StixelNet

A Deep Convolutional Network for Obstacle Detection and Road Segmentation

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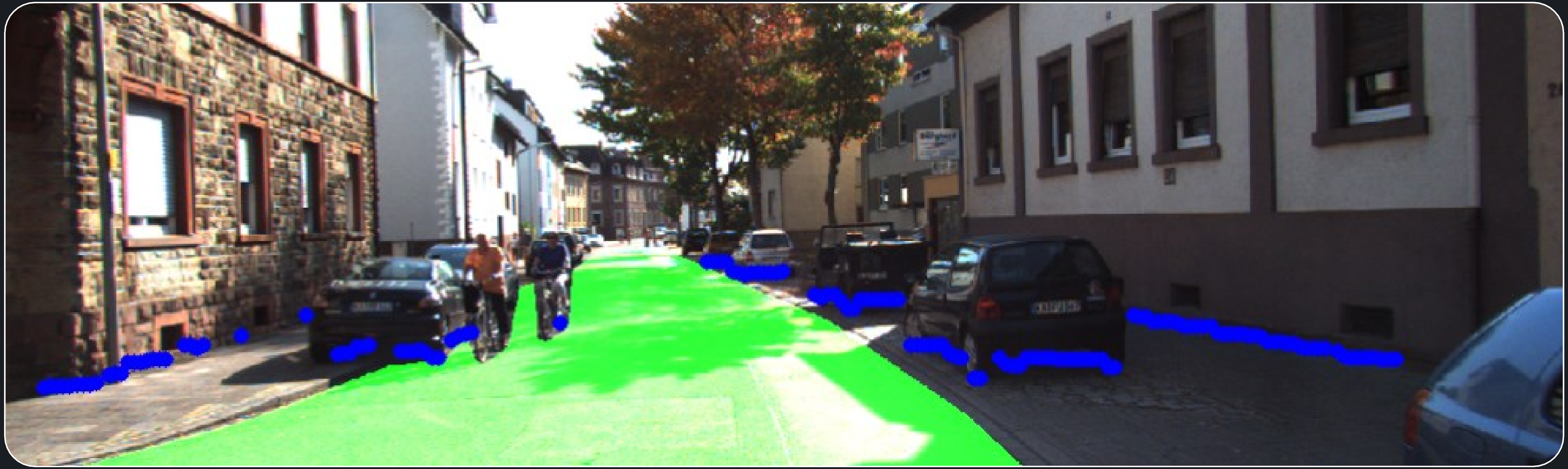
Problem formulation

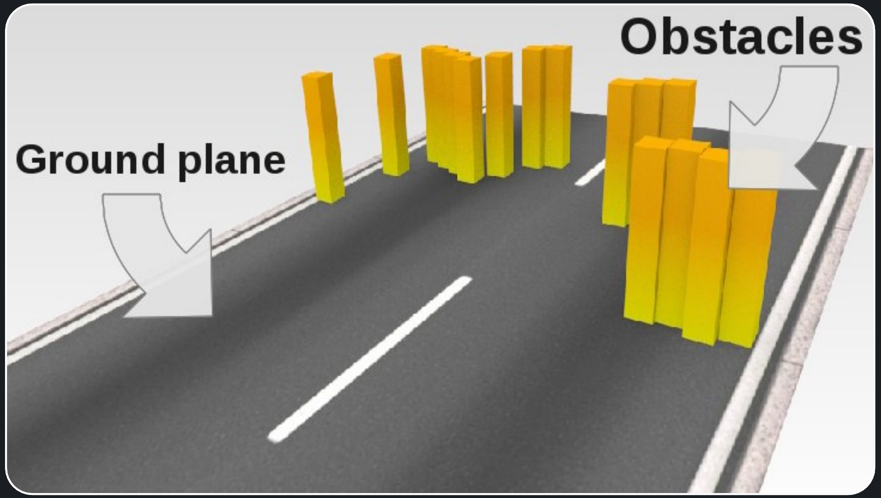


General obstacle detection / Free-space
3D sensors (Stereo, Lidar)

Road segmentation
Mono-camera using over-segmentation

Our approach
Solve both with a mono-camera

Stixel representation



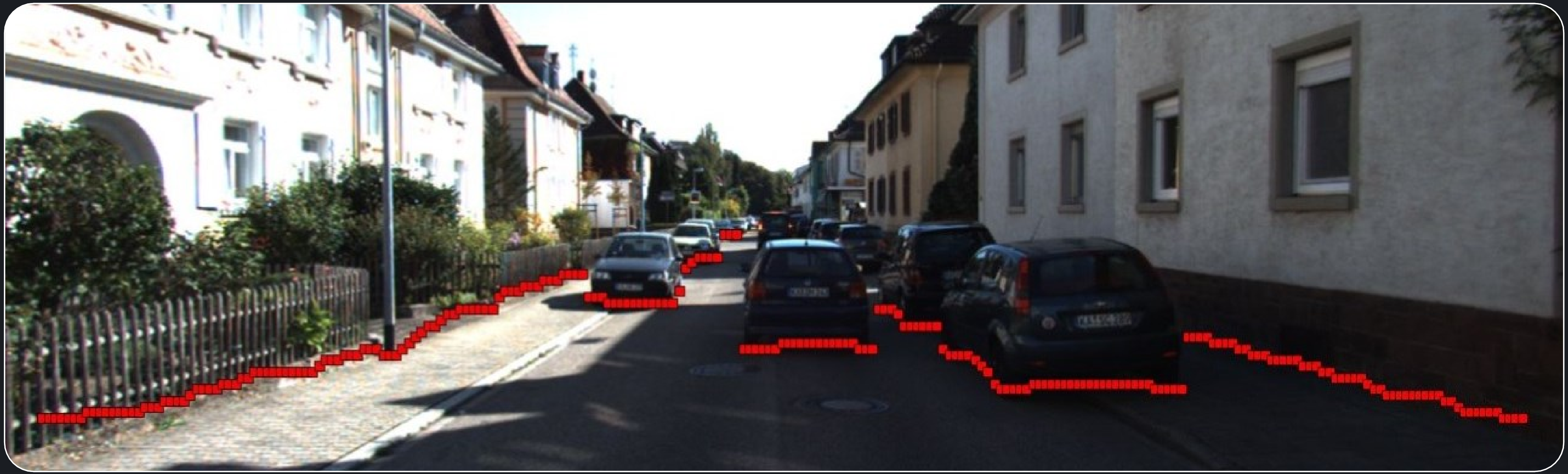
[Badino, Franke, Pfeiffer 2009]

Compact, local representation

Stereo vision:

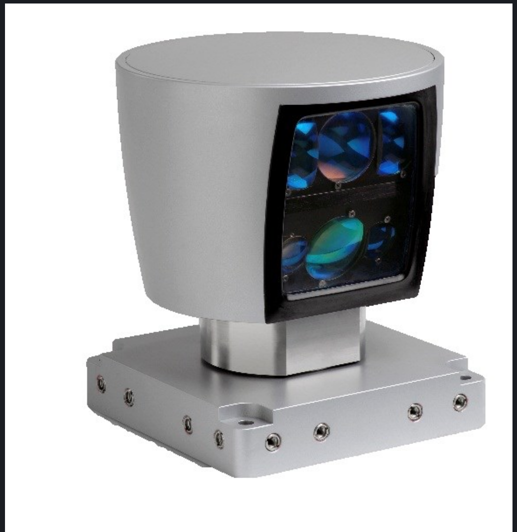
1. Ground plane estimation
2. Free-space estimation
3. Depth and height from point cloud:

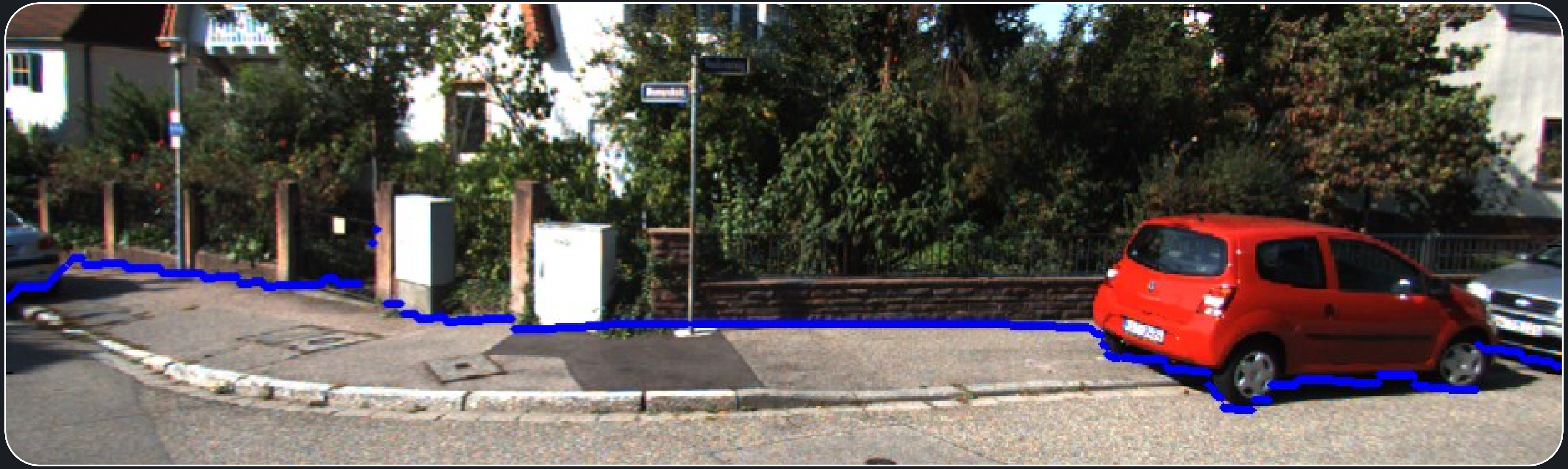
Monocular obstacle detection



Solved with CNN

Automated ground truthing



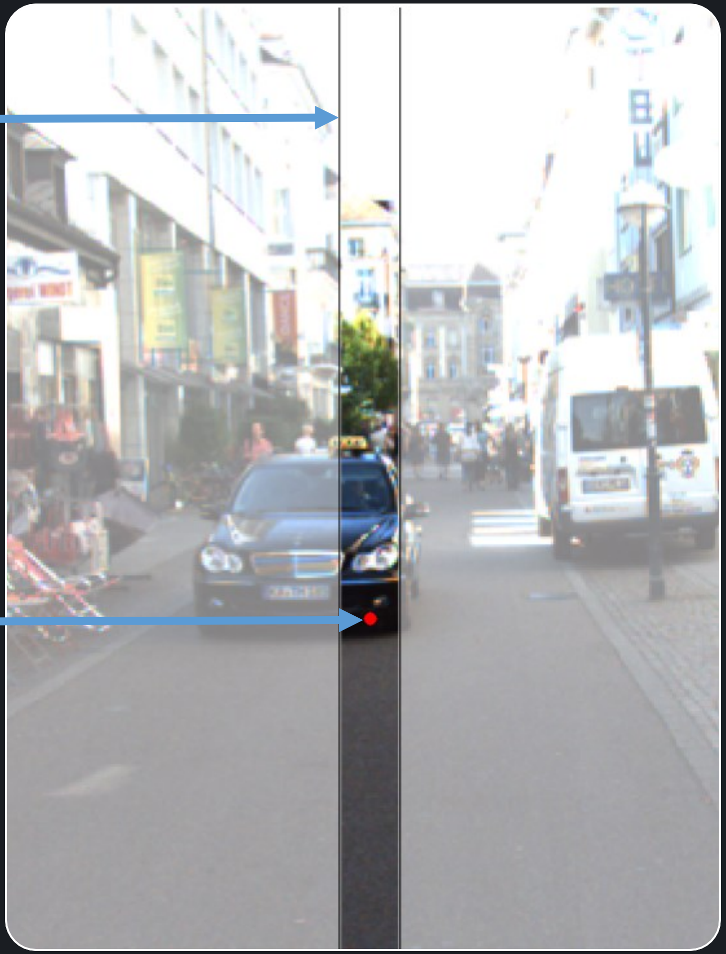


(*) **Road segmentation** requires manual annotation

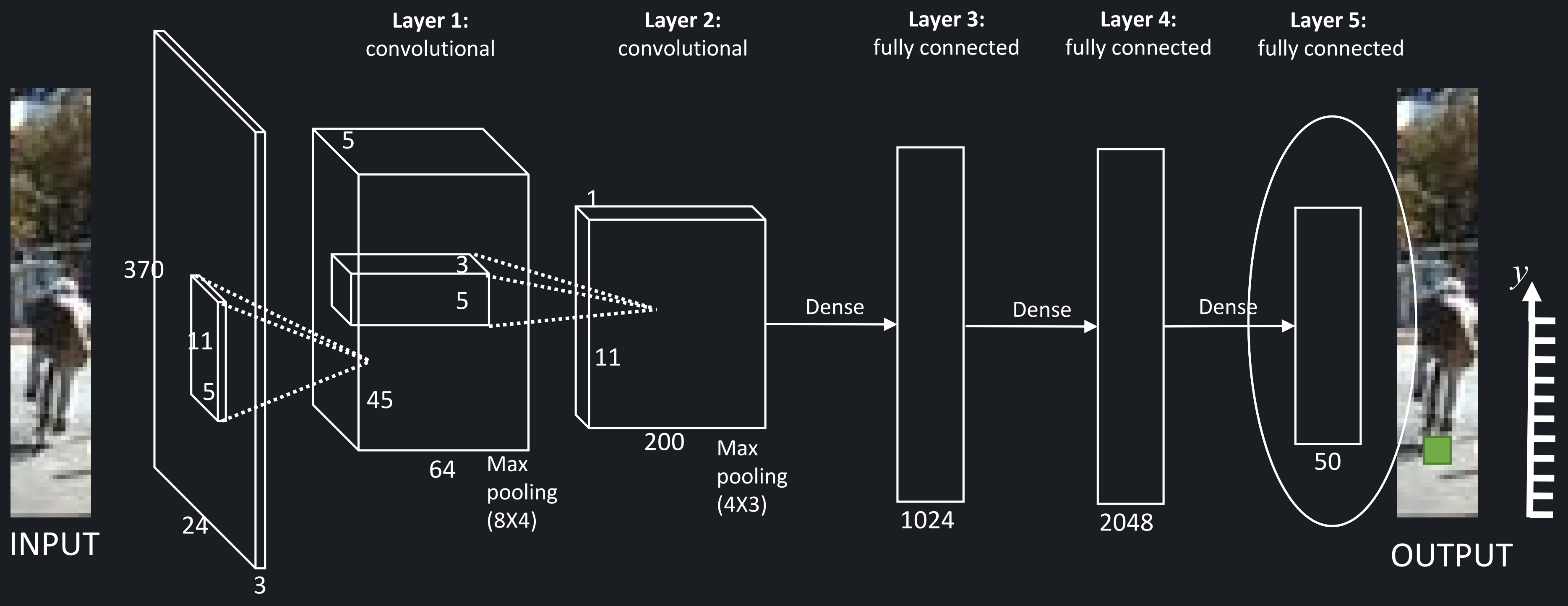
StixelNet column based approach

INPUT

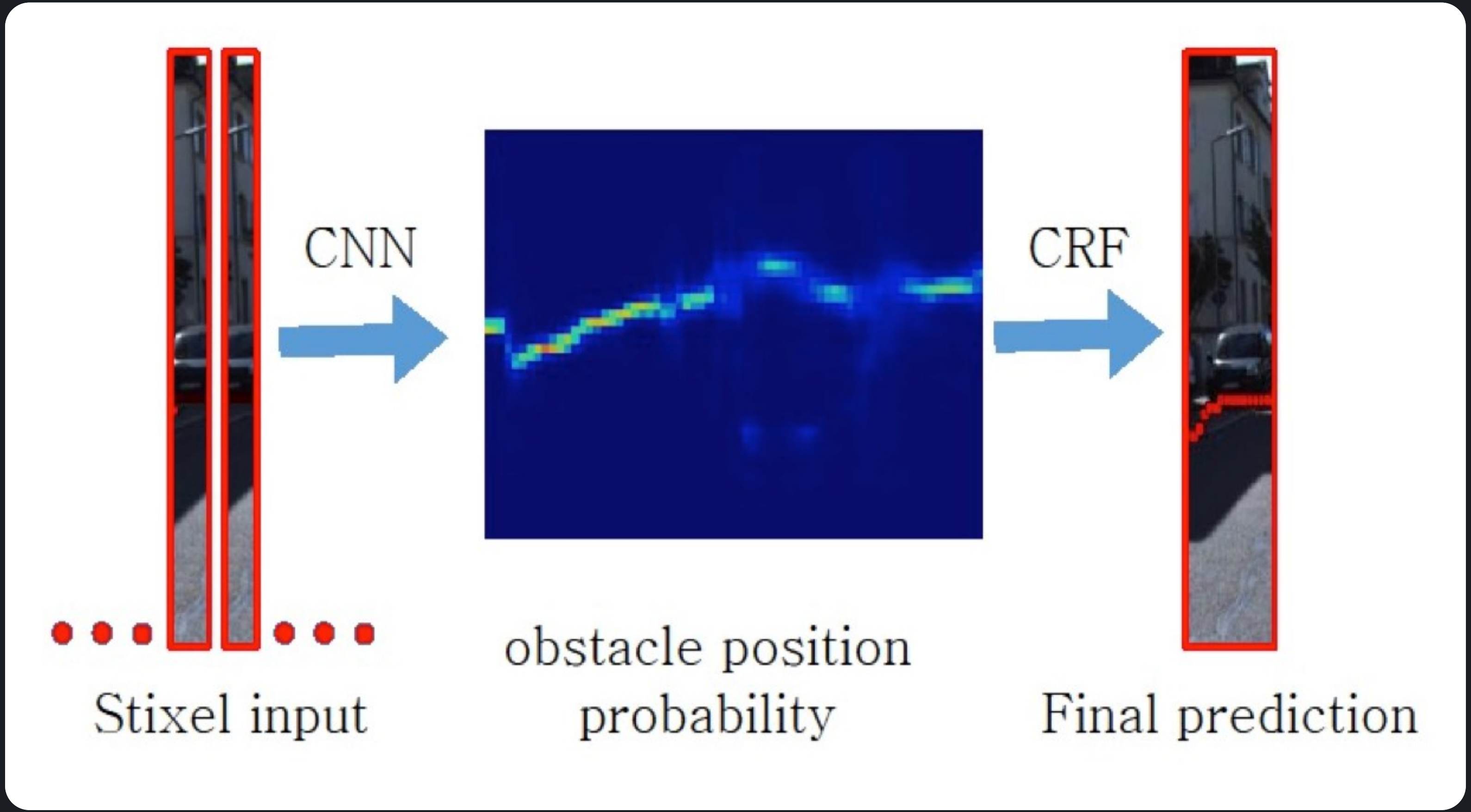
OUTPUT



StixelNet 5 Layer CNN



Obstacle detection flowchart



Training loss function

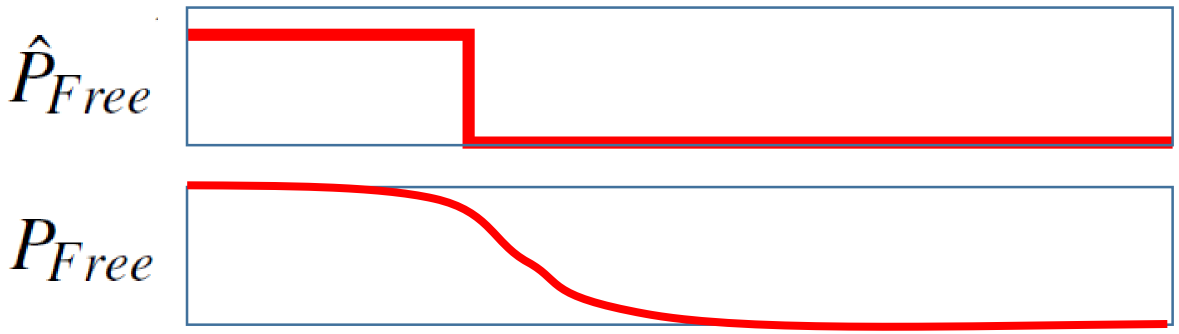
Euclidian loss:

- Natural loss for regression
- Doesn't provide full distribution
- Can't handle ambiguities
- Poor performance

KL-loss:

$$D_{KL}(\hat{P}_{Free} || P_{Free})$$

- Full distribution
- Improved results

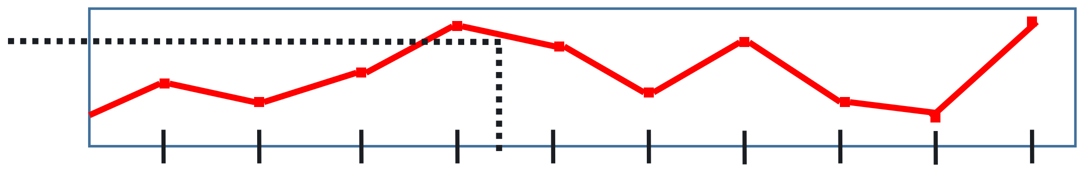


Training loss function

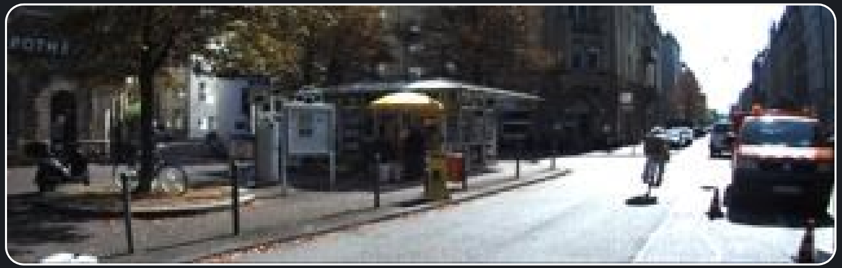
Softmax-loss

- classification to 50 bins
- Full distribution
- Boundary problem

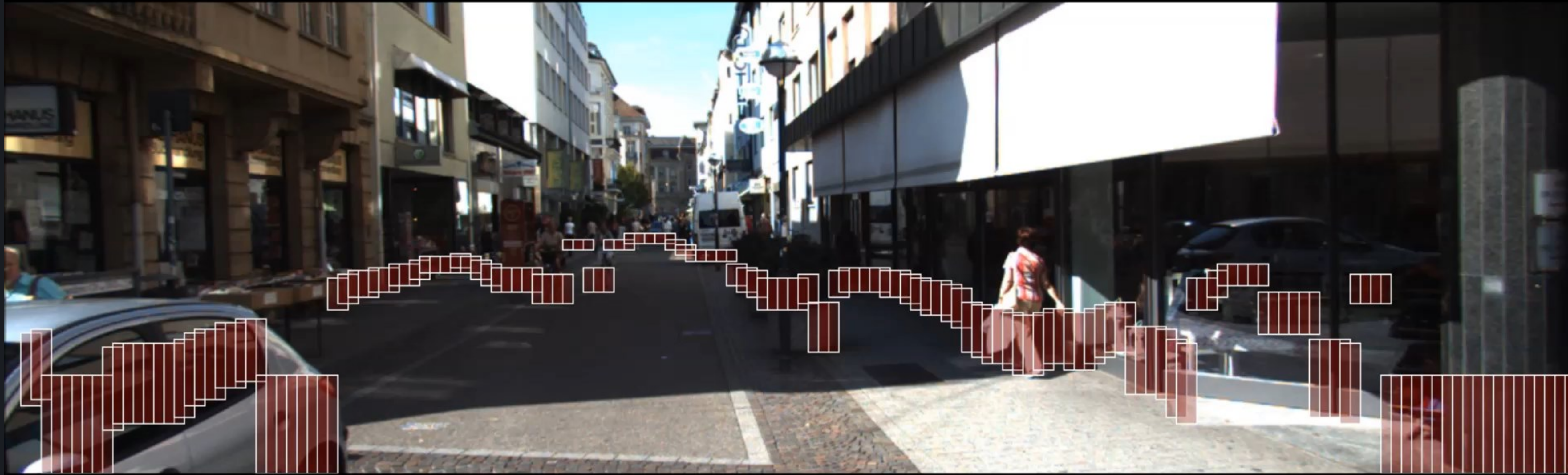
Piecewise-linear (PL) loss:



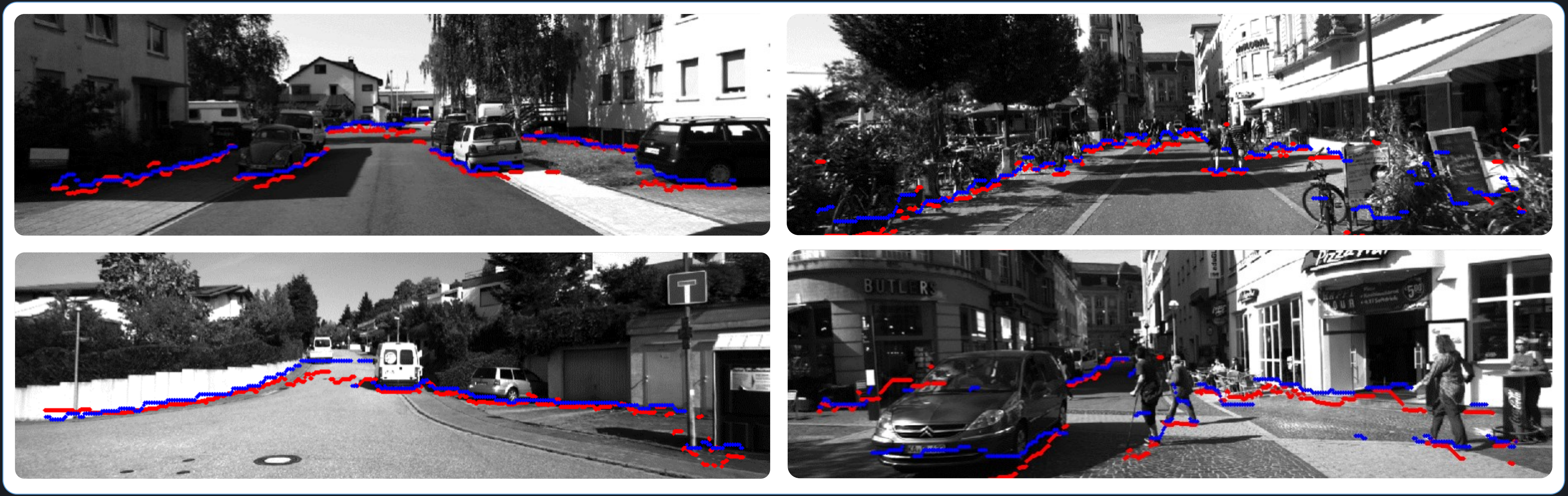
Results KITTI dataset [Geiger et al. 2013]



- Raw images: 56 sequences (50 Train, 6 Test).
- 6,000 train images (every 5th frame) and 800 test.
- Ground truth result:
- After GT: 331K training columns and 57K testing



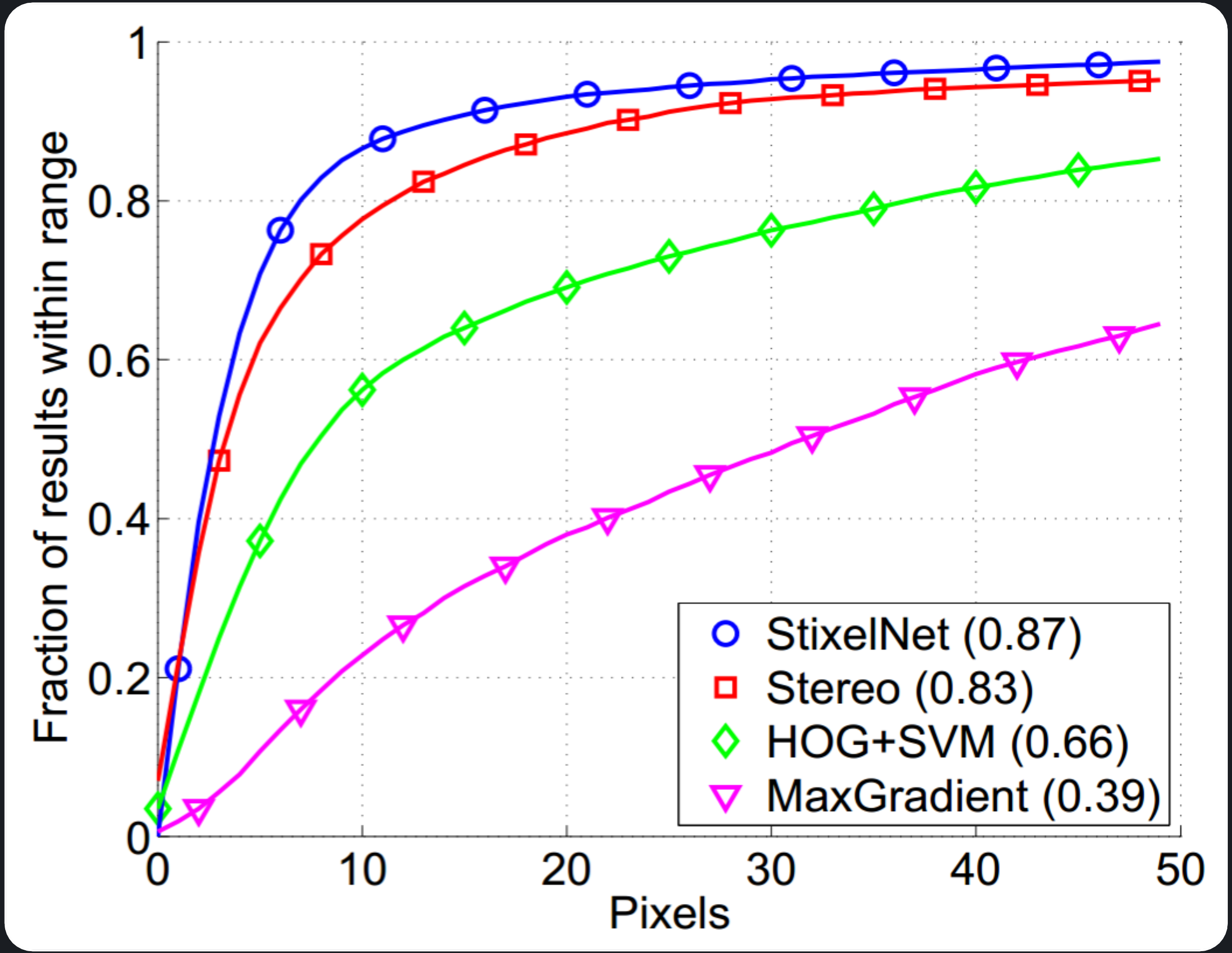
Comparison with stereo-based



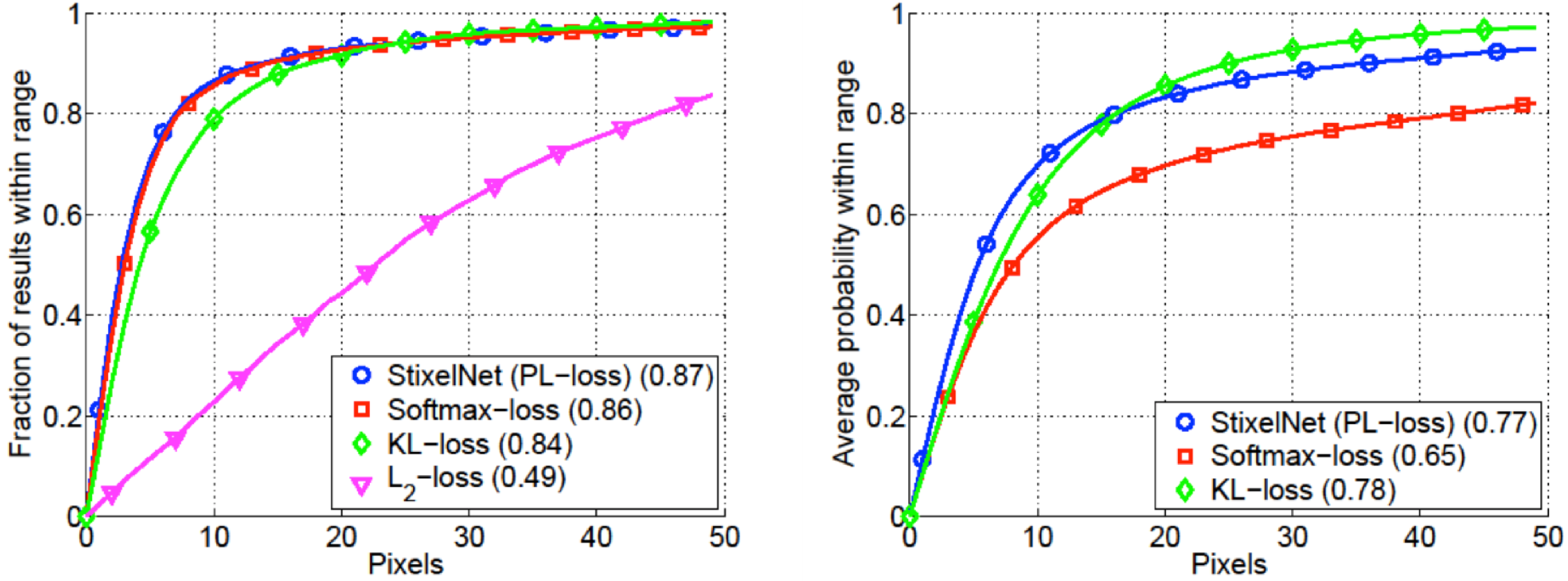
Stereo [Badino et al. 2009]

“StixelNet”

Results


Fraction of results within range
1
0.8
0.6
0.4
0.2
0
0
10
20
30
40
50
Pixels
StixelNet (0.87)
Stereo (0.83)
HOG+SVM (0.66)
MaxGradient (0.39)

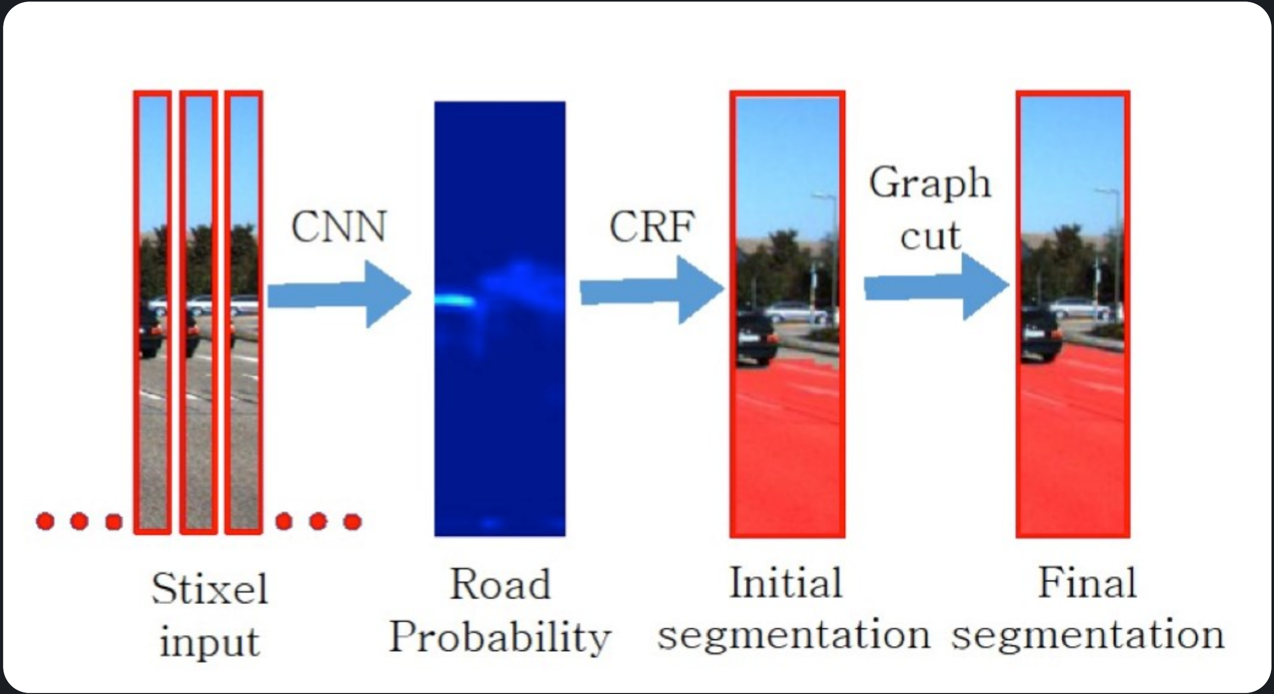
Results Loss-function



Drivable Road segmentation

Data: KITTI road segmentation challenge (manually annotated)

Fine-tuning from StixelNet



Road segmentation results

KITTI Road segmentation challenge

Thank you

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