

# X-PDNet: Accurate Joint Plane Instance Segmentation and Monocular Depth Estimation by Cross-Task Distillation and Boundary Correction

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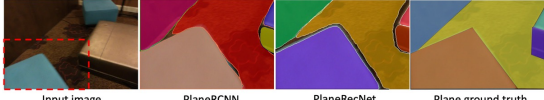
## 1 Overview

- Design X-PDNet, a multitask learning framework for joint plane instance segmentation and monocular depth estimation.
- Propose a novel Depth-Guided Boundary Preserving Loss that uses depth information to precise the plane instance segmentation results at boundary related regions.
- Contribute a manually annotated test set as a standard dataset for the plane instance segmentation problem.

## Acknowledgement

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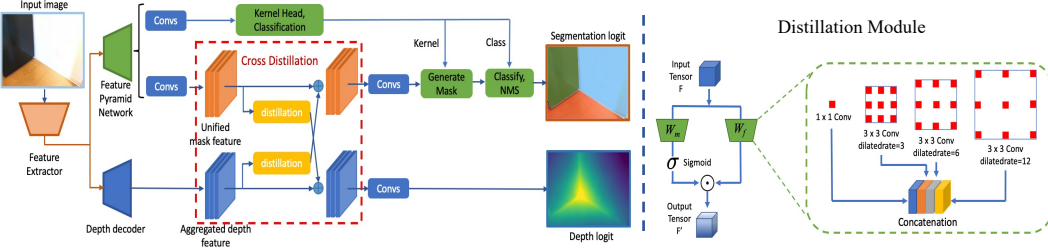
## 2 Related Works & Limitations



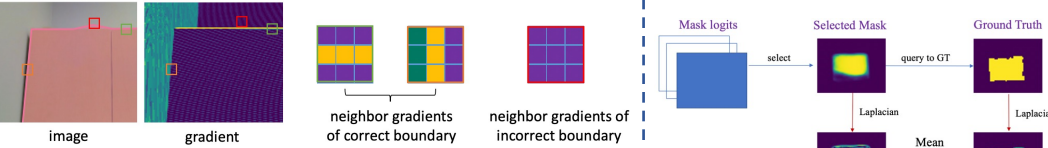
- Poor quality of plane instance ground truth in existing datasets
- Lack of boundary preserving loss => incorrect prediction at boundary regions
- Traditional boundary regression loss is vulnerable to incorrect GT boundary

## 3 Methods

Propose the X-PDNet, with the Cross-Task feature distillation design, which promotes early information sharing between cross for the specific task optimization



Propose a novel Depth Guided Boundary Preserving Loss, which employs depth information to combats with incorrect ground truth boundary, pricise predicted plane instance at boundary related areas



$$\text{Gradient: } G_{gt} = \text{abs}(G_x) + \text{abs}(G_y) \text{ with } G_x = \text{Sobel}_x(D_{gt}), G_y = \text{Sobel}_y(D_{gt}).$$

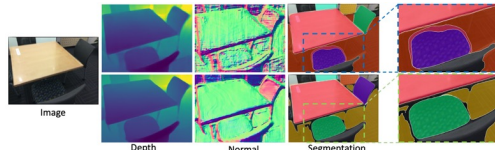
For each GT boundary point, measure the standard deviation of a set of points constructed from its gradient and that of its neighbors.

Then utilize set of std values to reweight the boundary regression loss

## 4 Experimental results

Methods	Dataset	Segmentation Metrics					Depth Metrics						
		$AP_m$	$AP_m^{50}$	$AP_m^{75}$	$AP_b$	$AP_b^{50}$	$rel \downarrow$	$log_{10} \downarrow$	$RMS \downarrow$	$\delta_1$	$\delta_2$	$\delta_3$	
PlaneAE	ScanNet	5.92	14.72	4.00	7.86	17.83	6.25	0.111	0.049	0.409	0.864	0.967	0.991
PlaneRCNN	ScanNet	14.23	28.23	12.88	17.51	33.00	16.00	0.124	0.050	0.265	0.865	0.972	0.994
PlaneRecNet	ScanNet	16.61	31.59	15.56	21.05	36.45	20.29	0.076	0.032	0.180	0.950	0.992	0.998
X-PDNet	ScanNet	17.62	33.05	16.60	22.23	37.53	21.91	0.069	0.029	0.175	0.955	0.993	0.999
PlaneRecNet	2D-3D-S	24.10	38.99	24.39	27.13	41.14	27.23	0.062	0.027	0.294	0.966	0.990	0.996
X-PDNet	2D-3D-S	25.20	39.63	25.79	28.62	41.80	29.15	0.061	0.026	0.294	0.966	0.991	0.996

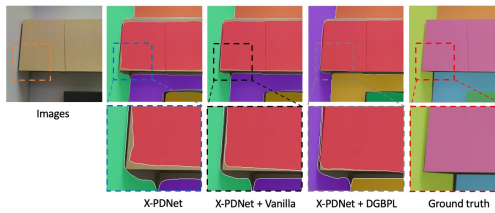
Table 1: Evaluation of plane instance segmentation and depth estimation on ScanNet and 2D-3D-S datasets. X-PDNet outperforms existing methods in most metrics.



Example produced by the baseline (above) and X-PDNet (below)

Methods	Eval set	Boundary IoU	Segmentation Metrics					
			$AP_m$	$AP_m^{50}$	$AP_m^{75}$	$AP_b$	$AP_b^{50}$	$AP_b^{75}$
X-PDNet	Provided by [1]	-	25.20	39.63	25.79	28.62	41.80	29.15
X-PDNet+Vanilla	Provided by [1]	-	26.49	41.61	27.09	30.23	44.18	30.7
X-PDNet+DGBPL	Provided by [1]	-	25.86	41.79	26.34	29.94	45.55	29.98
X-PDNet	Manually annotated	13.36	24.09	36.84	25.08	25.80	37.08	26.72
X-PDNet+Vanilla	Manually annotated	14.82	25.27	38.24	26.59	27.08	38.93	27.77
X-PDNet+DGBPL	Manually annotated	16.68	26.12	39.47	26.68	28.18	40.86	27.46

Table 2: Evaluation of segmentation results on 2D-3D-S annotation provided by [1] and human labelling evaluation datasets.



Planes predicted by X-PDNet, with Vanilla, and with DGBPL