

Active Perception using Light Curtains for Autonomous Driving

Webpage: <http://siddancha.github.io/projects/active-perception-light-curtains>



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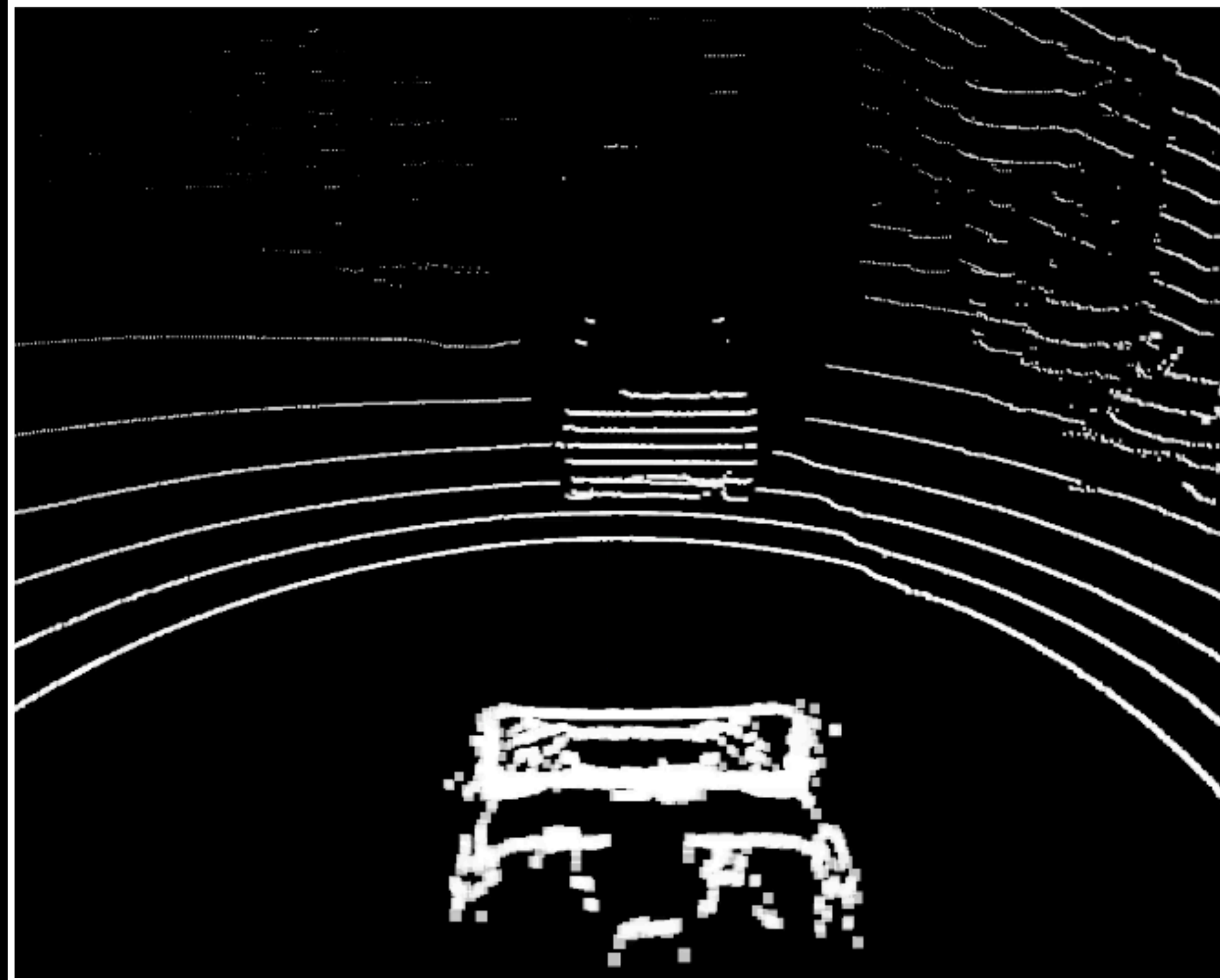


David
Held

**Carnegie
Mellon
University**



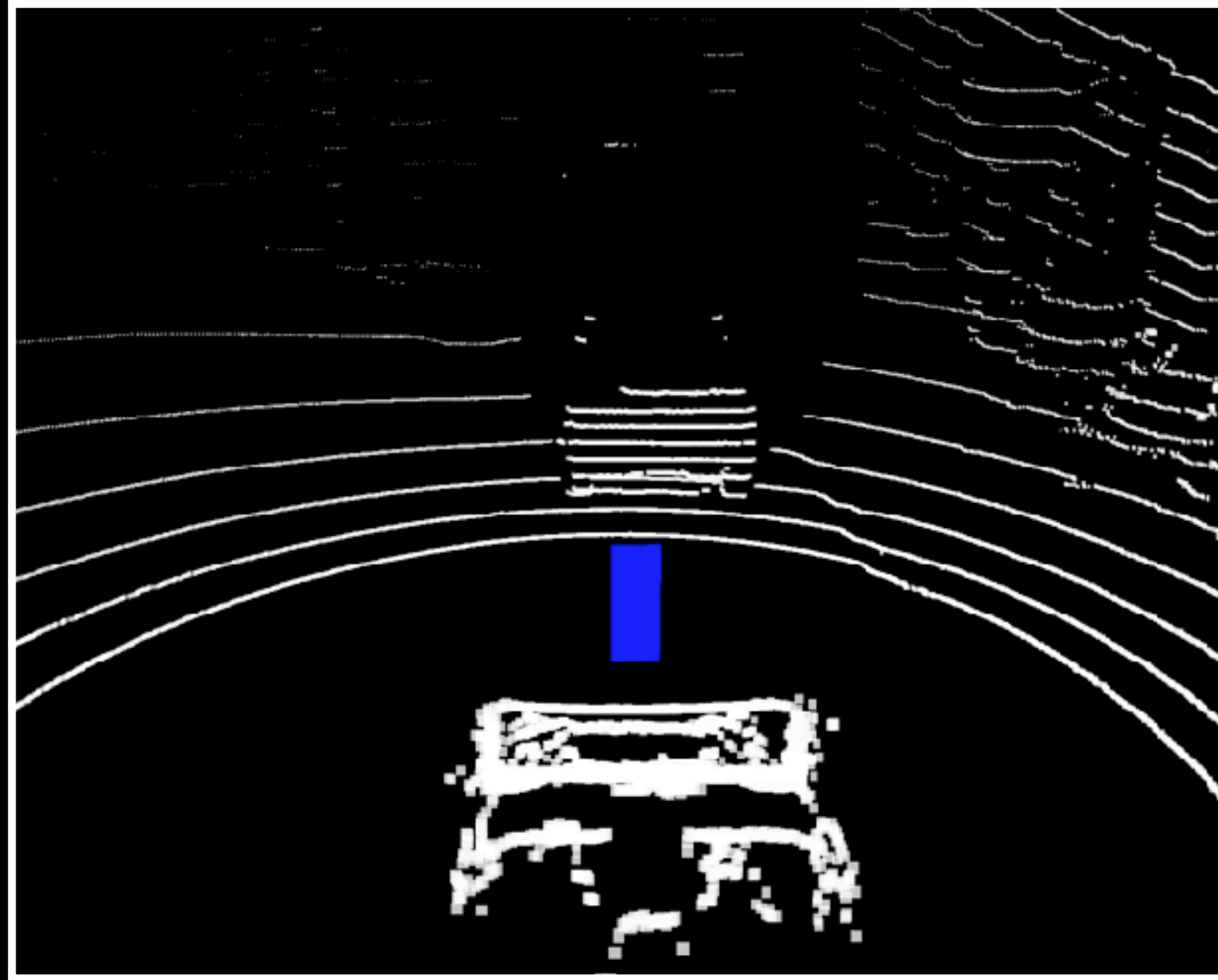
LiDARs perform fixed scans



LiDAR

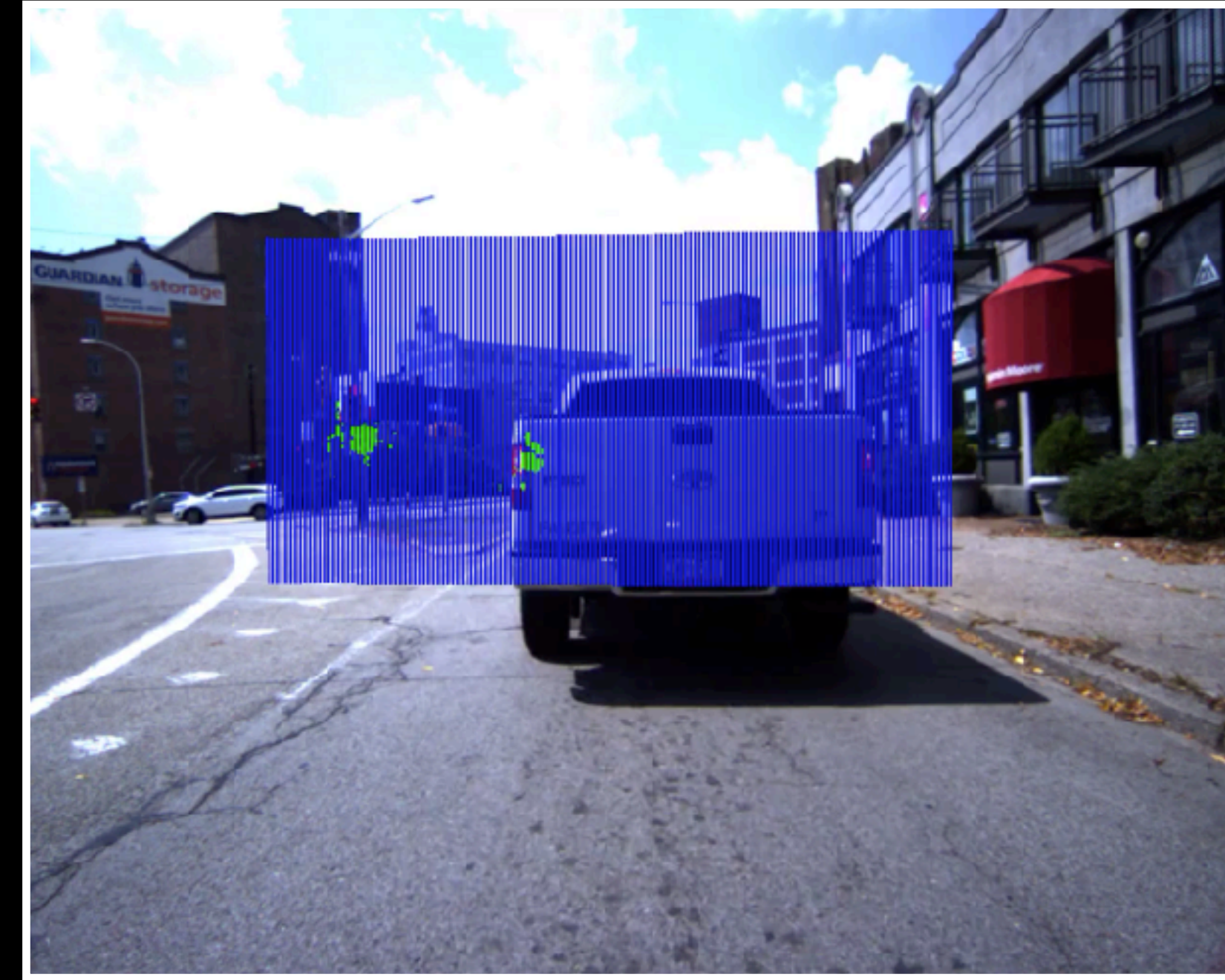
- Sparse point clouds.
- Expensive: Velodyne 64 beam LiDAR can cost > \$80,000.

Light curtains are *controllable*



LiDAR

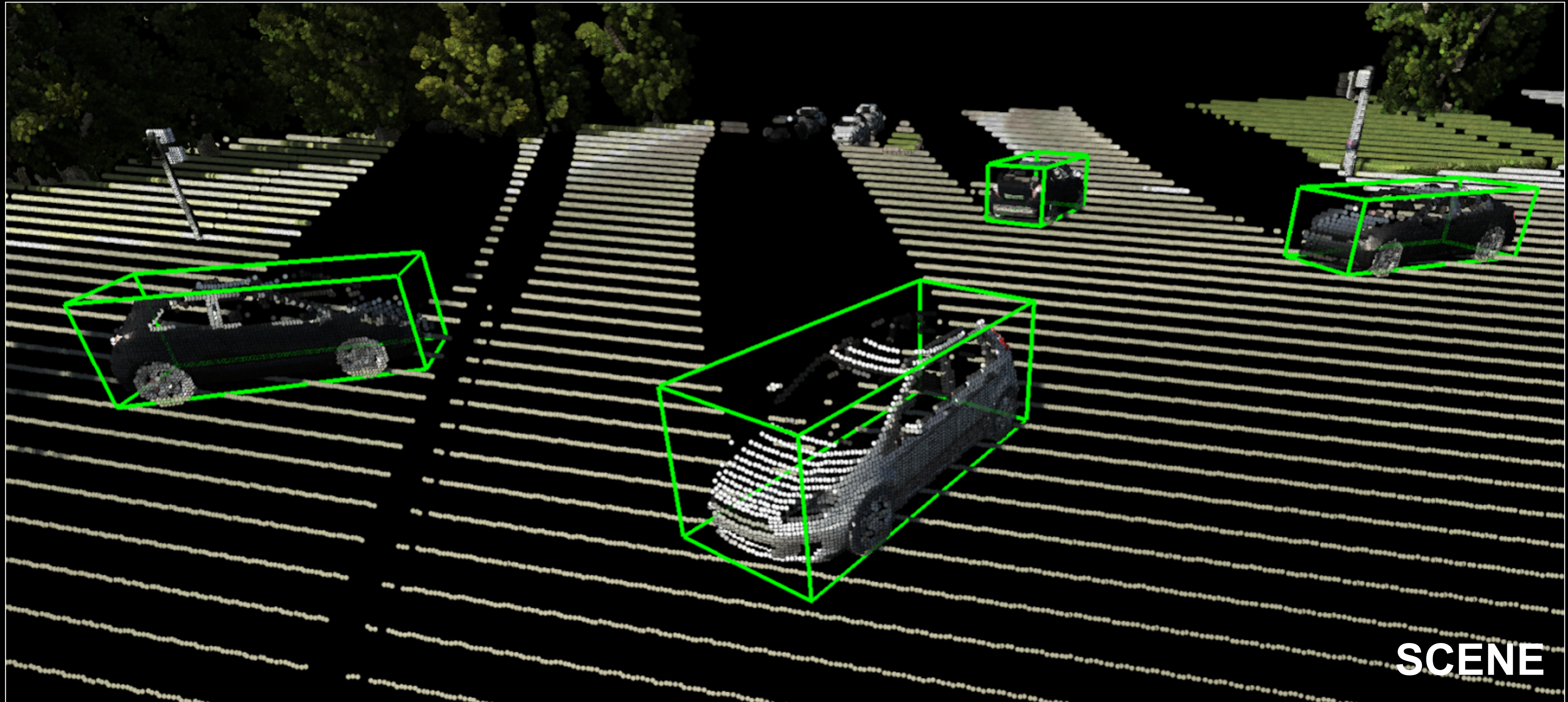
- Sparse point clouds.
- Expensive: Velodyne 64 beam LiDAR can cost > \$80,000.



Light Curtain

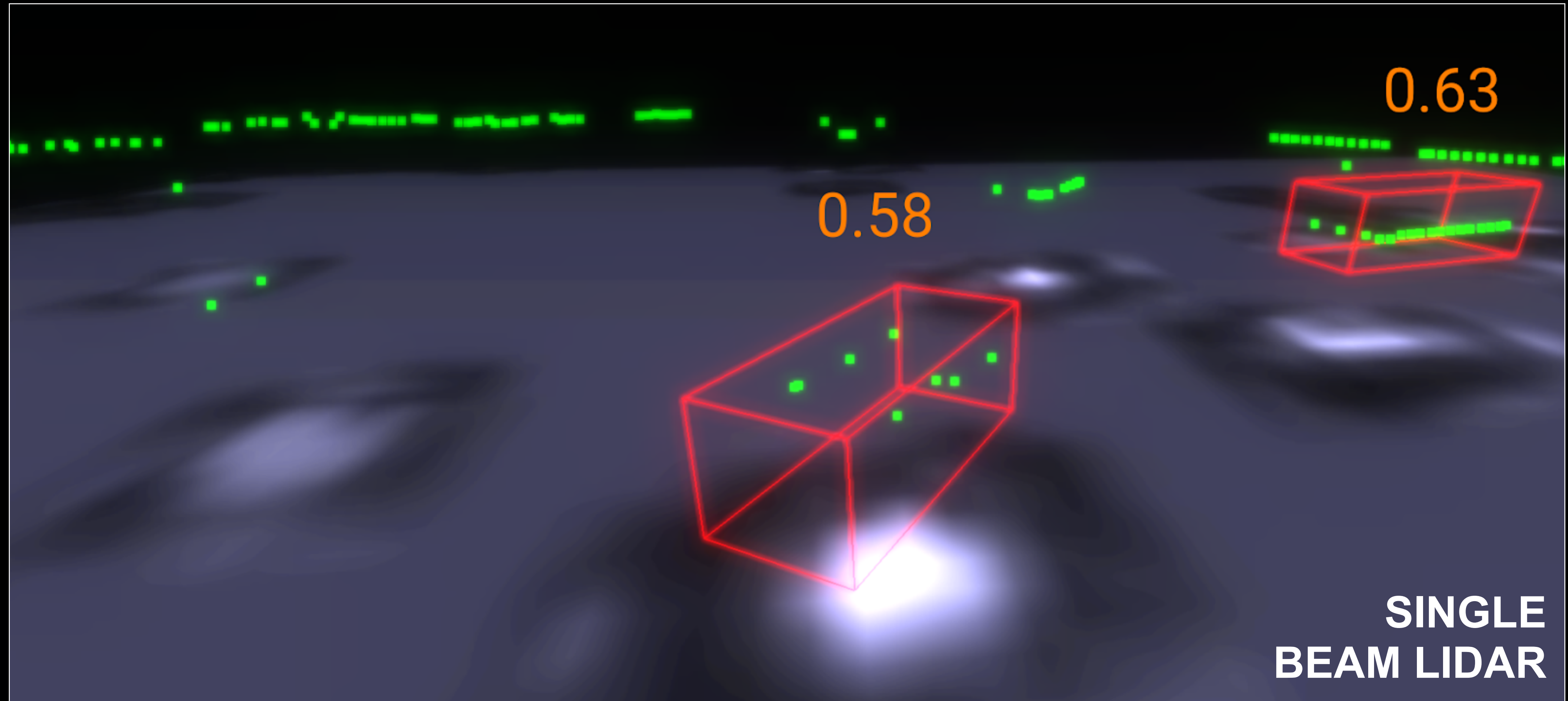
- Dense point cloud where curtain is placed.
- Inexpensive: Lab-built prototype costs ~\$1000.

Active Detection using Light Curtains



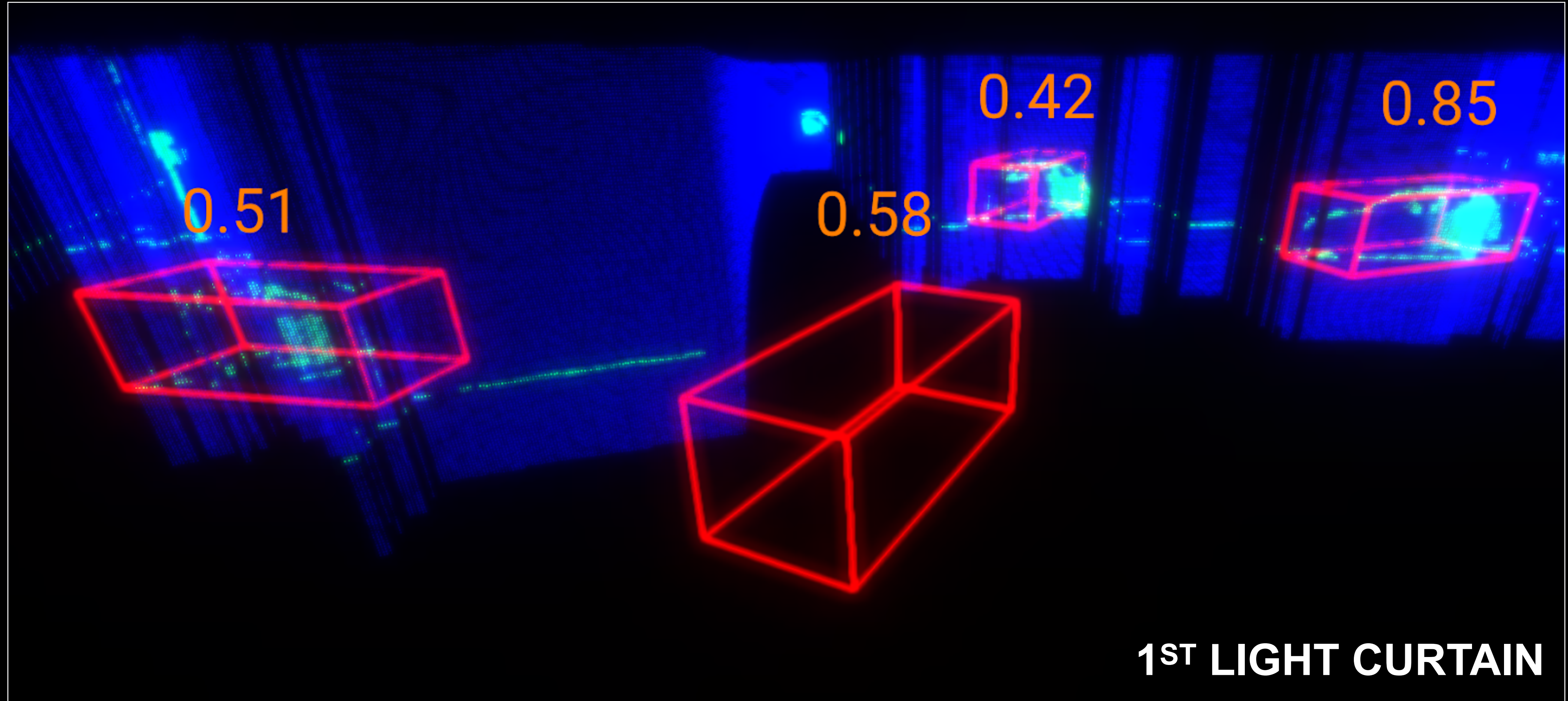
SCENE

Single-beam LiDAR produces sparse points

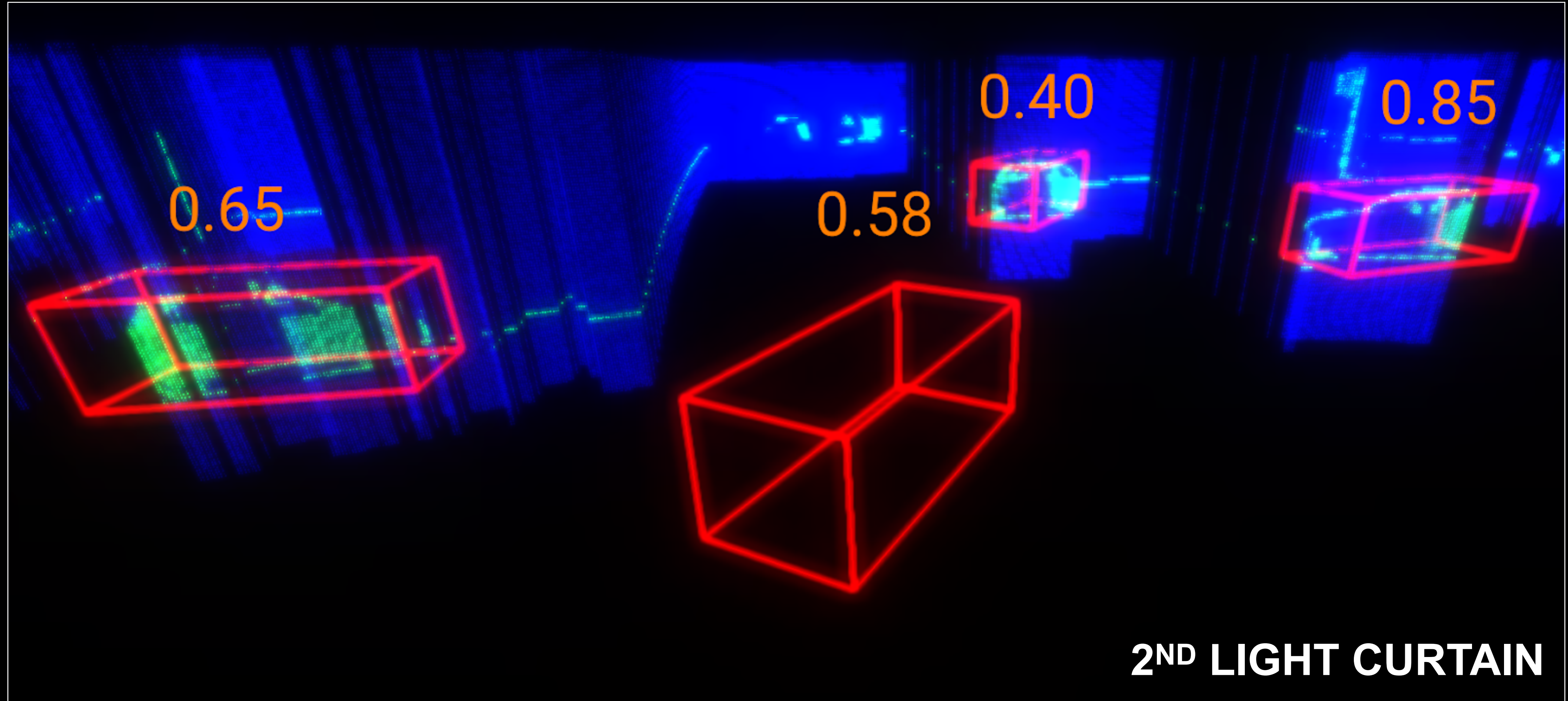


*White: more uncertain Black: less uncertain

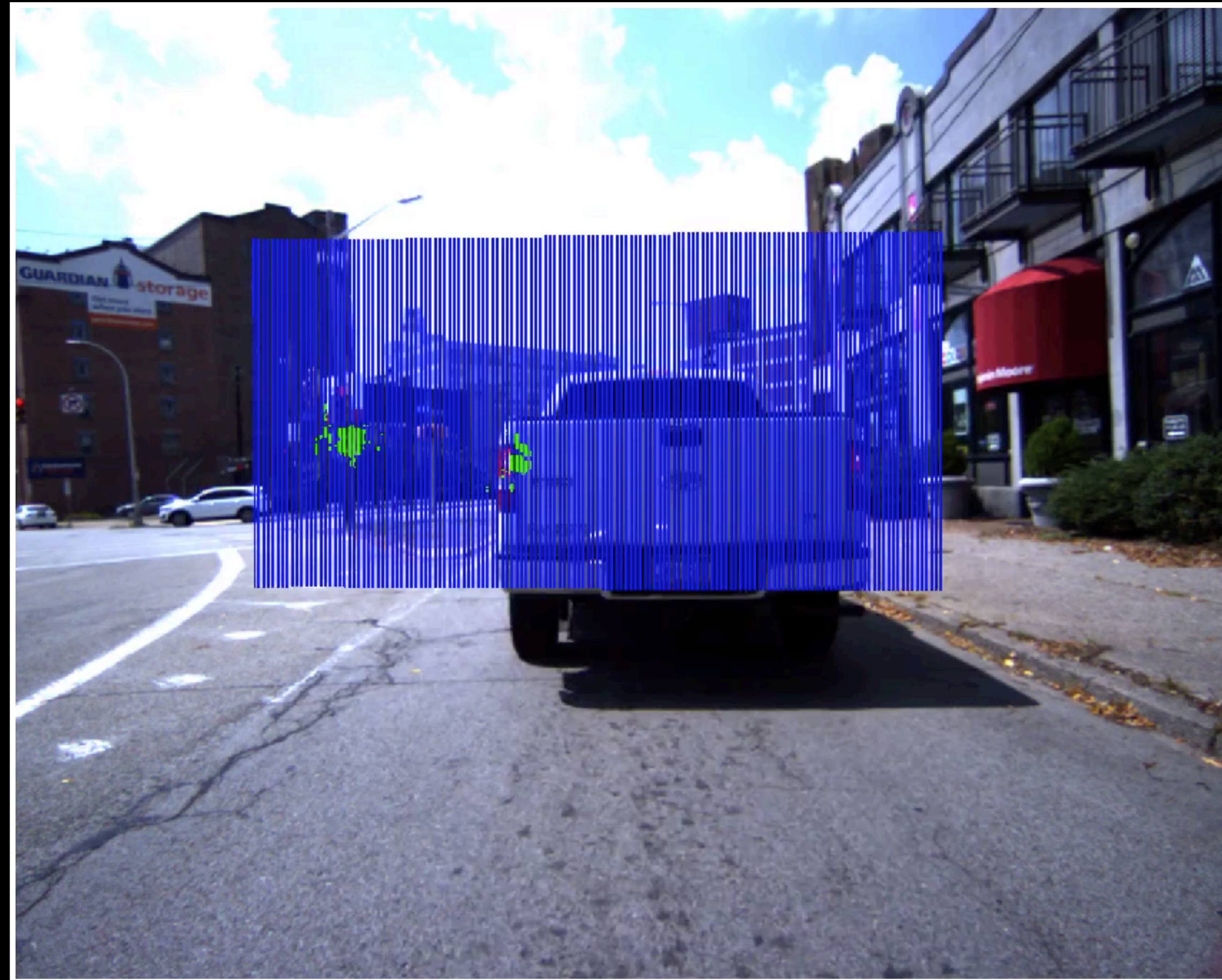
Light curtain improves detection



Light curtain improves detection



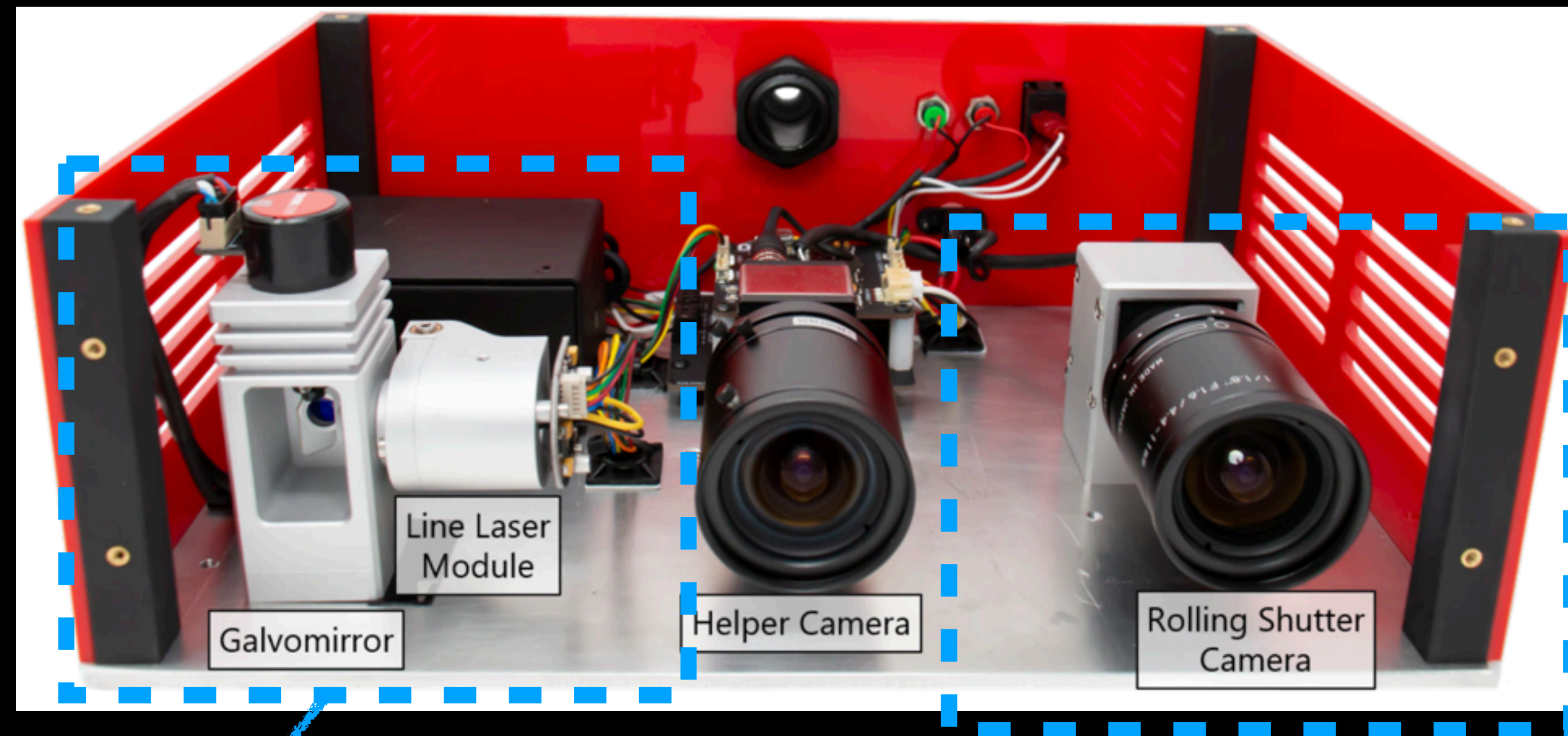
Background: what are light curtains?



“Agile Depth Sensing Using Triangulation Light Curtains”, Bartels et. al.

http://www.cs.cmu.edu/~ILIM/agile_depth_sensing

A light curtain has two major components



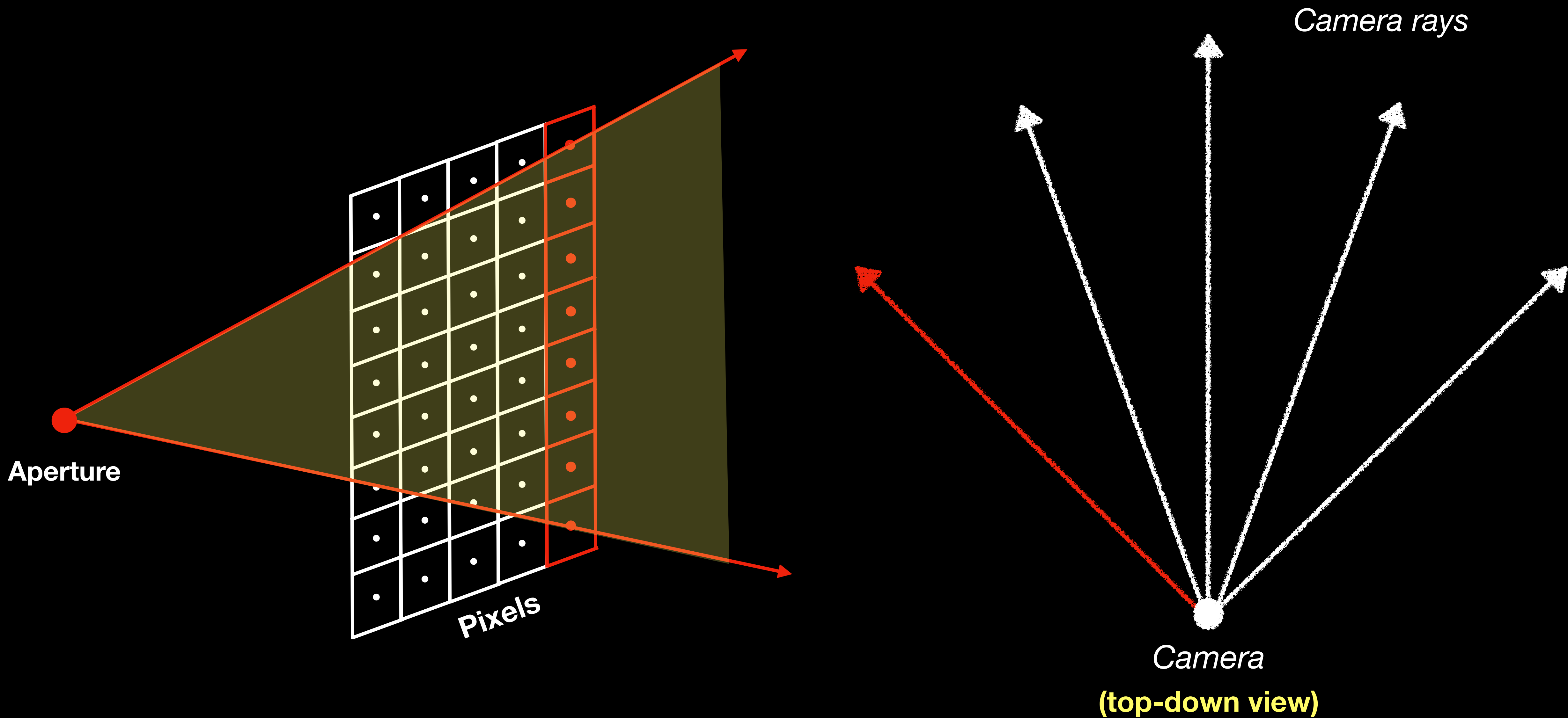
Laser

Camera

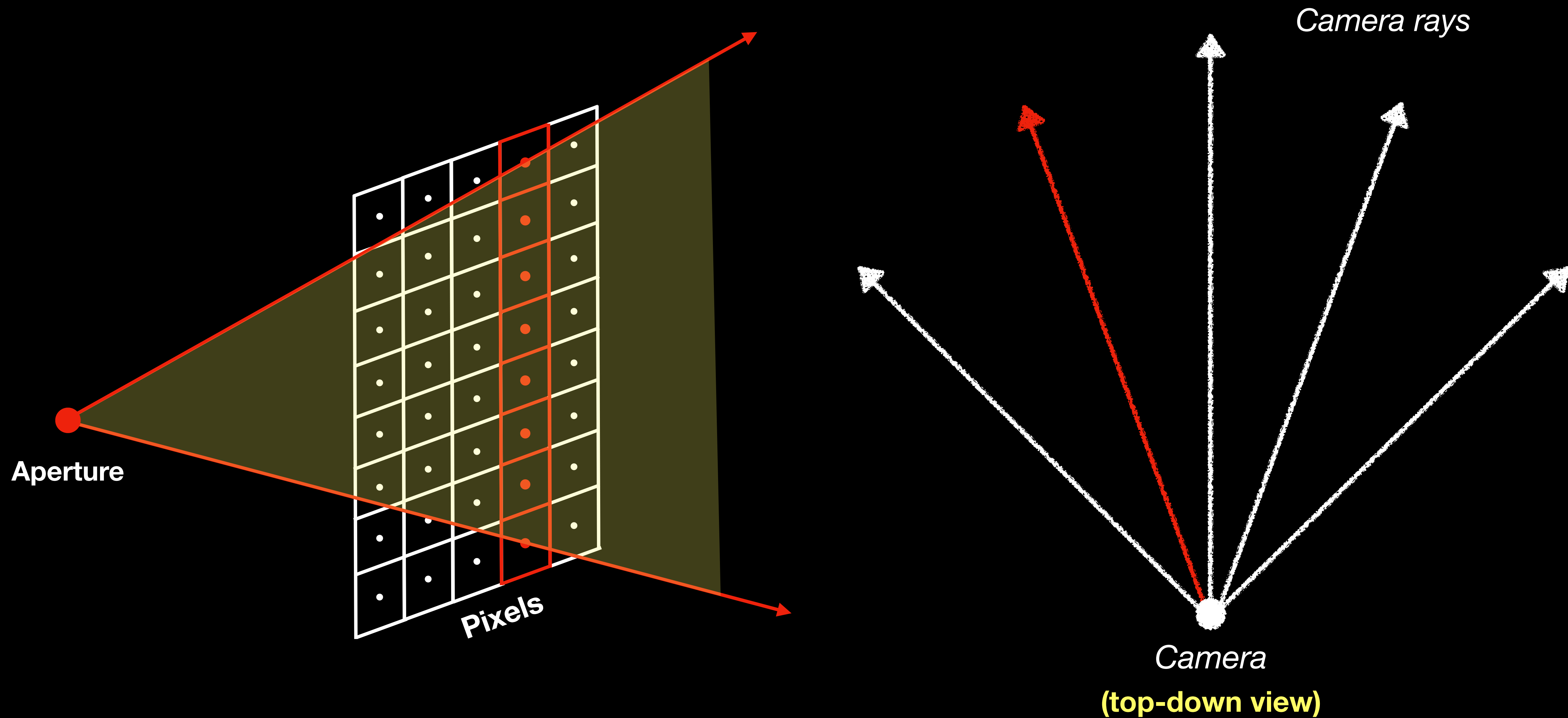
"Agile Depth Sensing Using Triangulation Light Curtains", Bartels et. al.

http://www.cs.cmu.edu/~ILIM/agile_depth_sensing

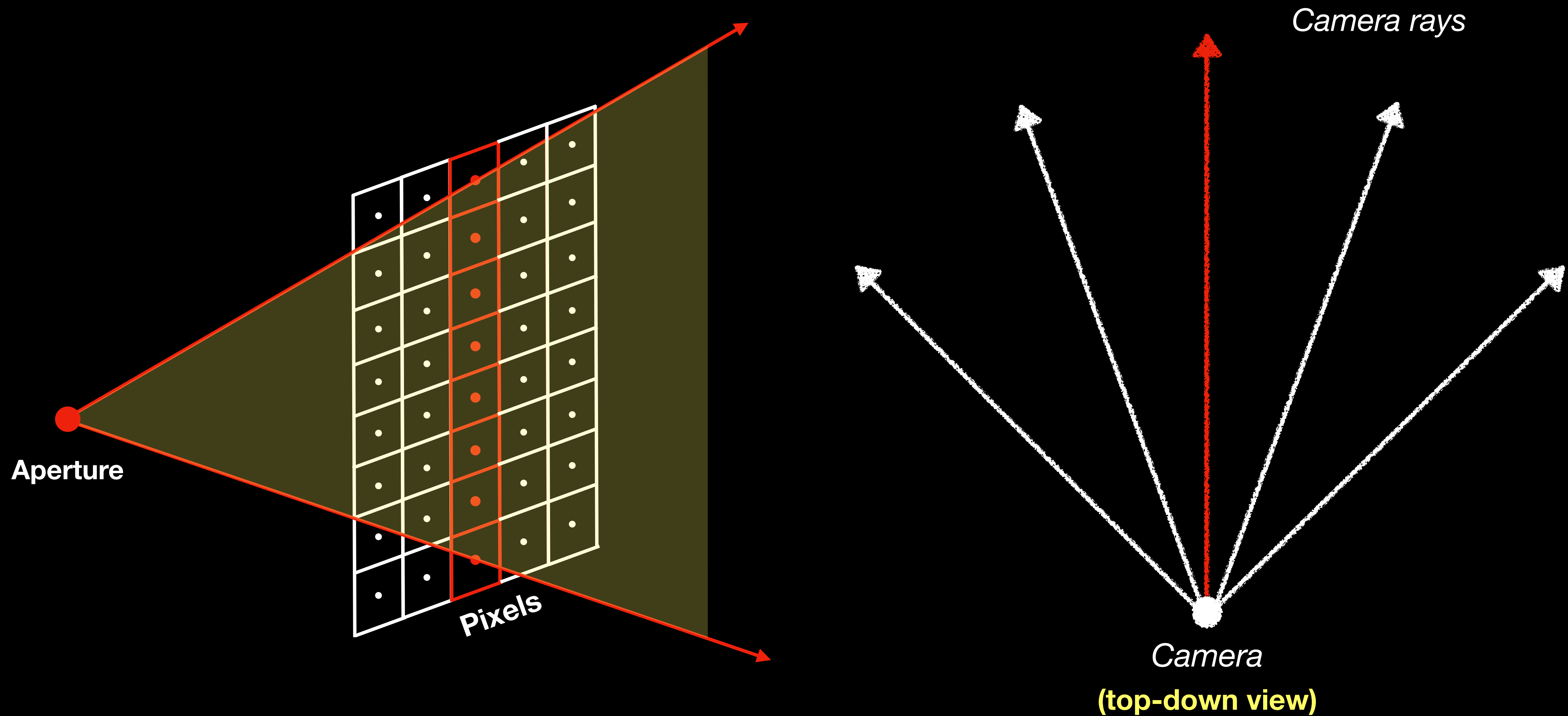
Rolling-shutter camera



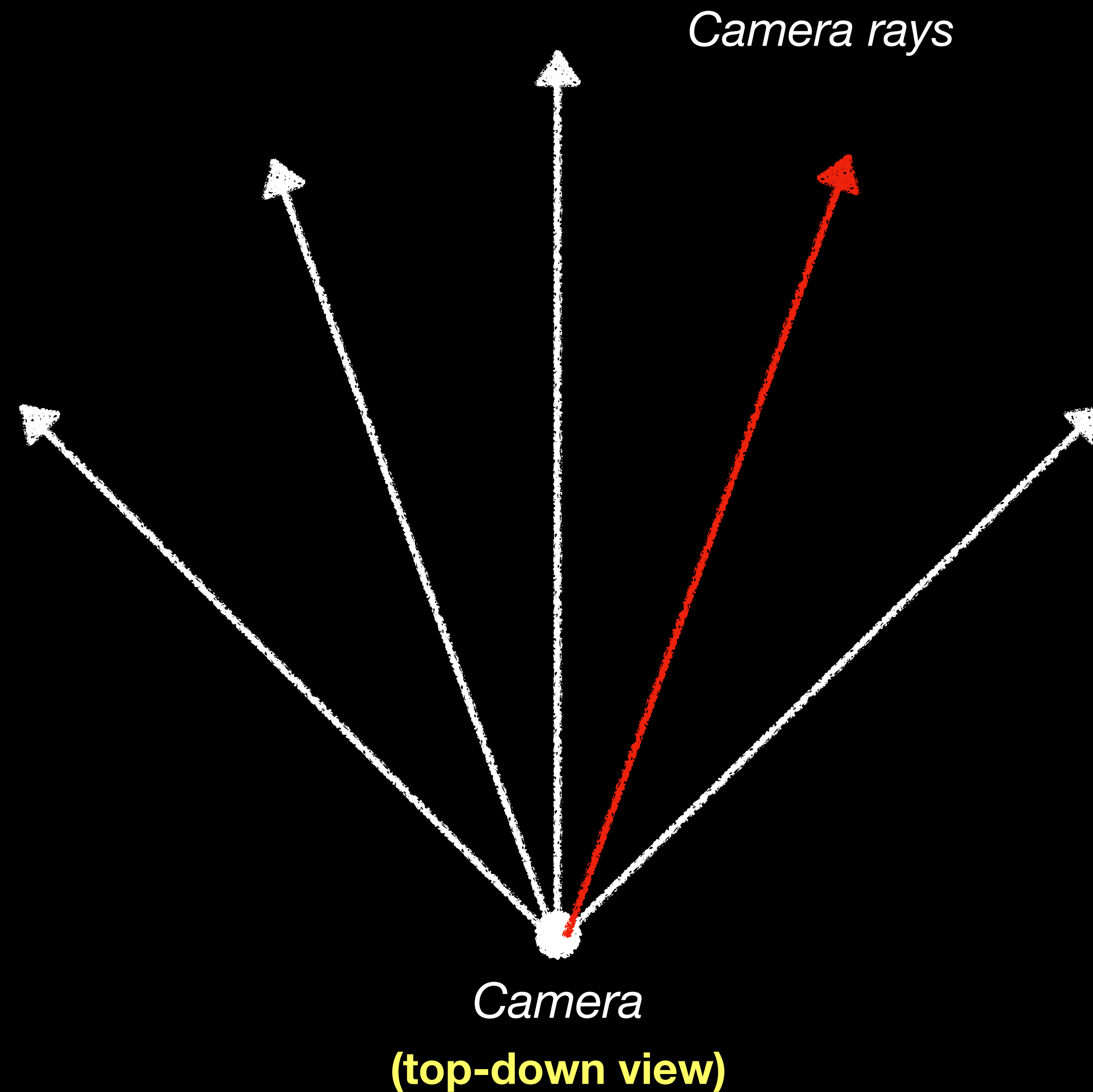
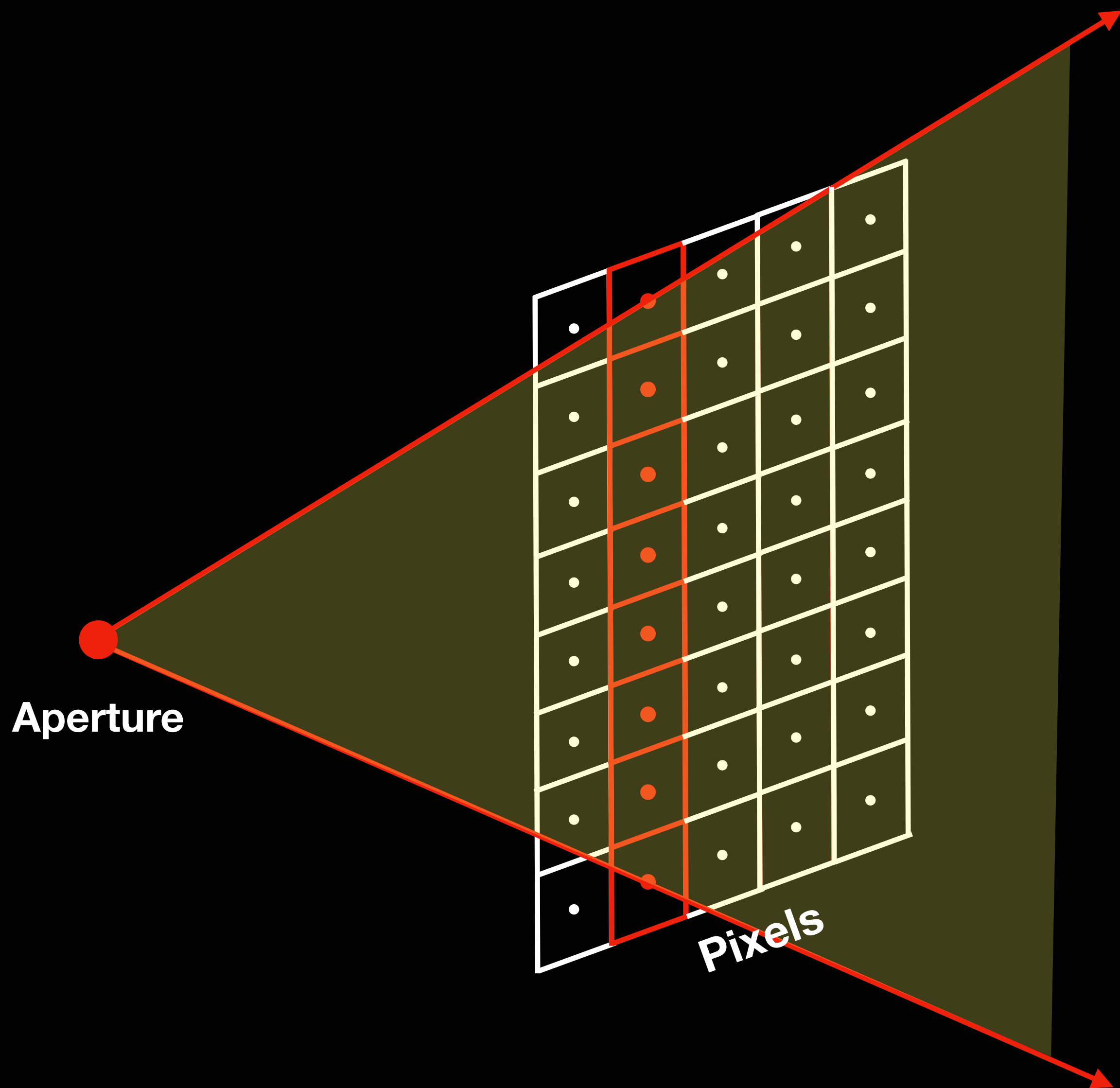
Rolling-shutter camera



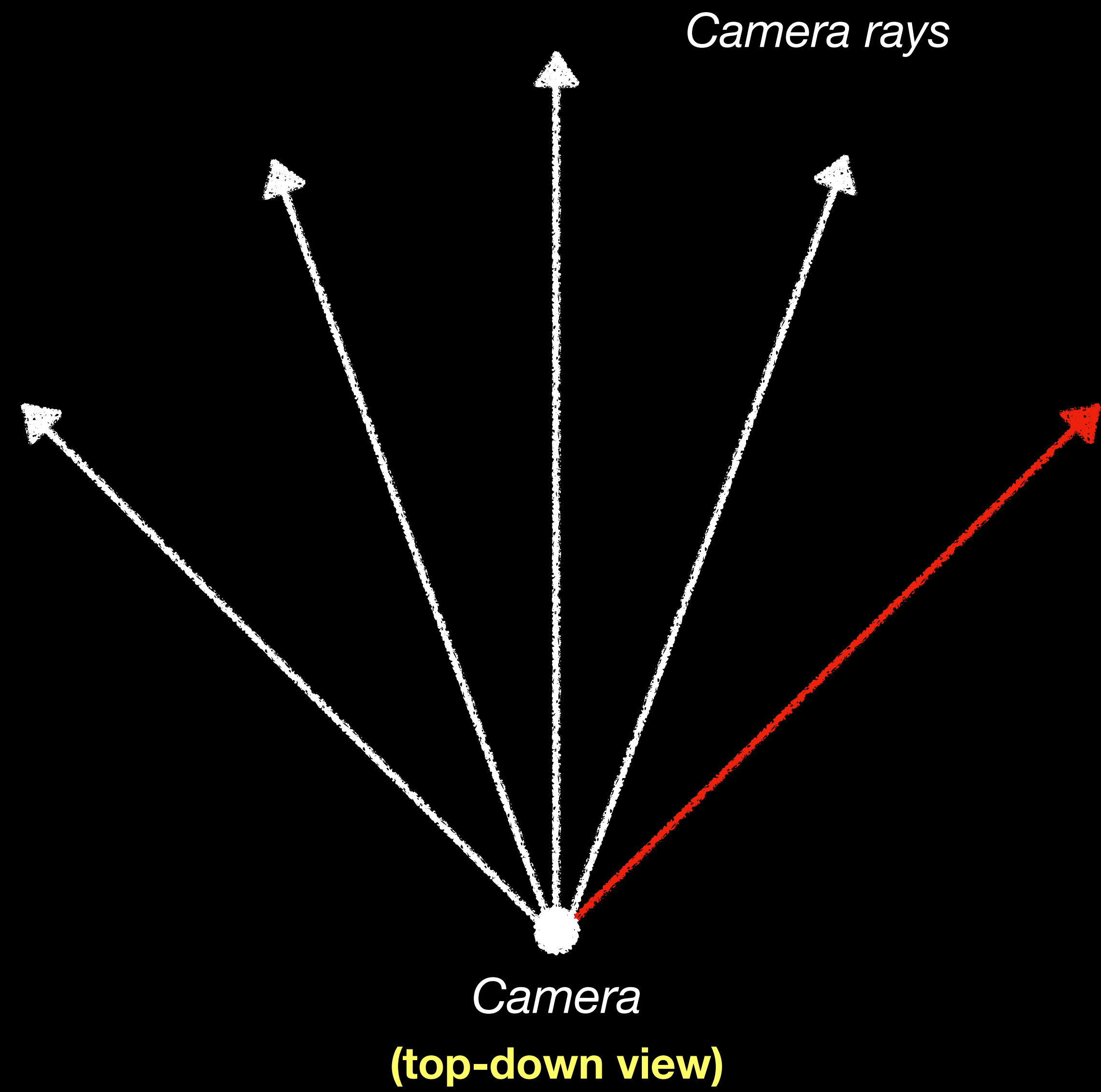
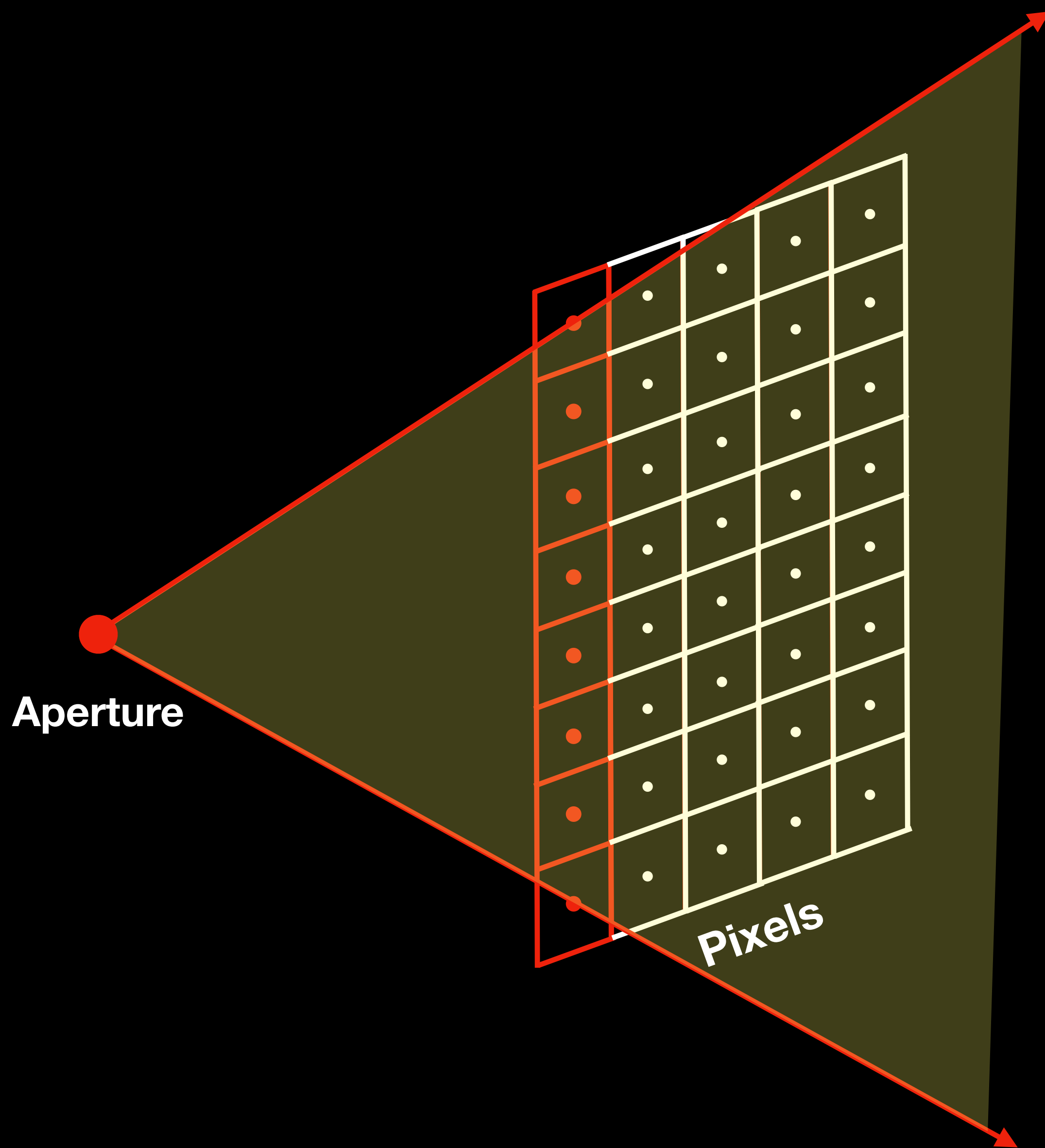
Rolling-shutter camera



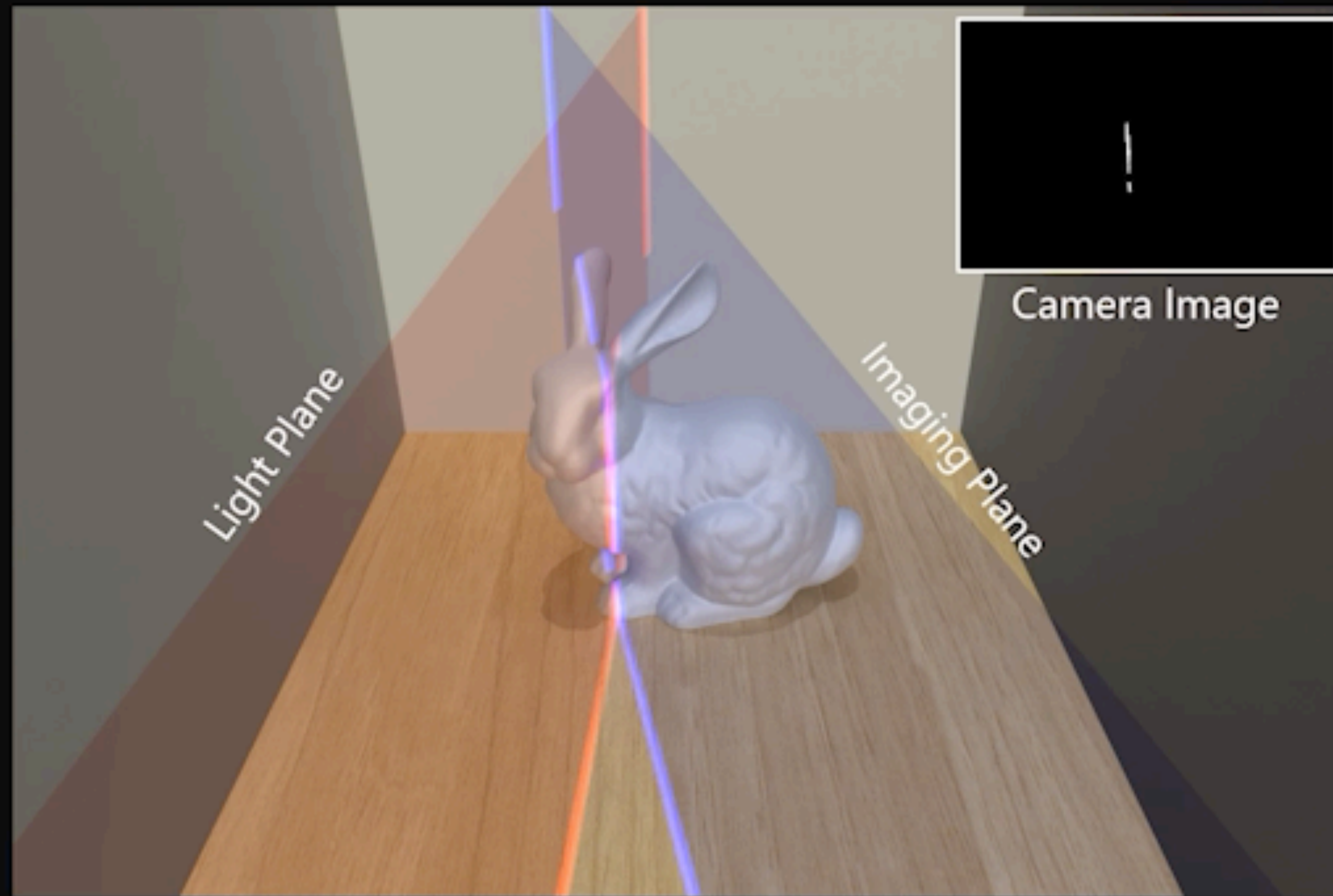
Rolling-shutter camera



Rolling-shutter camera



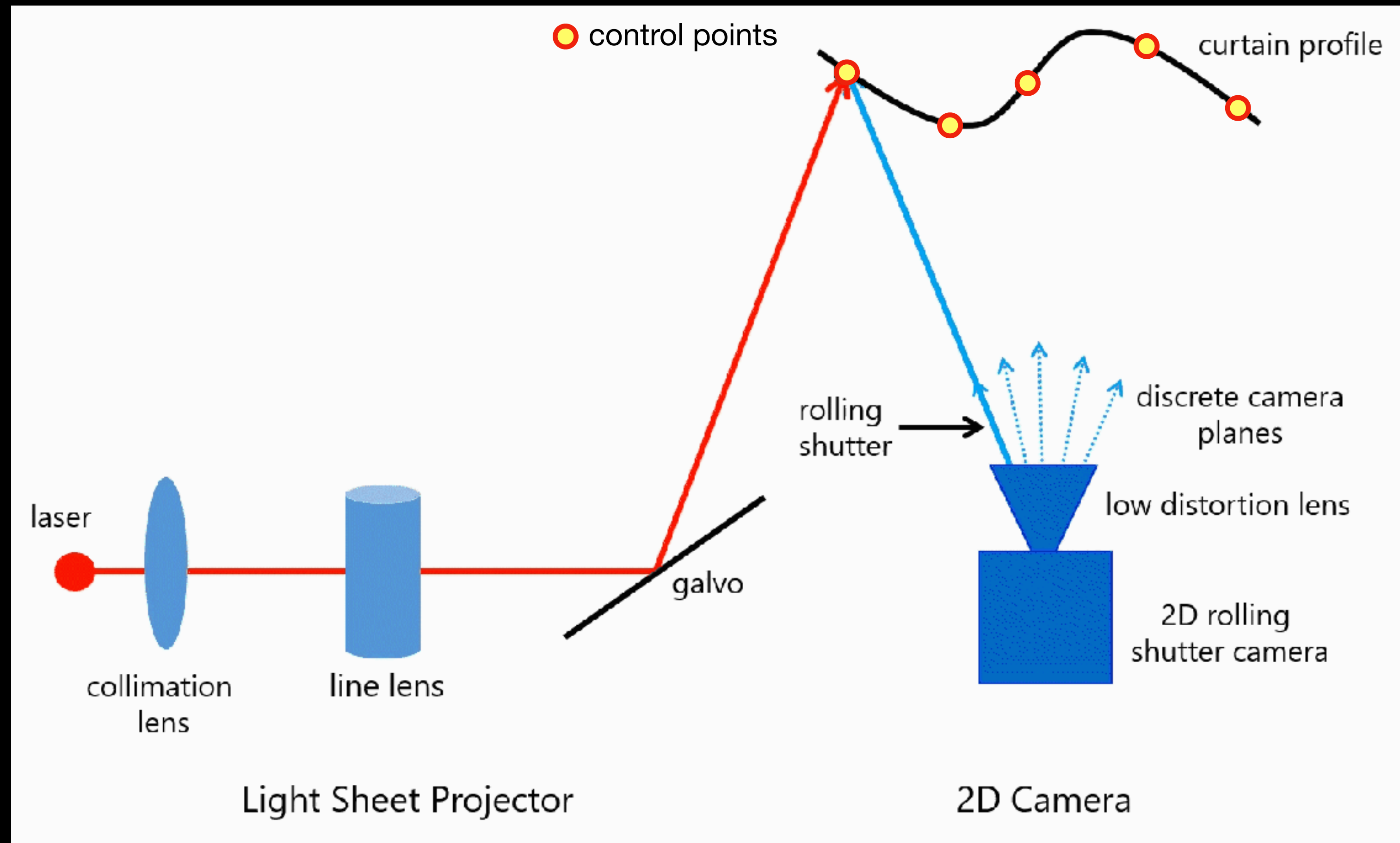
Programmable Light Curtain Principle



"Agile Depth Sensing Using Triangulation Light Curtains", Bartels et. al.

http://www.cs.cmu.edu/~ILIM/agile_depth_sensing

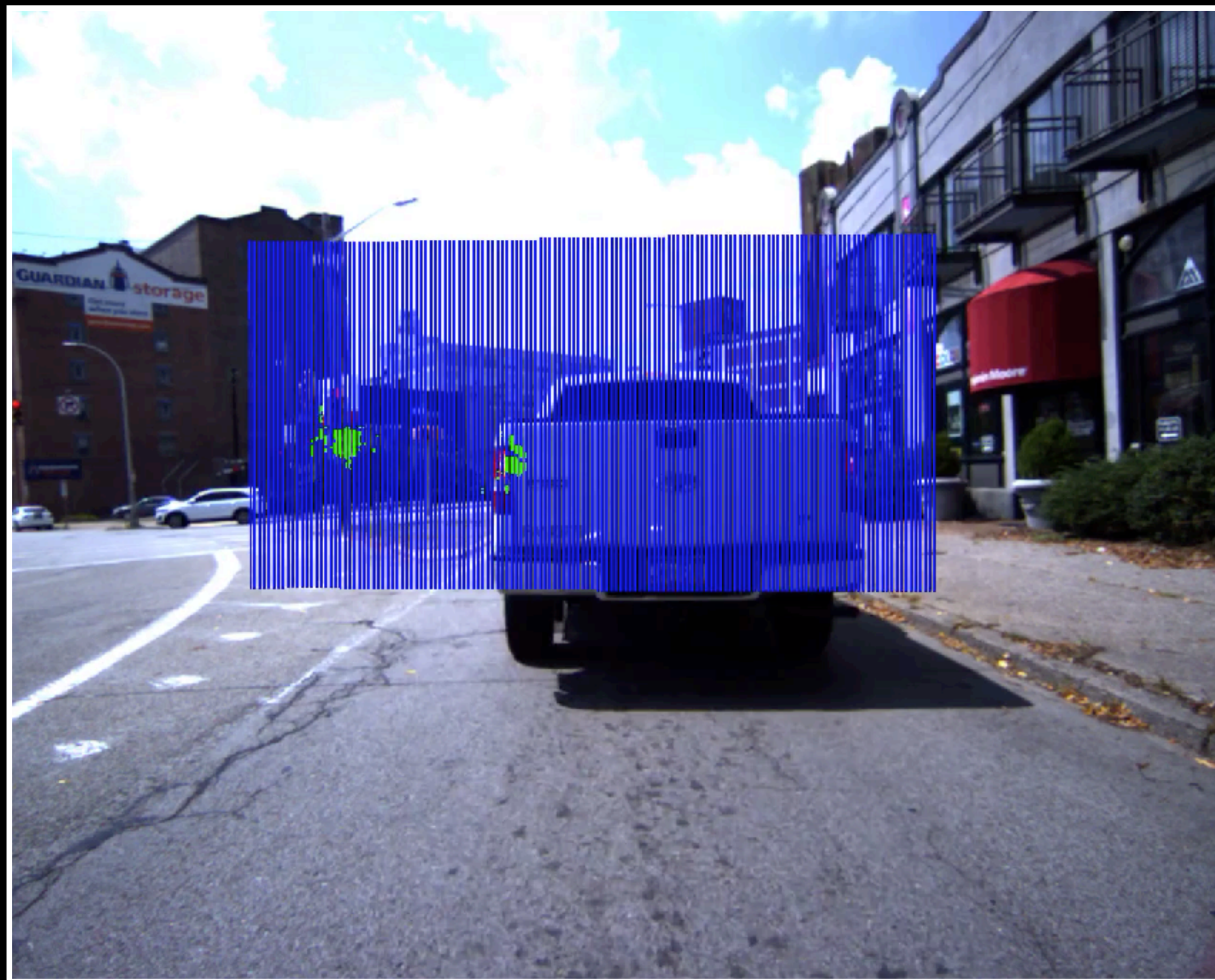
Light curtain working principle



“Agile Depth Sensing Using Triangulation Light Curtains”, Bartels et. al.

http://www.cs.cmu.edu/~ILIM/agile_depth_sensing

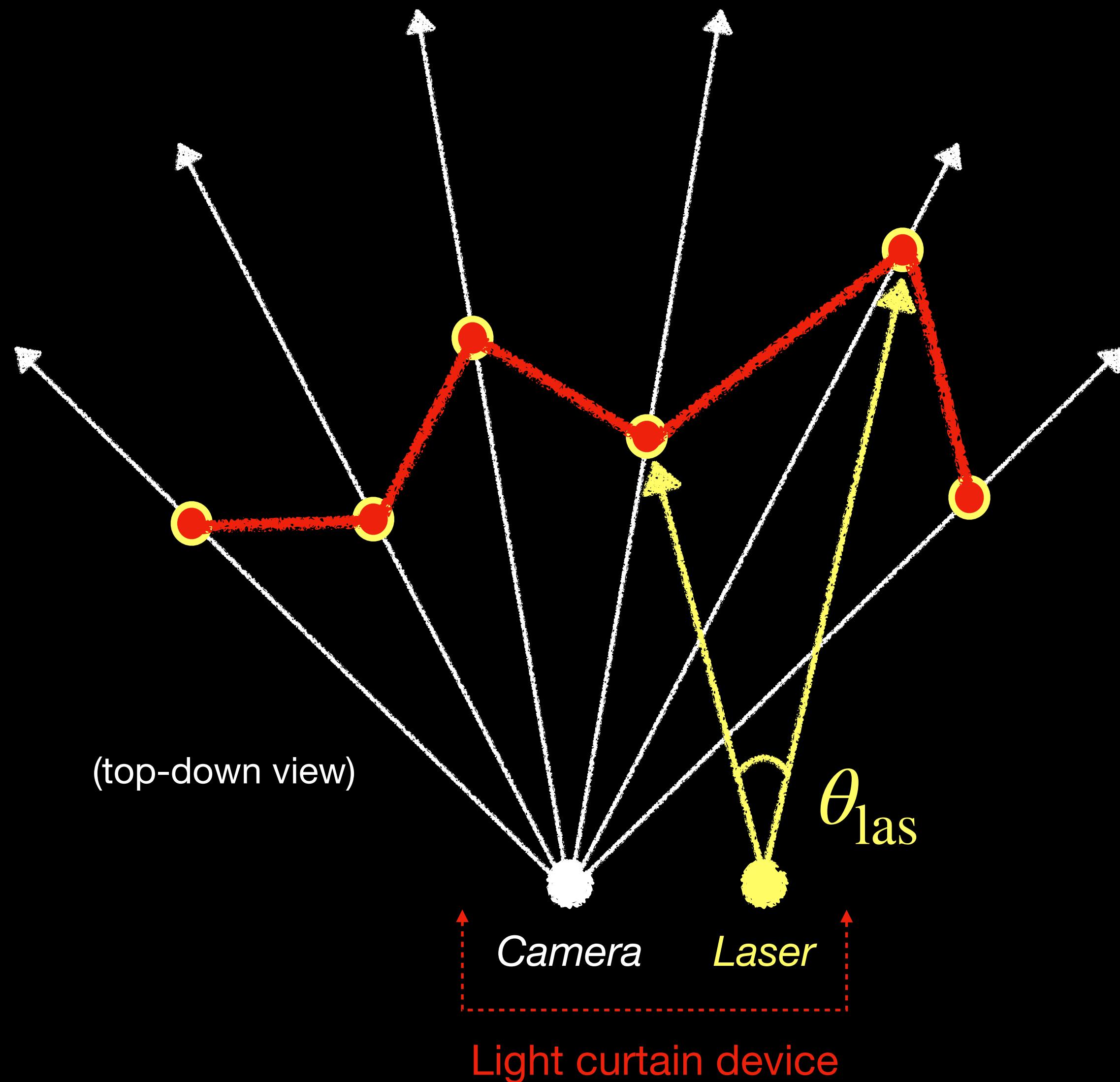
Light curtain output



“Agile Depth Sensing Using Triangulation Light Curtains”, Bartels et. al.

http://www.cs.cmu.edu/~ILIM/agile_depth_sensing

Light curtain constraints



● Control points

— Light curtain

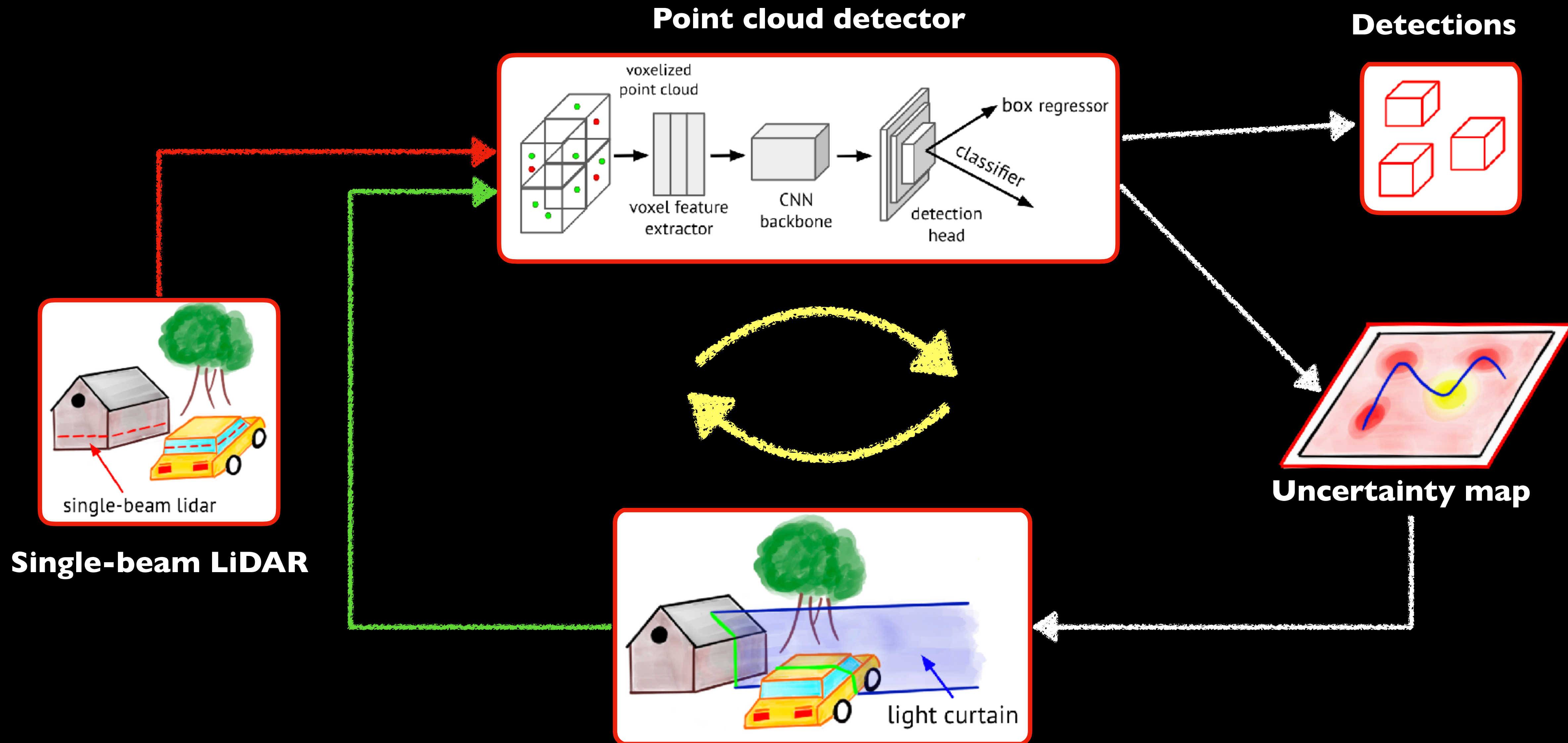
Light curtain velocity constraint

$$\theta_{las} \leq \omega_{max} \cdot \Delta t$$

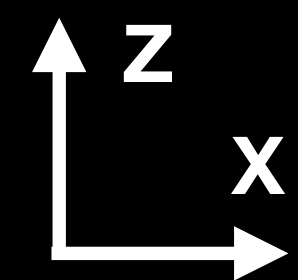
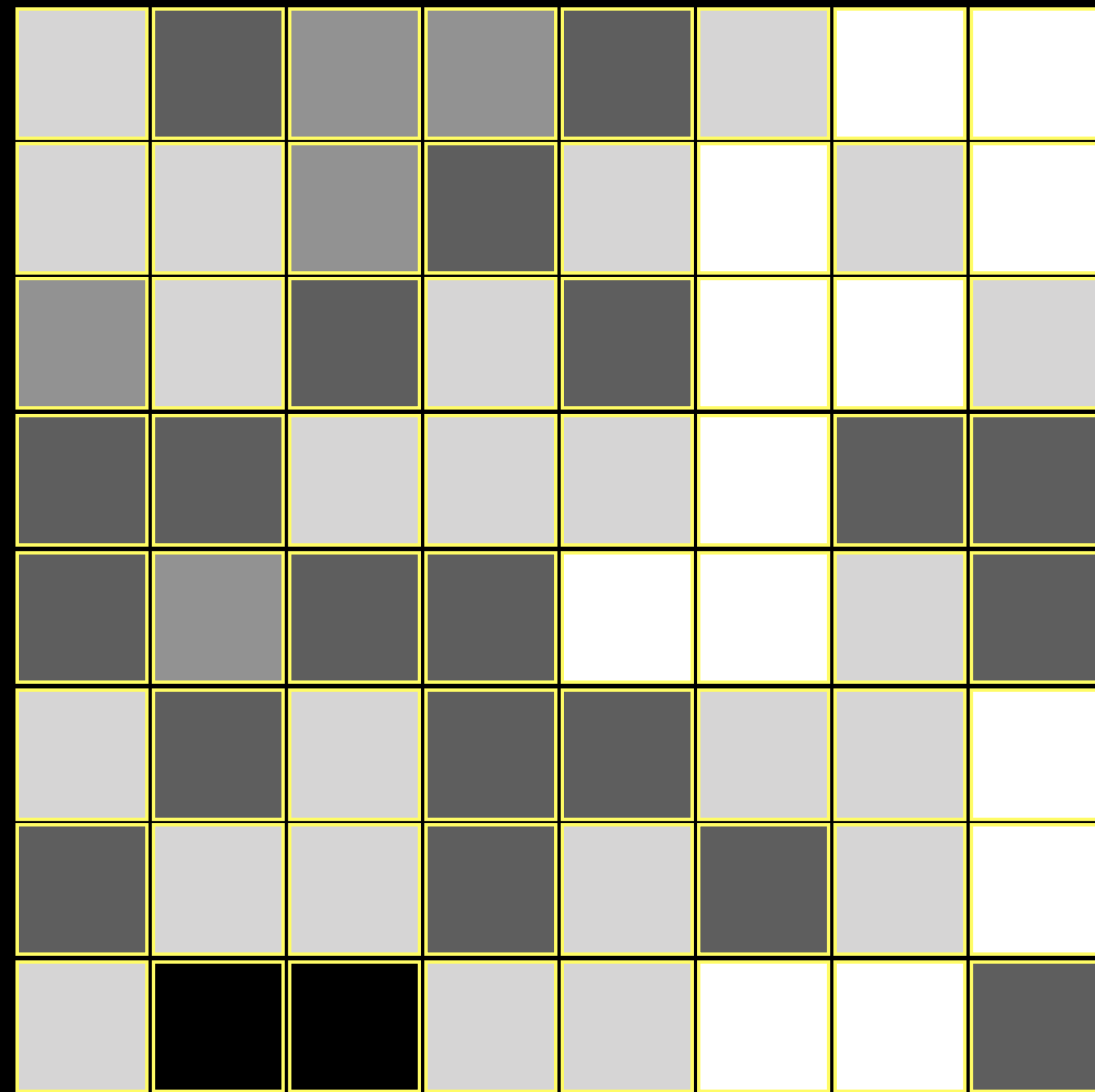
Laser max
velocity limit

Camera sweep
time between
consecutive
rays

Active 3D Detection Pipeline



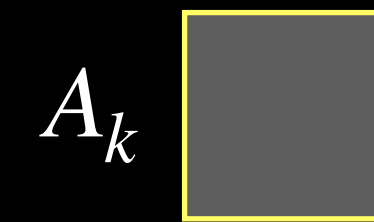
Detector Uncertainty



Uncertainty map
(top-down view)

Binary detection

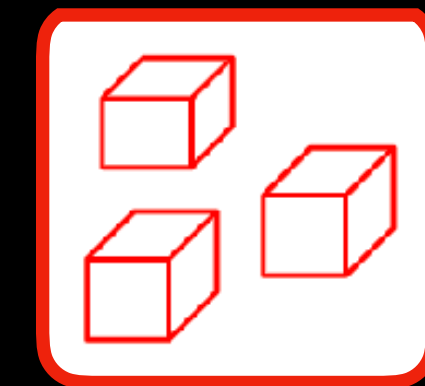
Anchor Box
(top down view)



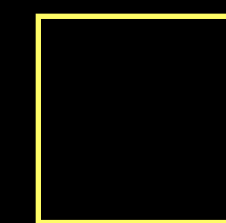
$$0 \leq p_k \leq 1$$

$p_k = \text{confidence}$

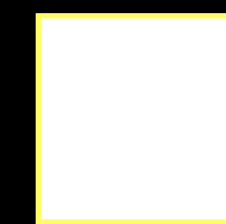
Detections



$$p_k > \text{threshold}$$

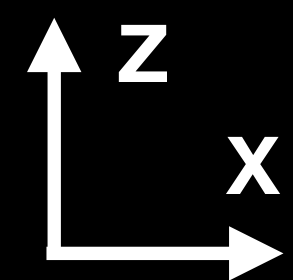
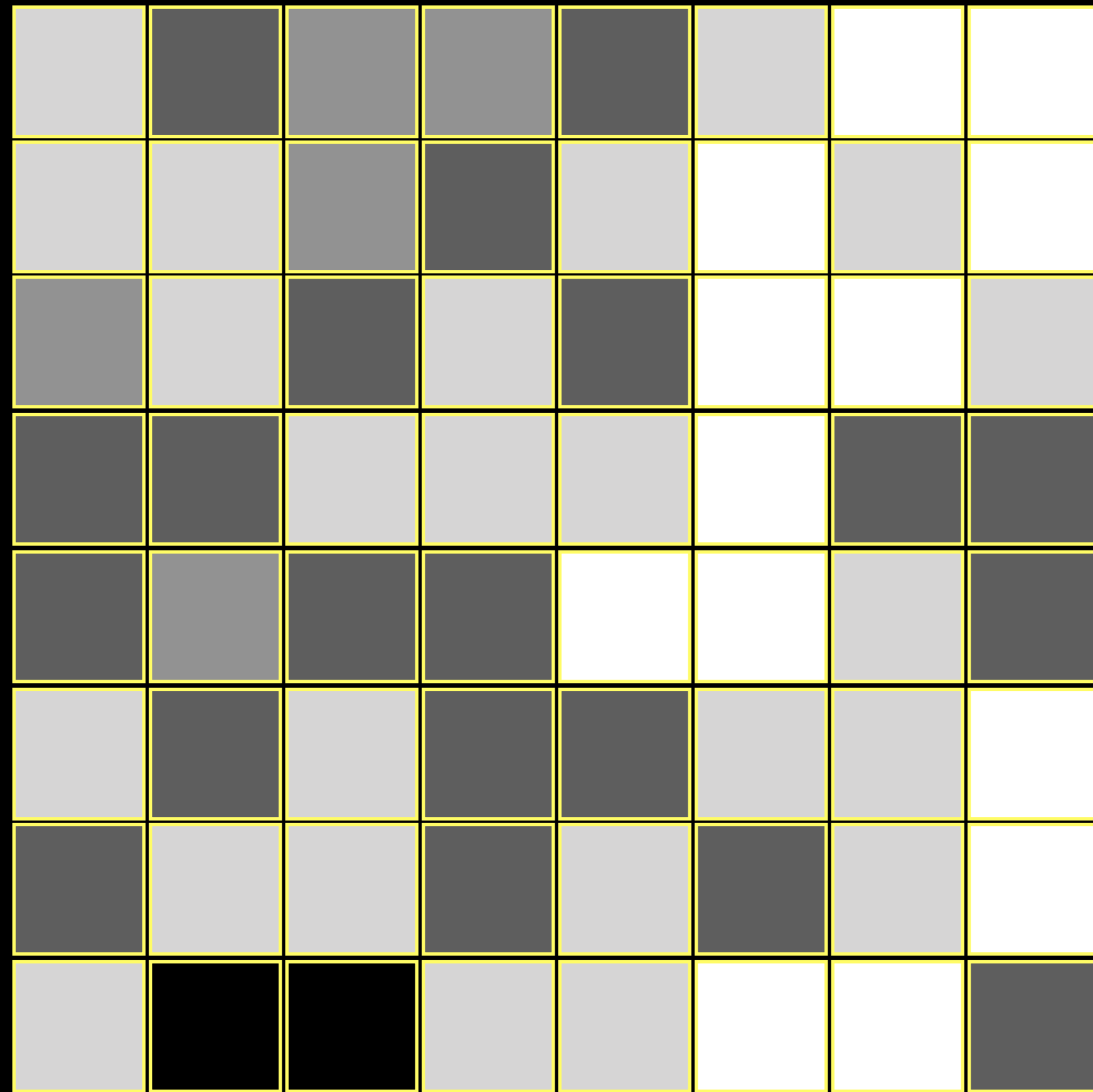


Lowest uncertainty
(low/high confidence)



Highest uncertainty
(medium confidence)

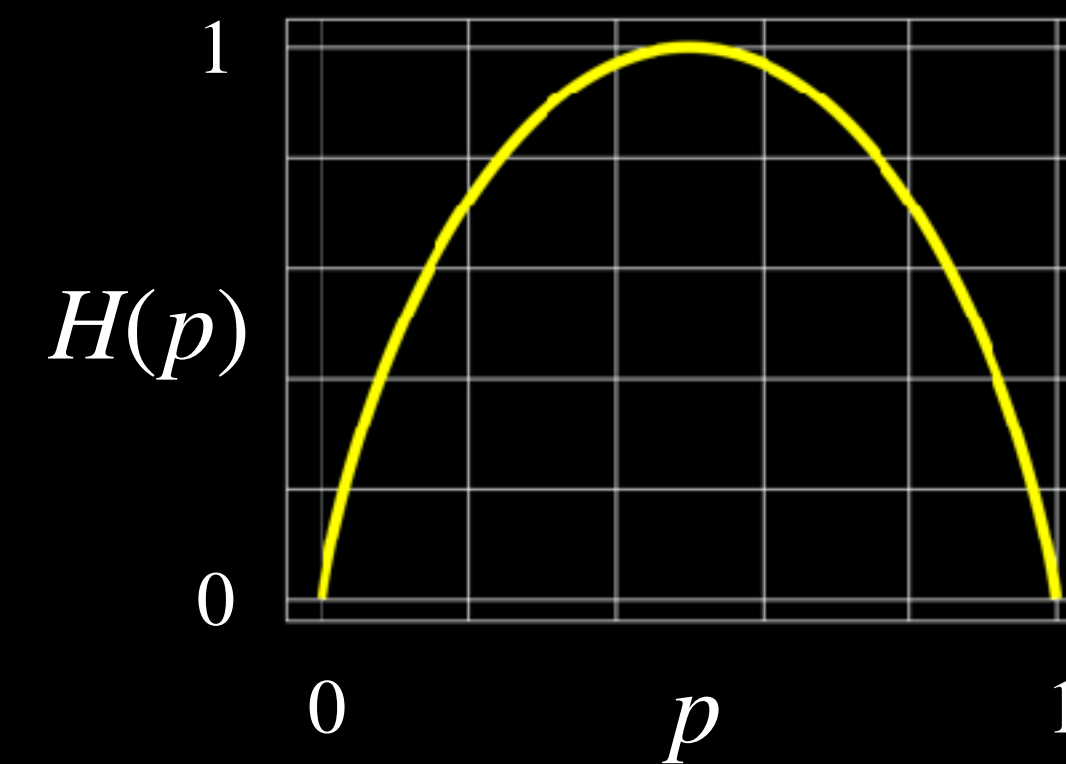
Confidence → Uncertainty



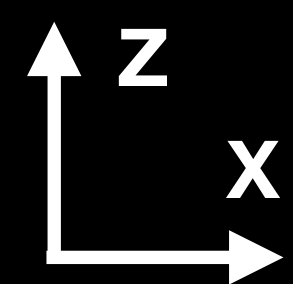
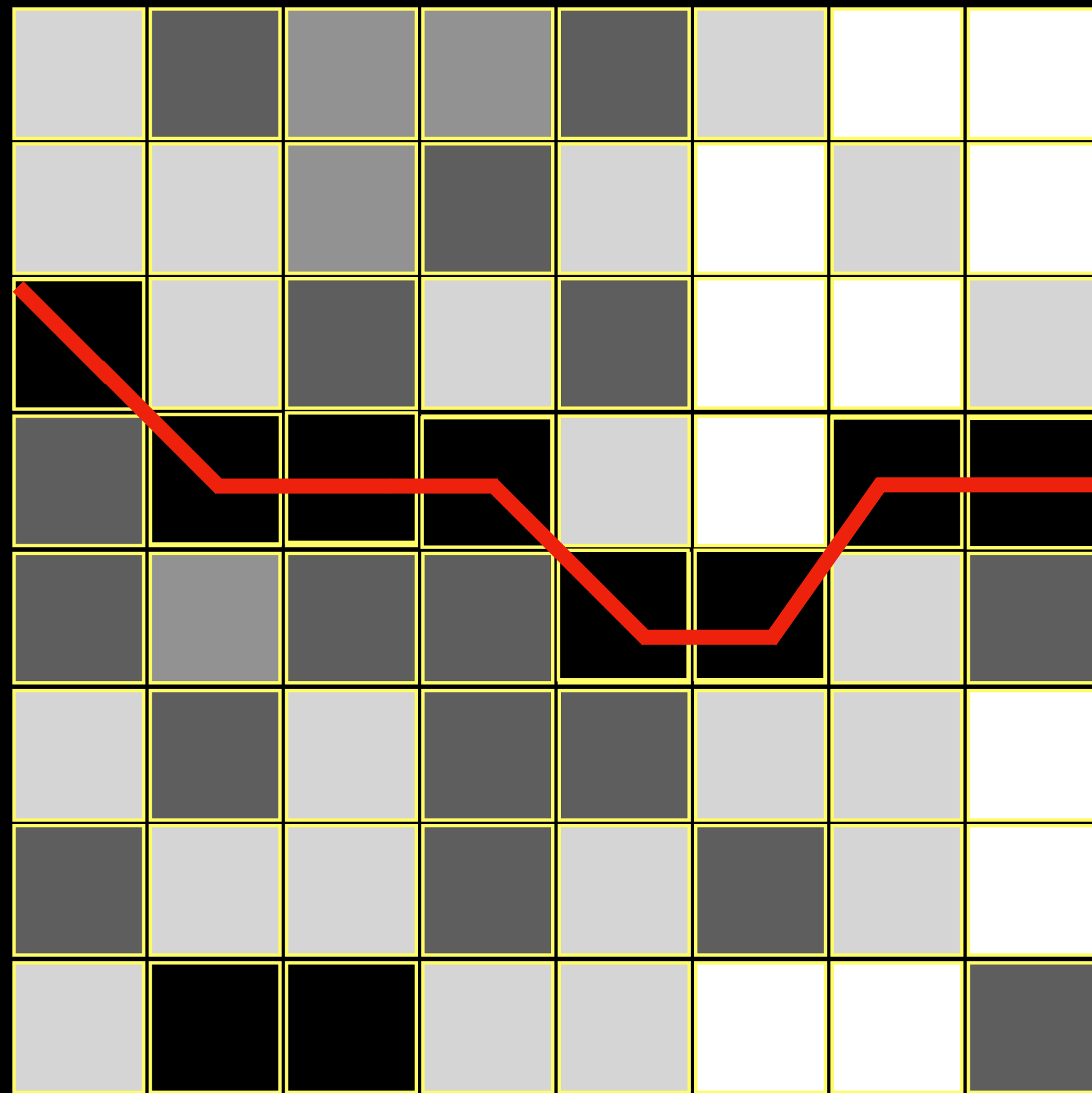
Uncertainty map
(top-down view)

Binary entropy

$$H(p) = -p \log_2 p - (1 - p) \log_2(1 - p)$$



Maximizing Information Gain



Uncertainty map
(top-down view)

Assumption 1

probabilities at each anchor locations are independent

$$H(p_{1:k}) = \sum_k H(p_k)$$

Assumption 2

a *light curtain* resolves uncertainties *fully and locally*

Information Gain

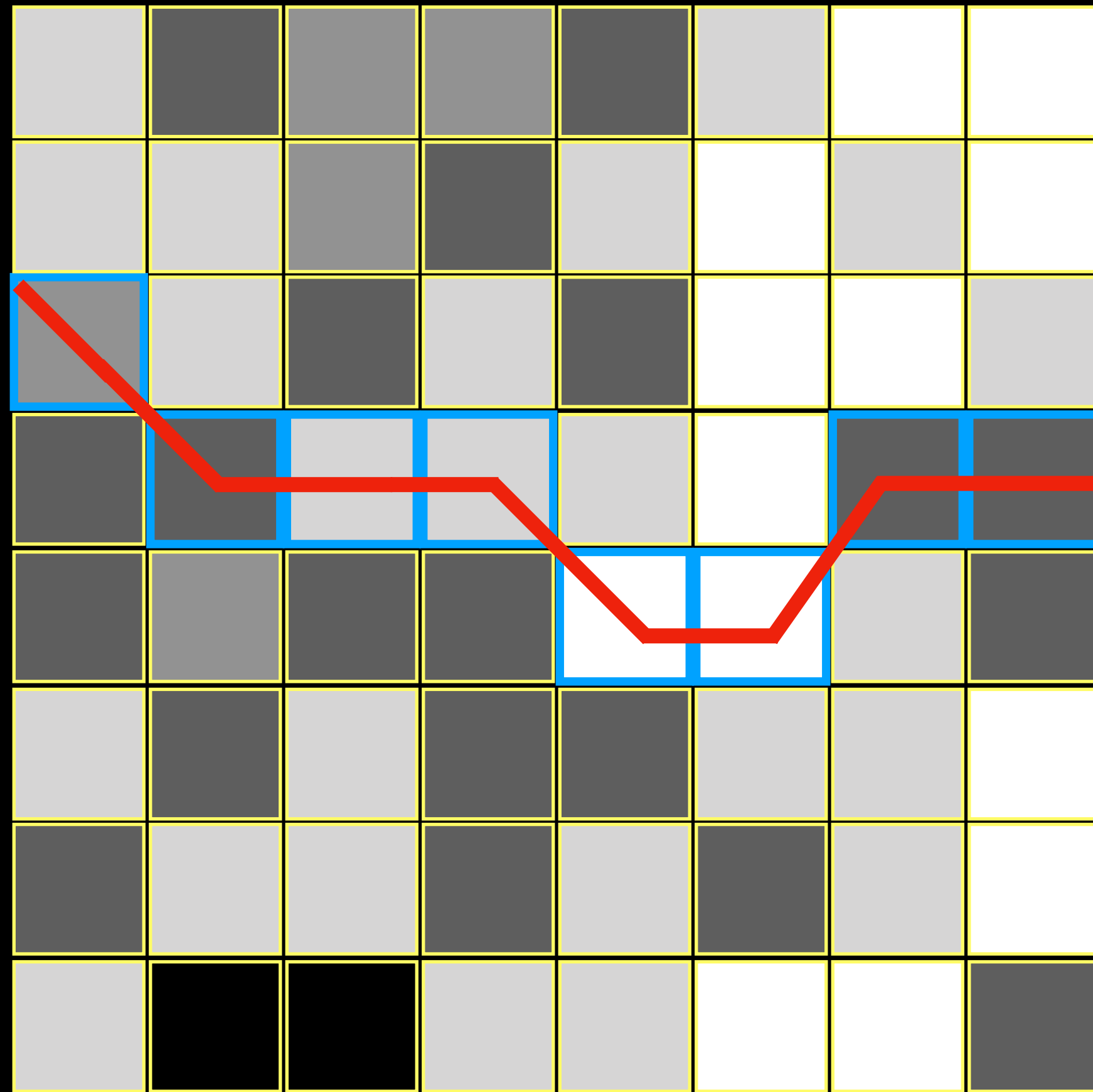
= H after placement - H before placement

$$= \sum_k H(p_k^t) - \sum_k H(p_k^{t-1})$$

$$= \sum_k H(p_k), \text{ where } k\text{-th anchor lies under the curtain}$$

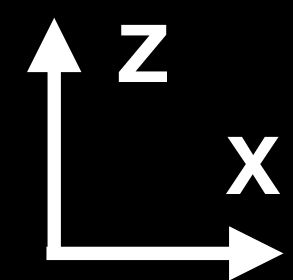
$$= \sum \left(\text{Diagram showing a red line passing through a grid of cells, representing the information gain from a light curtain placement. The diagram shows a red line moving across a grid of cells, with some cells highlighted in gray to indicate the path of the curtain. The entire diagram is enclosed in large parentheses.$$

Maximization Objective



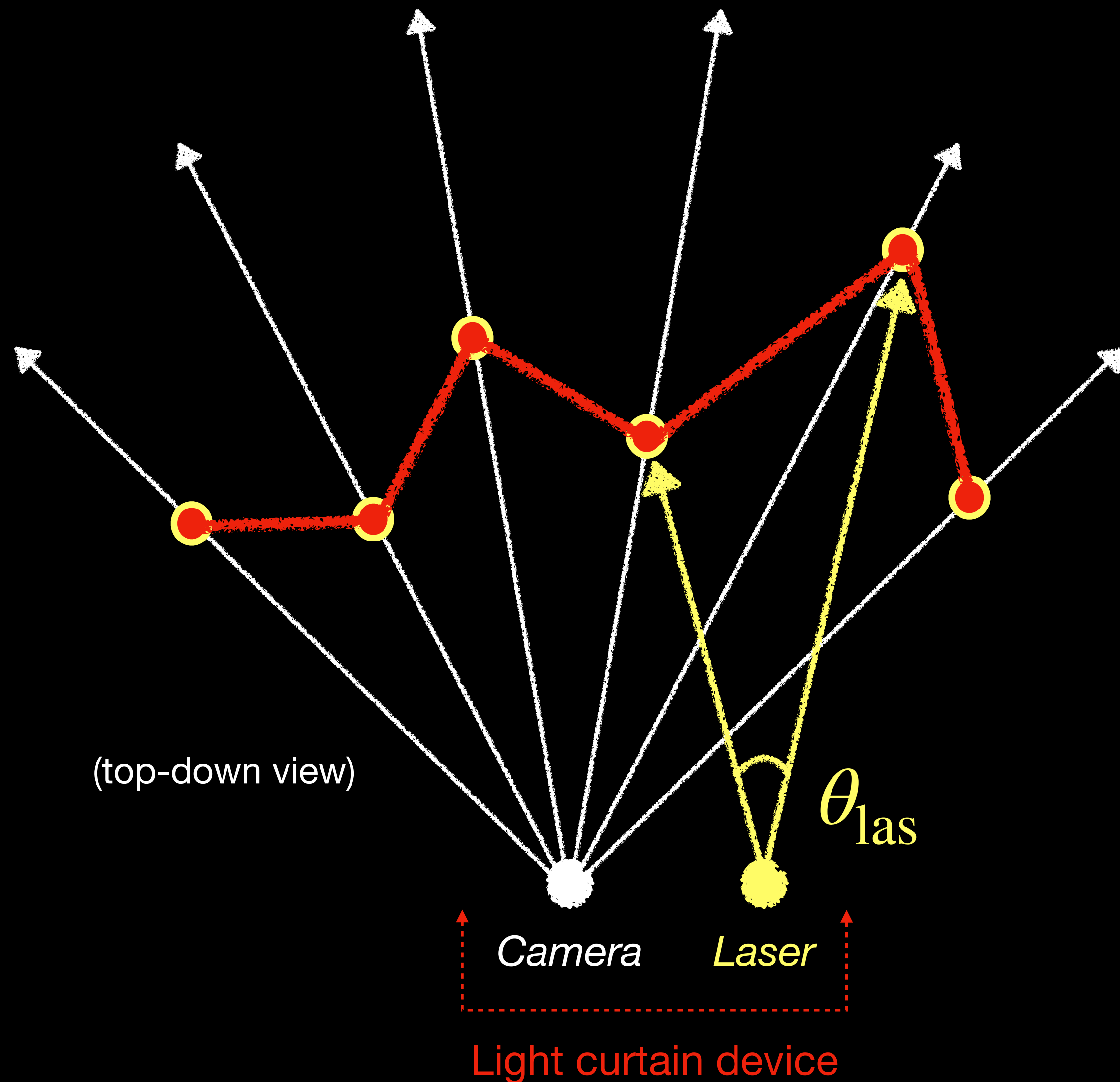
Objective to place light curtains:

Maximize the sum of binary entropies of regions covered by the light curtain!



Uncertainty map
(top-down view)

Light curtain parametrization



Control points

Light curtain

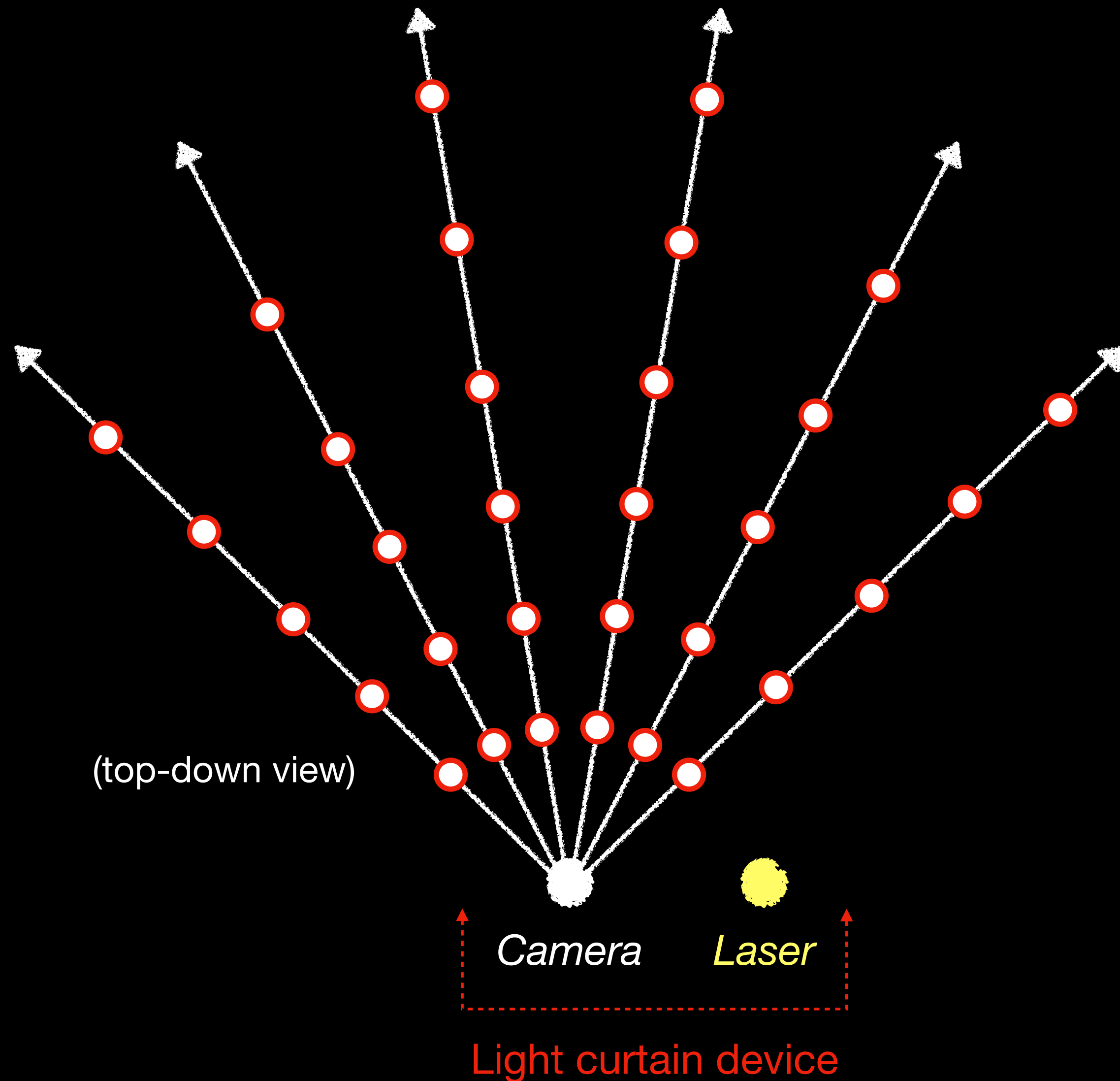
Light curtain constraint

$$\theta_{las} \leq \omega_{max} \cdot \Delta t$$

Laser max
velocity limit

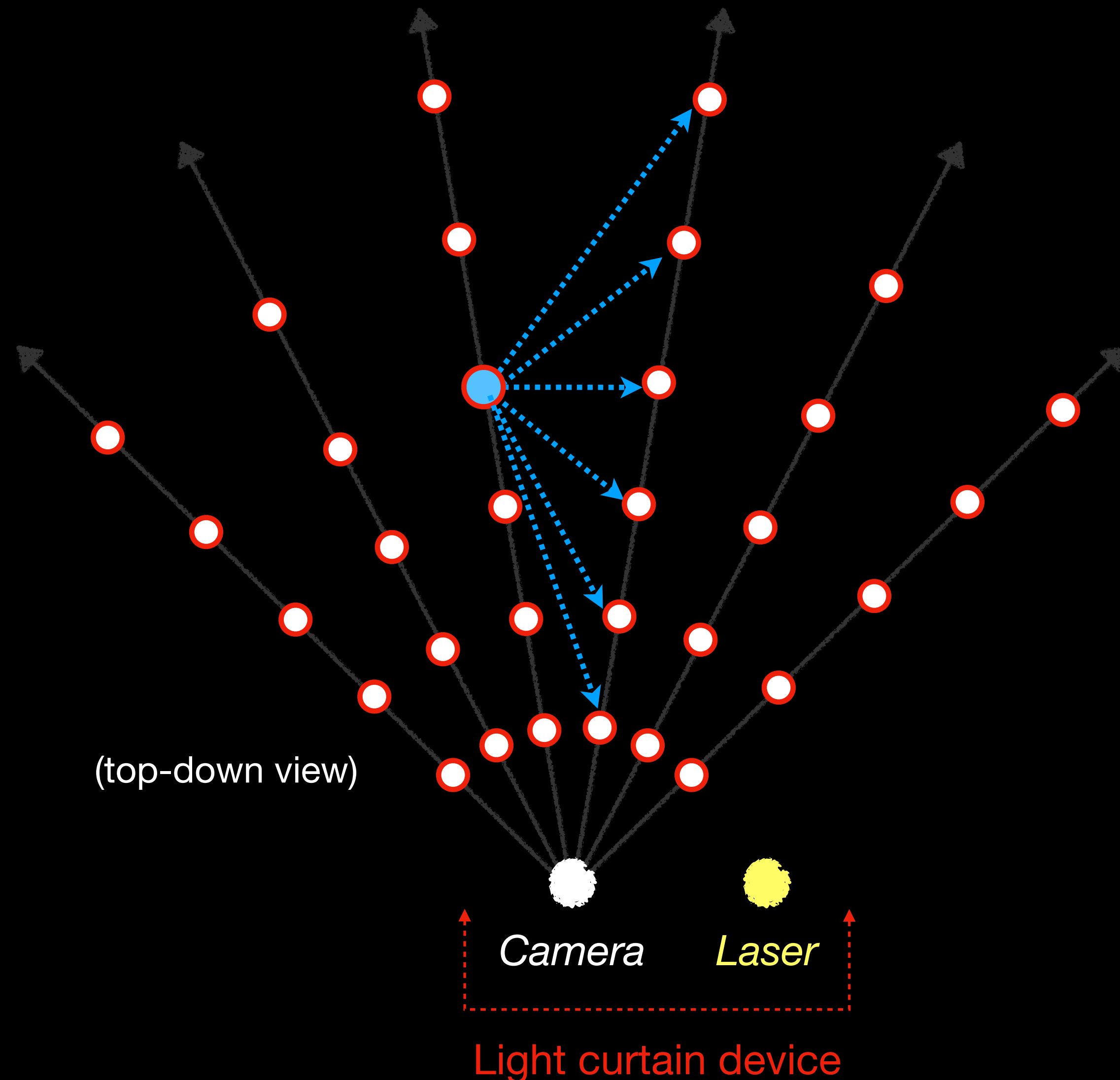
Camera sweep
time between
consecutive
rays

Constructing a *Constraint Graph*



Step 1 ● *Graph node*
Select equally spaced points as candidate control points on each camera ray. These are the *nodes* of the graph.

Constructing a *Constraint Graph*



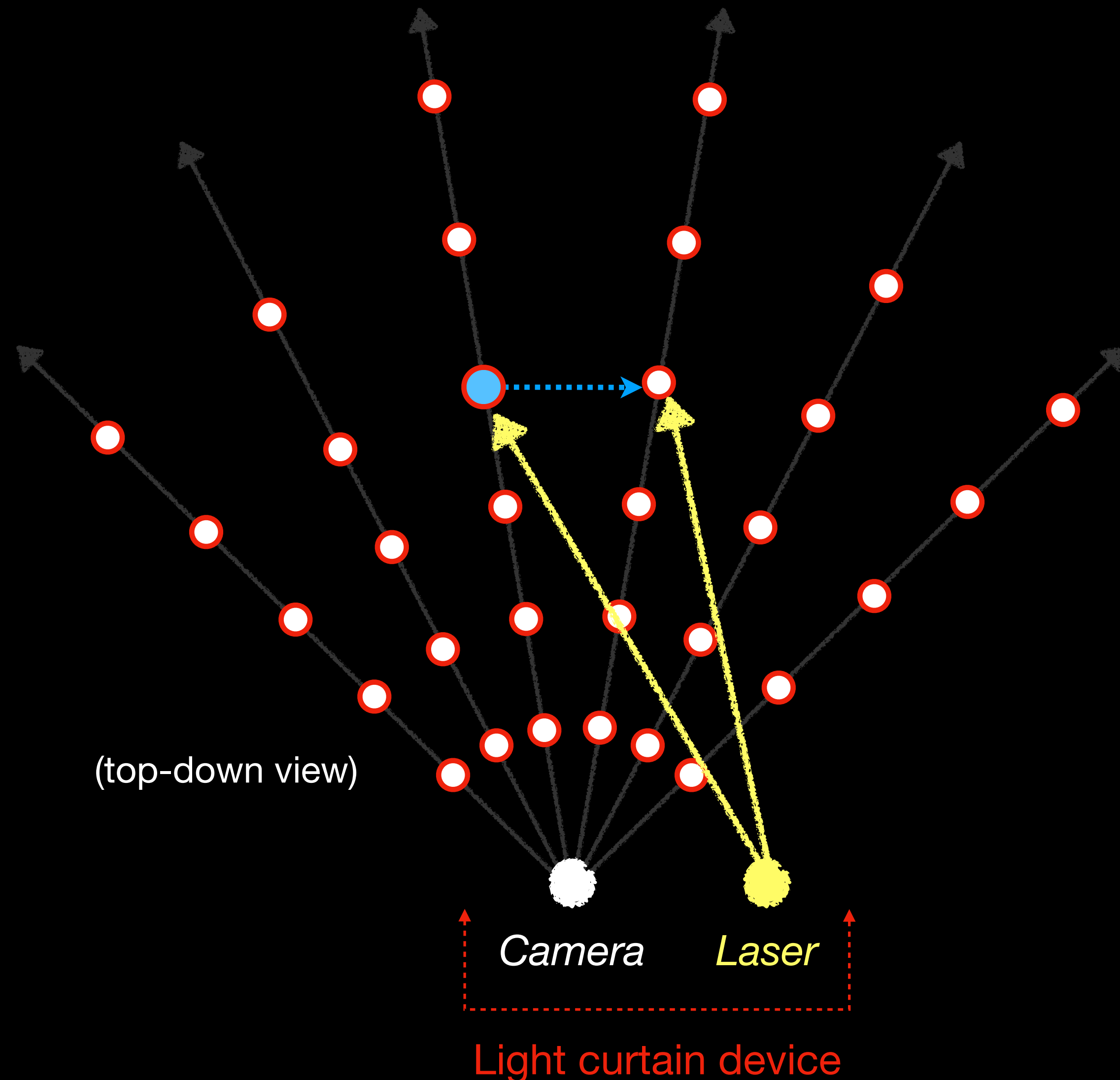
Step 1 ● *Graph node*

Select equally spaced points as candidate control points on each camera ray. These are the nodes of the graph.

Step 2

For each node, consider all nodes on the next ray.

Constructing a *Constraint Graph*



Step 1 ● *Graph node*

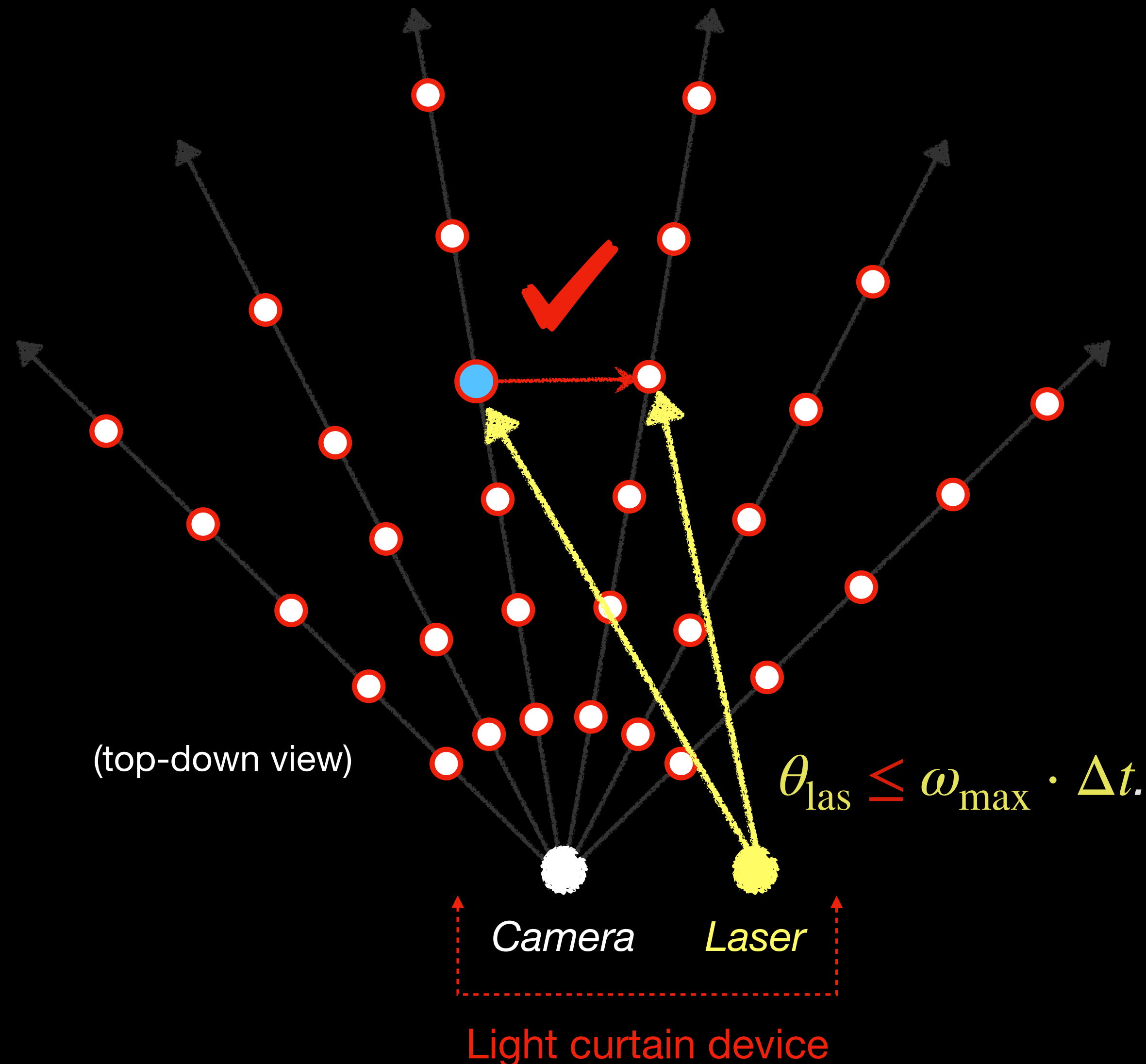
Select equally spaced points as candidate control points on each camera ray. These are the *nodes* of the graph.

Step 2

For each node, consider all nodes on the next ray.

Add those nodes that satisfy the velocity constraint $\theta_{\text{las}} \leq \omega_{\text{max}} \cdot \Delta t$ as edges.

Constructing a *Constraint Graph*



Step 1 ● *Graph node*

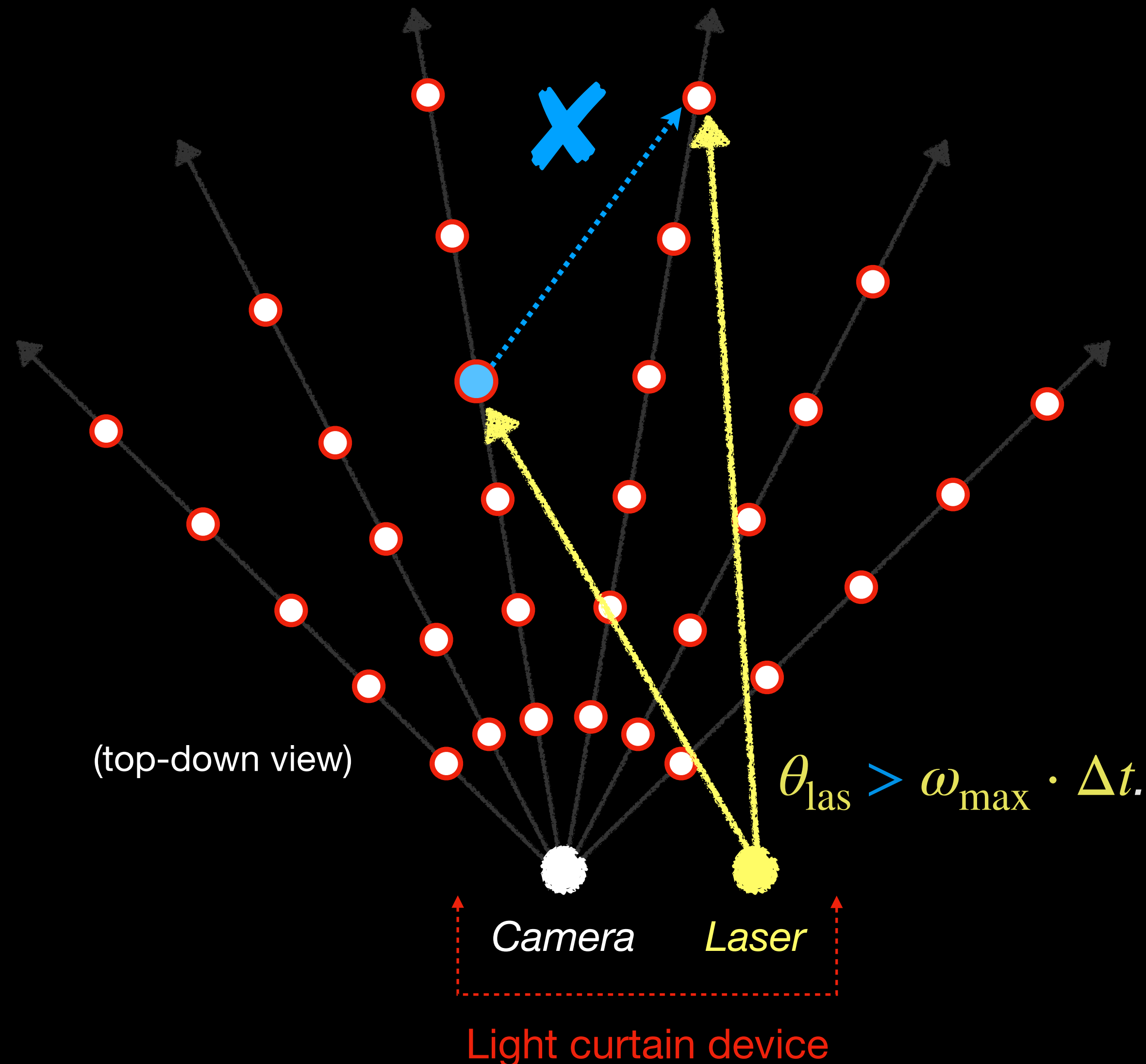
Select equally spaced points as candidate control points on each camera ray. These are the *nodes* of the graph.

Step 2 → *Graph edge*

For each node, consider all nodes on the next ray.

Add those nodes that satisfy the velocity constraint $\theta_{\text{las}} \leq \omega_{\text{max}} \cdot \Delta t$ as edges.

Constructing a *Constraint Graph*



Step 1 ● *Graph node*

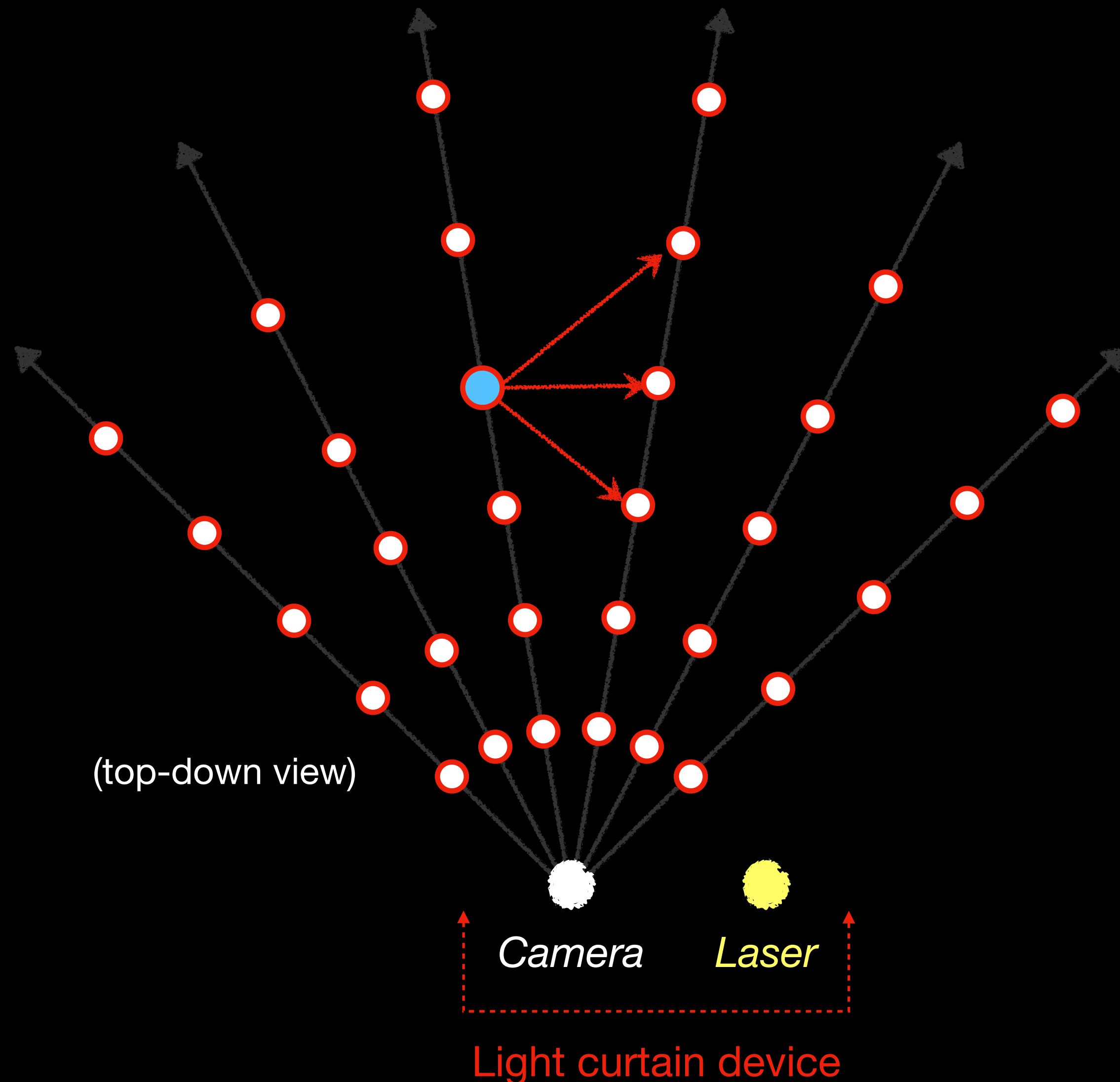
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Constructing a *Constraint Graph*



Step 1 ● *Graph node*

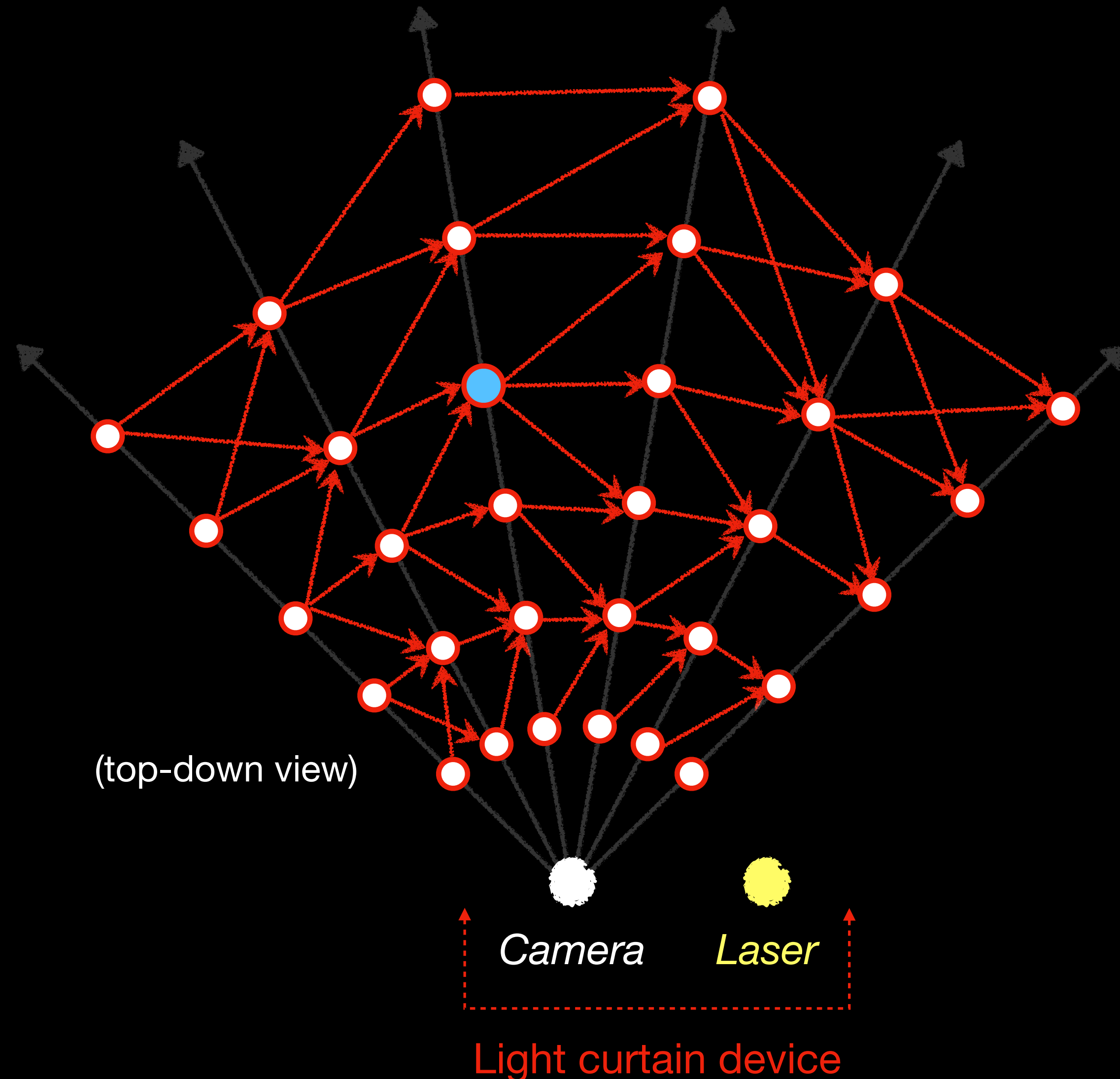
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Constructing a *Constraint Graph*



Step 1 ● *Graph node*

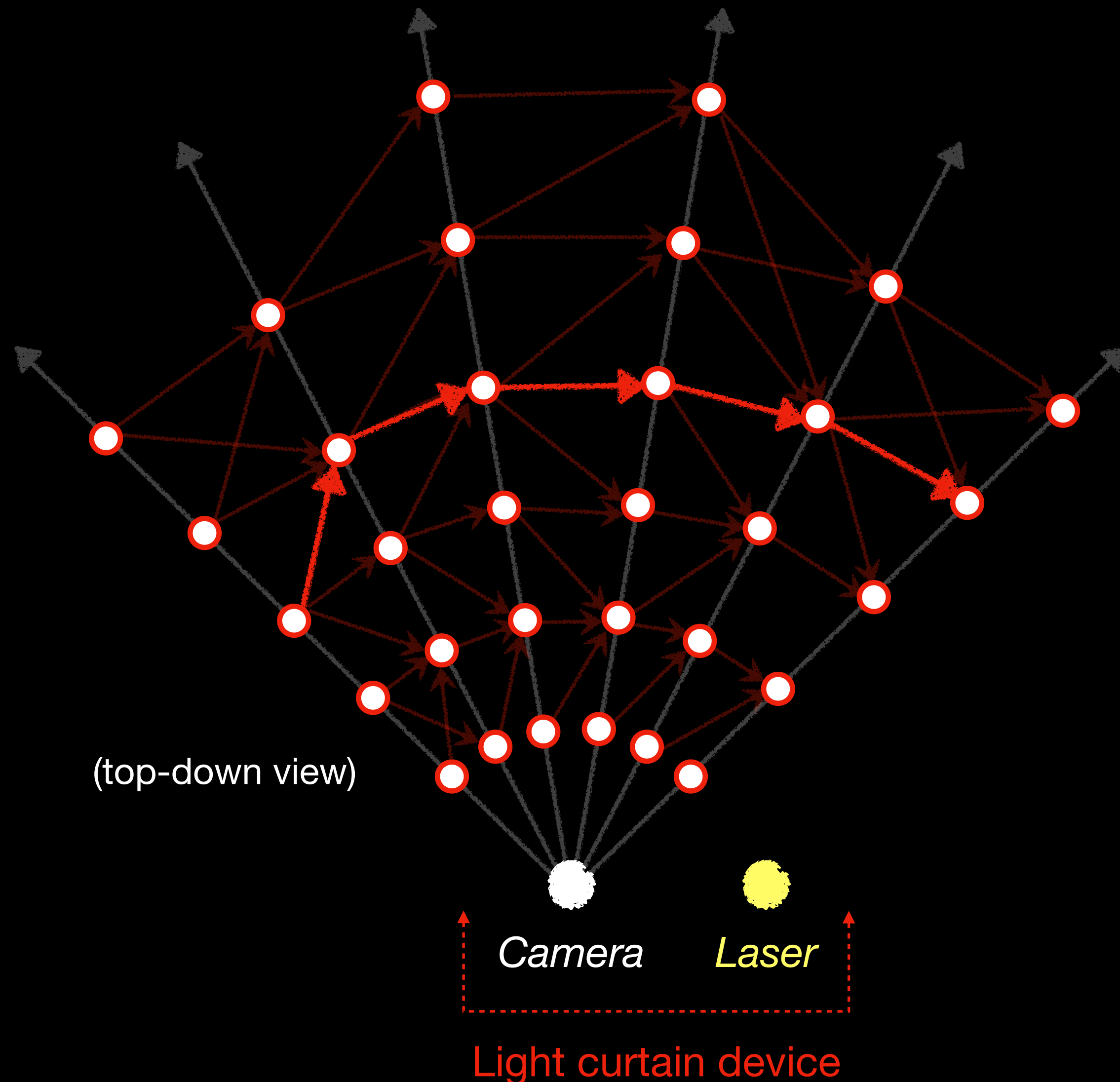
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Constructing a *Constraint Graph*



Step 1 ● *Graph node*

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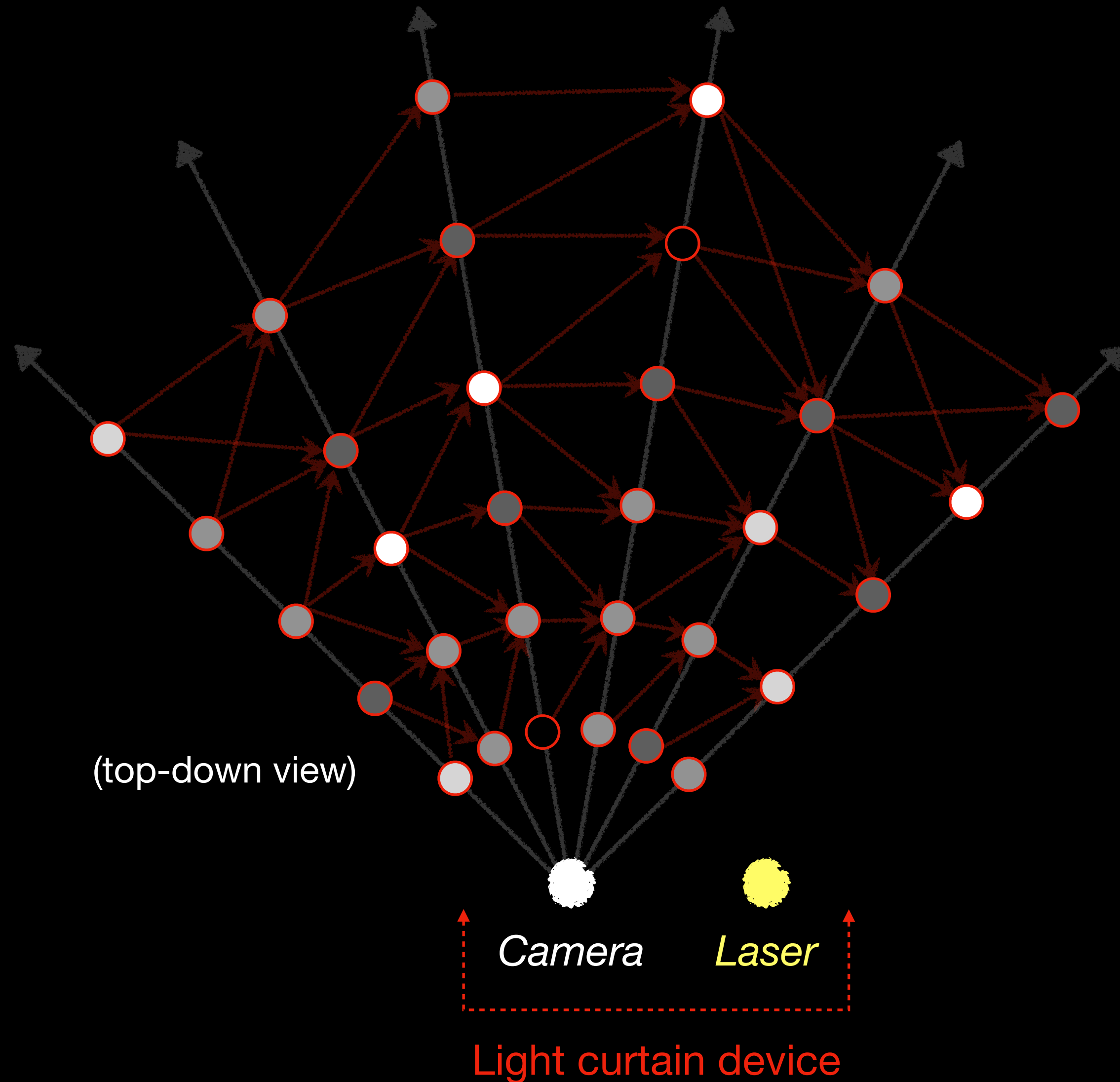
Step 2 → *Graph edge*

For each node, consider all nodes on the next ray.

Add those nodes that satisfy the velocity constraint $\theta_{\text{las}} \leq \omega_{\text{max}} \cdot \Delta t$ as edges.

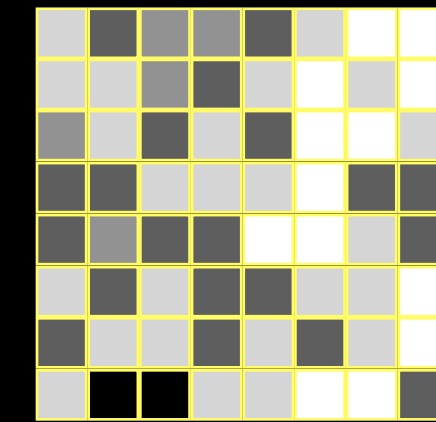
Then, any path in the graph is a *valid curtain!*

Uncertainty maximizing Light Curtain



Step 1 ● Graph node → Graph edge
Construct the constraint graph

Step 2 Assign uncertainty to each node by interpolating from the uncertainty map

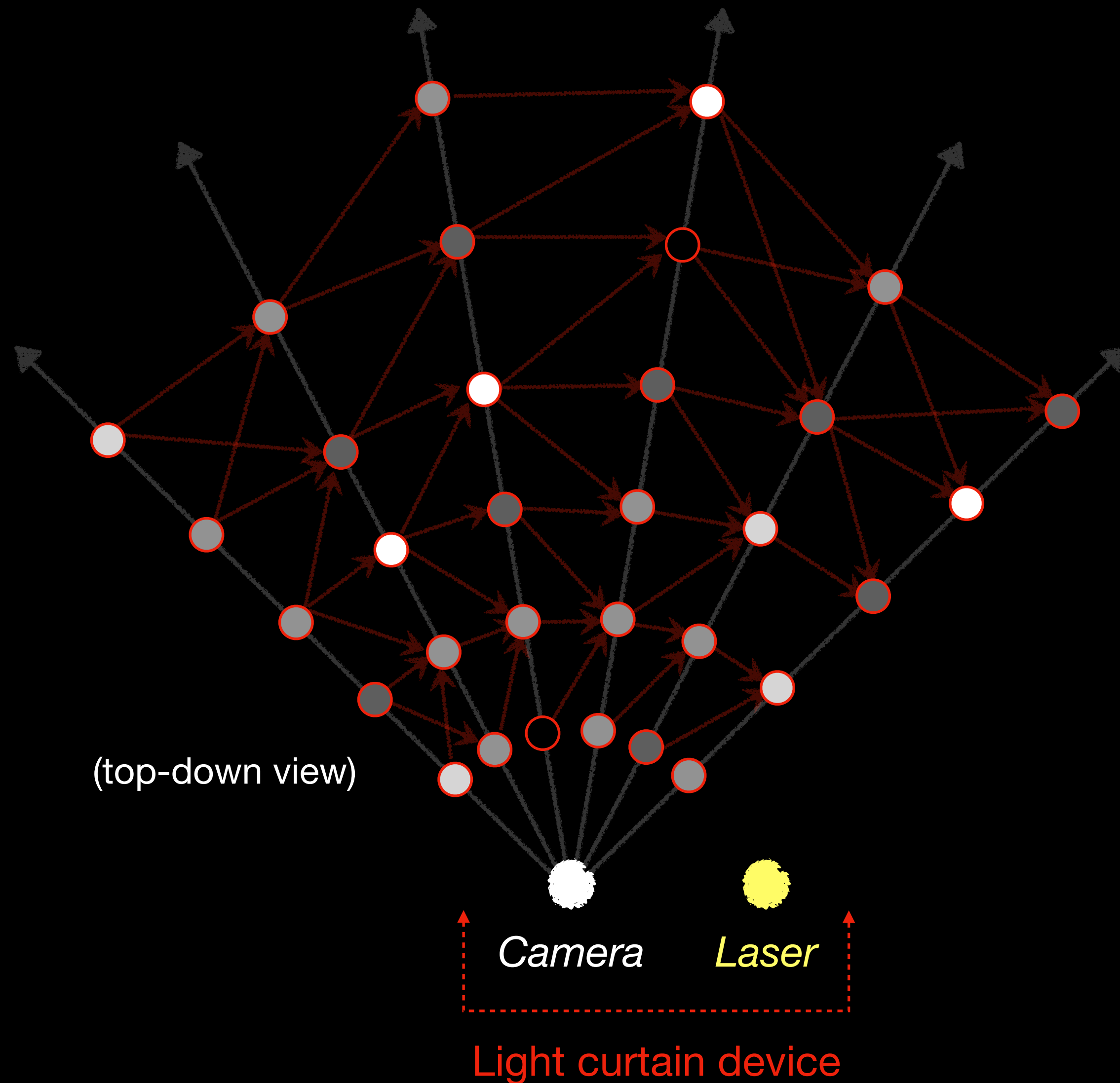


Step 3 Perform dynamic programming

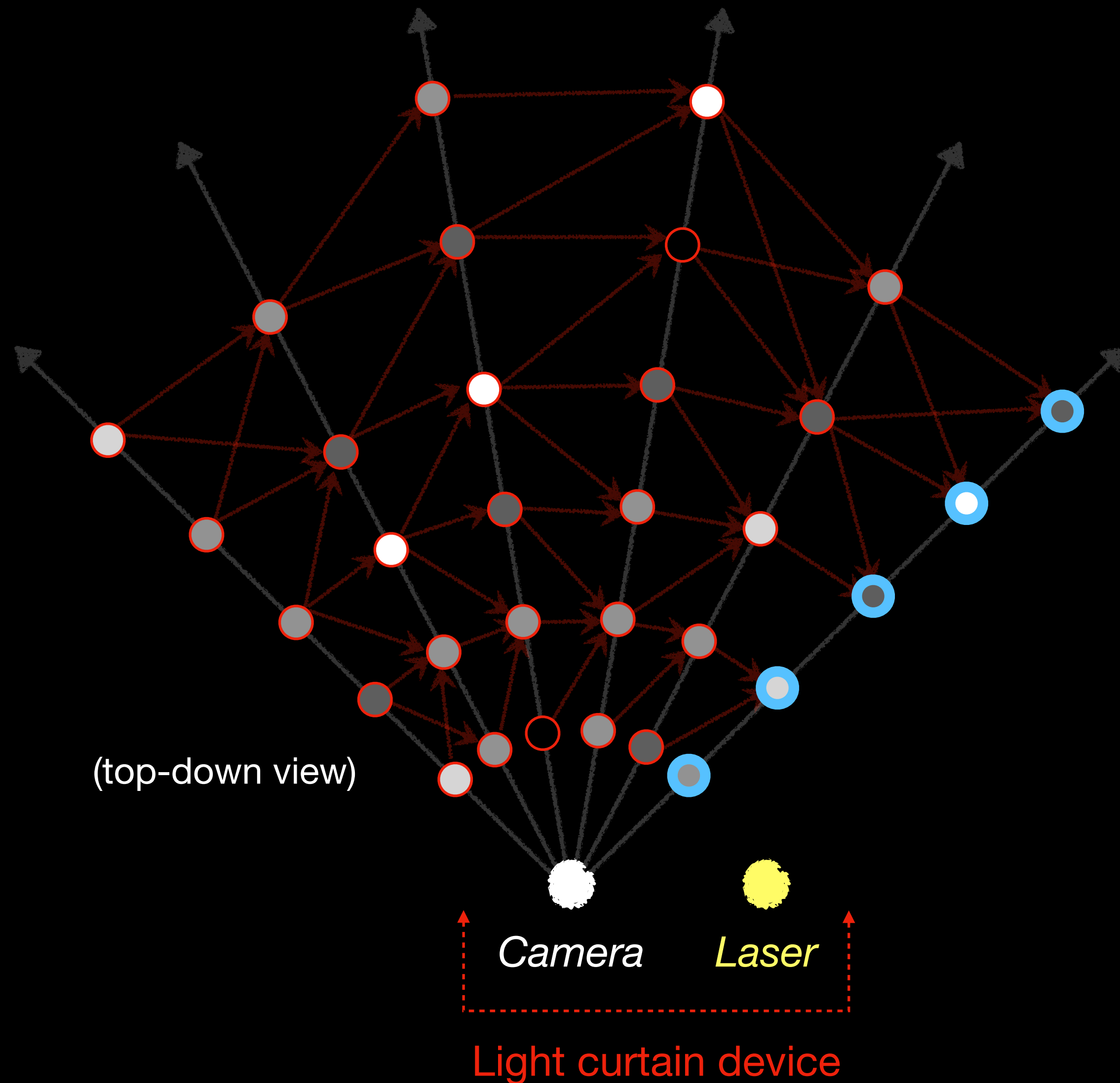
Dynamic Programming

● Graph node → Graph edge

For each node, find the partial curtain starting from that node that maximizes sum of uncertainties



Dynamic Programming

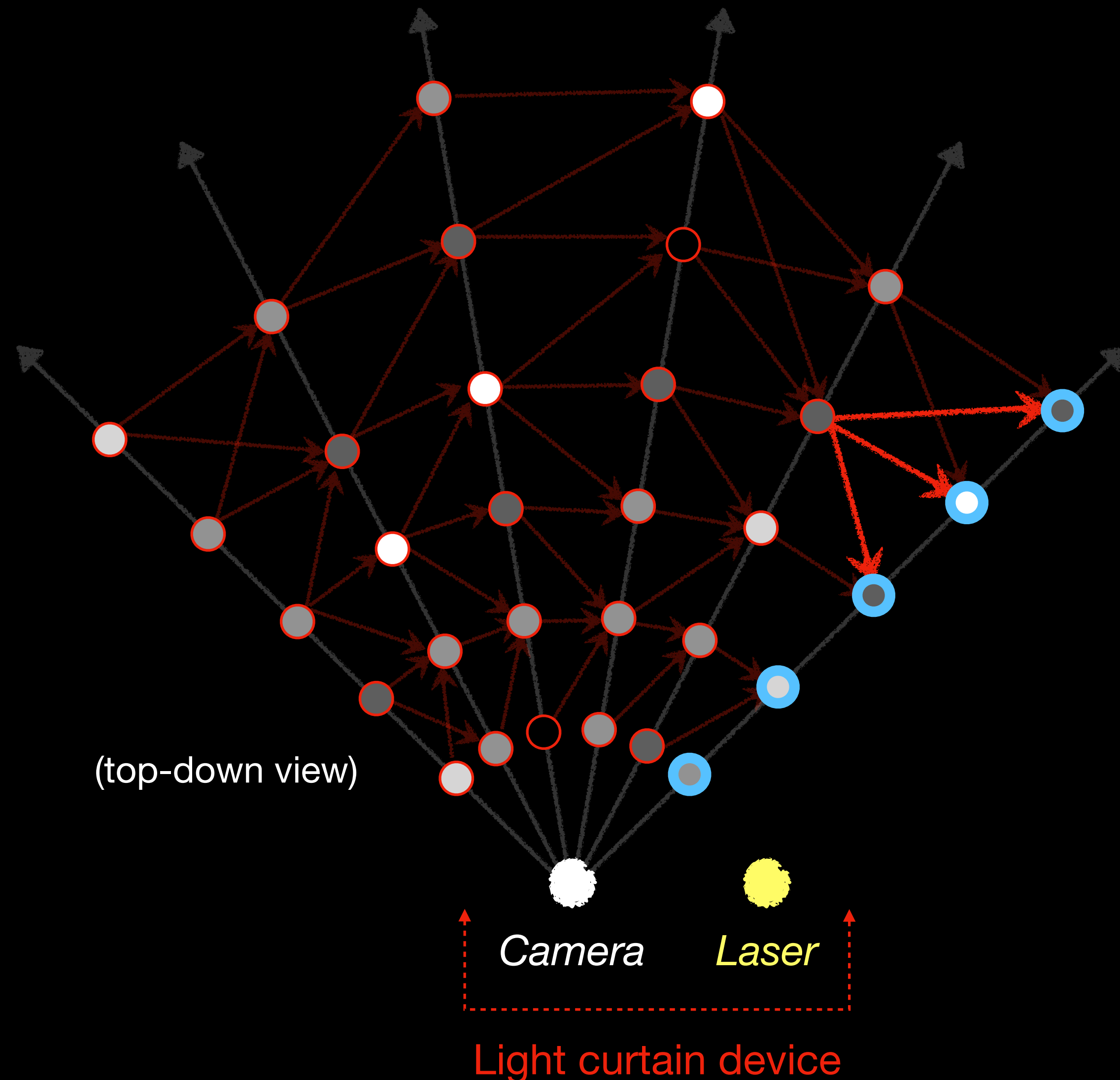


● Graph node → Graph edge

For each node, find the partial curtain starting from that node that maximizes sum of uncertainties

- Start from nodes on rightmost ray. Partial curtain starts and ends there.

Dynamic Programming

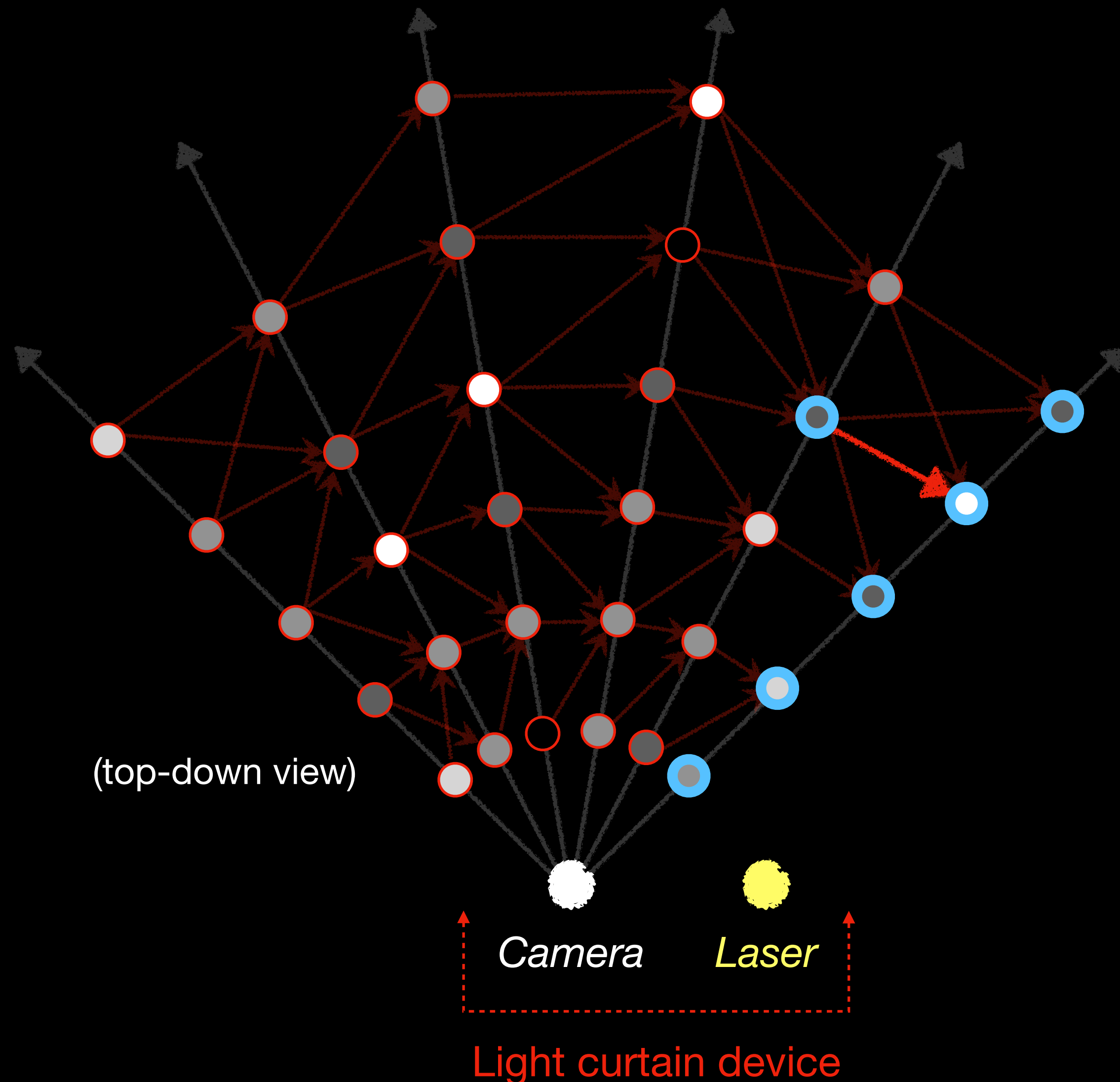


● Graph node → Graph edge

For each node, find the partial curtain starting from that node that maximizes sum of uncertainties

- *Start from nodes on rightmost ray. Partial curtain starts and ends there.*
- *For each node in the previous ray*
 - *Look at all its edges →*

Dynamic Programming

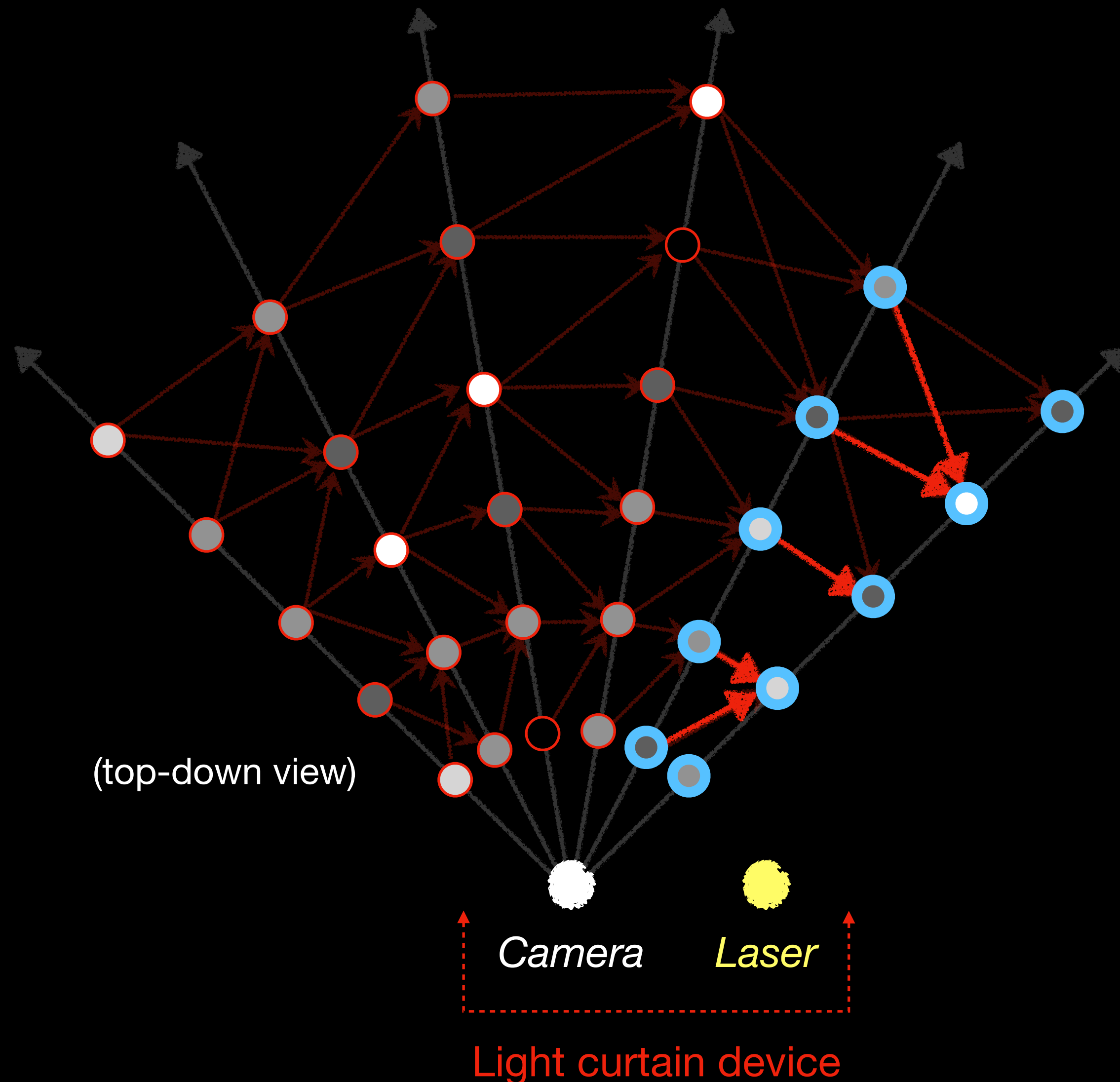


○ Graph node → Graph edge

For each node, find the partial curtain starting from that node that maximizes sum of uncertainties

- *Start from nodes on rightmost ray. Partial curtain starts and ends there.*
- *For each node in the previous ray*
 - *Look at all its →*
 - *Select the one with highest uncertainty. Add own uncertainty to the sum.*

Dynamic Programming

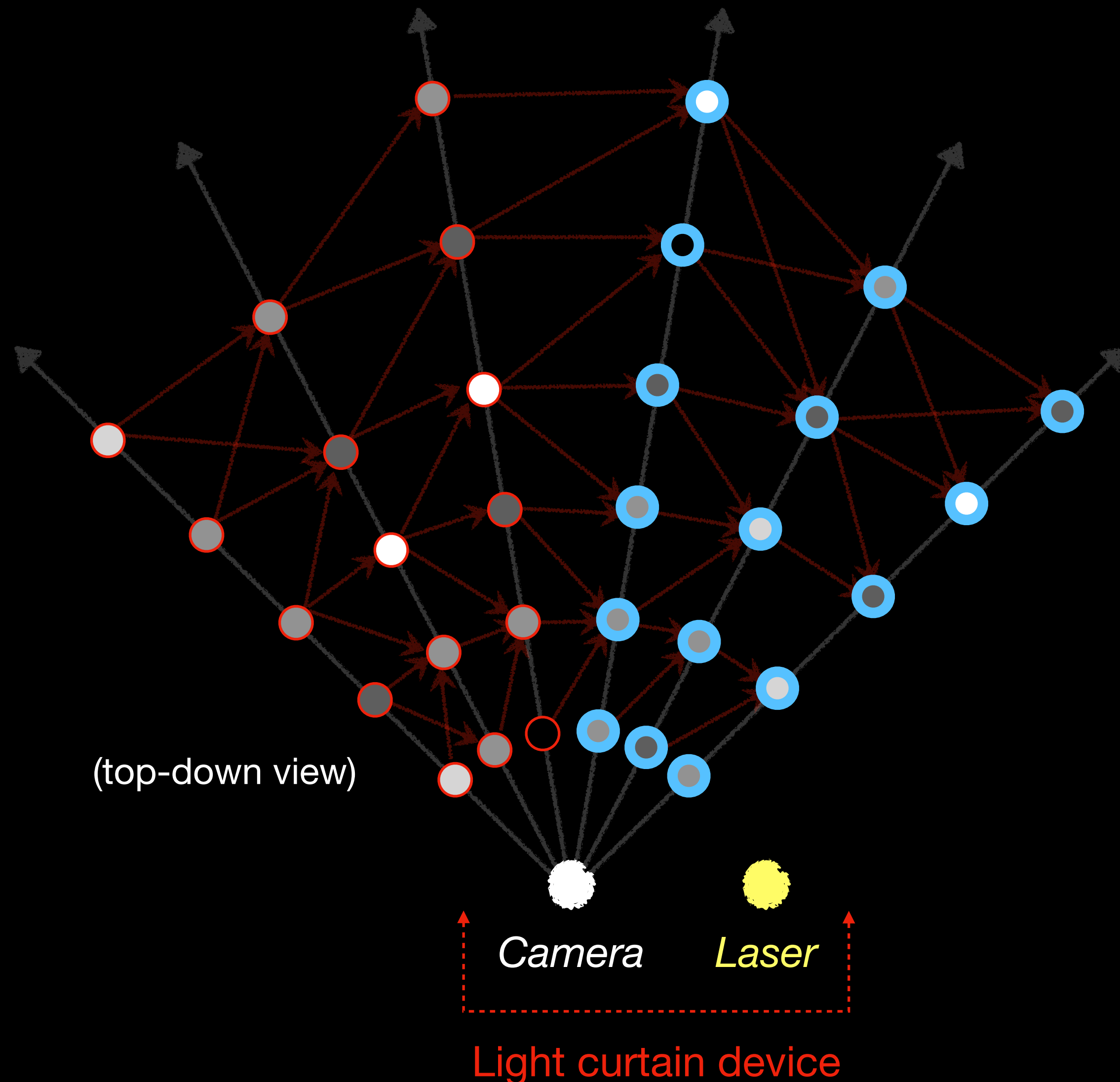


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For each node, find the partial curtain starting from that node that maximizes sum of uncertainties

- *Start from nodes on rightmost ray. Partial curtain starts and ends there.*
- *For each node in the previous ray*
 - *Look at all its →*
 - *Select the one with highest uncertainty. Add own uncertainty to the sum.*
 - *Repeat for all nodes in ray*

Dynamic Programming

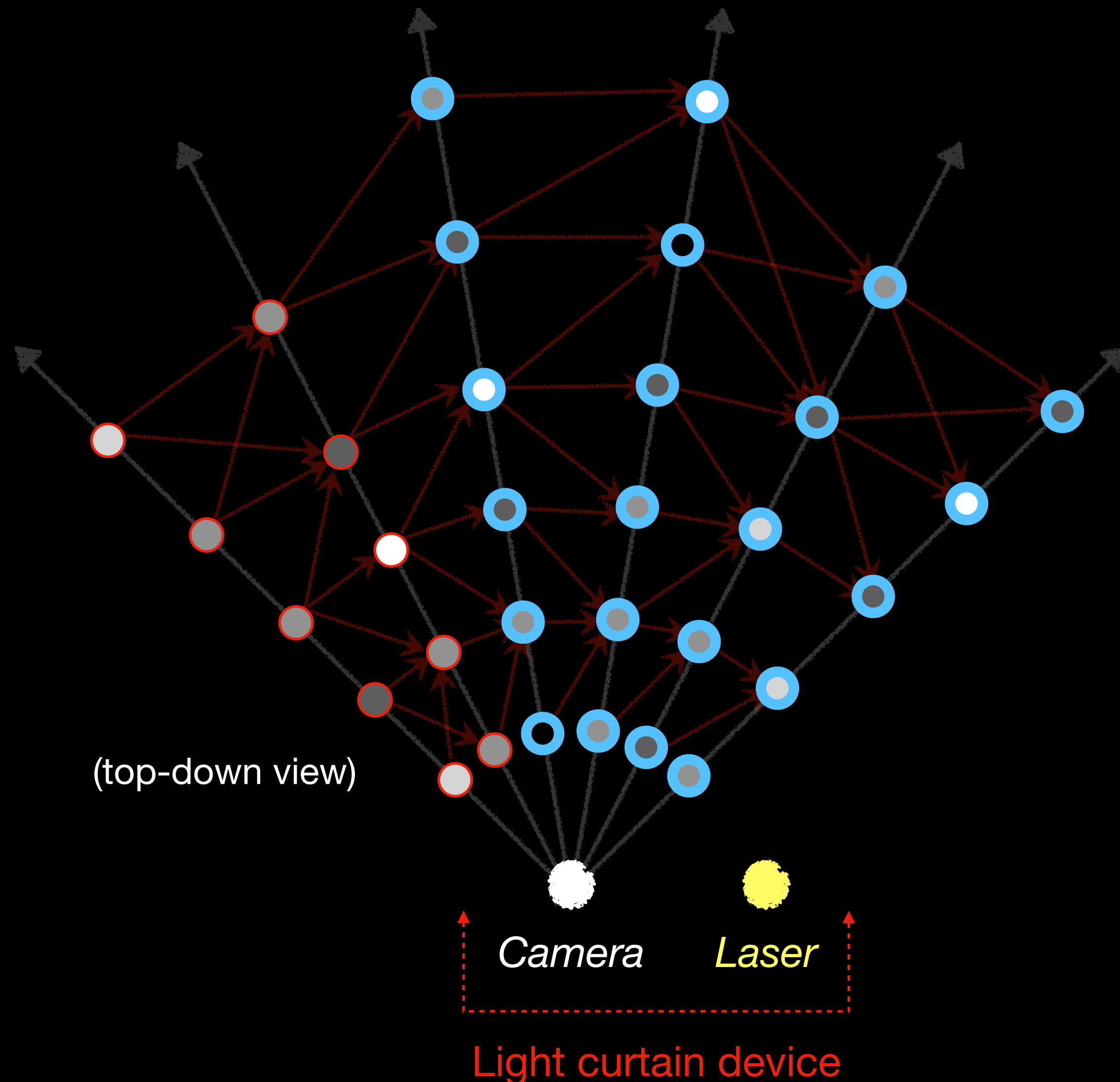


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 - *Repeat for all nodes in ray*
- *Repeat over each previous ray*

Dynamic Programming

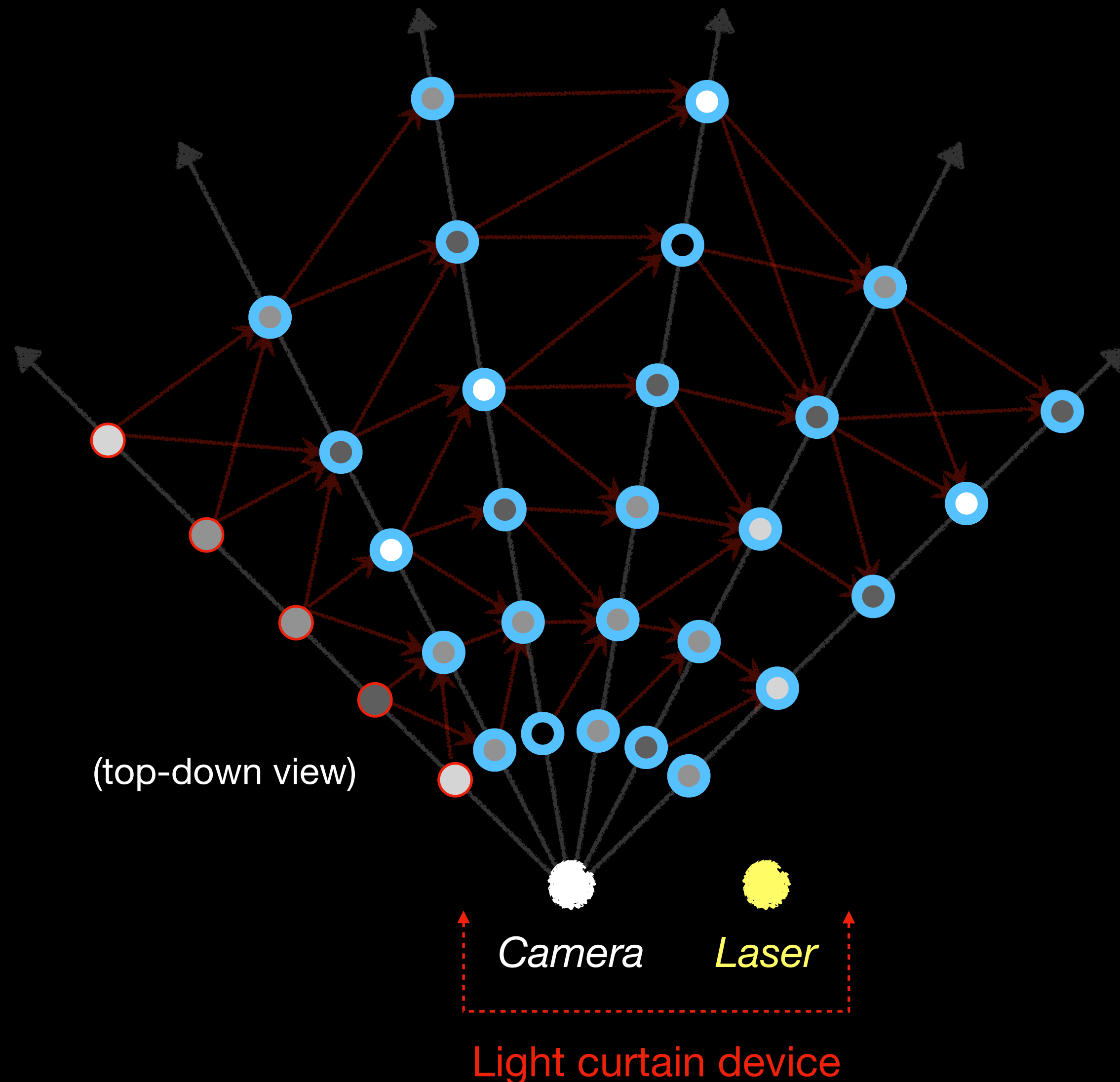


● Graph node → Graph edge

For each node, find the partial curtain starting from that node that maximizes sum of uncertainties

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 - *Repeat for all nodes in ray*
- *Repeat over each previous ray*

Dynamic Programming

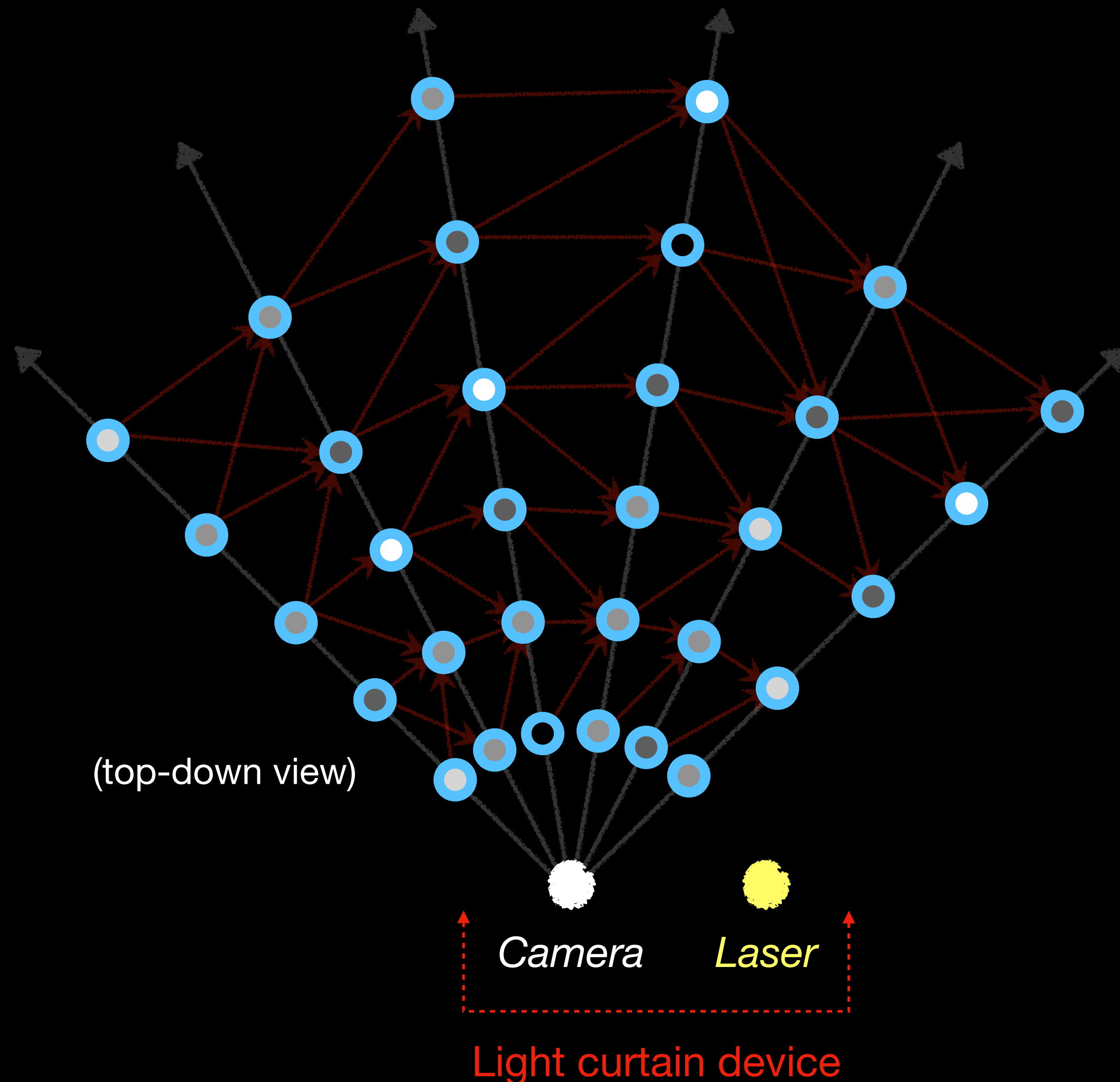


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- *Repeat over each previous ray*

Dynamic Programming

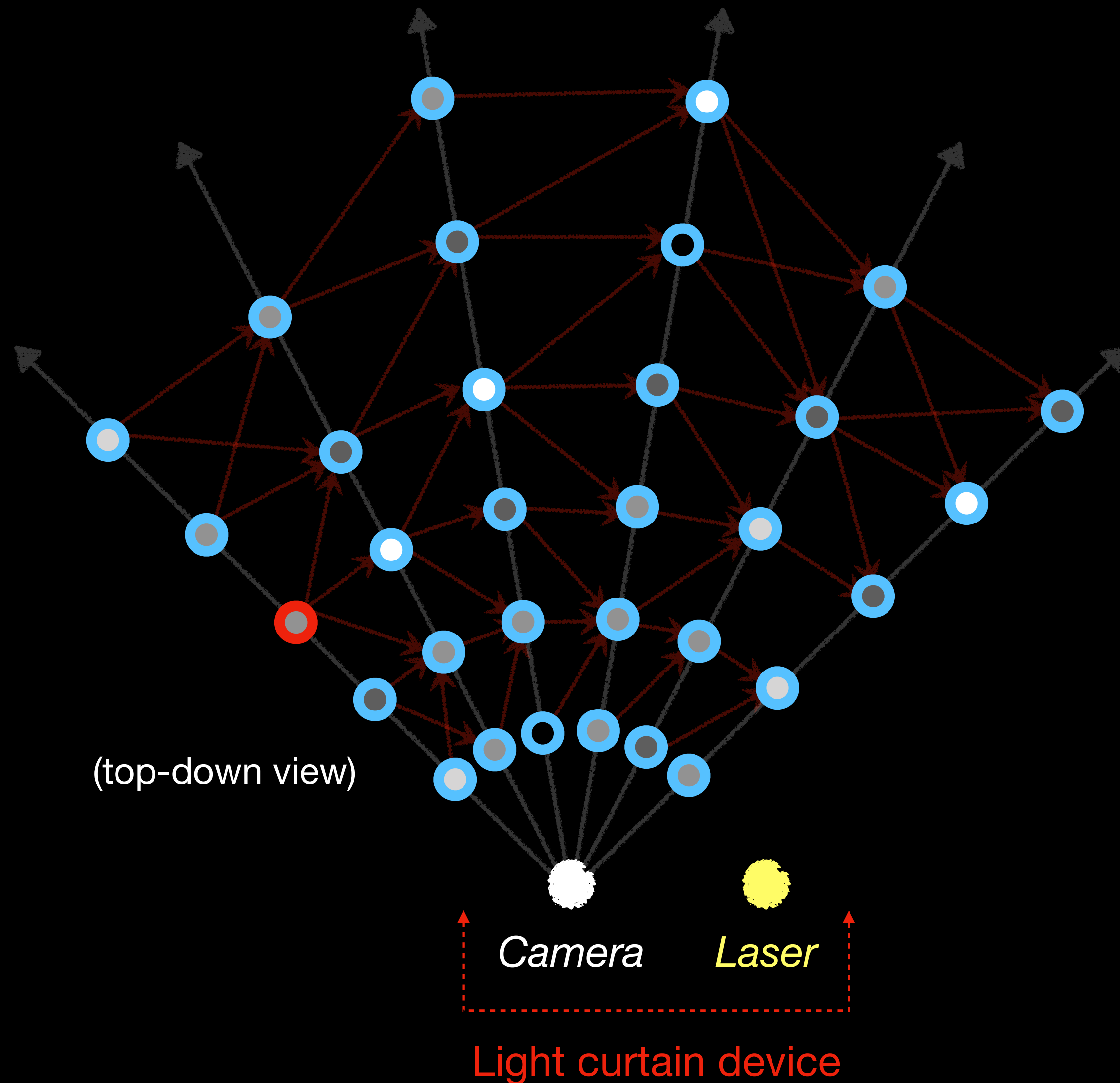


● Graph node → Graph edge

For each node, find the partial curtain starting from that node that maximizes sum of uncertainties

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 - *Select the one with highest uncertainty. Add own uncertainty to the sum.*
 - *Repeat for all nodes in ray*
- *Repeat over each previous ray*

Dynamic Programming

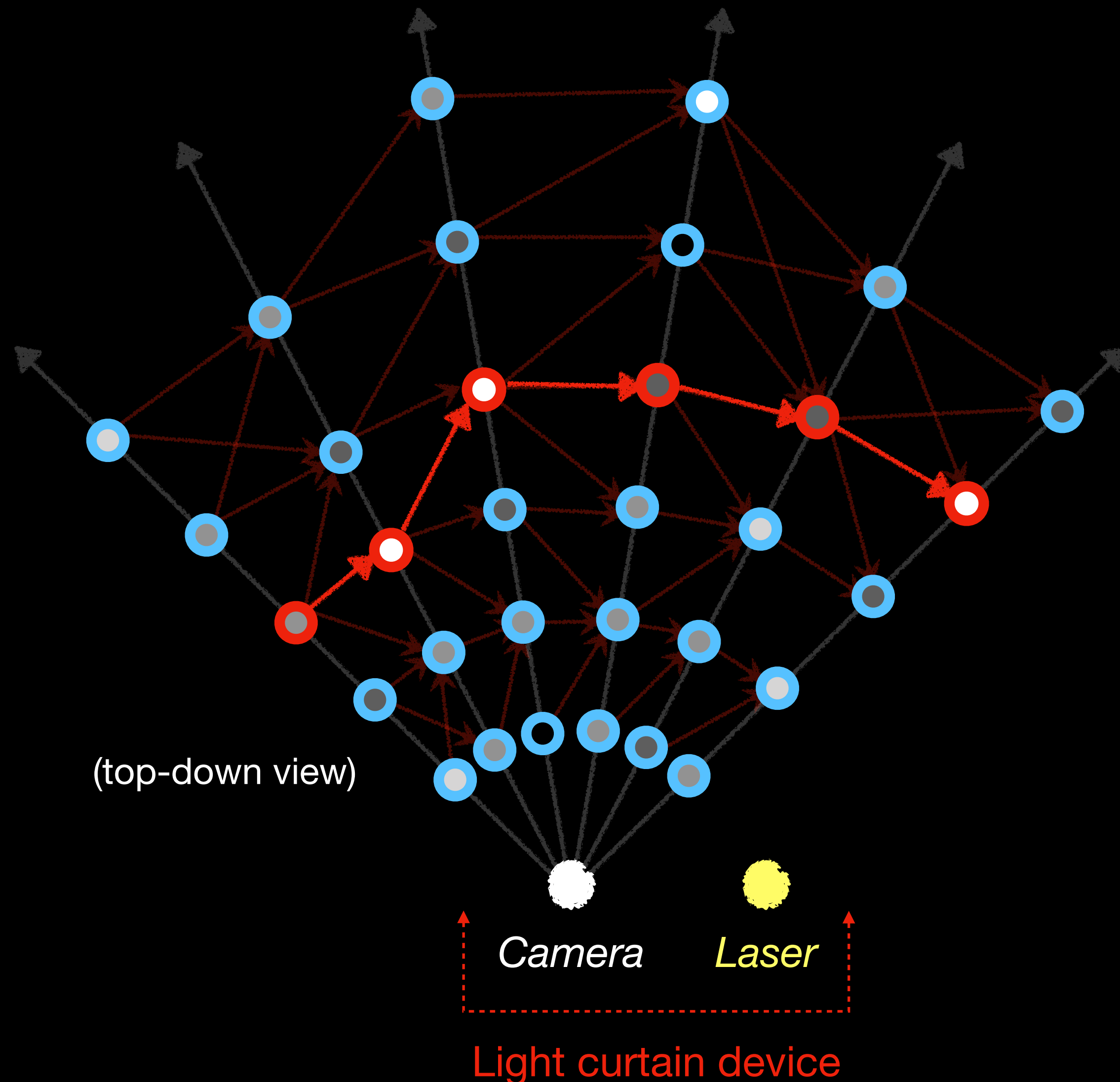


● Graph node → Graph edge

For each node, find the partial curtain starting from that node that maximizes sum of uncertainties

- Select the ● in the first ray that has the highest sum.

Dynamic Programming



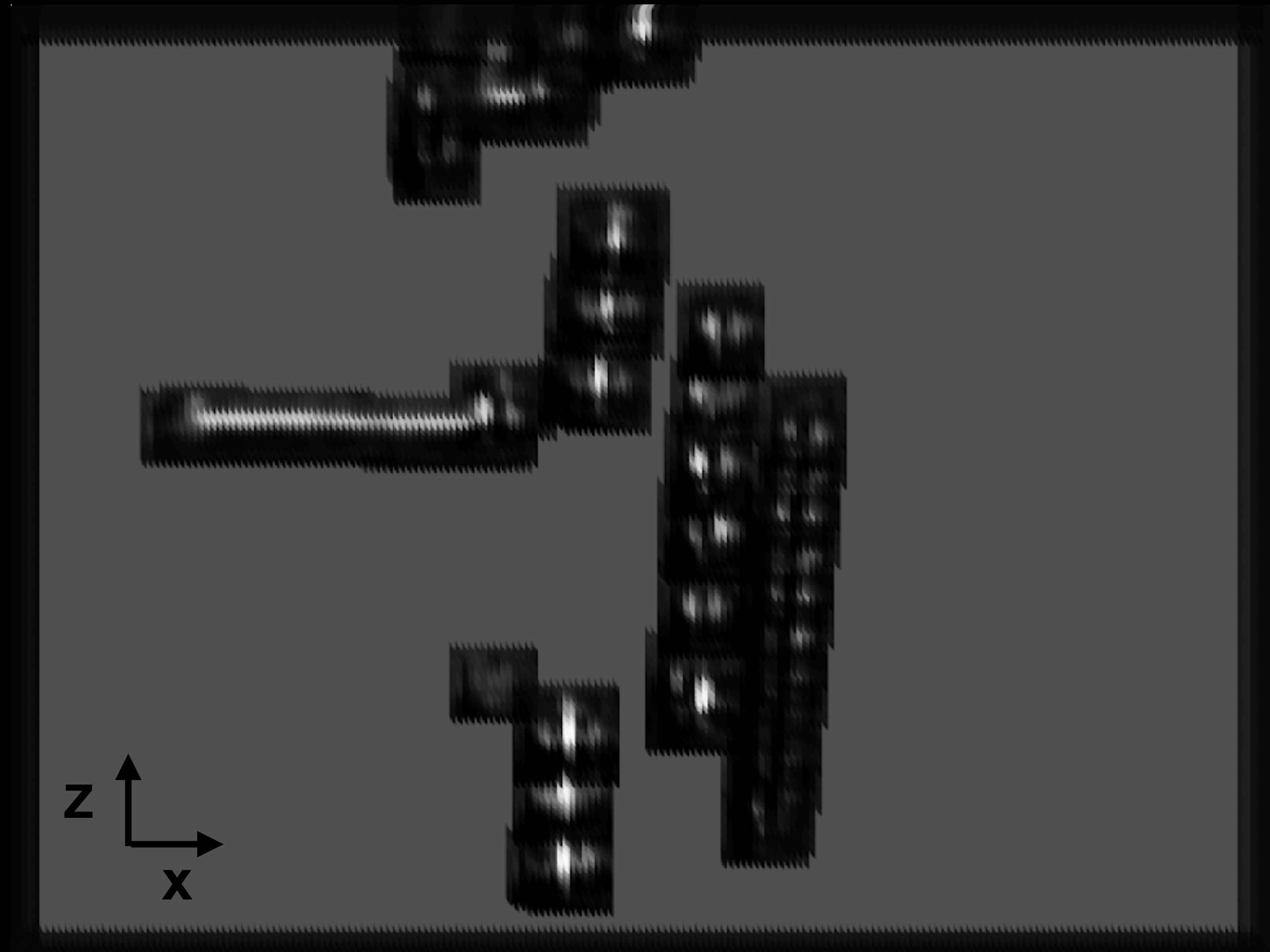
● Graph node → Graph edge

For each node, find the partial curtain starting from that node that maximizes sum of uncertainties

- Select the ● in the first ray that has the highest sum.
- Backtrack connecting each node to its best neighbor.

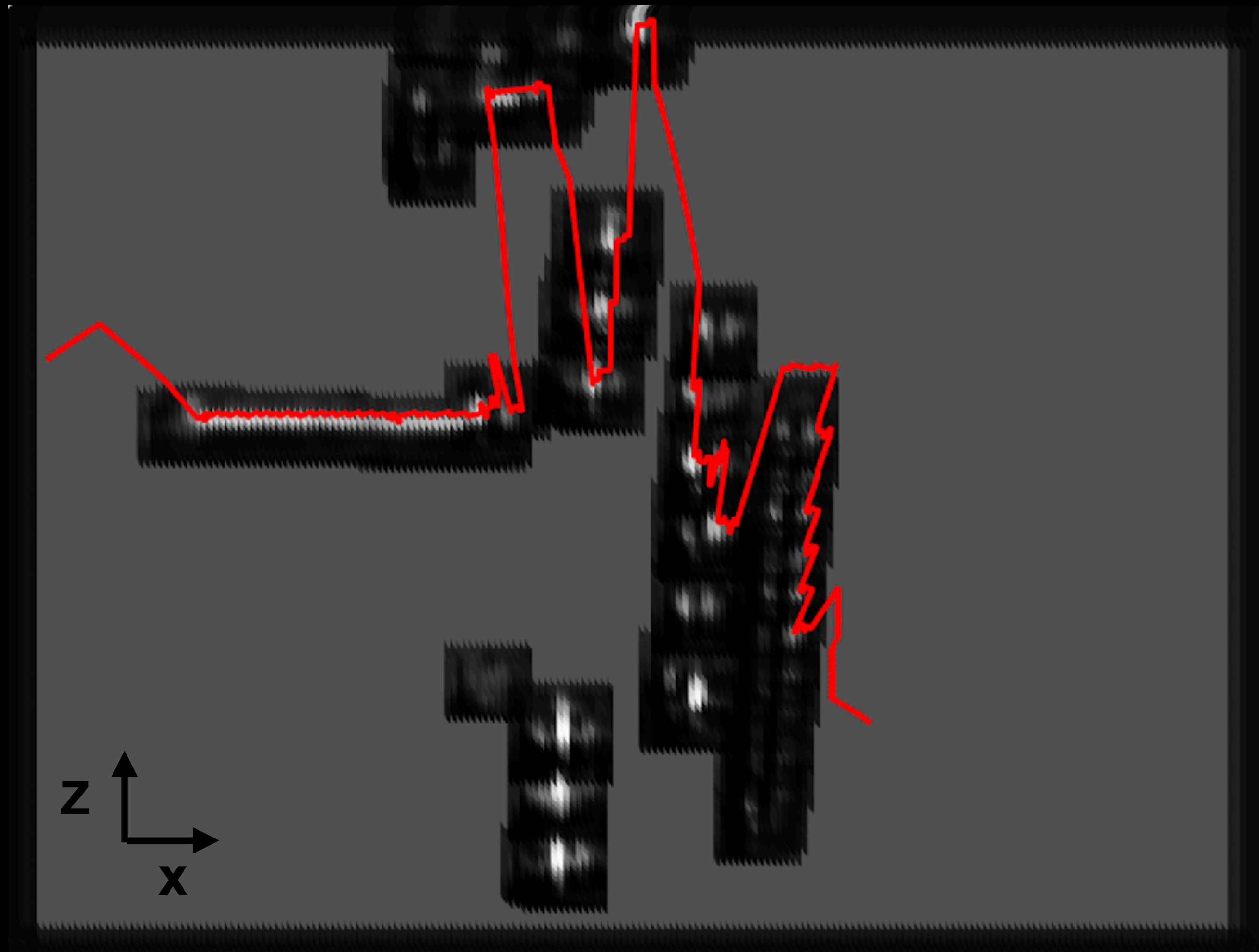
This is the light curtain that maximizes the sum of uncertainties!

Result



Uncertainty map
(top-down view)

Result

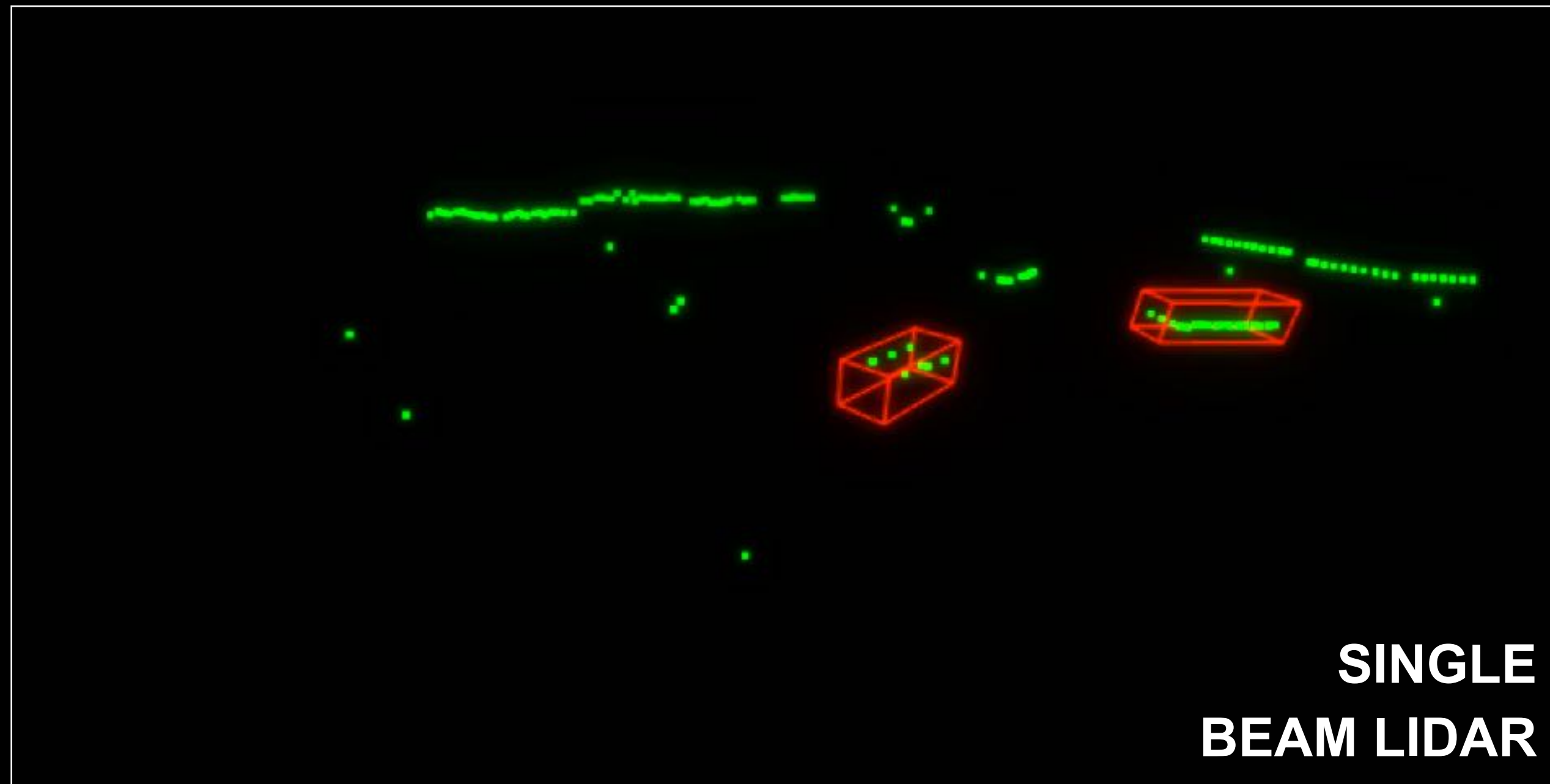
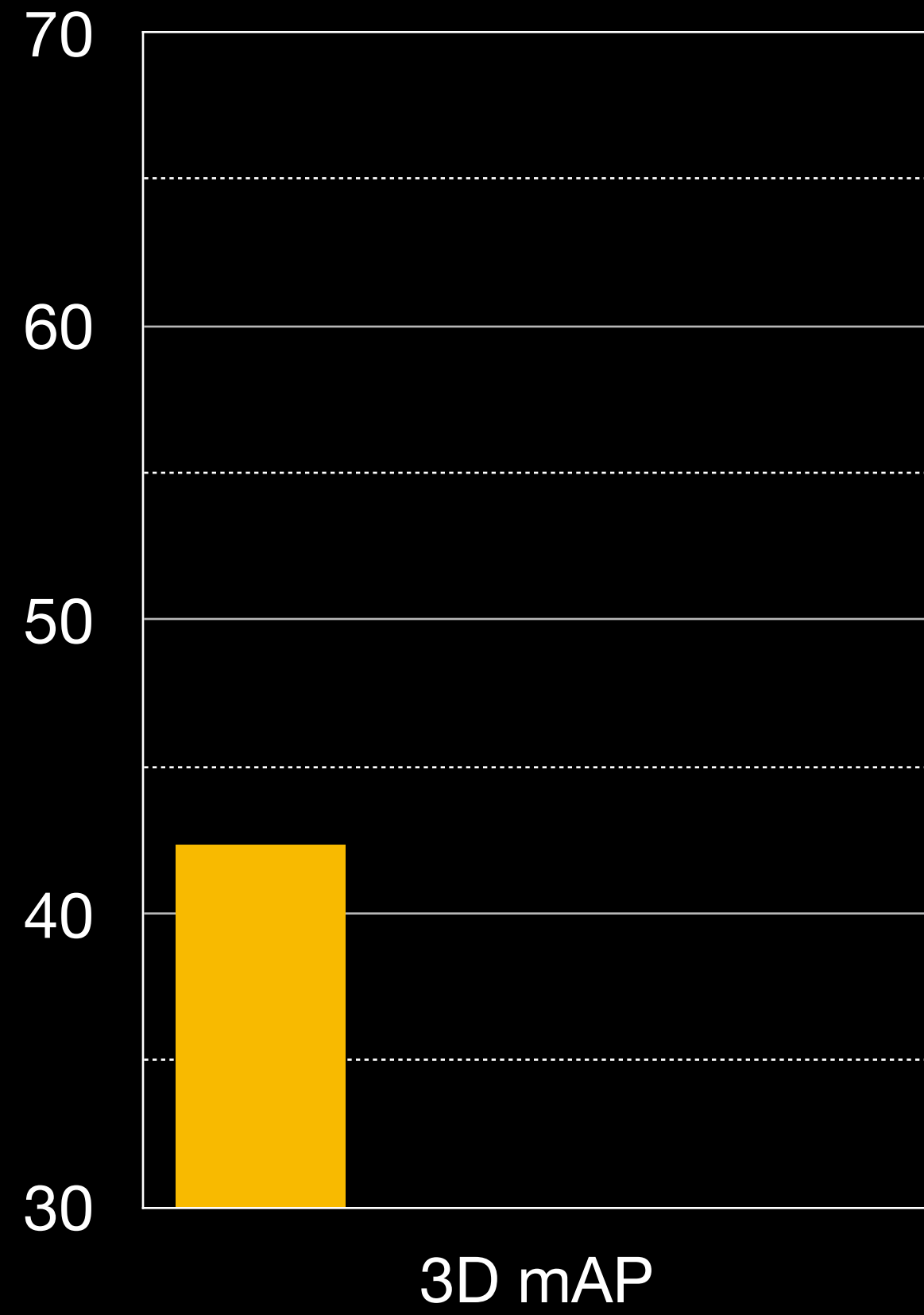


Uncertainty map
(top-down view)

Successive light curtain placements improve detection performance

Virtual KITTI

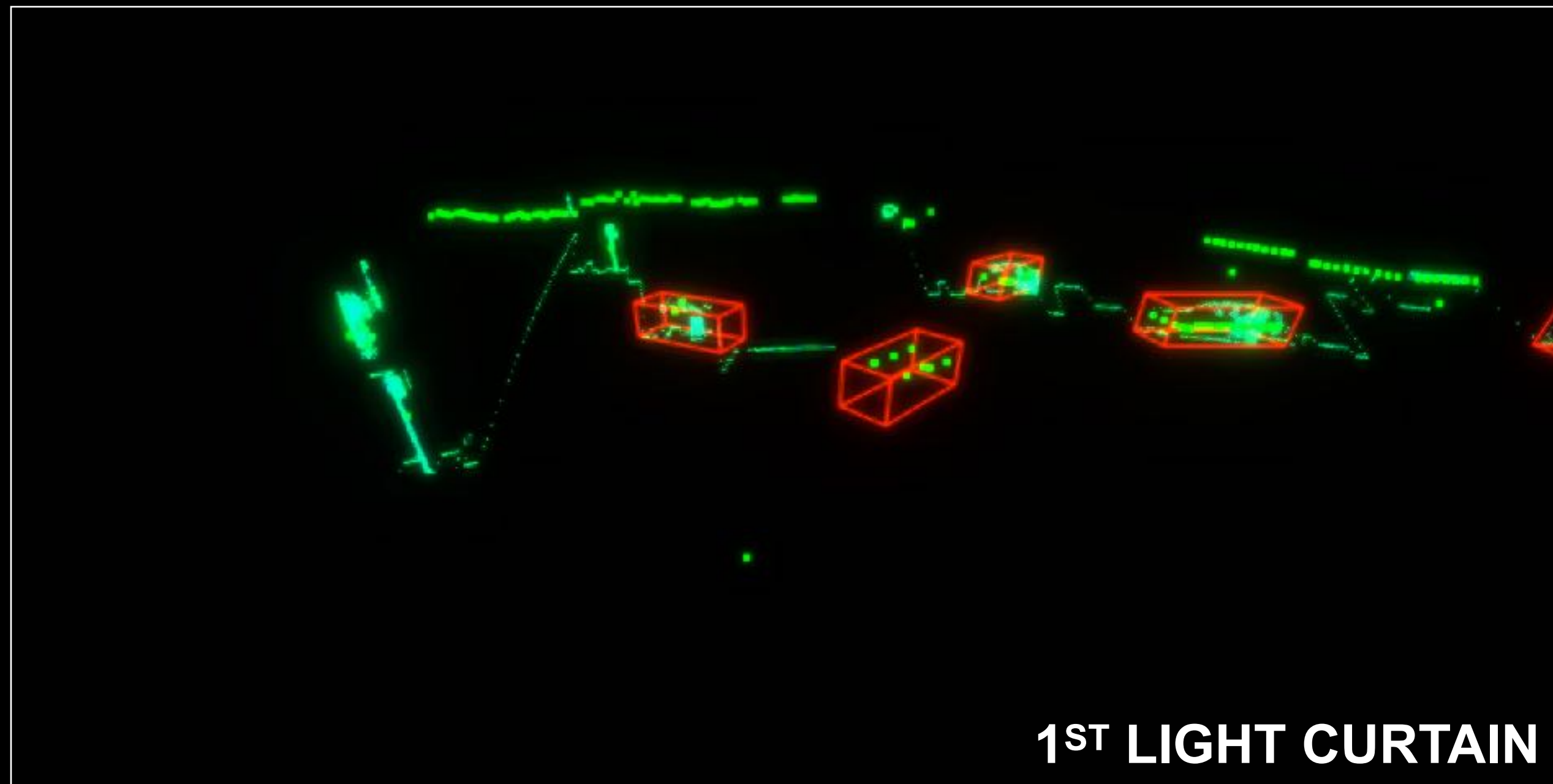
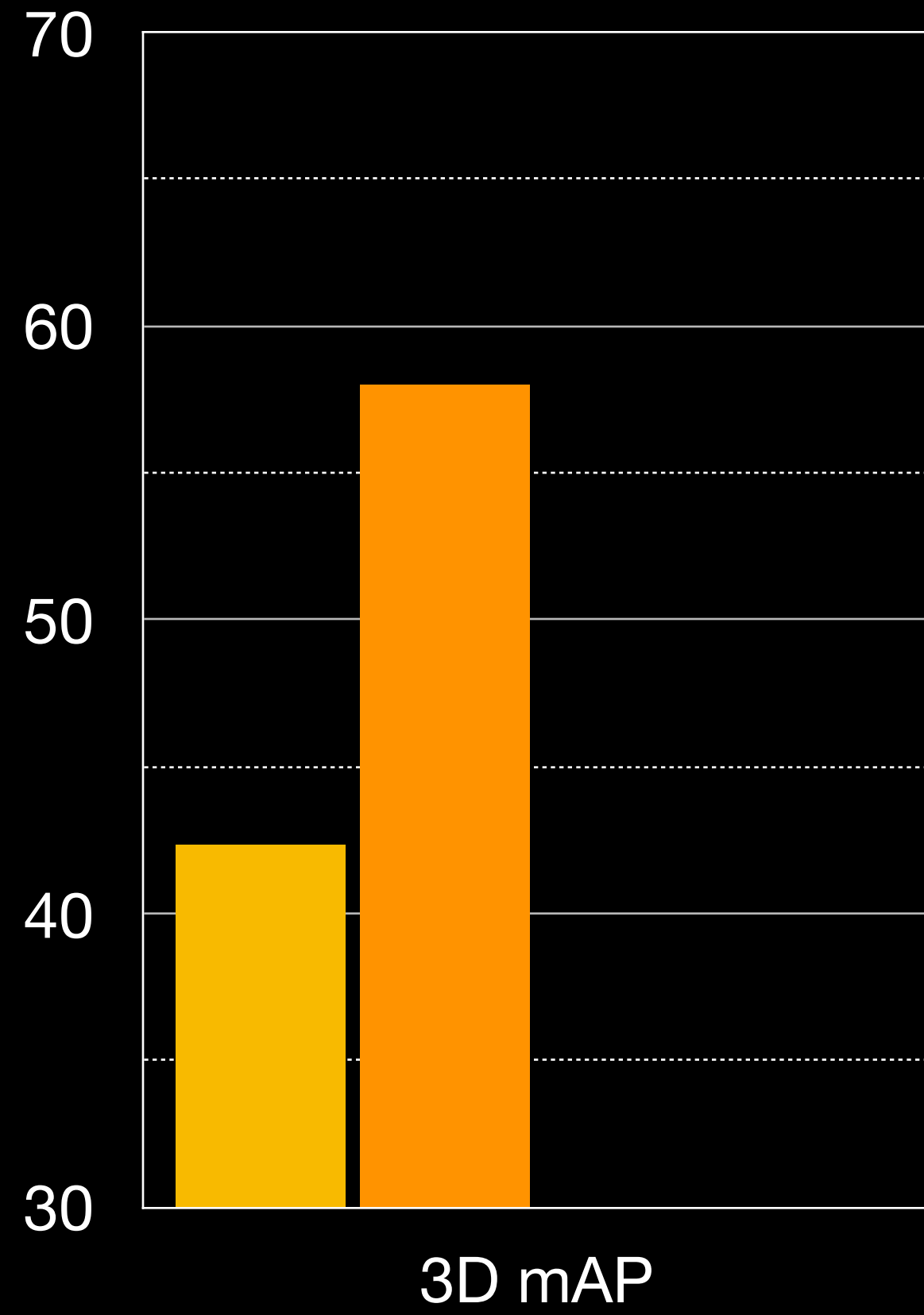
0.5 IoU



Successive light curtain placements improve detection performance

Virtual KITTI

0.5 IoU



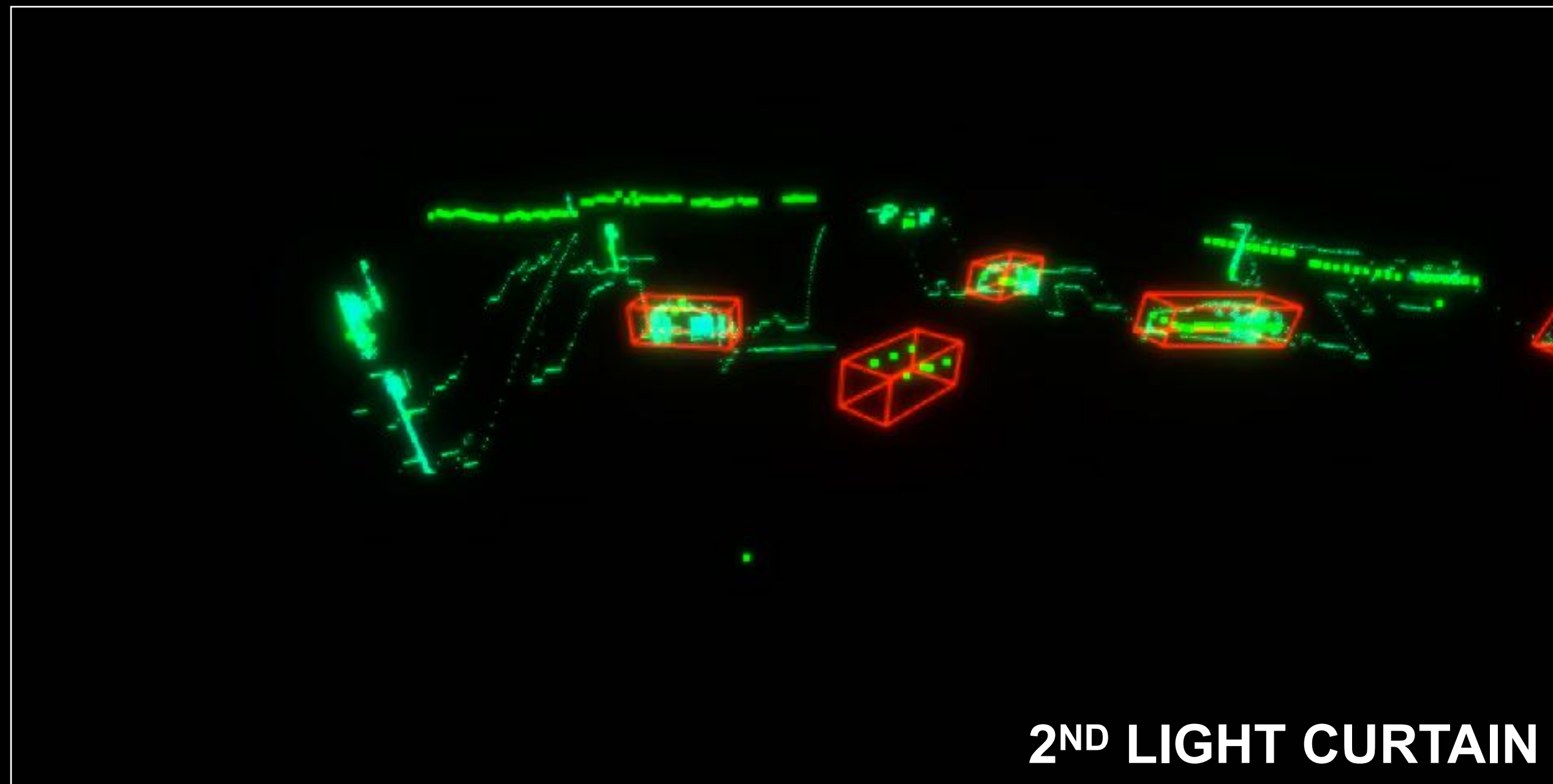
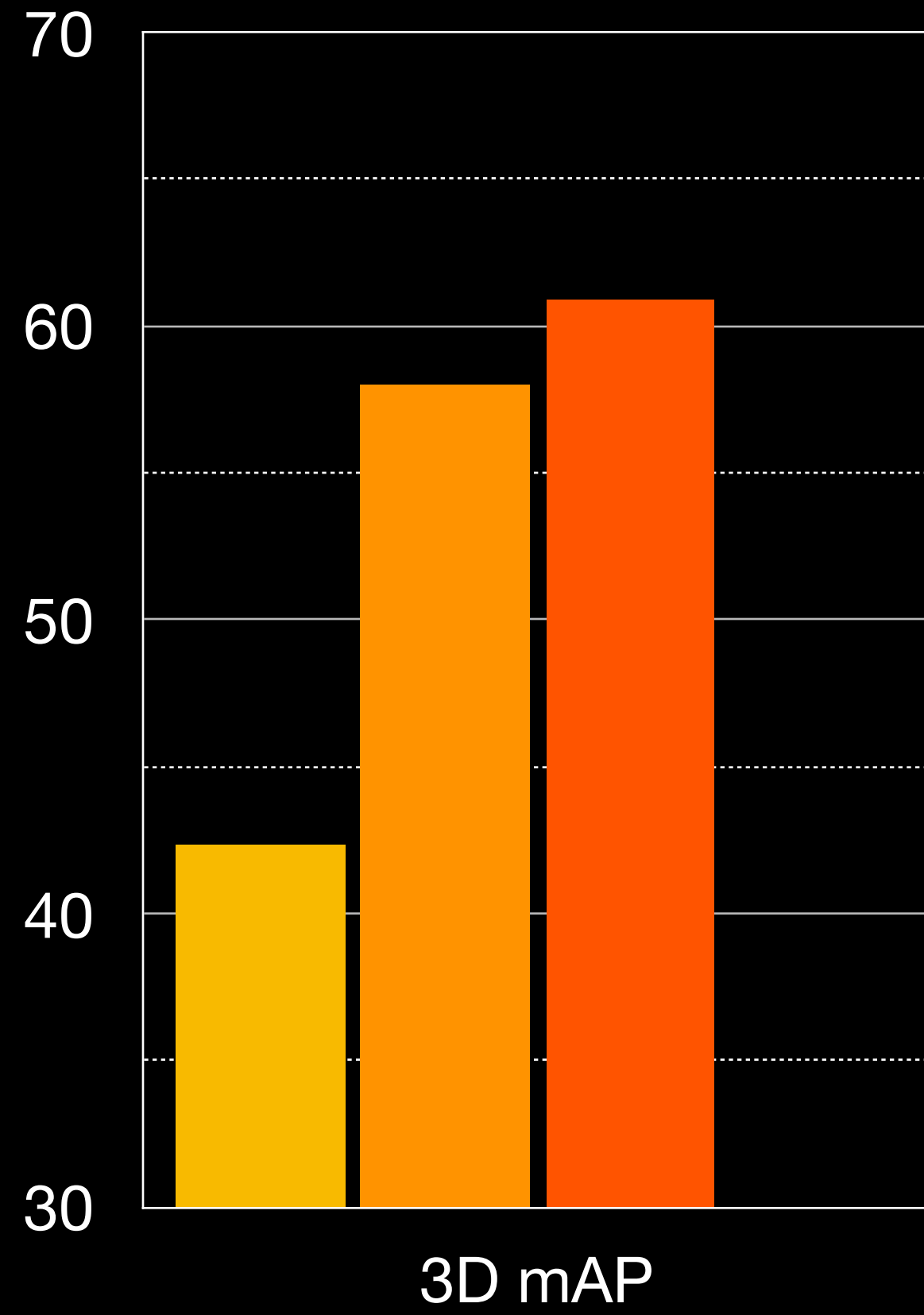
LiDAR

1 Light curtain

Successive light curtain placements improve detection performance

Virtual KITTI

0.5 IoU



LiDAR

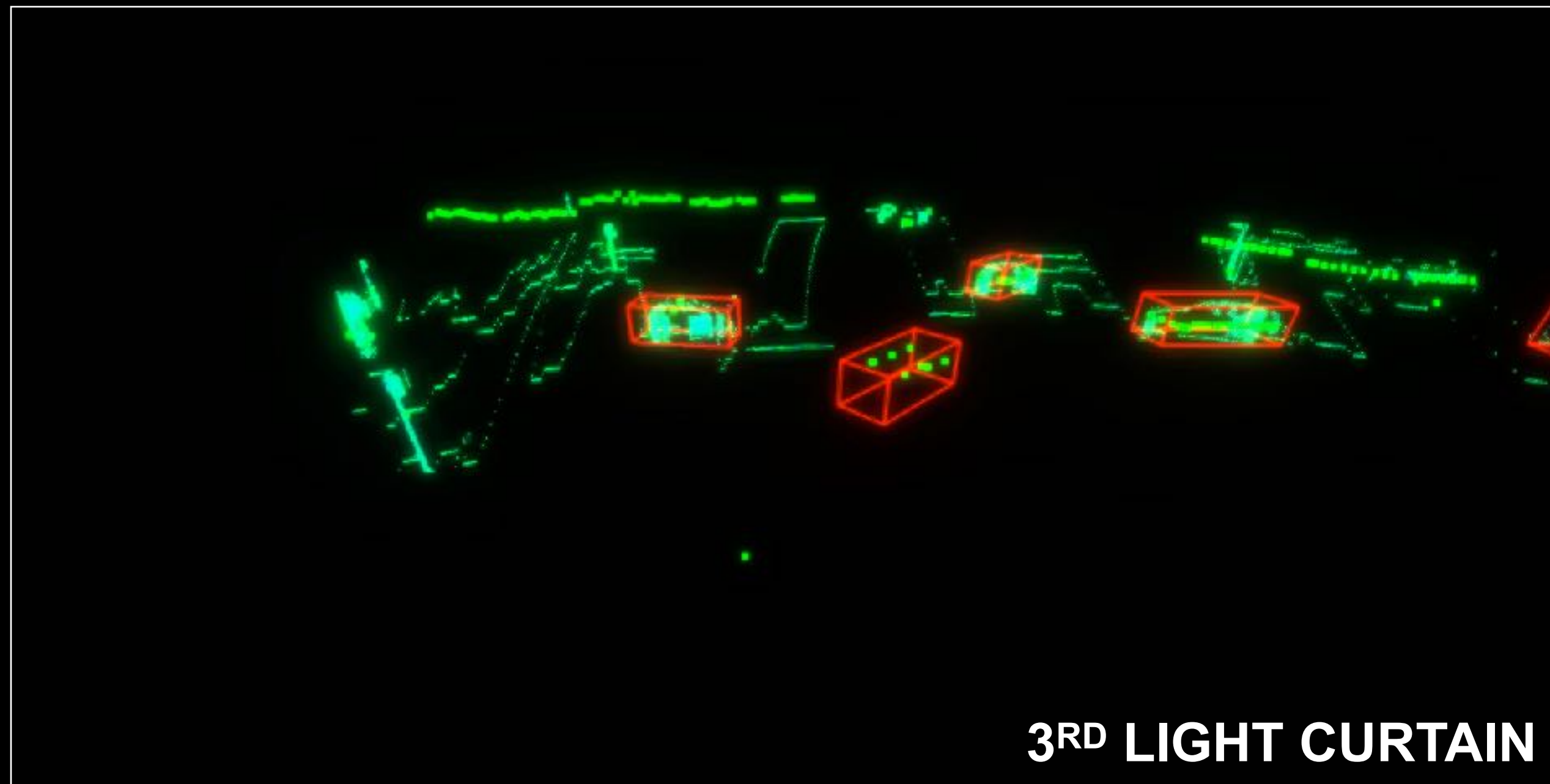
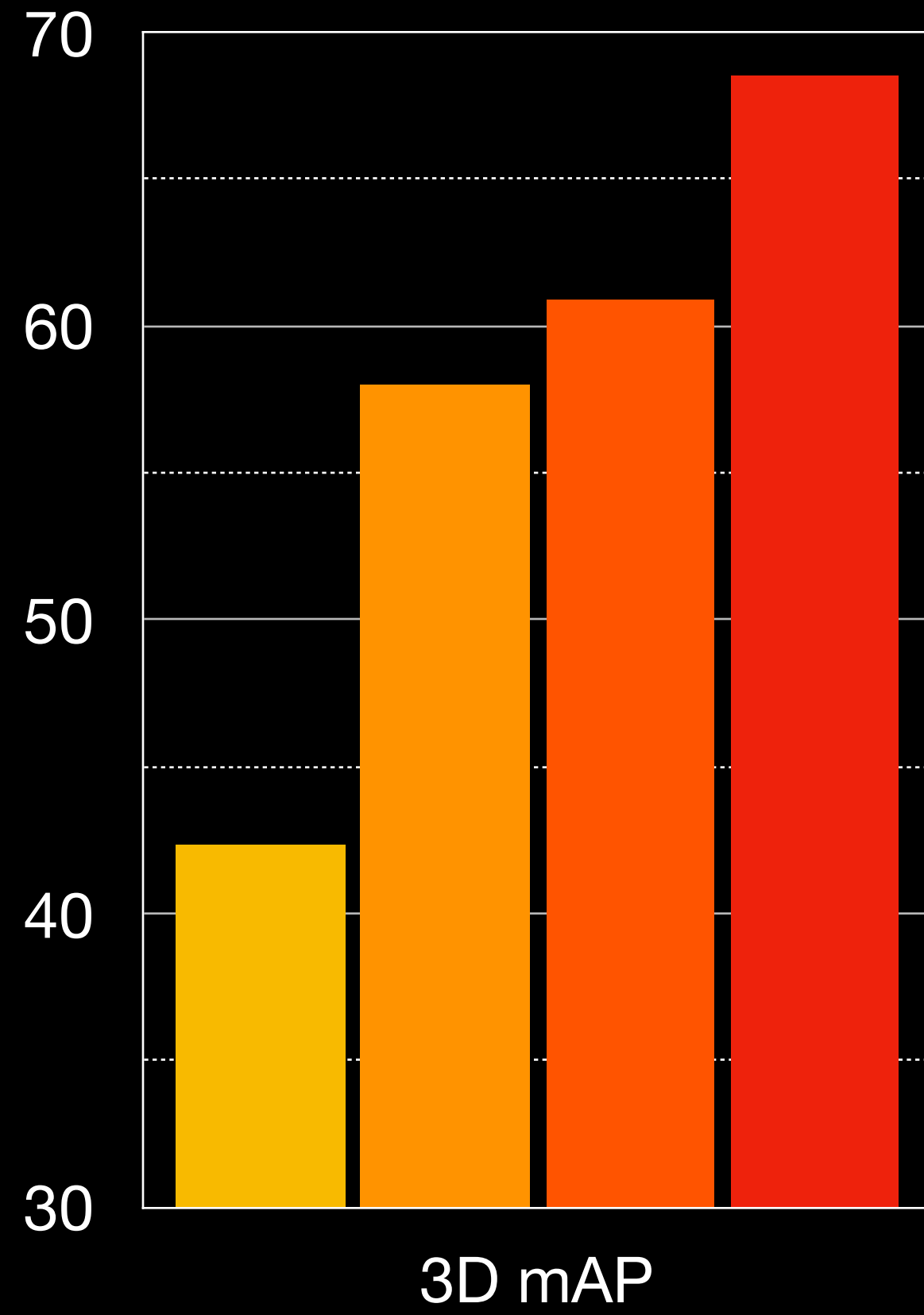
1 Light curtain

2 Light curtains

Successive light curtain placements improve detection performance

Virtual KITTI

0.5 IoU



LiDAR

1 Light curtain

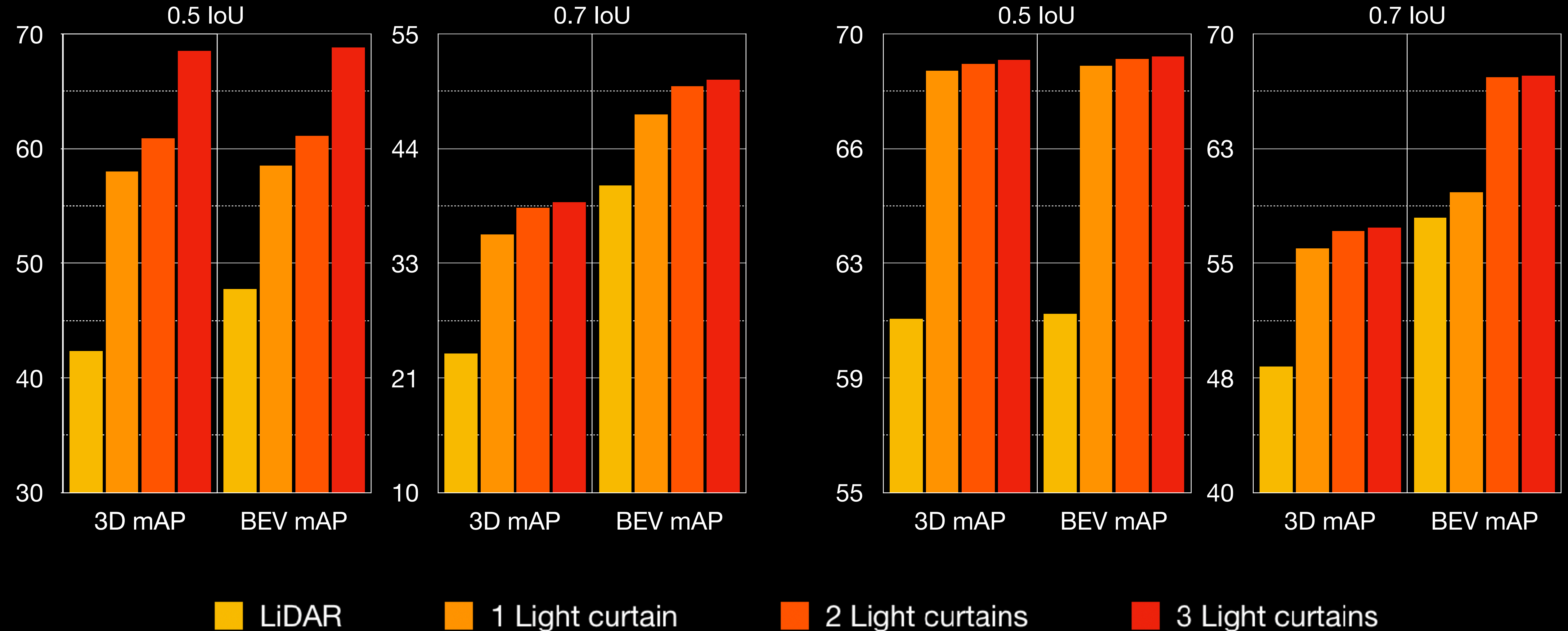
2 Light curtains

3 Light curtains

Successive light curtain placements improve detection performance

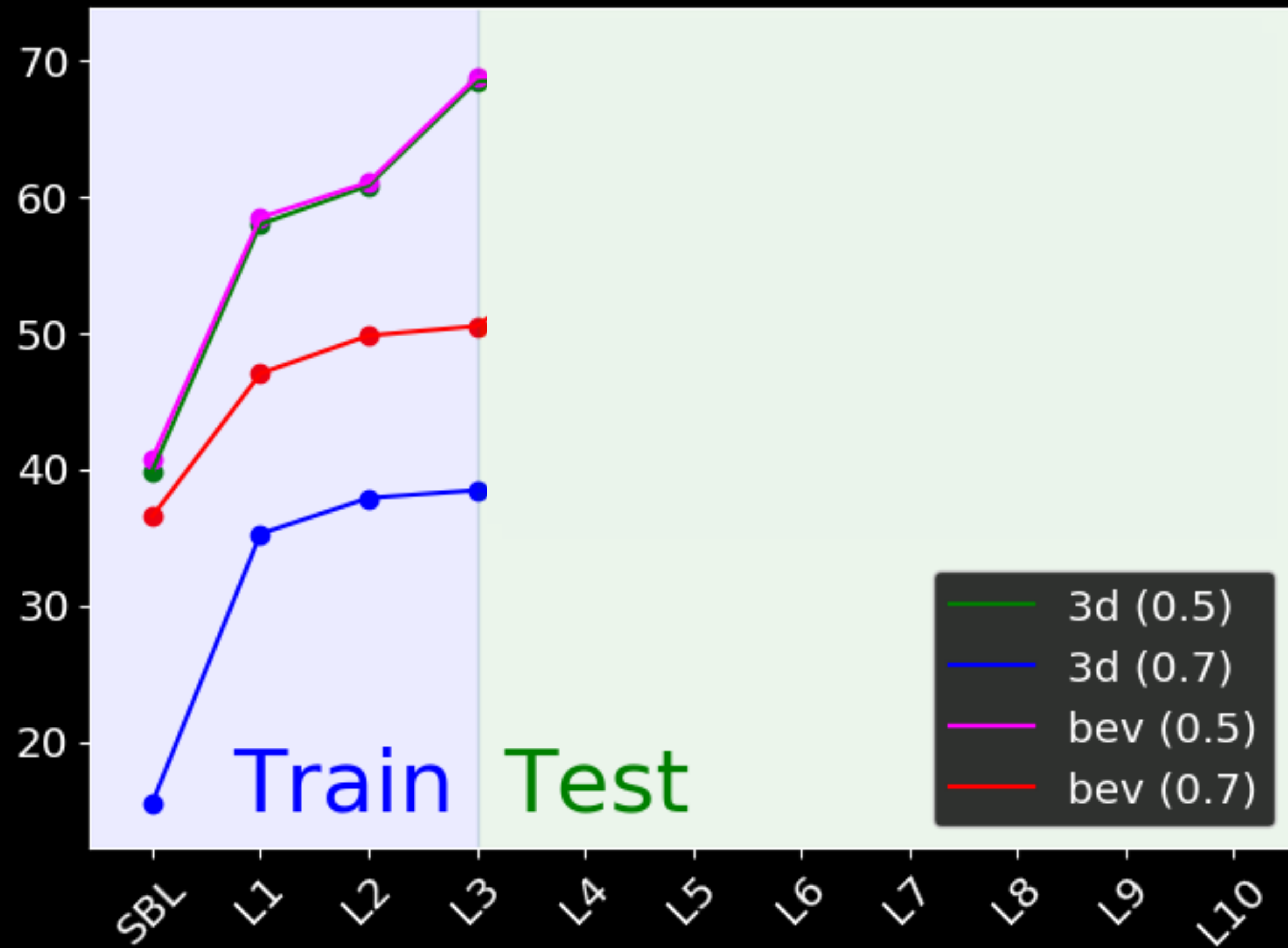
Virtual KITTI

SYNTHIA

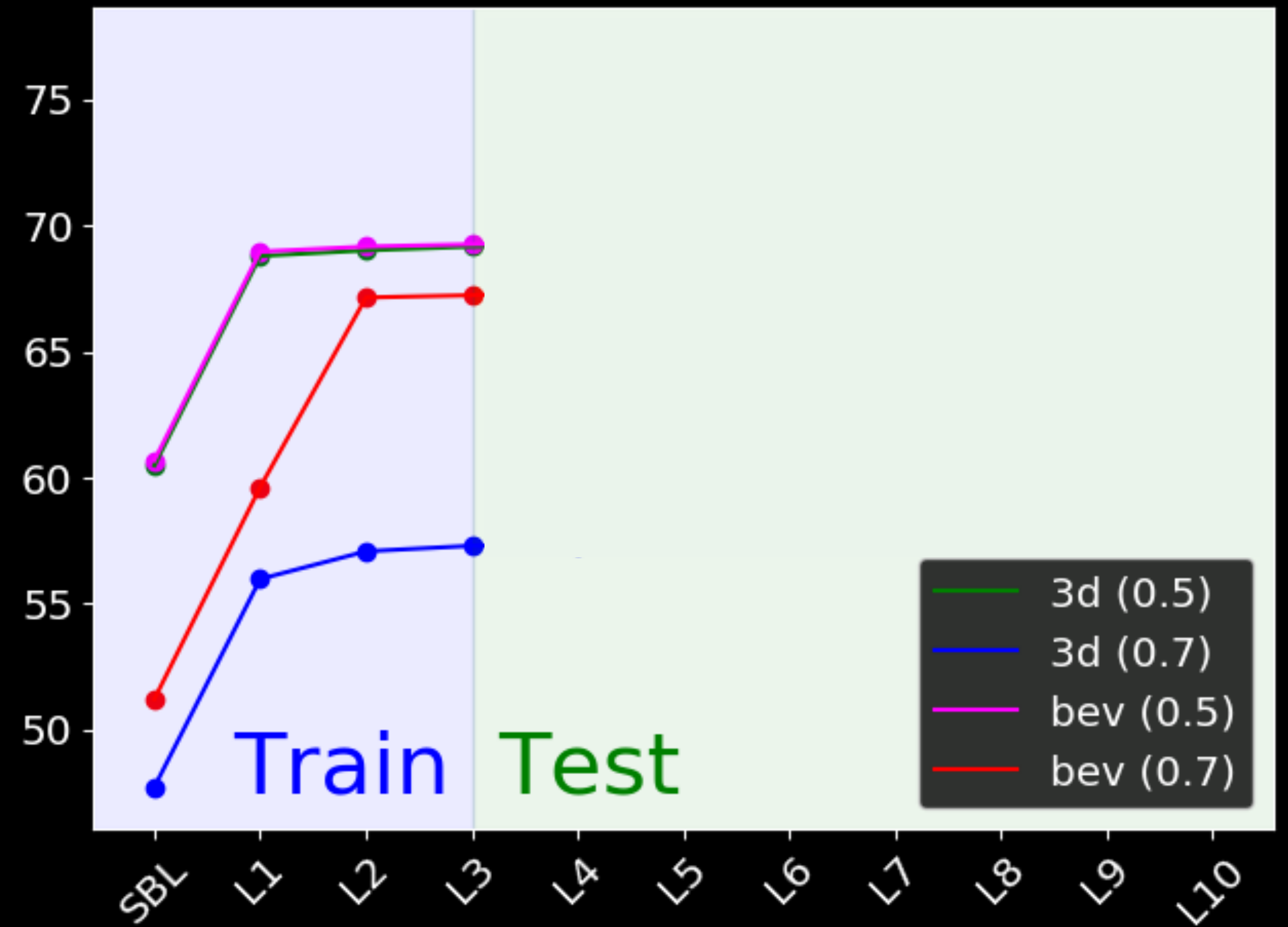


Performance generalizes to additional curtains

Generalization in Virtual KITTI

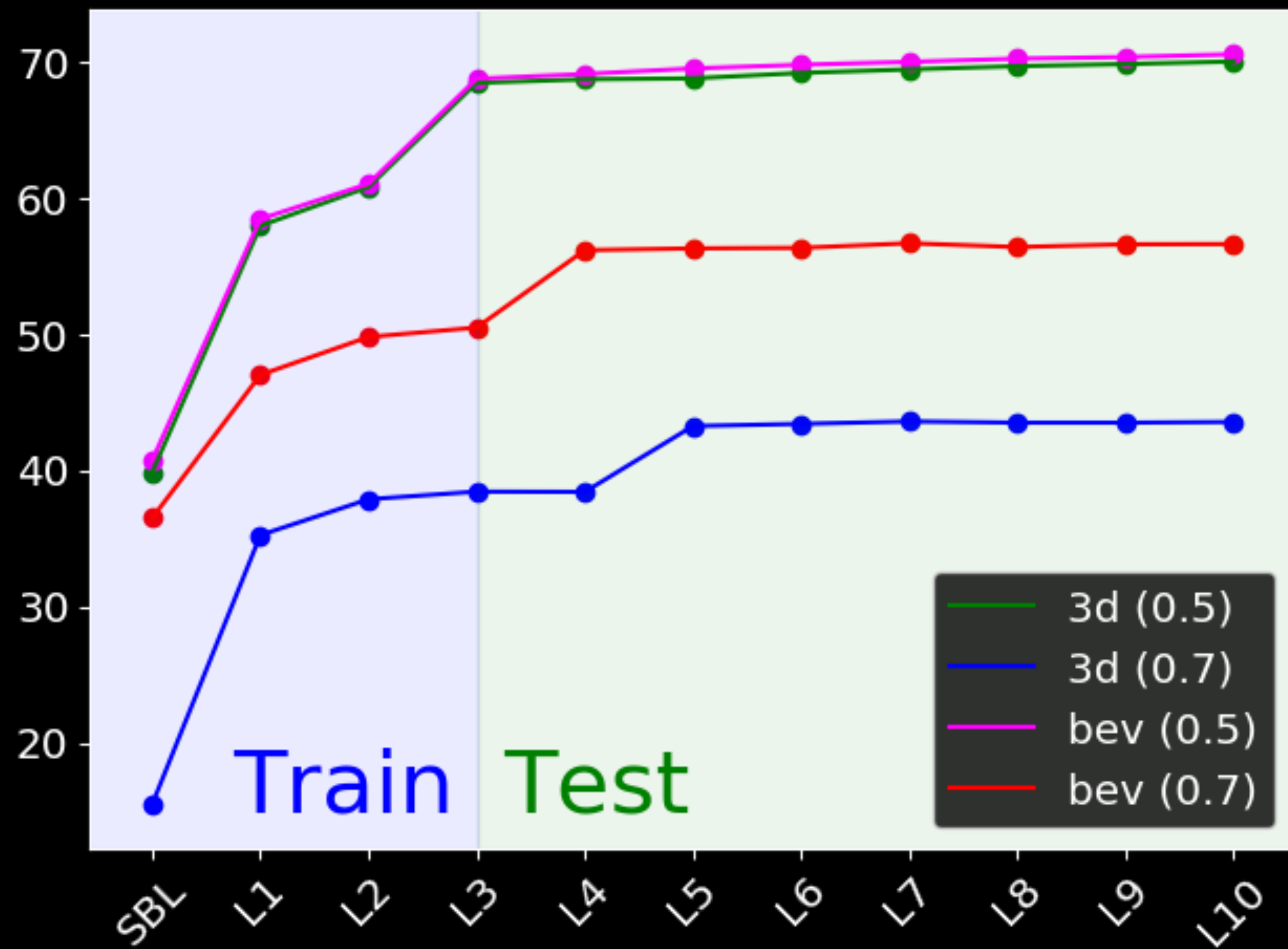


Generalization in SYNTHIA

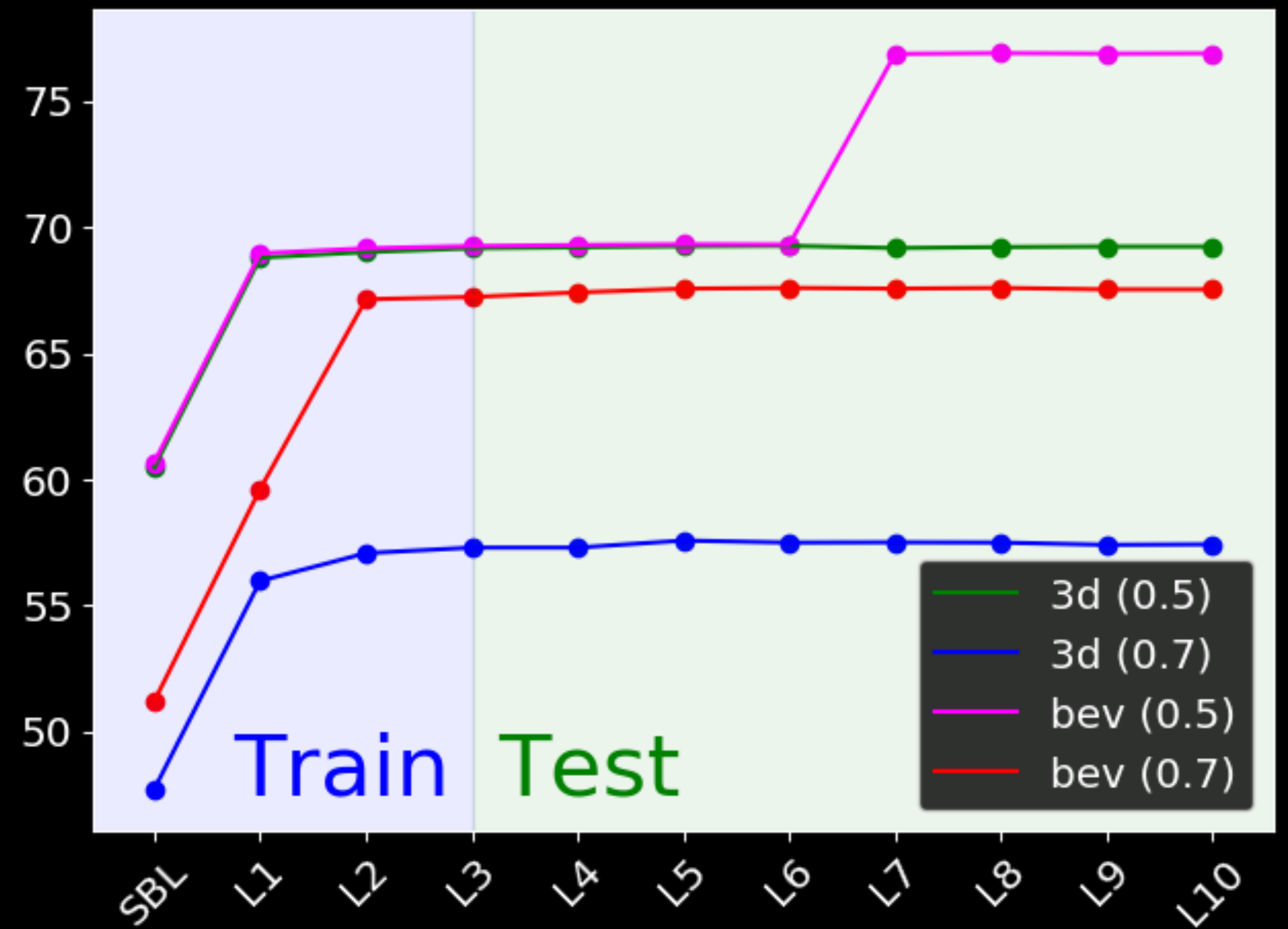


Performance generalizes to additional curtains

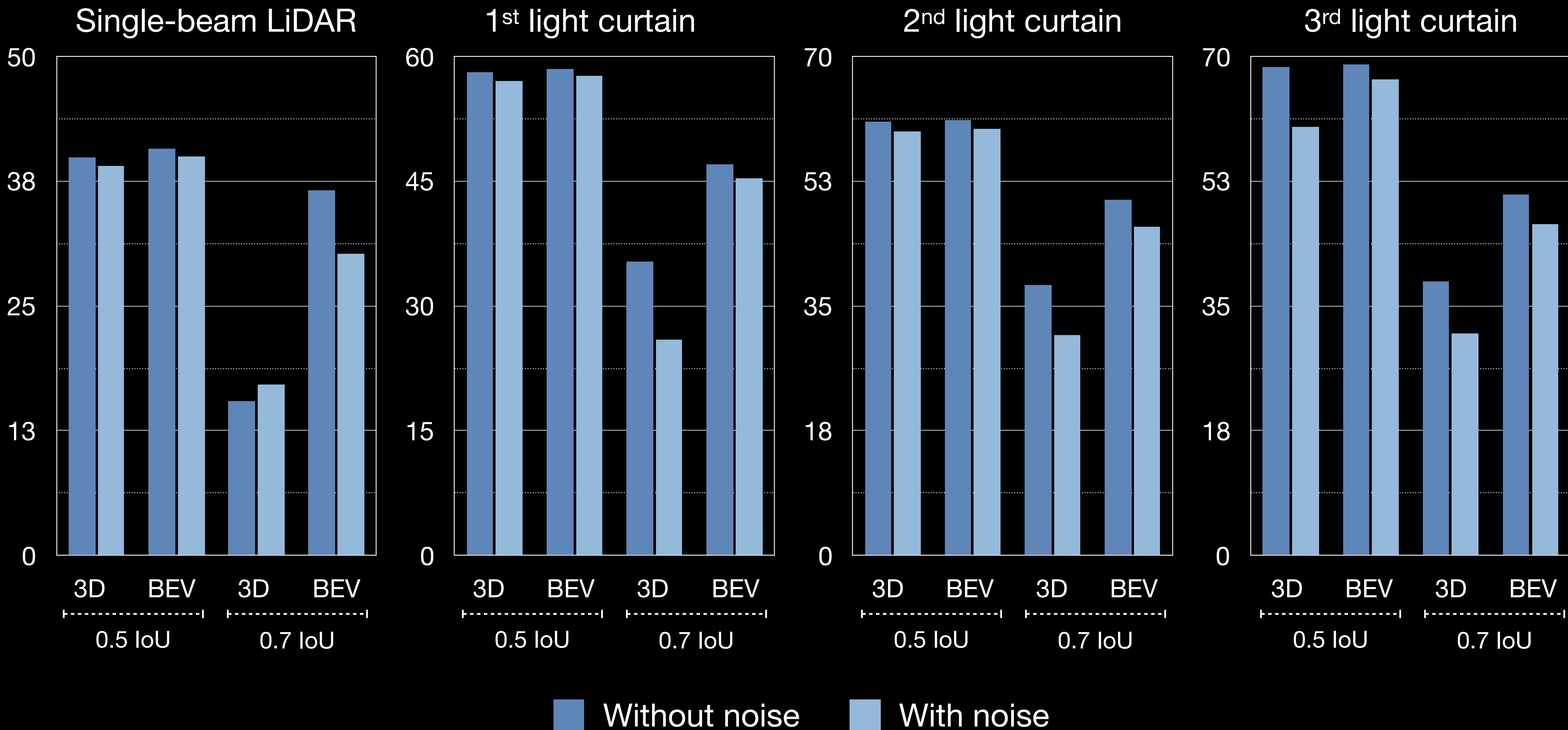
Generalization in Virtual KITTI



Generalization in SYNTHIA

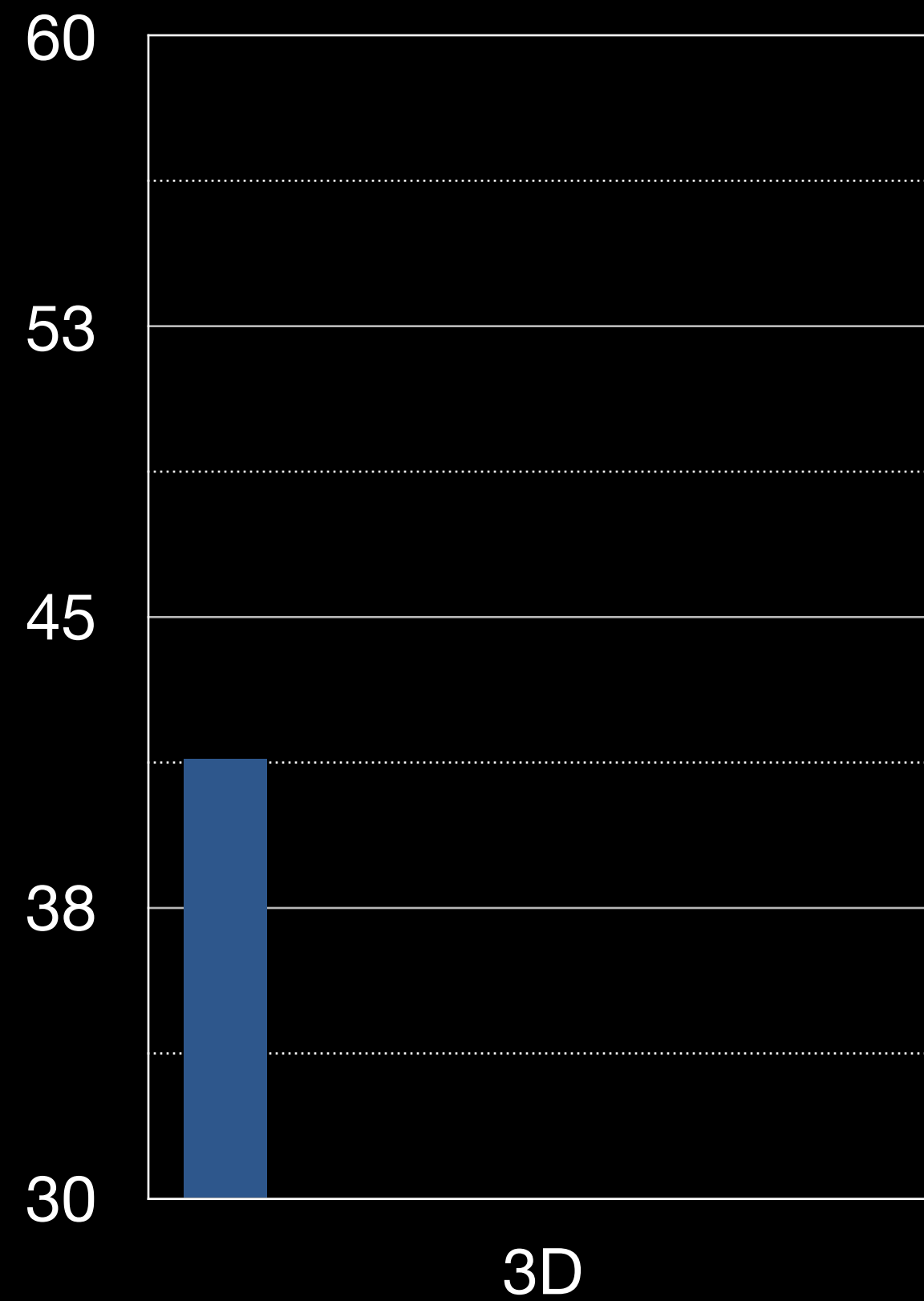


Performance generalizes to additional noise



Comparison to baselines

Virtual KITTI
0.5 IoU

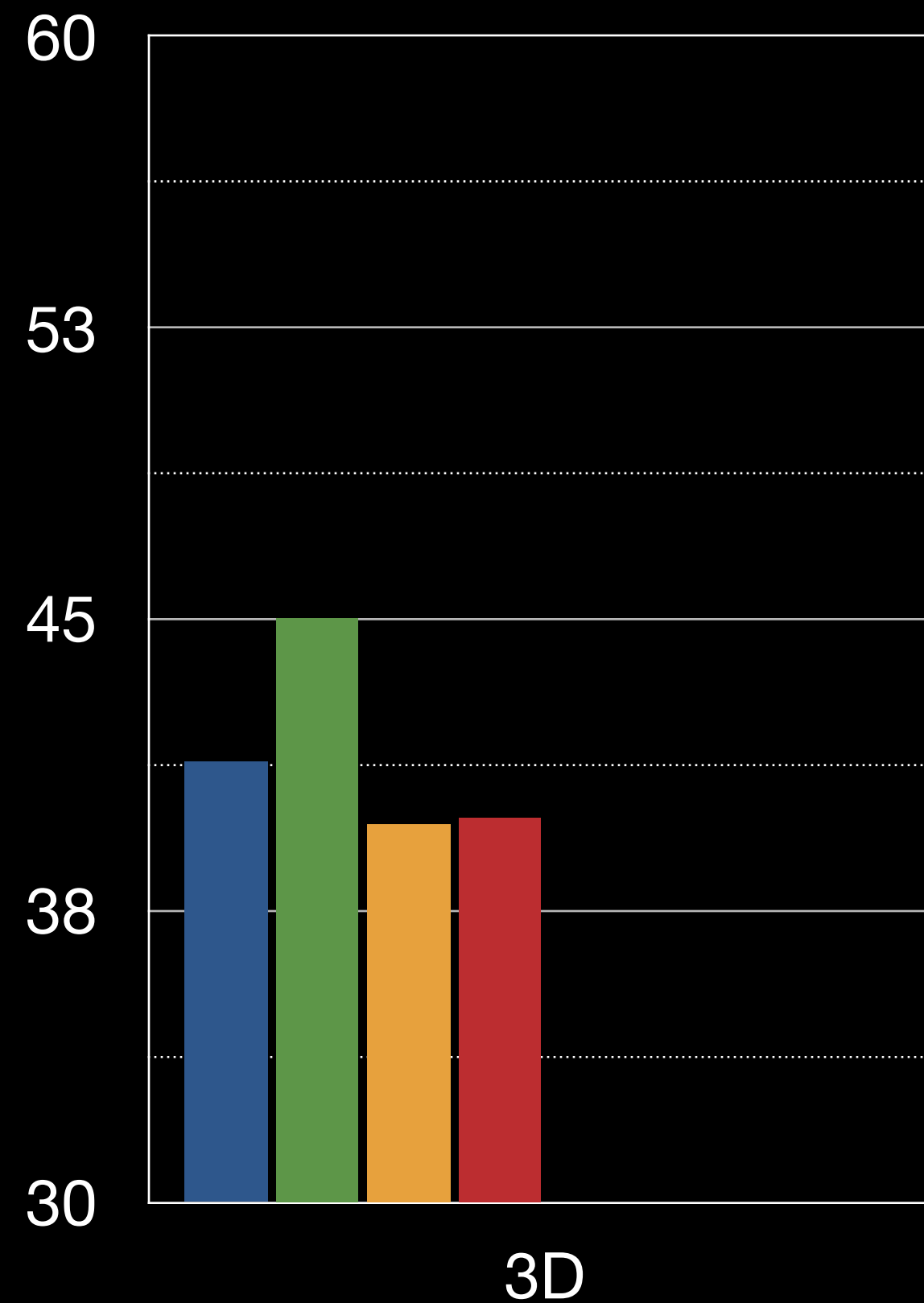


■ Random

Comparison to baselines

Virtual KITTI

0.5 IoU



■ Random

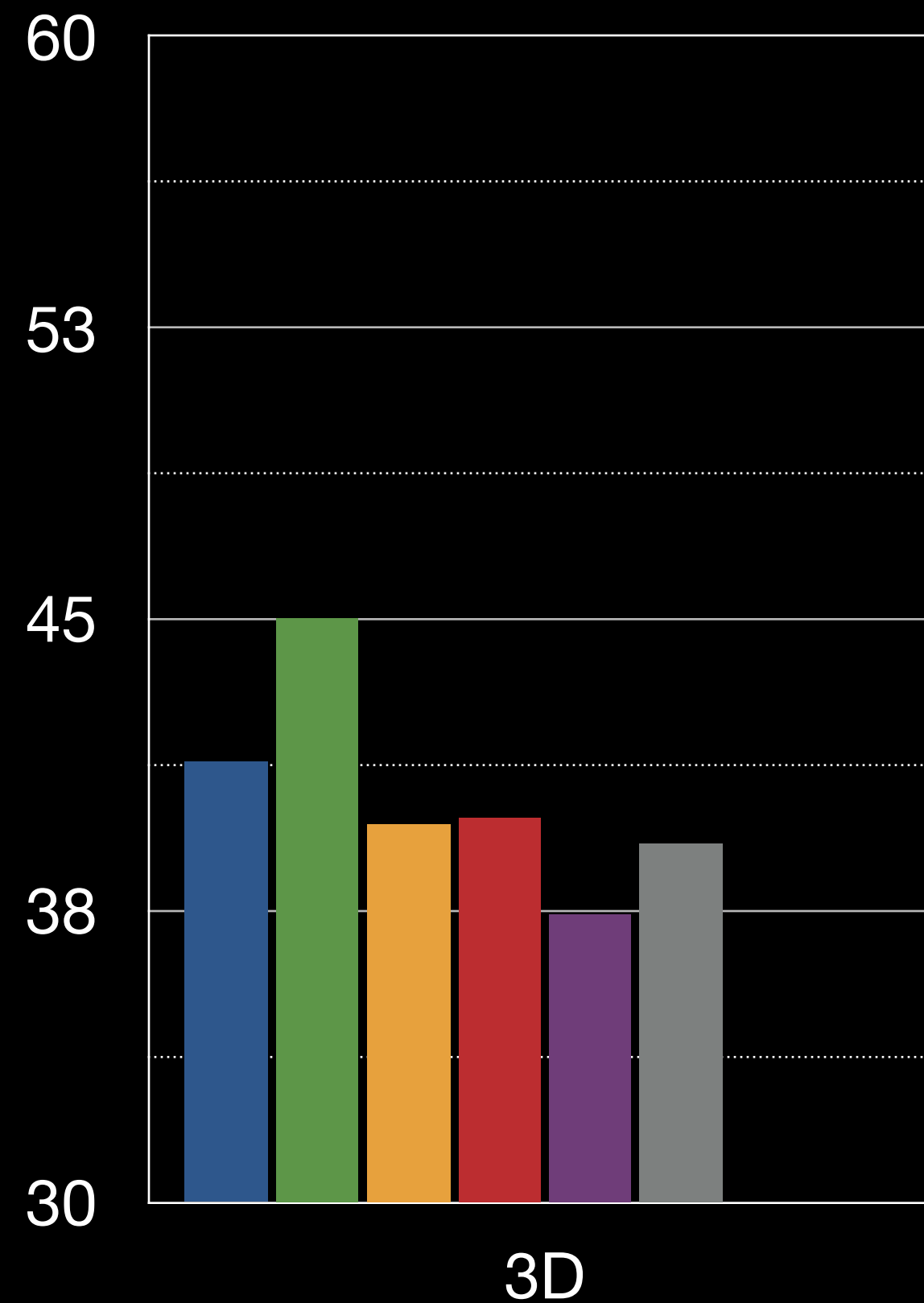
■ Fixed depth: 15m

■ Fixed depth: 30m

■ Fixed depth: 45m

Comparison to baselines

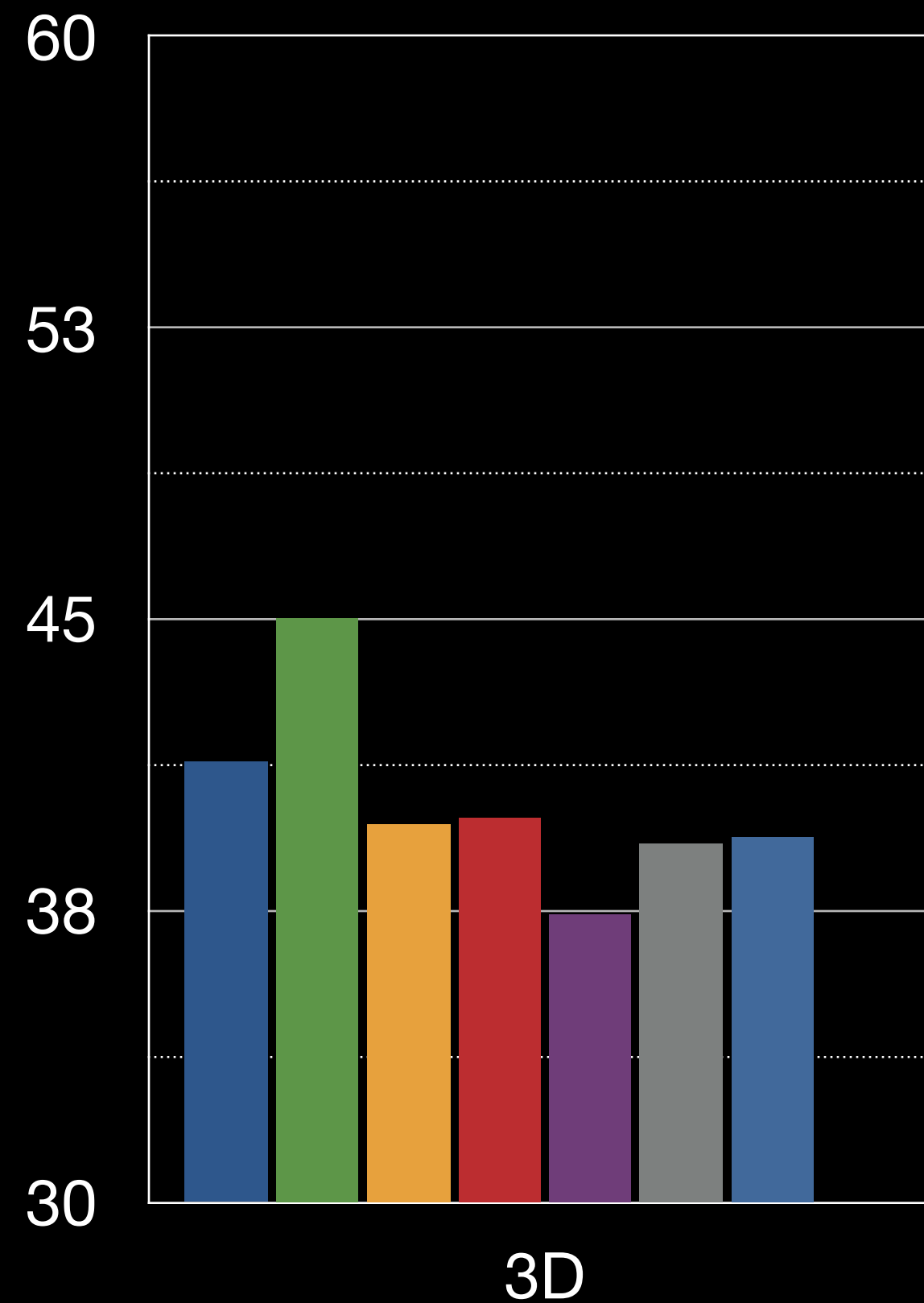
Virtual KITTI
0.5 IoU



Comparison to baselines

Virtual KITTI

0.5 IoU



Random

Fixed depth: 15m

Fixed depth: 30m

Fixed depth: 45m

GreedyOpt: Random tie break

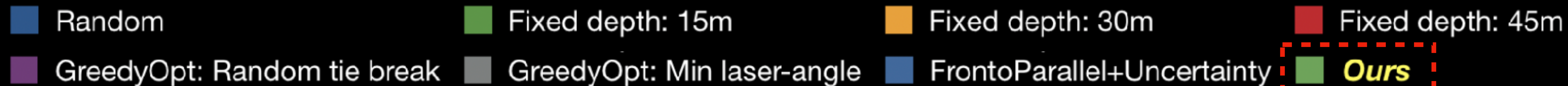
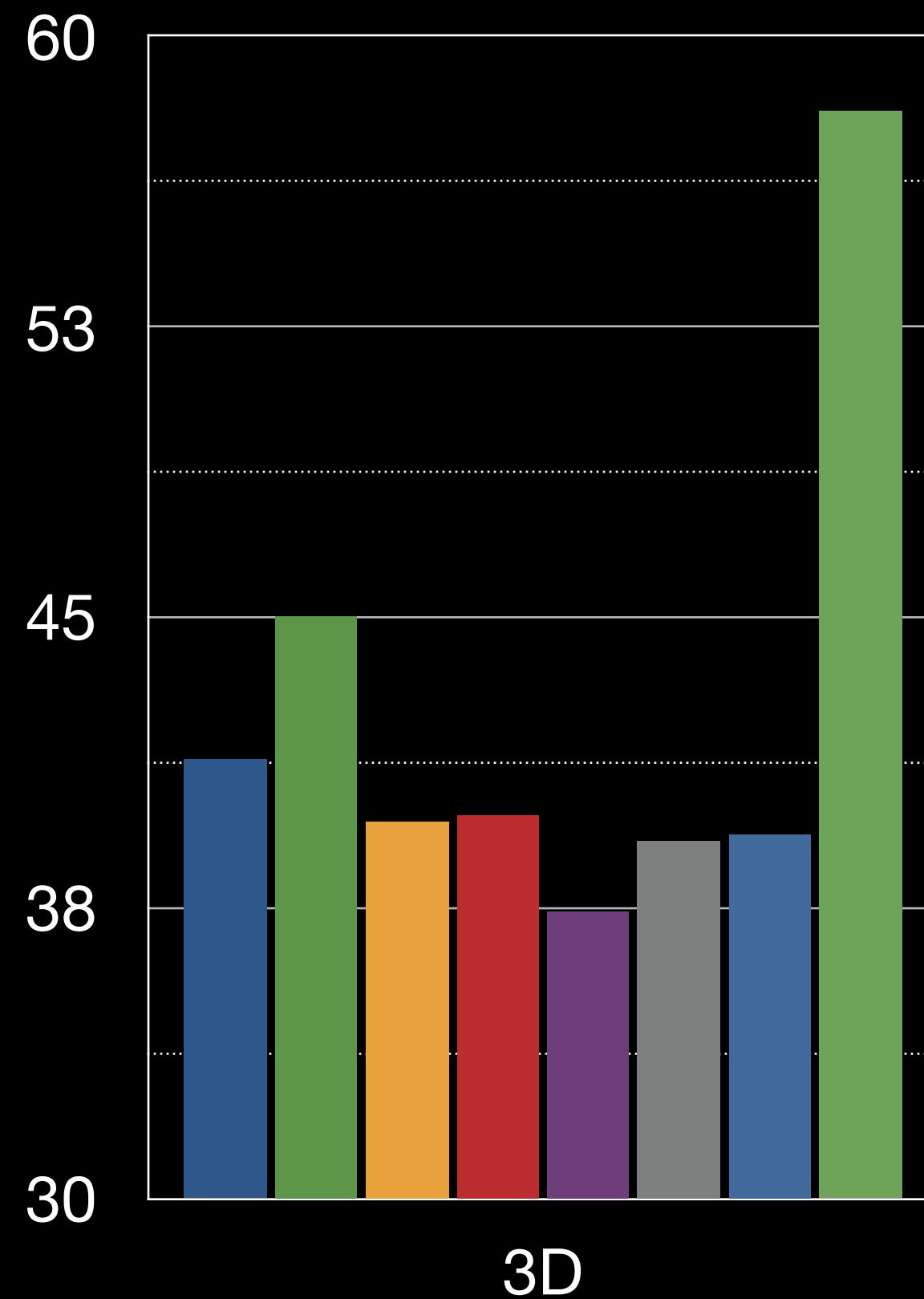
GreedyOpt: Min laser-angle

FrontoParallel+Uncertainty

Comparison to baselines

Virtual KITTI

0.5 IoU



Comparison to baselines

Virtual KITTI

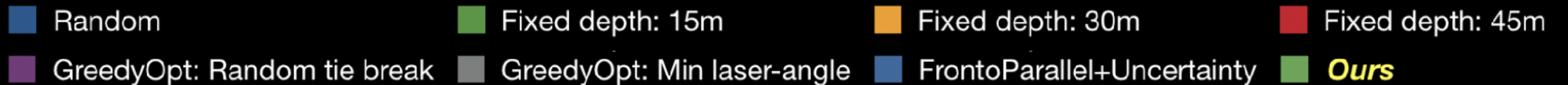
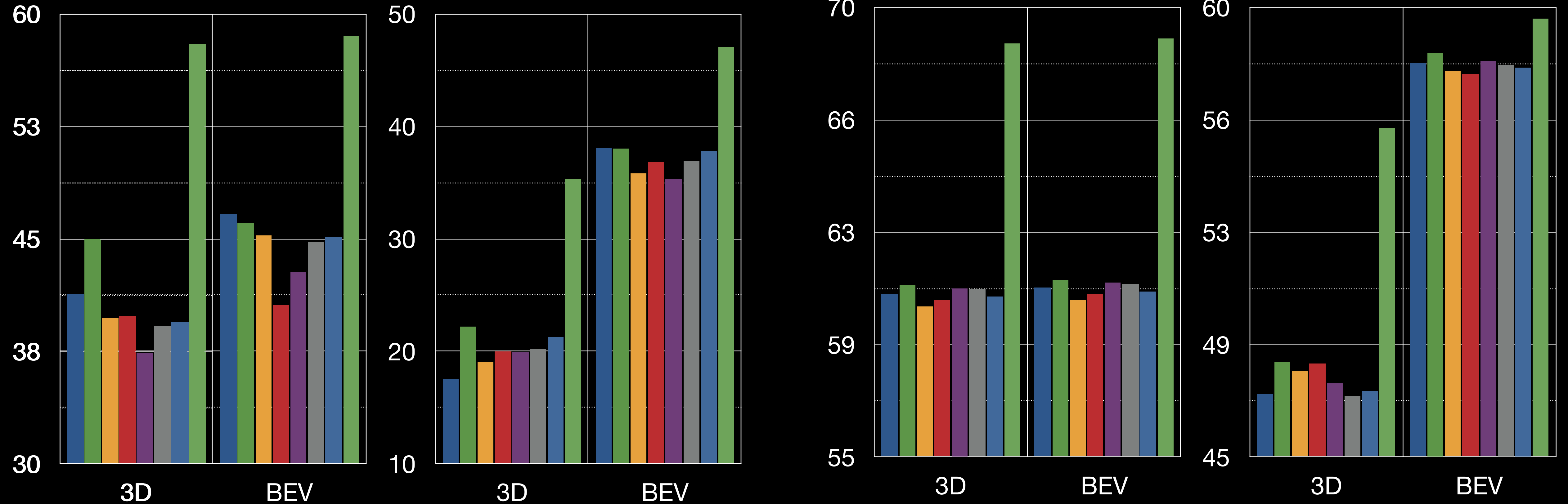
0.5 IoU

0.7 IoU

SYNTHIA

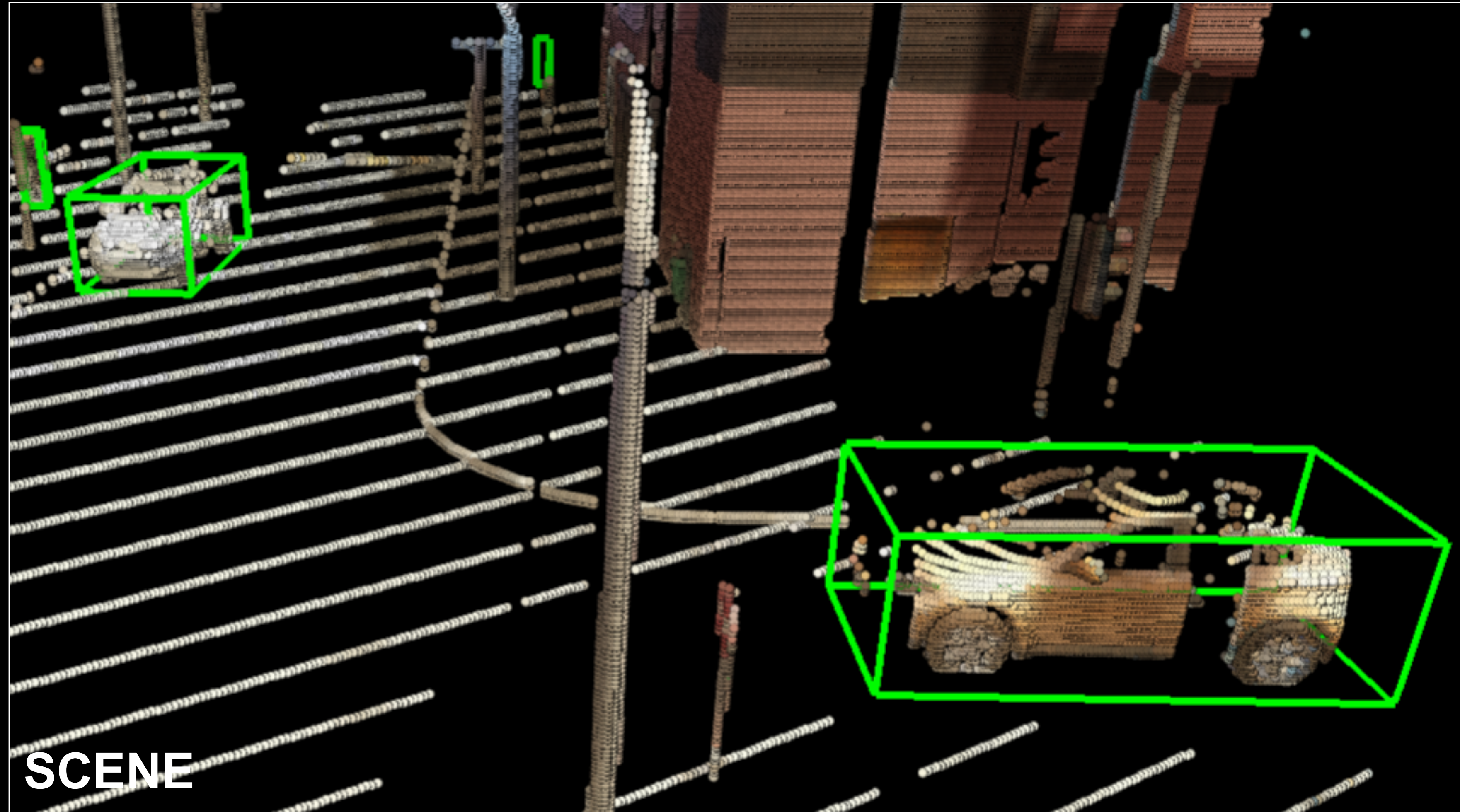
0.5 IoU

0.7 IoU



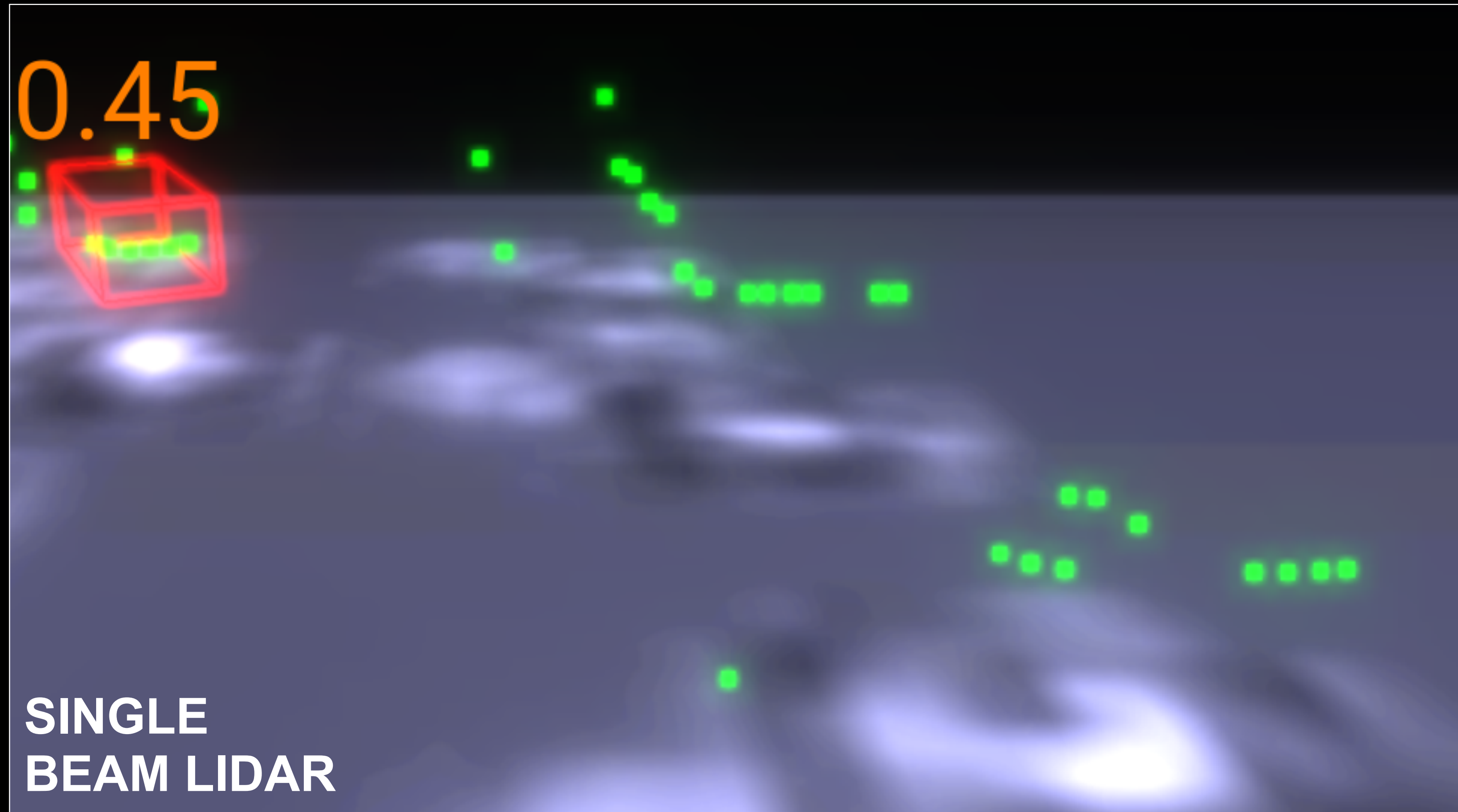
Detecting false negatives missed by LiDAR

(zoomed in)



Detecting false negatives missed by LiDAR

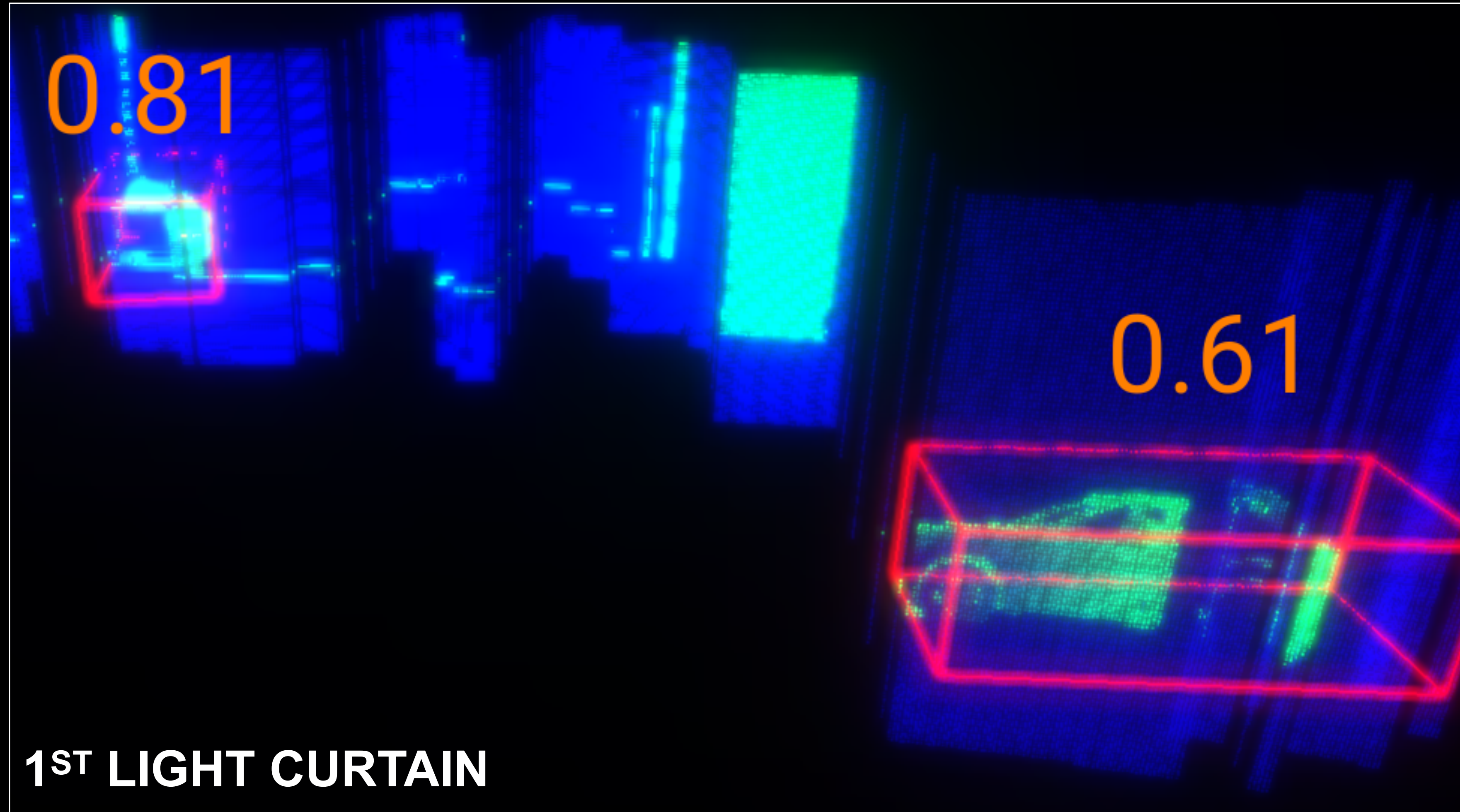
(zoomed in)



*White: more uncertain Black: less uncertain

Detecting false negatives missed by LiDAR

(zoomed in)



Removing false positives detected by LiDAR

(zoomed in)



Removing false positives detected by LiDAR

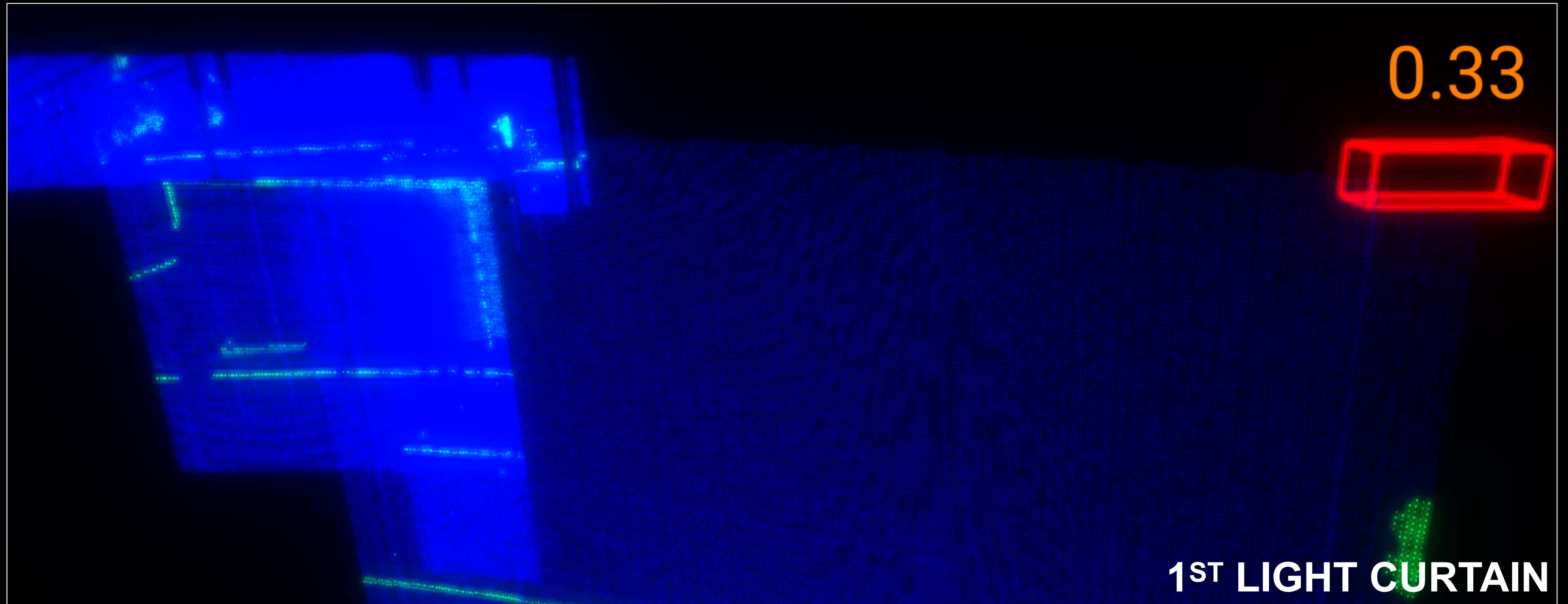
(zoomed in)



*White: more uncertain Black: less uncertain

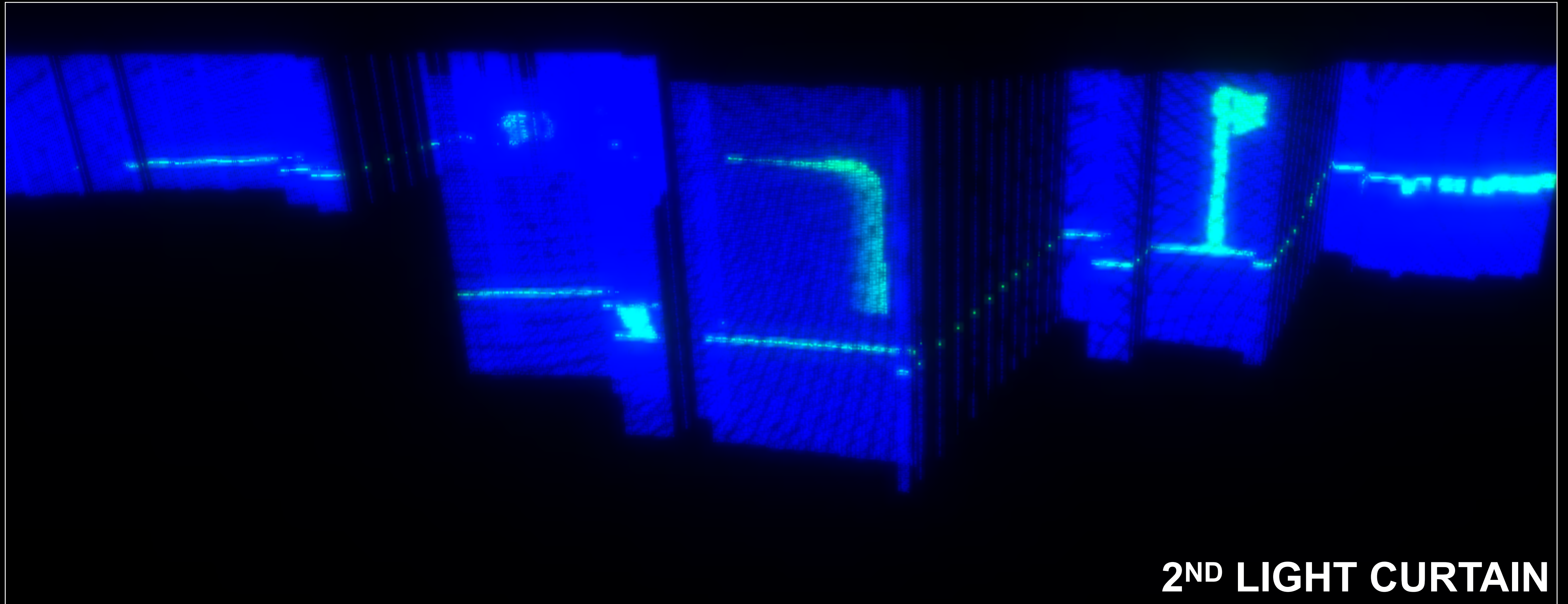
Removing false positives detected by LiDAR

(zoomed in)



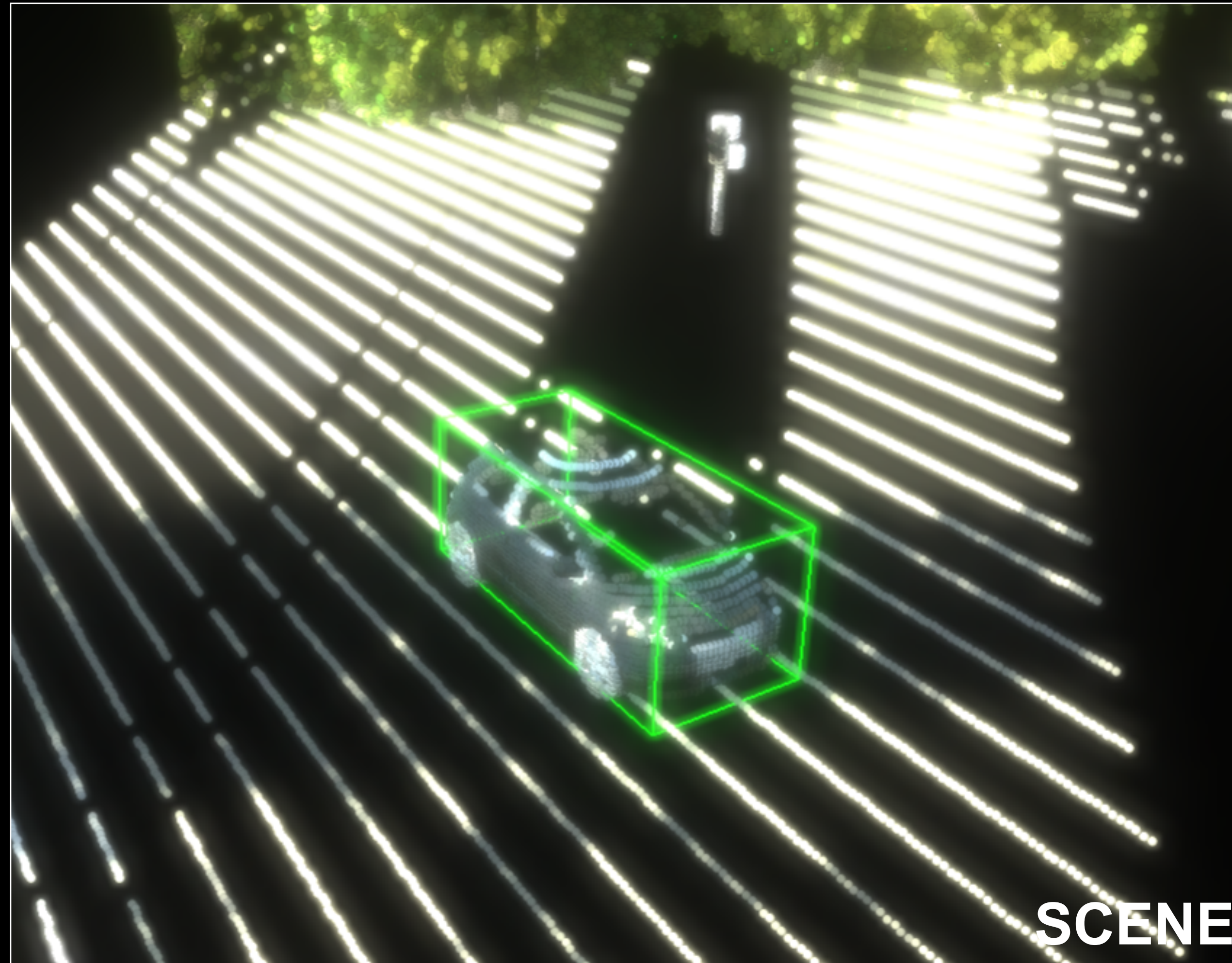
Removing false positives detected by LiDAR

(zoomed in)

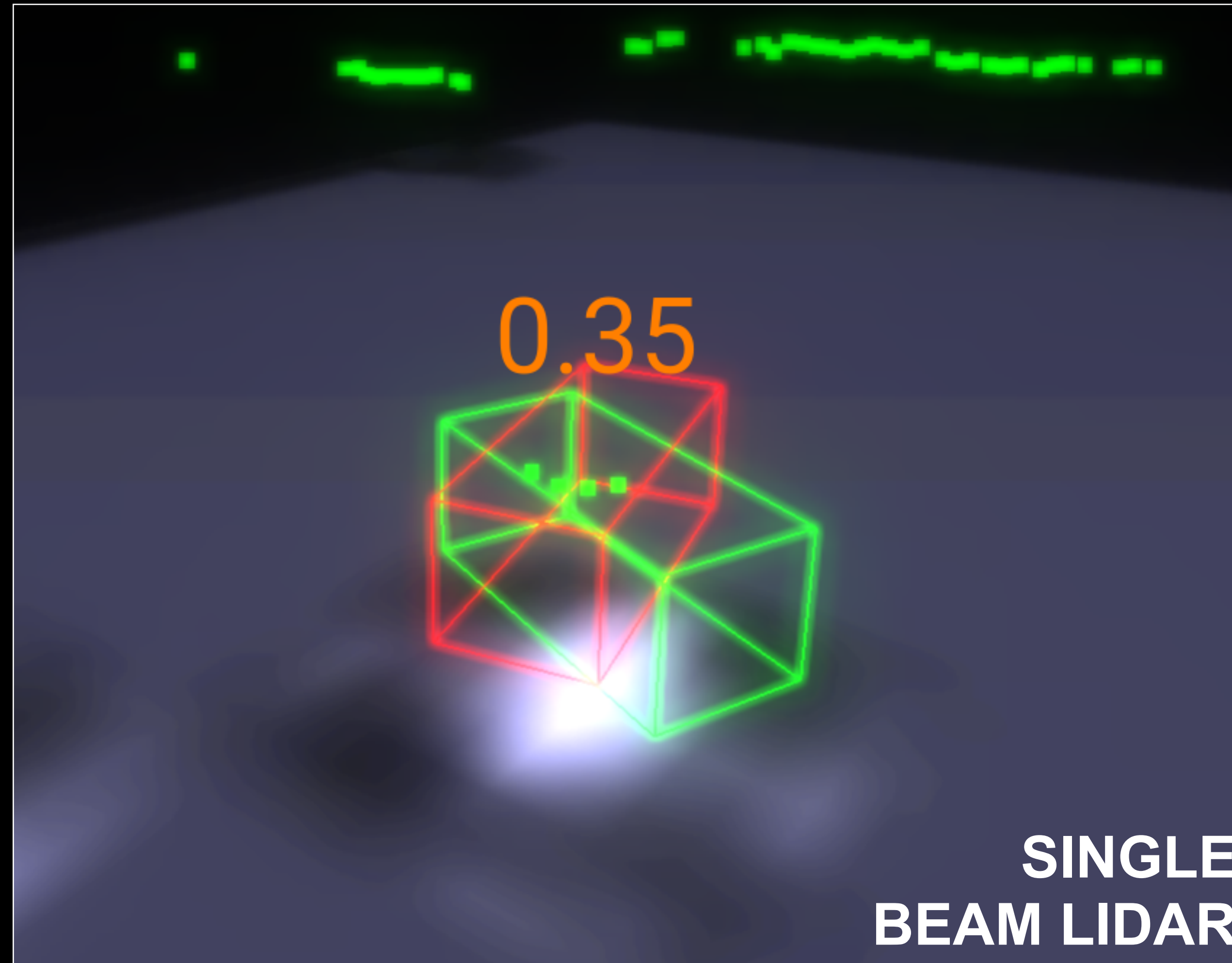


Correcting misaligned detection

(zoomed in)

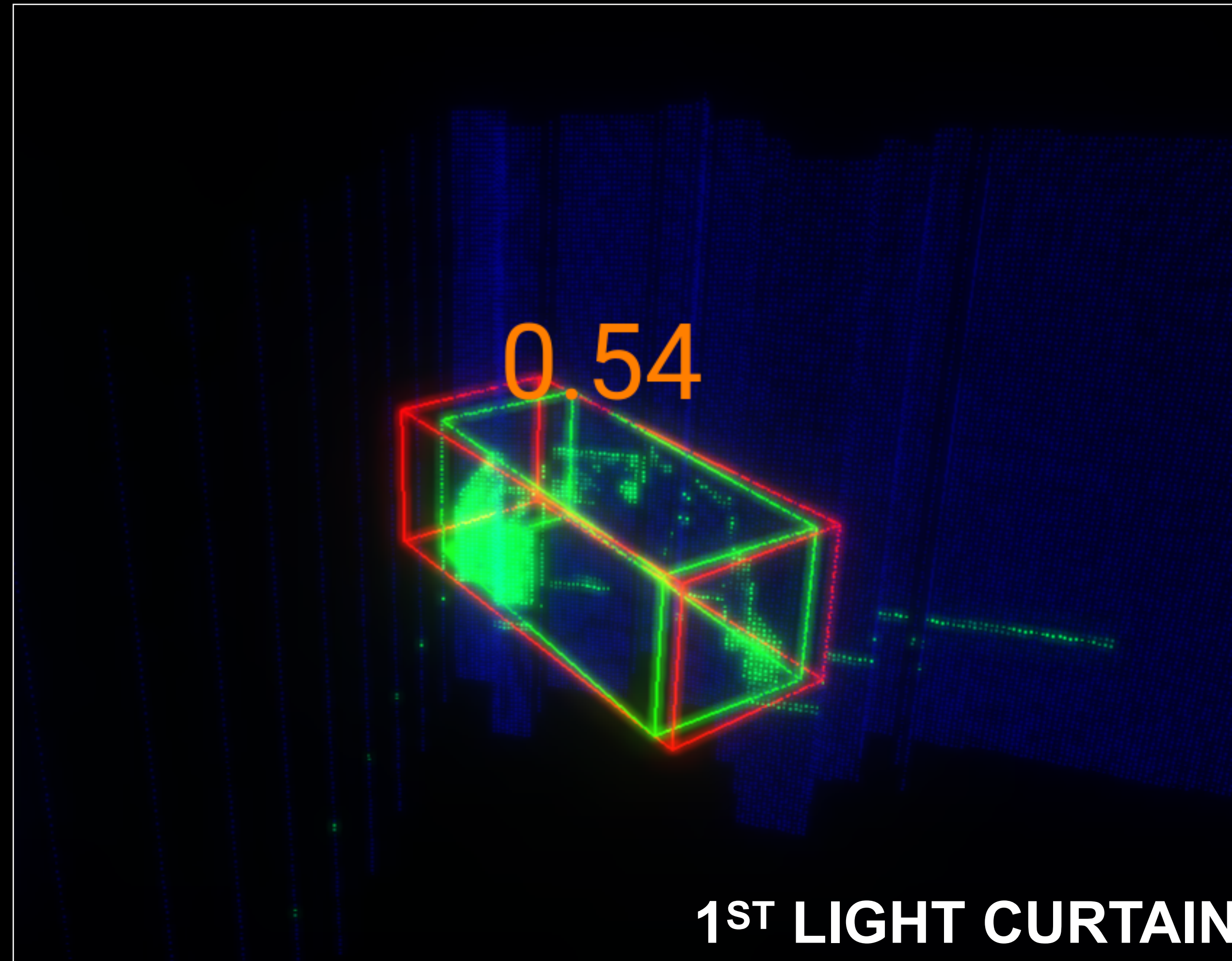


Correcting misaligned detection (zoomed in)



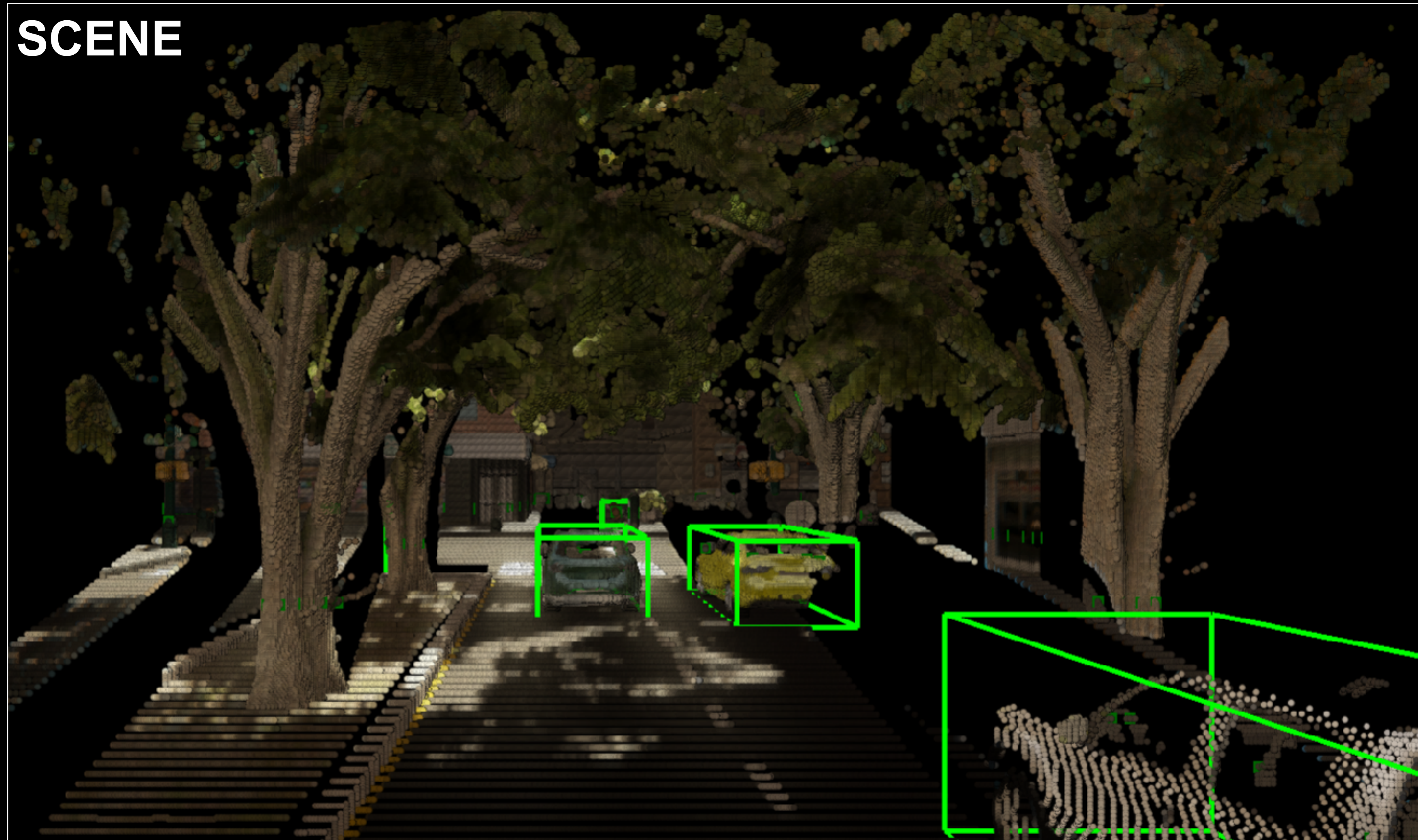
*White: more uncertain Black: less uncertain

Correcting misaligned detection (zoomed in)



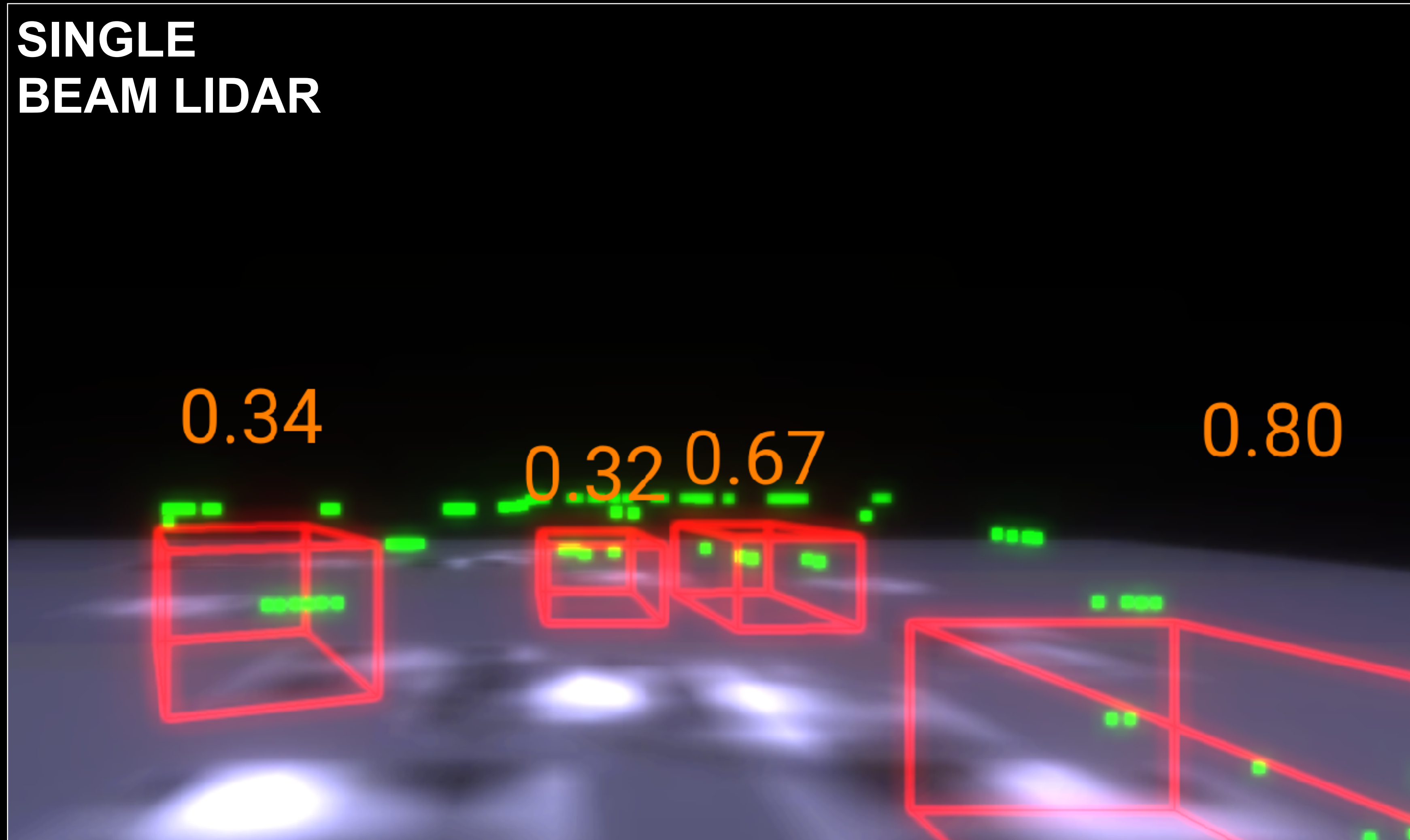
Failure case: many curtains might be required

(zoomed in)



Failure case: many curtains might be required

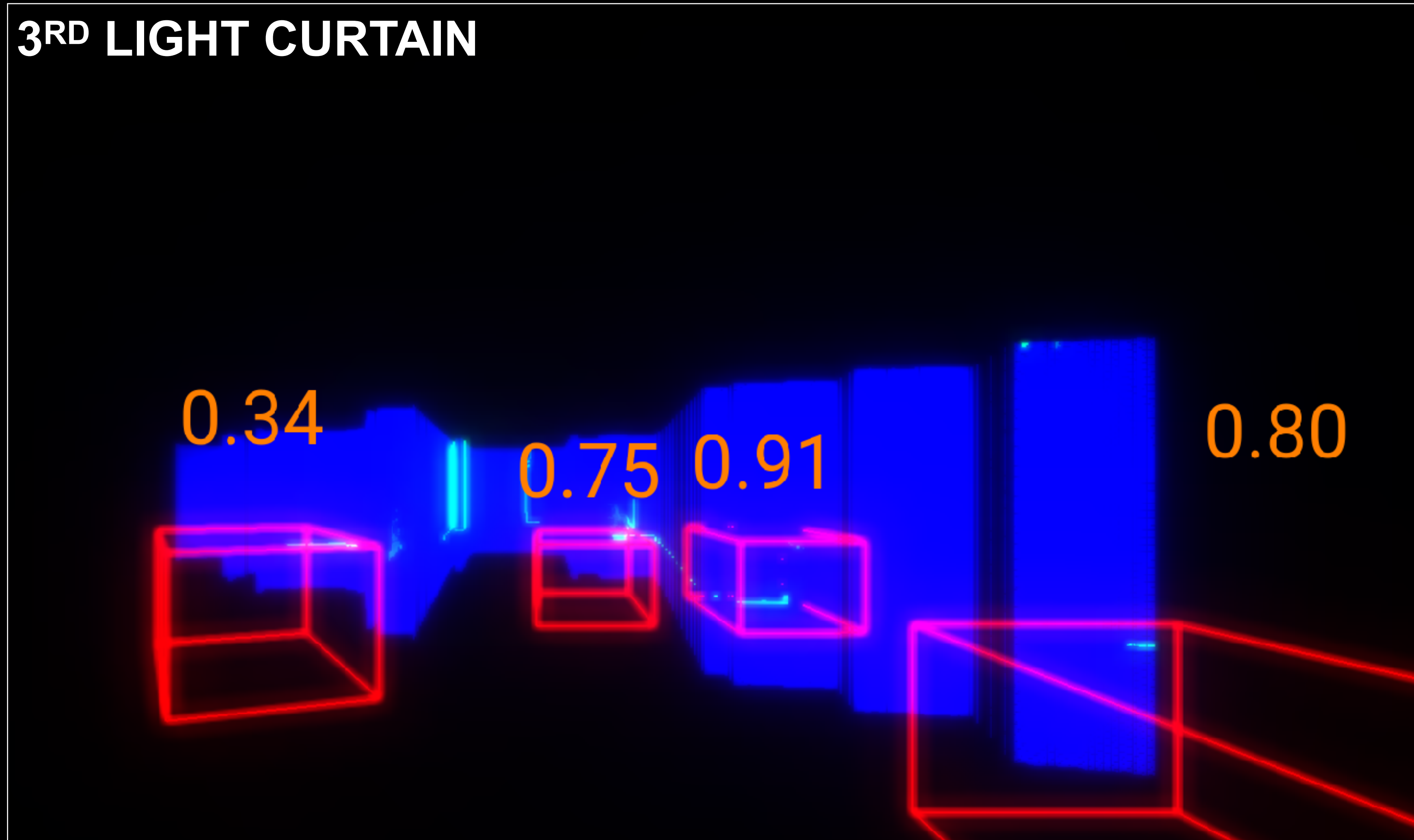
(zoomed in)



*White: more uncertain Black: less uncertain

Failure case: many curtains might be required

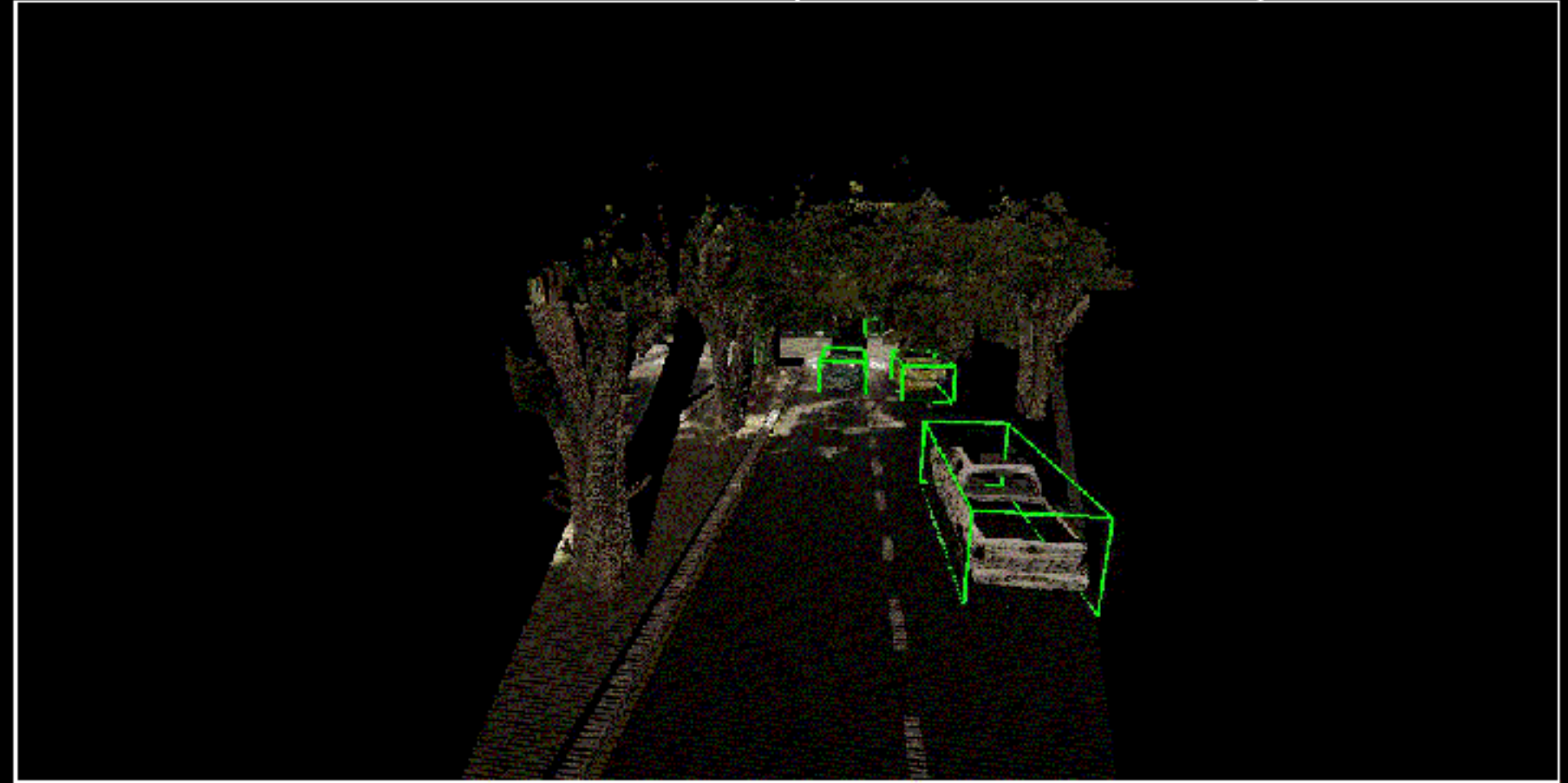
(zoomed in)



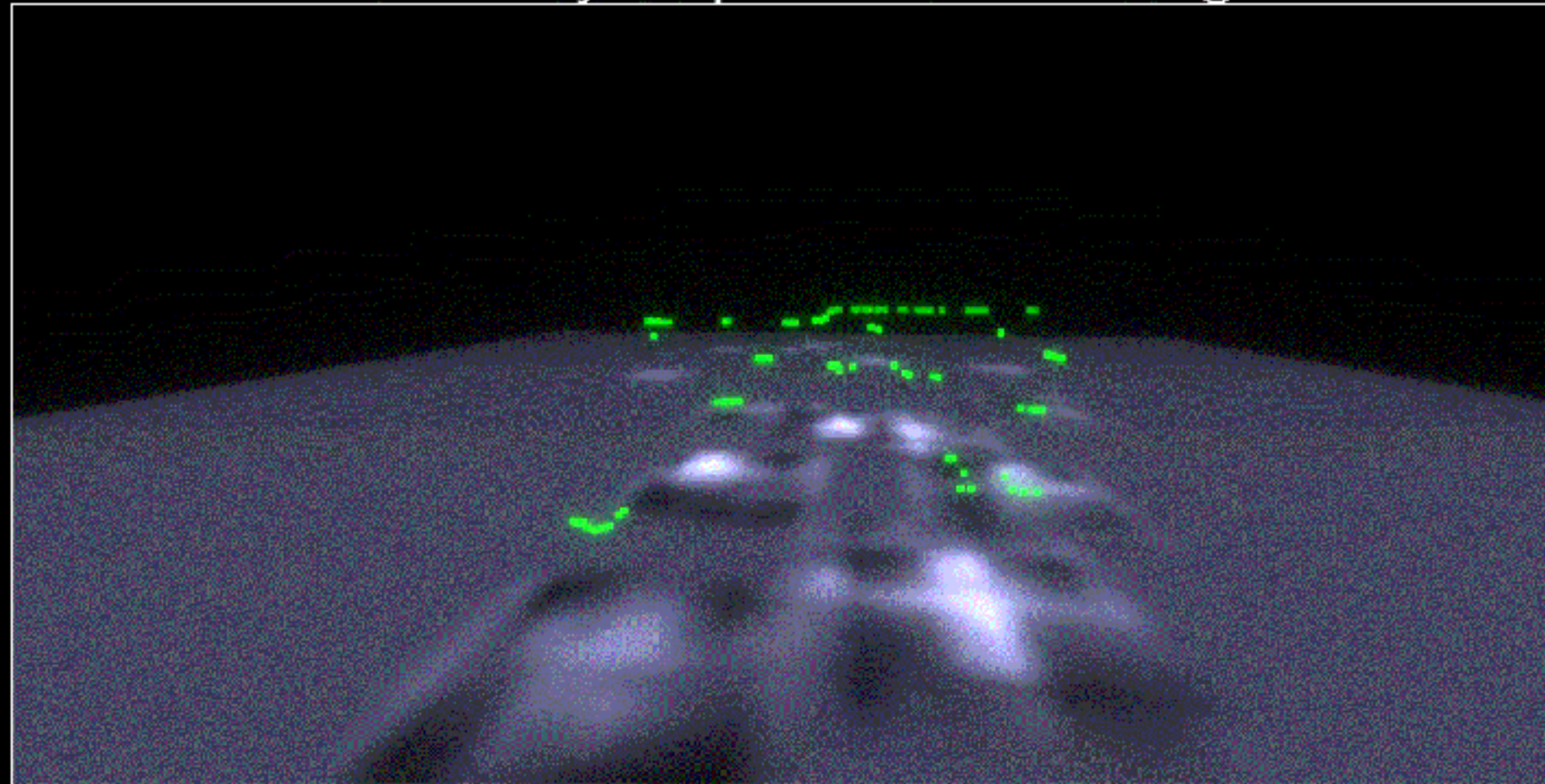
*White: more uncertain Black: less uncertain

Failure case: many curtains might be required

Dense Depth Map (visualization only)



Uncertainty Map + Sensor Readings



Cumulative Detector Input + Detections

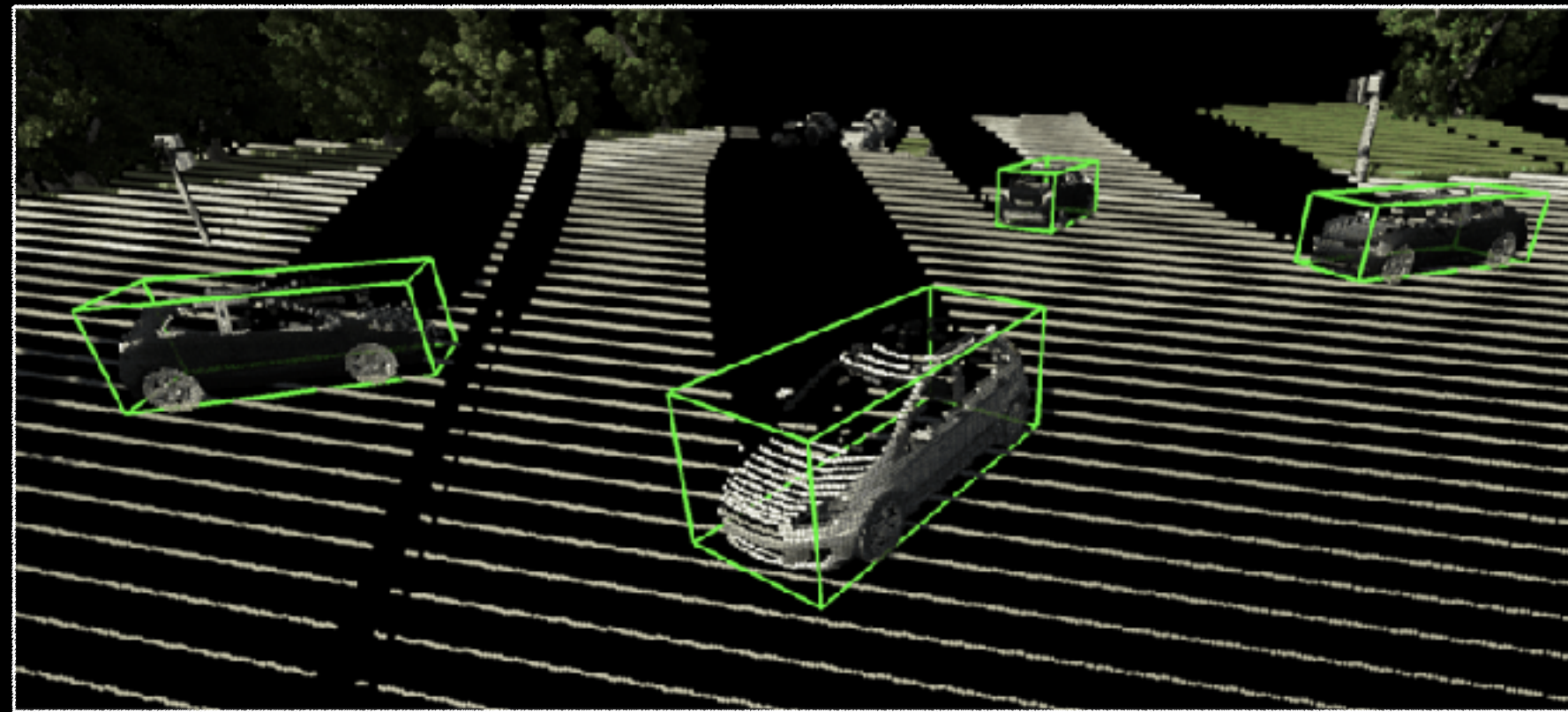


Single Beam LiDAR

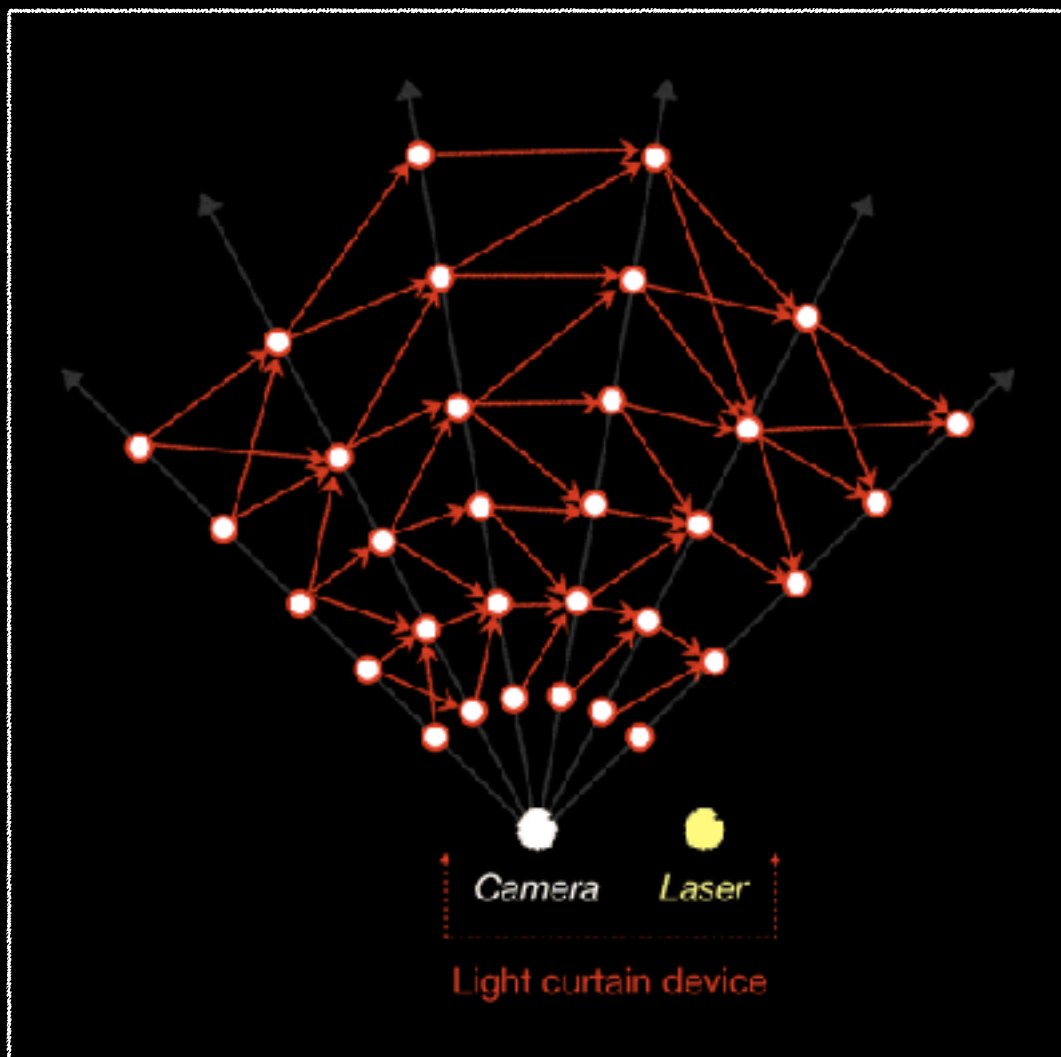
*White: more uncertain Black: less uncertain

Conclusions

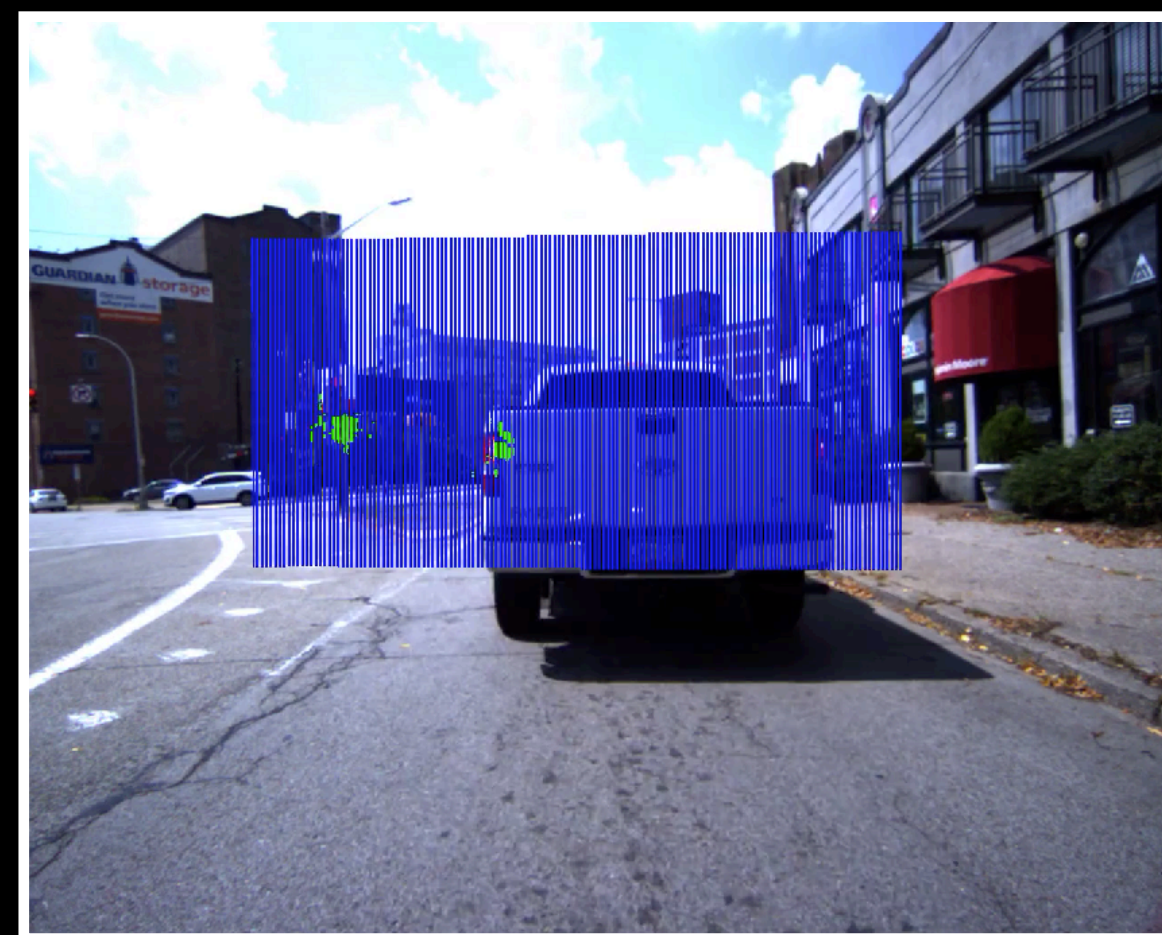
Active Detection



Dynamic Programming



Light Curtain



- We propose for a method for **active detection** using **light curtains** for autonomous driving.
- We derive an **information-gain** based objective for light curtain placement.
- We propose a novel optimization algorithm by encoding the light curtain constraints into a **constraint graph**, and using **dynamic programming** to maximize the objective.
- We show that our method can successively **improve detection accuracy of LiDAR**, and is a step towards replacing expensive multi-beam LiDAR systems with inexpensive controllable sensors.

Active Perception using Light Curtains for Autonomous Driving



Webpage

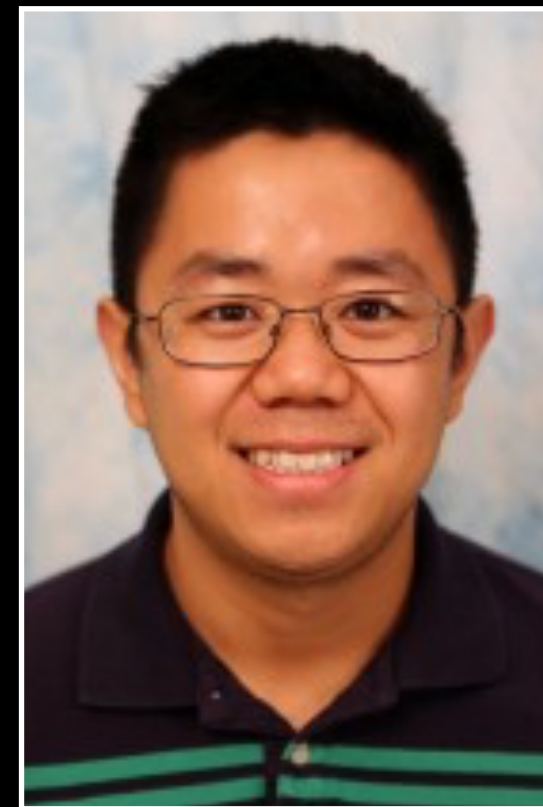
<http://siddancha.github.io/projects/active-perception-light-curtains>



Siddharth
Ancha



Yaadhav
Raaj



Peiyun
Hu



Srinivasa
Narasimhan



David
Held

**Carnegie
Mellon
University**

