Densely Connected Convolutional Networks

SKT Fellowship

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December 10, 2022

Introduction

About DenseNet

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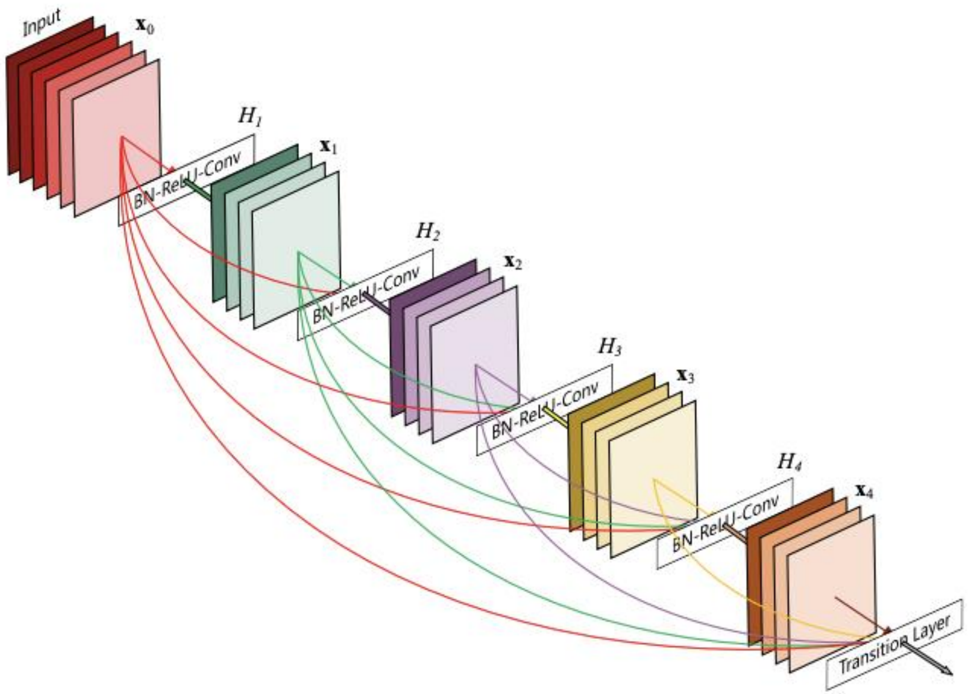
4. Advantages of DenseNet

- Strong Gradient Flow
- Parameters & Computational Efficiency
- Maintain Low Complexity Features

What is DenseNet

Densely Connected Network



Network가 Deep해짐에 따라 Vanishing gradient가 발생한다는 문제를 해결하기 위해 Skip-Connection 사용(Resnet)

Skip-Connection을 adjacent layer끼리 사용하는 것이 아닌 모든 layer에 연결하여 Dense Connectivity를 만듦

→ Dense-Connectivity로 인한 Gradient의 직접적 연결을 통해 Deep Network로 인해 발생하는 Optimize 문제를 해결

→ 적은 Parameters와 Narrow Network

ResNet to DenseNet

Why DenseNet is better

Resnet의 후속 연구를 통해 깊은 네트워크에서 모든 layer가 유의미하지 않음을 확인 (Stochastic Depth, dropout layers randomly

→ 깊은 레이어를 쌓는 것 보다 각 레이어를 병렬적으로 연결해 Compact Network를 생성함 (Feature reuse, Efficient)

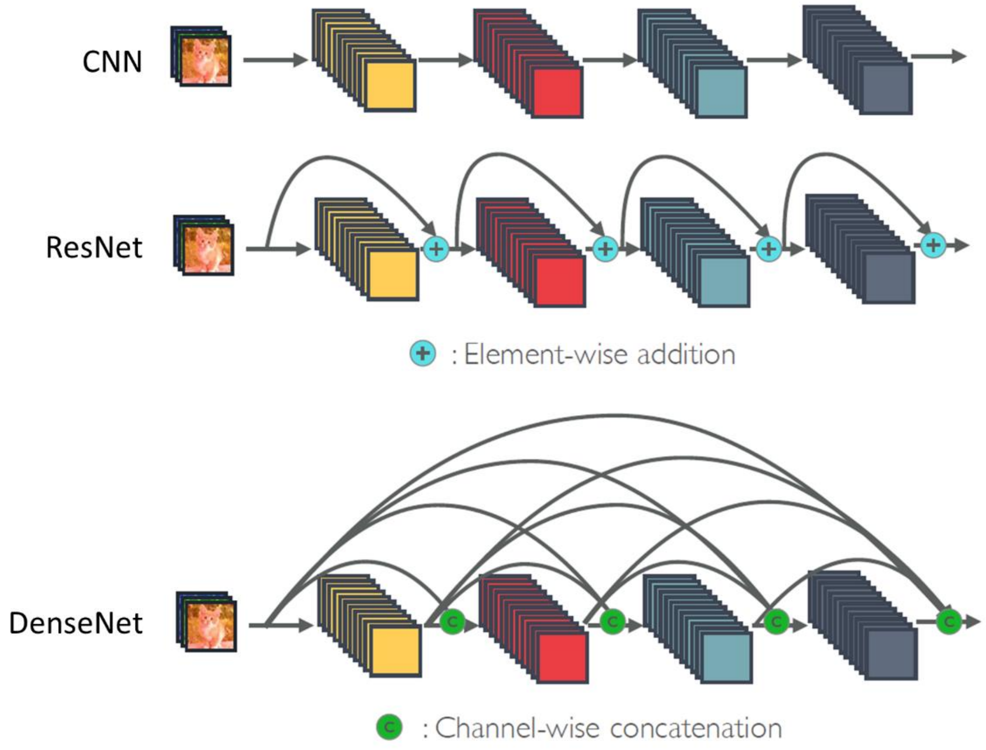
+ Summation Skip-Connection 방식이 input information과 skip-connected information을 혼합시켜 오히려 성능을 방해할 수 있다 (DenseNet은 concate을 통해 두 information을 구분)

Resnet

$$x_l = H_l(x_{l-1}) + x_{l-1}$$

Densenet

$$x_l = H_l([x_0, x_1, \ldots, x_{l-1}])$$

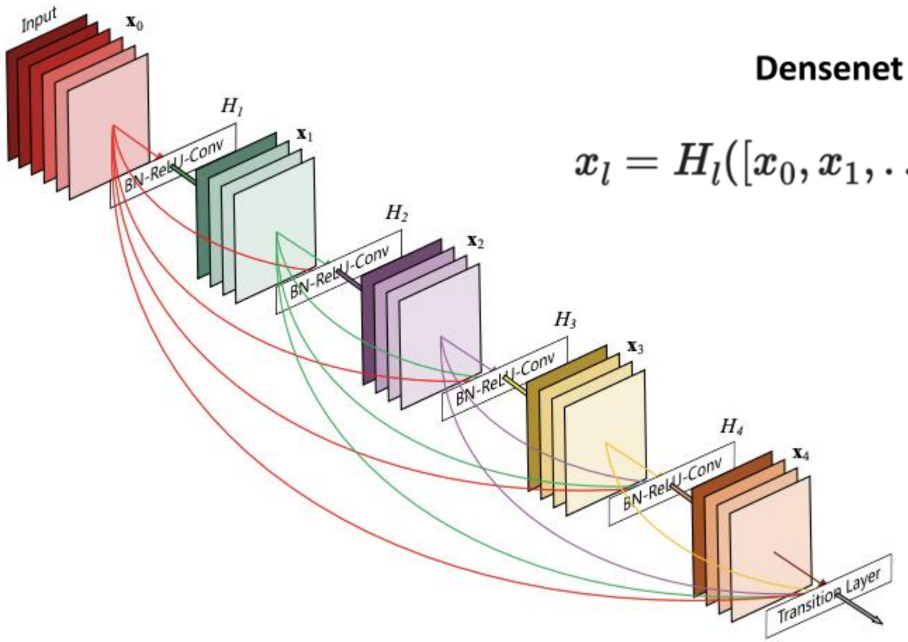


DenseNet – Dense Connectivity

DenseNet Structure

H_I(X_I)에서 나온 값을 모두 합쳐 input information으로 활용

Composite function H_1을 BN – RELU – 3X3 CONV로 구성하고 input과 output size를 유지한다 (Basic DenseNet)



Densenet

$$x_l = H_l([x_0, x_1, \ldots, x_{l-1}])$$

DenseNet – Pooling layers

DenseNet Structure

Information들의 concate을 위해선 information들의 size가 모두 동일해야한다 But, CNN의 기본 개념은 **차원, 크기 축소에 따른 특징 추출에** 있다 (Pooling)

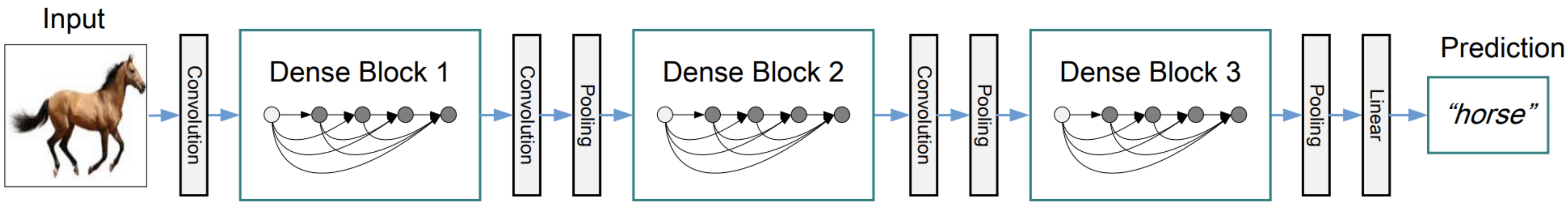


Figure 2: A deep DenseNet with three dense blocks. The layers between two adjacent blocks are referred to as transition layers and change feature-map sizes via convolution and pooling.

→ Network를 Dense Blocks로 나눈다

→ 각 Dense Block은 Dense Connectivity 상태이며 size가 동일하다

→ Dense Block 사이에 transition layers (CONV, POOL)를 통해 차원 축소를 한다

DenseNet – Pooling layers

DenseNet Structure

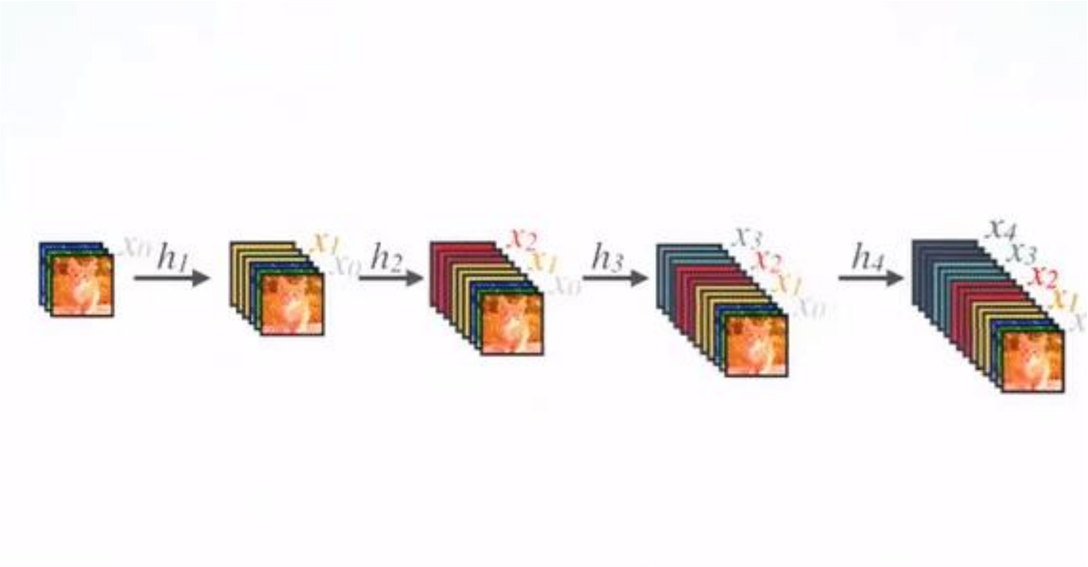
Layers	Output Size	DenseNet-121	DenseNet-169	DenseNet-201	DenseNet-264
Convolution	112×112	7×7 conv, stride 2			
Pooling	56×56	3×3 max pool, stride 2			
Dense Block (1)	56×56	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 6$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 6$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 6$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 6$
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	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 24$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 32$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 48$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 64$
Transition Layer (3)	14×14	1×1 conv			
	7×7	2×2 average pool, stride 2			
Dense Block (4)	7×7	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 16$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 32$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 32$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 48$
Classification Layer	1×1	7×7 global average pool			
		1000D fully-connected, softmax			

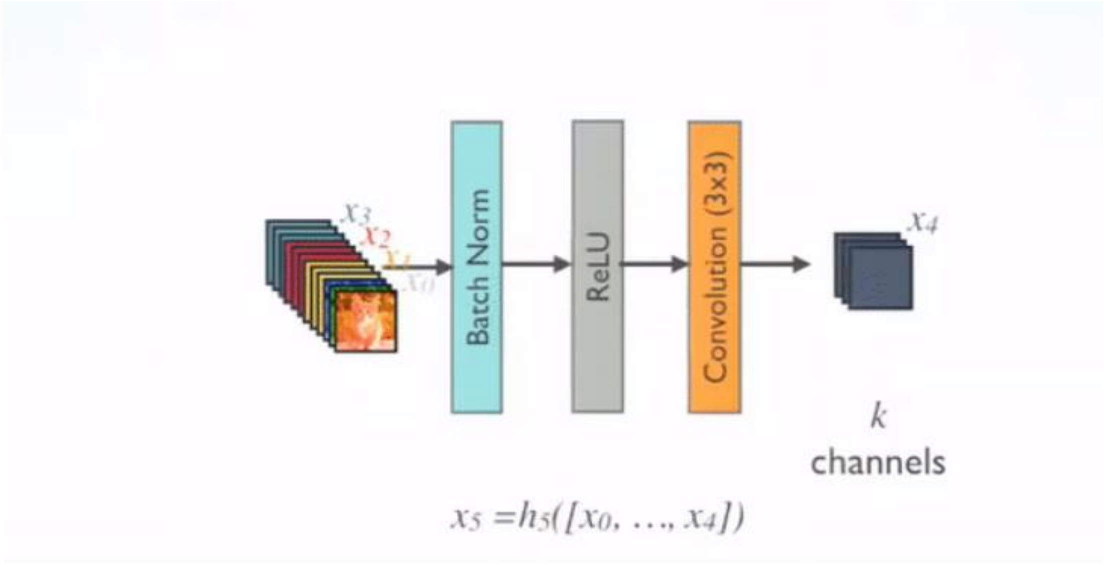
DenseNet – Growth Rate

DenseNet Structure

H_l을 통해 k feature-maps가 생성된다고 했을 때, l_th layer는 k_0 + k(l-1) feature-maps를 갖는다
(k : hyper-parameters, Network Depth를 결정)

→ DenseNet이 narrow 할 수 있는 이유

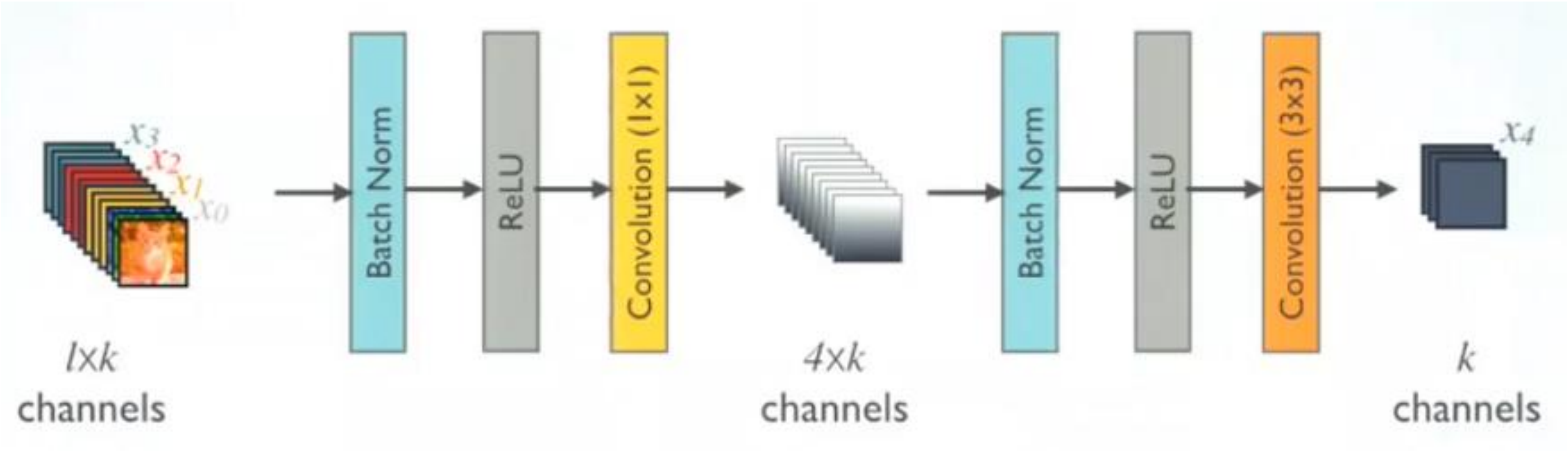




DenseNet – Bottleneck layers

DenseNet Structure

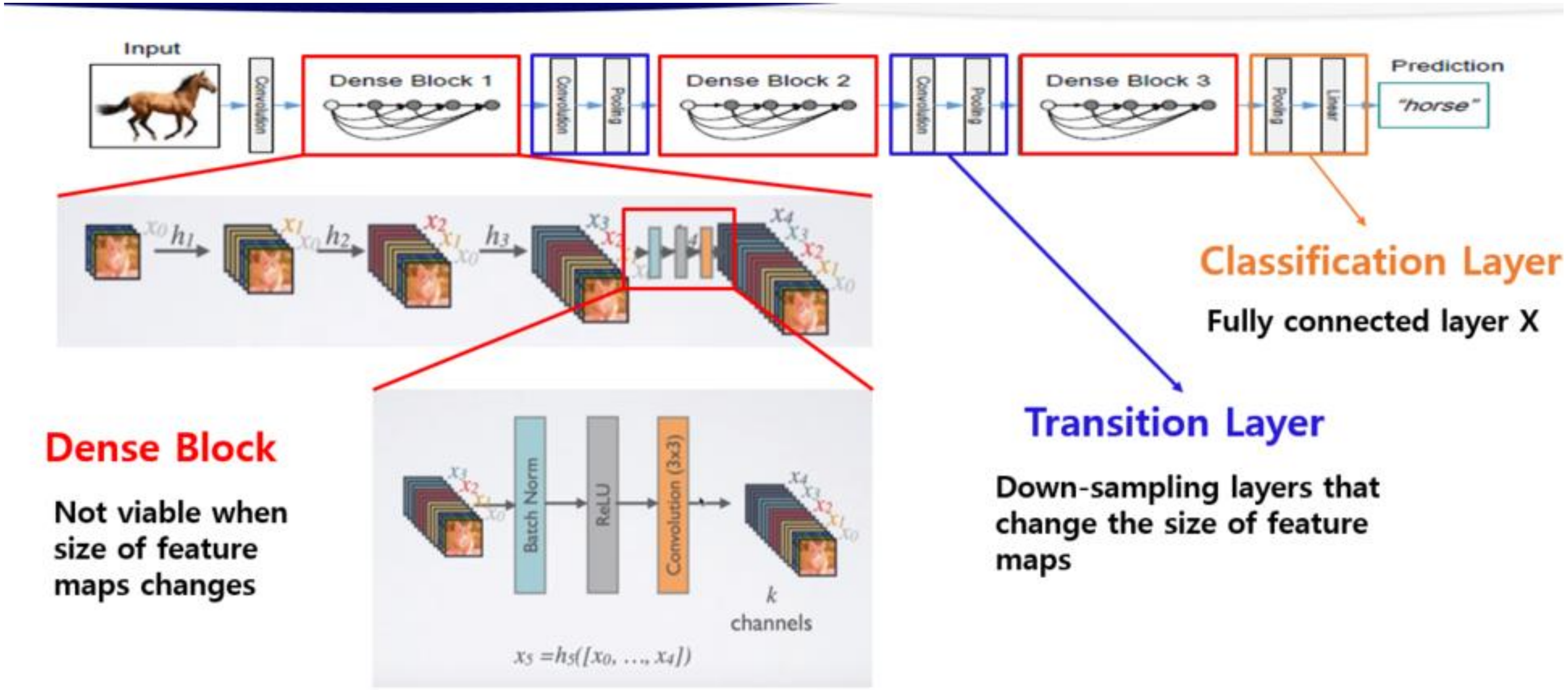
H_l : 더 efficient한 network를 위해 Conv(1x1)을 통해 각 layer의 input Channel을 줄이고 계산 (Densenet-B)



DenseNet – Compression

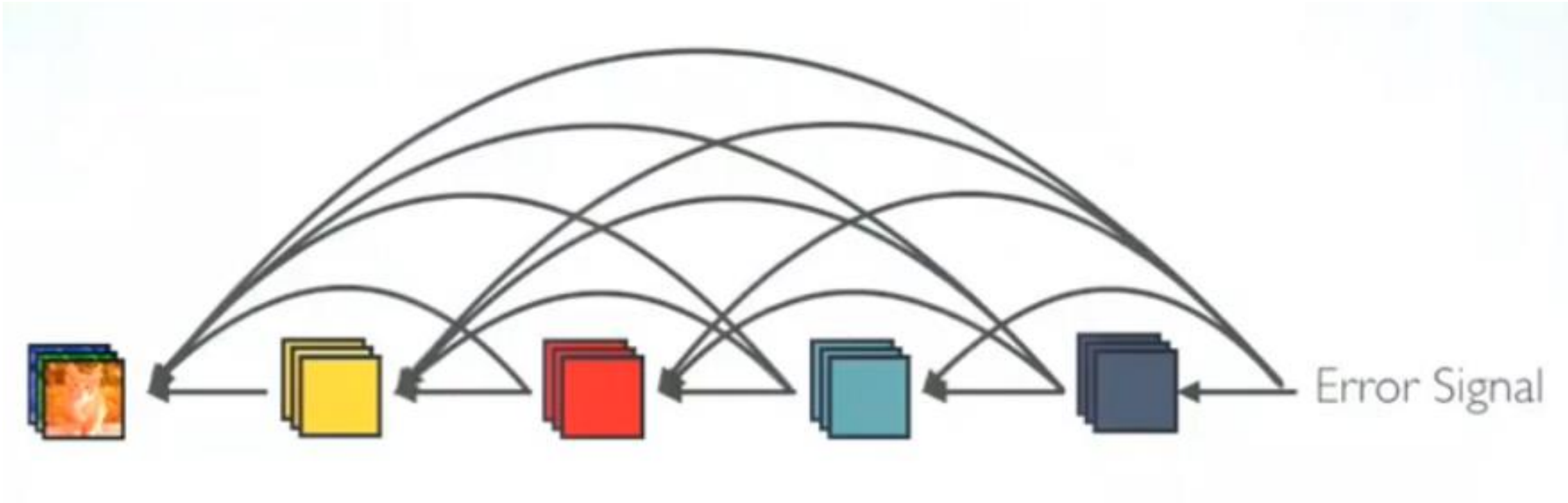
DenseNet Structure

Network의 Compactness를 위해 Dense Block에서 뿐만이 아니라 Transition layer에서도 thelta를 통해 Channels의 크기를 축소 (Densenet-BC)



Advatages of DenseNet – Strong Gradient Flow

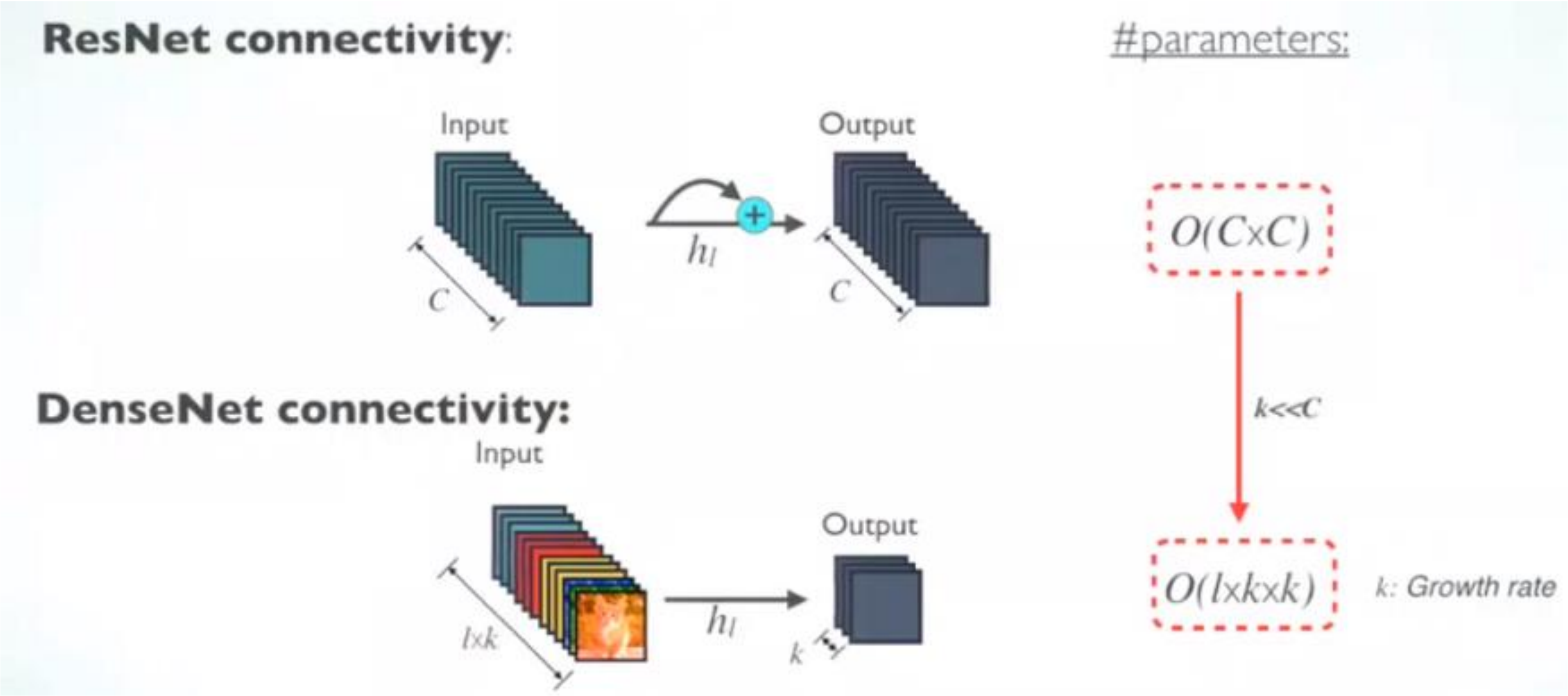
Avoid Vanishing Gradient



초기 layers와도 직접적인 연결을 통해 Vanishing Gradient 없이 back-propagation 진행

Advatages of DenseNet – Parameters & Computational Efficiency

Cost Efficient Modeling



Fixed Growth rate, Bottleneck을 통해 Narrow한 Network를 만들어 기존 CNN, ResNet에 비해 적은 Computational Cost

Advatages of DenseNet – Maintain Low Complexity Features

Use all size of complexity

Low & High level feature들을 병렬적으로 사용함으로서 적은 데이터로도 특징 추출이 잘 일어날 수 있게 함
(모든 Complexity의 Features 사용)