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**CVPR** VANCOUVER, CANADA



# LinK: Linear Kernel for LiDAR-based 3D Perception

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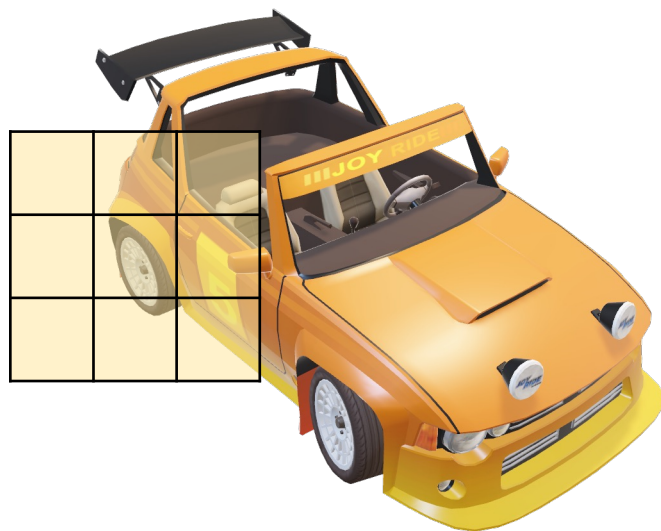
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# Problem

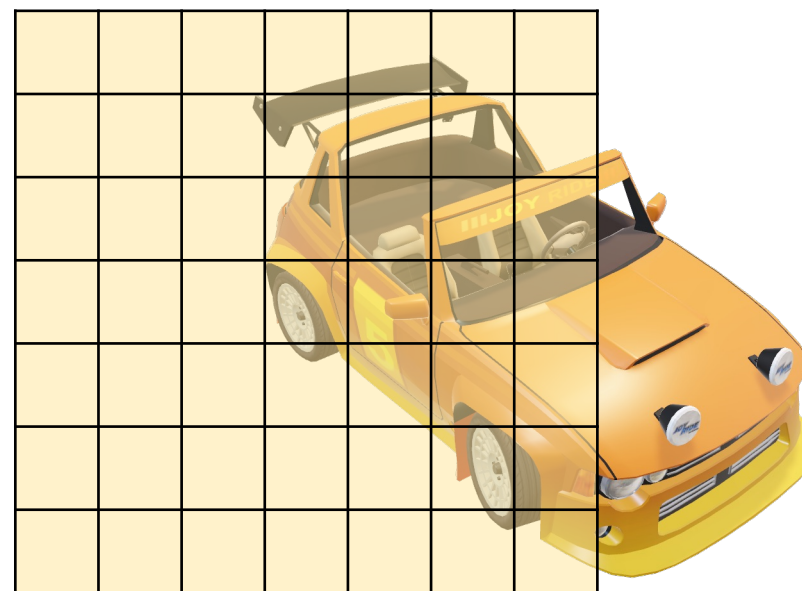
❖ How to scale up kernels in 3D?

Small kernel



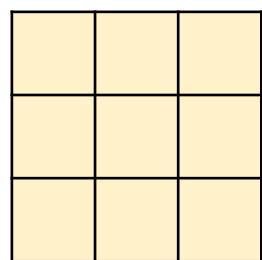
Large kernel {

- More informative context
- Better shape prior
- ...

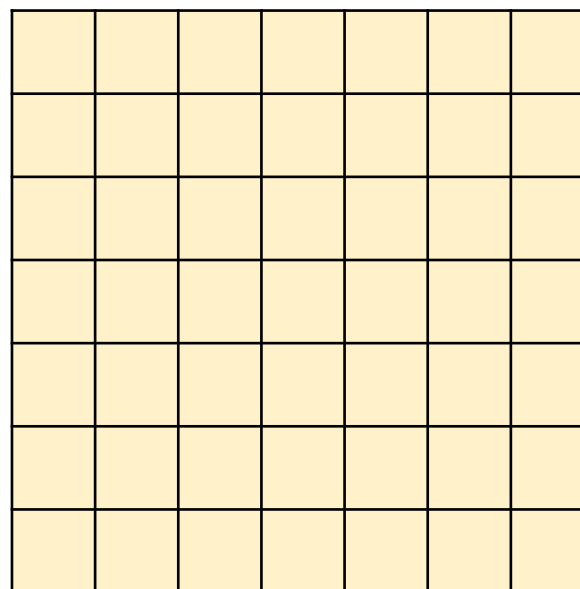
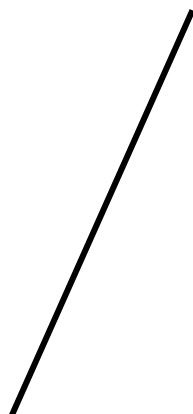


# Difficulties

➤ Cubically increasing **overhead**

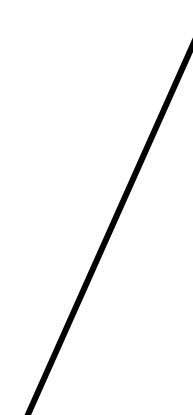


3×3×3



7×7×7

$$\left(\frac{7}{3}\right)^3 \approx \mathbf{12.7 \uparrow}$$



Larger **r** kernel

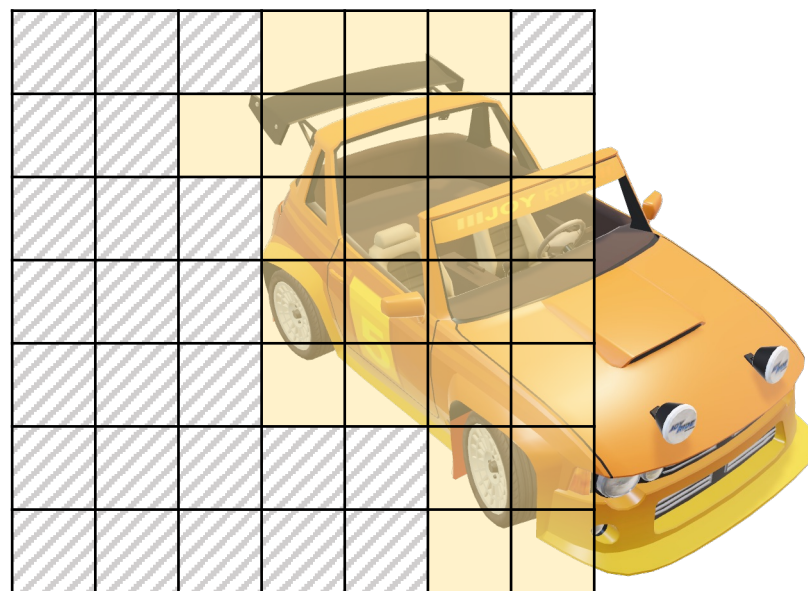
.....

21×21×21

$$\left(\frac{21}{3}\right)^3 = \mathbf{343 \uparrow}$$

# Difficulties

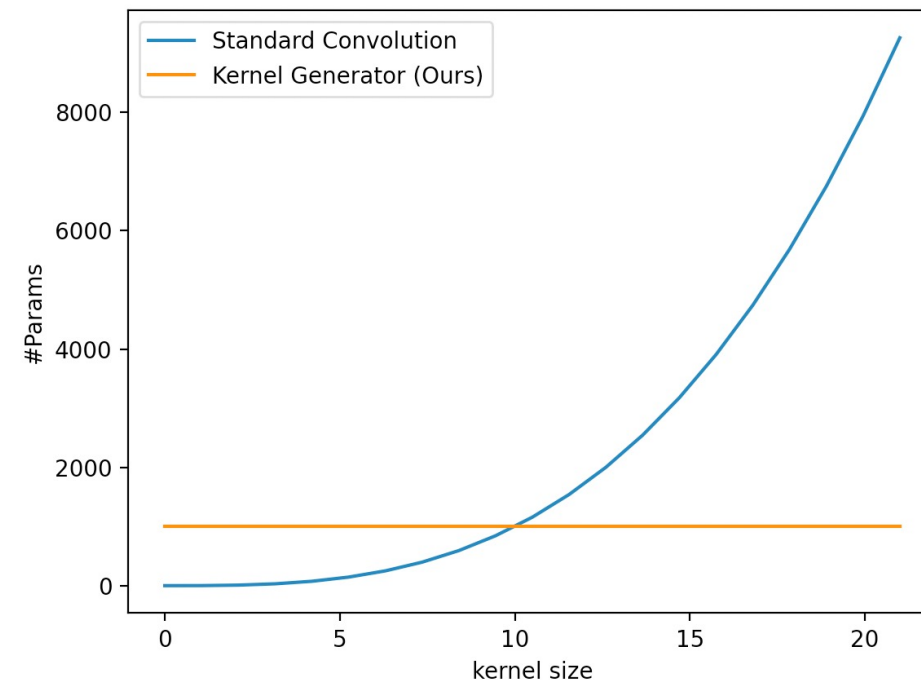
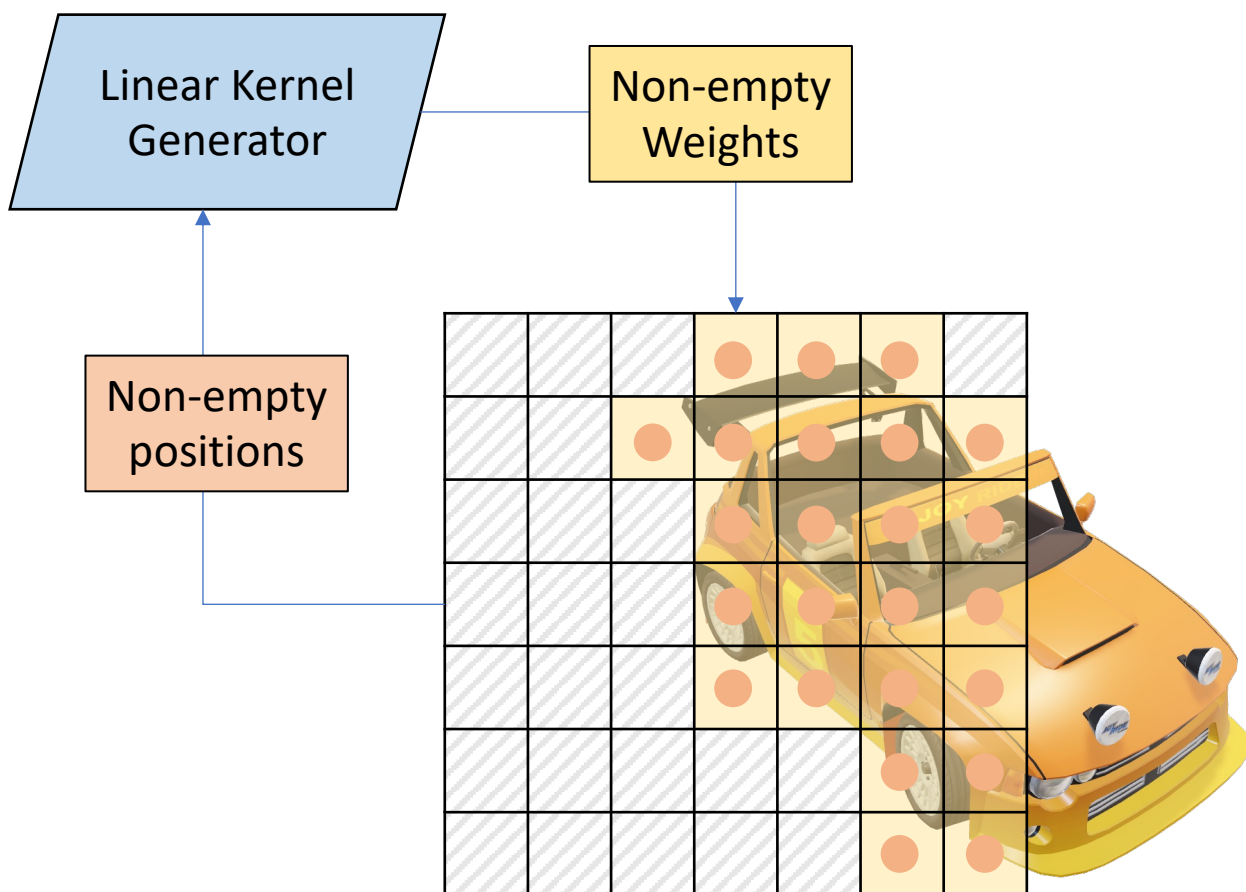
- Sparsity slows down the **optimization**



Empty area fails to be updated in backward process

# Our Solution

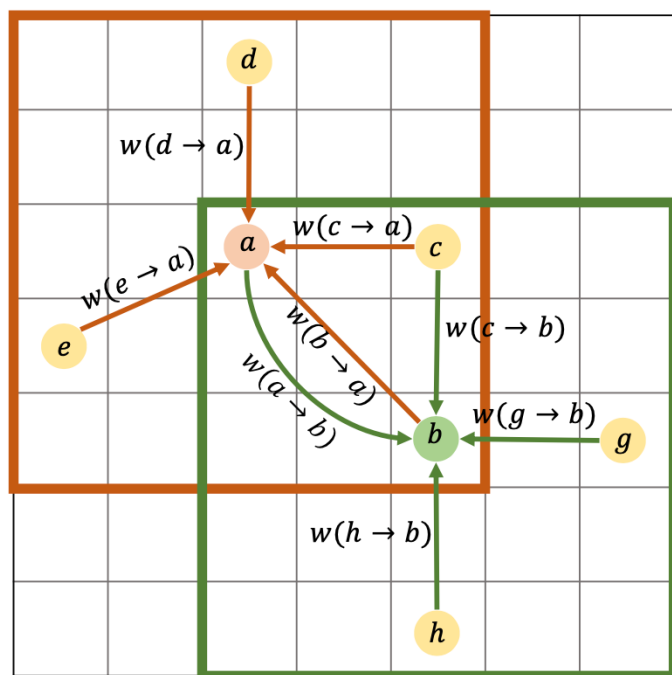
## ➤ Linear Kernel Generator



- ✓ Constant amount of learnable params, **not increase along with the kernel size**;
- ✓ Layer-wise sharing generator makes it friendly to optimization process.

# Our Solution

## ➤ Pre-aggregation



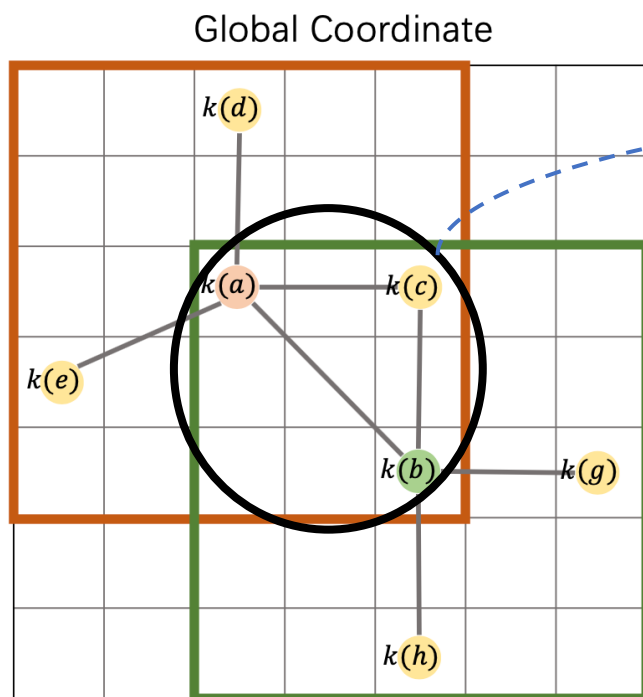
Local offset

$$\begin{array}{l}
 \{a, b, c\} \begin{cases}
 a = w(a - a) \cdot f_a + w(b - a) \cdot f_b + w(c - a) \cdot f_c \\
 b = w(a - b) \cdot f_a + w(b - b) \cdot f_b + w(c - b) \cdot f_c
 \end{cases}
 \end{array}$$

The overlap area is processed repeatedly!

# Our Solution

## ➤ Pre-aggregation



$$f_O = k(a) \cdot f_a + k(b) \cdot f_b + k(c) \cdot f_c.$$

$$w(x - y) = k(x)k(-y)$$

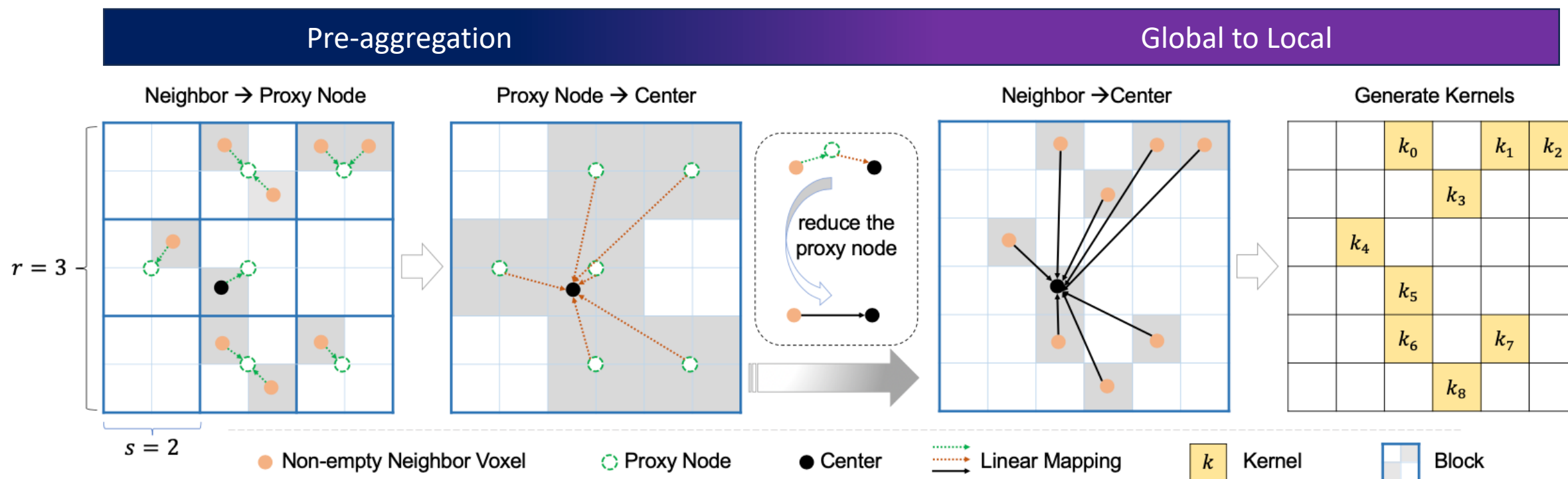
$$\begin{cases} f_{O \rightarrow a} = f_O \cdot k(-a) = \sum_{p \in O} w(p - a) \cdot f_{a+(p-a)}, \\ f_{O \rightarrow b} = f_O \cdot k(-b) = \sum_{p \in O} w(p - b) \cdot f_{b+(p-b)}. \end{cases}$$

Global coordinate

Pre-aggregation with global coordinate makes the overlap area reusable!

# Our Solution

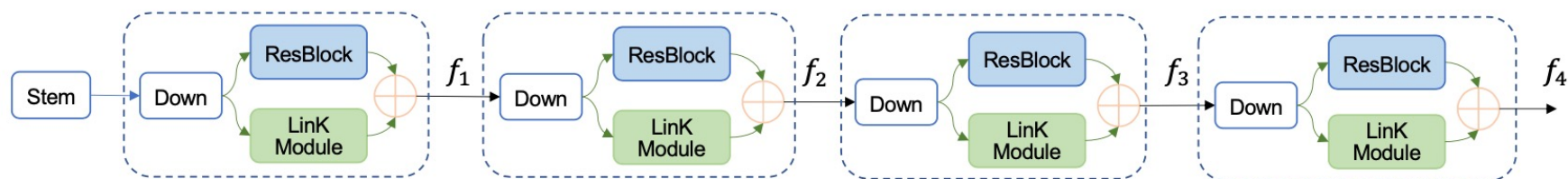
## ➤ Full pipeline of Link



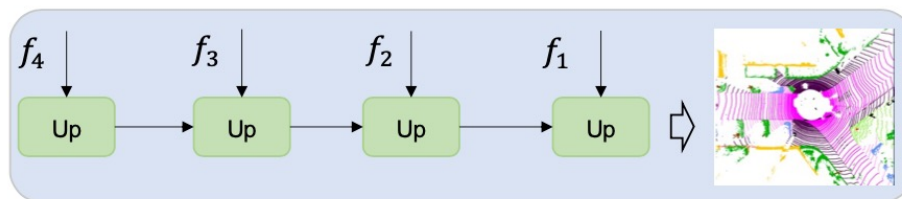


# Our Solution

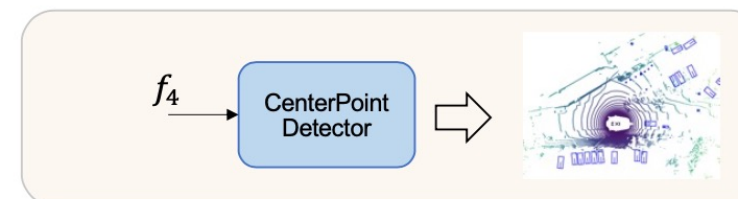
## ➤ Network Architecture



(a) Backbone.



(b) Segmentation Head.



(c) CenterPoint Detector.

(a) Architecture of the LinK-based backbone; (b) the constructed network for 3D semantic segmentation; (c) the constructed network for 3D object detection.

# Experiment: Detection

Table 1. Results on the test phase of nuScenes Detection. **Bold**: best results. \* denotes using TTA.

Methods	Source	NDS	mAP	car	truck	bus	trailer	construction _vehicle	pedestrian	motorcycle	bicycle	traffic_cone	barrier
PointPillars [31]	<i>CVPR19</i>	45.3	30.5	68.4	23.0	28.2	23.4	4.1	59.7	27.4	1.1	30.8	38.9
3DSSD [47]	<i>CVPR20</i>	56.4	42.6	81.2	47.2	61.4	30.5	12.6	70.2	36.0	8.6	31.1	47.9
CenterPoint [36]	<i>CVPR21</i>	65.5	58.0	84.6	51.0	60.2	53.2	17.5	83.4	53.7	28.7	76.7	70.9
HotSpotNet [48]	<i>ECCV20</i>	66.0	59.3	83.1	50.9	56.4	53.3	23.0	81.3	63.5	36.6	73.0	71.6
TransFusion-L [39]	<i>CVPR22</i>	70.2	65.5	86.2	<b>56.7</b>	66.3	58.8	28.2	86.1	68.3	44.2	<b>82.0</b>	<b>78.2</b>
Focals Conv [49]	<i>CVPR22</i>	70.0	63.8	<b>86.7</b>	56.3	<b>67.7</b>	59.5	23.8	<b>87.5</b>	64.5	36.3	81.4	74.1
LargeKernel [1]	<i>arXiv22</i>	70.5	65.3	85.9	55.3	66.2	60.2	26.8	85.6	72.5	46.6	80.0	74.3
LinK	<i>Ours</i>	<b>71.0</b>	<b>66.3</b>	86.1	55.7	65.7	<b>62.1</b>	<b>30.9</b>	85.8	<b>73.5</b>	<b>47.5</b>	80.4	75.5
VISTA* [50]	<i>CVPR22</i>	70.4	63.7	84.7	54.2	64.0	55.0	29.1	83.6	71.0	45.2	78.6	71.8
UVTR-LiDAR* [51]	<i>NeurIPS22</i>	69.7	63.9	86.3	52.2	62.8	59.7	33.7	84.5	68.8	41.1	74.7	74.9
MDRNet* [52]	<i>arXiv22</i>	72.8	68.4	<b>87.9</b>	58.5	67.3	64.1	30.2	<b>89.0</b>	77.0	50.7	<b>85.0</b>	74.7
LargeKernel3D* [1]	<i>arXiv22</i>	72.8	68.8	87.3	59.1	68.5	65.6	30.2	88.3	77.8	53.5	82.4	75.0
LinK*	<i>Ours</i>	<b>73.4</b>	<b>69.8</b>	87.3	<b>60.2</b>	<b>69.8</b>	<b>65.9</b>	<b>34.0</b>	88.2	<b>78.8</b>	<b>54.3</b>	83.0	<b>76.8</b>

# Experiment: Segmentation

Table 2. SemanticKITTI test results. **Red**: surpassing the baseline; **bold**: best results; 'P': point cloud; 'R': range map; 'V': voxel.

Method	Input	mIoU	Car	Bicycle	Motorcycle	Truck	Other-vehicle	Person	Bicyclist	Motorcyclist	Road	Parking	Sidewalk	Other-ground	Building	Fence	Vegetation	Trunk	Terrain	Pole	Traffic-sign
RandLA-Net [41]	P	53.9	94.2	26.0	25.8	40.1	38.9	49.2	48.2	7.2	90.7	60.3	73.7	20.4	86.9	56.3	81.4	61.3	66.8	49.2	47.7
RangeNet++ [60]	R	52.2	91.4	25.7	34.4	25.7	23.0	38.3	38.8	4.8	91.8	65.0	75.2	27.8	87.4	58.6	80.5	55.1	64.6	47.9	55.9
SqueezeSegV3 [61]	R	55.9	92.5	38.7	36.5	29.6	33.0	45.6	46.2	20.1	91.7	63.4	74.8	26.4	89.0	59.4	82.0	58.7	65.4	49.6	58.9
SalsaNext [62]	R	59.5	91.9	48.3	38.6	38.9	31.9	60.2	59.0	19.4	91.7	63.7	75.8	29.1	90.2	64.2	81.8	63.6	66.5	54.3	62.1
SPVNAS [42]	P+V	67.0	97.2	50.6	50.4	56.6	58.0	67.4	67.1	50.3	90.2	67.6	75.4	21.8	91.6	66.9	86.1	73.4	71.0	64.3	67.3
Cylinder3D [43]	V	67.8	97.1	67.6	64.0	59.0	58.6	73.9	67.9	36.0	91.4	65.1	75.5	32.3	91.0	66.5	85.4	71.8	68.5	62.6	65.6
(AF)2-S3Net [63]	V	69.7	94.5	65.4	<b>86.8</b>	39.2	41.1	<b>80.7</b>	<b>80.4</b>	<b>74.3</b>	91.3	68.8	72.5	<b>53.5</b>	87.9	63.2	70.2	68.5	53.7	61.5	<b>71.0</b>
DRINet [64]	P+V	67.5	96.9	57.0	56.0	43.3	54.5	69.4	75.1	58.9	90.7	65.0	75.2	26.2	91.5	67.3	85.2	72.6	68.8	63.5	66.0
RPVNet [44]	R+P+V	70.3	<b>97.6</b>	<b>68.4</b>	68.7	44.2	61.1	75.9	74.4	73.4	<b>93.4</b>	<b>70.3</b>	<b>80.7</b>	33.3	<b>93.5</b>	<b>72.1</b>	<b>86.5</b>	<b>75.1</b>	<b>71.7</b>	<b>64.8</b>	61.4
Mink(baseline) [15]	V	68.0	97.1	51.8	56.4	43.3	56.8	70.2	75.7	51.8	89.9	67.8	74.8	32.9	91.5	66.5	86.2	74.6	71.0	63.5	70.0
LinK(Ours)	V	<b>70.7</b>	<b>97.4</b>	<b>58.4</b>	<b>56.6</b>	<b>52.9</b>	<b>64.2</b>	<b>72.3</b>	<b>77.0</b>	<b>69.1</b>	<b>90.6</b>	<b>68.2</b>	<b>76.2</b>	<b>34.5</b>	<b>92.0</b>	<b>68.8</b>	85.7	74.3	70.5	<b>64.8</b>	69.5

# Experiment: Ablations

□ How does large kernel work?

✓ Large objects benefit greatly.

Table 5. Performance on different scale objects.

Category	Size( $m^3$ )	Detection		Segmentation	
		Center Point	+LinK	Mink	+LinK
Truck	$6 \times 2 \times 2$	51.0	(+4.7)55.7	43.3	(+9.6)52.9
Person	$0.4 \times 0.4 \times 2$	83.4	(+2.4)85.8	70.2	(+2.1)72.3

□ The influence of kernel size

Table 1. Different kernel sizes for segmentation. Without TTA.

$r \times s$	mIoU(%)@SemKITTI val
$3 \times 2$	66.9
$3 \times 3$	67.3
$3 \times 5$	67.5
$3 \times 7$	67.2

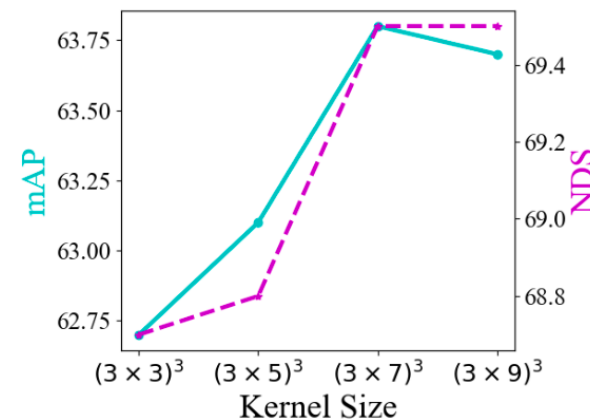


Figure 7. Detection performance with different kernel sizes.



# Visualizations

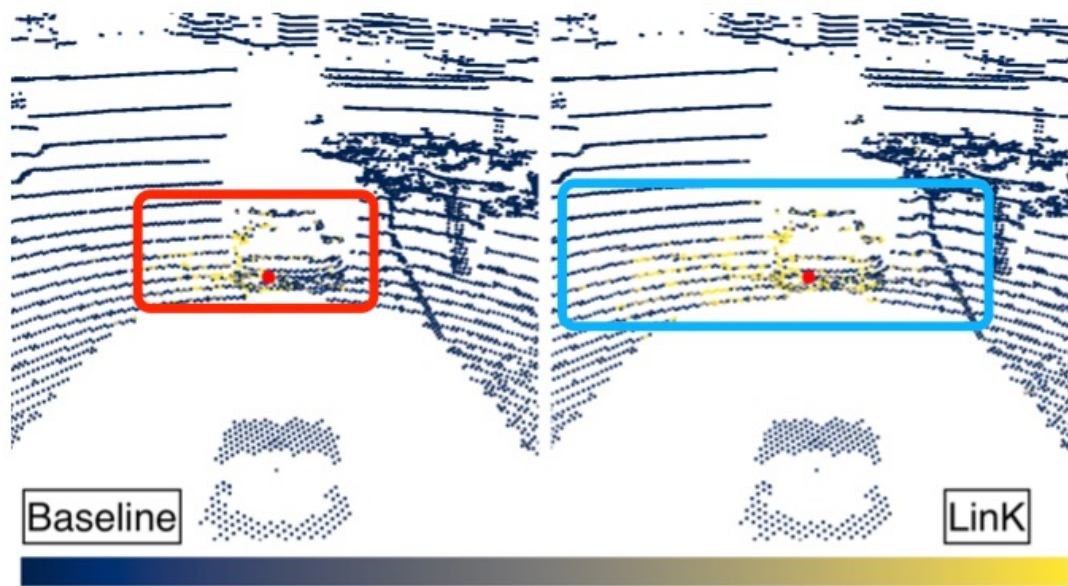
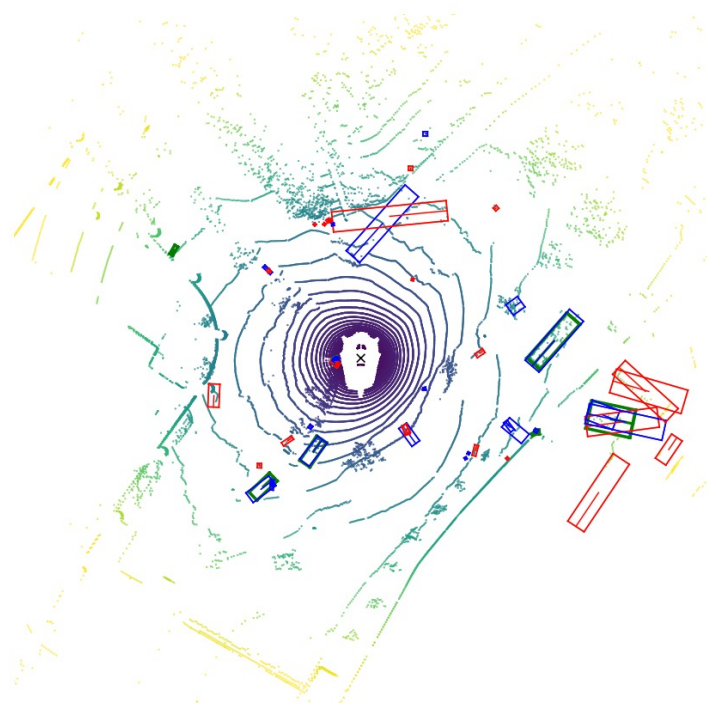
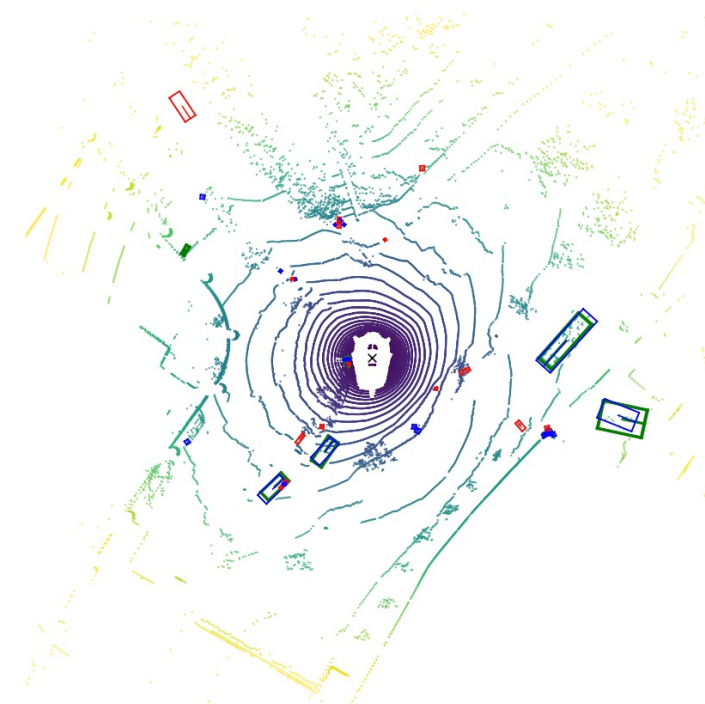


Figure 6. The effective receptive field (ERF) of the detection. The brightness indicates the degree of activation. LinK enjoys a wider-range perception.

# Visualizations



(a) Baseline



(b) LinK

*Thanks!*



Code

## Contact

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- Haisong Liu: [liuhs@smail.nju.edu.cn](mailto:liuhs@smail.nju.edu.cn)



Paper