Neural Network Part 3: Convolutional Neural Networks

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Computer Sciences 760

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Some of the slides in these lectures have been adapted/borrowed from materials developed by Mark Craven, David Page, Jude Shavlik, Tom Mitchell, Nina Balcan, Matt Gormley, Elad Hazan, Tom Dietterich, Pedro Domingos, and Kaiming He.

Goals for the lecture

you should understand the following concepts

- convolutional neural networks (CNN)
- convolution and its advantage
- pooling and its advantage

Convolutional neural networks

- Strong empirical application performance

- Convolutional networks: neural networks that use convolution in place of general matrix multiplication in at least one of their layers

$$h = \sigma(W^T x + b)$$

for a specific kind of weight matrix W

Convolution

Convolution: math formula

- Given functions $u(t)$ and $w(t)$, their convolution is a function $s(t)$

$$s(t) = \int u(a)w(t-a)da$$

- Written as

$$s = (u * w) \quad \text{or} \quad s(t) = (u * w)(t)$$

Convolution: discrete version

- Given array u_t and w_t, their convolution is a function s_t

$$s_t = \sum_{a=-\infty}^{+\infty} u_a w_{t-a}$$

- Written as

$$s = (u * w) \quad \text{or} \quad s_t = (u * w)_t$$

- When u_t or w_t is not defined, assumed to be 0

Illustration 1

w = [z, y, x]
u = [a, b, c, d, e, f]

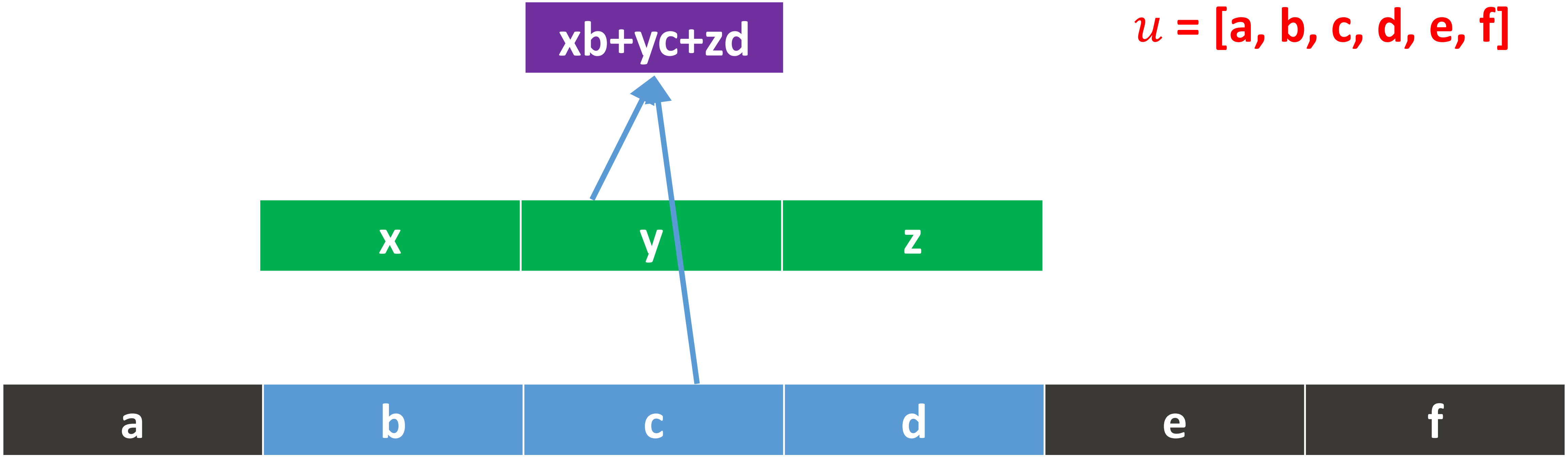


Illustration 1

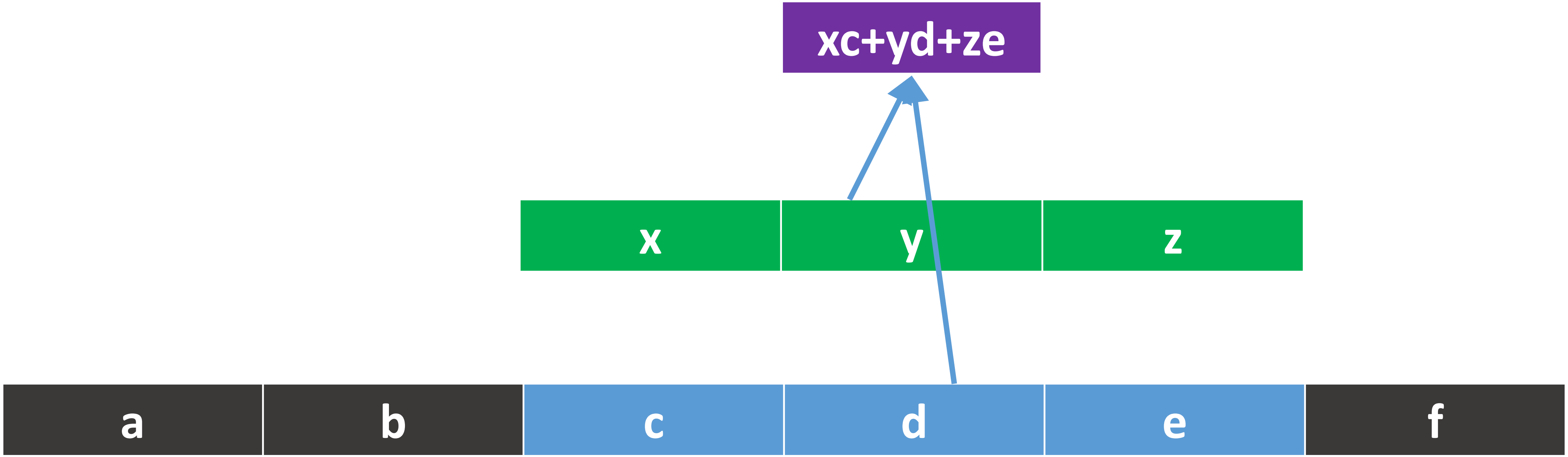


Illustration 1

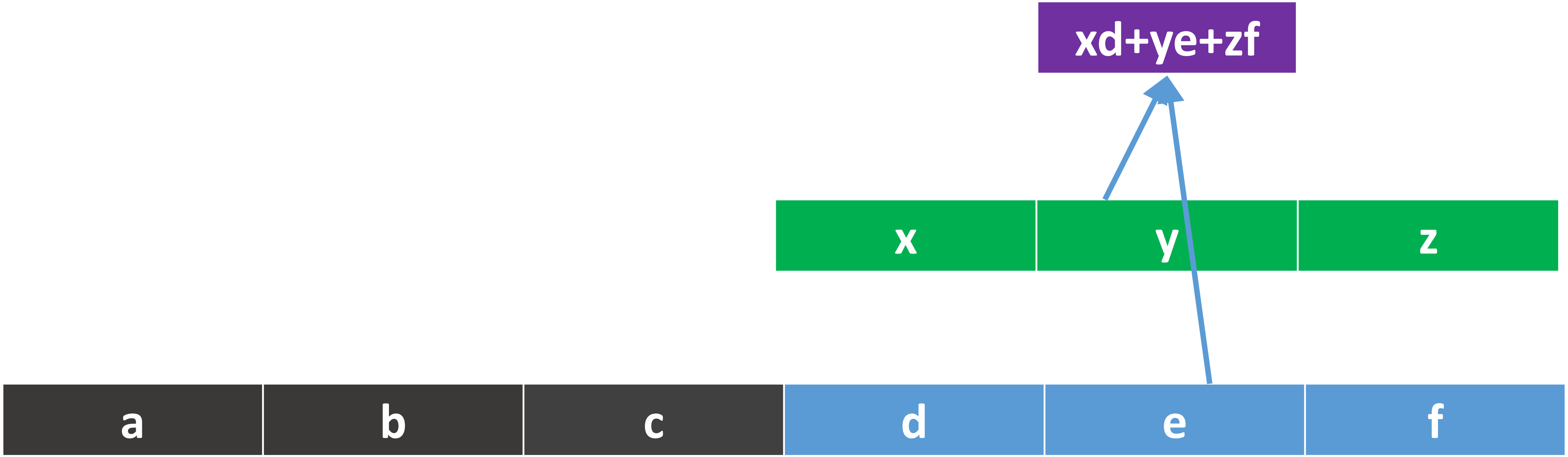


Illustration 1: boundary case

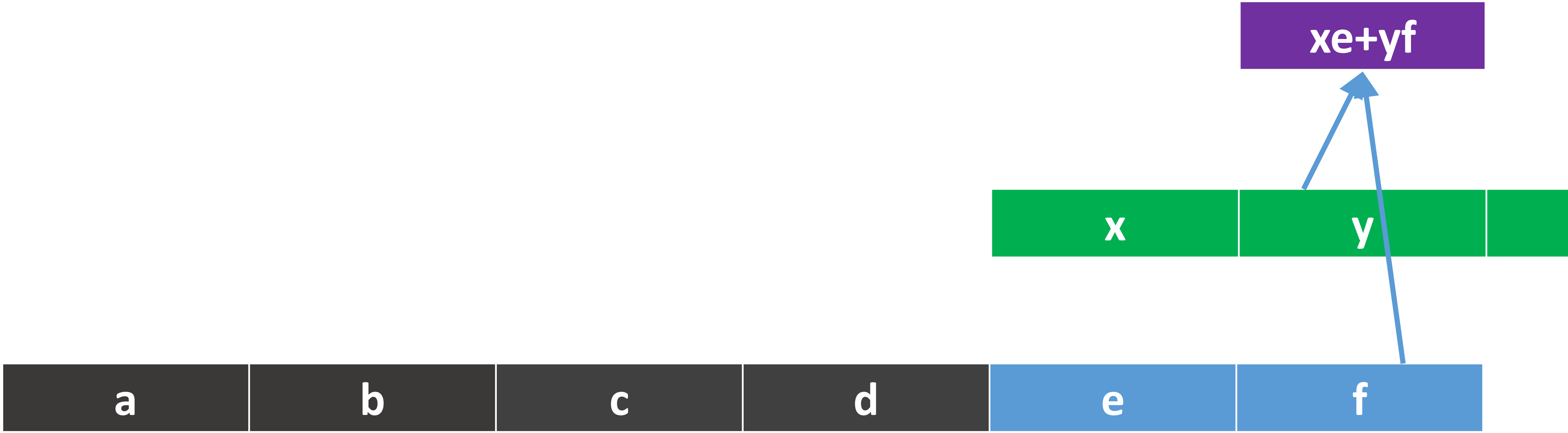


Illustration 1 as matrix multiplication

$$\begin{bmatrix} y & z & & & & \\ x & y & z & & & \\ & x & y & z & & \\ & & x & y & z & \\ & & & x & y & z \\ & & & & x & y \end{bmatrix} \qquad \begin{bmatrix} a \\ b \\ c \\ d \\ e \\ f \end{bmatrix}$$

Illustration 2: two dimensional case

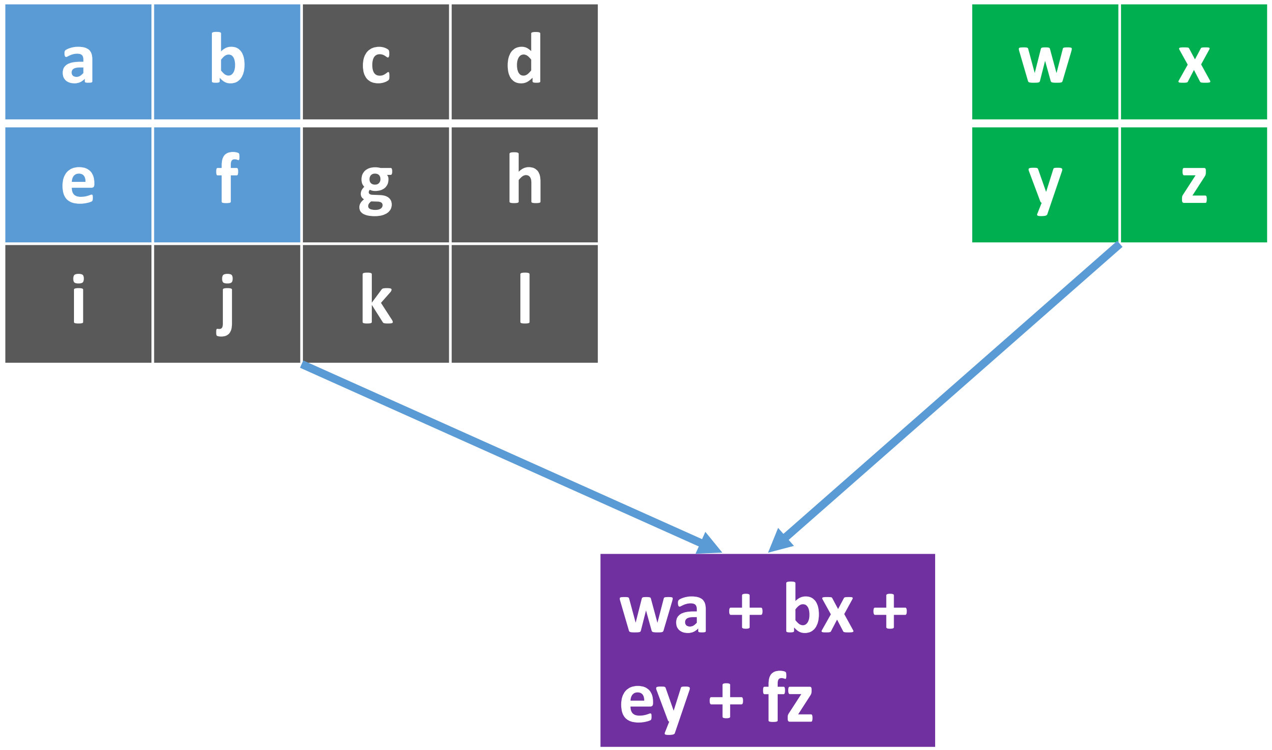


Illustration 2

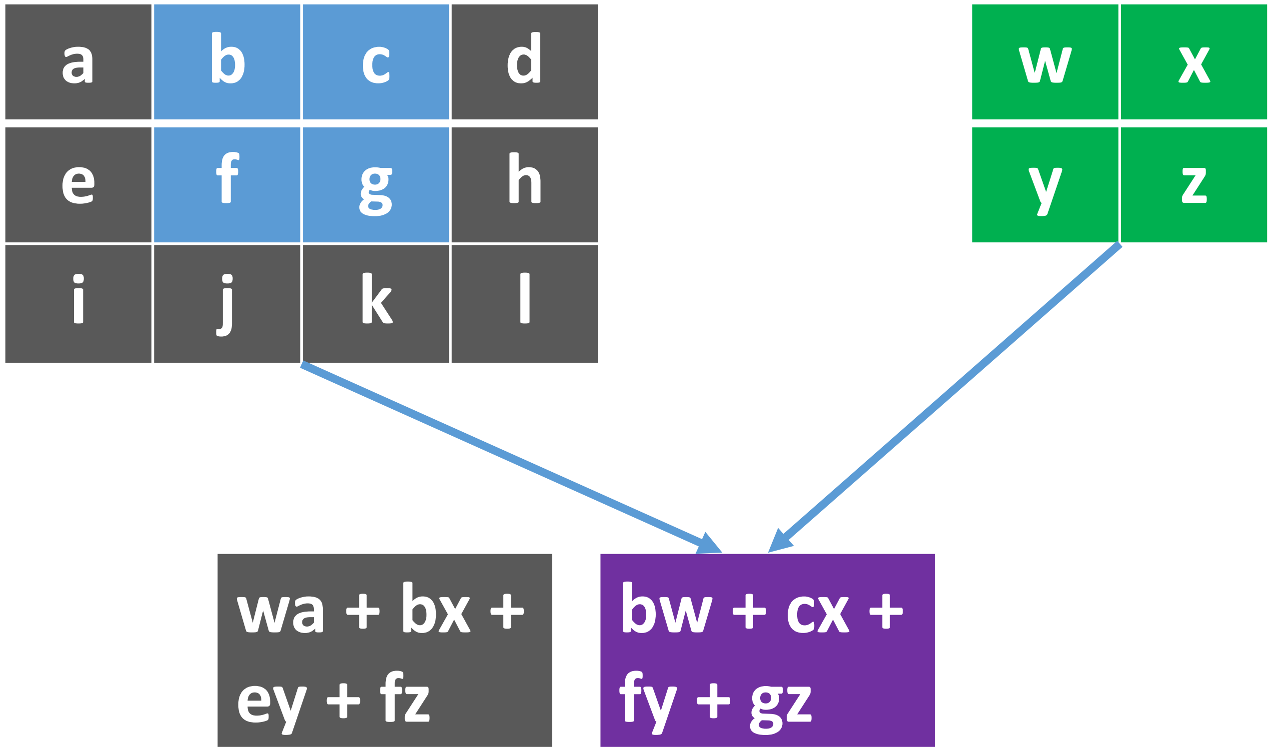
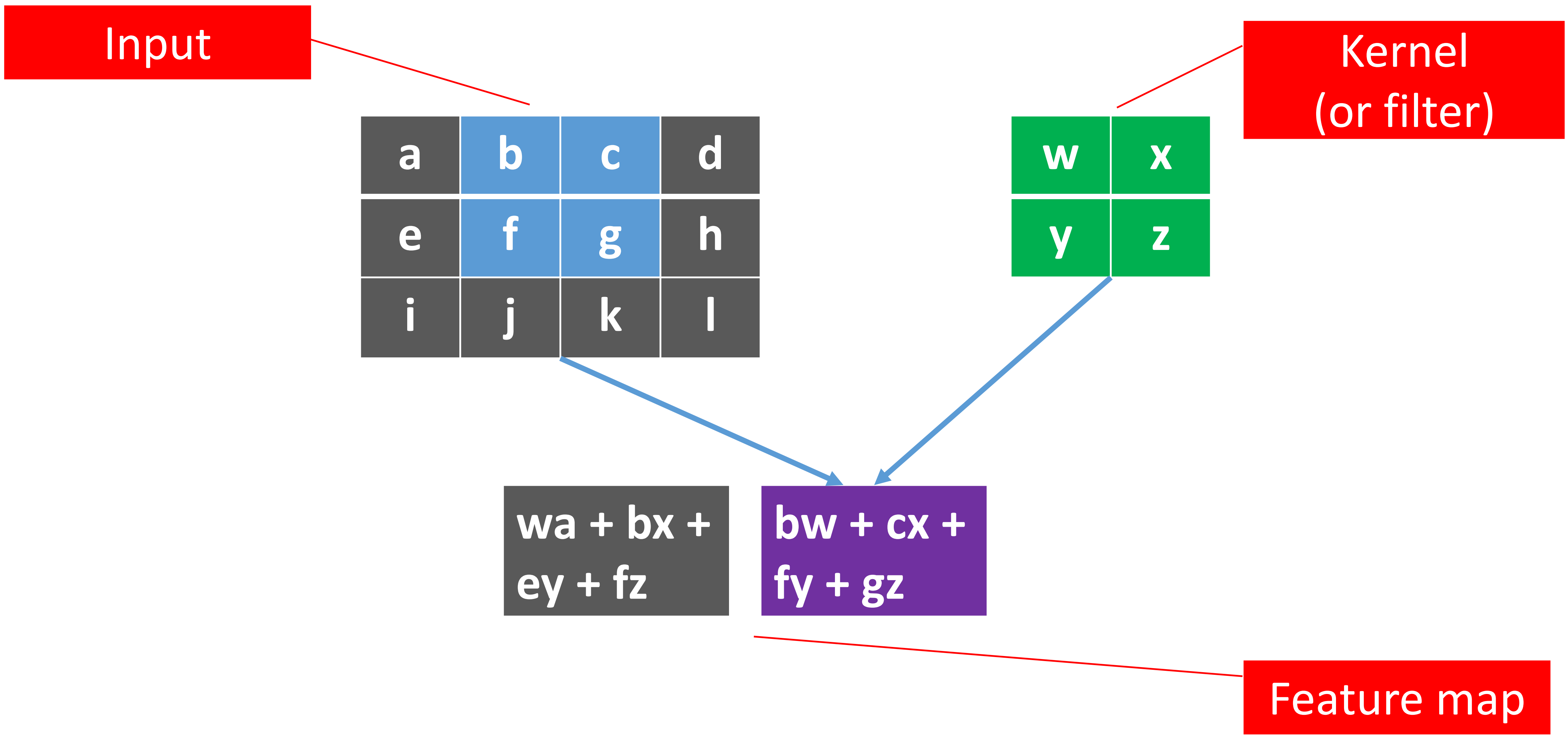
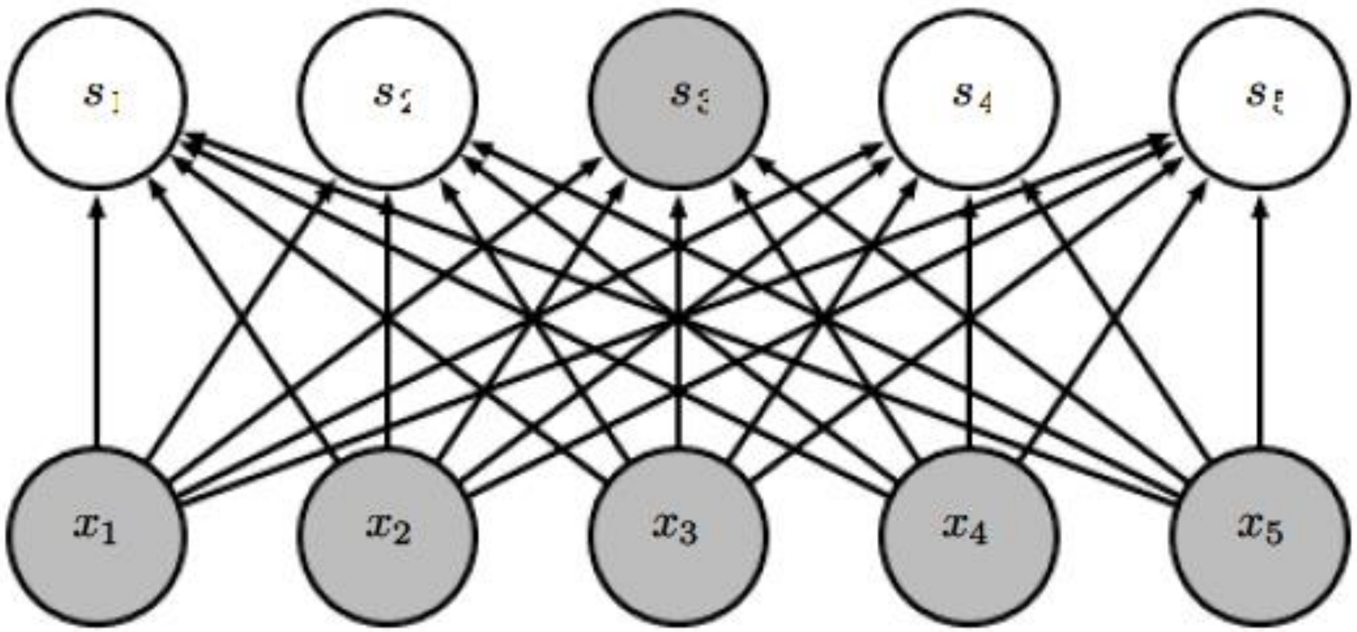


Illustration 2



Advantage: sparse interaction

Fully connected layer, $m \times n$ edges



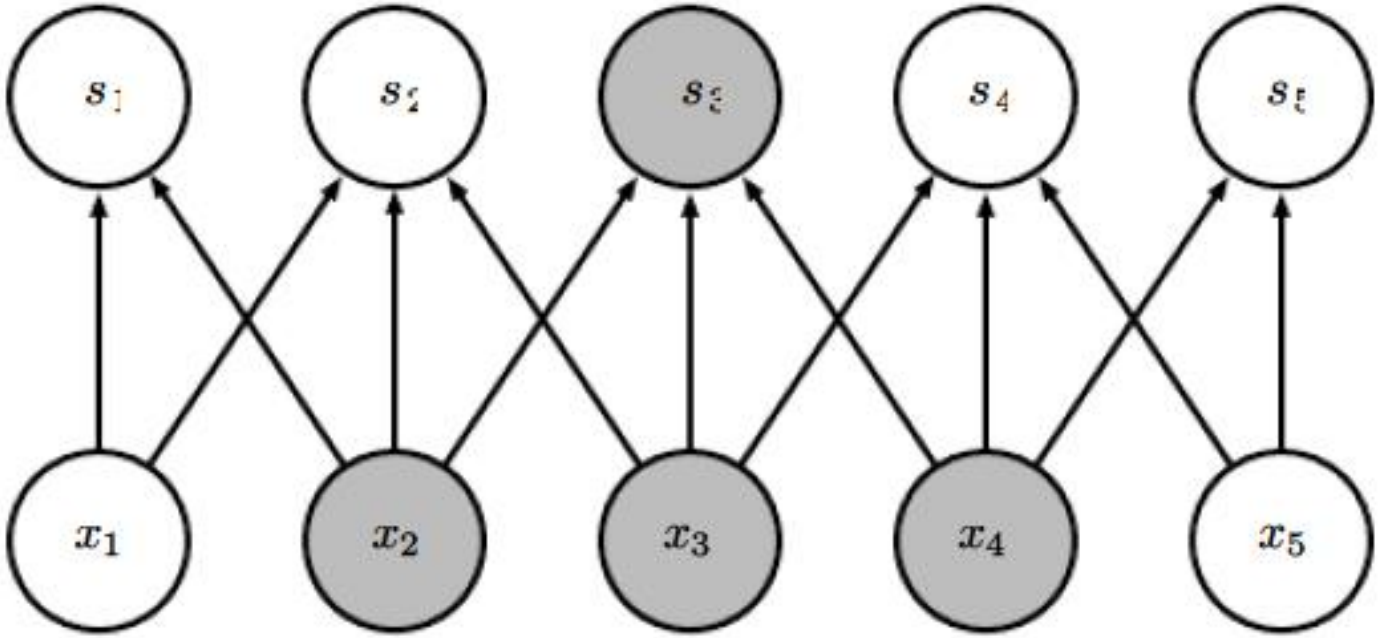
m output nodes

n input nodes

Figure from *Deep Learning,* by Goodfellow, Bengio, and Courville

Advantage: sparse interaction

Convolutional layer, $\leq m \times k$ edges



m output nodes

k kernel size

n input nodes

Figure from *Deep Learning,* by Goodfellow, Bengio, and Courville

Advantage: sparse interaction

Multiple convolutional layers: larger receptive field

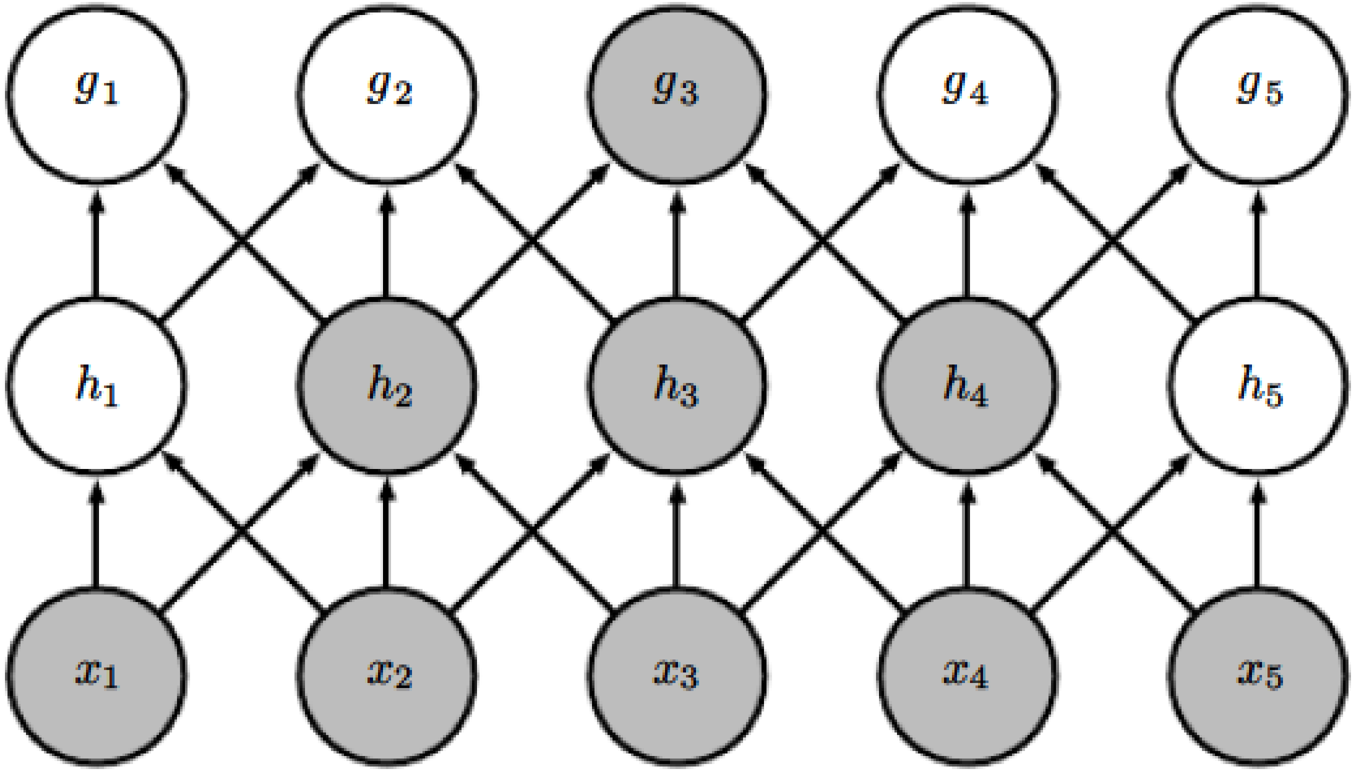
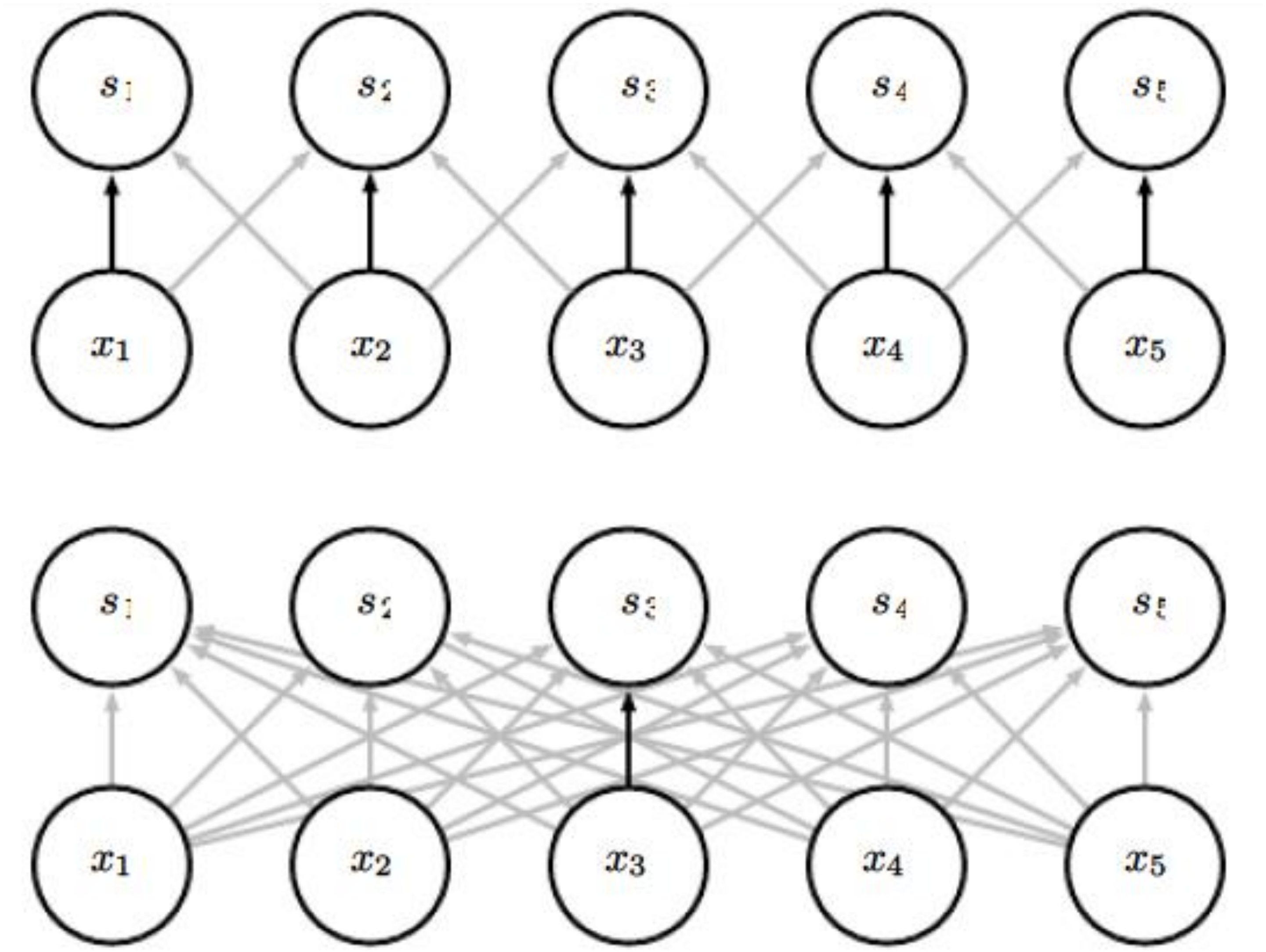


Figure from *Deep Learning,* by Goodfellow, Bengio, and Courville

Advantage: parameter sharing/weight tying



The same kernel are used repeatedly. E.g., the black edge is the same weight in the kernel.

Figure from *Deep Learning,* by Goodfellow, Bengio, and Courville

Advantage: equivariant representations

- Equivariant: transforming the input = transforming the output

- Example: input is an image, transformation is shifting
- Convolution(shift(input)) = shift(Convolution(input))

- Useful when care only about the existence of a pattern, rather than the location

Pooling

Terminology

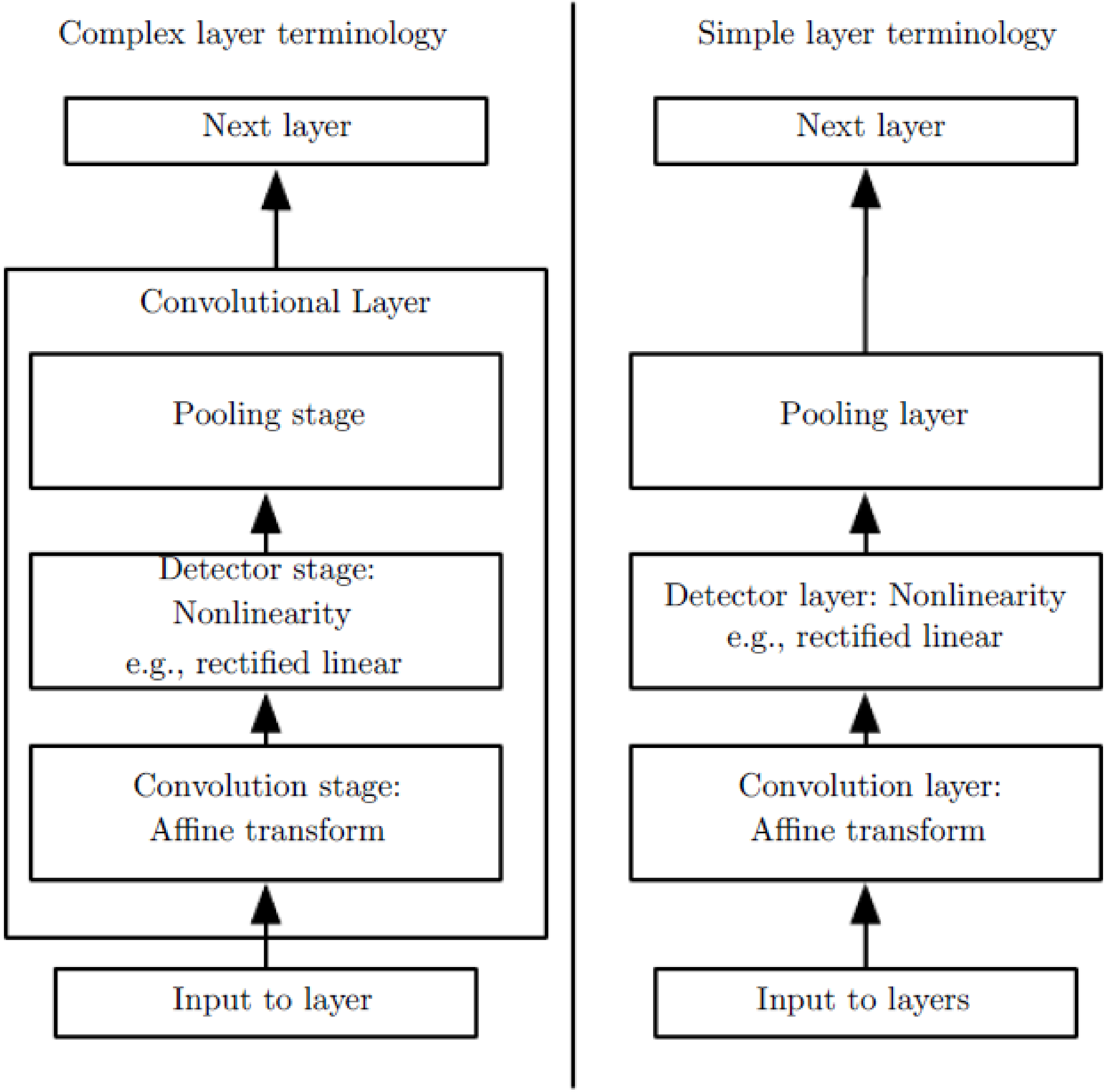


Figure from *Deep Learning,* by Goodfellow, Bengio, and Courville

Pooling

- Summarizing the input (i.e., output the max of the input)

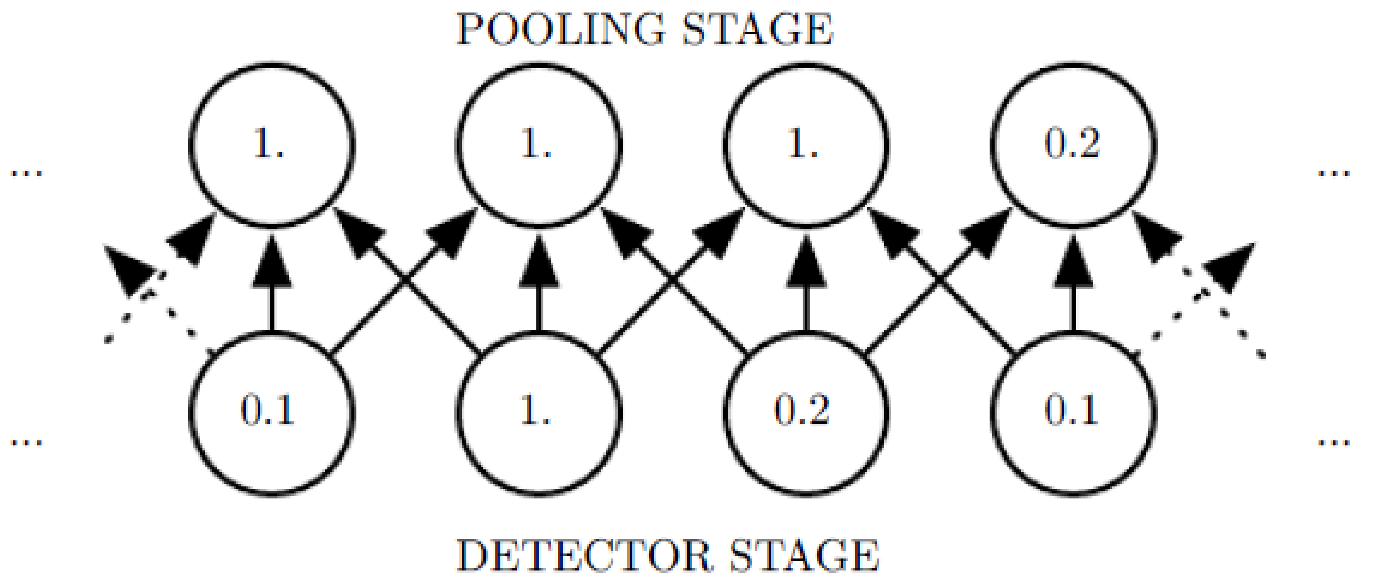
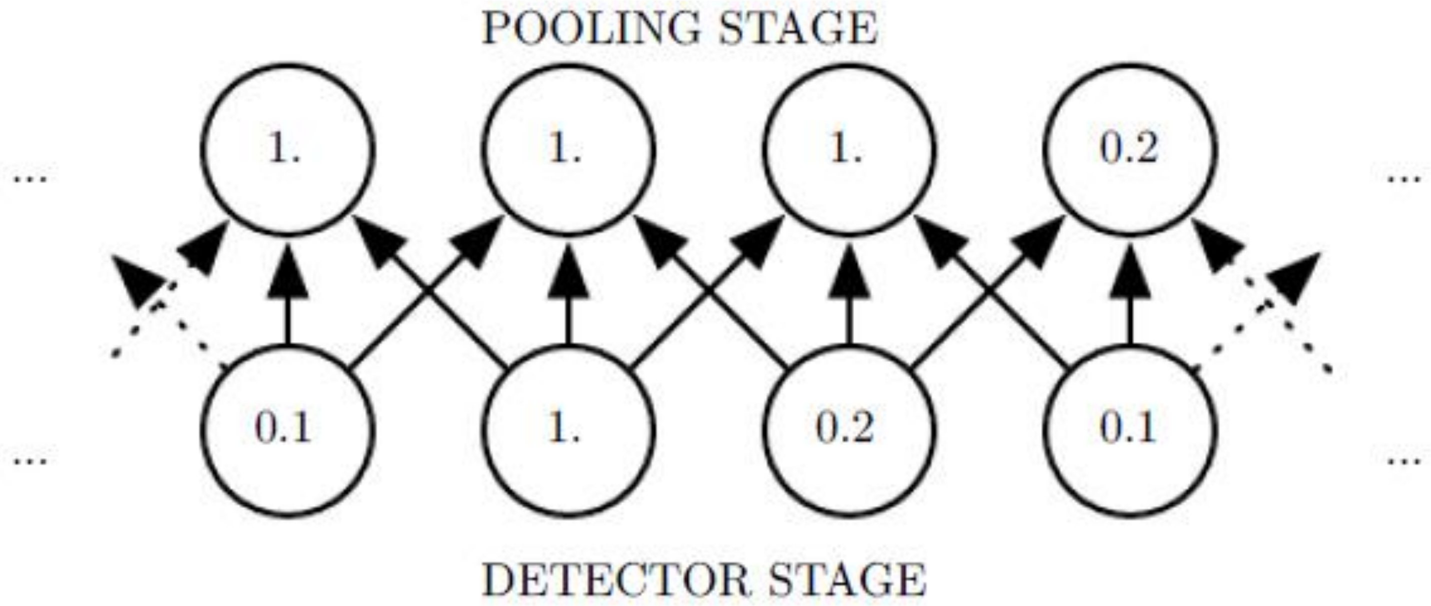


Figure from *Deep Learning,* by Goodfellow, Bengio, and Courville

Advantage

Induce invariance



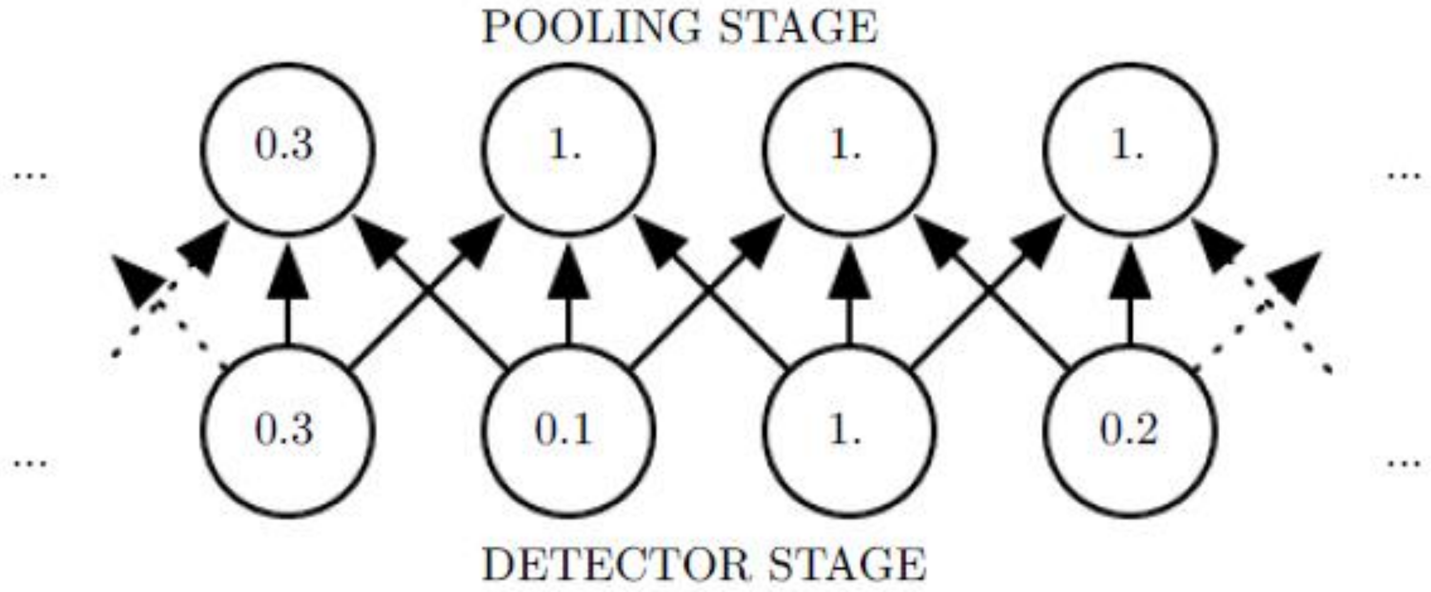


Figure from *Deep Learning,* by Goodfellow, Bengio, and Courville

Motivation from neuroscience

- David Hubel and Torsten Wiesel studied early visual system in human brain (V1 or primary visual cortex), and won Nobel prize for this

- V1 properties
  - 2D spatial arrangement
  - Simple cells: inspire convolution layers
  - Complex cells: inspire pooling layers

Example: LeNet

LeNet-5

- Proposed in *“Gradient-based learning applied to document recognition”* , *by Yann LeCun, Leon Bottou, Yoshua Bengio and Patrick Haffner, in Proceedings of the IEEE, 1998*

LeNet-5

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- Apply convolution on 2D images (MNIST) and use backpropagation

LeNet-5

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- Apply convolution on 2D images (MNIST) and use backpropagation

- Structure: 2 convolutional layers (with pooling) + 3 fully connected layers
  - Input size: 32x32x1
  - Convolution kernel size: 5x5
  - Pooling: 2x2

LeNet-5

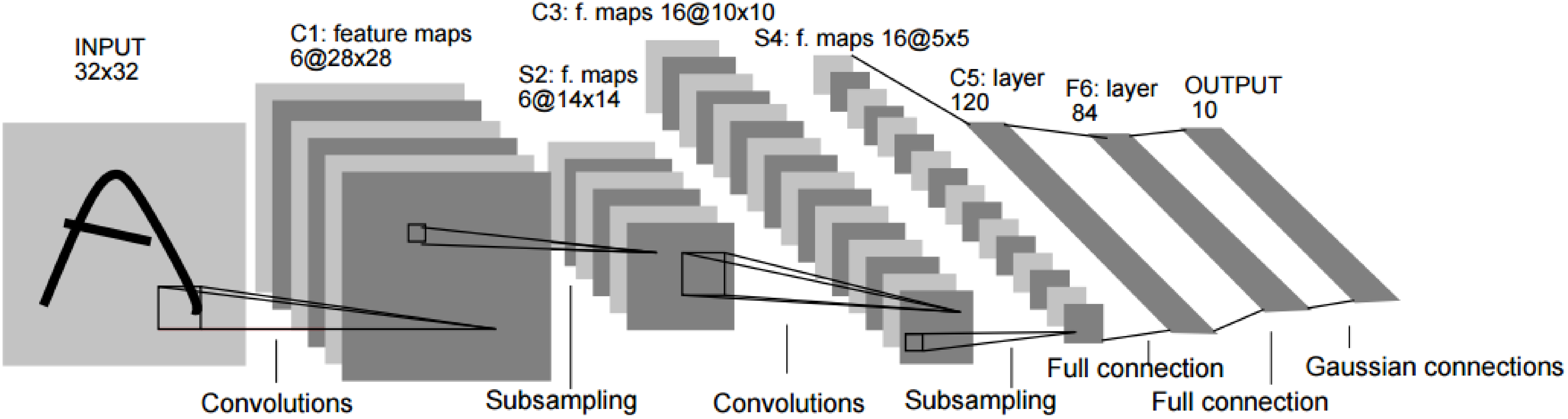
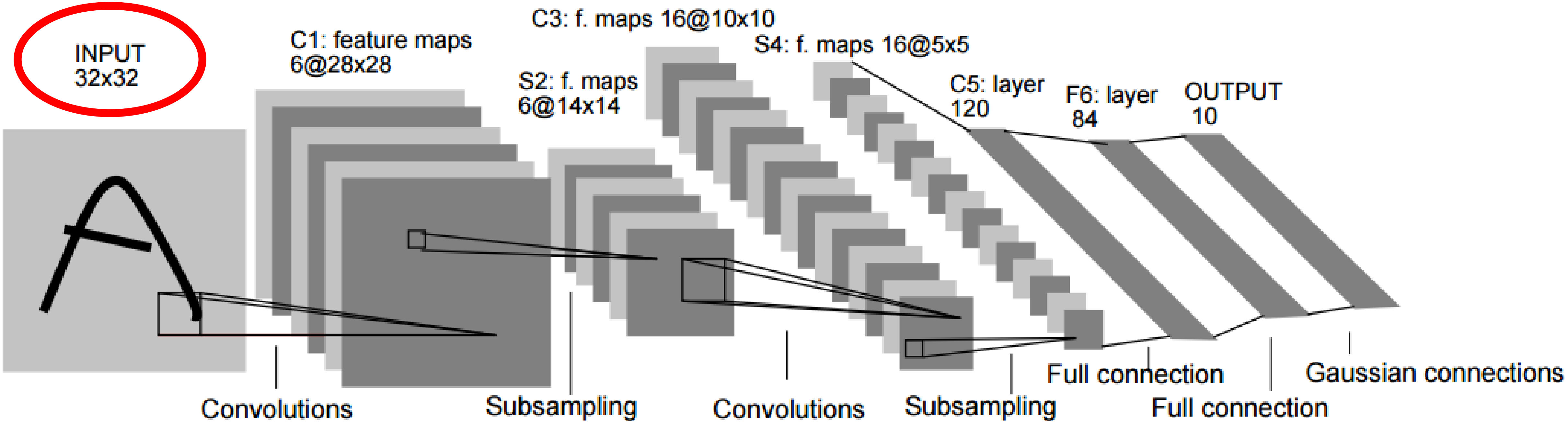


Figure from *Gradient-based learning applied to document recognition, by Y. LeCun, L. Bottou, Y. Bengio and P. Haffner*

LeNet-5



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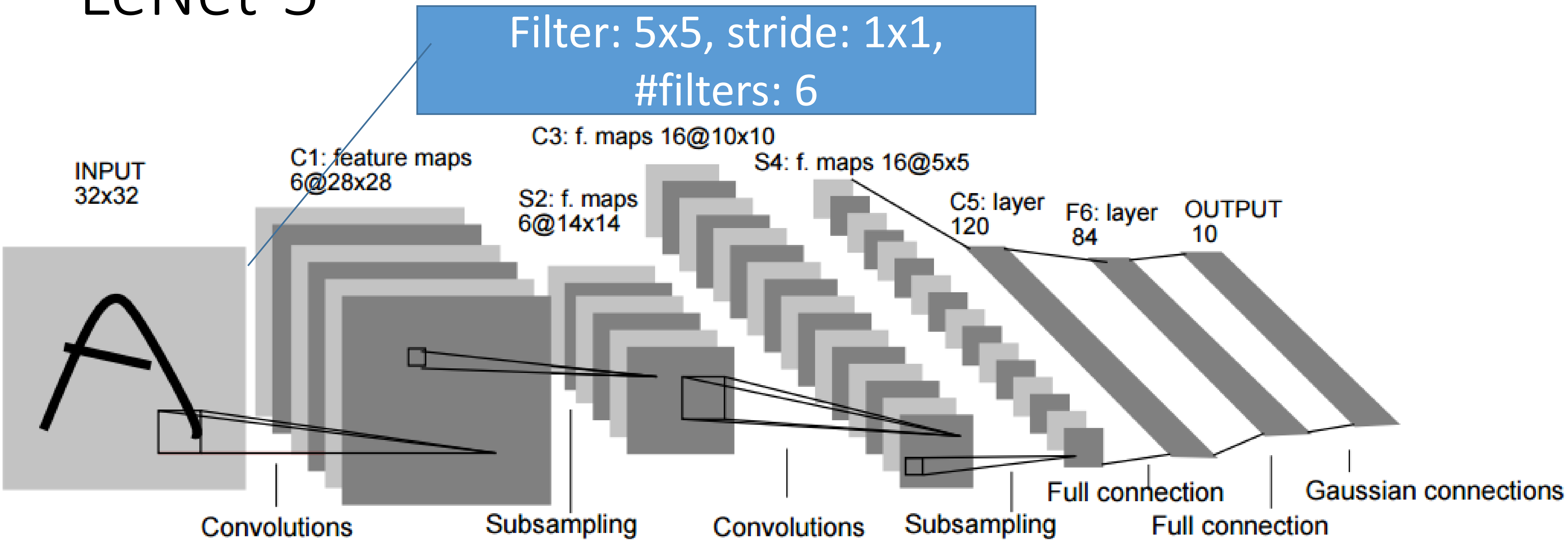
LeNet-5



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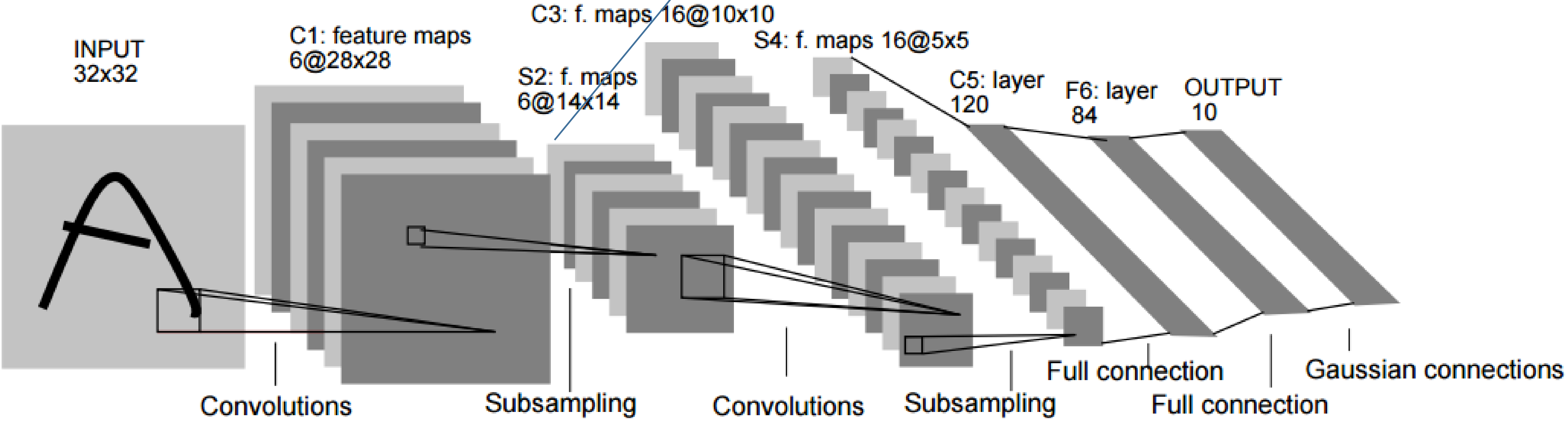
LeNet-5

Pooling: 2x2, stride: 2



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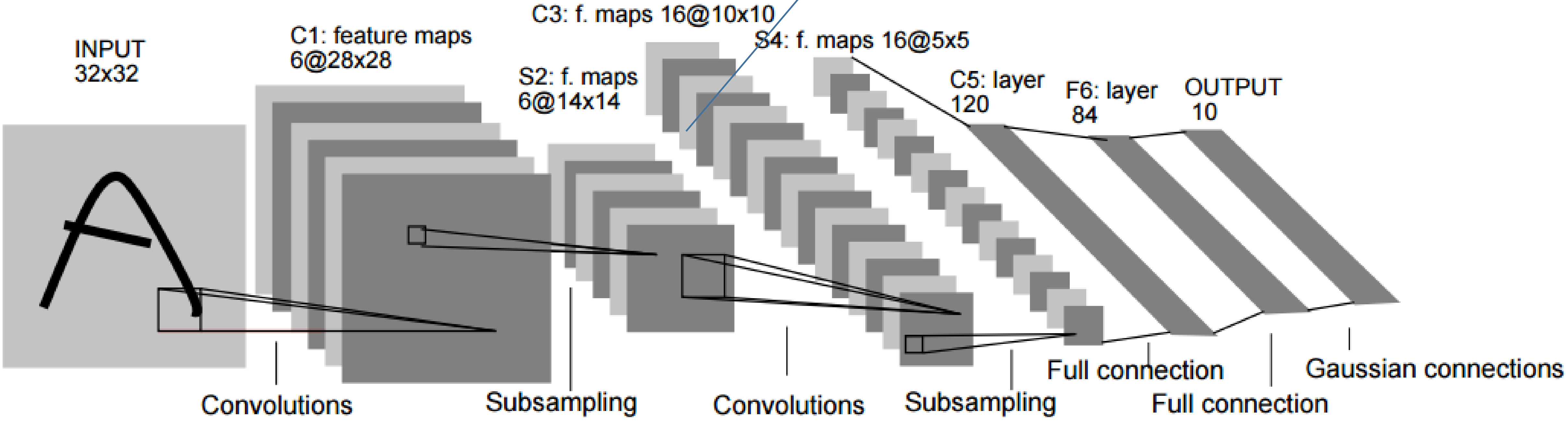
LeNet-5

Filter: 5x5x6, stride: 1x1, #filters: 16



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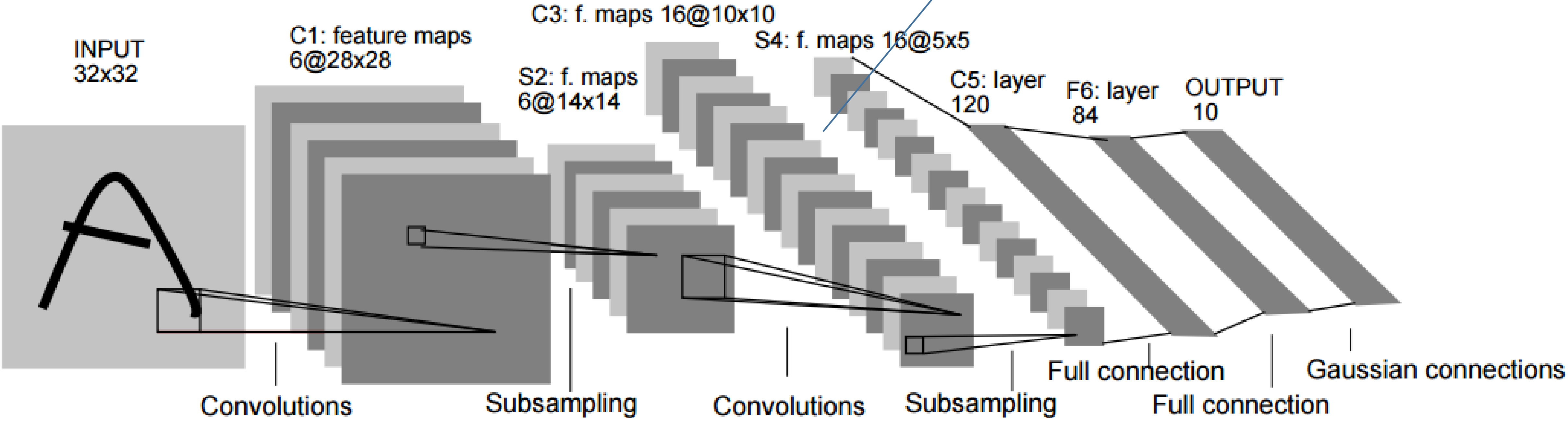
LeNet-5

Pooling: 2x2, stride: 2



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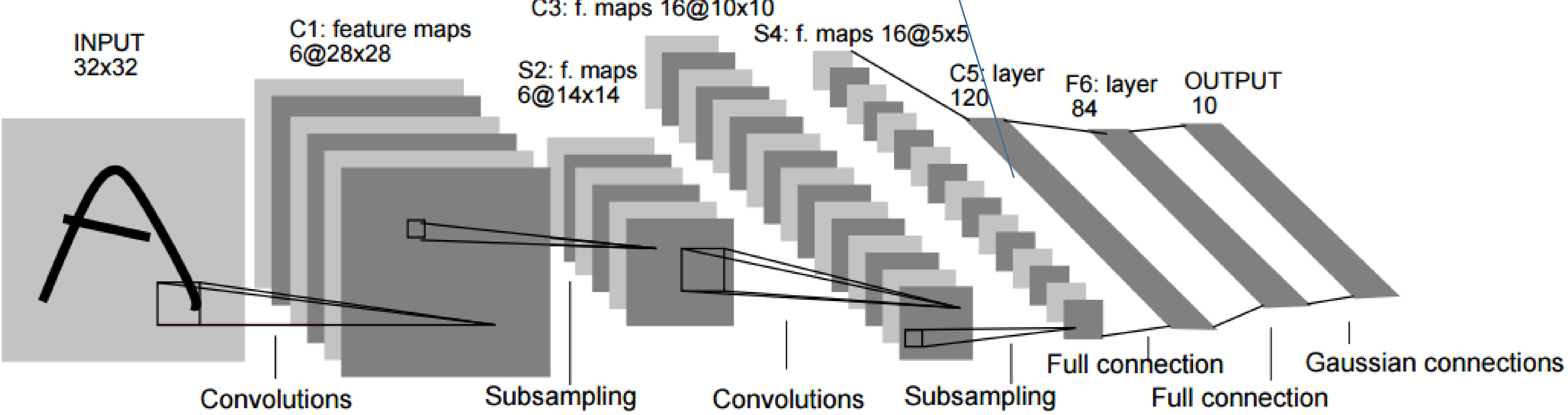
LeNet-5

Weight matrix: 400x120



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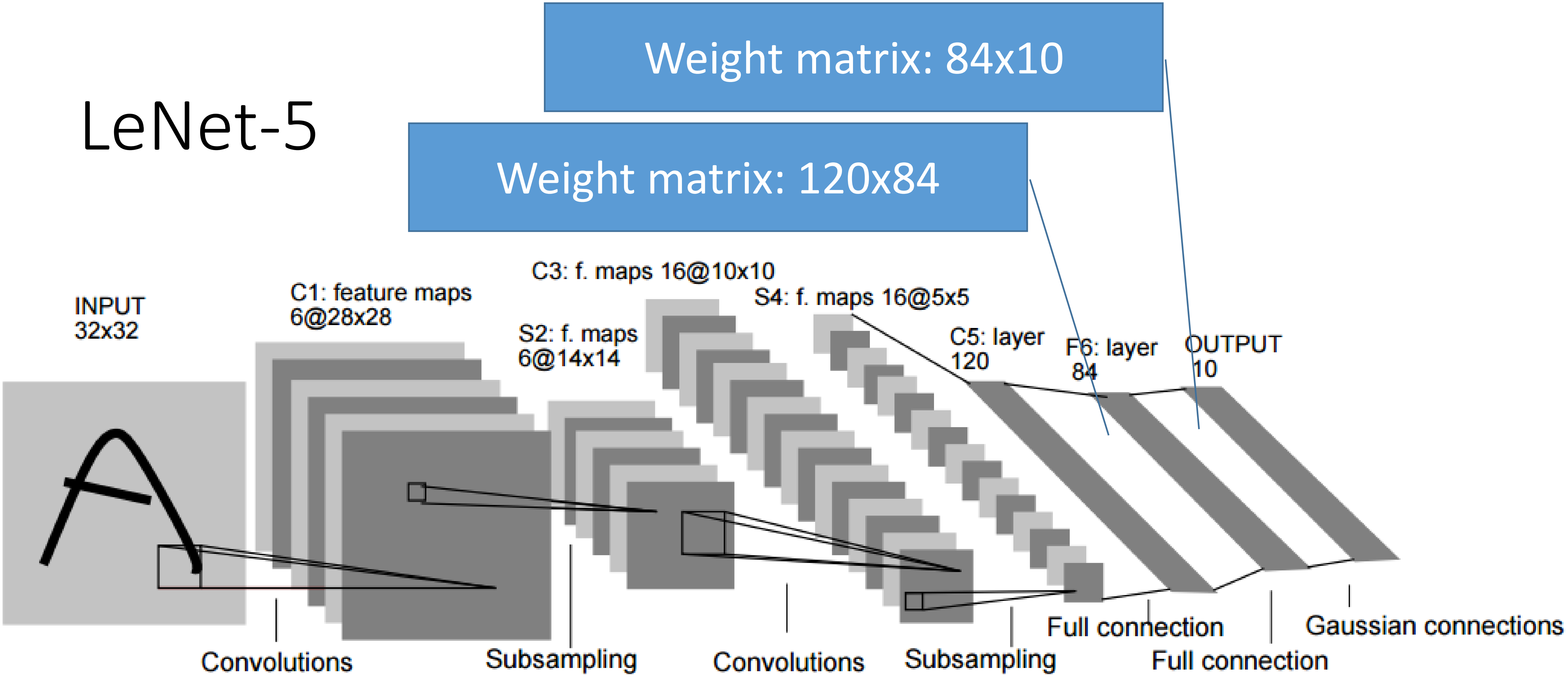

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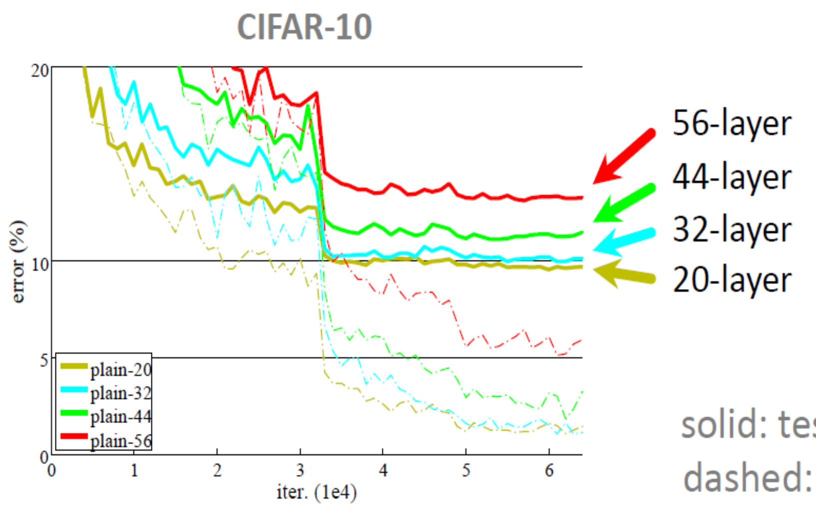
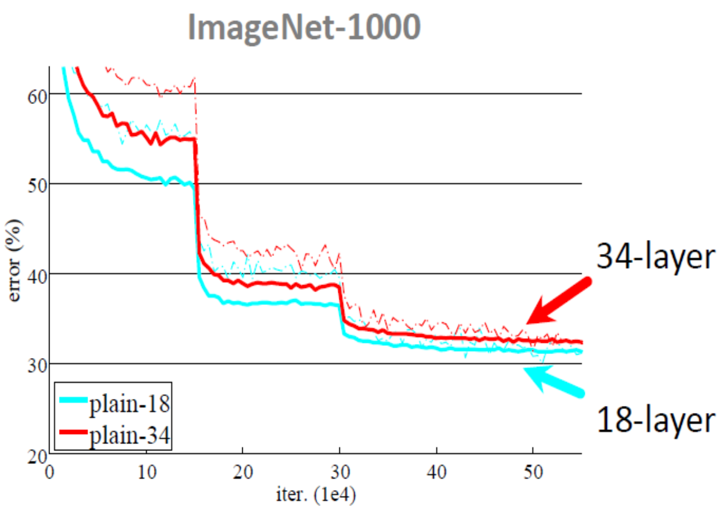
Example: ResNet

Plain Network

- “Overly deep” plain nets have higher training error
- A general phenomenon, observed in many datasets



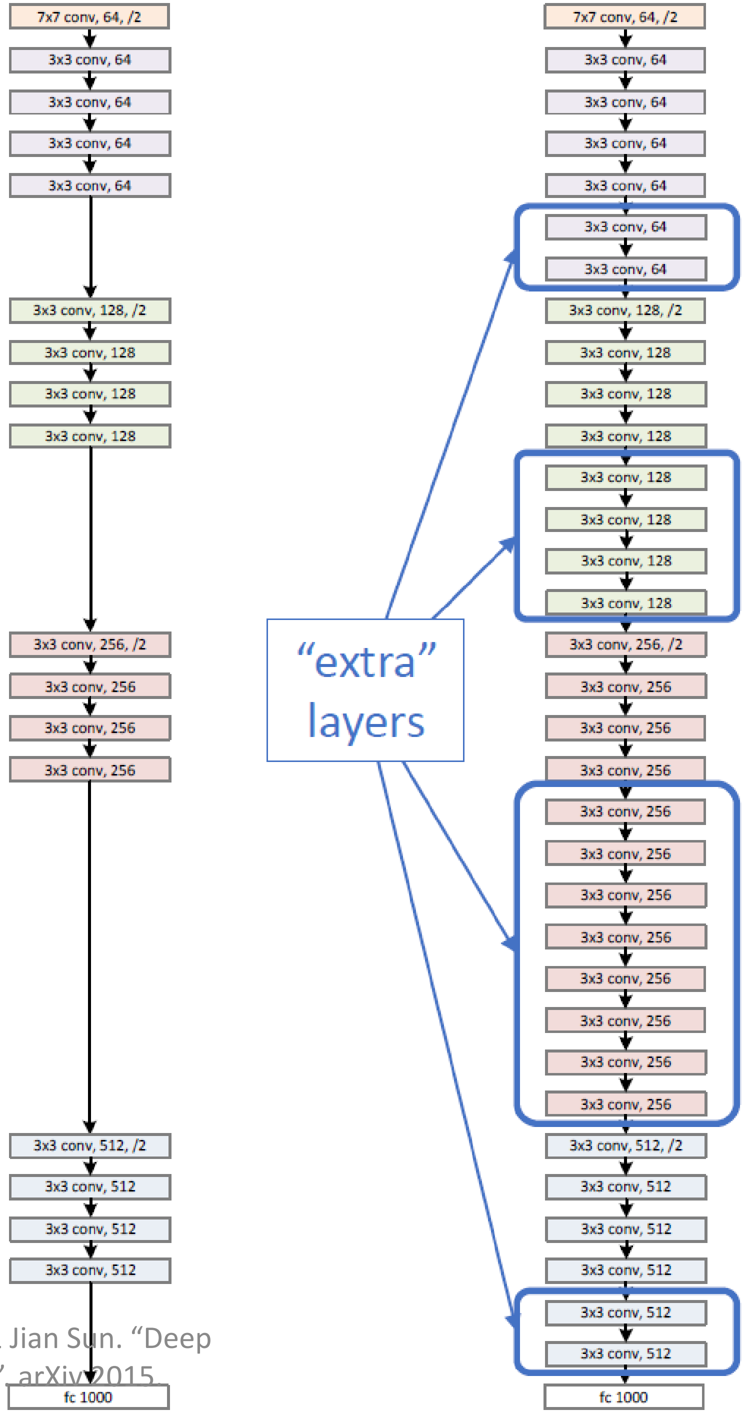
solid: test/val
dashed: train



Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. “Deep Residual Learning for Image Recognition”. arXiv 2015.

Residual Network

- Naïve solution
  - If extra layers are an identity mapping, then a training errors does not increase



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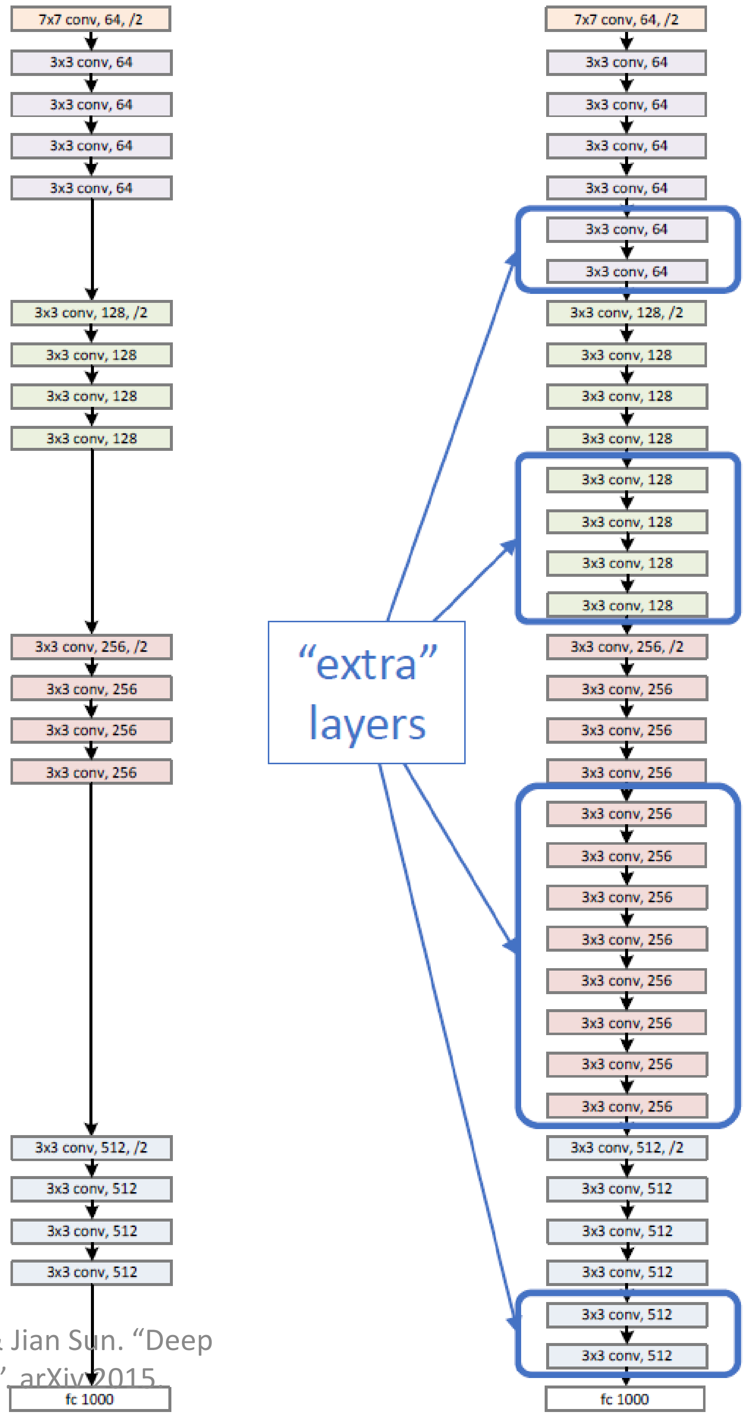
Residual Network

- Deeper networks also maintain the tendency of results
  - Features in same level will be almost same
  - An amount of changes is fixed
  - Adding layers makes smaller differences
  - Optimal mappings are closer to an identity



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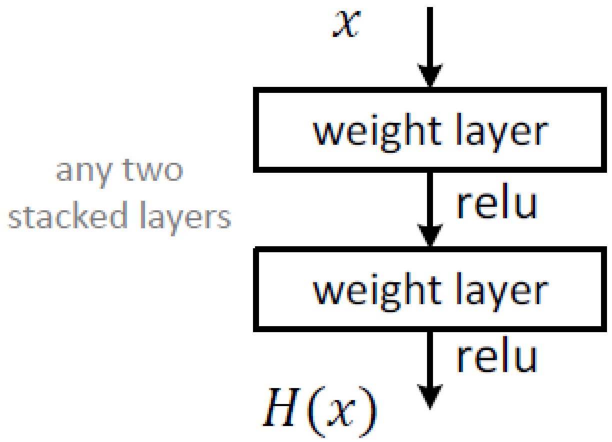
Residual Network

- Plain block
  - Difficult to make identity mapping because of multiple non-linear layers



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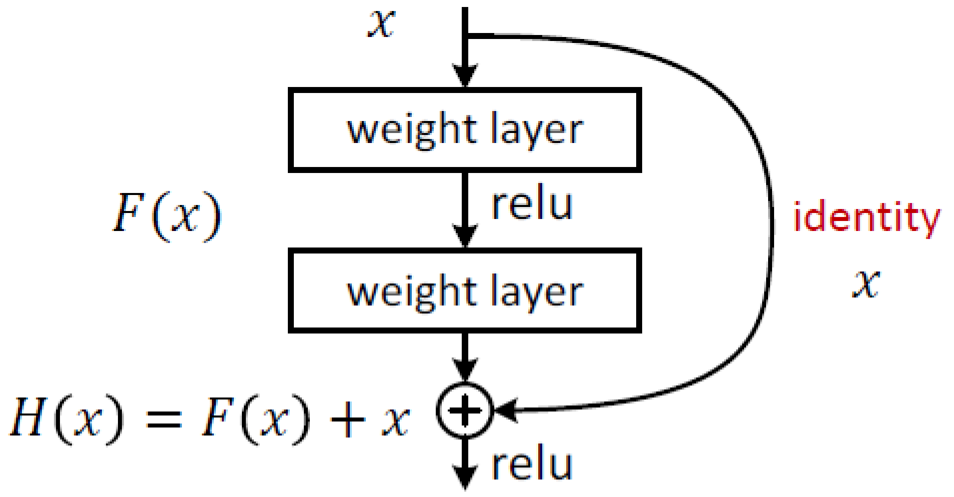
Residual Network

- Residual block
  - If identity were optimal, easy to set weights as 0
  - If optimal mapping is closer to identity, easier to find small fluctuations

-> Appropriate for treating perturbation as keeping a base information



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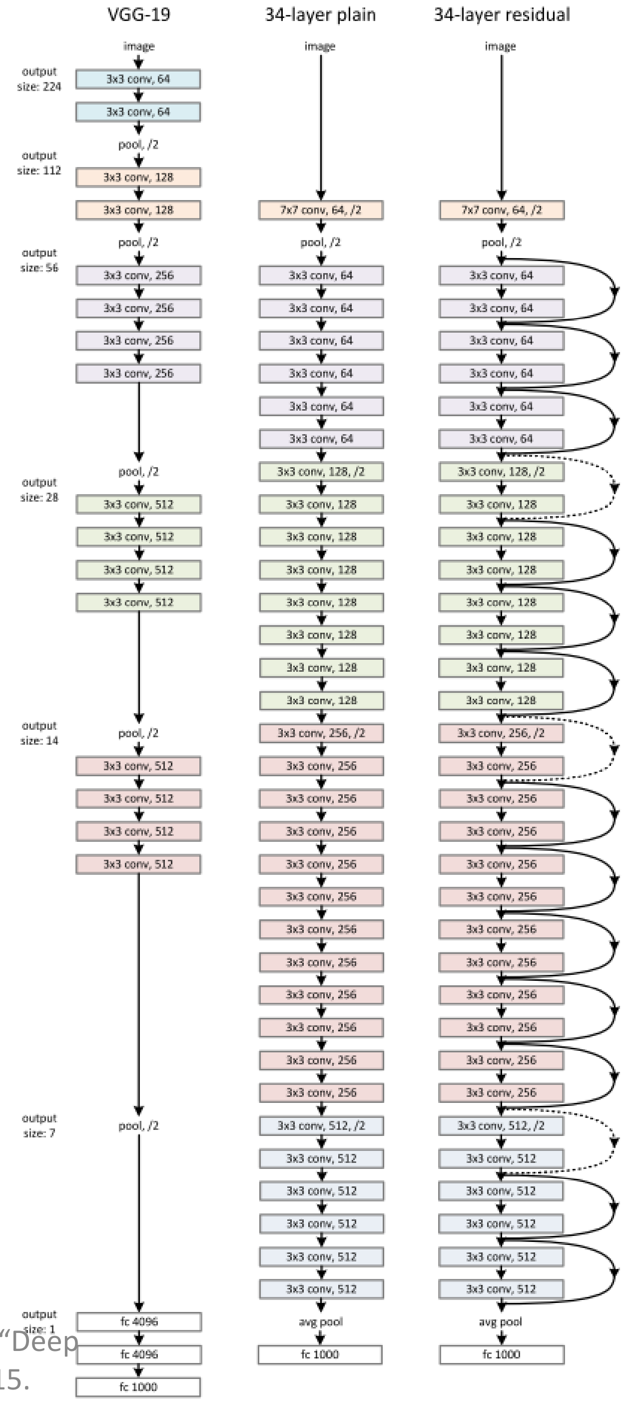
Network Design

- Basic design (VGG-style)
  - All 3x3 conv (almost)
  - Spatial size/2 => #filters x2
  - Batch normalization
  - Simple design, just deep
- Other remarks
  - No max pooling (almost)
  - No hidden fc
  - No dropout



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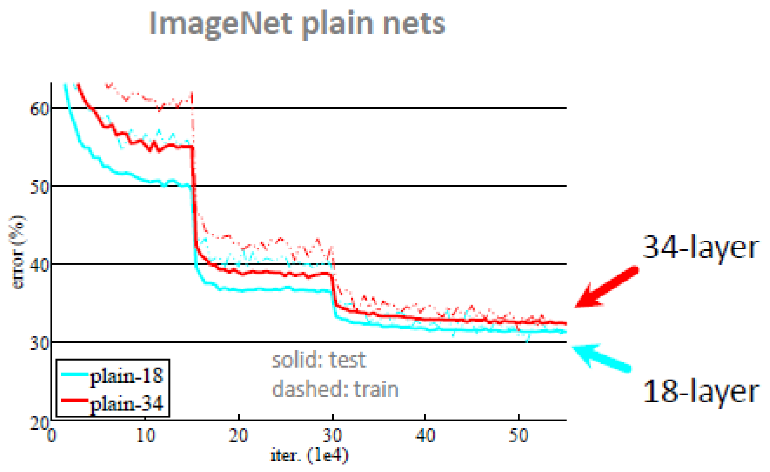
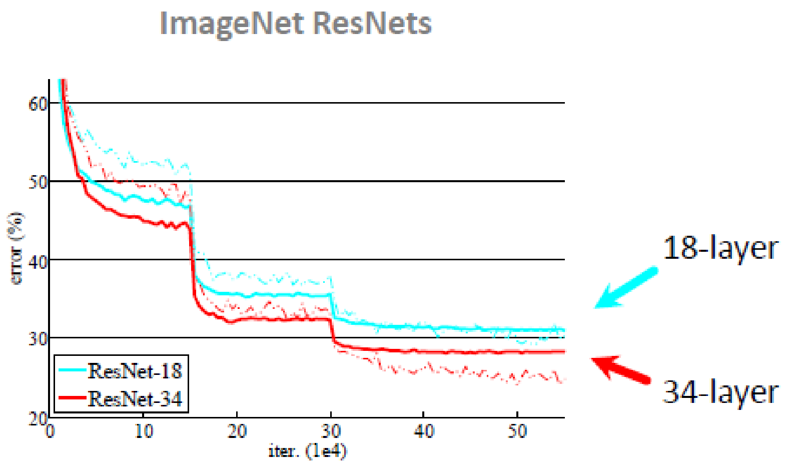
Results

- Deep Resnets can be trained without difficulties
- Deeper ResNets have lower training error, and also lower test error





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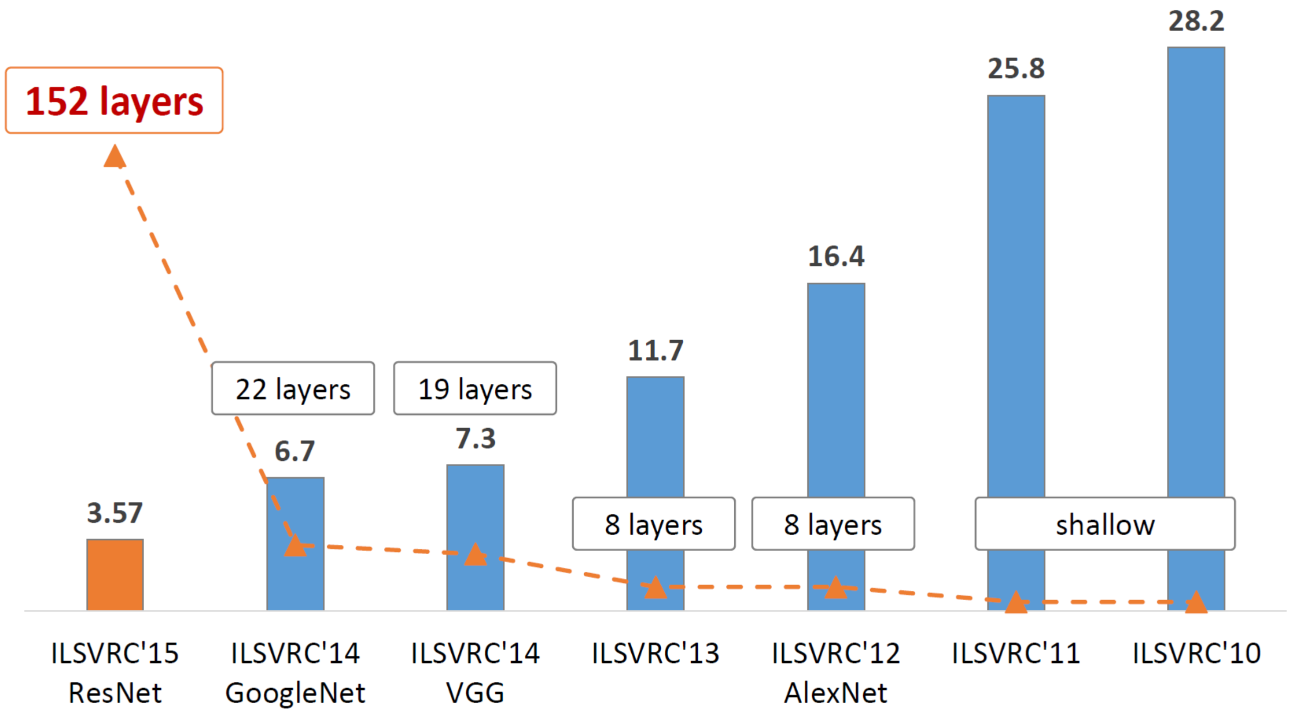
Results

- 1st places in all five main tracks in "ILSVRC & COCO 2015 Competitions"
  - ImageNet Classification
  - ImageNet Detection
  - ImageNet Localization
  - COCO Detection
  - COCO Segmentation

Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. "Deep Residual Learning for Image Recognition". arXiv 2015.

Quantitative Results

- ImageNet Classification



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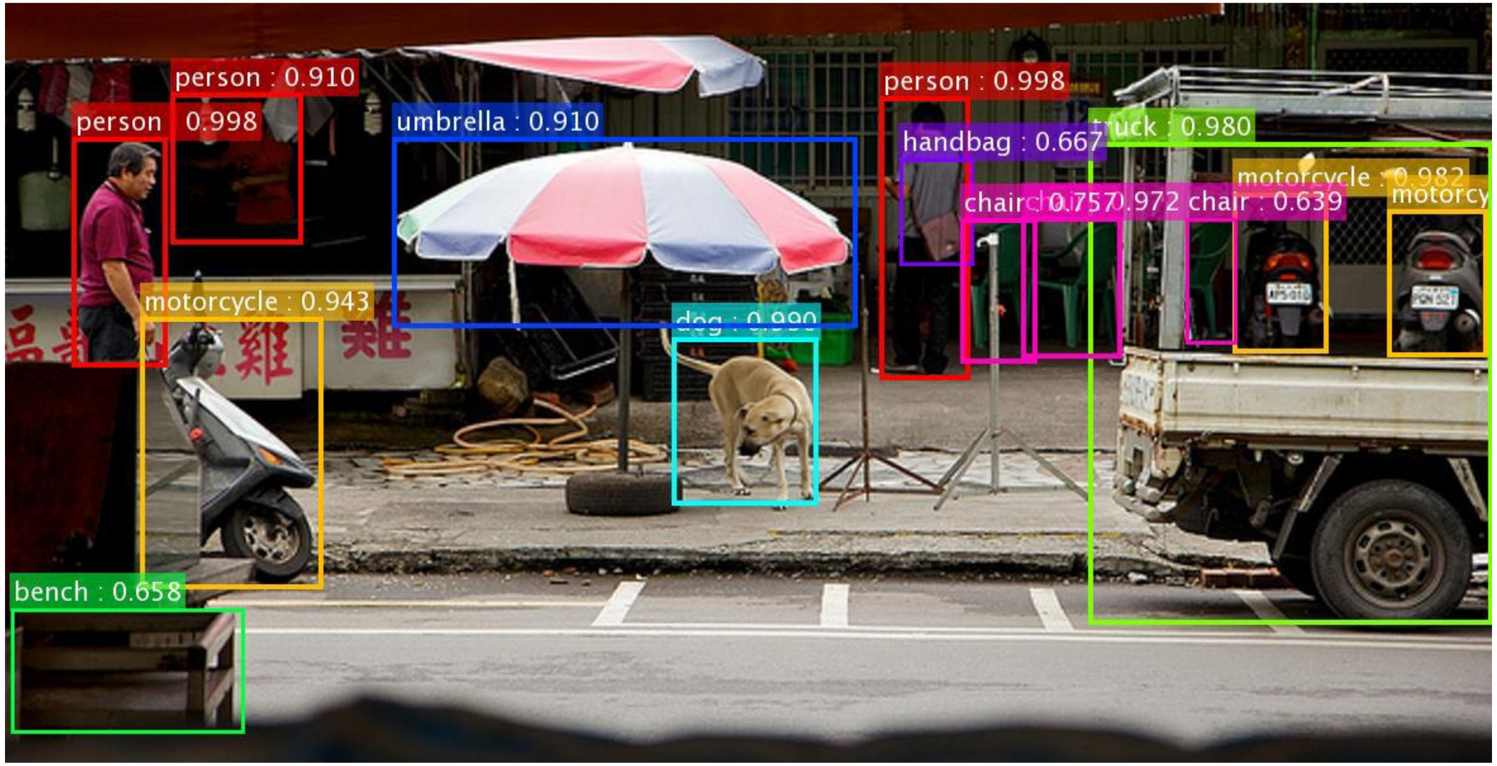
Qualitative Result

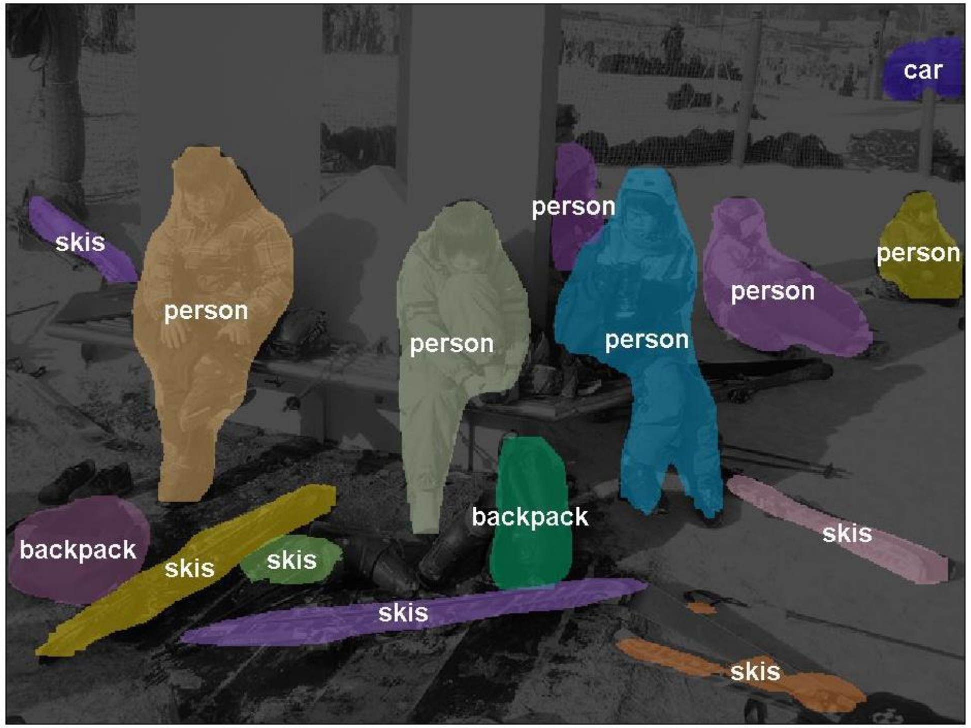
- Object detection
  - Faster R-CNN + ResNet



Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. “Deep Residual Learning for Image Recognition”. arXiv 2015.
Jifeng Dai, Kaiming He, & Jian Sun. “Instance-aware Semantic Segmentation via Multi-task Network Cascades”. arXiv 2015.

Qualitative Results

- Instance Segmentation



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