# Modern CNN

## More Accurate or More Efficient

# DenseNet

## Densely Connected Convolutional Networks


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### Abstract

*Recent work has shown that convolutional networks can be substantially deeper, more accurate, and efficient to train if they contain shorter connections between layers close to the input and those close to the output. In this paper, we embrace this observation and introduce the Dense Convolutional Network (DenseNet), which connects each layer to every other layer in a feed-forward fashion. Whereas traditional convolutional networks with L layers have L connections—one between each layer and its subsequent layer—our network has $\frac{L(L+1)}{2}$ direct connections. For each layer, the feature-maps of all preceding layers are used as inputs, and its own feature-maps are used as inputs into all subsequent layers. DenseNets have several compelling advantages: they alleviate the vanishing-gradient problem, strengthen feature propagation, encourage fea-*

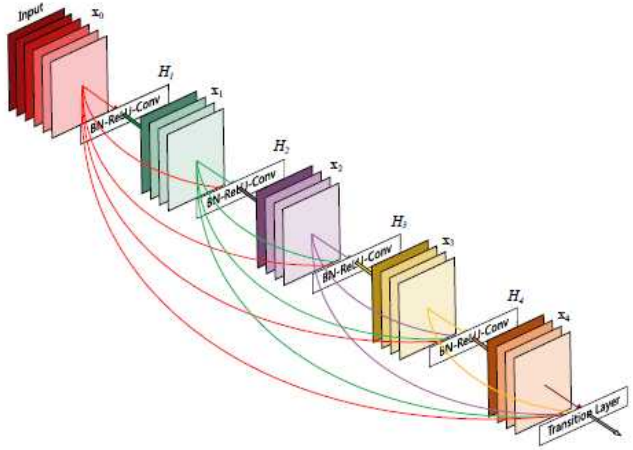
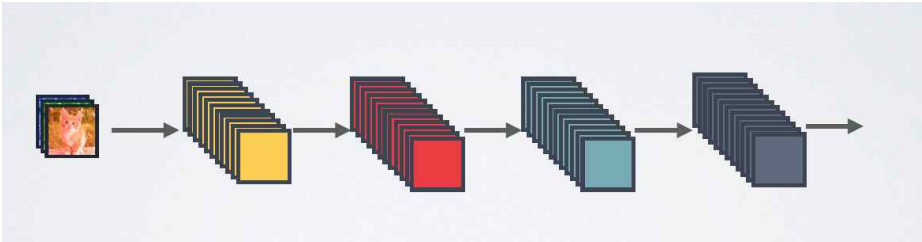



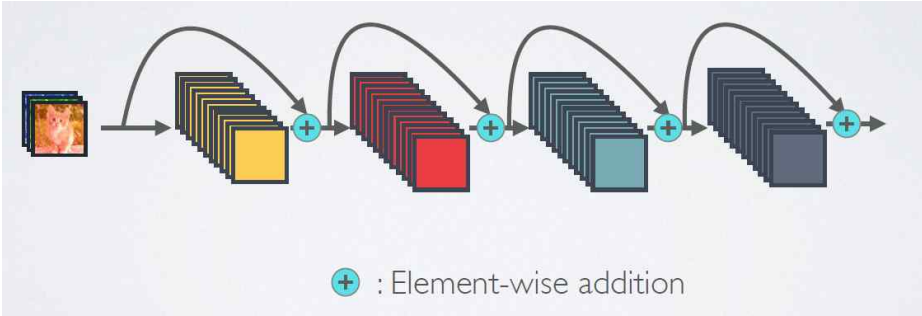

**Figure 1:** A 5-layer dense block with a growth rate of $k = 4$. Each layer takes all preceding feature-maps as input.

# Dense Connectivity

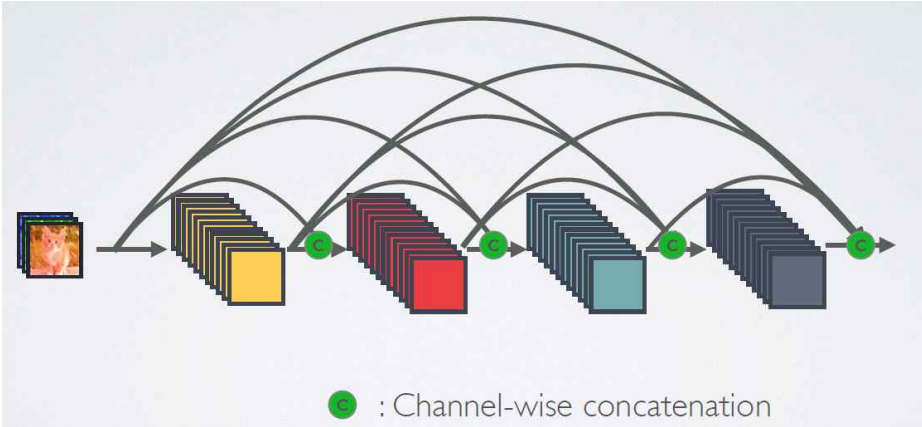
- Standard Connectivity



- ResNet Connectivity




- Dense Connectivity

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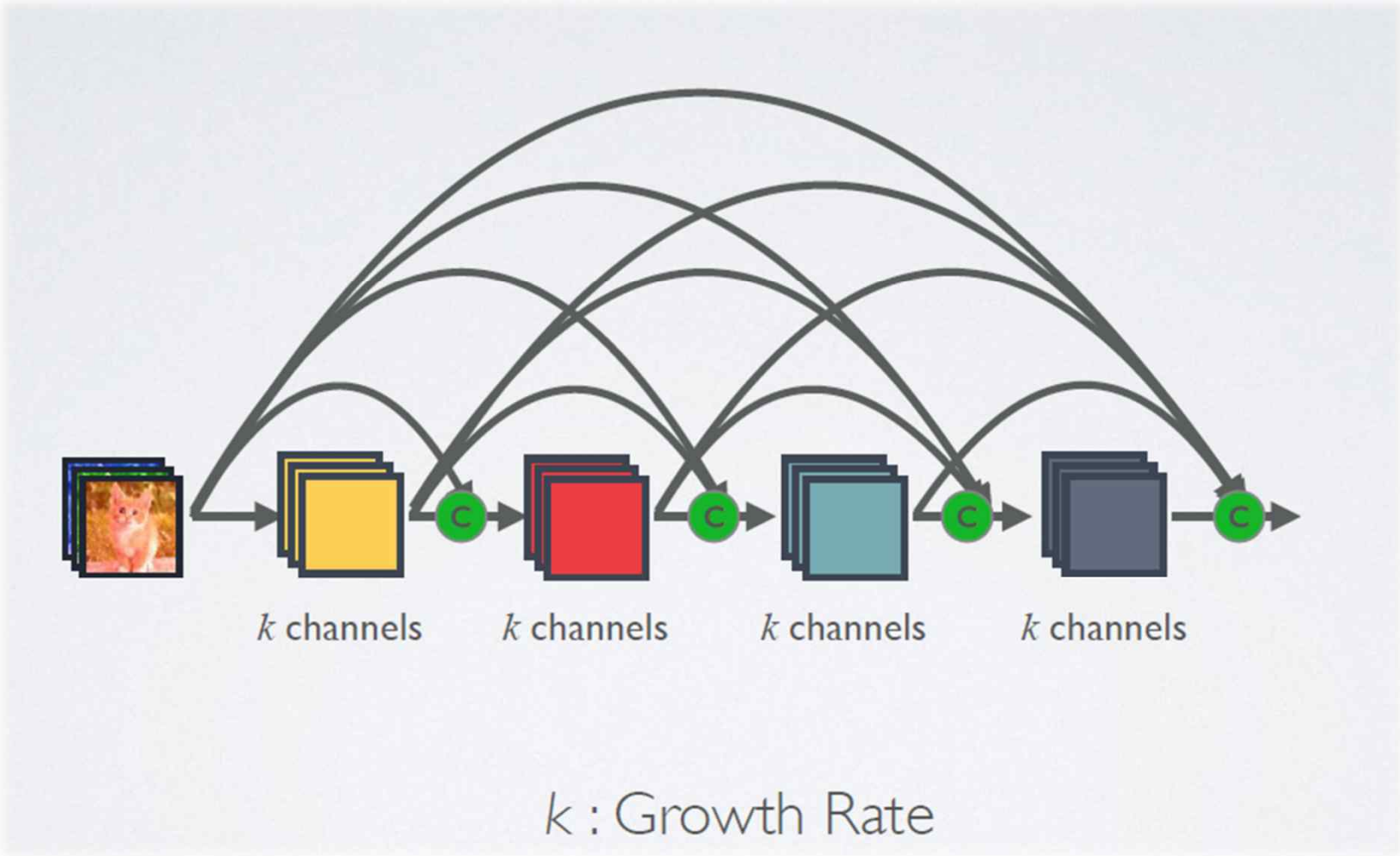
# Dense and Slim

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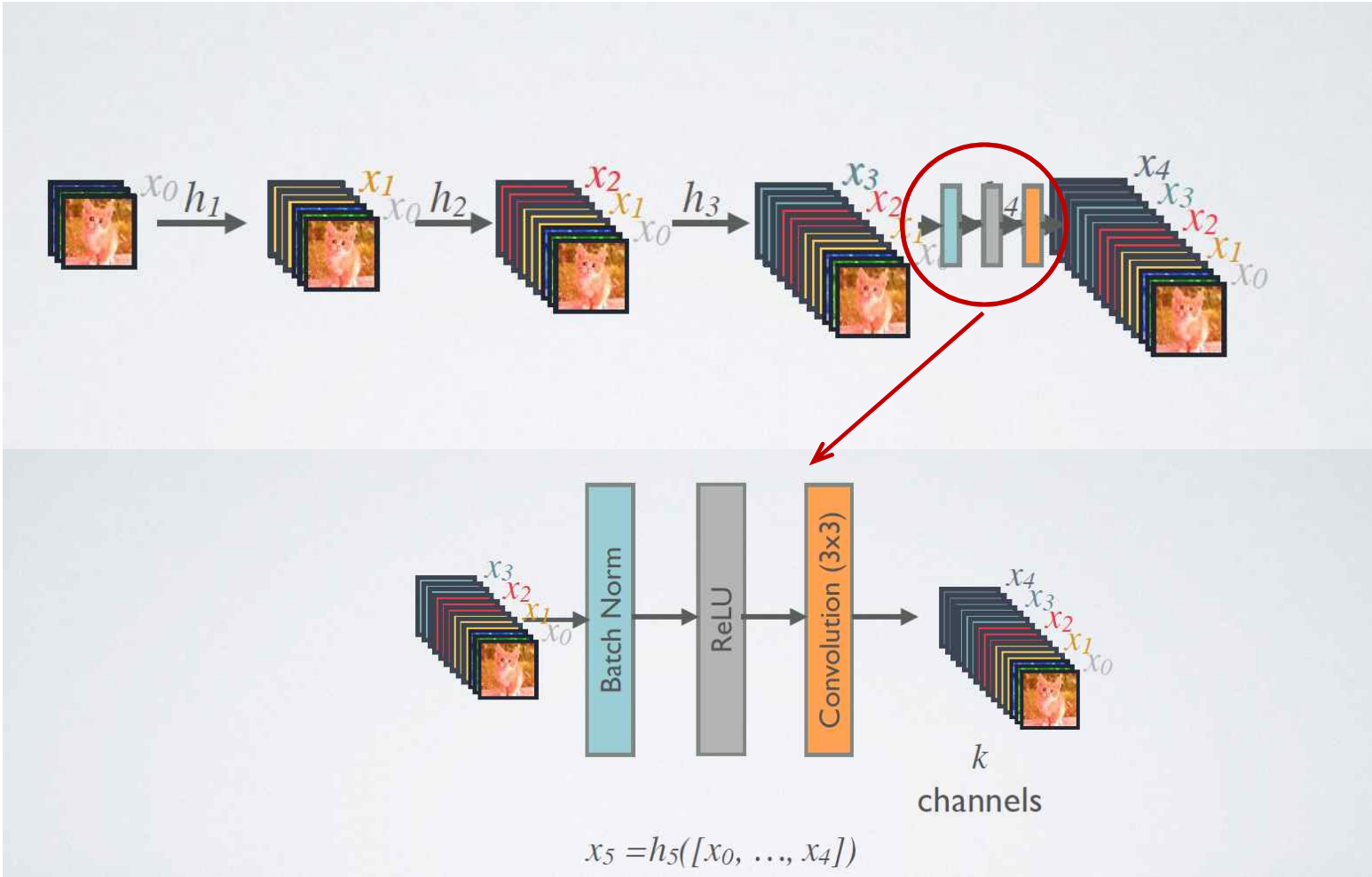
# Forward Propagation

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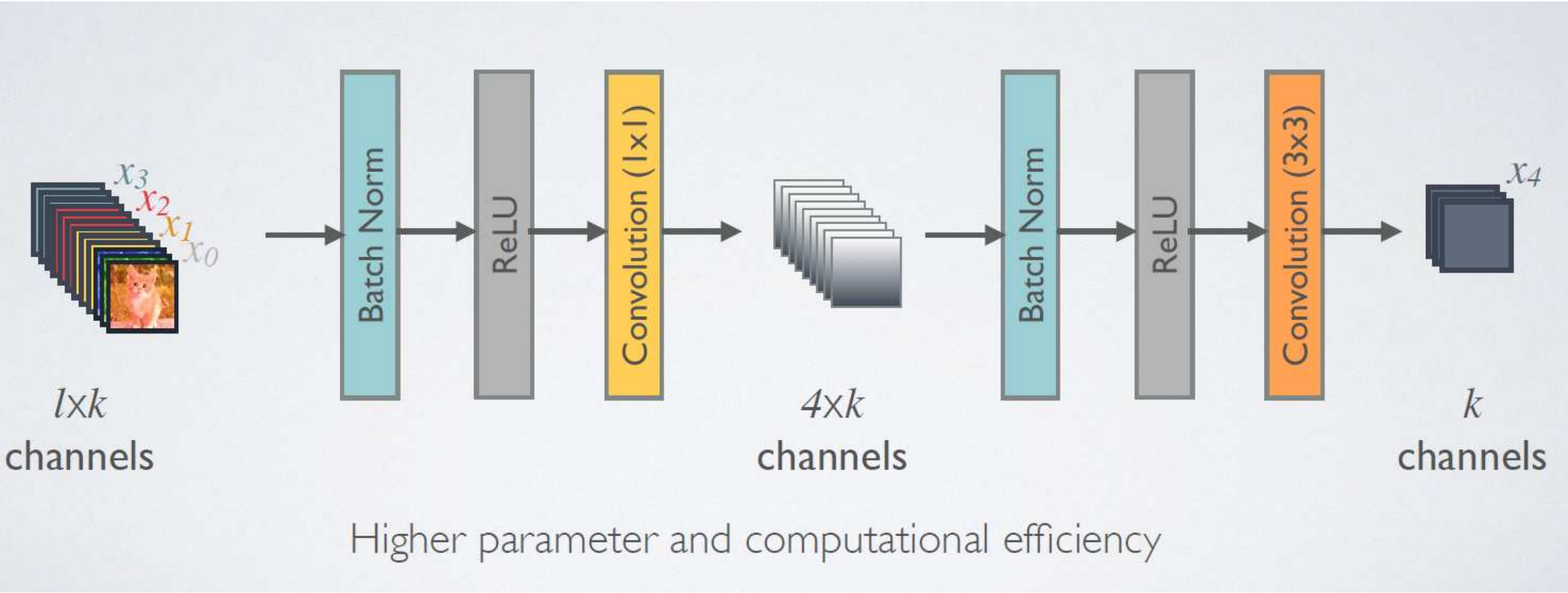
# Composite Layer in DenseNet with Bottleneck Layer

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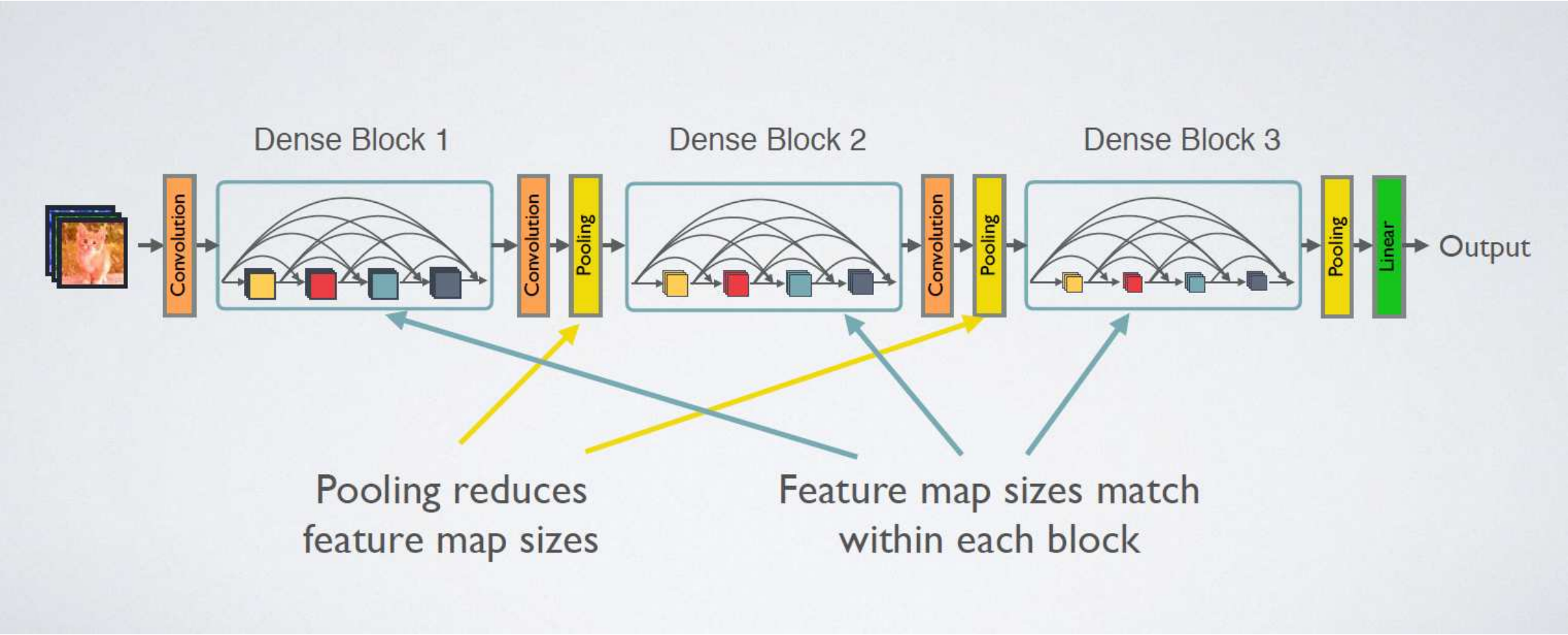
# DenseNet

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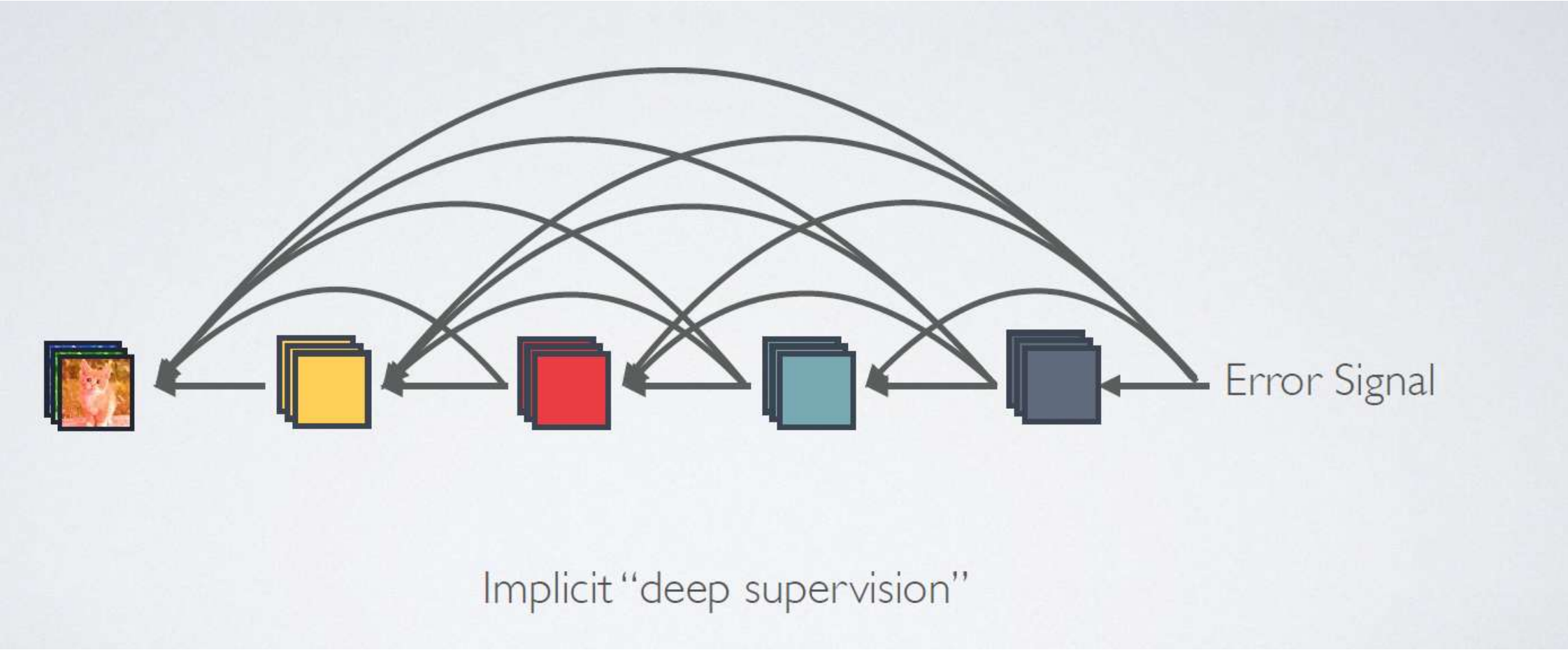
# Advantage 1 : Strong Gradient Flow

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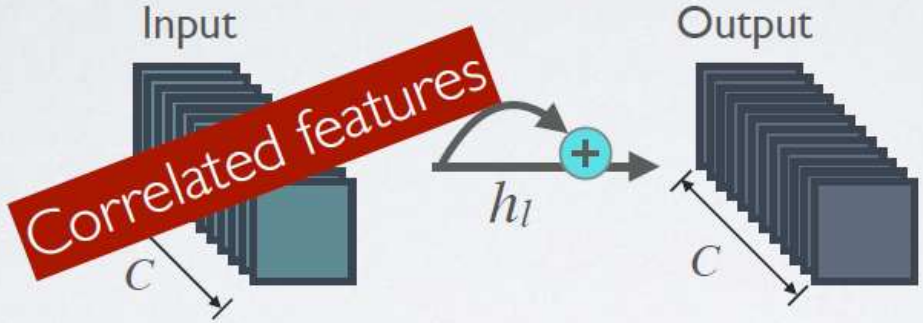
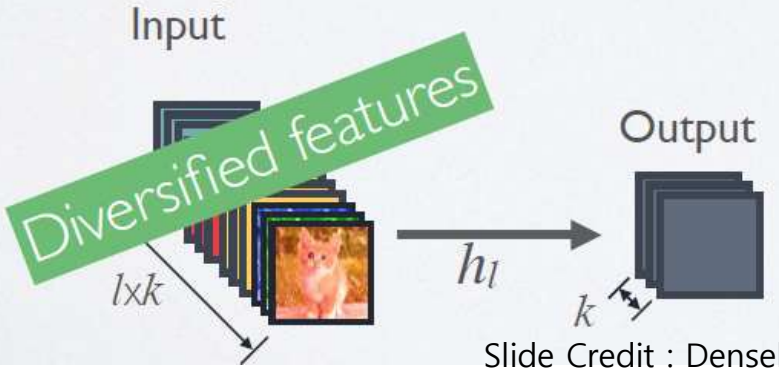
# Advantage 2 : Parameter & Computational Efficiency

**ResNet connectivity**:




**DenseNet connectivity:**




#parameters:

$O(C \times C)$

$k << C$

$O(l \times k \times k)$

$k$: Growth rate

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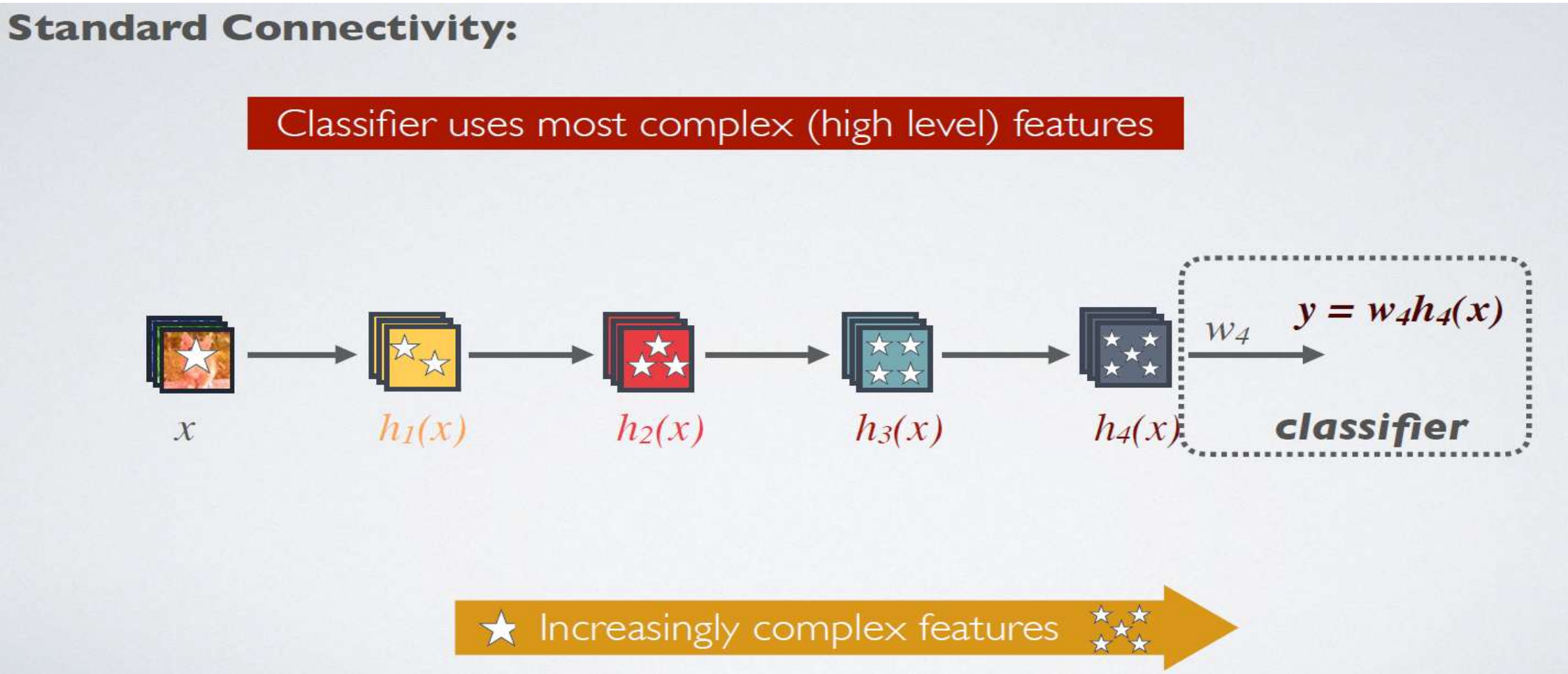
# Advantage 3 : Maintains Low Complexity Features

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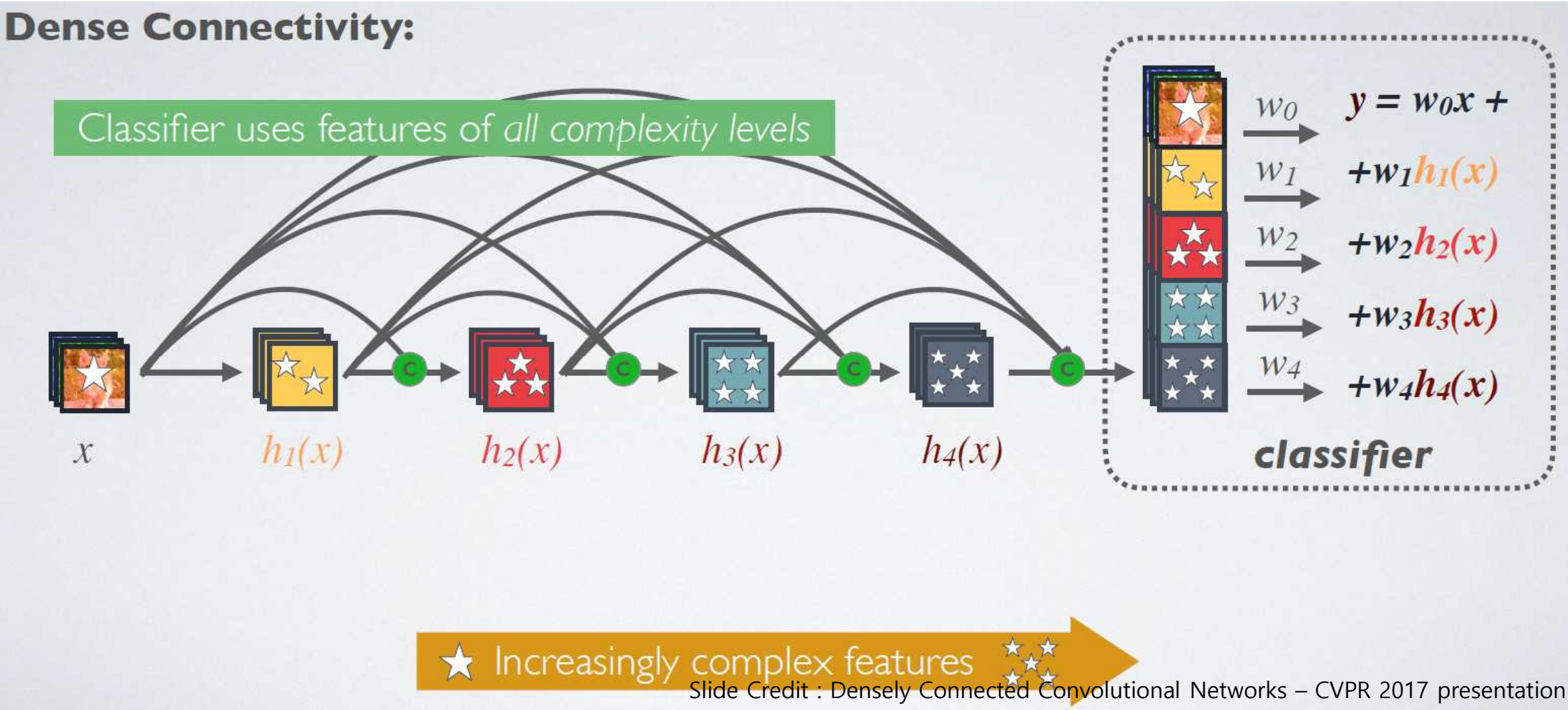
# Advantage 3 : Maintains Low Complexity Features

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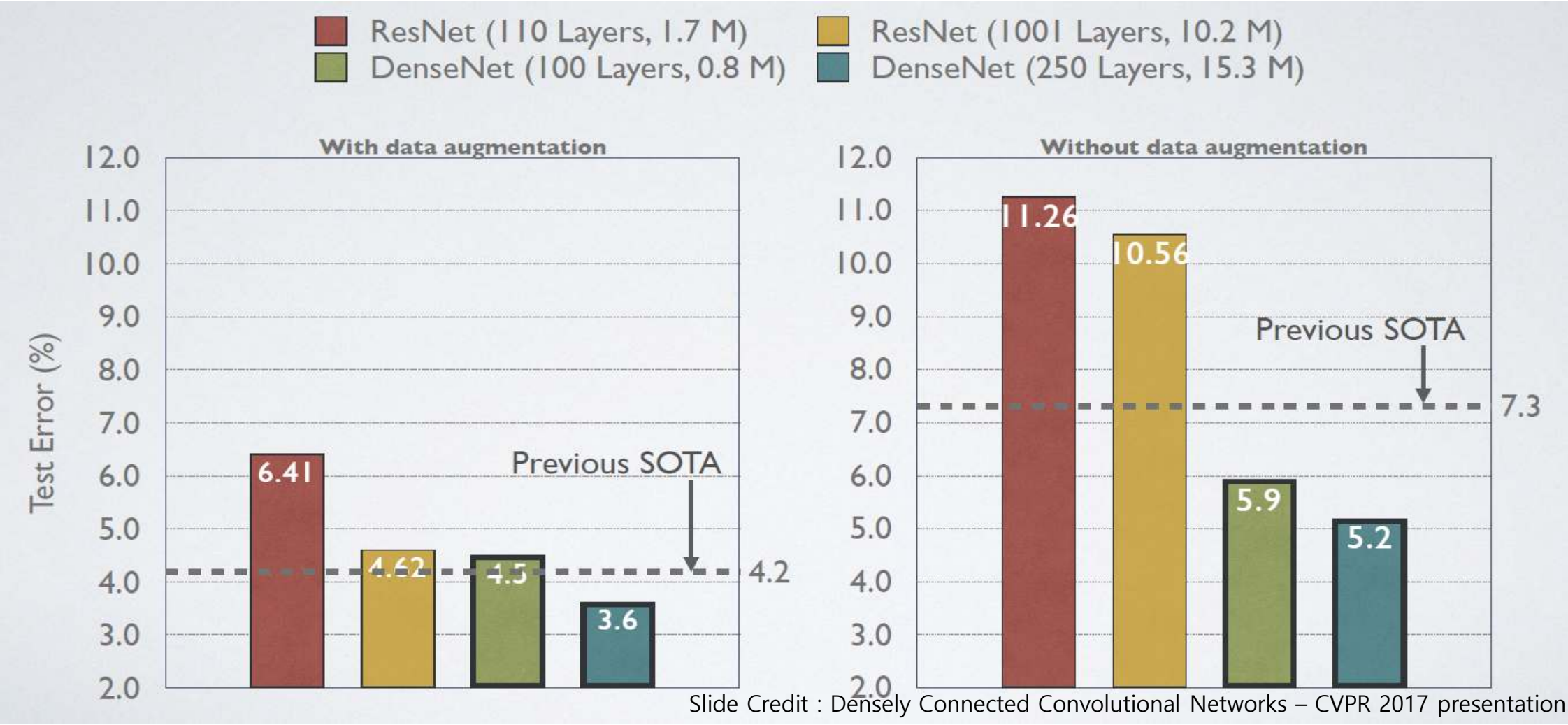
# Results on CIFAR-10

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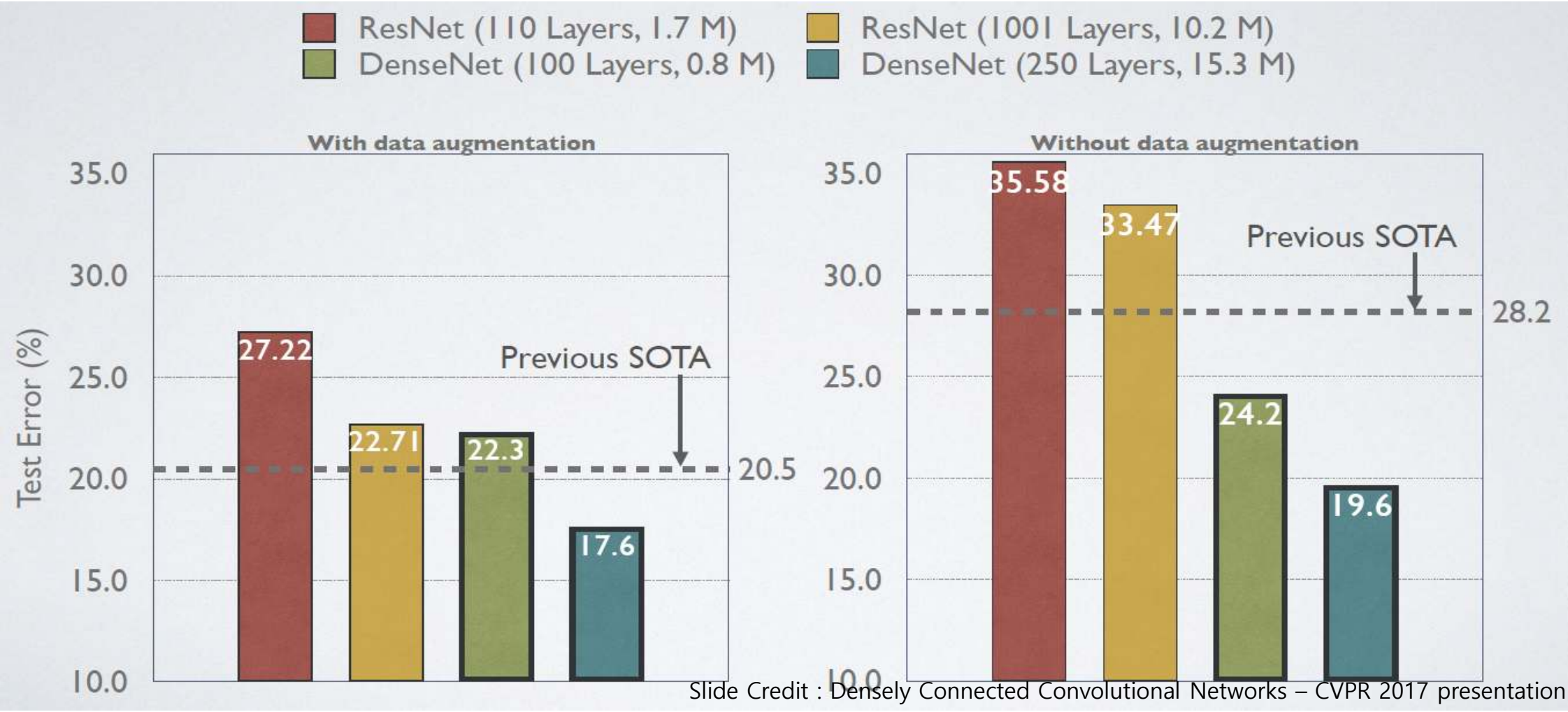
# Results on CIFAR-100

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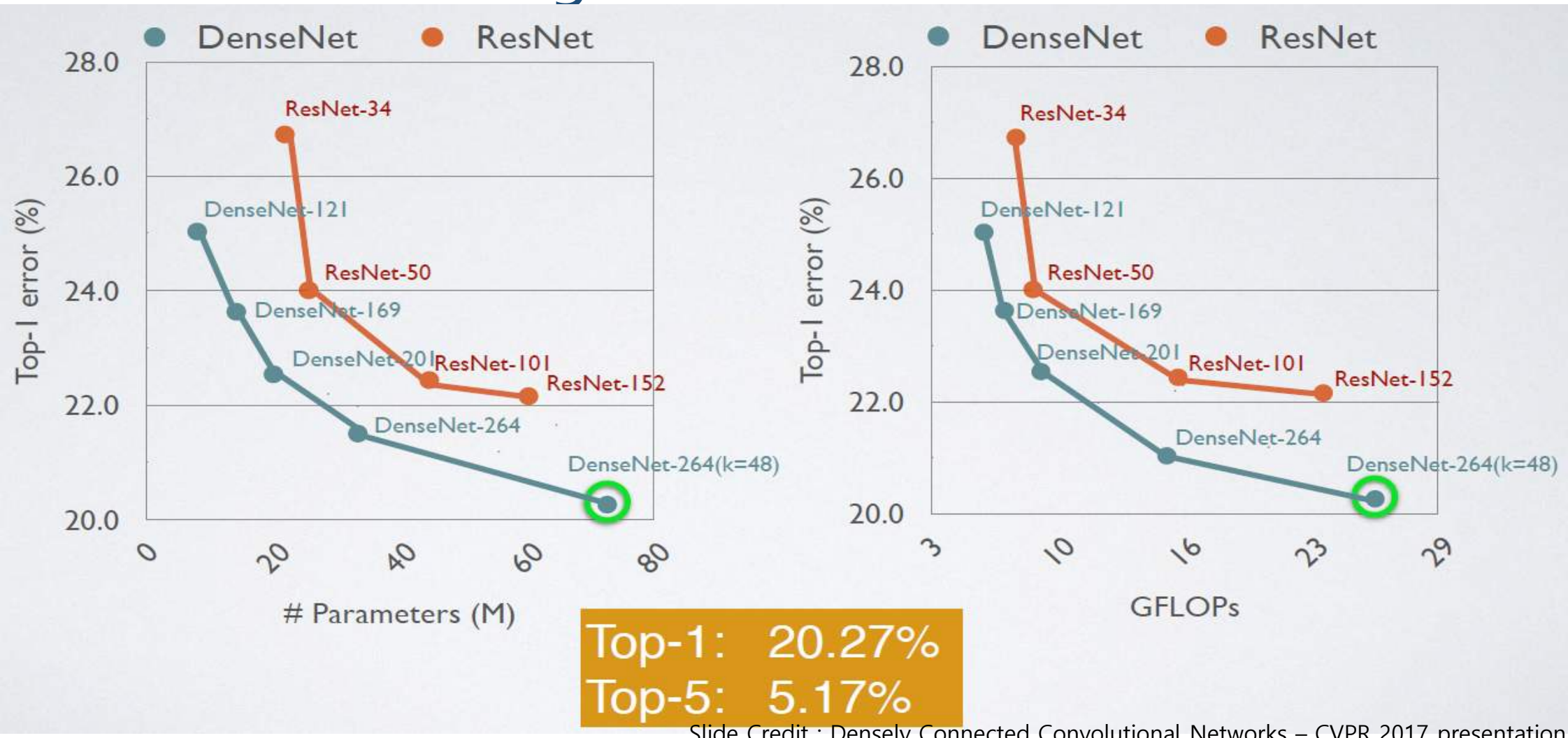
# Results on ImageNet




Top-1: 20.27%
Top-5: 5.17%

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# ResNeXt

## Aggregated Residual Transformations for Deep Neural Networks

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### Abstract

*We present a simple, highly modularized network architecture for image classification. Our network is constructed by repeating a building block that aggregates a set of transformations with the same topology. Our simple design results in a homogeneous, multi-branch architecture that has only a few hyper-parameters to set. This strategy exposes a new dimension, which we call "cardinality" (the size of the set of transformations), as an essential factor in addition to the dimensions of depth and width. On the ImageNet-1K dataset, we empirically show that even under the restricted condition of maintaining complexity, increasing cardinality is able to improve classification accuracy. Moreover, in-*

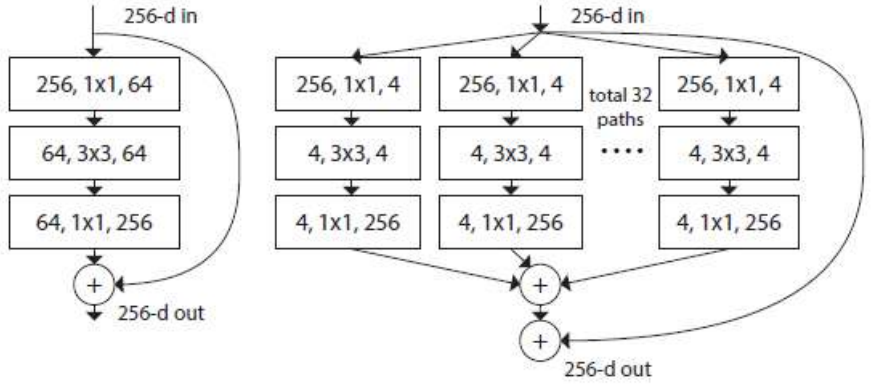



Figure 1. **Left**: A block of ResNet [14]. **Right**: A block of ResNeXt with cardinality = 32, with roughly the same complexity. A layer is shown as (# in channels, filter size, # out channels).

# ImageNet 2016 Results

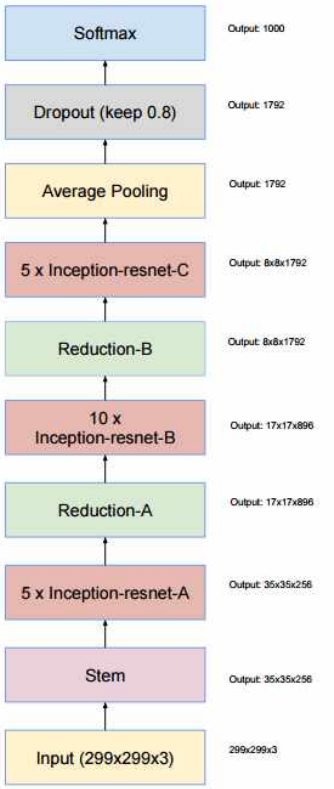
| Team name | Entry description | **Classification error** | Localization error |
|---|---|---|---|
| Trimps-Soushen | Ensemble 2 | 0.02991 | 0.077668 |
| Trimps-Soushen | Ensemble 3 | 0.02991 | 0.077087 |
| Trimps-Soushen | Ensemble 4 | 0.02991 | 0.077429 |
| ResNeXt | Ensemble C, weighted average, tuned on val. [No bounding box results] | 0.03031 | 0.737308 |
| CU-DeepLink | GrandUnion + Fused-scale EnsembleNet | 0.03042 | 0.098892 |
| CU-DeepLink | GrandUnion + Multi-scale EnsembleNet | 0.03046 | 0.099006 |
| CU-DeepLink | GrandUnion + Basic Ensemble | 0.03049 | 0.098954 |
| ResNeXt | Ensemble B, weighted average, tuned on val. [No bounding box results] | 0.03092 | 0.737484 |
| CU-DeepLink | GrandUnion + Class-reweighted Ensemble | 0.03096 | 0.099369 |
| CU-DeepLink | GrandUnion + Class-reweighted Ensemble with Per-instance Normalization | 0.03103 | 0.099349 |
| ResNeXt | Ensemble C, weighted average. [No bounding box results] | 0.03124 | 0.737526 |
| Trimps-Soushen | Ensemble 1 | 0.03144 | 0.079068 |
| ResNeXt | Ensemble A, simple average. [No bounding box results] | 0.0315 | 0.737505 |
| SamExynos | 3 model only for classification | 0.03171 | 0.236561 |
| ResNeXt | Ensemble B, weighted average. [No bounding box results] | 0.03203 | 0.737681 |
| KAISTNIA_ETRI | Ensembles A | 0.03256 | 0.102015 |
| KAISTNIA_ETRI | Ensembles C | 0.03256 | 0.102056 |
| KAISTNIA_ETRI | Ensembles B | 0.03256 | 0.100676 |

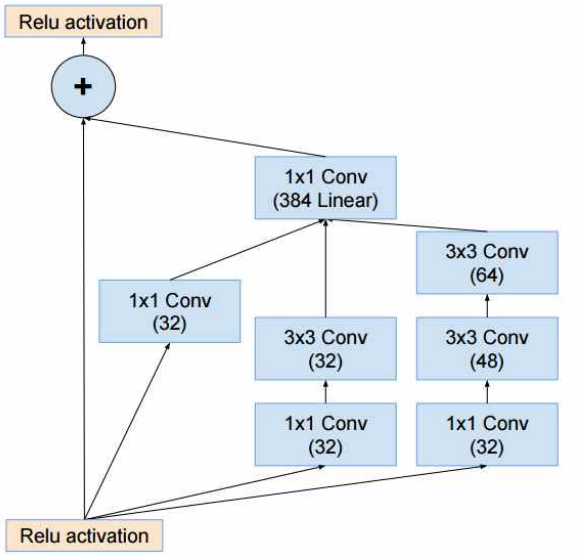
# Growing Number of Hyper-parameters

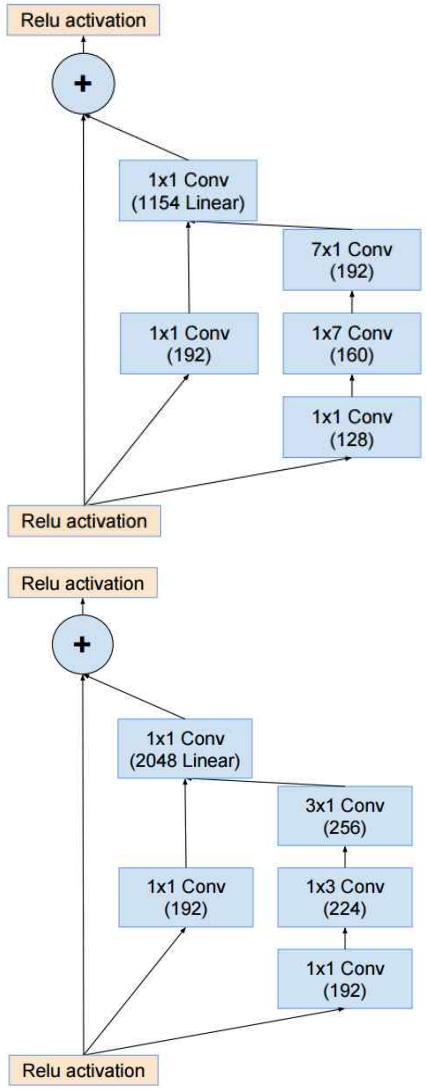
- VGGNet exhibit a simple yet effective strategy of constructing very deep network – stacking building blocks of the same shape
- ResNet inherit this strategy with stacking modules of the same topology
- Unlike VGGNet, the family of Inception models have demonstrated that carefully designed topologies are able to achieve compelling accuracy
  - Important common property is split-transform-merge strategy
  - Split – 1x1 conv, transform – 3x3, 5x5 conv, merge - concatenation

# Inception Learns ResNet

- Inception + ResNet



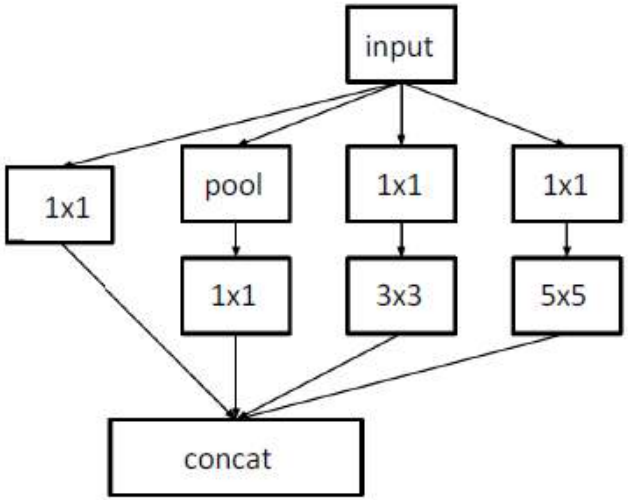



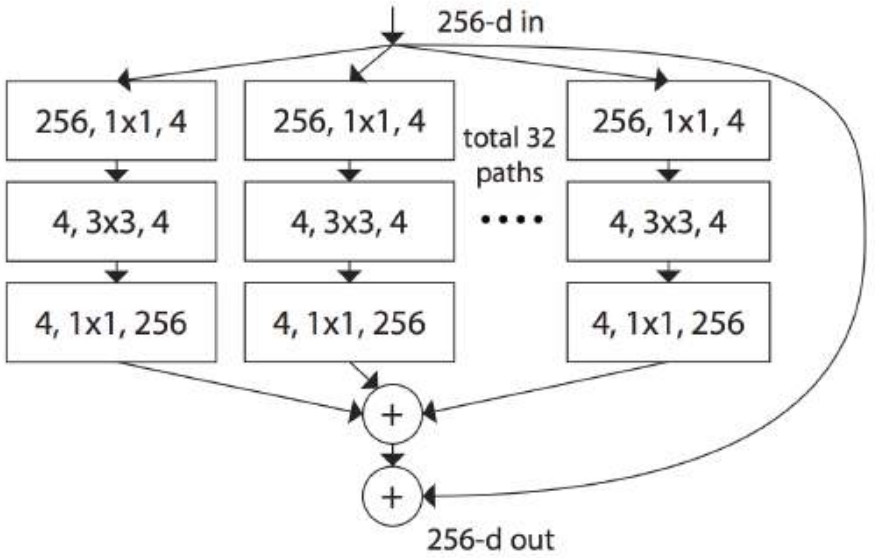

"Inception-v4, Inception-ResNet and the Impact of Residual Connections on Learning"

# ResNet Learns Inception??

- Multi-branch + ResNet

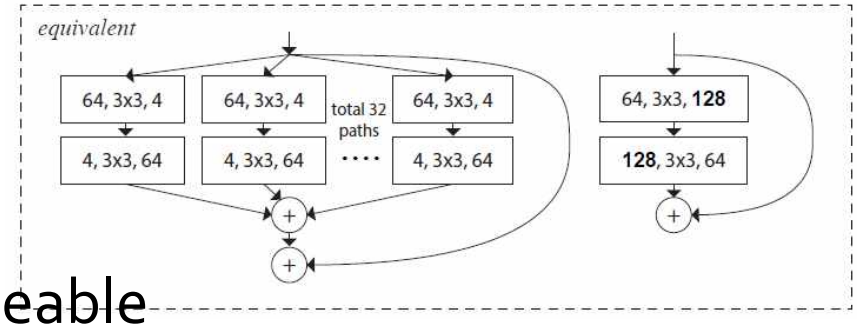



**Inception**:
heterogeneous multi-branch

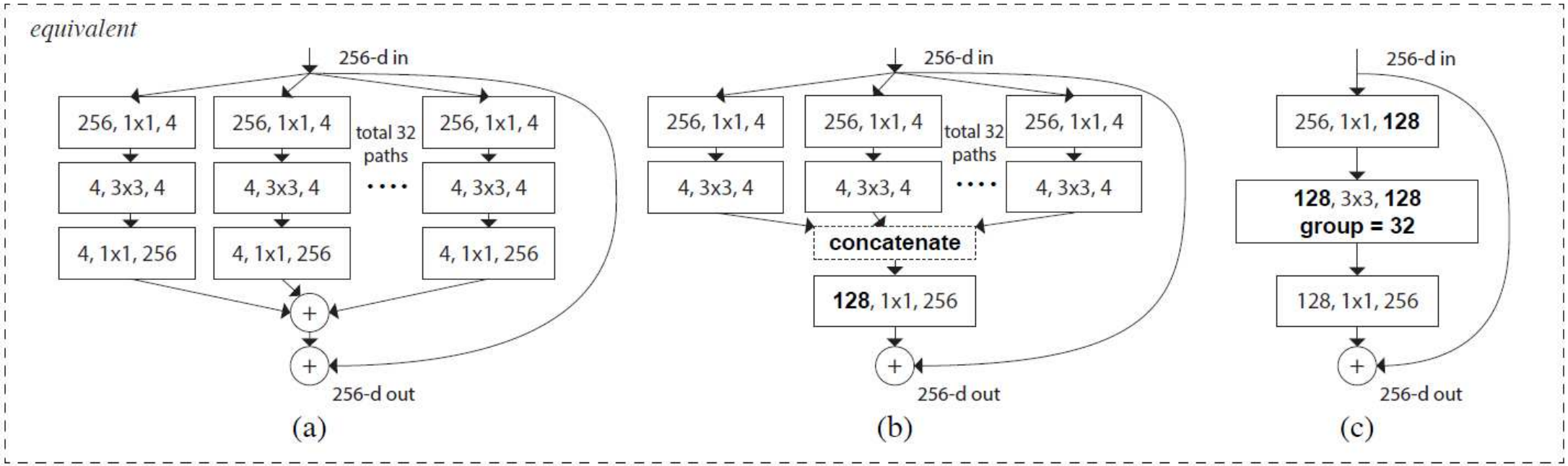



**ResNeXt**:
uniform multi-branch

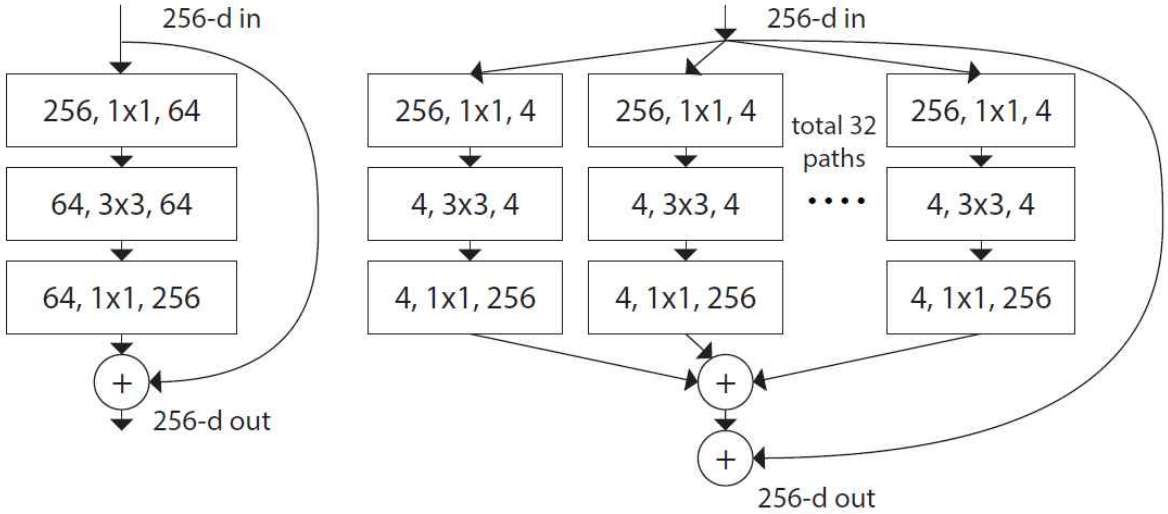
# ResNeXt




- Concatenation and Addition are interchangeable
- Uniform multi-branching can be done by group-conv



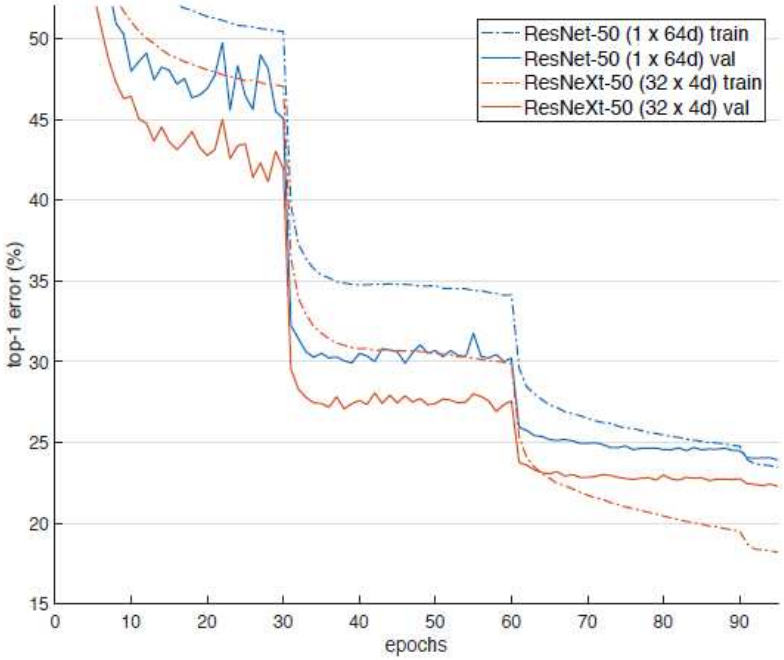
# Model Capacity (# of parameters)

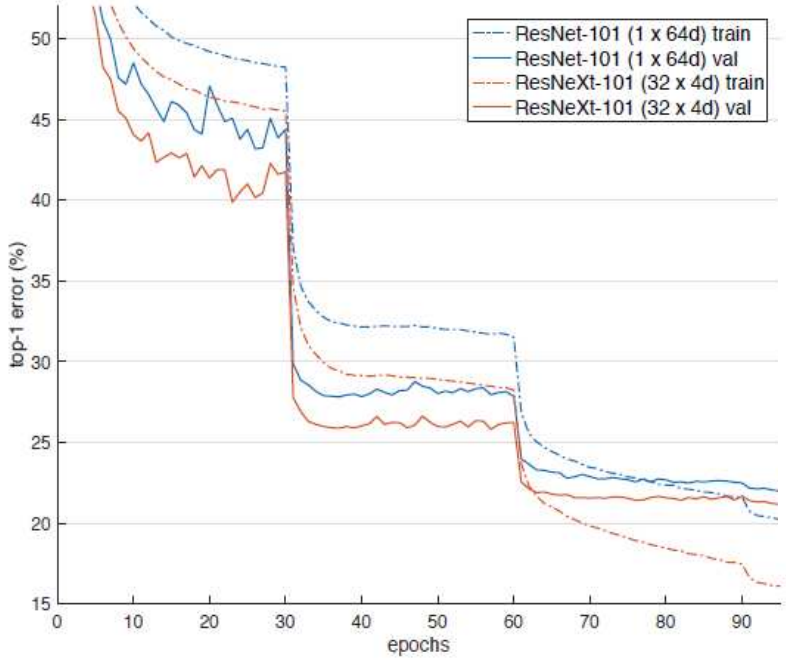



- Original ResNet(left) : 256x64 + 3x3x64x64 + 64x256 = 70k
- ResNeXt(right – with bottleneck width d and cardinality C) :

  C x (256xd + 3x3xdxd + dx256) = 70k, when C =32 and d=4

# Results – Cardinality vs Width




| | setting | top-1 error (%) |
|---|---|---|
| ResNet-50 | 1 × 64d | 23.9 |
| ResNeXt-50 | 2 × 40d | 23.0 |
| ResNeXt-50 | 4 × 24d | 22.6 |
| ResNeXt-50 | 8 × 14d | 22.3 |
| ResNeXt-50 | 32 × 4d | **22.2** |
| ResNet-101 | 1 × 64d | 22.0 |
| ResNeXt-101 | 2 × 40d | 21.7 |
| ResNeXt-101 | 4 × 24d | 21.4 |
| ResNeXt-101 | 8 × 14d | 21.3 |
| ResNeXt-101 | 32 × 4d | **21.2** |

# Results – Increasing Cardinality vs Deeper/Wider

| | setting | top-1 err (%) | top-5 err (%) |
|---|---|---|---|
| *1× complexity references:* | | | |
| ResNet-101 | 1 × 64d | 22.0 | 6.0 |
| ResNeXt-101 | 32 × 4d | 21.2 | 5.6 |
| *2× complexity models follow:* | | | |
| ResNet-**200** [15] | 1 × 64d | 21.7 | 5.8 |
| ResNet-101, wider | 1 × **100**d | 21.3 | 5.7 |
| ResNeXt-101 | **2** × 64d | 20.7 | 5.5 |
| ResNeXt-101 | **64** × 4d | **20.4** | **5.3** |

# Squeeze-and-Excitation Networks

Squeeze-and-Excitation Networks

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Gang Sun[0000−0001−6913−6799] Enhua Wu[0000−0002−2174−1428]

**Abstract**—The central building block of convolutional neural networks (CNNs) is the convolution operator, which enables networks to construct informative features by fusing both spatial and channel-wise information within local receptive fields at each layer. A broad range of prior research has investigated the spatial component of this relationship, seeking to strengthen the representational power of a CNN by enhancing the quality of spatial encodings throughout its feature hierarchy. In this work, we focus instead on the channel relationship and propose a novel architectural unit, which we term the "Squeeze-and-Excitation" (SE) block, that adaptively recalibrates channel-wise feature responses by explicitly modelling interdependencies between channels. We show that these blocks can be stacked together to form SENet architectures that generalise extremely effectively across different datasets. We further demonstrate that SE blocks bring significant improvements in performance for existing state-of-the-art CNNs at minimal additional computational cost. Squeeze-and-Excitation Networks formed the foundation of our ILSVRC 2017 classification submission which won first place and reduced the top-5 error to 2.251%, surpassing the winning entry of 2016 by a relative improvement of ∼25%. Models and code are available at https://github.com/hujie-frank/SENet.

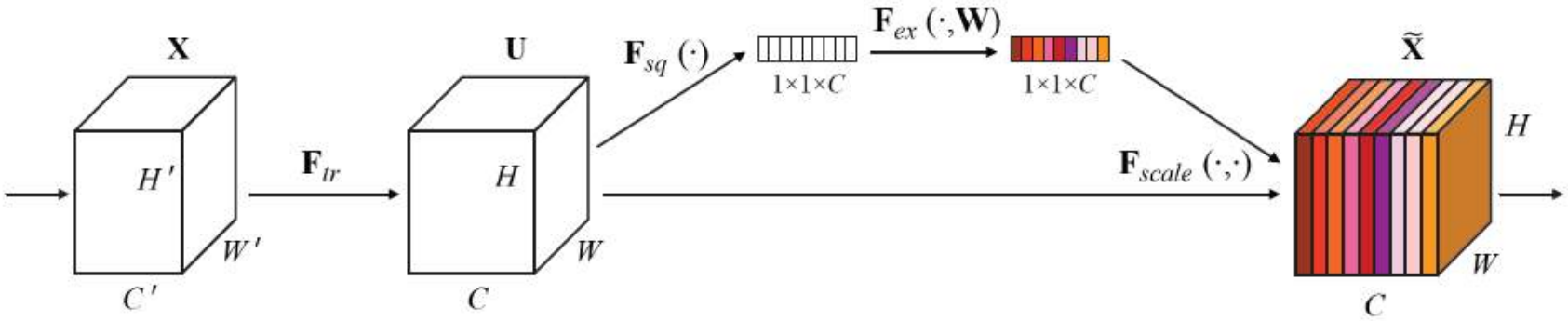
**Index Terms**—Squeeze-and-Excitation, Image classification, Convolutional Neural Network.

# Squeeze-and-Excitation Networks

| Team name | Entry description | **Classification error** | Localization error |
|---|---|---|---|
| WMW | Ensemble C [No bounding box results] | 0.02251 | 0.590987 |
| WMW | Ensemble E [No bounding box results] | 0.02258 | 0.591018 |
| WMW | Ensemble A [No bounding box results] | 0.0227 | 0.591153 |
| WMW | Ensemble D [No bounding box results] | 0.0227 | 0.591039 |
| WMW | Ensemble B [No bounding box results] | 0.0227 | 0.59106 |
| Trimps-Soushen | Result-1 | 0.02481 | 0.067698 |
| Trimps-Soushen | Result-2 | 0.02481 | 0.06525 |
| Trimps-Soushen | Result-3 | 0.02481 | 0.064991 |
| Trimps-Soushen | Result-4 | 0.02481 | 0.065261 |
| Trimps-Soushen | Result-5 | 0.02481 | 0.065302 |
| NUS-Qihoo_DPNs (CLS-LOC) | [E2] CLS:: Dual Path Networks + Basic Ensemble | 0.0274 | 0.088093 |
| NUS-Qihoo_DPNs (CLS-LOC) | [E1] CLS:: Dual Path Networks + Basic Ensemble | 0.02744 | 0.088269 |
| BDAT | provide_class | 0.02962 | 0.086942 |
| BDAT | provide_box | 0.03158 | 0.081392 |
| MIL_UT | Ensemble of 9 models (classification-only) | 0.03205 | 0.596164 |
| SIIT_KAIST-SKT | ensemble 2 | 0.03226 | 0.128924 |
| MIL_UT | Ensemble of 10 models (classification-only) | 0.03228 | 0.596174 |

# Squeeze-and-Excitation Blocks

- Improving the quality of representations produced by a network by explicitly modelling the interdependencies between the channels of its convolutional features

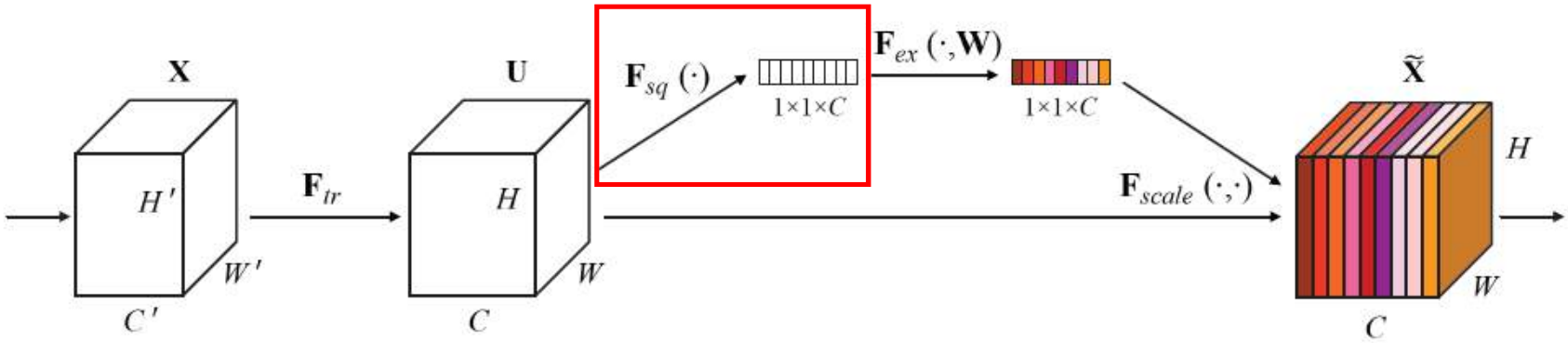


# Standard Convolution

- In standard convolution case, the output is produced by a summation through all channels
- Channel dependencies are implicitly embedded in output feature maps
- But, they are entangled with the local spatial correlation captured by filters

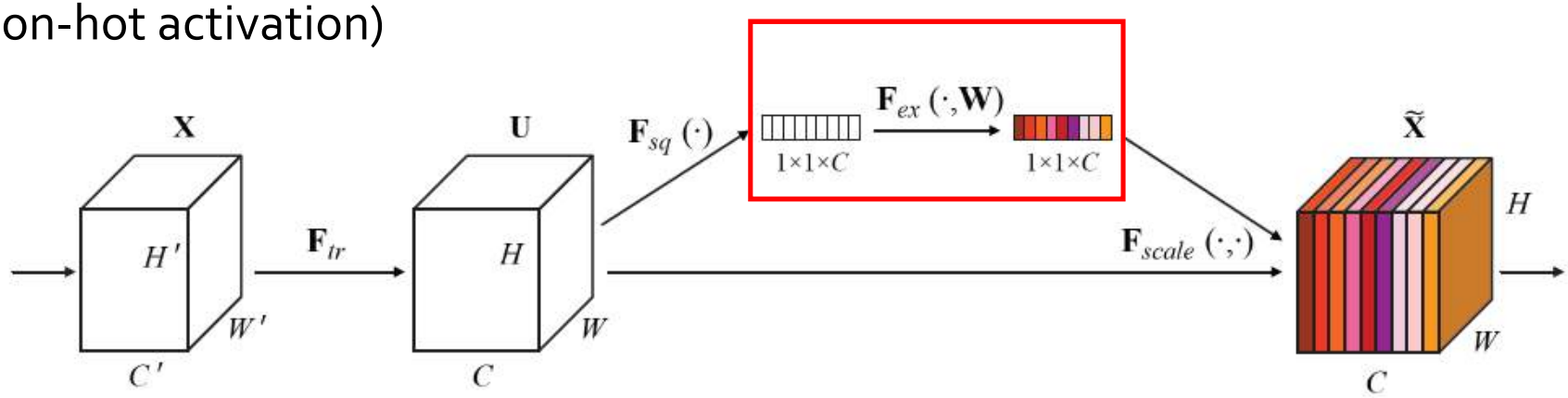
# Squeeze : Global Information Embedding

- Authors propose to squeeze global spatial information into a channel descriptor.
- This is achieved by using global average pooling to generate channel-wise statistics.
- The output of the transformation(GAP) can be interpreted as a collection of the local descriptors whose statistics are expressive for whole image



# Excitation : Adaptive Recalibration

- To make use of the information aggregated in the squeeze operation, authors follow it with a second operation which aims to fully captured channel-wise dependencies.
- The function must meet two criteria
  - It must be flexible(it must be capable of learning a nonlinear interaction btw channels)
  - It must learn a non-mutually-exclusive relationship(rather than enforcing a on-hot activation)

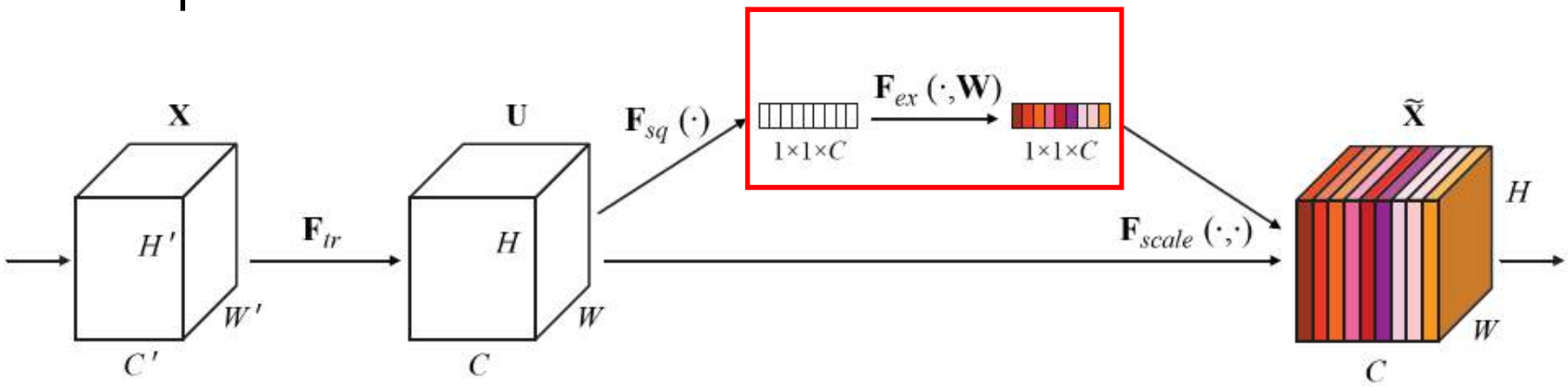


# Excitation : Adaptive Recalibration

- To meet these criteria, authors opt to employ a simple gating mechanism with a sigmoid activation (σ : sigmoid, δ : ReLU)

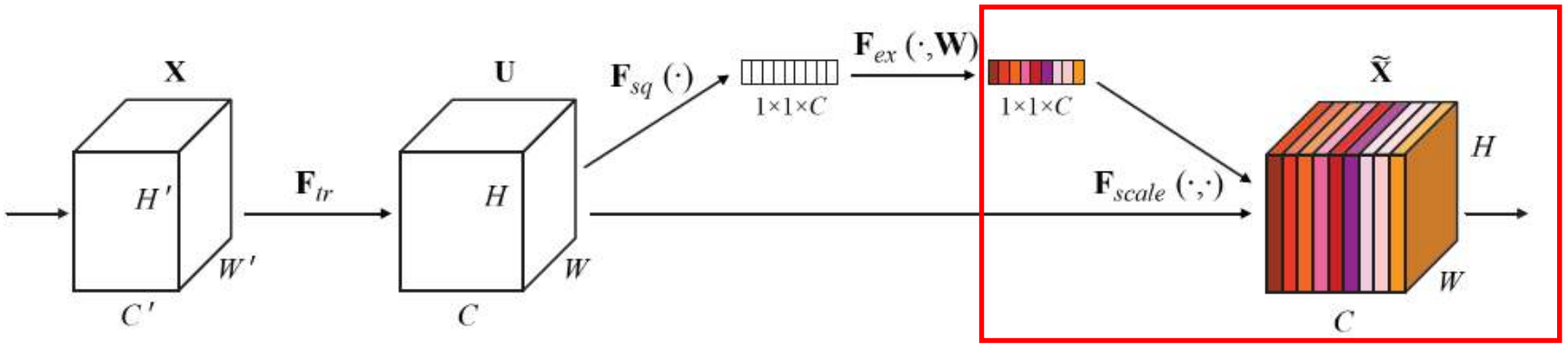
$$\mathbf{s} = \mathbf{F}_{ex}(\mathbf{z}, \mathbf{W}) = \sigma(g(\mathbf{z}, \mathbf{W})) = \sigma(\mathbf{W}_2\delta(\mathbf{W}_1\mathbf{z})),$$

- Forming a bottleneck with two fully connected layers around the non-linearity. A dimensionality-reduction layer with parameters W1 and reduction ratio r, a ReLU and then a dimensionality-increasing layer with parameters W2



# Excitation : Adaptive Recalibration

- The final output of the block is obtained by rescaling the transformation output with the activations – channel-wise multiplication



# Instantiation

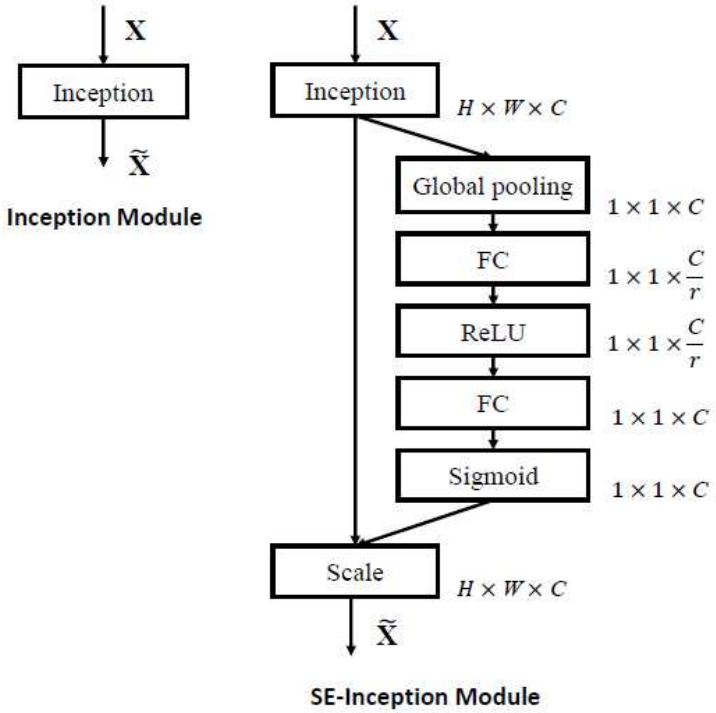



Fig. 2. The schema of the original Inception module (left) and the SE-Inception module (right).

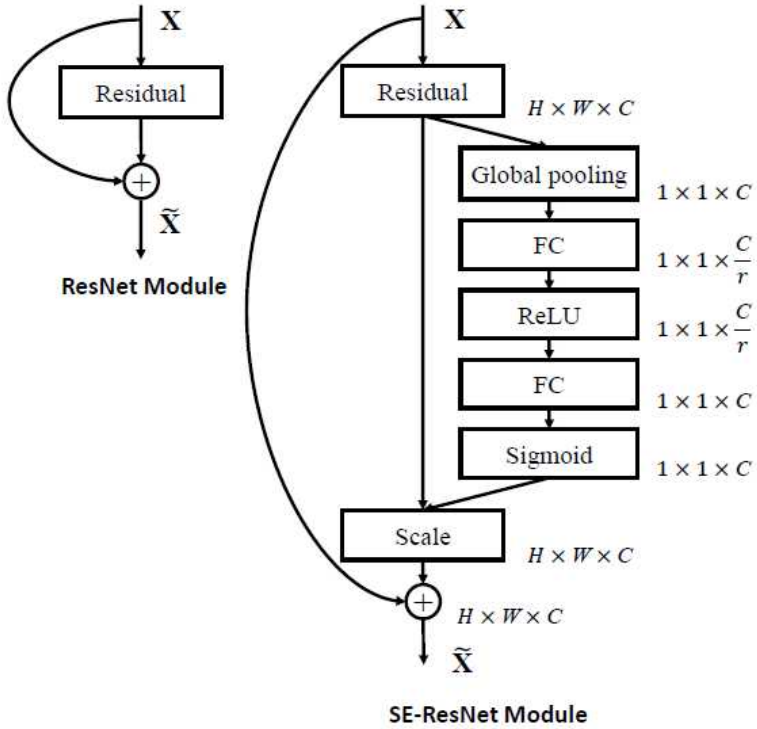


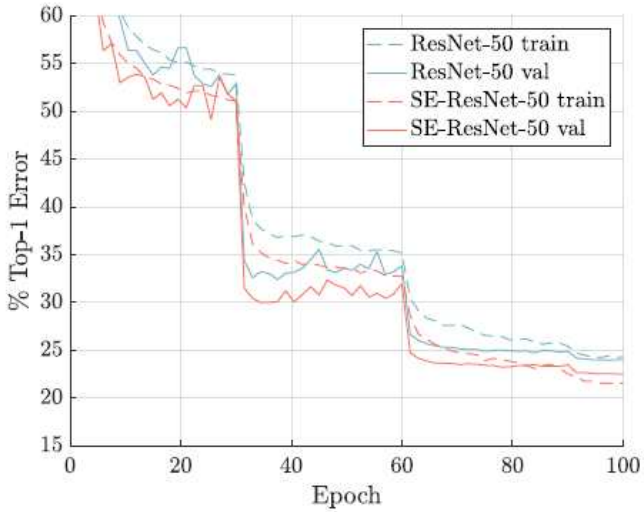

Fig. 3. The schema of the original Residual module (left) and the SE-ResNet module (right).

# Example Architecture

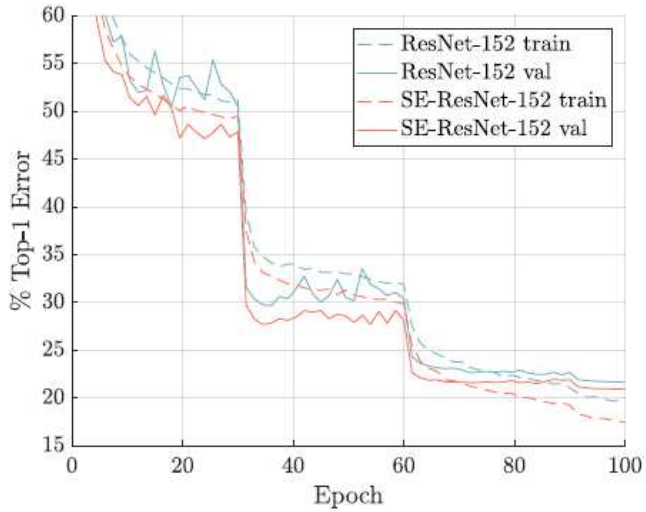
TABLE 1
(Left) ResNet-50. (Middle) SE-ResNet-50. (Right) SE-ResNeXt-50 with a 32×4d template. The shapes and operations with specific parameter settings of a residual building block are listed inside the brackets and the number of stacked blocks in a stage is presented outside. The inner brackets following by *fc* indicates the output dimension of the two fully connected layers in an SE module.

| Output size | ResNet-50 | SE-ResNet-50 | SE-ResNeXt-50 ($32 \times 4$d) |
|---|---|---|---|
| $112 \times 112$ | conv, $7 \times 7$, 64, stride 2 | | |
| $56 \times 56$ | max pool, $3 \times 3$, stride 2 | | |
| | $\begin{bmatrix} \text{conv}, 1 \times 1, 64 \\ \text{conv}, 3 \times 3, 64 \\ \text{conv}, 1 \times 1, 256 \end{bmatrix} \times 3$ | $\begin{bmatrix} \text{conv}, 1 \times 1, 64 \\ \text{conv}, 3 \times 3, 64 \\ \text{conv}, 1 \times 1, 256 \\ fc, [16, 256] \end{bmatrix} \times 3$ | $\begin{bmatrix} \text{conv}, 1 \times 1, 128 \\ \text{conv}, 3 \times 3, 128 \quad C = 32 \\ \text{conv}, 1 \times 1, 256 \\ fc, [16, 256] \end{bmatrix} \times 3$ |
| $28 \times 28$ | $\begin{bmatrix} \text{conv}, 1 \times 1, 128 \\ \text{conv}, 3 \times 3, 128 \\ \text{conv}, 1 \times 1, 512 \end{bmatrix} \times 4$ | $\begin{bmatrix} \text{conv}, 1 \times 1, 128 \\ \text{conv}, 3 \times 3, 128 \\ \text{conv}, 1 \times 1, 512 \\ fc, [32, 512] \end{bmatrix} \times 4$ | $\begin{bmatrix} \text{conv}, 1 \times 1, 256 \\ \text{conv}, 3 \times 3, 256 \quad C = 32 \\ \text{conv}, 1 \times 1, 512 \\ fc, [32, 512] \end{bmatrix} \times 4$ |
| $14 \times 14$ | $\begin{bmatrix} \text{conv}, 1 \times 1, 256 \\ \text{conv}, 3 \times 3, 256 \\ \text{conv}, 1 \times 1, 1024 \end{bmatrix} \times 6$ | $\begin{bmatrix} \text{conv}, 1 \times 1, 256 \\ \text{conv}, 3 \times 3, 256 \\ \text{conv}, 1 \times 1, 1024 \\ fc, [64, 1024] \end{bmatrix} \times 6$ | $\begin{bmatrix} \text{conv}, 1 \times 1, 512 \\ \text{conv}, 3 \times 3, 512 \quad C = 32 \\ \text{conv}, 1 \times 1, 1024 \\ fc, [64, 1024] \end{bmatrix} \times 6$ |
| $7 \times 7$ | $\begin{bmatrix} \text{conv}, 1 \times 1, 512 \\ \text{conv}, 3 \times 3, 512 \\ \text{conv}, 1 \times 1, 2048 \end{bmatrix} \times 3$ | $\begin{bmatrix} \text{conv}, 1 \times 1, 512 \\ \text{conv}, 3 \times 3, 512 \\ \text{conv}, 1 \times 1, 2048 \\ fc, [128, 2048] \end{bmatrix} \times 3$ | $\begin{bmatrix} \text{conv}, 1 \times 1, 1024 \\ \text{conv}, 3 \times 3, 1024 \quad C = 32 \\ \text{conv}, 1 \times 1, 2048 \\ fc, [128, 2048] \end{bmatrix} \times 3$ |
| $1 \times 1$ | global average pool, 1000-d $fc$, softmax | | |

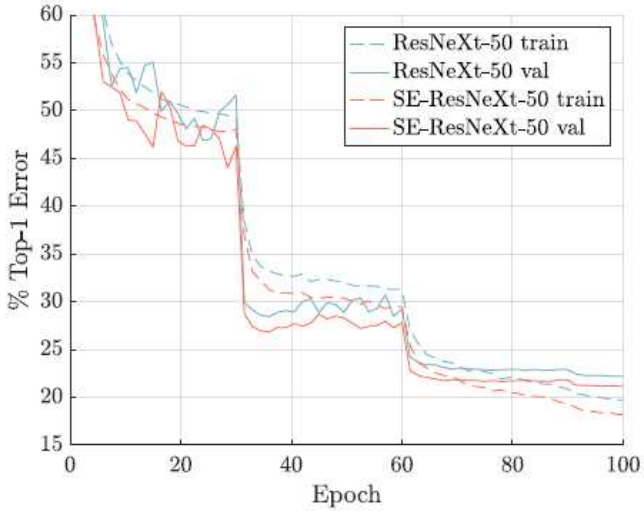
# Results



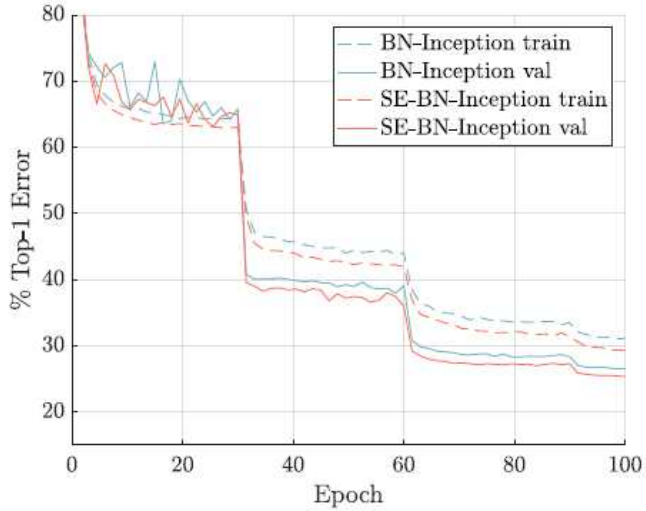

(a) ResNet-50 and SE-ResNet-50




(b) ResNet-152 and SE-ResNet-152




(c) ResNeXt-50 and SE-ResNeXt-50




(d) BN-Inception and SE-BN-Inception

# NASNet

## Learning Transferable Architectures for Scalable Image Recognition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### Abstract

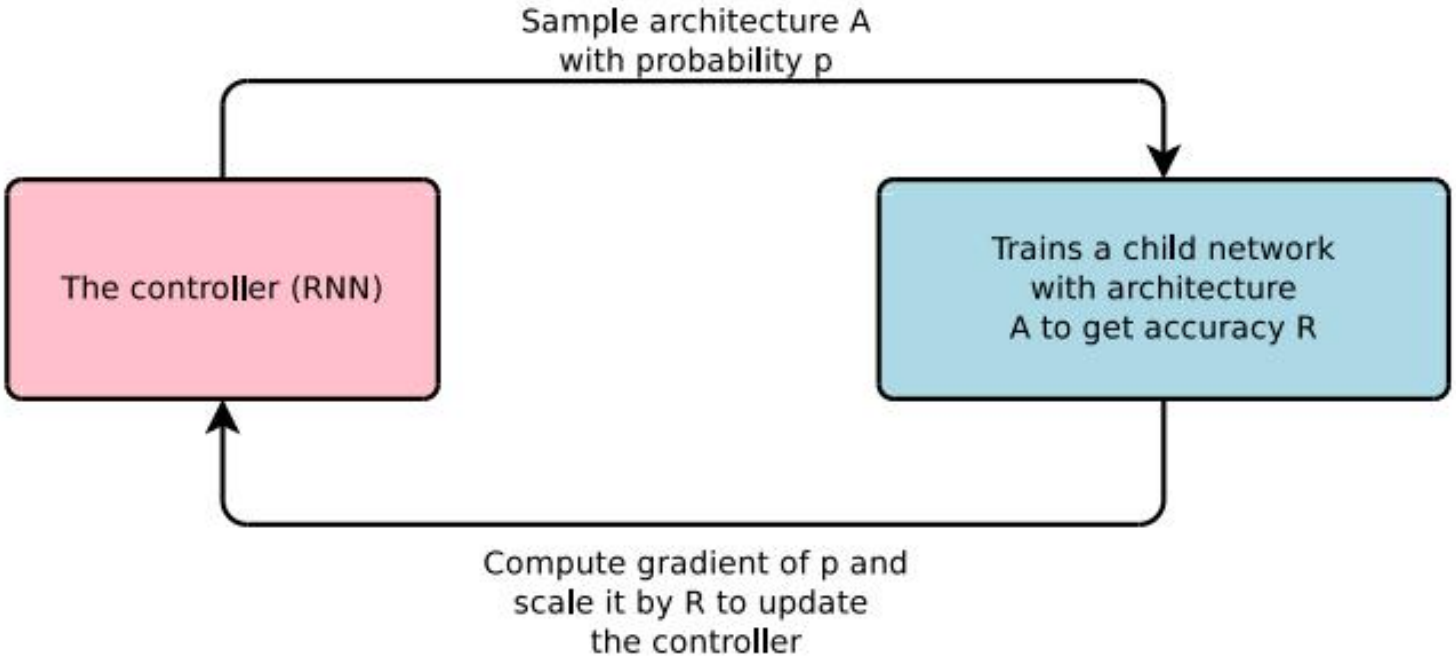
*Developing neural network image classification models often requires significant architecture engineering. In this paper, we attempt to automate this engineering process by learning the model architectures directly on the dataset of interest. As this approach is expensive when the dataset is large, we propose to search for an architectural building block on a small dataset and then transfer the block to a larger dataset. Our key contribution is the design of a new search space which enables transferability. In our experiments, we search for the best convolutional layer (or "cell") on the CIFAR-10 dataset and then apply this cell to the ImageNet dataset by stacking together more copies of this*


cation represents one of the most important breakthroughs in deep learning. Successive advancements on this benchmark based on convolutional neural networks (CNNs) have achieved impressive results through significant architecture engineering [52, 58, 20, 59, 57, 67].

In this paper, we consider learning the convolutional architectures directly from data with application to ImageNet classification. In addition to being an difficult and important benchmark in computer vision, features derived from ImageNet classifiers are of great importance to many other computer vision tasks. For example, features from networks that perform well on ImageNet classification provide state-of-the-art performance when transferred to other computer vision tasks where labeled data is limited [13].

# Neural Architecture Search

- B. Zoph and Q. V. Le., "Neural architecture search with reinforcement learning", ICLR-2017



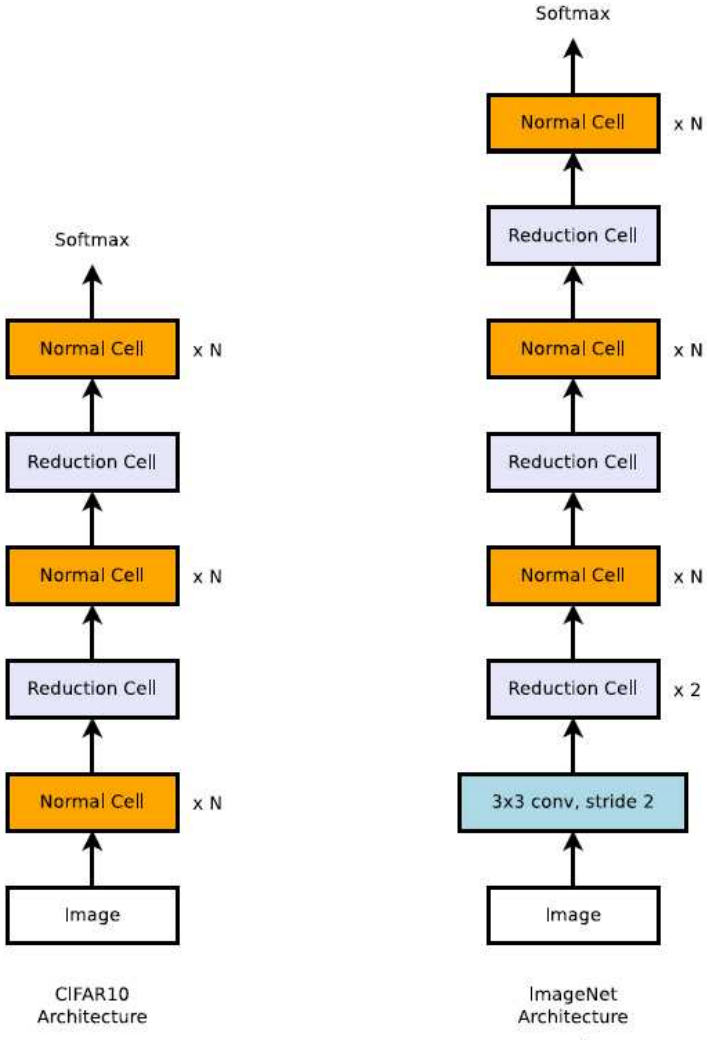
# Motivation & Idea

- NAS used 800 GPUs for 28days resulting in 22,400 GPU-hours → too long (ImageNet dataset)
- Many state-of-the-art models have repeated modules
- Searching for a good architecture on the far smaller CIFAR-10 dataset, and automatically transfer the learned architecture to ImageNet
- Achieving this transferability by designing a search space so that the complexity of the architecture is independent of the depth of the network
- All convolutional networks in search space are composed of convolutional layers(or "cells") with identical structure but different weights

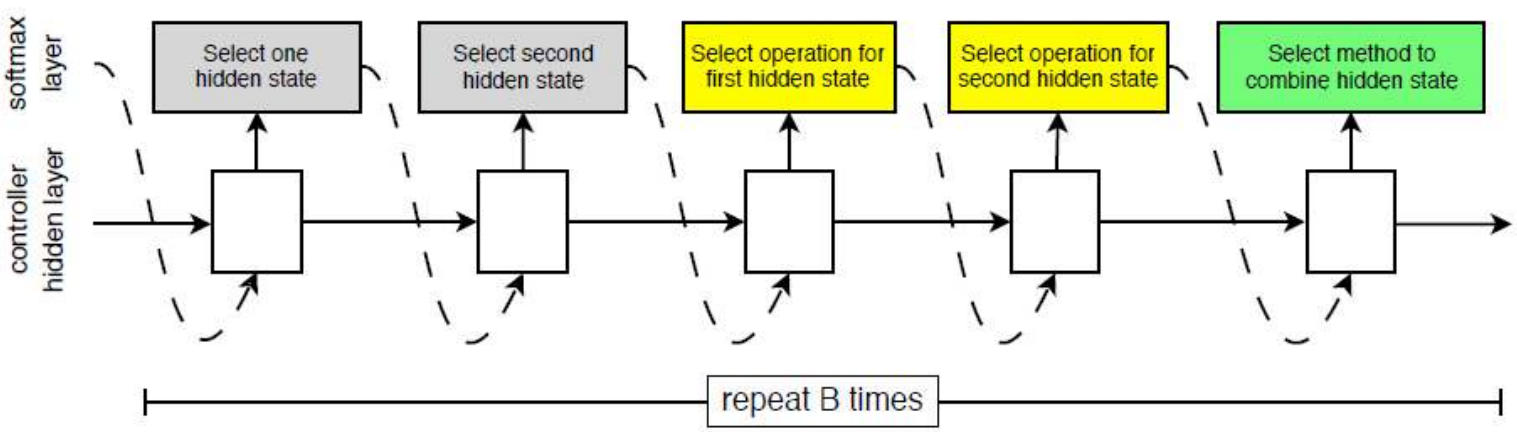
# Method

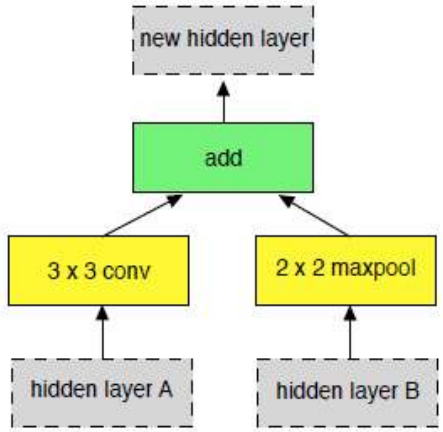
- Overall architectures of the convolutional nets are manually predetermined
  - Normal Cell – convolutional cells that return a feature map of the same dimension
  - Reduction Cell – convolutional cells that return a feature map where the feature map height and width is reduced by a factor of two
- Using common heuristic to double the number of filters in the output whenever the spatial activation size is reduced

# Scalable Architectures for Image Classification



# Models and Algorithms




**Step 1.** Select a hidden state from $h_i, h_{i-1}$ or from the set of hidden states created in previous blocks.

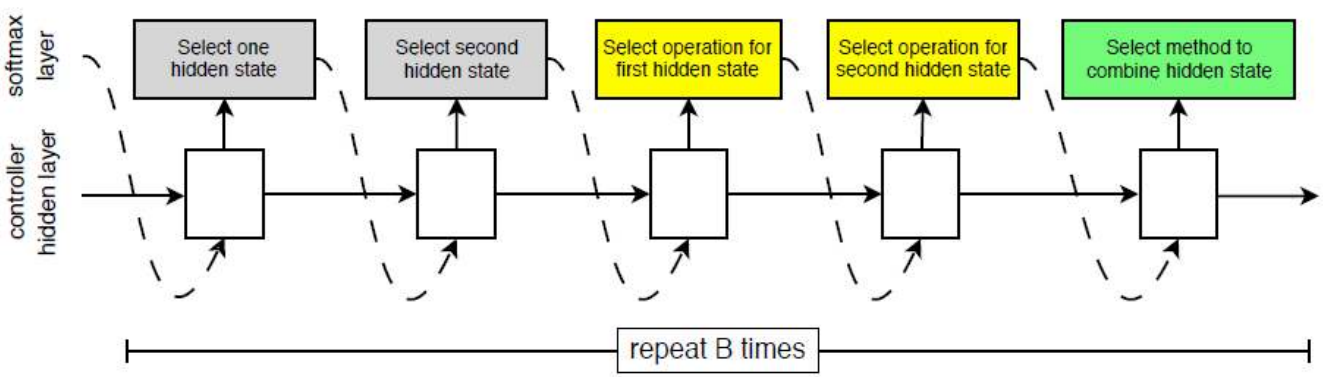
**Step 2.** Select a second hidden state from the same options as in Step 1.

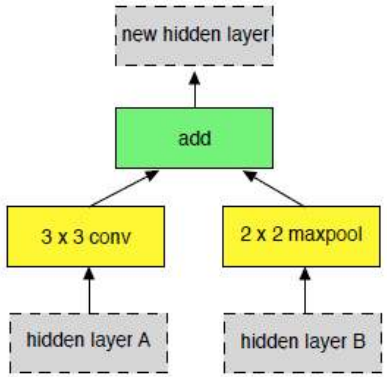
**Step 3.** Select an operation to apply to the hidden state selected in Step 1.

**Step 4.** Select an operation to apply to the hidden state selected in Step 2.

**Step 5.** Select a method to combine the outputs of Step 3 and 4 to create a new hidden state.

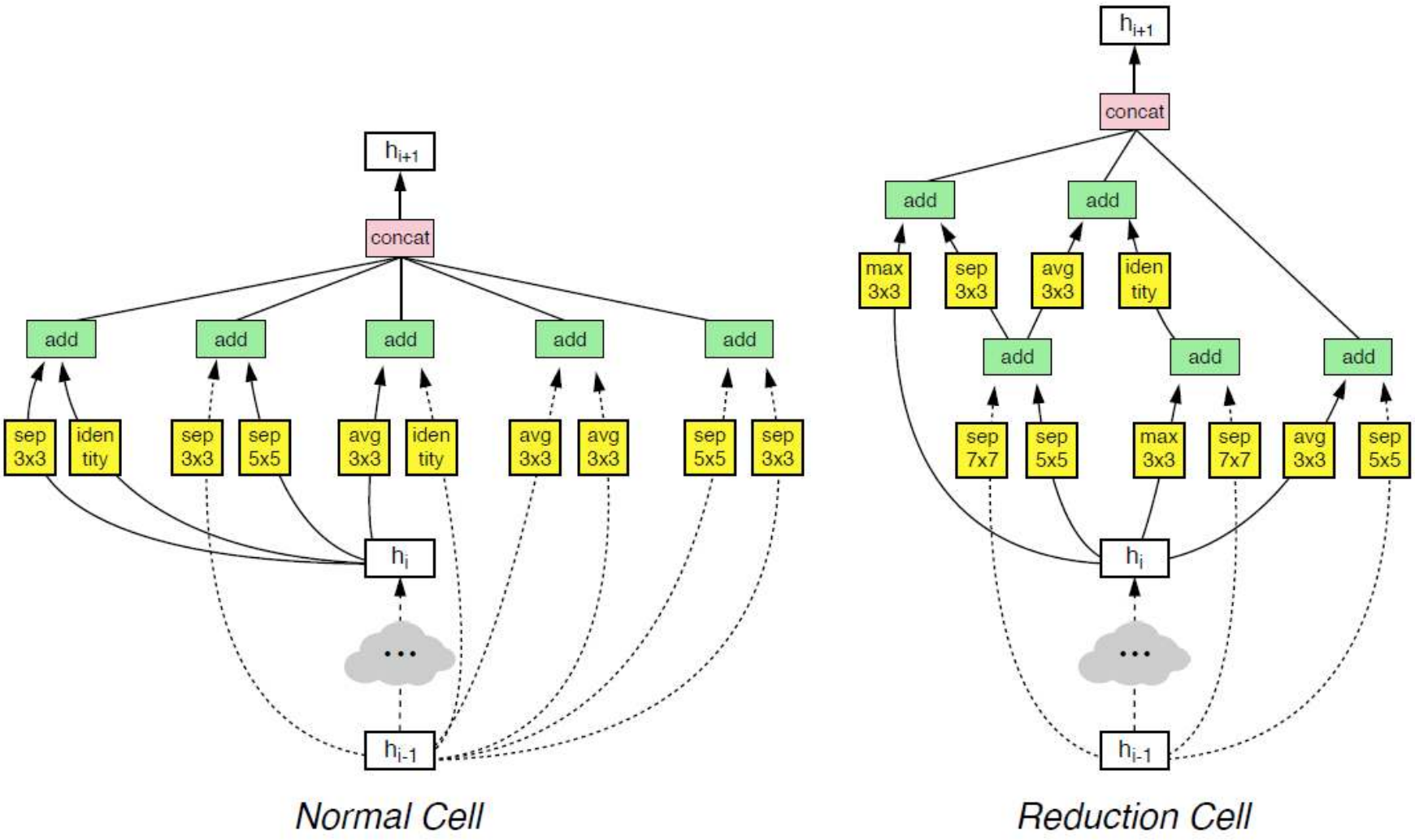
# Search Space in a Cell (Step 3 and 4)



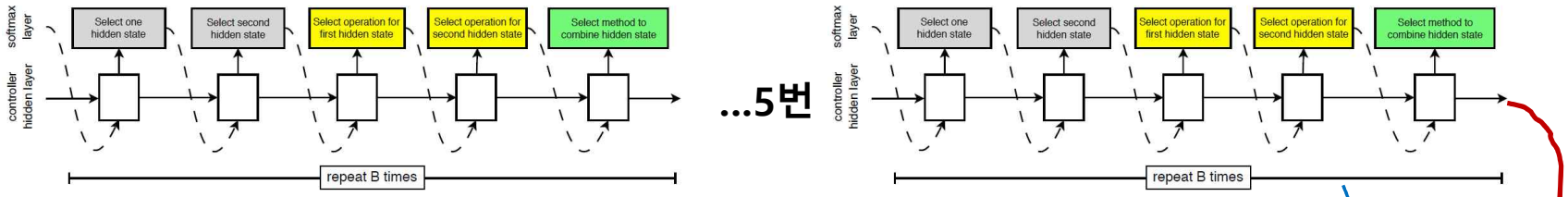




- identity
- 1x7 then 7x1 convolution
- 3x3 average pooling
- 5x5 max pooling
- 1x1 convolution
- 3x3 depthwise-separable conv
- 7x7 depthwise-separable conv
- 1x3 then 3x1 convolution
- 3x3 dilated convolution
- 3x3 max pooling
- 7x7 max pooling
- 3x3 convolution
- 5x5 depthwise-seperable conv

# Best Architecture (NASNet-A)



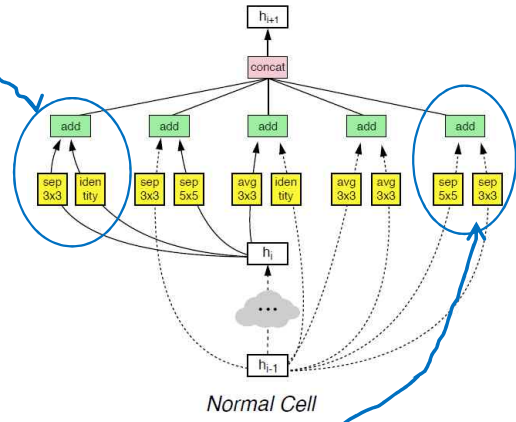
# Best Architecture (NASNet-A)



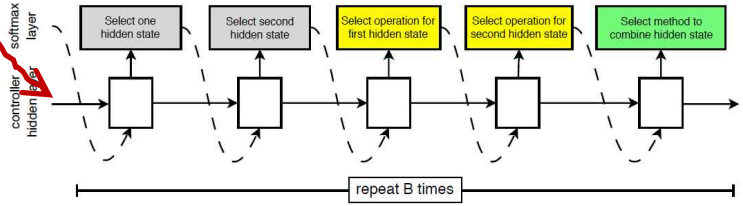

...5번



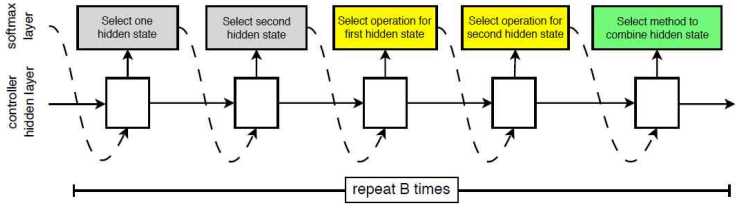

## <Normal Cell>



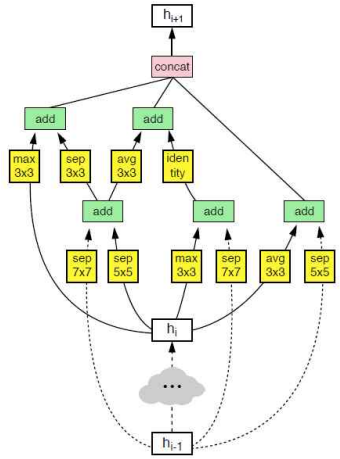

*Normal Cell*




...5번

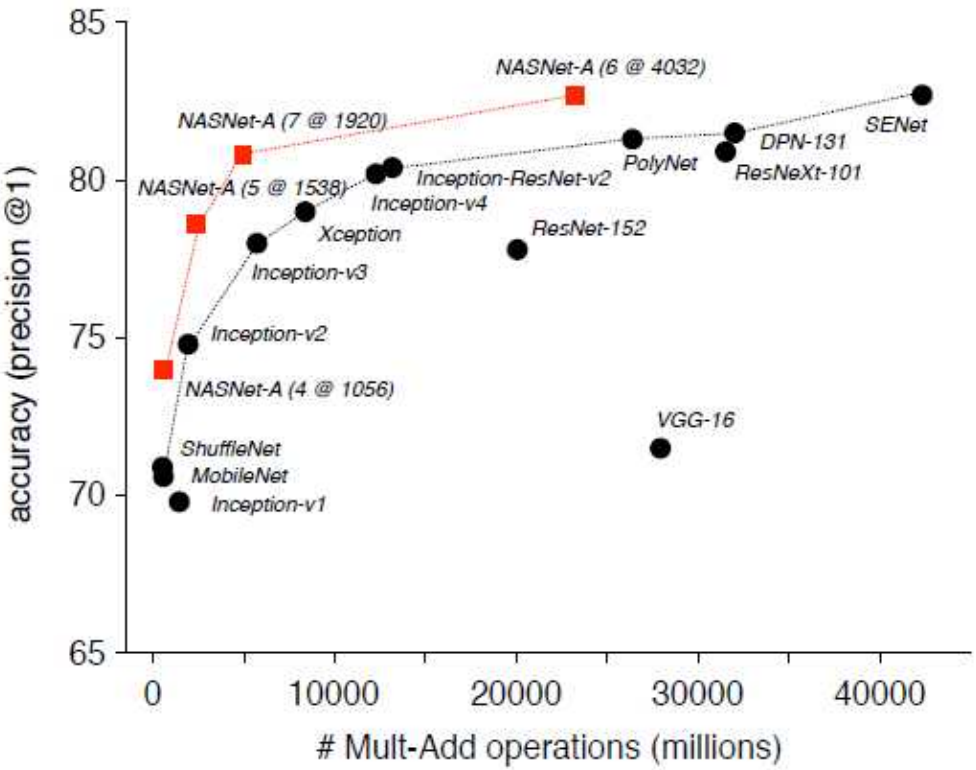


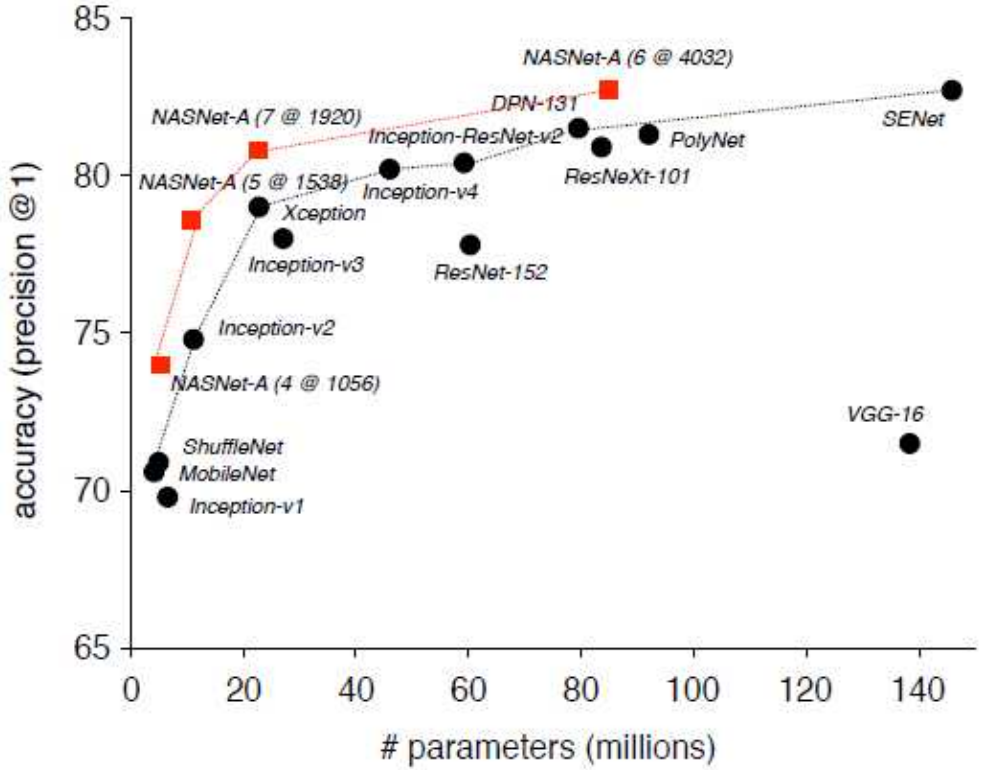

## <Reduction Cell>



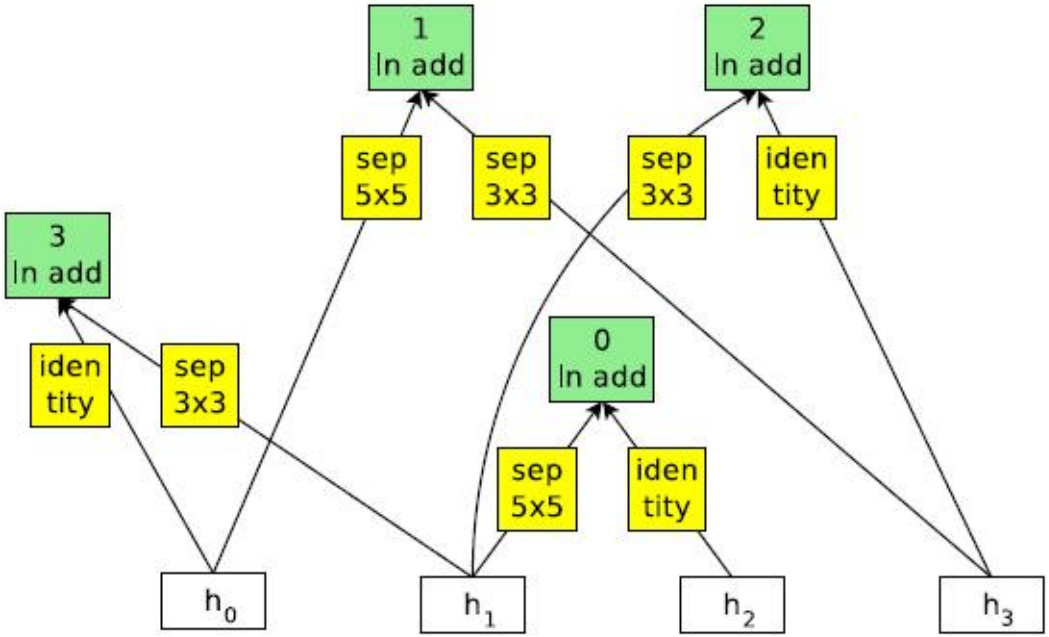

*Reduction Cell*

# Results on ImageNet

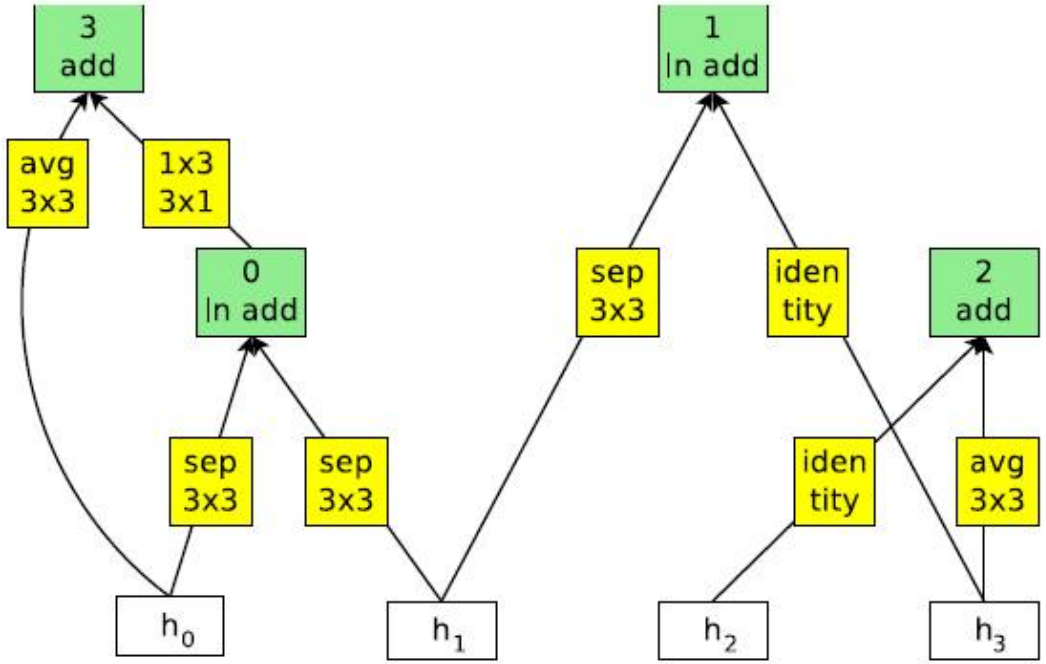


# NASNet-B

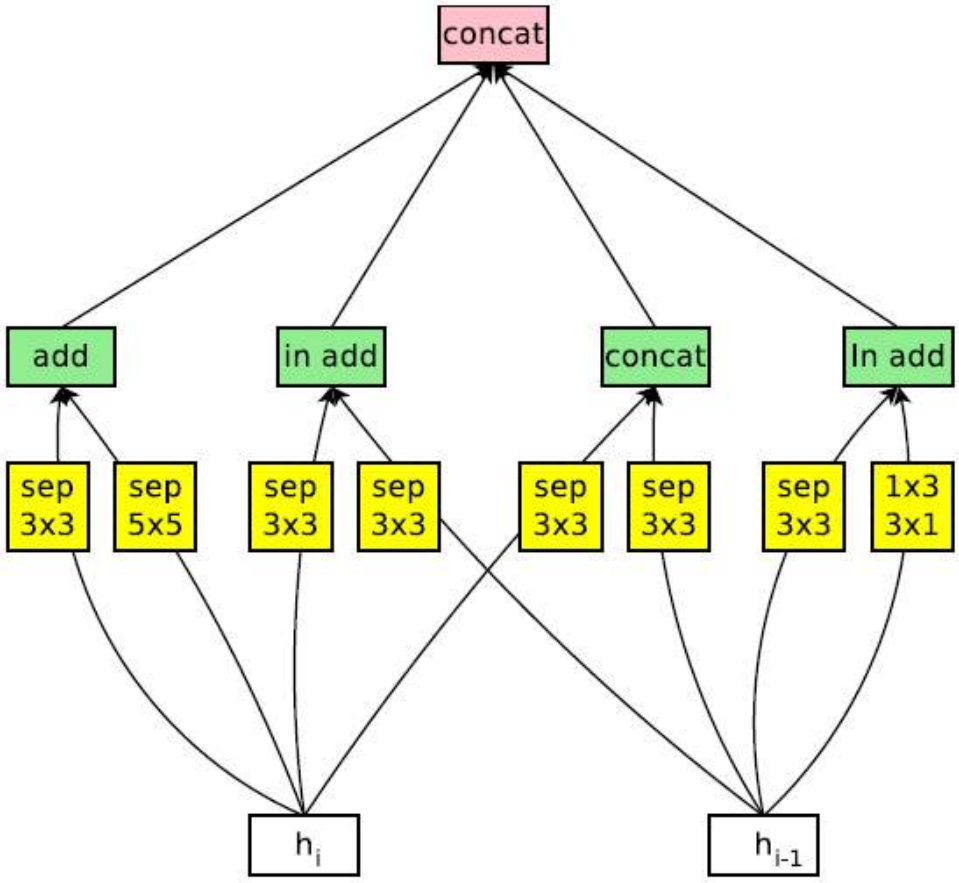



Normal Cell

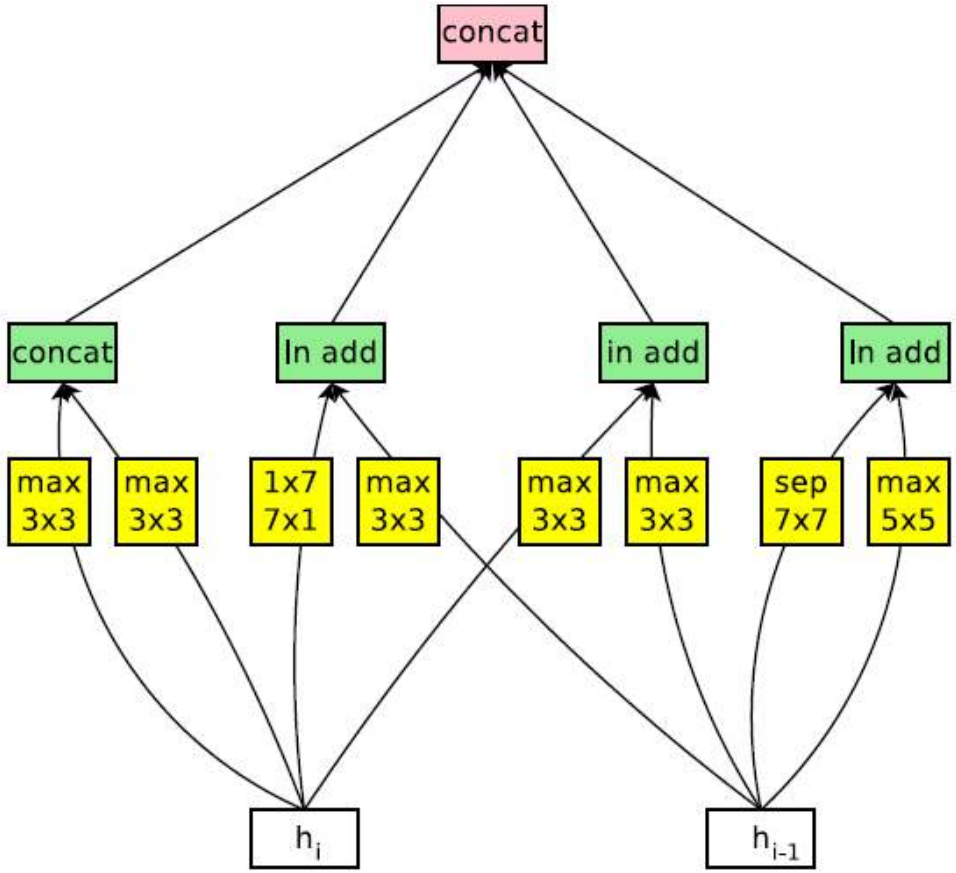



Reduction Cell

# NASNet-C




Normal Cell




Reduction Cell

# Randomly Wired Neural Networks

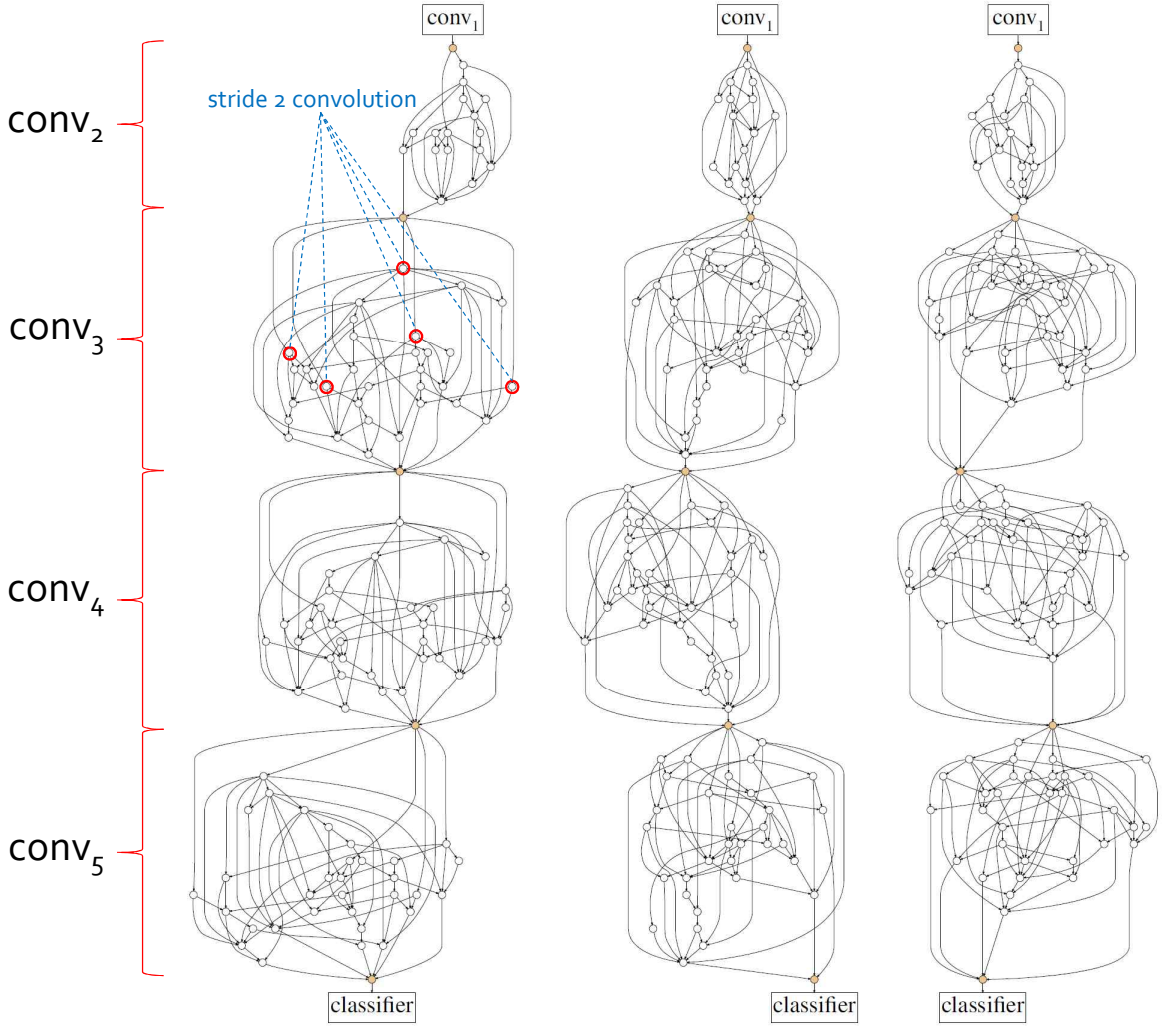



Figure 1. **Randomly wired neural networks** generated by the classical Watts-Strogatz (WS) [50] model: these three instances of random networks achieve (left-to-right) 79.1%, 79.1%, 79.0% classification accuracy on ImageNet under a similar computational budget to ResNet-50, which has 77.1% accuracy.

# SqueezeNet

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

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### ABSTRACT

Recent research on deep convolutional neural networks (CNNs) has focused primarily on improving accuracy. For a given accuracy level, it is typically possible to identify multiple CNN architectures that achieve that accuracy level. With equivalent accuracy, smaller CNN architectures offer at least three advantages: (1) Smaller CNNs require less communication across servers during distributed training. (2) Smaller CNNs require less bandwidth to export a new model from the cloud to an autonomous car. (3) Smaller CNNs are more feasible to deploy on FPGAs and other hardware with limited memory. To provide all of these advantages, we propose a small CNN architecture called SqueezeNet. SqueezeNet achieves AlexNet-level accuracy on ImageNet with 50x fewer parameters. Additionally, with model compression techniques, we are able to compress SqueezeNet to less than 0.5MB (510× smaller than AlexNet).

The SqueezeNet architecture is available for download here: https://github.com/DeepScale/SqueezeNet

# SqueezeNet

- Architectural Design Strategies
  - Replace 3x3 filters with 1x1 filters
  - Decrease the number of input channels to 3x3 filters
    - Total quantity of parameters in 3x3 conv layer is (number of input channels) x (number of filters) x (3x3)
  - Downsample late in the network so that convolution layers have large activation maps
    - large activation maps (due to delayed downsampling) can lead to higher classification accuracy

# The Fire Module

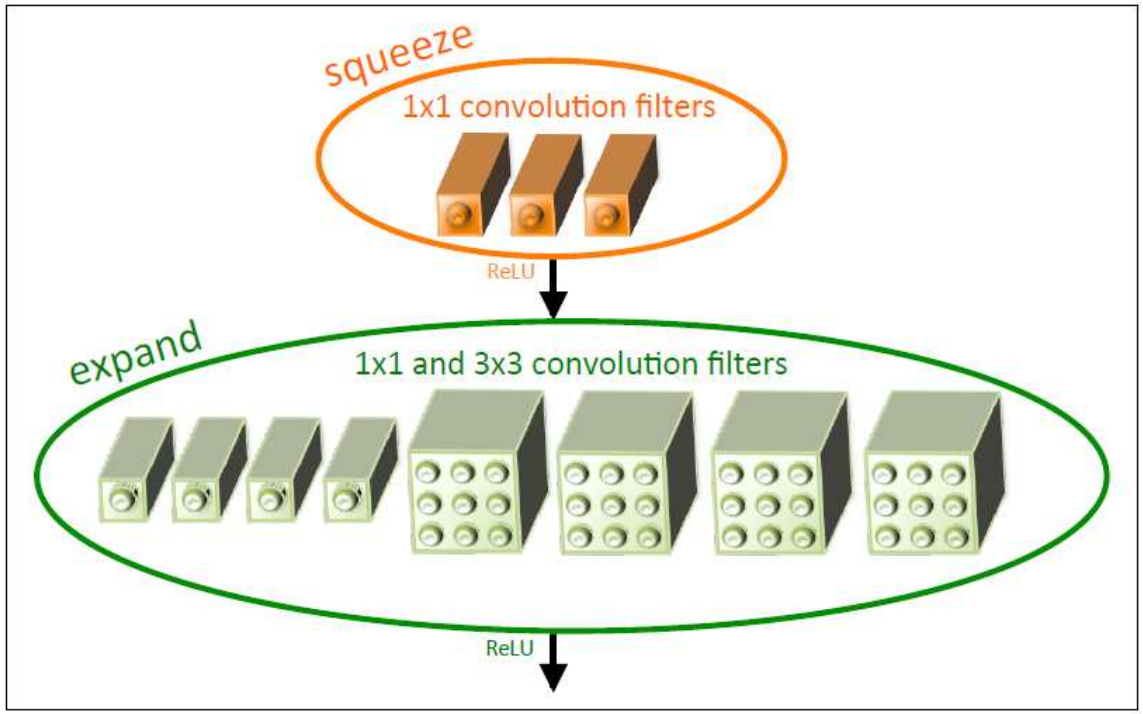
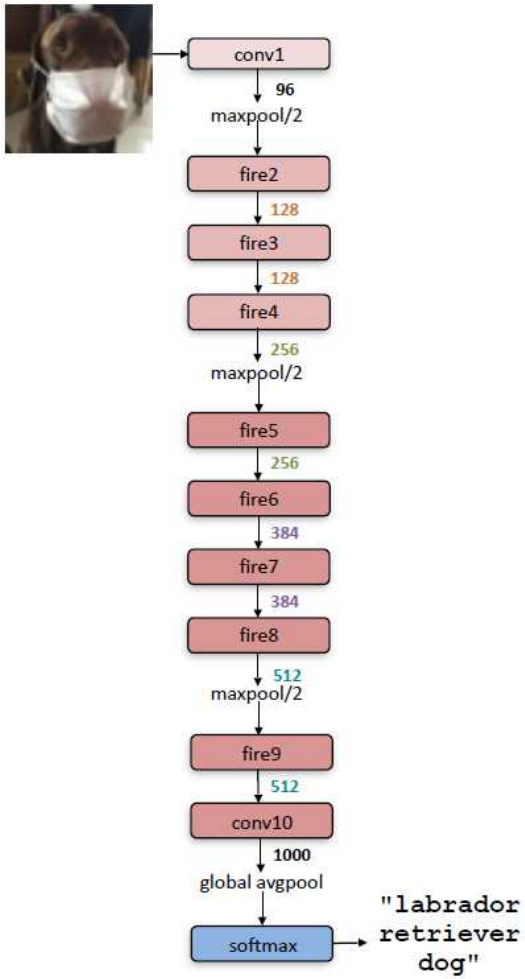
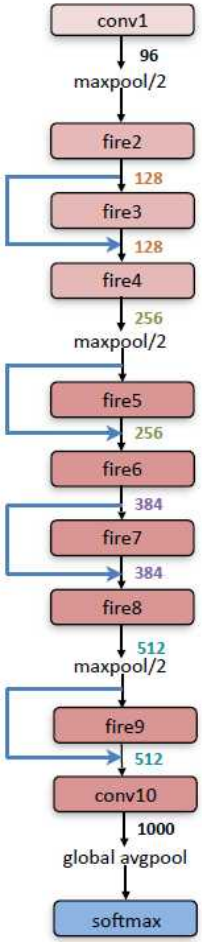
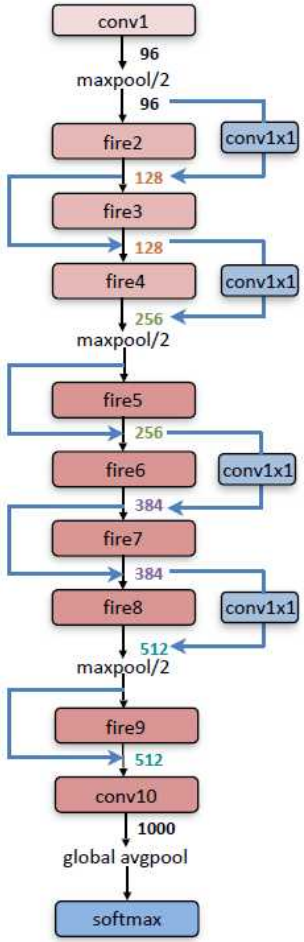



Figure 1: Microarchitectural view: Organization of convolution filters in the **Fire module**. In this example, $s_{1x1} = 3$, $e_{1x1} = 4$, and $e_{3x3} = 4$. We illustrate the convolution filters but not the activations.

# Macroarchitectural View



# SqueezeNet Architecture

| 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) |

# Results

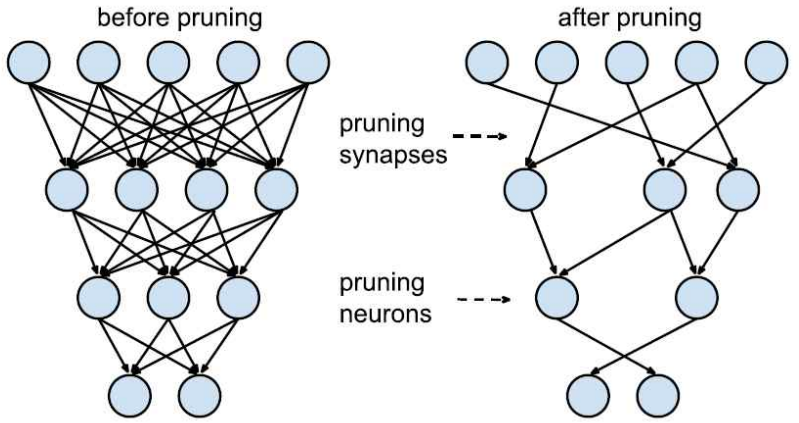
Table 2: Comparing SqueezeNet to model compression approaches. By *model size*, we mean the number of bytes required to store all of the parameters in the trained model.

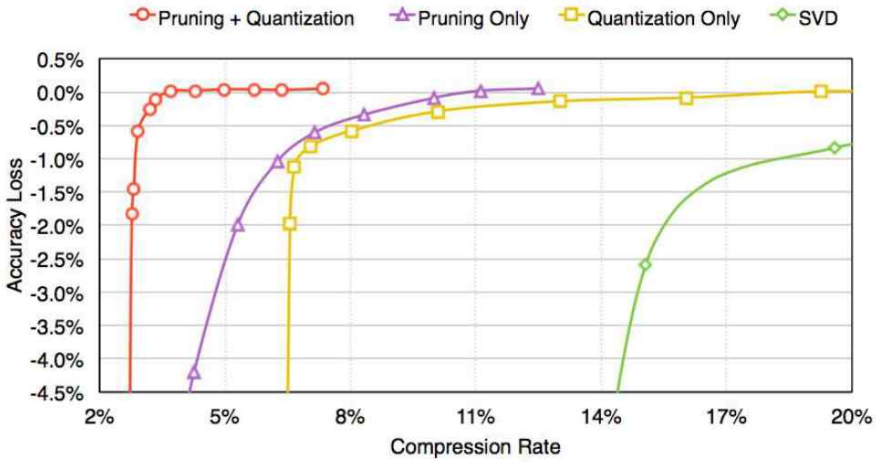
| CNN architecture | Compression Approach | Data Type | Original → Compressed Model Size | Reduction in Model Size vs. AlexNet | Top-1 ImageNet Accuracy | Top-5 ImageNet Accuracy |
|---|---|---|---|---|---|---|
| AlexNet | None (baseline) | 32 bit | 240MB | 1x | 57.2% | 80.3% |
| AlexNet | SVD (Denton et al., 2014) | 32 bit | 240MB → 48MB | 5x | 56.0% | 79.4% |
| AlexNet | Network Pruning (Han et al., 2015b) | 32 bit | 240MB → 27MB | 9x | 57.2% | 80.3% |
| AlexNet | Deep Compression (Han et al., 2015a) | 5-8 bit | 240MB → 6.9MB | 35x | 57.2% | 80.3% |
| SqueezeNet (ours) | None | 32 bit | 4.8MB | **50x** | 57.5% | 80.3% |
| SqueezeNet (ours) | Deep Compression | 8 bit | 4.8MB → 0.66MB | **363x** | 57.5% | 80.3% |
| SqueezeNet (ours) | Deep Compression | 6 bit | 4.8MB → 0.47MB | **510x** | 57.5% | 80.3% |

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

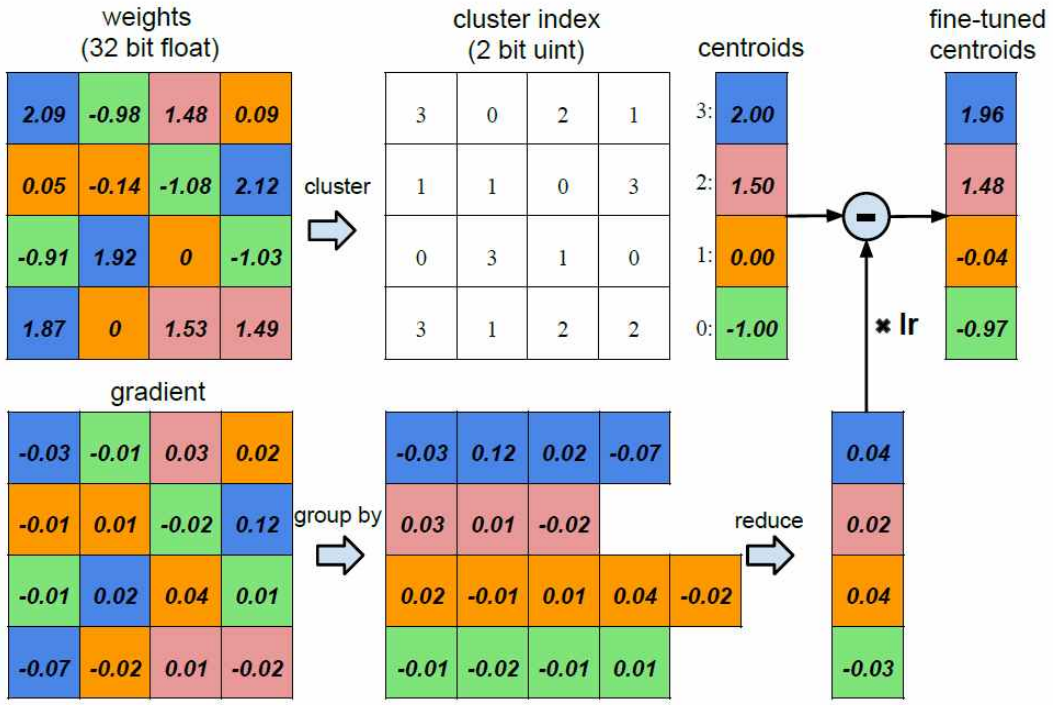
| Architecture | Top-1 Accuracy | Top-5 Accuracy | Model Size |
|---|---|---|---|
| Vanilla SqueezeNet | 57.5% | 80.3% | 4.8MB |
| SqueezeNet + Simple Bypass | **60.4%** | **82.5%** | 4.8MB |
| SqueezeNet + Complex Bypass | 58.8% | 82.0% | 7.7MB |

# Network Pruning & Deep Compression




AlexNet on ImageNet



# Xception

## Xception: Deep Learning with Depthwise Separable Convolutions

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### Abstract

*We present an interpretation of Inception modules in convolutional neural networks as being an intermediate step in-between regular convolution and the depthwise separable convolution operation (a depthwise convolution followed by a pointwise convolution). In this light, a depthwise separable convolution can be understood as an Inception module with a maximally large number of towers. This observation leads us to propose a novel deep convolutional neural network architecture inspired by Inception, where Inception modules have been replaced with depthwise separable convolutions. We show that this architecture, dubbed Xception, slightly outperforms Inception V3 on the ImageNet dataset (which Inception V3 was designed for), and significantly outperforms Inception V3 on a larger image classification dataset comprising 350 million images and 17,000 classes. Since the Xception architecture has the same number of parameters as Inception V3, the performance gains are not due to increased capacity but rather to a more efficient use of model parameters.*

as GoogLeNet (Inception V1), later refined as Inception V2 [7], Inception V3 [21], and most recently Inception-ResNet [19]. Inception itself was inspired by the earlier Network-In-Network architecture [11]. Since its first introduction, Inception has been one of the best performing family of models on the ImageNet dataset [14], as well as internal datasets in use at Google, in particular JFT [5].

The fundamental building block of Inception-style models is the Inception module, of which several different versions exist. In figure 1 we show the canonical form of an Inception module, as found in the Inception V3 architecture. An Inception model can be understood as a stack of such modules. This is a departure from earlier VGG-style networks which were stacks of simple convolution layers.

While Inception modules are conceptually similar to convolutions (they are convolutional feature extractors), they empirically appear to be capable of learning richer representations with less parameters. How do they work, and how do they differ from regular convolutions? What design strategies come after Inception?

# Xception

- Observation
  - Inception module try to explicitly factoring two tasks done by a single convolution kernel: mapping cross-channel correlation and spatial correlation
- Inception hypothesis
  - By inception module, these two correlations are sufficiently decoupled

  → Would it be reasonable to make a much stronger hypothesis than the Inception hypothesis?

# Xception

Figure 1. A canonical Inception module (Inception V3).

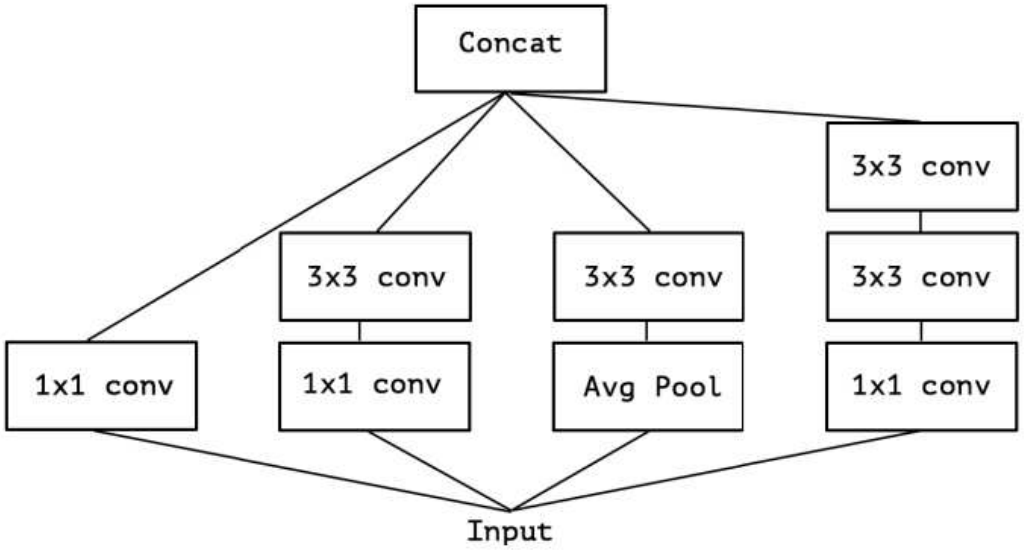
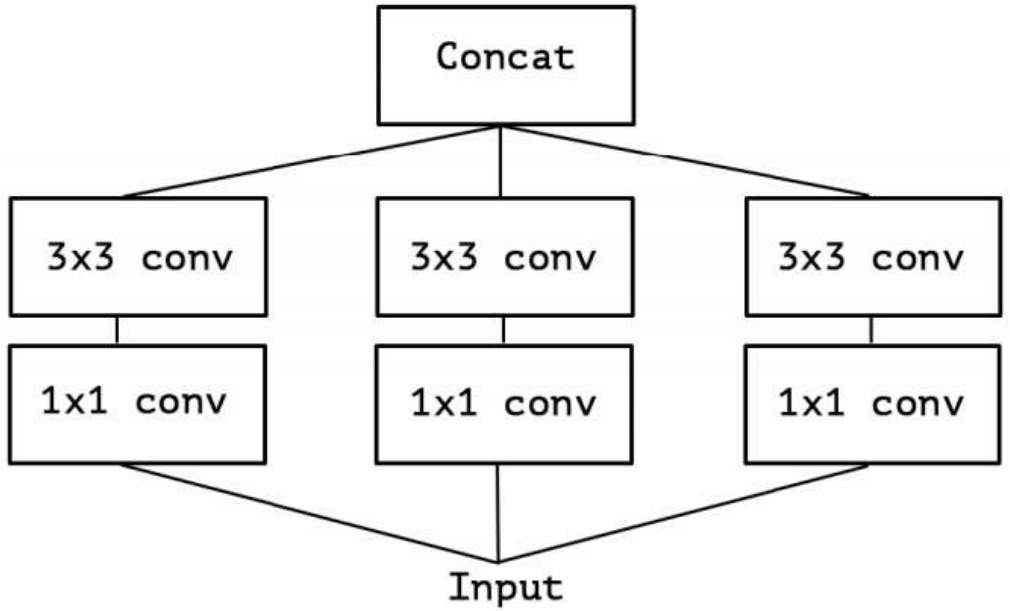



Figure 2. A simplified Inception module.



# Equivalent Reformulation

Figure 2. A simplified Inception module.

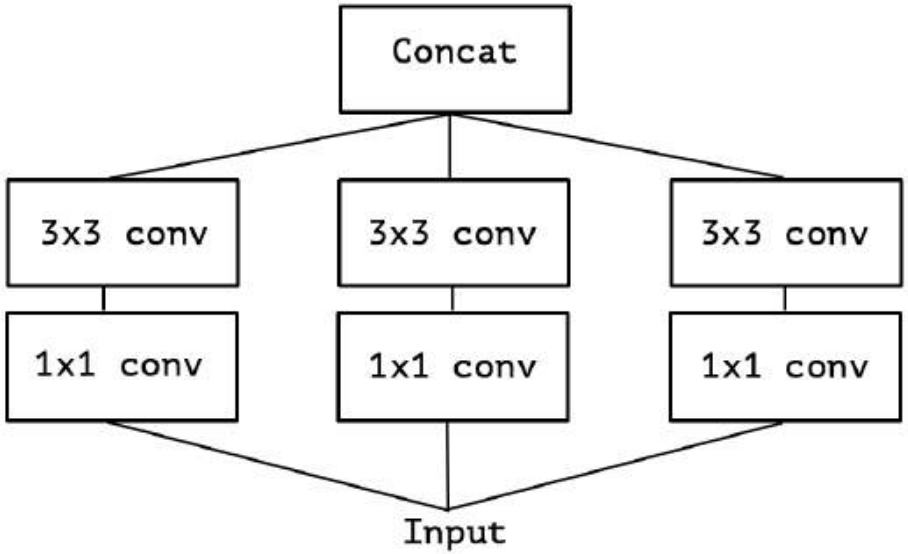
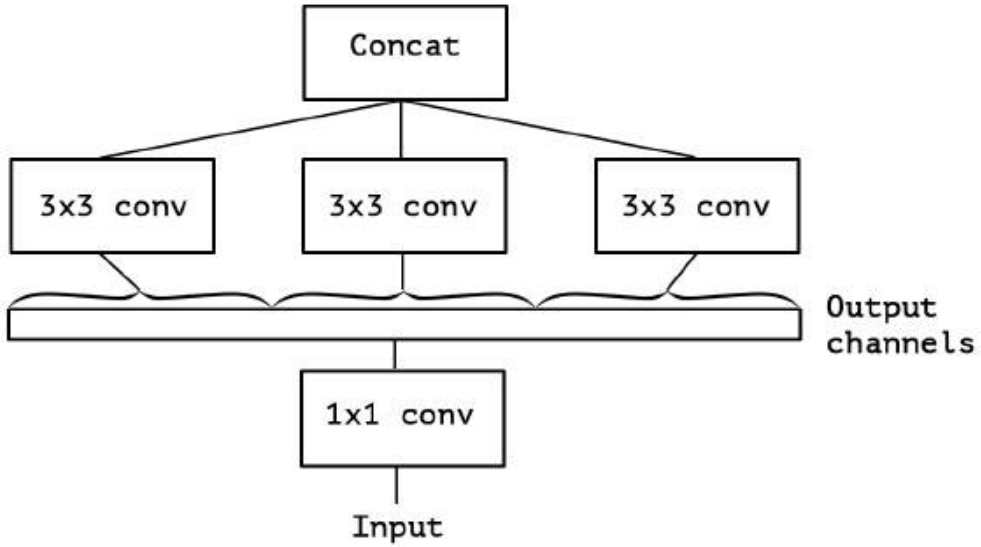
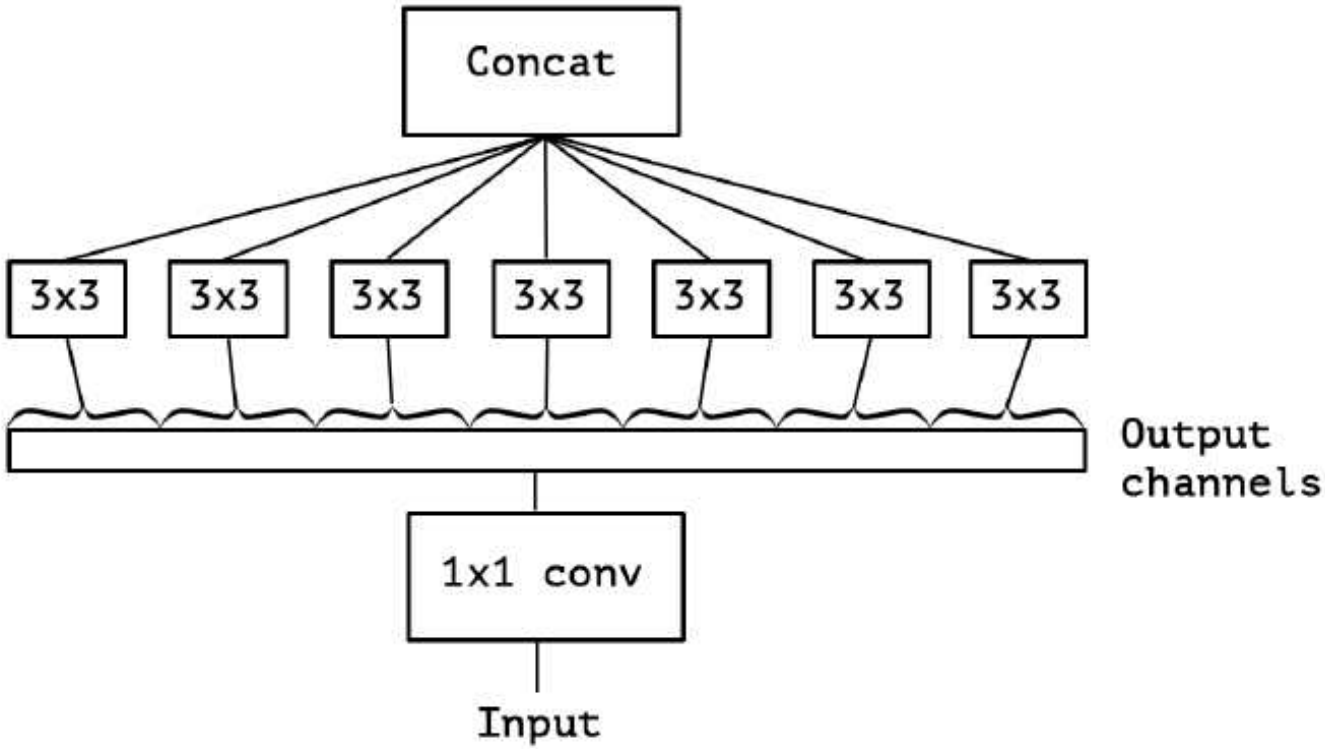



Figure 3. A strictly equivalent reformulation of the simplified Inception module.



# Extreme Version of Inception Module

Figure 4. An "extreme" version of our Inception module, with one spatial convolution per output channel of the 1x1 convolution.



# Xception vs Depthwise Separable Convolution

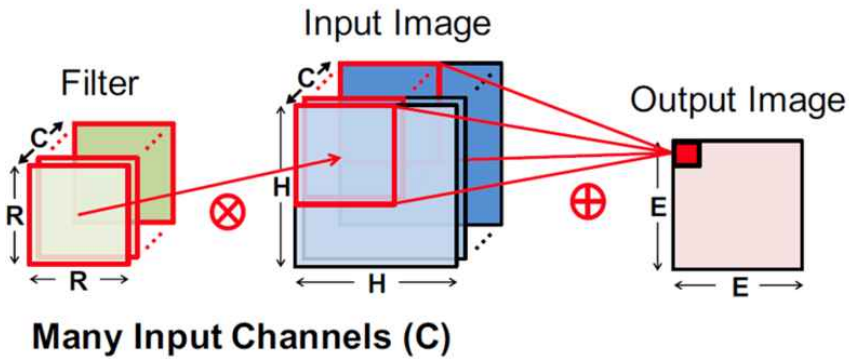
- The order of the operations
- The presence or absence of a non-linearity after the first operation

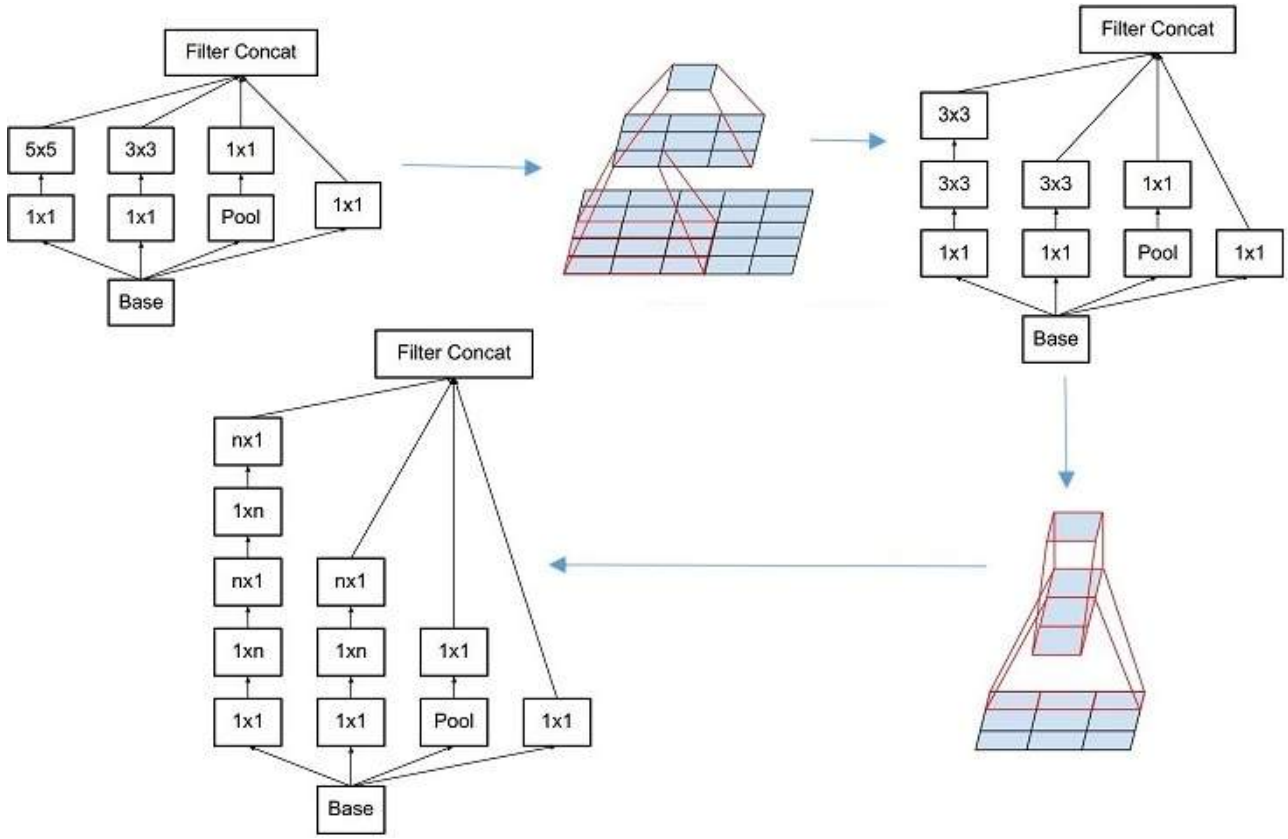

**Inception modules lie in between!**

**Xception Hypothesis**

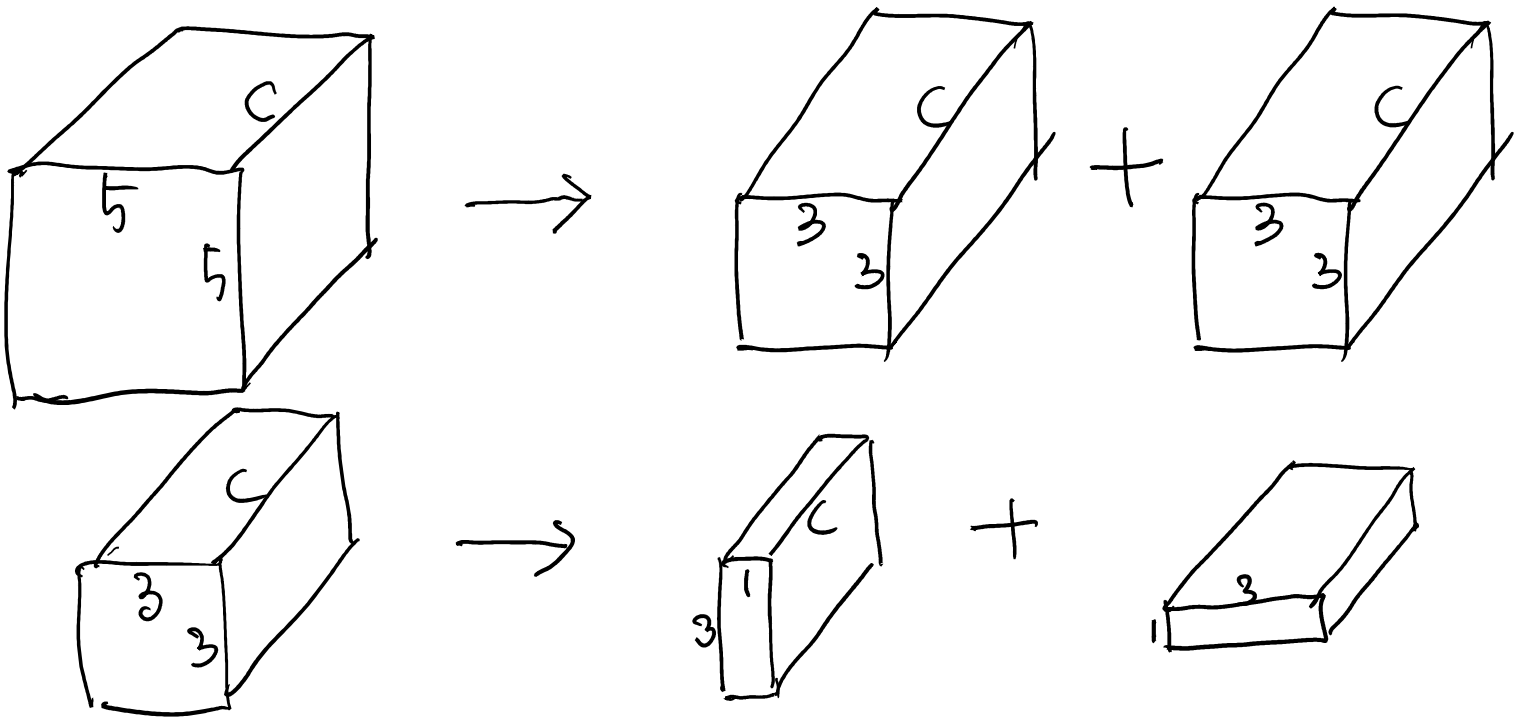
: Make the mapping that *entirely* decouples
the cross-channels correlations and spatial correlations

# Filter Factorization of CNN

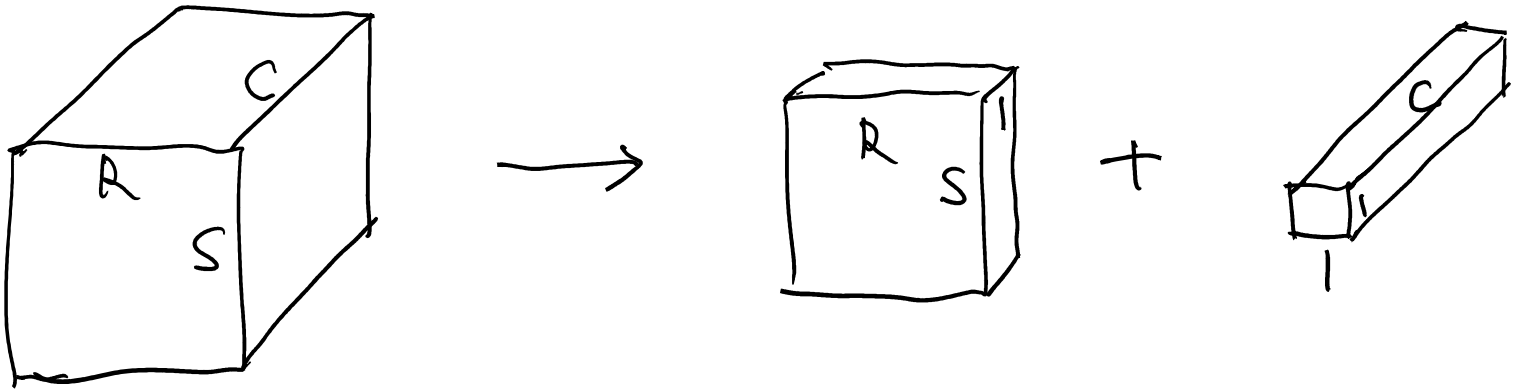


# Filter Factorization



# Depthwise Separable Convolution



# Results

Table 1. Classification performance comparison on ImageNet (single crop, single model). VGG-16 and ResNet-152 numbers are only included as a reminder. The version of Inception V3 being benchmarked does not include the auxiliary tower.

| | Top-1 accuracy | Top-5 accuracy |
|---|---|---|
| **VGG-16** | 0.715 | 0.901 |
| **ResNet-152** | 0.770 | 0.933 |
| **Inception V3** | 0.782 | 0.941 |
| **Xception** | **0.790** | **0.945** |

**ImageNet**

Table 2. Classification performance comparison on JFT (single crop, single model).

| | FastEval14k MAP@100 |
|---|---|
| **Inception V3 - no FC layers** | 6.36 |
| **Xception - no FC layers** | 6.70 |
| **Inception V3 with FC layers** | 6.50 |
| **Xception with FC layers** | **6.78** |

**JFT**

# MobileNets

## MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications

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Weijun Wang Tobias Weyand Marco Andreetto Hartwig Adam

Google Inc.

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### Abstract

*We present a class of efficient models called MobileNets for mobile and embedded vision applications. MobileNets are based on a streamlined architecture that uses depth-wise separable convolutions to build light weight deep neural networks. We introduce two simple global hyper-parameters that efficiently trade off between latency and accuracy. These hyper-parameters allow the model builder to choose the right sized model for their application based on the constraints of the problem. We present extensive experiments on resource and accuracy tradeoffs and show*

models. Section 3 describes the MobileNet architecture and two hyper-parameters width multiplier and resolution multiplier to define smaller and more efficient MobileNets. Section 4 describes experiments on ImageNet as well a variety of different applications and use cases. Section 5 closes with a summary and conclusion.

### 2. Prior Work

There has been rising interest in building small and efficient neural networks in the recent literature, e.g. [16, 34, 12, 36, 22]. Many different approaches can be generally

# MobileNets

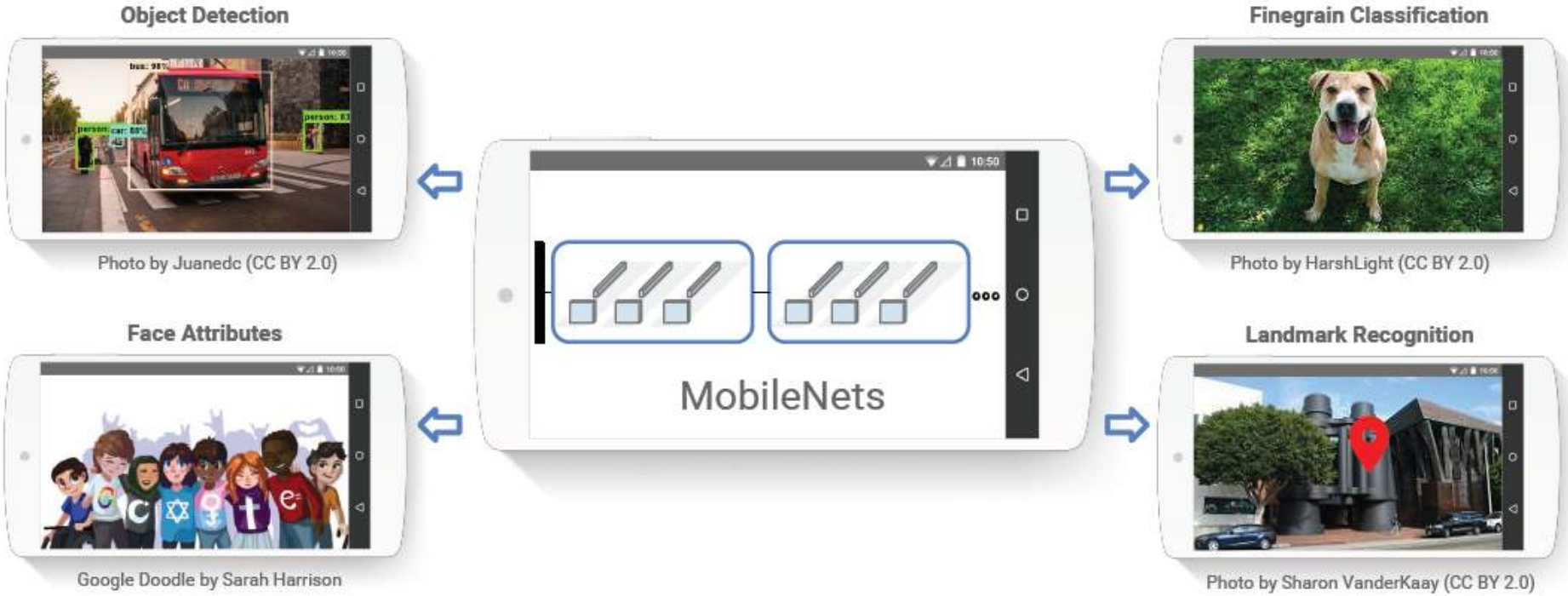
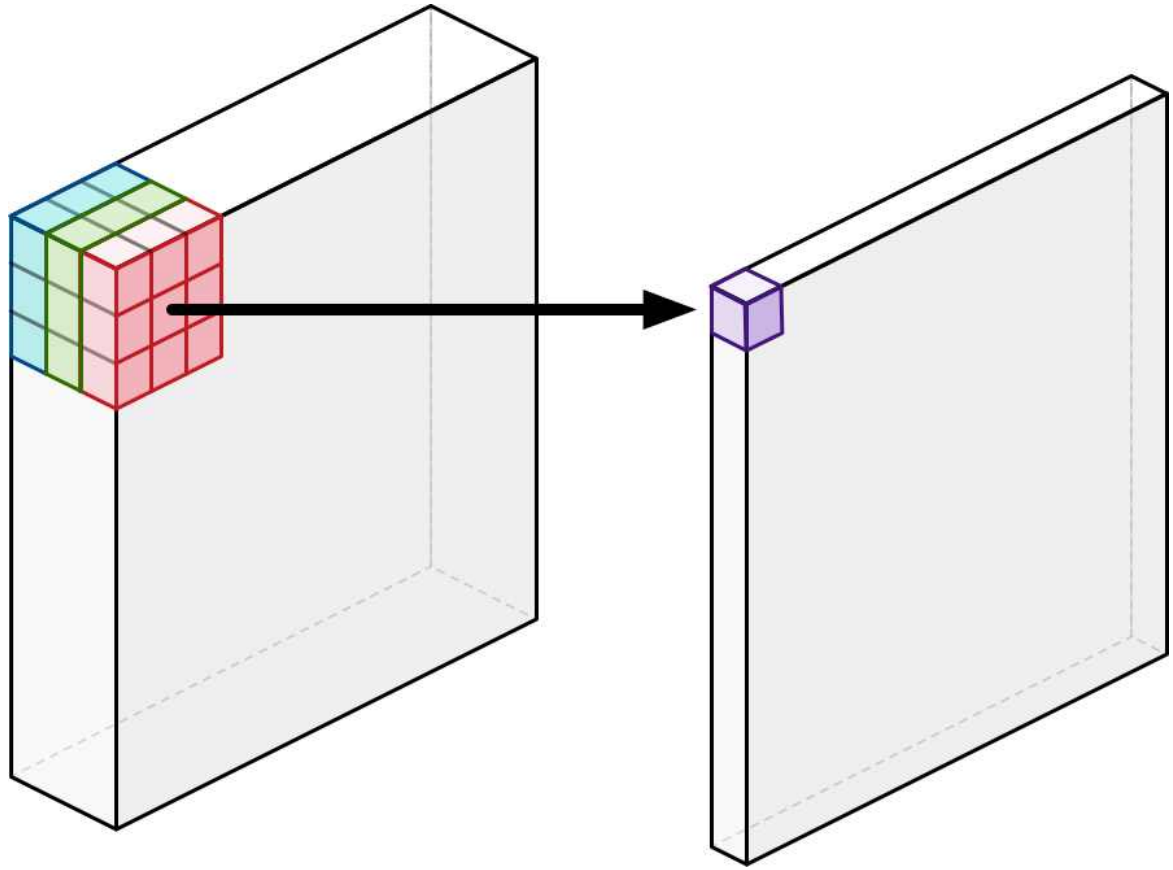



Figure 1. MobileNet models can be applied to various recognition tasks for efficient on device intelligence.

# Standard Convolution

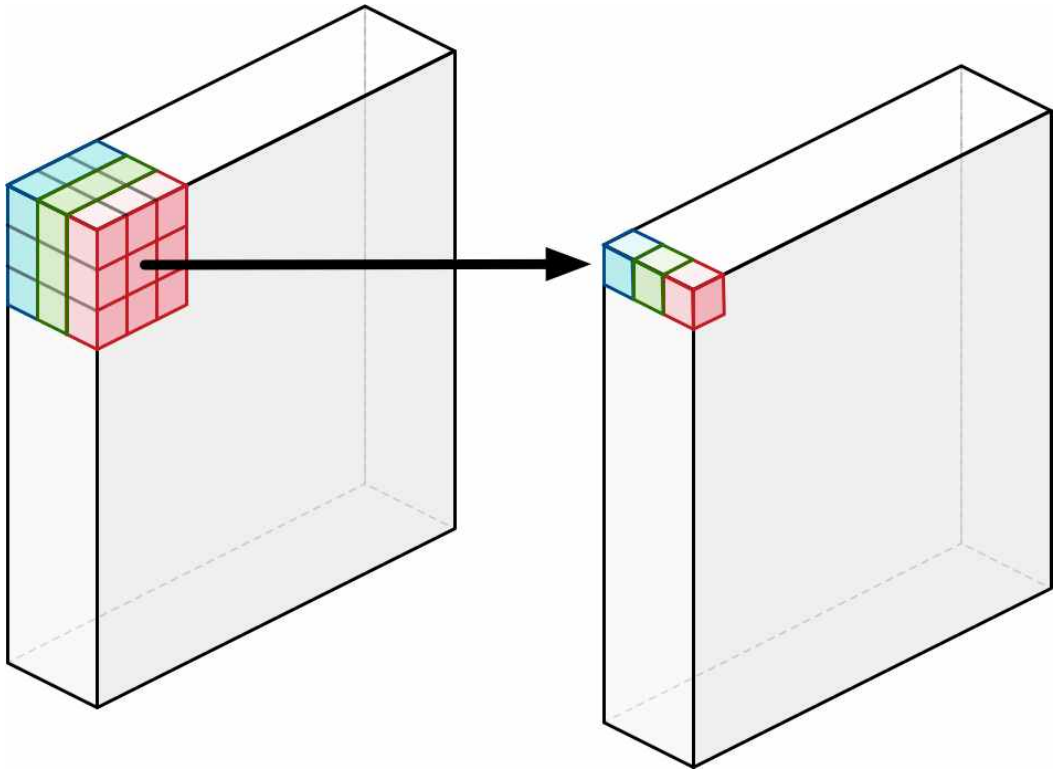


**Standard convolution**

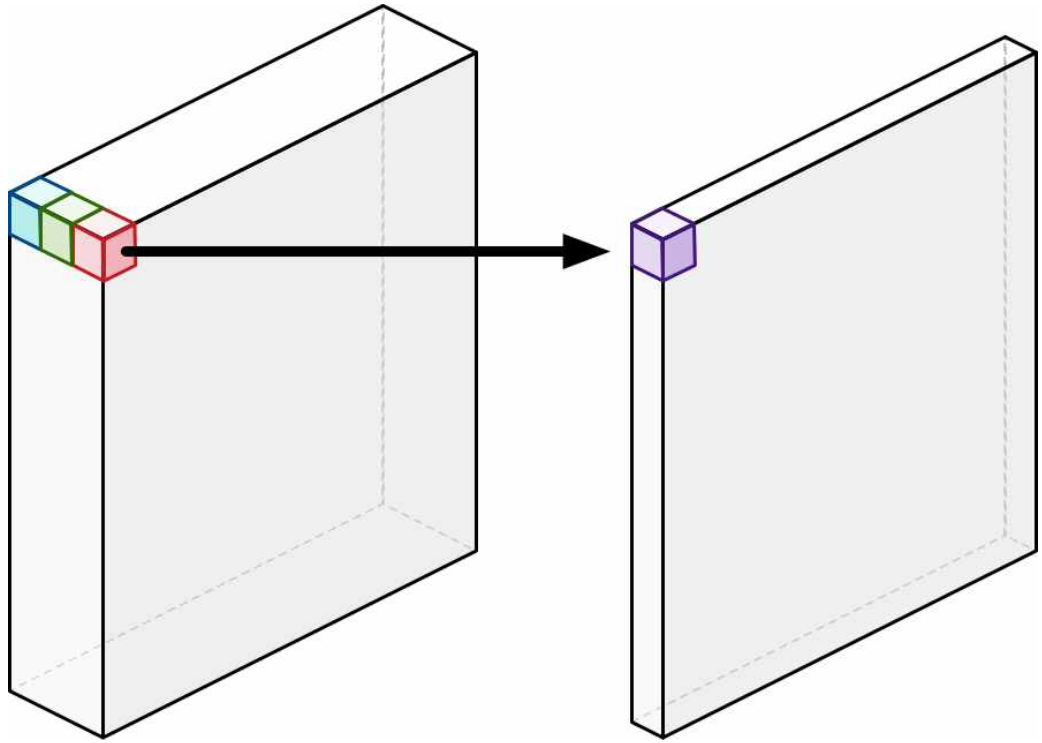
Figures from http://machinethink.net/blog/googles-mobile-net-architecture-on-iphone/

# Depthwise Separable Convolution

- Depthwise Convolution + Pointwise Convolution(1x1 convolution)



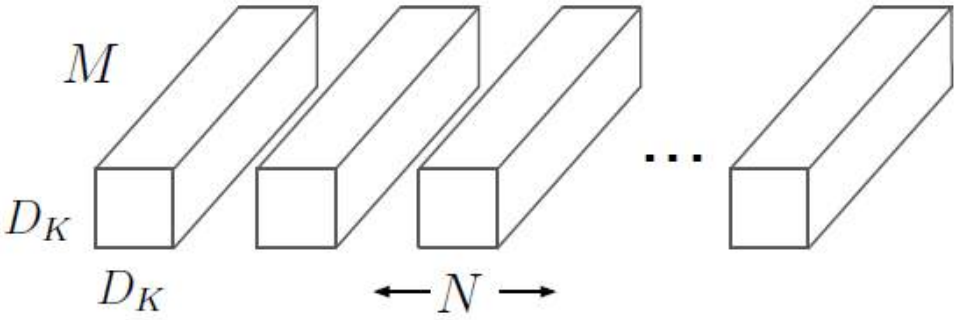
**Depthwise convolution**



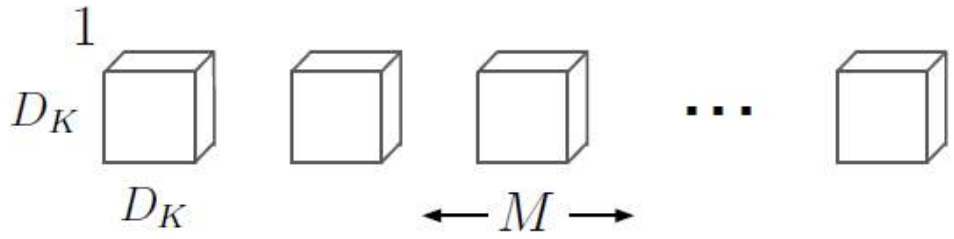
**Pointwise convolution**

Figures from http://machinethink.net/blog/googles-mobile-net-architecture-on-iphone/

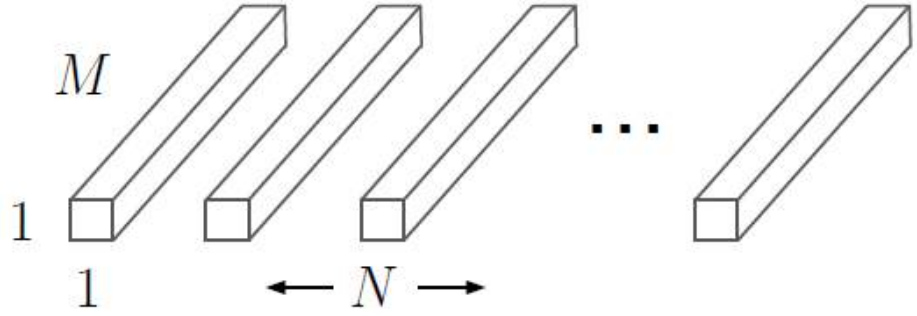
# Standard Convolution vs Depthwise Separable Convolution




(a) Standard Convolution Filters




(b) Depthwise Convolutional Filters




(c) $1 \times 1$ Convolutional Filters called Pointwise Convolution in the context of Depthwise Separable Convolution

# Standard Convolution vs Depthwise Separable Convolution

- Standard convolutions have the computational cost of
  - $D_K \times D_K \times M \times N \times D_F \times D_F$
- Depthwise separable convolutions cost
  - $D_K \times D_K \times M \times D_F \times D_F + M \times N \times D_F \times D_F$
- Reduction in computations
  - $1 / N + 1 / D_K^2$
  - If we use 3x3 depthwise separable convolutions, we get between 8 to 9 times less computations

# Depthwise Separable Convolutions

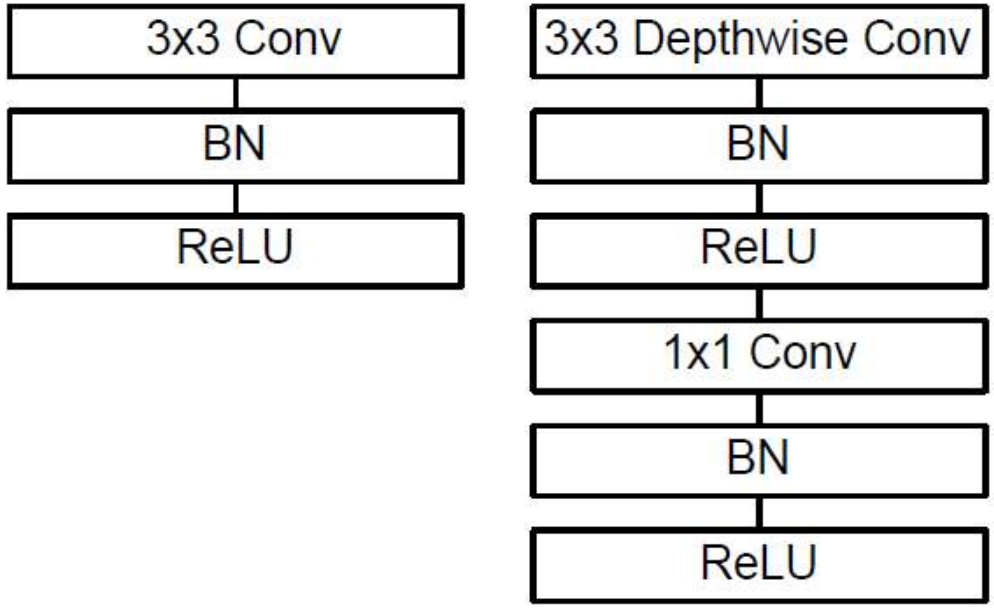



Figure 3. Left: Standard convolutional layer with batchnorm and ReLU. Right: Depthwise Separable convolutions with Depthwise and Pointwise layers followed by batchnorm and ReLU.

# Model Structure

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 $7 \times 7$ | $7 \times 7 \times 1024$ |
| FC / s1 | $1024 \times 1000$ | $1 \times 1 \times 1024$ |
| Softmax / s1 | Classifier | $1 \times 1 \times 1000$ |

Table 2. Resource Per Layer Type

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

# Width Multiplier & Resolution Multiplier

- For a given layer and width multiplier α, the number of input channels M becomes αM and the number of output channels N becomes αN – where α  with typical settings of 1, 0.75, 0.5 and 0.25
- The second hyper-parameter to reduce the computational cost of a neural network is a resolution multiplier ρ
- Computational cost:

$$D_K \times D_K \times \alpha M \times \rho D_F \times \rho D_F + \alpha M \times \alpha N \times \rho D_F \times \rho D_F$$

# Width Multiplier & Resolution Multiplier

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 |

# Experiments – Model Choices

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 |

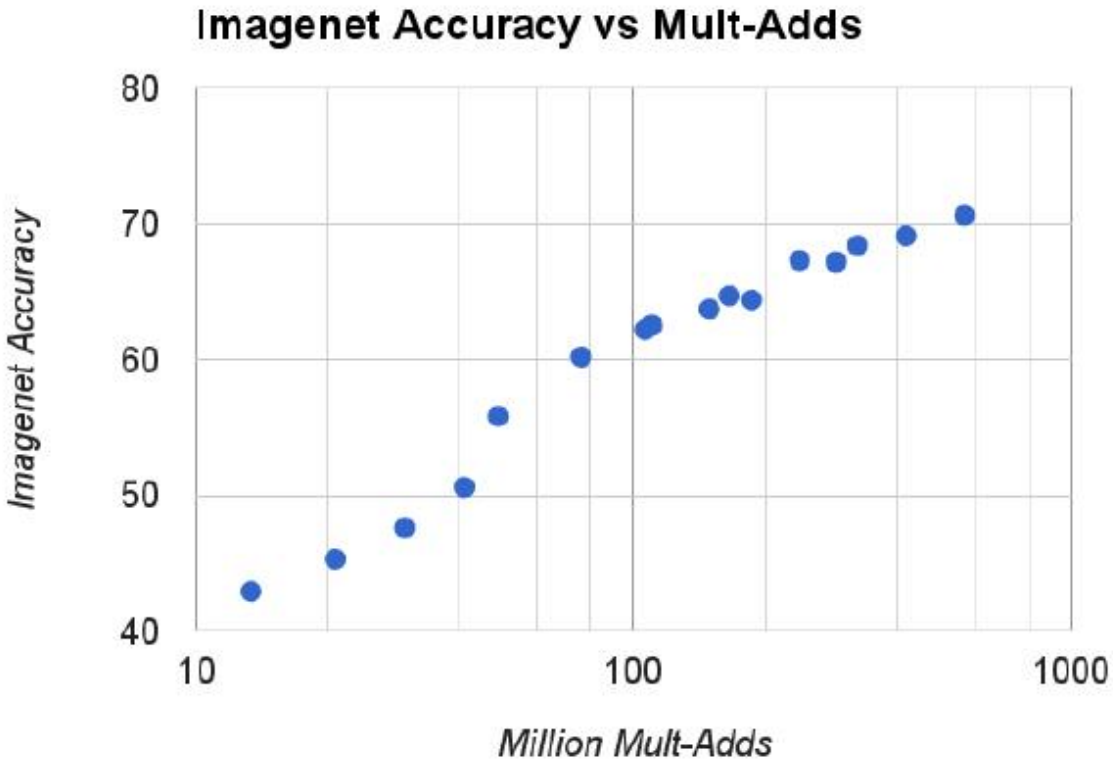
Table 6. MobileNet Width Multiplier

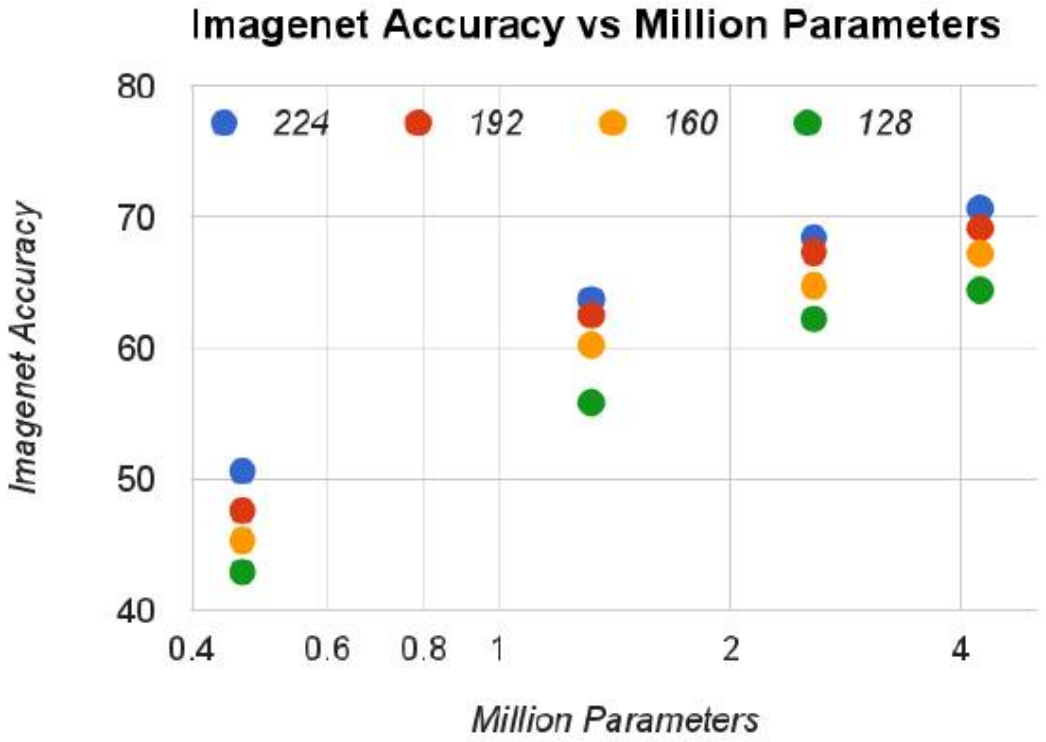
| Width Multiplier | ImageNet Accuracy | Million Mult-Adds | Million Parameters |
|---|---|---|---|
| 1.0 MobileNet-224 | 70.6% | 569 | 4.2 |
| 0.75 MobileNet-224 | 68.4% | 325 | 2.6 |
| 0.5 MobileNet-224 | 63.7% | 149 | 1.3 |
| 0.25 MobileNet-224 | 50.6% | 41 | 0.5 |

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 |

# Model Shrinking Hyperparameters



# ShuffleNet

## ShuffleNet: An Extremely Efficient Convolutional Neural Network for Mobile Devices

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Megvii Inc (Face++)
{zhangxiangyu,zxy,linmengxiao,sunjian}@megvii.com



### Abstract

*We introduce an extremely computation-efficient CNN architecture named ShuffleNet, which is designed specially for mobile devices with very limited computing power (e.g., 10-150 MFLOPs). The new architecture utilizes two new operations, pointwise group convolution and channel shuffle, to greatly reduce computation cost while maintaining accuracy. Experiments on ImageNet classification and MS COCO object detection demonstrate the superior performance of ShuffleNet over other structures, e.g. lower top-1 error (absolute 7.8%) than recent MobileNet [12] on ImageNet classification task, under the computation budget of 40 MFLOPs. On an ARM-based mobile device, ShuffleNet achieves ~13× actual speedup over AlexNet while maintaining comparable accuracy.*

*tions* to reduce computation complexity of $1 \times 1$ convolutions. To overcome the side effects brought by group convolutions, we come up with a novel *channel shuffle* operation to help the information flowing across feature channels. Based on the two techniques, we build a highly efficient architecture called *ShuffleNet*. Compared with popular structures like [30, 9, 40], for a given computation complexity budget, our ShuffleNet allows more feature map channels, which helps to encode more information and is especially critical to the performance of very small networks.

We evaluate our models on the challenging ImageNet classification [4, 29] and MS COCO object detection [23] tasks. A series of controlled experiments shows the effectiveness of our design principles and the better performance over other structures. Compared with the state-of-the-art architecture *MobileNet* [12], ShuffleNet achieves superior performance by a significant margin, e.g. absolute 7.8%

# Toward More Efficient Network Architecture

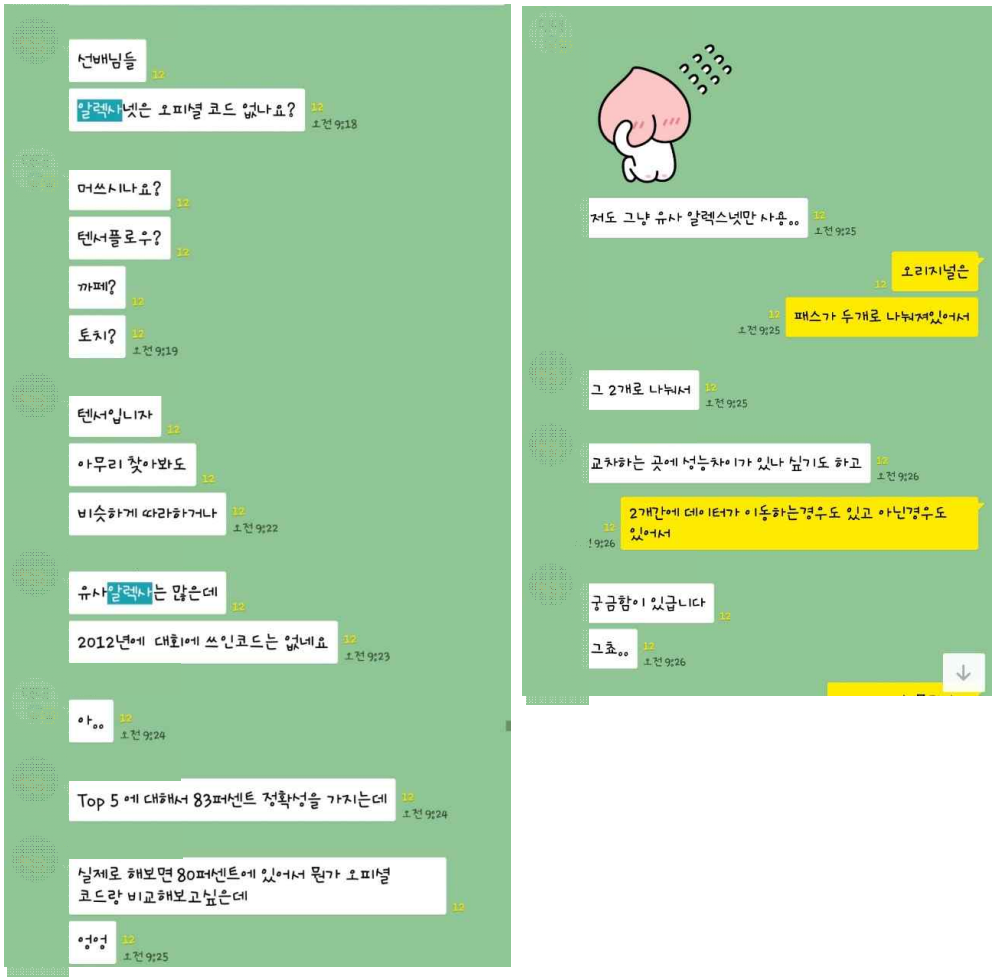
- The 1x1 convolution accounts for most of the computation

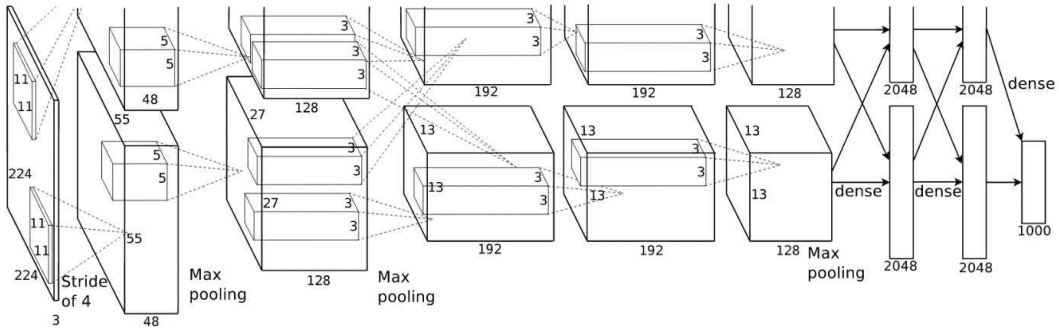
Table 2. Resource Per Layer Type

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

- Can we reduce more?

# A Secret of AlexNet

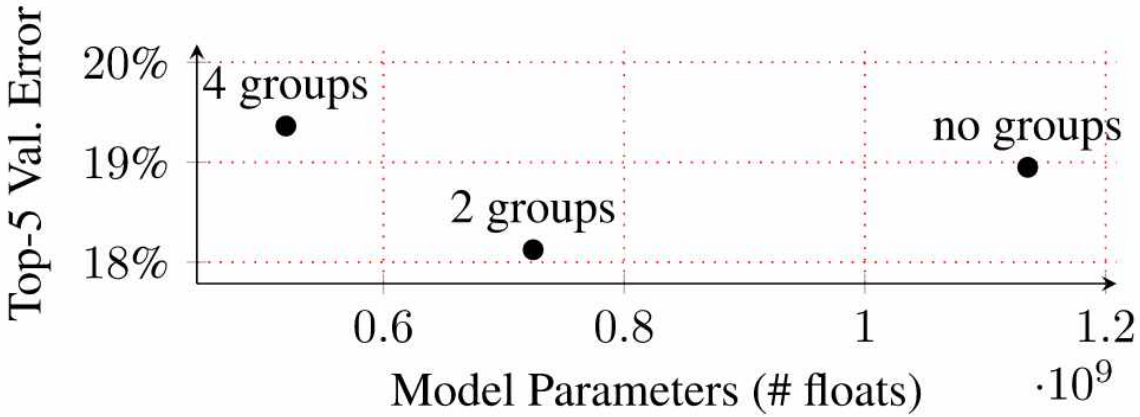



Grouped Convolution!

# Grouped Convolution of AlexNet

- AlexNet's primary motivation was to allow the training of the network over two Nvidia GTX580 GPUs with 1.5GB of memory each
- AlexNet without filter groups is not only less efficient(both in parameters and compute), but also slightly less accurate!



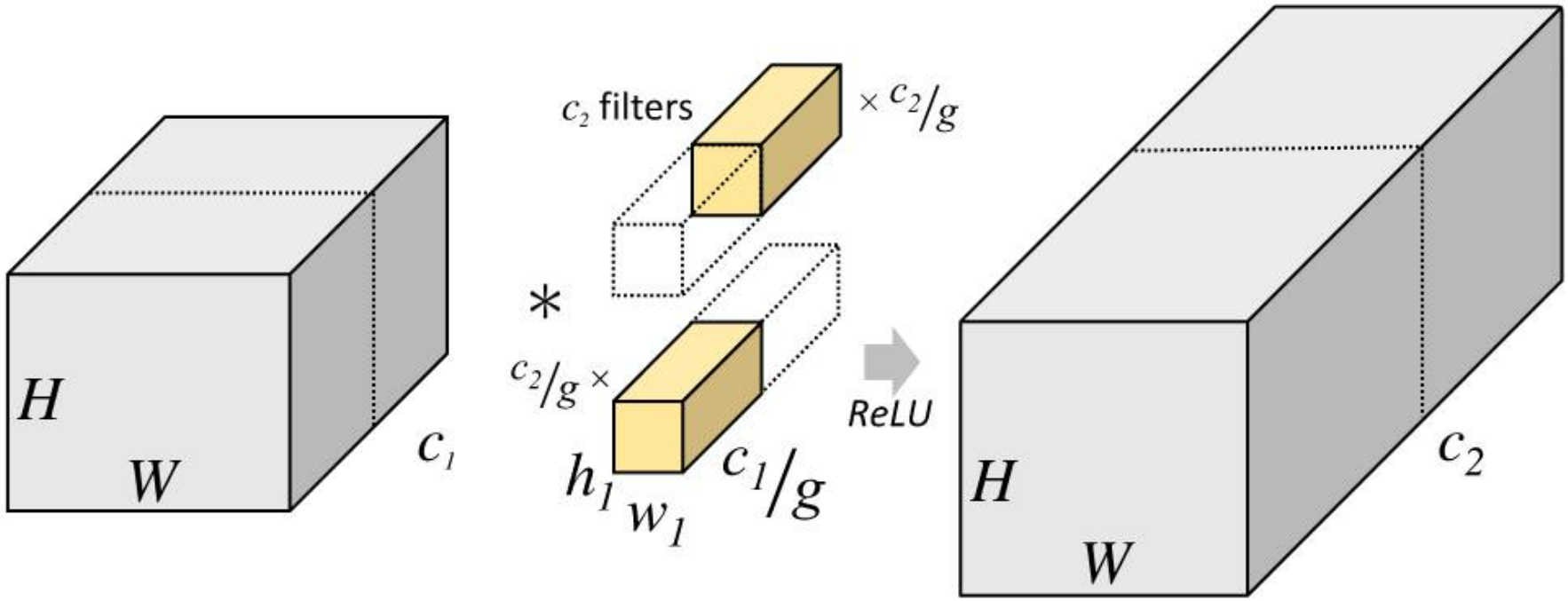

AlexNet trained with varying numbers of filter groups, from 1 (i.e. no filter groups), to 4. When trained with 2 filter groups, AlexNet is more efficient and yet achieves the same if not lower validation error.

Figure from https://blog.yani.io/filter-group-tutorial/

# Main Ideas of ShuffleNet

- (Use depthwise separable convolution)
- Grouped convolution on 1x1 convolution layers – pointwise group convolution
- Channel shuffle operation after pointwise group convolution

# Grouped Convolution

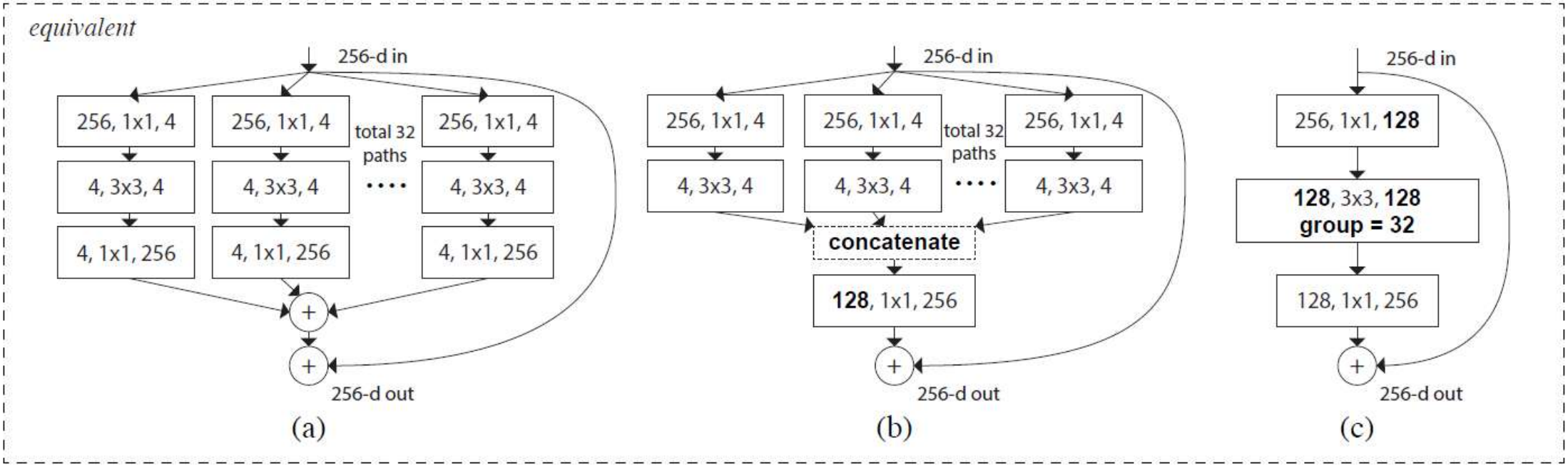



A convolutional layer with 2 filter groups. Note that each of the filters in the grouped convolutional layer is now exactly half the depth, i.e. half the parameters and half the compute as the original filter.

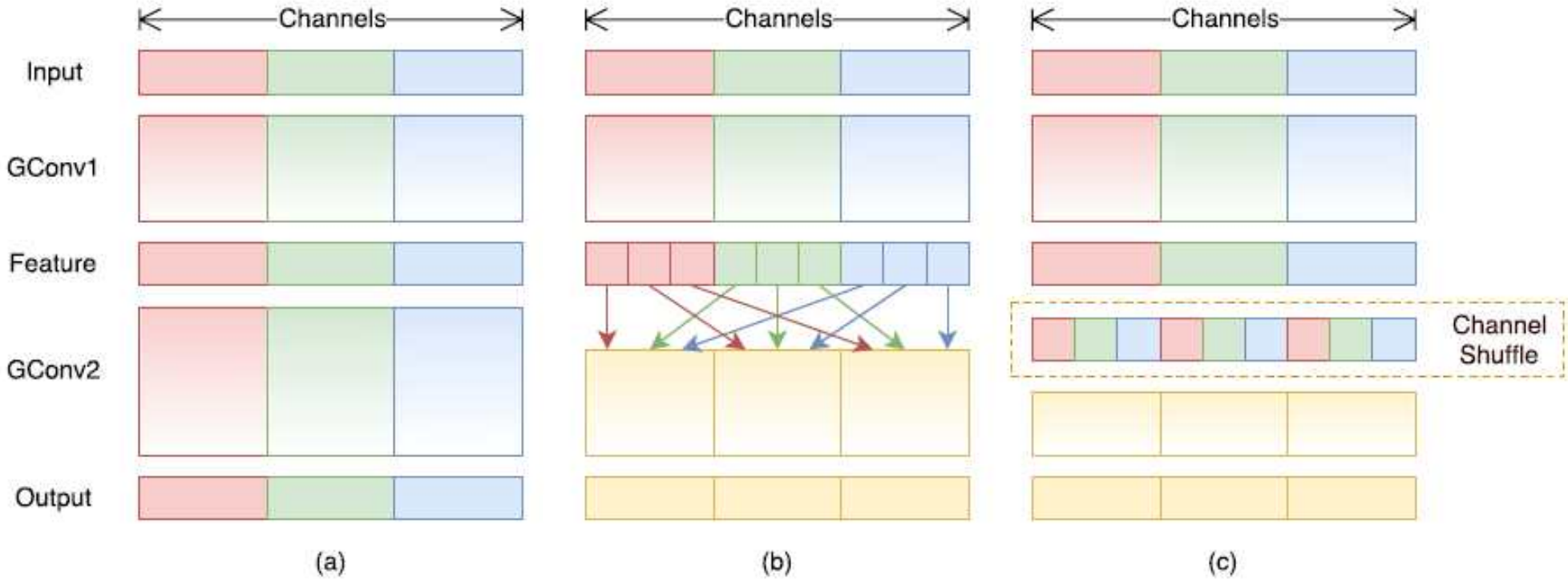
Figure from https://blog.yani.io/filter-group-tutorial/

# ResNeXt

- Equivalent building blocks of RexNext (cardinality=32)



# 1x1 Grouped Convolution with Channel Shuffling




- If multiple group convolutions stack together, there is one side effect(a)
  - Outputs from a certain channel are only derived from a small fraction of input channels
- If we allow group convolution to obtain input data from different groups, the input and outputchannels will be fully related.

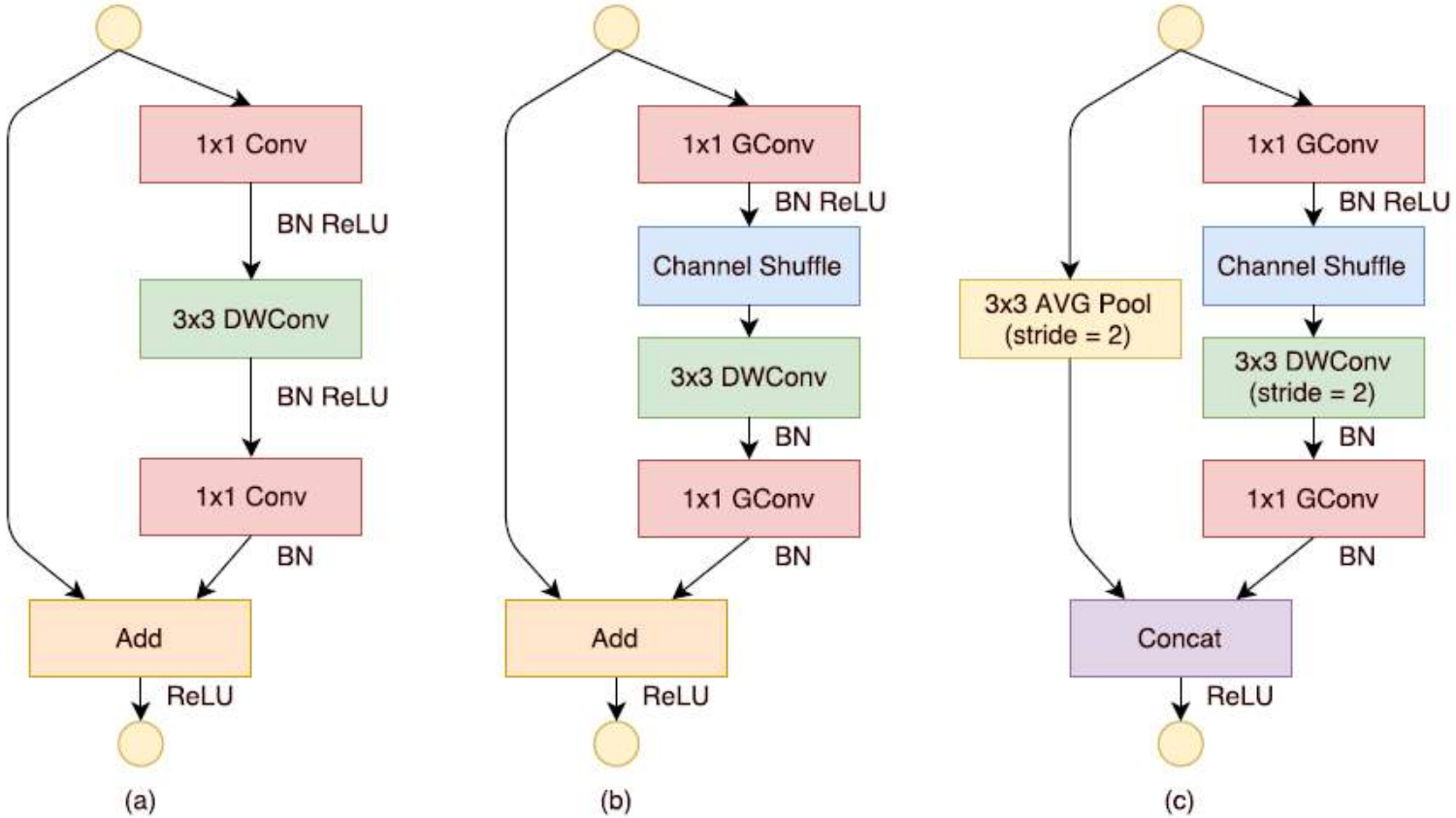
# Channel Shuffle Operation

- Suppose a convolutional layer with g groups whose output has g x n channels; we first reshape the output channel dimension into (g, n), transposing and then flattening it back as the input of next layer.
- Channel shuffle operation is also differentiable

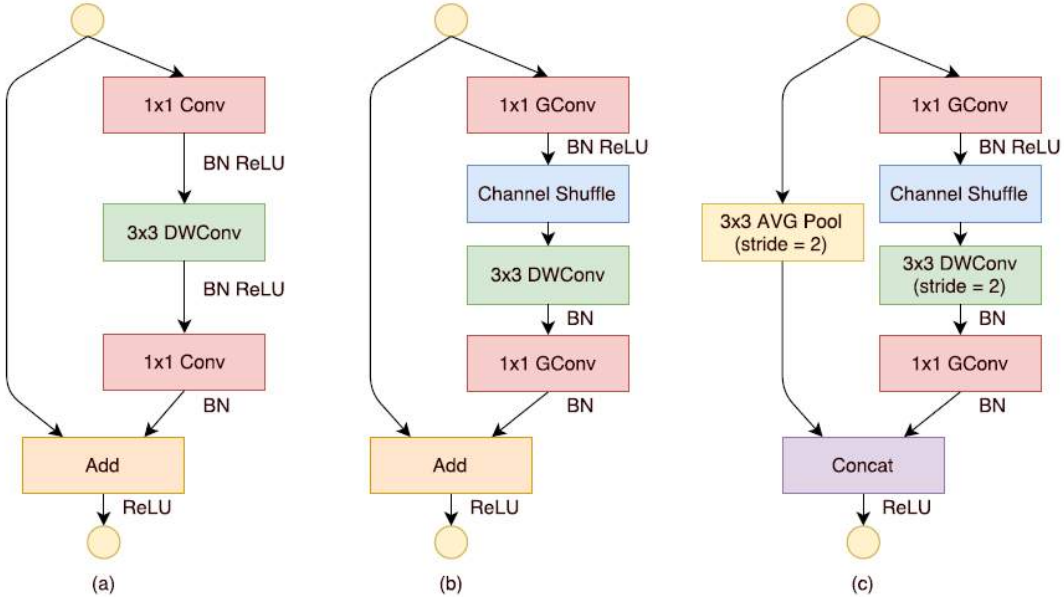
```
def channel_shuffle(name, x, num_groups):
    with tf.variable_scope(name) as scope:
        n, h, w, c = x.shape.as_list()
        x_reshaped = tf.reshape(x, [-1, h, w, num_groups, c // num_groups])
        x_transposed = tf.transpose(x_reshaped, [0, 1, 2, 4, 3])
        output = tf.reshape(x_transposed, [-1, h, w, c])
        return output
```

Tensorflow Implementation from https://github.com/MG2033/ShuffleNet

# ShuffleNet Units



# ShuffleNet Units




- From (a), replace the first 1x1 layer with pointwise group convolution followed by a channel shuffle operation
- ReLU is not applied to 3x3 DWConv
- As for the case where ShuffleNet is applied with stride, simply make to modifications
  - Add 3x3 average pooling on the shortcut path
  - Replace element-wise addition with channel concatenation to enlarge channel dimension with little extra computation

# Experimental Results

- It is clear that ShuffleNet models are superior to MobileNet for all the complexities though ShuffleNet network is specially designed for small models (< 150 MFLOPs)
- Results show that the shallower model is still significantly better than the corresponding MobileNet, which implies that the effectiveness of ShuffleNet mainly results from its efficient structure, not the depth.

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

Table 5. ShuffleNet vs. MobileNet [12] on ImageNet Classification

# Experimental Results

- Results show that with similar accuracy ShuffleNet is much more efficient than others.

| Model | Cls err. (%) | Complexity (MFLOPs) |
|---|---|---|
| VGG-16 [30] | 28.5 | 15300 |
| ShuffleNet 2× ($g = 3$) | 26.3 | **524** |
| GoogleNet [33]* | 31.3 | 1500 |
| ShuffleNet 1× ($g = 8$) | 32.4 | **140** |
| AlexNet [21] | 42.8 | 720 |
| SqueezeNet [14] | 42.5 | 833 |
| ShuffleNet 0.5× ($g = 4$) | 41.6 | **38** |

Table 6. Complexity comparison. **Implemented by BVLC (https://github.com/BVLC/caffe/tree/master/models/bvlc_googlenet)*

# SqueezeNext

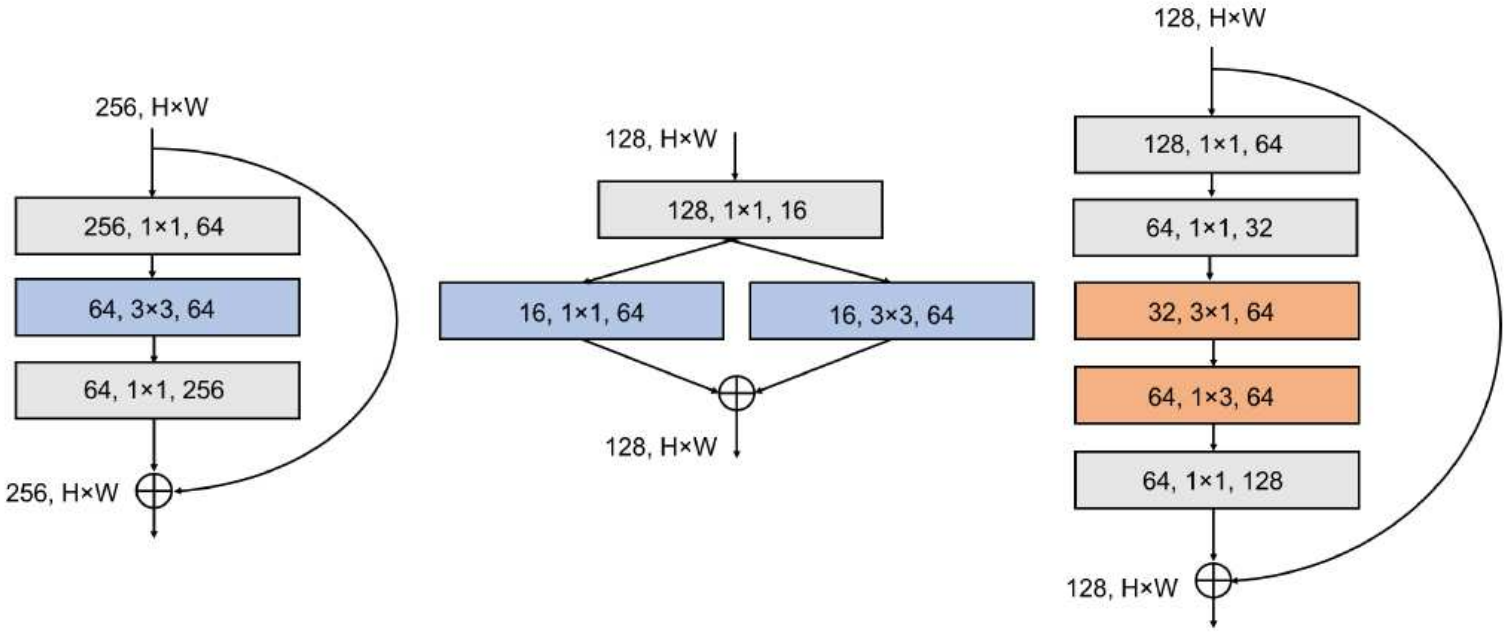
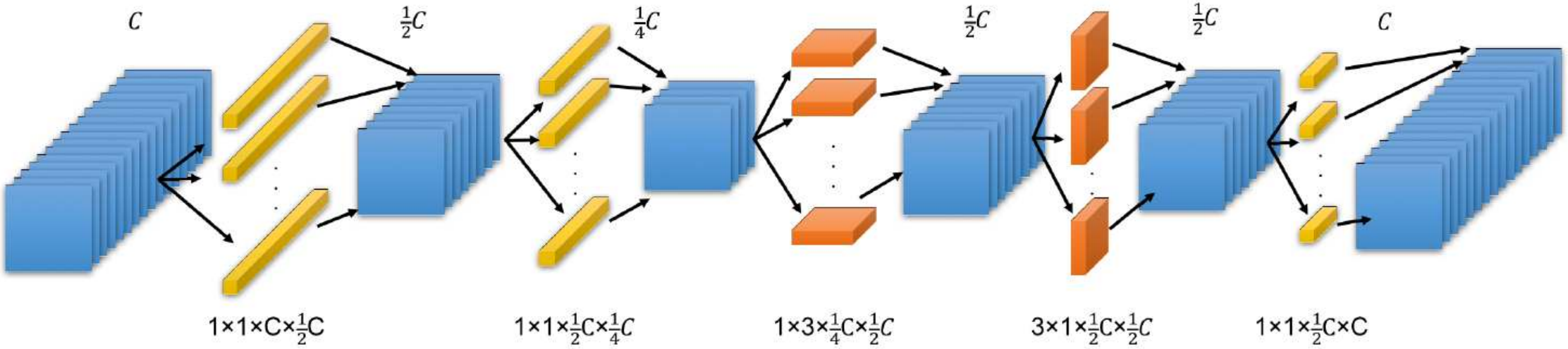



**Figure 1:** *Illustration of a ResNet block on the left, a SqueezeNet block in the middle, and a SqueezeNext (SqNxt) block on the right. SqueezeNext uses a two-stage bottleneck module to reduce the number of input channels to the $3 \times 3$ convolution. The latter is further decomposed into separable convolutions to further reduce the number of parameters (orange parts), followed by a $1 \times 1$ expansion module.*

# SqueezeNext Block



# Block Arrangement in 1.0-SqNxt-23

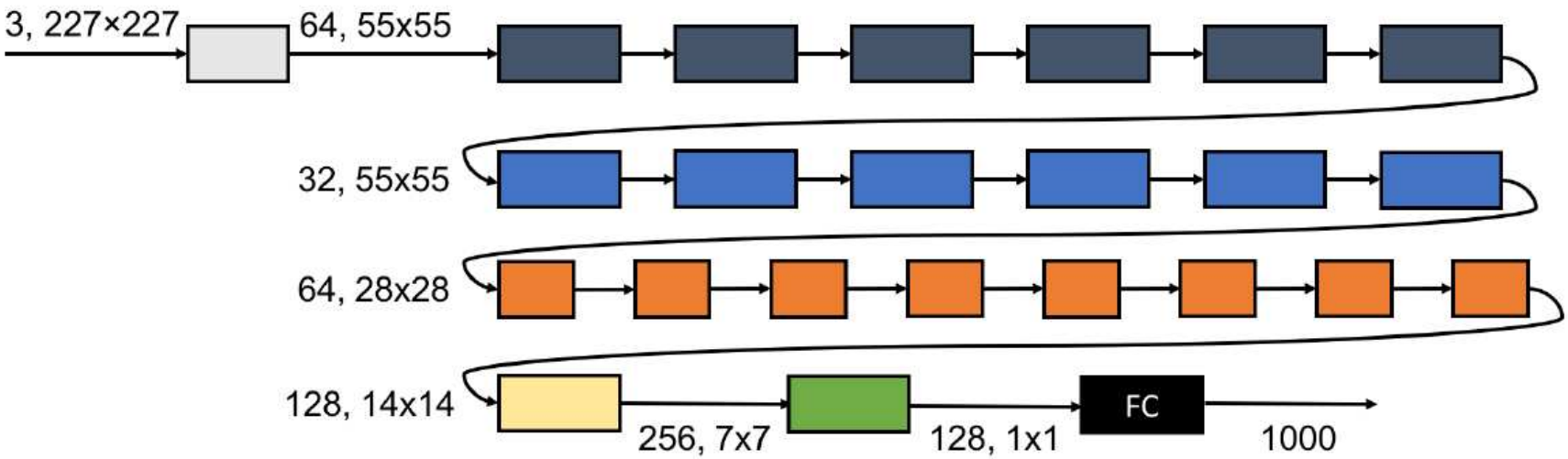
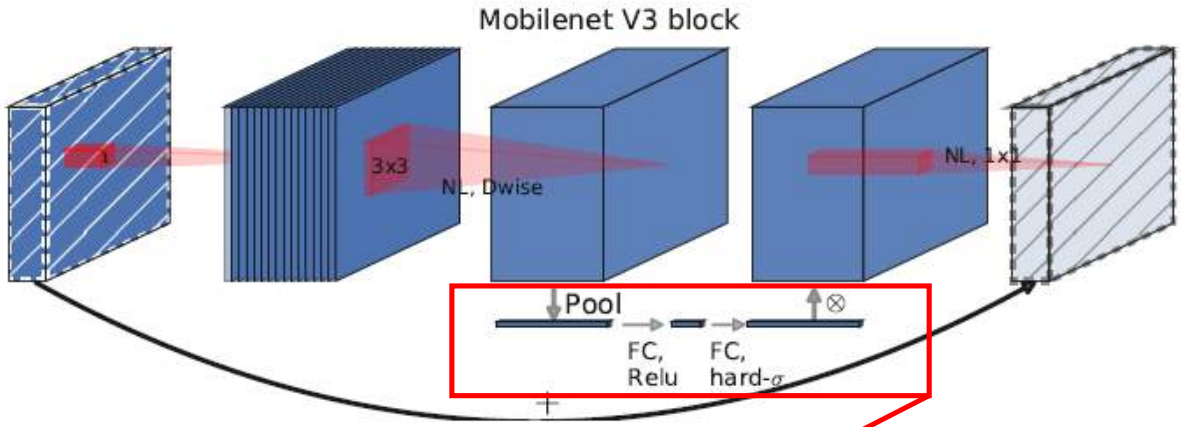
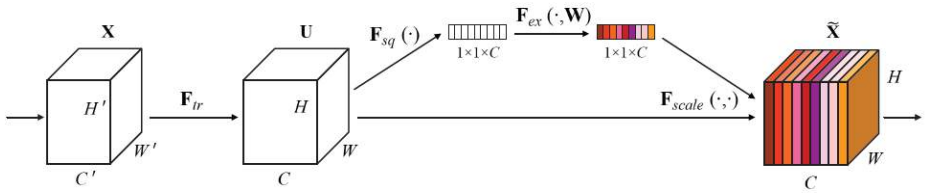



**Figure 3:** *Illustration of block arrangement in 1.0-SqNxt-23. Each color change corresponds to a change in input feature map's resolution. The number of blocks after the first convolution/pooling layer is* $Depth = [6, 6, 8, 1]$*, where the last number refers to the yellow box. This block is followed by a bottleneck module with average pooling to reduce the channel size and spatial resolution (green box), followed by a fully connected layer (black box). In optimized variations of the baseline, we change this depth distribution by decreasing the number of blocks in early stages (dark blue), and instead assign more blocks to later stages (Fig. 9). This increases hardware performance as early layers have poor compute efficiency.*

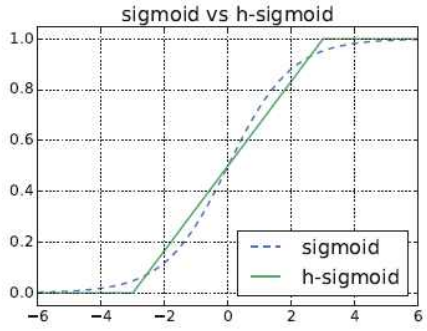
# MobileNet V2, V3

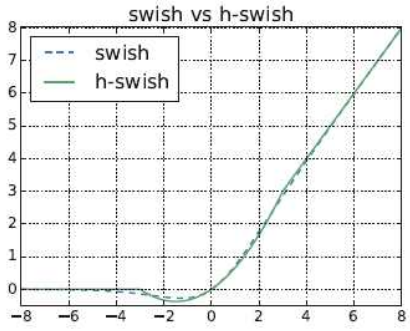


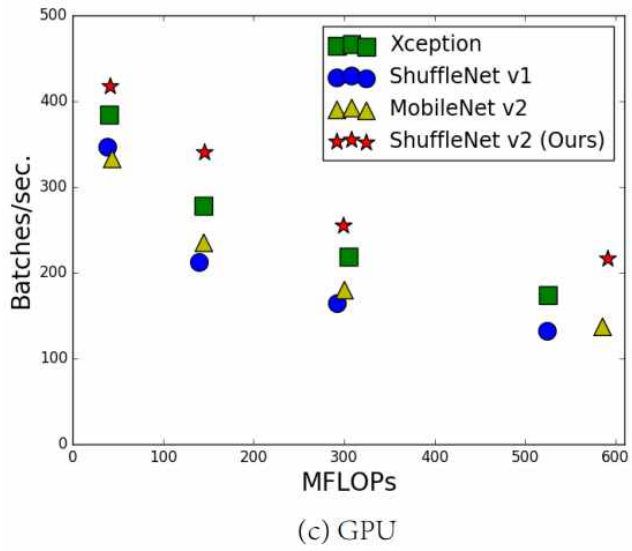

$$\text{swish}\, x = x \cdot \sigma(x)$$

$$\text{h-swish}[x] = x\frac{\text{ReLU6}(x+3)}{6}$$

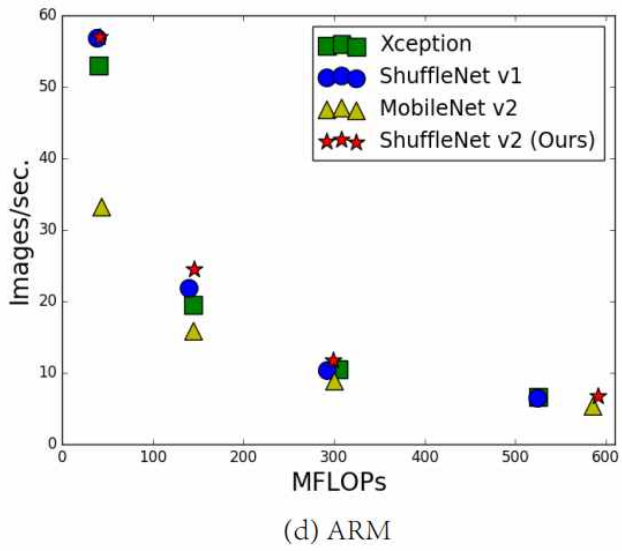


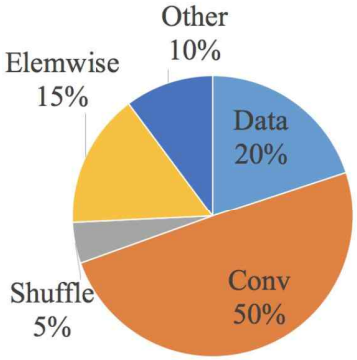
# ShuffleNet V2



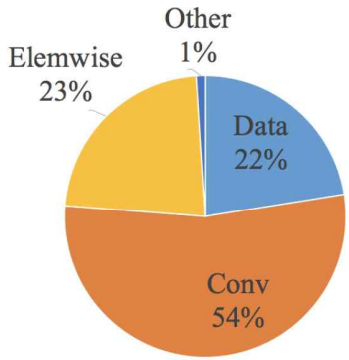

(c) GPU



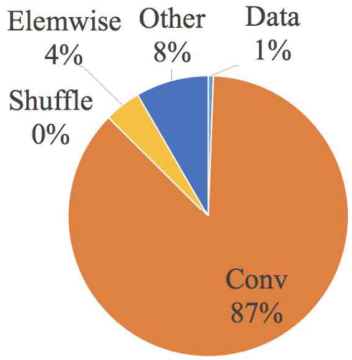

(d) ARM



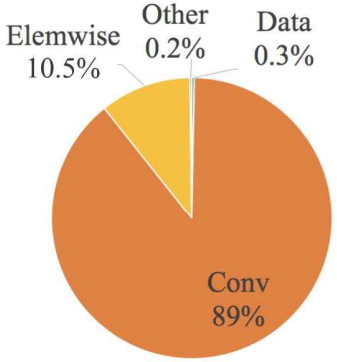

ShuffleNet V1 on GPU




MobileNet V2 on GPU




ShuffleNet V1 on ARM




MobileNet V2 on ARM

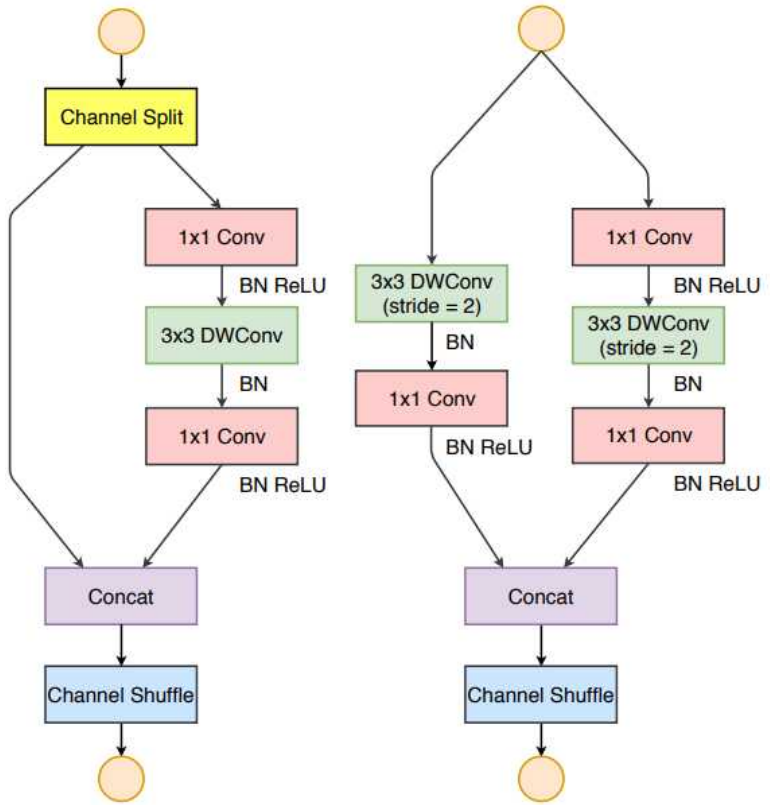
# ShuffleNet V2 – Guide 1

- **Equal channel width minimizes memory access cost (MAC).**
- Let h and w be the spatial size of the feature map, the FLOPs of the 1 x 1 convolution is $B = hwc_1c_2$.
- The memory access cost (MAC), or the number of memory access operations, is $MAC = hw(c_1 + c_2) + c_1c_2$.
- MAC has a lower bound given by FLOPs. It reaches the lower bound when the numbers of input and output channels are equal.

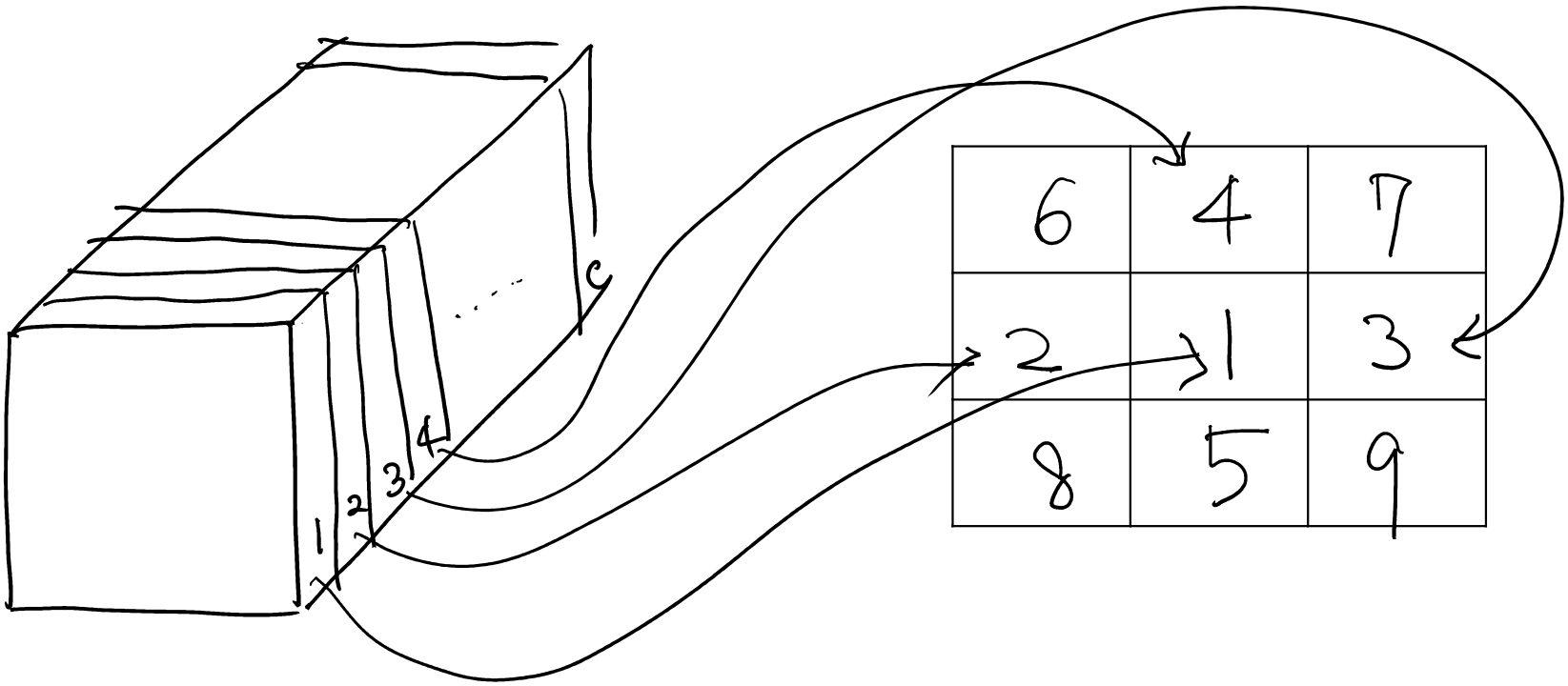
$$MAC \geq 2\sqrt{hwB} + \frac{B}{hw}$$

# ShuffleNet V2

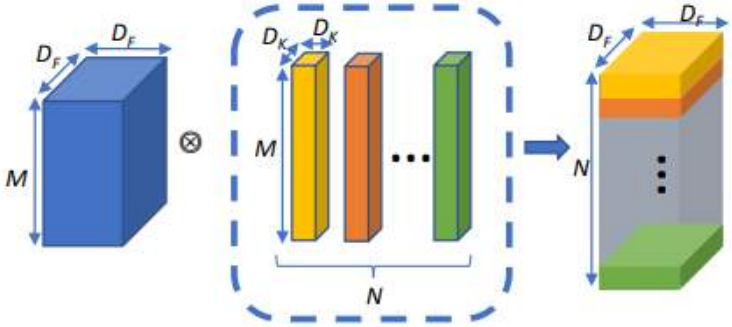
1. Use "balanced" convolutions (equal channel width).
2. Be aware of the cost of using group convolution.
3. Reduce the degree of fragmentation.
4. Reduce element-wise operations.



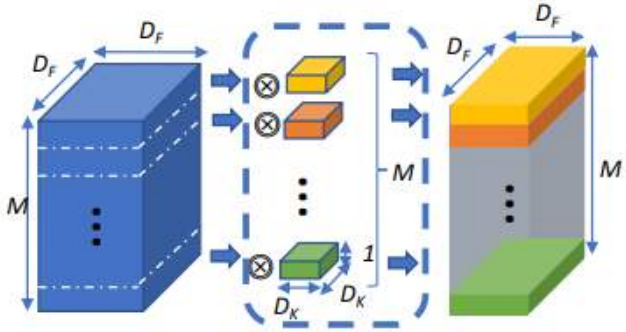
# ShiftNet



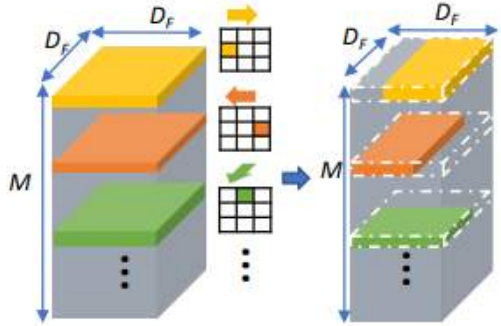
# ShiftNet



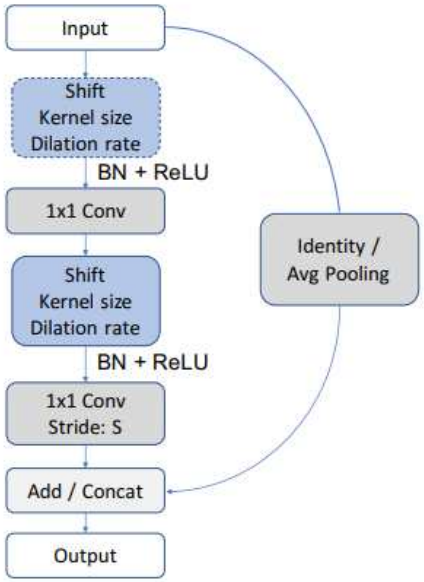

(a) Spatial Convolution




(b) Depth-wise convolution

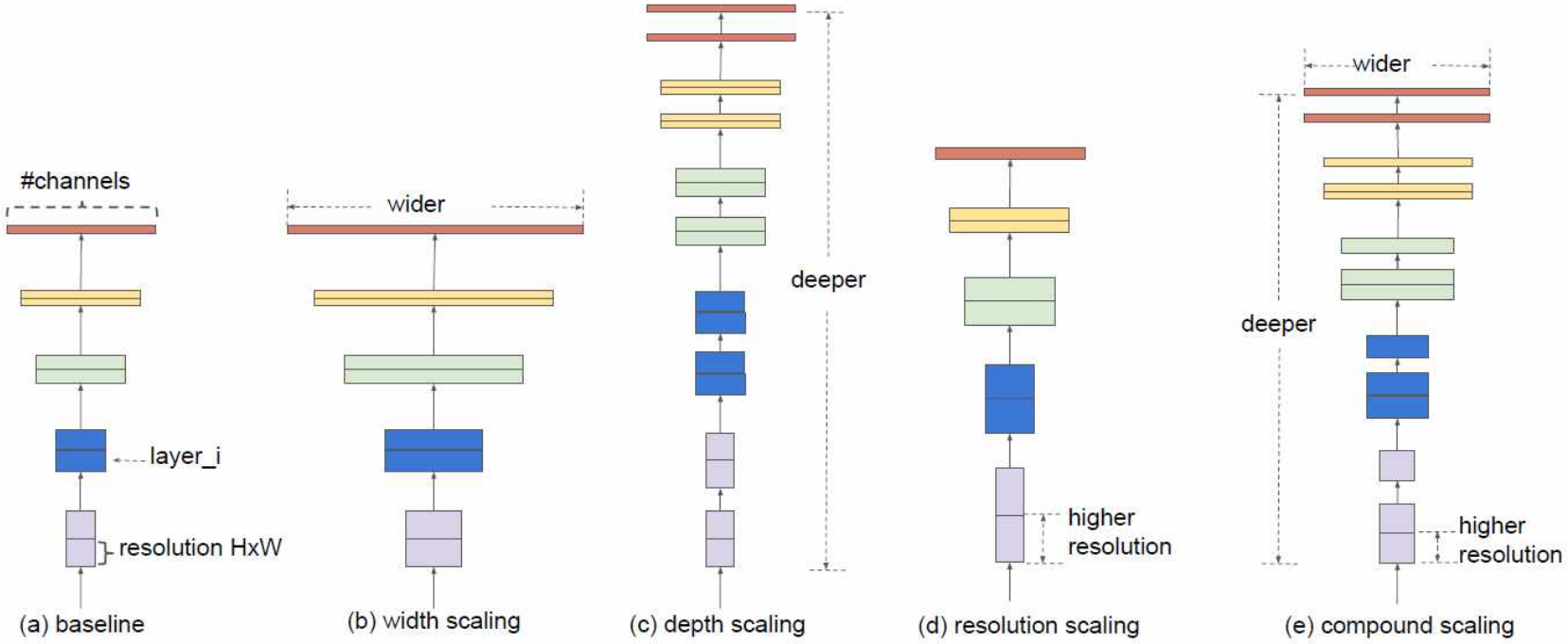



(c) Shift

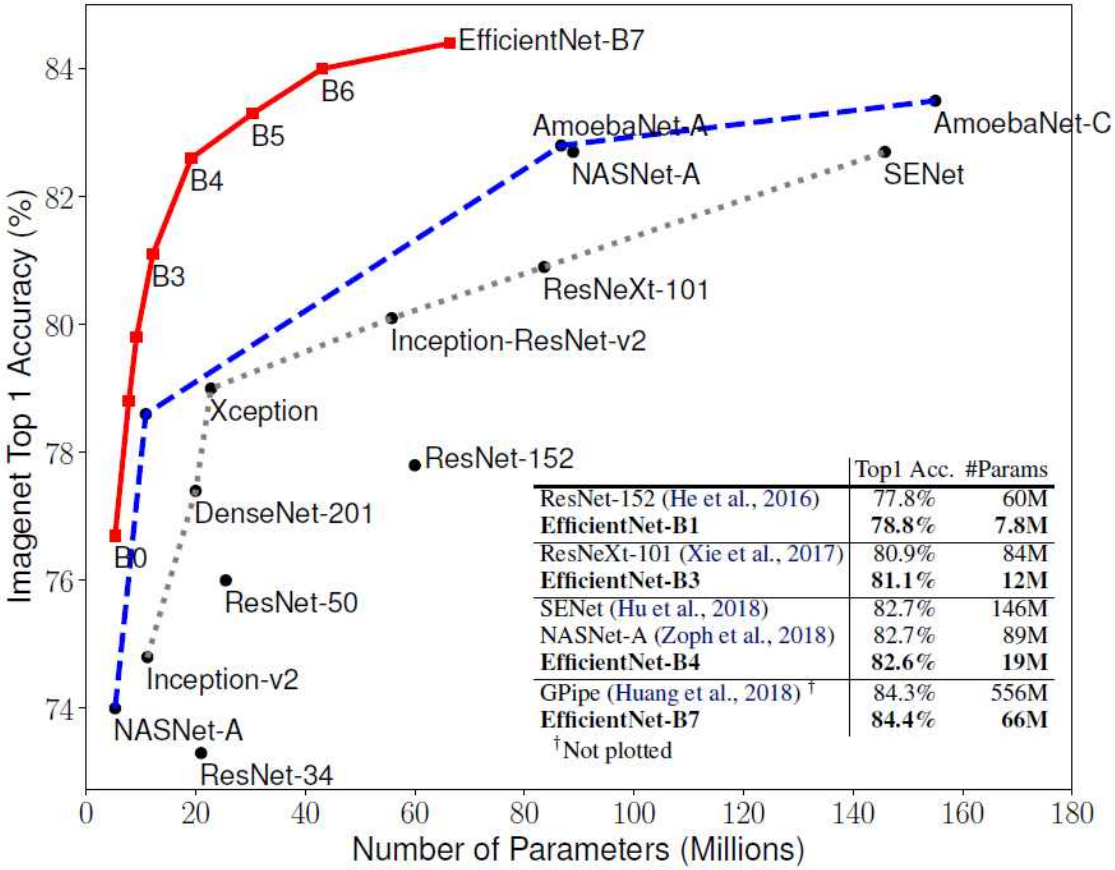


# EfficientNet

$$\text{depth: } d = \alpha^\phi$$
$$\text{width: } w = \beta^\phi$$
$$\text{resolution: } r = \gamma^\phi$$
$$\text{s.t. } \alpha \cdot \beta^2 \cdot \gamma^2 \approx 2$$
$$\alpha \geq 1, \beta \geq 1, \gamma \geq 1$$

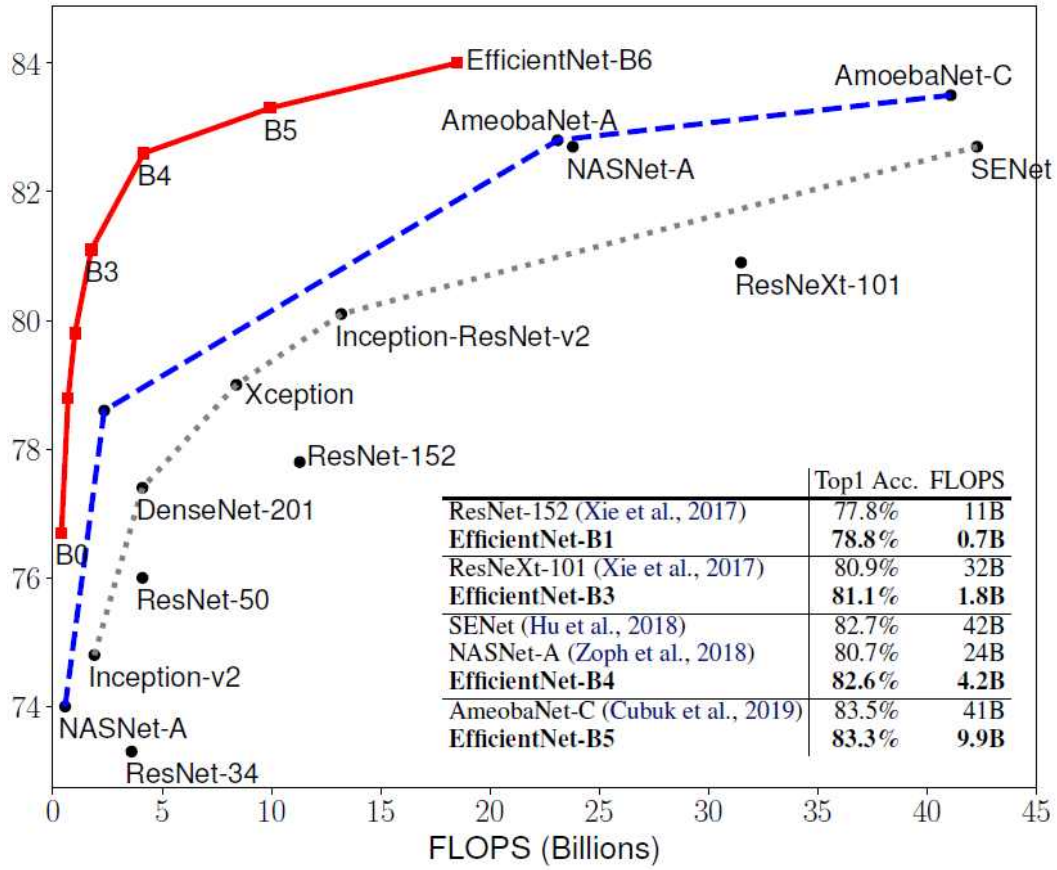


# EfficientNet




| | Top1 Acc. | #Params |
|---|---|---|
| ResNet-152 (He et al., 2016) | 77.8% | 60M |
| **EfficientNet-B1** | **78.8%** | **7.8M** |
| ResNeXt-101 (Xie et al., 2017) | 80.9% | 84M |
| **EfficientNet-B3** | **81.1%** | **12M** |
| SENet (Hu et al., 2018) | 82.7% | 146M |
| NASNet-A (Zoph et al., 2018) | 82.7% | 89M |
| **EfficientNet-B4** | **82.6%** | **19M** |
| GPipe (Huang et al., 2018) † | 84.3% | 556M |
| **EfficientNet-B7** | **84.4%** | **66M** |

†Not plotted




| | Top1 Acc. | FLOPS |
|---|---|---|
| ResNet-152 (Xie et al., 2017) | 77.8% | 11B |
| **EfficientNet-B1** | **78.8%** | **0.7B** |
| ResNeXt-101 (Xie et al., 2017) | 80.9% | 32B |
| **EfficientNet-B3** | **81.1%** | **1.8B** |
| SENet (Hu et al., 2018) | 82.7% | 42B |
| NASNet-A (Zoph et al., 2018) | 80.7% | 24B |
| **EfficientNet-B4** | **82.6%** | **4.2B** |
| AmeobaNet-C (Cubuk et al., 2019) | 83.5% | 41B |
| **EfficientNet-B5** | **83.3%** | **9.9B** |