ECE 598NSG/498NSU
Deep Learning in Hardware
Fall 2020

Low-complexity DNNs

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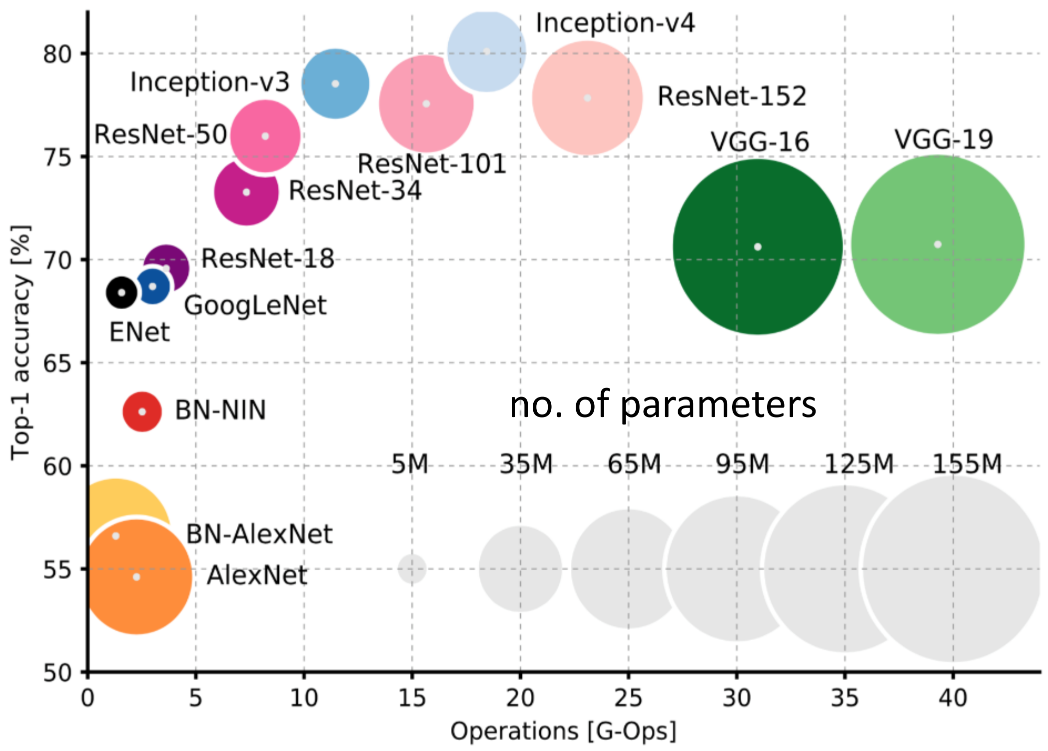
Today

- Motivation
- Low-complexity network - MobileNet
- Low-complexity network – SqueezeNet
- Low-complexity network – ShuffleNet
- Low-complexity network – ThunderNet

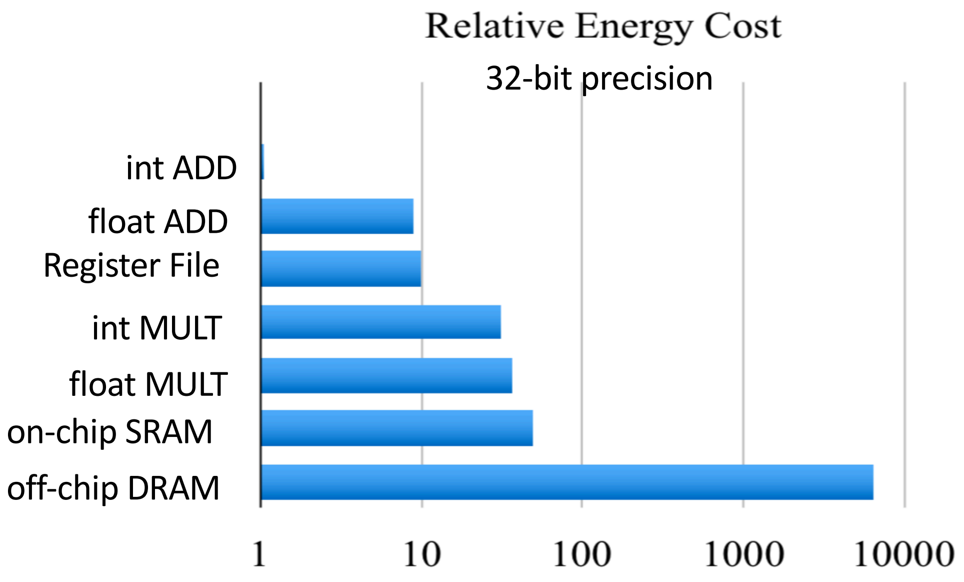
Motivation

- faster training
- easier '*over the air*' updates to Edge devices
- fewer off-chip accesses during inference – lower latency and energy costs of inference
  - e.g., FPGA on-chip memory < 10 MB

Memory Access Energy in DNNs



[Canziani-arXiv-2017]



[Horowitz-ISSCC-2014]

- Require large no. of parameters → don't fit within on-chip SRAM
- off-chip DRAM accesses are 100x more energy expensive

Low-Complexity DNNs

- Two approaches
- 1: design a low-complexity network from scratch
  - based on design intuitions (MobileNet, SqueezeNet)
- 2: reduce the complexity of a large network
  - model compression
  - factorization
  - distillation
  - binarization/ternarization
- need to address complexity vs. accuracy trade-off

Three Low-Complexity Networks

- MobileNet
- SqueezeNet
- ShuffleNet

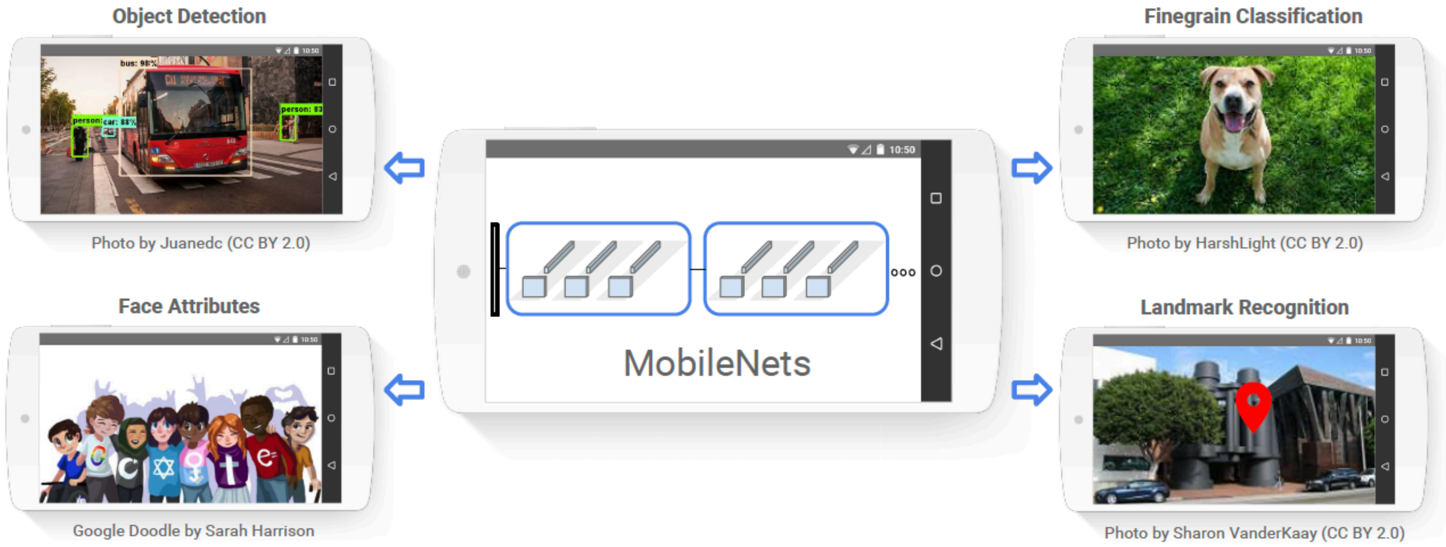
MobileNet

MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications

Andrew G. Howard Menglong Zhu Bo Chen Dmitry Kalenichenko
Weijun Wang Tobias Weyand Marco Andreetto Hartwig Adam

Google Inc.

intrinsically a low-complexity network → embedded vision apps.



	# of Layers	# of parameters CONV	# of parameters FC	# of MACs CONV	# of MACs FC	Top-1 error %	Top-5 error %
AlexNet	5C – 3F	3.7M	58.6M	1,077M	58.6M	42.9	15.3
VGGNet	13/16/19C – 3F	14.7M	123.6M	15,360M	123.6M	28.07	9.33
ResNet	18/34/50/101/152C – 1F	21M	512K	3,643M	512K	21.53	5.6
DenseNet	120/160/168/200C – 1F	~ 52M	1.152M	**> 7B**	1.152M	20.85	5.3
MobileNet	27C – 1F	3.1M	1M	532M	1M	29.4	11.022

[source: Dbouk]

- Objective: to design small, low-latency models for embedded platforms
- 5X smaller model complexity than ResNet but higher error rates

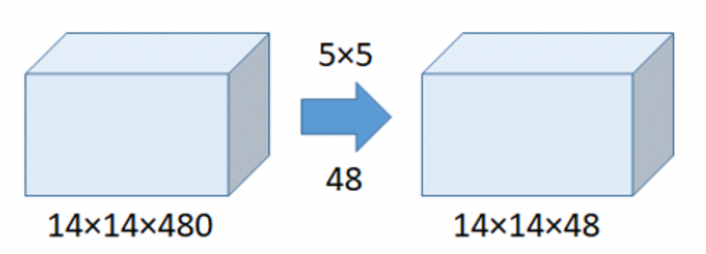
- optimizes size and latency
- parametrized network -> can design many versions
- two parameters: width and resolution multipliers
- built from

depth-wise separable convolutions →

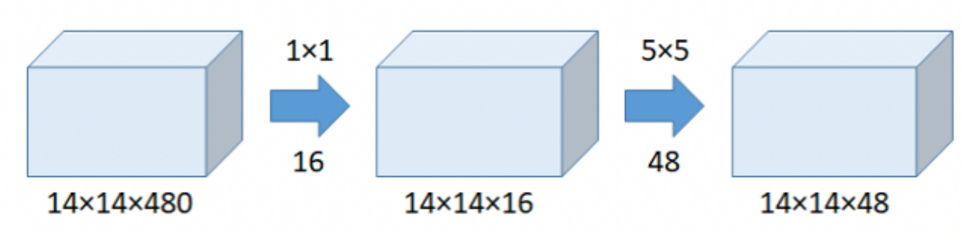
standard convolution = depth-wise separable x point-wise

convolutions

- depth-wise separable convolutions – first proposed in (Sifre, Ph.D. thesis, 2014) – use pointwise convolutions to reduce input dimension of larger filters
- Used by Inception modules in GoogleNet



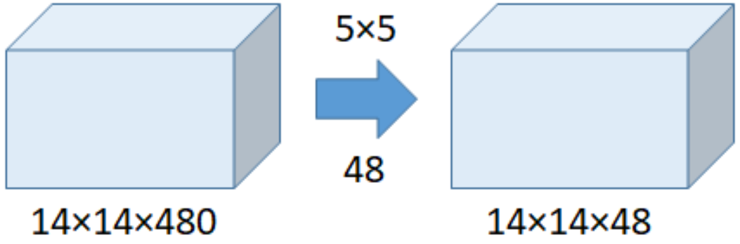
total #MACs = 112.9M



total #MACs = 5.3M

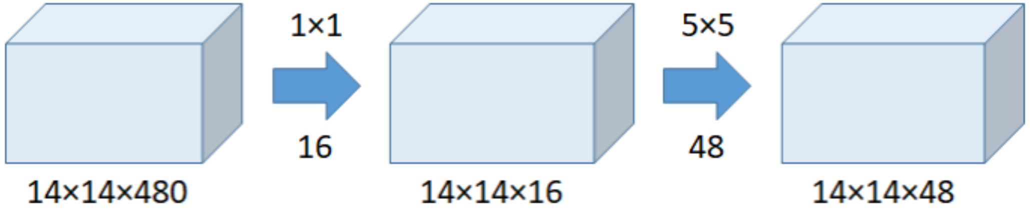
- depth-wise separable convolutions – first proposed in (Sifre, Ph.D. thesis, 2014) → factorize convolutions to save complexity
- better than reducing size of filters for accuracy
- Used by Inception modules in GoogleNet

standard convolution



total #MACs = 112.9M

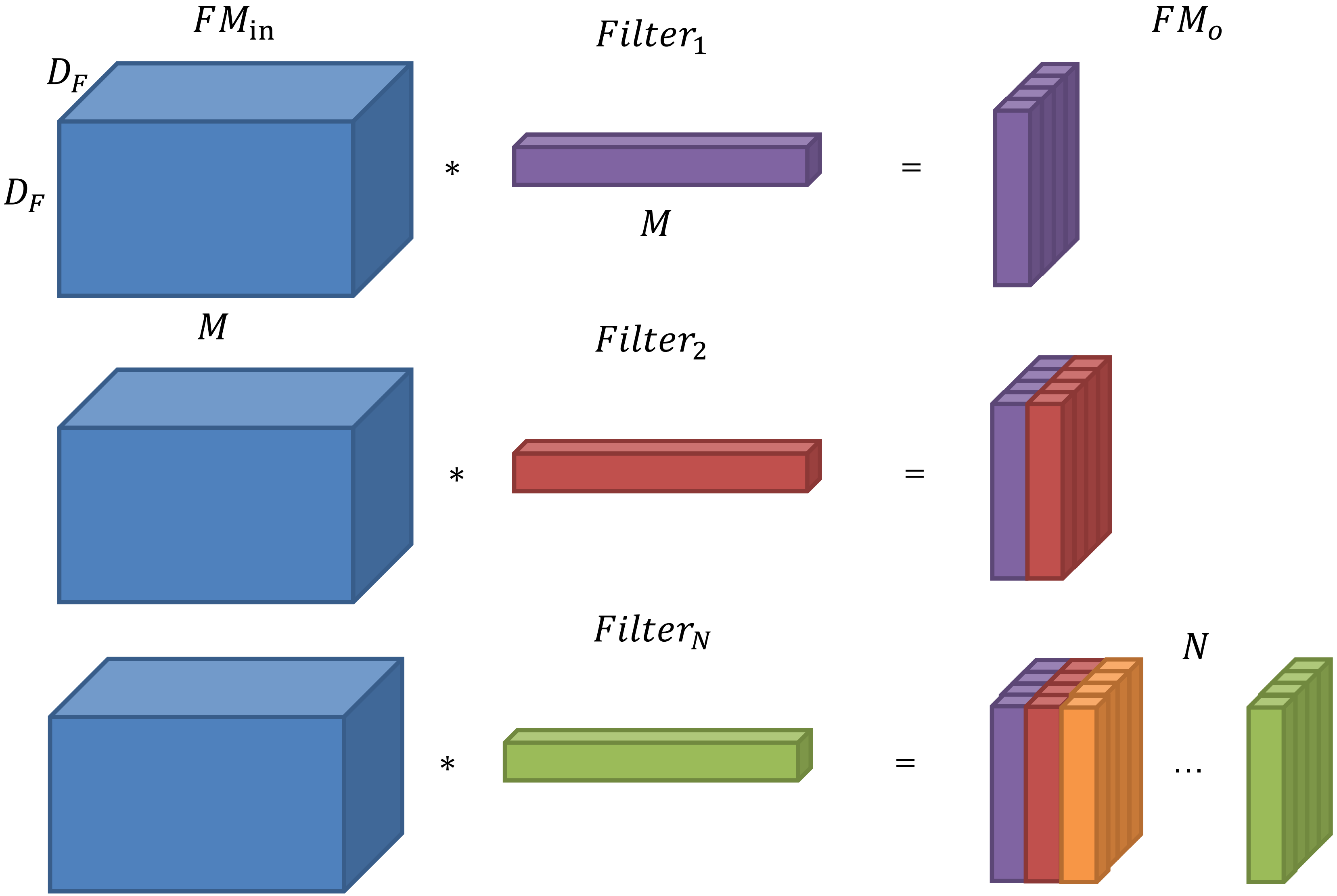
factorized convolution



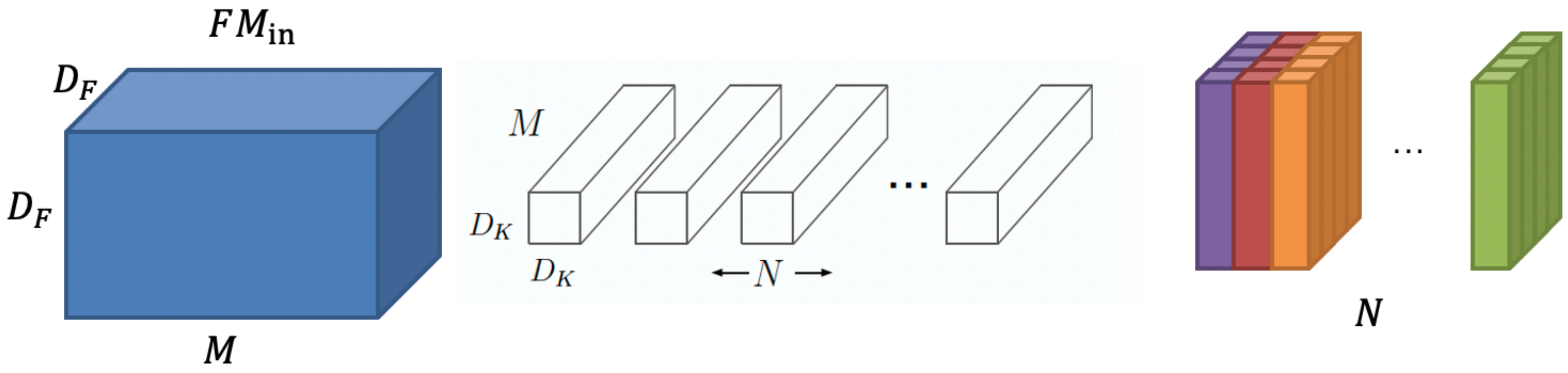
total #MACs = 5.3M

input and output FM sizes in both are the same → reduces impact on accuracy

Standard Convolution



Standard Convolution Filters

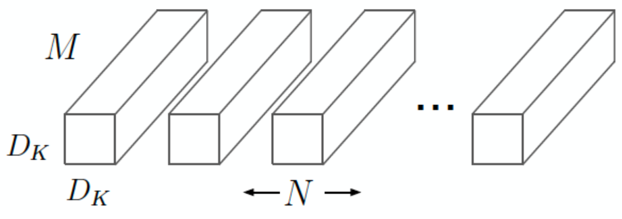


- Kernel size: $D_K^2 \times M \times N$
- Computational cost: $D_K^2 \times M \times N \times D_F^2$

Depth-wise Separable Convolutions

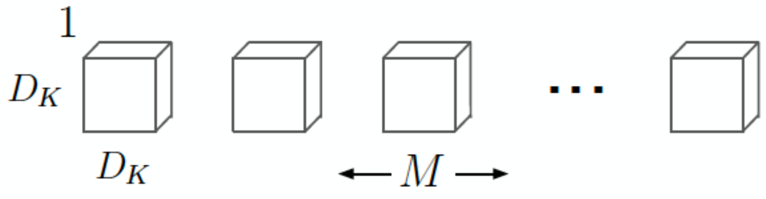
- breaks the relationship between N and kernel size
- depth-wise separable convolution = depth-wise convolution $\times$ point-wise convolution

standard



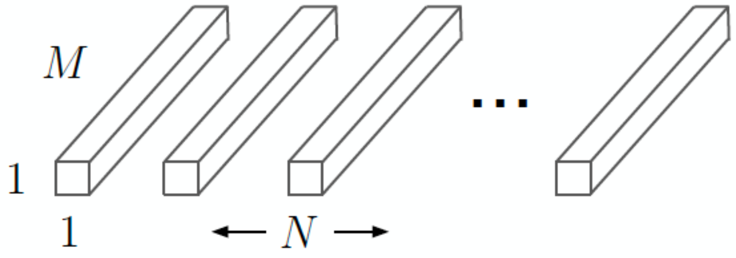
=

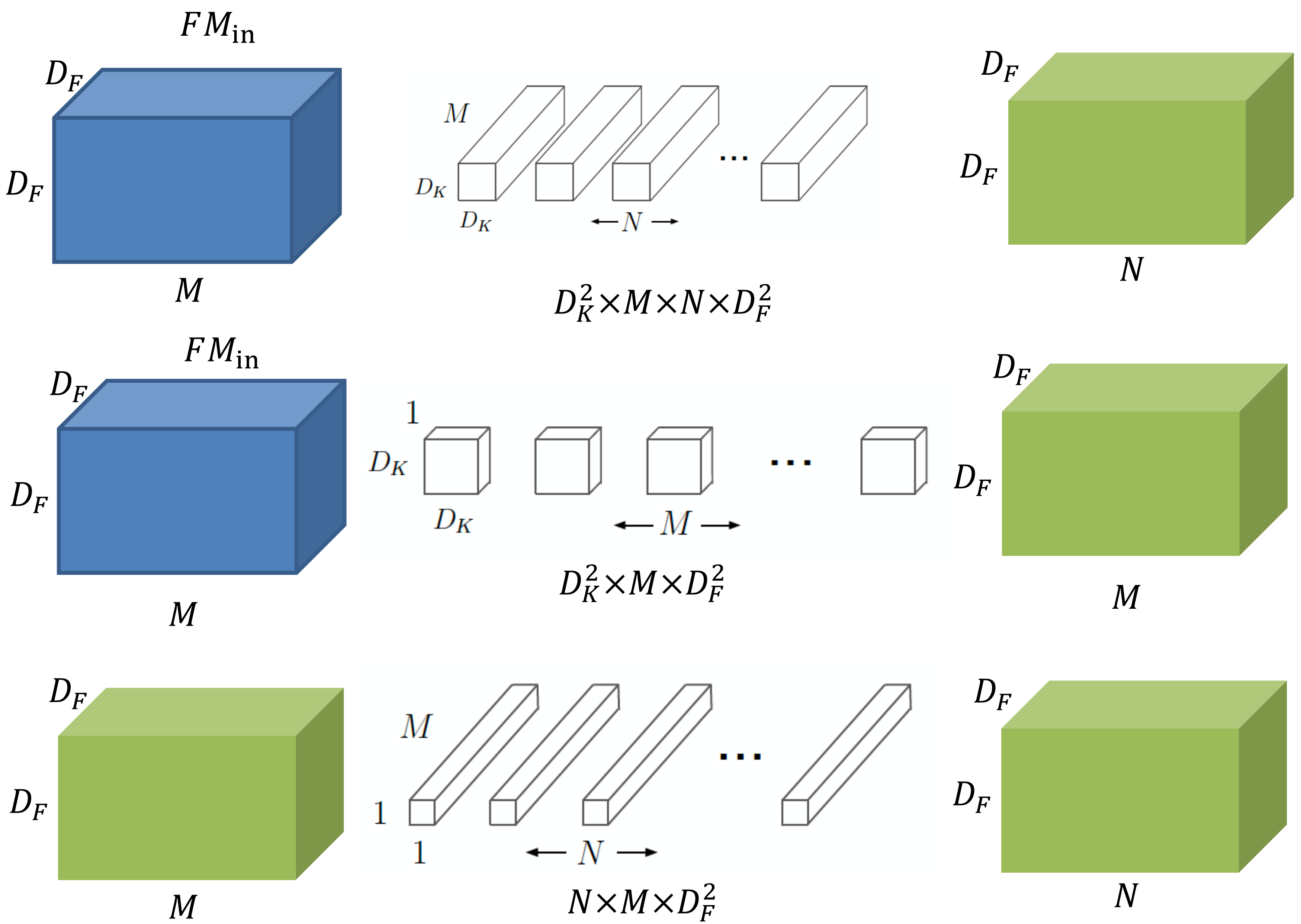
depth-wise (in-plane conv)



X

point-wise (cross-plane conv)




FM_{in}
D_F
D_F
M
M
D_K
D_K
N
D_F
D_F
N
$D_K^2 \times M \times N \times D_F^2$
FM_{in}
D_F
D_F
M
1
D_K
D_K
M
D_F
D_F
M
$D_K^2 \times M \times D_F^2$
D_F
D_F
M
M
1
1
N
D_F
D_F
N
$N \times M \times D_F^2$

Computational Cost

- Standard: $D_K^2 \times M \times N \times D_F^2$

- Depth-wise separable: $D_K^2 \times M \times D_F^2 + N \times M \times D_F^2$
- second term usually dominates

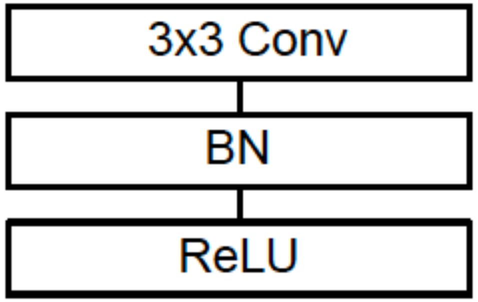
- Savings:

$$\frac{D_K^2 \times M \times D_F^2 + N \times M \times D_F^2}{D_K^2 \times M \times N \times D_F^2} = \frac{1}{N} + \frac{1}{D_K^2}$$

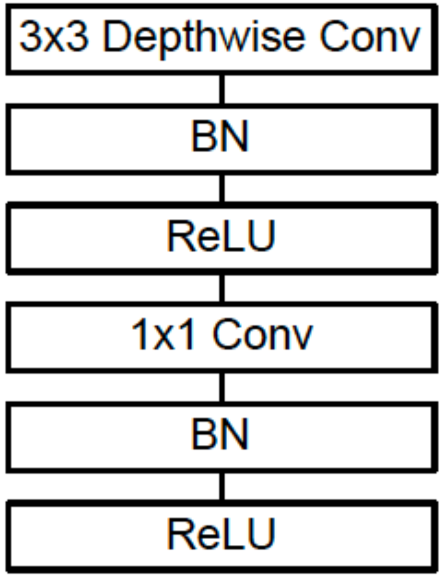
- MobileNet: $D_K = 3 \rightarrow 8\times$-to-$9\times$ savings in complexity

Network Architecture

Standard CONV layer



MobileNet CONV layer

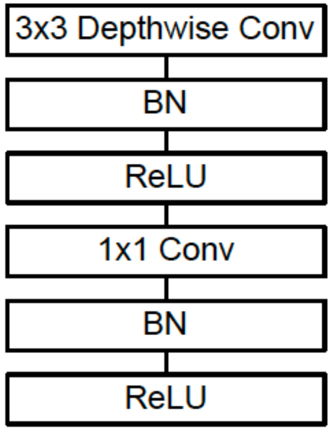


- MobileNet Layer 1 is standard CONV

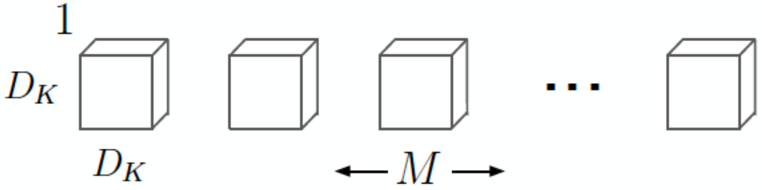
MobileNet Architecture – 28 Layers

Table 1. MobileNet Body Architecture

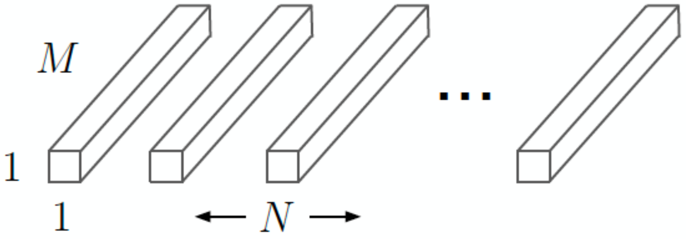
Type / Stride	Filter Shape	Input Size
Conv / s2	$3 \times 3 \times 3 \times 32$	$224 \times 224 \times 3$
Conv dw / s1	$3 \times 3 \times 32$ dw	$112 \times 112 \times 32$
Conv / s1	$1 \times 1 \times 32 \times 64$	$112 \times 112 \times 32$
Conv dw / s2	$3 \times 3 \times 64$ dw	$112 \times 112 \times 64$
Conv / s1	$1 \times 1 \times 64 \times 128$	$56 \times 56 \times 64$
Conv dw / s1	$3 \times 3 \times 128$ dw	$56 \times 56 \times 128$
Conv / s1	$1 \times 1 \times 128 \times 128$	$56 \times 56 \times 128$
Conv dw / s2	$3 \times 3 \times 128$ dw	$56 \times 56 \times 128$
Conv / s1	$1 \times 1 \times 128 \times 256$	$28 \times 28 \times 128$
Conv dw / s1	$3 \times 3 \times 256$ dw	$28 \times 28 \times 256$
Conv / s1	$1 \times 1 \times 256 \times 256$	$28 \times 28 \times 256$
Conv dw / s2	$3 \times 3 \times 256$ dw	$28 \times 28 \times 256$
Conv / s1	$1 \times 1 \times 256 \times 512$	$14 \times 14 \times 256$
$5\times$ Conv dw / s1	$3 \times 3 \times 512$ dw	$14 \times 14 \times 512$
$5\times$ Conv / s1	$1 \times 1 \times 512 \times 512$	$14 \times 14 \times 512$
Conv dw / s2	$3 \times 3 \times 512$ dw	$14 \times 14 \times 512$
Conv / s1	$1 \times 1 \times 512 \times 1024$	$7 \times 7 \times 512$
Conv dw / s2	$3 \times 3 \times 1024$ dw	$7 \times 7 \times 1024$
Conv / s1	$1 \times 1 \times 1024 \times 1024$	$7 \times 7 \times 1024$
Avg Pool / s1	Pool 7×7	$7 \times 7 \times 1024$
FC / s1	1024×1000	$1 \times 1 \times 1024$
Softmax / s1	Classifier	$1 \times 1 \times 1000$



$D_K \times D_K \times M$



$1 \times 1 \times M \times N$



Computational Costs by Layer Type

Table 2. Resource Per Layer Type

Type	Mult-Adds	Parameters
Conv 1×1	94.86%	74.59%
Conv DW 3×3	3.06%	1.06%
Conv 3×3	1.19%	0.02%
Fully Connected	0.18%	24.33%

- most of the cost in point-wise convolutions → 95% time and 75% of storage in point
- point-wise convolutions = dot-products

Parameterizing MobileNet

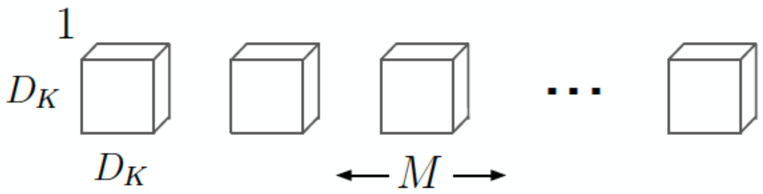
- how to generate MobileNets with different size, accuracy, latency trade-offs?

- parameterize the network with:
  – width multiplier – scales the number of channels
  – resolution multiplier – scales the 2D size of the FMs

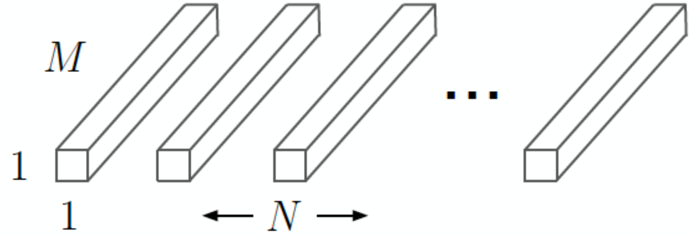
Width Multiplier

- width multiplier ($\alpha \in (0,1]$): $N \to \alpha N$; $M \to \alpha M$ ($\alpha = 1$: baseline)

depth-wise



point-wise

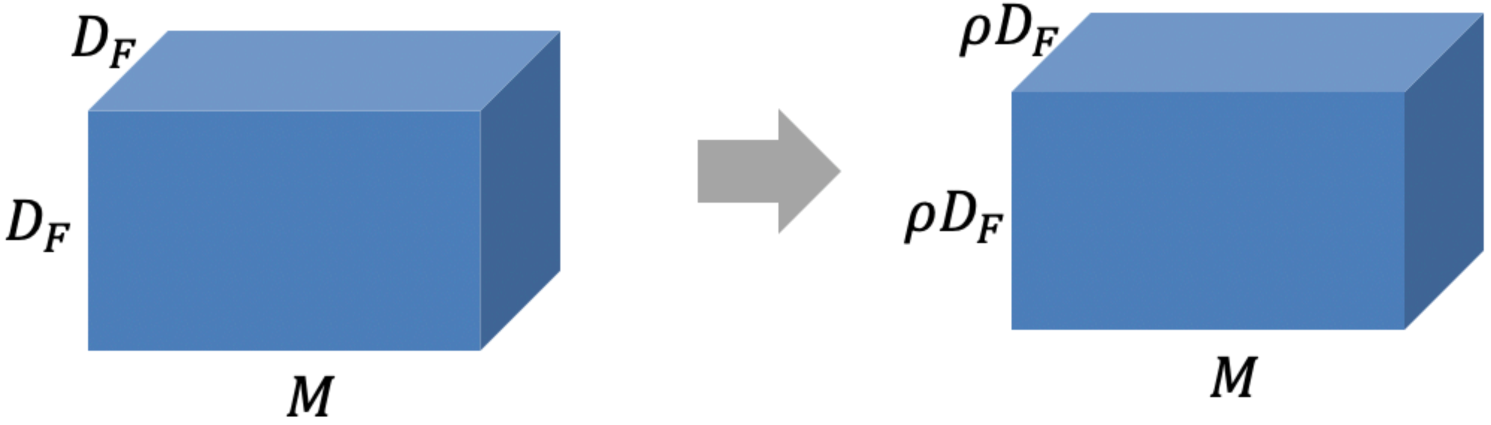


- computational cost reduced roughly by α^2

$$D_K^2 \times M \times D_F^2 + N \times M \times D_F^2 \to D_K^2 \times \alpha M \times D_F^2 + \alpha N \times \alpha M \times D_F^2$$

Resolution Multiplier

- resolution multiplier ($\rho \in (0,1]$): $D_F \to \rho D_F$; ($\rho = 1$: baseline) – implicitly set via assigning input resolution



- computational cost: reduced roughly by ρ^2

$$D_K^2 \times M \times D_F^2 + N \times M \times D_F^2 \to D_K^2 \times M \times \rho^2 D_F^2 + N \times M \times \rho^2 D_F^2$$

Total Cost with Both Multipliers

Table 3. Resource usage for modifications to standard convolution. Note that each row is a cumulative effect adding on top of the previous row. This example is for an internal MobileNet layer with $D_K = 3$, $M = 512$, $N = 512$, $D_F = 14$.

Layer/Modification	Million Mult-Adds	Million Parameters
Convolution	462	2.36
Depthwise Separable Conv	52.3	0.27
$\alpha = 0.75$	29.6	0.15
$\rho = 0.714$	15.1	0.15

- Baseline: $D_K^2 \times M \times D_F^2 + N \times M \times D_F^2$
- Reduced: $D_K^2 \times \alpha M \times \rho^2 D_F^2 + \alpha N \times \alpha M \times \rho^2 D_F^2$
- overall: computational cost reduced by $(\alpha\rho)^2$

Accuracy vs. Size

Table 4. Depthwise Separable vs Full Convolution MobileNet

Model	ImageNet Accuracy	Million Mult-Adds	Million Parameters
Conv MobileNet	71.7%	4866	29.3
MobileNet	70.6%	569	4.2

Table 5. Narrow vs Shallow MobileNet

Model	ImageNet Accuracy	Million Mult-Adds	Million Parameters
0.75 MobileNet	68.4%	325	2.6
Shallow MobileNet	65.3%	307	2.9

- Shallow MobileNet – remove 5 layers with 14×14×512 FMs
- narrow network preserves depth → good for accuracy

Accuracy vs. Size

Table 6. MobileNet Width Multiplier

Width Multiplier	ImageNet Accuracy	Million Mult-Adds	Million Parameters
1.0 MobileNet-224	70.6%	569	4.2
0.75 MobileNet-224	68.4%	325	2.6
0.5 MobileNet-224	63.7%	149	1.3
0.25 MobileNet-224	50.6%	41	0.5

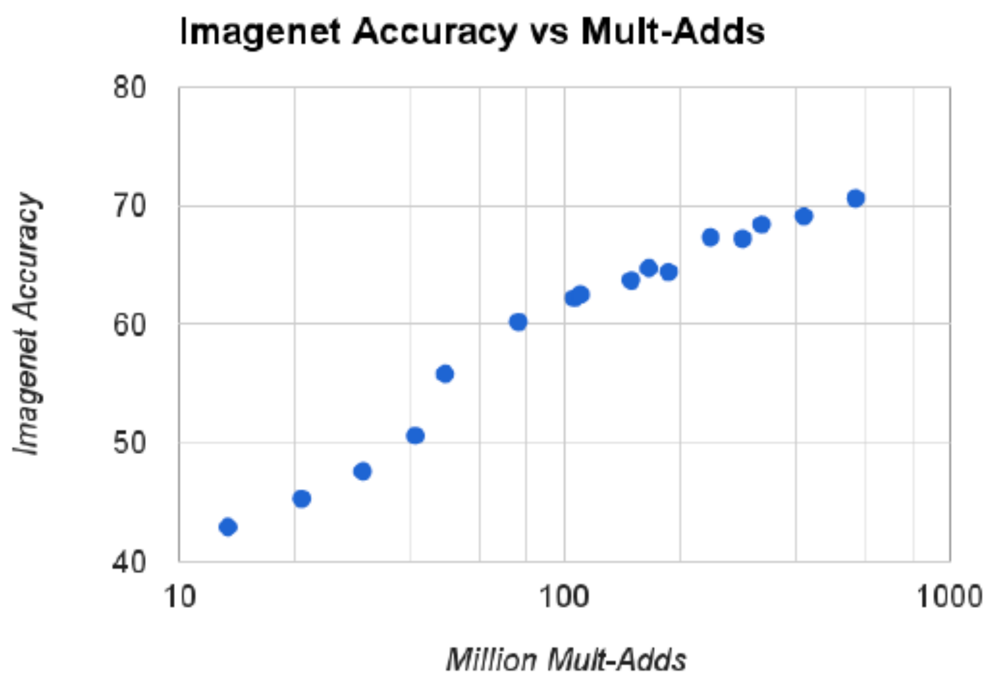
sharp drop

Table 7. MobileNet Resolution

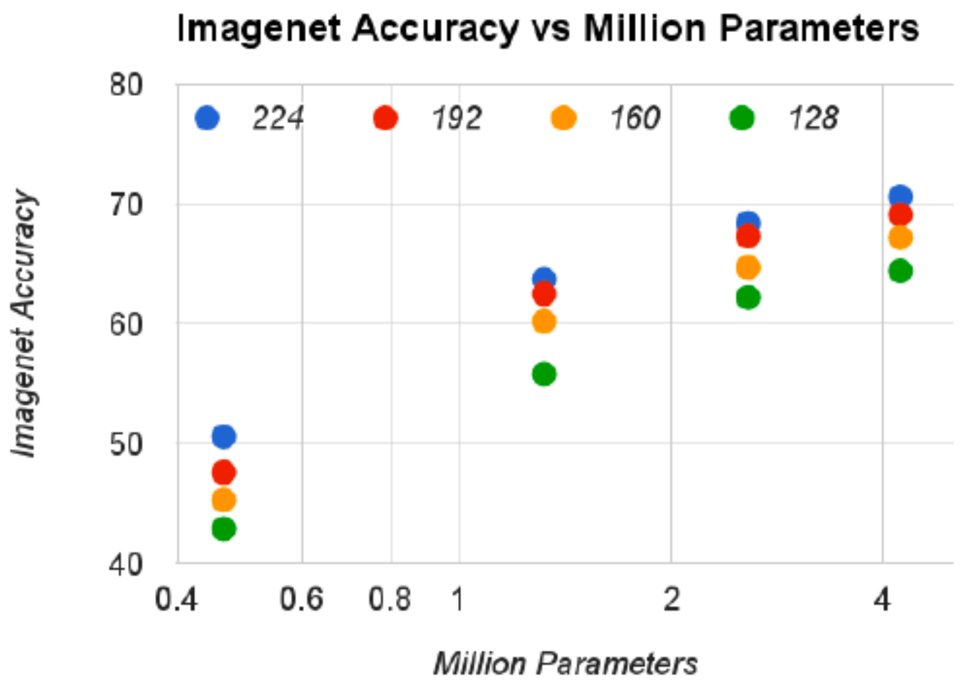
Resolution	ImageNet Accuracy	Million Mult-Adds	Million Parameters
1.0 MobileNet-224	70.6%	569	4.2
1.0 MobileNet-192	69.1%	418	4.2
1.0 MobileNet-160	67.2%	290	4.2
1.0 MobileNet-128	64.4%	186	4.2

smooth roll-off

Accuracy vs. Storage/Complexity Trade-off



log-linear dependence



log-linear dependence

- Networks generated as a cross-product:

$$\alpha \in \{1, 0.75, 0.5, 0.25\} \times \rho \in \{224, 192, 160, 128\}$$

SqueezeNet

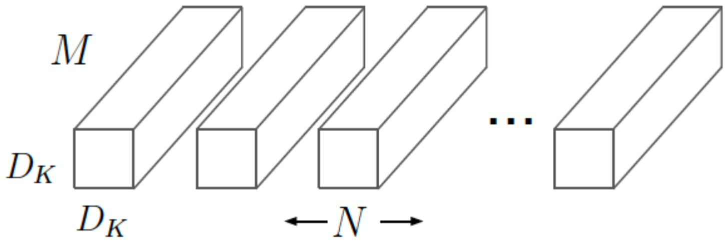
SQUEEZENET: ALEXNET-LEVEL ACCURACY WITH 50X FEWER PARAMETERS AND <0.5MB MODEL SIZE

Forrest N. Iandola[1], Song Han[2], Matthew W. Moskewicz[1], Khalid Ashraf[1], William J. Dally[2], Kurt Keutzer[1]
[1]DeepScale* & UC Berkeley [2]Stanford University

- another low-complexity network
- based on a set of design intuitions to reduce network size

Design Strategies

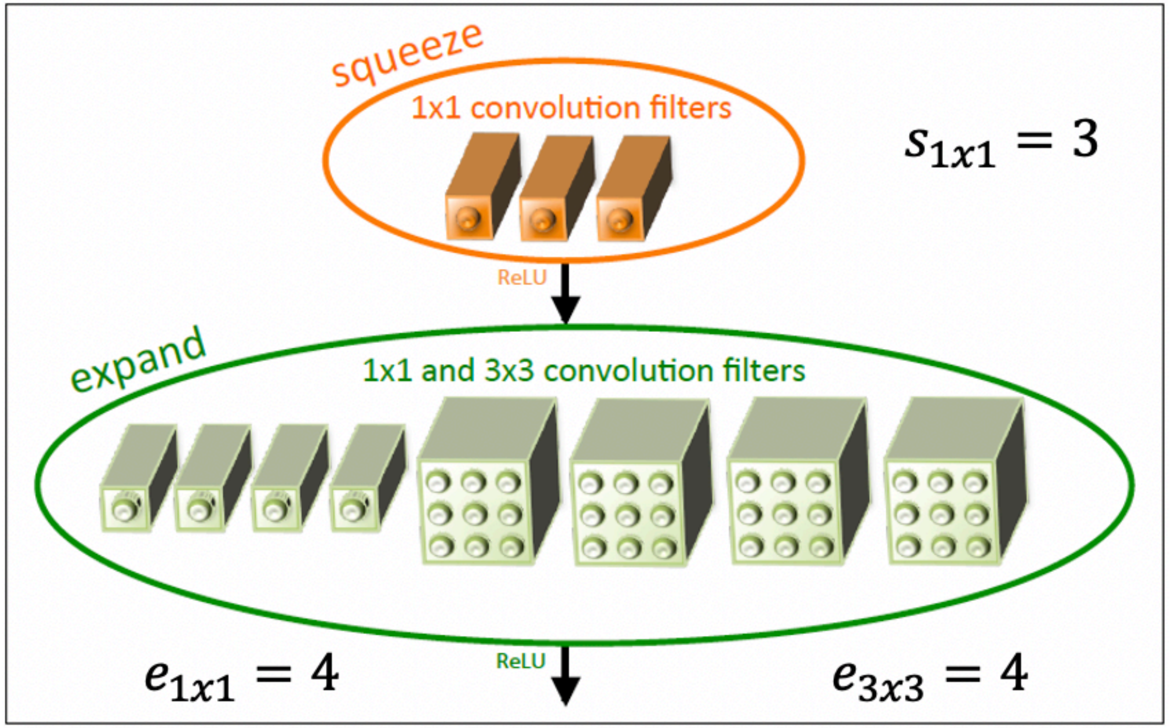
- **S1**: replace 3×3 filters with 1×1 filters → $9\times$ fewer parameters
- **S2**: decrease the number of input channels to 3×3 filters → reduces the number of parameters (width multiplier)



reduce M when $D_K = 3$

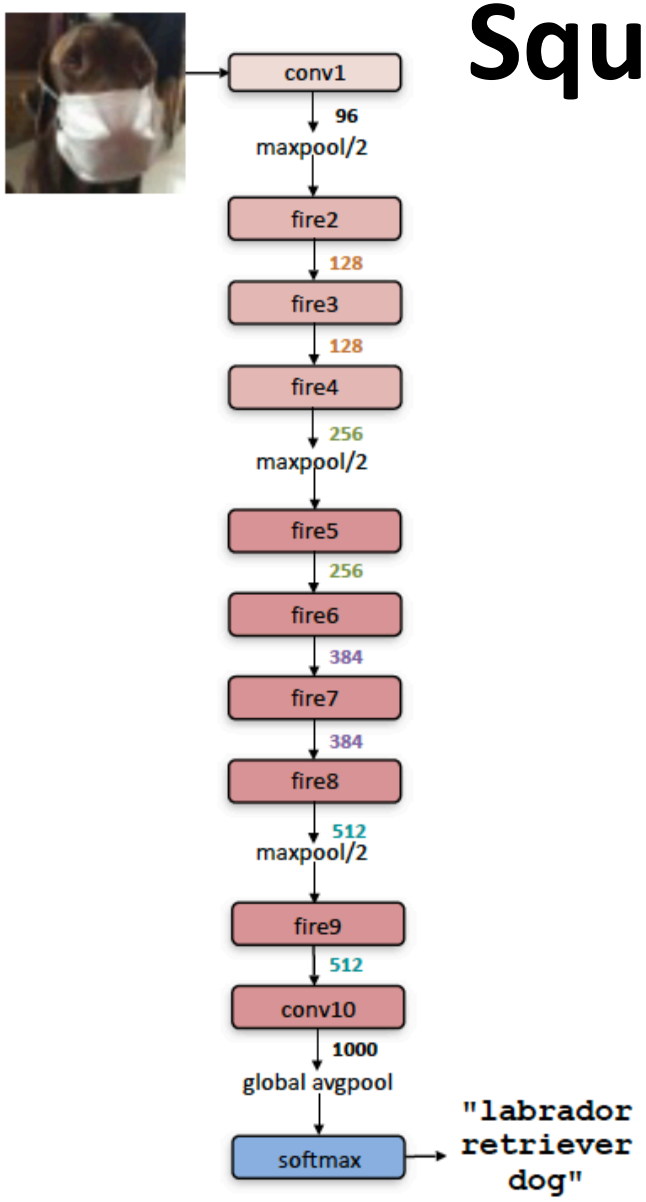
- **S3**: downsample late in network → conv layers have large activation maps → better accuracy

Fire Module



- concatenation of squeeze (**S1**) and expand layers
- parameterized by 3 variables: $s_{1x1}, e_{1x1}, e_{3x3}$
- Set: $s_{1x1} < e_{1x1} + e_{3x3}$ per **S2**

SqueezeNet Architecture



- Conv1: standard; no FC layer
- 8 Fire modules (fire2-9)
- max pooling after conv1, fire4, fire8, conv10 (per **S3**)

Table 1: SqueezeNet architectural dimensions. (The formatting of this table was inspired by the Inception2 paper (Ioffe & Szegedy, 2015).)

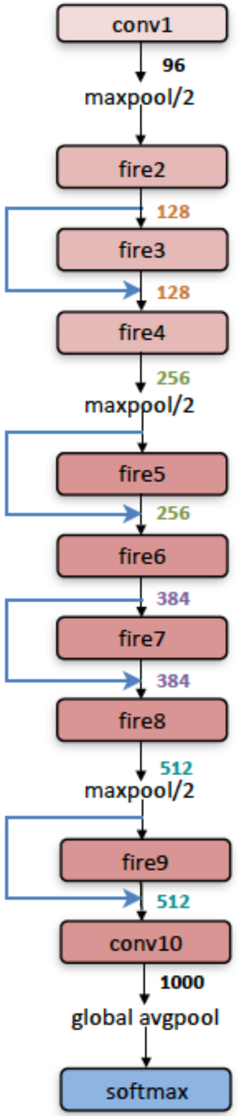
layer name/type	output size	filter size / stride (if not a fire layer)	depth	s_{1x1} (#1x1 squeeze)	e_{1x1} (#1x1 expand)	e_{3x3} (#3x3 expand)	s_{1x1} sparsity	e_{1x1} sparsity	e_{3x3} sparsity	# bits	#parameter before pruning	#parameter after pruning
input image	224x224x3										-	-
conv1	111x111x96	7x7/2 (x96)	1					100% (7x7)		6bit	14,208	14,208
maxpool1	55x55x96	3x3/2	0									
fire2	55x55x128		2	16	64	64	100%	100%	**33%**	6bit	11,920	5,746
fire3	55x55x128		2	16	64	64	100%	100%	**33%**	6bit	12,432	6,258
fire4	55x55x256		2	32	128	128	100%	100%	**33%**	6bit	45,344	20,646
maxpool4	27x27x256	3x3/2	0									
fire5	27x27x256		2	32	128	128	100%	100%	**33%**	6bit	49,440	24,742
fire6	27x27x384		2	48	192	192	100%	**50%**	**33%**	6bit	104,880	44,700
fire7	27x27x384		2	48	192	192	**50%**	100%	**33%**	6bit	111,024	46,236
fire8	27x27x512		2	64	256	256	100%	**50%**	**33%**	6bit	188,992	77,581
maxpool8	13x12x512	3x3/2	0									
fire9	13x13x512		2	64	256	256	**50%**	100%	**30%**	6bit	197,184	77,581
conv10	13x13x1000	1x1/1 (x1000)	1					**20%** (3x3)		6bit	513,000	103,400
avgpool10	1x1x1000	13x13/1	0									
	activations	parameters					compression info				1,248,424 (total)	**421,098** (total)

Design Intuitions

- add 1 pixel zero-padding to input of 3×3 expand filters $\rightarrow$ 3×3 and 1×1 filters output activations have identical dimensions
- ReLU is applied to activations from squeeze and expand layers (Nair & Hinton, 2010)
- dropout (Srivastava et. al., 2014) with ratio 50% after fire9
- no FC layer (inspired by NiN Lin et al., 2013)
- linearly decrease learning rate from 0.04 down (Mishkin et al., 2016)
- expand layer implemented in Caffe as concatenation of 1×1 filters and 3×3 filters

SqueezeNet Variants

with simple bypass



- similar to ResNet
- simple bypass applies to fire modules with same # of input and output dimensions
- complex bypass applied to fire modules with differing input/output dimensions (adds extra parameters)
- Squeeze layers limit information; bypass layers compensate for it

with complex bypass

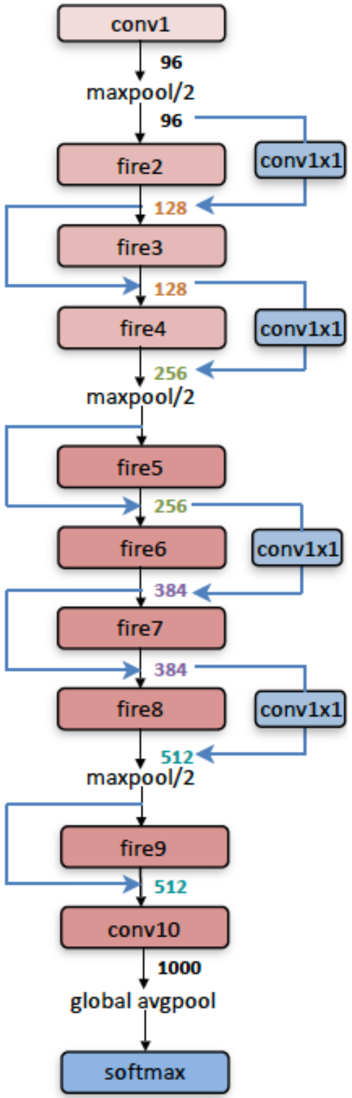


Table 3: SqueezeNet accuracy and model size using different macroarchitecture configurations

Architecture	Top-1 Accuracy	Top-5 Accuracy	Model Size
Vanilla SqueezeNet	57.5%	80.3%	4.8MB
SqueezeNet + Simple Bypass	**60.4%**	**82.5%**	4.8MB
SqueezeNet + Complex Bypass	58.8%	82.0%	7.7MB

- also applied model compression -> low-complexity model is further compressible

ShuffleNet

ShuffleNet: An Extremely Efficient Convolutional Neural Network for Mobile Devices

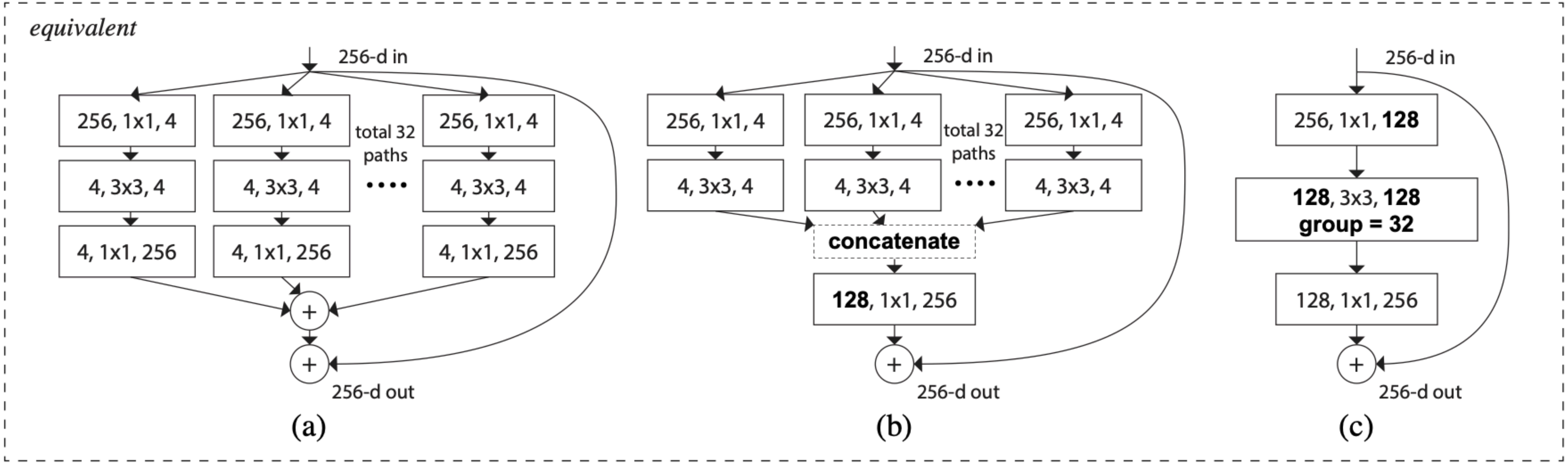
Xiangyu Zhang*   Xinyu Zhou*   Mengxiao Lin   Jian Sun
Megvii Inc (Face++)
{zhangxiangyu,zxy,linmengxiao,sunjian}@megvii.com

- Another low complexity network for mobile devices
- Channel shuffle and ShuffleNet Unit

Design Strategy

- Channel Shuffle: related input and output channels by cross talking
- Replace standard convolution with 1x1 Point-wise **Group** convolution and 3x3 Depth-wise Separable convolution

Group Convolution



[Xie et al., '17, ResNext]

- Used by AlexNet for distributing computations across GPUs
- Split input features into *M* groups
- Each group responsible for certain depth
- Concatenation each group at the end

Channel Shuffle

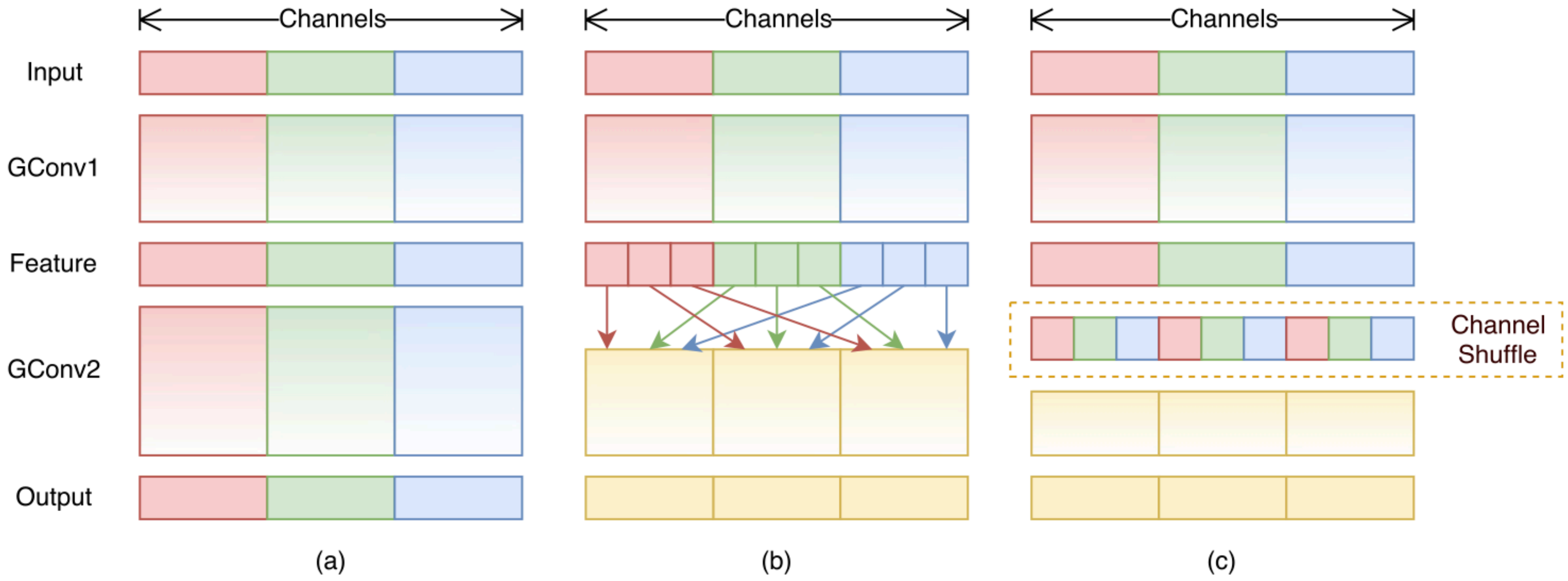


Figure 1. Channel shuffle with two stacked group convolutions. GConv stands for group convolution. a) two stacked convolution layers with the same number of groups. Each output channel only relates to the input channels within the group. No cross talk; b) input and output channels are fully related when GConv2 takes data from different groups after GConv1; c) an equivalent implementation to b) using channel shuffle.

- Allow information flow between channel groups and strengthen representation
- Differentiable operation, meaning end-to-end training is available

ShuffleNet Unit

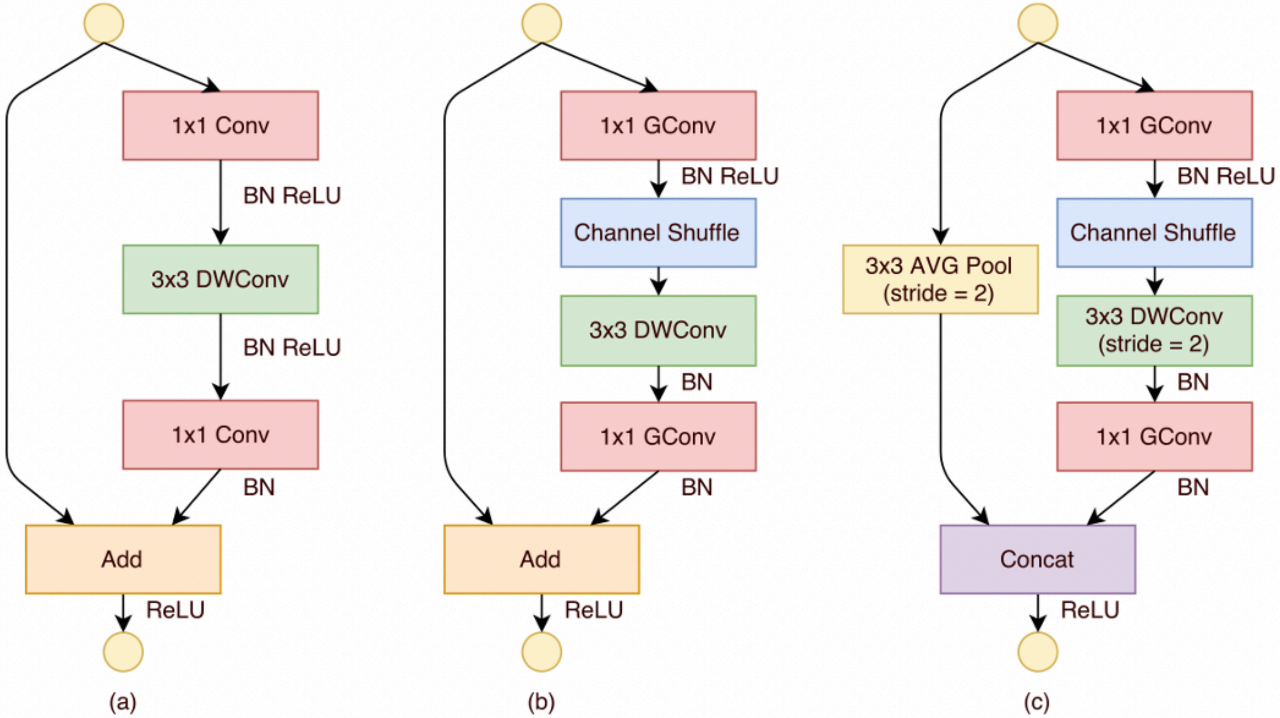


Figure 2. ShuffleNet Units. a) bottleneck unit [9] with depthwise convolution (DWConv) [3, 12]; b) ShuffleNet unit with pointwise group convolution (GConv) and channel shuffle; c) ShuffleNet unit with stride = 2.

- Consist of 1x1 group convolution followed by channel shuffle, 3x3 depthwise separable Convolution, and 1x1 group convolution
- Batch Normalization and ReLU after each convolution except the last 1x1 GConv
- Element-wise addition or concatenation to inputs at the final step

ShuffleNet Architecture

Layer	Output size	KSize	Stride	Repeat	Output channels (g groups)				
					$g = 1$	$g = 2$	$g = 3$	$g = 4$	$g = 8$
Image	224×224				3	3	3	3	3
Conv1	112×112	3×3	2	1	24	24	24	24	24
MaxPool	56×56	3×3	2						
Stage2	28×28		2	1	144	200	240	272	384
	28×28		1	3	144	200	240	272	384
Stage3	14×14		2	1	288	400	480	544	768
	14×14		1	7	288	400	480	544	768
Stage4	7×7		2	1	576	800	960	1088	1536
	7×7		1	3	576	800	960	1088	1536
GlobalPool	1×1	7×7							
FC					1000	1000	1000	1000	1000
Complexity					143M	140M	137M	133M	137M

- Conv1: standard
- 3 stages of ShuffleNet unit groups
  - Each contains ShuffleNet units with stride = 1 and stride = 2
  - The number of units in each stage is specified by the number of repeats

Accuracy vs. Use of Channel Shuffle

Model	Cls err. (%, no shuffle)	Cls err. (%, shuffle)	Δ err. (%)
ShuffleNet 1x ($g = 3$)	34.5	**32.6**	1.9
ShuffleNet 1x ($g = 8$)	37.6	**32.4**	5.2
ShuffleNet 0.5x ($g = 3$)	45.7	**43.2**	2.5
ShuffleNet 0.5x ($g = 8$)	48.1	**42.3**	5.8
ShuffleNet 0.25x ($g = 3$)	56.3	**55.0**	1.3
ShuffleNet 0.25x ($g = 8$)	56.5	**52.7**	3.8

- Small number represents better performance
- Channel Shuffle brings up to 6% decrease on classification error

Accuracy vs. Architecture

Complexity (MFLOPs)	VGG-like	ResNet	Xception-like	ResNeXt	ShuffleNet (ours)
140	50.7	37.3	33.6	33.3	**32.4** ($1\times$, $g = 8$)
38	-	48.8	45.1	46.0	**41.6** ($0.5\times$, $g = 4$)
13	-	63.7	57.1	65.2	**52.7** ($0.25\times$, $g = 8$)

Model	Complexity (MFLOPs)	Cls err. (%)	Δ err. (%)
1.0 MobileNet-224	569	29.4	-
ShuffleNet $2\times$ ($g = 3$)	524	**26.3**	3.1
ShuffleNet $2\times$ (with *SE*[13], $g = 3$)	527	**24.7**	4.7
0.75 MobileNet-224	325	31.6	-
ShuffleNet $1.5\times$ ($g = 3$)	292	**28.5**	3.1
0.5 MobileNet-224	149	36.3	-
ShuffleNet $1\times$ ($g = 8$)	140	**32.4**	3.9
0.25 MobileNet-224	41	49.4	-
ShuffleNet $0.5\times$ ($g = 4$)	38	**41.6**	7.8
ShuffleNet $0.5\times$ (shallow, $g = 3$)	40	42.8	6.6

- Achieve best performance across all network architectures

Summary of Methods for Designing Low-Complexity Networks

Summary

- Trade-off between complexity and accuracy
- Based on design intuitions to preserve accuracy
- separable convolutions
- use of point-wise convolutions
- delaying max-pooling
- others

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