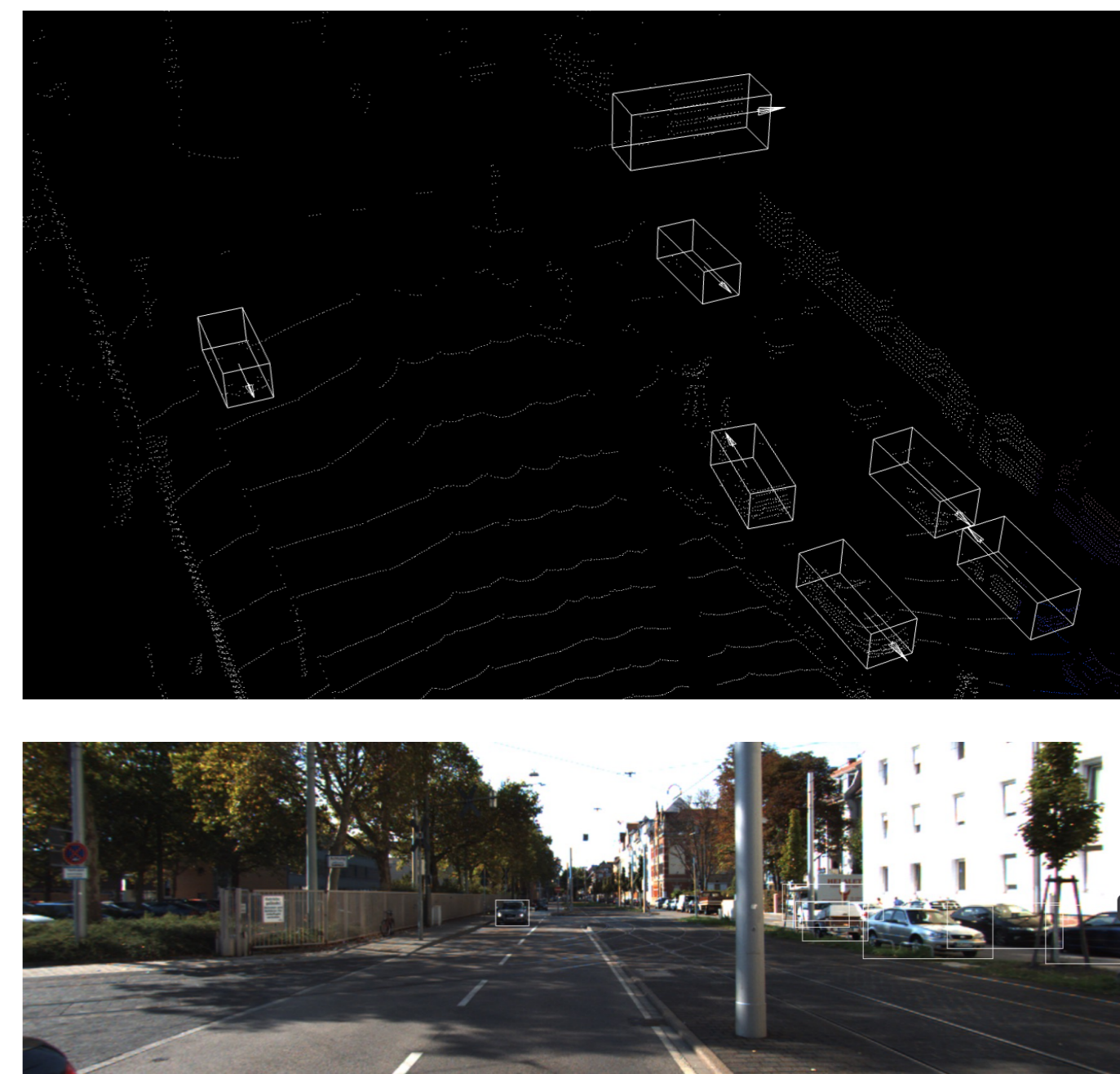
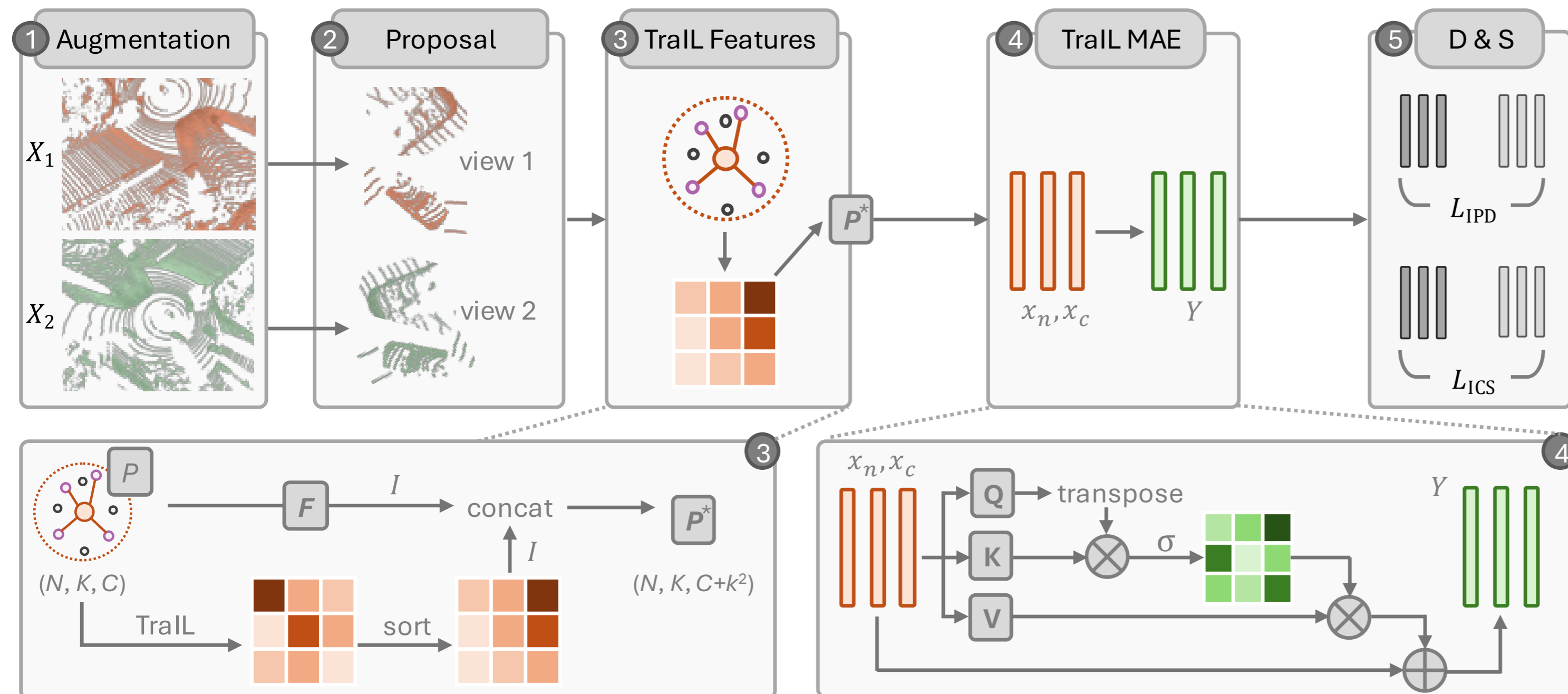


# Trall-Det: Transformation-Invariant Local Feature Networks for 3D LiDAR Object Detection with Unsupervised Pre-Training

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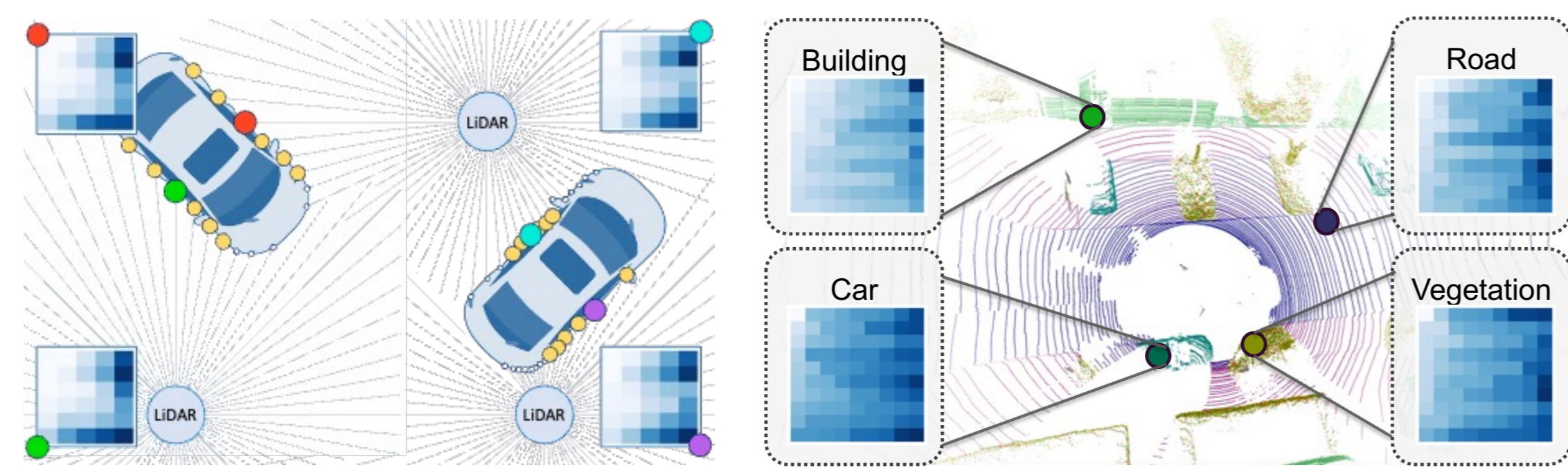
BMVC 2024



## Motivations & Contributions

### Trall-Det Architecture

- To Enhance local geometry representation and detection accuracy, our Trall features and Trall-Det architecture significantly improve 3D LiDAR object detection pre-training in autonomous driving.



- A transformation-invariant local feature (Trall) for 3D object detection, ensuring robustness to rigid transformations.
- An embedding method using Multi-head Self-Attention Encoder (MAE) for capturing geometric relations between points.
- A novel pre-training architecture (Trall-Det) for 3D object detection that surpasses recent approaches.

## Results & Conclusion

We use the standard SSL framework - pretrain a backbone network on large unlabeled data, then fine-tune it on downstream tasks with limited labeled data.

**Table: Data-efficient 3D Object Detection on KITTI.**

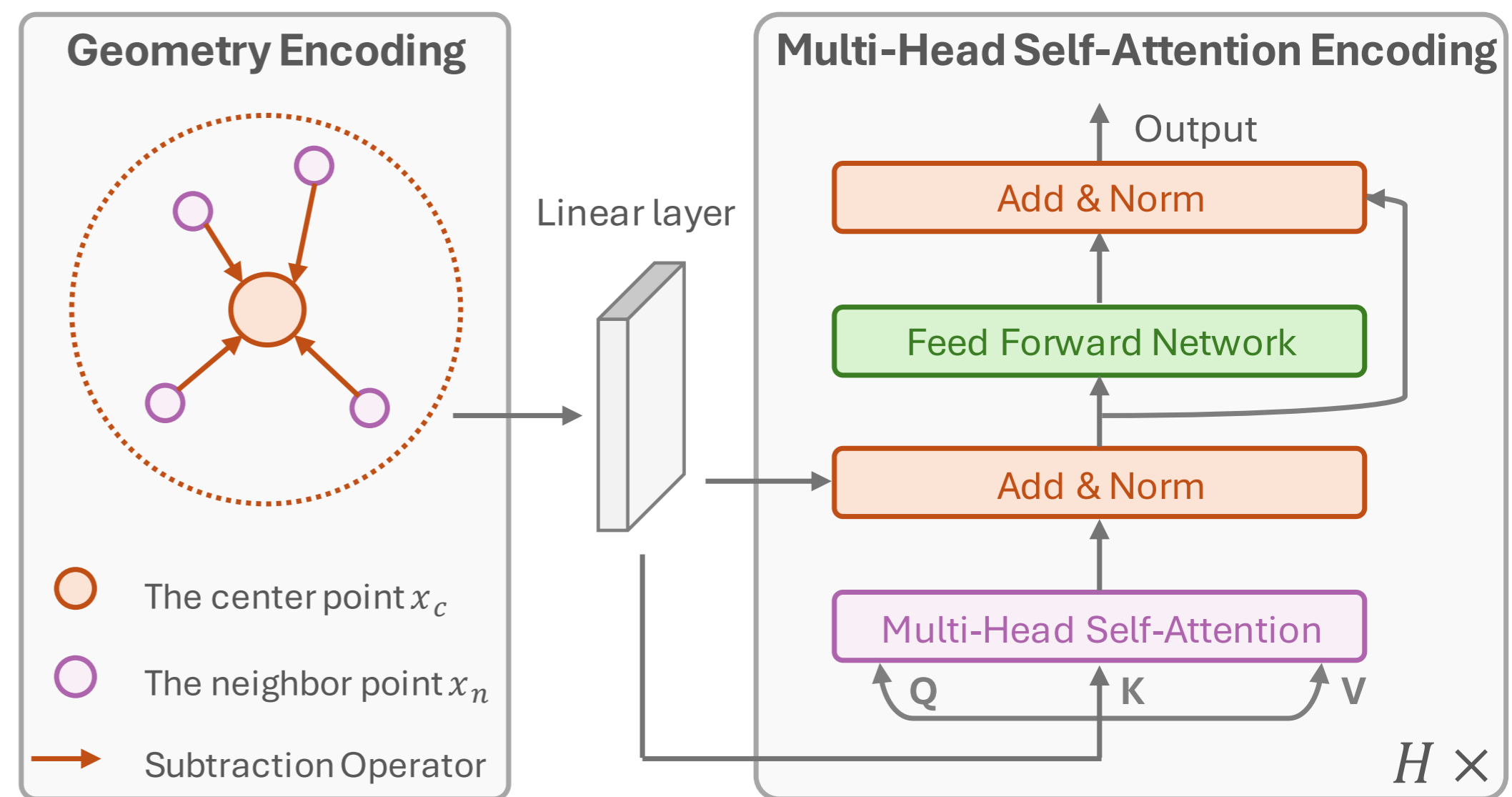
Fine-tuning with various label ratios	Detector	Pre-train. Schedule	mAP (Mod.)	Car			Pedestrian			Cyclist		
				Easy	Mod.	Hard	Easy	Mod.	Hard	Easy	Mod.	Hard
20% (~ 0.7k frames)	PointRCNN	Scratch	63.51	88.64	75.23	72.47	55.49	48.90	42.23	85.41	66.39	61.74
		Prop.Con. [52]	66.20	88.52	77.02	72.56	58.66	51.90	44.98	90.27	69.67	65.05
		★ Ours	<b>67.80</b>	<b>89.07</b>	<b>78.86</b>	<b>73.63</b>	<b>59.12</b>	<b>53.37</b>	<b>46.11</b>	<b>92.95</b>	<b>71.16</b>	<b>66.12</b>
	PV-RCNN	Scratch	66.71	91.81	82.52	80.11	58.78	53.33	47.61	86.74	64.28	59.53
		Prop.Con. [52]	68.13	<b>91.96</b>	82.65	80.15	<b>62.58</b>	55.05	<b>50.06</b>	<b>88.58</b>	66.68	<b>62.32</b>
		★ Ours	<b>69.30</b>	91.88	<b>82.73</b>	<b>80.39</b>	62.22	<b>56.94</b>	49.85	88.43	<b>68.24</b>	61.19
50% (~ 1.8k frames)	PointRCNN	Scratch	66.73	89.12	77.85	75.36	61.82	54.58	<b>47.90</b>	86.30	67.76	63.26
		Prop.Con. [52]	69.23	89.32	79.97	<b>77.39</b>	62.19	54.47	46.49	<b>92.26</b>	73.25	68.51
		★ Ours	<b>69.77</b>	<b>90.47</b>	<b>81.23</b>	76.82	<b>64.15</b>	<b>54.79</b>	47.28	91.16	<b>73.29</b>	<b>71.13</b>
	PV-RCNN	Scratch	69.63	91.77	82.68	81.90	63.70	57.10	52.77	89.77	69.12	64.61
		Prop.Con. [52]	71.76	<b>92.29</b>	82.92	82.09	<b>65.82</b>	59.92	55.06	91.87	72.45	<b>67.53</b>
		★ Ours	<b>73.24</b>	90.15	<b>84.20</b>	<b>85.01</b>	64.28	<b>61.43</b>	<b>56.09</b>	<b>92.42</b>	<b>74.10</b>	66.23
100% (~ 3.7k frames)	PointRCNN	Scratch	69.45	90.02	80.56	<b>78.02</b>	62.59	55.66	48.69	89.87	72.12	67.52
		DepthCon. [55]	70.26	89.38	80.32	77.92	65.55	57.62	50.98	90.52	72.84	68.22
		Prop.Con. [52]	70.71	89.51	80.23	77.96	66.15	<b>58.82</b>	52.00	91.28	73.08	68.45
	PV-RCNN	★ Ours	<b>71.41</b>	<b>90.82</b>	<b>81.95</b>	77.85	<b>66.28</b>	58.73	<b>53.96</b>	<b>92.41</b>	<b>73.55</b>	<b>71.53</b>
		Scratch	70.57	-	84.50	-	-	57.06	-	-	70.14	-
		GCC-3D [24]	71.26	-	-	-	-	-	-	-	-	-
PV-RCNN	STRL [14]	71.46	-	84.70	-	-	57.80	-	-	71.88	-	
	PointCon. [46]	71.55	91.40	84.18	82.25	65.73	57.74	52.46	91.47	72.72	67.95	
	Prop.Con. [52]	72.92	<b>92.45</b>	84.72	82.47	<b>68.43</b>	60.36	<b>55.01</b>	92.77	73.69	69.51	
	★ Ours	<b>73.89</b>	92.10	<b>85.39</b>	<b>84.12</b>	68.01	<b>61.25</b>	54.29	<b>93.46</b>	<b>75.04</b>	<b>72.49</b>	

## Methodology

### Trall Features

- Trall is defined for a point cloud patch  $X$  with  $K$  points where  $K > k$  and  $k$  is the count of the nearest neighbours of a point, forming an  $K \times k$  matrix  $\text{Trall}(X; k)$ . Each row  $i$  of this matrix includes the ordered distances from the  $i$ -th point in  $X$  to its  $k$  nearest neighbours.

### Multi-attention Geometric Encoding

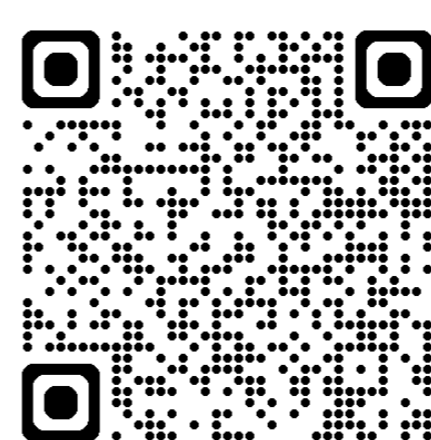


We propose the multi-attention geometric encoding. It computes asymmetric geometric features from the proposal  $P^*$  using center and neighbor points via subtraction. These features are refined with a proposal-aware encoding module using multi-head self-attention.

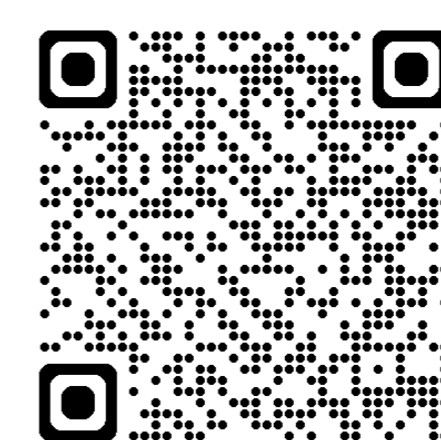
$$\mathbf{Q} = \delta(x_c), \quad \mathbf{K} = \theta(x_n - x_c), \quad \mathbf{V} = \gamma(x_n - x_c),$$

$$S^{(\text{att})}(\mathbf{Q}, \mathbf{K}, \mathbf{V}) = \text{softmax}\left(\frac{\mathbf{Q}_h \mathbf{K}_h^T}{\sqrt{D'}}\right) \cdot \mathbf{V}.$$

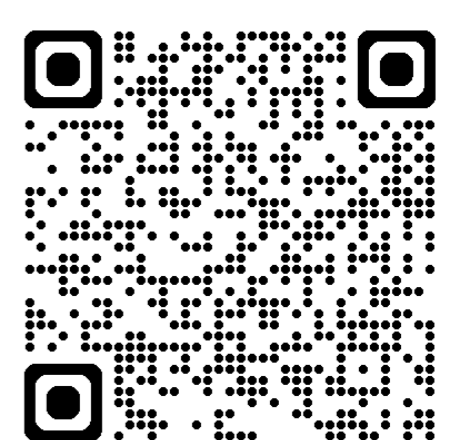
## Links & Connections



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