

Was kann Künstliche Intelligenz leisten?

Fach Digitale Transformation, *CAS Paralegal*

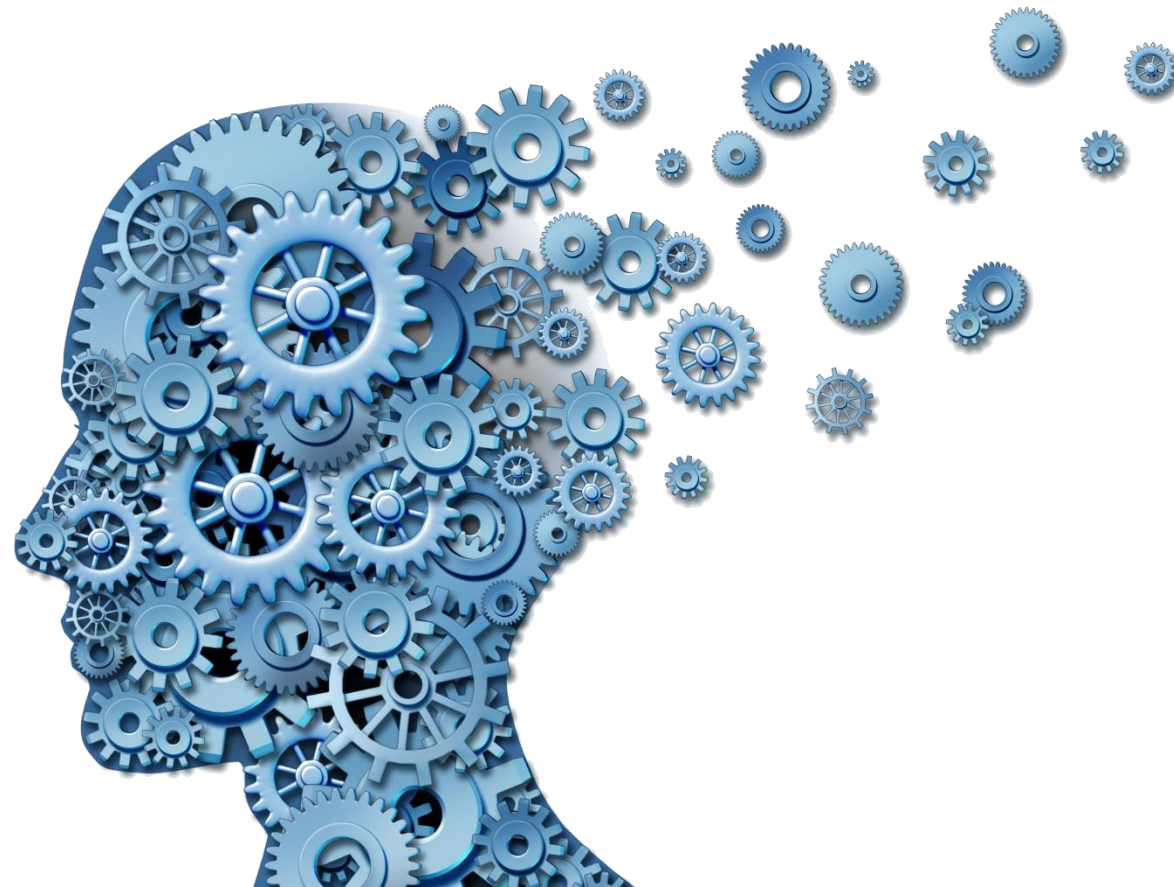
06. September 2019

Thilo Stadelmann

Was ist KI?

Warum ist das jetzt aktuell?

Wie funktioniert das?



Swiss Alliance for
Data-Intensive Services



datalab

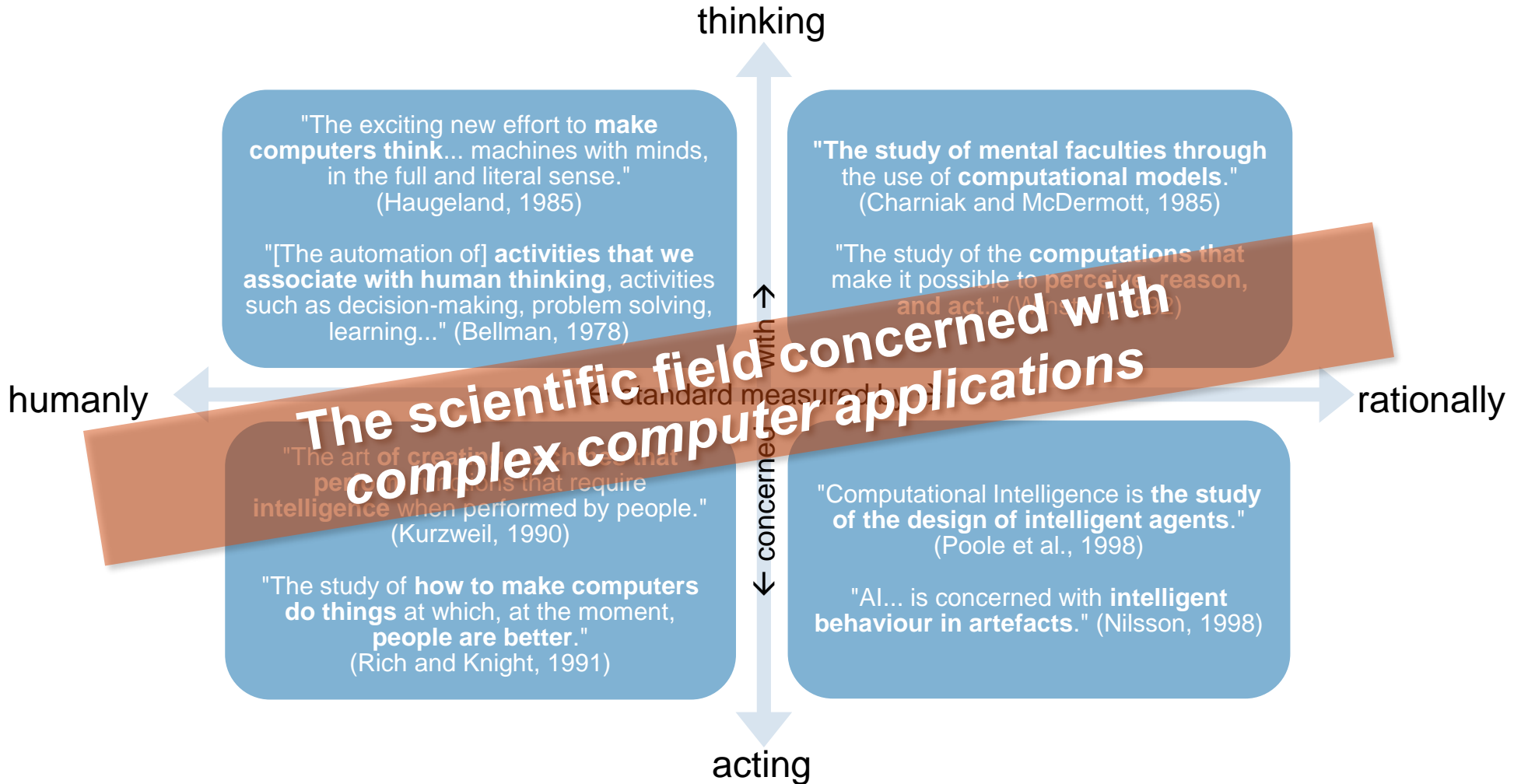
www.zhaw.ch/datalab

Was → Warum? → Wie?

1

Was ist Künstliche Intelligenz?

Was ist künstliche Intelligenz?



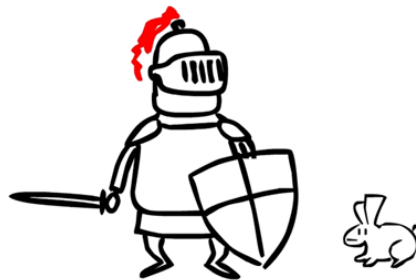
Pragmatisches Designparadigma: Rationale Agenten

Agents

- an **entity that perceives and acts**
- a **function from percept histories to actions** $f: P^* \rightarrow A$

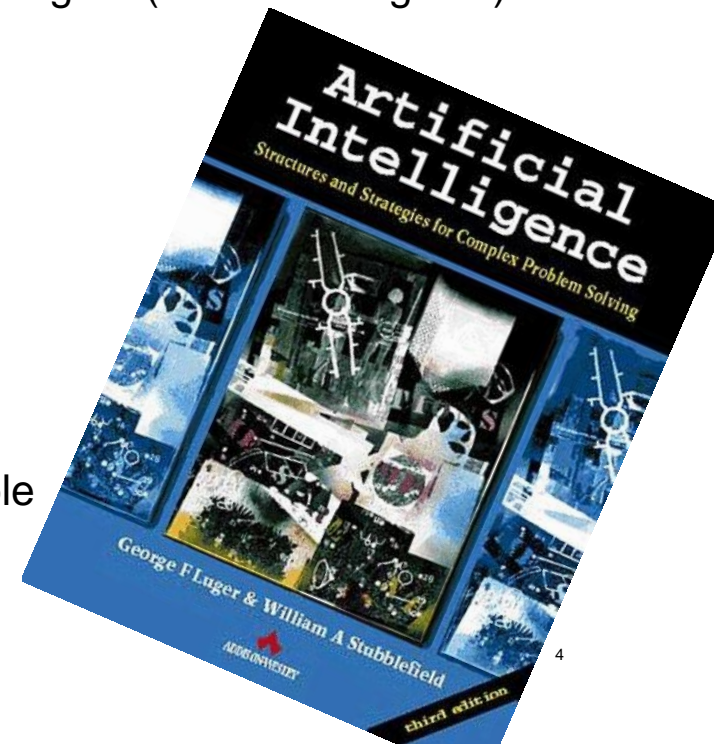
Rational agents

- **For any** given class of **environments** and **tasks**, we **seek** the agent (or class of agents) with the **best performance**

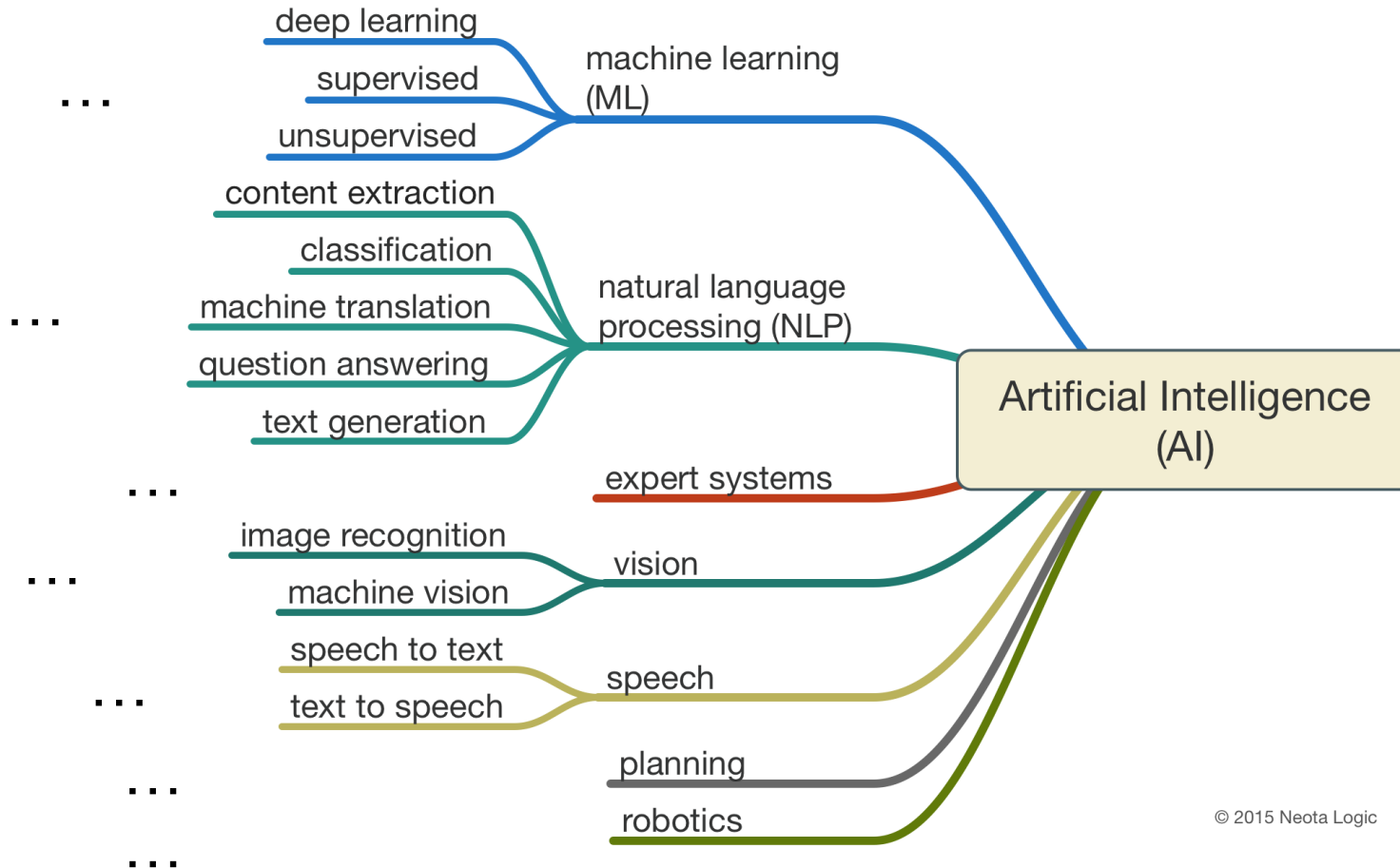


Caveat

- Computational limitations make perfect rationality unachievable
→ **Design best program for given machine resources**

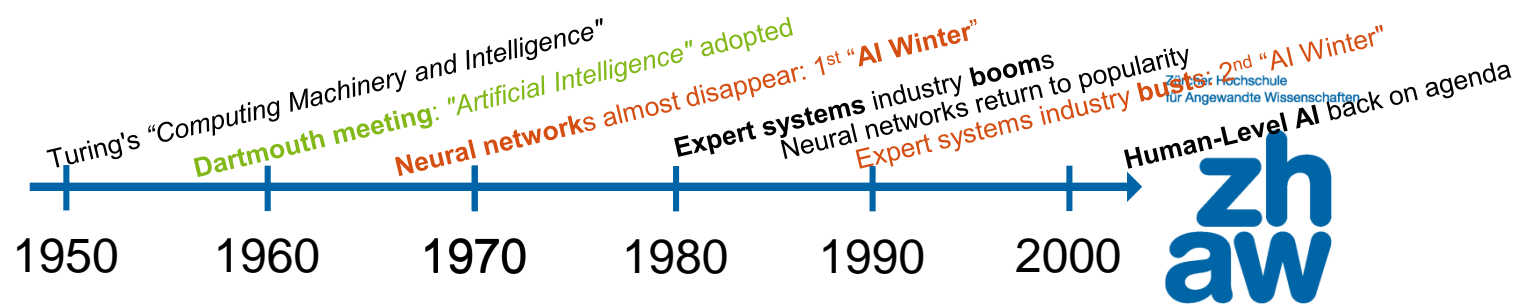


Was gehört zu künstlicher Intelligenz?

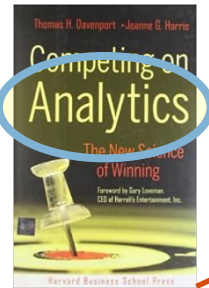


© 2015 Neota Logic

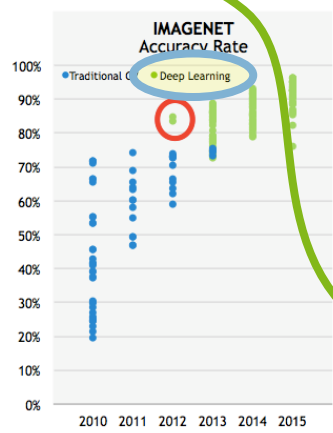
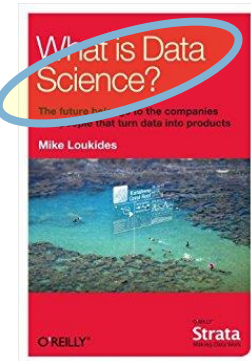
KI im Kontext



2007



2012



2016

future of life INSTITUTE
 News: AI Biotech Nuclear Climate Partner Orgs
 Technology is giving life the potential to flourish like never before...
 The open letter was announced July 28 at the opening of the IJCAI 2015 conference on July 28.
 Journalists who wish to see the press release may contact Toby Walsh.
 Hosting, signature verification and list management are supported by FLI: for administrative questions about this letter, please contact M. Tegmark.
AUTONOMOUS WEAPONS: AN OPEN LETTER FROM AI & ROBOTICS RESEARCHERS
 Autonomous weapons select and engage targets without human intervention. They might include, for example, armed quadcopters that can search for and eliminate people meeting certain pre-defined criteria, but do not include cruise missiles or remotely piloted drones for which humans make all targeting decisions. Artificial Intelligence (AI) technology has reached a point where the deployment of such systems is — practically if not legally — feasible within years, not decades, and the stakes are high: autonomous weapons have been dubbed as the third revolution in warfare, after gunpowder and nuclear arms.
 Many arguments have been made for and against autonomous weapons, for example that replacing human soldiers by machines is good by reducing casualties on both sides but bad by thereby lowering the threshold for going to battle. The key question for humanity today is whether to start a global AI arms race to prevent it from starting, if any major military power pushes ahead with AI weapon development, a global arms race is virtually inevitable. The endpoint of this technological trajectory is obvious: autonomous weapons will become the Kalashnikovs of tomorrow. Unlike nuclear weapons, they are easy to produce, easy to transport, and they can be mass-produced. They will become ubiquitous and cheap for all significant military powers to mass-produce. They will appear on the black market and in the hands of terrorists, dictators wishing to better control their populace, warlords who wish to perpetrate ethnic cleansing, etc. Autonomous weapons are ideal for tasks such as assassinations, destabilizing nations, subduing populations and

Was kann KI bereits heute?

1. Play a decent game of **table tennis**
2. **Drive** safely along a curving **mountain road**
3. Drive safely along **Technikumstrasse** Winterthur
4. **Buy** a week's worth of **groceries on the web**
5. Buy a week's worth of groceries **at Migros**
6. **Play** a decent game of **bridge**
7. **Discover** and prove a new mathematical **theorem**
8. **Design** and execute a **research program** in molecular biology
9. Write an **intentionally funny** story
10. Give competent **legal advice** in a specialized area of law
11. **Translate** spoken English **into spoken** Swedish in real time
12. **Converse** successfully with another person for an hour
13. Perform a complex **surgical operation**
14. **Unload** any **dishwasher** and put everything away
15. Compete in the game show **Jeopardy!**
16. **Write clickbait** articles fully automatized

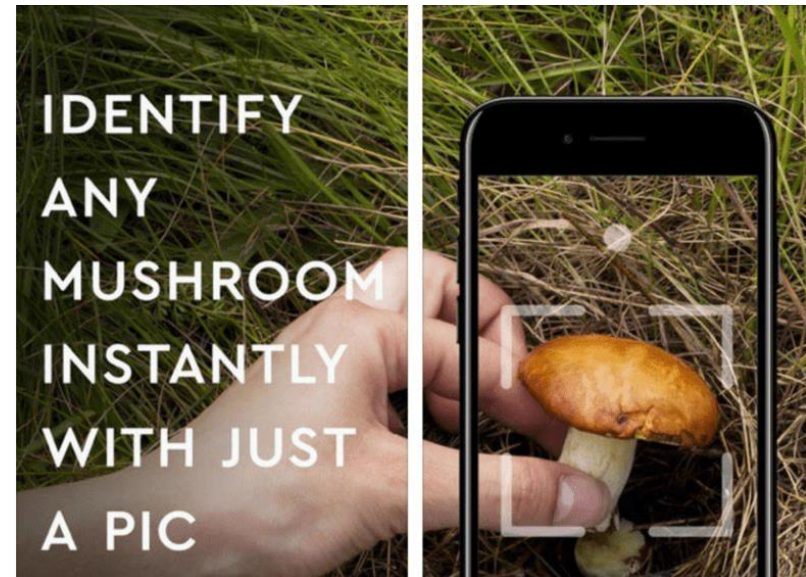
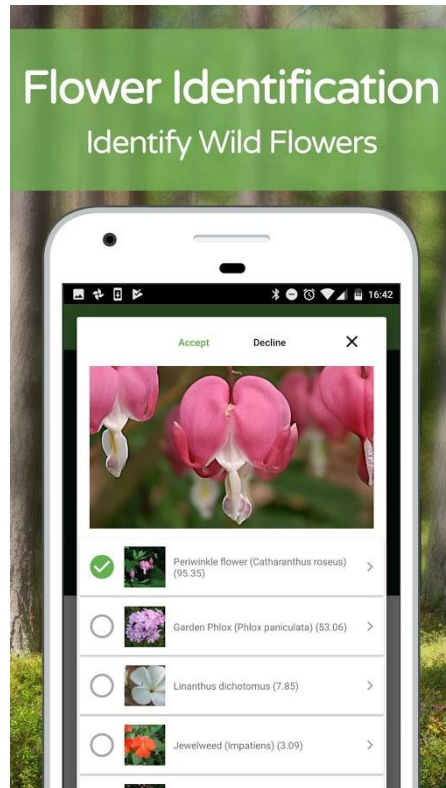
- ok
- ok
- ok (only since recently)
- ok
- no
- ok
- not complete
- not complete
- no
- ok
- ok
- no
- not complete
- no
- ok
- ok



IN CS, IT CAN BE HARD TO EXPLAIN THE DIFFERENCE BETWEEN THE EASY AND THE VIRTUALLY IMPOSSIBLE.

Beispiel: Machbar vs. gefährlich

Technologie: Computer Vision mit Deep Learning



<https://www.cultofmac.com/495088/avoid-potentially-deadly-ai-app/>

Beispiel: Markterfolg vs. regulatorische Hürden

Technologie: Recommender Systems

Customers Who Bought This Item Also Bought

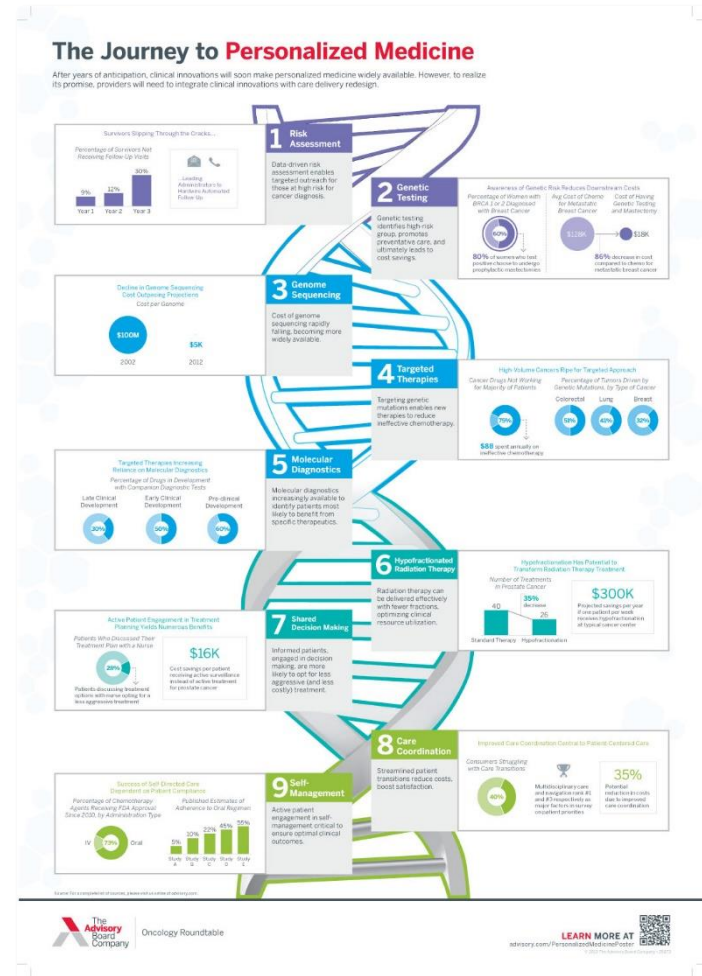
Reckoning with Risk: Learning to Live with Uncertainty by Gerd Gigerenzer
★★★★☆ (8) £6.49

Gut Feelings: The Intelligence of the Unconscious by Gerd Gigerenzer
£10.27

Bounded Rationality: The Adaptive Toolbox (Dahlerup) by G Gigerenzer
£20.95

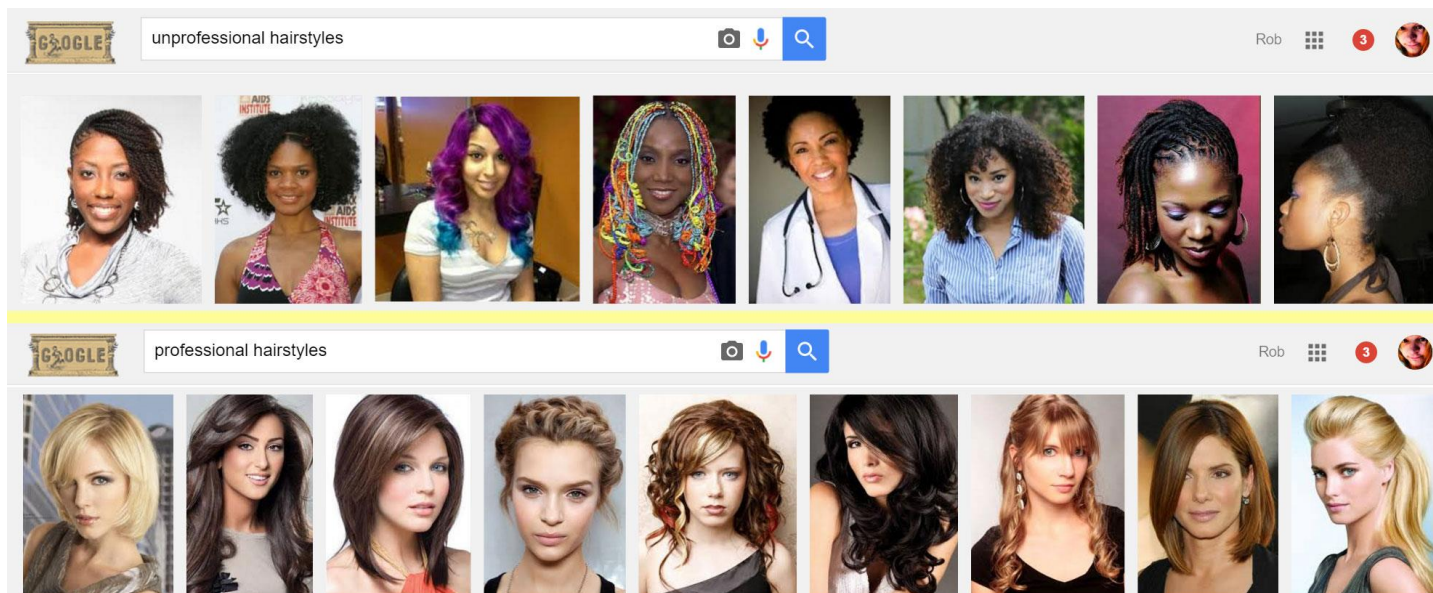
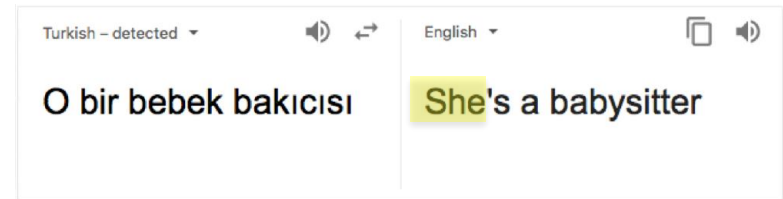
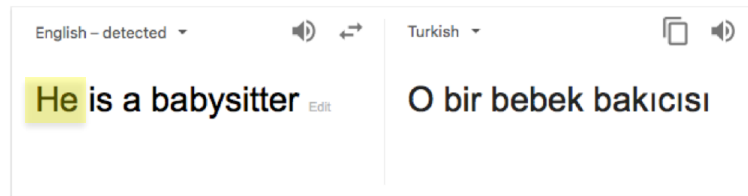
What Do Customers Ultimately Buy After Viewing This Item?

- 68% buy Simple Heuristics That Make Us Smart (Evolution & Cognition)**
£18.99
- 17% buy Gut Feelings: Short Cuts to Better Decision Making**
£6.74
- 9% buy Influence: The Psychology of Persuasion** ★★★★★ (12)
£7.09



Beispiel: Statistik vs. Bias

Technologie: Machine Learning



See also: Nassim Nicholas Talib, «*The Black Swan: The Impact of the Highly Improbable*», 2007

Beispiel: künstl. Intelligenz vs. natürl. Dummheit

Technologie: Machine Learning mit nachgelagerten Regeln

SKYLIGHT ABOUT US SERVICES BLOG

18 July 2019

Cylance, I Kill You!

Read about our Journey of dissecting the brain of a leading AI based Endpoint Protection Product, culminating in the creation of a universal bypass

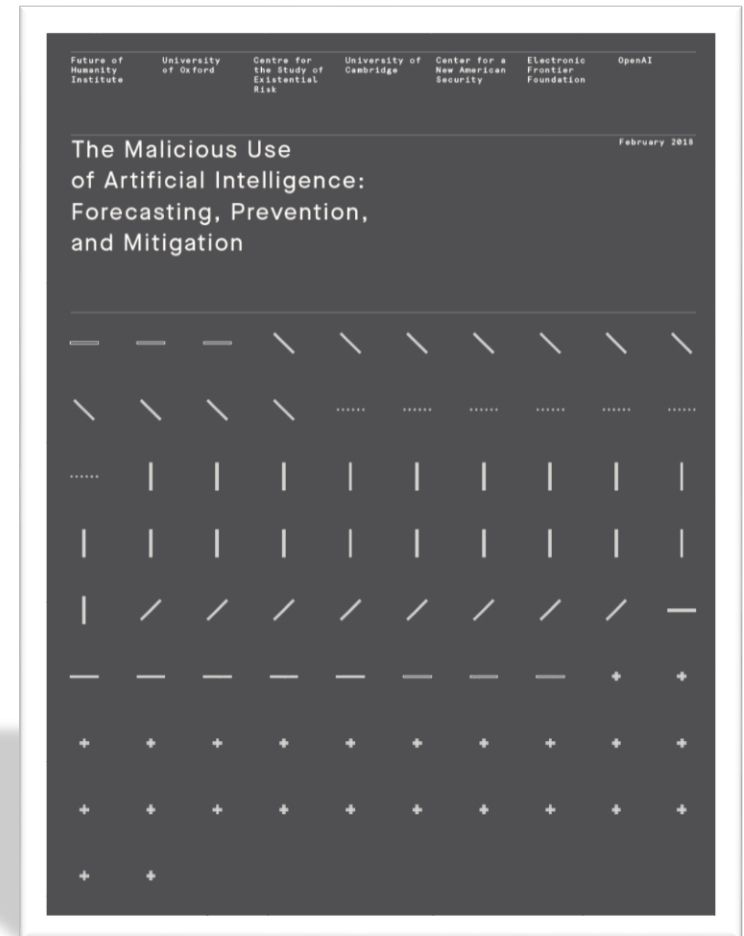
TL;DR

AI applications in security are clear and potentially useful, however AI based products offer a new and unique attack surface. Namely, if you could truly understand how a certain model works, and the type of features it uses to reach a decision, you would have the potential to fool it consistently, creating a universal bypass.

By carefully analyzing the engine and model of Cylance's AI based antivirus product, we identify a peculiar bias towards a specific game. Combining an analysis of the feature extraction process, its heavy reliance on strings, and its strong bias for this specific game, we are capable of crafting a simple and rather amusing bypass. Namely, by appending a selected list of strings to a malicious file, we are capable of changing its score significantly, avoiding detection. This method proved successful for 100% of the top 10 Malware for May 2019, and close to 90% for a larger sample of 384 malware.

Gefahren durch KI?

- KI ist per Definition eine **“dual use Technology”**
→ siehe Report von Brundage et al., 2018
- Aber: **“natürliche Dummheit”** ist die grössere Bedrohung
- **Algorithmische Ethik** und **erklärbare KI** sind in den letzten Jahren zu einem top Forschungsfeld geworden – nicht wegen der unkalkulierbaren Risiken per se, sondern:



Was → Warum? → Wie?

2

**Warum ist das jetzt aktuell?
(Eine kurze Geschichte der letzten Jahre)**

Google Acquires Artificial Intelligence Startup DeepMind For More Than \$500M

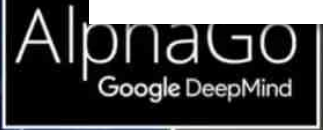
Zürcher Hochschule für Angewandte Wissenschaften



Posted Jan 26, 2014 by Catherine Shu (@catherineshu)



Google will buy reports that th in talks to buy couldn't disclose deal terms.



The acquisition was originally confirmed by Google to Re/code.

Nature
NATIONAL WEEKLY JOURNAL OF SCIENCE

At last — a computer program that can beat a champion Go player **PAGE 484**

ALL SYSTEMS GO

CONSERVATION
SONGBIRDS A LA CARTE
Illegal harvest of millions of Mediterranean birds
PAGE 452

RESEARCH ETHICS
SAFEGUARD TRANSPARENCY
Don't let openness backfire on individuals
PAGE 459

POPULAR SCIENCE
WHEN GENES GOT 'SELFISH'
Dawkins's calling card forty years on
PAGE 462

NATURE.COM/NATURE
28 January 2015 £10
Vol 529, No 7587



Deep neural networks can now transfer the style of one photo onto another

And the results are impressive

by James Vincent | @jvincent | Mar 30, 2017, 1:53pm EDT

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Computing

Algorithm Artistic Other In

A deep neural n
other images.

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The nature of arti
of Vincent Van C
Edvard Munch's
humans recogni:



Original photo Reference photo Result

Ad closed by Google

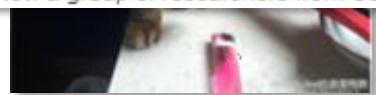
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You've probably heard of an AI technique known as "style transfer" — or, if you haven't heard of it, you've seen it. The process uses neural networks to apply the look and feel of one image to another, and appears in apps like [Prisma](#) and [Facebook](#). These style transfers, however, are stylistic, not photorealistic. They look good because they look like they've been painted. Now a group of researchers from Cornell University and Adobe have augmented

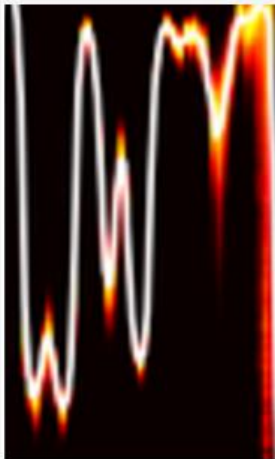
NOW TRENDING



WaveNet lässt Computersprache natürlich klingen

von Henning Steier / 12.9.2018

Die Google-Tochter DeepMind macht auch Musik.

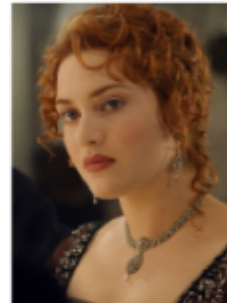


DeepMind lässt WaveNet Spr...

Die Google-Tochter DeepMind hat ein Spiel «Go» Schlagzeilen: es ist eines der besten menschlichen Spieler. Das Londoner Unternehmen erzeugt Sprache, die sehr natürlich klingt. Im Blogbeitrag des Unternehmens wird erklärt, wie es im Masstab nimmt. Man hat...

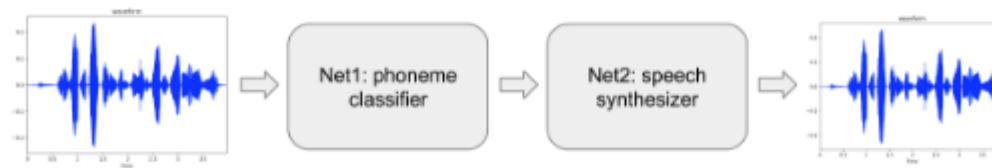
Intro

What if you could imitate a famous celebrity's voice or sing like a famous singer? This project started with a goal to convert someone's voice to a specific target voice. So called, it's voice style transfer. We worked on this project that aims to convert someone's voice to a famous English actress [Kate Winslet's voice](#). We implemented a deep neural networks to achieve that and more than 2 hours of audio book sentences read by Kate Winslet are used as a dataset.



Model Architecture

This is a many-to-one voice conversion system. The main significance of this work is that we could generate a target speaker's utterances without parallel data like <source's wav, target's wav>, <wav, text> or <wav, phone>, but only waveforms of the target speaker. (To make these parallel datasets needs a lot of effort.) All we need in this project is a number of waveforms of the target speaker's utterances and only a small set of <wav, phone> pairs from a number of anonymous speakers.



A's Waveforms

Speech Recognition

Speech Synthesis

B's Waveforms

Train1 \w small parallel dataset

Train2 \w large non-parallel dataset

"My name is Avin!"



"My name is Avin!"



nerierte Sprache
is Texteingabe»

nerierte Musik
ne Inhaltsvorgabe»



1 Second

...und die Liste liesse sich fortsetzen!

Brandon Amos About Blog

Image Completion with Deep Learning in TensorFlow

August 9, 2016



- Introduction
- Step 1: Interpreting images as samples from a probability distribution
 - How would you fill in the missing information?
 - But where does statistics fit in? These are images.
 - So how can we complete images?
- Step 2: Quickly generating fake images
 - Learning to generate new samples from an unknown probability distribution
 - [ML-Heavy] Generative Adversarial Net (GAN) building blocks
 - Using $G(z)$ to produce fake images
 - [ML-Heavy] Training DCGANs
 - Existing GANs
 - [ML-Heavy] Training DCGANs
 - Running DCGANs
- Step 3: Finding the right image completion
 - Image completion
 - [ML-Heavy] Training DCGANs
 - [ML-Heavy] Training DCGANs
 - Completing y
- Conclusion
- Partial bibliography
- Bonus: Incomplete

Introduction

Content-aware fill is a popular technique for image completion and inpainting. In this post, we'll do content-aware fill, inpainting, and semantic image inpainting. This post shows how to use deep learning for image completion. Some deeper portions for this section can be skipped if you're not interested in images of faces. I have a video on image completion.tensorflow.

We'll approach image completion in three steps:

1. We'll first interpret
2. This interpretation
3. Then we'll find the



Andrej Karpathy blog

The Unreasonable Effectiveness of Recurrent Neural Networks

May 23, 2015



TECH

Nvidia AI Generates Fake Faces Based On Real Celebs

BY STEPHANIE MLDT 10.31.2017 :: 10:00AM EST

32 SHARES



I'm getting a distinctly mid-90s "The Rachel" vibe from the woman in the top left corner (via Nvidia)

STAY ON TARGET

AI Shelley Pens Truly Creepy Horror Stories-And You Can Help

Neural Network Serves Up Truly Frightening Halloween Costume Ideas

Celebrity scandals are about to get a lot more complicated.

Nvidia has **developed** a way of producing photo-quality, AI-generated human profiles—by using famous faces.

the morning paper

The amazing power of word vectors

APRIL 21, 2016

For today's post, I've drawn material not just from one paper, but from five! The subject matter is 'word2vec' – the work of Mikolov et. al. at Google on efficient vector representations of words (and what you can do with them). The papers are:

- ★ **Efficient Estimation of Word Representations in Vector Space** – Mikolov et al. 2013
- ★ **Distributed Representations of Words and Phrases and their Compositionality** – Mikolov et al. 2013
- ★ **Linguistic Regularities in Continuous Space Word Representations** – Mikolov et al. 2013
- ★ **word2vec Parameter Learning Explained** – Rong 2014
- ★ **word2vec Explained: Deriving Mikolov et al's Negative Sampling Word-Embedding Method** – Goldberg and Levy 2014

hand,

From the first of these papers ('Efficient estimation...') we get a description of the *Continuous Bag-of-Words* and *Continuous Skip-gram* models for learning word vectors (we'll talk about what a word vector is in a moment...). From the second paper we get more illustrations of the power of word vectors, some additional information on optimisations for the skip-gram model (hierarchical softmax and negative sampling), and a discussion of applying word vectors to phrases. The third paper ('Linguistic

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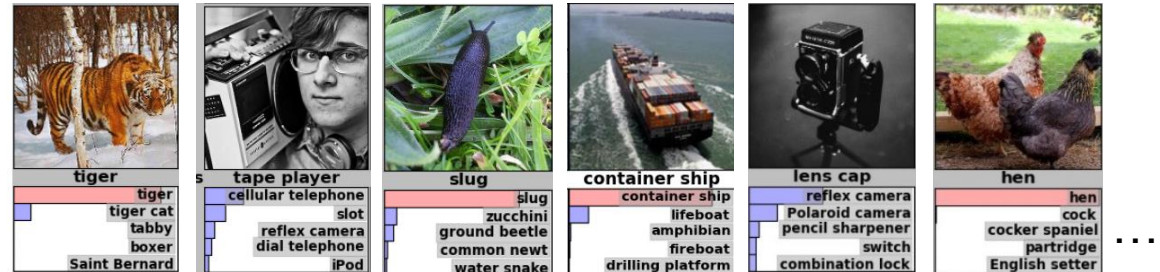
Law,
is,

Was ist passiert?

Der ImageNet Wettbewerb



1000 Kategorien
1 Mio. Beispiele



2015: Computer *haben* "Sehen" gelernt

4.95% Microsoft (06. Februar)
→ Besser als Menschen (5.10%)

4.80% Google (11. Februar)

4.58% Baidu (11. Mai)

3.57% Microsoft (10. Dezember)

A. Krizhevsky verwendet als erster ein sog. «Deep Neural Network» (CNN)

Was → Warum? → Wie?

3

Wie geht das?

Grundlage

Induktives überwachtetes Lernen

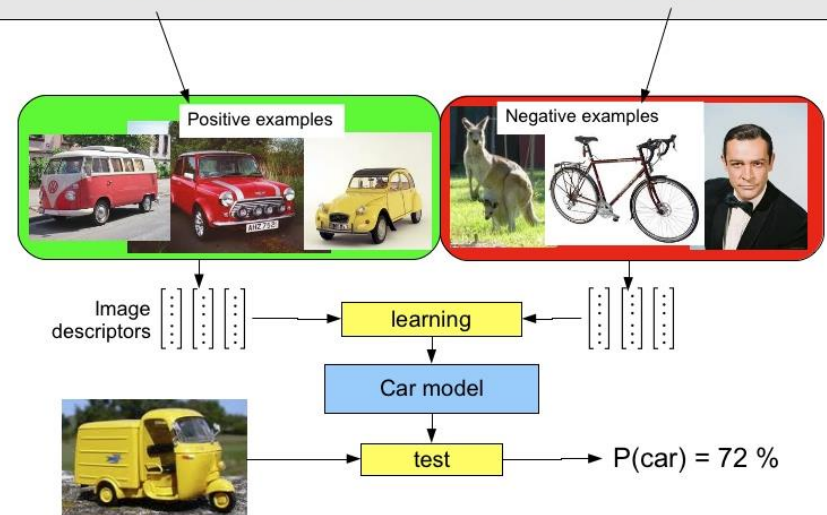
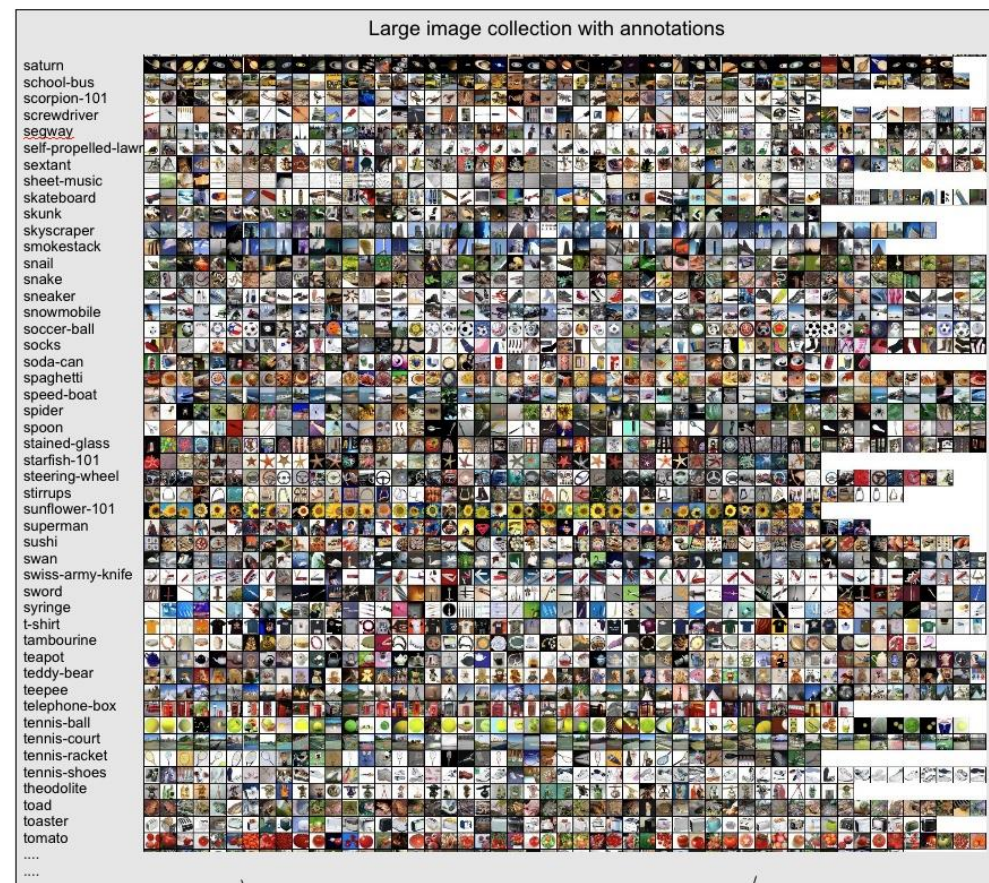
Annahme

- Ein an *genügend viele* Beispiele angepasstes Modell...
- ...wird auch auf unbekannte Daten **generalisieren**

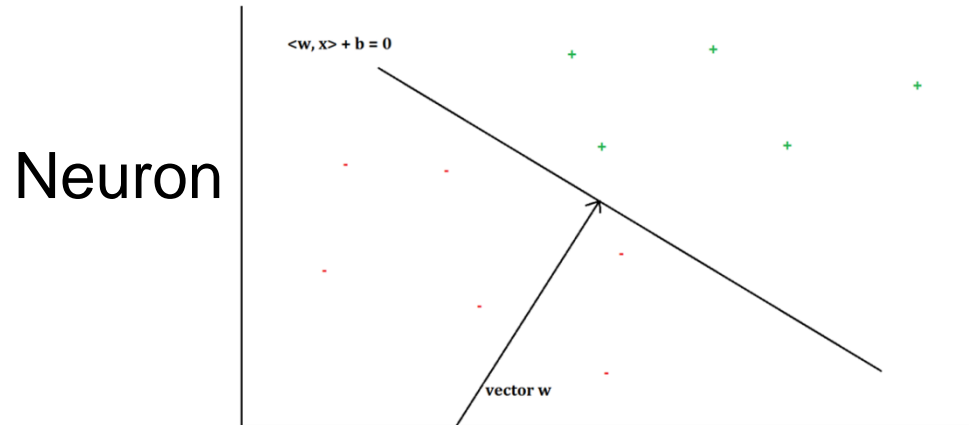
Methode

- **Suchen der Parameter einer gegebenen Funktion...**
- ...so dass für alle Beispiele Eingabe (Bild) auf Ausgabe («Auto») abgebildet wird

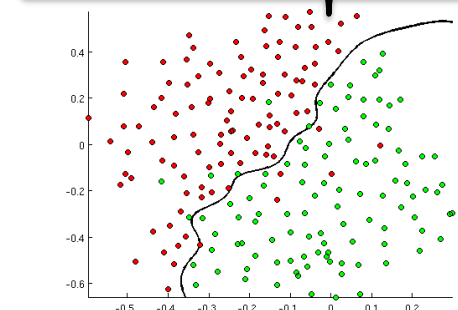
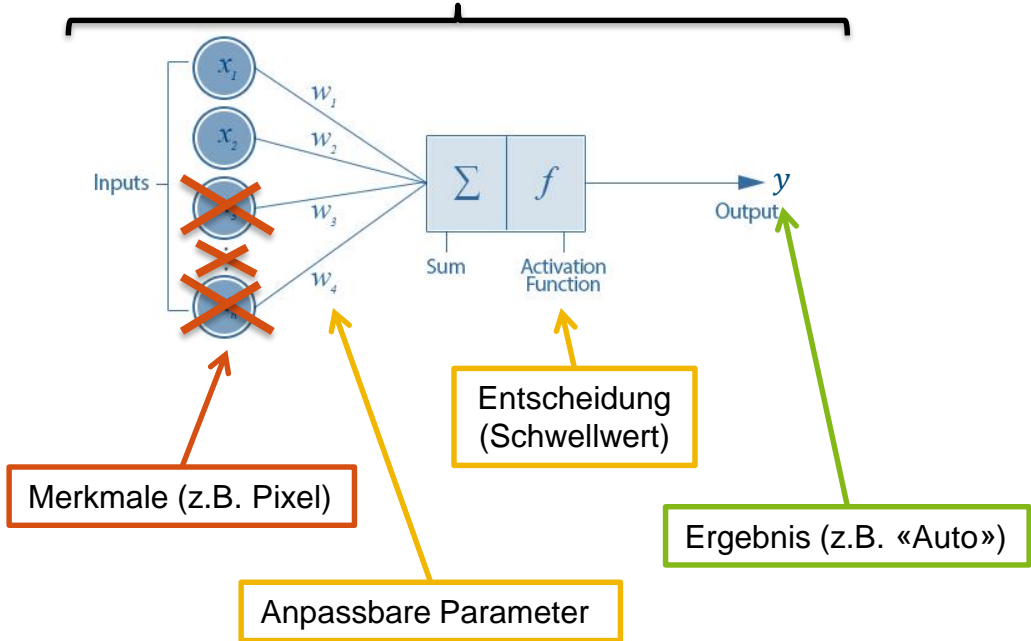
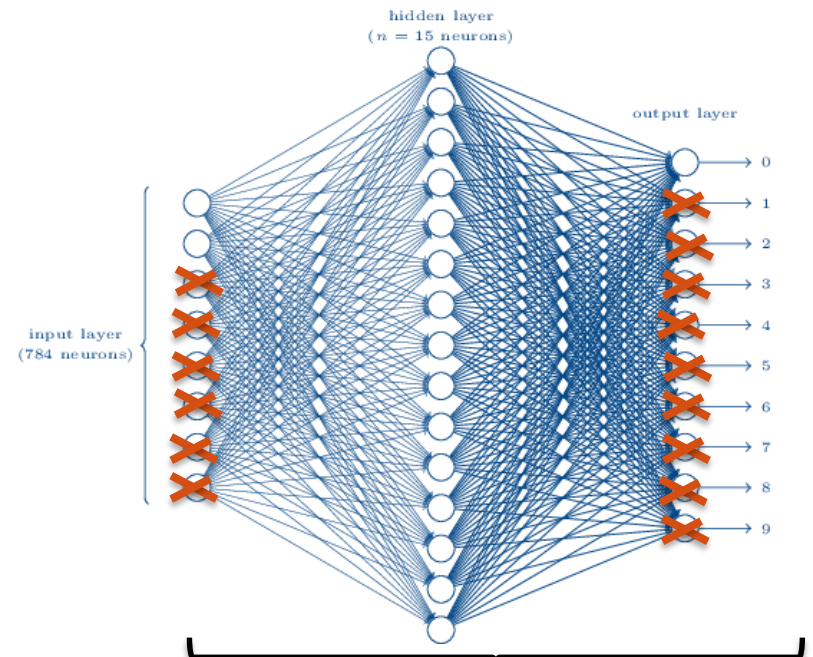
$$f(x) = y$$



Suche der Parameter *einer Funktion?*



Neuronales Netz



Schlussfolgerungen

- Deep Learning hat zu Paradigmenwechsel in *Mustererkennungsaufgaben* geführt
- Die Zeit vom Grundlagenresultat zur praktischer Anwendung beträgt wenige Monate
- Es gibt Methoden zum Hineinschauen in neuronale Black Boxes (siehe Anhang)
- Spezifische Aufgaben lassen sich sehr gut automatisieren (z.B. Ähnlichkeitssuche)



Zu mir:

- Prof. KI/ML, Scientific Director ZHAW digital
- Email: stdm@zhaw.ch
- Telefon: 058 934 72 08
- Web: <https://stdm.github.io/>
- Twitter: @thilo_on_data
- LinkedIn: thilo-stadelmann



Mehr zum Thema:

- Data+Service Alliance: www.data-service-alliance.ch
- KI: <https://sgaico.swissinformatics.org/>
- Zusammenarbeit: datalab@zhaw.ch



ANHANG

Developing for algorithmic fairness

FAT / ML

The FAT ML code of conduct

See <http://www.fatml.org/resources/principles-for-accountable-algorithms>

Purpose

- Help developers to **build algorithmic systems in publicly accountable ways**
- Accountability: the **obligation to report, explain, or justify** algorithmic decision-making & **mitigate** any **negative social impacts** or potential harms

Premise

- *A **human ultimately responsible** for decisions made/informed by an algorithm*

Principles

- **Responsibility, Explainability, Accuracy, Auditability, Fairness**

Make available somebody who will take care of adverse individual / societal effects

Explain any **algorithmic decision** in non-technical terms to end users

Report all **sources of uncertainty / error** in algorithms & data

Enable 3rd parties to **probe & understand** system **behavior**

Ensure algorithmic **decisions are not discriminatory** w.r.t. to people groups

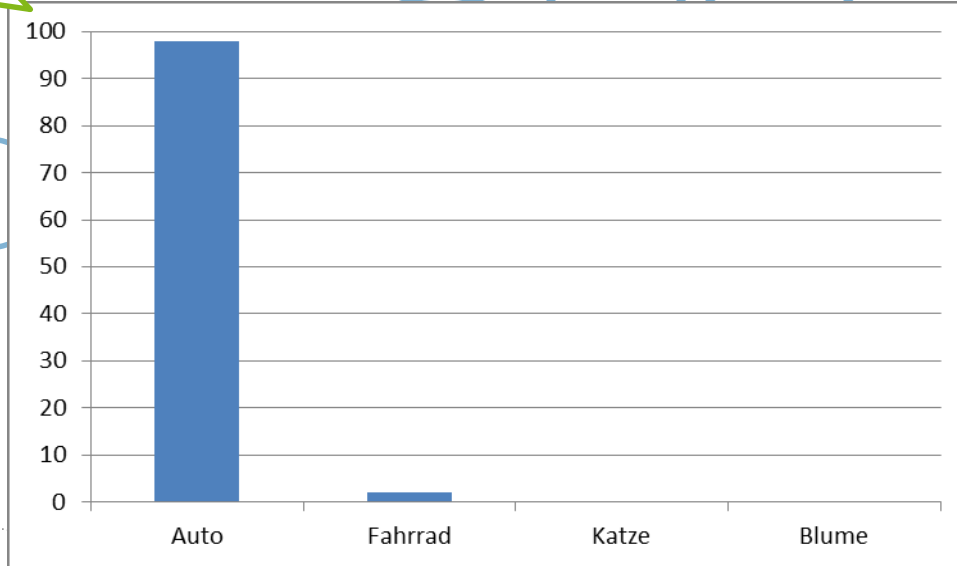
Making it actionable

- **Publish a Social Impact Statement**
- ...use above **principles as a guiding structure**
- ...**revisit three times** during development process: design stage, pre-launch, post-launch

Suche der Parameter einer Funktion?

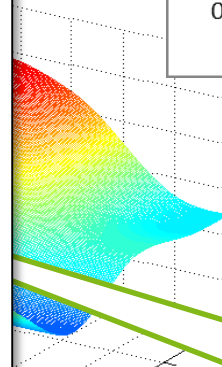
Wahrscheinlichkeit [%] für bestimmtes Ergebnis

- Unser Neuronales Netz: $f_W(x) = y$
mit Bild x , echtem Resultat y und Parametern W
($W = \{w_1, w_2, \dots\}$ anfangs zufällig gewählt)
- Fehlermass: $l(W) = \frac{1}{N} \sum_{i=1}^N (f_W(x_i) - y_i)^2$
Durchschnitt der quadratischen Abweichungen
über alle Bilder (Loss)



$$l(W) = \frac{1}{N} \sum_{i=1}^N (f_W(x_i) - y_i)^2$$

↙ Durchschnitt (über alle Beispiele)
↘ Differenz IST – SOLL (Fehler)
↓ Bestraft grosse Fehler überproportional stärker



← Fehlerlandschaft

Methode: Anpassung der Gewichte von f in Richtung der steilsten Steigung (abwärts) von J

Was «sieht» das Neuronale Netz?

Hierarchien komplexer werdender Merkmale

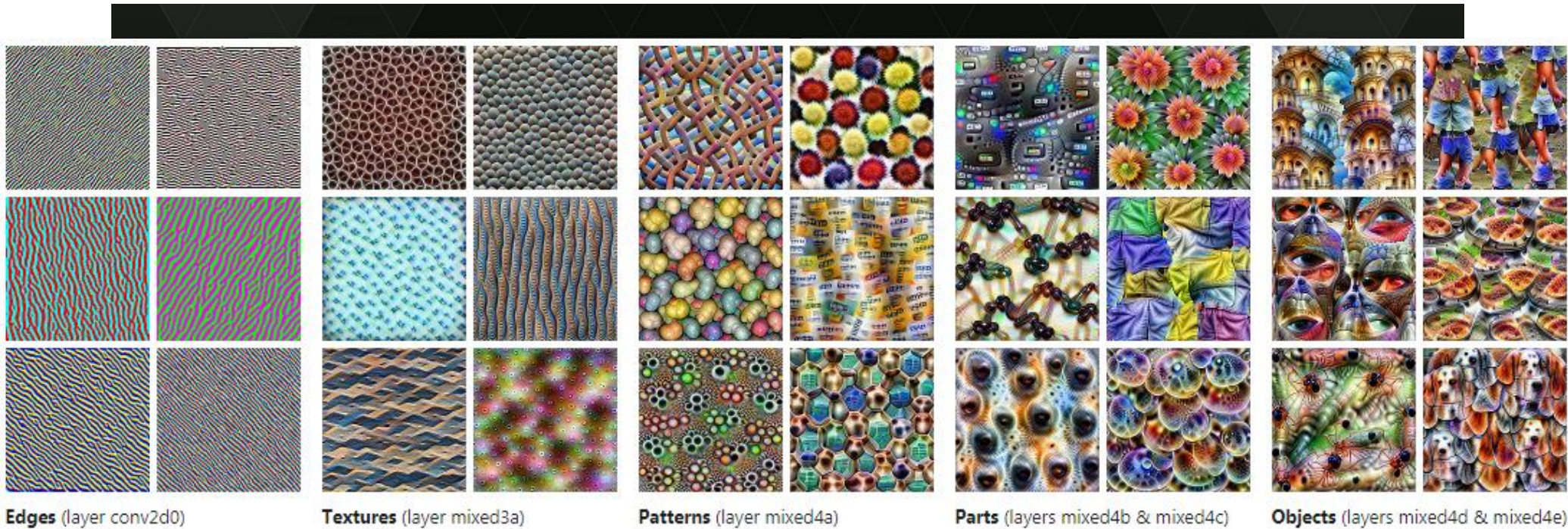


Image source: "Unsupervised Learning of Hierarchical Representations with Convolutional Deep Belief Networks" ICML 2009 & Comm. ACM 2011.
Honglak Lee, Roger Grosse, Rajesh Ranganath, and Andrew Ng.

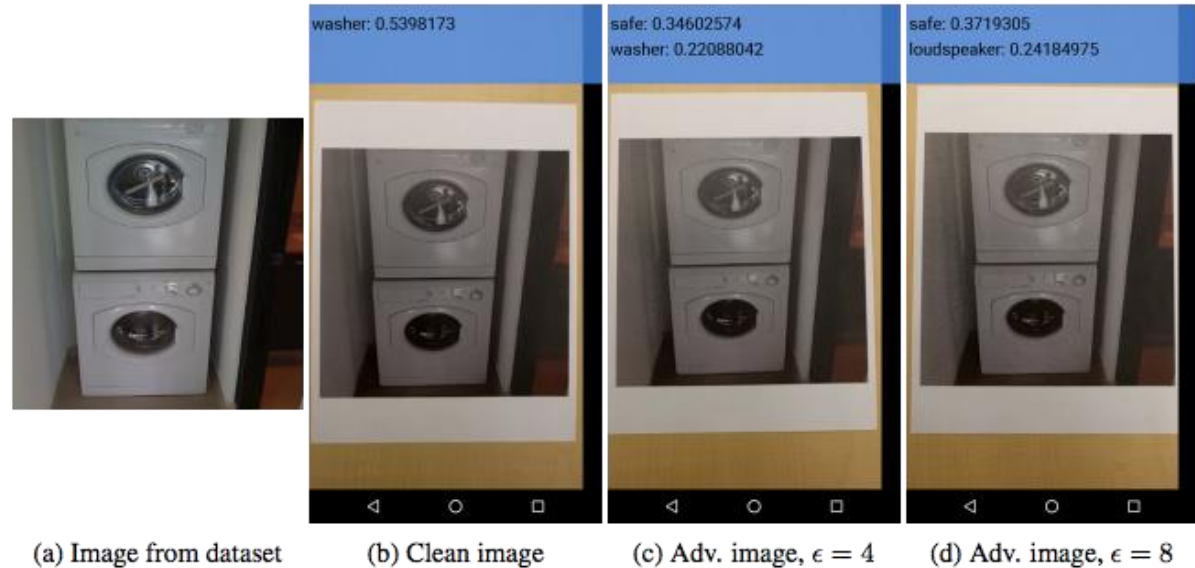
Quellen: <https://www.pinterest.com/explore/artificial-neural-network/>
Olah, et al., "Feature Visualization", Distill, 2017, <https://distill.pub/2017/feature-visualization/>.

Wie schlussfolgert die Maschine?

«Debugging» für Einblicke in die vermeintliche «Black Box»

Verdeutlichen ein Problem:

- Adversarial Examples



(a) Image from dataset

(b) Clean image

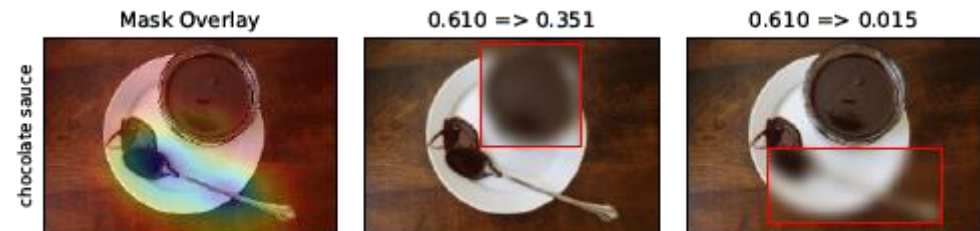
(c) Adv. image, $\epsilon = 4$

(d) Adv. image, $\epsilon = 8$

<https://blog.openai.com/adversarial-example-research/>

Bieten eine Lösung:







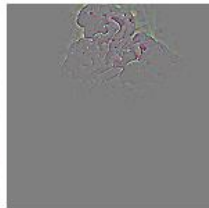
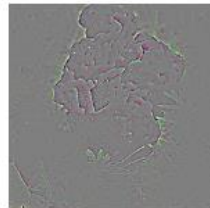
- Saliency Maps



Ruth C. Fong & Andrea Vedaldi, «Interpretable Explanations of Black Boxes by Meaningful Perturbation», 2017

Trace & detect adversarial attacks

...using average local spatial entropy of feature response maps

	Original	Adversarial	Original	Adversarial
Image:				
Feature response:				
Local spatial entropy:	