

Artificial Intelligence

V01: The field of Artificial Intelligence

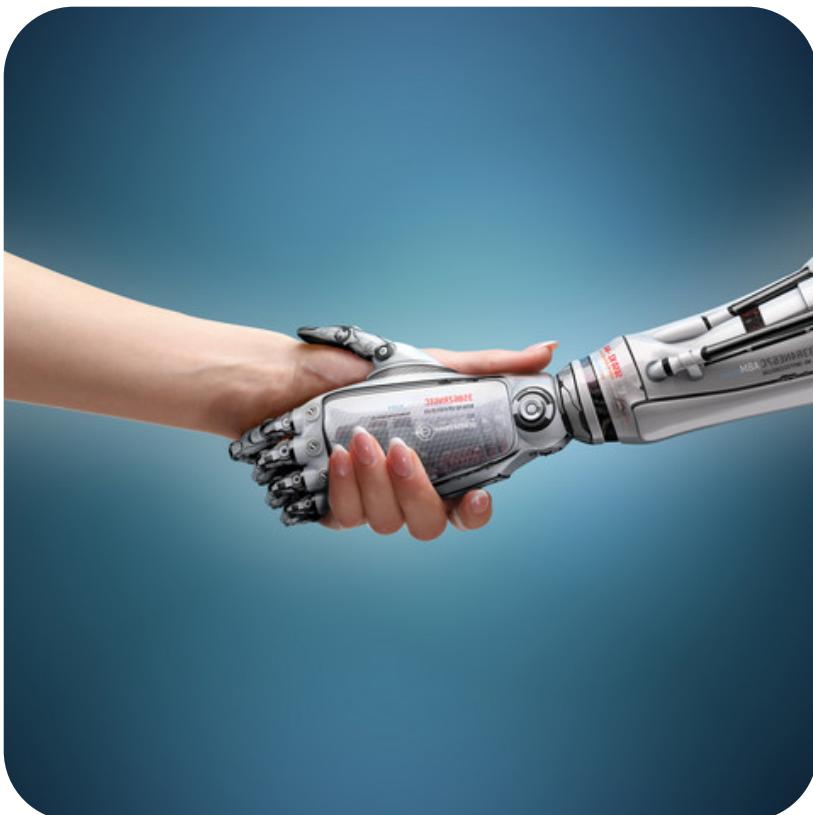
Logistics of this module

What is AI?

A brief history

The state of the Art

Based on material by Stuart Russell, UC Berkeley





0. LOGISTICS OF THIS MODULE

About me

Frank-Peter Schilling

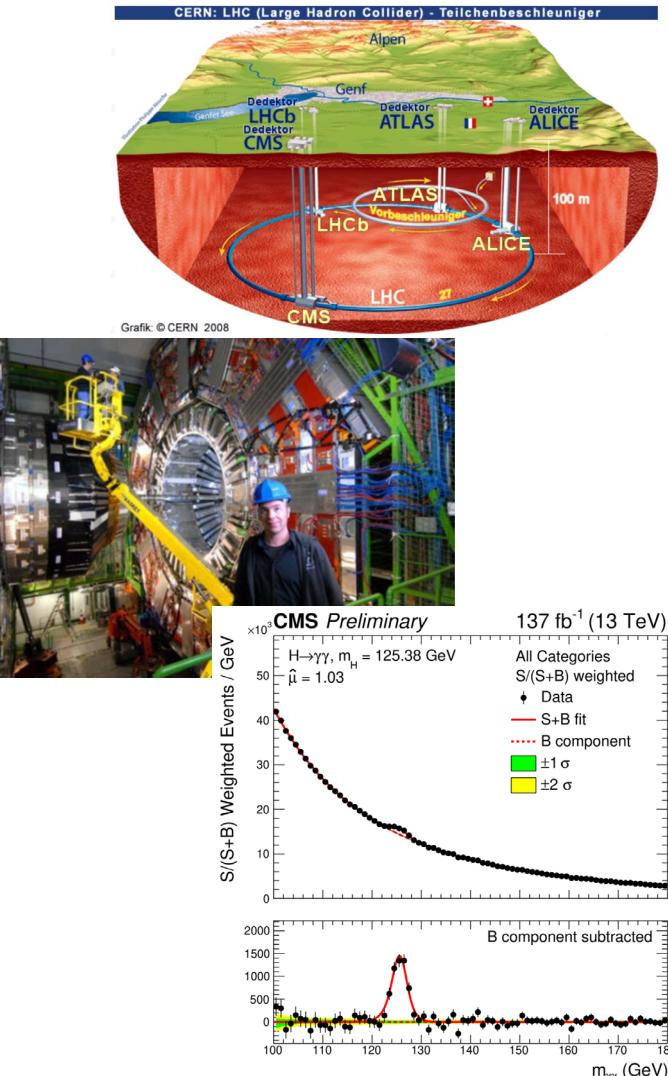
- PhD in Physics (Univ. Heidelberg)
- 15 years of research in particle physics at the DESY (Hamburg) and CERN (Geneva) laboratories
- Statistical big data analysis, machine learning, software development, project management, publications, ...
- Since 2018 at ZHAW

At ZHAW

- Senior researcher @ CAI, focus on AI and Deep Learning (Computer Vision with deep neural networks)
- Applied research projects with industrial partners
- Lectures and seminars on AI / ML for BSc / MSc students

Coordinates

- Campus Winterthur, TNO3.64, Email: scik@zhaw.ch
- Web: <https://www.zhaw.ch/en/about-us/person/scik/>



About You



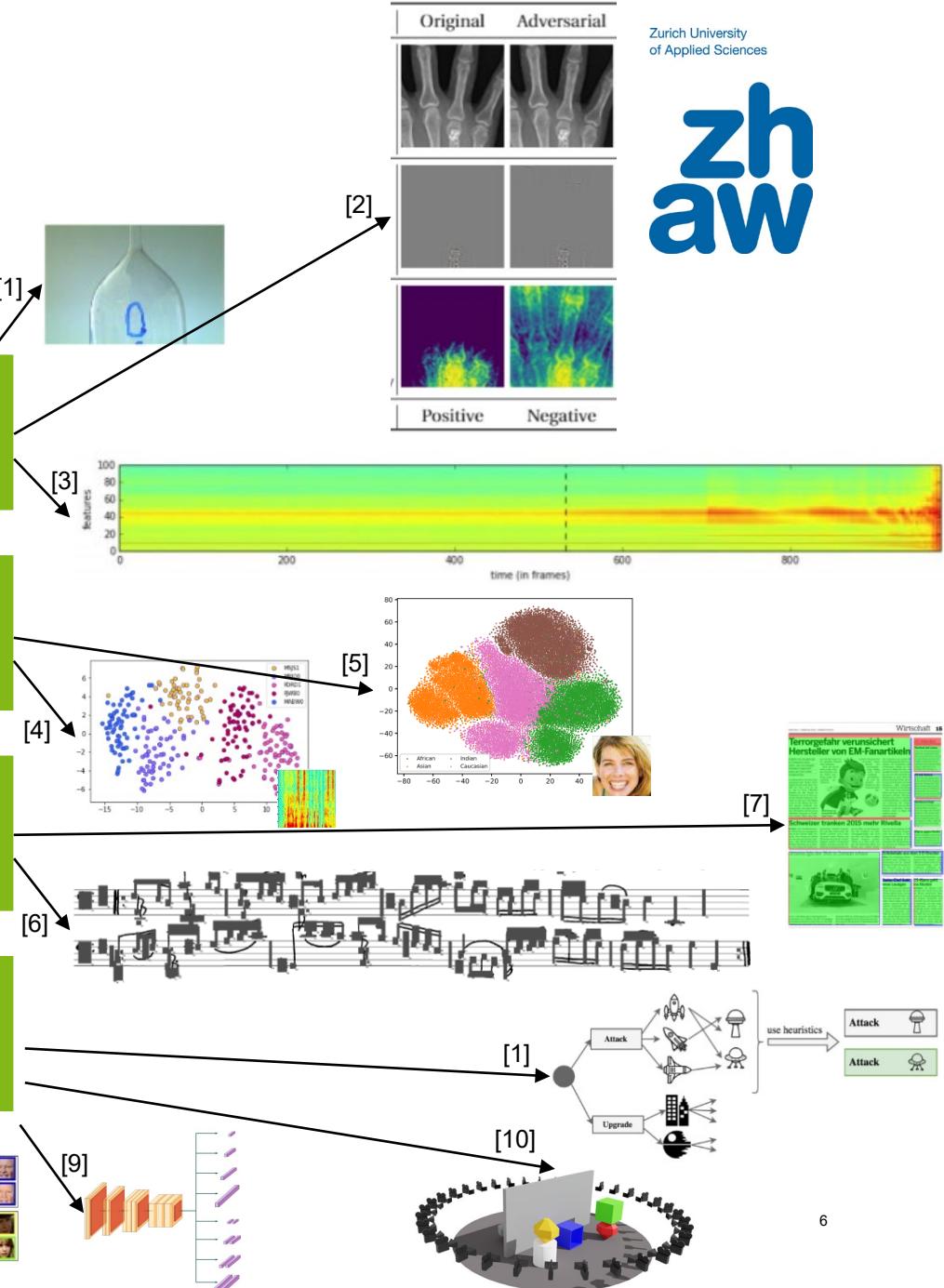
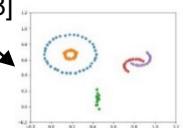
About our research

(see also <https://stdm.github.io>)



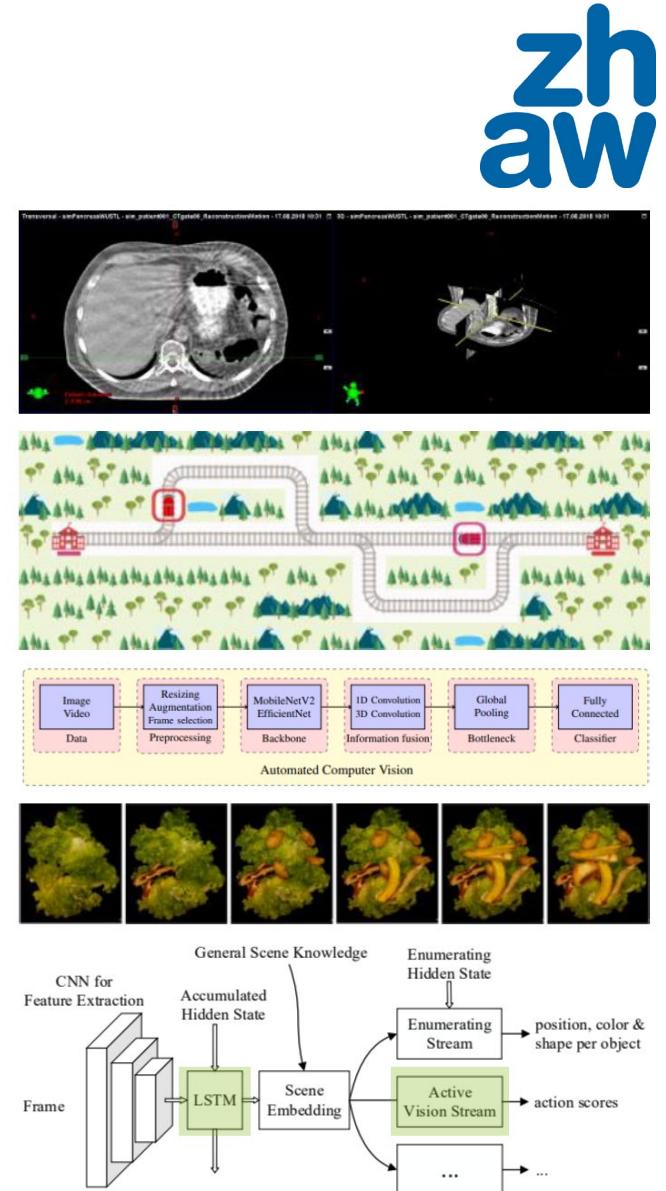
Machine learning-based Pattern Recognition

- Robust applications
- Biometrics
- Document Analysis
- Learning to act



Recent work in progress

- Learning to reduce **motion artifacts** in 3D CT scans
- Learning an artificial communication language for **multi-agent reinforcement learning** in logistics (notable rank in Flatland 2019 competition)
- **Automated deep learning** (top rank in AutoDL2020 challenge)
- Learning to **segment and classify food waste** in professional kitchens under adversarial conditions
- Improving **robotic vision** through active vision and combined supervised and reinforcement learning



CAI Highlights

Zurich University
of Applied Sciences



Mentoring
programme
for students!



About ZHAW Datalab

Est. 2013



Forerunner

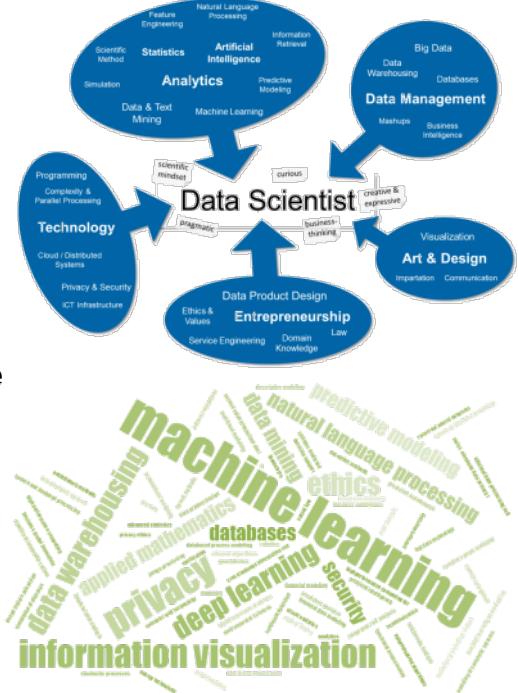
- **One of the first** interdisciplinary data science initiatives in Europe
- One of the first interdisciplinary centers at ZHAW

Foundation

- **People:** ca. 100 researchers from **9 institutes / 4 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**



Literature

Russell, Norvig, «*Artificial Intelligence – A Modern Approach*»,
4th edition 2020 (we use the “global edition”)

- Commonly known as *AIMA* or the *Intelligent Agent Book*
- *The textbook on AI: concise, complete, comprehensible*
- Among the 25 most cited scientific reference on CiteSeer

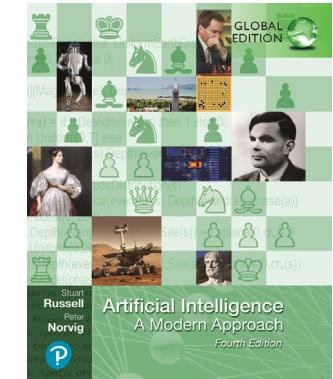
➔ **Lectures build on certain AIMA chapters**

https://swisscovery.slsp.ch/discovery/search?query=any.contains.russell%20norvig%20artificial%20intelligence%20modern%20approach&tab=41SLSP_NETWORK&search_scope=DN_and_CI&vid=41SLSP_NETWORK:VU1_UNION&offset=0

<http://aima.cs.berkeley.edu/global-index.html>

<https://www.amazon.de/Artificial-Intelligence-Modern-Approach-Global/dp/1292401133/>

<https://biz.delivros-orellfussli.ch/de/detail/ISBN-9781292401133/Norvig-Peter/Artificial-Intelligence-A-Modern-Approach-4th-Global-Edition>



Other good & informative reads

- Nilsson, «*The Quest for Artificial Intelligence*», 2010 (free PDF!)
→ *A History of Ideas and Achievements*
- Minski, «*The Society of Mind*», 1985
→ A collection of essays to explain how intelligence emerges from unintelligent parts
- Lytton, «*From Computer to Brain*», 2013
→ *Foundations of Computational Neuroscience*
- Bengio, «*Learning Deep Architectures for AI*», 2009
→ Deep machine learning from an AI perspective



Logistics



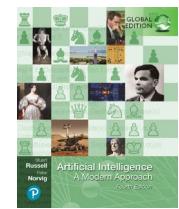
Lecture

- Starts on time, ends on time
- Gadgets (notebooks, tablets) are used for class purposes only



Self-study

- Read & experiment as much as possible at home (ca. **3h / week**)
- **Reading** corresponding **AIMA** chapters is **mandatory** (→ see later)



Material

- Everything on Moodle: <https://moodle.zhaw.ch/course/view.php?id=2069>
(slides & lab material will probably be updated directly before their use)



Grading

- Final exam (SEP): 90 minutes written test, **closed book**, **1 A4 sheet of handwritten notes** allowed
(← this might change due to COVID-19) max. 80 points
- Labs: **2 graded labs** of **your choice**, **demonstrated** until one week after the official end of this lab max. 20 points

→ See terms & conditions on Moodle

Fall term 2021: Schedule AI1 Winti & Zurich



Read this
on time!

| SW | Topic | Lecture | Lab | AIMA | Winti | ZH |
|----|--------------------------|--|---|----------------------|--------|--------|
| 1 | Introduction | Welcome & P01: Future & AI | Will be discussed during lecture time | - | 21.09. | 20.09. |
| 2 | | V01: The field of artificial intelligence | -"- (P01.1: Your view of AI) | ch. 1.1-1.4 | 28.09. | 27.09. |
| 3 | | V02: Intelligent agents | -"- (P01.2: ...revisited) | ch. 2 | 05.10. | 04.10. |
| 4 | Search | V03: Problem solving through search | P02: 2048 (P02.1: Learn Python) | ch. 3 | 12.10. | 11.10. |
| 5 | | V04: Local and adversarial search | -"- (P02.2: Heuristic agent) | ch. 6 (+4) | 19.10. | 18.10. |
| 6 | | V05: Constraint satisfaction problems | -"- (P02.3: Expectimax agent) | ch. 5 | 26.10. | 25.10. |
| 7 | Planning | V06a: Knowledge, reasoning & logic | P03: CSP & Logic (P03.1: Sudoku) | ch. 7 | 02.11. | 01.11. |
| 8 | | V06b: Datalog | -"- (P03.2: Datalog) | ch. 8 (+9) | 09.11. | 08.11. |
| 9 | | V07: Planning | -"- | ch. 11 | 16.11. | 15.11. |
| 10 | Learning | V08: Supervised learning with neural networks | AIMA Catchup Week | ch. 19.1-19.6 | 23.11. | 22.11. |
| 11 | | V09: Unsupervised learning with autoencoders | P04: Using neural nets (P04.1: Autoencoders) | ch. 19.8-19.9 | 30.11. | 29.11. |
| 12 | | V10: Generative adversarial learning for image synthesis | -"- (P04.2: Image synthesis) | ch. 21 | 07.12. | 06.12. |
| 13 | Selected chapters | V11: Reinforcement learning for game play | P05: Tic-tac-toe | ch. 22.1, 22.3, 22.7 | 14.12. | 13.12. |
| 14 | | V12: AI & society, Exam preparation, FAQ | -"- | ch. 1.5, 28 | 21.12. | 20.12. |

Questions regarding the exam will be answered **up to this point** (last week of the semester) – please prepare your material / questions in advance

All materials (V/P), up-to-date schedule, terms & conditions etc. → Moodle

Superior educational objectives

- You **Know** the breadth of AI problem solving strategies
- ...thus **identify** such challenges in practice
- ...and **develop** corresponding solutions on your own.

- You can **explain** the discussed algorithms and methodologies
- ...and are able to **transfer** it to the real world.

- ➔ This course is concerned with **methodology** and a good understanding of **what** may work **where**
- ➔ It thus **sacrifices depth** in how to implement concrete solutions **or proofs** why things work

P01: AI and the Future

Reading assignment & Blog posts

Two essays about AI, its impact on society, the potential pro's/con's of a superhuman AI (AGI) and the future

- Dirk Helbing, “What’s Wrong with AI? A Discussion Paper”, SI Magazine, 2020
 - <https://magazine.swissinformatics.org/en/whats-wrong-with-ai/>
- Rodney Brooks, “The Seven Deadly Sins of AI Predictions”, MIT Technology Review, October 2017
 - <https://www.technologyreview.com/2017/10/06/241837/the-seven-deadly-sins-of-ai-predictions/>

The screenshot shows the homepage of SI Magazine. At the top right is the zhaw logo. Below it is the SI Magazine logo with the tagline "SWISSINFORMATICS SOCIETY'S NEW ONLINE PLATFORM". The main navigation menu includes links for HOME, NEWS (with a dropdown for DEUTSCH), EVENTS, TECHNOLOGIE, LERNEN, SOCIETY, and WIRTSCHAFT. Below the menu are links for INTERVIEWS, BÜCHER, KULTUR, GESUNDHEIT, SI HOMEPAGE, and SI TWEETS. A search bar at the bottom right contains the text "SUCHE ...".

What’s Wrong with AI? A Discussion Paper

0

AI ON THE RISE

There are probably not many people who would doubt that we have arrived in an age of Big Data and Artificial Intelligence (AI). Of course, this opens up many previously untapped opportunities, ranging from production to automated driving and everyday applications. In fact, not only digital assistants such as Google Home, Siri or Alexa, but also many web services and apps, smartphones and home appliances, cleaning robots and even toys already use AI or at least some kind of machine learning.

Technology visionaries such as Ray Kurzweil predicted that AI would have the power of an insect brain in 2000, the power of a mouse brain around 2010, human-like brainpower around 2020 and the power of *all*/human brains on Earth before the middle of this century. Many do not share this extremely techno-optimistic view, but it cannot be denied that IBM’s Deep Blue computer beat the Chess genius Kasparov back in 1997, IBM’s Watson computer won the knowledge game Jeopardy back in 1997, and Google’s AlphaGo system beat the 18-time world champion Lee Sedol in the highly complex strategy game “Go” in 2016 – about 10 to 20 years before many experts had expected this to happen. When AlphaZero managed to outperform AlphaGo without human training, just by playing Go a lot of times against itself, the German news journal “Spiegel” wrote on October 29, 2017: “Gott braucht keine Lehrmeister”^[1] (“God does not need a teacher.”).

AI as God?

This was around the time when Anthony Levandowski, a former head of Google’s self-driving car project, founded a religion that worships an AI God.^[2] By that time, many considered Google to be almost all-knowing. With the Google Loon project, they were also working on omni-presence. Omnipotence was still a bit of a challenge, but as the world learned by the end of 2015, it was possible to manipulate people’s attention, opinions, emotions, decisions, and behaviors with personalized information.^[3] In a sense, our brains had been hacked. However, only in summer 2017 did a previous member of a Google control room, Tristan Harris, reveal in his TED talk, “How a handful of companies control billions of minds every day”.^[4] At the same time, Google was trying to build superintelligent systems and to become something like an emperor over life and death, namely with its Calico project.^[5]

P01

AI & The Future (cont.)

16.2.2018

The Seven Deadly Sins of AI Predictions - MIT Technology Review

- **Tasks:**
 - Part P01.1:
 - Read 1st article and write a blog post about it
 - Part P01.2:
 - Read 2nd article and write a new blog post about it
- **Tips:**
 - Use a platform of your choice (blogger, github etc.)
 - Should be accessible at least for tutor and your fellow students
 - **Content**
 - Summarize the main points of the essays
 - Highlight what you liked / found important
 - Formulate your own opinion (where did you (dis)agree and why?)
 - **The 2nd post**
 - Should also revisit your first post in light of what you learned so far about what AI can (not) do
 - **Comment on posts of your fellow students (links will be shared)**
 - **Use possibilities of medium (figs, links, references etc.)**



JOOST SWARTE

Intelligent Machines

The Seven Deadly Sins of AI Predictions

Mistaken extrapolations, limited imagination, and other common mistakes that distract us from thinking more productively about the future.

by Rodney Brooks October 6, 2017



We are surrounded by hysteria about the future of artificial intelligence and robotics—hysteria about how powerful they will become, how quickly, and what they will do to jobs.

I recently saw a story in MarketWatch that said robots will take half of today's jobs in 10 to 20 years. It even had a graphic to prove the numbers.

The claims are ludicrous. (I try to maintain professional language, but sometimes ...) For instance, the story appears to say that we will go from one million grounds and maintenance workers in the U.S. to only 50,000 in 10

END for today ...

Educational objectives for this lecture



- **Know** the history and breadth of the discipline of Artificial Intelligence
- **Define** what is meant by the term AI (and what is not)
- Be able to **engage** in an educated discussion on the state of the art and future of AI (→ see P01)

“In which we try to explain why we consider artificial intelligence to be a subject most worthy of study, and in which we try to decide what exactly it is, this being a good thing to decide before embarking.”

➔ Reading: AIMA, ch. 1





1. WHAT IS AI?

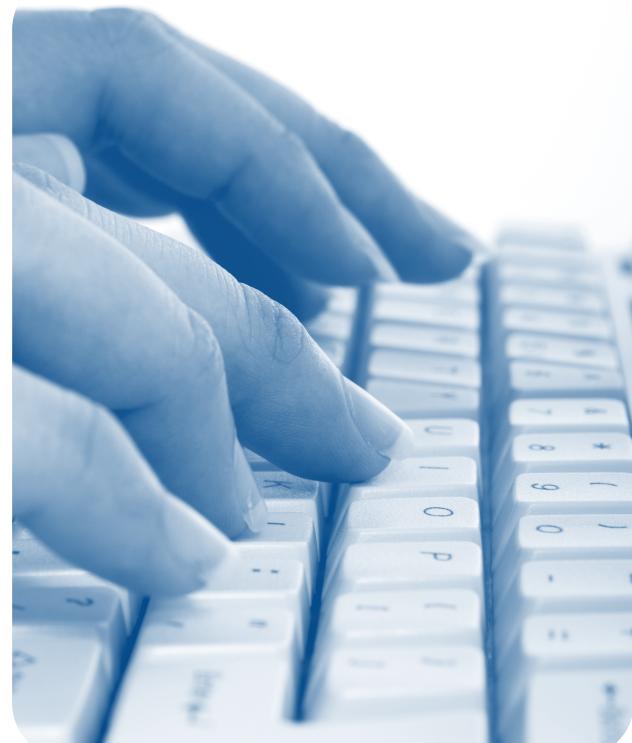
Exercise: What is AI for you?

- Think about a concise, one to two sentence definition of AI
- Is it discriminative enough (i.e., doesn't it work as a definition for something else, e.g. more general or more specific)?
- Is it wide enough (i.e., does it encompass all that AI is, not just what it does, or where it comes from)?
- Does it help to think what intelligence is for you? What is intelligence for you, anyway?
- Discuss with your neighbors

Personal answer stdm:

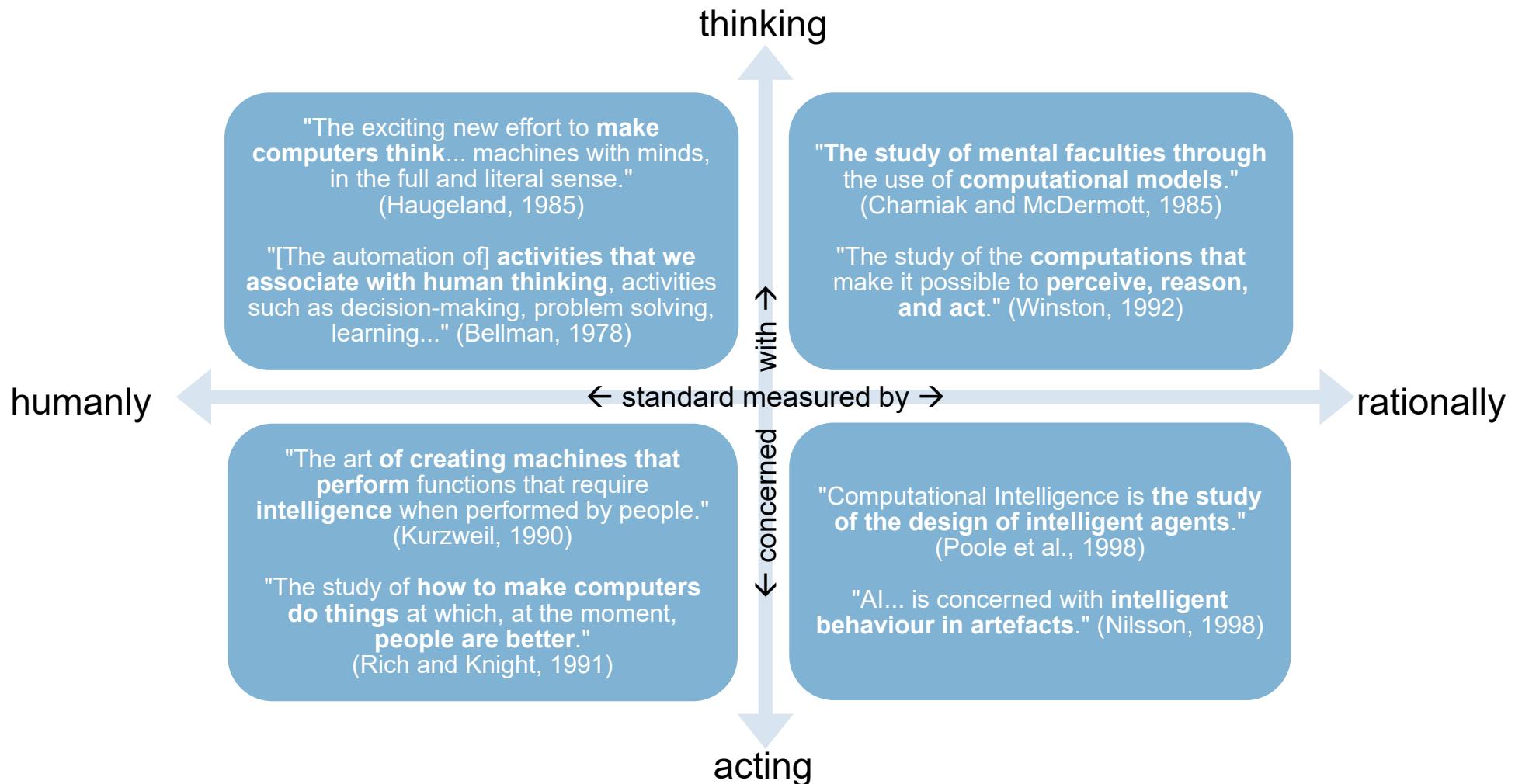
**AI: The scientific field concerned with
*complex computer applications***

**Intelligence: the power to *continually surprise*
me in a *positive way***



AI definitions

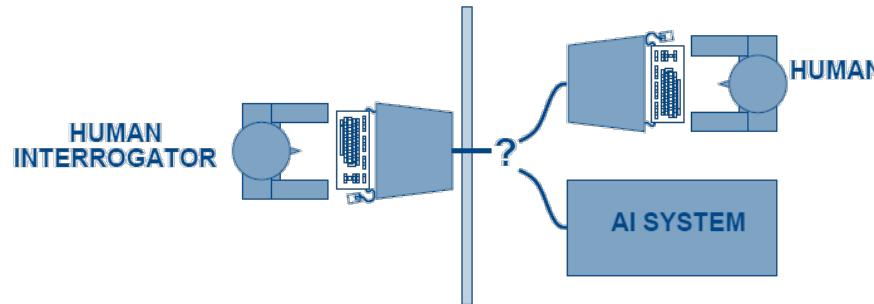
Or: schools of thought



Acting humanly: The Turing test

Turing, "Computing machinery and intelligence", 1950

- “**Can machines think?**” → “*Can machines behave intelligently?*”
- Operational test for intelligent behaviour: the **Imitation Game**



- Predicted that by 2000, a machine might have a 30% chance of fooling a lay person for 5 minutes
- Anticipated all major arguments against AI in following 50 years
- Suggested all major components of AI: [natural language processing](#), [knowledge representation](#), [automated reasoning](#), [machine learning](#) (+[computer vision](#), [robotics](#)) for full Turing test incl. video)

Problem: **Not reproducible, constructive**, or amenable to **mathematical analysis**

Thinking humanly: Cognitive science

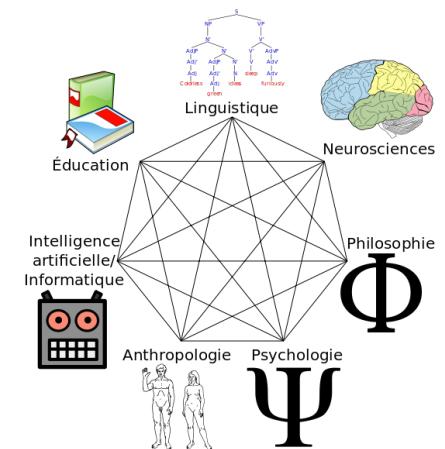
Understanding the human mind by computer modelling

1960s “cognitive revolution”

- information-processing psychology replaced prevailing orthodoxy of **behaviourism**

Requires scientific theories of internal activities **of the brain**

- What level of abstraction? “Knowledge” or “circuits”?
- How to validate? Requires...
 - ...predicting and testing behaviour of human subjects (top-down) or
 - ...direct identification from neurological data (bottom-up)



Today

- Both approaches (roughly, **cognitive science** and **cognitive neuroscience**) are now distinct from AI
- Both share with AI the following characteristic:
 - The **available theories do not explain** (or engender) anything resembling human-level general intelligence
 - Hence, all three fields share one principal direction

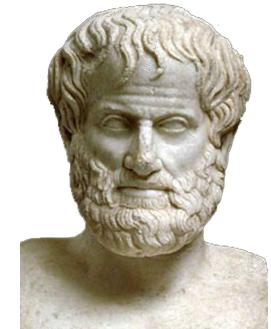
Thinking rationally: Laws of thought

How to make provably correct inference?

Several Greek schools developed various forms of **logic**

- Aristotle: What are correct arguments/thought processes?
- **Notation** and **rules of derivation** for thoughts
- May or may not have proceeded to the idea of mechanization

- **Normative** (or **prescriptive**) rather than descriptive
- Direct line through mathematics and philosophy to modern AI



Problems

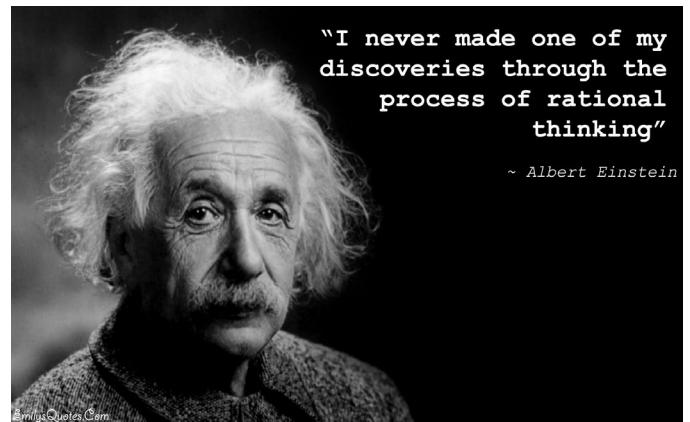
1. Not all intelligent behaviour is mediated by logical deliberation (e.g., uncertainty exists)
2. What is the **purpose of thinking**? What thoughts **should** I have out of all the thoughts (logical or otherwise) that I **could** have?

Acting rationally

Rational behaviour: **doing the right thing**

*that which is expected to maximize goal achievement,
given the available information*

- Doesn't necessarily involve thinking (e.g.: blinking reflex) but thinking should be in the service of rational action



Aristotle (Nicomachean ethics)

- **Every art and every inquiry, and similarly every action and pursuit, is thought to aim at some good**

Rational agents

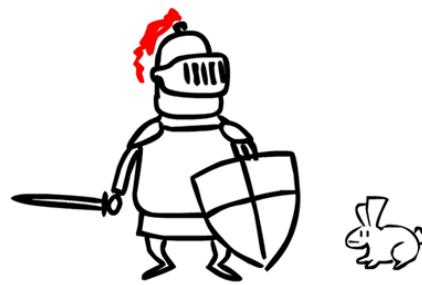
A practical way and goal of this course

Agents

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

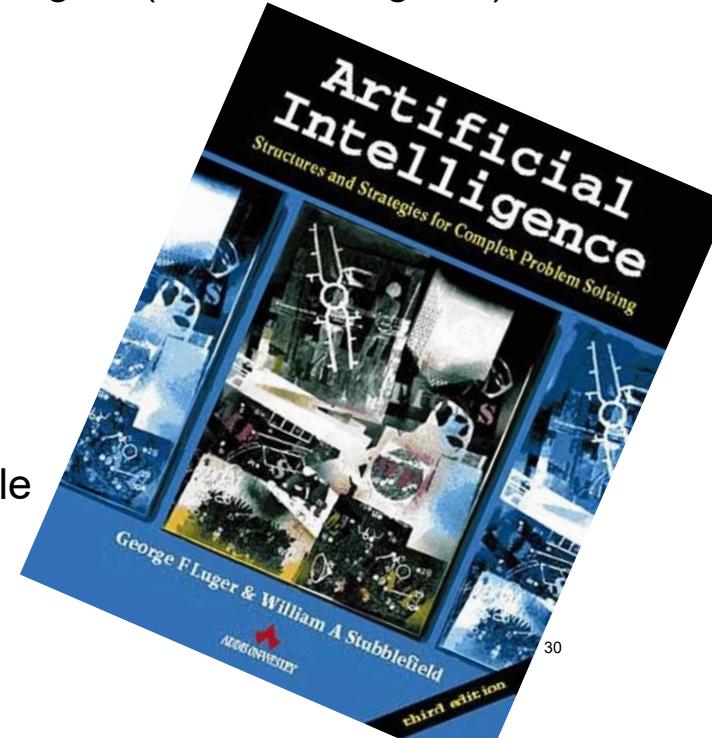
Rational agents

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

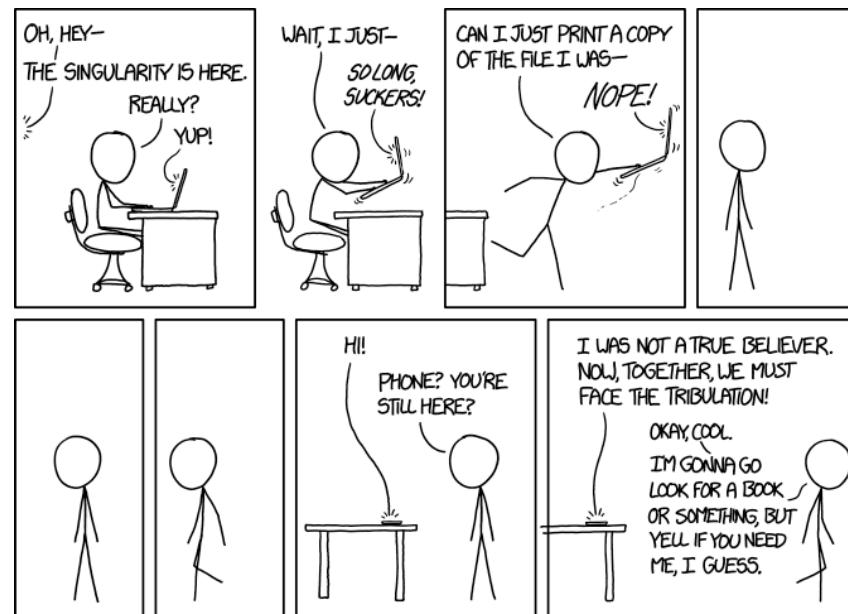


Caveat

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

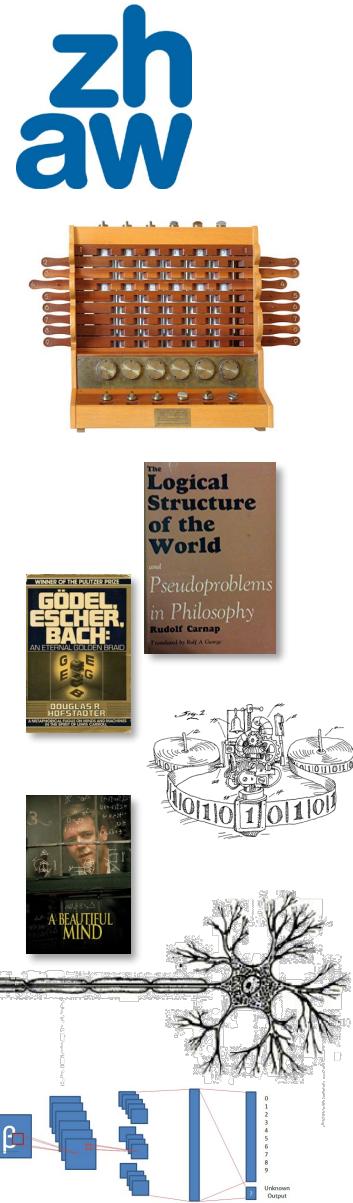


2. A BRIEF HISTORY

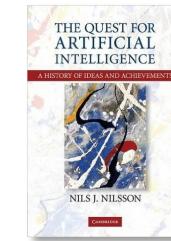


AI prehistory

AI paybacks to **computer science**: e.g. time sharing, interactive interpreters, GUI & mice, linked list, symbolic/functional/declarative/OO programming

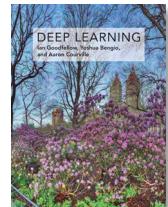
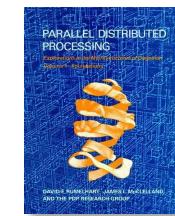
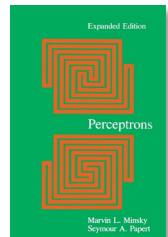


| | |
|-----------------------|--|
| Philosophy | logic , methods of reasoning mind as physical system (roots of calculation machines) foundations of learning, language, rationality (induction, empiricism, rationalism, utilitarianism) |
| Mathematics | formal representation and proof algorithms, computation (complexity, (un)decidability, (in)tractability) Probability |
| Psychology | adaptation phenomena of perception and motor control experimental techniques (controlled experiments, behaviourism) |
| Economics | formal theory of rational decisions , game theory |
| Linguistics | knowledge representation, natural language processing Grammar |
| Neuroscience | plastic physical substrate for mental activity |
| Control theory | Cybernetics (homeostatic systems: stability via feedback loops) simple optimal agent designs (objective function optimization) |



Potted history of AI

- 1943** McCulloch & Pitts: Boolean circuit model of brain
- 1950** Turing's “*Computing Machinery and Intelligence*”
- 1952-69** “Look, Ma, no hands!”
- 1950s** Early AI programs, including Samuel's **checkers program**, Newell & Simon's **Logic Theorist**, Gelernter's Geometry Engine
- 1956** **Dartmouth meeting**: “*Artificial Intelligence*” adopted
- 1965** Robinson's complete algorithm for logical reasoning
- 1966-74** AI discovers computational complexity
Neural network (NN) research almost disappears: 1st “**AI Winter**”
- 1969-79** Early development of knowledge-based systems
- 1980-88** **Expert systems** industry booms
- 1988-93** Expert systems industry busts: 2nd “**AI Winter**”
- 1985-95** Neural networks return to popularity
- 1988** Resurgence of **probability**; general increase in technical depth
“Nouvelle AI”: Artificial Life, Genetic Algorithms, soft computing
- 1995** **Agents**, agents, everywhere...
- 2003** Human-level AI back on the agenda
- Since 2010** **Machine learning** widely applied in industry (trends of big data, data science)
Superhuman performance in pattern recognition via NN under guise of “**deep learning**”
- Since 2016** **Buzzword** again, used to sell everything “digital”
- 2018** CLAIRE initiative for AI research in Europe



3. THE STATE OF THE ART

Which of the following can be done at present?

- | | |
|---|------------------------|
| 1. Play a decent game of table tennis | ok |
| 2. Drive safely along a curving mountain road | ok |
| 3. Drive safely along Technikumstrasse Winterthur | ok (only as prototype) |
| 4. Buy a week's worth of groceries on the web | ok |
| 5. Buy a week's worth of groceries at Migros | no |
| 6. Play a decent game of bridge | ok |
| 7. Discover and prove a new mathematical theorem | not completely |
| 8. Design and execute a research program in molecular biology | not completely |
| 9. Write an intentionally funny story | no |
| 10. Give competent legal advice in a specialized area of law | ok |
| 11. Translate spoken English into spoken Swedish in real time | ok |
| 12. Converse successfully with another person for an hour | no (but some minutes) |
| 13. Perform a complex surgical operation | not completely |
| 14. Unload any dishwasher and put everything away | no |
| 15. Compete in the game show Jeopardy! | ok |
| 16. Write clickbait articles fully automatized | ok |
| 17. Write mathematical articles fully automatized | not completely |

Learning to produce text char by char

See <http://karpathy.github.io/2015/05/21/rnn-effectiveness>

```
\begin{proof}
```

We may assume that \mathcal{I} is an abelian sheaf on \mathcal{C} .

\item Given a morphism $\Delta : \mathcal{F} \rightarrow \mathcal{I}$
is an injective and let \mathfrak{q} be an abelian sheaf on X .

Let \mathcal{F} be a fibered complex. Let \mathcal{F} be a category.

```
\begin{enumerate}
```

\item \hyperref[setain-construction-phantom]{Lemma}

\label{lemma-characterize-quasi-fir}

Let \mathcal{F} be an abelian quasi-

Let \mathcal{F} be a coherent \mathcal{O} -

\mathcal{F} is an abelian catena-

\item The following are equivalent

```
\begin{enumerate}
```

\item \mathcal{F} is an \mathcal{O} -

```
\end{lemma}
```

Proof. Omitted. \square

Lemma 0.1. Let \mathcal{C} be a set of the construction.

Let \mathcal{C} be a gerber covering. Let \mathcal{F} be a quasi-coherent sheaves of \mathcal{O} -modules. We have to show that

$$\mathcal{O}_X = \mathcal{O}_X(\mathcal{L})$$

Proof. This is an algebraic space with the composition of sheaves \mathcal{F} on $X_{\text{étale}}$ we have

$$\mathcal{O}_X(\mathcal{F}) = \{\text{morph}_1 \times_{\mathcal{O}_X} (\mathcal{G}, \mathcal{F})\}$$

where \mathcal{G} defines an isomorphism $\mathcal{F} \rightarrow \mathcal{G}$ of \mathcal{O} -modules. \square

Lemma 0.2. This is an integer \mathcal{Z} is injective.

Proof. See Spaces, Lemma ??.

Lemma 0.3. Let S be a scheme. Let X be a scheme and X is an affine open covering. Let $\mathcal{U} \subset \mathcal{X}$ be a canonical and locally of finite type. Let X be a scheme. Let X be a scheme which is equal to the formal complex.

The following to the construction of the lemma follows.

Let X be a scheme. Let X be a scheme covering. Let

$$b : X \rightarrow Y' \rightarrow Y \rightarrow Y' \times_X Y \rightarrow X.$$

be a morphism of algebraic spaces over S and Y .

Proof. Let X be a nonzero scheme of X . Let X be an algebraic space. Let \mathcal{F} be a quasi-coherent sheaf of \mathcal{O}_X -modules. The following are equivalent

- (1) \mathcal{F} is an algebraic space over S .
- (2) If X is an affine open covering.

Consider a common structure on X and X the functor $\mathcal{O}_X(U)$ which is locally of finite type. \square

This since $\mathcal{F} \in \mathcal{F}$ and $x \in \mathcal{G}$ the diagram

$$\begin{array}{ccc} S & \xrightarrow{\quad} & \\ \downarrow & & \downarrow \\ \xi & \xrightarrow{\quad} & \mathcal{O}_{X'} \\ \text{gor}_s & & \uparrow \\ & & = \alpha' \xrightarrow{\quad} \\ & & = \alpha' \xrightarrow{\quad} \alpha \end{array}$$

is a limit. Then \mathcal{G} is a finite type and assume S is a flat and \mathcal{F} and \mathcal{G} is a finite type f_s . This is of finite type diagrams, and

- the composition of \mathcal{G} is a regular sequence,
- $\mathcal{O}_{X'}$ is a sheaf of rings.

Proof. We have see that $X = \text{Spec}(R)$ and \mathcal{F} is a finite type representable by algebraic space. The property \mathcal{F} is a finite morphism of algebraic stacks. Then the cohomology of X is an open neighbourhood of U . \square

Proof. This is clear that \mathcal{G} is a finite presentation, see Lemmas ??.
A reduced above we conclude that U is an open covering of C . The functor \mathcal{F} is a field

$$\mathcal{O}_{X,s} \longrightarrow \mathcal{F}_{\mathbb{Z}}^{-1}(\mathcal{O}_{X_{\text{étale}}}) \longrightarrow \mathcal{O}_{X_s}^{-1}\mathcal{O}_{X_s}(\mathcal{O}_{X_s}^{\text{pt}})$$

is an isomorphism of covering of \mathcal{O}_{X_s} . If \mathcal{F} is the unique element of \mathcal{F} such that X is an isomorphism.

The property \mathcal{F} is a disjoint union of Proposition ?? and we can filtered set of presentations of a scheme \mathcal{O}_X -algebra with \mathcal{F} are opens of finite type over S .

If \mathcal{F} is a scheme theoretic image points. \square

If \mathcal{F} is a finite direct sum \mathcal{O}_{X_s} is a closed immersion, see Lemma ???. This is a sequence of \mathcal{F} is a similar morphism.

Computer vision and control

From Yann LeCun's NIPS'2016 keynote

Image captioning, Semantic Segmentation with ConvNets Y LeCun

[Farabet et al. ICML 2011]
[Farabet et al. PAMI 2013]

A man riding skis on a snow covered ski slope.
NP: a man, skis, the snow, a person, a woman, a snow covered slope, a slope, a snowboard, a skier, man.
VP: wearing, riding, holding, standing on, skiing down.
PP: on, in, of, with, down.
A man wearing skis on the snow.

A man is doing skateboard tricks on a ramp.
NP: a skateboard, a man, a trick, his skateboard, the air, a skateboarder, a ramp, a skate board, a person, a woman.
VP: doing, riding, is doing, performing, flying through.
PP: on, of, in, at, with.
A man riding a skateboard on a ramp.

The girl with blue hair stands under the umbrella.
NP: a woman, an umbrella, a man, a person, a girl, umbrellas, that, a little girl, a cell phone.
VP: holding, wearing, is holding, holds, carrying.
PP: with, on, of, in, under.
A woman is holding an umbrella.

VizDoom Champion: Actor-Critic RL system from FAIR Y LeCun
Won the VizDoom 2016 competition.
[Wu & Tian, submitted to ICLR 2017]

[Lebret, Pinheiro, Collobert 2015][Kulkarni 11][Mitchell 12][Vinyals 14][Mao 14][Karpathy 14][Donahue 14]...

The story of Rocket AI @ NIPS'2016

Or: The danger of hype



Quoting from the blog post (<https://medium.com/the-mission/rocket-ai-2016s-most-notorious-ai-launch-and-the-problem-with-ai-hype-d7908013f8c9#.9qjgyxre5>):

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.

Review

- AI is a traditional **sub discipline of computer science** with strong **interdisciplinary roots**
- Among several definitions of the field, to “**act rationally**” lends itself best to **practical exploitation**
- The state of the art comprises **numerous human-level systems** for narrow tasks (“**Artificial Narrow Intelligence**”, as opposed to “Artificial General Intelligence”)
- **AI people** tend to be visionaries motivated by **solving certain applications**, *by the way* discovering new methodologies and principles (like programming paradigms, multi-threading, etc.): **“Just do it”**





APPENDIX

Secrets of success

Do program, do take notes (yourself)!

Formulate goals,
cross-connect
knowledge

Know your learning style (Kolb):
do you need additional material
to our deductive (general theory
→ example) approach to AI?

*«Most of the things you need will be brought to you;
most of the things you want you have to go get.»*
(Bill Johnson)

Use self study
possibilities



Unintentionally funny stories

One day Joe Bear was hungry. He asked his friend Irving Bird where some honey was. Irving told him there was a beehive in the oak tree. Joe threatened to hit Irving if he didn't tell him where some honey was. The End.

Joe Bear was hungry. He asked Irving Bird where some honey was. Irving refused to tell him, so Joe offered to bring him a worm if he'd tell him where some honey was. Irving agreed. But Joe didn't know where any worms were, so he asked Irving, who refused to say. So Joe offered to bring him a worm if he'd tell him where a worm was. Irving agreed. But Joe didn't know where any worms were, so he asked Irving, who refused to say. So Joe offered to bring him a worm if he'd tell him where a worm was...

Henry Squirrel was thirsty. He walked over to the river bank where his good friend Bill Bird was sitting. Henry slipped and fell in the river. Gravity drowned. The End.

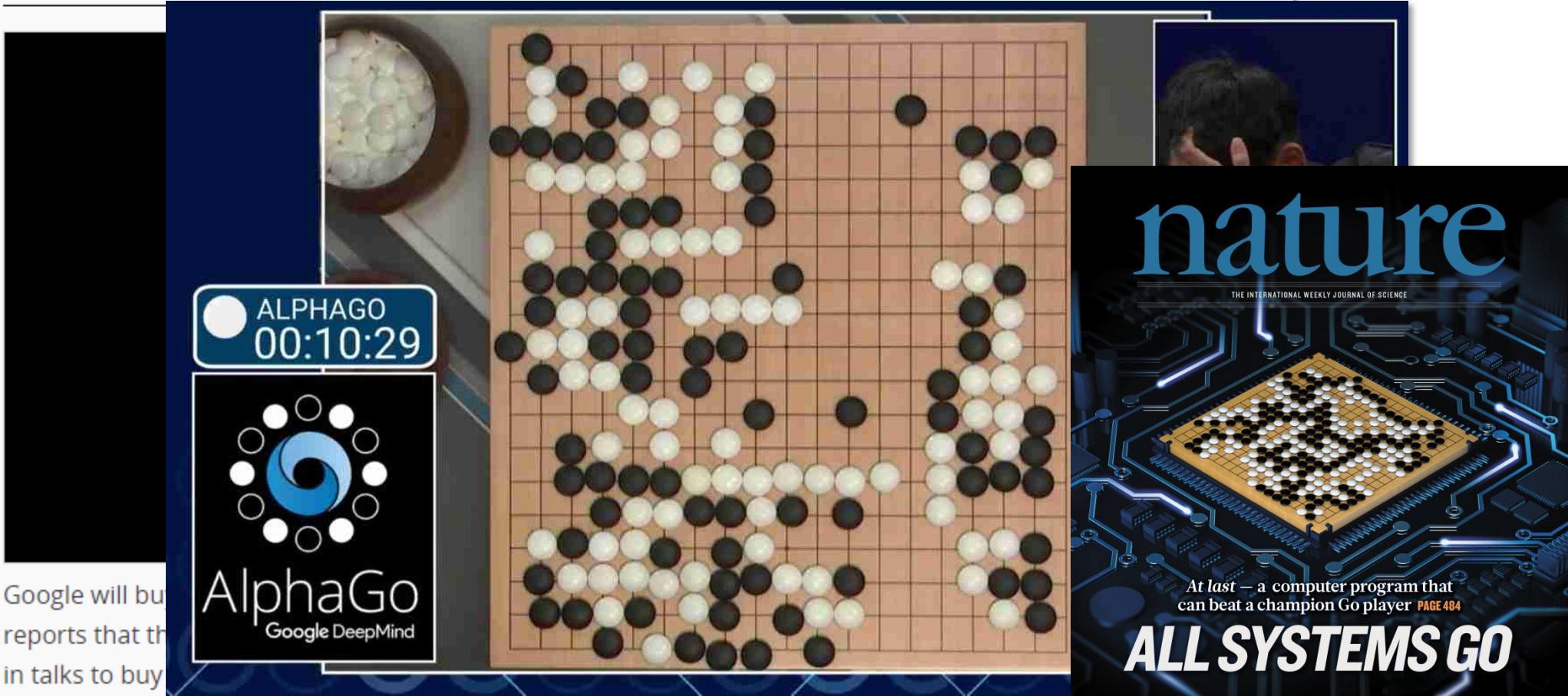
Once upon a time there was a dishonest fox and a vain crow. One day the crow was sitting in his tree, holding a piece of cheese in his mouth. He noticed that he was holding the piece of cheese. He became hungry, and swallowed the cheese. The fox walked over to the crow. The End.

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

Zurich University
of Applied Sciences



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.

Google's WaveNet uses neural nets to generate eerily convincing speech and music

Posted Sep 9, 2016 by Devin Coldevey



Generating speech from a piece of text is a common and important task undertaken by computers, but it's pretty rare that the result could be mistaken for ordinary speech. A new technique from researchers at Alphabet's DeepMind takes a completely different approach, producing speech and even music that sounds eerily like the real thing.

Early systems used a large library of the parts of speech (phonemes and morphemes) and a large ruleset that described all the ways letters combined to produce those sounds. The pieces were joined, or concatenated, creating functional speech synthesis that can handle most words, albeit with unconvincing cadence and tone. Later systems parameterized the generation of sound, making a library of speech fragments unnecessary. More compact — but often less effective.

WaveNet, as the system is called, takes things deeper. It simulates the sound of speech at as low a level as possible: one sample at a time. That means building the waveform from scratch — 16,000 samples per second.

Zurich University
of Applied Sciences

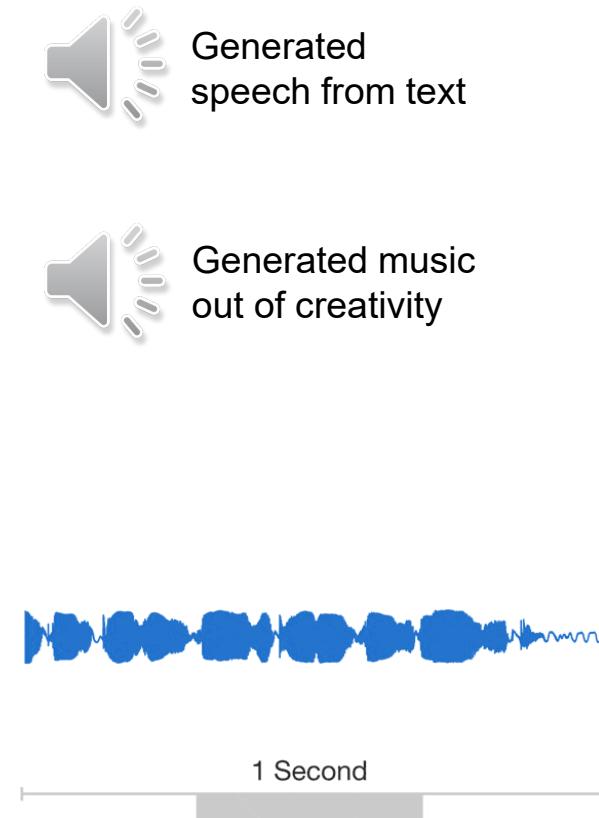


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Computing

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

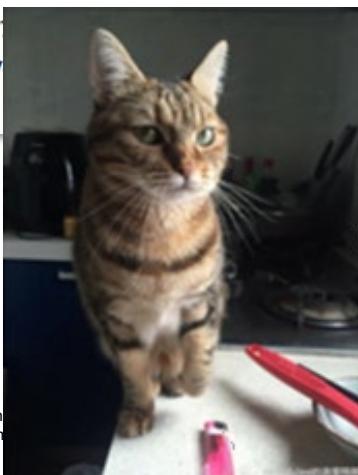
A deep neural network has learned to transfer artistic styles to other images.

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*, or Edvard Munch's *The Scream*, or any other image that humans recognize easily.



...and the list could be continued

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 statistic 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] Generating images with GANs
 - Running DCGANs
- Step 3: Finding the right way to do image completion
 - Image completion with GANs
 - [ML-Heavy] Generating images with GANs
 - [ML-Heavy] Generating images with GANs
 - Completing your images with GANs
- Conclusion
- Partial bibliography
- Bonus: Incomplete list of papers

Introduction

Content-aware fill is a powerful technique for image completion and inpainting. It can do content-aware fill, image completion, and semantic image inpainting. "Semantic Image Inpainting" shows how to use deep learning to fill in some deeper portions of images. This section can be skipped if you're not interested in image completion from images of faces. I have a blog post about image completion: [imagecompletion.tensorflow](#).

We'll approach image completion by first:

1. We'll first interpret what we want to do.
2. This interpretation will lead us to a solution.
3. Then we'll find the right way to implement it.



Andrey 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.

Based on the King Lear image: [http://www.english-test.net/testes/composition/king-lear.html](#). On 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 of

