– SSDA 2019 / Islamabad –
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Convolutional Neural Networks (CNNs)

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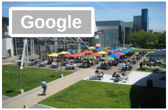
DCSM Department
RheinMain University of Applied Sciences

Outline

Introduction



Working Group "Learning and Visual Systems" > lavis.cs.hs-rm.de

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Visualization

Prof. Dr. Dirk Krechel

Content Analytics
Knowledge Management

Prof. Dr. Ulrich Schwanecke

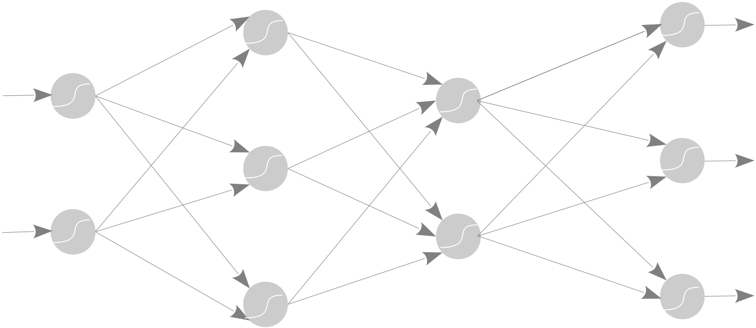
Computer Vision
Mixed Reality

Prof. Dr. Adrian Ulges

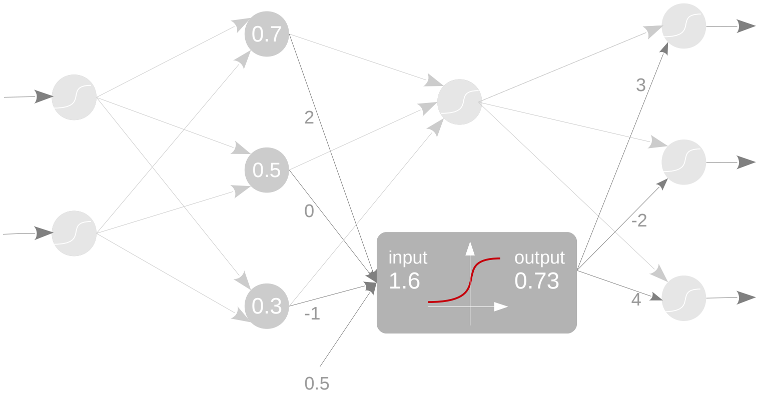
Machine Learning
Data Science

Outline

Neural Networks



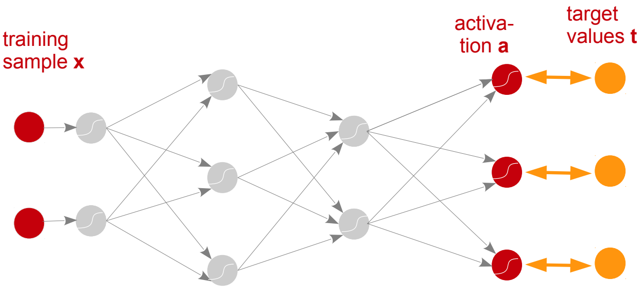
Neural Networks



Each neuron...

1. ... weighs its inputs
2. ... aggregates incoming energy
3. ... applies an activation function

Neural Networks Training: Backpropagation



Training = Adjusting Weights

- iteratively, pick a training sample.
- compute the deviation from the target with a **loss** function.

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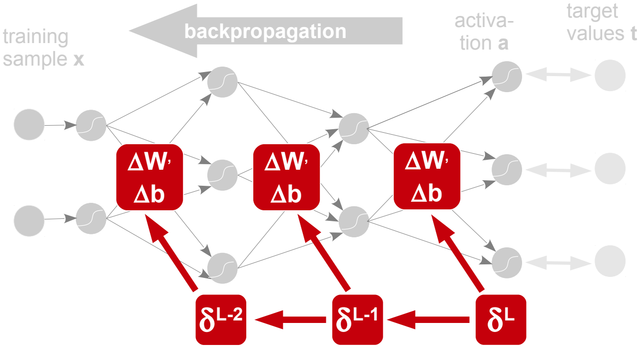

Training = Adjusting Weights

- iteratively, pick a training sample.
- compute the deviation from the target with a **loss** function.
- minimize loss by **gradient descent**.

Enter: Deep Learning

	SVMs	**Deep Learning**
	1990s – 2000s	2012 – today
nonlinearity through...	kernels	stacking layers *(at least 3)*

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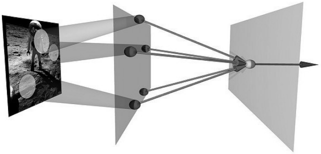
facilitated by ...	—	▸ hardware *(GPUs)* ▸ clever topologies *(CNNs, LSTMs)* ▸ tweaks *(losses+activations, optimizers, shortlinks, regularizers, attention)*

Neural Networks on Images: General Thoughts



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- Why not connect a neuron with **all pixels**?

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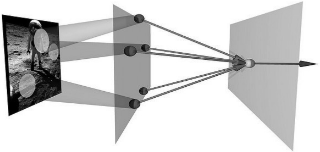

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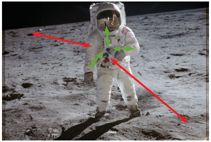

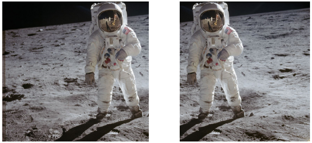

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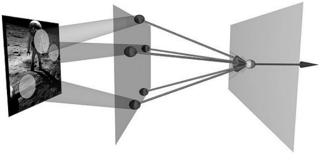

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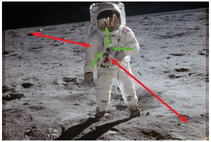

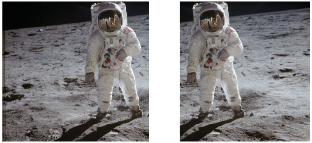

1. pixels interact mostly **locally**
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→ **Convolution gives us just that!**

Outline

Correlation/Convolution

A convolution is a transformation of **signals** *(here, images)*:

Definition (Input Images)

Let the input to a neural network be a (grayscale) **image x** *of size* $N \times M$*. Each pixel* (i, j) *has a value* $x(i, j) \in \mathbb{R}$*.*

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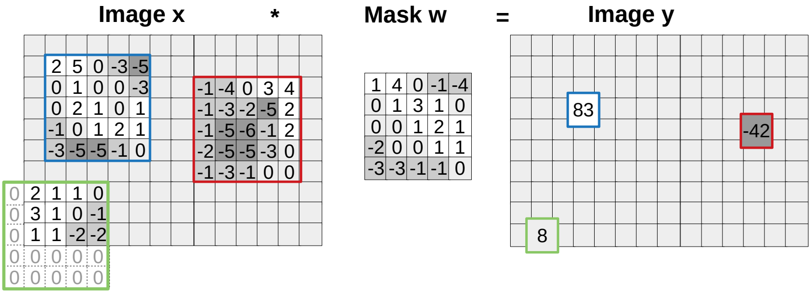
Definition (Convolution)

We define a **filter mask w** *as a matrix of size* $W \times W$*.*
Then the **convolution** *of image* **x** *with mask* **w** *is defined as:*

$$y(i,j) := \sum_{k,l=-W/2}^{W/2} w(k,l) \cdot x(i+k, j+l) \quad \text{// correlation}$$

$$y(i,j) := \sum_{k,l=-W/2}^{W/2} w(k,l) \cdot x(i-k, j-l) \quad \text{// convolution}$$

Correlation/Convolution (cont'd)



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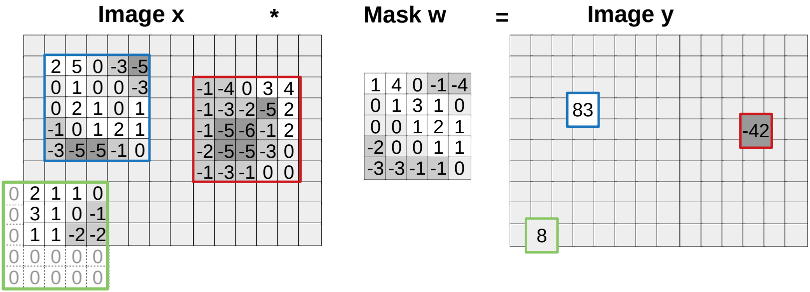
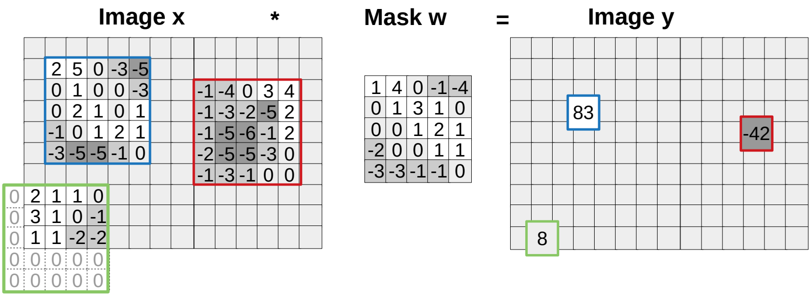


Remarks

- **Intuition**: **Shift the filter mask** over the image.
  At each position, compute the **weighted sum**.

Correlation/Convolution (cont'd)



Remarks

- **Intuition**: **Shift the filter mask** over the image.
  At each position, compute the **weighted sum**.
- At the **boundary**, the mask reaches outside the image.
  We can **pad** the input image *(here: zero padding)*.

Convolution = Feature Detection image: [2]

- By carefully designing filter masks, convolution allows us to scan the image for certain **features** *(here, the t-junction in the "4")*.

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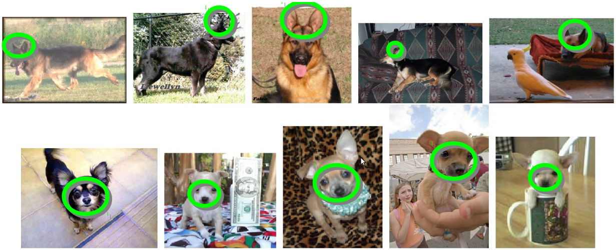
- The resulting **feature map** shows where "interesting" regions in the image are.



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Idea: a neural network that applies convolutions (=CNN)

- **Layer 1**: run filters over the image.
- **Layer 2**: classify based on feature maps.

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- **Layer 1**: run filters over the image.
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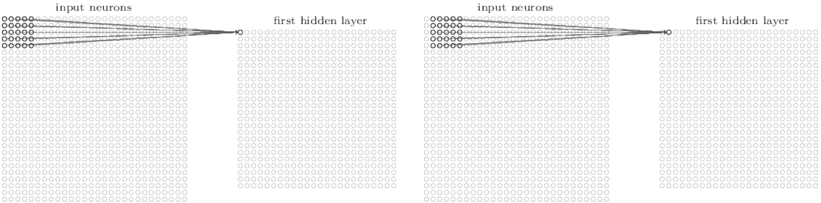
- **Such a convolutional neural network can learn its filter masks by backpropagation!**



Convolutional Layers: Multi-Channel Input

- In practice, inputs to a convolution can have **multiple channels** *(e.g. color images: R,G,B)*.

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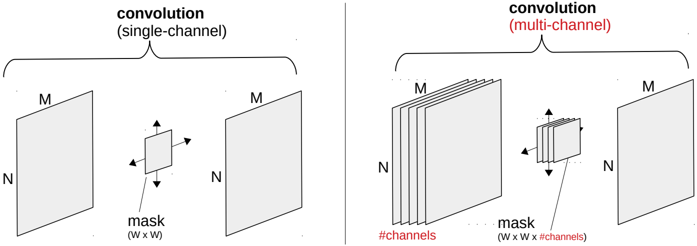

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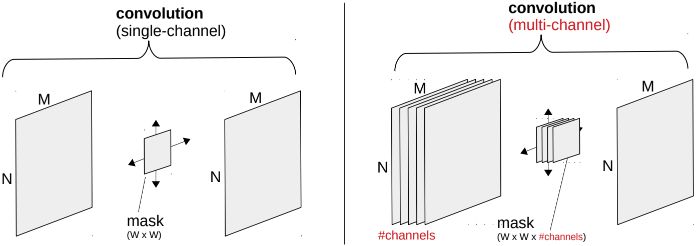


- We extend the convolution to sum **over the channels** too:

$$y(i,j) := \sum_{k,l=-W/2}^{W/2} \sum_{c=1}^{\#channels} w(k,l,c) \cdot x(i+k, j+l, c)$$

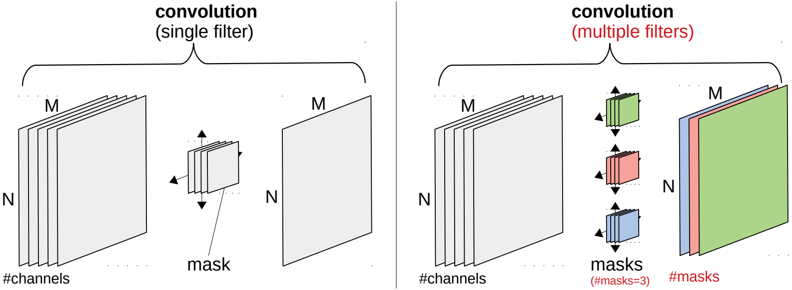
- Input and mask become 3D data "cubes" *(tensors)*.

Convolutional Layers: Multi-Channel Output

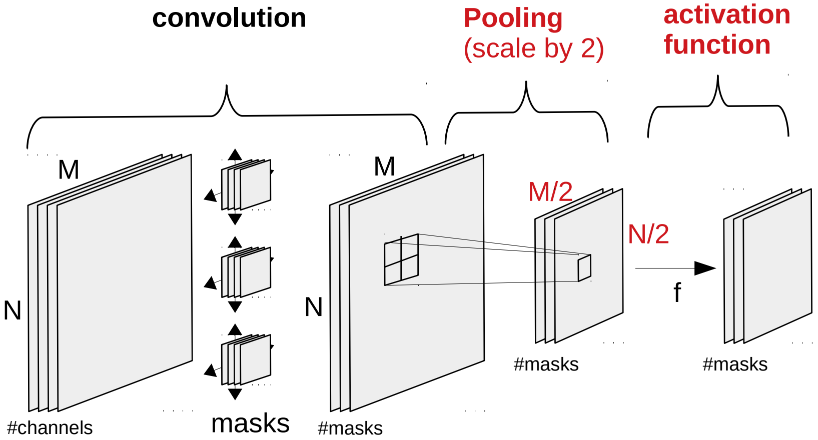
- In practice, we are not interested in detecting only <u>one</u> feature.
- We apply **multiple filters**, obtaining **multiple** feature maps.

Convolutional Layers: Multi-Channel Output

- In practice, we are not interested in detecting only one feature.
- We apply **multiple filters**, obtaining **multiple** feature maps.
- For K filters, we obtain a $N \times M \times K$ output tensor.



Convolutional Layers: Pooling



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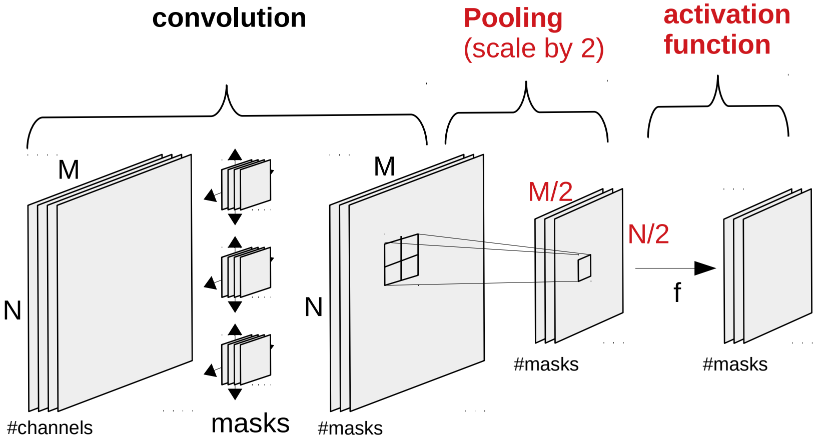

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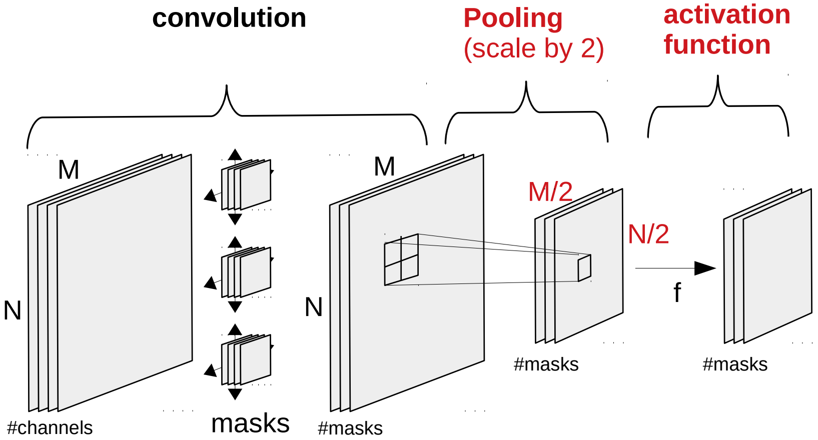

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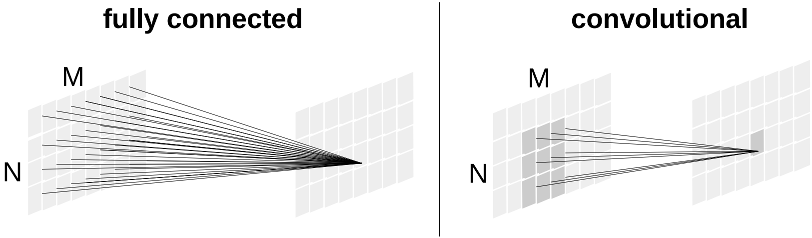
- We also apply an activation function for each pixel.

Convoution = Few Weights



Fully Connected Layer

- $N \times M$ pixels left, $N \times M$ pixels right.
- All are connected pairwise: $(N \times M)^2$ edges!
- **Example**: 320×240 input → 5.8 bio. parameters ☹

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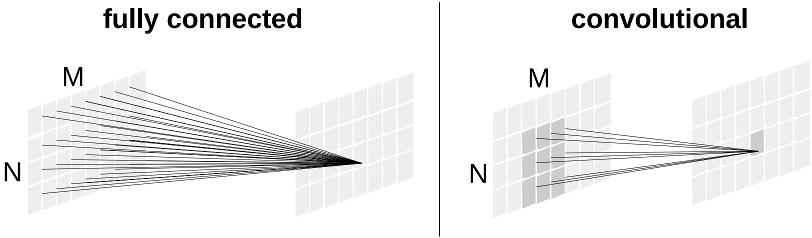

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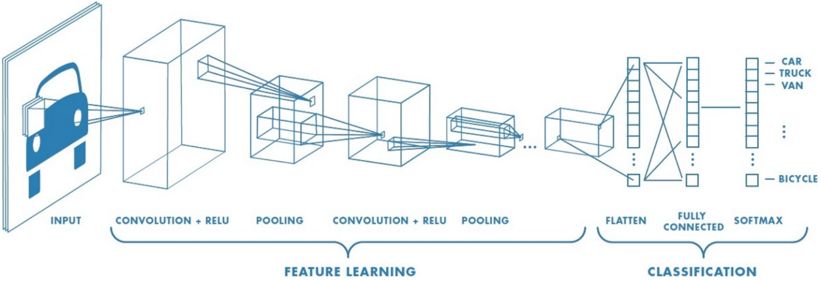
Convolutional Layer

- Each pixel has a small local **receptive field**.
- K filters. Each filter has $W \times W$ values.
- **Example**: 20 filters, 5×5 → 500 parameters ☺

Outline

From CNNs to Deep CNNs



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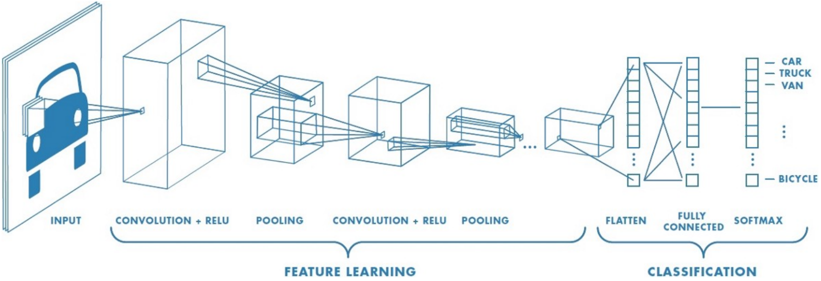
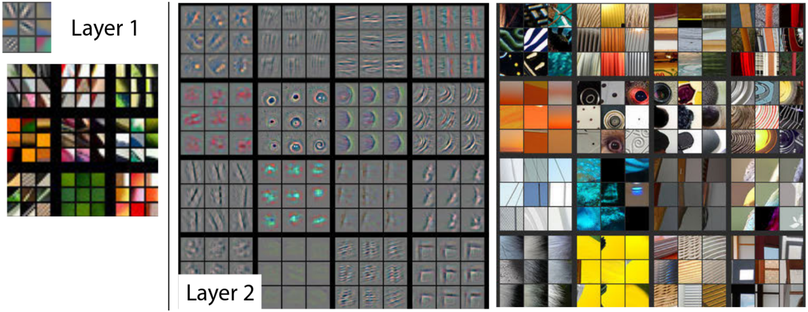


- State-of-the-Art CNNs are deep: They repeat convolution and pooling multiple times.
- Spatial resolution decreases.
- The number of kernels increases.

Deep CNNs images: [6]

With more layers, the level of abstraction increases



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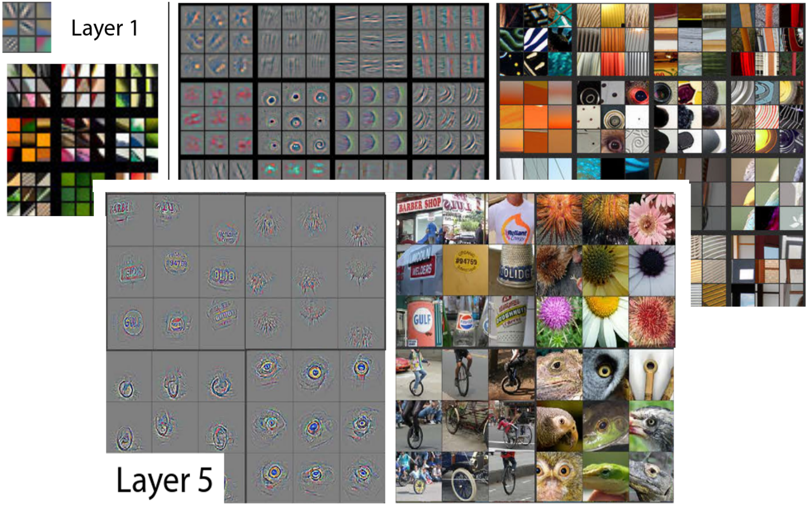
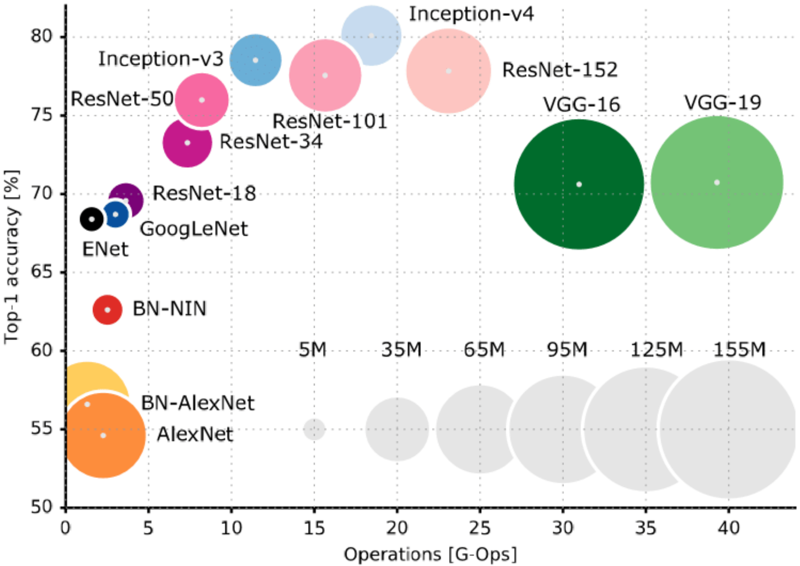
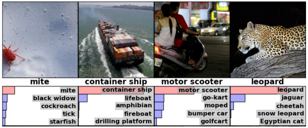


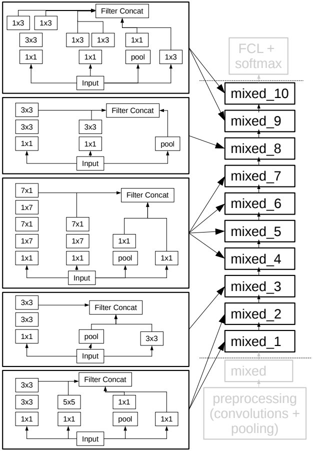
DeepCNNs: Architectures image: [5]

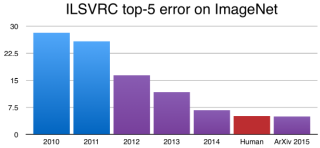


Example: Inception v3 [1]



- A **deep CNN** *(convolutional neural network)*
- 22 layers, about 25 mio. parameters
- 5 bio. multiply-adds per inference
- pre-trained on 1.2 mio. images to recognize 1000 object categories





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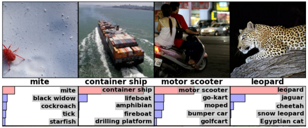

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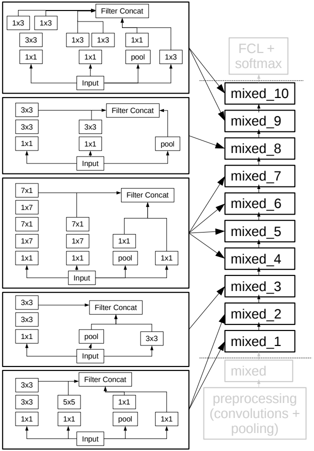

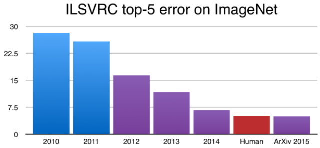

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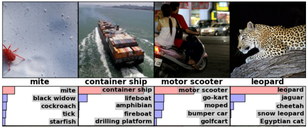

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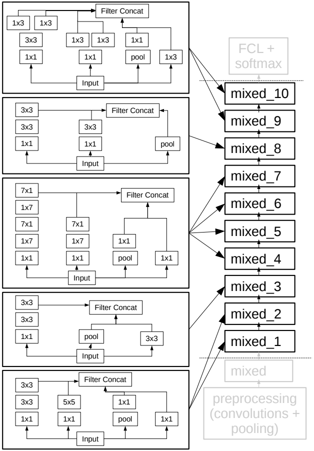
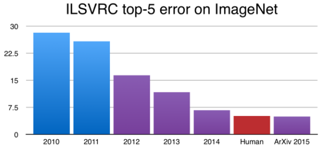
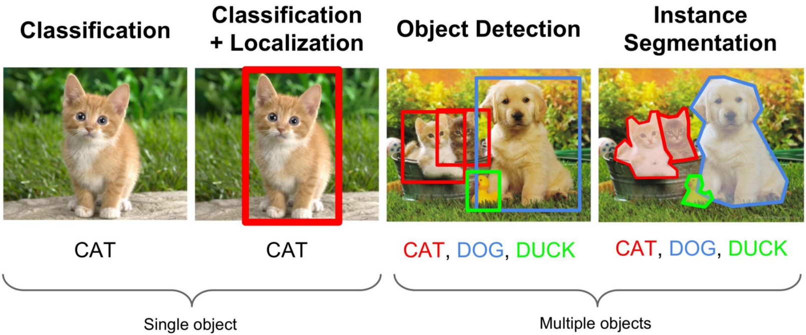
- good basis for **transfer learning**.



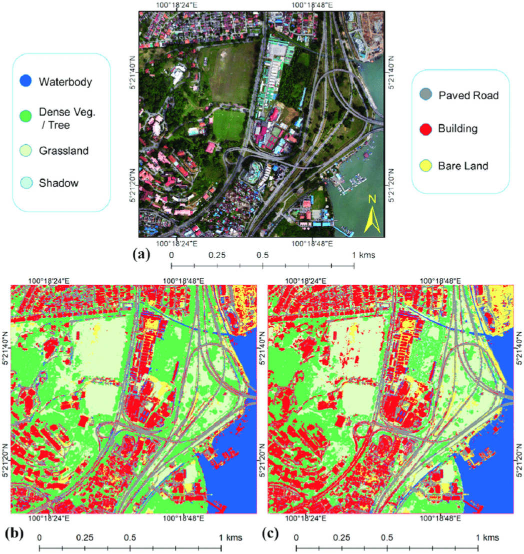


Tasks



- segmentation
- object detection
- object categorization
- similarity matching
- ...

Tasks (cont'd) image: [3]



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Deep Learning Toolboxes

Deep Learning has become easy...

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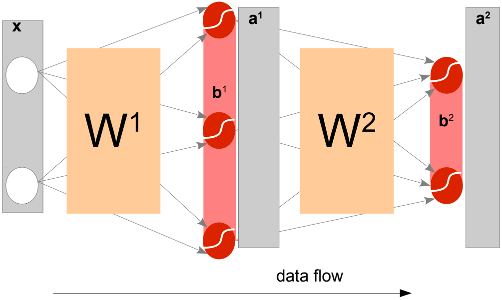
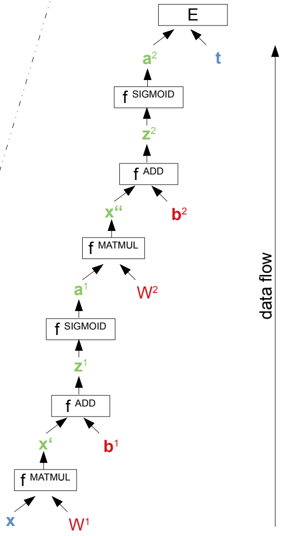
- **Visualization** of network behavior *(e.g., tensorboard)*

Neural Networks as Flow Graphs





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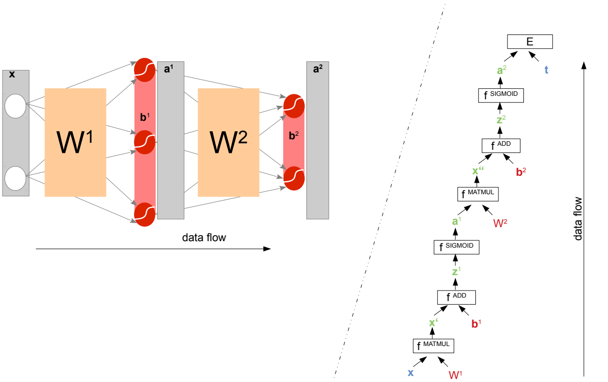
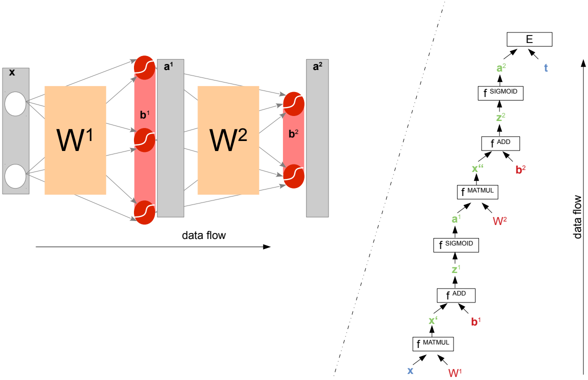


Deep Learning Frameworks view NNs as so-called flow graphs:

- The boxes correspond to operations/functions:
  Matrix multiplications, vector-adds, sigmoids, ...
- The nodes are data objects: vectors, matrices, or more generally n-dimensional *tensors*.

Neural Networks as Flow Graphs



There are three different kinds of tensors:

1. **Inputs**: features $\mathbf{x}$, targets $\mathbf{t}$, ...
2. **Parameters**: weight matrices (W^2, W^3), biases $(\mathbf{b}^2, \mathbf{b}^3)$, ...
3. **Results** from applying operations / functions $(\mathbf{a}^2, \mathbf{a}^3)$

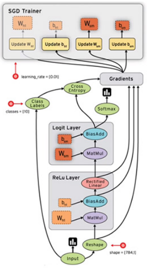
Tensorflow

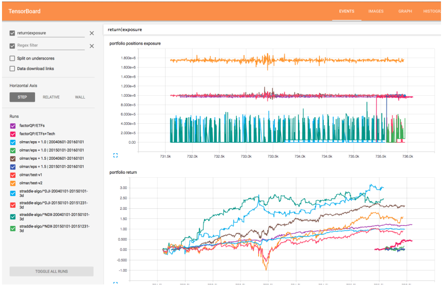
Tensorflow is the most commonly used deep learning framework.

Features

- developed by Google
- open-source (License: Apache 2.0)
- Interfaces: Python, C/C++
- Platforms: Linux, Mac OS X, Windows, Android

Tensorboard: Illustrations





Outline

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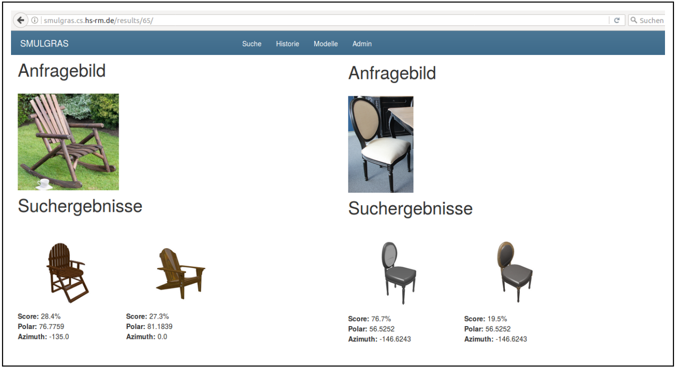
Image-Graphics Retrieval

- R&D Project SMULGRAS (1 year, 2016-17)
- development of 2D-to-3D image-graphics search



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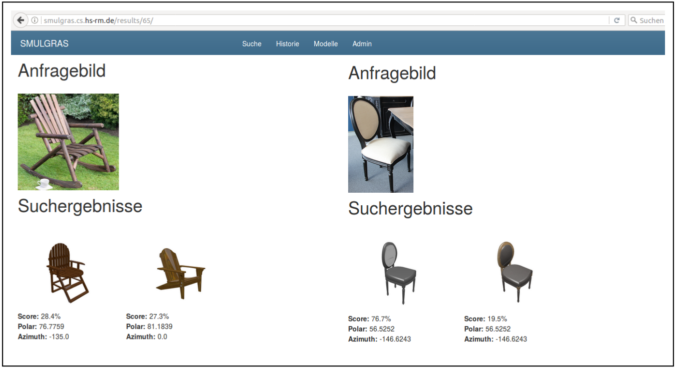

- Applications: customized product design, community-based modeling, copyright infringement, ...

Image-Graphics Retrieval

Challenges

photo to 3D model
(≈ 3D object recognition)

pose estimation

3D model registration

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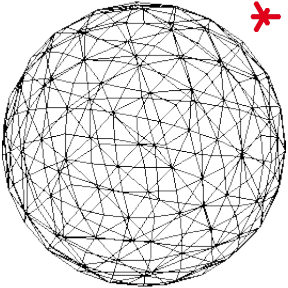
Preprocessing: Rendering

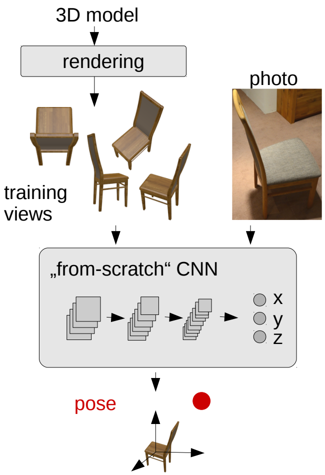


- representation of 3D model
  with rendered **views**
- **camera** sampling: Monte carlo / subdivision
- camera points at **object center**, roll $= 0°$
- **background**: plain, Flickr skybox
- **graphics**: high (raytracing, casted shadows)
  low (Phong shading)

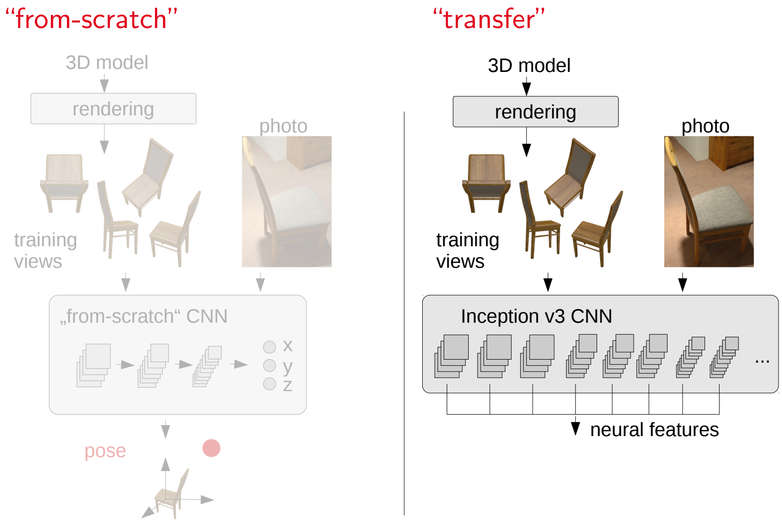
View-based Approach: Two Models

“from-scratch”

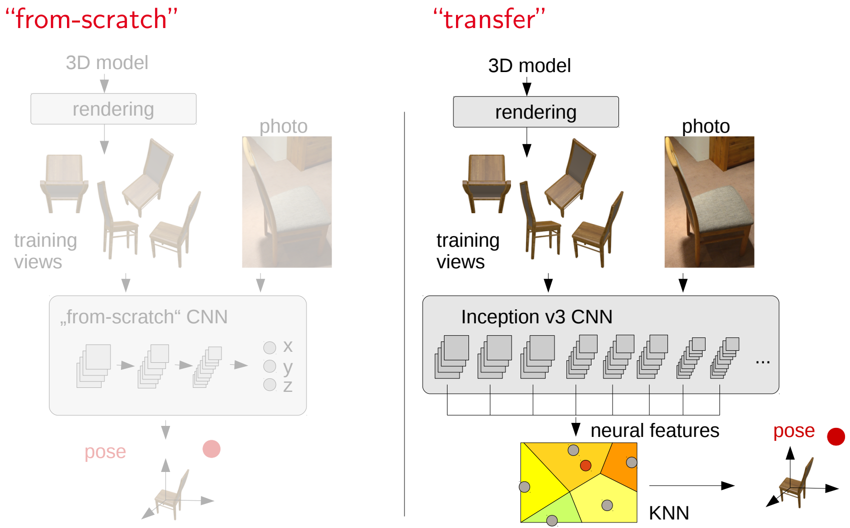
“transfer”



View-based Approach: Two Models



View-based Approach: Two Models



Experiments: Sample Results

- 200 models of chairs
  (≈ 40,000 views, subset of [4])
- 340 (calibrated) photos of chairs
  (self-captured, ground truth
  by chessboard marker)

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Recognition

Pose Estimation

Experiments: Pose Estimation

Setup

   

- 200-400 random training views per chair
- **accuracy measure**: angle between camera positions c and c’

$$E(c, c') := arccos\left(\frac{c^T \cdot c'}{||c|| \cdot ||c'||}\right)$$

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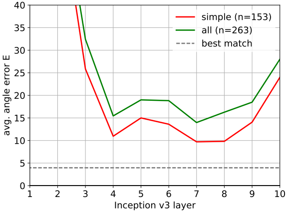
Results: Transfer Learning

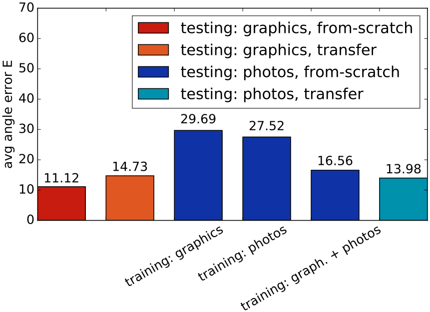


- best generalization: Inception Layer 7 (768x8x8 dimensions)

Experiments: Comparing both models

Testing on graphics

- generalization between models
- best results with from-scratch CNN
- average angle error of about **11.12°** (compared to 14.73°)



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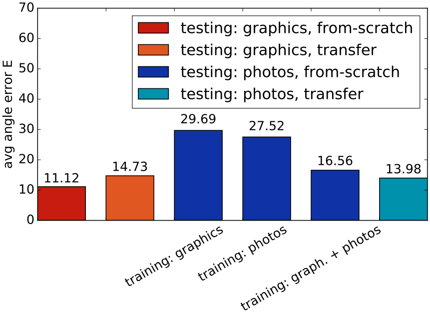

Testing on photos

- **from-scratch CNN**: strong **domain drift** observed
- **transfer learning**: model outperforms all from-scratch runs

Experiments: Sample results

- from-scratch CNN (left) and transfer learning (right)
- Example 1: Angle error of about 30°
- Example 4: Angle error of about 13.5°

The End

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