Table 10: Comparisons of self-distillation versus baselines.

Method	# epochs	NDS ↑	mAP ↑	mATE ↓	mASE ↓	mAOE ↓	mAVE ↓	mAAE ↓
Baseline (w/o distillation)	1	41.32	37.78	44.99	27.65	64.43	144.26	39.30
Self-distillation (pillar→pillar)	1	42.12	38.89	44.01	27.78	64.01	144.01	39.21
Baseline (w/o distillation)	6	57.44	45.68	37.55	26.48	36.15	34.39	19.38
Self-distillation (pillar→pillar)	6	57.93	46.06	36.78	26.54	35.45	33.11	19.10
Baseline (w/o distillation)	20	59.44	48.19	34.16	25.94	30.66	30.02	19.32
Self-distillation (pillar→pillar)	20	60.54	48.71	32.54	26.15	33.95	26.60	18.73

Table 11: Time complexity.

Models	PointPillars	Pillar-OD	CenterPoint	Object DGCNN (ours)
FPS	8.4	9.3	8.5	6.5

Supplementary Material

Results of distillation with longer training.

In this section, we provide results when the model is distilled with 1, 6, and 20 epochs. The teacher model and the student model are both constructed with a PointPillars backbone. Table 10 shows the results. In all regimes, the models with distillation improve over their baselines, which verifies the efficacy of the set-to-set distillation.

Time complexity.

We compare the time complexity of PointPillars, Pillar-OD, CenterPoint, and our proposed model. Table 11 shows that our model is more efficient than others at inference time thanks to its NMS-free characteristic. The performance is measured on a single Nvidia RTX 3090.

Visualization.

We provide visualization of predictions by our model in Figure 3. Without NMS, our model makes a sparse set of predictions.

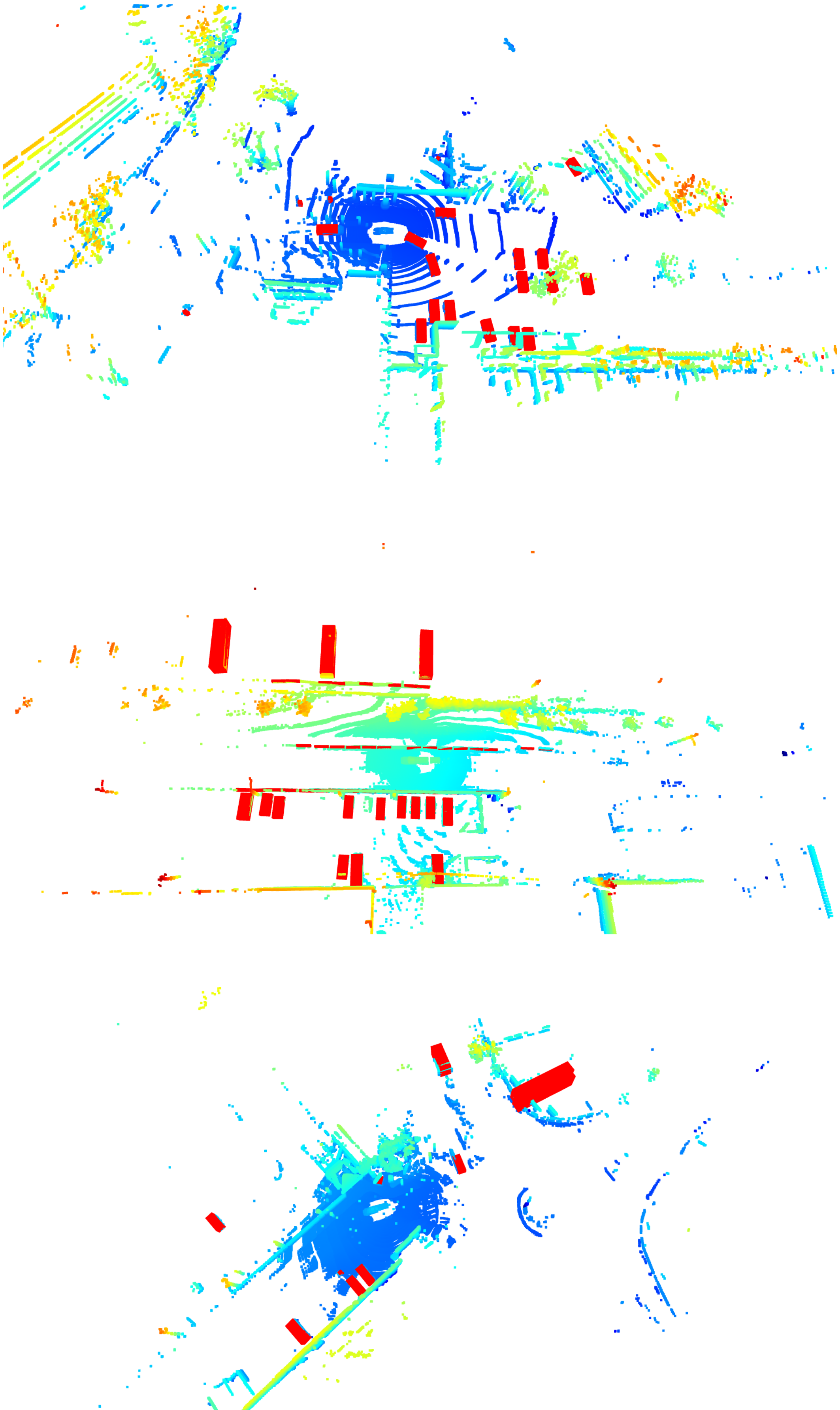

Figure 3: Visualizations. Our model makes a sparse set of predictions (boxes in red) without using NMS.