Not All Points Are Equal: Learning Highly Efficient Point-based Detectors for 3D LiDAR Point Clouds

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ABSTRACT

- Single-stage point-based 3D detector (**IA-SSD**)
  - Reduce memory and computational costs:
    - ➢ Two-learnable, task-oriented, instance-aware downsampling
    - ➢ Contextual centroid perception
- Compare with task-agnostic sampling
- Outperform in terms of detection accuracy and runtime efficiency

PREVIOUS WORKS

- **Voxel-based** Detectors: first convert raw point clouds into intermediate regular representation

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  Good detection performance with complex modules (two- stage) to overcome quantization error but greatly increasing computational costs

- **Point-based** Detectors: directly operate on raw point clouds (PointNet or variants)

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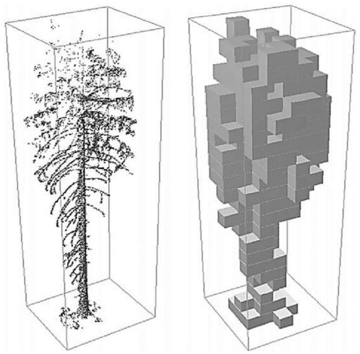
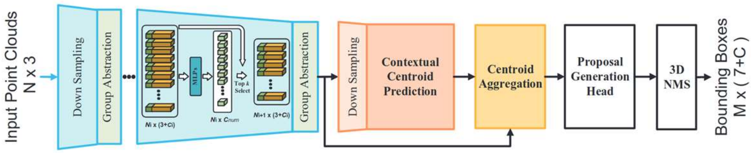
  Limited detection performance and expensive computational/memory costs due to the unstructured and orderless nature of 3d point clouds.



METHODS

The single-stage point-based 3D Detector **IA-SSD** main differences with previous point-based detectors:

1. Instance-aware sampling
2. Contextual instance centroid perception



In this paper, we argue that ***not all points are equally important to the task of object detection***. We only care about the foreground points.

1. **Feature extraction:** Set Abstraction layers
2. **Instance-aware Downsampling Strategy**: preserve foreground points
   - ***Class-aware Sampling:*** 2 MLPs used to learn semantic categories of each point
   - ***Centroid-aware Sampling:*** give higher weights to points closer to the instance centroid

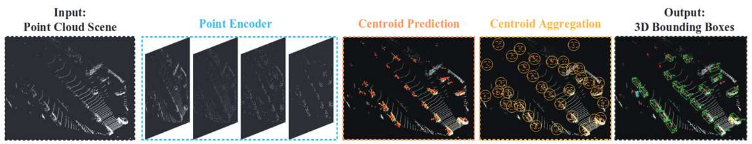
$$L_{cls} = -\sum_{i=1}^{C} (Mask_i * s_i \log(\hat{s_i}) + (1 - s_i)\log(1 - \hat{s_i}))$$

3. **Contextual Instance Centroid Perception**: exploit also surrounding points from a large context around the objects

$$L_{cent} = -\frac{1}{|F_+|}\frac{1}{|S_+|}\sum_i \sum_j (|\Delta\widehat{c_{ij}} - \Delta c_{ij}| + |\widehat{c_{ij}} - \overline{c_i}|) I_s(p_{ij})$$

4. Centroid-based Instance Aggregation: MLPs and symmetric function to learn a feature representation for each instance using the neighboring points.

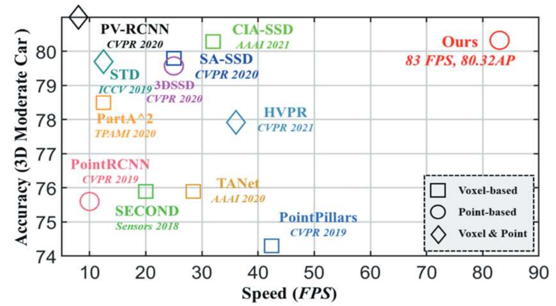
5. Proposal Generation Head: multidimensional representation of the bounding box with location, scale and orientation. Then filtering using 3D-NMS with a IoU threshold.



RESULTS

Sampling strategies	4096 points			1024 points			512 points			256 points		
	Car	*Ped.*	*Cyc.*	*Car*	*Ped.*	*Cyc.*	*Car*	*Ped.*	*Cyc.*	*Car*	*Ped.*	*Cyc.*
Random [14]	96.6%	99.1%	97.4%	87.5%	92.7%	84.1%	78.8%	84.9%	73.3%	67.4%	72.1%	57.3%
D-FPS [32]	98.3%	100%	97.2%	97.9%	99.3%	97.2%	96.8%	90.6%	90.8%	91.4%	69.1%	71.6%
Feat-FPS [52]	98.3%	100%	97.2%	97.7%	98.0%	97.2%	96.3%	87.6%	94.5%	95.3%	80.1%	91.7%
Cls-aware (Ours)	98.3%	100%	97.2%	97.9%	99.3%	97.2%	97.9%	99.0%	95.4%	97.9%	97.4%	92.7%
Ctr-aware (Ours)	98.3%	100%	97.2%	97.9%	99.3%	97.2%	97.9%	99.0%	97.2%	97.9%	98.4%	97.2%

	Method	Reference	Type	3D Car (IoU=0.7)			3D Ped. (IoU=0.5)			3D Cyc. (IoU=0.5)			Speed
				Easy	*Mod.*	*Hard*	*Easy*	*Mod.*	*Hard*	*Easy*	*Mod.*	*Hard*	
Voxel-based	VoxelNet [61]	CVPR 2018	1-stage	77.47	65.11	57.73	39.48	33.69	31.5	61.22	48.36	44.37	4.5
	SECOND [49]	Sensors 2018	1-stage	84.65	75.96	68.71	45.31	35.52	33.14	75.83	60.82	53.67	20
	PointPillars [18]	CVPR 2019	1-stage	82.58	74.31	68.99	51.45	41.92	38.89	77.10	58.65	51.92	42.4
	3D IoU Loss [59]	3DV 2019	1-stage	86.16	76.50	71.39	-	-	-	-	-	-	12.5
	Associate-3Ddet [7]	CVPR 2020	1-stage	85.99	77.40	70.53	-	-	-	-	-	-	20
	SA-SSD [11]	CVPR 2020	1-stage	88.75	79.79	74.16	-	-	-	-	-	-	25
	CIA-SSD [58]	AAAI 2021	1-stage	89.59	80.28	72.87	-	-	-	-	-	-	32
	TANet [24]	AAAI 2020	2-stage	84.39	75.94	68.82	53.72	<u>44.34</u>	40.49	75.70	59.44	52.53	28.5
	Part-A^2 [39]	TPAMI 2020	2-stage	87.81	78.49	73.51	53.10	43.35	40.06	79.17	63.52	56.93	12.5
Point-Voxel	Fast Point R-CNN [3]	ICCV 2019	2-stage	85.29	77.40	70.24	-	-	-	-	-	-	16.7
	STD [53]	ICCV 2019	2-stage	87.95	79.71	75.09	53.29	42.47	38.35	78.69	61.59	55.30	12.5
	PV-RCNN [36]	CVPR 2020	2-stage	<u>90.25</u>	<u>81.43</u>	<u>76.82</u>	52.17	43.29	40.29	78.60	63.71	<u>57.65</u>	12.5
	VIC-Net [16]	ICRA 2021	1-stage	88.25	80.61	75.83	43.82	37.18	35.35	78.29	63.65	57.27	17
	HVPR [29]	CVPR 2021	1-stage	86.38	77.92	73.04	53.47	43.96	<u>40.64</u>	-	-	-	36.1
Point-based	PointRCNN [38]	CVPR 2019	2-stage	86.96	75.64	70.70	47.98	39.37	36.01	74.96	58.82	52.53	10
	3D IoU-Net [19]	Arxiv 2020	2-stage	87.96	79.03	72.78	-	-	-	-	-	-	10
	Point-GNN [40]	CVPR 2020	1-stage	88.33	79.47	72.29	51.92	43.77	40.14	78.60	63.48	57.08	1.6
	3DSSD [52]	CVPR 2020	1-stage	88.36	79.57	74.55	<u>54.64</u>	44.27	40.23	<u>82.48</u>	64.10	56.90	25
	3DSSD† (Reproduced)	CVPR 2020	1-stage	87.73	78.58	72.01	35.03	27.76	26.08	66.69	59.00	55.62	23
	3DSSD‡ (OpenPCDet)	CVPR 2020	1-stage	87.91	79.55	74.71	3.63	3.18	2.57	27.08	21.38	19.68	28
	IA-SSD (single-class)	-	**1-stage**	**88.87**	**80.32**	**75.10**	**49.01**	**41.20**	**38.03**	**80.78**	<u>**66.01**</u>	<u>**58.12**</u>	<u>**85**</u>
	IA-SSD (multi-class)	-	**1-stage**	**88.34**	**80.13**	**75.04**	**46.51**	**39.03**	**35.60**	**78.35**	**61.94**	**55.70**	<u>**83**</u>



LIMITATIONS

The instance-aware downsampling relies on the semantic prediction of each point, which is susceptible to class imbalances distribution.