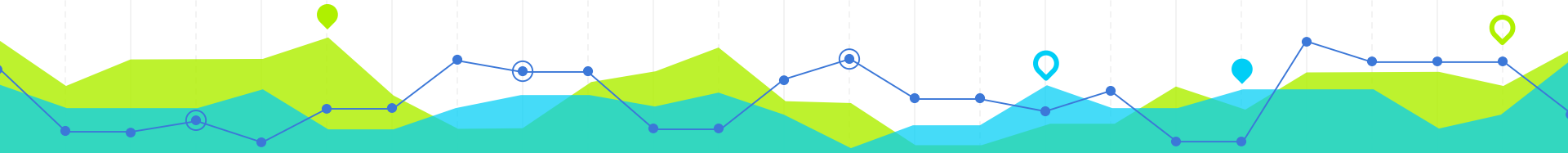
Densly Connected Convolutional Neural Networks



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Aug. 2017
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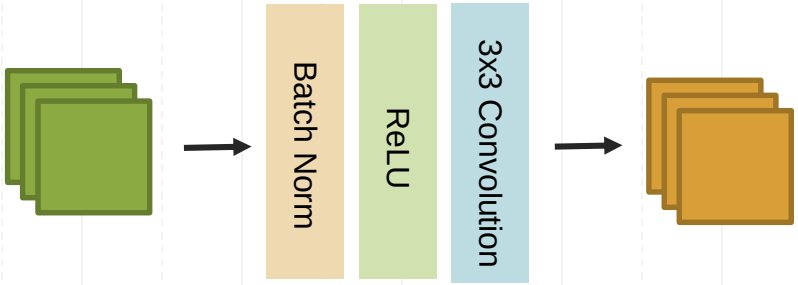
Seoul National University

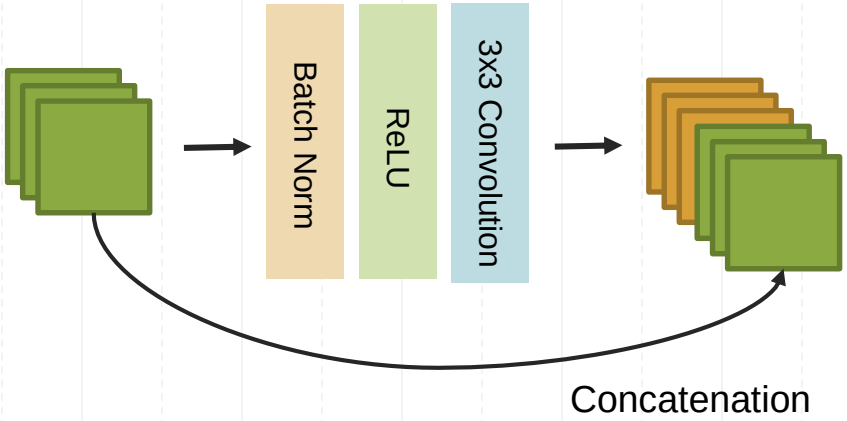
THROUGHOUT THE SLIDES

- Lots of the slides are originated from CVPR 2017 slides presented by Gao Huang et al.
- Check https://www.youtube.com/watch?v=-W6y8xnd--U

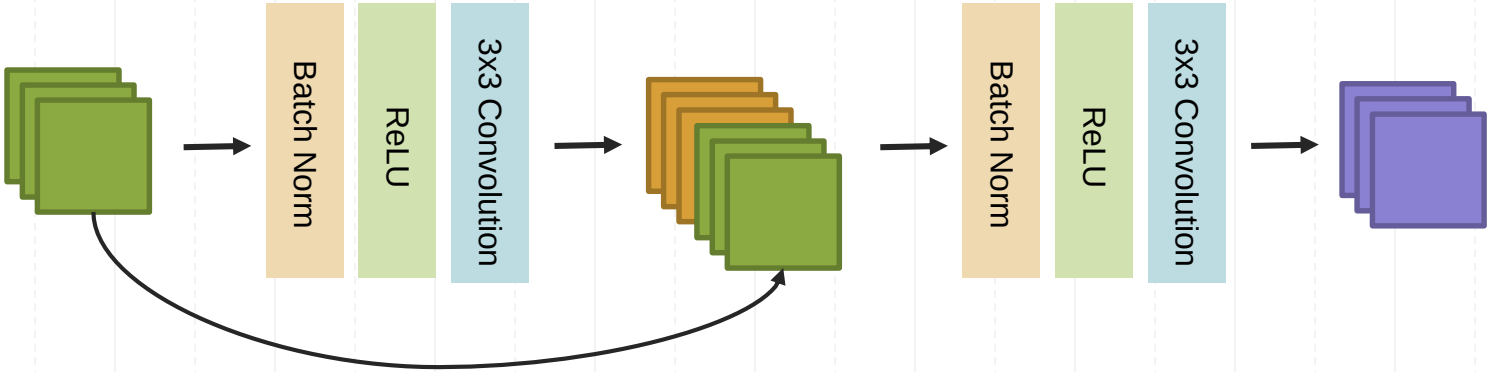
COMPOSITE LAYER



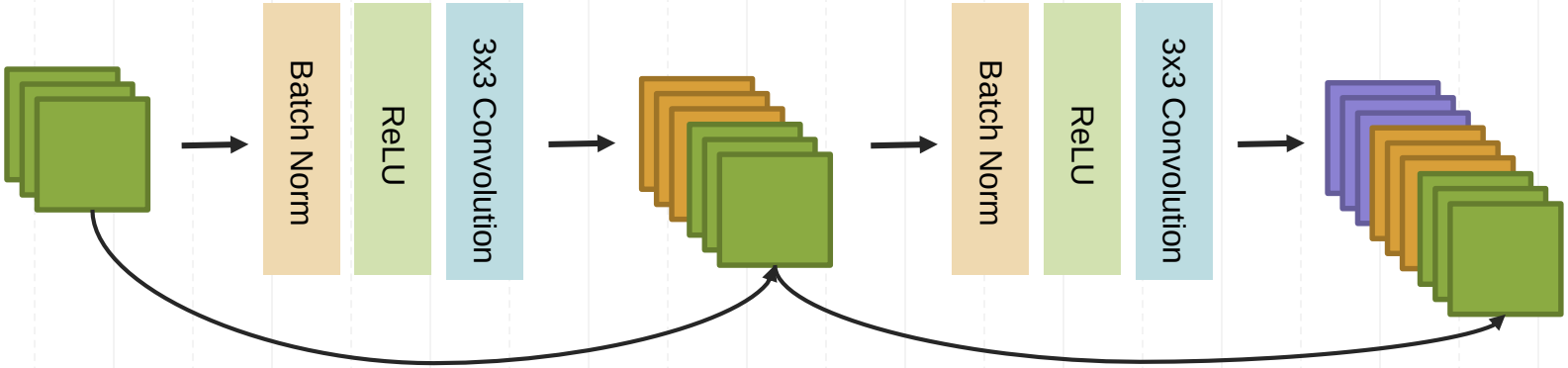
DENSE CONNECTIVITY



DENSE CONNECTIVITY

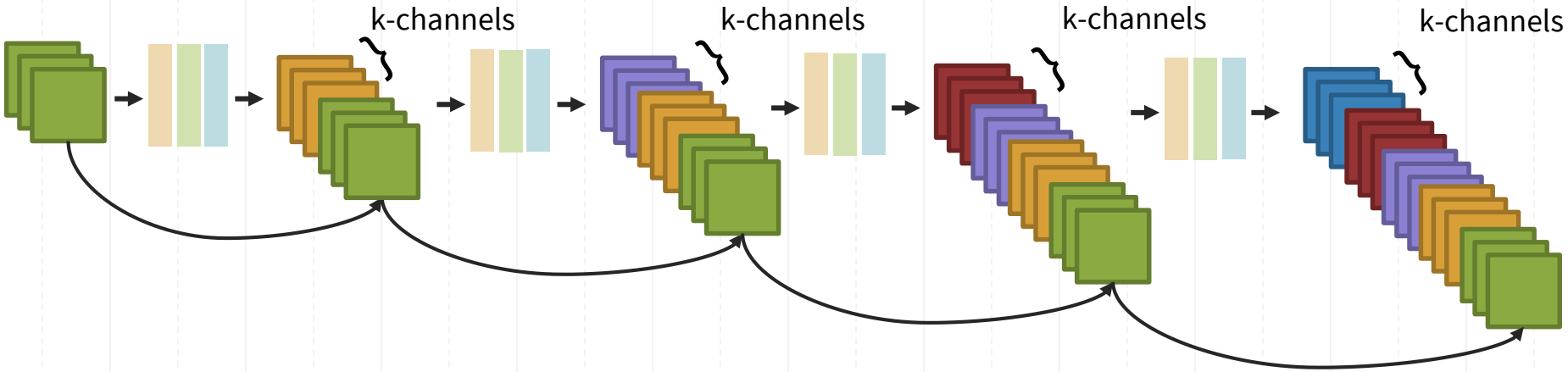


DENSE CONNECTIVITY



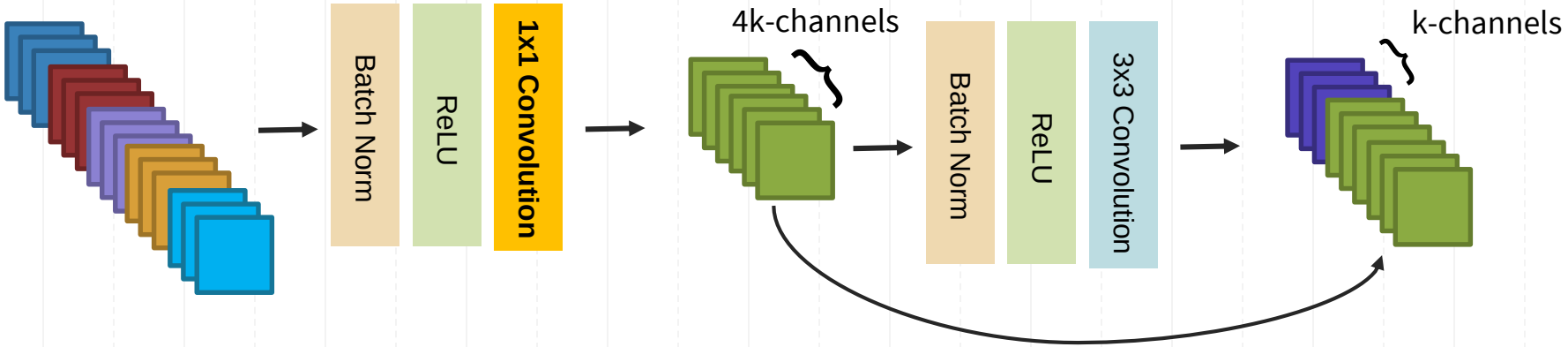
THIN FEATURE MAPS

- Channels are linearly increased.



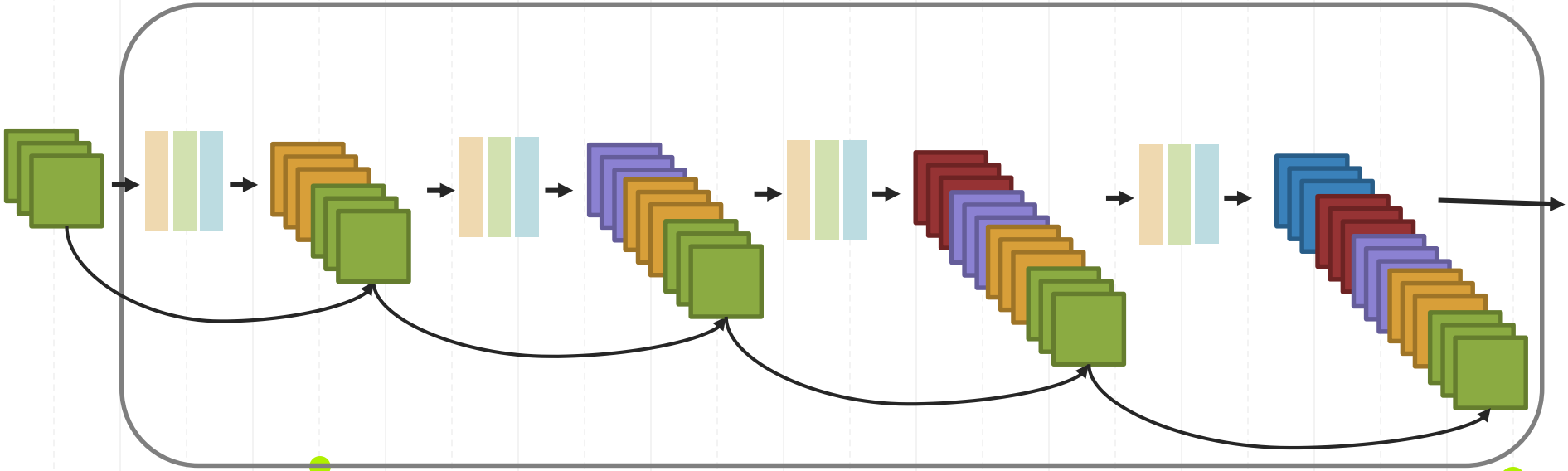
BOTTLENECK LAYER

- Reduce the number of channels to $4k$ before composite layer by **1x1 convolution**.
- It's optional.

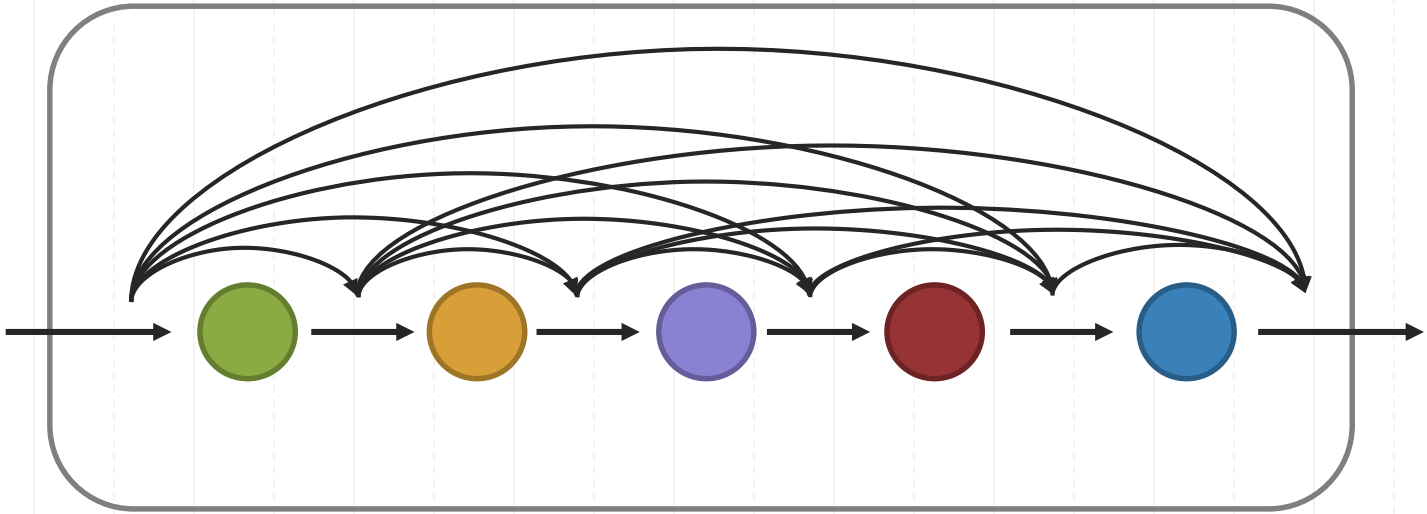


DENSE BLOCK

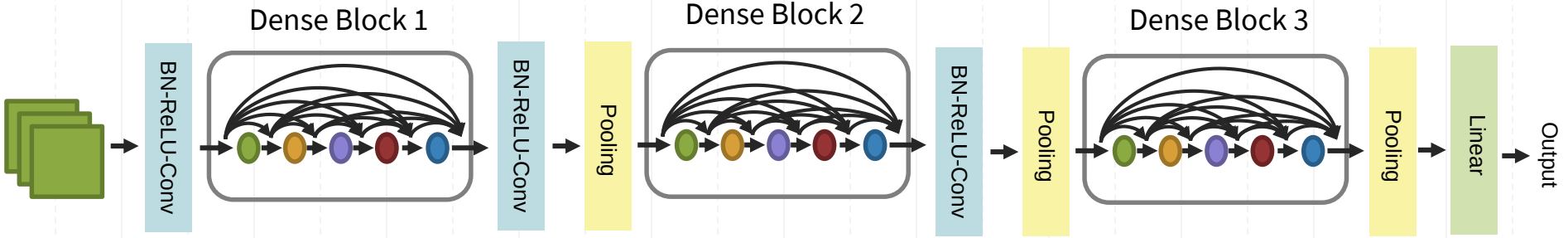
- Bottleneck layers are omitted for simple illustration. ☺



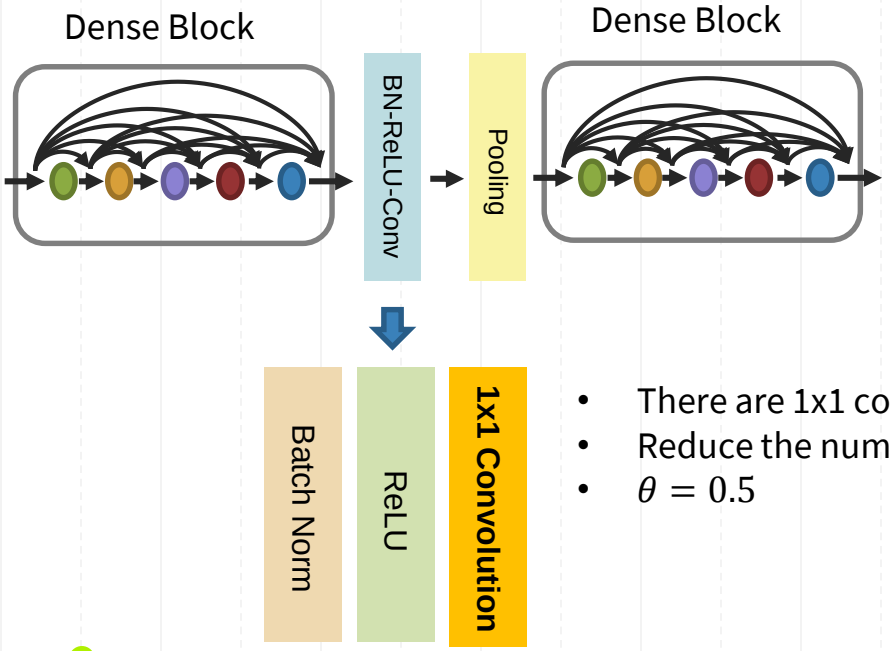
SIMPLE ILLUSTRATION OF DENSE BLOCK



DENSENET


Dense Block 1
Dense Block 2
Dense Block 3
BN-ReLU-Conv
BN-ReLU-Conv
BN-ReLU-Conv
Pooling
Pooling
Pooling
Linear
Output

COMPRESSION



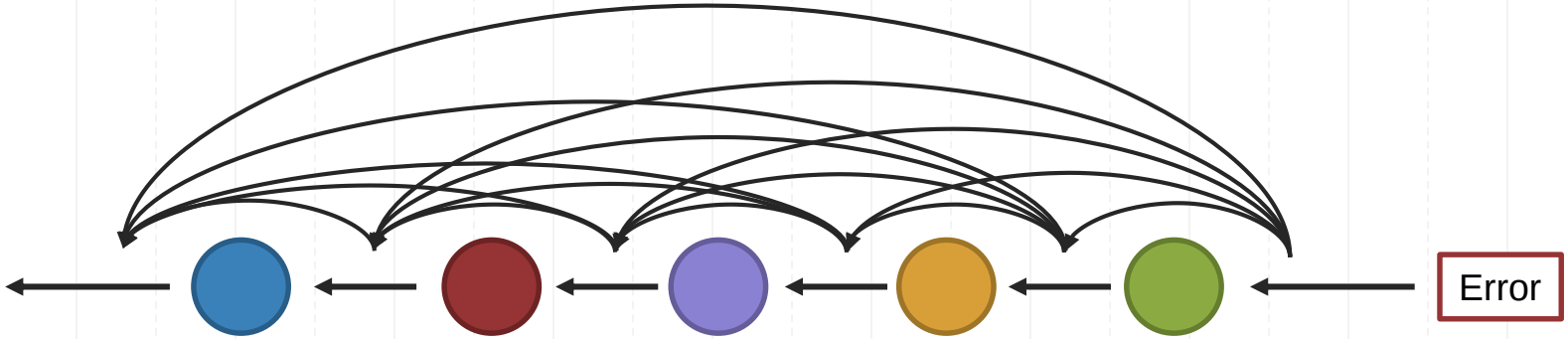
- There are 1x1 convolution between dense blocks.
- Reduce the number of channels by $0 < \theta \leq 1$.
- $\theta = 0.5$

ARCHITECTURES OF DENSENET

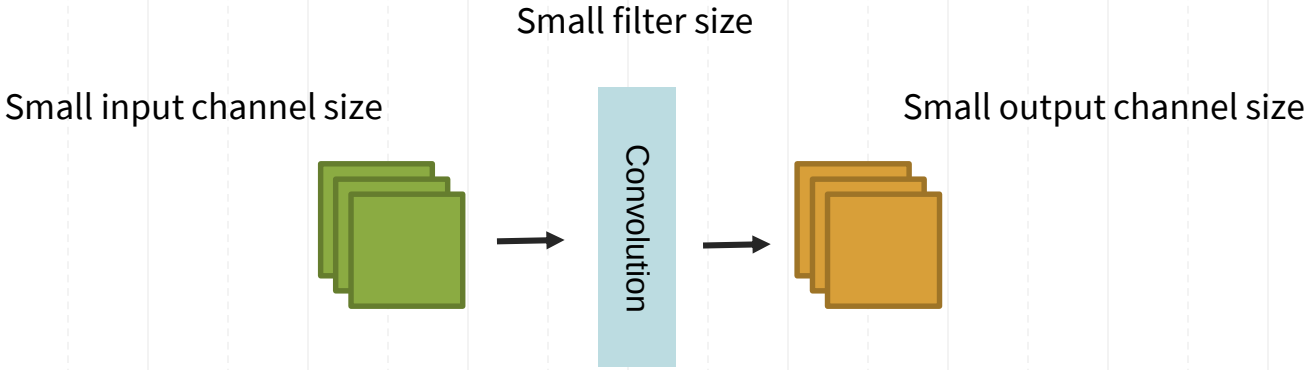
Layers	Output Size	DenseNet-121($k = 32$)	DenseNet-169($k = 32$)	DenseNet-201($k = 32$)	DenseNet-161($k = 48$)
Convolution	112 × 112	7 × 7 conv, stride 2			
Pooling	56 × 56	3 × 3 max pool, stride 2			
Dense Block (1)	56 × 56	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 6$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 6$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 6$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 6$
Transition Layer (1)	56 × 56	1 × 1 conv			
	28 × 28	2 × 2 average pool, stride 2			
Dense Block (2)	28 × 28	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 12$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 12$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 12$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 12$
Transition Layer (2)	28 × 28	1 × 1 conv			
	14 × 14	2 × 2 average pool, stride 2			
Dense Block (3)	14 × 14	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 24$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 32$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 48$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 36$
Transition Layer (3)	14 × 14	1 × 1 conv			
	7 × 7	2 × 2 average pool, stride 2			
Dense Block (4)	7 × 7	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 16$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 32$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 32$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 24$
Classification Layer	1 × 1	7 × 7 global average pool			
		1000D fully-connected, softmax			

Table 1. DenseNet architectures for ImageNet. The growth rate for the first 3 networks is $k = 32$, and $k = 48$ for DenseNet-161. Note that each "conv" layer shown in the table corresponds the sequence BN-ReLU-Conv.

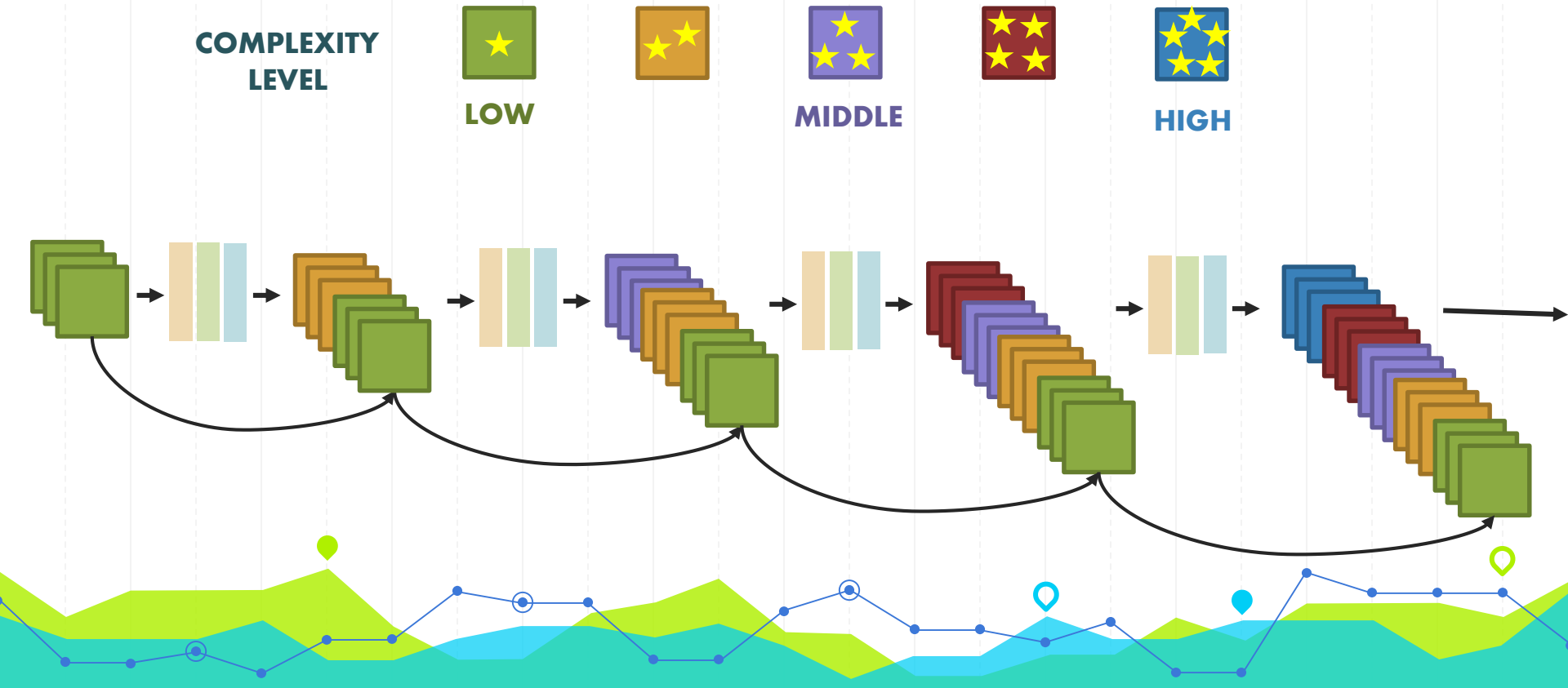
ADVANTAGE 1: STRONG GRADIENT FLOW



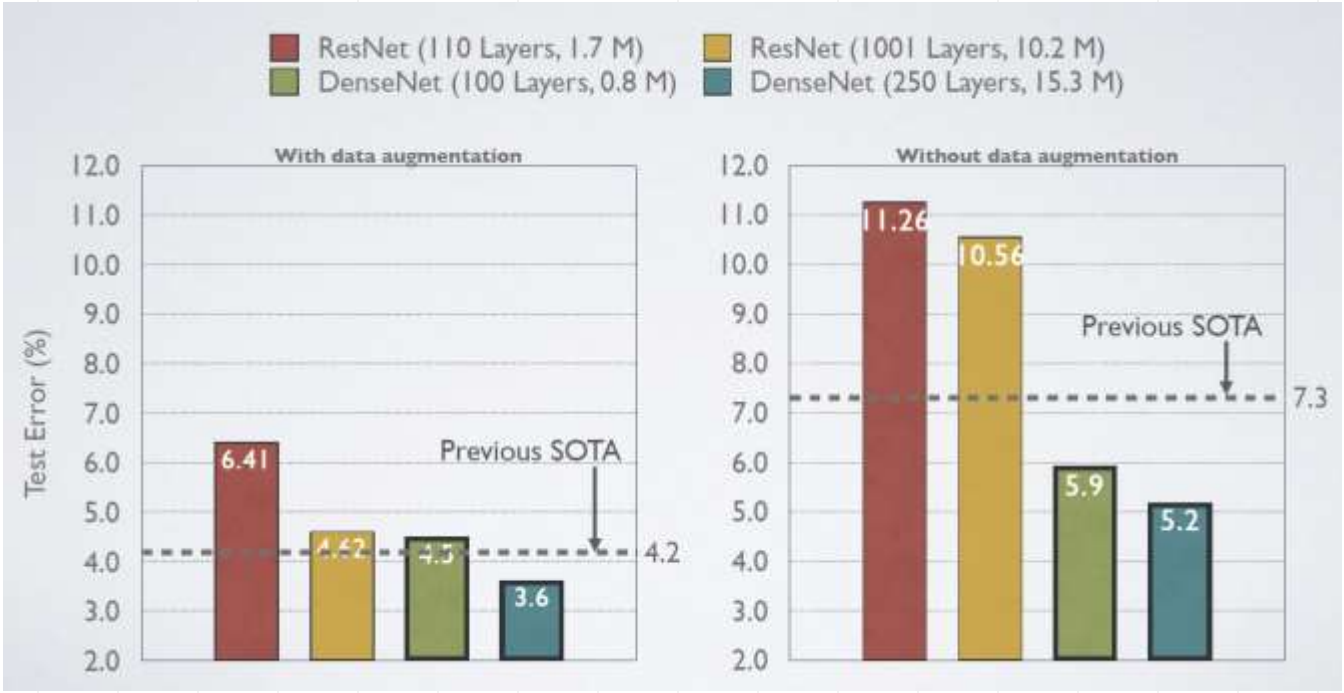
ADVANTAGE 2: PARAMETER & COMPUTATIONAL EFFICIENCY



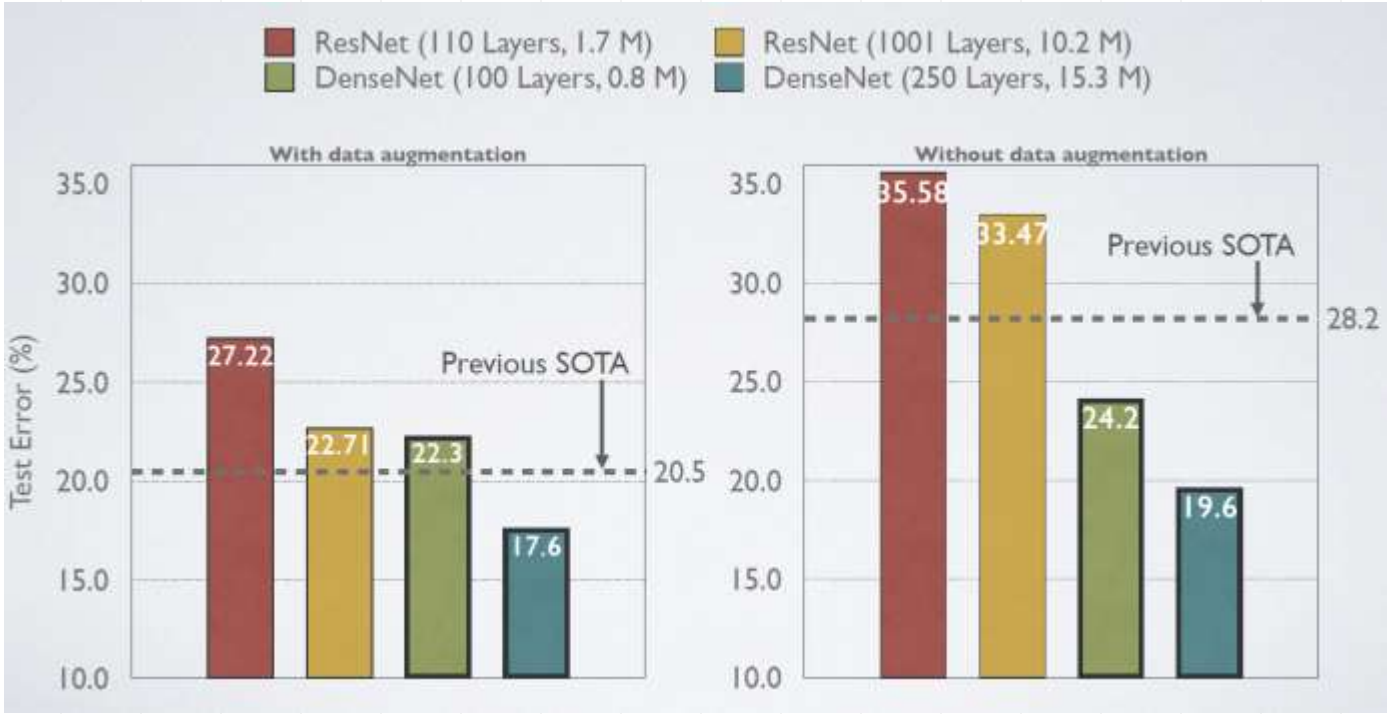
ADVANTAGE 3: MAINTAINS LOW COMPLEXITY FEATURES



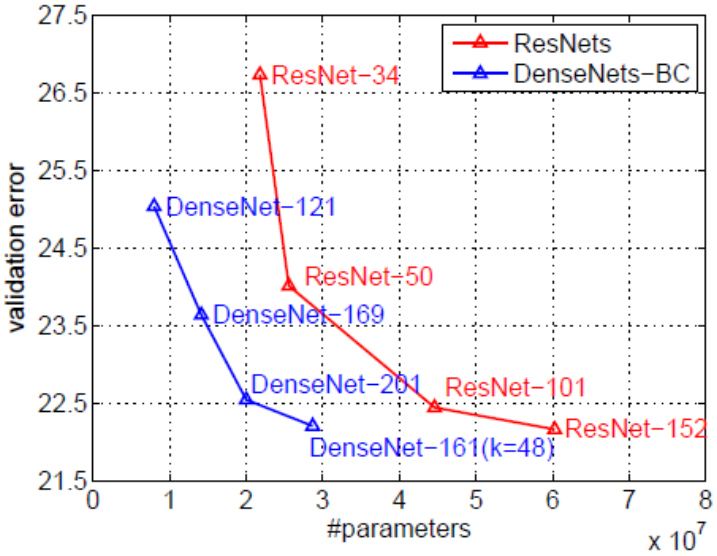
RESULTS ON CIFAR-10

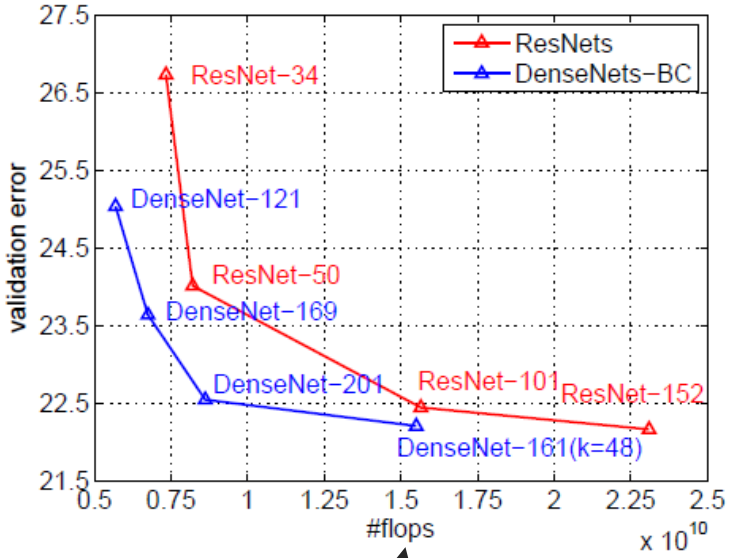


RESULTS ON CIFAR-100



RESULTS ON IMAGENET

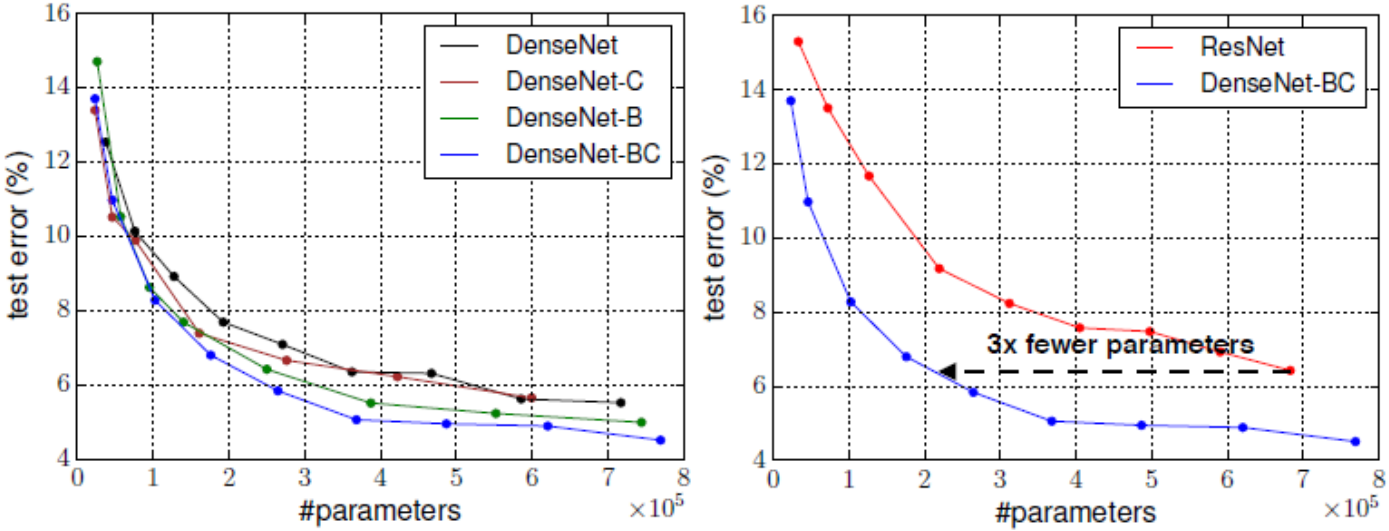


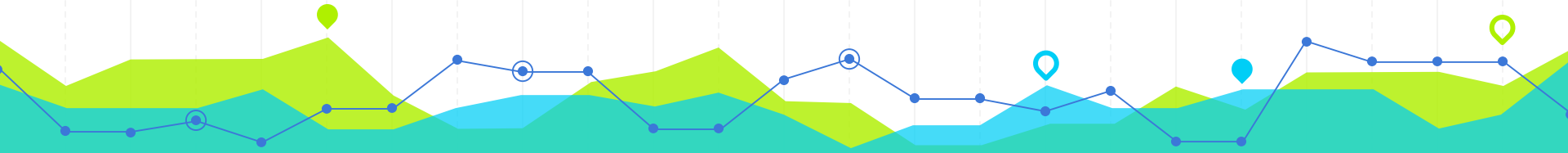


Floating-point operations

COMPARISON OF DENSENET VARIATIONS

- DenseNet-B : There are bottleneck layers.
- DenseNet-C : Compression ratio θ is less than 1. (See the previous slide named “Compression”)
- DenseNet-BC : Joint of ‘B’ and ‘C’.





Thank You!