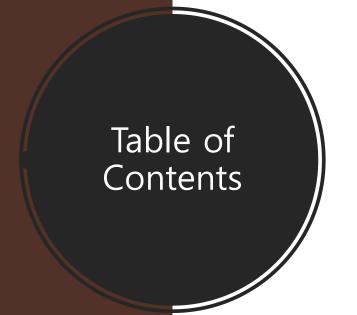
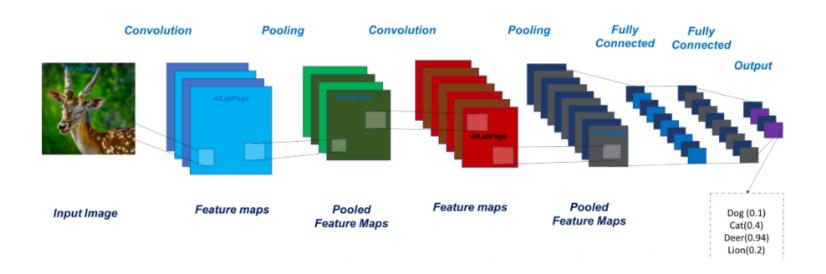
## Convolutional Neural Network

Kim Gwangho, Seo Youjung, Lee Hyunbin

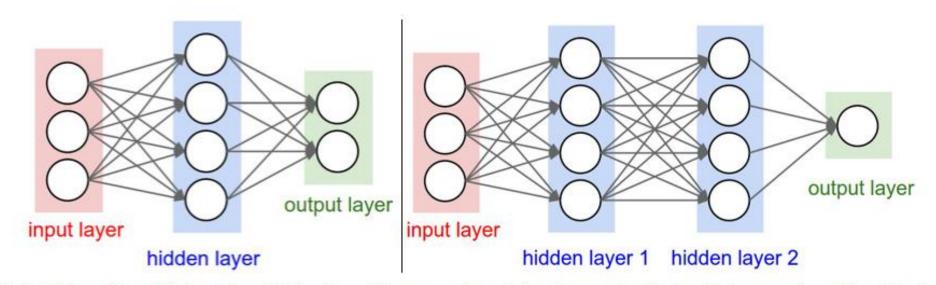




- What is Convolutional Neural Network?(1-5)
- Feature Map(Filter, Stride, Padding, Output Size)
- 중간정리
- Pooling(Max, Average Pooling)
- ReLU, Training(경사하강법, Adam, SGD)
- Structure Diagram
- Code(Keras)

Source: mcai https://mc.ai

## Regular Neural Network(Fully Connected Layer)



**Left:** A 2-layer Neural Network (one hidden layer of 4 neurons (or units) and one output layer with 2 neurons), and three inputs. **Right:** A 3-layer neural network with three inputs, two hidden layers of 4 neurons each and one output layer. Notice that in both cases there are connections (synapses) between neurons across layers, but not within a layer.

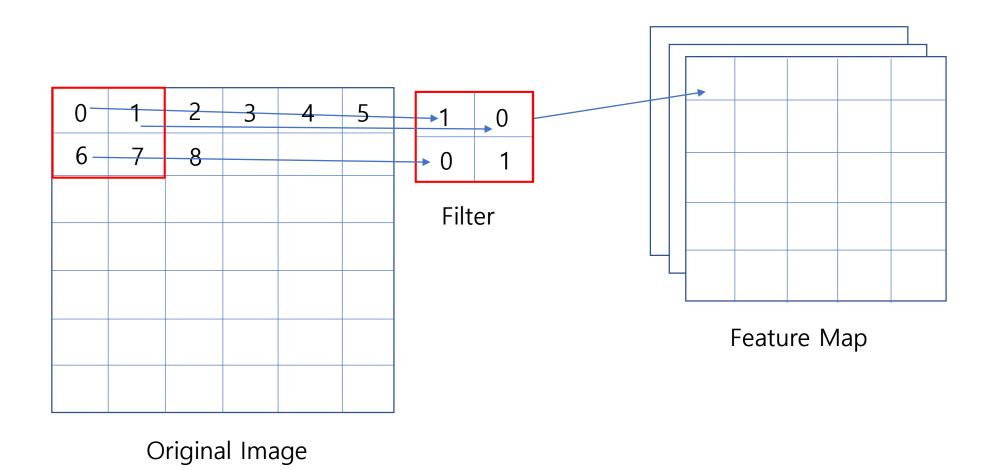
- 1. Connected with all of the adjacent neurons
- 2. Ignore spatial Image
- 3. Not applicable to colored image

Source: CS231n

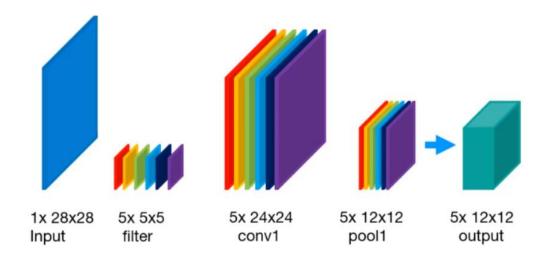
http://cs231n.github.io/convoluti

onal-networks/

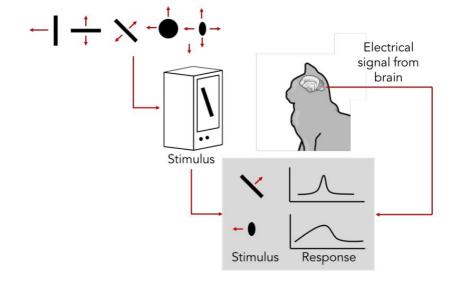
### Convolutional Neural Network



#### What is CNN?



- ✓ Image is cut down to filters to be made as convolutional layers.
- ✓ Each output is added altogether to make up a output result.

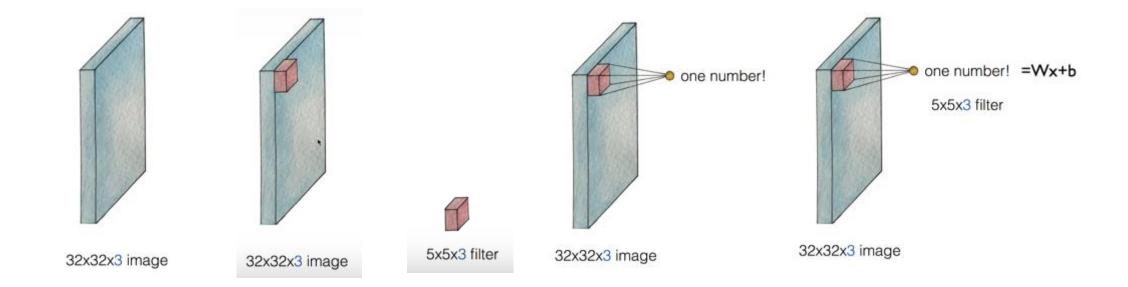


<u>Cat image</u> by CNX OpenStax is licensed under CC BY 4.0; changes made

### Hubel & Wiesel Experiment

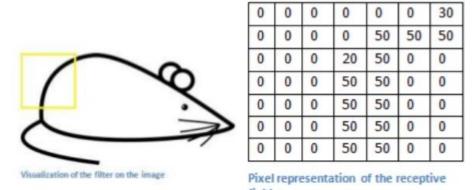
✓ Different cells respond to different stimulus of an image i.e: cells that respond to edges, oriented edges, shapes.

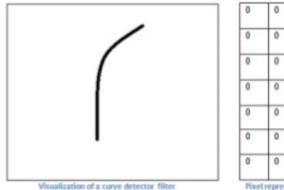
#### Filter



- ✓ One variable from one filter is made that represent a part of an image.
- ✓ In Wx+b, W indicate the filter 5x5x3 filter(using activation function)
- $\checkmark$  Filter value = Wx1 + Wx2 + Wx3 +  $\cdots$  + WxN + b + (ReLU Wx + b)
- ✓ Filter value stays fixed throughout the entire process.

#### Filter



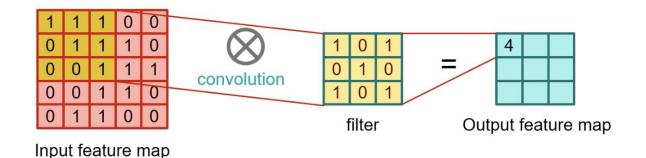


| 0 | 0 | 0 | 0  | 0  | 30 | 0 |
|---|---|---|----|----|----|---|
| 0 | 0 | 0 | 0  | 30 | 0  | 0 |
| 0 | 0 | 0 | 30 | 0  | 0  | 0 |
| 0 | 0 | 0 | 30 | 0  | 0  | 0 |
| 0 | 0 | 0 | 30 | 0  | 0  | 0 |
| 0 | 0 | 0 | 30 | 0  | 0  | 0 |
| 0 | 0 | 0 | 0  | 0  | 0  | 0 |

Pixel representation of filter

### Feature Map

$$1x1 + 1x0 + 1x1 + 0x0 + 1x1 + 1x0 + 0x1 + 0x0 + 1x1 = 4$$



- ✓ Filter is images which has the contents we'd like to detect.
- ✓ Size of filter is determined by how much pixel we'd like to detect at once.

What happens when filter slides through the image?

| <b>1</b> <sub>×1</sub> | 1,0  | 1,  | 0 | 0 |
|------------------------|------|-----|---|---|
| 0,0                    | 1,   | 1,0 | 1 | 0 |
| <b>0</b> <sub>×1</sub> | 0,×0 | 1,  | 1 | 1 |
| 0                      | 0    | 1   | 1 | 0 |
| 0                      | 1    | 1   | 0 | 0 |

| 4 |  |
|---|--|
|   |  |
|   |  |

**Image** 

Convolved Feature

- Key idea is to observe parts of the image rather than the whole.
- Feature map indicates distinctive feature of image (ex.sharpness, blue, edges)

✓ Stride = a value of how much we would like the filter to move(이동크기)



Filter =  $3 \times 3$ , Stride = 1



Filter =  $3 \times 3$ , Stride = 2

### **Padding**

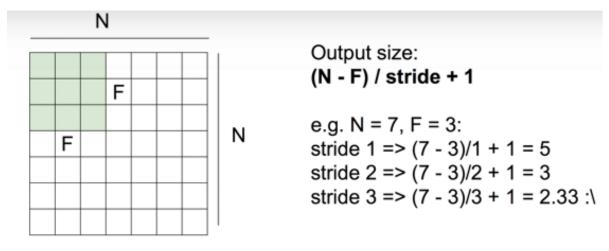
| 0 | 0 | 0 | 0 | 0 | 0 |  |  |
|---|---|---|---|---|---|--|--|
| 0 |   |   |   |   |   |  |  |
| 0 |   |   |   |   |   |  |  |
| 0 |   |   |   |   |   |  |  |
| 0 |   |   |   |   |   |  |  |
|   |   |   |   |   |   |  |  |
|   |   |   |   |   |   |  |  |
|   |   |   |   |   |   |  |  |
|   |   |   |   |   |   |  |  |

e.g. input 7x7
3x3 filter, applied with stride 1
pad with 1 pixel border => what is the output?

#### 7x7 output!

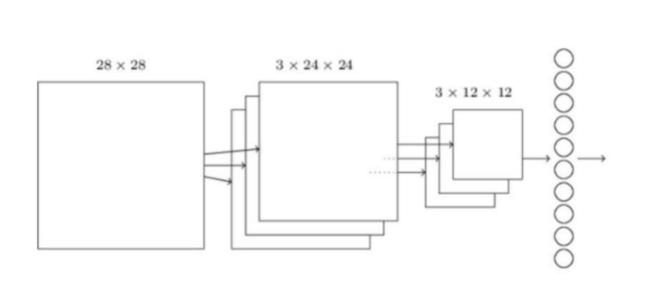
in general, common to see CONV layers with stride 1, filters of size FxF, and zero-padding with (F-1)/2. (will preserve size spatially)

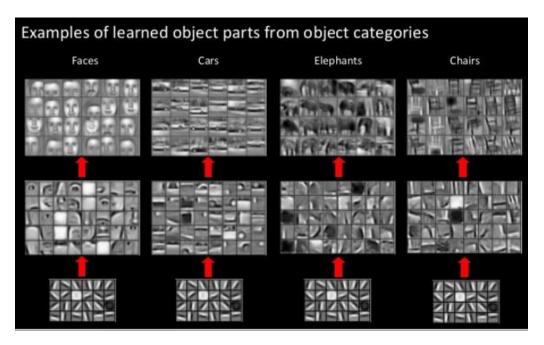
### Output Size



- ✓ To try to preserve as much output as possible.
- ✓ To identify the edges of the image

7 x 7 input spatially Assume 3 x 3 filter =  $5 \times 5$ 

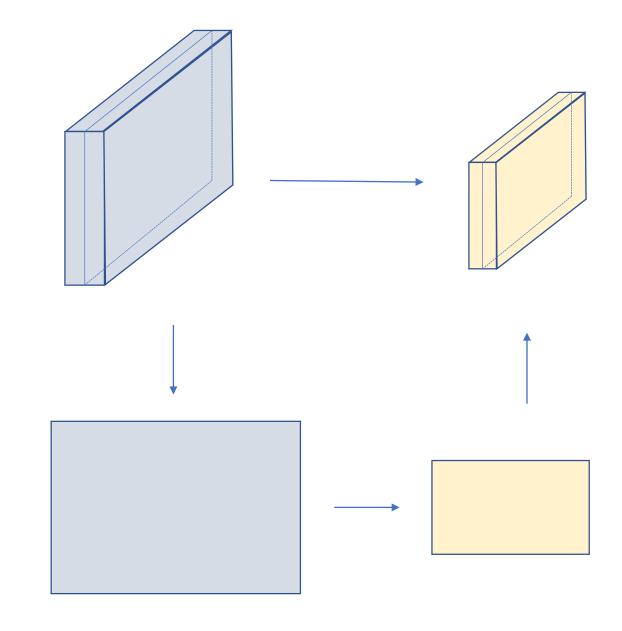




- ✓ A set of convolutional layer and pooling layer are obtained of which the layer are able to identify the images.
- ✓ <a href="https://www.youtube.com/watch?v=f0t-OCG79-U">https://www.youtube.com/watch?v=f0t-OCG79-U</a>

### Pooling

- Pooling layers reduce the dimensions of the data by replacing data of specific area to representative value.
- Reduction size of feature
- Reduction amount of calculation



| 60 | 88 | 10 | 94 | 74 | 42 | 53 | 60 | 48 |
|----|----|----|----|----|----|----|----|----|
| 75 | 48 | 9  | 14 | 61 | 17 | 26 | 93 | 43 |
| 13 | 70 | 26 | 53 | 31 | 47 | 8  | 52 | 93 |
| 64 | 23 | 70 | 2  | 28 | 36 | 9  | 25 | 68 |
| 63 | 10 | 66 | 74 | 30 | 67 | 80 | 8  | 10 |
| 38 | 38 | 77 | 47 | 52 | 42 | 21 | 88 | 40 |
| 92 | 31 | 25 | 91 | 87 | 34 | 75 | 66 | 40 |
| 17 | 44 | 53 | 29 | 69 | 62 | 29 | 29 | 68 |
| 66 | 59 | 76 | 19 | 26 | 25 | 25 | 21 | 28 |
|    |    |    |    |    |    |    |    |    |

| 88 | 94 | 93 |  |
|----|----|----|--|
| 77 | 74 | 88 |  |
| 92 | 91 | 75 |  |
|    |    |    |  |

Max Pooling

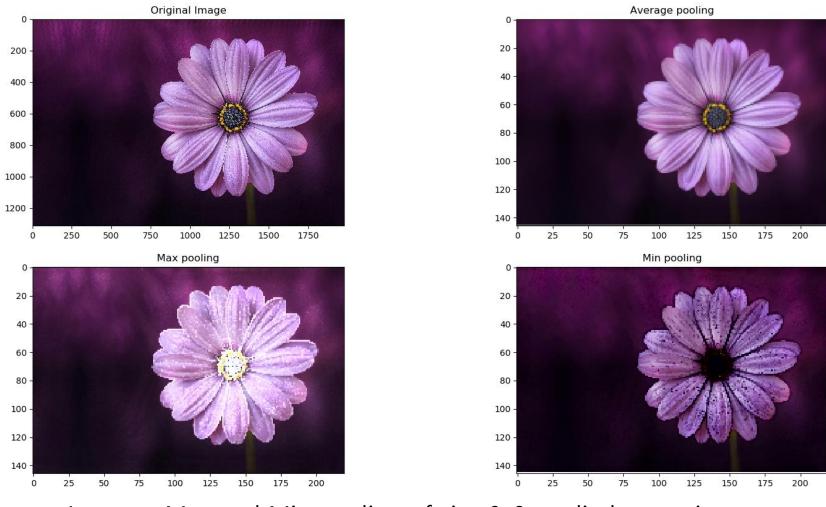
 Reduce dimension of the data by replacing <u>maximum</u> value of specific area.

| 60 | 88 | 10 | 94 | 74 | 42 | 53 | 60 | 48 |
|----|----|----|----|----|----|----|----|----|
| 75 | 48 | 9  | 14 | 61 | 17 | 26 | 93 | 43 |
| 13 | 70 | 26 | 53 | 31 | 47 | 8  | 52 | 93 |
| 64 | 23 | 70 | 2  | 28 | 36 | 9  | 25 | 68 |
| 63 | 10 | 66 | 74 | 30 | 67 | 80 | 8  | 10 |
| 38 | 38 | 77 | 47 | 52 | 42 | 21 | 88 | 40 |
| 92 | 31 | 25 | 91 | 87 | 34 | 75 | 66 | 40 |
| 17 | 44 | 53 | 29 | 69 | 62 | 29 | 29 | 68 |
| 66 | 59 | 76 | 19 | 26 | 25 | 25 | 21 | 28 |
|    |    |    |    |    |    |    |    |    |

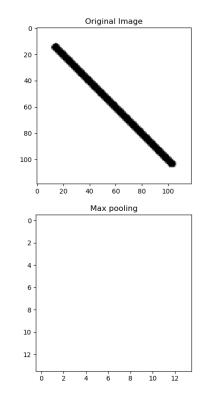
| 44.33 | 48.11 | 52.89 |  |
|-------|-------|-------|--|
| 49.89 | 42    | 38.78 |  |
| 51.44 | 49.11 | 42.33 |  |
|       |       |       |  |

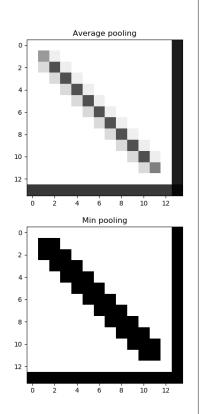
Average Pooling

• Reduce dimension of the data by replacing <u>average</u> value of specific area.

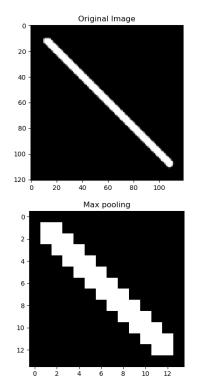


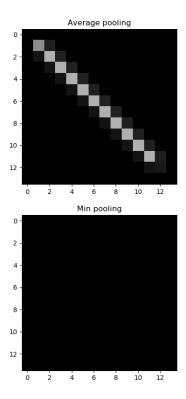
Average, Max and Min pooling of size 9x9 applied on an image





Min pooling gives better result for images with white background and black object



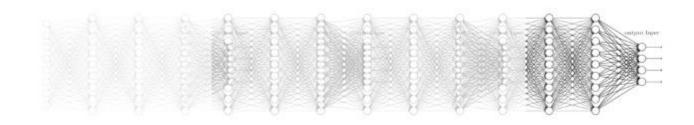


Max pooling gives better result for the images with black background and white object

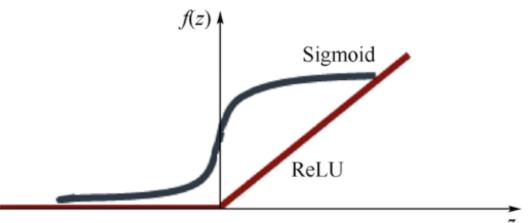
### ReLU

To avoid Vanishing gradient

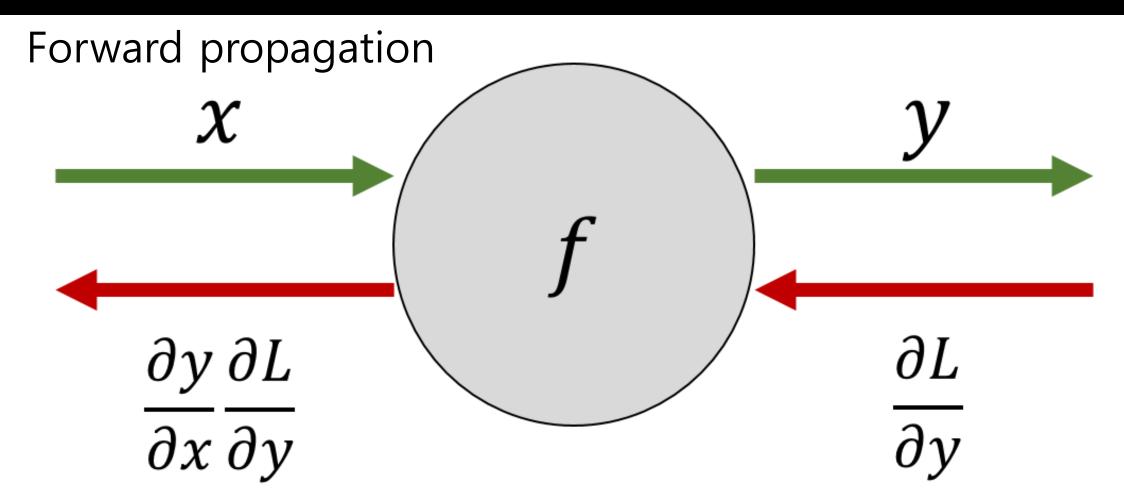
### Vanishing gradient (NN winter2: 1986-2006)



Sigmoid!



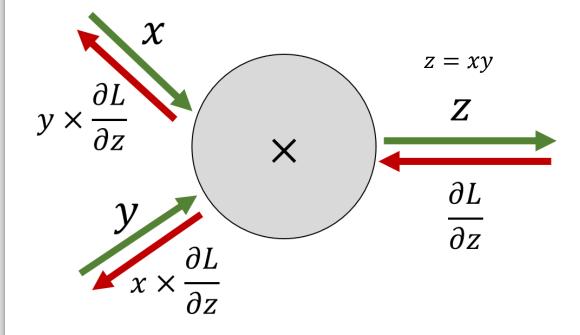
## Backpropagation



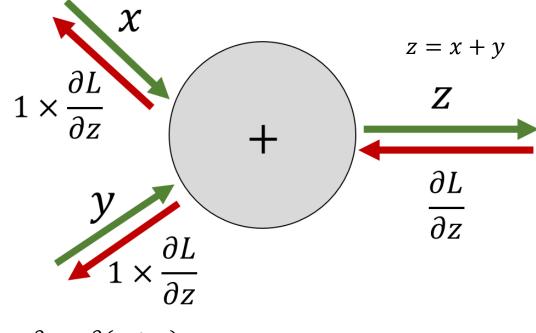
Backward propagation

$$\frac{\partial z}{\partial x} = \frac{\partial (xy)}{\partial x} = y$$

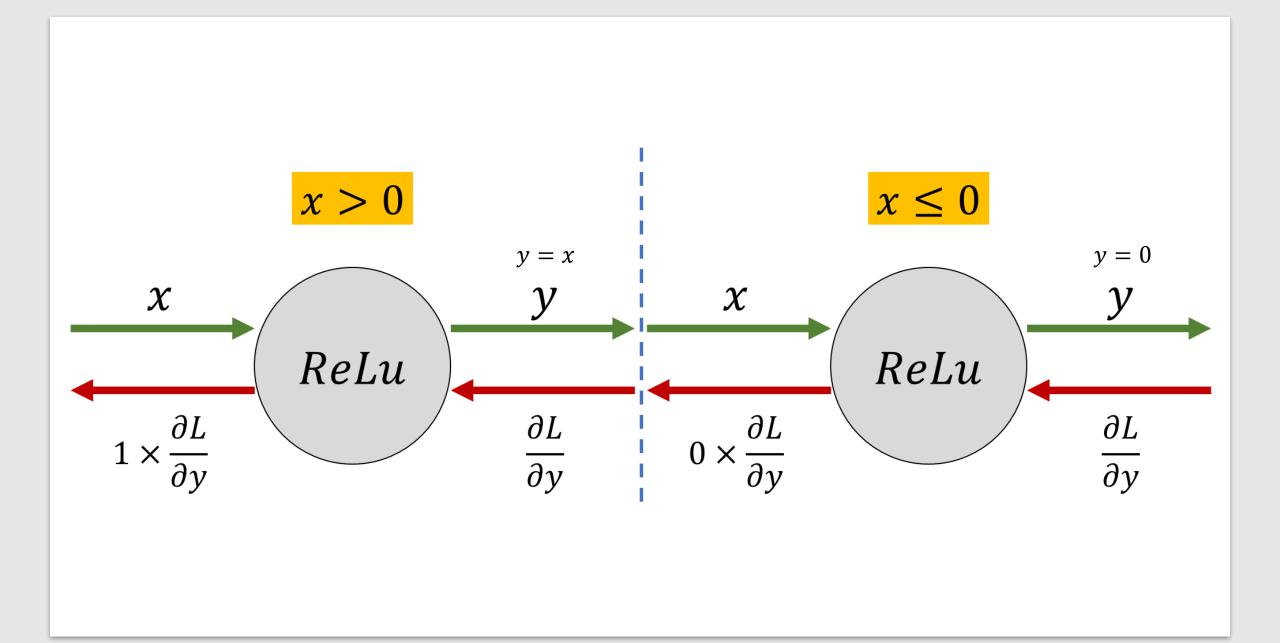
 $\frac{\partial z}{\partial y} = \frac{\partial (xy)}{\partial y} = x$ 

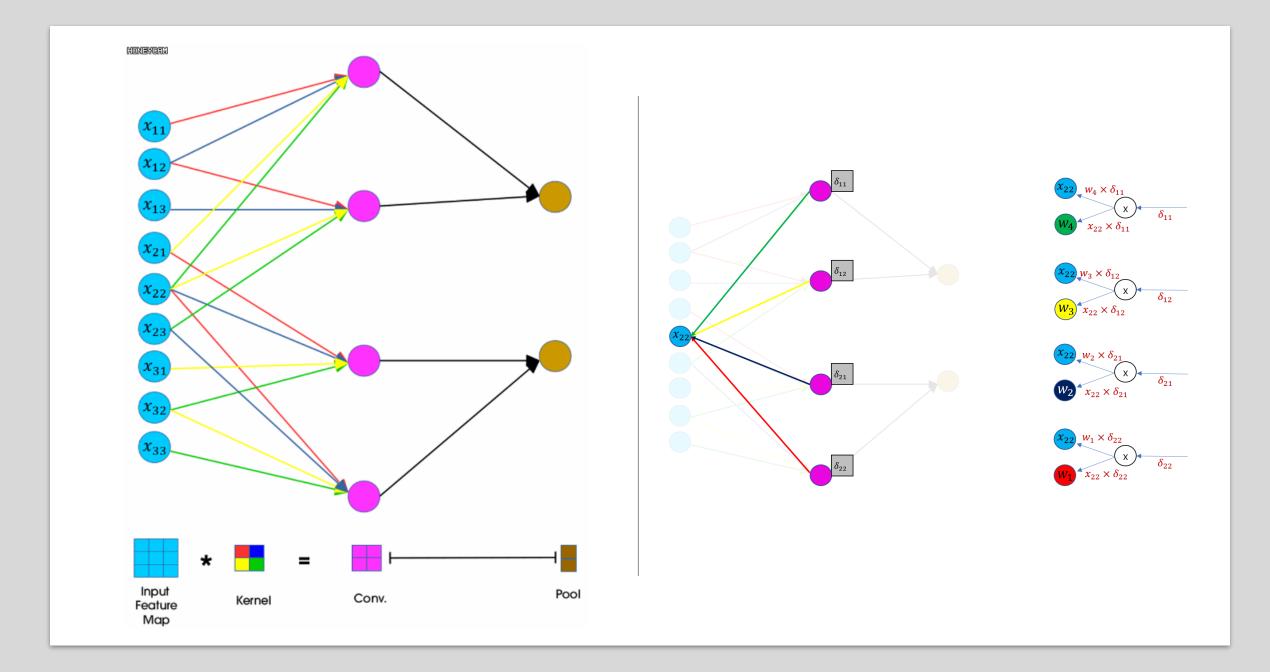


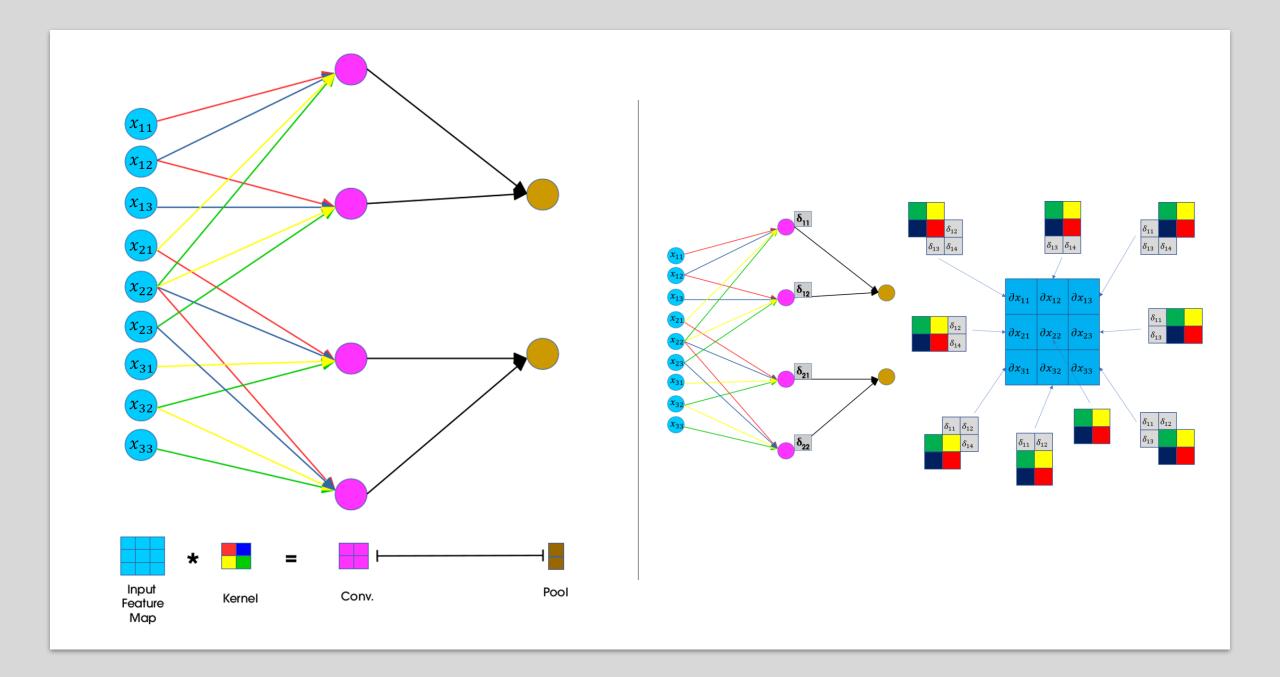
$$\frac{\partial z}{\partial x} = \frac{\partial (x+y)}{\partial x} = 1$$



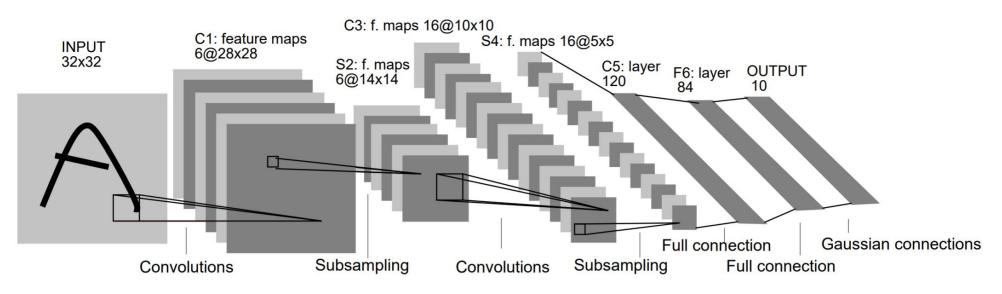
$$\frac{\partial z}{\partial y} = \frac{\partial (x+y)}{\partial y} = 1$$





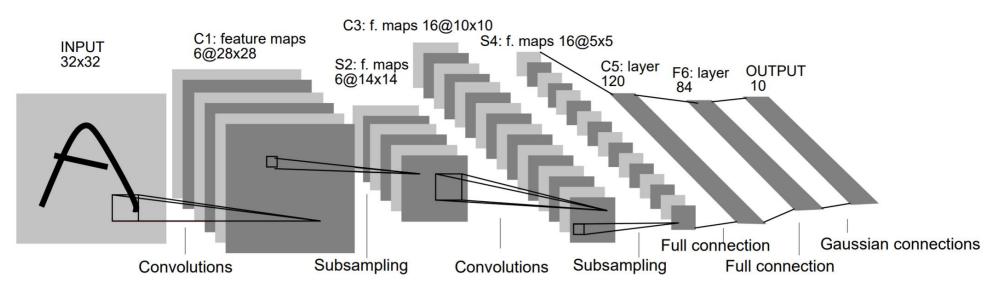


### LeNet 5 - Overview



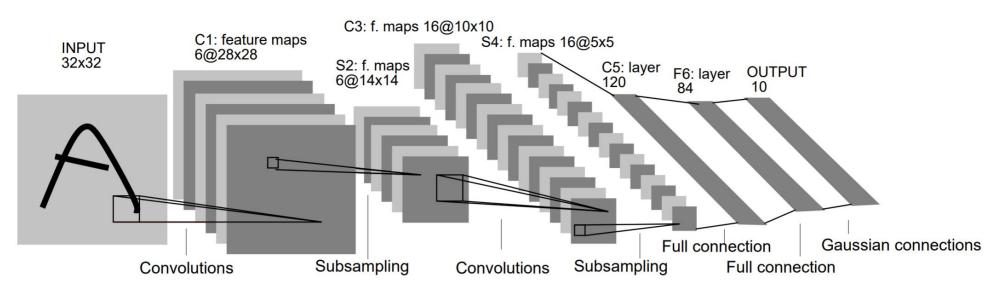
- Three key ideas: Local Receptive Fields, Shared Weights, Sub-sampling(Pooling)
- Input: 32x32 pixel image
- Largest character is 20x20
   (All important info should be in the center of the receptive field of the feature detectors)
- pixel values are normalized (Mean of pixels=0, Std of pixels=1)

## LeNet 5 - Layer C1



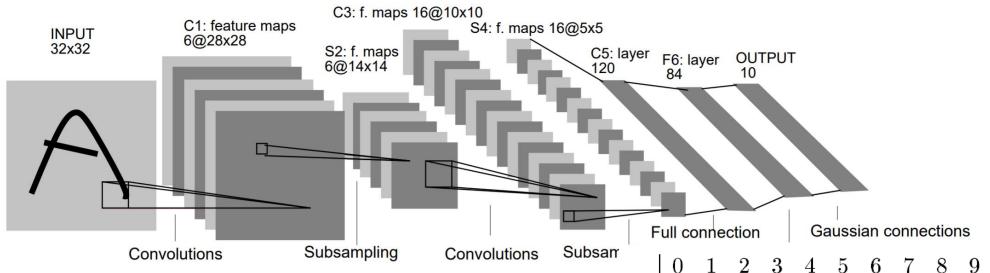
- Convolutional layer with 6 feature maps of output size 28x28.
- Each unit of C1 has a 5x5 receptive field in the input layer
- Parameters: (5x5+1)x6 = 156
- Connections:  $\{28x28\}x\{(5x5+1)x6\} = 122304$

## LeNet 5 - Layer S2



 Subsampling layer with 6 feature maps of output size 14x14 (2x2 non overlapping receptive fields in C1 Layer)

# LeNet 5 - Layer C3



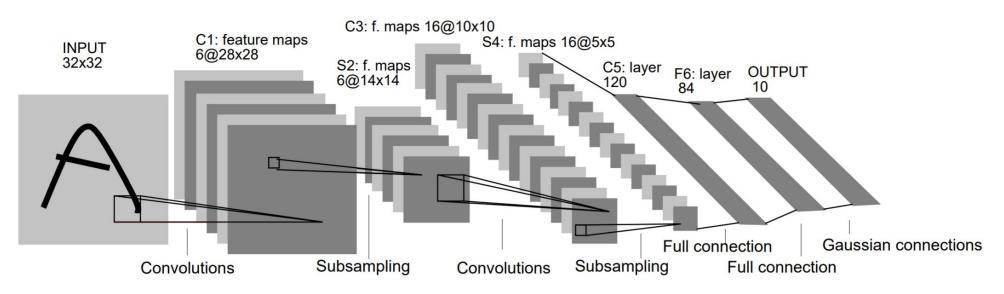
- Convolutional layer with 16 feature maps of size 10x10
- Parameters: (5x5+1)x16 = 1516
- Connections: 10x10x(5x5+1)x6 = 151600

| 1 dii connection |              |   |   |   |              | 14001 | arr o | 311110 | Otioi        |   |    |              |    |              |    |    |
|------------------|--------------|---|---|---|--------------|-------|-------|--------|--------------|---|----|--------------|----|--------------|----|----|
|                  | 0            | 1 | 2 | 3 | 4            | 5     | 6     | 7      | 8            | 9 | 10 | 11           | 12 | 13           | 14 | 15 |
| 0                | X            |   |   |   | Χ            | Χ     | Χ     |        |              | Χ | Χ  | Χ            | Χ  |              | Χ  | X  |
| 1                | X            | Χ |   |   |              | Χ     | Χ     | Χ      |              |   | X  | X            | X  | X            |    | X  |
| 2                | $\mathbf{X}$ | Χ | Χ |   |              |       | Χ     | Χ      | X            |   |    | X            |    | X            | X  | X  |
| 3                |              | Χ | Χ | Χ |              |       | Χ     | Χ      | Χ            | Χ |    |              | Χ  |              | Χ  | Χ  |
| 4                |              |   | Χ | X | Χ            |       |       | Χ      | Χ            | Χ | X  |              | Χ  | X            |    | X  |
| 5                |              |   |   | X | $\mathbf{X}$ | X     |       |        | $\mathbf{X}$ | X | X  | $\mathbf{X}$ |    | $\mathbf{X}$ | X  | X  |
|                  |              |   |   |   |              |       |       |        |              |   |    |              |    |              |    |    |

TABLE I

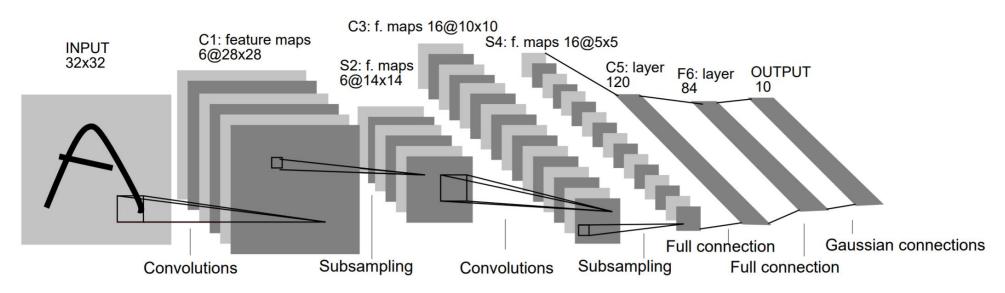
Each column indicates which feature map in S2 are combined by the units in a particular feature map of C3.

## LeNet 5 - Layer S4



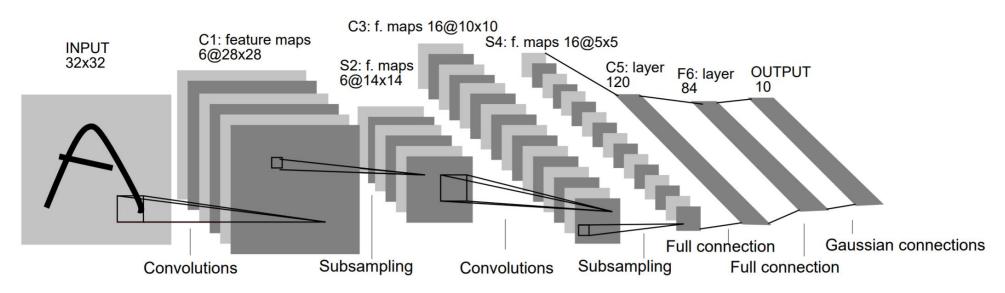
- Subsampling layer with 16 feature maps of size 5x5
- 2x2 non overlapping receptive fields in C3 Layer

# LeNet 5 - Layer C5



- Convolutional layer with 120 feature maps of size 1x1
- Parameters: 120x(16x25+1) = 48120
- Connections: 120x(5x5+1)x16 = 48120

## LeNet 5 - Layer F6



- 84 Fully connected units. 84x(120+1) = 10164 is parameters and connections count
- Output layer: 10 classes
- Weight update: Backpropagation

# Code Using Colab

 https://colab.research.google.com/drive/1a5I75n01V7vpyZOVa 9NGaqsRSMKOM9fH#scrollTo=5nAlPe4IF\_oT&forceEdit=true& sandboxMode=true

• <a href="https://colab.research.google.com/drive/1mRH80iQBMqQc0aft">https://colab.research.google.com/drive/1mRH80iQBMqQc0aft</a> 8Pf8Bk4BZwPVA2Mh#forceEdit=true&sandboxMode=true

## 참고 문헌

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- http://blog.naver.com/PostView.nhn?blogId=laonple&logNo=22064 8539191
- https://reniew.github.io/07/
- https://bskyvision.com/418