

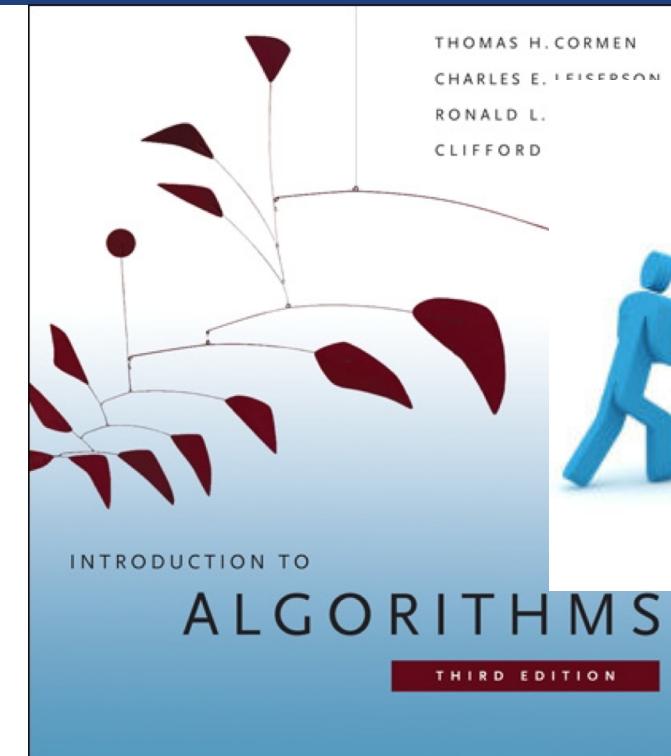
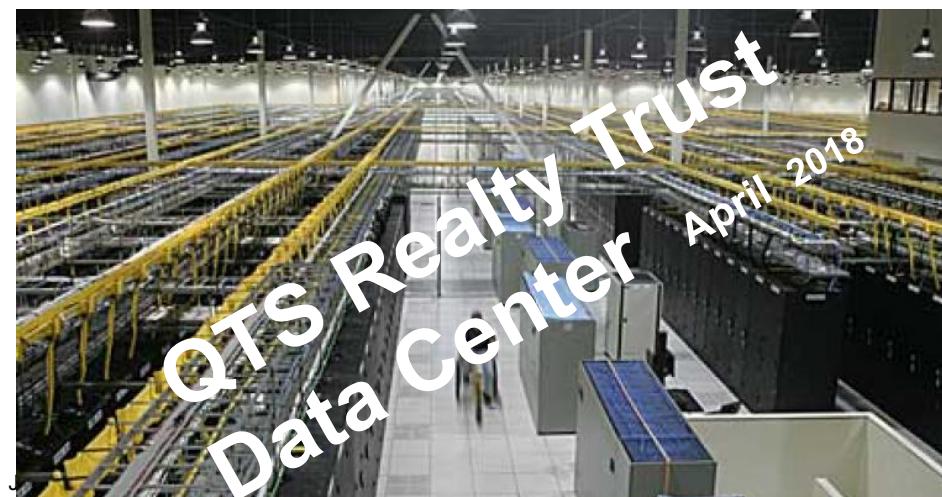
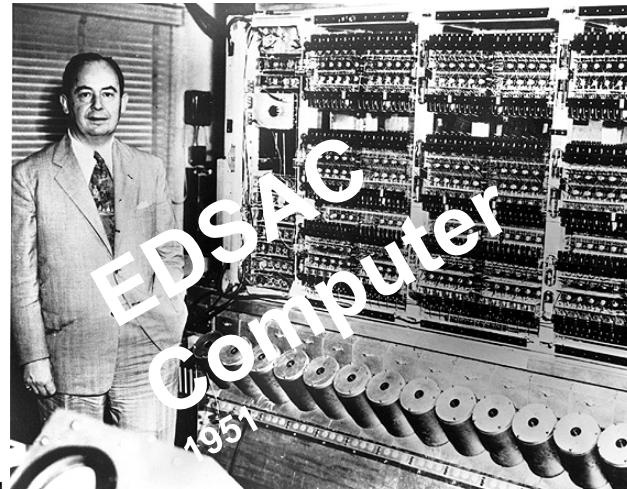


Advanced Machine Learning, Lecture 2019 Philosophical Motivation

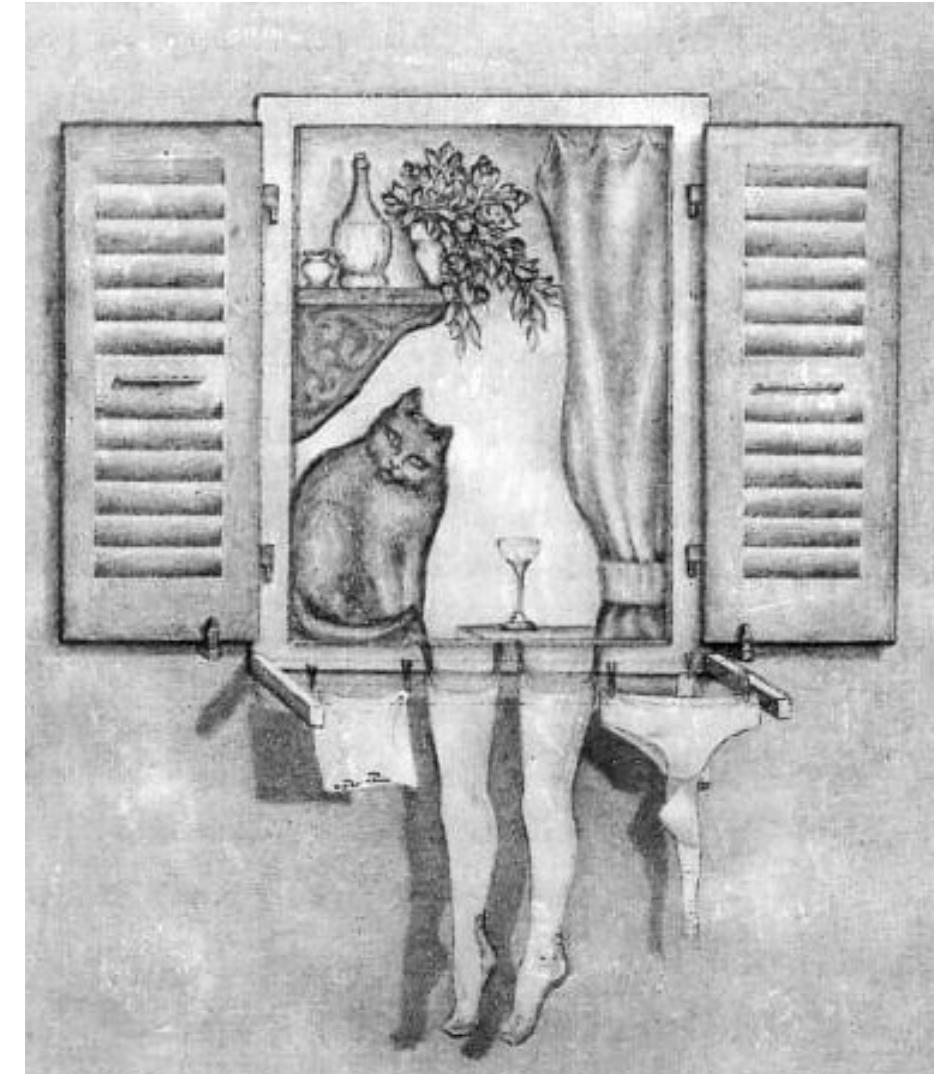
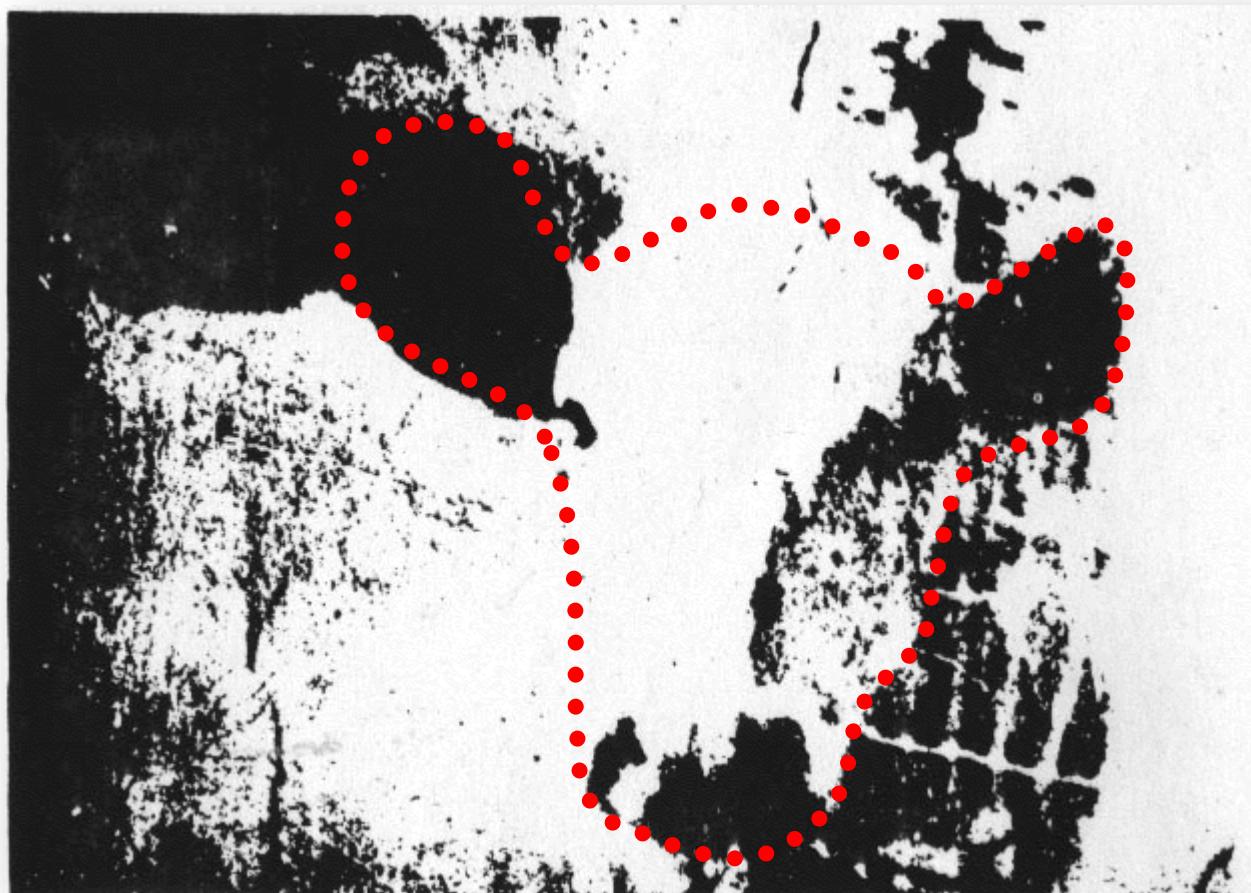
Joachim M. Buhmann

Institute for Machine Learning, D-INFK, ETH Zurich

Our world, in which we live!

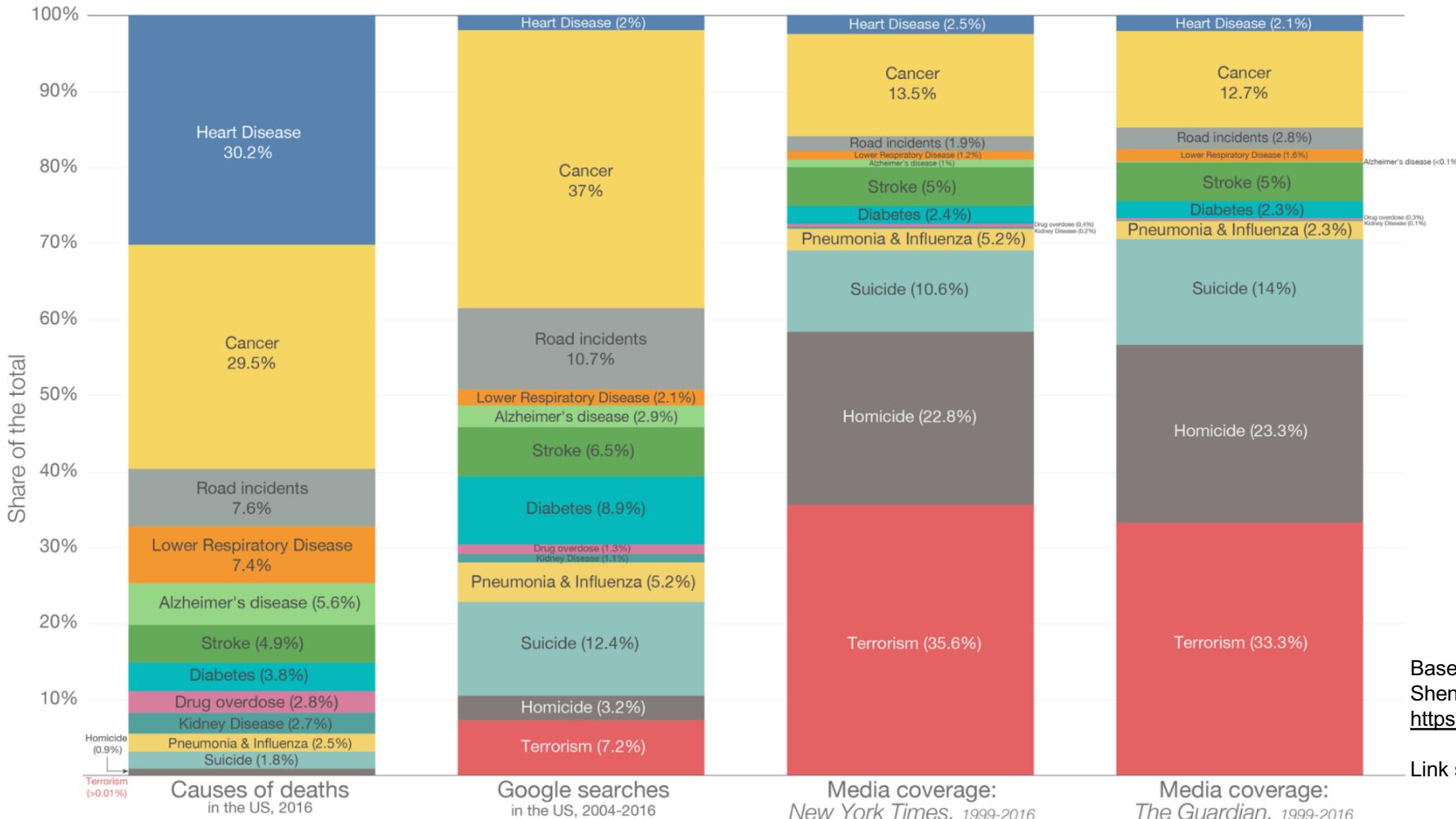


Seeing patterns in data (vision) is difficult!



Causes of death in the US

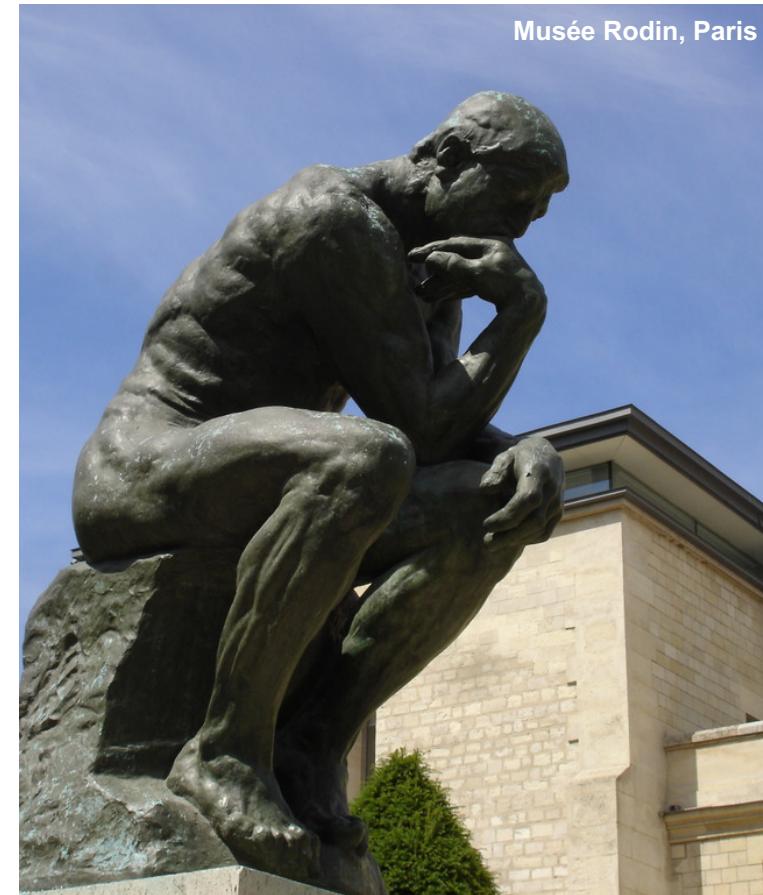
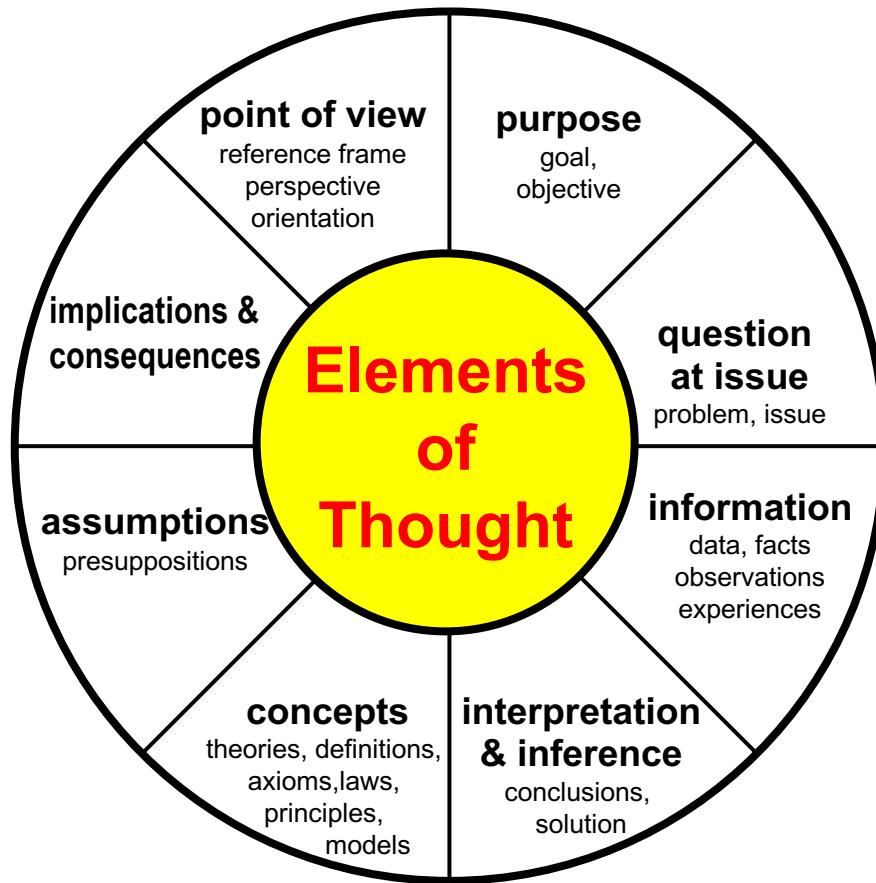
What Americans die from, what they search on Google, and what the media reports on



Based on data from
Shen et al. (2018) – Death: reality vs. reported.
<https://owenshen24.github.io/charting-death>

Link shared by Alessandro Curioni, IBM Research

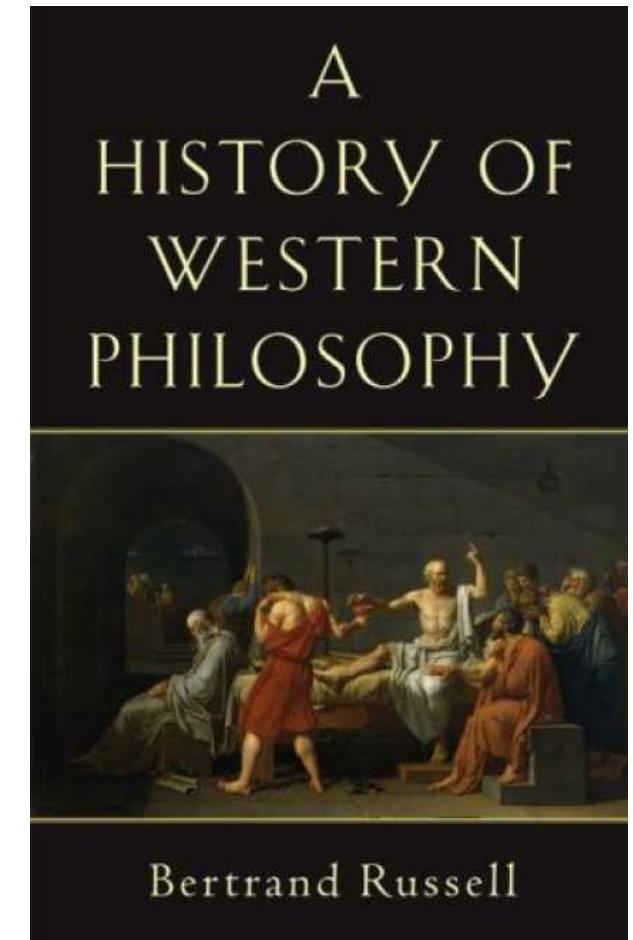
Elements of thinking



What is learning and understanding?

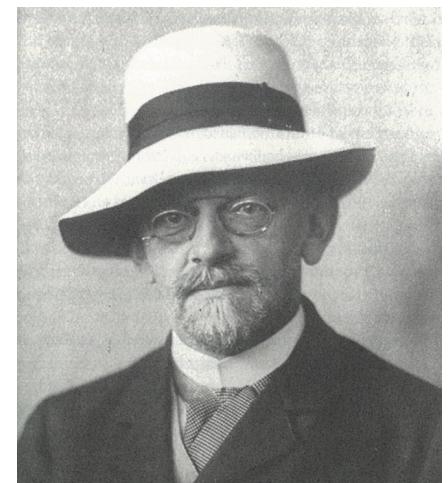
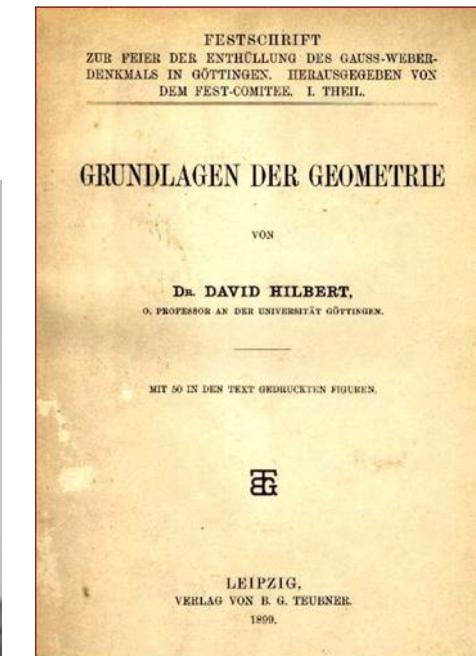
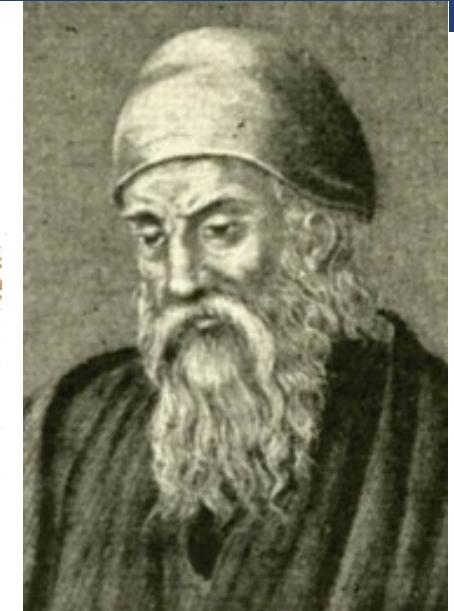
- **Thought processes**
 - **deduction**: draw conclusions from axioms, i.e., derive theorems from obviously true statements
 - **induction**: abstraction, i.e., conclude general laws from special cases
 - ... intuition, creativity, causality ...
- **Understanding and explanation**

Why and how does something work?
- **Planning**
 - **counterfactual reasoning**: What would be, if ...?
 - **causal thinking**: Why? What cause?



Power of deduction

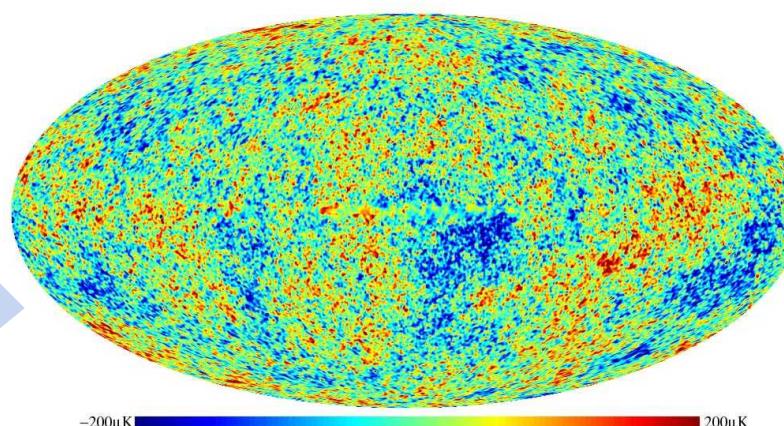
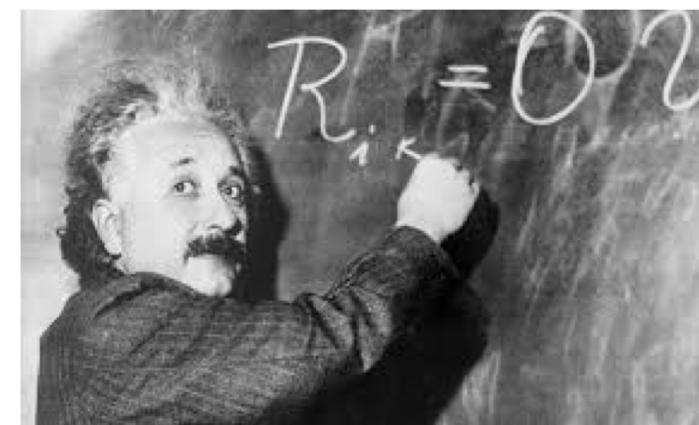
- **Euclid** (300BC) *Elements*,
 - Axiomatization of geometry with 5 postulates
- **David Hilbert** (1899)
Grundlagen der Geometrie
 - 20 Axioms are the foundation of Euclid's geometry!
- **David Mumford** (1937 - ...)
 - Algebraic geometry
 - Bayesian reasoning & AI



Induction – reference to “reality”

Axioms are generally accepted **fundamental principles!** Where do they come from?

Empiricism and data



Deduction and induction as computational processes

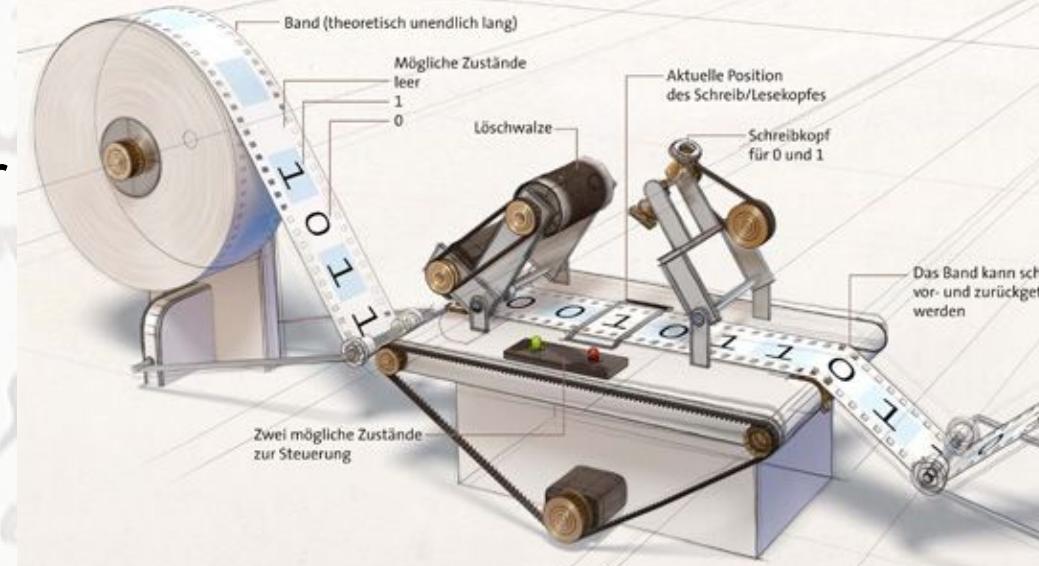
- **Leibniz: *Characteristica Universalis***

Thinking is achieved by computing

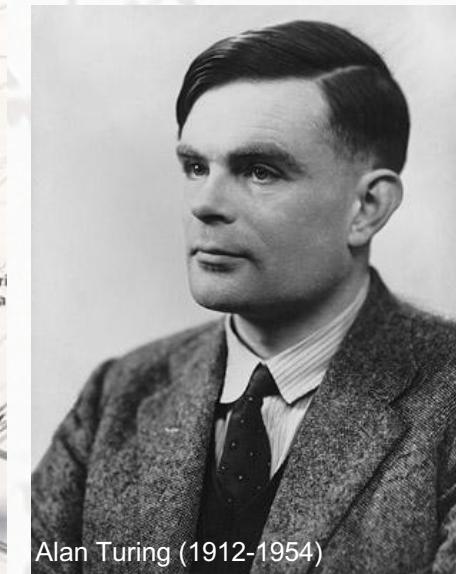
- First mechanical calculators
- Binary system



- This is computer



Gottfried Wilhelm Leibniz
(1646-1716)

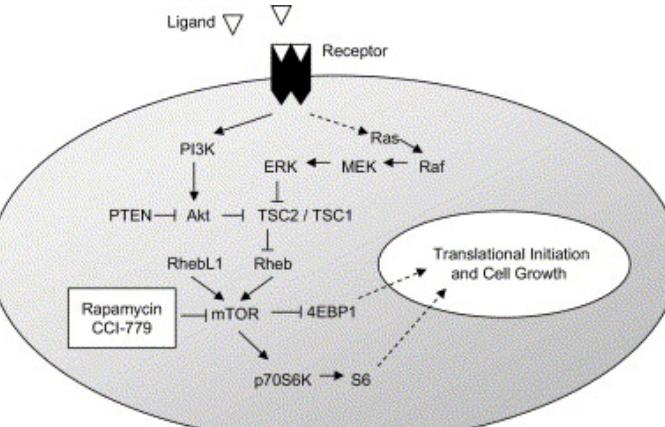
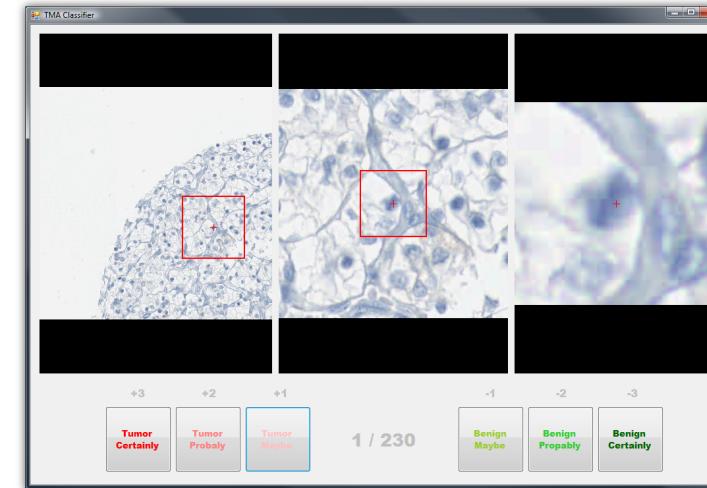
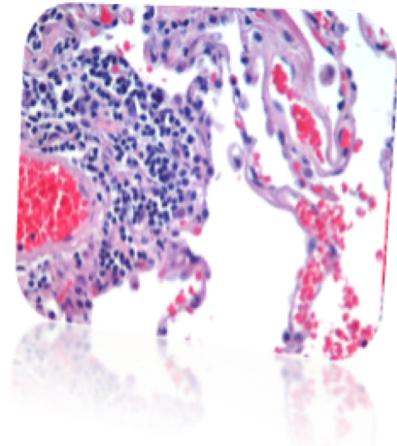


Alan Turing (1912-1954)

IT value generation in personalized medicine

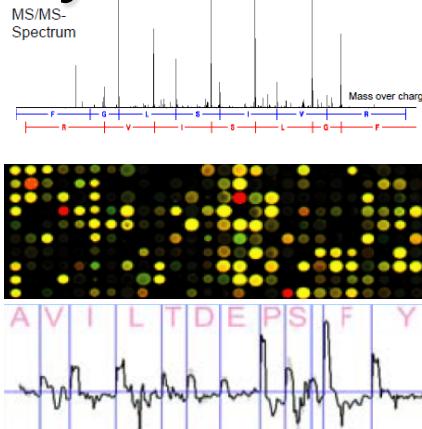


Thomas Fuchs
MSKCC, PAIGE.AI



Activation of the mTOR Signaling Pathway in Renal Clear Cell Carcinoma. Robb et al., J Urology 177:346 (2007)

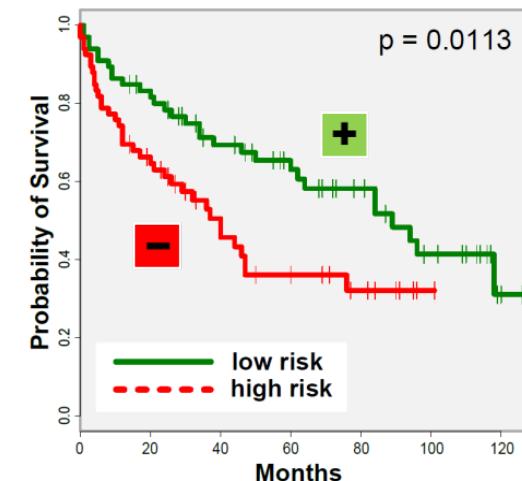
my Data



Institute for Machine Learning
Information Science and Engineering Group

my Information

our Knowledge

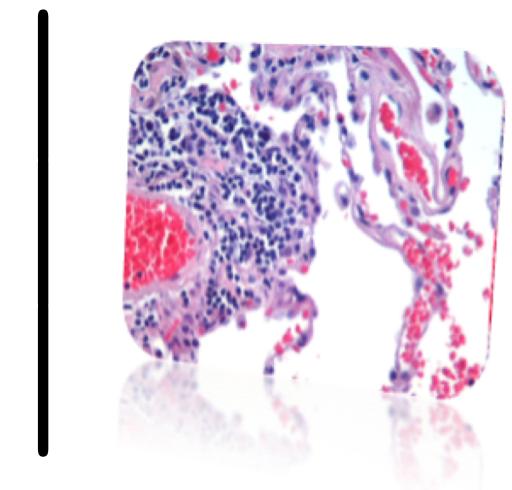
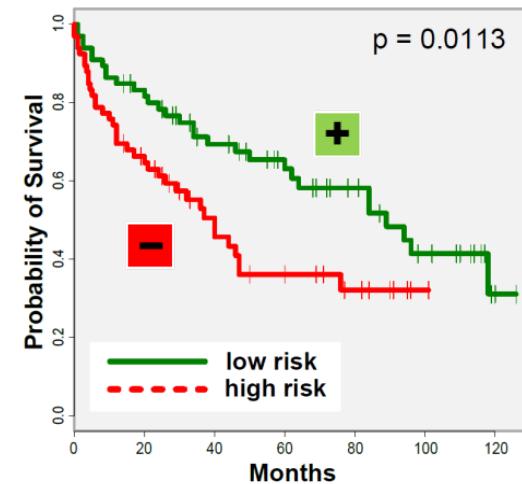


Joachim M. Buhmann

my Value

Fundamental data science questions - Which posterior distribution is encoded by algorithm \mathcal{A} ?

P(\mathcal{A})

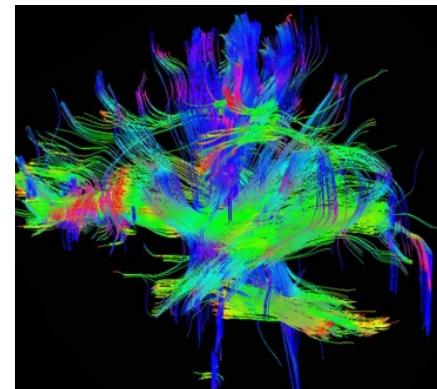
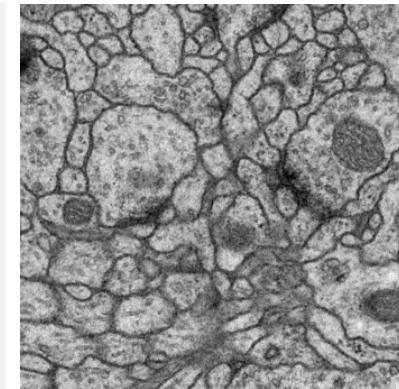
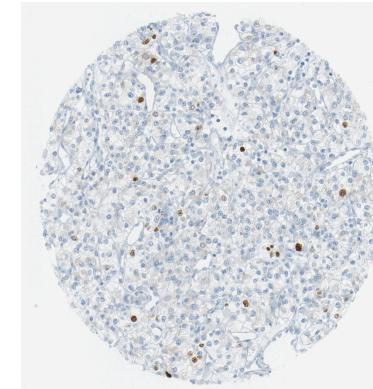
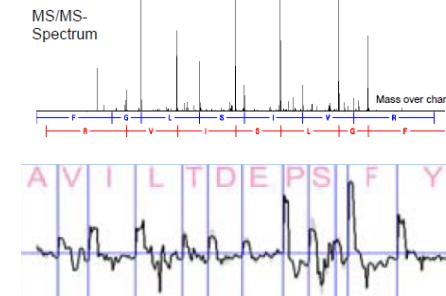
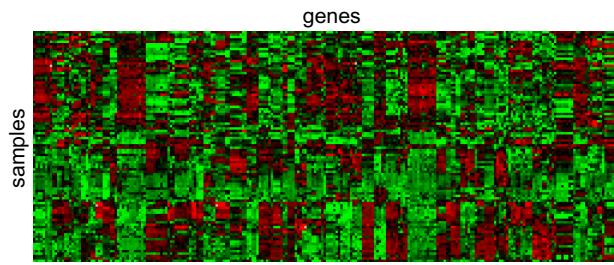


Big Data in der Medizin

Worüber reden wir eigentlich?

Heterogene Datenquellen

Patientendaten



Diagnose-, Prognose- und Therapiedaten der Mediziner



Bezeichnung	Einheit	U-GW	O-GW	22.01.97 15:57:00	29.02.08 14:30:35	19.03. 14:25:00
CRP	mg/l	8	<8			
Hämoglobin	g%	13	18	15.3	15.5	
Hämatokrit	vol%	41	54	45.6	47.0	
Erythrozyten	Mio/mm ³	4.5	6.5	4.95	5.29	
MCH	pg	27	31	30.8	29.2	
MCV	fL	83	95	92	90	
MCHC	%	32	36	33.4	32.3	
Leukozyten	mm ³	4	9	4.2	4.7	
Thrombozyten	mm ³	150	400	243	238	
Natrium	mmol/l	136	149	139	143	
Kalium	mmol/l	3.6	5	4.4	4.8	
Chlорid	mmol/l	98	106	100	101	
Glukose	mmol/l	3.9	6.1	3.5*	5.0	
HbA1c	%	4.2	6.5		5.0	
Kreatinin	umol/l	53	97	87	89	
AST	U/L	8	38	32	24	
GPT/ALT	U/L	4	44	31	17	
Akt. Phos.	U/L	36	126		43	
Cholesterin, total *	mmol/l			3.69	6.10	5.47
HDL-Cholesterin *	mmol/l			0.87	1.17	0.88
Triglycidole *	mmol/l			1.17	1.13	1.27
LDL-Cholesterin *	mmol/l			2.29	4.42	4.02
VLDL				53	51	57

„Selbstvermessung“

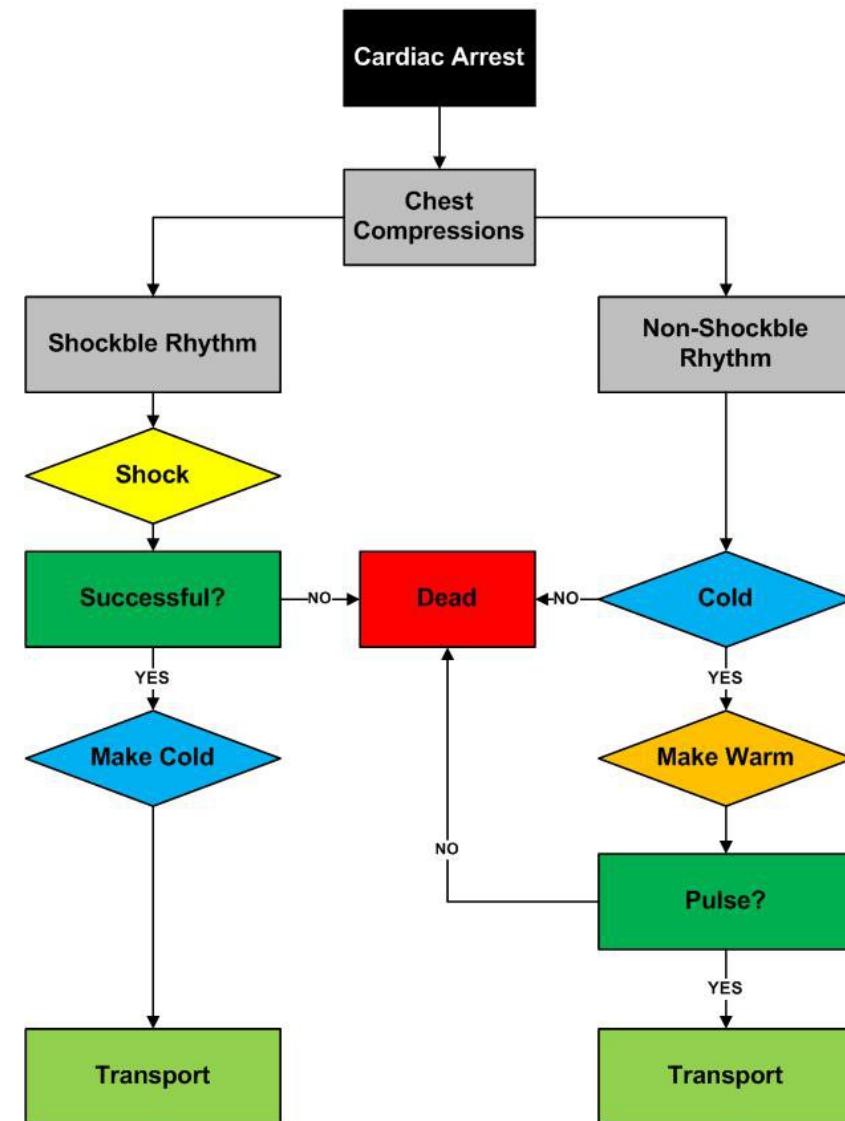


The Algorithm: Idiom of Modern Science

(Bernard Chazelle)

- Informally, an **algorithm** is any well-defined computational procedure, that takes some value as **input** and produces some value as **output**. (CLRS)
- **Analysis of algorithms**
 - ✓ Runtime
 - ✓ Memory consumption
 - ✗ Robustness
 - ✗ Generalization
- Learning algorithms „explore“ a complex stochastic reality!

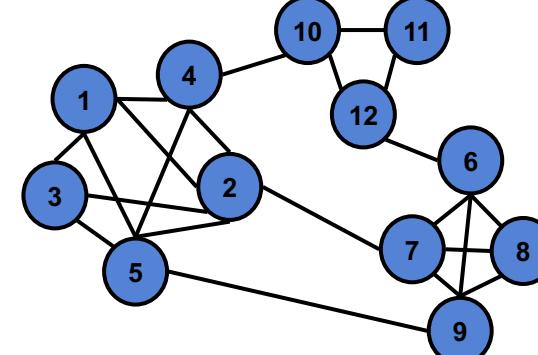
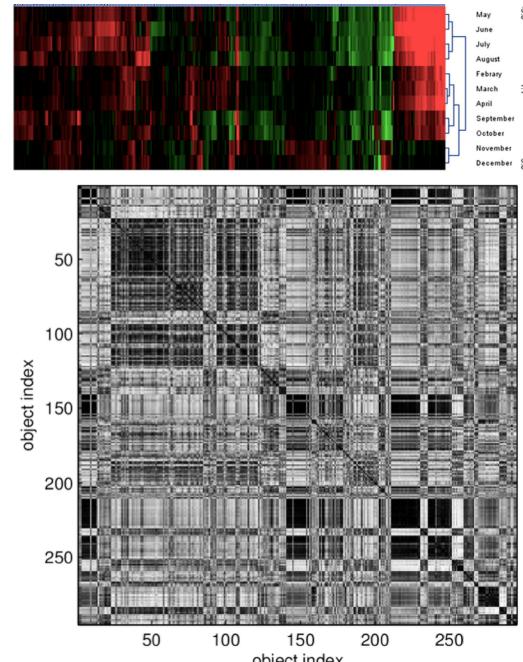
2015 ACLS CARDIAC ARREST ALGORITHM



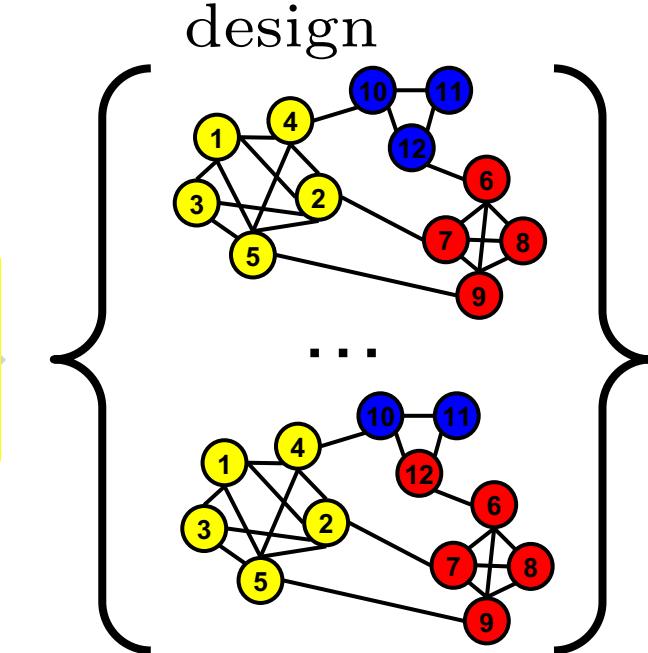
Algorithmics for Data Science – what is the problem?

- Random inputs imply random outputs

$$\underbrace{\text{input } \mathbf{X} \sim P(\mathbf{X})}_{\text{given}} \implies \underbrace{\mathcal{A}}_{\text{algorithm}} \implies \underbrace{\text{output } c \sim P(c|\mathbf{X})}_{\text{design}}$$

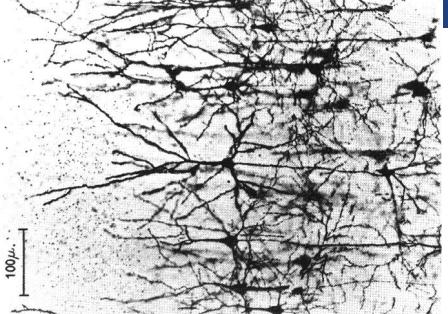
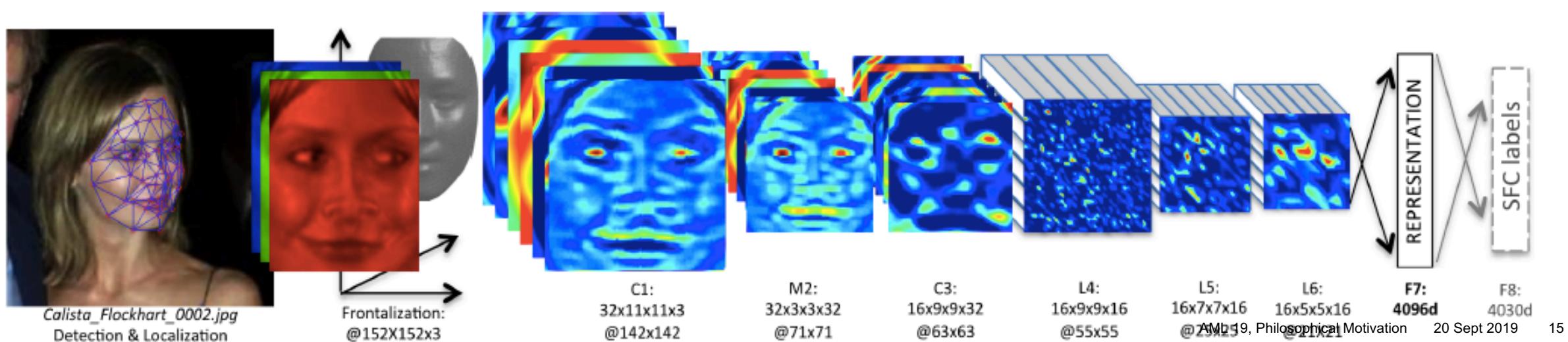


$\mathcal{A}?$



Learning machines master algorithmic induction and «imitate» humans

- **Biological neural networks** are adaptive and can learn.
- **Artificial neural networks** mimic these learning capabilities.
- **DeepFace** network of FaceBook



Neural networks visualized by brain scans. © VAN WEDELEN



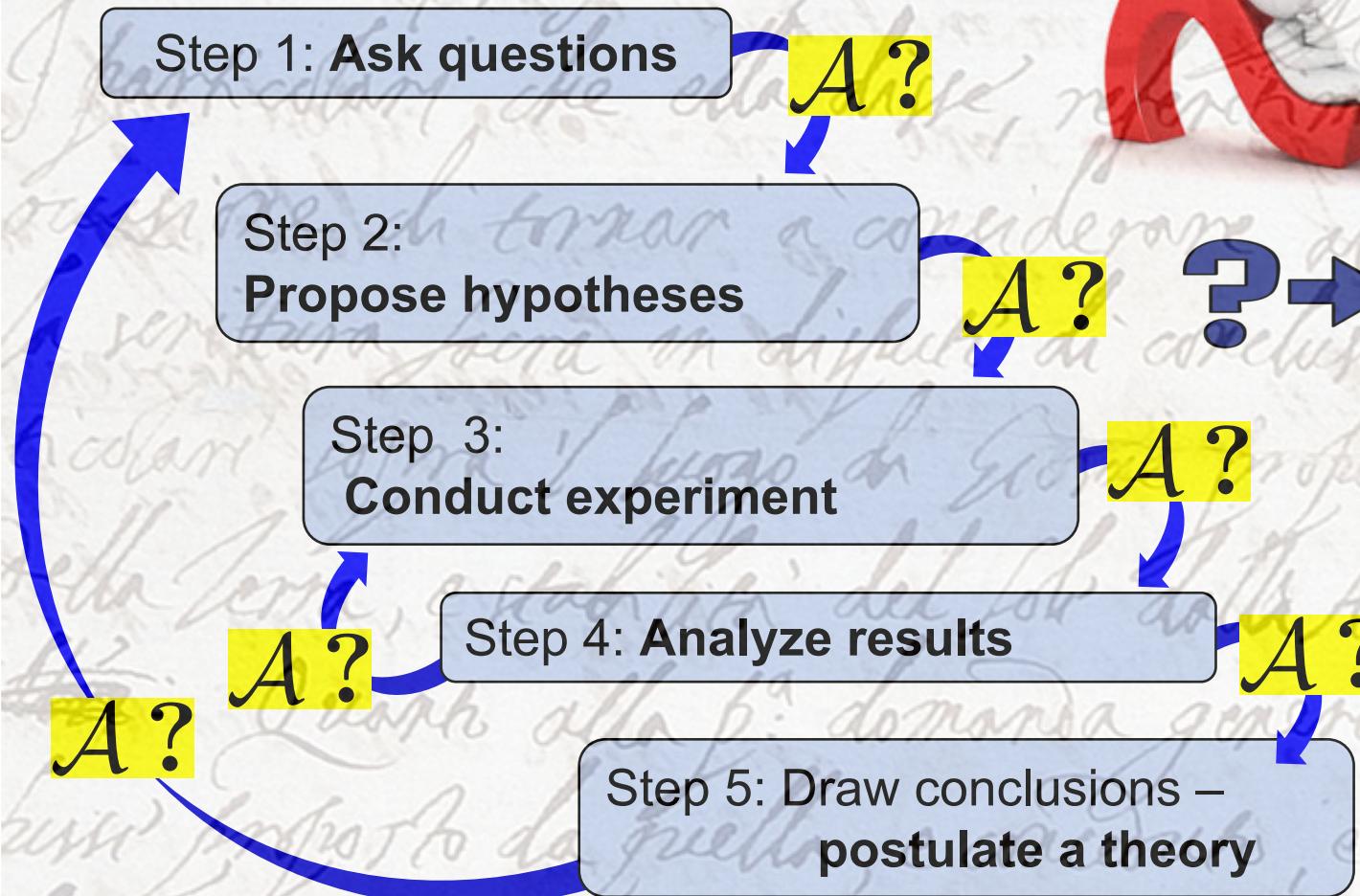
"Deep Network" Halluzinationen

(Courtesy of **Sebastian Nowozin**, 2016)

Image interpolation with neural networks



What is missing? The Scientific Method



Core question for computer science: How can we validate (data science) algorithms?

I. **Algorithms with random variables as input compute random variables as output!**

How can we prove correctness of such algorithms?

II. **Algorithms have to compute typical solutions!**

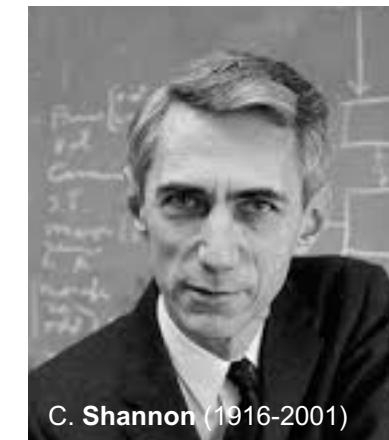
What does this mean for algorithm design?

III. **When do algorithms generalize over noise/model mismatch?**

IV. **How can algorithms autonomously improve performance?**



A. Kolmogorov (1903-1987)



C. Shannon (1916-2001)



V. Vapnik
(1936 -)