RAAK Top-up AIoTValley

Artificial Intelligence
Training session 3
Deep learning

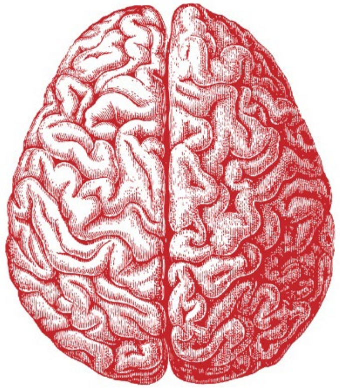
Jeroen Linssen

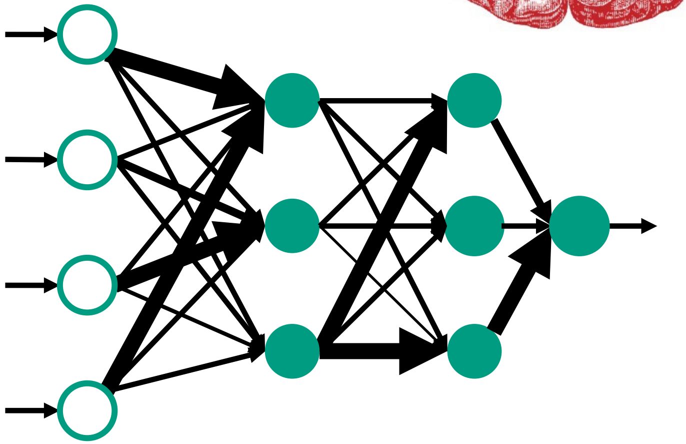
2021-06-18

SAXION UNIVERSITY OF APPLIED SCIENCES

TVALLEY

BOOST





Modus operandi

Webinar, but interactive

Ask questions in chat

Assistance by Linda Maalderink

Max. 3 hours with 2 breaks

Session is being recorded

 &  = self-service

Introduction square

Motivation

RAAK projects + BOOST

Involved partners

Learning goals

RAAK-mkb Focus op Vision & Data in Smart Industry

Focus op Vision (2019 – 2021)

- Enabling companies in ‘maakindustrie’ to use computer vision
- Disseminating knowledge on (AI for) vision

Data in Smart Industry (2017 – 2020)

- Enabling companies in ‘maakindustrie’ to use data for process optimization
- Disseminating knowledge on IoT and AI for data acquisition and analysis

AIoTValley (2020 – 2021)

- ‘Top-up’ of DSI to create open access educational material
- Including AI and IoT in TValley (robotics & mechatronics fieldlab)

Overview

Fundamentals of deep learning

Typical tasks

Network types

Use cases

Frameworks & deployment

Hands-on practice

Recap & outlook

Learning goals

Deep learning

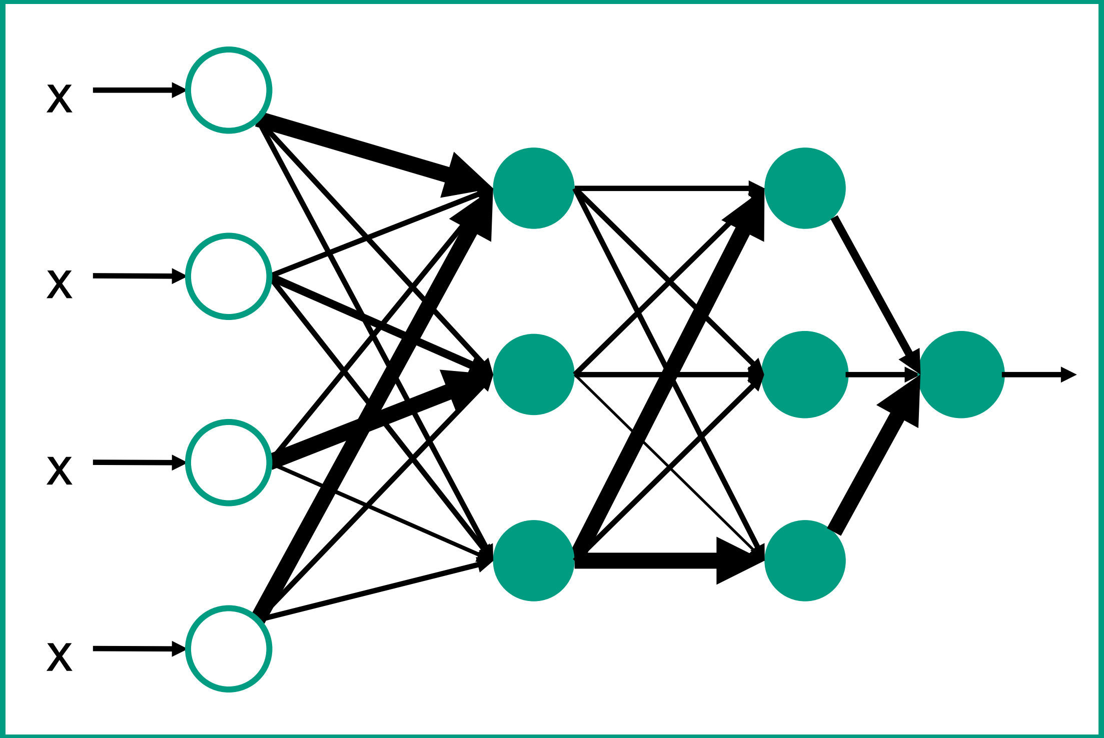
- Fundamentals and key concepts
- Training models
- Availability and usability

Disclaimers

- High-level
- Almost no math
- No tweaking, configuring, special cases

Fundamentals of deep learning

Cats, networks, activation functions and layers upon layers of math.

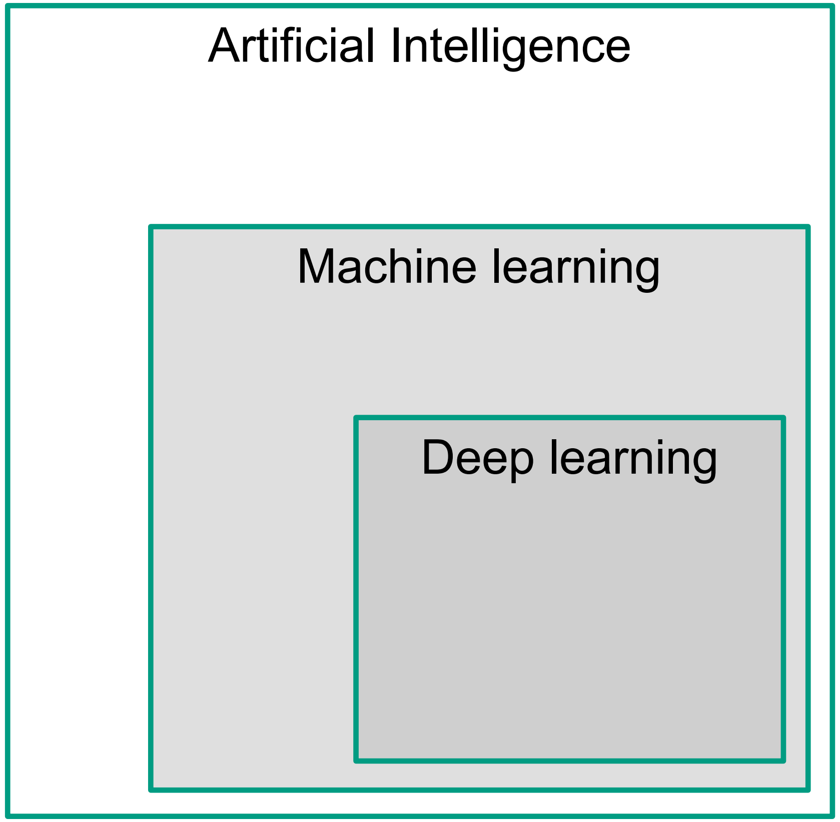


Some material gratefully borrowed and adapted from https://github.com/glouppe/info8010-deep-learning under a BSD-3 license, and from the Saxion HBO-ICT specialization Big Data Technologies.

Deep learning

Machine learning:
Defining a model with several parameters and optimize this model by training it on a dataset.

Deep learning:
Machine learning, but with ‘deep’ neural networks.



Difficult problems

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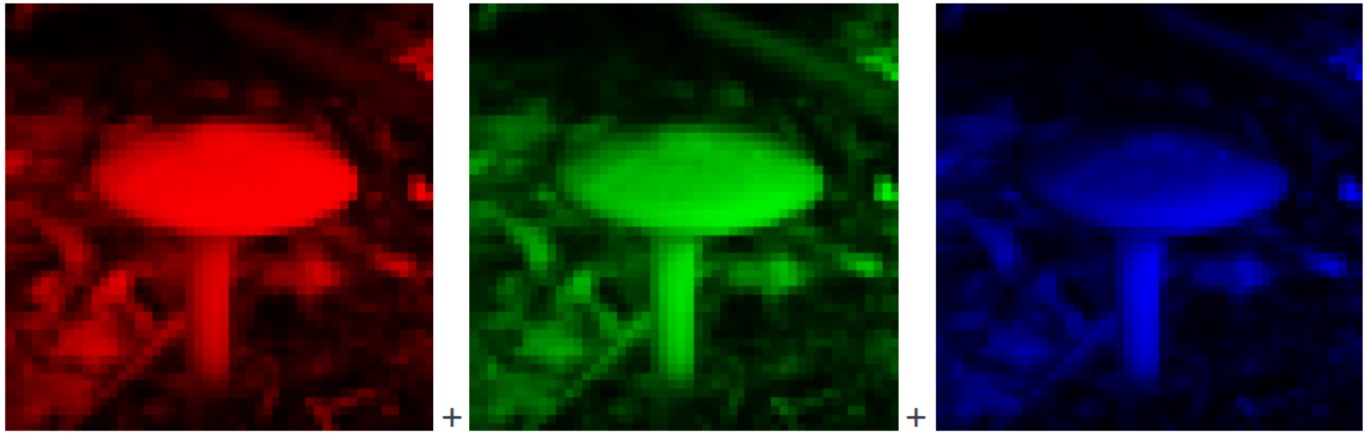
Human versus computer

This is a mushroom.



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        [0.2509804 , 0.1882353 , 0.20392157, 1.        ],
        [0.4117647 , 0.34117648, 0.37254903, 1.        ],
        ...,
        [0.20392157, 0.23529412, 0.17254902, 1.        ],
        [0.16470589, 0.18039216, 0.12156863, 1.        ],
        [0.18039216, 0.18039216, 0.14117648, 1.        ]],

       [[0.1254902 , 0.11372549, 0.09411765, 1.        ],
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        [0.21176471, 0.2       , 0.20392157, 1.        ],
        ...,
        [0.1764706 , 0.24705882, 0.12156863, 1.        ],
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        [0.16470589, 0.20784314, 0.11764706, 1.        ]],

       [[0.14117648, 0.12941177, 0.10980392, 1.        ],
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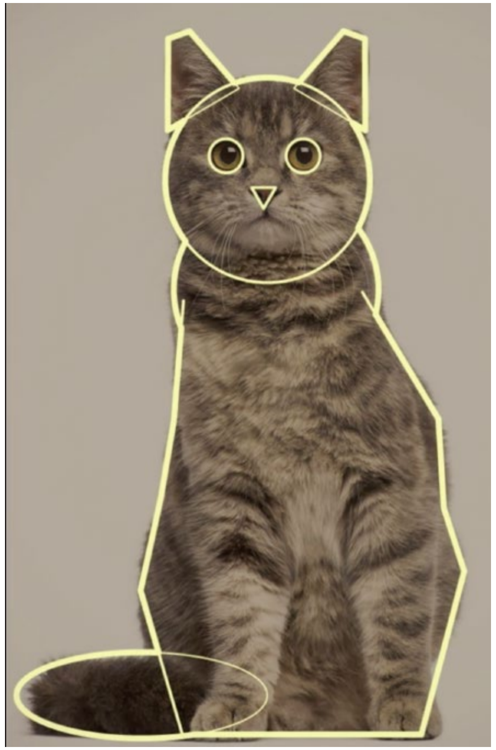
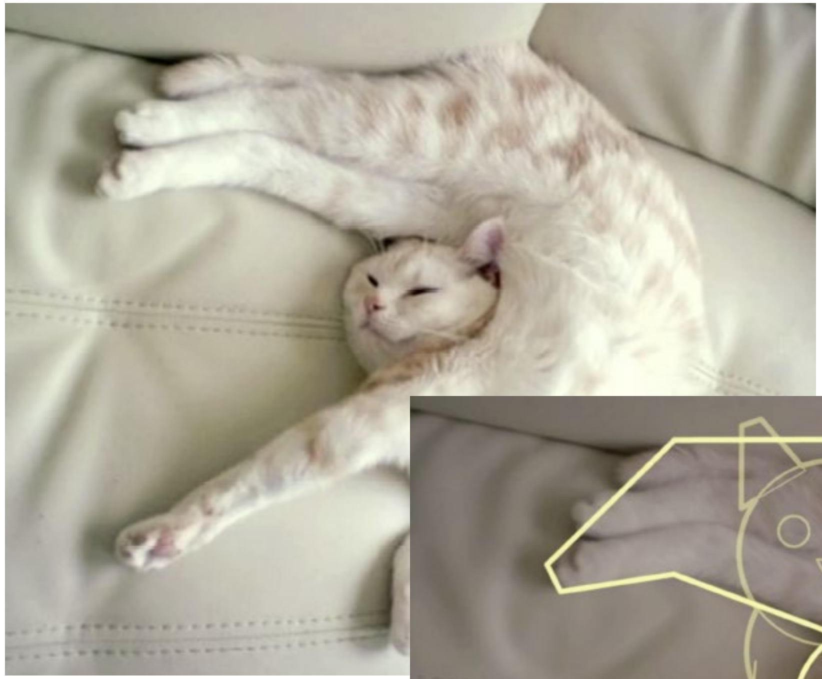
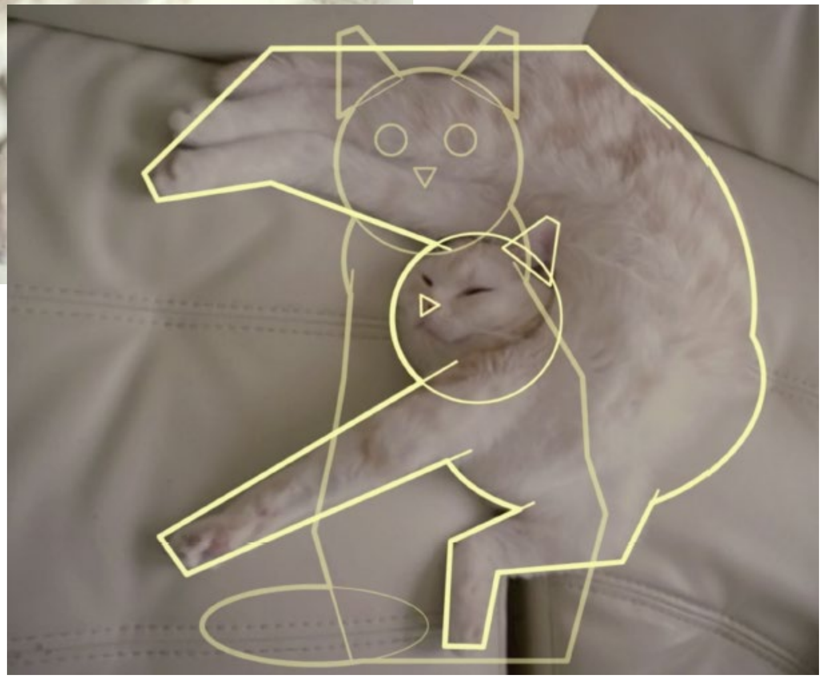
       ...,
```

Logical approach to recognition

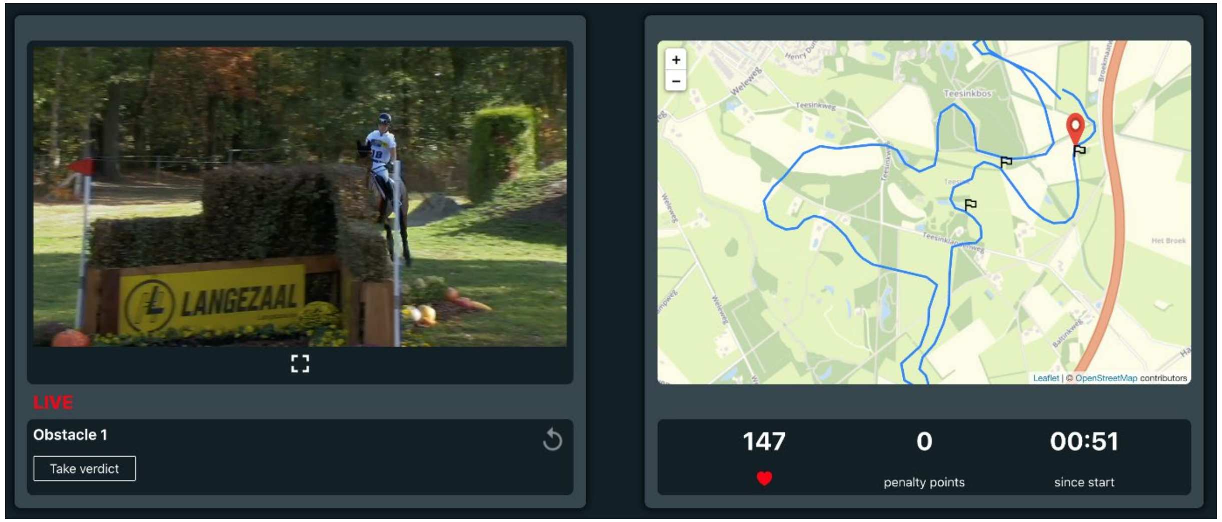






Just a few examples

Horse/rider detection for the Military event in Boekelo



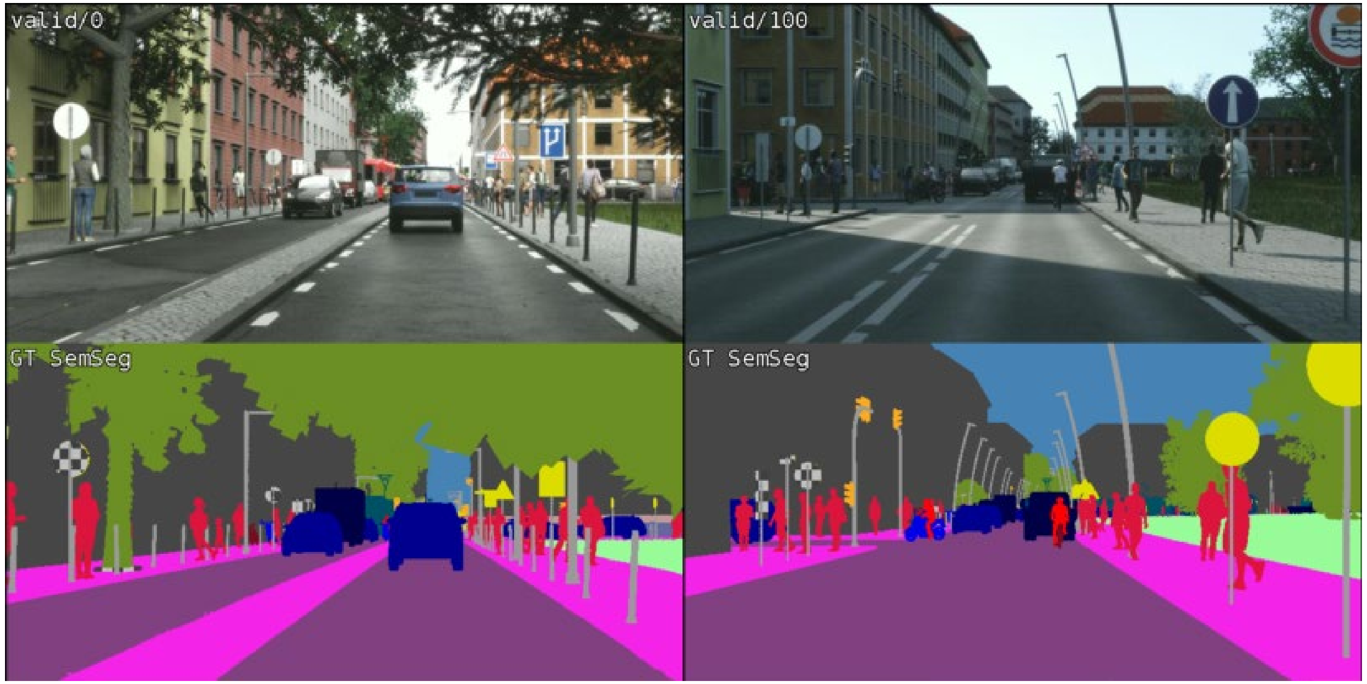
https://www.rtvoost.nl/nieuws/1534373/Publiek-Military-Boekelo-bepaalt-in-de-toekomst-zelf-welke-hindernis-op-hun-scherm-te-zien-is

Fitting Fashion Using Machine Learning

https://youtu.be/XvOM29ZtIeU

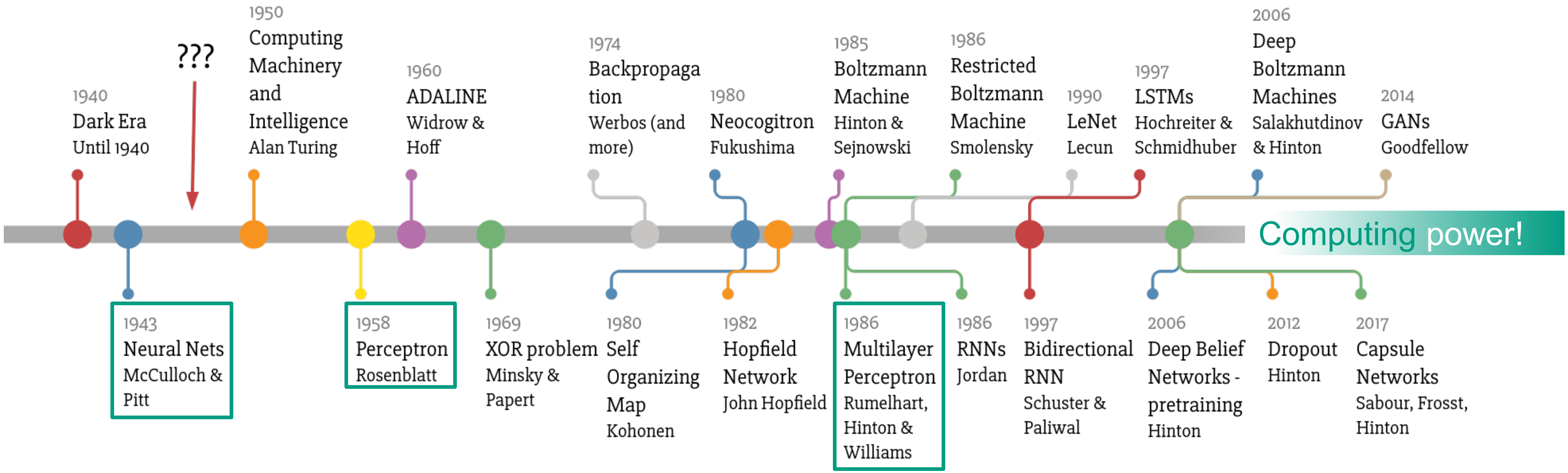
Just a few examples

Google Assistant
(speech recognition
& understanding)



Contextual awareness for autonomous cars

A short history



Made by Favio Vázquez

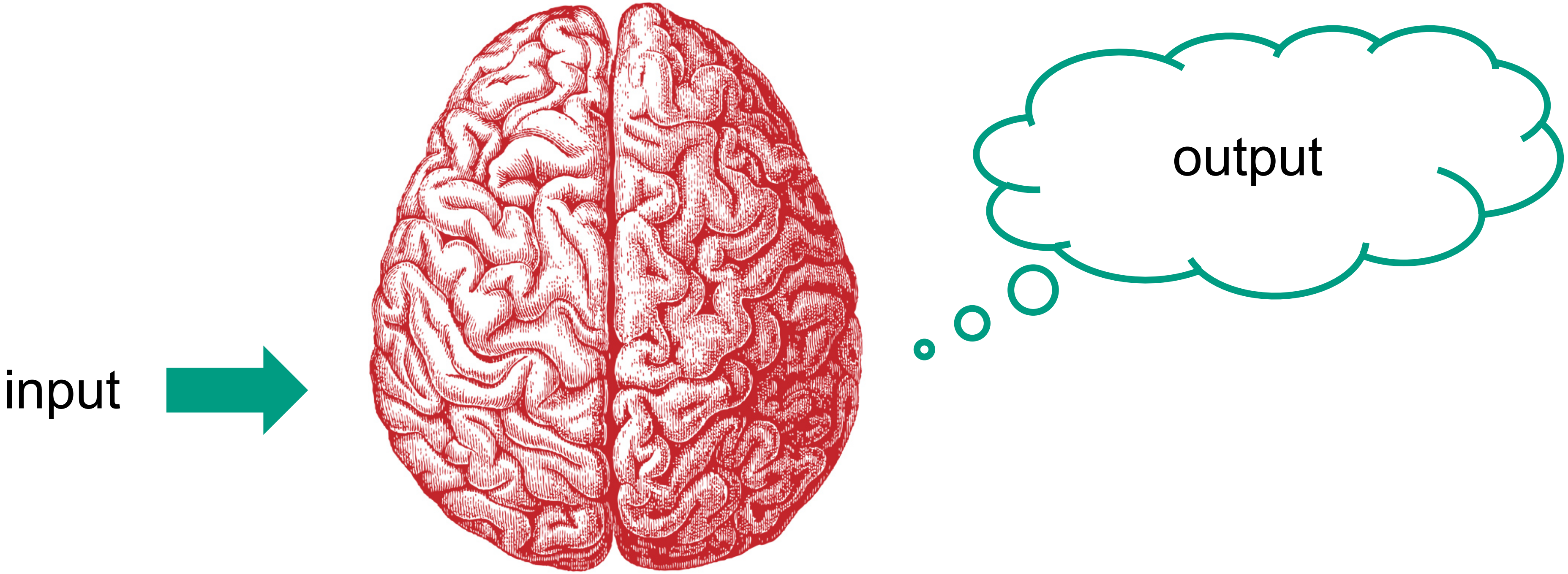
ARTIFICIAL INTELLIGENCE

=

(AUTOMATED)

PATTERN RECOGNITION + PLANNING FOR ACTION

Neural networks in the brain

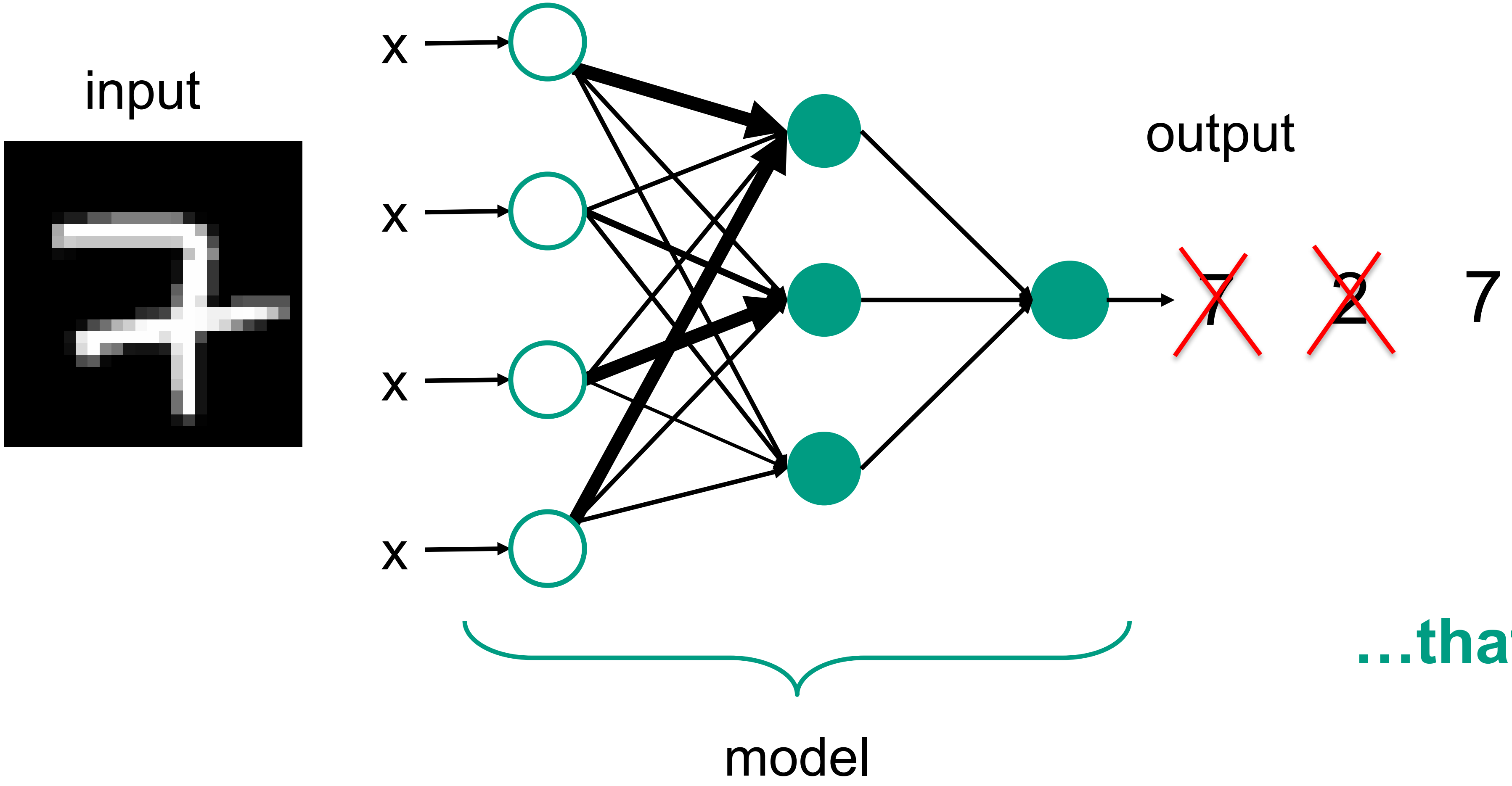


100 000 000 000 neurons

~7 000 connections per neuron

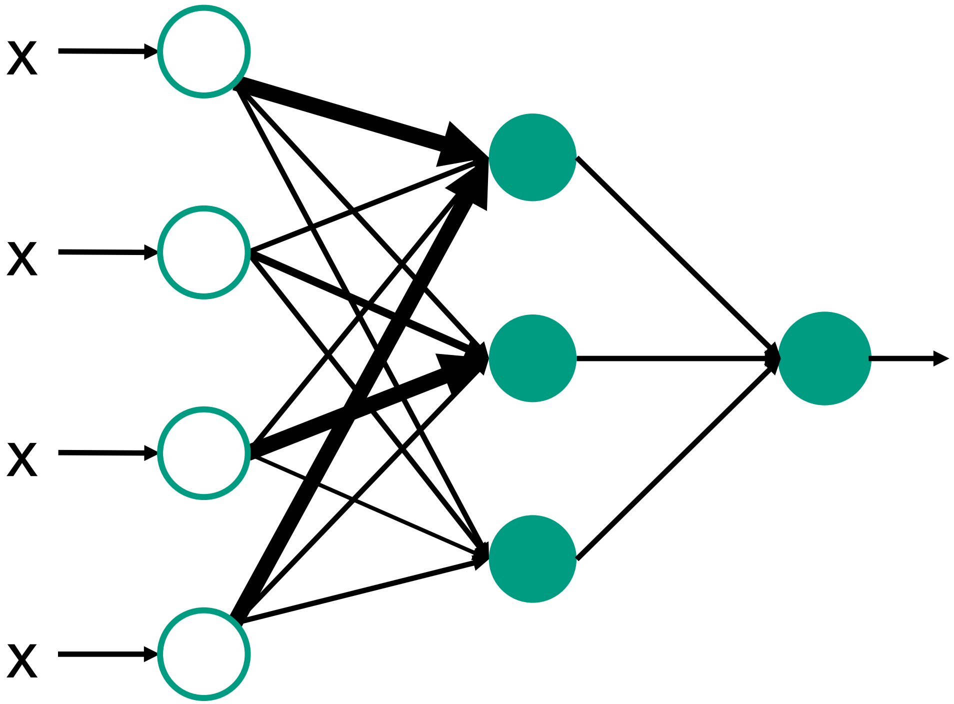
~1 000 000 000 000 000 connections in total

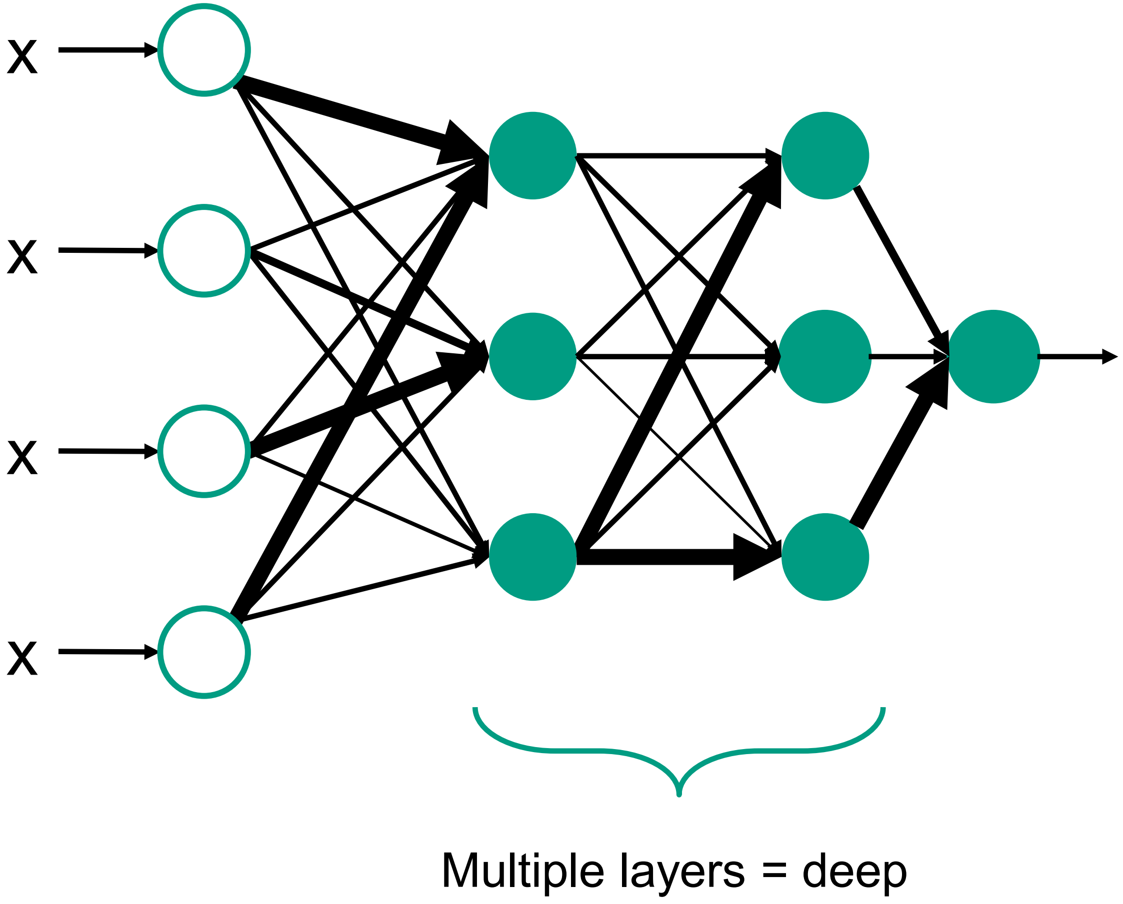
Artificial neural networks



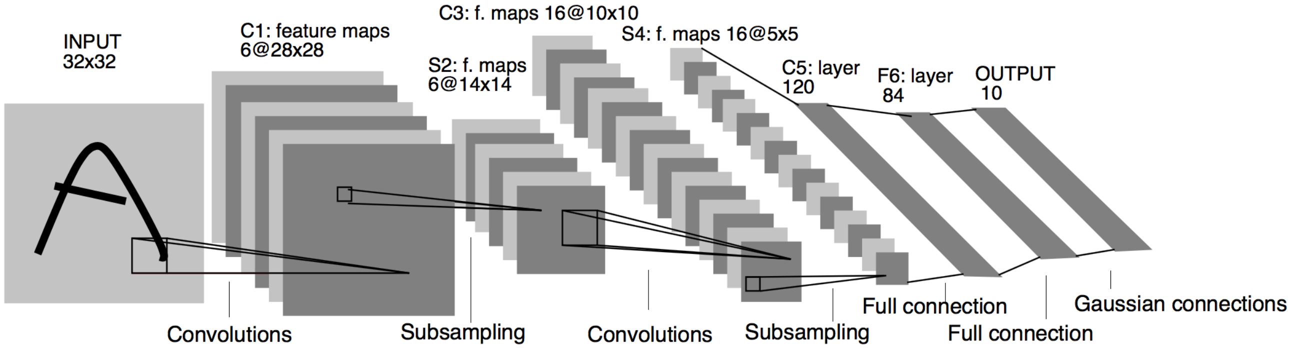
…that's it!

What’s so deep about it?



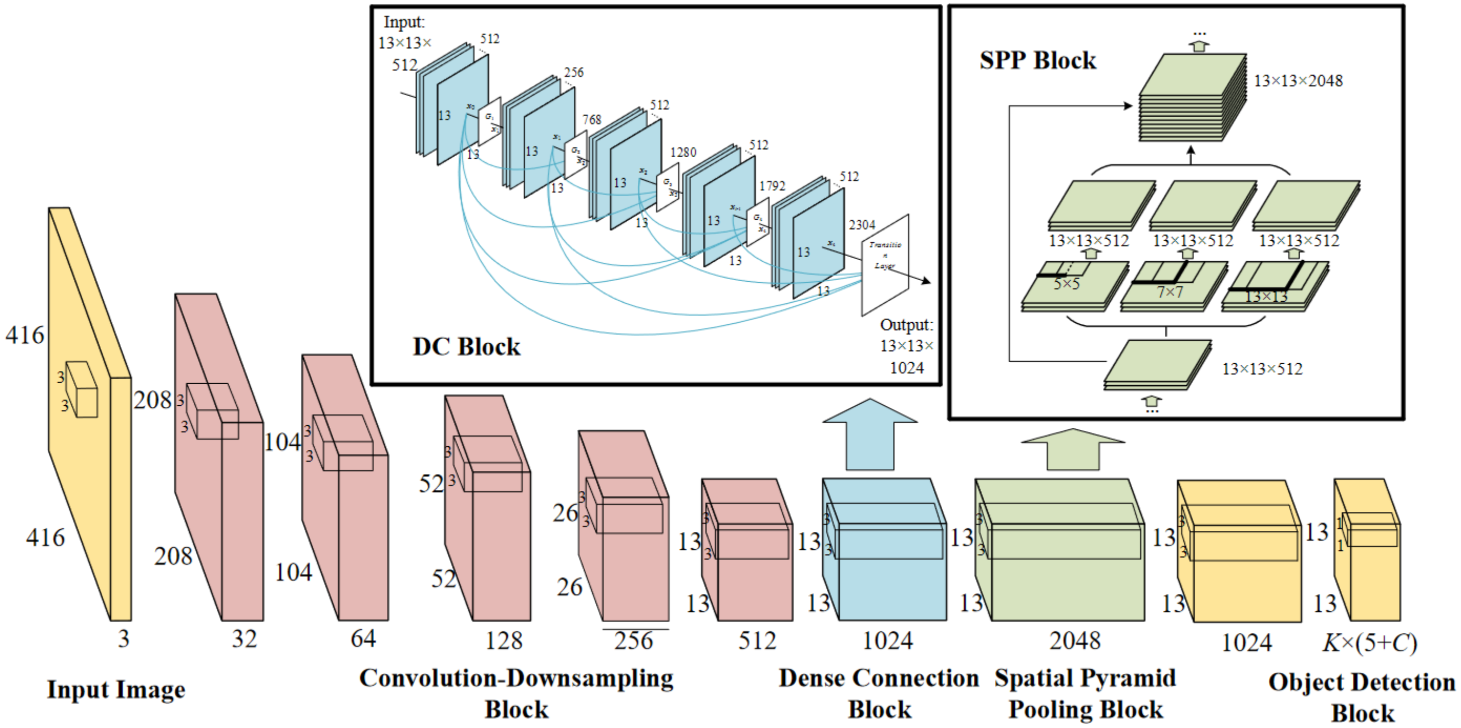


Layers and layers of learning



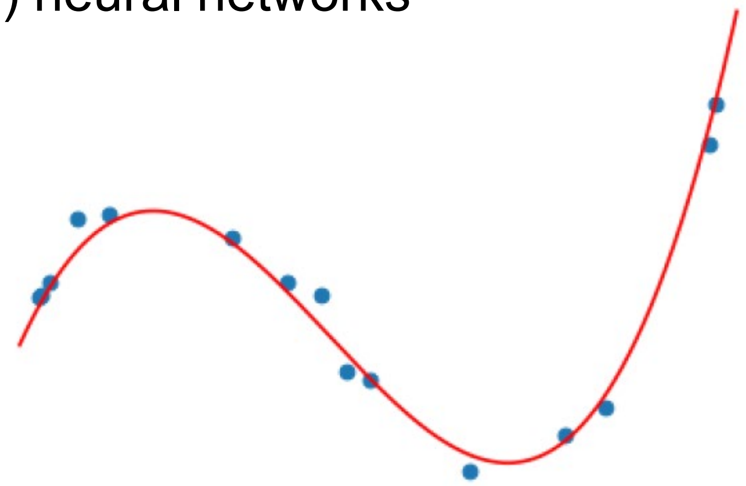
LeNet (1998)

YOLOv4 (2020)



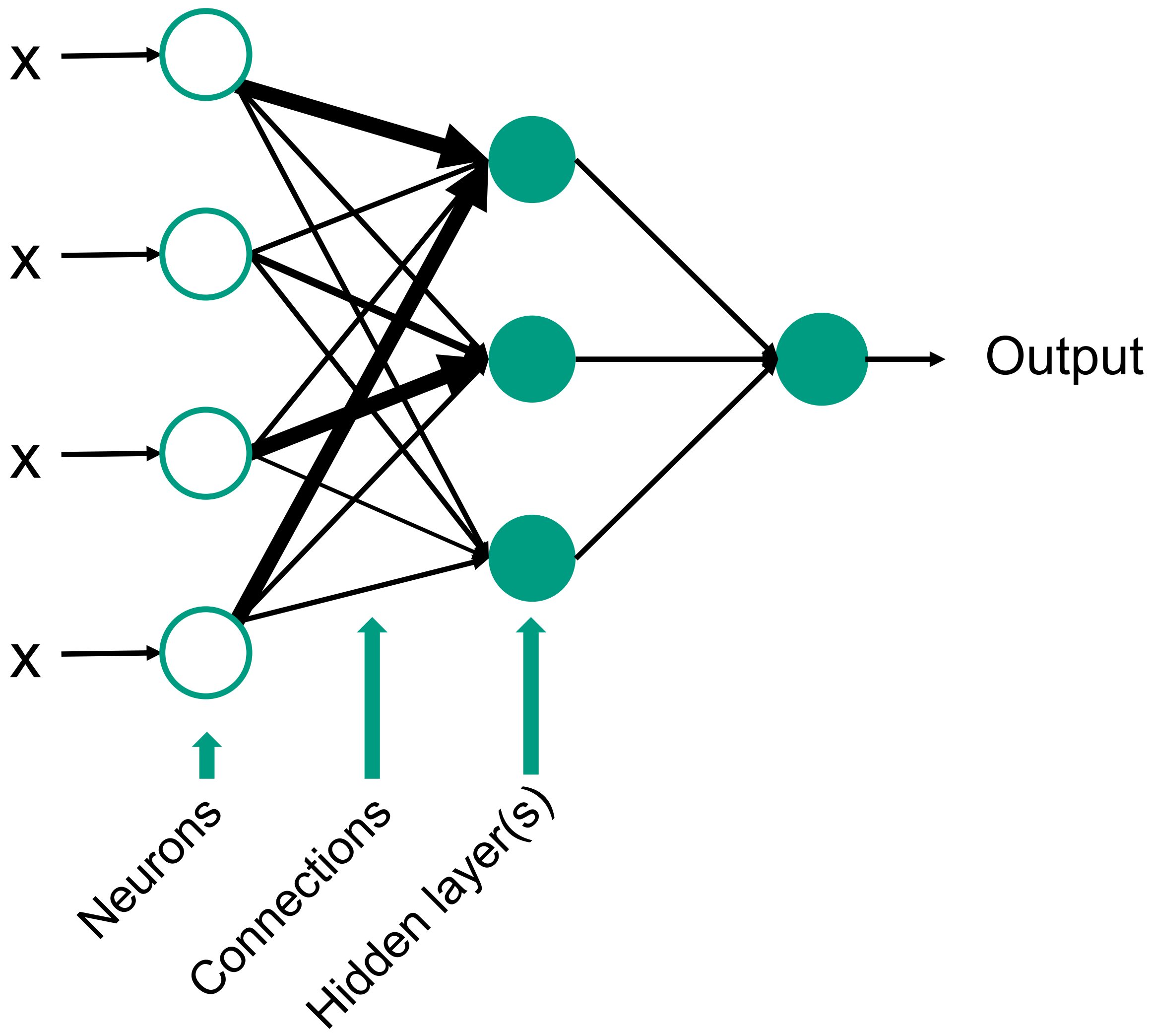
A step back

- Pattern recognition through machine learning
- Using statistics to determine functions
  - Prediction
  - Classification
- Deep learning employs (artificial!) neural networks



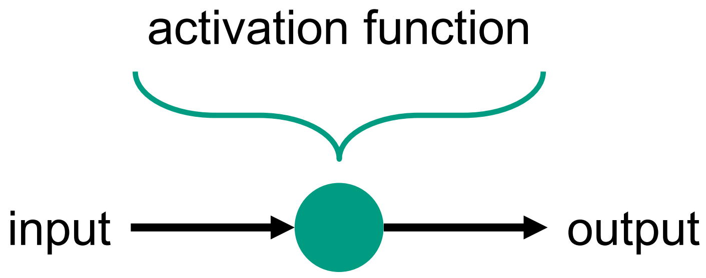
Key concepts in deep learning

- **(Multi-layer) perceptrons**
- Activation functions
- Gradient descent
- Backpropagation

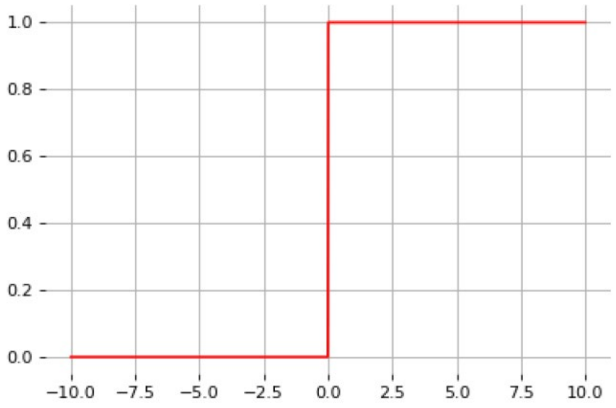


Key concepts in deep learning

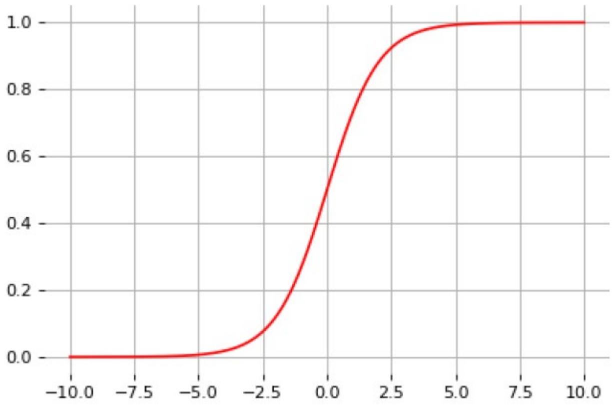
- (Multi-layer) perceptrons
- **Activation functions:** when does a neuron ‘fire’?
- Gradient descent
- Backpropagation



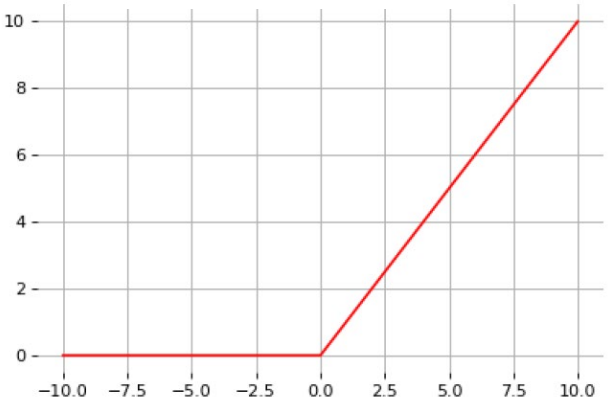
$$\mathrm{sign}(x) = \begin{cases} 1 & \text{if } x \geq 0 \\ 0 & \text{otherwise} \end{cases}$$



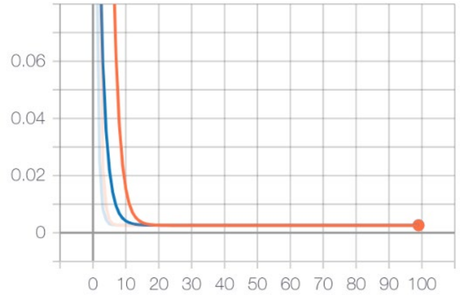
$$\sigma(x) = \frac{1}{1 + \exp(-x)}$$



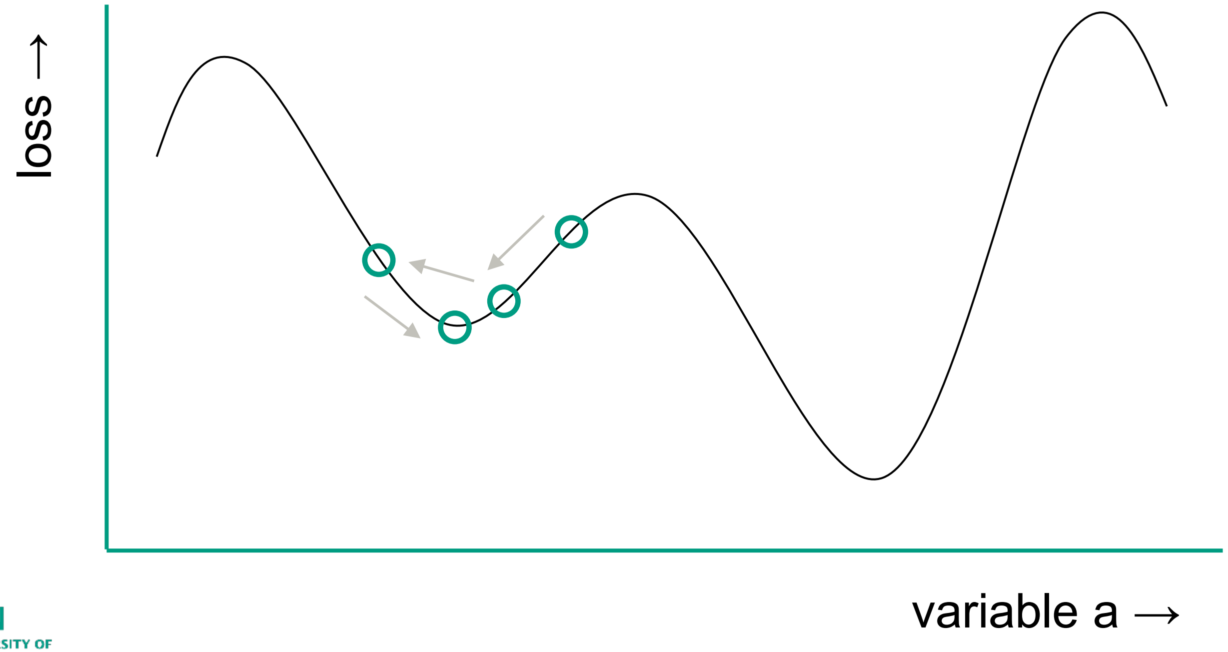
$$\mathrm{ReLU}(x) = \max(0, x)$$

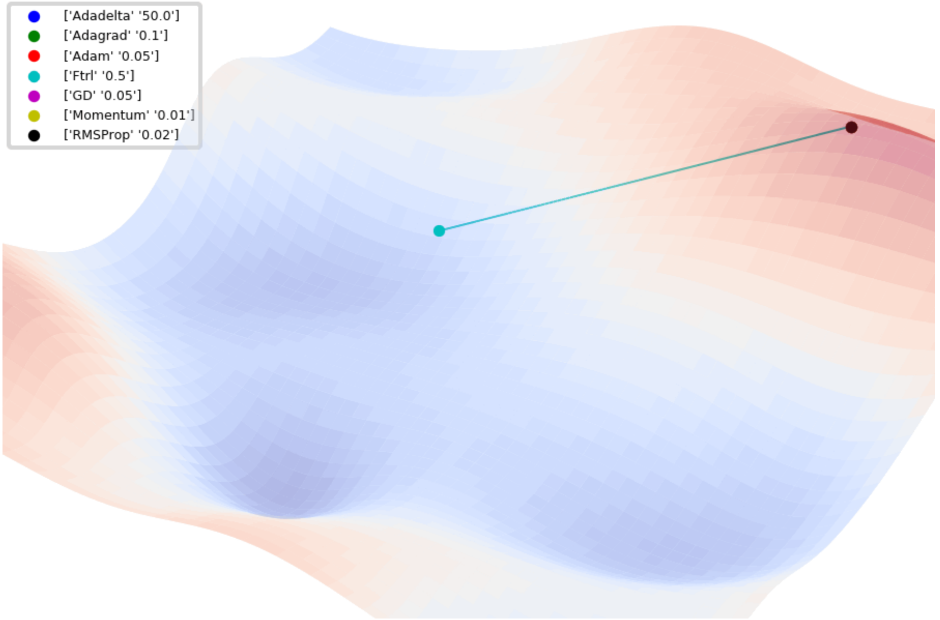


Key concepts in deep learning



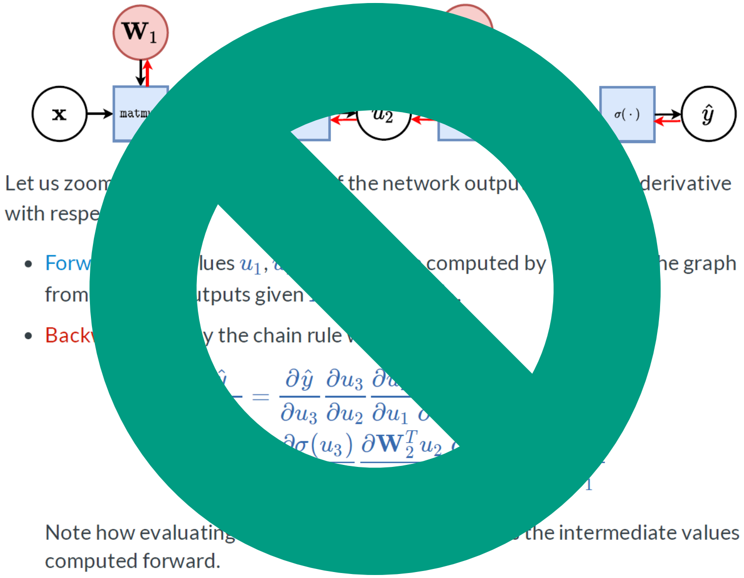
- (Multi-layer) perceptrons
- Activation functions
- **Gradient descent:** minimizes ‘loss’ as an alternative to ‘error’.
- Backpropagation





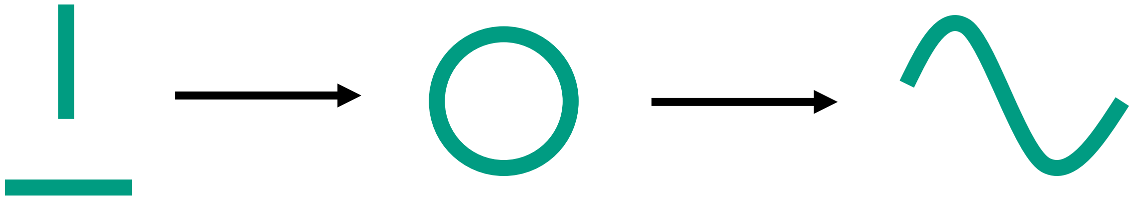
Key concepts in deep learning

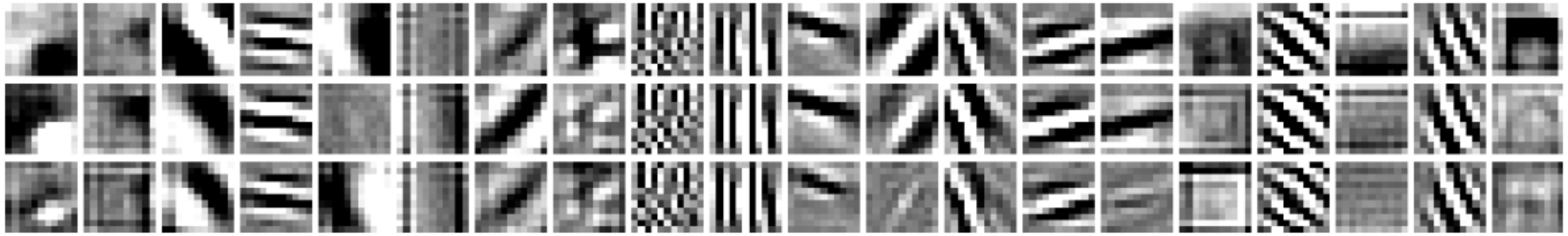
- (Multi-layer) perceptrons
- Activation functions
- Gradient descent
- **Backpropagation:**
  backtracking ALL the function results, the ‘ASSEMBLY’ of deep learning.



Convolutional neural networks

- **Convolutions** help find structure in large signals.
- Excellent for visual data.
- Each convolutional layer learns **filters** for a specific **feature**.





AlexNet’s first 20 filters.

INTERMISSION 1

Typical tasks

Using deep learning to improve computer vision and get insight into (un?)structured data.

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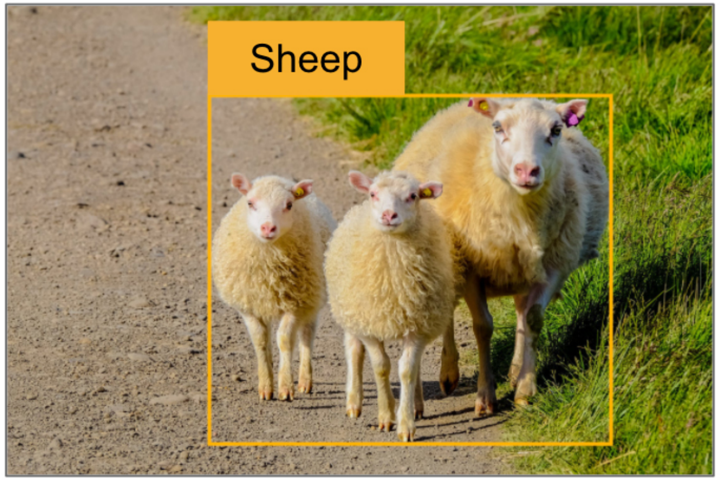
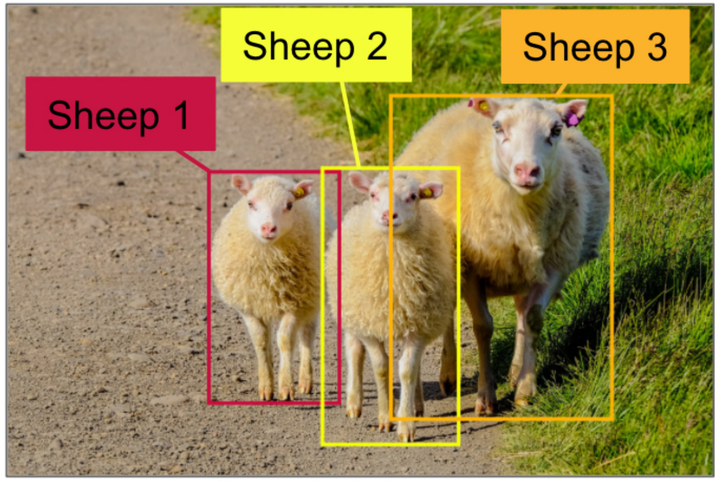
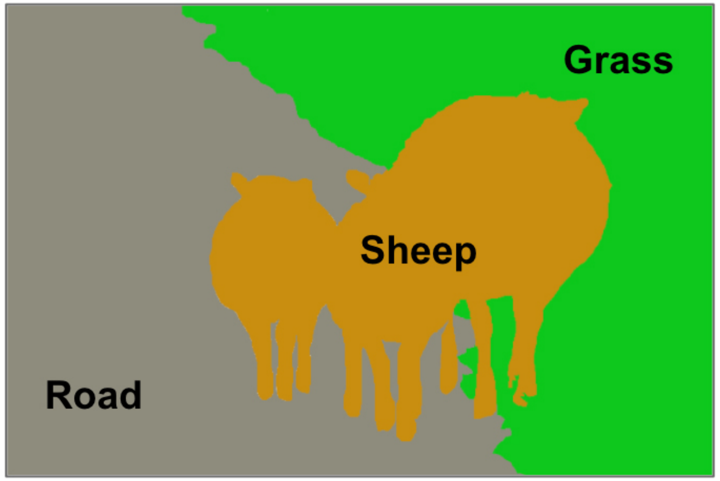
Typical deep learning: computer vision



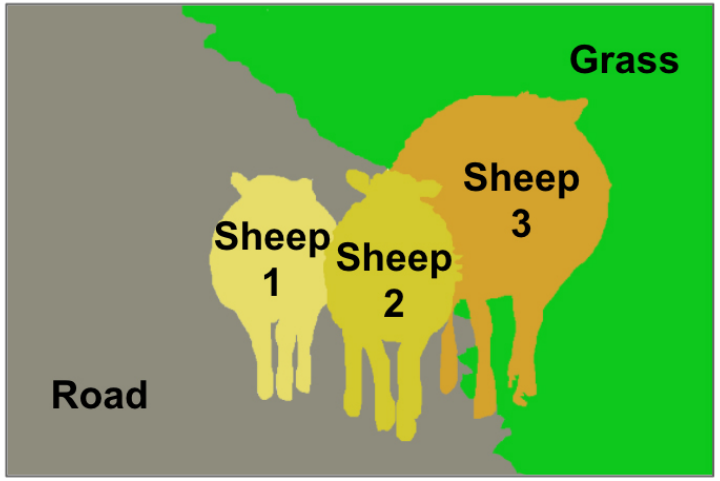
Classification + Localization



Object Detection



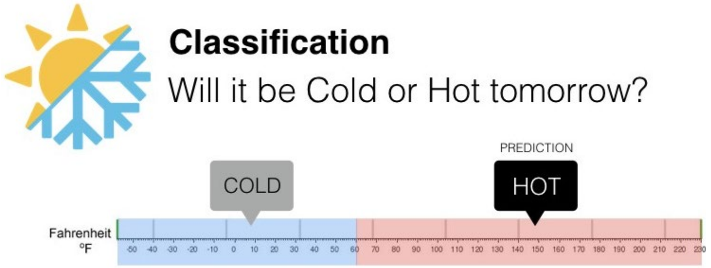
Semantic Segmentation



Instance Segmentation

Classification

- *What* is this object?



- The model learns characteristics of an object class.

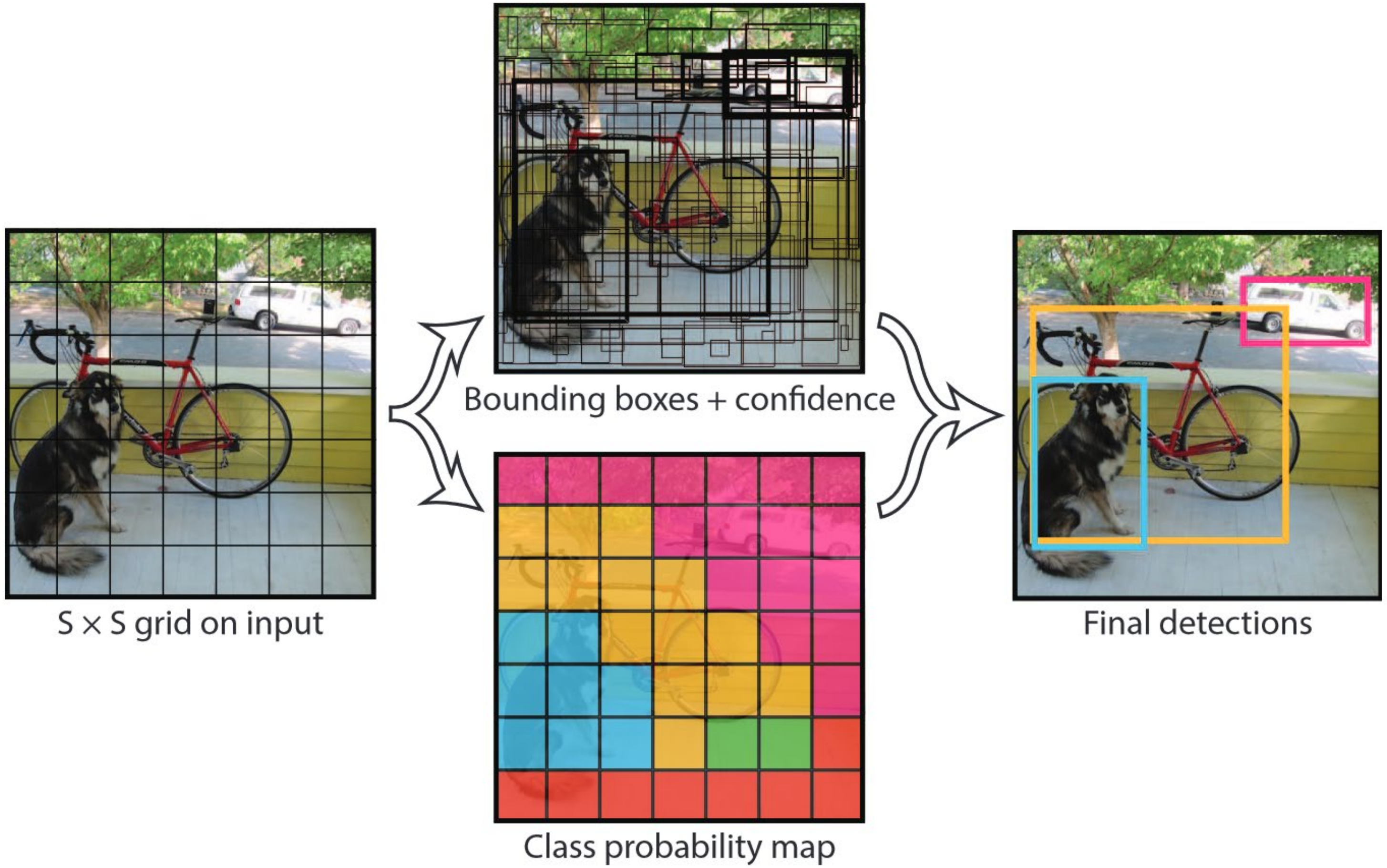
Detection

- *Where* is an object?
  (And what is it?)
- The model learns how to look for objects.

- YOLO: You Only Look Once

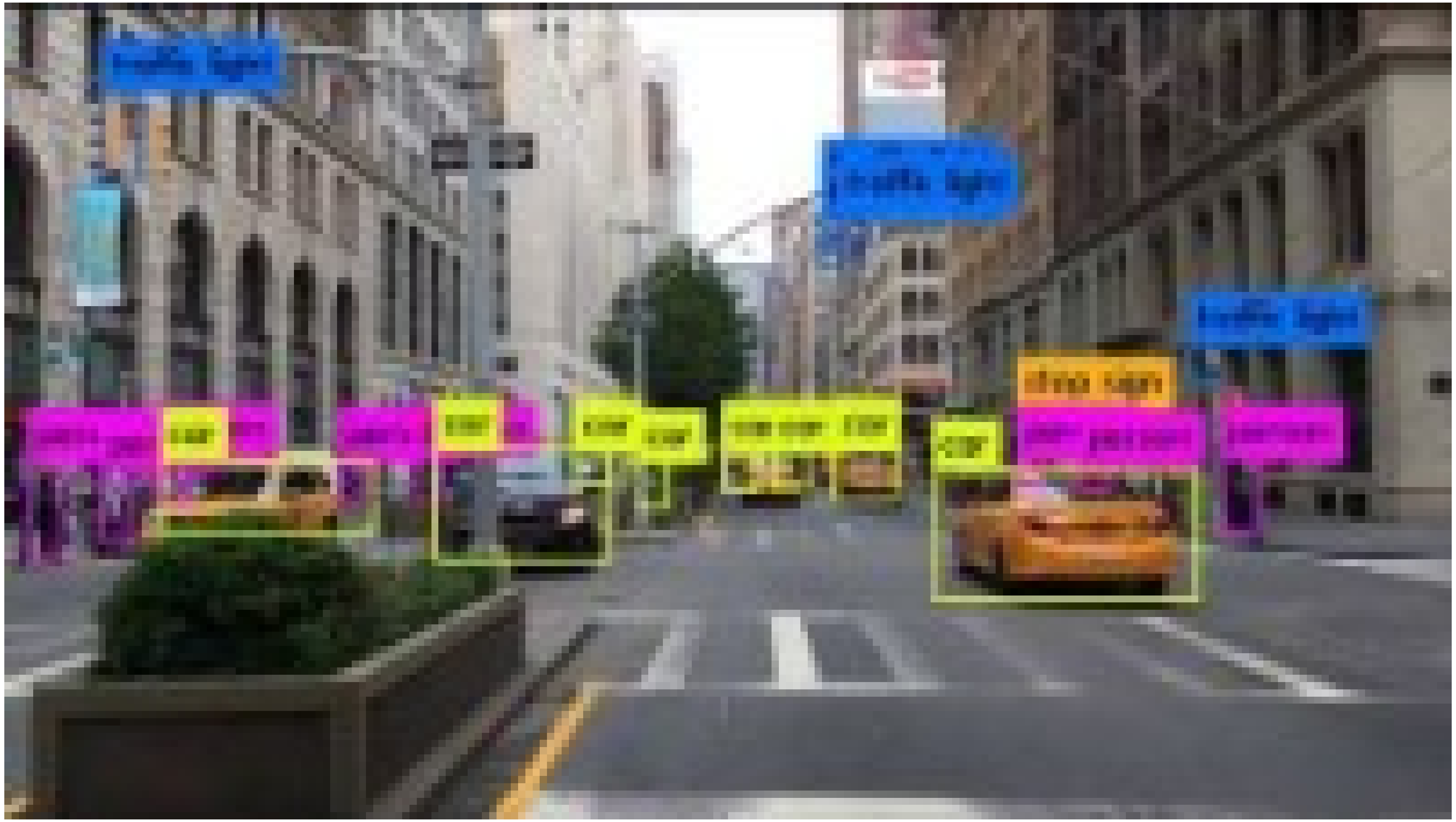
```
NOW HERE'S THE REAL LICENSE:

0. Darknet is public domain.
1. Do whatever you want with it.
2. Stop emailing me about it!
```



https://pjreddie.com/darknet/yolo/

YOLO in action

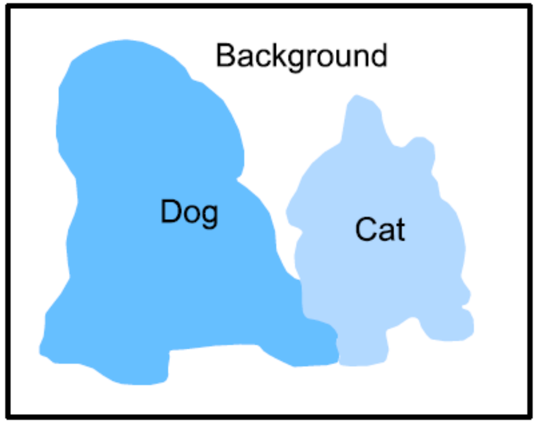


https://youtu.be/YmbhRxQkLMg

Segmentation

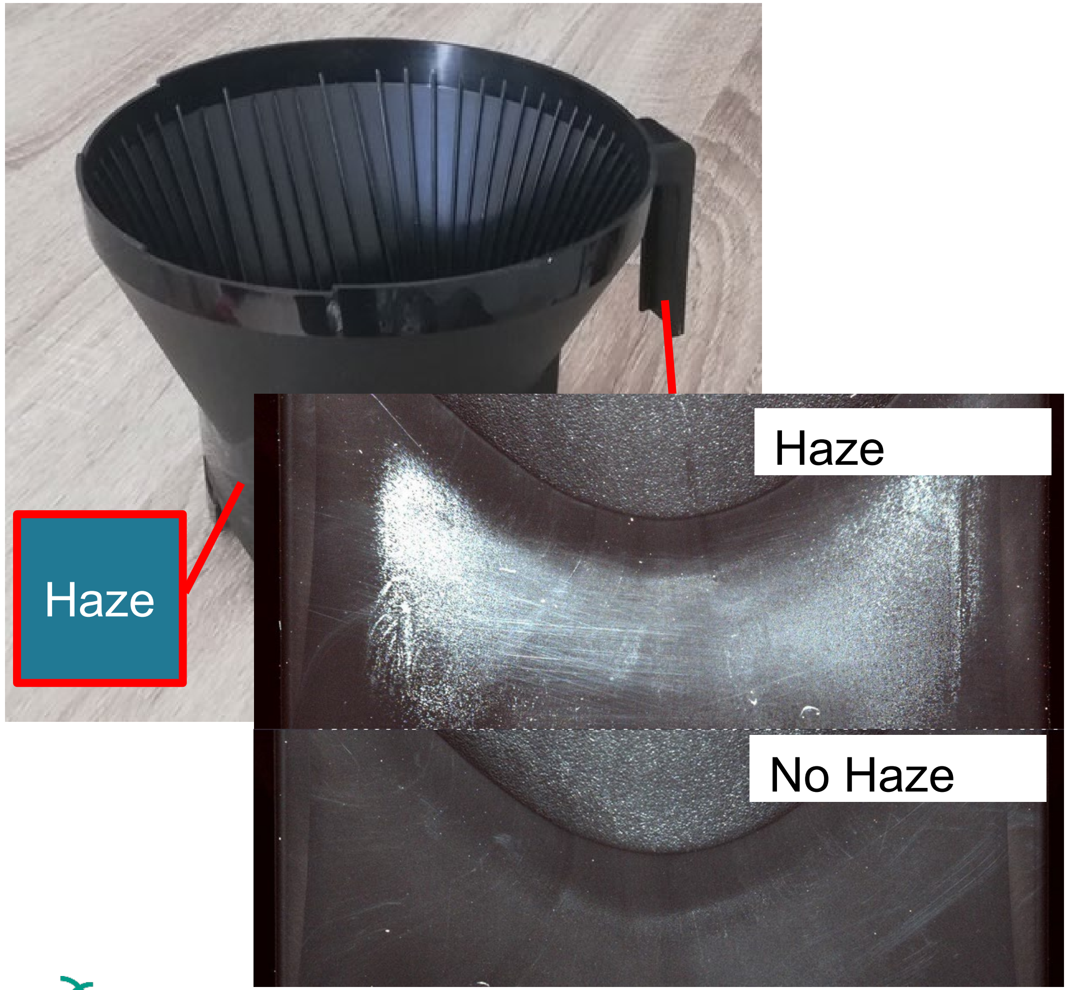
- *Which parts of an image* belong to a specific type?
- The model learns to decide which pixels have a specific (joint class).

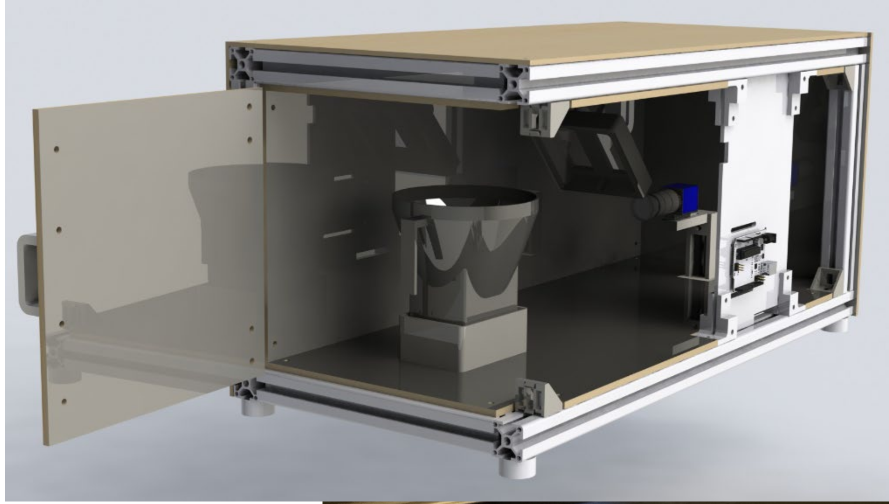
- Intuition: similar pixels are a cluster and could be a ‘semantic category’.
- Actual intuition for solution: down-sample image, then up-sample again.

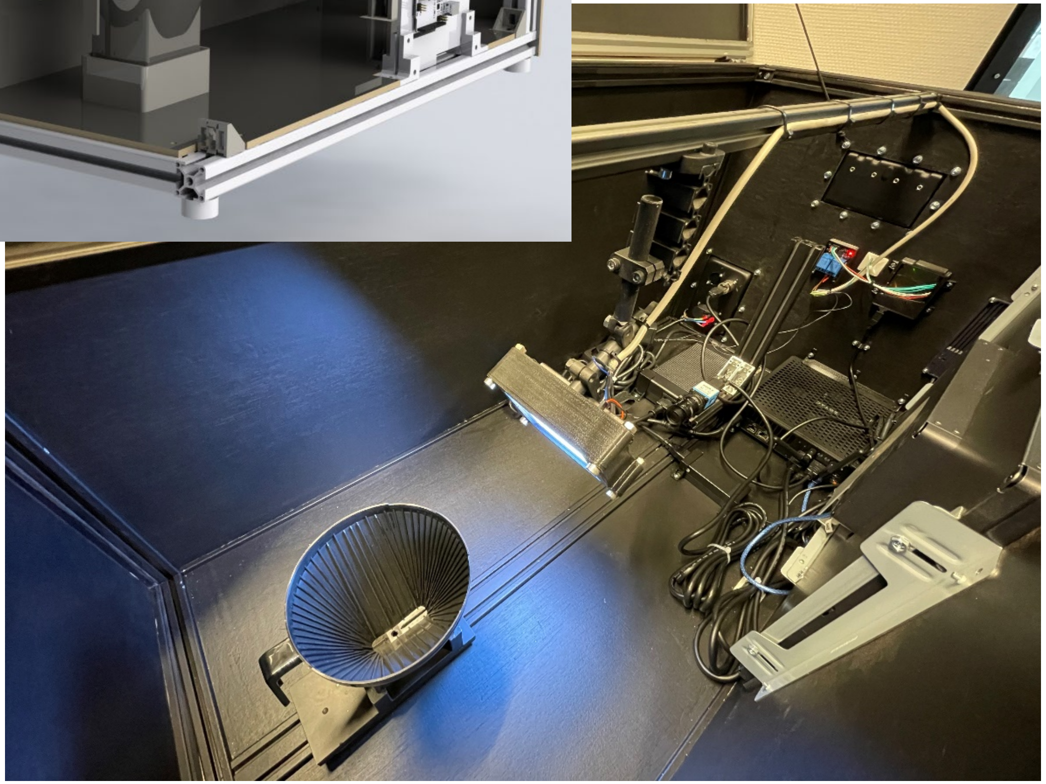


https://youtu.be/OOT3UIXZztE

Example: flaw detection on plastic products







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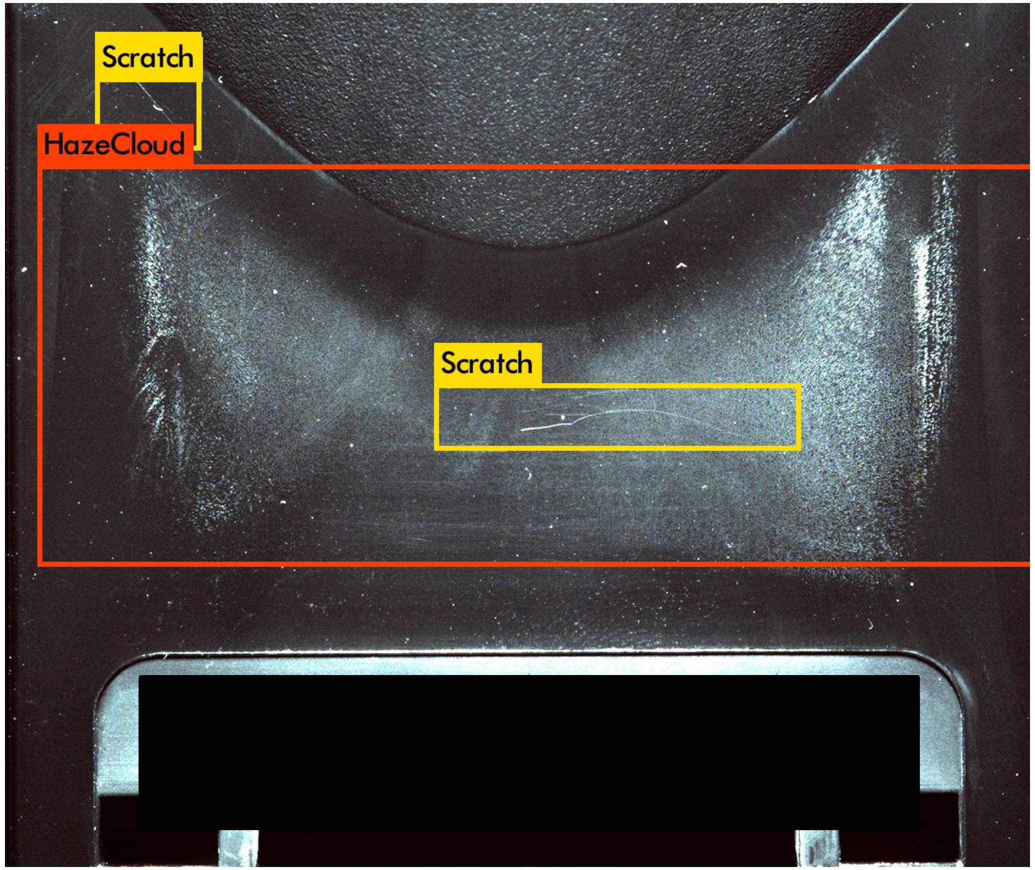
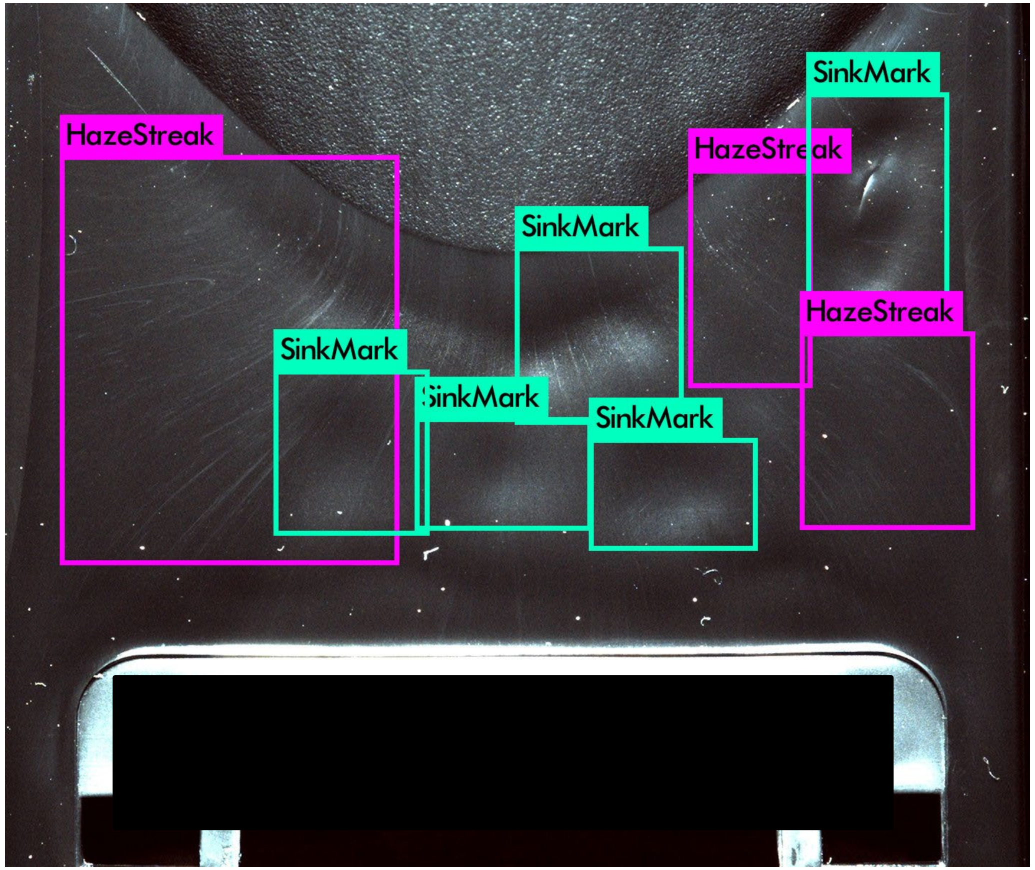
Example: flaw detection on plastic products

Timmerije
NEXT LEVEL IN PLASTICS





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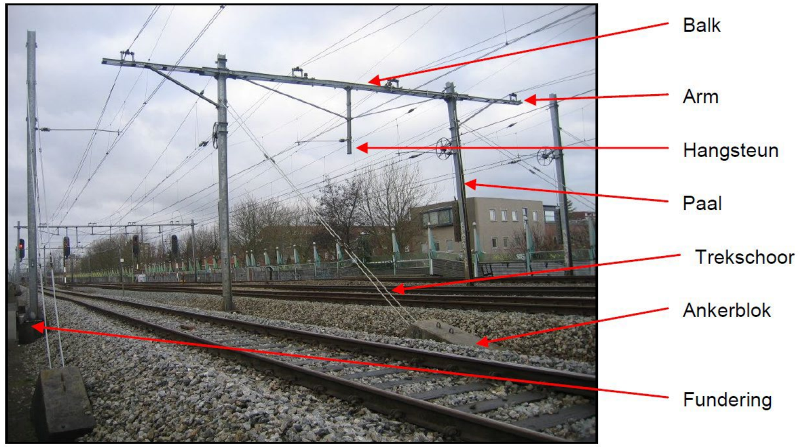
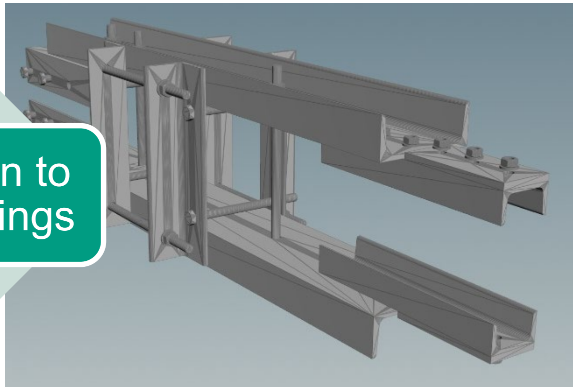
Example: Digitalisatie Bovenleidingen & Draagconstructies

Strukton Rail

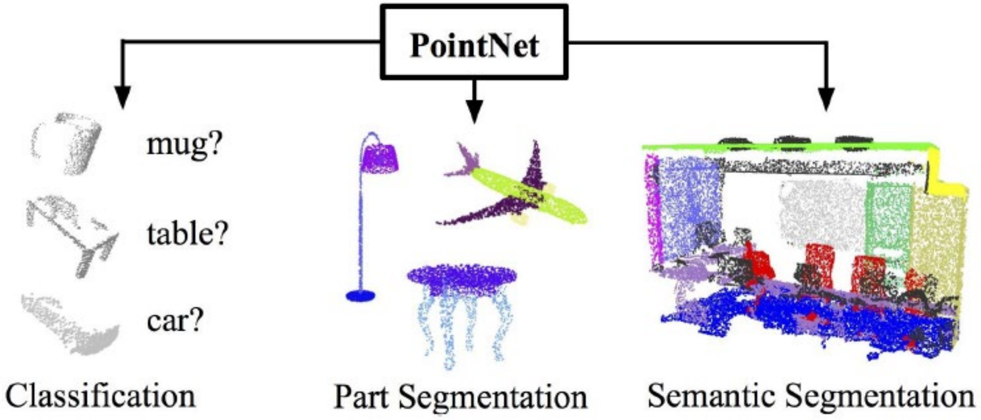
- 3,000 km of railway tracks in NL to be digitized
- Lidar: point clouds
- Instance segmentation
- 1 km: 2.5 billion points
- 1 arch: 3 million points

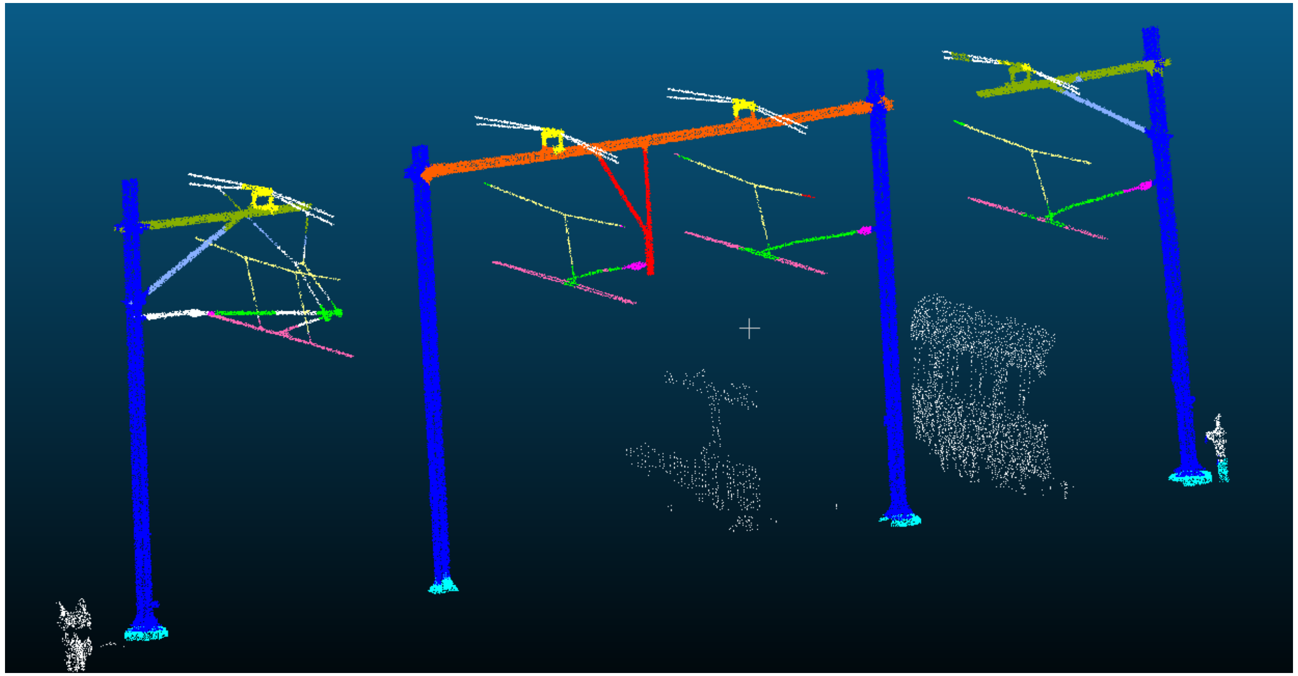


Point cloud → Pre-processing → Object segmentation → Conversion to CAD drawings



Example: Digitalisatie Bovenleidingen & Draagconstructies





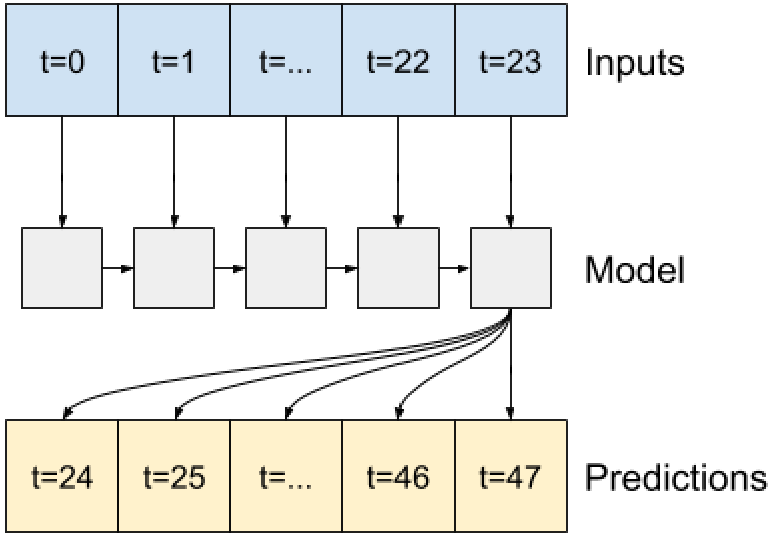
- Labelling of all data
- Density of objects
- Computing power

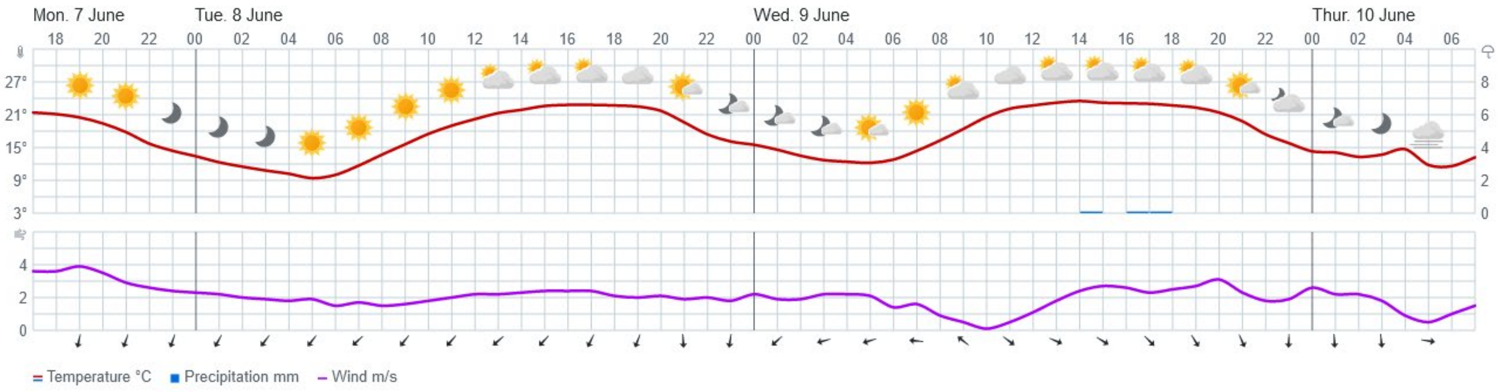
Network types for different applications

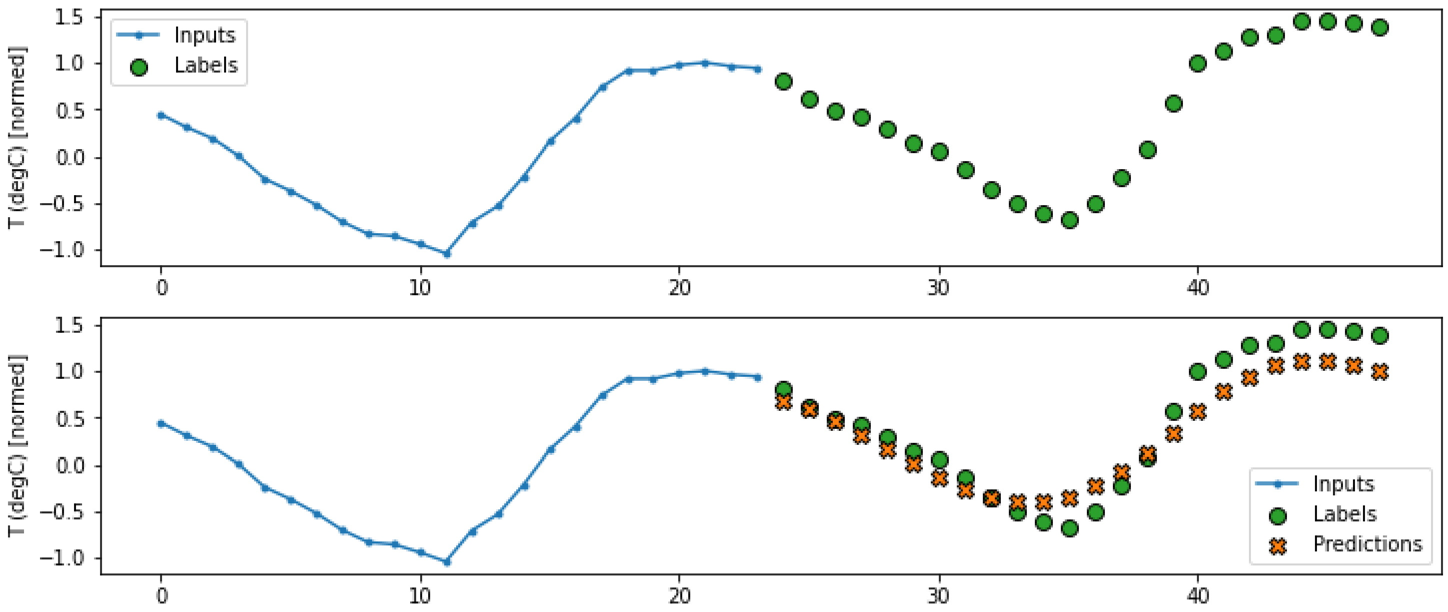
- **RNNs**: sequential data
- **GANs**: generating data
- **Reinforcement learning**: getting better using rewards and penalties
- **Transfer learning**: re-using existing models

Recurrent Neural Networks

- Sequences: text, speech, motion
- Rhythm/periodicity







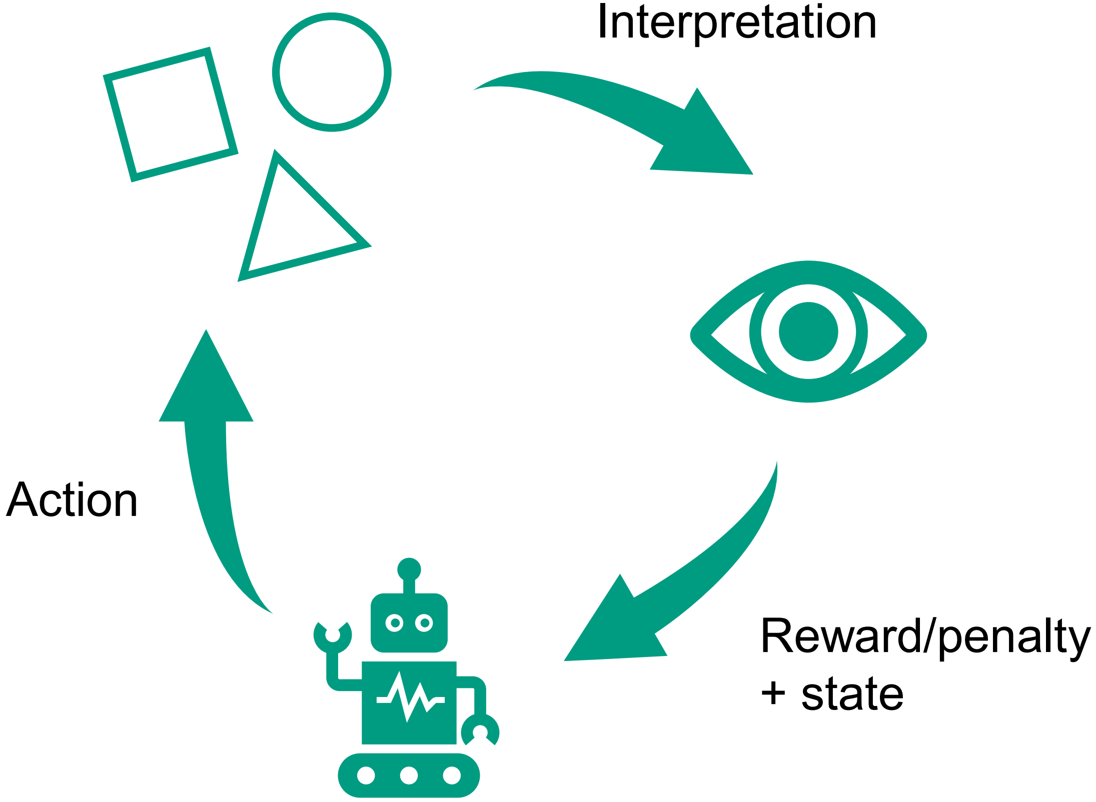
Generative Adversarial Networks

- Make a model ‘fool’ another model
- Two neural networks contest:
  - Generator creates data to be close to reality
  - Discriminator checks data for falsehood
- One of the techniques for *deepfakes*

https://youtu.be/0sR1rU3gLzQ

thispersondoesnotexist.com

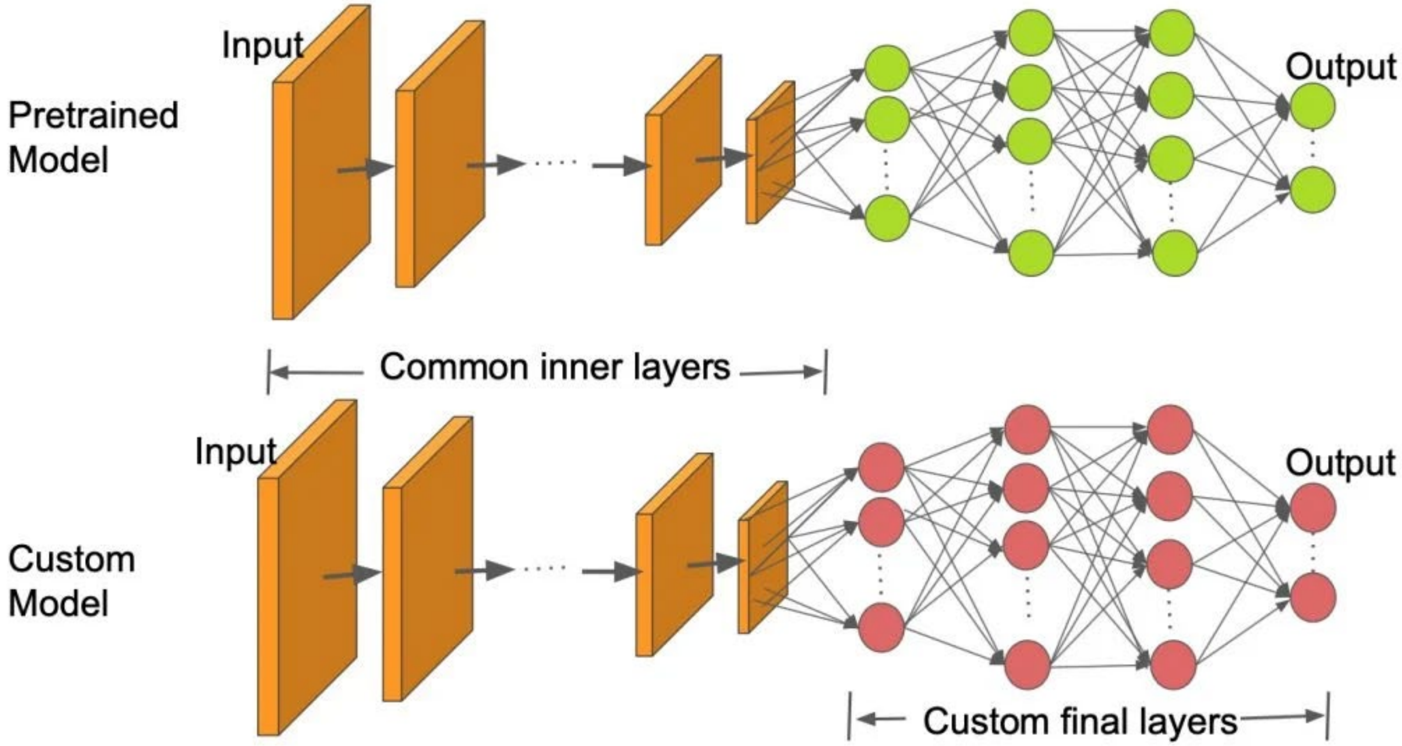
Reinforcement learning



https://youtu.be/goxCjGPQH7U

Transfer learning

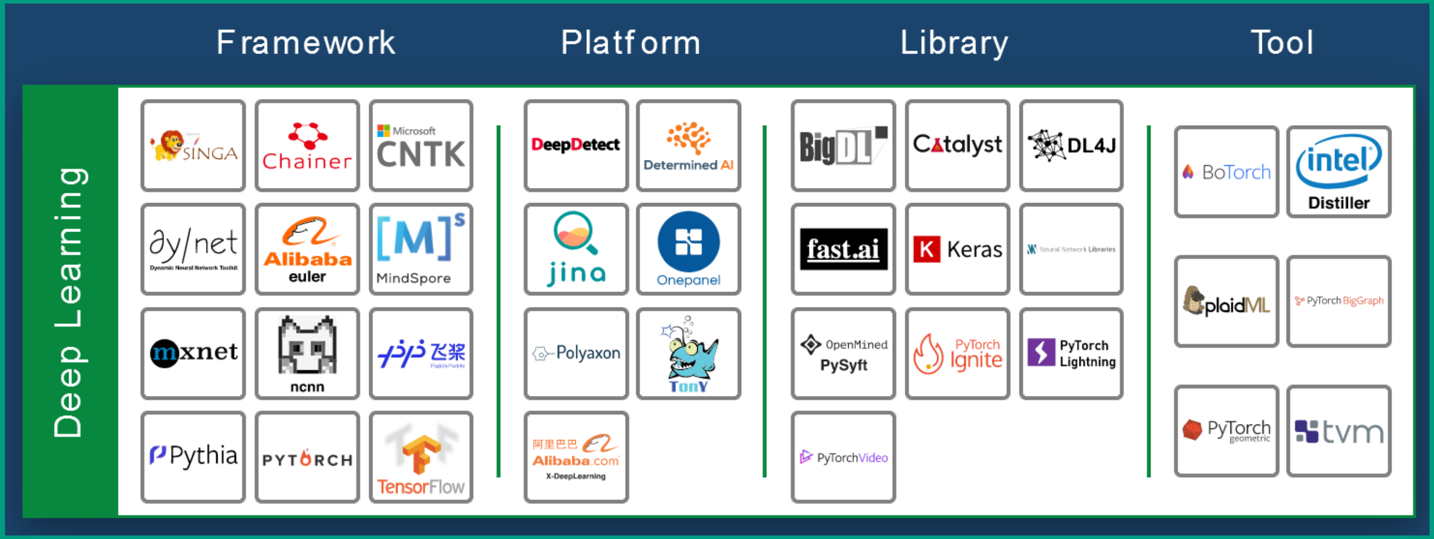
- Don’t reinvent the wheel!
- Use parts of the model to train a new model



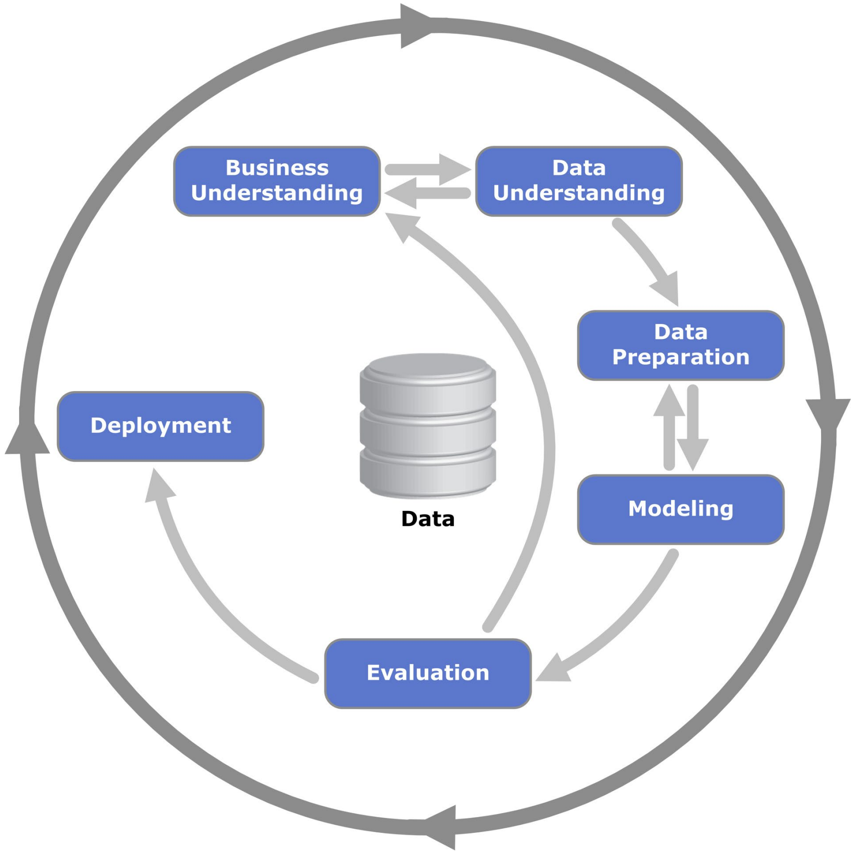
INTERMISSION 2

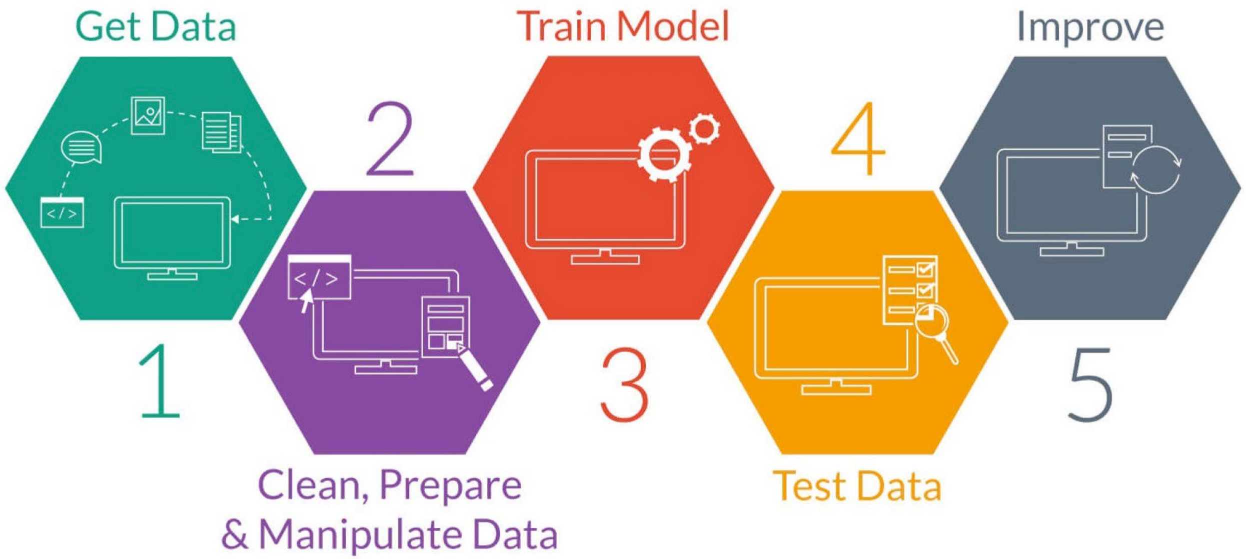
Frameworks & deployment

Choices guaranteed to confuse everybody: frameworks, platforms, libraries, visual/code, etc.



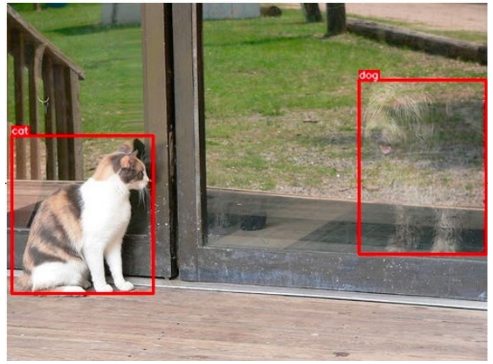
But first… our process!

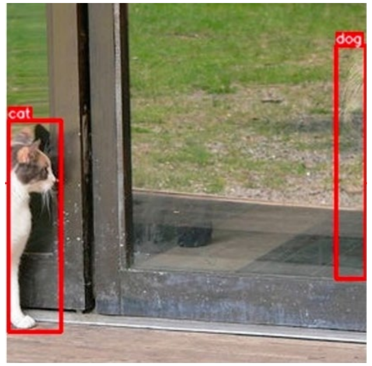




Data preparation

- Checklist
  - Data
  - **Labels**
- Generating additional data: augmentation
  - Few examples
  - Class imbalance: few examples of one class
  - Increase model robustness, simulate possible modifications

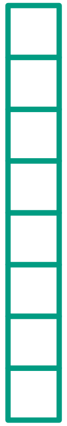




Network design (modelling)

Input

- Type of data
- Dimensions



- Experimentation!
- Size and number of layers
- Type of layers
- Activation functions
- (Automated) weight optimization

Layers

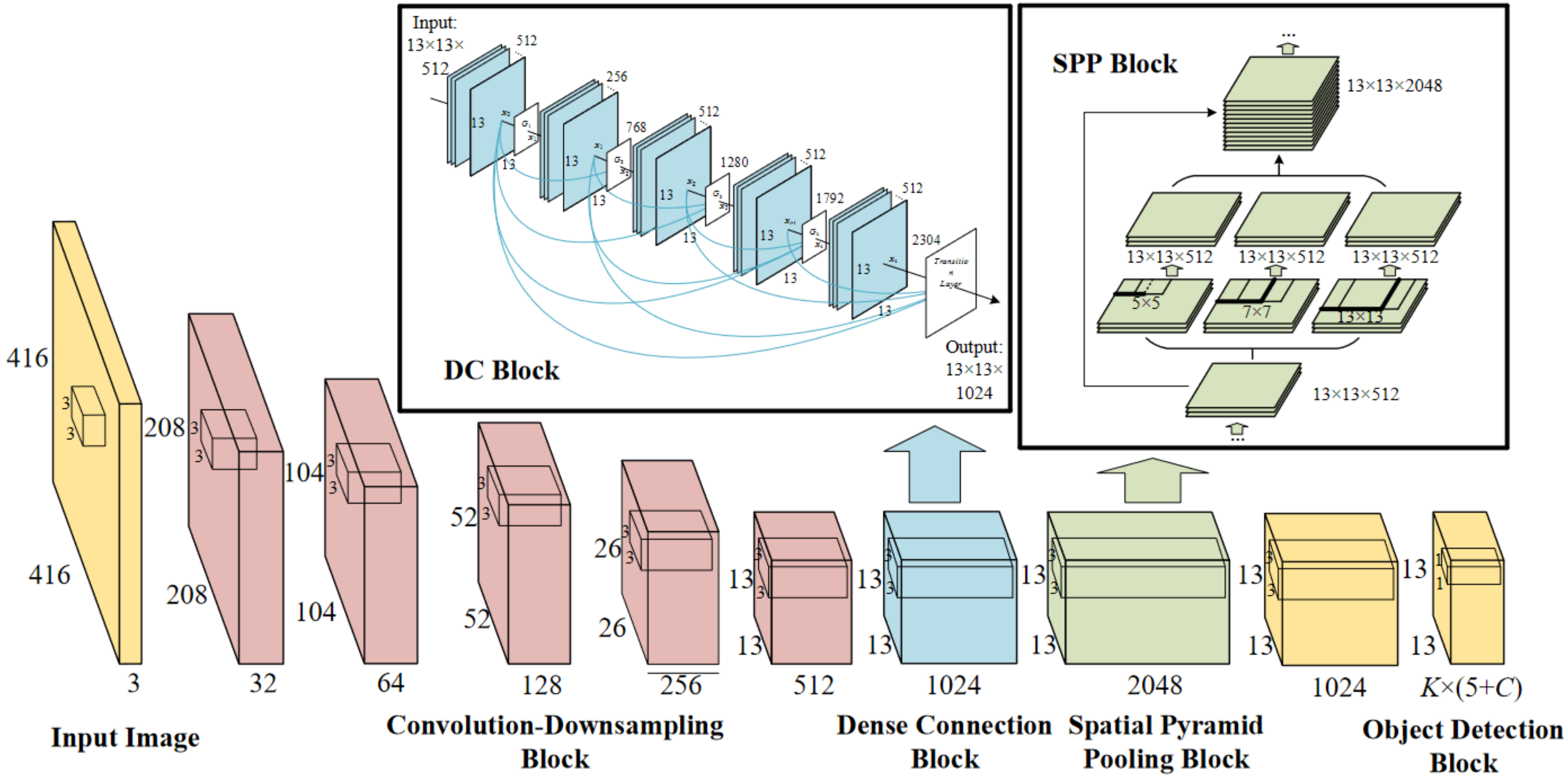
Output

- Type of data
- Dimensions

- **‘7’**
- **‘dog’**
- **Location of object**

Example networks

YOLOv4 (2020)

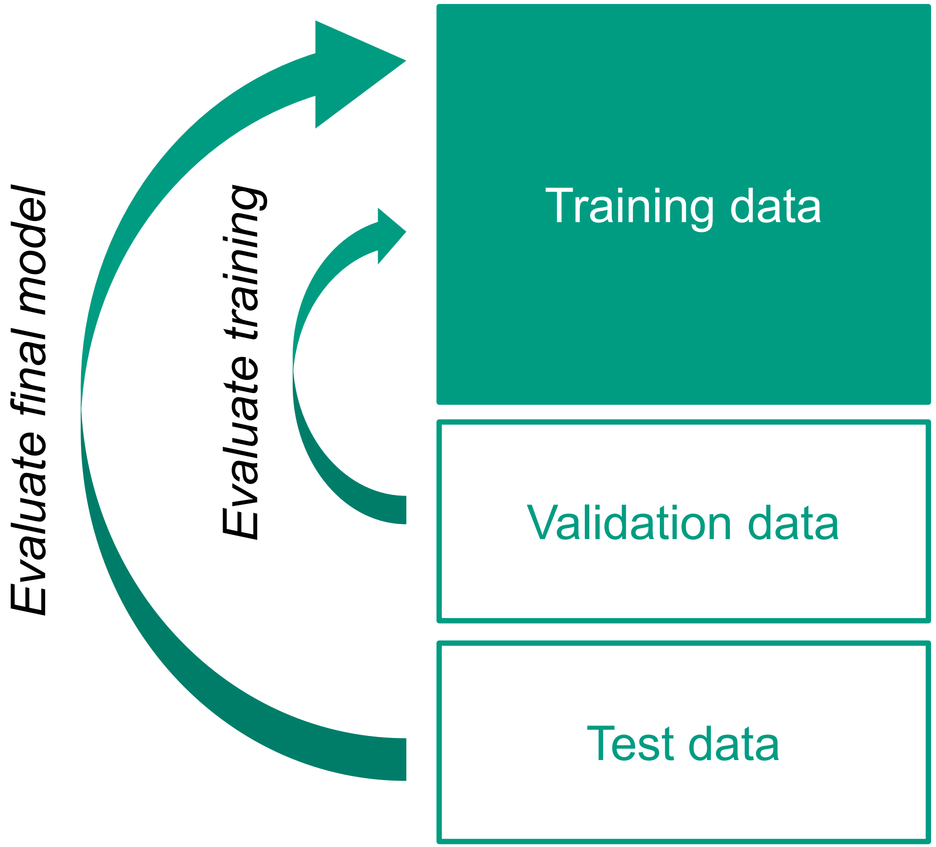


Network training

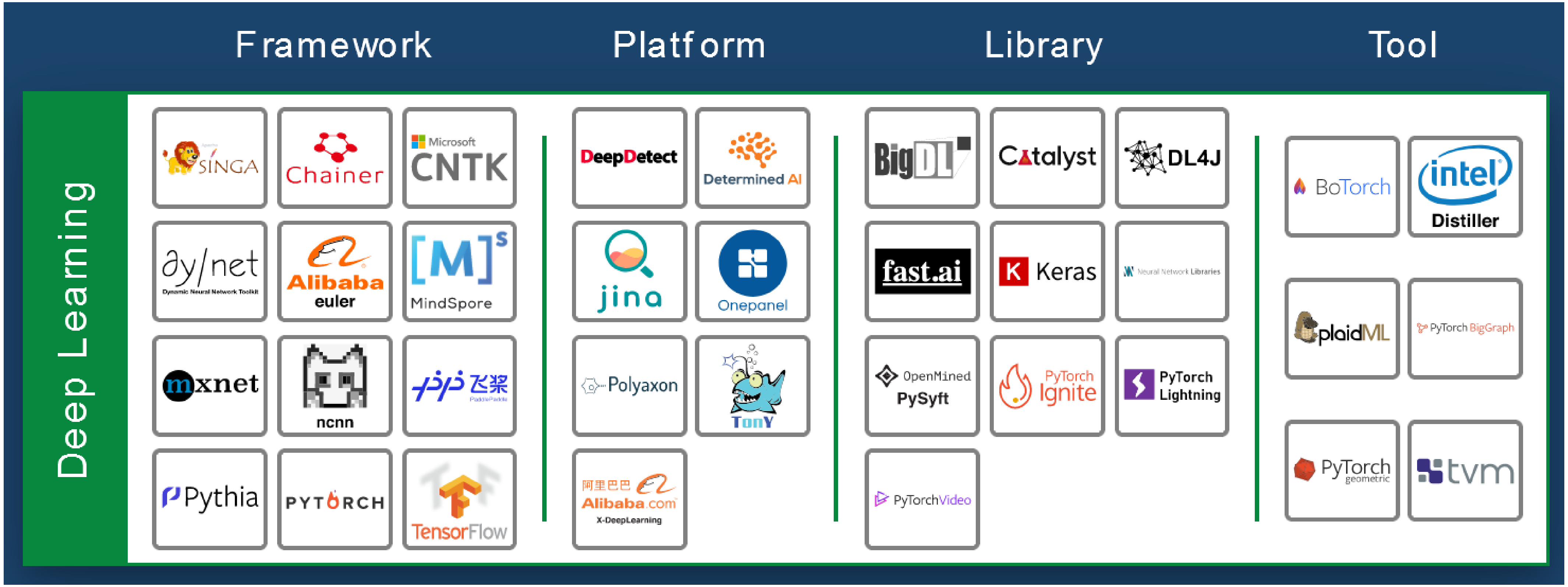
1. **Configuration**
   a. Network design
   b. Optimizer: how to automatically adapt parameters
   c. Loss function: goal for the model to minimize

2. **Define train instructions**
   a. Size of training 'batches'
   b. Number of training rounds ('epochs')

3. **Test!**
   a. Predict on a new sample
   b. Evaluate…



The forest of frameworks

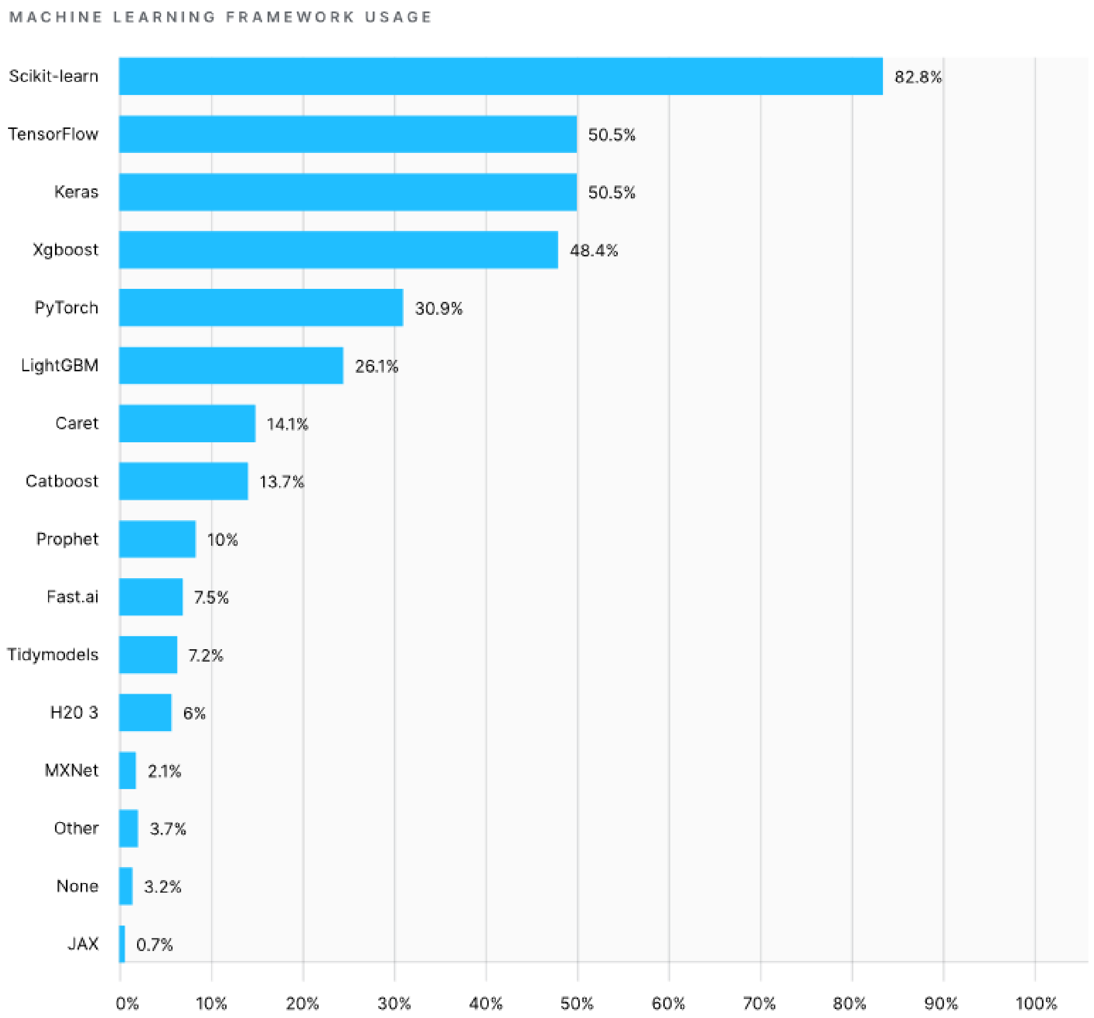


https://landscape.lfai.foundation/

Choose your framework wisely

- Firstly: all deep learning frameworks are suitable.

- Factors to consider:
  - Available knowledge
    - Programming language
    - Connectivity and integration (IT, databases)
  - Cloud or on-premises
  - Availability and maintenance: is it up-to-date?
  - Efficiency and cost-effectiveness



https://www.kaggle.com/kaggle-survey-2020

Challenges on the horizon

- Automation!
  - Integration with IT infrastructure
  - DataOps/MLOps as a response to Development and Operations (DevOps)

- Explainability: ‘understanding what layers do’

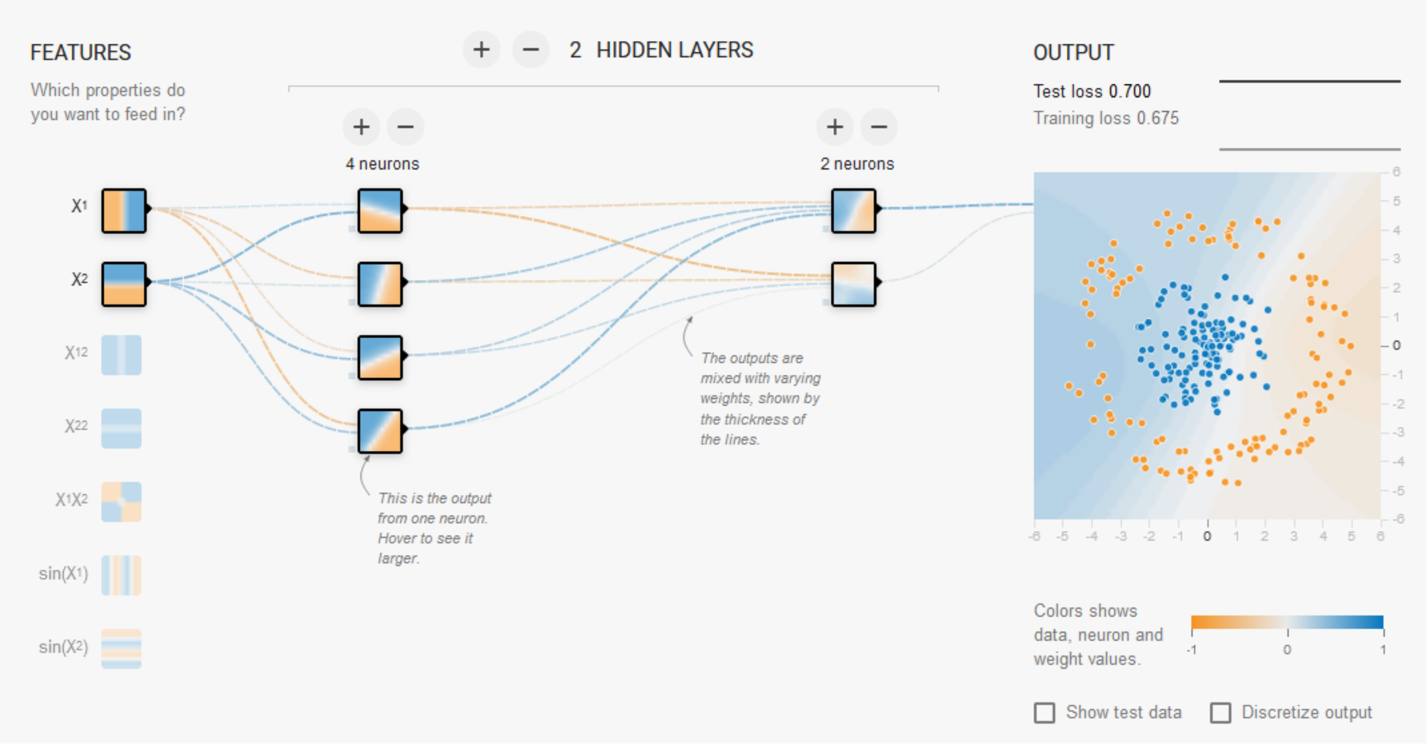
- The data conundrum
  - Responsible, ethical use
  - Bias and completeness
  - See: FAIR data and Responsible Data Science (redasci.org)

Hands-on practice

A few short examples of actual deep learning – at home, in your browser!

Let’s train a bit

https://cs.stanford.edu/people/karpathy/convnetjs/demo/mnist.html



http://deeperplayground.org

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And now for some home-made coding

Just one brief example of MNIST again…
https://colab.research.google.com/drive/1AJlI9cmPspY8t-wbOCJss5Rc7zR7Jc4u?usp=sharing

```
[ ]  model = keras.Sequential(
         [
             keras.Input(shape=input_shape),
             layers.Conv2D(32, kernel_size=(3, 3), activation="relu"),
             layers.MaxPooling2D(pool_size=(2, 2)),
             layers.Conv2D(64, kernel_size=(3, 3), activation="relu"),
             layers.MaxPooling2D(pool_size=(2, 2)),
             layers.Flatten(),
             layers.Dropout(0.5),
             layers.Dense(num_classes, activation="softmax"),
         ]
     )

     model.summary()
```

For the enthusiasts: https://keras.io/examples/

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Recap

Learning goals

- Deep learning = artificial neural networks with multiple layers.
- Models can be trained with sufficient data.
- Many tools are available; preferences and possibilities for integration determine choice.

- AI is not magic when you understand it.

Open questions?

All learning material will be made available.

Must we fear AI?

Bloomberg

Technology

AI Will Give Us Better French Fries

By Lydia Mulvany
April 26, 2018, 6:27 PM GMT+2

No One Is Sure How Good, or Bad, AI Will Get

LISTEN TO ARTICLE

Tired of disappointing french fries? The machines are here to help.

Newsweek

U.S. EDITION Thu, Jun 07, 2018 SIGN IN SUBSCRIBE

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TECH & SCIENCE

ARTIFICIAL INTELLIGENCE COULD RESULT IN ‘CATASTROPHIC’ NUCLEAR WAR BY 2040, THINK TANK WARNS

BY DANA DOVEY ON 4/25/18 AT 2:30 PM

LATEST NEWS


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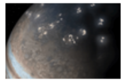
Stolen Columbus Letter Returned To Spain By ICE


Jupiter's Lightning Is the Polar Opposite of Earth's


Human Tastes 'Super Beefy' Says Man Who Ate His Foot


Atlanta Democrat Apologizes For Flag-Burning D-Day Meme


GOP Congressman Hits Trump for ‘Spygate’ Conspiracy


'Morning Joe' Host Calls Giuliani a 'Misogynistic Fool'

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Challenges in AI

Methodology

Interdisciplinarity

Artificial vs Natural Stupidity?

BUSINESS NEWS OCTOBER 10, 2018 / 5:12 AM / 6 DAYS AGO

Amazon scraps secret AI recruiting tool that showed bias against women

Jeffrey Dastin 8 MIN READ

SAN FRANCISCO (Reuters) - Amazon.com Inc's (AMZN.O) machine-learning specialists uncovered a big problem: their new recruiting engine did not like women.

Computer Facts
@computerfact
Follow

concerned parent: if all your friends jumped off a bridge would you follow them?
machine learning algorithm: yes.

8:20 PM - 15 Mar 2018

7,220 Retweets **14,676** Likes

5 closing thoughts on AI

1. Build a vision: what now, what later?

2. Think before you apply.

3. Data is key, but people are more important.

4. Work your way up: start with data, an infrastructure, simple analyses, and then expand into more complex AI techniques.

5. Collaborate! Find universities (of applied sciences) like Saxion to help you explore possibilities.

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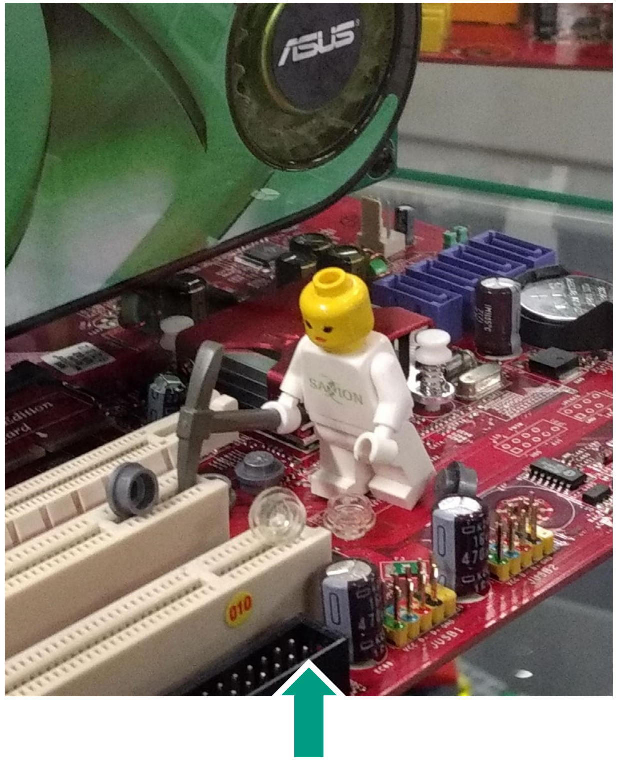
Thanks for your attention! Want more?



(Data mining)

This is the finish line… for now!

- Case studies
- Applied research
- Student assignments

Send an email!

j.m.linssen@saxion.nl

Visit our websites!

saxion.nl/ami

tvalley.nl

boostsmartindustry.nl

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Media sources

Deep learning timeline: https://www.kdnuggets.com/2018/03/weird-introduction-deep-learning.html
Autonomous driving: https://florian.world/deep-learning-for-autonomous-driving/
We need to go deeper meme: https://knowyourmeme.com/memes/we-need-to-go-deeper
LeNet architecture: https://medium.com/@pechyonkin/key-deep-learning-architectures-lenet-5-6fc3c59e6f4, LeCun, Y., Bottou, L., Bengio, Y., & Haffner, P. (1998). Gradient-based learning applied to document recognition. *Proceedings of the IEEE*, *86*(11), 2278-2324.
Gradient descent algorithms: https://github.com/Jaewan-Yun/optimizer-visualization
Loss function: https://www.tensorflow.org/tensorboard/scalars_and_keras
Machine learning workflow: https://quantumcomputingtech.blogspot.com/2019/09/supervised-machine-learning-workflow.html
Computer vision tasks: https://www.oreilly.com/content/introducing-capsule-networks/
Cat/dog segmentation: https://d2l.ai
Recurrent neural network: https://www.tensorflow.org/tutorials/structured_data/time_series#recurrent_neural_network
Transfer learning: https://learnopencv.com/image-classification-using-transfer-learning-in-pytorch/
Data preparation/augmentation: https://albumentations.ai
Machine learning framework usage: https://www.kaggle.com/kaggle-survey-2020
Deep learning on MNIST in browser: https://cs.stanford.edu/people/karpathy/convnetjs/demo/mnist.html

License for material on deep learning

https://github.com/glouppe/info8010-deep-learning