

3D Computer Graphics and Animation

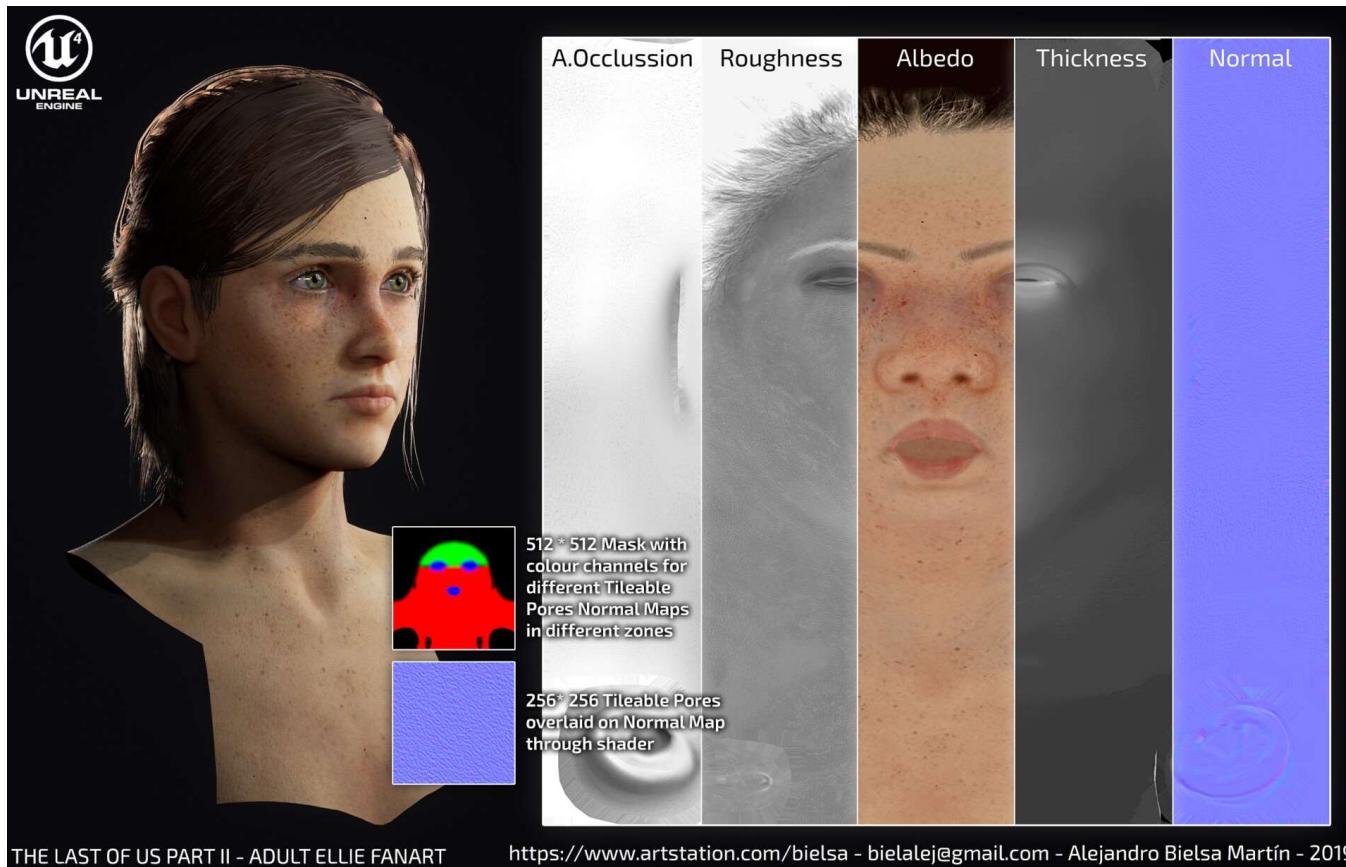
Filtered Shadows The line begins to blur...

Elmar Eisemann

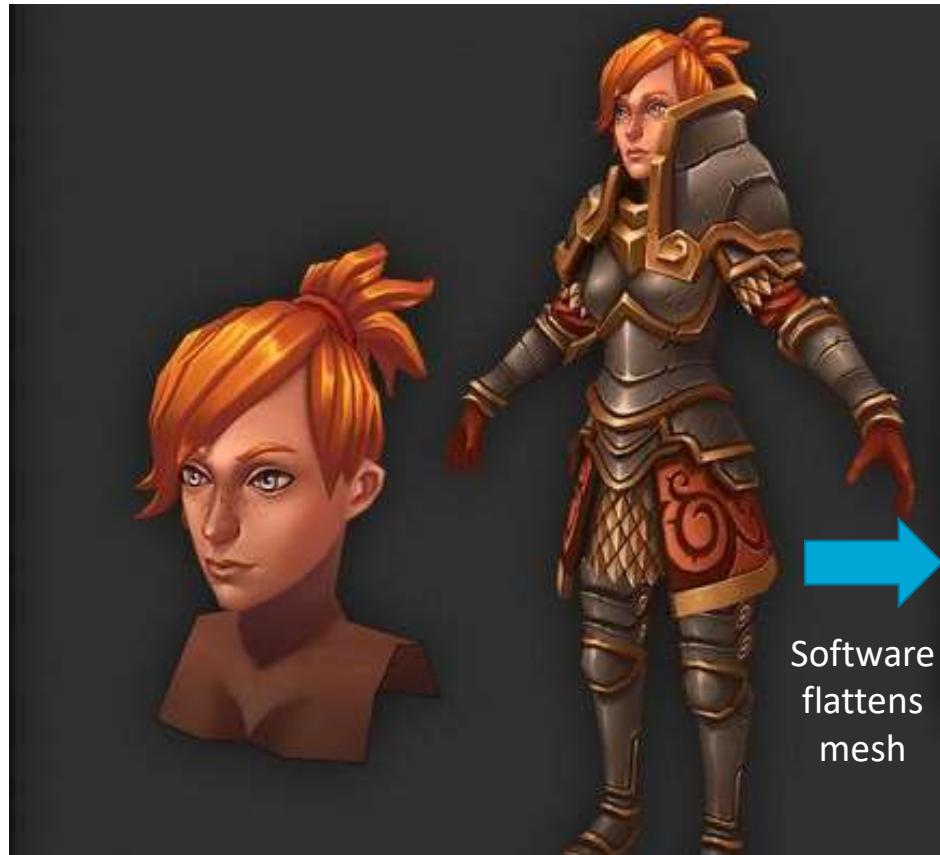
Delft University of Technology



Professional Example

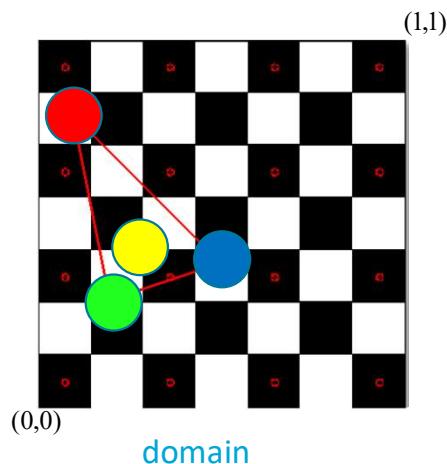


Texture Mapping: Special Software

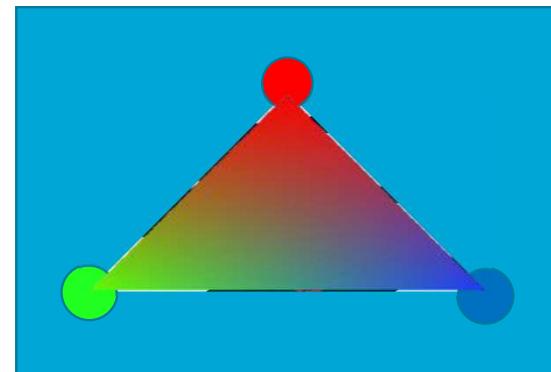


Textures

- Image mapped on the surface via texture coordinates
 - Specified at each vertex `glTexCoord{123}{fi}`
 - Interpolated over triangles

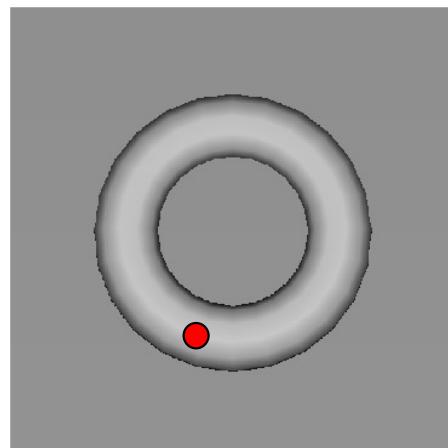
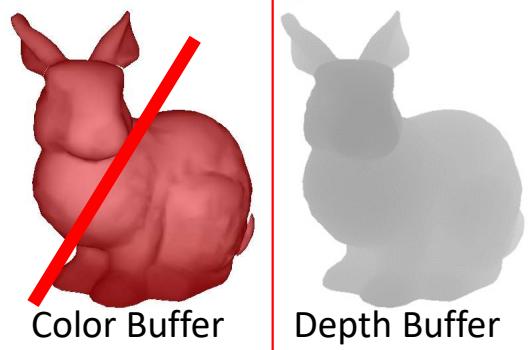


```
TextureCoords(0.2f, 0.3f);  
Vertex(-1.0f, 0.0f);  
  
TextureCoords(0.5f, 0.4f);  
Vertex(+1.0f, 0.0f);  
  
TextureCoords(0.1f, 0.8f);  
Vertex( 0.0f, 1.0f);
```

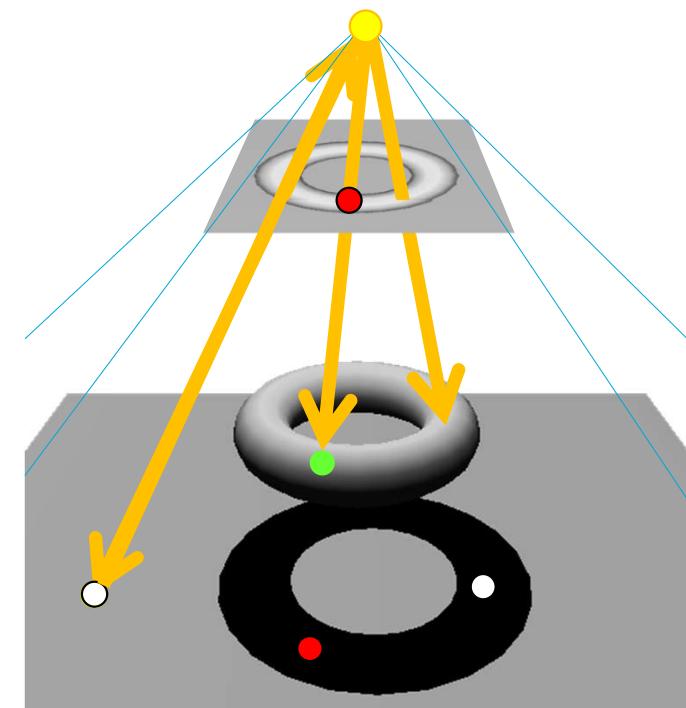


3D View

Shadow Mapping [Williams78]

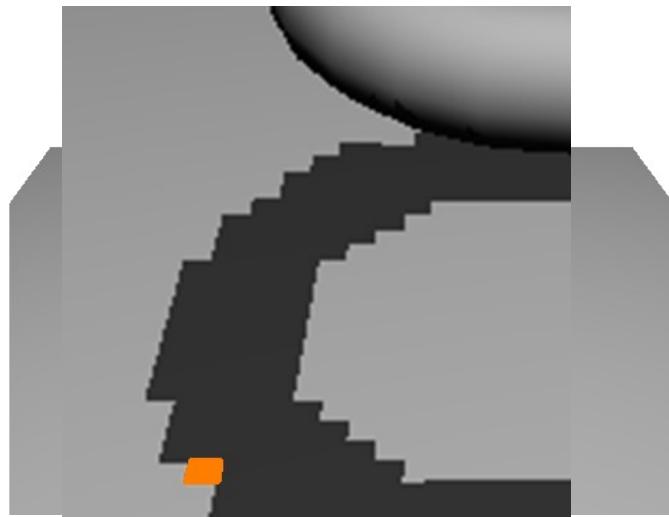


1. render view from light
use **depth buffer**

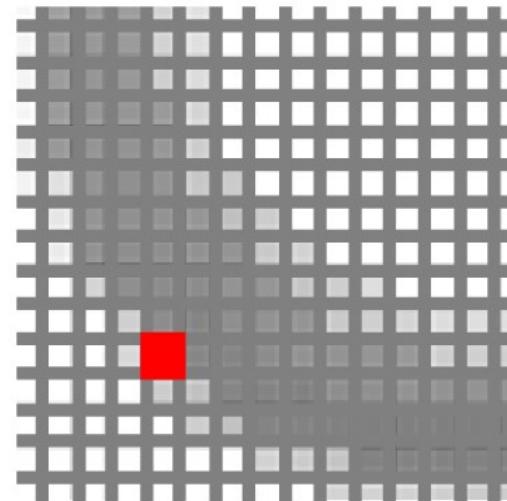


2. render from viewpoint

Shadows and Rasterization



from viewpoint

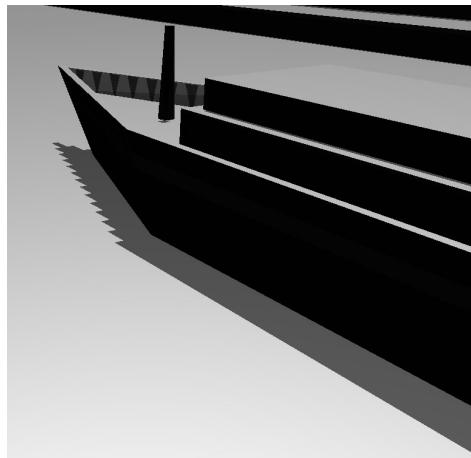


from light

Texture Problems for Shadow Mapping

Reconstruction

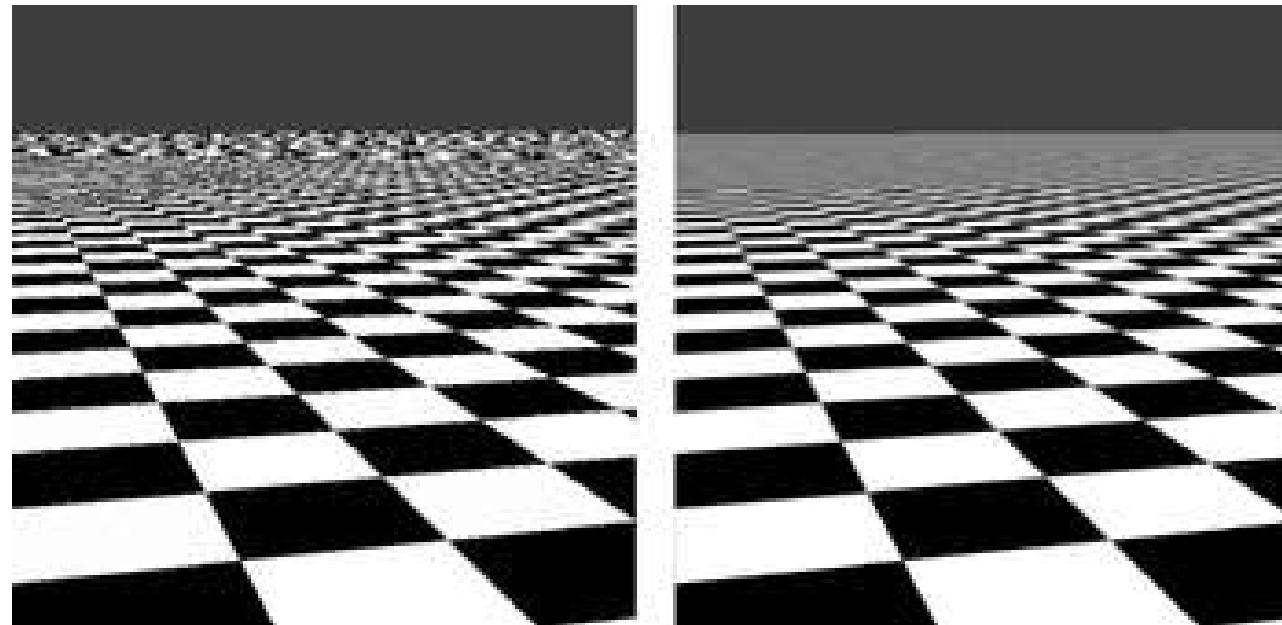
- Staircase artifacts



Texture Oversampling



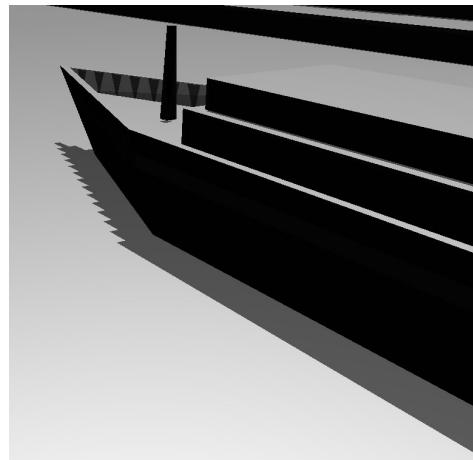
Texture Undersampling



Texture Problems for Shadow Mapping

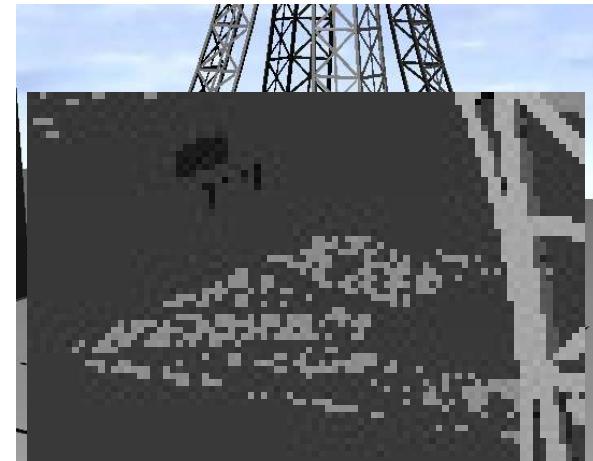
Reconstruction

- Staircase artifacts

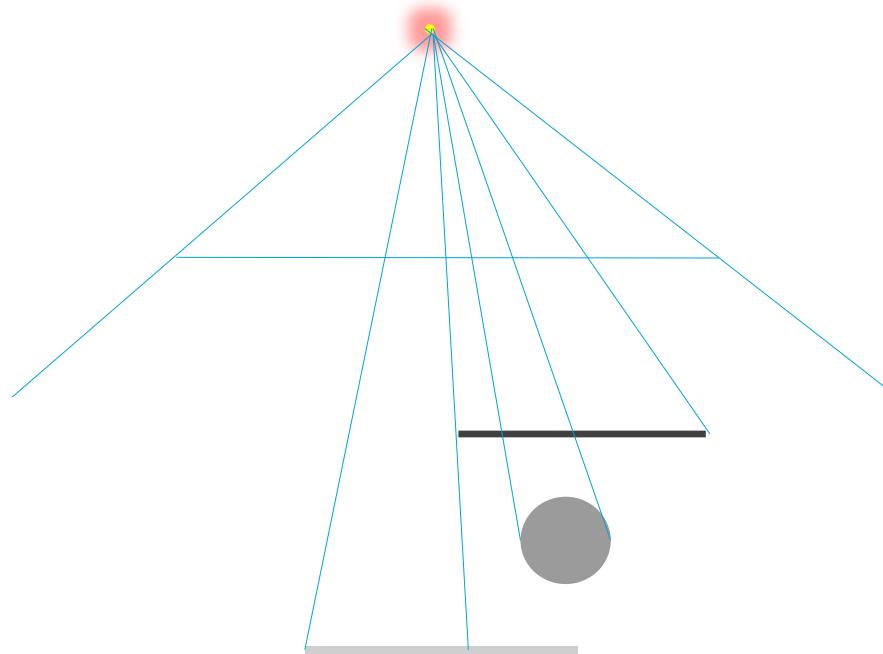


Undersampling

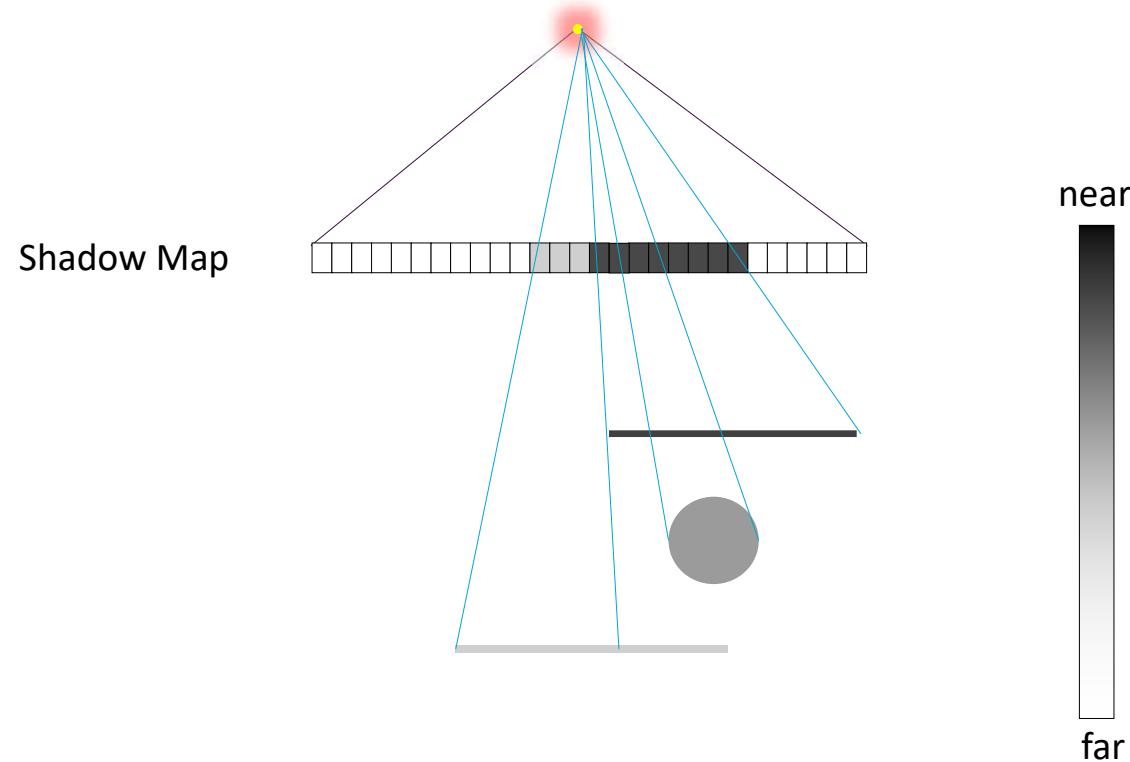
- Noise



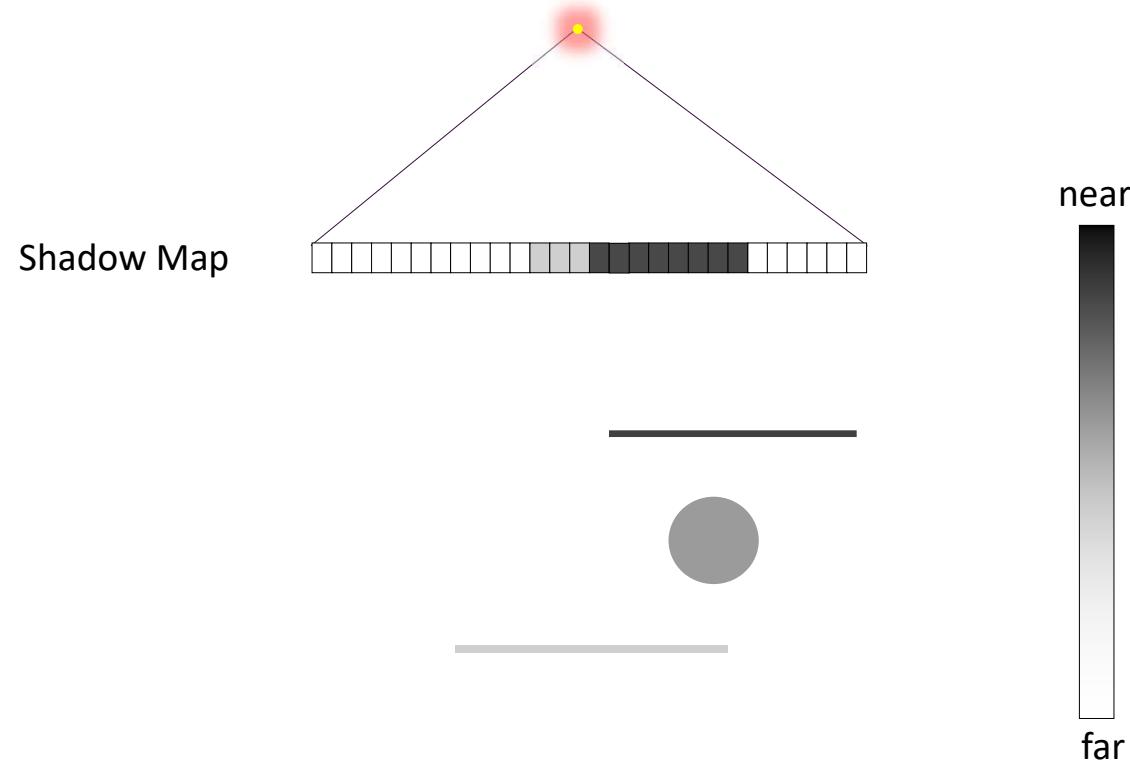
Shadow Mapping



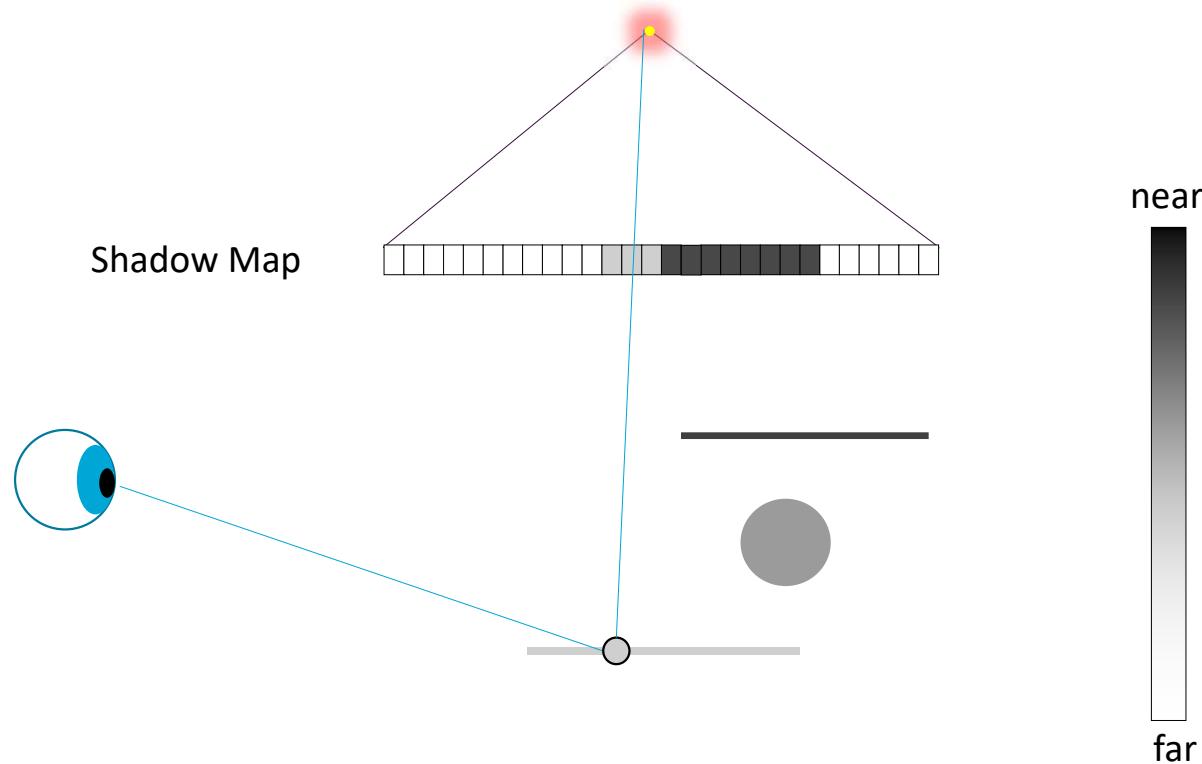
Shadow Mapping



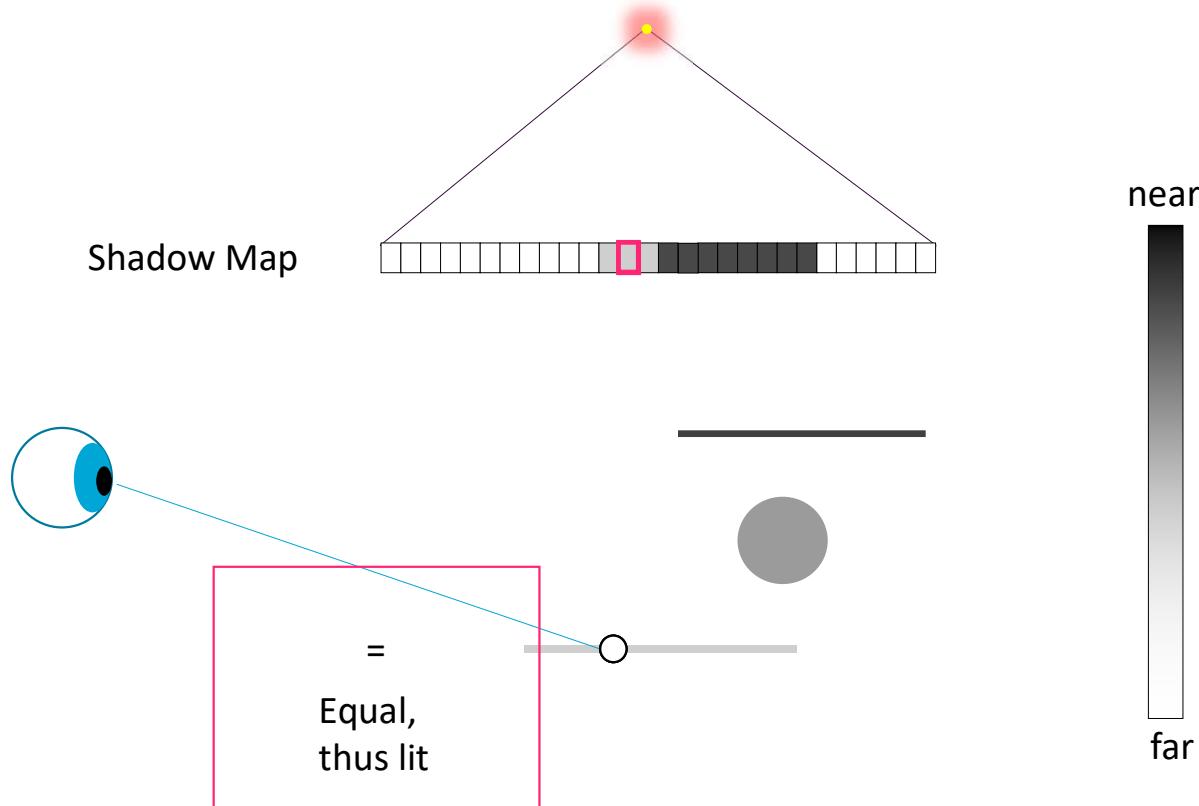
Shadow Mapping



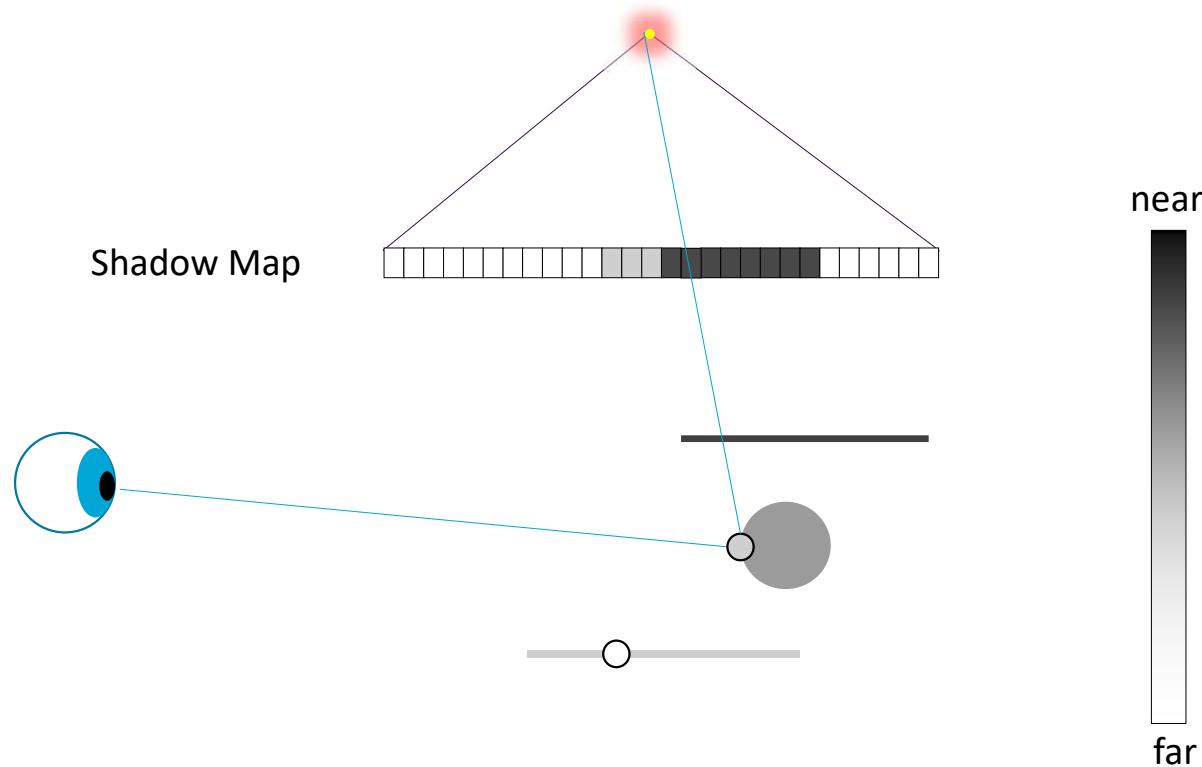
Shadow Mapping



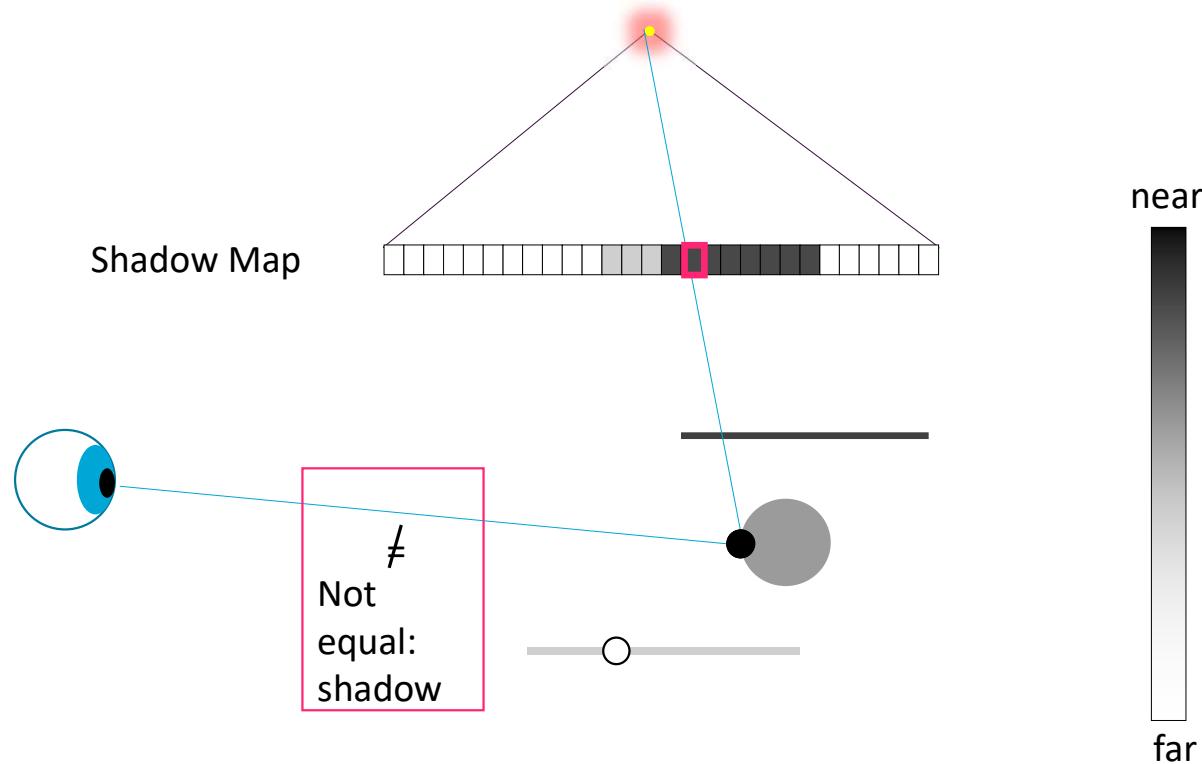
Shadow Mapping



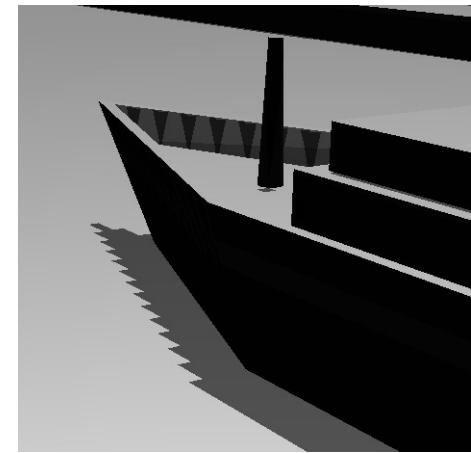
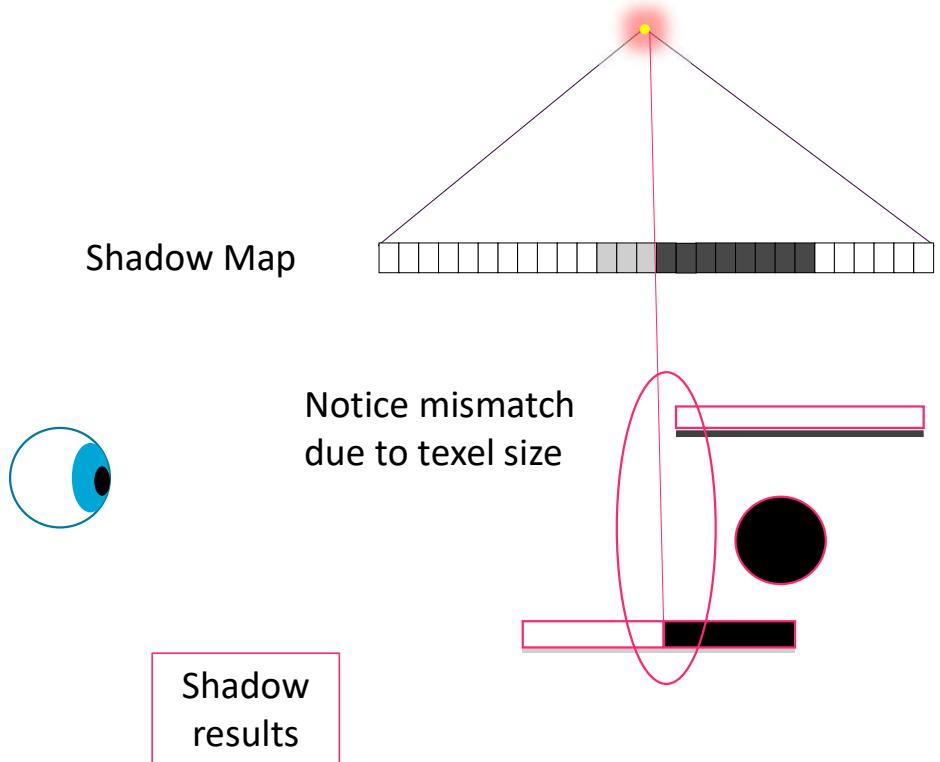
Shadow Mapping



Shadow Mapping



Shadow Mapping

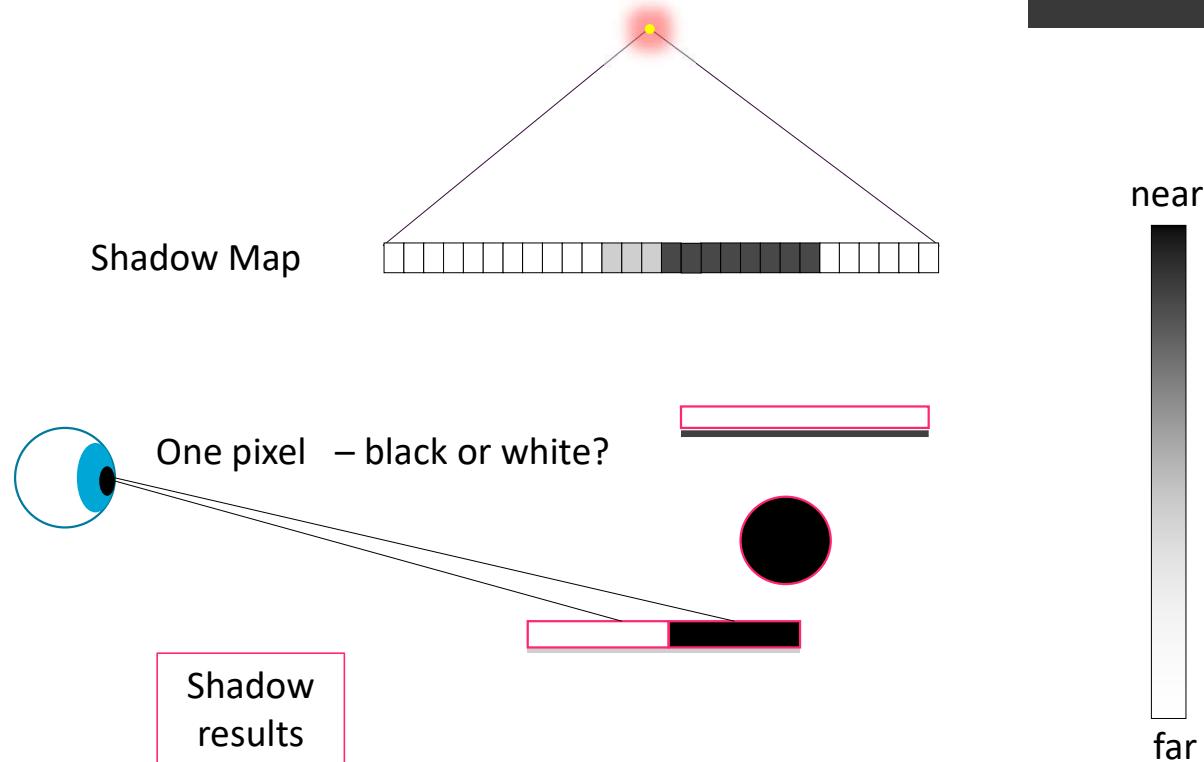
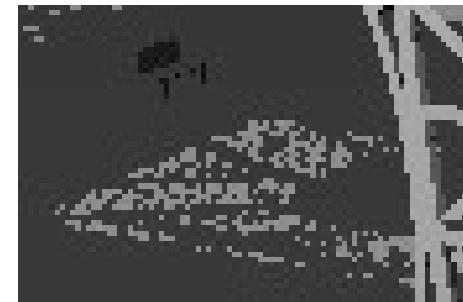


near

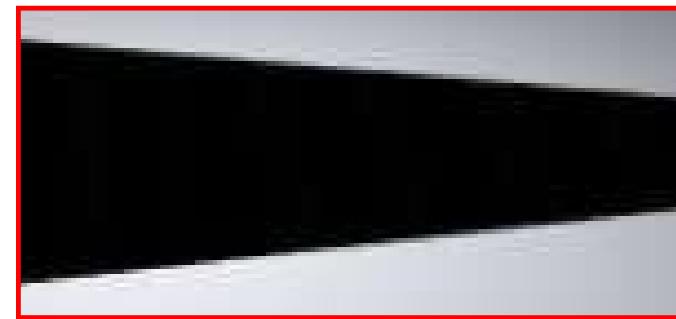
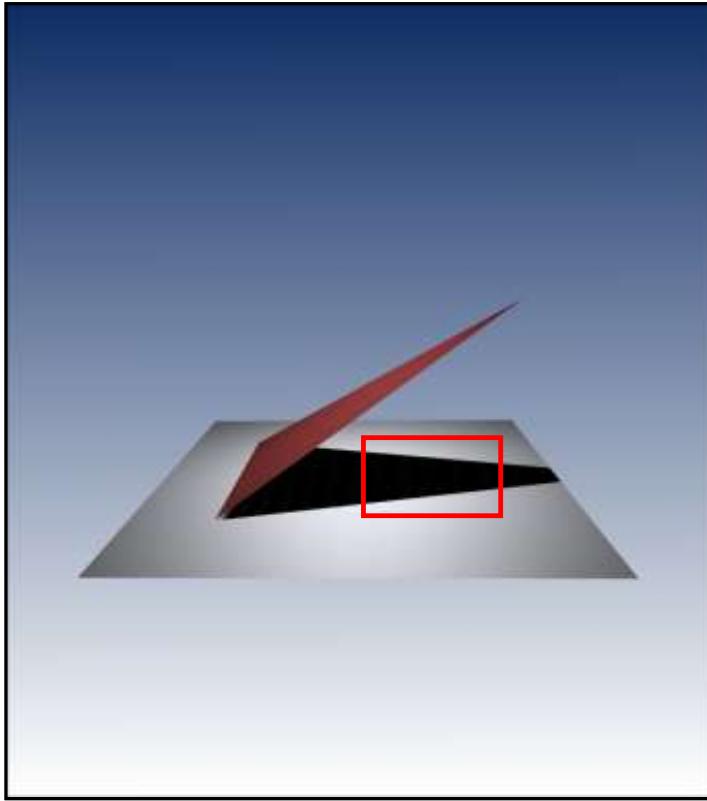


far

Shadow Mapping

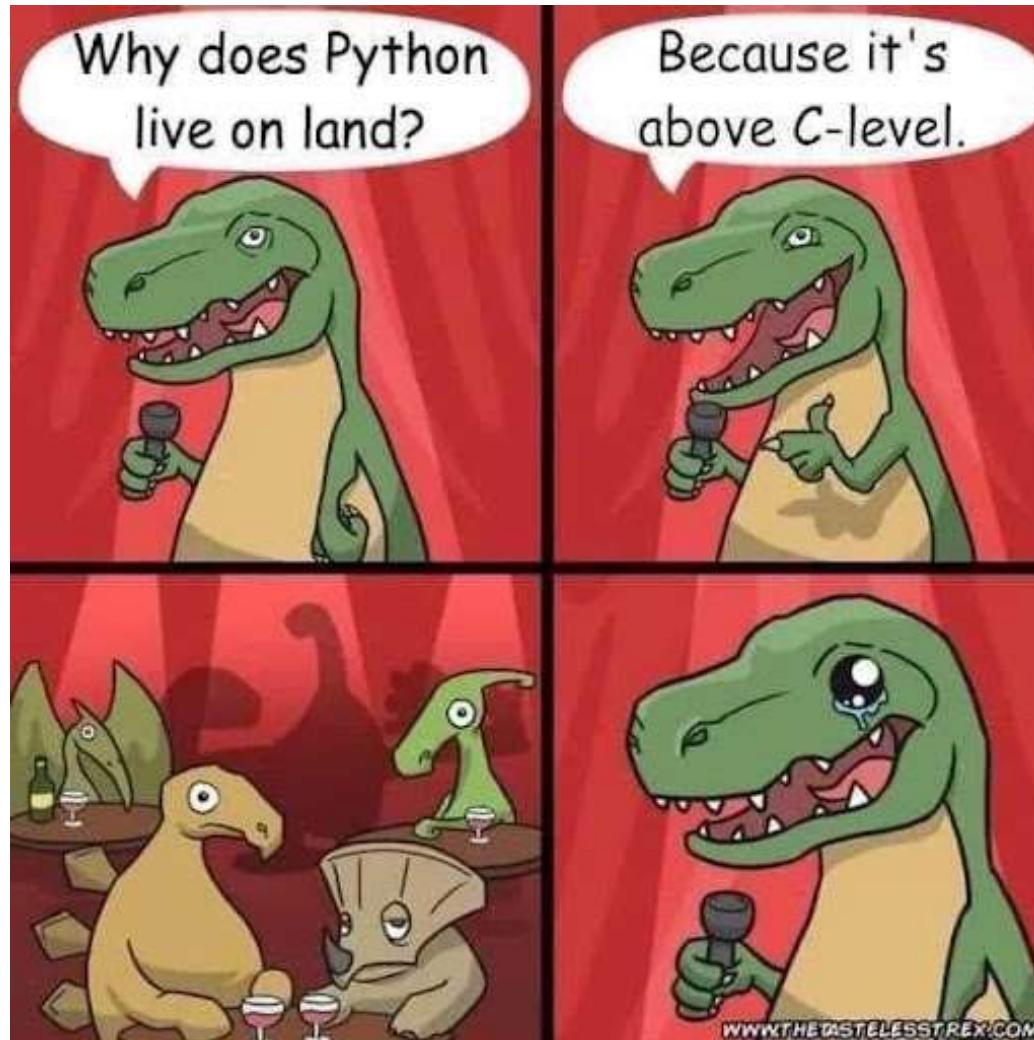


Filtered Hard Shadows

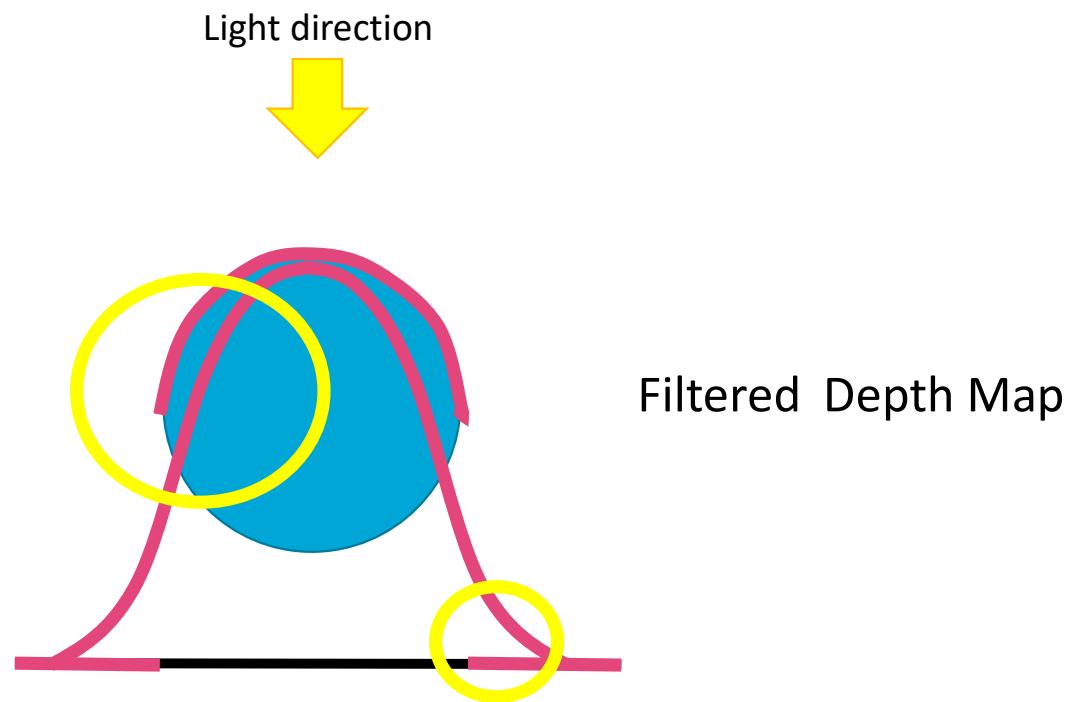


Filtered Shadow Mapping

Questions?



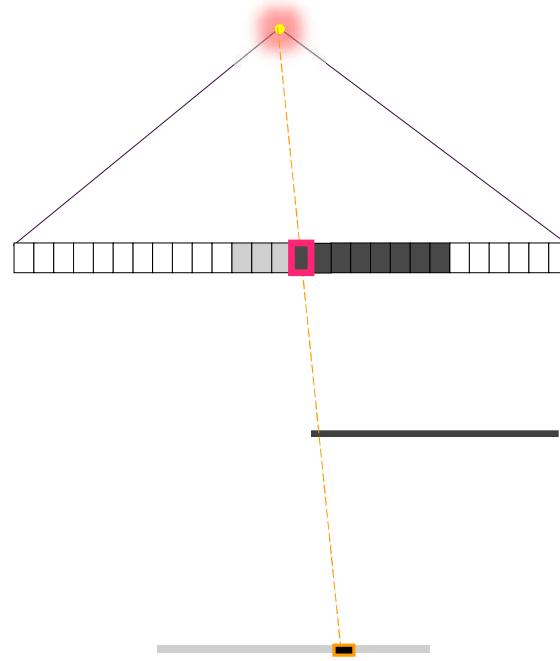
Can we just filter the Depth Map?



Percentage-Closer Filtering



unfiltered

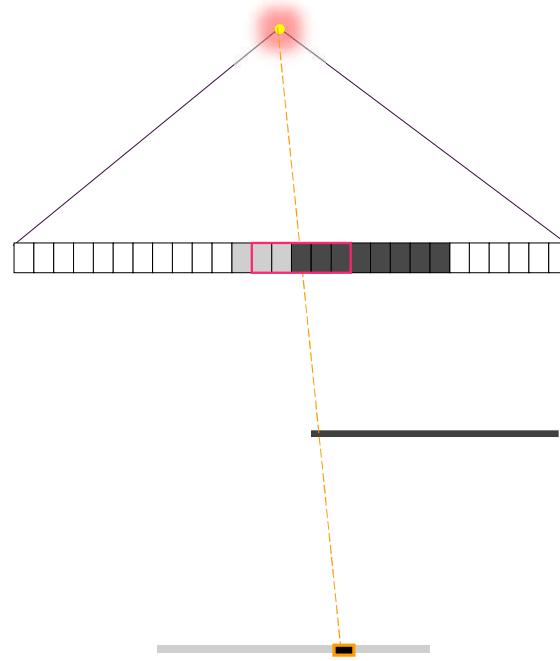


[Reeves et al. '87]

Percentage-Closer Filtering

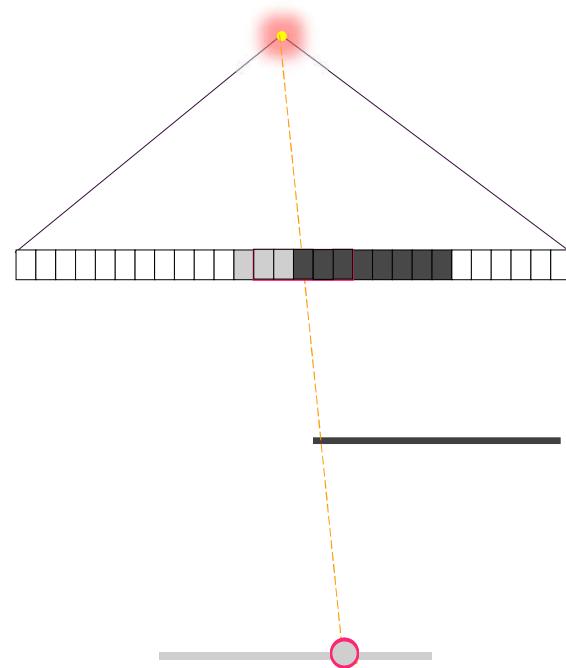
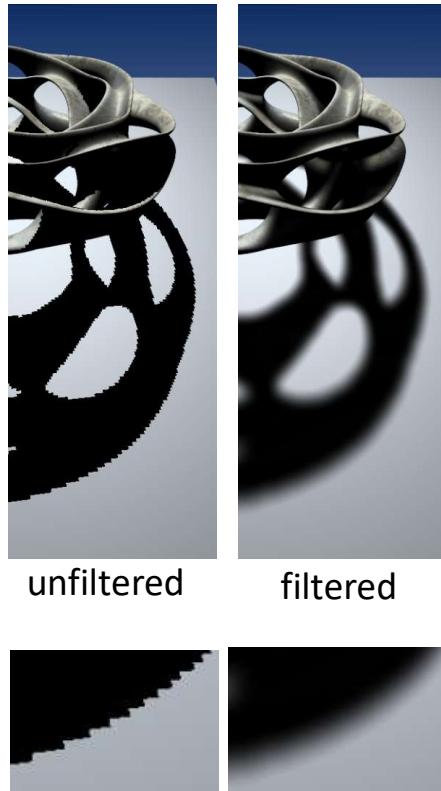


unfiltered



[Reeves et al. '87]

Percentage-Closer Filtering



[Reeves et al. '87]

40 % lit, 60% shadow

\neq	shadow
\neq	shadow
\neq	shadow
=	lit
=	lit



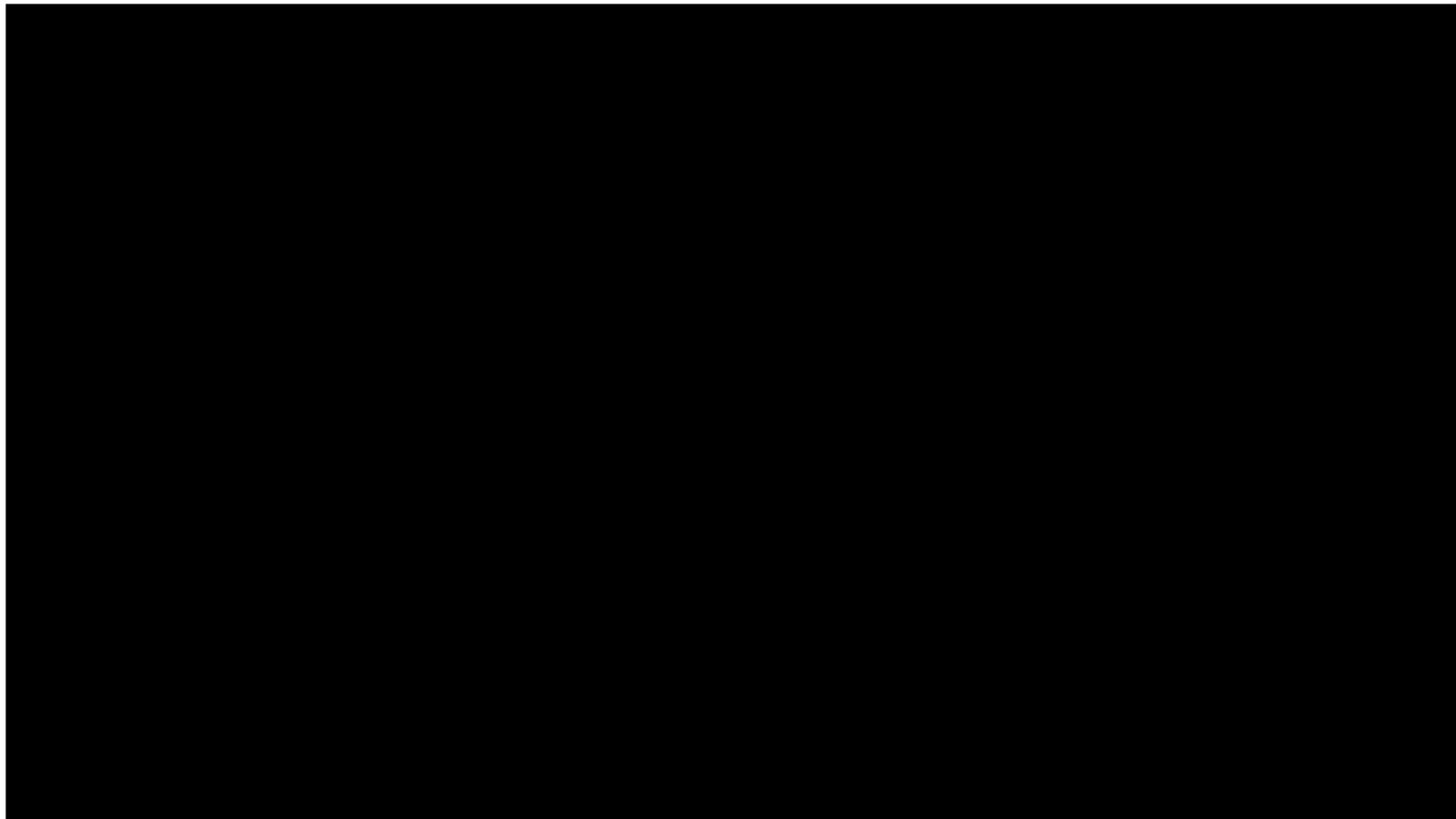
compare first, then average!

Attention

- Percentage-Closer Filtering is
NOT computing soft shadows



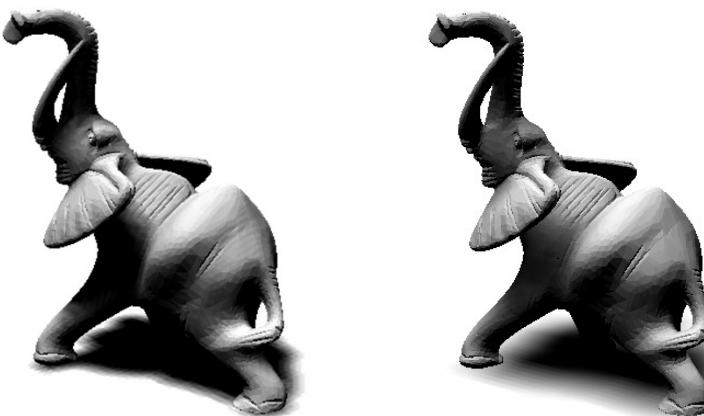
Pixar



Shadows computed with Percentage-Closer Filtering (PCF)

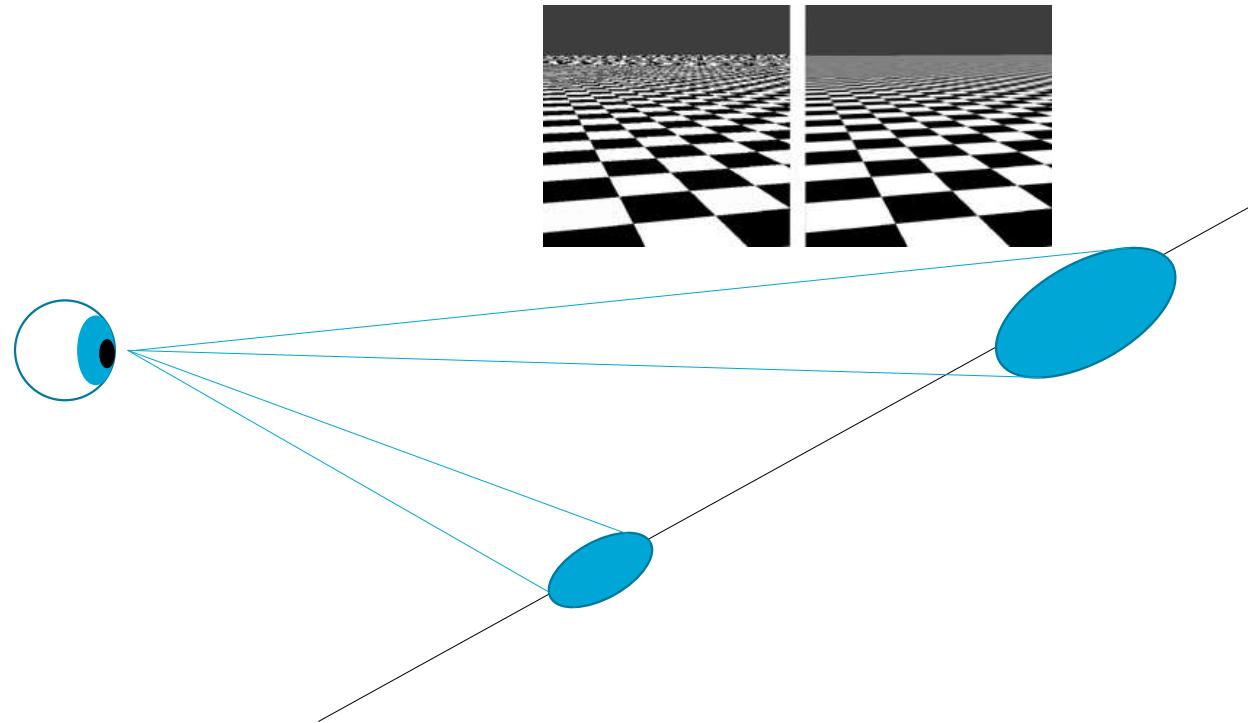
Percentage-Closer-like Filtering

- + Standard (simple to implement)
- + Hides discretization



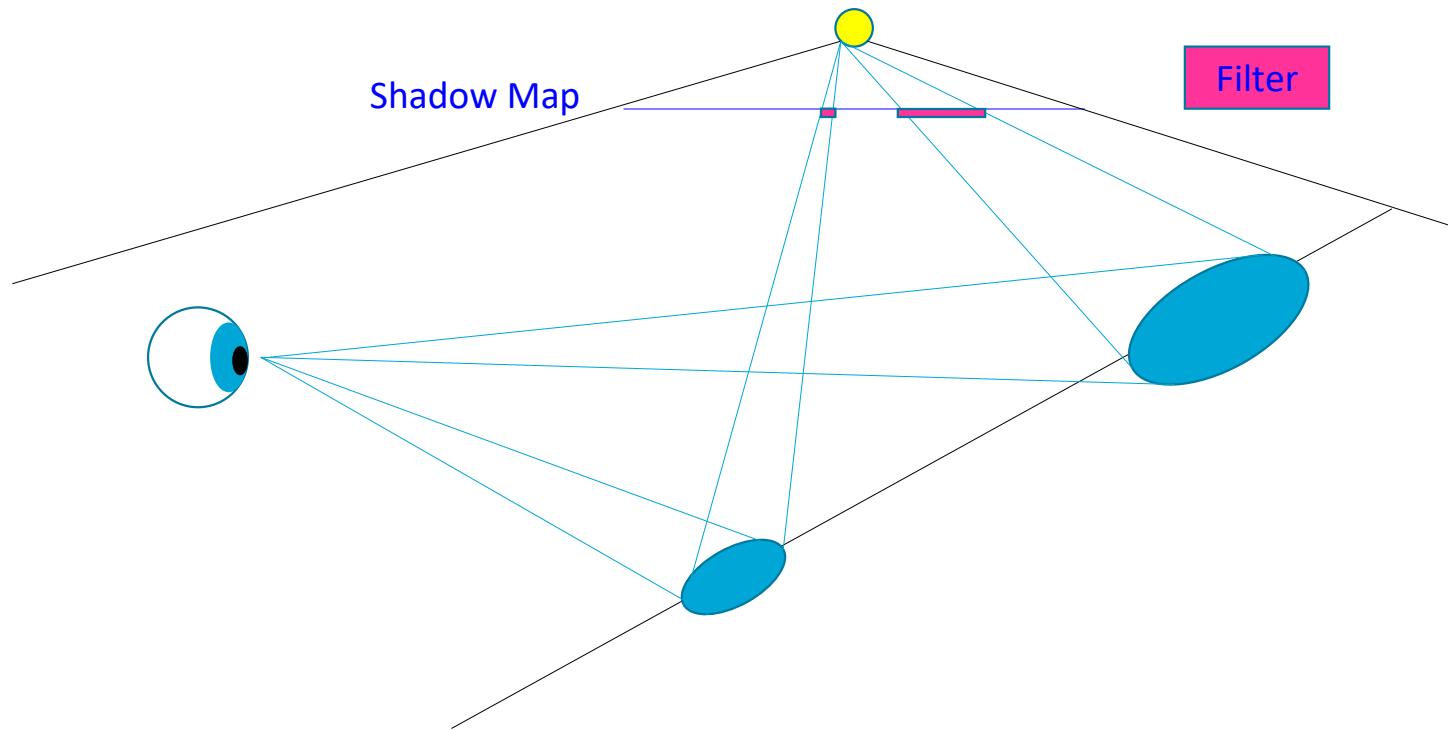
How to choose the PCF Filter size?

- Choose filter according to viewing distance

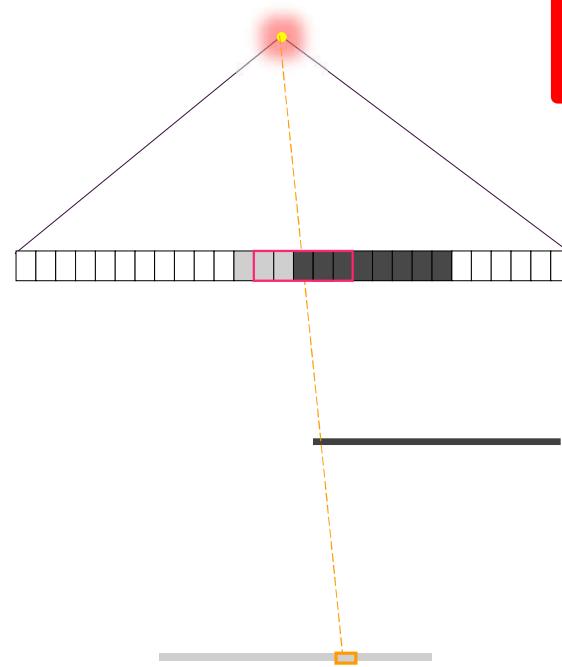
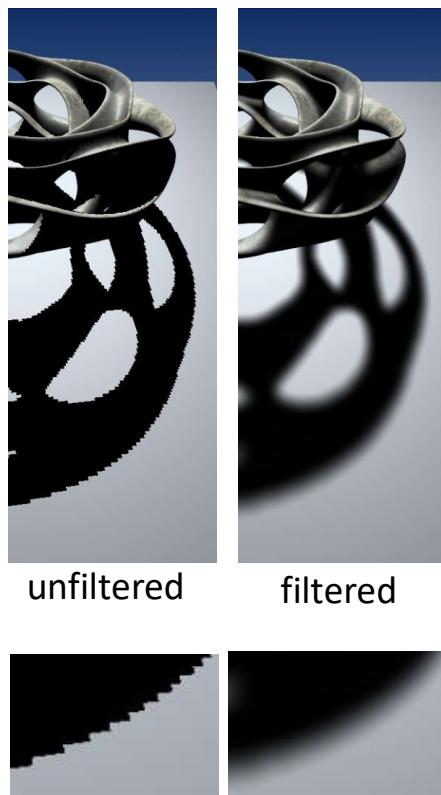


How to choose the PCF Filter size?

- Choose filter according to viewing distance
- PCF Filter can become very large



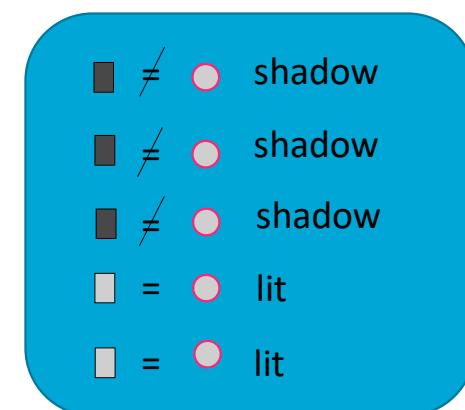
Percentage-Closer Filtering



[Reeves et al. '87]

Attention:
 Large neighborhood
 = costly evaluation!
 E.g., 5x5 implies 25 lookups

40 % lit, 60% shadow



compare first, then average!

Adapted PCF Filter Kernel

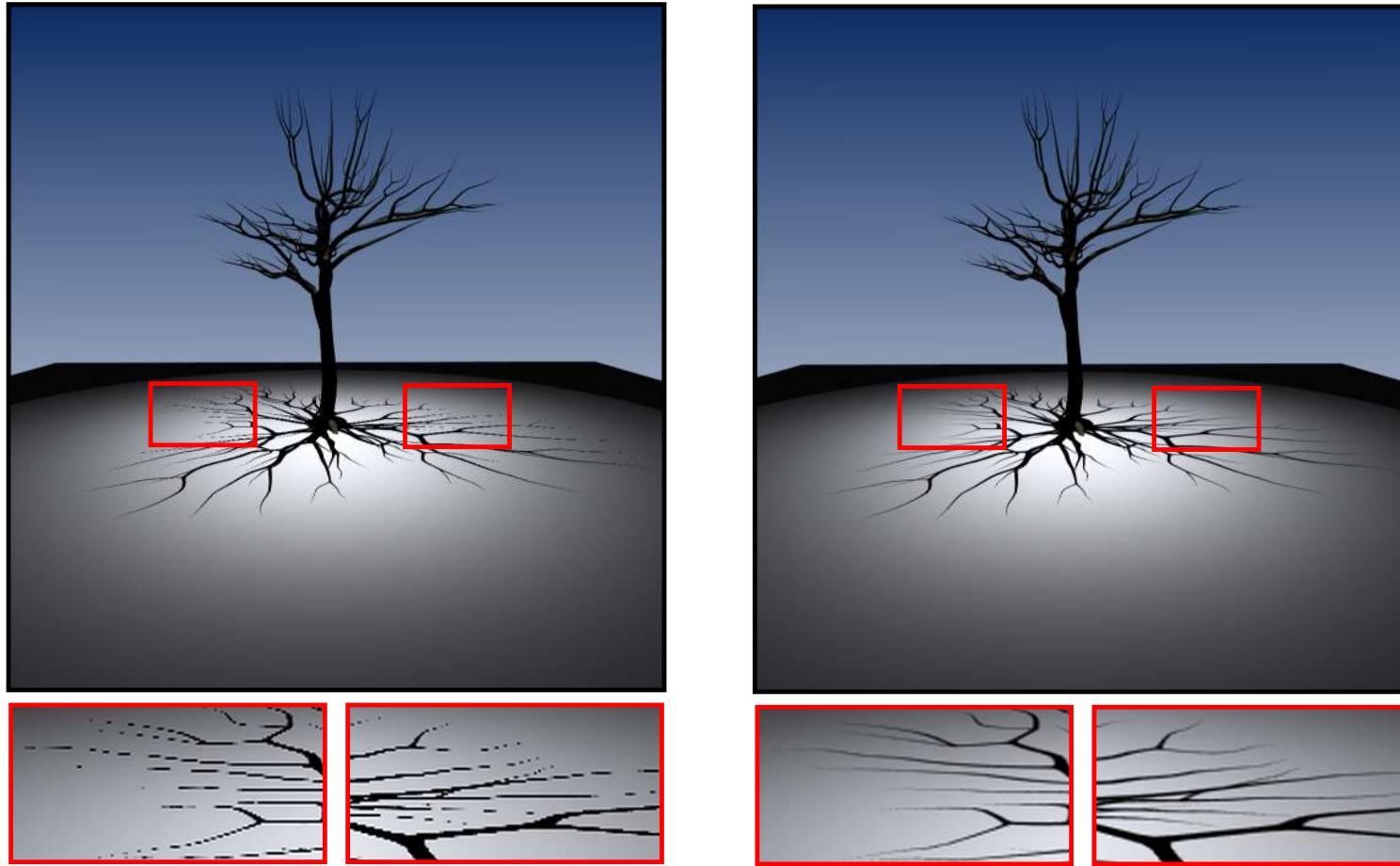
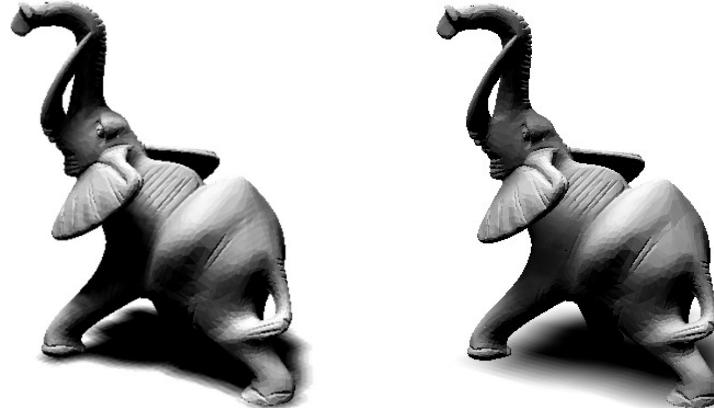


Illustration courtesy of Annen et al.

Percentage-Closer-like Filtering

- + Standard (simple to implement)
 - + Hides discretization
 - Costly for large kernels
- Topic of today!



Any Questions...

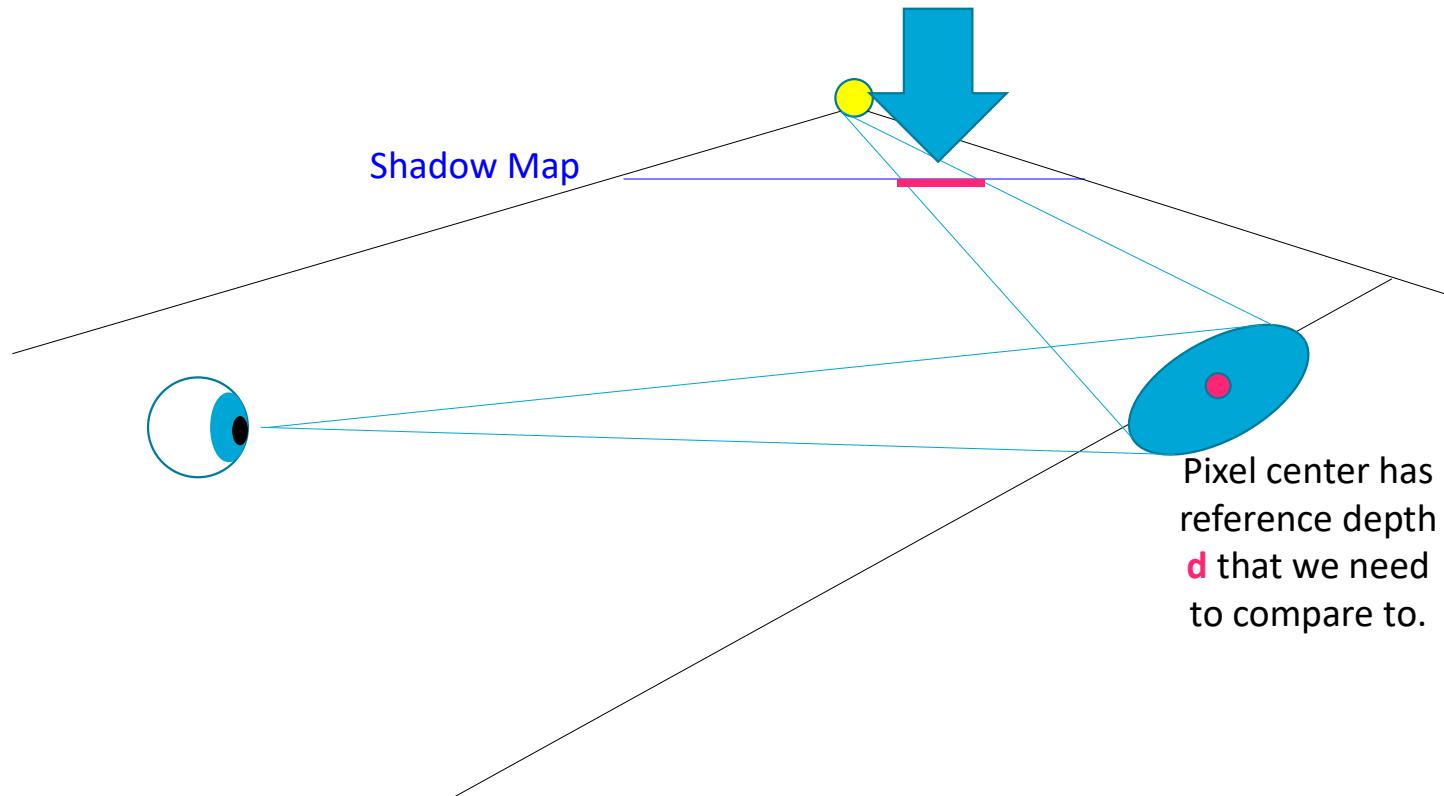
besides: How can we accelerate PCF?



Improvements

- Variance Shadow maps [Lauritzen&Donnelly06]
- Convolution Shadow Maps [Annen et al. 07]
- Exponential Shadow Maps [Annen et al. 08, Salvi08]

How evaluate PCF in this region quickly?

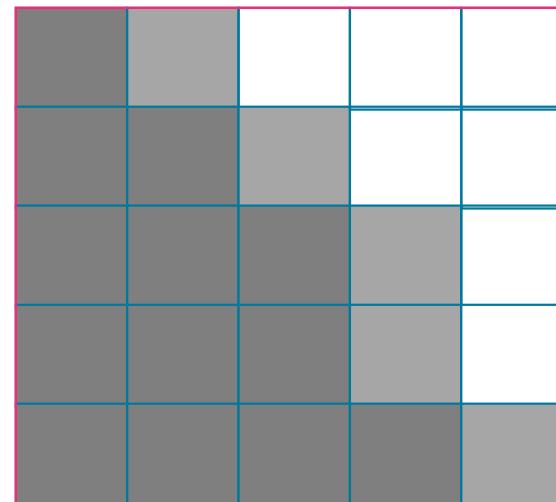


Variance SMs [Lauritzen & Donnelly 2006]

- Avoid many lookups and comparisons

- Solution:
 - FIRST filter
 - SECOND one lookup

Reference d

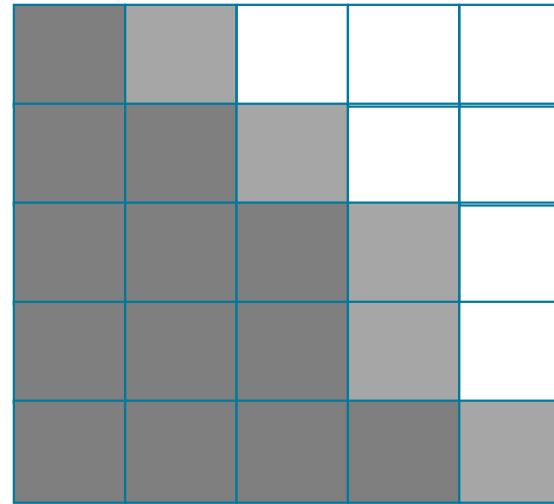


Filtered
binary
result

Wait a second... didn't we just say:
We cannot first filter then compare???

Variance SMs [Lauritzen & Donnelly 2006]

- Reformulation:
- Given depth d
- What is probability
that $d < x$
for all x in window?

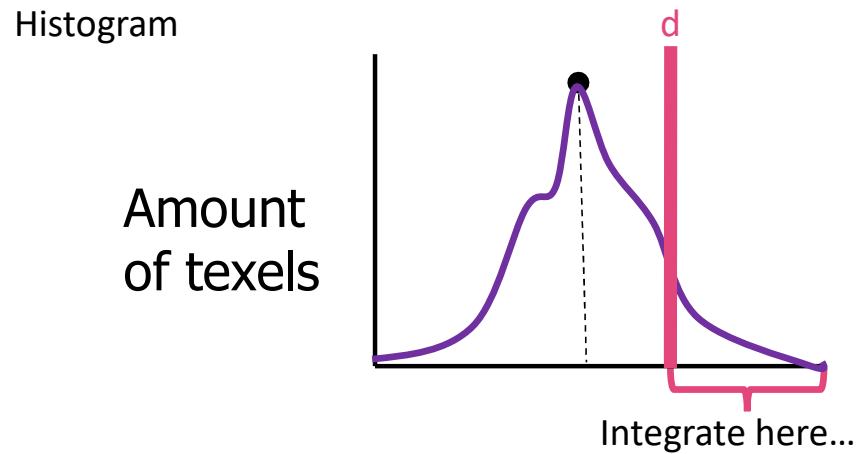


It is the same
computation!

→ Idea: Use statistics to “guess” the outcome

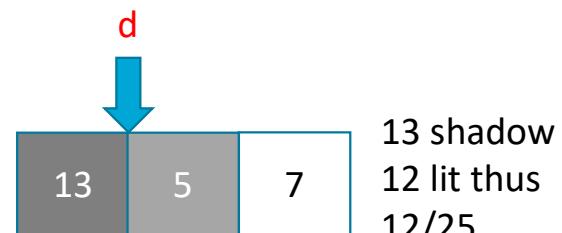
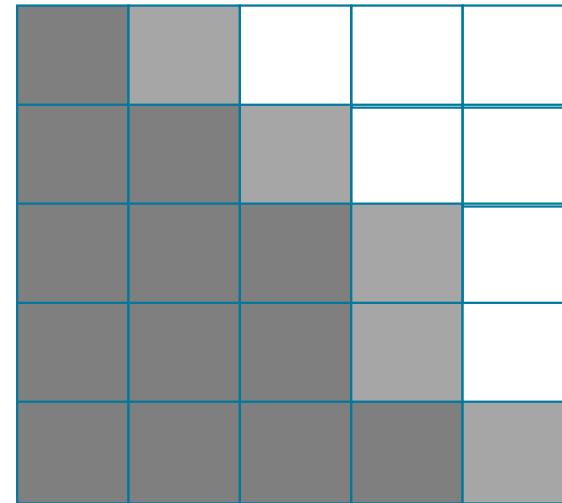
Theoretical Approach

- Take the depth distribution (like a histogram) and compare to d



The integrated part tells you how many depth values are larger than d and would therefore not occlude it.

But building up the actual distribution requires us to do again lots of lookups...



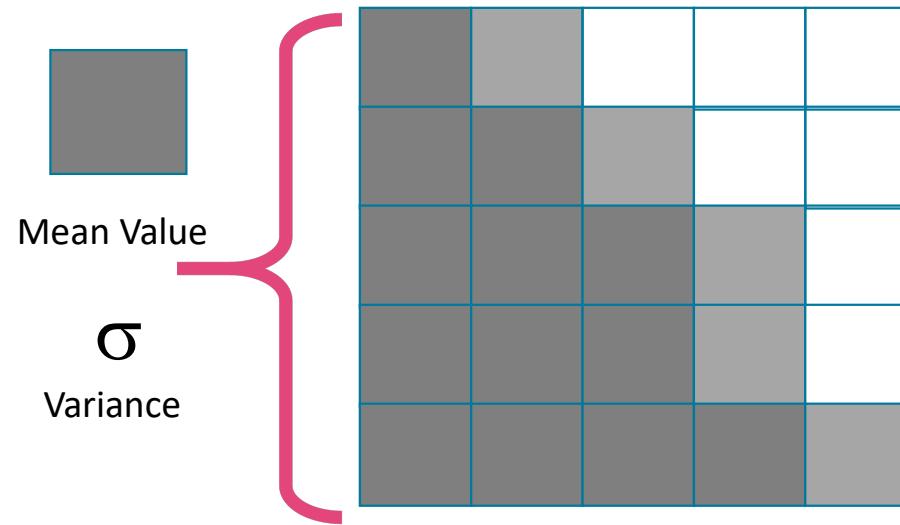
Approximate Distribution

- Instead of looking at individual depth values,
consider an approximate **distribution** :



Use **mean and variance**

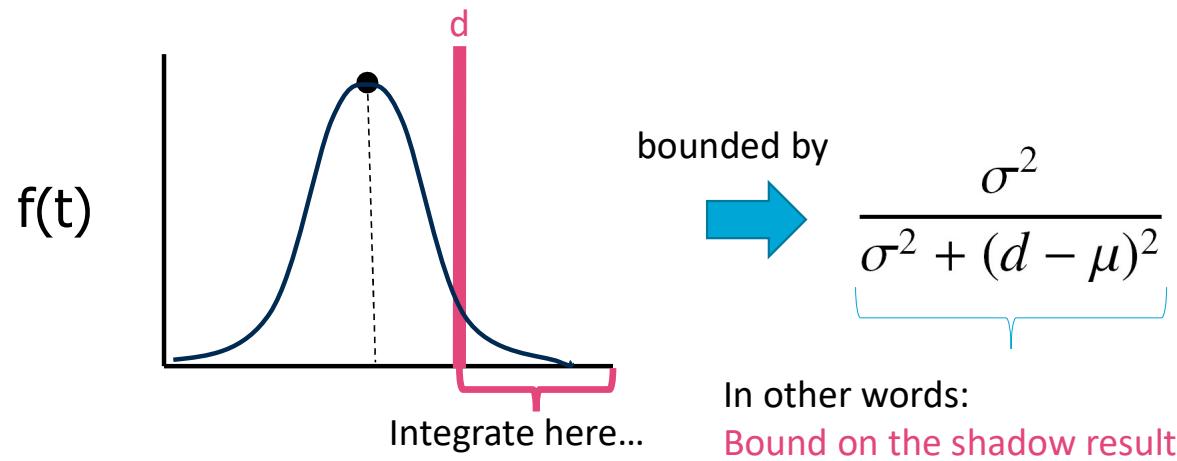
Approximate Distribution



Suppose a “Magic Transformation” for the moment

What can we do with Distribution?

For a depth-value distribution
the test result can be bounded



Lauritzen and Donnelly'06:
“Just assume equality and you have a fast and good-looking method!”

Where does this bound come from?

- Chebyshev Inequality:

$$\text{Probability}(d < D) \leq \frac{\sigma^2}{\sigma^2 + (d - \mu)^2}$$

(for $d \leq \mu$, for $d \geq \mu$ assume 1)

where D is random Variable from an arbitrary

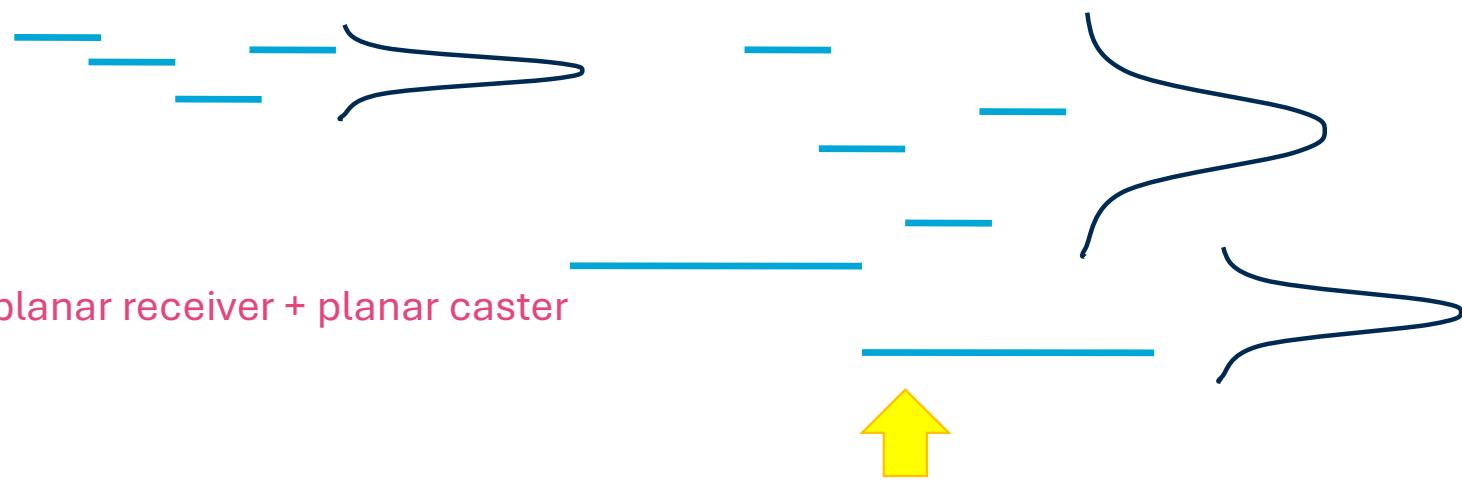
depth distribution (mean μ , variance σ^2)

Estimating shadows

- Using:

$$\frac{\sigma^2}{\sigma^2 + (d - \mu)^2}$$

- Small sigma leads to quick fall-off
- Large sigma leads to slow fall-off



- Accurate for planar receiver + planar caster

Estimating shadows



Light direction

- What is the problem?

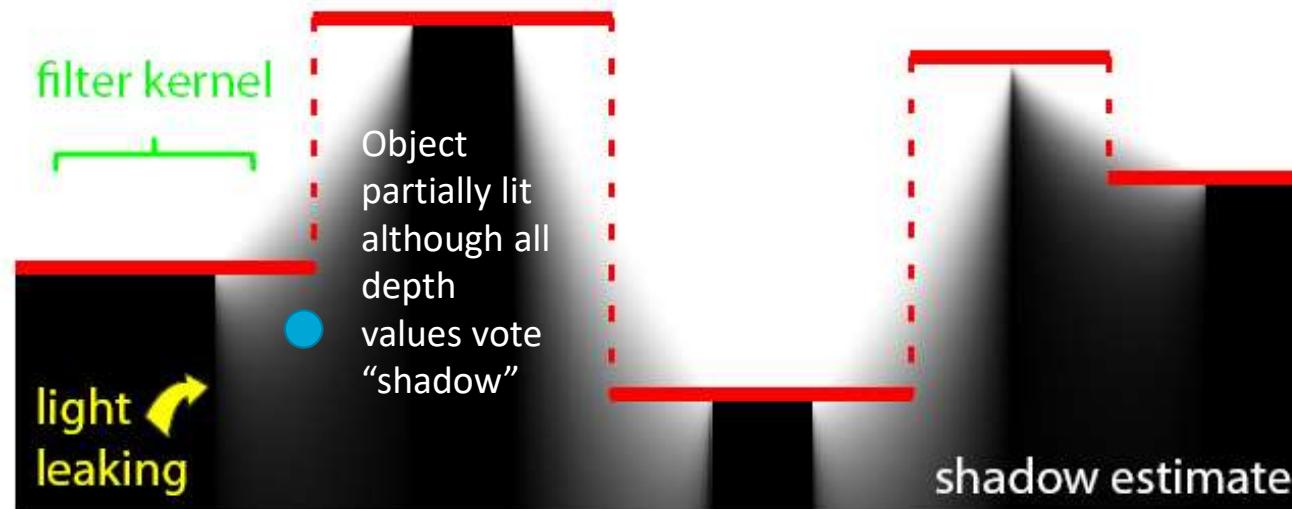


Estimating shadows



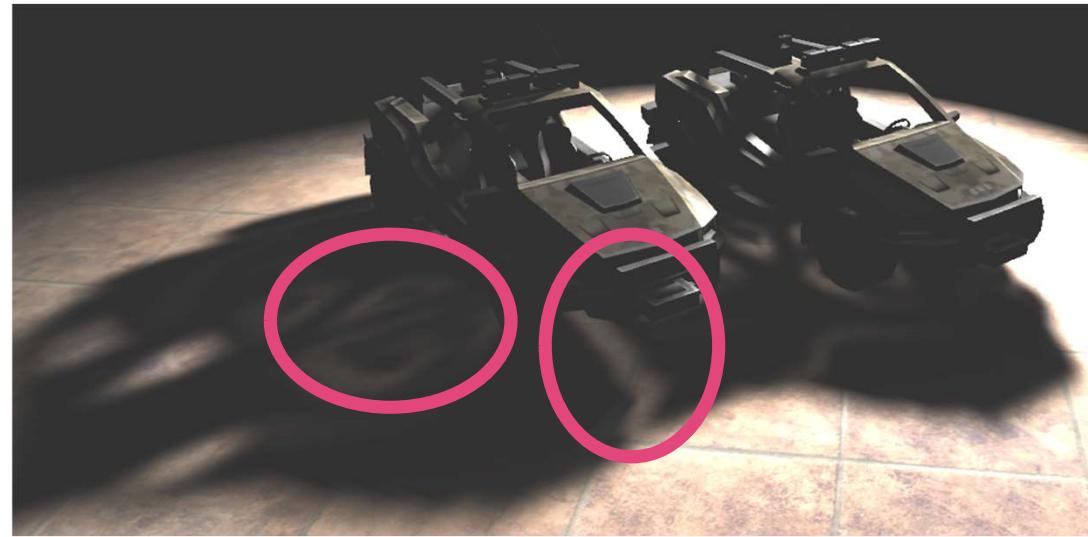
Light direction

- What is the problem?
- Solution is an upper bound, not accurate in general!



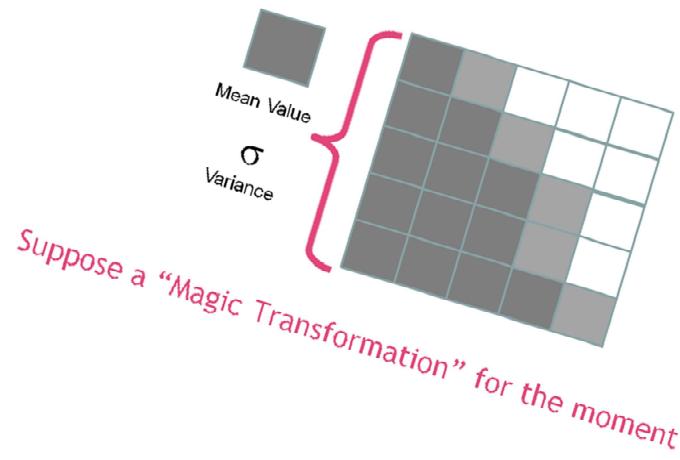
Variance SMs [Lauritzen & Donnelly 2006]

- Light leaks



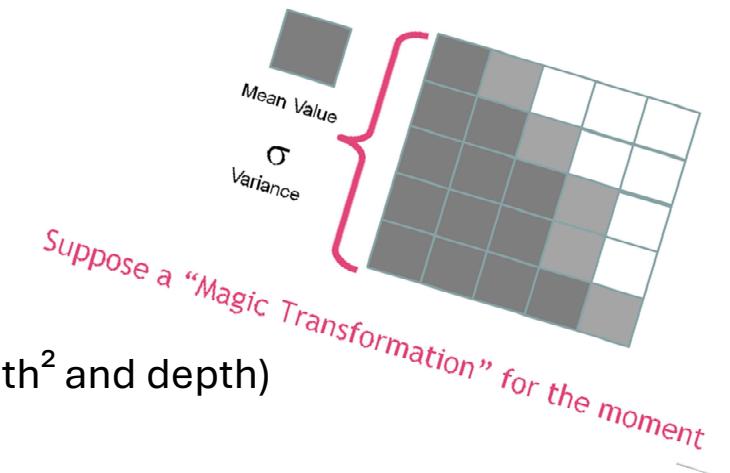
But there was still some detail...

- “Magic Transformation”



Transforming Depth Values to Distribution

- Mean Value: $\mu = E(d)$
an average of depth values
- Variance: $\sigma^2 = E(d^2) - E(d)^2$
easy to compute given two average values (depth² and depth)



➡ Need to quickly average values in a window

Mmm... I heard that one before...

Applied to Variance Shadow Maps

- All techniques compatible with

Variance Shadow Maps:

1. Create Shadow Map and Squared Shadow Map (d, d^2)

2. Create filtered maps

$(E(d), E(d^2))$

3. Use maps for shadow computation

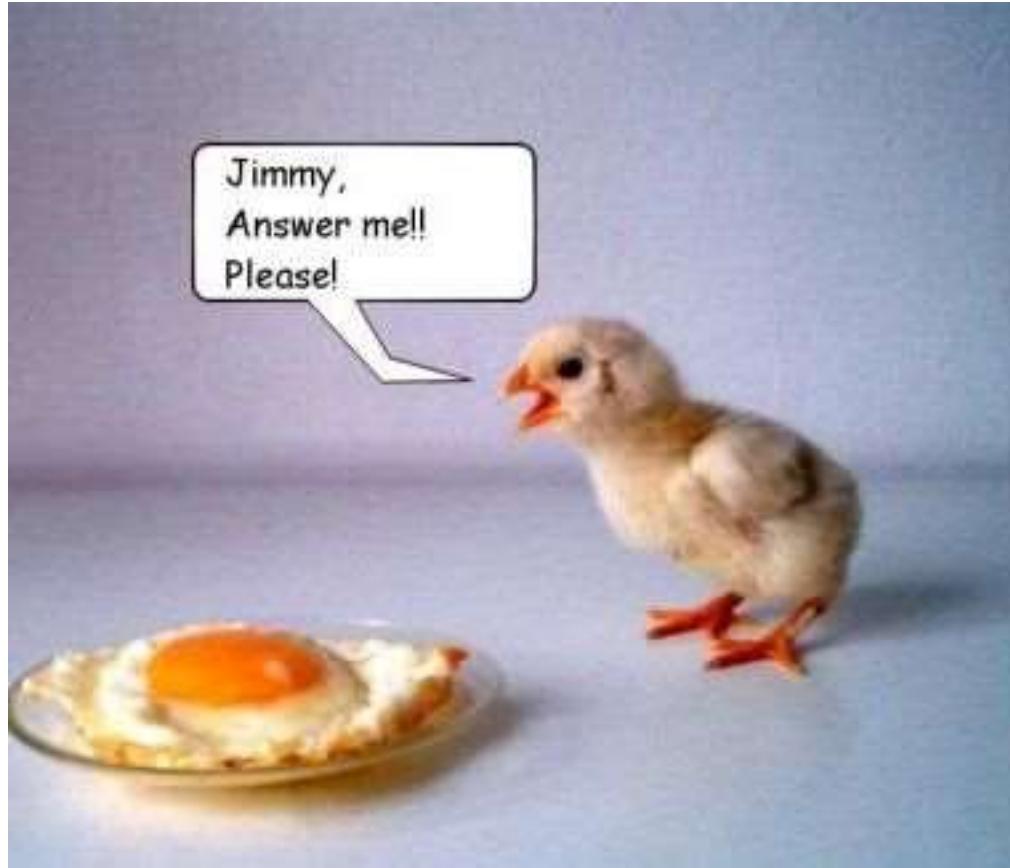
$(\mu = E(d), \sigma^2 = E(d^2) - E(d)^2)$

Variance SMs [Lauritzen & Donnelly 2006]

- + Very efficient
- + Independent of Filter size
- Light leaks



Questions?



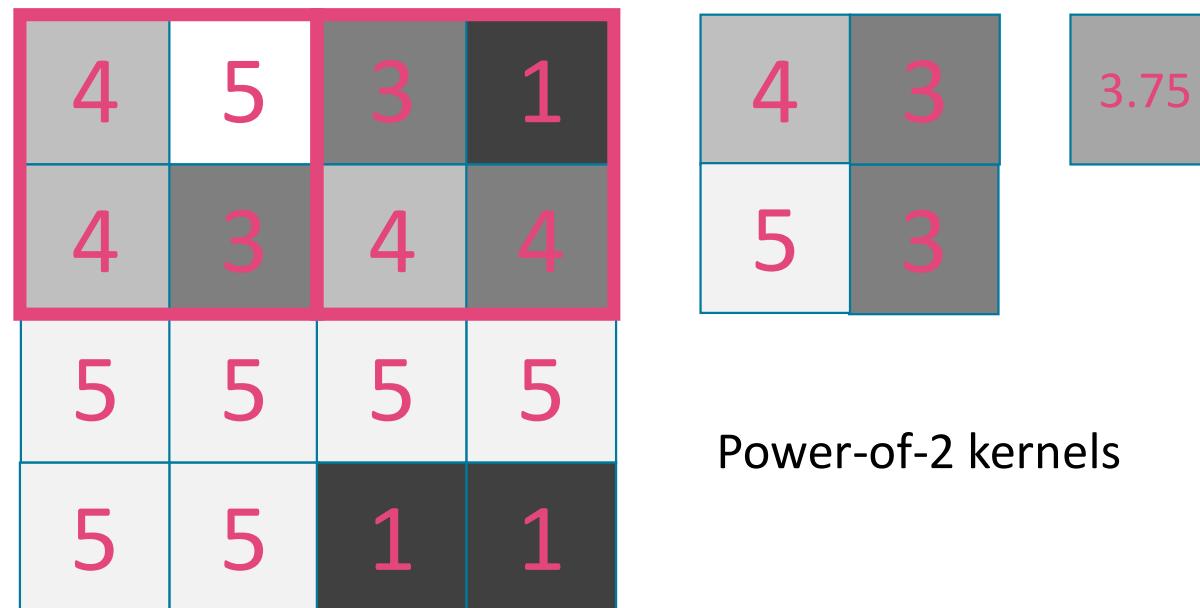
Sidenote: Computing Averages on the GPU

- MipMapping
- N-Buffer
- Summed-Area Tables



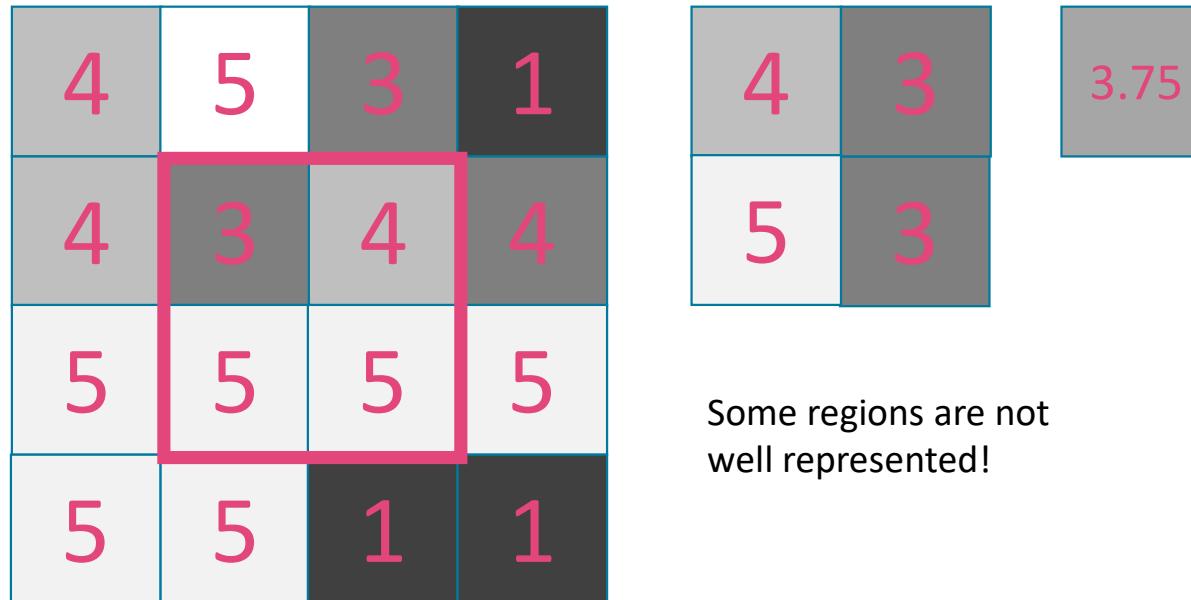
Computing Averages: MipMaps [Williams1983]

- Power of 2 hierarchy
- Average 4 pixels together for next level



Computing Averages: MipMaps [Williams1983]

- Power of 2 hierarchy
- Average 4 pixels together for next level



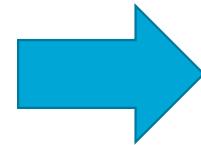
Some regions are not
well represented!

Computing Averages: N-Buffers [Décoret2005]

- Multi-Level Representation
- Each Level **same** resolution
- Level i : Pixel contains average of 2^i window

4	5	3	1
4	3	4	4
5	5	5	5
5	5	1	1

Level 0

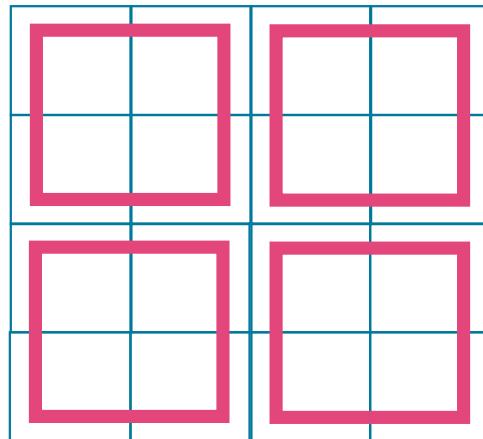


4	4	3	2.5
4.25	4.25	4.5	4.5
5	4	3	3
5	3	1	1

Level 1

Computing Averages: N-Buffers [Décoret2005]

- Efficient Recursive Construction:
 - Use level i for level $i+1$ (4 LU per texel)



= 4 *



Computing Averages: Fast Summed-Area Tables [Crow1984]

1	0	0	1
0	1	1	0
1	0	0	0
0	1	0	1

FSAT

		4	

Computing Averages: Fast Summed-Area Tables [Crow1984]

1	0	0	1
0	1	1	0
1	0	0	0
0	1	0	1

FSAT

		4	5

Computing Averages: Fast Summed-Area Tables [Crow1984]

1	0	0	1
0	1	1	0
1	0	0	0
0	1	0	1

FSAT

		4	5
			7

Computing Averages: Fast Summed-Area Tables [Crow1984]

1	0	0	1
0	1	1	0
1	0	0	0
0	1	0	1

FSAT

1	1	1	2
1	2	3	4
2	3	4	5
2	4	5	7

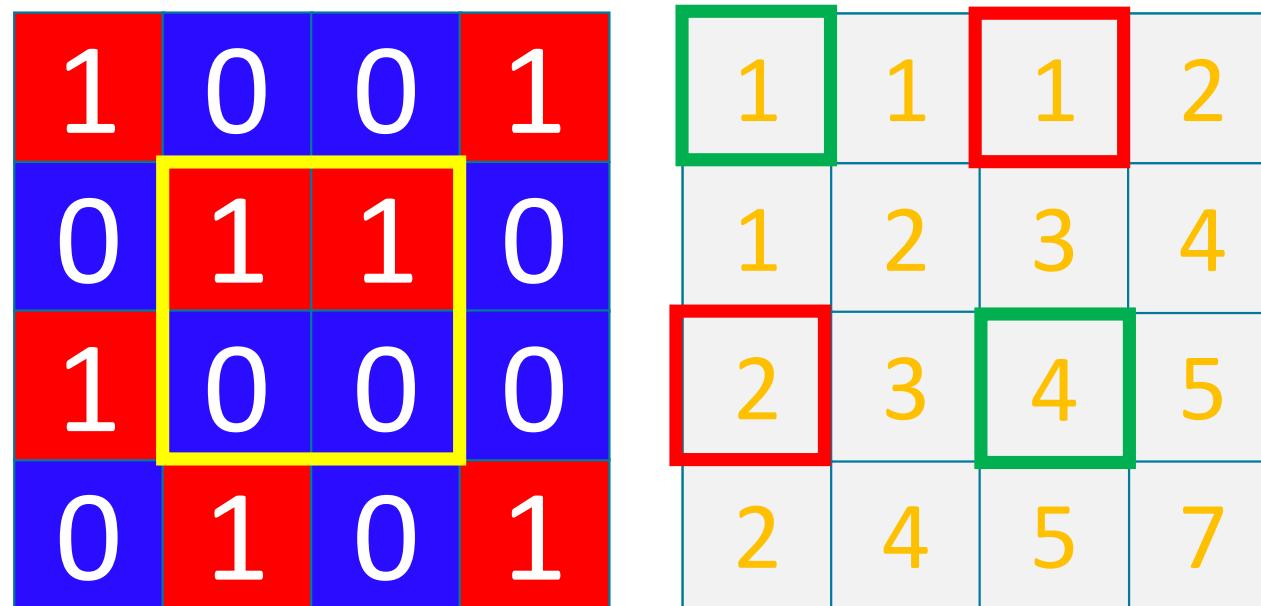
Computing Averages: Fast Summed-Area Tables [Crow1984]

1	0	0	1
0	1	1	0
1	0	0	0
0	1	0	1

FSAT

1	1	1	2
1	2	3	4
2	3	4	5
2	4	5	7

Computing Averages: Fast Summed-Area Tables [Crow1984]



$$4 - 1 - 2 + 1 = 2$$

Computing Averages: Fast Summed-Area Tables [Crow1984]

Get average of any window with just 4 value lookups!

FSAT

1	0	0	1
0	1	1	0
1	0	0	0
0	1	0	1

1	1	1	2
1	2	3	4
2	3	4	5
2	4	5	7

Fast Summed-Area Tables

- Efficient GPU Construction [Hensley et al. 2005]

Comparison

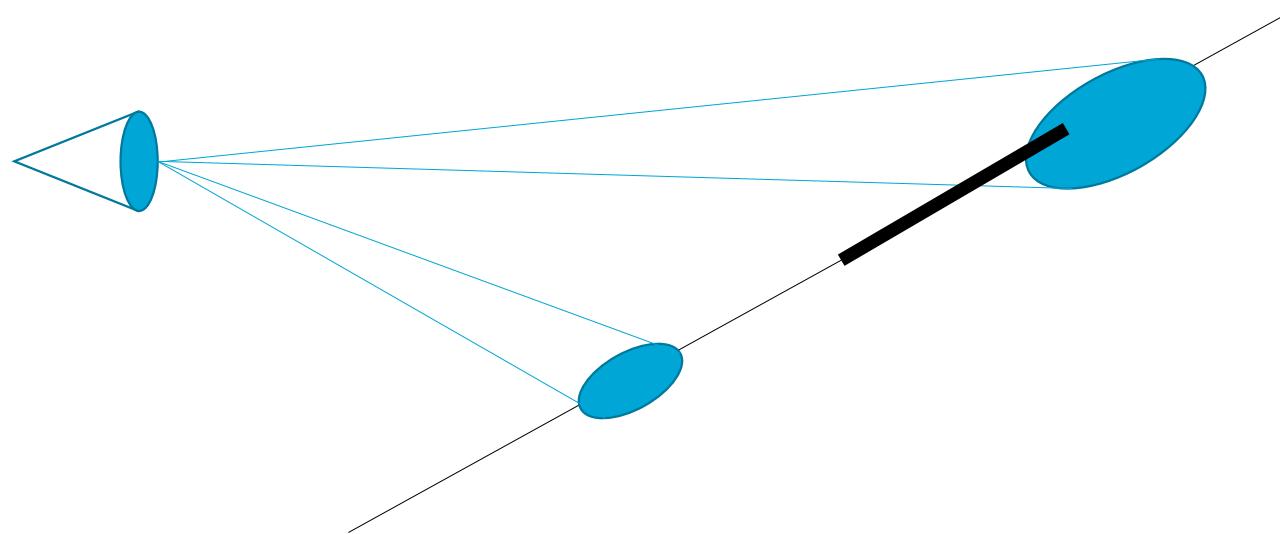


Filtering Quality

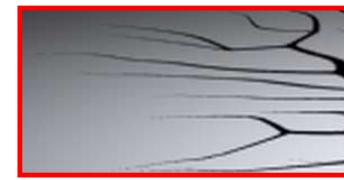
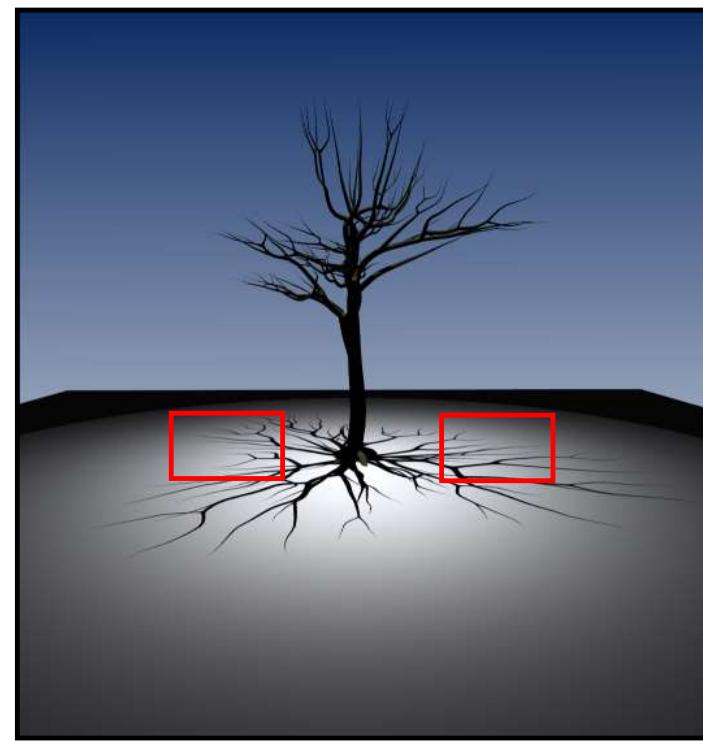
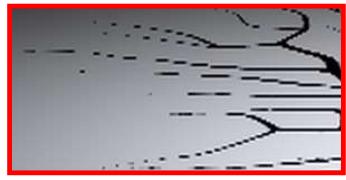
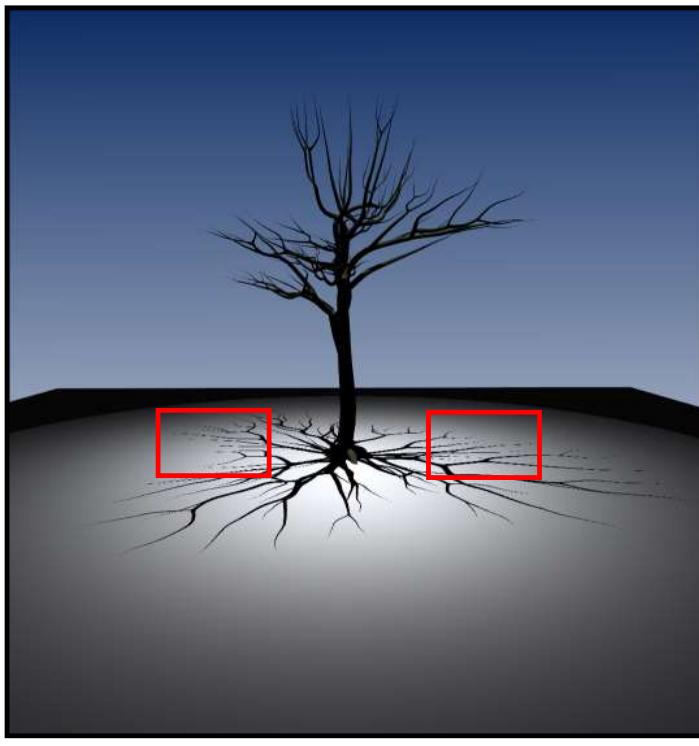
- MipMaps : fastest, but lowest quality
- N-Buffer : average construction time, medium quality
(higher memory consumption)
- FSAT: slower construction time, highest quality
(slightly more costly lookups)
- Please note:
All methods allow to choose the region size on the fly (i.e., varying filter size)

Perspective Foreshortening

- Choose kernel according to viewing distance



Perspective foreshortening



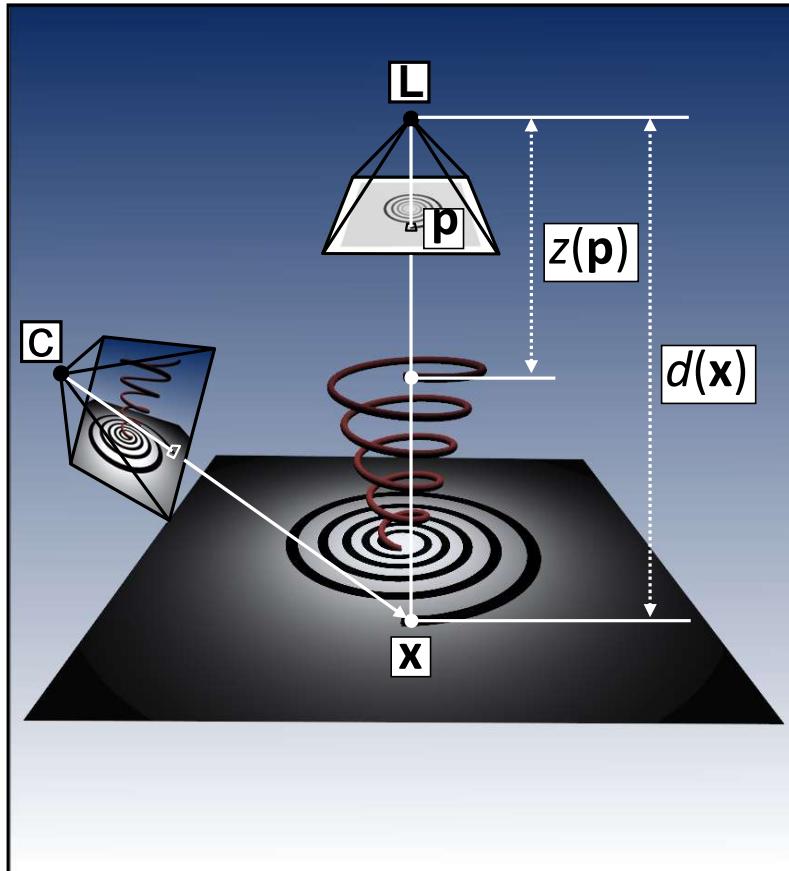
Questions?



Approximate the Shadow Function

- Convolution Shadow Maps [Annen et al. 2007]
- Exponential Shadow Maps [Annen et al. 2008, Salvi 2008]

Shadow Mapping [Williams 1978]



Animation courtesy of Annen et al.

- $\mathbf{x} \in \mathbb{R}^3$
- $\mathbf{p} \in \mathbb{R}^2$

Shadow Test:

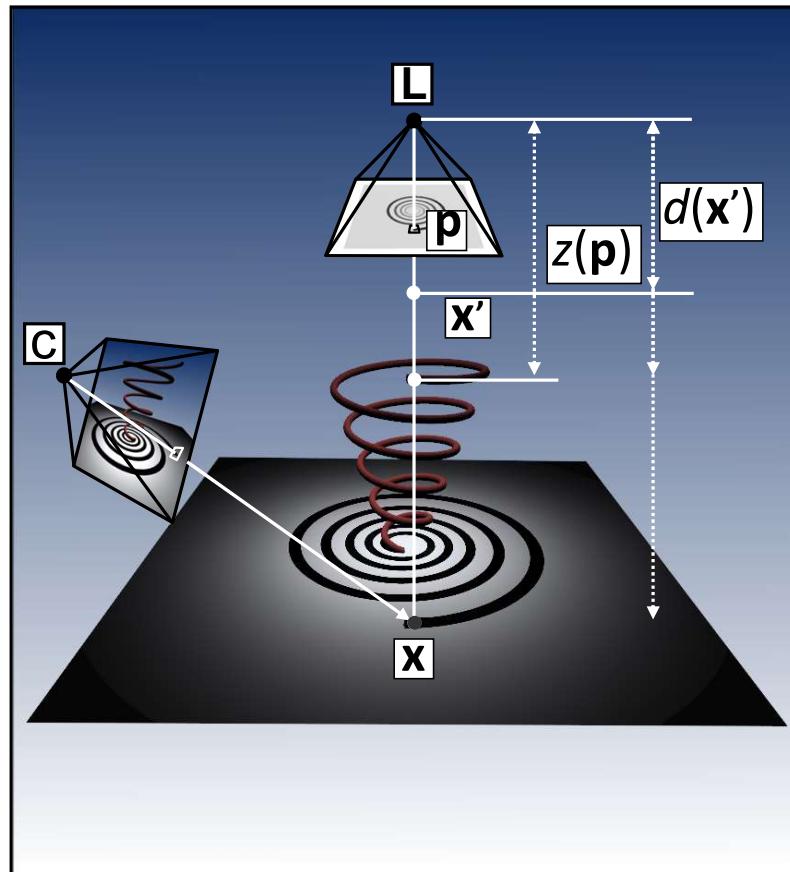
$$t(d(\mathbf{x}), z(\mathbf{p})) :=$$

$$s(d(\mathbf{x}) - z(\mathbf{p})),$$

where

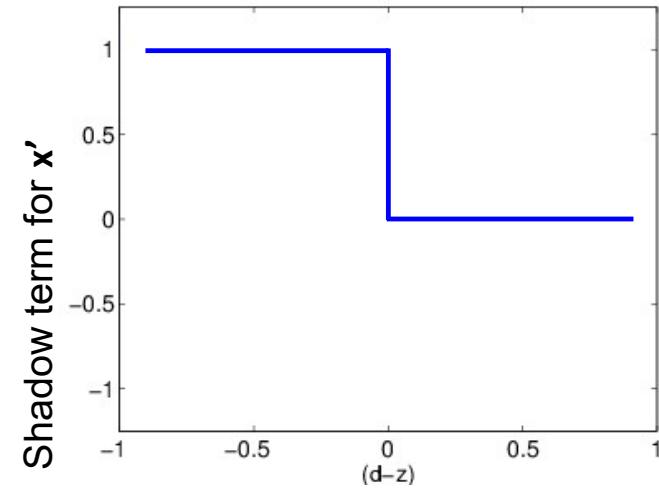
$$s(\mathbf{x}) := \begin{cases} 1 & \text{if } \mathbf{x} \leq 0 \\ 0 & \text{else} \end{cases}$$

Shadow Test: $s(x)$



Animation courtesy of Annen et al.

- What kind of function is $s(x)$?



- Heaviside Step Function: $H(t)$

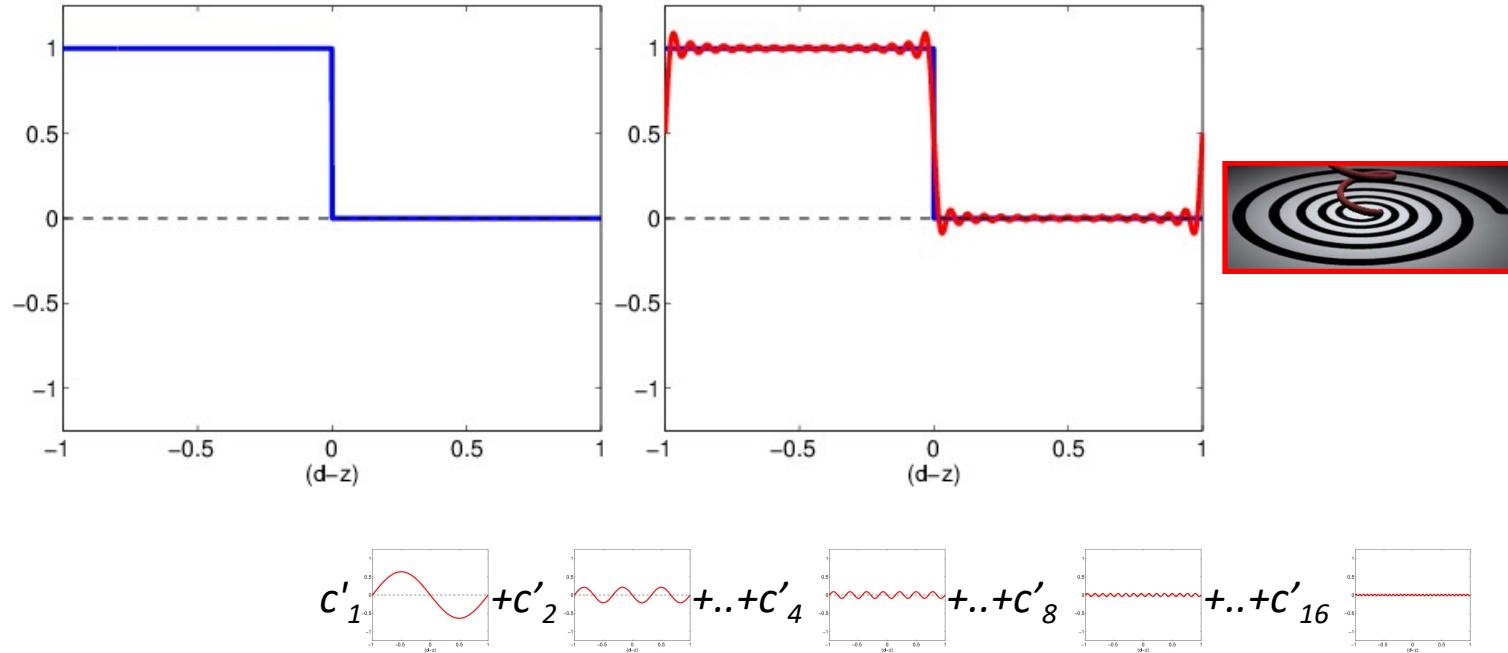
Fourier Analysis

- Check out:
- <https://betterexplained.com/articles/an-interactive-guide-to-the-fourier-transform/>

$$f(x) = \frac{a_0}{2} + \sum_{k=1}^{\infty} \left(a_k \cos \frac{k2\pi x}{T} + b_k \sin \frac{k2\pi x}{T} \right)$$

Fourier Analysis

- Approximate shadow test with Fourier series

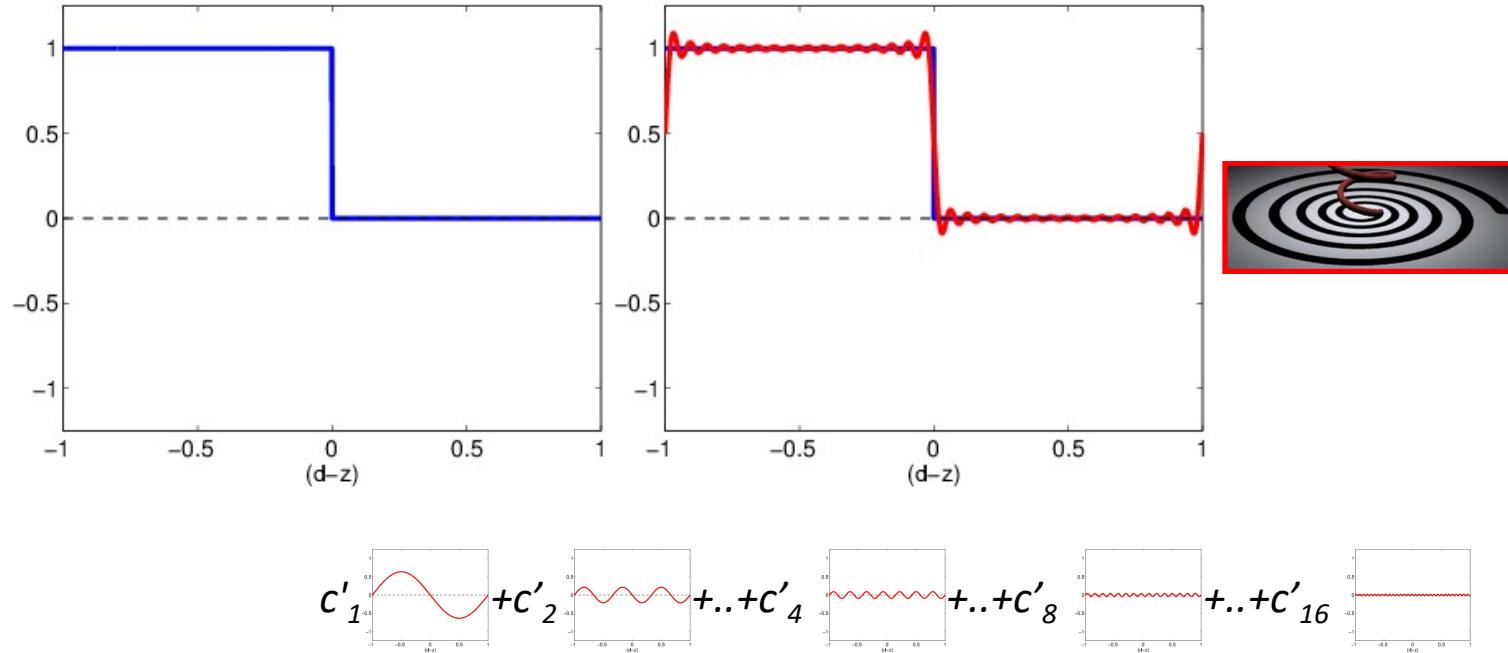


We can write the shadow test as:

$$f(d-z) = \sum_{i=1}^{\infty} c_i(d) B_i(z)$$

Fourier Analysis

- Approximate shadow test with Fourier series



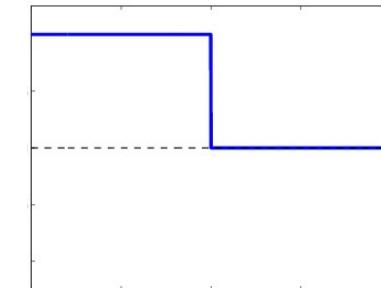
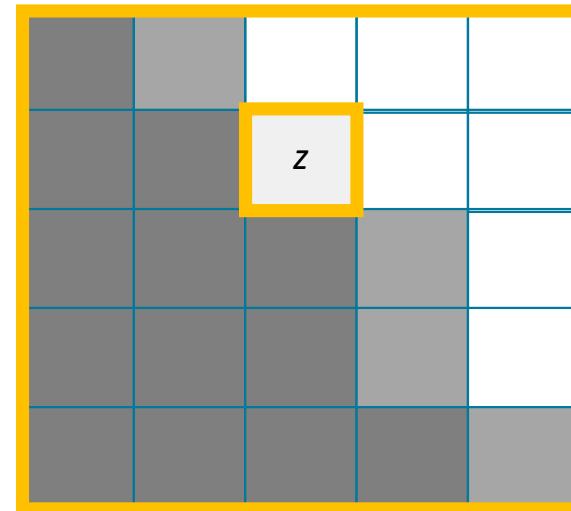
We can write the
shadow test as:

$$f(d-z) = \sum_{i=1}^{\infty} c_i(d) B_i(z) = s(d-z)$$

Fourier Analysis

- Why is this useful???

$$\sum_{s=1}^N f(d-z_s) = \sum_{s=1}^N \sum_{i=1}^{\infty} c_i(d) B_i(z_s)$$



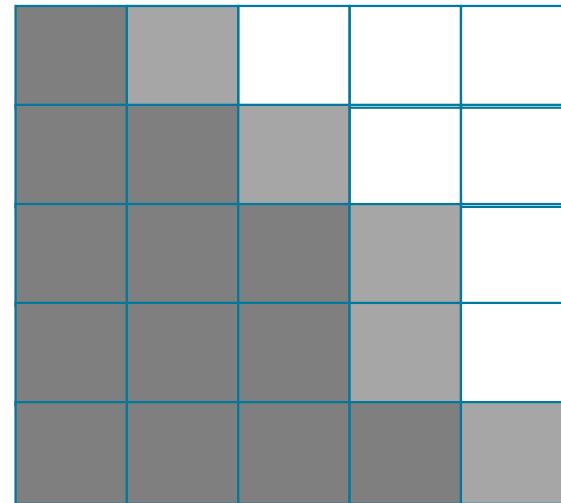
Fourier Analysis

- Why is this useful???

$$\sum_{s=1}^N f(d - z_s) = \sum_{i=1}^{\infty} c_i(d)$$

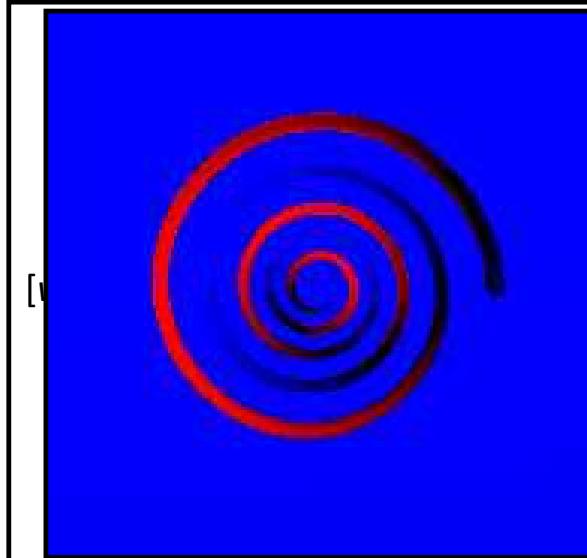
Average of result of
Bi's applied to SM

$$\sum_{s=1}^N B_i(z_s)$$

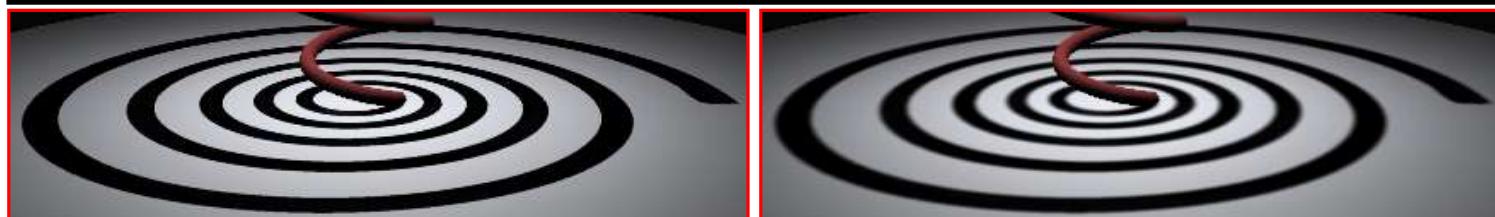
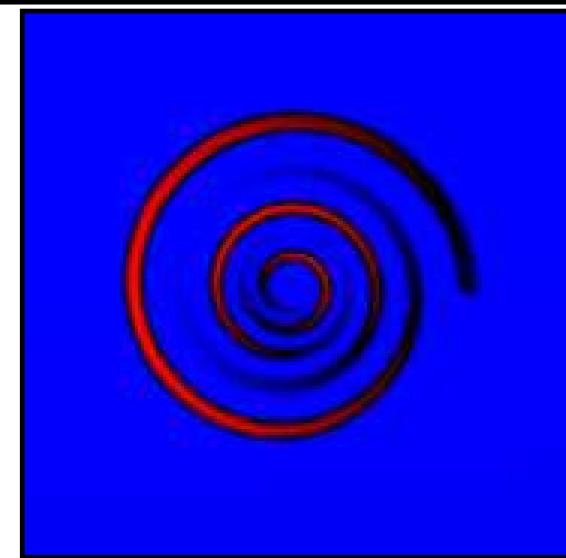


Filtering Example

Original $B_i(z)$



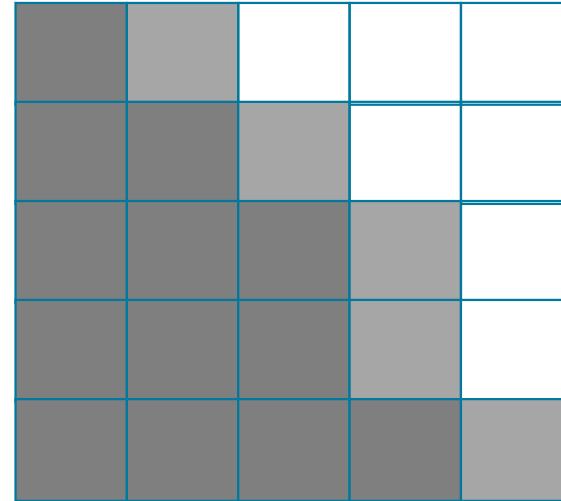
After filtering $B_i(z)$



- We can use any fast averaging method

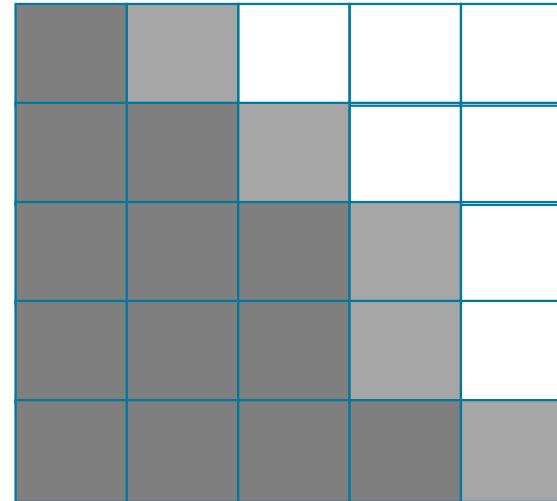
Reality strikes back...

$$\sum_{s=1}^N f(d-z_s) = \sum_{i=1}^{\infty} c_i(d) \sum_{s=1}^N B_i(z_s)$$



Reality strikes back...

$$\sum_{s=1}^N f(d-z_s) \approx \sum_{i=1}^M c_i(d) \sum_{s=1}^N B_i(z_s)$$



Truncation can lead to ringing

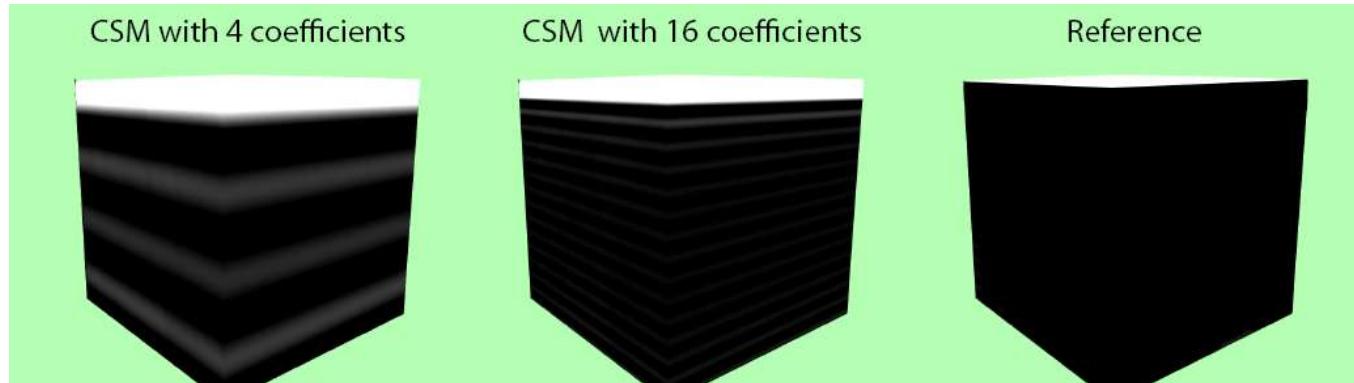
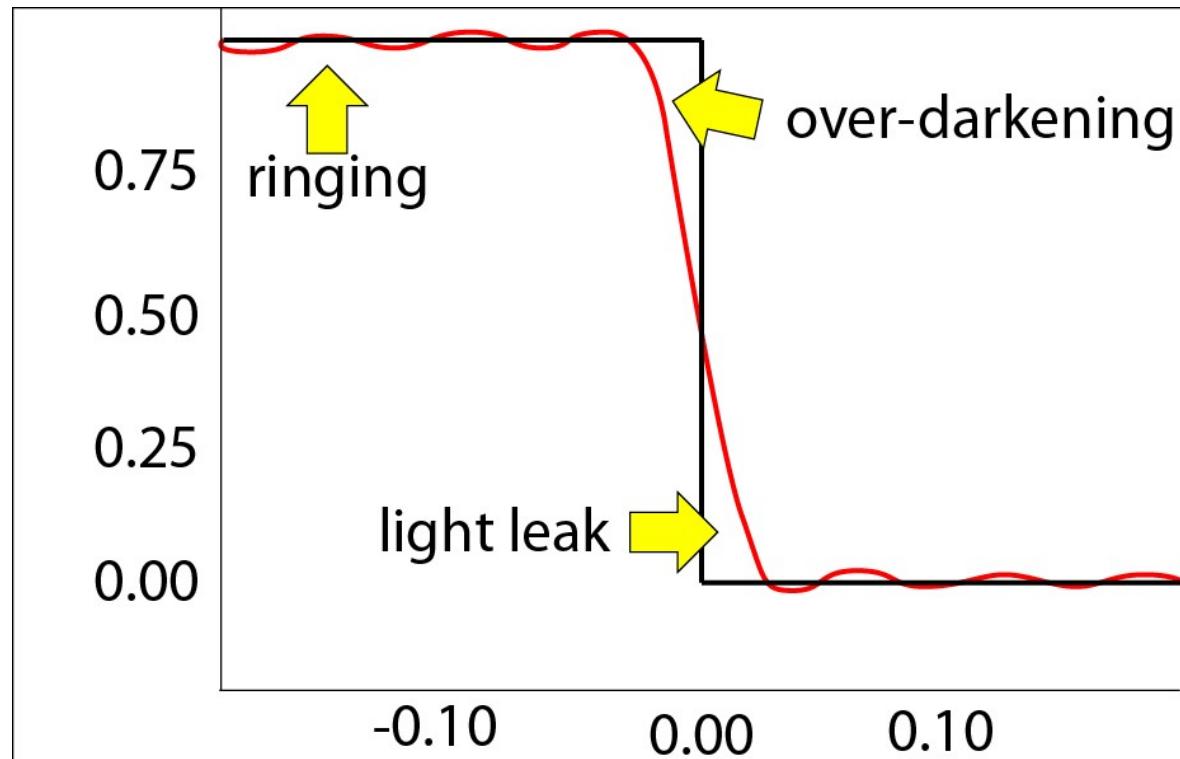


Illustration shows the shadow calculation not considering diffuse lighting

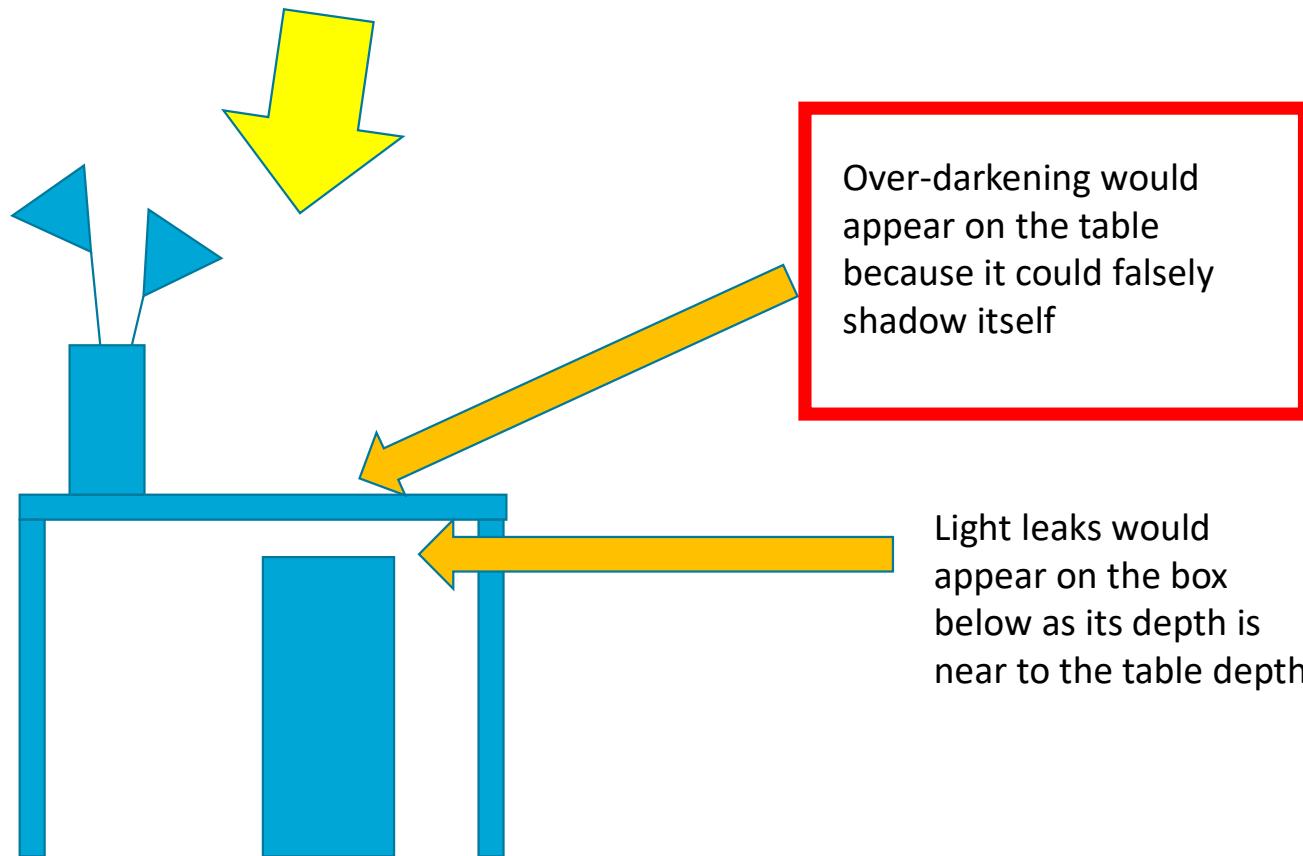
Reduce Ringing



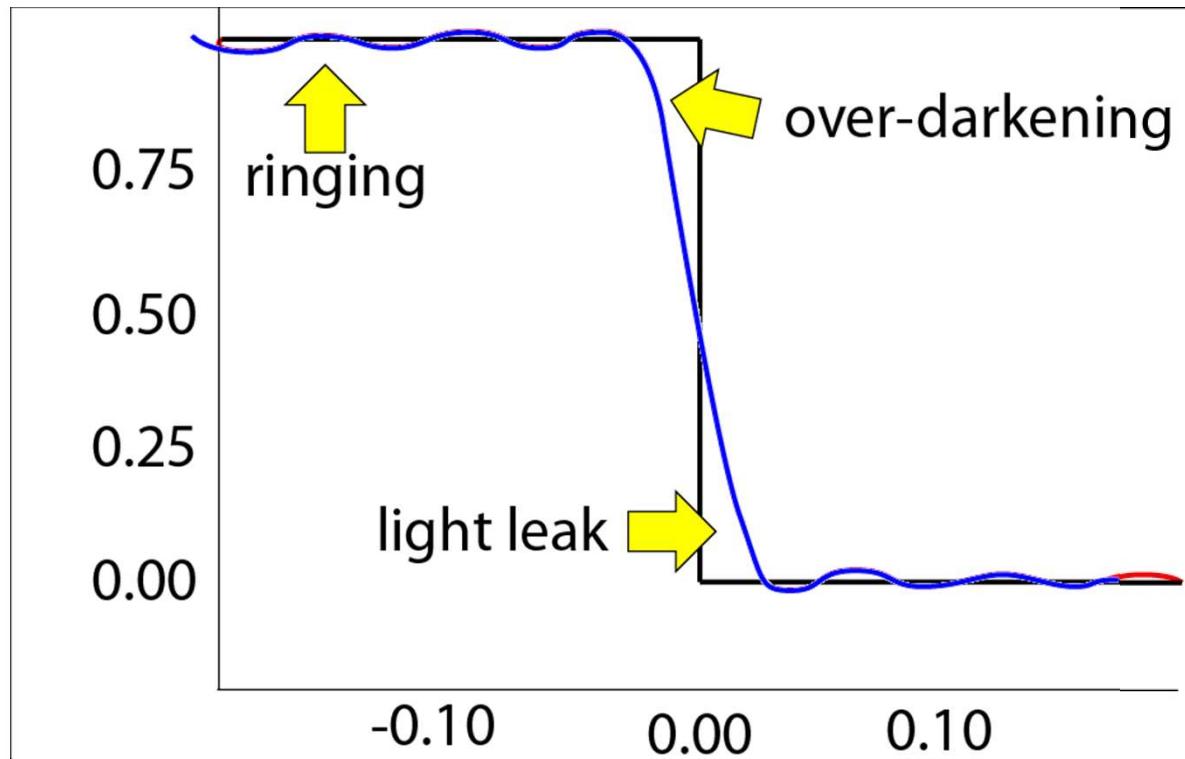
What is worse? Light leaks or over-darkening?

Light Leaks vs. Over-darkening

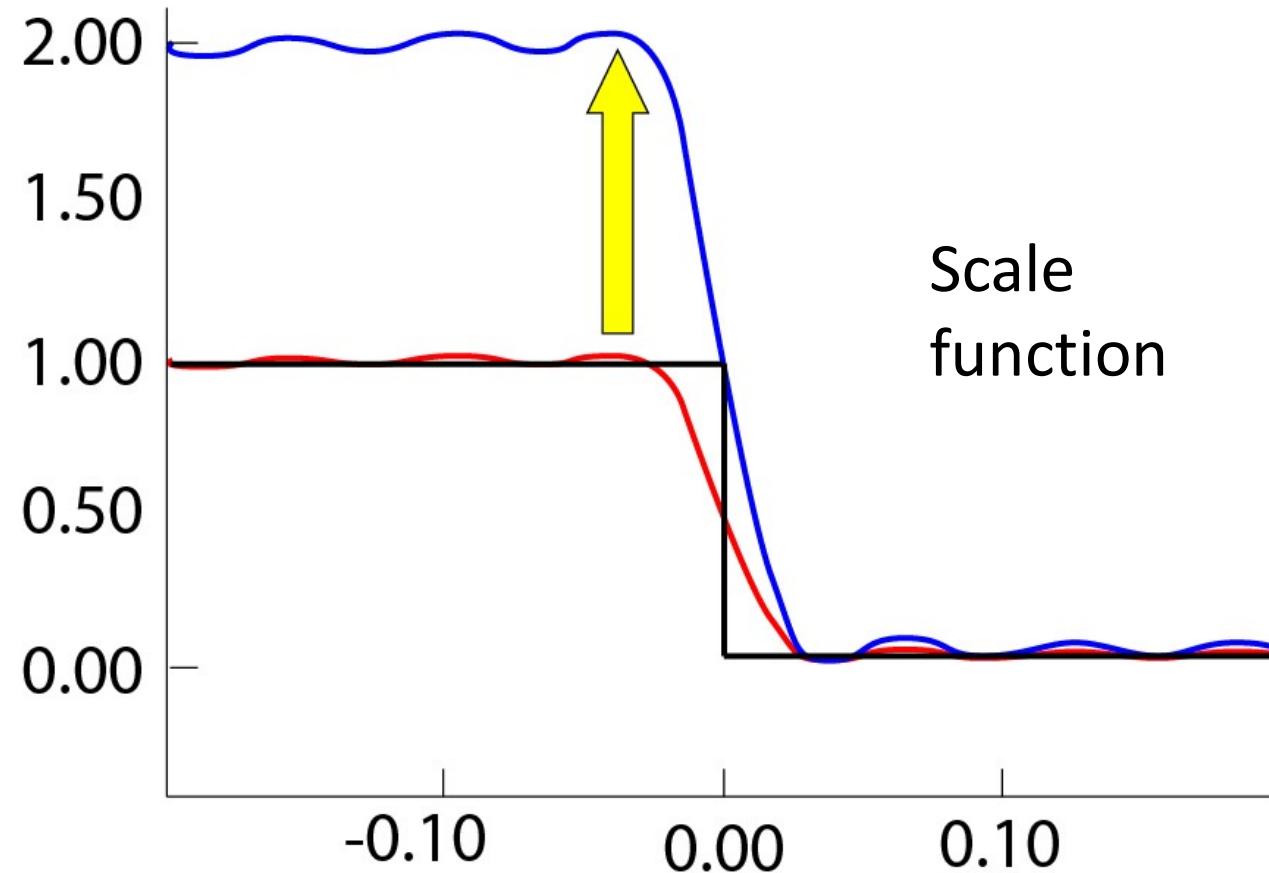
Light direction



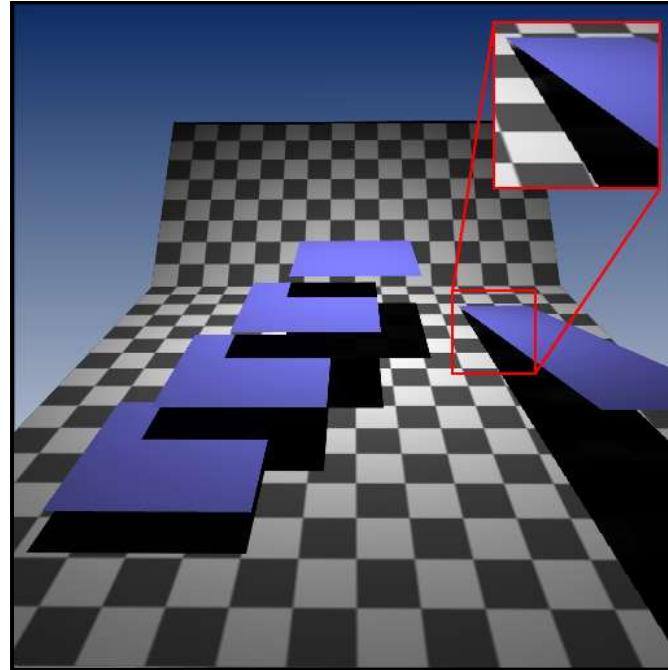
Reduce Ringing



Reduce Ringing

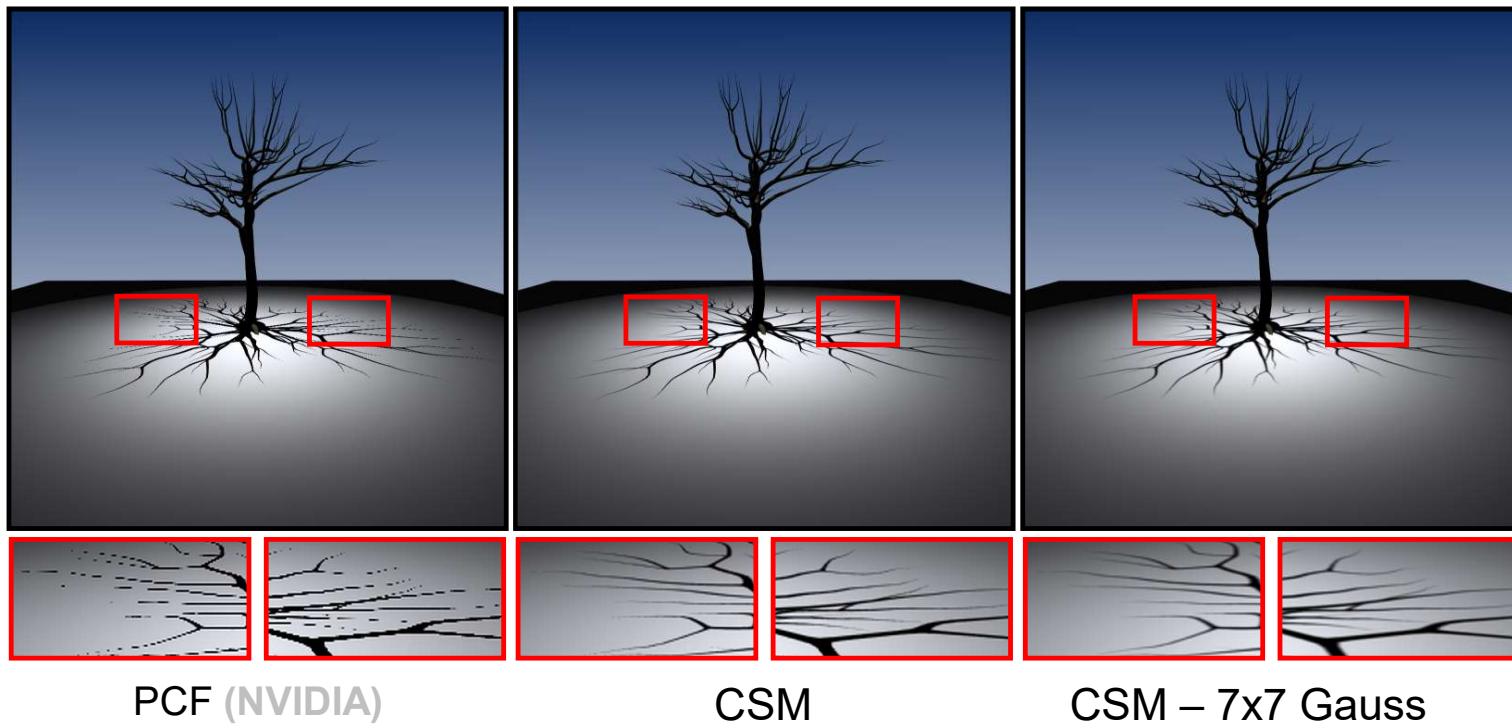


Influence of reconstruction order M



- Memory consumption increases as M grows
- Performance (filtering) decreases as M grows

Results



CSM [Annen et al. 2007]

- + Beautiful theoretical result
- + high-quality smoothing
(includes anisotropic blur)
- ~ relatively fast (for M=8)
- Relatively high memory consumption

Questions



Exponential Shadow Maps

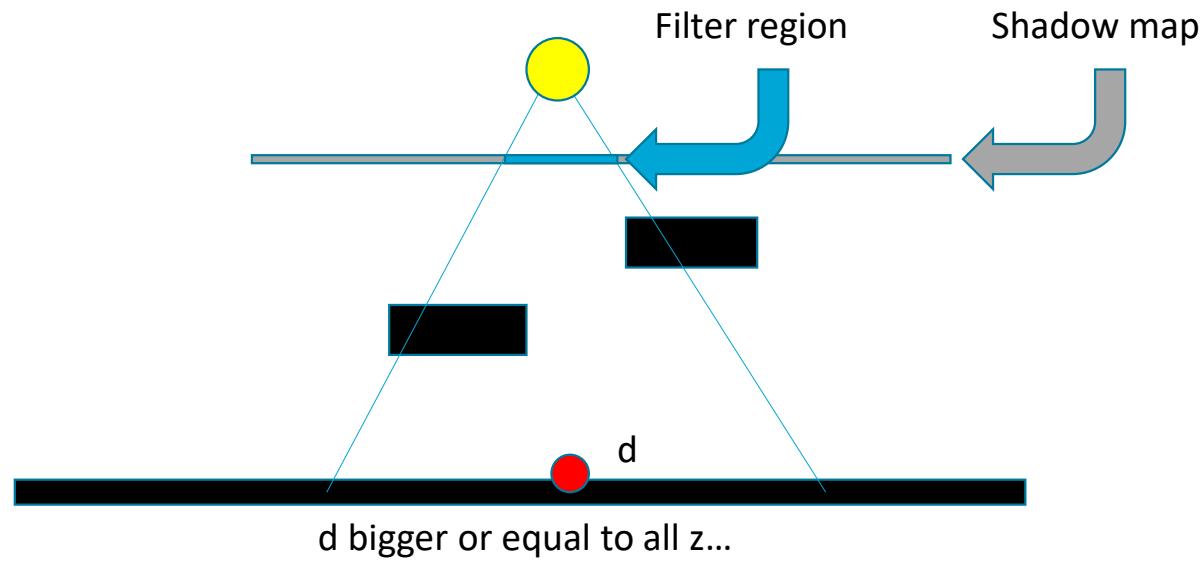
[Annen et al. 2008, Salvi2008]

- Are there other ways so that the shadow test could be decomposed into a filtered part depending only on SM values?

Exponential SM [Annen et al. 2008, Salvi2008]

- Assumption:

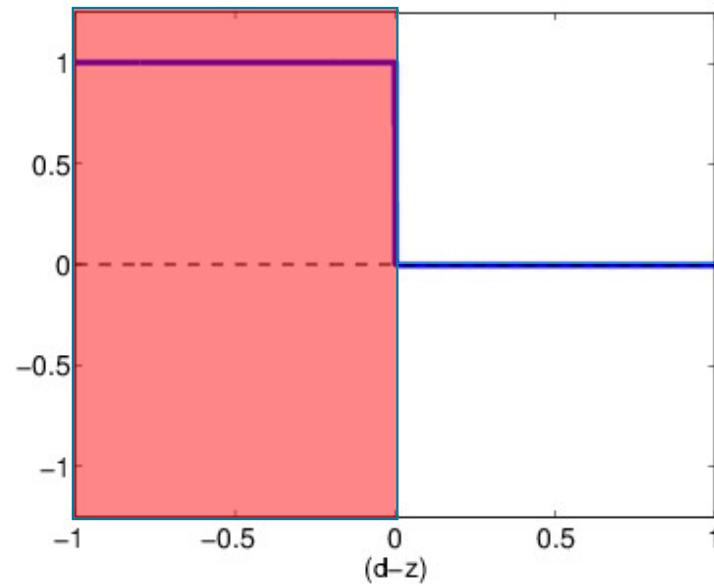
Tested pixel is the farthest from the light
in the filter region of the shadow map



Exponential SM [Annen et al. 2008, Salvi2008]

- Assumption:

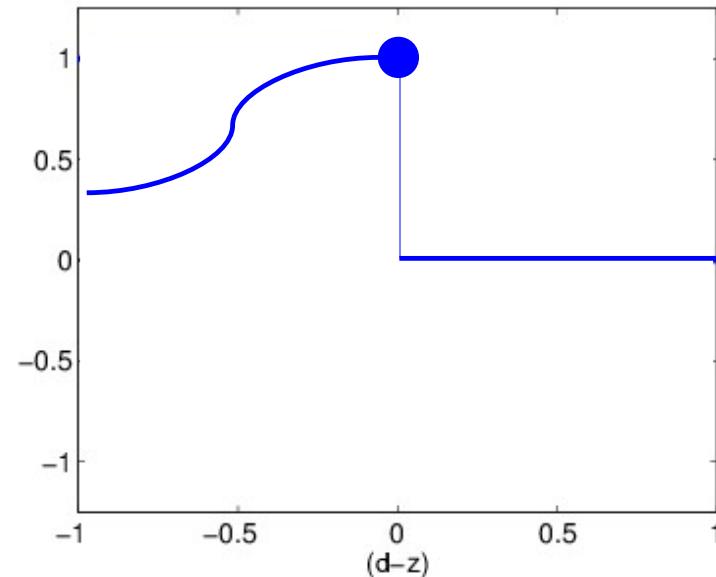
Tested pixel is the farthest from the light
in the filter region of the shadow map
-> others are either equal or closer



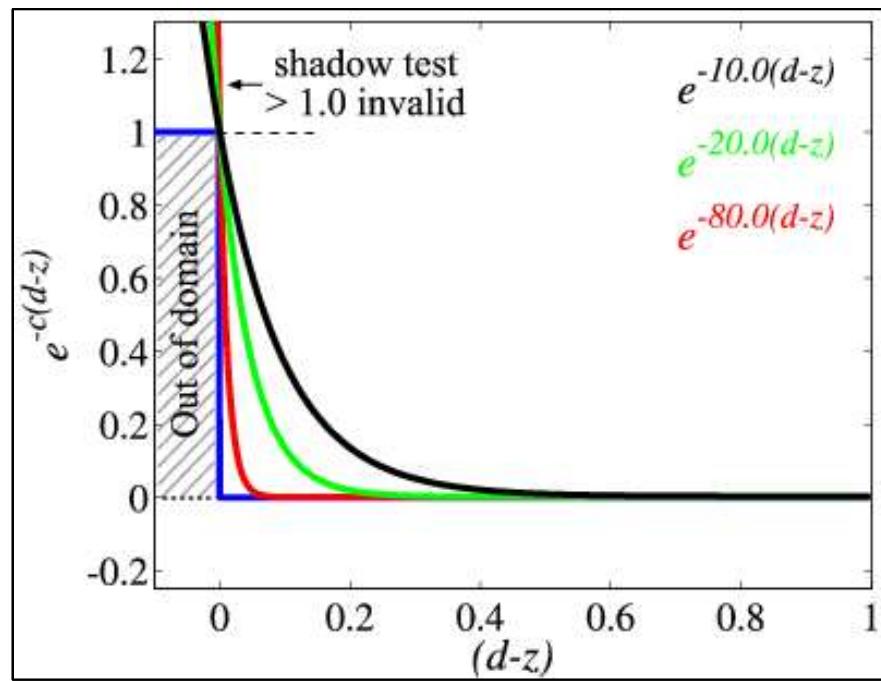
Exponential SM [Annen et al. 2008, Salvi2008]

- Assumption:

Tested pixel is the farthest from the light
in the filter region of the shadow map
-> others are either equal or closer



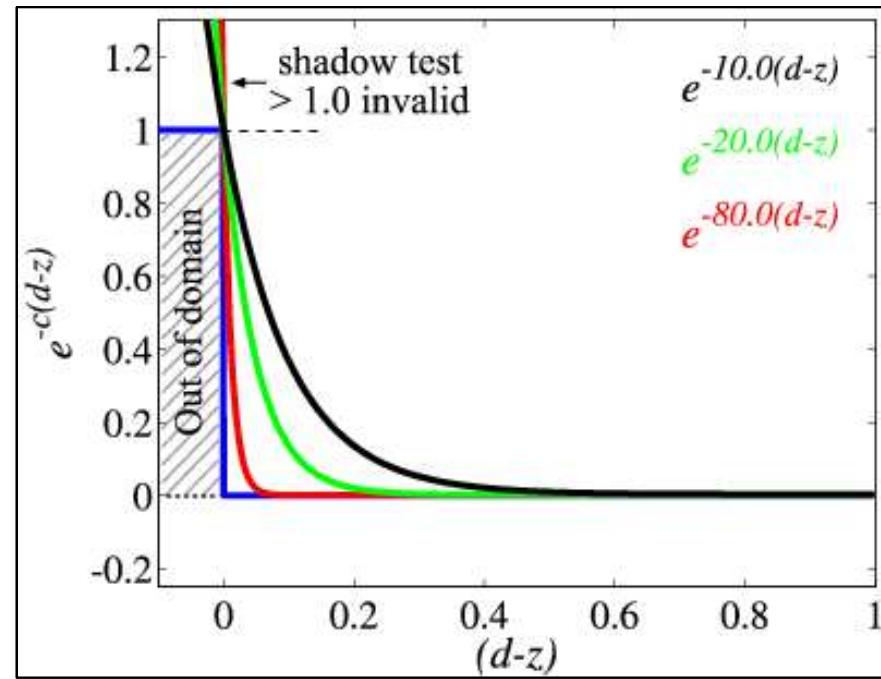
Exponential SM [Annen et al. 2008, Salvi2008]



Exponential SM [Annen et al. 2008, Salvi2008]

- Shadow function assumed to be:

$$s(d-z) \approx e^{-c(d(x) - z(p))}$$

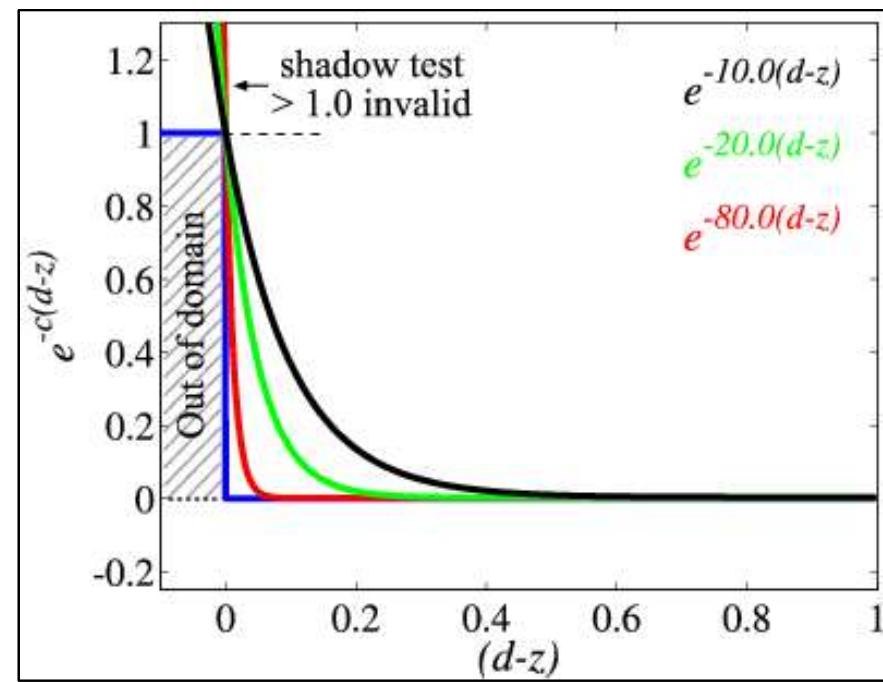


Exponential SM [Annen et al. 2008, Salvi2008]

- Shadow function assumed to be:

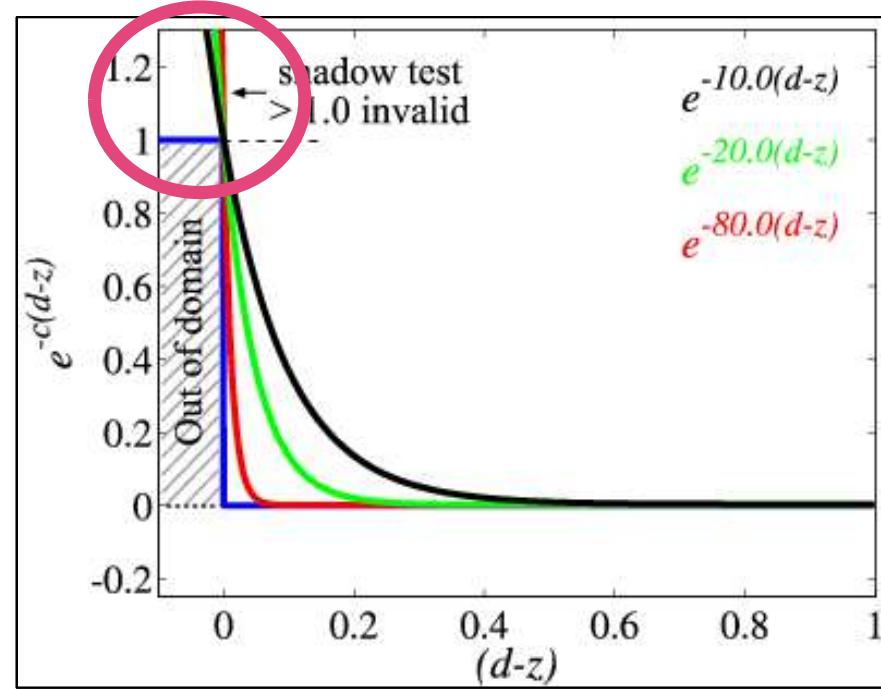
$$s(d-z) \approx e^{-c(d(x) - z(p))} = e^{-c(d(x))} e^{cz(p)}$$

decomposition



Problem: Overshooting

- Remember the assumption:
- We need: $d > z$! Otherwise, the approximation can be very wrong!



Detection of Erroneous Pixels

Hacky fix:

Detect the locations where the assumption fails
and those pixels use PCF computation



ESM [Annen et al. 2008, Salvi2008]

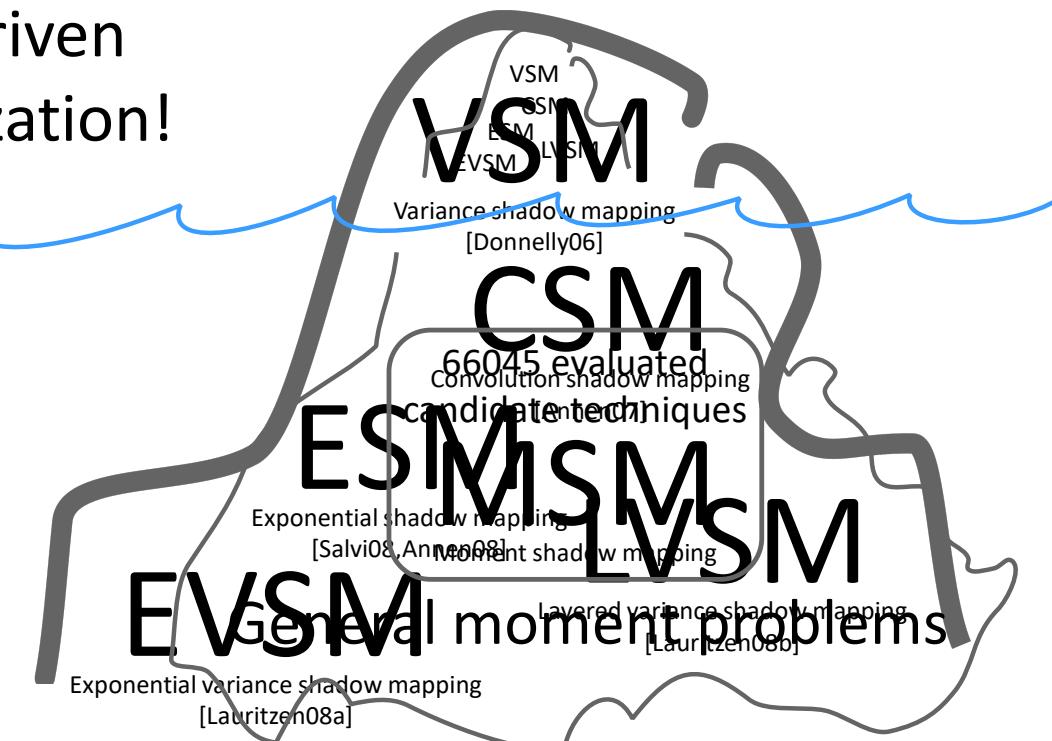
- + Faster than CSM some scenes
(depends on correction)
- + Same quality as CSM
- + Memory consumption lower than CSM
- + Creation of ESM is faster

- Correction cost unpredictable
- Should be used with smaller kernels

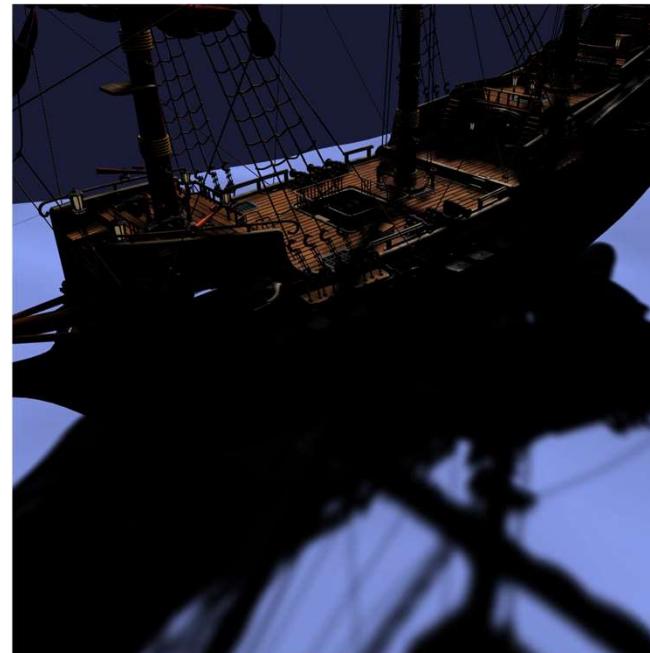
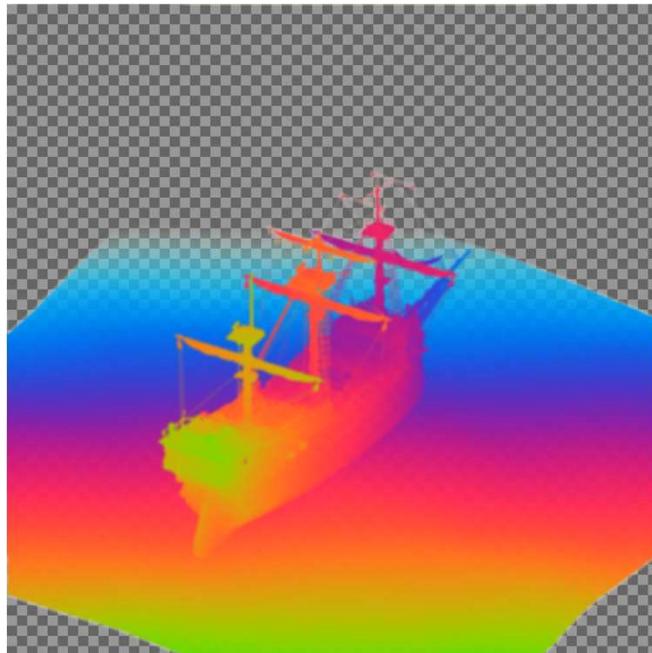
What is the best?

- Moment Shadow Maps! [Peters & Klein i3D05]

Data-driven
optimization!



Moment Shadow Mapping



Summary

- Combat Aliasing for Shadow mapping
- Discussed main algorithms and limitations
- Filtering methods
 - MipMapping
 - NBuffers
 - Summed Area Tables

Overview

- Really fast:

Variance SM

- Best tradeoff Quality/Performance:

Exponential Shadow Maps

Moment Shadow Maps

BUT all these methods filter hard shadows.

There is no real penumbra computation...

Unreal Engine 5



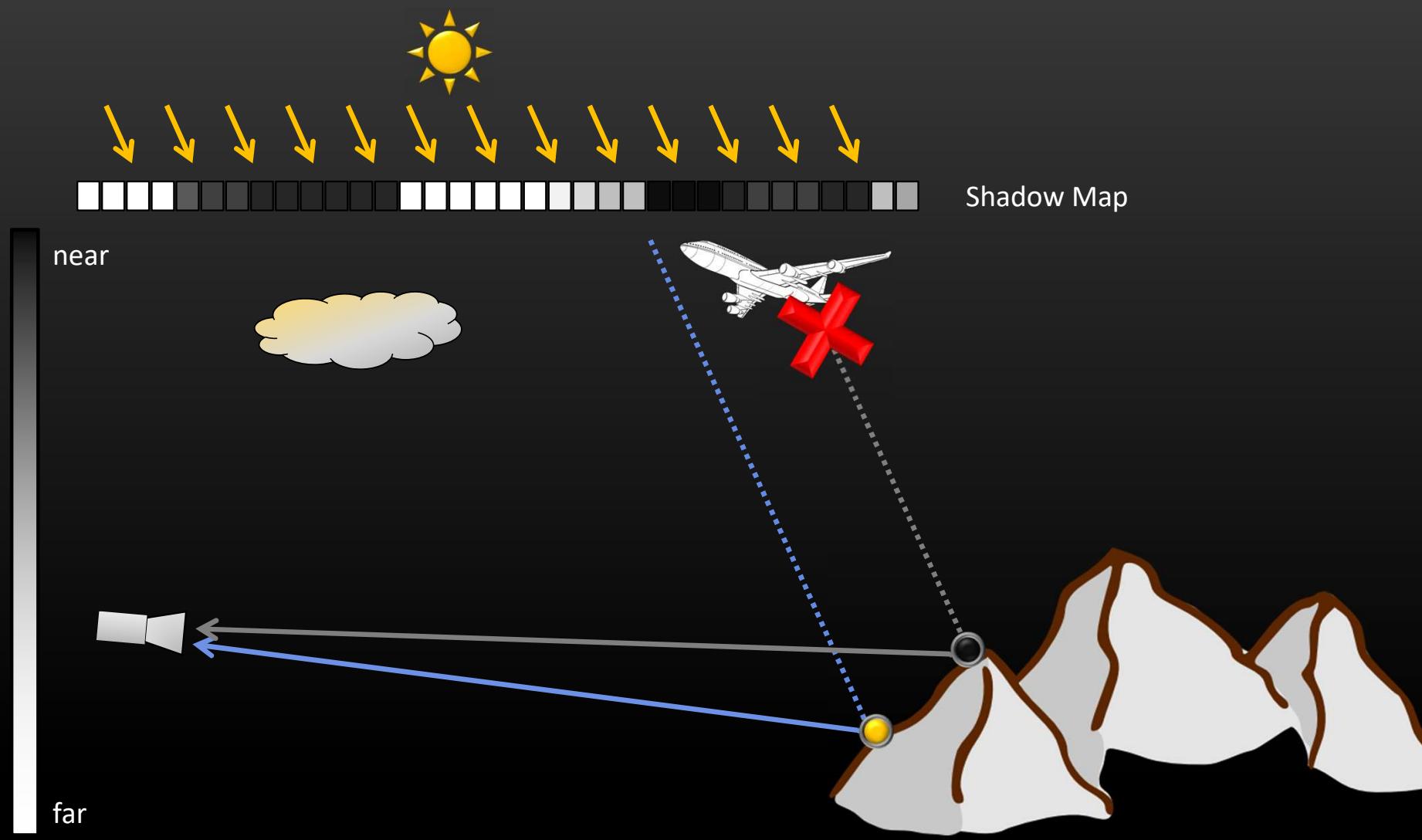
Unreal Engine 5

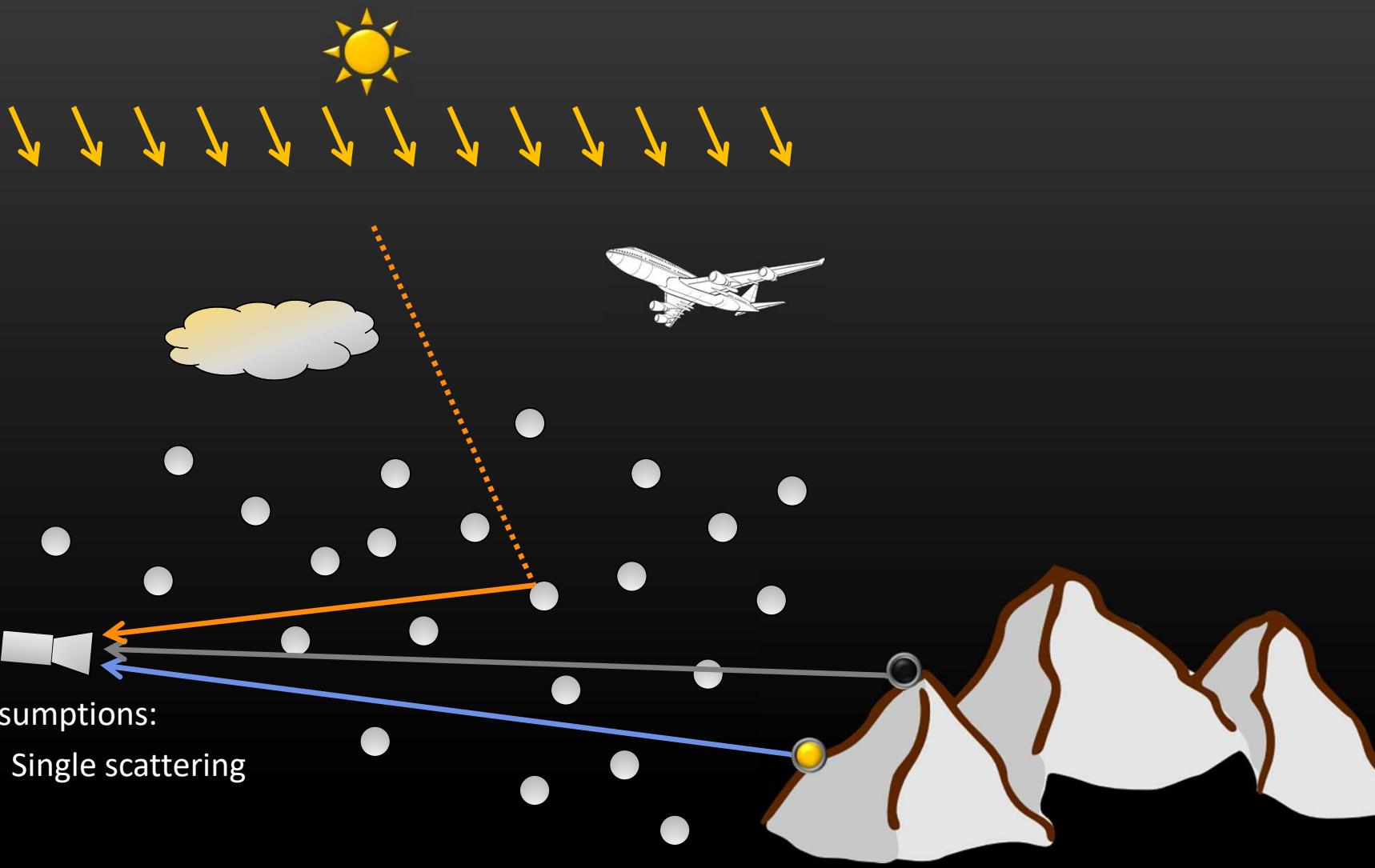


Additional Application of Soft Shadows



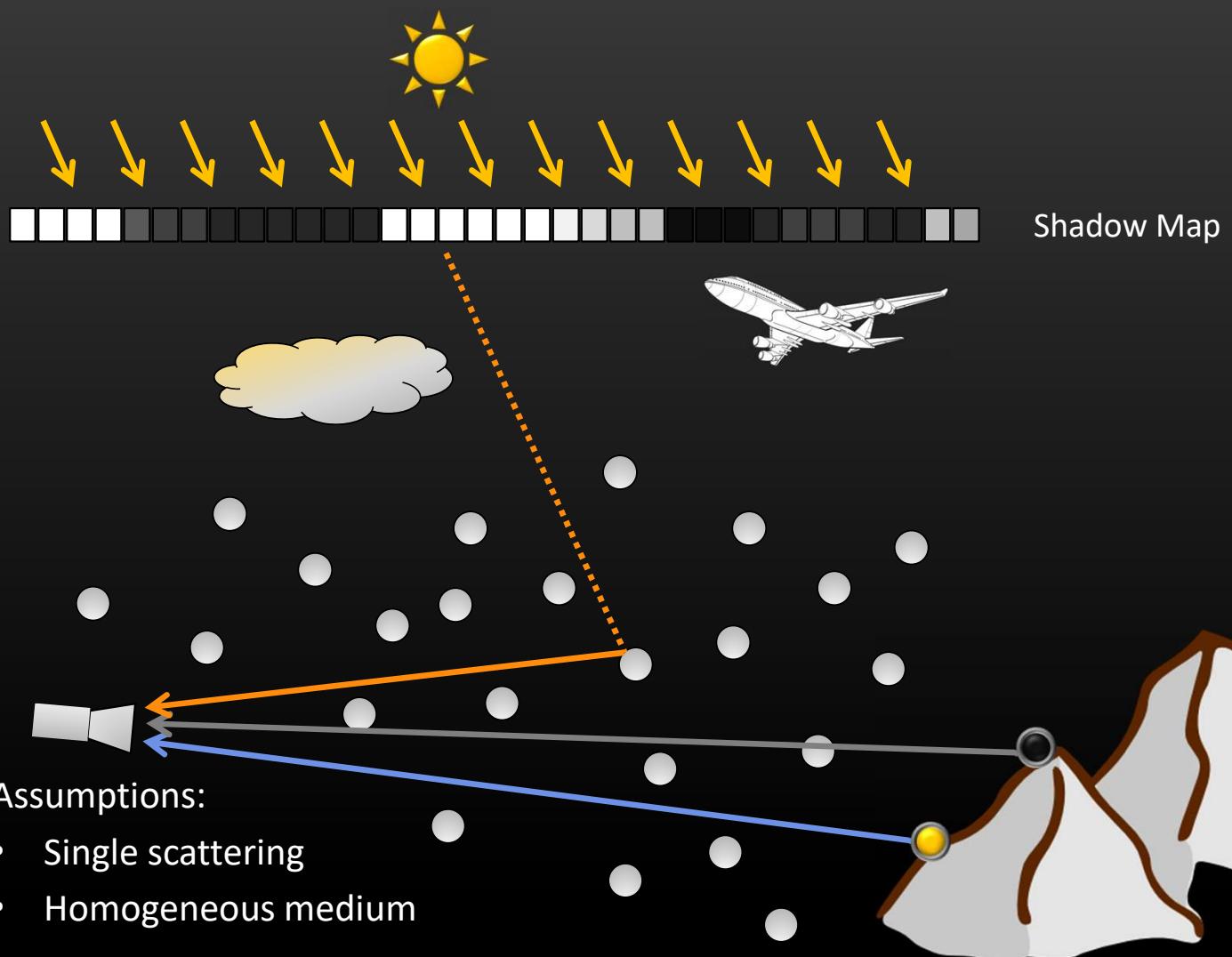
Fredo Durand

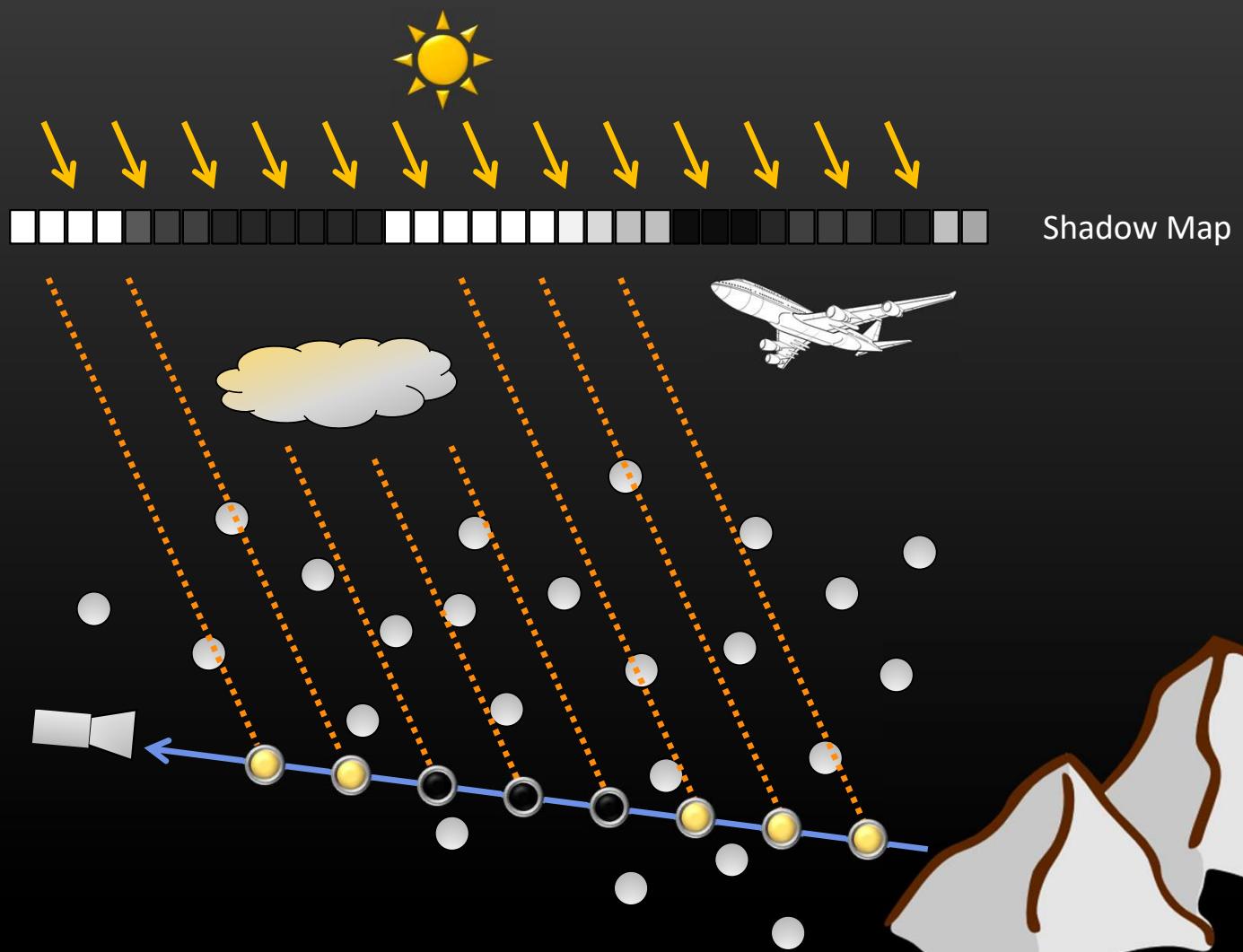


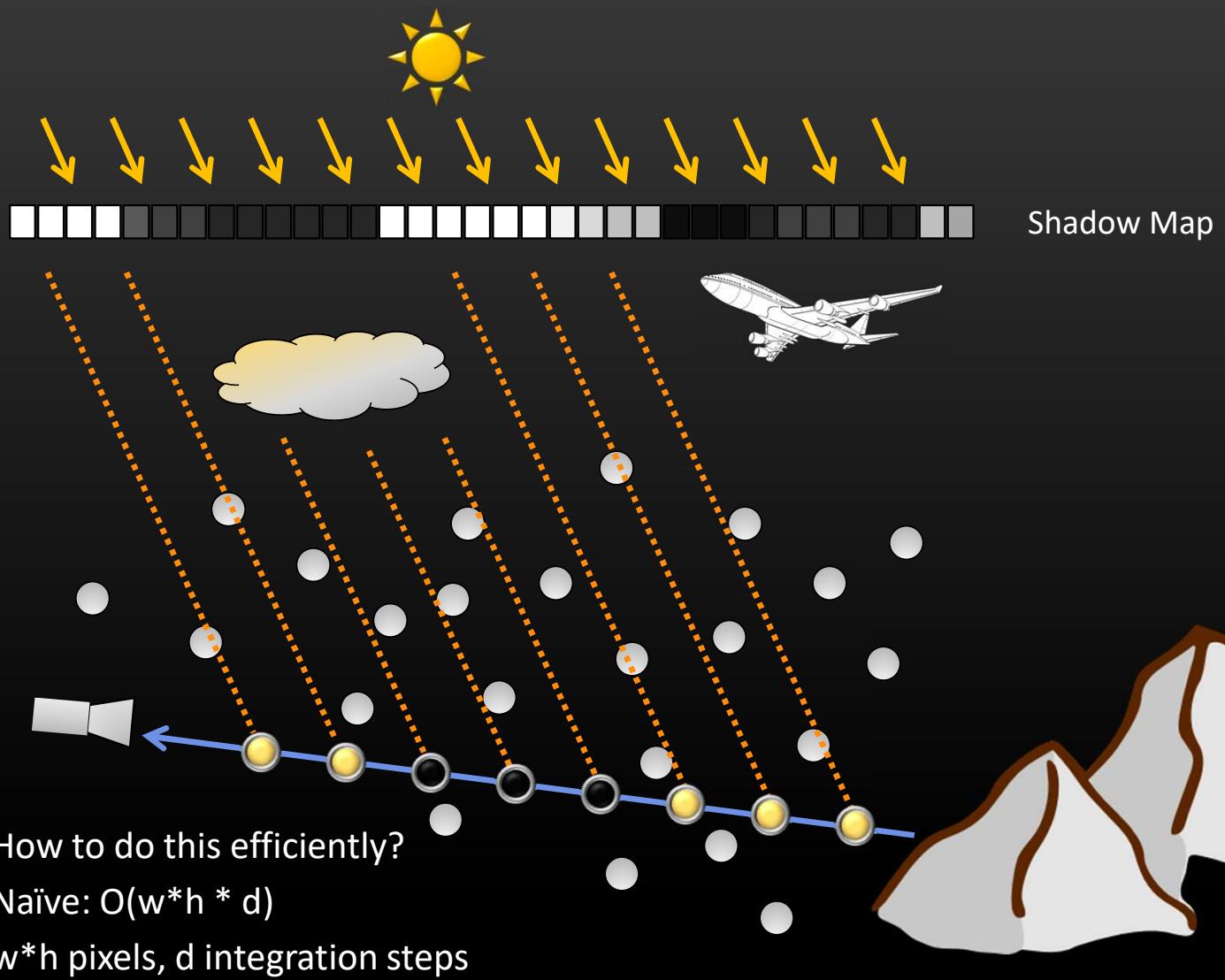


Assumptions:

- Single scattering





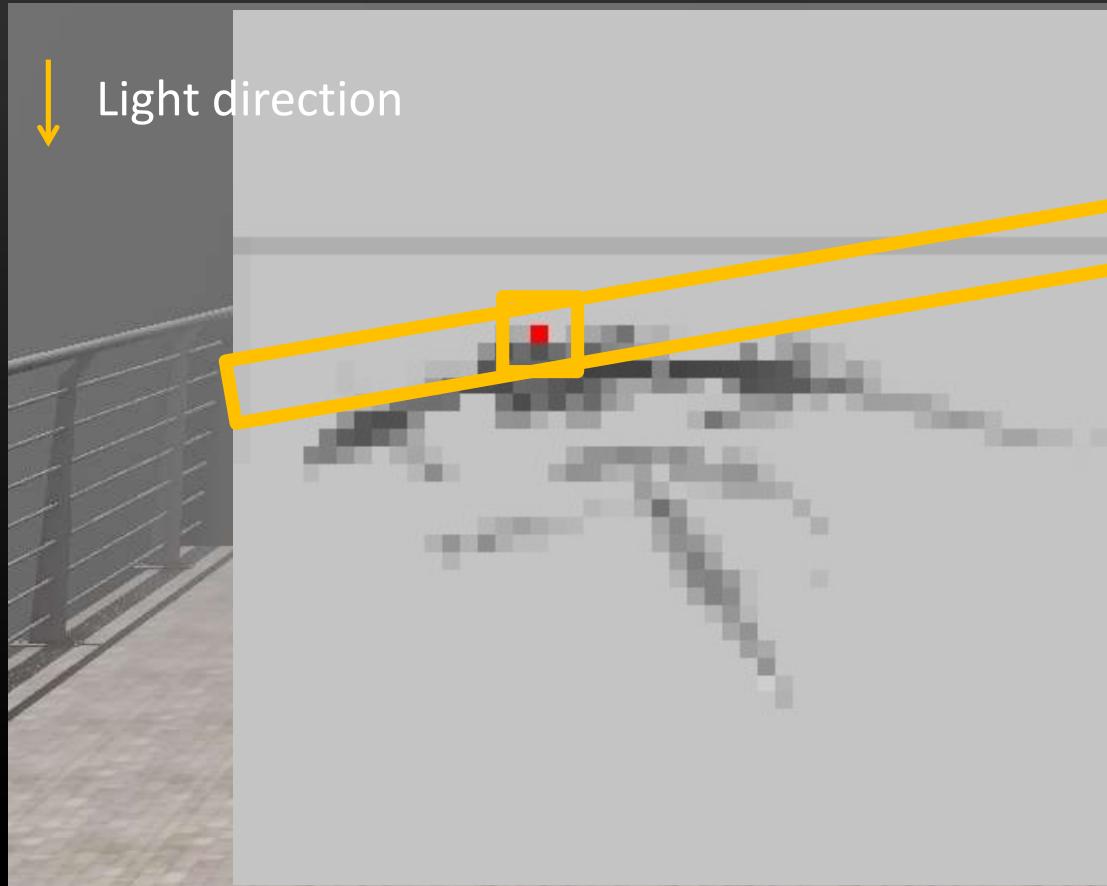


Link to Percentage Closer Filtering

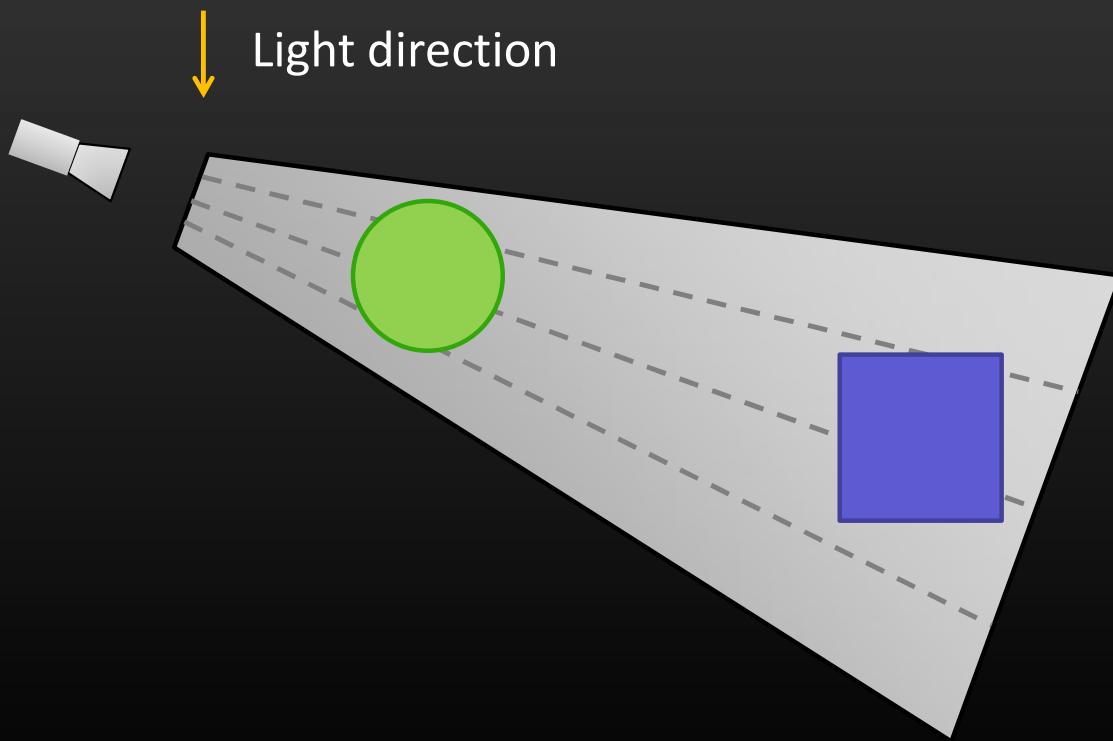
Percentage Closer
Filtering

Visibility function V

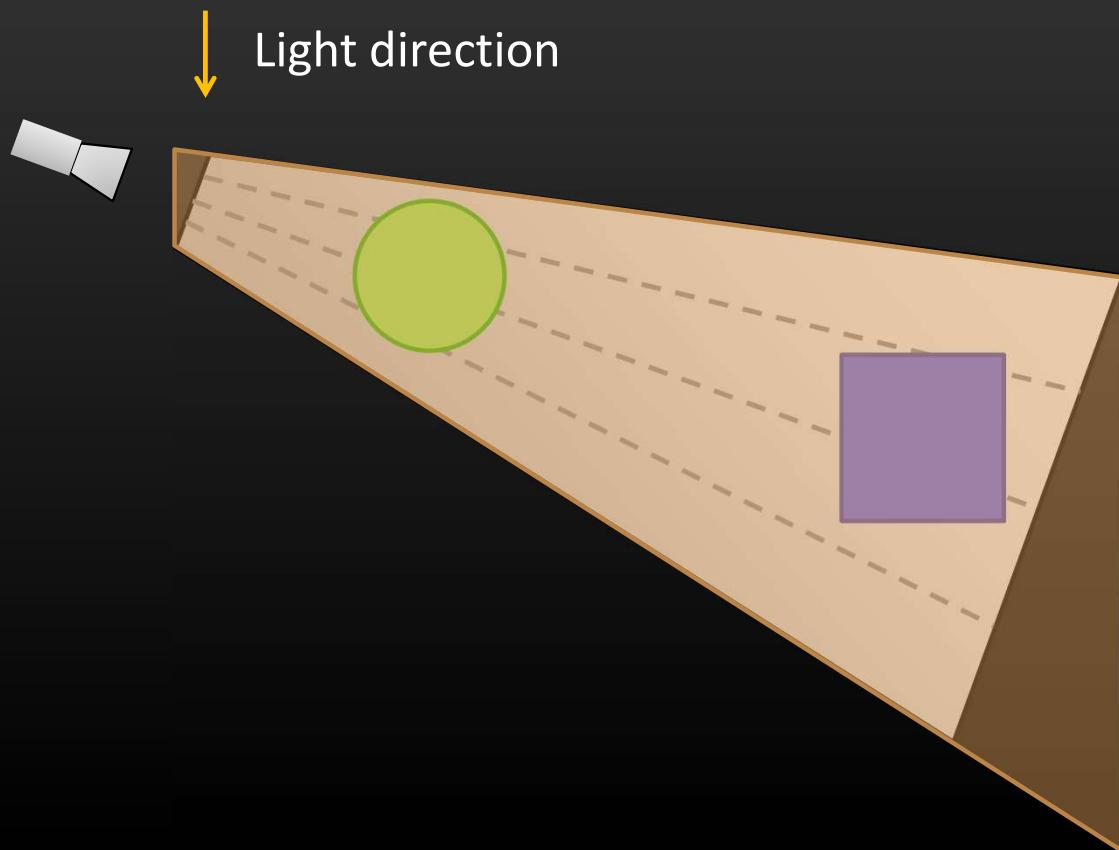
$$\sum_{s=1}^N V(d, z_s)$$



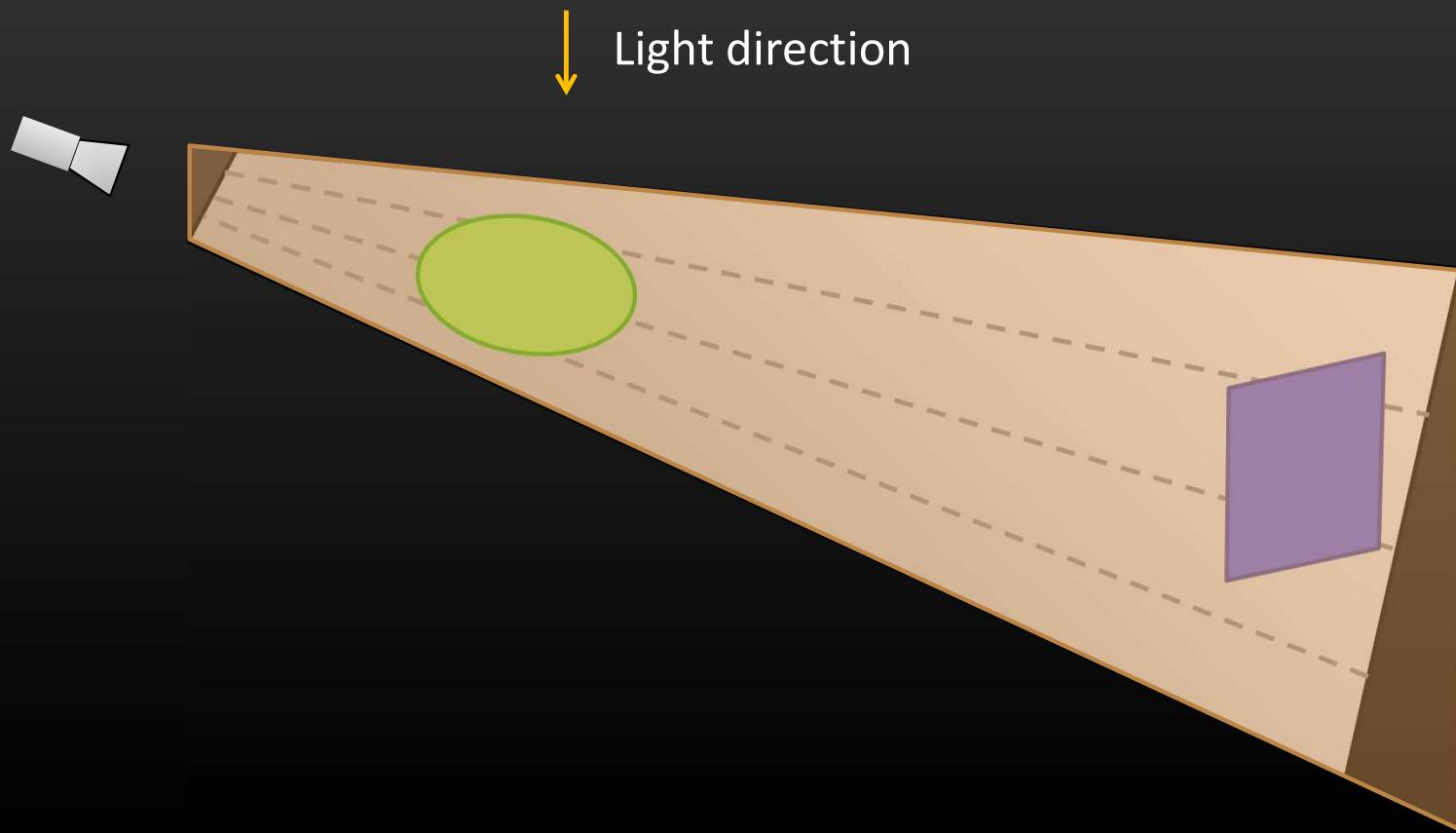
Rectified Shadow Map



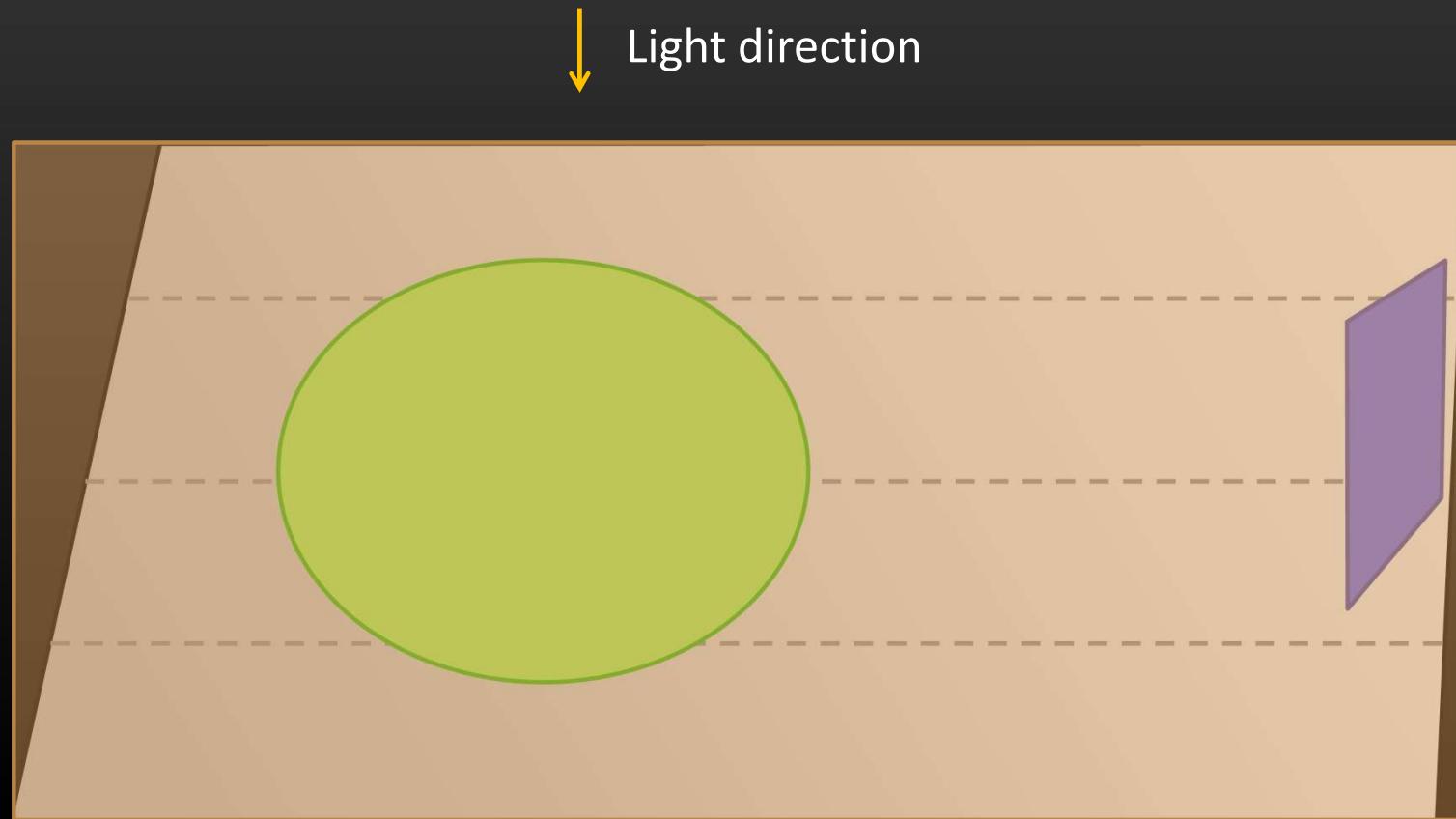
Rectified Shadow Map



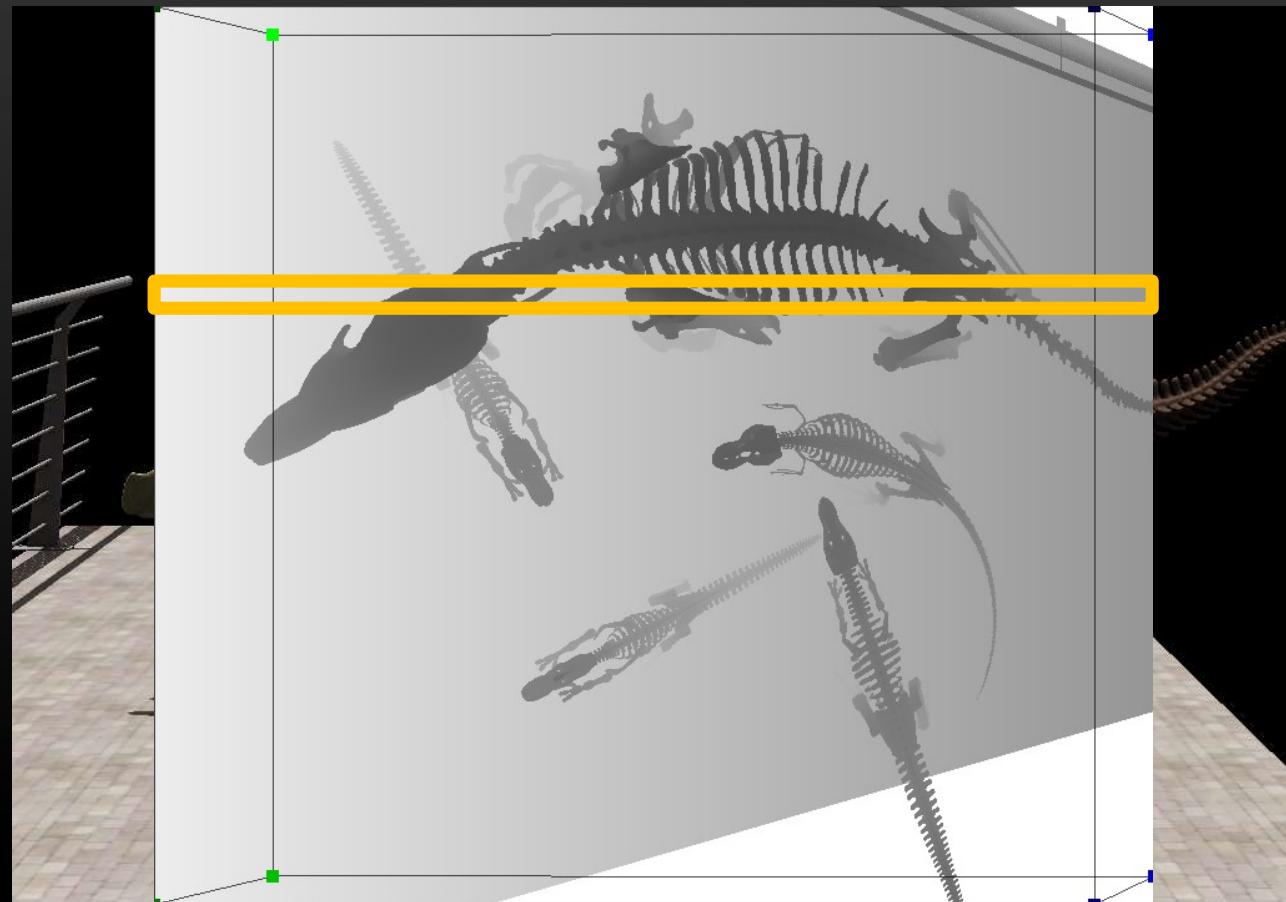
Rectified Shadow Map



Rectified Shadow Map

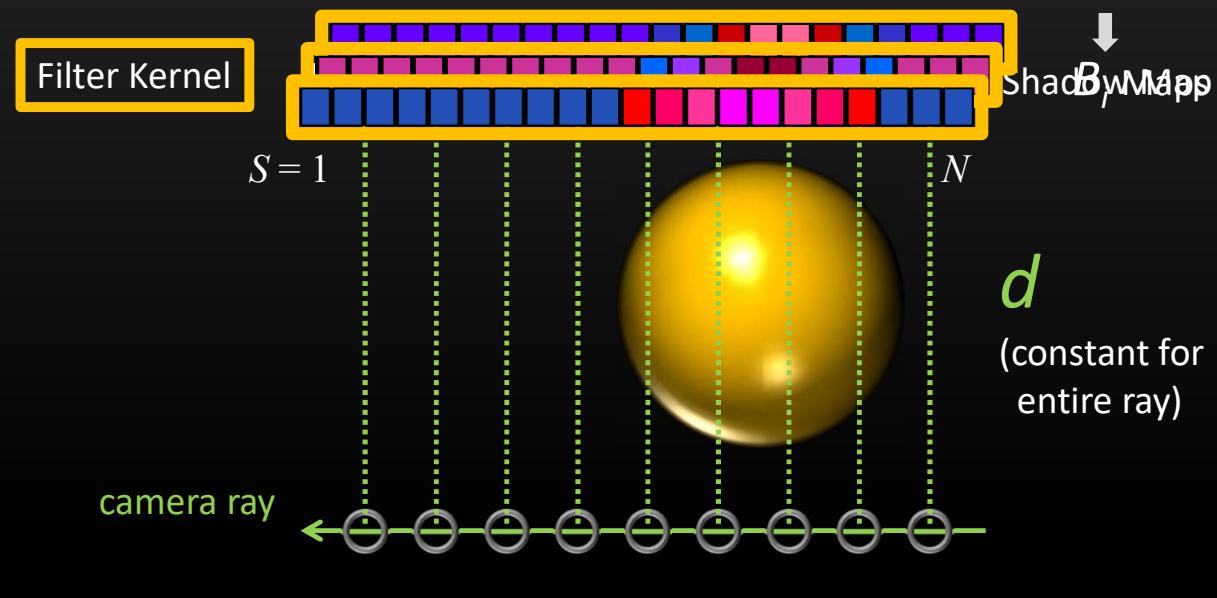


Rectified Shadow Map



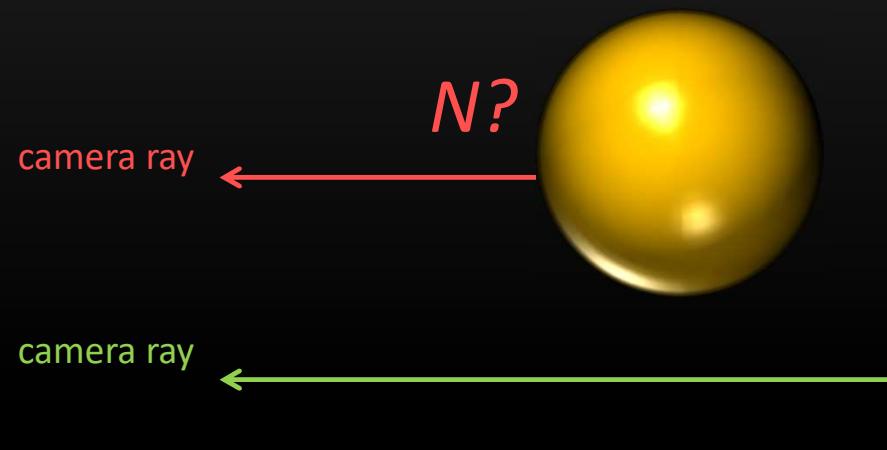
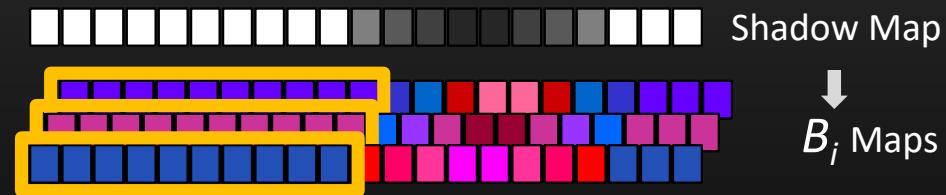
Filtering for camera rays

$$\sum_{s=1}^N V(\mathbf{d}, z_s) = \sum_{i=1}^{\infty} a_i(\mathbf{d}) \boxed{\sum_{s=1}^N B_i(z_s)}$$

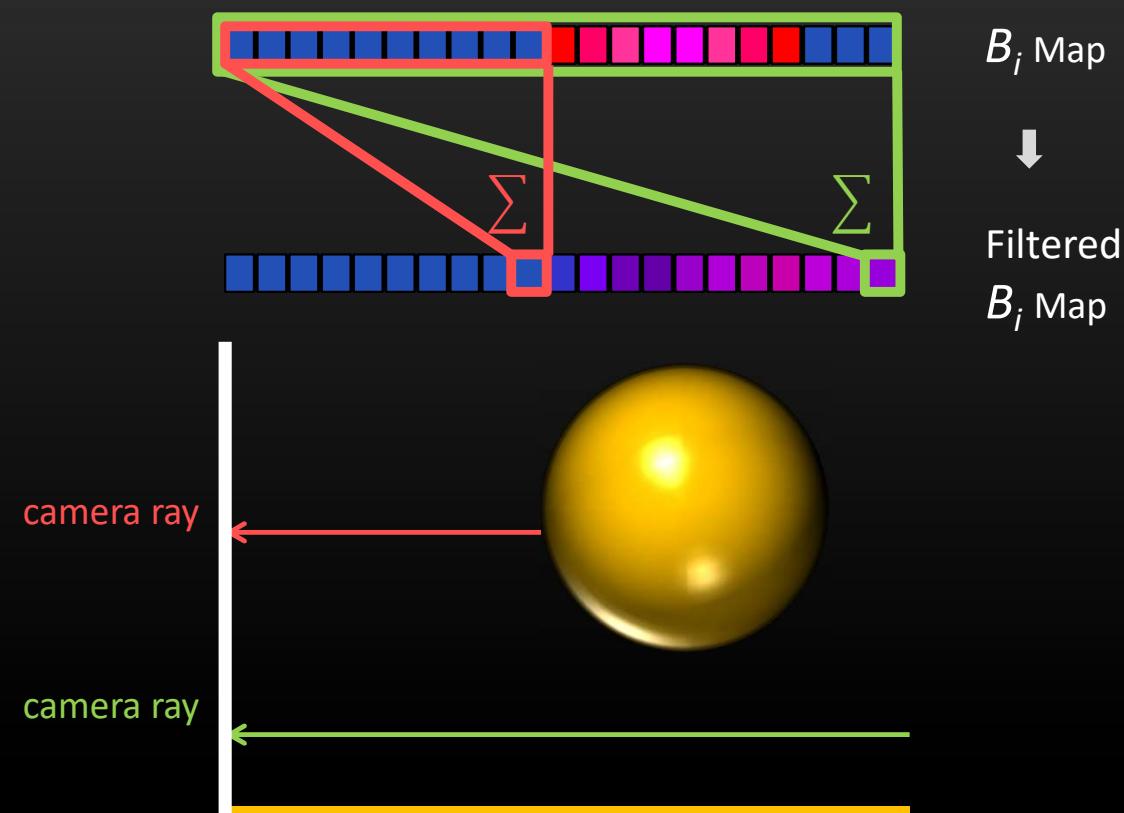


Filtering for camera rays

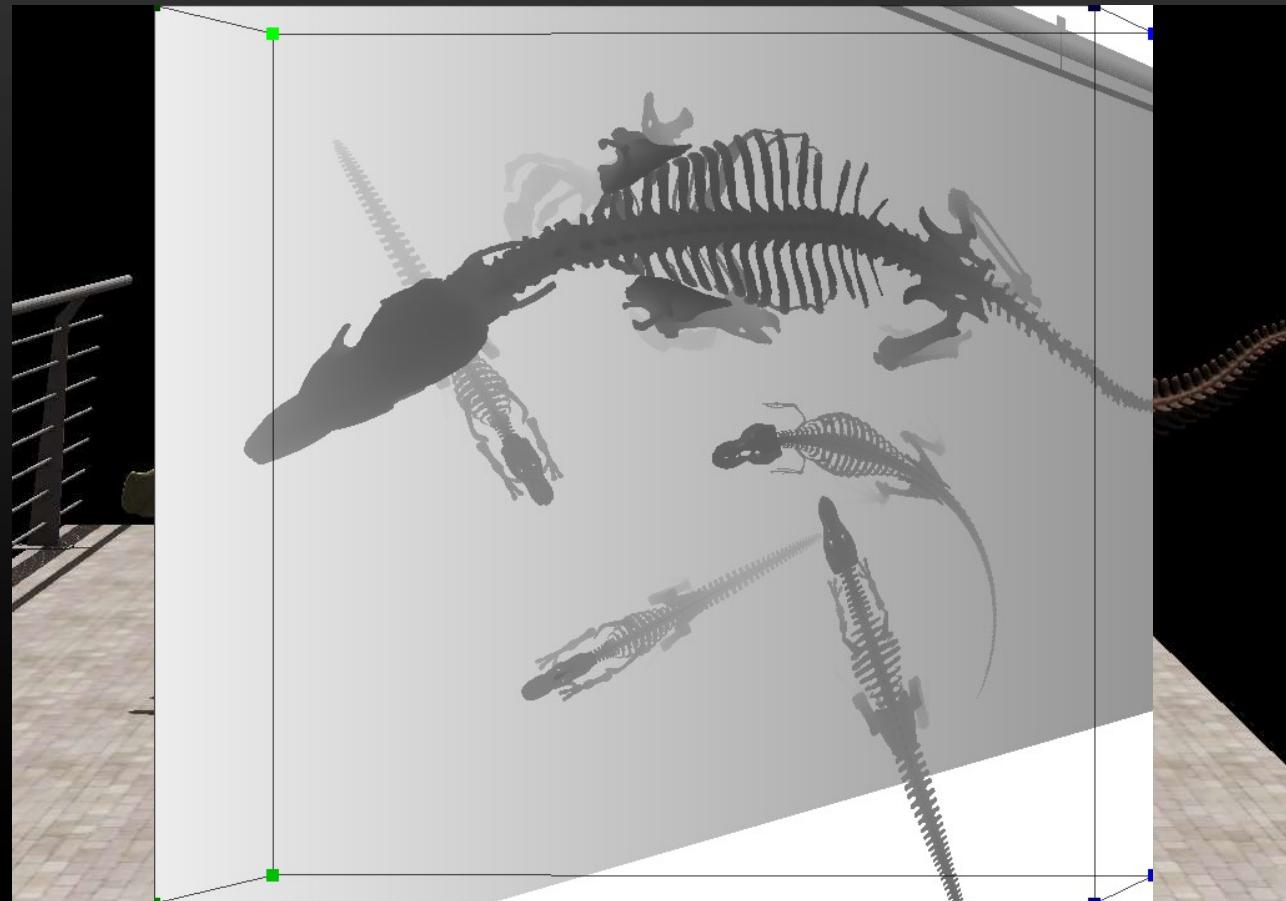
$$\sum_{s=1}^N V(\mathbf{d}, z_s) = \sum_{i=1}^{\infty} a_i(\mathbf{d}) \sum_{s=1}^N B_i(z_s)$$



Like Summed Area Tables but for a single row!



Rectified Shadow Map



Wrap up



Prefiltered Single Scattering

Oliver Klehm¹ Hans-Peter Seidel¹ Elmar Eisemann²

¹MPI Informatik

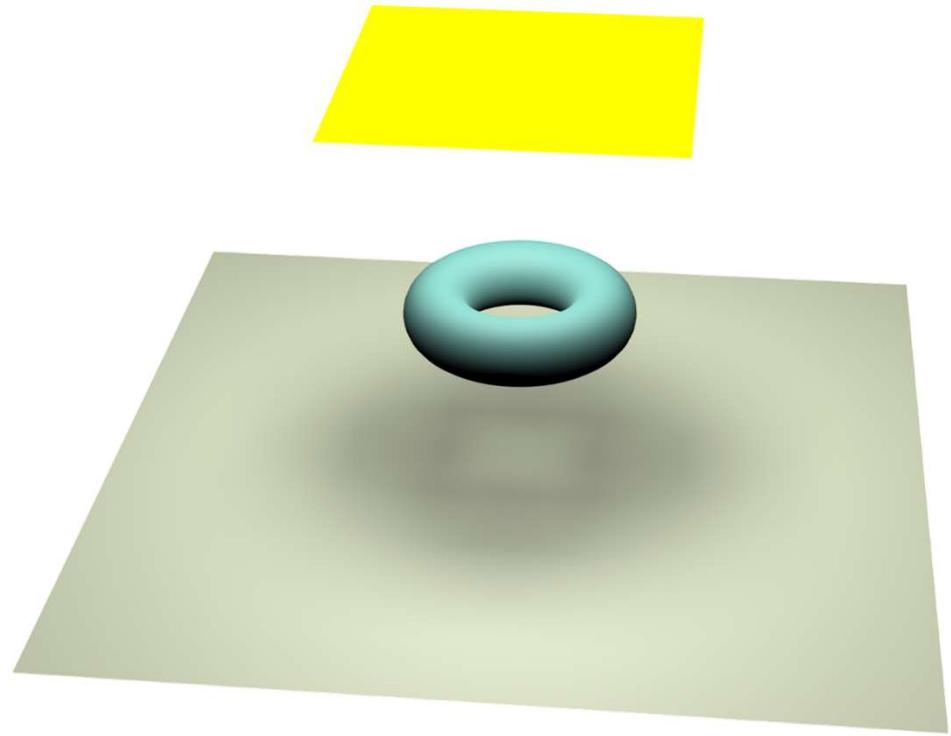
²Delft University of Technology

Comparison



Outlook

- We are not here yet:



... but we will get there...

Thank you very much
for your attention!

