

Beyond the Hype

Fundamentals and Limits of Artificial Intelligence

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Shortlink

Shortlink to

- these slides
- source code examples

⇒ *link.simplexacode.ch/8yn4*

Terms and Definitions

- algorithm
- artificial intelligence (AI)
- machine learning
- artificial neural networks (ANNs)
- deep learning
- convolutional neural networks (CNNs)

algorithm:

- sequence of instructions for processing data
- examples: sorting algorithms, JPEG compression, AI methods

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artificial intelligence (AI):

- John McCarthy: “the science and engineering of making intelligent machines”
- Merriam-Webster: “a branch of computer science dealing with the simulation of intelligent behavior in computers”

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machine learning:

- learning from examples
- generalizing after the end of the learning phase

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artificial neural networks (ANNs):

- *one* method for machine learning
- neurons receiving input signals, weighting them, and calculating an output signal each

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deep learning:

- at least 2 hidden layers between input and output layer
- in practice: several hundred hidden layers

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convolutional neural networks (CNNs):

- class of deep neural networks specifically designed for pixel data and image recognition
- inspired by the behavior of the visual cortex of the brain

What Is Intelligence? | Poldi and Nora



What Is Intelligence? | Poldi and Nora



“Guten Morgen
mein kleiner Spatz!”

What Is Intelligence? | Poldi and Nora



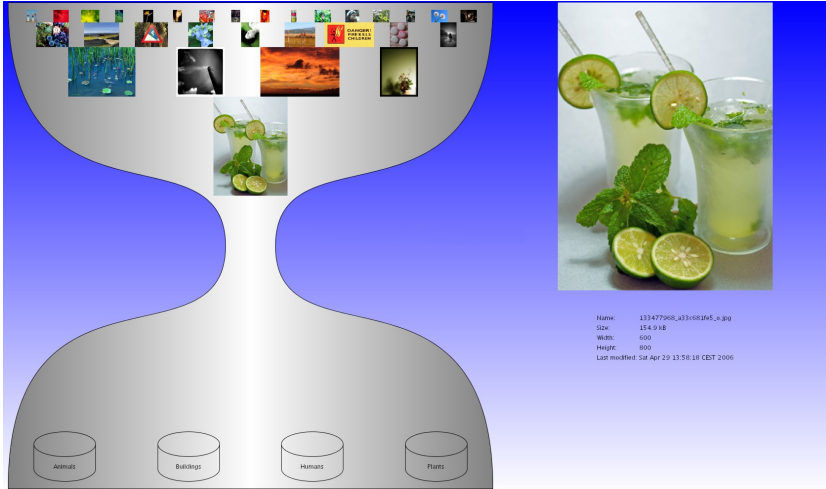
“Komm zum Herrchen!”

What Is Artificial Intelligence? | Gesture-based Image Selection UI

- Gesture-based Image Selection User Interface for Large Screen Interaction Environments, Bachelor Thesis, Computer Graphics Lab, ETH Zurich, 2006
- 3 position coordinates (cameras)
- 2 acceleration coordinates (accelerometers)



Demo | Gesture-based Image Selection User Interface



What AI Can Do

- recognize faces and objects in images (Facebook)
- estimate ages of people (How old do I look?¹)
- recognize speech (Siri)
- filter personal preferences
- recommend videos, music, and products (Netflix)
- write newspaper articles (robot journalism)
- filter out spam
- play games (Google DeepMind)
- drive and park cars autonomously
- route ridesharing fleets (Uber, Lyft)
- optimize picker routes (Zalando)
- check symptoms (Ada)
- diagnose certain types of cancer²
- predict crimes (Precobs (Germany), COMPAS (United States))

¹<https://www.how-old.net>

²A. Grävemeyer, KI erkennt Krebs – Neuronale Netze in der Radiologie, c't 14/2018

What AI *Cannot* Do

- understand society, ethics, money, competition, love, or sexual desire
- differentiate between originals and parodies (GEMA)
- form the singularity in the future
- be as intelligent as humans
- learn like humans

- \implies AI systems are geeks.
- \implies Every system masters exactly one thing.
- \implies Specialists cannot unite to form an “artificial superintelligence”.

Demo | MNIST Database | Training Phase

- handwritten digits
- 60,000 training images
- 10,000 test images
- `exec(open('mnist_database.py').read())`



0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3
4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4
5 5 5 5 5 5 5 5 5 5 5 5 5 5 5 5
6 6 6 6 6 6 6 6 6 6 6 6 6 6 6 6
7 7 7 7 7 7 7 7 7 7 7 7 7 7 7 7
8 8 8 8 8 8 8 8 8 8 8 8 8 8 8 8
9 9 9 9 9 9 9 9 9 9 9 9 9 9 9 9

³R. Schwaiger et al., Neuronale Netze programmieren mit Python, Rheinwerk Verlag, 2019

How ANNs Work

- ① Set parameters of every neuron to random values.
- ② Give feedback to the network after each training example.
- ③ Readjust all parameters according to their contribution to the error.
- ④ Repeat steps 2 and 3 until the error rate is below a certain threshold.
- ⑤ Freeze all parameters after the end of the training phase.

Demo | Neural Network Playground

playground.tensorflow.org

Demo | MNIST Database | Test Phase

```
model.evaluate(testImages, testLabels)
```

3 Main Ingredients of Deep Learning

- ① masses of data
- ② indexed data (e.g., tagged objects in images)
- ③ computing power (e.g., cloud, data centers, or specialized hardware)

Demo | Pretrained Inception-v3 Convolutional Neural Network

- `inception_v3.py`
- `picture.jpg`

Weaknesses of Deep Learning

- thousands or millions of training data (e.g., tagged images)
- very time-consuming and CPU-intensive⁴
- biases and errors (see next slide)⁵
- manipulations (see slide after next)
- segregation and combination problems⁶
- exploding and vanishing gradients, overfitting, and saturation⁷

⁴C. Heitzmann, Warum künstliche Intelligenz so schwierig ist – Einführung in die Komplexität von Algorithmen, JavaSPEKTRUM 3/2019, link.simplexacode.ch/mysk

⁵P. Merkert, Statistik ist nicht Denken, c't 24/2018

⁶P. Merkert, Statistik ist nicht Denken, c't 24/2018

⁷R. Schwaiger et al., Neuronale Netze programmieren mit Python, Rheinwerk Verlag, 2019

Weaknesses of Deep Learning | Biases and Errors

- recognize huskies only with snow in the background
- recognize trains only based on platforms and tracks, not locomotives or cars
- classify black people as gorillas (Google)
- favor male over female job applicants (Amazon)
- tag people in kitchen situations as female (imSitu)
- produce false-positives with deadly consequences (SKYNET)



8



COOKING	
ROLE	VALUE
AGENT	WOMAN
FOOD	PASTA
HEAT	STOVE
TOOL	SPATULA
PLACE	KITCHEN

COOKING	
ROLE	VALUE
AGENT	WOMAN
FOOD	FRUIT
HEAT	?
TOOL	KNIFE
PLACE	KITCHEN

COOKING	
ROLE	VALUE
AGENT	WOMAN
FOOD	MEAT
HEAT	STOVE
TOOL	SPATULA
PLACE	OUTSIDE

COOKING	
ROLE	VALUE
AGENT	WOMAN
FOOD	?
HEAT	STOVE
TOOL	SPATULA
PLACE	KITCHEN

COOKING	
ROLE	VALUE
AGENT	MAN
FOOD	?
HEAT	STOVE
TOOL	SPATULA
PLACE	KITCHEN

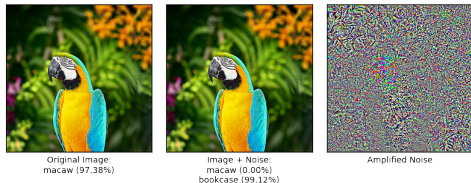
9

⁸Pixabay

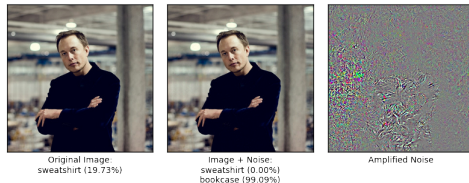
⁹J. Zhao et al., Men Also Like Shopping, University of Virginia, 2017

Weaknesses of Deep Learning | Manipulations

- trick antivirus software by appending specific strings¹⁰
- noise patterns and optical illusions



11



12

¹⁰J. Schmidt, Antivirus: Cylance-KI böse ausgetrickst, heise Security, 2019

¹¹M. E. Hvass Pedersen, TensorFlow Tutorial #11, Adversarial Examples, github.com/Hvass-Labs/

¹²M. E. Hvass Pedersen, TensorFlow Tutorial #11, Adversarial Examples, github.com/Hvass-Labs/

Weaknesses of Deep Learning | Manipulations

- Face Swap



13

¹³all pictures: www.dailymail.co.uk/femail/article-4261400/The-biggest-face-swap-FAILS.html

3 Main Reasons for Flawed Deep Learning

- ① no contextual understanding
- ② too little traceability
- ③ too much tinkering

Reasons for Flawed Deep Learning | No Contextual Understanding

- AI can perfectly find correlations between X and Y .
- AI *cannot* find the causation of any relationship between X and Y .
- in general: Correlation does not imply causation.
- examples from daily life:
 - more wind \longleftrightarrow faster windmills
 - children watching TV \longleftrightarrow children being more violent
 - increase in ice cream sales \longleftrightarrow increase in drowning deaths

Reasons for Flawed Deep Learning | Too Little Traceability

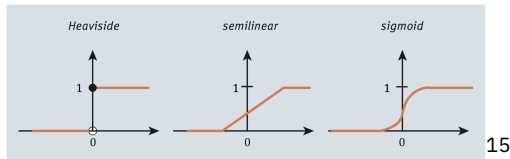
- “black box” because / in spite of loads of parameters
- no traceability, no insight, and no debugging tools
- biased systems because of biased training data
- \Rightarrow “explainable AI”
- examples:
 - decision-making of cars right before a crash
 - medical decisions
 - rejected loans¹⁴

¹⁴cf. GDPR, Article 22, “Automated individual decision-making, including profiling”

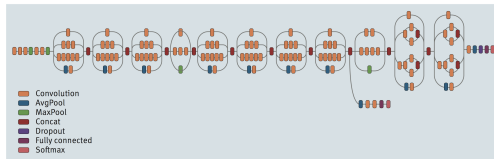
Reasons for Flawed Deep Learning | Too Much Tinkering

- initializations
- network types
- activation functions

- gradient optimizations
- early stoppings
- dropouts



15



16

¹⁵R. Schwaiger et al., Neuronale Netze programmieren mit Python, Rheinwerk Verlag, 2019

¹⁶R. Schwaiger et al., Neuronale Netze programmieren mit Python, Rheinwerk Verlag, 2019

Demo | Convolution Matrices

setosa.io/ev/image-kernels

Conclusion

- ① There is and never will be “the AI”, but very specific AI implementations that excel within their very specific domains, e.g.:
 - speech recognition
 - computer vision
 - logistics
- ② Both AI systems and human experts will be important and support each other in the future.
- ③ AI implementations can only be as good as their developers understand the underlying problems and solutions.

Questions?

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