2nd week
CV study

Speaker:류창훈

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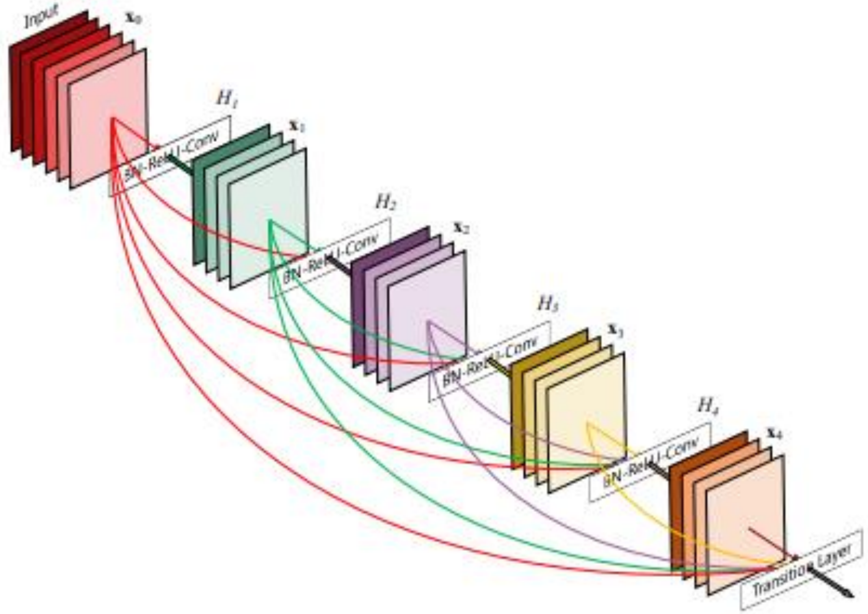
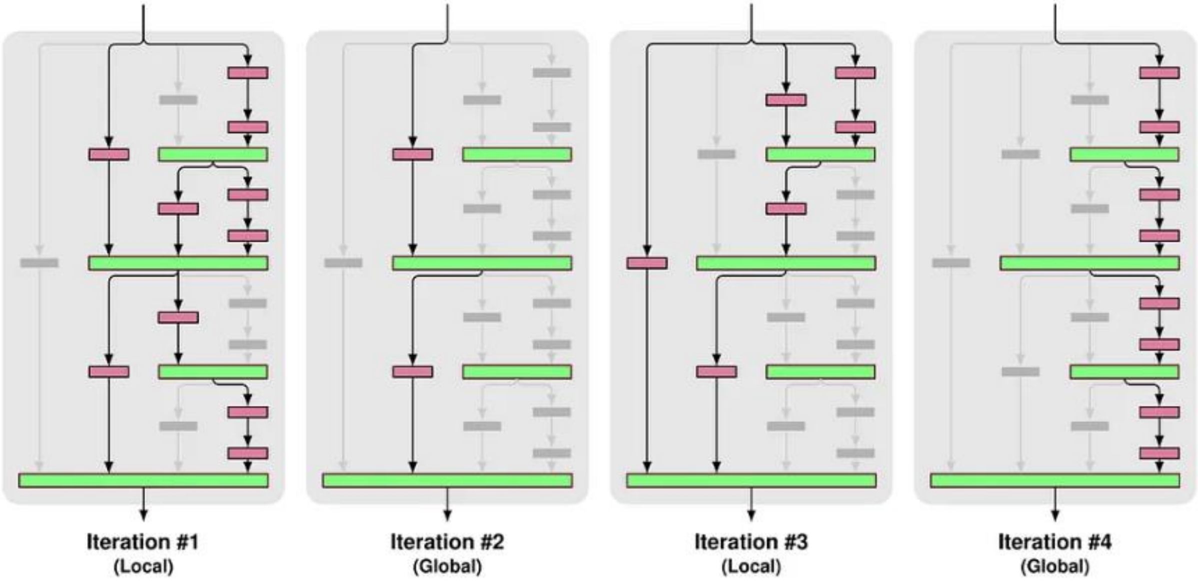
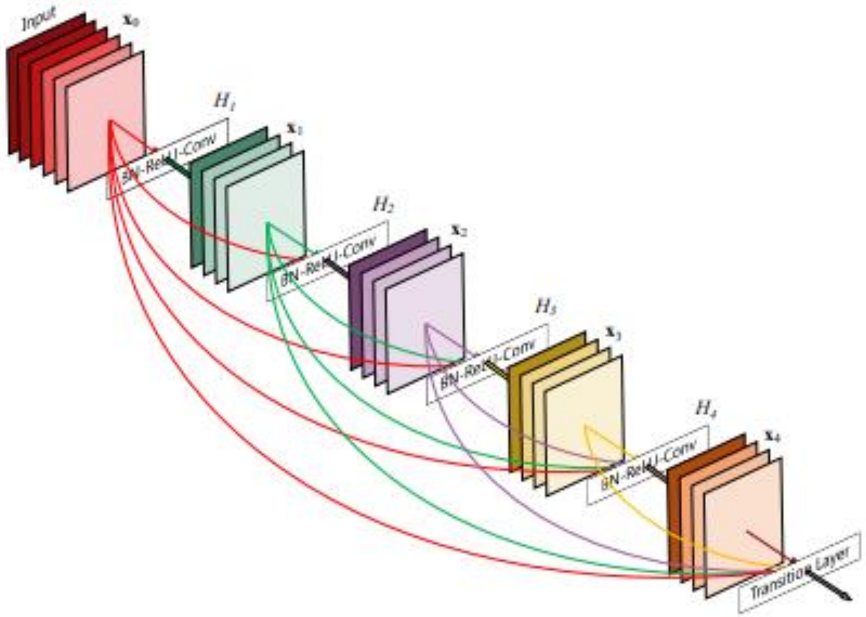
Densely Connected Convolutional Networks(DenseNet)



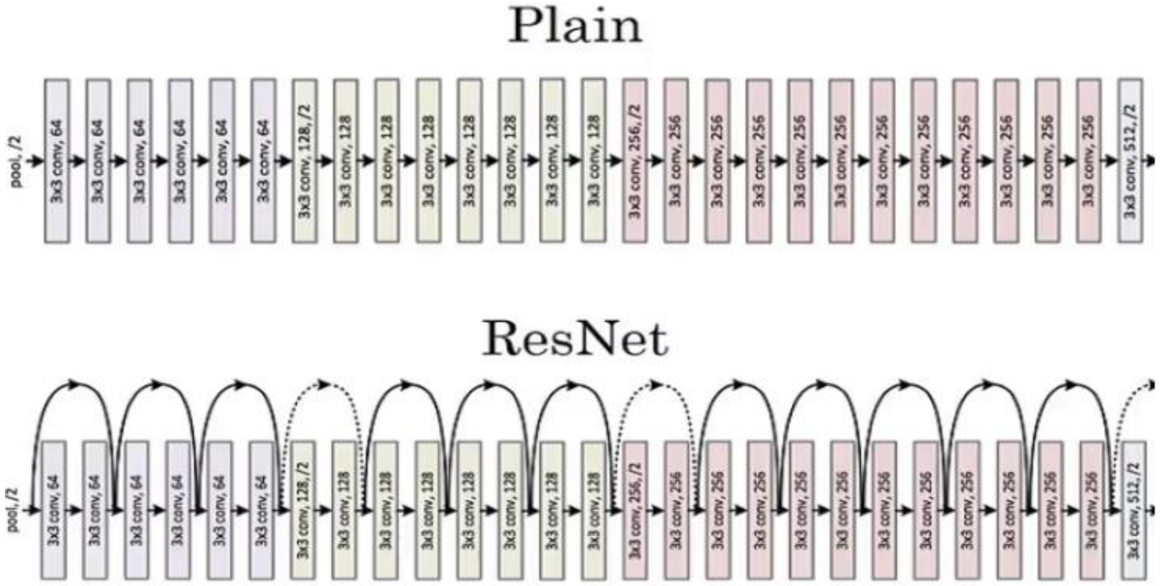
DenseNet



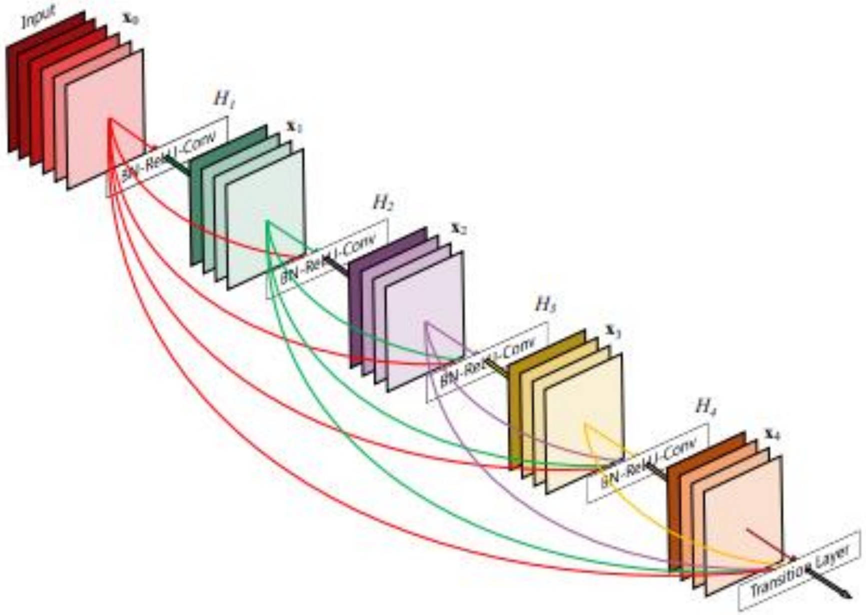
FractalNet



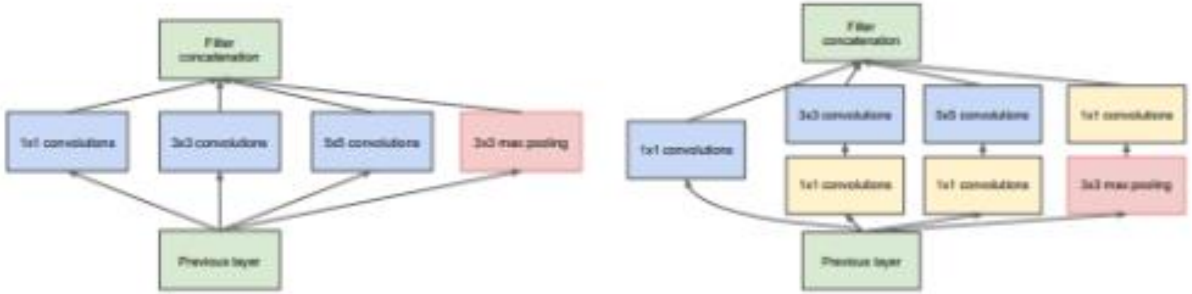
DenseNet



ResNet



DenseNet



(a) Inception module, naïve version (b) Inception module with dimension reductions

Figure 2: Inception module

GoogleNet

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input:
L개의 Layer에 L개의 input

각 Layer마다 L(L+1) / 2 개의 connect.

전체 sum 하는 구조가 아닌, 각각 연결만 한 구조.

획기적.

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계층마다 가중치 값 갖고 있음.

각 계층마다 연결만 하는 구조.

결국 Parameter값 감소.

모든 특성도 고려하는 효과.

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Related Work:

기존의 계단식 구조 + 바이패스 경로(HighwayNet)

여기에 무작위(확률적)로 레이어 제거 기능 추가.
(훨씬 더 많은 레이어 고려 가능)

바이패스 경로:
일부 레이어를 건너뛰는 방식.

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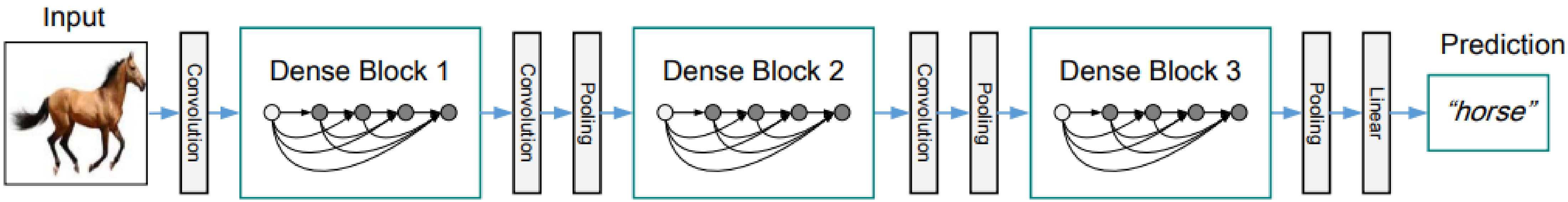

특징 재사용,
각 레이어에서 피쳐맵 연결,
효율적, 다양성 증가.

$$\mathbf{x}_\ell = H_\ell(\mathbf{x}_{\ell-1}) + \mathbf{x}_{\ell-1}.$$

➔ **ResNet**

$$\mathbf{x}_\ell = H_\ell([\mathbf{x}_0, \mathbf{x}_1, \ldots, \mathbf{x}_{\ell-1}]),$$

➔ **Dense 연결**

ℓ^{th} layer has $k_0 + k \times (\ell - 1)$

transition layer:

다운 샘플링 위함.

뜬금없는 1x1 layer,(Bottle Neck)

2x2 average pooling

$$\ell^{th} \text{ layer has } k_0 + k \times (\ell - 1)$$

각 층들은 위와 같은 입력값.

애초에 연결만 한 구조라

이렇게 적은 입력 값들로 기존의 정확도 따라잡음.

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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			

Method	Depth	Params	C10	C10+	C100	C100+	SVHN
Network in Network [22]	-	-	10.41	8.81	35.68	-	2.35
All-CNN [32]	-	-	9.08	7.25	-	33.71	-
Deeply Supervised Net [20]	-	-	9.69	7.97	-	34.57	1.92
Highway Network [34]	-	-	-	7.72	-	32.39	-
FractalNet [17]	21	38.6M	10.18	5.22	35.34	23.30	2.01
with Dropout/Drop-path	21	38.6M	7.33	4.60	28.20	23.73	1.87
ResNet [11]	110	1.7M	-	6.61	-	-	-
ResNet (reported by [13])	110	1.7M	13.63	6.41	44.74	27.22	2.01
ResNet with Stochastic Depth [13]	110	1.7M	11.66	5.23	37.80	24.58	1.75
	1202	10.2M	-	4.91	-	-	-
Wide ResNet [42]	16	11.0M	-	4.81	-	22.07	-
	28	36.5M	-	4.17	-	20.50	-
with Dropout	16	2.7M	-	-	-	-	1.64
ResNet (pre-activation) [12]	164	1.7M	11.26^*	5.46	35.58^*	24.33	-
	1001	10.2M	10.56^*	4.62	33.47^*	22.71	-
DenseNet ($k = 12$)	40	1.0M	**7.00**	5.24	**27.55**	24.42	1.79
DenseNet ($k = 12$)	100	7.0M	**5.77**	**4.10**	**23.79**	**20.20**	1.67
DenseNet ($k = 24$)	100	27.2M	**5.83**	**3.74**	**23.42**	**19.25**	**1.59**
DenseNet-BC ($k = 12$)	100	0.8M	**5.92**	4.51	**24.15**	22.27	1.76
DenseNet-BC ($k = 24$)	250	15.3M	**5.19**	**3.62**	**19.64**	**17.60**	1.74
DenseNet-BC ($k = 40$)	190	25.6M	-	**3.46**	-	**17.18**	-

CIFAR-10

CIFAR-100

SVHN

ImageNet

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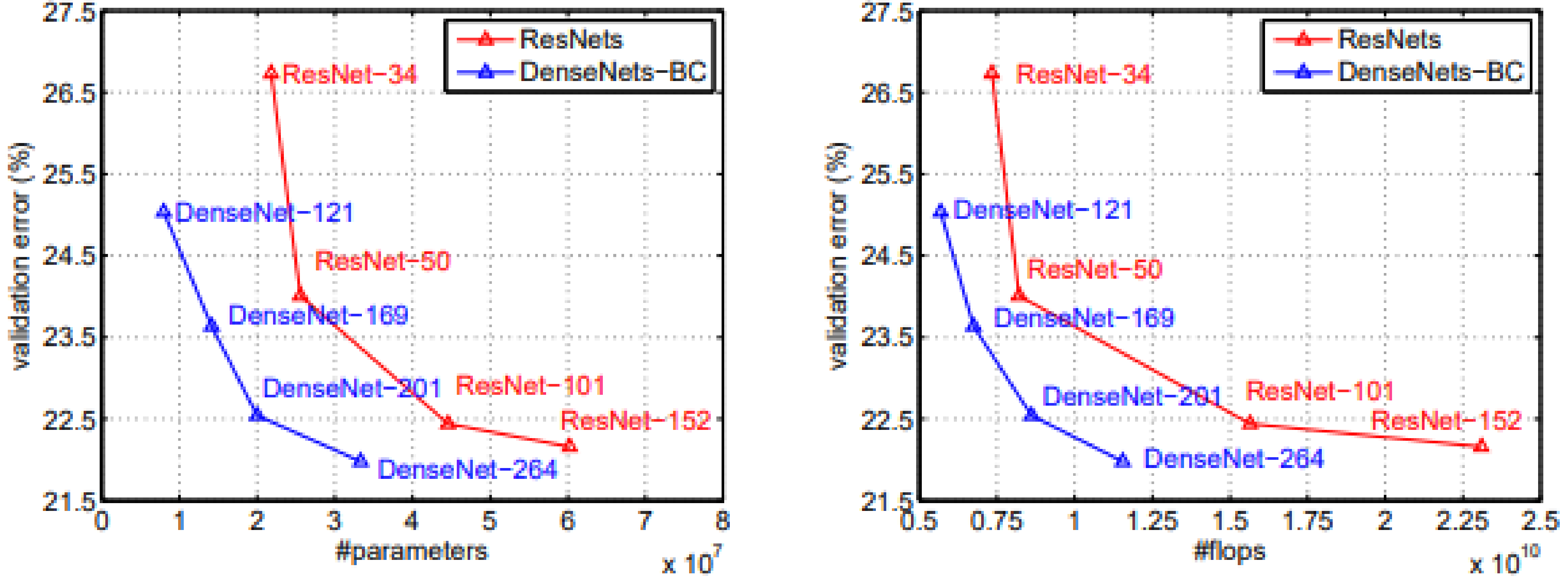

ResNets
DenseNets-BC
ResNet-34
DenseNet-121
ResNet-50
DenseNet-169
DenseNet-201
ResNet-101
ResNet-152
DenseNet-264
validation error (%)
#parameters
x 10^7
#flops
x 10^10

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출처:

https://arxiv.org/pdf/1608.06993v5.pdf

https://medium.com/@sunnerli/an-interesting-idea-toward-cnn-residual-4bb54040b9a

https://www.linkedin.com/pulse/residual-net-resnet-carmel-shalgi

https://pytorch.kr/hub/pytorch_vision_googlenet/

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