Machine Learning

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Overview

Why is machine learning of interest?

Thesis: Learning is one of the three fundamental mechanisms for the design and the improvement of autonomous, intelligent systems

1: Evolution

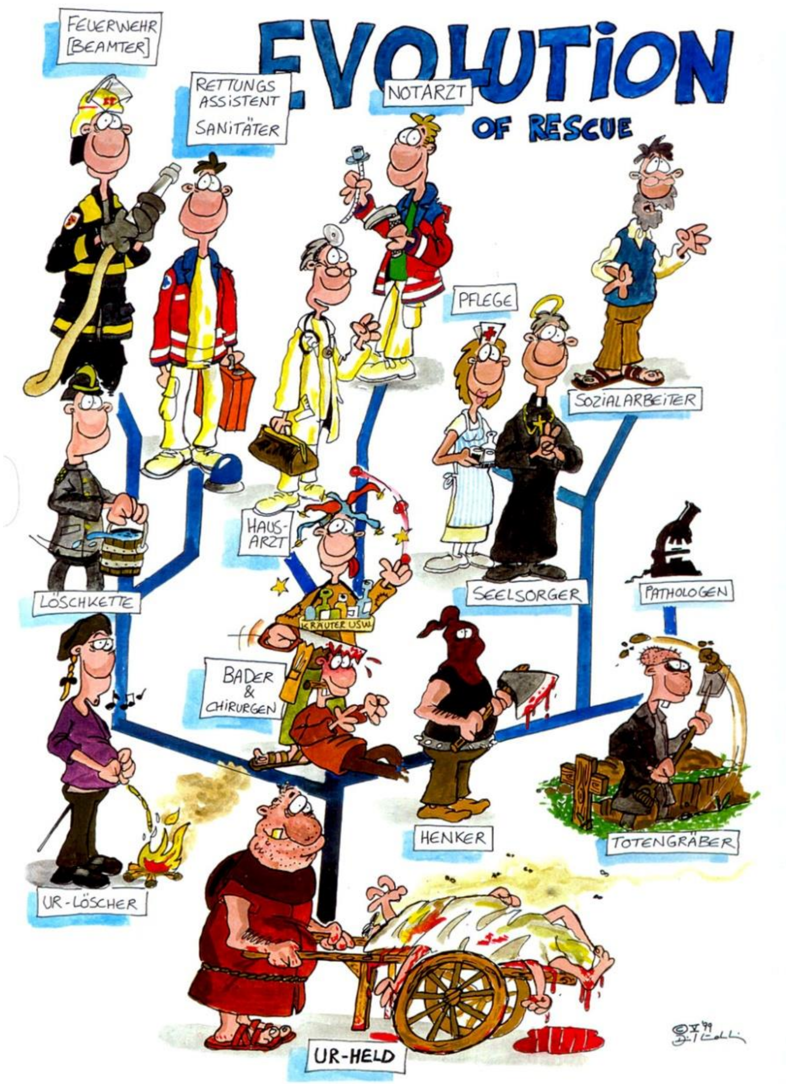
- Improvement via trial and error
- Biological evolution
- The “**Blind Watchmaker**“ (Richard Dawkins, 1986)
- Technical evolution: evolutionary improvement of technical solutions (advancement of the state of the art by trial and error in all competing companies world wide)

Advantages:

- Simple (blind); self-optimizing

Disadvantages:

- Time constant: years, decades, centuries, wasteful
- Software/hardware is limited by slowly evolving DNA (bacteria)



2: Learning

Biological Learning:

- Lifelong optimization (improvement) of the behavior of an individual via interaction with the environment
- The **“Learning (Apprentice) Watchmaker**” that learns from a teacher and personal experience
- Basic properties of animals (“natural law”)
- Feedback of the learning success (reinforcement)
- Time constants: milliseconds (memorization) / lifelong

Machine Learning

- Broadest sense: attempt to mimic biological and human learning for technical purposes
- Autonomous optimization of a technical system via interaction with the environment or by analyzing acquired data; “learning instead of programming“
- Analysis of dependencies between observations/events

3: Intelligent Design

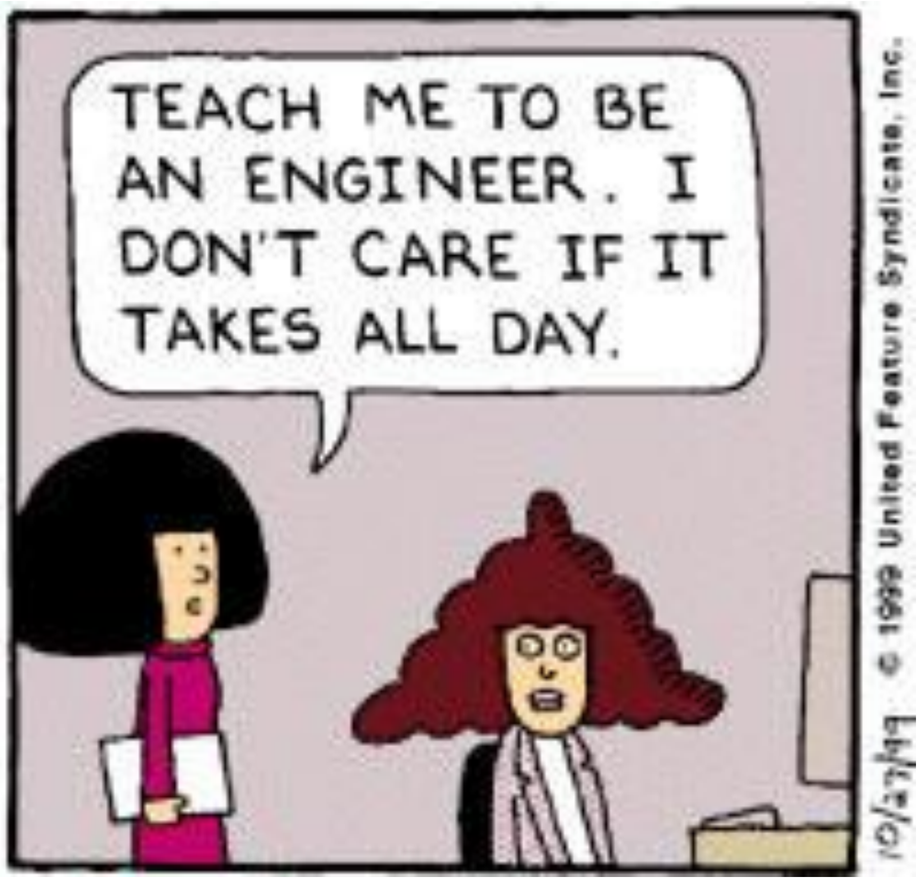
- Almost all technical solutions are based on intelligent design
- Engineer: the “**Knowledgeable Watchmaker**“
- (We don’t mean the “Divine Watchmaker” of Fontenelle, 1686, and Paley, 1802)
- Key for human success is breaking the genome bottleneck through cultural transmission (language and, even more importantly, written transmission!)
- Programmer (AI Coder: OpenAI Codex, GitHub Copilot, …)

Advantages:

- Explicit knowledge: the system is well understood and can be analyzed / improved via analytic thinking
- Time constant: years
- Can be taught (in school)

Disadvantage:

- Need for an (expensive) designer (human)



Technical Progress

Advancing the state of the art of **engineering** by informed **trial and errors** by a set of **knowledgeable (learning) actors** (companies), driven by customer needs, competition and business opportunities

Occasional paradigm changes in technology and business models which might affect own business (search in service reports, digitalization) or might open up completely new businesses (Google, LLMs, …)

Characterization of Learning

Learning is an exclusive property of living beings (and computers?)

- Even quite primitive animals can learn (adaption)

Biological Learning:

- (beneficial? permanent?) Modifications in the (central?) nervous system (based on interactions with the environment?)
- *Better Brain Hypothesis: My brain today is “better” than my brain yesterday*

Machine Learning:

- Beneficial changes in a technical system based on the analysis of data or based on the interaction with the environment, by employing learning algorithms

Is Learning Memorization?

Declarative Memories

- Episodic Memory (evens we remember)
- Semantic Memories (facts we know)

Nondeclarative memories

- Skills that we have learned
- Learning to perceive and act better

Working Memory: Central Executive

Is ChatGPT memorization?

Etymological Origin

Etymologically

- Old English: *leornian*
- From Proto-Germanic *liznojan* (with a base sense of "to follow or find the track")
- From Proto-Indo-European *leis* (track)
  - Related to German *Gleis* (track)

Comment: Even etymologically, "learning" has something to do with the idea of "following traces / leaving traces"

Overview

Non-Technical Perspectives

A	Philosophy
B	Psychology, Cognition and Cognitive Neuroscience
C	Cellular Neuroscience

A: Philosophy

Epistemology (*Erkenntnistheorie)*

- Epistemology is the theory of knowledge (and justified belief)
- What can mankind really know and how can **mankind acquire knowledge** (learn)?
- How can we know and study how the world functions?
- What is knowledge?
- [Be aware that until quite recently, in western civilization, these questions were only allowed to be addressed in a religious context]

Basic Mechanisms for Gaining Knowledge: Deduction and Induction

Deduction

- From the general to the specific **(top-down)**
- Axioms are given and theorems are derived via the machinery of deductive reasoning
- Axioms:
  - Can be **simple facts** (“Jack has blue eyes”) (data, measurements, Knowledge Graphs**)**
  - Can be **complex axioms** (“If something is a dog, it is also a mammal”)
- Relationship to language theory:
  - Do we speak in axioms?
- Technical: basis for **classical Artificial Intelligence** (1954 ….)

Induction:

- Generalizes observations (**bottom-up**), to generalize and to justify theories
- Inferring the validity of a hypothesis via observations and experiences
- Simple facts (“Jack’s height is 180 cm”) as in deduction
- Learned, often statistical, dependencies instead of assumed axioms!
- Closer to reality but learned dependencies might be difficult to explain
- Technical: basis for Machine Learning and modern **Artificial Intelligence**

Rationalism (17th Century) (~Louis XIV)

- From Latin: ratio = „reason“: *let’s trust mostly our reasoning capabilities* *(complex axioms)*
- Priority of **rational reasoning** in knowledge acquisition (in contrast to other forms such as the senses or religious convention); search for optimal problem solution
- Representatives: Socrates (ca 470–399 BC), Plato (– 348/347 BC), **René Descartes** (1596–1650) (thinking defines who we are, not experience), Baruch Spinoza (1632–1677), Gottfried Leibniz (1646–1716)
- Since the enlightenment, rationalism is usually associated with the introduction of mathematical methods into philosophy, as in Descartes, Leibniz, and Spinoza. This is commonly called continental rationalism, because it was predominant in the continental schools of Europe, whereas in Britain empiricism dominated
- Proponents of some varieties of rationalism argue that, starting with foundational basic principles, like the axioms of geometry, one could deductively derive the rest of all possible knowledge

Empiricism (17/18th Century) (~Rise of Prussia, Age of Enlightenment)

- *Let's not speculate as much, let's trust the facts (observations, data, measurements)*
- The English term empirical derives from the Ancient Greek word empeiria, which translates to the Latin experientia; mostly a bottom-up approach
- More of a British tradition and in contrast to continental Europe's Rationalism
- „There is nothing in the mind that was not first in the senses." John Locke postulated that, at birth, the mind was a blank slate or tabula rasa (individual/mankind)
- Representatives: Aristotle (384 – 322 BC), Francis Bacon (1562-1626), John Locke (1632-1704), **David Hume** (1711-1776)
- Aristotle/Locke: "One idea was thought to follow another in consciousness if it were associated by some principle" "The principal laws of association are contiguity, repetition, attention, pleasure-pain, and similarity. Both philosophers taught that the mind at birth is a blank slate and that all knowledge has to be acquired by learning. The laws they taught still make up the backbone of modern *learning theory*" (Wikipedia)
- Descriptive: how do humans act and acquire knowledge
- Rationalism/Empiricism reminds one of the distinction between Probability/Statistics

Idealism: The Discovery of the Individual; (dominant Philosophy of the 18th/19th century) (~French Revolution)

- **Idealism:** each form of matter, including human behavior, is a reflection of ideas
- *Mind over matter: <u>Let's trust mostly our mental self</u>; people are driven by ideas, visions*
- *What is an ideal (society); <u>ethics</u>: what should we do?*
- In philosophy, idealism assert that reality, or reality as we can know it, is fundamentally mental, mentally constructed (*constructivism*), or otherwise immaterial (*anti-realism* in opposition to ***realism, objectivism***)
- Suggests the priority of ideals, principles, values, and goals over concrete realities ("continental")
- Human ideas — especially beliefs and values — shape society
- **Plato's idealism**: reality is just a reflection of non-physical Ideas (<u>ontological</u> idealism). The material world is an illusion (**George Berkeley,** 1685-1753); also a tradition in Hinduism and **Buddhism**. <u>Epistemologically,</u> a skepticism about the possibility of knowing any mind-independent thing (also: Kant)
- **Immanuel Kant** (1724-1804) (attempt of a synthesis of **Rationalism and Empiricism;** as enlightenment)
- Beginning with Immanuel Kant, German idealists such as Hegel, Fichte, Schelling, and Schopenhauer dominated 19th-century philosophy
- Modern cognitive relevance: Semiotic triangle: objective world (can we describe it? From grand unified theory, to biology, to our daily life) --- the world in our mind (cognitive neuroscience) --- linguistics
- Romantic movement: <u>let's trust your feelings</u> (enlightenment ←→ romantic movement)

Positivism and the Scientific Method: (~19th Century, 1st Half, Restauration, Revolutions, Imperialisms)

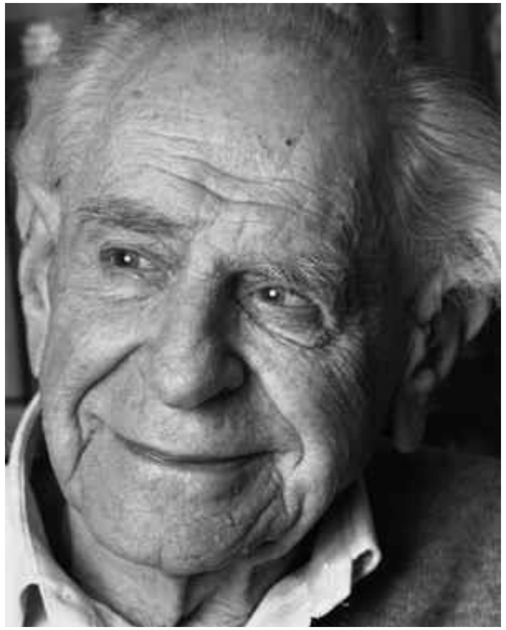
- **Knowledge is derived from positive (in the sense of certain) findings**
- *Let's trust mostly science: the scientific method, the circular dependence of theory and observation, must replace metaphysics in the history of thought*
- Positivism is defined as the belief that all true knowledge is scientific, and that all things are ultimately measurable (scientific revolution, Galileo Galilei)
- Data derived from sensory experience, and logical and mathematical treatments of such data, are together the exclusive source of all authentic knowledge
- Even society might operate according to laws like the physical world. Introspective and intuitional attempts to gain knowledge are rejected. Philosopher and founding sociologist, **Auguste Comte**: society operates according to its own laws, much as the physical. Also: Ernst Mach, Émile Durkheim
- "The Unreasonable Effectiveness of Mathematics in the Natural Sciences" (Eugene Wigner, 1960)
- Materialism (Ludwig Feuerbach, Karl Marx): history is not driven by ideas but by laws (historic-dialectic materialism) (by most not considered to belonging to Positivism)

Neopositivism or Logical Positivism (20th Century) (~WW I, II)

- *Mathematical formalization of knowledge; let's trust mathematics*
- Motivated by attempts to formalize all of mathematics by Gottlob Frege (1848-1925), and then, in the *Principia Mathematica*, by Bertrand Russell (1872-1970) and Alfred North Whitehead (1861-1947) [However, in 1931, Gödel's incompleteness theorem proved definitively that *Principia Mathematica*, and in fact any other attempt, could never succeed: For any set of axioms and inference rules proposed to encapsulate mathematics, either the system must be inconsistent, or there must in fact be some truths of mathematics which could not be deduced from them.]
- Logical positivists (or 'neopositivists') attempts to reduce statements and propositions to pure logic; Wiener Kreis, **Rudolf Carnap** (1891-1970); great influence in US; the Wiener Kreis was initially formed to study the *Tractatus* of Ludwig Wittgenstein (1889-1951); Wittgenstein focused at first on logical formal language, and later in life on the intricacies of human language

Critical Rationalism

- *Critical Rationalism* (Karl Popper (1902-1994): *Only falsifiable theories should be pursued* (If it's not falsifiable, it is not scientific)
- Is induction sound? Hume (1711-1776) advocated a practical skepticism based on common sense, where the inevitability of induction is accepted ("Will the sun rise tomorrow?"")
- If no finite set of observation can ever prove a theory, how can we ever accept a scientific theory as being true?
- Popper accepts Empiricism as a valid means to increase knowledge, if one accepts that theories can only be falsified (shown to be false) but never be proven (shown to be correct)!
- A theory has falsifiability or refutability if there is the possibility of showing it to be false: only falsifiable theories should be pursued
- The Logic of Scientific Discovery (Logik der Forschung, 1935)



Objective truth?

Reactions to Positivism
(~20th century)

Sometimes associated with *Continental Philosophy* in contrast to *Analytic Philosophy*

Question: Can the scientific method also be applied to the human mind and sociology?

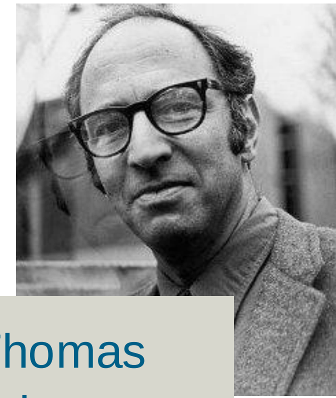
Anti-Positivism, Critical Theory: *Criticism as science as an ideology in sociology*

- Max Weber (1864-1920): sociology as a “science” as it is able to identify causal relationships. But: one seeks relationships not as "ahistorical, invariant, or generalizable“ as those pursued by natural scientists
- Rejections of 'scientism'; or science as ideology (Frankfurter Schule: Herbert Marcuse, Theodor Adorno, Max Horkheimer, Walter Benjamin, Erich Fromm, Jürgen Habermas)

Postpositivism: *Science is not independent of the scientist and of culture*

- Whereas for positivists: researcher and the researched person are independent of each other
- Postpositivists: theories/background/knowledge/values of the researcher can influence what is observed (Kuhn; critical of the Wiener Kreis)

Cultural Influence and Sociology of Science (~20th Century, 2nd Half)



Structure of Scientific Revolutions (Paradigm Shifts): The Structure of Scientific Revolutions (Thomas Kuhn, 1922 –1996): Science does not progress via a linear accumulation of new knowledge, but undergoes periodic revolutions, also called "paradigm shifts" in which the nature of scientific inquiry within a particular field is abruptly transformed (Kuhn did not consider himself a relativist)

Relativism: A form of truth relativism, which is the doctrine that there are no absolute truths, i.e., that truth is always <u>relative to some particular frame of reference, such as a language or a culture</u>

- Paul Feyerabend (1924 – 1994): Scientific knowledge is not cumulative or progressive; there can be no demarcation in terms of method between science and any other form of investigation

Postmodernism (1970 -) (Michel Foucault, Jacques Derrida): <u>let's mistrust anyone and anything including absolute truth; it is about power; let's focus on our/my and everyone elses suffering:</u> Postmodern criticism include objective reality, morality, truth, human nature, reason, science, language, social progress

- "Continental philosophers generally reject scientism, the view that the natural sciences are the best or most accurate way of understanding all phenomena" (Wikipedia: Contemporary philosophy)
- <u>Structuralism</u>: *scientific* study of underlying related meta-structures in different cultures (Saussure, Levi-Strauss); <u>post-structuralism</u>: structures are not universal but societal constructions (*political* perspective) (see: constructivism in idealism, Kant)

Philosophy as a Basis for Classical Artificial Intelligence and Machine Learning

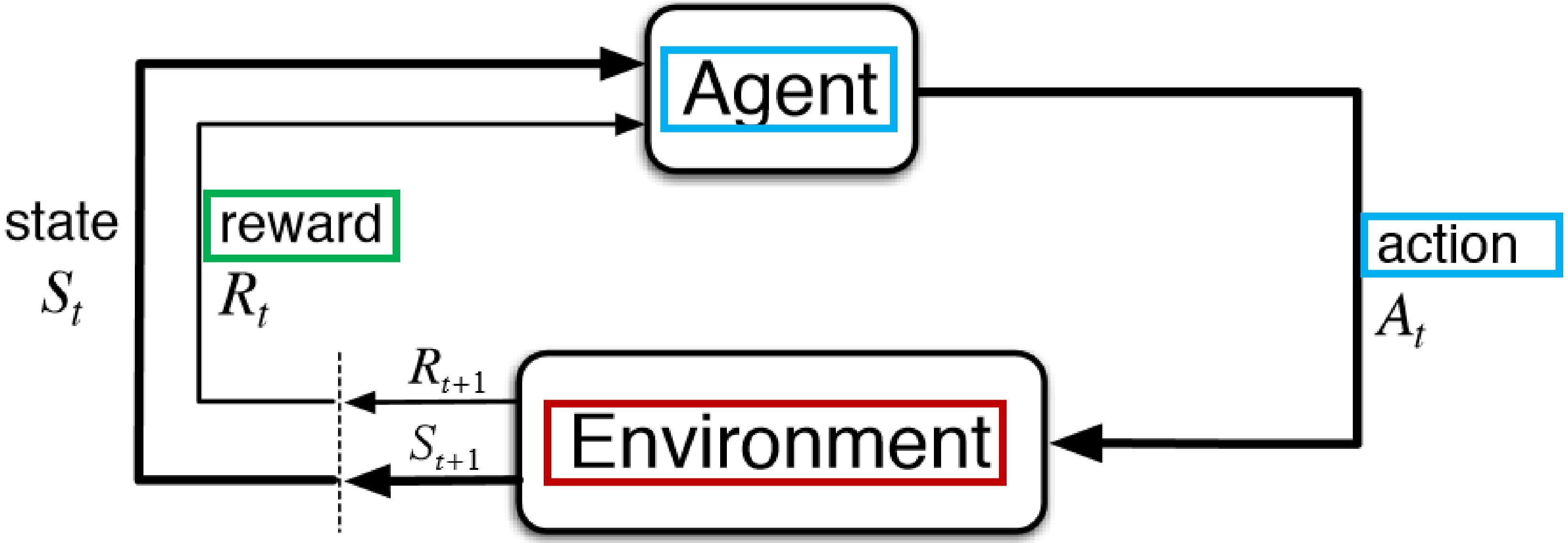
- Poppers *falsificationism* has great influence in science today, in general
- Logical positivism (Ludwig Wittgenstein) as a motivation for early AI research (dominance of logic-based top-down approaches)
- Empiricism as a basis for Machine Learning

- Personal conclusion: All philosophical schools provide some models on some aspect of nature, human beings, and society but none seems to explain all aspects
- At a given instance in time, some schools are more in focus than others

Philosophy and Reinforcement Learning

- Rationalism: The agent should act rationally (optimally)

- Idealism / enlightenment: what are the ideals/goals we should aim for?



- Positivism: There is an objective model
- Empiricism: The model can be learned from observations

B: Psychology, Cognition and Cognitive Neuroscience

- Psychology is the study of the faculty of the mind, in particular of learning and behavior
- Whereas philosophy is concerned with the question, what mankind can learn and know (phylogenetic), here the question is **how an individual learns** (a child) (ontogenetic)
    - **Psychology:** humans are mostly the system that produces data to be studies (e.g., happiness as a function of income; child development)
    - **Cognition:** also models the inner working of the system, i.e., the brain (Bayesian brain)
    - **Cognitive Neuroscience:** connecting psychology and cognition with neuroscience (e.g., the role of the hippocampus in episodic memory)

Psychology as Empirical Science

Revolutionary idea: Humans can the subject of scientific studies!

Begin of empirical (experimental) psychology:

- Herrmann von Helmholtz (1821-1894, Berlin)
- Wilhelm Wundt (1832-1920, Leipzig) (Assistant to Helmholtz)
    - Wundt is considered to be the founder of psychology as a separate scientific field
    - From 1858 to 1863, he was assistant to Hermann von Helmholtz. “Theorie der Sinneswahrnehmungen”
    - First experimental psychological lab worldwide
- Gustav Theodor Fechner (1801–1887, Leipzig): Founder of Psychophysics
    - “The Scientific Study of the Relation between Stimulus and Sensation“
- Hermann Ebbinghaus (1850-1909): first rigorous experimental studies on human memory

Psychoanalysis and Psychiatry

- Psychoanalysis was founded by Sigmund Freud (1856-1939)
- Hypothesis: people can be cured by making conscious their unconscious thoughts and motivations, thus gaining "insight"

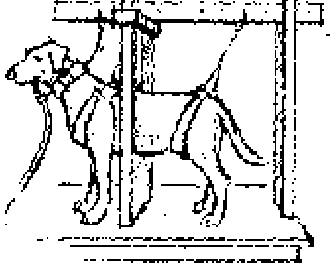
- Psychoanalysis is not part of psychology, and by some critics regarded as a pseudoscience (difficulty with falsification)

- Psychoanalysis maintains a strong influence on **psychiatry** (a branch of medicine: diagnosis, prevention, study and treatment of mental disorders)

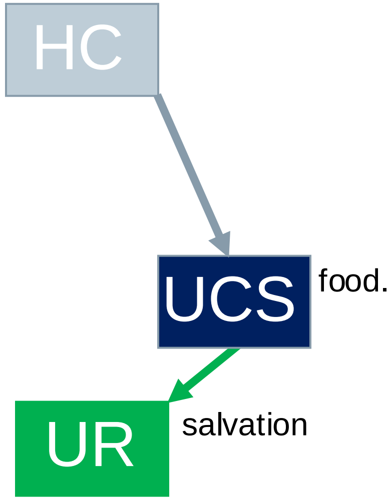
Behaviorisms (1920-1960)

- „Belief in the existence of consciousness goes back to the ancient days of superstition and magic“
- Founded also as reaction to Sigmund Freud’s Psychoanalysis (“continental”)
- Rejection of theories that need to assume mental states (no interest in explainability?)
- The inner structure (of the brain) is irrelevant
- The functioning can only be deduced from input (stimulus) and output (reaction)
- “Input” can include personal history
- Humans are just another animal (Freud exclusively focused on humans)
- Humans start tabula rasa (nature versus **nurture**)
- Representatives: Iwan Pawlow (1849-1936), John Watson (1878-1958), B. F. Skinner (1904-1990)

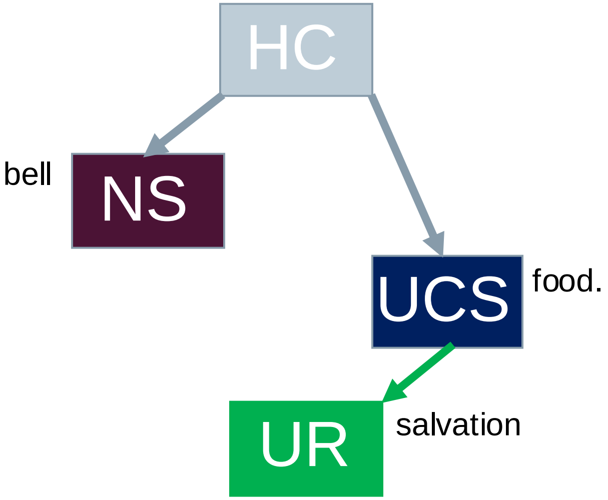
Classical Conditioning: ´Learning to predict important events (Pawlow)



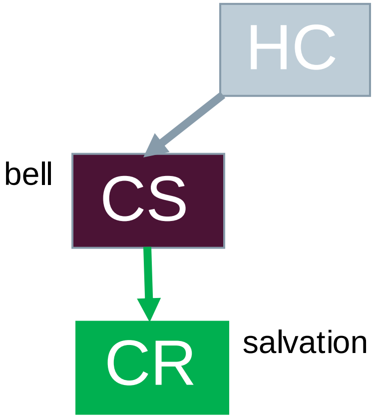
Phase 1:
Unconditional stimulus/response



Phase 2:
Neutral stimulus



Phase 3:
Conditional stimulus/response



The **unconditional stimulus (UCS, food)** produces the **unconditional response (UR, salvation)**

A hidden cause (**HC**, experimenter) might produce both the **UCS** and the **neutral stimulus (NS, bell),** which comes slightly earlier than the food

The dog leans that after the **conditional stimulus (bell),** food follows and as a **conditional response (CR) starts salvation**

- As a predictive model this makes absolutely sense but it might not reflect causality or be interpretable

Another example. **UC**: A stomach virus (UCS) would produce a response of nausea (R). **C**: Chocolate (CS) which was eaten before the person was sick with a virus, but was not the cause, now produces a response of nausea (CR).

See: Classical Conditioning (National Library of Medicine)

Learning in Psychology

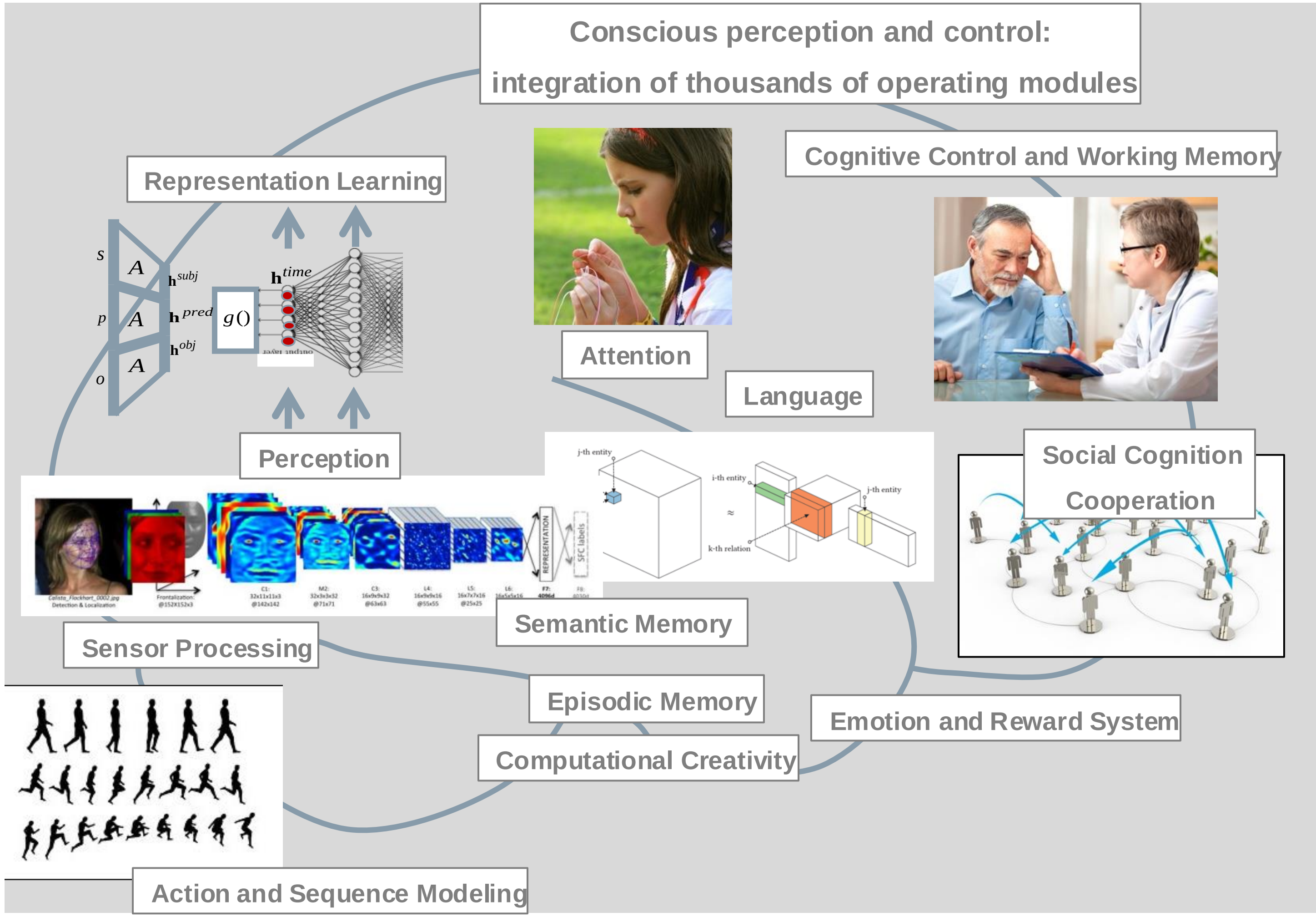
- **Habituation, Sensitization, Familiarization**
  - Learning about repeated events
- **Classical Conditioning: <u>learning to predict</u>**
  - By learning the association (Bell~Food); learning to predict
- **Operand Conditioning: <u>learning to act</u>**
  - Reward depends on the action of the subject
  - Learning the outcome of <u>behavior</u>
  - Learning new behavioral patterns (Thorndike)
  - Reinforcement Learning
- **Social Learning**
  - Observing, interacting and reinacting
  - Learning to copy behavior

Cognitive Psychology and Cognition

- Attempt to understand the inner working of the „Black Box“: the study of mind itself is a worthy scientific pursuit
- Reaction to Behaviorism [whose scientific methodologies are the basis for much of psychology today]
- Human behavior is more than stimulus-response: Development is an active process of a subject
- Reintroduction of mental processes: explainability
- Acting is dominated not only by a stimulus but by active reasoning
- The link between stimulus and behavior is the cognitive representation
- Williams James (1842-1910), Herrmann von Helmholtz (1821-1894), Frederik Bartlett (1886-1969), George Miller (The magic number seven, 1956; information theory and memory), Noam Chomsky (Three Models of Language, 1956)
- Cognitive Science:
  - 1: Cognitivism (symbolic/logic)
  - 2: Connectionists (neural networks)
  - 3: Embodied cognition

Cognitive Neuroscience

- Personally, one of my favorite areas
- Combines psychology and cognition with modern research in neuroscience
- Integrated understanding of the human mind
    - From behavioral studies, structural analysis of the brain (including MRI, Diffusion Tensor Imaging), EEG, fMRI, insights from brain damage, …
- Highly recommended book:
    - Gazzaniga: Cognitive Neuroscience



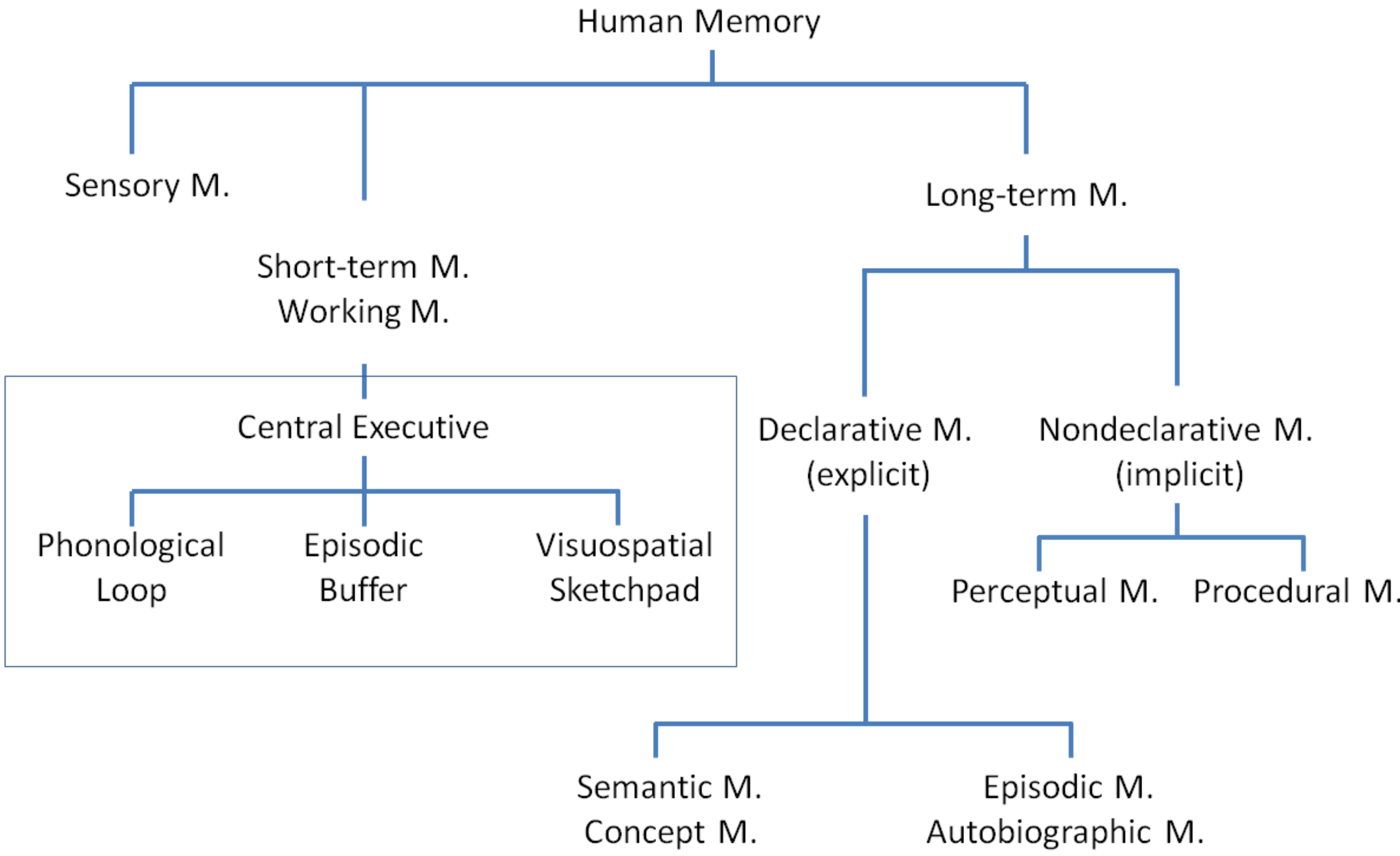
The Organization of Memory and Learning: Better Brain Hypothesis

Declarative Memories
- Episodic Memory (evens we remember)
- Semantic Memories (facts we know)

Nondeclarative memories
- Skills that we have learned
- Learning to perceive and act better

Working Memory: Central Executive

More (!) Insight by introspection? Learned causality and rules? Logical and other forms of reasoning? Learning to make the right decisions. Role of language in all of his? Learning in school? Learning about social roles (mine and others) and how to improve mine. Learning how others feel. Reinforcement Learning and internal rewards (dopamine)



Integrated Intelligence

Integrated Intelligence

Perception

(understand)

Integrated Intelligence

Episodic Memory

(remember)

Perception

(understand)

Integrated Intelligence

Semantic Memory

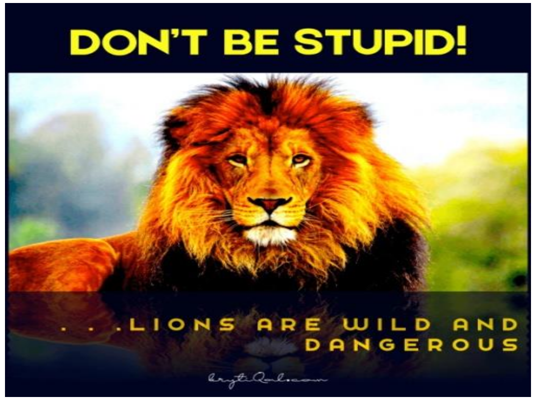
(know)

Episodic Memory

(remember)

Perception

(understand)



Integrated Intelligence

Semantic Memory

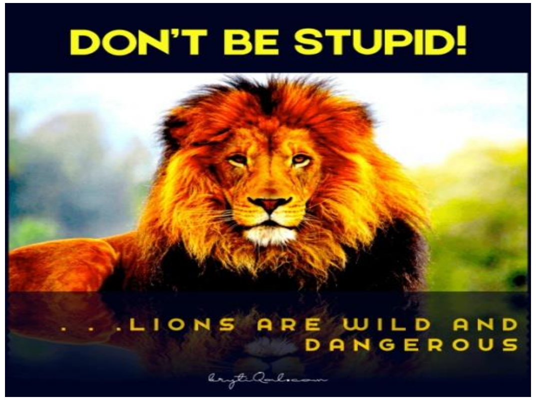
(know)

Episodic Memory

(remember)

Perception

(understand)



Integrated Intelligence

Declarative

Working Memory

- Prediction
- Decision Making, Reinforcement Learning
- Planning

Semantic Memory

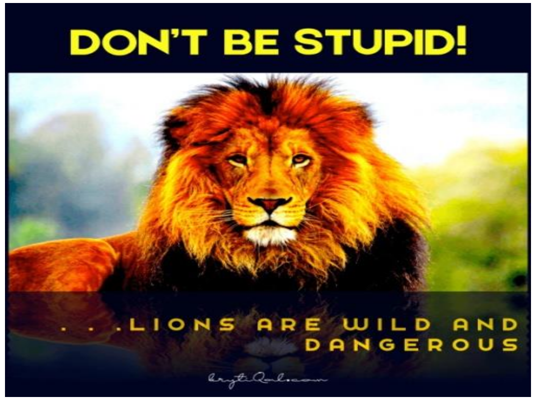
(know)

Episodic Memory

(remember)

Perception

(understand)



Integrated Intelligence

Working Memory

- Prediction
- Decision Making, Reinforcement Learning
- Planning

Semantic Memory

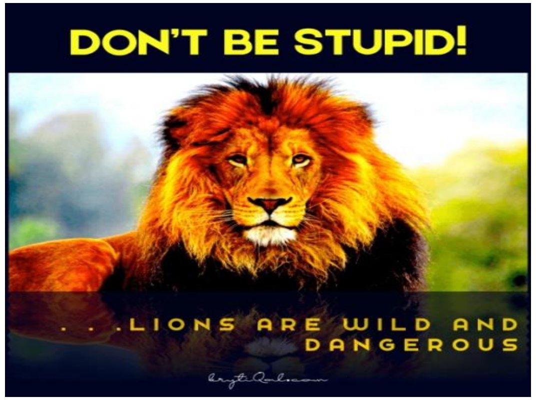
(know)

Episodic Memory

(remember)

Perception

(understand)

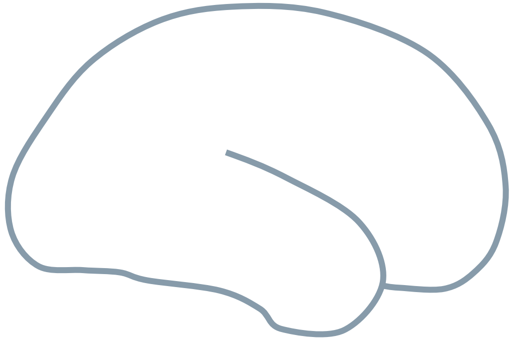


The Objective World, the Cognitive World and the Semantic World

The objective world (does it exist?)

looksAt(Sparky, Jack)

Cognitive/neuroscience Perspective
- grounding/embodiment



I think: Sparky looks at Jack

The language perspective

I say: “Sparky looks at Jack”

Influence on Machine Learning

Psychology

- The statistical approach of **psychology** greatly influenced Machine Learning
- A Neural Network as a model that predicts the response from stimuli, and other inputs

Cognition

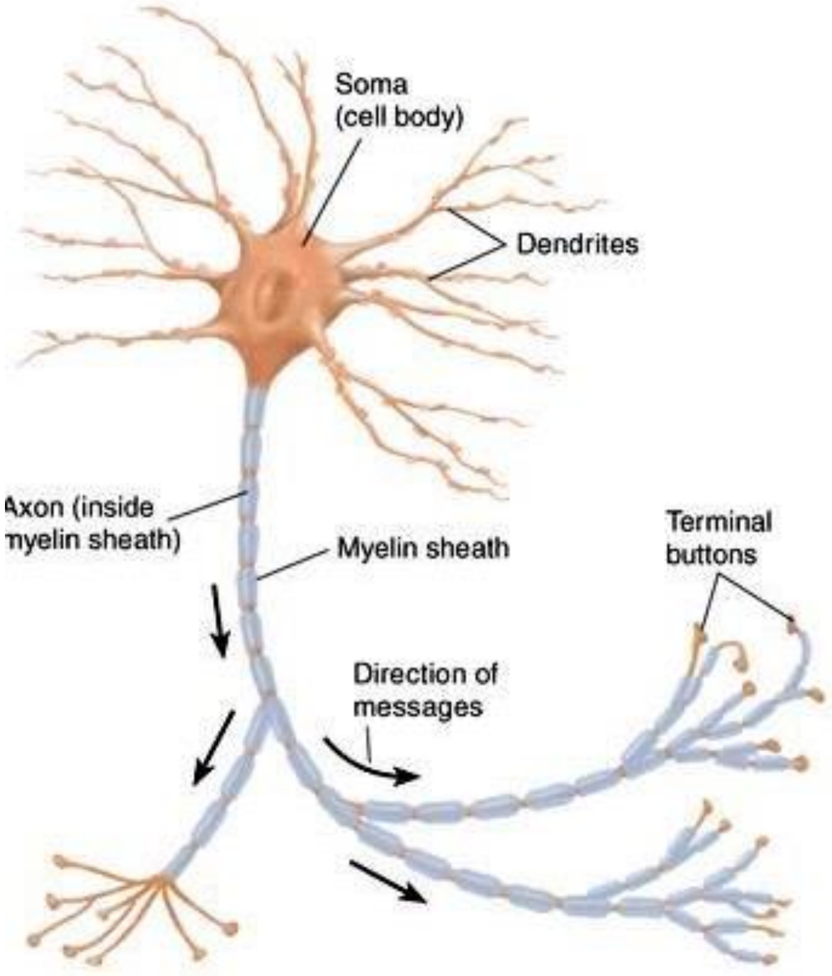
- Relating the inner working of a Neural Network to Cognition and the inner working of the brain
- Machine Learning motivates much research in Cognition
- Two of the co-inventors of the multilayer perceptron, (David Rumelhart and Geoffrey Hinton) are **cognitive psychologists**
- Geoffrey Hinton: founder of Deep Learning

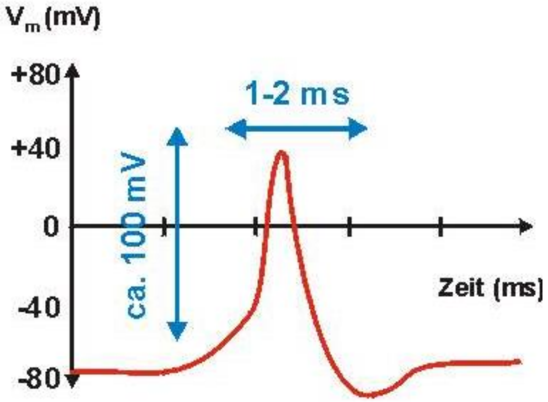
C: Neuroscience

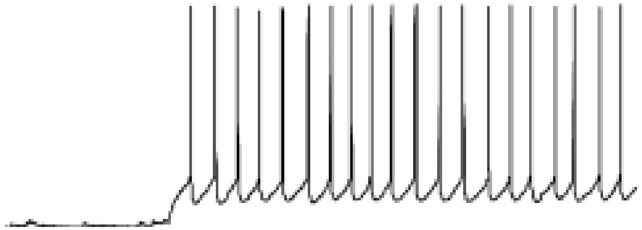
- Whereas before, we were concerned about a systemic view on brain function, here one is interested in the elementary mechanisms: **how does an individual learn and represents knowledge at the level of neurons and their networks, synapses, ion channels, biochemistry, …?**
- Simply put: how does the brain work?
- **Reductionism:** analyzing phenomena, in terms of other simpler or more fundamental phenomena
- There must be a physical change if something is learned!
- **Materialism:** matter is the fundamental substance in nature, and all things, including mental states and consciousness, are results of material interactions
- Central mechanism: Synapses change their efficiency
  - Short-term plasticity: the change lasts milliseconds to minutes
  - Long-term plasticity: the synaptic efficiency changes from hours to life-long

Neuron

- Integrate and fire neuron
- Resting potential: -70 mV.
- Depolarization of the **membrane potential** (by inputs from dendrites):
  - > -50mV
- Leads to an opening of the sodium channels; this leads to the generation of on **action potential**, which is transmitted via the axon
- Refractory period: during this time no new action potential can be generated (appr. 2ms)
- Systems theory: leaky integrator
- In some models: The firing rate is interpreted as a continuous neural output

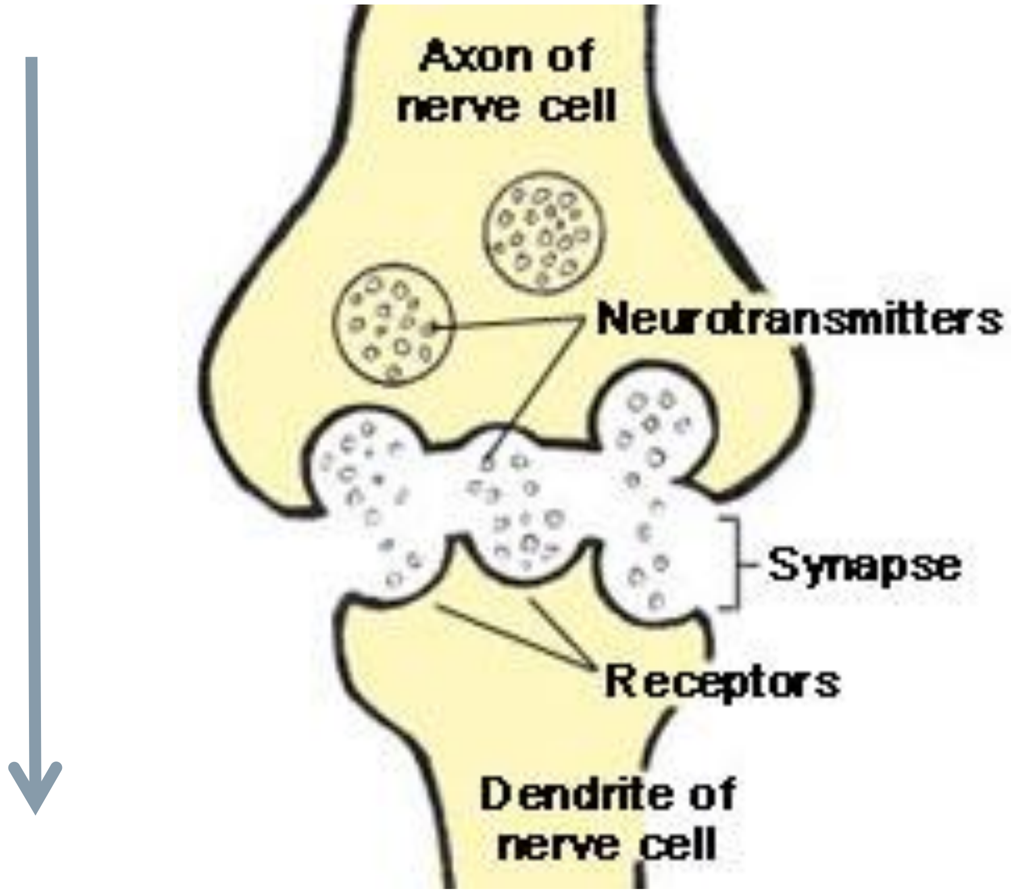






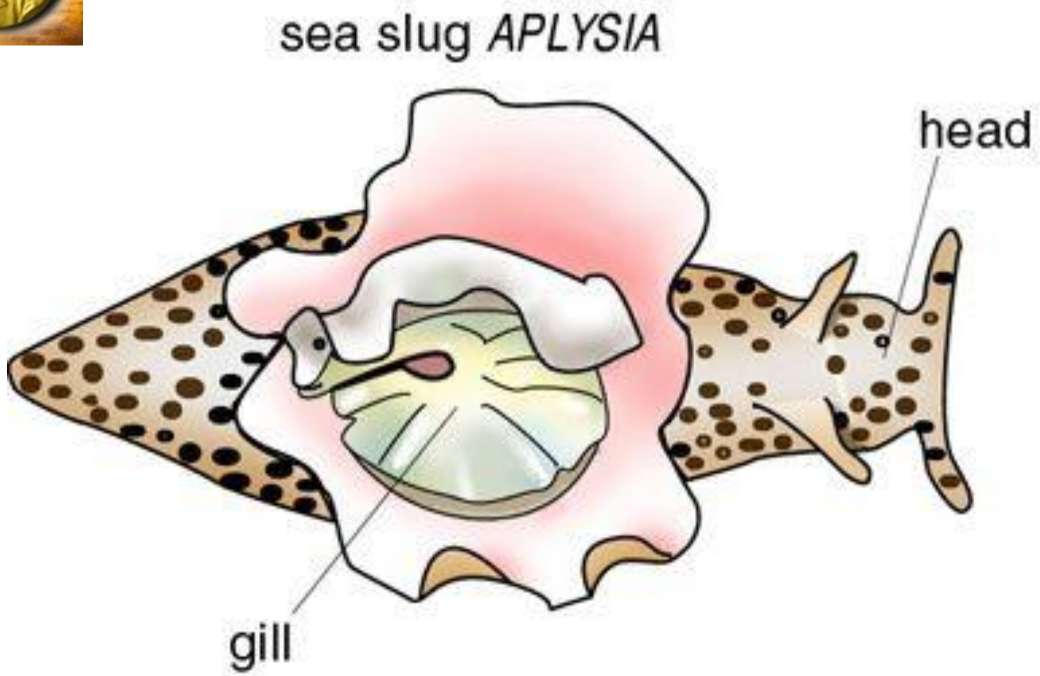
Synapse

- **Presynaptic (Axon):**
  - Presynaptic discharge of the action potential leads to the release of neurotransmitters (10 important types, but maybe 100 in total; from small to very large molecules)
- **Postsynaptic (Dendrite):**
  - Opening of ion channels and thus change of the postsynaptic membrane potential



Aplysia

- Eric Richard Kandel (1929-): US-American Neuroscientist with Austrian origin (Nobel price 2000)
- Study object: Californian see slug (Aplysia californica)
- Gill-withdrawal reflex with 24 sensory-neurons and 6 motor-neurons
- Habituation
    - Reduction of neurotransmitters with repeated stimuli
- Sensitization:
    - Increase of neurotransmitters with repeated (damaging) stimuli
- Association:
    - Light/electric chock



Hebb Learning in Psychology and Neurophysiology

- Kandel’s results supplied new evidence for the Hebb’s law
  - "When an axon of cell A is near enough to excite cell B and repeatedly or persistently takes part in firing it, some growth process or metabolic change takes place in one or both cells such that A's efficiency, as one of the cells firing B, is increased."
- In short:
  - “Neurons that fire together wire together” (long-term potentiation (LTP))
  - “Neurons out off sync, loose their link” (long-term depression (LTD))
- Hebb learning has been confirmed biologically, i.e., in the neurons of the hippocampus
- Hebb formulates learning much more abstractly than Kandel
  - Open question in Machine Learning: how much can one ignore biological details without loosing the essence (e.g. spiking, spike timing?)

Cellular Neuroscience and Neural Circuitry

- Cellular Neuroscience and Neural Circuitry are currently not a major focus in Machine Learning but are areas of interest
- Machine Learning tries to maintain some of the inherent properties of biological learning:
  - Distributed local computing: formalized neurons as building blocks
  - Multilayered hierarchical computing
  - Convolution architectures
  - Noise and fault tolerance: graceful degradation
- The neurobiological plausibility of Machine Learning architectures and algorithms is sometimes hotly debated (is the backpropagation learning rule biologically plausible?)

Psychology, Cognition and Cognitive Neuroscience

- All non-technical endeavors on human learning and intelligence provide insights on some aspects and study different levels of abstractions
- This reflects the state of our understanding
- As an outside observer: It appears that the different endeavors are more isolated from one another than one would expect

Overview

A	**Before the Computer Age to Today: Statistics**
B	**Neural Computation I (Perceptron)**
C	**Classical Artificial Intelligence**
D	**Neural Computation II (Multilayer Perceptron)**
E	**Mathematically Well-Founded Models**
F	**Neural Computation III (Deep Learning); AI II**
G	**Generative AI; Large Language Models; Foundation Models**

A: Before the Computer Age to Today: Statistics

- Thomas Bayes (1701 -1761): Updating the degree of belief in hypothesis based on observations (his work was published after his death by Richard Price)
- **A mathematical answer to the top-down versus bottom-up problem**
- **A priori assumption (top-down)**: $P(H=1)$, with $P(H=0) = 1 - P(H=1)$
  - Degree of belief in the truthfulness of a hypothesis H (top-down)
- **Likelihood (bottom up):** $P(D|H=1)$ and $P(D|H=0)$
  - $P(D|H=1)$: Plausibility of the data D (observations), if the hypothesis H is true
  - $P(D|H=0)$: Plausibility of the data D (observations), if the hypothesis H is false
- Then, the **a posteriori probability** (Bayes called it “inverse probability”) of the hypothesis being true is given by Bayes’ theorem:
  - $P(H=1|D) = P(D|H=1) P(H=1) / P(D)$
- With: $P(D) = P(D|H=1) P(H=1) + P(D|H=0) P(H=0)$
- Learning: updating ones prior belief based on data

Bayes’ rule was rediscovered independently by Pierre Simon Laplace (1749-1827), who gave it its modern mathematical form

Bayesian Statistics

- In statistics, the Bayesian interpretation of probability was developed mainly by Pierre-Simon Laplace (1749–1827)
- Bayes rule is a theorem in the mathematical probability theory
- The application of Bayes rule to problems in the real world is disputed (in particular if hypothesis on parameter distributions are used)
- Bayesian Statistics has great influence in the sciences, in particular in Bayesian Machine Learning and Cognition (Bayesian Brain Hypothesis)

- Example:
  - $P(H = Bronchitis \mid D = PositiveXRay)$

    $= P(D = PositiveXRay \mid H = Bronchitis)\, P(H = Bronchitis) / P(D = PositiveXRay)$

Bayesian Statistics is Based on the Concept of Subjective Probability

- With subjective probabilities I can make personal statements like:
  - *Before I throw a coin, I believe that the coin is a fair coin with 99%*
  - *I believe that the probability that party X wins the election is 45%*

- Cox's theorem implies that any plausibility model that meets his postulates is equivalent to the subjective probability model, i.e., can be converted to the probability model by rescaling (Richard Threlkeld Cox, 1898–1991)

- If a one corresponds to the belief that an event happens with certainty and if a zero corresponds to the belief that an event does not happen, and numbers in between corresponds to degrees of certainty, then these numbers exactly behave as probabilities

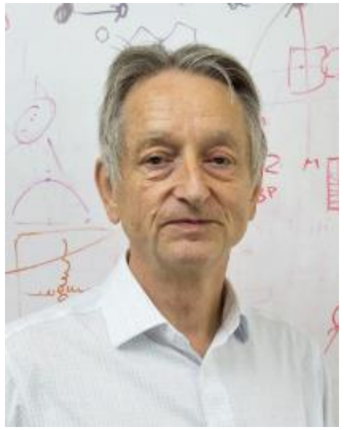
Critique on Bayesian Statistics


- **Karl Pearson** (1857–1936)
  - now considered the founder (“godfather”) of modern statistics (also referred to as classical or frequentist statistics)
  - "I felt like a buccaneer of Drake's days -... I interpreted that sentence of Francis Galton (1822-1911) [his advisor] to mean that there was a category broader than causation, namely correlation, of which causation was only the limit, and that this new conception of correlation brought psychology, anthropology, medicine, and sociology in large parts into the field of mathematical treatment."
- **Ronald Aylmer Fisher** (1890-1962)
  - Criticism of subjective probabilities: frequentists only make statements about repeatable experiments
  - One evaluates if the data contradict a hypothesis but one does not make statements about the probability of a hypothesis
- Other founding contributors: **Egon Pearson** (1895-1980), son of Karl P.; **Jerzy Neyman** (1894-1981)

Footnote: Incidentally: all of them were critical on Bayesian statistics, and also causal analysis

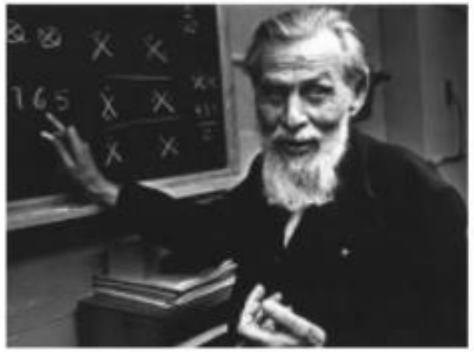
Comparison

- Bayesian modelling: *$P(H=1|D) \sim P(D|H=1)\, P(H=1)$*
  - *Model $P_w(D|H=1)$ and $P(H=1)$ separately*
- Classical statistics: hypothesis testing based on $P_w(D|H=1)$
  - Avoid the modelling of $P(H=1)$
- Supervised Machine Learning: model directly: $P_w(H=1|D)$
- (w are the model parameters)



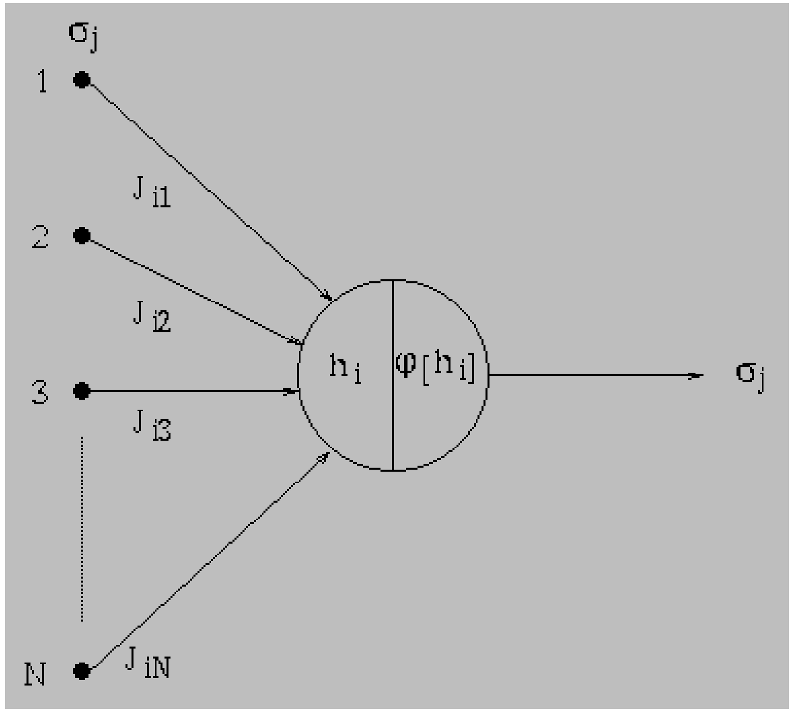
B: Neural Computation I

- Started with a focus on expressiveness of Neural Networks (and not their ability to learn)
- McCulloch and Pitts (1943)
  - First attempt to formalize brain functions via networks of simple computational nodes (network of simple logical units)
  - McCulloch-Pitts Neuron



Warren McCulloch
1898-1969

Walter Pitts
1923-1969



Expressiveness of Neural Networks

- John von Neumann (1903-1957) investigated the error tolerance of Neural Networks
  - “Computer and the Brain” (book, 1958)

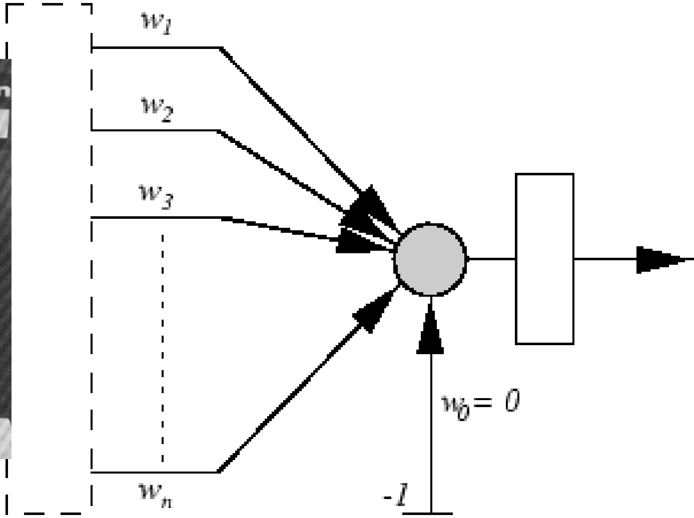
- John von Neumann concluded that the brain operates in part digitally, in part analogically, but uses a peculiar statistical language unlike that employed in the operation of man-made computers

Learning in Neuronal Structures

- Hebb (1949): Repeated activation of one neuron by another, across a particular synapse, increases its conductance (Hebb‘s theorem); "Neurons that fire together wire together"
  - Hebb tried to explain classical conditioning via neural mechanisms
- Wiener (1949): Cybernetics, or control and communications in the animal and the machine
  - The whole world -- even the universe -- could be seen as one big feedback system subject to the relentless advance of entropy, which subverts the exchange of messages that is essential to continued existence (1954)
  - “Cybernetics or Control and Communication in the Animal and the Machine” (book, 1948)

Perceptron and ADALINE

- **Marvin Minsky** (1927-2016) developed 1954 in his dissertation a neural computer he called SNARC (Stochastic Neural Analog Reinforcement Calculator)
- **Frank Rosenblatt** (1928-1971) developed in 1958 the *Perceptron learning rule* and formulated a convergence proof; Mark I Perceptron
  - Basis for MLP and Deep Learning
- **Bernard Widrow** (1929-) and **Ted Hoff** (1937-) developed in 1960 the *ADALINE* (ADaptive LINear Element)
  - Foundation of adaptive signal processing
- Marvin Minsky and Seymour Aubrey Papert (1928-2016) published 1969 the book „Perceptrons“ and demonstrated the limitations of the Perceptrons and of the ADALINE (Exclusive-Or Problem)



The New York Times

SUNDAY, JULY 13, 1958

overstepping the limits of toxicity, and (2) because cancer cells that are resistant to the action of the chemicals arise rapidly and in many ways.

There are "inadequate and intriguing hints," he said, "that the synthesis and use of large molecules of nucleic acids (chemicals that con-

versity College of Medicine said he regarded the discovery of lactone as "one of the most significant steps reported at the Congress" and expressed the hope that it will prove useful in the treatment of bladder cancer for the general population, when the chemical becomes generally available.

Electronic 'Brain' Teaches Itself

The Navy last week demonstrated the embryo of an electronic computer named the Perceptron which, when completed in about a year, is expected to be the first non-living mechanism able to "perceive, recognize and identify its surroundings without human training or control." Navy officers demonstrating a preliminary form of the device in Washington said they hesitated to call it a machine because it is so much like a "human being without life."

Dr. Frank Rosenblatt, research psychologist at the Cornell Aeronautical Laboratory, Inc., Buffalo, N. Y., designer of the Perceptron, conducted the demonstration. The machine, he said, would be the first electronic device to think as the human brain. Like humans, Perceptron will make mistakes at first, "but it will grow wiser as it gains experience," he said.

The first Perceptron, to cost about $100,000, will have about 1,000 electronic "association cells" receiving electrical impulses from an eyelike scanning device with 400 photocells. The human brain has ten billion responsive cells, including 100,000,000 connections with the eye.

Difference Recognized

The concept of the Perceptron was demonstrated on the Weather Bureau's $2,000,000 IBM 704 computer. In one experiment, the 704 computer was shown 100 squares situated at random either on the left or the right side of a field. In 100 trials, it was able to "say" correctly ninety-seven times whether a square was situated on the right or left. Dr. Rosenblatt said that after having seen only thirty to forty squares the device had learned to recognize the difference between right and left, almost the way a child learns.

When fully developed, the Perceptron will be designed to remember images and information it has perceived itself, whereas ordinary computers remember only what is fed into them on punch cards or magnetic tape.

Later Perceptrons, Dr. Rosenblatt said, will be able to recognize people and call out their names. Printed pages, longhand letters and even speech commands are within its reach. Only one more step of development, a difficult step, he said, is needed for the device to hear speech in one language and instantly translate it to speech or writing in another language.

Self-Reproduction

In principle, Dr. Rosenblatt said, it would be possible to build Perceptrons that could reproduce themselves on an assembly line and which would be "conscious" of their existence.

Perceptron, it was pointed out, needs no "priming." It is not necessary to introduce it to surroundings and circumstances, record the data involved and then store them for future comparison as is the case with present "mechanical brains." It literally teaches itself to recognize objects the first time it encounters them. It uses a camera-eye lens to scan objects or survey situations, and an electrical impulse system, patterned point-by-point after the human brain does the interpreting.

The Navy said it would use the principle to build the first Perceptron "thinking machines" that will be able to read or write.

C: Classical Artificial Intelligence

- After the book of Minsky and Papert, funding almost exclusively went into the emerging field of AI
- No more funding for the study of learning systems
- A brief history of classical AI (1950s to 1980s)

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- A brief history of classical AI (1960s to 1980s)

Roots of AI in Philosopy

- Motivated by attempts to formalize all of mathematics by Gottlob Frege (1848-1925), and then, in the *Principia Mathematica*, by Bertrand Russell (1872-1970) and Alfred North Whitehead (1861-1947)
- Logical positivists (or 'neopositivists') attempts to reduce statements and propositions to pure logic; Wiener Kreis, Rudolf Carnap (1891-1970); great influence in US (after 1936, worked in the US)
- Ludwig Wittgenstein (1889-1951): critical to the Wiener Kreis, but related, focusing on language

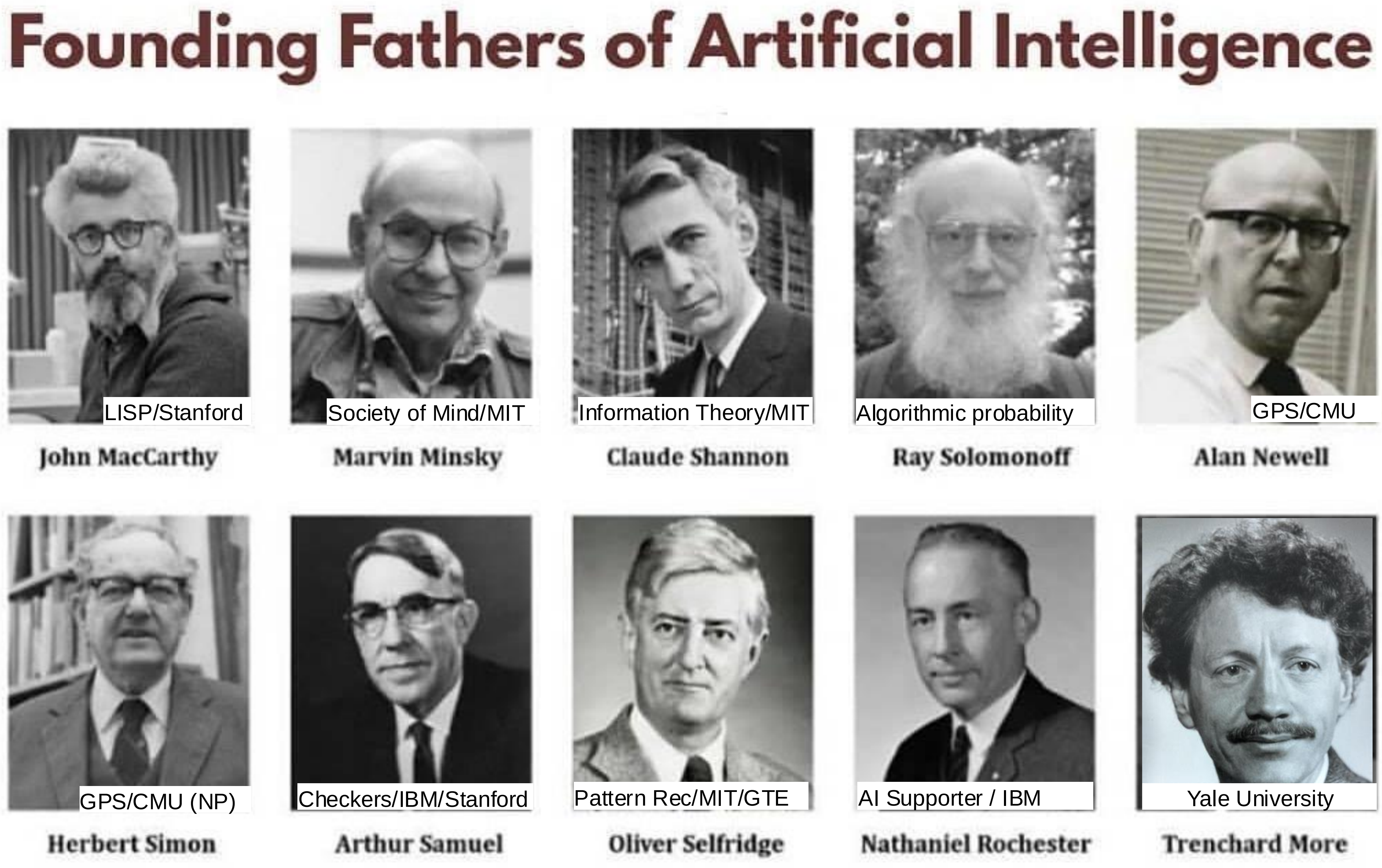
Perspectives of AI

- **Normative or prescriptive decision theory** is concerned with identifying the best decision to make, modeling an ideal decision maker who is able to compute with perfect accuracy and is fully rational. The practical application of this prescriptive approach (how people ought to make decisions) is called decision analysis, and is aimed at finding tools, methodologies and software (decision support systems) to help people make better decisions (tradition in Rationalism)
  - Rational (optimal) Reasoning: Logic
  - Rational (optimal) Acting: Agents

- In contrast, **positive or descriptive decision theory** is concerned with describing observed behaviors under the assumption that the decision-making agents are behaving under some consistent rules (tradition in Empiricism)
  - Understanding human thinking (Cognition)
  - Indistinguishably from human acting (Turing Test)

Birth of AI: Dartmouth Workshop (1956)

- **John McCarthy** (Dartmouth, later Stanford) (1927-2011)
  - Suggested the term *Artifical Intelligence* (to distinguish it from Cybernetics); inventor of LISP
- **Marvin Minsky** (1927-2016) (MIT)
  - SAINT (calculus integration); ANALOGY (geometric analogy); STUDENT (algebra); Blocks World; The Society of Mind (1985)
  - Critique on the dominating roles of Logic in AI and Statistics in Machine Learning
- **Claude Shannon** (1916-2001) (Bell Labs) Inventor of Information Theory
- **Arthur Samuel** (1901-1990) (IBM) checkers program
- **Ray Solomonoff** (1926-2009) (MIT) Founder of Algorithmic Probability
- **John von Neumann** (1903–1957) Institute for Advanced Study; Founder of Game Theory
- **Allen Newell** (1927-1992) (CMU), **Herbert Simon** (1916-2001) (CMU) (Nobel P. 1978) General Problem Solver (GPS): a program to solve general problems (terminated after 10 years)
  - Representative of strong AI: Intelligence is independent of substrate
- **Nathaniel Rochester** (chief architect of the IBM 700 series), **Trenchard More** (Yale), **Oliver Selfridge** (MIT), **Cliff Shaw**



Founding Fathers of Artificial Intelligence
LISP/Stanford
John MacCarthy
Society of Mind/MIT
Marvin Minsky
Information Theory/MIT
Claude Shannon
Algorithmic probability
Ray Solomonoff
GPS/CMU
Alan Newell
GPS/CMU (NP)
Herbert Simon
Checkers/IBM/Stanford
Arthur Samuel
Pattern Rec/MIT/GTE
Oliver Selfridge
AI Supporter / IBM
Nathaniel Rochester
Yale University
Trenchard More

Early Classical AI Phase

Early Enthusiasm (1952-1969)

- In the first AI phase there was an unlimited expectation with respect to the capabilities of computers to „solve tasks for which intelligence is required, if they would be executed by humans“
- Herbert Simon (1957)
  - Within the next 10 years a computer will be world champion in chess and will derive an important mathematical theorem
  - In don‘t want to chock you …There are now in the world machines that think … in a visible future the range of problems they can handle will be coextensive with the range to which the human mind has been applied…
- In 1958 McCarthy proposed to formalize the complete human knowledge in form of a homogeneous formal representation, first order predicate logic

First Reality-Dose (1966-1973)

- Project to translate Russian into English was stopped: "the spirit is willing but the flesh is weak“ became "the vodka is good but the meat is rotten"
- Reasoning did not scale up

Late Classical AI Phase

Knowledge-based Systems(1969-1979)

- Expert systems: In an expert system, there is a formal knowledge representation, for example as a set of rules, and these are applied to known facts to infer new facts
- Bruce Buchanan: DENDRAL (1969); inferring molecular structure from mass spectroscopy data; first knowledge intensive system
- Ed Feigenbaum (Stanford): Heuristic Programming Project (HPP)
- Feigenbaum, Buchanan, Shortliffe; MYCIN: Diagnose blood infections; extensive interviewing of experts; uncertainty factors
- Progress in NLP: Eugene Charniak, Roger Shank

AI becomes an Industry (1980- and a few years later)

- McDermott: R1 (DEC, 1982); Configuration of computer systems; each major company has an AI group
- Fifth Generation Project in Japan (1981); 10-year project: intelligent computers based on PROLOG

Collapse (1984) of many Silicon Valley start-ups (Beginning of the AI winter)

(In UK funding had stopped even earlier after the publication of the Lighthill report (1973): criticized the utter failure of AI to achieve its "grandiose objectives“)

Machine Learning in Classical AI

- Machine Learning was not in focus in classical AI (“only deductive inference is sound”)
- The field wanted to distinguish itself from statistics and probability
- Focus on *symbolic* Machine Learning

- Out off this tradition
  - Case-based reasoning (CBR) (Schank, 1977)
  - Learning of decision trees (Ross Quinlan‘s ID3, 1979, Rivest)
  - Inductive Logic Programming (Stephen Muggleton, 1991)
    - Intuitively attractive: The goal is to extract simple logical rules
    - Powerful: One can learn (first-order) Prolog Rules (Turing-equivalent)

D: Neural Computation II

- There was increasing interest in neural computation around the mid 80s; end of the neural winter (1969-1982)
- Descartes (and classical AI): the mind (thinking, soul) is entirely distinct from the body and can be successfully explained and understood **without** reference to the body or to its processes
  - Maybe the substrate is relevant after all; embodied AI
- Learning in focus; in opposition to rule-based approaches
- Fascination brain: despite the biological complexity there should be a simple organizational principal, which leads to intelligence via learning. Maybe intelligence can only be reached via learning?
- Technically high-performing solutions

Hopfield Networks

- John Hopfield (1933-): Neural networks and physical systems with emergent collective computational abilities (1982, 1984)

- Achievements:
  - Associative content-addressable memory (Hebb learning)
  - Solving combinatorial optimization problems (travelling salesman) (new interest in Hopfield nets in in quantum computing, e.g., quantum annealing)
- Important: he made the link to statistical physics (spin-glasses), which brought in many physicists
- Interesting computational features: nonlinear, parallel, error tolerant, with feedback
- Implementation as optical computer?
- Relationship to brain functioning?
  - At the end: solutions were not technically competitive
- Prior work on associative memory: W. K. Taylor (1956); Karl Steinbuch (1961); James A. Anderson (1968), D. J. Willshaw (1969), Stephen Grossberg (1967), Teuvo Kohonen (1974)
- Prior work on links to statistical physics: E. R. Caianiello (1961), W.A. Little and Gordon L. Shaw (1975)

Boltzmann Machine, Multilayer Perceptron

Ackley, Hinton, Sejnowsky (1985): Boltzmann Machine

- Discriminative Learning; close connection to Statistical Physics
- Theoretically very interesting but not as practical as the MLP
- Come-back in Deep Learning as restricted Boltzmann Machine

Rumelhart, Hinton, Williams (1986): Multilayer Perceptron (MLP)

- MLP: a robust powerful tool for modeling high-dimensional nonlinear dependencies
- Beyond the limitations of the Perceptron: Solution to the exclusive-or-problems, Nettalk
- MLP: superior modeling tool for high-dimensional problems
- Breakthrough in Neural Computation
- Interest in Statistics and from statisticians

- Since 1988 a certain hype („Learning instead of programming“)

E: Mathematically Well-Founded Models

- In the middle 1990s the interest in neural networks slowly faded
  - Limited interest by other fields in this “heuristic” approach
  - Connection to Neuroscience became less strong
- Neural computation transformed into Machine Learning
  - (The term was used earlier only for symbolic machine learning)
- Keywords: Statistical Machine Learning; Bayesian networks and Graphical Models; VC-Theory; Kernel Systems; Gaussian Processes; Infinite Models
- Most famous model: Support Vector Machine
- High recognition and deep impact on other fields: Bioinformatics, Vision, Natural Language Processing, Information Retrieval, Search Engines, …
- AI increasingly became influenced by Machine Learning (other fields became NIPS-ified)

F: Neural Computation III, AI II

- By around 2010 theoreticians dominated the core of Machine Learning
- The field converged to a number of beautiful theories but in terms of practical usefulness, there was little progress (in some areas, the SVM excelled, but in some applications, a neural network from 1986 was equally good and sometimes even better than an SVM)
- This situation totally changed with deep learning
  - Sometimes after 2010 (2012?) the deep learning revolution got started
  - Big names; Geoffrey Hinton, Yoshua Bengio, Yann LeCun, Andrew Ng, Jürgen Schmidhuber, …
- Some difficult benchmarks were improved by a factor of 10 (ImageNet)!
- Dominates: Vision research, NLP, …
- Immediately in products: Speech recognition, face recognition, language translation, …
- The perceived AI revolution is due to Deep Learning

G: Generative AI; Large Language Models; Foundation Models

- GPT: Generative Pre-trained Transformer
- ChatGPT(Chatbots)
    - “An earthquake”

- Vision-language Models:

> VT: I am a student at LMU Munich: should I study machine learning?
>
> Whether or not you should study machine learning depends on your interests, career goals, and the direction you want to take in your academic and professional life.
>
> If you are interested in computer science, mathematics, and statistics, and enjoy solving complex problems using data-driven approaches, then studying machine learning could be a good fit for you. Machine learning is a rapidly growing field with numerous applications in various industries, including healthcare, finance, and technology. It offers a wide range of career opportunities in research, development, and implementation of machine learning models and algorithms.
>
> However, if your interests lie elsewhere, such as in the humanities or social sciences, machine learning may not be as relevant to your academic and career goals. It's important to explore different fields of study and career paths before making a decision.
>
> Ultimately, the decision to study machine learning should be based on your interests, aptitude, and career goals. You can talk to your academic advisor, career counselor, or professionals in the field to get a better understanding of the potential benefits and drawbacks of studying machine learning.

Power of Foundation Models / Large Language Models

For example, when I gave GPT-3 the prompt:

In 1958, Frank Rosenblatt introduced the Perceptron, an early version of a neural net that could only detect the location of a square on a printed card. Fifty years later, neural nets are capable of . . .

The software dutifully completed the thought, and then continued on, picking up on the historical framing of the initial text:

. . . detecting and classifying faces, finding patterns in data, and emulating the human brain. While the neural net matured in academia, it also found its way into the tech industry. In the late 1980s and early 90s, neural nets were used in speech recognition and character recognition applications. The growth in computing power and the ability to collect larger data sets allowed other neural net applications to emerge.

New York Times, 2022-04-22

Overview

The Lecture

- Technical foundation of approaches which are in focus today
- From applied mathematics
  - **Linear Algebra (vectors, matrices, …)**
  - Calculus: how to calculate derivatives, chain rule, …
  - Optimization: necessary conditions to be in an optimum; gradient descent optimization
  - **Probability, Bayesian and Frequentist Statistics**
    - Lectures from different experts agree on what should be done, but might differ in in the reason why something should be done (PAC, VC-theory, Frequentist Statistics, Bayesian Statistics, …)
    - I present the path I find most useful

- Often: Machine Learning is based on the minimization of a data-dependent cost function (optimization) with respect to unknown model parameters. The cost function is derived using probabilistic assumptions (probability) and model performance is analyzed by statistical methods. With quadratic loss functions, solutions can be derived with methods from linear algebra by setting derivatives to zero (calculus)

Recommended Literature

- Andrew Ng’s Coursera and Stanford courses on Machine Learning and Deep Learning
- The Elements of **Statistical Learning**: Data mining, Inference and Prediction. Hastie, Tibshirani, Friedman: Springer (2nd Ed.). [Modern Statistics; frequentist] Download at http://www-stat.stanford.edu/~tibs/ElemStatLearn/
- “Probabilistic Machine Learning: An Introduction” (2022) Probabilistic Machine Learning: Advanced Topics”; Kevin Murphy: MIT Press [**Bayesian orientation**, available for free download]
- Pattern Classification. Duda, Hart, Storck: Wiley [Pattern recognition]
- Pattern Recognition and Machine Learning. Bishop: Springer [Bayesian touch]
- Artificial Intelligence-a Modern Approach. Russel and Norvig, Prentice Hall [All of AI]
- Machine Learning. Tom Mitchell: McGraw-Hill [Some excellent Chapters; some outdated]

Specific Topics

- **Data Mining:** Concepts and Techniques. Han and Kamber: Morgan Kaufmann [Data mining]
- **Kernel Methods** for Pattern Analysis. John Shawe-Taylor and Nello Cristianini: Cambridge UP
- **Reinforcement Learning**: an Introduction. Sutton and Barto: MIT Press
- **Bayesian Data Analysis**. Gelman, Carlin, Stern, Rubin: Chapman
- **Statistik.** Fahrmeir, Kuenstler, Pigeot, Tutz: Springer (introduction to classical statistics)
- **Probability**, Random Variables and Stochastic Processes. Papoulis, McGraw, Hill
- **Cognitive Neuroscience:** The Biology of the Mind. Gazzaniga, Ivry, Mangun, Norton
- **Computational Learning Theory:** Understanding Machine Learning: From Theory to Algorithms. Shai Shalev-Shwartz and Shai Ben-David. Cambridge University Press. (covers VC-Theory, Statistical Learning Theory)

Deep Learning

- Deep Learning. Ian Goodfellow, Yoshua Bengio, and Aaron Courville (2016). http://www.deeplearningbook.org/
- **Deep Learning: Foundations and Concepts.** Christopher M. Bishop and Hugh Bishop (2023)
- **Understanding Deep Learning.** Simon J.D. Prince (2023)
  - They're similar and both very good. I'd say prince is more intuitive with great diagrams, but bishop is more willing to dive into the maths. you can find pdfs of both online, have a skim through both and just choose whichever style you prefer. (Reddit)

Lecture Overview

Introduction (History of everything)

Perceptron, Linear Algebra (Review), Linear Regression (Adaline)

Basis functions

Complexity Analysis

Neural Networks

Deep Learning

Sequential Data (including LSTM, Attention)

Manifold Learning (including AE, GAN)

Kernels

Probability (Review)

Frequentists versus Bayesians

Linear Classifiers, SVM

Model Comparison

Bayes nets

(Reinforcement Learning)

Notes on Privacy Policy:

Moodle, LMU-Cast and Uni2Work

Moodle, LMU Cast and Uni2Work are websites from the Ludwig-Maximilians-Universität München and follow the privacy policy which can be read here: https://www.en.uni-muenchen.de/funktionen/privacy/index.html

News

Organization

- **Course:** 3+2 hours weekly (equals 6 ECTS)
- **Lecture:** Prof. Dr. Volker Tresp
- **Assistants:**
- **Register**: Moodle

Time and Locations

All times are c.t. (cum tempore)

Component	When	Where	Starts at
Lecture	Thu, 9:00 c.t. - 12:00 h	Geschw.-Scholl-Pl. 1 - B 006	17.10.2024
Tutorial	Mon, 16:00 c.t. - 18:00	Geschw.-Scholl-Pl. 1 - E 216	21.10.2024