Automatic Network Pruning via Hilbert-Schmidt Independence Criterion Lasso under Information Bottleneck Principle Supplementary Material

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Model	**Method**	**Pruned Top-1 Acc.(diff.)**	**FLOPs↓**
VGG-16	CPGMI[3]	73.53%(−0.27%)	37%
	CPMC[5]	73.01%(−0.79%)	48%
	PGMPF[1]	73.45%(−0.35%)	48%
	PGMPF-SFP[1]	73.66%(−0.14%)	48%
	APIB (ours)	**73.89**%(**+0.09%**)	**48**%
ResNet-56	NSPPR[6]	72.46%(−0.03%)	25%
	DLRFC[2]	71.41%(+0.27%)	26%
	APIB (ours)	**73.31**%(**+0.79%**)	**26**%
	PGMPF[1]	70.21%(−2.71%)	53%
	APIB (ours)	**70.89**%(**−1.63%**)	**53**%

Table 1. Pruning results of VGG-16 and ResNet-56 on CIFAR-100.

1. Overview

In this supplementary material, we provide the experimental results about CIFAR-100 and time cost comparison.

2. Experiments on CIFAR-100

We conduct experiments on CIFAR-100 using ResNet-56 and VGG-16, the results show that APIB yield a state-of-the-art performance.

3. Time cost comparison

We compare the time cost of APIB and baselines for pruning ResNet50 with a sparsity of 76%. APIB significantly reduces pruning time compared to Hrank and CHIP[4], which calculate rank or channel independence based on feature maps.

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Method	L1	FPGM	APIB	Hrank	CHIP
Time	7s	8s	63s	9112s	545618s

Table 2. Time cost required by APIB and other baselines.

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