MCUNetV2: Memory-Efficient Patch-based Inference for Tiny Deep Learning

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[1] Massachusetts Institute of Technology
[2] MIT-IBM Watson AI Lab

Deep Learning Going “Tiny”

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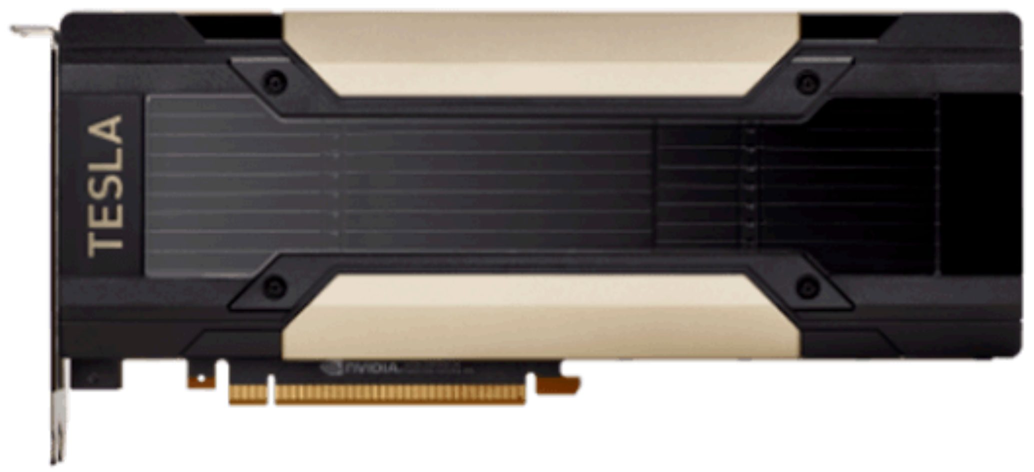


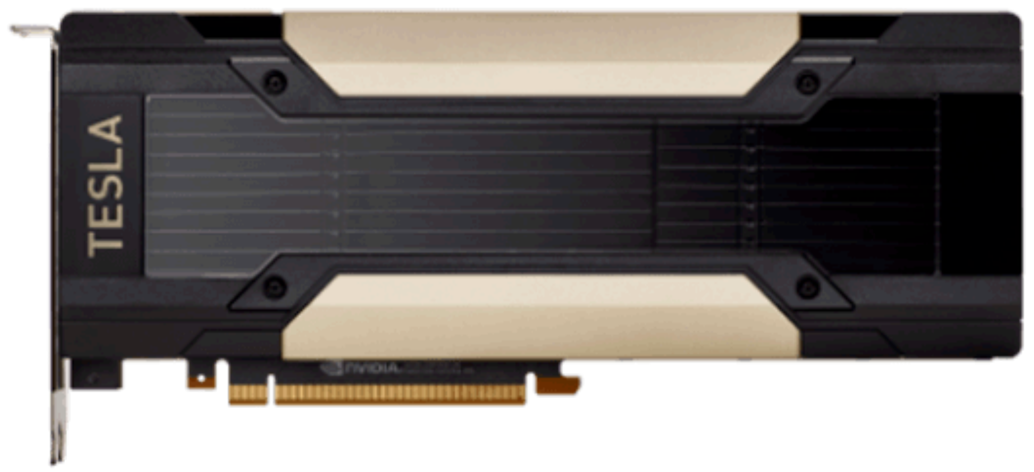
Cloud AI

Data centers
Expensive
Privacy issue

Mobile AI

Smartphones
Accessible
Process locally

Deep Learning Going “Tiny”



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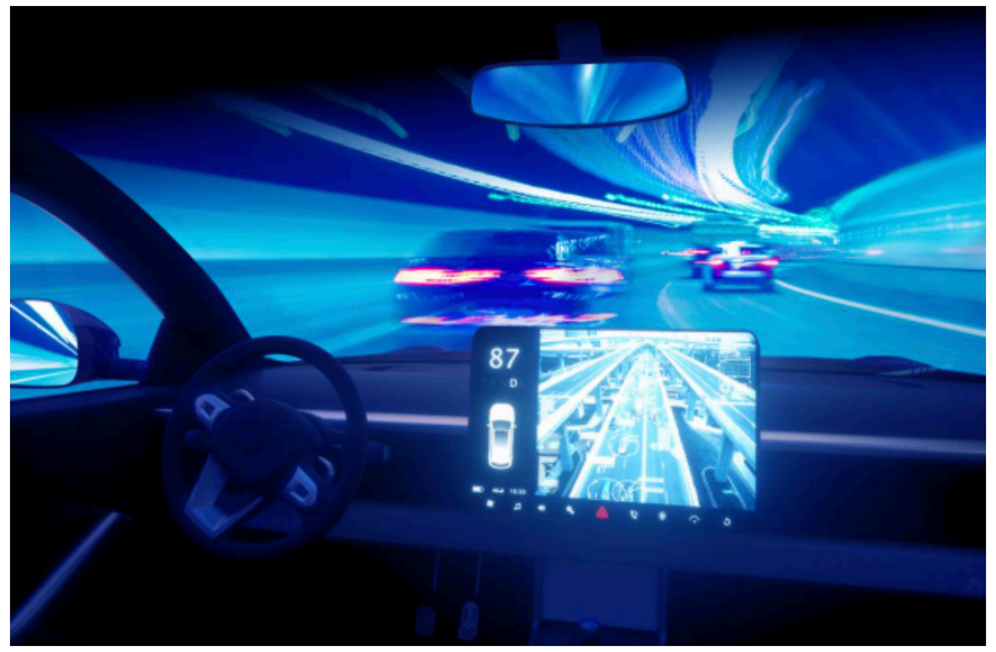
- Billions of <u>IoT devices</u> around the world based on <u>microcontrollers</u>

Smart Home

Smart Manufacturing

Personalized Healthcare

Driving Assist



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- Billions of <u>IoT devices</u> around the world based on <u>microcontrollers</u>
- **Low-cost**: low-income people can have access. Democratize AI.

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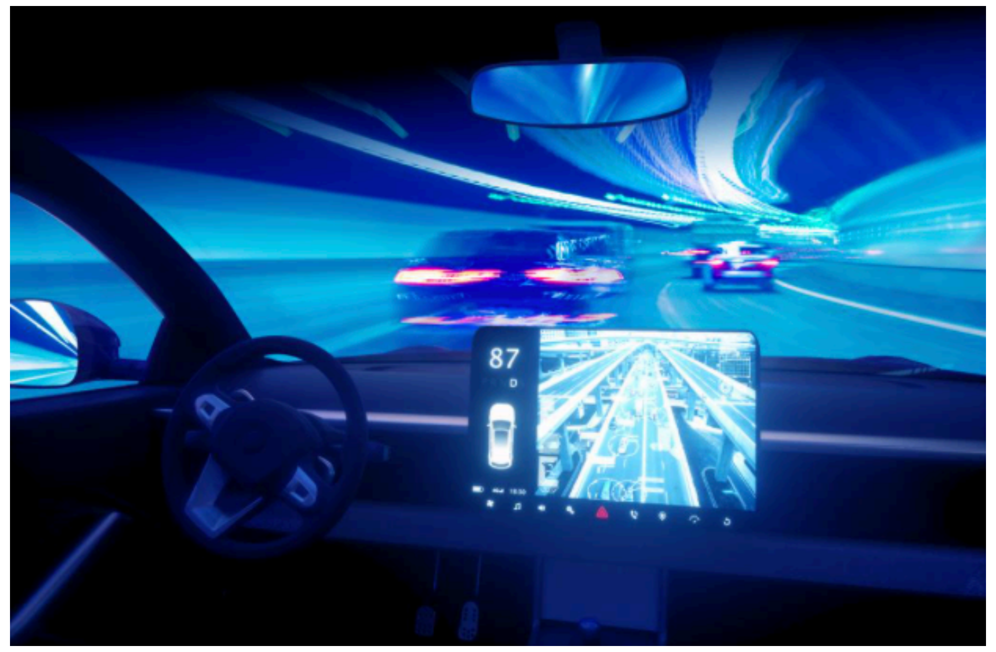

Can we go even smaller?

- The future belongs to Tiny AI.
- Billions of <u>IoT devices</u> around the world based on <u>microcontrollers</u>
- **Low-cost**: low-income people can have access. Democratize AI.
- **Low-power**: reduce carbon. Green AI.

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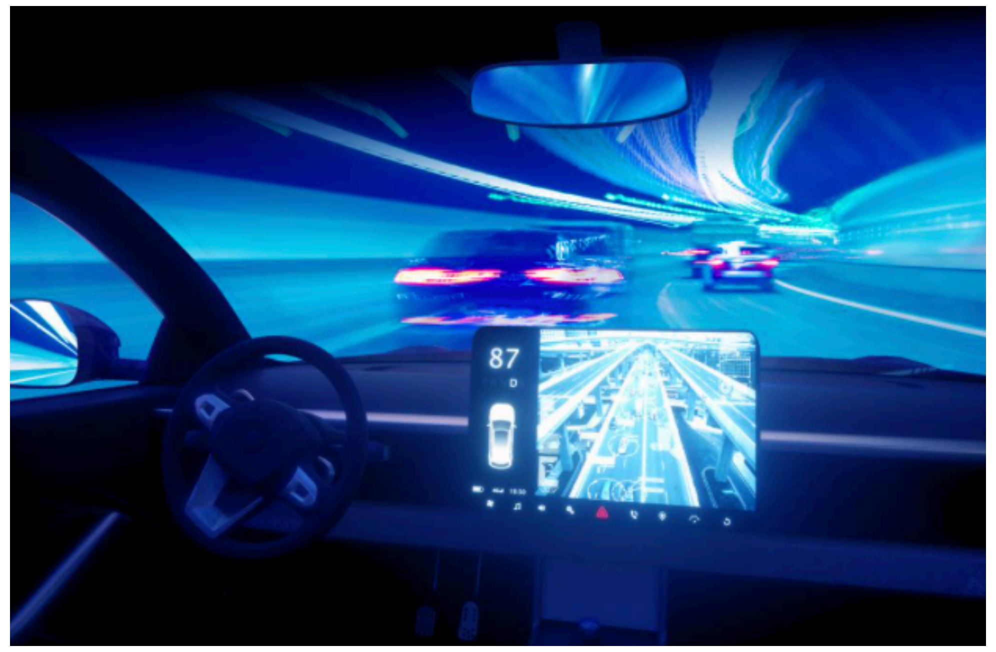

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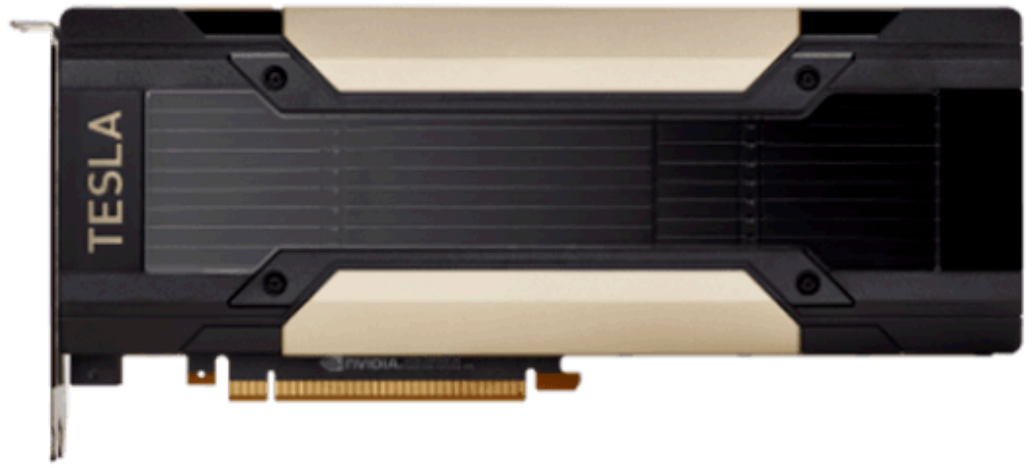


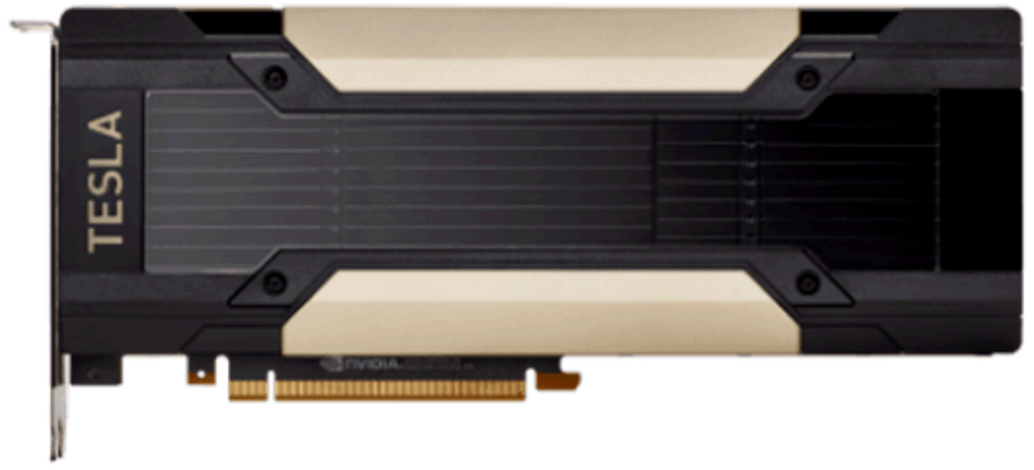
	Cloud AI	Mobile AI	Tiny AI
Memory	32GB	4GB	256kB

16,000x smaller

100,000x smaller

But Tiny AI is Difficult

- Tiny model design is <u>fundamentally different</u> from mobile AI, due to <u>limited memory</u>.
- Existing work optimize for #parameters/#FLOPs, but <u>#activation</u> is the real bottleneck.
- CANNOT directly scale.



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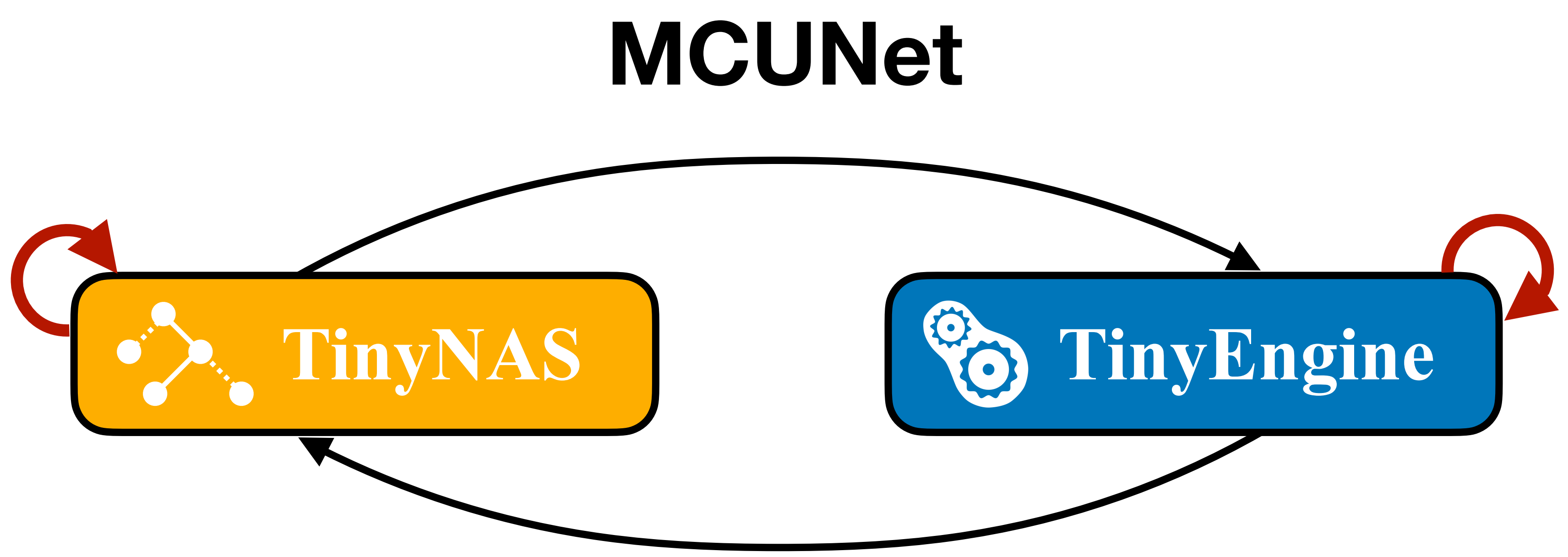
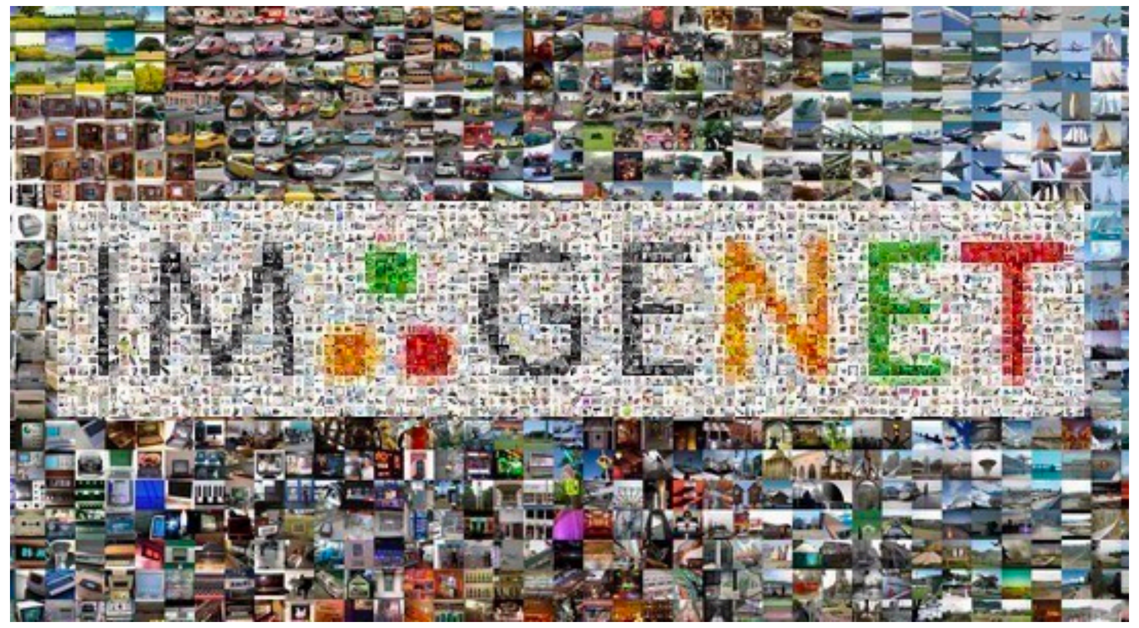
Breaking the Memory Bottleneck of TinyML

Toy applications





Real-life applications

* Lin *et al.*, MCUNet: Tiny Deep Learning on IoT Devices

Breaking the Memory Bottleneck of TinyML

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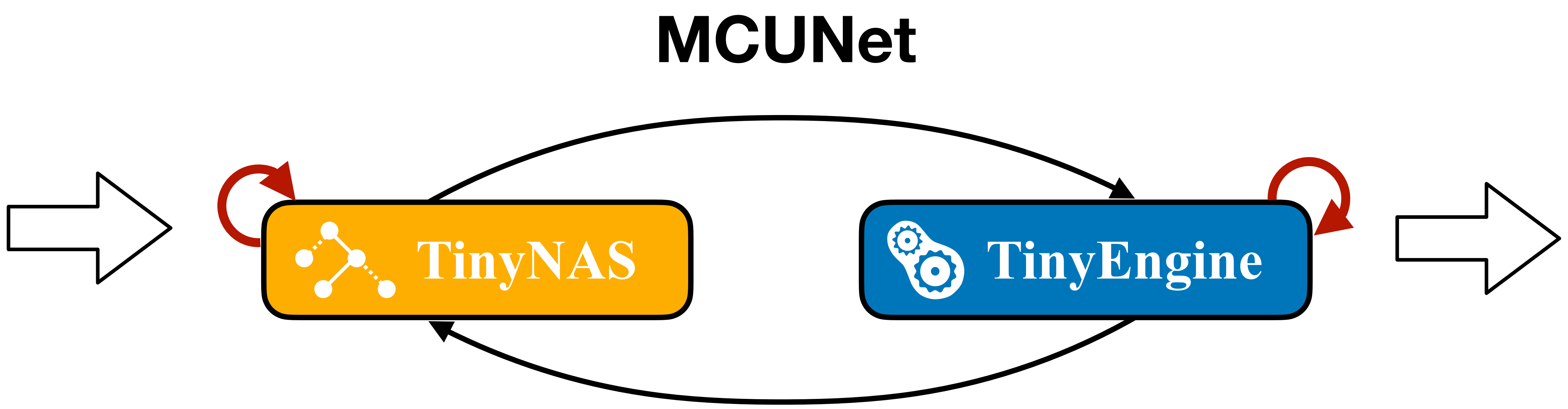

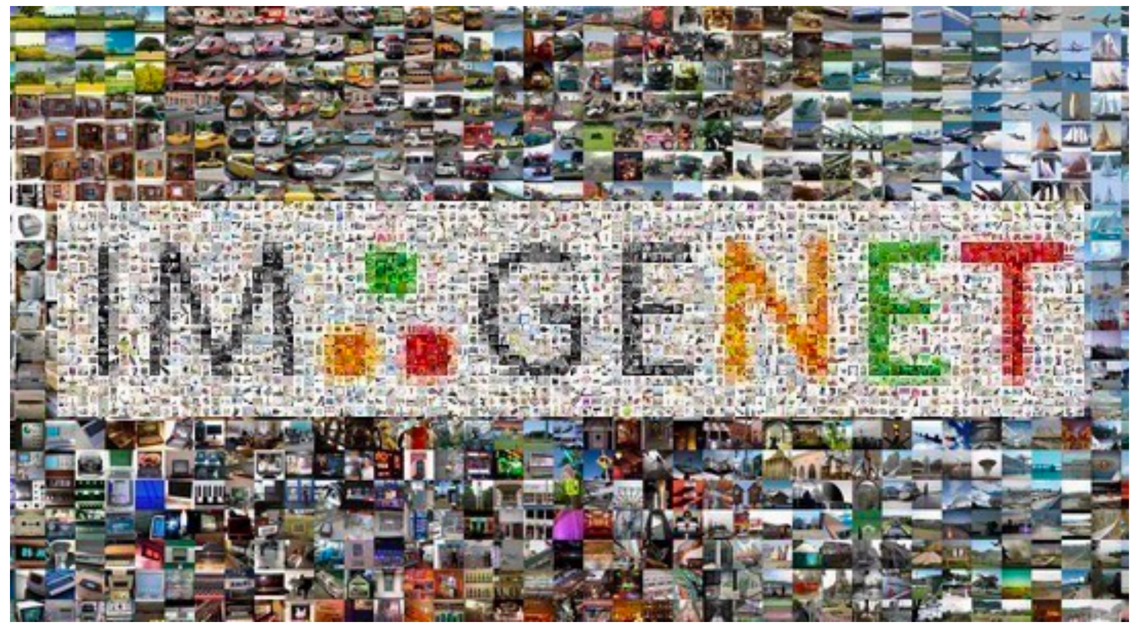

Real-life applications

- Problems:
  - Insufficient/imbalanced memory utilization across blocks
  - Poor performance on applications beyond classification (e.g., detection)

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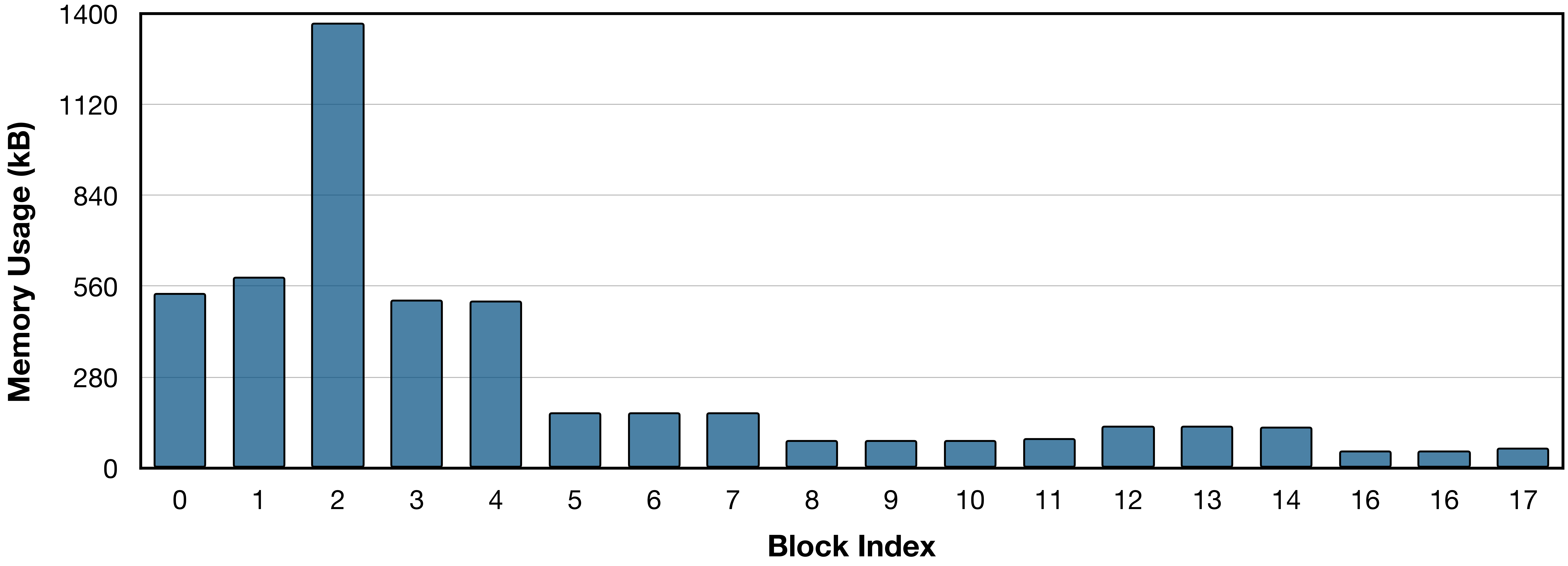
Imbalanced Memory Distribution of CNNs

- Per-block memory usage of MobileNetV2



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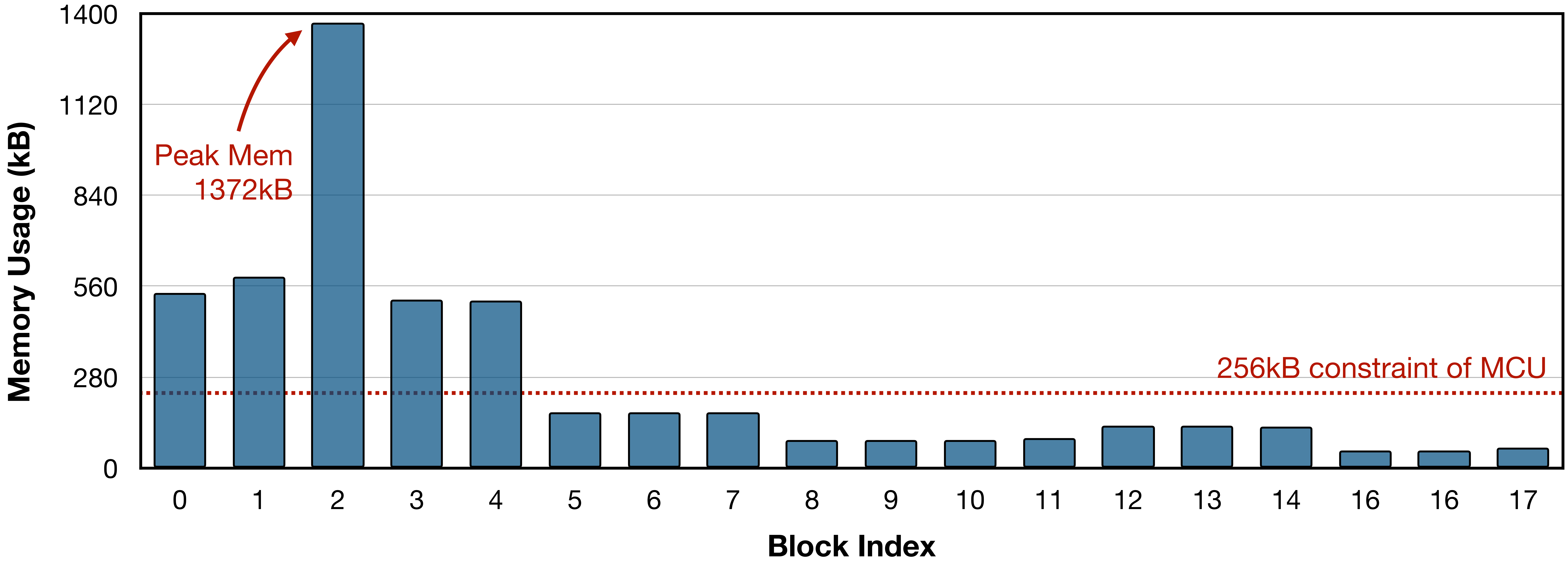

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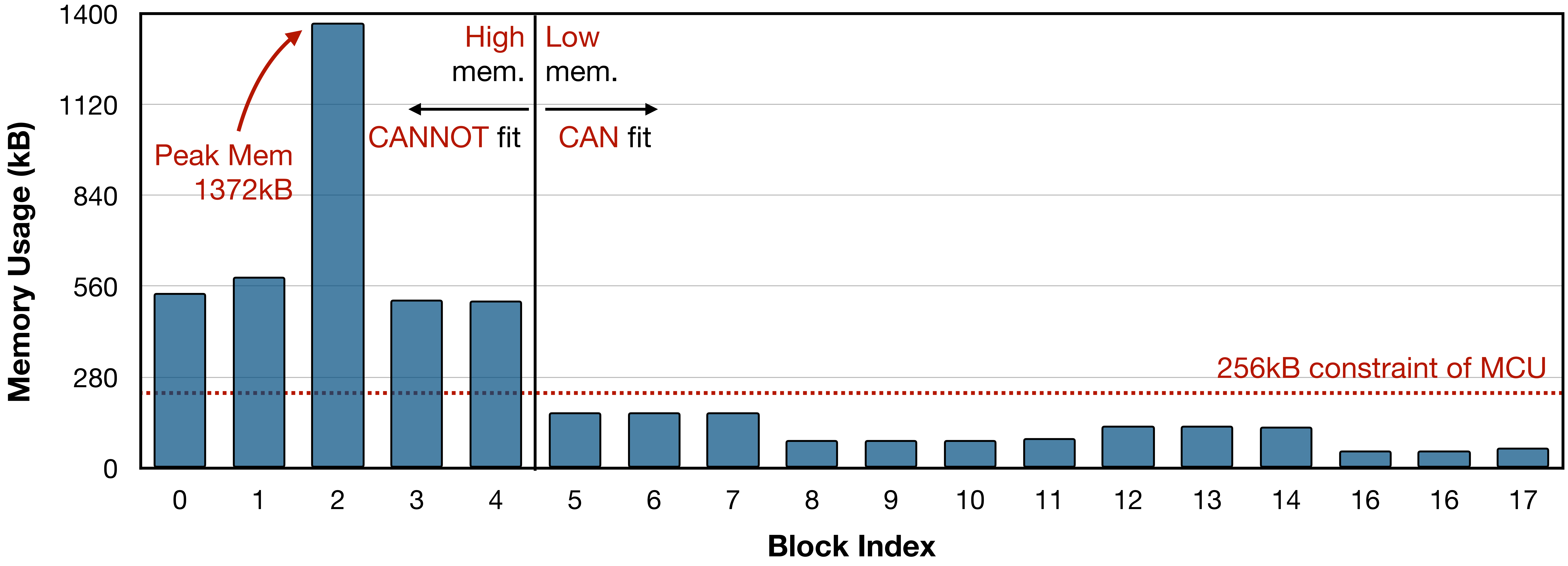

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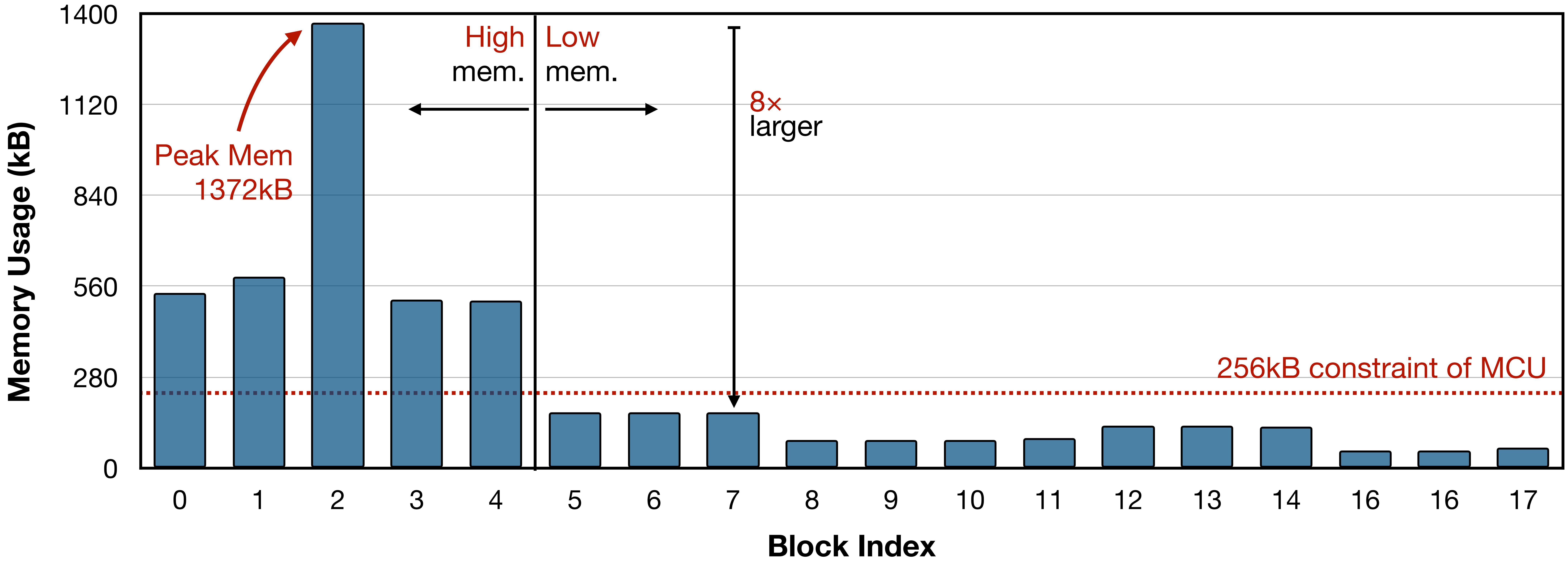
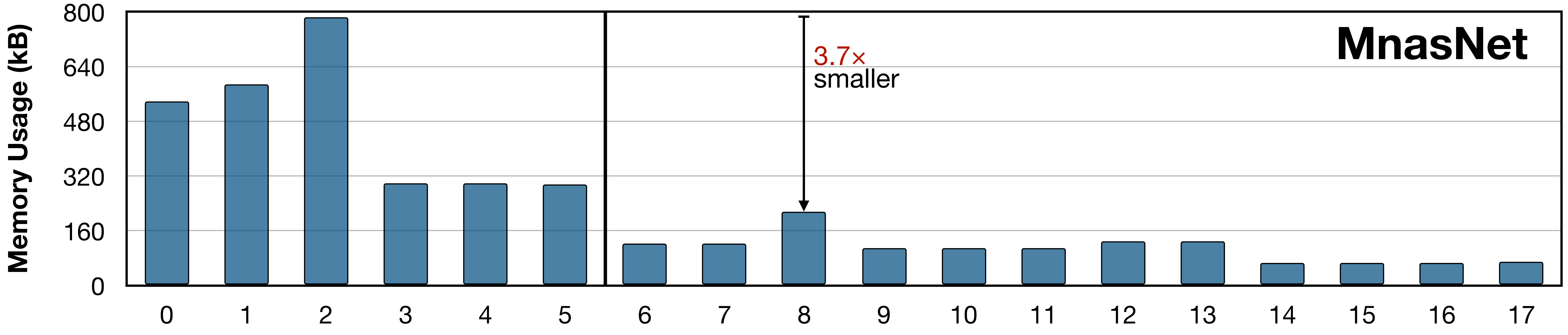
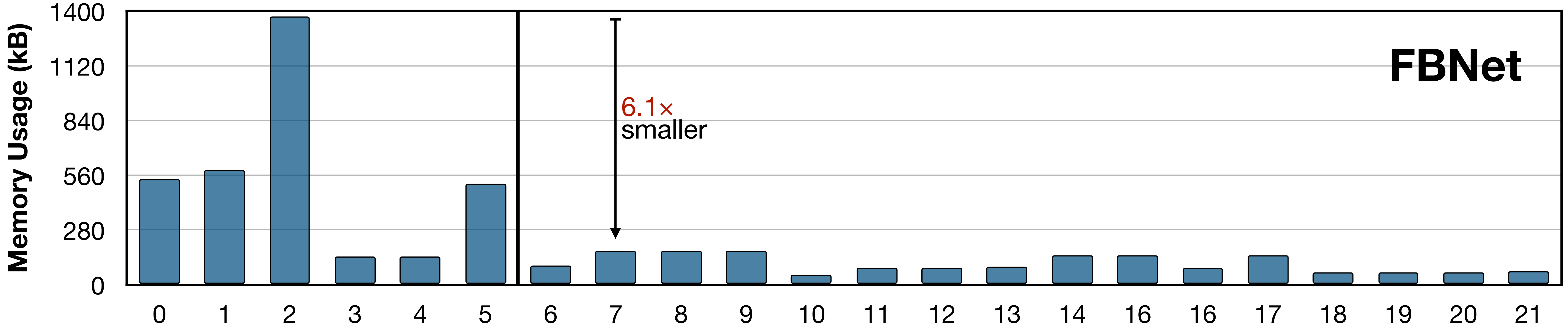


Imbalanced Memory Distribution of CNNs

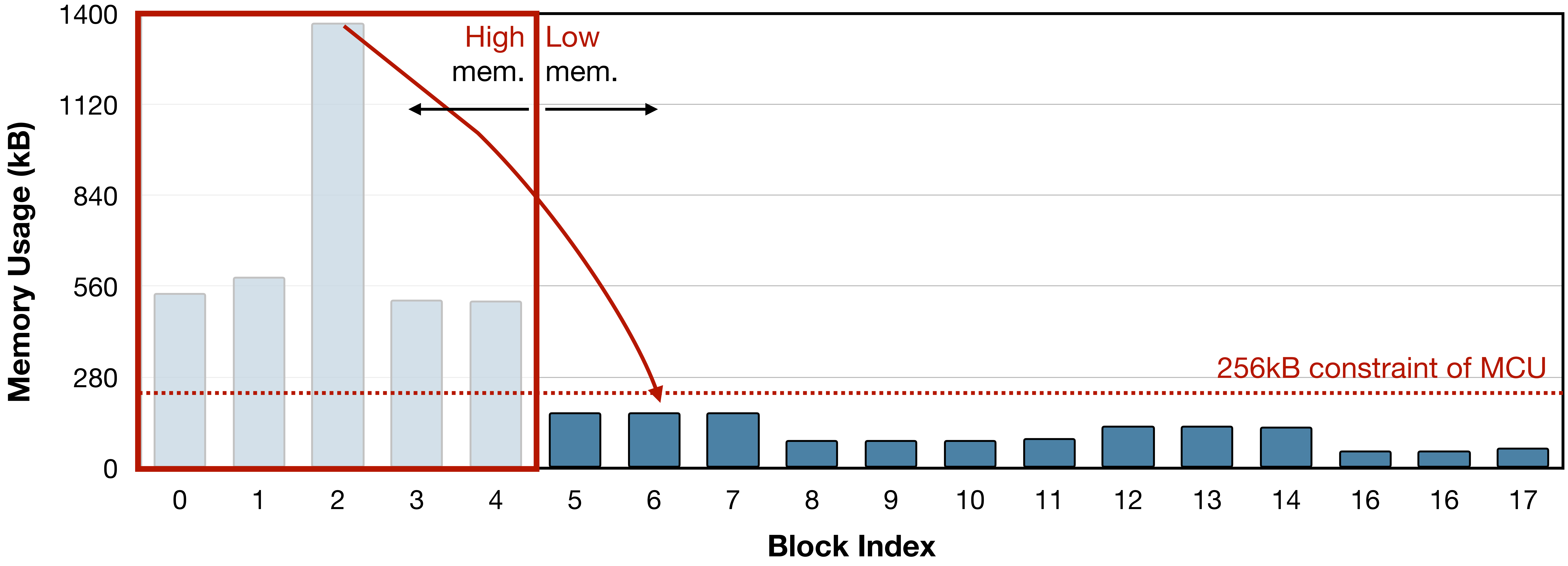
- Common case in efficient CNN design



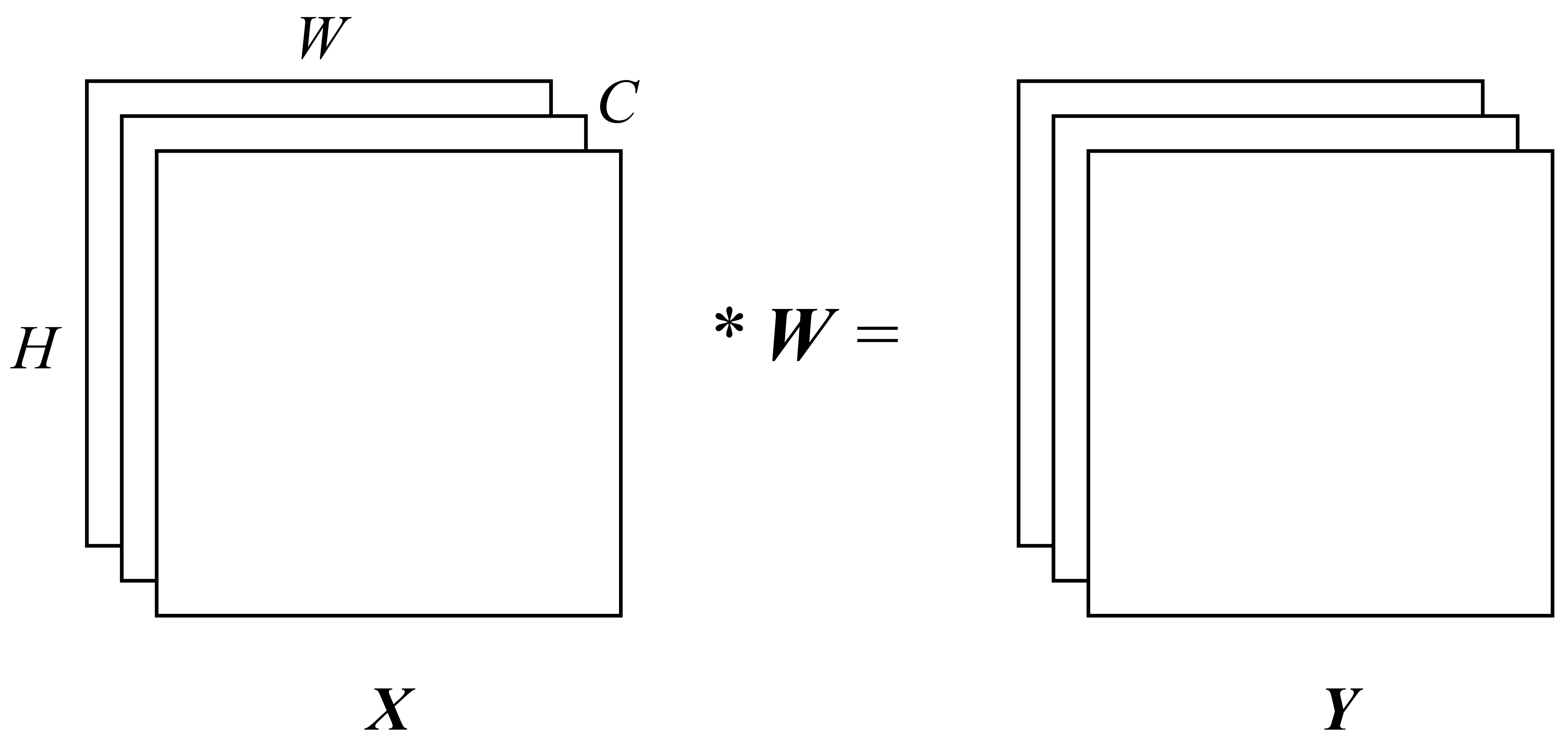


Imbalanced Memory Distribution of CNNs

Reduce memory usage of the initial stage
-> Reduce the overall memory usage



1. Saving Memory with Patch-based Inference



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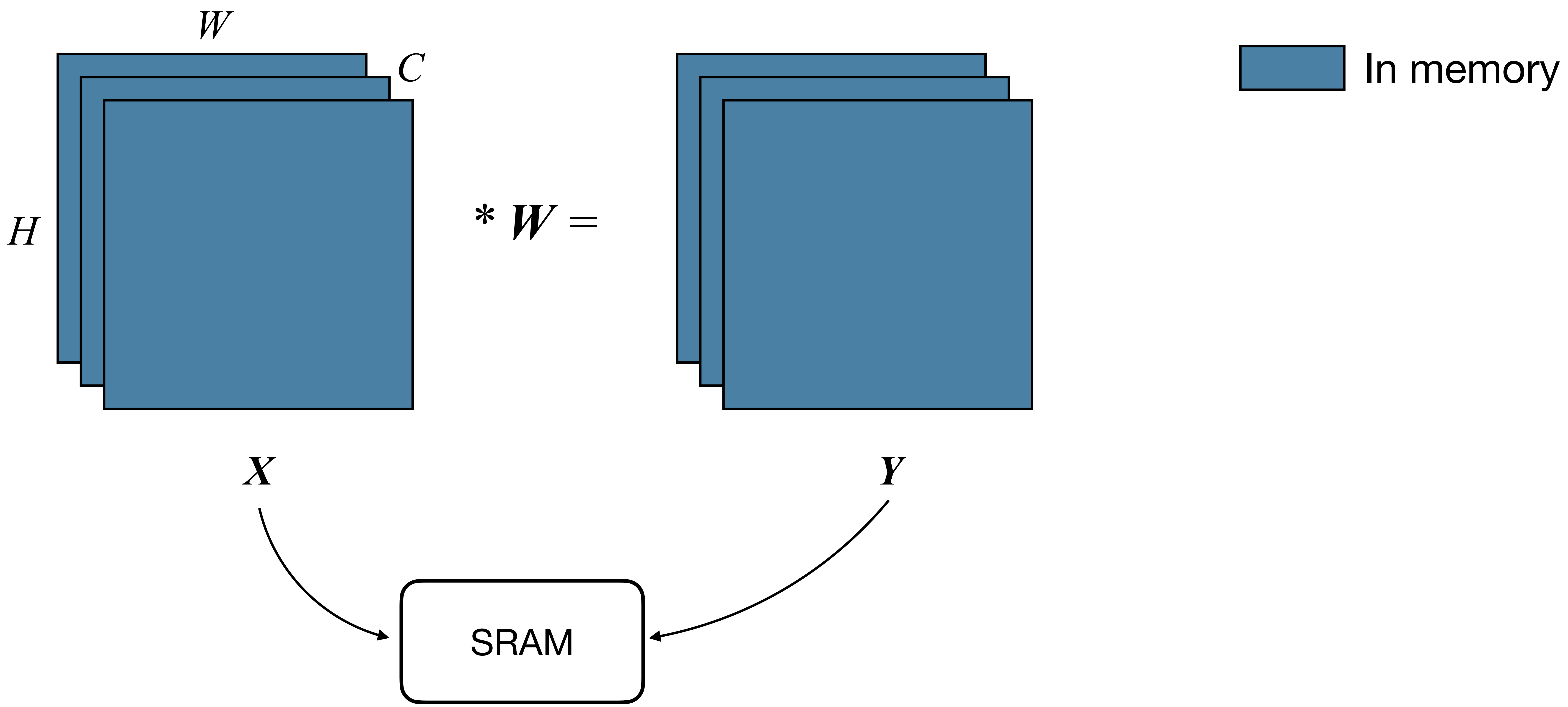
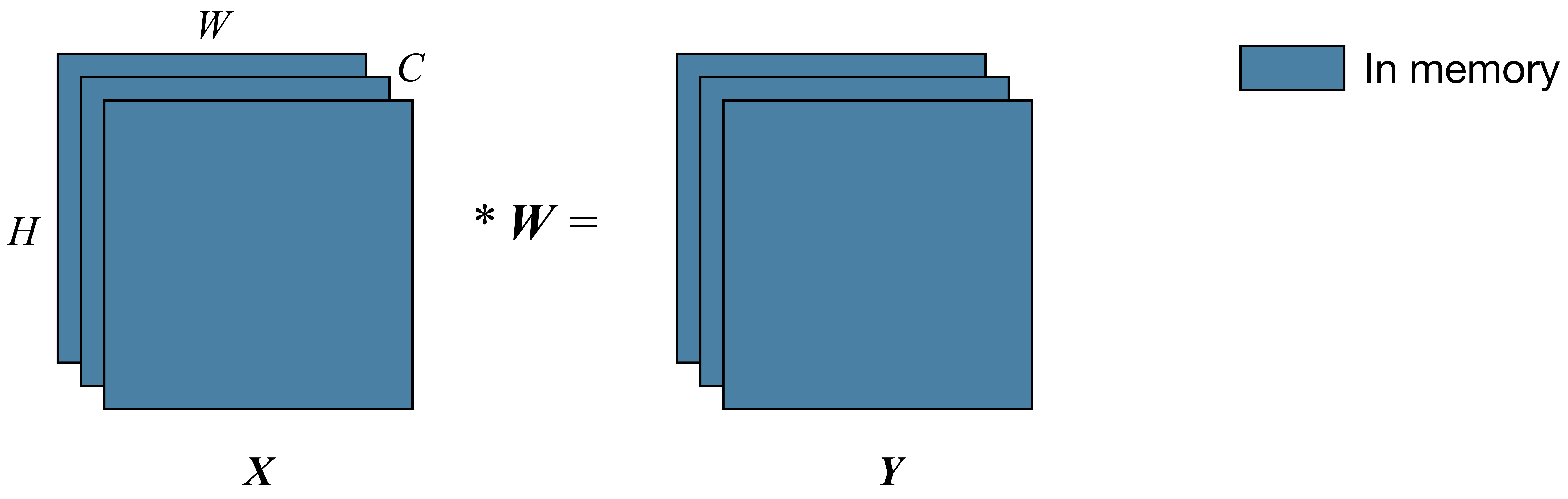


* weights are usually partially fetched from Flash

1. Saving Memory with Patch-based Inference

1. Per-layer inference

Peak Mem $= 2\ WHC$



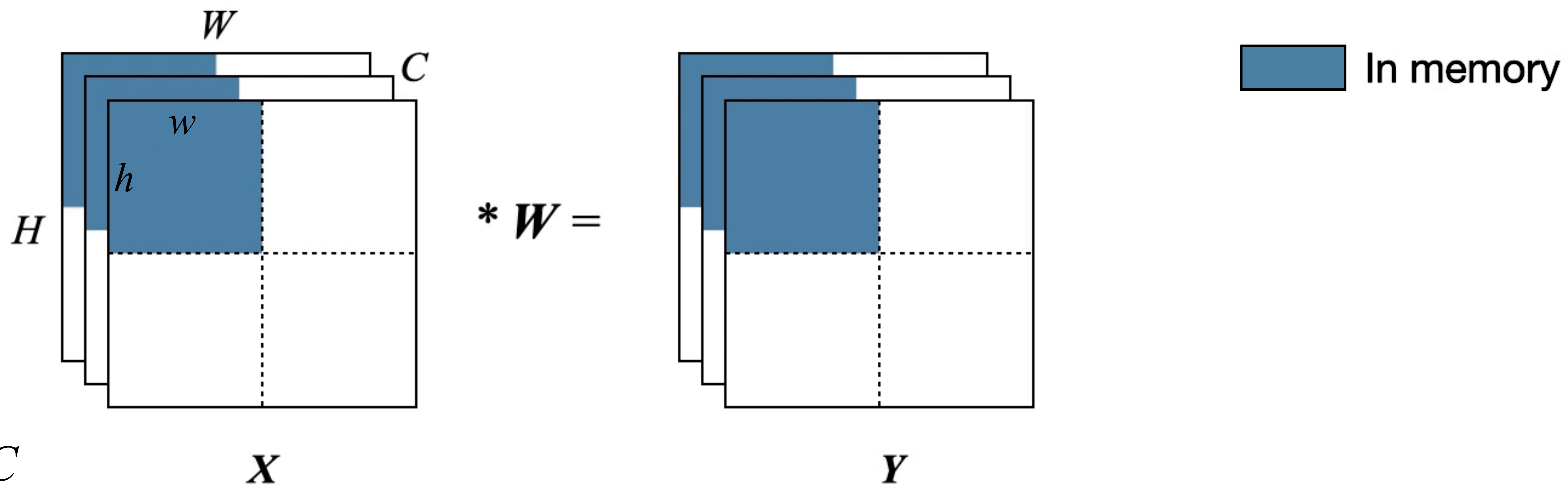
1. Saving Memory with Patch-based Inference

1. Per-layer inference

Peak Mem = $2\ WHC$

2. Per-patch inference

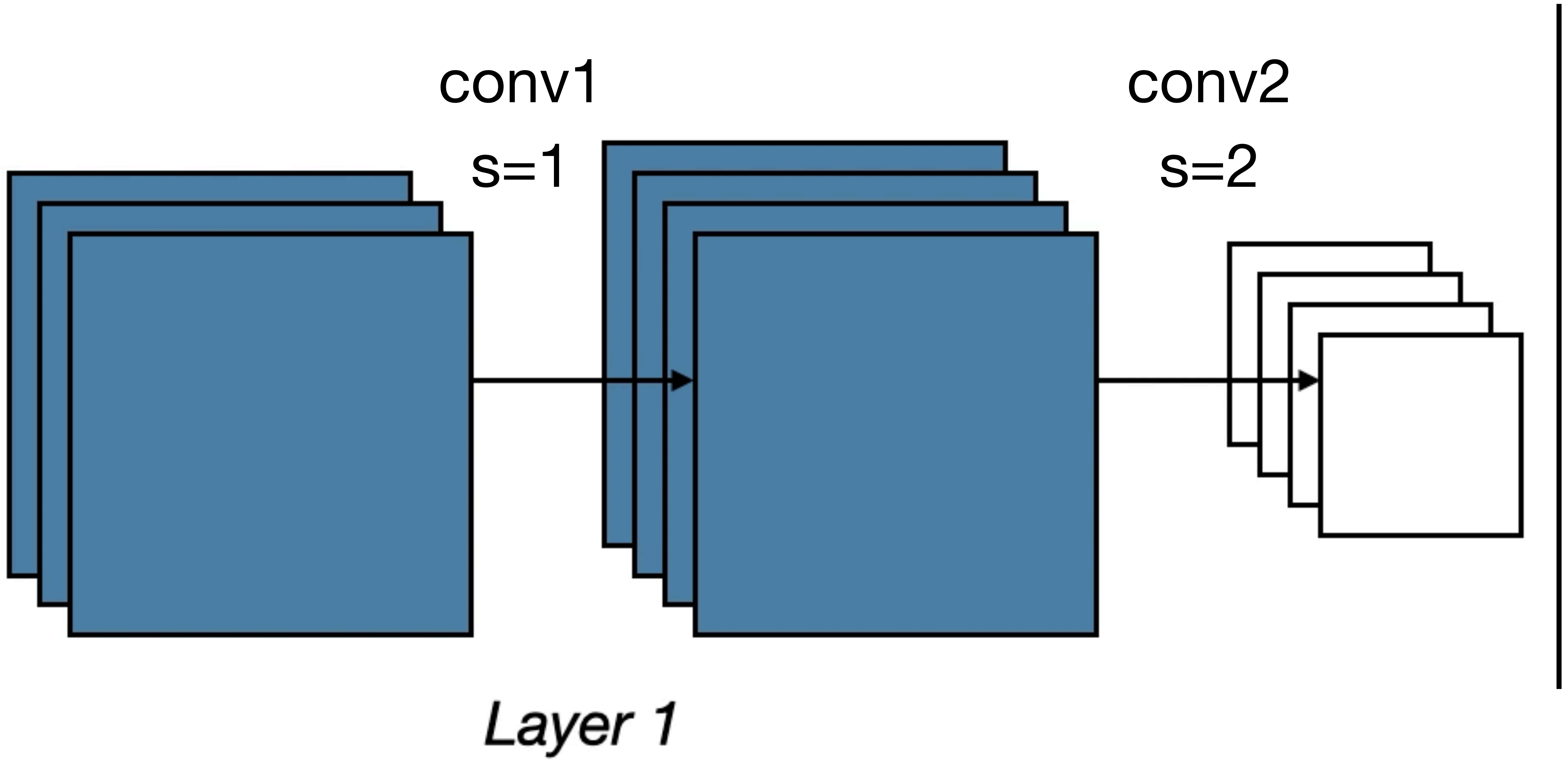
Peak Mem = $2\ whC << 2WHC$



* *can use more than 2x2 patches*

1. Saving Memory with Patch-based Inference

- a practical 2-layer example



per-layer inference

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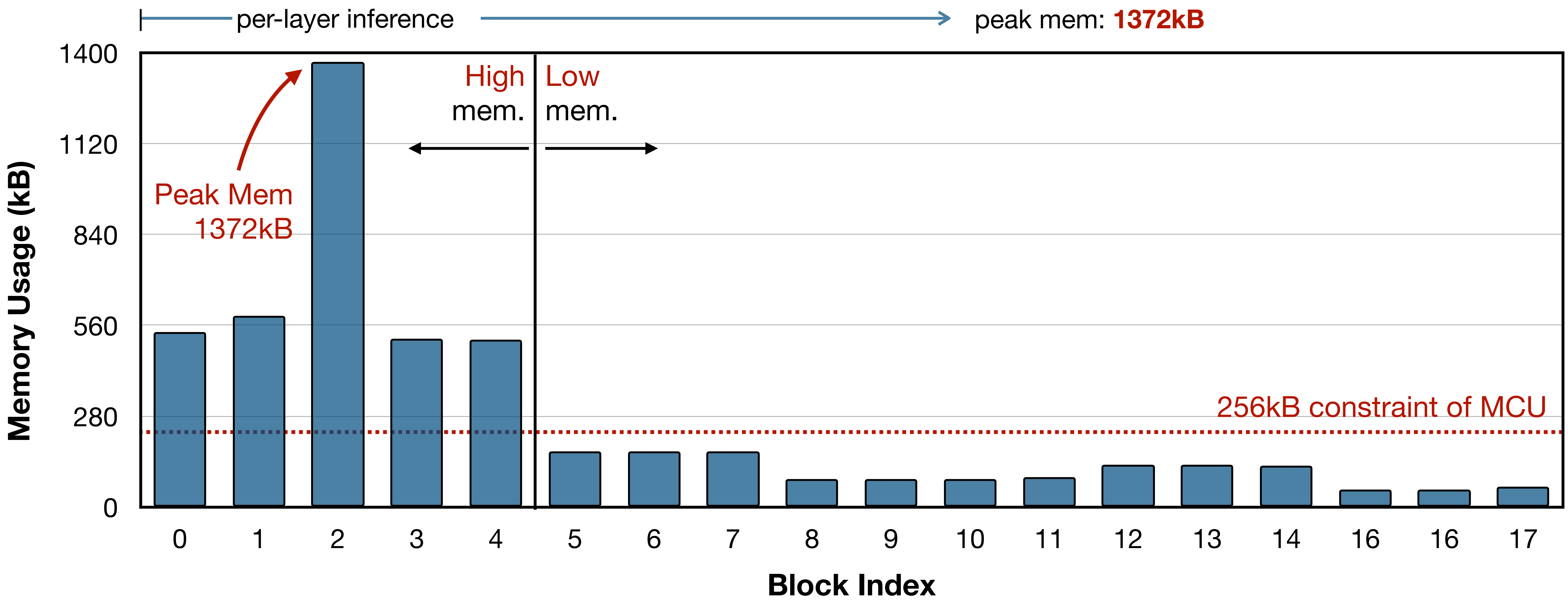
- Applying to MobileNetV2



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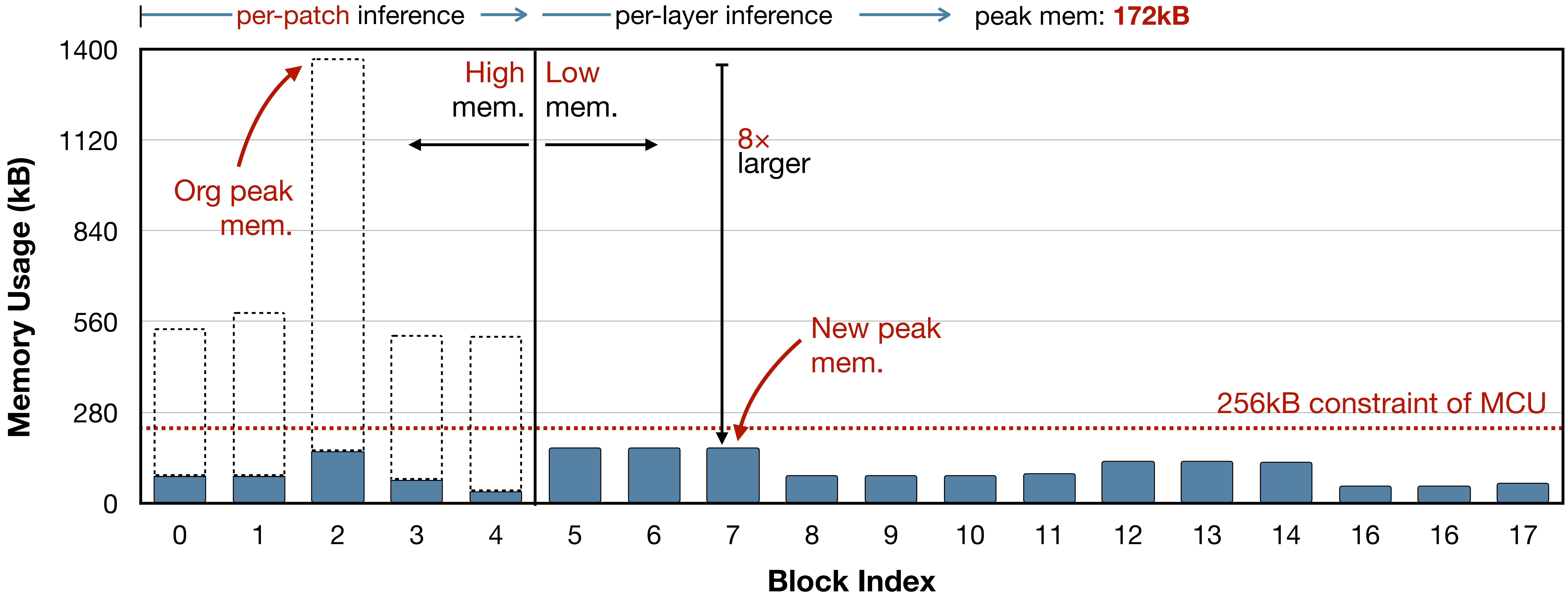
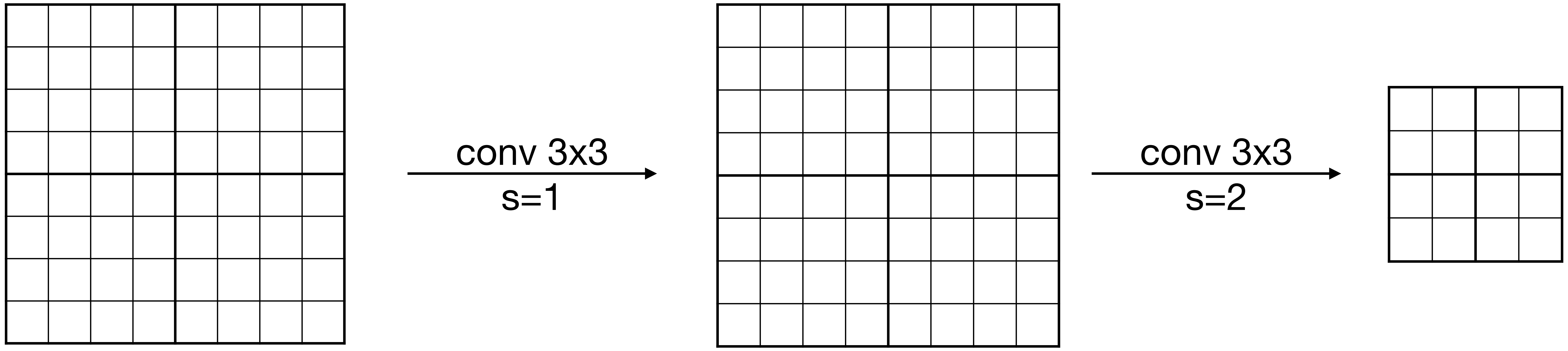


Problem: Computation Overhead from Overlapping

- Using 2x2 patches



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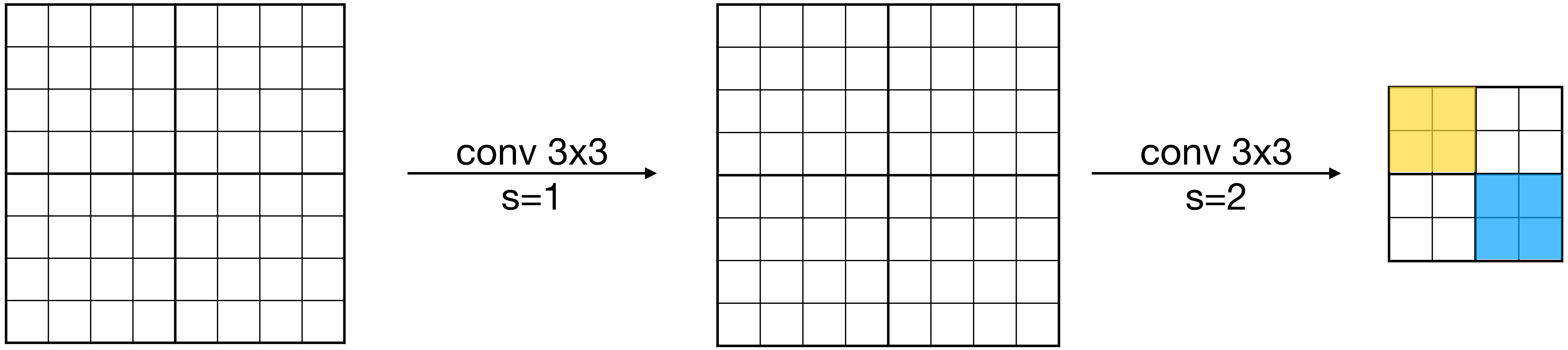

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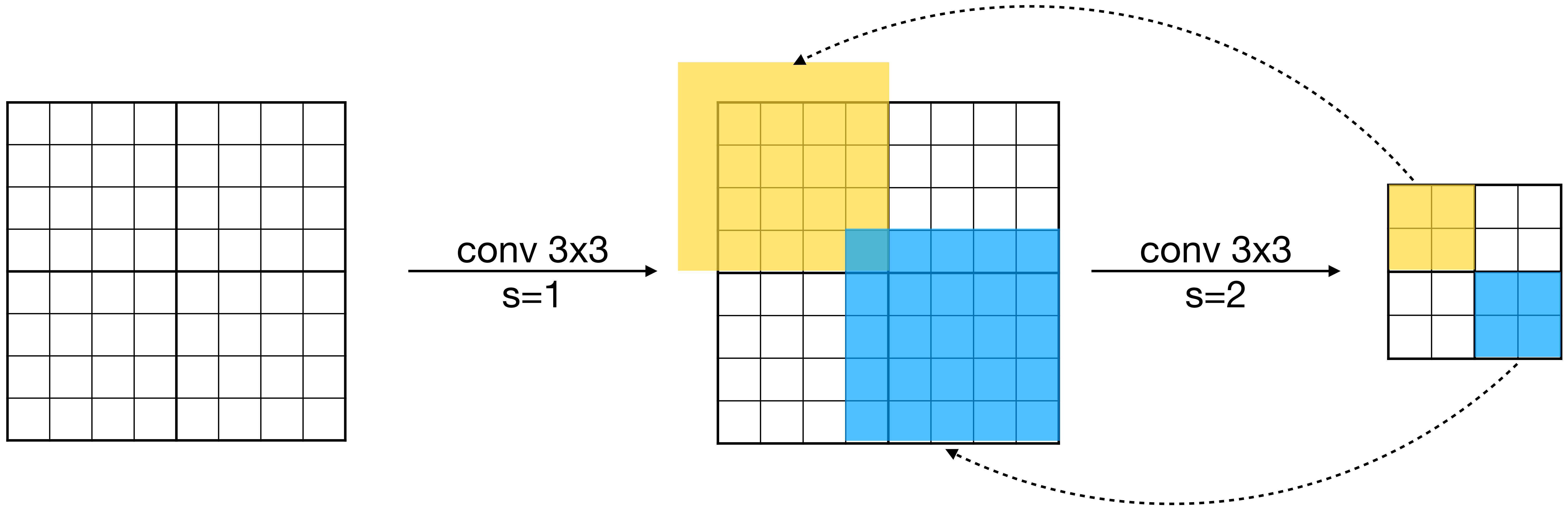

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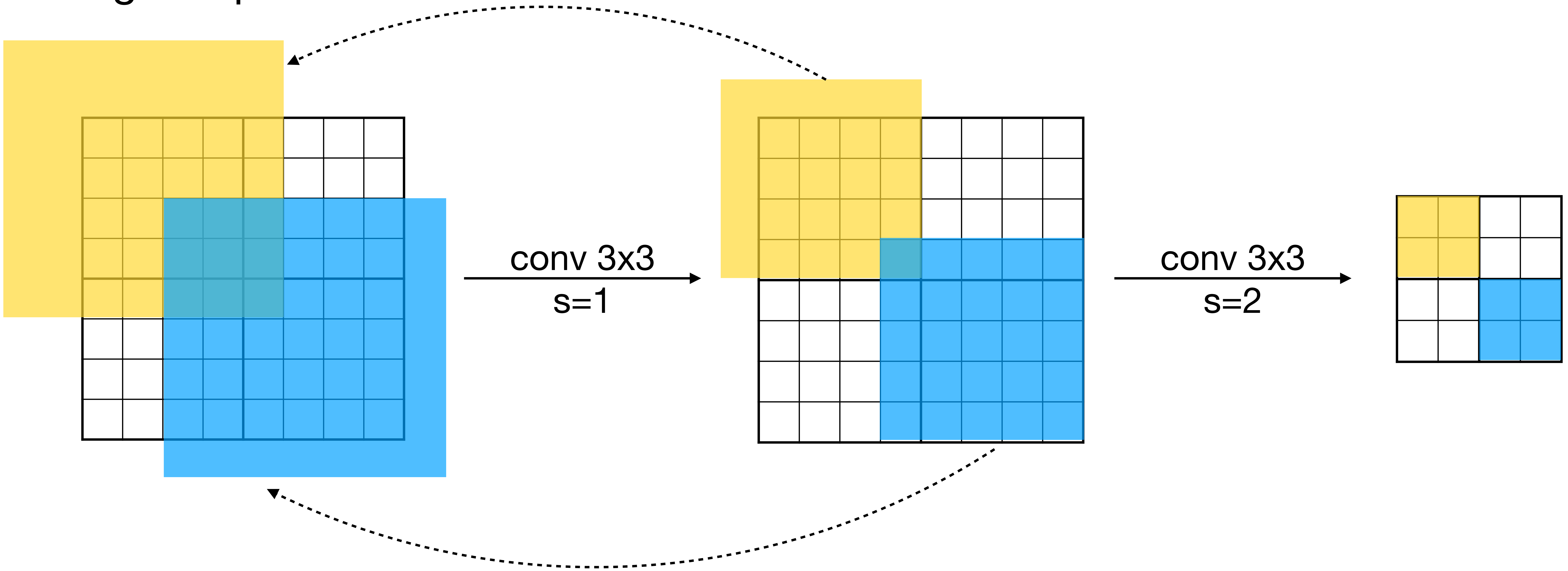

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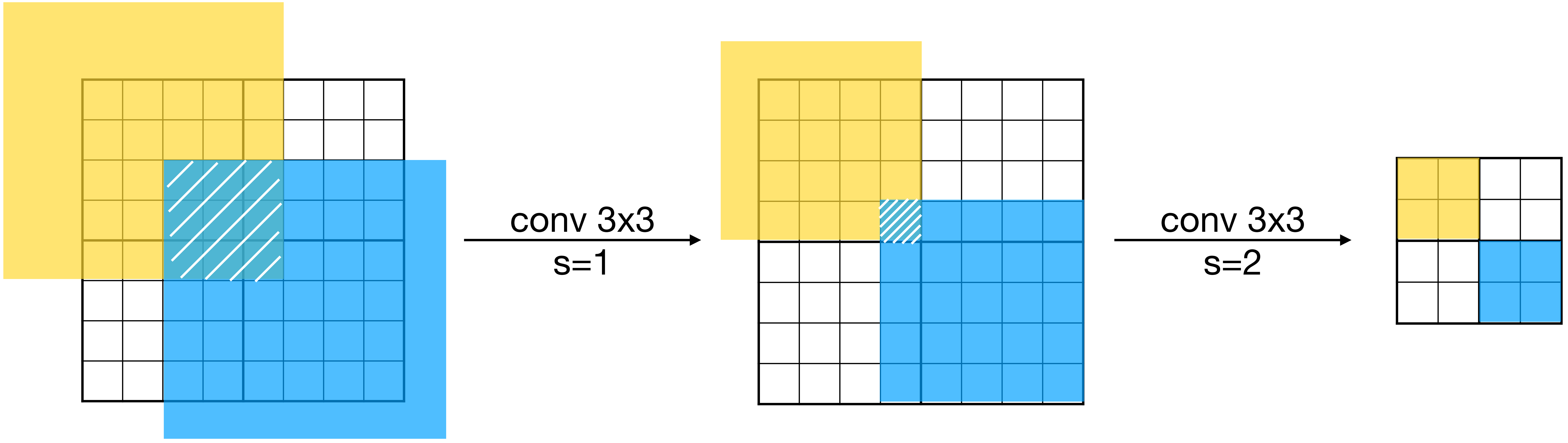
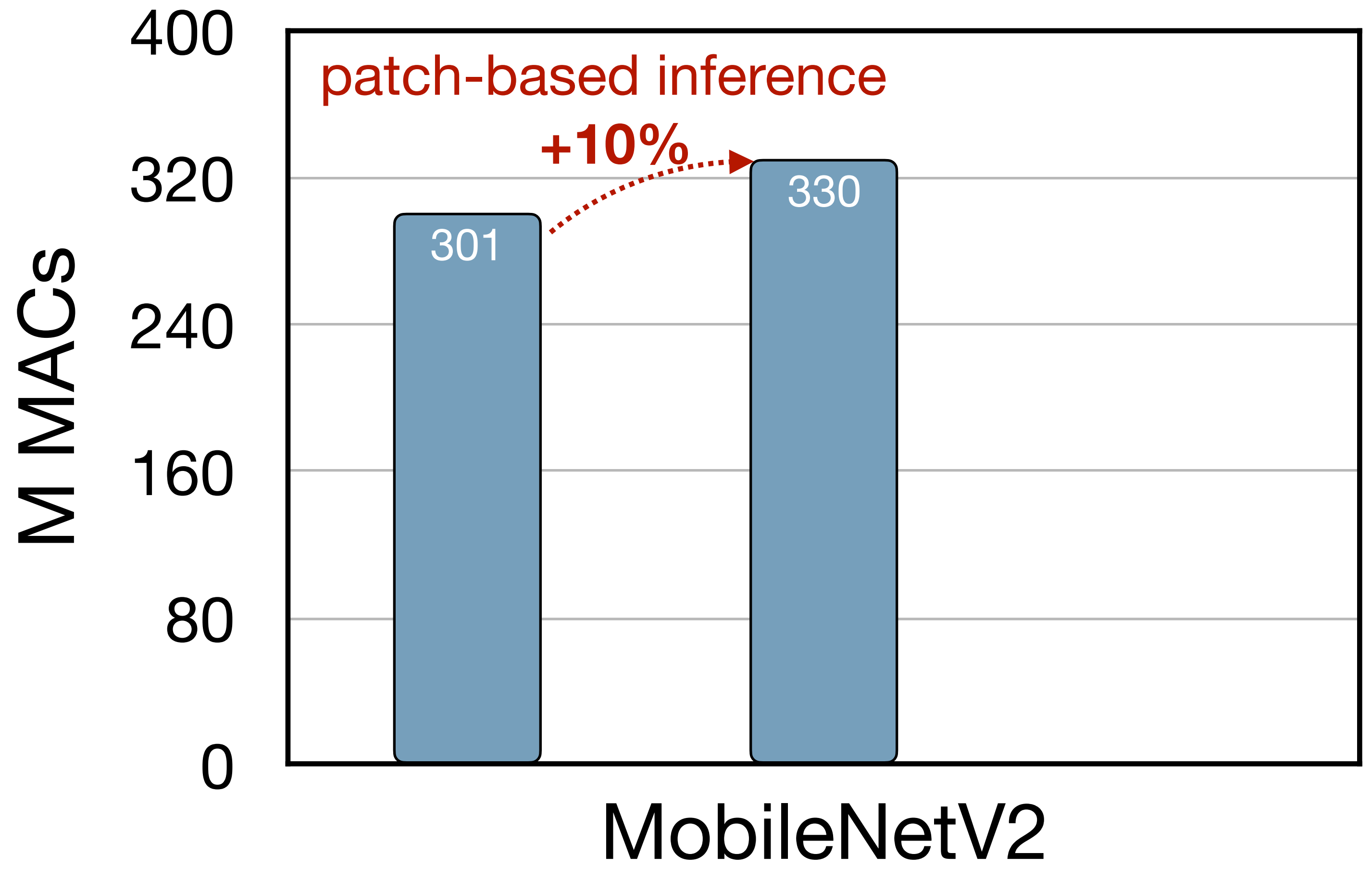
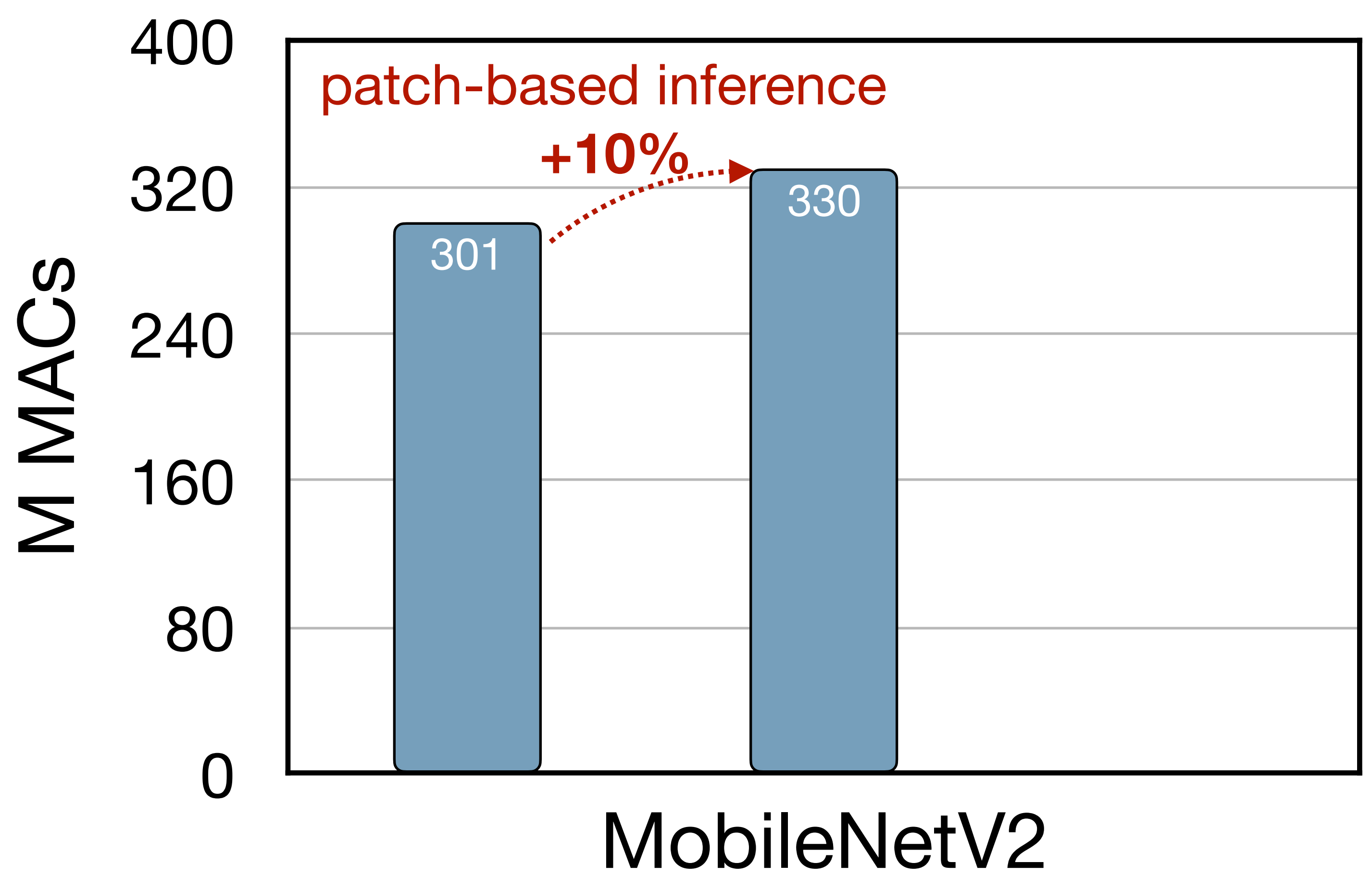


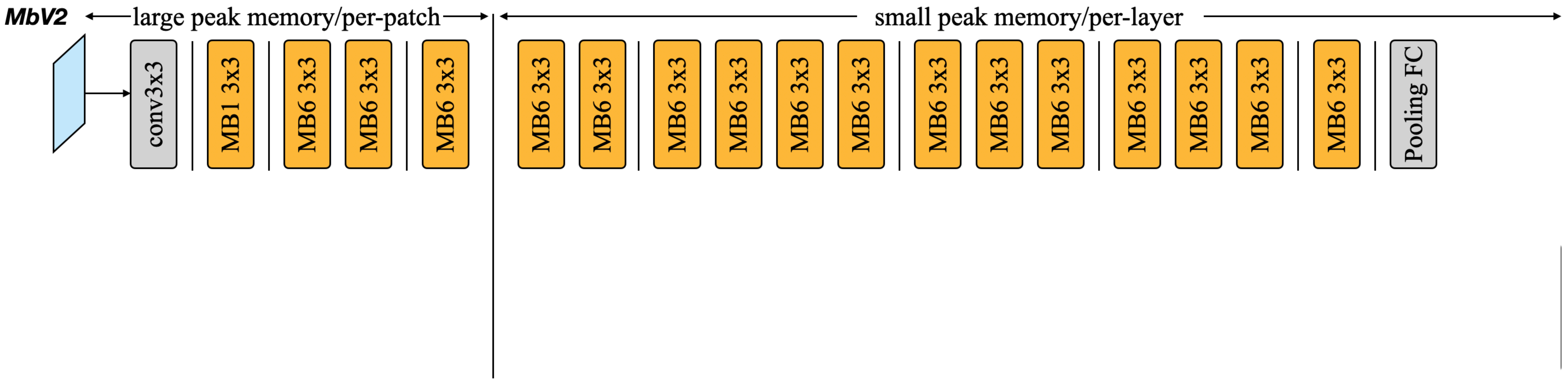
Spatial overlapping gets larger as **receptive field** grows!

Problem: Computation Overhead from Overlapping



2. Network Redistribution to Reduce Overhead





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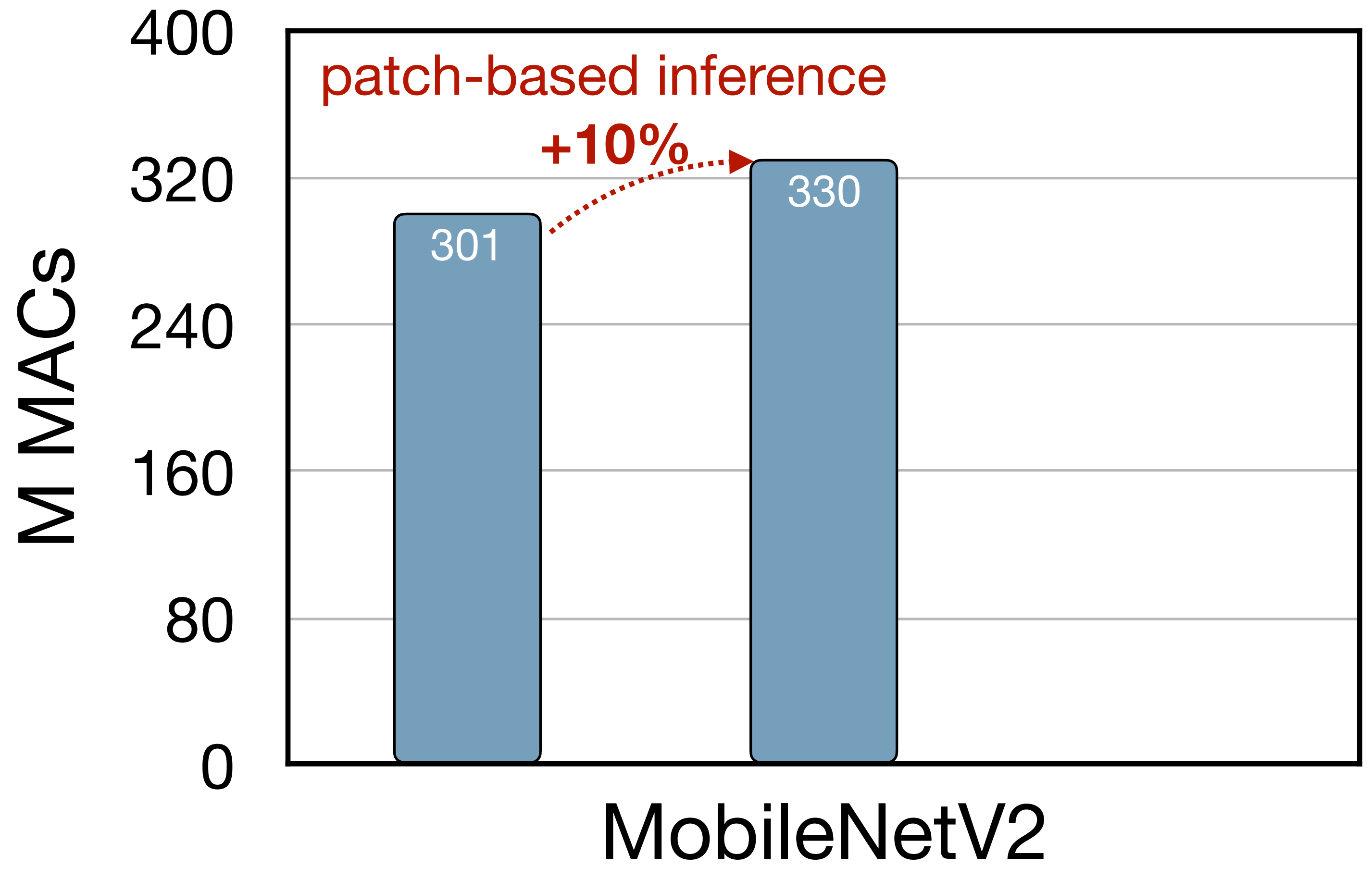

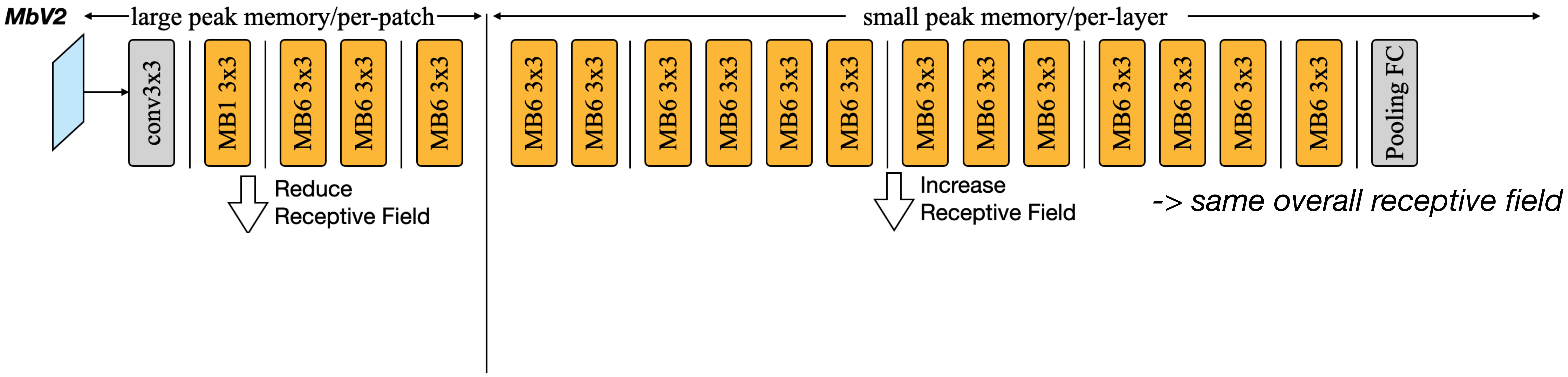

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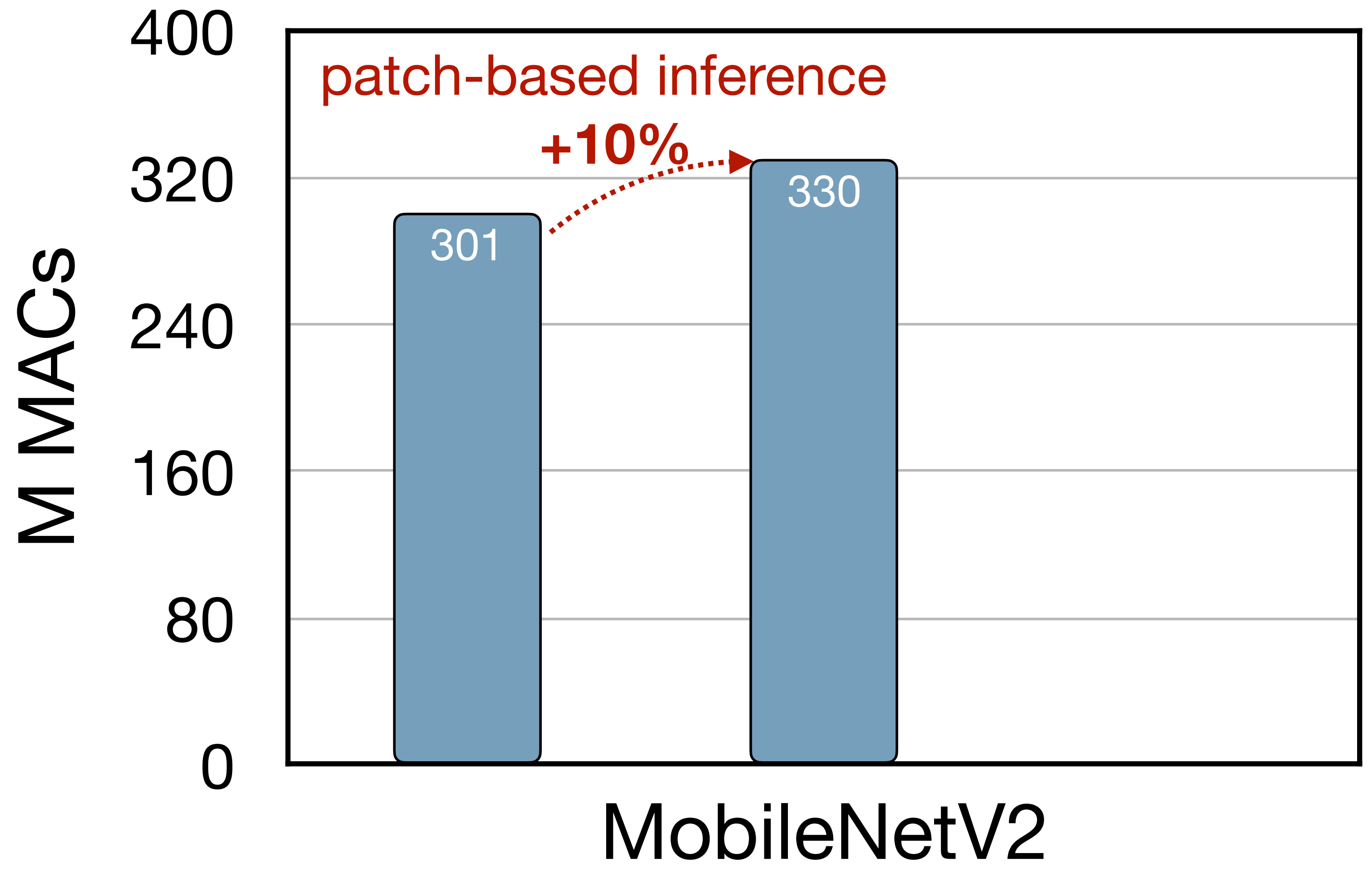

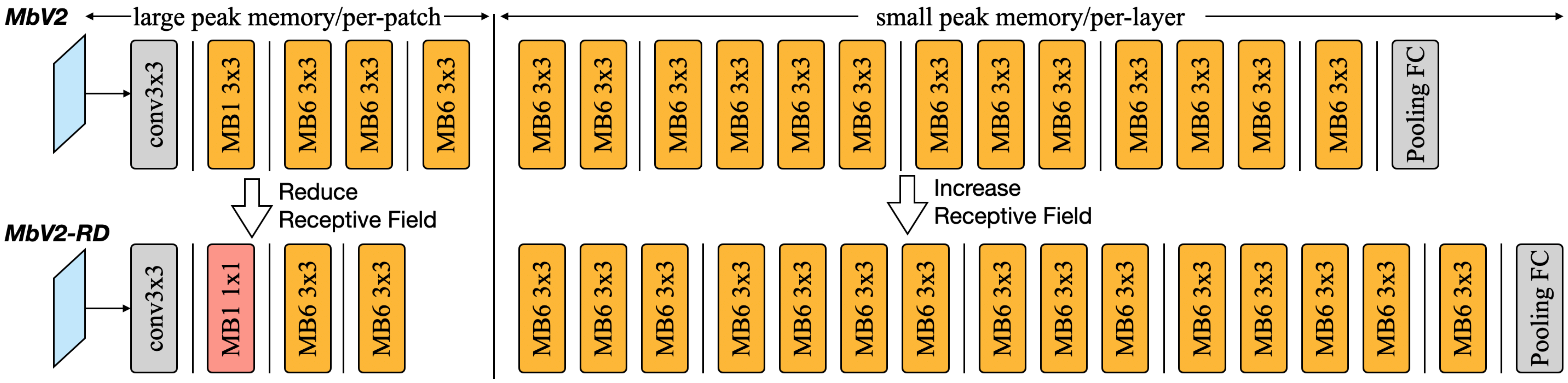

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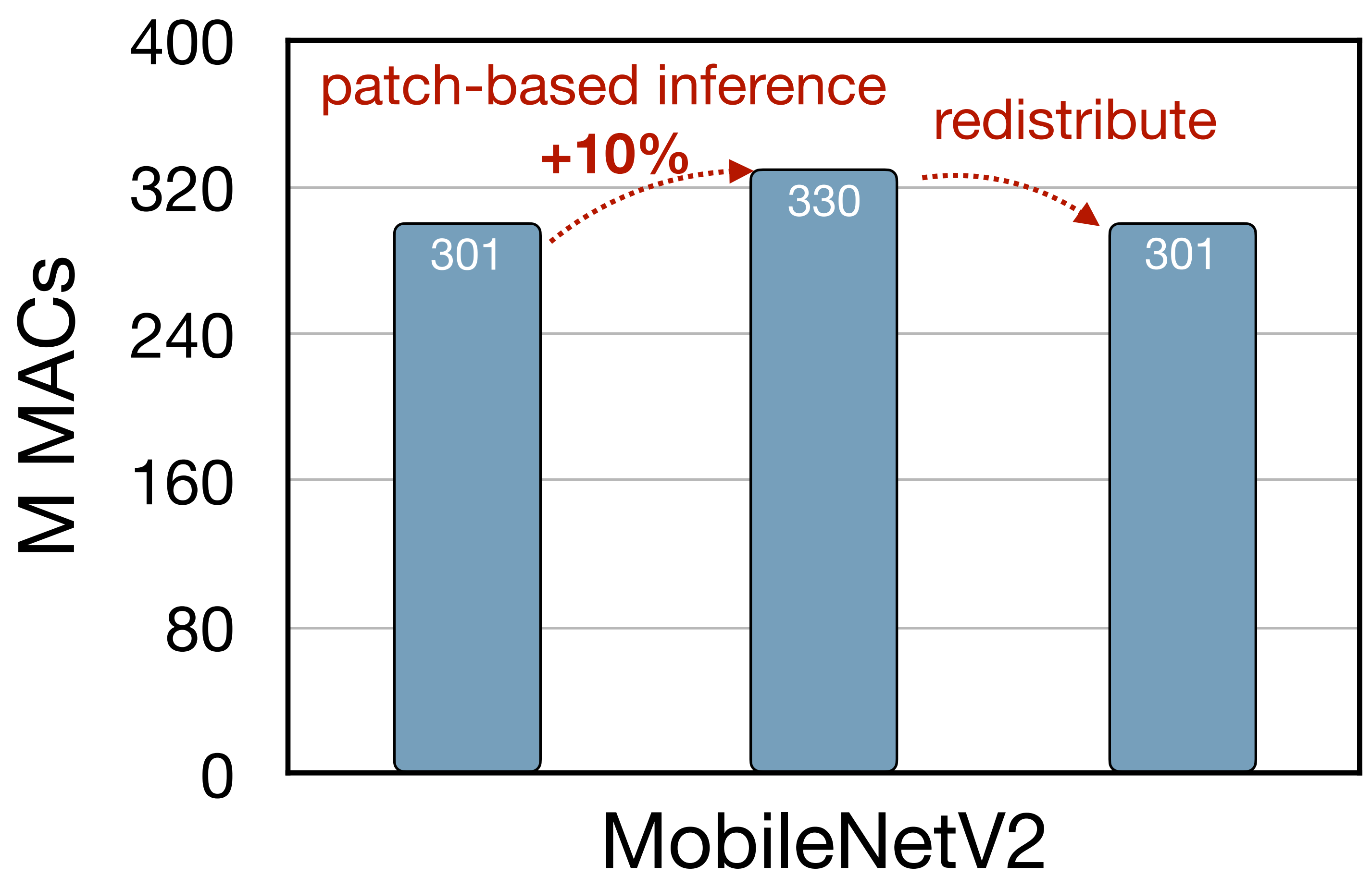
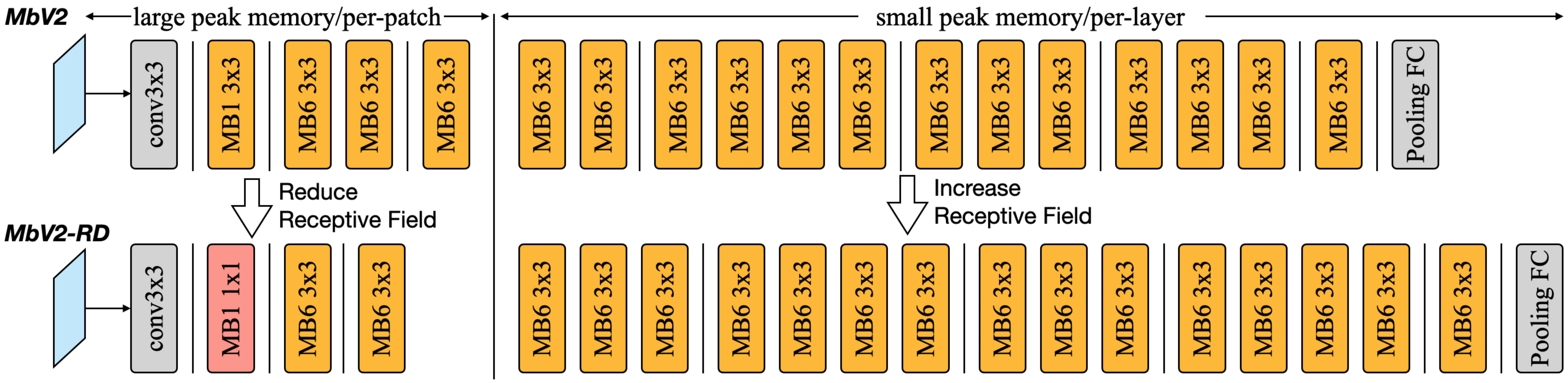


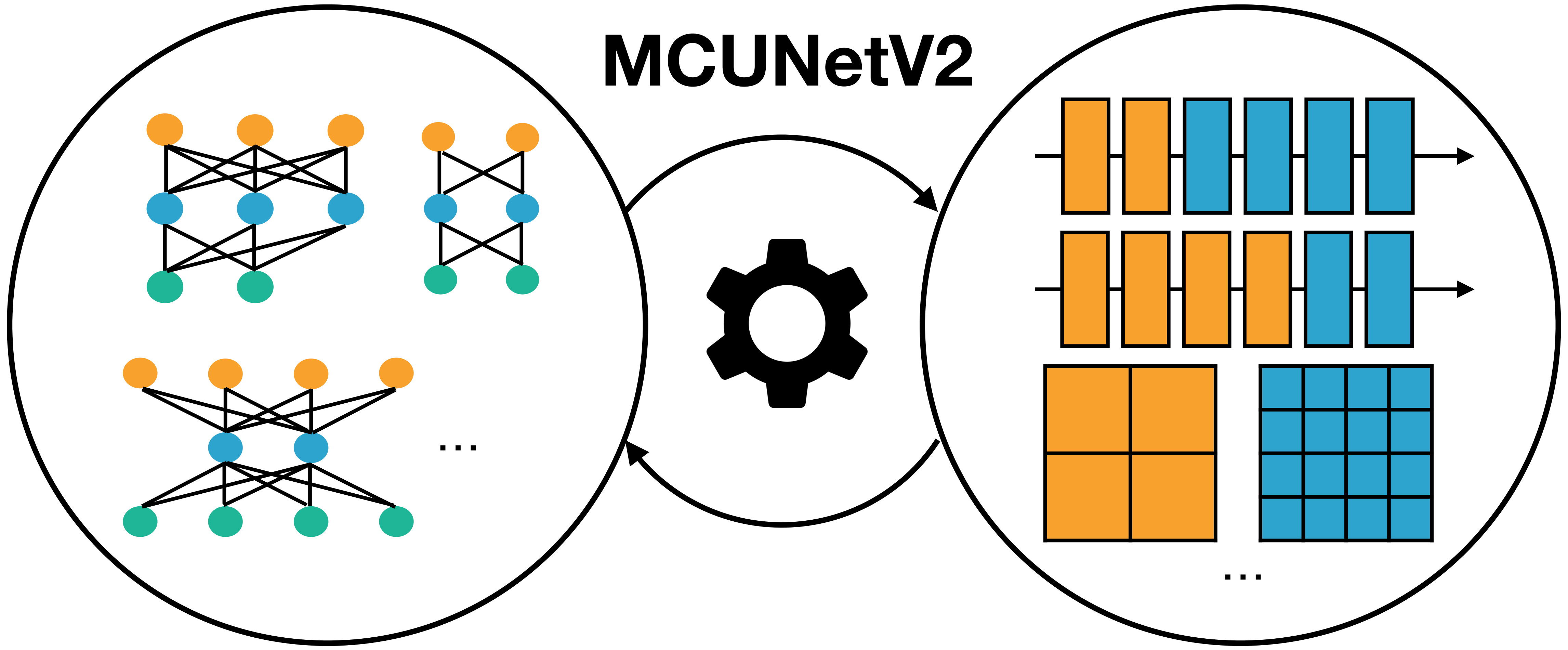
Same performance on:

- Image classification
- Object detection
- ….

Negligible overhead



3. Joint Automated Search for Optimization



Neural architecture
#layers
#channels
kernel size
...

Inference scheduling
#patches
#layers for patch-based
other knobs from TinyEngine*
...

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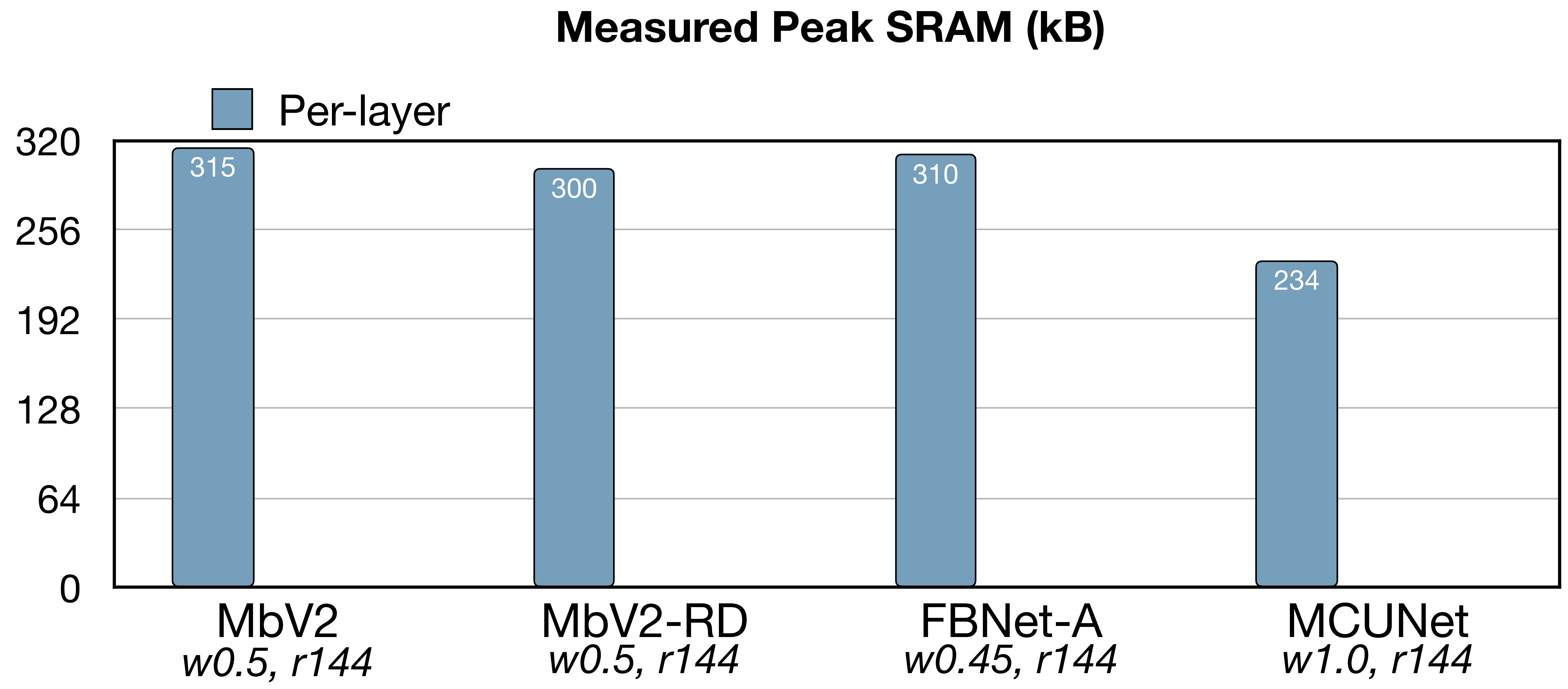
Reducing the Peak Memory of CNNs

- Baseline: TinyEngine, the SOTA system stack for tinyML
- Measured on STM32F746 MCU



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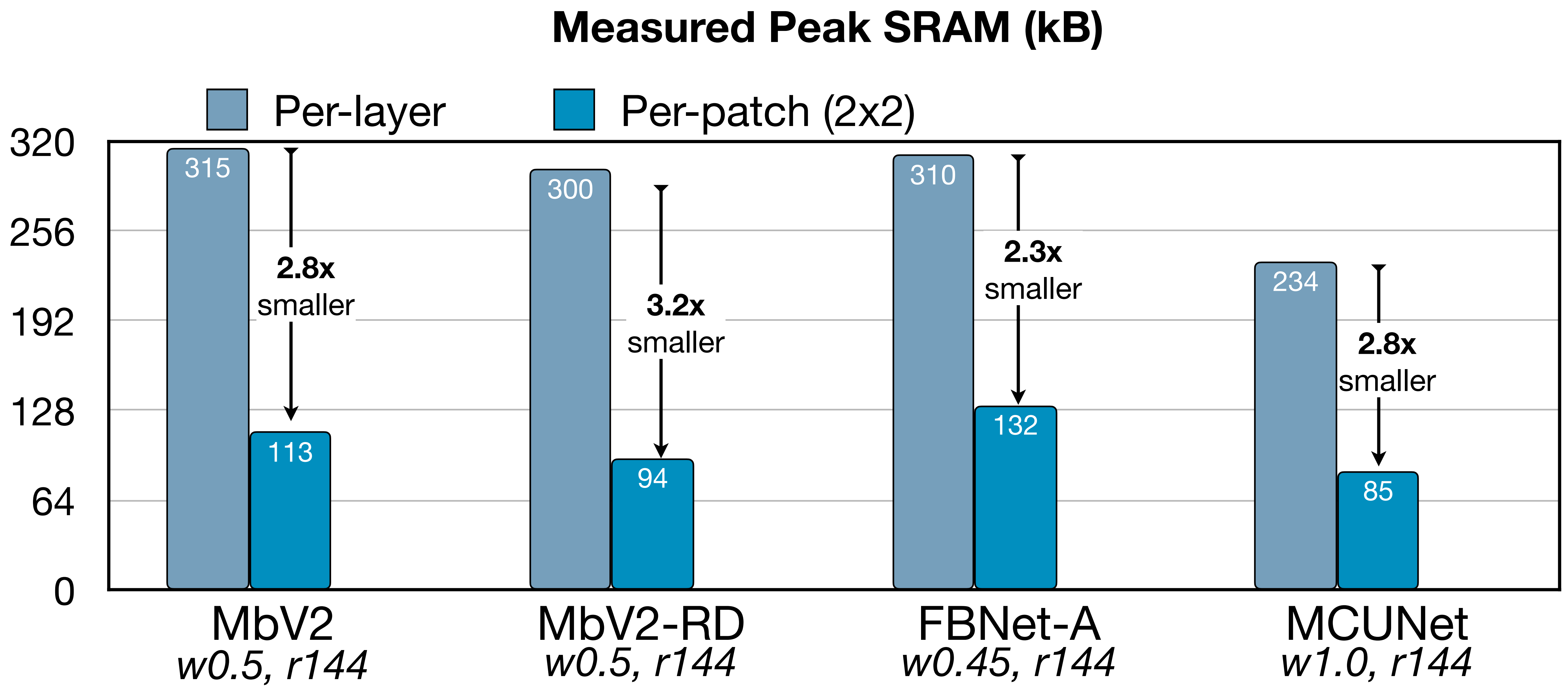

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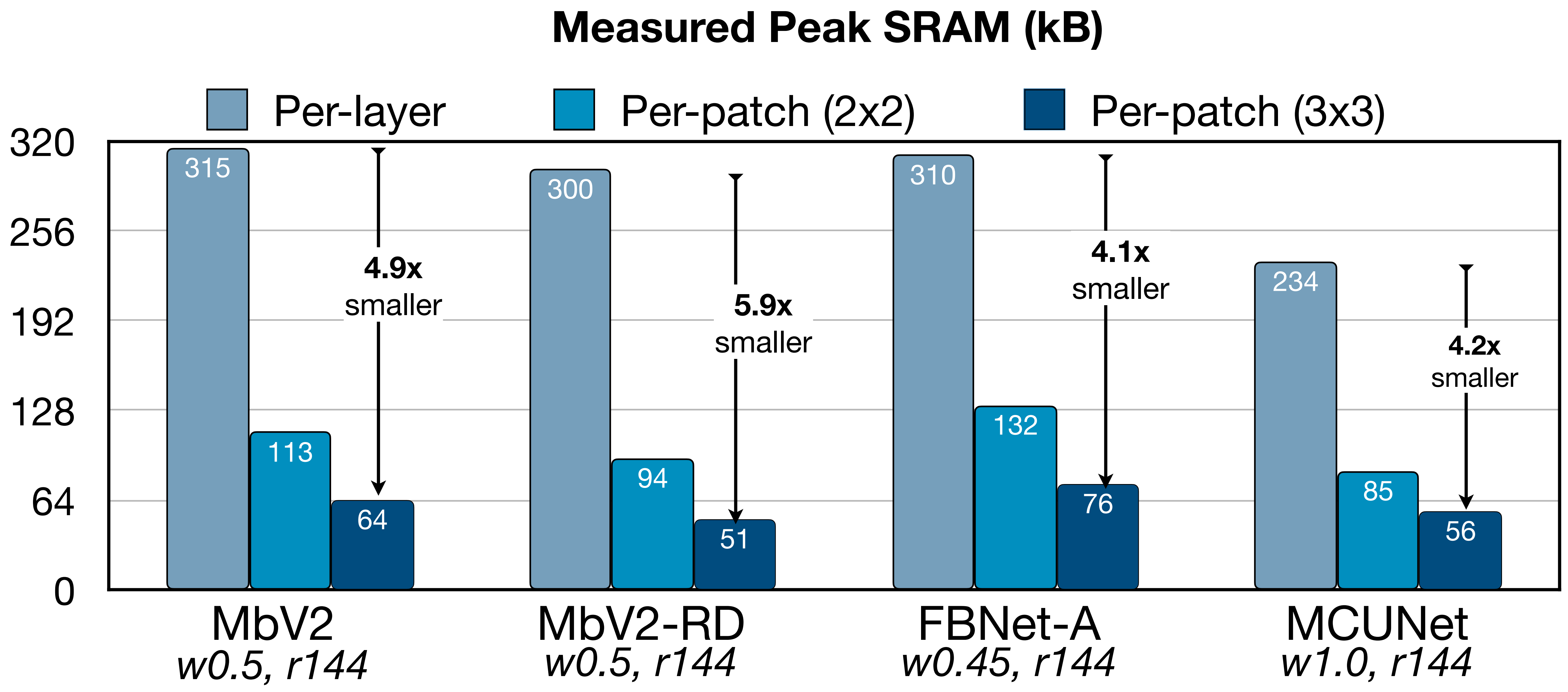

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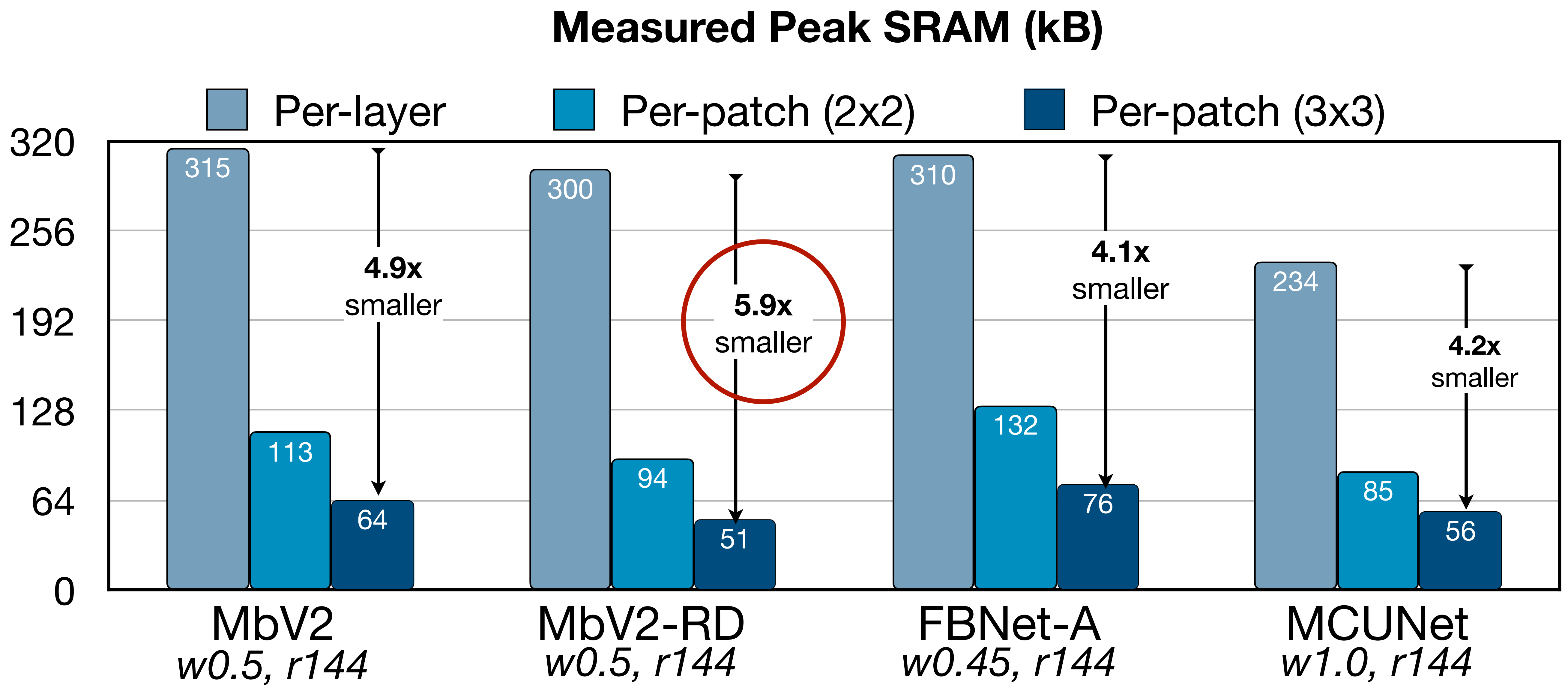
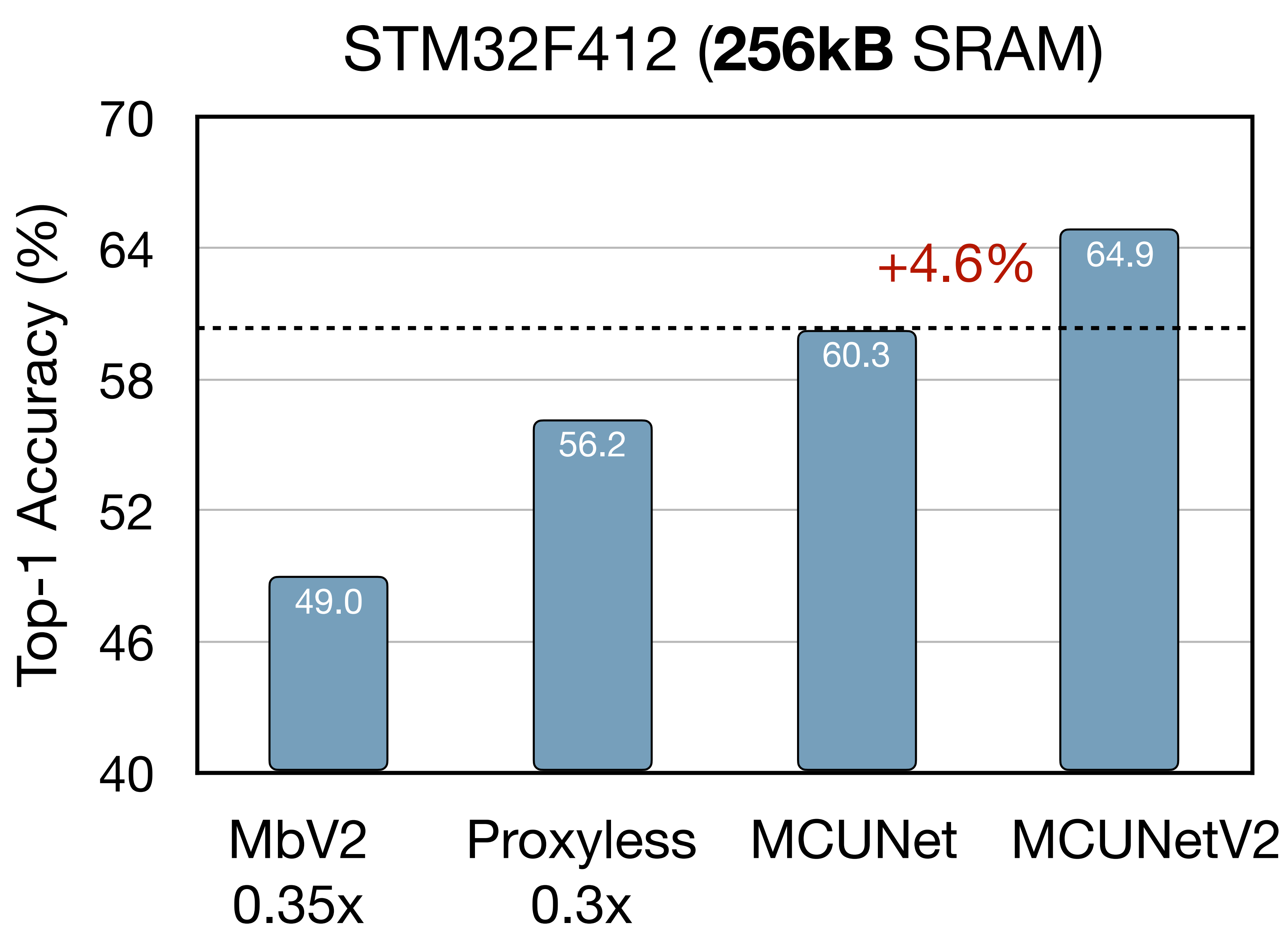
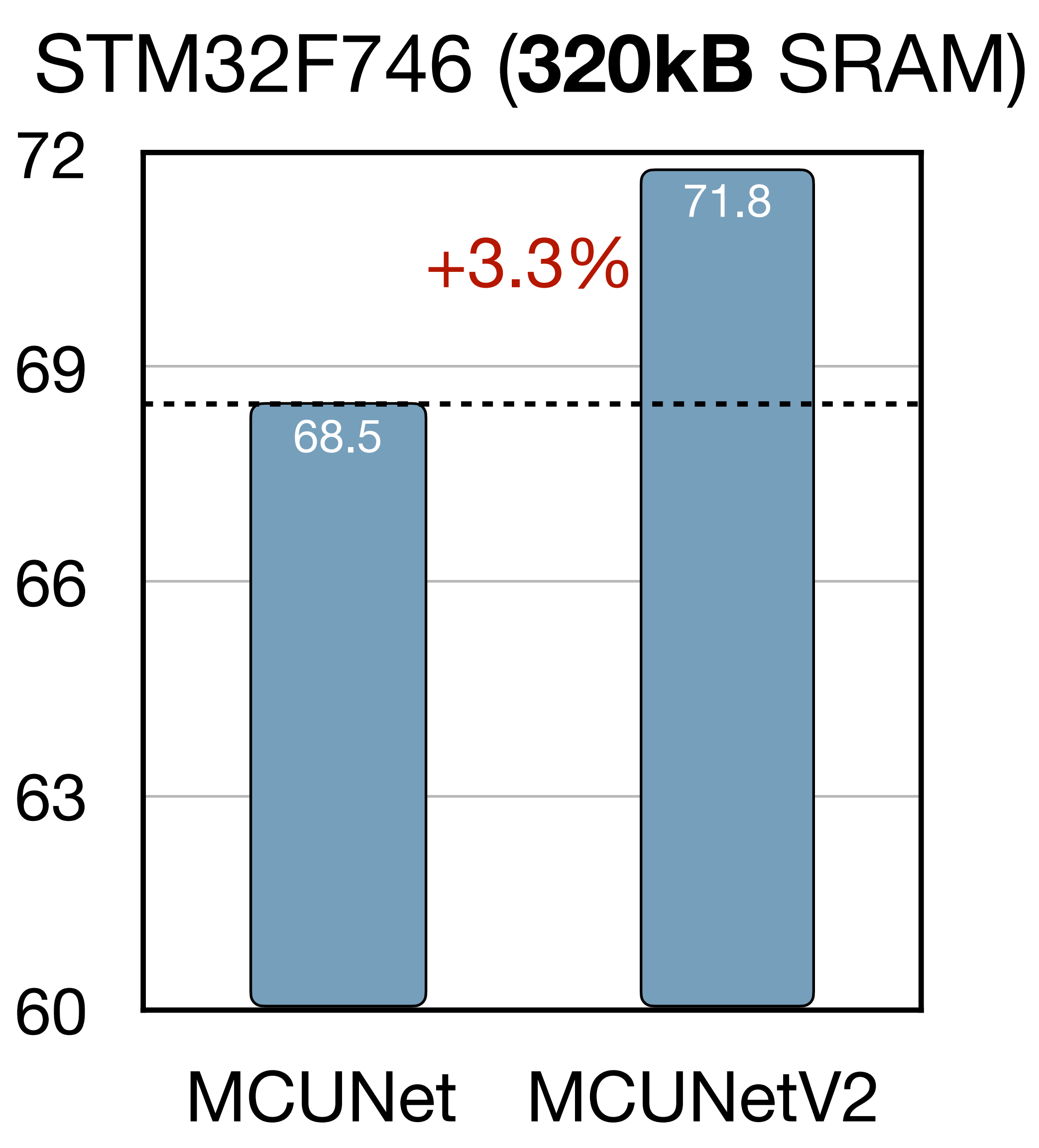


MCUNetV2 for Tiny Image Classification

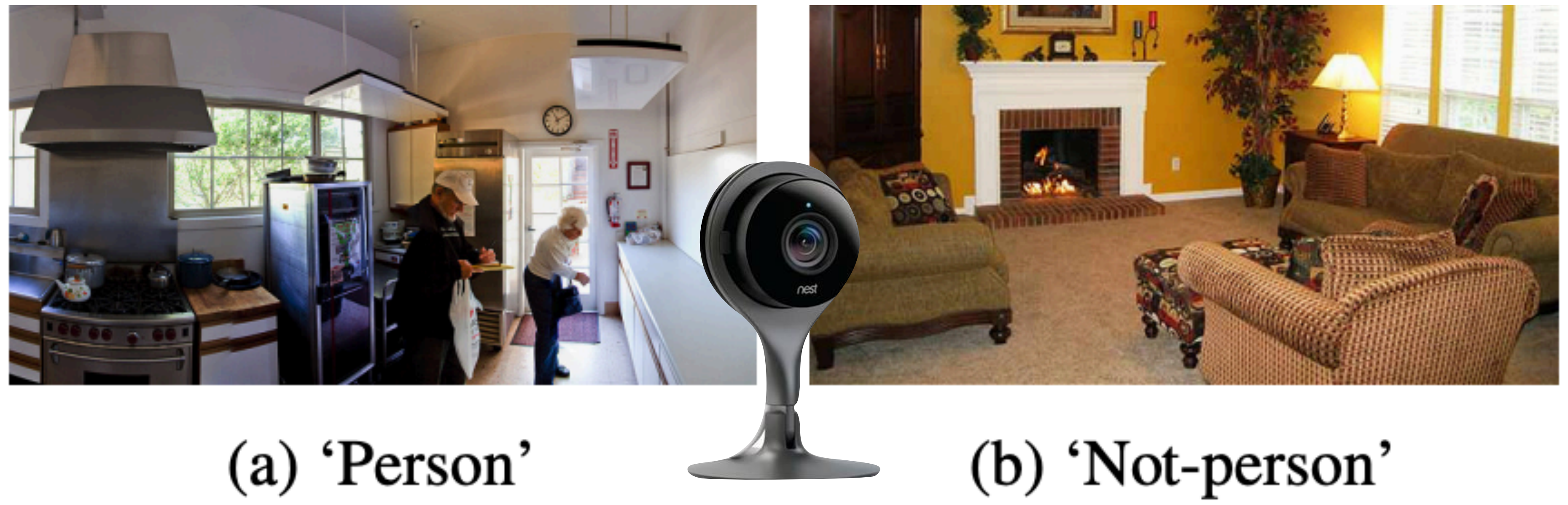
- Large-scale **ImageNet** classification
- Models are quantized to int8
- Serving using TinyEngine.



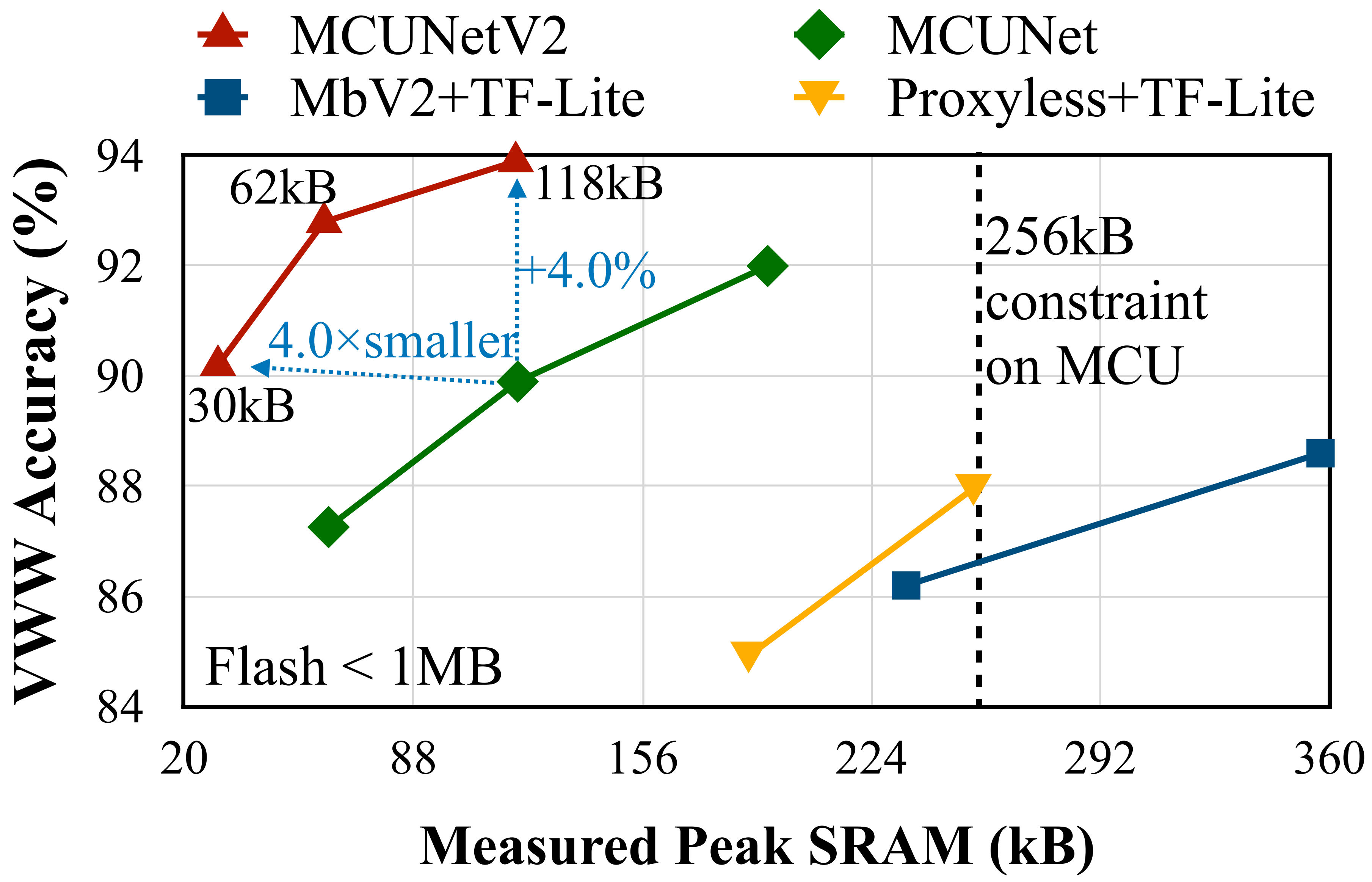


MCUNetV2 for Tiny Image Classification

- TinyML application: **Visual Wake Words (VWW)**
- Higher accuracy, lower SRAM



(a) 'Person' (b) 'Not-person'



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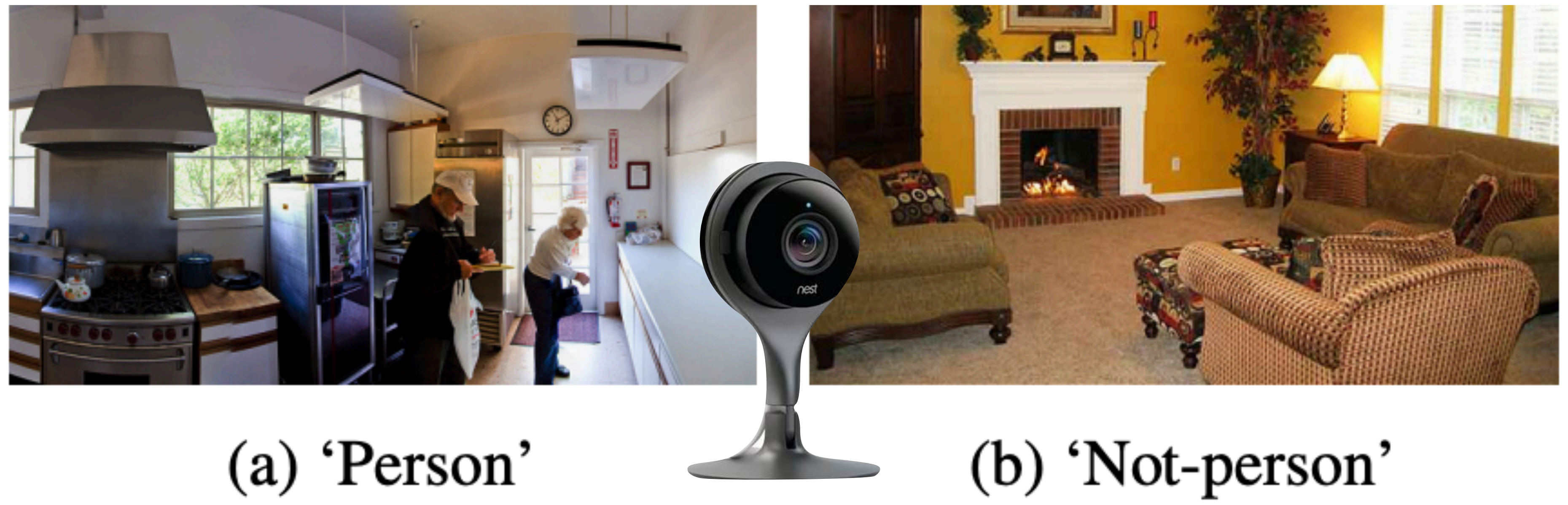

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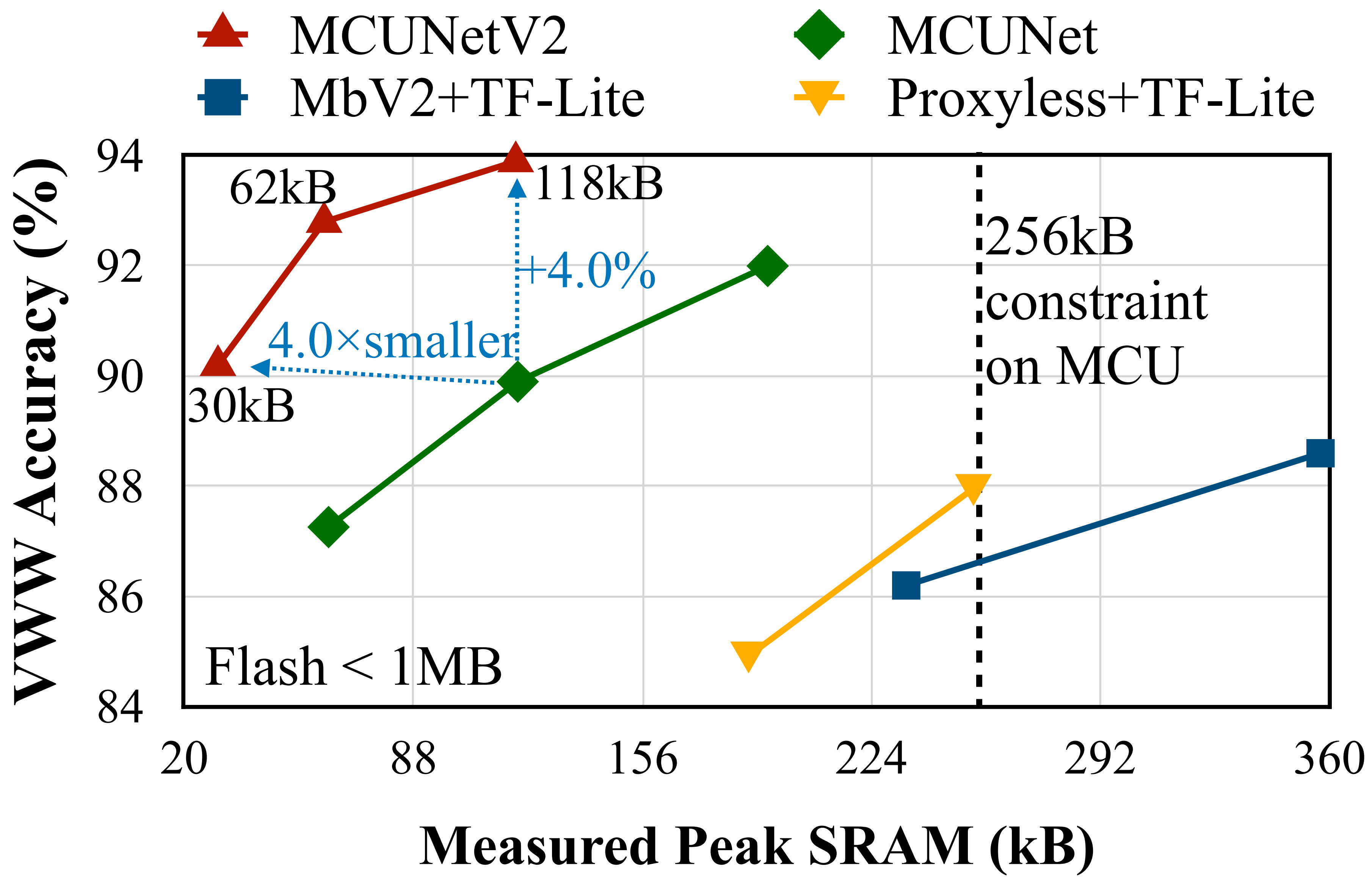
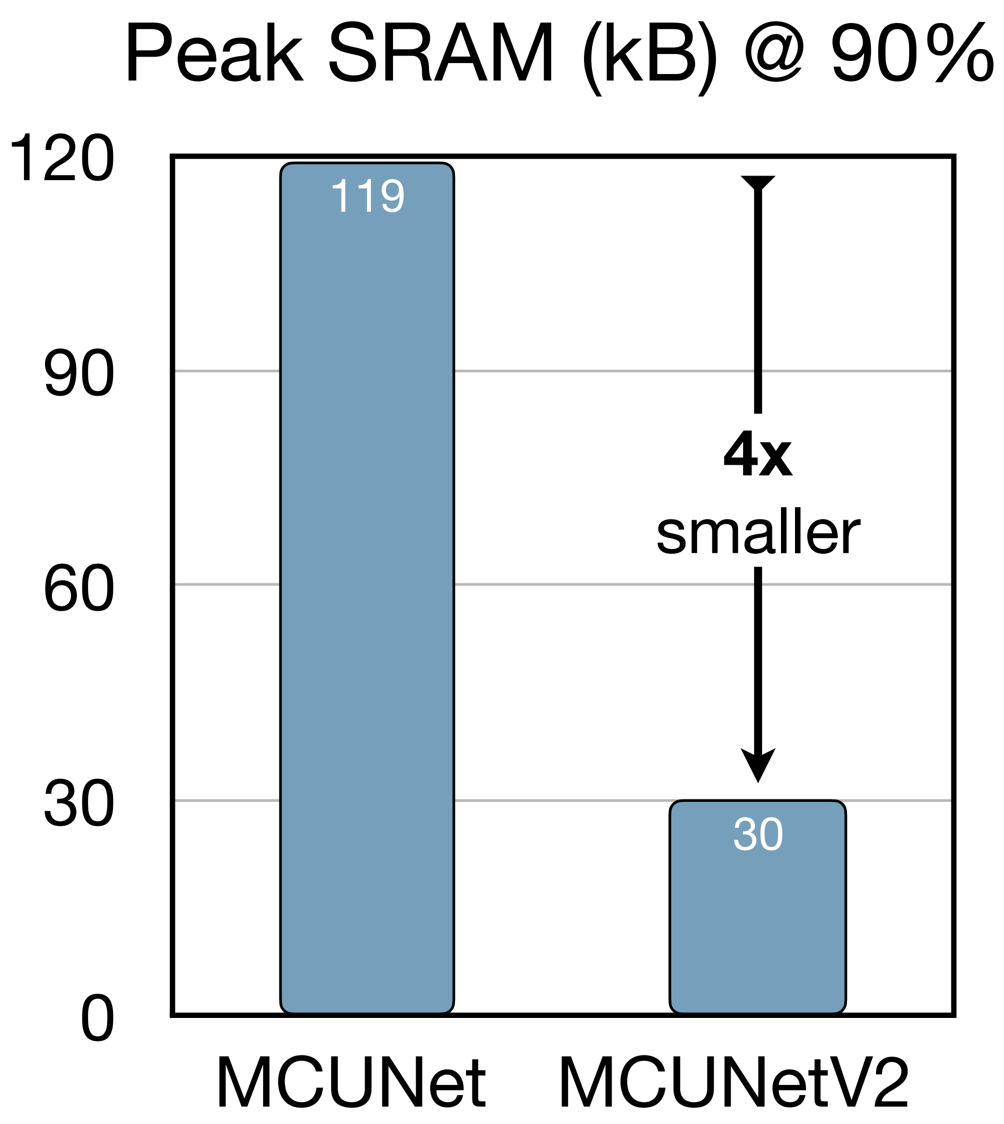
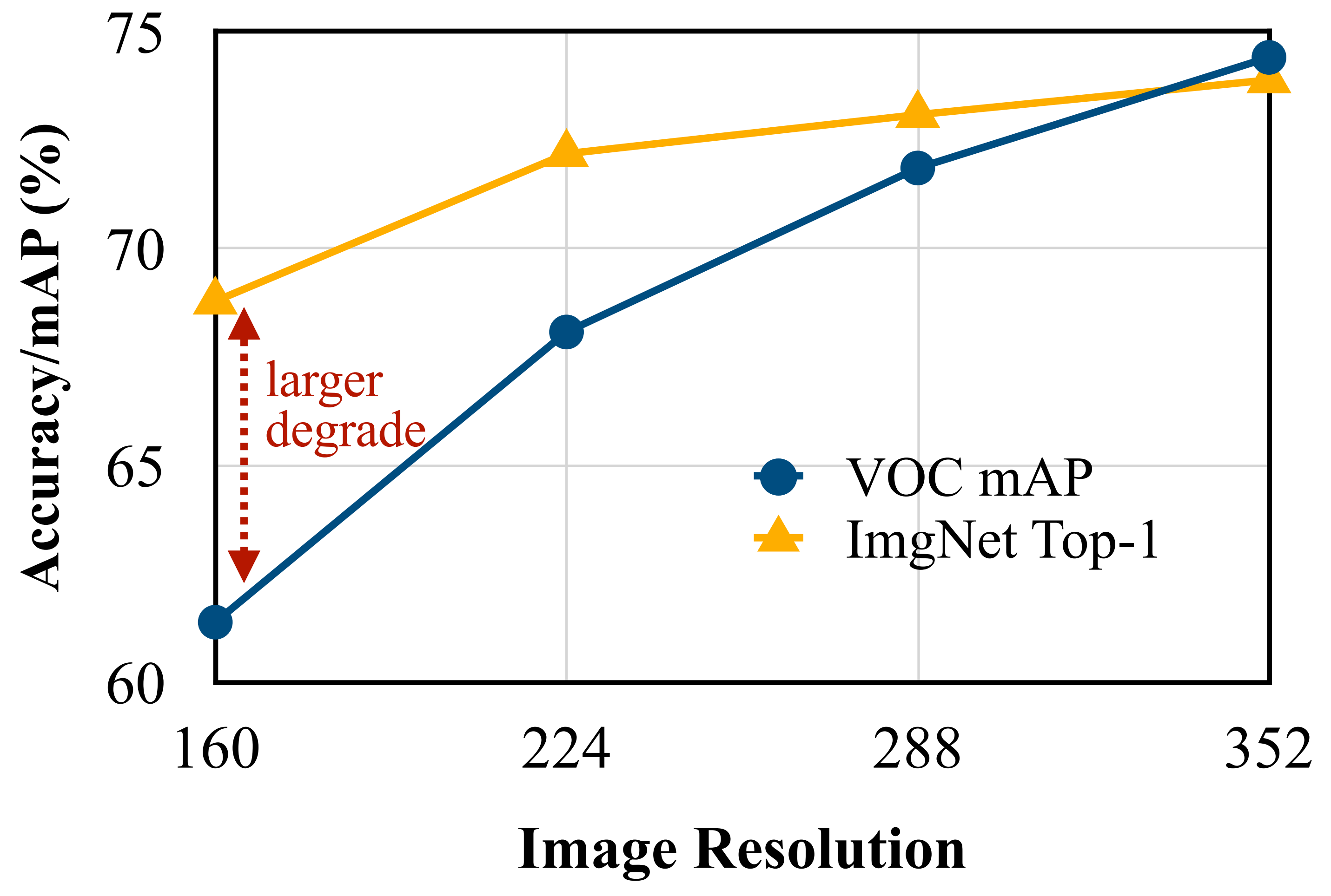




MCUNetV2 for Tiny Object Detection

- Object detection is more sensitive to input resolution



MCUNetV2 for Tiny Object Detection

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- Patch-based inference allows for a larger resolution, improving detection performance

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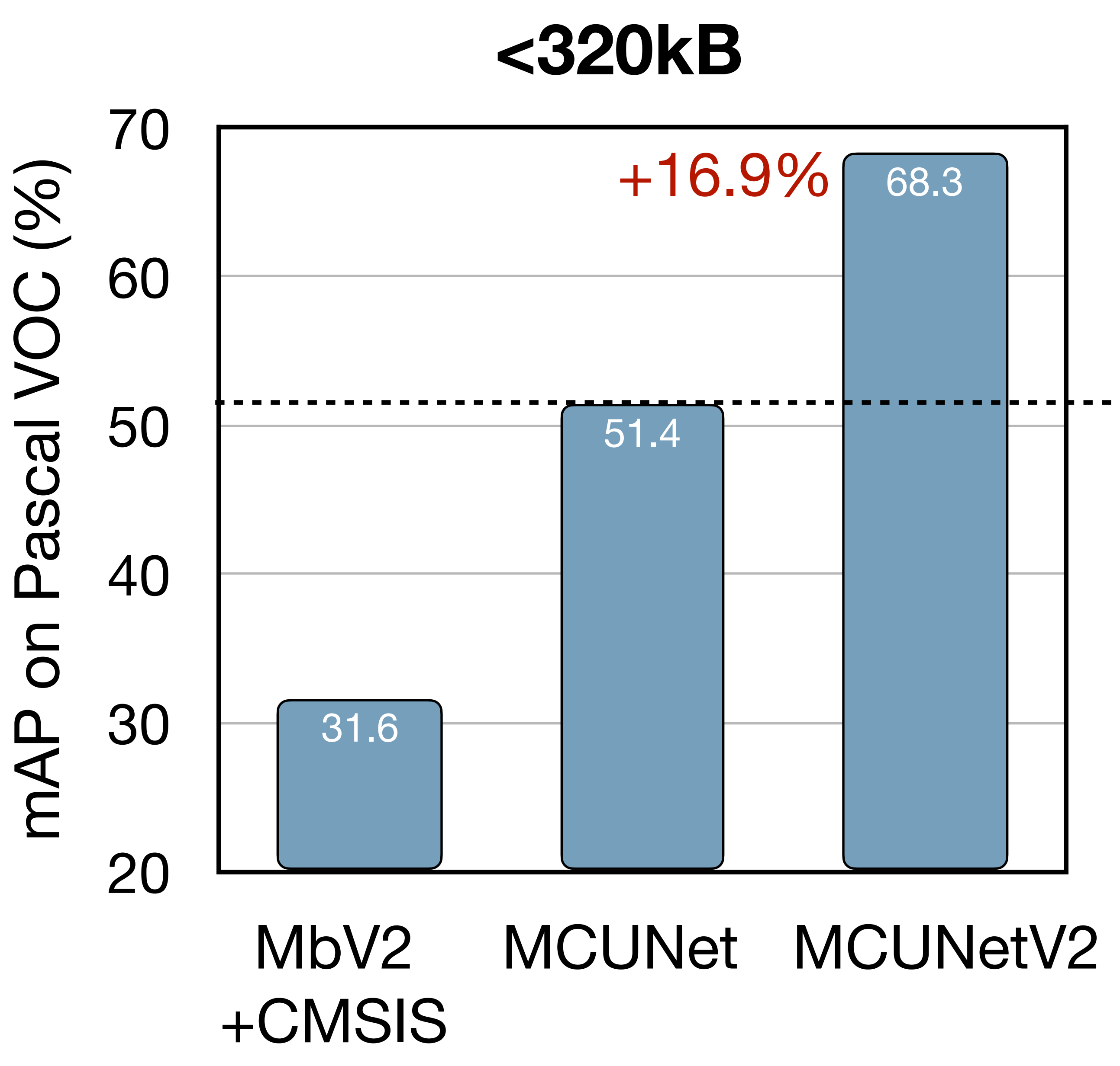
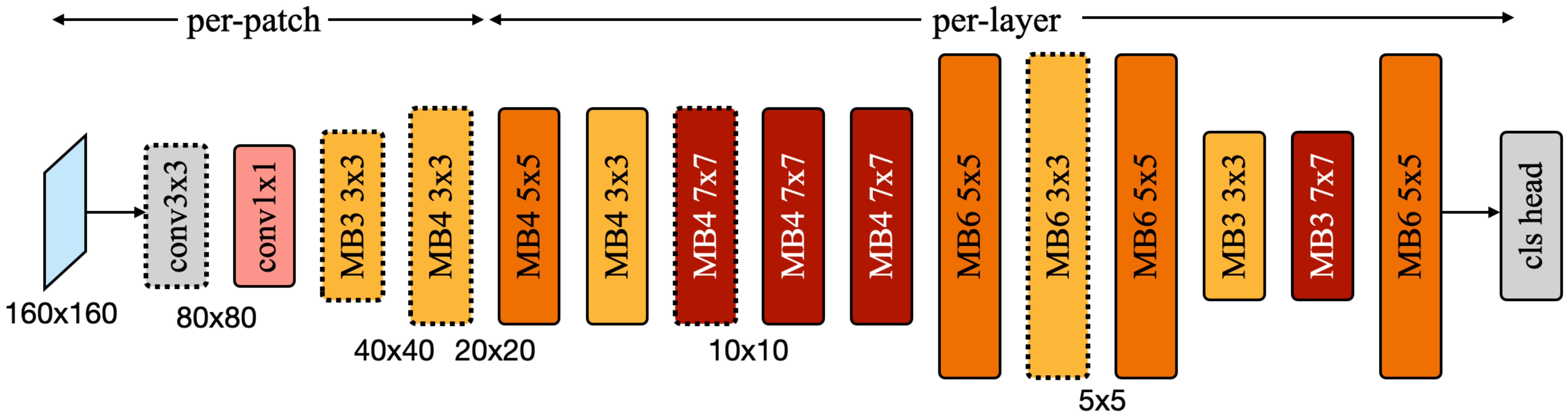


MCUNetV2 for Tiny Object Detection

- Face detection on WIDER Face
- More robust results at a smaller peak memory

(a) RNNPool-Face-Quant (b) MCUNetV2

Dissecting MCUNetV2 Architecture



Sample arch from VWW. ***Legend:*** `MB{expansion}_{k_size}x{k_size}`

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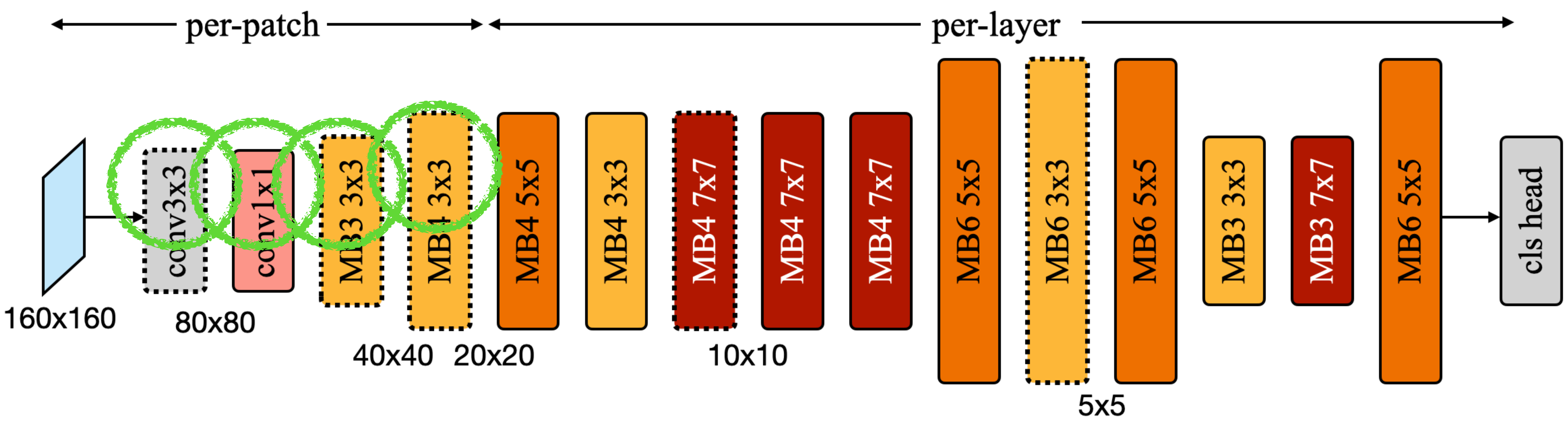

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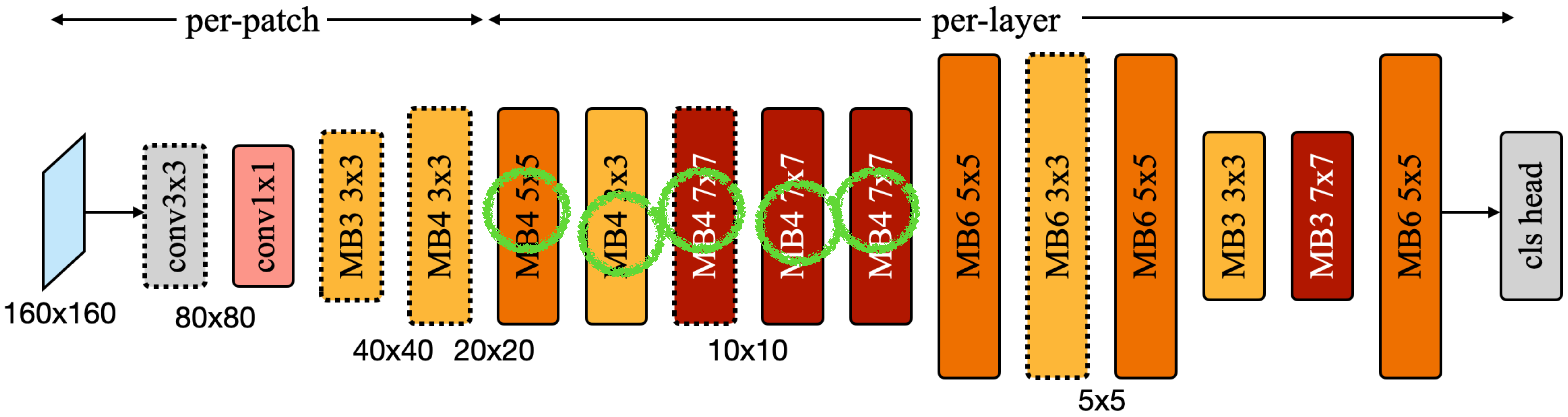

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- Kernel size in per-patch stage is small to reduce spatial overlapping
- Expansion ratio in middle stage is small to reduce peak memory

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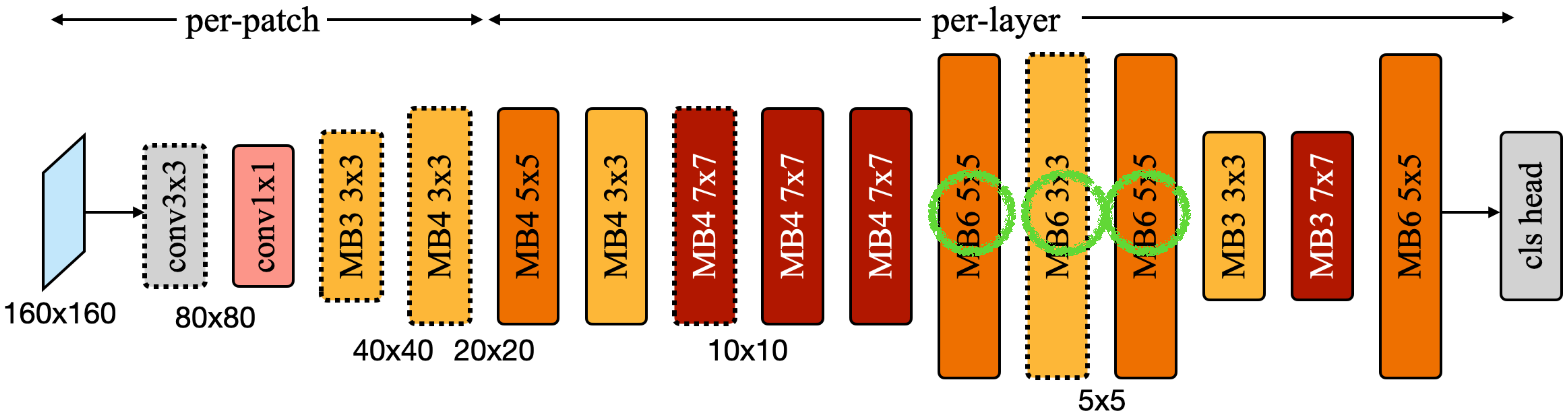
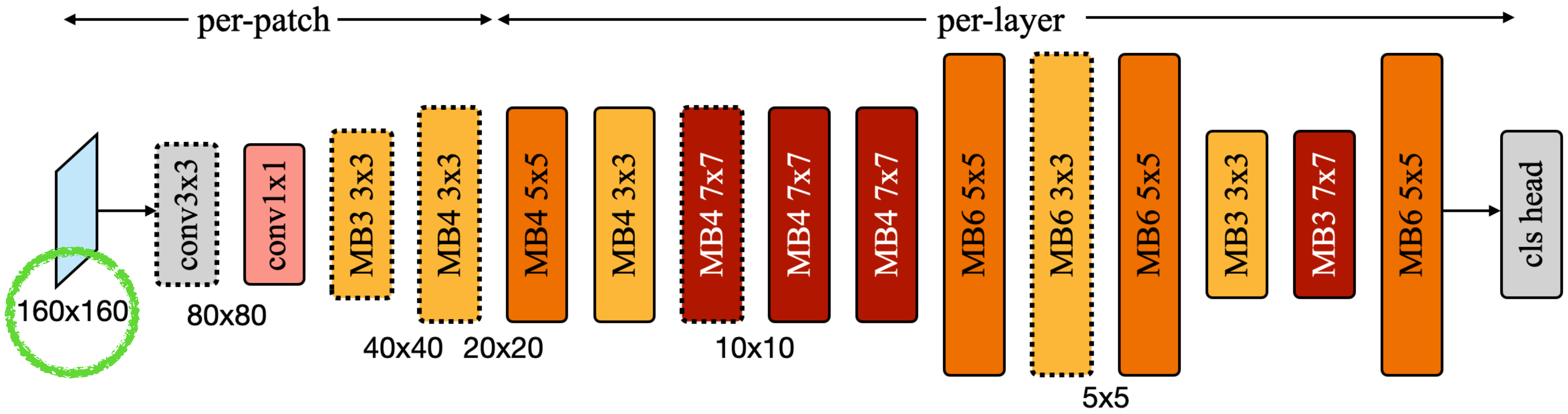


Sample arch from VWW. ***Legend:*** `MB{expansion}_{k_size}x{k_size}`

- Kernel size in per-patch stage is small to reduce spatial overlapping
- Expansion ratio in middle stage is small to reduce peak memory; large in later stage to boost performance.

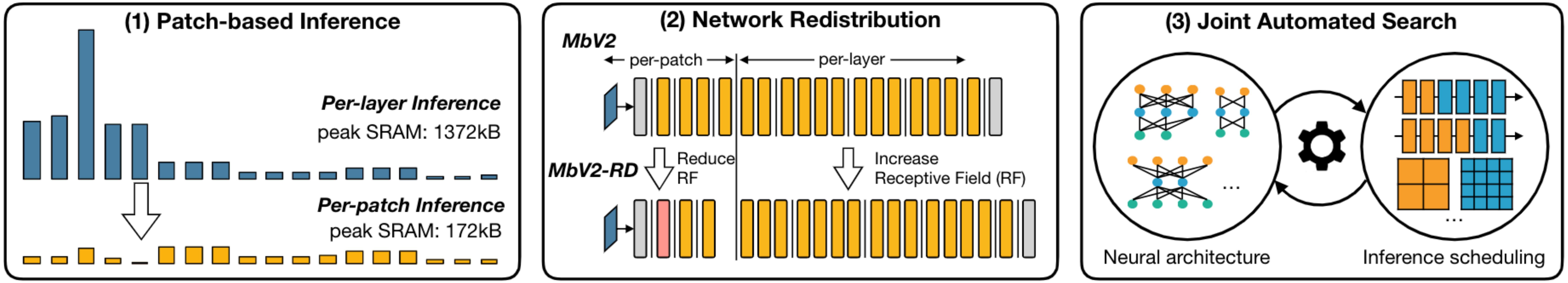
Dissecting MCUNetV2 Architecture



Sample arch from VWW. ***Legend:*** `MB{expansion}_{k_size}x{k_size}`

- Kernel size in per-patch stage is small to reduce spatial overlapping
- Expansion ratio in middle stage is small to reduce peak memory; large in later stage to boost performance.
- Larger input resolution for resolution-sensitive datasets like VWW (MCUNet: 128x128)

Thanks for listening!



MCUNetV2