# Compact Geometric Structures in Graphics

Norbert Bus

October 8, 2015

UNIVERSITÉ PARIS-EST

ESIEE PARIS

# Outline

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## A Compact Structure

Well-Separated Pair Decomposition

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Well-Separated Pair Decomposition

## Global Illumination

Well-Separated Pair Decomposition

IlluminationCut

# Well-Separated Pair Decomposition

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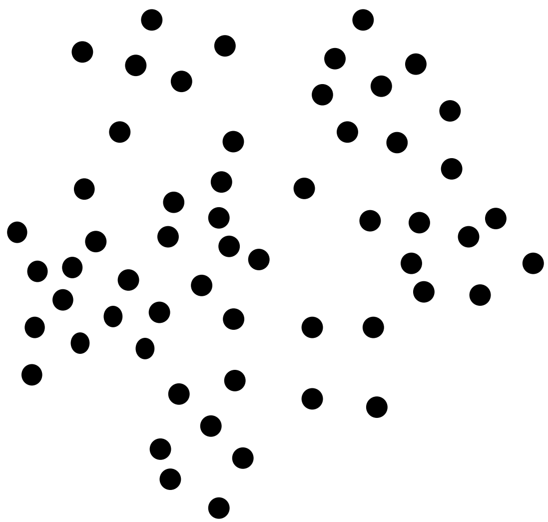

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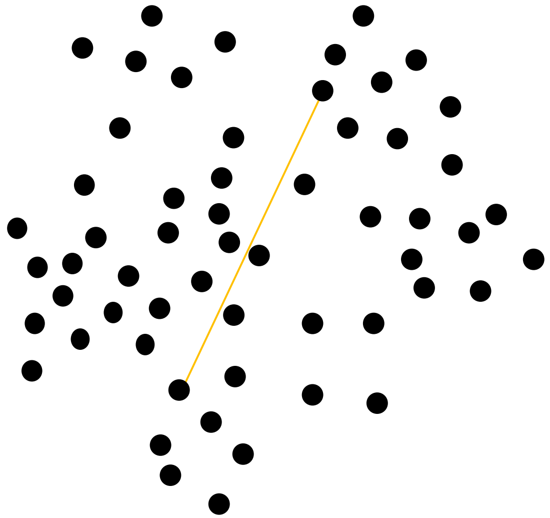

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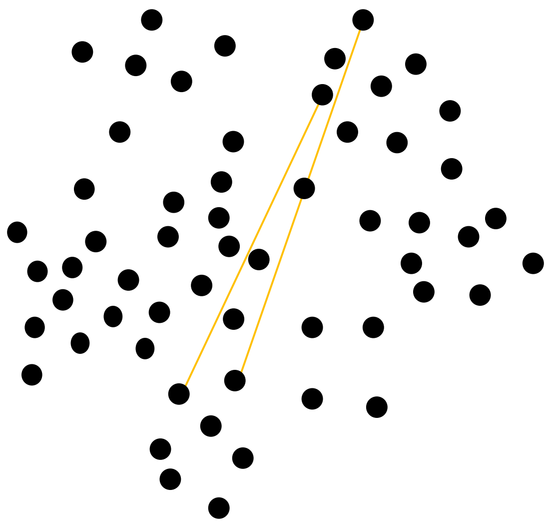

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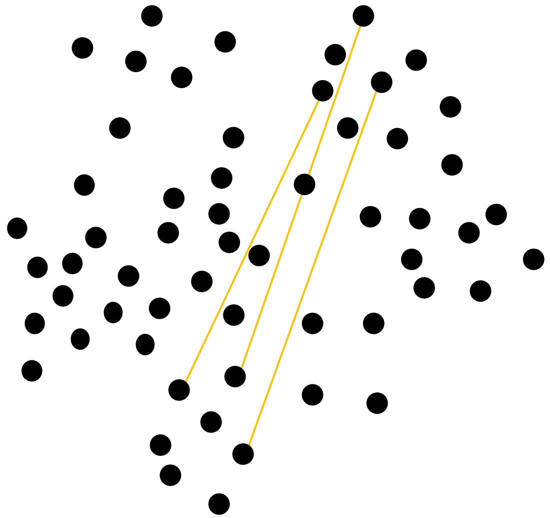

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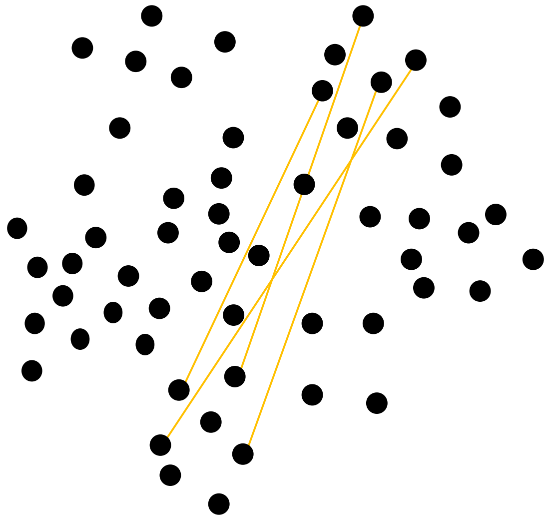

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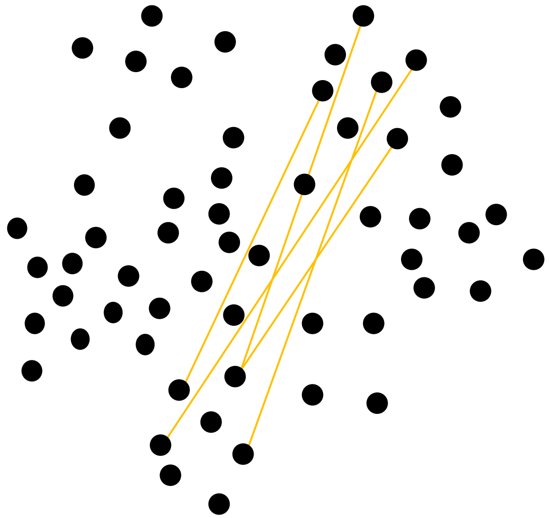

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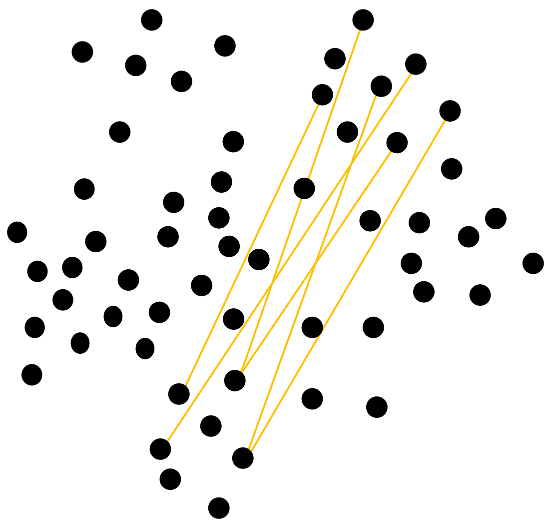

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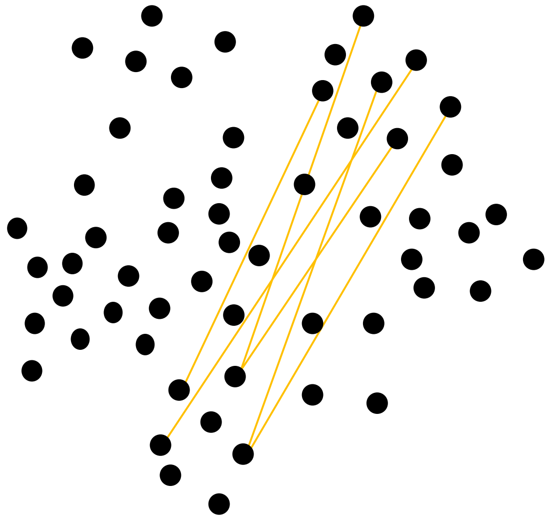

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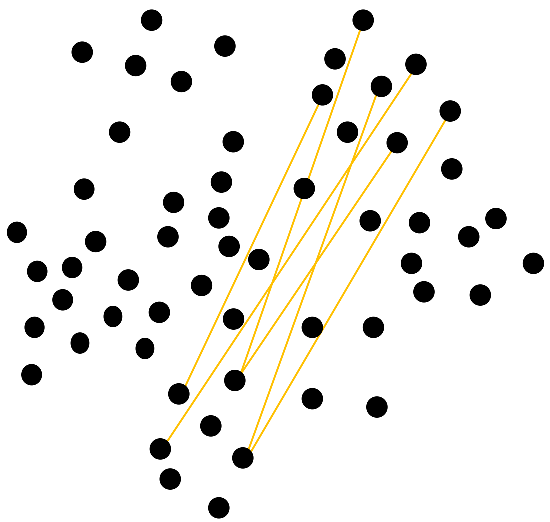

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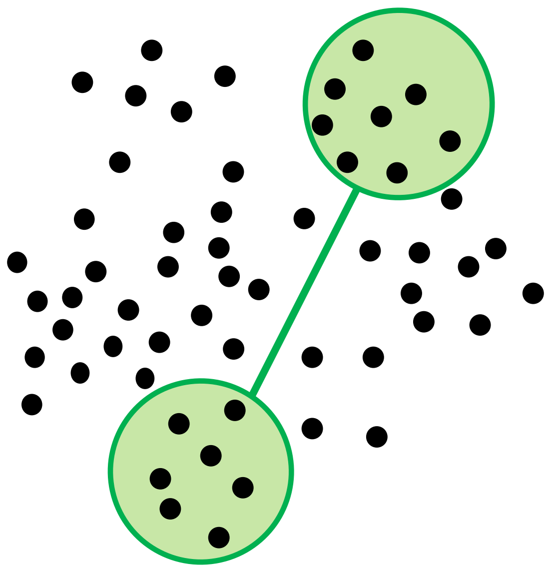

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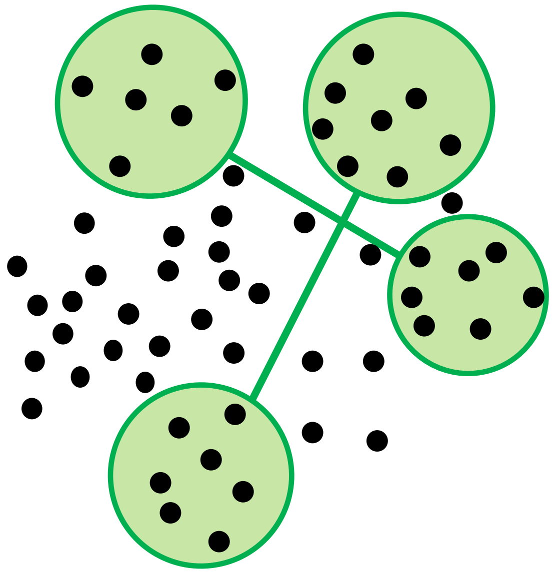

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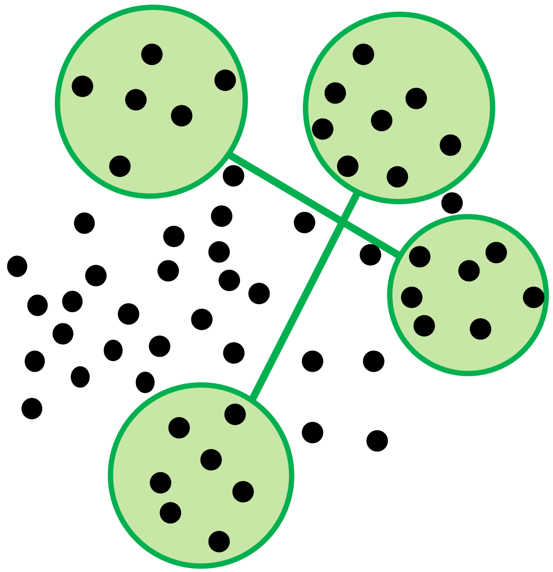

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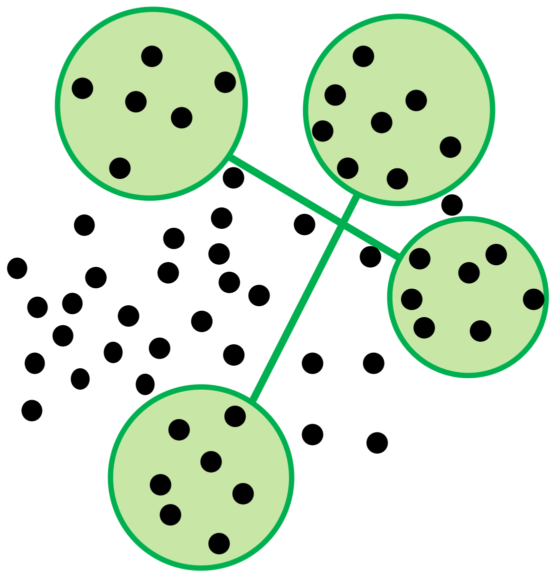

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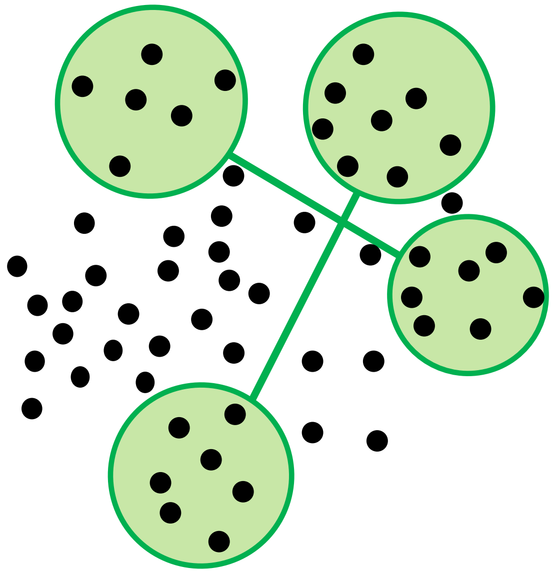

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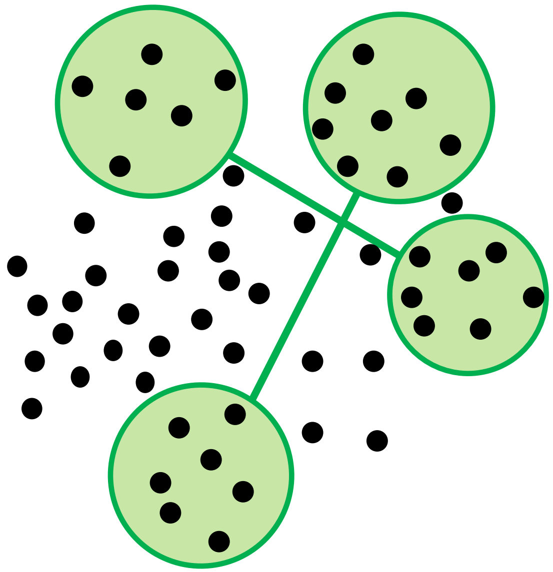

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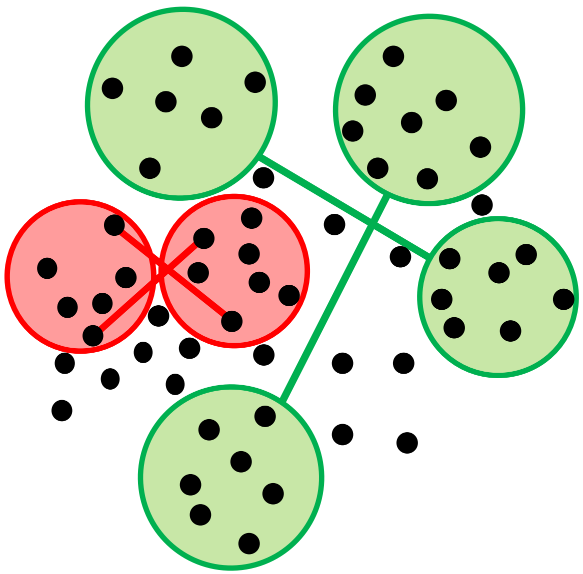

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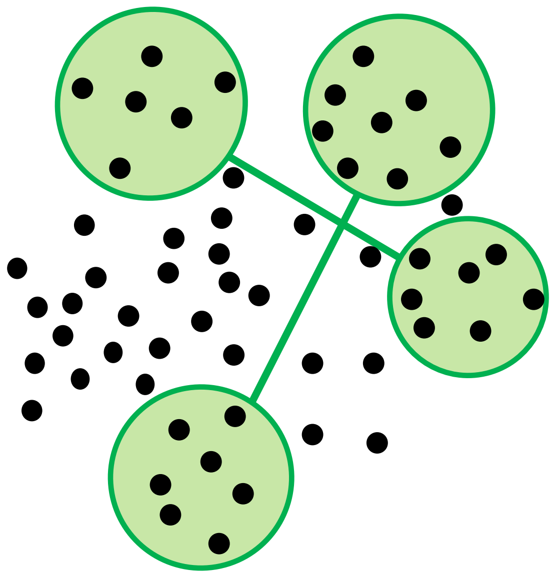

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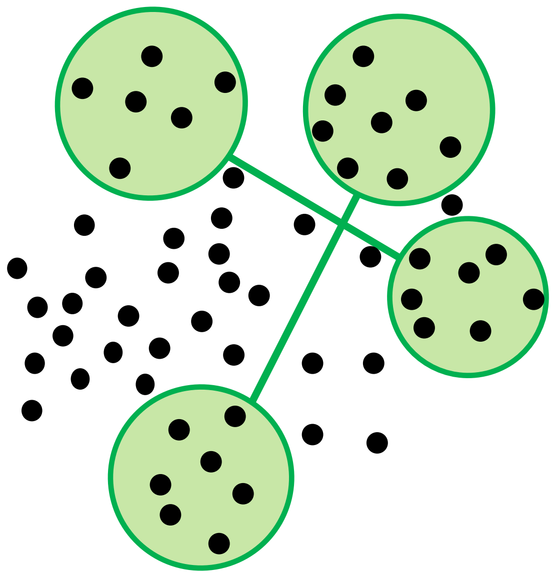

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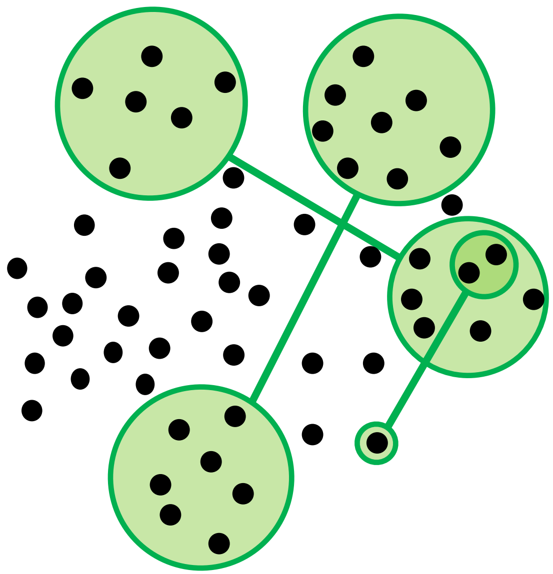

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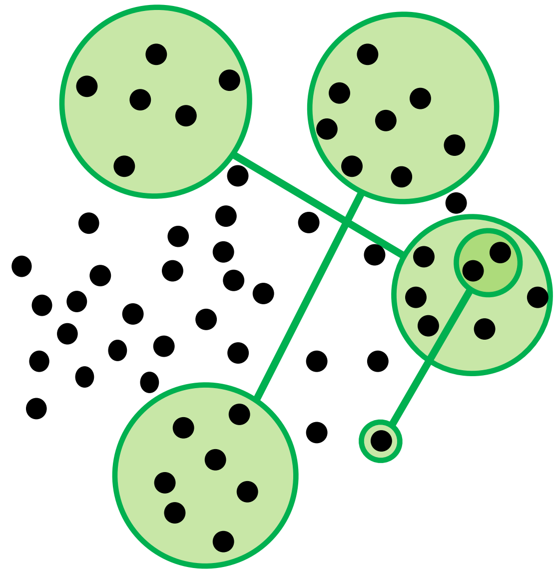

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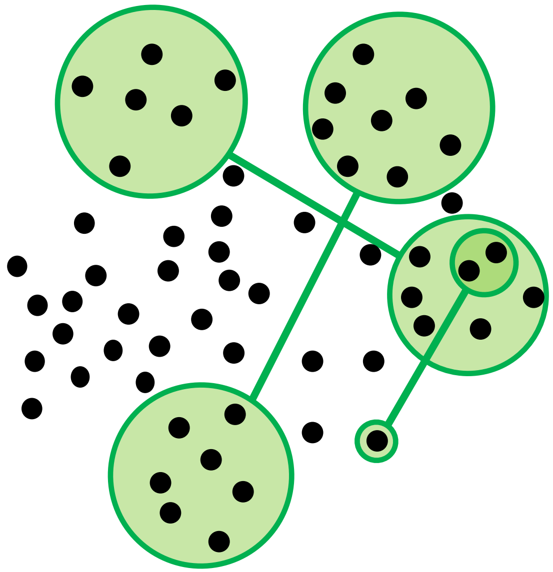

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**Theorem:** $O(n)$ pairs are sufficient

[Callahan, Kosaraju 1995]

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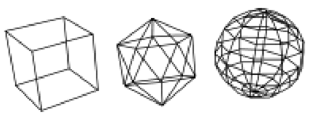

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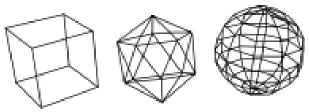

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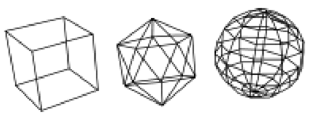

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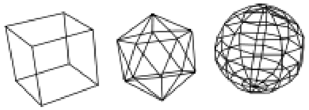

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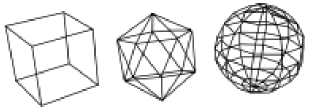

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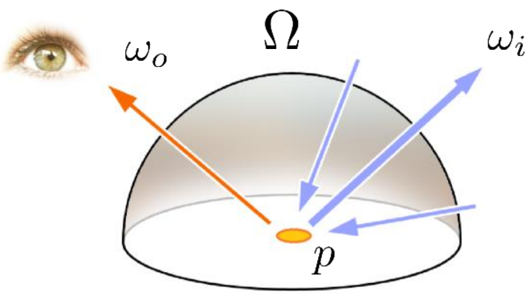
Solving the rendering equation (simple form):




$$L_o(p, \omega_o) = L_e(p, \omega_o) + \int_\Omega f_r(p, \omega_i, \omega_o) L_i(p, \omega_i)(\omega_i \cdot n) d\omega_i$$

[Kajiya 1986]

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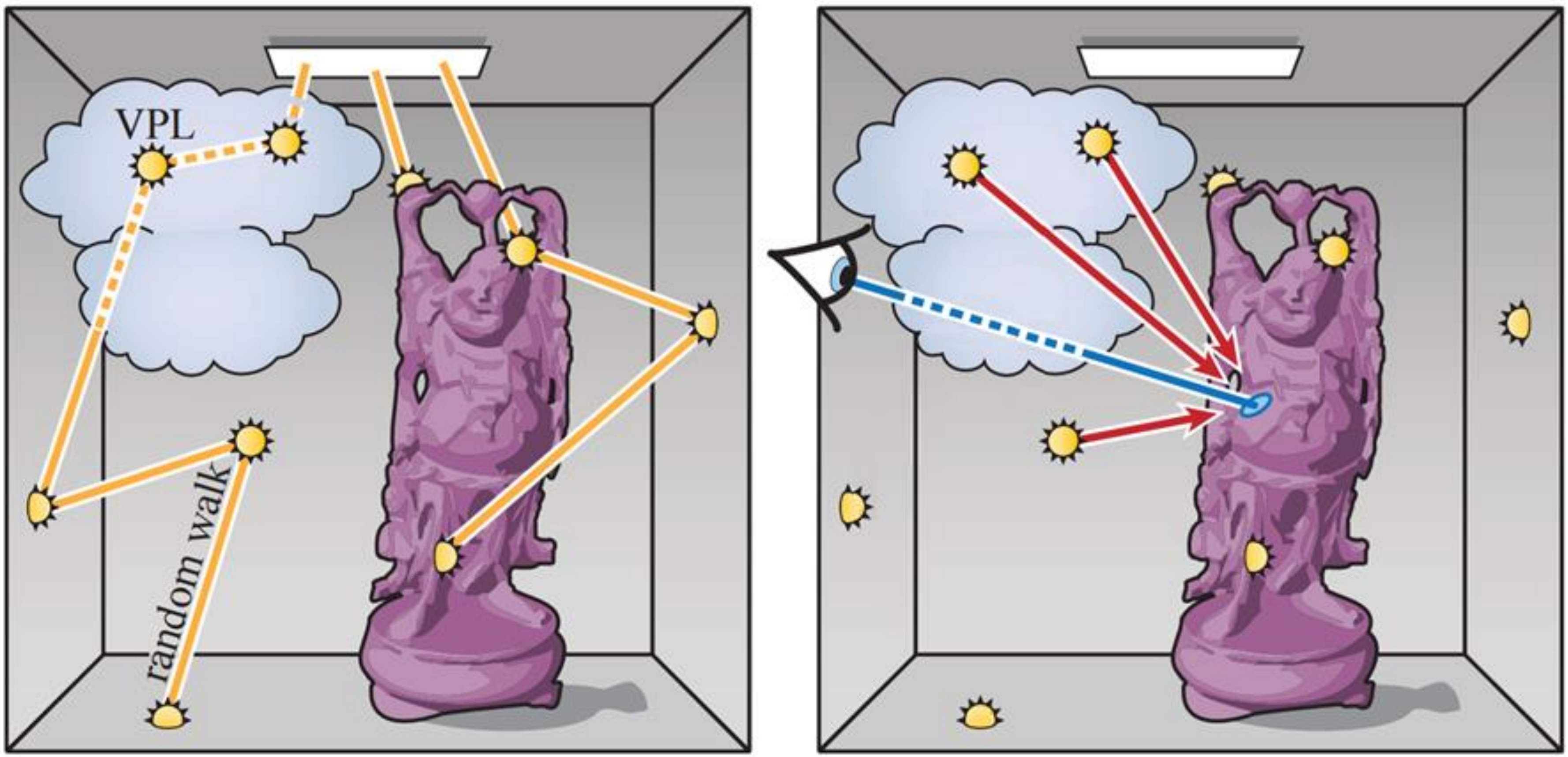

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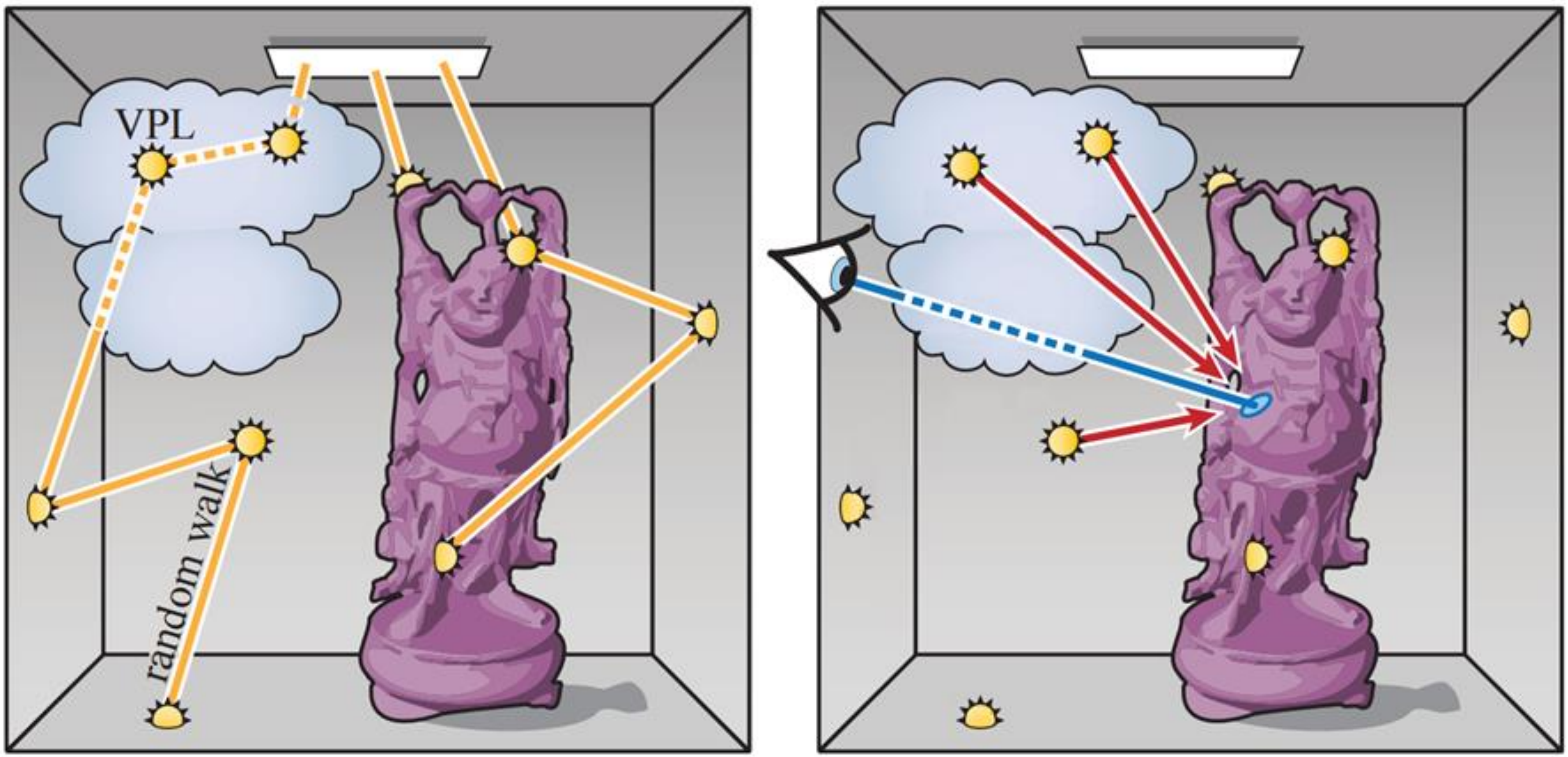


$$L(p, \omega) =$$

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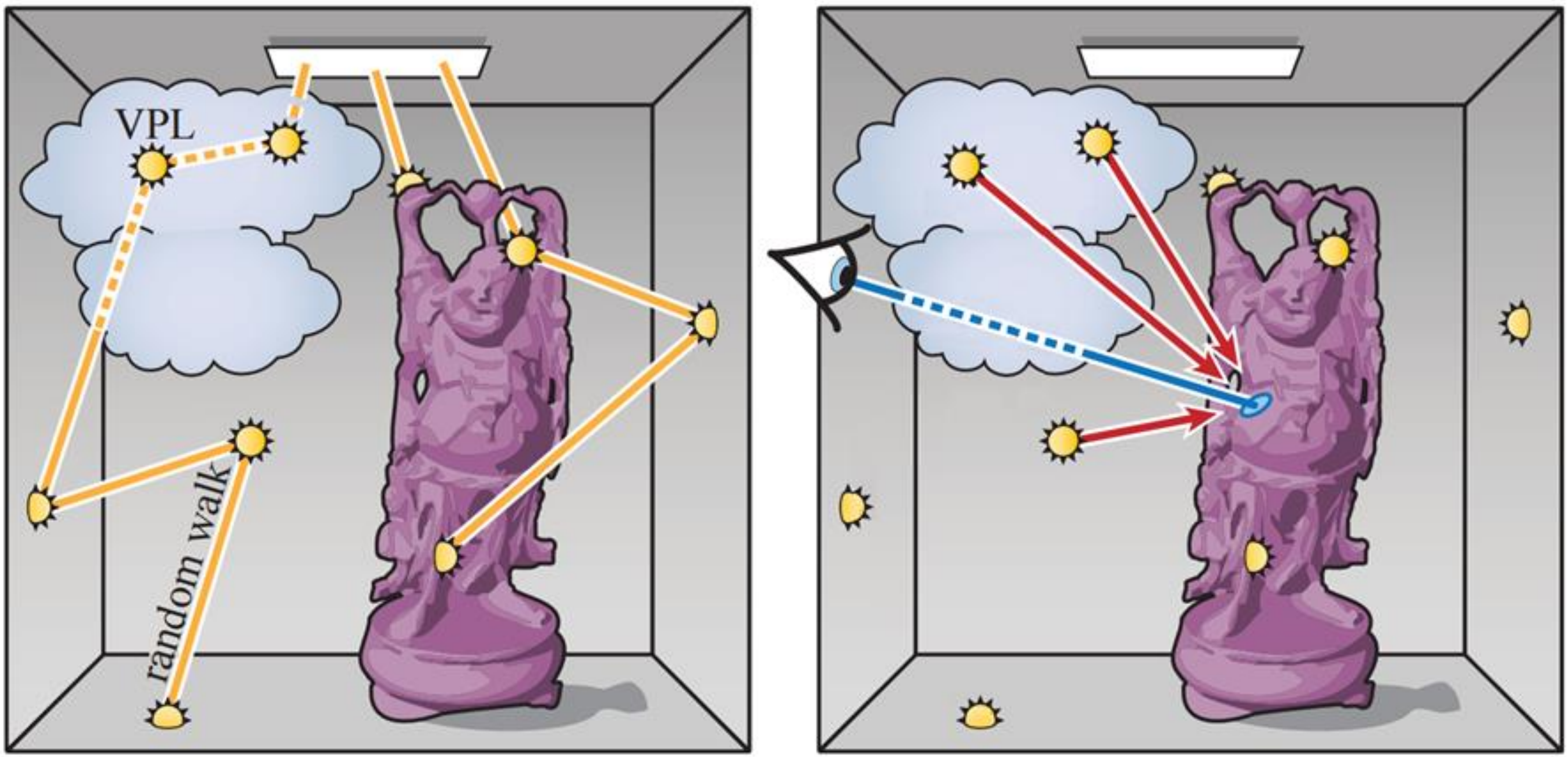


$$L(p,\omega) = \sum_{s\in S}$$

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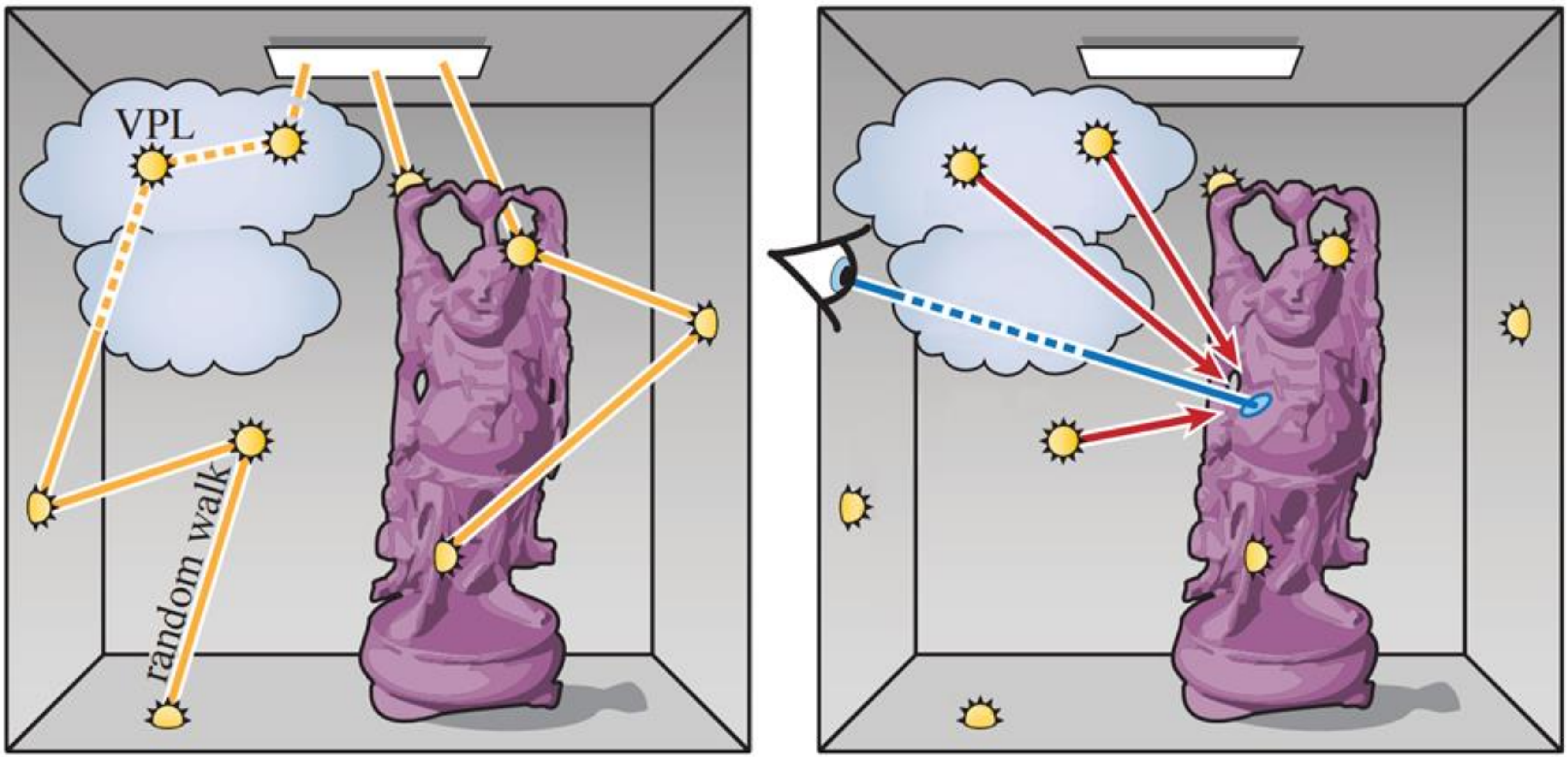


$$L(p,\omega) = \sum_{s \in S} I_s$$

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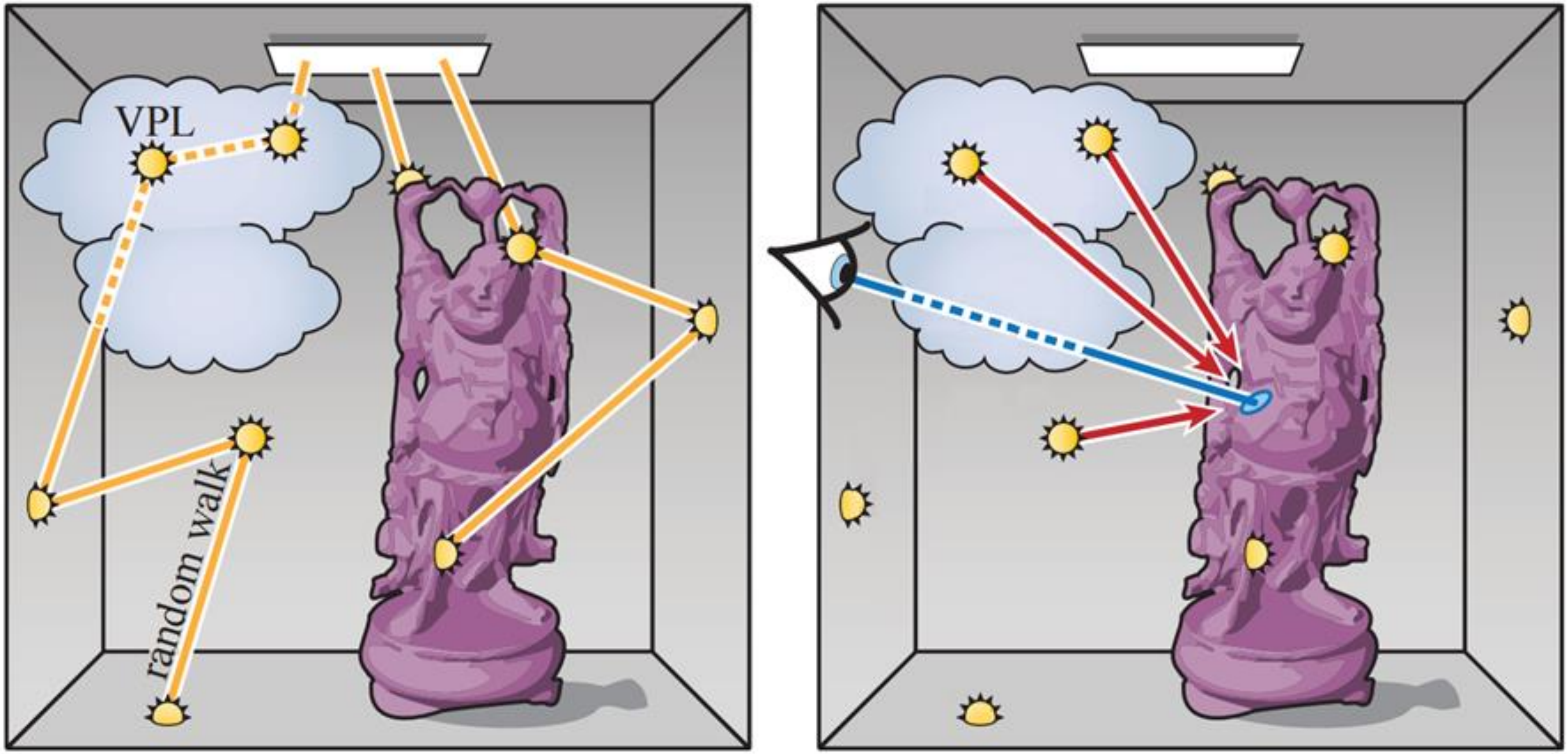


$$L(p, \omega) = \sum_{s \in S} I_s \; V_s(p)$$

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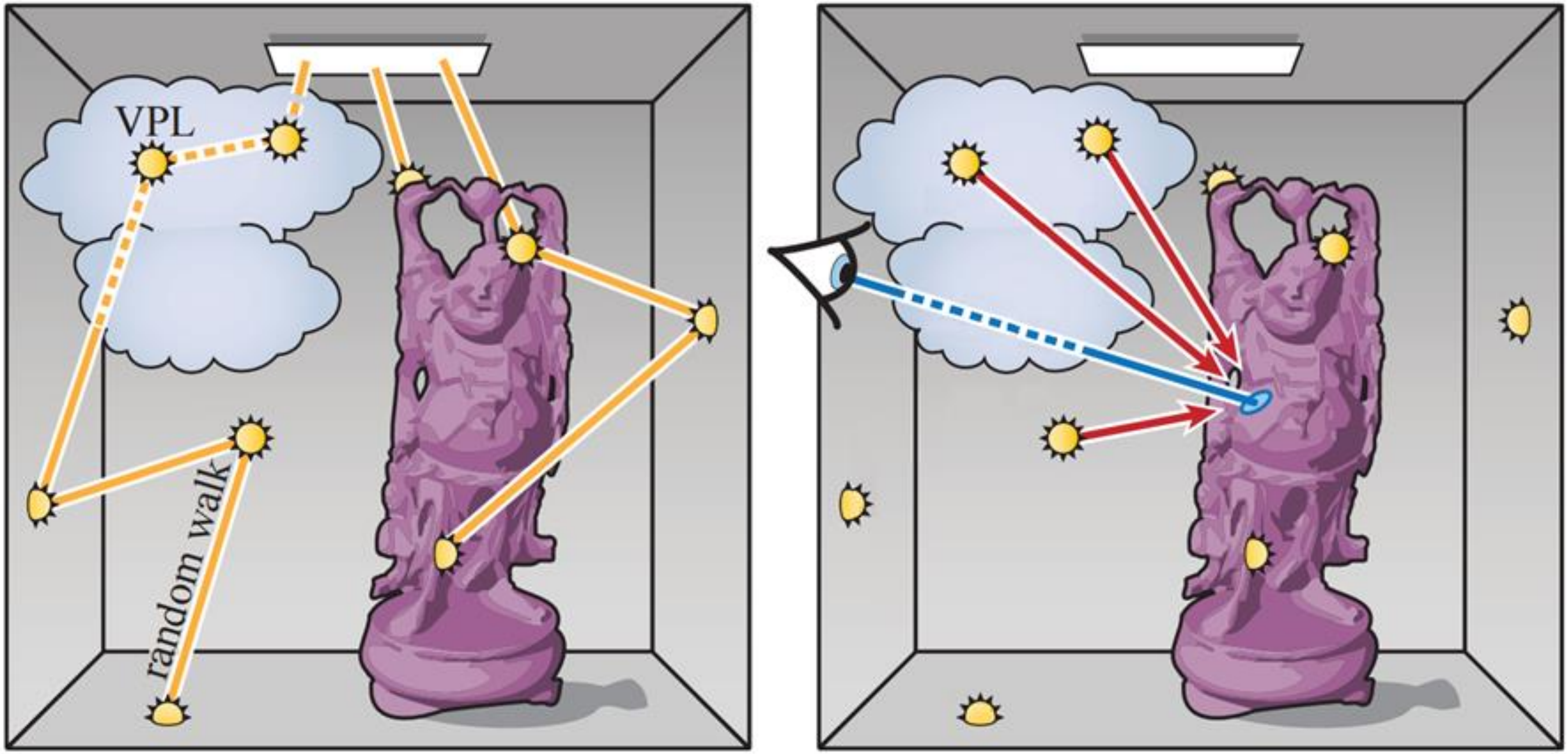


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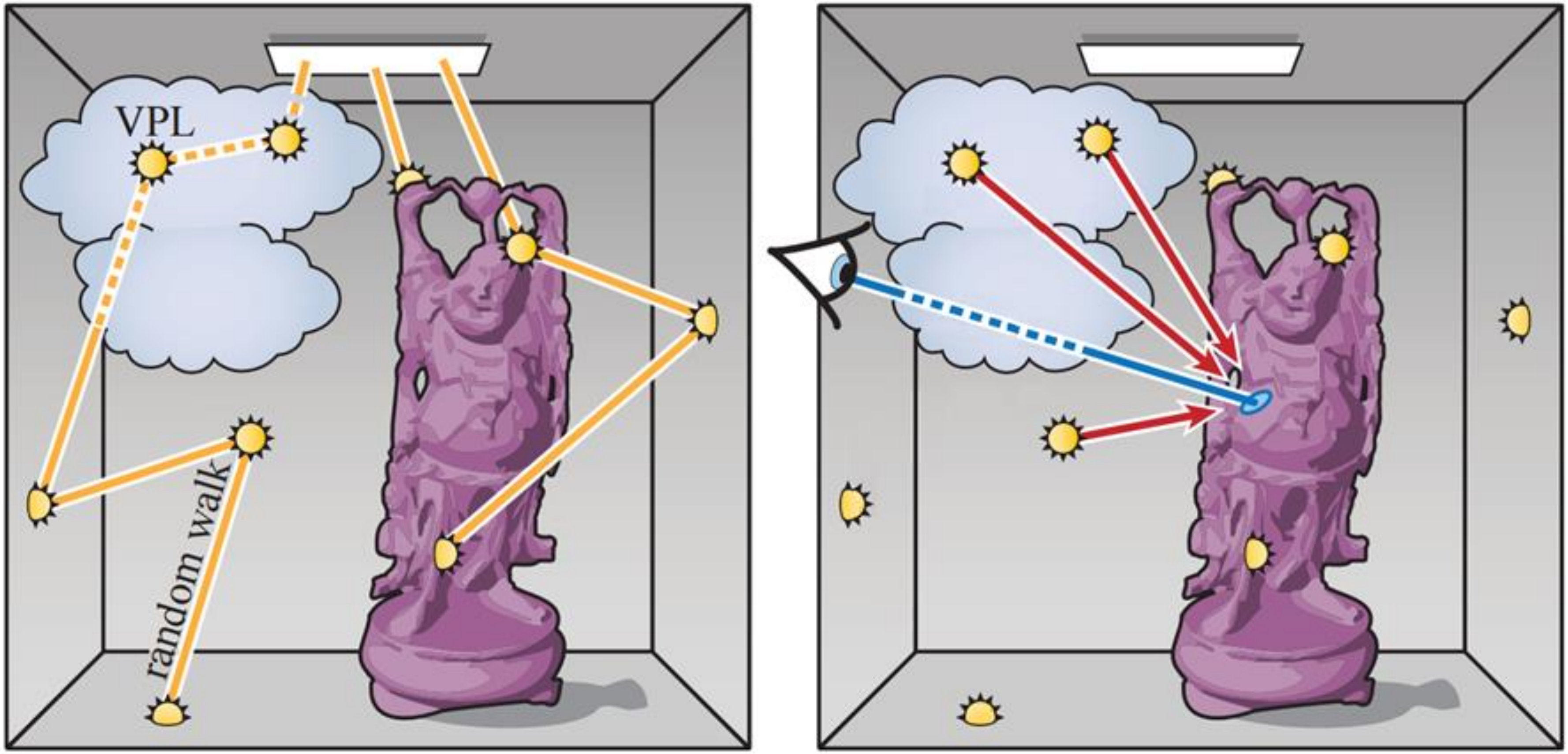


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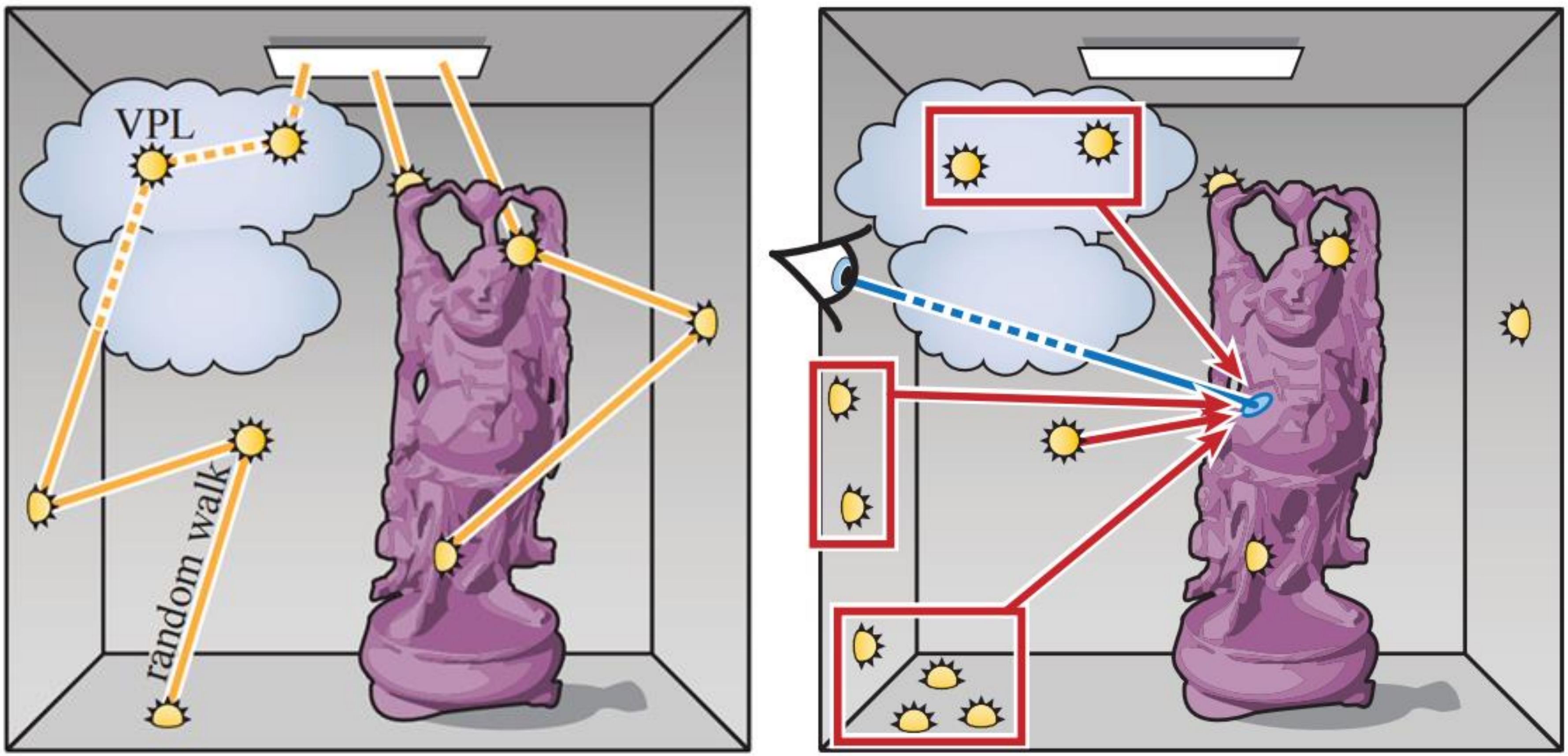


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Millions of VPLs $\rightarrow$ Cluster lights

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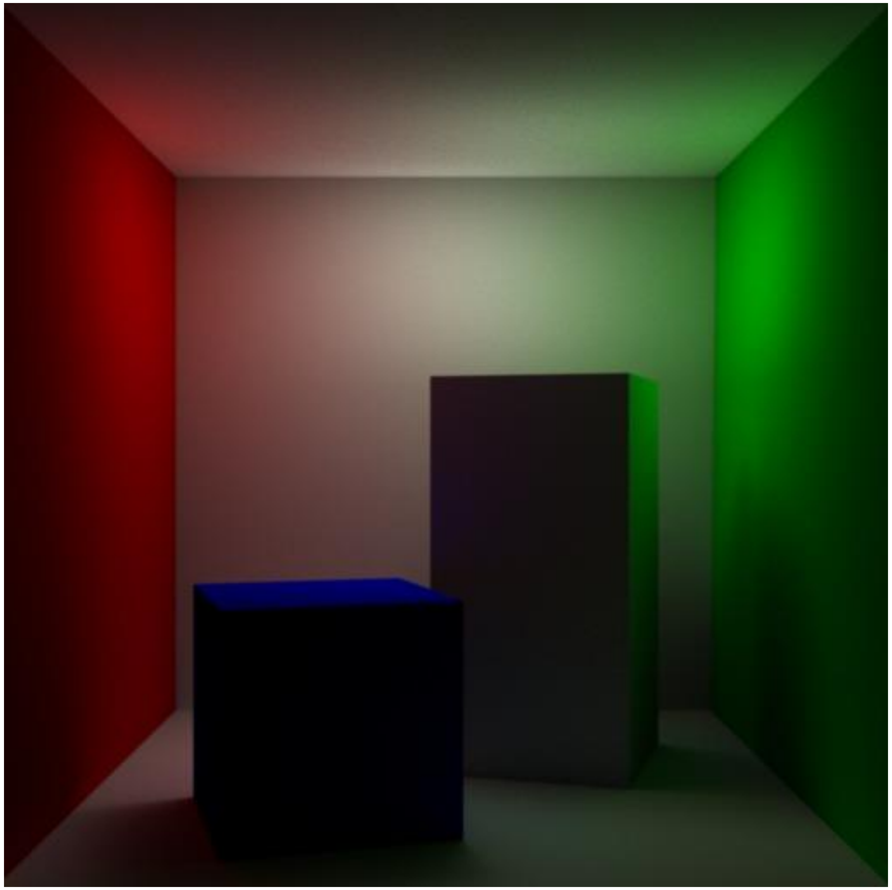

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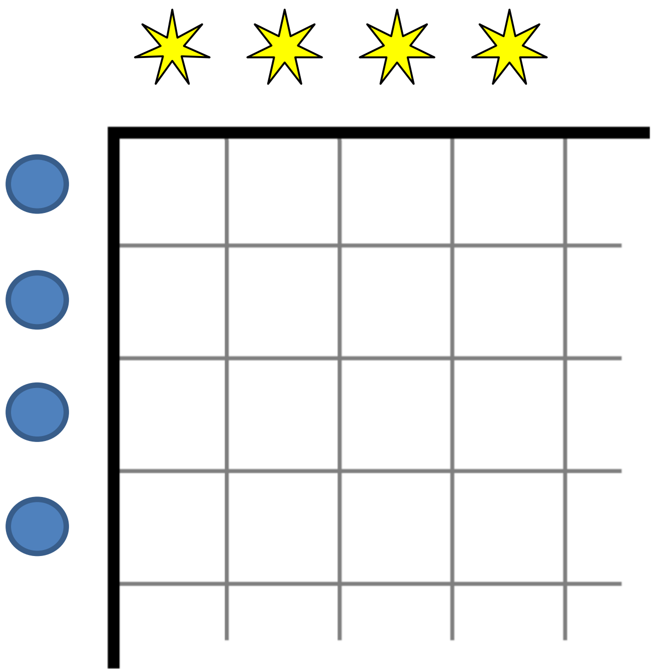

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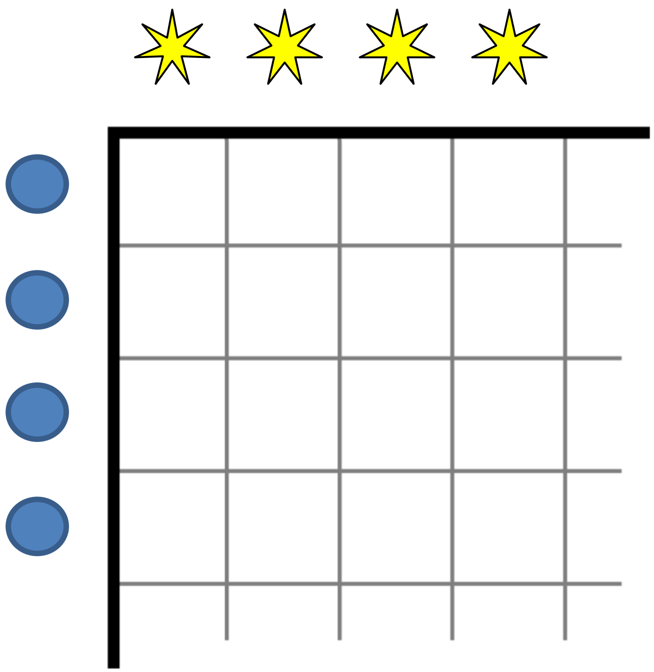

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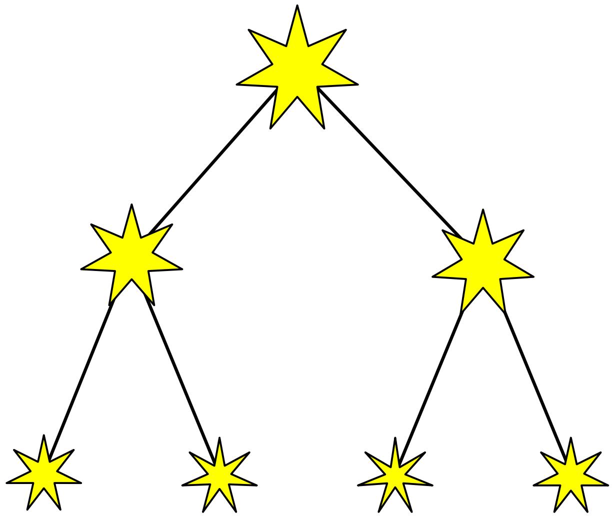
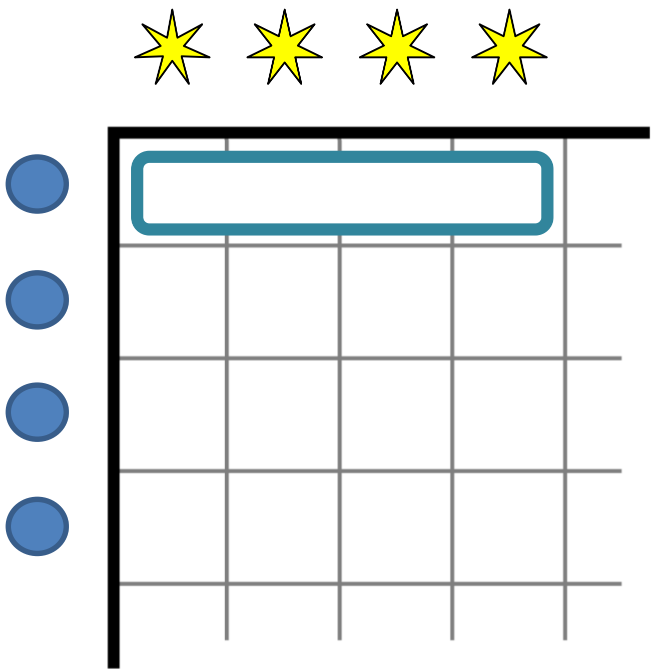


light tree

# Clustering: Lightcuts

[Walter et al, SIGGRAPH 2005]



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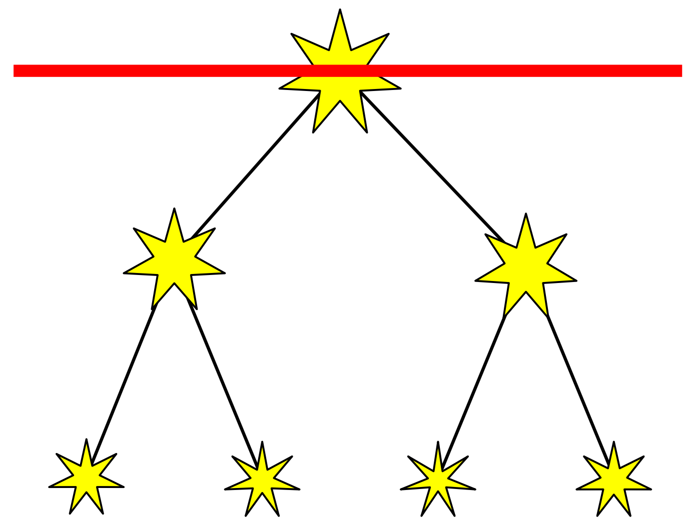

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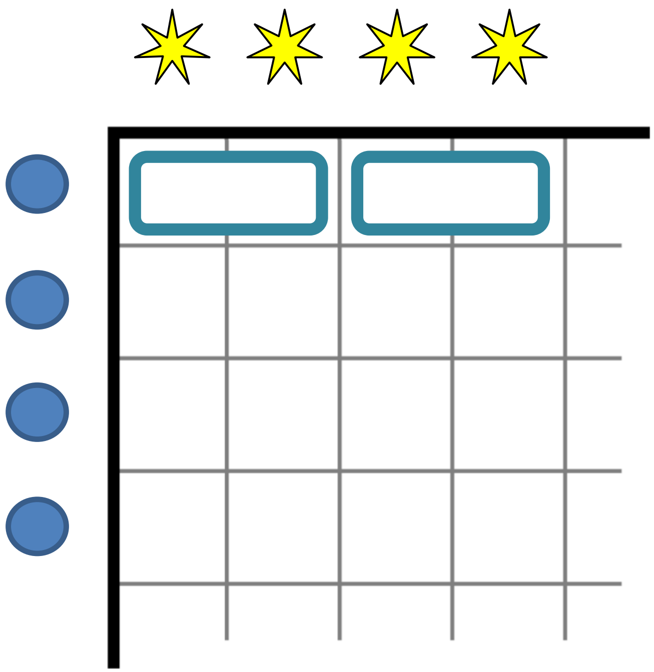

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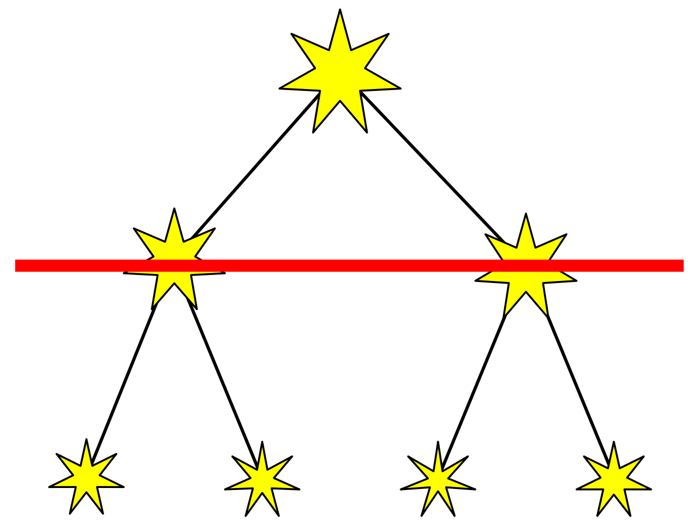

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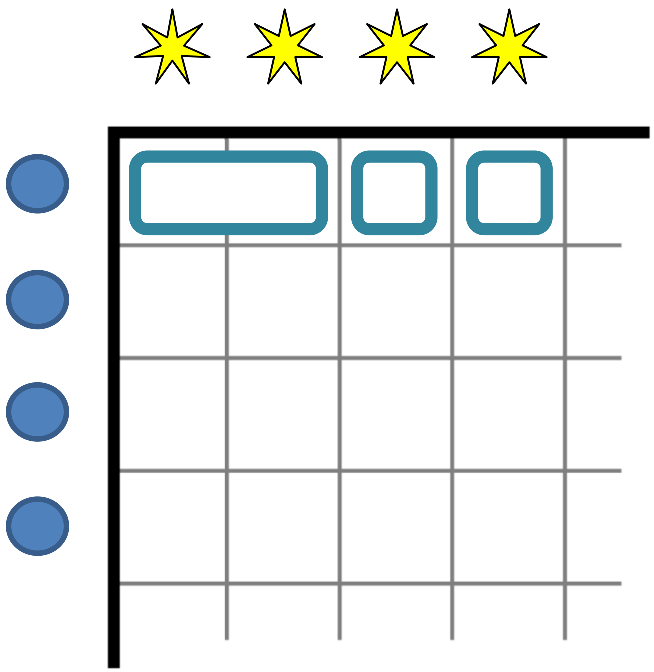

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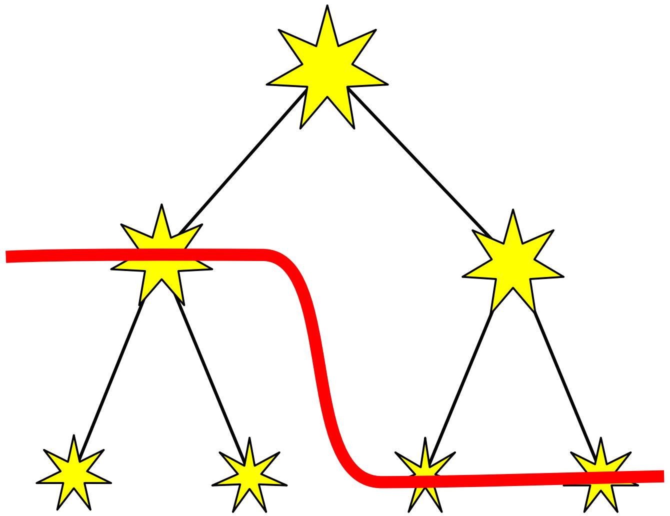

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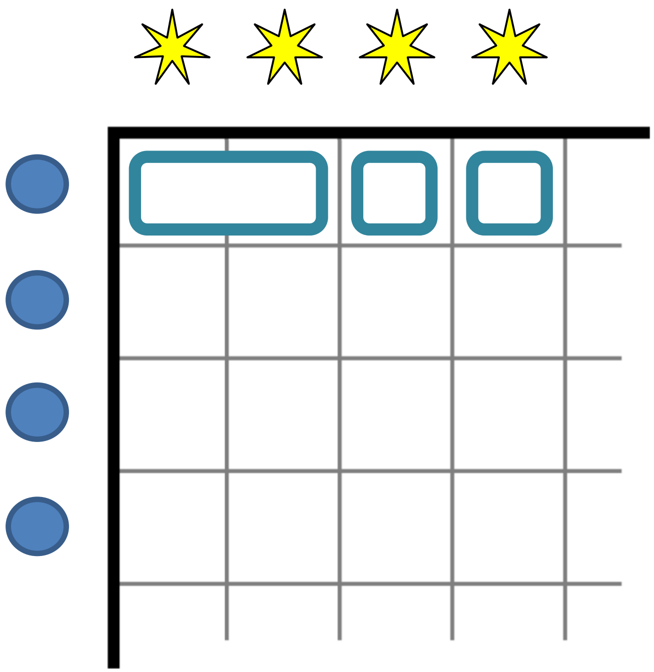

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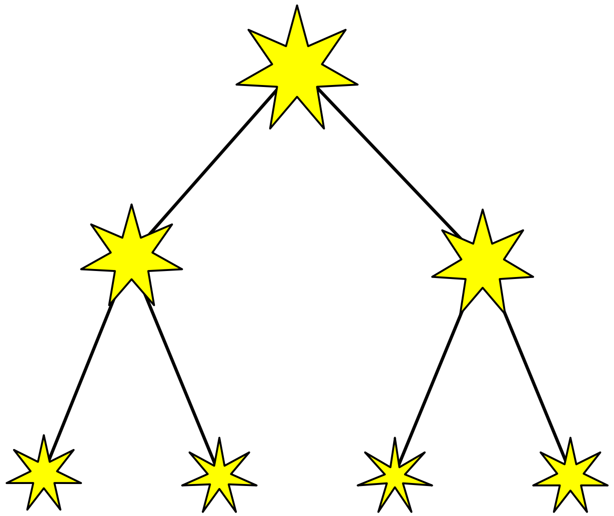

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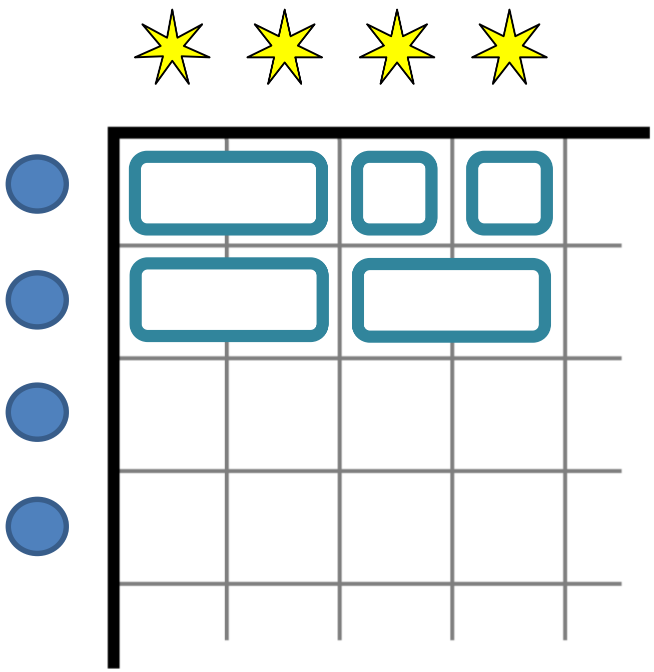

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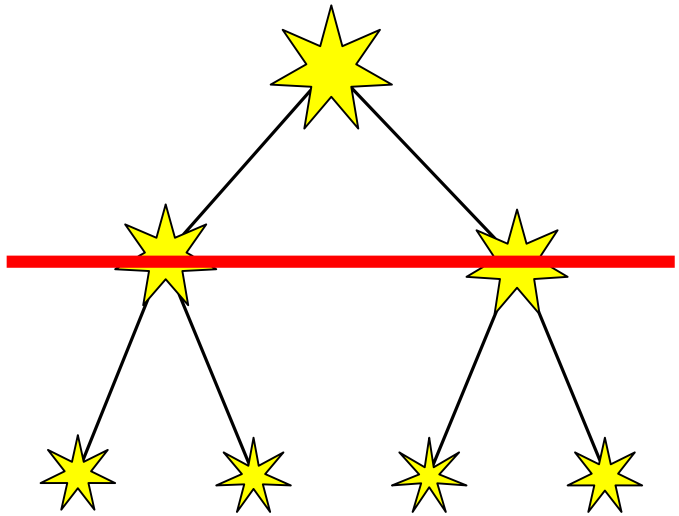

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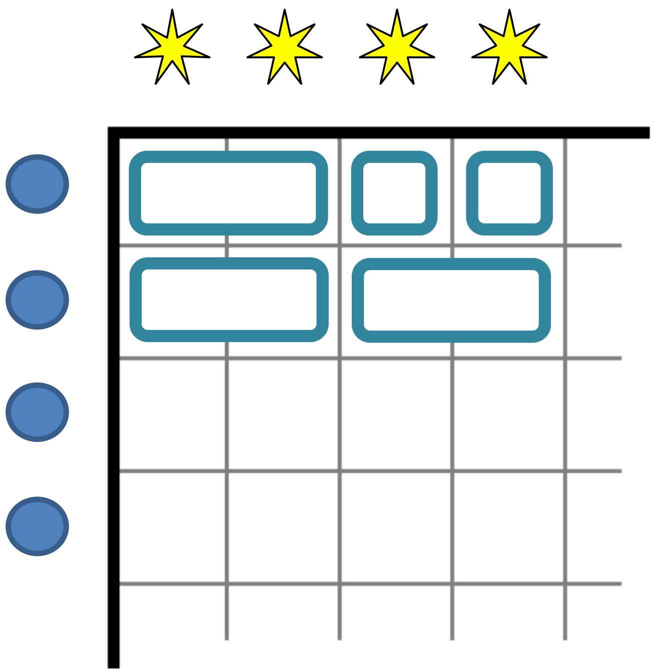

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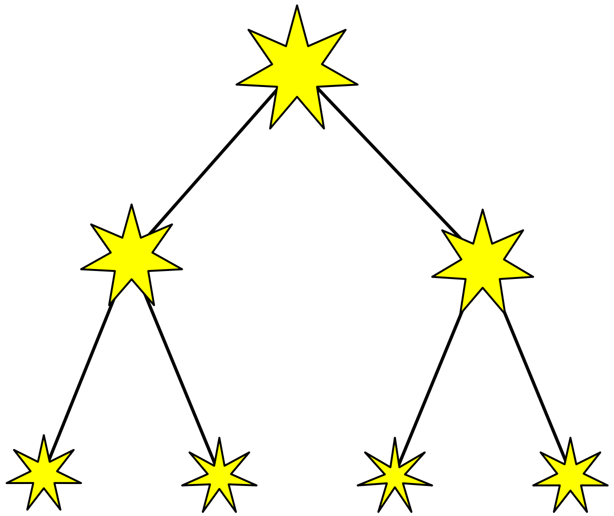

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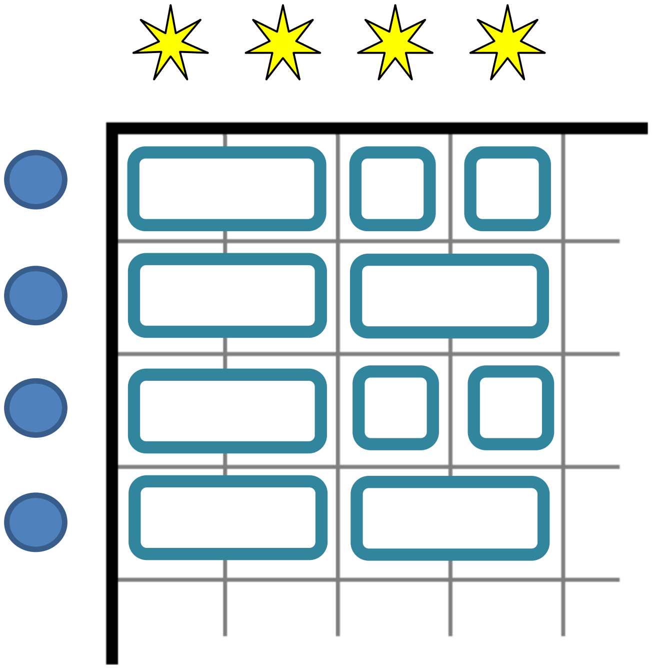

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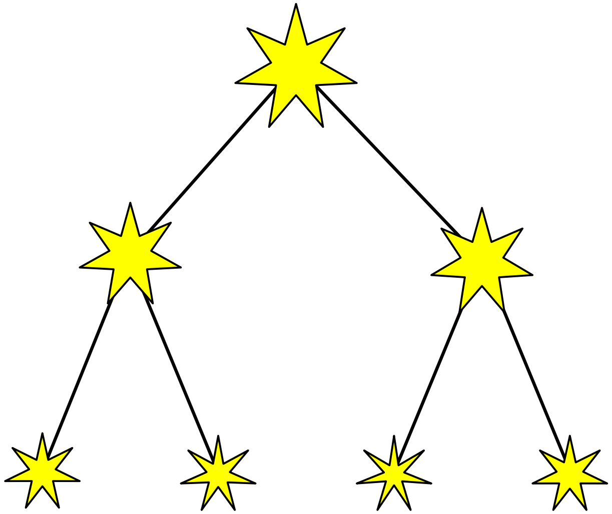

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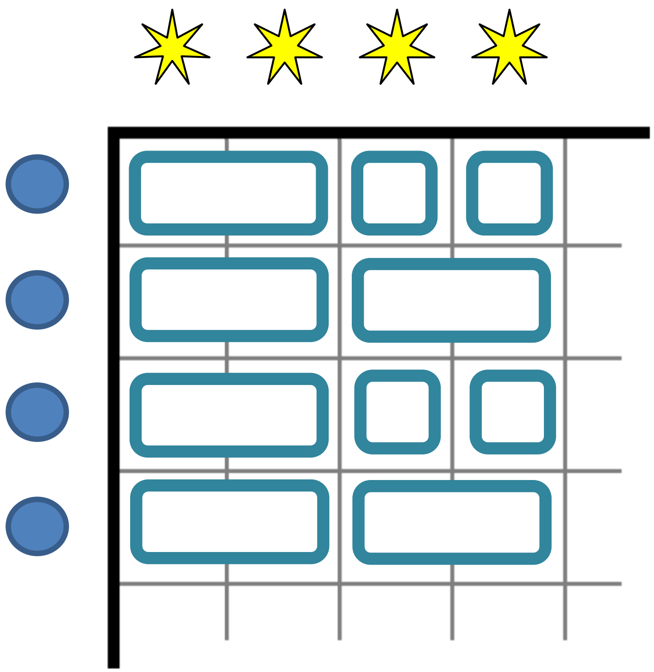

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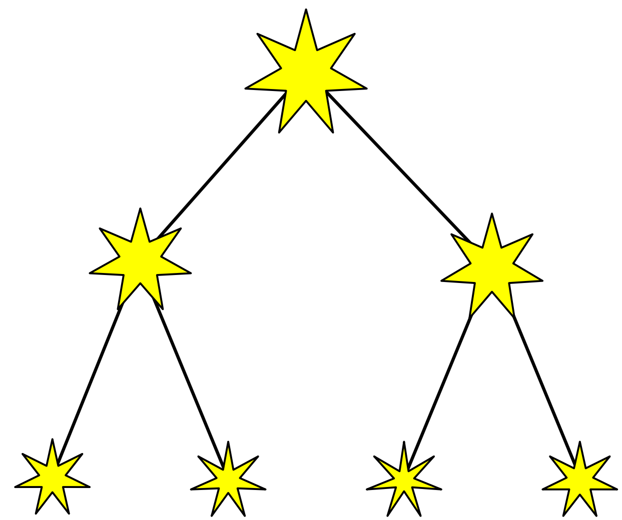

light tree

Selecting the cut is still expensive

# Global Illumination Using Well-Separated Pair Decomposition

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**WSPD:**

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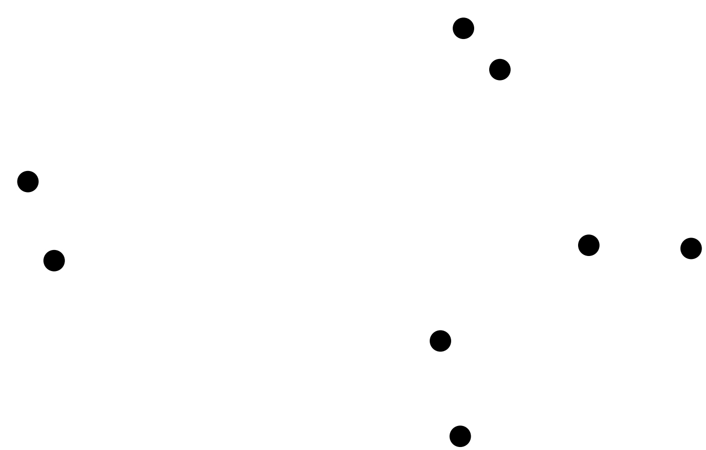

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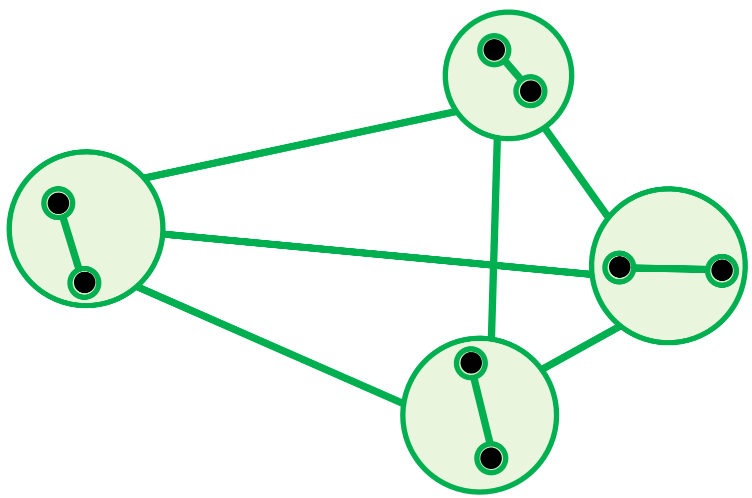

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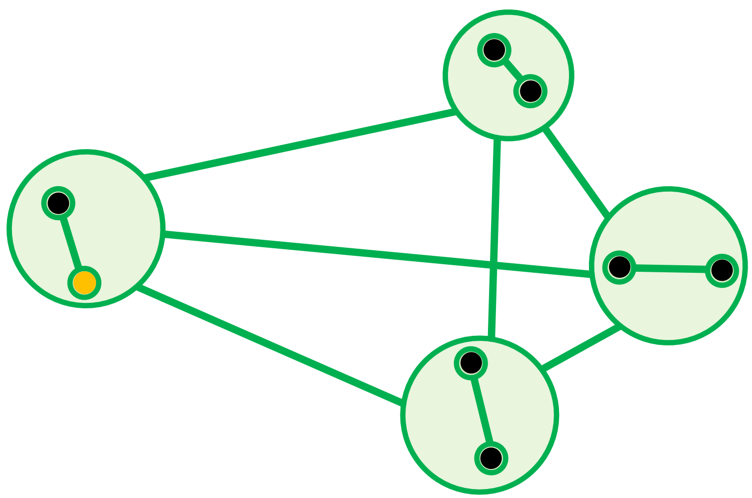

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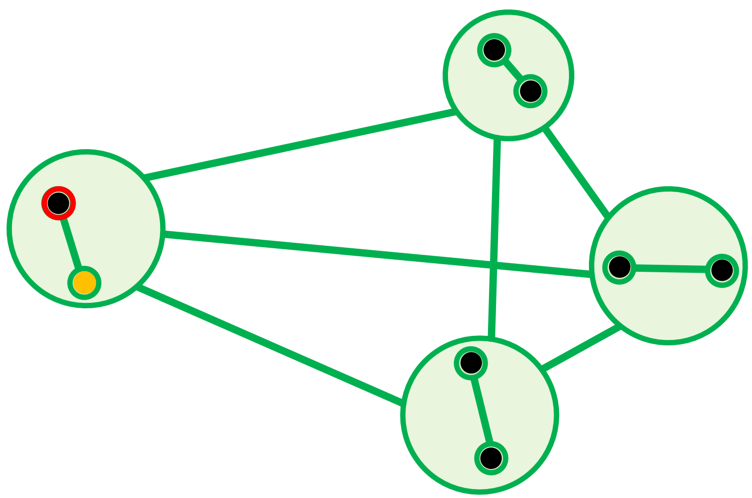

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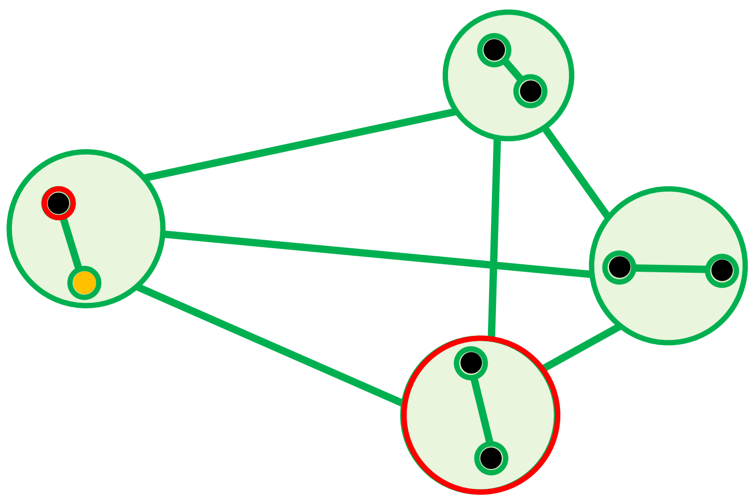

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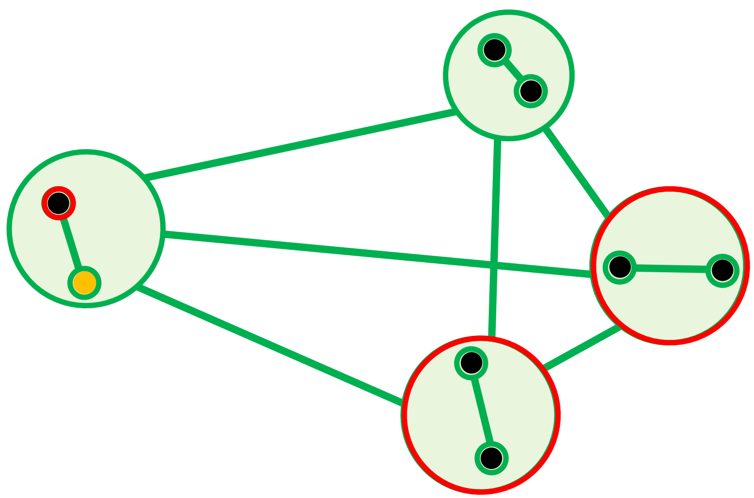

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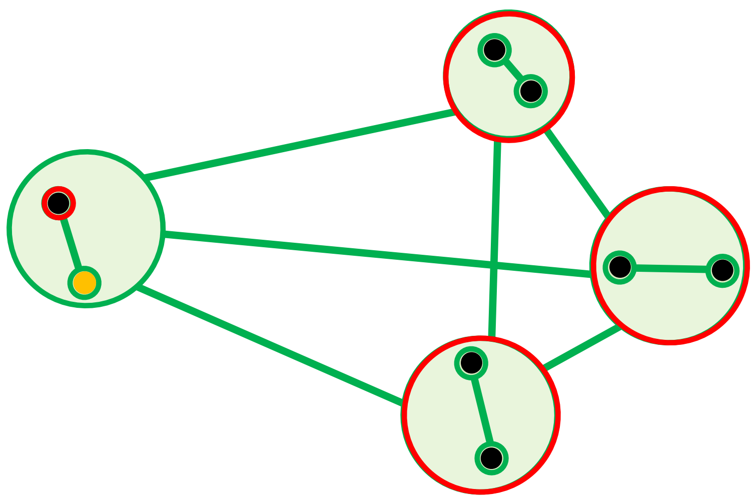

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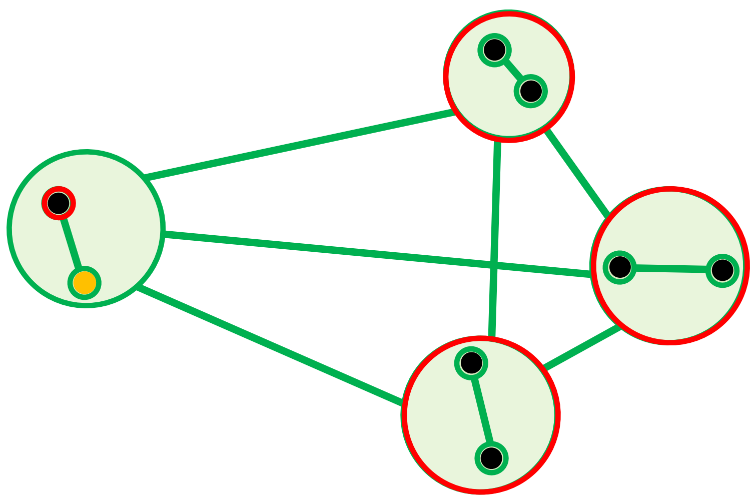

Use the WSPD to store all clusterings compactly

# Global Illumination Using Well-Separated Pair Decomposition

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**Algorithm:**

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**Algorithm:**

Preprocessing phase

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## Algorithm:

### Preprocessing phase

Create WSPD of VPLs – stores clusterings

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Adjust it to be more adapted to illumination

# Global Illumination Using Well-Separated Pair Decomposition

**Algorithm:**

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Rendering

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Adjust it to be more adapted to illumination

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Pick the closest VPL and take its clustering

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Only requires provably minor adjustment for each shaded point

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Create WSPD of VPLs – stores clusterings

Adjust it to be more adapted to illumination

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Pick the closest VPL and take its clustering

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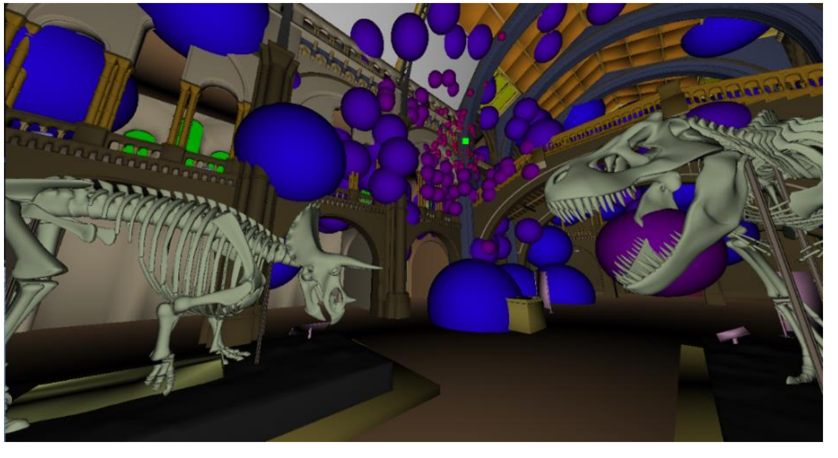
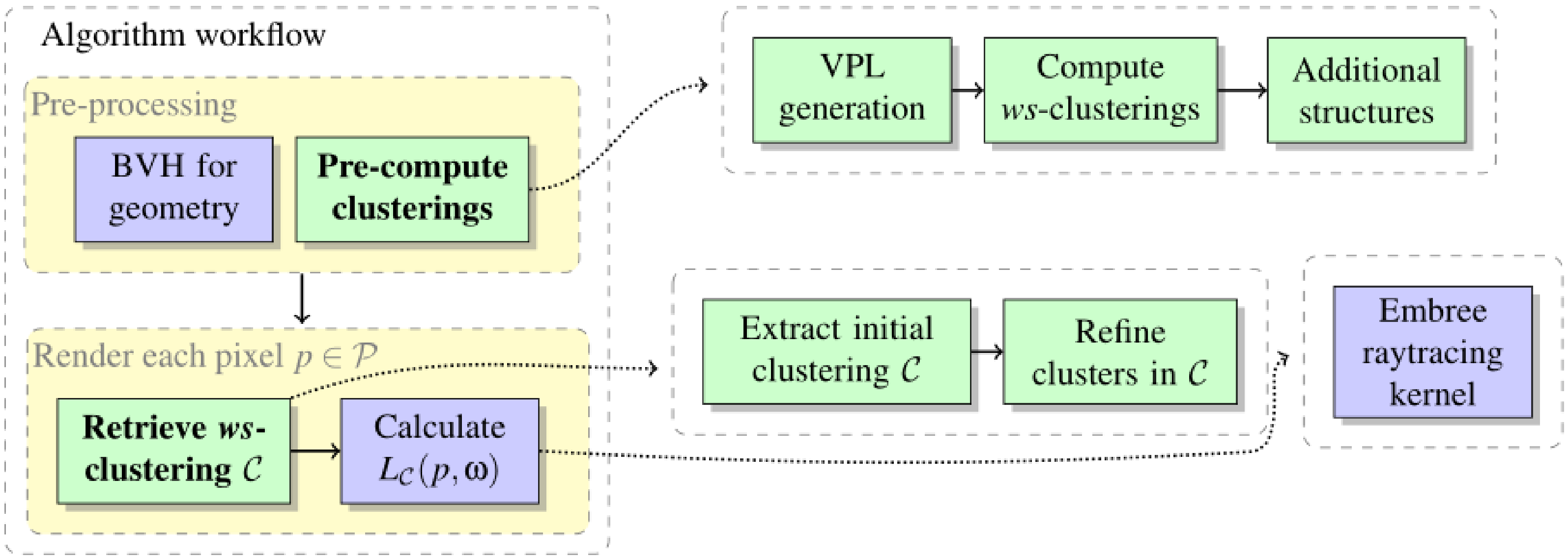
**Theorem:**
Let $p$ be an arbitrary point and $s$ be its nearest neighbor. There is only $O(\frac{1}{\epsilon^6})$ refinement needed to create a well-separated clustering for $p$.



# System overview

Easy to integrate into existing framework



# Results

# Results

Lightcuts

WSPD

# Results

Lightcuts

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# Results

Lightcuts

Time: 515.06 sec
RMSE: 0.00467

WSPD

Time: 190.27 sec (2.7x)
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+ very fast rendering

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# Results

Lightcuts

Time: 515.06 sec
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+ very fast rendering
− long preprocessing
− diffuse only BRDF

# Clustering: Lightcuts

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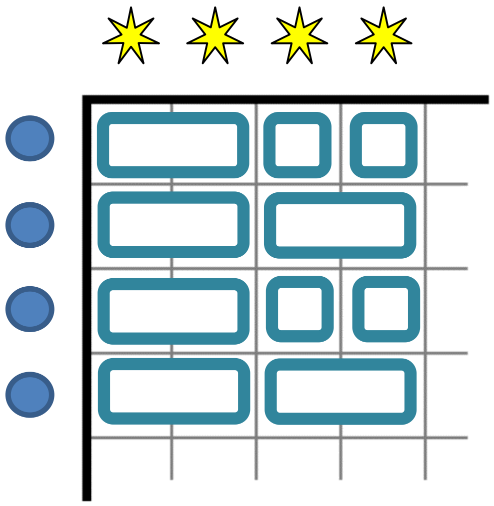
Observe what happens over many pixels



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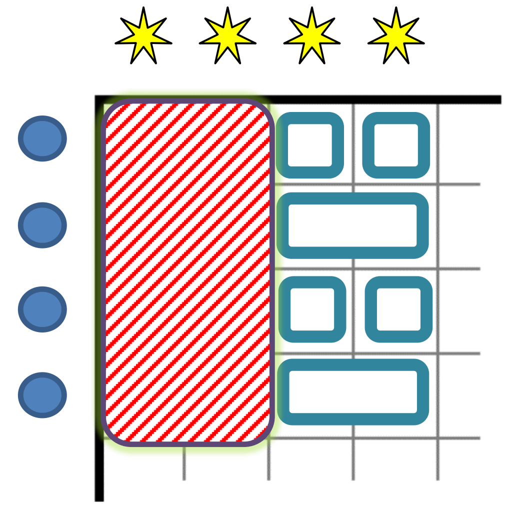

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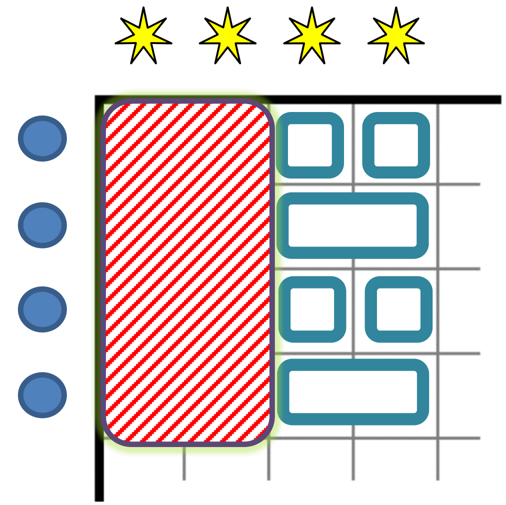
Repeated calculations for the same clusters



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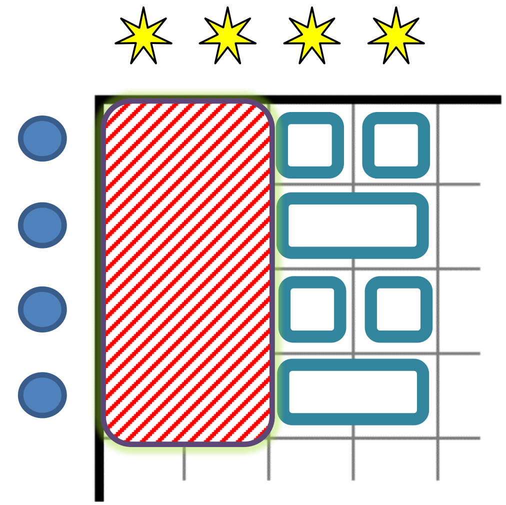

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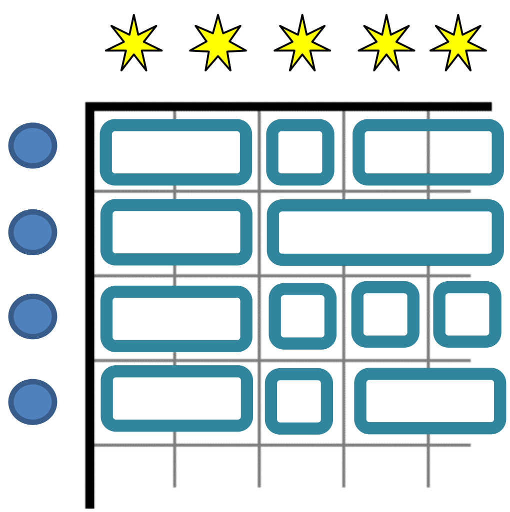
Cluster similar shaded points



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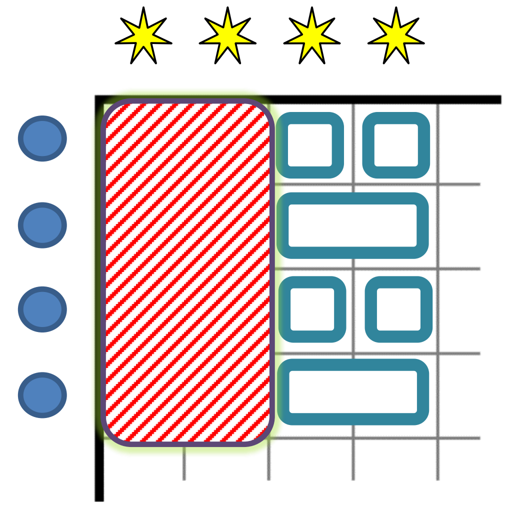

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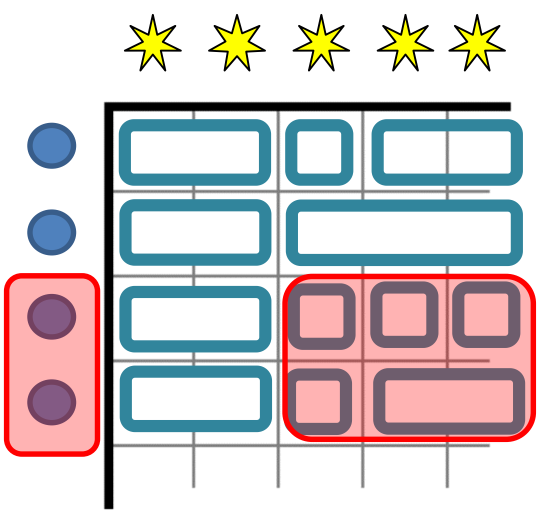

suboptimal

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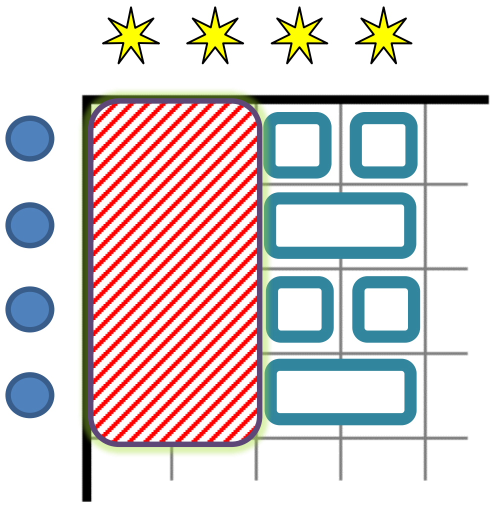

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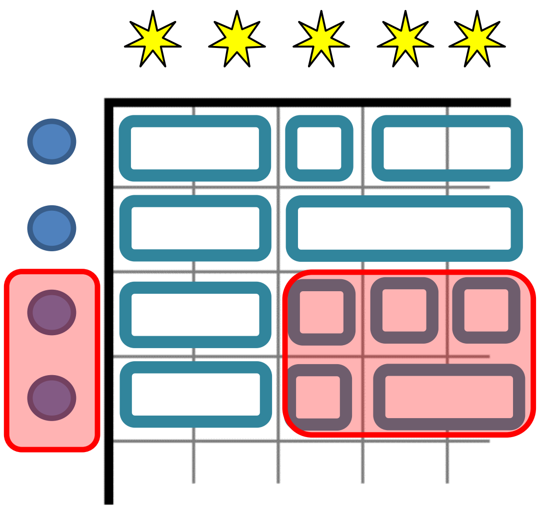

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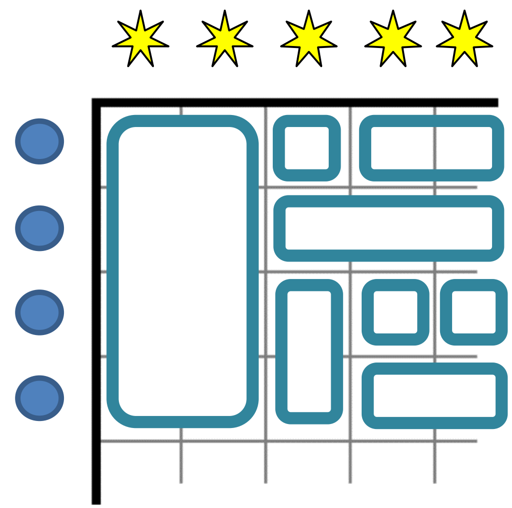

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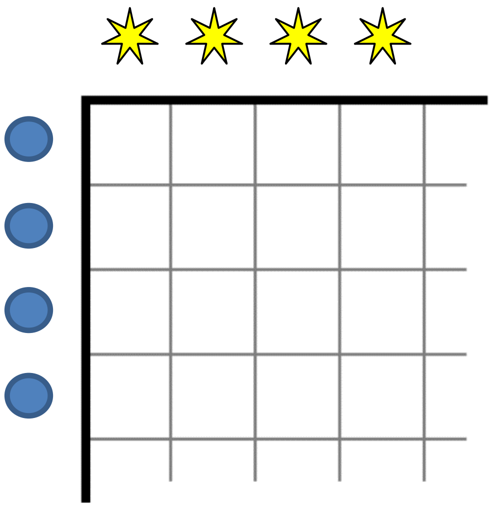
# IlluminationCut



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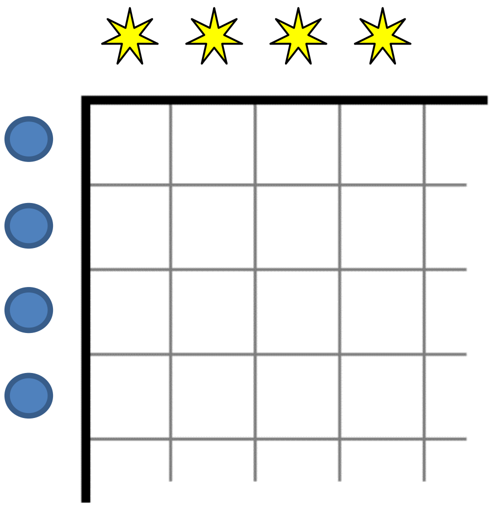

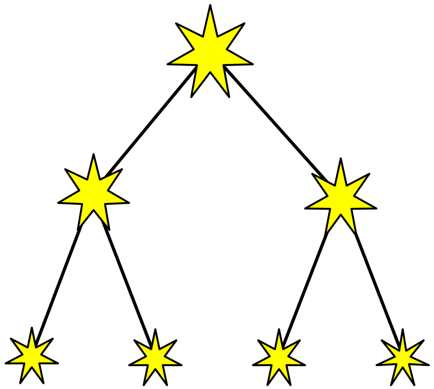

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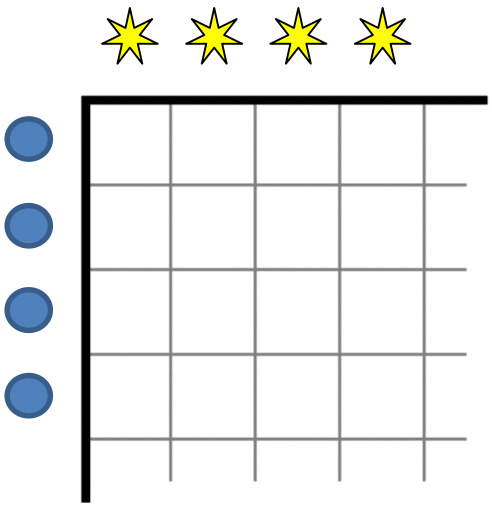

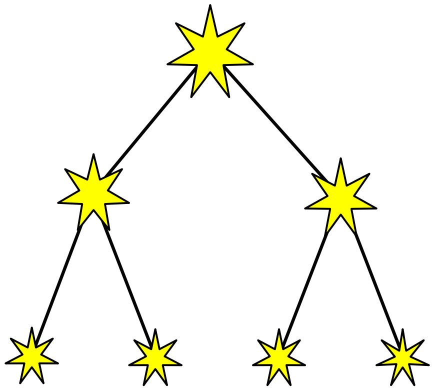

Instead of clustering the points
use a hierarchical clustering structure

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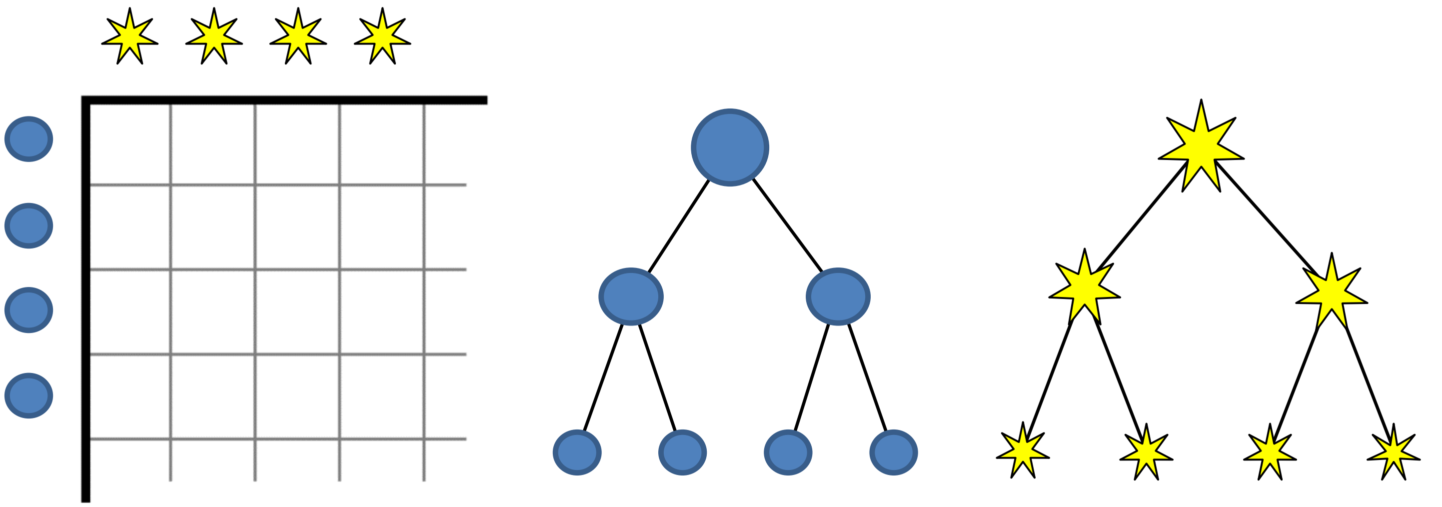

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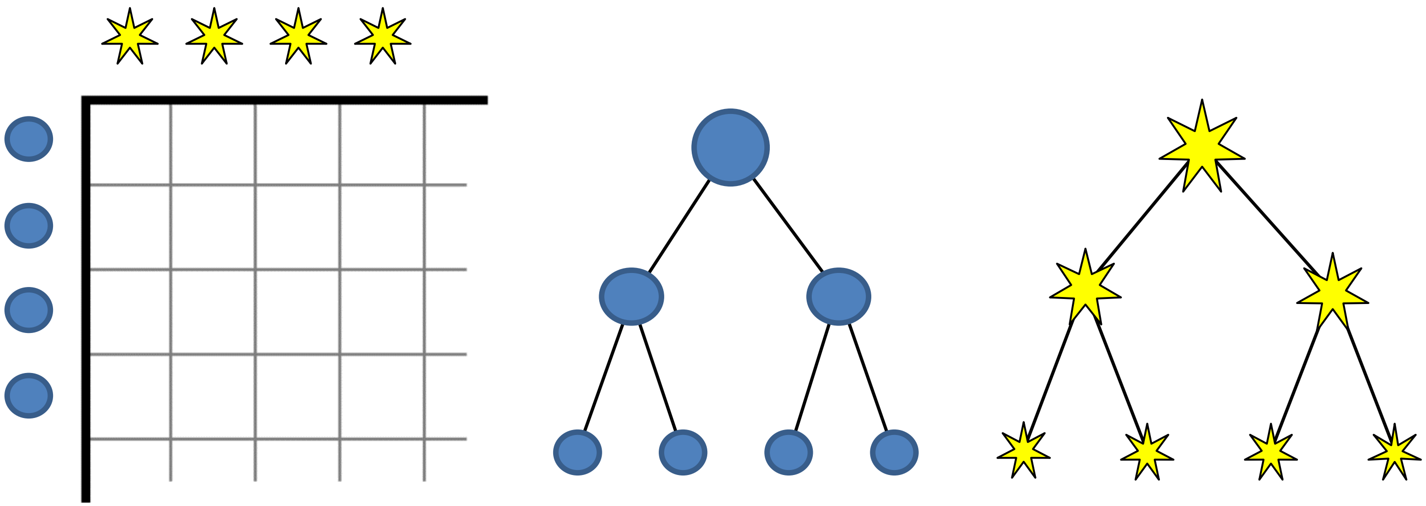

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Create pairs of shaded point and VPL groups
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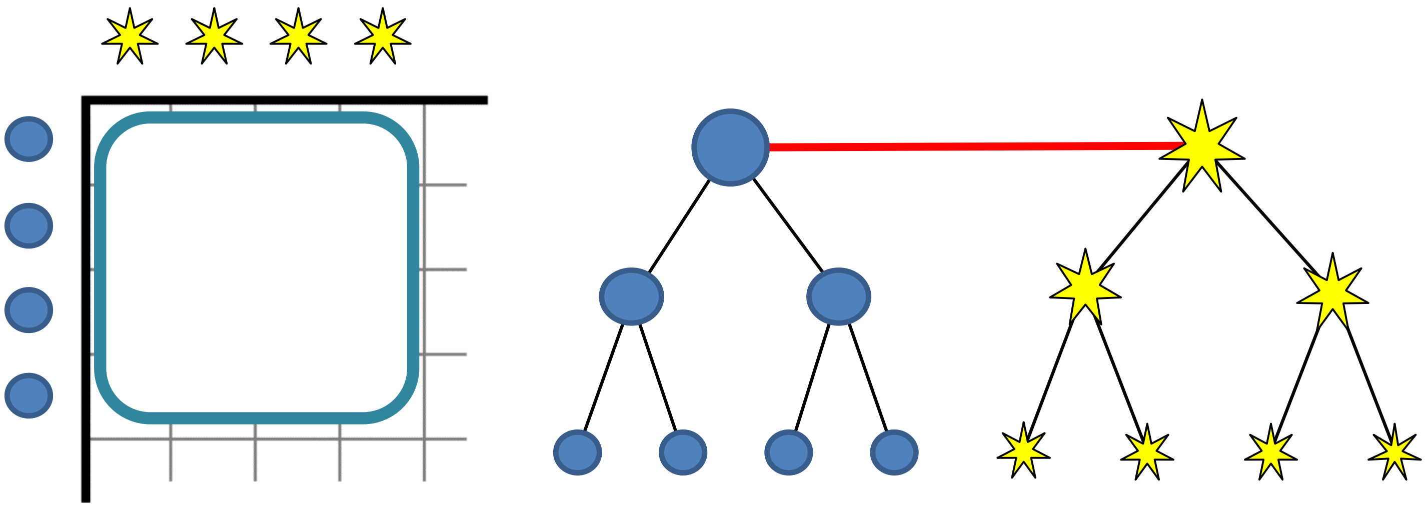

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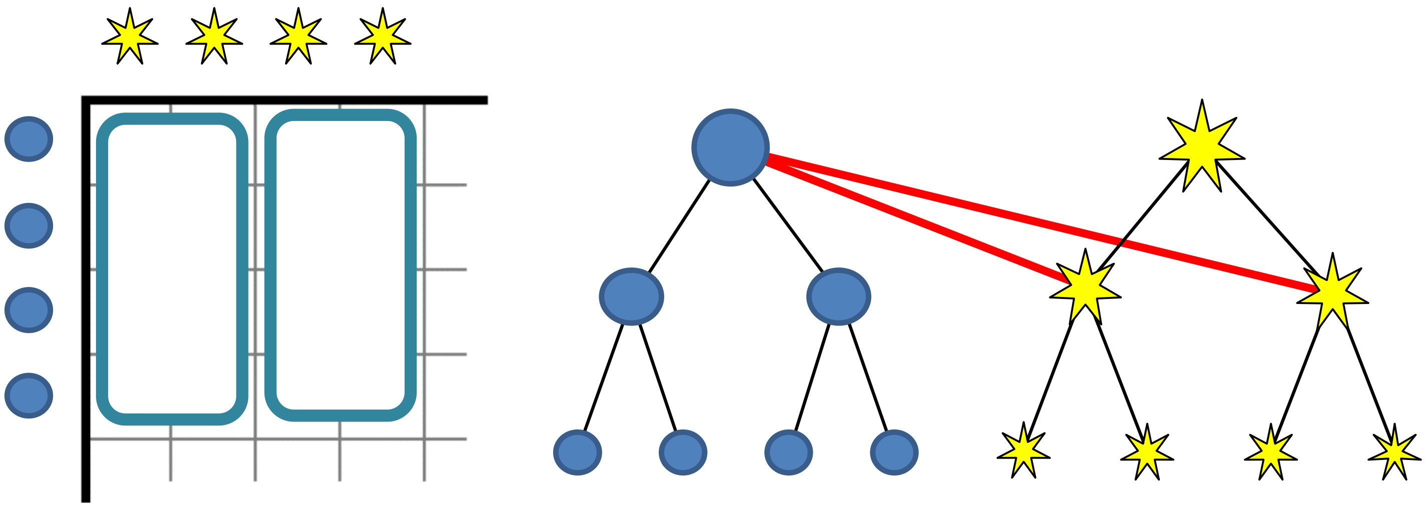

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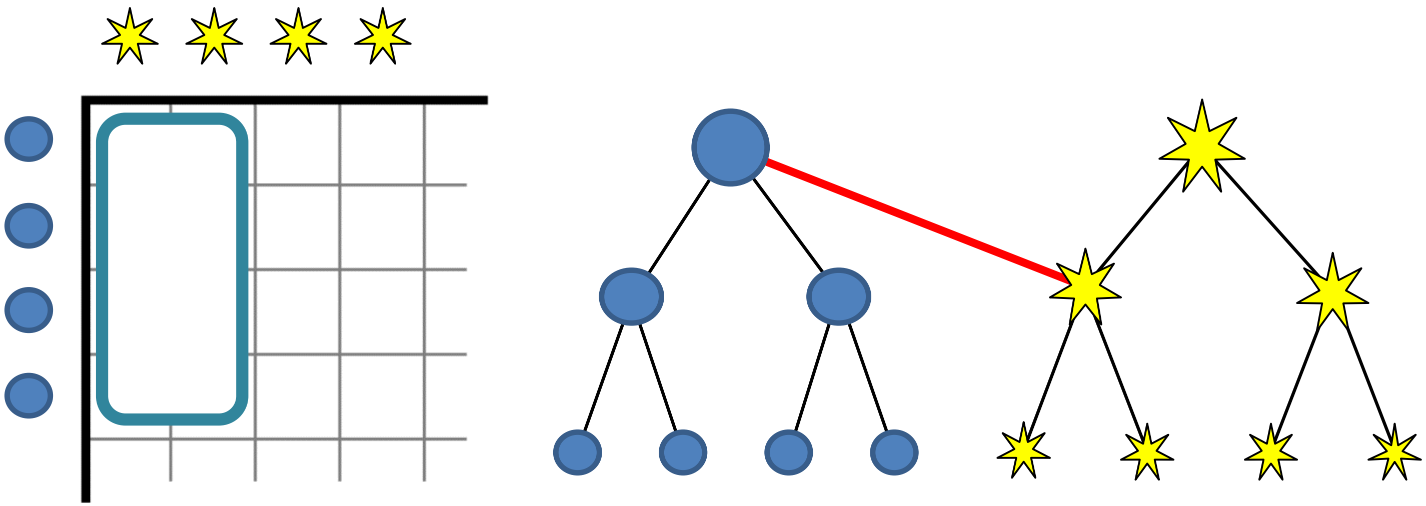

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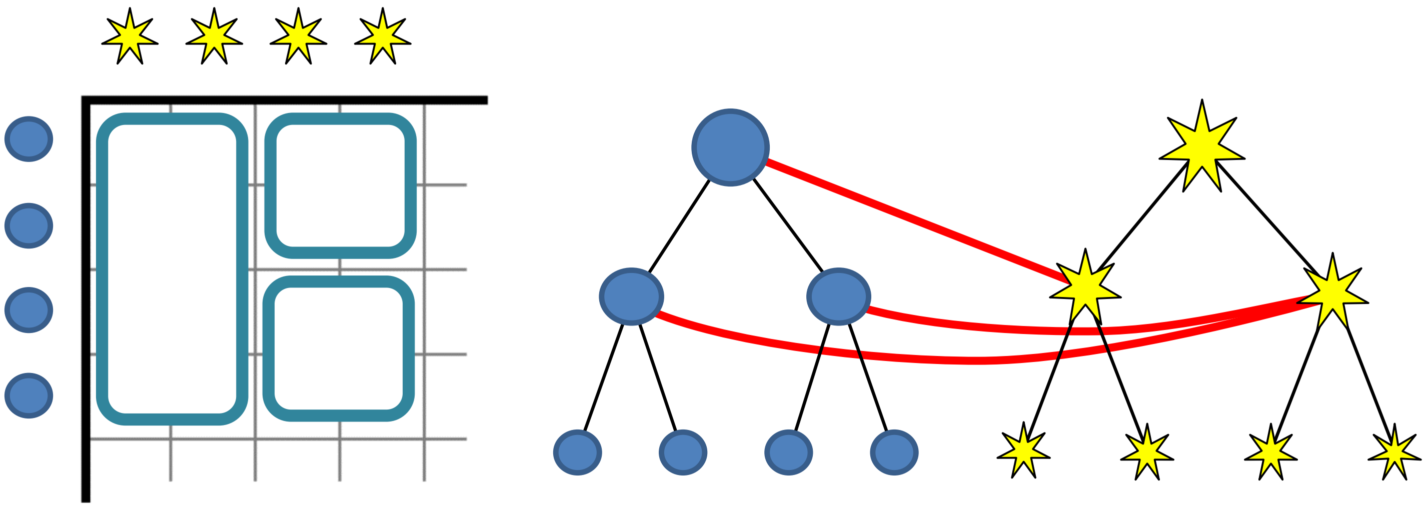

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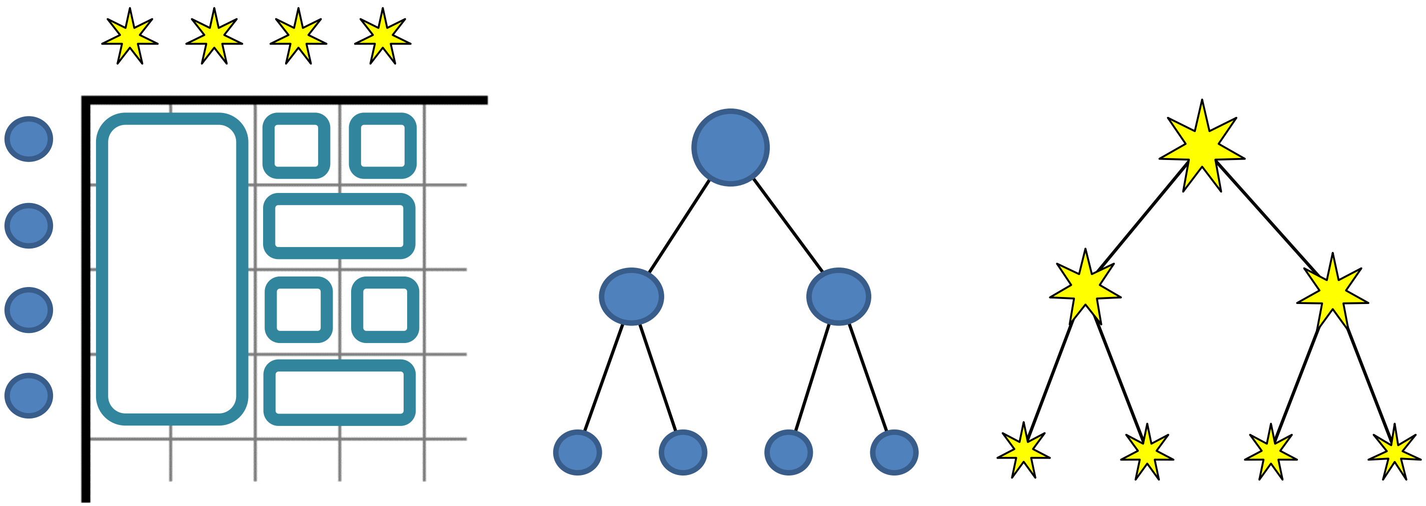

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# Efficiency

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Clustering costs (amortized)

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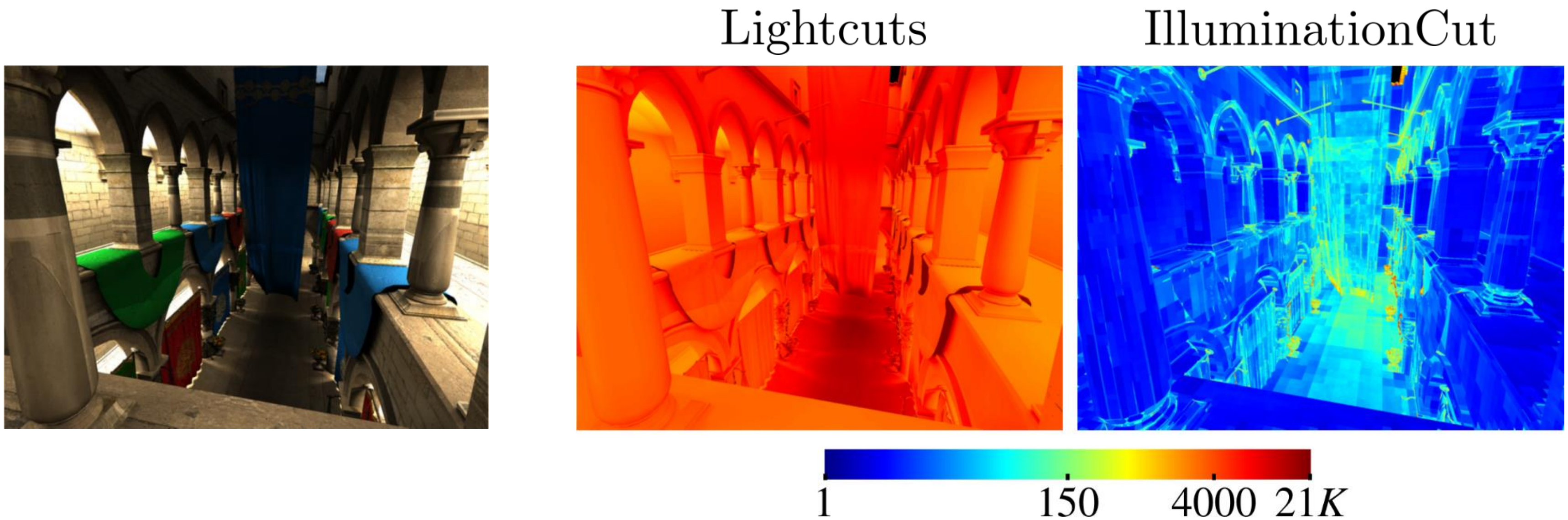

# Results

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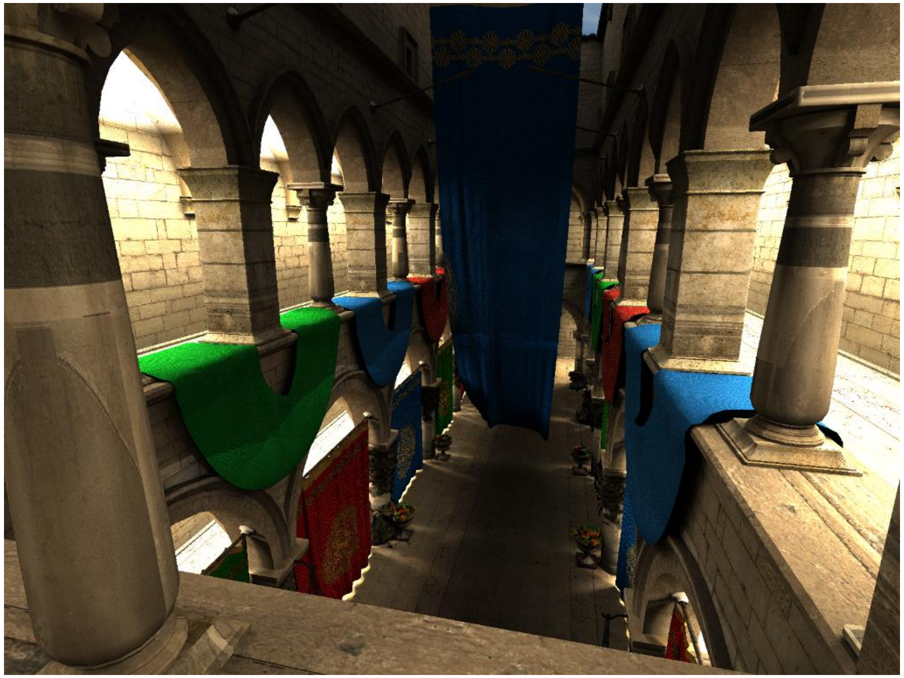
Lightcuts



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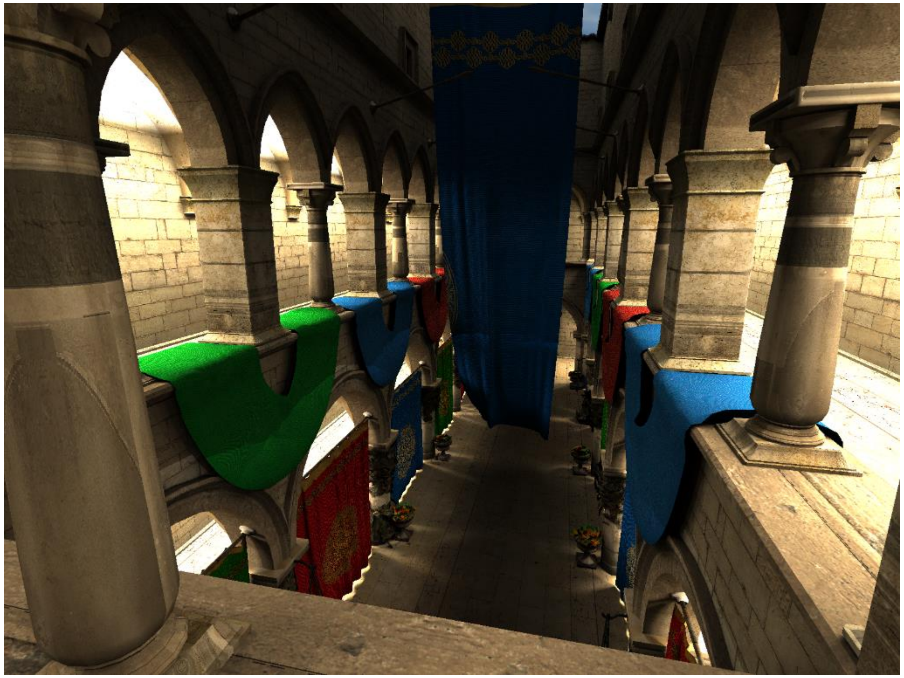

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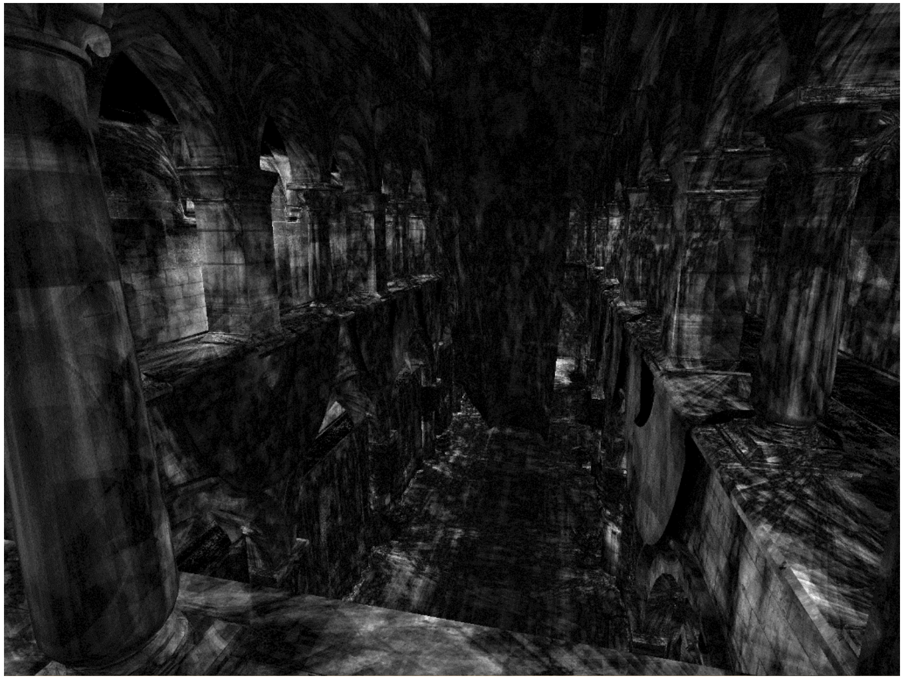

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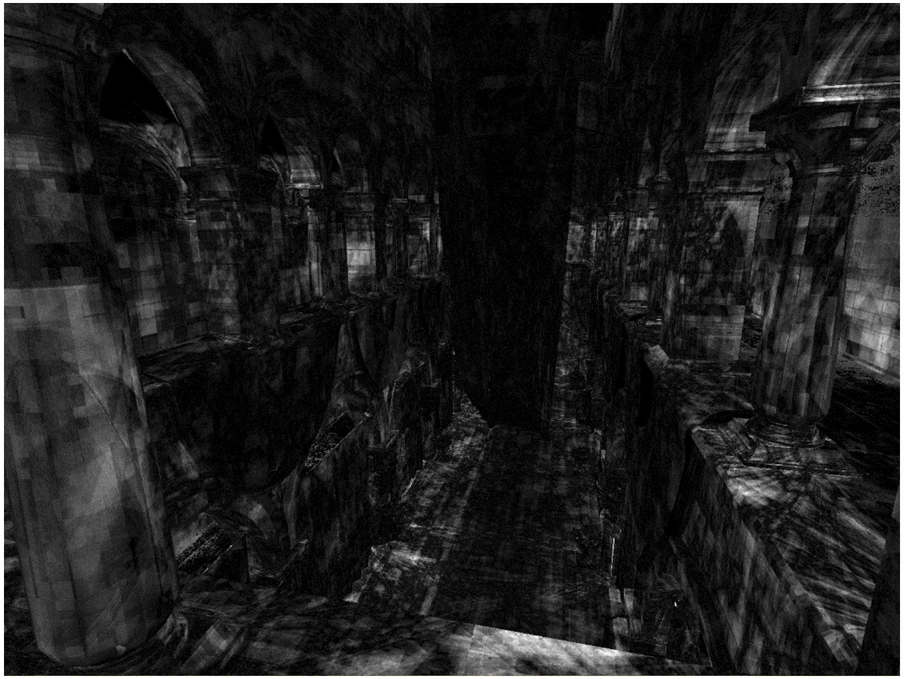
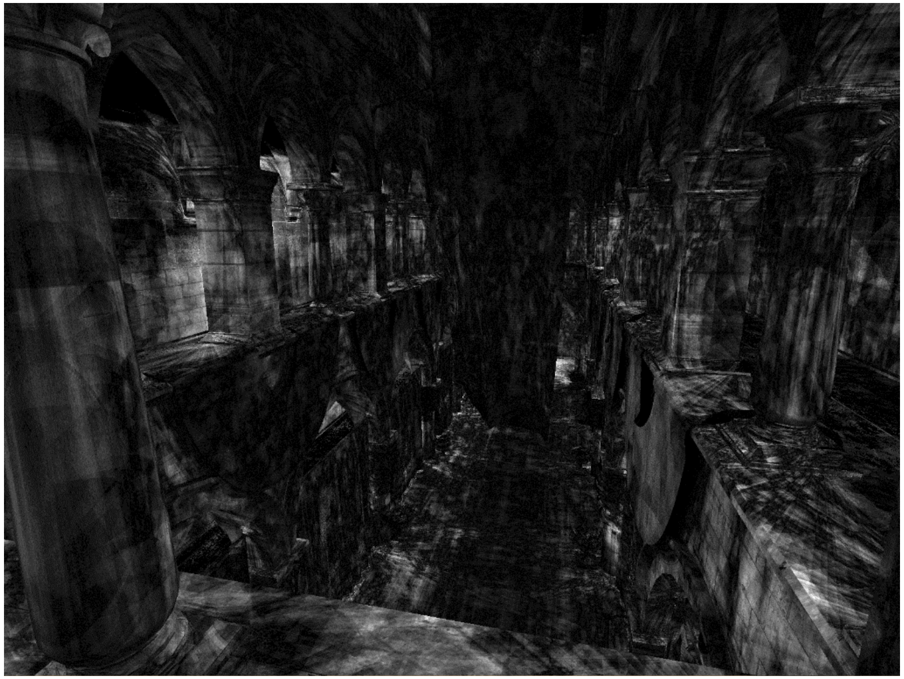


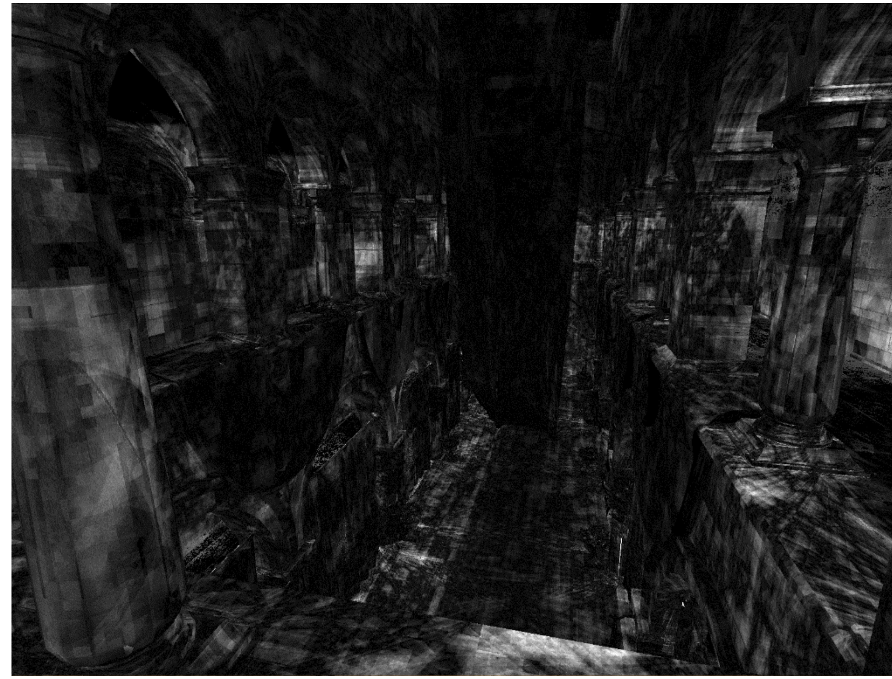
# Results

Lightcuts



Time: 233.31 sec
RMSE: 0.00591

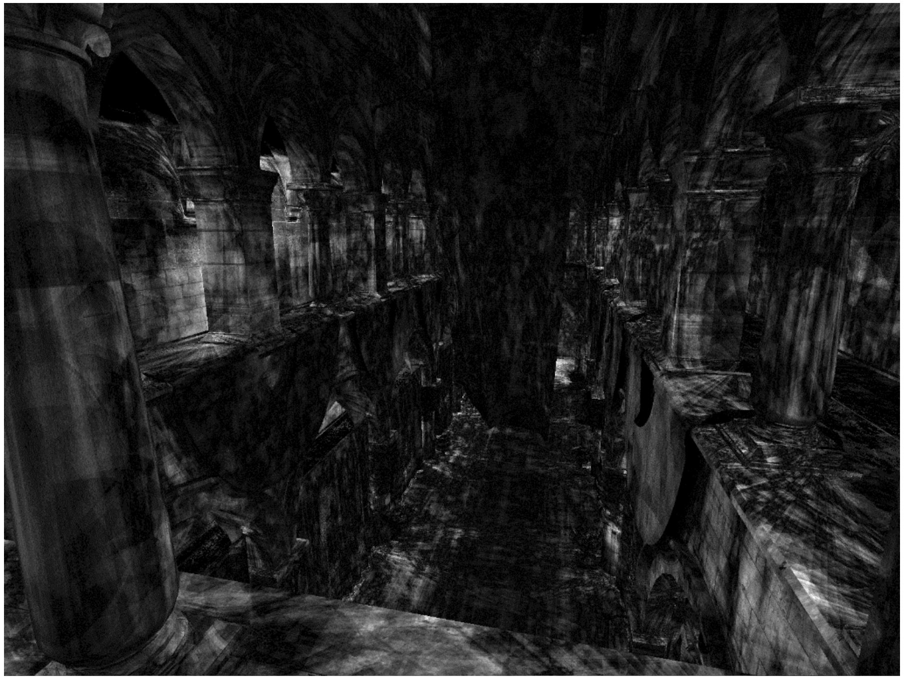
IlluminationCut



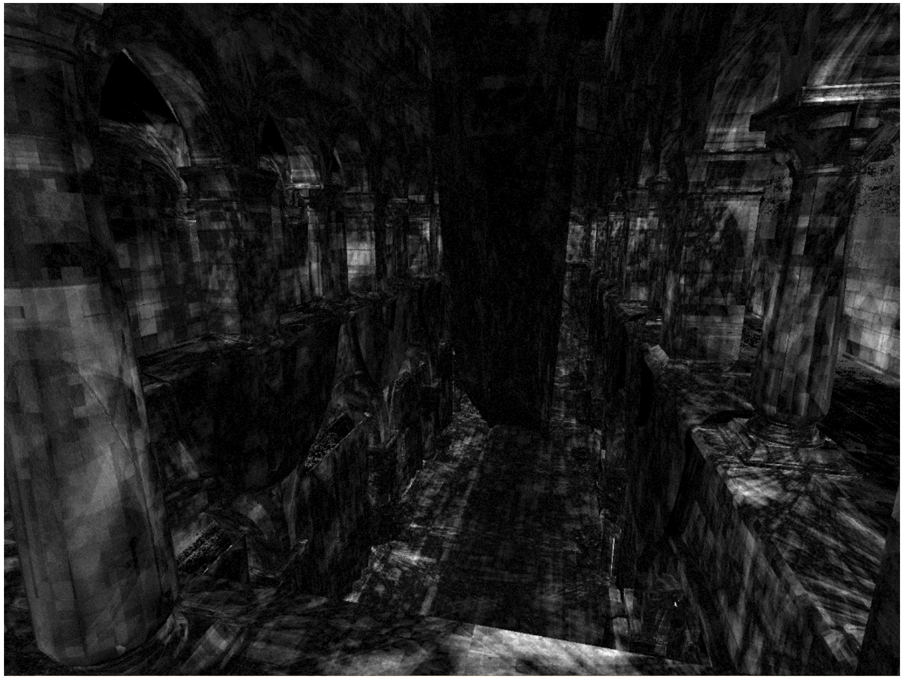
Time: 71.83 sec (3.3x)
RMSE: 0.00574

# Results

Lightcuts



IlluminationCut



# Results

Lightcuts

IlluminationCut

# Results

Lightcuts

Time: 183.07 sec
RMSE: 0.01033

IlluminationCut

Time: 43.04 sec (4.2x)
RMSE: 0.01256

# Results

Lightcuts

Time: 183.07 sec
RMSE: 0.01033

IlluminationCut

Time: 43.04 sec (4.2x)
RMSE: 0.01256

+ very fast rendering

# Results

Lightcuts

Time: 183.07 sec
RMSE: 0.01033

IlluminationCut

Time: 43.04 sec (4.2x)
RMSE: 0.01256

+ very fast rendering
+ specular BRDF

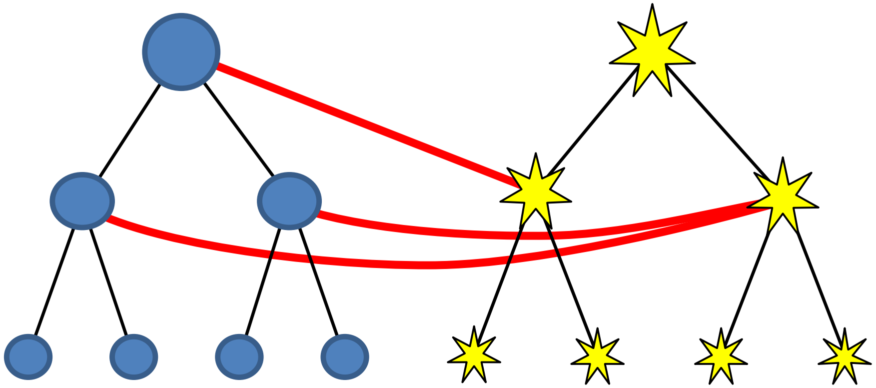
# Visibility Sampling

# Visibility Sampling

Additional benefit of group pairs:

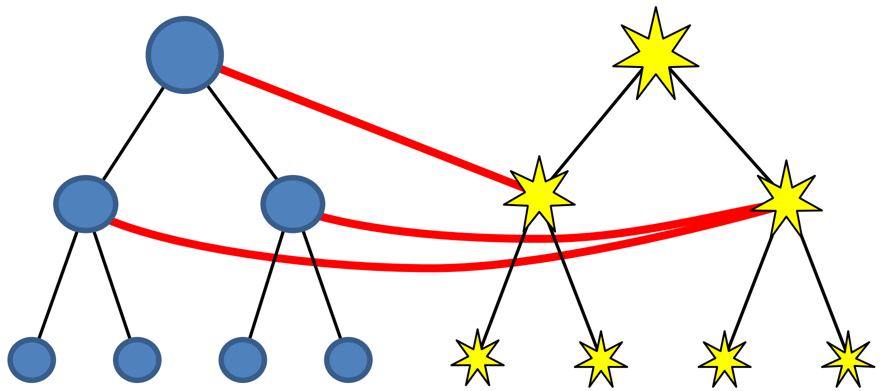
# Visibility Sampling

Additional benefit of group pairs:



# Visibility Sampling

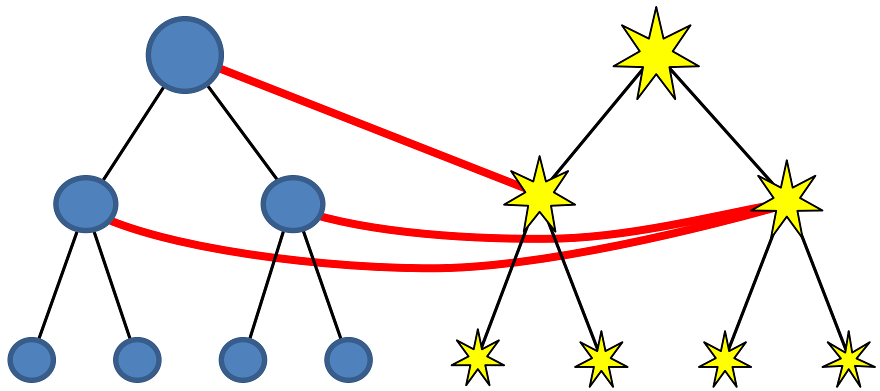
Additional benefit of group pairs:



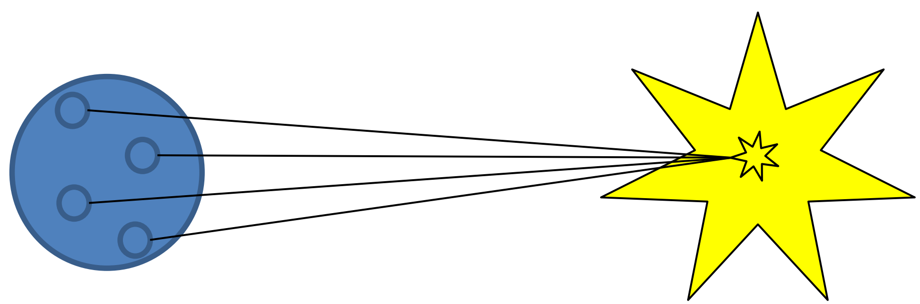
Very similar illumination → we can save shadow rays

# Visibility Sampling

Additional benefit of group pairs:

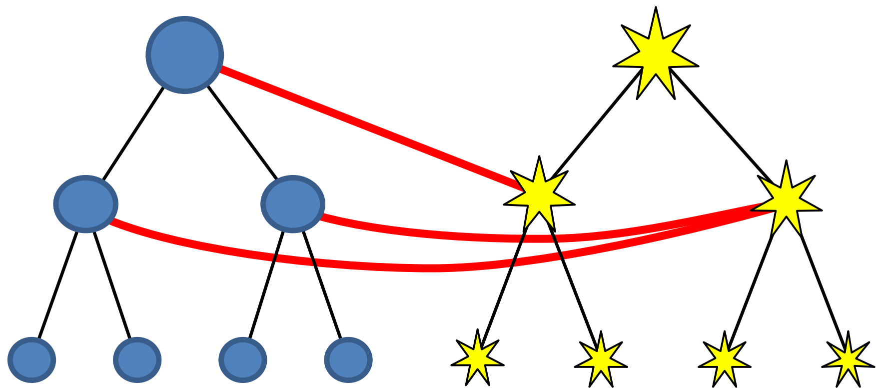


Very similar illumination $\rightarrow$ we can save shadow rays

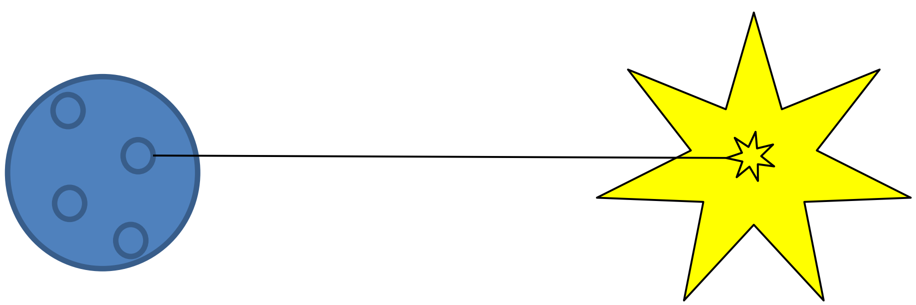


# Visibility Sampling

Additional benefit of group pairs:



Very similar illumination → we can save shadow rays



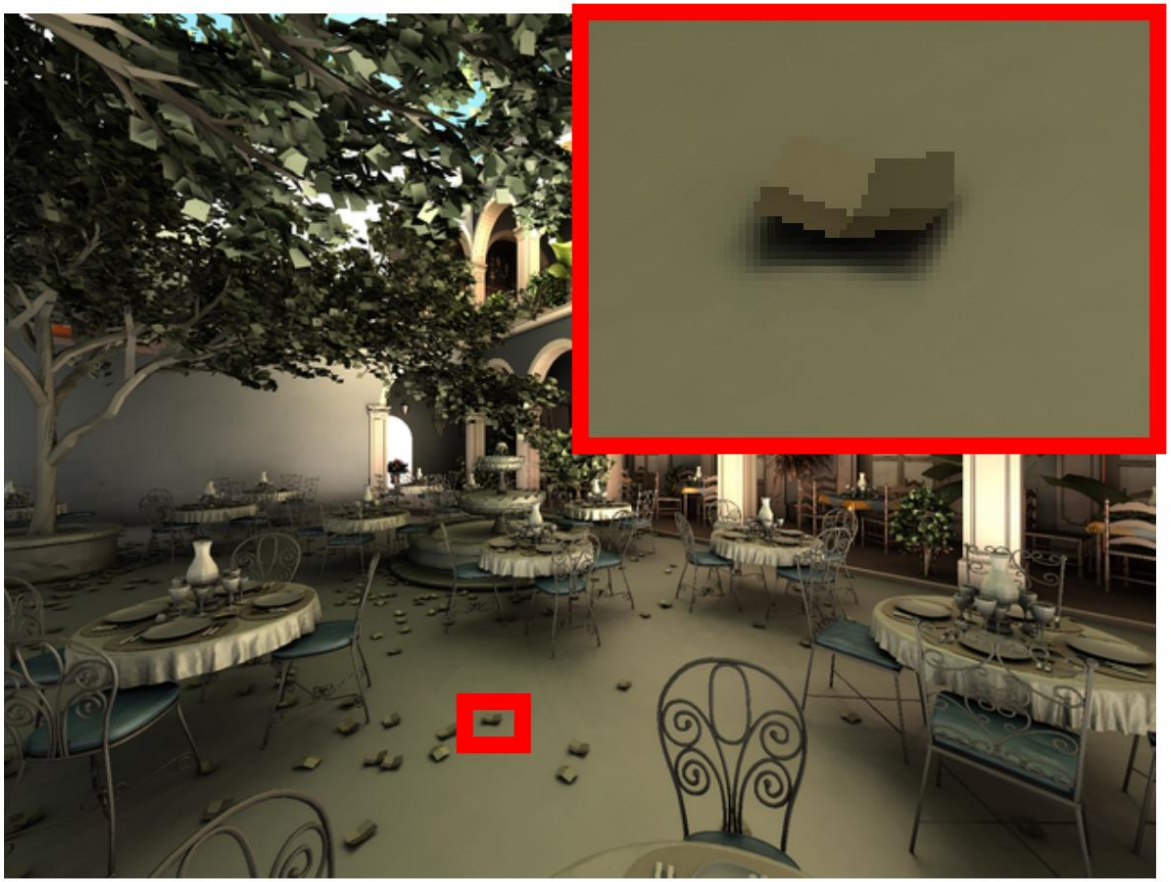
# Results

# Results

Reference

# Results

Reference



# Results

IlluminationCut – Visibility sampling

# Results

IlluminationCut – Visibility sampling

\+ even more fast rendering

9.6x speedup

# Published source code

# Published source code

## Implementation

Most of the state-of-the-art many-lights methods within one framework

Lightcuts

IlluminationCut

LightSlice

Multidimensional Lightcuts

Matrix Row-Column Sampling

Global Illumination Using WSPD

# Implementation

Most of the state-of-the-art many-lights methods within one framework

Lightcuts IlluminationCut LightSlice

Multidimensional Lightcuts Matrix Row-Column Sampling

Global Illumination Using WSPD

Embree – Intel®

- interactive frame rates with progressive path tracing



Thank you!