

## D. Experiments for coreset

### D.1. Experiments on S3DIS

The **S3DIS** (Armeni et al., 2016) is a large-scale indoor 3D point cloud dataset. It consists of 13 semantic categories, including ceiling, floor, wall, beam, column, window, door, table, chair, sofa, bookcase, board, and clutter. We first extract individual point cloud shapes from the dataset and then perform sampling on each shape, representing it with 300 points to form our point cloud dataset.

**Efficiency of our coreset method:** The green dashed line represents the results on the full dataset. From Figure 10, it can be seen that our CS method significantly outperforms the US method.

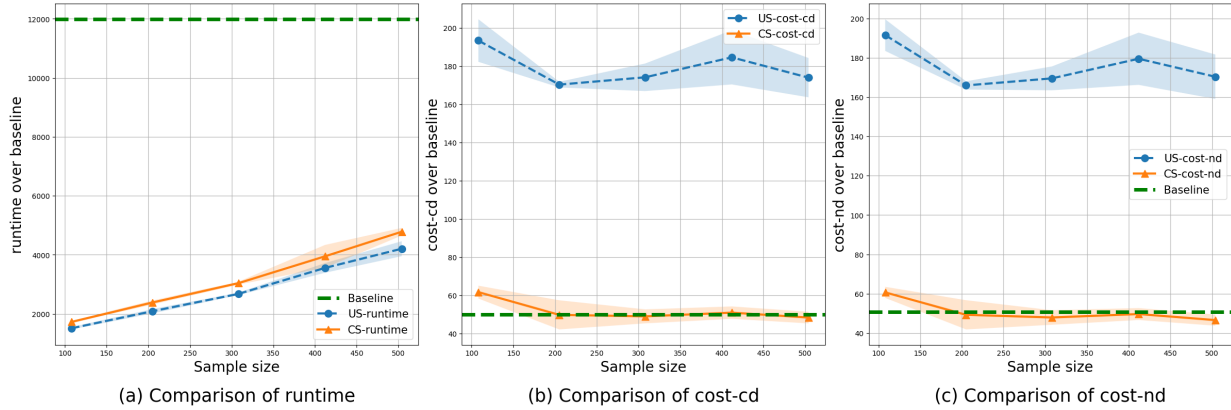


Figure 10: Comparison of the US method and our CS method across varying sample sizes on S3DIS dataset.

**Results on different  $k$ :** From Table 7, our CS method consistently has an advantage over the US method for different  $k$ .

Table 7: Comparison of the US method and our CS method with varying values of  $k$  on S3DIS dataset. We fix the sample size as 504,  $\sigma = 1$ , and  $\zeta = 0.1$ .

$k$	SM	cost-nd( $\downarrow$ )	cost-cd( $\downarrow$ )	Runtime( $\downarrow$ )
10	US	170.37 $\pm$ 11.29	173.89 $\pm$ 10.28	4205.60 $\pm$ 252.75
	CS	<b>46.53</b> $\pm$ 2.83	<b>48.33</b> $\pm$ 3.04	4225.40 $\pm$ 129.21
20	US	160.31 $\pm$ 0.38	166.94 $\pm$ 0.07	5160.80 $\pm$ 145.69
	CS	<b>27.77</b> $\pm$ 2.80	<b>28.77</b> $\pm$ 2.30	5244.40 $\pm$ 86.73
30	US	160.12 $\pm$ 0.43	166.12 $\pm$ 1.71	5958.20 $\pm$ 322.21
	CS	<b>24.49</b> $\pm$ 5.45	<b>25.33</b> $\pm$ 5.66	5897.80 $\pm$ 209.25

**Ablation experiments on  $\tau$ :** From Table 8, a smaller  $\tau$  leads to faster computation and lower cost. Thus, we recommend using a relatively small  $\tau$ .

Table 8: Comparison of our CS method using varying parameter  $\tau$  of noise. We fix the sample size as 504,  $\sigma = 1$ , and  $\zeta = 0.1$ .

$\tau$	SM	SS	cost-nd( $\downarrow$ )	cost-cd( $\downarrow$ )	Runtime ( $\downarrow$ )
1	CS	504	55.15	60.03	3453.58
2	CS	504	50.42	52.05	3333.24
3	CS	504	50.70	51.38	3395.46
4	CS	504	49.65	50.48	3407.61
5	CS	504	<b>43.64</b>	<b>44.89</b>	4032.00
10	CS	504	46.53	48.33	4225.40
20	CS	504	49.00	51.02	5145.33
50	CS	504	57.75	58.37	11173.33
100	CS	504	53.51	57.49	31920.00

**Selection of  $\zeta$ :** Each of our data items contains 0.1 mass of noise, but we run experiments with varying  $\zeta$ . The results in Table 6 confirm that slightly overestimating  $\zeta$  has only a minor impact, while underestimating it severely degrades the solution quality. Therefore, when the actual noise mass is unknown, we recommend setting  $\zeta$  slightly larger than the expected noise mass.

Table 9: Comparison of our CS method with varying values of  $\zeta$  on S3DIS dataset with 0.1 mass of noise. We fix the sample size as 504 and  $\sigma = 1$ .

$\zeta$	SM	cost-nd( $\downarrow$ )	cost-cd( $\downarrow$ )	Runtime( $\downarrow$ )
0.05	CS	104.96 $\pm$ 11.80	206.60 $\pm$ 6.81	3991.60 $\pm$ 278.49
0.1	CS	46.53 $\pm$ 2.83	48.33 $\pm$ 3.04	4225.40 $\pm$ 129.21
0.2	CS	43.52 $\pm$ 52.93	52.93 $\pm$ 7.41	4148.60 $\pm$ 156.73
0.3	CS	45.62 $\pm$ 3.32	59.94 $\pm$ 3.96	4237.60 $\pm$ 40.49

## D.2. Experiments on KITTI

The **KITTI** dataset (Geiger et al., 2012) is a widely used benchmark for autonomous driving, containing 3D LiDAR scans. We use its 3D object detection subset, which contains point clouds for various categories such as *Pedestrian*, *Cyclist*, *Car*, *Van*, *Truck*, *Person\_sitting*, *Tram*, and *Misc*. We extract object-level point cloud instances from the dataset and uniformly sample each to 300 points, forming our point cloud dataset.

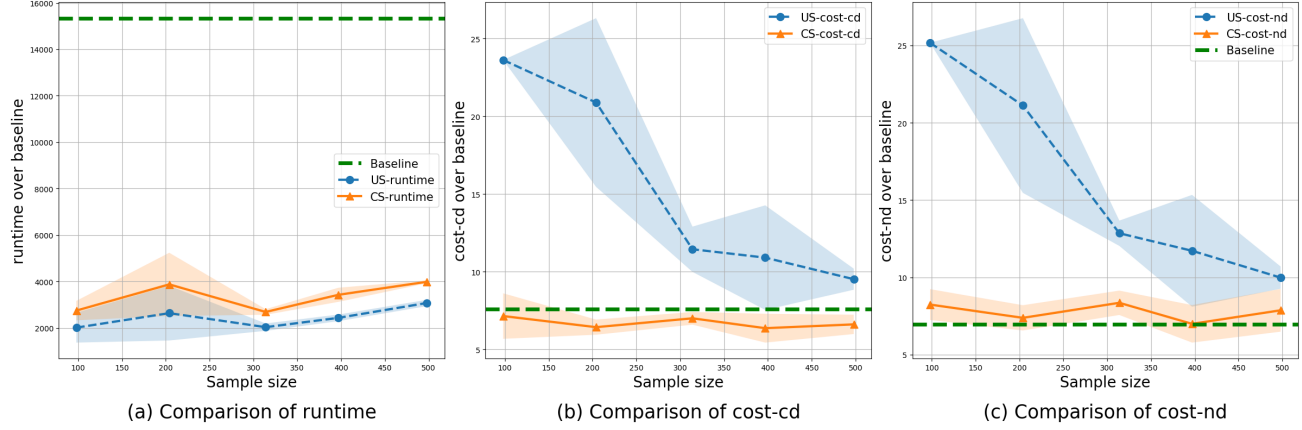


Figure 11: Comparison of the US method and our CS method across varying sample sizes on KITTI dataset.

**Efficiency of our coreset method:** The green dashed line represents the results on the full dataset. From Figure 11, it can be seen that our CS method significantly outperforms the US method.

Table 10: Comparison of the US method and our CS method with varying values of  $k$  on KITTI dataset. We fix the sample size as 498,  $\sigma = 1$ , and  $\zeta = 0.1$ .

$k$	SM	cost-nd( $\downarrow$ )	cost-cd( $\downarrow$ )	Runtime( $\downarrow$ )
10	US	$9.52 \pm 0.68$	$9.98 \pm 0.72$	$3074.89 \pm 135.57$
	CS	<b><math>6.62 \pm 0.62</math></b>	<b><math>7.87 \pm 1.38</math></b>	$3987.10 \pm 62.02$
20	US	$6.02 \pm 0.72$	$6.44 \pm 0.47$	$3345.67 \pm 36.58$
	CS	<b><math>3.58 \pm 0.29</math></b>	<b><math>5.00 \pm 0.62</math></b>	$4314.92 \pm 66.38$
30	US	$5.06 \pm 0.00$	$5.85 \pm 0.14$	$3525.40 \pm 94.05$
	CS	<b><math>2.90 \pm 0.38</math></b>	<b><math>3.68 \pm 0.06</math></b>	$4605.90 \pm 125.72$

**Results on different  $k$ :** From Table 10, our CS method consistently has an advantage over the US method for different  $k$ .

### D.3. Experiments on ShapeNetCore

**ShapeNetCore** (Chang et al., 2015) is a dataset containing a large collection of 3D object models. It includes 55 categories, such as chairs, tables, cars, airplanes, and other common objects. We extract object-level point cloud instances from the dataset and uniformly sample each to 300 points, forming our point cloud dataset.

**Efficiency of our coreset method:** The green dashed line represents the results on the full dataset. From Figure 12, it can be seen that our CS method significantly outperforms the US method.

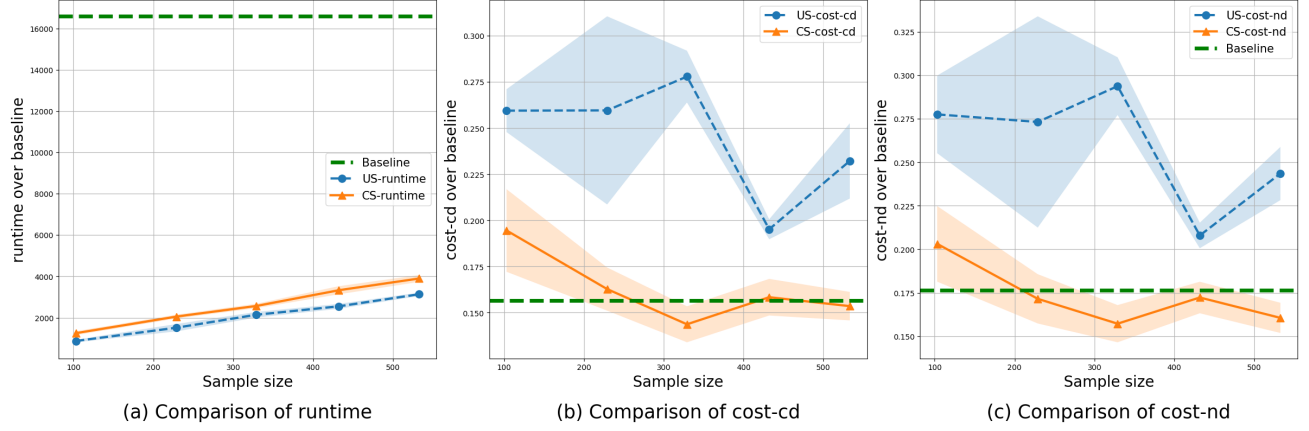


Figure 12: Comparison of the US method and our CS method across varying sample sizes on ShapeNetCore dataset.

**Results on different  $k$ :** From Table 11, our CS method consistently has an advantage over the US method for different  $k$ .

Table 11: Comparison of the US method and our CS method with varying values of  $k$  on ShapeNetCore dataset. We fix the sample size as 533,  $\sigma = 1$ , and  $\zeta = 0.1$ .

$k$	SM	cost-nd( $\downarrow$ )	cost-cd( $\downarrow$ )	Runtime( $\downarrow$ )
10	US	$0.23 \pm 0.02$	$0.24 \pm 0.02$	$3132.53 \pm 81.48$
	CS	<b><math>0.15 \pm 0.01</math></b>	<b><math>0.16 \pm 0.01</math></b>	$3896.53 \pm 166.72$
20	US	$0.18 \pm 0.03$	$0.20 \pm 0.03$	$3712.89 \pm 180.86$
	CS	<b><math>0.13 \pm 0.01</math></b>	<b><math>0.14 \pm 0.01</math></b>	$4430.57 \pm 59.18$
30	US	$0.17 \pm 0.01$	$0.18 \pm 0.01$	$4476.98 \pm 48.44$
	CS	<b><math>0.11 \pm 0.01</math></b>	<b><math>0.13 \pm 0.02</math></b>	$5170.38 \pm 17.25$

#### D.4. Experiments on ScanObjectNN

**ScanObjectNN** (Uy et al., 2019) is a real-world 3D object classification benchmark, which is captured from real scans, making it more challenging than synthetic datasets such as ModelNet10. We extract object-level point cloud instances from the dataset and uniformly sample each to 300 points, forming our point cloud dataset.

**Efficiency of our coreset method:** The green dashed line represents the results on the full dataset. From Figure 13, it can be seen that our CS method significantly outperforms the US method.

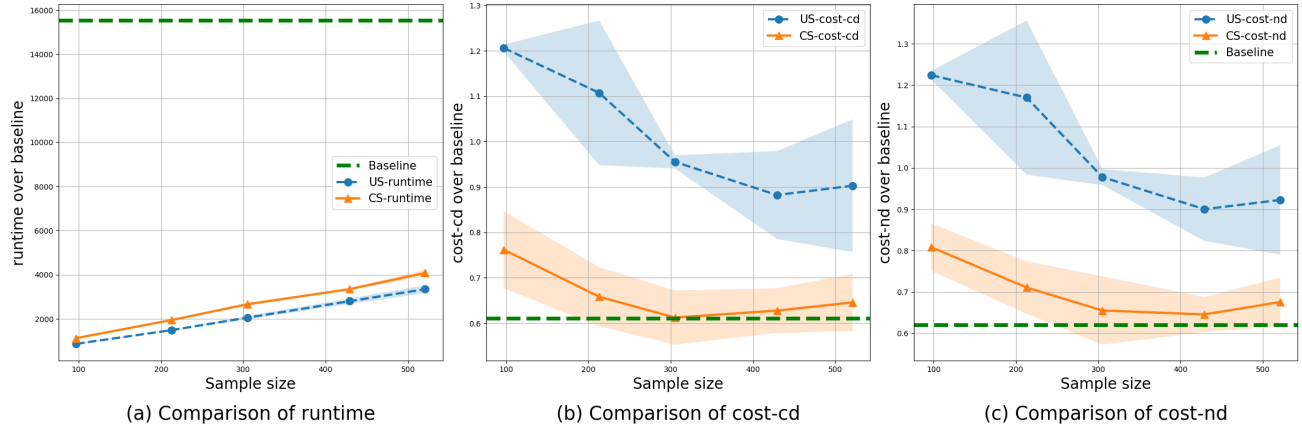


Figure 13: Comparison of the US method and our CS method across varying sample sizes on ScanObjectNN dataset.

**Results on different  $k$ :** From Table 12, our CS method consistently has an advantage over the US method for different  $k$ .

Table 12: Comparison of the US method and our CS method with varying values of  $k$  on ScanObjectNN dataset. We fix the sample size as 521,  $\sigma = 1$ , and  $\zeta = 0.1$ .

$k$	SM	cost-nd( $\downarrow$ )	cost-cd( $\downarrow$ )	Runtime( $\downarrow$ )
10	US	0.90 $\pm$ 0.15	0.92 $\pm$ 0.13	3345.48 $\pm$ 179.84
	CS	<b>0.65</b> $\pm$ 0.06	<b>0.68</b> $\pm$ 0.06	4082.18 $\pm$ 142.71
20	US	0.73 $\pm$ 0.02	0.73 $\pm$ 0.02	3631.17 $\pm$ 181.59
	CS	<b>0.56</b> $\pm$ 0.02	<b>0.57</b> $\pm$ 0.02	4477.70 $\pm$ 185.45
30	US	0.72 $\pm$ 0.05	0.72 $\pm$ 0.05	4205.75 $\pm$ 214.16
	CS	<b>0.38</b> $\pm$ 0.02	<b>0.39</b> $\pm$ 0.03	4934.63 $\pm$ 127.15