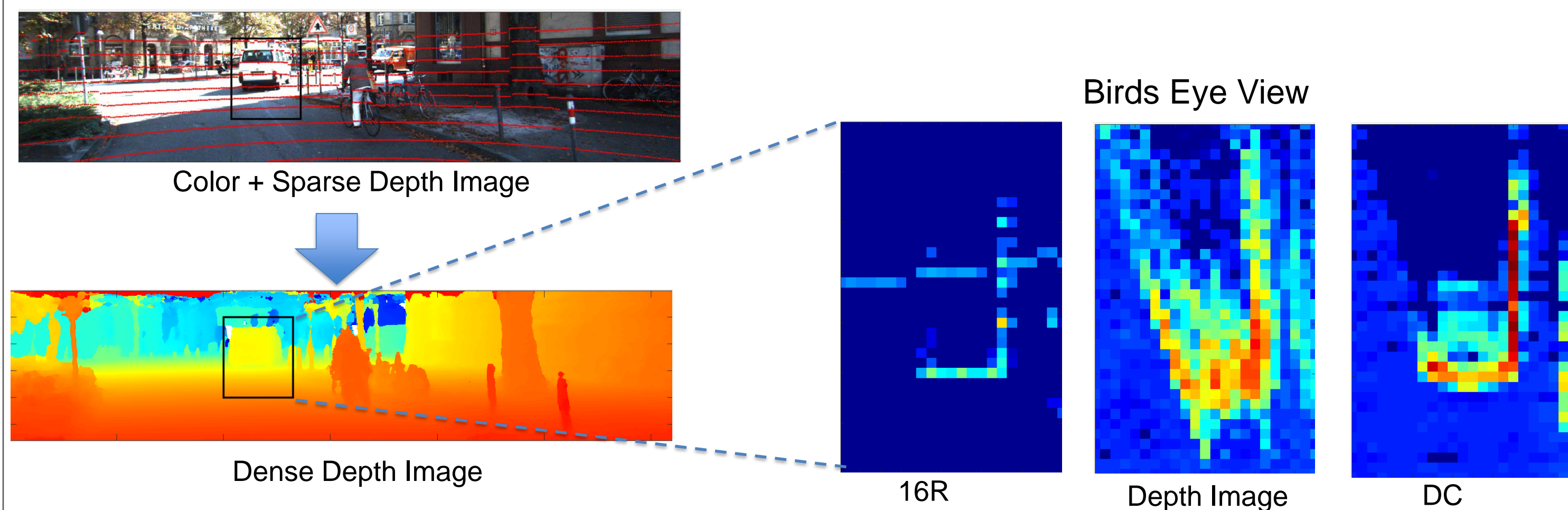


## Problem Statement

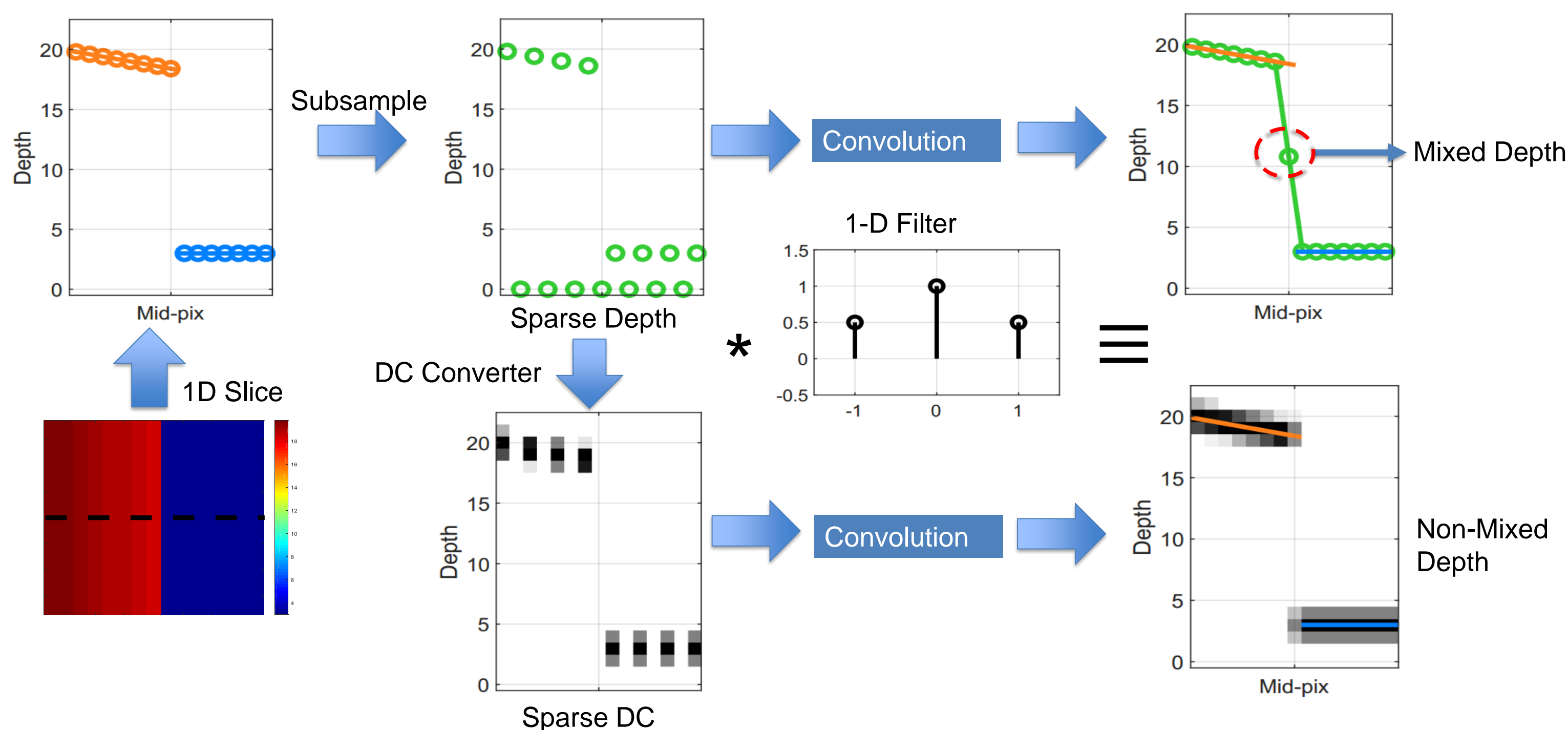
- Given sparse depth and color image can we estimate **dense** depth, **without smearing depth**, across object **boundaries**?

## Contributions:

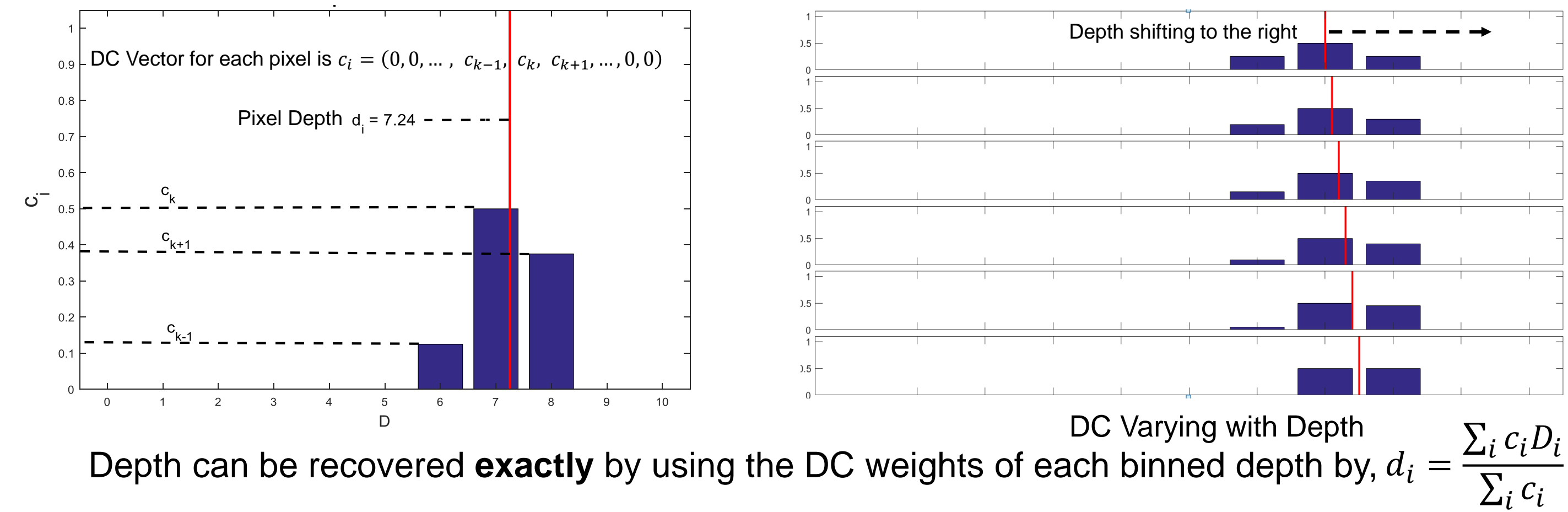
- New depth representation (depth coefficients) that prevent smearing across boundaries.
- Learning by Cross-Entropy Loss.
- Improved object detection performance from super-resolved depth.



## Motivation by Convolution



## Depth Coefficients (DC): Representation of Depth



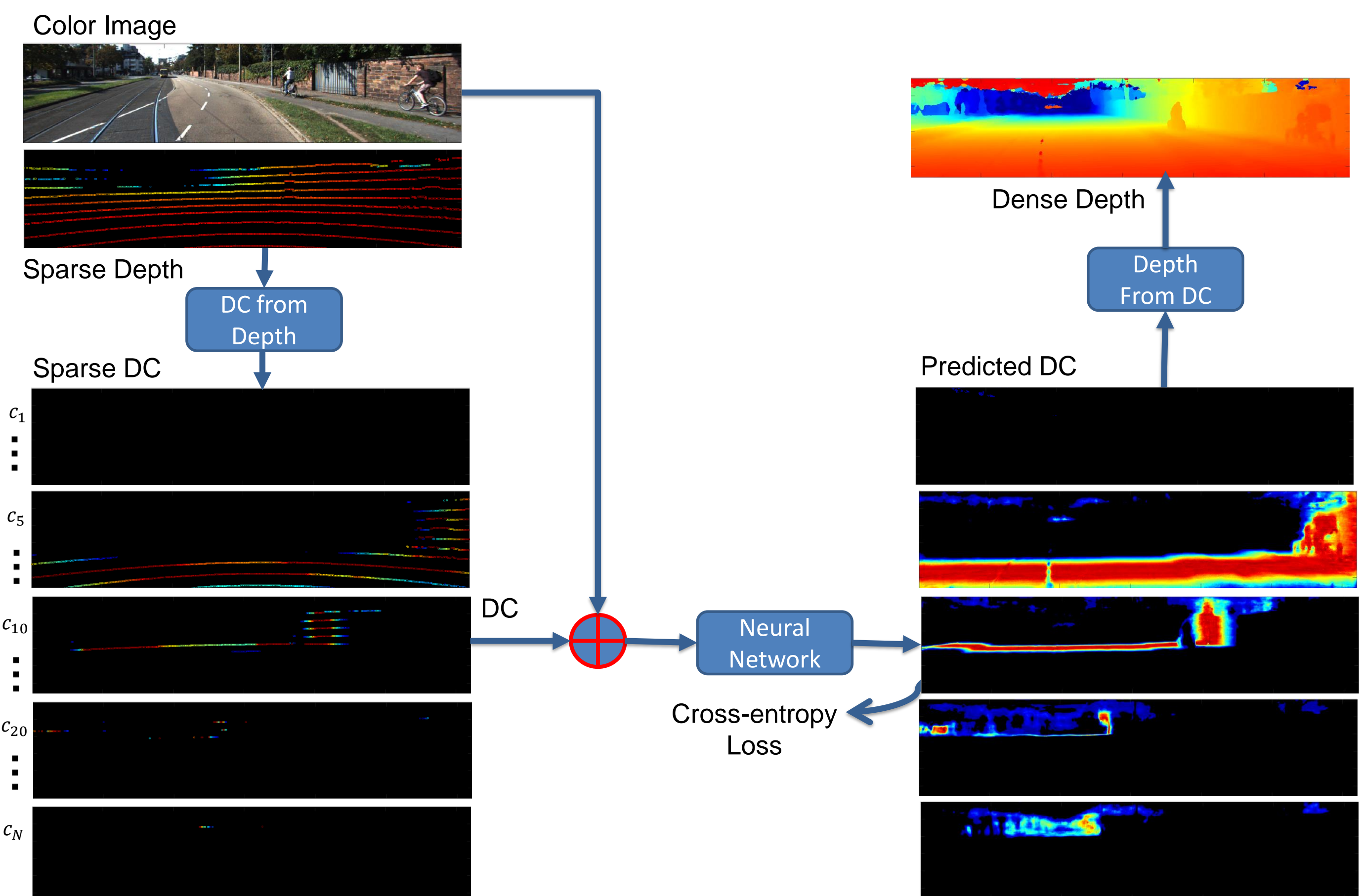
## Loss Function

We use the **Cross-entropy** loss as opposed to **MSE** or **MAE**

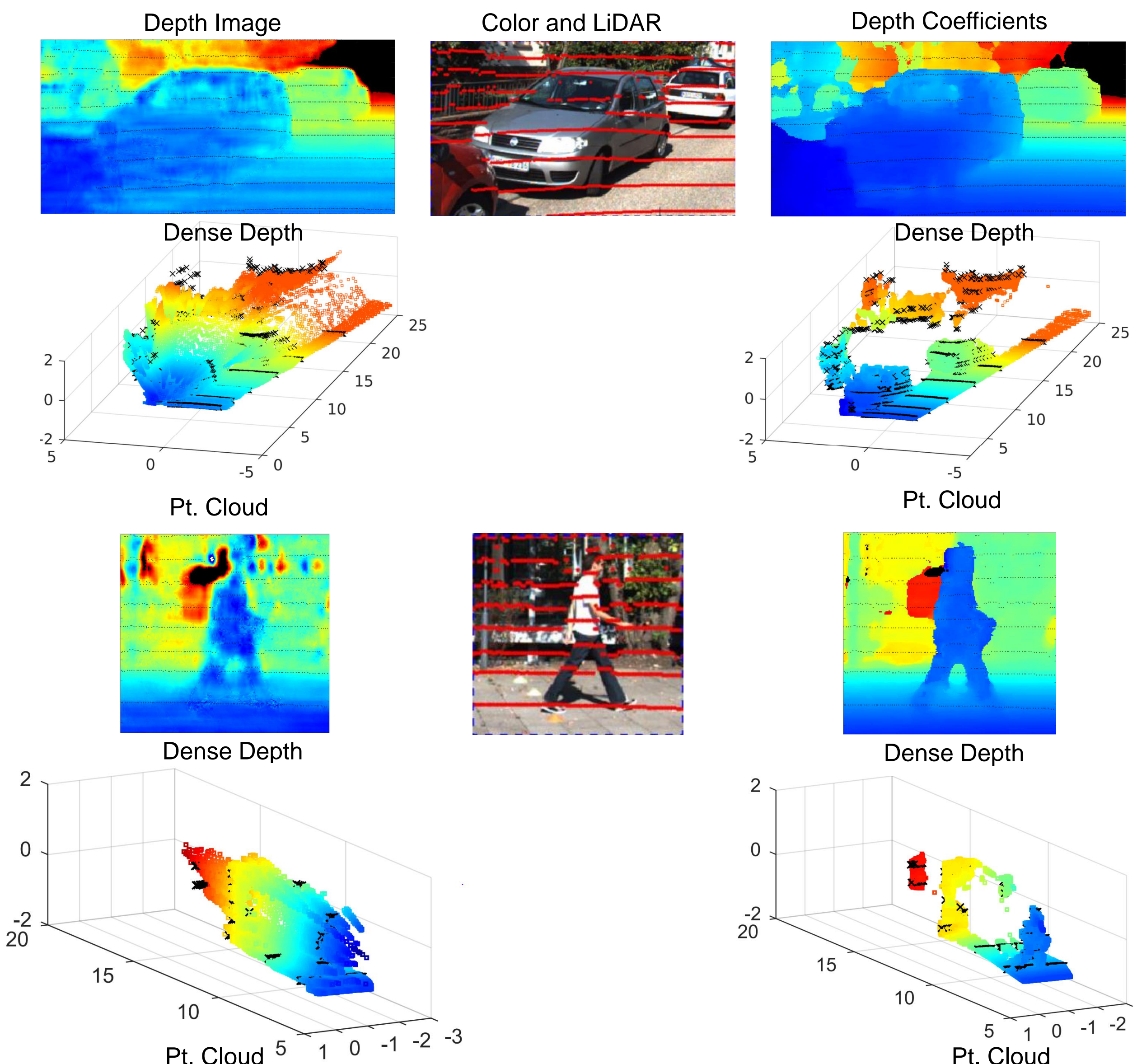
$$L_i^{ce}(c_{ij}) = -\sum_{j=1}^N c_{ij} \log(\hat{c}_{ij})$$

N: Total no. of pixels.  
i: ith binned depth

## Using DC with a Neural Network



## Sample Results



## Quantitative Results

Meth.	MAE	RMSE	Input	Loss	MAE	RMSE	Upsamp	3D Bounding Box			Bird's Eye View Box		
DI [1]	65.2	174.3	DI [1]	MSE	6.63	15.28		Easy	Med.	Hard	Easy	Med.	Hard
DC	<b>37.8</b>	<b>160.6</b>	DC	MSE	6.10	15.32	16R	54.4	36.2	31.3	73.6	<b>58.1</b>	<b>50.4</b>
Table 1. KITTI Validation Benchmark with 16R LiDAR Scans.							DI[1]	36.7	23.0	18.5	56.2	33.8	29.7
Table 2. NYU2 Test Benchmark with Uniform-500 Samples.							DC	<b>64.9</b>	<b>41.9</b>	<b>34.7</b>	<b>78.1</b>	54.0	45.6

Units are in cm  
DI: Depth Image  
DC: Depth Coefficients

Table 3. Object Detection Results based on Frustum Point-Net [2].

