Lightweight Object Detection: A Brief Report

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January 22, 2024

1. Content and Achievements
   - NAS
   - Channel Pruning
   - SCConv
   - PConv
   - Re-Parameterization
   - NMS

2. Design and Results

3. References

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- Zero-Cost NAS, proxy is defined as the entropy of S.

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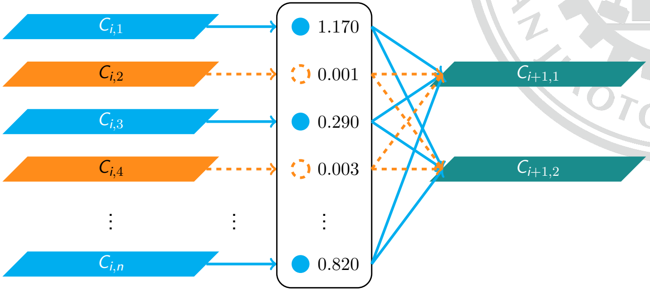

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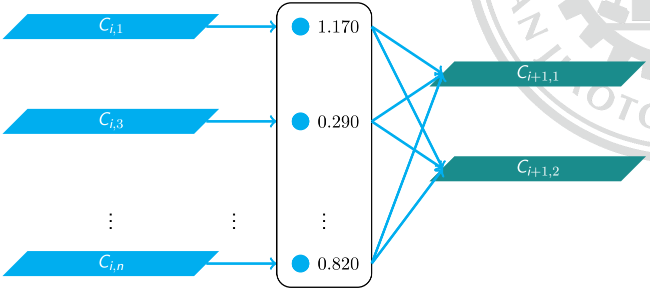

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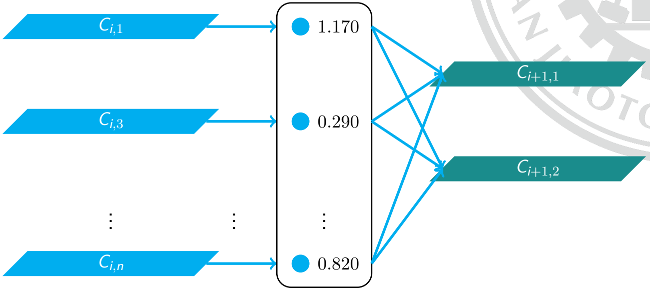

- mAP $= 10.3\%$ after sparsifying

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parameter	**value**
dataset	CIFAR-10
epoch	200

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Model	**Acc(%)**	**FLOPs(G)**	**Params(M)**
ResNet-50	94.93	2.62	23.52
ResNet-50 with SCConv	92.03	1.86	15.91

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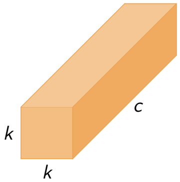

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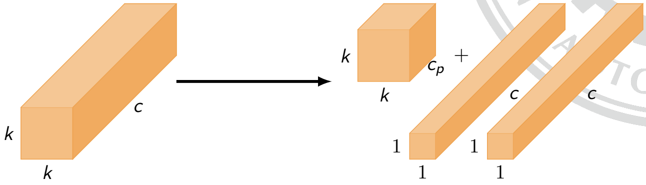

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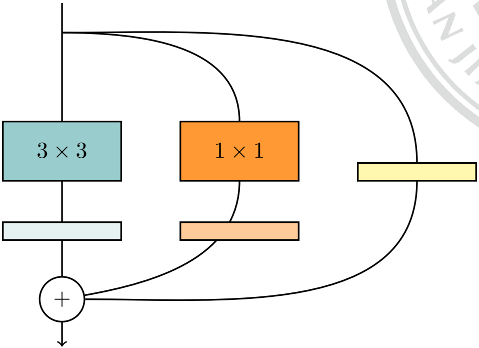

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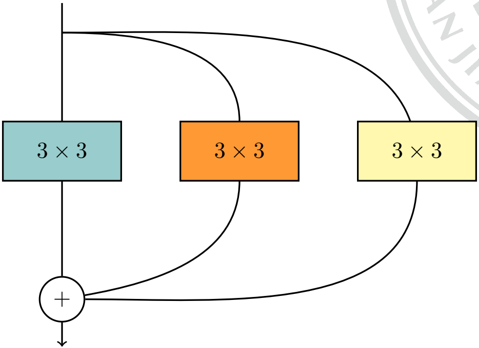

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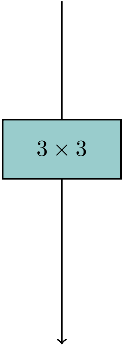

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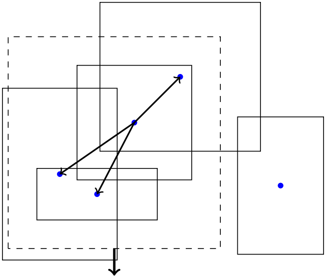

$K=3$, IoU/Density Query Box

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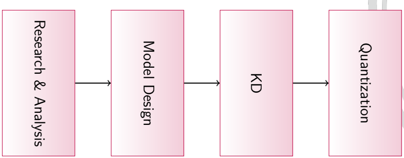

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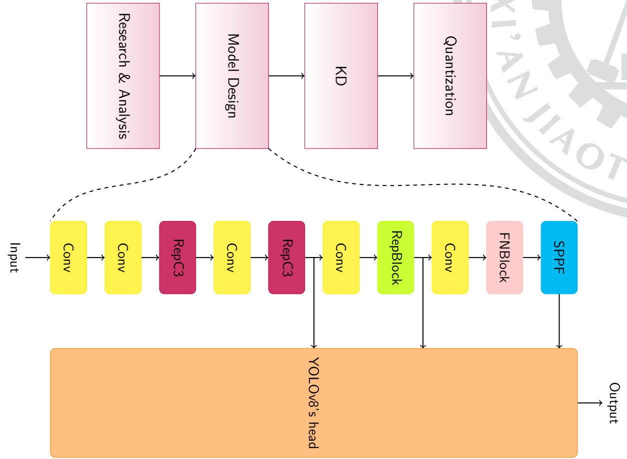
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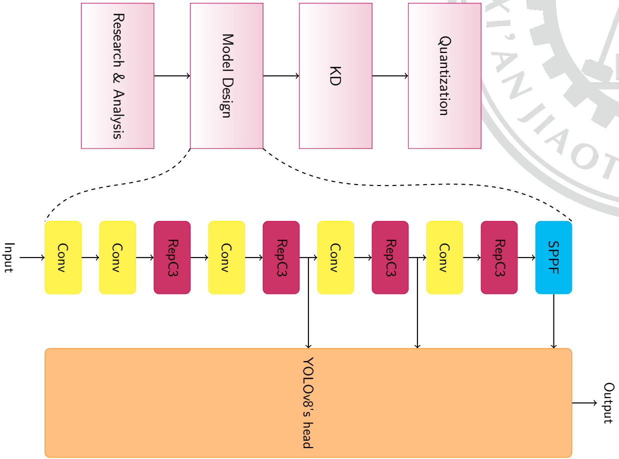
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	Model	$\mathbf{mAP}^{\mathbf{val}}_{\mathbf{50-95}}$	**latency(ms)**	**FPS(/s)**
env_1 [1]	yolov5s.pt	37.4	2.78	359.71
	yolov5su.pt	43.1	1.70	588.24($\uparrow 63.53\%$)
	yolov8n.pt	37.4	1.43	699.30($\uparrow 94.41\%$)
	yolov6n.pt	37.5	3.05	327.87($\downarrow 8.85\%$)
env_2 [2]	yolov8n.pt	37.4	2.18	458.72
	xjtun.pt(Ours)	36.7	1.91	523.56

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- Conclusion: The FPS improvement is at least 95% with 0.7% accuracy decrease.

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[1] Jierun Chen, Shiu-hong Kao, Hao He, Weipeng Zhuo, Song Wen, Chul-Ho Lee, and S-H Gary Chan.
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[4] Zhuang Liu, Jianguo Li, Zhiqiang Shen, Gao Huang, Shoumeng Yan, and Changshui Zhang.
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Thanks!