
# *Modern Convolution Network Design*

杨健程 YANG Jiancheng

Oct 25, 2017

上海交通大學
SHANGHAI JIAO TONG UNIVERSITY


**Top-5 Error**

# What's Next?

# Agenda

*Times are last modified version on arXiv

- **Deeper** and easy to train (Res / Dense)
  - Pre-Activation (2016.07)
  - DenseNet (2016.12)
  - Dual Path Networks (2017.07)
- **Wider** and light-weight (Group Conv)
  - Xception (2017.04)
  - ResNeXt (2017.04)
  - ShuffleNet (2017.07)
  - Merge-and-Run (2017.07)
  - Interleaved Group Conv (2017.07)
- **Global Context**
  - Dilated Conv: Dilated-8 (2016.04) and Dilated Residual Network (2017.05)
  - Squeeze-and-Excitation (2017.09)

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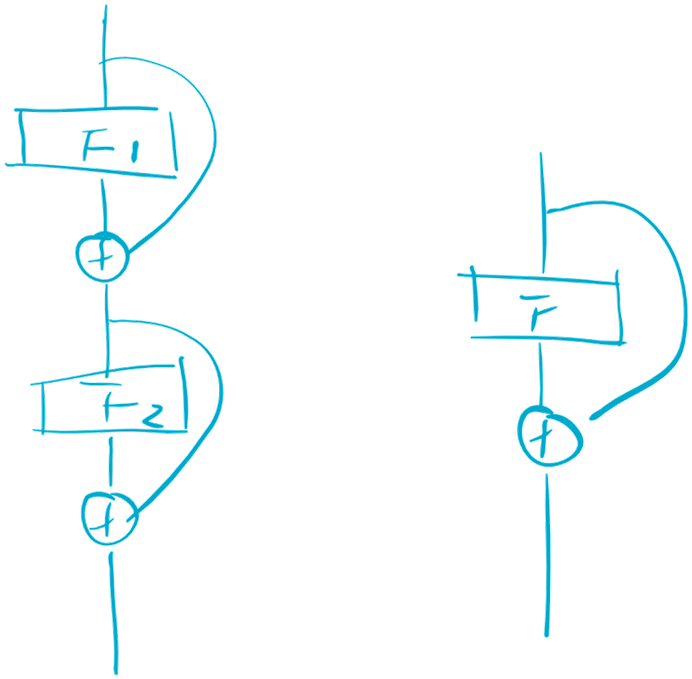
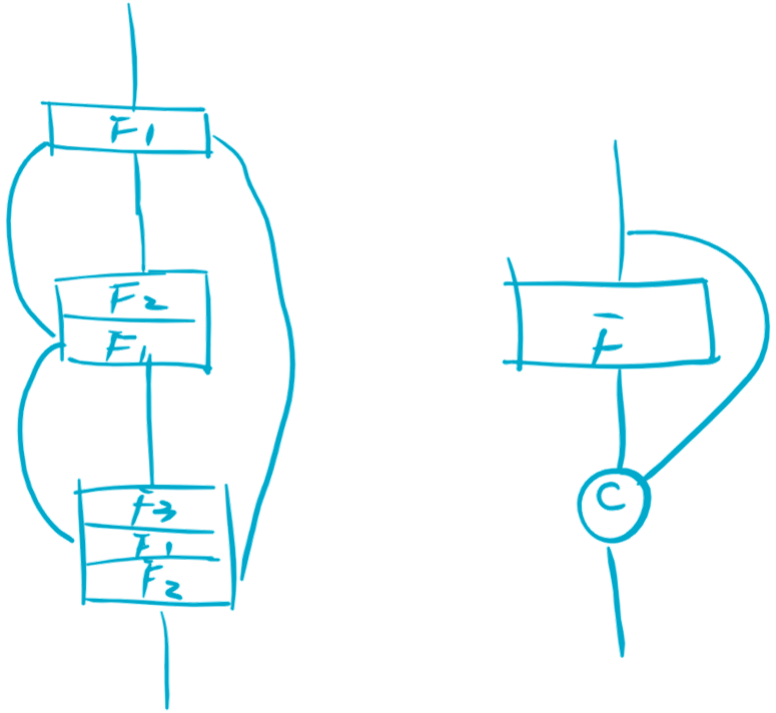
## Deeper and easy to train

# Res / Dense



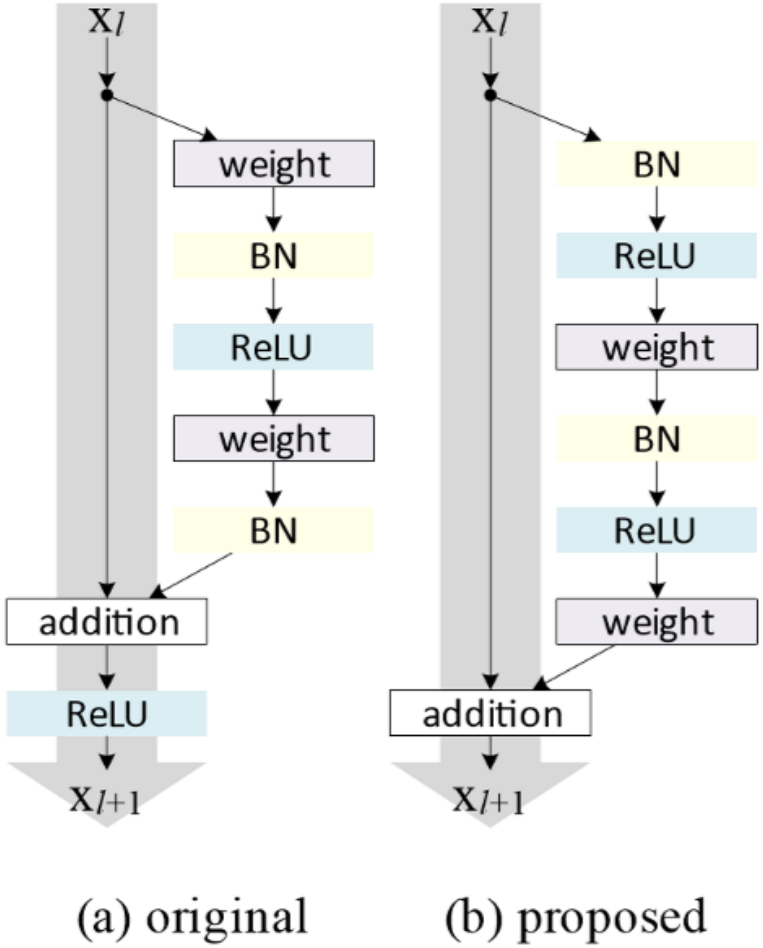

ResNet and Residual Block




DenseNet and Dense Block

## Deeper and easy to train

# Pre-Activation




(a) original (b) proposed

- 1. Ease of Optimization

$$\mathbf{x}_L = \mathbf{x}_l + \sum_{i=l}^{L-1} \mathcal{F}(\mathbf{x}_i, \mathcal{W}_i), \tag{4}$$

$$\frac{\partial \mathcal{E}}{\partial \mathbf{x}_l} = \frac{\partial \mathcal{E}}{\partial \mathbf{x}_L}\frac{\partial \mathbf{x}_L}{\partial \mathbf{x}_l} = \frac{\partial \mathcal{E}}{\partial \mathbf{x}_L}\left(1 + \frac{\partial}{\partial \mathbf{x}_l}\sum_{i=l}^{L-1}\mathcal{F}(\mathbf{x}_i, \mathcal{W}_i)\right). \tag{5}$$

We also find that the impact of $f$ = ReLU is not severe when the ResNet has fewer layers (*e.g.*, 164 in Fig. 6(right)). The training curve seems to suffer

- 2. Reducing Overfitting

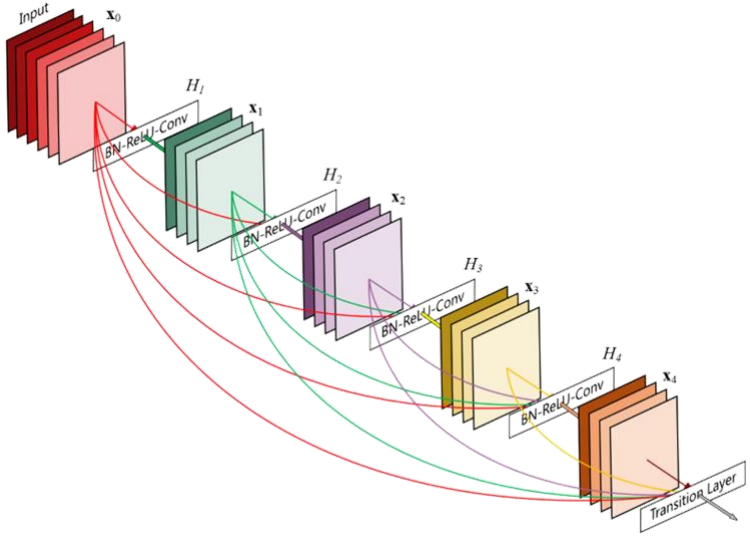
the next weight layer. On the contrary, in our pre-activation version, the inputs to all weight layers have been normalized.

- ResNet1001 / ResNet200 / ResNet v2
- Bottleneck usage is the same as before

## Deeper and easy to train

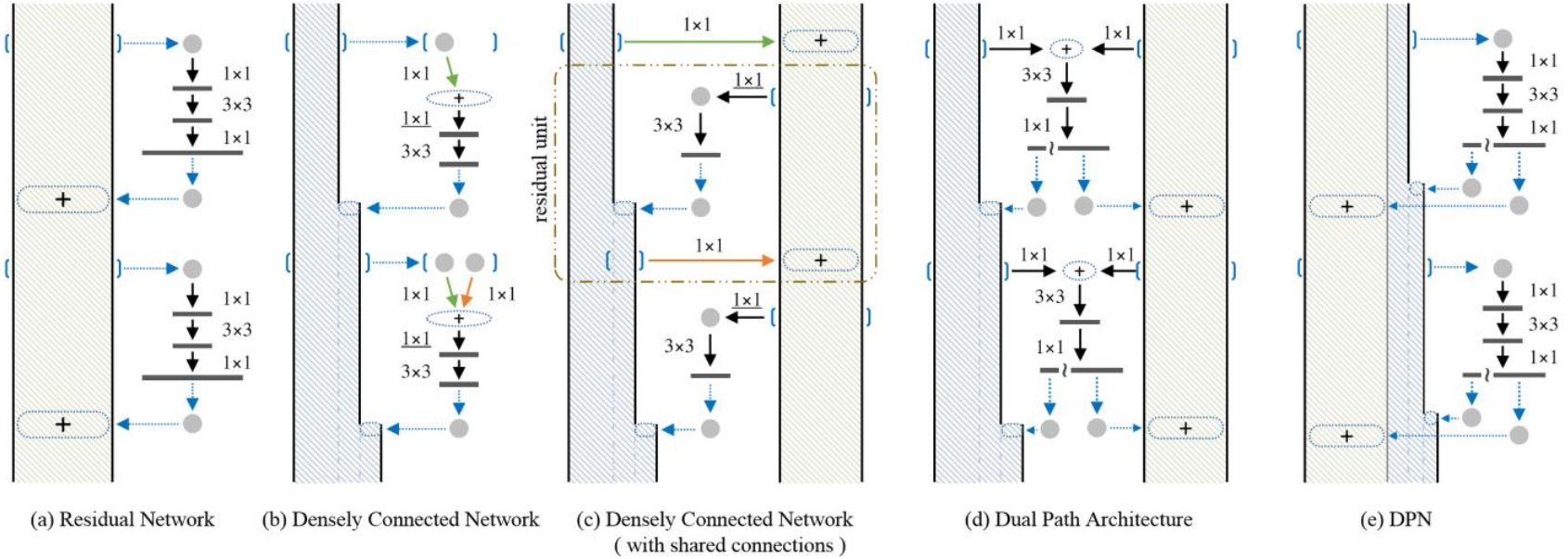
# DenseNet

- DenseNet-BC
  - Bottleneck
  - Compression
- 1 / 3 parameters of ResNet counterpart
- Less prone to overfitting
- Able to train from scratch
- Large memory consuming



## Deeper and easy to train
# Dual Path Networks

- Res + Dense




- split => one Res path + one Dense path => merge

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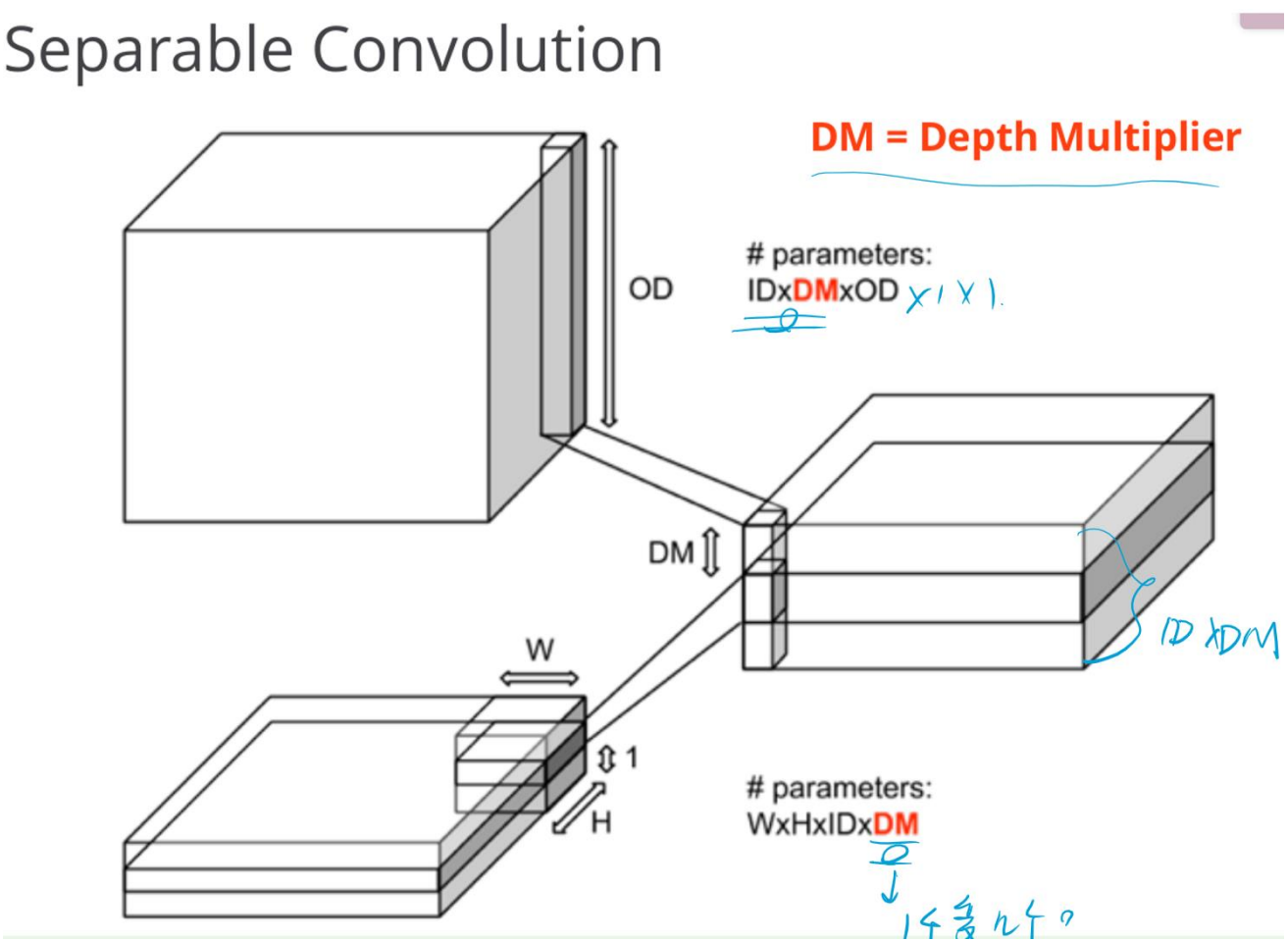
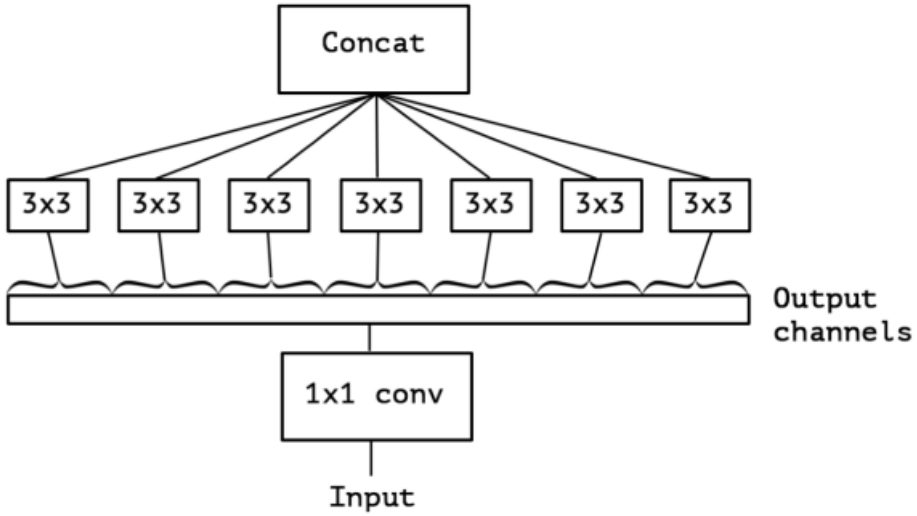
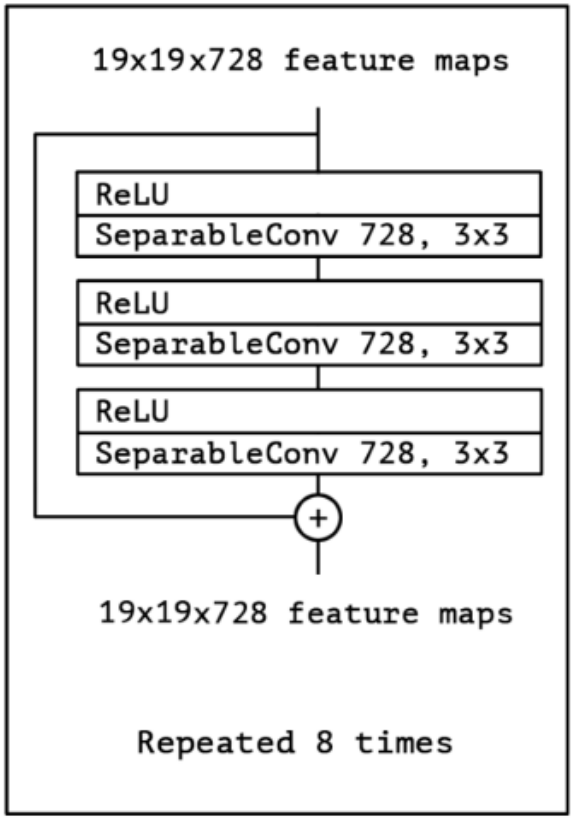
## Wider and light-weight
# Group Convolution




depthwise spatial convolution + pointwise convolution

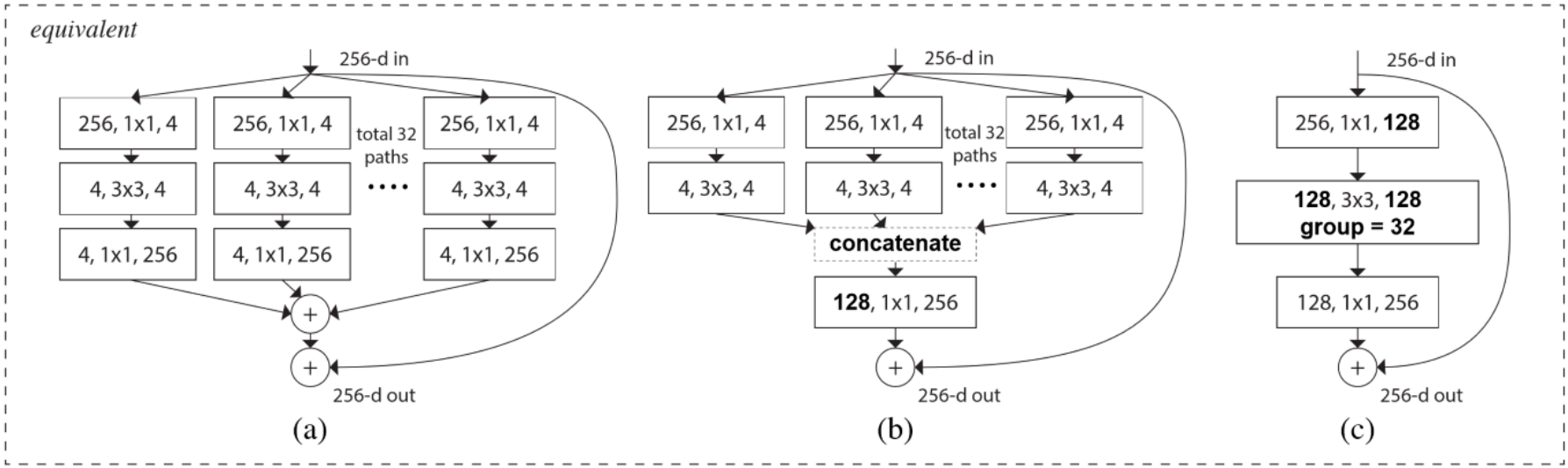
# Wider and light-weight
# Xception



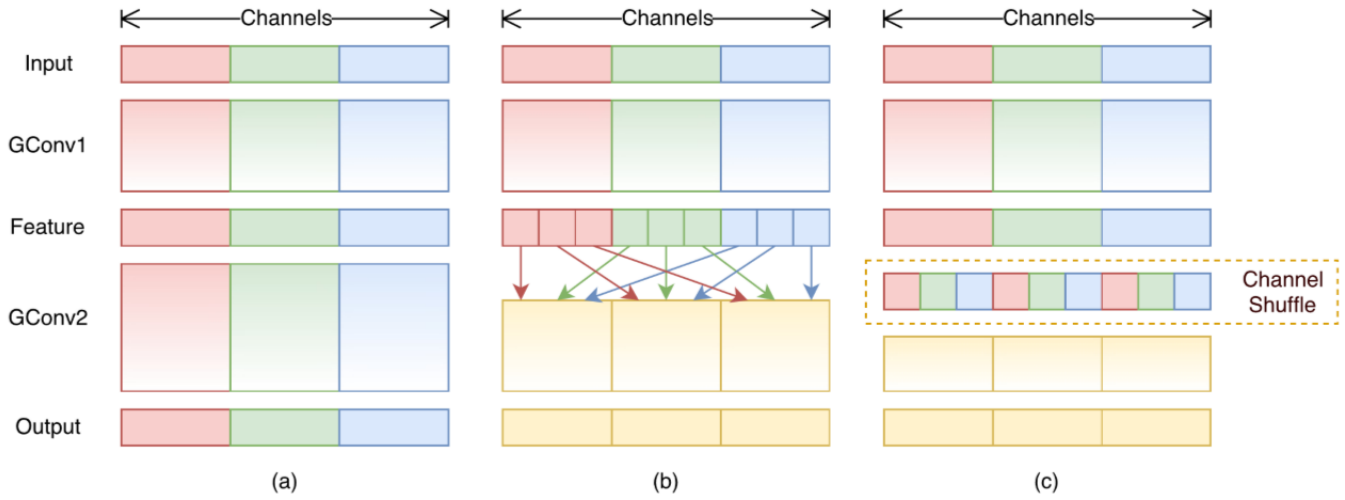

- Extreme version of Inception: 1x1 + act + depthwise 3x3 +act
- √ SeparableConv: depthwise 3x3 + 1x1 +act
- $DM = 1\ (no\ depth\ expansion)$
- Conv means Conv+BN

# Wider and light-weight
# ResNeXt



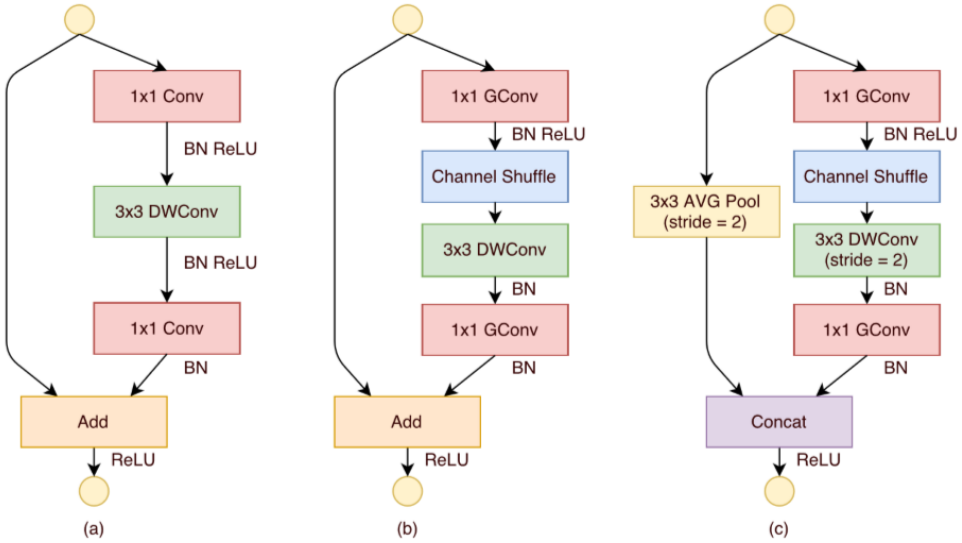

- ResNet: $c \times 1 \times 1 \times m + m \times 3 \times 3 \times m + m \times 1 \times 1 \times c = 2cm + 9m^2 (c \to m \to c)$
- ResNeXt: $c \times 1 \times 1 \times m + g \times \frac{m}{g} \times 3 \times 3 \times \frac{m}{g} + m \times 1 \times 1 \times c = 2cm + \frac{9m^2}{g} \left( c \to \frac{m}{g} \to c \right)$
- $m = \frac{c}{2}$

# Wider and light-weight
# ShuffleNet




- Based on Xception, also focus on 1x1 conv (pointwise gconv)
- Use “channel shuffle” to encourage inter-channel communication
- Very efficient on small models (never mention on large models)

# Wider and light-weight
# ShuffleNet




- ResNeXt: $c \times 1 \times 1 \times m + g \times \frac{m}{g} \times 3 \times 3 \times \frac{m}{g} + m \times 1 \times 1 \times c = 2cm + \frac{9m^2}{g} \left( c \to \frac{m}{g} \to c \right)$
- ShuffleNet: $\mathrm{g} \times \frac{c}{g} \times 1 \times 1 \times \frac{m}{g} + m \times 3 \times 3 + \mathrm{g} \times \frac{m}{g} \times 1 \times 1 \times \frac{c}{g} = \frac{2cm}{g} + 9m \left( \frac{c}{g} \to m(DW) \to \frac{c}{g} \right)$
- $m = \frac{c}{4}$

# Wider and light-weight
# Merge-and-Run

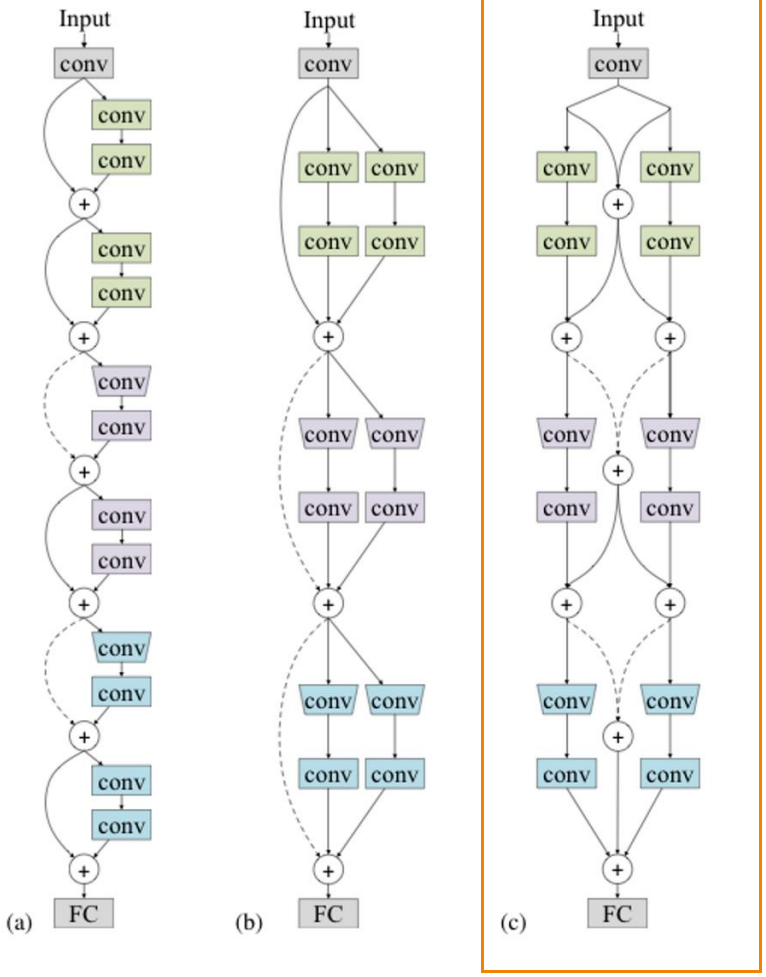
- Like ResNeXt
- Improved information flow

**Information flow improvement.** We transform Equation 3 into the matrix form,

$$\begin{bmatrix} \mathbf{x}_{2(t+1)} \\ \mathbf{x}_{2(t+1)+1} \end{bmatrix} = \begin{bmatrix} H_{2t}(\mathbf{x}_{2t}) \\ H_{2t+1}(\mathbf{x}_{2t+1}) \end{bmatrix} + \frac{1}{2} \begin{bmatrix} \mathbf{I} & \mathbf{I} \\ \mathbf{I} & \mathbf{I} \end{bmatrix} \begin{bmatrix} \mathbf{x}_{2t} \\ \mathbf{x}_{2t+1} \end{bmatrix}, \tag{4}$$

where $\mathbf{I}$ is an $d \times d$ identity matrix and $d$ is the dimension of $\mathbf{x}_{2t}$ (and $\mathbf{x}_{2t+1}$). $\mathbf{M} = \frac{1}{2} \begin{bmatrix} \mathbf{I} & \mathbf{I} \\ \mathbf{I} & \mathbf{I} \end{bmatrix}$ is the transformation matrix of the merge-and-run mapping.

- Shorter paths
- Increased width



## Wider and light-weight
# Interleaved Group Convolution

- Highly related to ShuffleNet (Channel Shuffle operation)

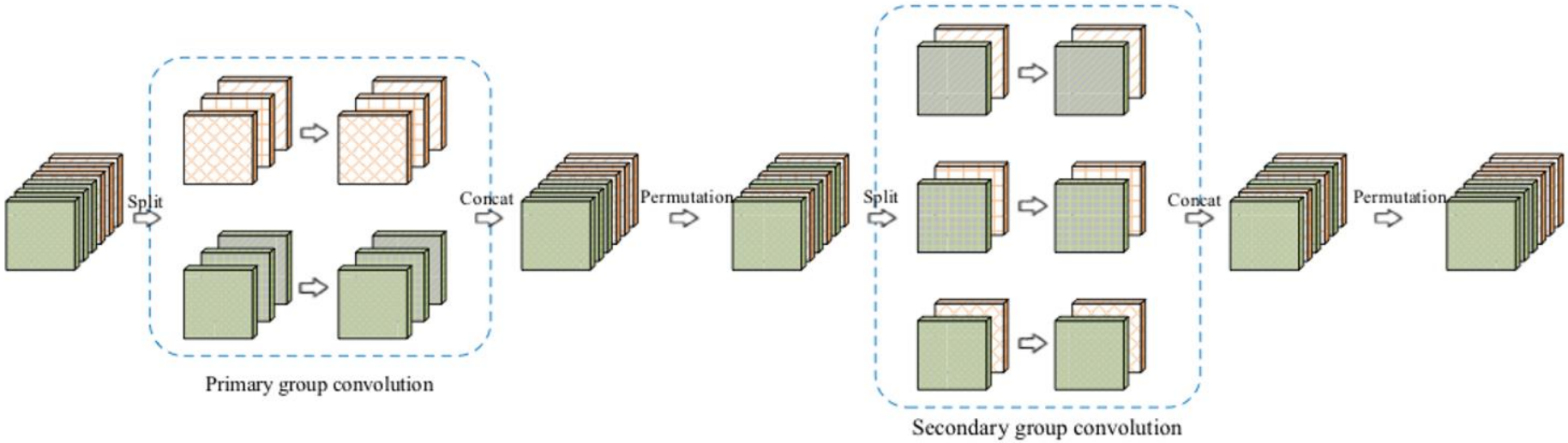



Figure 1. Illustrating the interleaved group convolution, with $L = 2$ primary partitions and $M = 3$ secondary partitions. The convolution for each primary partition in primary group convolution is spatial. The convolution for each secondary partition in secondary group convolution is point-wise ($1 \times 1$). Details are given in Section 3.1.

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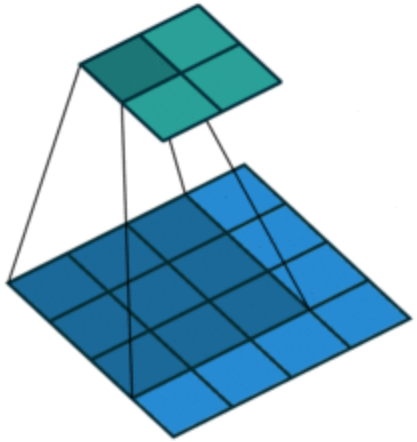
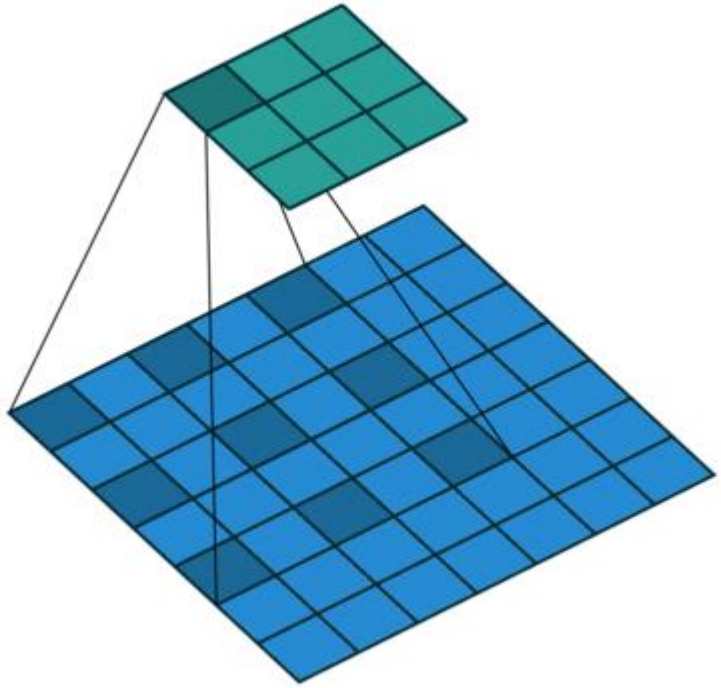
## Global Context
# Dilated Convolution

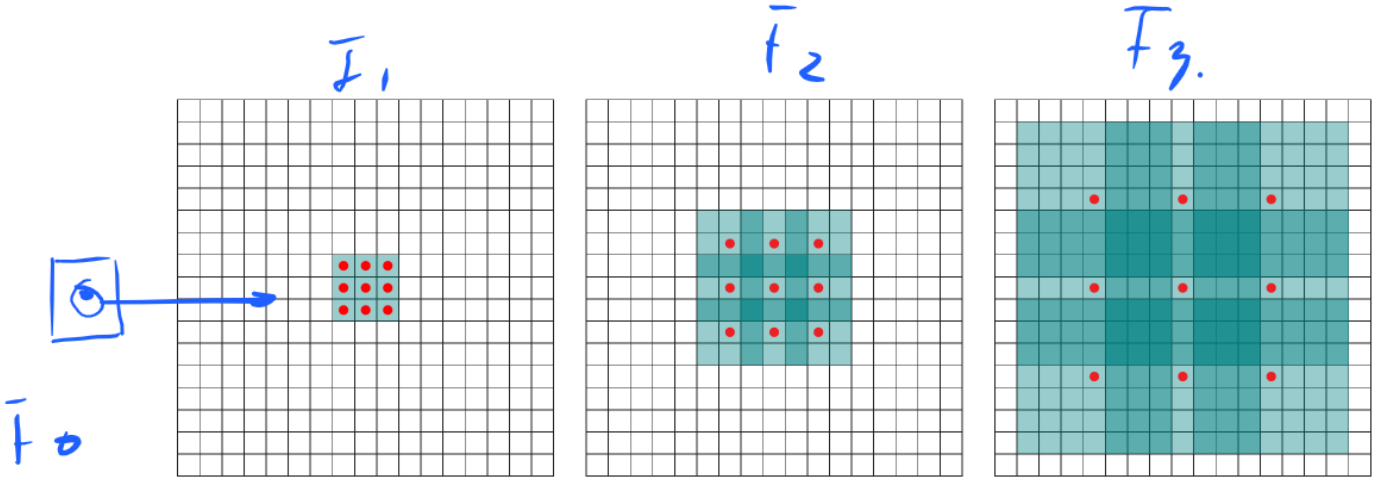


Regular Conv
No padding, no strides



Dilated Conv
No padding, no stride

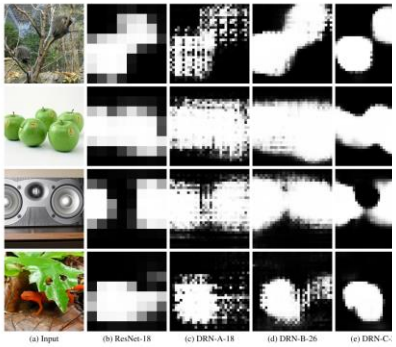
# Global Context
## Dilated-8

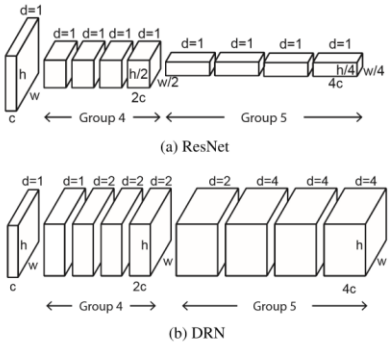



| Layer | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---|---|---|---|---|---|---|---|
| Convolution | 3×3 | 3×3 | 3×3 | 3×3 | 3×3 | 3×3 | 3×3 | 1×1 |
| Dilation | 1 | 1 | 2 | 4 | 8 | 16 | 1 | 1 |
| Truncation | Yes | Yes | Yes | Yes | Yes | Yes | Yes | No |
| Receptive field | 3×3 | 5×5 | 9×9 | 17×17 | 33×33 | 65×65 | 67×67 | 67×67 |
| Output channels | | | | | | | | |
| Basic | $C$ | $C$ | $C$ | $C$ | $C$ | $C$ | $C$ | $C$ |
| Large | $2C$ | $2C$ | $4C$ | $8C$ | $16C$ | $32C$ | $32C$ | $C$ |

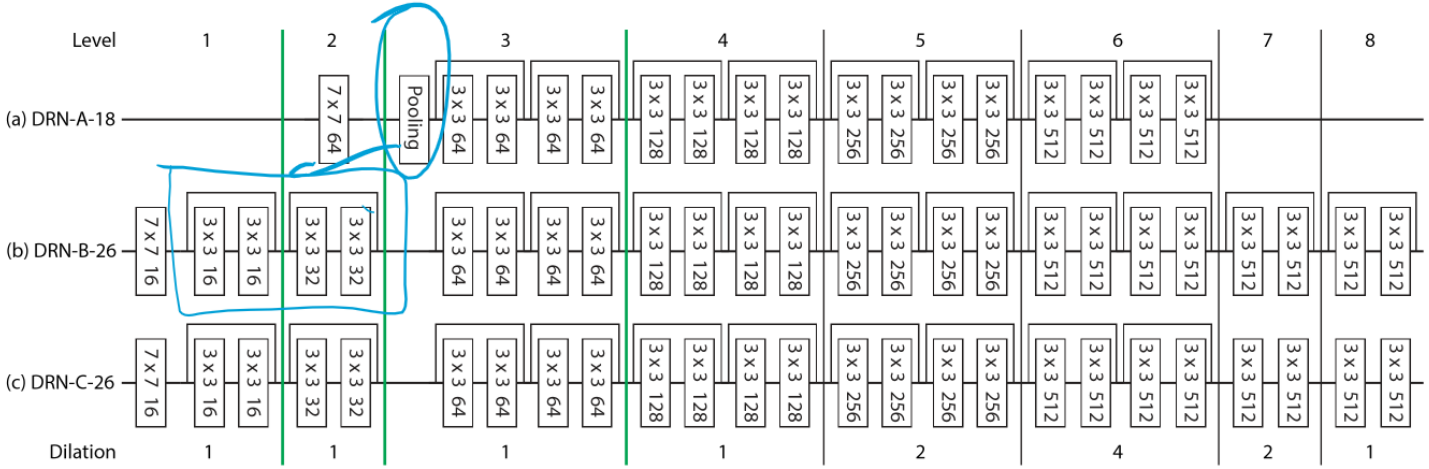
## Global Context

# Dilated Residual Network



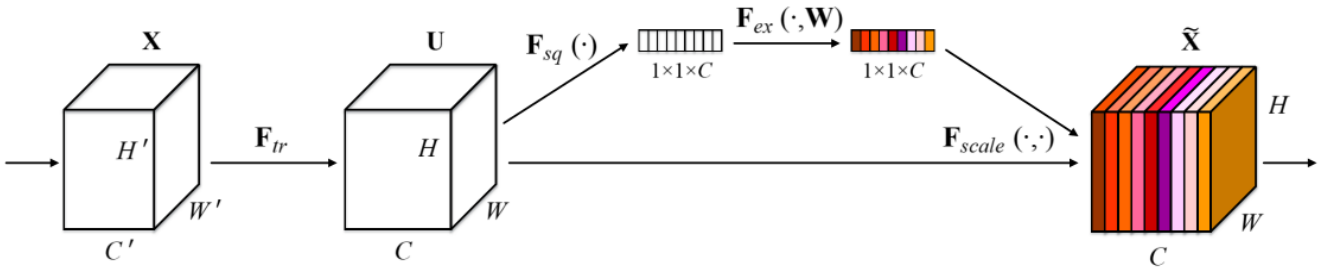


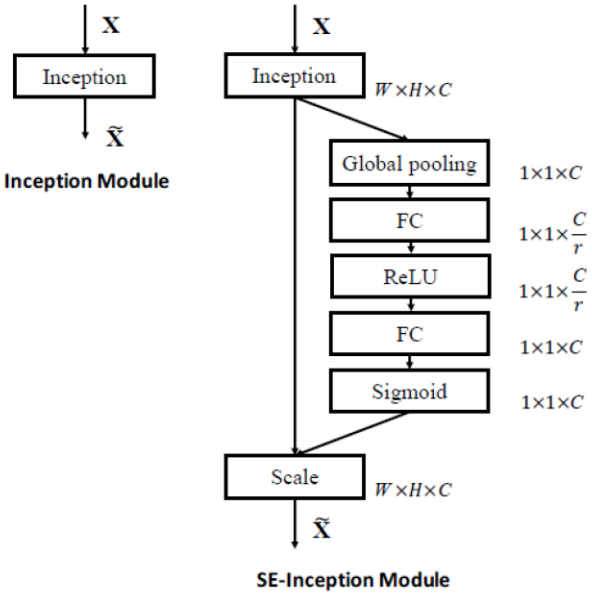

- Low resolution problem
- Degridding for dilated conv
- High res means high memory cost

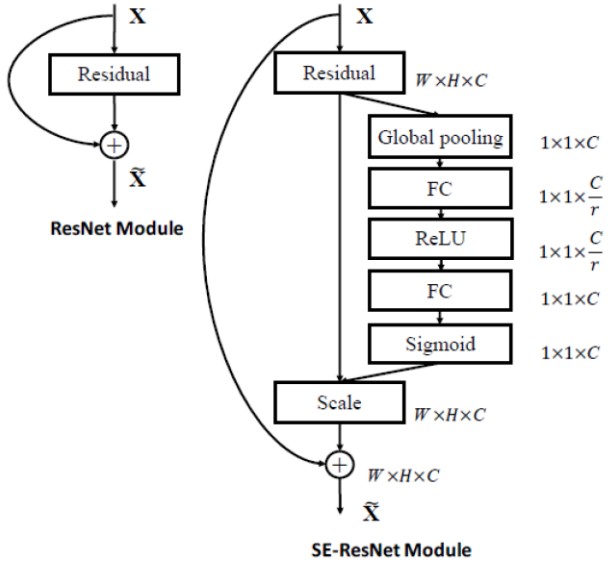


## Global Context

# Squeeze-and-Excitation



# Global Context
# Squeeze-and-Excitation


- Squeeze: Global Information Embedding
  - Larger than local receptive field of regular conv
- Excitation: Adaptive Recalibration
  - Capture channel-wise dependencies
- Details of ImageNet 2017 best entry (SENet)
  a) Based on ResNeXt-152
  b) Halved bottleneck
  c) 7x7 conv=> 2 stack of 3x3 conv
  d) Down-sampling 1x1 stride-2 conv => 3x3 stride-2 conv
  e) Dropout before fc
  f) Label smoothing
  g) BN parameter frozen for last few epochs
  h) 2048 batch size with initial learning rate of 0.1 SGD on 64 GPUs

# Thank You