



# ATML Tutorial 07

Advanced Topics in Machine Learning

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# Today

- Batch normalization
- Convolution layers

# Batch Normalization

Normalize input to intermediate layers

$x$  - data of size  $M \times N$

- $M$  - mini batch size - number of training examples
- $N$  - number of features

$$y = \frac{x - E[x]}{\sqrt{Var[x] + \epsilon}} * \gamma + \beta$$

Vector of means of each feature (size  $N$ )

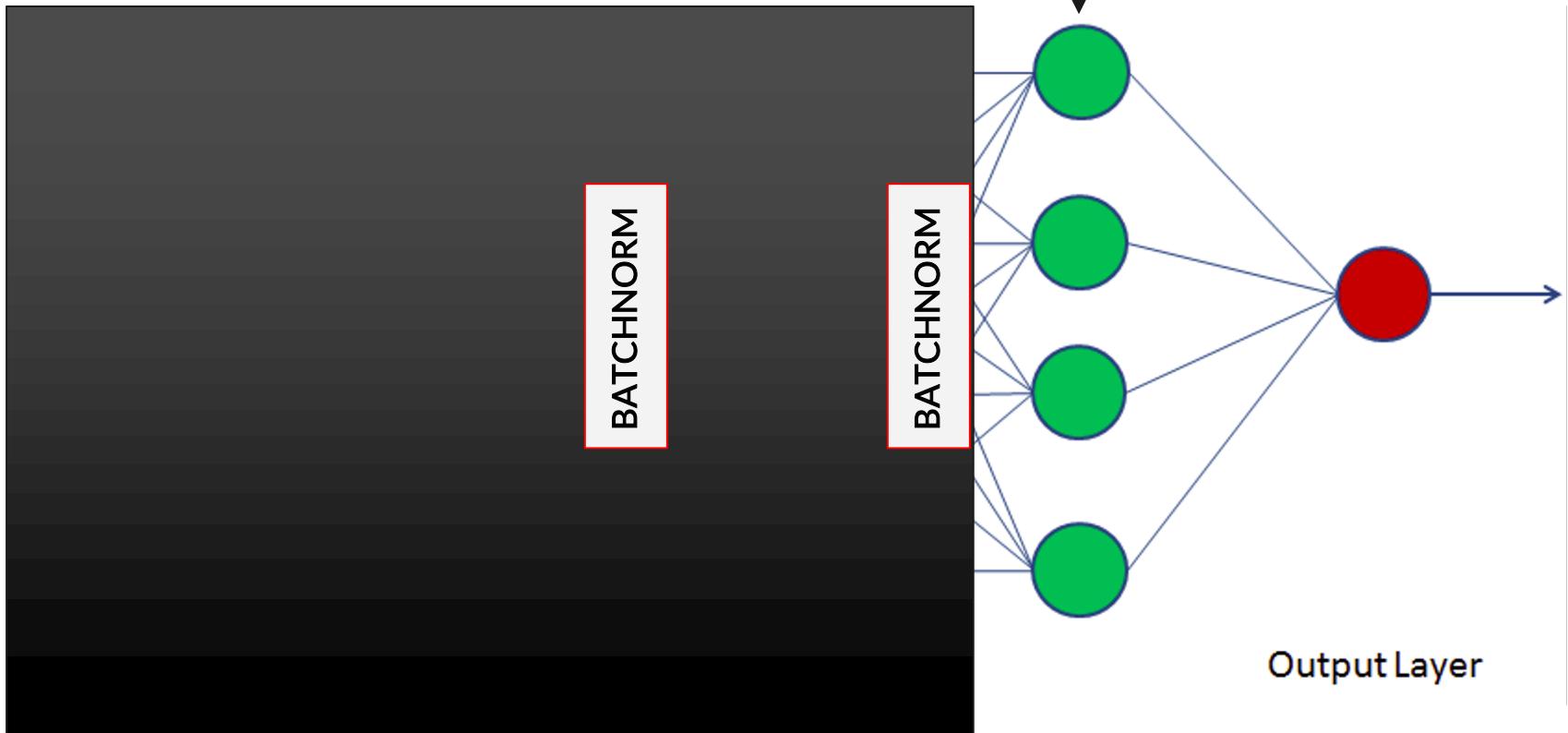
Scaling and shift (learnable parameters)

Vector of variances of each feature

$$y = \frac{x - \mathbb{E}[x]}{\sqrt{\text{Var}[x] + \epsilon}} * \gamma + \beta$$

# Batch Normalization

As we update previous layers, Now the input to each layer is normalized to work  
input to this layer can be shifted This layer also  
shift is reduced for a certain input  
that's not the expected input layers can learn more "independently"



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## Batch Normalization - inference

In training phase: we compute mean and variance within a mini-batch

In evaluation phase: we want to get the same result regardless of batch size; we don't want any randomness that comes from sampling a mini-batch

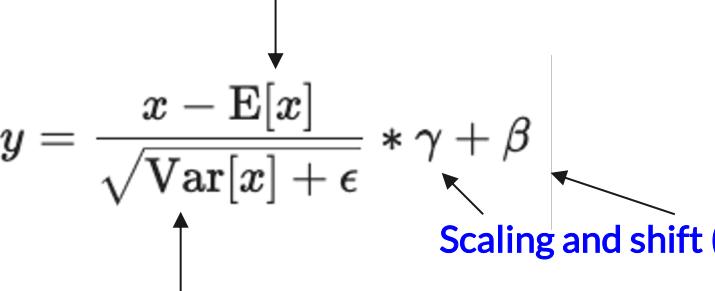
Solution: during training, global running mean and variance are computed

$$y = \frac{x - \mathbb{E}[x]}{\sqrt{\text{Var}[x] + \epsilon}} * \gamma + \beta$$

Global features mean

Global features variance

Scaling and shift (learnable parameters)

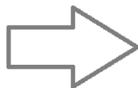


# Convolutions

Before: MLP - look at the entire image at once

- spatial information is lost
- very sensitive to shifts etc.

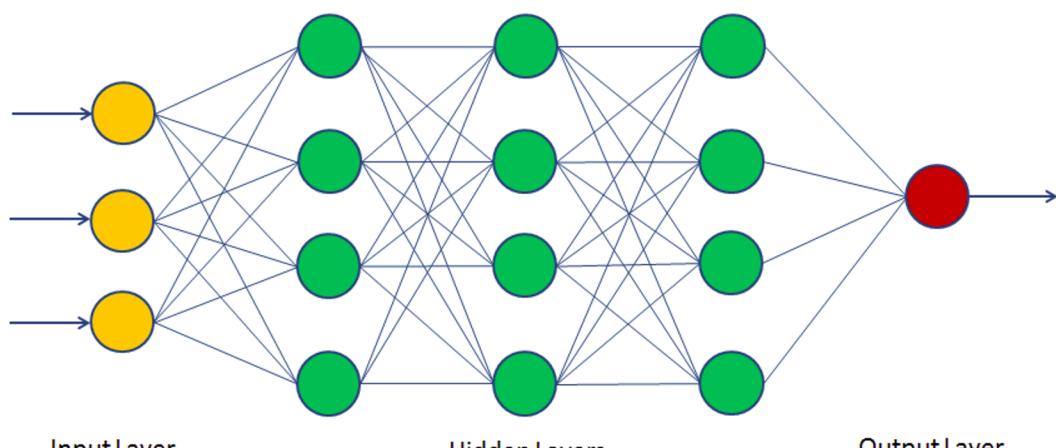
1	1	0
4	2	1
0	2	1



1
1
0
4
2
1
0
2
1

Image

Flattened image



MLP

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# Convolutions

Convolutions: Learn to detect local features

Multiply a small kernel (filter) at every image location

Example: edge detector

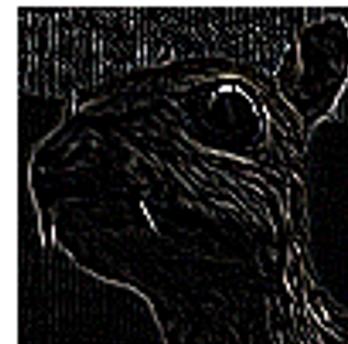
Input image



Convolution  
Kernel

$$\begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix}$$

Feature map



# Convolutions

Convolutions: Learn to detect local features

7	2	3	3	8
4	5	3	8	4
3	3	2	8	4
2	8	7	2	7
5	4	4	5	4

\*

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

=

6		

$$\begin{aligned} & 7 \times 1 + 4 \times 1 + 3 \times 1 + \\ & 2 \times 0 + 5 \times 0 + 3 \times 0 + \\ & 3 \times -1 + 3 \times -1 + 2 \times -1 \\ & = 6 \end{aligned}$$

# Convolutions

Convolutions: Learn to detect local features

7	2	3	3	8
4	5	3	8	4
3	3	2	8	4
2	8	7	2	7
5	4	4	5	4

\*

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

=

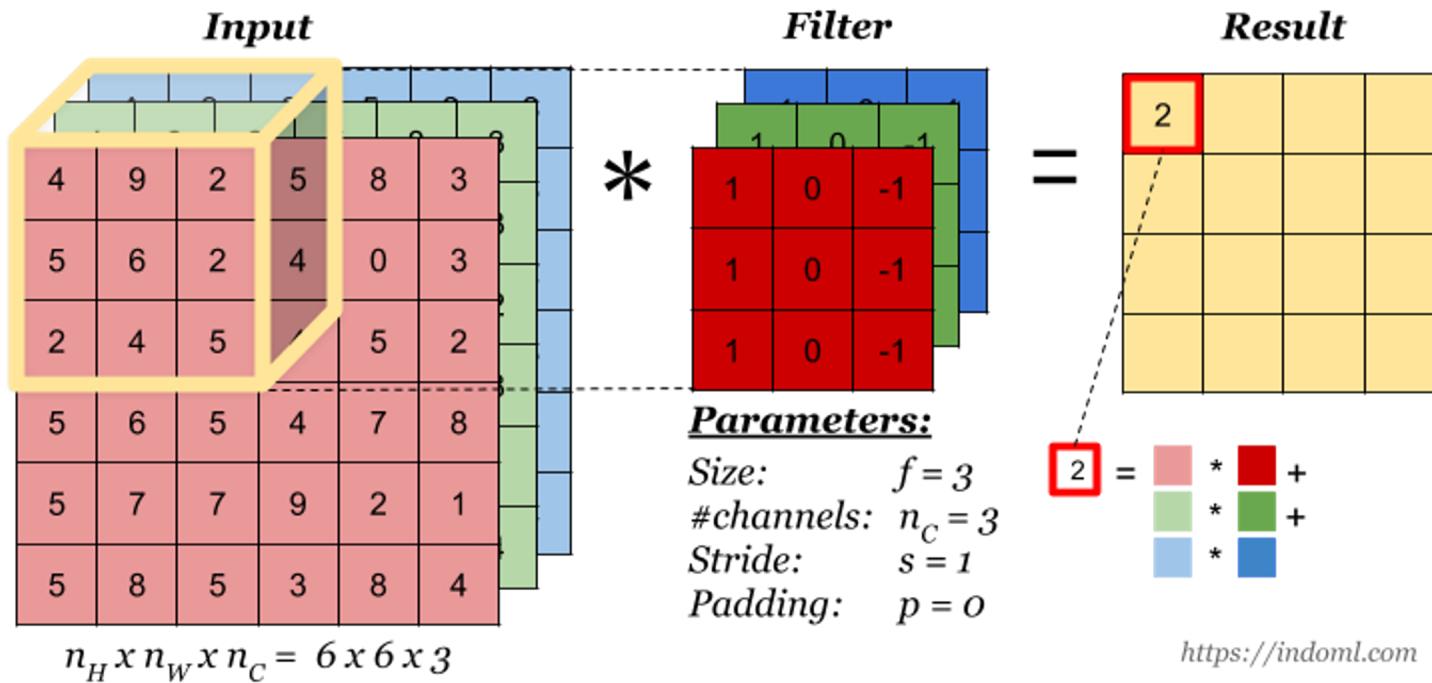
6		

$$\begin{aligned} & 7 \times 1 + 4 \times 1 + 3 \times 1 + \\ & 2 \times 0 + 5 \times 0 + 3 \times 0 + \\ & 3 \times -1 + 3 \times -1 + 2 \times -1 \\ & = 6 \end{aligned}$$

# Convolutions

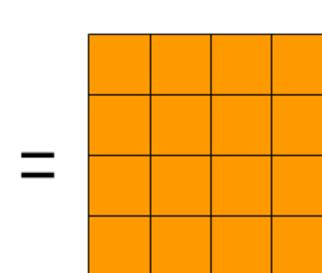
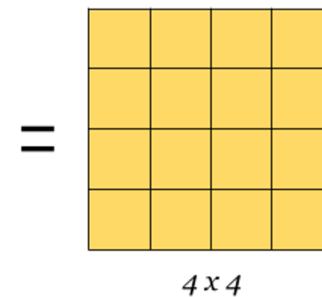
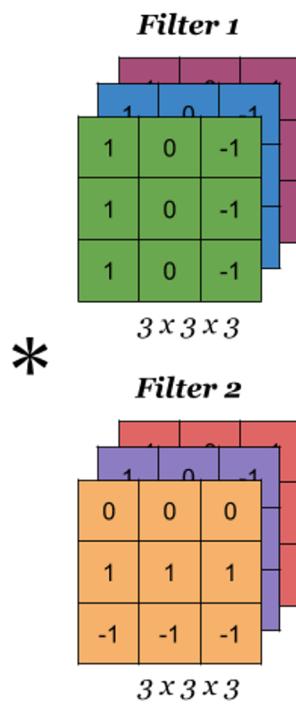
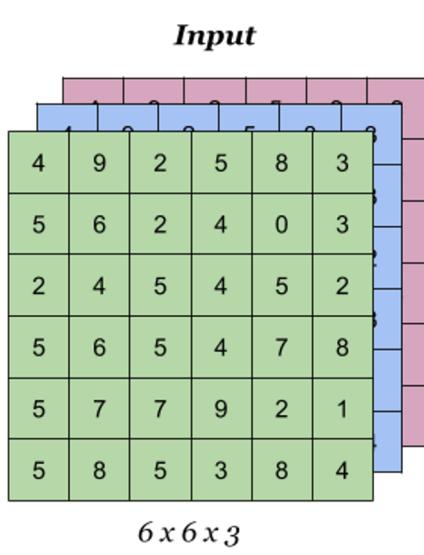
We can apply convolutions on volumes (e.g. RGB image)

Filter depth must match input depth



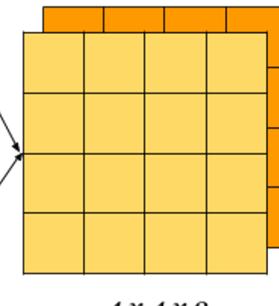
# Convolutions

We can use multiple filters



**Feature map -**  
“image” with information  
detected features

*Output*

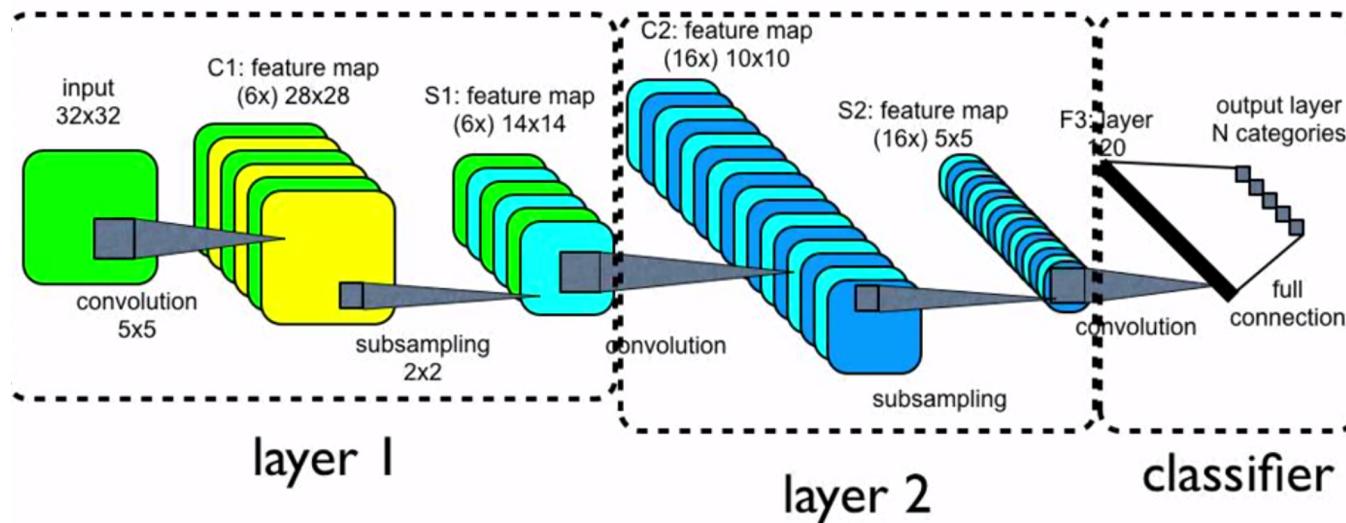


Number of output channels

# Convolutions

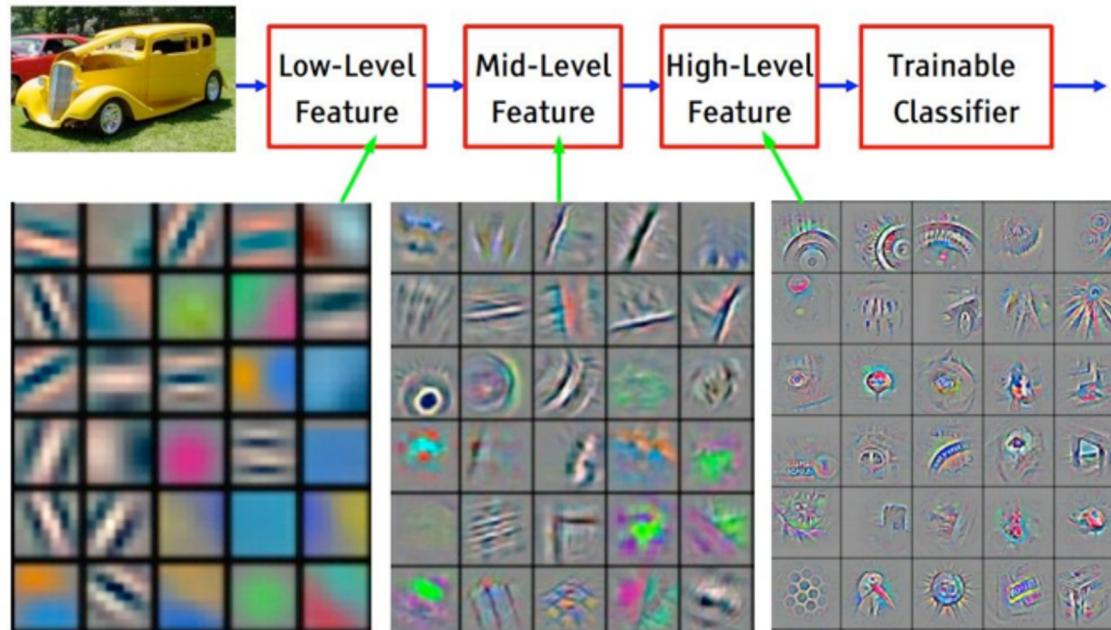
We can stack convolution layers

## Convolutional Neural Networks



# Convolutions

Learning hierarchy of features



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

# Pooling layers

Commonly used after some convolutional layers to reduce feature map size

