HAN

Minor Computer Vision

Artificial Intelligence & Deep Learning

Germonde Mooij - Bio

… – 1995 PhD, Computational Physics (AMOLF, Amsterdam)

1996 – 2016 Shell expat Reservoir Engineer (Scotland, Syria, Gabon)

2016 – 2019 Master Artificial Intelligence at Radboud University & UMC

-> Deep Learning

2019 – 2021 Decision Engineering consultancy

2021 – … Senior Data Science Researcher at HAN

Goto https://www.menti.com and use the code 1938 3907

What applications of computer vision are you interested i

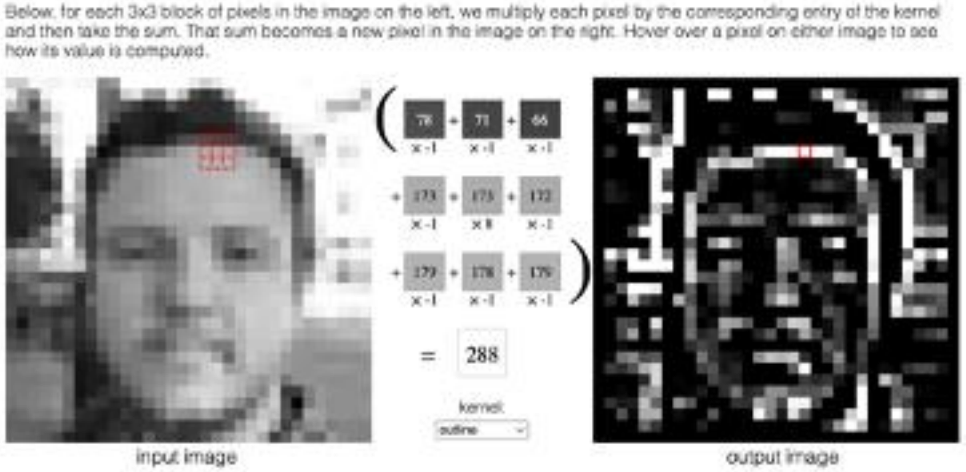
mentimeter

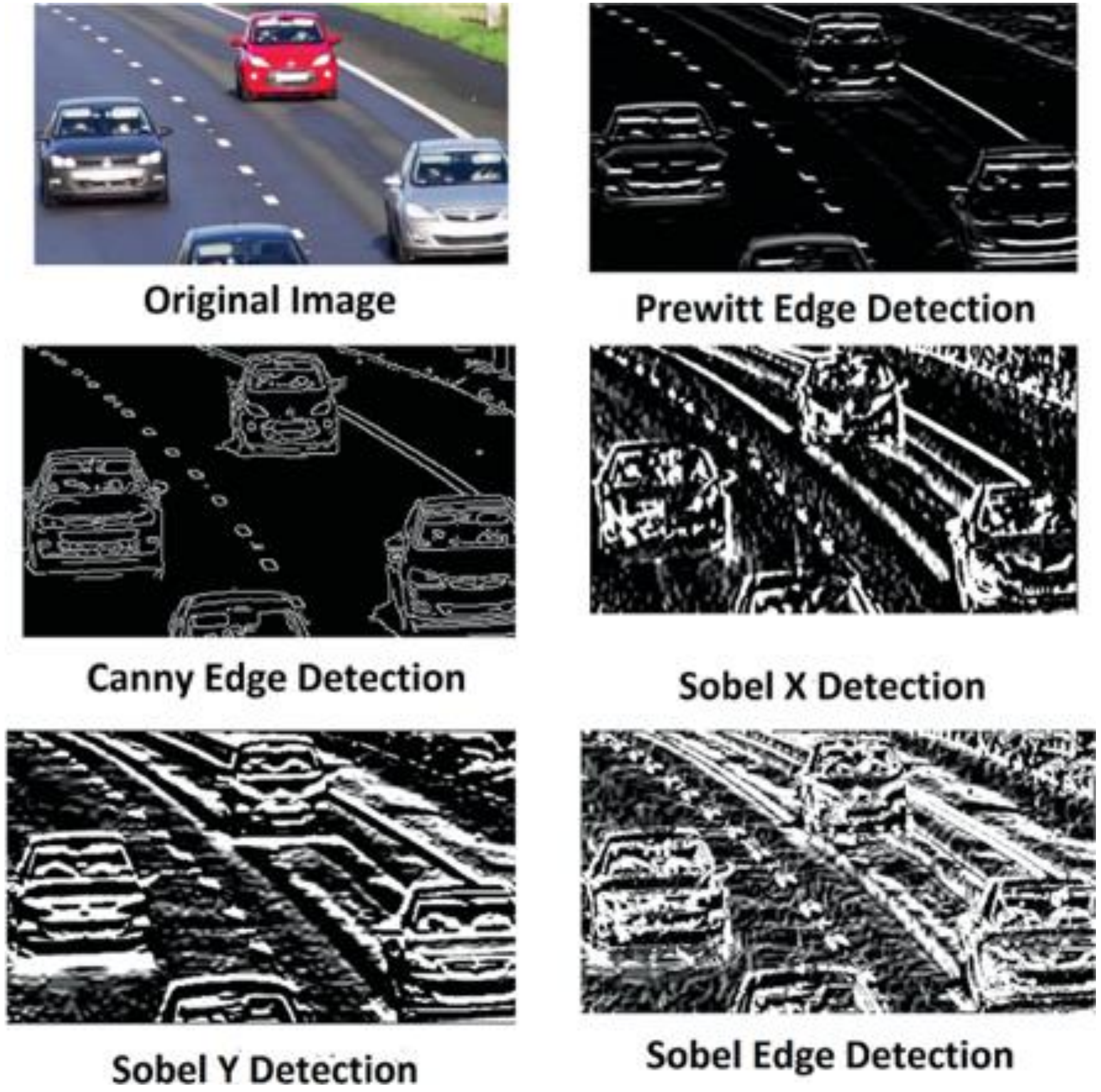
Computer Vision

Edge detection with convolutional filters

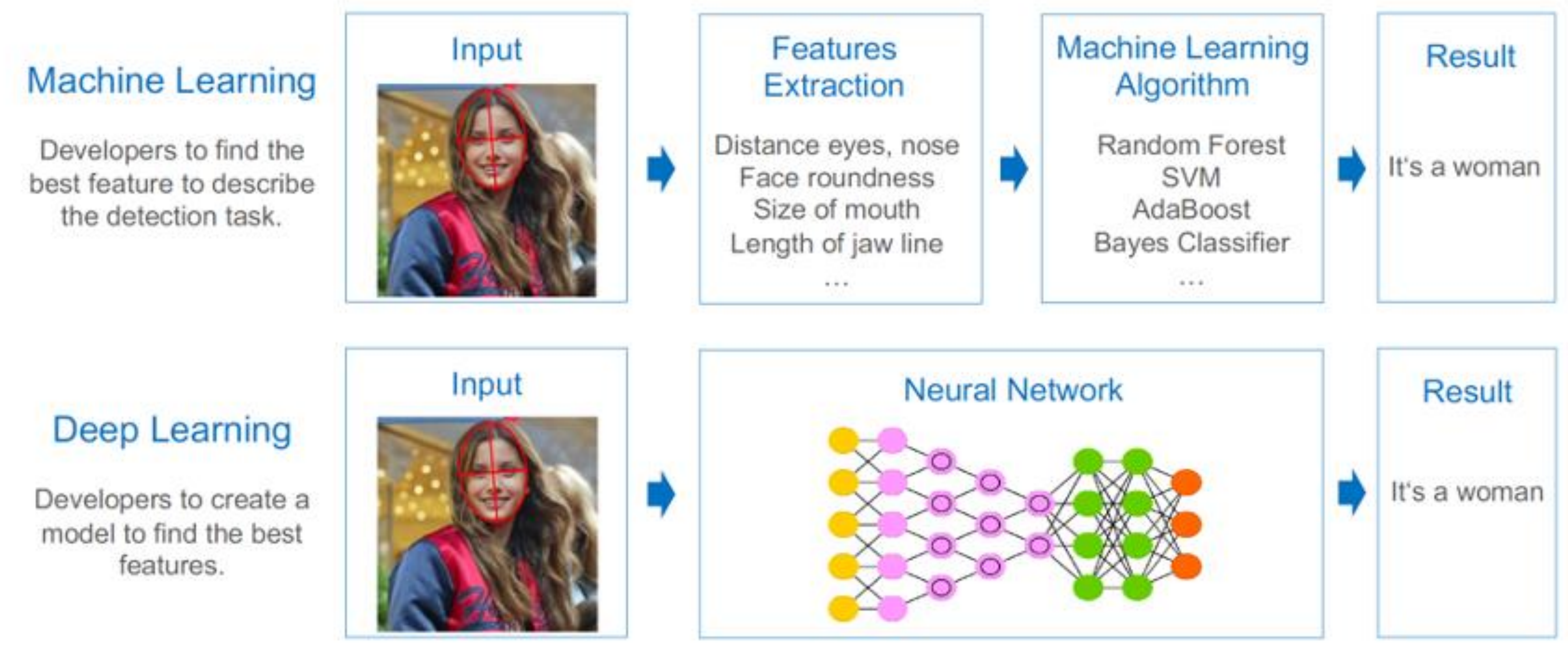
- Filters detecting changes in neighbouring pixels
- Smoothing, filling, object separation tools

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





Machine Learning & Deep Learning



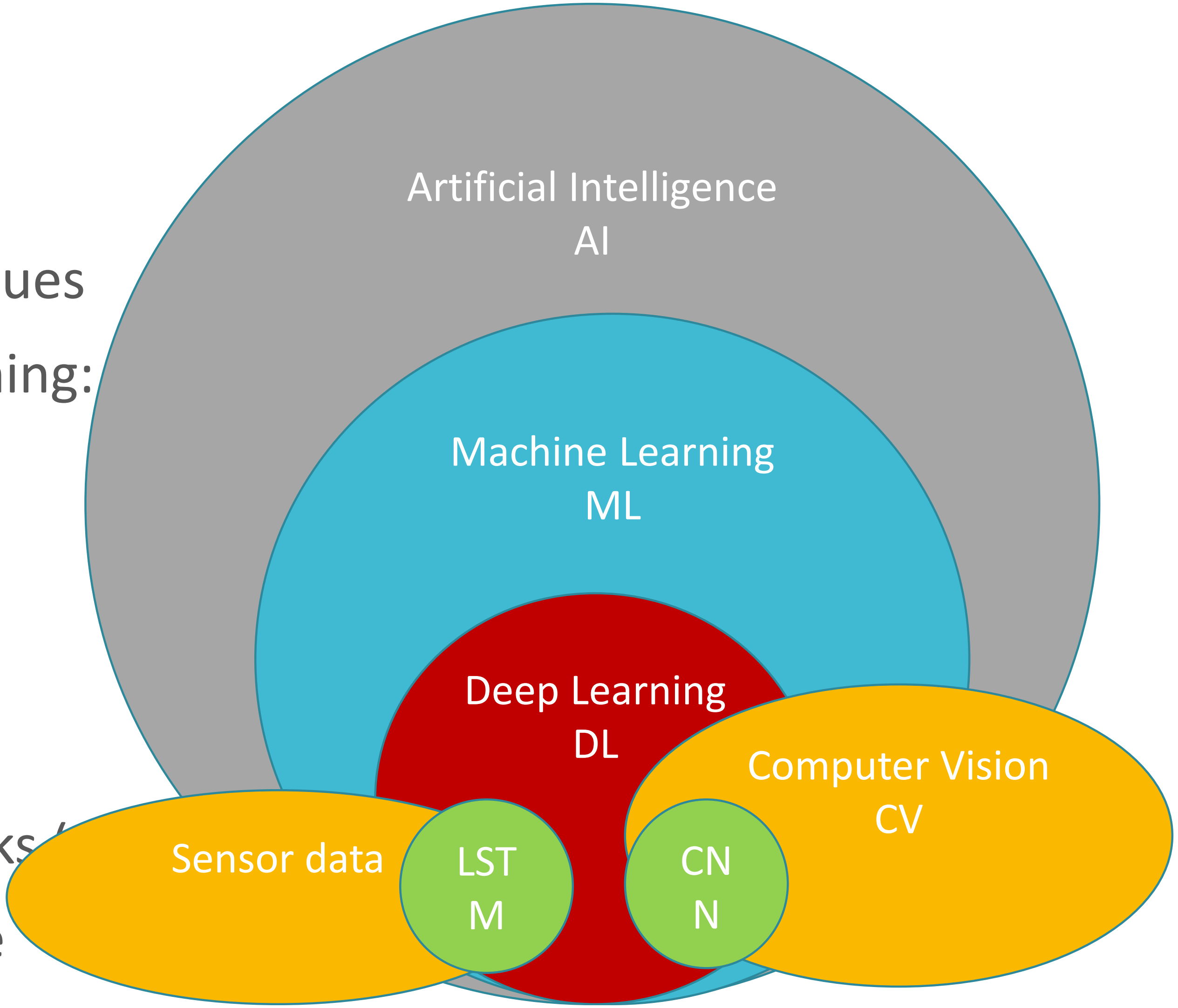
Source: Florian Bauman, Dell, "Challenges of deep learning in the automotive industry" (May 21, 2019)

Artificial Intelligence

The definition of AI is very broad and changes over time. Usually it covers the most advanced techniques

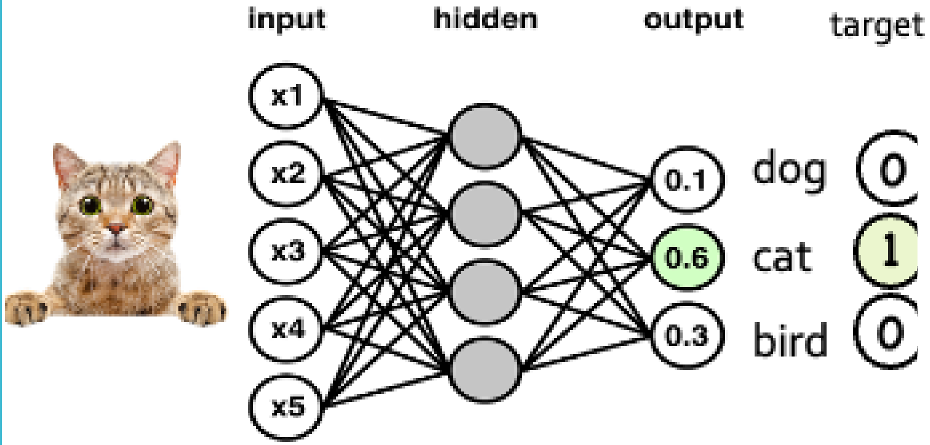
So <u>currently</u> often AI = Deep Learning:

- CNN or LSTM architecture
- ImageNet competitions
- Transfer learning
- Autoencoders
- Generative Adversarial Networks /
- Adversarial attacks and defense



What is a neural network?

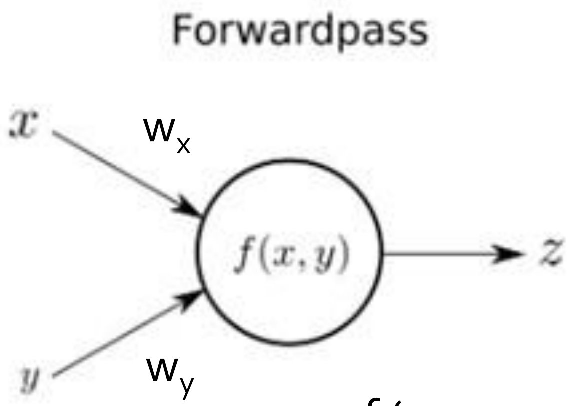
- Nodes (with bias)
- Connections (weights)
- Fully connected network (FCN)



- Activation layer
- Forward pass (prediction)

Neural network forward pass is **basic math**.

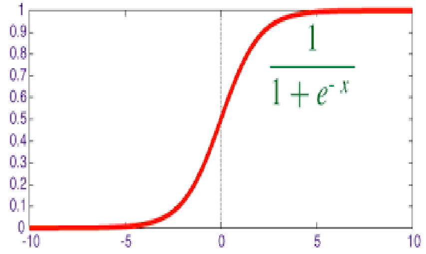
- Training a neural network: minimize the loss



$z = f\,(w_x x + w_y y)$

Loss = (z - target)^2

f = Non-linear activation function
= e.g. sigmoid function



What is a neural network?

- Backpropagation (=learning, training)

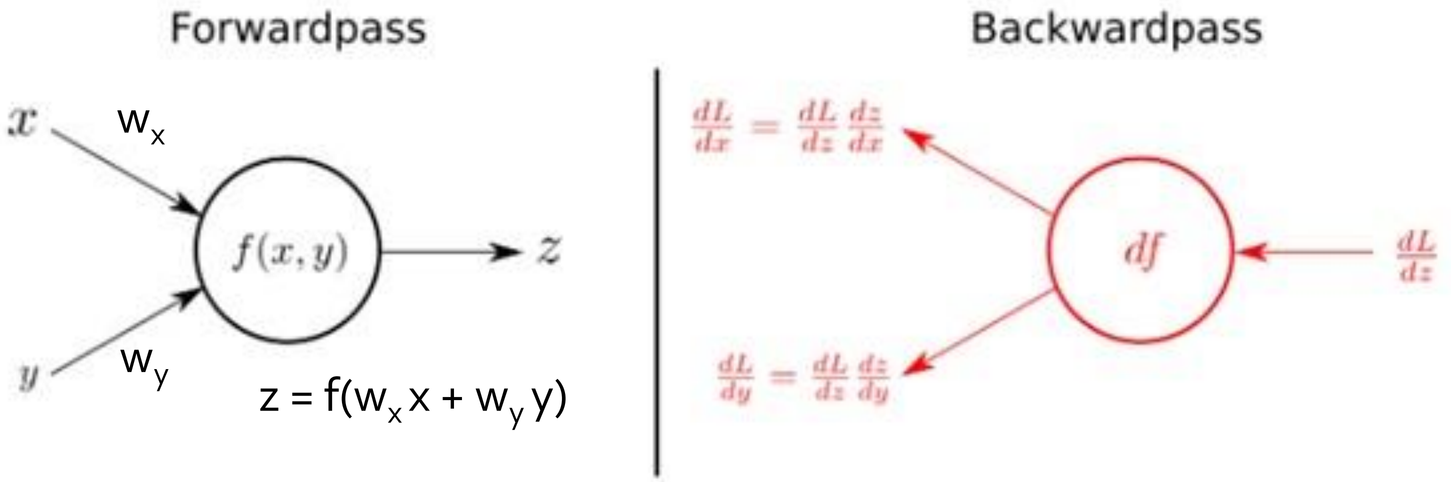
Gradient Descent in 1D

Hyperparameter stap grootte
λ = learning rate

- too high: target missed
- too low: slow learning

Neural network backpropagation is also **basic math**.
Do you remember the chain rule for derives?

- Formula for Loss is differentiable
- Gradient descent to minimize Loss

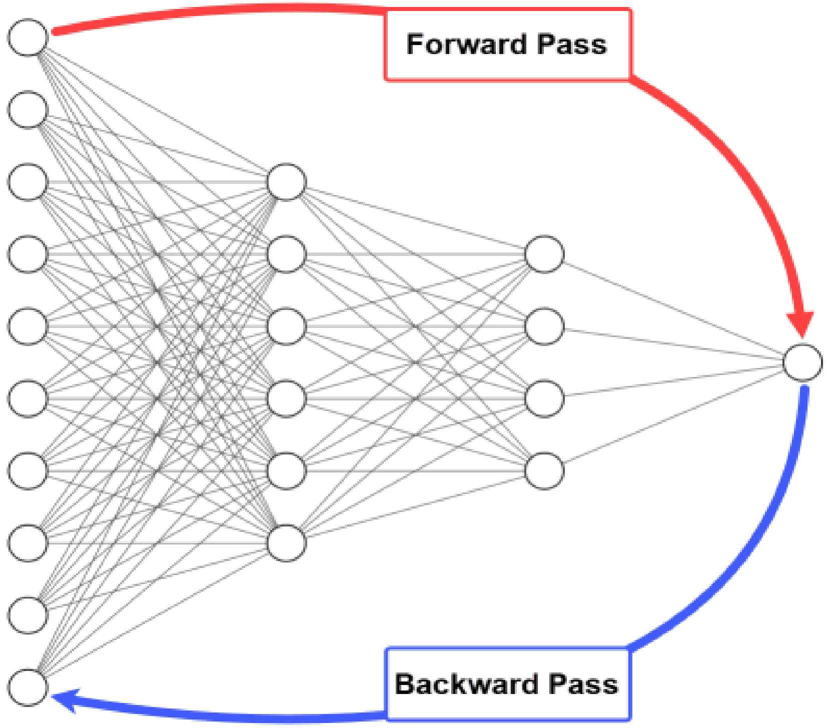


Loss L = (z - truth)^2

Repeat forward and backward passes until the loss is acceptably low

What is training a neural network?

Train a neural network to correctly predict a target by many iterations of forward and backward passes. E.g. 10 epochs where 1 epoch = # images in dataset .



Minimize Loss

Many types of Neural Network architectures

Depending on data type

- Unstructured data like text - embedding to structured data
- Timeseries - recurrent networks e.g. LSTMS
- Images - CNNs

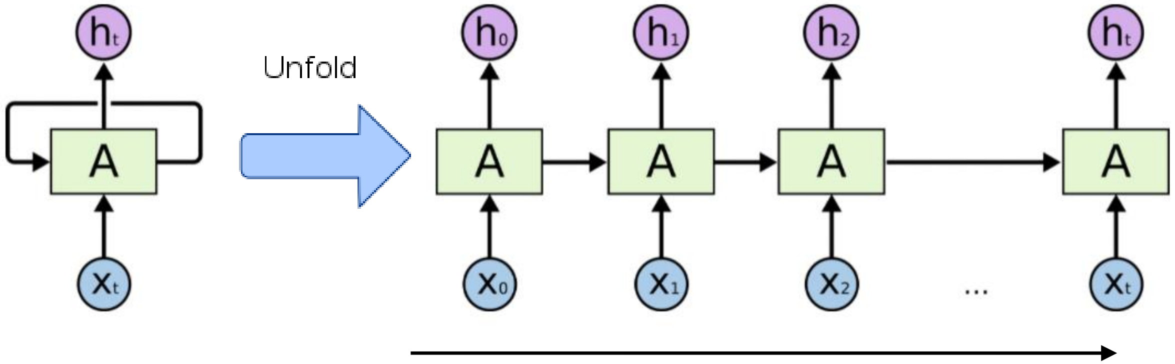
Depending on task

- Classification - ImageNet networks
- Object detection - Yolo, RCNN
- Segmentation - U-Net, some GANs
- Generation - decoder/encoders, GANs

Time series

For time series the Deep Learning architecture used most is recursive neural networks (RNN), and long-short-term-memory neural networks in particular (LSTM). E.g. in Google Translate.

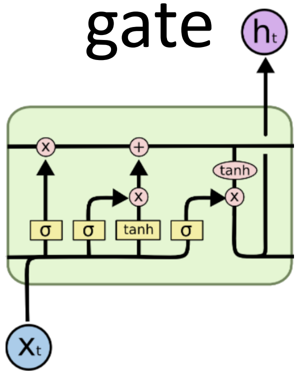
RNN



Time series

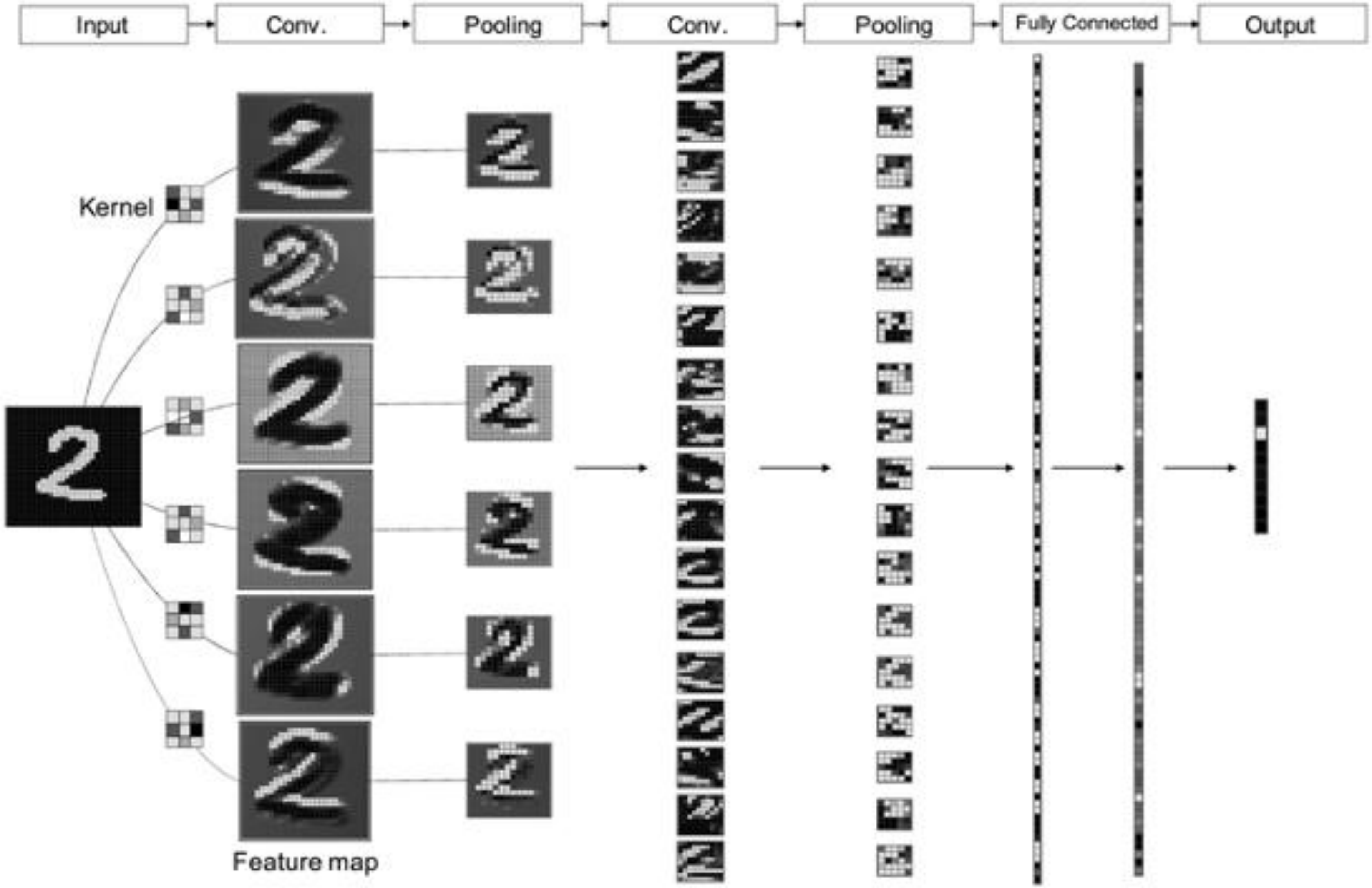
LSTM

gate



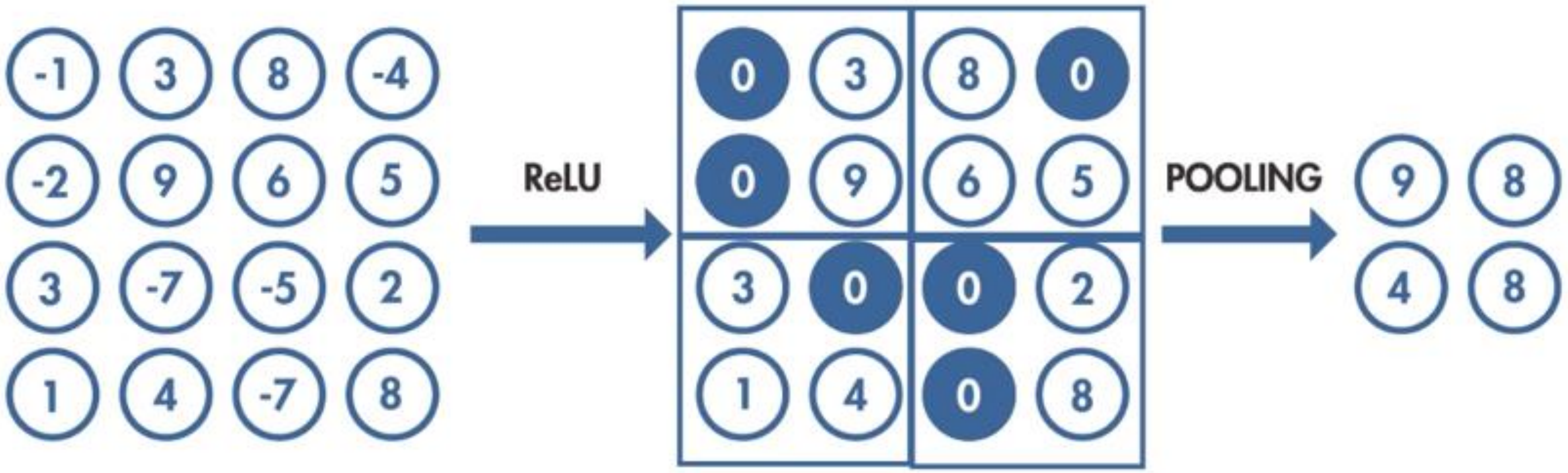
Images

Neural network model layers = architecture



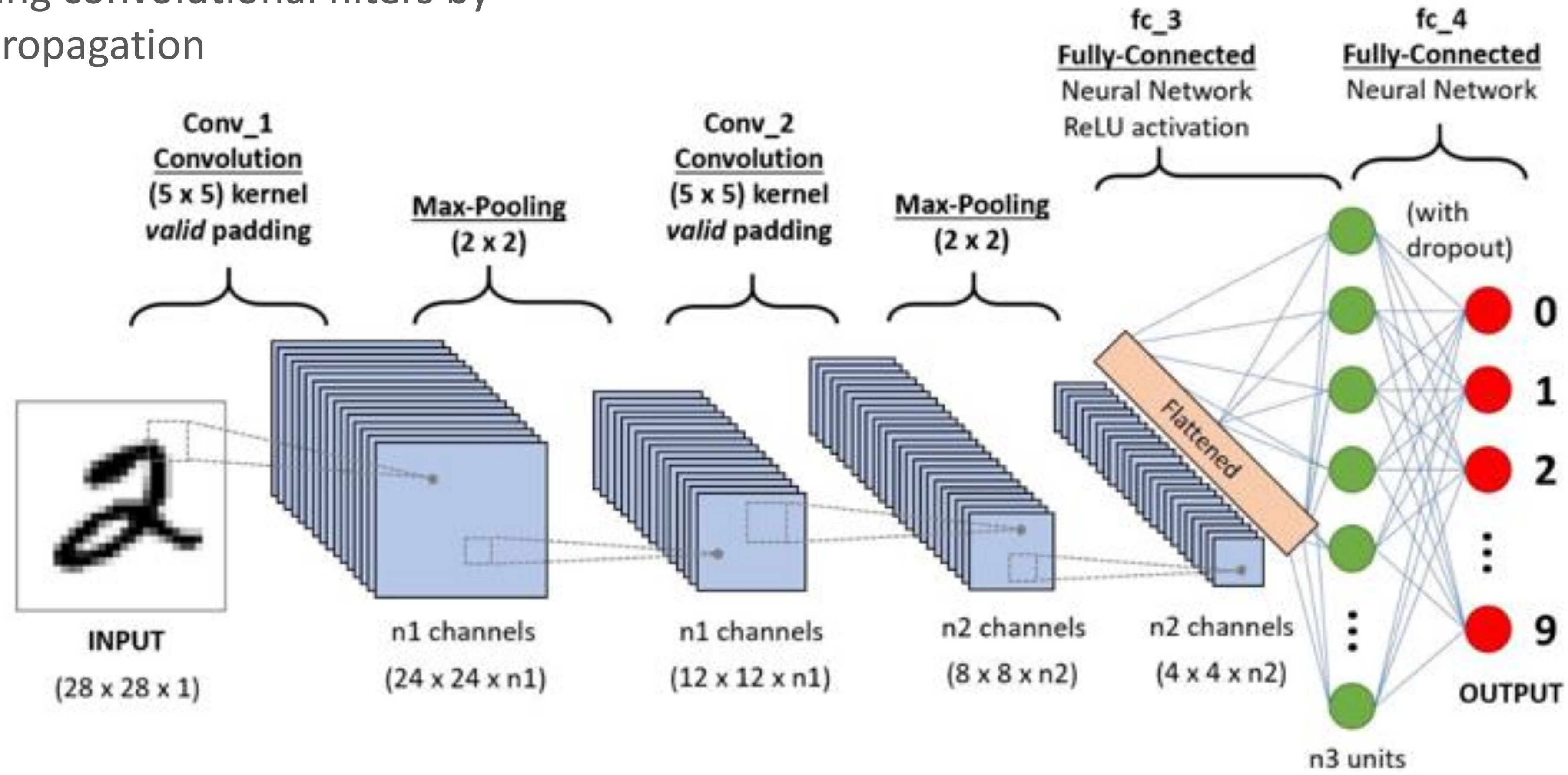
Convolutional Neural Network (CNN)

Activation (Relu) and Pooling (MaxPooling)



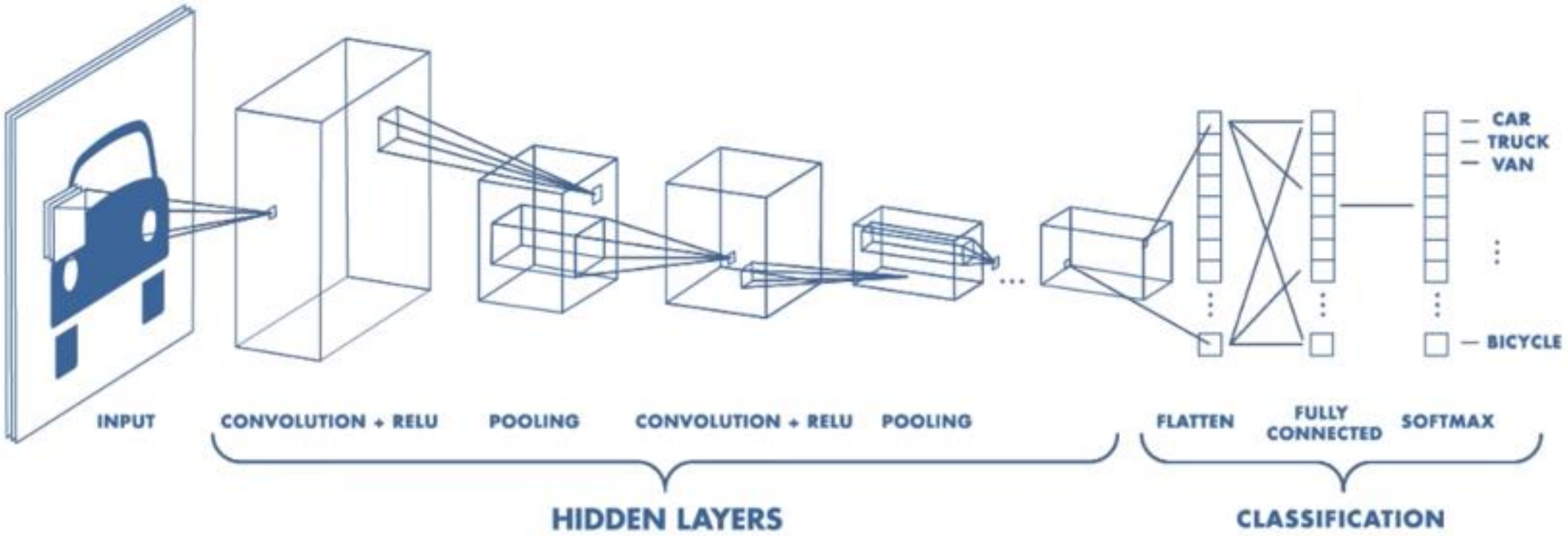
Convolutional Neural Net (CNN)

Learning convolutional filters by backpropagation



https://medium.com/@RaghavPrabhu/understanding-of-convolutional-neural-network-cnn-deep-learning-99760835f148

Output



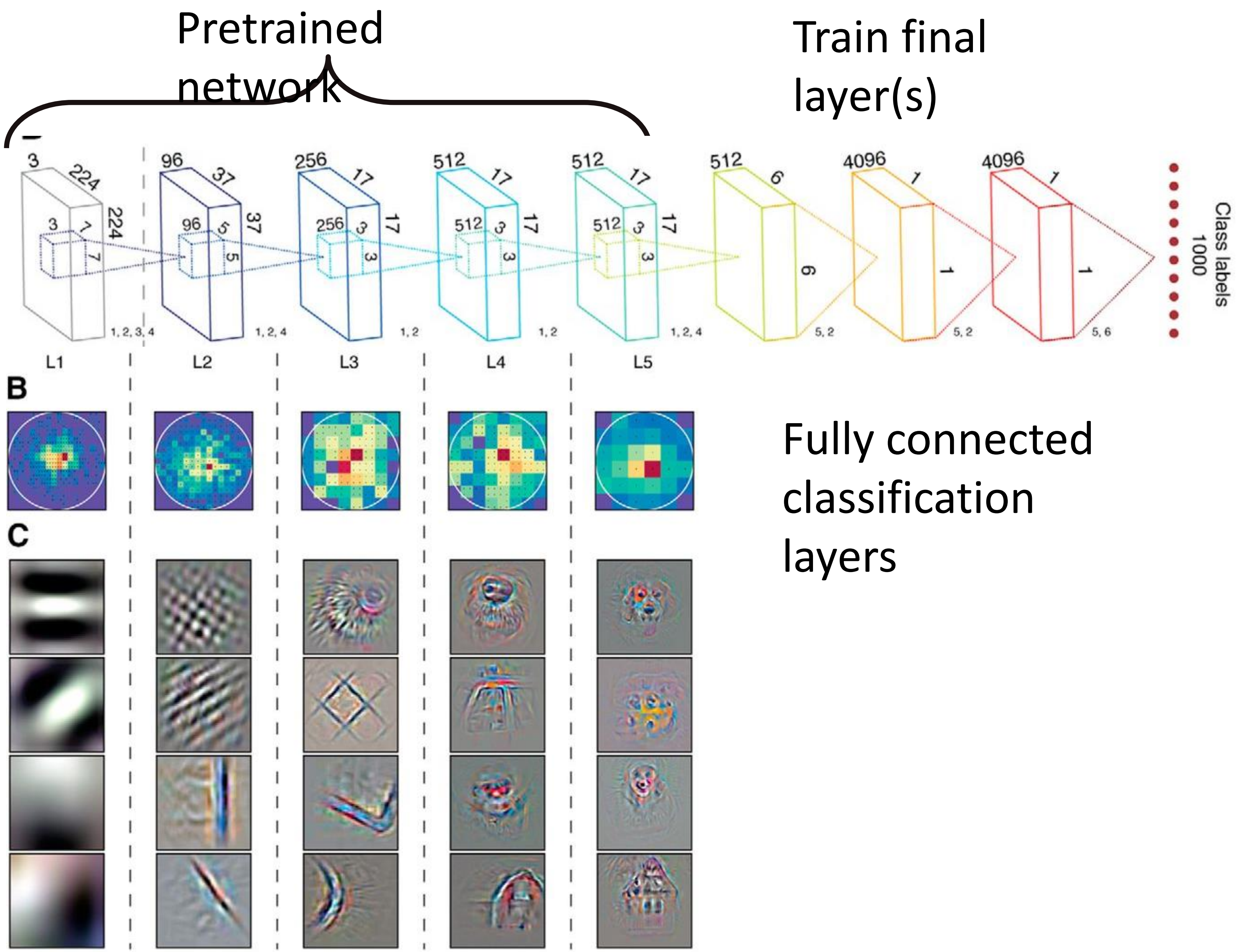
CAR
TRUCK
VAN
BICYCLE
INPUT
CONVOLUTION + RELU
POOLING
CONVOLUTION + RELU
POOLING
FLATTEN
FULLY CONNECTED
SOFTMAX
HIDDEN LAYERS
CLASSIFICATION

Transfer learning

Advantages:

Reduces training time and need for training images

Believed to work because of learned feature hierarchy: deeper layers detect more complex shapes with larger receptive fields

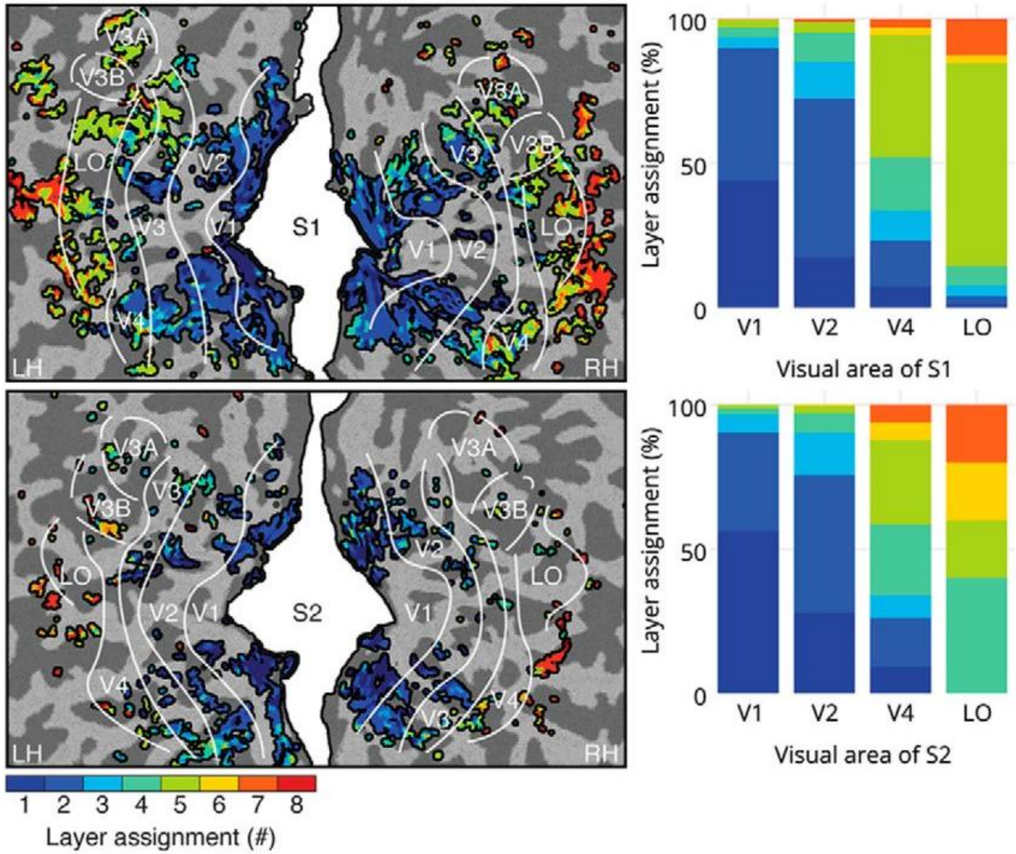


Human visual cortex

Some evidence of similar hierarchy in human visual cortex, in the direction from the area where visual stimuli enter the brain

Research at Radboud in Nijmegen:

Neuroscience at Donders Institute Artificial Intelligence group of Marcel van Gerven



Guclu and van Gerven, AI department at Radboud University: [Deep Neural Networks Reveal a Gradient in the Complexity of Neural Representations across the Ventral Stream]

ImageNet competition

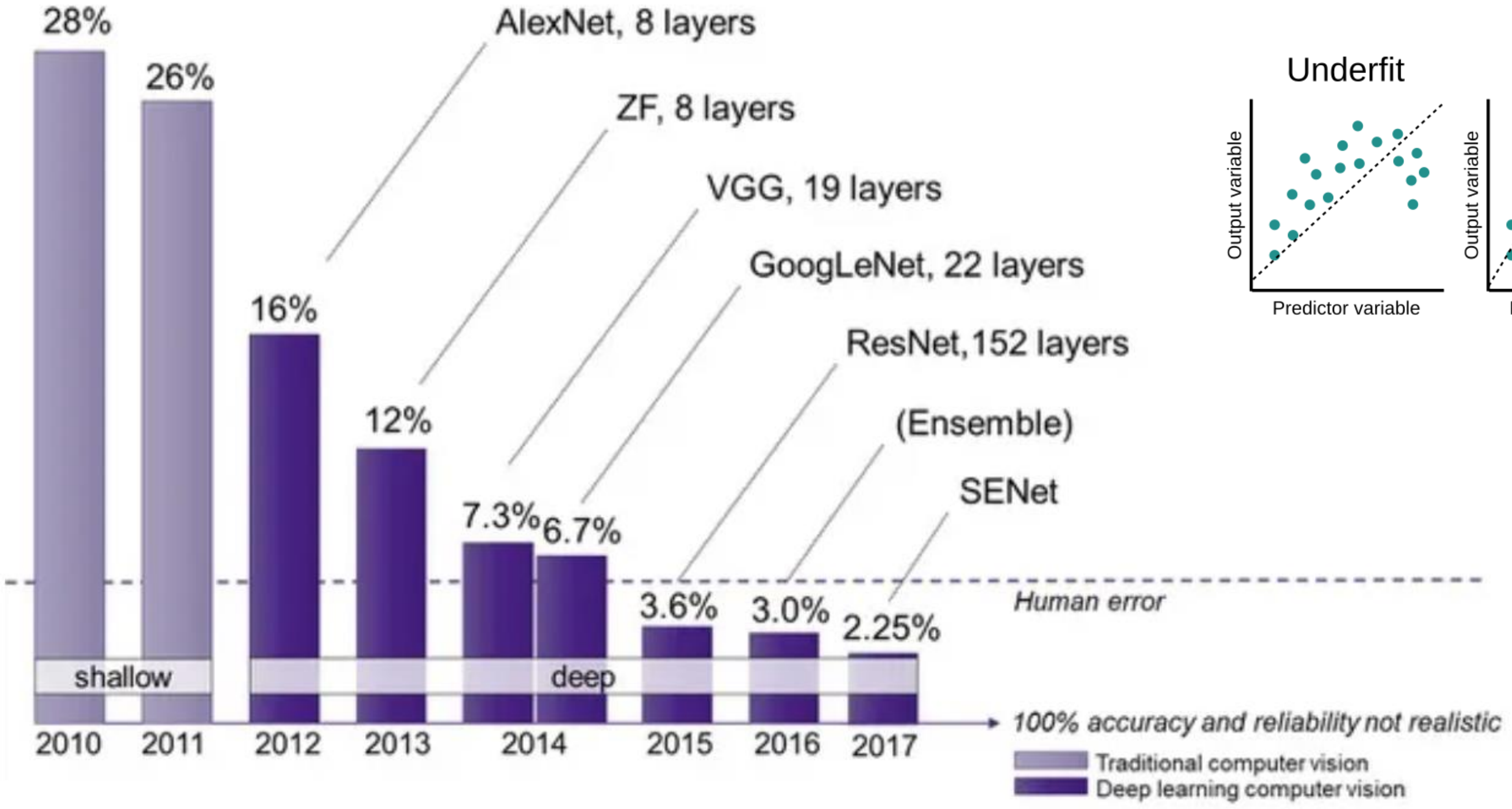
Benchmark public dataset used since 2010

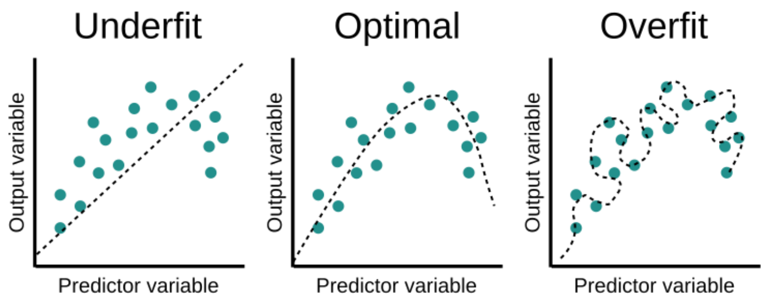
- Total number of non-empty WordNet synsets: 21,841
- Total number of images: 14,197,122
- Number of images with bounding box annotations: 1,034,908
- Number of synsets with SIFT features: 1000
- Number of images with SIFT features: 1.2 million

ImageNet competition

Deeper networks :

- Overfitting -> regularization
- Vanishing gradients -> skip connections, gradient boosting



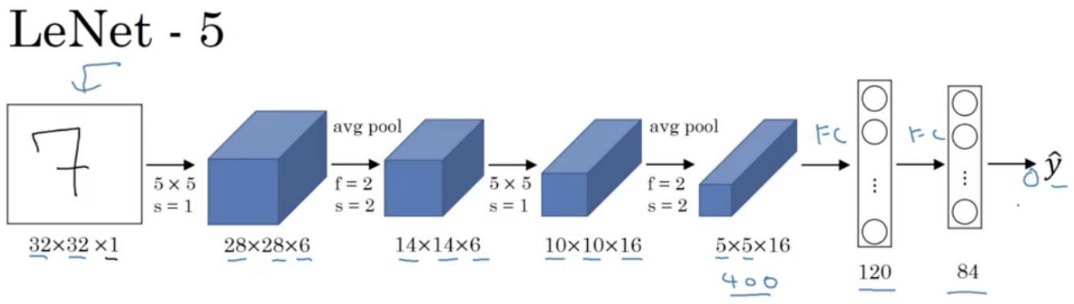


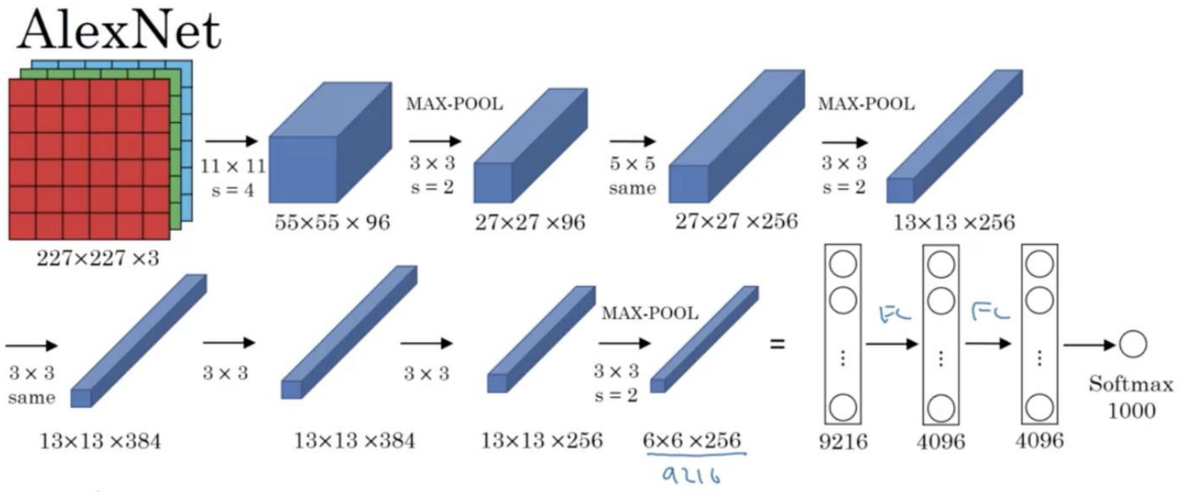
ImageNet competition

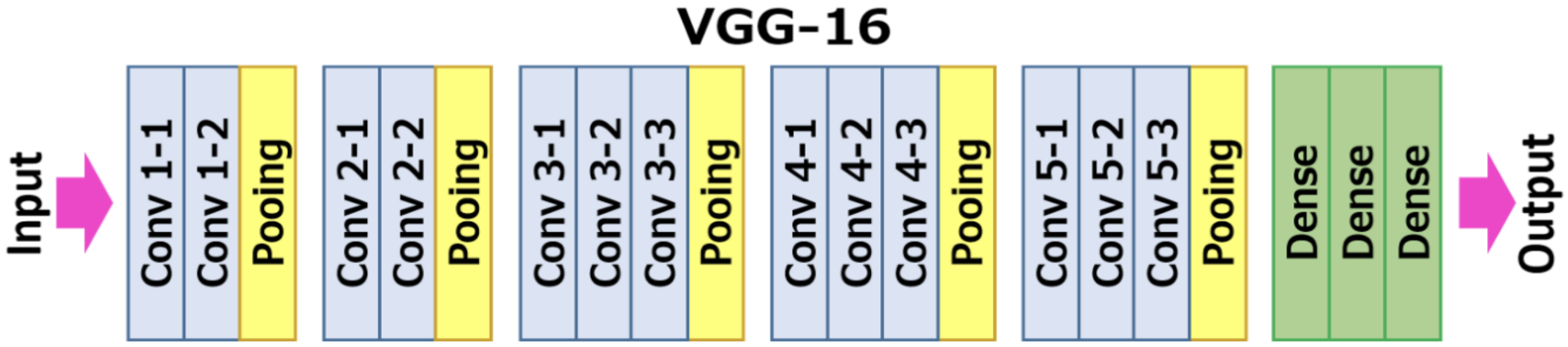
Winners

2012: AlexNet

2013: VGG-16







ImageNet competition

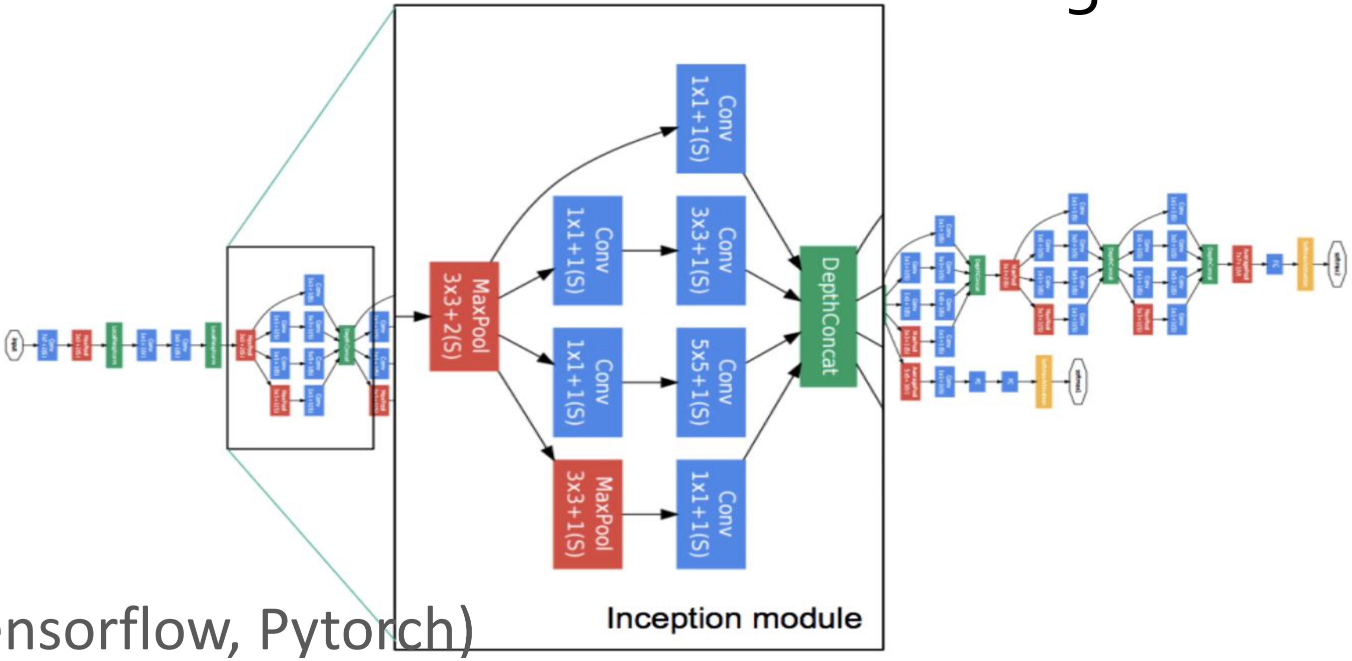
Winners

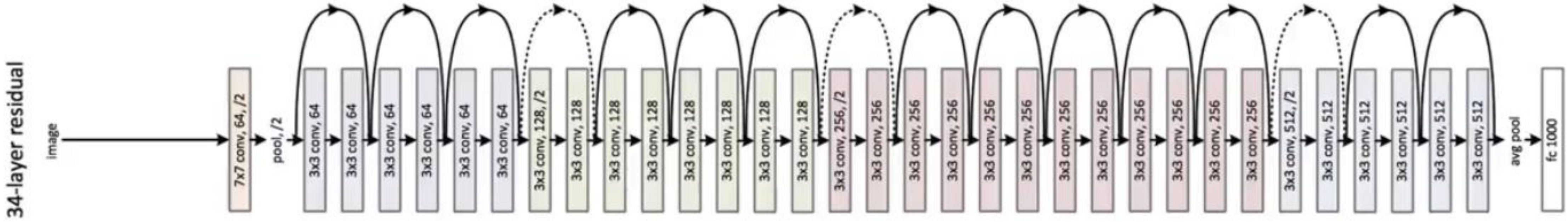
2014: GoogleNet

2015: ResNet – skip connections

Trained networks are available in
Deep Learning frameworks (like Tensorflow, Pytorch)

GoogleNet





Zero- or low-code applications

Google Teachable Machines

https://teachablemachine.withgoogle.com/

Zero-code, pretrained network

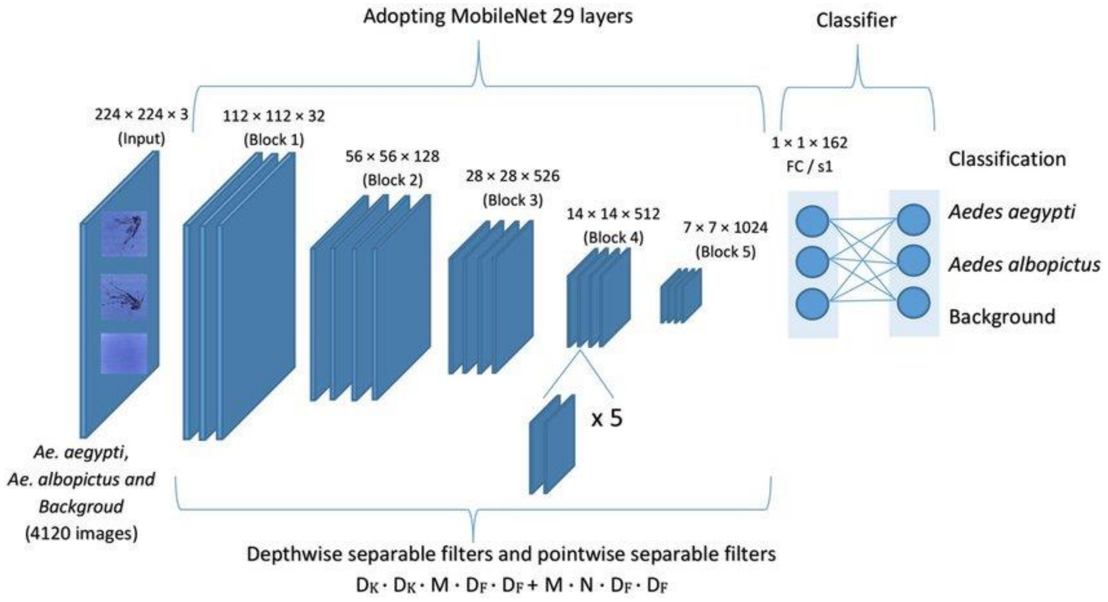
Based on Tensorflow templates.

Try your own image classification training

Test if it learns what you intended.

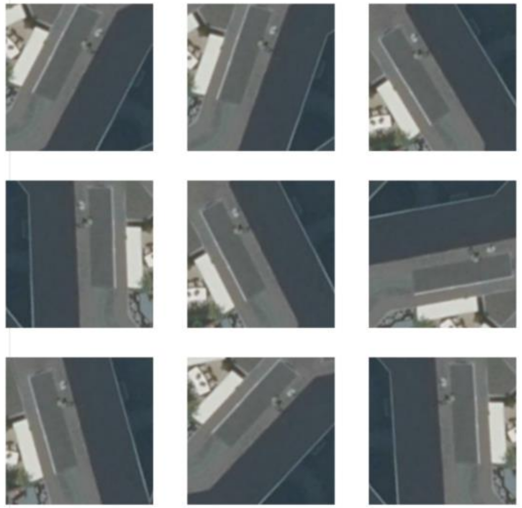
MobileNet

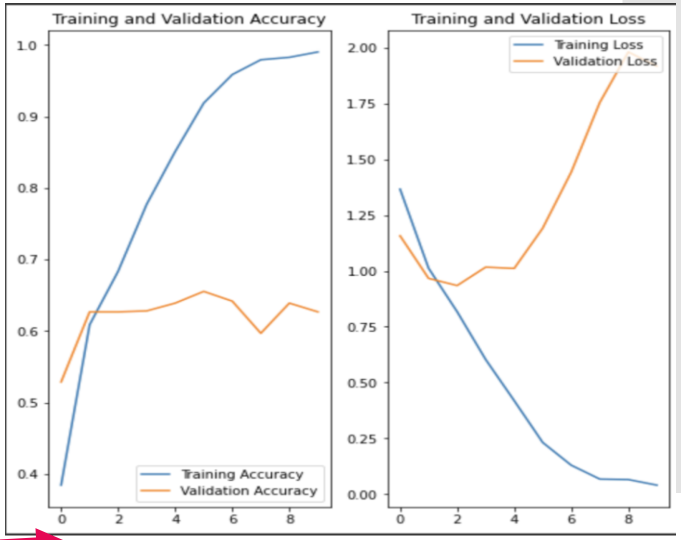
Smaller model developed for use on Mobile phones



Steps in Tensorflow tutorial

1. Import Python packages
2. Collect labelled set of images
   - Normalize images
   - Shuffle images
3. Load a pretrained neural network model (Keras)
   - Define trainable top layer or layers (finetu
4. Split in train/validate/test sets
5. Training set
   - Augment data
   - Train the model -> training score
6. Validation set
   - Check the model -> validation score
   - Choose best scoring model
7. Check the final model on the test set -> test scc





Tensorflow tutorials on Colab

https://colab.research.google.com/github/tensorflow/docs/blob/master/site/en/tutorials/

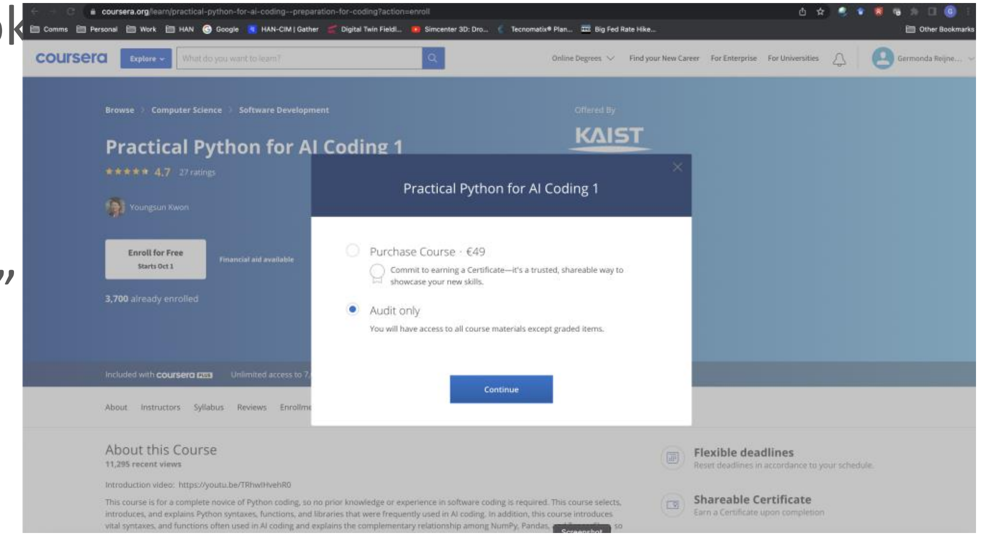
Image classification: images/classification.ipynb

Synthetic image generation: generative/dcgan.ipynb

Style transfer CycleGAN: generative/cyclegan.ipynb

https://www.coursera.org/learn/practical-python-for-ai-coding--preparation-for-coding

Coursera course how to run this Jupyter Notebook classification.ipynb on your laptop, free to Audit:

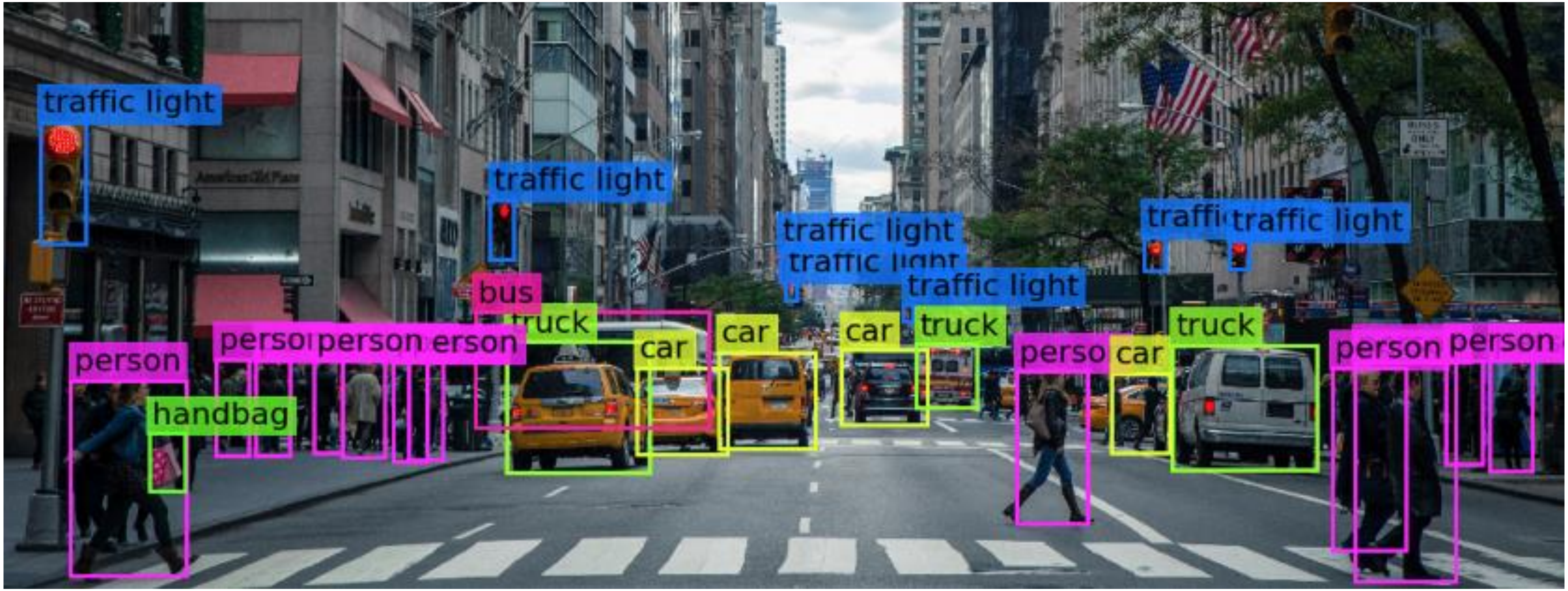


Any issues, google “stackoverflow”+ “some error”

Chances are someone will have asked about this

Object Detection

Detect objects in traffic with bounding boxes and names

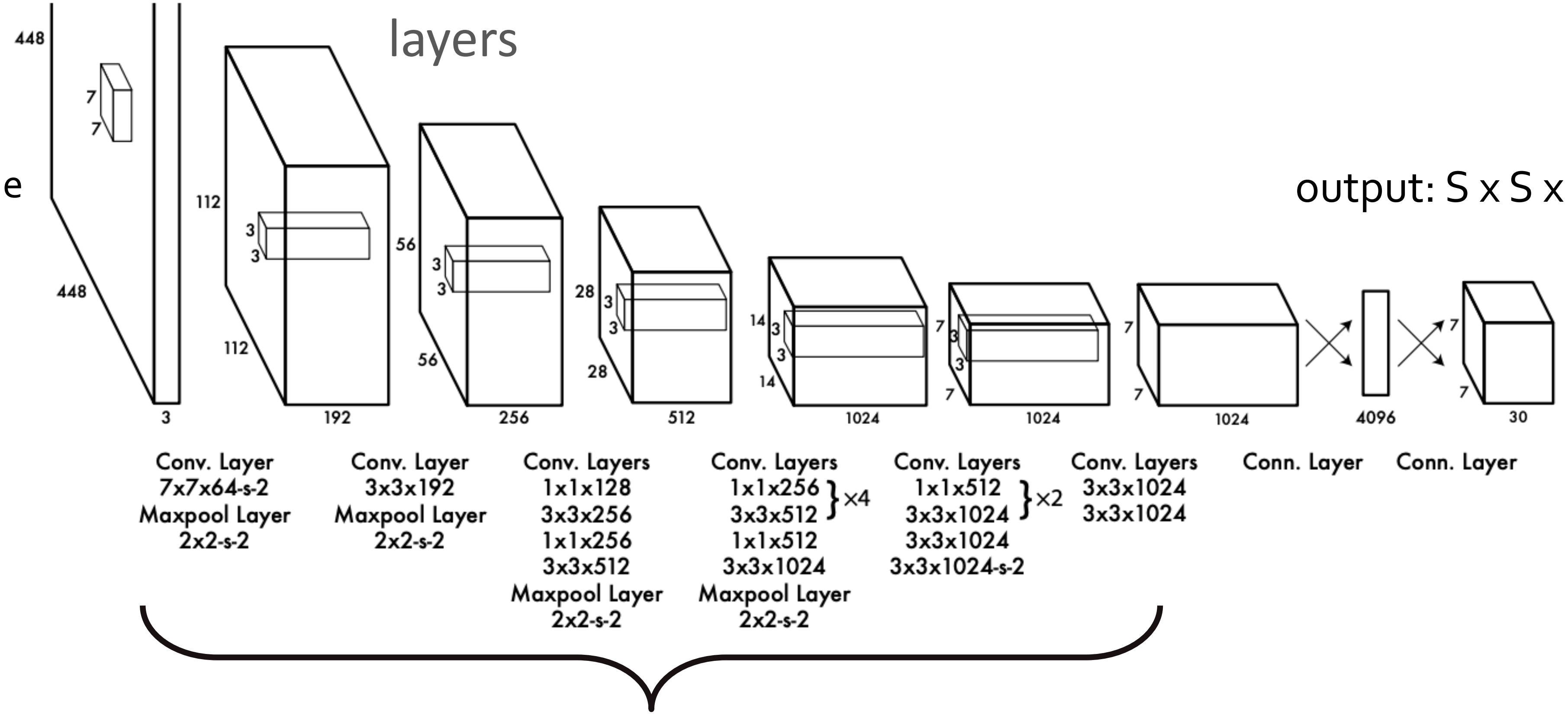


YOLO

blocks of [CNN + non-linear activation + Maxpool] layers

Input image

output: S x S x 6 B



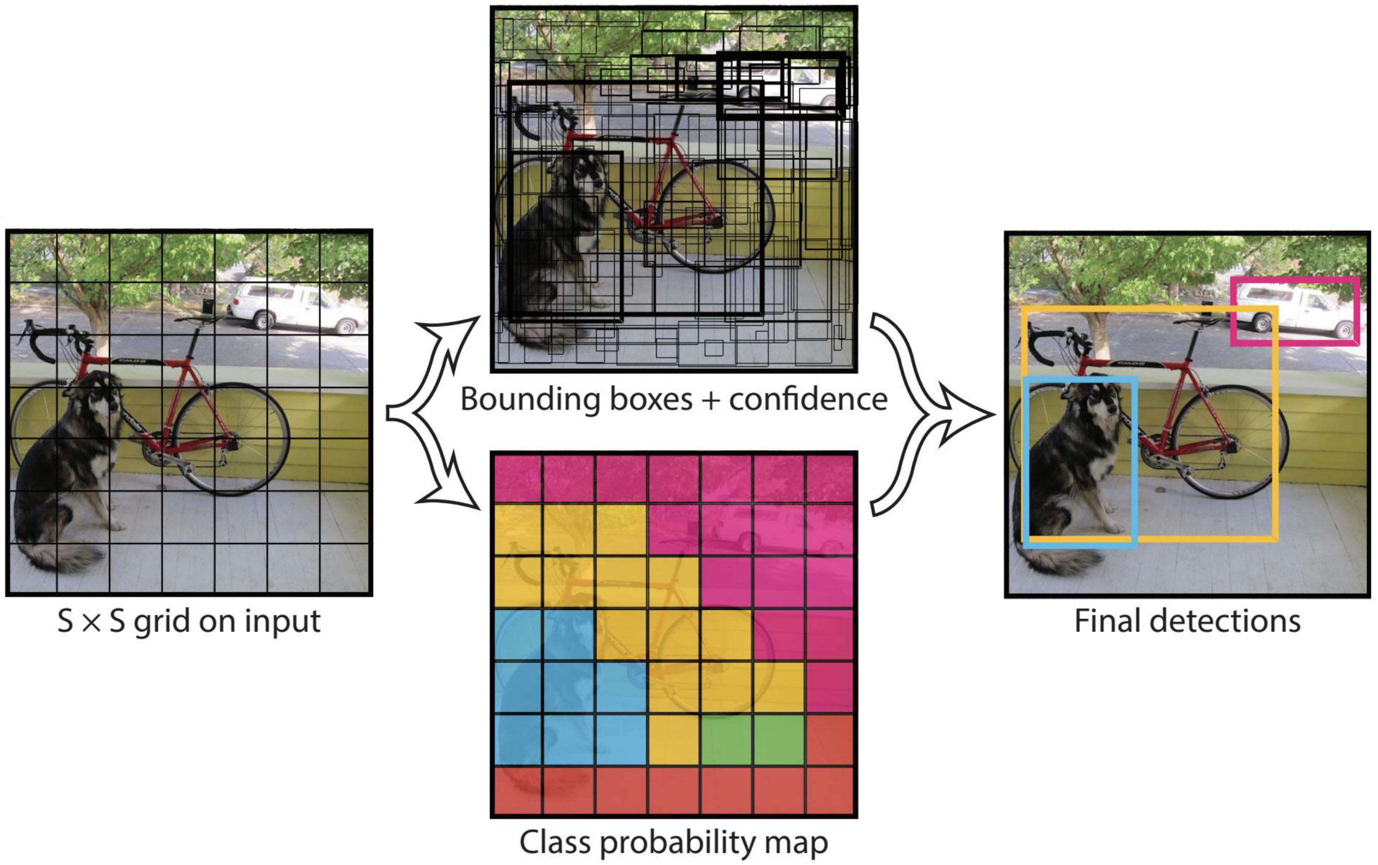
Pretraining for 1 week (!)

Fast training final layers

YOLO

You-Only-Look-Once (YOLO, 2016 Redmon)

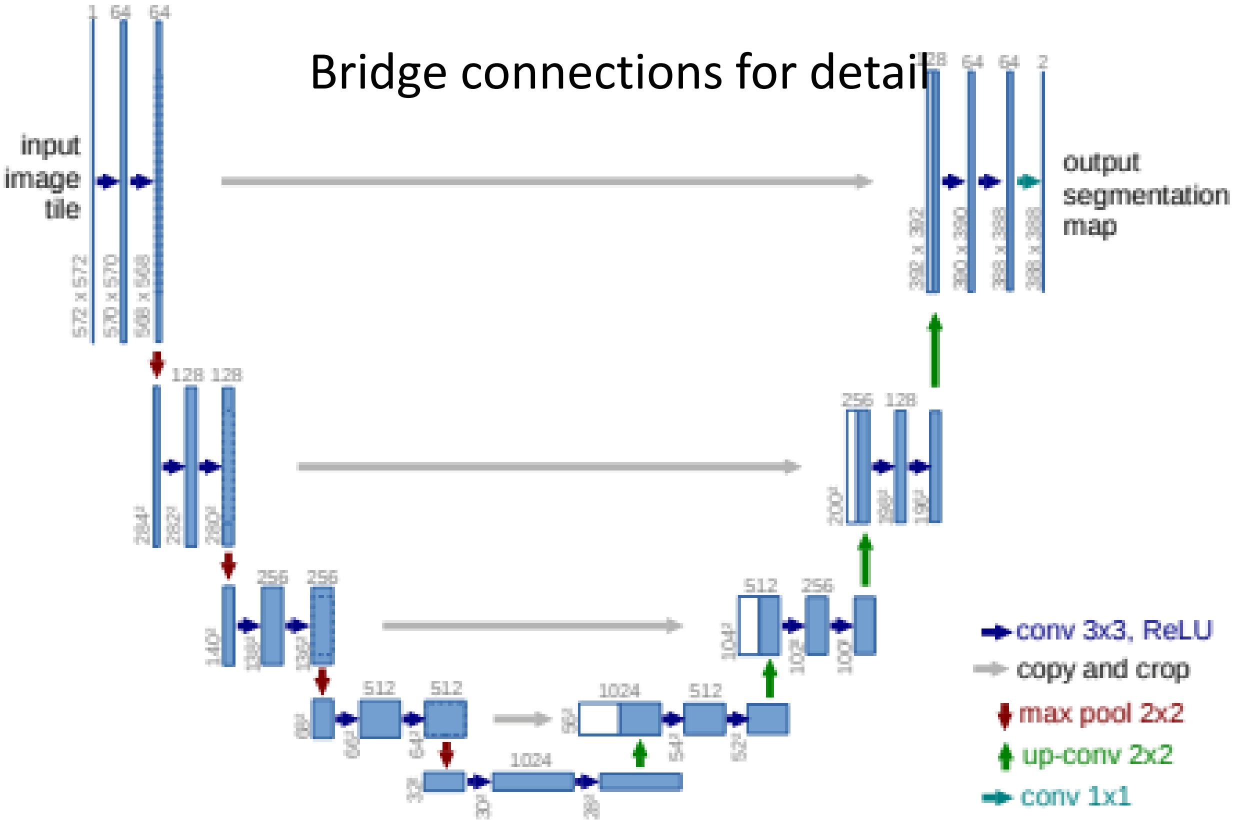
1. Every cell predicts B bounding boxes and probability it contains an object
   [x, y, w, h, P(object)]
2. Trained to maximize overlap with groundtruth bounding box
3. If cell contains object, train to predict P(class|object)
4. Use model to predict B x [x, y, w, h, P(object)] + P(Class|object) for each cell in an SxS grid
5. Take cell bounding box highest P(Class)

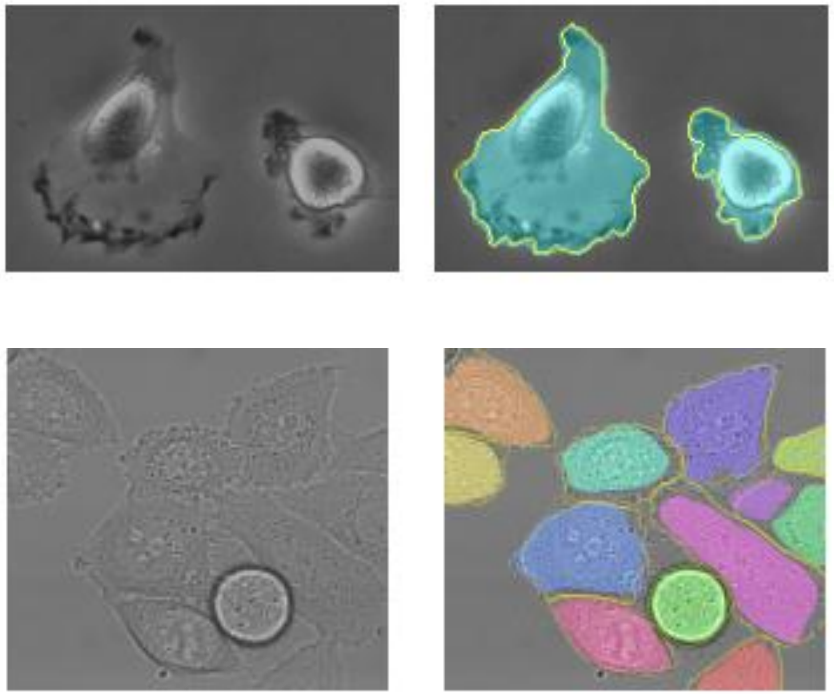


Segmentation

U-Net Ronneberger et al 2015 https://arxiv.org/abs/1505.04597v1

Bridge connections for detail



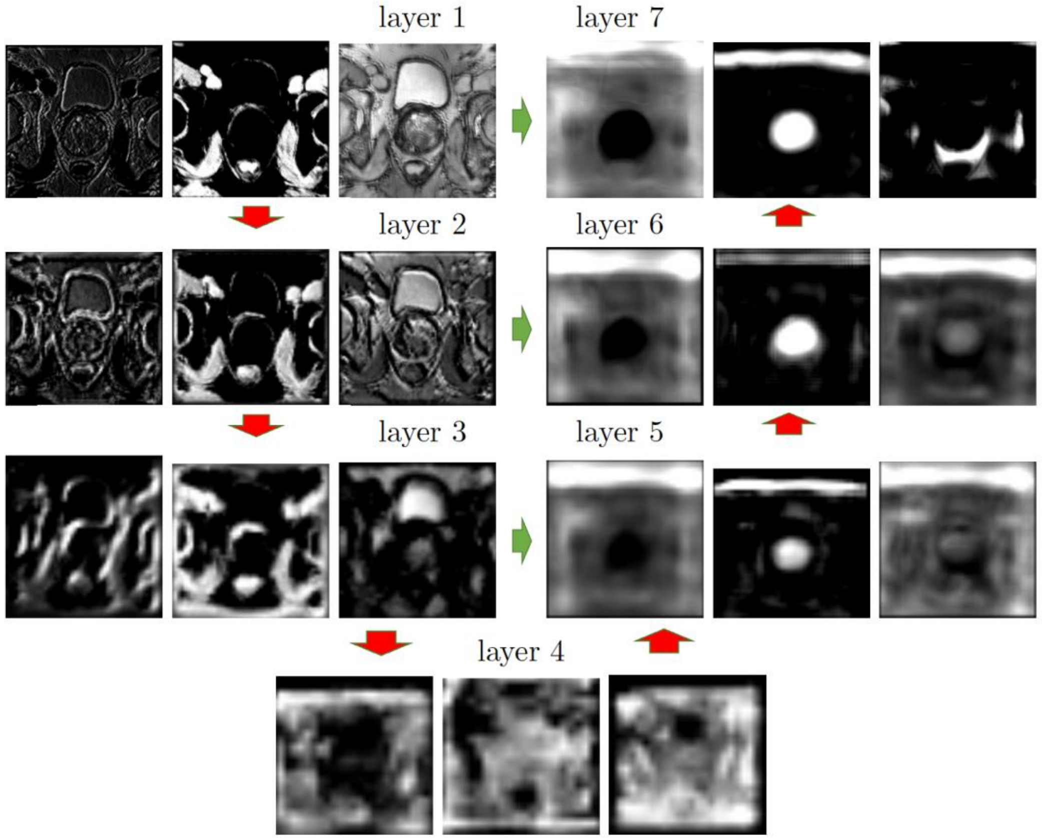


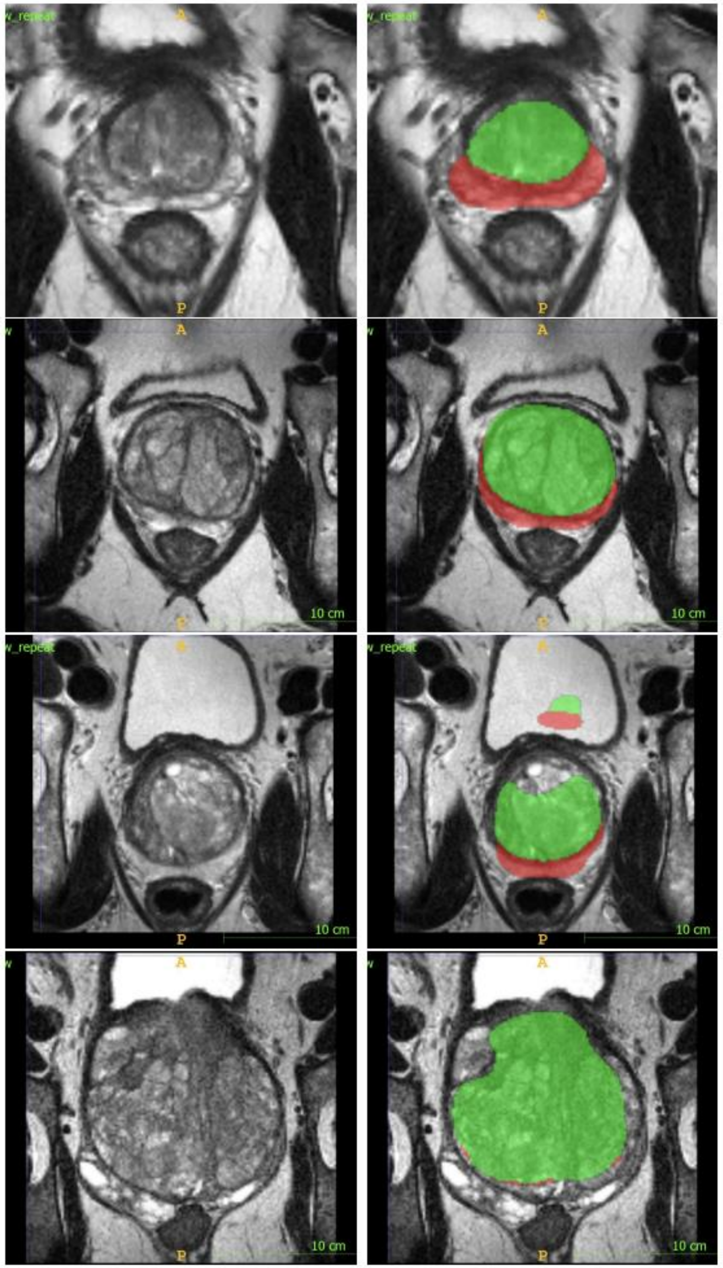
Use case in medical imaging

Prostate MRI, pictures of feature maps:

Layer1: shape edge detail

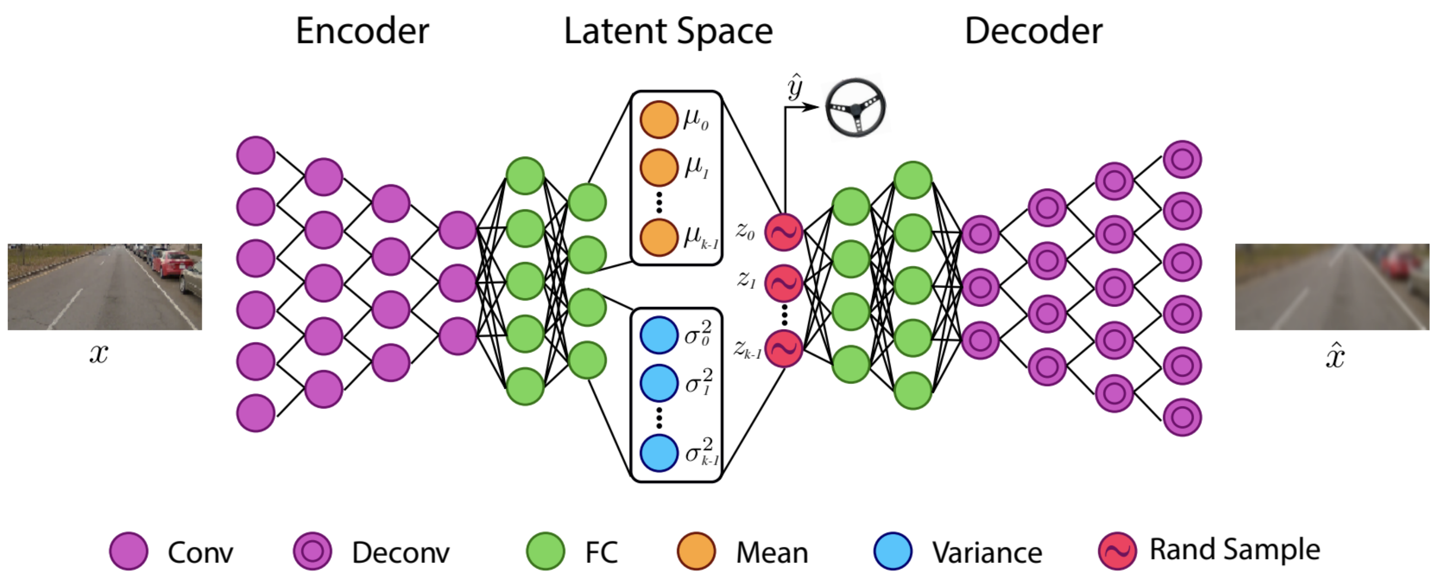
layer7: colour coding of shap





Generative Models

Variational Autoencoders (VAE, 2014 Diederik Kingma and Max Welling)



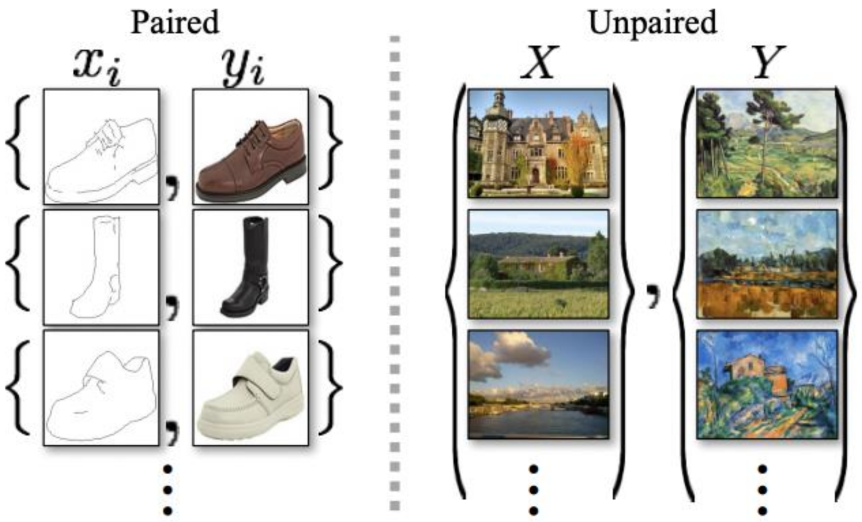
Loss = difference between output image and input image

The bottle neck middle layer parameters that encode the image (e.g. kind of lines on the road, weather), and by varying them the decoder can generate new images

https://www.youtube.com/watch?v=ZwSdzcV-jr4

Generative modelling

Training images can be paired or un-paired

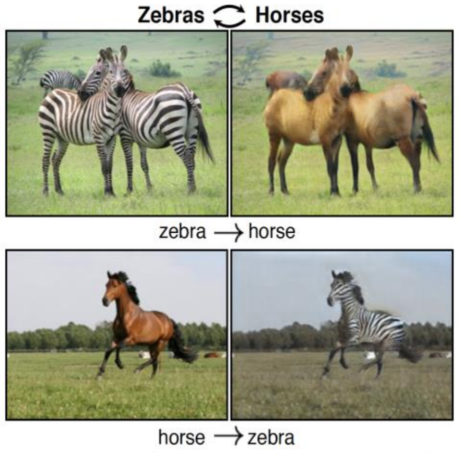


Pix2Pix

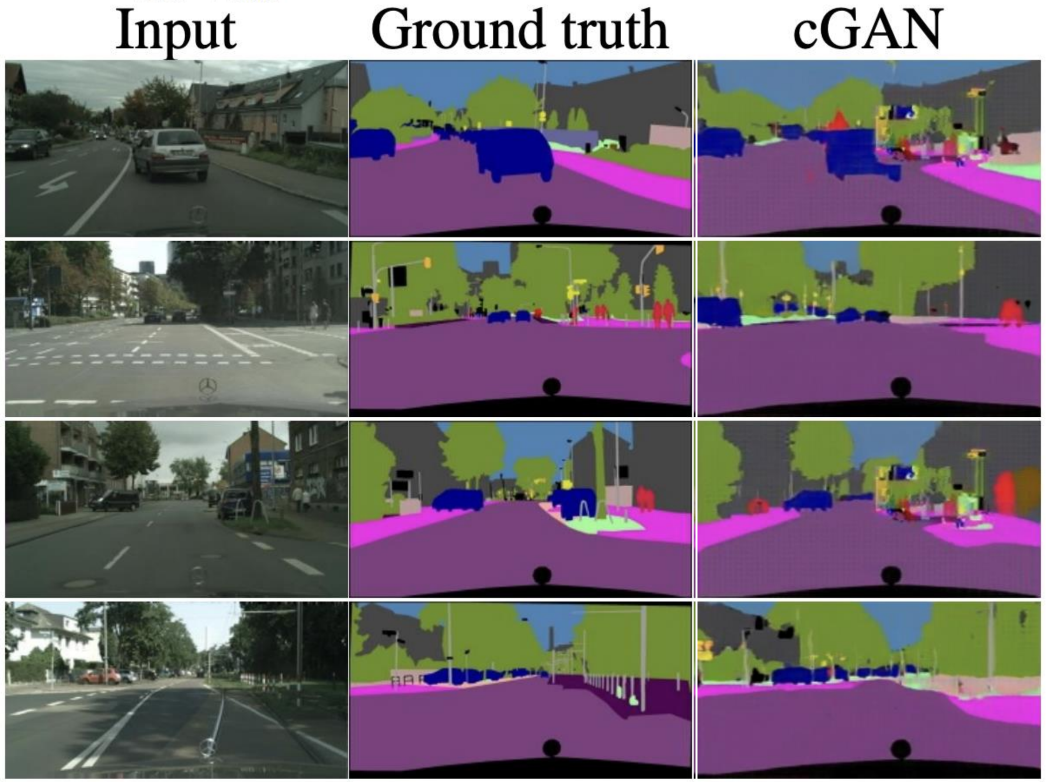
cycleGAN

[2016 Pix2Pix (Isola et al): https://paperswithcode.com/paper/image-to-image-translation-with-conditional](https://paperswithcode.com/paper/image-to-image-translation-with-conditional)

[2018 cycleGAN (Zhu et al): https://paperswithcode.com/paper/unpaired-image-to-image-translation-using](https://paperswithcode.com/paper/unpaired-image-to-image-translation-using)

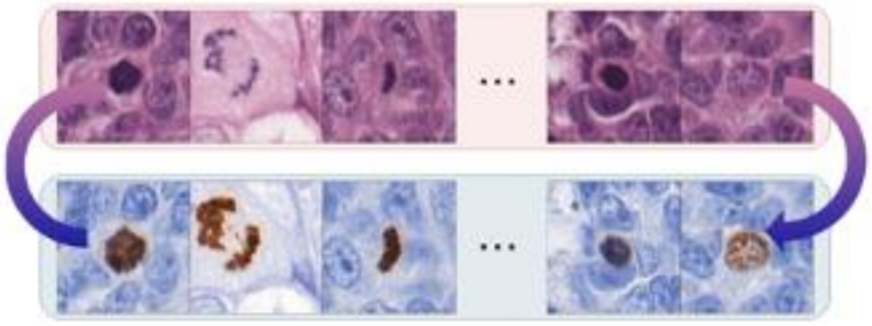


Mistakes happen

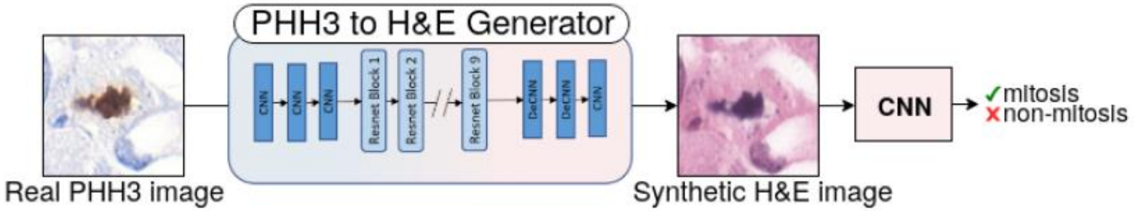


Use case in medical imaging

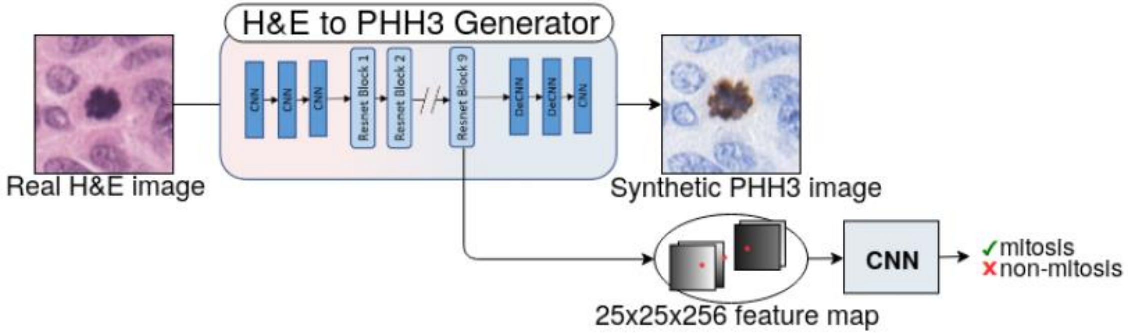
Synthetically staining cancerous nuclei in pathologicy tissues (my Master thesis in 2019)



Classifying and counting cancerous nuclei



(a) Learning from synthetic GAN images.

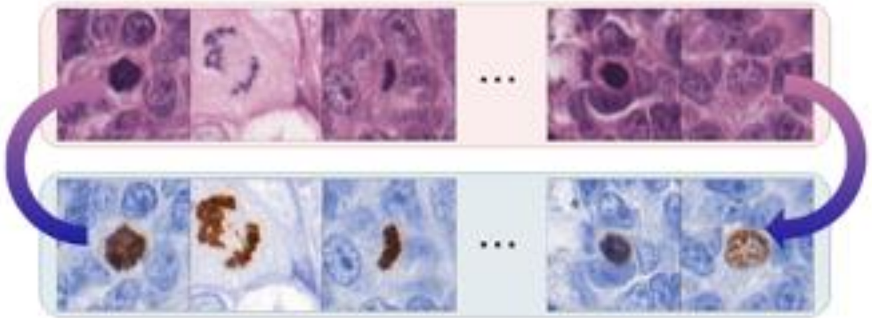


Good or bad?

As with any technology it is good or bad depending on how you use it.

So be critical as new t

need more governme



Use cases:

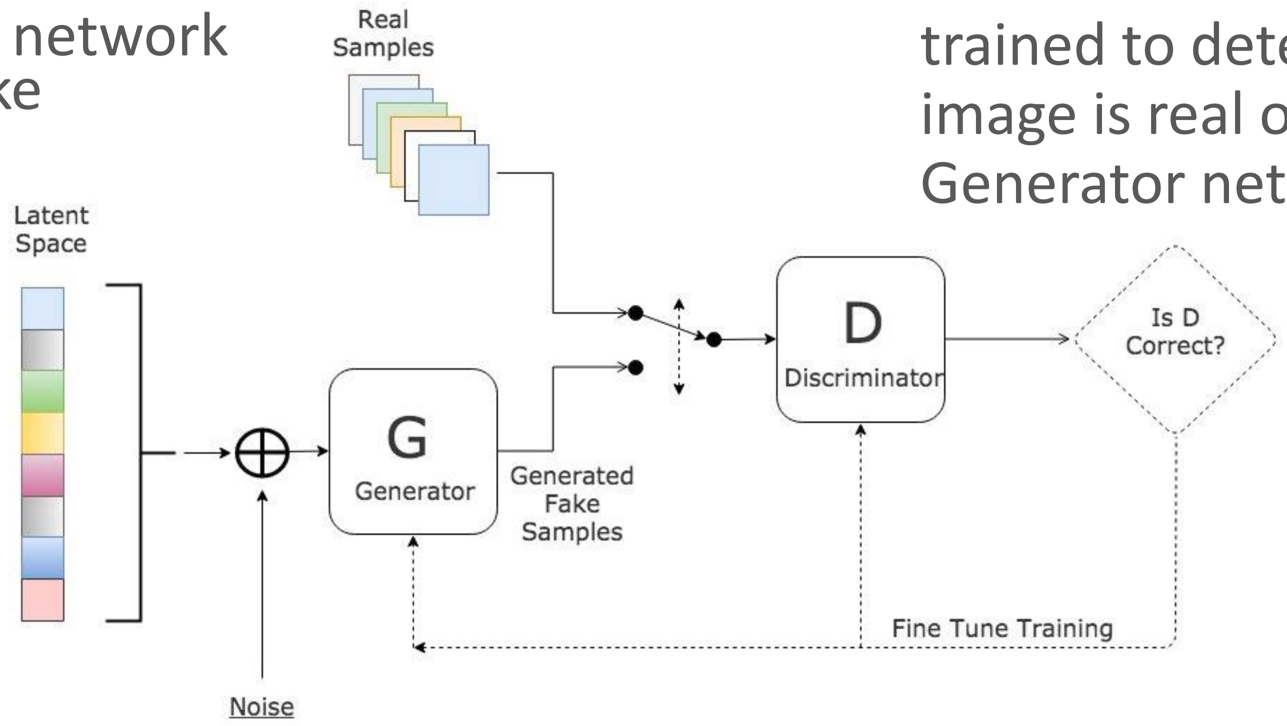
- Staining cancerous nodules in pathologicy tissues
- Synthetic images for training software autonomous cars
- Creative fun https://deepdreamgenerator.com/
- Deep fakes https://www.youtube.com/watch?v=gLoI9hAX9dw

Generative models

Generative Adversarial Networks (GANs)

1. A Generator network produces fake images

2. A Discriminator network is trained to detect if an input image is real or generated by a Generator network.



3. The Generator is trained to fool the Discriminator, so it becomes good at generating realistic images.

Generative models

CycleGAN

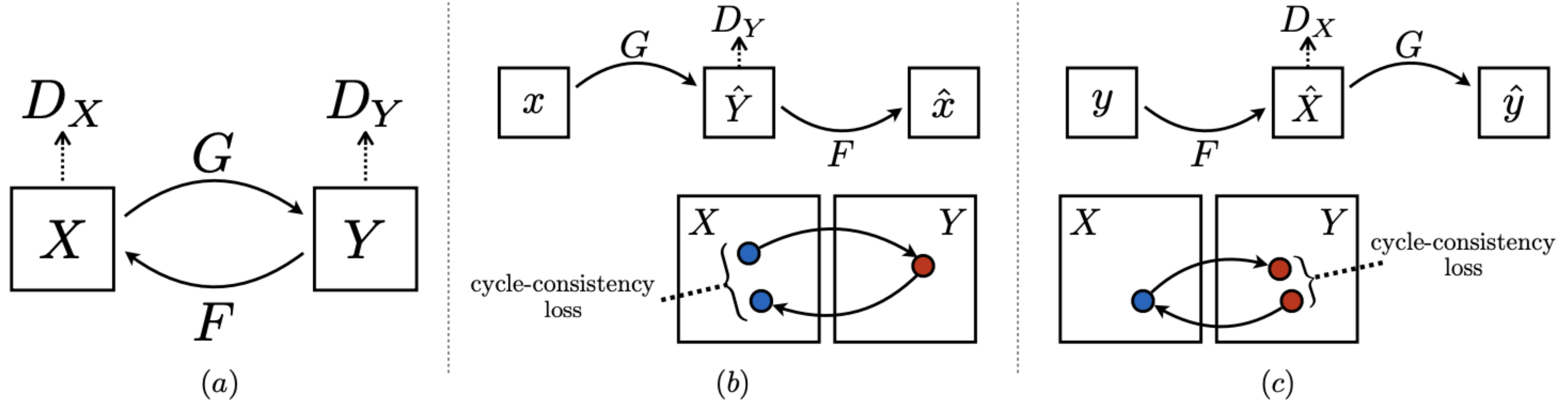


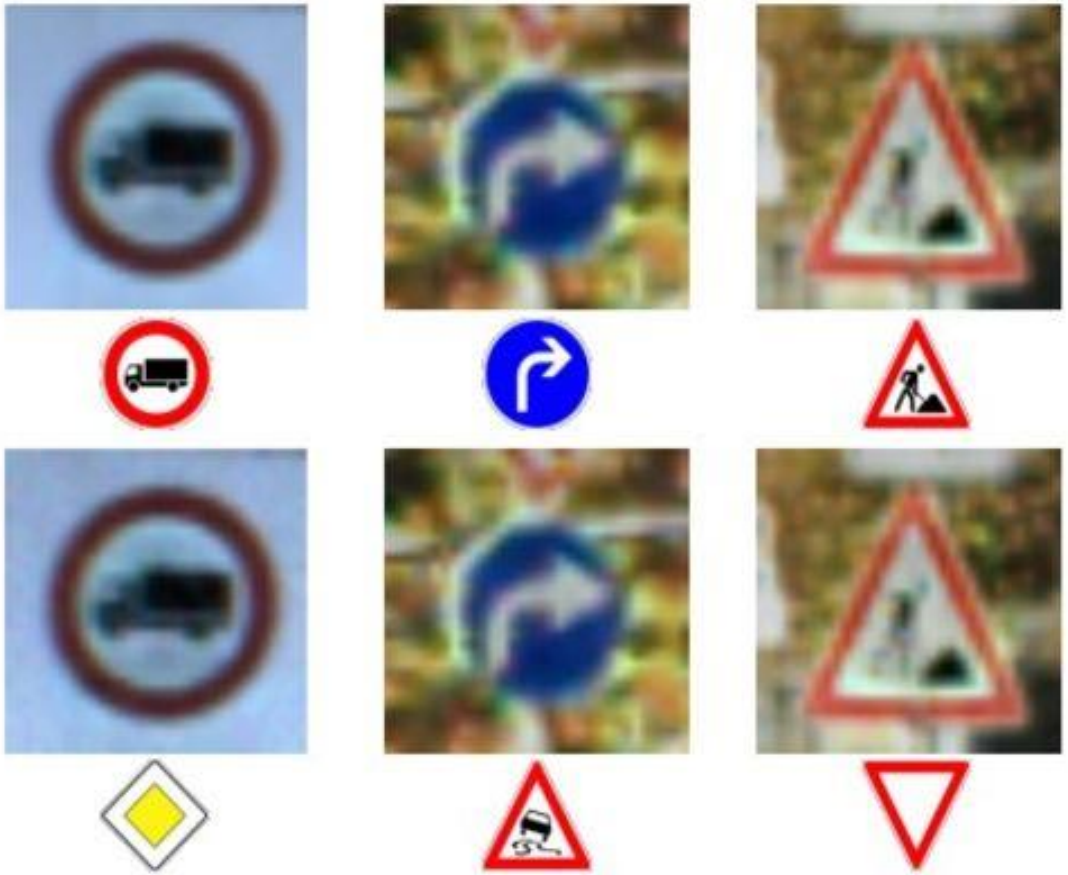
Figure 3: (a) Our model contains two mapping functions $G : X \rightarrow Y$ and $F : Y \rightarrow X$, and associated adversarial discriminators D_Y and D_X. D_Y encourages G to translate X into outputs indistinguishable from domain Y, and vice versa for D_X and F. To further regularize the mappings, we introduce two *cycle consistency losses* that capture the intuition that if we translate from one domain to the other and back again we should arrive at where we started: (b) forward cycle-consistency loss: $x \rightarrow G(x) \rightarrow F(G(x)) \approx x$, and (c) backward cycle-consistency loss: $y \rightarrow F(y) \rightarrow G(F(y)) \approx y$

Adversarial attacks and defense

Small difference to images that will amplify through network, are selected on purpose to attack neural network application.

There is research on such adversarial attacks, to a defend against them even before the applications are operational.

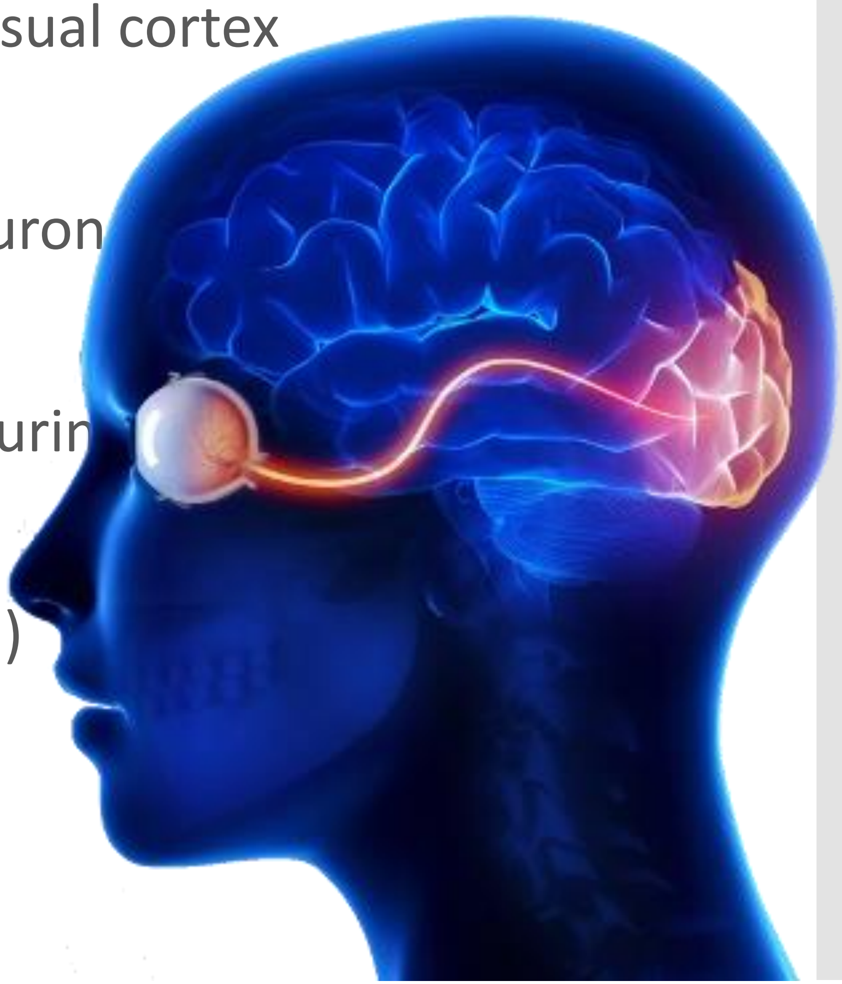
Development of testing platform with certification for AI applications



Human brain

Our brain does a lot more than the early stages of the visual cortex

- Pay attention to what is important (e.g. inhibitory neuron
- Predict what will happen (research predictive coding)
- Generalization through model of environment (e.g. durin
- Recognise things never seen before
- Anticipate intentions of other people (theory of mind)



Neuroscience and AI research help each other
(Nijmegen Radboud Donders Institute and AI Research)

Ethics

Important to understand AI and its impact when applying it

- Explainability
- Safety
- Privacy
- Liability
- Regulations
- Human behaviour

Thank you

Questions?