

1 1 Supplementary Material

2 **More results on ShapeNet-55/34.** In order to have an intuitive evaluation of reconstructed results,
 3 we also provide qualitative evaluations in Fig. 1 compared with results generated from the baseline.
 4 We can clearly see the results not only have better numerical performance (Tab. 3) but also the model
 5 trained with InfoCD did a better job in reconstructing the surface areas and preserving the details
 6 with less noise.



Figure 1: Visual comparison of point cloud completion results on ShapeNet-55 dataset. **Row-1:** Inputs of incomplete point clouds. **Row-2:** Outputs of SeedFormer with CD. **Row-3:** Outputs of SeedFormer with InfoCD. **Row-4:** Ground truth.

7 We report complete results of our method on ShapeNet-55 in Tab. 3 and results of novel categories
 8 on ShapeNet-34 in Tab. 1. We also provide the complete results on ShapeNet-34 in Tab. 2 of two
 9 popular baselines. The models are tested under three difficulty levels: simple, moderate and hard.
 10 For ShapeNet-55, we can see that with the help of InfoCD, the baseline achieves best scores on all
 11 categories. We also provide the complete results on ShapeNet-55 in Tab. 4 of two popular baselines.

Table 1: Detailed results for the novel objects on ShapeNet-34. *S.*, *M.* and *H.* stand for the simple,
 moderate and hard settings.

CD- ℓ_2 ($\times 1000$)	PCN [1]			TopNet [2]			PFNet [3]			GRNet [4]			SeedFormer [5]			InfoCD + S.		
	S.	M.	H.	S.	M.	H.	S.	M.	H.	S.	M.	H.	S.	M.	H.	S.	M.	H.
bag	2.48	2.46	3.94	2.08	1.95	4.36	3.88	4.42	9.67	1.47	1.88	3.45	0.49	0.82	1.45	0.41	0.75	1.40
basket	2.79	2.51	4.78	2.46	2.11	5.18	4.47	4.55	14.46	1.78	1.94	4.18	0.60	0.85	1.98	0.55	0.80	1.81
birdhouse	3.53	3.47	5.31	3.17	2.97	5.89	3.9	4.65	9.88	1.89	2.34	5.16	0.72	1.19	2.31	0.67	1.02	2.18
bowl	2.66	2.35	3.97	2.46	2.16	4.84	4.35	5.0	14.59	1.77	1.97	3.9	0.60	0.77	1.50	0.51	0.65	1.42
camera	4.84	5.3	8.03	4.24	4.43	8.11	6.78	8.04	13.91	2.31	3.38	7.2	0.89	1.77	3.75	0.82	1.67	3.63
can	1.95	1.89	5.21	2.02	1.7	5.82	2.95	3.47	23.02	1.53	1.8	3.08	0.56	0.89	1.57	0.47	0.72	1.35
cap	7.21	7.14	10.94	4.68	4.23	9.17	14.11	14.86	28.23	3.29	4.87	13.02	0.50	1.34	5.19	0.38	1.12	4.23
keyboard	1.07	1.0	1.23	0.79	0.77	1.55	1.13	1.16	2.58	0.73	0.77	1.11	0.32	0.41	0.60	0.23	0.31	0.52
dishwasher	2.45	2.09	3.53	2.51	1.77	4.72	3.44	3.78	9.31	1.79	1.7	3.27	0.63	0.78	1.44	0.55	0.72	1.35
earphone	7.88	6.59	16.53	5.33	4.83	11.67	20.31	23.21	39.49	4.29	4.16	10.3	1.18	2.78	6.71	1.05	2.21	6.77
helmet	6.15	6.41	9.16	4.89	4.86	8.73	8.78	10.07	21.2	3.06	4.38	10.27	1.10	2.27	4.78	1.01	2.17	4.76
mailbox	2.74	2.68	4.31	2.35	2.2	4.91	5.2	5.33	10.94	1.52	1.9	4.33	0.56	0.99	2.06	0.47	0.87	1.95
microphone	4.36	4.65	8.46	3.03	3.2	7.15	6.39	7.99	19.41	2.29	3.23	8.41	0.80	1.61	4.21	0.61	1.56	4.02
microwaves	2.59	2.35	4.47	2.67	2.12	5.41	3.89	4.08	9.01	1.74	1.81	3.82	0.64	0.83	1.69	0.61	0.75	1.51
pillow	2.09	2.16	3.54	2.08	2.05	4.01	4.15	4.29	12.01	1.43	1.69	3.43	0.43	0.66	1.45	0.38	0.52	1.35
printer	3.28	3.6	5.56	2.9	2.96	6.07	5.38	5.94	10.29	1.82	2.41	5.09	0.69	1.25	2.33	0.62	1.17	2.15
remote	0.95	1.08	1.58	0.89	0.89	2.28	1.51	1.75	6.0	0.82	1.02	1.29	0.27	0.42	0.61	0.21	0.34	0.50
rocket	1.39	1.22	2.01	1.14	0.96	2.03	1.84	1.51	4.01	0.97	0.79	1.6	0.28	0.51	1.02	0.17	0.41	0.95
skateboard	1.97	1.78	2.45	1.23	1.2	2.01	2.43	2.53	4.25	0.93	1.07	1.83	0.35	0.56	0.92	0.27	0.51	0.81
tower	2.37	2.4	4.35	2.2	2.17	5.47	3.38	4.15	13.11	1.35	1.8	3.85	0.51	0.92	1.87	0.46	0.81	1.72
washer	2.77	2.52	4.64	2.63	2.14	6.57	4.53	4.27	9.23	1.83	1.97	5.28	0.61	0.87	1.94	0.51	0.72	1.83
mean	3.22	3.13	5.43	2.65	2.46	5.52	5.37	5.95	13.55	1.84	2.23	4.95	0.61	1.07	2.35	0.54	1.01	2.18

Table 2: More detailed results for the novel objects on ShapeNet-34. *S.*, *M.* and *H.* stand for the simple, moderate and hard settings.

CD- ℓ_2 ($\times 1000$)	FoldingNet [6]			InfoCD + FoldingNet			PoinTr [7]			InfoCD + PoinTr		
	S.	M.	H.	S.	M.	H.	S.	M.	H.	S.	M.	H.
bag	2.15	2.27	3.99	1.75	1.98	3.47	0.96	1.34	2.08	0.52	0.85	1.59
basket	2.37	2.2	4.87	1.90	1.94	4.46	1.04	1.4	2.9	0.59	0.84	2.06
birdhouse	3.27	3.15	5.62	2.81	2.84	5.18	1.22	1.79	3.45	0.75	1.24	2.58
bowl	2.61	2.3	4.55	2.18	2.01	4.08	1.05	1.32	2.4	0.60	0.77	1.47
camera	4.4	4.78	7.85	4.01	4.45	7.36	1.63	2.67	4.97	1.00	1.95	4.26
can	1.95	1.73	5.86	1.52	1.41	1.38	0.8	1.17	2.85	0.51	0.83	1.81
cap	6.07	5.98	11.49	5.63	5.67	11.98	1.4	2.74	8.35	0.57	1.30	5.42
keyboard	0.98	0.96	1.35	0.53	0.64	0.84	0.43	0.45	0.63	0.29	0.34	0.54
dishwasher	2.09	1.8	4.55	1.55	1.45	4.09	0.93	1.05	2.04	0.55	0.73	1.49
earphone	6.86	6.96	12.77	6.43	6.62	12.26	2.03	5.1	10.69	1.05	2.49	7.91
helmet	4.86	5.04	8.86	4.41	4.71	8.34	1.86	3.3	6.96	1.11	2.40	5.88
mailbox	2.2	2.29	4.49	1.83	1.94	4.02	1.03	1.47	3.34	0.53	0.94	2.21
microphone	2.92	3.27	8.54	2.51	2.92	8.01	1.25	2.27	5.47	0.83	1.52	4.00
microwaves	2.29	2.12	5.17	1.83	1.81	1.75	1.01	1.18	2.14	0.63	0.81	1.75
pillow	2.07	2.11	3.73	1.64	1.82	3.22	0.92	1.24	2.39	0.48	0.69	1.59
printer	3.02	3.23	5.53	2.61	2.97	5.02	1.18	1.76	3.1	0.71	1.27	2.52
remote	0.89	0.92	1.85	0.42	0.61	1.38	0.44	0.58	0.78	0.26	0.38	0.57
rocket	1.28	1.09	2.0	0.81	0.77	1.51	0.39	0.72	1.39	0.30	0.53	1.01
skateboard	1.53	1.42	1.99	1.16	1.10	1.48	0.52	0.8	1.31	0.36	0.60	0.88
tower	2.25	2.25	4.74	1.80	1.93	4.22	0.82	1.35	2.48	0.50	0.93	1.98
washer	2.58	2.34	5.5	1.12	2.07	5.02	1.04	1.39	2.73	0.60	0.87	2.08
mean	2.79	2.77	5.49	2.42	2.49	5.01	1.05	1.67	3.45	0.61	1.06	2.55

12 **References**

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