MUXConv: Information Multiplexing in Convolutional Neural Networks

Zhichao Lu, Kalyanmoy Deb and Vishnu Naresh Boddeti
Michigan State University
{luzhicha, kdeb, vishnu}@msu.edu
https://github.com/human-analysis/MUXConv

MUXConv

- New layer: Multiplexed Convolutions (Spatial + Channel Multiplexing)
- Idea: increase flow of information between space and channels
- Goal: smaller model size, increased efficiency, maintain/increase performance

Spatial Multiplexing: Idea

Spatial Multiplexing

Subpixel

Superpixel

Spatial Multiplexing: Evaluation

- Consistent improvement on accuracy over the original depth-wise separable convolution
- Particularly effective in low MAdds Regime

Channel Multiplexing:Idea

Channel Multiplexing: Evaluation

- Consistently outperforming existing scaling methods

Tri-Objective Search: Idea

- Simultaneously optimize for accuracy ("), #Params (#), and #MAdds (#)
- User preference guided search through PBI[1] decomposition

[1] Qingfu Zhang and Hui Li. Moea/d: A multiobjective evolutionary algorithm based on decomposition. IEEE Transactions on Evolutionary Computation, 11(6):712731, 2007

Tri-Objective Search: Evaluation

- NASBench101: our search is more ef cient than regularized evolution [2]

[2] Esteban Real, Alok Aggarwal, Yanping Huang, and Quoc VLe. Regularized evolution for image classi er architecture search. In AAAI, 2019

ImageNet-1K Classi cation

Model	Type	#MAdds	Ratio	#Params	Ratio	CPU(ms)	GPU(ms)	Top-1 (%)	Top-5 (%)
MUXNet-xs (ours)	auto	66M[z]	1.0x	1.8M[z]	1.0x	6.8	18	66.7	86.8
MobileNetV2_0.5	manual	97M	1.5x	2.0M	1.1x	6.2	17	65.4	86.4
MobileNetV3 small	combined	66M	1.0x	2.9M	1.6x	6.2[z]	14	67.4	-
MUXNet-s (ours)	auto	117M[z]	1.0x	2.4M[z]	1.0x	9.5	25	71.6	90.3
MobileNetV1	manual	575M	4.9x	4.2M	1.8x	7.3	20	70.6	89.5
Shuf eNetV2	manual	146M	1.3x	-	-	6.8	11[z]	69.4	-
ChamNet-C	auto	212M	1.8x	3.4M	1.4x	-	-	71.6	-
MUXNet-m (ours)	auto	218M[z]	1.0x	3.4M[z]	1.0x	14.7	42	75.3	92.5
MobileNetV2	manual	300M	1.4x	3.4M	1.0x	8.3[z]	23	72.0	91.0
Shuf eNetV2 2	manual	591M	2.7x	7.4M	2.2x	11.0	22[z]	74.9	-
MnasNet-A1	auto	312M	1.4x	3.9M	1.1x	9.3[z]	32	75.2	92.5
MobileNetV3 large	combined	219M	1.0x	5.4M	1.6x	10.0[z]	33	75.2	-
MUXNet-l (ours)	auto	318M[z]	1.0x	4.0M[z]	1.0x	19.2	74	76.6	93.2
MnasNet-A2	auto	340M	1.1x	4.8M	1.2x	-	-	75.6	92.7
FBNet-C	auto	375M	1.2x	5.5M	1.4x	9.1[z]	31	74.9	-
Ef cientNet-B0	auto	390M[z]	1.2x	5.3M	1.3x	14.4	46	76.3	93.2
MixNet-M	auto	360M[z]	1.1x	5.0M	1.2x	24.3	79	77.0	93.3

[z] indicates the objective that the method explicitly optimizes through NAS.

Additional Experiments

Generalization to ImageNet-V2

PASCAL VOC2007 Detection

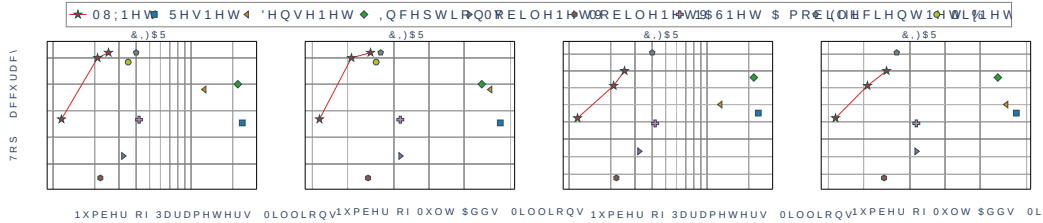
Network	#MAdds	#Params	mAP (%)
VGG16 + SSD	35B	26.3M	74.3
MobileNet + SSD	1.6B	9.5M	67.6
MobileNetV2 + SSDLite	0.7B	3.4M	67.4
MobileNetV2 + SSD	1.4B	8.9M	73.2
MUXNet-m + SSDLite	0.5B	3.2M	68.6
MUXNet-l + SSD	1.4B	9.9M	73.8

ADE20K Semantic Segmentation

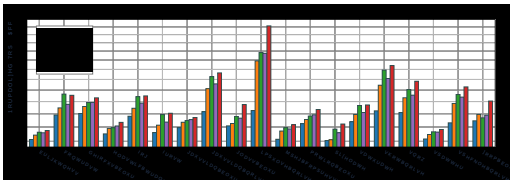
Network	#MAdds	#Params	mIoU (%)	Acc (%)
ResNet18 + C1	1.8B	11.7M	33.82	76.05
MobileNetV2 + C1	0.3B	3.5M	34.84	75.75
MUXNet-m + C1	0.2B	3.4M	32.42	75.00
ResNet18 + PPM	1.8B	11.7M	38.00	78.64
MobileNetV2 + PPM	0.3B	3.5M	35.76	77.77
MUXNet-m + PPM	0.2B	3.4M	35.80	76.33

Additional Experiments

Transfer Learning on CIFAR



Robustness to Degradations



Visualization on Segmentation Results