Lecture 11:
CNN Architectures
Part 2

Administrative: A1 grades released

- A1 grades are out on Canvas
- We will accept regrade requests until **Friday 2/19 5pm ET**
  - To request a regrade (or for questions about late days, etc): **Make a private post on Piazza under the regrade folder**
  - **Do not make regrade requests via Canvas or Email**

Administrative: A1 grades released

- Some students lost points for not including plots etc. From assignment page:

  - **Run all cells, and do not clear out the outputs, before submitting.** You will only get credit for code that has been run.

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- If you are affected by this on A1, or think you will be affected by this on A2 or A3, **make a regrade request on Piazza by Tuesday 5pm ET and you can resubmit your notebook only with no penalty**

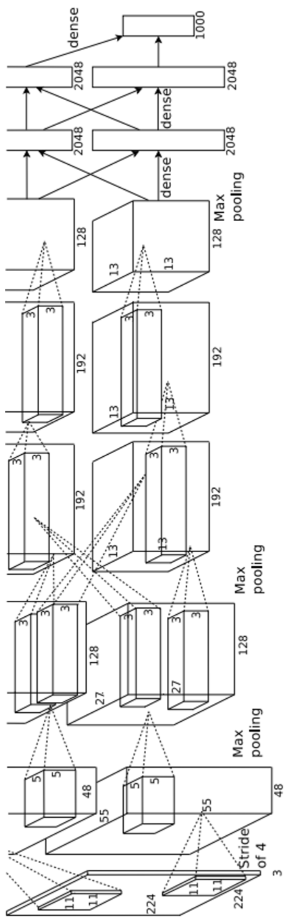
Administrative: Midterm

- Wednesday, February 23
- Will be remote as a Canvas quiz (most likely)
- Exam is 90 minutes
- You can take it any time in a 24-hour window
- We will have 3-4 “on-call” periods during the 24-hour window where GSIs will answer questions within ~15 minutes
- Open note
- True / False, multiple choice, short answer
- For short answer questions requiring math, either write LaTeX or upload an image with handwritten math
- **We will try to get practice midterm out this week**

Last Time: Training Deep Networks

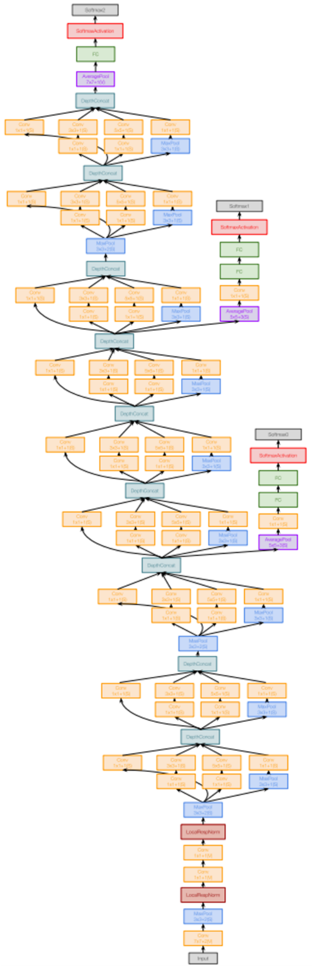
1. **One time setup**
   Activation functions, data preprocessing,
   weight initialization, regularization
2. **Training dynamics**
   Learning rate schedules;
   hyperparameter optimization
3. **After training**
   Model ensembles

Previously: CNN Architectures

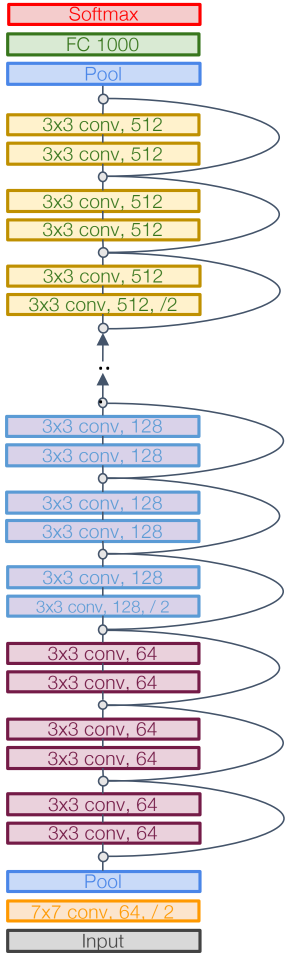


AlexNet

VGG

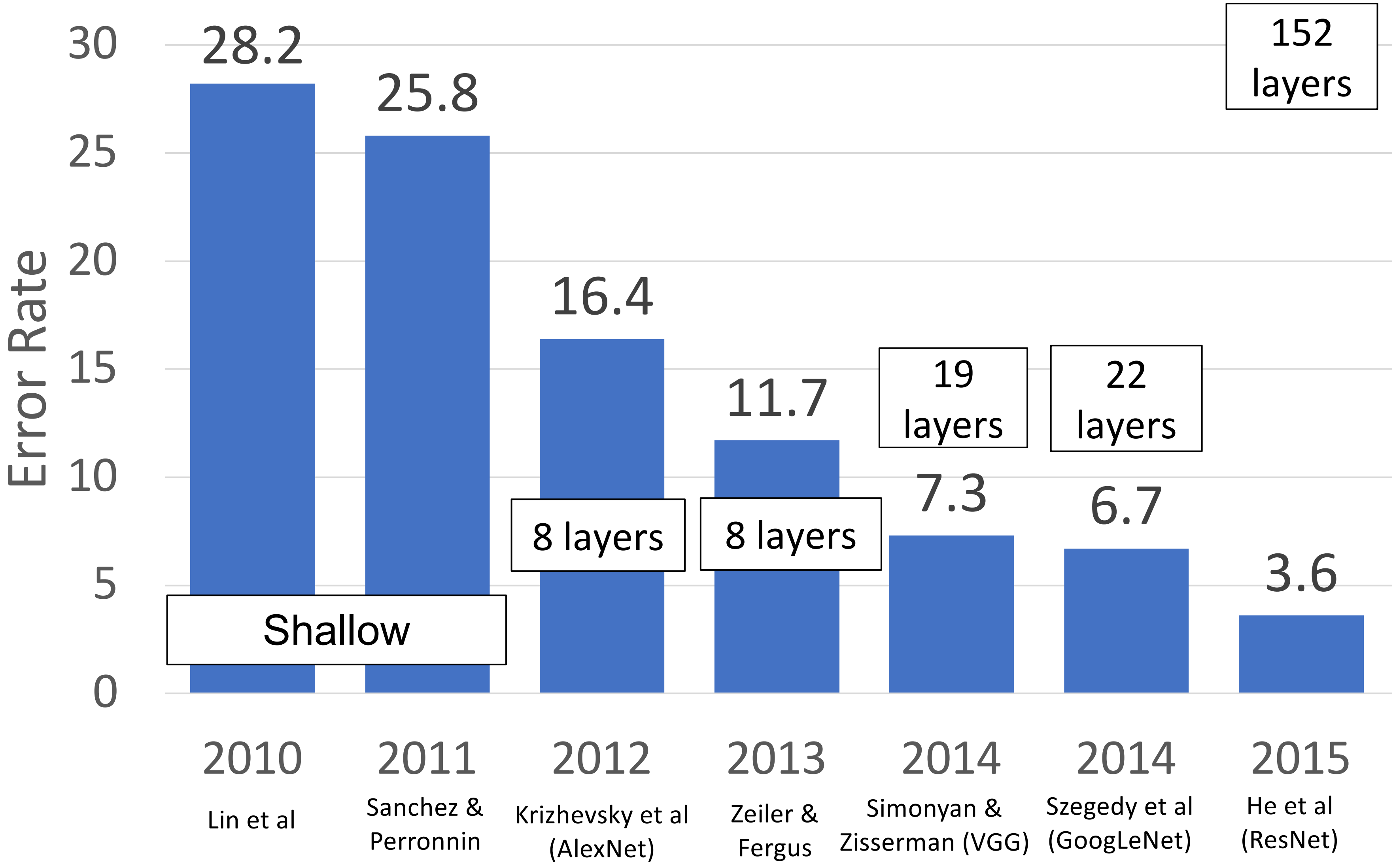


GoogLeNet

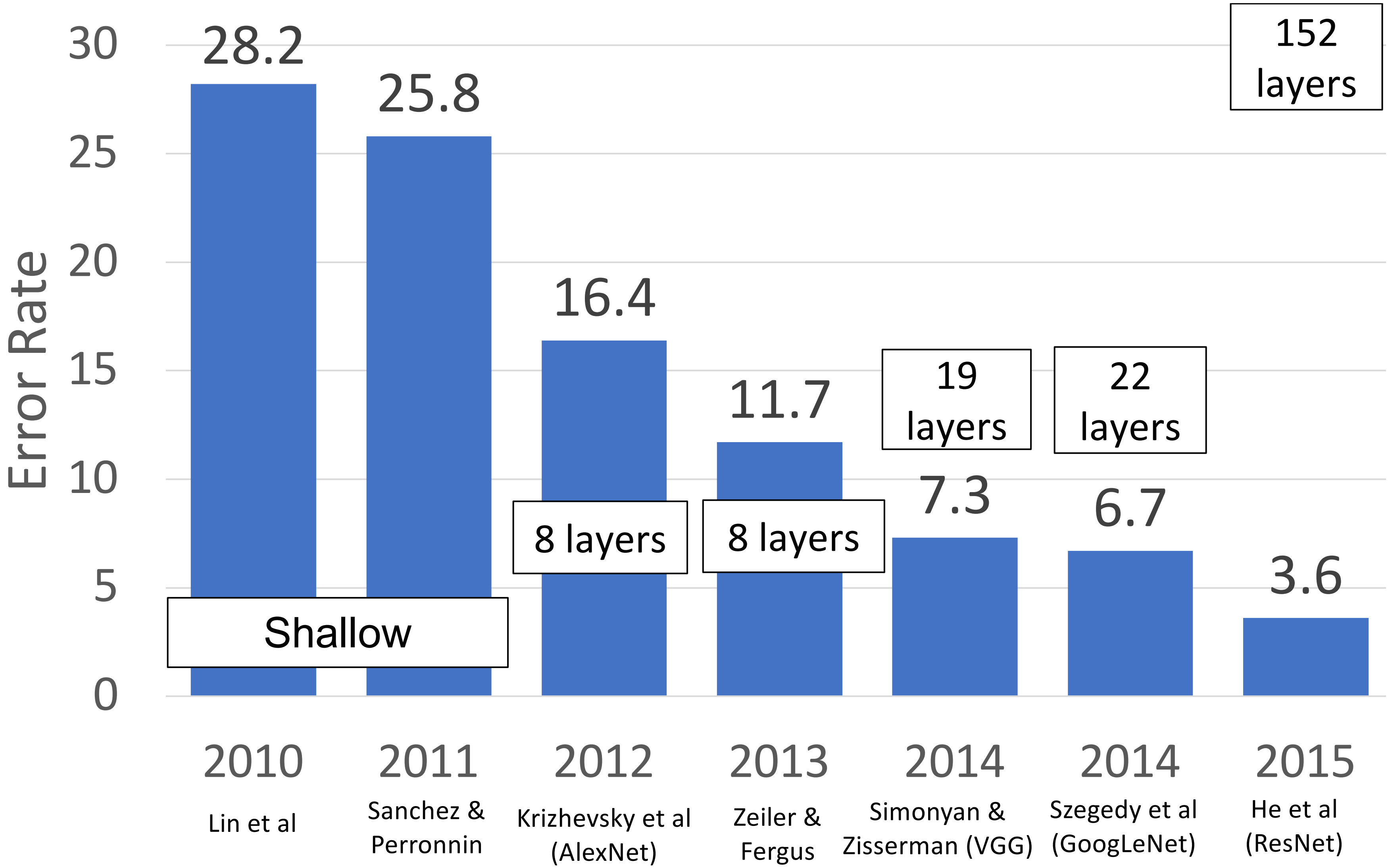


ResNet

ImageNet Classification Challenge



ImageNet Classification Challenge

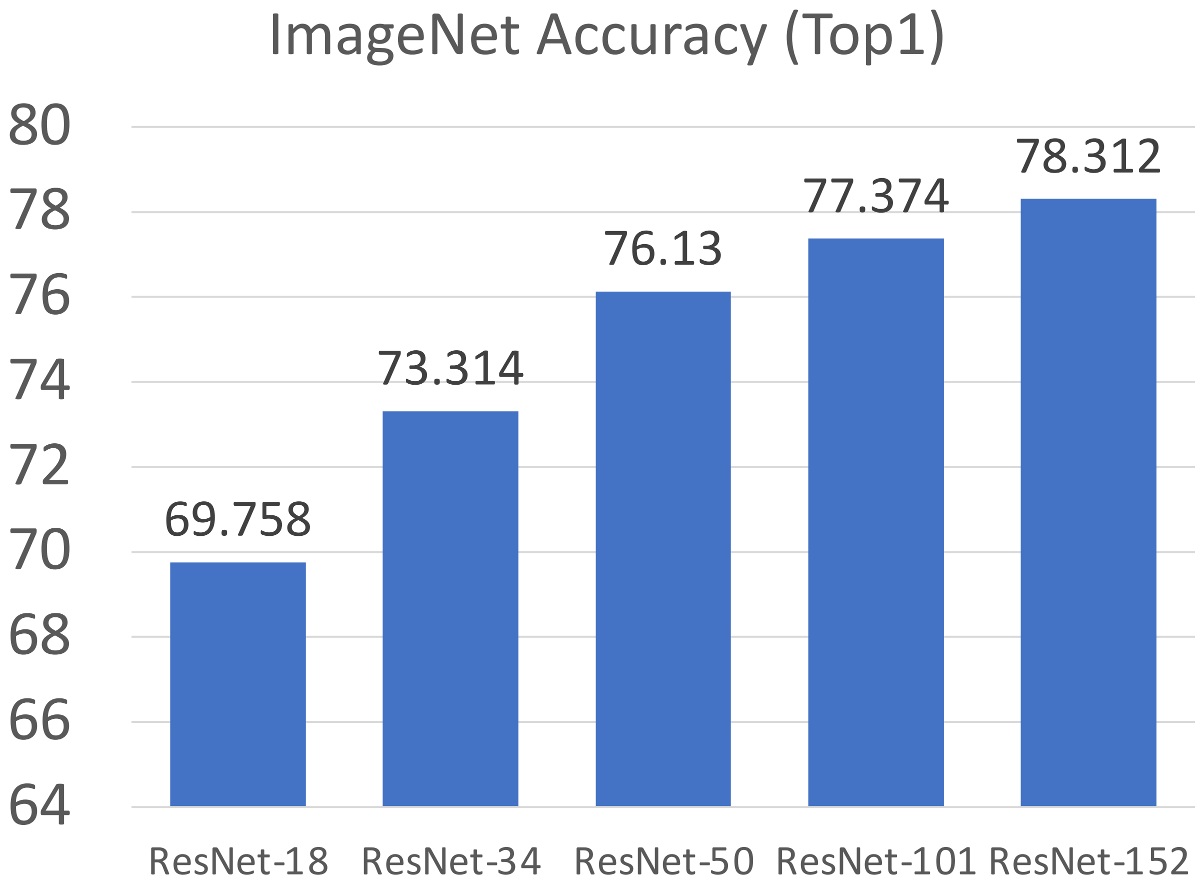


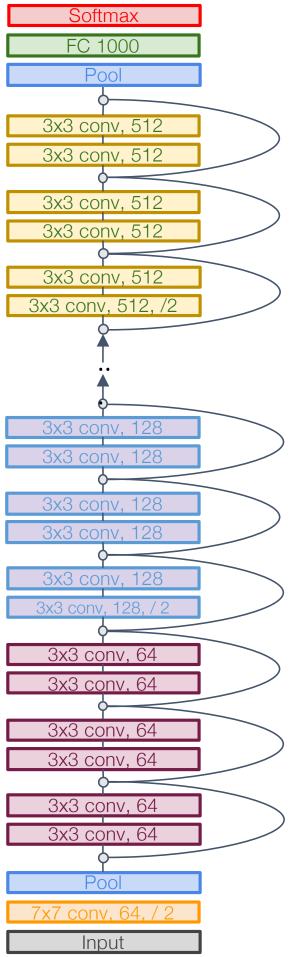
Today:
More recent CNN architectures

Post-ResNet Architectures

ResNet made it possible to increase accuracy with larger, deeper models

Many followup architectures emphasize **efficiency**: can we improve accuracy while controlling for model "complexity"?





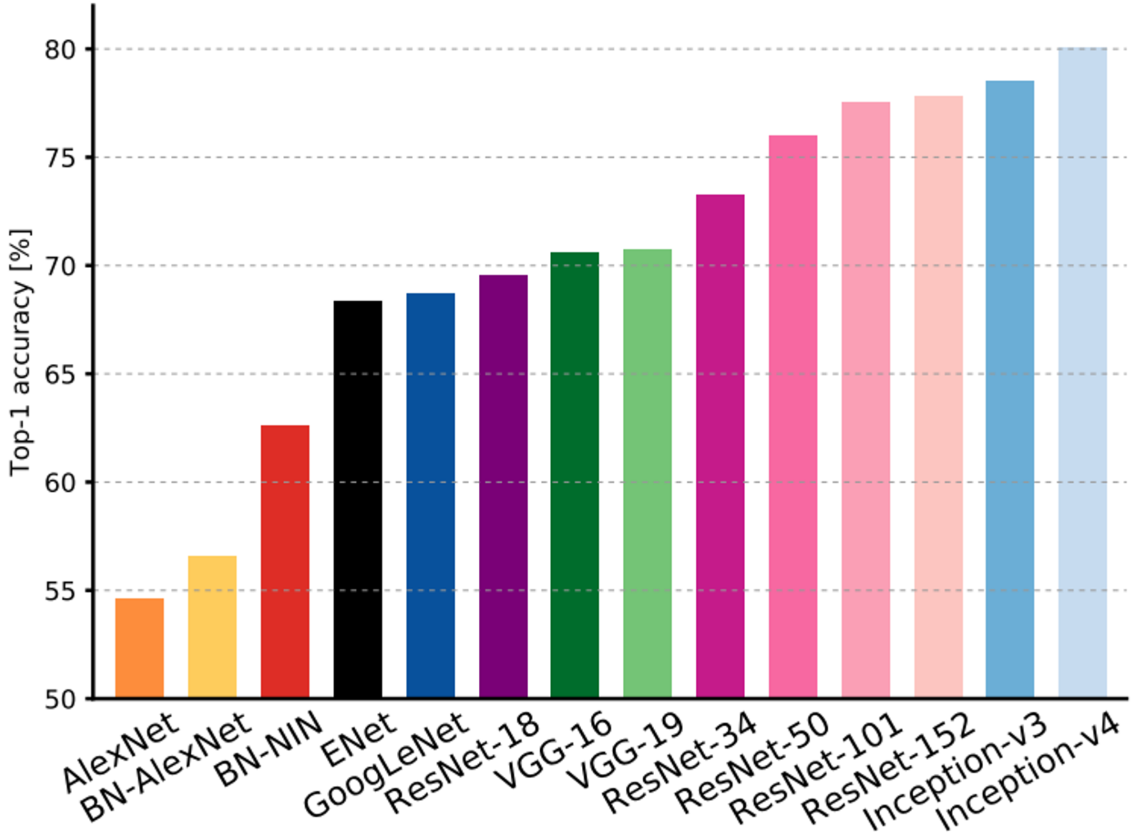
Measures of Model Complexity

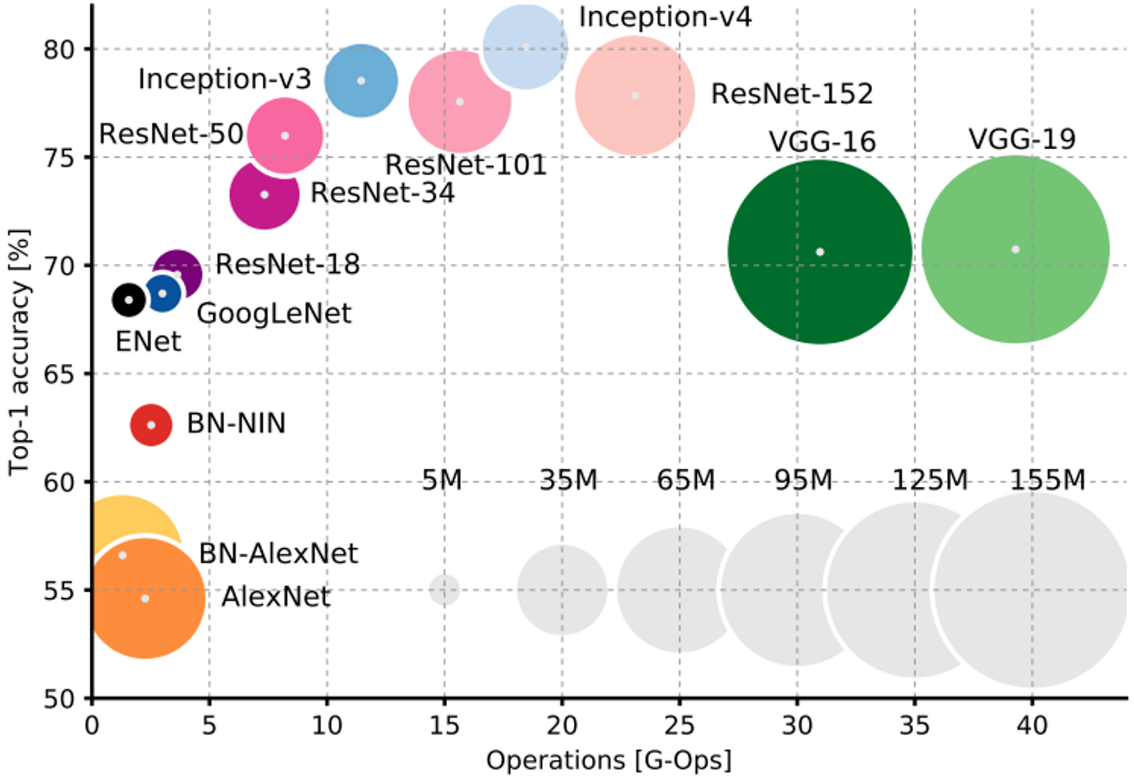
Parameters: How many learnable parameters does the model have?

Floating Point Operations (FLOPs): How many arithmetic operations does it take to compute the forward pass of the model?
Watch out, lots of subtlety here:
- Many papers only count operations in conv layers (ignore ReLU, pooling, BatchNorm)
  Most papers use "1 FLOP" = "1 multiply and 1 addition" so dot product of two N-dim vectors takes N FLOPs; some papers say MADD or MACC instead of FLOP
- Other sources (e.g. NVIDIA marketing material) count "1 multiply and one addition" = 2 FLOPs, so dot product of two N-dim vectors takes 2N FLOPs

Network Runtime: How long does a forward pass of the model take on real hardware?

Comparing Complexity



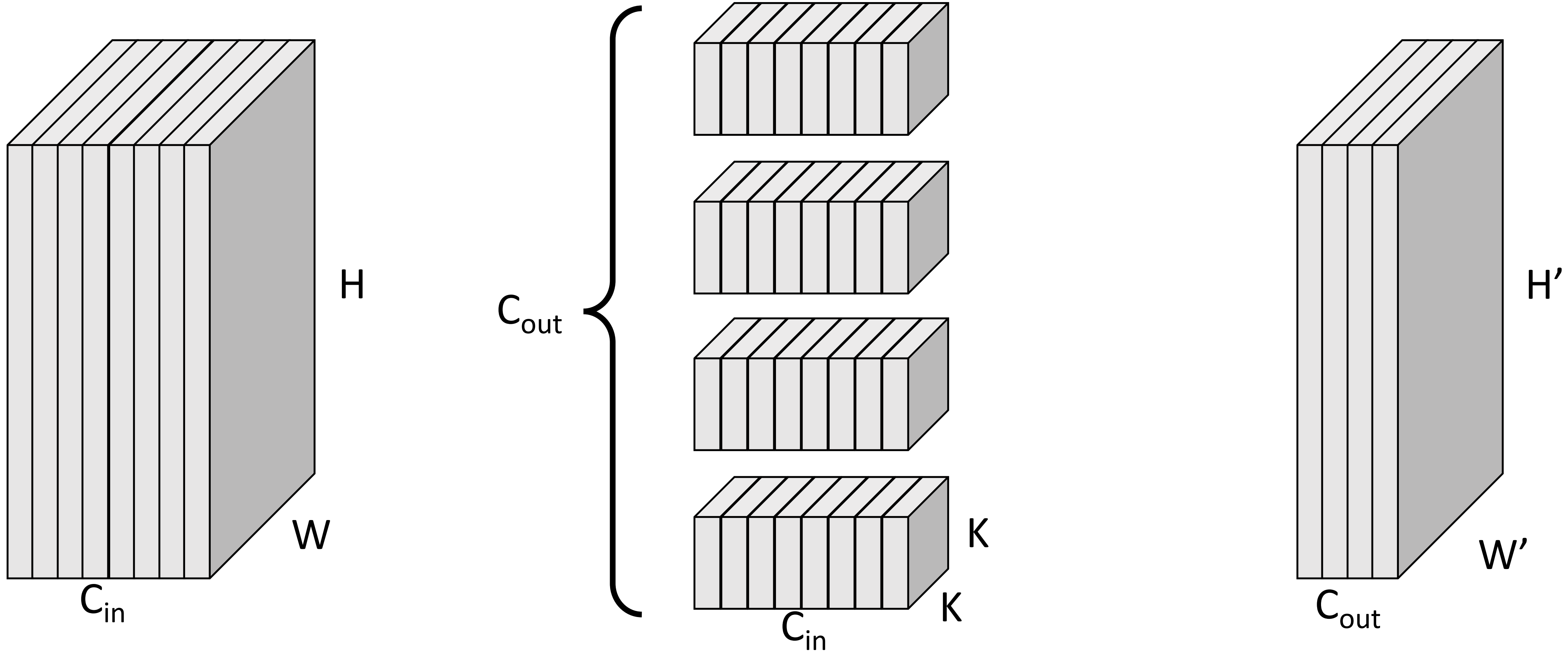


Canziani et al, "An analysis of deep neural network models for practical applications", 2017

Key ingredient:
Grouped / Separable convolution

Recall: Convolution Layer

Each filter has the same number of channels as the input



Input: C_{in} x H x W

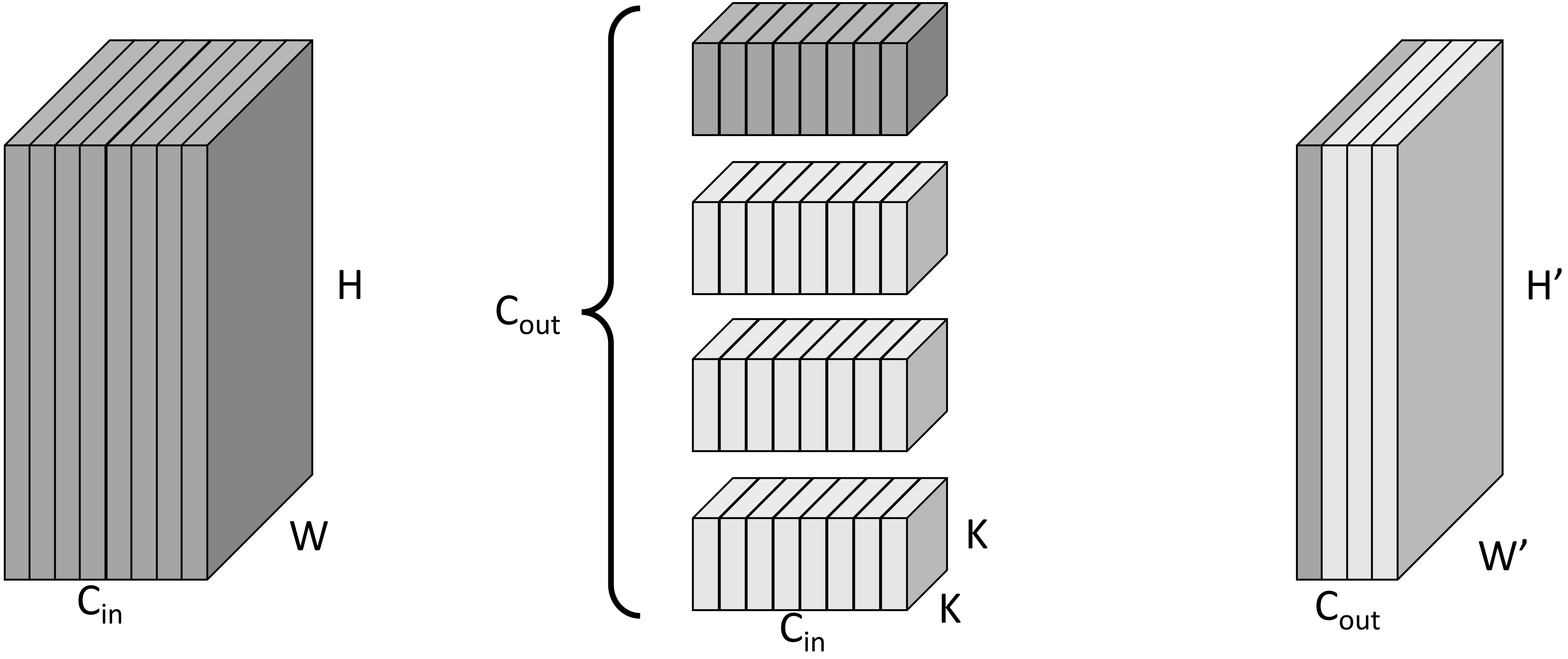
Weights: C_{out} x C_{in} x K x K

Output: C_{out} x H' x W'

Recall: Convolution Layer

Each filter has the same number of channels as the input

Each plane of the output depends on the full input and one filter



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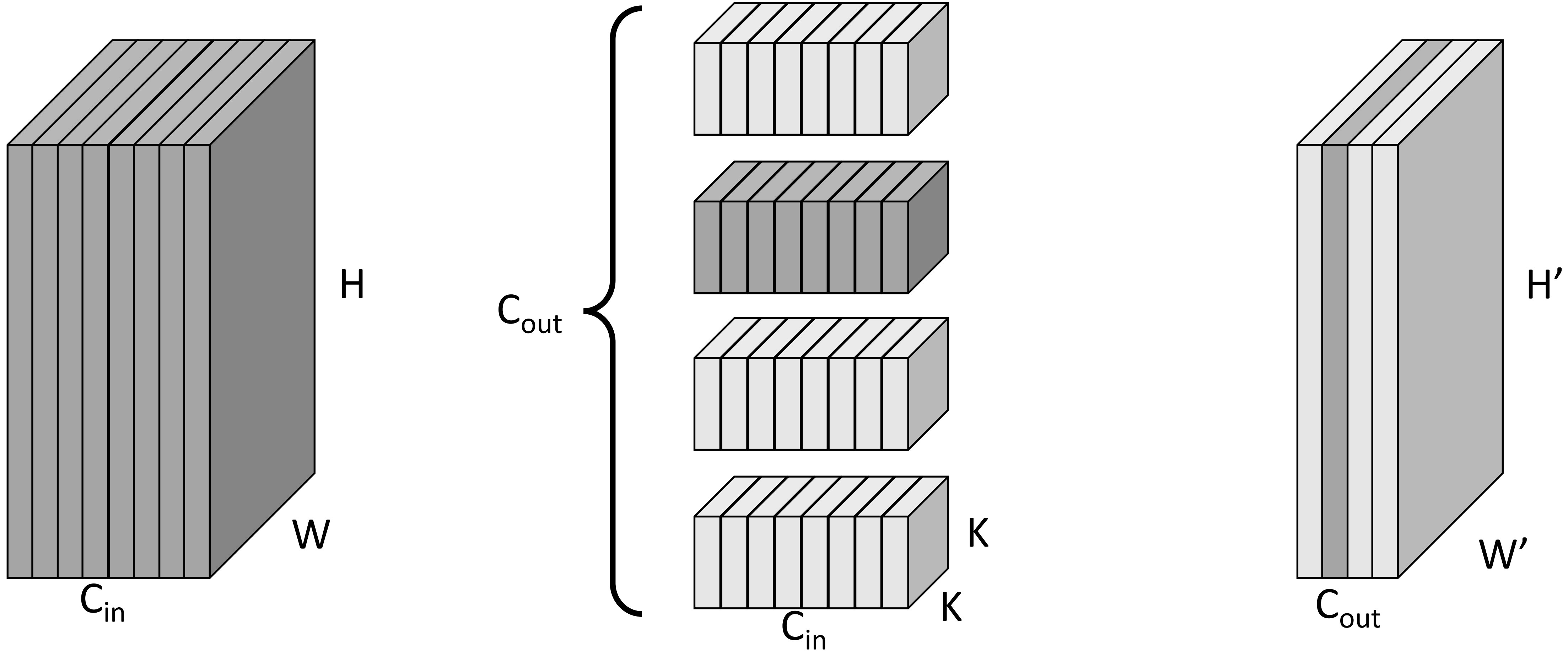

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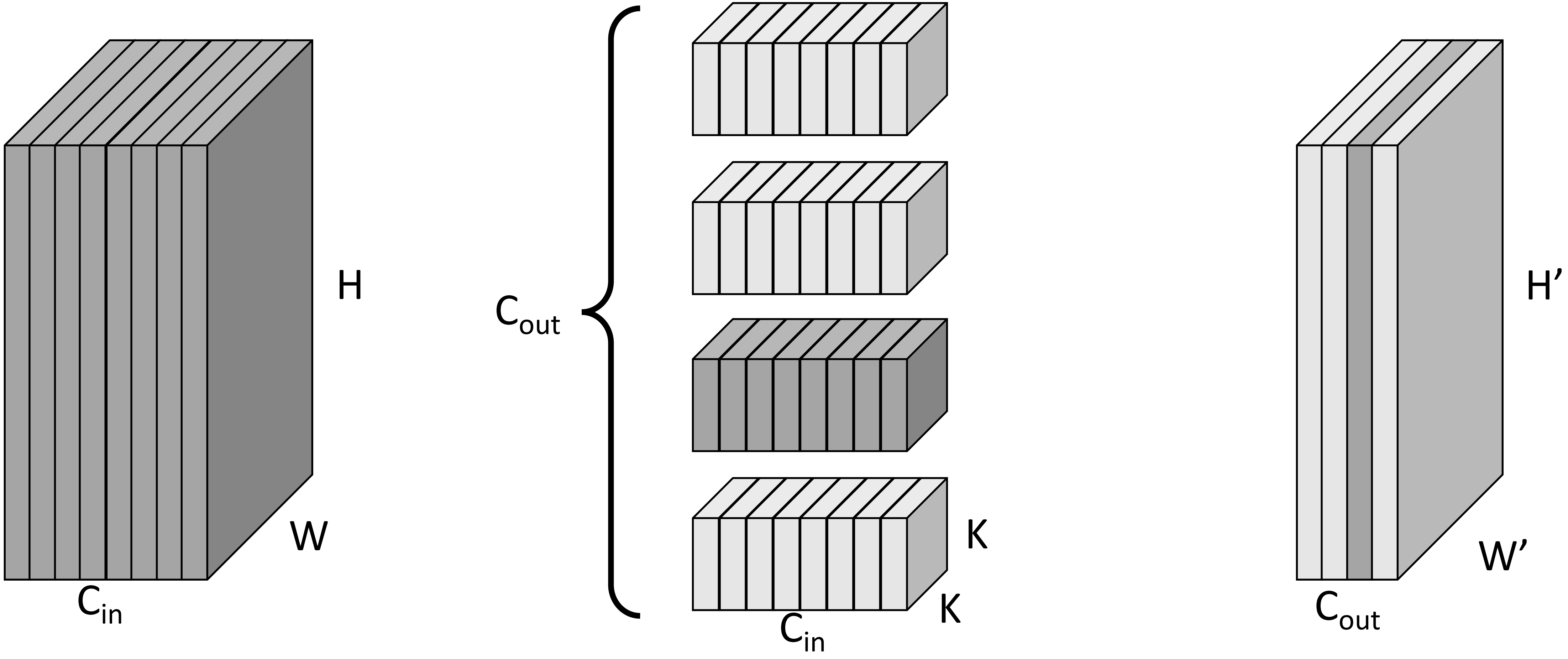

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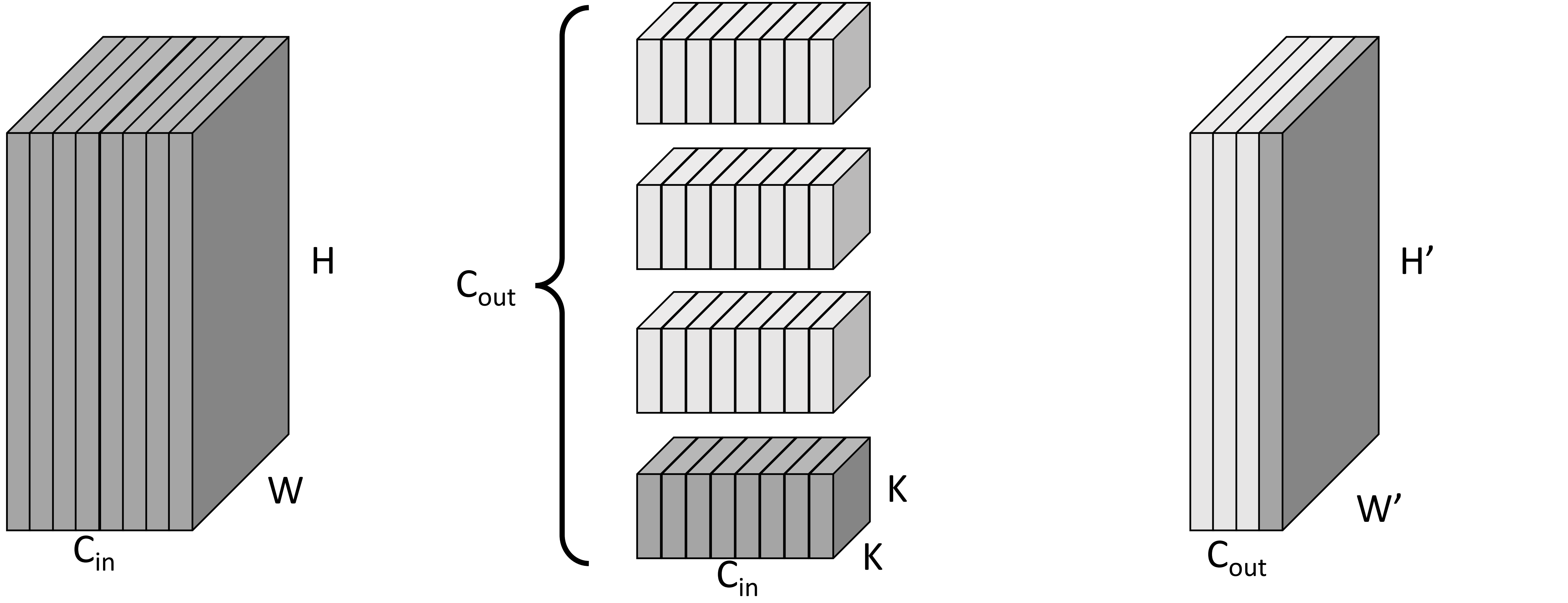

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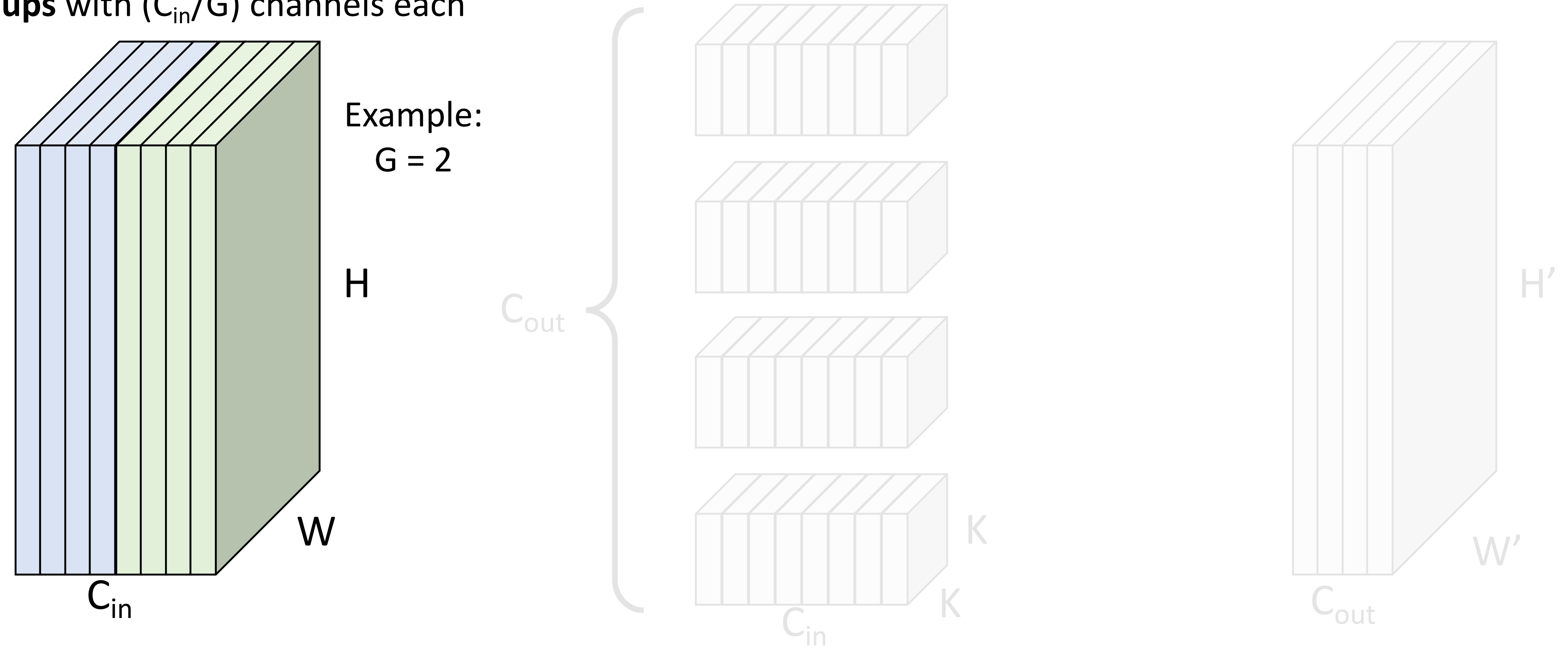
Grouped Convolution

Grouped Convolution

Divide channels of input into G **groups** with (C_{in}/G) channels each



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Grouped Convolution

Divide filters into G groups; each group looks at a **subset** of input channels

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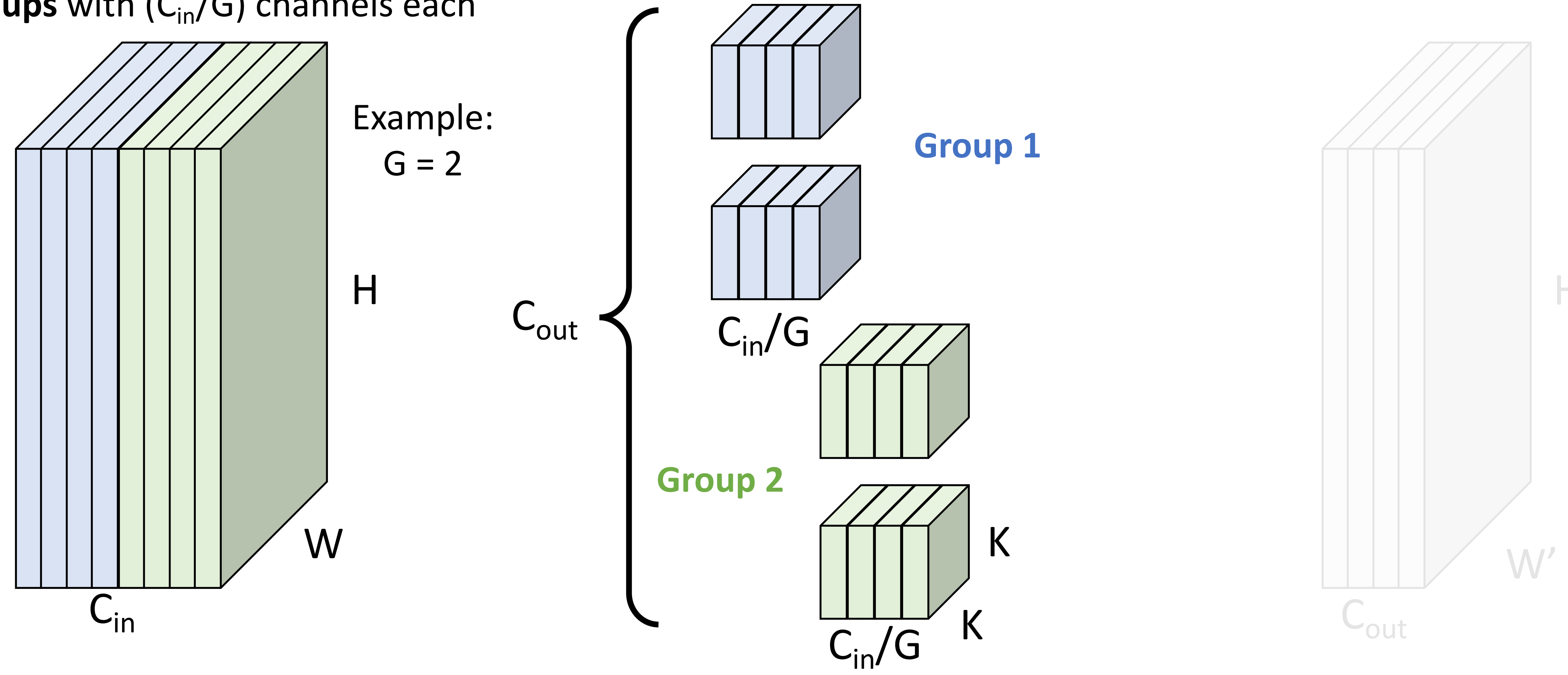

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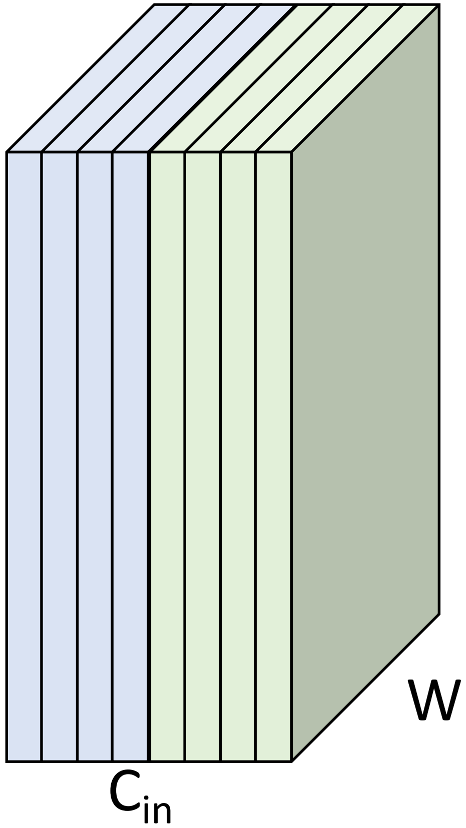
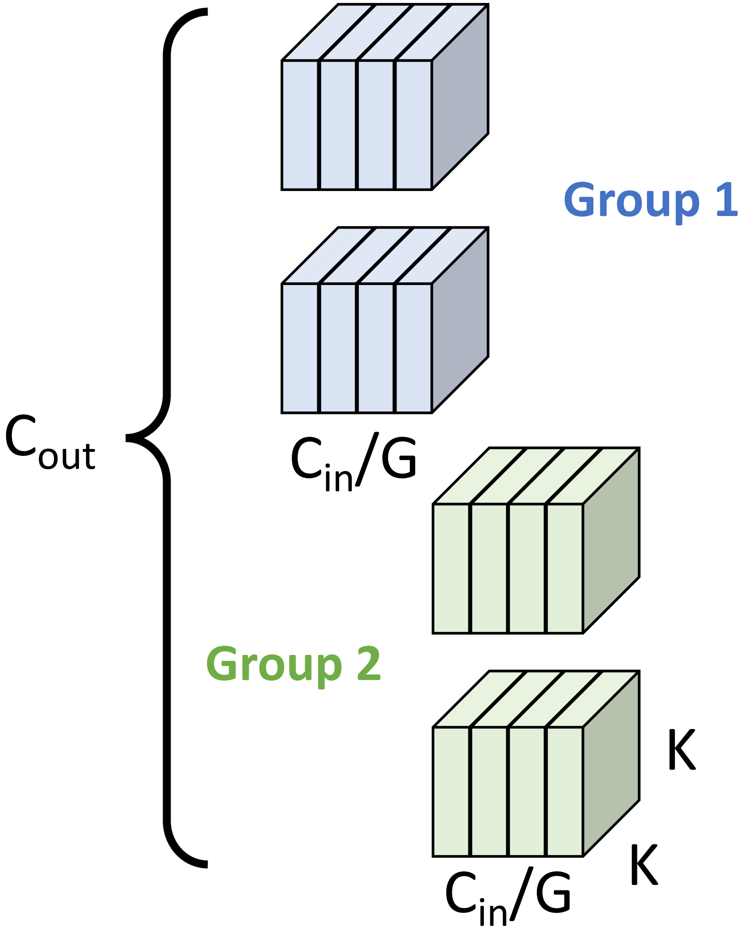
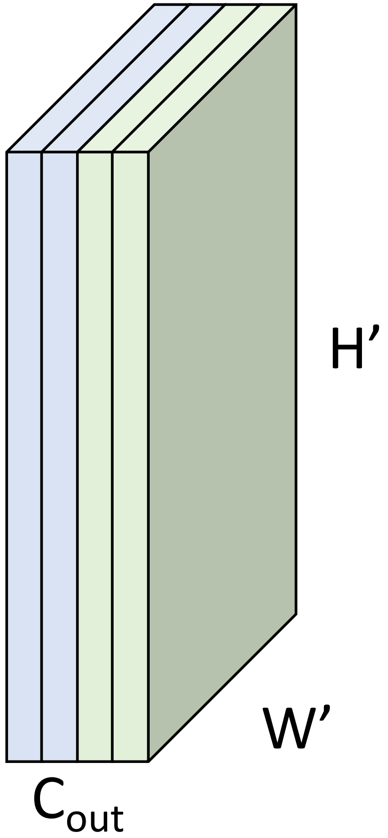


Example:
G = 2





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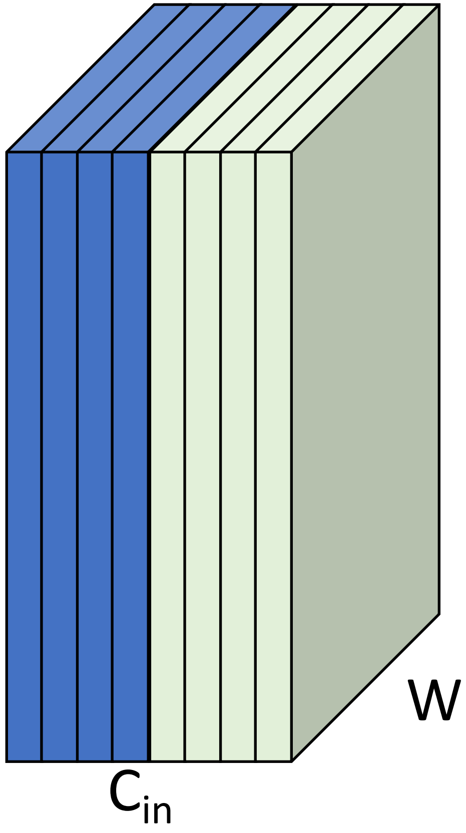

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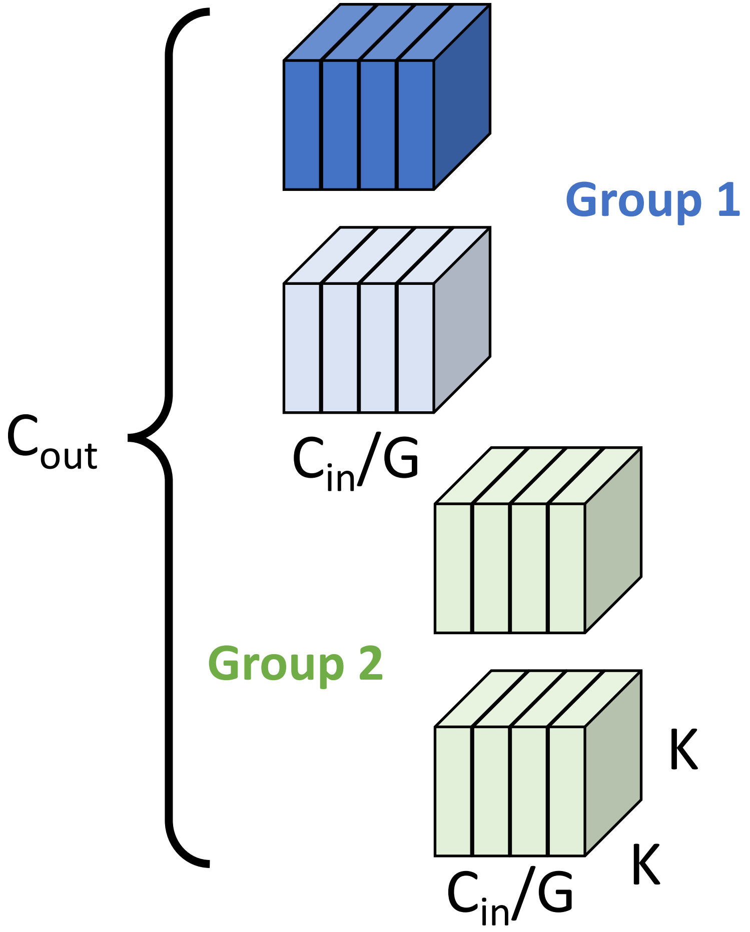

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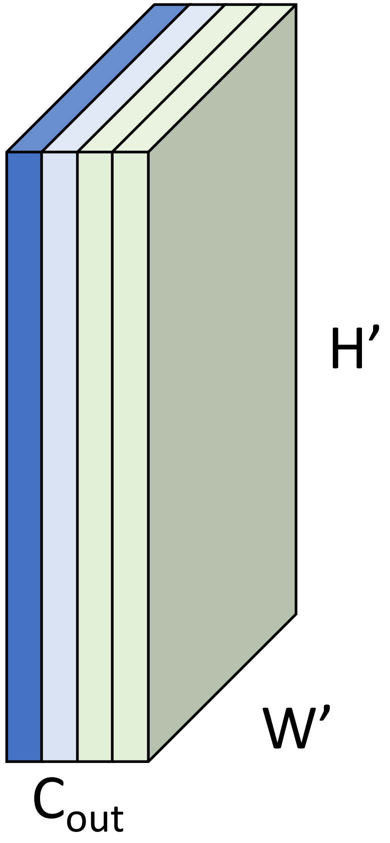

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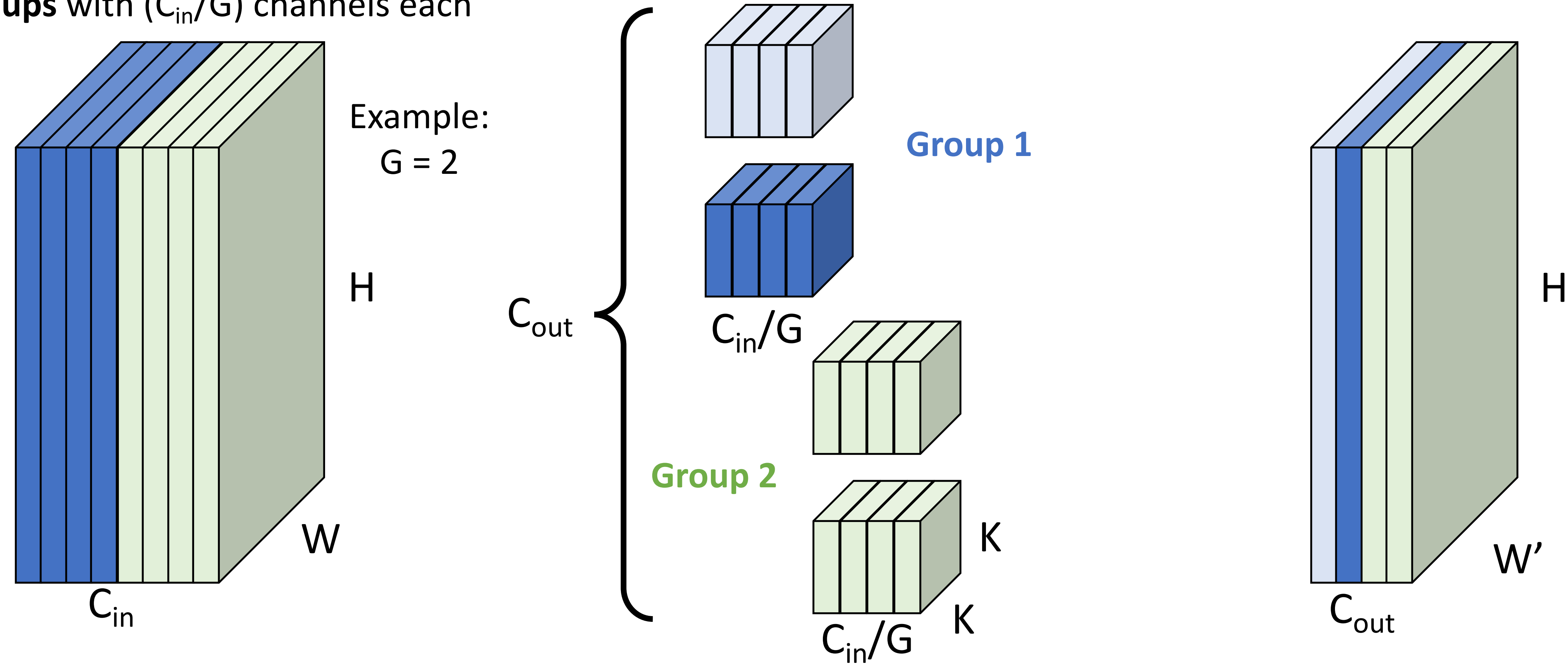

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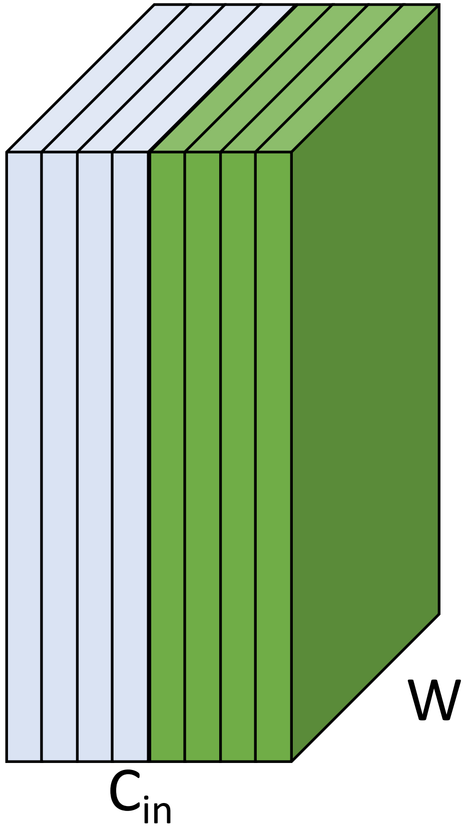

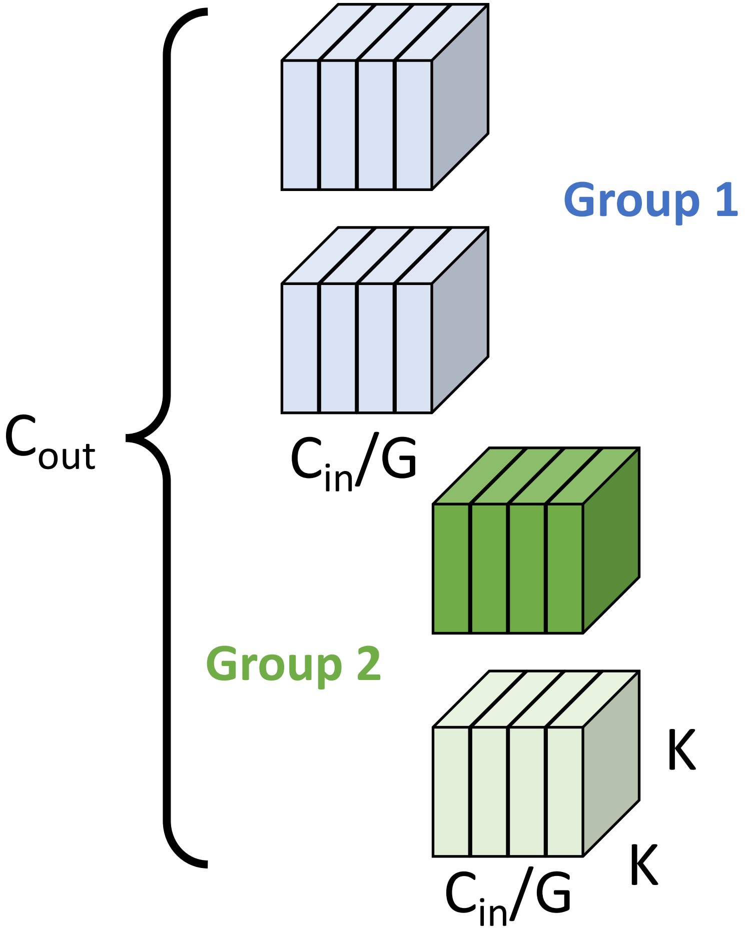

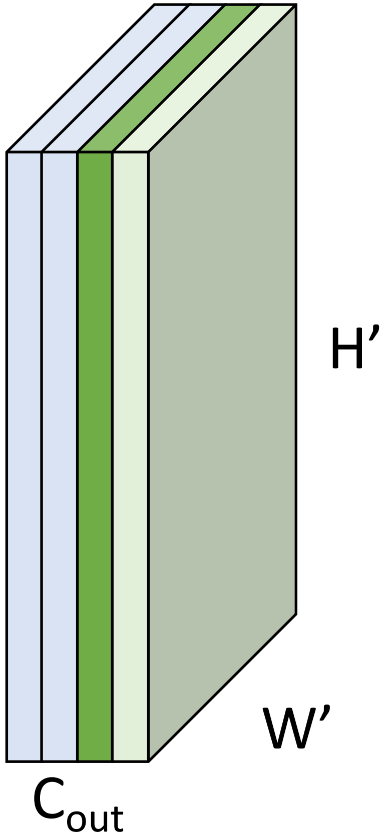

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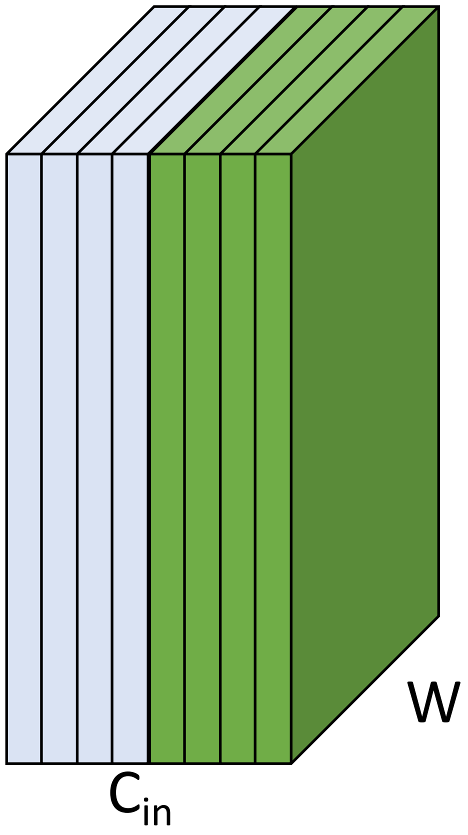

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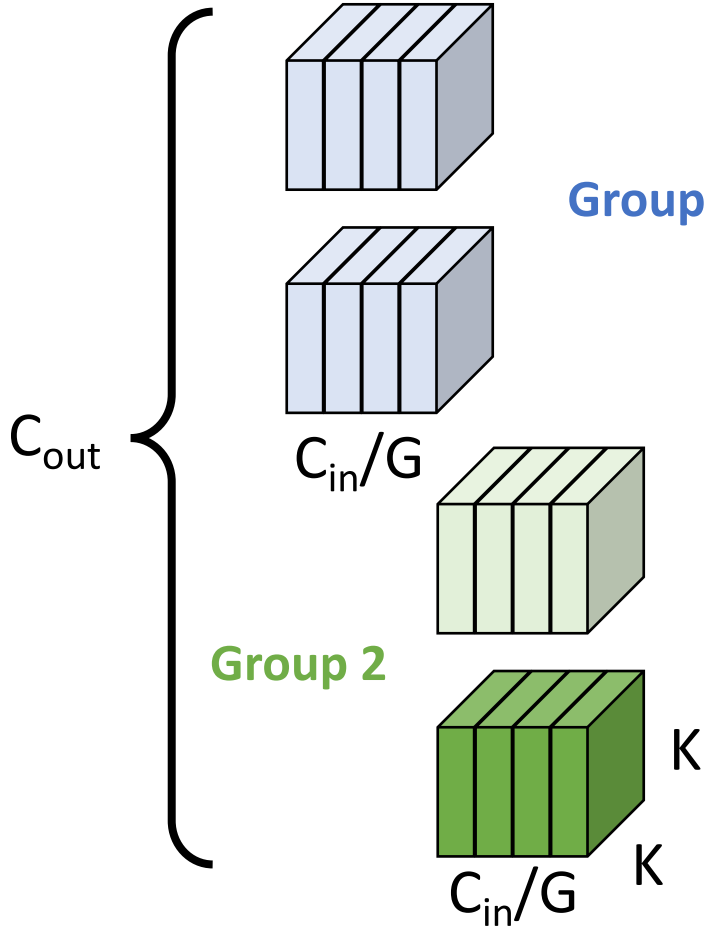

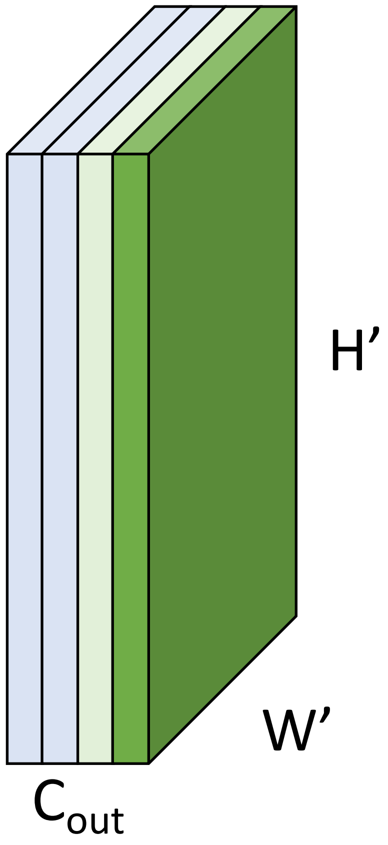

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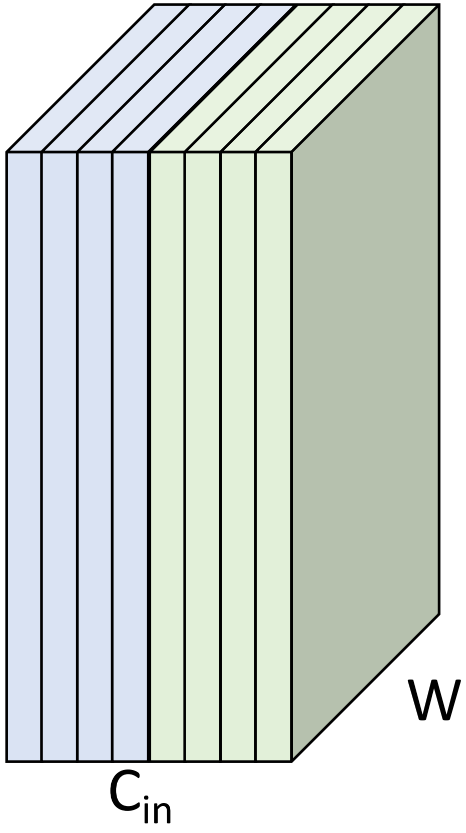

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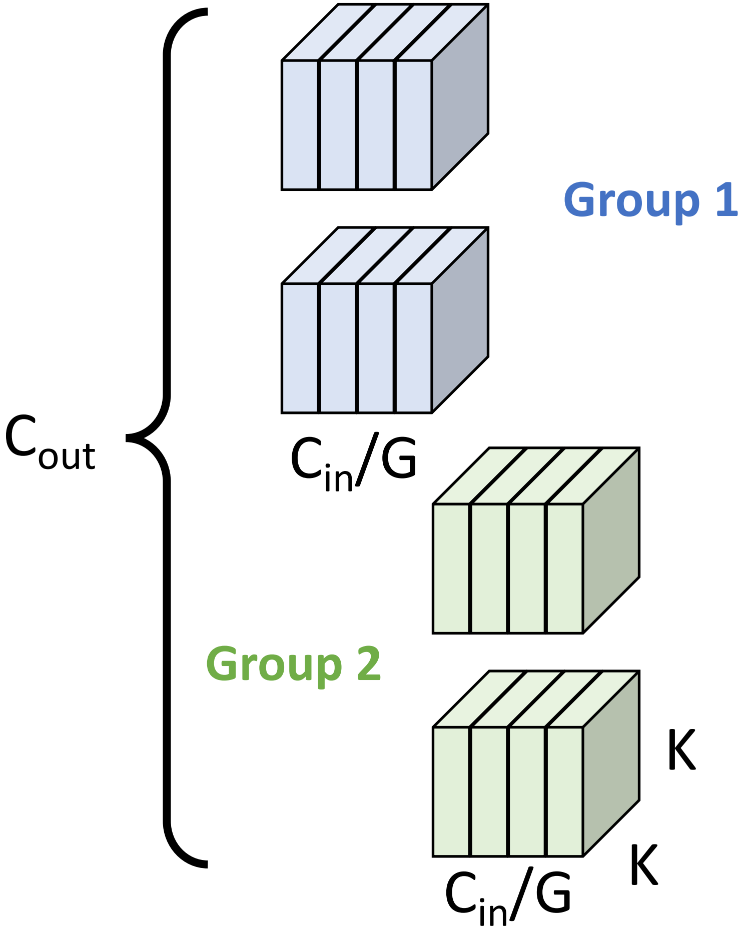

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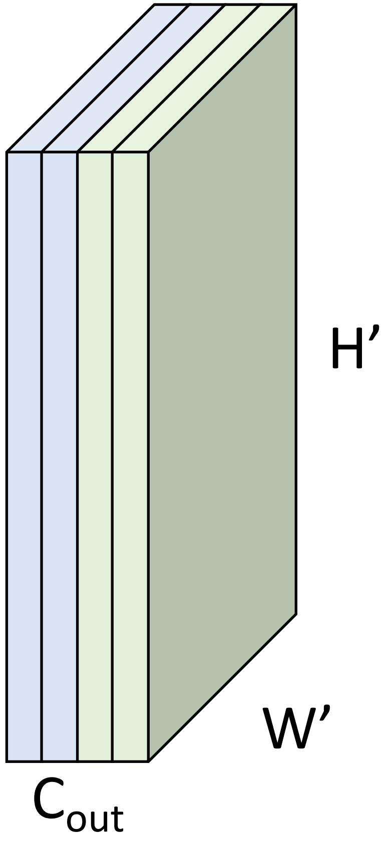

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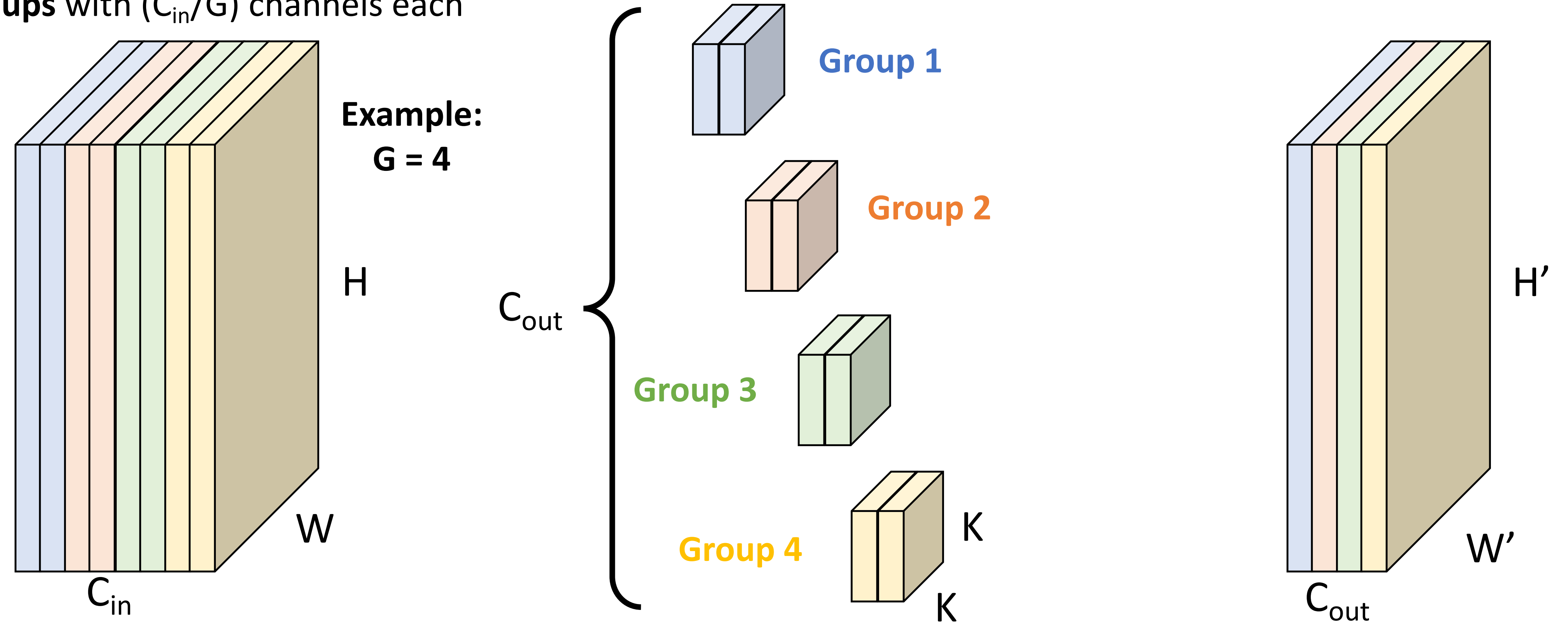


Input: C_{in} x H x W

Weights: C_{out} x (C_{in}/G) x K x K

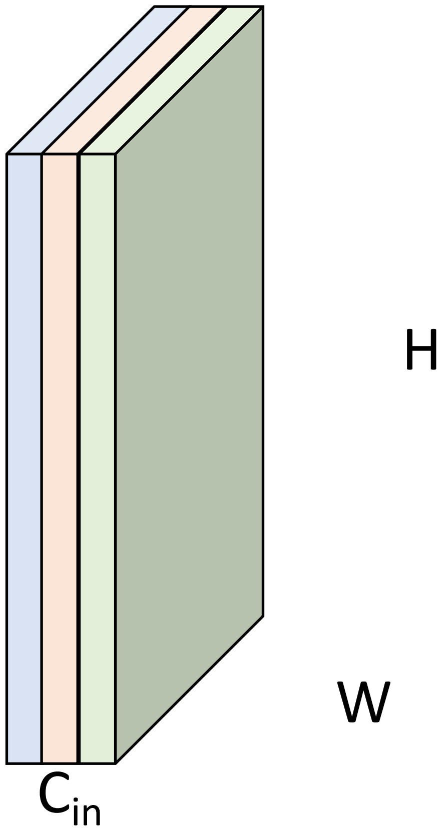
Output: C_{out} x H' x W'

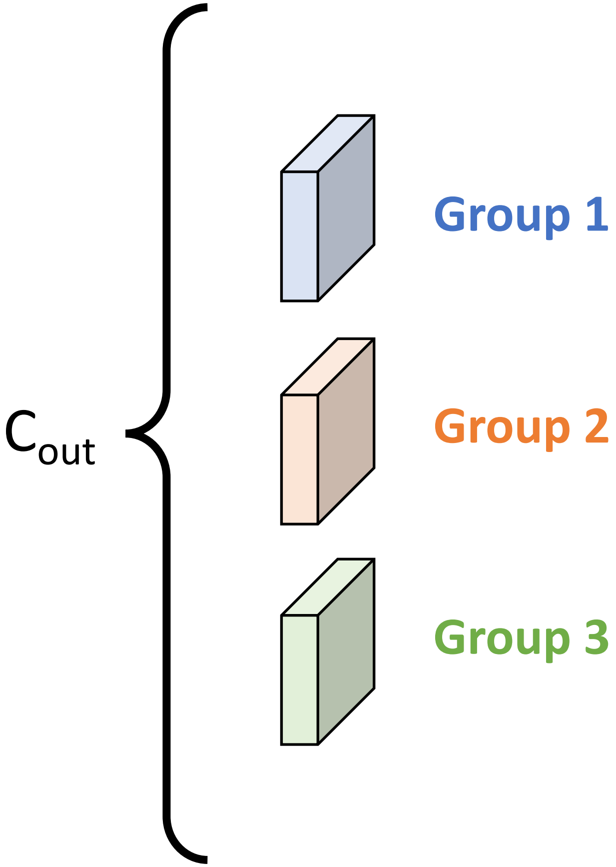
Special Case: **Depthwise Convolution**

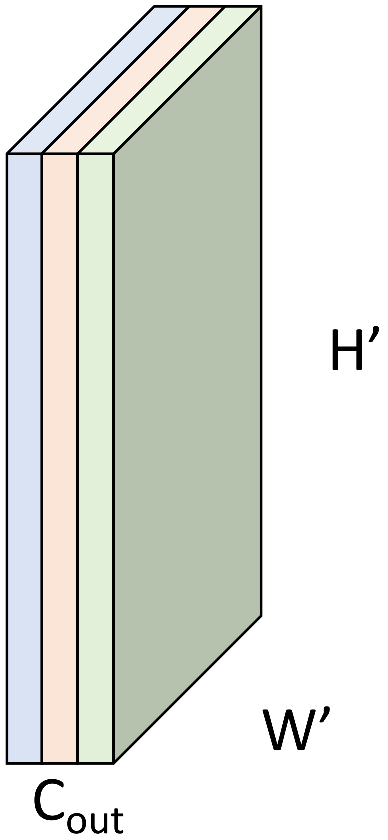
Number of groups equals number of input channels

Common to also set $C_{out} = G$

Output only mixes *spatial* information from input; *channel* information not mixed







Input: C_{in} x H x W

Weights: C_{out} x 1 x K x K

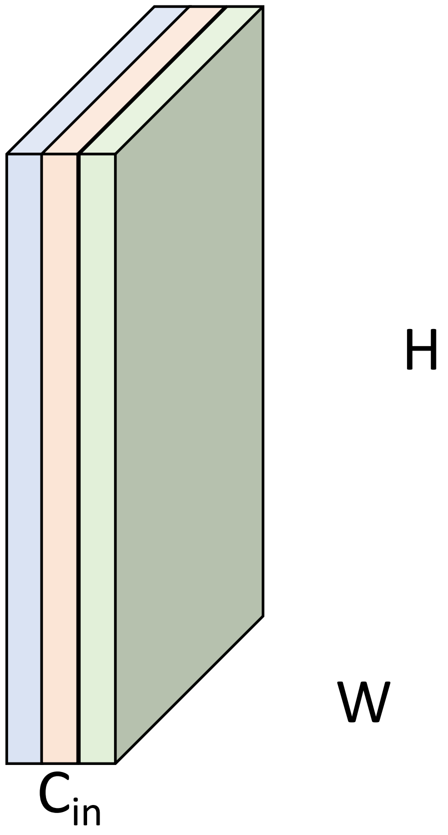
Output: C_{out} x H’ x W’

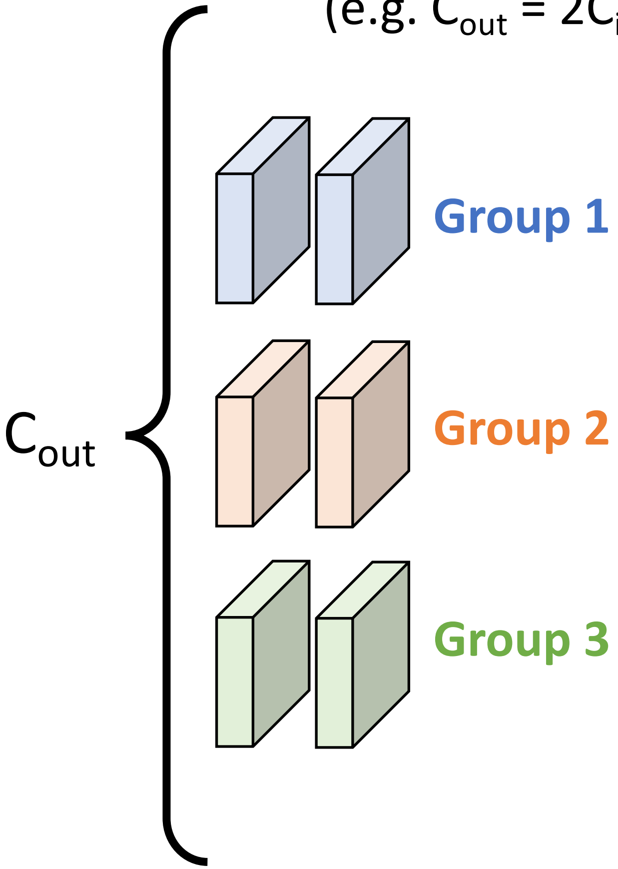
Special Case: **Depthwise Convolution**

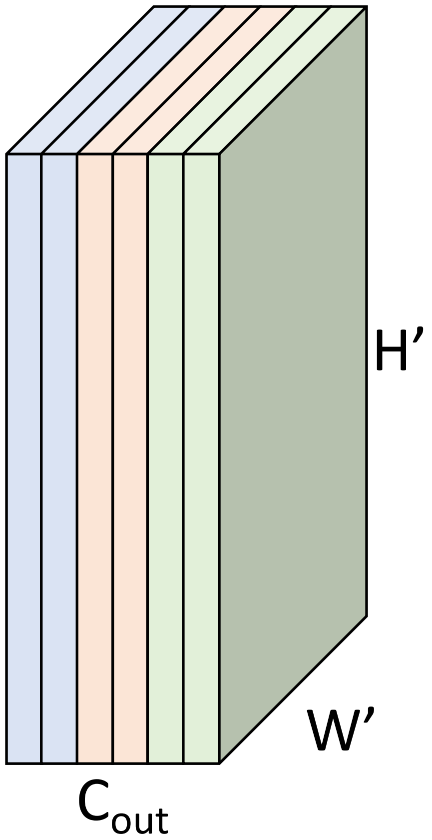
Output only mixes *spatial* information from input; *channel* information not mixed

Number of groups equals number of input channels

Can still have multiple filters per group (e.g. $C_{out} = 2C_{in}$)







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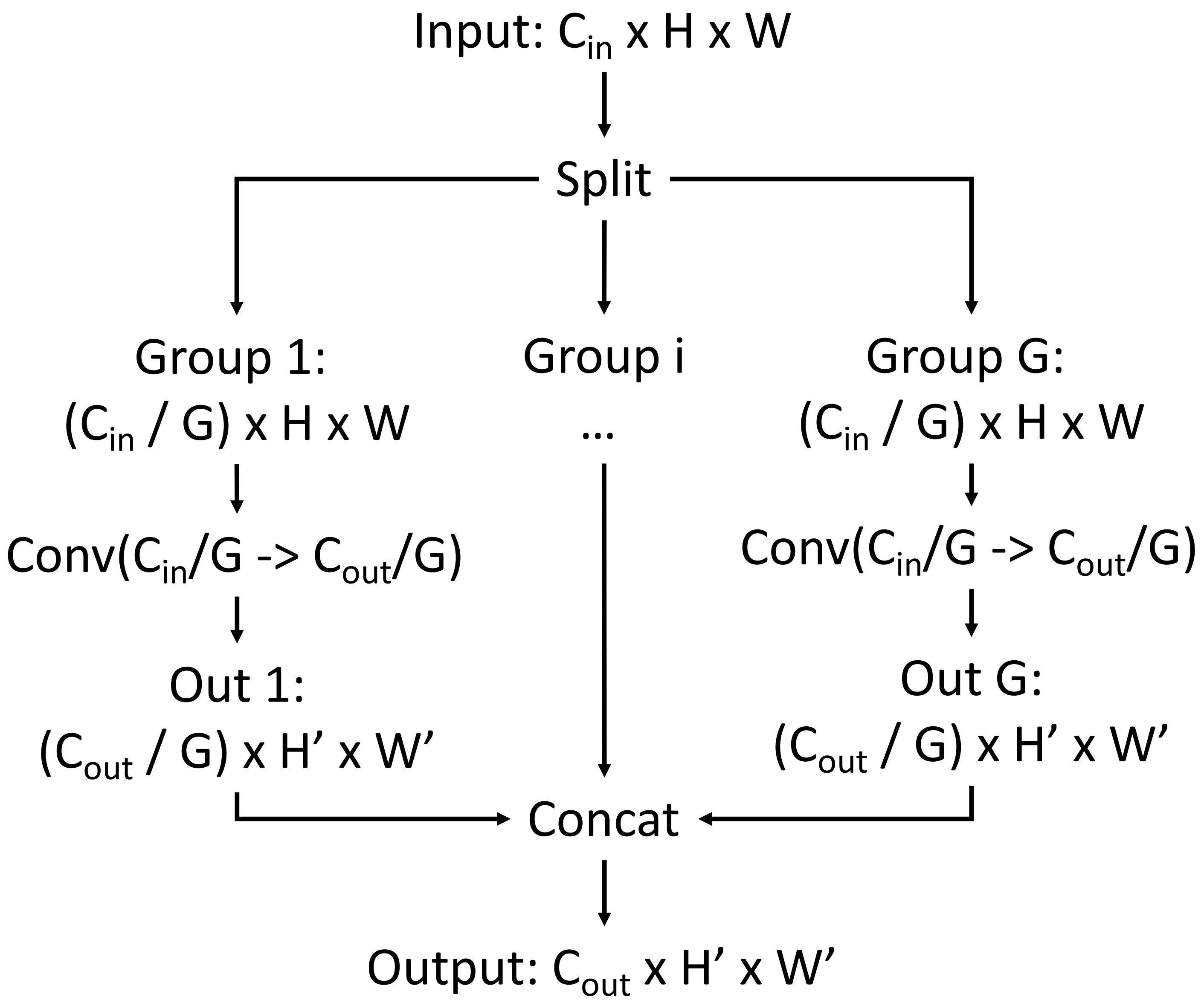
Output: C_{out} x H’ x W’

Grouped Convolution

<u>Grouped Convolution (G groups)</u>:
G parallel conv layers; each “sees” C_{in}/G input channels and produces C_{out}/G output channels

Input: $C_{in} \times H \times W$
Split to $G \times [(C_{in} / G) \times H \times W]$
Weight: $G \times (C_{out} / G) \times (C_{in} / G) \times K \times K$
G parallel convolutions
Output: $G \times [(C_{out} / G) \times H' \times W']$
Concat to $C_{out} \times H' \times W'$
FLOPs: $C_{out}C_{in}K^2HW/G$



Grouped Convolution vs Standard Convolution

<u>Grouped Convolution (G groups)</u>:
G parallel conv layers; each "sees" C_{in}/G input channels and produces C_{out}/G output channels

Input: C_{in} x H x W
Split to G x [(C_{in} / G) x H x W]
Weight: G x (C_{out} / G) x (C_{in} x G) x K x K
G parallel convolutions
Output: G x [(C_{out} / G) x H' x W']
Concat to C_{out} x H' x W'
FLOPs: $C_{out}C_{in}K^2HW/G$

<u>Standard Convolution (groups=1)</u>

Input: C_{in} x H x W
Weight: C_{out} x C_{in} x K x K
Output: C_{out} x H' x W'
FLOPs: $C_{out}C_{in}K^2HW$

All convolutional kernels touch all C_{in} channels of the input

Using G groups reduces FLOPs by a factor of G!

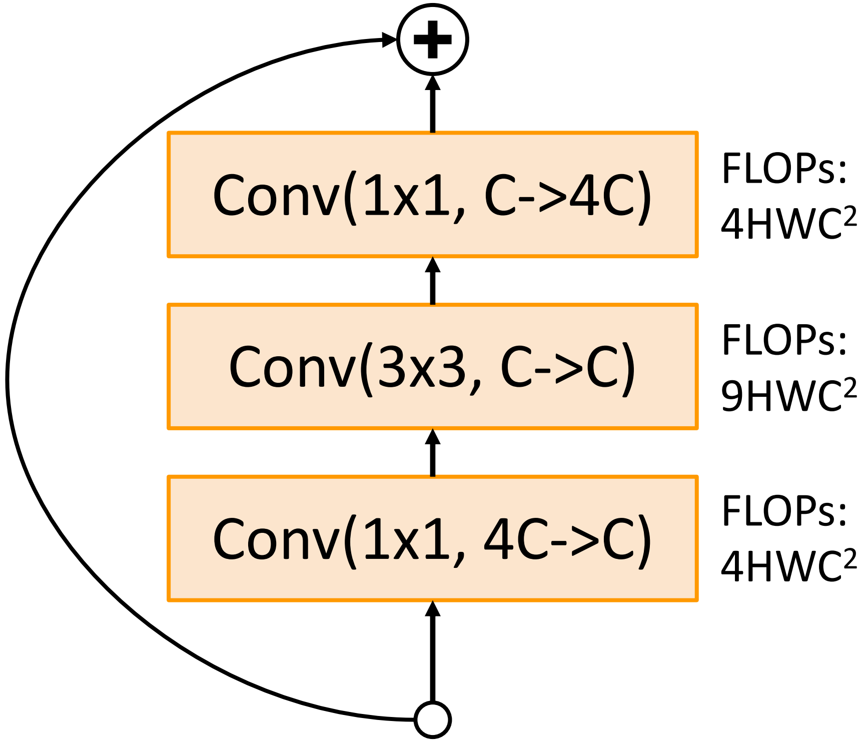
Grouped Convolution in PyTorch

PyTorch convolution gives an option for groups!

Conv2d

CLASS `torch.nn.Conv2d(in_channels, out_channels, kernel_size, stride=1, padding=0, dilation=1, groups=1, bias=True, padding_mode='zeros')` [SOURCE]

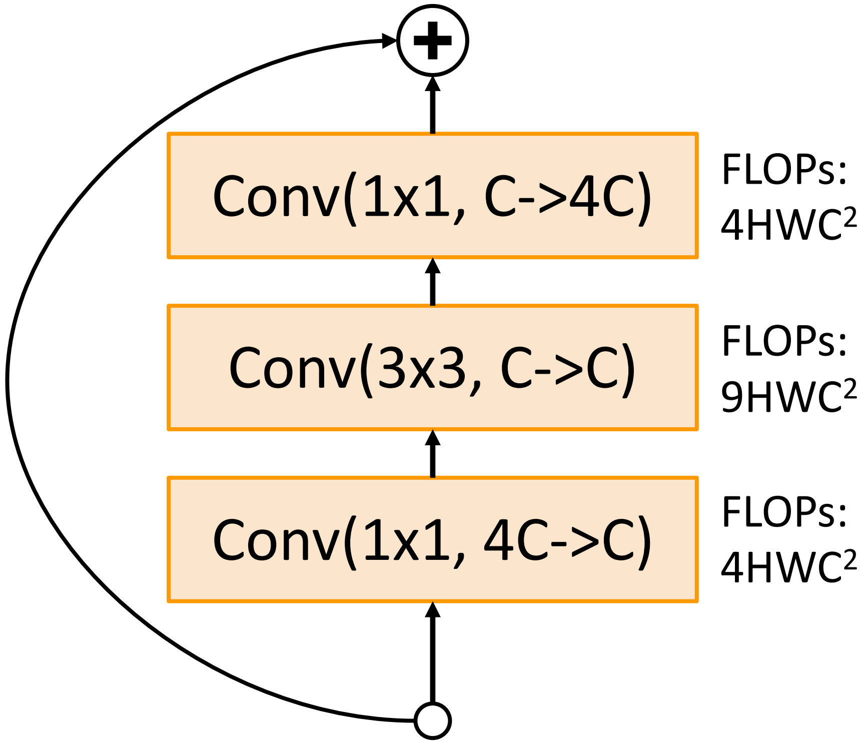
Improving ResNets



"Bottleneck"
Residual block

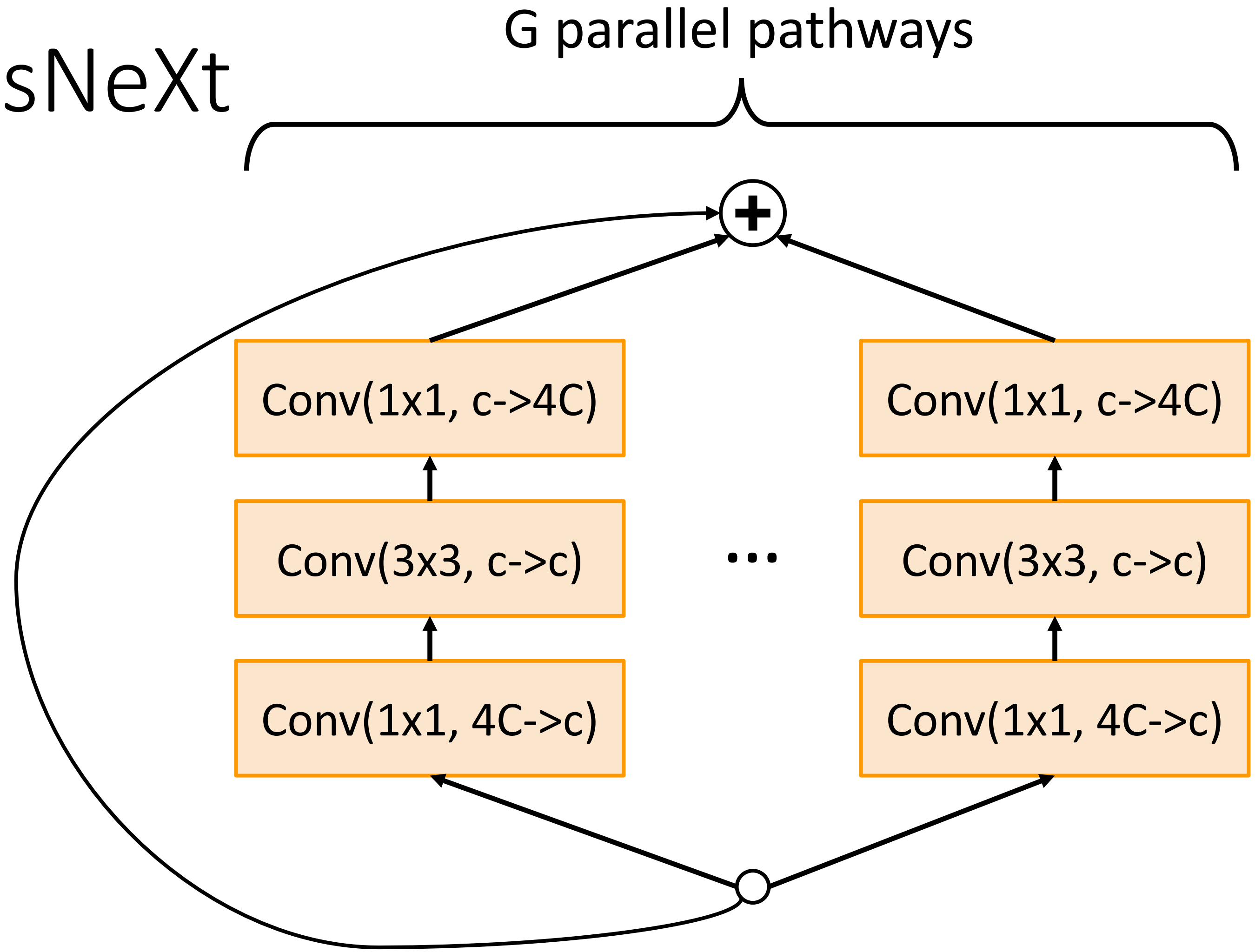
Total FLOPs:
$17HWC^2$

Improving ResNets: ResNeXt



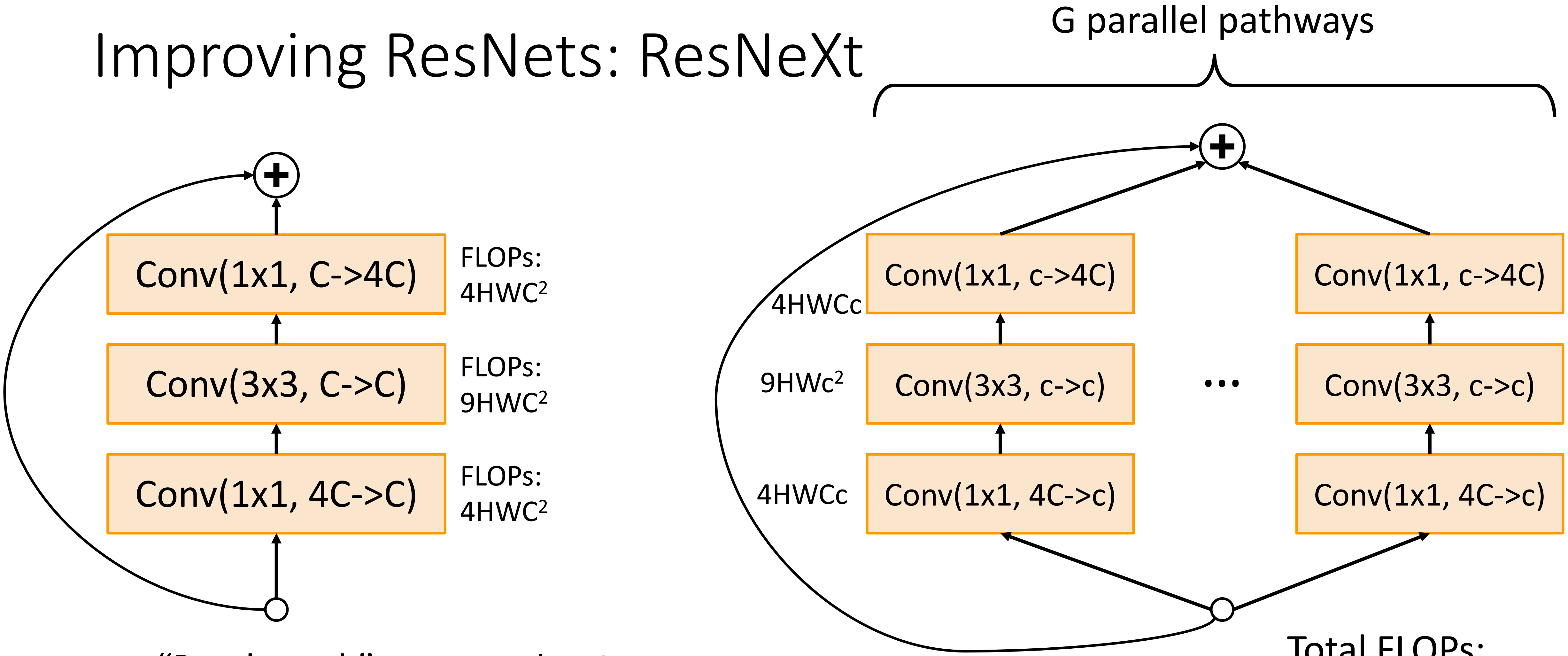
“Bottleneck” Residual block

Total FLOPs: $17HWC^2$



Xie et al, “Aggregated residual transformations for deep neural networks”, CVPR 2017

Improving ResNets: ResNeXt



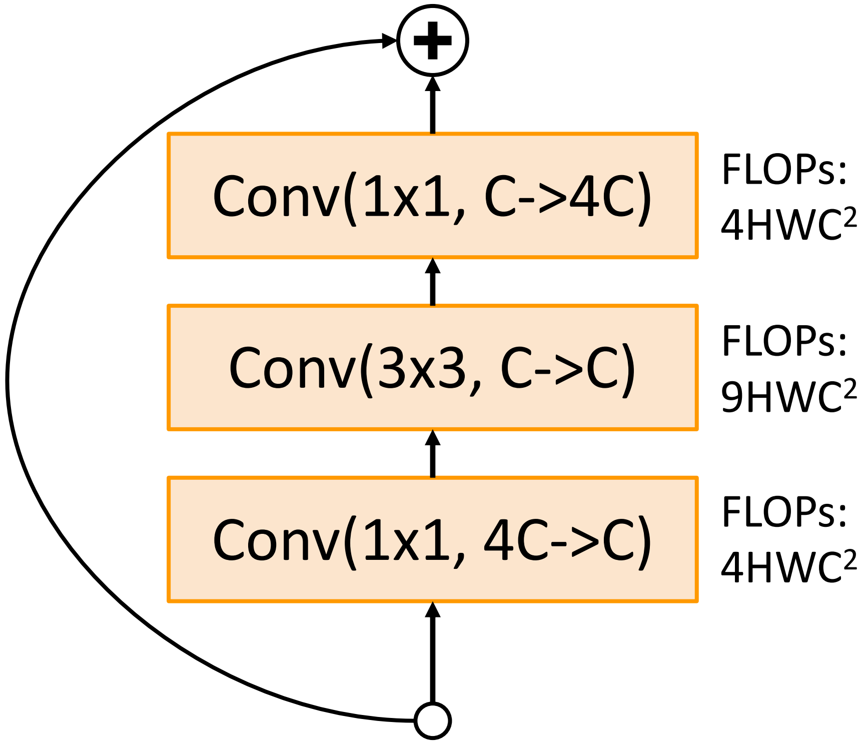
"Bottleneck" Residual block

Total FLOPs: $17HWC^2$

Total FLOPs: $(8Cc + 9c^2)*HWG$

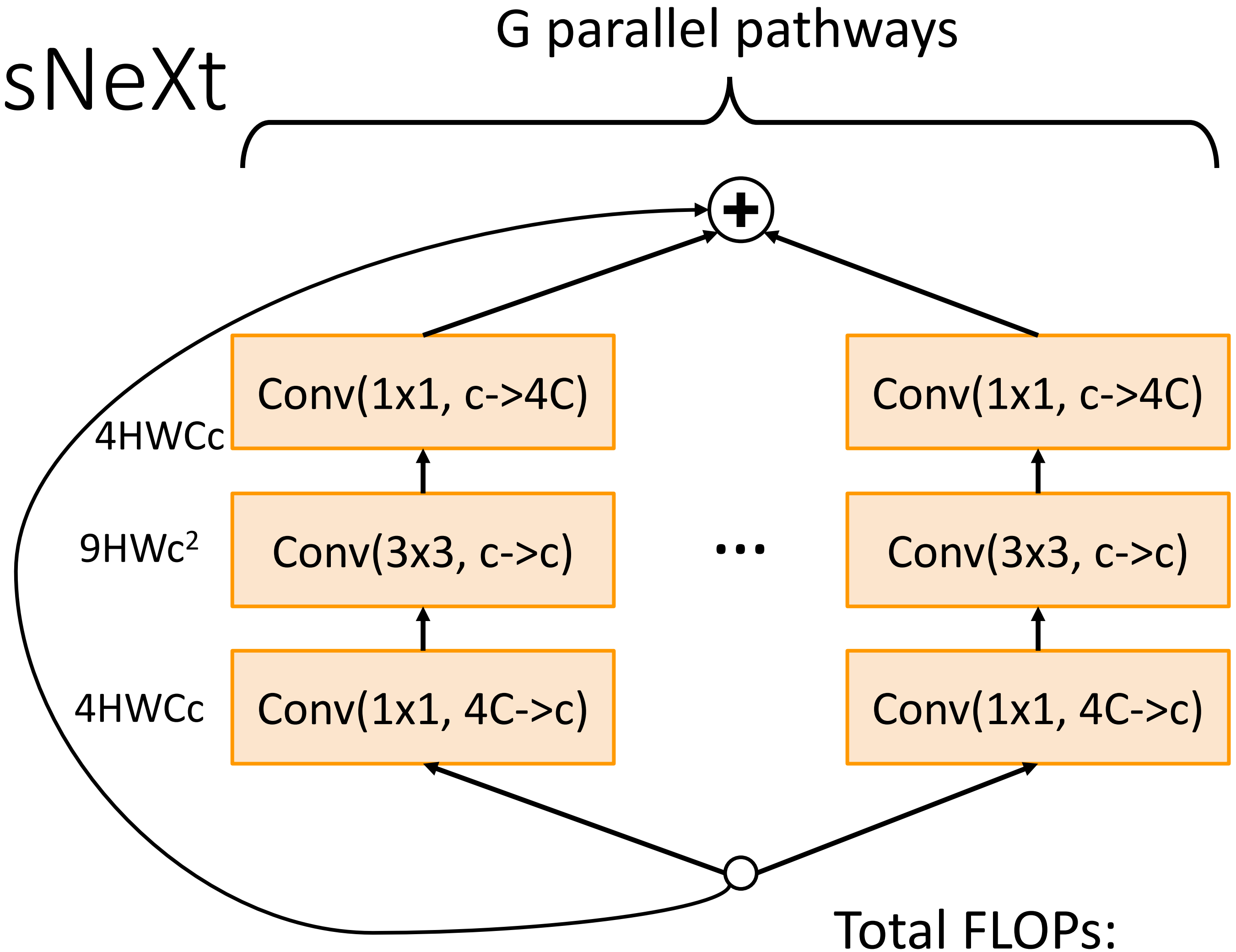
Xie et al, "Aggregated residual transformations for deep neural networks", CVPR 2017

Improving ResNets: ResNeXt



“Bottleneck” Residual block

Total FLOPs: $17HWC^2$



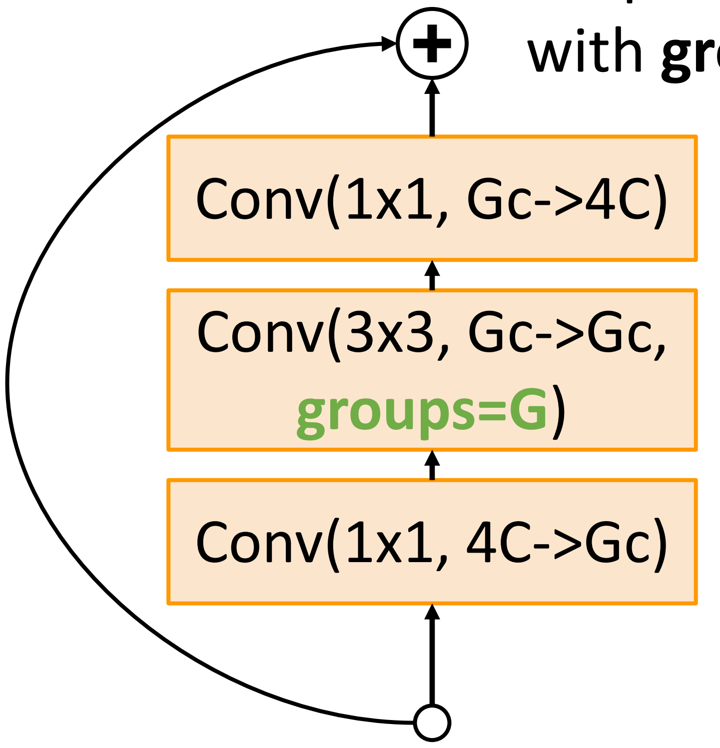
Total FLOPs: $(8Cc + 9c^2)*HWG$

Same FLOPs when $9Gc^2 + 8GCc - 17C^2 = 0$

Example: C=64, G=4, c=24; C=64, G=32, c=4

Xie et al, “Aggregated residual transformations for deep neural networks”, CVPR 2017

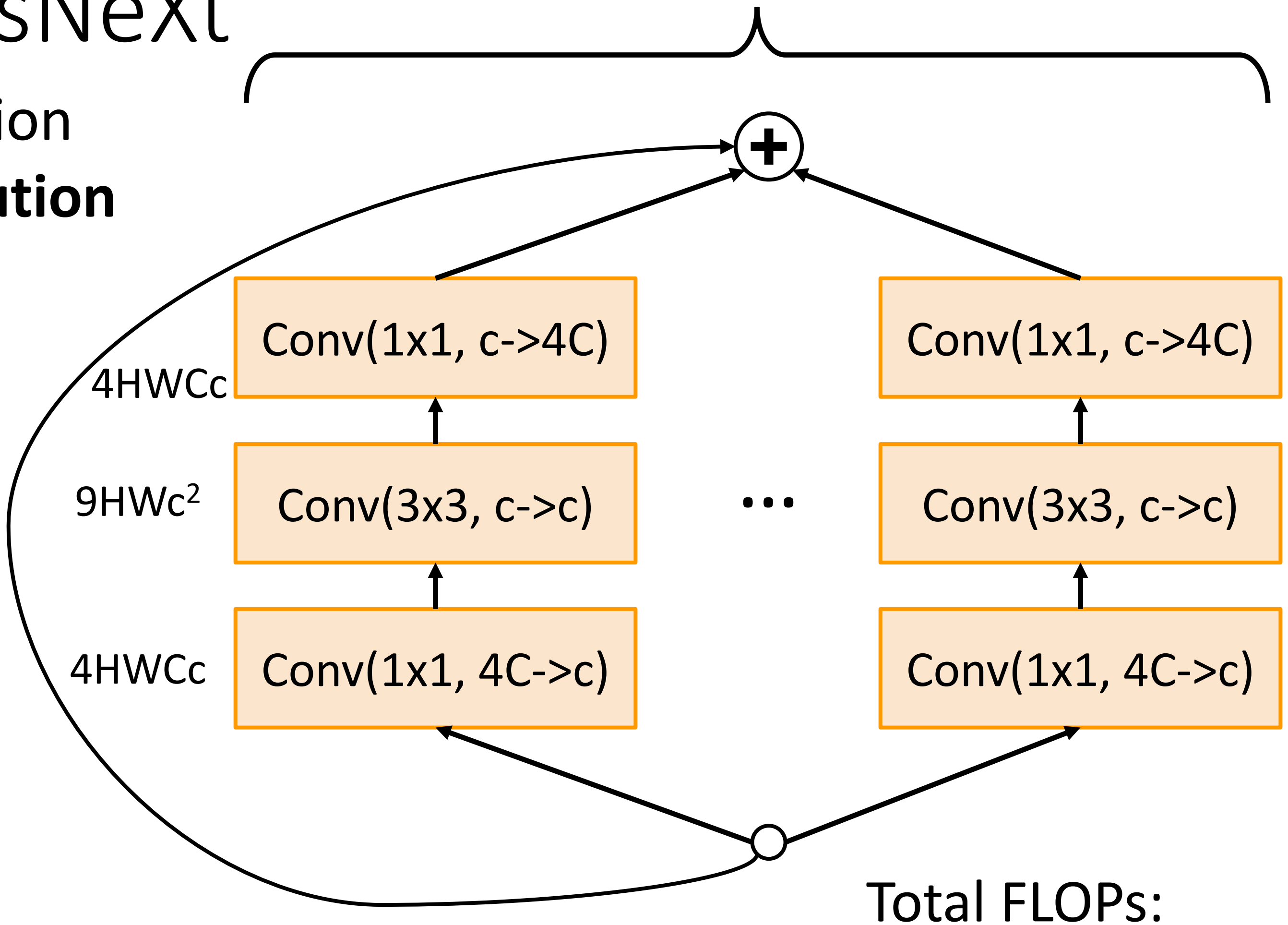
Improving ResNets: ResNeXt



ResNeXt block:
Grouped convolution

Equivalent formulation with **grouped convolution**

G parallel pathways



Total FLOPs:
$(8Cc + 9c^2)*HWG$

Same FLOPs when
$9Gc^2 + 8GCc - 17C^2 = 0$

Example: C=64, G=4, c=24; C=64, G=32, c=4

Xie et al, "Aggregated residual transformations for deep neural networks", CVPR 2017

ResNeXt: Maintain computation by adding groups!

Model	Groups	Group width	Top-1 Error
ResNet-50	1	64	23.9
ResNeXt-50	2	40	23
ResNeXt-50	4	24	22.6
ResNeXt-50	8	14	22.3
ResNeXt-50	32	4	22.2

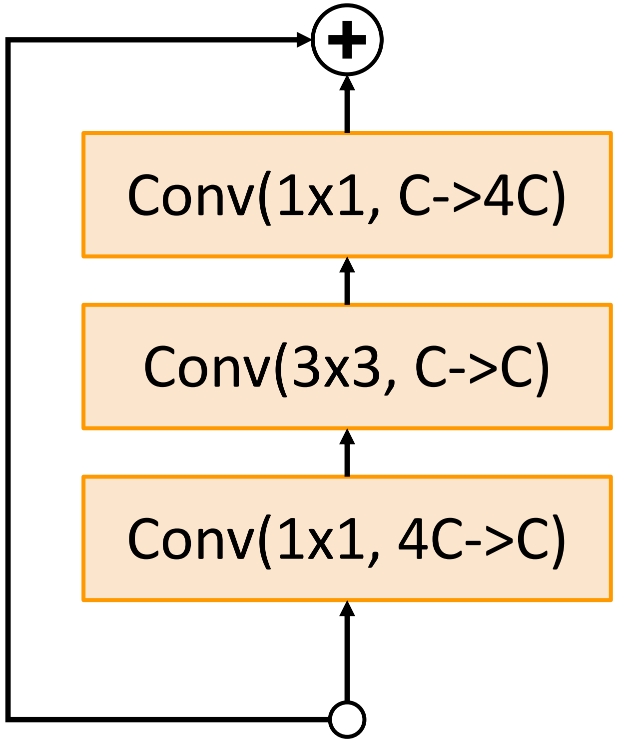
Model	Groups	Group width	Top-1 Error
ResNet-101	1	64	22.0
ResNeXt-101	2	40	21.7
ResNeXt-101	4	24	21.4
ResNeXt-101	8	14	21.3
ResNeXt-101	32	4	21.2

Adding groups improves performance **with same FLOPs!**

Often denoted e.g. ResNeXt-50-32x4d: 32 groups,
Blocks in first stage have 4 channels per group (#channels still doubles at each stage)

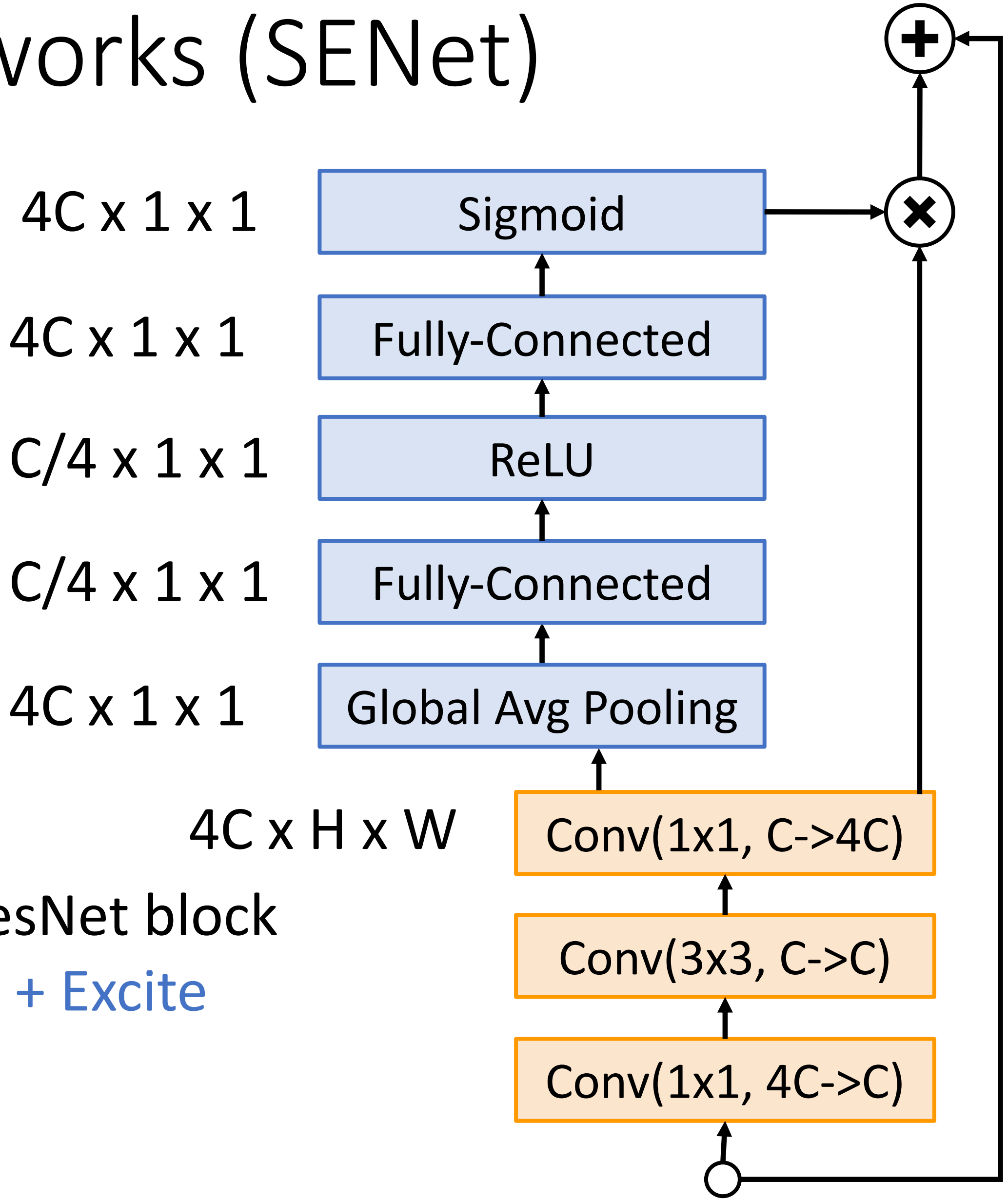
Xie et al, “Aggregated residual transformations for deep neural networks”, CVPR 2017

Squeeze-and-Excitation Networks (SENet)



Bottleneck ResNet block

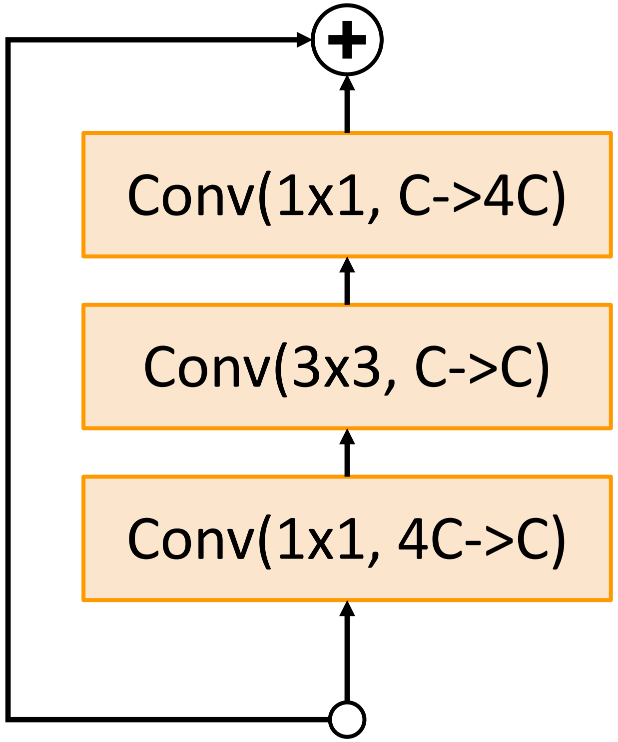
Adds **global context** to each ResNet block



Bottleneck ResNet block
with Squeeze + Excite

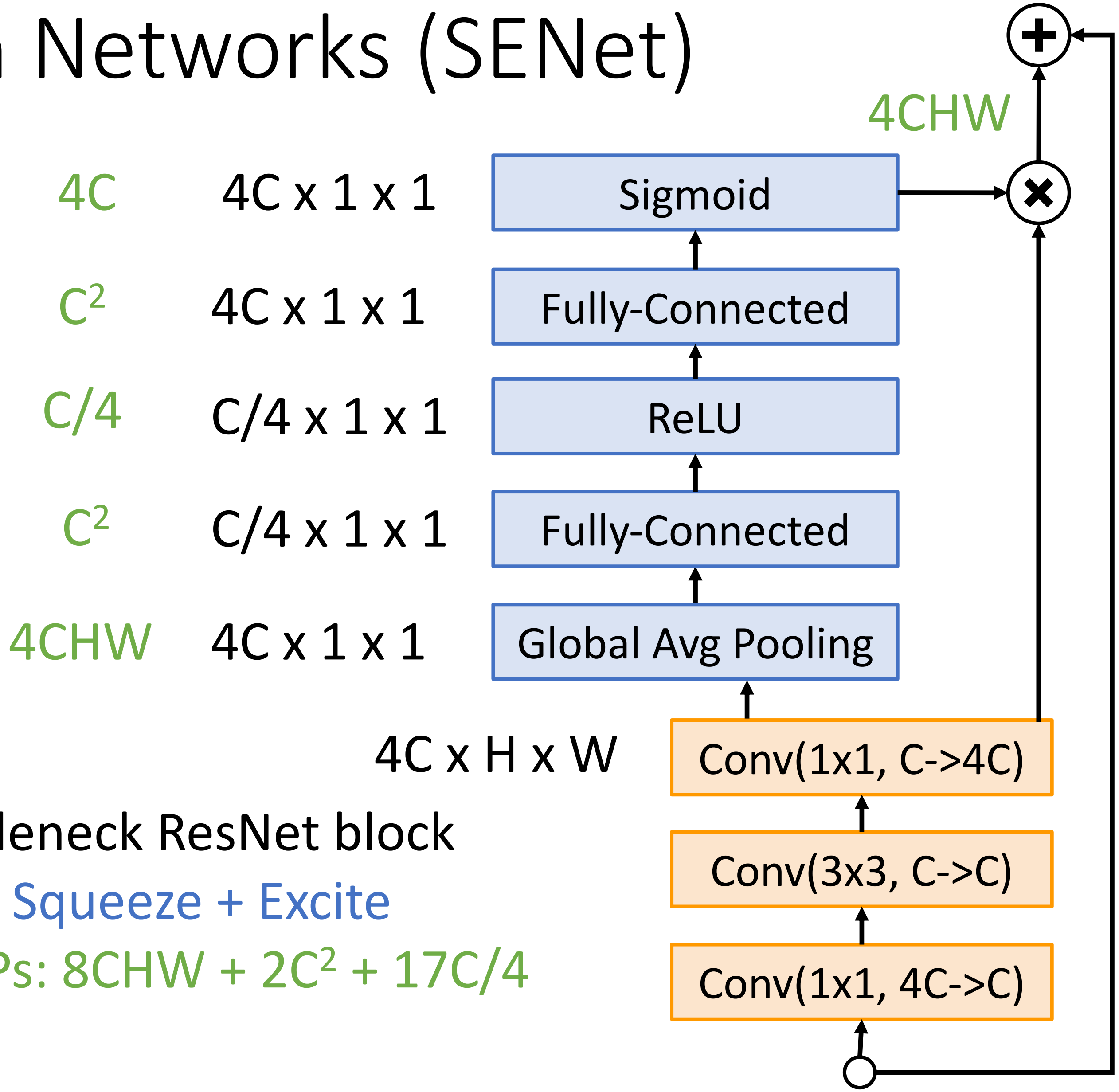
Hu et al, "Squeeze-and-Excitation networks", CVPR 2018

Squeeze-and-Excitation Networks (SENet)



Bottleneck ResNet block
FLOPs: $17HWC^2$

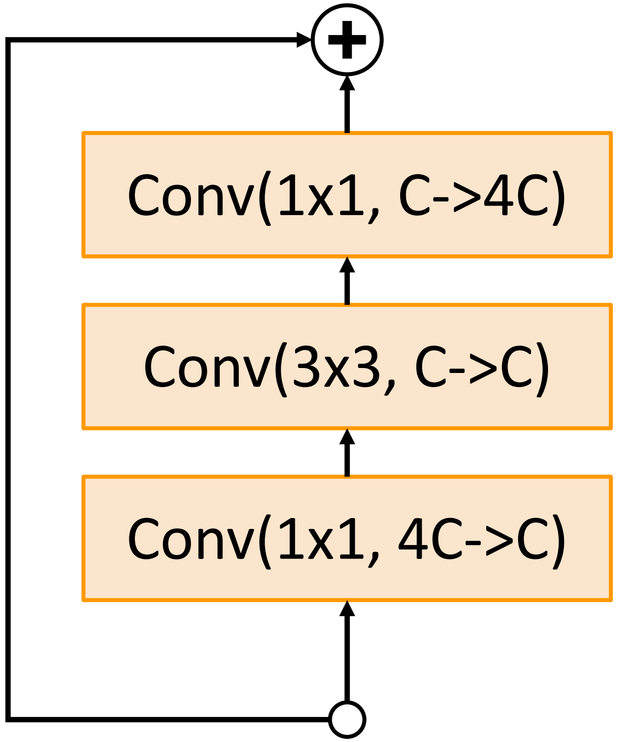
Adds **global context** to each ResNet block



Bottleneck ResNet block
with Squeeze + Excite
FLOPs: $8CHW + 2C^2 + 17C/4$

Hu et al, "Squeeze-and-Excitation networks", CVPR 2018

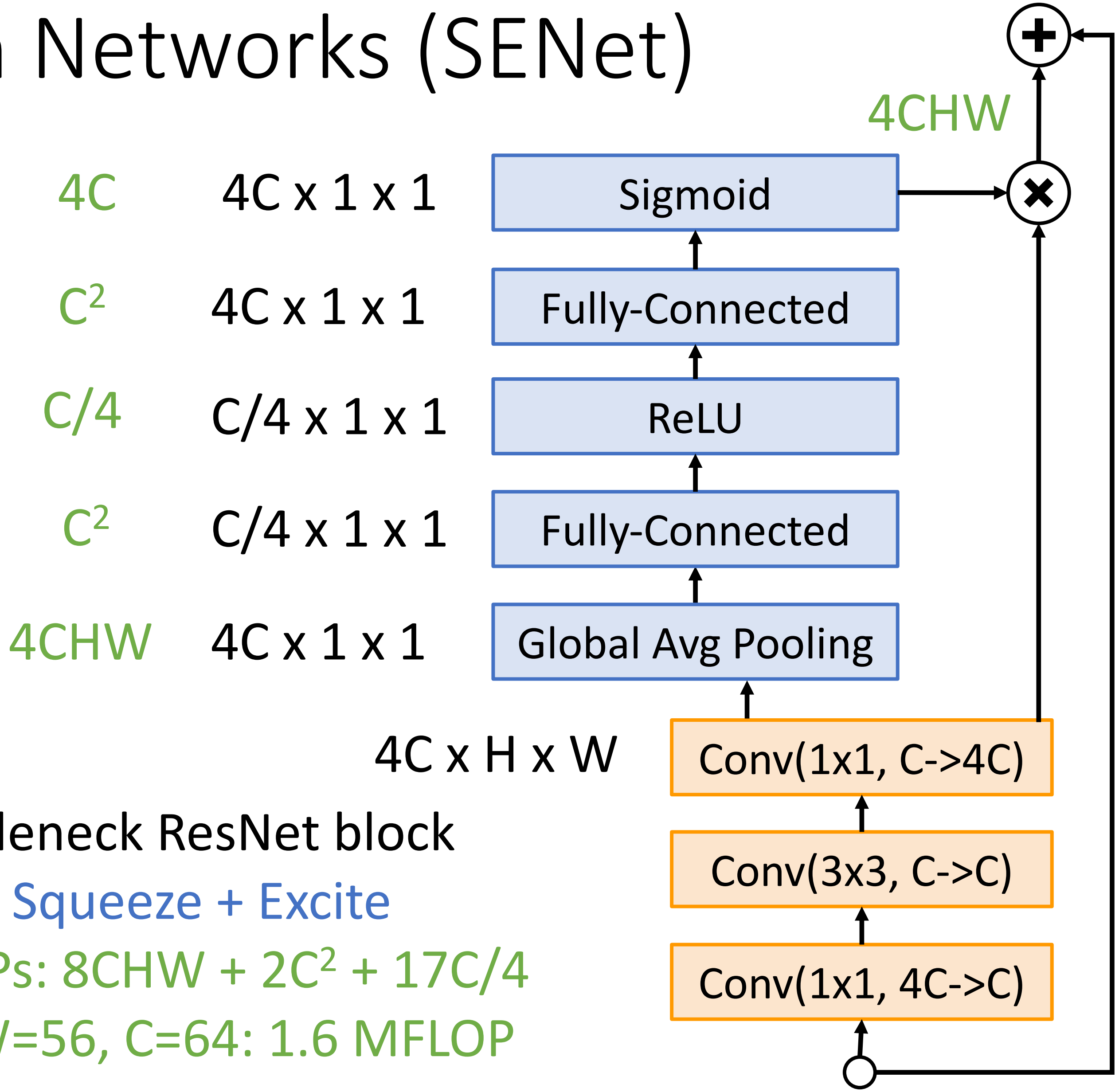
Squeeze-and-Excitation Networks (SENet)



Bottleneck ResNet block
FLOPs: $17HWC^2$
H=W=56, C=64: 218 MFLOP

Adds **global context** to each ResNet block

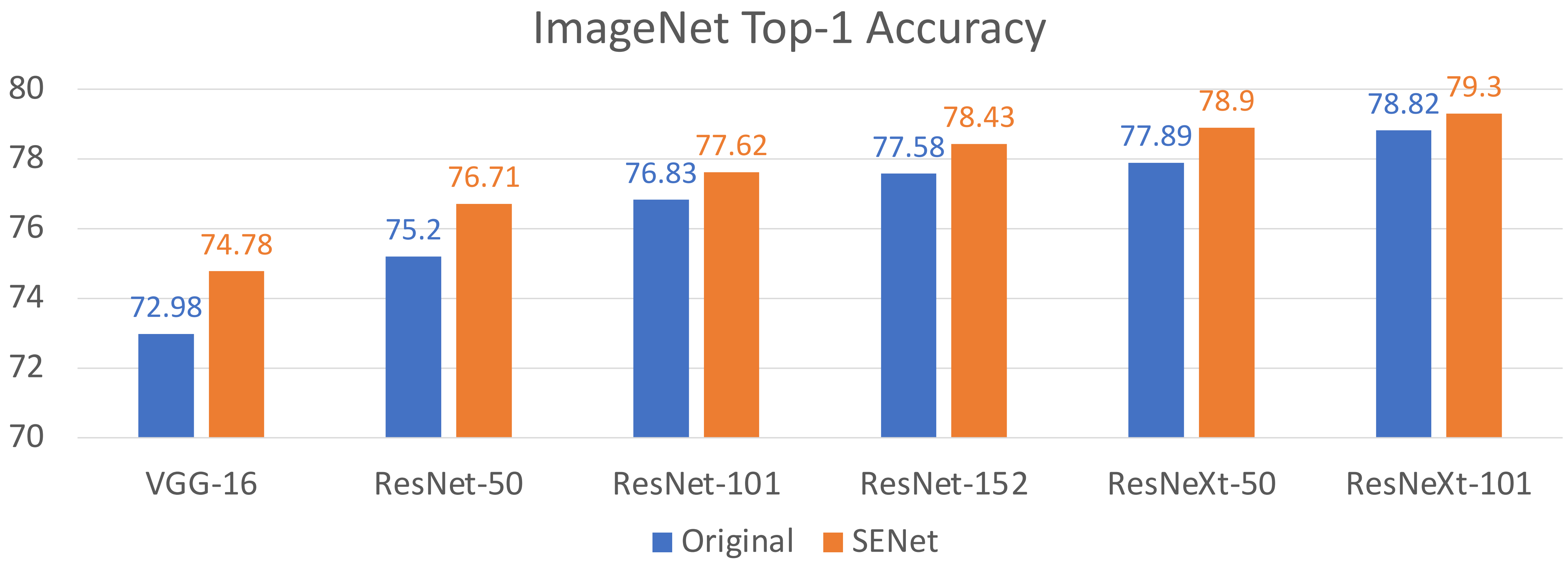
Increases overall FLOPs by < 1%!



Bottleneck ResNet block
with Squeeze + Excite
FLOPs: $8CHW + 2C^2 + 17C/4$
H=W=56, C=64: 1.6 MFLOP

Hu et al, "Squeeze-and-Excitation networks", CVPR 2018

Squeeze-and-Excitation Networks (SENet)



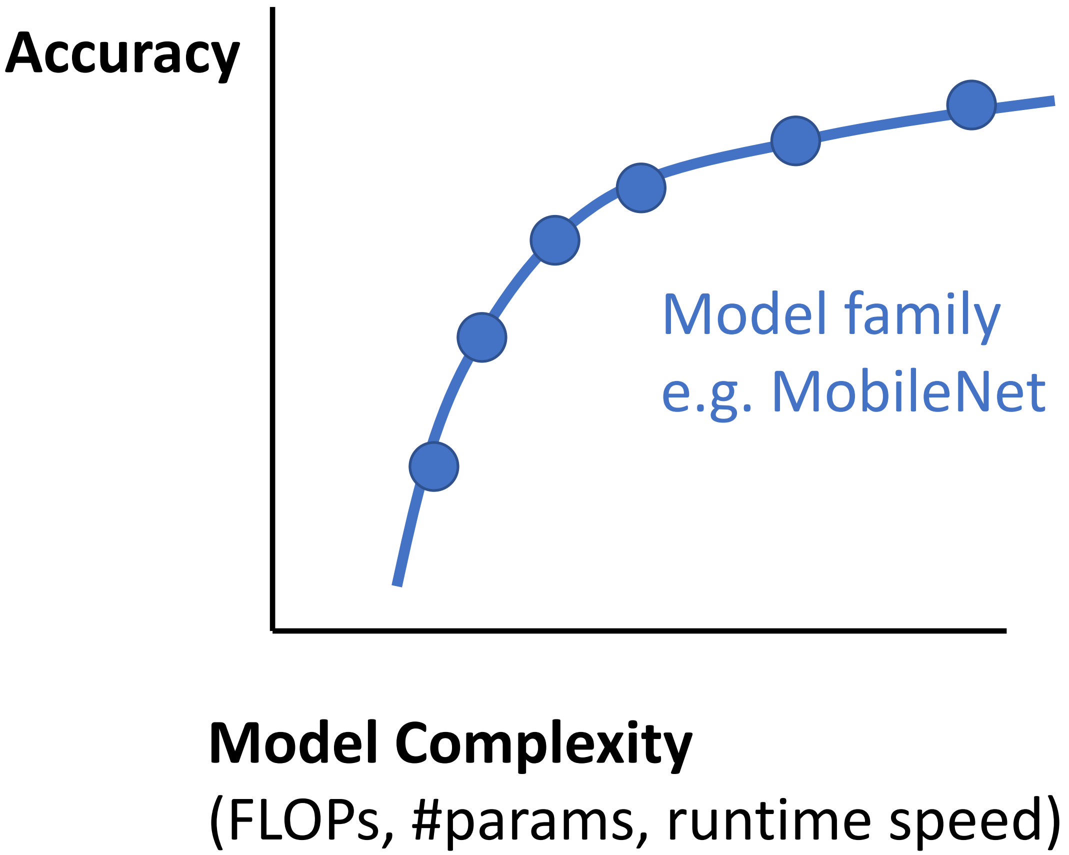
Add SE to any architecture, enjoy 1-2% boost in accuracy

Hu et al, "Squeeze-and-Excitation networks", CVPR 2018

Tiny Neural Networks for Mobile Devices

Instead of pushing for the largest network with biggest accuracy, consider tiny networks and accuracy / complexity tradeoff

Compare **families of models**:

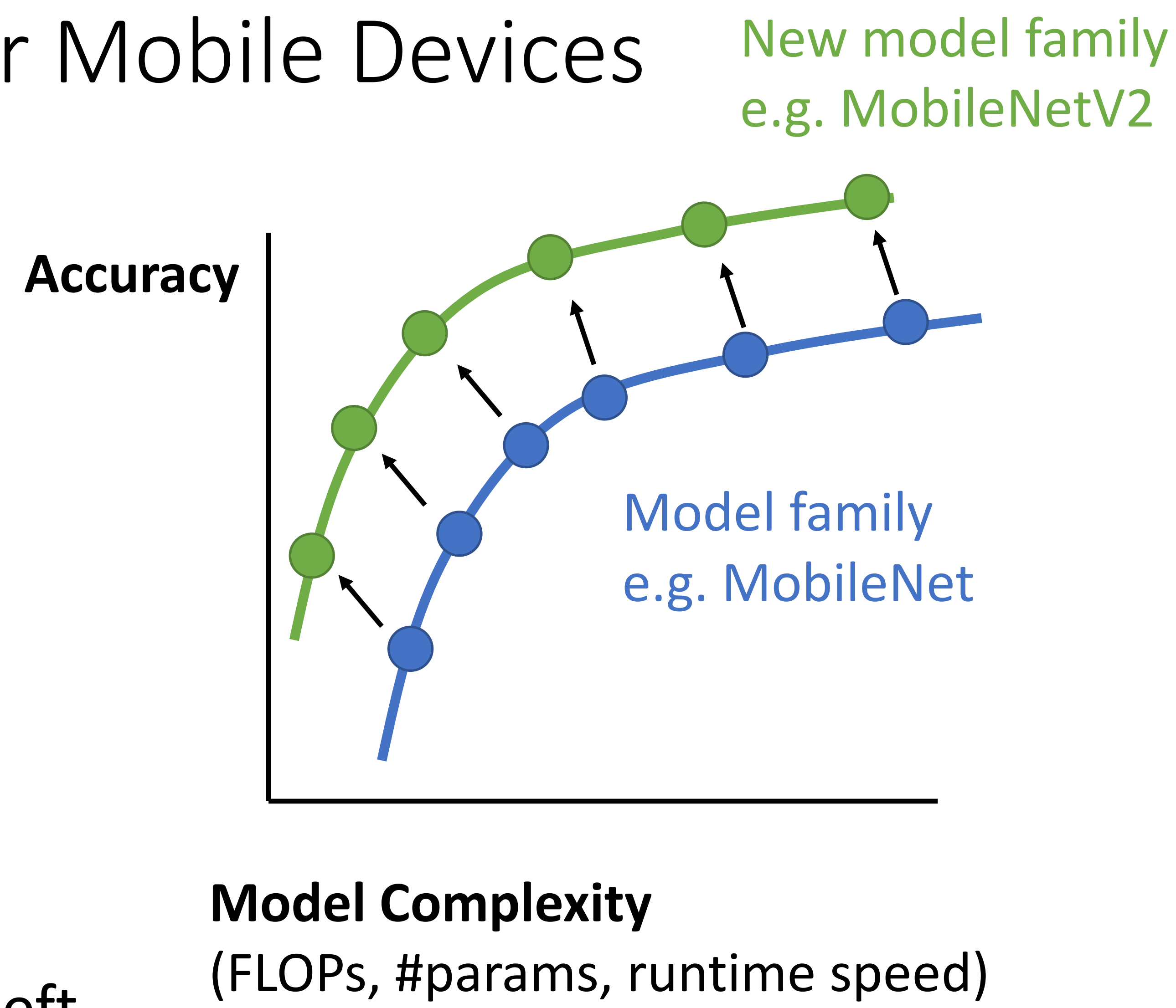


Tiny Neural Networks for Mobile Devices

Instead of pushing for the largest network with biggest accuracy, consider tiny networks and accuracy / complexity tradeoff

Compare **families of models**:

One family is better than another if it moves the whole curve up and to the left



MobileNets: Tiny Networks (For Mobile Devices)

Standard Convolution Block

Total cost: $9C^2HW$

ReLU

↑

Batch Norm

↑

Conv(3x3, C->C) — $9C^2HW$

$$\text{Speedup} = 9C^2/(9C+C^2)$$
$$= 9C/(9+C)$$
$$\Rightarrow 9 \text{ (as } C\to\text{inf)}$$

Depthwise Separable Convolution

Total cost: $(9C + C^2)HW$

ReLU

↑

Batch Norm

↑

C^2HW — Conv(1x1, C->C) — "Pointwise Convolution"

↑

ReLU

↑

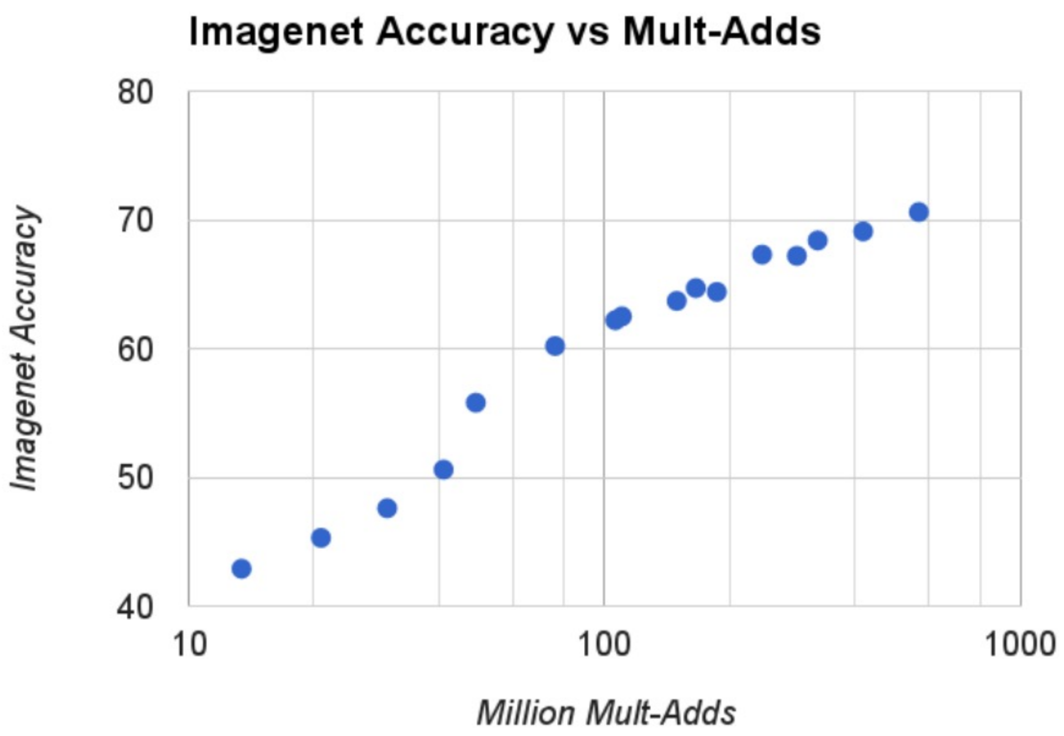
Batch Norm

↑

$9CHW$ — Conv(3x3, C->C, groups=C) — "Depthwise Convolution"

Howard et al, "MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications", arXiv 2017
Chollet, "Xception: Deep Learning with Depthwise Separable Convolutions", CVPR 2017

MobileNets: Tiny Networks (For Mobile Devices)



Depthwise Separable Convolution

Total cost: $(9C + C^2)HW$

ReLU

↑

Batch Norm

↑

C^2HW Conv(1x1, C->C) "Pointwise Convolution"

↑

ReLU

↑

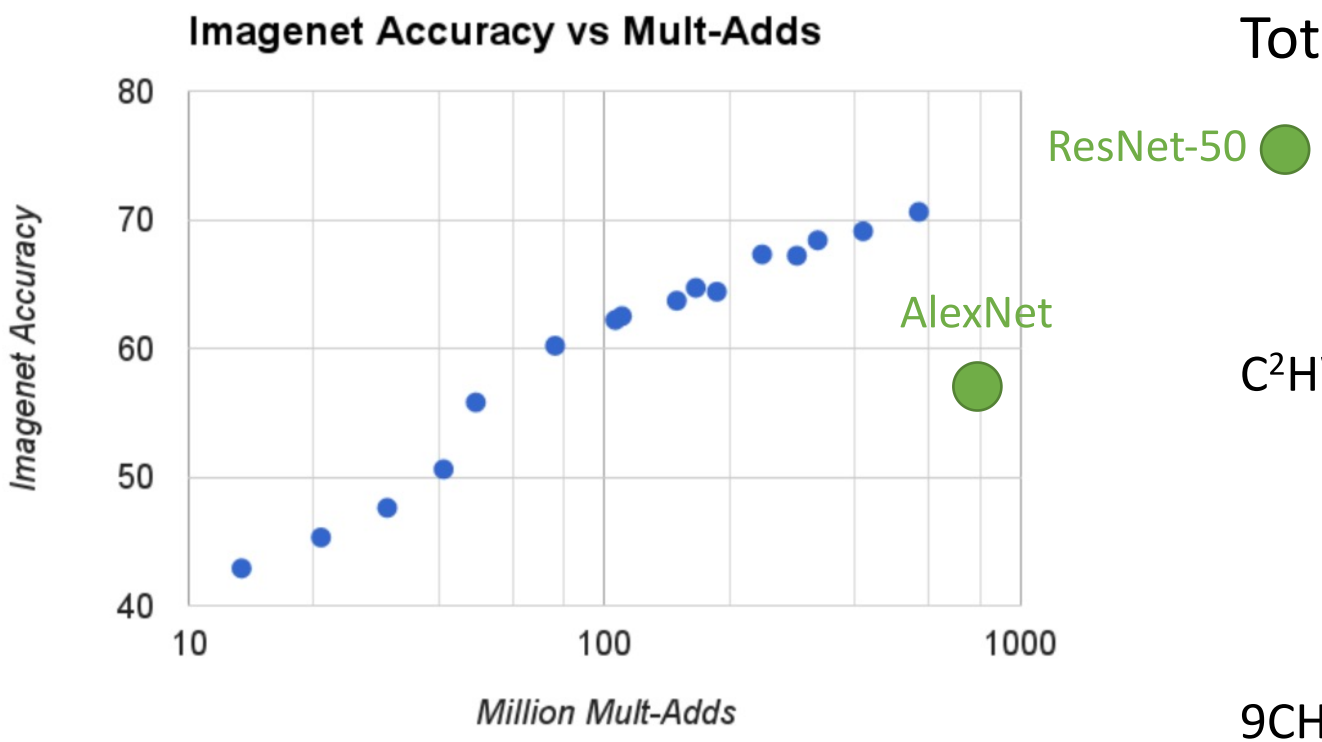
Batch Norm

↑

9CHW Conv(3x3, C->C, groups=C) "Depthwise Convolution"

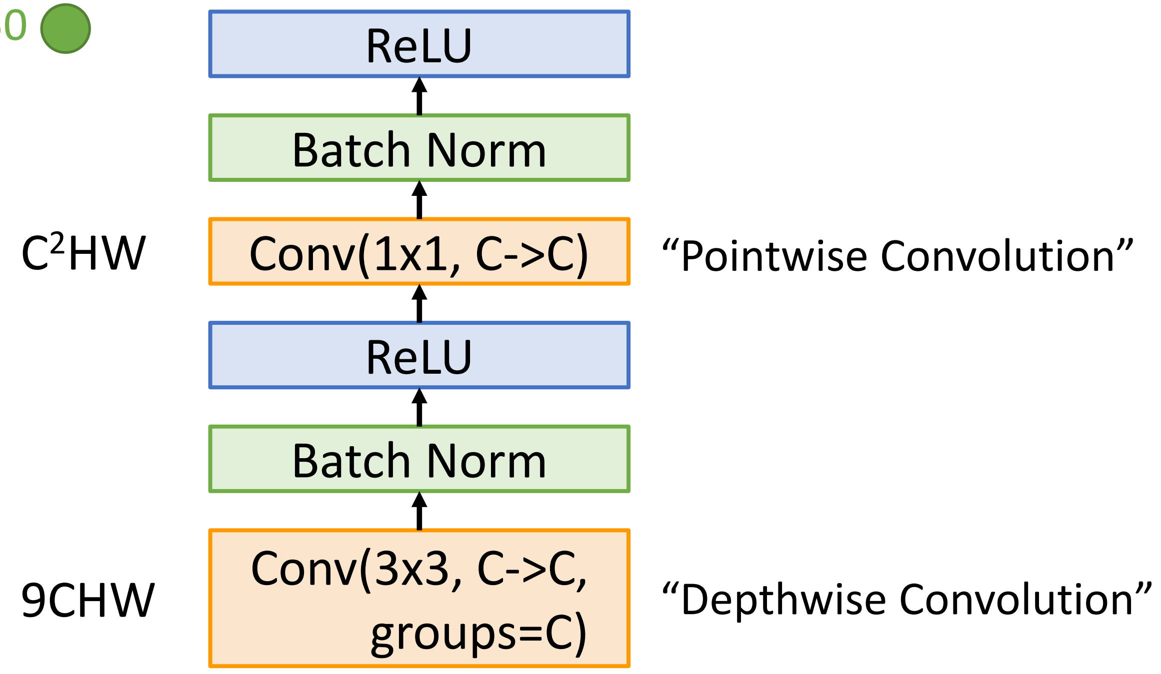
Howard et al, "MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications", 2017

MobileNets: Tiny Networks (For Mobile Devices)



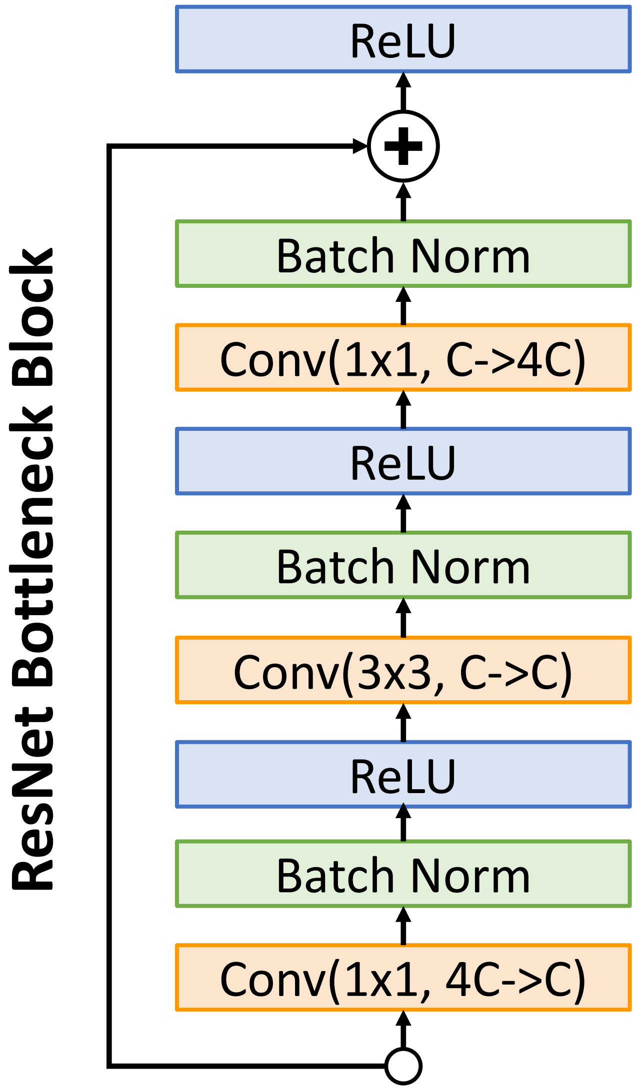
Depthwise Separable Convolution

Total cost: $(9C + C^2)HW$



Howard et al, "MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications", 2017

MobileNetV2: Inverted Bottleneck, Linear Residual



Nonlinearity outside residual

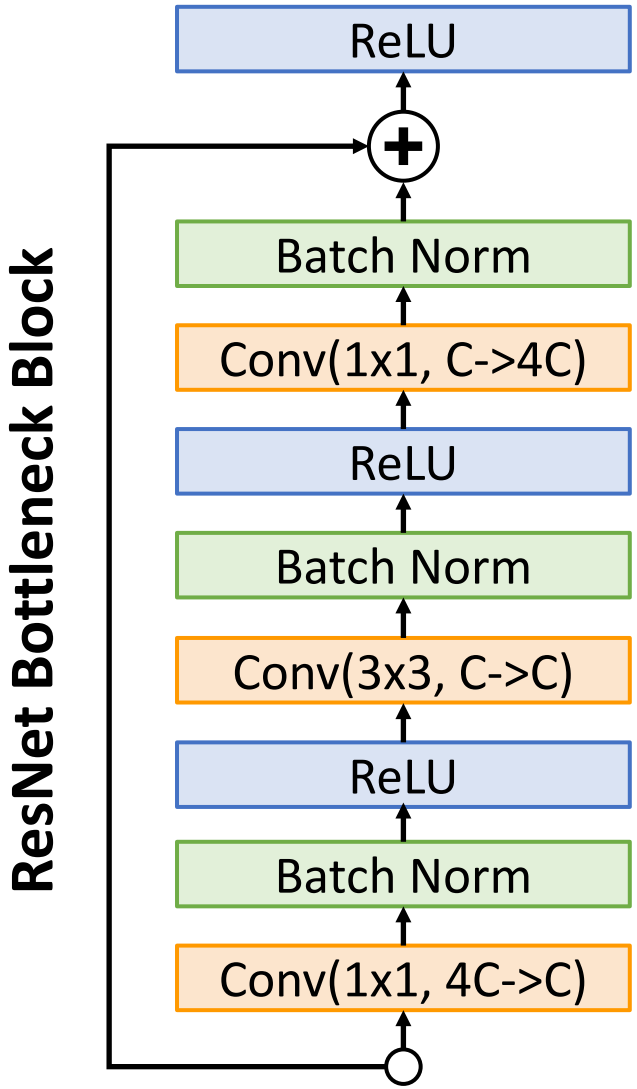
1x1 conv **expands** channels output ($4HWC^2$ FLOP)

3x3 conv uses **fewer** channels than input ($9HWC^2$ FLOP)

1x1 conv **reduces** channels before 3x3 conv ($4HWC^2$ FLOP)

Sandler et al, "MobileNetV2: Inverted Residuals and Linear Bottlenecks", CVPR 2018

MobileNetV2: Inverted Bottleneck, Linear Residual



Nonlinearity outside residual

1x1 conv **expands** channels output (4HWC² FLOP)

3x3 conv uses **fewer** channels than input (9HWC² FLOP)

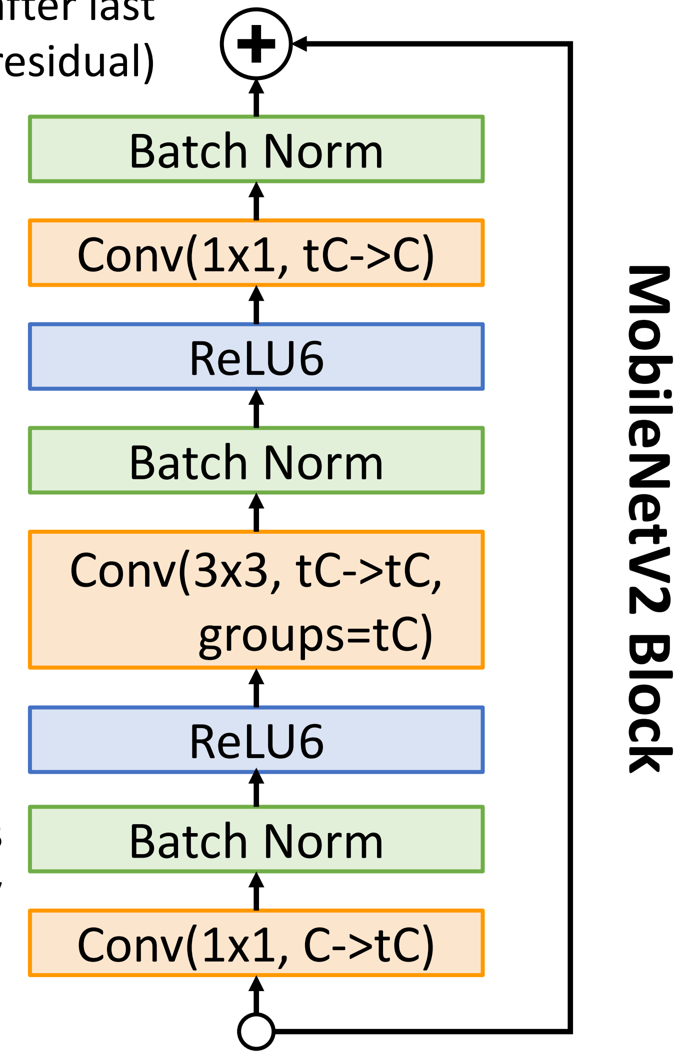
1x1 conv **reduces** channels before 3x3 conv (4HWC² FLOP)

No nonlinearity after last conv! (linear residual)

1x1 conv **reduces** channels before output (tHWC² FLOP)

3x3 Depthwise conv with **more** channels than input (9tHWC FLOP)

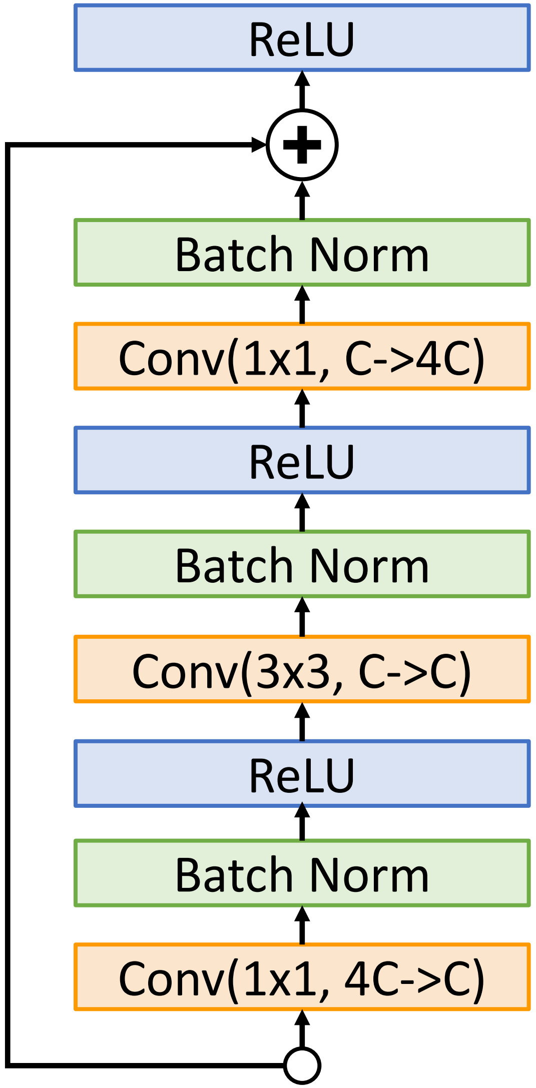
1x1 conv **increases** channels before 3x3 conv (inverted bottleneck) (tHWC² FLOP)



Sandler et al, "MobileNetV2: Inverted Residuals and Linear Bottlenecks", CVPR 2018

MobileNetV2: Inverted Bottleneck, Linear Residual

ResNet Bottleneck Block



Nonlinearity outside residual

Total FLOP: 17HWC²

1x1 conv **expands** channels output (4HWC² FLOP)

3x3 conv uses **fewer** channels than input (9HWC² FLOP)

1x1 conv **reduces** channels before 3x3 conv (4HWC² FLOP)

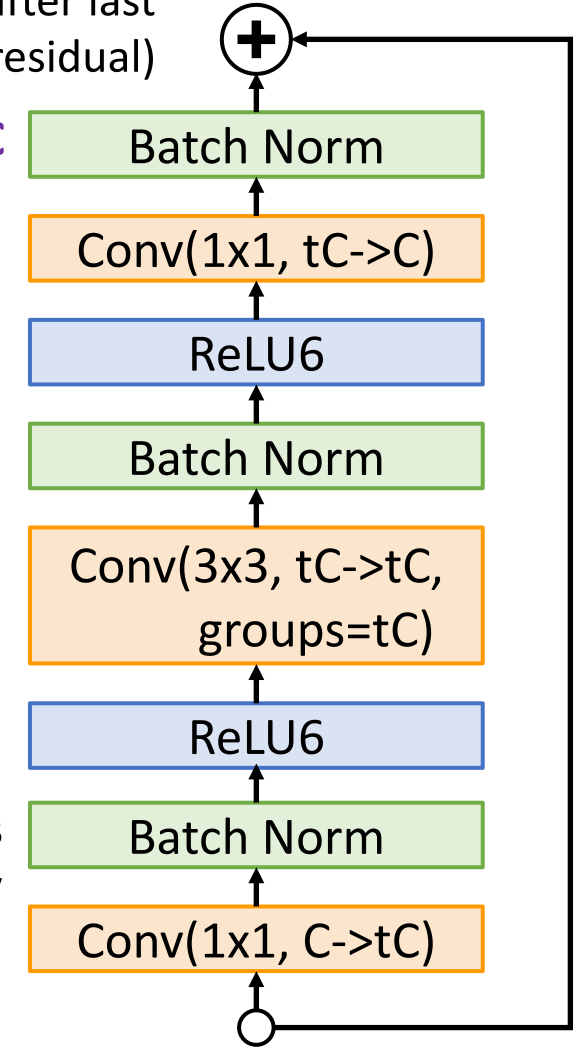
No nonlinearity after last conv! (linear residual)

Total FLOP: 2tHWC² + 9tHWC

1x1 conv **reduces** channels before output (tHWC² FLOP)

3x3 Depthwise conv with **more** channels than input (9tHWC FLOP)

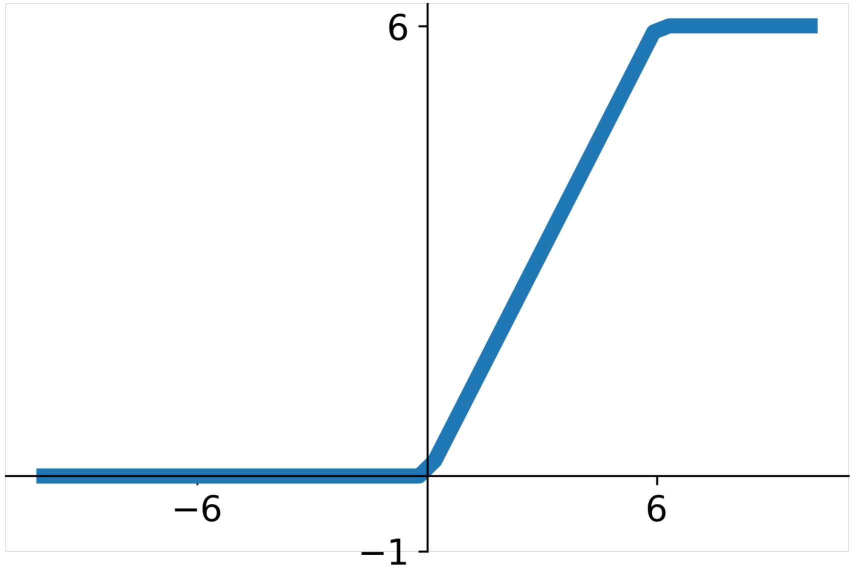
1x1 conv **increases** channels before 3x3 conv (inverted bottleneck) (tHWC² FLOP)



MobileNetV2 Block

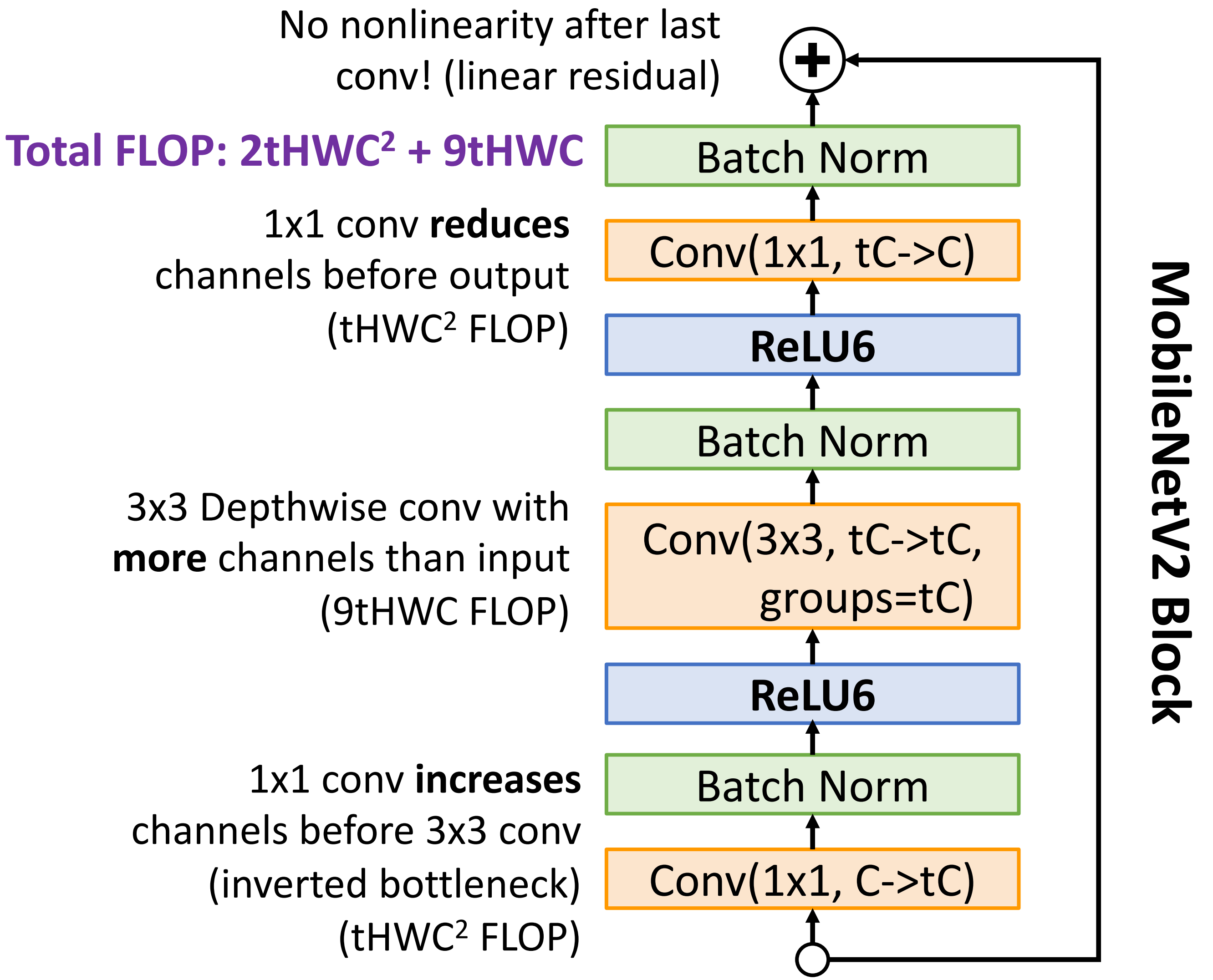
Sandler et al, "MobileNetV2: Inverted Residuals and Linear Bottlenecks", CVPR 2018

MobileNetV2: Inverted Bottleneck, Linear Residual



$$ReLU6(x) = \begin{cases} 0 & if\ x \leq 0 \\ x & if\ 0 < x < 6 \\ 6 & if\ x \geq 6 \end{cases}$$

Keeps activations in reasonable range when running inference in low precision

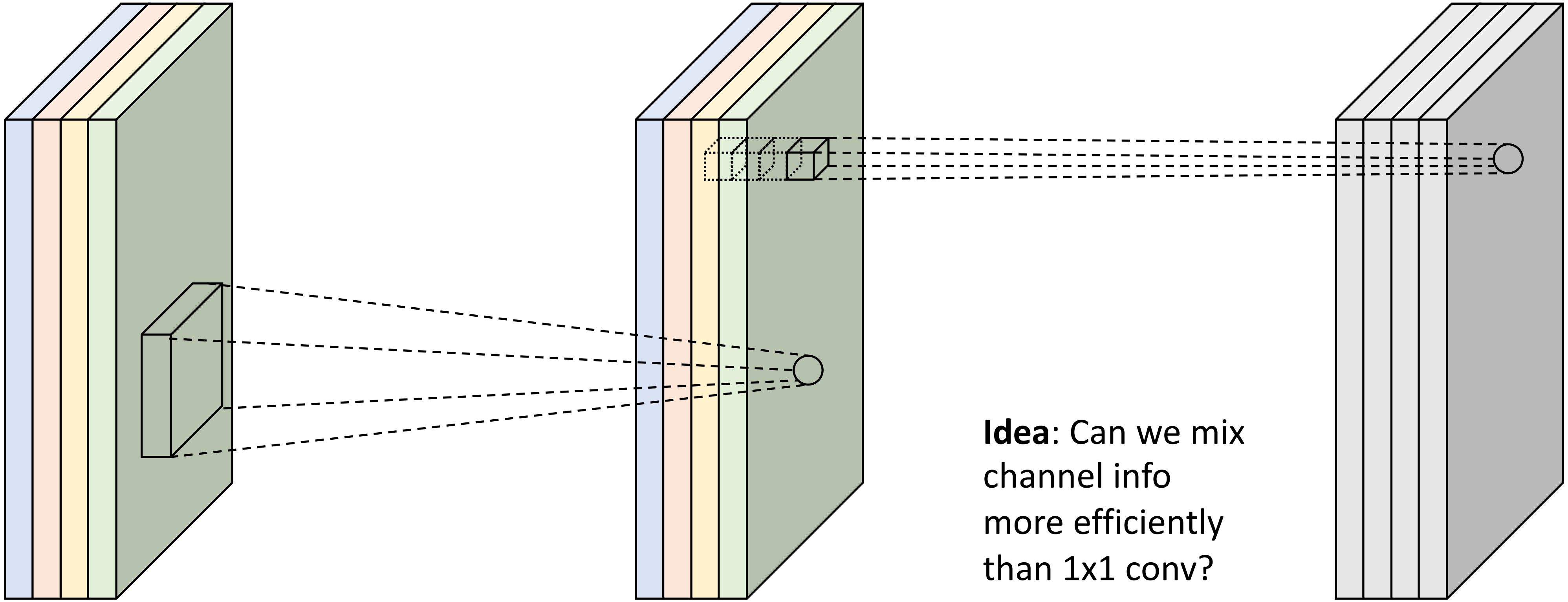


Sandler et al, "MobileNetV2: Inverted Residuals and Linear Bottlenecks", CVPR 2018

MobileNetV2: Inverted Bottleneck, Linear Residual

3x3 Depthwise Convolution:
Mixes data across space,
Keeps data across channels separate

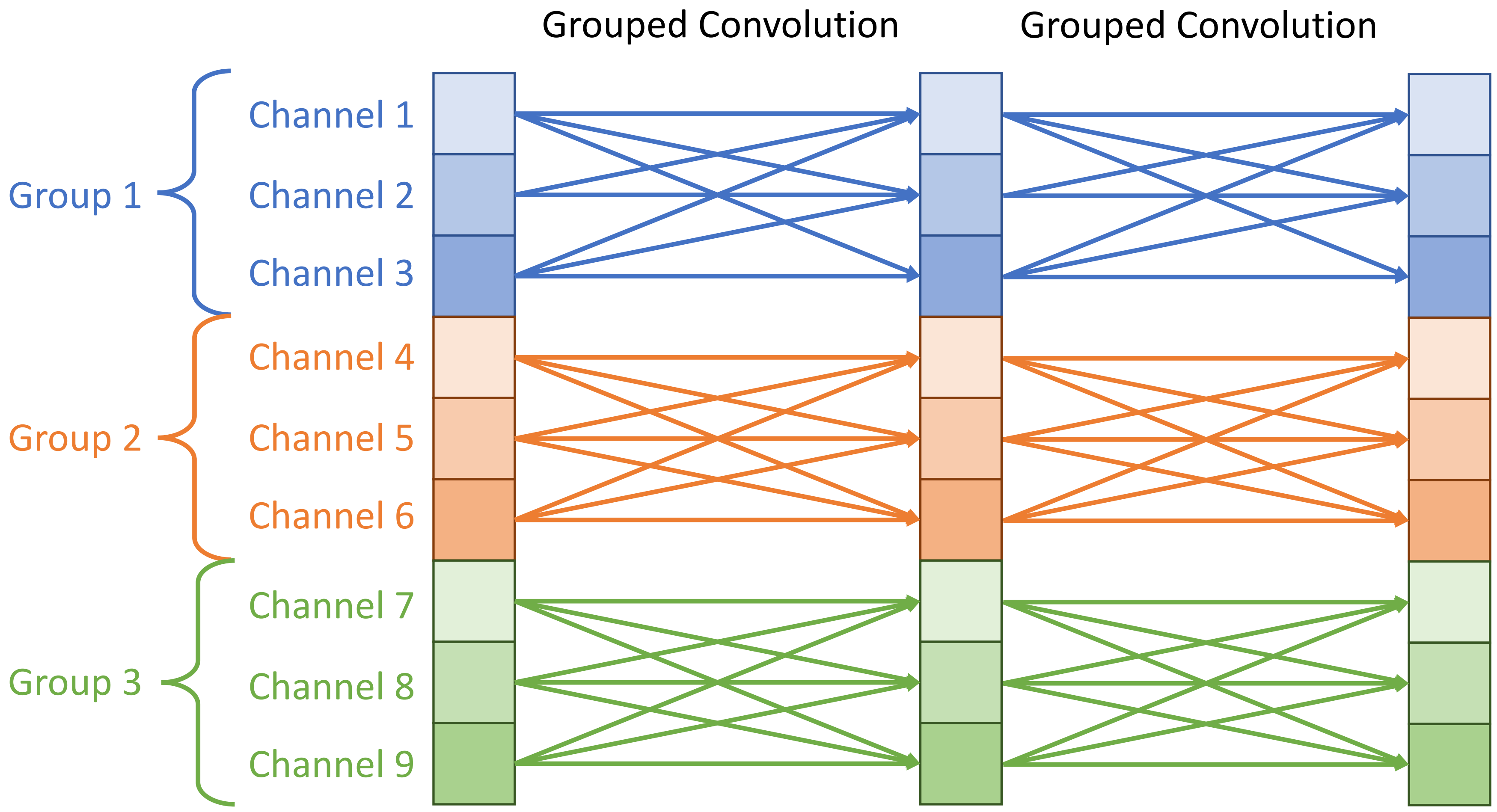
1x1 Convolution:
Keeps data across space separate,
Mixes data across channels



Idea: Can we mix channel info more efficiently than 1x1 conv?

Sandler et al, "MobileNetV2: Inverted Residuals and Linear Bottlenecks", CVPR 2018

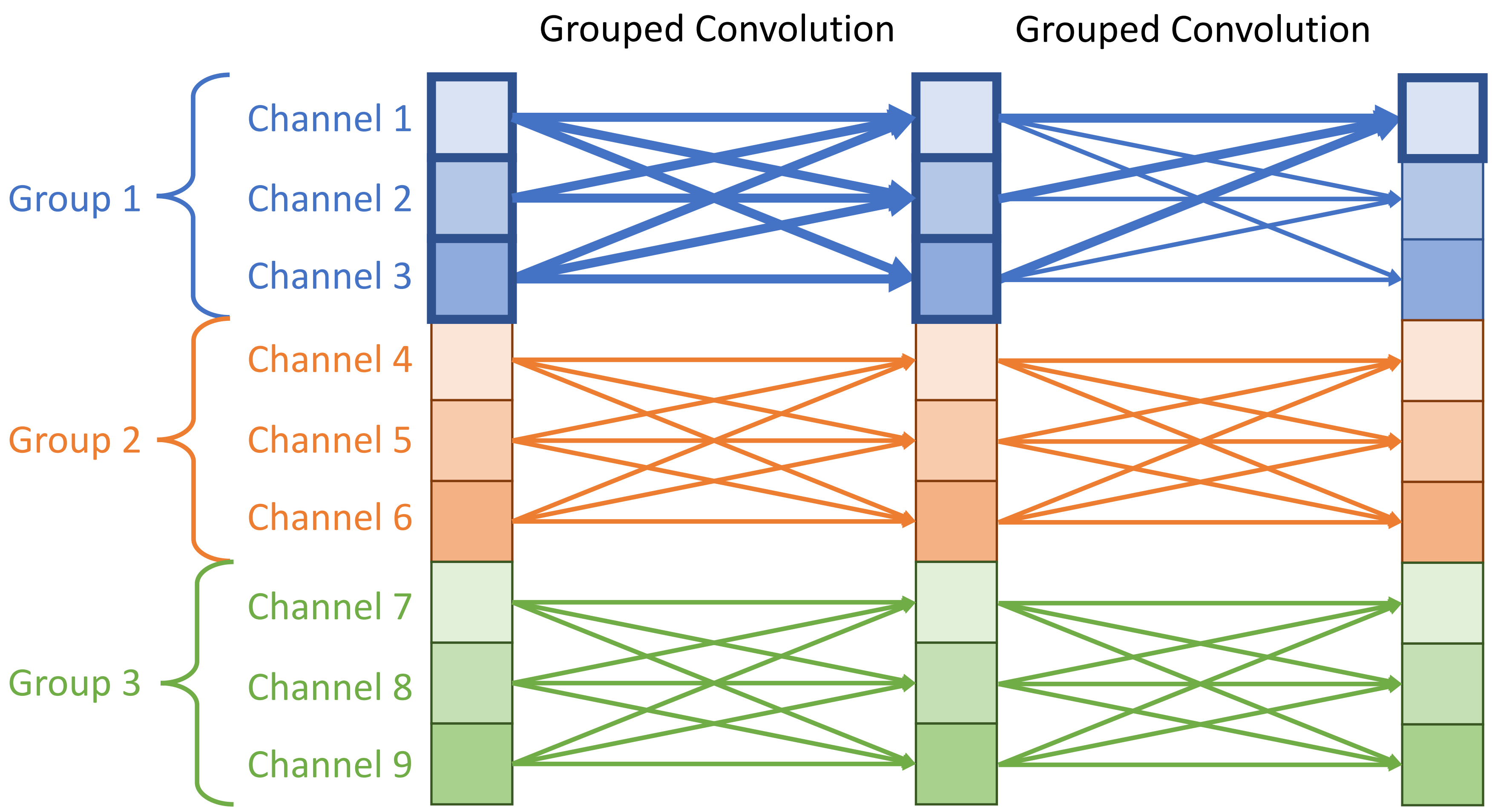
Stacking Grouped Convolutions



Zhang et al, "ShuffleNet: An Extremely Efficient Convolutional Neural Network for Mobile Devices", CVPR 2018

Problem: Information is never mixed across channels from different groups!

Stacking Grouped Convolutions

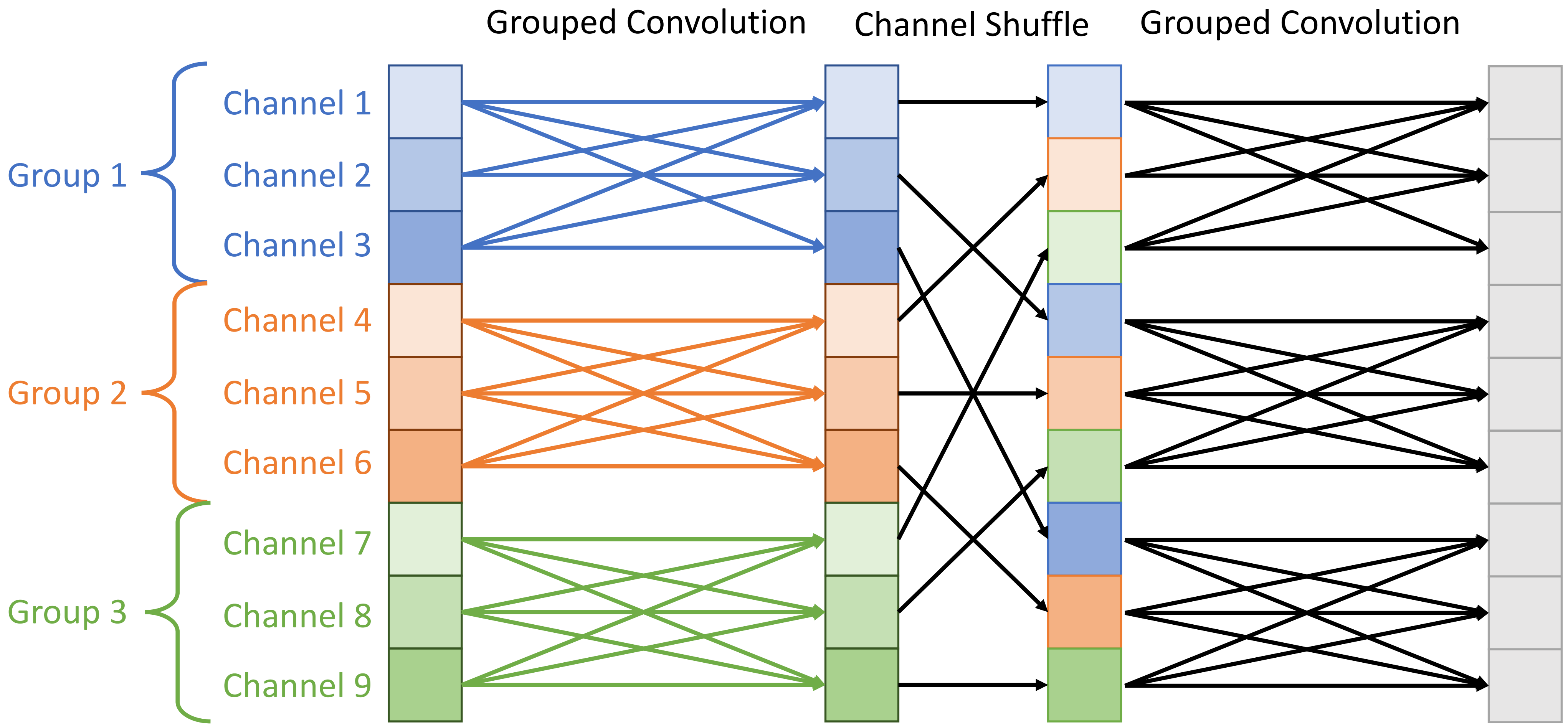


Zhang et al, "ShuffleNet: An Extremely Efficient Convolutional Neural Network for Mobile Devices", CVPR 2018

Problem: Information is never mixed across channels from different groups!

Stacking Grouped Convolutions

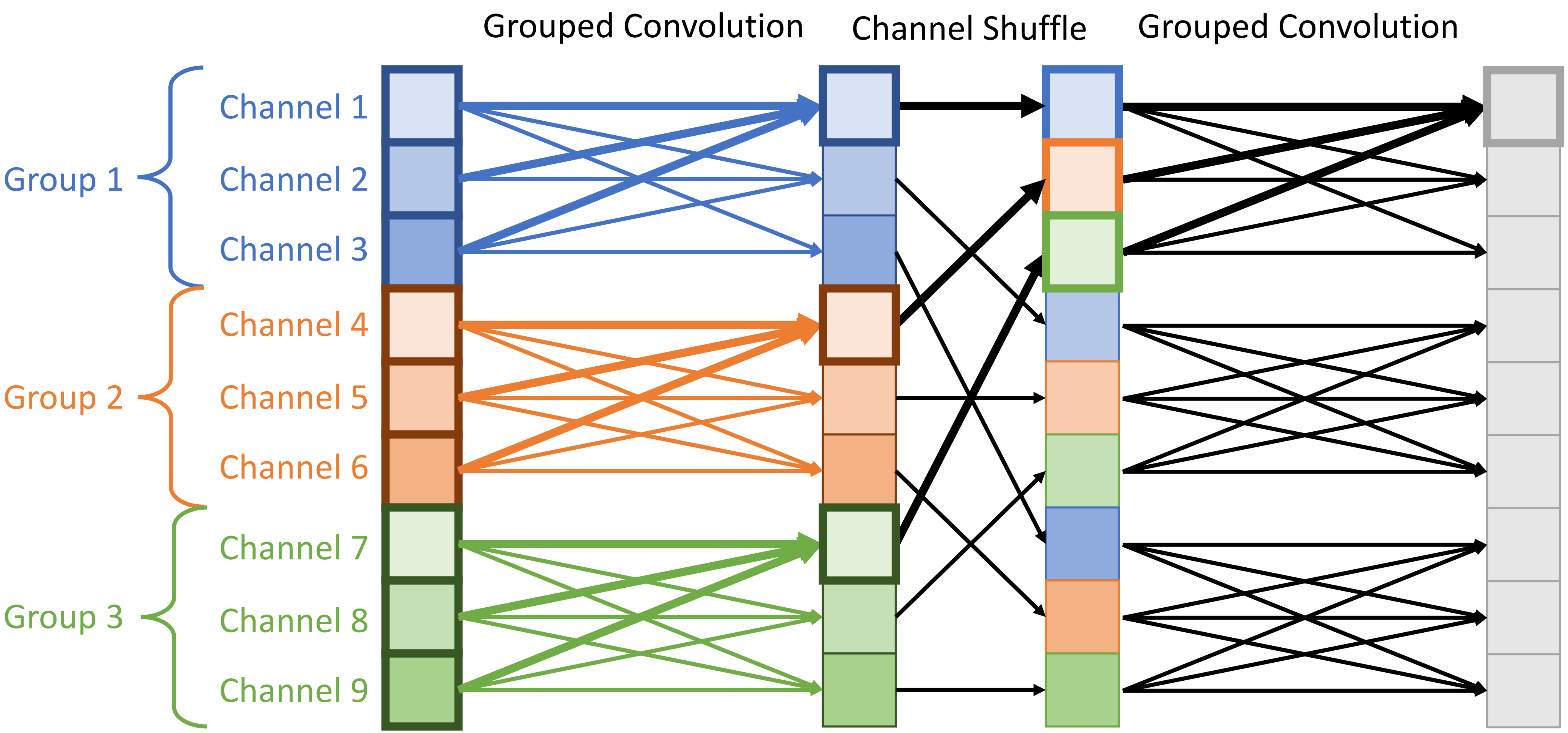
Insert "Channel Shuffle" operators that permute channels between convolutions



Zhang et al, "ShuffleNet: An Extremely Efficient Convolutional Neural Network for Mobile Devices", CVPR 2018

Stacking Grouped Convolutions

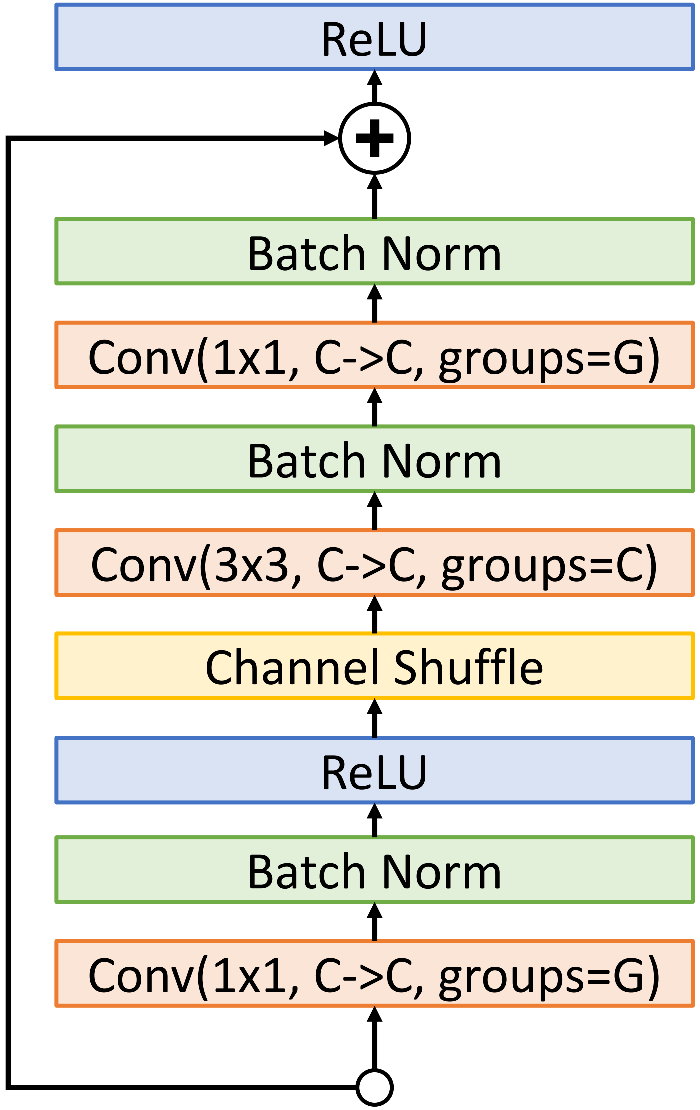
Insert "Channel Shuffle" operators that permute channels between convolutions



Now channel information is fully "mixed" after two grouped convolutions – no need for any ungrouped convolutions!

Zhang et al, "ShuffleNet: An Extremely Efficient Convolutional Neural Network for Mobile Devices", CVPR 2018

ShuffleNet



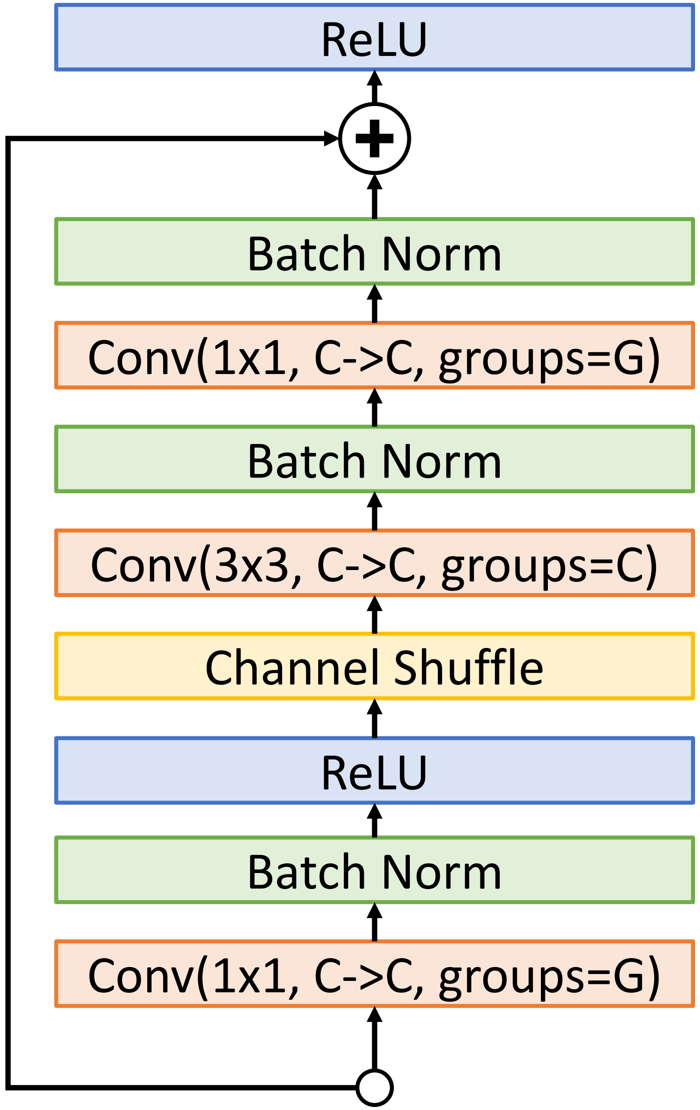
1x1 grouped conv

3x3 depthwise conv,
No nonlinearity here!

1x1 grouped conv

Zhang et al, "ShuffleNet: An Extremely Efficient Convolutional Neural Network for Mobile Devices", CVPR 2018

ShuffleNet



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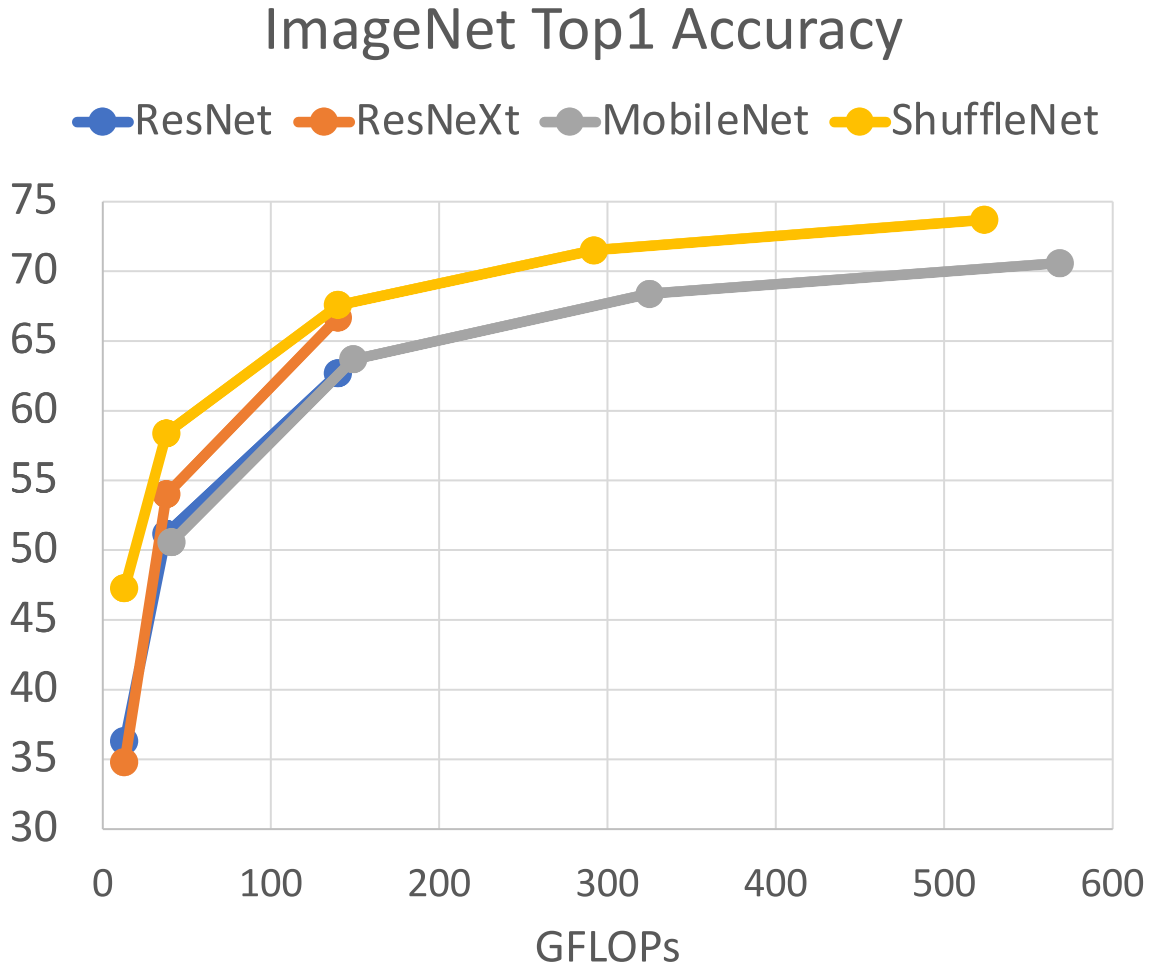
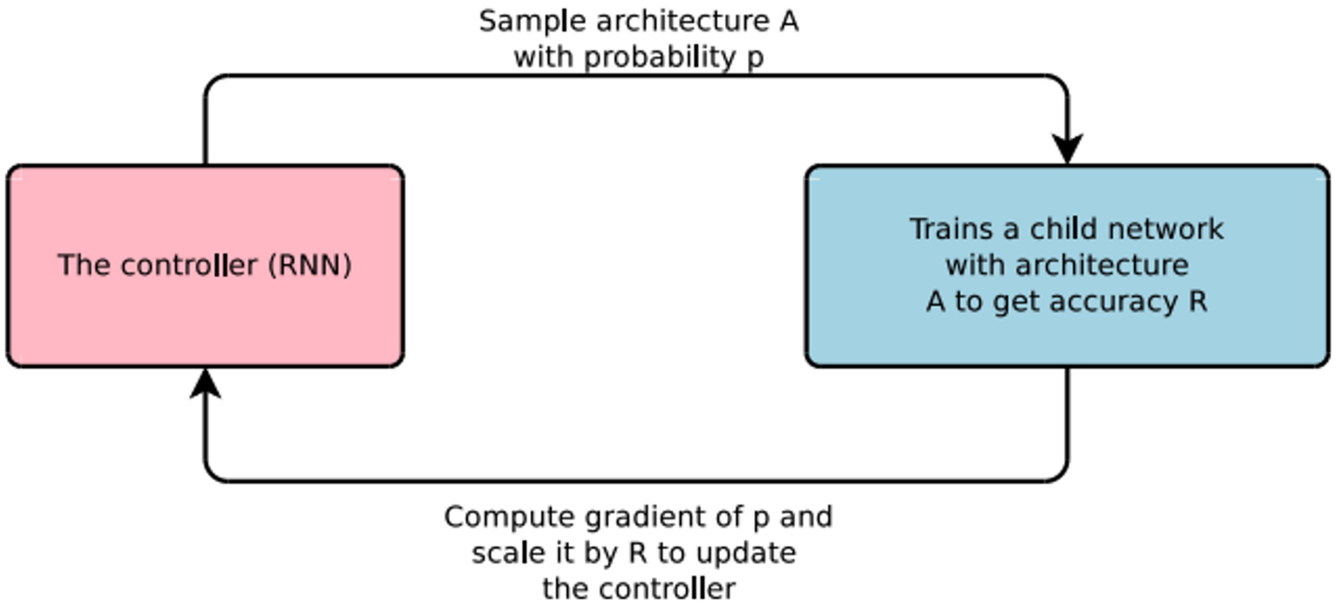


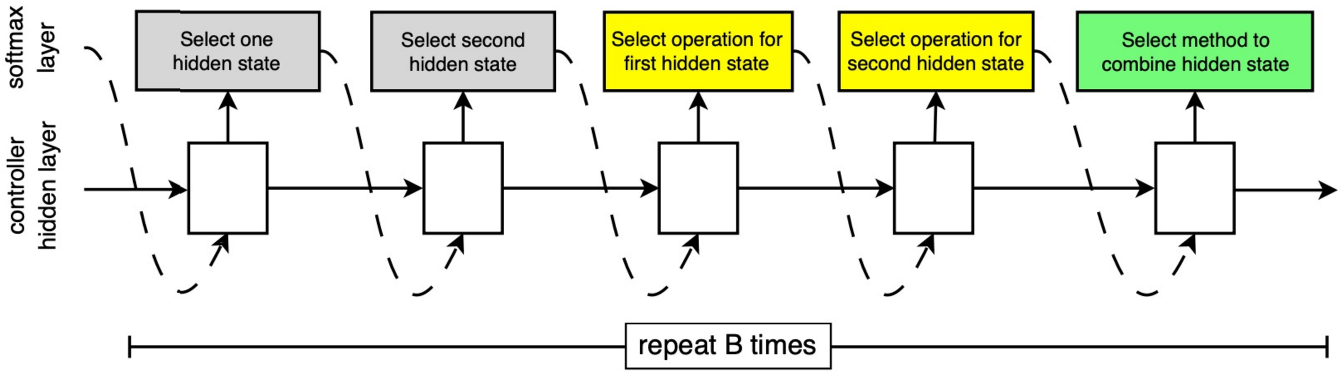
Zhang et al, "ShuffleNet: An Extremely Efficient Convolutional Neural Network for Mobile Devices", CVPR 2018

Neural Architecture Search (NAS)

Designing neural network architectures is hard – let's automate it!

- One network (**controller**) outputs network architectures
- Sample **child networks** from controller and train them
- After training a batch of child networks, make a gradient step on controller network (Using **policy gradient**)
- Over time, controller learns to output good architectures!





Zoph and Le, "Neural Architecture Search with Reinforcement Learning", ICLR 2017
Zoph et al, "Learning transferable architectures for scalable image recognition", CVPR 2018

Neural Architecture Search (NAS)

Search for reusable "block" designs which can use the following operators:

- Identity
- 1x1 conv
- 3x3 conv
- 3x3 dilated conv
- 1x7 then 7x1 conv
- 1x3 then 3x1 conv
- 3x3, 5x5, or 7x7 depthwise-separable conv
- 3x3 avg pool
- 3x3, 5x5, or 7x7 max pool

Zoph and Le, "Neural Architecture Search with Reinforcement Learning", ICLR 2017
Zoph et al, "Learning transferable architectures for scalable image recognition", CVPR 2018

Neural Architecture Search (NAS)

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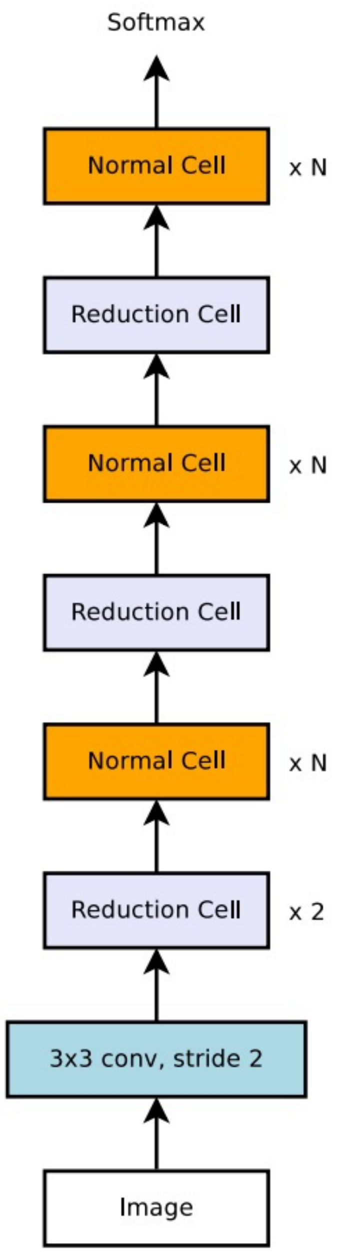
- 3x3, 5x5, or 7x7 depthwise-separable conv
- 3x3 avg pool
- 3x3, 5x5, or 7x7 max pool

The "Normal cell" maintains the same image resolution

The "Reduction cell" reduces image resolution by 2x

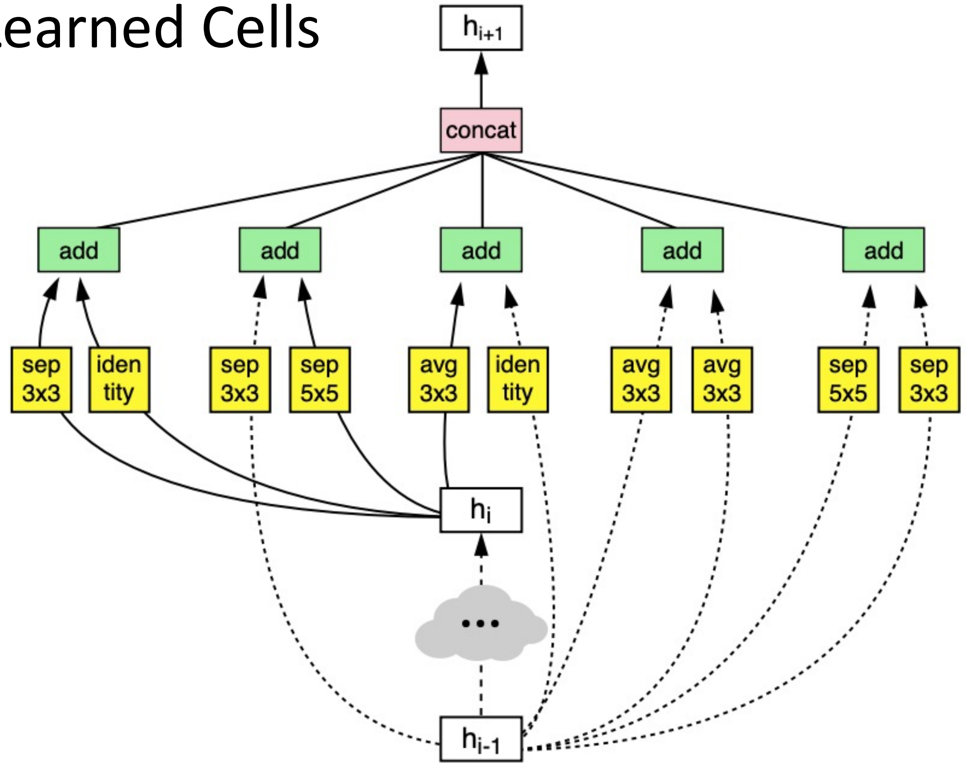
Combine two learned cells in a regular pattern to create overall architecture



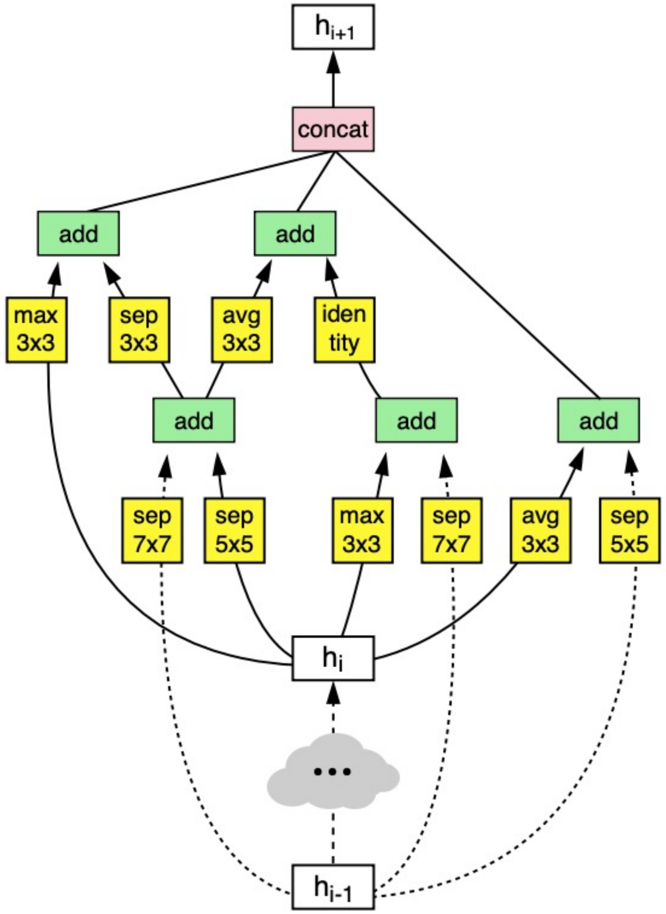
Zoph and Le, "Neural Architecture Search with Reinforcement Learning", ICLR 2017
Zoph et al, "Learning transferable architectures for scalable image recognition", CVPR 2018

Neural Architecture Search (NAS)

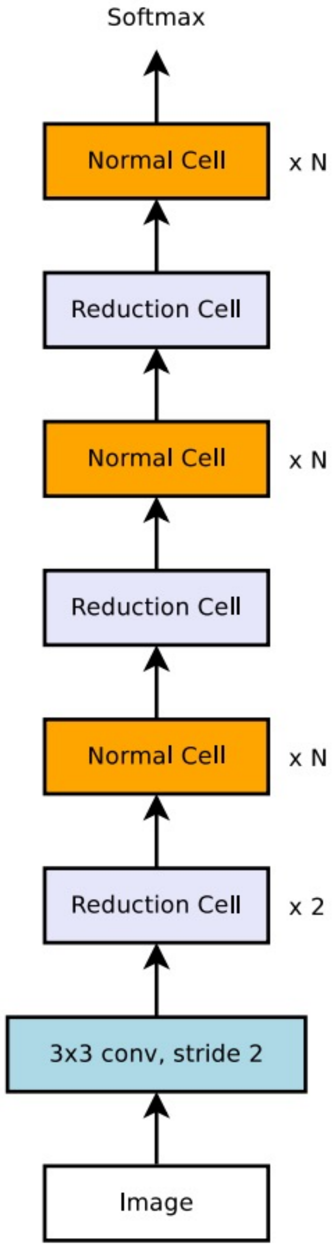
Learned Cells



Normal Cell

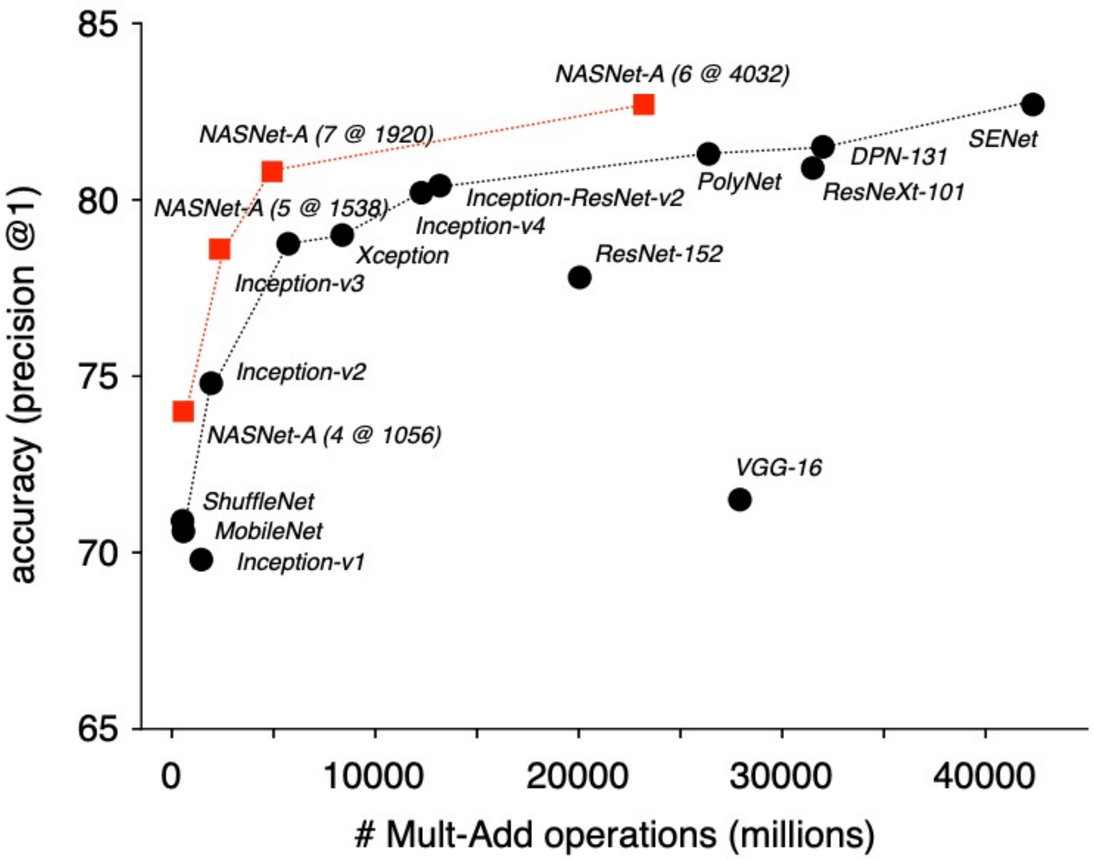


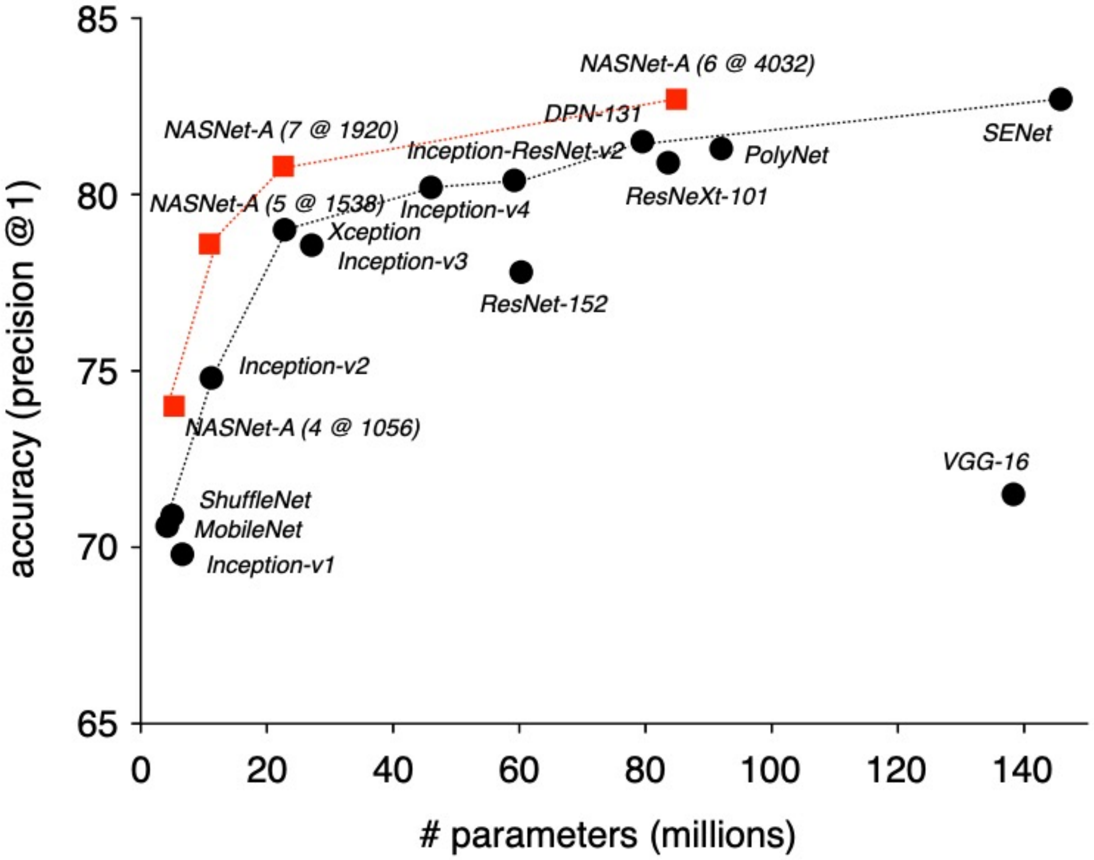
Reduction Cell



Zoph and Le, "Neural Architecture Search with Reinforcement Learning", ICLR 2017
Zoph et al, "Learning transferable architectures for scalable image recognition", CVPR 2018

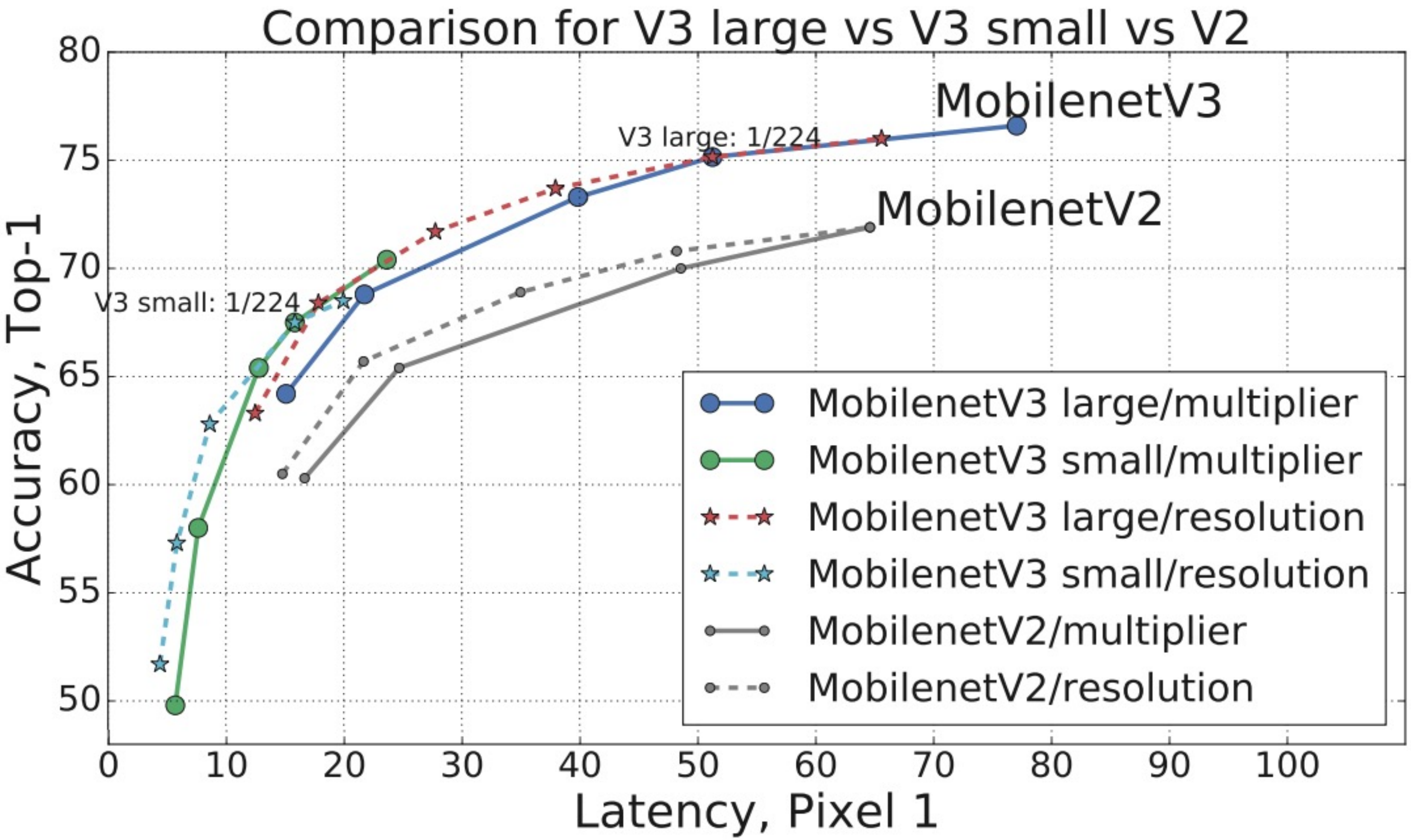
Neural Architecture Search (NAS)





Zoph and Le, “Neural Architecture Search with Reinforcement Learning”, ICLR 2017
Zoph et al, “Learning transferable architectures for scalable image recognition”, CVPR 2018

NAS for MobileNetV3

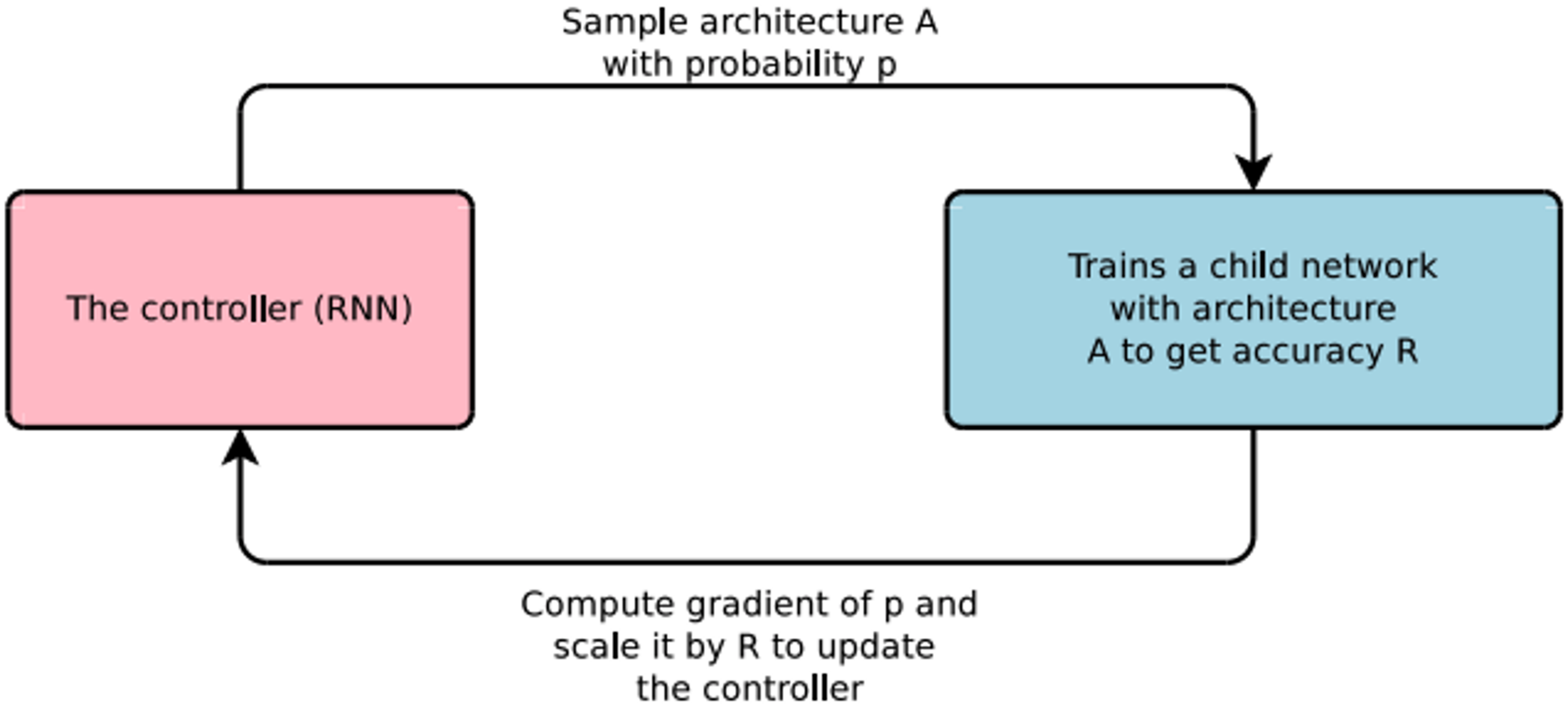


Howard et al, "Searching for MobileNetV3", ICCV 2019

Big Problem: NAS is Very Expensive!

Original NAS paper: Each update to the controller requires training **800 child models** for 50 epochs on CIFAR10; Total of **12,800** child models are trained

Later work improved efficiency, but still expensive



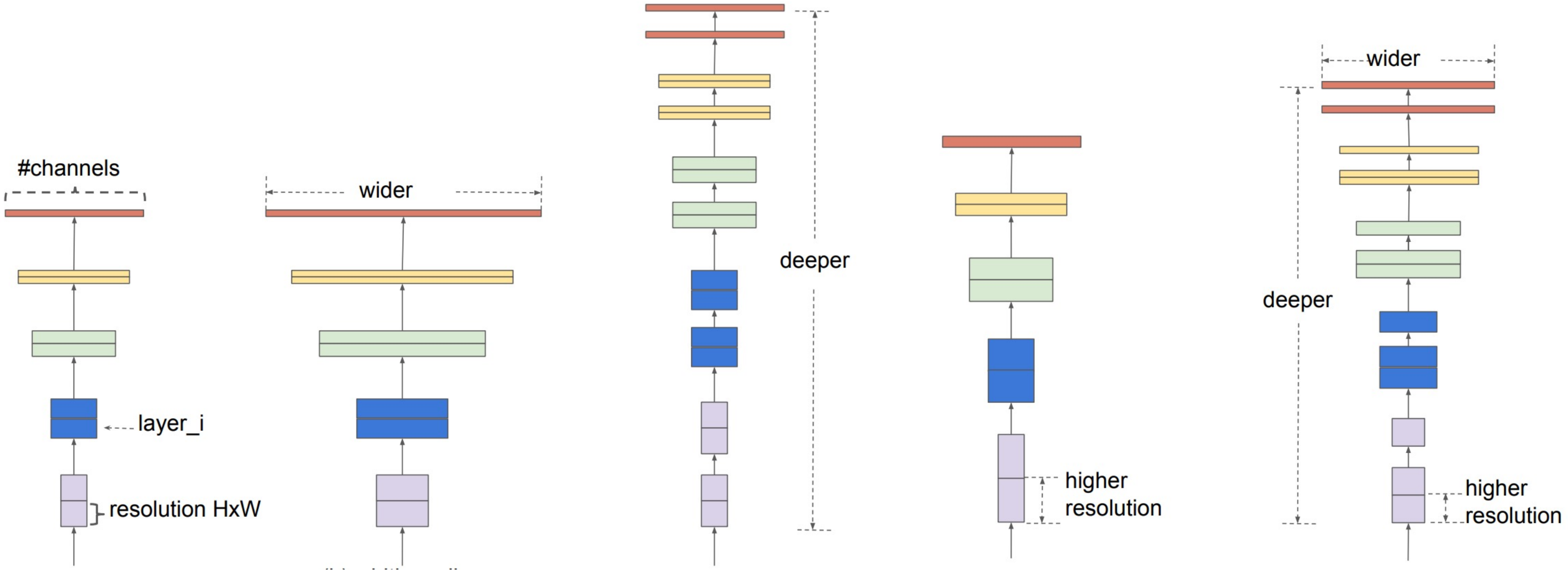
Zoph and Le, “Neural Architecture Search with Reinforcement Learning”, ICLR 2017

Neural Architecture Search: Many followups

Zoph and Le, ”Neural Architecture Search with Reinforcement Learning”, ICLR 2017
Pham et al, “Efficient neural architecture search via parameter sharing”, ICML 2018
Brock et al, “SMASH: One-Shot Model Architecture Search through HyperNetworks”, ICLR 2018
Ramachandran et al, “Searching for Activation Functions”, ICLR 2018 Workshop
Zoph et al, “Learning transferable architectures for scalable image recognition”, CVPR 2018
Liu et al, “Progressive Neural Architecture Search”, CVPR 2018
Liu et al, “DARTS: differentiable Architecture Search”, ICLR 2019
Cai et al, “ProxylessNAS: Direct Neural Architecture Search on Target Task and Hardware”, ICLR 2019
Xie et al, “SNAS: Stochastic Neural Architecture Search”, ICLR 2019
Real et al, “Regularized evolution for image classifier architecture search”, AAAI 2019
Tan et al, “MnasNet: Platform-Aware Neural Architecture Search for Mobile”, CVPR 2019
Howard et al, “Searching for MobileNetV3”, CVPR 2019
Wu et al, “FBNet: Hardware-Aware Efficient ConvNet Design via Differentiable Neural Architecture Search”, CVPR 2019
Liu et al, “Auto-DeepLab: Hierarchical Neural Architecture Search for Semantic Image Segmentation”, CVPR 2019
Ghiasi et al, “NAS-FPN: Learning Scalable Feature Pyramid Architecture for Object Detection”, CVPR 2019
Cubuk et al, “AutoAugment: Learning Augmentation Strategies from Data”, CVPR 2019

Model Scaling

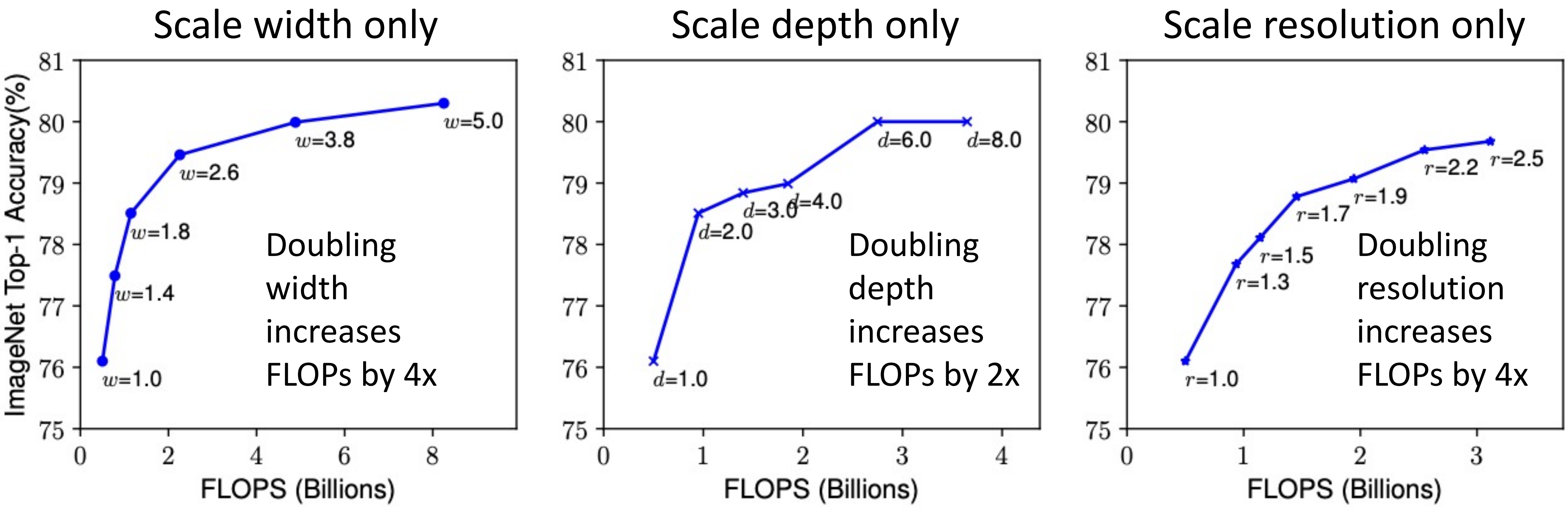
Starting from a given architecture, how should you **scale it up** to improve performance?



Baseline Architecture	**Width** : Increase channels in all layers	**Depth**: Use more layers	**Resolution**: Higher res input image	**Compound**: Scale all jointly

Tan and Le, "EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks", ICML 2019

Model Scaling: EfficientNets



Scaling any of width, depth, or resolution has diminishing returns.
For optimal results, need to scale them all jointly!

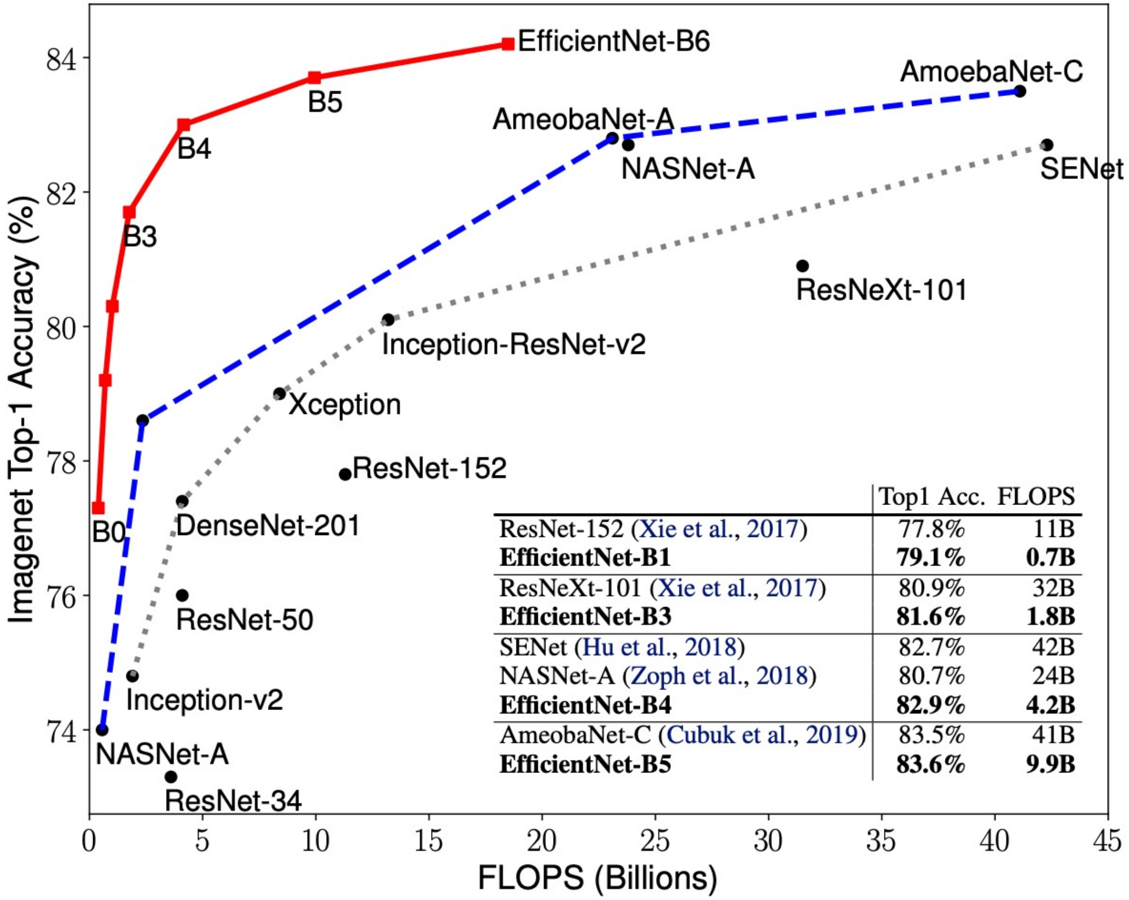
Tan and Le, “EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks”, ICML 2019

Model Scaling: EfficientNets

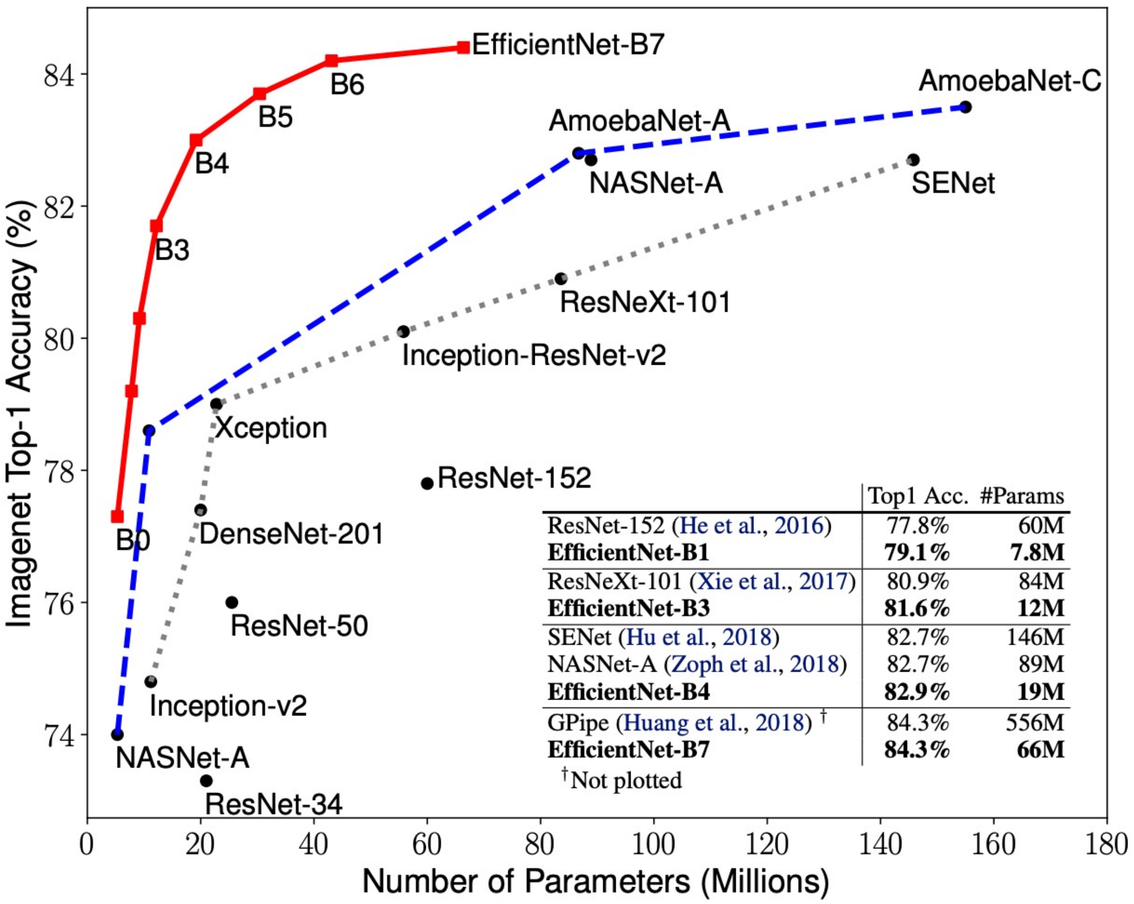
1. Use NAS to get initial EfficientNet-B0 architecture; uses depthwise conv, inverted bottlenecks, and SE
2. Find optimal scaling factors α for depth, β for width, γ for resolution with $\alpha, \beta, \gamma \geq 1$ and $\alpha\beta^2\gamma^2 \approx 2$ via grid search on scaling up initial architecture; found $\alpha = 1.2, \beta = 1.1, \gamma = 1.15$
3. Scale initial architecture to arbitrary FLOPs: scaling by $\alpha^\phi, \beta^\phi, \gamma^\phi$ will increase FLOPs by a factor of $\approx 2^\phi$

Tan and Le, "EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks", ICML 2019

Model Scaling: EfficientNets



	Top1 Acc.	FLOPS
ResNet-152 (Xie et al., 2017)	77.8%	11B
EfficientNet-B1	**79.1%**	**0.7B**
ResNeXt-101 (Xie et al., 2017)	80.9%	32B
EfficientNet-B3	**81.6%**	**1.8B**
SENet (Hu et al., 2018)	82.7%	42B
NASNet-A (Zoph et al., 2018)	80.7%	24B
EfficientNet-B4	**82.9%**	**4.2B**
AmeobaNet-C (Cubuk et al., 2019)	83.5%	41B
EfficientNet-B5	**83.6%**	**9.9B**

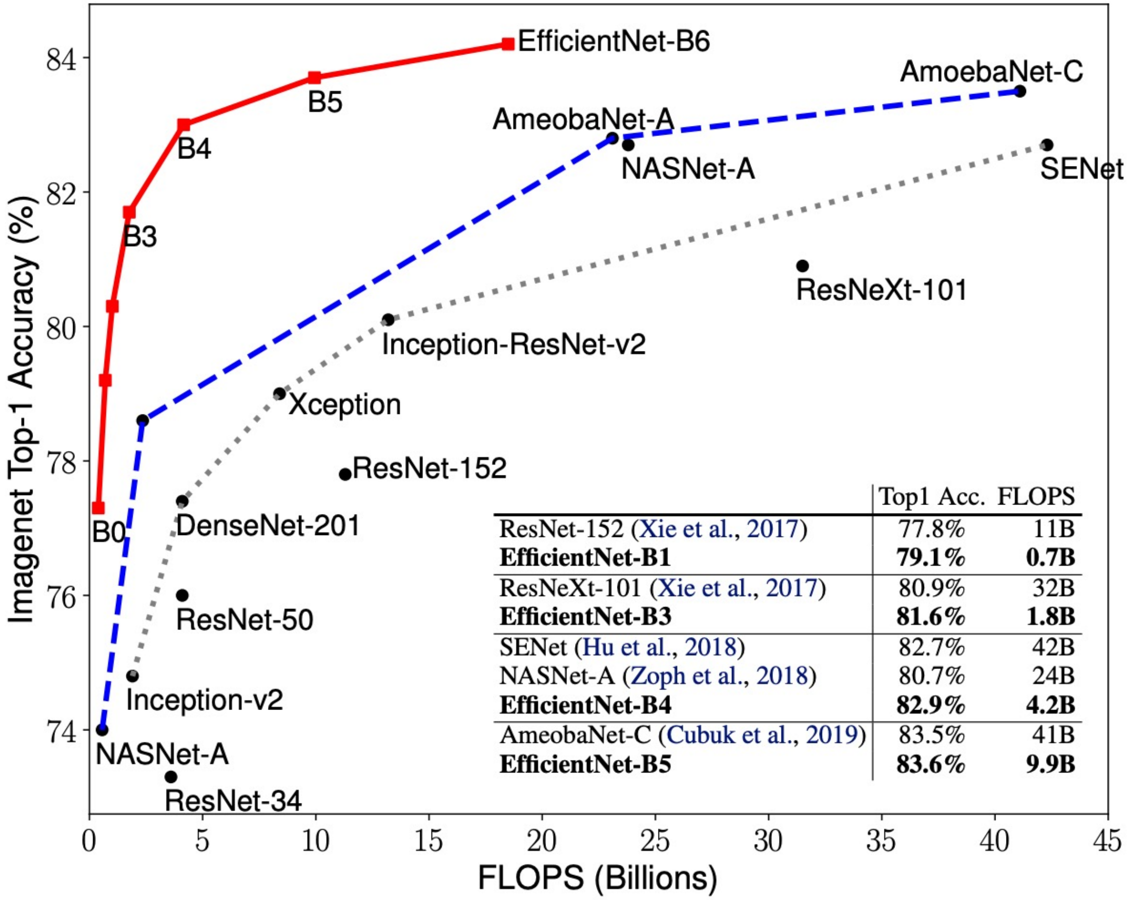


	Top1 Acc.	#Params
ResNet-152 (He et al., 2016)	77.8%	60M
EfficientNet-B1	**79.1%**	**7.8M**
ResNeXt-101 (Xie et al., 2017)	80.9%	84M
EfficientNet-B3	**81.6%**	**12M**
SENet (Hu et al., 2018)	82.7%	146M
NASNet-A (Zoph et al., 2018)	82.7%	89M
EfficientNet-B4	**82.9%**	**19M**
GPipe (Huang et al., 2018) †	84.3%	556M
EfficientNet-B7	**84.3%**	**66M**

†Not plotted

Tan and Le, “EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks”, ICML 2019

Model Scaling: EfficientNets



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Big problem: Real-world runtime does not correlate well with FLOPs!

- Runtime depends on the device (mobile CPU, server CPU, GPU, TPU); A model which is fast on one device may be slow on another
- Depthwise convolutions are efficient on mobile, but not on GPU / TPU – they become memory-bound
- The “naïve” FLOP counting we have done for convolutions can be incorrect – alternate conv algorithms can reduce FLOPs in some settings (FFT for large kernels, Winograd for 3x3 conv)
- EfficientNet was designed to minimize FLOPs, not actual runtime – so it is surprisingly slow!

Tan and Le, “EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks”, ICML 2019

Vasilache et al, “Fast Convolutional Nets With fbfft: A GPU Performance Evaluation”, ICLR 2015
Lavin and Gray, “Fast Algorithms for Convolutional Neural Networks”, CVPR 2016

Beyond NAS – back to hand-designed models!

Work in the last ~year has started to turn away from NAS;
instead smartly tweak ResNet-style models to improve performance,
scaling, runtime on GPU / TPU

NFNets: Remove Batch Normalization
ResNet-RS: Modern ResNet training recipe, better scaling
RegNets: Simple block design, optimize macro architecture and scaling

Training ResNets without Batch Normalization

- Batch Normalization has good properties:
  - Makes it easy to train deep networks >= 10 layers
  - Makes learning rates, initialization less critical
  - Adds regularization
  - "Free" at inference: can be merged into linear layers
- But also has bad properties:
  - Doesn't work with small minibatches
  - Different behavior at train and test
  - Slow at training time

NFNets are ResNets without Batch Normalization!

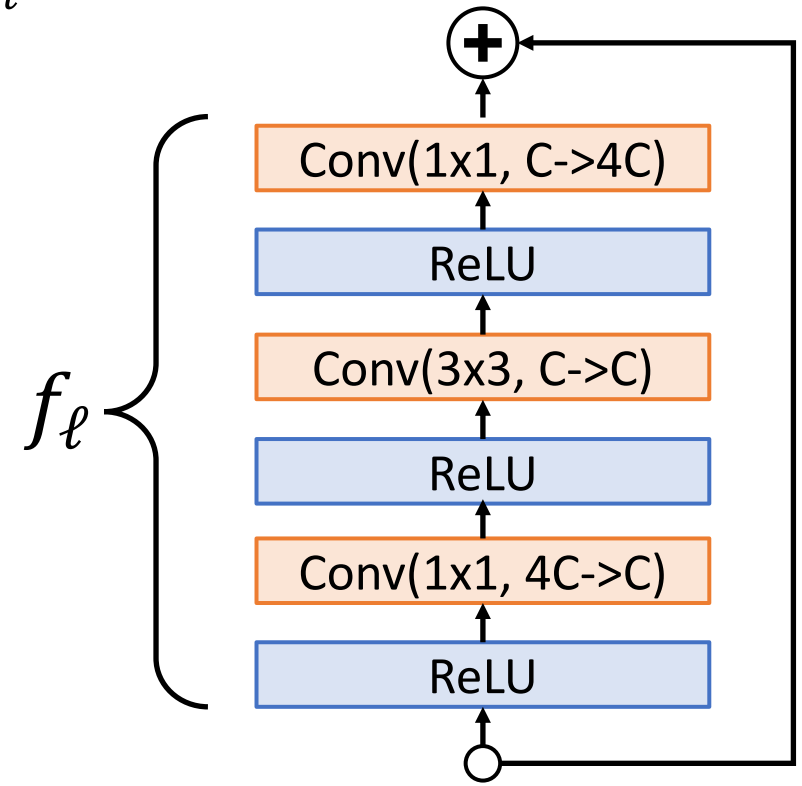
Brock et al, "Characterizing Signal Propagation to Close the Performance Gap in Unnormalized ResNets", ICLR 2021
Brock et al, "High-Performance Large-Scale Image Recognition without Normalization", ICML 2021

NFNets

Consider a pre-activation ResNet block $x_{\ell+1} = f_\ell(x_\ell) + x_\ell$

Problem: Variance grows with each block:

$$Var(x_{\ell+1}) = Var(x_\ell) + Var\big(f_\ell(x_\ell)\big)$$



He et al, "Identity Mappings in Deep Residual Networks", ECCV 2016

Brock et al, "Characterizing Signal Propagation to Close the Performance Gap in Unnormalized ResNets", ICLR 2021
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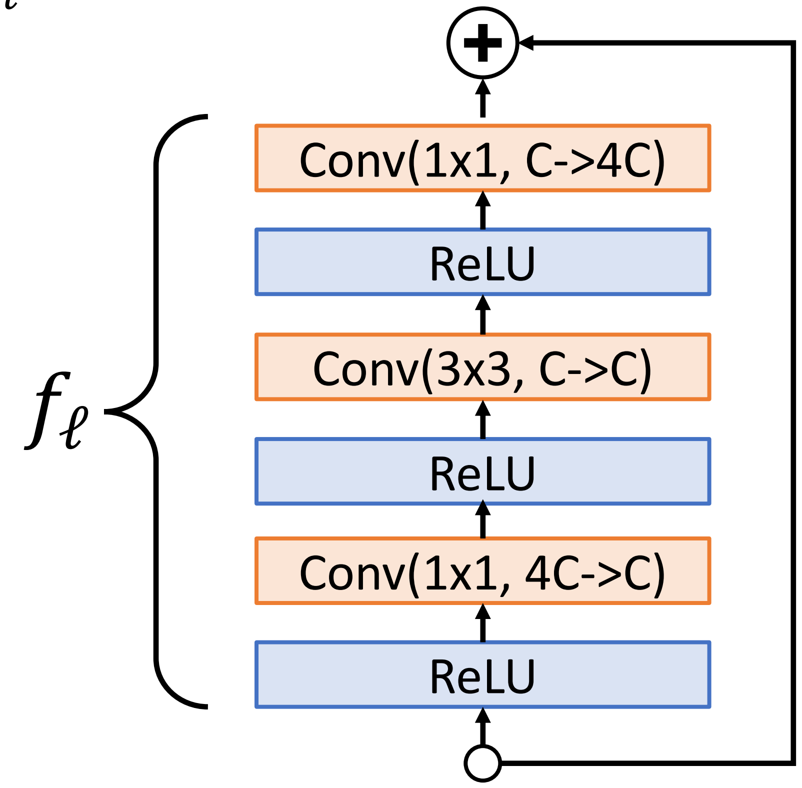

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Brock et al, “Characterizing Signal Propagation to Close the Performance Gap in Unnormalized ResNets”, ICLR 2021
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NFNets: Scaled Residual Blocks

Consider a pre-activation ResNet block $x_{\ell+1} = f_\ell(x_\ell) + x_\ell$

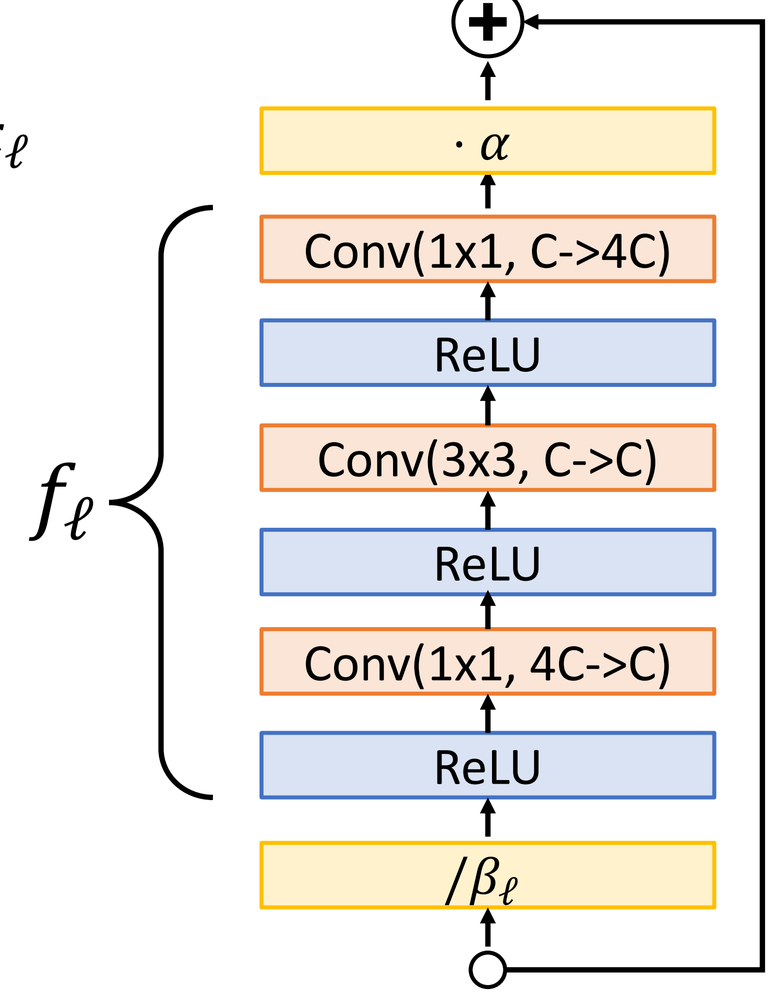
Problem: Variance grows with each block:

$$Var(x_{\ell+1}) = Var(x_\ell) + Var\big(f_\ell(x_\ell)\big)$$

Solution: Re-parameterize block:

$$x_{\ell+1} = x_\ell + \alpha f_\ell(x_\ell / \beta_\ell)$$

α is a hyperparameter, $\beta_\ell = \sqrt{Var(x_\ell)}$ at initialization; both are constants during training



Brock et al, "Characterizing Signal Propagation to Close the Performance Gap in Unnormalized ResNets", ICLR 2021
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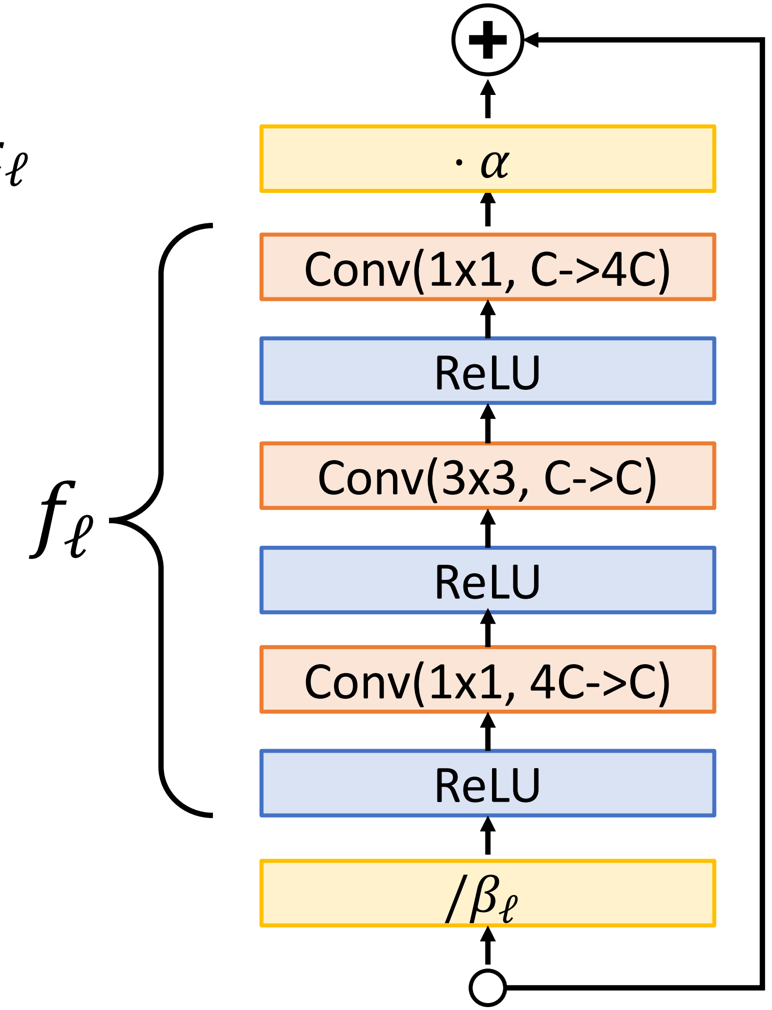
Now $Var\big(x_{\ell+1)}\big) = Var(x_\ell) + \alpha^2$; resets to $1 + \alpha^2$ after each downsampling block



Brock et al, "Characterizing Signal Propagation to Close the Performance Gap in Unnormalized ResNets", ICLR 2021
Brock et al, "High-Performance Large-Scale Image Recognition without Normalization", ICML 2021

NFNets: Weight Standardization

Rather than normalizing *activations* during training,
instead normalize *weights*!

Brock et al, "Characterizing Signal Propagation to Close the Performance Gap in Unnormalized ResNets", ICLR 2021
Brock et al, "High-Performance Large-Scale Image Recognition without Normalization", ICML 2021

NFNets: Weight Standardization

Rather than normalizing *activations* during training, instead normalize *weights*!

Learn weights W but convolve with weights $\widehat{W}$ where

$$\widehat{W}_{i,j} = \gamma \cdot \frac{W_{i,j} - mean(W_i)}{std(W_i)\sqrt{N}}$$

W_i is a single conv filter, $N = K^2 C_{in}$ is the "fan-in" of the kernel
γ is a constant that depends on the nonlinearity

Brock et al, "Characterizing Signal Propagation to Close the Performance Gap in Unnormalized ResNets", ICLR 2021
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γ is a constant that depends on the nonlinearity

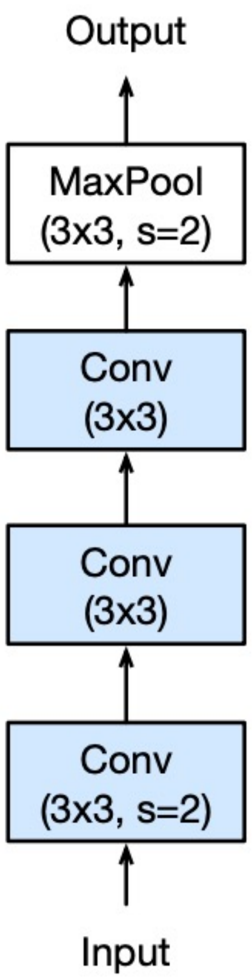
For ReLU: $\gamma = \sqrt{2 / \big(1 - (1/\pi)\big)}$

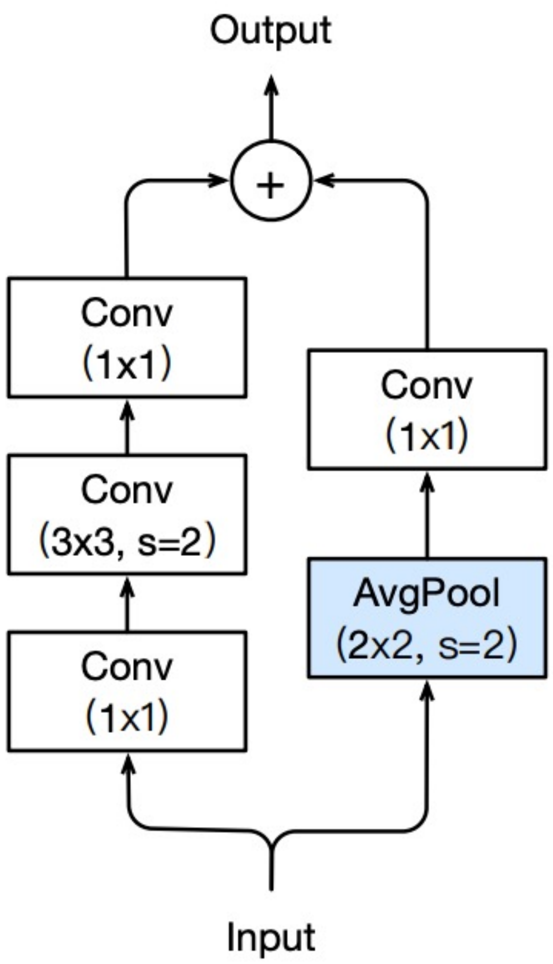
Compute $\widehat{W}$ each iteration during training (and backprop through it); at inference use fixed $\widehat{W}$ (zero-overhead like BN)

Brock et al, "Characterizing Signal Propagation to Close the Performance Gap in Unnormalized ResNets", ICLR 2021
Brock et al, "High-Performance Large-Scale Image Recognition without Normalization", ICML 2021

NFNets: Other Tricks

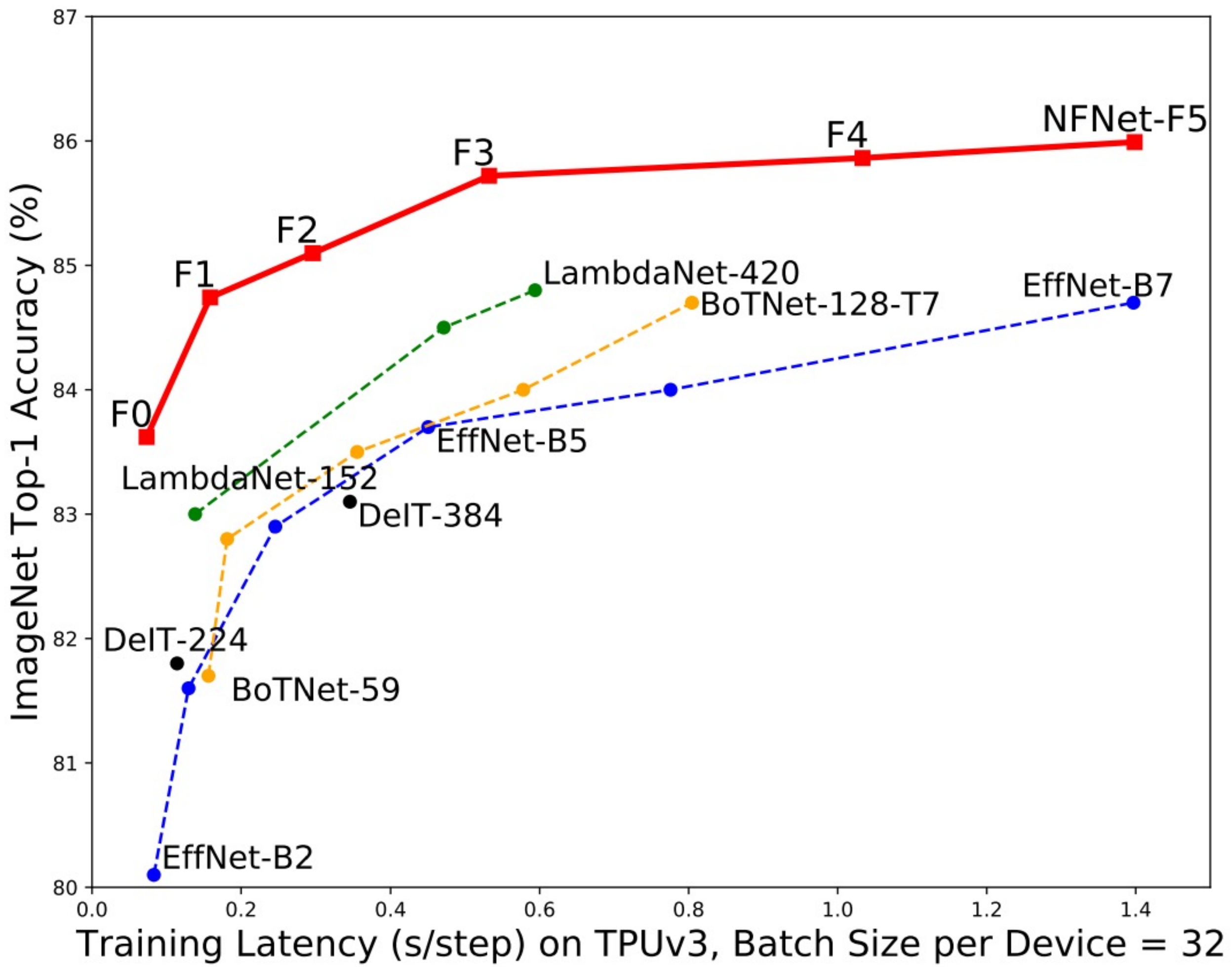
- **Adaptive Gradient Clipping:** Clip (raw) gradients during training if they get too large
- **Tweak ResNet architecture:**
  - Start from SE-ResNeXt
  - Tweak stem and downsampling blocks (ResNet-D)
  - Change ReLU to GeLU
  - Group width = 128 at all layers
  - Change stage widths: [256, 512, 1024, 1024] -> [256, 512, 1536, 1536]
  - Change stage depths: [3, 4, 6, 3] -> [1, 2, 6, 3]
- **Stronger regularization:** MixUp, RandAugment, CutMix, DropOut, Stochastic Depth





Brock et al, "Characterizing Signal Propagation to Close the Performance Gap in Unnormalized ResNets", ICLR 2021
Brock et al, "High-Performance Large-Scale Image Recognition without Normalization", ICML 2021
Hu et al, "Bag of Tricks for Image Classification with Convolutional Neural Networks", CVPR 2019

NFNets: Other Tricks



Always be careful with plots like this – different papers use different metric for x-axis:

- FLOPs
- Params
- Test-time runtime
- Training-time runtime
- Runtime on CPU / GPU / TPU / ?

Brock et al, "Characterizing Signal Propagation to Close the Performance Gap in Unnormalized ResNets", ICLR 2021
Brock et al, "High-Performance Large-Scale Image Recognition without Normalization", ICML 2021

Revisiting ResNets

Starting from baseline ResNet-200 model, improve performance with small tweaks:

Model	IN Top1	Δ
Baseline ResNet-200:	79.0	
+Cosine LR decay	79.3	+0.3
+Longer training (90->350 epochs)	78.8	-0.5
+EMA of weights	79.1	+0.3
+Label smoothing	80.4	+1.3
+Stochastic Depth	80.6	+0.2
+RandAugment	81.0	+0.4
+Dropout on FC	80.7	-0.3
+Less weight decay	82.2	+1.5
+Squeeze and Excite	82.9	+0.7
+ResNet-D	83.4	+0.5

Bello et al, “Revisiting ResNets: Improved Training and Scaling Strategies”, NeurIPS 2021

Revisiting ResNets

To get networks of different sizes, brute-force search over:

- Initial network width: 0.25x, 0.5x, 1.0x, 1.5x, or 2.0x baseline model
- Overall network depth: 26, 50, 101, 200, 300, 350, or 400 layers
- Input image resolution: 128, 160, 224, 320, or 448 pixels

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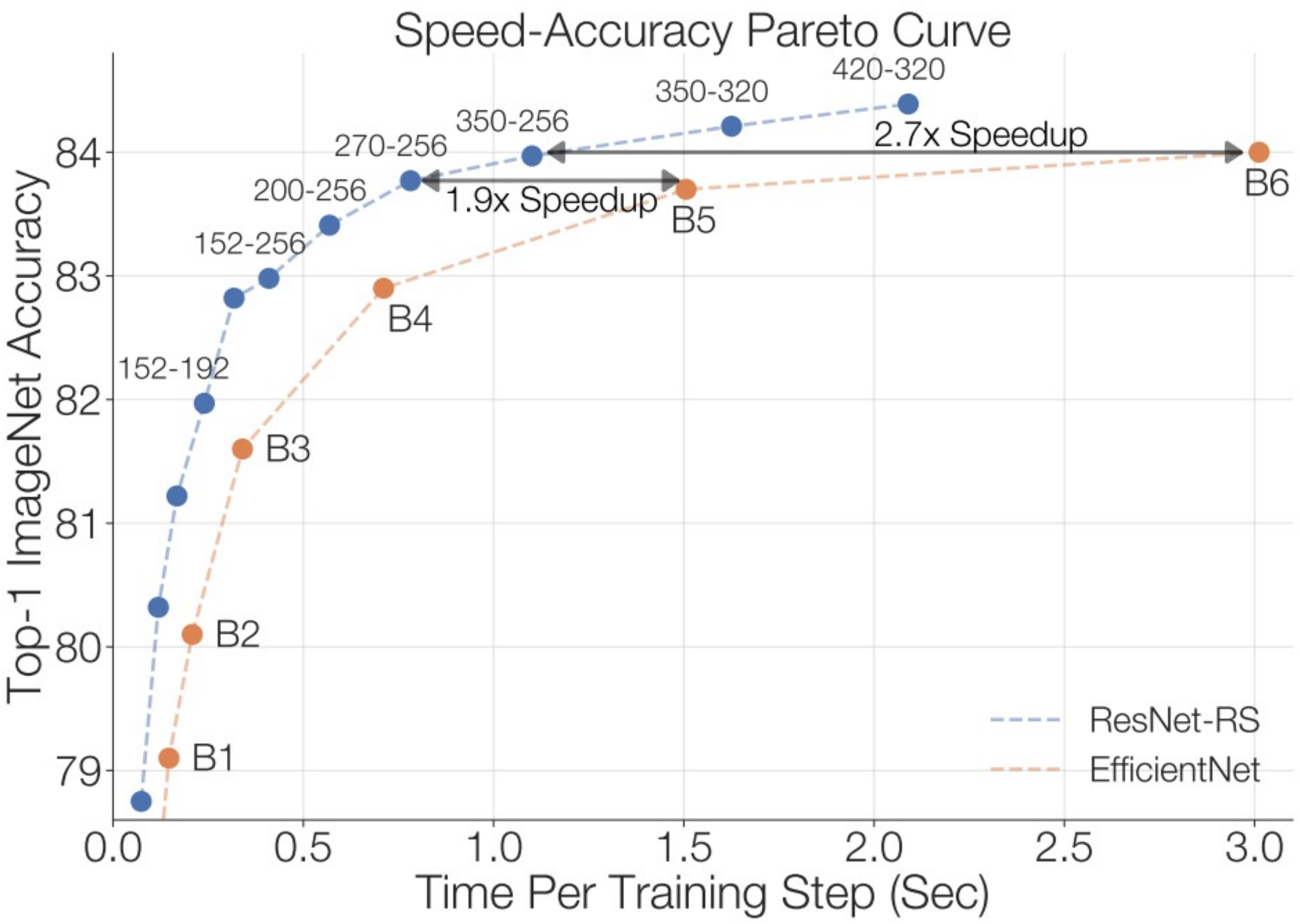
- Input image resolution: 128, 160, 224, 320, or 448 pixels

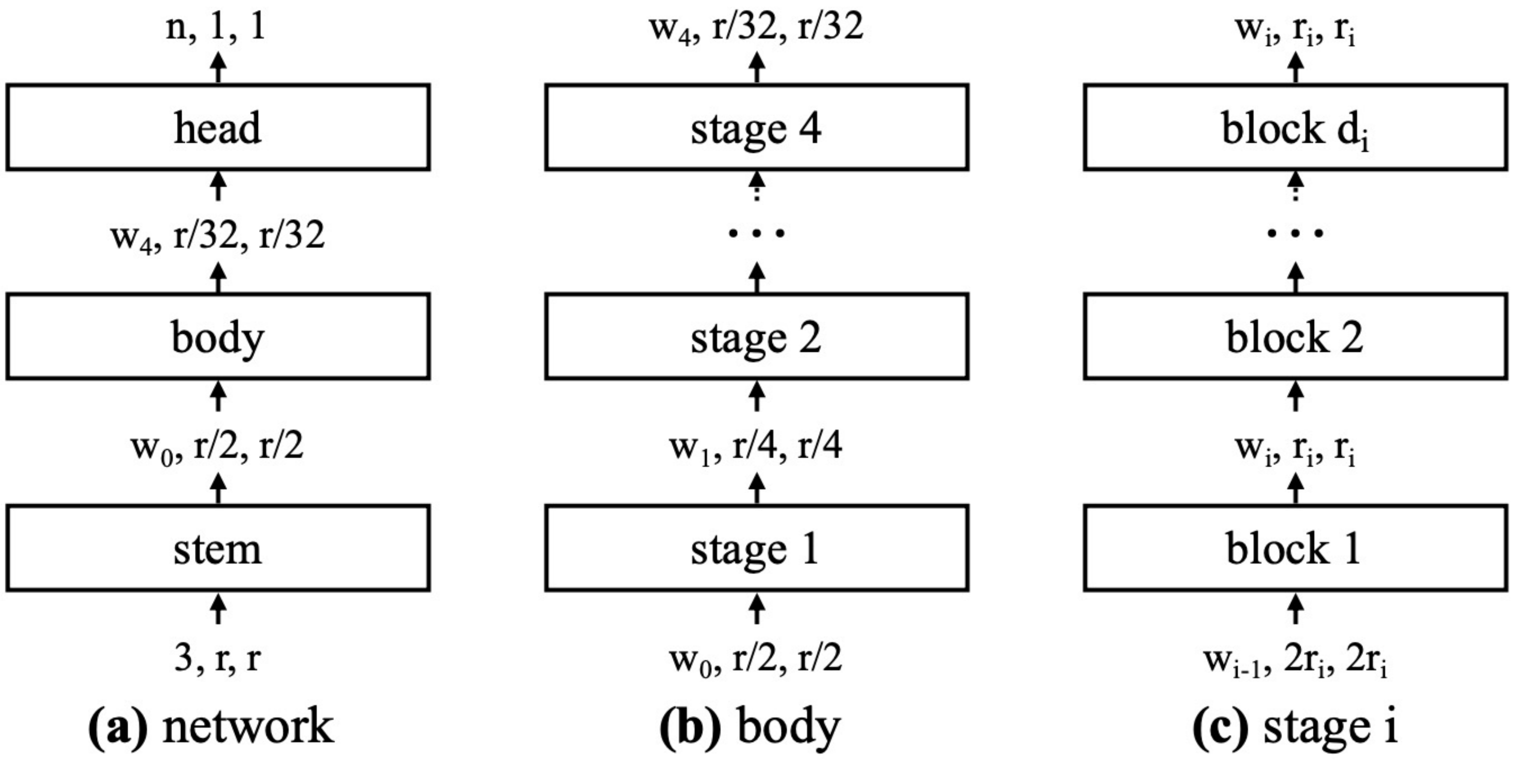
Significantly faster than EfficientNets at same accuracy (times on TPU)



Bello et al, "Revisiting ResNets: Improved Training and Scaling Strategies", NeurIPS 2021

RegNets: Network Design Spaces

Network design is simple: **Stem** of 3x3 convs, a **body** of 4 *stages*, and a **head;** Each stage has multiple **blocks**: First block downsamples by 2x, others keep resolution the same



Radosavovic et al, "Designing Network Design Spaces", CVPR 2020
Dollar et al, "Fast and Accurate Model Scaling", CVPR 2021

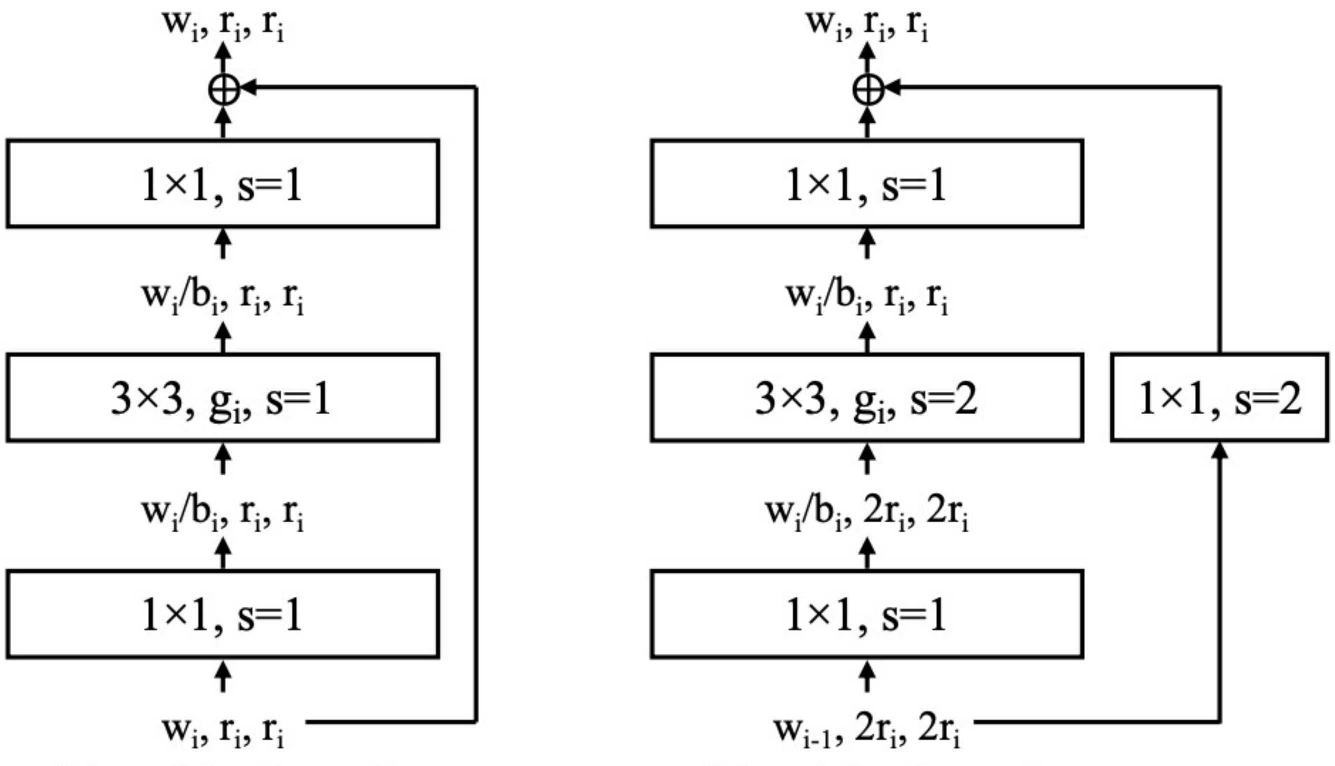
RegNets: Network Design Spaces

Block design is simple, generalizes ResNext

Each stage has 4 parameters:

- Number of blocks
- Number of input channels w
- Bottleneck ratio b
- Group width g

The *design space* for the network has just 16 parameters

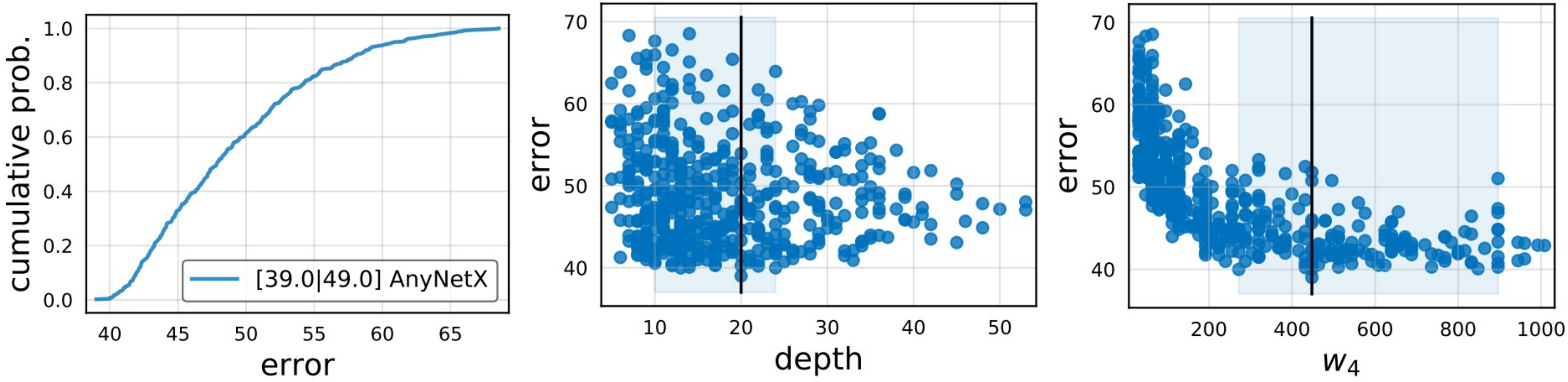


(a) X block, s=1 **(b)** X block, s=2

Radosavovic et al, "Designing Network Design Spaces", CVPR 2020
Dollar et al, "Fast and Accurate Model Scaling", CVPR 2021

RegNets: Network Design Spaces

Randomly sample architectures from the design space, examine trends:



Radosavovic et al, "Designing Network Design Spaces", CVPR 2020
Dollar et al, "Fast and Accurate Model Scaling", CVPR 2021

RegNets: Network Design Spaces

Use results to *refine* the design space: Reduce degrees of freedom from 16 to bias toward better-performing architectures:

- Share bottleneck ratio across all stages (16 -> 13 params)
- Share group width across all stages (13 -> 10 params)
- Force width, blocks per stage to increase *linearly* across stages

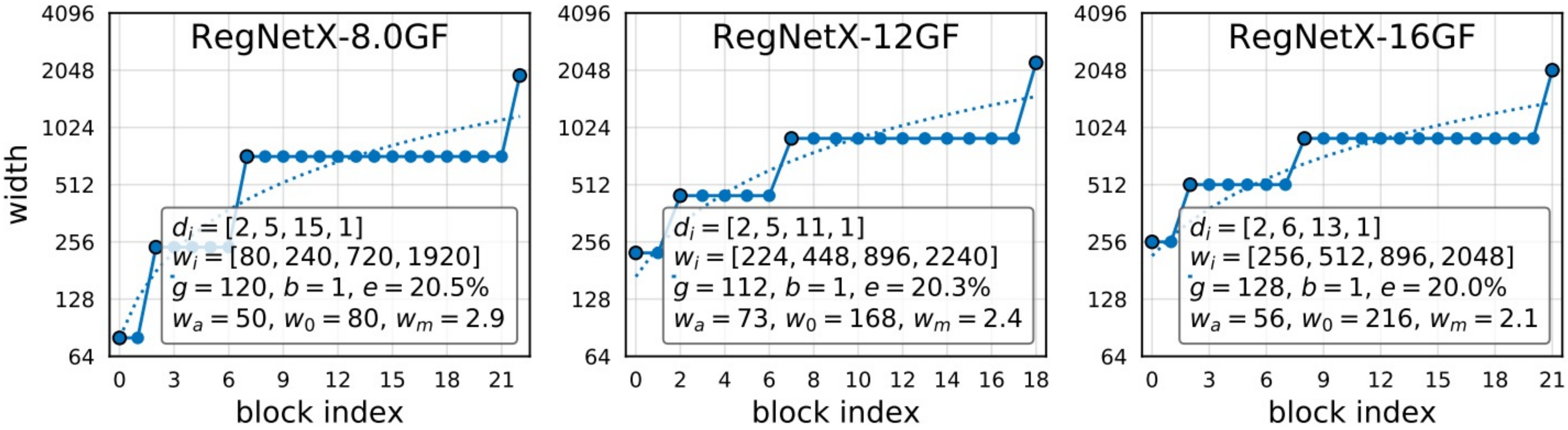
Final design space has 6 parameters:

- Overall depth d, bottleneck ratio b, group width g
- Initial width w_0, width growth rate w_a, blocks per stage w_m

Radosavovic et al, "Designing Network Design Spaces", CVPR 2020
Dollar et al, "Fast and Accurate Model Scaling", CVPR 2021

RegNets: Network Design Spaces

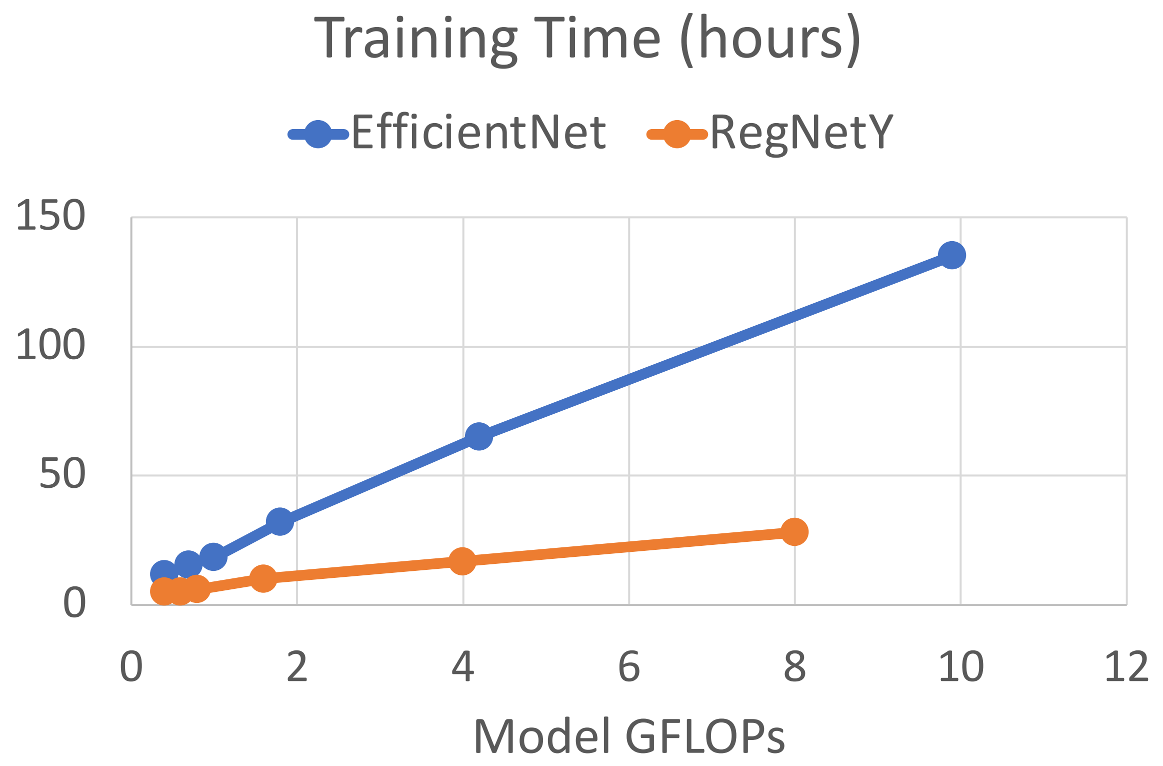
Random search finds good-performing models at varying FLOP budgets

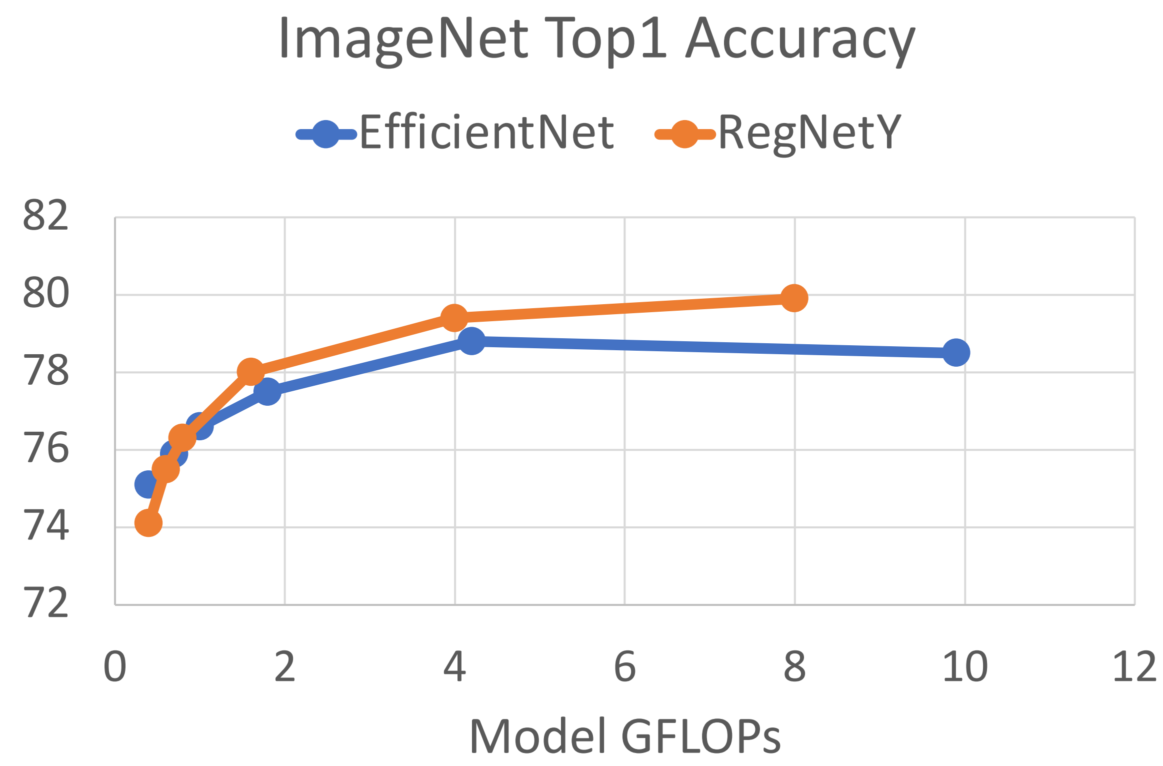


RegNetX is as described above, RegNetY also adds SE

Radosavovic et al, “Designing Network Design Spaces”, CVPR 2020
Dollar et al, “Fast and Accurate Model Scaling”, CVPR 2021

RegNets: Network Design Spaces

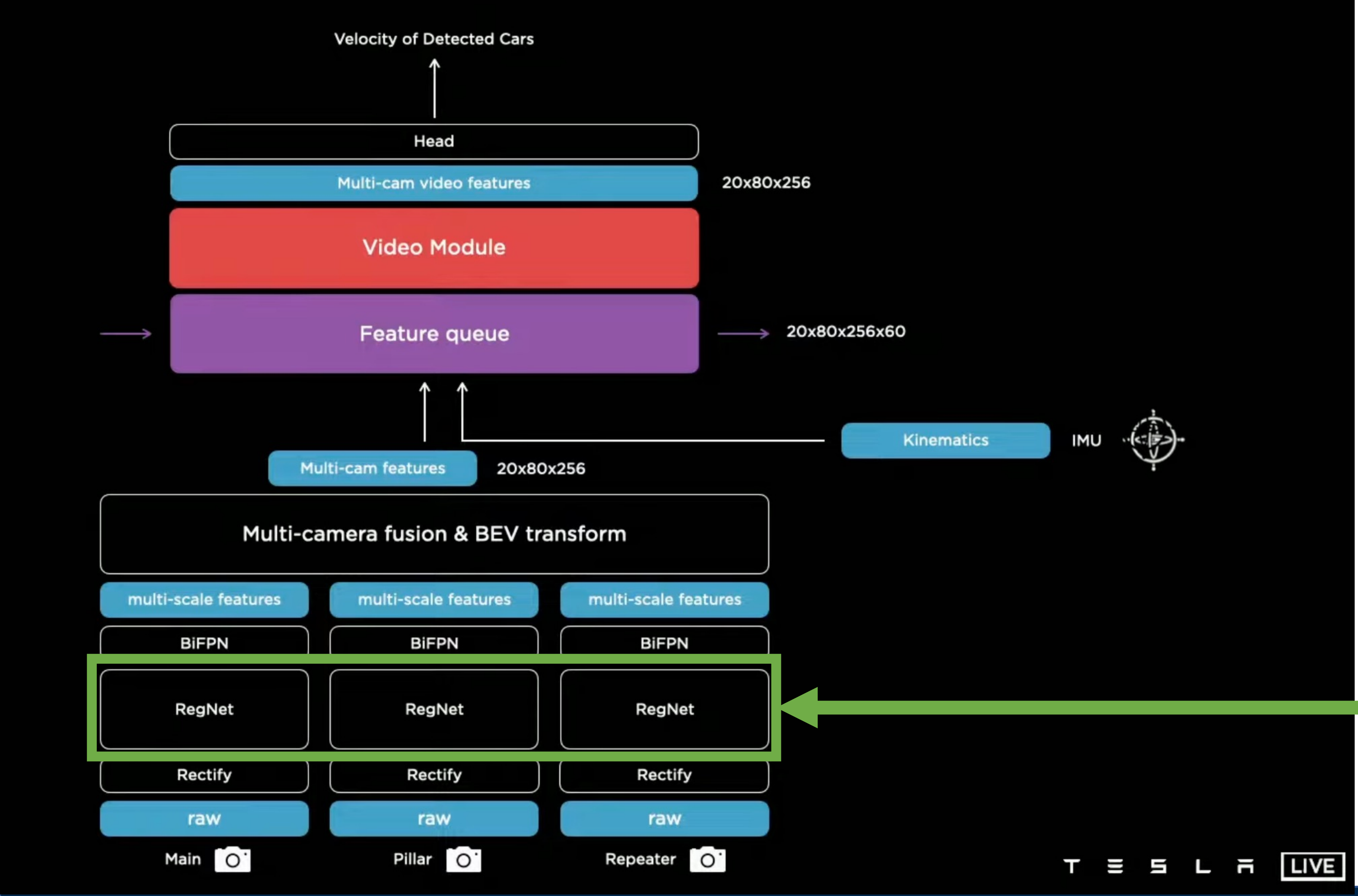




At same FLOPs, RegNet models get similar accuracy as EfficientNets but are up to 5x faster in training (each iteration is faster)

Radosavovic et al, “Designing Network Design Spaces”, CVPR 2020
Dollar et al, “Fast and Accurate Model Scaling”, CVPR 2021

Video Neural Net Architecture



Tesla Vision system uses RegNets to process inputs from each camera

Tesla AI Day 2021, https://www.youtube.com/watch?v=j0z4FweCy4M

CNN Architectures Summary

- Early work (AlexNet -> VGG -> ResNet): **bigger networks work better**
- New focus on **efficiency**: Improve accuracy, control for network complexity
- **Grouped and Depthwise Convolution** appear in many modern architectures
- **Squeeze-and-Excite** adds accuracy boost to just about any architecture while only adding a tiny amount of FLOPs and runtime
- Tiny networks for **mobile devices** (MobileNet, ShuffleNet)
- **Neural Architecture Search (NAS)** promised to automate architecture design
- More recent work has moved towards **careful improvements to ResNet-like architectures**
- ResNet and ResNeXt are still surprisingly strong and popular architectures!
- RegNet seems like a promising and efficient architecture to use

A Sneak Peek…

A lot of recent work has started to move away from CNNs entirely!

New classes of models: Vision Transformers, MLP-like models

We will learn more after Spring Break (Lectures 17 and 18)

Next Time: How do we implement all this?

Deep Learning Software