

Supplementary for SD-MTCNN: Self-Distilled Multi-Task CNN

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In the supplementary document, we report the followings,

- Analysis in terms of the evalution of different performance metrics.
- We showcase some of the qualitative results for the CityScapes dataset.
- Detailed baseline analysis for Mini-Taskonomy, NYUv2 for two tasks, and Cityscapes, respectively.

1 Training performance analysis on NYUv2 dataset

We showcase the validation error at the Teacher end (SD-MTCNN) for segmentation (mIoU), depth perception (relative error), and surface-normal estimation (median error) of the NYUv2 dataset for 100 iterations (Figure 1) and compare the same with the performance of the vanilla Segnet (Baseline-1 main paper).

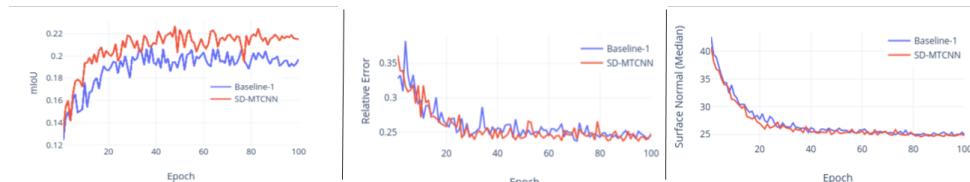


Figure 1: Performance graph between SD-MTCNN (Eq. 5 main paper) and SD-Vanilla Segnet (Baseline-1 main paper) for three tasks on the NYUv2 dataset. From left to right: mIoU (semantic segmentation), relative error (depth estimation), and median error (surface normal).

2 Baseline analysis for Mini-Taskonomy, NYUv2 (two tasks), and CityScapes

We mention the performance of different baseline approaches as detailed in Section 4.2 (main paper) for Mini-Taskonomy, NYUv2 (2 tasks), and CityScapes in Table 1 and 2, respectively. Figure 2 showcases the performance comparison of SD-MTCNN with the traditional distillation strategy for a case from the CityScapes dataset qualitatively.

Method	Segmentation \uparrow		Depth error \downarrow		SN \uparrow	Key \downarrow	Edge \downarrow
	IoU	mIoU	Abs.	Rel.			
Vanilla Segnet \dagger	89.04	50.38	0.0336	0.3607	0.8805	0.0153	0.0103
SD-Vanilla Seg. $^T(\star)\ddagger$	89.30	53.53	0.0301	0.3628	0.8988	0.0149	0.0108
SD-Vanilla Seg. S	88.39	48.93	0.0432	0.4150	0.8543	0.0343	0.0122
SD-Vanilla Seg. $^T(\star\star)\ddagger$	89.17	49.88	0.0352	0.3755	0.8896	0.0192	0.0108
SD-Vanilla Seg. S	80.38	10.27	0.0744	2.8007	0.8482	0.0469	0.0764
Trad. K.D. \mp	88.70	48.82	0.0293	0.3987	0.8818	0.0153	0.0105
SD-MTCNN $^T(\star)\#$	89.03	54.87	0.0325	0.4619	0.8933	0.0151	0.0102
SD-MTCNN S	88.90	54.21	0.0418	0.5523	0.8659	0.0331	0.0120
SD-MTCNN $^T(\star\star)\#$	88.97	55.19	0.0331	0.5683	0.8852	0.0173	0.0106
SD-MTCNN S	88.76	54.07	0.0423	1.0034	0.8664	0.0335	0.0131
SD-MTCNN $^T(full)\star$	89.36	55.36	0.0290	0.3572	0.9058	0.0138	0.0097
SD-MTCNN S	89.02	54.78	0.0370	0.4010	0.8608	0.0327	0.0118
SD-MTCNN $^T(\star\star)full$	89.21	55.26	0.0327	0.4318	0.8907	0.0147	0.0101
SD-MTCNN S	88.93	53.68	0.0419	0.5221	0.8616	0.0340	0.0129
Ablation on U-Net							
U-Net	89.11	52.76	0.0328	0.5294	0.8901	0.0121	0.0105
U-Net $^T(\star)full$	89.61	55.96	0.0277	0.3519	0.9080	0.0125	0.0099
U-Net S	89.37	55.17	0.0322	0.5213	0.8730	0.0211	0.0121
U-Net $^T(\star\star)full$	89.17	55.02	0.0272	0.3883	0.8942	0.0133	0.0104
U-Net S	88.54	54.39	0.0367	0.5575	0.8691	0.0237	0.0136

Table 1: 5-task validation results on the Mini-Taskonomy dataset for semantic segmentation, depth estimation, surface normal prediction, key-point estimation, and edge prediction on Segnet based models and ablation analysis on U-Net architecture. T Teacher, S Student. \dagger Baseline-1, \ddagger Baseline-2, \mp Baseline-3, # Baseline-4, (\star) by Eq. 5, $(\star\star)$ by Eq. 6. We compare SD-MTCNN(\star) against all the (\star) baselines and similar for ($\star\star$).

Dataset	NYUv2				CityScapes			
Method	Segmentation \uparrow		Depth error \downarrow		Segmentation \uparrow		Depth error \downarrow	
	IoU	mIoU	Abs.	Rel.	IoU	mIoU	Abs.	Rel.
Vanilla Segnet \dagger	50.64	14.90	0.6244	0.2612	89.73	49.71	0.0161	35.91
SD-Vanilla Seg. T (\star) \ddagger	56.52	18.44	0.5793	0.2502	92.37	54.61	0.0137	28.97
SD-Vanilla Seg. S	52.77	15.79	0.6083	0.2576	89.60	49.11	0.0164	37.94
SD-Vanilla Seg. T ($\star\star$) \ddagger	54.37	16.94	0.6051	0.2468	90.44	52.02	0.0148	27.94
SD-Vanilla Seg. S	23.06	6.55	1.7556	0.6943	49.98	14.83	0.0769	214.8
Trad. K.D. \mp	50.92	15.76	0.6201	0.2689	89.78	49.87	0.0156	27.15
SD-MTCNN T (\star) $\#$	56.32	21.22	0.6885	0.2560	92.13	55.48	0.0149	6.98
SD-MTCNN S	55.93	21.64	0.7066	0.2683	91.12	52.54	0.0164	14.06
SD-MTCNN T ($\star\star$) $\#$	56.16	21.89	0.6897	0.2620	91.64	54.03	0.0148	9.82
SD-MTCNN S	55.84	20.35	0.7166	0.2662	90.96	51.94	0.0164	12.40
SD-MTCNN T (\star) <i>full</i>	57.18	23.01	0.5847	0.2466	92.54	56.70	0.0131	27.68
SD-MTCNN S	55.80	23.19	0.6033	0.2588	91.60	54.09	0.0150	33.23
SD-MTCNN T ($\star\star$) <i>full</i>	56.29	22.63	0.6042	0.2544	91.57	54.63	0.0134	31.11
SD-MTCNN S	56.09	22.50	0.6103	0.2674	90.99	53.27	0.0151	34.82

Table 2: 2-task validation results on the NYUv2 and CityScapes datasets for 13-classes and 7-classes resp. with semantic segmentation and depth estimation on Segnet based models. T Teacher, S Student. \dagger Baseline-1, \ddagger Baseline-2, \mp Baseline-3, $\#$ Baseline-4, (\star) by Eq. 5, ($\star\star$) by Eq. 6. We compare SD-MTCNN(\star) against all the (\star) baselines and similar for ($\star\star$).

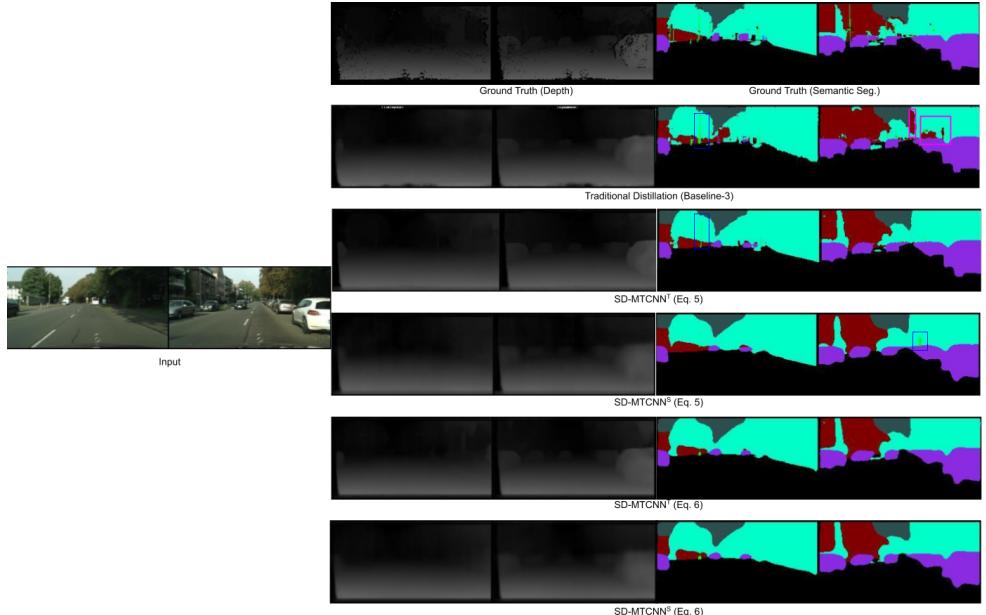


Figure 2: Visualization of segmentation and depth estimation on the CityScapes dataset. From top to bottom: ground truth, and predictions of Baseline-3 (Trad. Dist.), SD-MTCNN T and SD-MTCNN S (by Eq. 5 and Eq. 6 our model), respectively. The blue boxes show the correct predictions, whereas red boxes show the wrong predictions.