CNN for CV

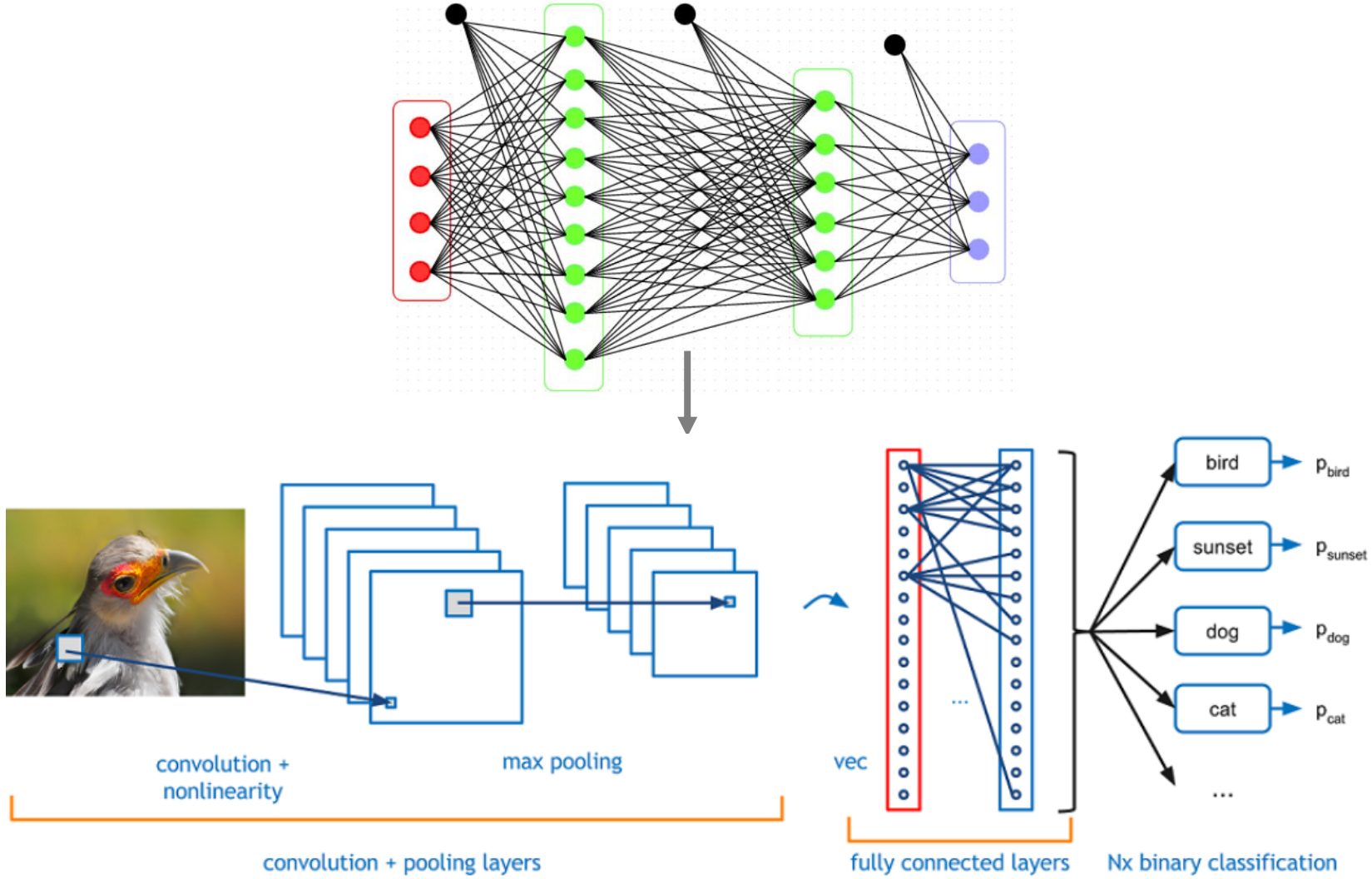
AI for CV Group
2019

Week 6.
CNN I. Outline & Layers

Contents:

I. CNN Outlines

I. CNN Outlines



I. CNN Outlines

A. What CNN does in CV:

I. CNN Outlines

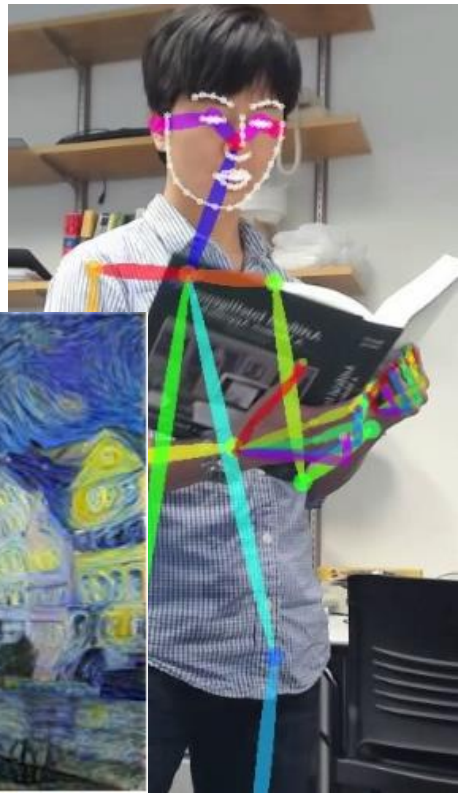
A. What CNN does in CV:

Everything

(Almost)

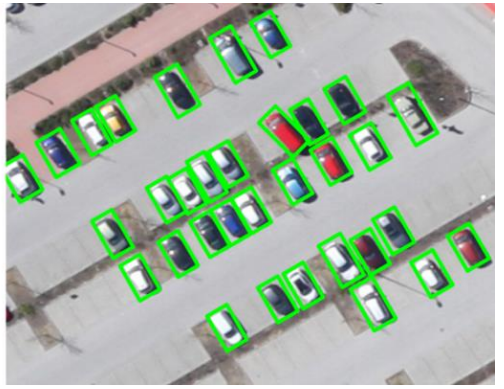
I. CNN Outlines

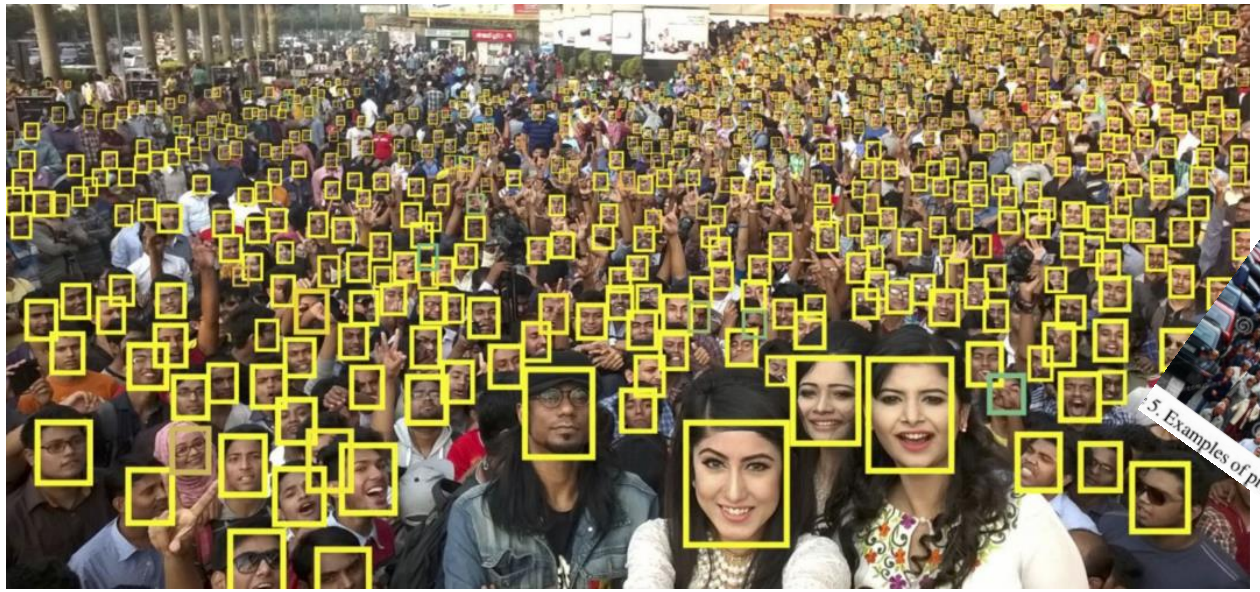
A. What CNN does in CV:

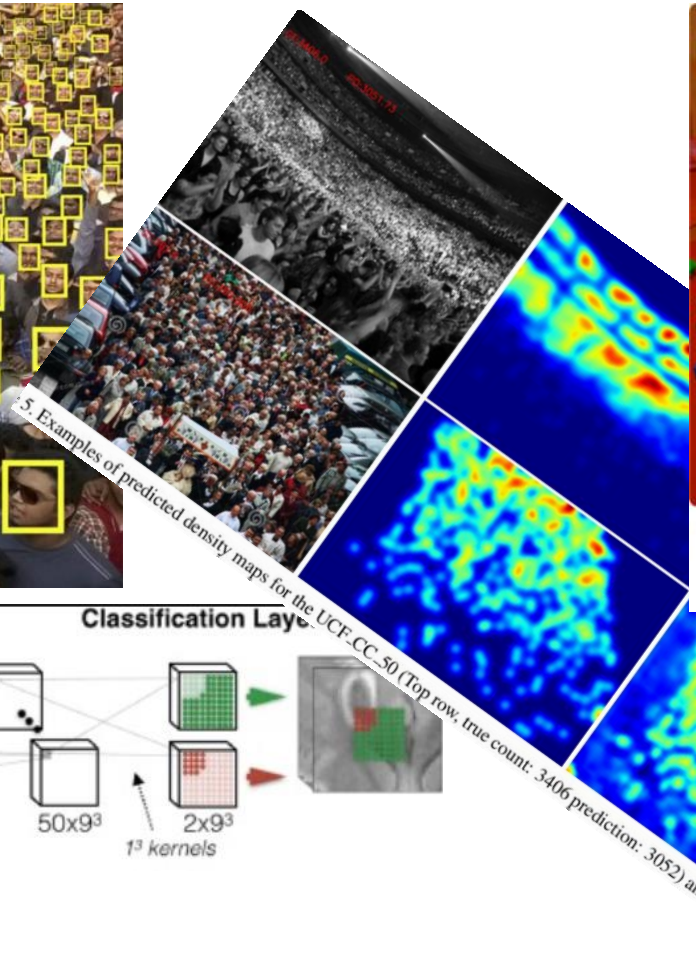


I. CNN Outlines

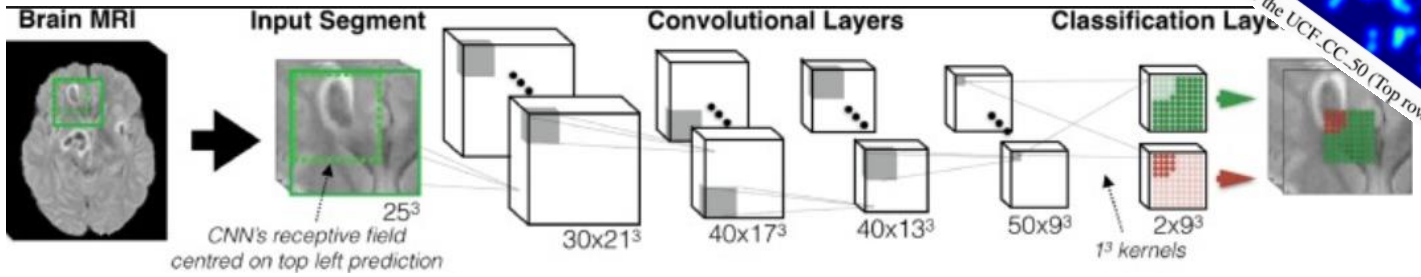
A. What CNN does in CV:







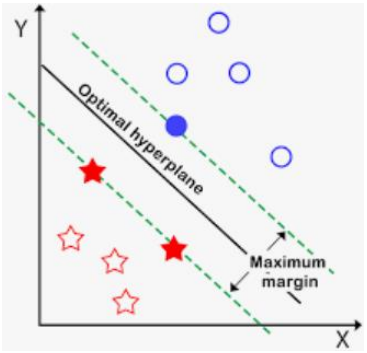
"two young girls are playing with lego toy."

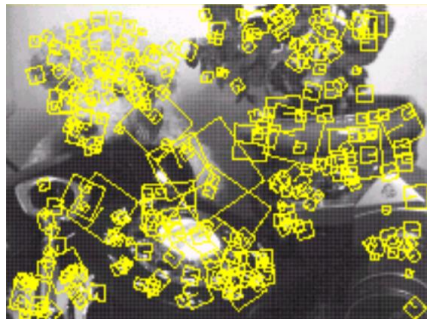


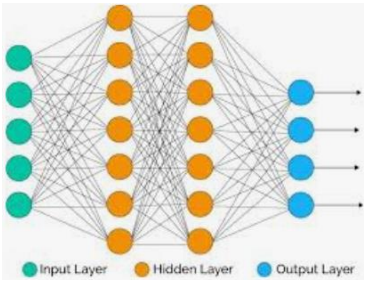
I. CNN Outlines

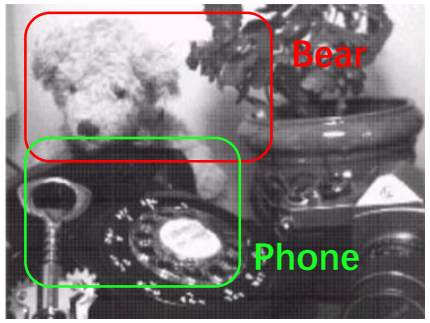
B. CNN Outlines:

Old Fashion Way:









Input → Feature → Classic ML Tools → Target

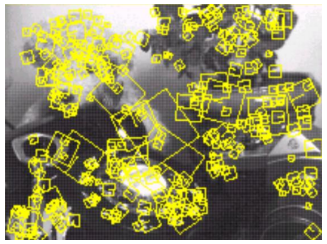
Get Manually — Choose Carefully — Use Hopelessly

I. CNN Outlines

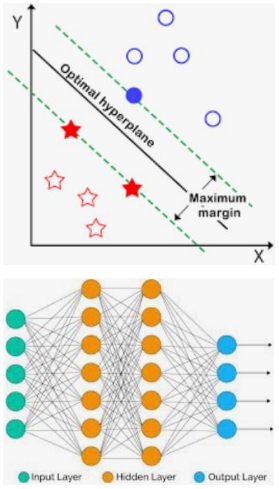
B. CNN Outlines:

Old Fashion Way:

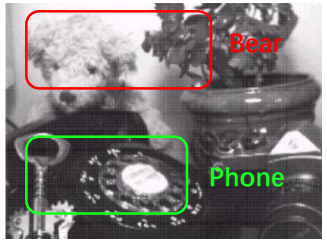
Input



Feature



Classic ML Tools



Target

Get Manually

Choose Carefully

Use Hopelessly

Pros & Cons

- Mathematical
- Explainable

- Difficult & Messy
- Separated Processes
- Poor results
- Hard to learn & implement

I. CNN Outlines

B. CNN Outlines:

CNN / Modern Way:

I. CNN Outlines

B. CNN Outlines:

CNN / Modern Way:

Pros & Cons

- End-to-end
- Easy to implement
- No need to learn part by part

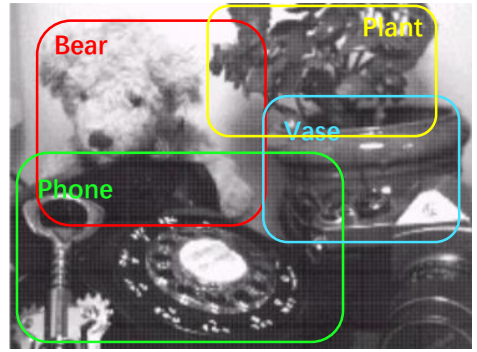
- Unexplainable

Put In

CNN

Only Focus On This Part

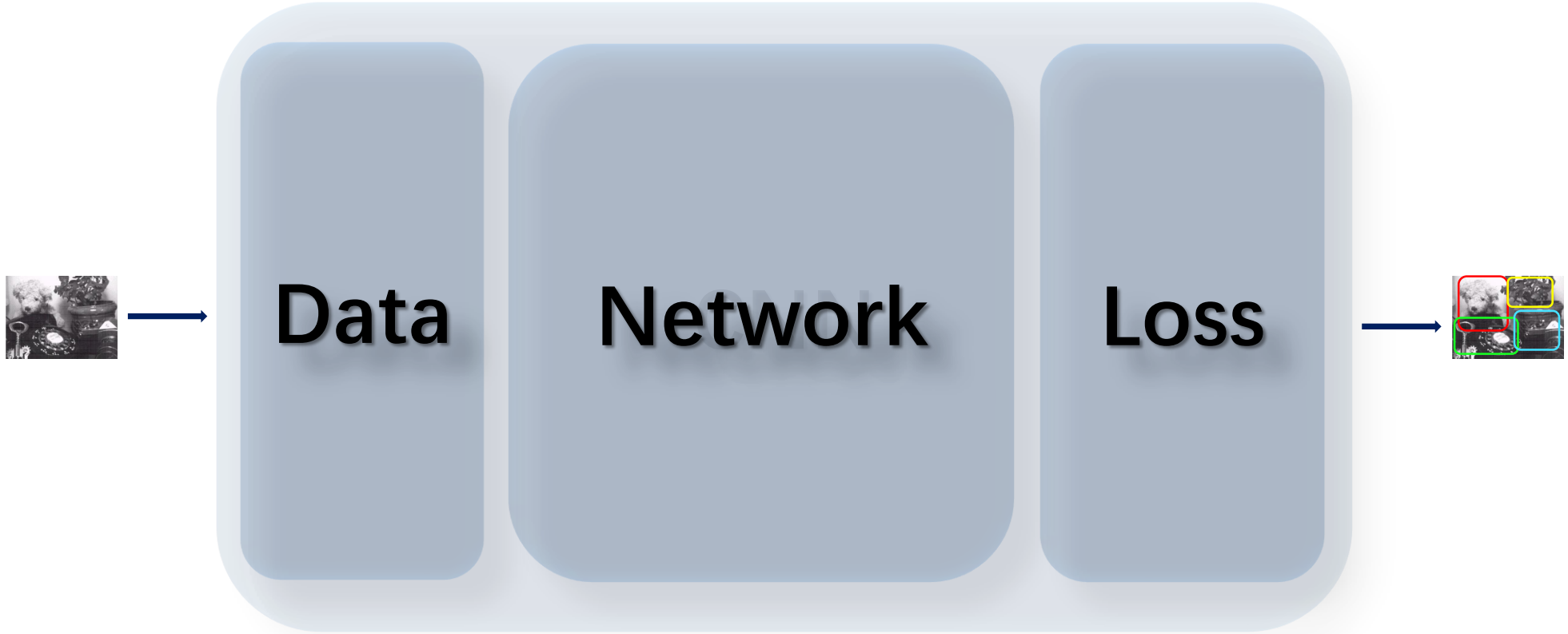
Use The Result



I. CNN Outlines

B. CNN Outlines:

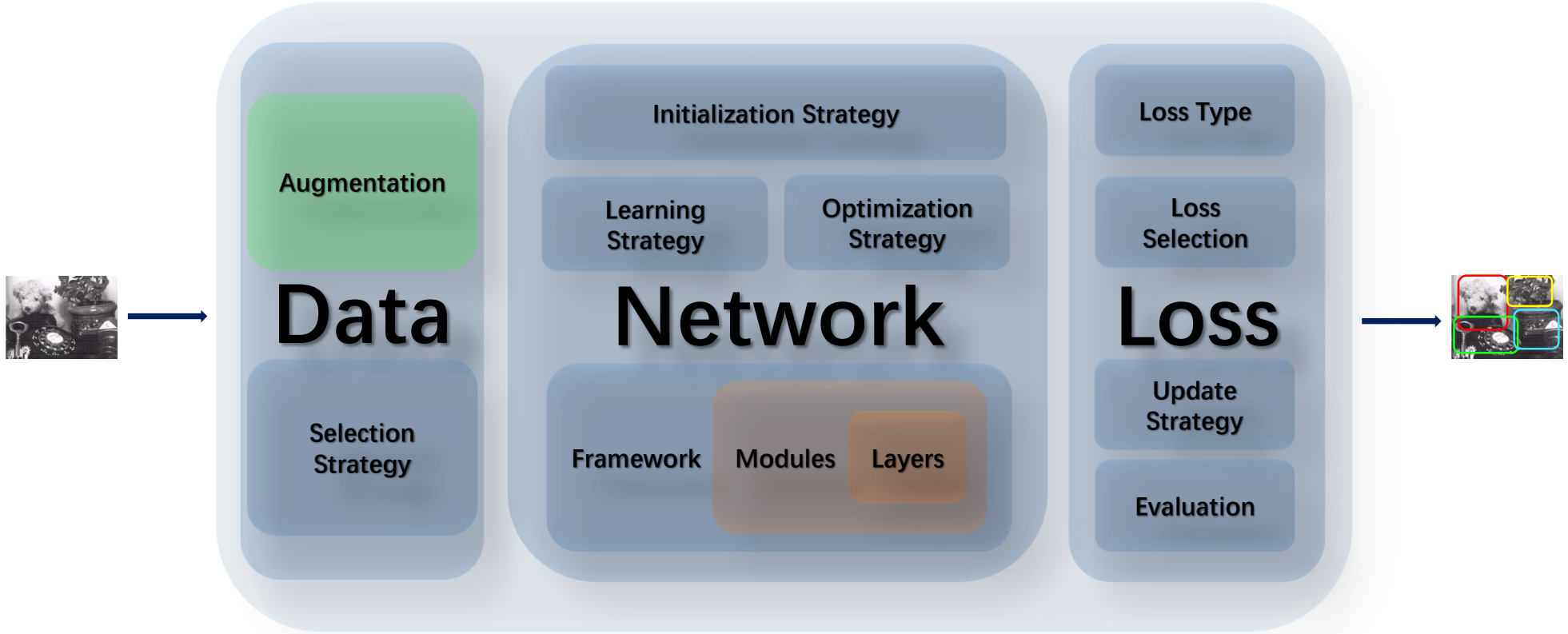
CNN / Modern Way:



I. CNN Outlines

B. CNN Outlines:

CNN / Modern Way:

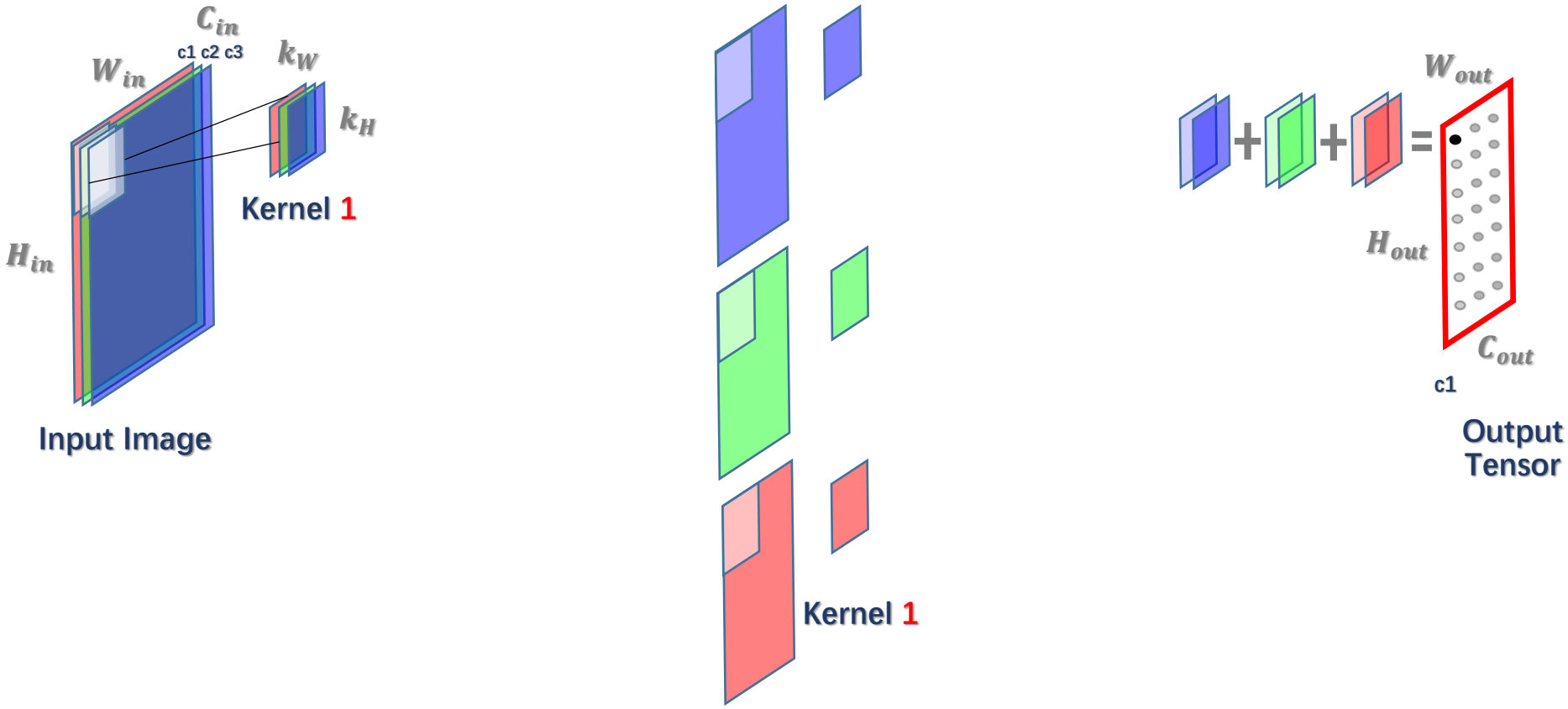


II. Fundamental Layers

II. Fundamental Layers

C. Layers Concepts & Implements

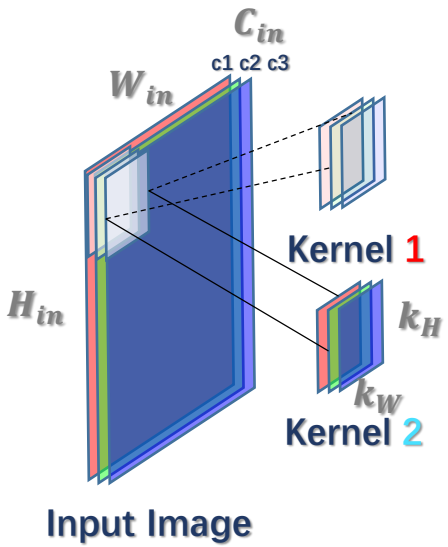
C1. Convolution AGAIN!

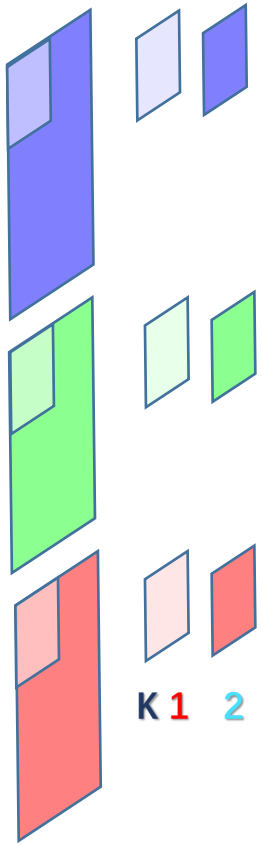


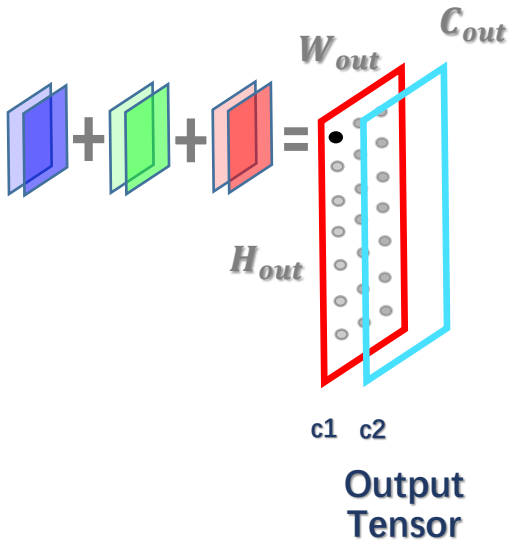
II. Fundamental Layers

C. Layers Concepts & Implements

C1. Convolution - General



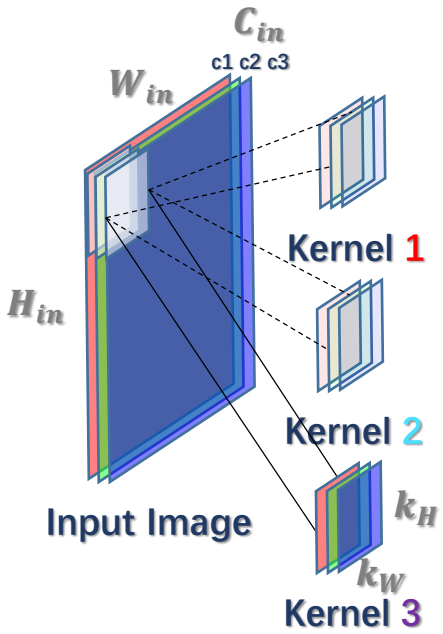


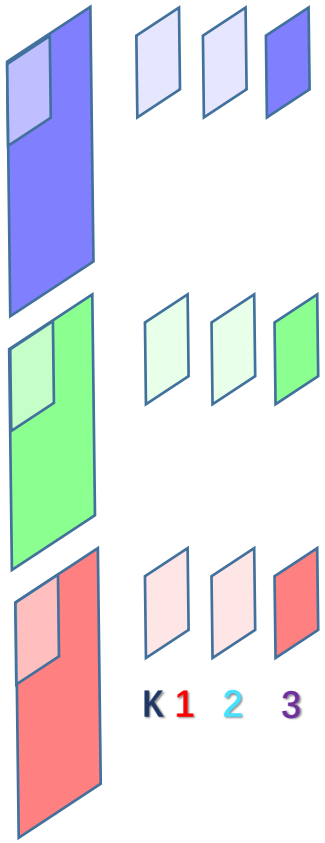


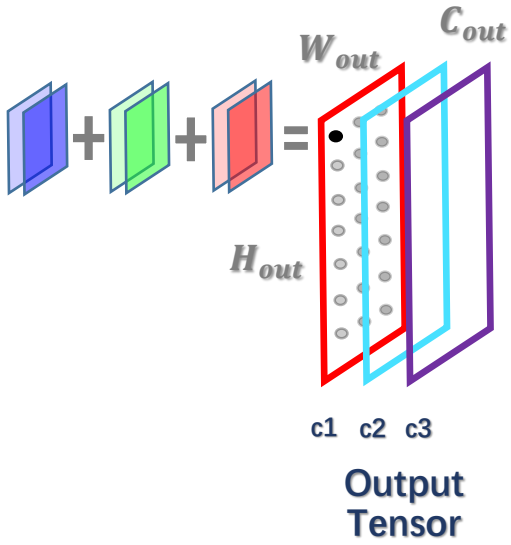
II. Fundamental Layers

C. Layers Concepts & Implements

C1. Convolution - General



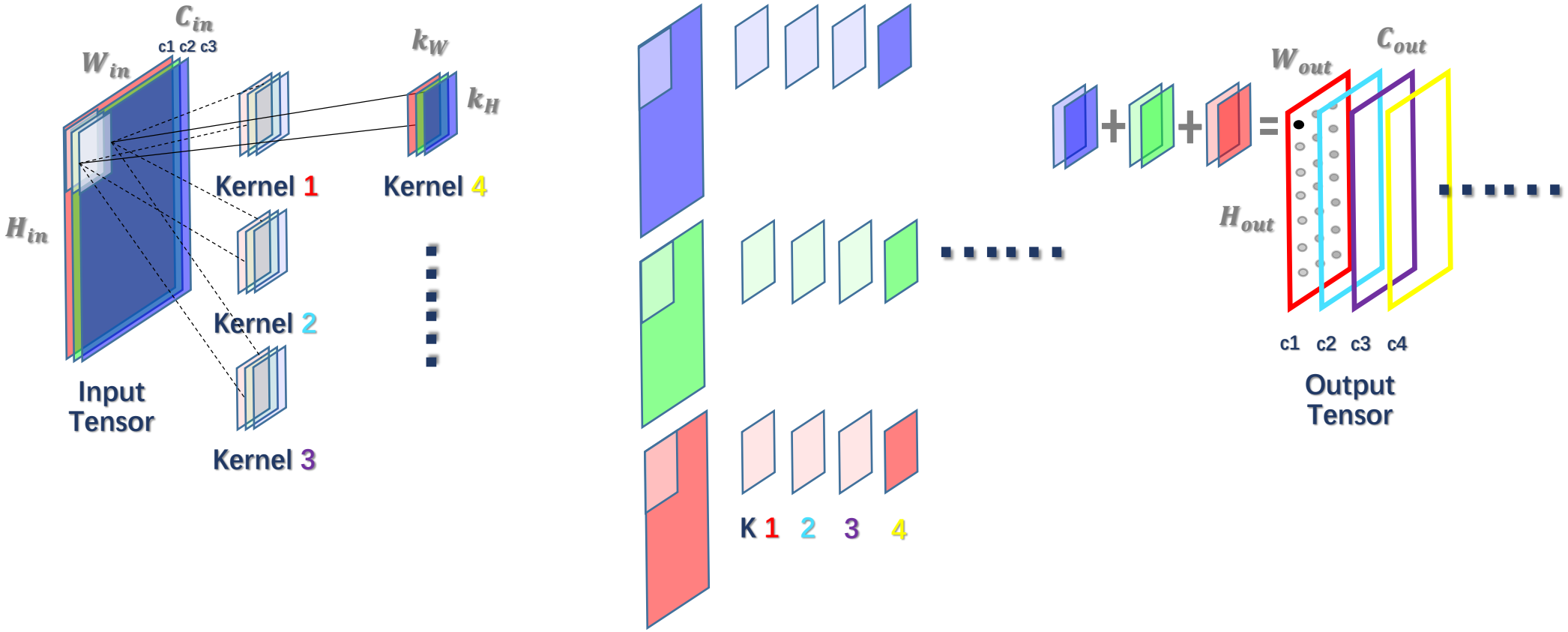




II. Fundamental Layers

C. Layers Concepts & Implements

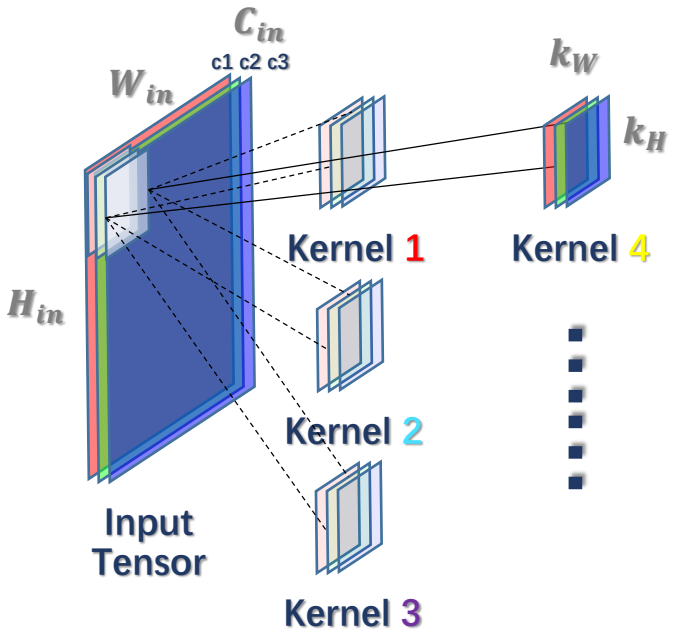
C1. Convolution - General



II. Fundamental Layers

C. Layers Concepts & Implements

C1. Convolution - General

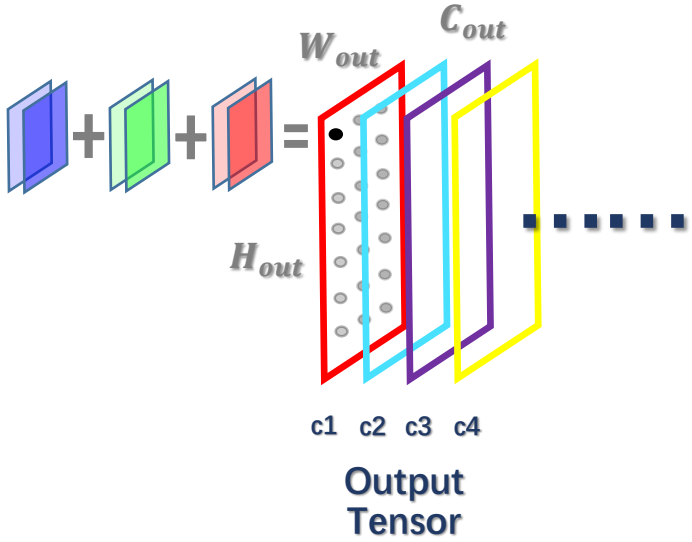


Output Tensor Shape:

$C_{out} = \#\ of\ Kernel$

$W_{out} = ?$

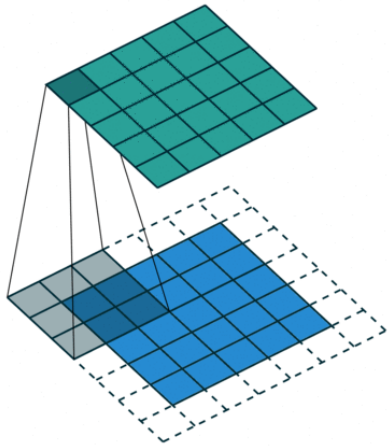
$H_{out} = ?$



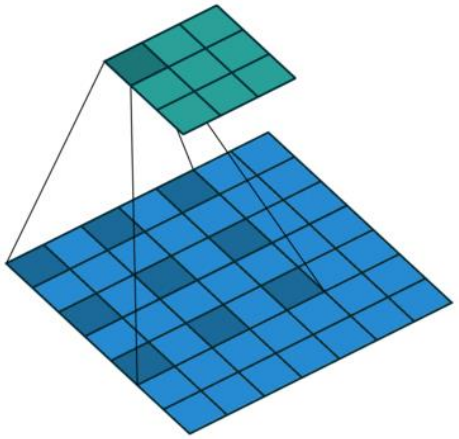
II. Fundamental Layers

C. Layers Concepts & Implements

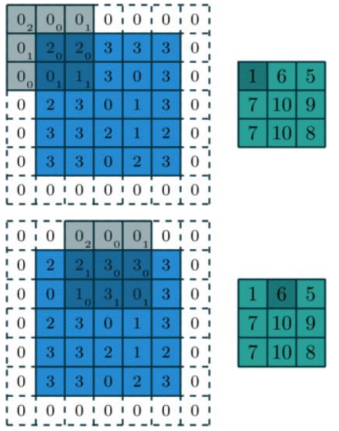
C1. Convolution - General



Padding:
Get same input size



Dilation:
Bigger receptive field

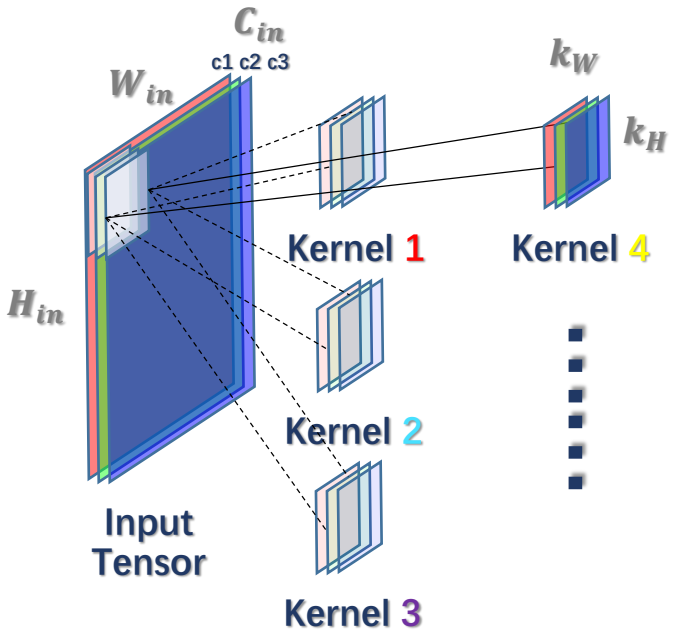


Stride:
Downsample

II. Fundamental Layers

C. Layers Concepts & Implements

C1. Convolution - General



Output Tensor Shape:

$$C_{out} = \#\ of\ Kernel$$

$$H_{out} = \left\lfloor \frac{H_{in} + 2 \times pad_H - dilation_H \times (k_H - 1) - 1}{stride_H} + 1 \right\rfloor$$

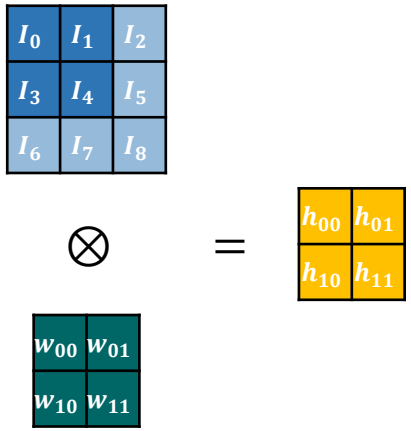
$$W_{out} = \left\lfloor \frac{W_{in} + 2 \times pad_W - dilation_W \times (k_W - 1) - 1}{stride_W} + 1 \right\rfloor$$

II. Fundamental Layers

C. Layers Concepts & Implements

C1. Convolution - Calculation

Forward



$$\begin{cases} h_{00} = w_{00}I_0 + w_{01}I_1 + w_{10}I_3 + w_{11}I_4 \\ h_{01} = w_{00}I_1 + w_{01}I_2 + w_{10}I_4 + w_{11}I_5 \\ h_{10} = w_{00}I_3 + w_{01}I_4 + w_{10}I_6 + w_{11}I_7 \\ h_{11} = w_{00}I_4 + w_{01}I_5 + w_{10}I_7 + w_{11}I_8 \end{cases}$$

$$\boldsymbol{h = CI}$$

II. Fundamental Layers

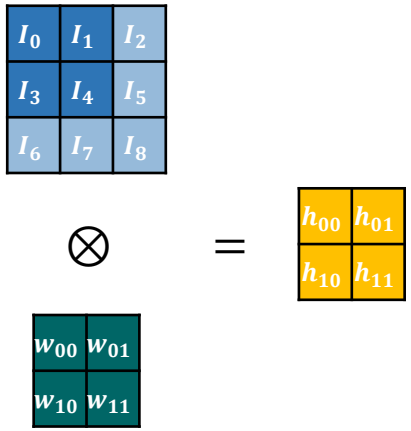
C. Layers Concepts & Implements

C1. Convolution - Calculation

Forward

$$\boldsymbol{h = CI}$$

$$\begin{cases} h_{00} = w_{00}I_0 + w_{01}I_1 + w_{10}I_3 + w_{11}I_4 \\ h_{01} = w_{00}I_1 + w_{01}I_2 + w_{10}I_4 + w_{11}I_5 \\ h_{10} = w_{00}I_3 + w_{01}I_4 + w_{10}I_6 + w_{11}I_7 \\ h_{11} = w_{00}I_4 + w_{01}I_5 + w_{10}I_7 + w_{11}I_8 \end{cases}$$

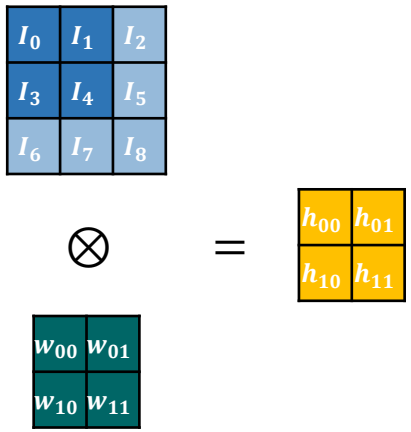


II. Fundamental Layers

C. Layers Concepts & Implements

C1. Convolution - Calculation

Transposed Weight Matrix C

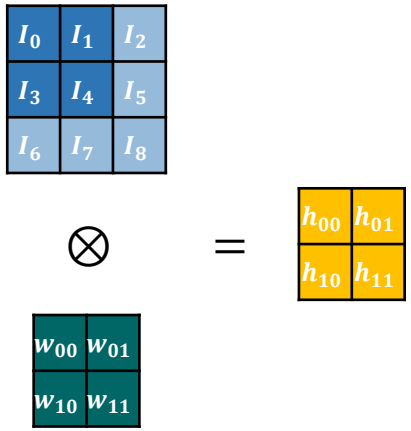


II. Fundamental Layers

C. Layers Concepts & Implements

C1. Convolution - Calculation

Backward / BP



$$Loss = \partial h_{00} + \partial h_{01} + \partial h_{10} + \partial h_{11}$$

$$\begin{cases} h_{00} = w_{00}I_0 + w_{01}I_1 + w_{10}I_3 + w_{11}I_4 \\ h_{01} = w_{00}I_1 + w_{01}I_2 + w_{10}I_4 + w_{11}I_5 \\ h_{10} = w_{00}I_3 + w_{01}I_4 + w_{10}I_6 + w_{11}I_7 \\ h_{11} = w_{00}I_4 + w_{01}I_5 + w_{10}I_7 + w_{11}I_8 \end{cases}$$

$$\partial w = ?$$
$$\partial I = ?$$

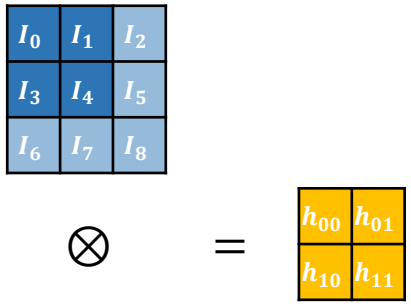
II. Fundamental Layers

C. Layers Concepts & Implements

C1. Convolution - Calculation

Backward / BP

$$Loss = \partial h_{00} + \partial h_{01} + \partial h_{10} + \partial h_{11}$$



$$\begin{cases} h_{00} = w_{00}I_0 + w_{01}I_1 + w_{10}I_3 + w_{11}I_4 \\ h_{01} = w_{00}I_1 + w_{01}I_2 + w_{10}I_4 + w_{11}I_5 \\ h_{10} = w_{00}I_3 + w_{01}I_4 + w_{10}I_6 + w_{11}I_7 \\ h_{11} = w_{00}I_4 + w_{01}I_5 + w_{10}I_7 + w_{11}I_8 \end{cases}$$

$$\partial w = \frac{\partial L}{\partial h}\frac{\partial h}{\partial w}$$

$$\partial I = \frac{\partial L}{\partial h}\frac{\partial h}{\partial I}$$

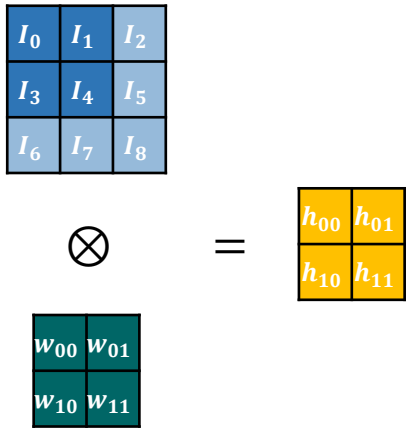
$$\begin{cases} \partial w_{00} = \partial h_{00}I_0 + \partial h_{01}I_1 + \partial h_{10}I_3 + \partial h_{11}I_4 \\ \partial w_{01} = \partial h_{00}I_1 + \partial h_{01}I_2 + \partial h_{10}I_4 + \partial h_{11}I_5 \\ \partial w_{10} = \partial h_{00}I_3 + \partial h_{01}I_4 + \partial h_{10}I_6 + \partial h_{11}I_7 \\ \partial w_{11} = \partial h_{00}I_4 + \partial h_{01}I_5 + \partial h_{10}I_7 + \partial h_{11}I_8 \end{cases}$$

II. Fundamental Layers

C. Layers Concepts & Implements

C1. Convolution - Calculation

Backward / BP



$$\partial w = \frac{\partial L}{\partial h}\frac{\partial h}{\partial w}$$

$$\partial I = \frac{\partial L}{\partial h}\frac{\partial h}{\partial I}$$

$$\begin{aligned} \partial w_{00} &= \partial h_{00} \\ \partial w_{01} &= \partial h_{01} \\ \partial w_{10} &= \partial h_{10} \\ \partial w_{11} &= \partial h_{11} \end{aligned} \qquad I_M \cong \boldsymbol{C}$$

II. Fundamental Layers

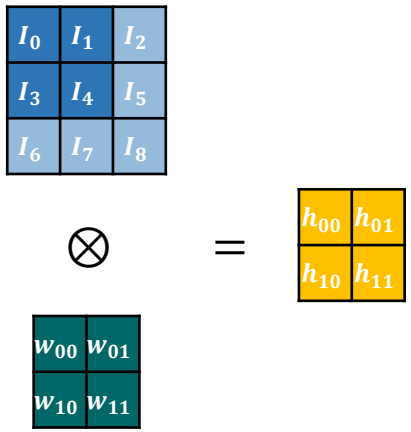
C. Layers Concepts & Implements

C1. Convolution - Calculation

Backward / BP

$$\partial w = \frac{\partial L}{\partial h}\frac{\partial h}{\partial w}$$

$$\partial I = \frac{\partial L}{\partial h}\frac{\partial h}{\partial I}$$



$$\begin{aligned}\partial w_{00} &= \\ \partial w_{01} &= \\ \partial w_{10} &= \\ \partial w_{11} &=\end{aligned} \quad I_C \cong \boldsymbol{C} \quad \begin{aligned}\partial h_{00}\\ \partial h_{01}\\ \partial h_{10}\\ \partial h_{11}\end{aligned}$$

II. Fundamental Layers

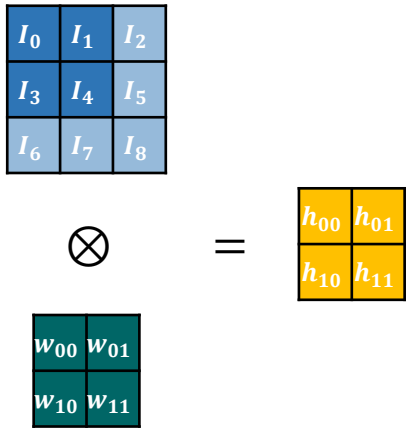
C. Layers Concepts & Implements

C1. Convolution - Calculation

Backward / BP

$$Loss = \partial h_{00} + \partial h_{01} + \partial h_{10} + \partial h_{11}$$

$$\begin{cases} h_{00} = w_{00}I_0 + w_{01}I_1 + w_{10}I_3 + w_{11}I_4 \\ h_{01} = w_{00}I_1 + w_{01}I_2 + w_{10}I_4 + w_{11}I_5 \\ h_{10} = w_{00}I_3 + w_{01}I_4 + w_{10}I_6 + w_{11}I_7 \\ h_{11} = w_{00}I_4 + w_{01}I_5 + w_{10}I_7 + w_{11}I_8 \end{cases}$$



$$\partial w = \frac{\partial L}{\partial h}\frac{\partial h}{\partial w}$$

$$\partial I = \frac{\partial L}{\partial h}\frac{\partial h}{\partial I}$$

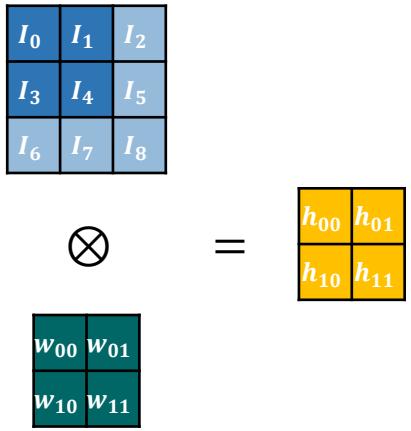
$$\begin{cases} \partial I_0 = \partial h_{00} w_{00} \\ \partial I_1 = \partial h_{00} w_{01} + \partial h_{01} w_{00} \\ \partial I_2 = \partial h_{01} w_{01} \\ \partial I_3 = \partial h_{00} w_{10} + \partial h_{10} w_{00} \\ \vdots \end{cases}$$

II. Fundamental Layers

C. Layers Concepts & Implements

C1. Convolution - Calculation

Backward / BP



$$\partial w = \frac{\partial L}{\partial h}\frac{\partial h}{\partial w}$$

$$\partial I = \frac{\partial L}{\partial h}\frac{\partial h}{\partial I}$$

$$\begin{matrix} \partial I_0 = \\ \partial I_1 = \\ \partial I_2 = \\ \partial I_3 = \\ \vdots \end{matrix} \boldsymbol{C}^T \begin{matrix} \partial h_{00} \\ \partial h_{01} \\ \partial h_{10} \\ \partial h_{11} \end{matrix}$$

II. Fundamental Layers

C. Layers Concepts & Implements

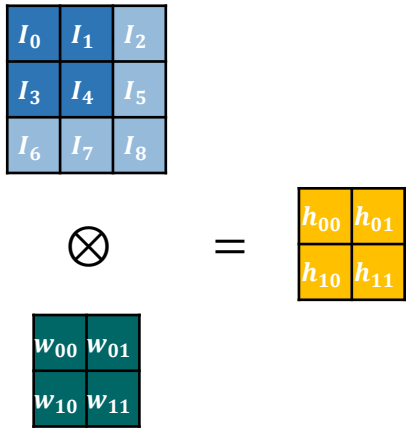
C1. Convolution - Calculation

Backward / BP

$$\partial w = \frac{\partial L}{\partial h}\frac{\partial h}{\partial w}$$

$$\partial I = \frac{\partial L}{\partial h}\frac{\partial h}{\partial I}$$

$$\begin{matrix} \partial I_0 = \\ \partial I_1 = \\ \partial I_2 = \\ \partial I_3 = \\ \vdots \end{matrix} \boldsymbol{C}^T \begin{matrix} \partial h_{00} \\ \partial h_{01} \\ \partial h_{10} \\ \partial h_{11} \end{matrix}$$



II. Fundamental Layers

C. Layers Concepts & Implements

C1. Convolution - Calculation

$$\partial I = \frac{\partial L}{\partial h}\frac{\partial h}{\partial I}$$

Thinking

Conv Forward

I → h

3x3 → 2x2

Downsample

$$\begin{matrix} I_0 & I_1 & I_2 \\ I_3 & I_4 & I_5 \\ I_6 & I_7 & I_8 \end{matrix} \otimes \begin{matrix} w_{00} & w_{01} \\ w_{10} & w_{11} \end{matrix} = \begin{matrix} h_{00} & h_{01} \\ h_{10} & h_{11} \end{matrix}$$

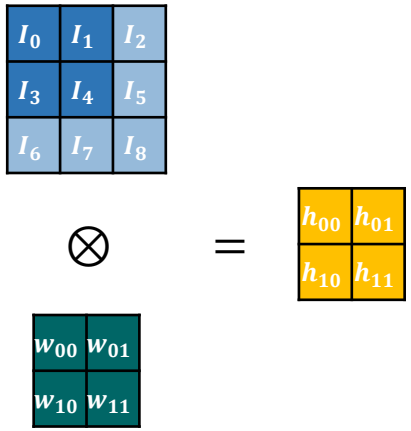
$$\begin{matrix} \partial I_0 = \\ \partial I_1 = \\ \partial I_2 = \\ \partial I_3 = \\ \vdots \end{matrix} \boldsymbol{C^T} \begin{matrix} \partial h_{00} \\ \partial h_{01} \\ \partial h_{10} \\ \partial h_{11} \end{matrix}$$

II. Fundamental Layers

C. Layers Concepts & Implements

C1. Convolution - Calculation

$$\partial I = \frac{\partial L}{\partial h}\frac{\partial h}{\partial I}$$



Thinking

Conv Forward

I → h

3x3 → 2x2

Downsample

Conv Backward

∂h → ∂I

2x2 → 3x3

UPSAMPLE

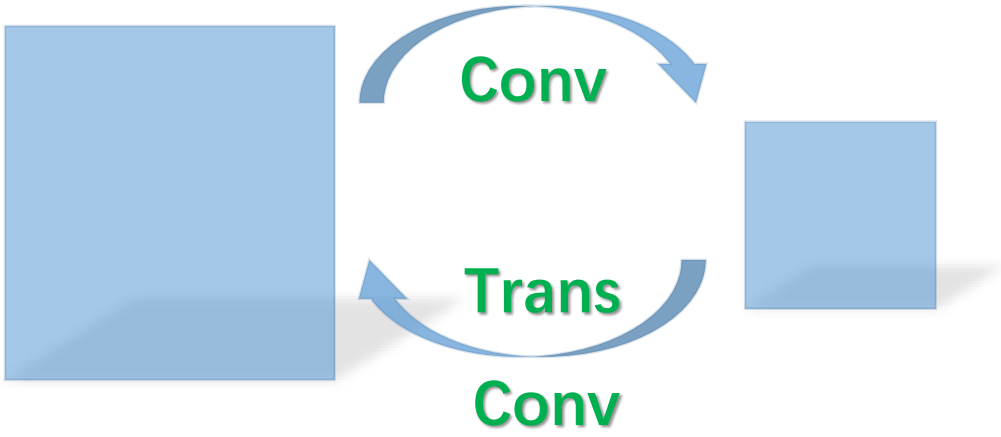
$$\begin{matrix}\partial I_0 = \\ \partial I_1 = \\ \partial I_2 = \\ \partial I_3 = \\ \vdots\end{matrix} \boldsymbol{C^T} \begin{matrix}\partial h_{00} \\ \partial h_{01} \\ \partial h_{10} \\ \partial h_{11}\end{matrix}$$

II. Fundamental Layers

C. Layers Concepts & Implements

C1. Convolution

-Transposed Conv / Deconv / Fractionally Strided Conv

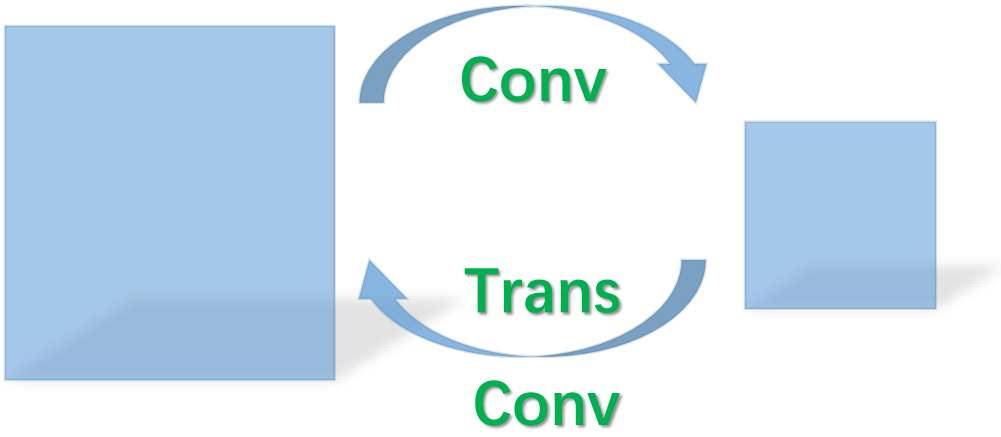


II. Fundamental Layers

C. Layers Concepts & Implements

C1. Convolution

-Transposed Conv / Deconv / Fractionally Strided Conv

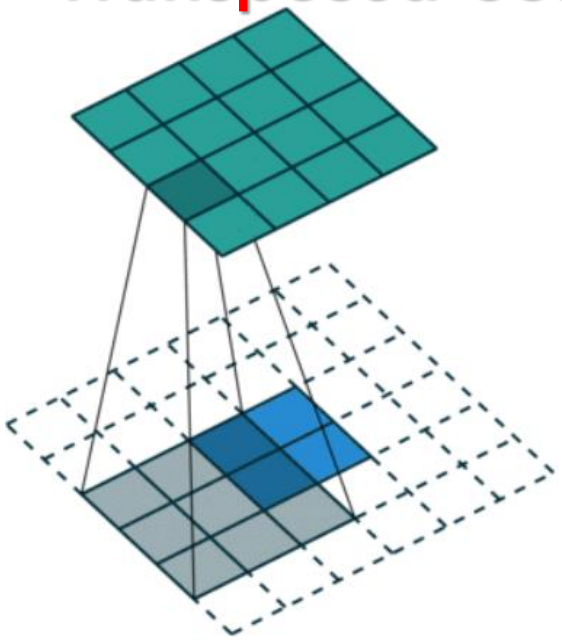


II. Fundamental Layers

C. Layers Concepts & Implements

C1. Convolution

-Transposed Conv / Deconv / Fractionally Strided Conv



Transposed Conv + Padding

⇕

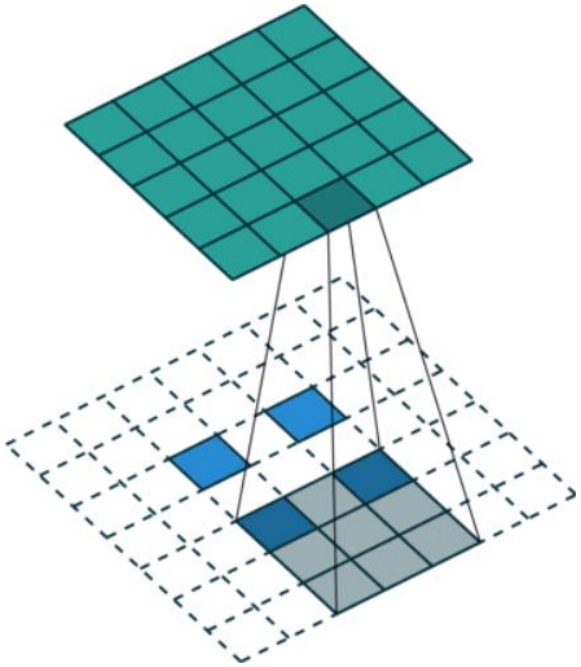
Conv

II. Fundamental Layers

C. Layers Concepts & Implements

C1. Convolution

-Transposed Conv / Deconv / Fractionally Strided Conv



Conv with stride > 0

Add 0 among elements when transposed conv

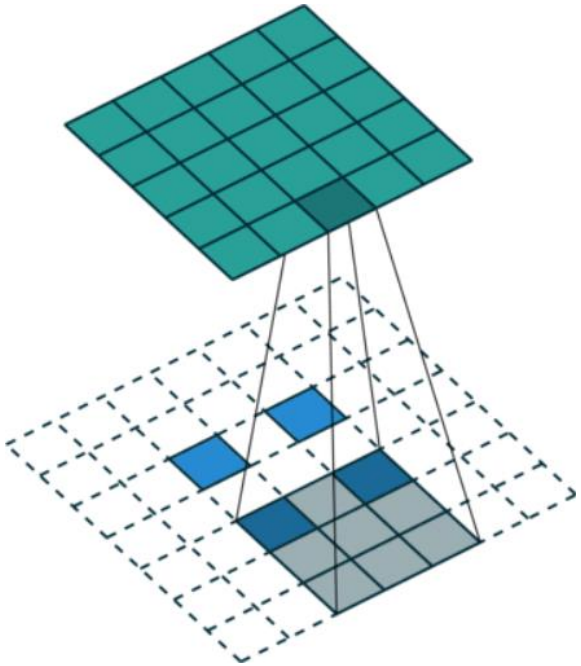
$$Stride_{trans\_conv} = \frac{1}{Stride_{conv}}$$

II. Fundamental Layers

C. Layers Concepts & Implements

C1. Convolution

-Transposed Conv / Deconv / Fractionally Strided Conv



Output Tensor Shape:

$$C_{out} = \#\ of\ Kernel$$

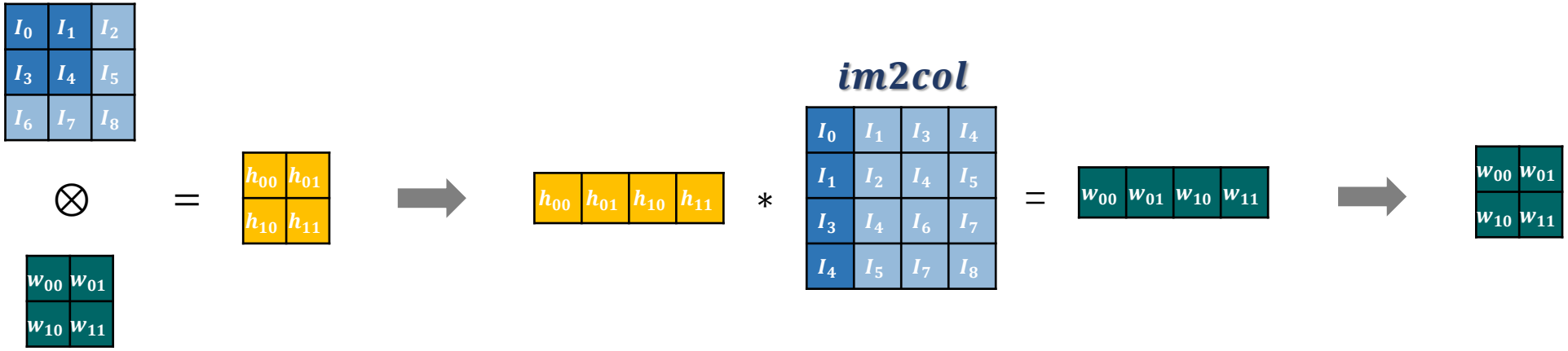
$$H_{out} = (H_{in} - 1) \times stride_H - 2 \times pad_H + k_H + out\_pad_H$$

$$W_{out} = (W_{in} - 1) \times stride_W - 2 \times pad_W + k_W + out\_pad_W$$

II. Fundamental Layers

C. Layers Concepts & Implements

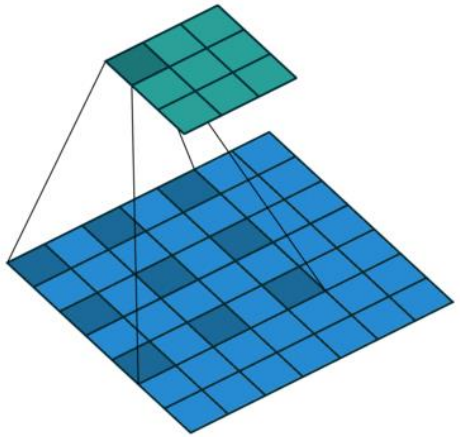
C1. Convolution-In Reality



II. Fundamental Layers

C. Layers Concepts & Implements

C1. Convolution - Dilated Conv



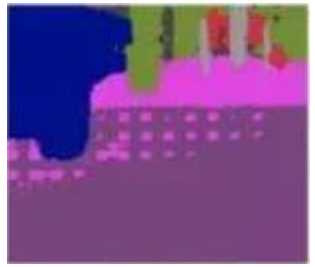
Get better view;

Mostly used in segmentation

Some drawbacks;

Some improvements

Will revisit in Segmentation part



Dilated Conv

Hybrid
Dilated Conv

Ground Truth

II. Fundamental Layers

C. Layers Concepts & Implements

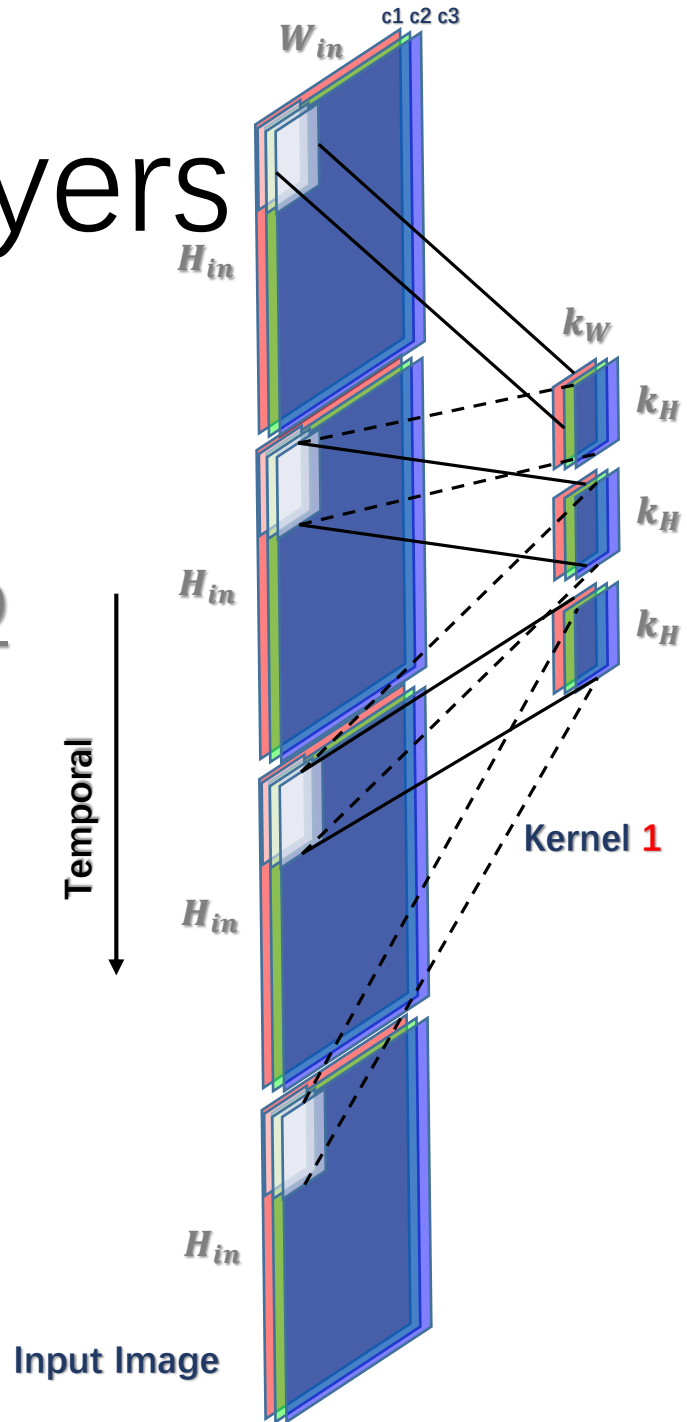
C1. Convolution-3D Conv / C3D

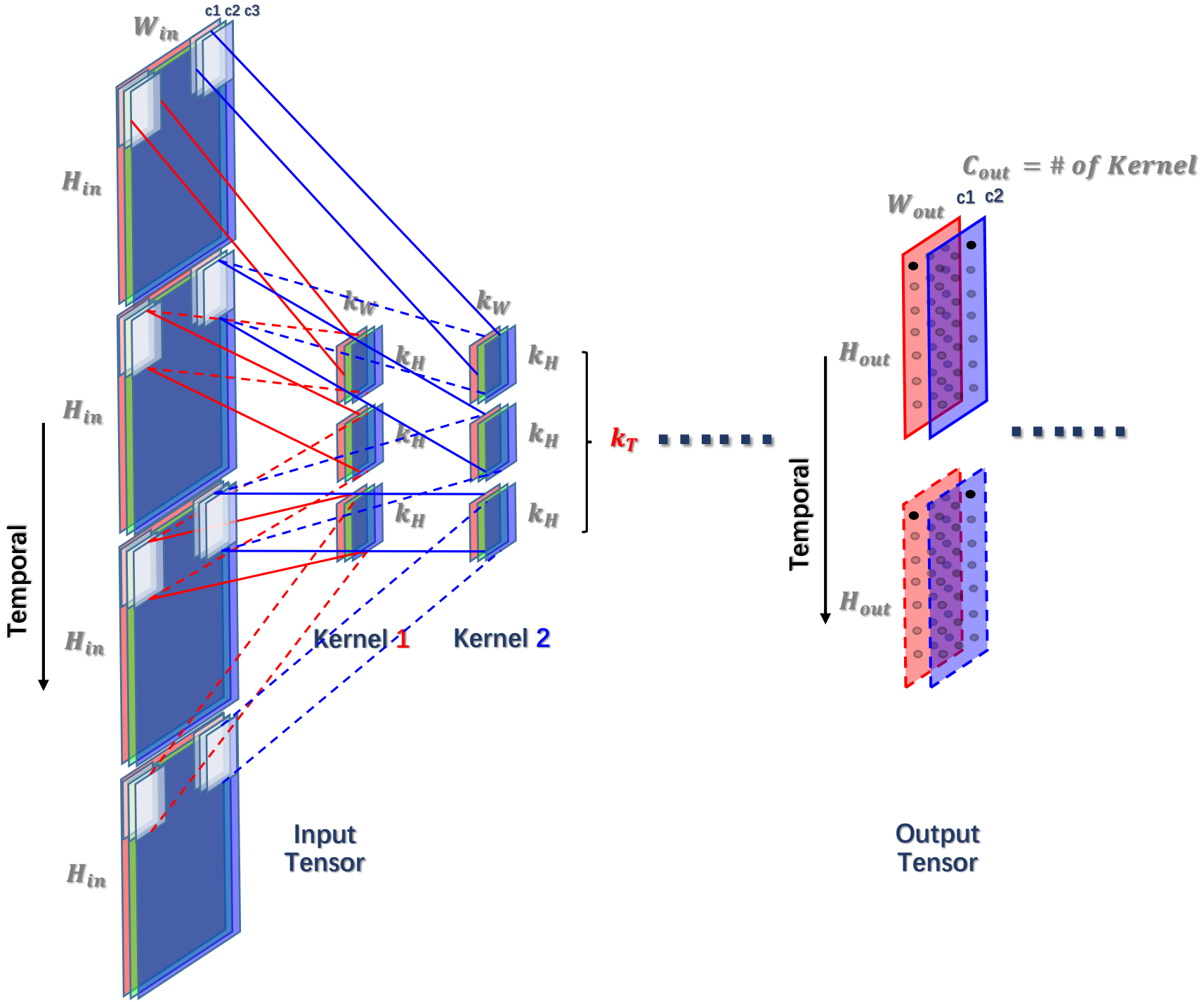
Trend:

CNN can do every thing.

Necessity:

Time info is critical




W_{in}
c1 c2 c3
H_{in}
H_{in}
H_{in}
H_{in}
Temporal
k_W
k_W
k_H
k_H
k_H
k_H
k_H
k_H
k_T
Kernel 1
Kernel 2
Input
Tensor
C_{out} = # of Kernel
W_{out}
c1 c2
H_{out}
H_{out}
Temporal
Output
Tensor

Question:

Write code of 2D image median filtering

Attentions:

1. ***Padding***
2. ***Stride***
3. ***Kernel Size***
4. ***How to get the median number***

II. Fundamental Layers

C. Layers Concepts & Implements

C1. Convolution – Other Convs

Depthwise Convolution

Group Convolution

Will Revisit Later

II. Fundamental Layers

C. Layers Concepts & Implements

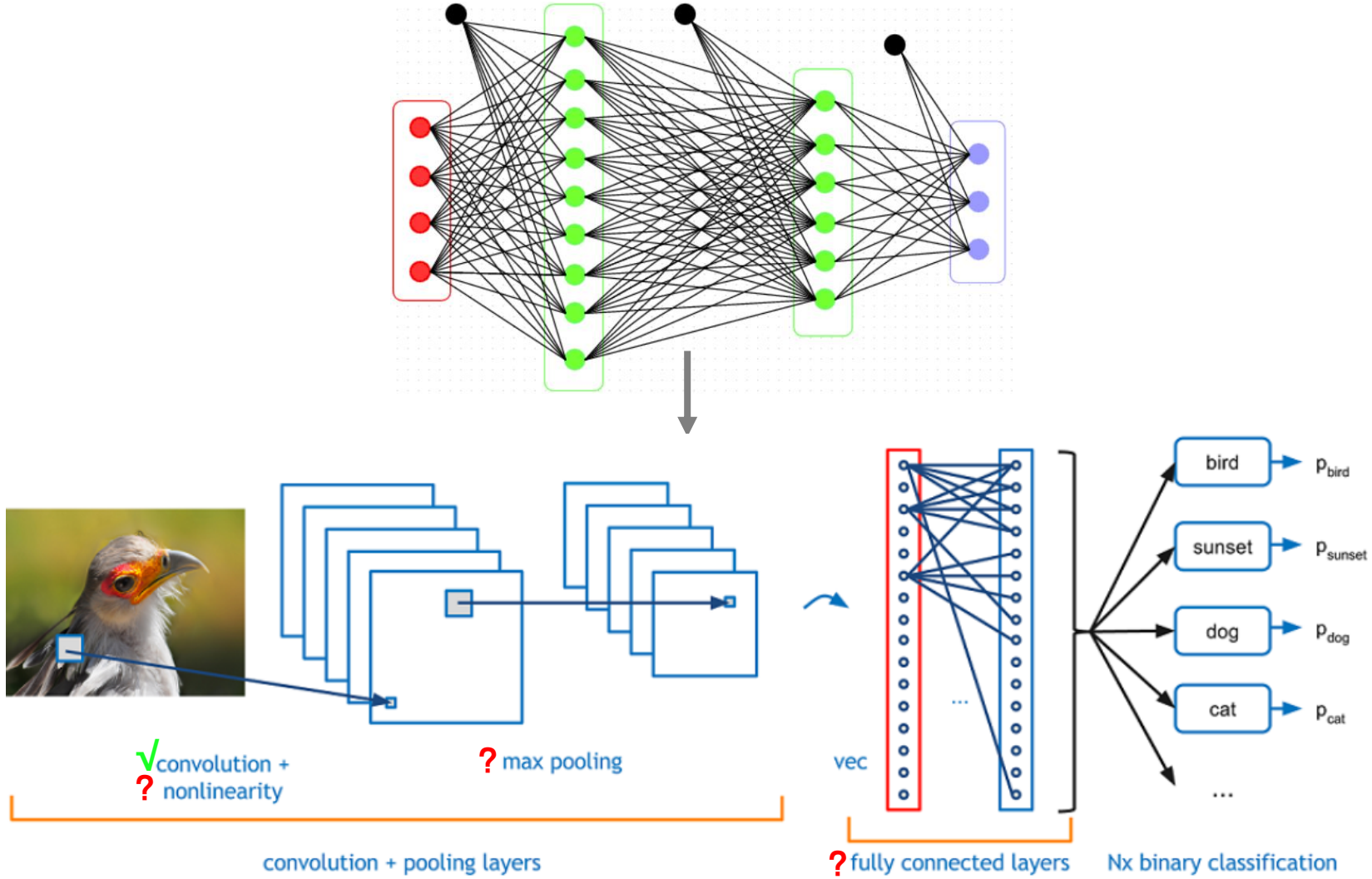
C1. Convolution – Advanced Convs

Deformable Convolution

(2017, MSRA)

Read If U Have Interests

I. CNN Outlines - Revisit



II. Fundamental Layers

C. Layers Concepts & Implements

C2. ReLU - Nonlinearity

Questions:

1. ***What is nonlinearity***
2. ***What is nonlinearity for***
3. ***What is ReLU***
4. ***Why ReLU***

Answers:

1.
2.
3.
4.

II. Fundamental Layers

C. Layers Concepts & Implements

C2. ReLU - Nonlinearity

Questions:

1. ***What is nonlinearity***
2. ***What is nonlinearity for***
3. ***What is ReLU***
4. ***Why ReLU***

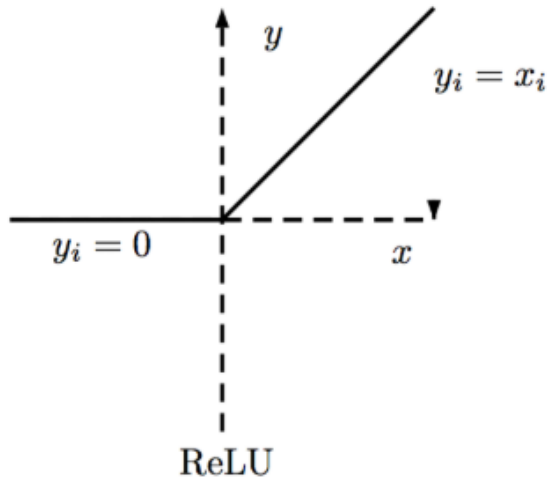
Answers:

1. $d_{out} \neq k\, d_{in}$
2. ***to fit the complex system***
3.
4.

II. Fundamental Layers

C. Layers Concepts & Implements

C2. ReLU - Nonlinearity

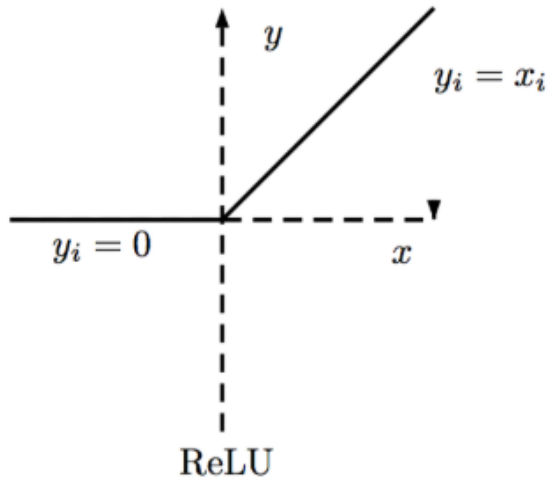


$$ReLU(x) = \max(0, x)$$

II. Fundamental Layers

C. Layers Concepts & Implements

C2. ReLU - Nonlinearity



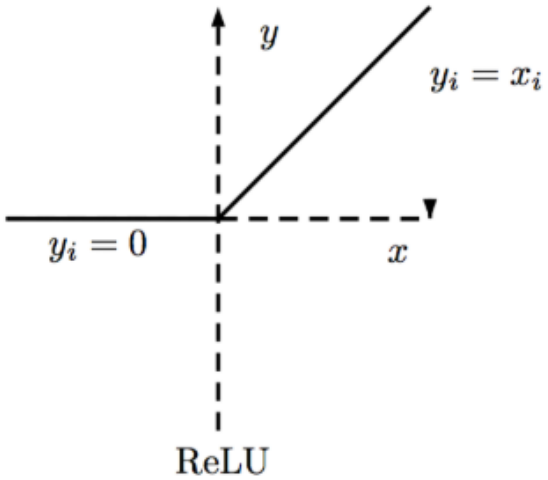
$$ReLU(x) = \max(0, x)$$

$$\frac{\partial L}{\partial x} = \begin{cases} 0, & x \leq 0 \\ 1, & x > 0 \end{cases}$$

II. Main Layers

C. Layers Concepts & Implements

C2. ReLU - Nonlinearity



$$ReLU(x) = \max(0, x)$$

$$\frac{\partial L}{\partial x} = \begin{cases} 0, & x \leq 0 \\ 1, & x > 0 \end{cases}$$

Good Enough?

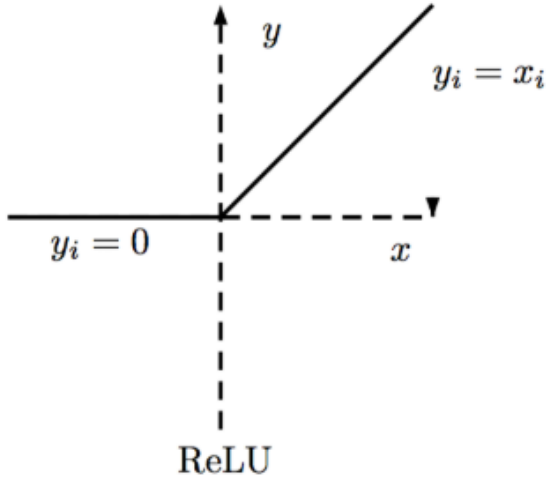
Partial elements die. Loss info

What Else Could Do?

II. Fundamental Layers

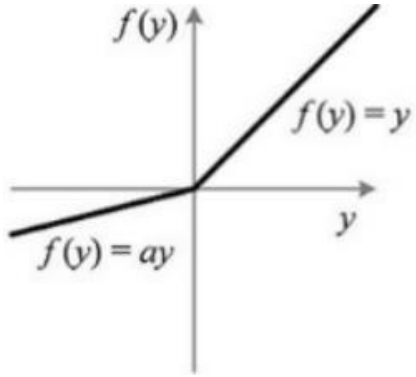
C. Layers Concepts & Implements

C2. ReLU - Nonlinearity



$$ReLU(x) = \max(0, x)$$

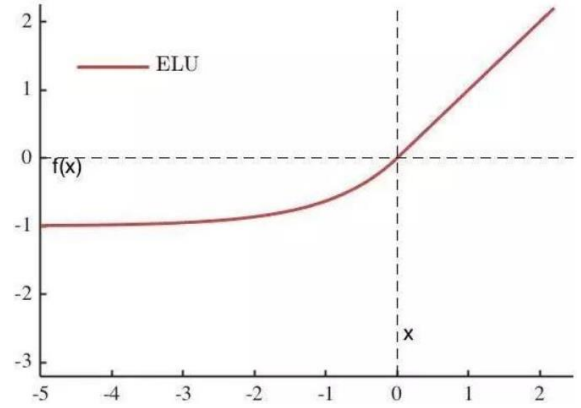
(rectified linear unit)



$$Leaky\_ReLU(x) = \max(0.01x, x)$$

$$PReLU(x) = \max(\alpha x, x)$$

(parametric relu)



$$ELU(x) = \begin{cases} \alpha(\exp(x) - 1), & x \le 0 \\ x, & x > 0 \end{cases}$$

(exponential relu)

$$\frac{\partial L}{\partial x} = \begin{cases} ELU(x) + \alpha, & x \le 0 \\ 1, & x > 0 \end{cases}$$

II. Fundamental Layers

C. Layers Concepts & Implements

C2. ReLU - Nonlinearity

Questions:

1. ***What is nonlinearity***
2. ***What is nonlinearity for***
3. ***What is ReLU***
4. ***Why ReLU***

Answers:

1. $d_{out} \neq k\, d_{in}$
2. ***to fit the complex system***
3. ***activation func like Sigmoid , Tanh ...***
4. ***easy to implement, calculate, loss-friendly***

II. Fundamental Layers

C. Layers Concepts & Implements

C2. ReLU - Nonlinearity

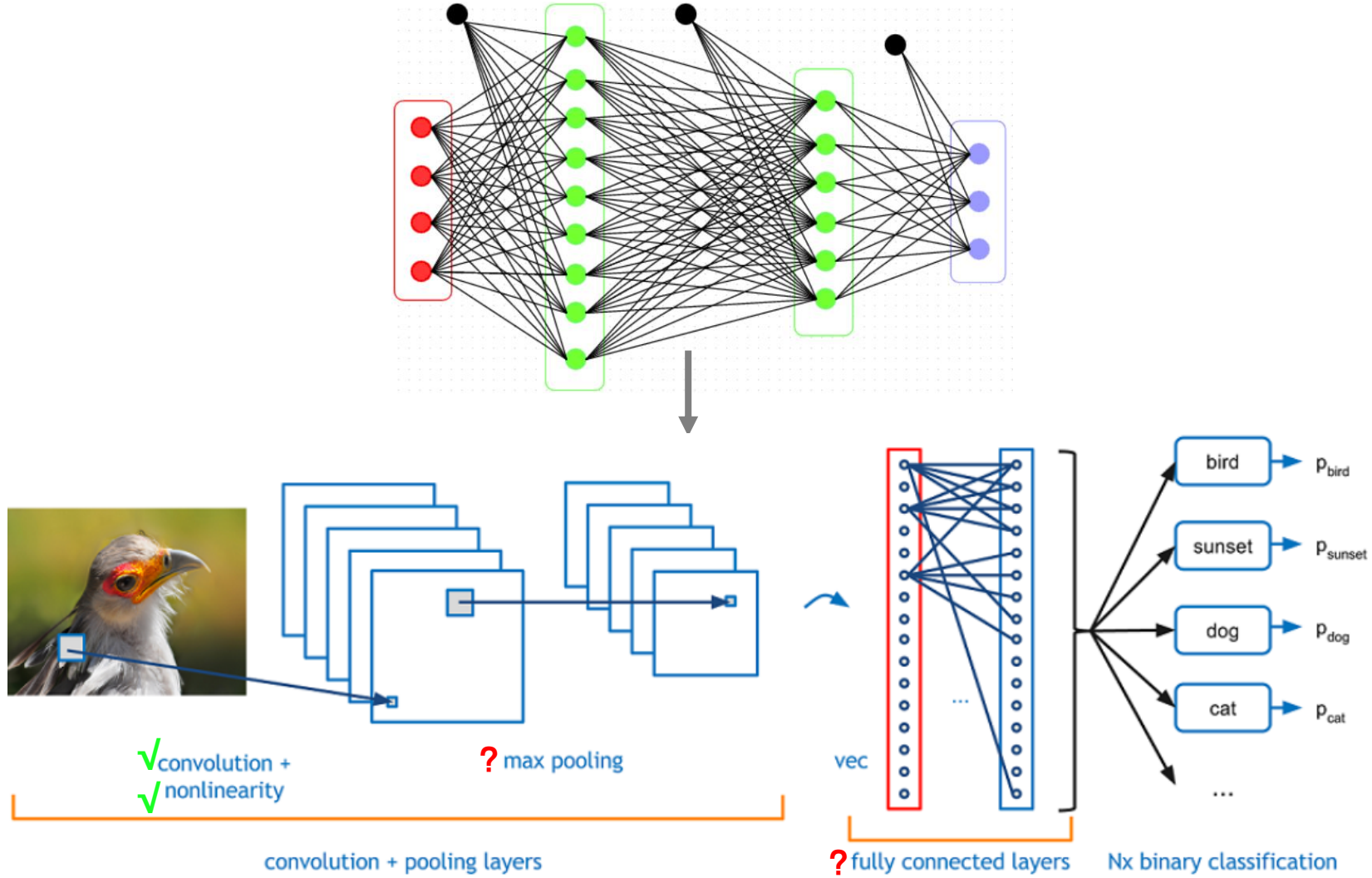
Questions:

5. ***Which one is better***
6. ***Any other types***

Answers

5. ***ReLU could be 1st choice***
   PReLU looks better
   Never use sigmoid in middle layers
6. ***Maxout, SeLU. (If U have interests)***

I. CNN Outlines - Revisit



II. Fundamental Layers

C. Layers Concepts & Implements

C3. Pooling

Questions:

1. ***What is pooling***
2. ***What is pooling for***
3. ***What kind of pooling***

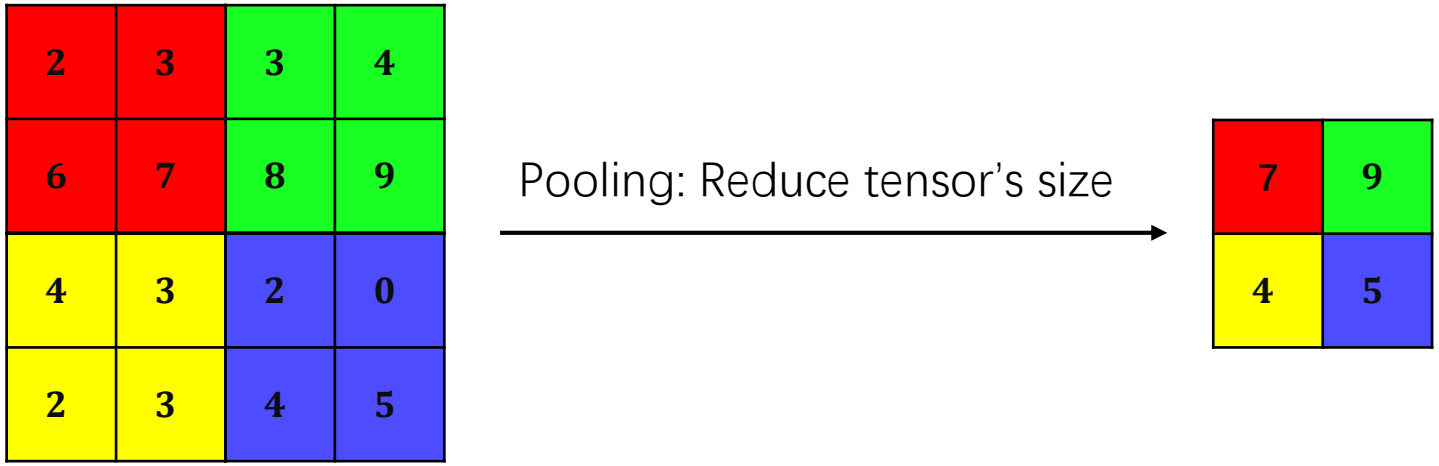
Answers:

1.
2.
3.

II. Fundamental Layers

C. Layers Concepts & Implements

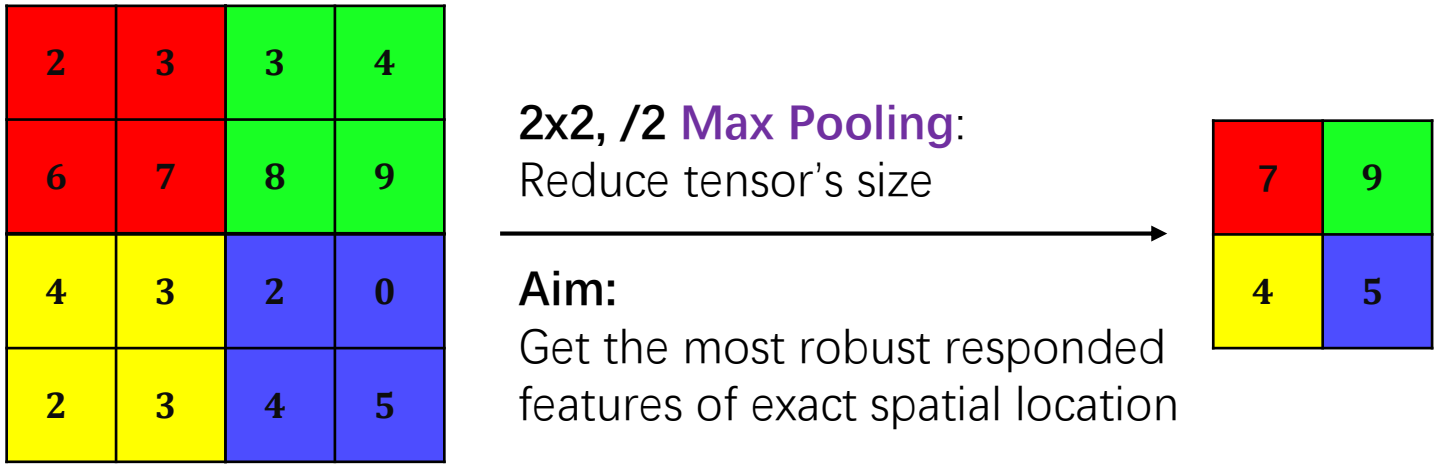
C3. Pooling (池化)



II. Fundamental Layers

C. Layers Concepts & Implements

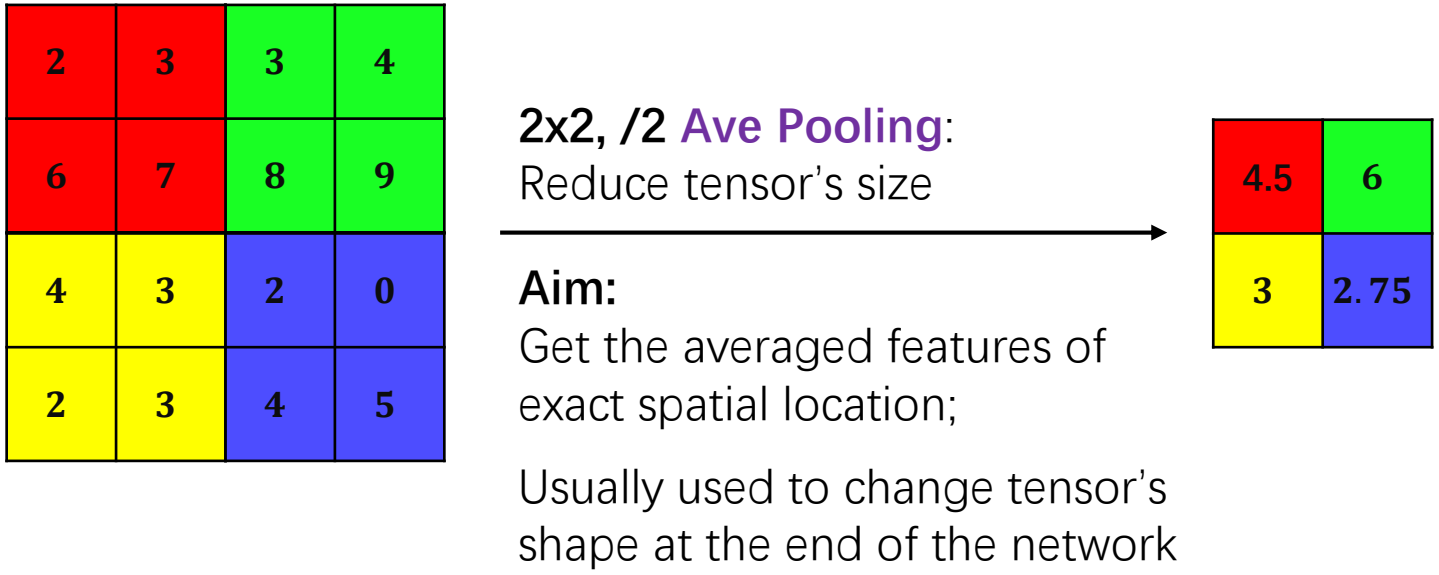
C3. Pooling (池化)



II. Fundamental Layers

C. Layers Concepts & Implements

C3. Pooling (池化)



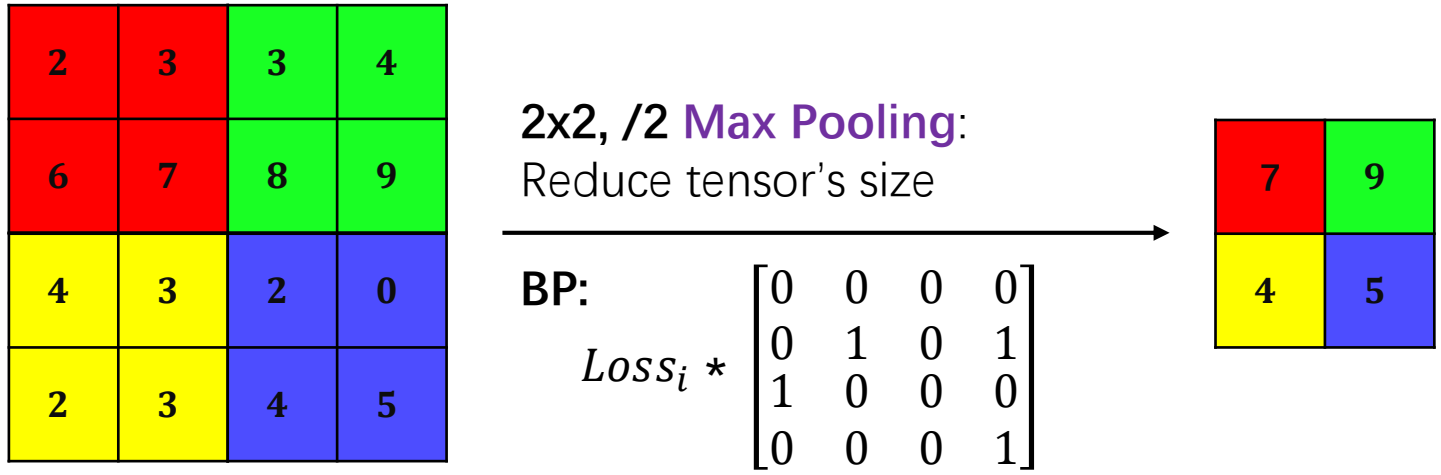
Aim:
Get the averaged features of exact spatial location;

Usually used to change tensor's shape at the end of the network

II. Fundamental Layers

C. Layers Concepts & Implements

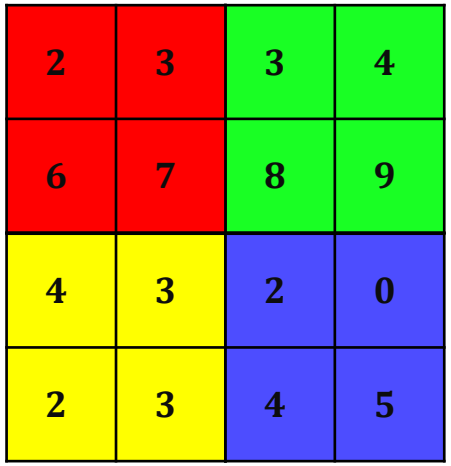
C3. Pooling - BP



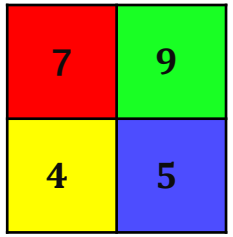
II. Fundamental Layers

C. Layers Concepts & Implements

C3. Pooling - BP



2x2, /2 Ave Pooling:
Reduce tensor's size



BP:

$$Loss_i * \begin{bmatrix} \frac{1}{4} & \frac{1}{4} & \frac{1}{4} & \frac{1}{4} \\ \frac{1}{4} & \frac{1}{4} & \frac{1}{4} & \frac{1}{4} \\ \frac{1}{4} & \frac{1}{4} & \frac{1}{4} & \frac{1}{4} \\ \frac{1}{4} & \frac{1}{4} & \frac{1}{4} & \frac{1}{4} \end{bmatrix}$$

II. Fundamental Layers

C. Layers Concepts & Implements

C3. Pooling

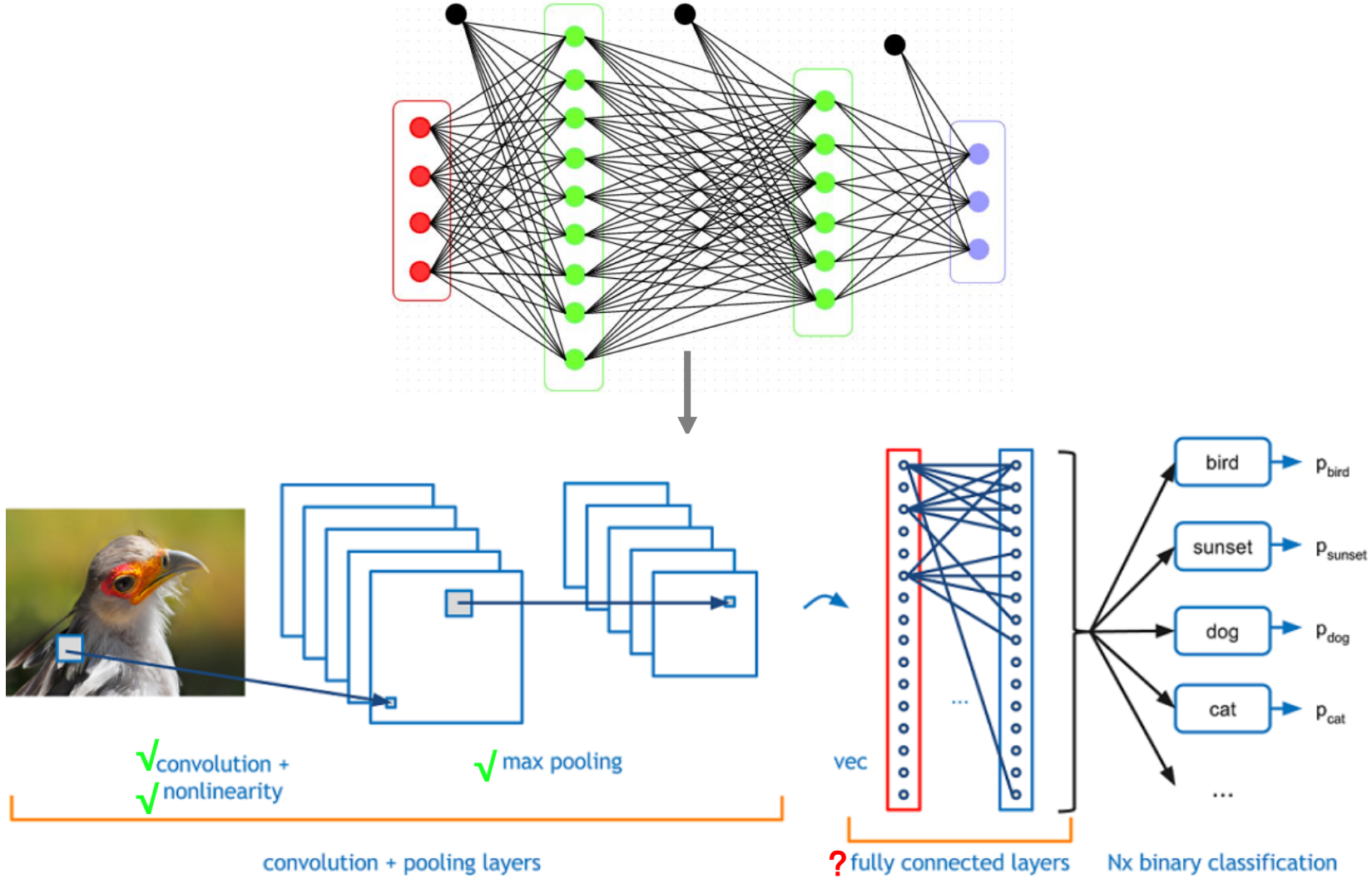
Questions:

1. ***What is pooling***
2. ***What is pooling for***
3. ***What kind of pooling***
4. ***How to do BP***

Answers:

1.
2.
3.
4.

I. CNN Outlines - Revisit



II. Fundamental Layers

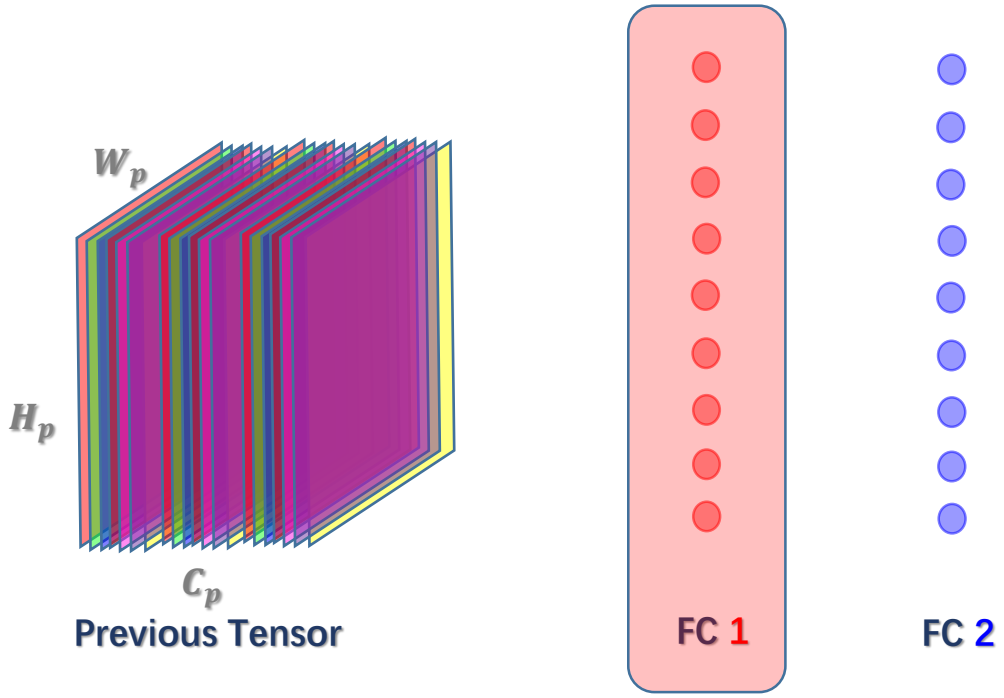
C. Layers Concepts & Implements

C4. Fully Connected / Inner Product

II. Fundamental Layers

C. Layers Concepts & Implements

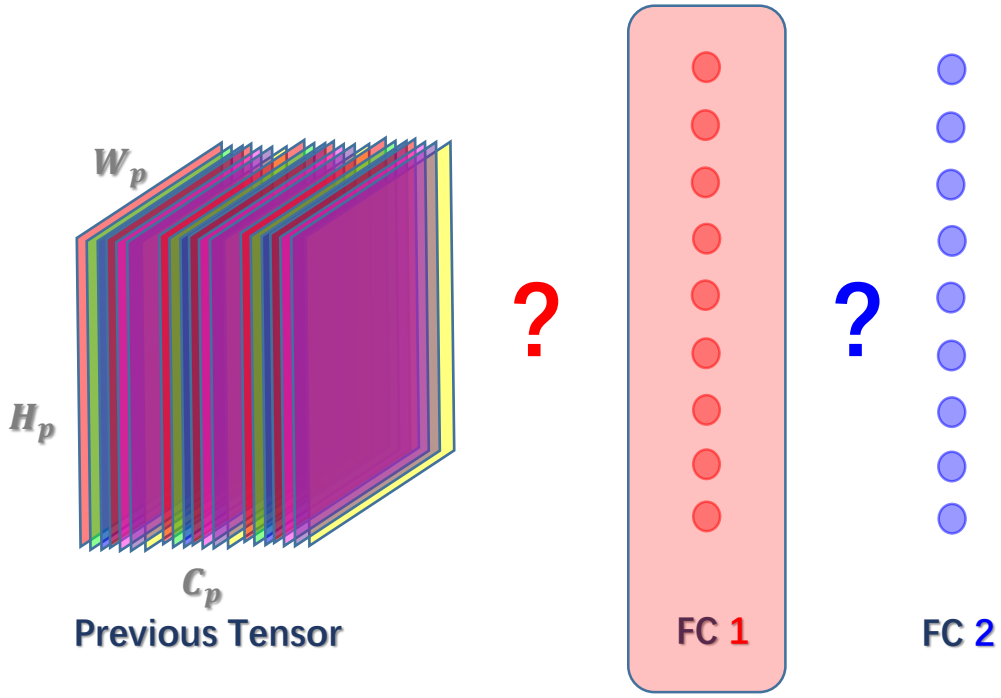
C4. Fully Connected / Inner Product



II. Fundamental Layers

C. Layers Concepts & Implements

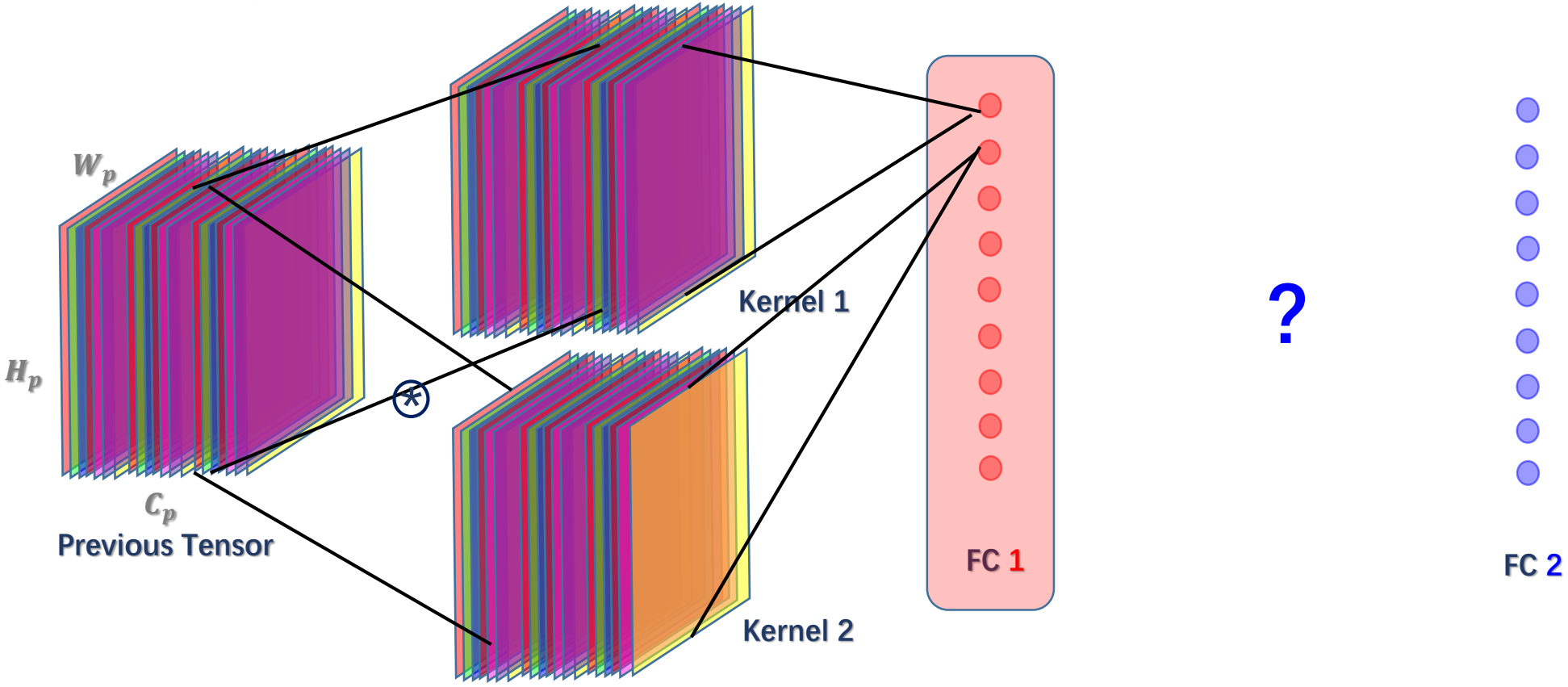
C4. Fully Connected / Inner Product



II. Fundamental Layers

C. Layers Concepts & Implements

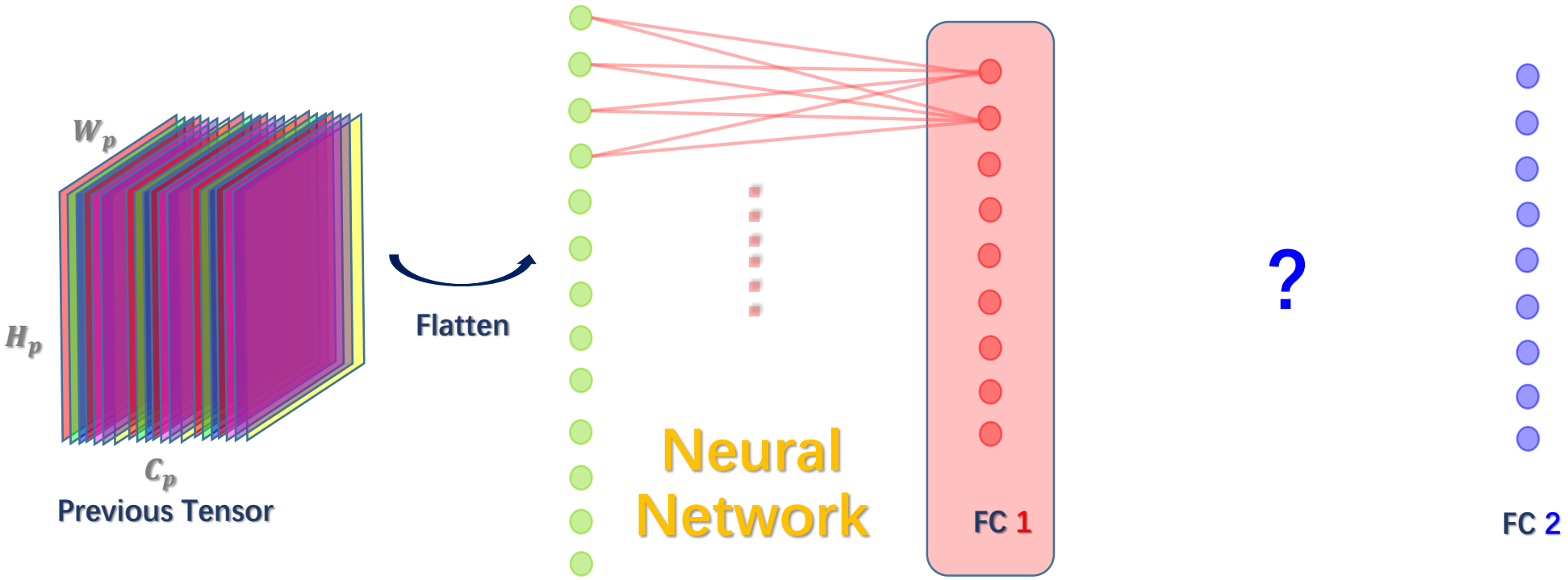
C4. Fully Connected / Inner Product



II. Fundamental Layers

C. Layers Concepts & Implements

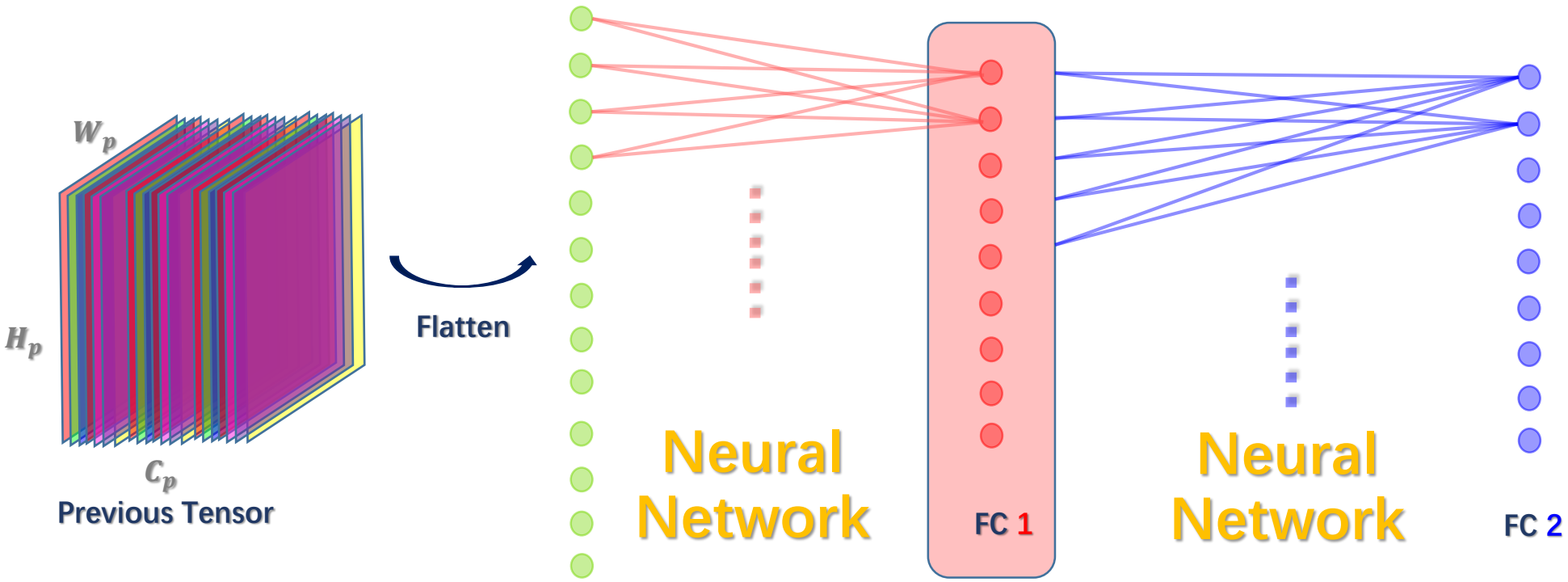
C4. Fully Connected / Inner Product



II. Fundamental Layers

C. Layers Concepts & Implements

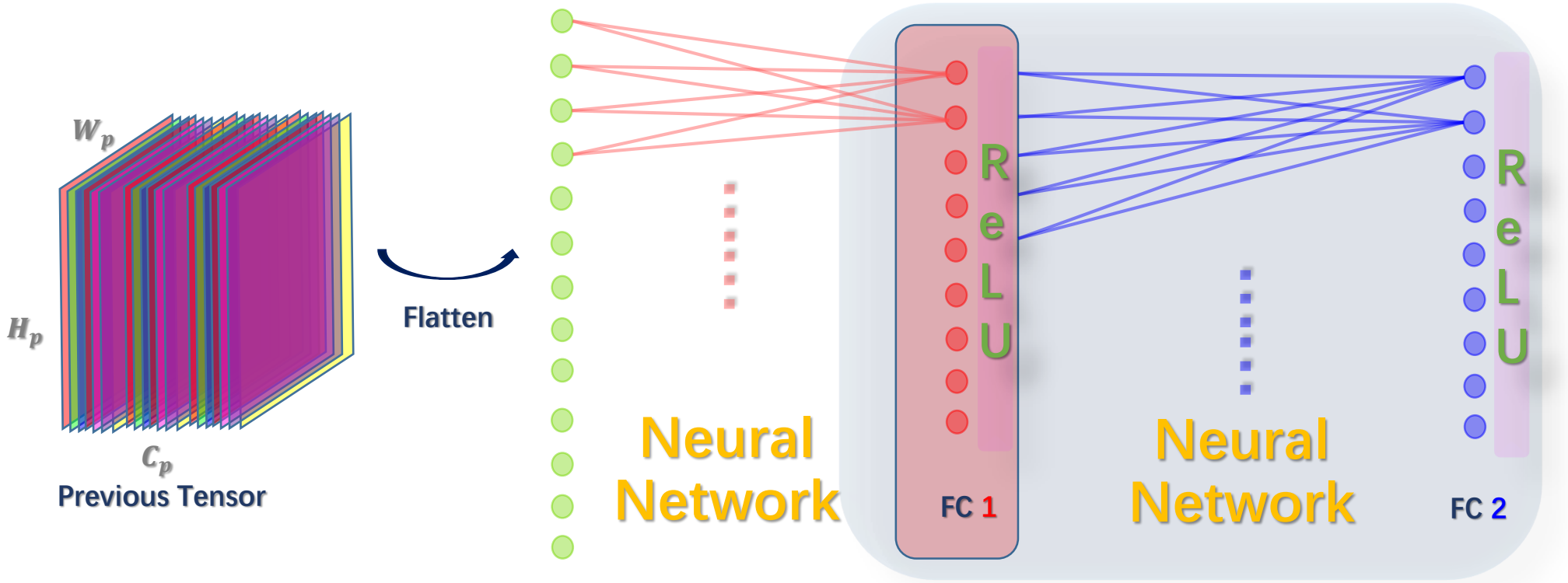
C4. Fully Connected / Inner Product



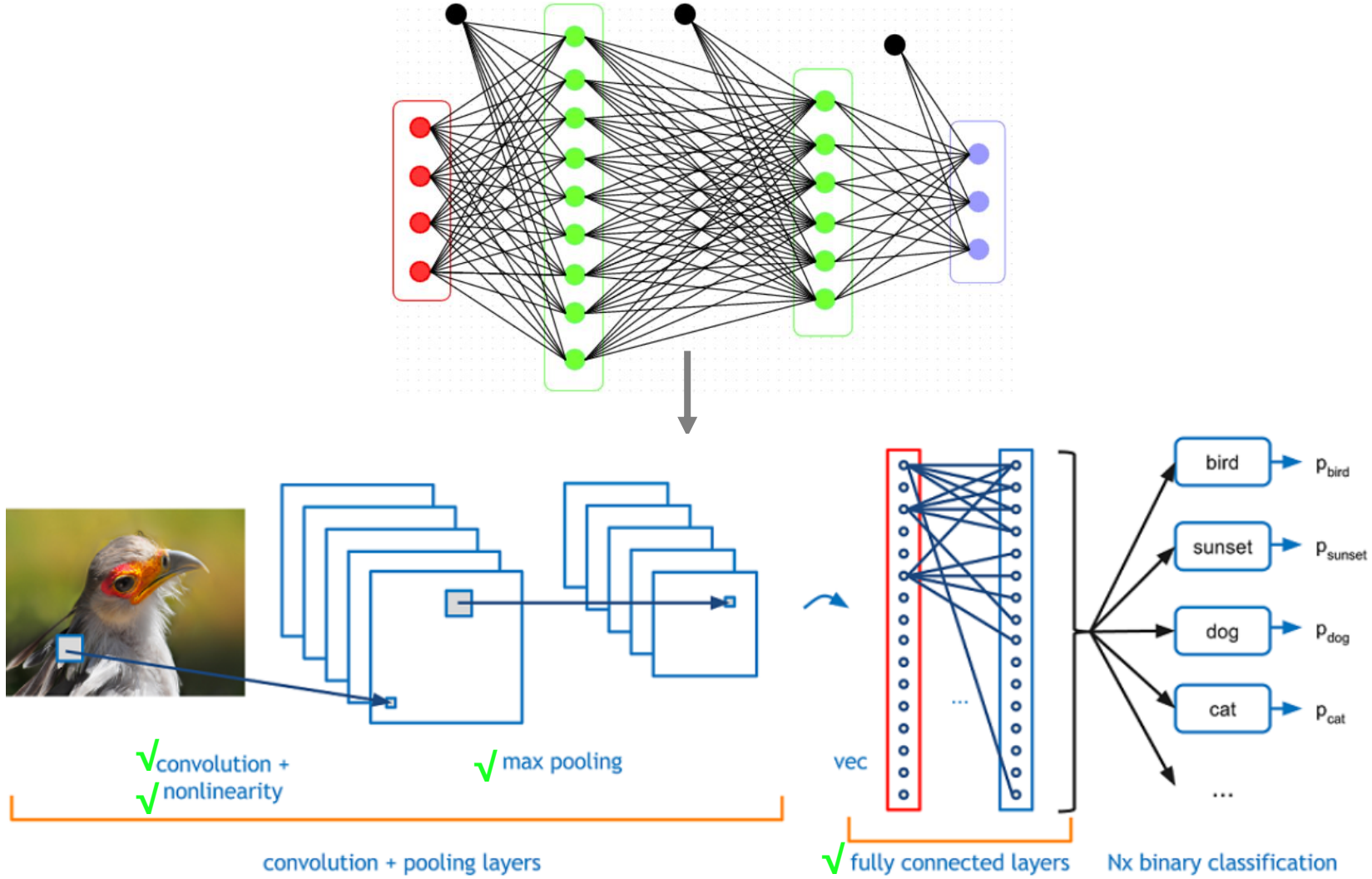
II. Fundamental Layers

C. Layers Concepts & Implements

C4. Fully Connected / Inner Product



I. CNN Outlines - Revisit



II. Fundamental Layers

C. Layers Concepts & Implements

C4. Fully Connected / Inner Product

Really?

II. Fundamental Layers

C. Layers Concepts & Implements

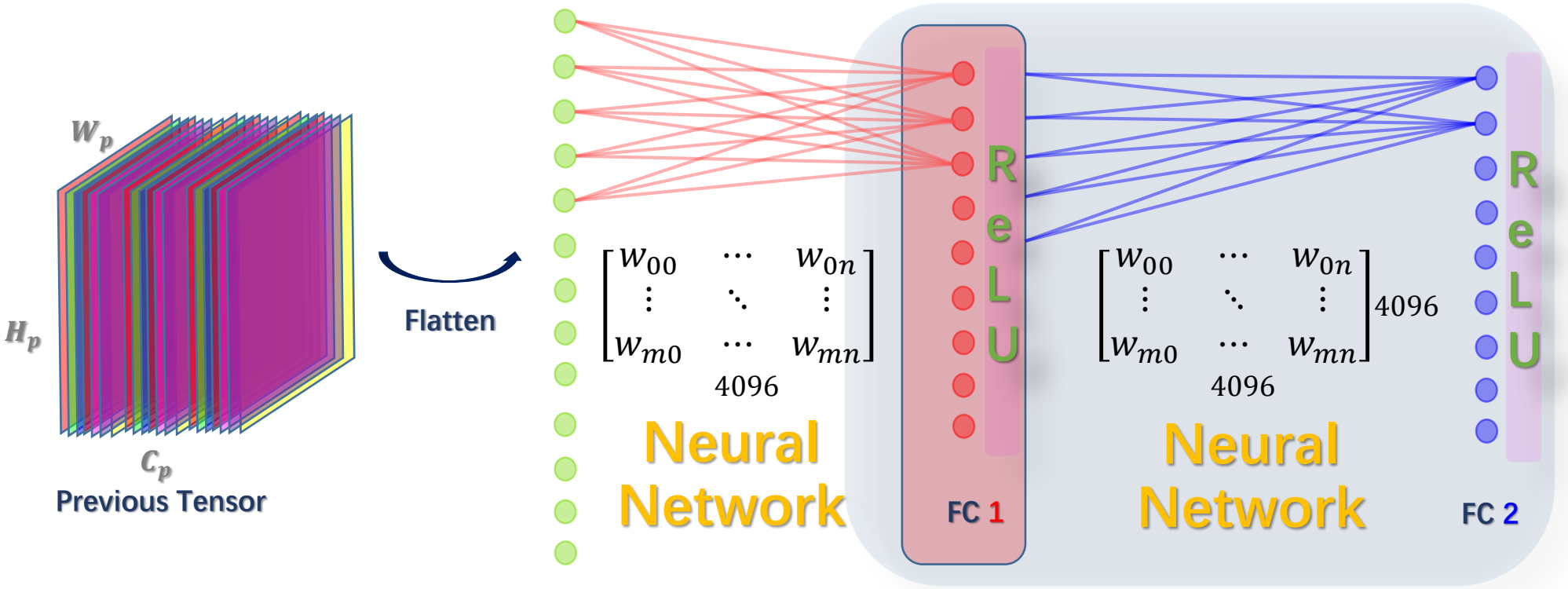
C4. Fully Connected / Inner Product

Any Thoughts?

II. Fundamental Layers

C. Layers Concepts & Implements

C4. Fully Connected / Inner Product



II. Fundamental Layers

C. Layers Concepts & Implements

C4. Fully Connected / Inner Product

1. **Too many parameters, sometimes**
2. **Too many calculations, sometimes**
3. **Too much resources needed, sometimes**
4. **Prone to over fit**

II. Fundamental Layers

C. Layers Concepts & Implements

C4. Fully Connected / Inner Product

1. **Too many parameters, sometimes**
2. **Too many calculations, sometimes**
3. **Too much resources needed, sometimes**
4. **Prone to over fit**

Any Features?

II. Fundamental Layers

C. Layers Concepts & Implements

C4. Fully Connected / Inner Product

1. Too many parameters, sometimes
2. Too many calculations, sometimes
3. Too much resources needed, sometimes
4. Prone to over fit

1. CNN-based feature vector
2. Global ave pooling as a trend

II. Fundamental Layers

C. Layers Concepts & Implements

C4. Fully Connected / Inner Product

Questions:

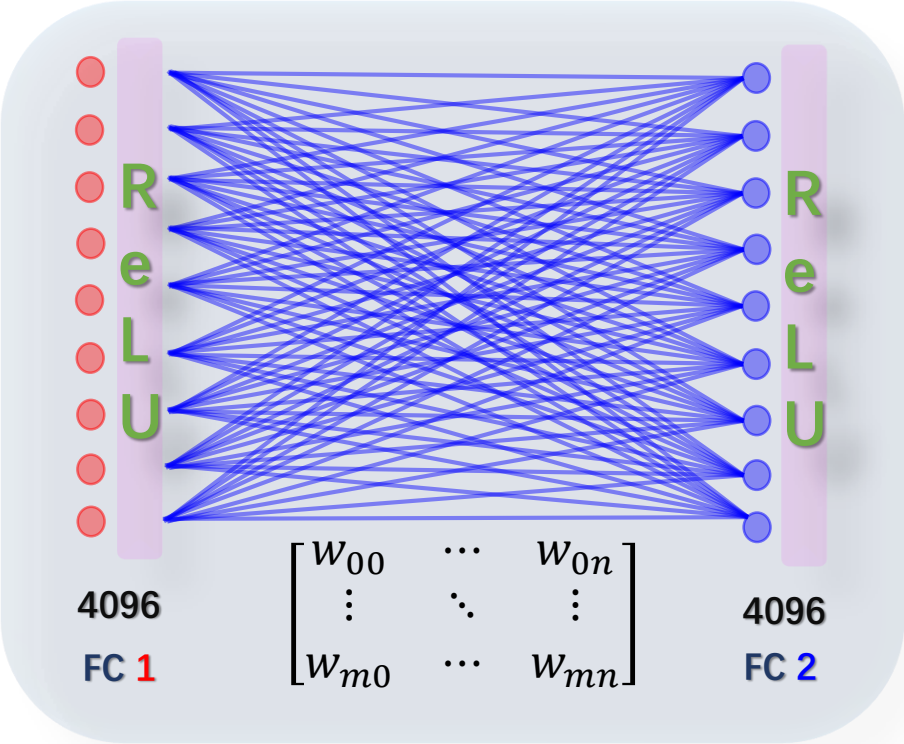
1. ***What if we need parameters to fit?***
2. ***But we don't want overfitting***
3. ***And time / resource consuming***

III. Functional Layers

II. Functional Layers

D. Functional Layers Concepts & Implements

D1. Dropout Layer

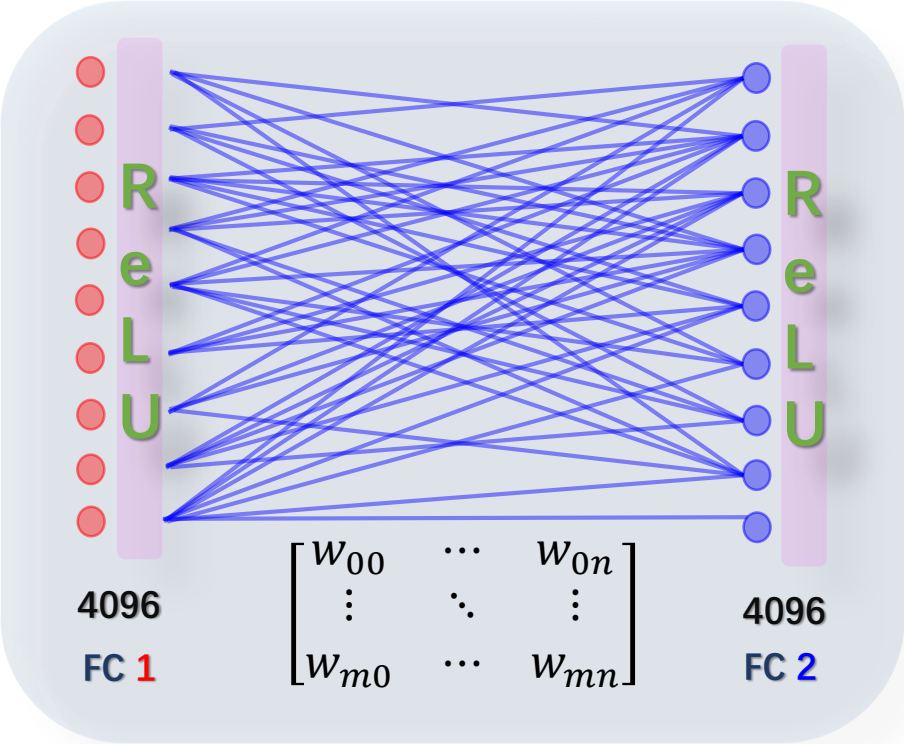


1. **Too many parameters**
2. **Too many calculations**
3. **Too much resources needed**
4. **Prone to over fit**

II. Functional Layers

D. Functional Layers Concepts & Implements

D1. Dropout Layer

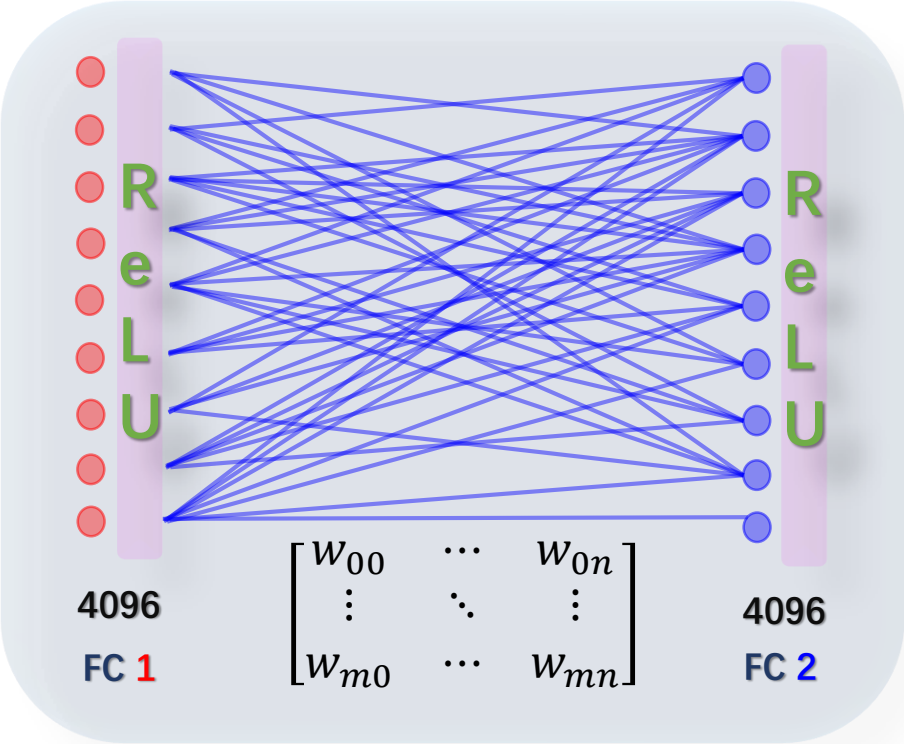


1. **Too many parameters**
2. **Too many calculations**
3. **Too much resources needed**
4. **Prone to over fit**

II. Functional Layers

D. Functional Layers Concepts & Implements

D1. Dropout Layer

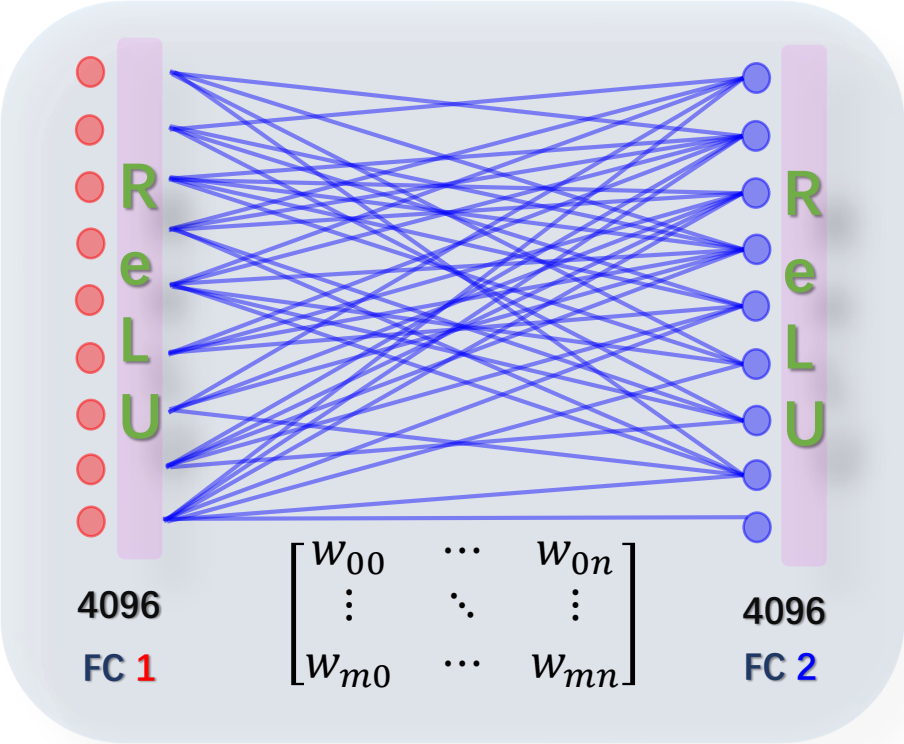


Randomly give up some connections under a particular ratio

II. Functional Layers

D. Functional Layers Concepts & Implements

D1. Dropout Layer



Train:

```
def dropout_train_step(X):
    ReLU1 = np.maximum(0, FC1)
    mask1 = np.random.rand(*ReLU1.shape) < p
    Dropout1 = ReLU1 * mask1
```

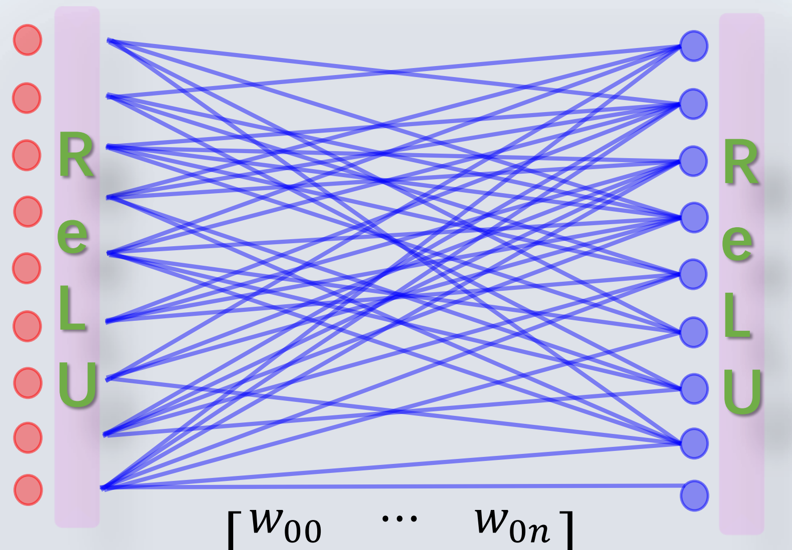
Test:

How ?

II. Functional Layers

D. Functional Layers Concepts & Implements

D1. Dropout Layer



$$\begin{bmatrix} w_{00} & \cdots & w_{0n} \\ \vdots & \ddots & \vdots \\ w_{m0} & \cdots & w_{mn} \end{bmatrix}$$

Train:

```
def dropout_train_step(X):
    ReLU1 = np.maximum(0, FC1)
    mask1 = np.random.rand(*ReLU1.shape) < p
    Dropout1 = ReLU1 * mask1
```

Test:

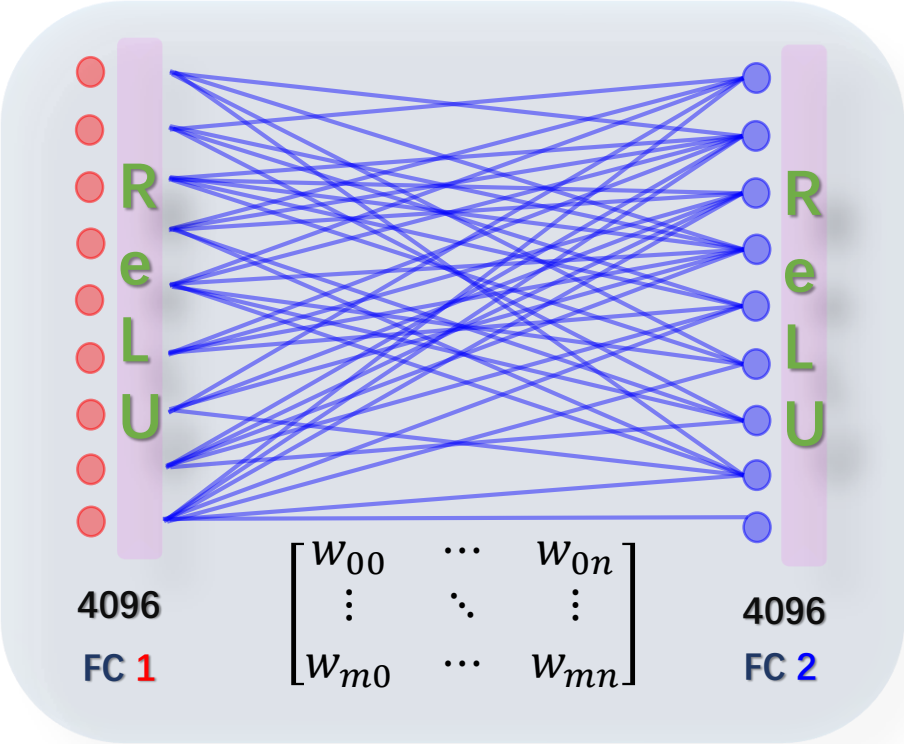
$$\begin{aligned} y &= w_0x_0 + w_1x_1 \\ &= w_0 * 1 + w_1 * 1 \end{aligned}$$

$$\begin{aligned} &= [(w_0 * 0 + w_1 * 0) + (w_0 * 0 + w_1 * 1) + \\ &\quad (w_0 * 1 + w_1 * 0) + (w_1 * 1 + w_1 * 1)] * \frac{1}{4} \\ &= \frac{1}{4} * (2w_0x_0 + 2w_1x_1) \\ &= \frac{1}{2} * (w_0x_0 + w_1x_1) \\ &= E(y) \end{aligned}$$

II. Functional Layers

D. Functional Layers Concepts & Implements

D1. Dropout Layer



Train:

```
def dropout_train_step(X):
    ReLU1 = np.maximum(0, FC1)
    mask1 = np.random.rand(*ReLU1.shape) < p
    Dropout1 = ReLU1 * mask1
```

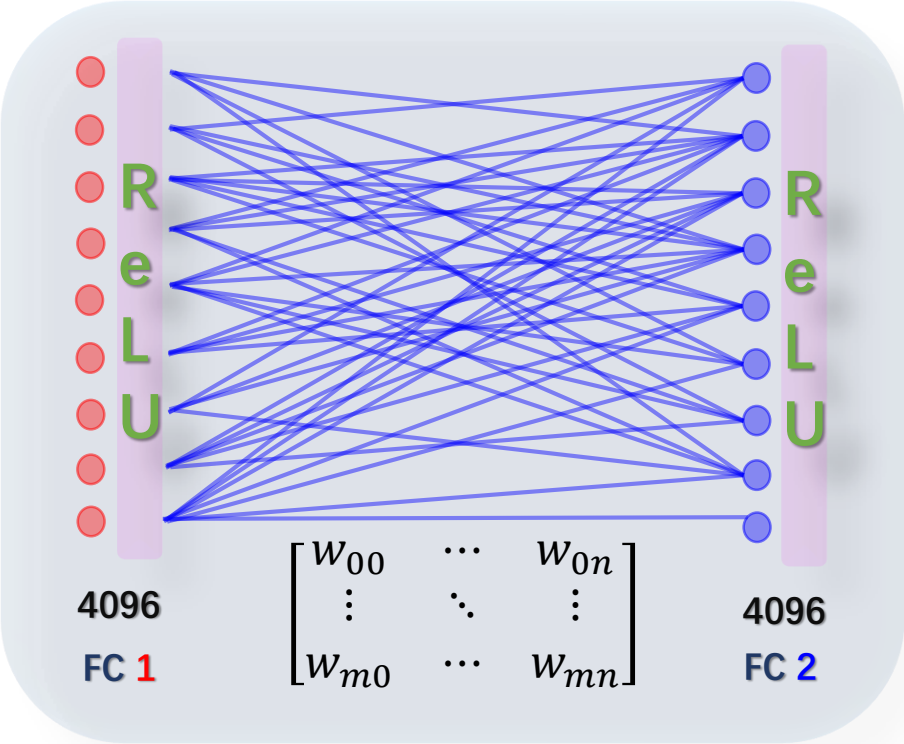
Test:

```
def dopout_test_step(X):
    ReLU1 = np.maximum(0, FC1) * p
```

II. Functional Layers

D. Functional Layers Concepts & Implements

D1. Dropout Layer



Train:

```
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    ReLU1 = np.maximum(0, FC1)
    mask1 = np.random.rand(*ReLU1.shape) < p
    Dropout1 = ReLU1 * mask1
```

Test:

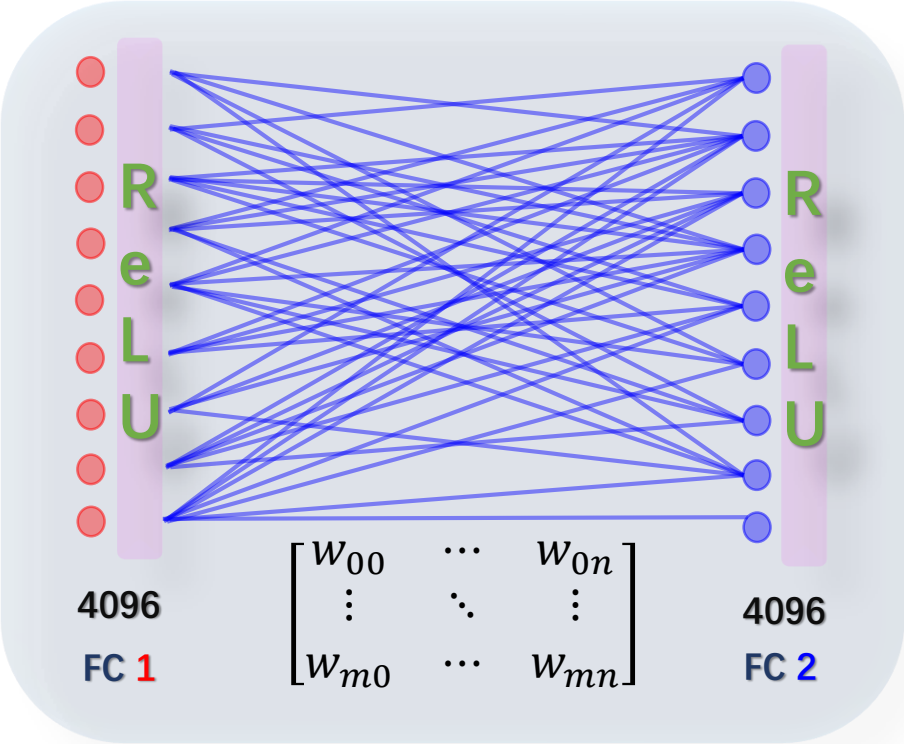
```
def dopout_test_step(X):
    ReLU1 = np.maximum(0, FC1) * p
```

We could do better

II. Functional Layers

D. Functional Layers Concepts & Implements

D1. Dropout Layer



Train:

```
def dropout_train_step(X):
    ReLU1 = np.maximum(0, FC1)
    mask1 = (np.random.rand(*ReLU1.shape) < p) / p
    Dropout1 = ReLU1 * mask1
```

Test:

```
def dopout_test_step(X):
    ReLU1 = np.maximum(0, FC1)
```

II. Functional Layers

D. Functional Layers Concepts & Implements

D2. Batch Normalization

II. Functional Layers

D. Functional Layers Concepts & Implements

D2. Batch Normalization

Questions:

1. ***What is BN***
2. ***What is BN for***
3. ***What kind N***
4. ***Where to put BN***
5. ***What does BN look like***
6. ***How to compute***

Answers:

1.
2.
3.
4.
5.
6.

II. Functional Layers

D. Functional Layers Concepts & Implements

D2. Batch Normalization

The deeper network, the harder to train

Vanishing gradient

II. Functional Layers

D. Functional Layers Concepts & Implements

D2. Batch Normalization

The deeper network, the more difficult to train

Vanishing gradient

Q. What kind of data is good to train

II. Functional Layers

D. Functional Layers Concepts & Implements

D2. Batch Normalization

The deeper network, the more difficult to train

Vanishing gradient

Q. What kind of data is good to train (why sigmoid is much worse?)

II. Functional Layers

D. Functional Layers Concepts & Implements

D2. Batch Normalization

The deeper network, the more difficult to train

Vanishing gradient

Q. What kind of data is good to train (why sigmoid is much worse?)

A:

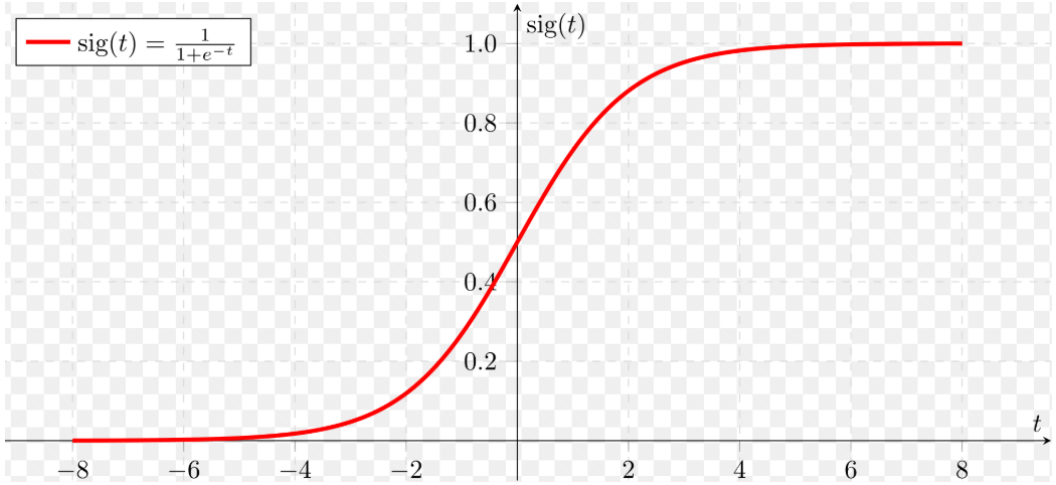
[Independent Identically Distribution & No Internal Covariate Shift]

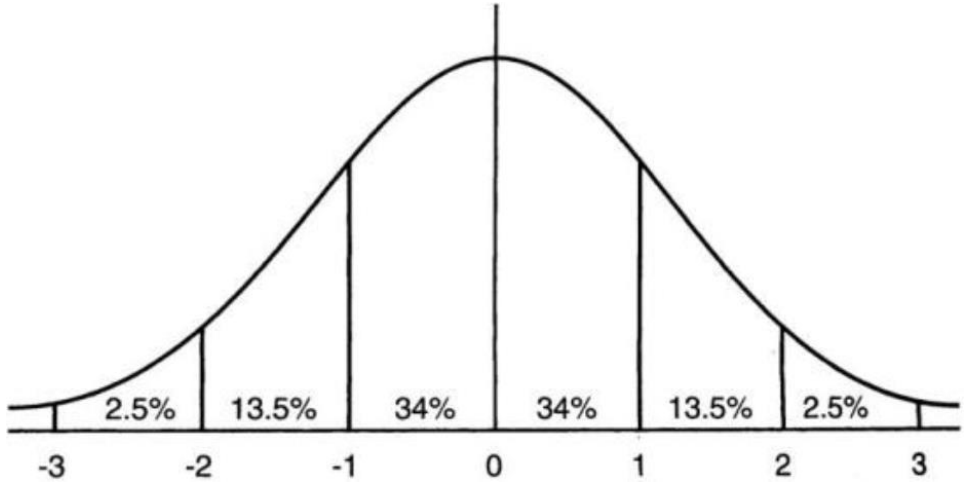
The distribution is coincident to data and to the range of activation function where there's largest gradient.

II. Functional Layers

D. Functional Layers Concepts & Implements

D2. Batch Normalization-Theory

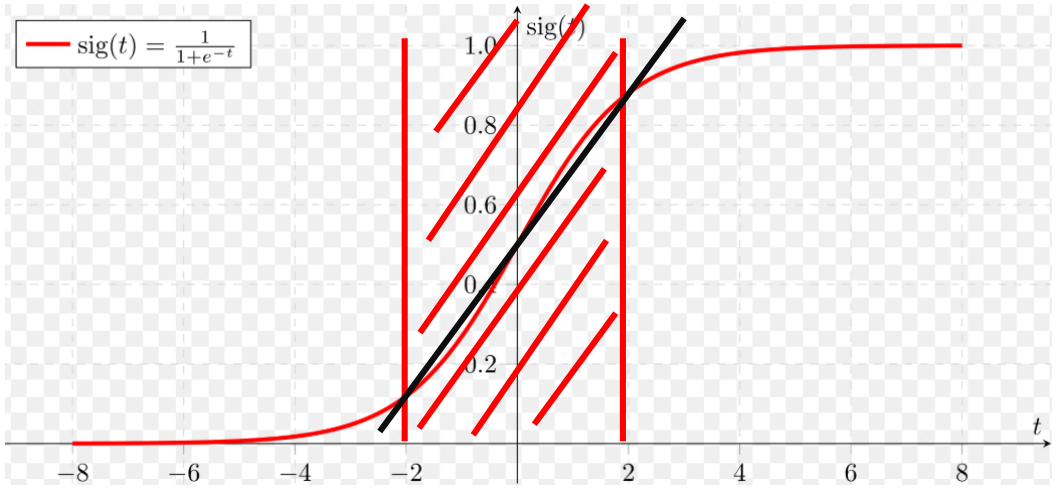


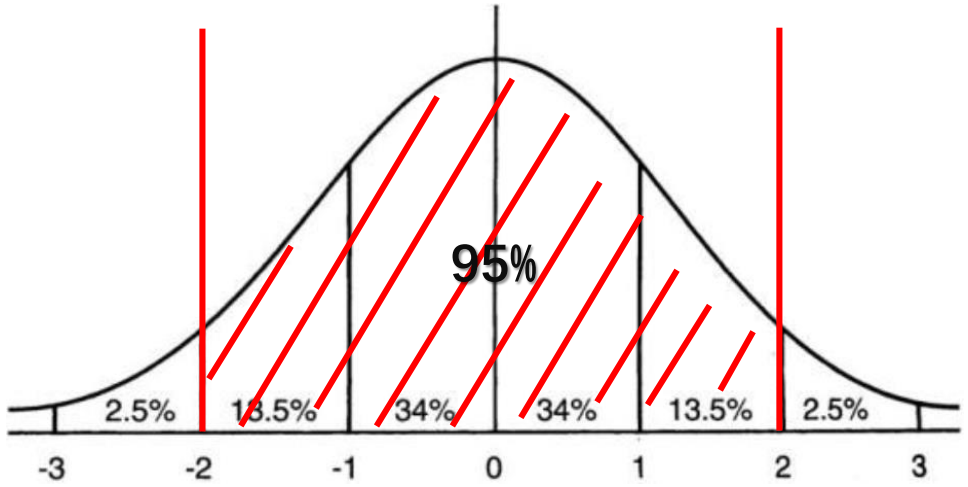


II. Functional Layers

D. Functional Layers Concepts & Implements

D2. Batch Normalization-Theory





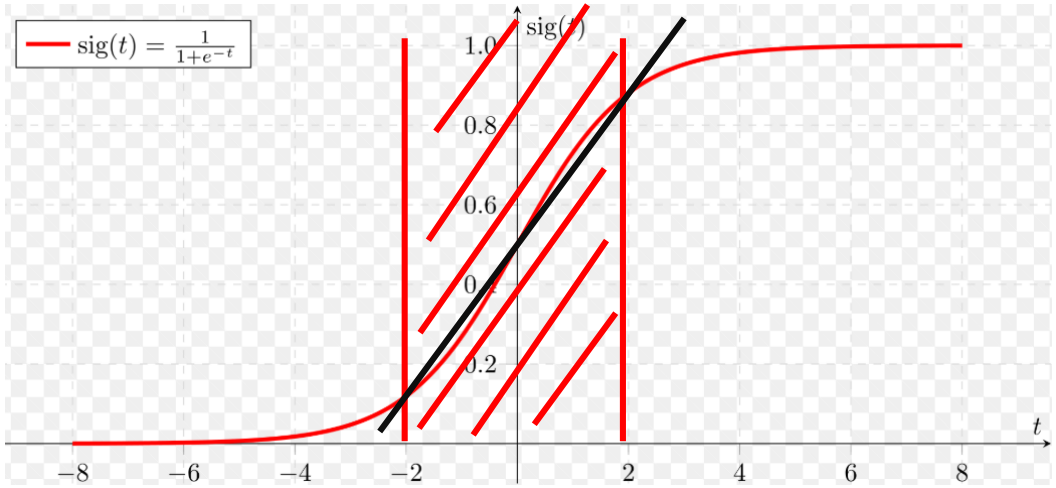
Layer-layer: Should have IID (Independent identical distribution)

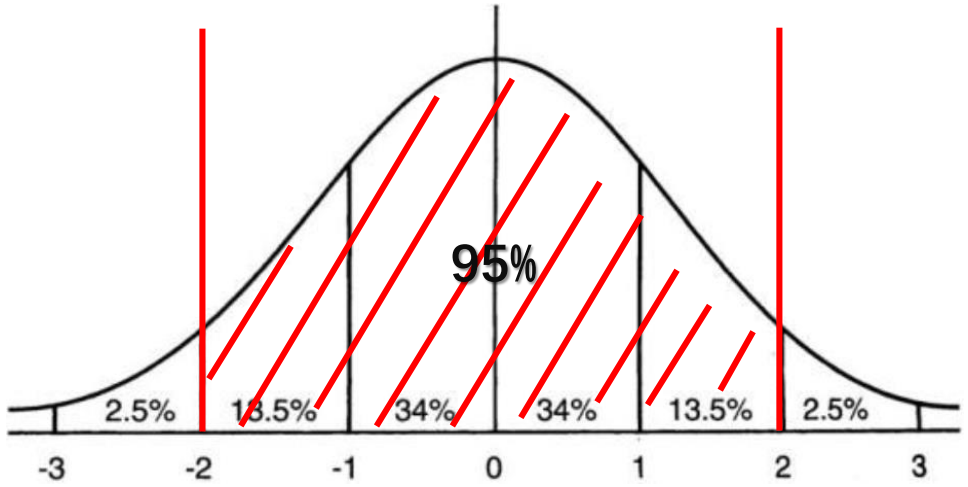
Solve: Internal Covariate Shift

II. Functional Layers

D. Functional Layers Concepts & Implements

D2. Batch Normalization-Theory





Gradient saturation: a. gradient losing; b. loss is reducing

BN: pull the data back to distribution having larger distribution.
Changing data distribution via changing data

II. Functional Layers

D. Functional Layers Concepts & Implements

D2. Batch Normalization-Theory

Input: Values of x over a mini-batch: $\mathcal{B} = \{x_{1...m}\}$;
Parameters to be learned: γ, β
Output: $\{y_i = \mathrm{BN}_{\gamma,\beta}(x_i)\}$

$$\mu_{\mathcal{B}} \leftarrow \frac{1}{m}\sum_{i=1}^{m} x_i \qquad \text{// mini-batch mean}$$

$$\sigma_{\mathcal{B}}^2 \leftarrow \frac{1}{m}\sum_{i=1}^{m}(x_i - \mu_{\mathcal{B}})^2 \qquad \text{// mini-batch variance}$$

$$\widehat{x}_i \leftarrow \frac{x_i - \mu_{\mathcal{B}}}{\sqrt{\sigma_{\mathcal{B}}^2 + \epsilon}} \qquad \text{// normalize}$$

$$y_i \leftarrow \gamma\widehat{x}_i + \beta \equiv \mathrm{BN}_{\gamma,\beta}(x_i) \qquad \text{// scale and shift}$$

II. Functional Layers

D. Functional Layers Concepts & Implements

D2. Batch Normalization-Theory

Input: Values of x over a mini-batch: $\mathcal{B} = \{x_{1...m}\}$;
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II. Functional Layers

D. Functional Layers Concepts & Implements

D2. Batch Normalization-Theory

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$$y_i \leftarrow \gamma\widehat{x}_i + \beta \equiv \mathrm{BN}_{\gamma,\beta}(x_i) \qquad \text{// scale and shift}$$

Phenomenon

1. Larger gradient -> more linear
2. More linear -> harder to fit complex system
3. Harder to fit -> bad result

Explanation

1. Finetune each input
2. Gradually map the normalized input to original one
3. Maintain the ability of fitting complex system

II. Functional Layers

D. Functional Layers Concepts & Implements

D2. Batch Normalization-Theory

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$$y_i \leftarrow \gamma\widehat{x}_i + \beta \equiv \mathrm{BN}_{\gamma,\beta}(x_i) \qquad \text{// scale and shift}$$

Benefits (more exp. in course)

1. Increase learning rate
2. Speed up training
3. Less prone to overfit
   Remove or use less dropout
   Reduce L2 regularization weight
4. Less image augmentation

II. Functional Layers

D. Functional Layers Concepts & Implements

D2. Batch Normalization-Practice

Where To Put?

Usually:

Conv -> Batch Norm -> ReLU->Pool

Some argues:

Conv -> ReLU -> Batch Norm ->Pool

II. Functional Layers

D. Functional Layers Concepts & Implements

D2. Batch Normalization-Practice

Train & Test?

Train:

Get mean & std for each batch

Test:

Use recorded mean & std (usually last trained batch's)

II. Functional Layers

D. Functional Layers Concepts & Implements

D2. Batch Normalization-Calculation

How To BP?

Input: Values of x over a mini-batch: $\mathcal{B} = \{x_{1...m}\}$;
Parameters to be learned: γ, β
Output: $\{y_i = \mathrm{BN}_{\gamma,\beta}(x_i)\}$

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$$\sigma_{\mathcal{B}}^2 \leftarrow \frac{1}{m}\sum_{i=1}^{m}(x_i - \mu_{\mathcal{B}})^2 \qquad \text{// mini-batch variance}$$

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$$y_i \leftarrow \gamma\widehat{x}_i + \beta \equiv \mathrm{BN}_{\gamma,\beta}(x_i) \qquad \text{// scale and shift}$$

II. Functional Layers

D. Functional Layers Concepts & Implements

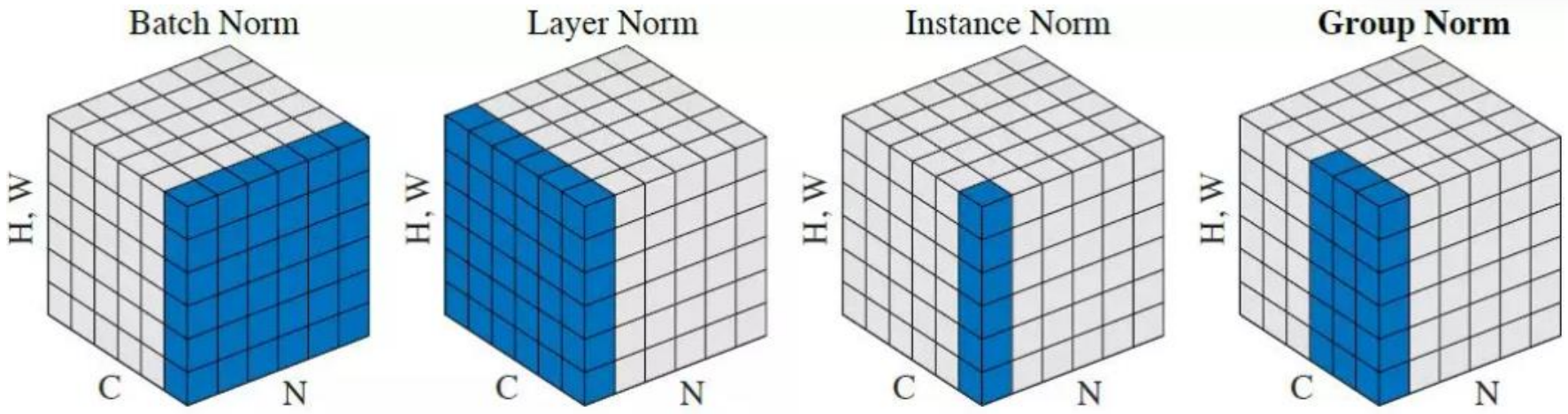
D2. Batch Normalization-Others

Group Norm, Instance Norm, Layer Norm

Reading [Optional] 😬

Answer me:

1. Area to use.
2. When to use.
3. How to use.
4. Compare each. Pros & Cons



Summary

I. Fundamental Layers

Conv: Conv, Dilated Conv, Transposed Conv, C3D (Deformable Conv)

ReLU: ReLU, Leaky-ReLU, PReLU, ELU (SeLU)

Pooling: Max Pooling, Ave Pooling

FC

II. Functional Layers

Dropout

Batch Normalization (Group / Layer / Instance Norm)