Tags2Parts: Discovering Semantic Regions from Shape Tags

Supplementary Material

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1. Weakly-supervised segmentation precision-recall plots.

In Figures 1, 2, 3, 4, 5, 6, we present full precision-recall plots from various experiments on weakly-supervised segmentation, including ablation studies and comparisons to prior work. The area under the curve (AUC) statistics summarizing these plots are presented in the main paper.

2. More segmentation statistics and complete visualizations

Tables 1, 2, 3 and 4 show the per-category performance of different deep and shallow WU-Net variants for strongly-supervised segmentation on the standard ShapeNet dataset, on (a) the train/test splits from Kalogerakis et al. [1], (b) on randomly rotated versions of the shapes in these splits, and (c) the splits from the recent ICCV challenge [4] (both accuracy and IOU statistics) respectively. Different variants of WU-Net-style networks are given abbreviated names: 3SU is a sequence of **3 s**hallow **U**'s (i.e. WU-Net), 1DUI is **1** single **d**eep **U** (**I**nception-style).

Our project website for this paper has visualizations of all segmentations of shapes in our datasets under both weak and strong supervision of WU-Net.

The performance of WU-Net on weakly-supervised segmentation of test set shapes mirrors that on the training set, as can be seen in Table 4 of the main paper as well as the visualizations on the website.

References

[1] E. Kalogerakis, M. Averkiou, S. Maji, and S. Chaudhuri. 3D shape segmentation with projective convolutional networks. In *CVPR*, 2017. 1, 3

[2] E. Kalogerakis, A. Hertzmann, and K. Singh. Learning 3D mesh segmentation and labeling. *Trans. Graph.*, 29(4), 2010. 3

[3] P. Shilane and T. Funkhouser. Distinctive regions of 3D surfaces. *Trans. Graph.*, 26(2), 2007. 2

[4] L. Yi et al. Large-scale 3D shape reconstruction and segmentation from ShapeNet Core55. *CoRR*, abs/1710.06104, 2017. 1, 4

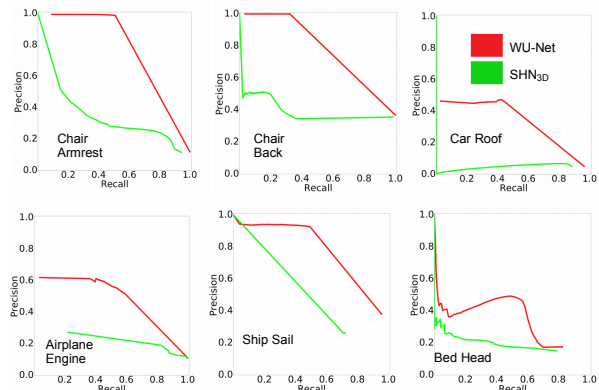Figure 1: WU-Net (red) consistently outperforms a Stacked Hourglass Network SHN_{3D} (3 deep U's without low resolution skip connections between different U's, green) on all categories (on training shapes, outputs symmetrized).
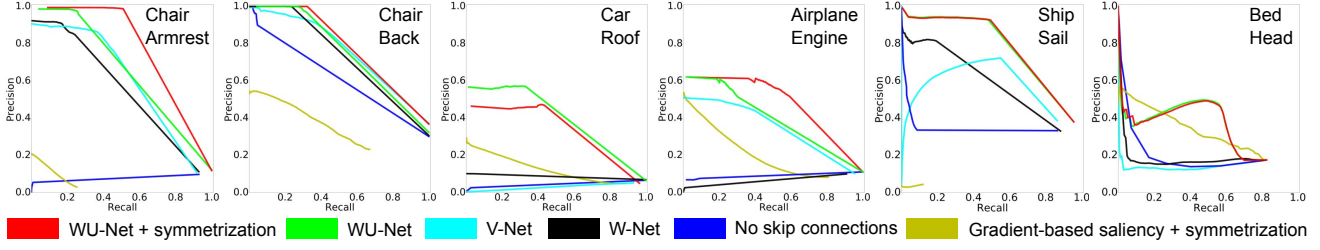
Figure 2: WU-Net vs various ablations for weakly-supervised segmentation (on training shapes).
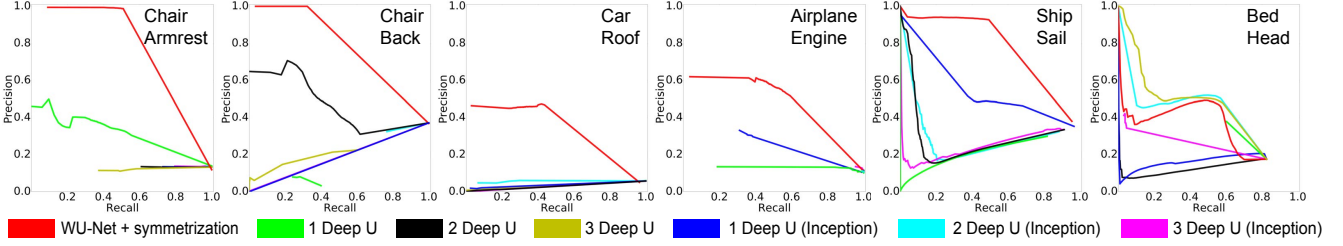
Legend: WU-Net + symmetrization | WU-Net | V-Net | W-Net | No skip connections | Gradient-based saliency + symmetrization

Figure 3: WU-Net vs Deep U alternatives (symmetrized) for weakly-supervised segmentation (on training shapes).

Legend: WU-Net + symmetrization | 1 Deep U | 2 Deep U | 3 Deep U | 1 Deep U (Inception) | 2 Deep U (Inception) | 3 Deep U (Inception)
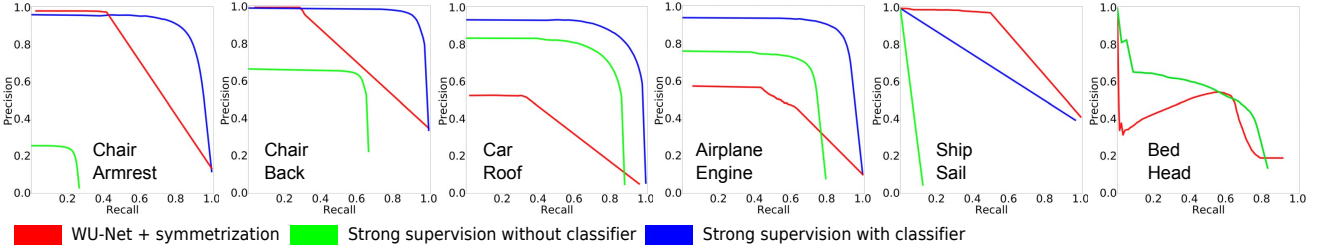
Figure 4: Weakly supervised WU-Net vs a strongly supervised baseline (on test shapes).

Legend: WU-Net + symmetrization | Strong supervision without classifier | Strong supervision with classifier

Figure 5: WU-Net vs Shilane and Funkhouser (SF) [3] at different scales (on training shapes). Note that SF requires knowledge of ground truth tags at test time, whereas our method does not use them.

Legend: WU-Net + symmetrization | SF 0.25 | SF 0.5 | SF 1.0 | SF 2.0

Figure 6: The statistical effect of increasing the kernel size for average pooling at the end of WU-Net.

Legend: No avg pooling | 2x2x2 (default) | 4x4x4 | 8x8x8

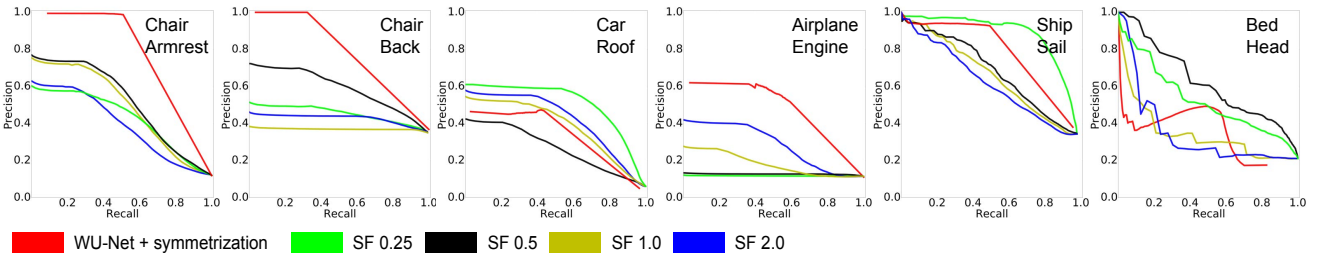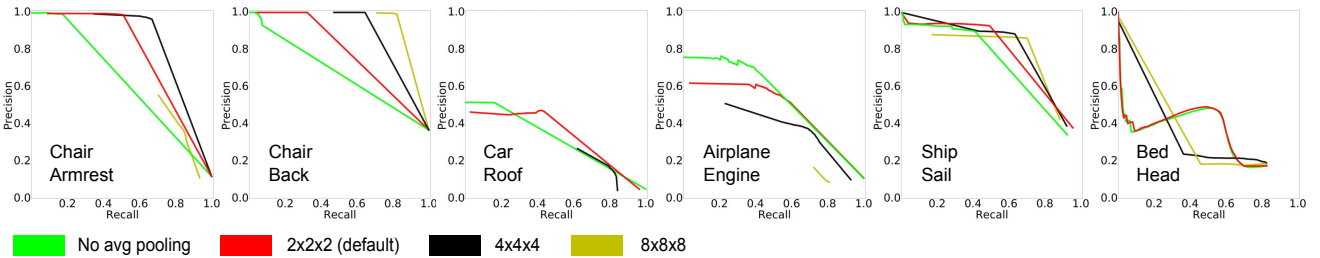| Category	#train/ #test	#labels	Shape-Boost	Shape-PFCN	1 SU	2 SU	3 SU (WU-Net)	4 SU	1 DU	2 DU	3 DU	1 DUI	2 DUI	3 DUI
Airplane	250/250	4	84.1	88.4	89.54	90.32	90.13	90.66	90.34	90.75	90.77	91.12	90.87	**90.97**
Bag	38/38	2	94.3	95.5	93.24	**96.51**	96.02	95.53	96.18	95.26	96.21	96.24	96.15	96.19
Bike	101/101	6	78.6	**87.5**	80.84	84.07	84.77	85.75	85.04	85.04	85.54	85.19	83.66	85.9
Cap	27/28	2	**94.8**	92	87.77	88.7	89.82	88.63	90.27	91.19	86.31	90.75	91.69	91.88
Car	250/250	4	75.5	86.6	88.91	89.61	89.44	89.67	89.7	89.87	90.02	90.13	90.15	**90.17**
Chair	250/250	4	71.9	83.7	90.47	92.01	91.82	91.9	92.24	92.01	92.11	92.32	92.3	**92.4**
Earphone	34/35	3	76	**82.9**	67.21	75.86	78.53	74.44	78.24	80.84	74.71	82.2	77.34	79.73
Guitar	250/250	3	86.9	89.7	95.89	96.22	95.98	96.09	96.22	96.23	96.19	96.26	96.23	**96.29**
Knife	196/196	2	84.1	87.1	83.81	90.33	90.96	**92.42**	91.57	91.34	91.37	91.69	91.83	90.91
Lamp	250/250	4	63.8	78.3	75.75	77.97	77.37	80.91	82.7	83.63	82.96	84.38	83.82	**85.09**
Laptop	222/222	2	79.4	95.2	**96.86**	96.57	96.61	96.63	96.33	96.48	96.51	96.56	96.62	96.84
Mug	92/92	3	98.1	98.1	98.94	99.09	99.05	**99.17**	99.14	98.81	99.16	99.16	99.14	99.15
Pistol	137/138	3	84.9	92.2	94.46	96.01	95.75	96.05	96.41	96.51	**96.7**	96.55	96.54	96.55
Rocket	33/33	3	**83.2**	81.5	75.64	75.35	79.94	75.36	76.29	76.98	75.61	77.93	78.05	79.73
Skateboard	76/76	3	89.6	92.5	94.54	94.32	**94.66**	94.23	93.91	92.97	93.62	94.33	94.36	94.36
Table	250/250	3	83.9	92.5	90.33	93.58	92.91	92.99	93.94	93.32	94.37	94.57	**94.92**	94.42
Category average			83.07	88.98	87.76	89.78	90.24	90.03	90.53	90.7	90.14	91.21	90.85	**91.29**

Table 1: Dataset statistics and strongly-supervised segmentation and labeling accuracy per category for test shapes in ShapeNetCore, versus ShapePFCN [1] and ShapeBoost [2], using the splits from [1].

Category	#train/ #test	#labels	Shape-Boost	Shape-PFCN	1 SU	2 SU	3 SU (WU-Net)	4 SU	1 DU	2 DU	3 DU	1 DUI	2 DUI	3 DUI
Airplane	250/250	4	84.1	**88.4**	70.15	80.76	78.83	76.99	79.77	80.54	78.54	79.97	81.29	80.88
Bag	38/38	2	94.3	**95.5**	93.67	93.2	92.45	93.49	93.09	93.5	93.01	93.04	93.69	93.22
Bike	101/101	6	78.6	**87.5**	73.17	71.98	73.86	74.63	71.73	72.65	73.35	71.92	72.18	72.22
Cap	27/28	2	**94.8**	92	73.43	70.79	72.98	72.54	70.23	68.22	74.31	73.37	72.84	75.03
Car	250/250	4	75.5	**86.6**	74.66	76.12	78.03	78.3	78.42	80.02	80.25	77.58	78.8	78.49
Chair	250/250	4	71.9	**83.7**	55.32	66.14	69.62	74.99	79.77	77.9	80.51	78.68	81.01	80.87
Earphone	34/35	3	76	**82.9**	61.93	65.75	66.98	65.44	66.9	68.52	66.02	65.97	64.42	66.4
Guitar	250/250	3	86.9	89.7	88.54	91.91	92.16	93.01	93.06	**94.17**	93.25	93.65	93.4	93.66
Knife	196/196	2	**84.1**	87.1	71.33	71.55	70.24	71.01	79.24	80.25	78.04	80.05	79.02	79.61
Lamp	250/250	4	63.8	**78.3**	58.5	58.65	60.63	64.05	66.68	65.87	68.64	71.14	69.34	70.98
Laptop	222/222	2	79.4	**95.2**	53.91	56.36	54.39	51.64	57.12	50.6	57.71	62.18	62.64	62.43
Mug	92/92	3	**98.1**	**98.1**	95.77	97.29	97.5	97.58	96.86	97.26	96.14	96.55	96.41	96.37
Pistol	137/138	3	84.9	**92.2**	67.2	61.88	66.69	65.06	77.14	77.87	76.92	74.59	74.71	74.11
Rocket	33/33	3	**83.2**	81.5	71.96	70.85	69.26	70.72	67.12	69.24	68.43	67.59	72.09	69.86
Skateboard	76/76	3	89.6	**92.5**	84.98	85.5	85.08	84.85	82.31	82.3	86.42	80.84	85.51	82.92
Table	250/250	3	83.9	**92.5**	74.77	76.9	73.45	75.34	85.27	86.32	86.89	86.19	87.29	87.05
Category average			83.07	**88.98**	73.08	74.73	75.14	75.6	77.79	77.83	78.65	78.33	79.04	79.01

Table 2: Dataset statistics and strongly-supervised segmentation and labeling accuracy per category for randomly rotated test shapes in ShapeNetCore, versus ShapePFCN [1] and ShapeBoost [2], on the splits from [1].

Category	#train/ #test	#labels	1 SU	2 SU	3 SU (WU-Net)	4 SU	1 DU	2 DU	3 DU	1 DUI	2 DUI	3 DUI
Airplane	1958/341	4	87.46	89.18	89.61	89.73	90.4	90.16	90.32	90.51	90.65	**90.74**
Bag	54/14	2	93.51	90.96	93.44	92.83	96.02	95.57	95.74	96.12	96.43	**96.56**
Bike	125/51	6	75.35	75.89	86.36	86.9	73.64	77.78	**87.1**	86.95	86.1	86.83
Cap	39/11	2	88.32	87.01	87.4	87.24	83.35	86.72	88.38	**90.62**	87.47	85.63
Car	659/158	4	89.24	90.34	90.41	**90.49**	90.25	89.94	90.19	90.24	90.21	90.42
Chair	2658/704	4	91.16	92.93	93.13	93.4	93.85	93.91	93.92	93.95	**94**	93.98
Earphone	49/14	3	70.54	90.35	91.6	91.61	91.68	92.1	**92.52**	87.3	91.5	91.64
Guitar	550/159	3	95.63	95.75	95.65	95.89	**96.11**	95.96	95.66	95.88	96.05	95.89
Knife	277/80	2	83.28	90.8	91.98	90.7	91.93	91.08	90.77	**92.31**	91.83	91.49
Lamp	1118/296	4	73.87	78.21	78.38	80.49	**88.27**	88.18	87.19	88.1	86.47	87.83
Laptop	324/83	2	96.66	96.88	96.79	**97.23**	96.15	95.9	95.56	96.73	96.51	96.8
Mug	130/38	3	99.29	99.43	99.42	99.39	99.44	**99.46**	99.4	99.34	99.38	99.43
Pistol	209/44	3	92.94	94.46	94.33	94.85	95.84	95.98	**96.01**	95.91	95.85	96
Rocket	46/12	3	**75.11**	73.67	74.46	74.76	72.93	69.85	74.94	71.45	74.01	74.2
Skateboard	106/31	3	94.5	94.13	93.73	94.1	94.68	**94.85**	94.57	94.19	93.9	94.34
Table	3835/848	3	85.25	87.03	88.94	88.14	93	92.64	92.17	**94.38**	93.78	92.22
Category average			87.01	89.19	90.35	90.48	90.47	90.63	**91.53**	91.5	91.51	91.5

Table 3: Dataset statistics and strongly-supervised segmentation and labeling accuracy per category for test shapes in ShapeNetCore on the new splits from the ShapeNet ICCV Challenge [4].

Method	avg	plane	bag	cap	car	chair	earphone	guitar	knife	lamp	laptop	bike	mug	pistol	rocket	skateboard	table
2 DUI	83.13	81	83.2	75.25	75.22	89.04	71.68	89.24	84.15	75.85	93.46	69.27	94.19	81.38	54.34	73.39	80.86
1 DUI	82.89	80.83	81.8	81.16	75.31	89.02	60.22	88.93	84.99	77.72	93.37	70.12	93.9	82	50.28	72.46	80.12
3 DUI	81.12	80.9	83.4	73.1	75.93	89.04	73.94	89.13	83.59	77.1	93.51	69.44	94.7	82.61	47.32	72.7	74.52
3 DU	81.13	80.35	78.91	76.67	75.63	88.87	74.96	88.16	82.94	75.56	92.53	69.17	94.49	82.22	49.6	73.77	75.39
1 DU	81.03	80.42	81.75	68.82	73.95	88.81	73.97	89.82	84.34	76.64	92.85	29.7	94.78	82.18	48.69	71.95	77.47
2 DU	80.97	79.91	79.56	74	74.36	88.75	70.5	89.08	83.12	75.45	92.93	34.75	94.92	82.95	46.14	74.15	77.38
4 SU	79.84	77.19	68.79	76.52	75.01	87.41	68.59	89.54	83.16	68.08	93.96	68.63	94.28	80.07	50.07	71.57	74.91
3 SU	79.35	76.51	71.2	76.39	75.07	86.95	69.24	89.08	84.64	66.87	93.26	61.91	94.66	77.18	51.56	71.04	74.62
2 SU	77.87	75.31	59.01	74.68	74.35	86.24	68.46	89.15	82.75	63.03	93.34	25.04	94.71	77.49	44.69	71.73	74.32
1 SU	74.35	70.86	73.46	78.06	69.05	81.31	37.21	88.49	71.97	58.67	93.01	24.66	93.73	74.71	46.46	73.23	72.23

Table 4: IOU scores for different versions of Deep and Shallow-U networks for strongly-supervised segmentation of test shapes in ShapeNetCore on the new splits from the ShapeNet ICCV Challenge [4].