Cornell Bowers C·IS
College of Computing and Information Science

Convolutional Neural Networks

CS4782: Intro to Deep Learning

Thanks to:

Varsha Kishore
Justin Lovelace
Anissa Dallmann
Stephanie Ginting
Alexander Scotte

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Logistics

- **HW1** has been released
  - Due next Thursday (February 13)
  - Homework clarifications are listed as pinned posts under HW1 on Ed
- CS 5782 - **Quiz 1** will be released today
  - 20 min duration - make sure to start well before it's due
  - Submission Due: Thursday 11:59 PM
- **Coding Assignment 1** to be released this week.
- Office hours are listed on the course website
- Post questions on Ed

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So far…

- MLPs learn complex decision boundaries
- Optimization algorithms use the gradient of the loss to find network parameters
- Different training strategies like regularization, early stopping and normalization can improve training and generalization

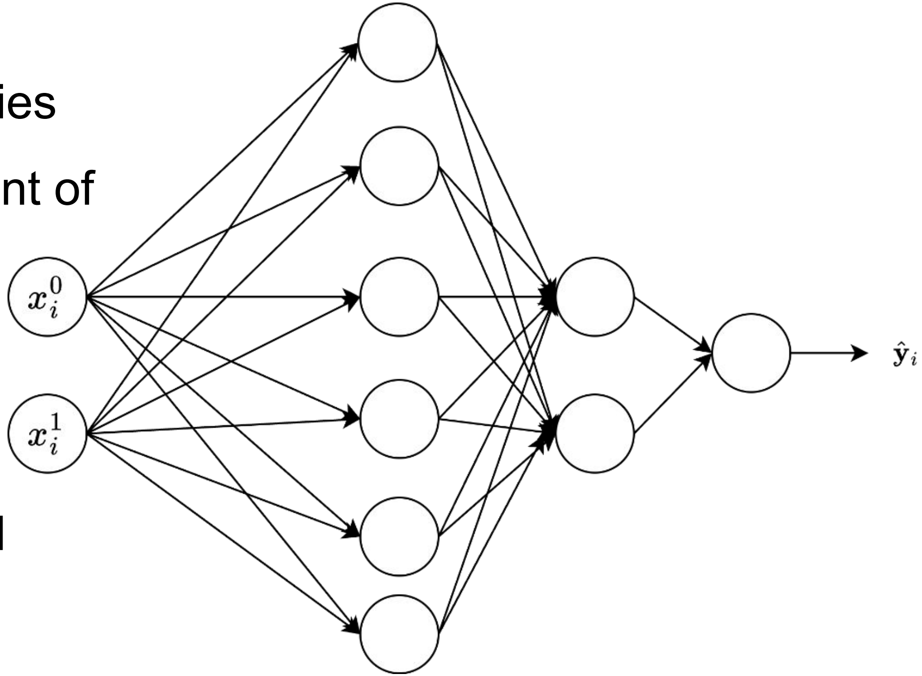

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Image Classification

input image

classification

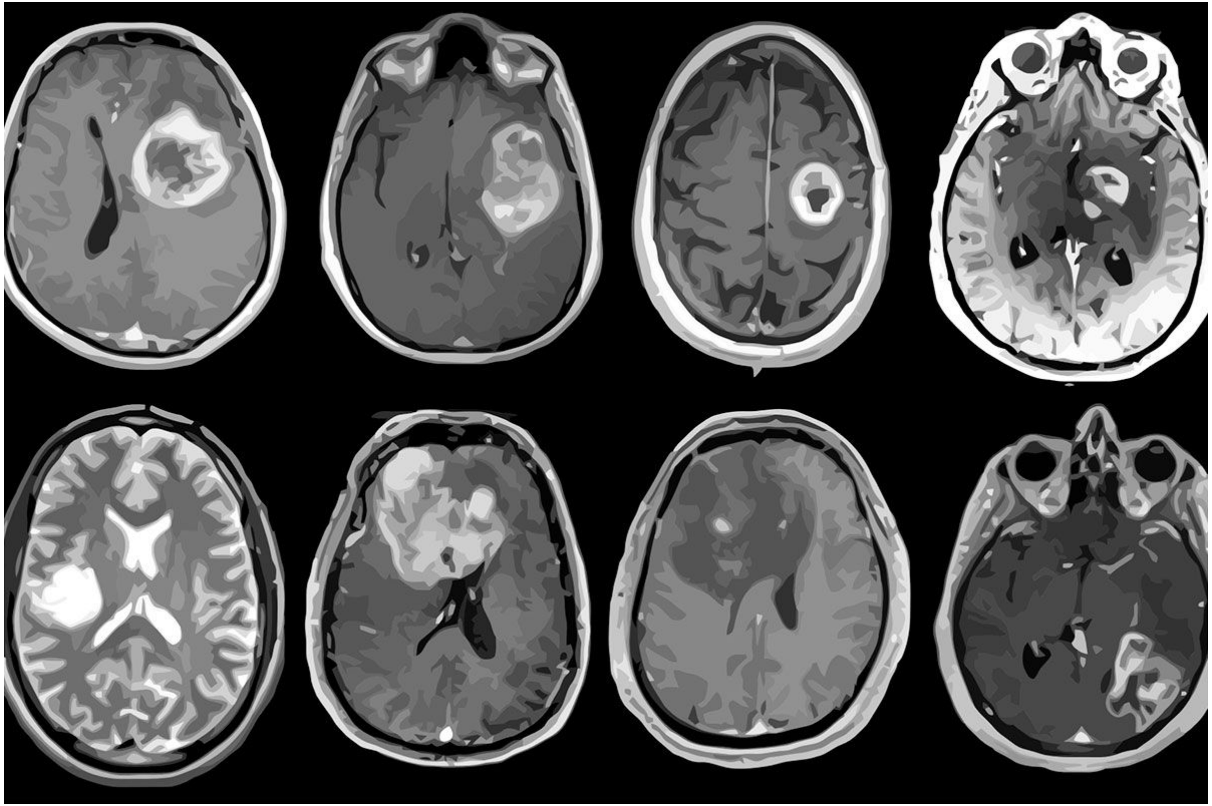
“dog”

input image

classification

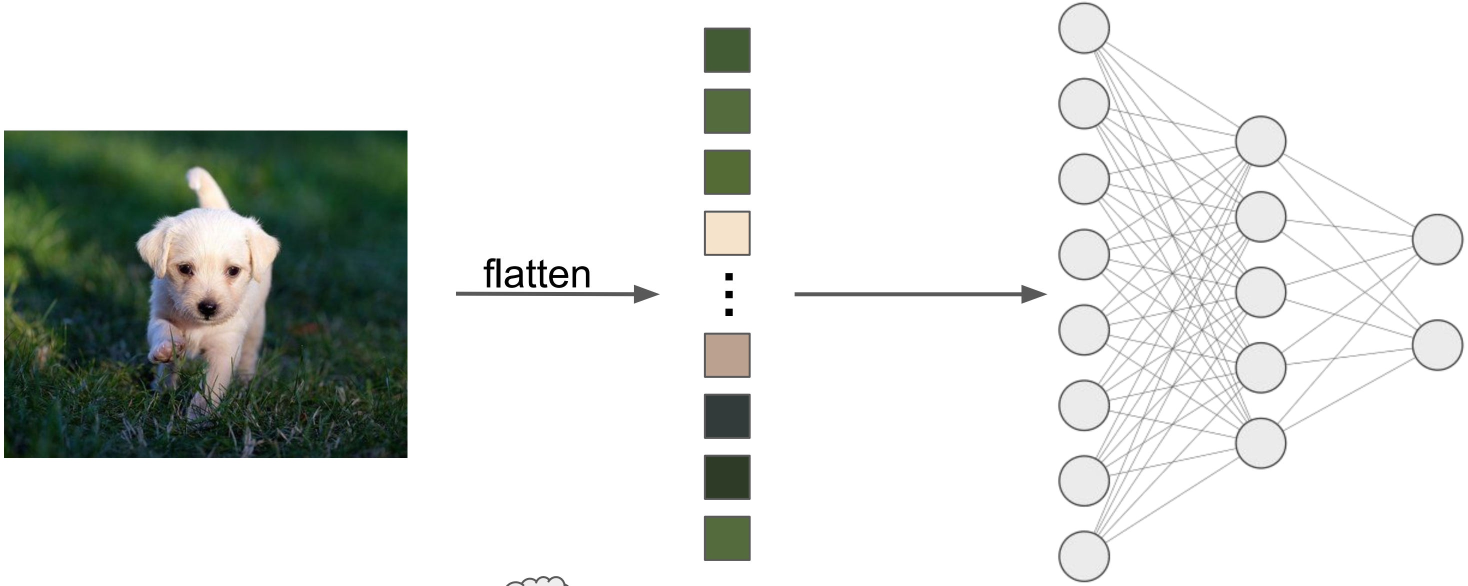
“cat”

Applications in Medicine



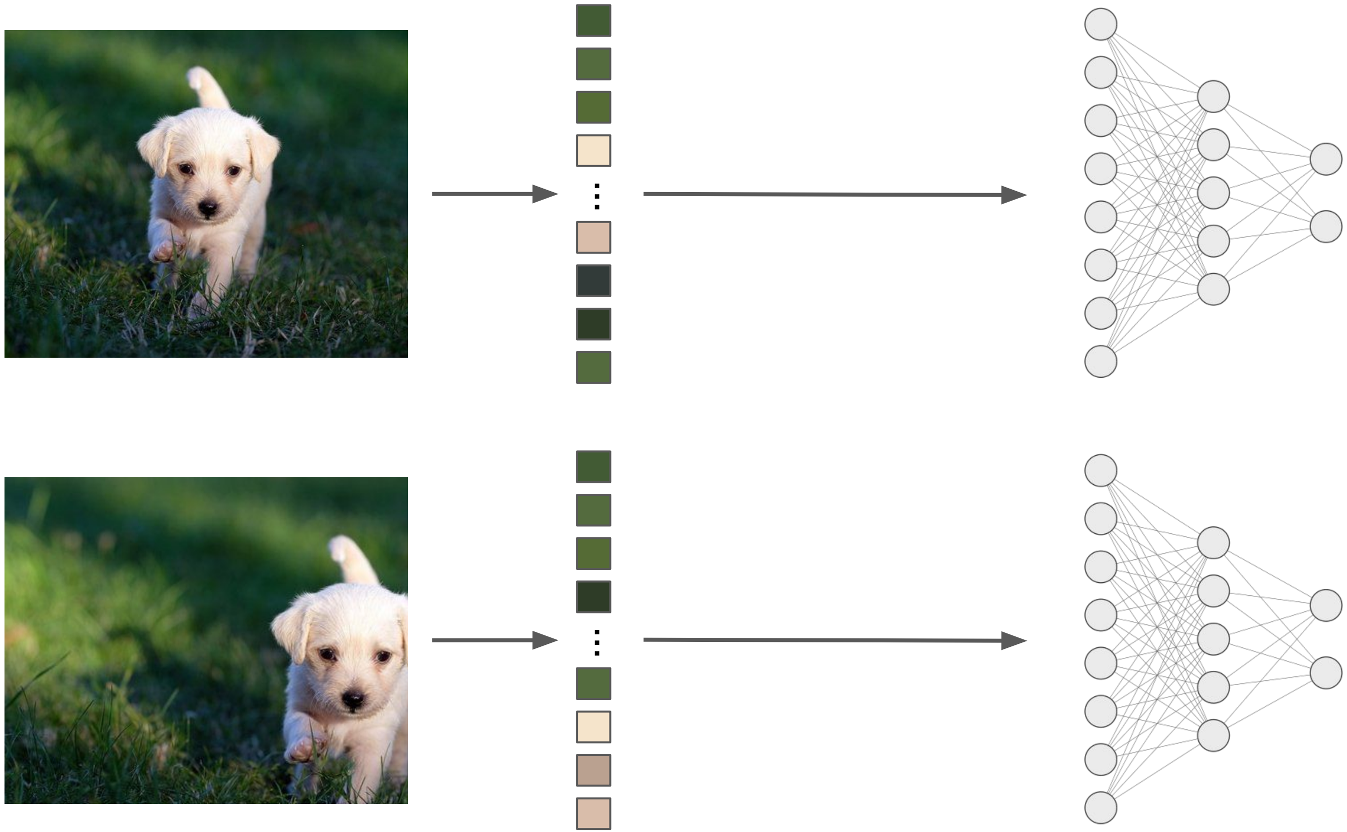
Applications in Autonomous Driving

Why not use a Multi-Layer Perceptron?



Which pixels were next to each other?

Why not use a Multi-Layer Perceptron?



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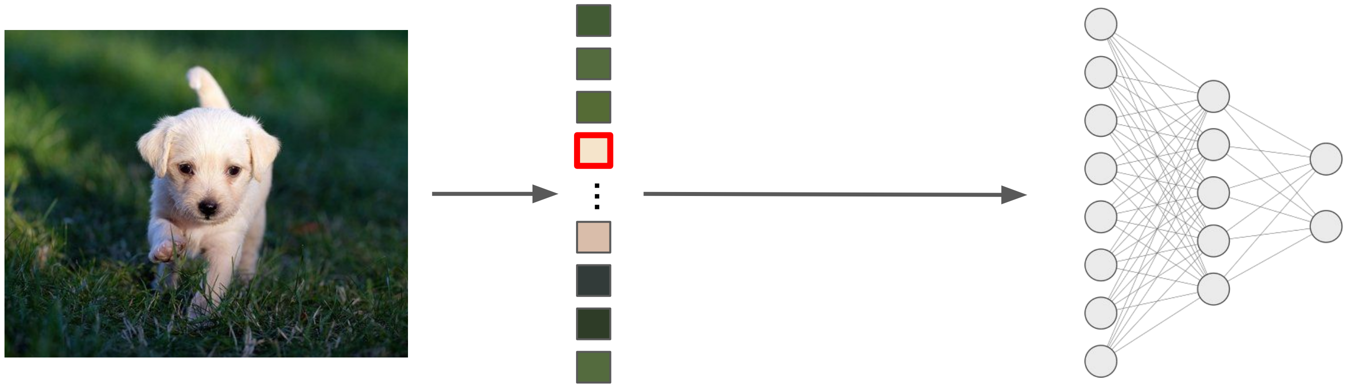
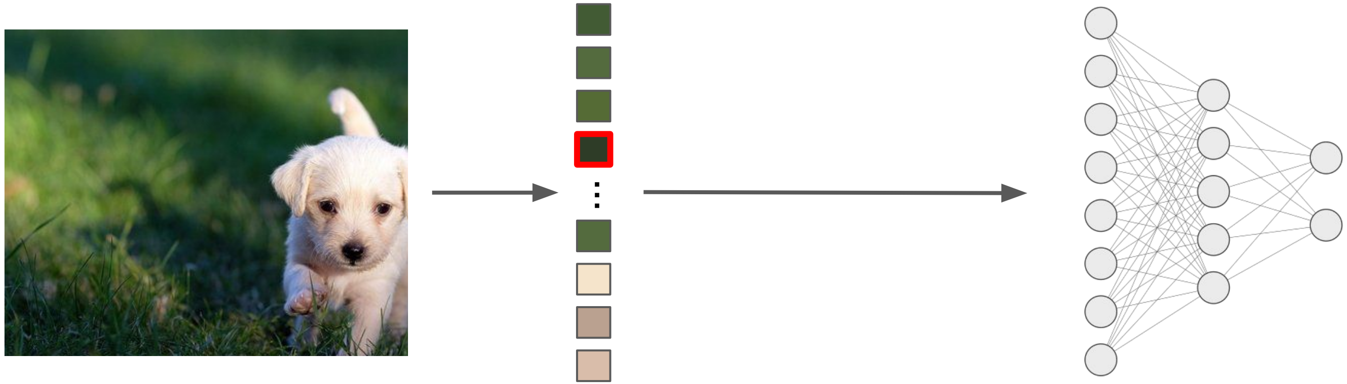
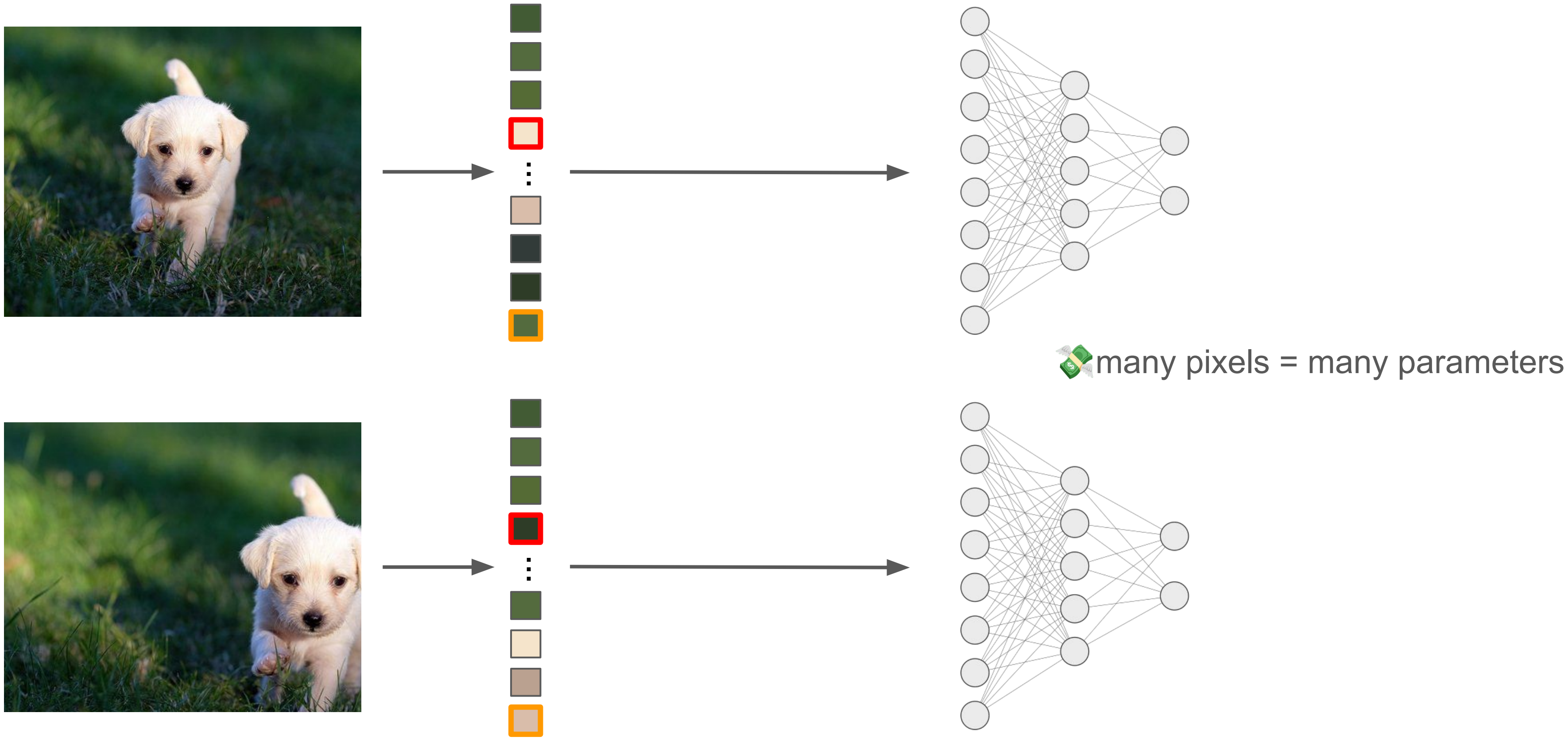
Why not use a Multi-Layer Perceptron?





Why not use a Multi-Layer Perceptron?



Convolutional Filters

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

“image”

*

0	1	0
1	0	1
0	1	0

convolutional filter

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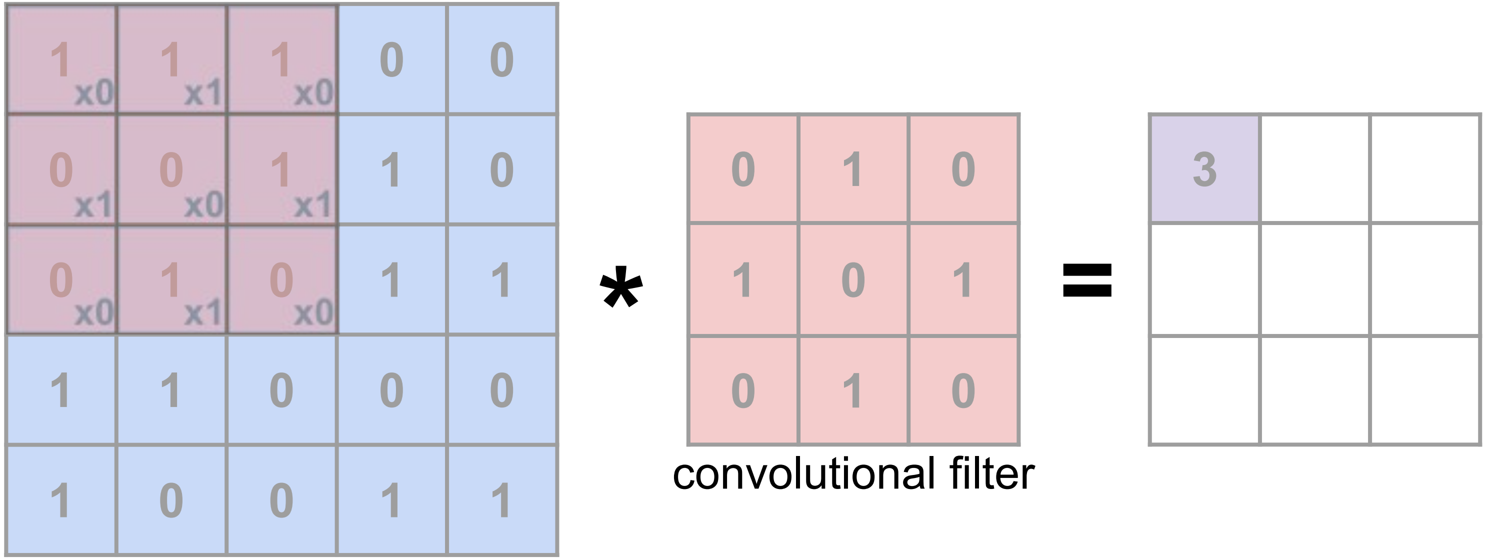
Convolutional Filters



“image”

convolutional filter

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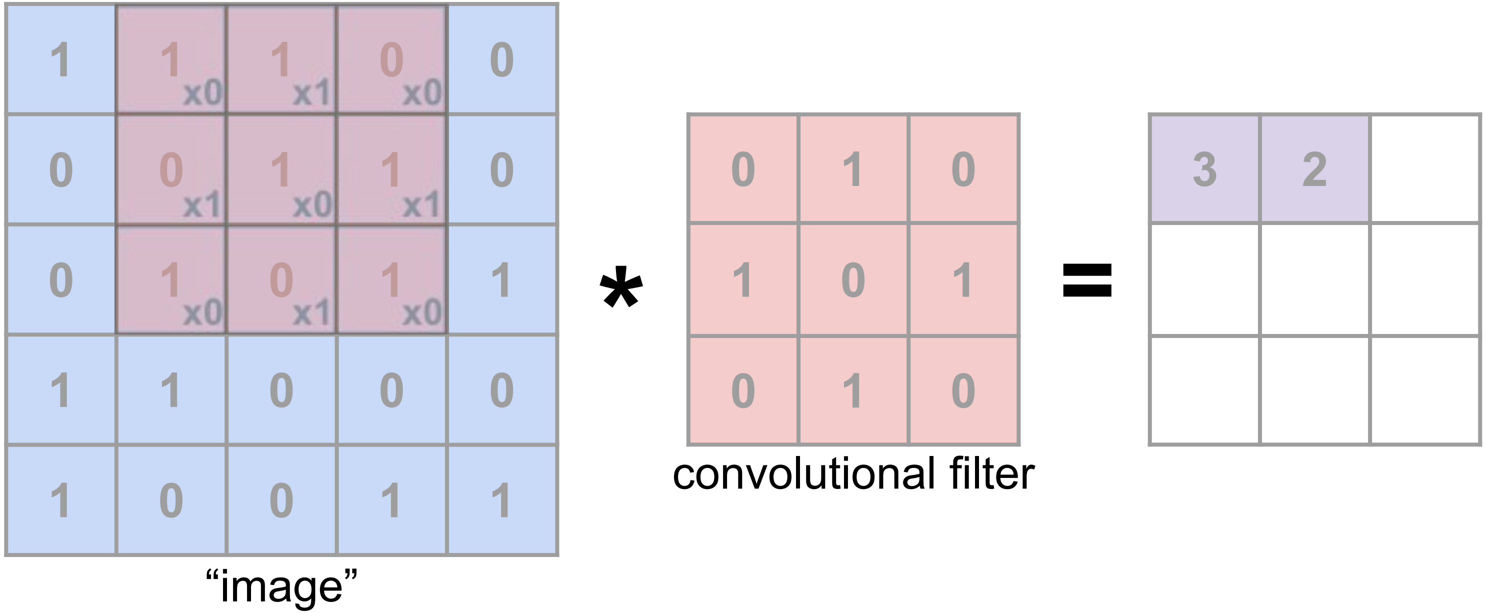
Convolutional Filters



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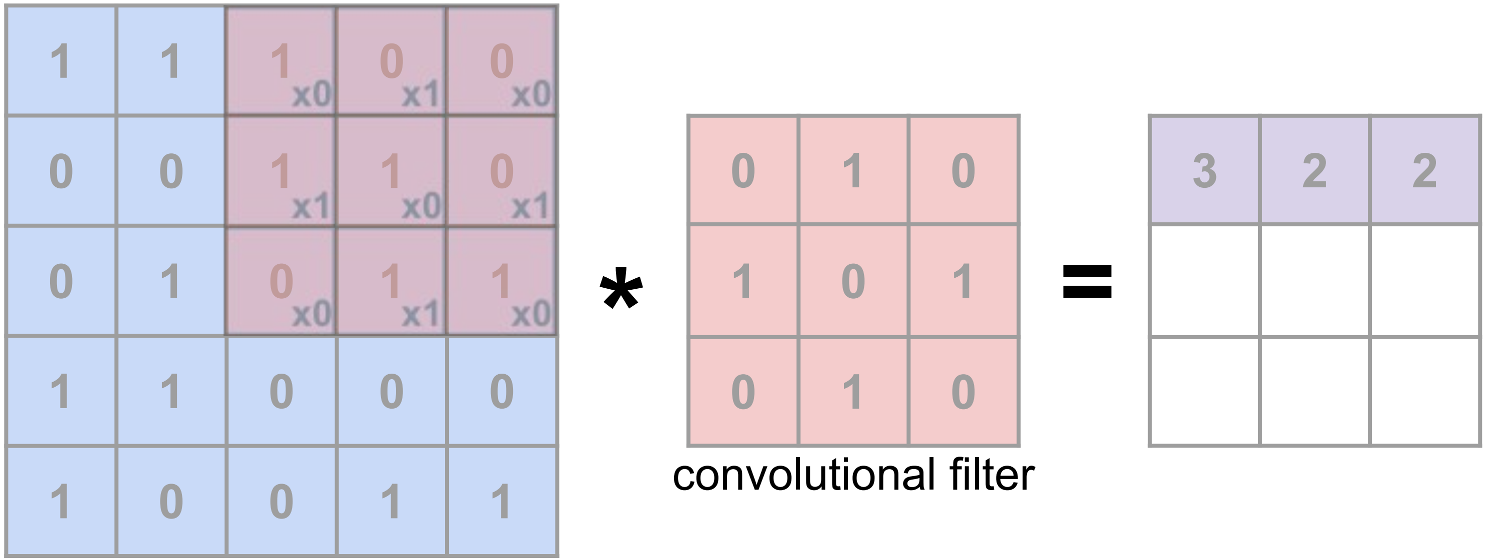
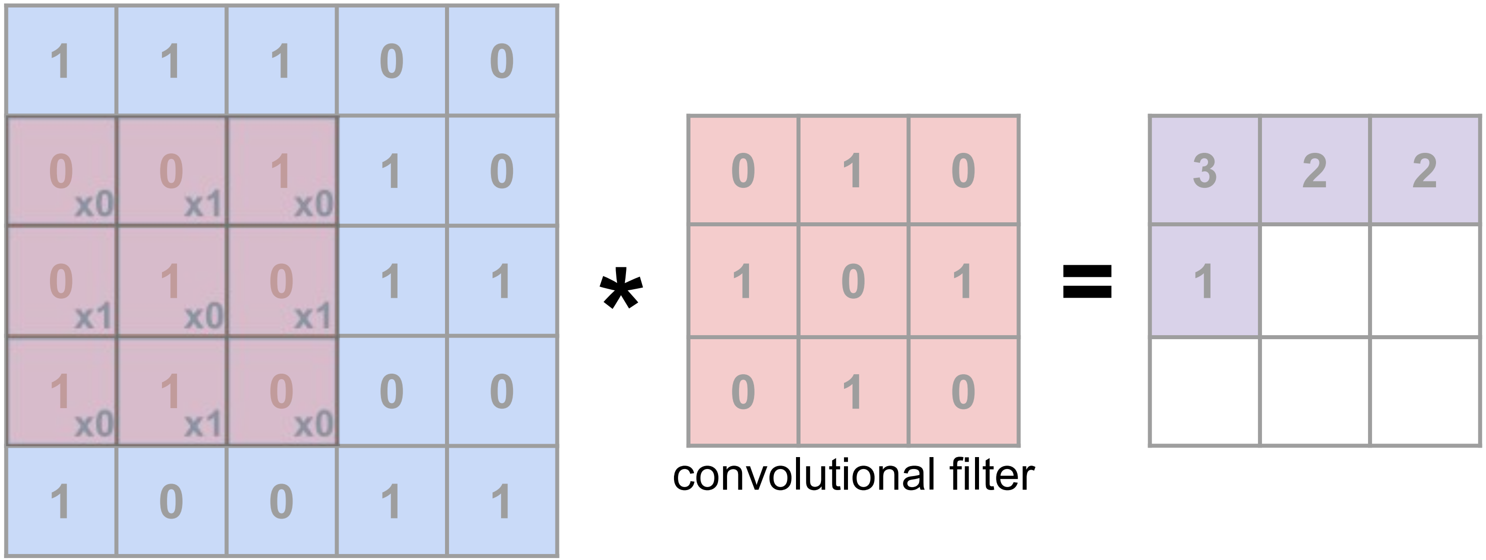
Convolutional Filters



convolutional filter

“image”

Convolutional Filters



convolutional filter

“image”

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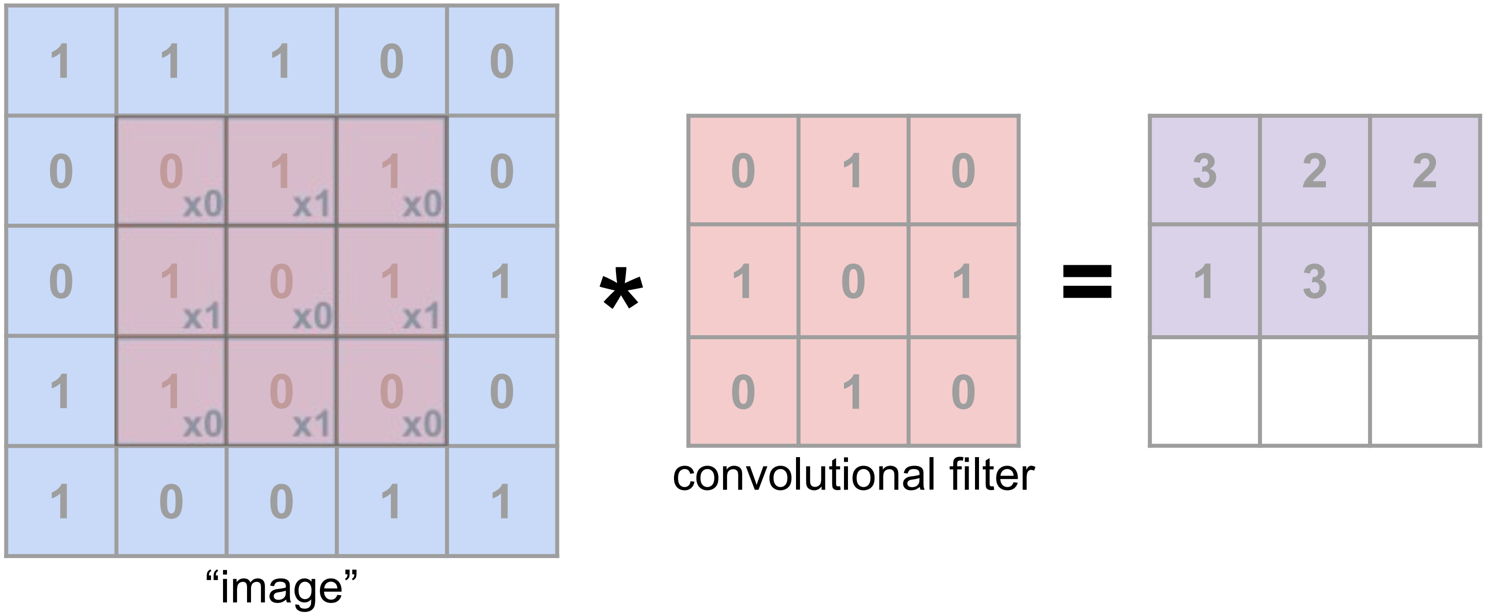
Convolutional Filters



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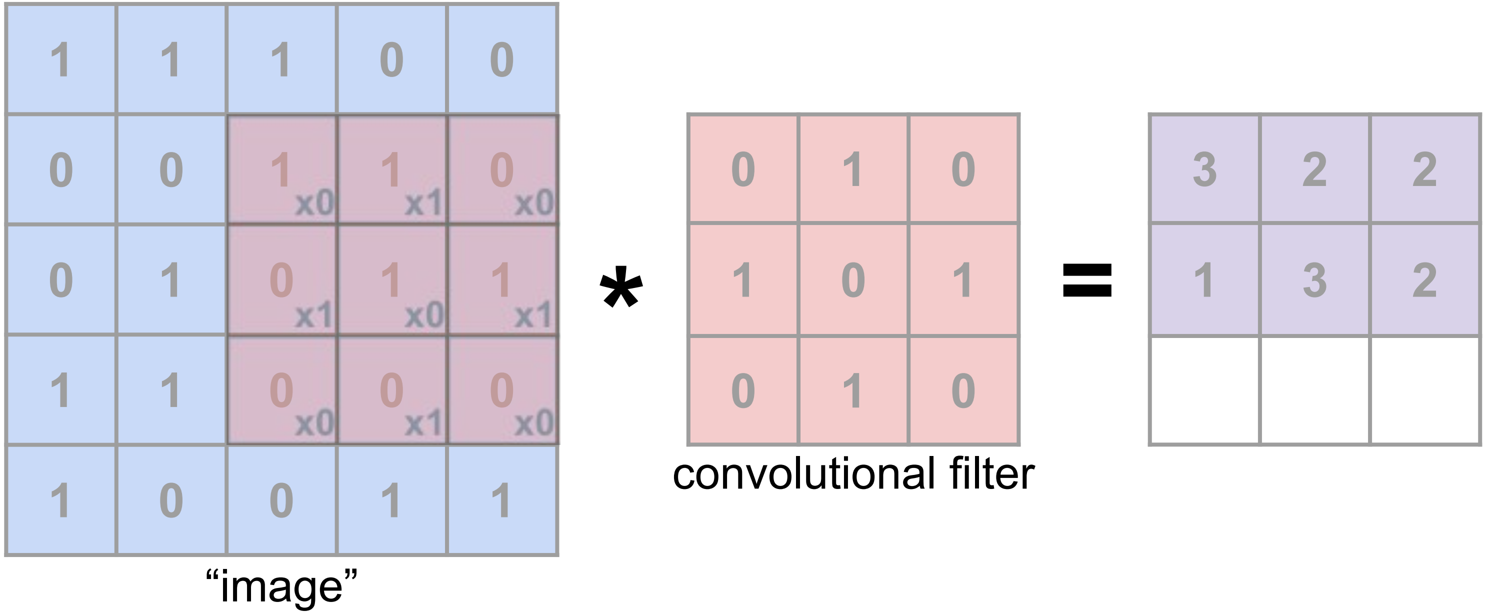
Convolutional Filters



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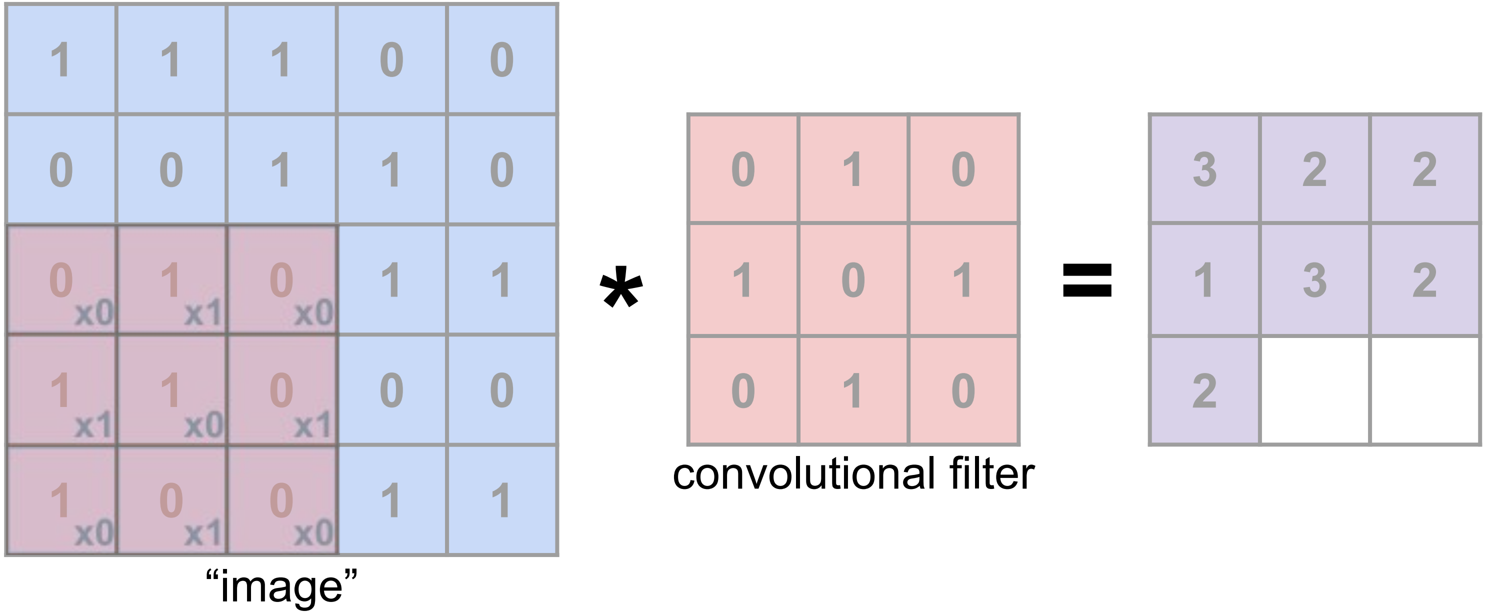
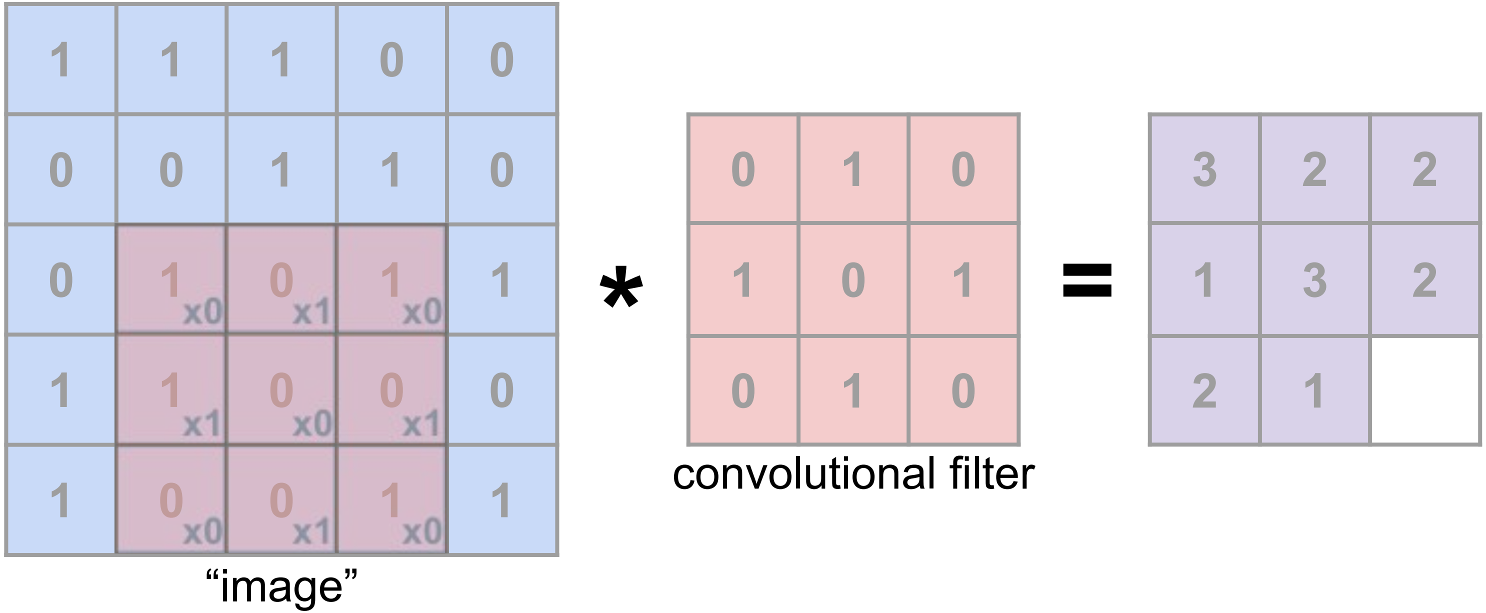
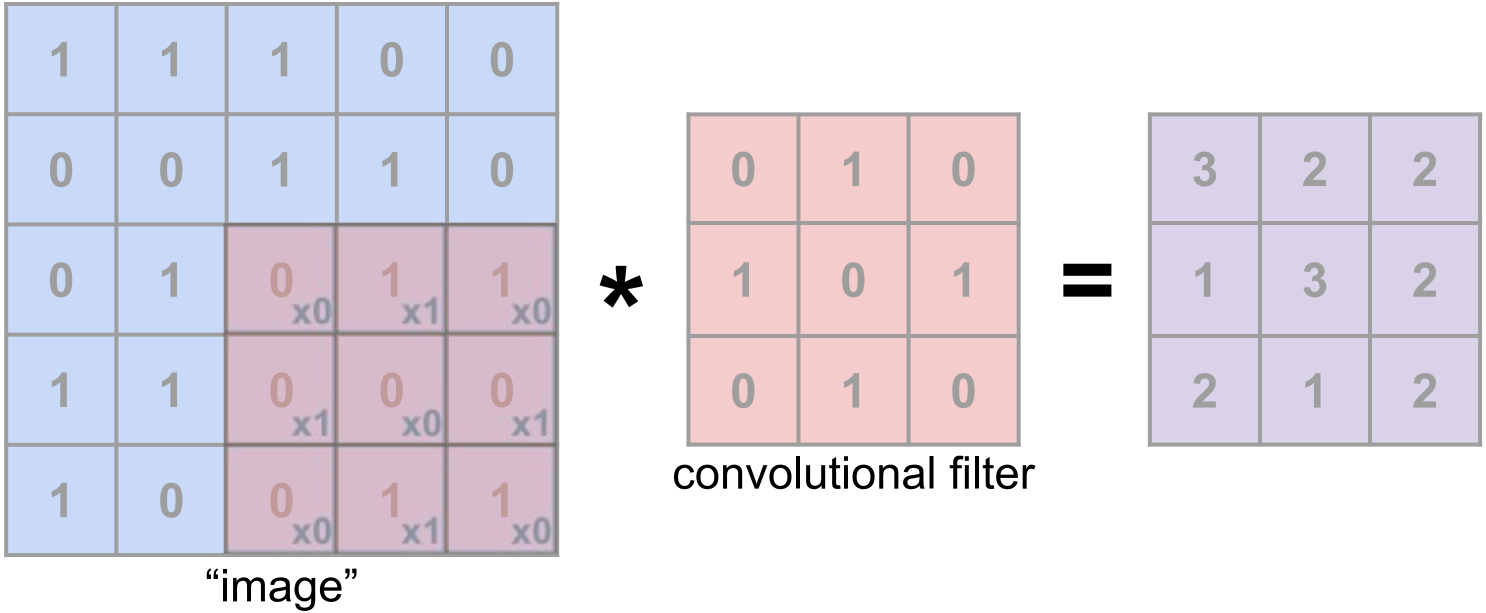
Convolutional Filters



Convolutional Filters



Convolutional Filters



Convolutional Filters

$$\underbrace{\begin{bmatrix} 1 & 1 & 1 & 0 & 0 \\ 0 & 0 & 1 & 1 & 0 \\ 0 & 1 & 0 & 1 & 1 \\ 1 & 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 1 & 1 \end{bmatrix}}_{\text{“image”}} * \underbrace{\begin{bmatrix} 0 & 1 & 0 \\ 1 & 0 & 1 \\ 0 & 1 & 0 \end{bmatrix}}_{\text{convolutional filter}} = \begin{bmatrix} 3 & 2 & 2 \\ 1 & 3 & 2 \\ 2 & 1 & 2 \end{bmatrix}$$

can learn this!

Convolutional Filters

- Aggregates information from local window around pixel
- Translational invariance
- Reduce number of parameters needed to be learned

$$\underset{\text{“image”}}{\begin{bmatrix} 1 & 1 & 1 & 0 & 0 \\ 0 & 0 & 1 & 1 & 0 \\ 0 & 1 & 0 & 1 & 1 \\ 1 & 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 1 & 1 \end{bmatrix}} * \underset{\text{convolutional filter}}{\begin{bmatrix} 0 & 1 & 0 \\ 1 & 0 & 1 \\ 0 & 1 & 0 \end{bmatrix}} = \begin{bmatrix} 3 & 2 & 2 \\ 1 & 3 & 2 \\ 2 & 1 & 2 \end{bmatrix}$$

Discuss with your Neighbor!

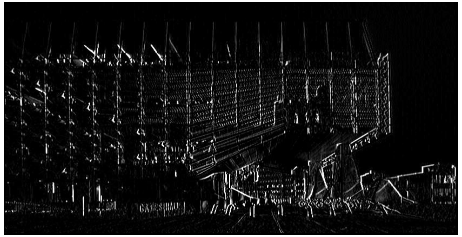
Match the following convolutional filters with the output they produce.

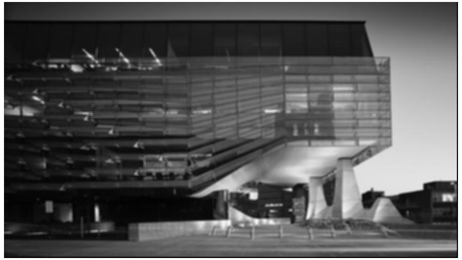
input image

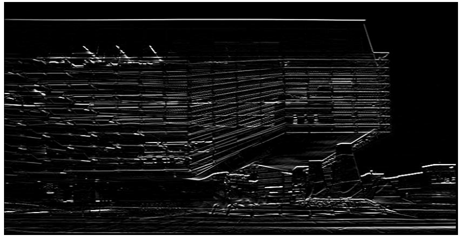
-1	-1	-1
0	0	0
1	1	1

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

1/9	1/9	1/9
1/9	1/9	1/9
1/9	1/9	1/9







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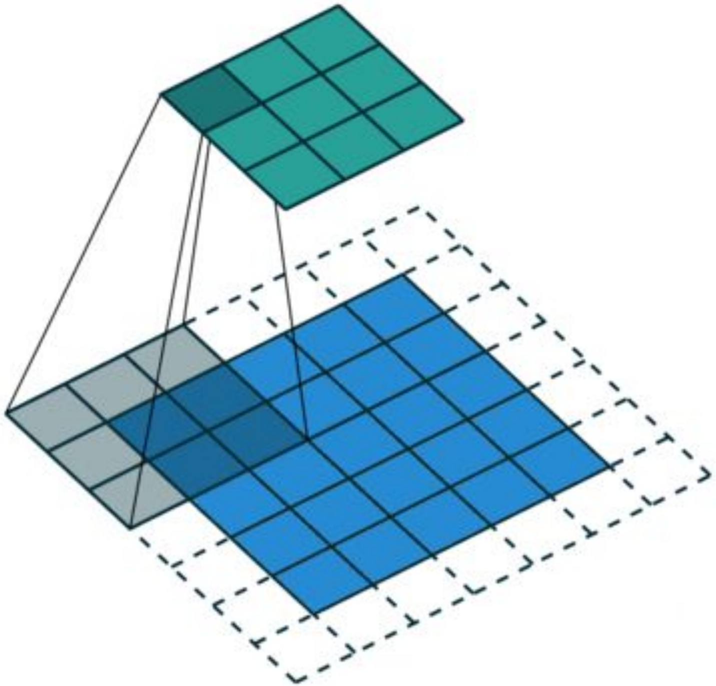
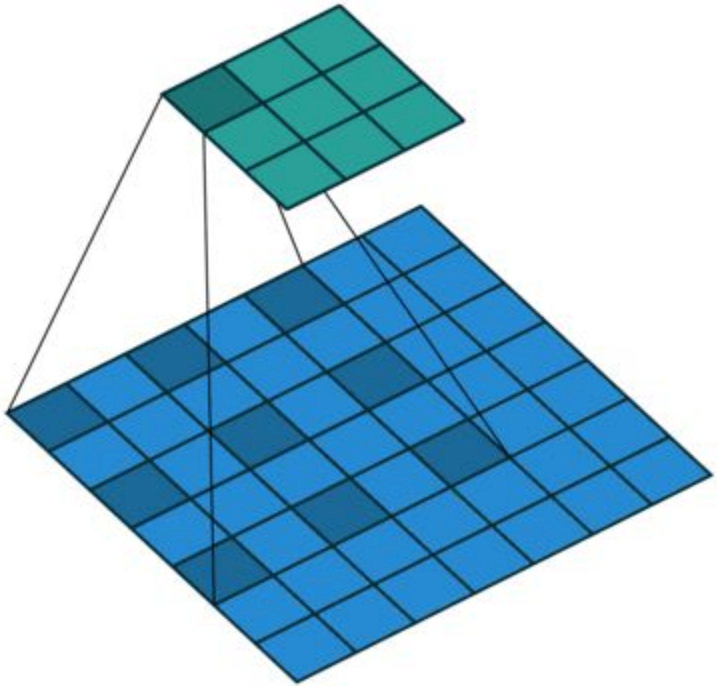
Dilated Convolutions





https://towardsdatascience.com/review-dilated-convolution-semantic-segmentation-9d5a5bd768f5

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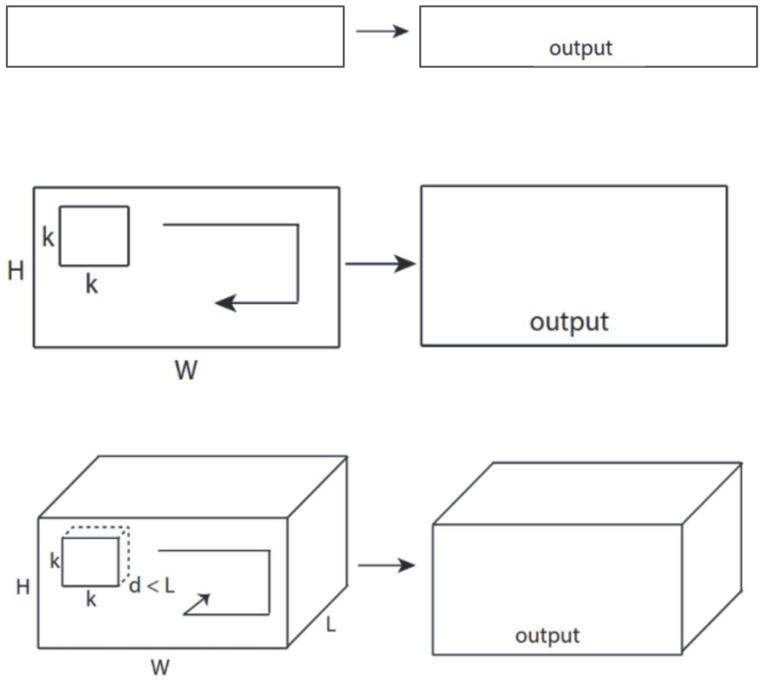
1D and 3D Convolutions



https://wandb.ai/ayush-thakur/dl-question-bank/reports/Intuitive-understanding-of-1D-2D-and-3D-convolutions-in-convolutional-neural-networks---VmlldzoxOTk2MDA

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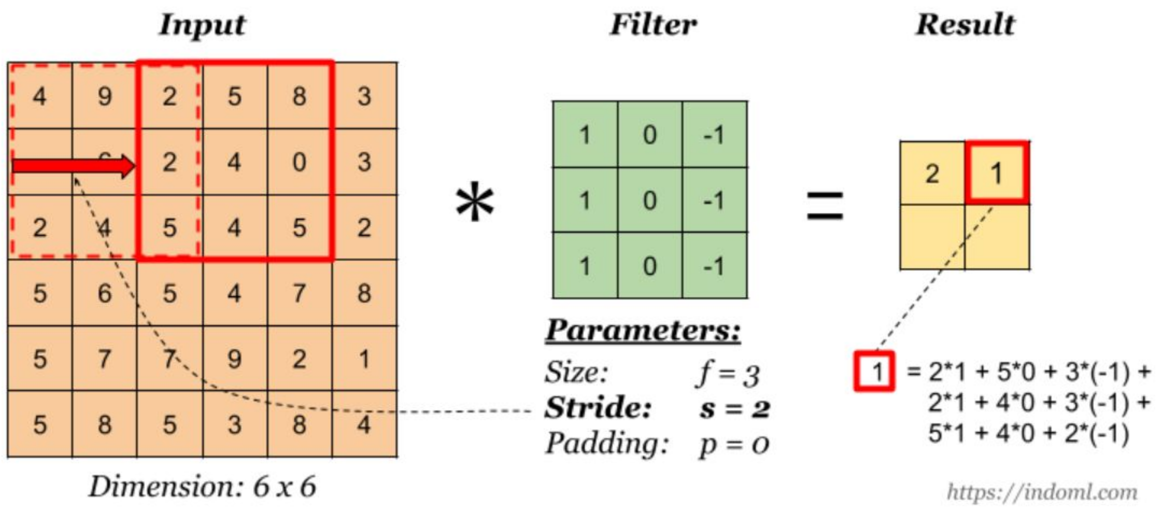
CNNs - Stride

- Stride controls how many units the filter / the receptive field shift at a time
- The size of the output image shrinks more as the stride becomes larger
- The receptive fields overlap less as the stride becomes larger



Filter with stride (s) = 2

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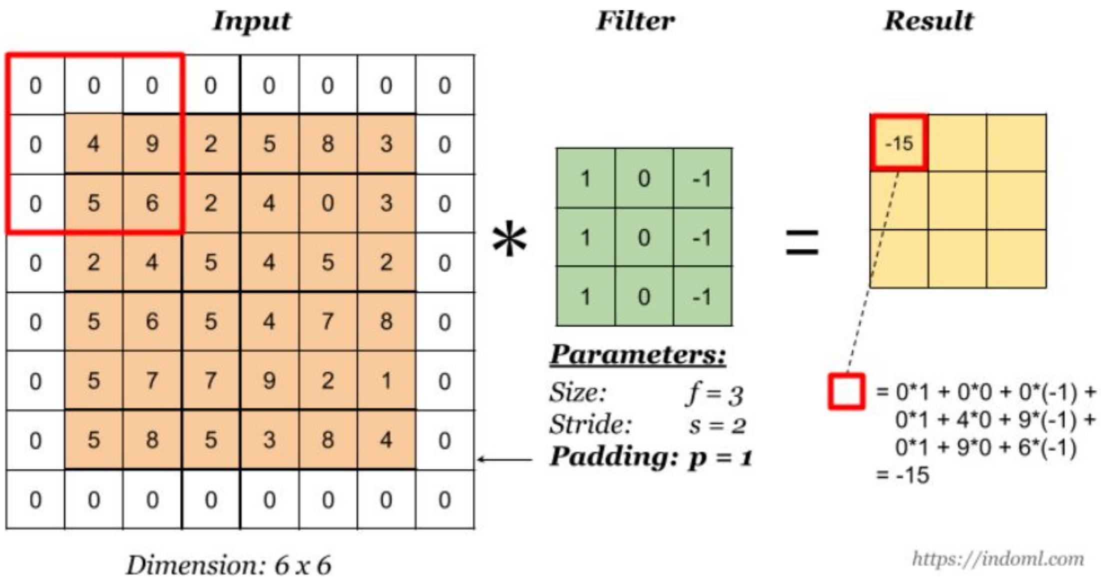
CNNs - Padding

- ❖ Padding adds layers of zeros (or other number) around image border
- ❖ Prevents image shrinking and loss of information from image boundary



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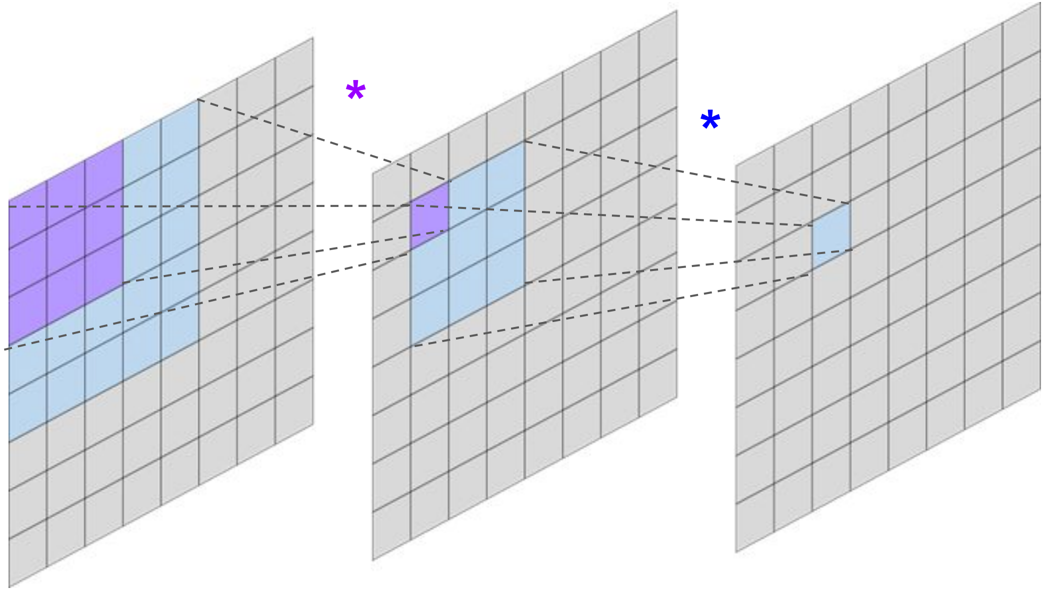
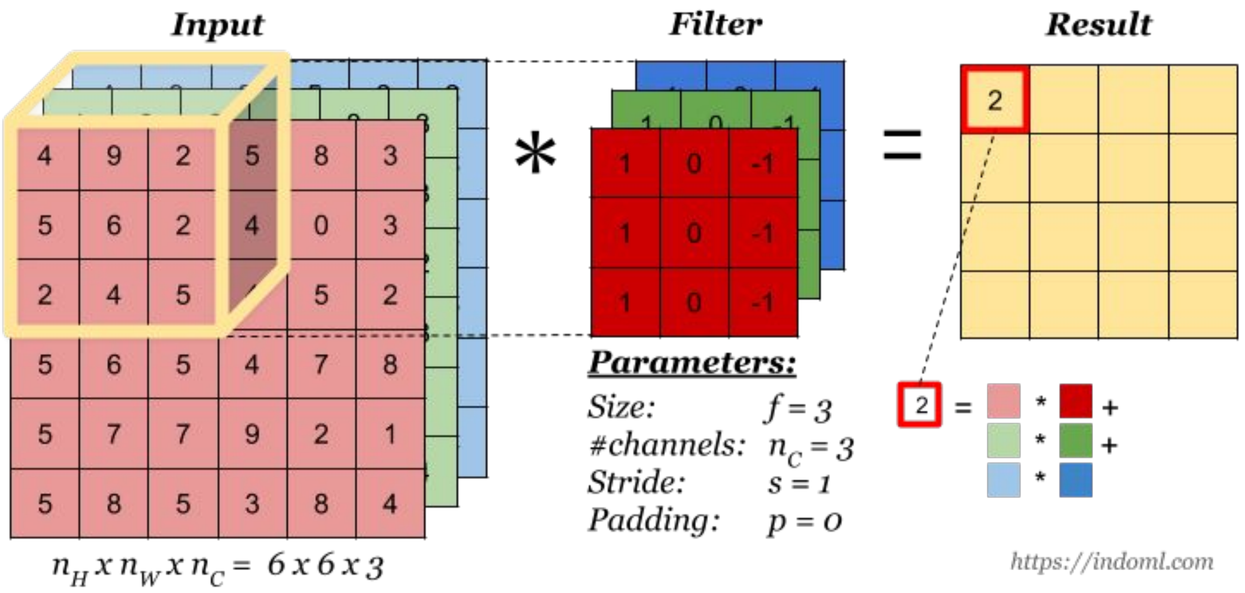
Stacking Convolutions



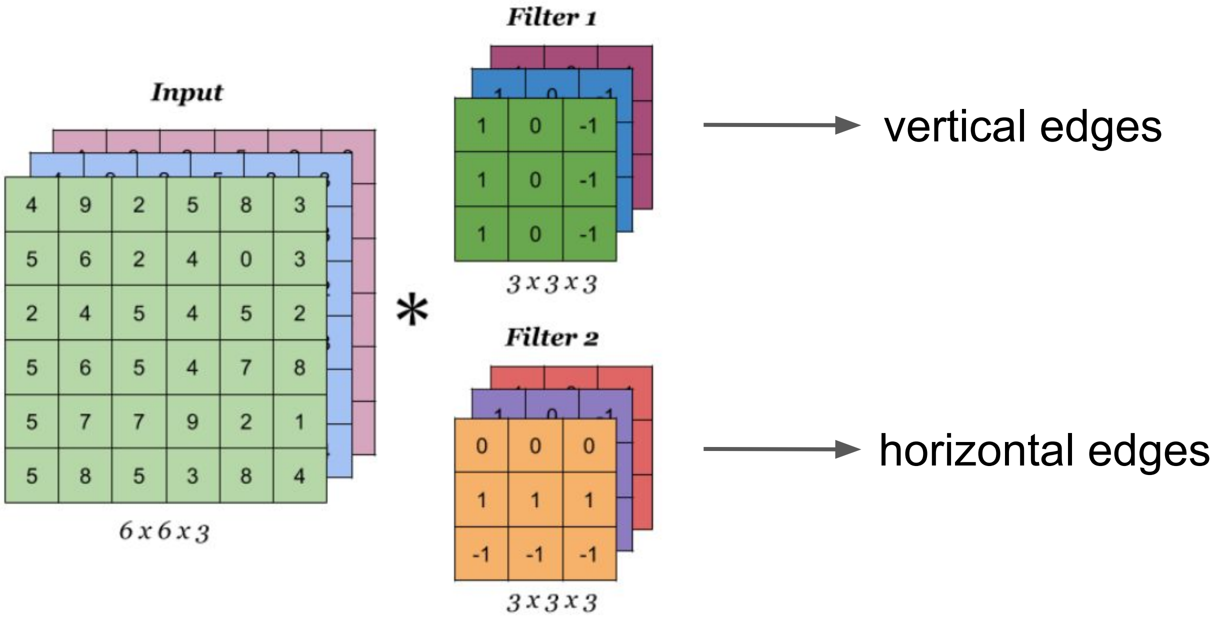
- Size of receptive field increases with each layer
- Capture more complex features

Convolution Over Volumes

What if our input image has more than one channel?



Convolution Operation with Multiple Filters



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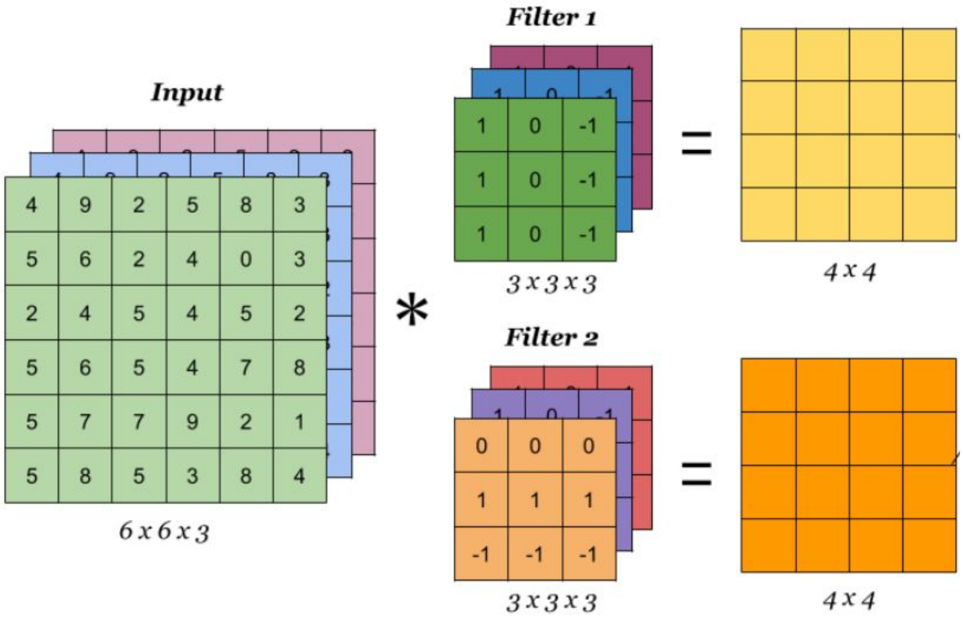
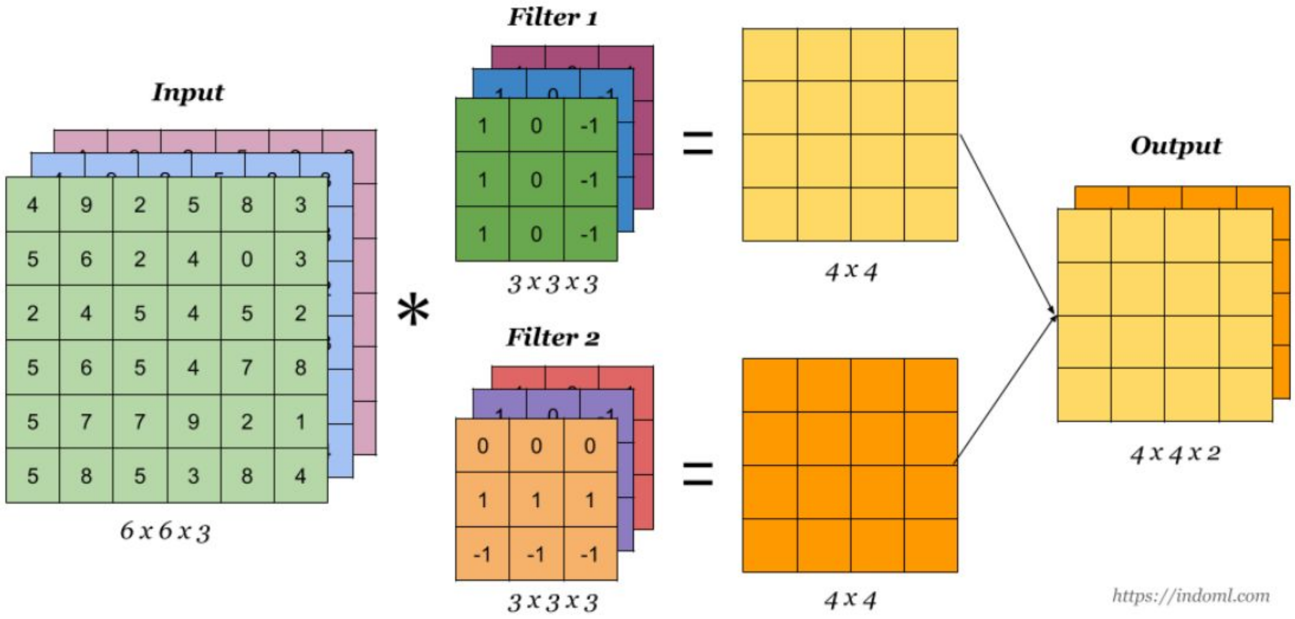
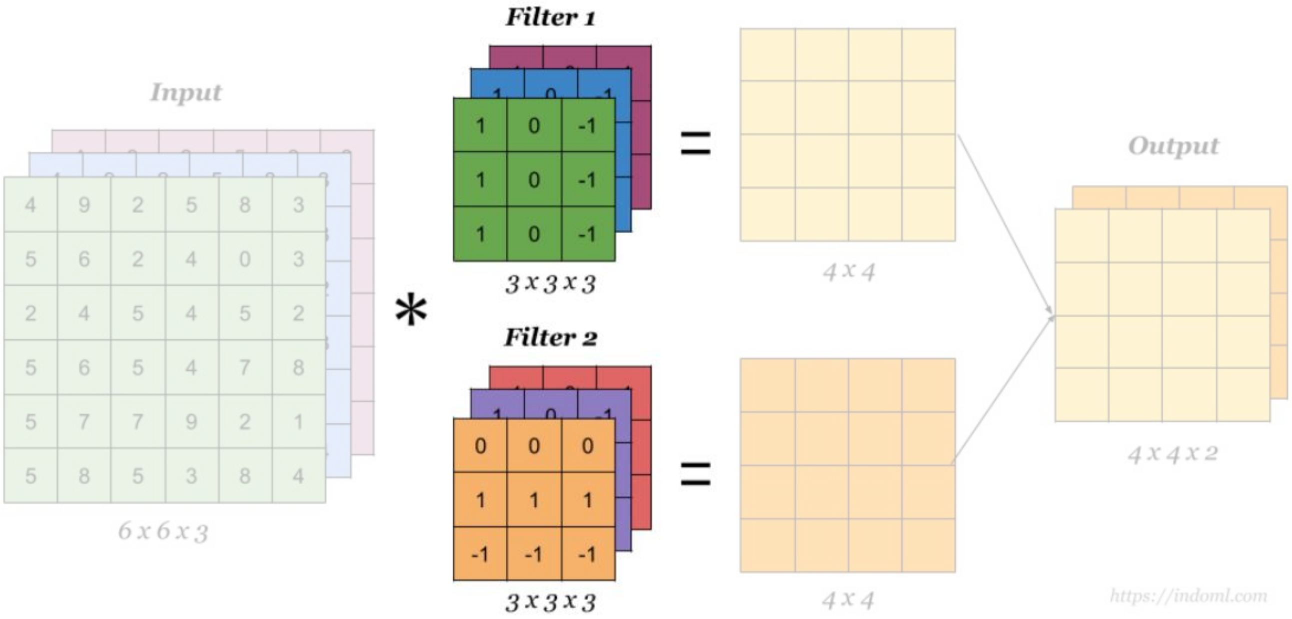
Convolution Operation with Multiple Filters



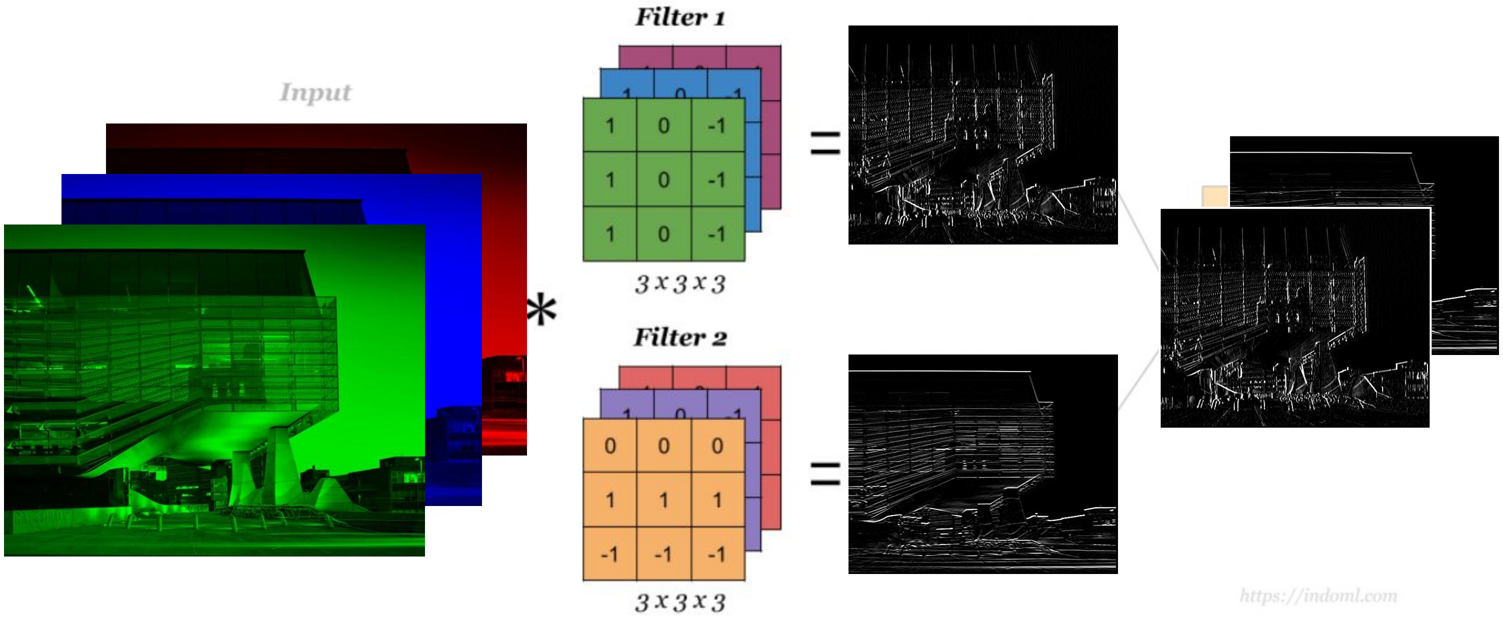
Convolution Operation with Multiple Filters



Convolution Operation with Multiple Filters

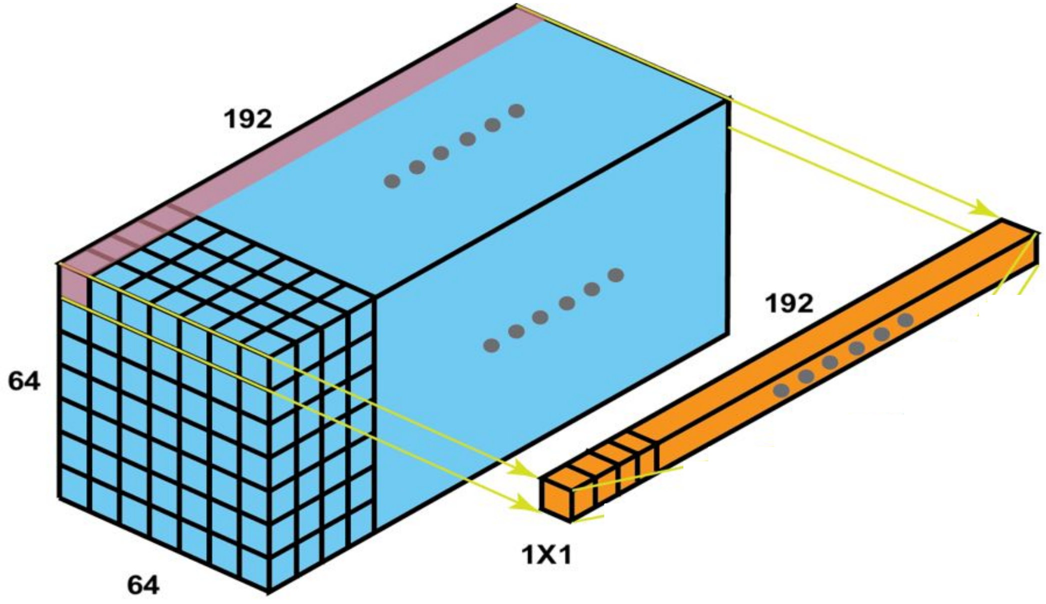


Convolution Operation with Multiple Filters



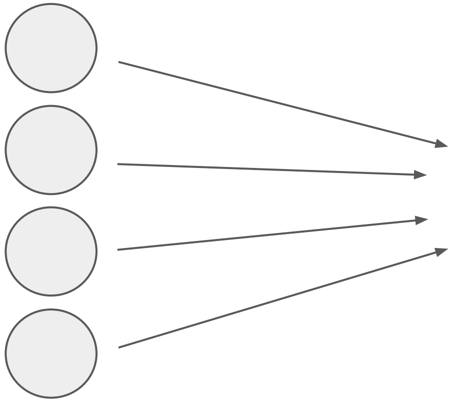
Discuss: 1x1 Convolutions

What is the result of convolving a 64x64x192 dimensional cube with a 1x1 filter?

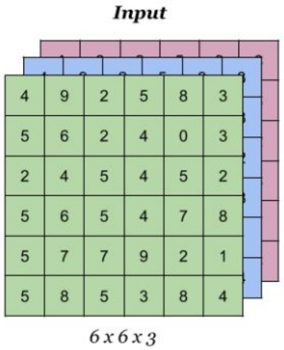


Convolution Layer

MLP Layer

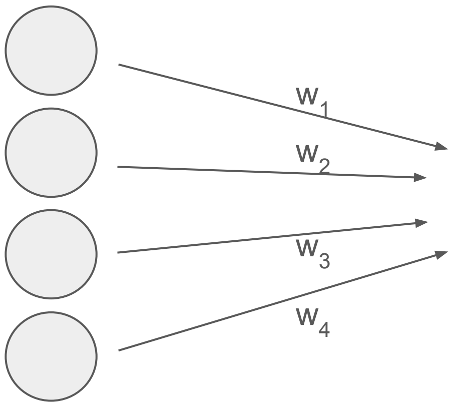


Convolution Layer

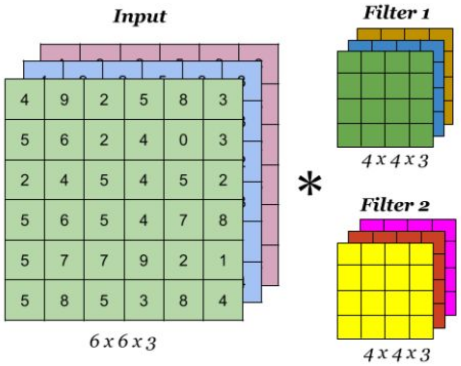


Convolution Layer

MLP Layer

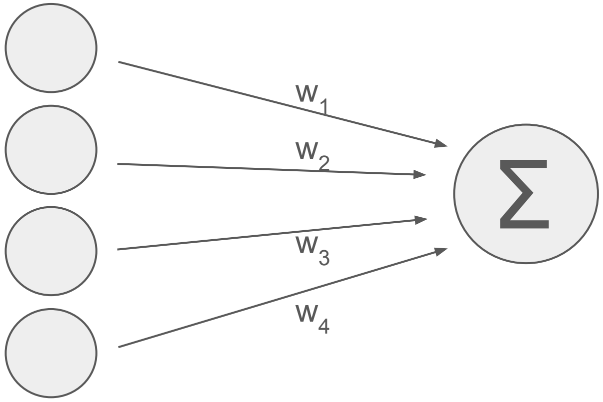


Convolution Layer

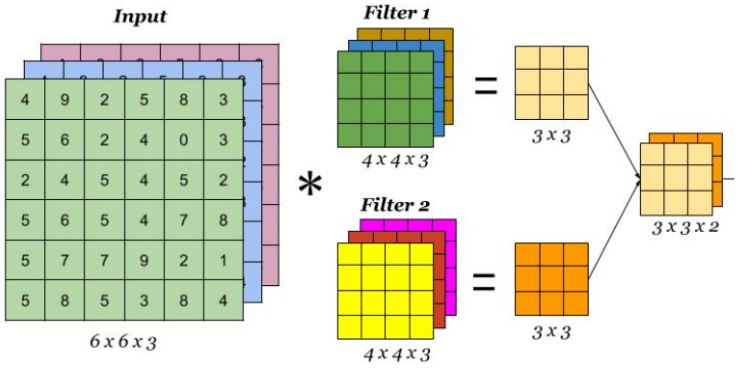


Convolution Layer

MLP Layer

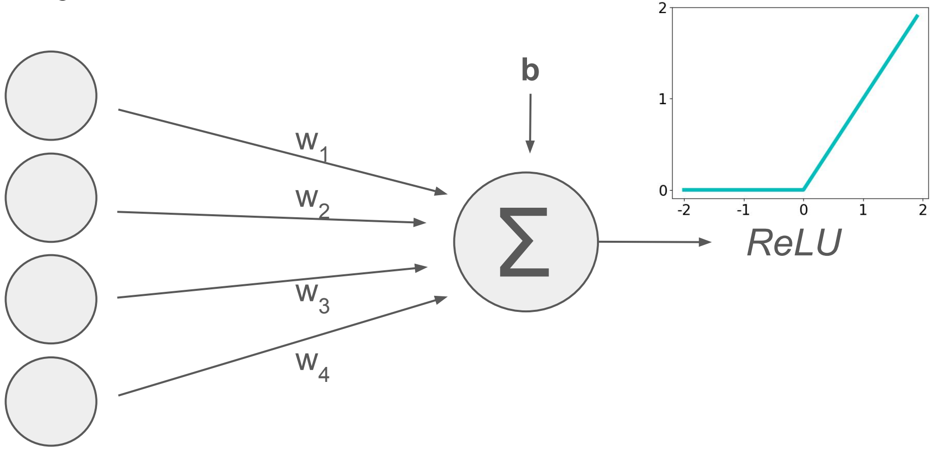


Convolution Layer

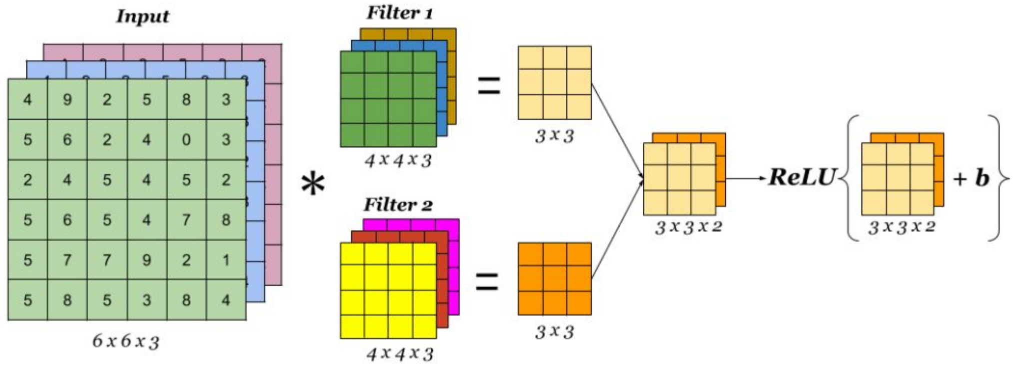


Convolution Layer

MLP Layer



Convolution Layer



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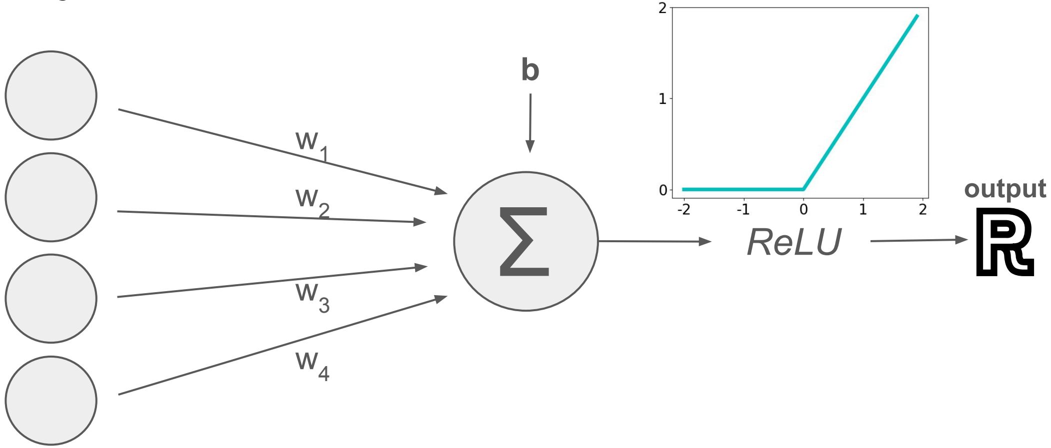
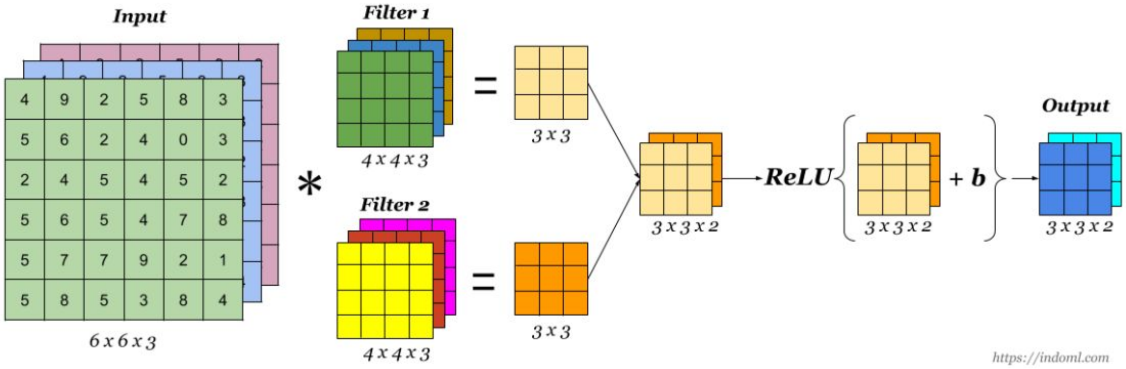
Convolution Layer

MLP Layer



Convolution Layer

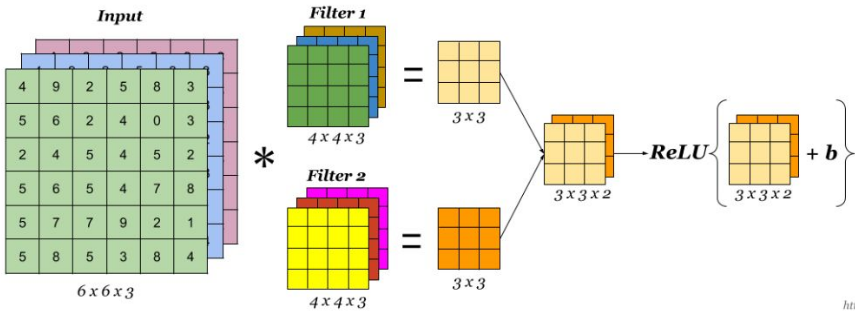


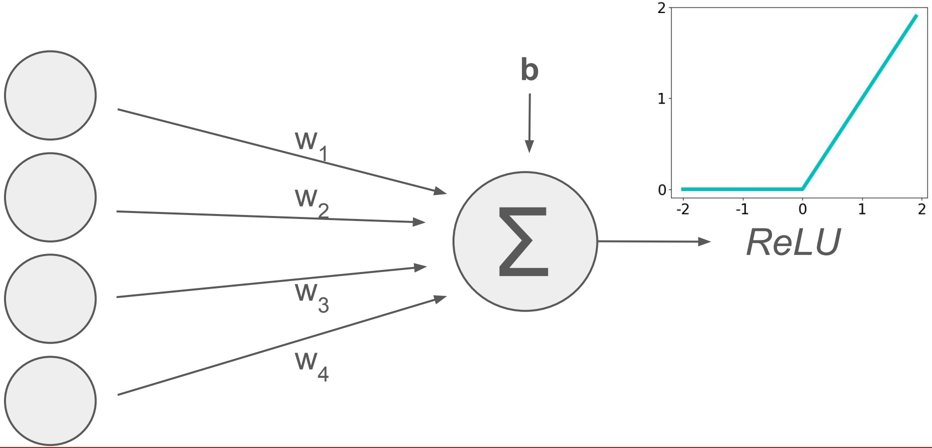
CNN/MLP Equivalence

Differences in a convolution layer:

- neurons are connected to a local region
- Weights are shared across multiple parameters

CONV layers can be converted to Fully connected layers and vice versa!





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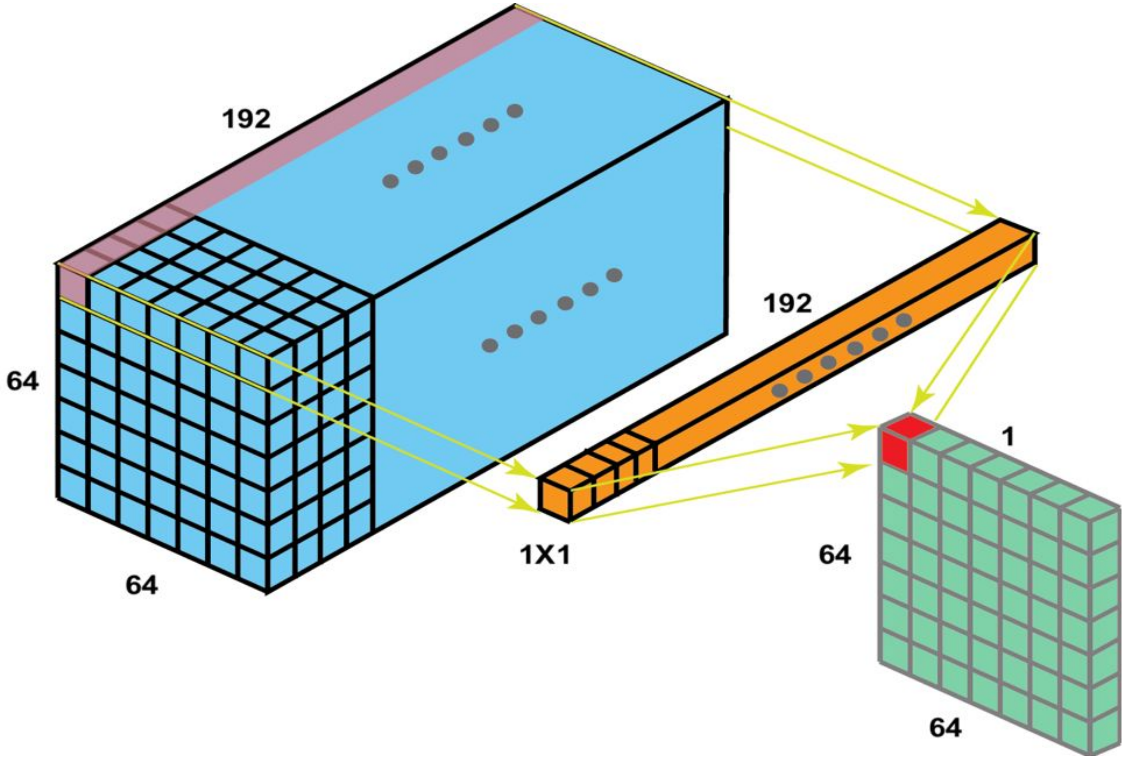
Discuss: Trade-offs between CNNs and MLPs

How would this image change if you used an MLP instead of a 1x1 convolution filter to produce a (64x64x1) feature map? Hint: think about parameter counts and feature interactions.



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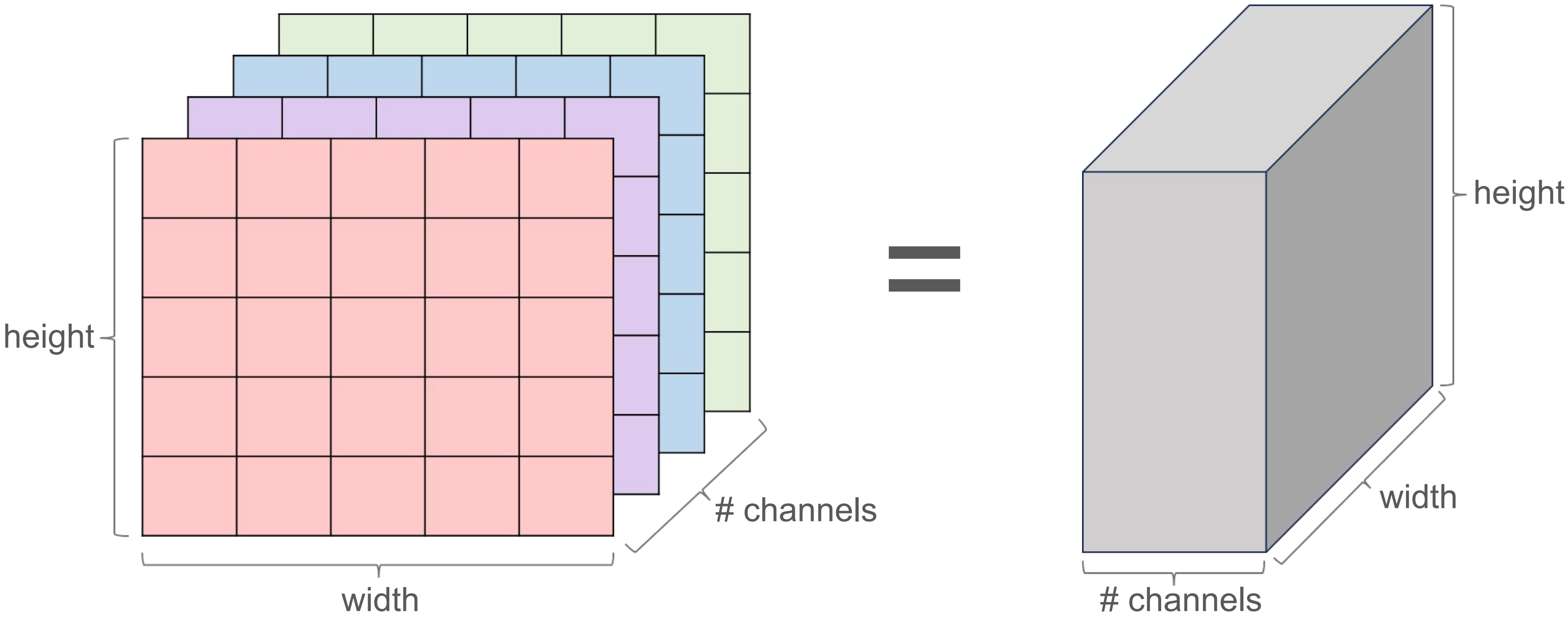
CNN Layer Output Visualization



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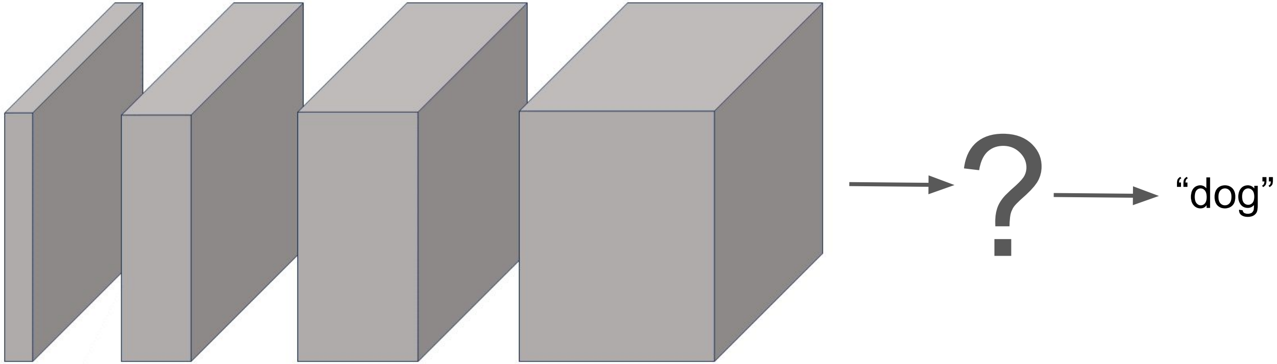
Convolutional Neural Networks (CNNs)

✅ **Convolutions**

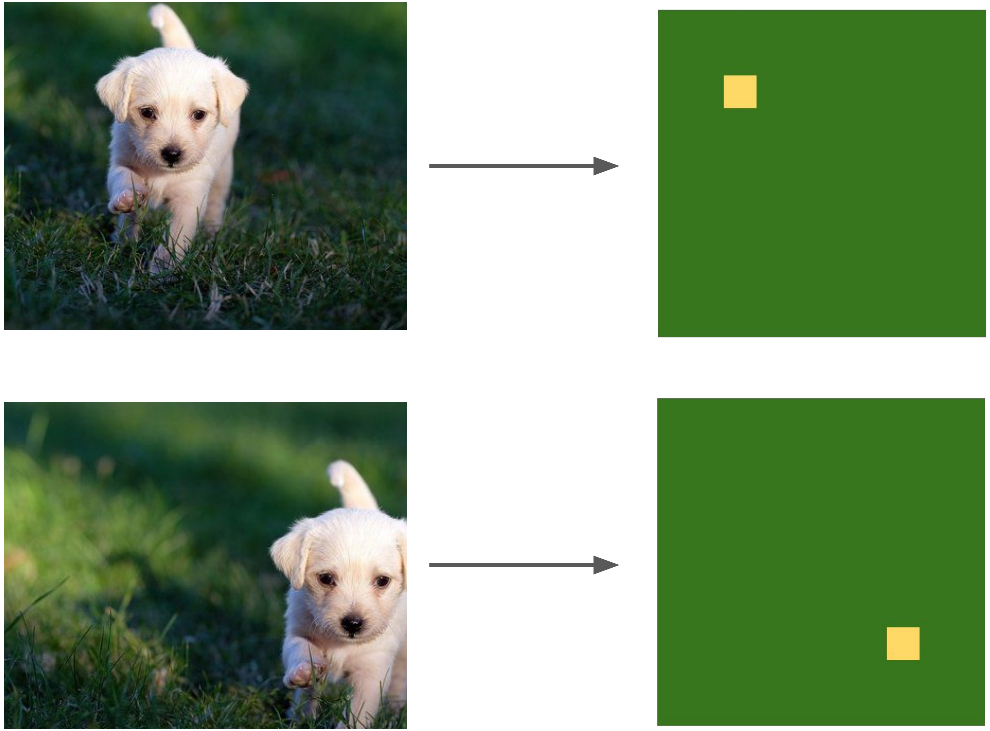
Maintain spatial relation between pixels

Reduce number of parameters through weight sharing

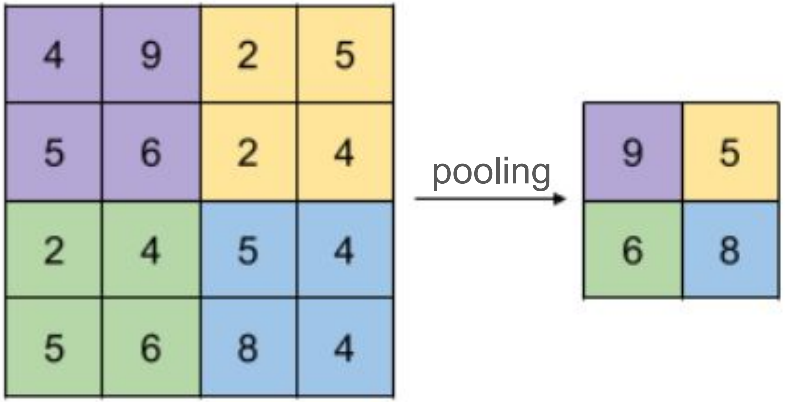
input image



Ensuring translational invariance



Max Pooling



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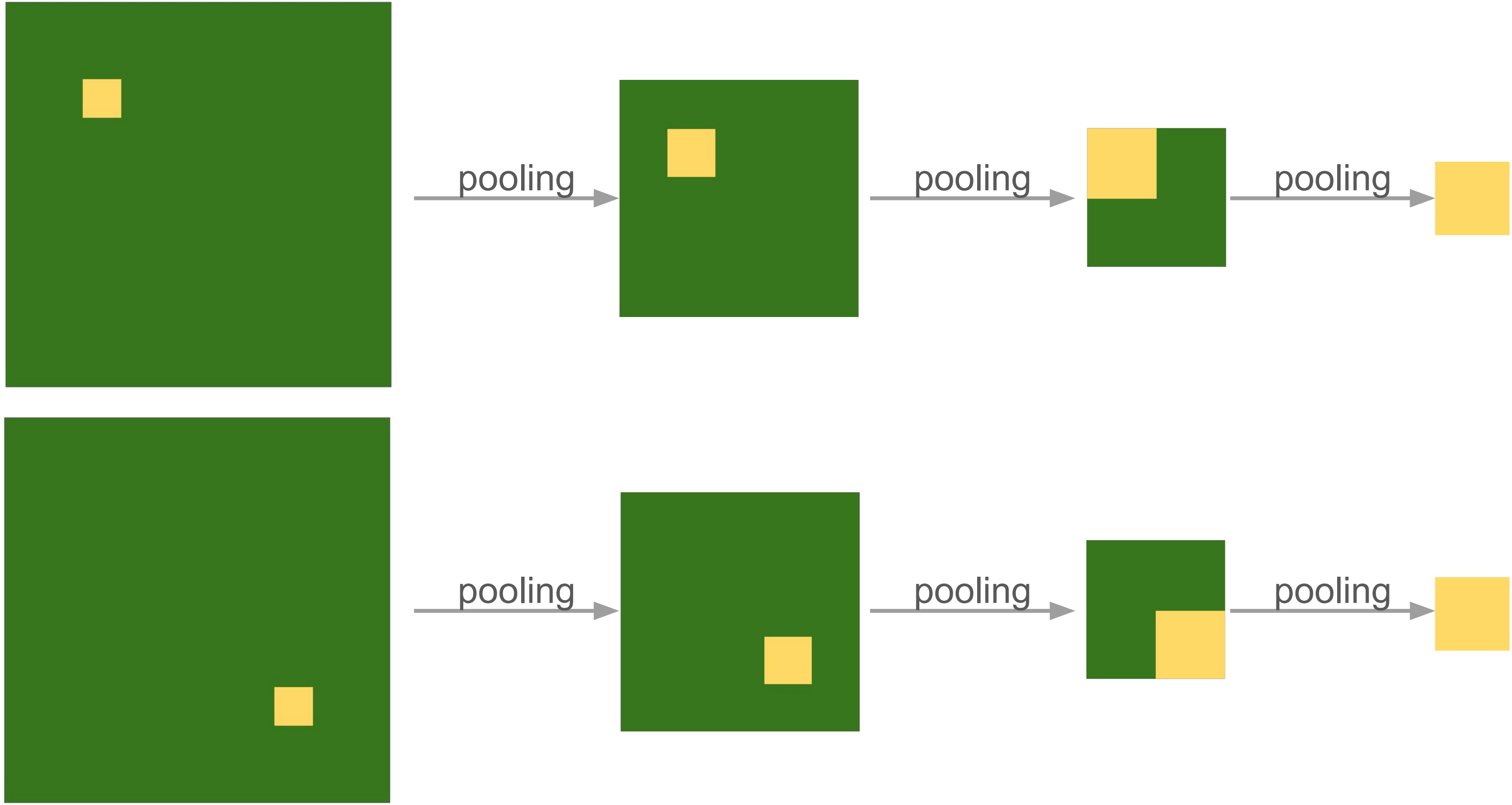
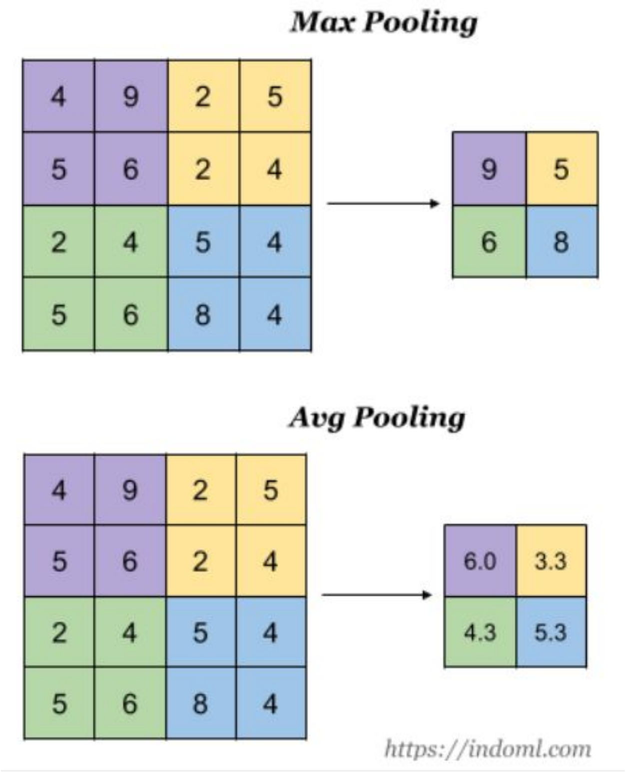
CNNs - Pooling



CNNs - Pooling

- ❖ Down sample feature maps that highlight the most present feature in the patch
- ❖ Improve efficiency by reducing computations with downsampling
- ❖ Increase receptive field size

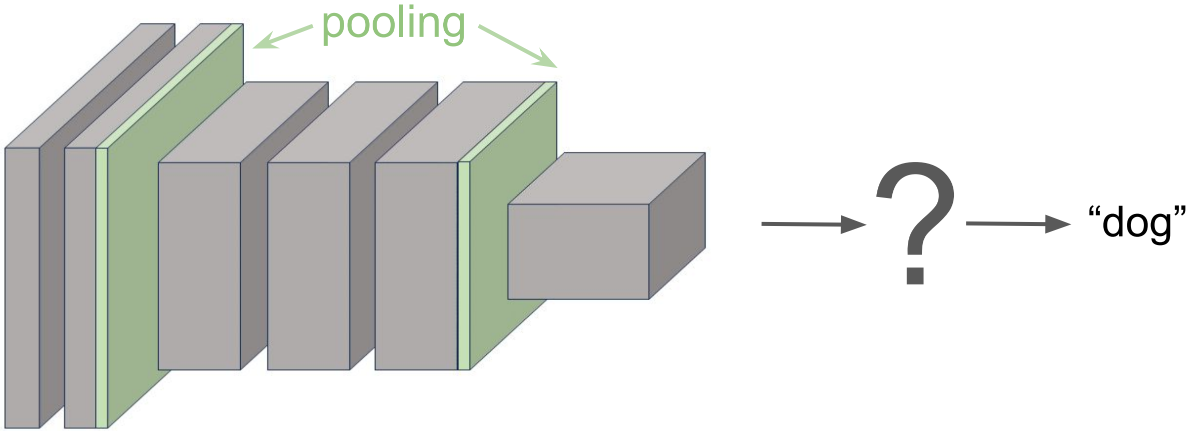


Convolutional Neural Networks (CNNs)

✅ Convolutions — Maintain spatial relation between pixels
Reduce number of parameters through weight sharing

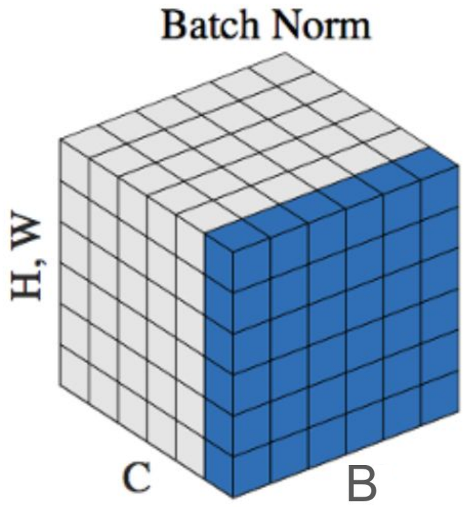
✅ **Pooling** — Captures key information from across different areas of the feature maps
Together with convolutions allows for translational invariance


input image



Normalization

- Normalize channels to mean 0 and variance 1 across each training batch
- Increases speed of training by enabling the use of larger learning rates
- Improves stability of training



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The Batch Normalization Algorithm

Input: Values of x over a mini-batch: $\mathcal{B} = \{x_{1 \ldots m}\}$;
Parameters to be learned: γ, β

Output: $\{y_i = \mathrm{BN}_{\gamma,\beta}(x_i)\}$

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

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

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

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

Algorithm 1: Batch Normalizing Transform, applied to activation x over a mini-batch.

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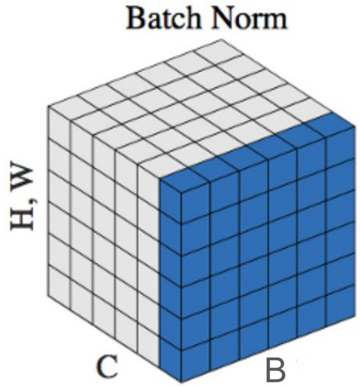
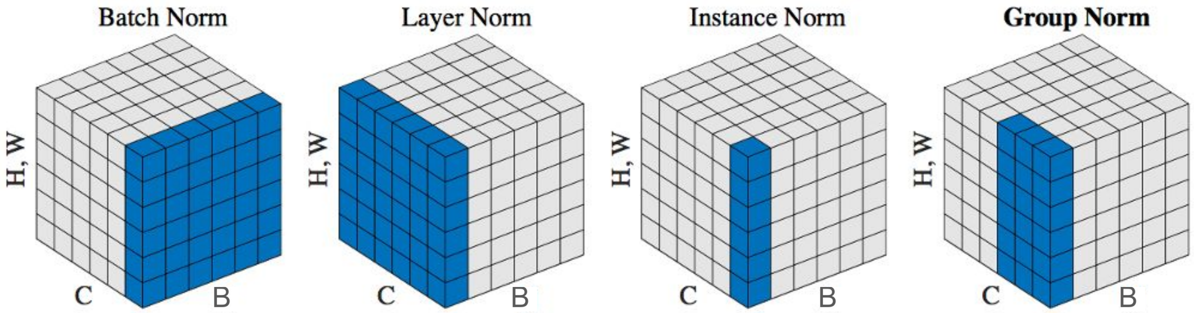
Discuss!

What is the dimension of the mean when you compute the batch norm of a volume of dimension (b x c x h x w)?



Normalization Layers

- Normalization layers improve training stability
- Can train with larger learning rates
  - Faster training
- A large learning rate acts as an implicit regularizer
  - Better generalization
- Normalization can also be applied across different dimensions for different use cases



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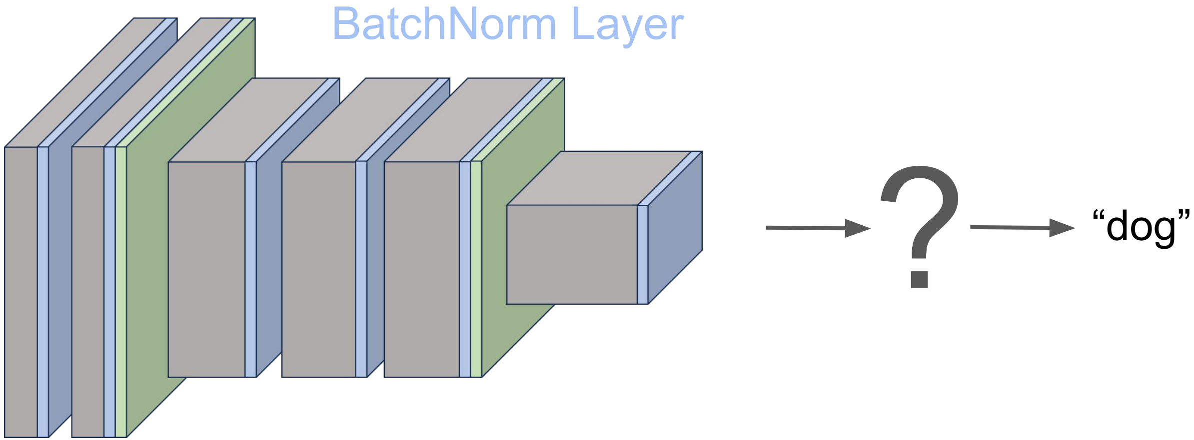
Convolutional Neural Networks (CNNs)

✅ Convolutions — Maintain spatial relation between pixels
Reduce number of parameters through weight sharing

✅ Pooling — Captures key information from across different areas of the feature maps
Together with convolutions allows for translational invariance

✅ **BatchNorm** — Increases speed and stability of training

input image



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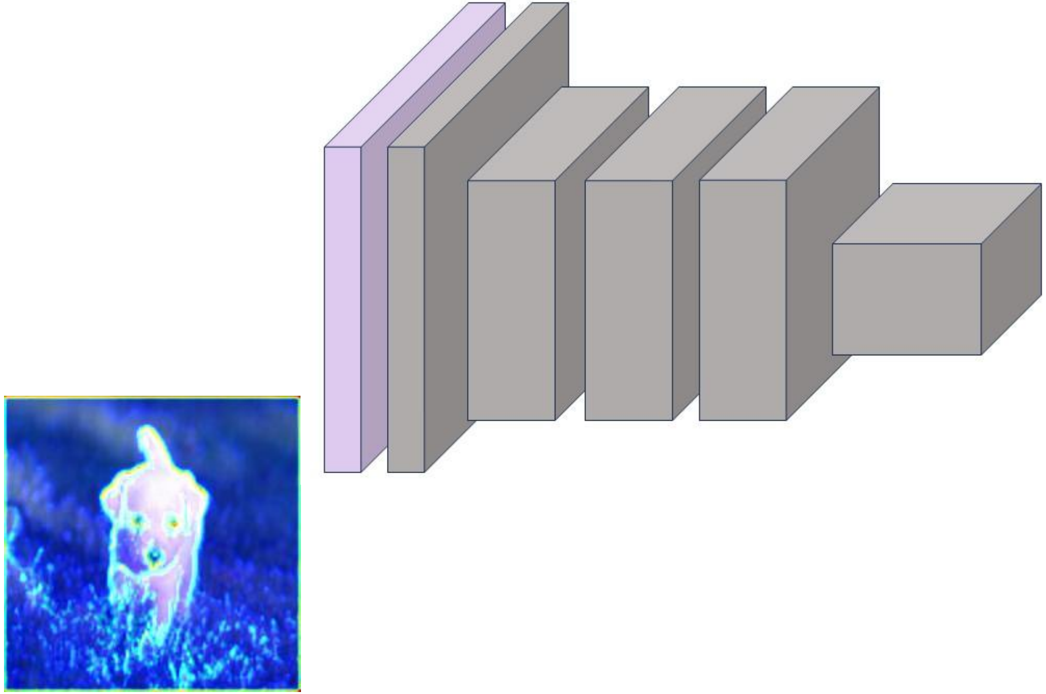
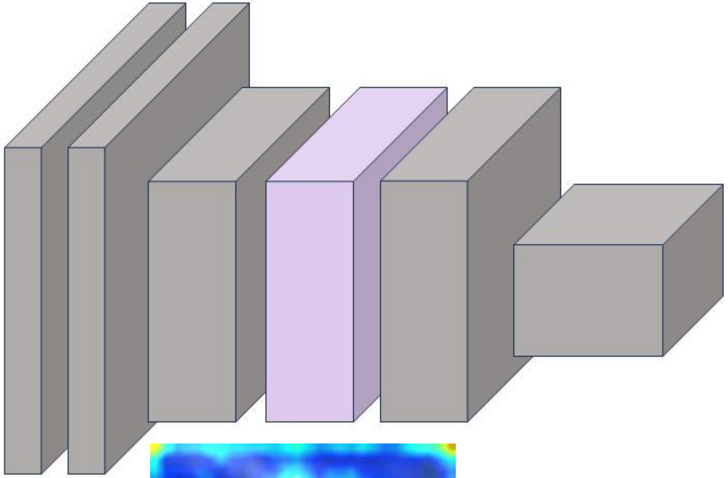
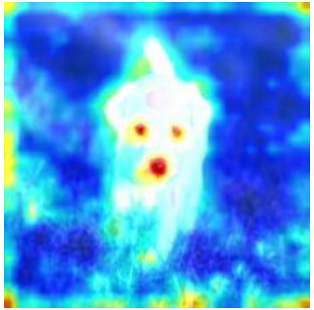
Convolutional Neural Networks (CNNs)

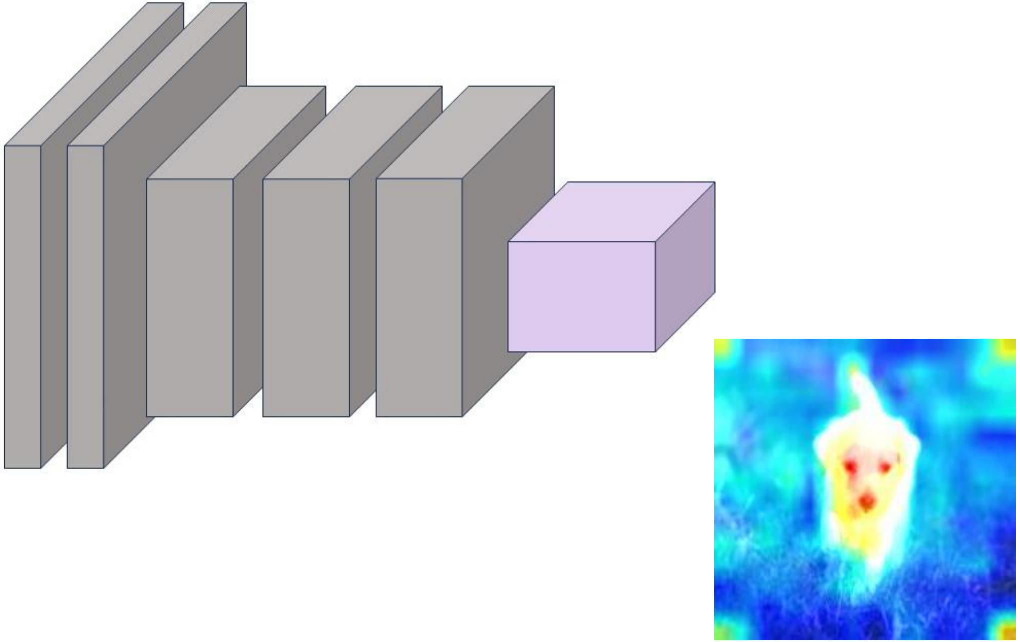


Convolutional Neural Networks (CNNs)





Convolutional Neural Networks (CNNs)



Convolutional Neural Networks (CNNs)

✅ Convolutions — Maintain spatial relation between pixels
Reduce number of parameters through weight sharing

✅ Pooling — Captures key information from across different areas of the feature maps
Together with convolutions allows for translational invariance

✅ BatchNorm — Increases speed and stability of training

input image

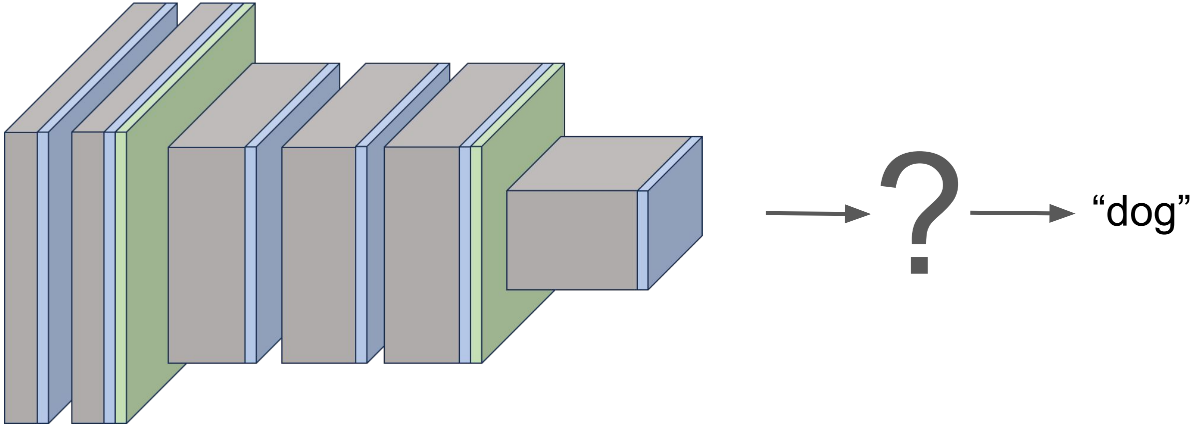


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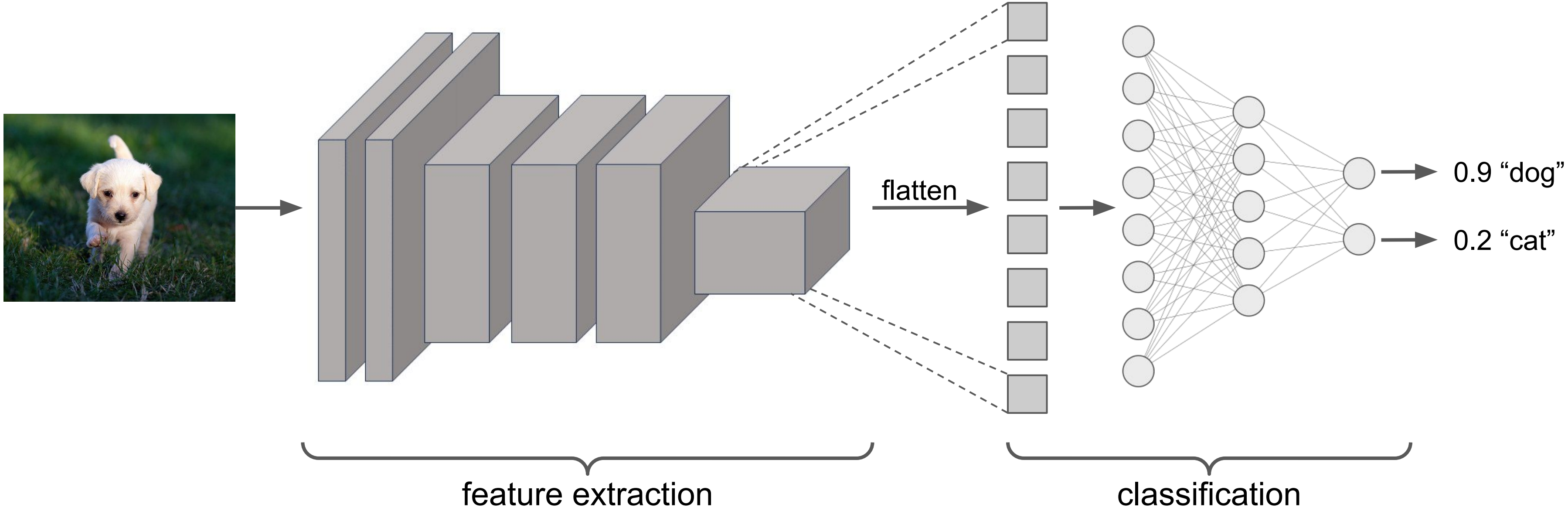
Image Classification



Practical Guide

- Input image dimensions is divisible by 2
- Small conv filters (3x3 or 5x5)
- Zero padding is used to maintain spatial resolution
- Max pooling for downsampling
- Pooling layers have a receptive field of 2 and stride of 2

Summary

- CNNs are primarily designed to process and analyze visual data, such as images and videos.
- Key components: convolution layers, pooling layers, activation functions, normalization layers
- Advantages:
  - Translational Invariance
  - Parameter sharing
  - Feature learning
- Can be trained with backprop
- Used for tasks such as segmentation, classification, object detection, etc.