

Hot Research Topics in AI for Engineering Applications

Bonus Content - Convolutional Neural Networks and Regularization in NNs
WS 2025/26

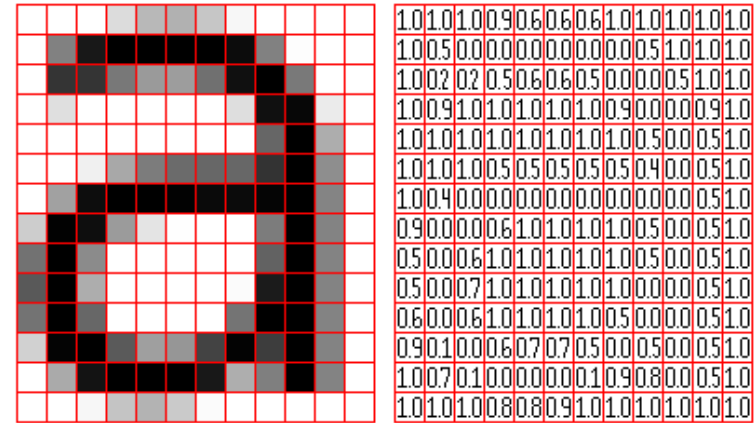
Convolutional Neural Networks

Convolutional Neural Networks

- **Convolutional Neural Networks** (CNNs) are a specific architecture of neural networks especially suited for **image processing** tasks
- Basic Idea
 - Implementation of a receptive field for each neuron
 - Conservation of a spatial context between layers
 - Each Neuron only depends on a number of spatially close neurons from the previous layer
- Ideas originate in the 1980s but were early on hindered by hardware limitations
- CNNs were successfully applied to yield unprecedented results on image analysis tasks in 2012 (AlexNet)

Digital Representation of Images

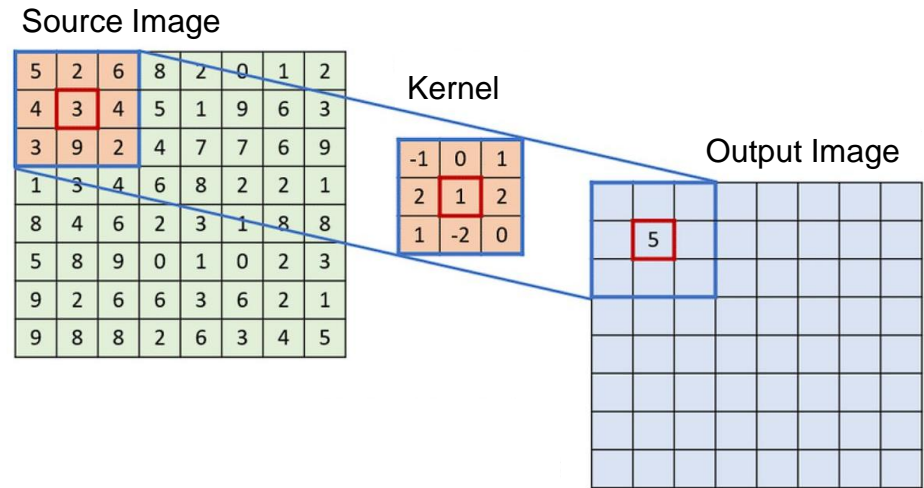
- Images can be digitally represented by 2-D matrices (greyscale)
 - Sampled into pixels
 - Each pixel has a value
 - High value = white
 - Low value = black
- In case of color images, 3-D matrices are used
 - 2-D spatial dimension
 - 3 color channels: red, green, blue



Source: https://pippin.gimp.org/image-processing/chap_dir.html

Convolution in Image Processing

- Convolution is a common local filtering technique in image processing
- A **kernel** of fixed size is applied at every image location
- Application of kernel corresponds to weighted sum of considered pixel values



Source: [Link](#)

Convolution in Image Processing

- Different kernels perform different operations

Line Detection



-1	-1	-1	1	2	-1
2	2	2	1	2	-1
-1	-1	-1	1	2	-1

Horizontal Lines

Vertical Lines

Edge Detection



-1	-1	-1	0	-1	0
-1	8	-1	-1	4	-1
-1	-1	-1	0	-1	0

Laplacian

Blur



$\frac{1}{9}$	$\frac{1}{9}$	$\frac{1}{9}$
$\frac{1}{9}$	$\frac{1}{9}$	$\frac{1}{9}$
$\frac{1}{9}$	$\frac{1}{9}$	$\frac{1}{9}$

Box blur

Gaussian

$\frac{4}{273}$	$\frac{16}{273}$	$\frac{26}{273}$	$\frac{16}{273}$	$\frac{4}{273}$
$\frac{7}{273}$	$\frac{26}{273}$	$\frac{41}{273}$	$\frac{26}{273}$	$\frac{7}{273}$
$\frac{4}{273}$	$\frac{16}{273}$	$\frac{26}{273}$	$\frac{16}{273}$	$\frac{4}{273}$
$\frac{1}{273}$	$\frac{4}{273}$	$\frac{7}{273}$	$\frac{4}{273}$	$\frac{1}{273}$

Source: [Link](#)

Convolutional Layers in Neural Networks

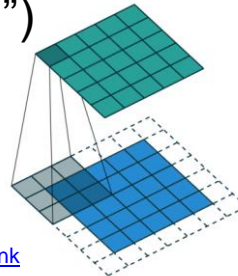
- Neurons in convolutional layers are arranged 3-dimensionally
 - 2 spatial dimensions
 - Additional dimension for multiple channels/filters
- Weighted sum z only considers neurons in spatial vicinity

$$z = \sum_{c=1}^C \sum_{i=-m}^m \sum_{j=-m}^m w_{cij} x_{cij} + b$$

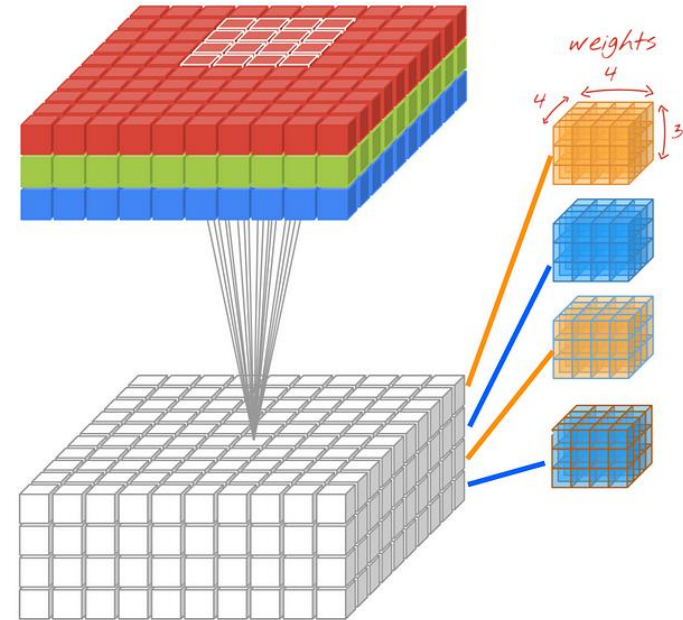
- Here, c is the depth dimension of the previous layer (e.g. RGB color channels in an input image)
- The size of the convolution kernel is $2m + 1$
- Activation function applied as before to compute neuron activation a

Convolutional Layers in Neural Networks

- In case of images, the input layer often contains 3 channels
- Spatial arrangement is preserved in convolutional layers
- Each layer contains a number of filters which are stacked in the third dimension
- Handling of boundary pixels needs to be considered, e.g. padding of constant (zero) boundary units (“same padding”)



Source: [Link](#)



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Pooling Layers

- Used to reduce spatial dimensions of layers in a CNN
- Third (depth) dimension is conserved (applied in each channel independently)
- Different types, most common are
 - Max Pooling
 - Average Pooling
- Parameters:
 - Filter Size – spatial dimension of pooling (usually rectangular window, e.g. 2x2)
 - Stride – distance at which the filter is applied (often equal to filter size)

2	2	7	3
9	4	6	1
8	5	2	4
3	1	2	6

Max Pool
→
Filter - (2 x 2)
Stride - (2, 2)

9	7
8	6

2	2	7	3
9	4	6	1
8	5	2	4
3	1	2	6

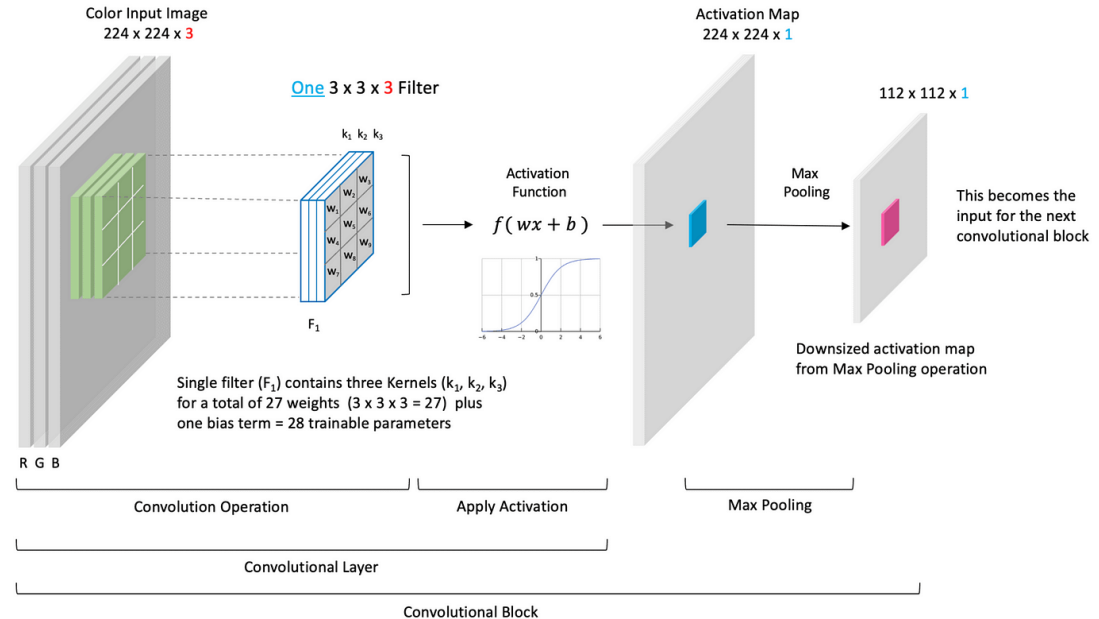
Average Pool
→
Filter - (2 x 2)
Stride - (2, 2)

4.25	4.25
4.25	3.5

Source: [Link](#)

Convolutional Blocks

- In CNNs, convolutional layers and pooling layers are often arranged alternately
- Sequence of convolutional layer followed by a pooling layer is often called a **convolutional block**


Source: [Link](#)

CNN Architectures

- CNNs originally consist of
 - Convolutional Blocks
 - Fully-connected layers toward the end
 - Softmax classifier at the end
- Conventions
 - Spatial dimensions decrease gradually
 - Channel/filter amount increases gradually

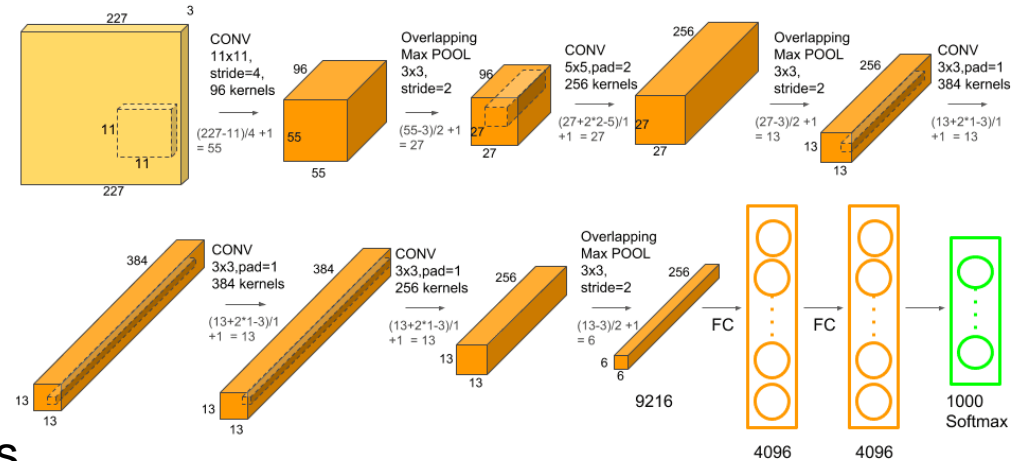


Figure: AlexNet architecture. [AlexNet](#) famously won the 2012 [ImageNet](#) image classification challenge reviving interest in CNNs for image analysis tasks.

Source: [Link](#)

Advanced CNN Architectures

- Newer CNN architecture often use additional concepts
 - Use different convolution kernel sizes in parallel (e.g. [Inception](#))
 - Depth-wise separable convolutions*
 - Skip connections, e.g. residual layers*
 - Transposed convolutions (up-sampling convolutions)*

Regularization in Neural Networks

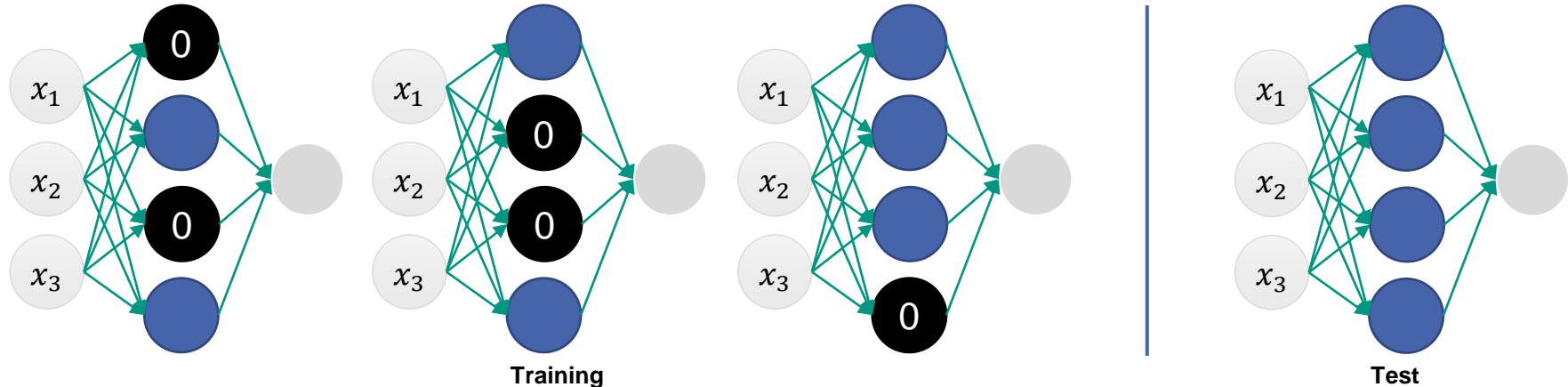
Regularization in Artificial Neural Networks

- L1 or L2 regularization (compare other ML models)
 - Add term to loss function penalizing (large) parameter weights
- Early Stopping
 - Monitor evaluation error during training → stop when it does no longer decrease
- Dropout
 - Random units are set to zero during training
- Batch Normalization^[1]
 - During training, normalize layer outputs according to training data specific mean and standard deviation
- Data Augmentation
 - Synthetically increase amount of training data

[1] Ioffe, Sergey. "Batch normalization: Accelerating deep network training by reducing internal covariate shift." *arXiv preprint arXiv:1502.03167* (2015).

Regularization in Artificial Neural Networks: Dropout

- Idea: Prevent feature co-adaptation
- Can be seen as a form of model bagging (training an ensemble model)
- Hyperparameter: Dropout probability p
 - With probability p , each unit is set to 0 during training
 - At test time, all units are used (weights reduced by $1 - p$)



Regularization in Artificial Neural Networks: Batch Normalization

- Additional layer in network architecture
- Normalizes unit outputs according to training data statistics
 - Computes unit value mean μ_B and standard variation σ_B of current batch
 - Keeps a moving average of unit mean $\hat{\mu}$ and standard variation $\hat{\sigma}$ over whole training data
 - Two learnable parameters: target mean β and variance γ

$$BN(x) = \gamma \cdot \frac{x - \hat{\mu}}{\hat{\sigma}} + \beta$$

- Originally applied before computation of activation function
- Can accelerate training, i.e. convergence
- Prevents overfitting to outliers

Regularization in Artificial Neural Networks: Data Augmentation

- Apply label-preserving transformations to input features
- Frequently used for arbitrary types of data
- Efficiently increases amount of training samples (especially important when data acquisition / labelling is costly)

Original



Flipped



Random Saturation



Random Brightness



Rotation



Source: [Link](#)