

IDa-Det: An Information Discrepancy-aware Distillation for 1-bit Detectors

Supplementary Material

Sheng Xu^{1†}, Yanjing Li^{1†}, Bohan Zeng^{1†}, Teli Ma², Baochang Zhang^{1,3*},
Xianbin Cao¹, Peng Gao², Jinhu Lü^{1,3}

¹ Beihang University, Beijing, China

² Shanghai Artificial Intelligence Laboratory, Shanghai, China

³ Zhongguancun Laboratory, Beijing, China

{shengxu, yanjingli, bohanzeng, bczhang}@buaa.edu.cn

1 More experiments

Framework	Backbone	Quantization Method	KD Method	W/A	Memory Usage (MB)	OPs ($\times 10^9$)	mAP
Faster-RCNN	ResNet-50	Real-valued	✗	32/32	164.88	127.76	80.7
		ReActNet	✗				73.1
		Ours	✗				76.5
		LWS-Det					76.9
		Ours	FGFI	1/1	29.61	21.95	77.2
		Ours	DeFeat				77.6
		IDa-Det					79.4

Table 1. Comparison of memory usage, FLOPs, and mAP (%) with state-of-the-art BNNs, other KD methods in both Faster-RCNN and SSD frameworks on VOC test2007. The best results are **bold**.

Due to the page length constraint, we move the experiments using Faster-RCNN [8] with ResNet-50 [3] backbone to the supplementary material. The architecture of ResNet-50 is modified in our experiments in accordance with [6]. We compare our IDa-Det with the state-of-the-art 1-bit ReActNet [7] and other KD methods, such as FGFI [9], DeFeat [2], and LWS-Det [10]. We also compare the detection performance of the 4-bit quantized FQN [4] and the DoReFa-Net [11] for further reference. First, on the VOC [1] dataset, our IDa-Det surpasses FGFI and DeFeat distillation method by 2.2%, and 1.7% with ResNet-50. Our IDa-Det significantly outperforms the prior state-of-the-art, *i.e.*, LWS-Det, by 2.5% with the same memory usage and FLOPs. Then, on the COCO [5] dataset, our

† Equal contribution.

* Corresponding author.

Framework	Backbone	Quantization Method	KD Method	W/A	mAP @[.5, .95]	AP ₅₀	AP ₇₅	AP _s	AP _m	AP ₁
Faster-RCNN	ResNet-50	Real-valued	✗	32/32	37.7	59.3	40.9	22.0	41.5	48.9
		FQN	✗	4/4	33.1	54.0	35.5	18.2	36.2	43.6
		ReActNet	✗		26.1	47.7	35.6	14.1	28.9	38.9
		Ours	✗		30.3	48.9	34.5	17.3	31.0	40.2
		LWS-Det		1/1	31.7	52.1	37.5	17.7	34.9	43.1
		Ours	FGFI		32.5	53.7	37.9	17.4	34.7	44.0
		Ours	DeFeat		32.7	54.2	36.9	18.0	35.0	43.9
		IDa-Det			34.0	54.5	38.0	18.9	35.7	44.7

Table 2. Comparison with state-of-the-art 1-bit detectors and KD methods on COCO minival. Optimal results are **bold**.

IDa-Det surpasses LWS-Det by 2.3%. Similarly, our IDa-Det outperforms other detectors on other APs with varying IoU thresholds.

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