2022 Enterprise Boost Program AI/ML Basic 05

08. 이미지를 위한 신경망

CNN으로 패션상품을 분류해보자!

전현상 Solutions Architect 2022.06.28



AI/ML Basic Tracks

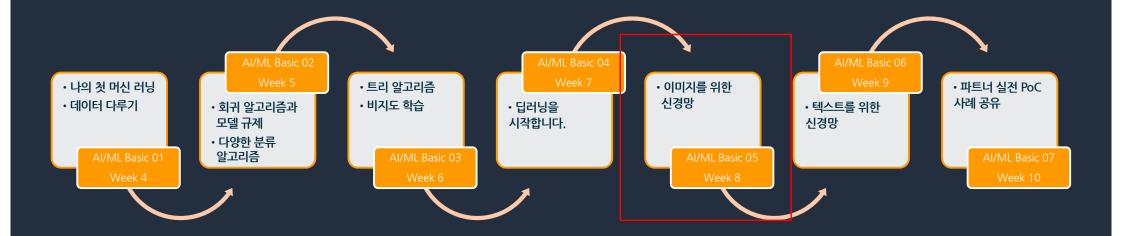




Table of contents

08. 이미지를 위한 신경망

08-1. 합성곱 신경망의 구성 요소

- Convolution operation
- Convolutional Layer

08-2. 합성곱 신경망의 시각화



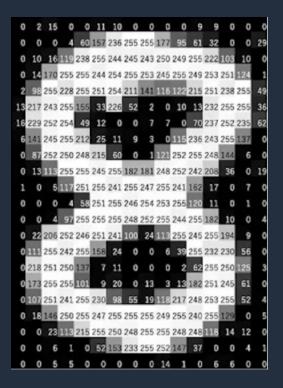
Convolutional Neural Networks



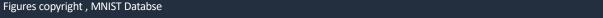
How images are stored in a Computer?

Grayscale image





(height x width) pixels





How images are stored in a Computer?

Colored image





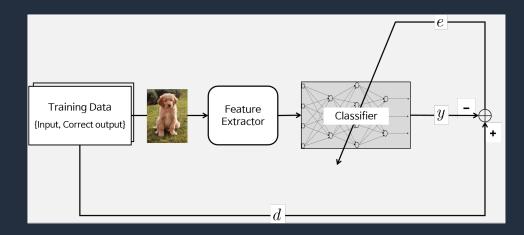
							141	142	143	144	145
							151	152	153	154	155
							161	162	163	164	165
			Ī	35	36	37	38	39	173	174	175
			Ī	45	46	47	48	49	183	184	185
			1	55	56	57	58	59	193	194	195
	_	_		65	66	67	68	69	1	_	
31	32	33	34	3	5 6	77	78	79	1 /	_	
41	42	43	44	4	5 6	87	88	89	١ ١	J	
51	52	53	54	54 55 64 65		_	_	_	1		
61	62	63	64			- [)				
71	72	73	74	7	5	- [2				
81	82	83	84	8	5						

(height x width) x 3 pixels

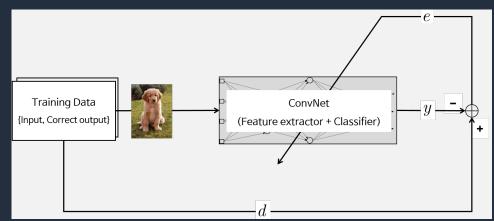


Image recognition

Perceptron neural network



Convolutional neural network



Feature extraction + Classification network

Feature extraction network + Classification network

Figures copyright , 김성필, 머신러닝에서 컨벌루션 신경망까지, 딥러닝 첫걸음



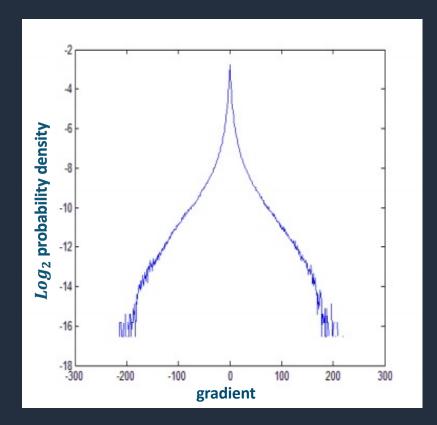
Statistics of image gradients









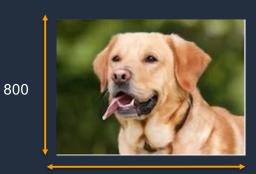


Logarithmic density of gradients from 10 natural images.



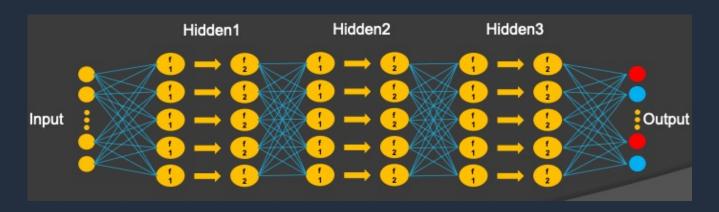
DNN Image recognition

Colored image



600

- 2차원 input data
- Pixel array: (800, 600, 3)
- Bytes: $800 \times 600 \times 3 = 1,440,000$ bytes



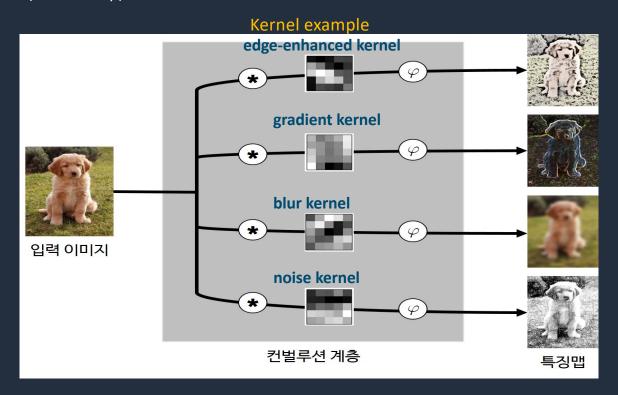
- Dense Layer에서는 모든 입력이 Hidden Layer에 연결(fully conecteted layer)
- Hidden Layer가 늘어날수록 back propagation에서 weight, bias update 계산량이 기하급수로 늘어남
- Image 의 평탄한 영역은 학습에 불필요한 영역, 특징이 잘 드러나지 않음
- 특징 추출기는 사람이 직접 설계
- 학습에서 모든 data(pixels)를 각각 node에 연결하는 것보다 효율적인 방법을 찾아보자.



CNN Image recognition

Convolution Layer

- 특징점(feature point) 추출filer(kernel)을 사용하여 입력데이터를 처리
- kernel의 개수가 특징맵(feature map)개수





CNN operation



Convolution?

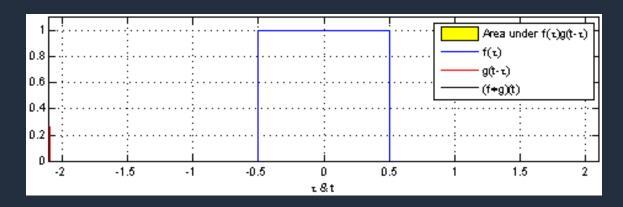
두 신호함수의 적분(중첩)

Convolution

$$(f * g)(t) = \int_{-\infty}^{\infty} f(\tau)g(t - \tau)d\tau$$



$$(f * g)(t) = \int_{-\infty}^{\infty} f(\tau)g(t+\tau)d\tau$$



Figures copyright, Convolution, Wikipedia.



2D convolution for image filtering

Convolution

$$f(x,y) * k(x,y) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(\tau_1, \tau_2) k(x - \tau_1, y - \tau_2) d\tau_1 d\tau_2$$

$$g = f * k \qquad g[i,j] = \sum_{u=-k}^{k} \sum_{v=-k}^{k} k[u,v] f[i-u,j-v]$$





2D Convolution ? Cross-Correlation

$$Y = I - K + 1$$

$$1 \cdot 1 + 2 \cdot 6 + -1 \cdot 5 + 0 \cdot 3 = 8$$

$$1 \cdot 6 + 2 \cdot 2 + -1 \cdot 3 + 0 \cdot 1 = 7$$

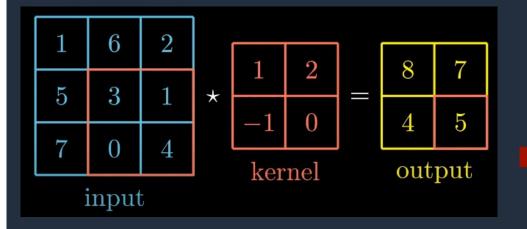
$$\begin{array}{|c|c|c|c|c|c|c|}
\hline
1 & 6 & 2 \\
5 & 3 & 1 \\
7 & 0 & 4
\end{array}$$

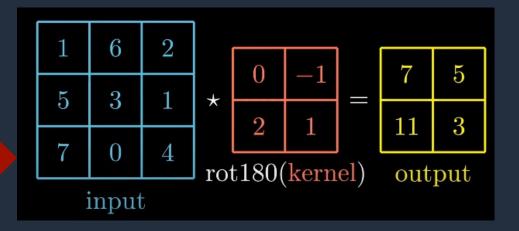
$$\star
\begin{array}{|c|c|c|c|c|}
\hline
1 & 2 \\
-1 & 0 \\
\hline
kernel & output
\end{array}$$

$$1 \cdot 3 + 2 \cdot 1 + -1 \cdot 0 + 0 \cdot 4 = 5$$



Convolution & Cross Correlation





Cross-Correlation
$$(f * g)(t) = \int_{-\infty}^{\infty} f(\tau)g(t+\tau)d\tau$$

Convolution
$$I*K = I * rot 180(K)$$

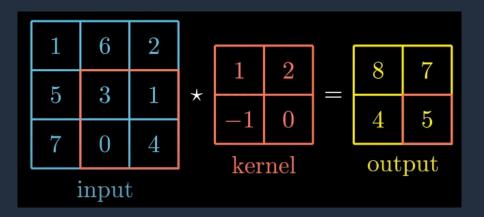
$$(f*g)(t) = \int_{-\infty}^{\infty} f(\tau)g(t-\tau)d\tau$$



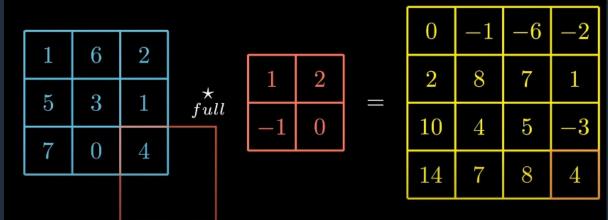
Convolution

Padding

valid



• full cross correlation(same)



Keras functional parameter : padding (default = 'valid')

- valid : kernel에 매칭되지 않는 부분 skip, (0,0)시작
- same : kernel에 매칭 되지 않는 부분 0 padding



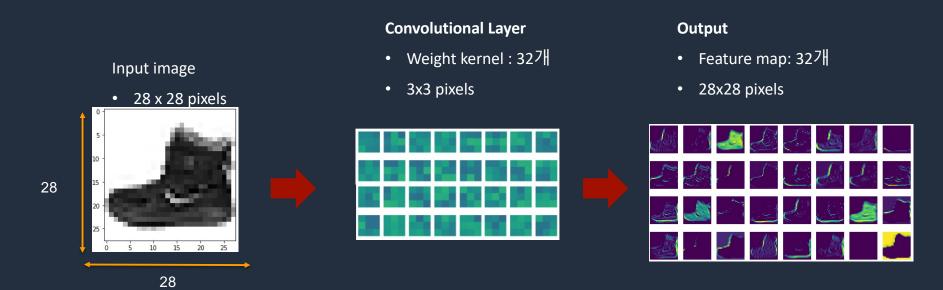
Convolution Layer



CNN for Image

Tensorflow keras CNN example

model.add(keras.layers.Conv2D(32, kernel_size=3, activation='relu', padding='same', input_shape=(28,28,1)))



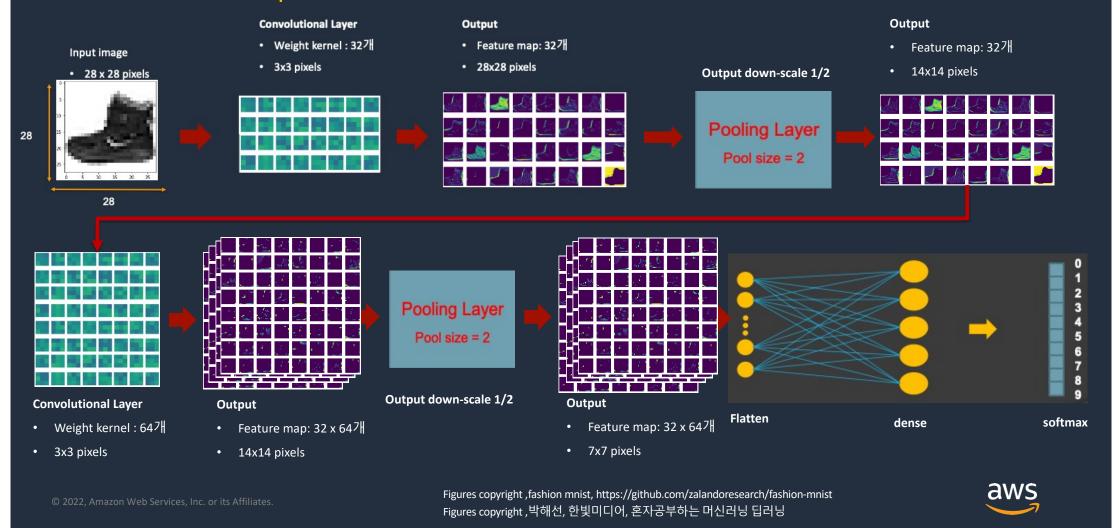
Weight Parameters:

- Input_channel * w_kernel * h_kernel* + biases
- $1 \times 3 \times 3 \times 32 + 32 = 320$



CNN for Image

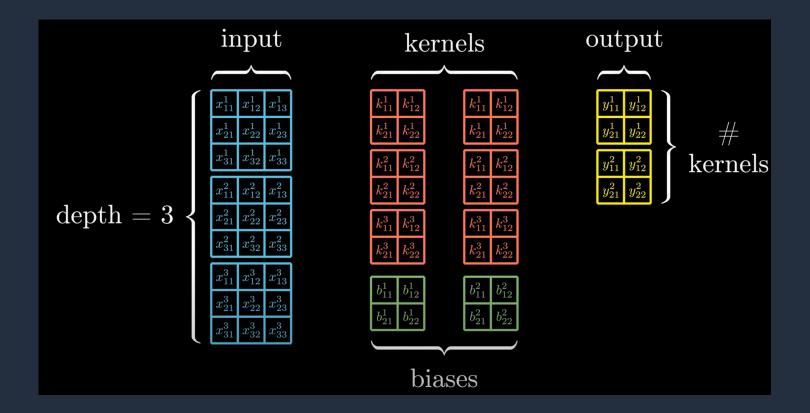
Tensorflow keras CNN example



Visualization of Multi-Layer Perceptron & CNN













$$Y_{1} = B_{1} + X_{1} * K_{11} + X_{2} * K_{12} + X_{3} * K_{13}$$

$$Y_{2} = B_{2} + X_{1} * K_{21} + X_{2} * K_{22} + X_{3} * K_{23}$$

$$\vdots$$

$$Y_{d} = B_{d} + X_{1} * K_{d1} + X_{2} * K_{d2} + X_{3} * K_{d3}$$

$$X_{1} = X_{11} = X_{21} = X_{22}$$

$$X_{2} = X_{22} = X_{22$$



$$Y_i = B_i + \sum_{j=1}^n X_j \star K_{ij}, \quad i = 1 \dots d$$

$$Y_1 = B_1 + X_1 \star K_{11} + \dots + X_n \star K_{1n}$$

$$Y_2 = B_2 + X_1 \star K_{21} + \dots + X_n \star K_{2n}$$

$$\vdots$$

$$Y_d = B_d + X_1 \star K_{d1} + \dots + X_n \star K_{dn}$$



$$Y_{i} = B_{i} + \sum_{j=1}^{n} X_{j} \star K_{ij}, \quad i = 1 \dots d$$

$$Y_{1} = B_{1} + X_{1} \star K_{11} + \dots + X_{n} \star K_{1n}$$

$$Y_{2} = B_{2} + X_{1} \star K_{21} + \dots + X_{n} \star K_{2n}$$

$$\vdots$$

$$Y_{d} = B_{d} + X_{1} \star K_{d1} + \dots + X_{n} \star K_{dn}$$

$$\begin{bmatrix} Y_1 \\ Y_2 \\ \vdots \\ Y_d \end{bmatrix} = \begin{bmatrix} B_1 \\ B_2 \\ \vdots \\ B_d \end{bmatrix} + \begin{bmatrix} K_{11} & K_{12} & \dots & K1n \\ K_{21} & K_{22} & \dots & K2n \\ \vdots & \vdots & \vdots & \vdots \\ K_{d1} & K_{d2} & \dots & Kdn \end{bmatrix} \cdot |\star \begin{bmatrix} X_1 \\ X_2 \\ \vdots \\ X_n \end{bmatrix}$$

$$Y = B + K \cdot |\star X$$

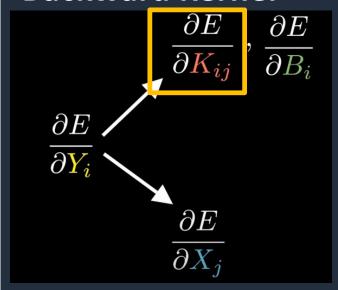


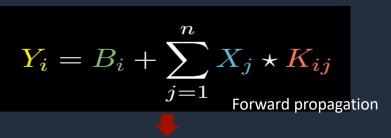
Convolution Layer

Backward Operation



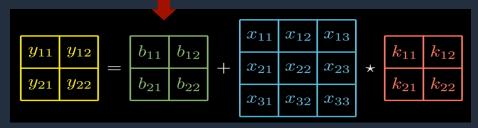
Backward Kernel





$$Y_i = B_i + X_1 \star K_{i1} + \dots + X_n \star K_{in}$$

Simplified example



$$y_{11} = b_{11} + k_{11}x_{11} + k_{12}x_{12} + k_{21}x_{21} + k_{22}x_{22}$$

$$\begin{cases} y_{12} = b_{12} + k_{11}x_{12} + k_{12}x_{13} + k_{21}x_{22} + k_{22}x_{23} \\ y_{21} = b_{21} + k_{11}x_{21} + k_{12}x_{22} + k_{21}x_{31} + k_{22}x_{32} \\ y_{22} = b_{22} + k_{11}x_{22} + k_{12}x_{23} + k_{21}x_{32} + k_{22}x_{33} \end{cases}$$



Backward Kernel

$$\begin{cases} y_{11} = b_{11} + k_{11}x_{11} + k_{12}x_{12} + k_{21}x_{21} + k_{22}x_{22} \\ y_{12} = b_{12} + k_{11}x_{12} + k_{12}x_{13} + k_{21}x_{22} + k_{22}x_{23} \\ y_{21} = b_{21} + k_{11}x_{21} + k_{12}x_{22} + k_{21}x_{31} + k_{22}x_{32} \\ y_{22} = b_{22} + k_{11}x_{22} + k_{12}x_{23} + k_{21}x_{32} + k_{22}x_{33} \end{cases}$$

$$\frac{\partial E}{\partial k_{11}} = \frac{\partial E}{\partial y_{11}} \frac{\partial y_{11}}{\partial k_{11}} + \frac{\partial E}{\partial y_{12}} \frac{\partial y_{12}}{\partial k_{11}} + \frac{\partial E}{\partial y_{21}} \frac{\partial y_{21}}{\partial k_{11}} + \frac{\partial E}{\partial y_{22}} \frac{\partial y_{22}}{\partial k_{11}}$$

$$\frac{\partial E}{\partial k_{11}} = \frac{\partial E}{\partial y_{11}} \frac{\partial y_{11}}{\partial k_{11}} + \frac{\partial E}{\partial y_{12}} \frac{\partial y_{12}}{\partial k_{11}} + \frac{\partial E}{\partial y_{21}} \frac{\partial y_{21}}{\partial k_{11}} + \frac{\partial E}{\partial y_{22}} \frac{\partial y_{22}}{\partial k_{11}}$$

$$x_{11} \qquad x_{12} \qquad x_{21} \qquad x_{22}$$

$$\frac{\partial E}{\partial k_{11}} = \frac{\partial E}{\partial y_{11}} x_{11} + \frac{\partial E}{\partial y_{12}} x_{12} + \frac{\partial E}{\partial y_{21}} x_{21} + \frac{\partial E}{\partial y_{22}} x_{22}$$



$$\frac{\partial E}{\partial k_{11}} = \frac{\partial E}{\partial y_{11}} x_{11} + \frac{\partial E}{\partial y_{12}} x_{12} + \frac{\partial E}{\partial y_{21}} x_{21} + \frac{\partial E}{\partial y_{22}} x_{22}$$

$$\frac{\partial E}{\partial k_{12}} = \frac{\partial E}{\partial y_{11}} x_{12} + \frac{\partial E}{\partial y_{12}} x_{13} + \frac{\partial E}{\partial y_{21}} x_{22} + \frac{\partial E}{\partial y_{22}} x_{23}$$

$$\frac{\partial E}{\partial k_{21}} = \frac{\partial E}{\partial y_{11}} x_{21} + \frac{\partial E}{\partial y_{12}} x_{22} + \frac{\partial E}{\partial y_{21}} x_{31} + \frac{\partial E}{\partial y_{22}} x_{32}$$

$$\frac{\partial E}{\partial k_{22}} = \frac{\partial E}{\partial y_{11}} x_{22} + \frac{\partial E}{\partial y_{12}} x_{23} + \frac{\partial E}{\partial y_{21}} x_{32} + \frac{\partial E}{\partial y_{22}} x_{33}$$



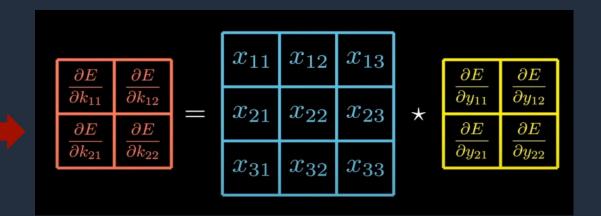
Backward Kernel

$$\frac{\partial E}{\partial k_{11}} = \frac{\partial E}{\partial y_{11}} x_{11} + \frac{\partial E}{\partial y_{12}} x_{12} + \frac{\partial E}{\partial y_{21}} x_{21} + \frac{\partial E}{\partial y_{22}} x_{22}$$

$$\frac{\partial E}{\partial k_{12}} = \frac{\partial E}{\partial y_{11}} x_{12} + \frac{\partial E}{\partial y_{12}} x_{13} + \frac{\partial E}{\partial y_{21}} x_{22} + \frac{\partial E}{\partial y_{22}} x_{23}$$

$$\frac{\partial E}{\partial k_{21}} = \frac{\partial E}{\partial y_{11}} x_{21} + \frac{\partial E}{\partial y_{12}} x_{22} + \frac{\partial E}{\partial y_{21}} x_{31} + \frac{\partial E}{\partial y_{22}} x_{32}$$

$$\frac{\partial E}{\partial k_{22}} = \frac{\partial E}{\partial y_{11}} x_{22} + \frac{\partial E}{\partial y_{12}} x_{23} + \frac{\partial E}{\partial y_{21}} x_{32} + \frac{\partial E}{\partial y_{22}} x_{33}$$



$$Y = B + X \star K \Rightarrow \frac{\partial E}{\partial K} = X \star \frac{\partial E}{\partial Y}$$

Simplified version

$$\frac{\partial E}{\partial K} = X \star \frac{\partial E}{\partial Y}$$

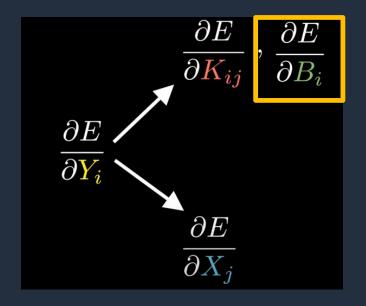
Actual version

$$Y_i = B_i + \sum_{j=1}^n X_j \star K_{ij}, \quad i = 1 \dots d$$

$$\frac{\partial E}{\partial K_{ij}} = X_j \star \frac{\partial E}{\partial Y_i}$$



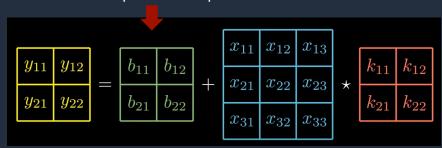
Backward bias



$$Y_i = B_i + \sum_{j=1}^n X_j \star K_{ij}$$
 Forward propagation

$$Y_i = B_i + X_1 \star K_{i1} + \dots + X_n \star K_{in}$$

Simplified example



$$y_{11} = b_{11} + k_{11}x_{11} + k_{12}x_{12} + k_{21}x_{21} + k_{22}x_{22}$$

$$\begin{cases} y_{12} = b_{12} + k_{11}x_{12} + k_{12}x_{13} + k_{21}x_{22} + k_{22}x_{23} \\ y_{21} = b_{21} + k_{11}x_{21} + k_{12}x_{22} + k_{21}x_{31} + k_{22}x_{32} \\ y_{22} = b_{22} + k_{11}x_{22} + k_{12}x_{23} + k_{21}x_{32} + k_{22}x_{33} \end{cases}$$



Backward bias

$$\begin{cases} y_{11} = b_{11} + k_{11}x_{11} + k_{12}x_{12} + k_{21}x_{21} + k_{22}x_{22} \\ y_{12} = b_{12} + k_{11}x_{12} + k_{12}x_{13} + k_{21}x_{22} + k_{22}x_{23} \\ y_{21} = b_{21} + k_{11}x_{21} + k_{12}x_{22} + k_{21}x_{31} + k_{22}x_{32} \\ y_{22} = b_{22} + k_{11}x_{22} + k_{12}x_{23} + k_{21}x_{32} + k_{22}x_{33} \end{cases}$$

$$\frac{\partial E}{\partial b_{11}} = \frac{\partial E}{\partial y_{11}} \begin{bmatrix} \partial y_{11} \\ \partial b_{11} \end{bmatrix} + \frac{\partial E}{\partial y_{12}} \begin{bmatrix} \partial y_{12} \\ \partial b_{11} \end{bmatrix} + \frac{\partial E}{\partial y_{21}} \begin{bmatrix} \partial y_{21} \\ \partial b_{11} \end{bmatrix} + \frac{\partial E}{\partial y_{22}} \begin{bmatrix} \partial y_{22} \\ \partial b_{11} \end{bmatrix}$$

$$1 \qquad 0 \qquad 0 \qquad 0$$

$$\frac{\partial E}{\partial b_{11}} = \frac{\partial E}{\partial y_{11}}$$

$$\frac{\partial E}{\partial b_{12}} = \frac{\partial E}{\partial y_{12}}$$

$$\frac{\partial E}{\partial b_{21}} = \frac{\partial E}{\partial y_{21}}$$

$$\frac{\partial E}{\partial b_{22}} = \frac{\partial E}{\partial y_{22}}$$

$$\frac{\partial E}{\partial B} = \frac{\partial E}{\partial \mathbf{Y}}$$

Simplified version

$$Y = B + X \star K \Rightarrow \frac{\partial E}{\partial B} = \frac{\partial E}{\partial Y}$$

$$\frac{\partial E}{\partial Y} = \begin{bmatrix} \frac{\partial E}{\partial y_{11}} & \frac{\partial E}{\partial y_{12}} \\ \frac{\partial E}{\partial y_{21}} & \frac{\partial E}{\partial y_{22}} \end{bmatrix} \longrightarrow \begin{bmatrix} \frac{\partial E}{\partial b_{11}} & \frac{\partial E}{\partial b_{12}} \\ \frac{\partial E}{\partial b_{21}} & \frac{\partial E}{\partial b_{22}} \end{bmatrix}$$

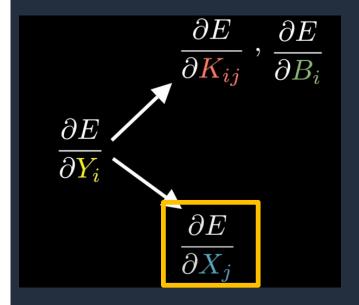
Actual version

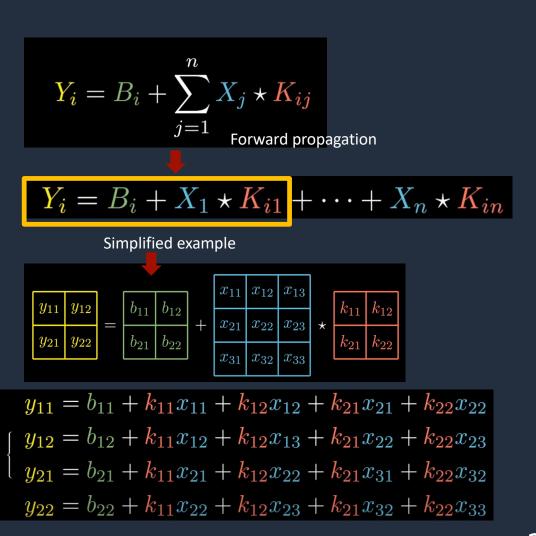
$$Y_i = B_i + \sum_{j=1}^n X_j \star K_{ij}, \quad i = 1 \dots d$$

$$\frac{\partial E}{\partial B_i} = \frac{\partial E}{\partial Y_i}$$



Backward input





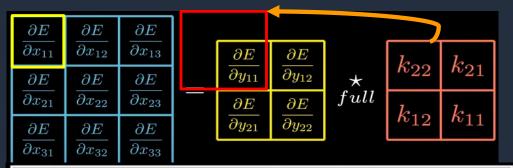


Backward bias

$$\begin{cases} y_{11} = b_{11} + k_{11}x_{11} + k_{12}x_{12} + k_{21}x_{21} + k_{22}x_{22} \\ y_{12} = b_{12} + k_{11}x_{12} + k_{12}x_{13} + k_{21}x_{22} + k_{22}x_{23} \\ y_{21} = b_{21} + k_{11}x_{21} + k_{12}x_{22} + k_{21}x_{31} + k_{22}x_{32} \\ y_{22} = b_{22} + k_{11}x_{22} + k_{12}x_{23} + k_{21}x_{32} + k_{22}x_{33} \end{cases}$$

$$\frac{\partial E}{\partial x_{11}} = \frac{\partial E}{\partial y_{11}} \begin{bmatrix} \frac{\partial y_{11}}{\partial x_{11}} \end{bmatrix} + \frac{\partial E}{\partial y_{12}} \begin{bmatrix} \frac{\partial y_{12}}{\partial x_{11}} \end{bmatrix} + \frac{\partial E}{\partial y_{21}} \begin{bmatrix} \frac{\partial y_{21}}{\partial x_{11}} \end{bmatrix} + \frac{\partial E}{\partial y_{22}} \begin{bmatrix} \frac{\partial y_{22}}{\partial x_{11}} \end{bmatrix}$$

$$k_{11} \qquad 0 \qquad 0 \qquad 0$$



$$Y = B + X \star K \Rightarrow \frac{\partial E}{\partial X} = \frac{\partial E}{\partial Y} f_{ull}^* K$$

$$\frac{\partial E}{\partial Y} = \begin{bmatrix} \frac{\partial E}{\partial y_{11}} & \frac{\partial E}{\partial y_{12}} \\ \frac{\partial E}{\partial y_{21}} & \frac{\partial E}{\partial y_{22}} \end{bmatrix} \rightarrow \begin{bmatrix} \frac{\partial E}{\partial x_{11}} & \frac{\partial E}{\partial x_{12}} & \frac{\partial E}{\partial x_{13}} \\ \frac{\partial E}{\partial x_{21}} & \frac{\partial E}{\partial x_{22}} & \frac{\partial E}{\partial x_{23}} \\ \frac{\partial E}{\partial x_{31}} & \frac{\partial E}{\partial x_{32}} & \frac{\partial E}{\partial x_{33}} \end{bmatrix}$$

Actual version

$$\frac{\partial E}{\partial X_j} = \sum_{i=1}^n \frac{\partial E}{\partial Y_i} *_{full} K_{ij}$$

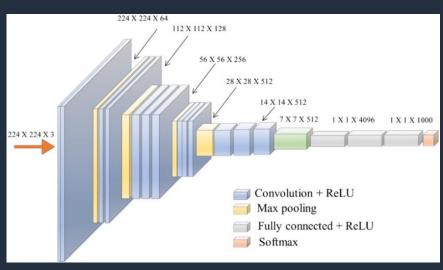


CNN Visualization



Deep CNN Layer Visualization

VGG16







Q&A





감사합니다

