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

Image Classification

input image

classification →

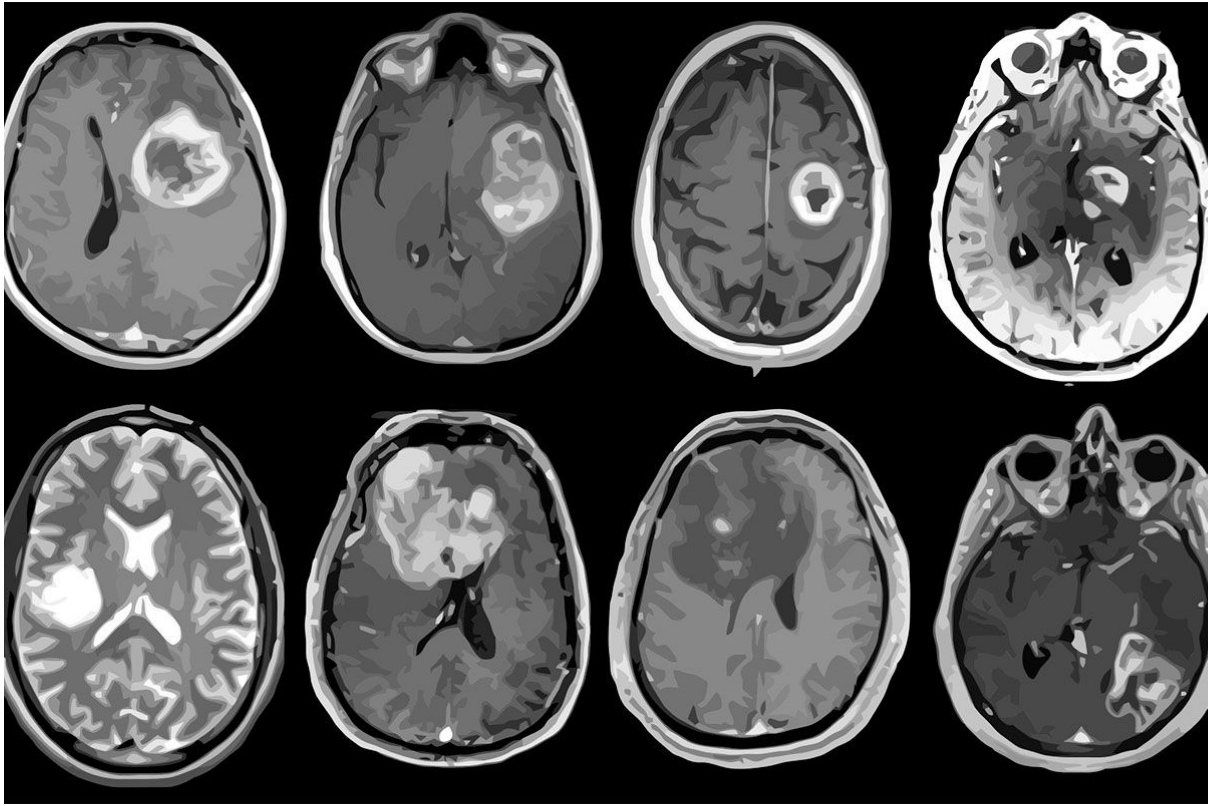
“dog”

input image

classification →

“cat”

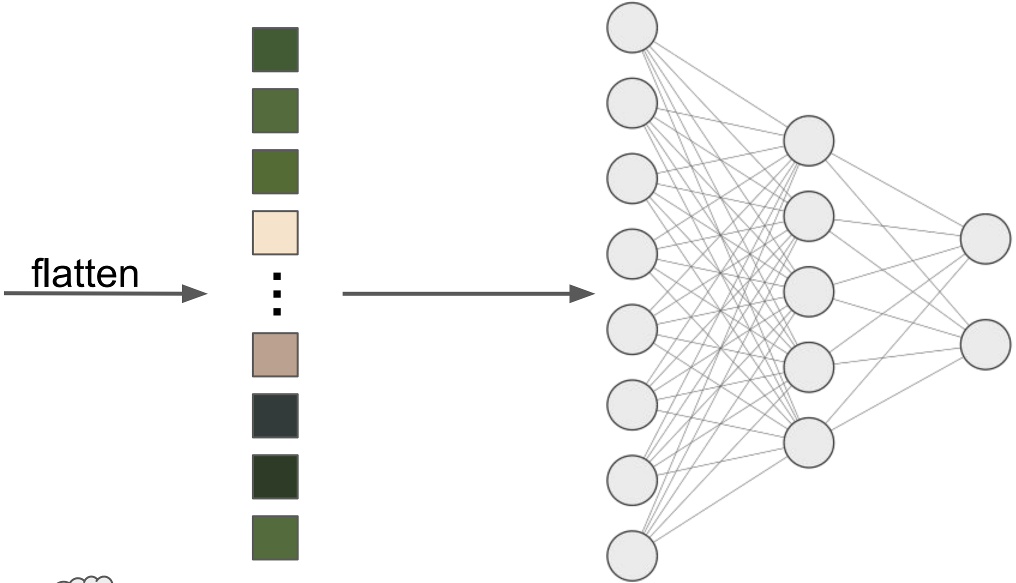
Applications in Medicine



Cornell Bowers C·IS

Applications in Autonomous Driving

Why not use a Multi-Layer Perceptron?



Which pixels were next to each other?

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”

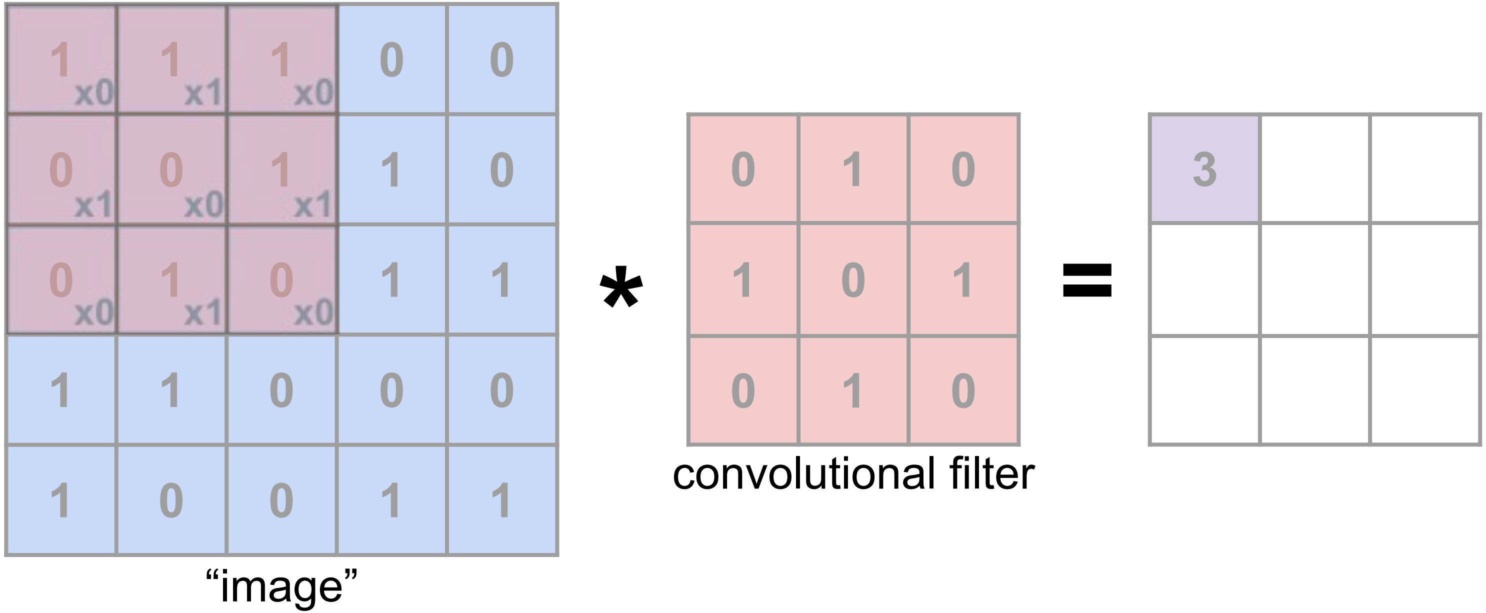
*

0	1	0
1	0	1
0	1	0

convolutional filter

Cornell Bowers C·IS

Convolutional Filters



Cornell Bowers C·IS

Discuss with your Neighbor!

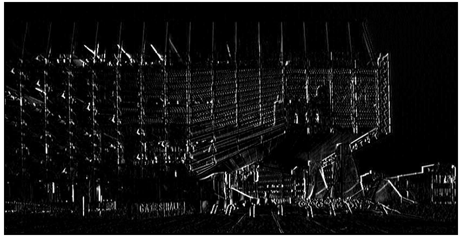
Match the following convolutional filters with the output they produce.

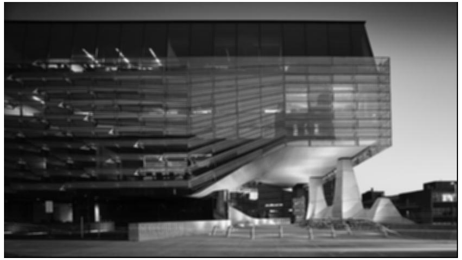
input image

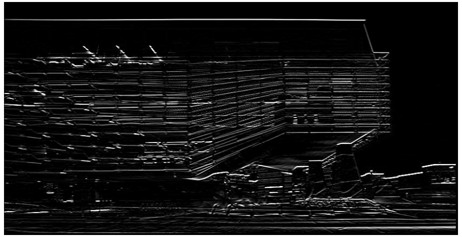
-1	-1	-1
0	0	0
1	1	1

-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



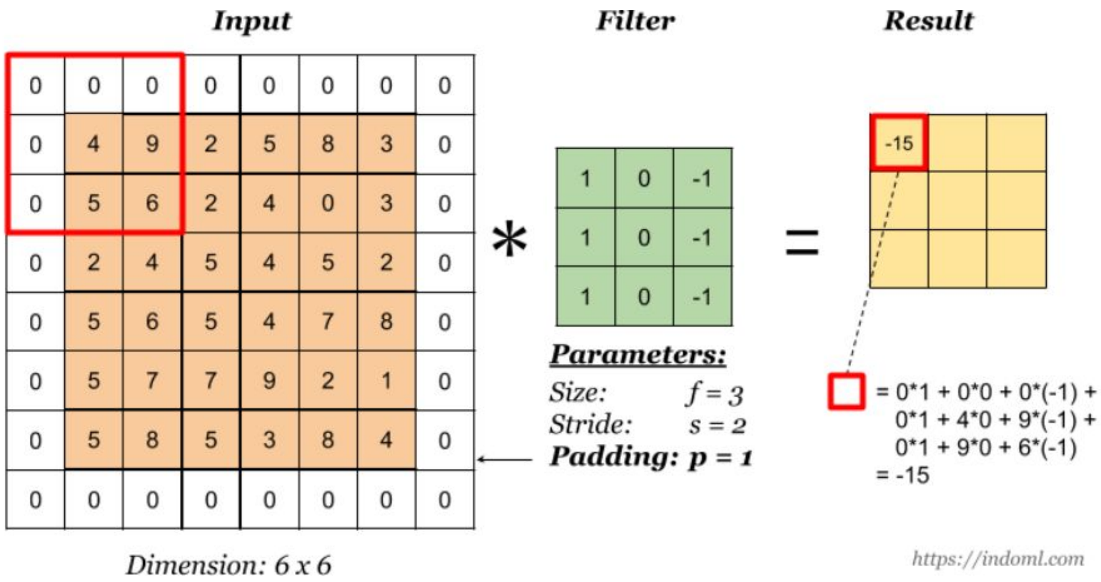




Cornell Bowers C·IS

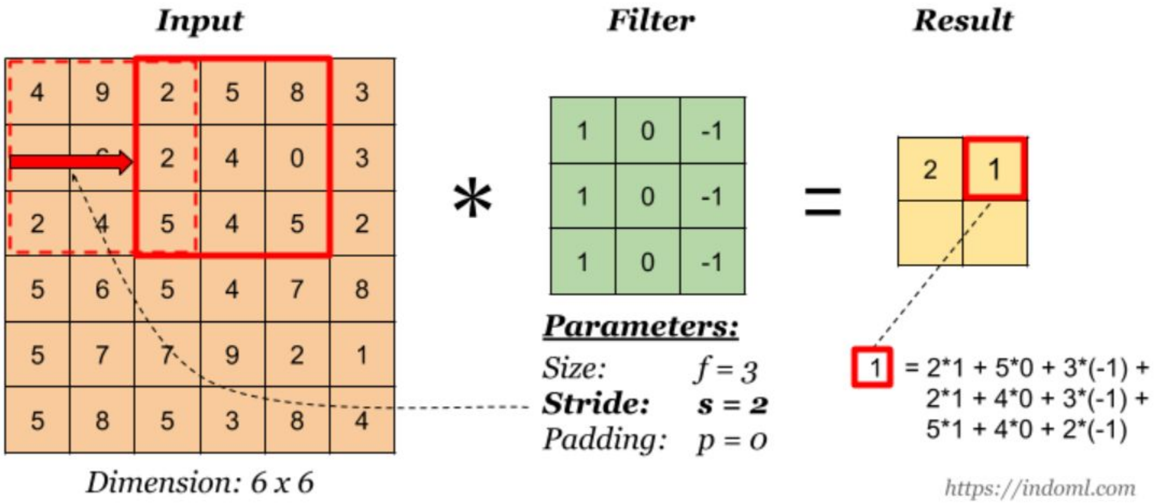
CNNs - Padding

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



CNNs - Stride

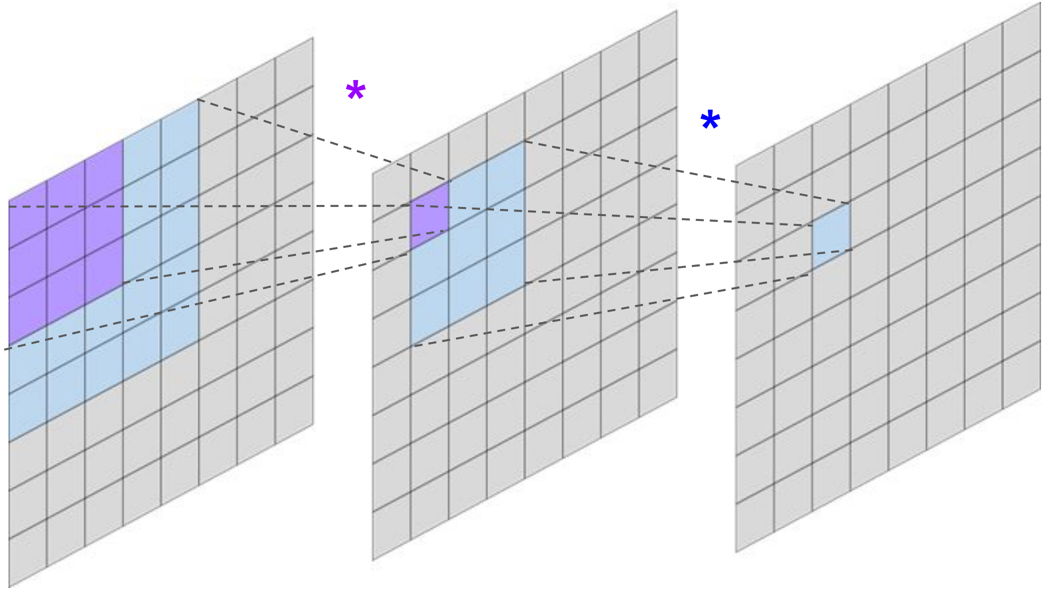
- Stride controls how many units the filter / the receptive field shift at a time
- The size of the output image shrinks more as the stride becomes larger
- The receptive fields overlap less as the stride becomes larger



Filter with stride (s) = 2

Cornell Bowers C·IS

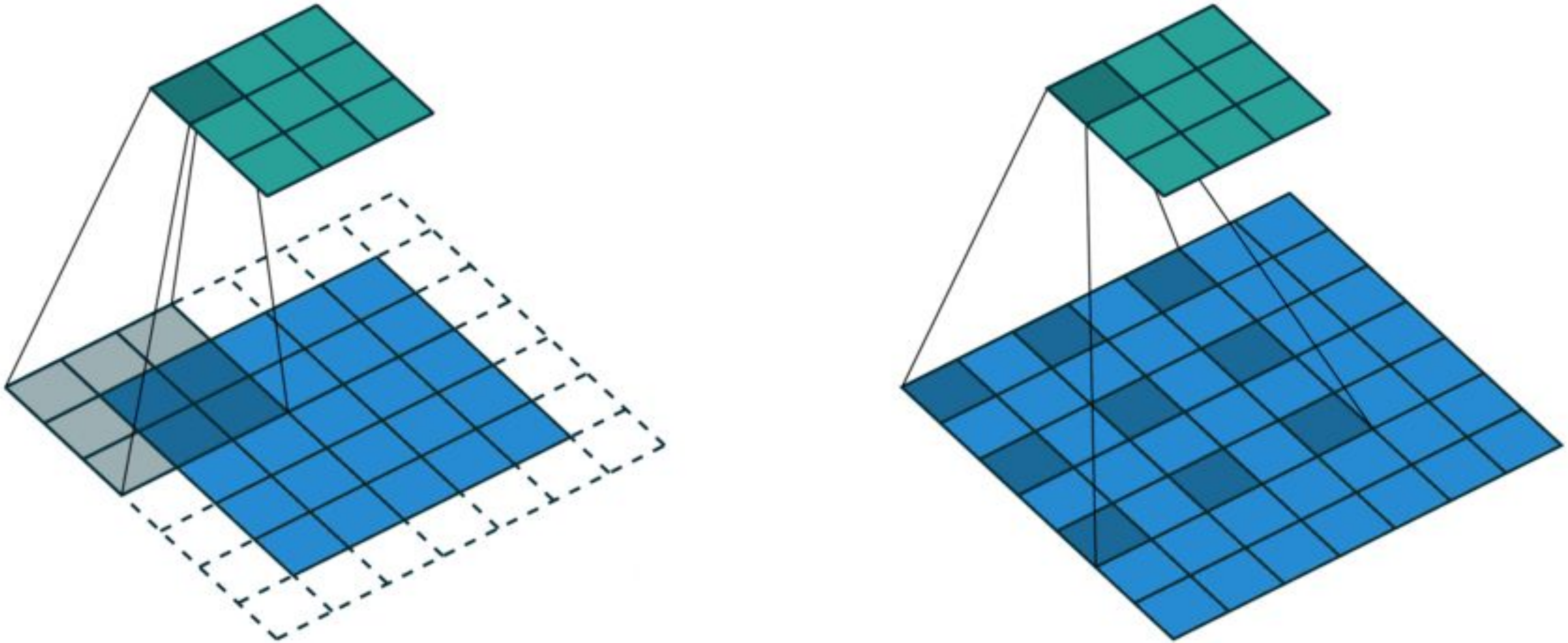
Stacking Convolutions



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

Cornell Bowers C·IS

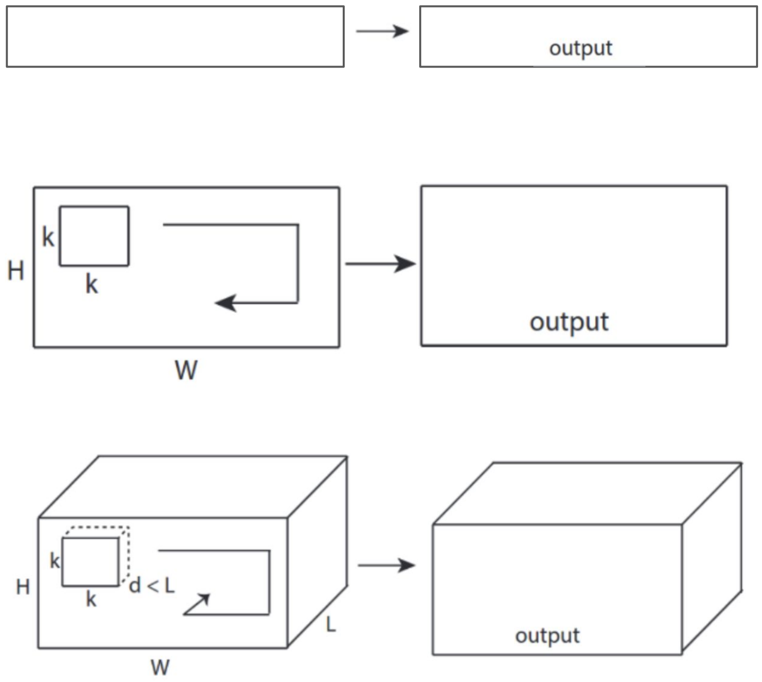
Dilated Convolutions



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

Cornell Bowers C·IS

1D and 3D Convolutions

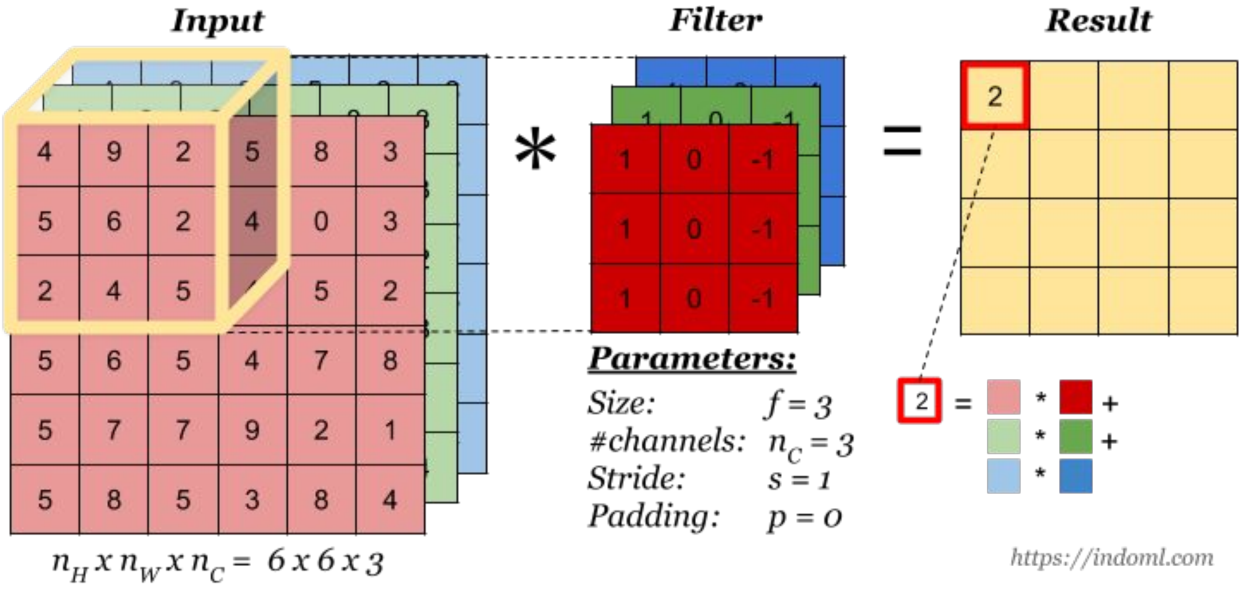


https://wandb.ai/ayush-thakur/dl-question-bank/reports/Intuitive-understanding-of-1D-2D-and-3D-convolutions-in-convolutional-neural-networks---VmlldzoxOTk2MDA

Cornell Bowers C·IS

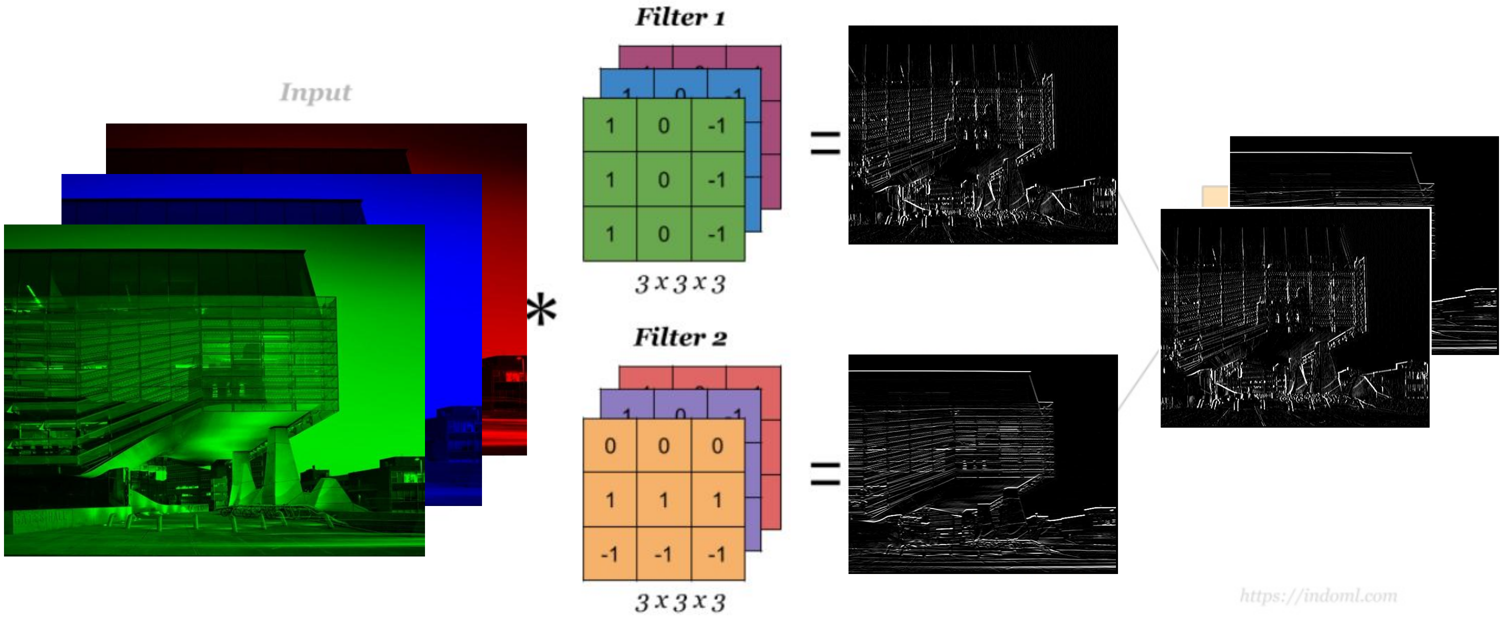
Multiple Input Channels: Convolution Over Volumes

What if our input image has more than one channel?



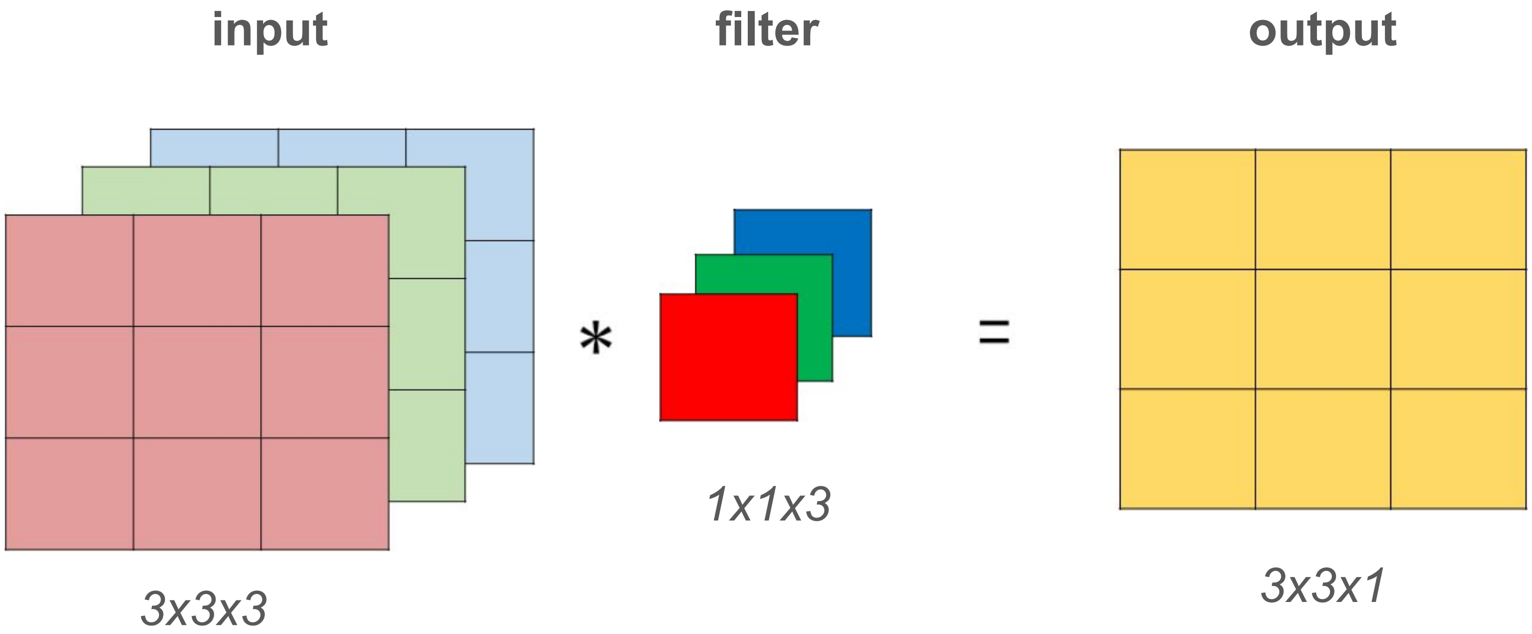
Cornell Bowers C·IS

Multiple Output Channels: Multiple Filters



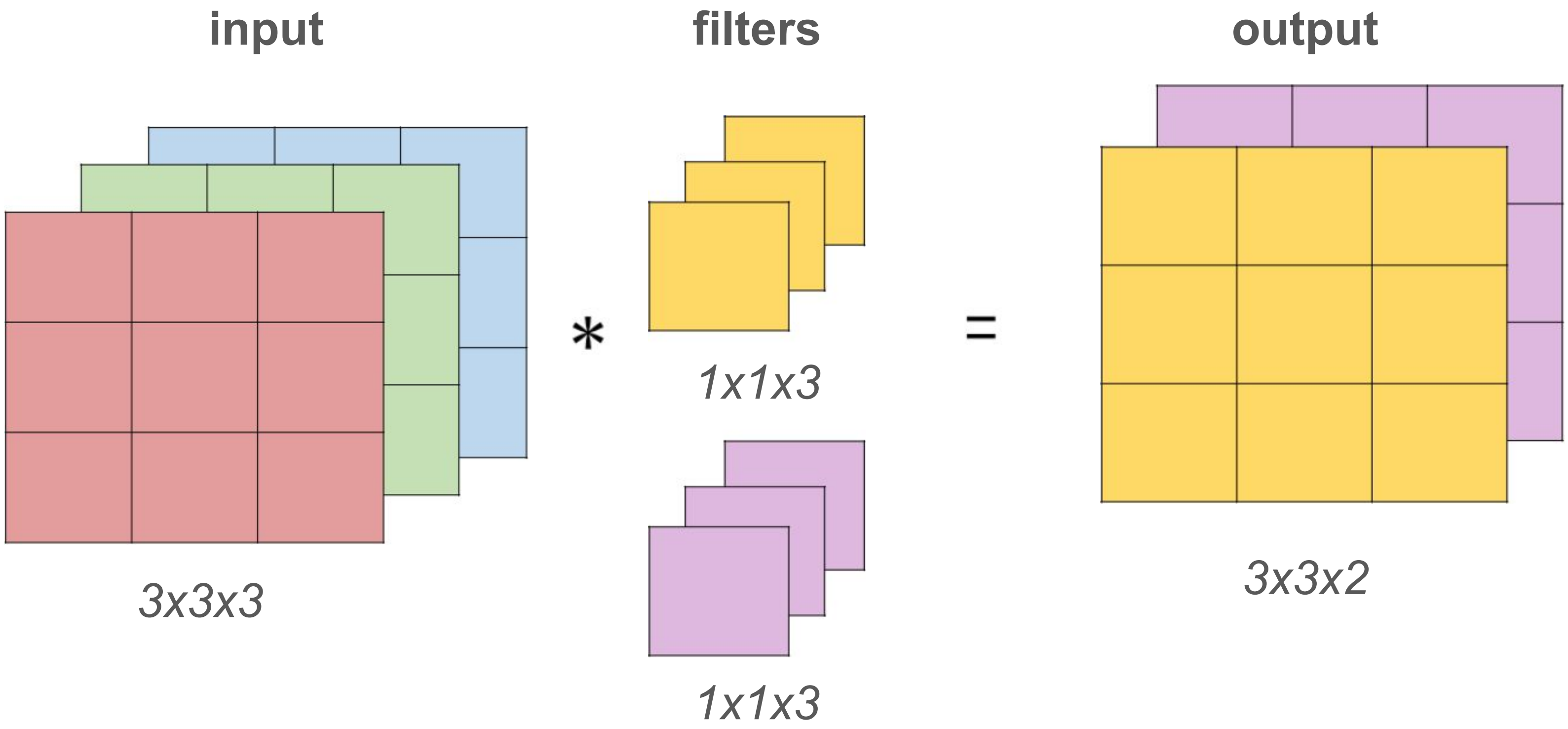
Cornell Bowers C·IS

Slight Detour: 1x1 convolutions



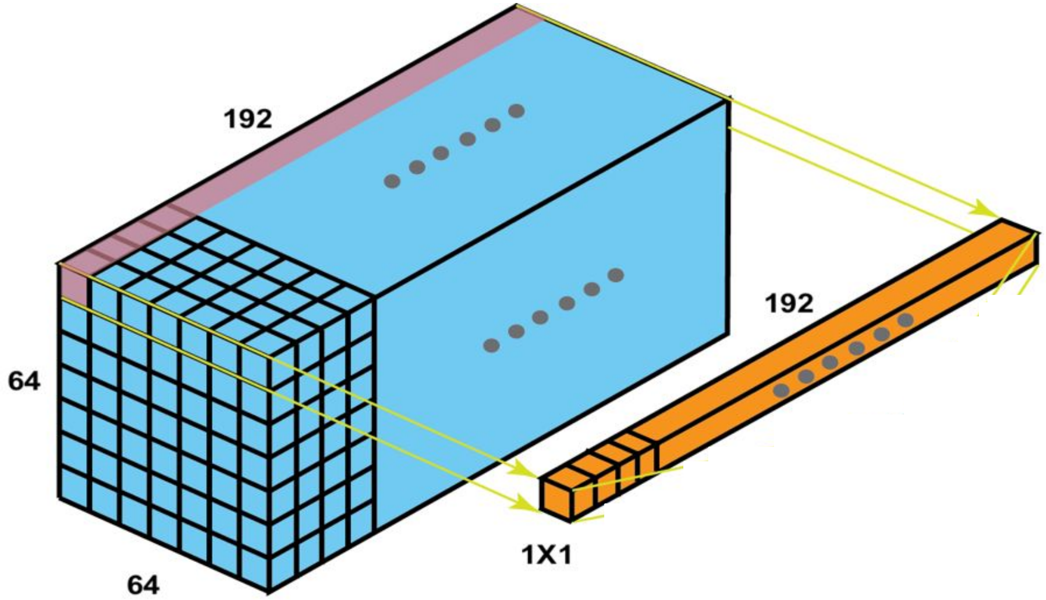
Cornell Bowers C·IS

Slight Detour: 1x1 convolutions



Discuss: 1x1 Convolutions

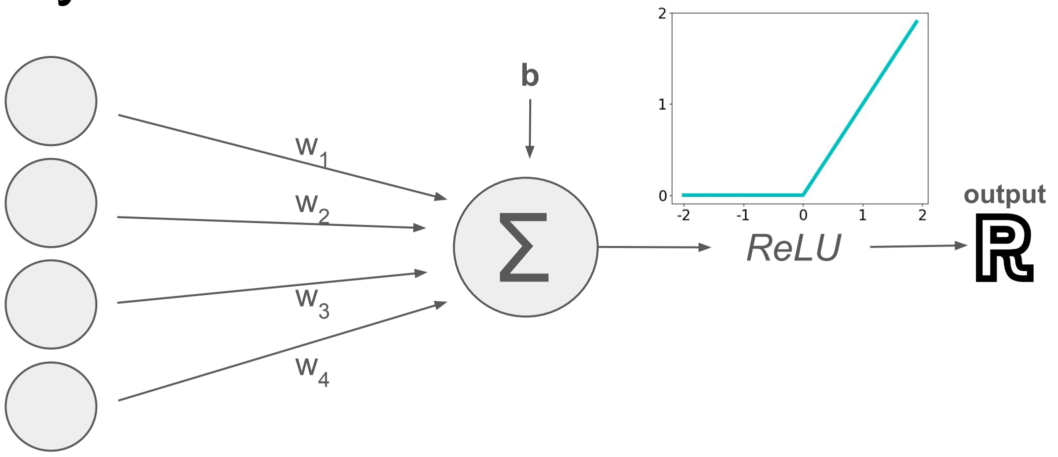
What is the result of convolving a 64x64x192 dimensional cube with a 1x1 filter?



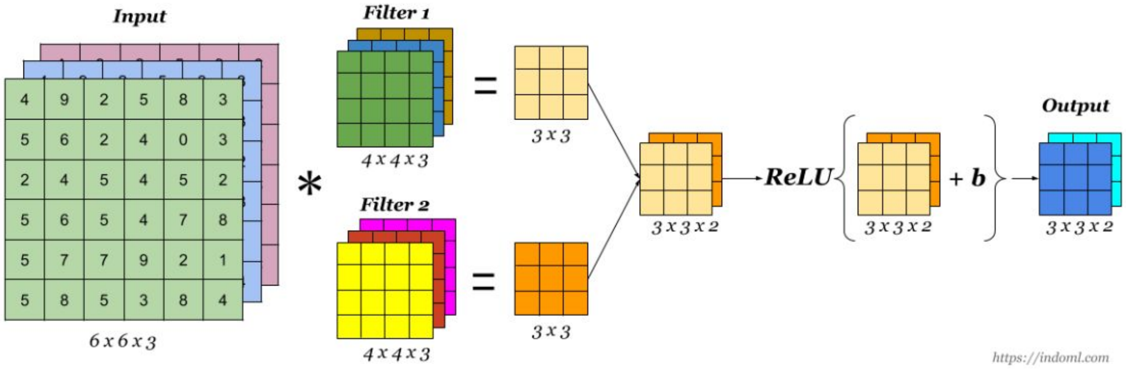
Cornell Bowers C·IS

Convolution Layer

MLP Layer



Convolution Layer

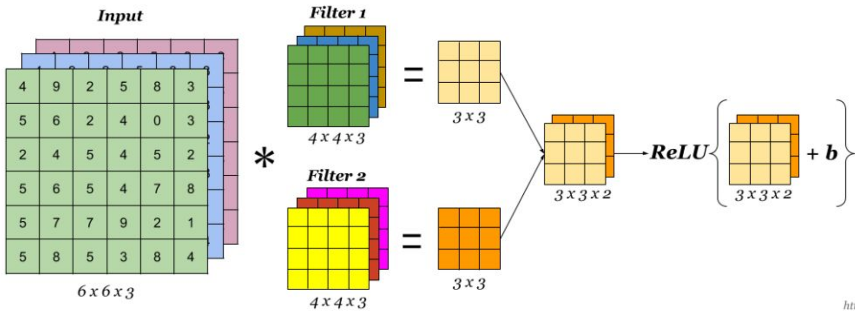


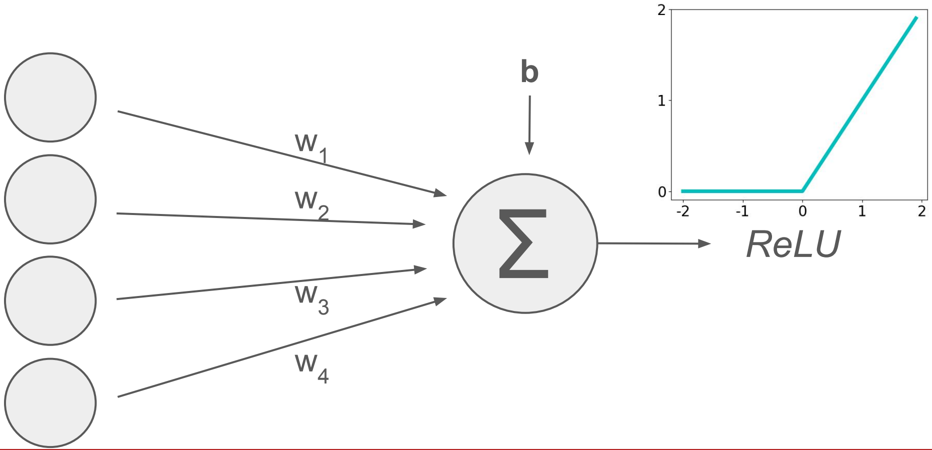
CNN/MLP Equivalence

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!

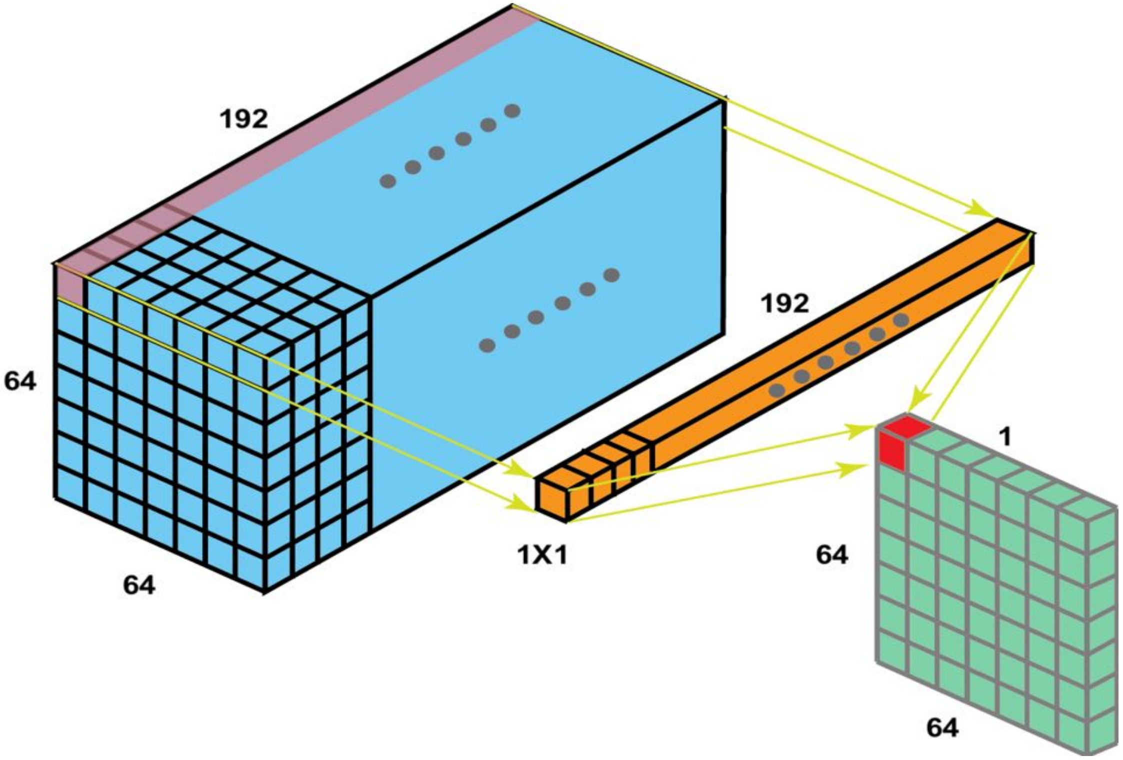




Cornell Bowers C·IS

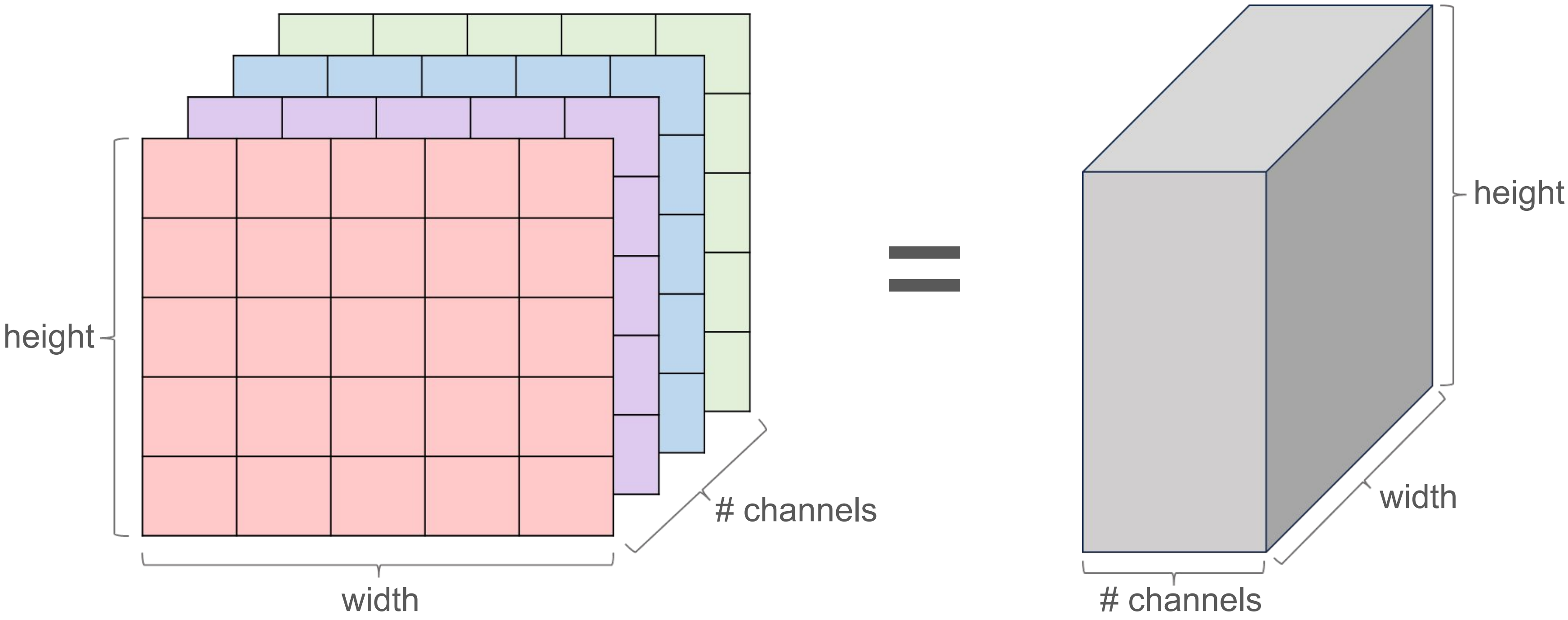
Discuss: Trade-offs between CNNs and MLPs

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.



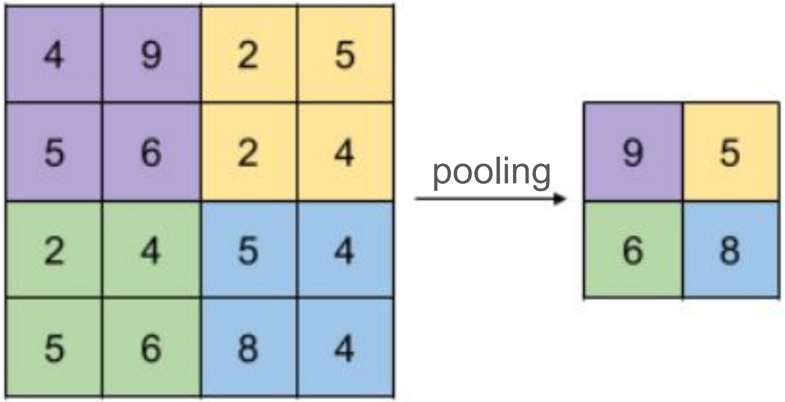
Cornell Bowers C·IS

CNN Layer Output Visualization



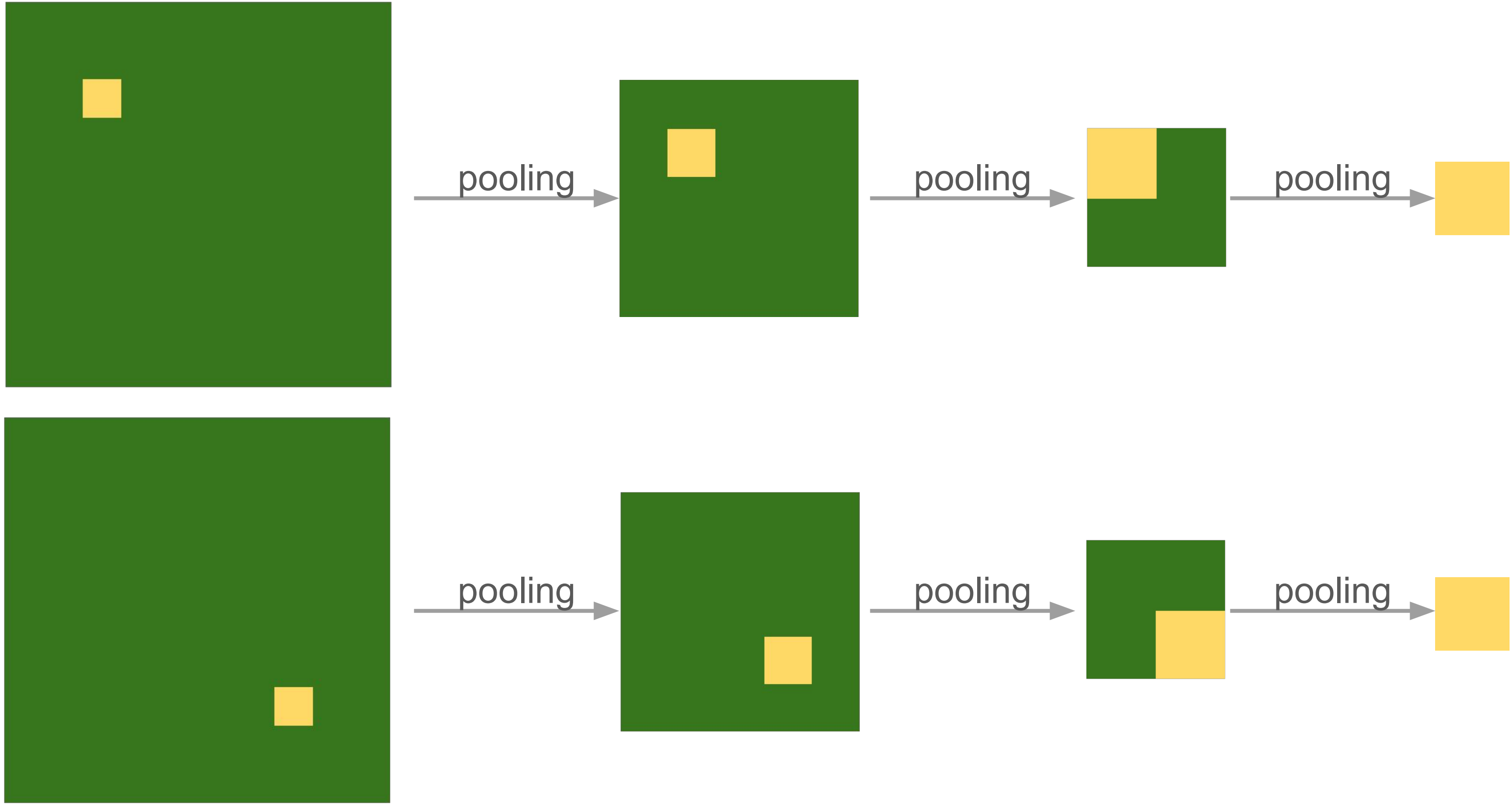
Cornell Bowers C·IS

Max Pooling



Cornell Bowers C·IS

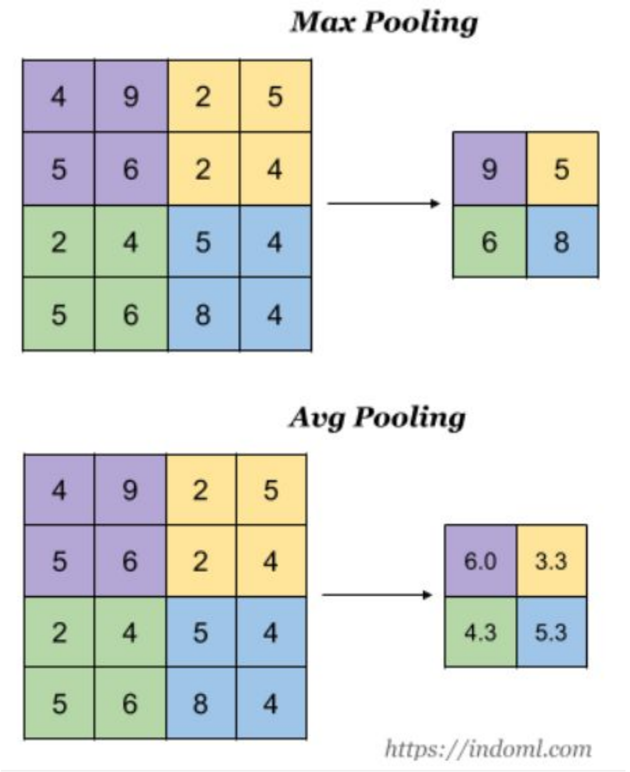
CNNs - Pooling



Cornell Bowers C·IS

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



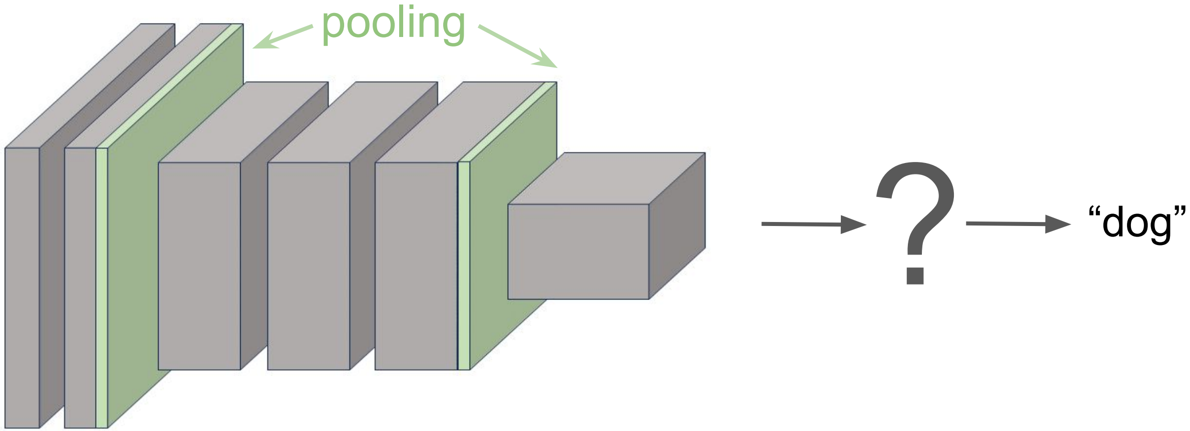
Cornell Bowers C·IS

Convolutional Neural Networks (CNNs)

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

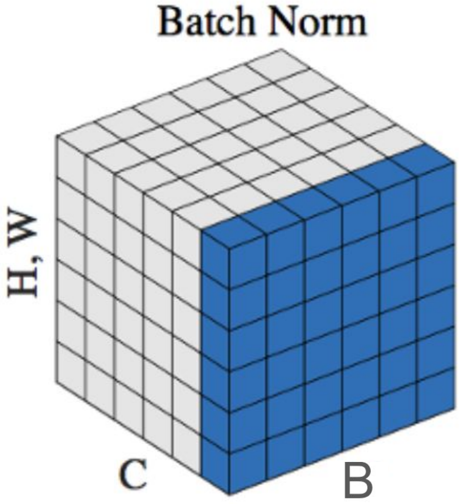
✅ **Pooling** — Captures key information from across different areas of the feature maps
Together with convolutions allows for translational invariance

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



Cornell Bowers C·IS

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

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

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

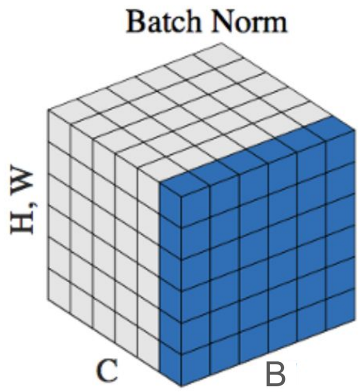
$$\widehat{x}_i \leftarrow \frac{x_i - \mu_{\mathcal{B}}}{\sqrt{\sigma_{\mathcal{B}}^2 + \epsilon}} \qquad \text{// normalize}$$

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

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

Discuss!

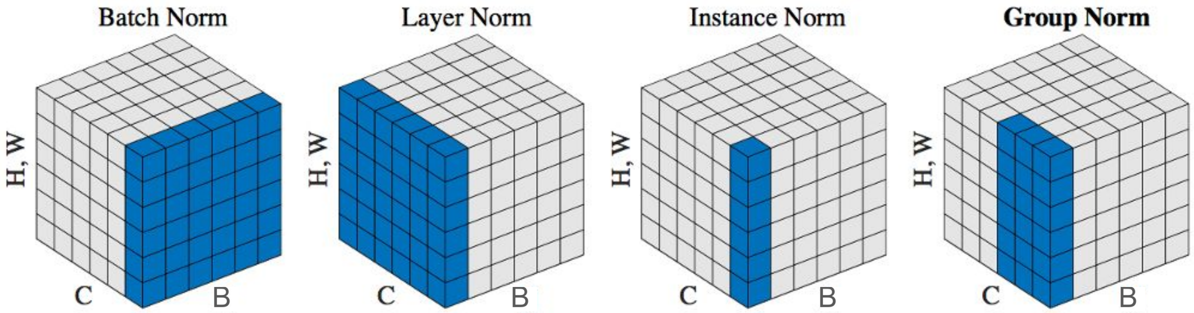
What is the dimension of the mean when you compute the batch norm of a volume of dimension (b x c x h x w)?



Cornell Bowers C·IS

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

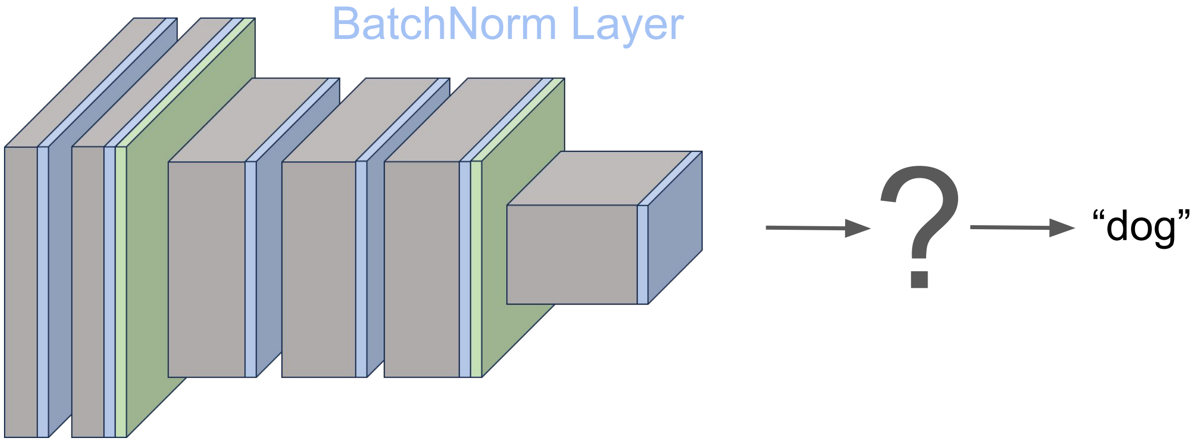


Cornell Bowers C·IS

Convolutional Neural Networks (CNNs)

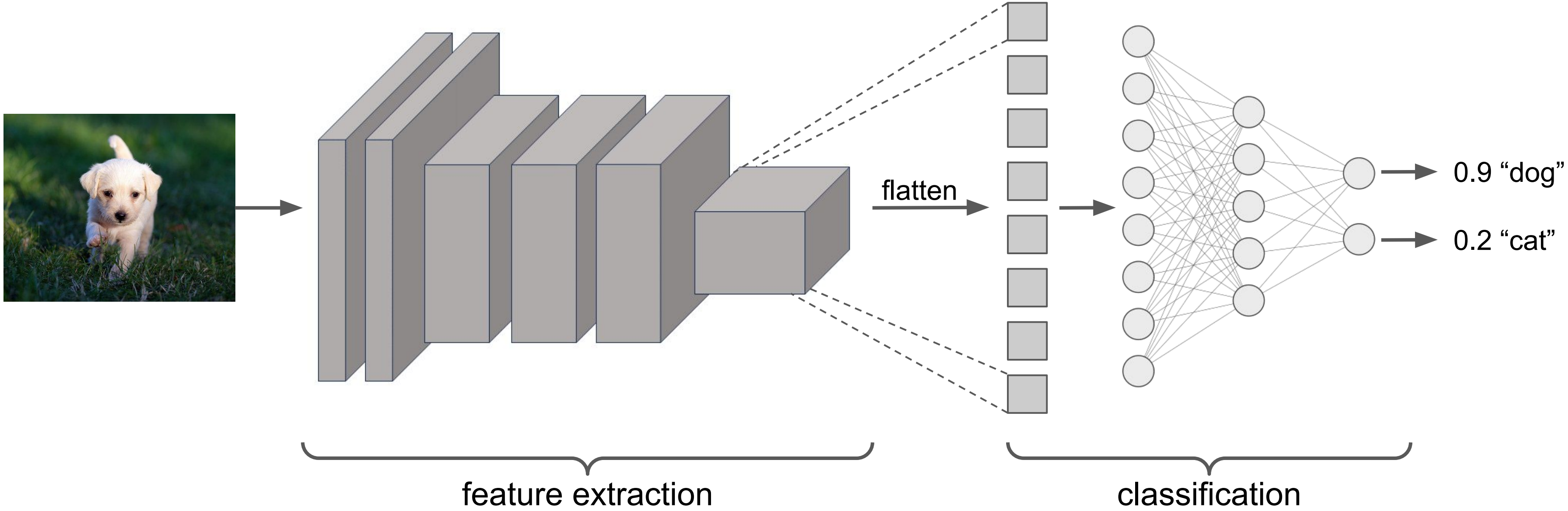
✅ Convolutions	Maintain spatial relation between pixels Reduce number of parameters through weight sharing
✅ Pooling	Captures key information from across different areas of the feature maps Together with convolutions allows for translational invariance
✅ **BatchNorm**	Increases speed and stability of training

input image



Cornell Bowers C·IS

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.