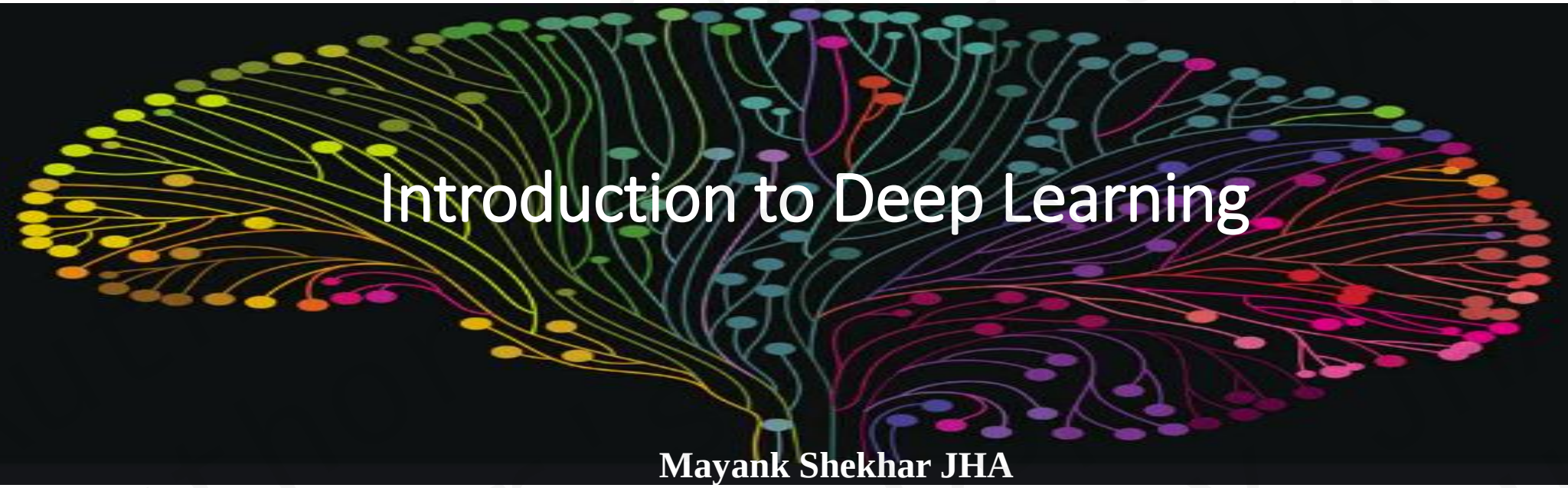

Introduction to Deep Learning

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Convolutional Neural Networks

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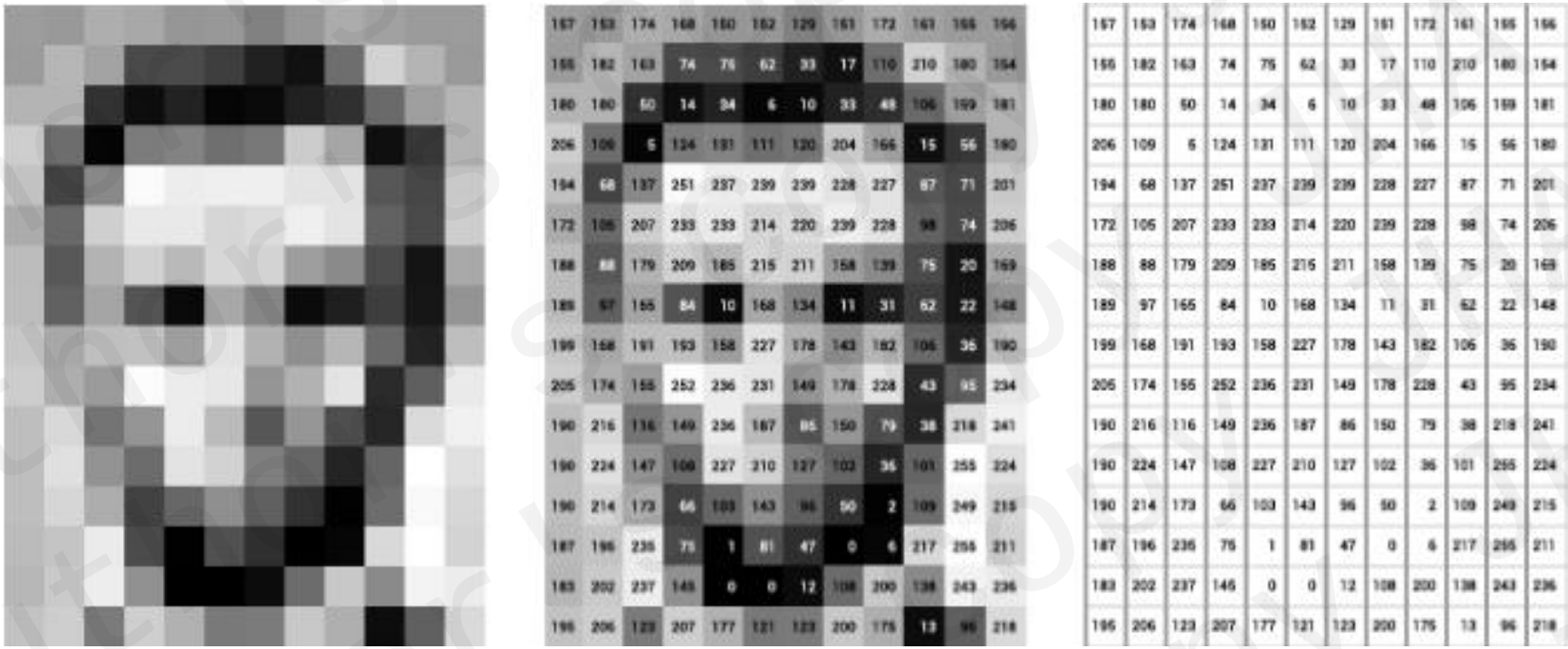
Images are just numbers for computer!



Source: OpenFrames

Images are matrix of numbers.

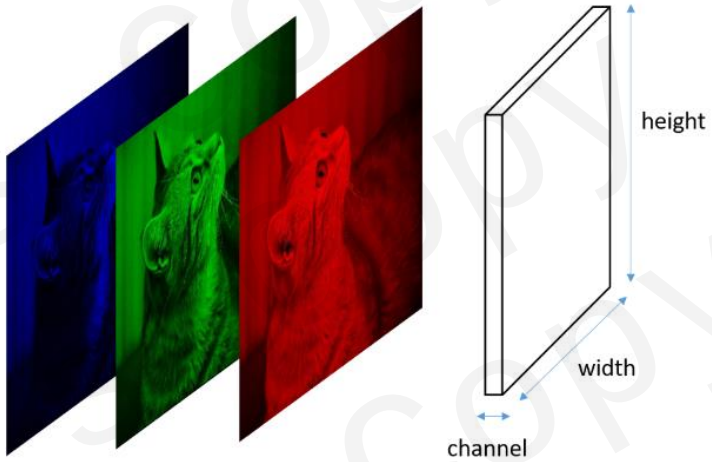
Gray Scale Images ➔ One channel Grey Scale ➔ 2D matrix of numbers (pixel values).

Each pixel =[0,255],

No of pixels proportional to image size → No of rows and columns.

Color images

Source: Broher



Source: Medium

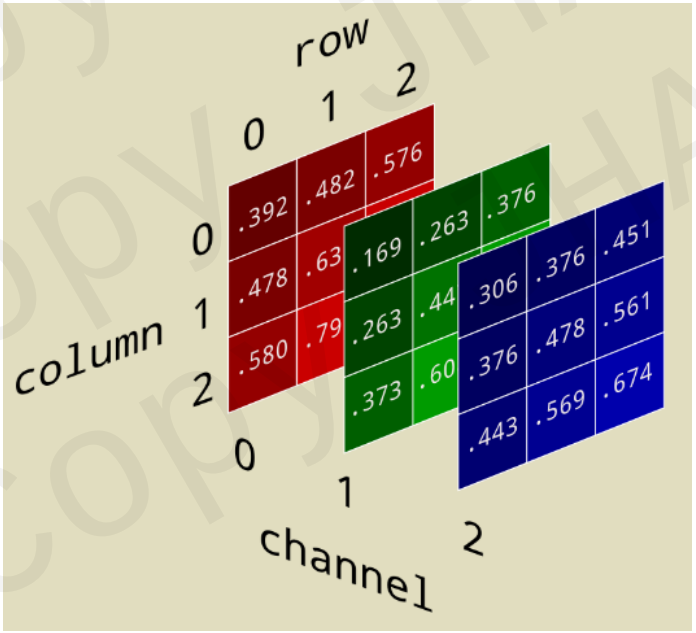
Colored Images: 3 channels of colors: 3D array

RGB channels ➔ 3D Arrays

Red: 2-D matrix

Green: 2-D matrix

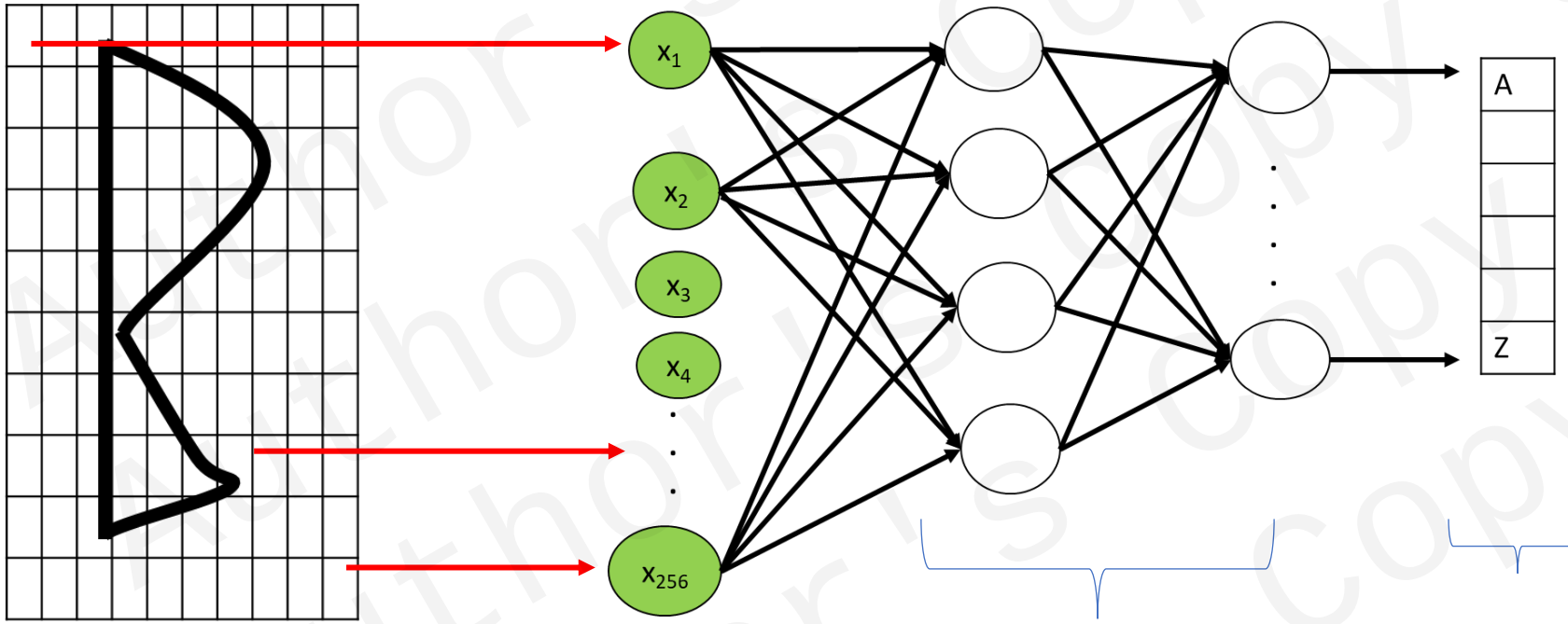
Blue: 2-D matrix



Drawbacks

Drawbacks

Explosion of training parameters



16 X 16 Image GreyScale

Deep Hidden layers

Multi class output

Colored Images: 3 channels of colors: 3D array

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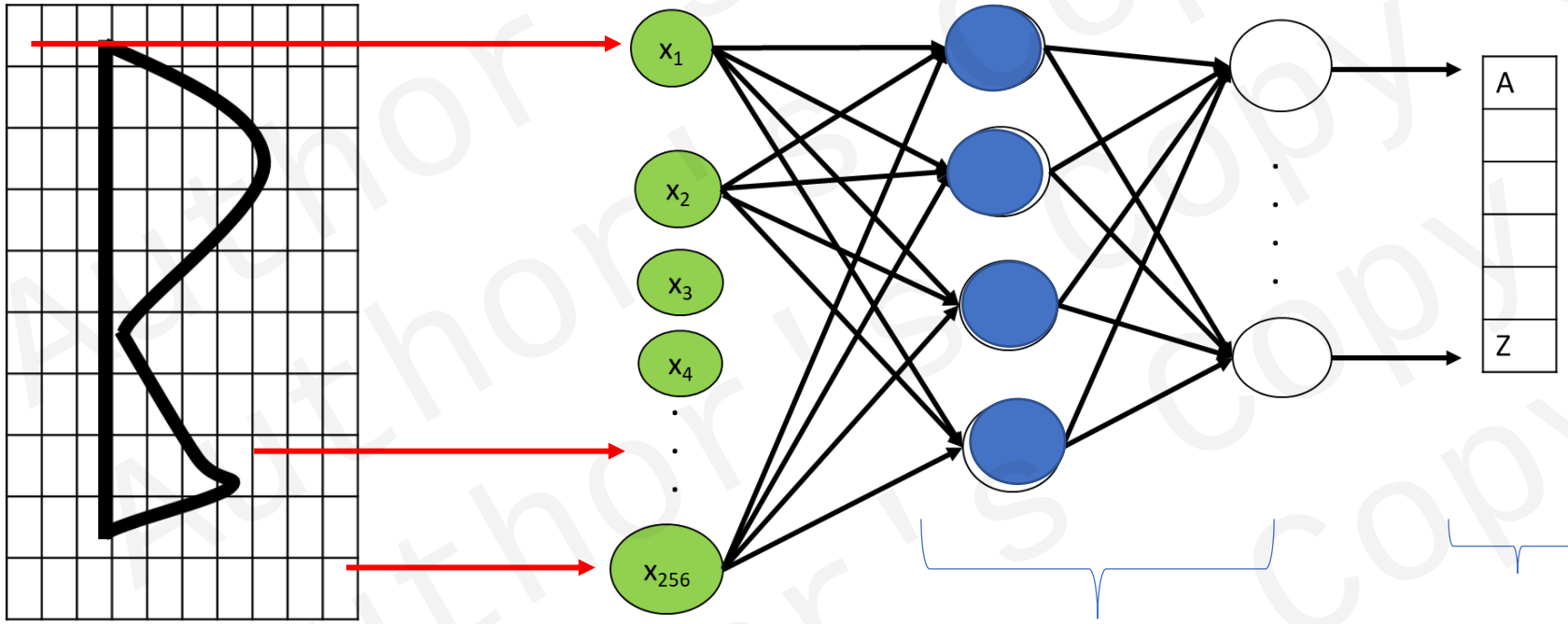
Drawbacks

Explosion of training parameters



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Deep Hidden layers

Multi class output

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Simple calculation for 1 layer , 100 hidden units:

256 inputs → 256 weights

100 hidden units → 256 x 100=25600 input weights

Bias → 100 bias

26 Outputs (A-Z)→ 26 X 100 output weights

Biases → 26

Total: 25600 + 100+ 2600 + 26 = 28326

That is just with one layer !!

Drawbacks: Trainable parameter explosion

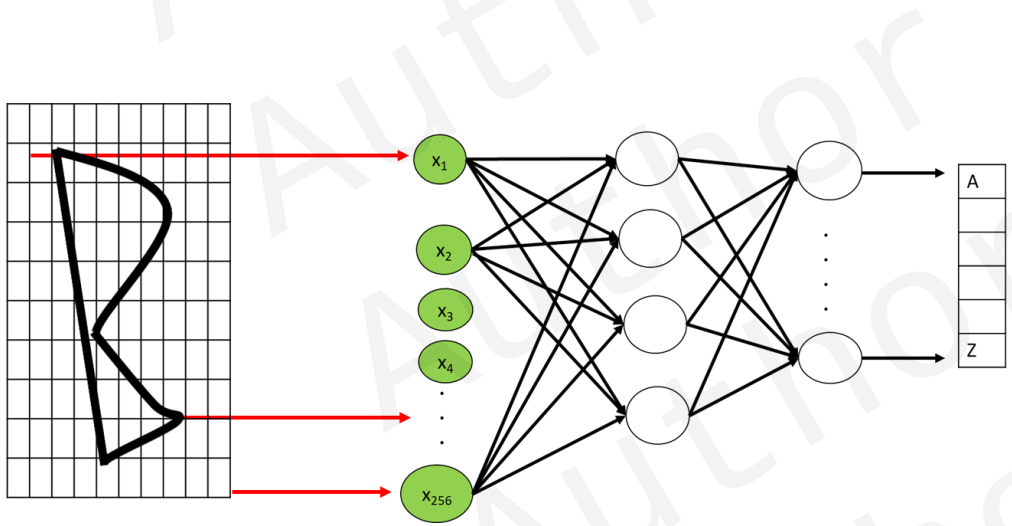
- Most images → high resolution (1MB or more) → several thousands of pixels ➔ several thousands inputs.
- Several hundreds of hidden layers with several hundreds of units.
- Total parameters to train → Extremely large → Computation intractable !!
- Strong regularization needed → difficult and little reproducibility.

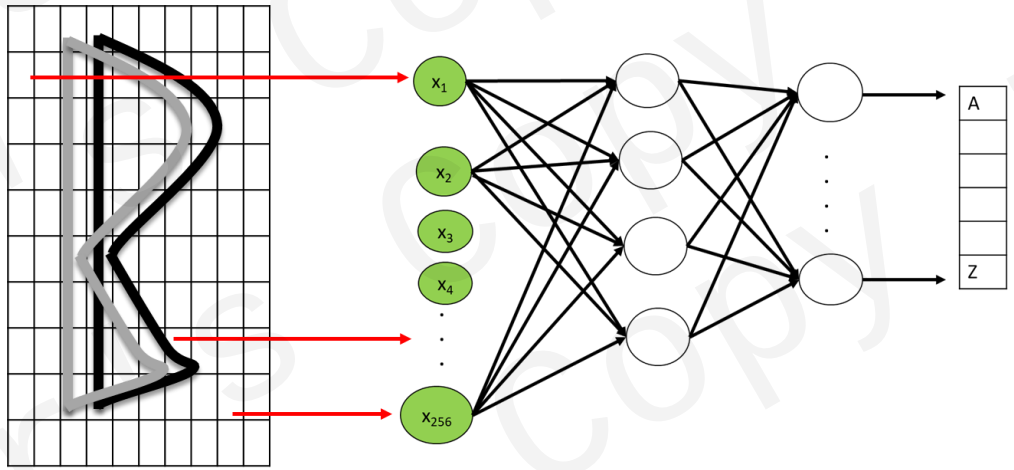
Drawbacks: Variance to distortions

- The orientation / location of object within an image should have little influence over it getting detected.

  This is not true with previous NNs (MLPs, ANNs).

- Variance to scaling, shifting and other distortions, influence of surroundings (global context).
- The topology of the data is ignored.
- Inherent distributions are not learnt well.





- Must avoid parameter explosion in face of large inputs.
- Identification of object should be invariant to scaling, shifting and different orientation.

- The object should be identifiable in any location / orientation ➔ placement of object in an image should not influence the outcome, only local information about the object should be sufficient.

Convolutional neural networks

JHA Mayank , Email: mayank-shekhar.jha [at] univ-lorraine.fr

Motivation

Convolutional layer: Motivation

Proposed by Yann LeCun and Yoshua Bengio in 1995.

- Convolutional Neural Networks are a special kind of multi-layer neural networks.
- Inspired by neuro-biology: brain's mechanism of understanding different attributes of an object
  - Attributes : shape, size, orientation and color.

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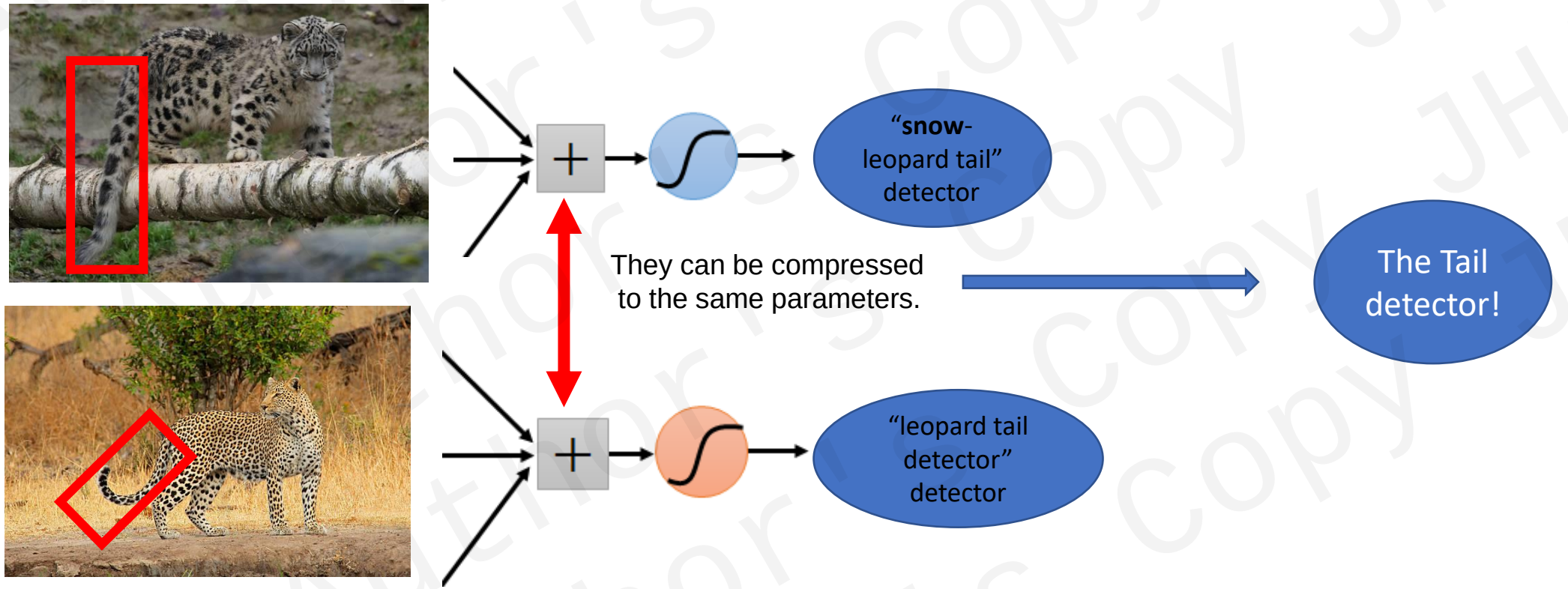

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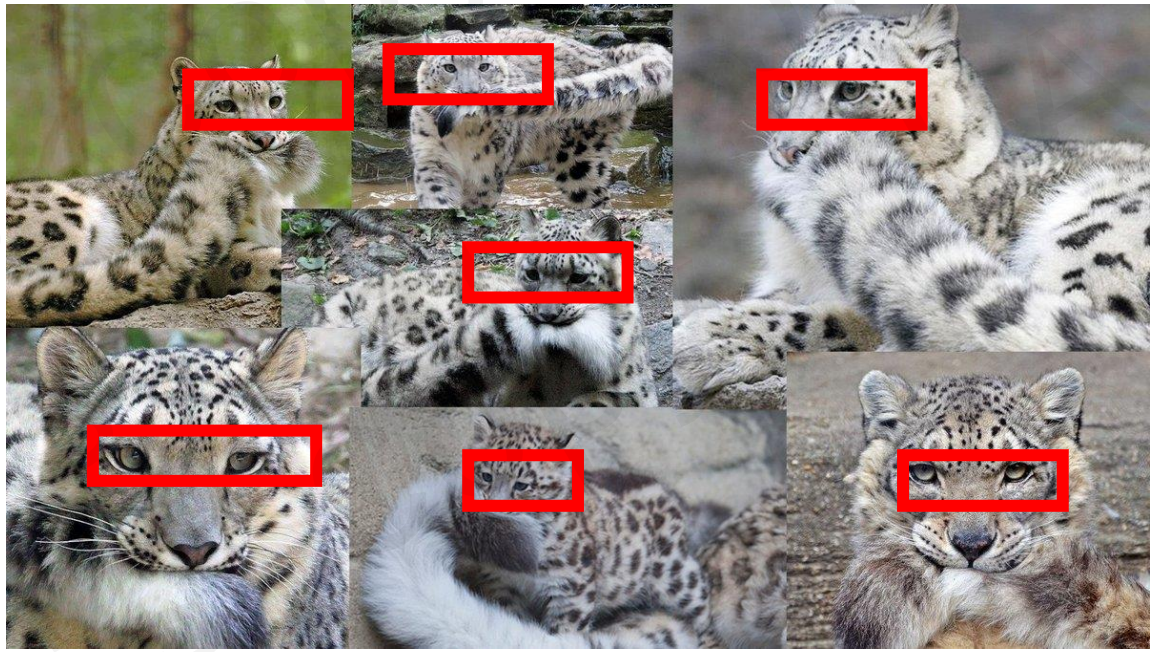
Intuition:

- Understanding the inherent data distribution.
- Using local information to extract topological properties from image.
- Implicitly extract relevant features.

Understanding the new data using learnt attributes.



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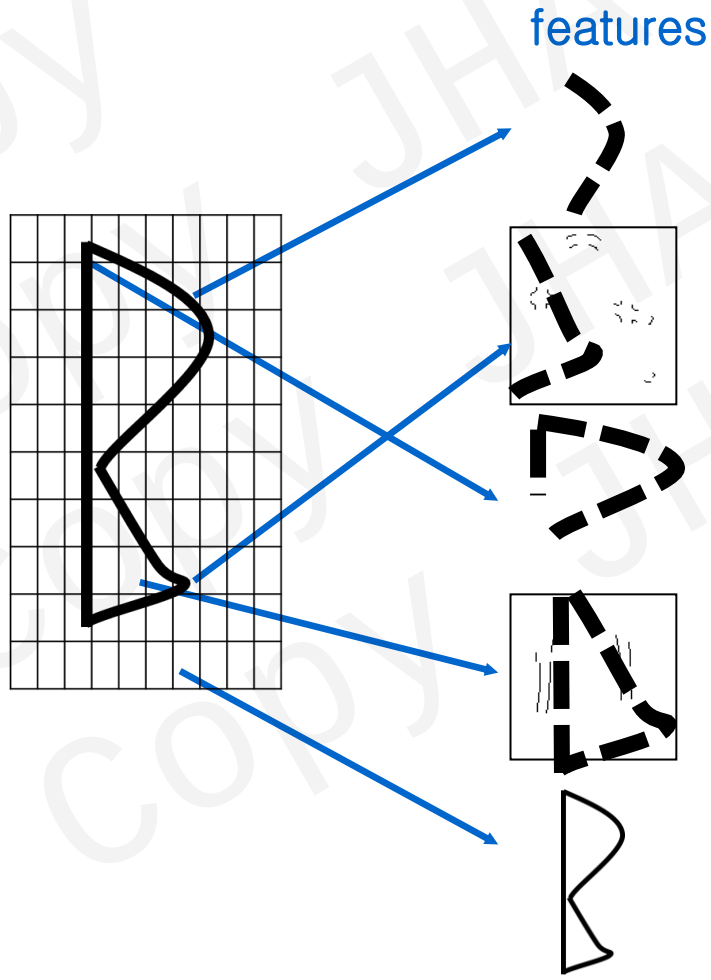
Understanding the new data using learnt attributes.

Example:

A door is always rectangular in shape,

A ship has a characteristic shape,

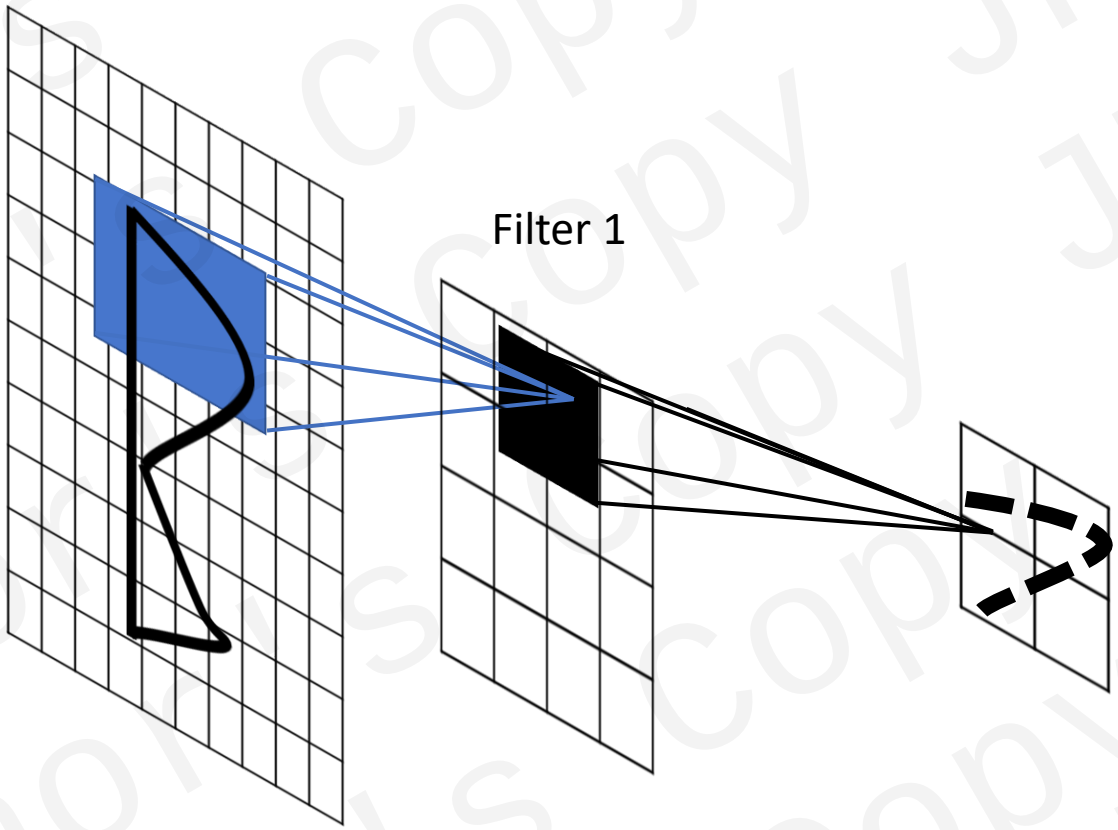
a car of any brand shall have a typical shape….



Intuition

Intuition

Shape 1 / feature 1



Intuition:

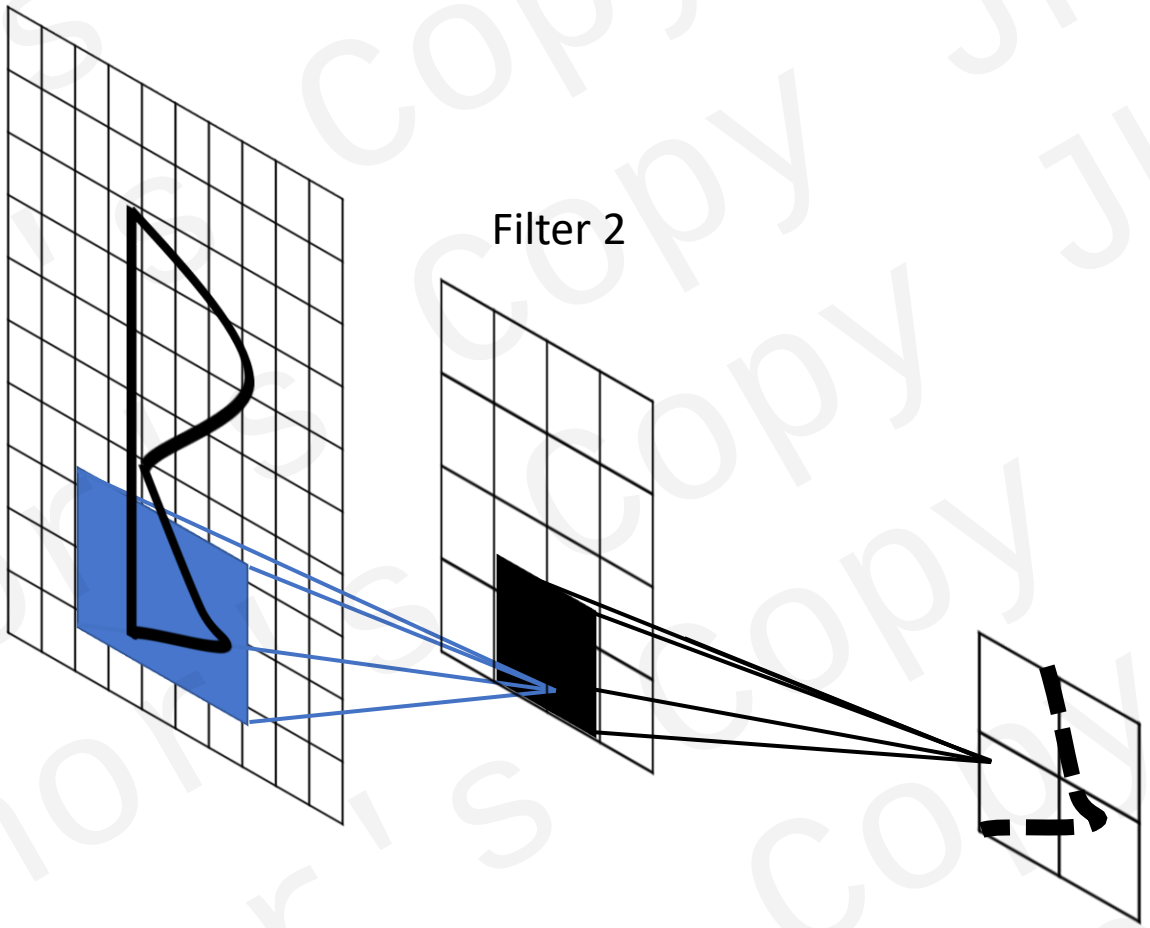
Use an image kernel to extract relevant features from the image.

Image kernel = image matrix.

Learn an appropriate filter weights through successive training (BP).

Intuition

Shape 2 / feature 2



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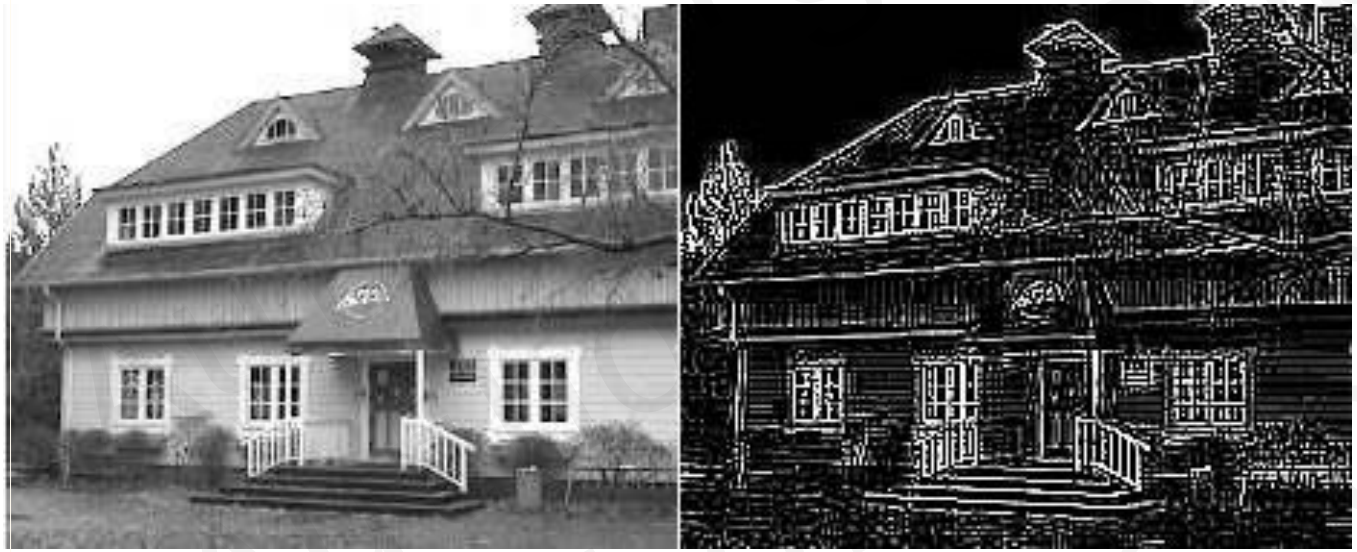
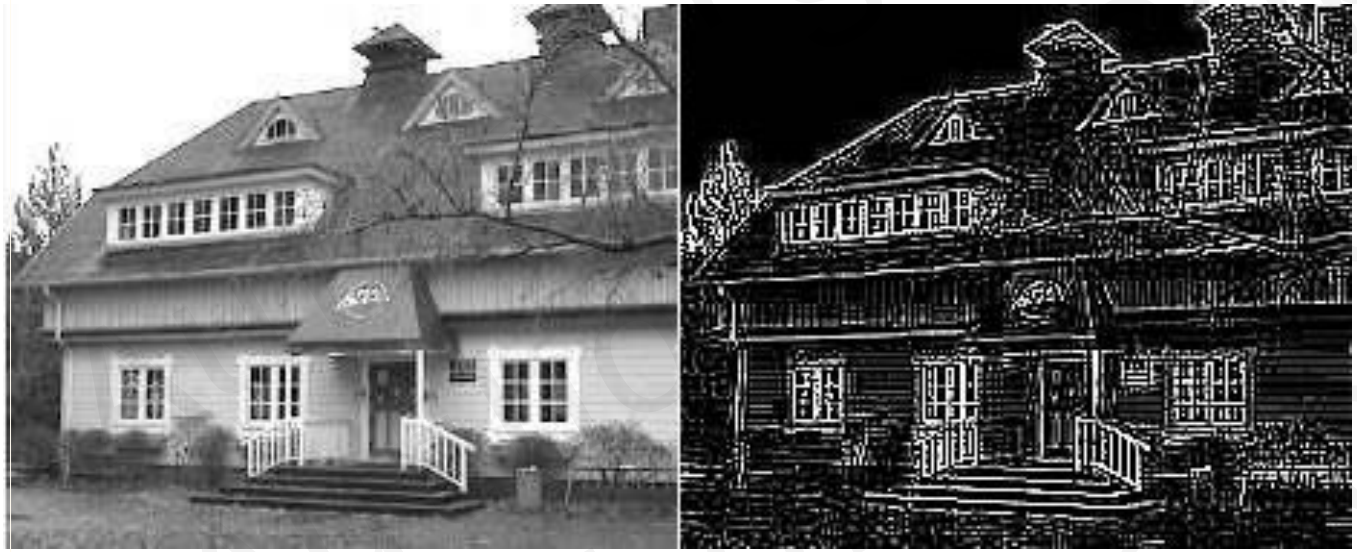


Source :Blog AndrewSzot

Intuition:

Edge Detection: An image kernel for edge detection.

Intuition



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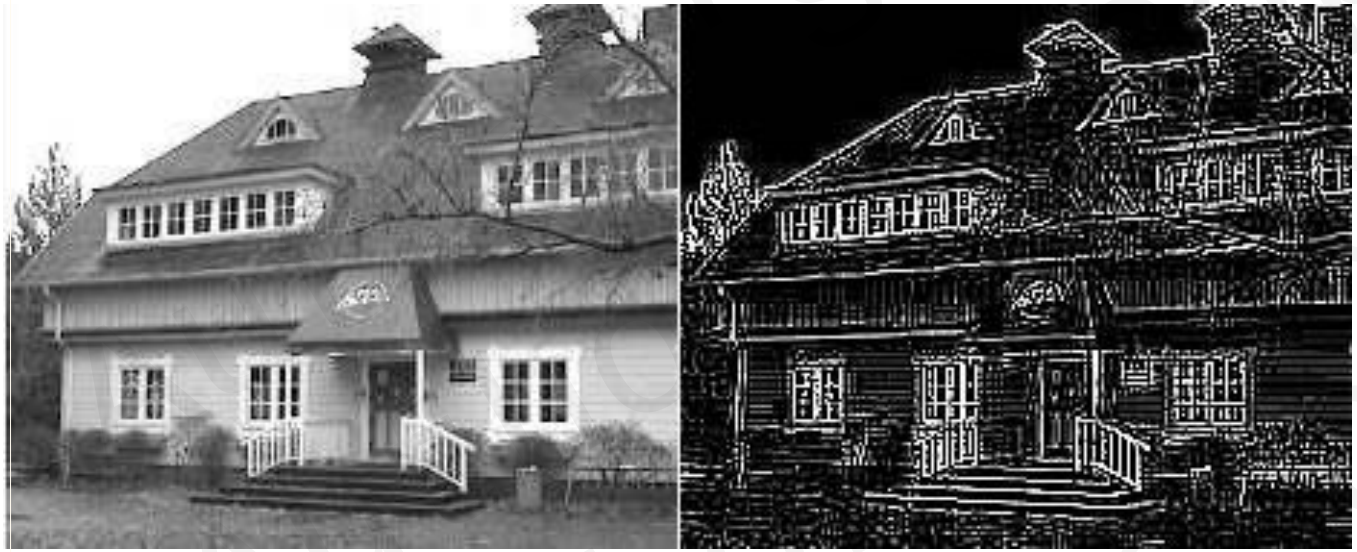
Intuition:

Edge Detection: image kernel for edge detection.

Different image kernels to extract different features.

Intuition



Source :Blog AndrewSzot

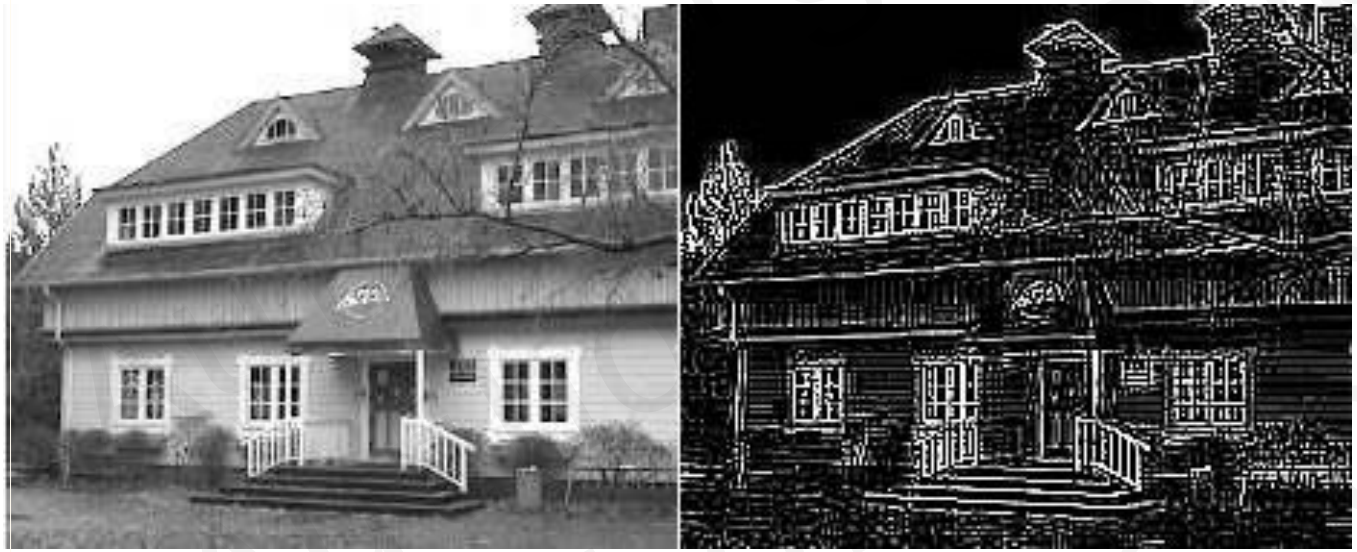
Intuition:

Edge Detection: image kernel for edge detection.

Multiple image kernels to extract different features.

Why not multiple kernels to extract set of features expected from object / required for the objective.

Intuition



Source :Blog AndrewSzot

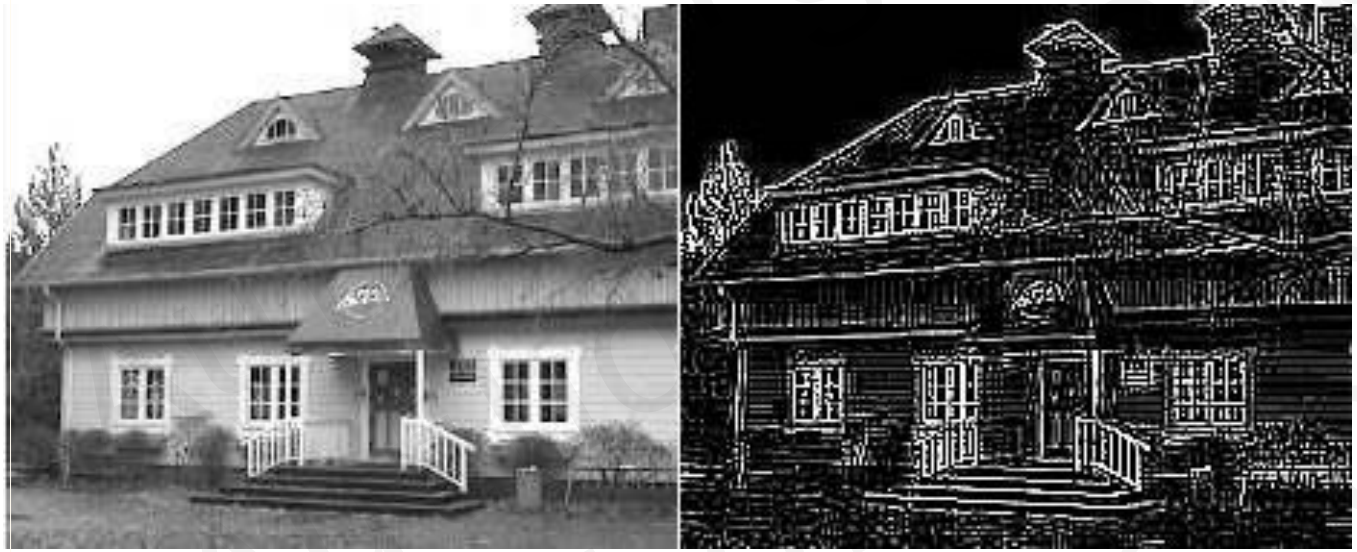
Intuition:

How to construct these filters? Edge detection is straight foreword. Not obvious in general.

Essence of CNN :

- learn the values (weights) of these filters (BP).
- stack multiple layers of feature detectors (kernels) on top of each other for abstracted levels of feature detection.

Intuition



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- learn the values (weights) of these filters (BP).
- stack multiple layers of feature detectors (kernels) on top of each other for abstracted levels of feature detection.
- extract relevant features: Convolution operation . What and How?

Convolution Operator

Convolution Operator

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

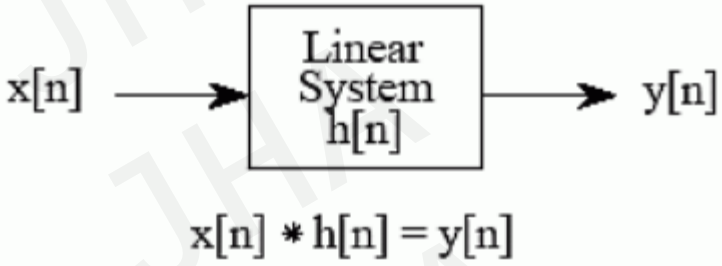
Reminders:

- origins in Signal Processing.
- convolution of two signals produces a third signal
- In signal processing, input signal convolution with impulse response of the system → output response

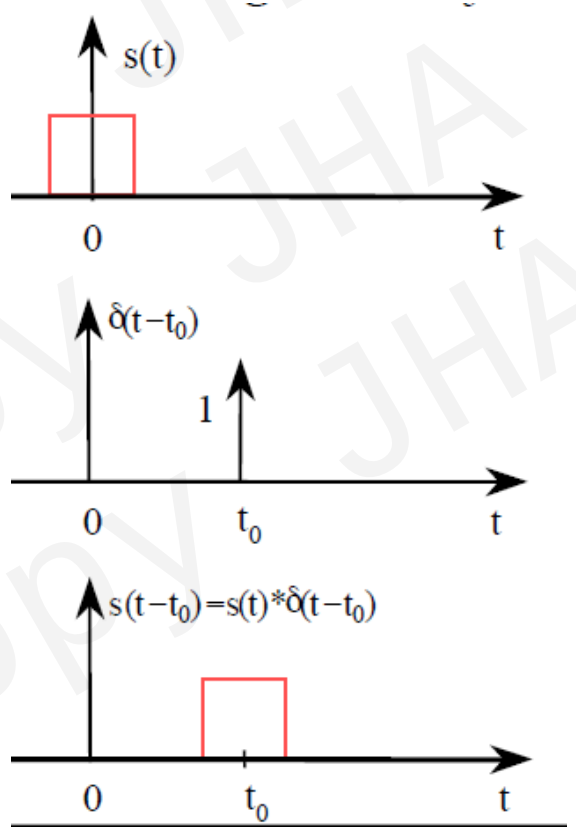
Convolution Operator

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

$$s(t) * \delta(t-t_0) = s(t-t_0)$$



Source: DSP Guide book



Source: DSP Course by Prof. Garnier, Polytech Nancy

Reminders:

- origins in Signal Processing.
- convolution of two signals produces a third signal
- input signal * impulse response of the system ➔ output response.

Convolution of a signal by Dirac impulse positioned at t_0 ➔ signal shift to t_0.

Convolution Operator

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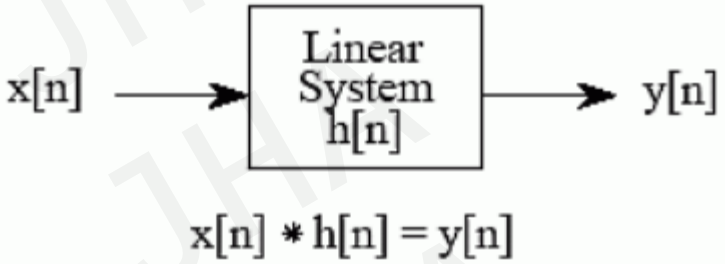
$$s(t) * \delta_{Te}(t) = \sum_{k=-\infty}^{+\infty} s(t - kTe)$$



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Reminders:

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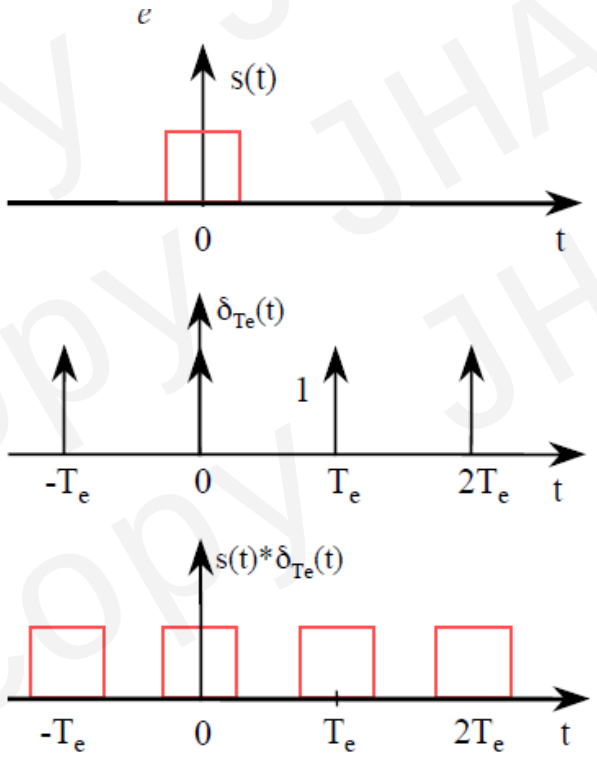
Convolution of a signal by Dirac train → periodic signal with period T_e



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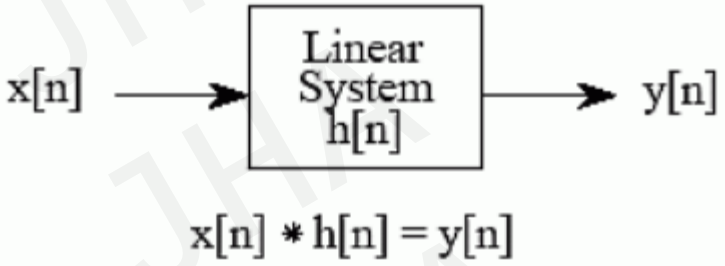

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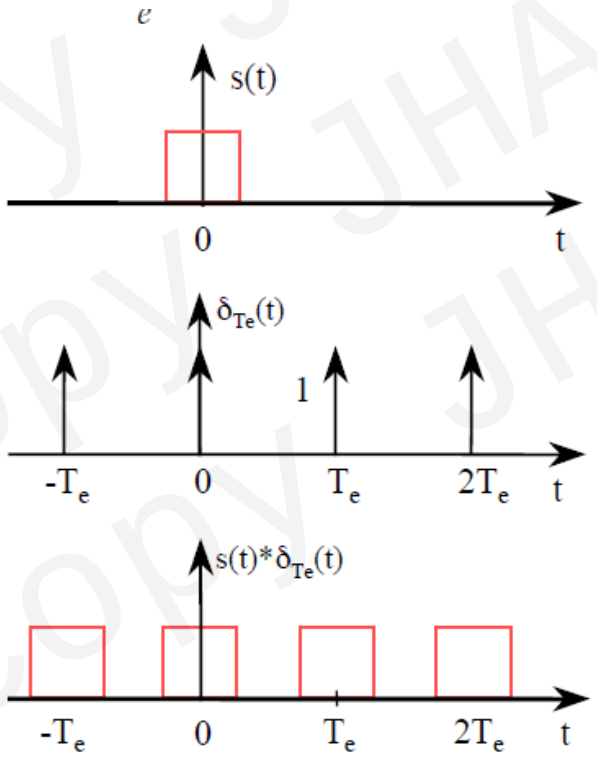
Convolution of a signal by Dirac train → periodic signal with period T_e

- Convolution operation constructs a system response signal.
- Convolution operation fundamental in assessing the similarity between two signals.



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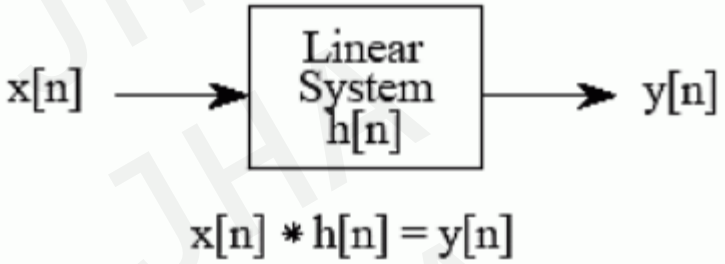
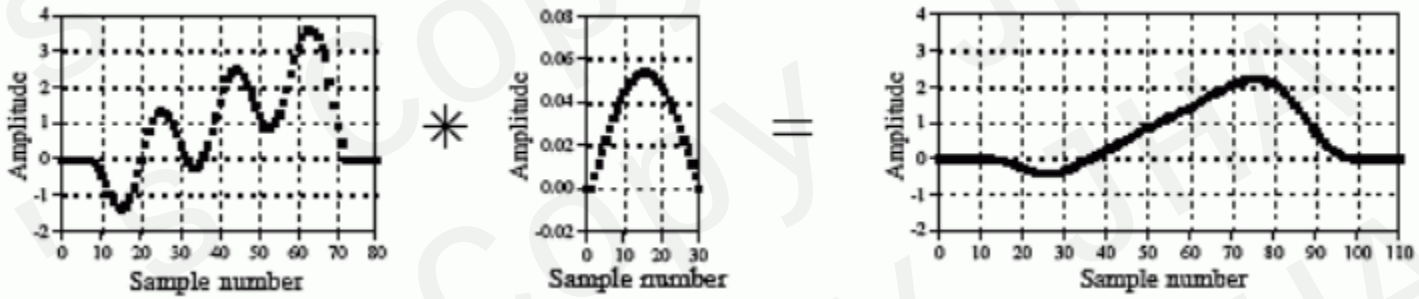


$$S(t) = (x * w) \times (t) = \sum_{a=-\infty}^{\infty} w(a)x(t-a)$$

Source: DSP Guide book



Reminders:

Low pass filtering:

Input: three cycles of sine wave plus a slow increasing ramp.

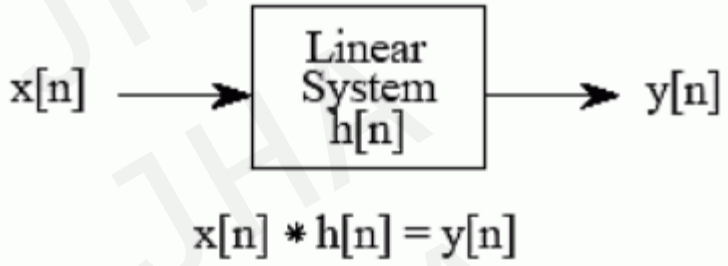
Low pass filter impulse response (or Convolution kernel / filter kernel)

Output = slow component ramp.

Convolution operation → extracts the weighted feature.

Convolution Operator

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



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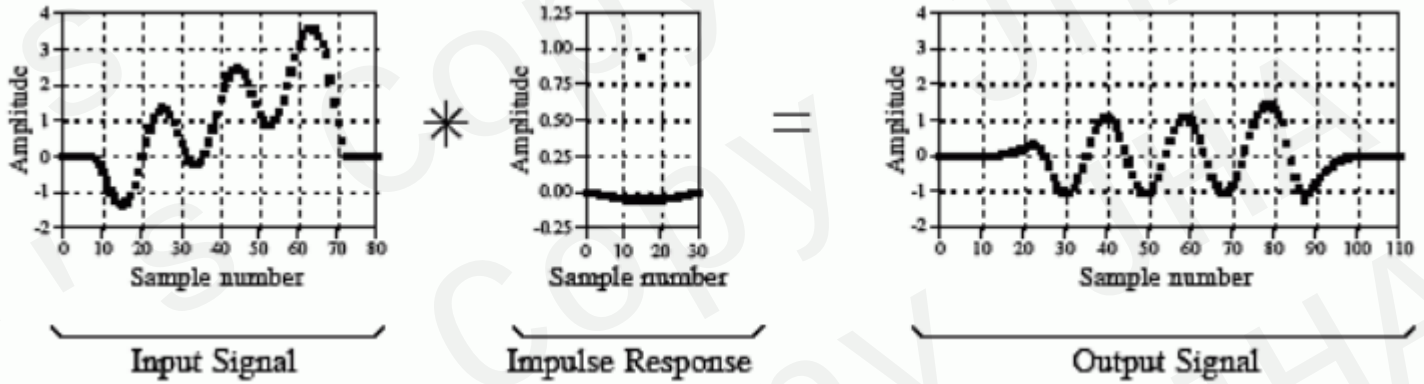

Reminders:

High pass filtering:

Input: three cycles of sine wave plus a slow increasing ramp.

High pass filter impulse response (or Convolution kernel / filter kernel)

Output = Fast component ramp.

Convolution operation → extracts the weighted feature.

Convolution Operator

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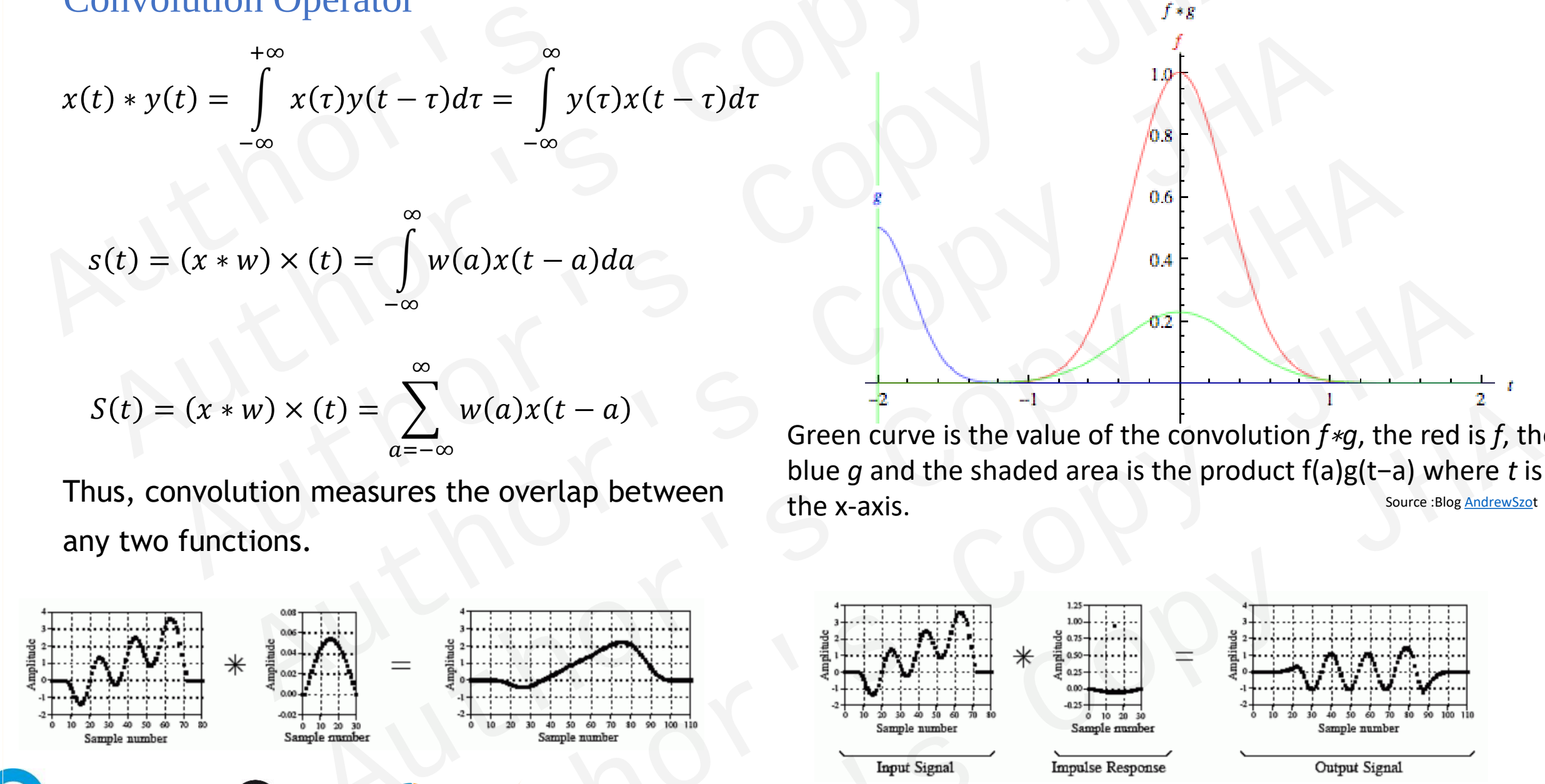
$$s(t) = (x * w) \times (t) = \int_{-\infty}^{\infty} w(a)x(t-a)da$$

$$S(t) = (x * w) \times (t) = \sum_{a=-\infty}^{\infty} w(a)x(t-a)$$

Thus, convolution measures the overlap between any two functions.

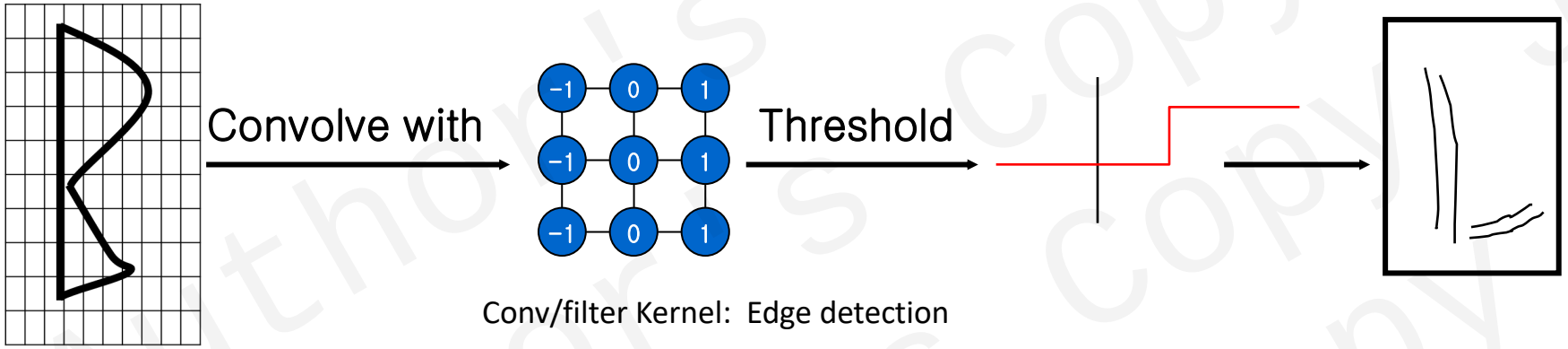


Green curve is the value of the convolution $f*g$, the red is f, the blue g and the shaded area is the product f(a)g(t−a) where t is the x-axis.

Source :Blog AndrewSzot

Convolution

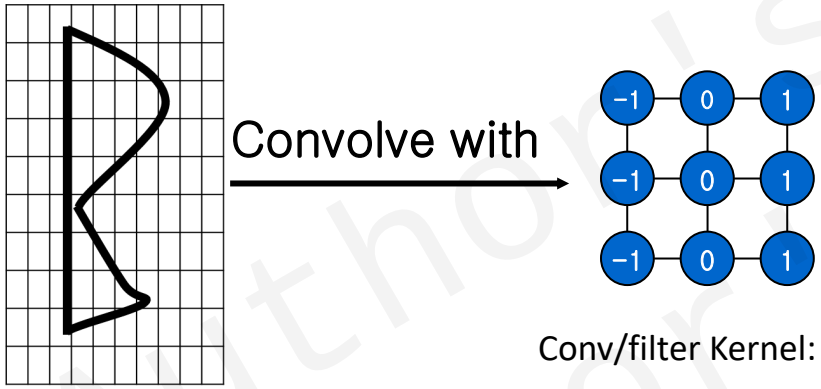
Convolution: CNN context.



Conv/filter Kernel: Edge detection

Back to CNNs:

Convolution Operator : CNN context.



Conv/filter Kernel: Edge detection

Back to CNNs:

Images can be represented as 2D array.

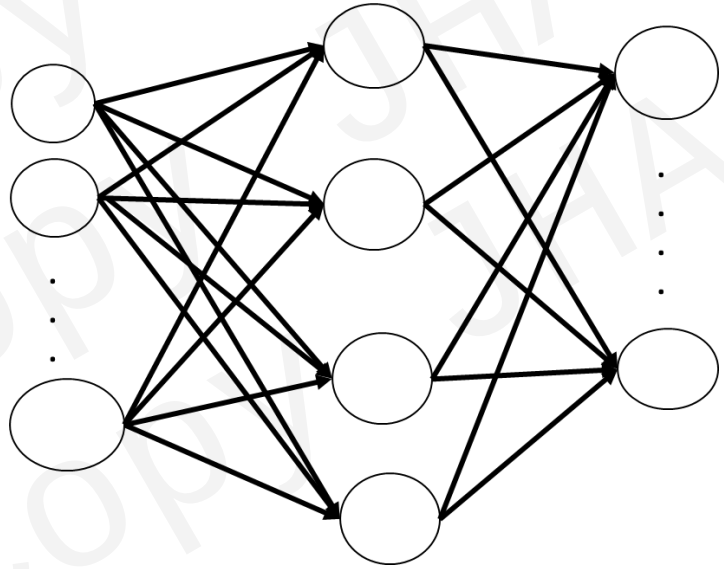
Consider (i,j) → any position in an image.

Consider Hidden layers as 2-D array ,

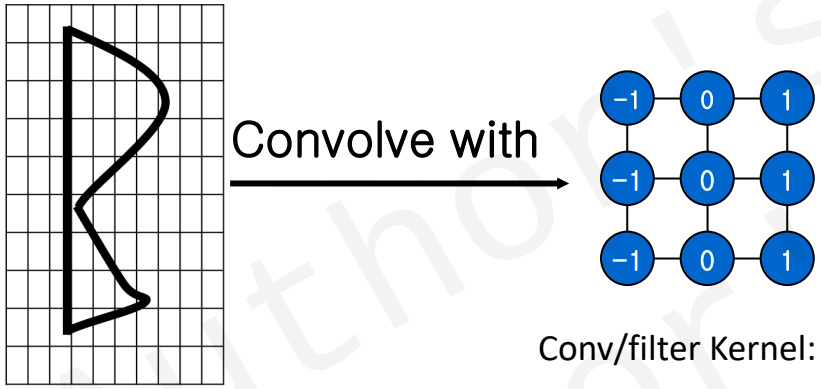
Then, dense layers → 4D tensors (Weights in a hidden layer X no of layers)

Weights matrices become weight tensors

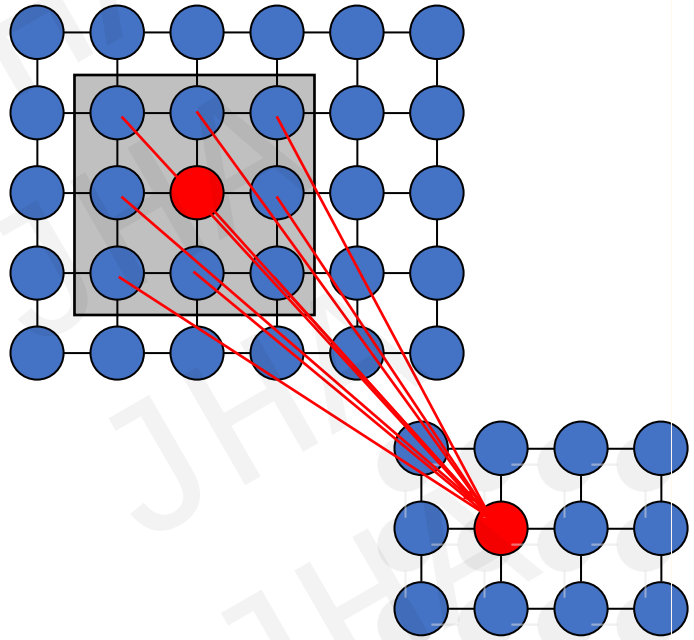
$$h[i,j] = \sum_{a,b} W(i,j,a,b) \cdot x(i+a, j+b)$$



Convolution Operator : CNN context.



Conv/filter Kernel: Edge detection

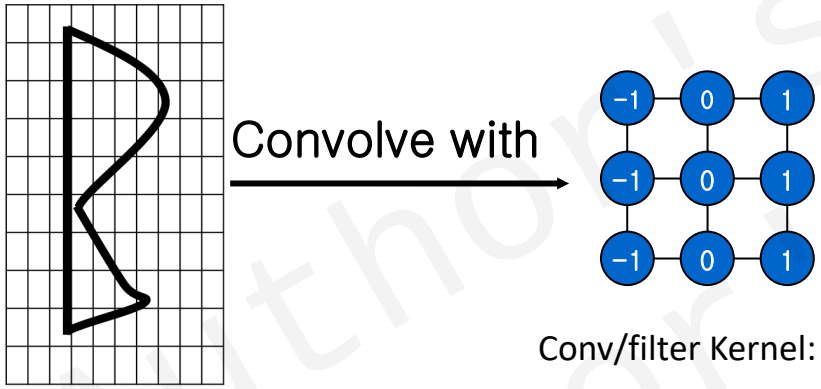


For any location, (i,j), consider an activation value in hidden layer $h[i,j]$

$h[i,j]$ is computed by summing over pixels in x and centered around (i,j).

$$h[i,j] = \sum_{a,b} W(i,j,a,b) \cdot x(i+a, j+b)$$

Convolution Operator : CNN context



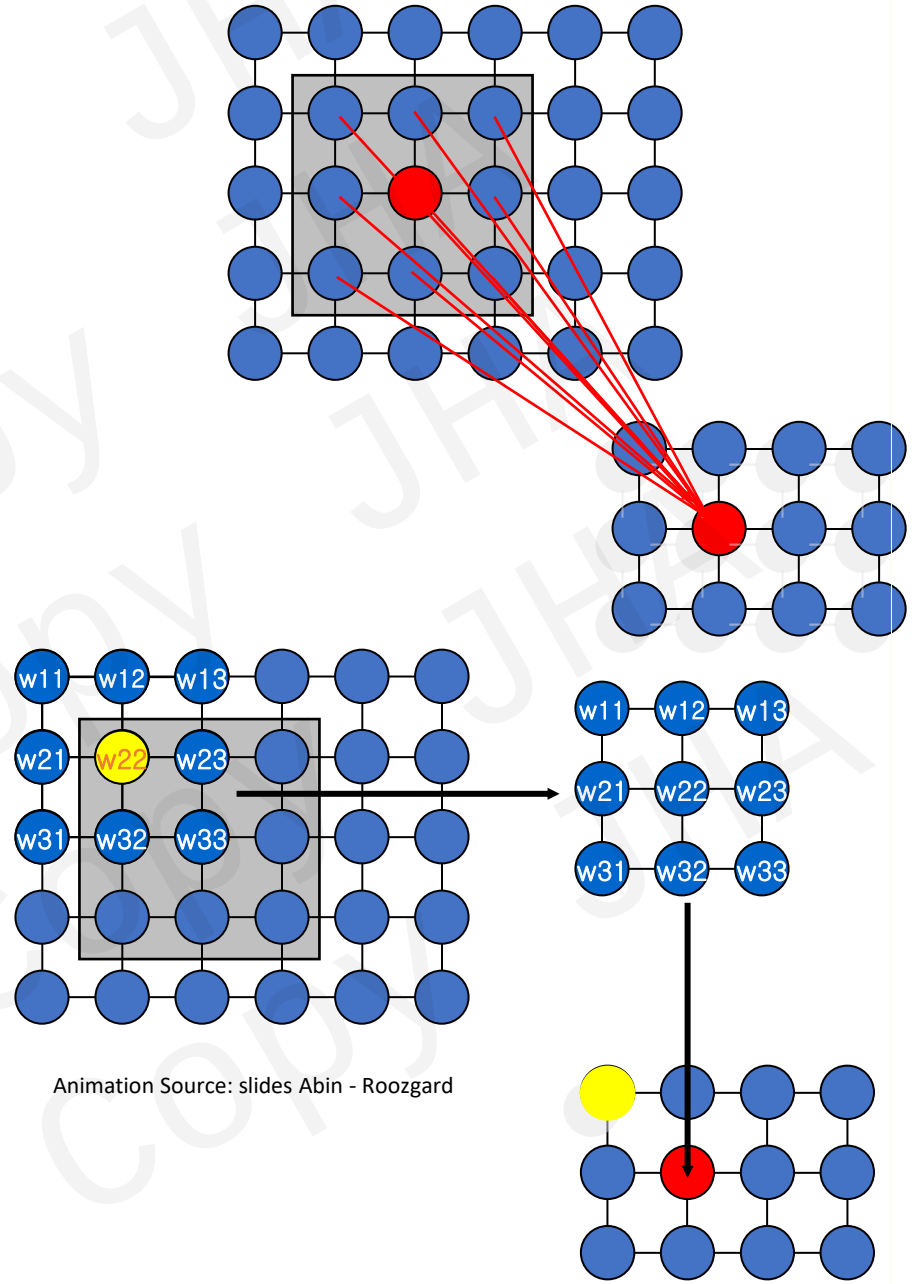
Conv/filter Kernel: Edge detection

For any location, (i,j), consider an activation value in hidden layer $h[i,j]$

$h[i,j]$ is computed by summing over pixels in x and centered around (i,j).

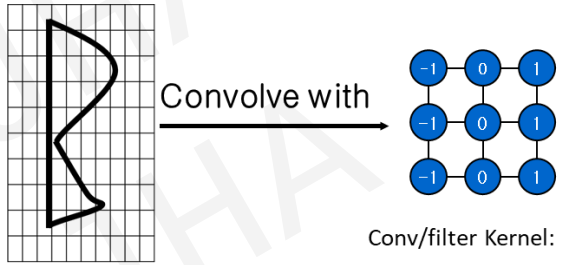
Run the image kernel (filter kernel, convolution) over entire a and b.

$$h[i,j] = \sum_{a,b} W(i,j,a,b) \cdot x(i+a, j+b)$$



Animation Source: slides Abin - Roozgard

Convolution Operator



Conv/filter Kernel: Edge detection

Invoke *Translation invariance:*

Now, activation *h should only change with* shift in inputs *x* .

Or, filter kernel (weights) should be same for all *(i,j)(*pixel positions)

➔This means same feature is searched over whole image.

➔In this way all neurons detect the same feature at different positions in the input image.

$$W[i,j,a,b] = V[a,b]$$

$$h[i,j] = \sum_{a,b} V[a,b].\cdot x[i+a, j+b]$$

Source :Blog AndrewSzot

Convolution Operator

Invoke *Locality:*

The feature should be recognized using local aspects, look in proximity and not very far.

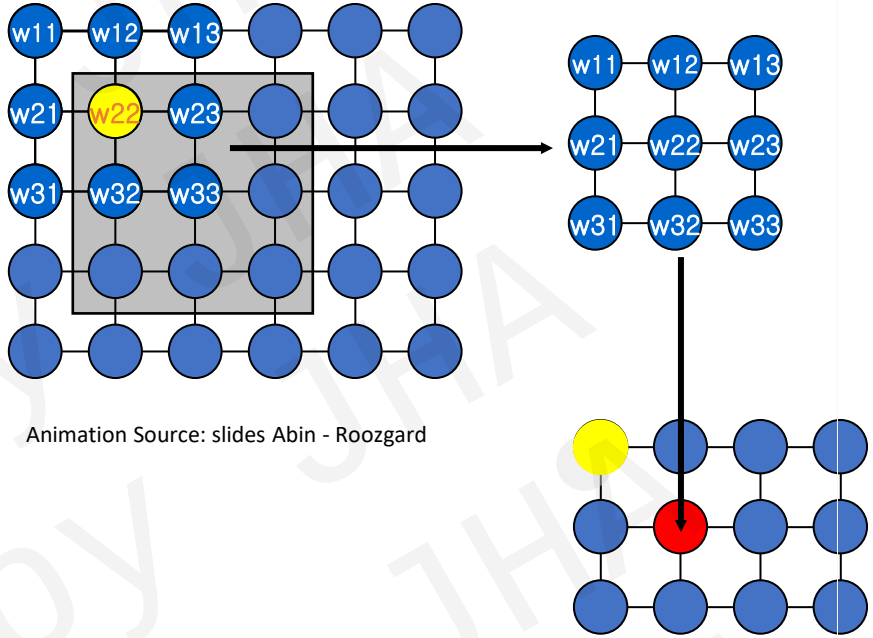
i.e. constrain the size of the kernel filter.

$$W[i,j,a,b] = V[a,b]$$

$$h[i,j] = \sum_{a,b} V[a,b] \cdot x[i+a, j+b]$$

$$for\ |a|,|b| > \Delta$$
$$put\ V[a,b] = 0$$

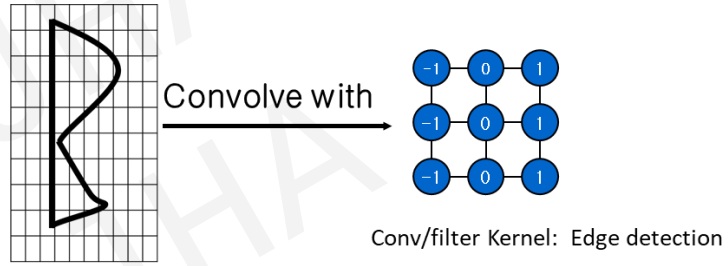
$$h[i,j] = \sum_{a=-\Delta}^{\Delta} \sum_{b=-\Delta}^{\Delta} V[a,b] \cdot x[i+a, j+b]$$



Animation Source: slides Abin - Roozgard

Source :Blog AndrewSzot

Example:



1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0
1	0	0	0	1	0
0	1	0	0	1	0
0	0	1	0	1	0

6 x 6 image

1	-1	-1
-1	1	-1
-1	-1	1

Filter 1

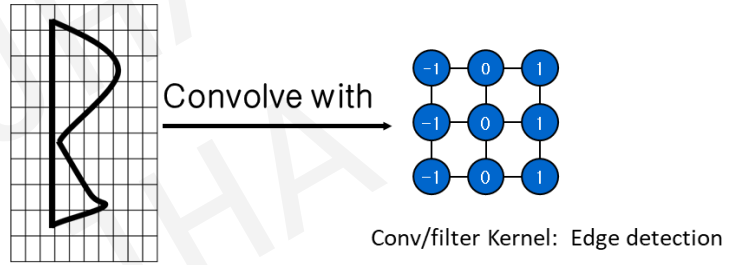
-1	1	-1
-1	1	-1
-1	1	-1

Filter 2

⋮ ⋮

Each filter detects a small feature (3 x 3).

Example:



1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0
1	0	0	0	1	0
0	1	0	0	1	0
0	0	1	0	1	0

6 x 6 image

1	-1	-1
-1	1	-1
-1	-1	1

Filter 1

convolve (slide) over all spatial locations

3			

⋮ ⋮

Each filter detects a small feature (3 x 3).

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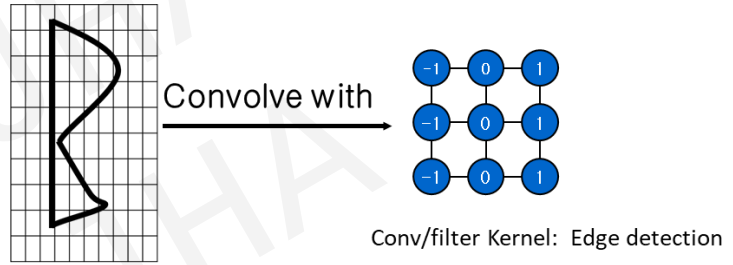
Example:



stride=1

1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0
1	0	0	0	1	0
0	1	0	0	1	0
0	0	1	0	1	0

6 x 6 image

1	-1	-1
-1	1	-1
-1	-1	1

Filter 1

convolve (slide) over all spatial locations

3	-1		

⋮ ⋮

Each filter detects a small feature (3 x 3).

Example:

stride=1

1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0
1	0	0	0	1	0
0	1	0	0	1	0
0	0	1	0	1	0

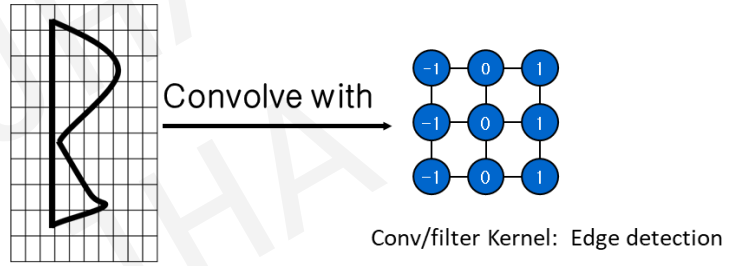
6 x 6 image

1	-1	-1
-1	1	-1
-1	-1	1

Filter 1

convolve (slide) over all spatial locations

3	-1	-3	

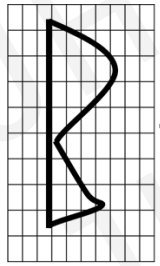


Conv/filter Kernel: Edge detection

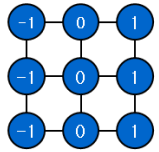
⋮ ⋮

Each filter detects a small feature (3 x 3).

Example:



Convolve with



Conv/filter Kernel: Edge detection

stride=1

1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0
1	0	0	0	1	0
0	1	0	0	1	0
0	0	1	0	1	0

6 x 6 image

1	-1	-1
-1	1	-1
-1	-1	1

Filter 1

convolve (slide) over all spatial locations

3	-1	-3	-1

⋮ ⋮

Each filter detects a small feature (3 x 3).

Example:

stride=1

1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0
1	0	0	0	1	0
0	1	0	0	1	0
0	0	1	0	1	0

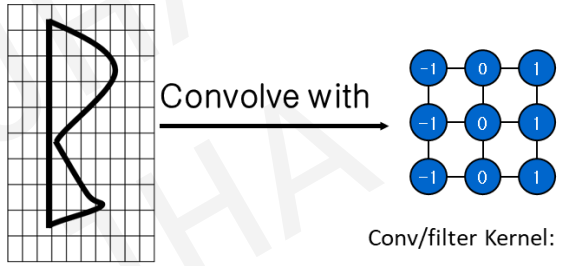
6 x 6 image

1	-1	-1
-1	1	-1
-1	-1	1

Filter 1

convolve (slide) over all spatial locations

3	-1	-3	-1
-3			



Conv/filter Kernel: Edge detection

⋮ ⋮

Each filter detects a small feature (3 x 3).

Example:

stride=1

1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0
1	0	0	0	1	0
0	1	0	0	1	0
0	0	1	0	1	0

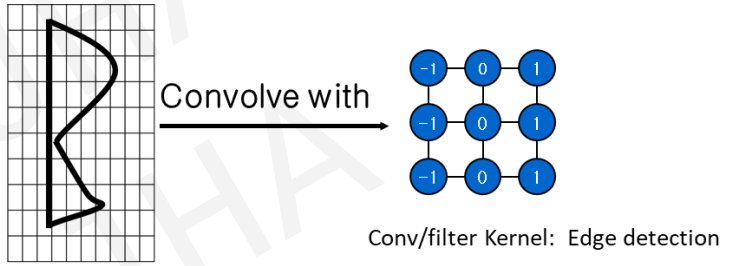
6 x 6 image

1	-1	-1
-1	1	-1
-1	-1	1

Filter 1

convolve (slide) over all spatial locations

3	-1	-3	-1
-3	1	0	



Conv/filter Kernel: Edge detection

⋮ ⋮

Each filter detects a small feature (3 x 3).

Example:

stride=1

1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0
1	0	0	0	1	0
0	1	0	0	1	0
0	0	1	0	1	0

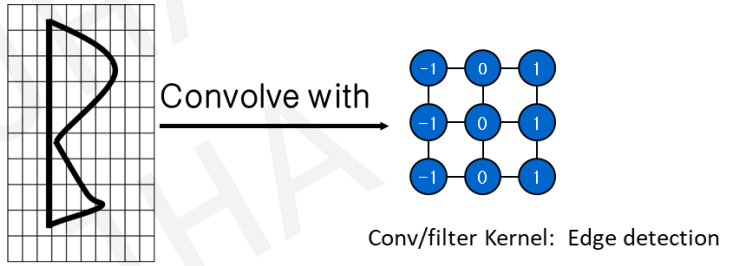
6 x 6 image

1	-1	-1
-1	1	-1
-1	-1	1

Filter 1

convolve (slide) over all spatial locations

3	-1	-3	-1
-3	1	0	



Conv/filter Kernel: Edge detection

⋮ ⋮

Each filter detects a small feature (3 x 3).

Example:

stride=1

1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0
1	0	0	0	1	0
0	1	0	0	1	0
0	0	1	0	1	0

6 x 6 image

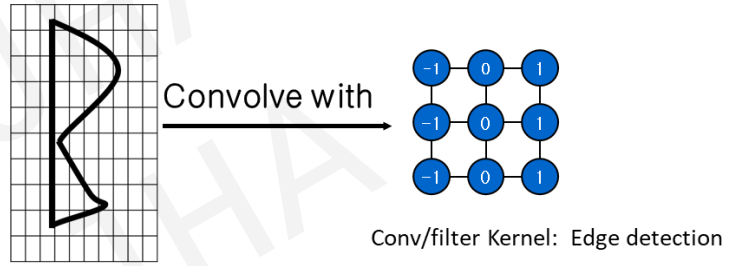
1	-1	-1
-1	1	-1
-1	-1	1

Filter 1

convolve (slide) over all spatial locations

3	-1	-3	-1
-3	1	0	-3
-3	-3	0	1
3	-2	-2	1

Feature Map

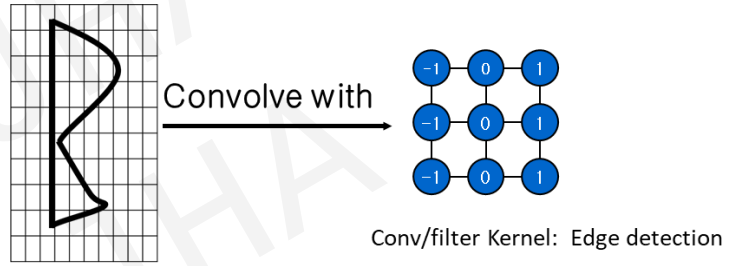


Conv/filter Kernel: Edge detection

⋮ ⋮

Each filter detects a small feature (3 x 3).

Example:



1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0
1	0	0	0	1	0
0	1	0	0	1	0
0	0	1	0	1	0

6 x 6 image

Filter 1

1	-1	-1
-1	1	-1
-1	-1	1

-1	1	-1
-1	1	-1
-1	1	-1

Filter 2

3	-1	-3	-1
-3	1	0	-3
-3	-3	0	1
3	-2	-2	1

Feature Map

⋮ ⋮

Each filter detects a small feature (3 x 3).

Example:

1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0
1	0	0	0	1	0
0	1	0	0	1	0
0	0	1	0	1	0

6 x 6 image

Filter 1

1	-1	-1
-1	1	-1
-1	-1	1

-1	1	-1
-1	1	-1
-1	1	-1

Filter 2

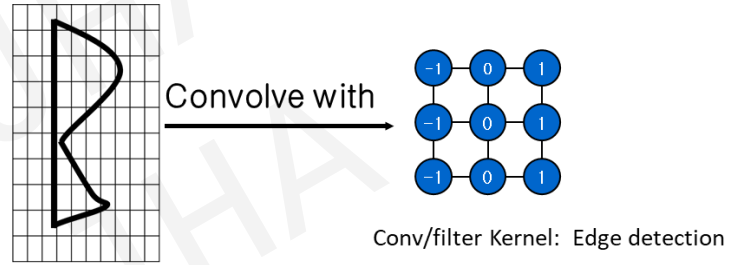
-1	-1	-1	-1
-1	-1	-2	1
-1	-1	-2	1
-1	0	4	3

Feature Maps

⋮ ⋮

Each filter detects a small feature (3 x 3).

Example:



1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0
1	0	0	0	1	0
0	1	0	0	1	0
0	0	1	0	1	0

6 x 6 image

Filter 1

1	-1	-1
-1	1	-1
-1	-1	1

-1	1	-1
-1	1	-1
-1	1	-1

Filter 2

-1	-1	-1	-1
-1	-1	-2	1
-1	-1	-2	1
-1	0	4	3

Feature Maps

⋮ ⋮

2 images of 4 x 4 matrix is produced.
This procedure is repeated for each filter

Example: Edge detection

1	1	0	0	0	0	1	1
1	1	0	0	0	0	1	1
1	1	0	0	0	0	1	1
1	1	0	0	0	0	1	1
1	1	0	0	0	0	1	1
1	1	0	0	0	0	1	1

H x W image

1	-1

Edge detector kernel

0	1	0	0	0	-1	0
0	1	0	0	0	-1	0
0	1	0	0	0	-1	0
0	1	0	0	0	-1	0
0	1	0	0	0	-1	0
0	1	0	0	0	-1	0

Feature Map

Kernel: if
horizontally elements are same , output is 0.
Else, non-zero.

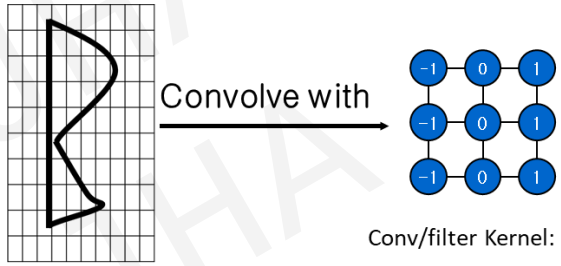
Detected:
1 for edge from white to **black**
-1 for edge from **black** to white

Difficult to handcraft such filters.
Thus, filter kernel weights must be learnt !!

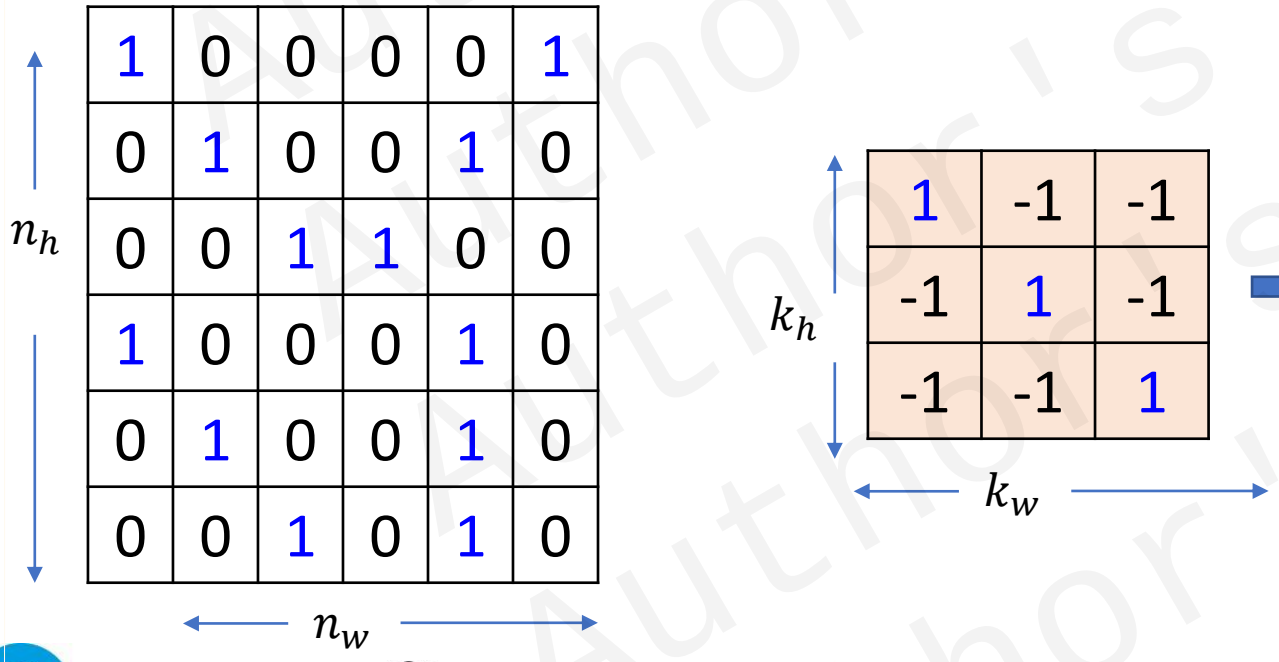
Remarks:

Output shape determined by shape of input and convolutional kernel window.

Small convolution with filter kernels → “smaller” outputs (feature maps).



Conv/filter Kernel: Edge detection



$$(n_h - k_h + 1) \times (n_w - k_w + 1)$$

Padding and Strides

Padding

- Multiple layers of convolution may reduce the information available at boundary.
- Padding prevents this problem.
- Adding zeros around the edges such that multiple convolution operation does not lead to information loss.
- Pixels added around edges.
- These pixels are zero in value.

	0	0	0	0	0	0	0	0
	0	1	0	0	0	0	1	0
	0	0	1	0	0	1	0	0
	0	0	0	1	1	0	0	0
	0	1	0	0	0	1	0	0
	0	0	1	0	0	1	0	0
	0	0	0	1	0	1	0	0
p_h	0	0	0	0	0	0	0	0

p_w

$$(n_h - k_h + p_h + 1) \times (n_w - k_w + p_w + 1)$$

Padding: In practice

- $p_h = k_h - 1$,
- $p_w = k_w - 1$,
- Kernel dimensions : k_w, k_h are chosen odd numbers (Ex: 1,3,5,7..)
- Padding dimensions are even. $p = k - 1$,
- then, each side padded with $p/2$ *zeros*
- *or,* padding dimensions = *(k-1)/2*

$$(n_h - k_h + p_h + 1) \times (n_w - k_w + p_w + 1)$$

	0	0	0	0	0	0	0	0
	0	1	0	0	0	0	1	0
	0	0	1	0	0	1	0	0
	0	0	0	1	1	0	0	0
	0	1	0	0	0	1	0	0
	0	0	1	0	0	1	0	0
	0	0	0	1	0	1	0	0
p_h	0	0	0	0	0	0	0	0

p_w

Strides

Stride=1

1	0	0	0	0	1	1
0	1	0	0	1	0	0
0	0	1	1	0	0	0
1	0	0	0	1	0	0
0	1	0	0	1	0	0
0	0	1	0	1	0	0
0	0	1	0	1	0	0

Input : 7x7 (spatially)

Filter kernel: 3X3

Stride=1

Output =5 x5

Number of rows and columns per slide → stride.

- Useful in reducing information (resolution) drastically.

Convolution : Strides

Stride=1

1	0	0	0	0	1	1
0	1	0	0	1	0	0
0	0	1	1	0	0	0
1	0	0	0	1	0	0
0	1	0	0	1	0	0
0	0	1	0	1	0	0
0	0	1	0	1	0	0

Input : 7x7 (spatially)

Filter kernel: 3X3

Stride=1

Output =5 x5

Convolution : Strides

Stride=1

1	0	0	0	0	1	1
0	1	0	0	1	0	0
0	0	1	1	0	0	0
1	0	0	0	1	0	0
0	1	0	0	1	0	0
0	0	1	0	1	0	0
0	0	1	0	1	0	0

Input : 7x7 (spatially)

Filter kernel: 3X3

Stride=1

Output =5 x5

Convolution : Strides

Stride=1

1	0	0	0	0	1	1
0	1	0	0	1	0	0
0	0	1	1	0	0	0
1	0	0	0	1	0	0
0	1	0	0	1	0	0
0	0	1	0	1	0	0
0	0	1	0	1	0	0

Input : 7x7 (spatially)

Filter kernel: 3X3

Stride=1

Output =5 x5

Convolution : Strides

Stride=1

1	0	0	0	0	1	1
0	1	0	0	1	0	0
0	0	1	1	0	0	0
1	0	0	0	1	0	0
0	1	0	0	1	0	0
0	0	1	0	1	0	0
0	0	1	0	1	0	0

Input : 7x7 (spatially)

Filter kernel: 3X3

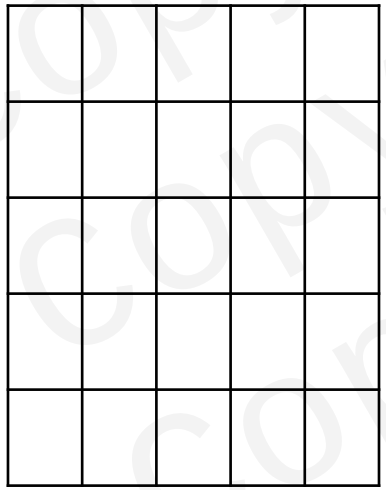
Stride=1

Output =5 x5

Convolution : Strides

Stride=1

1	0	0	0	0	1	1
0	1	0	0	1	0	0
0	0	1	1	0	0	0
1	0	0	0	1	0	0
0	1	0	0	1	0	0
0	0	1	0	1	0	0
0	0	1	0	1	0	0



Feature Map

Input : 7x7 (spatially)

Filter kernel: 3X3

Stride=1

Output =5 x5

Convolution : Strides

Stride=2

1	0	0	0	0	1	1
0	1	0	0	1	0	0
0	0	1	1	0	0	0
1	0	0	0	1	0	0
0	1	0	0	1	0	0
0	0	1	0	1	0	0
0	0	1	0	1	0	0

Input : 7x7 (spatially)

Filter kernel: 3X3

Stride=2

Output =3 x3

Convolution : Strides

Stride=2

1	0	0	0	0	1	1
0	1	0	0	1	0	0
0	0	1	1	0	0	0
1	0	0	0	1	0	0
0	1	0	0	1	0	0
0	0	1	0	1	0	0
0	0	1	0	1	0	0

Input : 7x7 (spatially)

Filter kernel: 3X3

Stride=2

Output =3 x3

Convolution : Strides

Stride=2

1	0	0	0	0	1	1
0	1	0	0	1	0	0
0	0	1	1	0	0	0
1	0	0	0	1	0	0
0	1	0	0	1	0	0
0	0	1	0	1	0	0
0	0	1	0	1	0	0

Input : 7x7 (spatially)

Filter kernel: 3X3

Stride=2

Output =3 x3

Convolution : Strides

Stride=2

1	0	0	0	0	1	1
0	1	0	0	1	0	0
0	0	1	1	0	0	0
1	0	0	0	1	0	0
0	1	0	0	1	0	0
0	0	1	0	1	0	0
0	0	1	0	1	0	0

Input : 7x7 (spatially)

Filter kernel: 3X3

Stride=2

Output =3 x3

Convolution : Strides

Stride=2

1	0	0	0	0	1	1
0	1	0	0	1	0	0
0	0	1	1	0	0	0
1	0	0	0	1	0	0
0	1	0	0	1	0	0
0	0	1	0	1	0	0
0	0	1	0	1	0	0

Input : 7x7 (spatially)

Filter kernel: 3X3

Stride=2

Output =3 x3

Convolution : Strides

Stride=2

1	0	0	0	0	1	1
0	1	0	0	1	0	0
0	0	1	1	0	0	0
1	0	0	0	1	0	0
0	1	0	0	1	0	0
0	0	1	0	1	0	0
0	0	1	0	1	0	0

Input : 7x7 (spatially)

Filter kernel: 3X3

Stride=2

Output =3 x3

Convolution : Strides

Stride=2

1	0	0	0	0	1	1
0	1	0	0	1	0	0
0	0	1	1	0	0	0
1	0	0	0	1	0	0
0	1	0	0	1	0	0
0	0	1	0	1	0	0
0	0	1	0	1	0	0

Input : 7x7 (spatially)

Filter kernel: 3X3

Stride=2

Output =3 x3 Feature map matrix

Convolution : Strides

Stride=2

1	0	0	0	0	1	1
0	1	0	0	1	0	0
0	0	1	1	0	0	0
1	0	0	0	1	0	0
0	1	0	0	1	0	0
0	0	1	0	1	0	0
0	0	1	0	1	0	0

Input : 7x7 (spatially)

Filter kernel: 3X3

Stride=2

Output =3 x3 Feature map matrix

In general, with stride =s

output size: $\left(\frac{n_h - \kappa_h + p_h}{s} + 1\right) \times \left(\frac{n_w - k_w + p_w}{s} + 1\right)$

Convolution : Strides

Stride=3

1	0	0	0	0	1	1
0	1	0	0	1	0	0
0	0	1	1	0	0	0
1	0	0	0	1	0	0
0	1	0	0	1	0	0
0	0	1	0	1	0	0
0	0	1	0	1	0	0

Input : 7x7 (spatially)

Filter kernel: 3X3

Stride=3 ?? (stride increased)

Cannot apply 3x3 filter kernel on 7X7 input → Does not fit.

Convolution : Strides

Stride=3

1	0	0	0	0	1	1
0	1	0	0	1	0	0
0	0	1	1	0	0	0
1	0	0	0	1	0	0
0	1	0	0	1	0	0
0	0	1	0	1	0	0
0	0	1	0	1	0	0

Input : 7x7 (spatially)

Filter kernel: 3X3

Stride=3 ?? (stride increased)

Cannot apply 3x3 filter kernel on 7X7 input → Does not fit.

Convolution : Strides

Stride=3

1	0	0	0	0	1	1
0	1	0	0	1	0	0
0	0	1	1	0	0	0
1	0	0	0	1	0	0
0	1	0	0	1	0	0
0	0	1	0	1	0	0
0	0	1	0	1	0	0

In general, with stride =s

output size: $\left(\frac{n_h - \kappa_h + p_h}{s} + 1\right) \times \left(\frac{n_w - k_w + p_w}{s} + 1\right)$

Input : 7x7 (spatially)

Filter kernel: 3X3

Stride=3 ?? (stride increased)

Cannot apply 3x3 filter kernel on 7X7 input → Does not fit.

Apply padding

0	0	0	0	0	0	0	0	0
0	1	0	0	0	0	1	1	0
0	0	1	0	0	1	0	0	0
0	0	0	1	1	0	0	0	0
0	1	0	0	0	1	0	0	0
0	0	1	0	0	1	0	0	0
0	0	0	1	0	1	0	0	0
0	0	0	1	0	1	0	0	0
0	0	0	0	0	0	0	0	0

Input : 7x7 (spatially)

Filter kernel: 3X3

Stride=3 ?? (stride increased)

Output= 3 X 3

In general, with stride =*s*

output size: $\left(\frac{n_h - \kappa_h + p_h}{s} + 1\right) \times \left(\frac{n_w - k_w + p_w}{s} + 1\right)$

Apply Padding: 1 pixel border on each side (p_h=2 , p_w=2)

Kernel =3X3, Stride =1 ,

output =7 X 7 !!

In practice:

Stride =1,

kernel dim: F X F where F is an odd number (Ex: 1,3,5,7..)

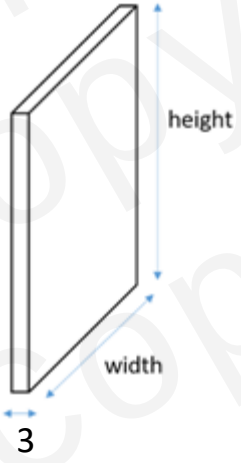
Padding on each side = (F-1)/2

Multi input and output channels

Multi input channels

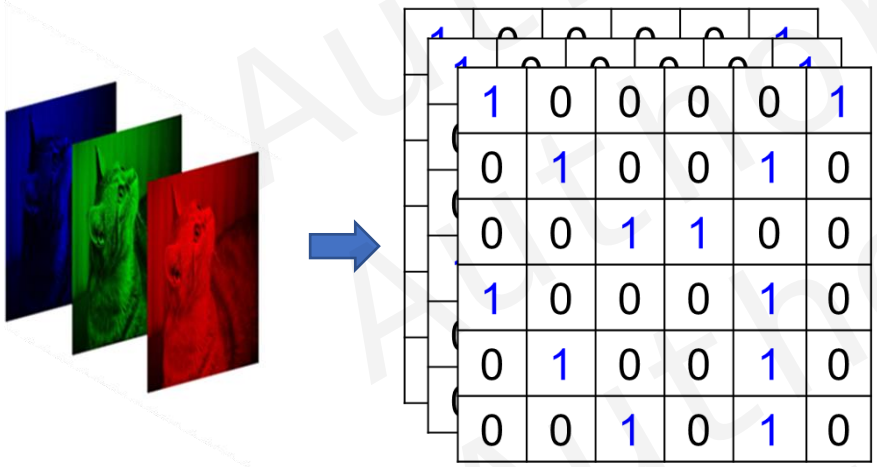
so far, greyscale images→ One channel.

Most images are colorful → 3 channels RGB



➔Input as multi-dimensional array : 3 X *h* X w

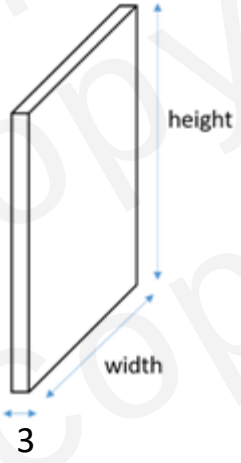
➔construct a convolution kernel with the same number of input channels as the input data (3 here)



Multi input channels

so far, greyscale images→ One channel.

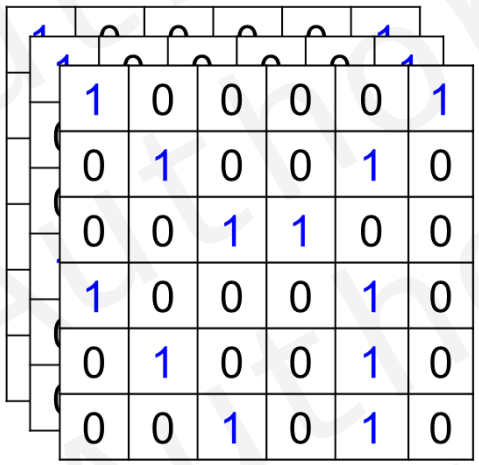
Most images are colorful → 3 channels RGB

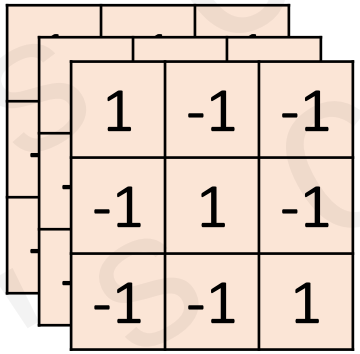


➔Input as multi-dimensional array : 3 X *h* X w

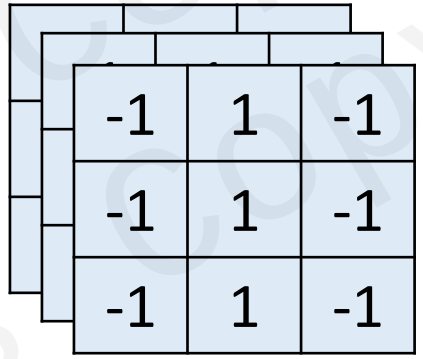
➔construct a convolution kernel with the same number of input channels as the input data (3 here)

➔Assign a 2-D kernel to each channel → concatenation gives 3D conv kernel.





Filter 1



Filter 2

Multi input channels

Convolution with 3 input channels:

- slide the 2D filter kernel on 2D input , for each channel.

1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0
1	0	0	0	1	0
0	1	0	0	1	0
0	0	1	0	1	0

*

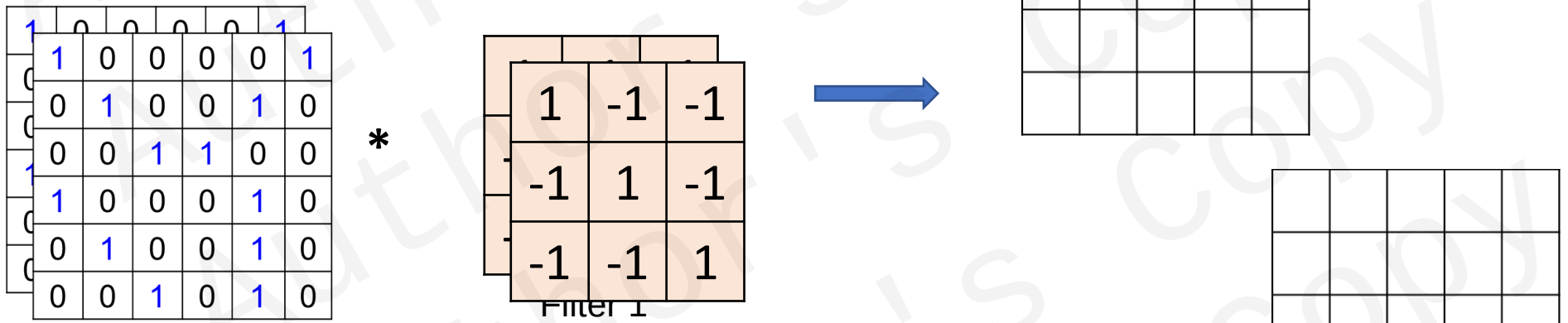
1	-1	-1
-1	1	-1
-1	-1	1

Filter 1

Multi input channels

Convolution with 3 input channels:

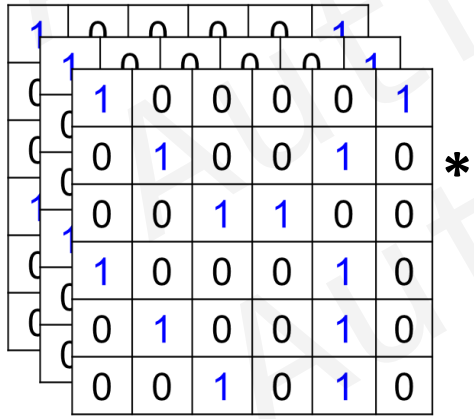
- slide the 2D filter kernel on 2D input , for each channel.

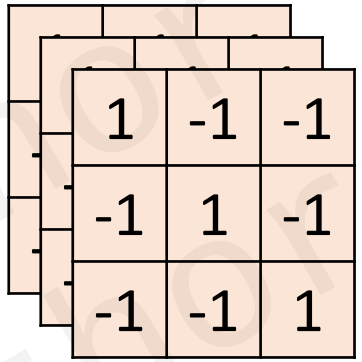


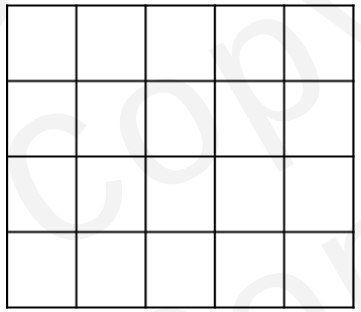
Multi input channels

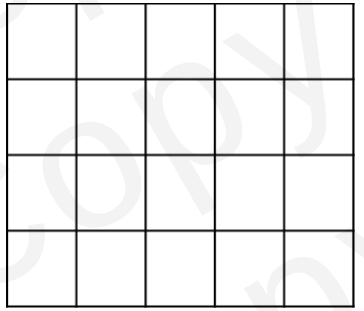
Convolution with 3 input channels:

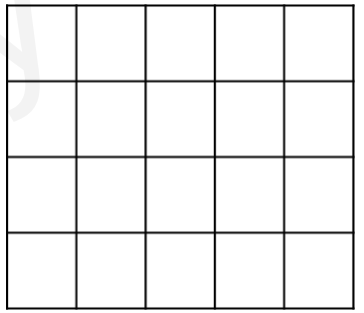
- slide the 2D filter kernel on 2D input , for each channel.







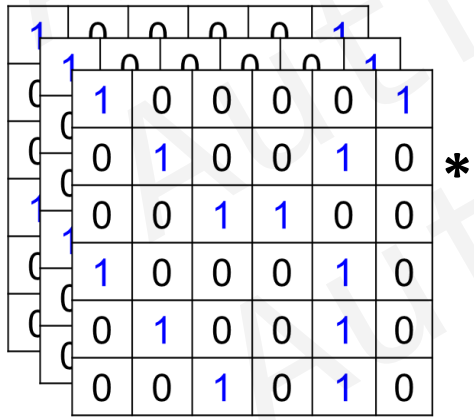


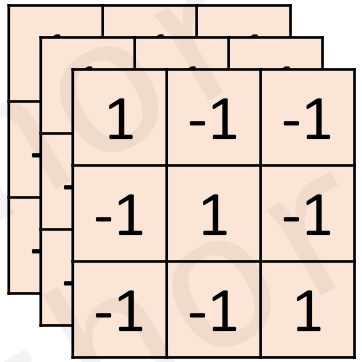


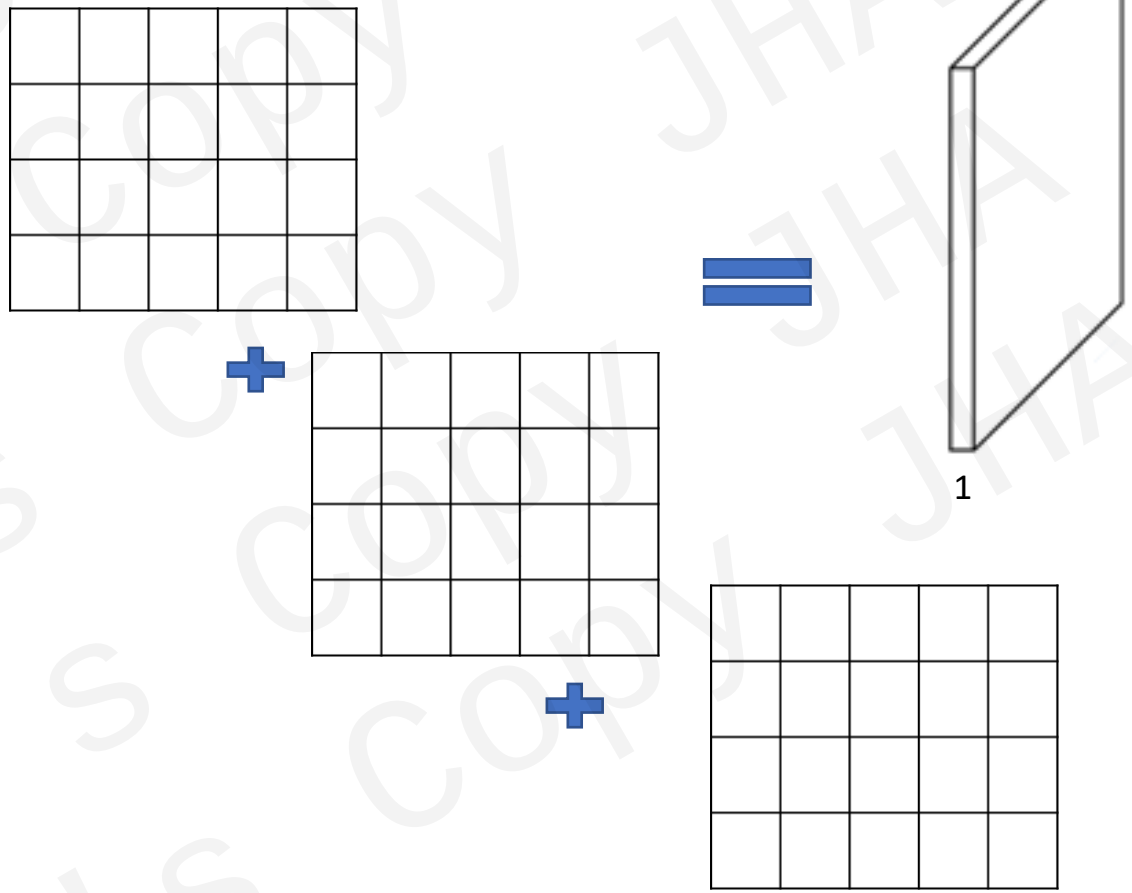
Multi input channels

Convolution with 3 input channels:

- slide the 2D filter kernel on 2D input , for each channel.
- add the three 2D feature maps to get the output➔ feature map (a **2D** array).
- generalizable to *n* input channels.



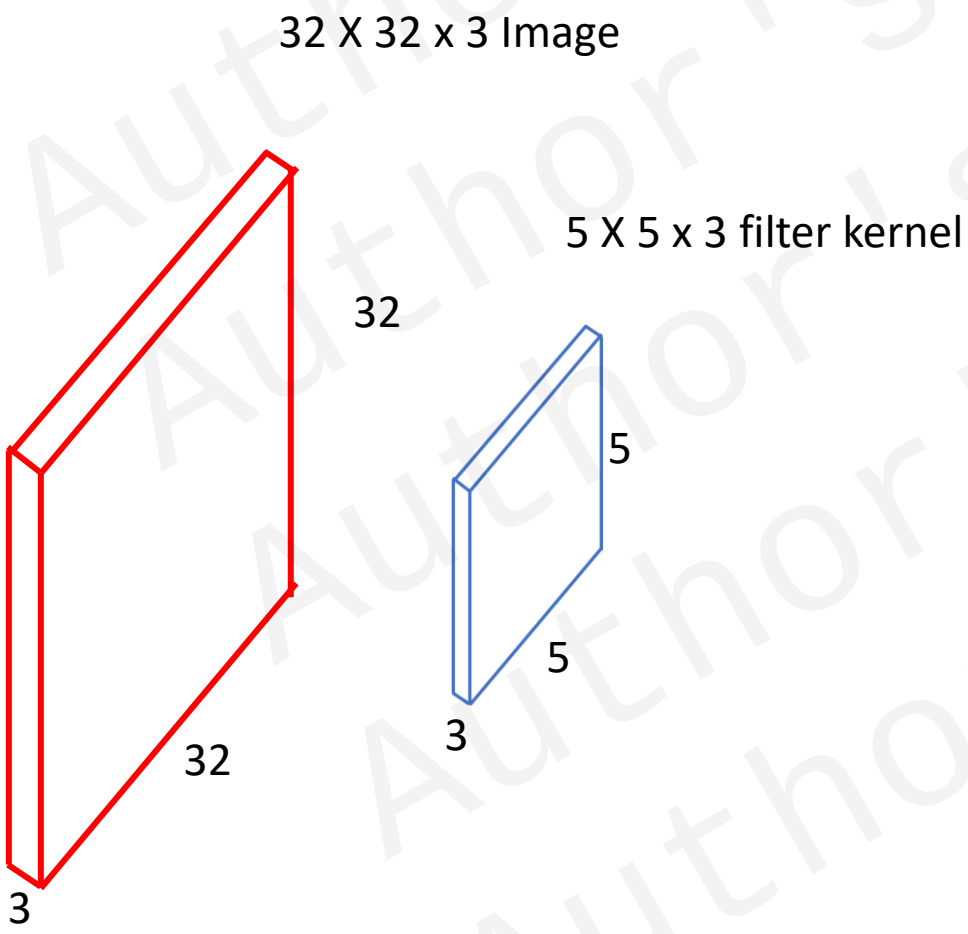




Multi input channels: Summary

Convolution of image (3 channels)

with 3 channel filter ➔ 1-D feature map.



Multi input channels: Summary

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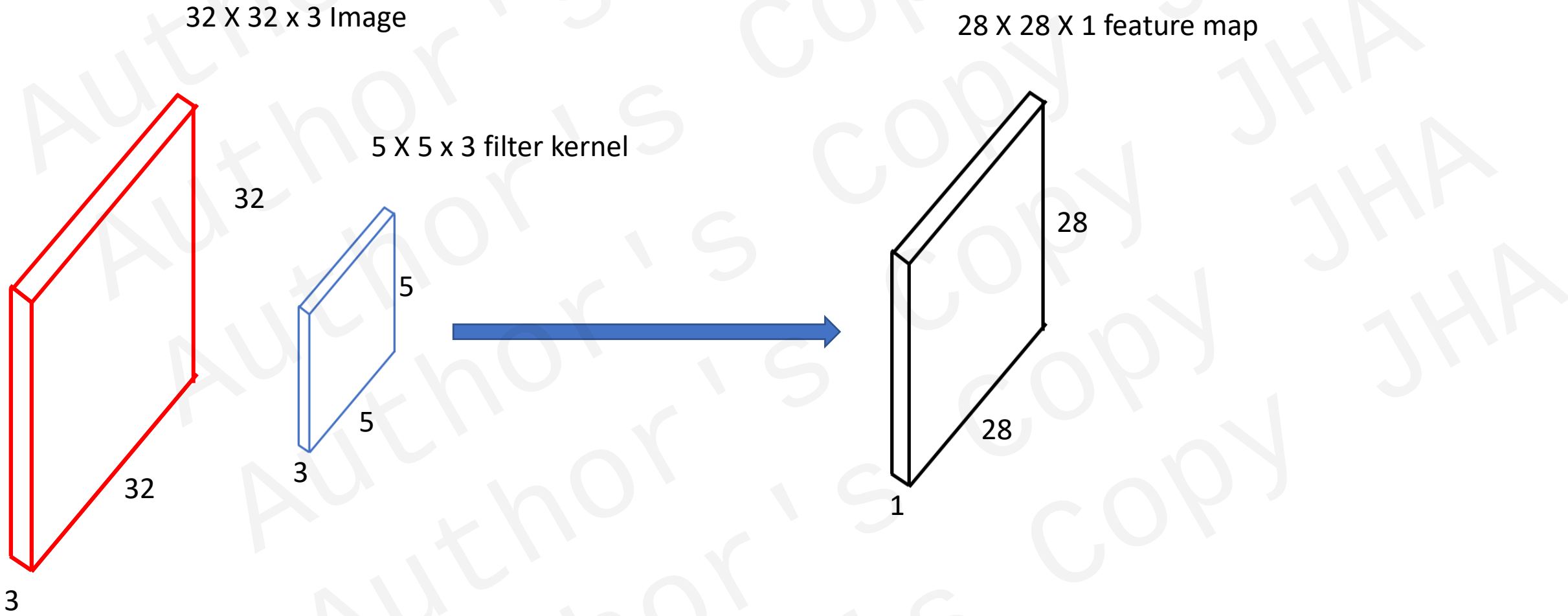
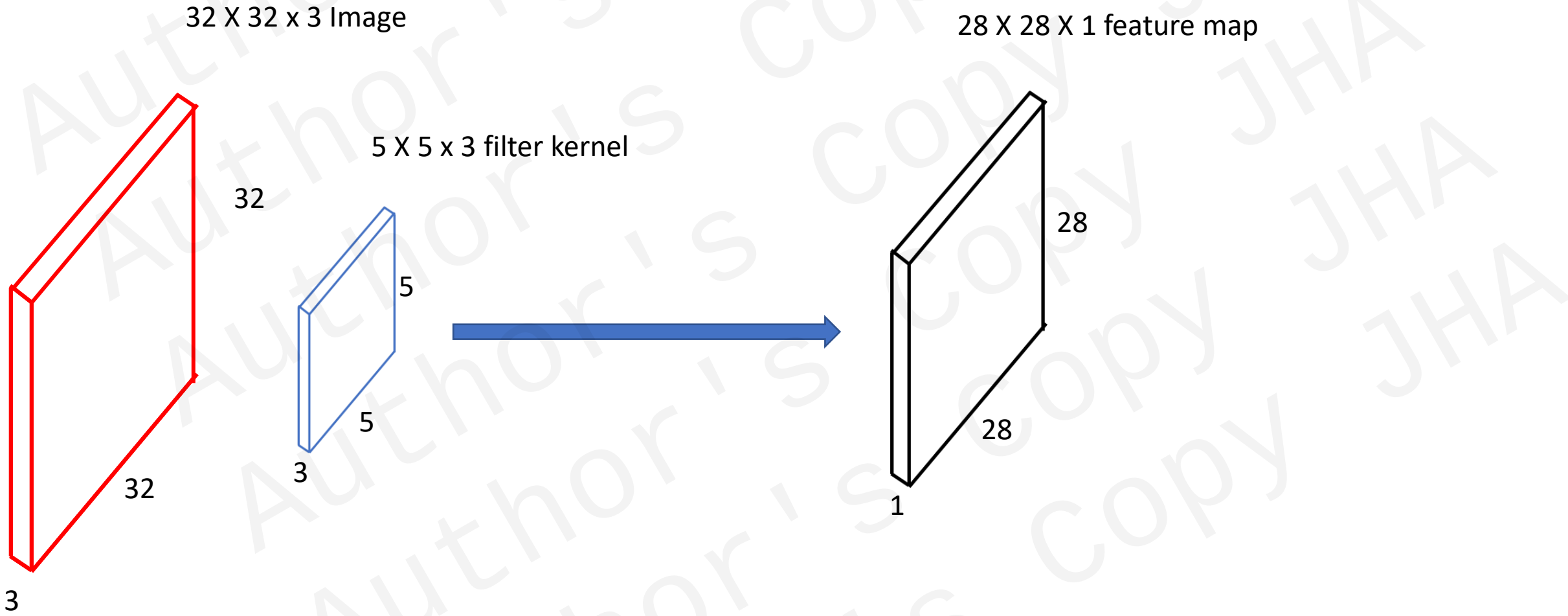


Multi input channels: Summary

Convolution of image (3 channels)

with 3 channel filter ➔ 1-D feature map.



Multi outputs

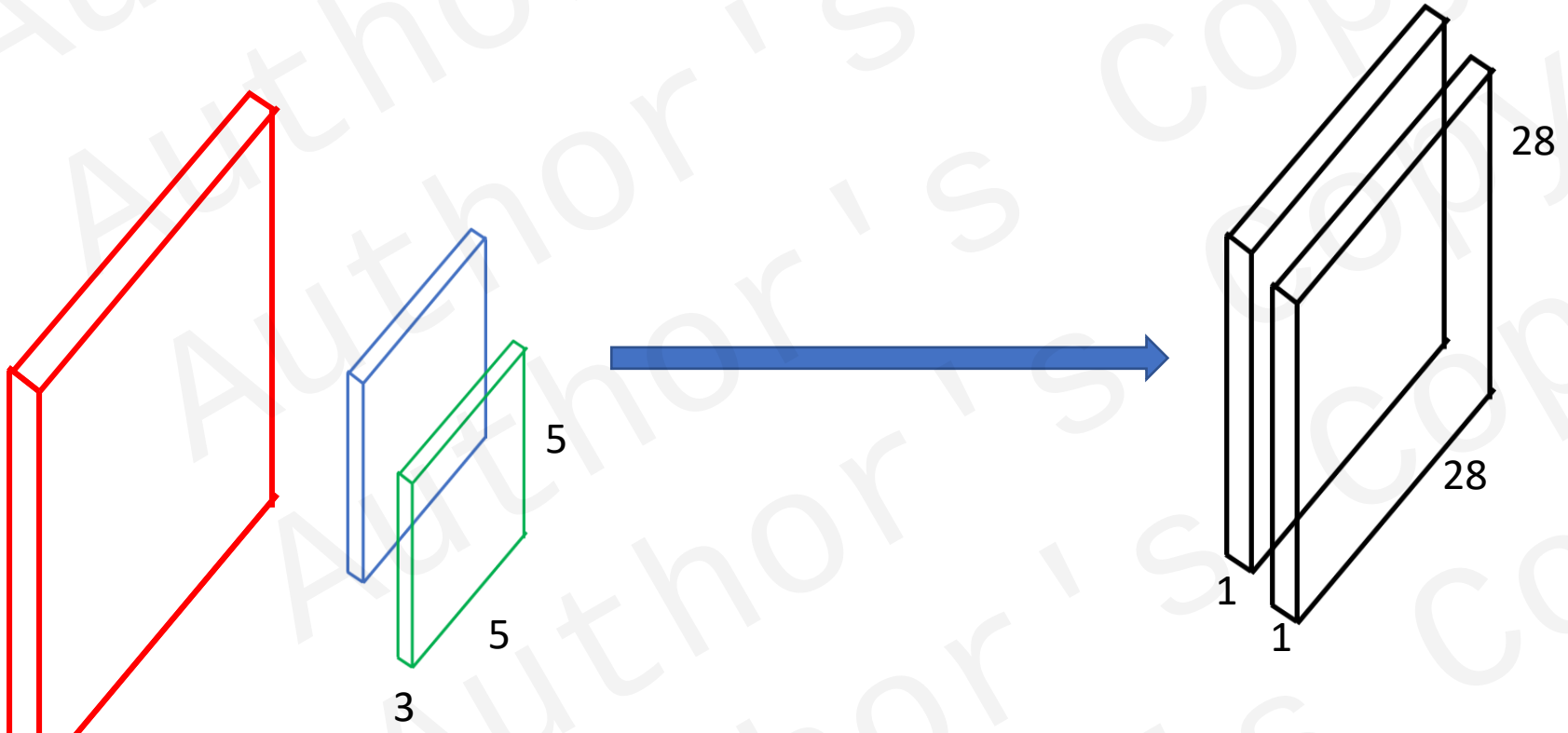
When more than one feature is to be extracted → multiple filters are used.

Output for each filter is desired. Output has multiple channels.

Convolution is performed with each filter kernel , for each output channel.

Output is concatenated along number of filter (output channel) dimension.

2 different filters ➔ convolution with each filter kernel and concatenated along output channel dimension.



Multi outputs

When more than one feature is to be extracted → multiple filters are used.

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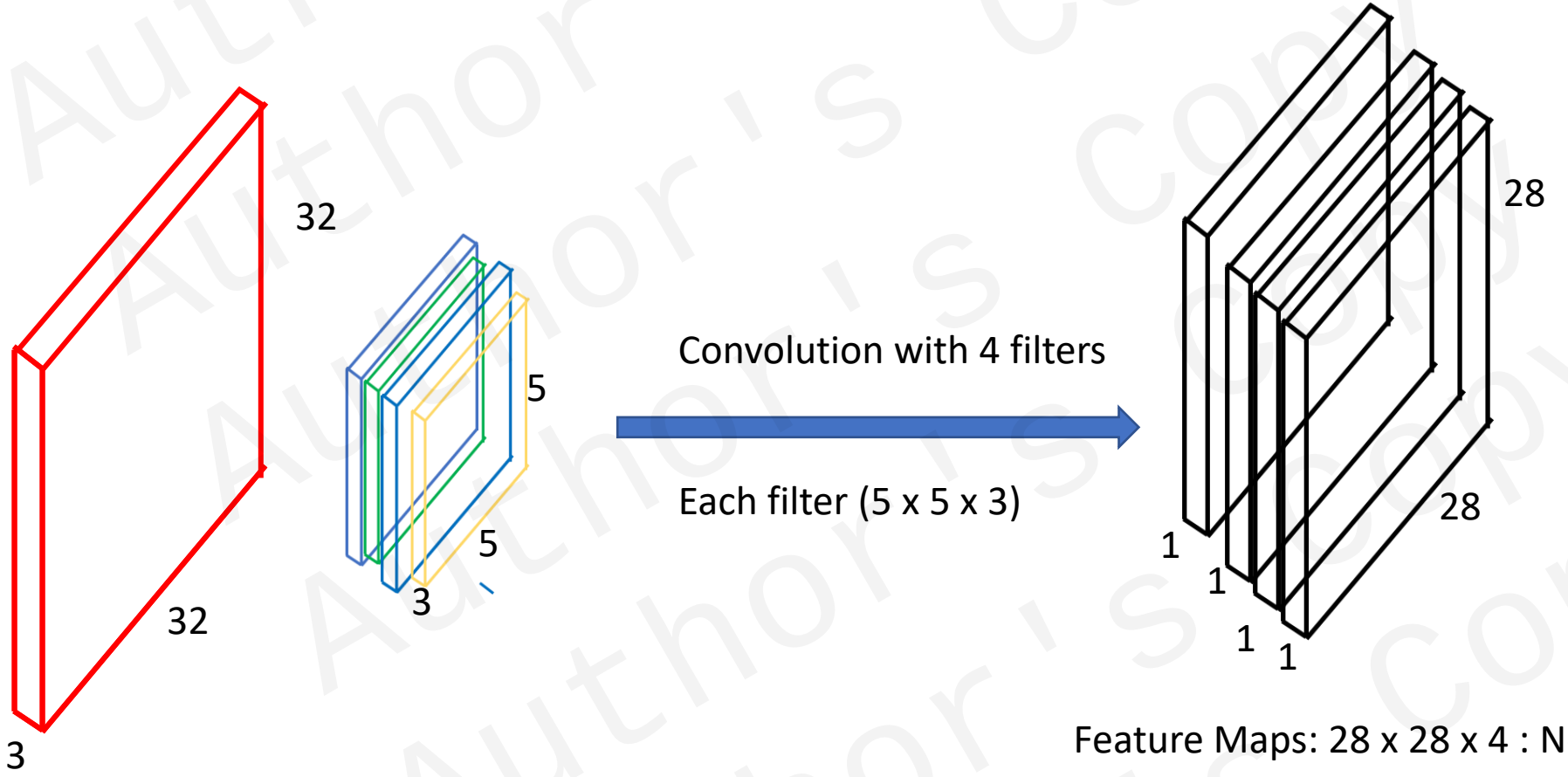
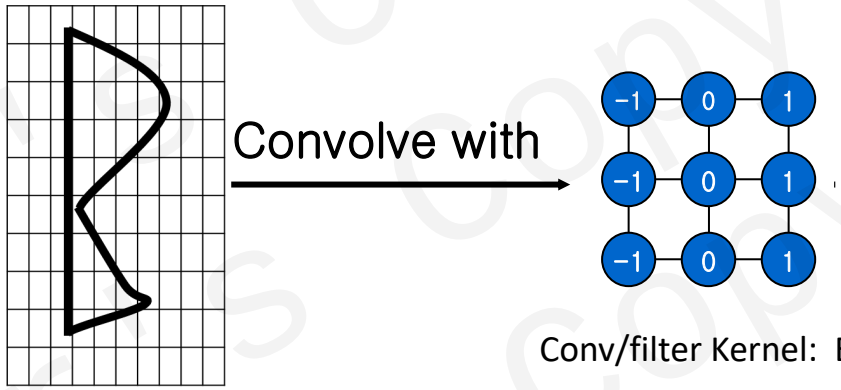


Feature Maps: 28 x 28 x 4 : New image!

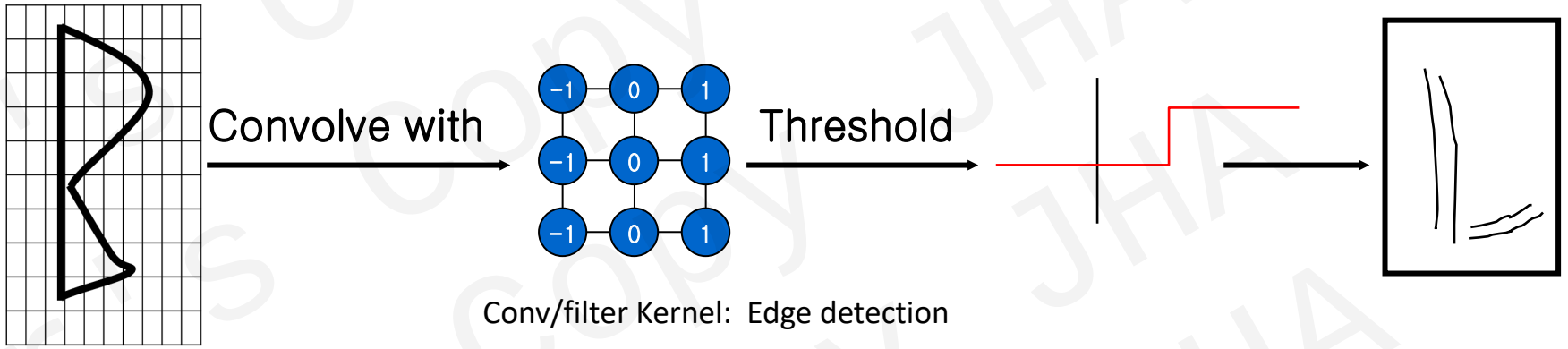
Summary

- So far: Just Convolutions!



Conv/filter Kernel: Edge detection

Summary

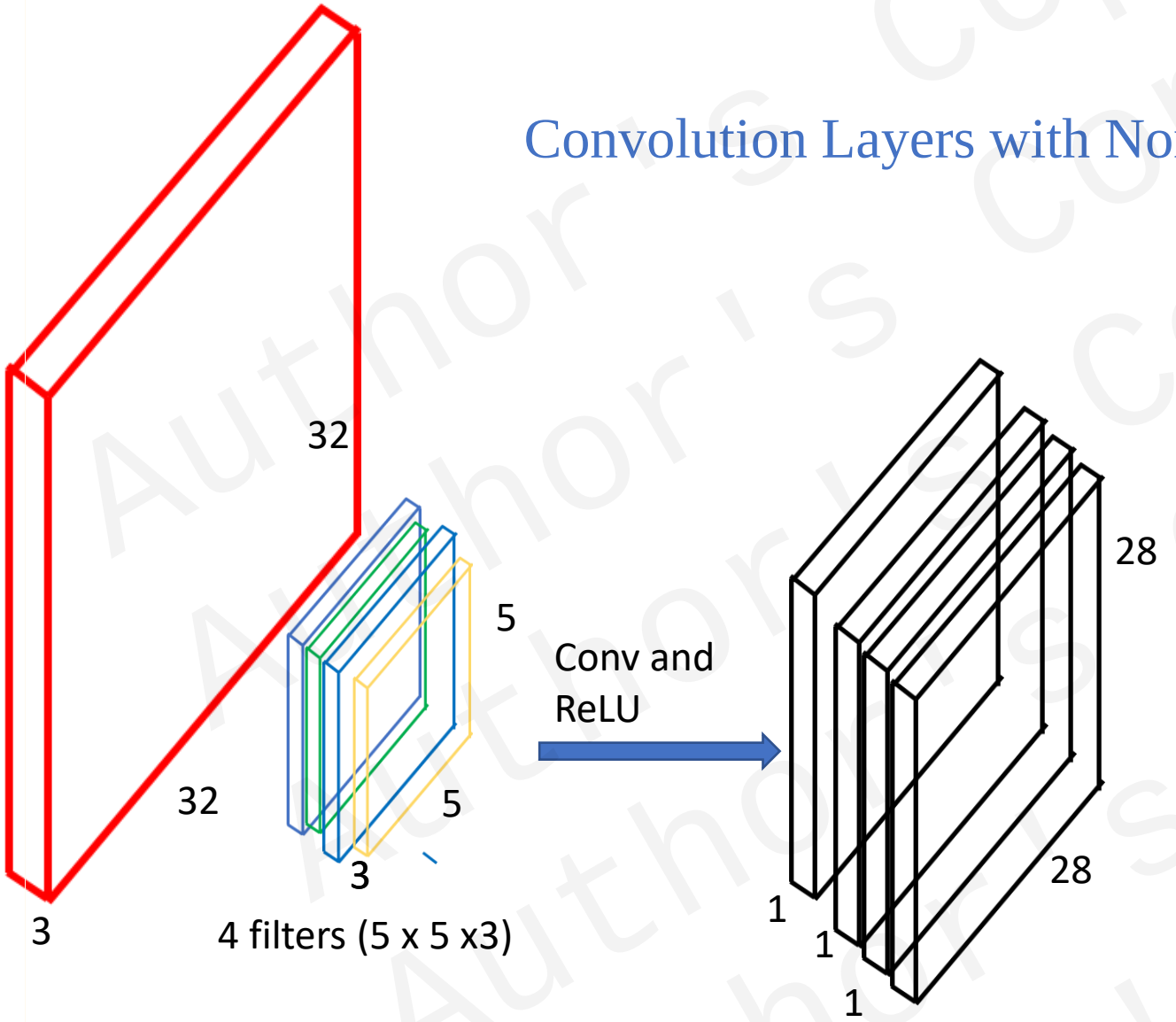


Conv/filter Kernel: Edge detection

- Apply Non-linearity (as seen earlier) : features pass thru activation functions → activation maps (terminology is loose , feature maps/activation maps both are used often to mean the same)

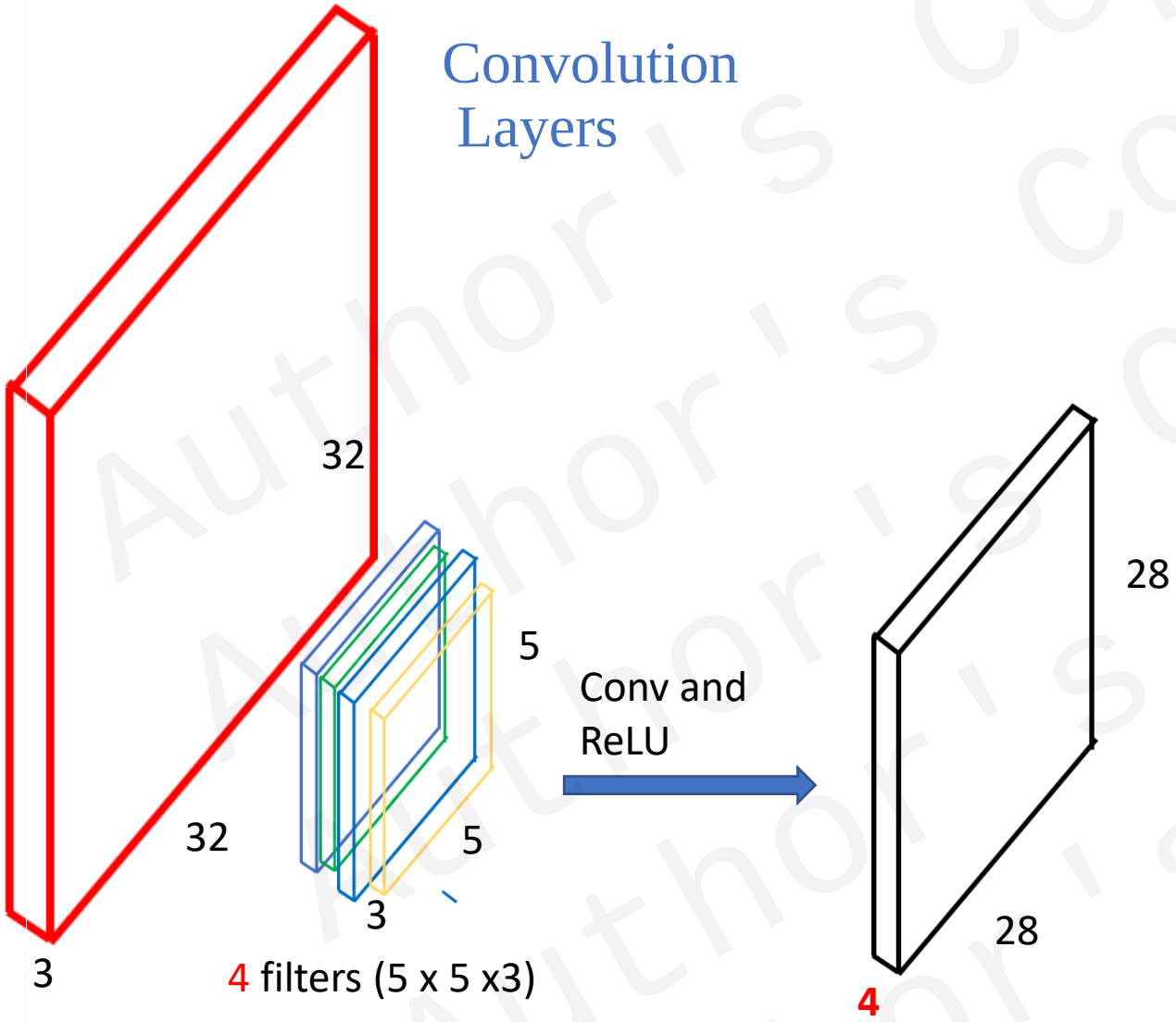
- In practice: ReLu is mostly preferred (fast convergence, no zero-gradient problem..

Convolution Layers with Non linearity Activation



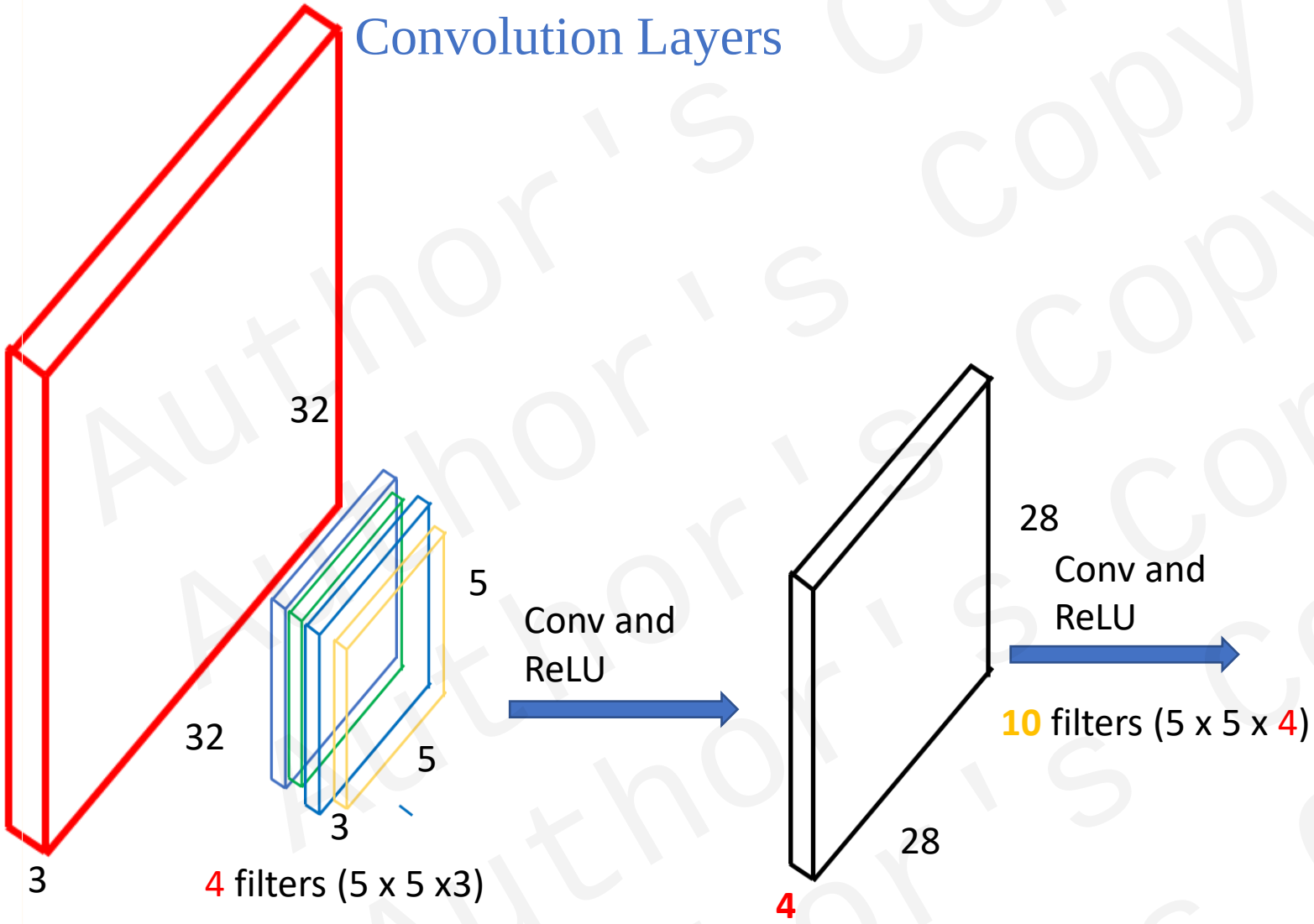
Feature Maps: 28 x 28 x 4 : New image!

Convolution Layers



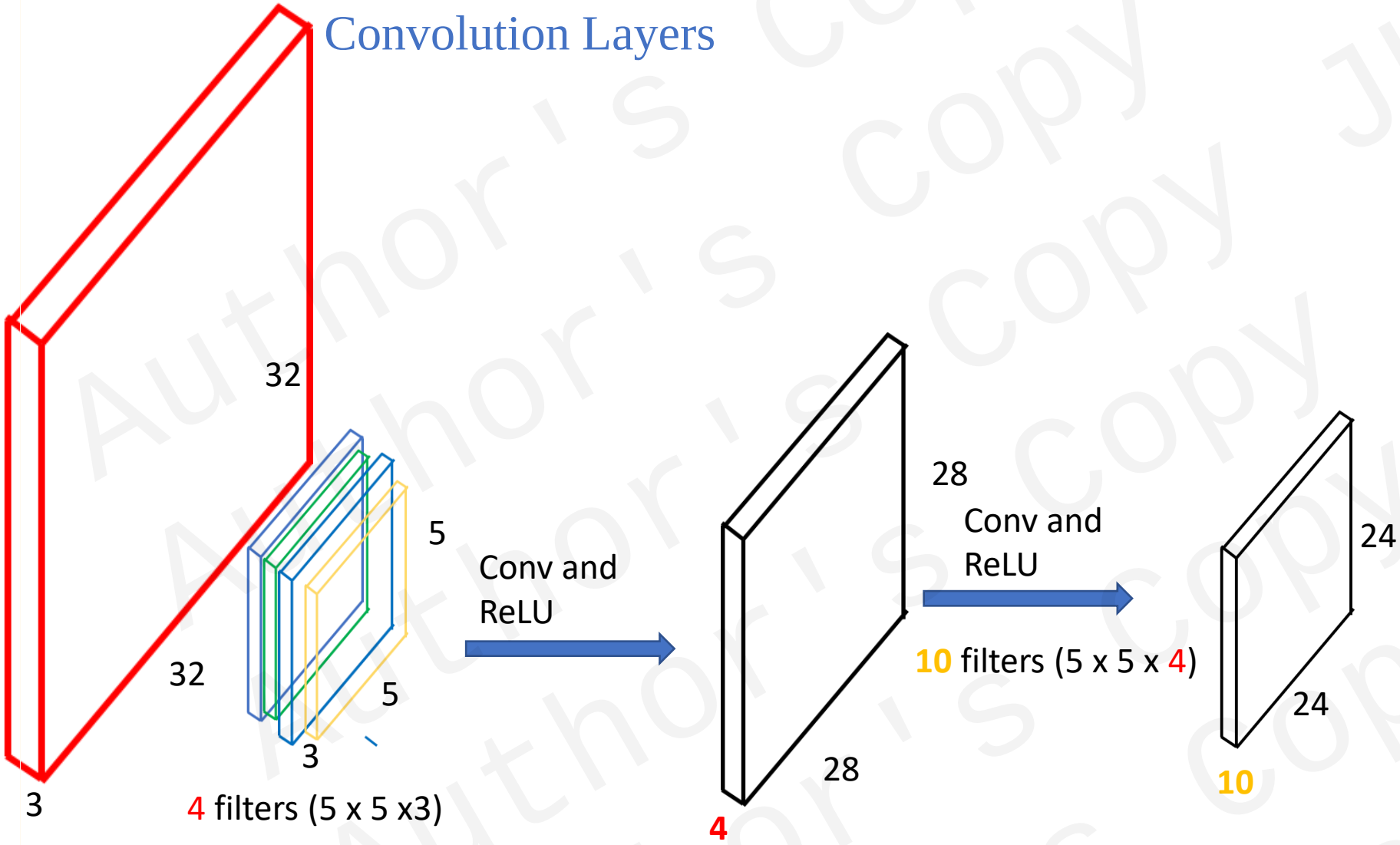
Feature Maps / Activation maps : 28 x 28 x 4

Convolution Layers



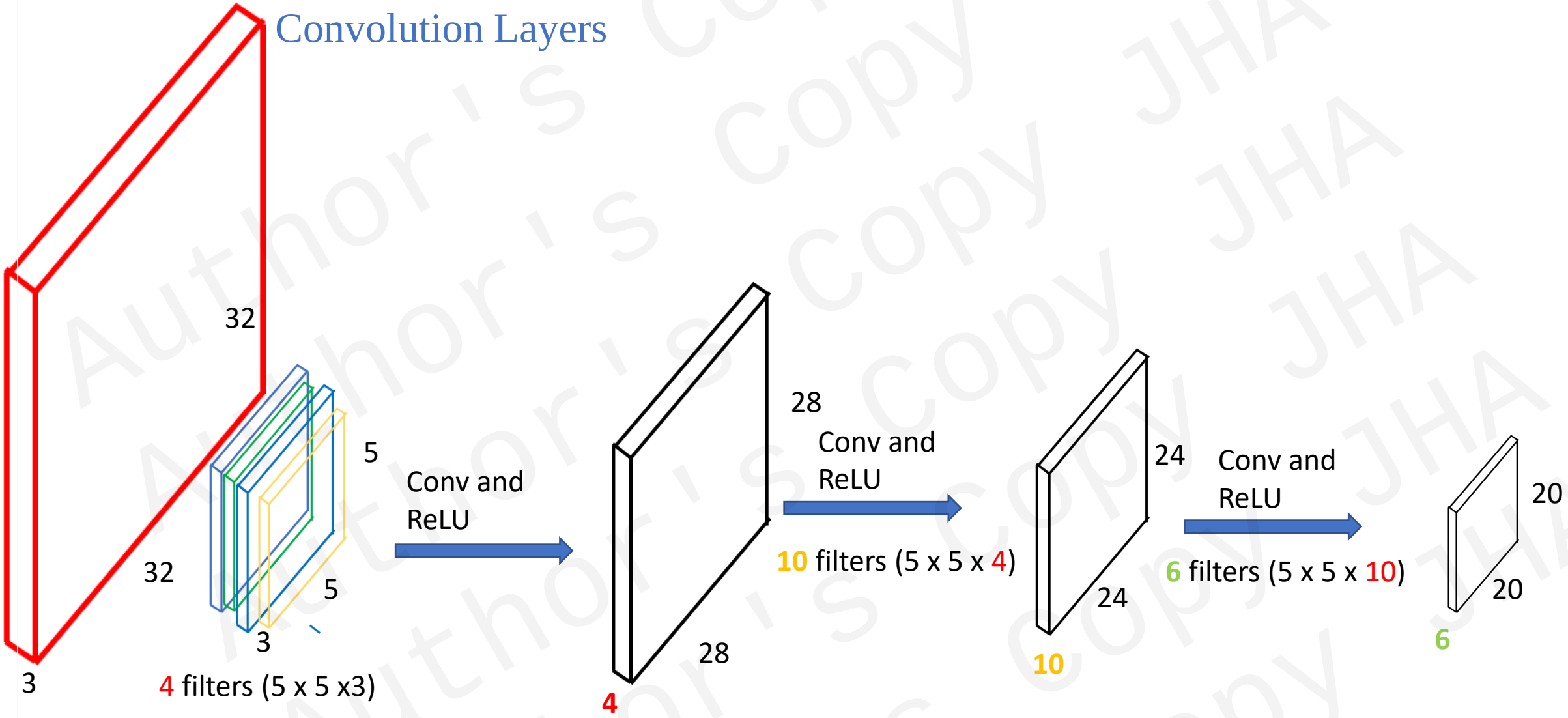
Feature Maps / Activation maps
: 28 x 28 x 4

Convolution Layers



Feature Maps / Activation maps
: 28 x 28 x 4

Convolution Layers



Feature Maps / Activation maps
: 28 x 28 x 4

Convolutional neural network (CovNets) CNNs

JHA Mayank , Email: mayank-shekhar.jha [at] univ-lorraine.fr

Convolution Layers

Remarks: Observe the reduction in size.

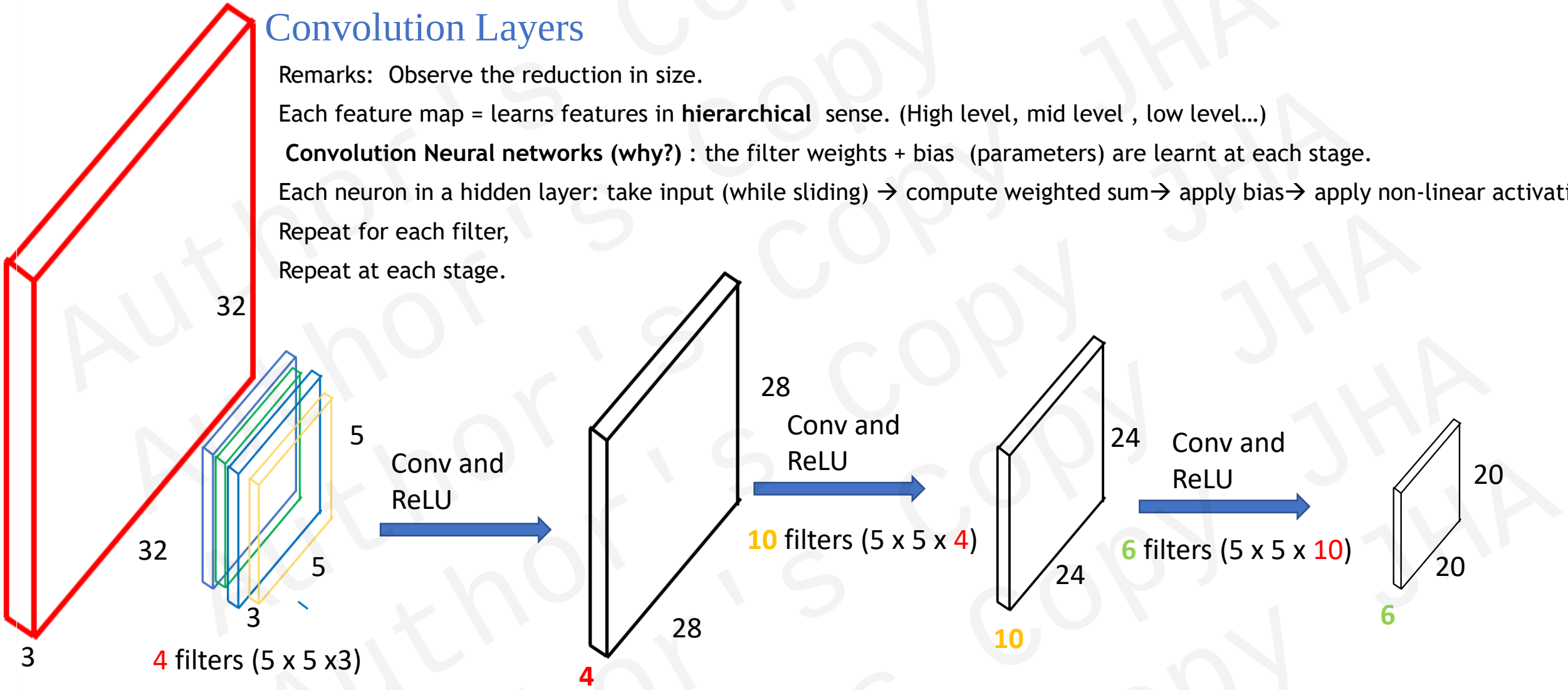
Each feature map = learns features in **hierarchical** sense. (High level, mid level , low level…)

Convolution Neural networks (why?) : the filter weights + bias (parameters) are learnt at each stage.

Each neuron in a hidden layer: take input (while sliding) → compute weighted sum→ apply bias→ apply non-linear activation

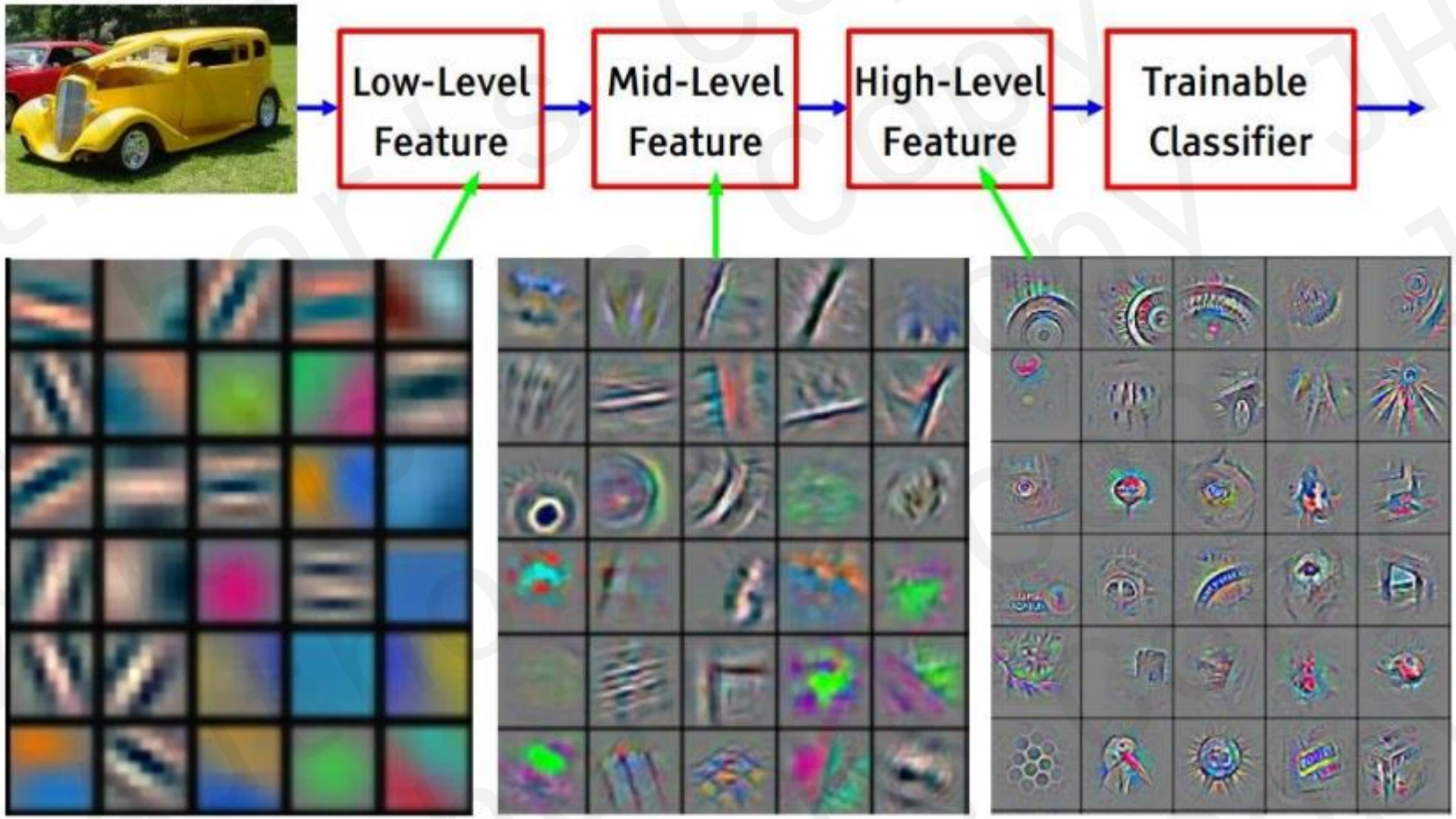
Repeat for each filter,

Repeat at each stage.



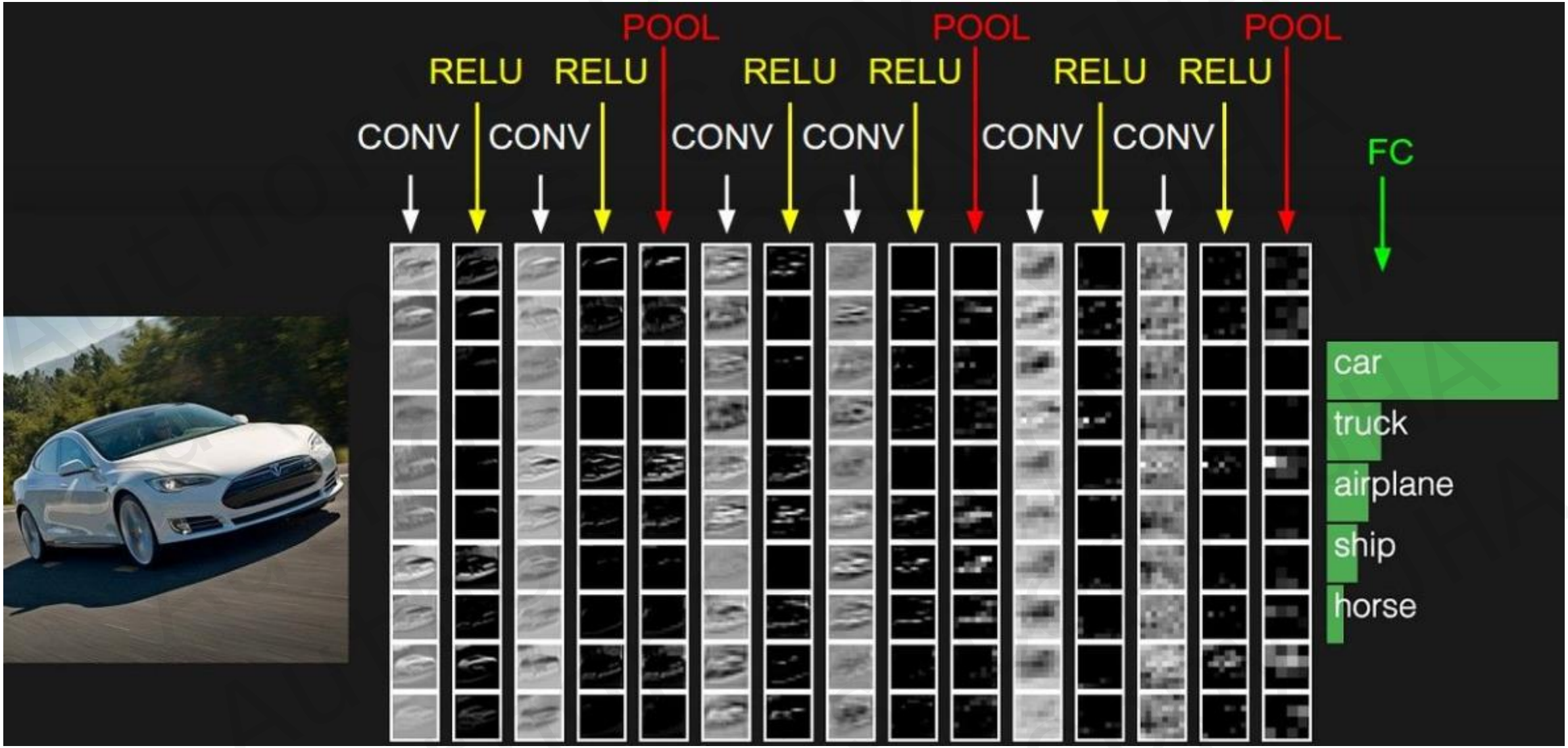
$$\sum_{i=1}^{5}\sum_{j=1}^{5} w_{i,j}x_{i+p,j+q} + b$$

Feature Maps / Activation maps : 28 x 28 x 4



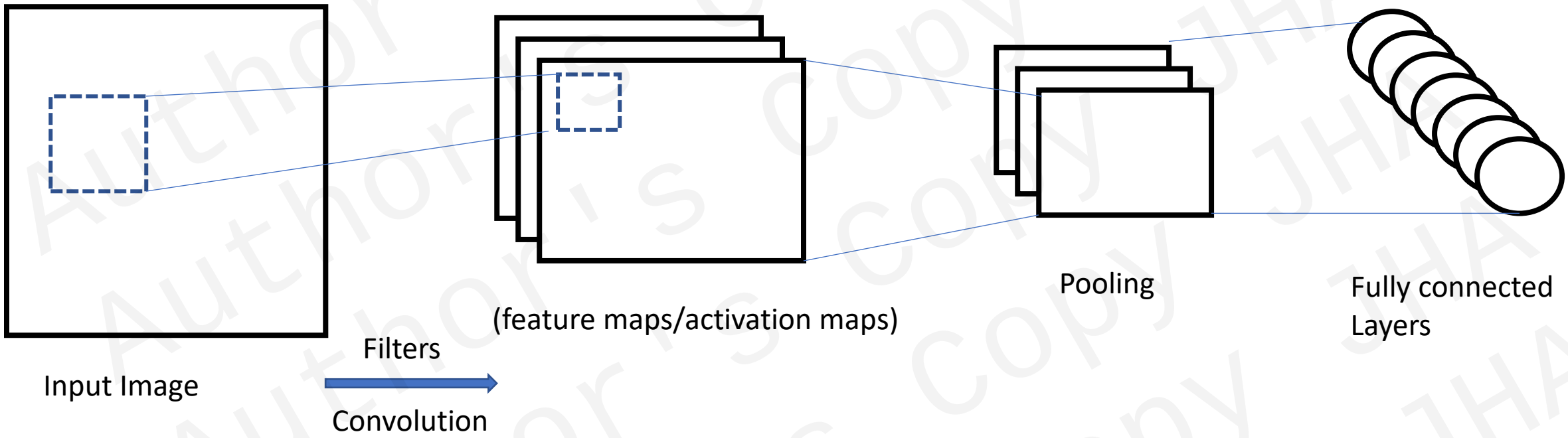
Feature visualization of convolutional net trained on ImageNet from [Zeiler & Fergus 2013]

Source: Dr. Fie Fie Li slides



Source: Prof. Fie Fie Li slides

CNNs for classification



- We discussed convolution operation and feature maps.
- Pooling:

Pooling

Pooling: Motivations

Down sampling:

- We want to reduce the resolution of images.
- The output should not depend on the dimensionality of the original image.

Invariance to translation:

In reality, objects hardly ever occur exactly at the same place.

- Detection should be invariant to translation to some extent.

Example: For instance, image with sharp feature and shifted by one pixel → detection result should not be vastly different from original image.

Pooling layers:

- reduce the sensitivity of Conv layer to location
- reduce the resolution through the processing pipeline.

Pooling layer : Max pooling or Average Pooling

0	3	1	6
2	1	0	2
-1	1	1	1
-1	0	-1	3

Max Pooling

Choose the maximum value in pooling window

0	3	1	6
2	1	0	2
-1	1	1	1
-1	0	-1	3

Average Pooling

Choose the average value in pooling window

Pooling layer : Max pooling or Average Pooling

0	3	1	6
2	1	0	2
-1	1		1
-1	0	-1	3

Max Pooling

Choose the maximum value in pooling window

3	

0	3	1	6
2	1	0	2
-1	1	1	1
-1	0	-1	3

Average Pooling

Choose the average value in pooling window

1.5	

Pooling layer : Max pooling or Average Pooling

0	3	1	6
2	1	0	2
-1	1	1	1
-1	0	-1	3

Max Pooling

Choose the maximum value in pooling window

3	6

0	3	1	6
2	1	0	2
-1	1	1	1
-1	0	-1	3

Average Pooling

Choose the average value in pooling window

1.5	2.25

Pooling layer : Max pooling or Average Pooling

0	3	1	6
2	1	0	2
-1	1	1	1
-1	0	-1	3

Max Pooling

Choose the maximum value in pooling window

3	6
1	

0	3	1	6
2	1	0	2
-1	1	1	1
-1	0	-1	3

Average Pooling

Choose the average value in pooling window

1.5	2.25
-0.25	

Pooling layer : Max pooling or Average Pooling

0	3	1	6
2	1	0	2
-1	1	1	1
-1	0	-1	3

Max Pooling

Choose the maximum value in pooling window

3	6
1	3

0	3	1	6
2	1	0	2
-1	1	1	1
-1	0	-1	3

Average Pooling

Choose the average value in pooling window

1.5	2.25
-0.25	1

Strides and padding also available for pooling.

In practice, pooling window size: 2 x 2 , stride = 2.

Note: Zero padding is NOT common for pooling layers.

Pooling

Pooling layers / Subsampling pixels does not change the object.

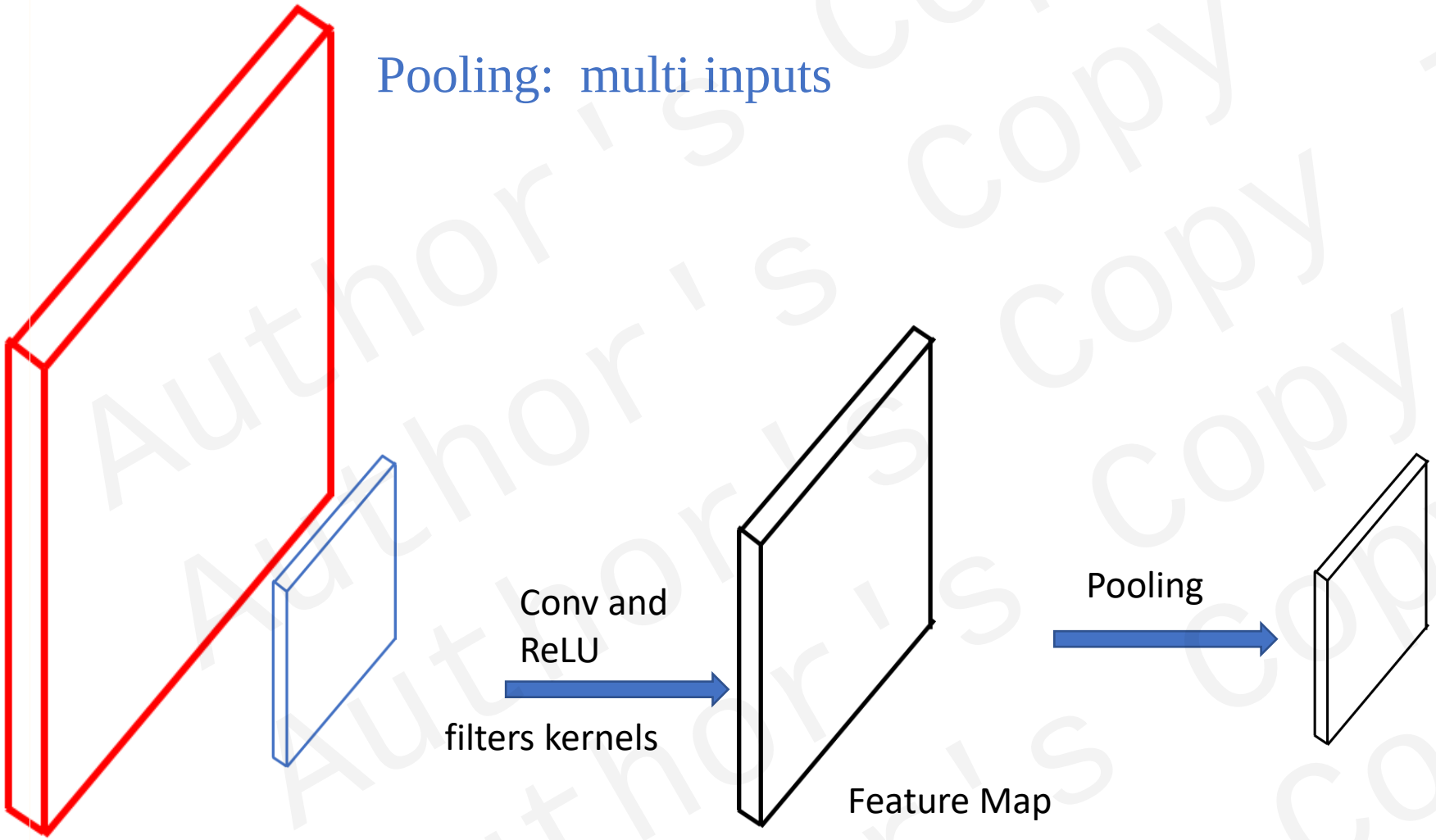
Changes the resolution , fewer parameters to characterize the image.

The subsampling layers reduce the spatial resolution of each feature map

By reducing the spatial resolution of the feature map, a certain degree of shift and distortion invariance is achieved.

Reduces the effect of noises and shift or distortion

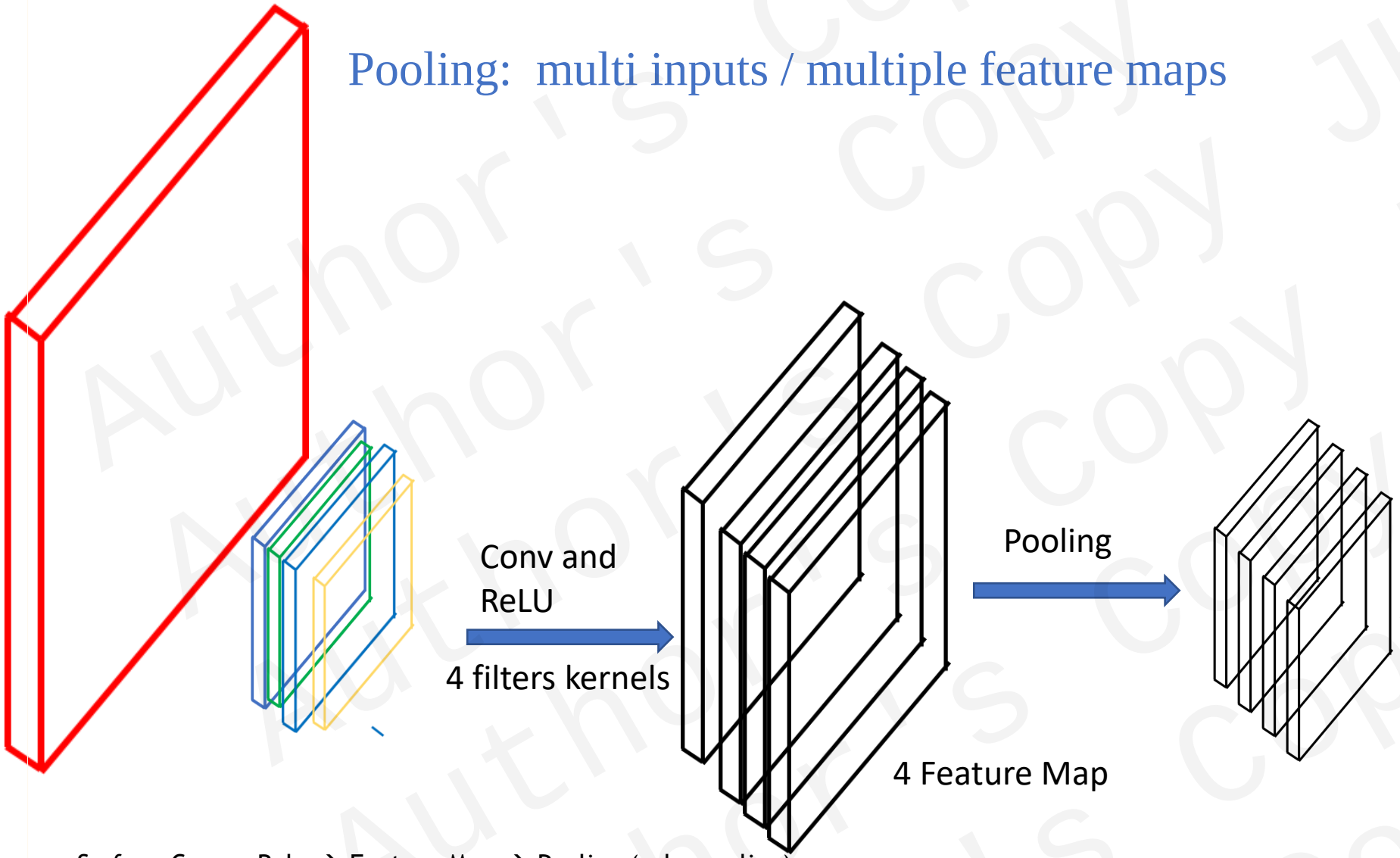
Pooling: multi inputs



So far: Conv + Relu → Feature Map → Pooling (subsampling)

When, multiple filters used:

Pooling: multi inputs / multiple feature maps

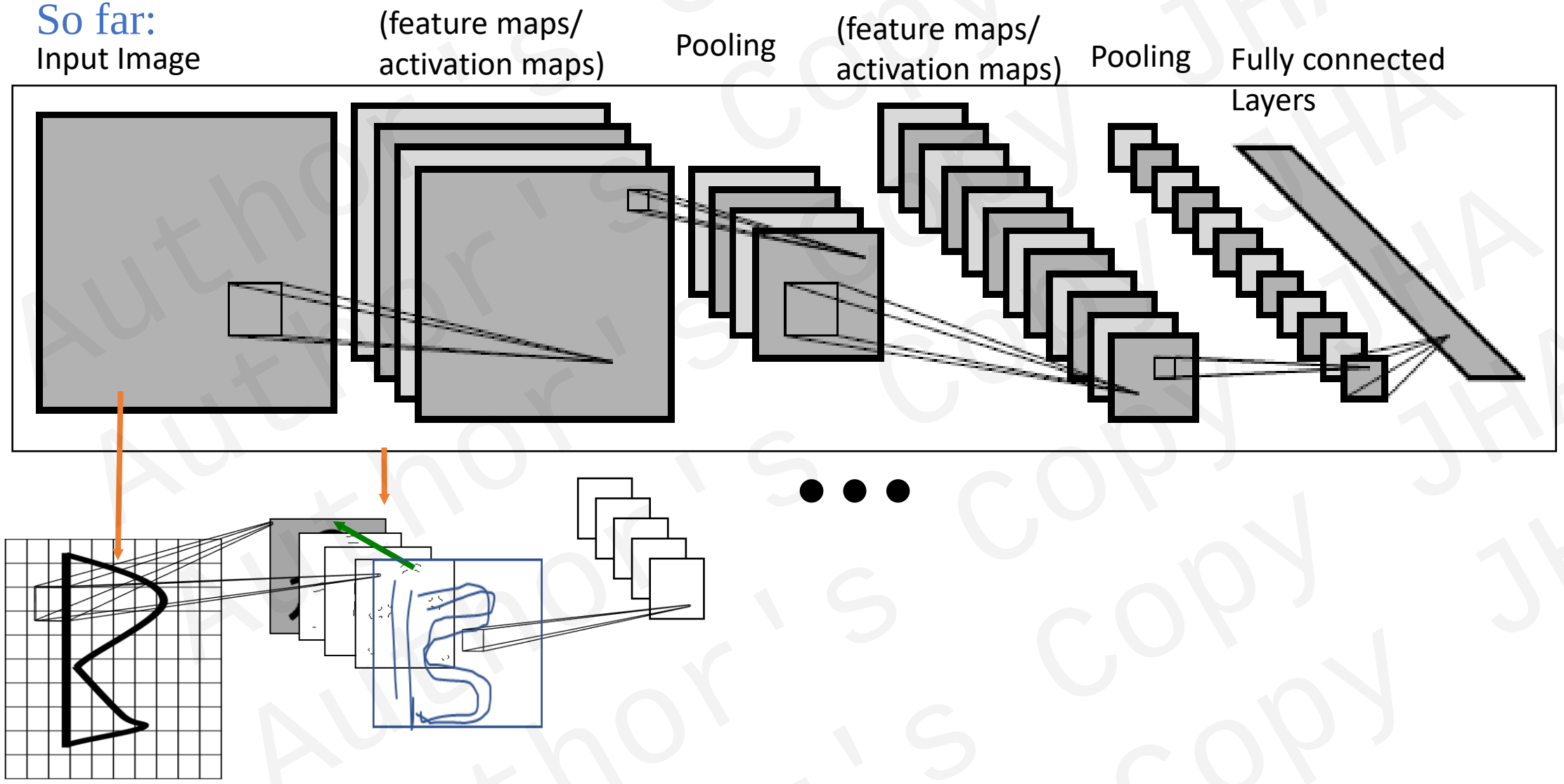


So far: Conv + Relu → Feature Map → Pooling (subsampling)

When, multiple filters used: Pooling done on each input feature map.

New set of images but smaller images.

So far:

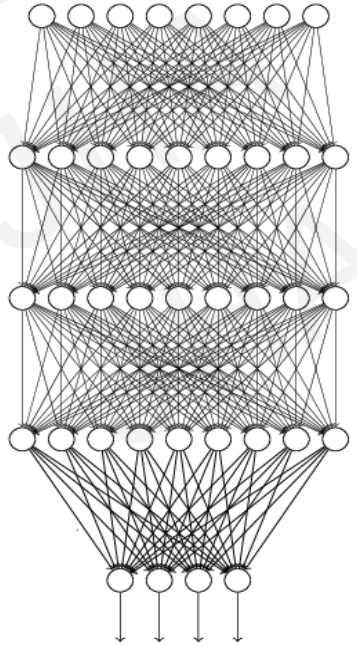


Convolution → Max Pooling → Convolution → Max Pooling → Flattening

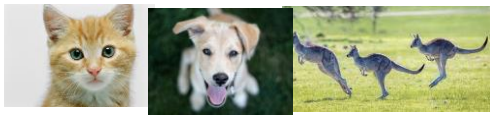
A new image

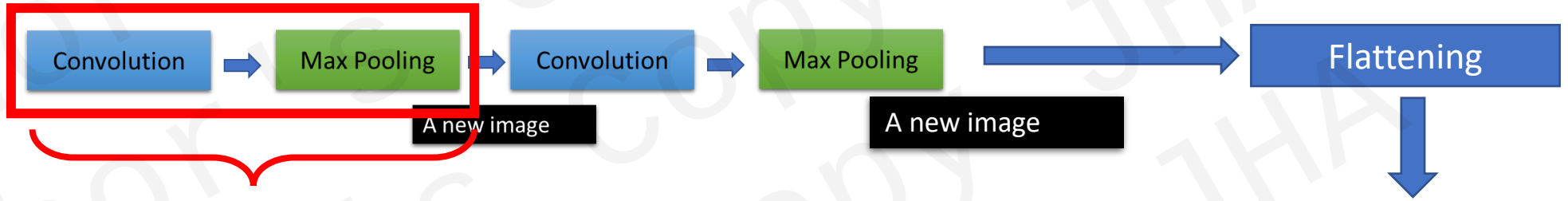
A new image

Fully Connected Feedforward network



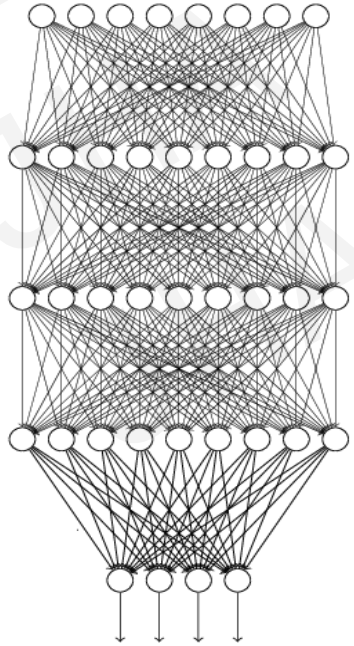
cat , dog , kangaroo……





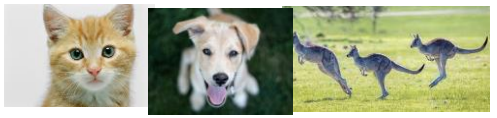
This can repeat many times
Pooling leads to subsampling

Fully Connected
Feedforward network

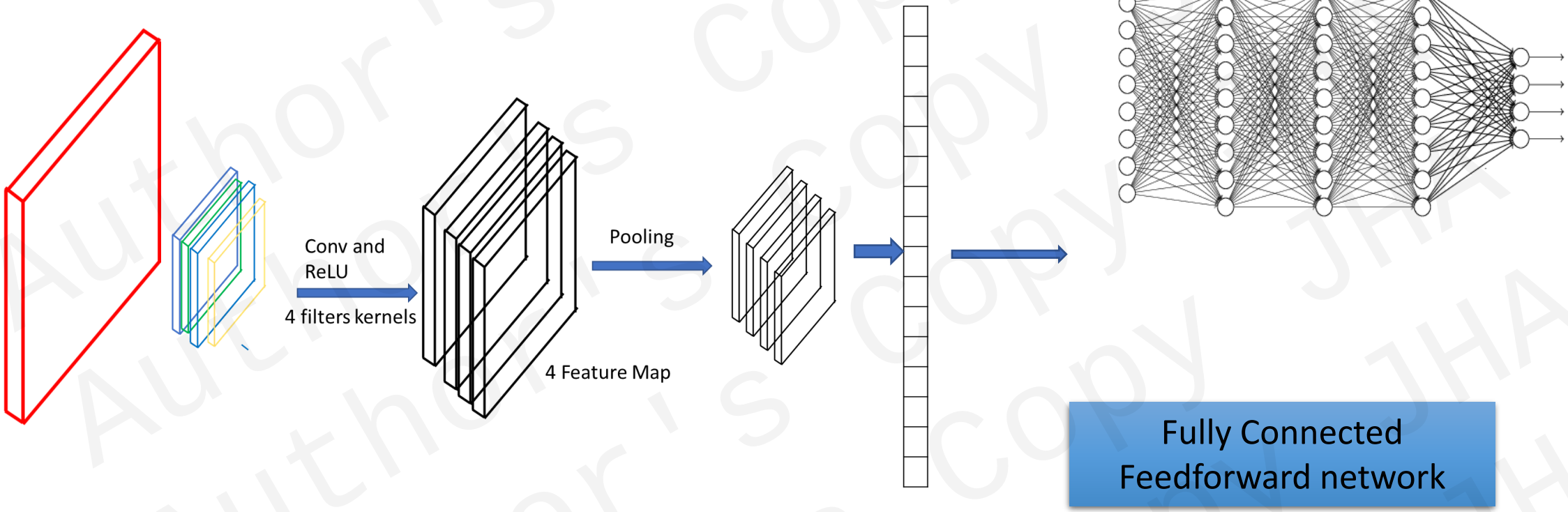


- At each stage, a new image (reduced resolution) is obtained, ready for convolution.
- At the end, the output structure is “flattened” to create a single long feature vector to be used by the dense layer for the final classification.

cat , dog , kangaroo……



Flattening



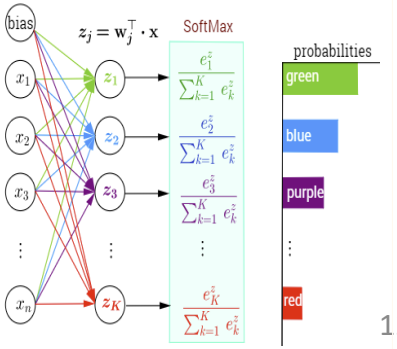
For classification, expect the net outputs distribution of probability of each class (multi class , softmax)

This has little to do with “spatial” 2D information.

This is abstract representation.

Output information → flatten→ create single long feature vector (like last lecture)→ feed to Dense ANNs.

Fully connected Dense Feed foreword networks can propagate this information.



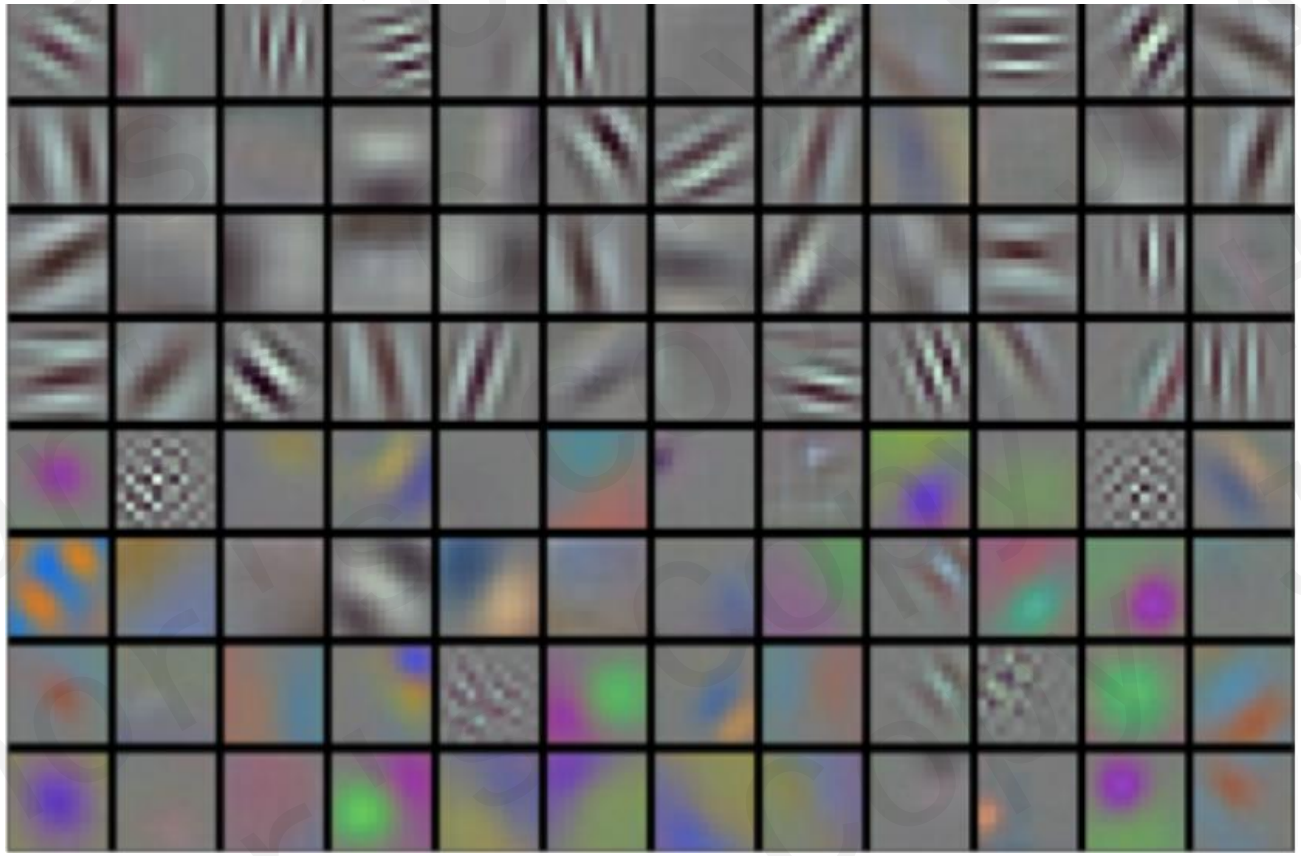
Demo: training on CIFAR-10 dataset

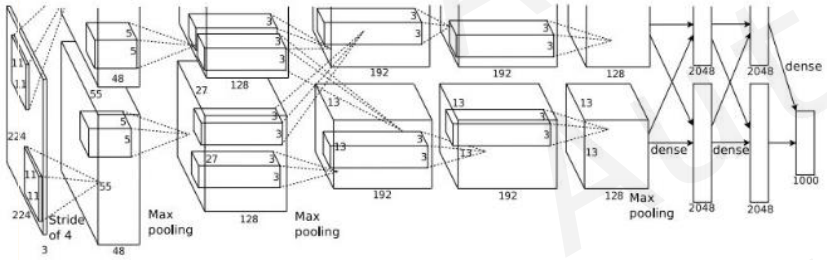
https://cs.stanford.edu/people/karpathy/convnetjs/demo/cifar10.htmlt

AlexNet: obtained above par state of art results on ImageNet challenge,

learnt good low level features,

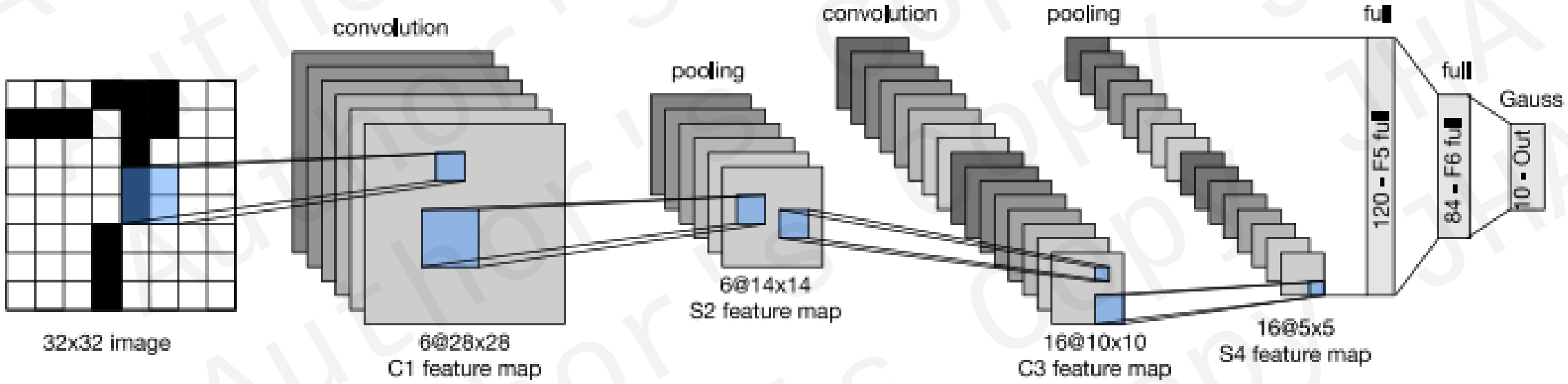
higher level features built upon these.





LeNet-5 (LeCun et al. 1998)

- state-of-the-art performance on hand digit recognition tasks.



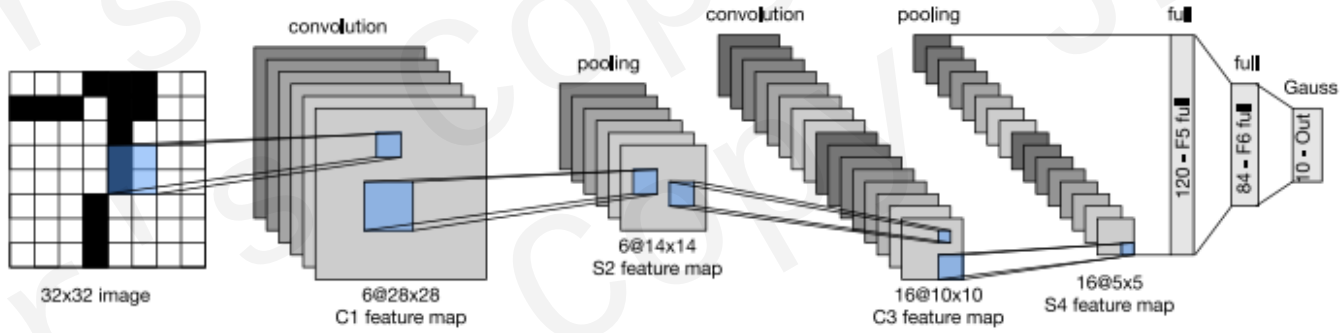
LeNet-5 (LeCun et al. 1998)

Advantages :

- convolution with learnable parameters (sharable parameters) ➔ effective way to extract similar features at multiple locations with few parameters .
- correlation with neighboring pixels (data) considered.
- optical character, fingerprint recognition…

Limitations:

- High computational burden: each pixel as separate input .
- Traditional activations functions: slow learning.



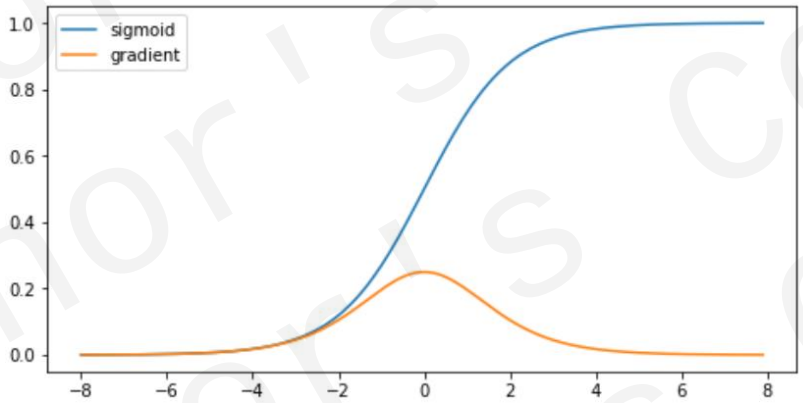
Stagnation of CNN : Early 2000

ML paradigm in 1990-1998:

- Typically such datasets were **hand generated** using very expensive sensors.
- Lacked richness, diversity ➔ insignificant improvement of performance (lack of complex training data, representations etc.
- Till 2012, feature representation had to be thought, or based on intuition.

CNNs:

- Backpropagation → not effective to reach global minima.
- Activation functions: Sigmoid function (variants)
  - vanishing gradient problem (exponential decay)
  - exploding gradient problem.



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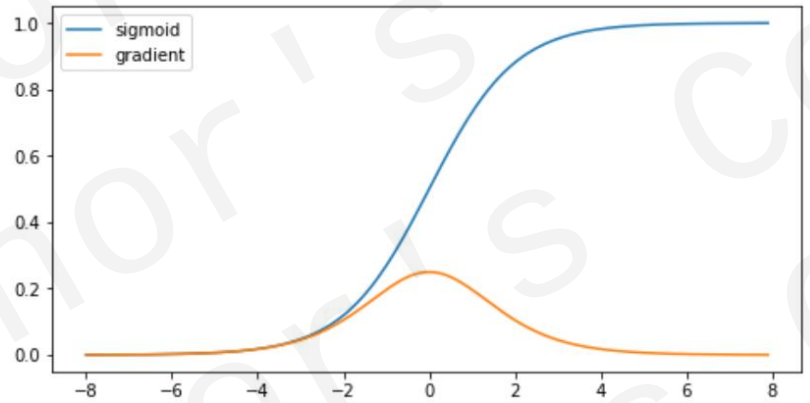
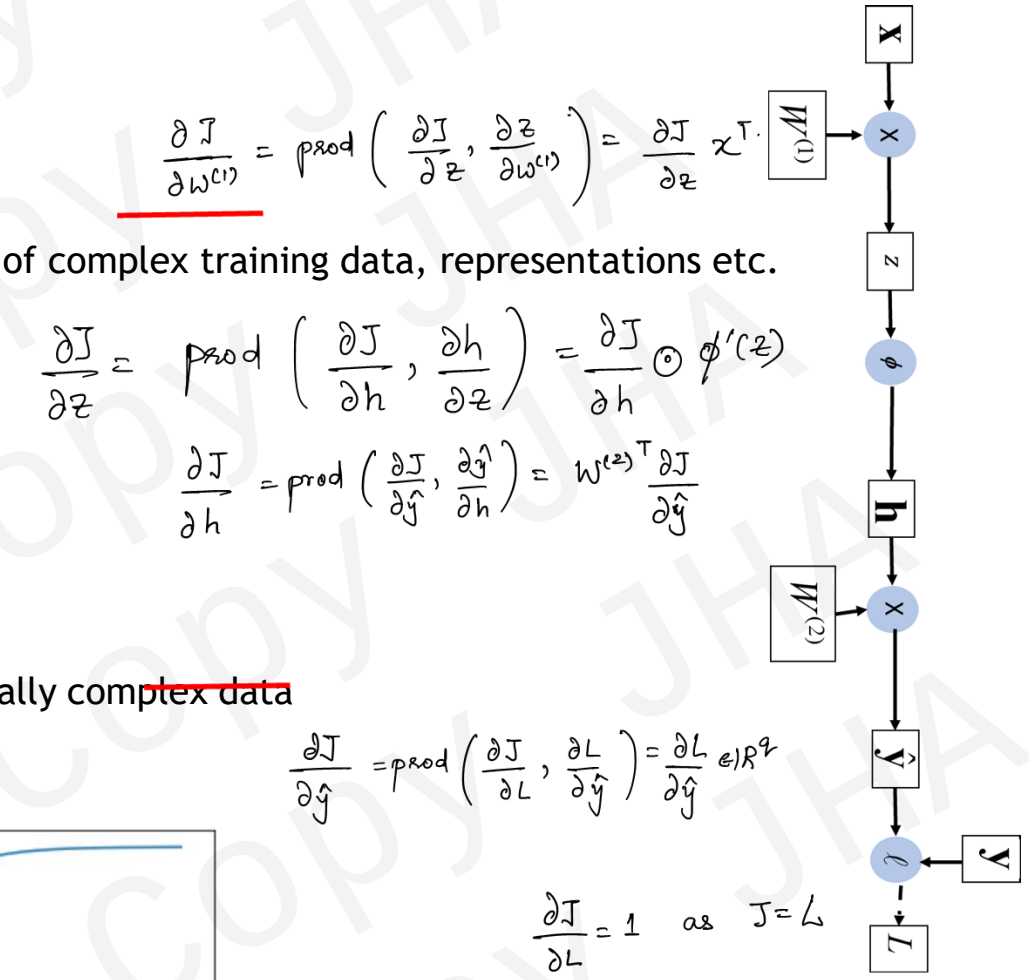
CNNs:

- Backpropagation → not effective to reach global minima.
- Activation functions: sigmoid function (variants)
  - vanishing gradient problem (exponential decay)
  - exploding gradient problem (no efficient initialization methods)
- Little attention : object detection, classification/prediction of spatio-temporally complex data
- Limited computational resources (no GPUs)

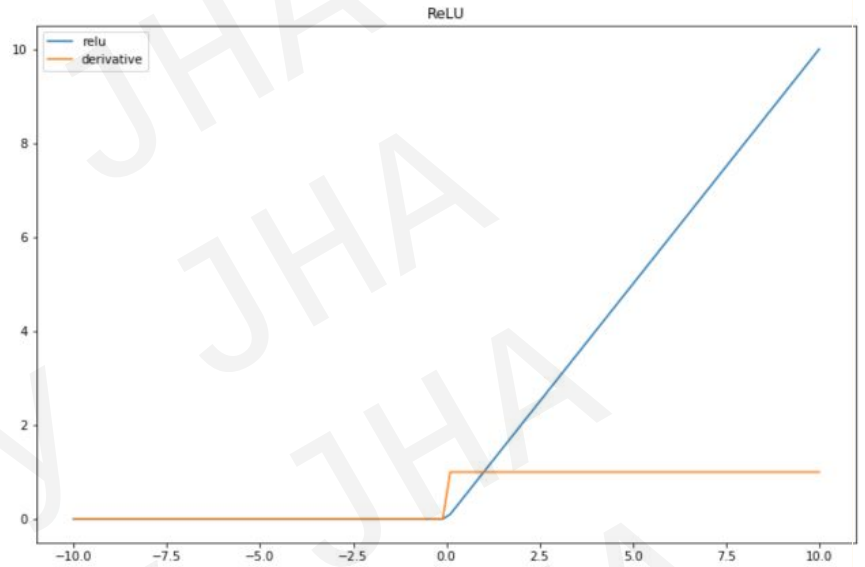


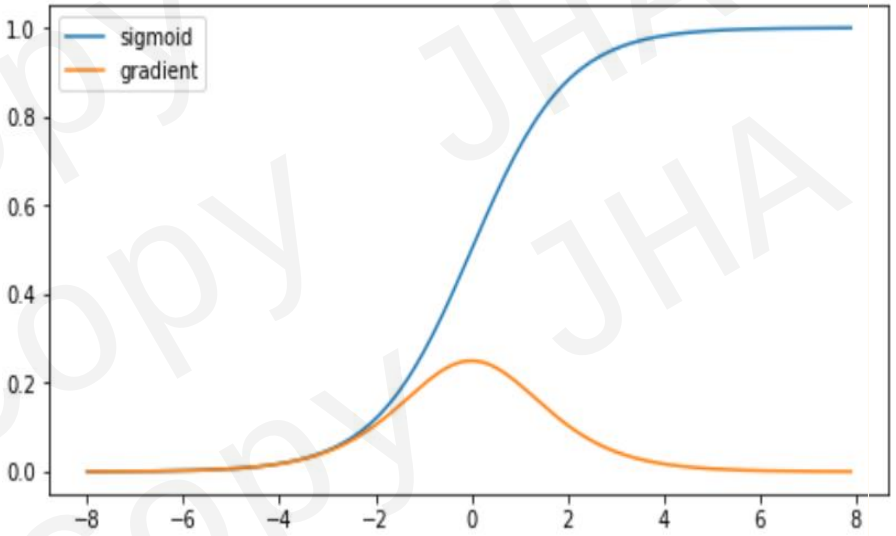


Revival of CNNs: 2006-2011

- Efficient initialization techniques:
  - greedy layer-wise pre-training (Hinton et al. 2006)
  - unsupervised/supervised training-based pre-training
  - Xavier initialization (Glorot and Bengio, 2010)
- Use of Non-saturating Activation Functions : ReLu (Glorot and Bengio, 2010)
- Max-pooling > Sub-sampling (Ranzato et al, 2007) → learnt better invariant features.

- Late 2006: GPUs for training CNNs.
- 2007: NVIDIA → CUDA programming → harness parallel processing power of GPUs





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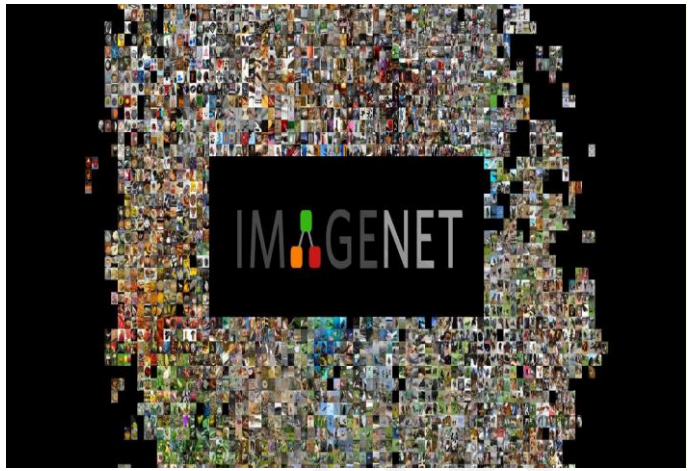

- Late 2006: GPUs for training CNNs.
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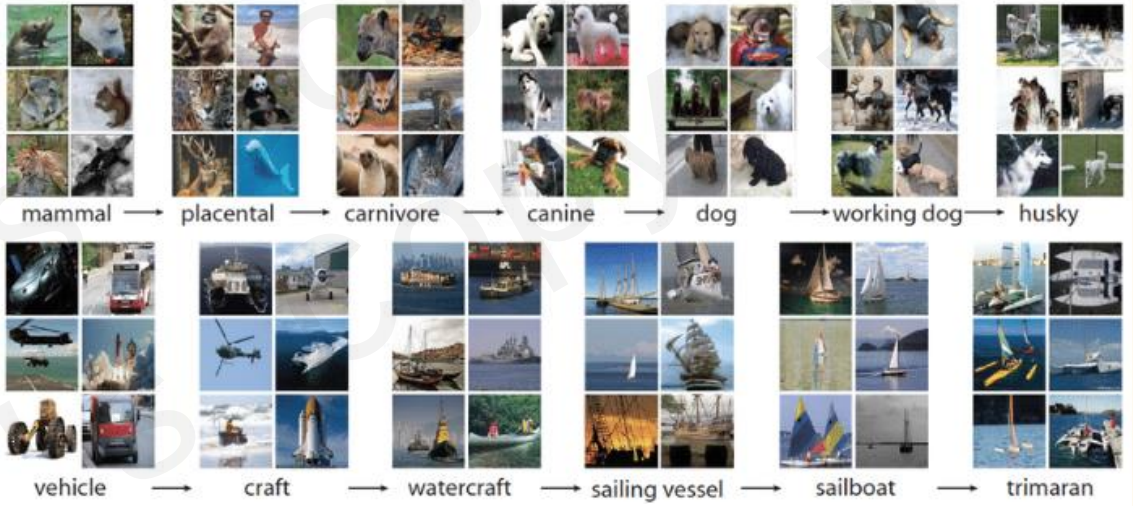
- 2010: Dr. Fei-Fei Li group (Stanford) → ImageNet platform

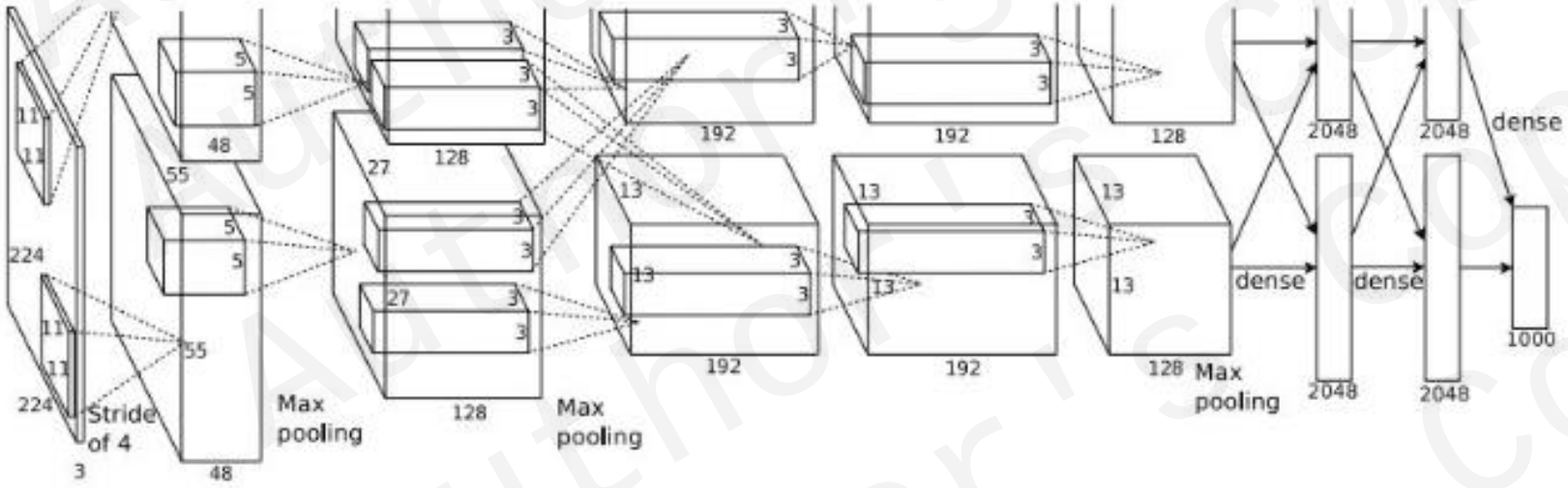
today ImageNet → 15 millions, large number categories and classes (target labels).

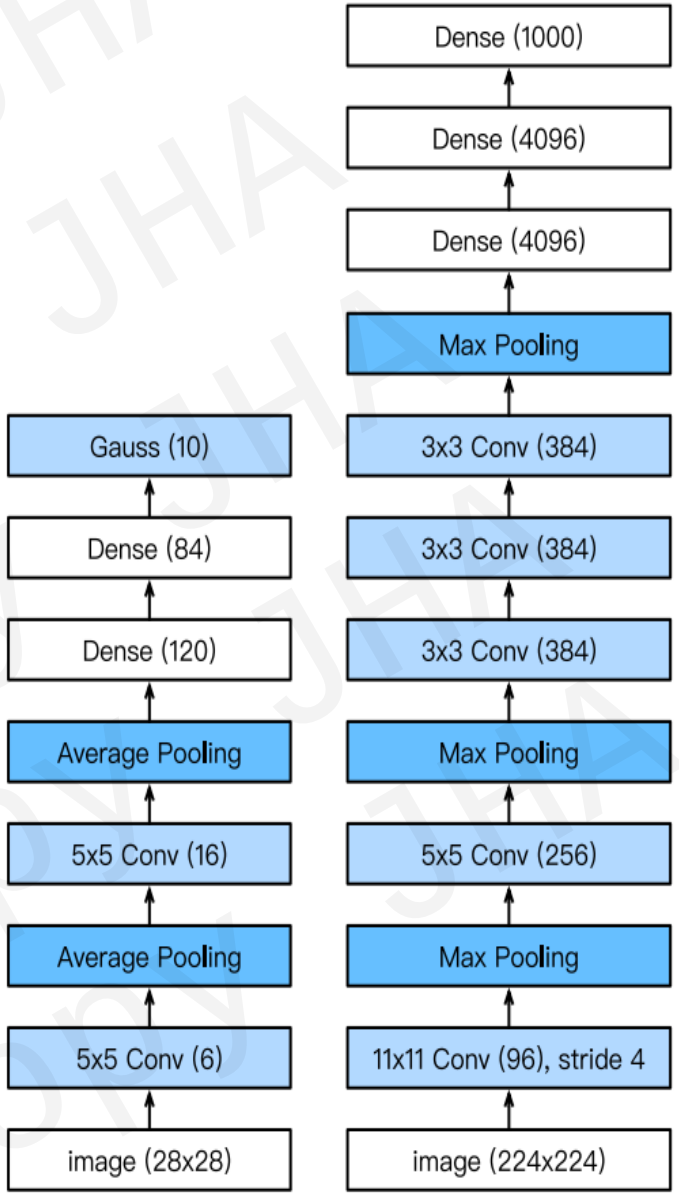
- ImageNet Large Scale Visual Recognition Challenge (ILSVRC) (2010-2017)



AlexNet (Krizhevsky et al. 2012)

- Considered first “modern deep architecture”
- Deeper than LeNet-5: from 5 to 8 layers

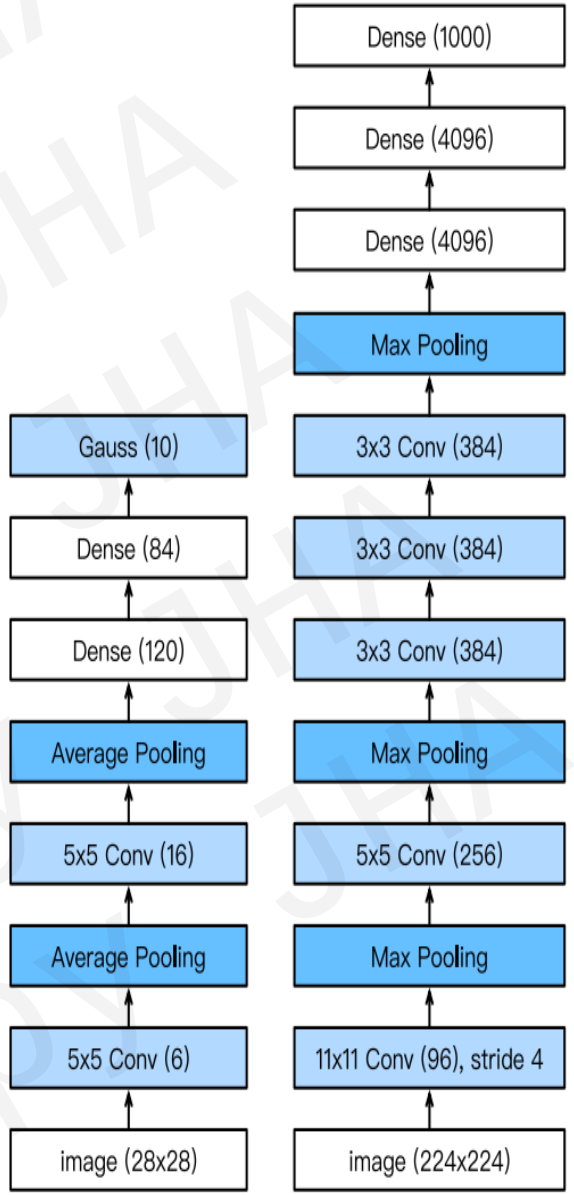




LeNet AlexNet

AlexNet (Krizhevsky et al. 2012)

- Considered first “modern deep architecture”, deeper than LeNet-5: from 5 to 8 layers,
- 60 Million parameters
- Depth increases overfitting: learning algo: skips some transformational units.
- ReLU : improve convergence ➔ reduce vanishing gradient problem.
- Heavy data augmentation for training: flipping, clipping, color change etc.
- Use of multiple GPUs for training : trained in parallel on two NVIDIA GTX 580
- Use of large filter (11X11, 5X5) as initial layers
- Overlapping pooling layers: (0.5% reduction in overfitting).
- Other adjustments:
  - Dropout for regularization
  - SGD Momentum



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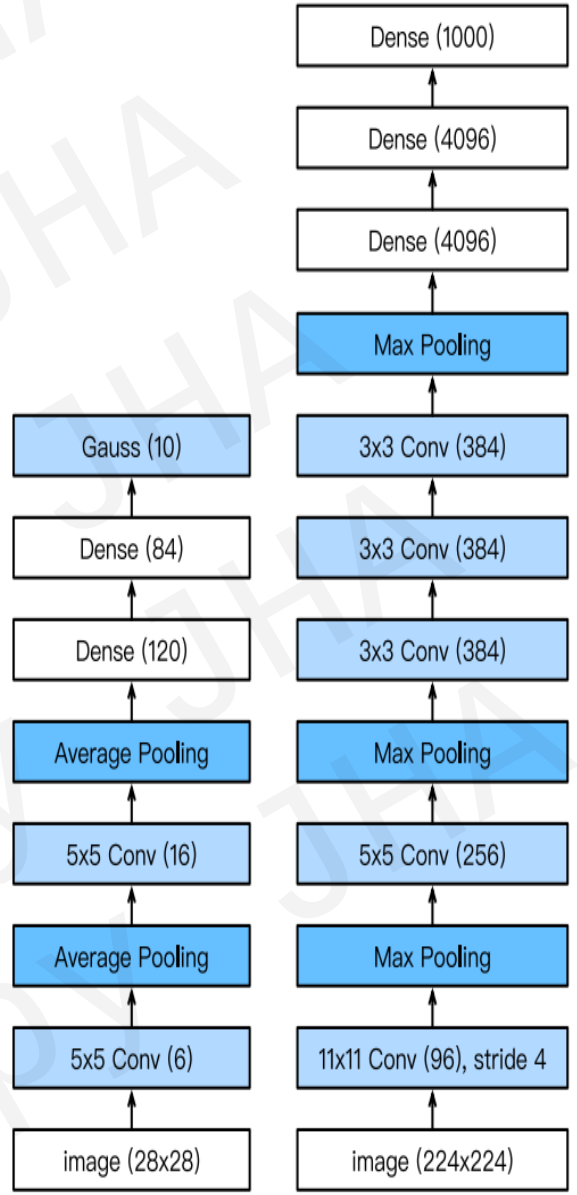
- Overlapping pooling layers: (0.5% reduction in overfitting).
- Other adjustments:
  - Dropout for regularization: 0.5
  - SGD Momentum
- Winner of ImageNet Large-Scale Visual Recognition Challenge (ILSVRC) 2012
  - Recognize off-center objects.
- Beginning of Modern era of Deep learning: SOTA
  - Deep Learning to new fields: medical imaging, data extraction, end to end learning…
- Missing ➔ A template for Deep NN design.



LeNet AlexNet

Visual Geometry Group or VGG (Simonyan and Zisserman 2015)

19 layers deeper compared to AlexNet

Addition:

- Studied the relation of depth with the representational capacity of the network.
- Replaced: large kernel-sized with small receptive field (multiple 3×3 kernels).
- All hidden layers: ReLu activation.
- Suggested that small size filters can improve the performance of the CNNs

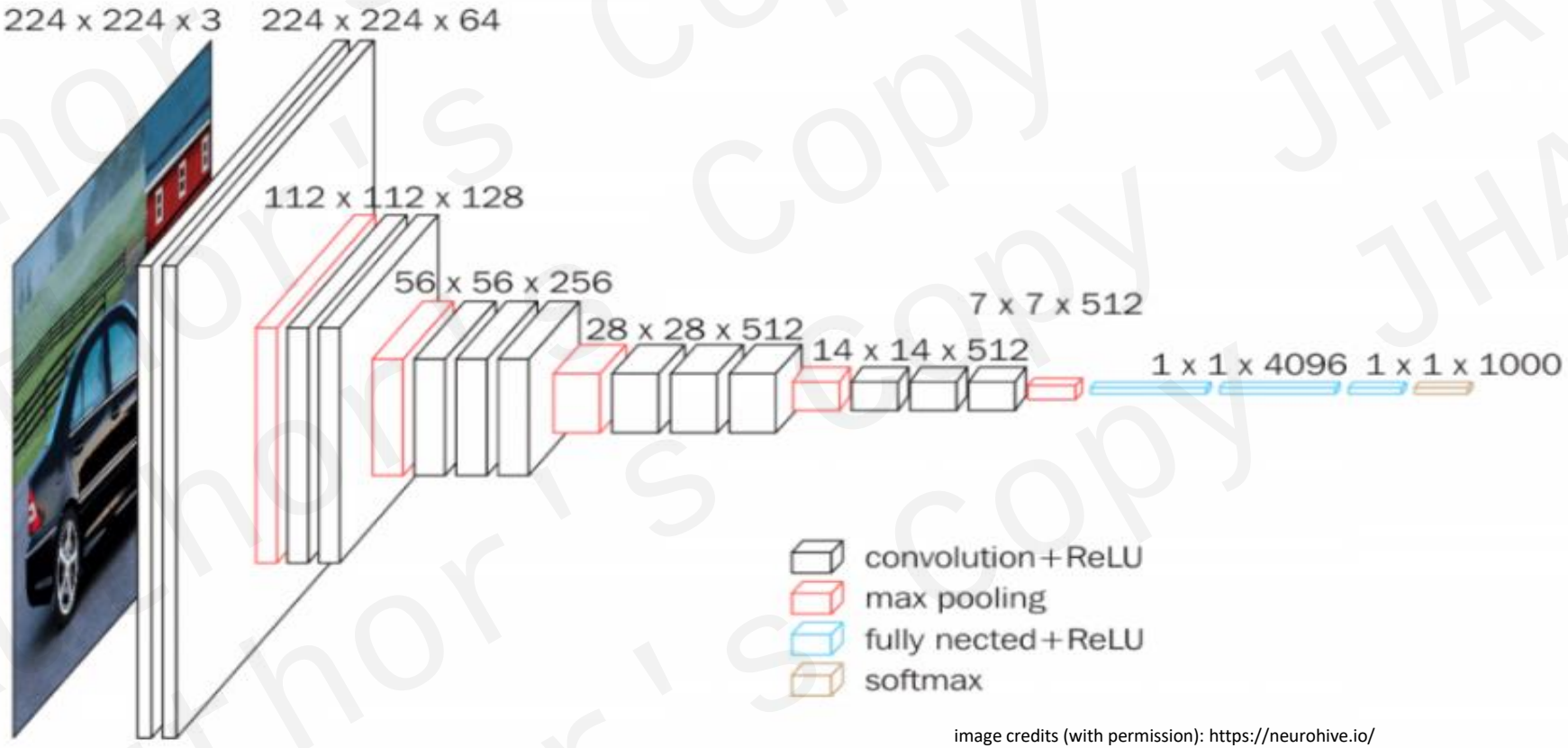


image credits (with permission): https://neurohive.io/

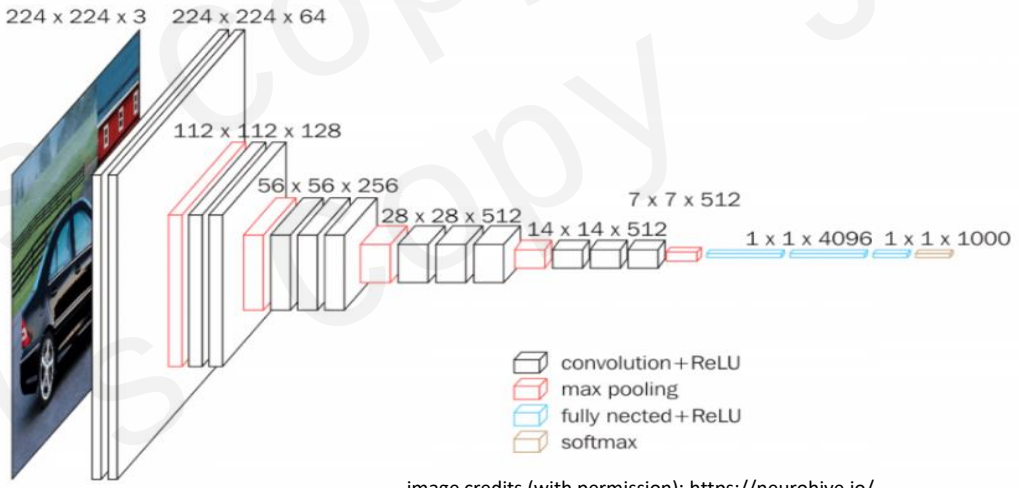
Visual Geometry Group or VGG (Simonyan and Zisserman 2015)

Dataset:

- ImageNet , inputs down-sampled → 256×256

Architecture:

- Image passed through a stack of convolutional (conv.) layers, with filters → with a very small receptive field: 3×3
  - The convolution stride is fixed to 1 pixel
  - the spatial padding of conv. layer input is such that the spatial resolution is preserved after convolution, i.e. the padding is 1-pixel for 3×3 conv. layers.
  - Spatial pooling is carried out by five max-pooling layers, which follow some of the conv. layers (not all the conv. layers are followed by max-pooling).
  - Max-pooling is performed over a 2×2 pixel window, with stride 2.
  - Complexity regulation: 1X1 convolutions between conv layers (learn linear combination of resultant feature maps)
  - Followed by: Three Fully-Connected (FC) layers : 4096, 4096,1000 (for ILSVRC classification)
  - The final layer is the soft-max layer.
  - The configuration of the fully connected layers is the same in all networks.



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Addition:

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- Replaced: large kernel-sized with small receptive field (multiple 3×3 kernels).
- All hidden layers: ReLu activation.

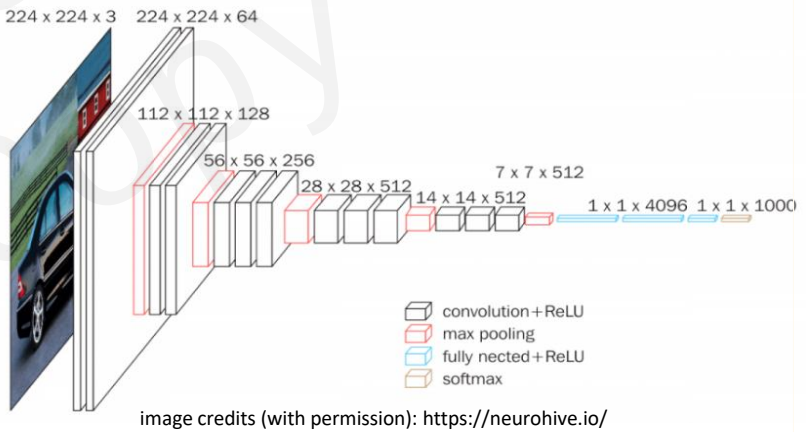
Advantages:

- Significantly outperformed previous generation models with respect to classification accuracy.
- Representation depth is beneficial for the classification accuracy.
- Suggested that small size filters can improve the performance of the CNNs.
- Several layers of deep and narrow convolutions (i.e., 3×3) were more effective than fewer layers of wider convolutions.
- 2nd Place 2014-ILSVRC

Set the trend: smaller sized filters.

Limitations:

- Very slow to train (For example: VGG16 was trained for weeks , NVIDIA Titan Black GPU's)
- Large no pf parameters 138 million parameters
- Heavy architecture → 533MB



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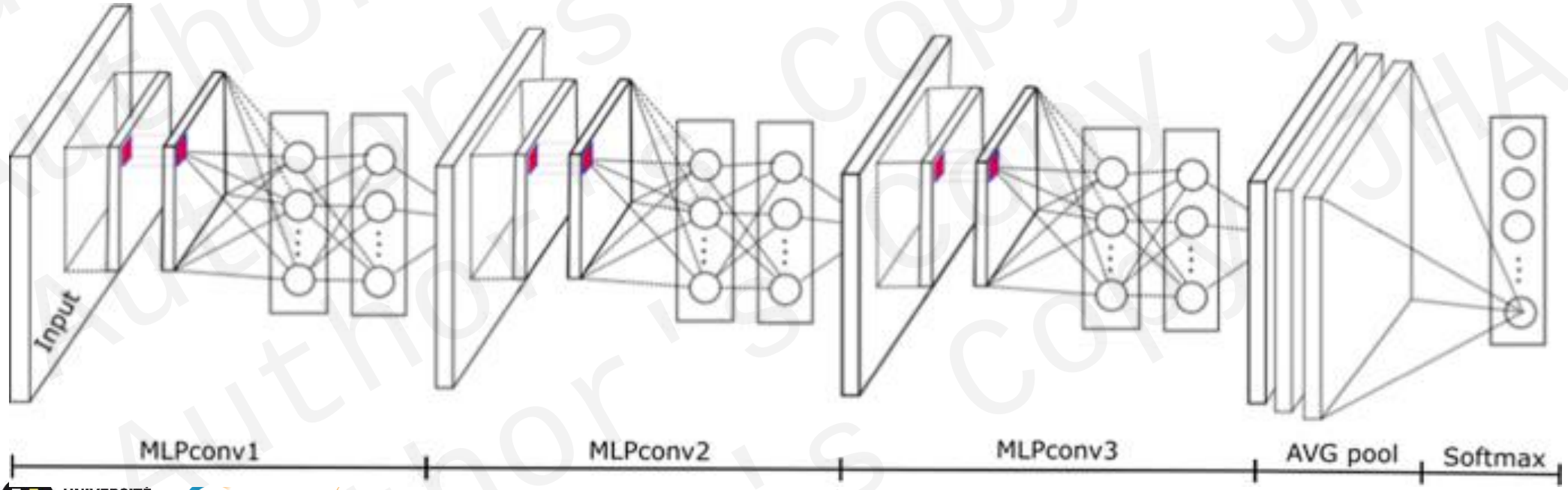
Network in Network (NiN) (Lin et al., 2013)

- Intuition:
  - to use an MLP on the channels for each pixel separately.
  - Apply a fully-connected layer at each pixel location (for each height and width).



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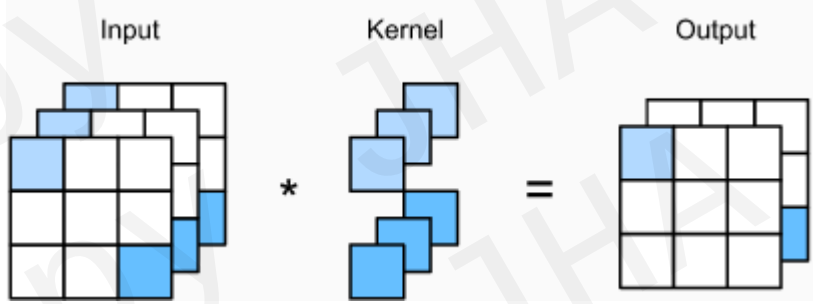
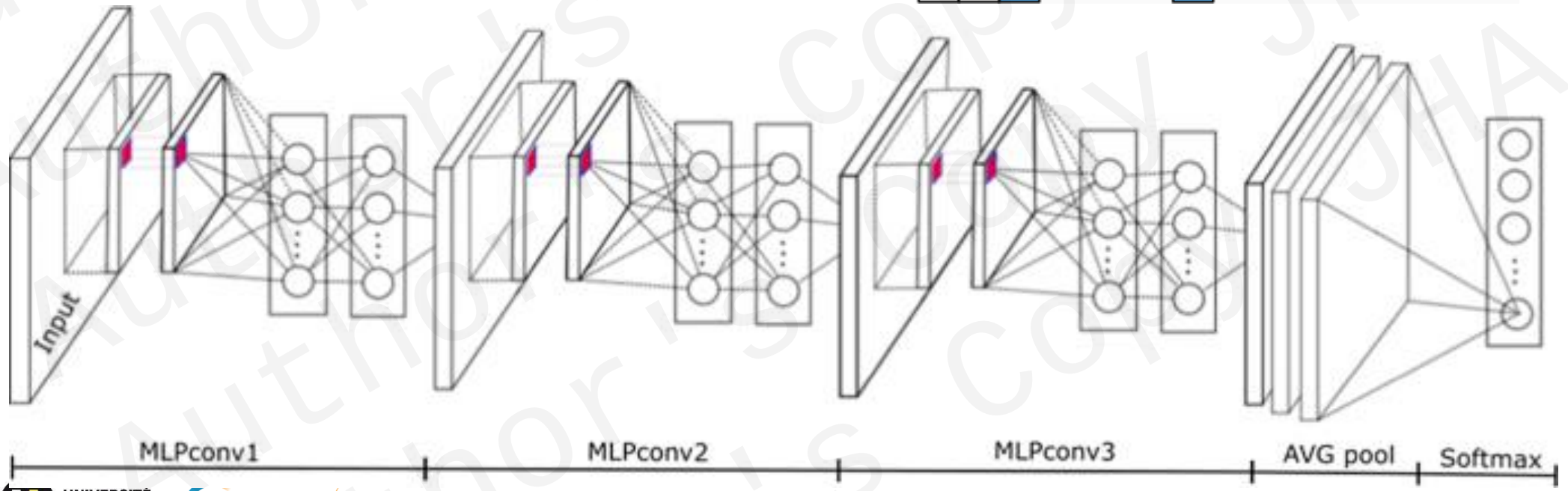
  - If we tie the weights across each spatial location becomes ➔ 1X1 convolution layer.
    or
    fully-connected layer acting independently on each pixel location





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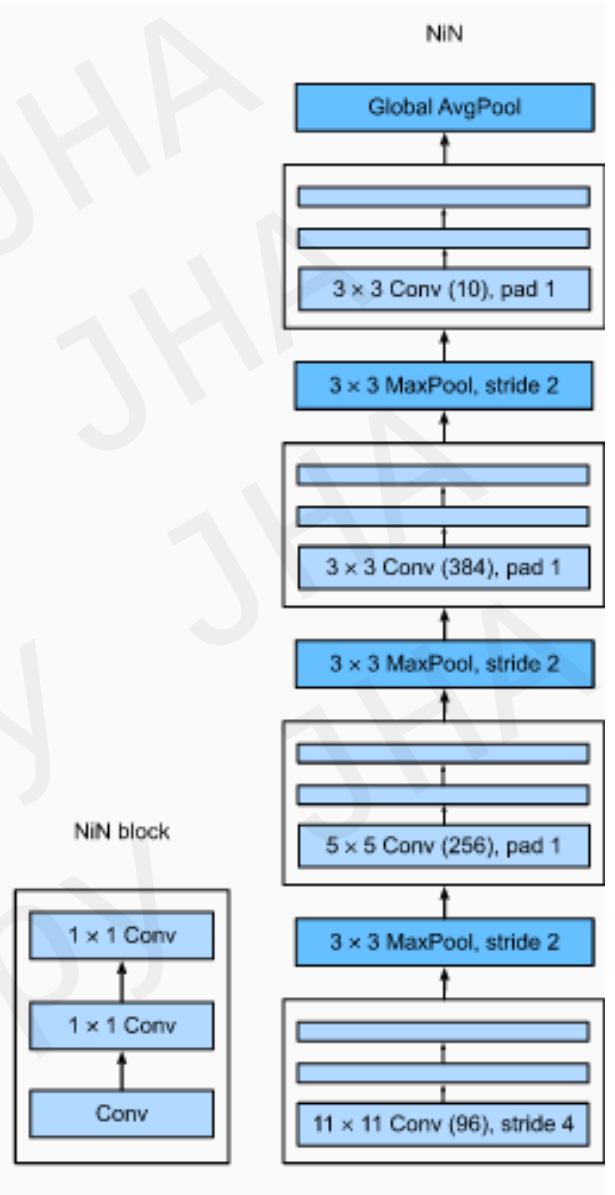
Network in Network (NiN) (Lin et al. 2013)

- Architecture:
  - inspired from AlexNet.
  - Convolutional layers: 11×11, 5×5, and 3×3
    - followed by two 1×1 convolutional layers that act as per-pixel fully-connected layers with ReLU activations
    - Each NiN block is followed by a maximum pooling layer (stride 2, window shape of 3×3).
  - The convolution window shape of the first layer is typically set by the user.
  - Output: number of output channels equal to the number of label classes, followed by a *global* average pooling layer.
  - Avoids fully-connected layers totally (against AlexNet, LeNet…)
- Advantages:
  - 1X1 convolutions ➔ allow for more per-pixel nonlinearity within convolutional stack.
  - NiN removes the fully-connected layers and replaces them with global average pooling.
    - Removing fully-connected layers reduces overfitting.
  - NiN has dramatically less parameters.



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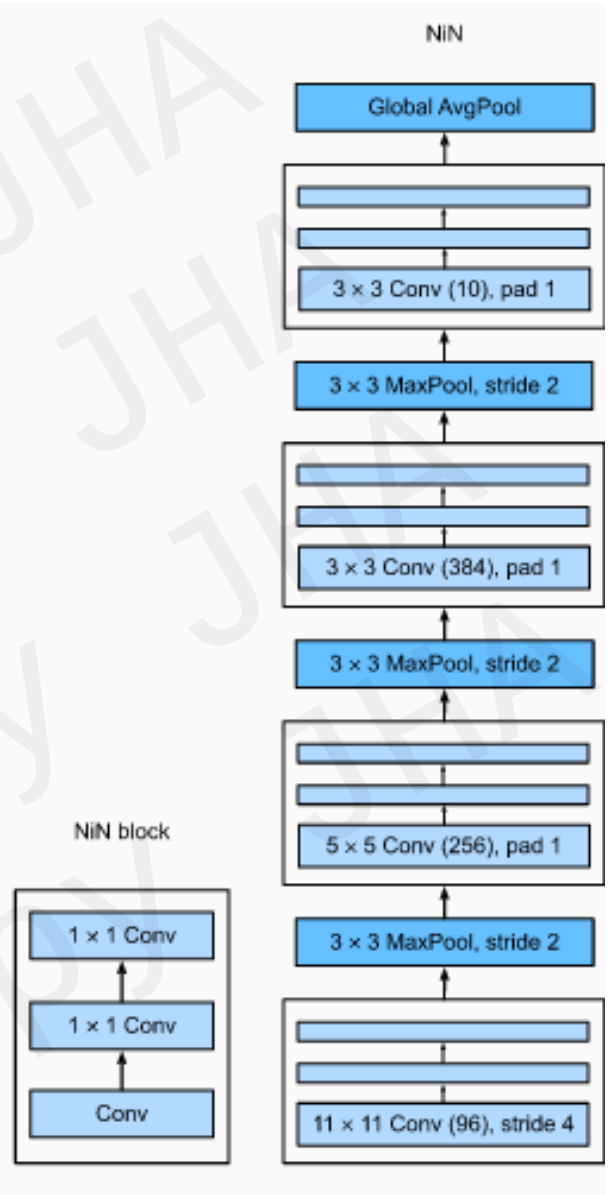

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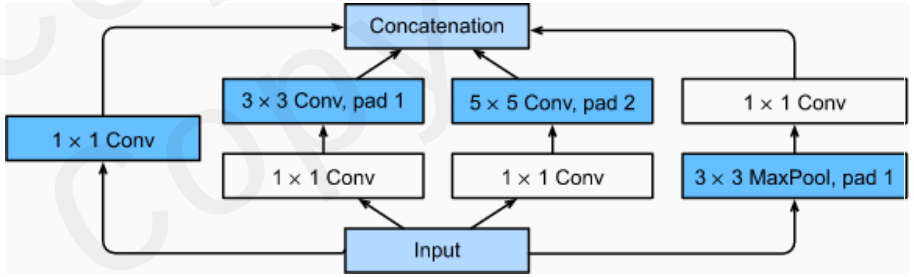
GoogLeNet (Szegedy et al., 2015)

- Winner of 2014 ILSVRC
- One focus: Which sized convolution kernels are best (1X1, 3X3, 11X11 …) ?
- Introduced *Inception* block:
  - incorporates multi-scale convolutional transformations using split, transform and merge idea.
  - encapsulates filters of different sizes (1x1, 3x3, and 5x5)
  - captures spatial information at different scales: fine and coarse grain level.



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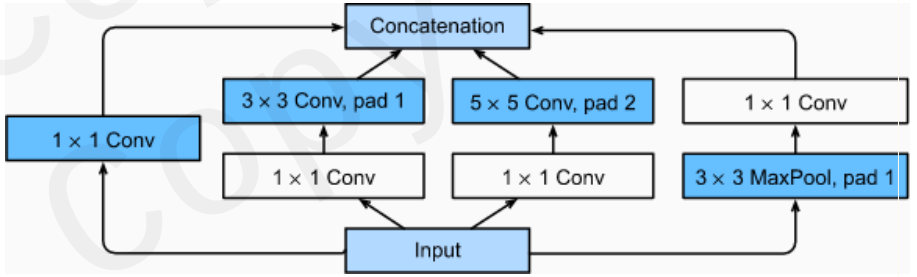

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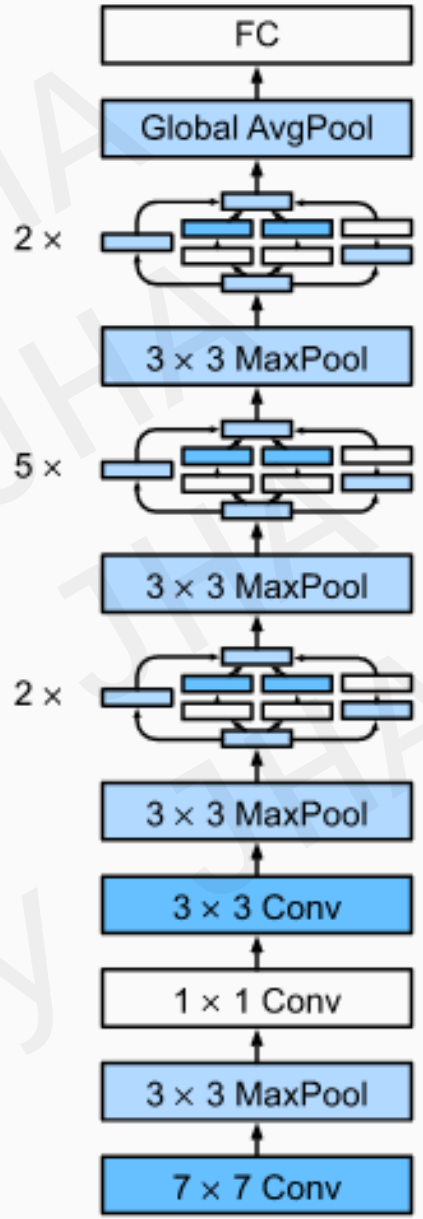
- Advantages:
  - Density reduced → use of global average pooling at the last layer and NOT instead of using a fully connected layer
  - Significant decrease in parameters: from 138 Million to 4 Million parameters.
  - Other novelties:
    - Batch Normalization
    - RmsProp as optimizer,…



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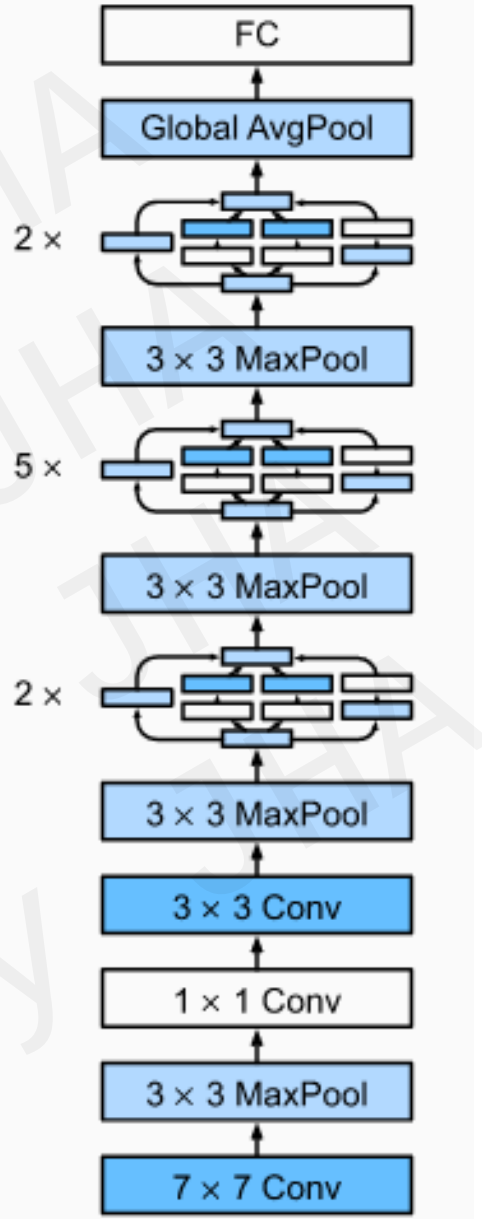
    - RmsProp as optimizer,…
- Limitations:
  - heterogeneous topology that needs to be customized from module to module
  - representation bottleneck that drastically reduces the feature space
  - in the next layer and thus sometimes may lead to loss of useful information.
- Variants: Inception V2, Inception V3



Source: Dive into Deep learning book

ResNet (He et al., 2015)

Problem: Deeper networks do not necessarily lead to better accuracy.

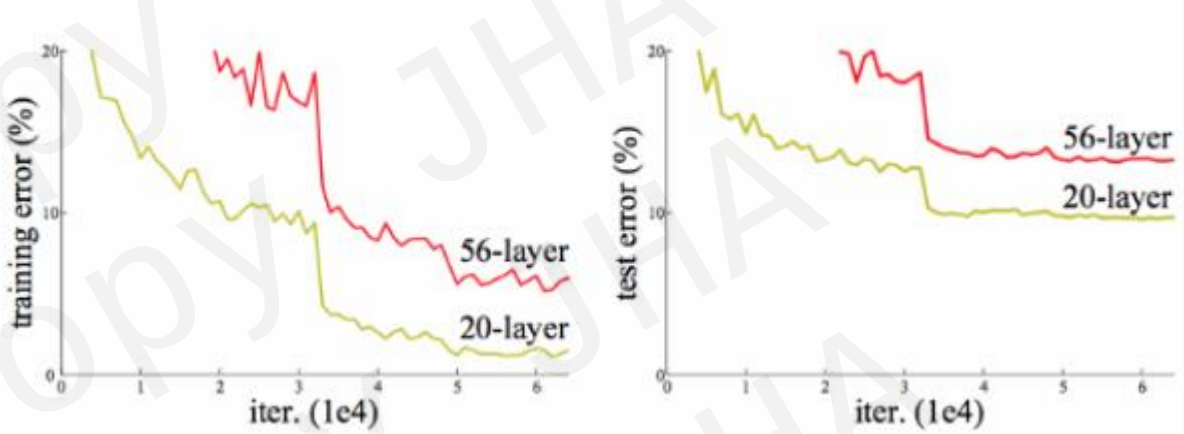
ResNet (He et al. 2015)

Problem: Deeper networks do not necessarily lead to better accuracy. WHY?

Vanishing gradients? (infinitesimally small gradients?)

ResNet (He et al. 2015)

Observation: Training accuracy dropped when the count of layers was increased.



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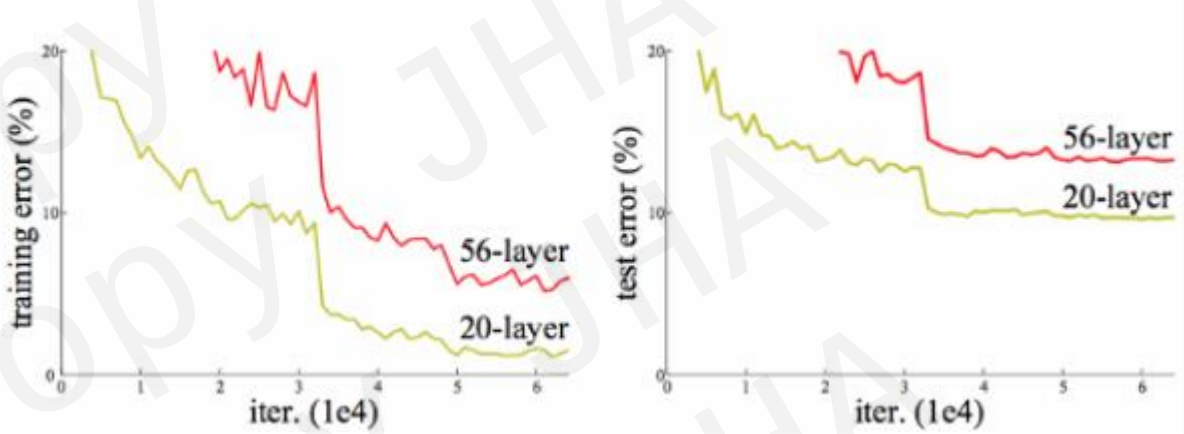
Overfitting ?



Source: Dive into Deep learning book

ResNet (He et al. 2015)

Observation: Training accuracy dropped when the count of layers was increased.

Degradation Problem:

With the network depth increasing, the accuracy saturates and then begins to degrade rapidly if more layers are introduced.

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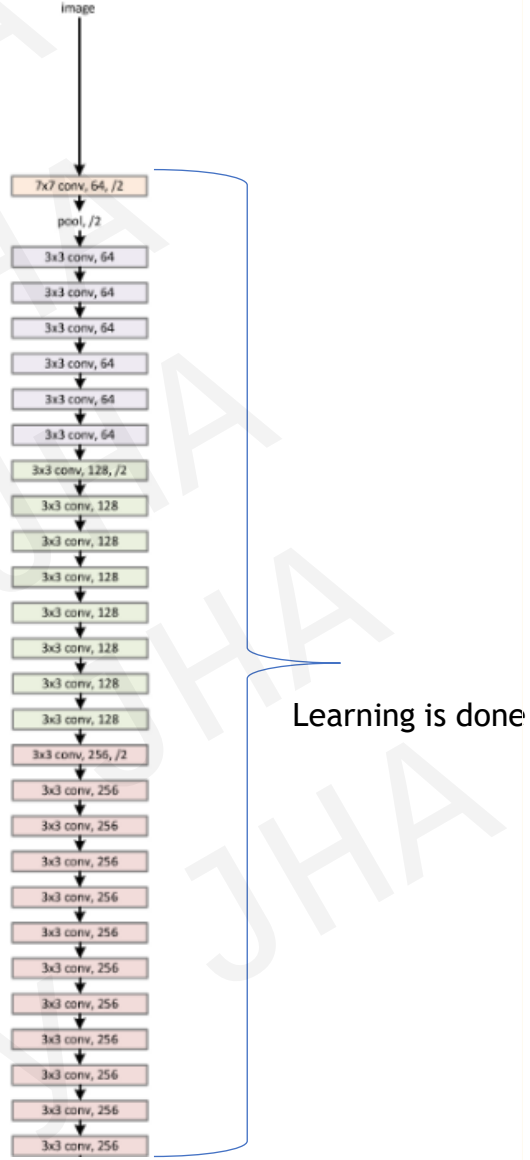

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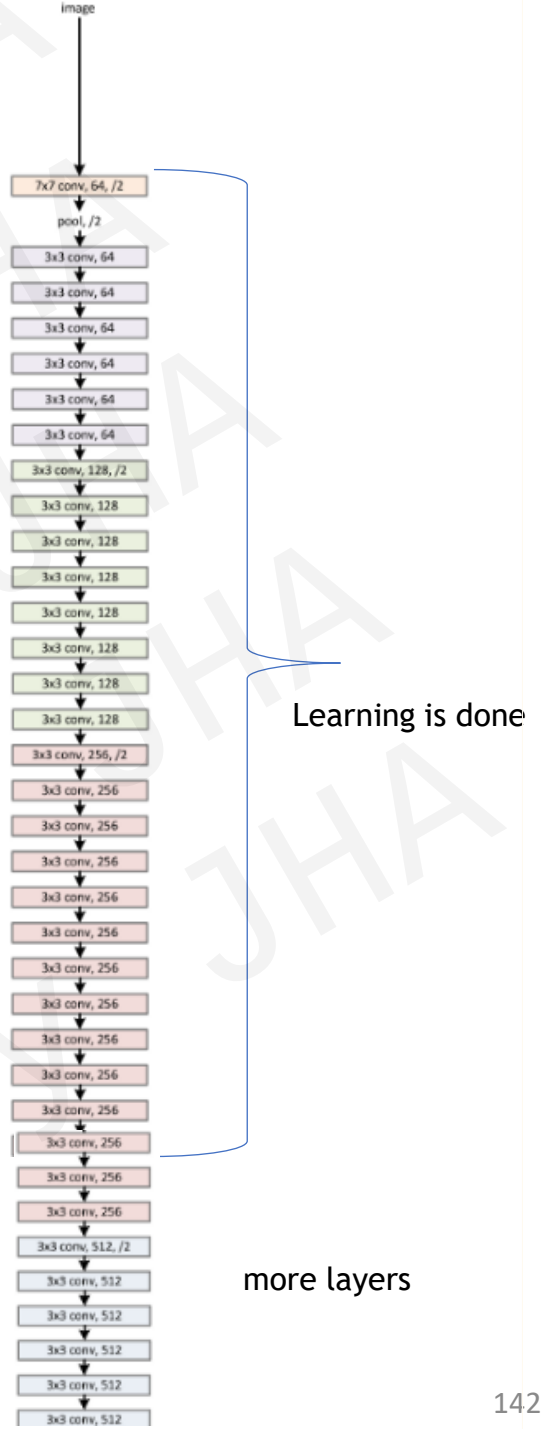

Should behave as Identity Function (let the input from previous layer flow ahead)

$$f(x) = x$$

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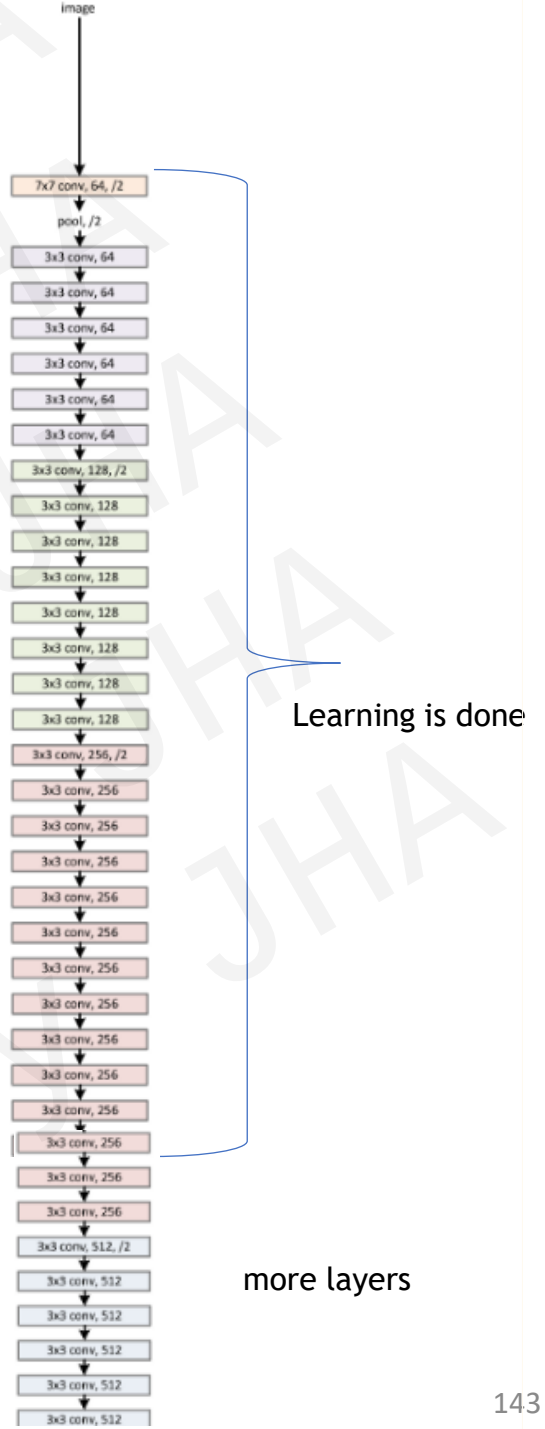

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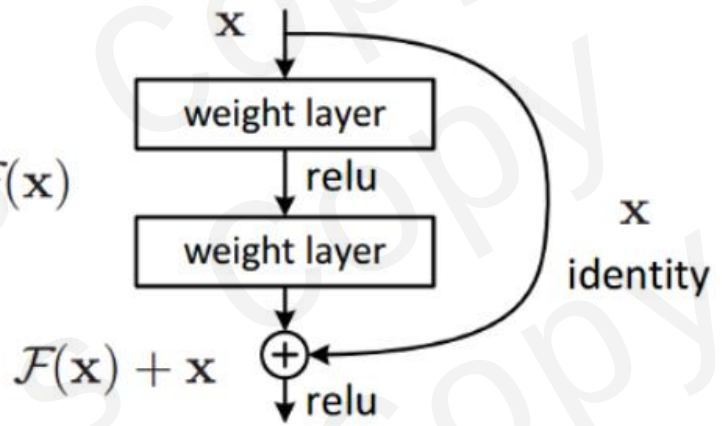
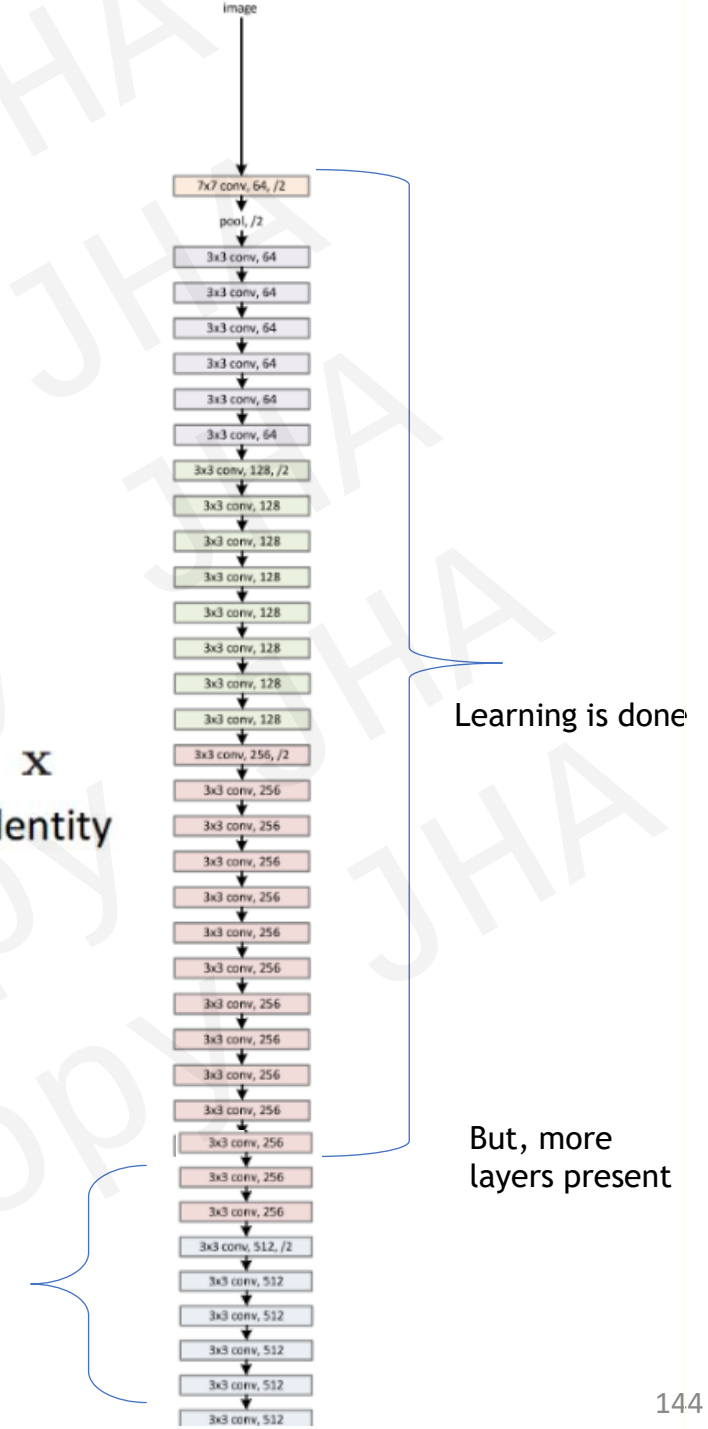
Intuition :

- Learn Residual mapping





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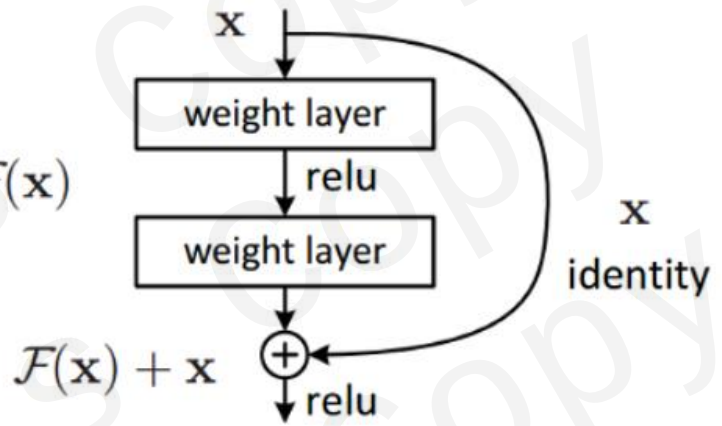
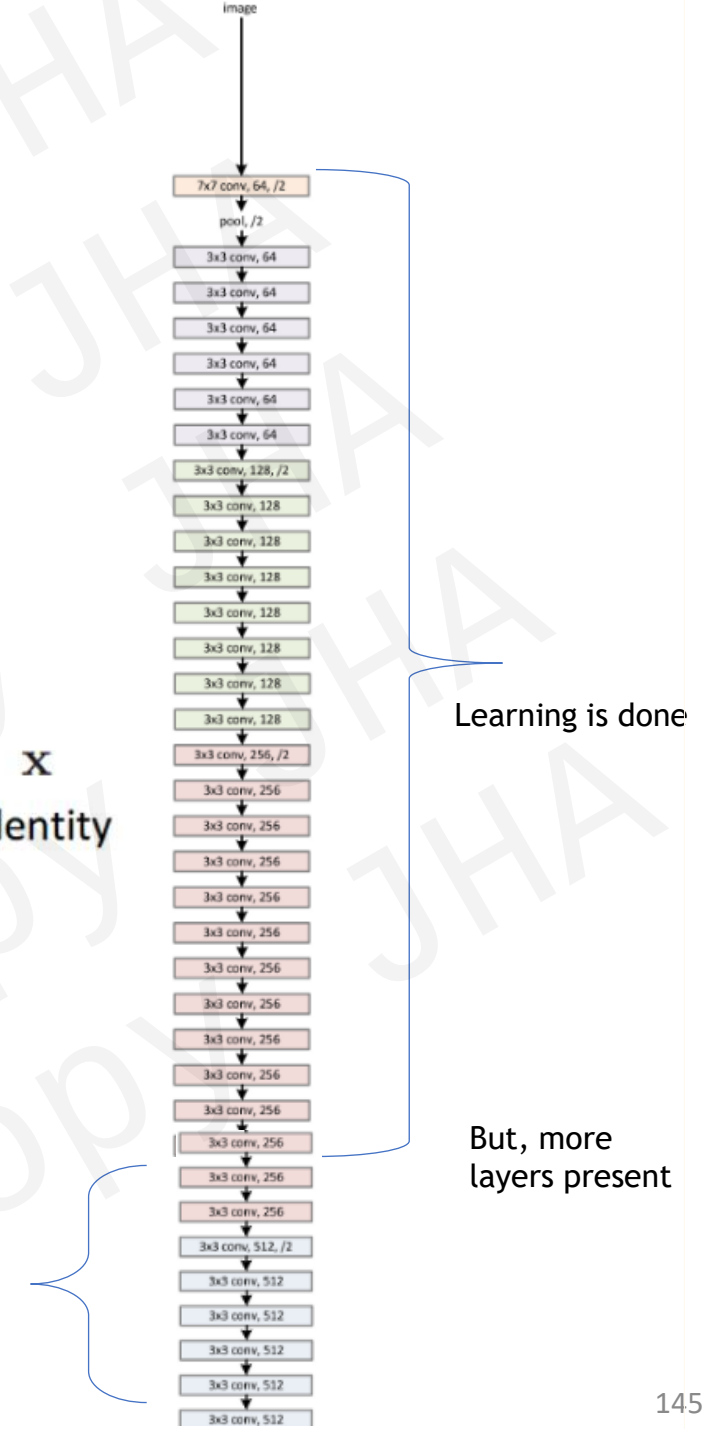
Intuition :

- Learn Residual mapping
- Use skip connections
- If any layer hurts performance ➔ skip it!
- Easier to learn $F(x) = 0$ so that it behaves as identity function.





Learning is done

But, more layers present

ResNet (He et al. 2015)

Architecture:

- Identity Block: skip connections
- Conv block: restructure incoming data
- 153 layers Deep
- Less computational complexity (but deeper : 20 X AlexNet, 8 X VGG)

Advantage:

- Residual mapping can learn the identity function more easily
- Stacking more layers ➔ equivalent to stacking identity mappings
- Inputs can forward propagate faster through the residual connections across layers.

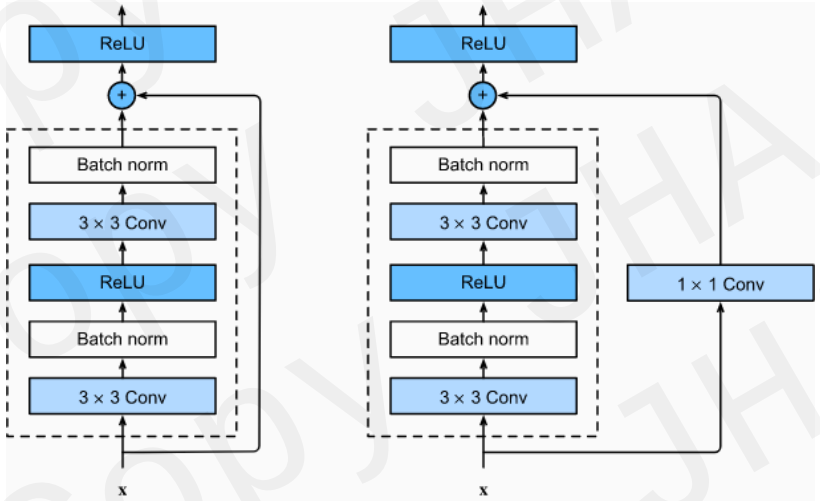
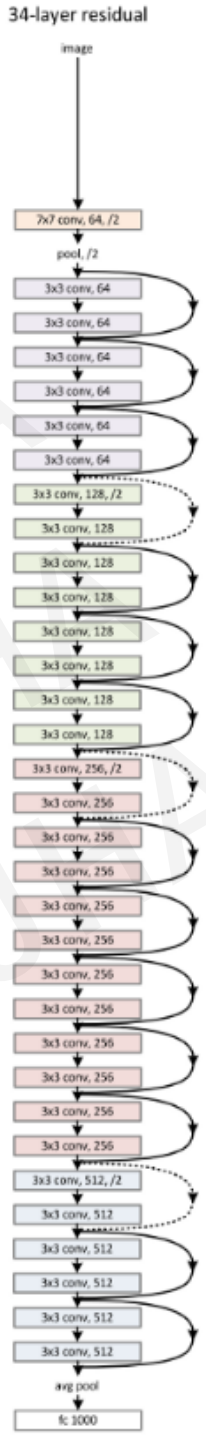


Image Credits: Dive into Deep learning



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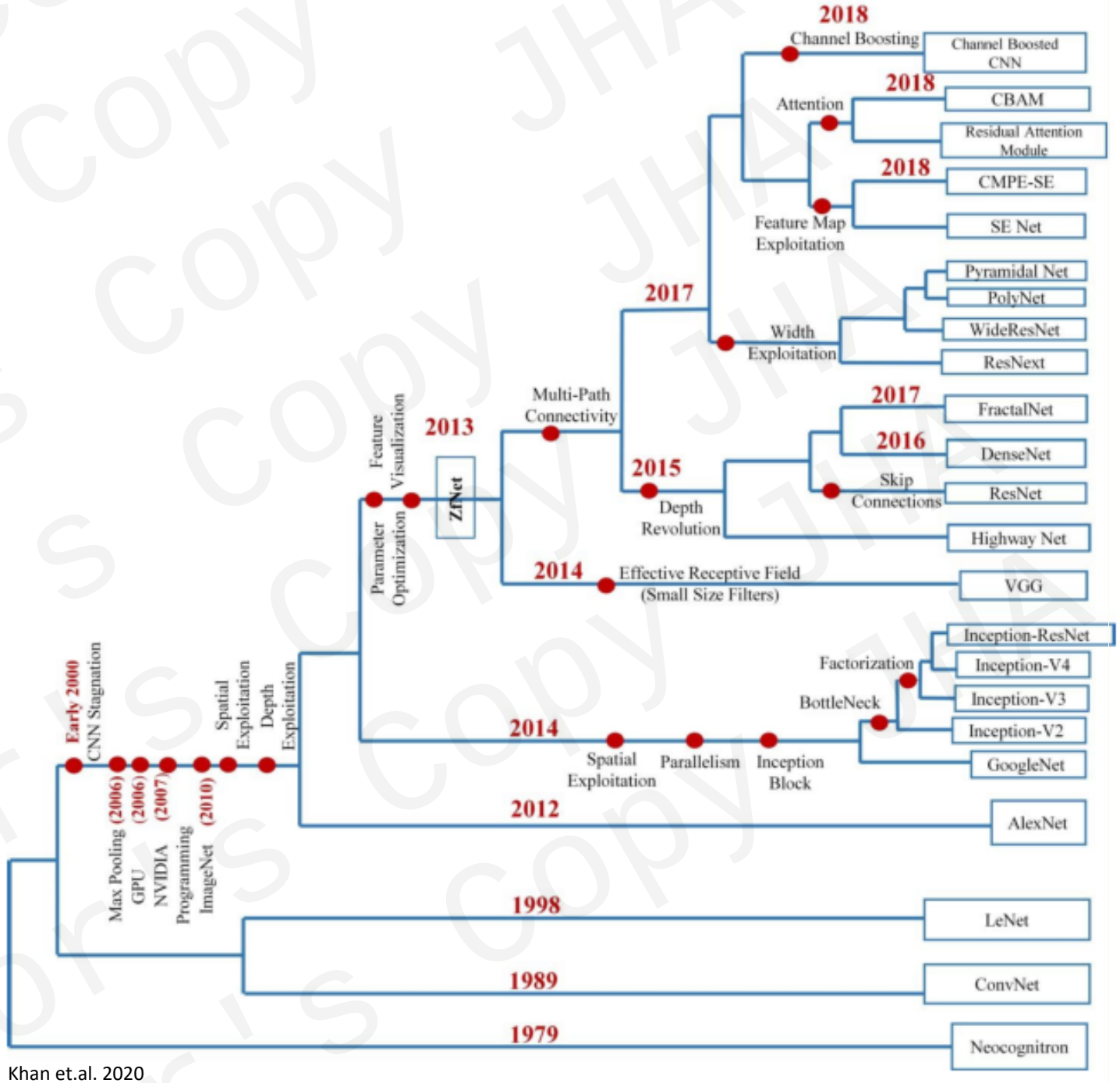
Where are we?



Khan et.al. 2020