(\omega_m, \omega) D(\omega_m) \langle \omega \cdot \omega_m \rangle d\omega$$

Our new model: microscopic self-shadowing

Local shadowing (1 or 6 parameters)



$$\sigma_t(\omega) = A(\omega) \rho \int_{S^2} D(\omega_m) \langle \omega \cdot \omega_m \rangle d\omega$$

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$$f_{ss}(\omega \rightarrow \omega') = \frac{\rho \alpha_{ss}(\lambda) A(\omega) A(\omega') D(\omega_h)}{4\sigma_{ss}(\omega)}$$

Our new model: microscopic self-shadowing

Local shadowing (1 or 6 parameters)


$$\sigma_t(\omega) = A(\omega) \rho \int_{S^2} D(\omega_m) \langle \omega \cdot \omega_m \rangle d\omega$$

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$$f_{ss}(\omega \rightarrow \omega') = \frac{\rho \alpha_{ss}(\lambda) A(\omega) A(\omega') D(\omega_h)}{4\sigma_{ss}(\omega)}$$

+ local multiple scattering terms, MS albedo

Local estimation of parameters

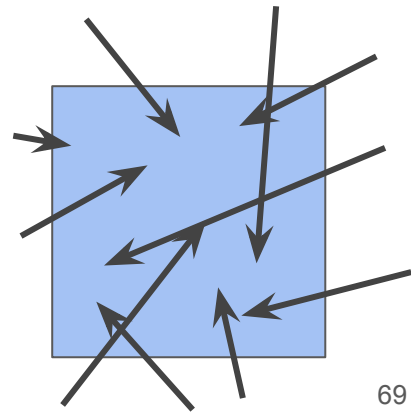
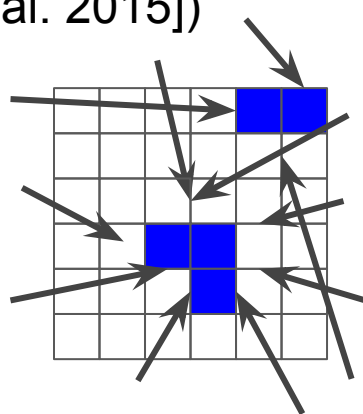
We estimate:

- Transparency (easy)
- Single scattering albedo (linear)
- Microflake distributions (linear, [Heitz et al. 2015])

Local estimation of parameters

We estimate:

- Transparency (easy)
- Single scattering albedo (linear)
- Microflake distributions (linear, [Heitz et al. 2015])
- **Density** and **shadowing parameters**
- **Multiple scattering albedo**

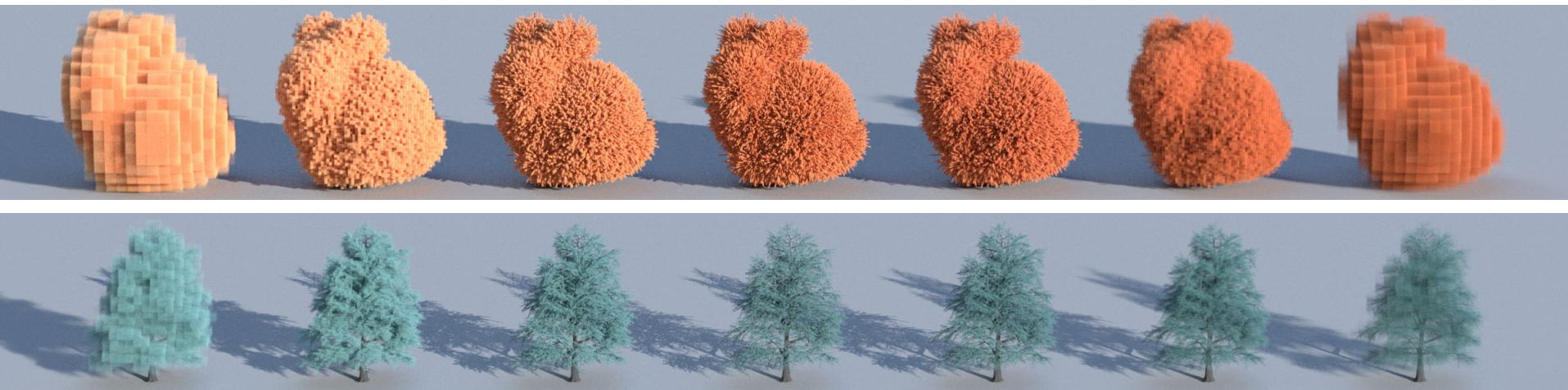


Results

Naive (linear)

Input

Our



LOD 5

LOD 3

LOD 1



LOD 1

LOD 3

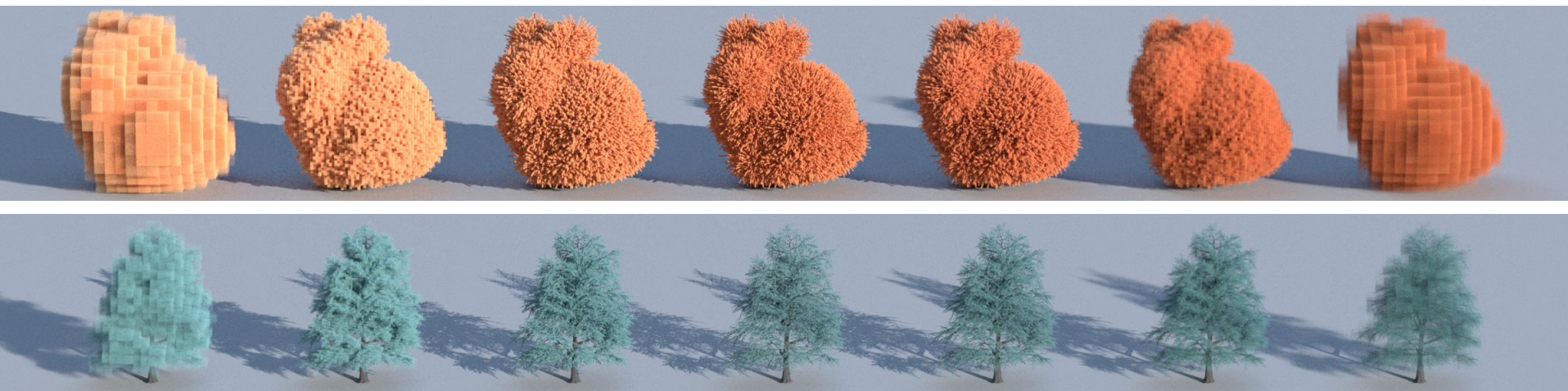
LOD 5

Results

Naive (linear)

Input

Our



LOD 5

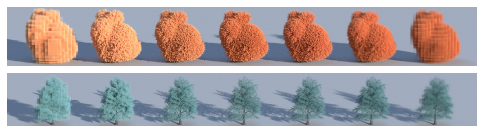
LOD 3

LOD 1

LOD 1

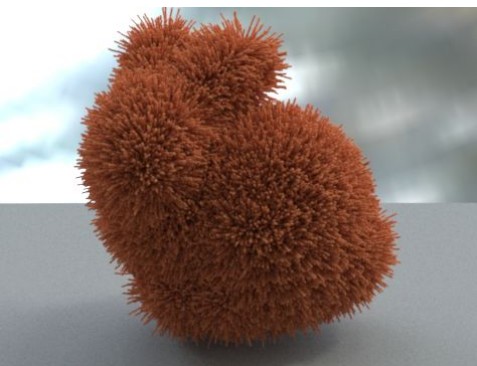
LOD 3

LOD 5

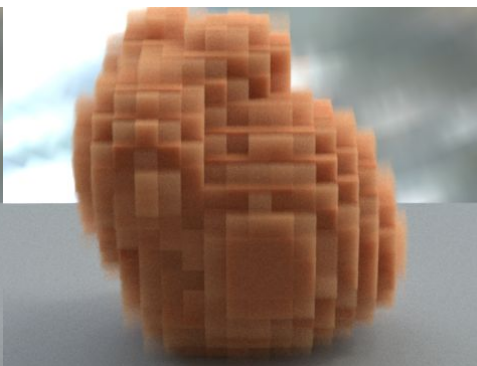


Results

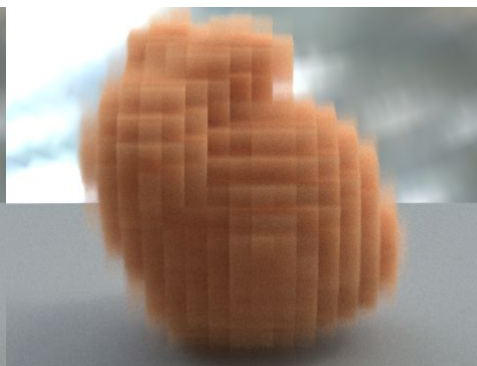
Input



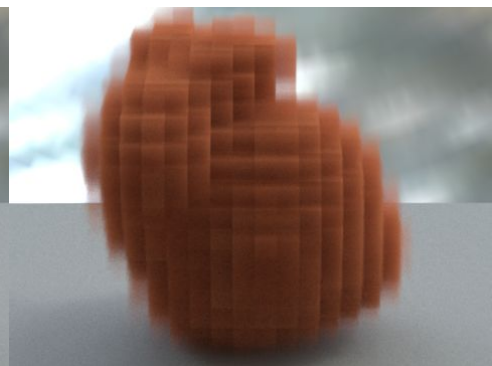
Naïve (linear)



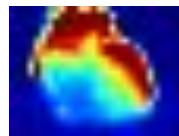
Naïve (correct transp.)



Our

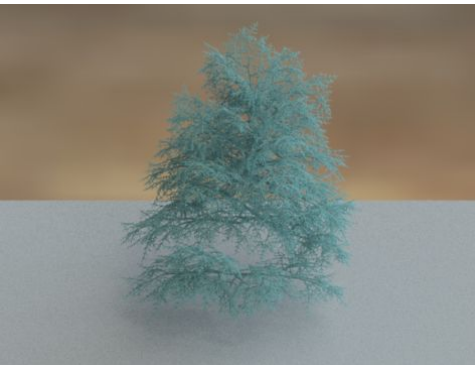


Errors:

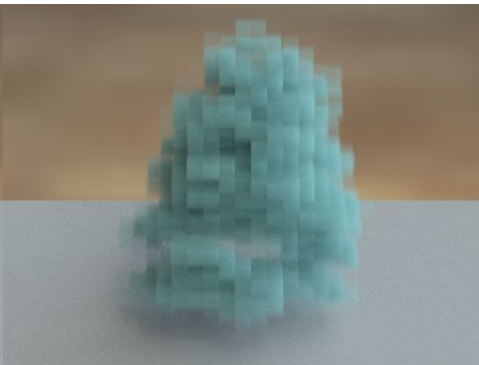


Results

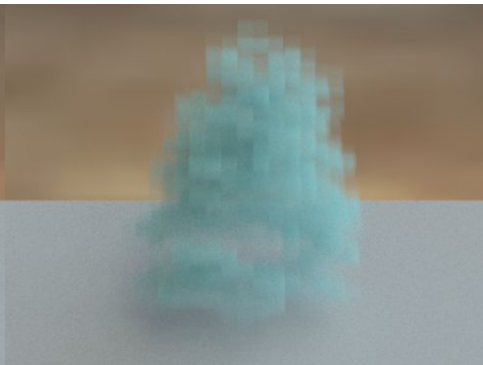
Input



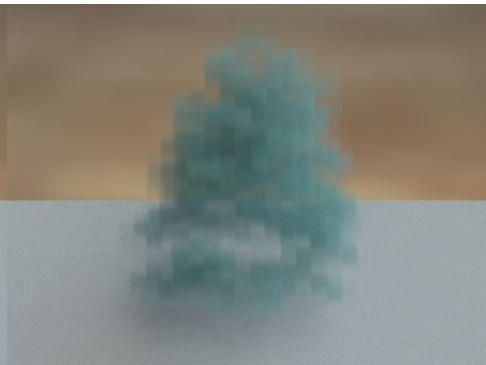
Naïve (linear)



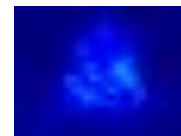
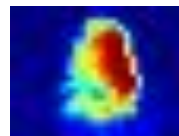
Naïve (correct transp.)



Our

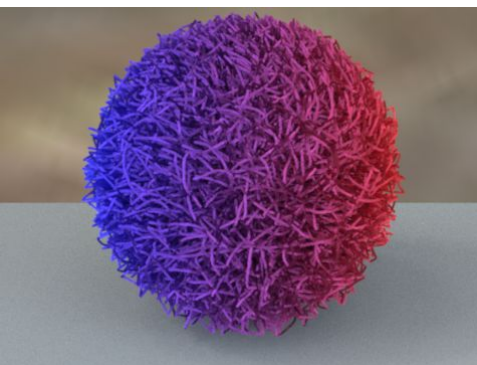


Errors:

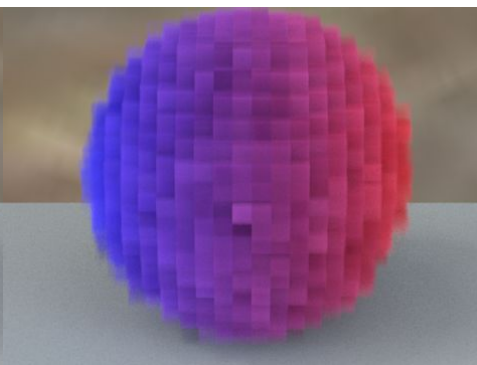


Results

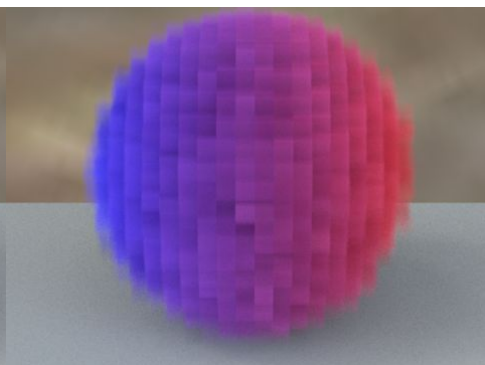
Input



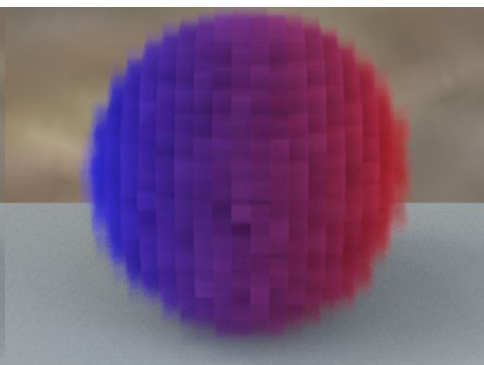
Naïve (linear)



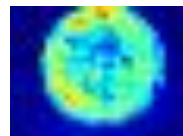
Naïve (correct transp.)



Our



Errors:



Results

Input



Naïve (linear)



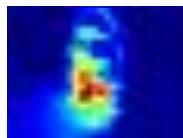
Naïve (correct transp.)



Our



Errors:

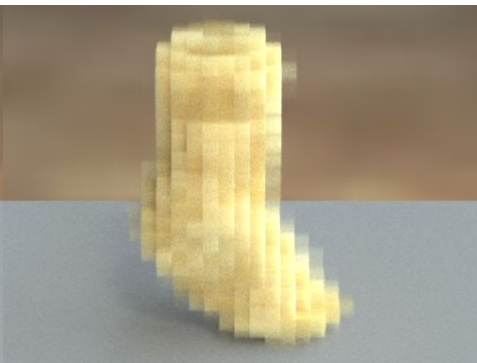


Results

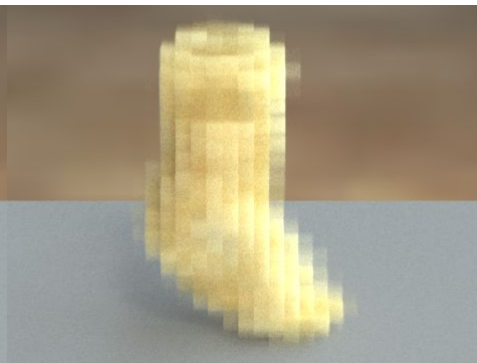
Input



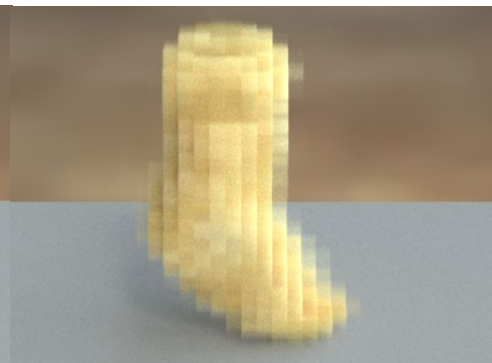
Naïve (linear)



Naïve (correct transp.)



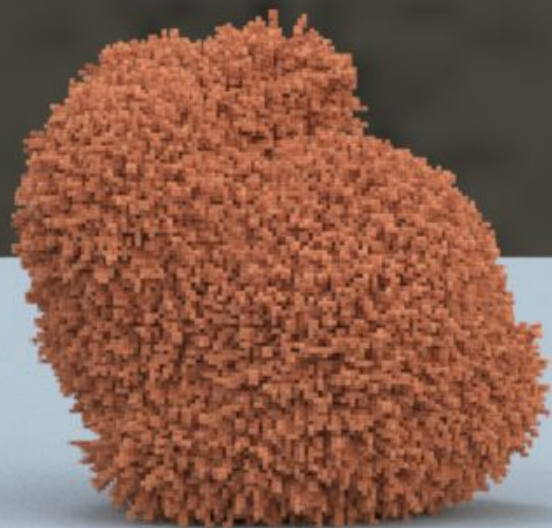
Our



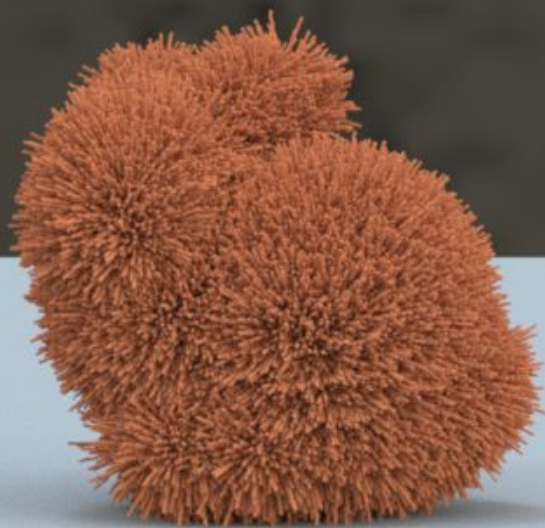
Errors:



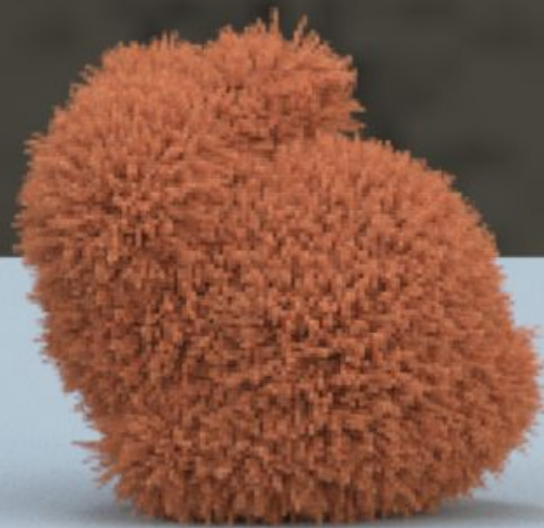
Results



LOD 2
[Zhao, Wu et al. 2016]



Input



LOD 2
Our, x10 faster

Results



Input

Results



LOD 1

Results



LOD 2

Results



LOD 3

Results



LOD 4

Results

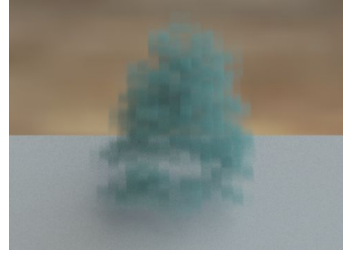


LOD 5

Main ideas

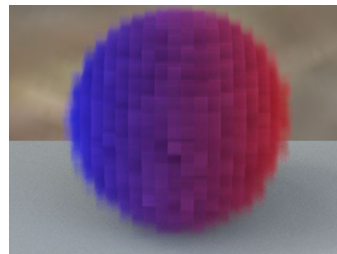
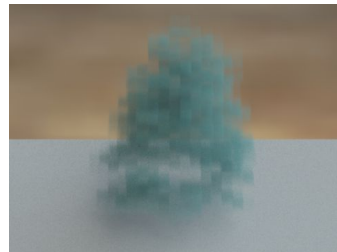
Main ideas

- **Correct transparency is important**



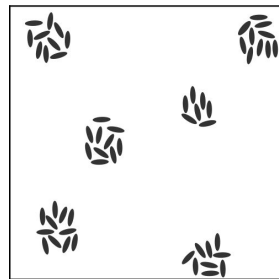
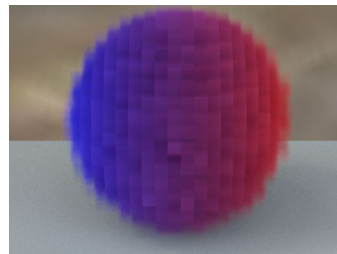
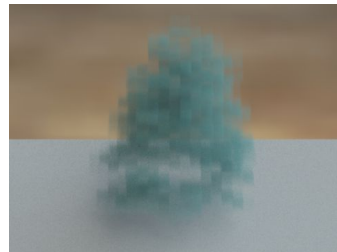
Main ideas

- **Correct transparency is important**
- **Local estimation of parameters:** fast, accurate, general



Main ideas

- **Correct transparency is important**
- **Local estimation of parameters:** fast, accurate, general
- **Our model:** good for correct color and transparency, still not perfect!



Acknowledgement

Shuang Zhao & Lifan Wu for their code and datasets!