Zürcher Hochschule
für Angewandte Wissenschaften

Der Motor der digitalen Transformation

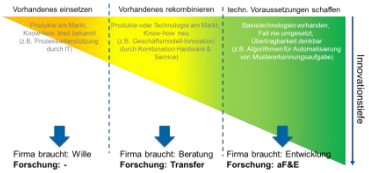
Big Data Forschung aus der Perspektive des ZHAW Datalab

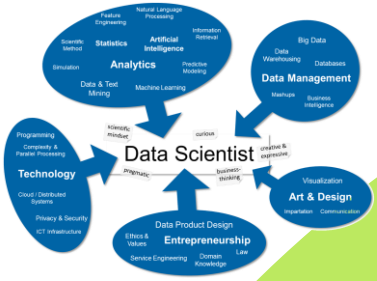
Strategietagung „Digitalisierung“ des Fachhochschulrats
Zürich, 17. November 2017

Thilo Stadelmann

datalab
www.zhaw.ch/datalab

Die nächsten 15 Minuten





Rolle der ZFH

Stand der Forschung

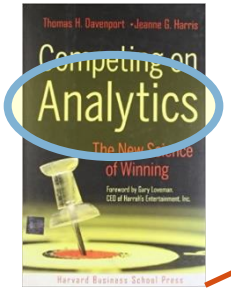
Data Science als Motor

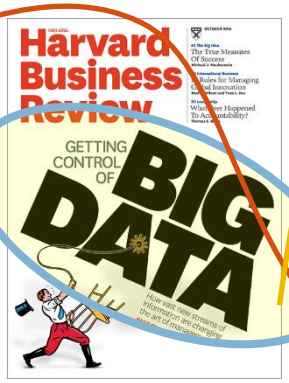
Ausblick

Zürcher Hochschule
für Angewandte Wissenschaften

Viele Begriffe, ein Trend: Digitalisierung

Schlagwörter und inhaltliche Treiber





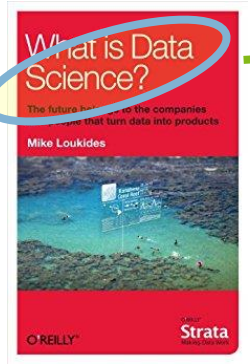
DIGITALisierung ZURICH 2025

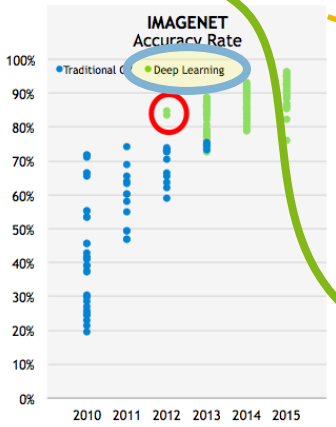
INDUSTRY 4.0 2025 INDUSTRIE INDUSTRIA

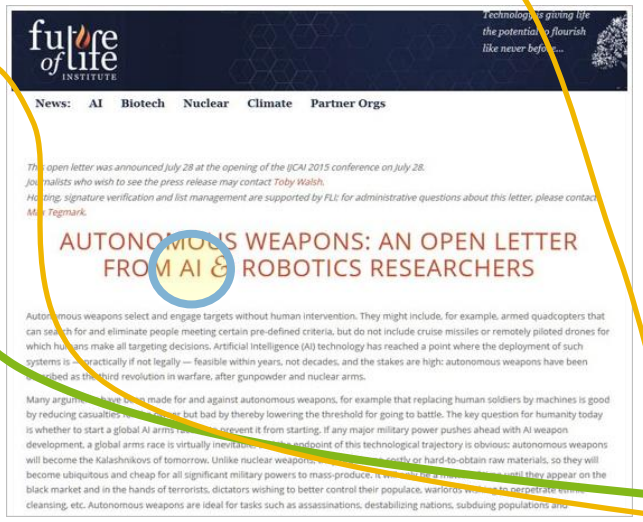
SWISS FINTECH INNOVATIONS

…

2007 2012 2016



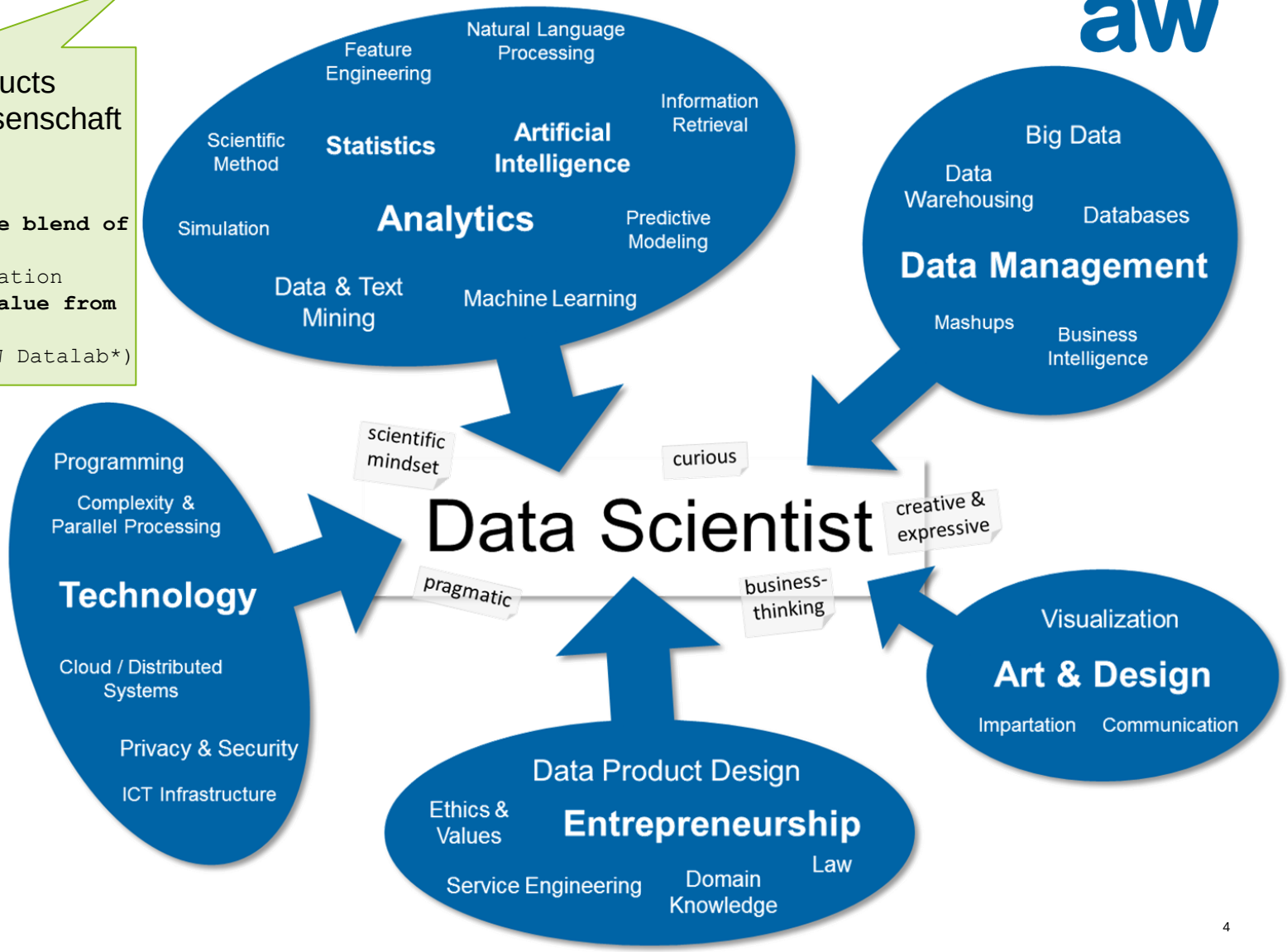




Was ist Data Science?

Ermöglicht Data Products
➔ **Angewandte** Wissenschaft
➔ Interdisziplinär

Data Science := "**Unique blend of skills** from analytics, engineering & communication aiming at **generating value from** the **data** itself […]"
(ZHAW Datalab*)



*) Stadelmann, Stockinger, Braschler, Cieliebak, Baudinot, Dürr and Ruckstuhl (2013). *Applied Data Science in Europe* . ECSS 2013, Amsterdam.

Teil 2

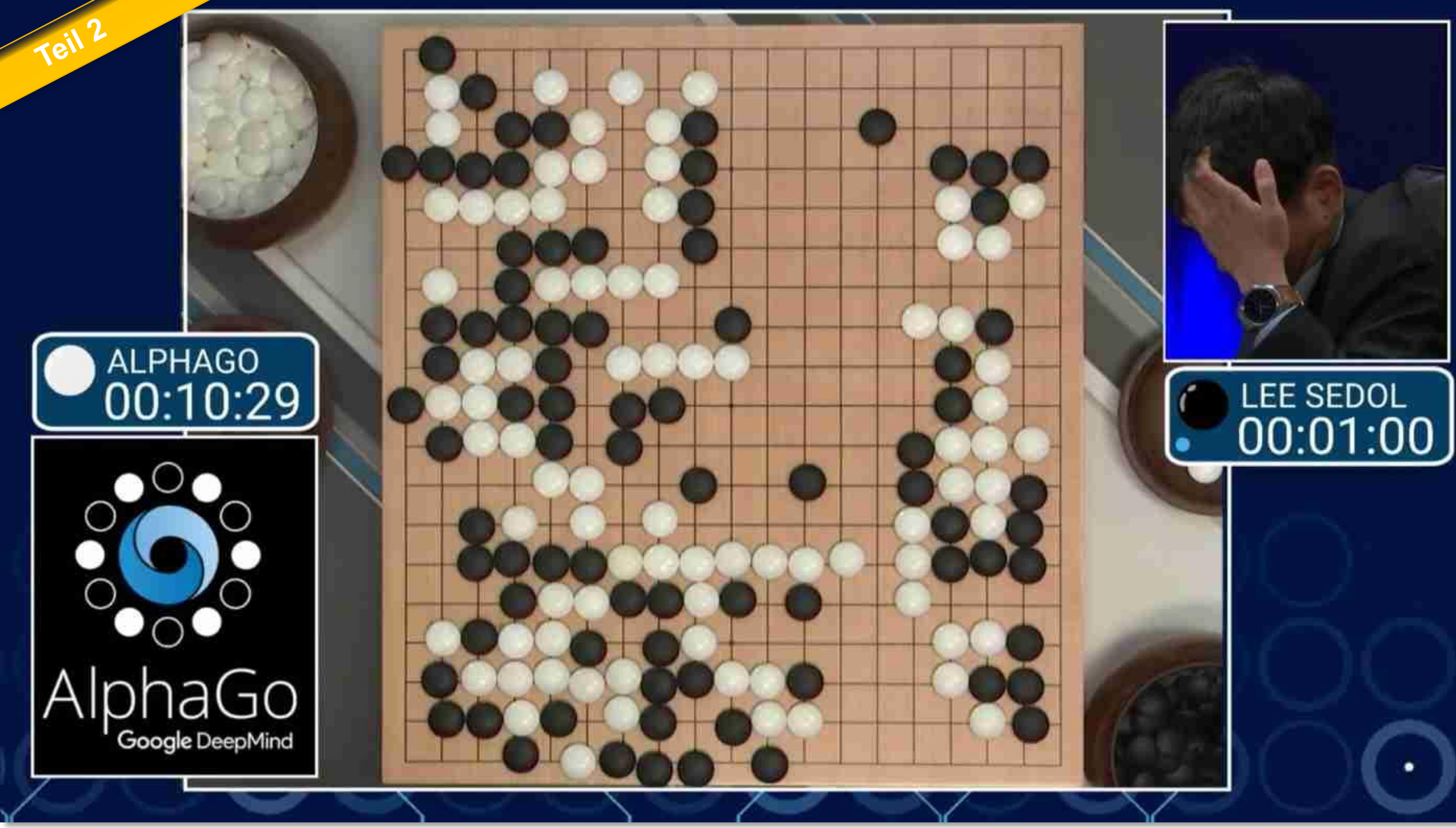
Zurich University of Applied Sciences

Der Stand der Forschung

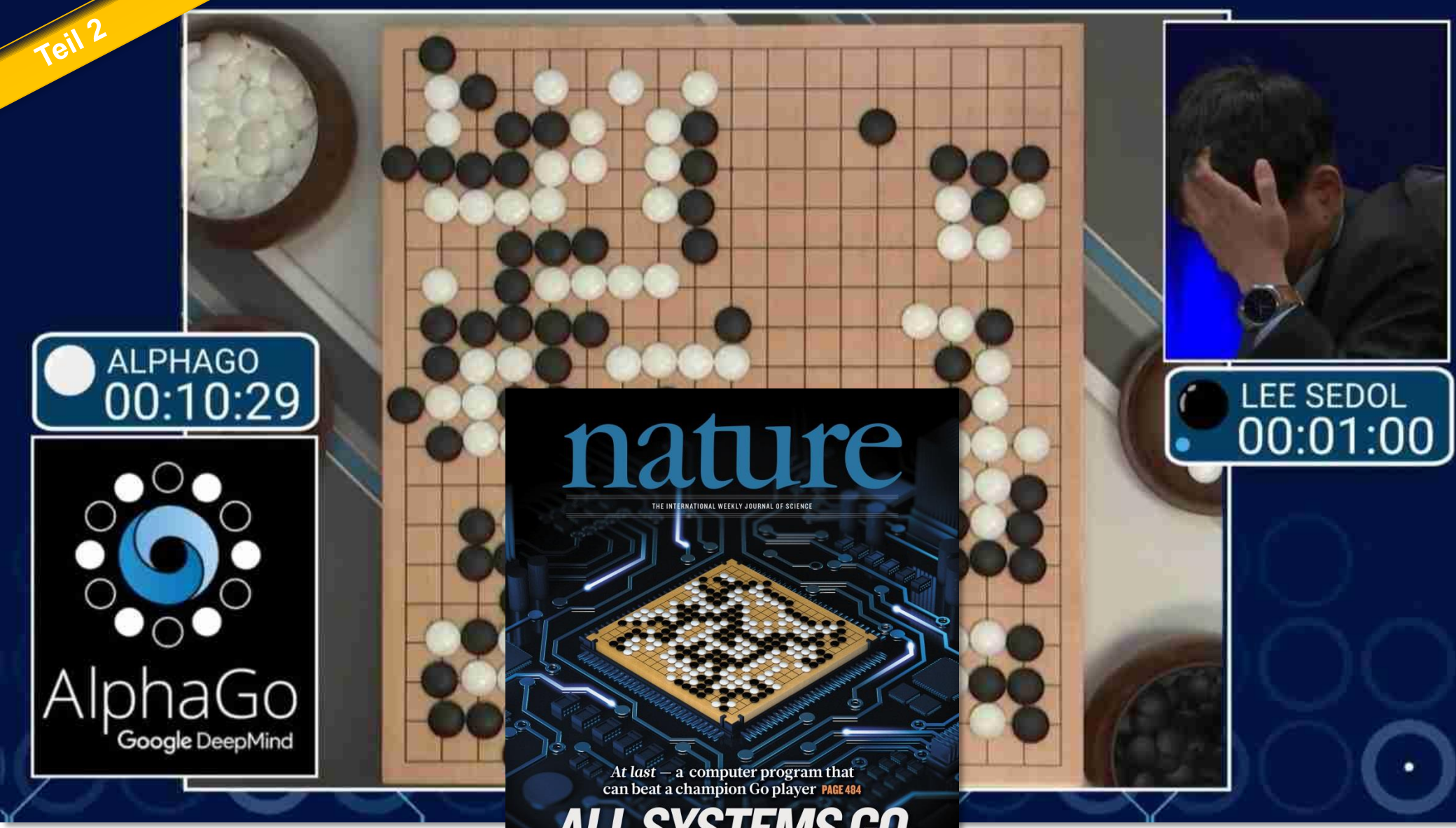
Durchbrüche allein im Bereich Deep Learning auf Big Data

Die **letzten 18 Monate** lieferten eine beeindruckende Liste **bedeutsame**r **Durchbrüche** in der Automatisierung **wahrnehmungsbezogener Aufgaben**.

➔ siehe die nächsten 2 Folien (weitere im Anhang)


Teil 2
ALPHAGO
00:10:29
AlphaGo
Google DeepMind
LEE SEDOL
00:01:00

Teil 2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nature
THE INTERNATIONAL WEEKLY JOURNAL OF SCIENCE
At last — a computer program that can beat a champion Go player PAGE 484
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Illegal harvest of millions of Mediterranean birds
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SAFEGUARD TRANSPARENCY
Don't let openness backfire on individuals
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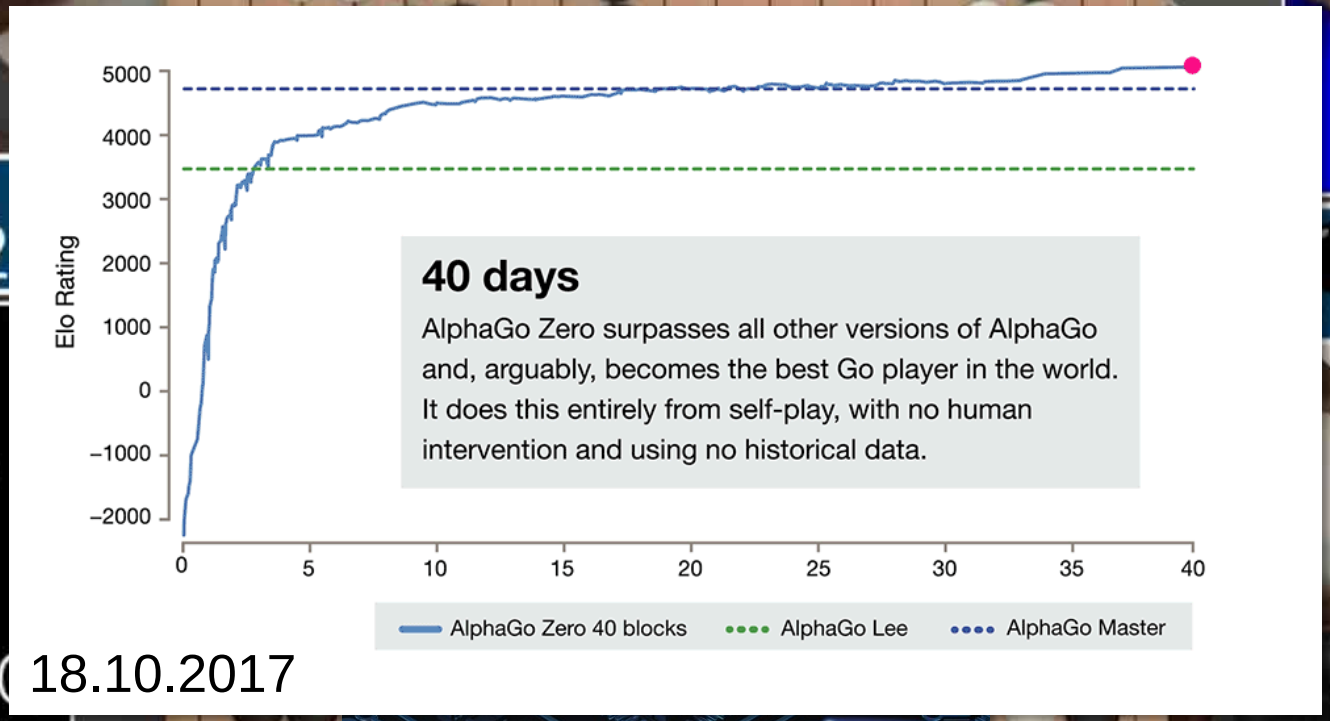
POPULAR SCIENCE
WHEN GENES GOT 'SELFISH'
Dawkins's calling card forty years on
PAGE 462
NATURE.COM/NATURE
28 January 2016 £10
Vol. 529, No. 7587

Teil 2



18.10.2017

Teil 2

…und viele weitere!

Zurich University of Applied Sciences

zh aw

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?
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  - Completing y
- Conclusion
- Partial bibliography
- Bonus: Incomplete

Introduction

Content-aware fill is a po completion and inpaintin do content-aware fill, im "Semantic Image Inpaint shows how to use deep l some deeper portions fo section can be skipped if from images of faces. I ha completion.tensorflow.

We'll approach image co

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

Andrej Karpathy blog About Hacker's guide to Neural Networks

The Unreasonable Effectiveness of Recurrent Neural Networks

May 21, 2015

There's something magical about Recurrent Neural Networks (RNNs). I still remember when I trained my first recurrent network for Image Captioning. Within a few dozen minutes of training my first baby model (with rather arbitrarily-chosen hyperparameters) started to generate very nice looking descriptions of images that were on the edge of making sense. Sometimes the ratio of how simple your model is to the quality of the results you get out of it blows past your expectations, and this was one of those times. What made this result so shocking at the time was that the common wisdom was that RNNs were supposed to be difficult to train (with more experience I've in fact reached the opposite conclusion). Fast forward about a year: I'm training RNNs all the time and I've witnessed their power and robustness many times, and yet their magical outputs still find ways of amusing me. This post is about sharing some of that magic with you.

> *We'll train RNNs to generate text character by character and ponder the question "how is that even possible?"*

By the way, together with this post I am also releasing code on Github that allows you to train character-level language models based on multi-layer LSTMs. You give it a large chunk of text and it will learn to generate text like it one character at a time. You can also use it to reproduce my experiments below. But we're getting ahead of ourselves; What are RNNs anyway?

Recurrent Neural Networks

Sequences. Depending on your background you might be wondering: *What makes Recurrent Networks so special?* A glaring limitation of Vanilla Neural Networks (and also Convolutional Networks) is that their API is too constrained: they accept a fixed-sized vector as input (e.g. an image) and produce a fixed-sized vector as output (e.g. probabilities of different classes). Not only that: These models perform this mapping using a fixed amount of computational steps (e.g. the number of layers in the model). The core reason that recurrent nets are more exciting is that they allow us to operate over sequences of vectors: Sequences in the input, the output, or in the most general case both. A few examples may make this more concrete:

```
VIOLA:
Why, Salisbury must find his flesh and thought
That which I am not aps, not a man and in fire,
To show the reining of the raven and the wars
To grace my hand reproach within, and not a fair are hand,
That Caesar and my goodly father's world;
When I was heaven of presence and our fleets,
We spare with hours, but cut thy council I am great,
Murdered and by thy master's ready there
My power to give thee but so much as hell:
Some service in the noble bondman here,
Would show him to her wine.

KING LEAR:
O, if you were a feeble sight, the courtesy of your law,
Your sight and several breath, will wear the gods
With his heads, and my hands are wonder'd at the deeds,
So drop upon your lordship's head, and your opinion
Shall be against your honour.
```

the right, a recurrent network generates images of digits by learning to sequentially add color to a canvas (Gregor et al.):

the morning paper

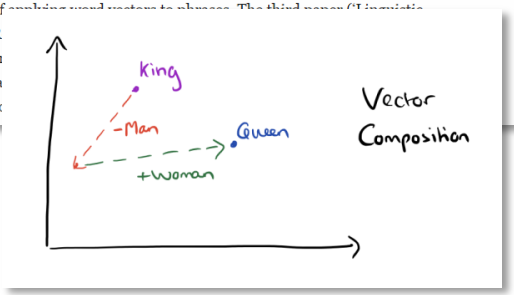
The amazing power of word vectors

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

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



Teil 2

…und viele weitere!

Zurich University of Applied Sciences

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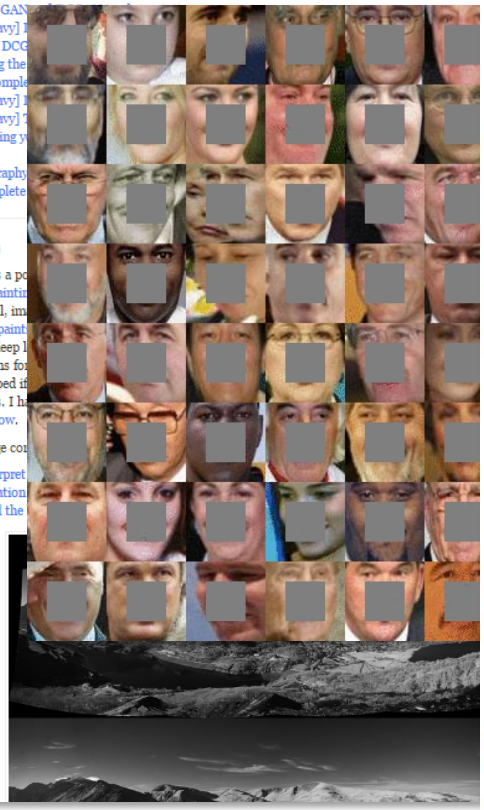

Andrej Karpathy blog About Hacker's guide to Neural Networks

The Unreasonable Effectiveness of Recurrent Neural Networks

GEEK.COM

TECH

Nvidia AI Generates Fake Faces Based On Real Celebs

BY STEPHANIE MLOT 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.

hand,

law,

is,

the morning paper

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APRIL 21, 2016

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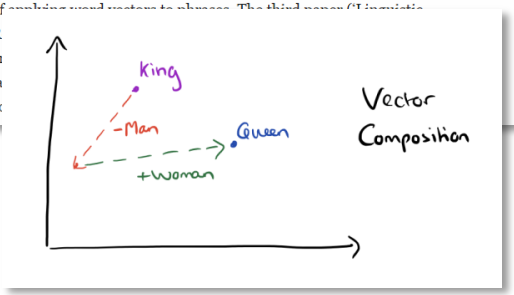


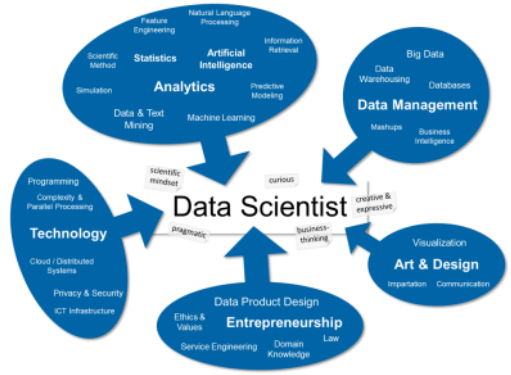
Teil 3

ZHAW Datalab: Est. 2013

Zurich University of Applied Sciences

Forerunner

- **One of the first** interdisciplinary data science initiatives in Europe
- One of the first interdisciplinary centers at ZHAW



Foundation

- **People**: ca. **70 researchers** from **5 institutes** / **3 departments** opted in
- Vision: **Nationally leading** and **internationally recognized** center of excellence
- Mission: **Generate projects** through critical mass and mutual relationships
- Competency: **Data product design** with structured and unstructured data

Success factors

- **Lean** organization and operation → geared towards projects
- Years of successful **pre-Datalab collaboration**

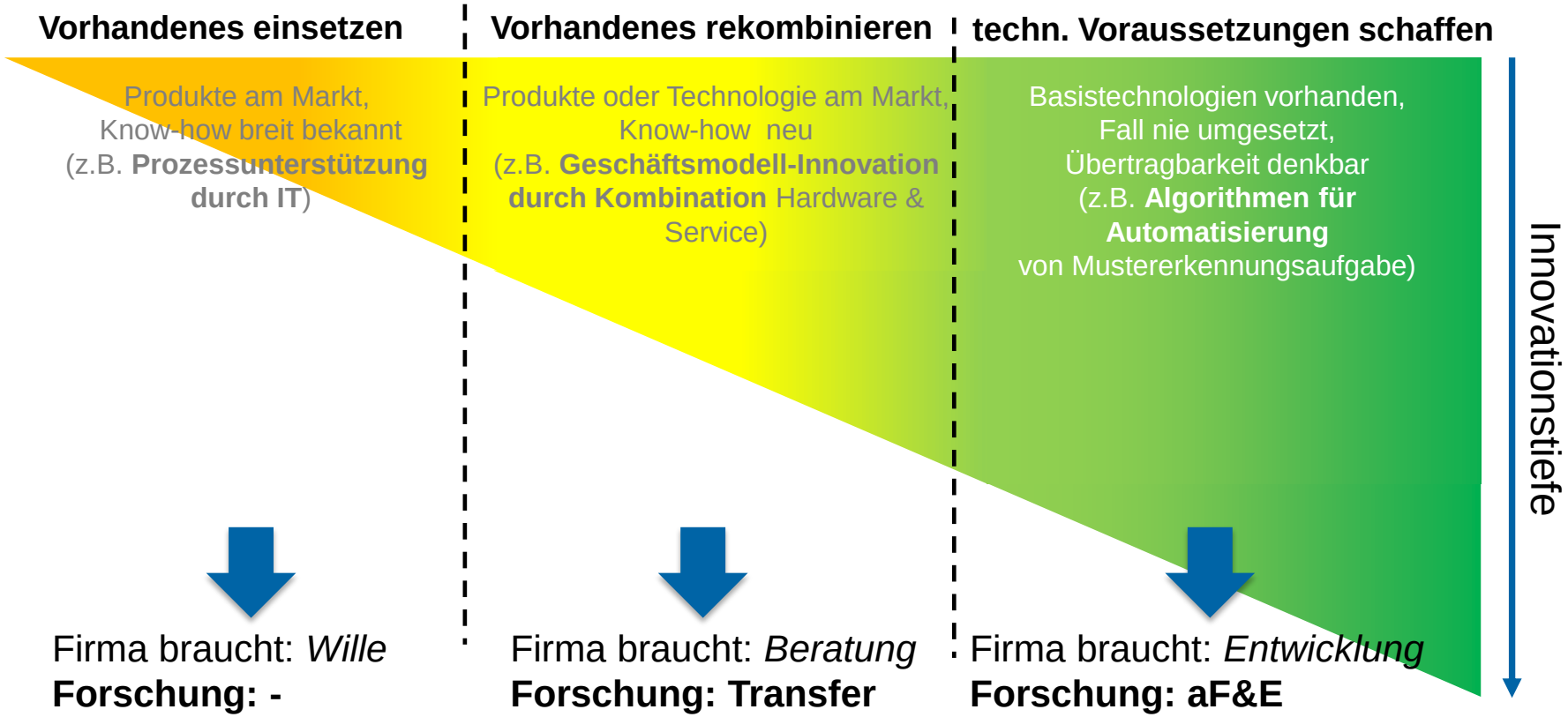
Teil 3

Zürcher Hochschule
für Angewandte Wissenschaften

Unsere Rolle als Forscher an Fachhochschulen

Innovation in Zeiten der Digitalisierung → siehe Konferenz Digitale Schweiz

3 Arten von betrieblicher Innovation in der Digitalisierung



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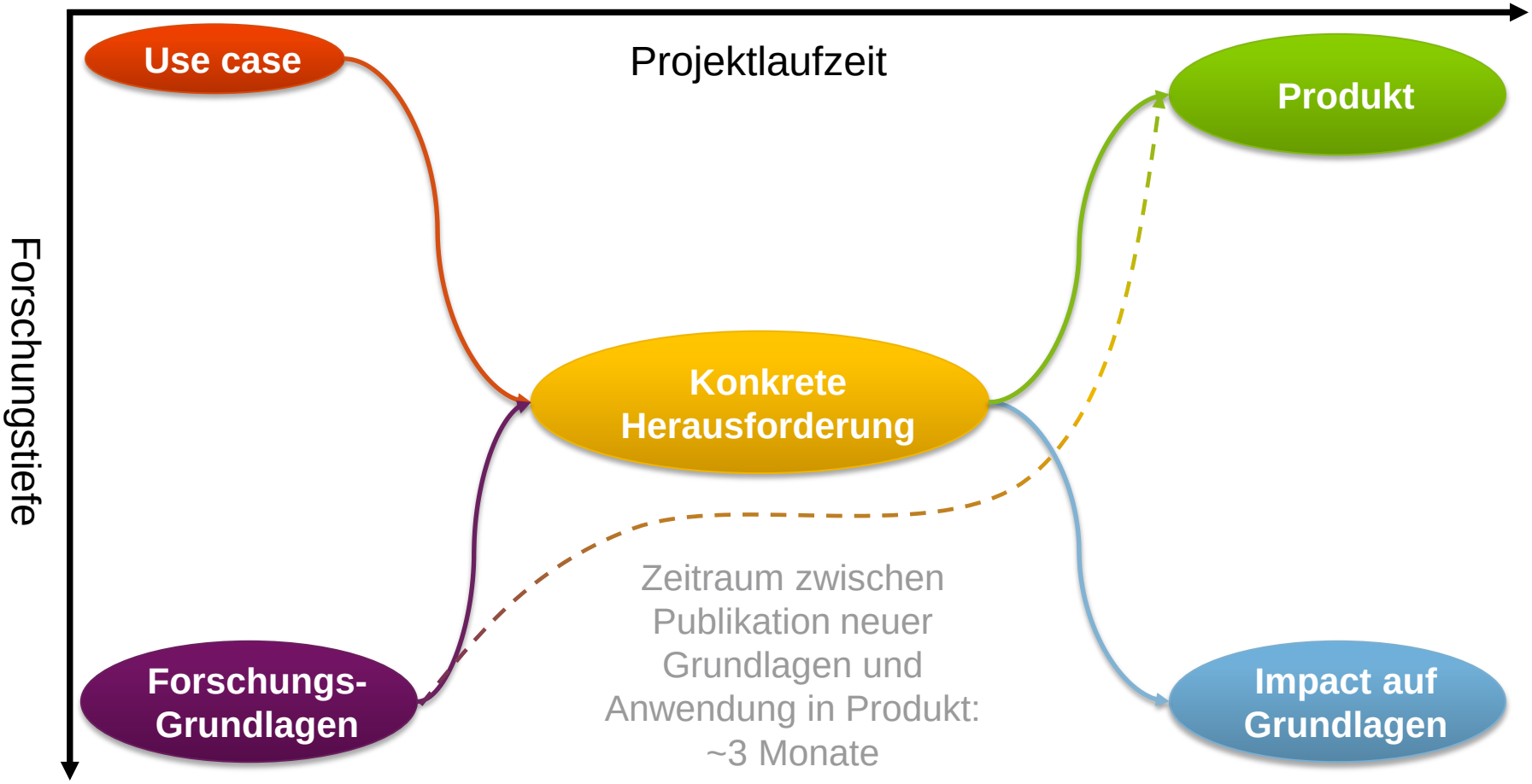
für Angewandte Wissenschaften

Parallelität von Grundlagen- und aF&E

Innovation in Zeiten der Digitalisierung, contd.



Teil 3

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für Angewandte Wissenschaften

Angewandte F&E im ZHAW Datalab

Drei Beispiele

- **Produktionsautomatisierung** für KMU mit *Deep Neural Networks*
- **Intuitive Suche** in Datenbanken für Bioinformatiker mit *Big Data Technologie*
- **Behandlungsplanung** für Aneurysmen mit *Maschinellem Lernen*

- (zwei weitere: siehe Anhang)

Teil 3

PANOPTES – Automated Article Segmentation of Newspaper Pages for "Real Time Print Media Monitoring“

M. Cieliebak & T. Stadelmann, ZHAW

Overview

Partners

Who are we

ARGUS der Presse AG
- Switzerland's leading media monitoring and information provider
- Experience of more than 100 years

ZHAW Datalab
- Interdisciplinary research group at Zurich University of Applied Sciences
- Combining the knowledge of different fields related to machine learning

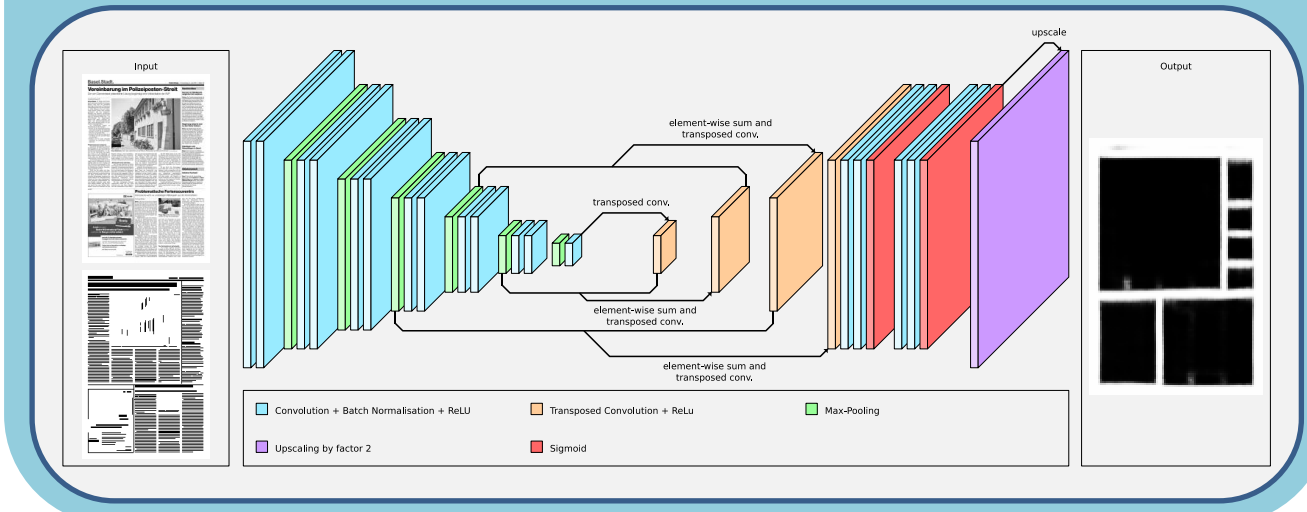
The Project

What do we do

Goal
- Real Time Print Media Monitoring
  - Extraction of relevant articles from newspaper pages
  - Delivering articles to customers

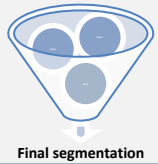
Problem
- Fully automated article segmentation
- Identification of article elements (e.g. title, subtitle, etc.)

Most Successful Approach [3]



Combination

Combination of rules, visual and textual features



Final segmentation

Result

References

[1] D. C. Ciresan, A. Giusti, L. M. Gambardella, and J. Schmidhuber. *Deep neural networks segment neuronal membranes in electron microscopy images.* In *NIPS*, pages 2852–2860, 2012.
[2] T. Mikolov, K. Chen, G. Corrado, and J. Dean. *Efficient Estimation of Word Representations in Vector Space.* In Proceedings of Workshop at *ICLR*, 2013.
[3] B. Meyer, T. Stadelmann, J. Stampfli, M. Arnold, M. Cieliebak. *Fully Convolutional Neural Networks for Newspaper Article Segmentation*. In Proceedings of ICDAR, Kyoto, Japan, 2018.

This project was funded by CTI under project number 17719.1 PFES-ES

Schweizerische Eidgenossenschaft
Confédération suisse
Confederazione Svizzera
Confederaziun svizra

Swiss Confederation

Federal Department of Economic Affairs, Education and Research EAER

Commission for Technology and Innovation CTI
Innovation Promotion Agency

Teil 3

Zürcher Hochschule
für Angewandte Wissenschaften

Bio-SODA: Enabling Complex, Semantic Queries to Bioinformatics Databases through Intuitive Searching over Data

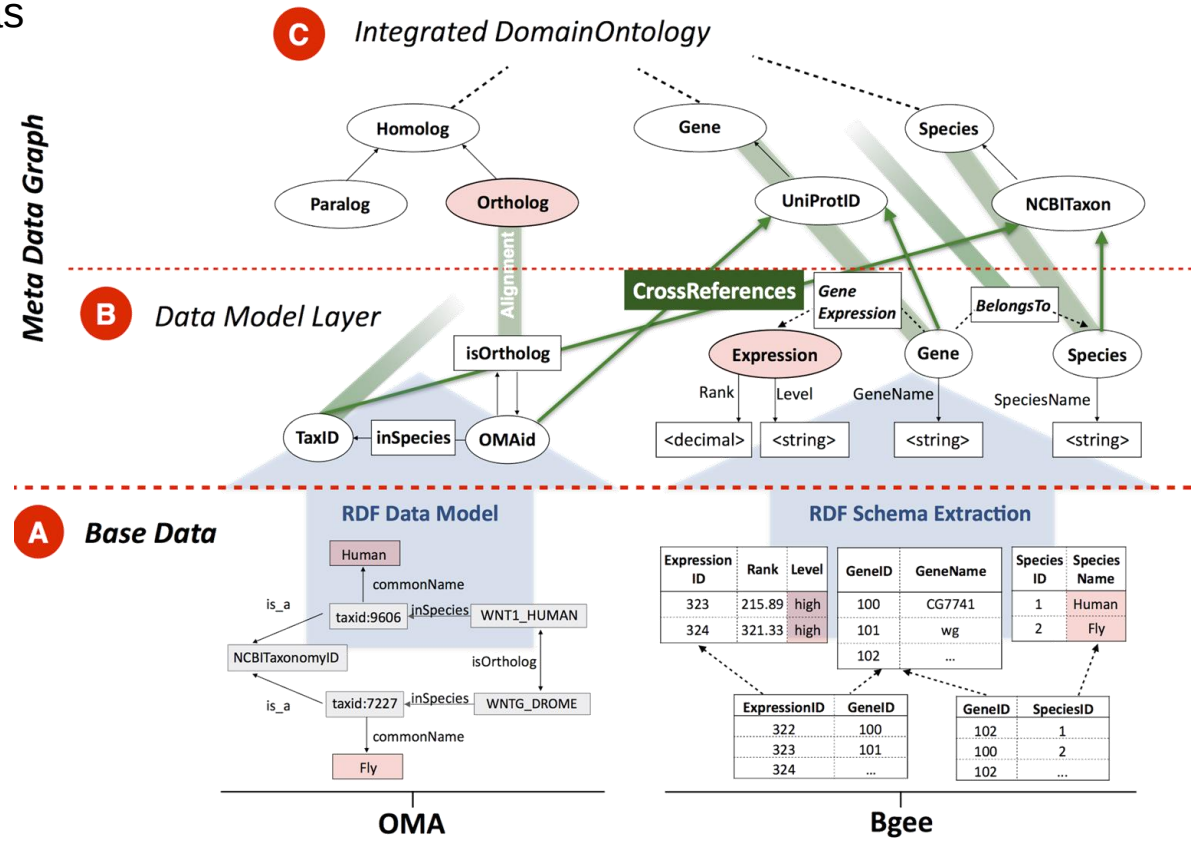
Intuitive exploration

- ✓ without knowing SPARQL, SQL, etc
- ✓ without knowing database schemas
- ✓ large datasets

Impact

- ➢ large bioinformatics user bases
- ➢ future federation of life sciences

Lead: Kurt Stockinger, ZHAW



75 NFP Big Data Nationales Forschungsprogramm

FNSNF Fonds national suisse Schweizerischer Nationalfonds Fondo nazionale svizzero Swiss National Science Foundation

Zurich University of Applied Sciences zhaw

UNIL | Université de Lausanne

SIB Swiss Institute of Bioinformatics

Teil 3

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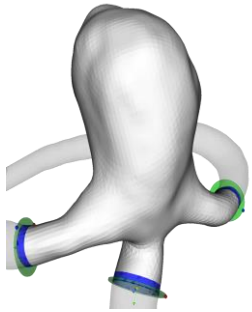
für Angewandte Wissenschaften

AneuX: Ist die Form signifikant für die Gefährdung eines Aneurysmas?

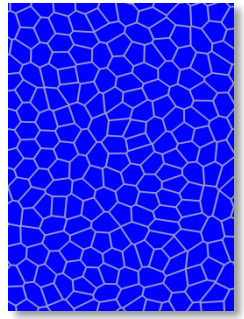
Aneurysm im Röntgenbild (XA)

Isoliertes Aneurysma Zur Formanalyse

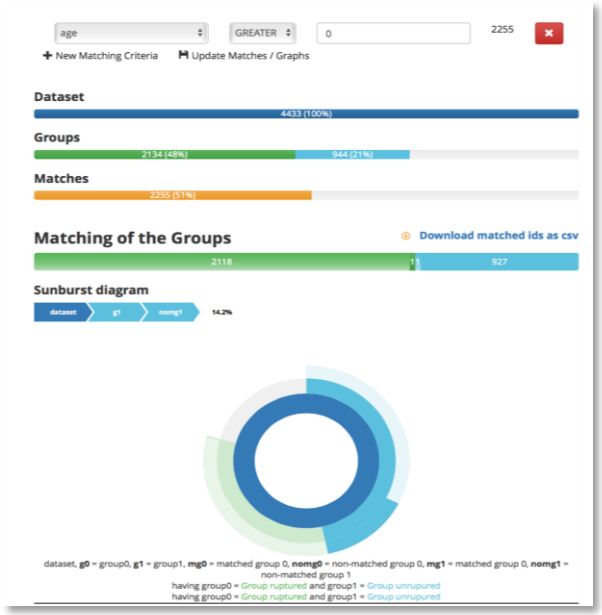


Zellen der Gefässwand

Modell der Gefässwand



Webtool für statistische Analyse



SystemsX.ch funding: 2M CHF, Begutachtung SNSF

- Morphologische Analyse von Aneurysmen mit Machine Learning
- Biologisch motiviertes Simulationsmodell für Zellwandveränderung
- Aufbau eines Krankheitsmodells für die Behandlungsplanung
- Aufbau einer Datenbank von Aneurysmen
- Erstellung von Werkzeuge zur Analyse der klinischen Daten und Bilddaten

Partner (Co-Antragsteller Sven Hirsch, ZHAW):

Zürcher Fachhochschule

AneuX
Shape as Biomarker
for Aneurysm Disease

HUG Hôpitaux Universitaires de Genève

Universität Zürich[UZH]

UNIVERSITÉ DE GENÈVE

cabmm

IT'IS FOUNDATION

Swiss Neuro Foundation

ETH zürich

Zürcher Hochschule
für Angewandte Wissenschaften

Schlussfolgerungen

Welche Rahmenbedingungen benötigen wir, um erfolgreich zu bleiben?

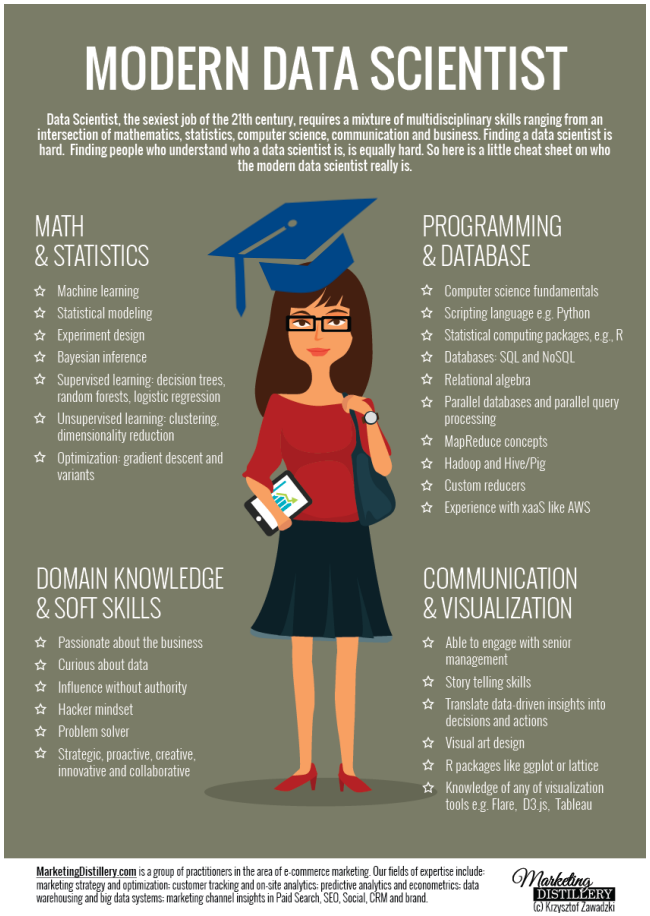
Drei Thesen

- Digitale Innovationen laufen in **extrem kurzen** Zyklen ab
- **Einfachere** digitale **Innovationen** bestehen in der neuartigen **Kombination** von vorhandenen **Technologien** mit einem geeigneten Prozess- und **Businessmodell**
- **Komplexere** digitale Innovationen verlangen eine **Gleichzeitigkeit** von **Grundlagen**forschung, **angewandter Forschung** und **Umsetzung**

Zwei Schlussfolgerungen

➔ Wir brauchen interdisziplinäre Data Science Ausbildung auf Master-Stufe
(M.Sc. Data Science)

➔ Wir brauchen die besten angewandten Forscher
(Tenure Track für Dozierende, PhD Studenten in Co-Betreuung mit Universitäten)



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ANHANG

Teil 2

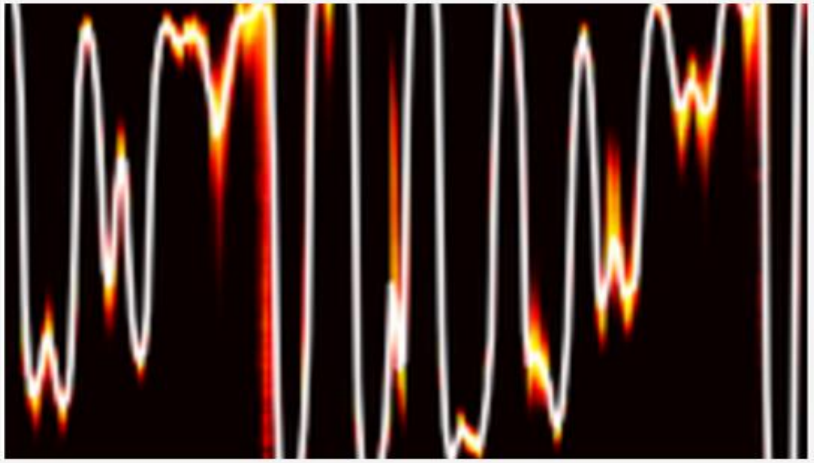
liche Intelligenz

WaveNet lässt Computersprache natürlich klingen

von Henning Steier / 12.9.2016, 10:05 Uhr

Die Google-Tochter DeepMind hat ein neuronales Netz präsentiert, das Rechner fast wie Menschen klingen lässt. Es macht auch Musik.

KOMMENTARE



DeepMind lässt WaveNet Sprachwellen erzeugen. (Symbolbild: PD)

Die Google-Tochter DeepMind machte zuletzt mit ihrem Sieg beim Spiel «Go» Schlagzeilen: Ihre Software AlphaGo schlug im Frühjahr einen der besten menschlichen Spieler, Lee Sedol. Nun hat das Londoner Unternehmen WaveNet präsentiert: Dieses neuronale Netz erzeugt Sprache, die sehr natürlich klingt – zumindest wenn man die im Blogeintrag des Unternehmens zu hörenden Klangbeispiele als Massstab nimmt. Man hat sogar das Gefühl, Atempausen zu hören.

MEISTGELESEN

Künstliche Intelligenz
Kein Google für jeden
KOMMENTAR / Henning Steier / 5.10.2016

Neue Produkte aus Mountain View
Google macht sich nicht nur im Wohnzimmer breit
Henning Steier / 4.10.2016

Dropbox
68 Millionen verschlüsselte Passwörter im Netz
5.10.2016

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Generierte Sprache
«aus Texteingabe»

Generierte Musik
«ohne Inhaltsvorgabe»

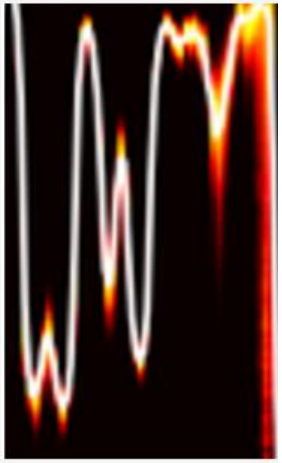
Teil 2

liche Intelligenz

WaveNet lässt Computersprache natürlich klingen

von Henning Steier / 12.9.201

Die Google-Tochter DeepM
macht auch Musik.



DeepMind lässt WaveNet Spra

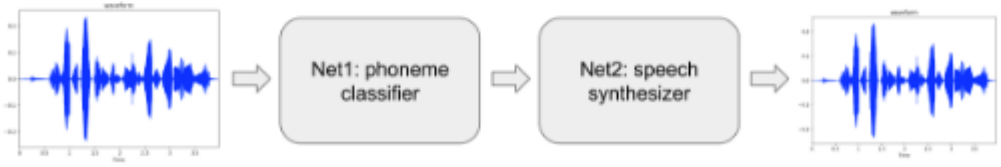
Die Google-Tochter Deep
Spiel «Go» Schlagzeilen:
einen der besten mensch
Londoner Unternehmen
erzeugt Sprache, die seh
im Blogeintrag des Unter
Massstab nimmt. Man ha

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.



02.11.2017

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nerierte Sprache
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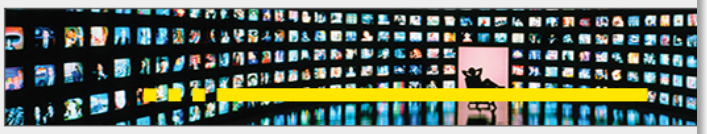
1 Second

Teil 2

MIT ...ology ...view

Topics+ Top Stories



Computing

Algorithm Clones Van Gogh's Artistic Style and Pastes It onto Other Images, Movies

A deep neural network has learned to transfer artistic styles to other images.

by Emerging Technology from the arXiv May 10, 2016

The nature of artistic style is something of a mystery to most people. Think of Vincent Van Gogh's *Starry Night*, Picasso's work on cubism, or Edvard Munch's *The Scream*. All have a powerful, unique style that humans recognize easily.

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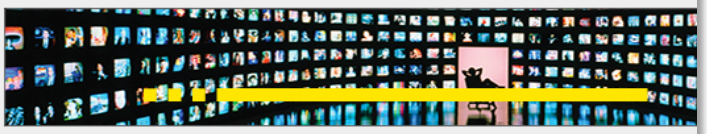

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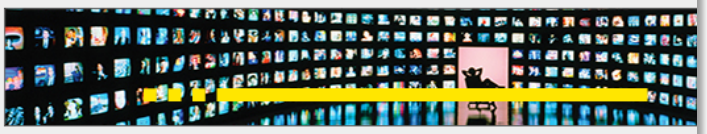

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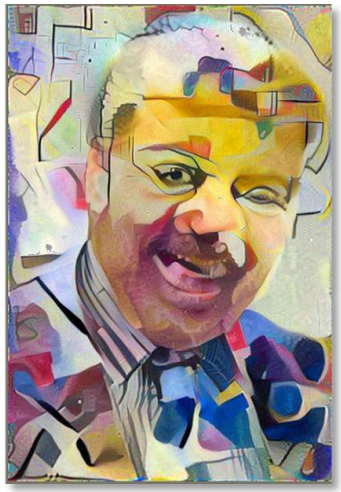

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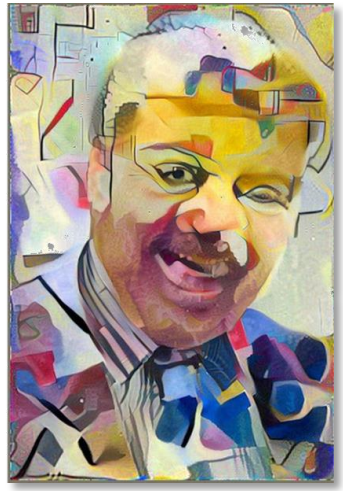


The nature of artistic style is something of a mystery to most people. Think of Vincent Van Gogh's *Starr*, or Edvard Munch's *The Scream* e th humans recognize easily.



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

And the results are impressive

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

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

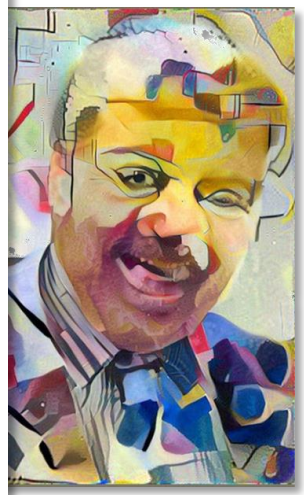
Computing

Algorith
Artistic
Other In

A deep neural n
other images.

by Emerging Tech

The nature of arti
of Vincent Van G
Edvard Munch's
humans recogniz



Teil 2

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Die Geschichte von Rocket AI @ NIPS'2016

Oder: Die Gefahr hinter Hype

Zitat aus dem Blogbeitrag (https://medium.com/the-mission/rocket-ai-2016s-most-notorious-ai-launch-and-the-problem-with-ai-hype-d7908013f8c9#.9gjgyxre5):

> **Turns out anyone can make a multi-million dollar company in 30 minutes** …with a website editor whilst in a Spanish mansion found on Airbnb. *'Temporally Recurrent Optimal Learning'* is a combination of buzzwords we put together to spell out TROL(L) that were conjured up over breakfast. If we hadn't put significant effort into making sure people realized it was a joke, Rocket AI would be in the press right now.
>
> Metrics for the Rocket AI launch party:
>
> Email RSVPs to party: 316
> People who emailed in their resume: 46
> Large name brand funds who contacted us about investing: 5
> Media: Twitter, Facebook, HackerNews, Reddit, Quora, Medium etc
> Time Planning: < 8 hours
> Money Spent: $79 on the domain, $417 on alcohol and snacks + (police fine)
> For reference, NIPS sponsorship starts at $10k.
>
> Estimated value of Rocket AI: *in the tens of millions.*

Teil 3

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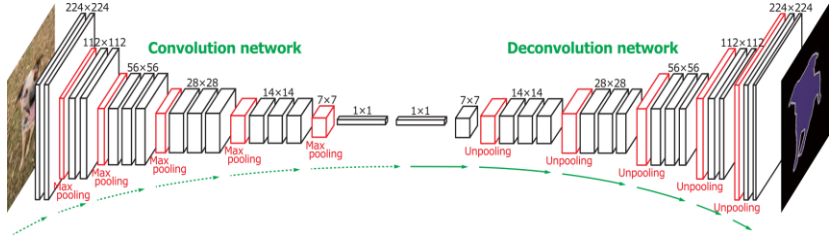
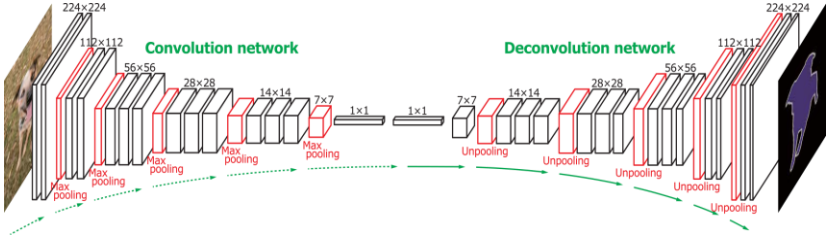
Erkennung von Musiknotation

Grundlage für Digitalisierung in Orchestern und Musikschulen

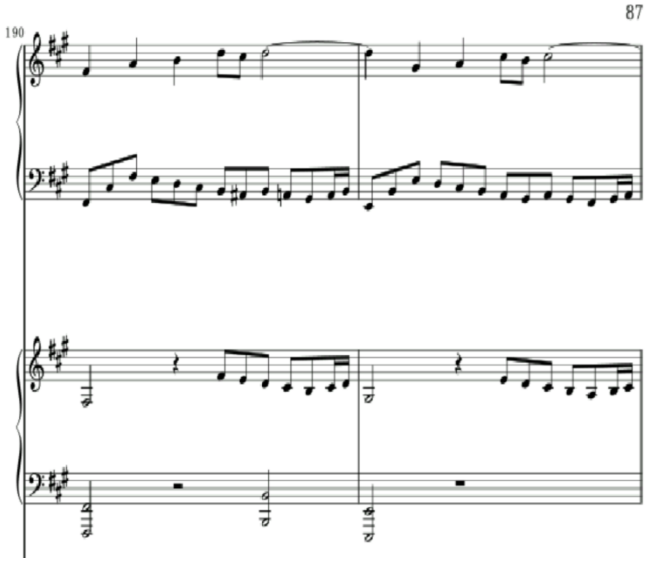




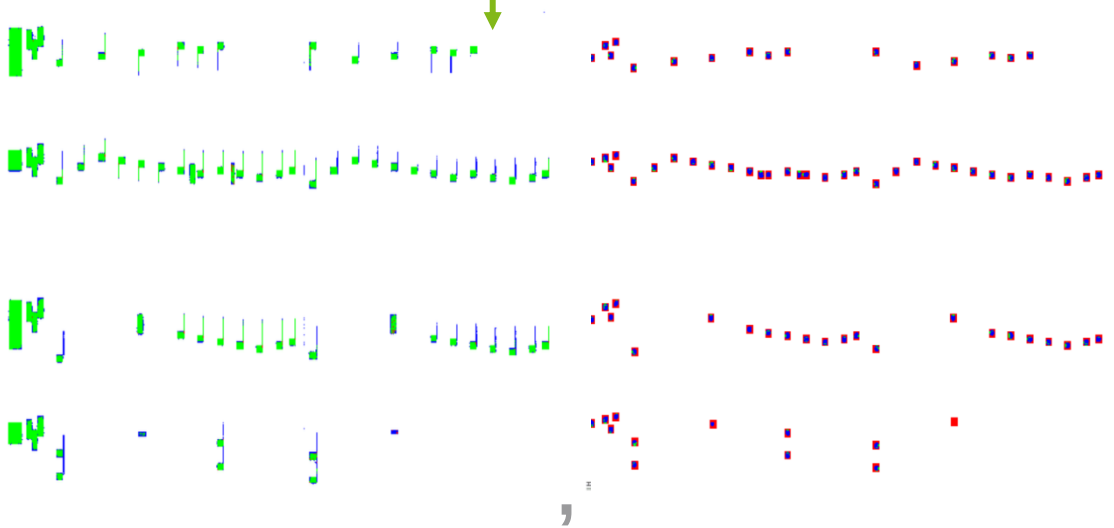
Bild

Label pro Pixel

Objekthaftigkeit



Benannte Symbole



Teil 3

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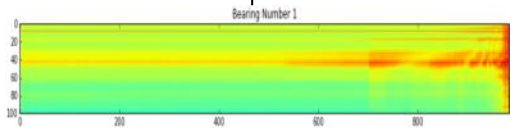
Datengetriebenes Condition Monitoring

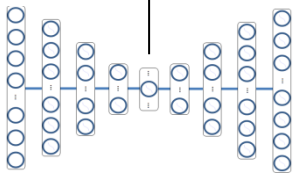
Predictive Maintenance von Rotationsmaschinen

Vibrations-Sensor

Merkmalsextraktion



z.B. neuronaler Autoencoder



Früherkennung von Fehlern