Image Recognition

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Fraunhofer
BIG DATA AI

Course Overview

1. Intro to Deep Learning	Recent successes, Machine Learning, Deep Learning & types
2. Intro to Tensorflow	Basics of Tensorflow, logistic regression
3. Building Blocks of Deep Learning	Steps in Deep Learning, basic components
4. Unsupervised Learning	Embeddings for meaning representation, Word2Vec, BERT
5. Image Recognition	Analyze Images: CNN, Vision Transformer
6. Generating Text Sequences	Text Sequences: Predict new words, RNN, GPT
7. Sequence-to-Sequence and Dialog Models	Transformer Translator and Dialog models
8. Reinforcement Learning for Control	Games and Robots: Multistep control
9. Generative Models	Generate new images: GAN and Large Language Models

: link to background material, : link to images used in lecture, G. : Terms that may be asked in the exam

Image Recognition

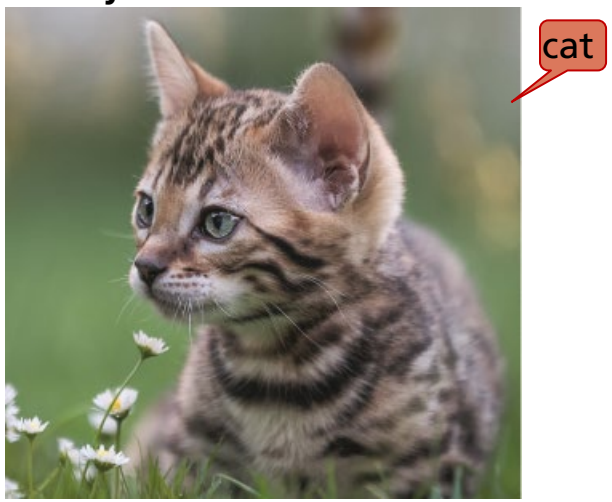
Agenda

1. Image Recognition Tasks
2. Convolutional Layers as local Feature Detectors
3. Simple Convolutional Neural Network
4. Advanced Convolutional Neural Networks
5. Vision Transformer
6. Semantic Segmentation
7. Summary

Different Types of Image Recognition

- Detect the objects in an image
  - Determine their type: classification
  - Find the location of an object
    - Bounding box
    - Pixel of an object
- Image Captioning: Describe the main contents of the image

Object classification

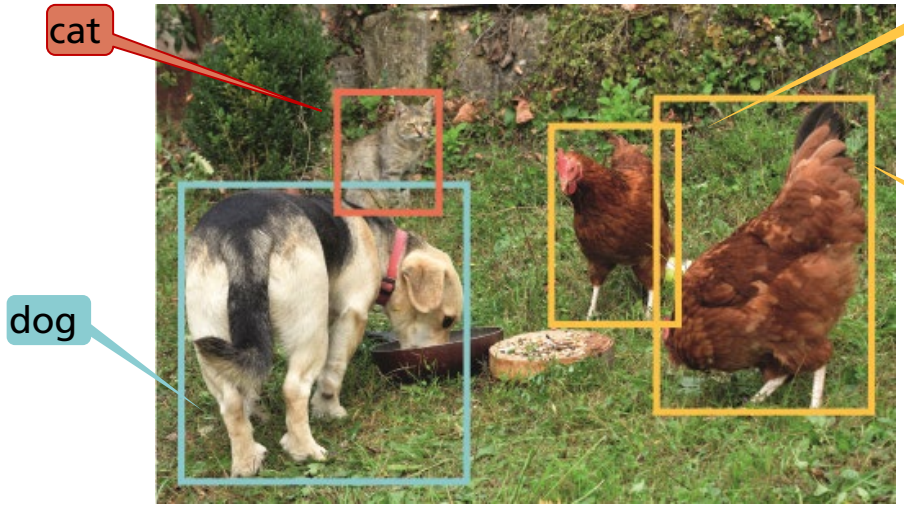


andreaskrappweis / istockphoto.com

Object localization

G. image recognition task

Object localization



Pavol Klimek / stock.adobe.com

Object segmentation

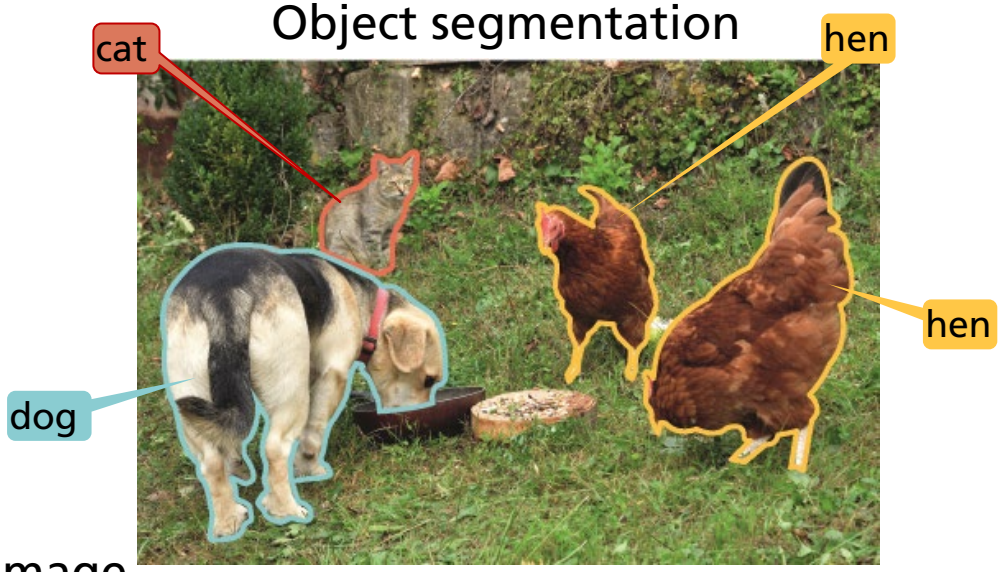


Image Captioning

Two hens, a dog and a cat on a meadow

ImageNet

www.image-net.org

Deng et al. 2009: **ImageNet**: A Large-Scale Hierarchical Image Database

22k categories and 15M images

Annotate the most prominent object

- Animals
  - Bird
  - Fish
  - Mammal
  - Invertebrate
- Plants
  - Tree
  - Flower
- Food
- Materials
- Structures
- Artifact
  - Tools
  - Appliances
  - Structures
- Person
- Scenes
  - Indoor
  - Geologic
- Sport

"bird" by Mathias Appel / CC0 1.0

"Palm tree" by L. Braughler / CC BY 2.0

"Б-396 Tango class submarine" by Peer.Gynt / CC BY-SA 2.0

"Soccer Practice" by mill56 / CC BY 2.0

ImageNet Classification Challenge

1000 object classes

1431167 images

Criterion: Top-5 error

GT: Stork

Output
Nest
Stork
Chicks
Twigs
Eggshell

✓

Output
Nest
Bird
Chicks
Twigs
Eggshell

✗

ImageNet Classification Challenge: Results

1000 object classes

1431167 images

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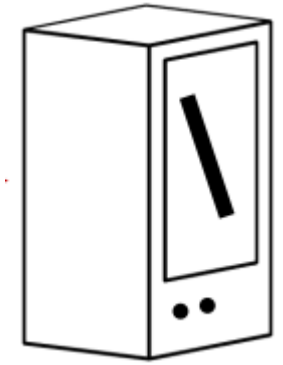
Hubel & Wiesel 1959

- Experiments with the visual cortex of cats
  - record nerve signals from single cells
- Simple cells:
  response to sticks of different orientation
- Complex cells:
  Response to light orientation & movement

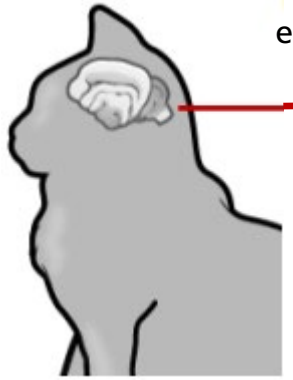
- Hypercomplex cells:
  response to movement with an end point

no response

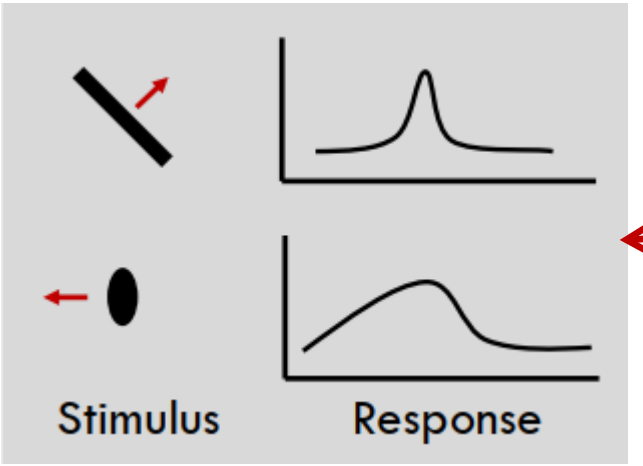
response
(end point)



Stimulus



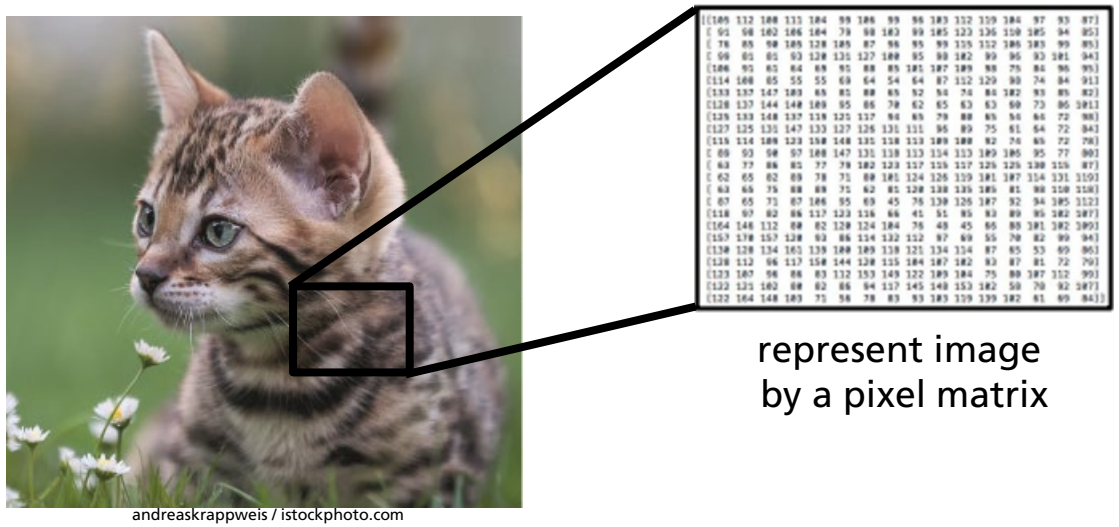
electrical signal
from brain



brain first detects local features
which are processed further

Local Feature Detection: Convolution

- Define a small kernel: matrix, e.g. 3x3
- move kernel over input pixel matrix
- multiply kernel values with pixel values
- store sum in output field



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represent image
by a pixel matrix

Image

50	200	235	201
15	135	88	100
0	42	77	165
6	108	250	144

*

Convolution Kernel

-1	-1	-1
-1	8	-1
-1	-1	-1

Kernel = **3x3**
Stride = **1**
Padding = **0**

=

Resulting Feature Matrix

0	0	0	0	0	0
0	50	200	235	201	0
0	15	135	88	100	0
0	0	42	77	165	0
0	6	108	250	144	0

*

-1	4
-3	2

Kernel = **2x2**
Stride = **2**
Padding = **1**

=

Example: Edge detection

- Apply kernel with specific values

Before any kernel convolution. By Michael Plotke CC BY-SA 3.0

kernel

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

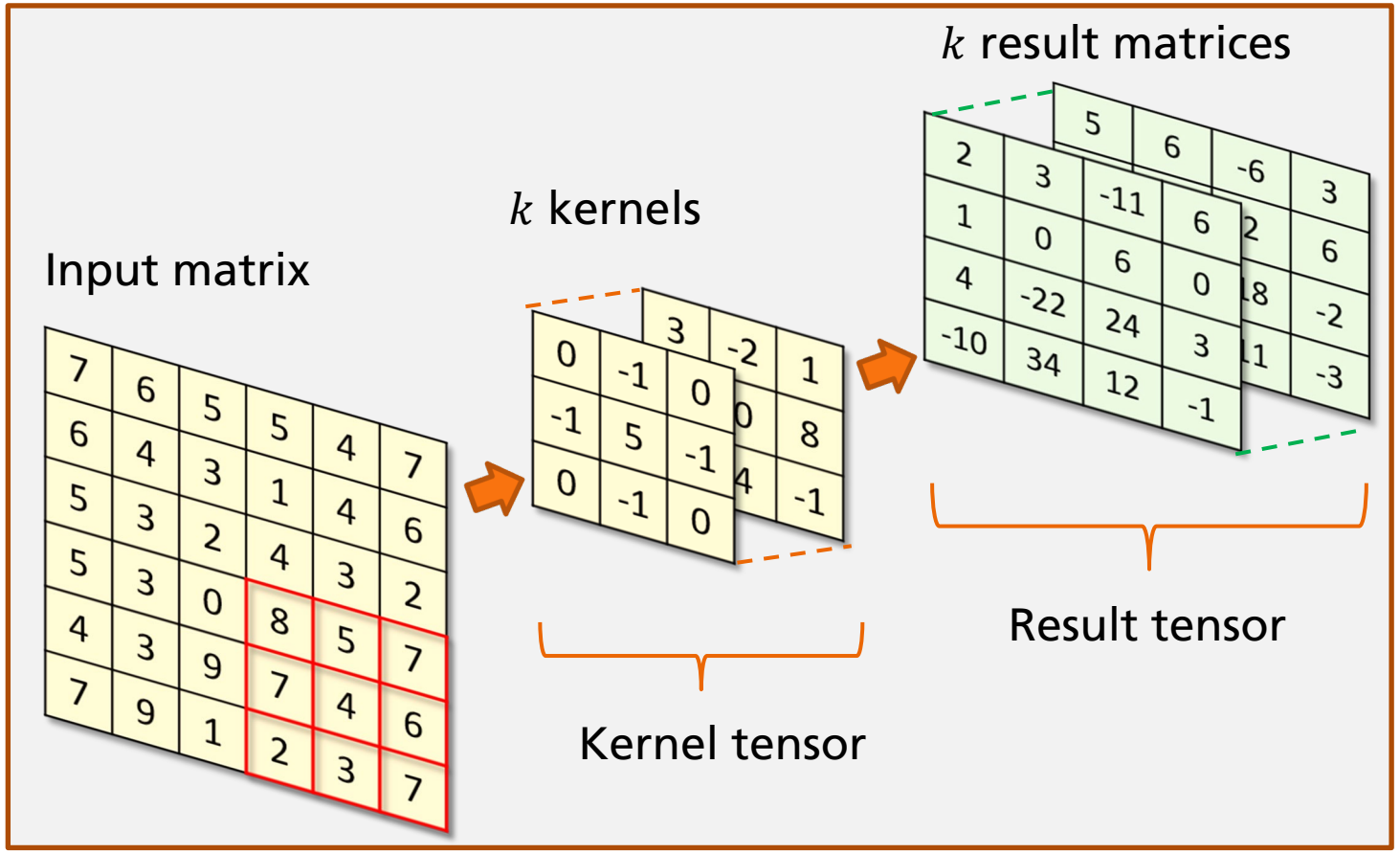
$$\odot \begin{bmatrix} 0 & -1 & 0 \\ -1 & 5 & -1 \\ 0 & -1 & 0 \end{bmatrix} =$$

$$\odot \begin{bmatrix} 1 & 1 & 1 \\ 1 & 8 & 1 \\ 1 & 1 & 1 \end{bmatrix} =$$

Kernel (image processing)

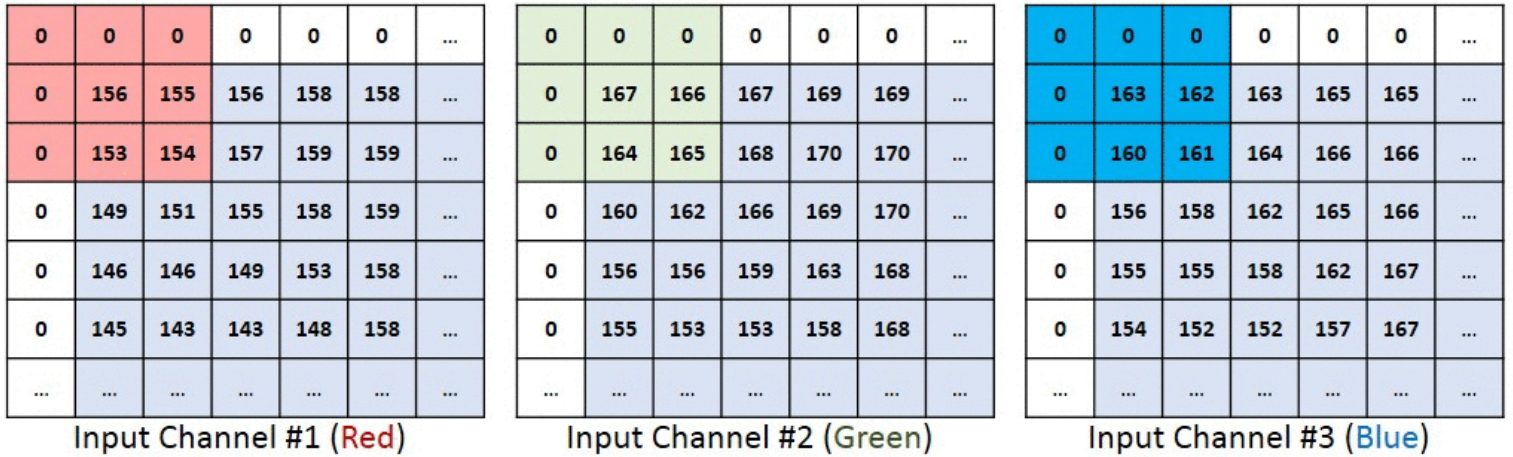
Convolution: Filter bank

- **Filter bank**: Convolutional layer with k independent kernels
- number of kernels can be selected
- Values in kernels are parameters: Adapted to training data
- Convolutions with multiple filters change the size of the output ("hidden units")



Convolution for RGB Images

- Apply 3x3x3 kernel to the three input pixel matrice



- kernel matrices: values are optimized

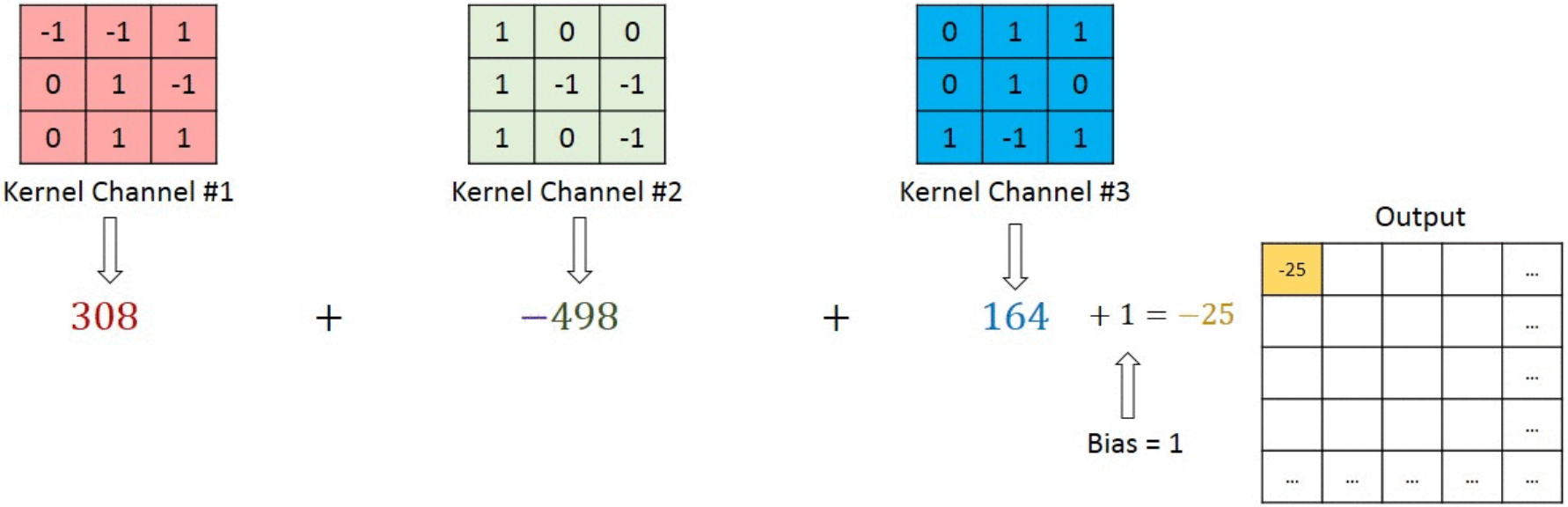
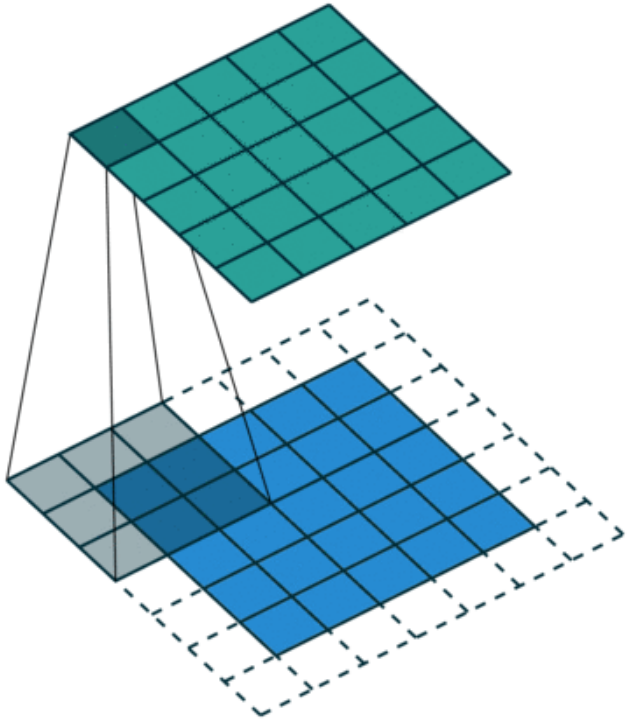


Image Margins and Strides

- images are often padded with 0s
- otherwise: result matrix is smaller

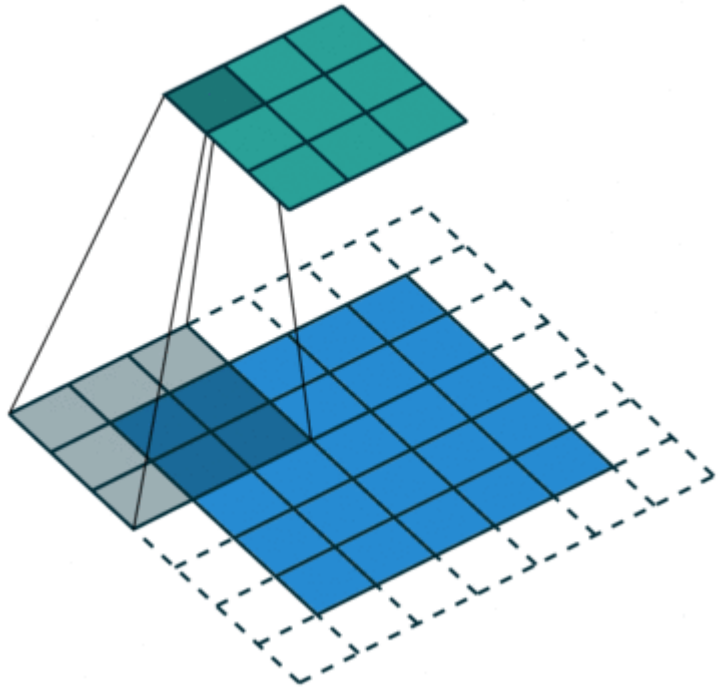
"same padding"

- Apply 3x3 kernel with stride 1



"valid padding"

- Apply 3x3 kernel with stride 2



Convolutional Layers

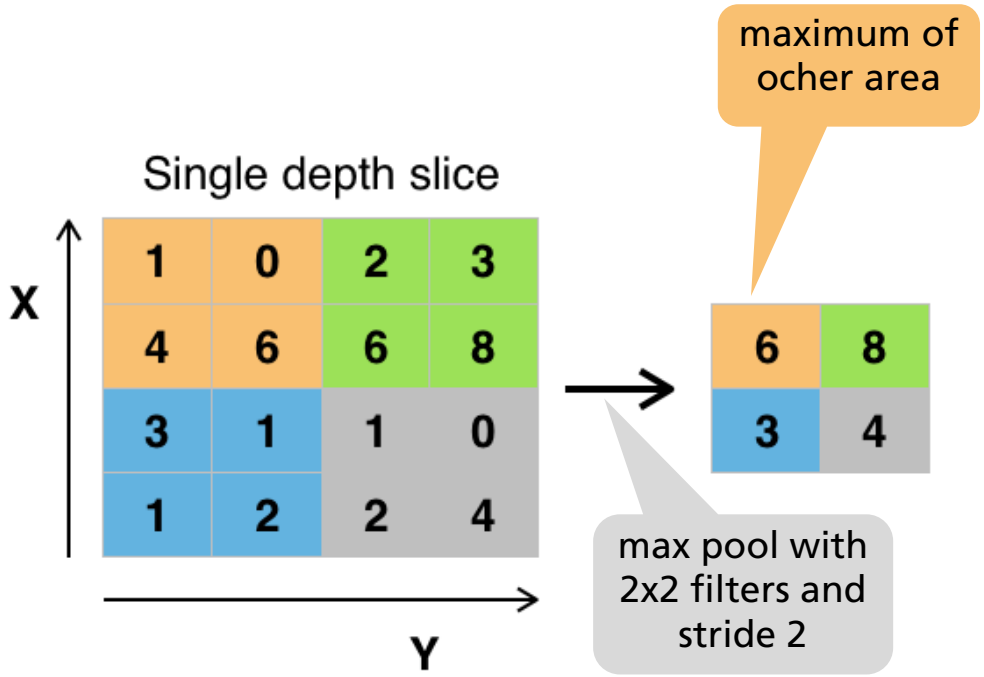
- Extract local features:
  - compute for receptive field of the kernel
  - specific bias for image recognition
- Same kernel is used for all positions in pixel matrix
  - parameter sharing
    - 1000x1000 pixel matrix and fully connected layer with 100 outputs
      ➔ 1000000*100 = 100M parameters
    - 1000x1000 pixel matrix and 100 kernels of size 3x3
      ➔ 900 parameters
- **Pro**: very flexible, few parameters
- **Con**: compute intensive (but there are special GPU-instructions to speed up)

Pooling Layer

- By selecting many kernels for the convolutional layer we get very many features
  - $m \times m$ input matrix, k kernels ➔ $\sim m * m * k$ output features
    ➔ need a way to reduce the number of features

Pooling layer

- Aggregate feature values in a feature matrix in a small field of size $r \times r$
- usually separate aggregation for each feature matrix
- reduction of number of features by factor $1/(r * r)$
- Aggregation function: mean, max, …
- max-Averaging usually has the best performance

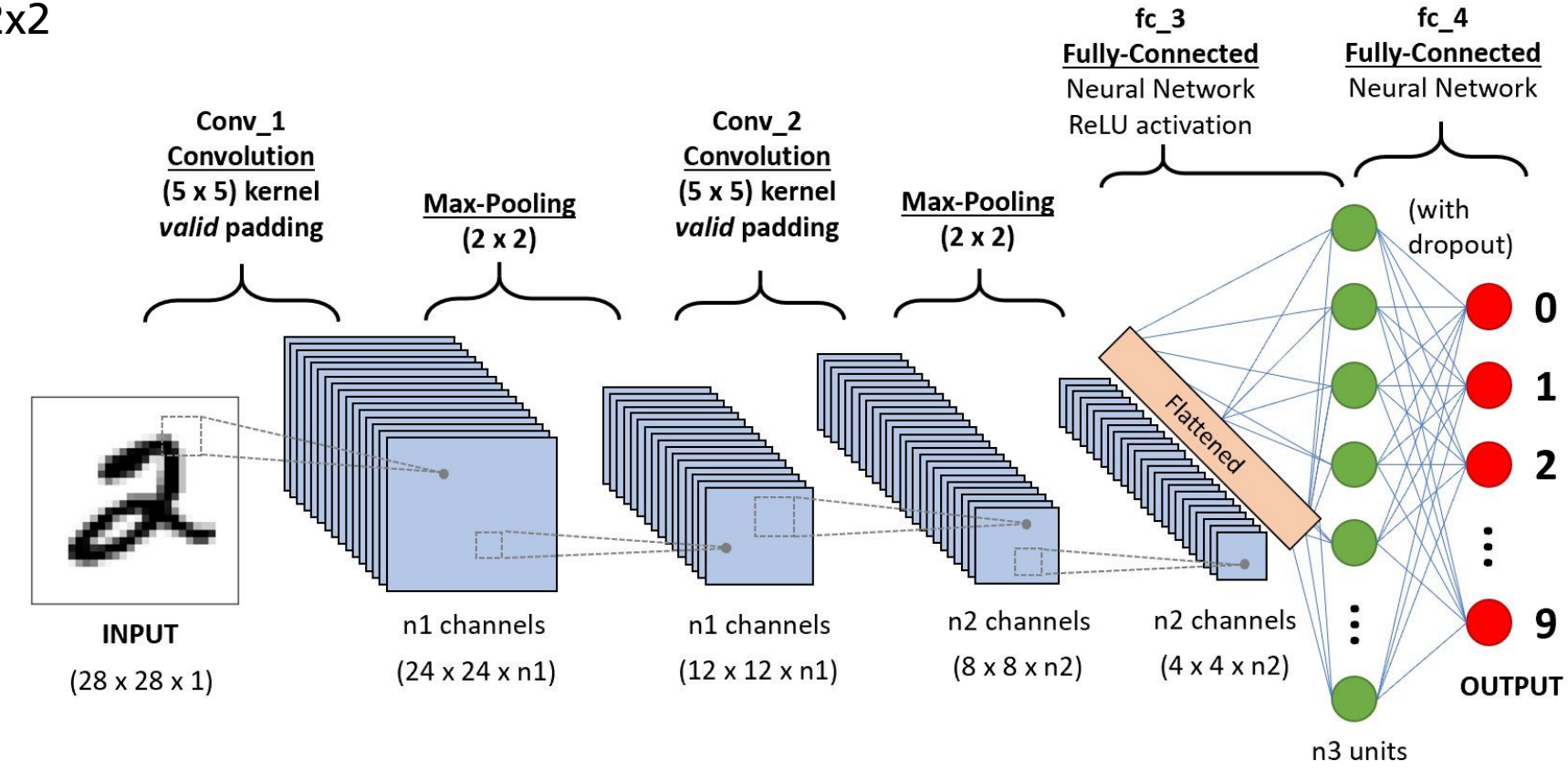


G. MaxPooling

pooling reduces the size of an image

Convolutional Neural Network

- Convolutional Neural networks (**CNN**) are a cascade of convolutional layers
  - convolution, e.g. with 5x5 kernels and ReLU activation
  - Max-Pooling, e.g. with 2x2
  - fully connect layer
  - final softmax-layer
    ➔ class probabilities
- Higher layers of CNN
  - have lower spatial resolution
  - more features per position



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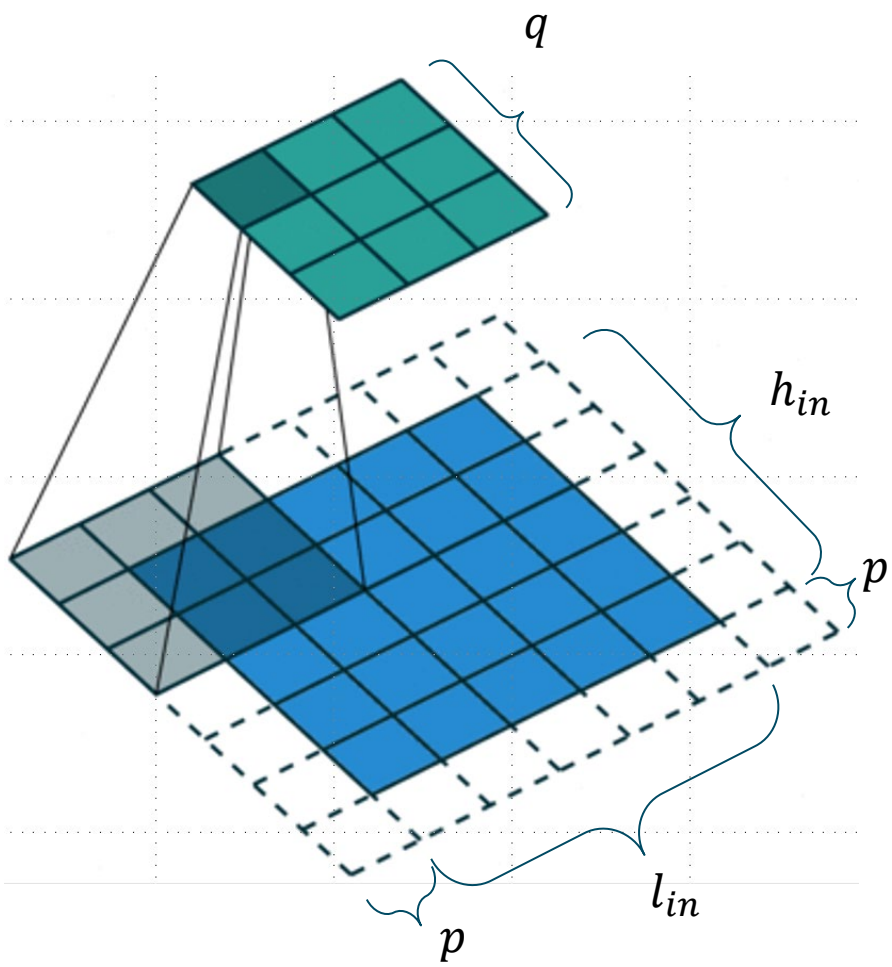
Convolutional Layer Dimensions

- Accepts an input tensor of size $l_{in} \times h_{in} \times m_{in}$ (width, height, num. features)
- Requires four hyperparameters:
  - number of filter / kernels k
  - their spatial extent $q \times q$
  - the stride (steplength) s
  - the amount of zero-padding p
- produces an output tensor of size $l_{out} \times h_{out} \times m_{out}$
  - $l_{out} = \frac{l_{in} - q + 2p}{s} + 1$
  - $l_{out} = \frac{l_{in} - q + 2p}{s} + 1$
  - $m_{out} = k$
- with parameter sharing: $q \times q \times m_{in}$ weights per kernel
  ➔ $(q \times q \times m_{in}) * k$ weights and k biases



Typical CNN Design: AlexNet

- convolutional layers (CONV) with Relu Activation
- max pooling (Max POOL)
- Dropout for regularization
- fully connected layers (FC) to aggregate
- Softmax to compute class probabilities

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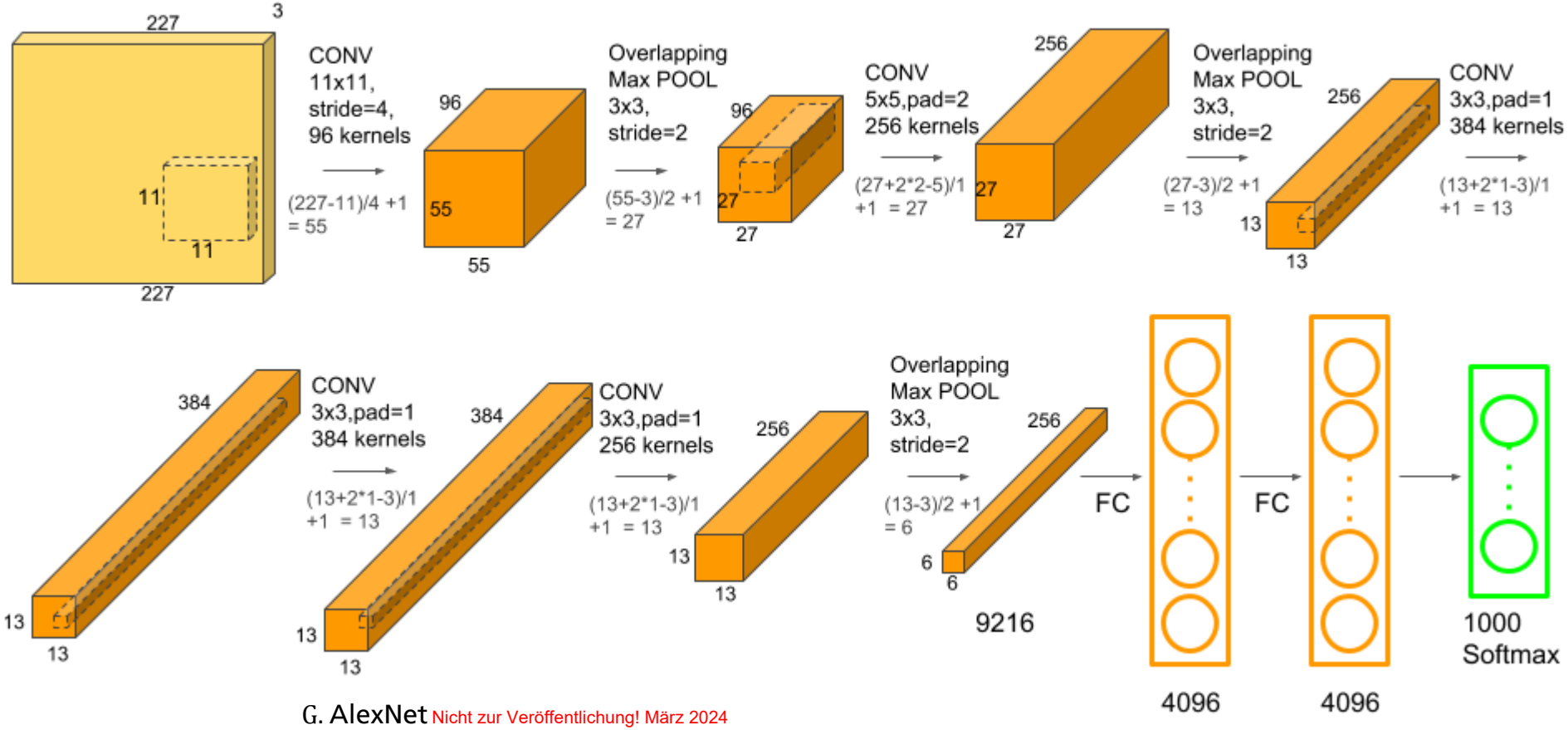
ImageNet Classification with Deep Convolutional Neural Networks by Alex Krizhevsky, Ilya Sutskever, and Geoffrey E. Hinton, 2012



G. AlexNet Nicht zur Veröffentlichung! März 2024

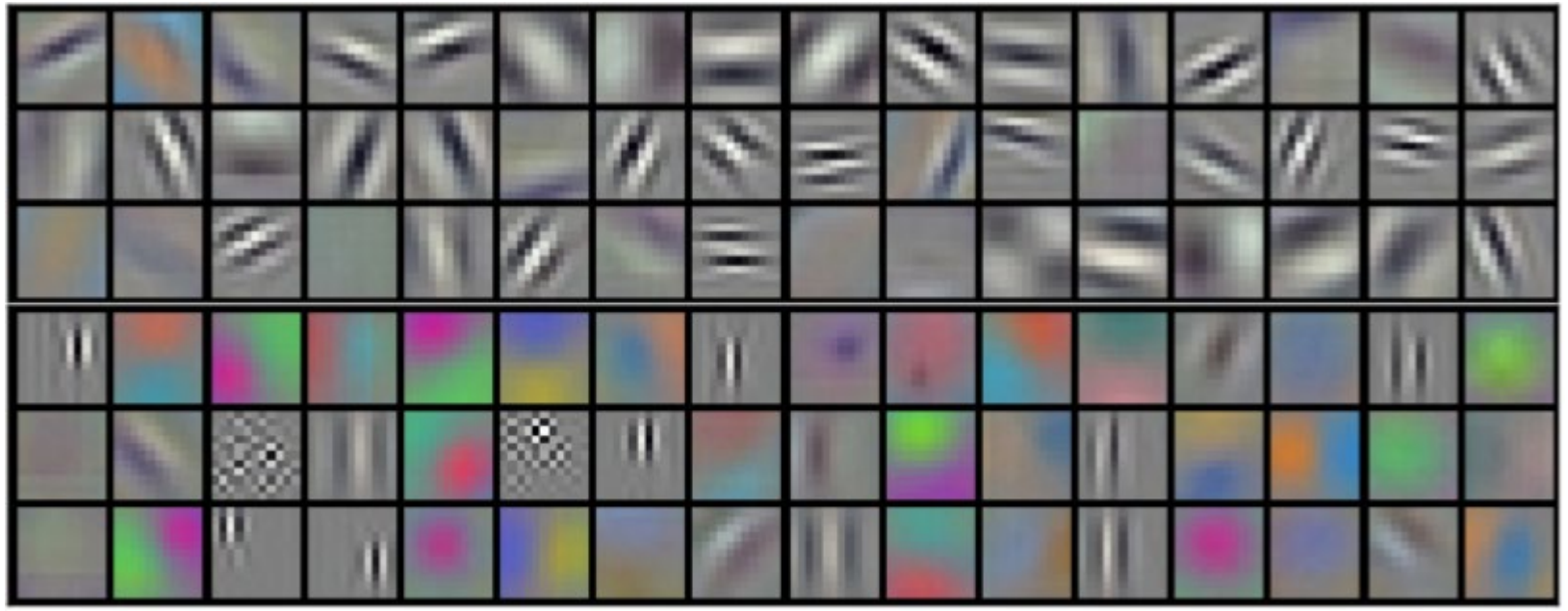
CNN Training

- Training set $(x_1, y_1), \ldots, (x_n, y_n)$ with Image-label pairs
- Initialize parameters $w^{(0)}$ (kernel values, etc.) randomly.
- loop over batches of training data
  1. forward propagation with the current $w^{(t)}$
  2. compute gradient for the next batch: $grad$
  3. update parameter
     $$w^{(t+1)} = w^{(t)} - \lambda * grad$$
  4. if $\|grad\|^2 < \epsilon$ stop
     else continue with step 1
- High computational effort: 90 epochs
  took 5-6 days on two NVIDIA GTX 580 3GB GPUs

Kernel (image processing)

Kernel Features

- Inputs with highest responds of different kernels
  - lines with different orientation and width
  - color blobs of different colors
  - textures

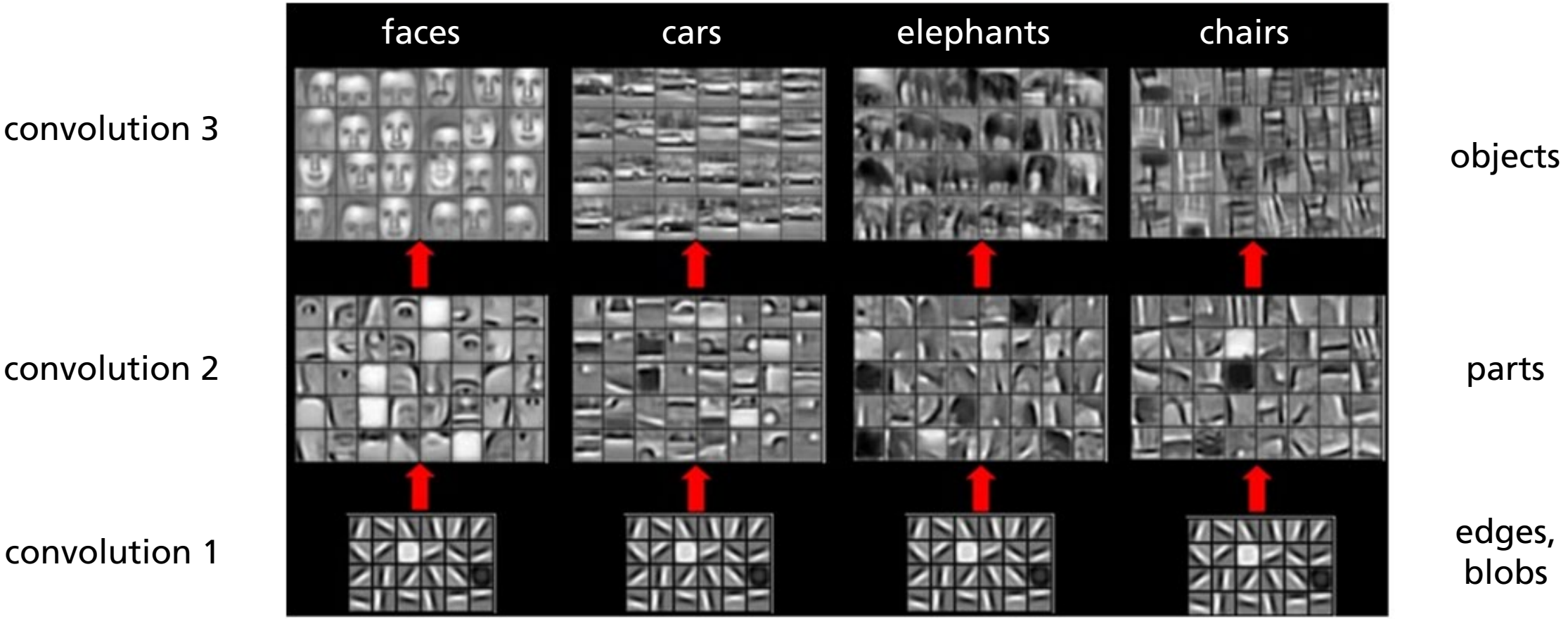


Krizhevsky et al. 2012 : ImageNet Classification with Deep ConvolutionalNeural Networks. p.6

reduced top-5 error in ImageNet
from 25.5% to 17.0%

33% reduction

CNN: Intermediate features



Hidden Vector Features

- compute feature vector $f(x)$ in the last hidden layer for test image x.
- compute feature vectors $f(x_i)$ in the last hidden layer for all training images x_i.
- determine the closest images

$$j = argmin_i \|f(x) - f(x_i)\|^2$$

- good characterization of the image by hidden vector

may be used for image search

input image

Closest training images

"Rose" by Oberau-Online / CC BY 2.0

"Rose laser バラ レーザー" by T.Kiya / CC BY-SA 2.0

"Rose Carina バラ カリーナ" by T.Kiya / CC BY-SA 2.0

"Rose, Princess Hanako, バラ, プリンセス ハナコ," by T.Kiya / CC BY-SA 2.0

[Krizhevsky et al. 2012] p.8

Image Recognition

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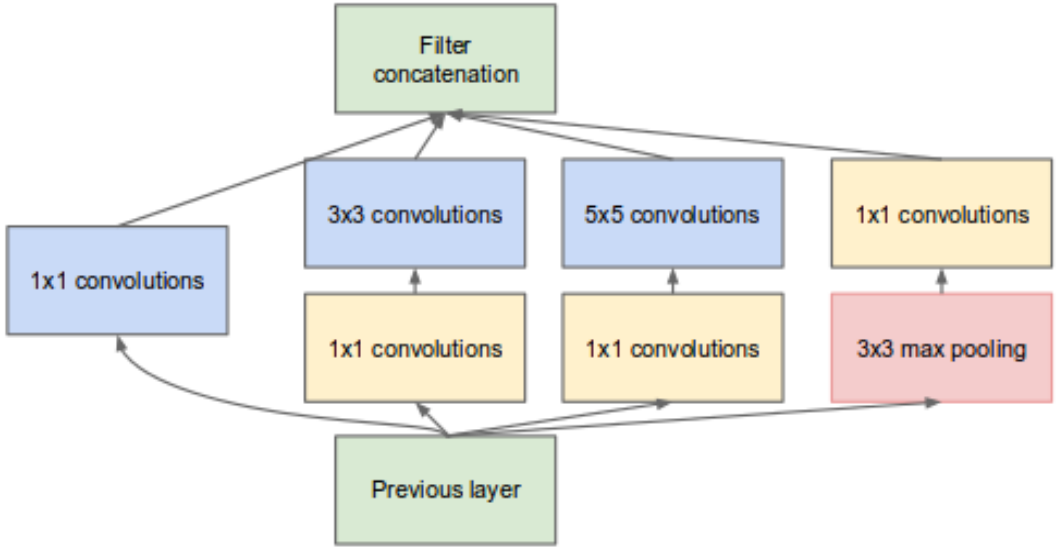
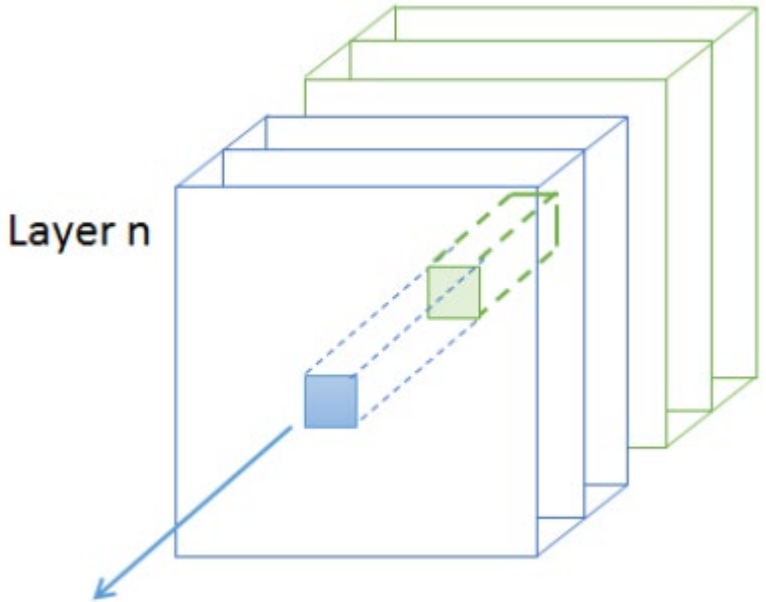
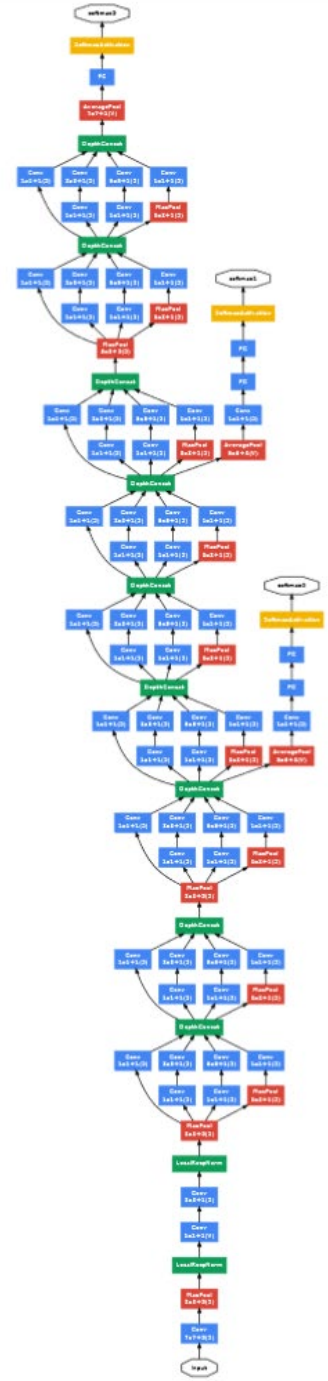
Inception Net

- First really deep net
  - ~ 160 layers
  - ~ 60 convolutions
- Only one fully connected layer
- uses dropout regularization
- **Inception Module**
  - process input with kernels of different size
  - 1x1 convolutions:
    at each position compute linear mapping for values at same position
    ➔ downsample features





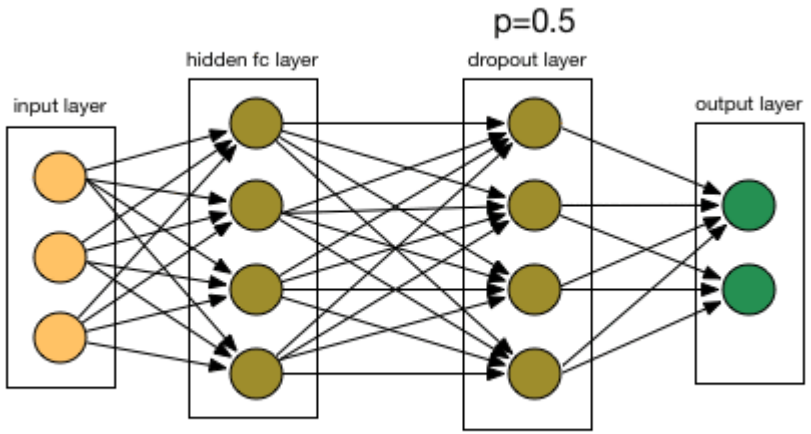


Szegedy et al. 2015: Going deeper with convolutions.

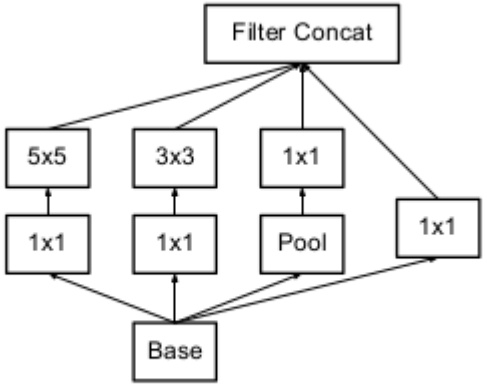
G. Inception Module

Inception Net

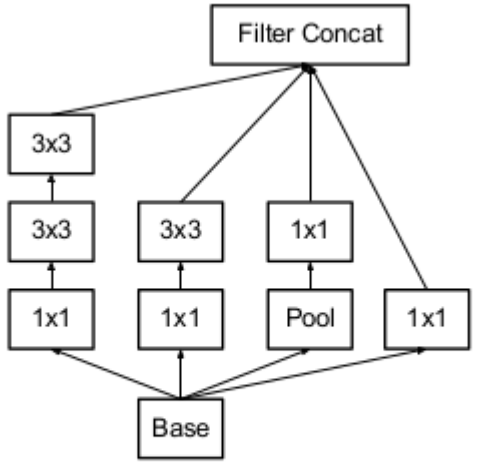
- **Regularization**:
  - Dropout layer: "drops" random portion of connections for one iteration
- **Separable convolution**
  - Replace larger kernels by 2 successive smaller kernels:
    e.g. 5x5 by 3x3 followed by 3x3
- less weights
  ➔ less memory & computation



Training time



Inception module version 1



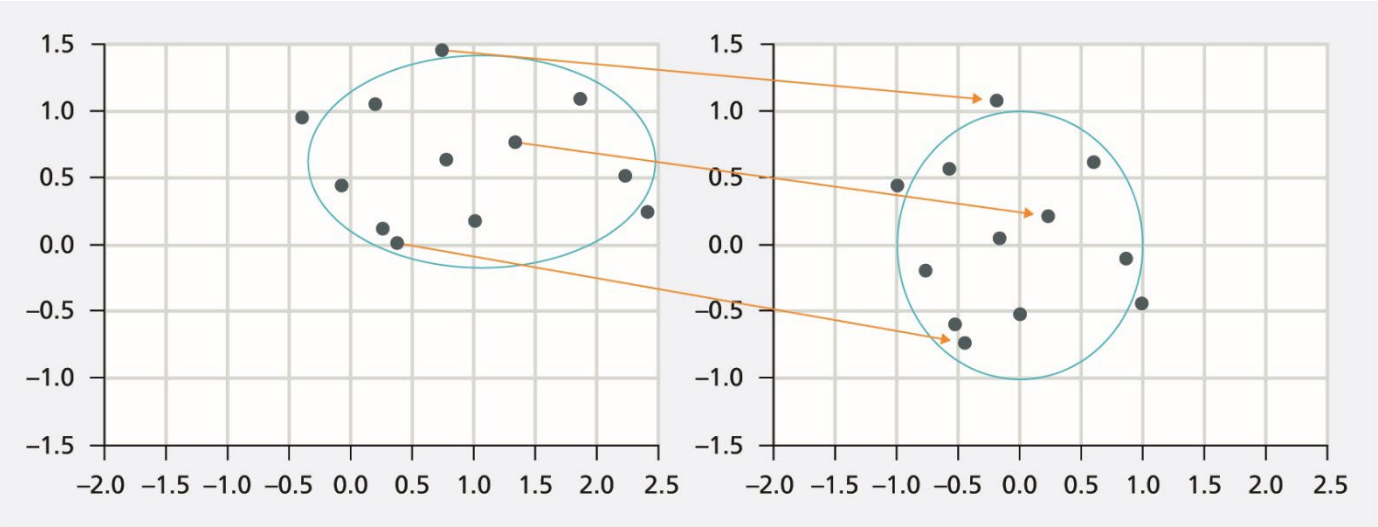
Inception module version 3

Szegedy et al. 2015: Going deeper with convolutions.

Inception Net

- **Regularization**:
  - Batch Normalization
- Renormalization of layer outputs (batch by batch)
  - Fixes the covariance-shift between batches
  - Avoids the "*vanishing gradient*" problem
  - need to compute batch statistics

- Input: values of a feature for a minibatch $x_1, \ldots, x_m$
- compute mean $\mu = \frac{1}{m}\sum_{i=1}^{m} x_i$
- compute variance $\sigma^2 = \frac{1}{m}\sum_{i=1}^{m}(x_i - \mu)^2$
- normalize $\hat{x}_i = \frac{x_i - \mu}{\sqrt{\sigma^2 + \epsilon}}$
- transform $y_i = \gamma\hat{x}_i + \beta$
  with trainable parameters γ and β



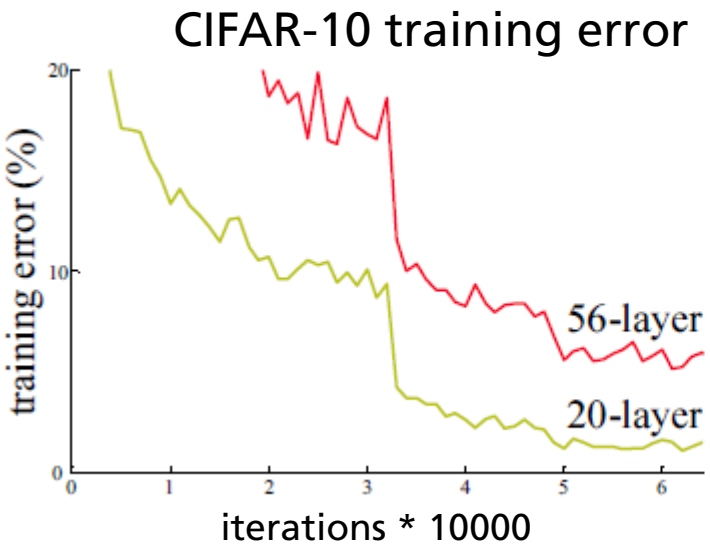
- Performance on the ImageNet benchmark
  - 3.58% top-5 error

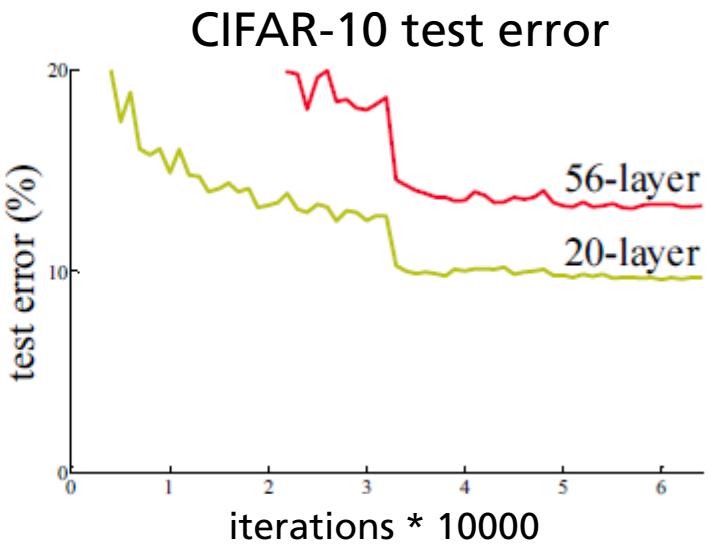
Szegedy et al. (2016). Rethinking the inception architecture for computer vision.

ResNet: newer architecture for deep CNNs

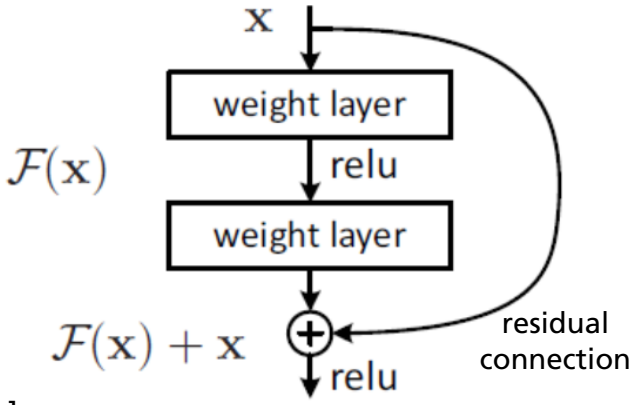
[He et al. 2015] p.770

- Training of deep networks is difficult
  - 20-layer network has lower error than a 56-layer network
  - deeper networks: **problem of vanishing/exploding gradients**





- Skip / residual connections
  - a skip / shortcut connection is added to add the input *x* to the output after few weight layers
  - The skip connection is added to output



at start with small weights
➔ identity connection

[He et al. 2015: Deep residual learning for image recognition.]

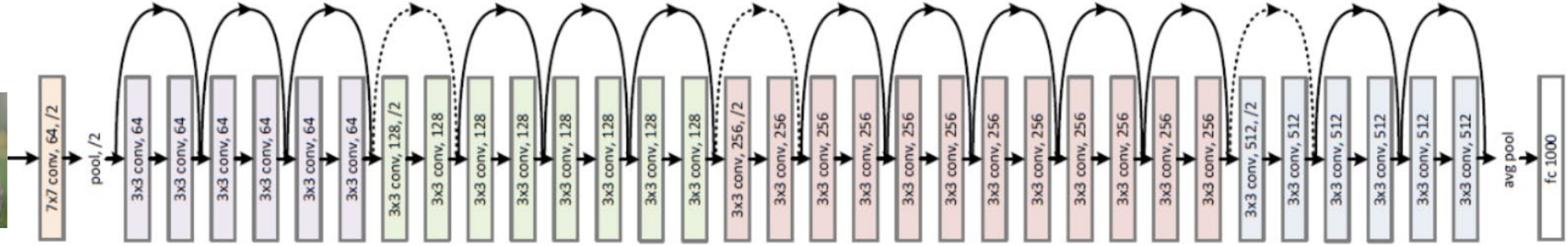
G. Residual Connection

ResNet

- Resnet architecture allows to use very many layers
- Batch normalization for regularization, no dropout
- SGD + Momentum
- minibatch size 256

- Experimental Results
  - Able to train very deep networks without degrading (152 layers on ImageNet, 1202 layers on Cifar)
  - Deeper networks now achieve lower training error as expected
  - 3.6% top 5 error in ImageNet '2015 better than human performance

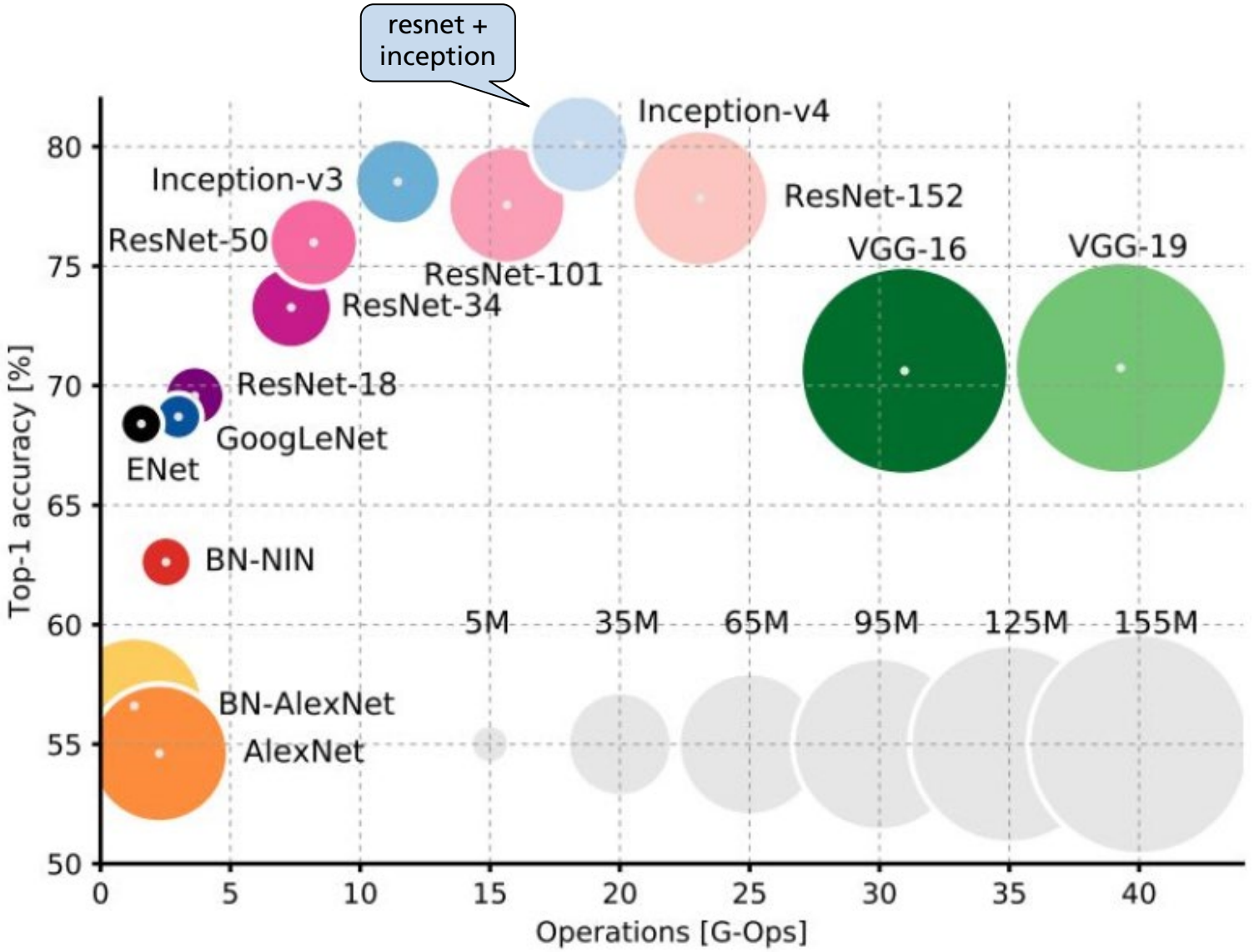
andreaskrappweis / istockphoto.com



[He et al. 2015] p.773

Comparing Complexity

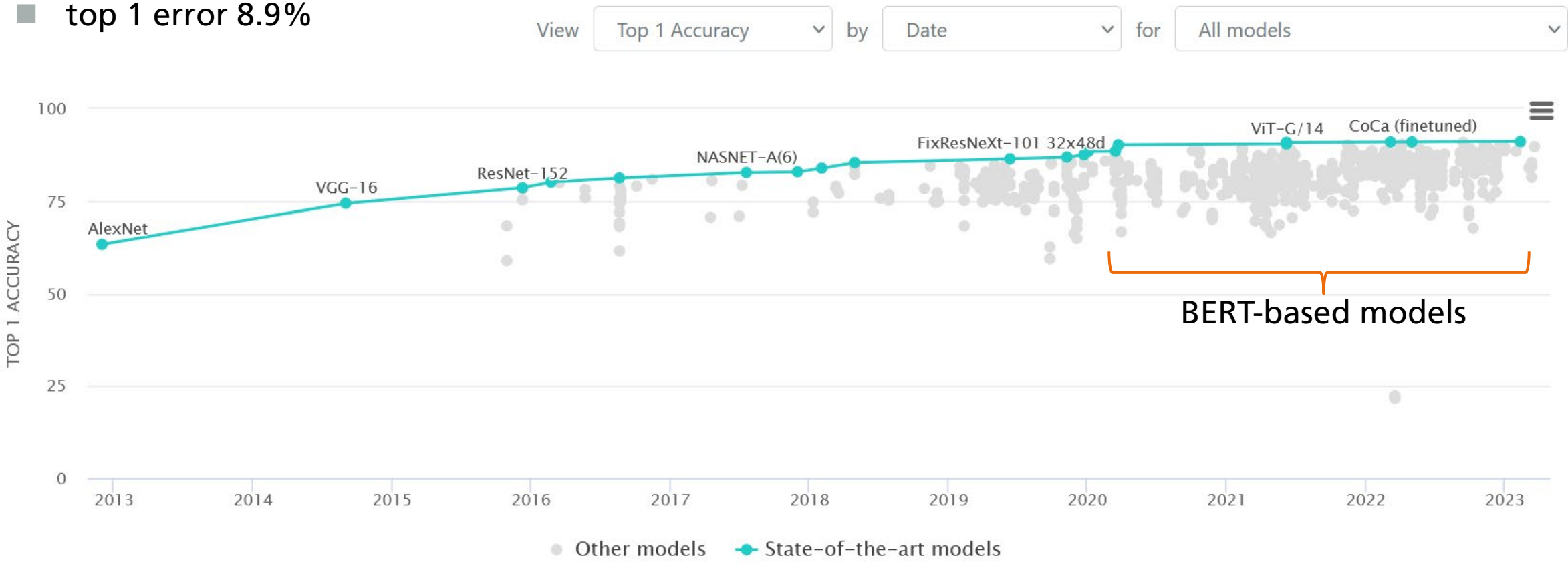
- ResNet has not very many parameters compared to its performance
- The computational effort is relatively low



[Canziani, Paszke, Culurciello 2017] p.2

Improving ResNet

- Current state-of-the art:
  - top-5 error 0.98%
  - top 1 error 8.9%



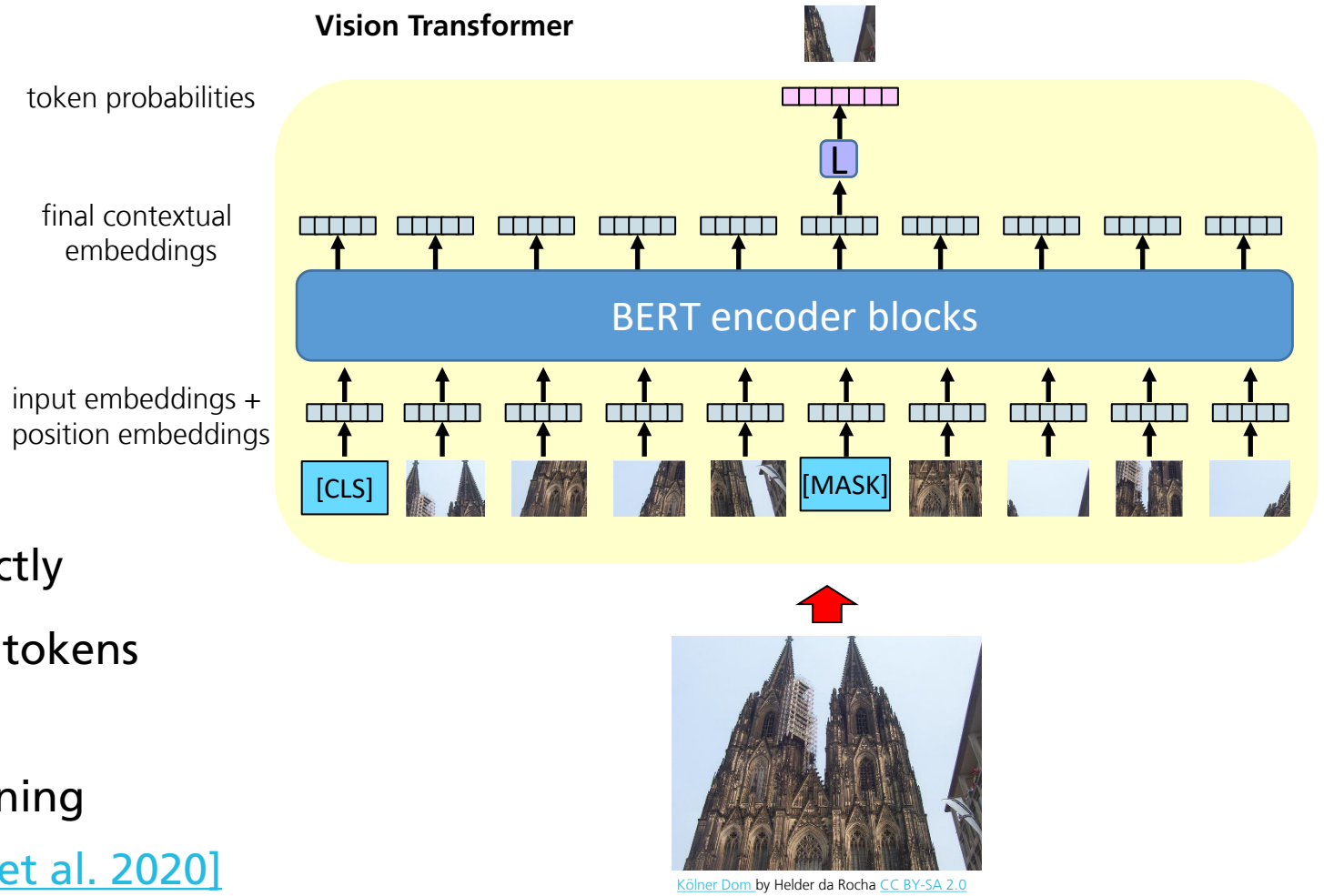
https://paperswithcode.com/sota/image-classification-on-imagenet

Image Recognition

1. Image Recognition Tasks
2. Convolutional Layers as local Feature Detectors
3. Simple Convolutional Neural Network
4. Advanced Convolutional Neural Networks
5. Vision Transformer
6. Semantic Segmentation
7. Summary

Vision Transformer

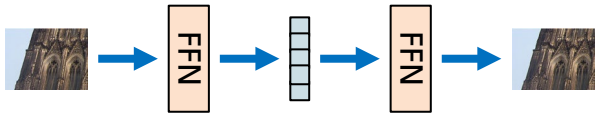
- An image can be partitioned into image tokens
  ➔ e.g. 16x16 pixel **image patches**
- Assign each image patch to an embedding vector, e.g. by linear map
- Apply BERT encoder blocks create contextual embeddings
- Pre-training:
  - Predict masked tokens
  - or predict ImageNet classes directly
- Model the relation between image tokens
  - can fill in missing tokens
  - solve additional tasks by fine-tuning
  - Vision Transformer [Dosovitskiy et al. 2020]



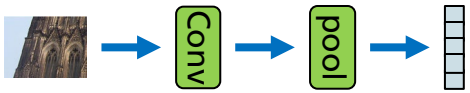
Kölner Dom by Helder da Rocha CC BY-SA 2.0

Vision Transformer Input Encoding

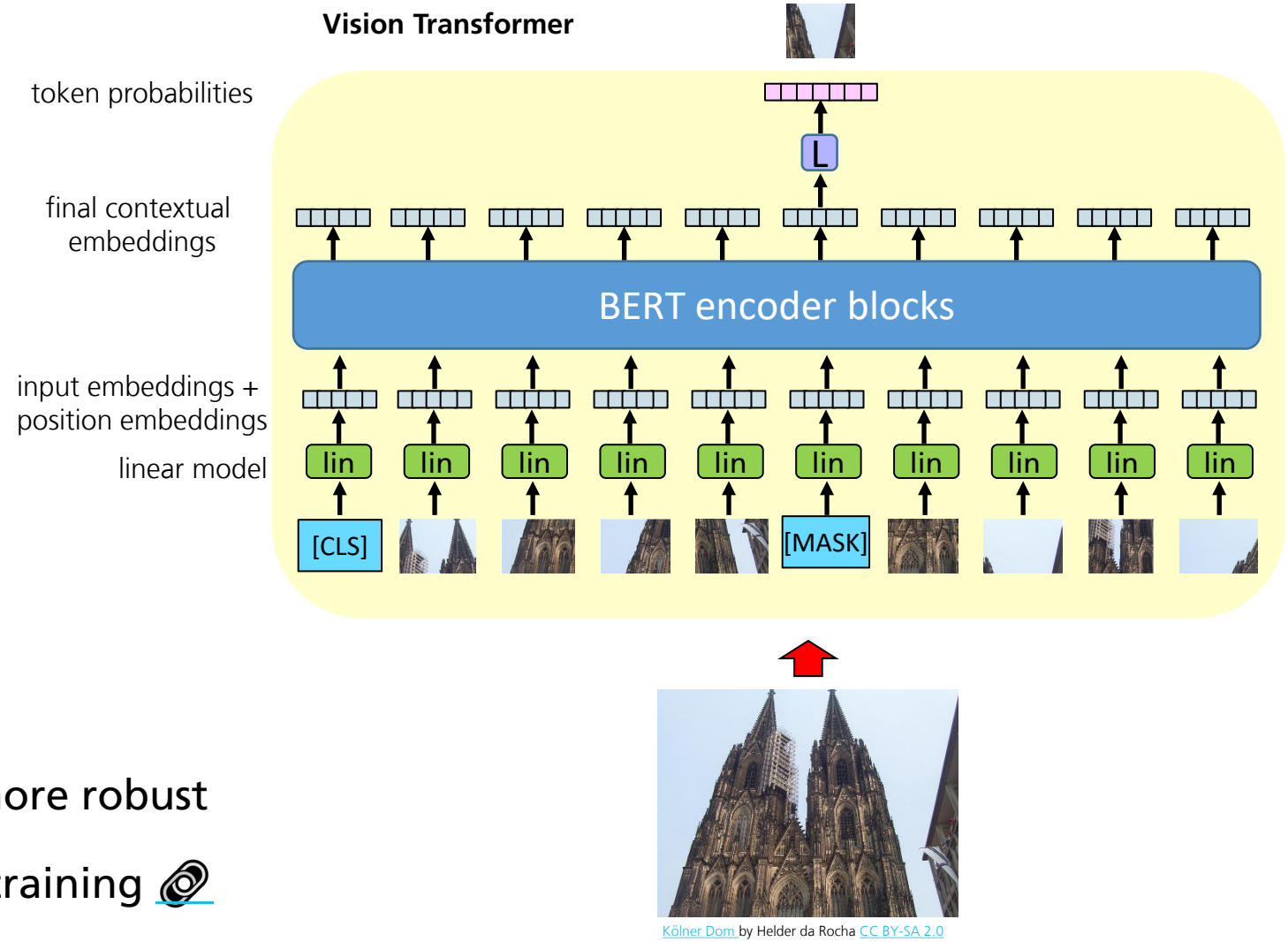
- Generate input embeddings
  - Flatten image patches to vectors and transform linearly $Ax + b$
- Alternative input embeddings
  - autoencoder for image patches



  - first local layers of CNN, e.g. ResNet 152



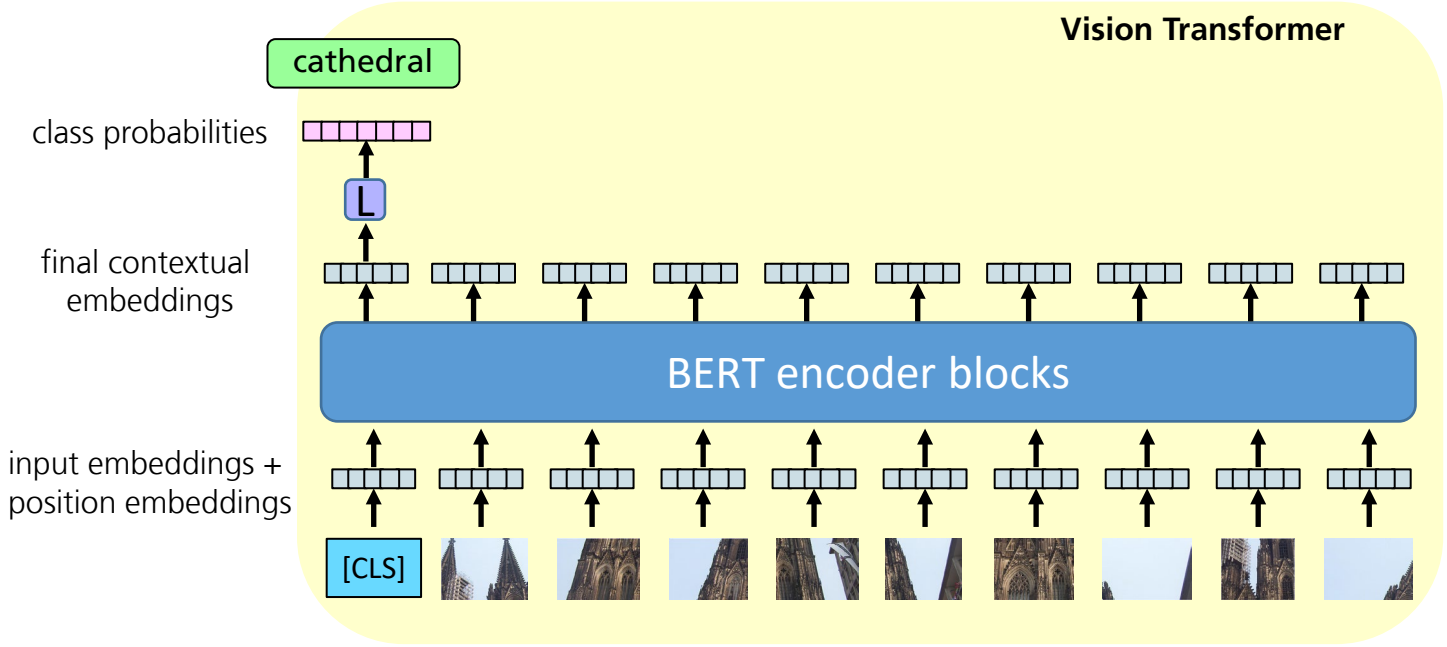
- Cluster inputs to discrete tokens: more robust
- Step-by-step implementation and training



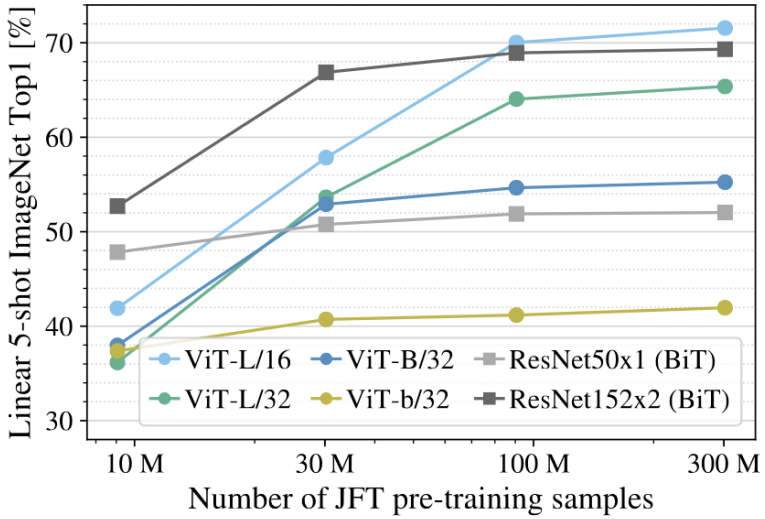
Kölner Dom by Helder da Rocha CC BY-SA 2.0

ImageNet Classification

- Pre-train vision transformer on a large unlabeled image dataset
- weight decay
  dropout
- Fine-tune on ImageNet classification task with 1000 object classes
- Size of pre-training data matters
  - 10 M images: 42% top-1 acc.
  - 300M images: 73% top 1 acc. **SOTA**
  - model needs more data to acquire knowledge about images



[Dosovitskiy et al. 2020]



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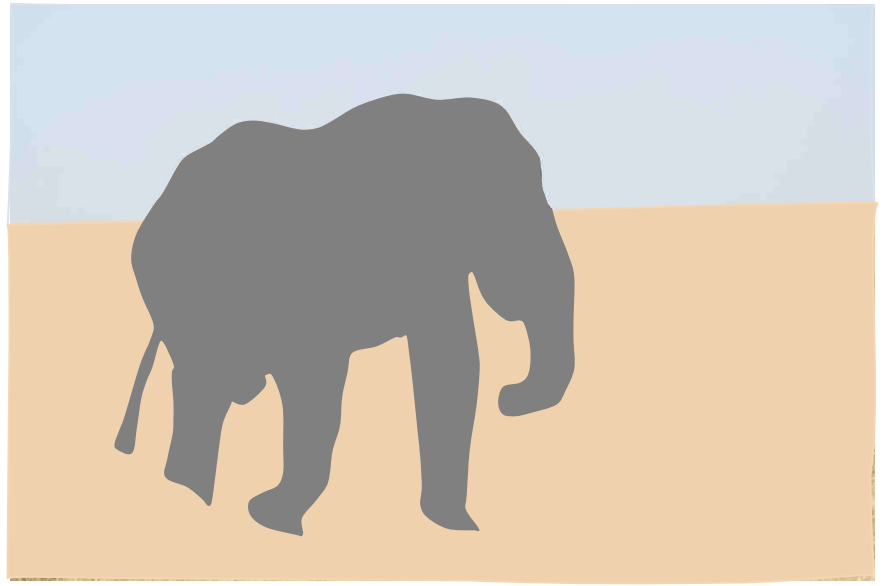
Semantic Segmentation

- Identify the pixels belonging to an object.
- Need to classify the objects of the image.
  - Integrate information in the image to a high level
  - propagate the classification information to each pixel.

Sky

Elephant

Ground



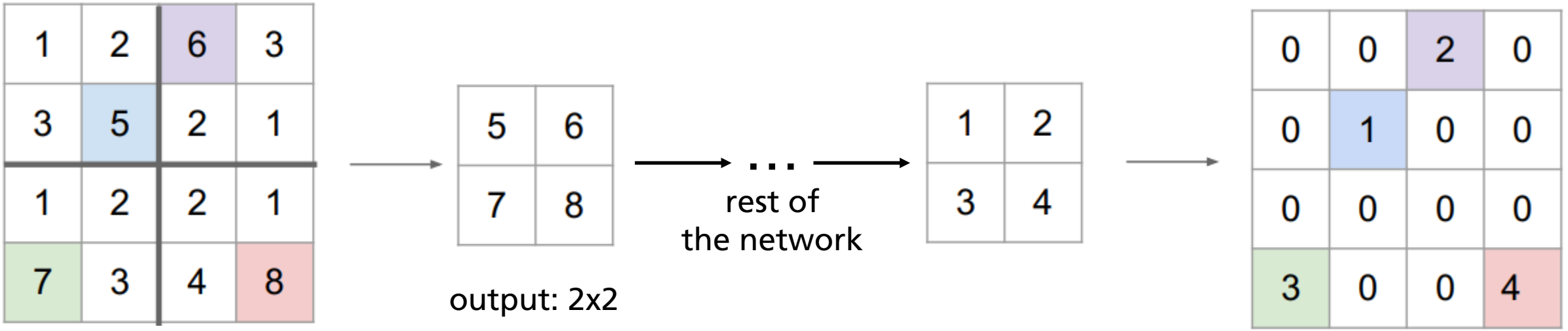
G. Segmentierung

Downsampling and Upsampling

- Max-Pooling performs downsampling
  ➔ reduce spatial resolution
- Create an inverse upsampling
  ➔ increase spatial resolution

Max Pooling
remember which element was max!

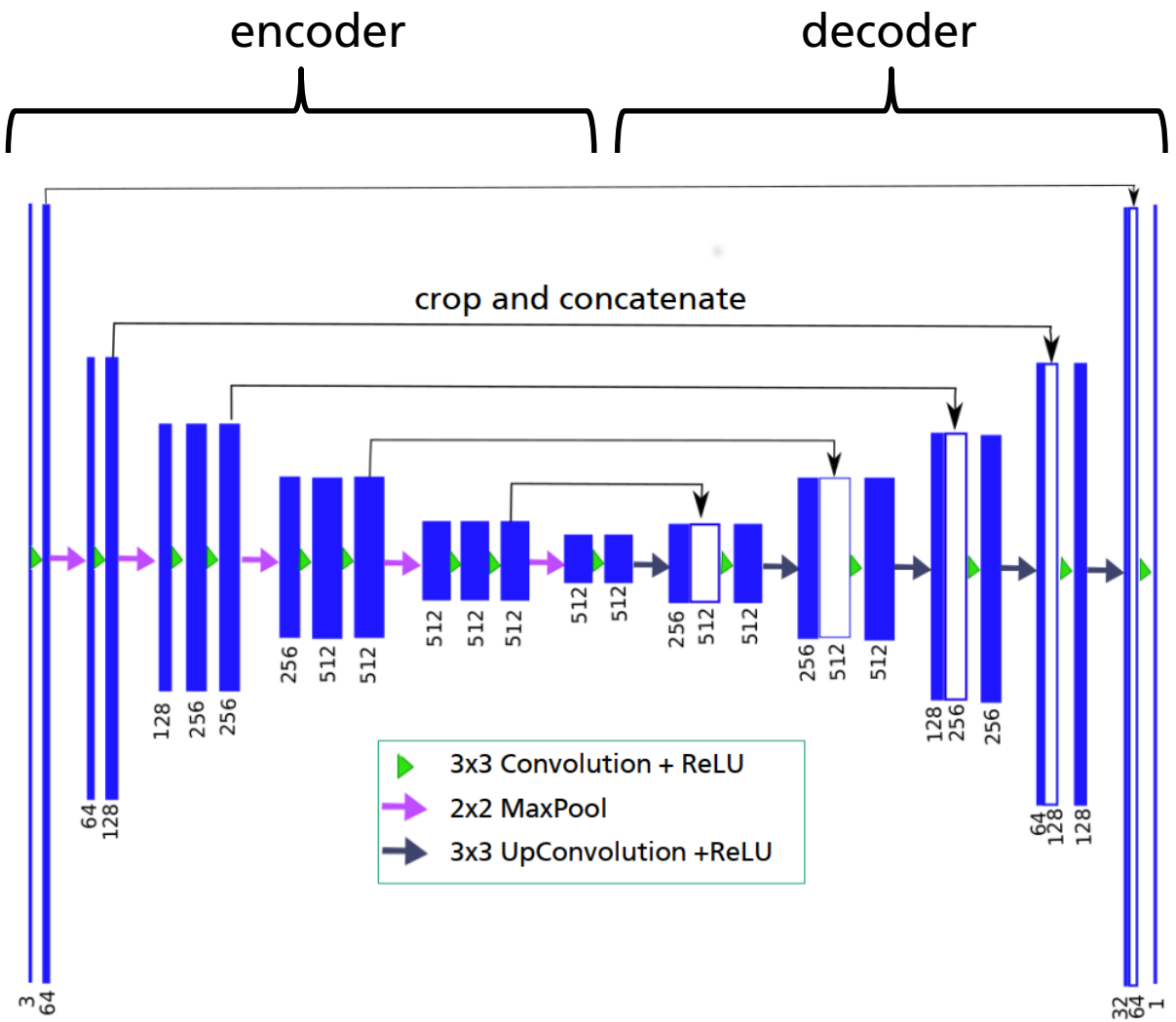
Max Unpooling
use max-position from pooling layer

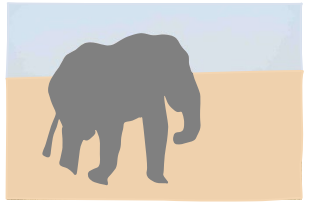


U-Net

- Reduces spatial resolution with maxpool
  - remember max-positions
- Distribute class information to positions by max-unpooling
- Training:
  get original image and segmented image

"Elephant" by gudi&cris / CC BY 2.0



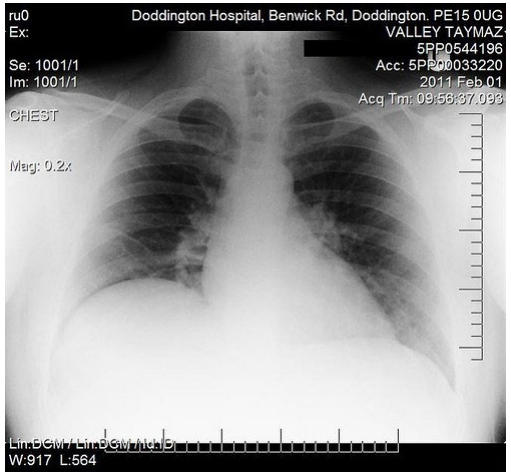


Ronneberger et al. 2015: U-Net: Convolutional Networks for Biomedical Image Segmentation

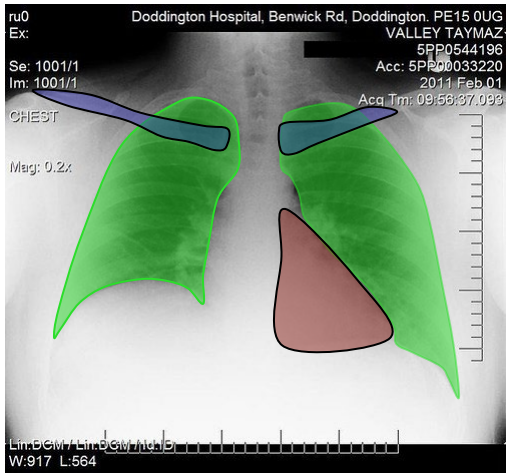
Semantic Segmentation: Application

- medical image processing

Input image

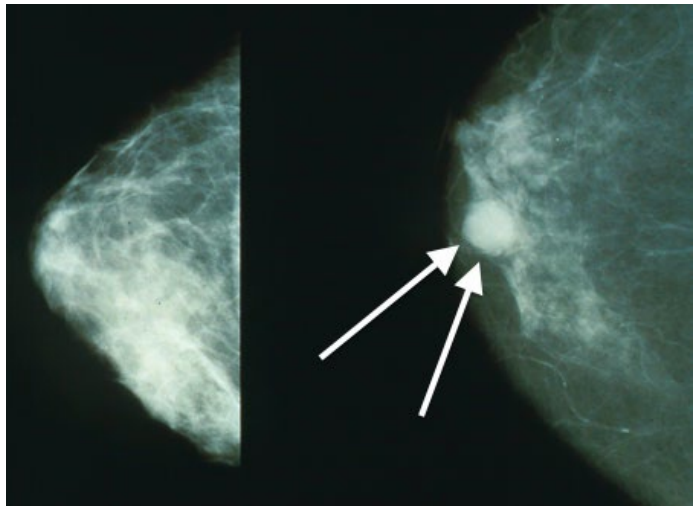


Segmented image



Application: Cancer Detection

- Skin cancer detection
  - Esteva et al. 2017
  - Deep neural network was pretrained on ImageNet data
  - Deep neural network is as good as trained dermatologists
- Brain tumor detection (with U-Net) p.9
- Brest cancer detection
  - McKinney et al. 2020
  - Reduction in false negatives and false positives
  - the AI system outperformed all six human experts: the area under the receiver operating characteristic curve (AUC-ROC) for the AI system was greater than the AUC-ROC for the average radiologist by an absolute margin of 11.5%.



Semantic Segmentation: Application

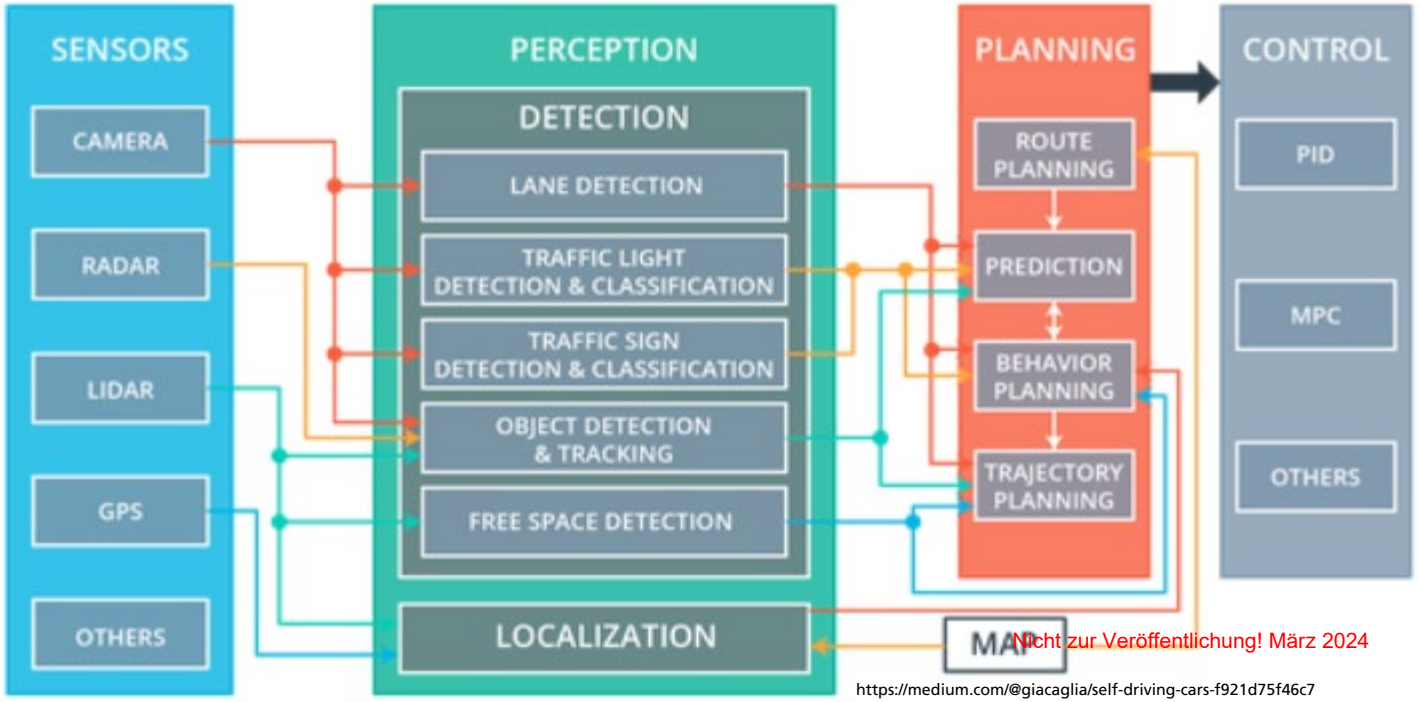
- self-driving cars

Video of segmented traffic

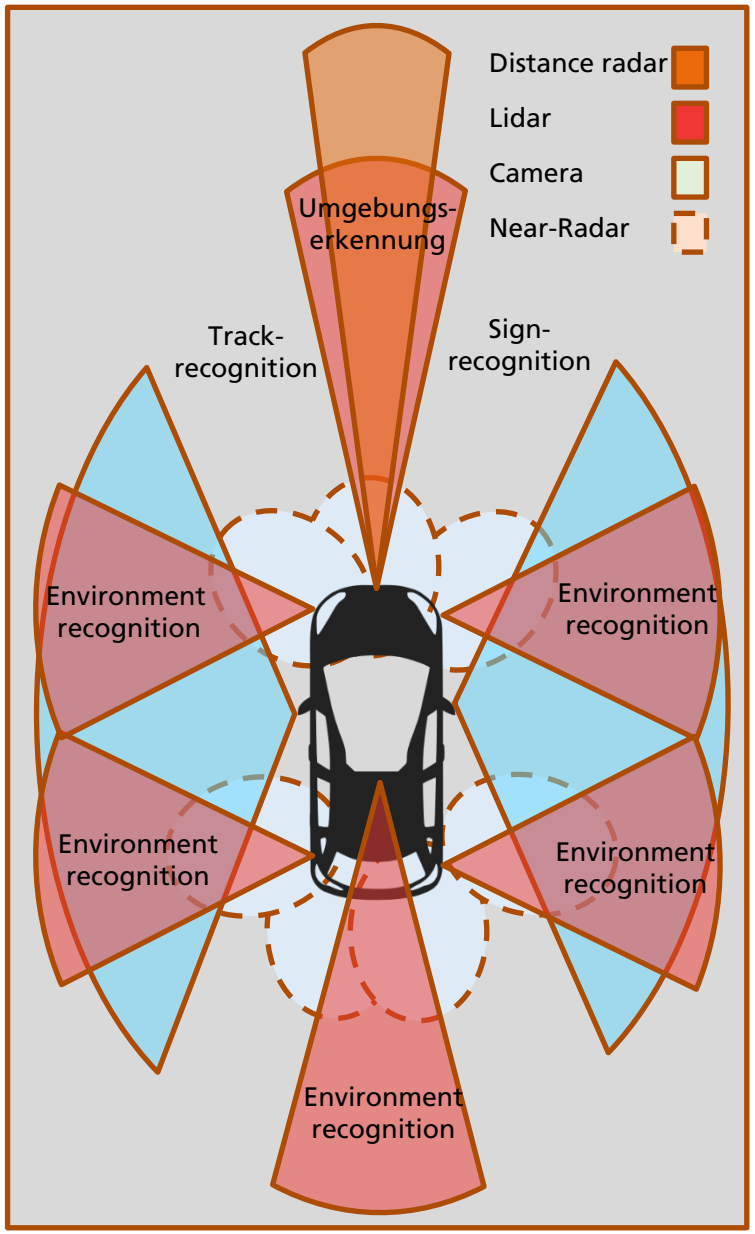
benchmark: Cityscapes test (https://paperswithcode.com/sota/semantic-segmentation-on-cityscapes)

Application: Self Driving Cars

- Integration of many sensors
  - Camera: important for lane, sign & object detection
  - Radar
  - Lidar: precision distance measuring
  - GPS for location detection
  - Movement & speed, acceleration



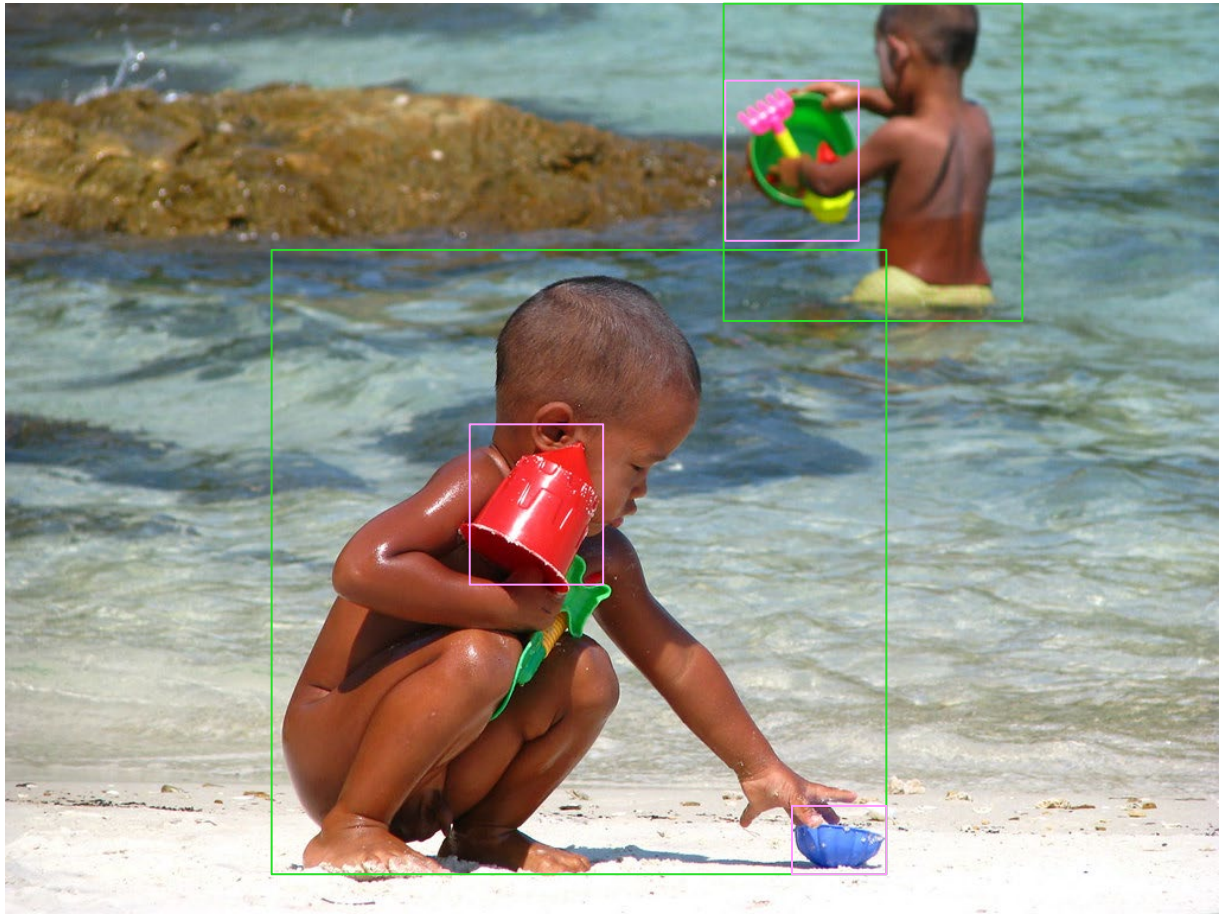
https://medium.com/@giacaglia/self-driving-cars-f921d75f46c7



Object detection and Captioning

- detect objects in the image
- assign properties
- find relations

- Training with image-caption pairs



Caption: Child playing on the beach and child playing in the water

Johnson et al. 2016: DenseCap: Fully Convolutional Localization Networks for Dense Captioning. 5th page

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Summary

- **Convolutional Networks**
  - Consist from Convolutions: kernels which are shifted over the input
  - A Convolutional layer contains many kernels ➔ different features
  - Maxpooling aggregates and reduces spatial resolution
  - Regularization: Dropout / Batch normalization
- Modern architectures
  - inception module: use parallel branches with different kernel sizes
  - ResNet: use residual connections as shortcut. Allows many layers. Good standard architecture
  - **Vision Transformer**: Use BERT-like architecture to classify images
    ➔ give better results but requires more unlabeled training data
- Semantic segmentation
  - reduce spatial resolution and subsequently increase spatial resolution
  - Max Pooling and Max Unpooling

Disclaimer

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