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EFFICIENT AND INTELLIGENT COMPUTING

DepthShrinker: A New Compression Paradigm Towards Boosting Real-Hardware Efficiency of Compact Neural Networks

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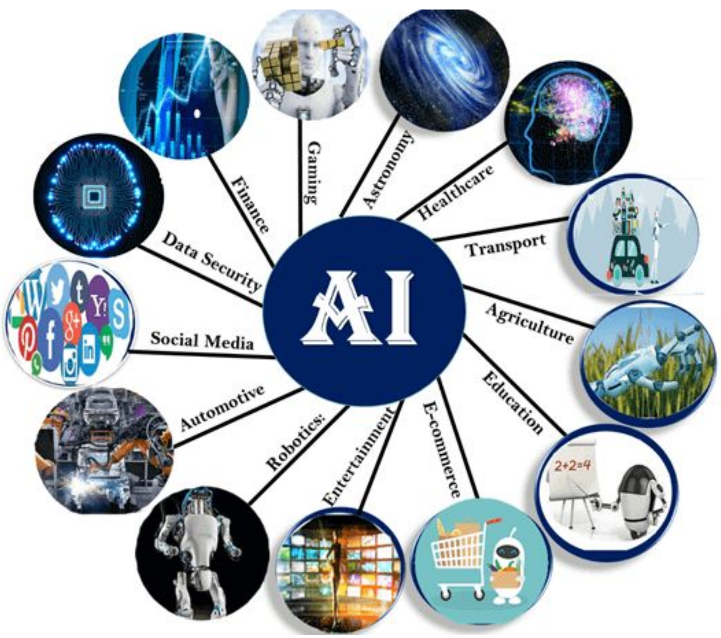
Meta

RICE Electrical and Computer Engineering

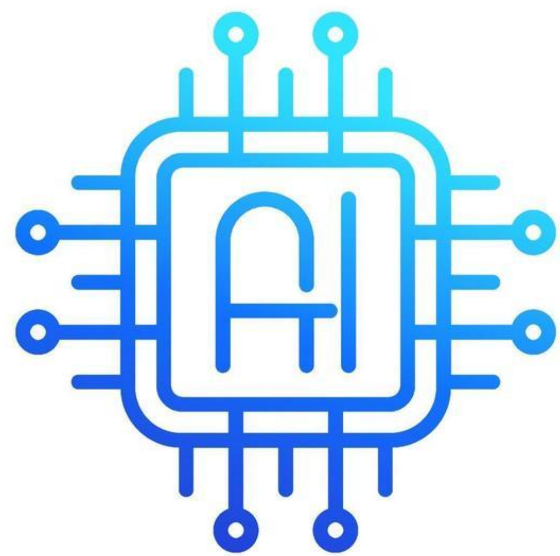
Background: Demanding Efficient ML

- **A growing demand**: Accelerate deep neural networks (DNNs) on real-world devices



Complex AI Models

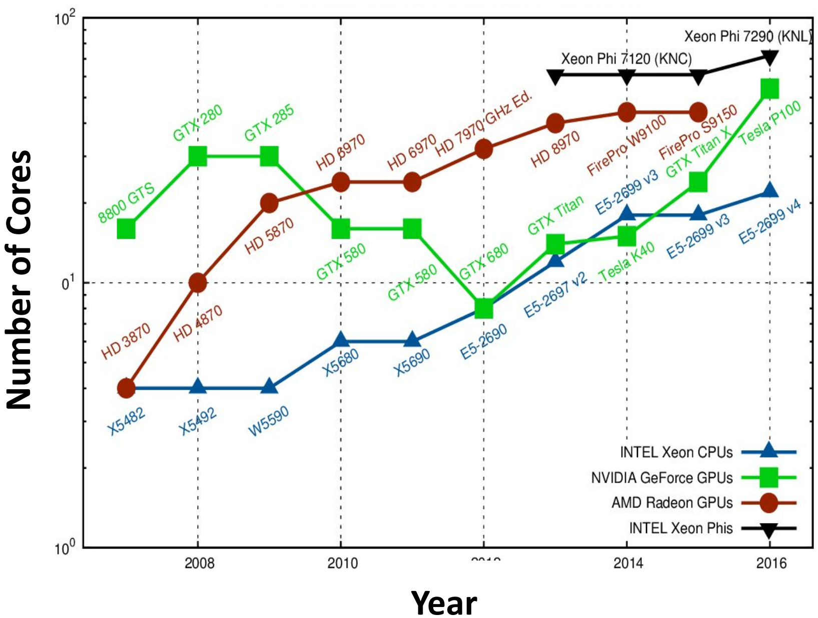
Bridge the Gap

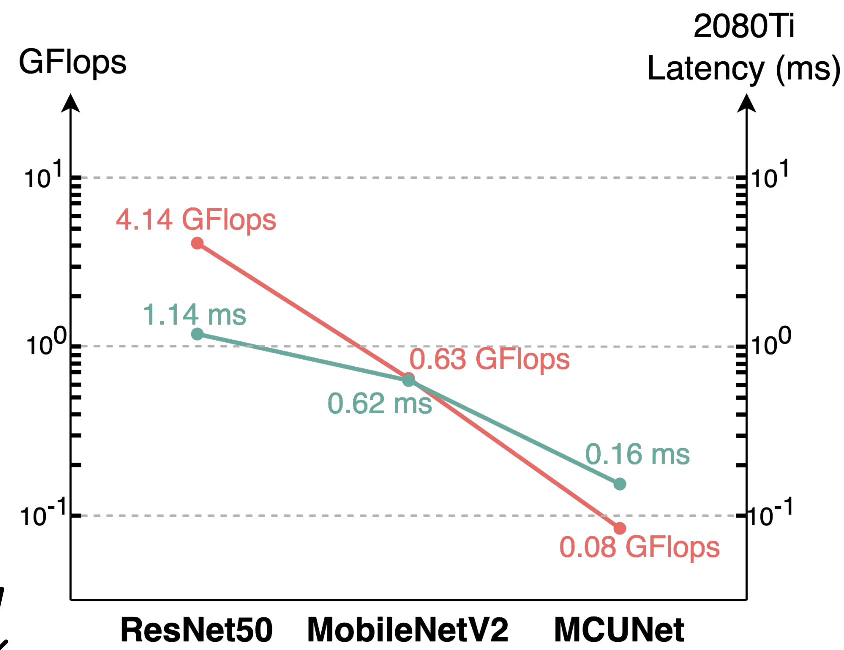


Computing Platforms with Limited Resources

Challenge: A Dilemma

- **A dilemma** between the trends of efficient DNN design vs. modern computing platform advances





Modern computing platforms: A higher degree of parallel computing [*K. Rupp*]

Efficient DNNs: Adopt Lightweight operators featuring low utilization

Our Driven Question and Proposed Solution

How can we build efficient/compact DNNs with boosted hardware utilization to harvest more parallelized capability of modern hardware?

Our Driven Question and Proposed Solution

How can we build efficient/compact DNNs with boosted hardware utilization to harvest more parallelized capability of modern hardware?

We propose ***DepthShrinker***:

- ➢ Shrinking consecutive operations into one single *dense* operation

Overview

- Background and Challenge
- **Motivating Profiling**
- The DepthShrinker Framework
- Experimental Results

Motivating Real-device Profiling

- **Goal**: Validate the hw benefits of dense operators

- **Profiling setup**
  - Replace each building block by one dense conv layer
  - Scale channel numbers to ensure the same FLOPs

- **Considered devices**: Desktop + Edge GPUs
  - NVIDIA Tesla V100 GPU
  - NVIDIA RTX 2080Ti GPU
  - Jetson TX2 Edge GPU

Motivating Real-device Profiling

- **Compact models vs. their dense counterparts**
  - Dense convs lead to higher throughputs
    - 3.45x ~ 4.38x on top of the MobileNetV2 family
    - 1.18x ~ 2.43x on top of the ResNet family
    - More notable on Desktop GPUs than Edge ones

Model	GFLOPs	Tesla V100 GPU		RTX 2080Ti GPU		TX2 Edge GPU	
		Original	Dense	Original	Dense	Original	Dense
MobileNetV2	0.33	3088	**12090** (↑**3.91**×)	2364	**9351** (↑**3.96**×)	115	**397** (↑**3.45**×)
MobileNetV2-1.4	0.63	2127	**8846** (↑**4.16**×)	1617	**6869** (↑**4.25**×)	73	**267** (↑**3.66**×)
Efficientnet-Lite0	0.41	2731	**11174** (↑**4.09**×)	2185	**9577** (↑**4.38**×)	98	**360** (↑**3.67**×)
ResNet-50	4.14	1079	**2182** (↑**2.02**×)	874	**1862** (↑**2.13**×)	45	**53** (↑**1.18**×)
ResNet-101	7.88	642	**1509** (↑**2.35**×)	538	**1279** (↑**2.38**×)	28	**44** (↑**1.57**×)
ResNet-152	11.62	449	**1082** (↑**2.41**×)	378	**917** (↑**2.43**×)	19	**30** (↑**1.58**×)

Overview

- Background and Challenge
- Motivating Profiling
- **The DepthShrinker Framework**
- Experimental Results

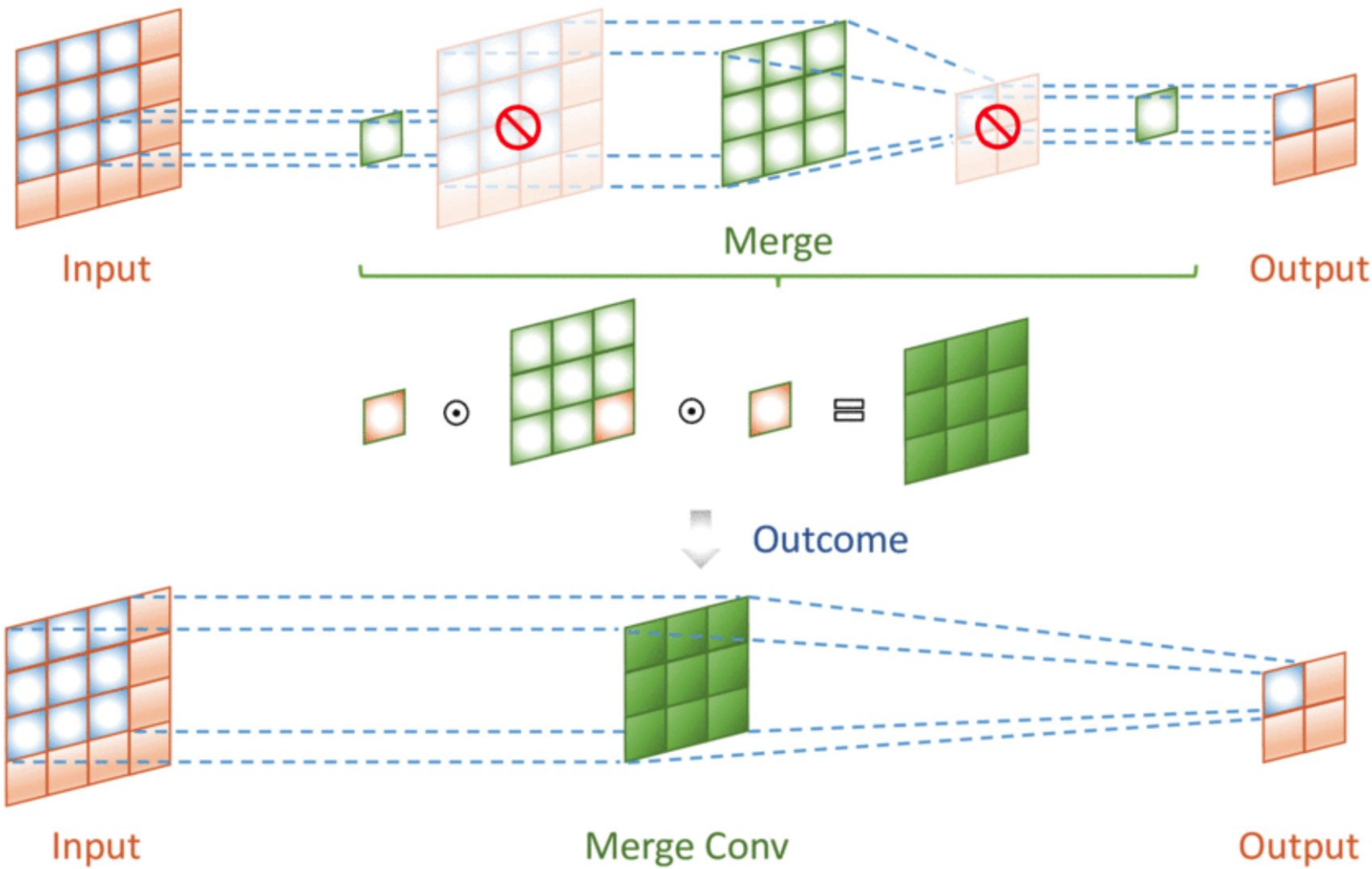
DepthShrinker: The Key Idea

- **Key idea**
  - Remove all the activation functions in one inverted residual block [*CVPR2018, M. Sandler*] and shrink it to one dense conv layer

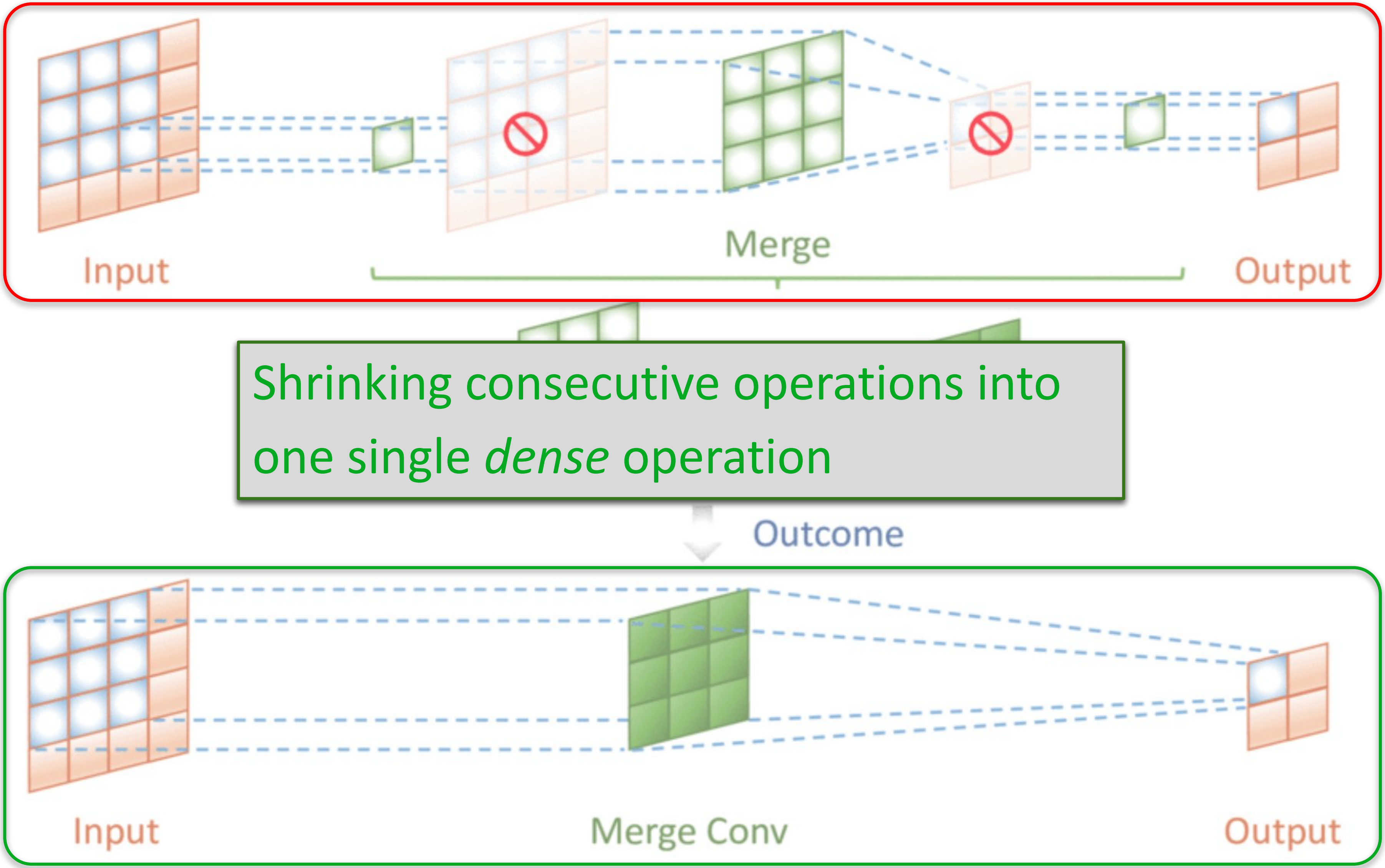
We propose ***DepthShrinker***:

➢ Shrinking consecutive operations into one single *dense* operation

DepthShrinker: The Key Idea



DepthShrinker: The Key Idea



Shrinking consecutive operations into one single *dense* operation

DepthShrinker: Research Questions

We propose ***DepthShrinker***:

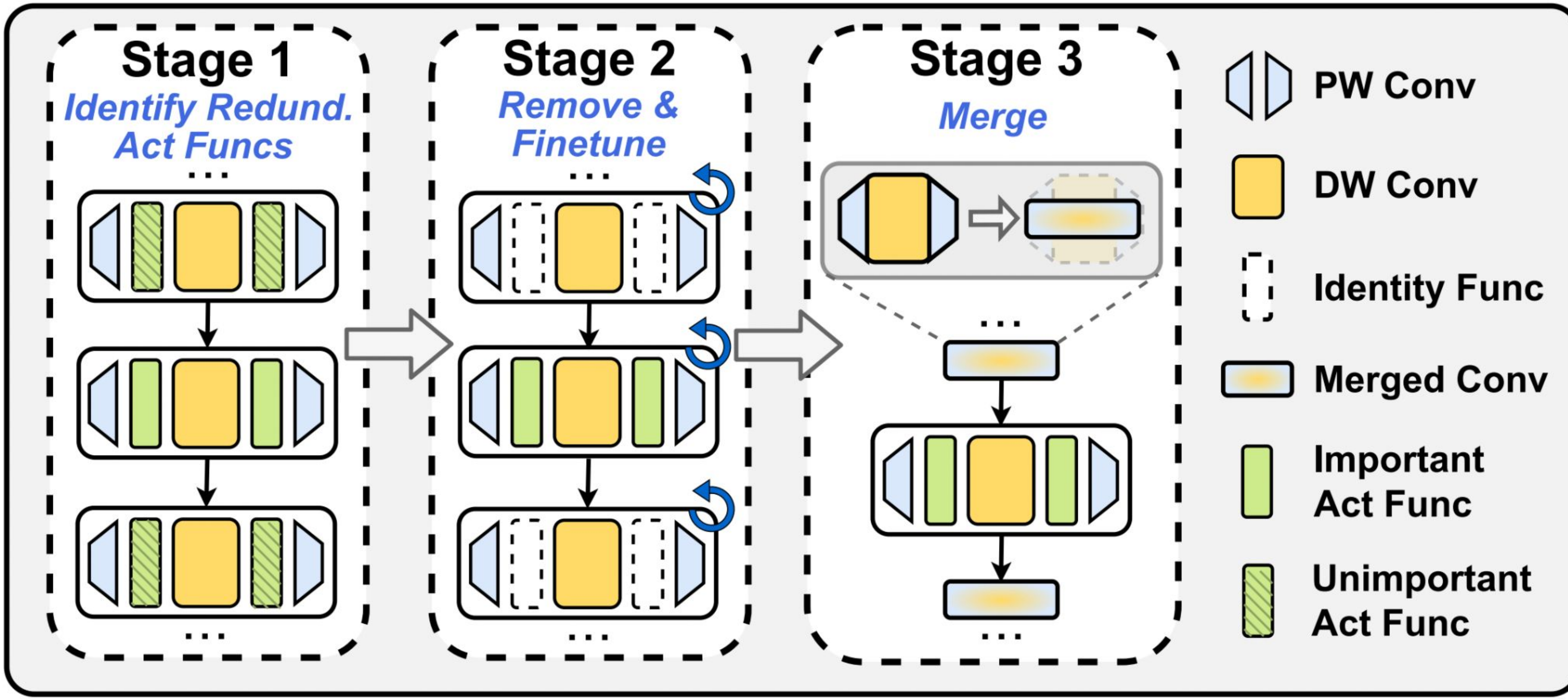
- ➢ Shrinking consecutive operations into one single *dense* operation

Two research questions to achieve ***DepthShrinker***:

- ➢ *Which activation functions to remove?*
- ➢ *How to restore the accuracy after the removal?*

DepthShrinker: Overview

- **DepthShrinker:** A three-stage framework



Identify Redundant Act Funcs

- **Search method**
  - Learnable binary masks on act funcs with *L0* sparsity

$$\underset{\theta,m}{\arg\min} \sum_i \ell(\hat{y}_{\theta,m}(x_i), y_i) \quad \text{s.t.} \quad \|m\|_0 \leqslant k$$

- **Learning scheme: Fully differentiable**
  - Forward: Activate top *k* act funcs
  - Backward: Update both model weights and masks via STE

Identify Redundant Act Funcs

- **Search method**
  - Learnable binary masks on act funcs with *L0* sparsity

$$\arg\min_{\theta,m} \sum_i \ell(\hat{y}_{\theta,m}(x_i), y_i) \quad \text{s.t.} \quad \|m\|_0 \leqslant k$$

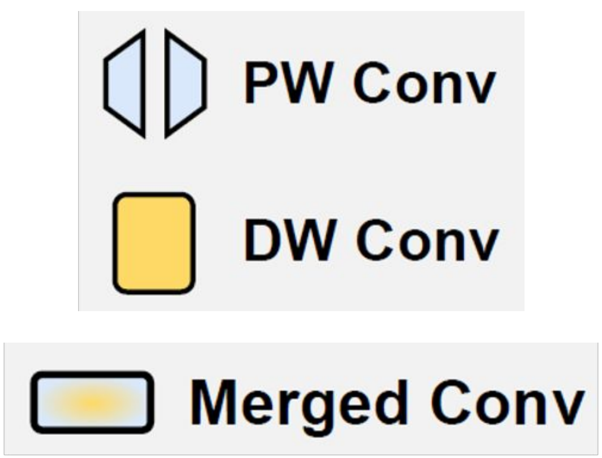
- **Other techniques in implementation**
  - Block-wise shrink: Share *m* for all act funcs in one block
  - Latency-aware decay on *m*: Penalize the importance of latency-bottleneck blocks

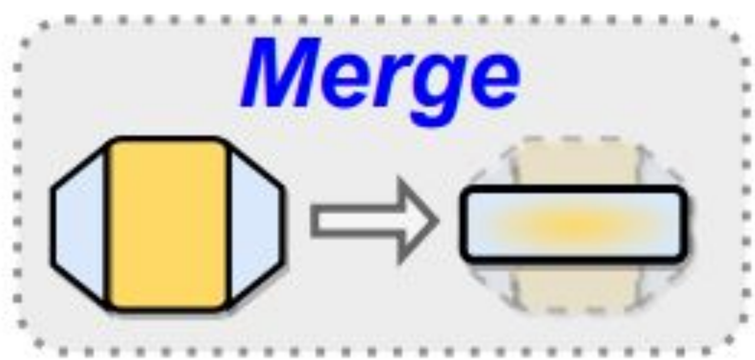
Merge Consecutive Linear OPs

One nice property during merging

- The resulting conv layer is only determined by
  - The number of the input channels in the first conv
  - The number of output channels in the last conv

➢ DepthShrinker can shrink the wide intermediate layers within inverted residual blocks





Overview

- Background and Challenge
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- The DepthShrinker Framework
- **Experimental Results**

Experiment: Setup

- **Models and datasets**
  - MobileNetV2 families @ ImageNet
  - EfficientNet-Lite families @ ImageNet

- **Considered devices**: Desktop + Edge
  - NVIDIA Tesla V100 GPU
  - NVIDIA RTX 2080Ti GPU
  - Jetson TX2 Edge GPU
  - CPU devices: Google Pixel 3 / Raspberry Pi 4

- **Metrics:** Accuracy / Throughput (FPS)

Experiment: Benchmark with Pruning

- **Benchmark with channel-wise pruning**
  - Consistently better Acc-FPS trade-off

Model	Acc (%)	MFLOPs	Tesla V100	RTX 2080Ti	TX2
MBV2-1.4	75.30	630	2127 ($\uparrow$1.00$\times$)	1617 ($\uparrow$1.00$\times$)	73 ($\uparrow$1.00$\times$)
MetaPruning-1.0$\times$	73.20	332	3159 ($\uparrow$1.49$\times$)	2527 ($\uparrow$1.56$\times$)	115 ($\uparrow$1.58$\times$)
MBV2-1.4-DS-A	74.65/75.29/75.65	519	3827 ($\uparrow$1.80$\times$)	2881 ($\uparrow$1.78$\times$)	134 ($\uparrow$1.84$\times$)
MBV2-1.4-DS-B	73.67/74.8/75.13	502	4778 ($\uparrow$2.25$\times$)	3356 ($\uparrow$2.08$\times$)	163 ($\uparrow$2.23$\times$)
MBV2-1.4-DS-C	73.38/74.55/74.91	492	4597 ($\uparrow$2.16$\times$)	3537 ($\uparrow$2.19$\times$)	159 ($\uparrow$2.18$\times$)
Uniform-0.65$\times$	67.20	182	4004 ($\uparrow$1.88$\times$)	3147 ($\uparrow$1.95$\times$)	161 ($\uparrow$2.21$\times$)
MetaPruning-0.65$\times$	71.70	160	4336 ($\uparrow$2.04$\times$)	3691 ($\uparrow$2.28$\times$)	179 ($\uparrow$2.45$\times$)
MBV2-1.4-DS-D	72.51/73.93/74.50	484	5560 ($\uparrow$2.61$\times$)	3926 ($\uparrow$2.43$\times$)	184 ($\uparrow$2.52$\times$)
MBV2-1.4-DS-E	72.20/73.85/74.43	474	5317 ($\uparrow$2.50$\times$)	4175 ($\uparrow$2.58$\times$)	179 ($\uparrow$2.45$\times$)
Uniform-0.35$\times$	54.60	68	6266 ($\uparrow$2.95$\times$)	5607 ($\uparrow$3.47$\times$)	263 ($\uparrow$3.60$\times$)
MetaPruning-0.35$\times$	64.50	52	7044 ($\uparrow$3.31$\times$)	6938 ($\uparrow$4.29$\times$)	377 ($\uparrow$5.16$\times$)
MBV2-1.4-DS-F	67.56/69.04/70.13	415	10804 ($\uparrow$5.08$\times$)	7687 ($\uparrow$4.75$\times$)	344 ($\uparrow$4.71$\times$)

Experiment: Benchmark with Pruning

- **Benchmark with channel-wise pruning**
  - Better scalability to extremely efficient cases
    - A 3.06% higher acc with 1.53x FPS

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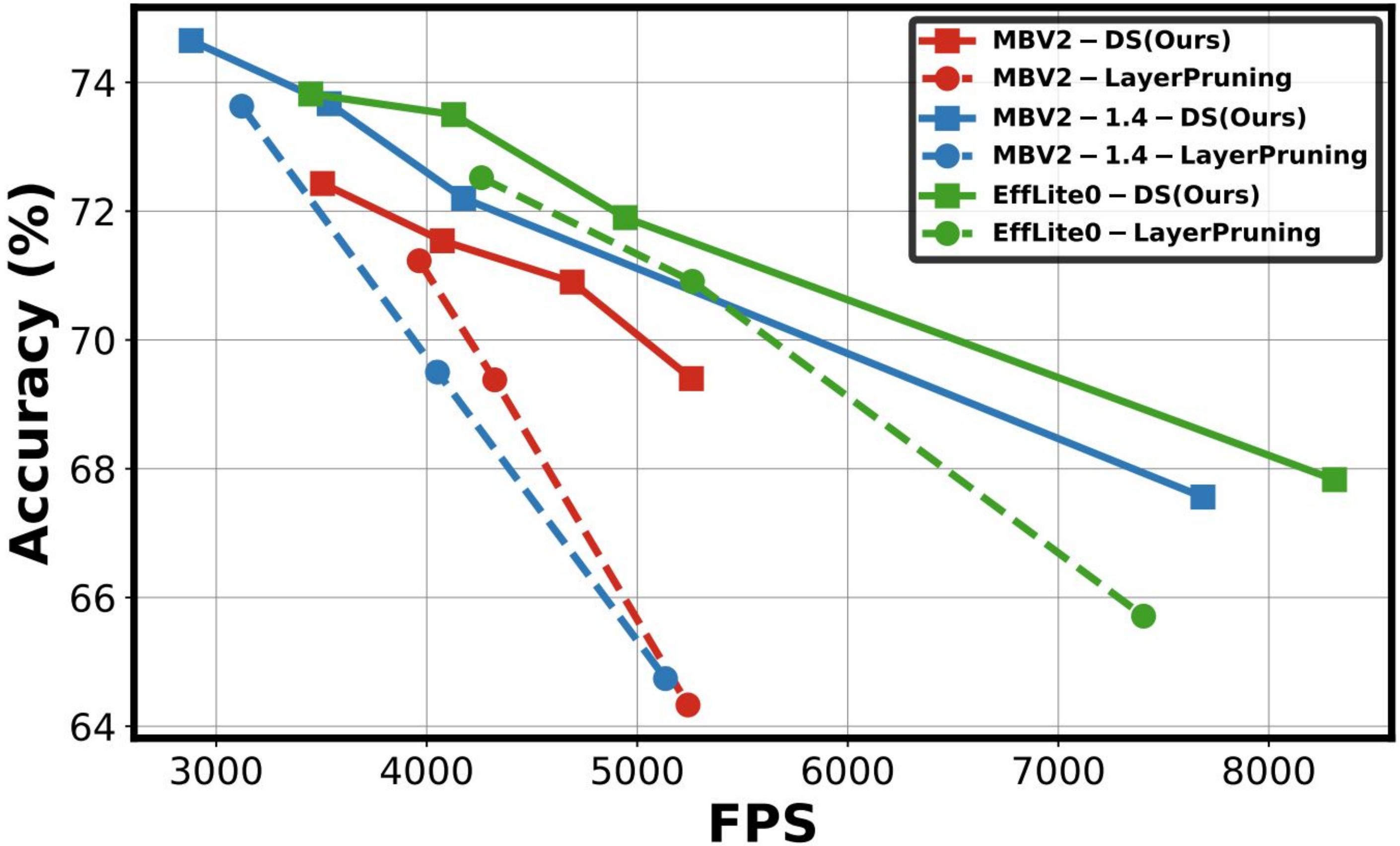
Experiment: Benchmark with Pruning

- **Benchmark with layer-wise pruning**
  - Much better acc under large compression ratios
    - Shrinking is a soft version of “hard pruning”



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