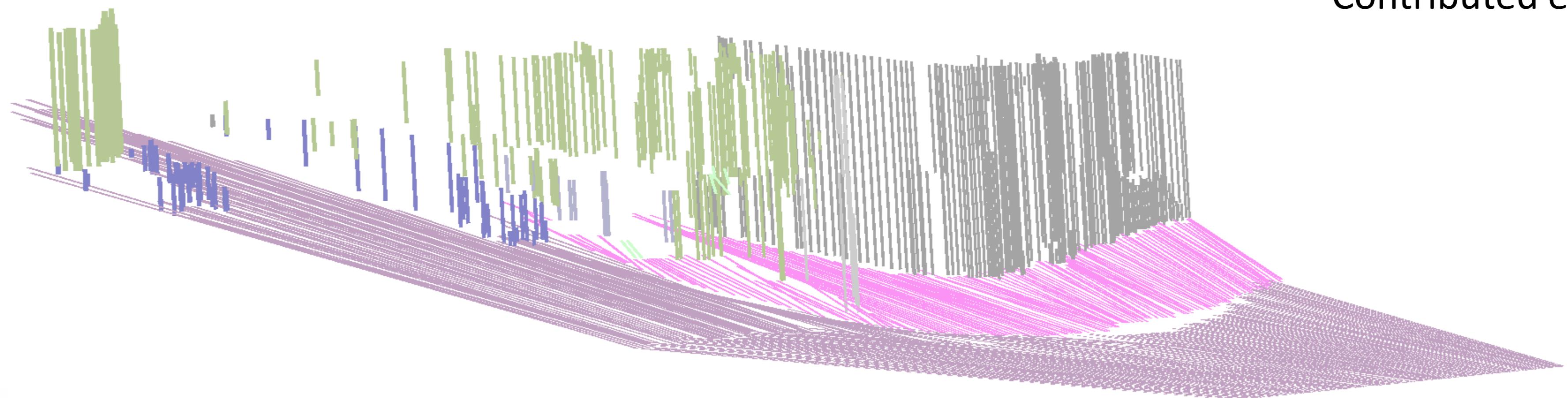


# Slanted Stixels: Representing San Francisco's Steepest Streets

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*Daniel Hernández-Juárez\*, Lukas Schneider\*, Antonio Espinosa, David Vázquez,  
Antonio M. López, Uwe Franke, Marc Pollefeys and Juan C. Moura*

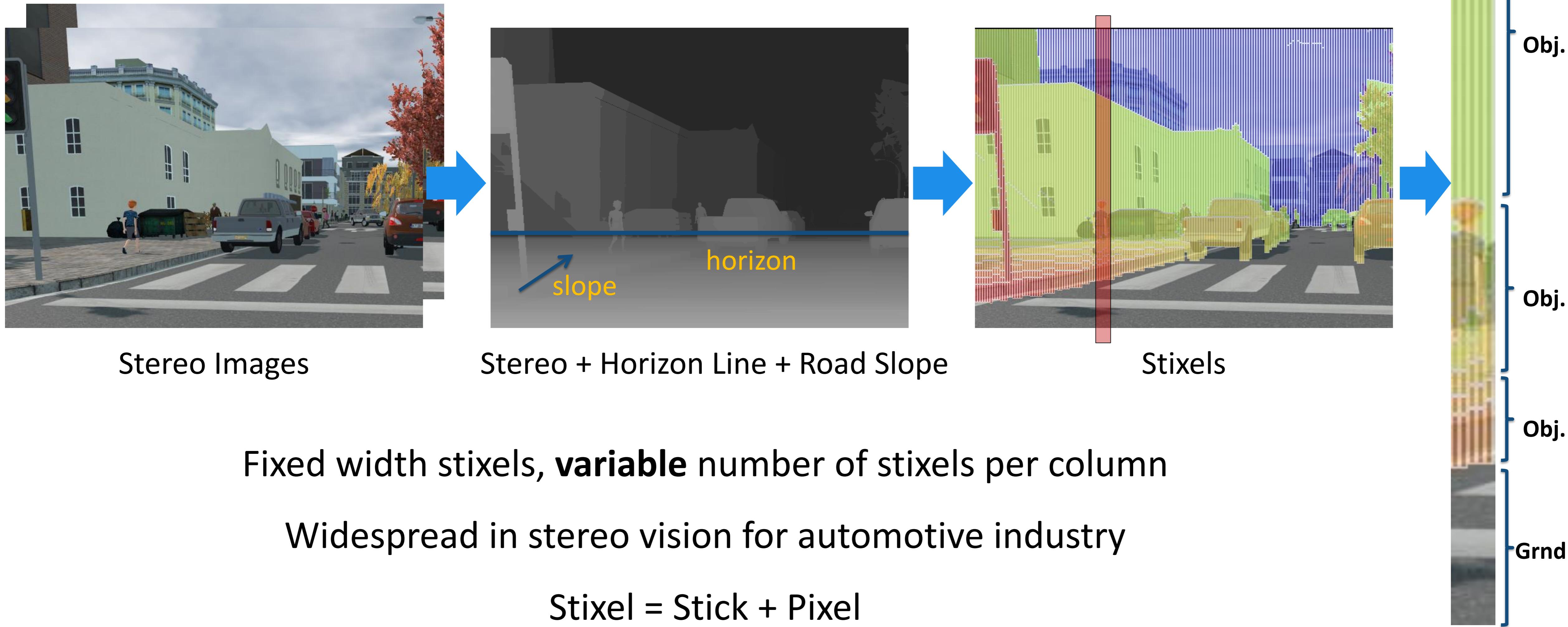
\* Contributed equally



DAIMLER



# Stixel World: Compact representation of the world

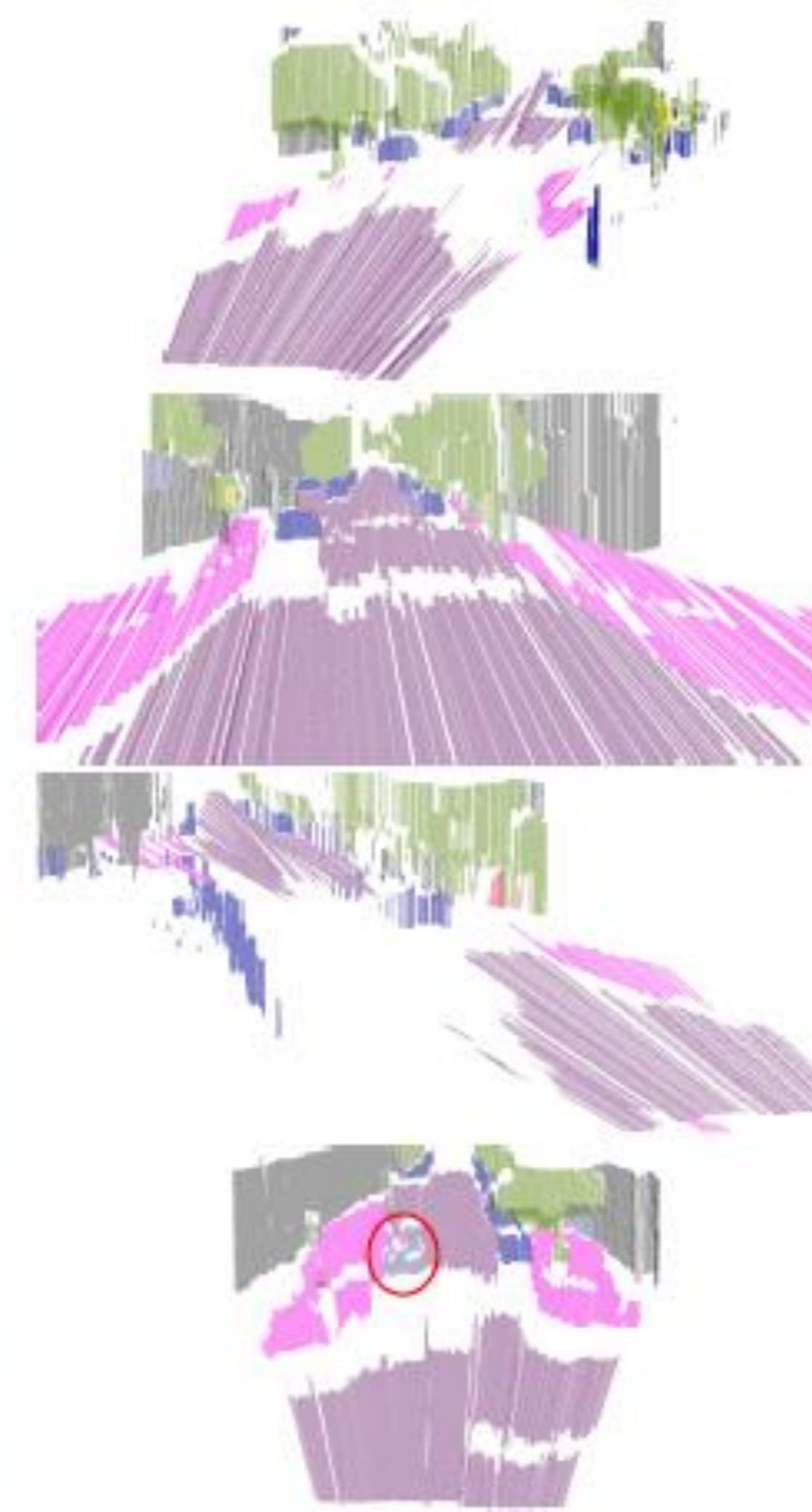


# Motivation & Objectives

Left Image



Original Stixels



## Previous work:

- Stixel World [Pfeiffer 2011]
- Semantic Stixels [Schneider 2016]

## Problem:

- Slanted roads not well modeled

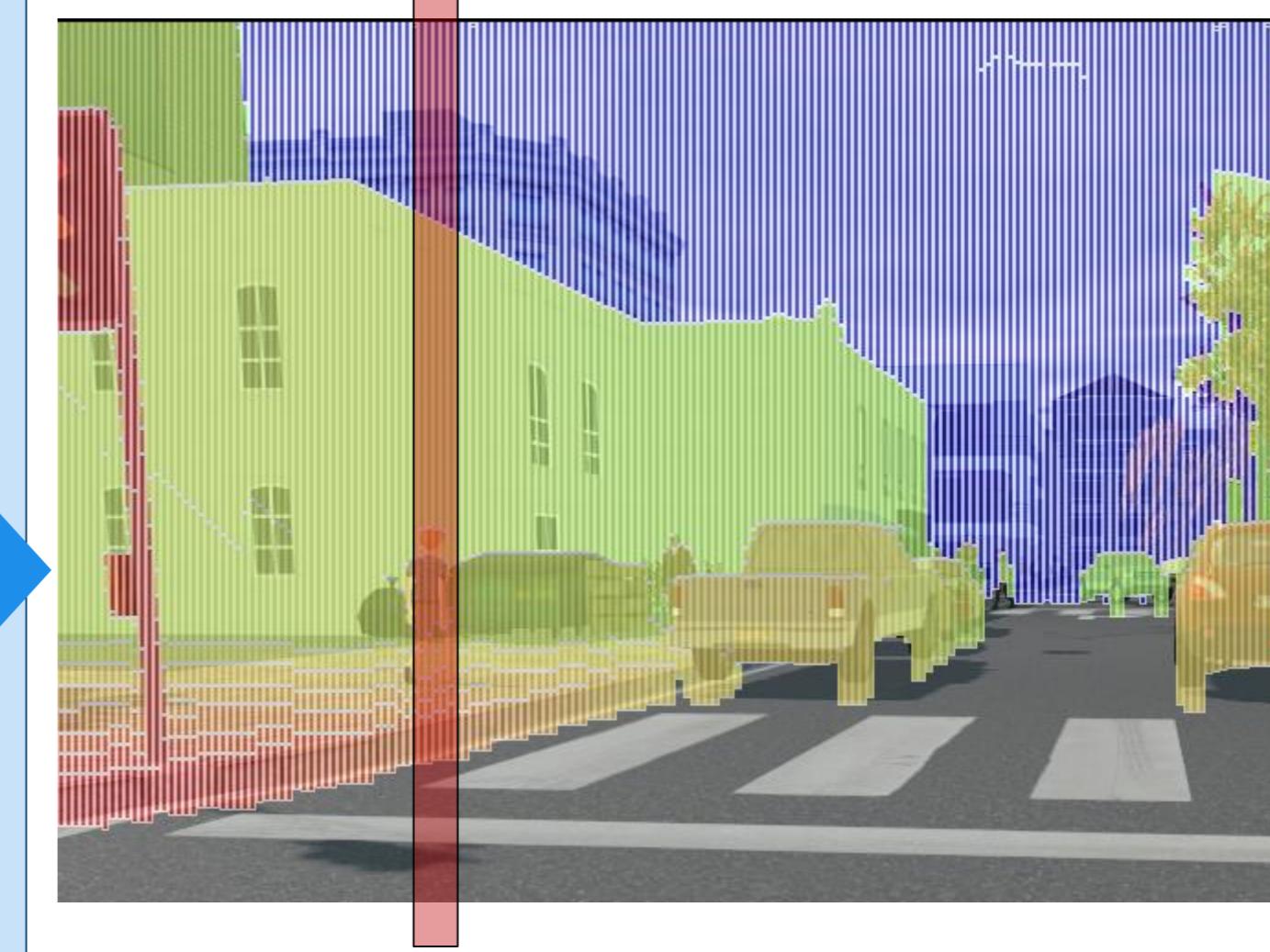
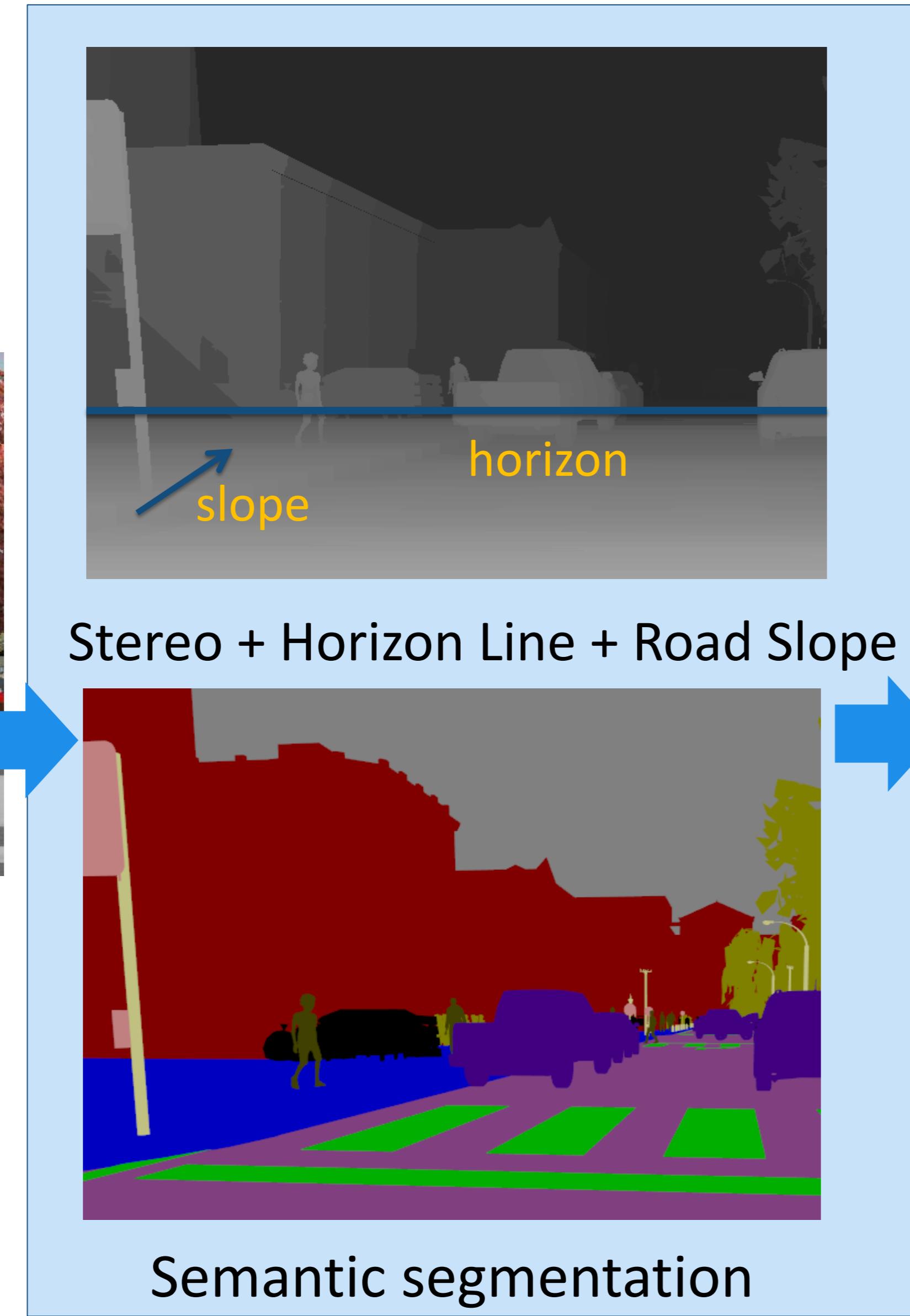
## Contribution:

- New model to represent slanted roads
- Proposal to reduce computational work

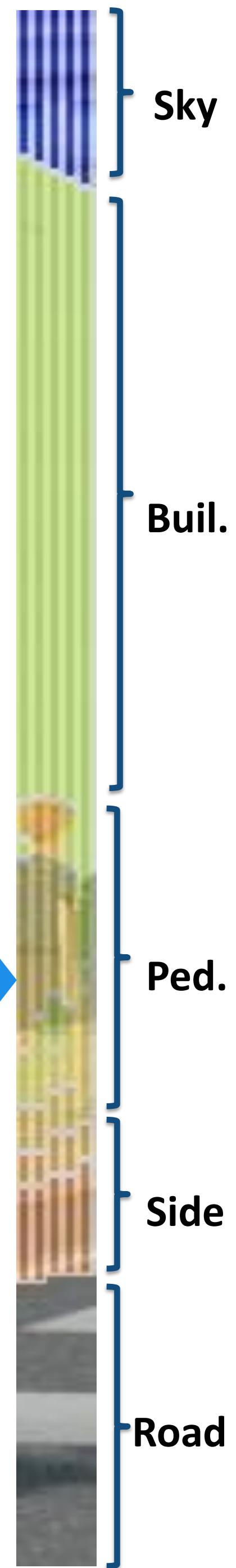
# Semantic Stixels: Unified approach



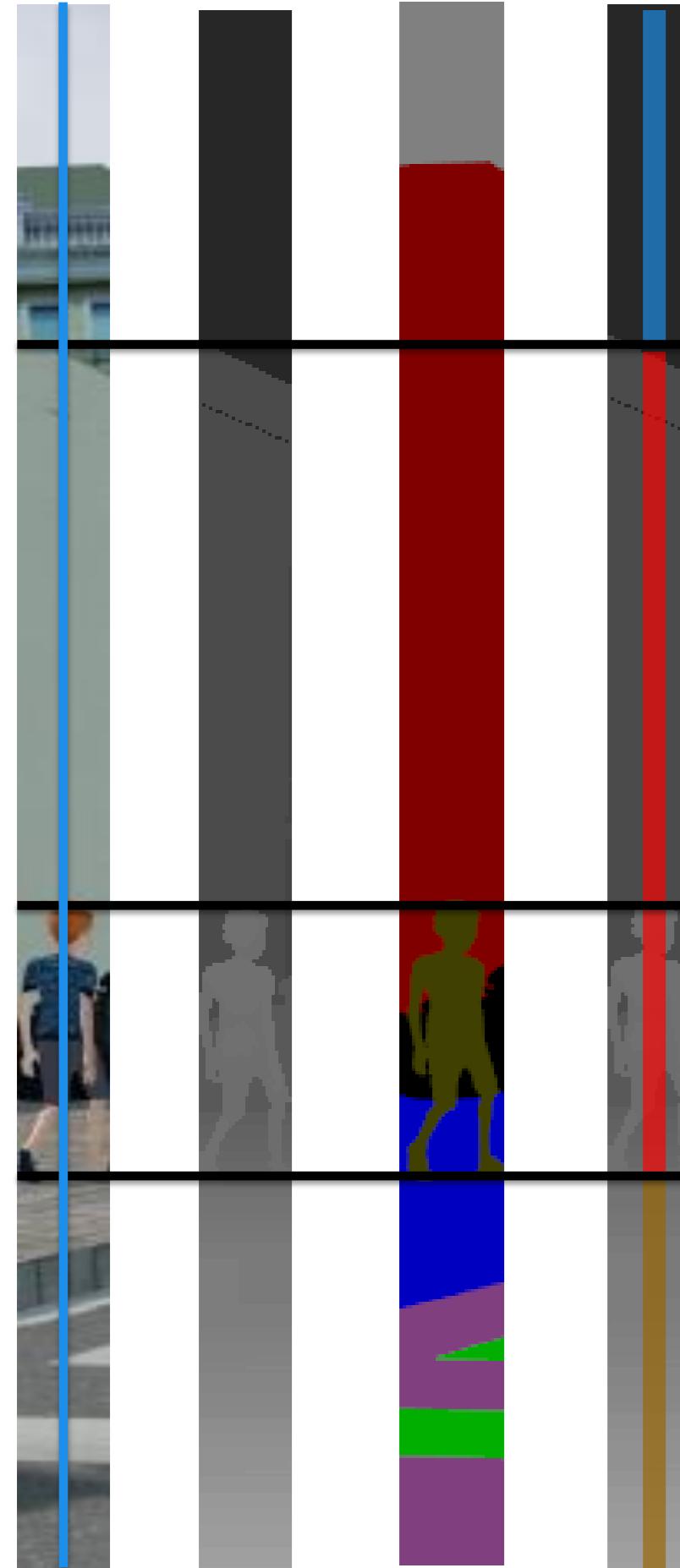
Stereo Images



Semantic Stixels



# Stixels: Original Model



## Stixel models:

- █ Sky: 0 disparity
- █ Object: Disparity mean
- █ Ground: Precomputed model

Assumption: Far away  
Assumption: Constant distance  
Assumption: Constant height

## Unified probabilistic approach:

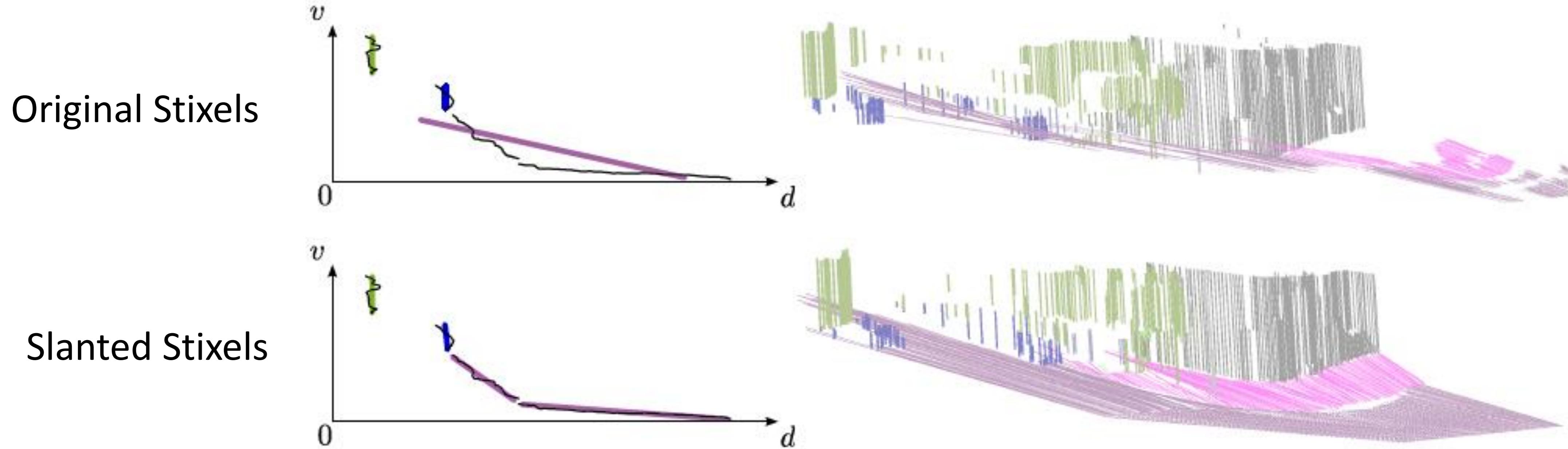
Disparity term considers the accordance of measurements to model  
Semantic energy favors classes that fit to the observed input

## Enforces constraints:

no sky below horizon, no neighbors objects at same disparity ...

**Computed independently for each column**

## New model: Slanted Stixels



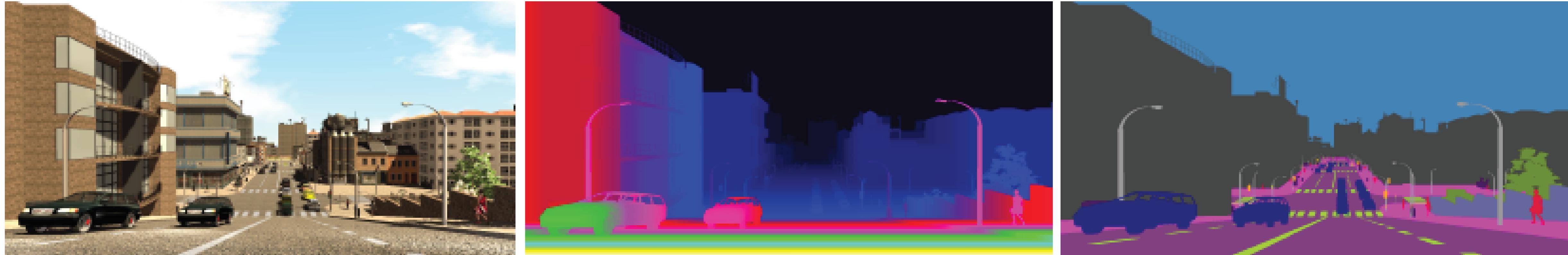
- New model to represent all classes:
- With priors according to the class:

$$\mu(s_i, v) = b_i * v + a_i$$

$$E_{plane}(s_i) = \left(\frac{a - \mu_{c_i}^a}{\sigma_{c_i}^a}\right)^2 + \left(\frac{b - \mu_{c_i}^b}{\sigma_{c_i}^b}\right)^2 - \log(Z)$$

- Each class has different parameters: slanted ground and objects and 0 disparity for sky
- Optimized jointly with Semantic Stixel probabilistic framework

# New dataset: SYNTHIA-San Francisco



sidewalk	building	vegetation	traffic light	traffic sign	bicycle	motorcycle	road lines
terrain	road	wall	pole	rider	truck	bus	train

- Generated with SYNTHIA toolkit to evaluate our algorithm, features slanted roads
- Photorealistic virtual sequence (2224 images), pixel-level depth and semantic ground truth
- Expensive to generate equivalent real-data sequence

## Results: Disparity Error

Metric	Dataset	Original	Ours
Disp Err (%)	Ladicky	17.3	16.9
	KITTI 15	10.9	11.0
	SYNTHIA-SF	30.9	<b>12.9</b>

Lower is better

- Much better accuracy for slanted road sequence, similar for others

# Results: Semantic segmentation IoU

Metric	Dataset	Original	Ours
Disp Err (%)	Ladicky	17.3	16.9
	KITTI 15	10.9	11.0
	SYNTHIA-SF	30.9	<b>12.9</b>
IoU (%)	Ladicky	63.5	63.4
	Cityscapes	65.7	65.8
	SYNTHIA-SF	46.0	<b>48.5</b>

Higher is better

- Better accuracy for slanted road sequence, similar for others

## Results: Frame-rate

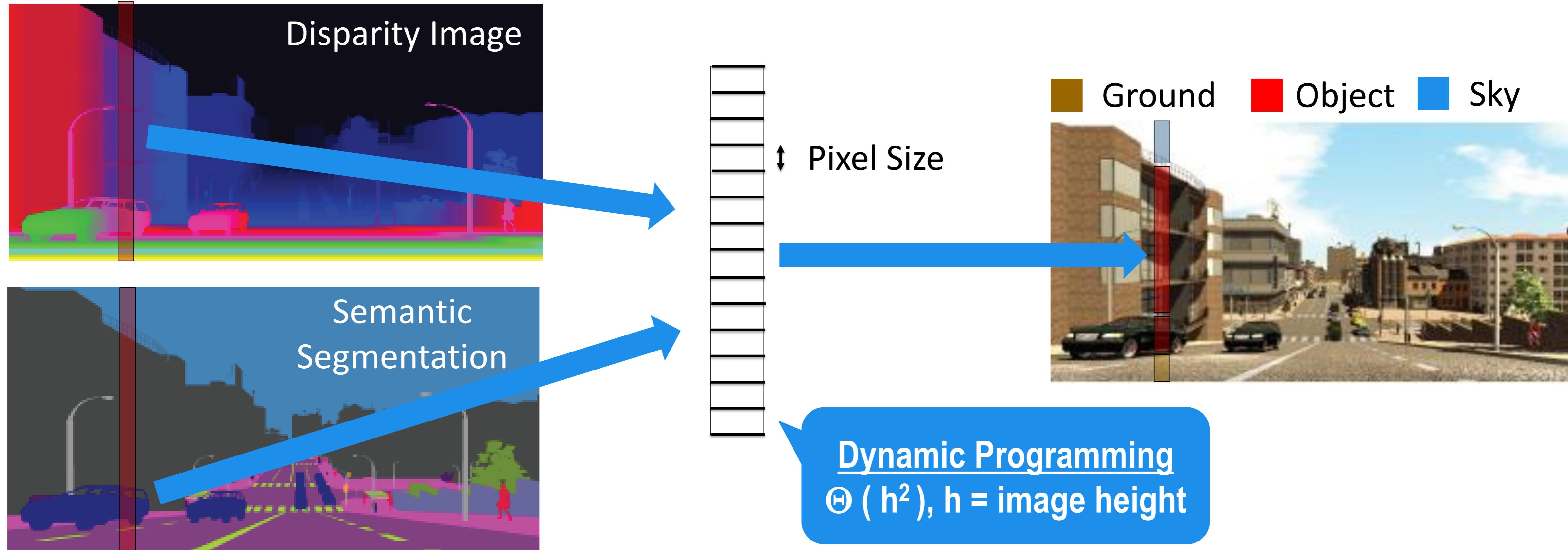
Metric	Dataset	Original	Ours
Disp Err (%)	Ladicky	17.3	16.9
	KITTI 15	10.9	11.0
	SYNTHIA-SF	30.9	<b>12.9</b>
IoU (%)	Ladicky	63.5	63.4
	Cityscapes	65.7	65.8
	SYNTHIA-SF	46.0	<b>48.5</b>
Frame-rate (Hz)	KITTI 15	<b>113</b>	61
	Cityscapes	<b>20.9</b>	6.6
	SYNTHIA-SF	<b>19.4</b>	4.7

Stixels time measured on  
6-core Intel i7

Higher is better

- Our version is slightly slower because of the increased complexity

# Stixel Computation Complexity: Dynamic Programming

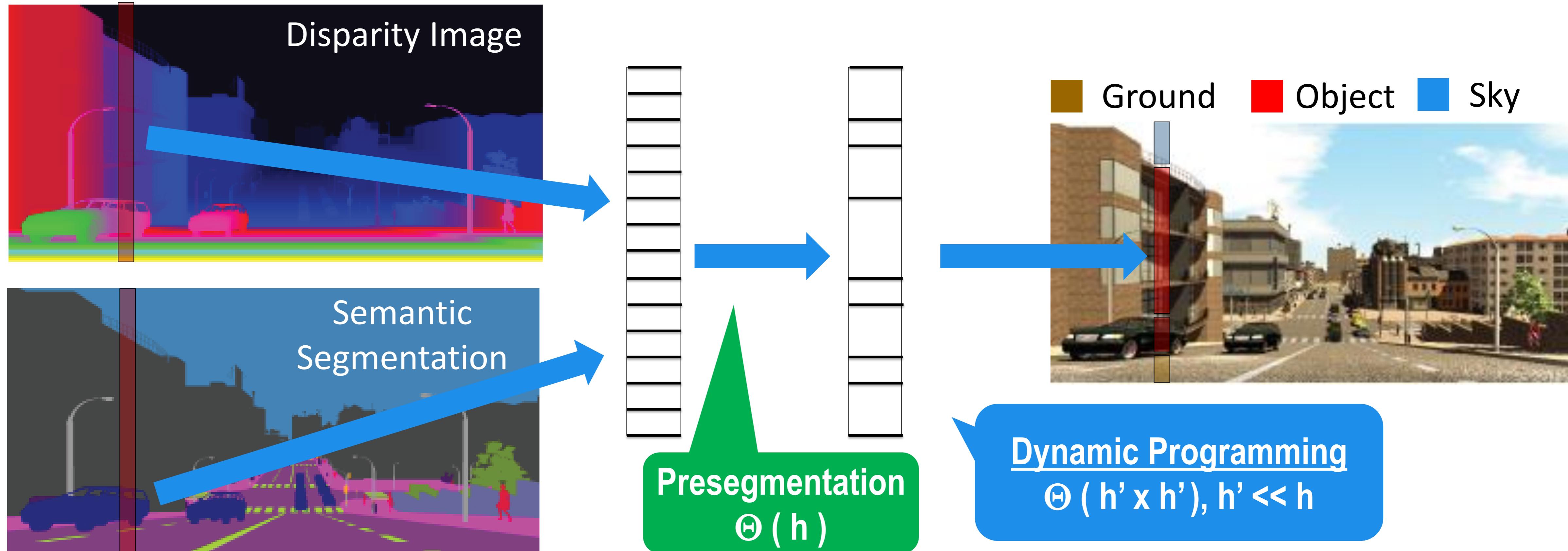


**First-order Markov property:** Only pair-wise Stixel relations are taken into account

**Combinatorial explosion (of possible configurations):**

Dynamic programming to evaluate efficiently

# Stixel Computation Complexity: Presegmentation



- Infer possible Stixel cuts (presegmentation) from image
- Avoid checking all possible Stixel combinations
- If given the correct Stixel cuts, same accuracy (or better!)

# Presegmentation Results: Disparity Error

Metric	Dataset	Presegmentation		Original	
		Original	Ours	Original	Ours
Disp Err (%)	Ladicky	17.3	16.9	18.5	17.8
	KITTI 15	10.9	11.0	11.8	11.7
	SYNTHIA-SF	30.9	<b>12.9</b>	33.9	<b>15.4</b>

Lower is better

- Depth error is higher because we do not check all combinations

# Presegmentation Results: Semantic segmentation IoU

Metric	Dataset	Presegmentation			
		Original	Ours	Original	Ours
Disp Err (%)	Ladicky	17.3	16.9	18.5	17.8
	KITTI 15	10.9	11.0	11.8	11.7
	SYNTHIA-SF	30.9	<b>12.9</b>	33.9	<b>15.4</b>
IoU (%)	Ladicky	63.5	63.4	63.9	63.7
	Cityscapes	65.7	65.8	65.7	65.8
	SYNTHIA-SF	46.0	<b>48.5</b>	46.9	<b>48.5</b>

Higher is better

- The same semantic segmentation accuracy is maintained

## Presegmentation Results: Frame-rate

Metric	Dataset	Presegmentation			
		Original	Ours	Original	Ours
Disp Err (%)	Ladicky	17.3	16.9	18.5	17.8
	KITTI 15	10.9	11.0	11.8	11.7
	SYNTHIA-SF	30.9	<b>12.9</b>	33.9	<b>15.4</b>
IoU (%)	Ladicky	63.5	63.4	63.9	63.7
	Cityscapes	65.7	65.8	65.7	65.8
	SYNTHIA-SF	46.0	<b>48.5</b>	46.9	<b>48.5</b>
Frame-rate (Hz)	KITTI 15	113	61	120	116
	Cityscapes	20.9	6.6	36.6	27.5
	SYNTHIA-SF	19.4	4.7	38.9	33.1

- Presegmentation speeds up both original and Slanted Stixels

Higher is better

# Presegmentation Results: Frame-rate

Metric	Dataset	Original		Presegmentation	
		Original	Ours	Original	Ours
Disp Err (%)	Ladicky	17.3	16.9	18.5	17.8
	KITTI 15	10.9	11.0	11.8	11.7
	SYNTHIA-SF	30.9	<b>12.9</b>	33.9	<b>15.4</b>
IoU (%)	Ladicky	63.5	63.4	63.9	63.7
	Cityscapes	65.7	65.8	65.7	65.8
	SYNTHIA-SF	46.0	<b>48.5</b>	46.9	<b>48.5</b>
Frame-rate (Hz)	KITTI 15	113	61	120	116
	Cityscapes	20.9	Up to 2x		36.6
	SYNTHIA-SF	19.4	4.7	38.9	33.1

Higher is better

# Presegmentation Results: Frame-rate

Metric	Dataset	Original		Presegmentation	
		Original	Ours	Original	Ours
Disp Err (%)	Ladicky	17.3	16.9	18.5	17.8
	KITTI 15	10.9	11.0	11.8	11.7
	SYNTHIA-SF	30.9	<b>12.9</b>	33.9	<b>15.4</b>
IoU (%)	Ladicky	63.5	63.4	63.9	63.7
	Cityscapes	65.7	65.8	65.7	65.8
	SYNTHIA-SF	46.0	<b>48.5</b>	46.9	<b>48.5</b>
Frame-rate (Hz)	KITTI 15	113	61	120	116
	Cityscapes	20.9	6.6	Up to 7x	
	SYNTHIA-SF	19.4	4.7	38.9	33.1

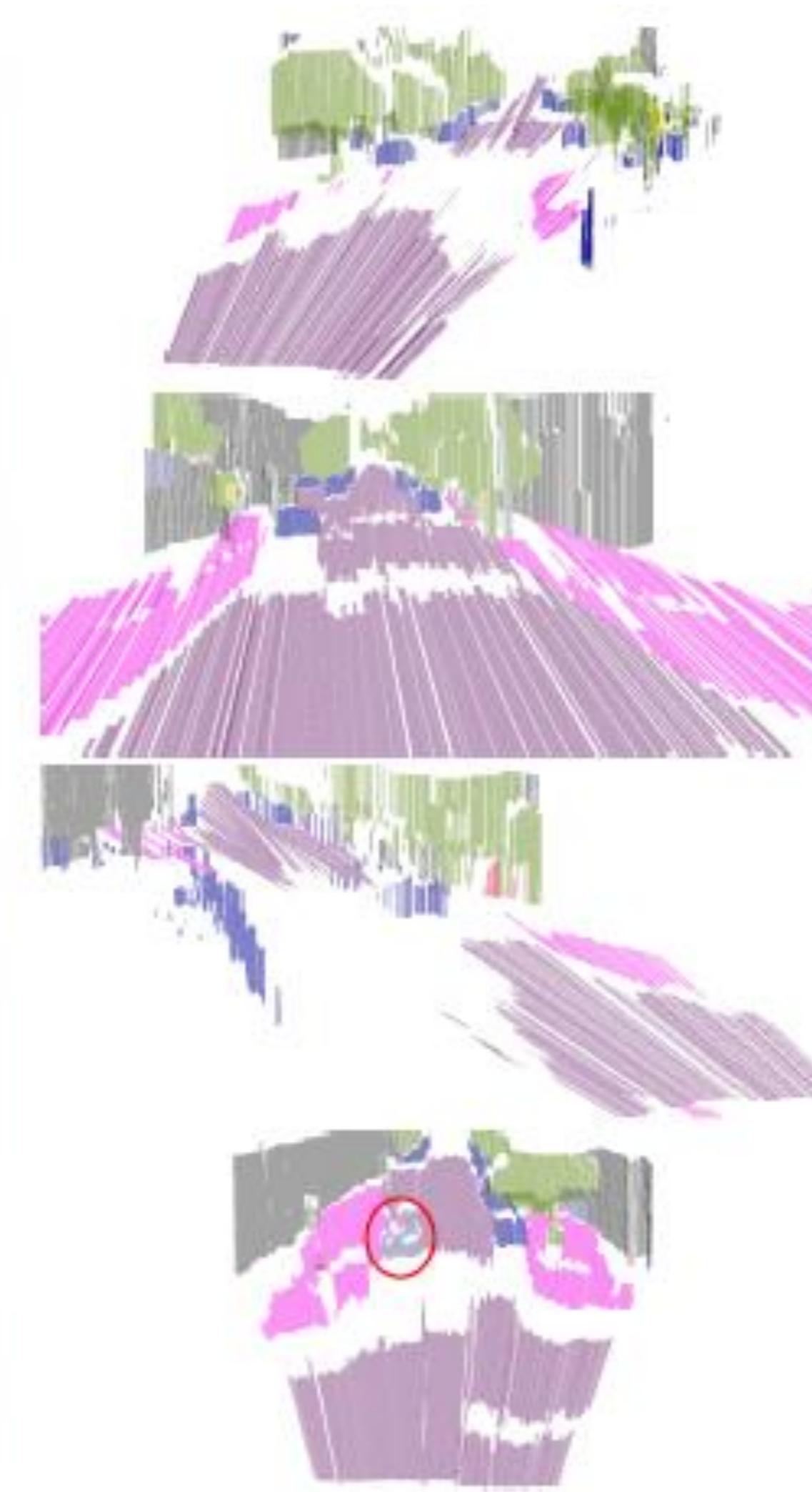
Higher is better

# Visual examples

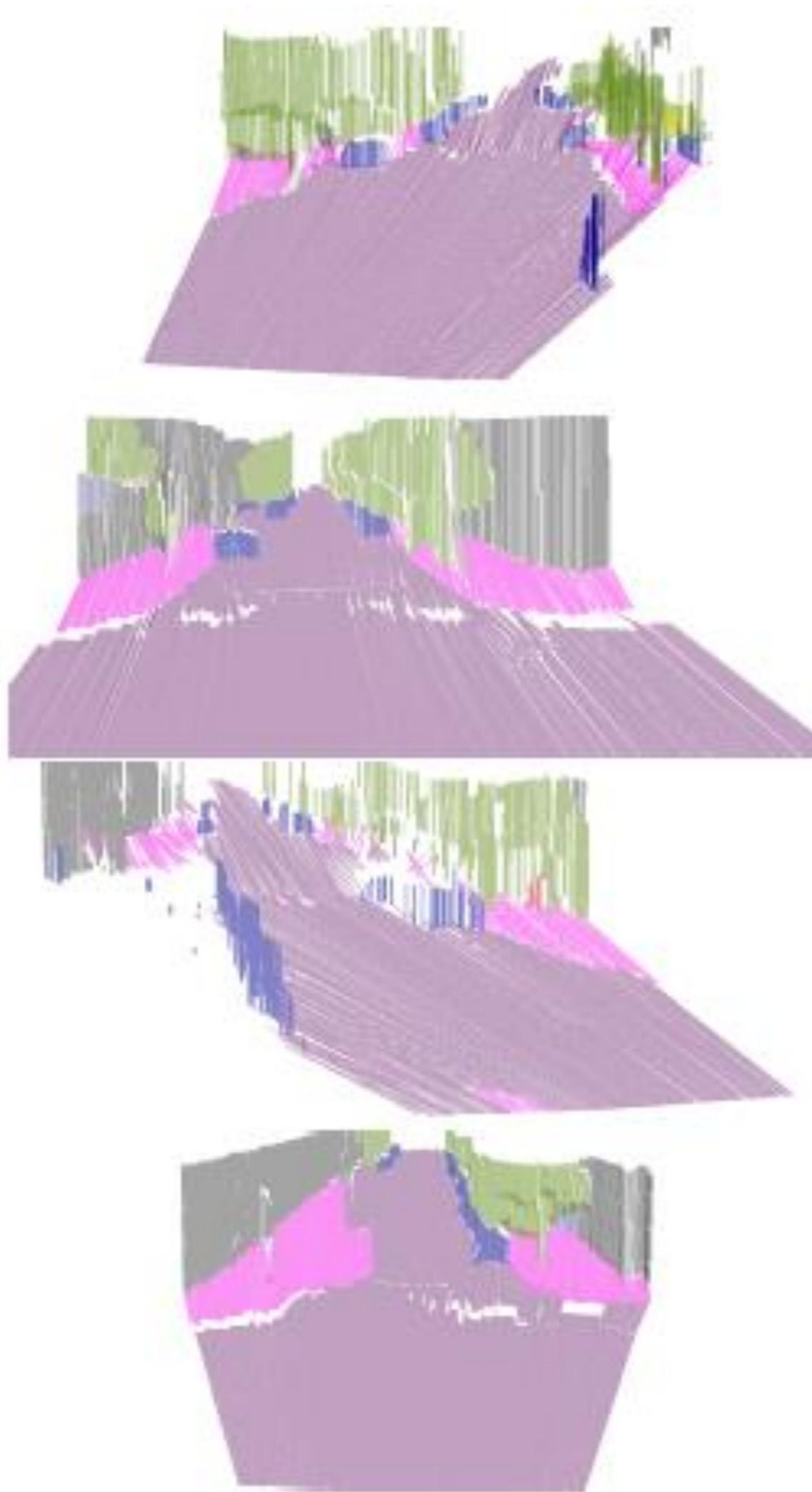
Left Image



Original Stixels



Slanted Stixels



## Visual example: Avoid emergency break

Left Image



Original Stixels



Slanted Stixels

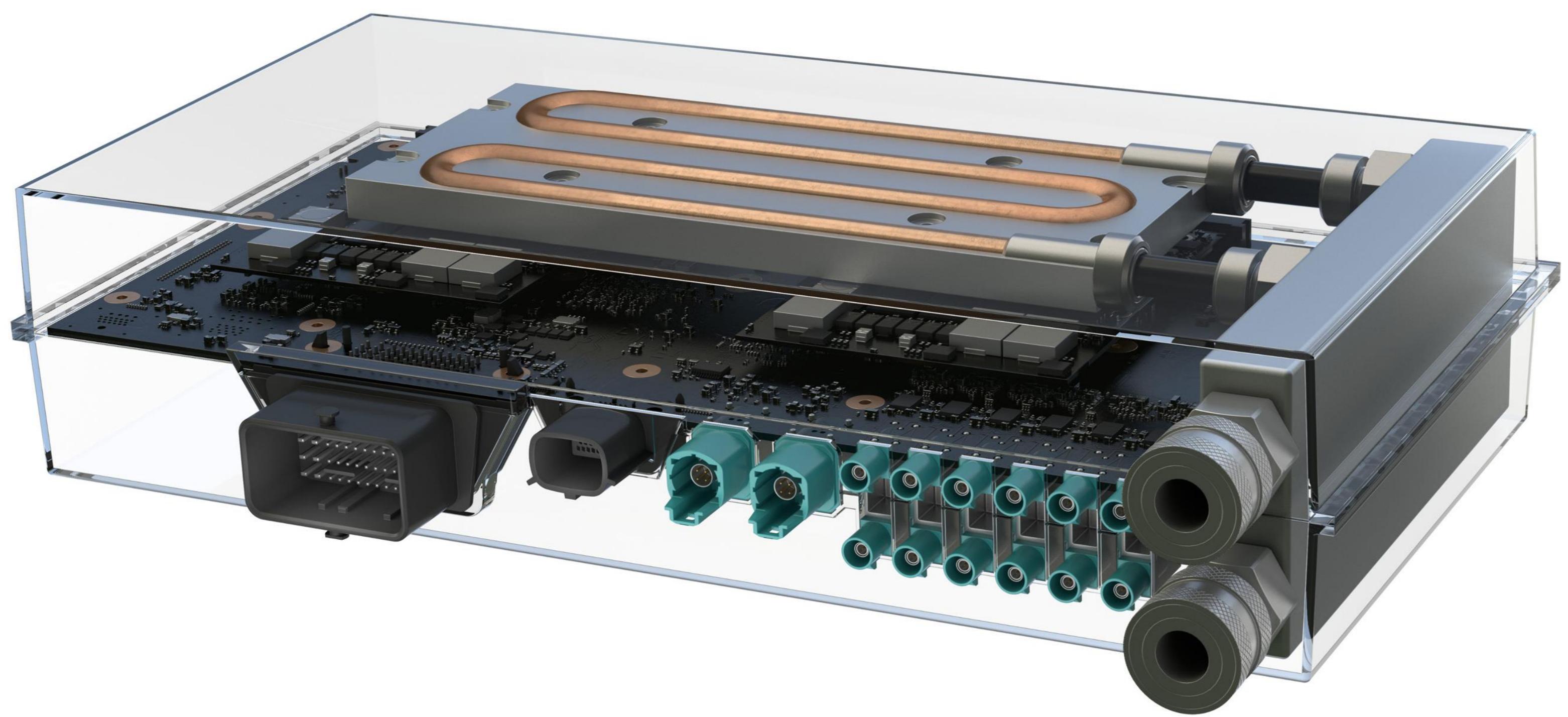


## Summary: Real sequence video



## Future work

- Improve presegmentation for better accuracy using a CNN
- Embedded GPU version on NVIDIA Drive PX 2 for autonomous driving



# Thank you

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