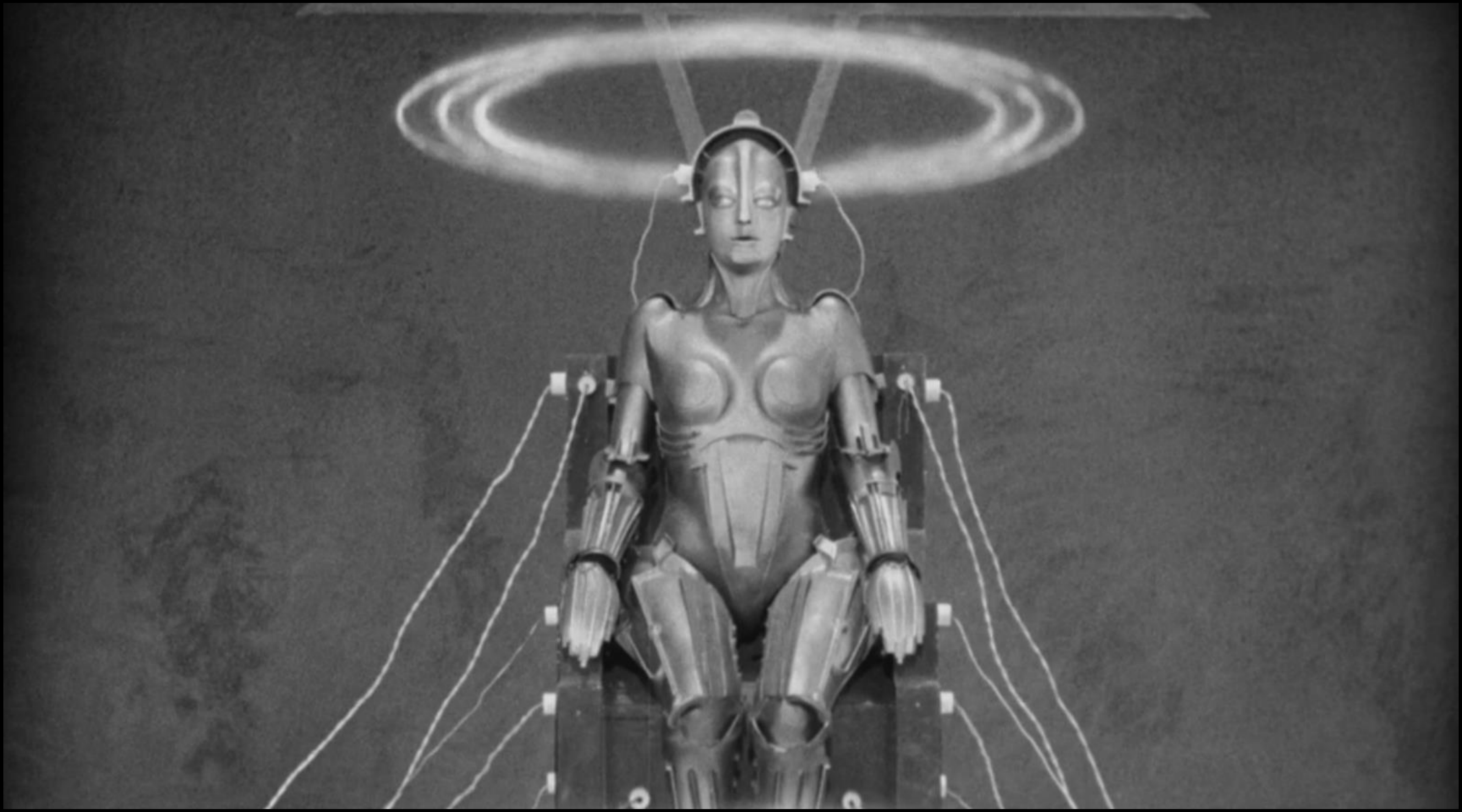
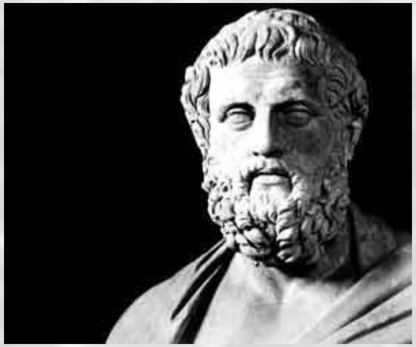


Foundations / A (Brief) History of AI

What is AI?

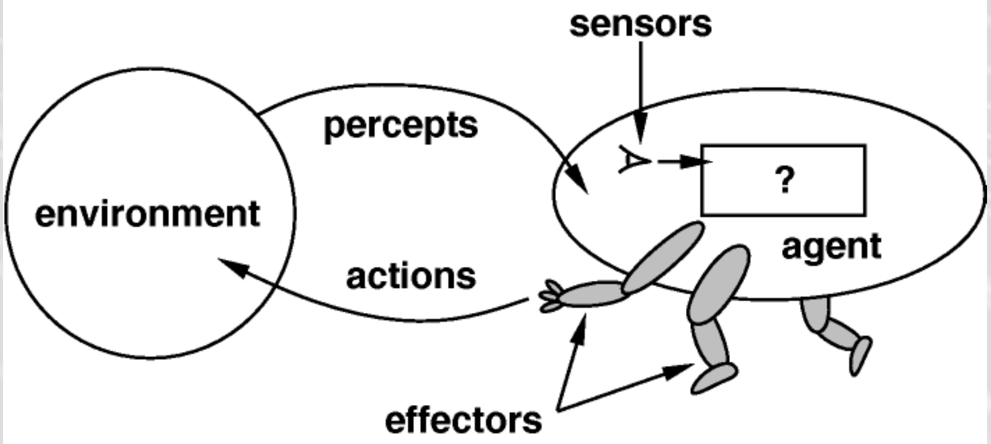
"Numberless are the world's wonders – but none more wonderful than mankind" – Sophocles, Antigone



(*) "AI" encompasses two general domains:

(1) **Behavior** (acting "humanly")

(2) **Rationality** (acting and thinking "rationally")



What is AI?

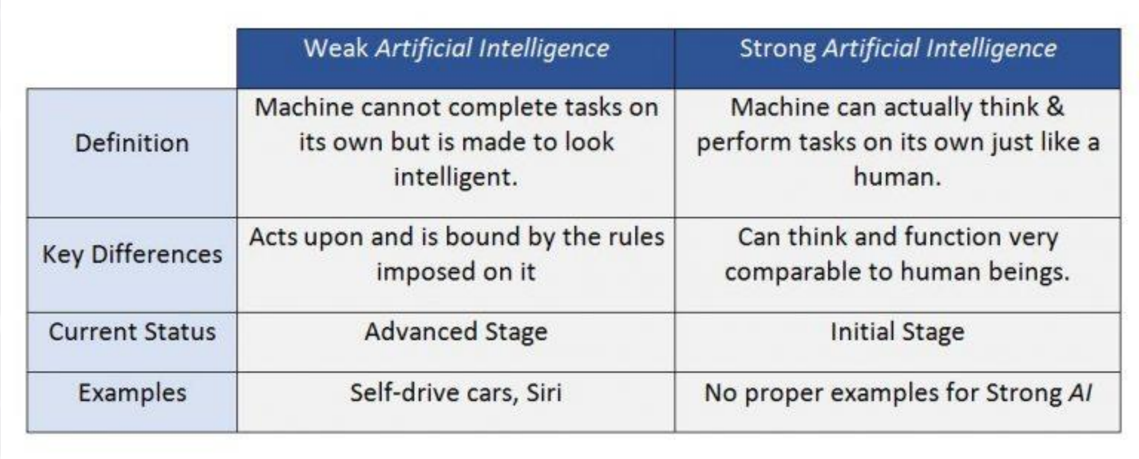
Rational Agent Model for AI:

(*) A **rational agent** "behaves as well as possible."

"Strong AI" vs. "Weak AI"

Strong AI: Machines are actually "thinking"

Weak AI: Machines *act* as if they were intelligent



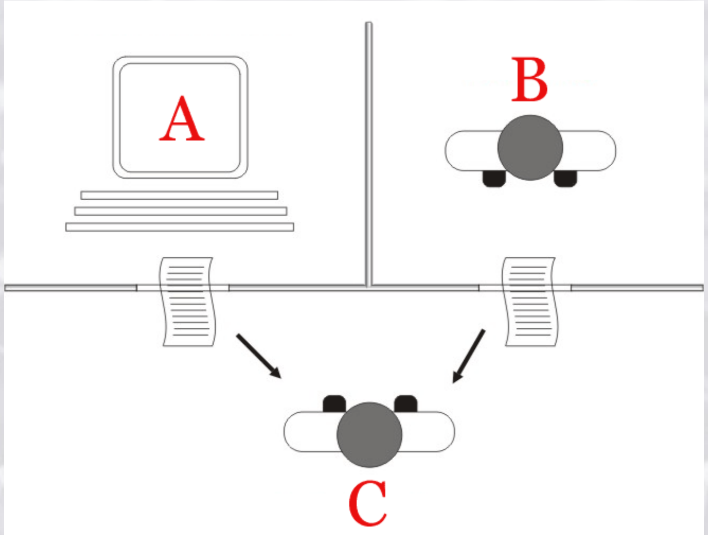
	Weak *Artificial Intelligence*	Strong *Artificial Intelligence*
Definition	Machine cannot complete tasks on its own but is made to look intelligent.	Machine can actually think & perform tasks on its own just like a human.
Key Differences	Acts upon and is bound by the rules imposed on it	Can think and function very comparable to human beings.
Current Status	Advanced Stage	Initial Stage
Examples	Self-drive cars, Siri	No proper examples for Strong *AI*

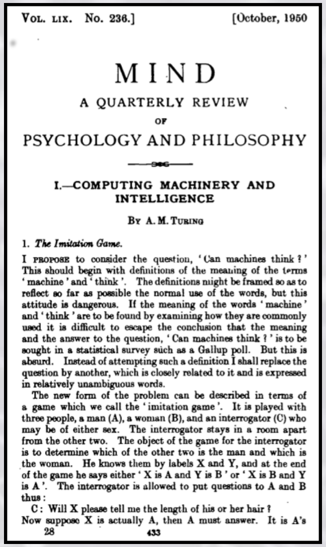
(*) Most (but not all) practitioners believe weak AI is (sometimes trivially) achievable – but disagree about the feasibility of strong AI.

(*) Few mainstream researchers believe that anything significant hinges on the outcome of this debate.

What is AI?

(*) Turing Test / "Total" Turing Test (1950) https://www.csee.umbc.edu/courses/471/papers/turing.pdf




VOL. LIX. No. 236.] [October, 1950

MIND

A QUARTERLY REVIEW

OF

PSYCHOLOGY AND PHILOSOPHY

I.—COMPUTING MACHINERY AND INTELLIGENCE

BY A. M. TURING

1. *The Imitation Game.*

I PROPOSE to consider the question, 'Can machines think ?' This should begin with definitions of the meaning of the terms 'machine' and 'think'. The definitions might be framed so as to reflect so far as possible the normal use of the words, but this attitude is dangerous. If the meaning of the words 'machine' and 'think' are to be found by examining how they are commonly used it is difficult to escape the conclusion that the meaning and the answer to the question, 'Can machines think ?' is to be sought in a statistical survey such as a Gallup poll. But this is absurd. Instead of attempting such a definition I shall replace the question by another, which is closely related to it and is expressed in relatively unambiguous words.

The new form of the problem can be described in terms of a game which we call the 'imitation game'. It is played with three people, a man (A), a woman (B), and an interrogator (C) who may be of either sex. The interrogator stays in a room apart from the other two. The object of the game for the interrogator is to determine which of the other two is the man and which is the woman. He knows them by labels X and Y, and at the end of the game he says either 'X is A and Y is B' or 'X is B and Y is A'. The interrogator is allowed to put questions to A and B thus:

C: Will X please tell me the length of his or her hair ?

Now suppose X is actually A, then A must answer. It is A's

28 433

(*) Again, few researchers believe the Turing test is crucial to the future development of AI – however, many fascinating & canonical issues are raised by Turing in this paper on the nature of AI.

Is intelligence a well-defined concept?

(*) A 1955 study found that in 19/20 "expert disciplines", an elementary mathematical model (e.g. regression, naïve Bayes) outperformed human practitioner.

Aspects of AI & AI Systems

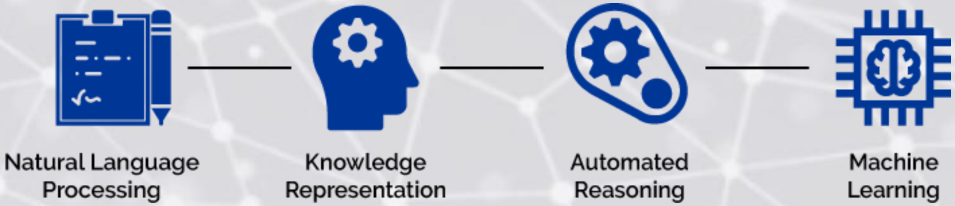
(*) NLP: Natural Language Processing

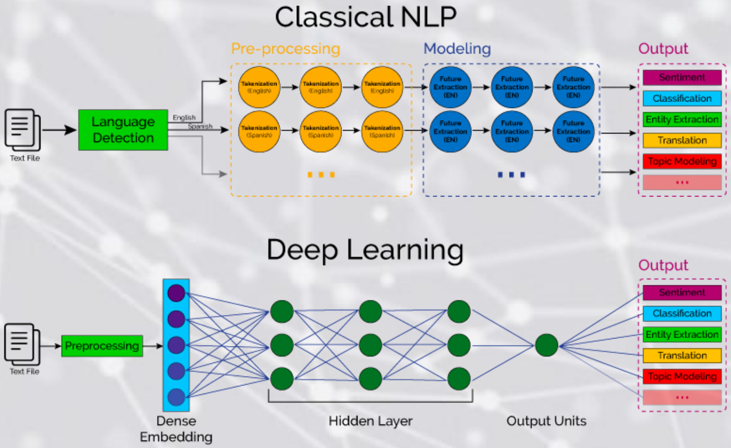
(*) Knowledge Representation: Store/retrieve what is known

(*) Automated Reasoning: Use stored information for inference/deduction

(*) Machine Learning: Detect/extrapolate patterns

(*) Agent's Representation of the World: Environment-knowledge representation





(Computer Vision + Robotics (sensors, actuators) + embodiment = "**Total Turing Test**"

Aspects of AI & AI Systems

(*) Sophia the robot (Hanson Robotics)

https://www.youtube.com/watch?v=T4q0WS0gxRY&t=1s

Ben Goertzel

Singularity Net

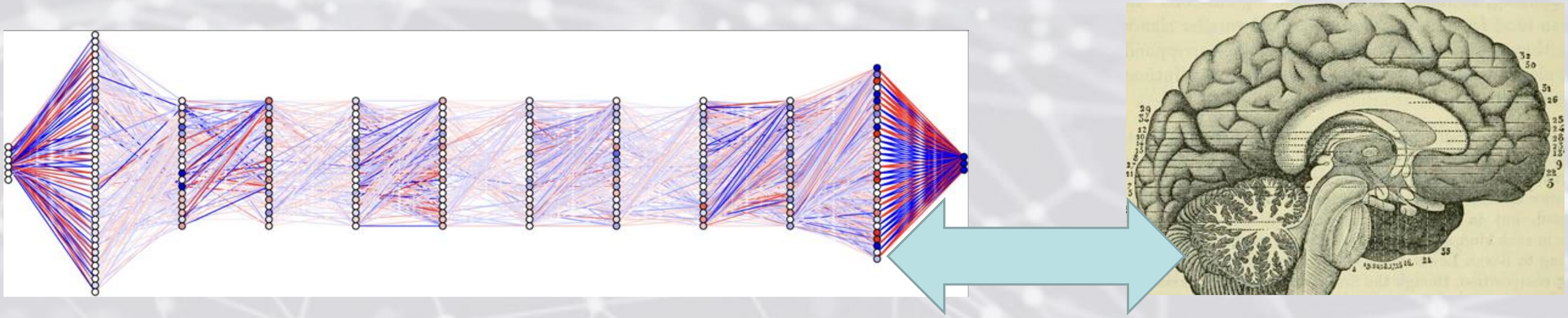
https://singularitynet.io/ http://goertzel.org/

Related Disciplines

Neuroscience: Direct study of nervous system (brain functions, etc.)

Psychology: Emphasis on Behaviorism (Skinner) – difficult to directly test.

Cognitive Science: "AI + Psychology" (use testable theories)

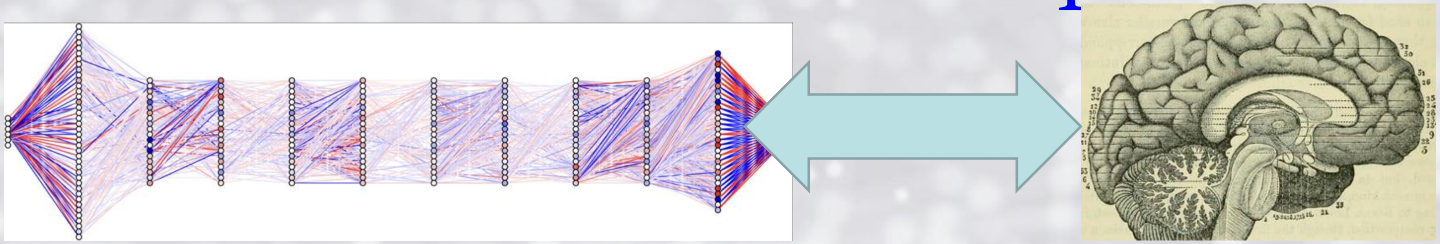


(*) Most researchers today accept the basic distinction between:

Phenomenal / observable works in AI vs Phenomenal / observable works in physical brains

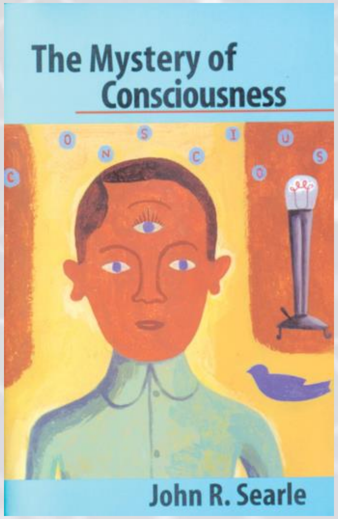
(*) Nevertheless, many important biological models have fruitfully inspired models in AI (e.g. computer vision)

Related Disciplines



(*) Still though, rarely (to date) do researchers begin with the premise: “let’s build a biological brain”

Why? Because we still don’t know how a biological brain works! Consciousness, for example, is still largely a mystery.

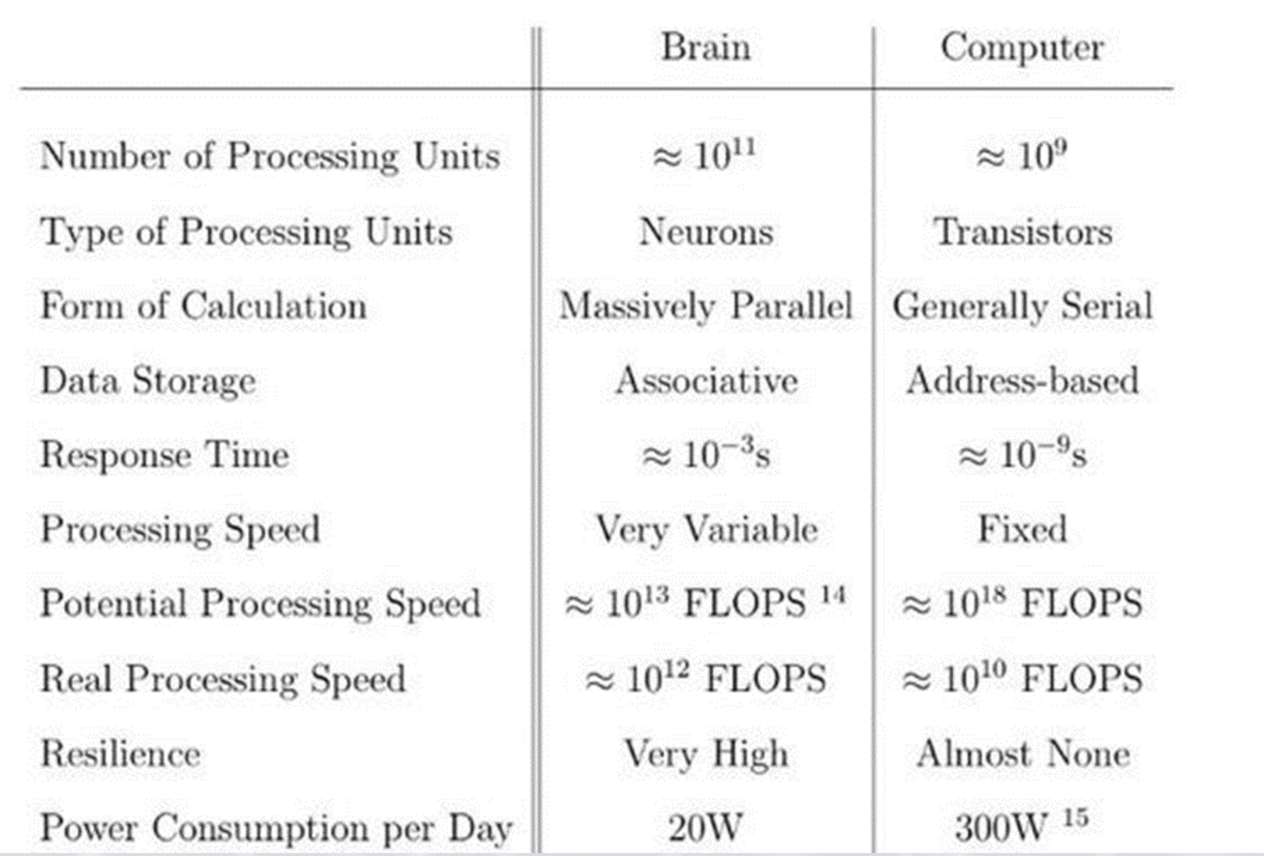


David Chalmers on consciousness: https://www.youtube.com/watch?v=uhRhtFFhNzQ

Computation Comparison

(*) Current computation benchmarks for computers are near that of the brain.

Q: But is computation enough? Probably not.



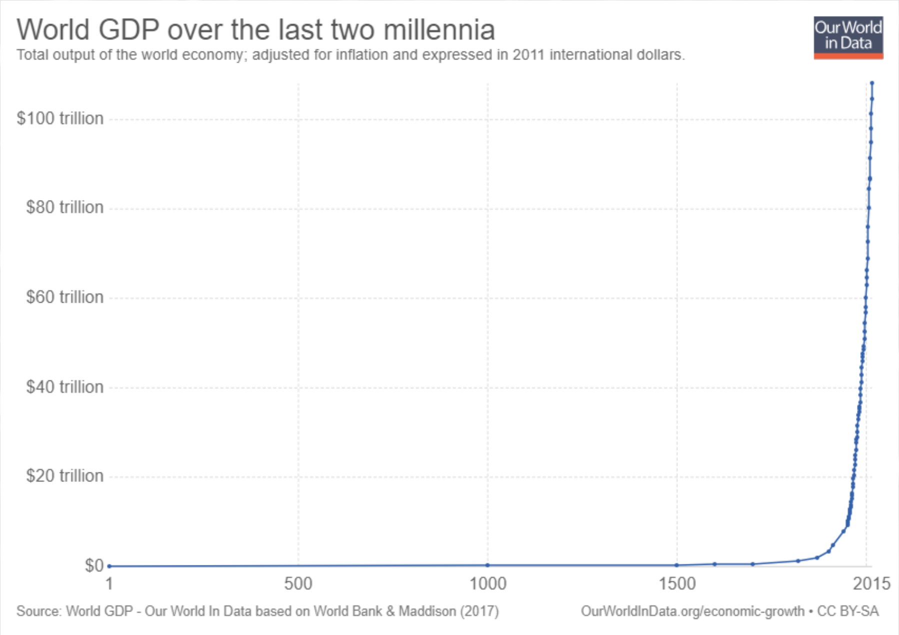
	Brain	Computer
Number of Processing Units	$\approx 10^{11}$	$\approx 10^{9}$
Type of Processing Units	Neurons	Transistors
Form of Calculation	Massively Parallel	Generally Serial
Data Storage	Associative	Address-based
Response Time	$\approx 10^{-3}$s	$\approx 10^{-9}$s
Processing Speed	Very Variable	Fixed
Potential Processing Speed	$\approx 10^{13}$ FLOPS [14]	$\approx 10^{18}$ FLOPS
Real Processing Speed	$\approx 10^{12}$ FLOPS	$\approx 10^{10}$ FLOPS
Resilience	Very High	Almost None
Power Consumption per Day	20W	300W [15]

Accelerated Growth

(*) A few hundred thousand years ago, in early human prehistory, growth was so slow that it took on the order of one million years for human productive capacity to increase sufficiently to sustain an additional one million individuals live at subsistence level.

(*) By 5000 BC, following the **Agricultural Revolution**, the rate of growth had increase to the point where the same amount of growth took just two centuries.

(*) Today, following the **Industrial Revolution**, **the world economy grows on average by that amount of ninety minutes**.

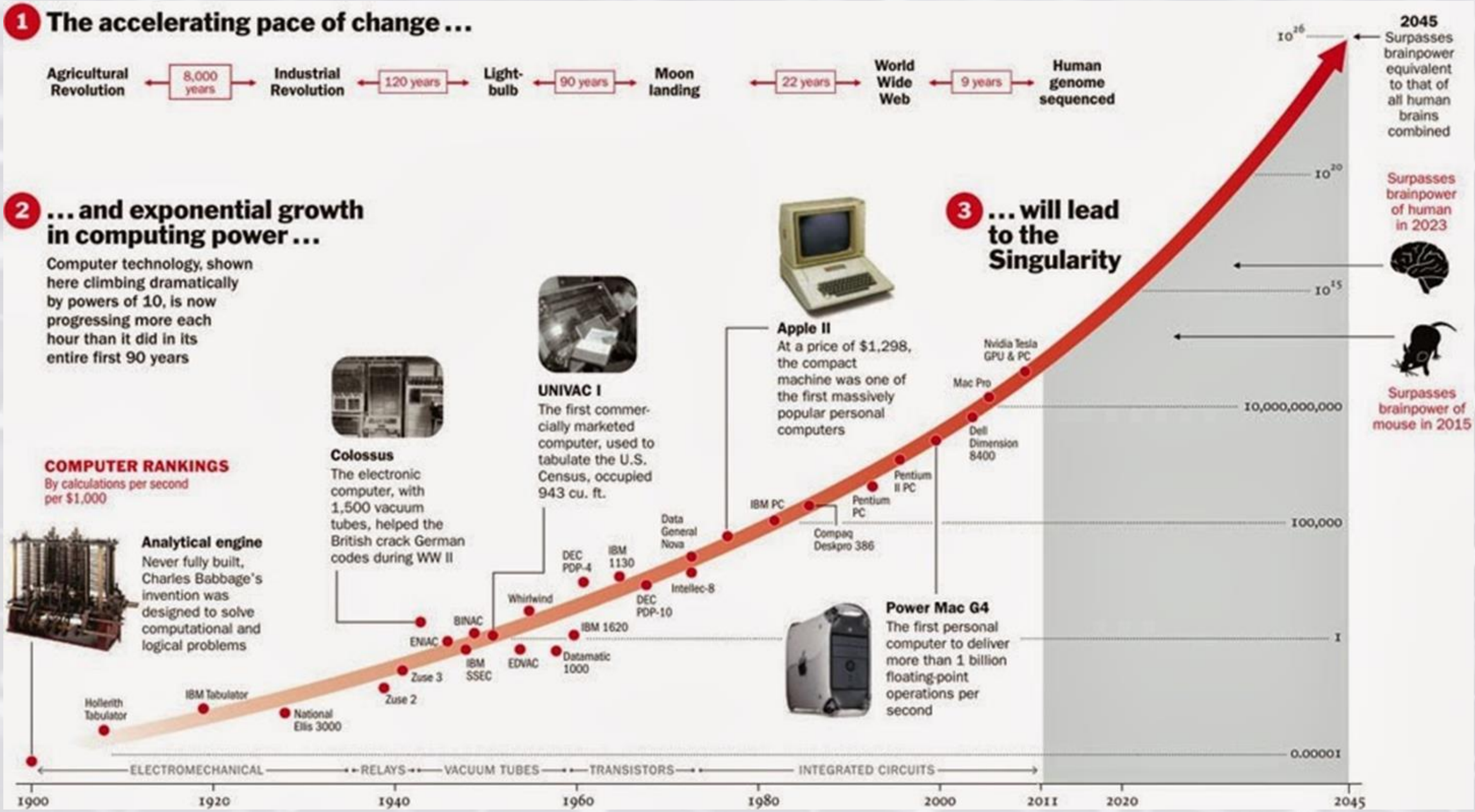

World GDP over the last two millennia

Total output of the world economy; adjusted for inflation and expressed in 2011 international dollars.

Source: World GDP - Our World In Data based on World Bank & Maddison (2017)

OurWorldInData.org/economic-growth • CC BY-SA

Accelerated Growth & Computation



1 The accelerating pace of change …

2 … and exponential growth in computing power …

Computer technology, shown here climbing dramatically by powers of 10, is now progressing more each hour than it did in its entire first 90 years

3 … will lead to the Singularity

COMPUTER RANKINGS

By calculations per second per $1,000

Analytical engine

Never fully built, Charles Babbage's invention was designed to solve computational and logical problems

Colossus

The electronic computer, with 1,500 vacuum tubes, helped the British crack German codes during WW II

UNIVAC I

The first commercially marketed computer, used to tabulate the U.S. Census, occupied 943 cu. ft.

Apple II

At a price of $1,298, the compact machine was one of the first massively popular personal computers

Power Mac G4

The first personal computer to deliver more than 1 billion floating-point operations per second

2045 Surpasses brainpower equivalent to that of all human brains combined

Surpasses brainpower of human in 2023

Surpasses brainpower of mouse in 2015

Accelerated Growth & Computation

Revolution in Egypt
Joe Klein: What the U.S. should do
On the Street: Hope meets anxiety
Muslim Brotherhood: What it wants
Oscars: Portraits of star power
TIME
2045
The Year Man Becomes Immortal

TYPE I CIVILIZATION harnesses all the resources of a planet. Carl Sagan estimated that Earth rates about 0.7 on the scale.

TYPE II CIVILIZATION harnesses all the radiation of a star. Humans might reach Type II in a few thousand years.

TYPE III CIVILIZATION harnesses all the resources of a galaxy. Humans might reach Type III in a few hundred thousand to a million years.

The Kardashev Scale

Rational Thinking

(*) Early codification of “right thinking – Aristotle (syllogisms)

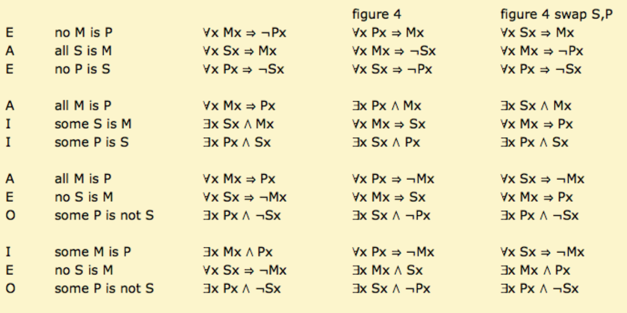
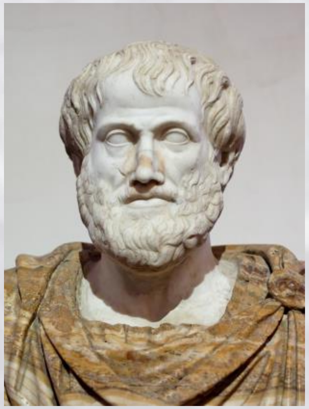


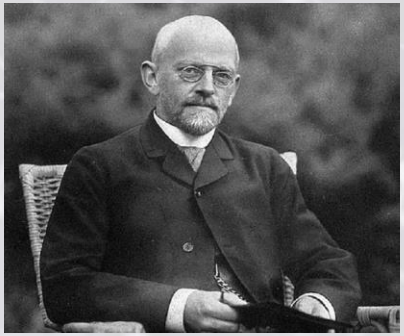
			figure 4	figure 4 swap S,P
E	no M is P	$\forall x\ Mx \Rightarrow \neg Px$	$\forall x\ Px \Rightarrow Mx$	$\forall x\ Sx \Rightarrow Mx$
A	all S is M	$\forall x\ Sx \Rightarrow Mx$	$\forall x\ Mx \Rightarrow \neg Sx$	$\forall x\ Mx \Rightarrow \neg Px$
E	no P is S	$\forall x\ Px \Rightarrow \neg Sx$	$\forall x\ Sx \Rightarrow \neg Px$	$\forall x\ Px \Rightarrow \neg Sx$
A	all M is P	$\forall x\ Mx \Rightarrow Px$	$\exists x\ Px \wedge Mx$	$\exists x\ Sx \wedge Mx$
I	some S is M	$\exists x\ Sx \wedge Mx$	$\forall x\ Mx \Rightarrow Sx$	$\forall x\ Mx \Rightarrow Px$
I	some P is S	$\exists x\ Px \wedge Sx$	$\exists x\ Sx \wedge Px$	$\exists x\ Px \wedge Sx$
A	all M is P	$\forall x\ Mx \Rightarrow Px$	$\forall x\ Px \Rightarrow \neg Mx$	$\forall x\ Sx \Rightarrow \neg Mx$
E	no S is M	$\forall x\ Sx \Rightarrow \neg Mx$	$\forall x\ Mx \Rightarrow Sx$	$\forall x\ Mx \Rightarrow Px$
O	some P is not S	$\exists x\ Px \wedge \neg Sx$	$\exists x\ Sx \wedge \neg Px$	$\exists x\ Px \wedge \neg Sx$
I	some M is P	$\exists x\ Mx \wedge Px$	$\forall x\ Px \Rightarrow \neg Mx$	$\forall x\ Sx \Rightarrow \neg Mx$
E	no S is M	$\forall x\ Sx \Rightarrow \neg Mx$	$\exists x\ Mx \wedge Sx$	$\exists x\ Mx \wedge Px$
O	some P is not S	$\exists x\ Px \wedge \neg Sx$	$\exists x\ Sx \wedge \neg Px$	$\exists x\ Px \wedge \neg Sx$



Logic: Is there a set of (finite, discoverable) laws that govern the operation of the mind?

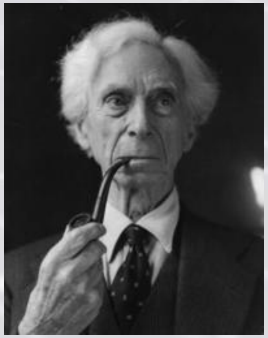
Issues with Logicist-AI methodology: Difficult to translate all real-world problems into symbolic form; tractability; some argue incompleteness (Gödel) renders logicist approac to mathematics/AI futile.

Hilbert -> Russell/Whitehead -> Gödel

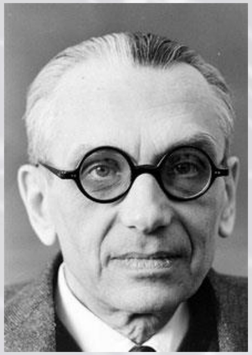


Hilbert’s

“Millennium Problems”



“Principia”

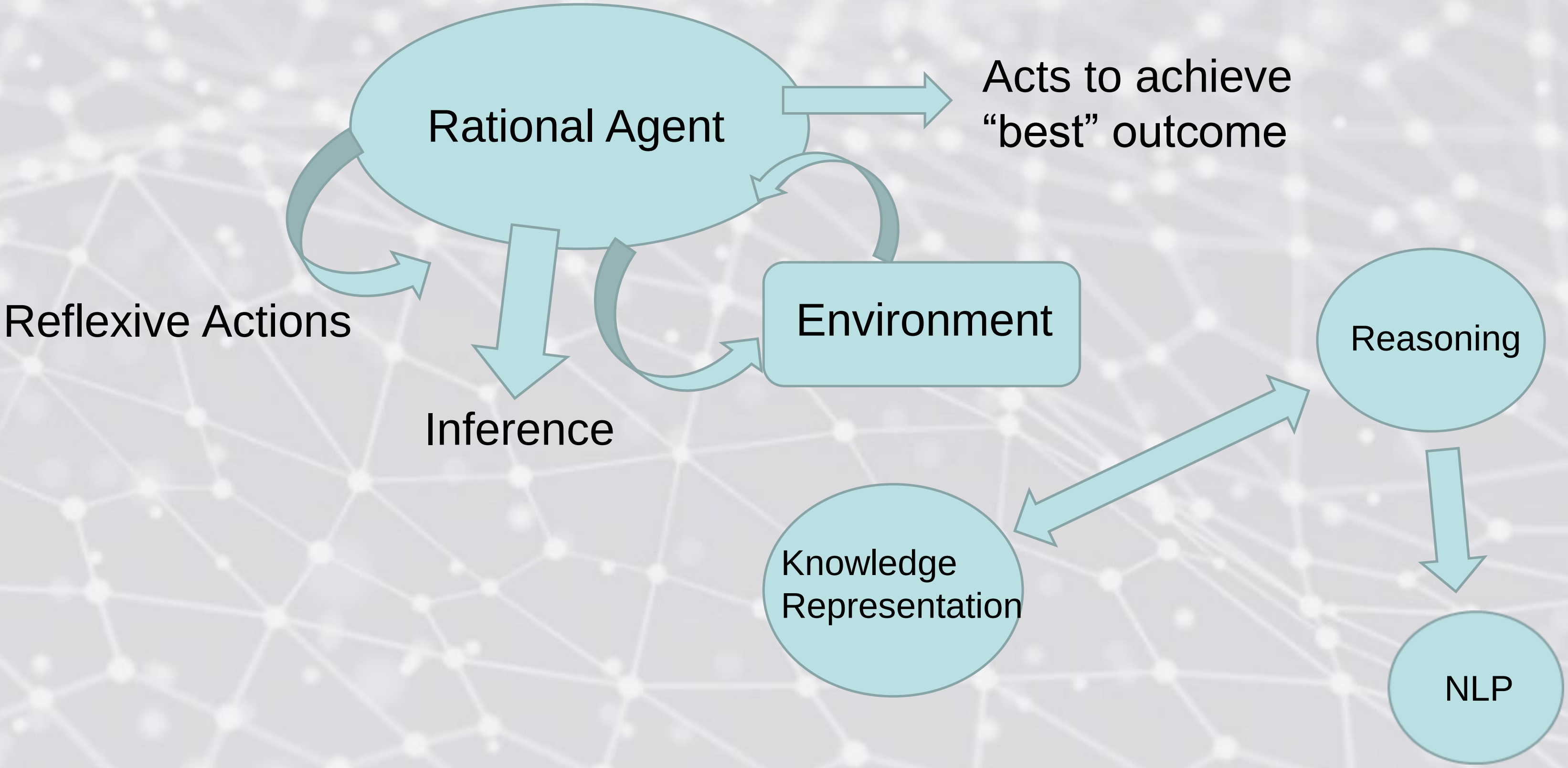


Incompleteness

Fundamental Fact: The attempt to establish an indubitable foundation for all of mathematics/science through logic directly inspired the gedanken experiments that led to the invention of the computer and the inception of AI as a formal discipline.

Rational Thinking

A more complete rational agent?



Rational Agent

Acts to achieve
“best” outcome

Reflexive Actions

Inference

Environment

Reasoning

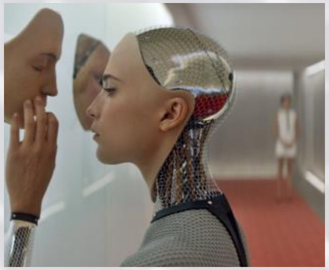
Knowledge
Representation

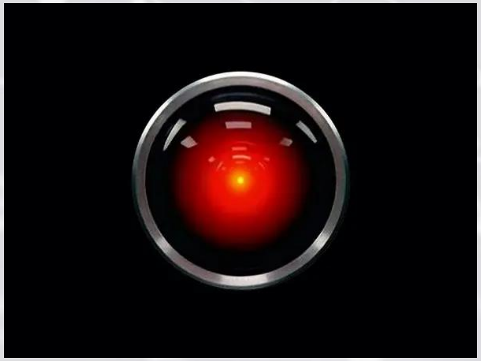
NLP

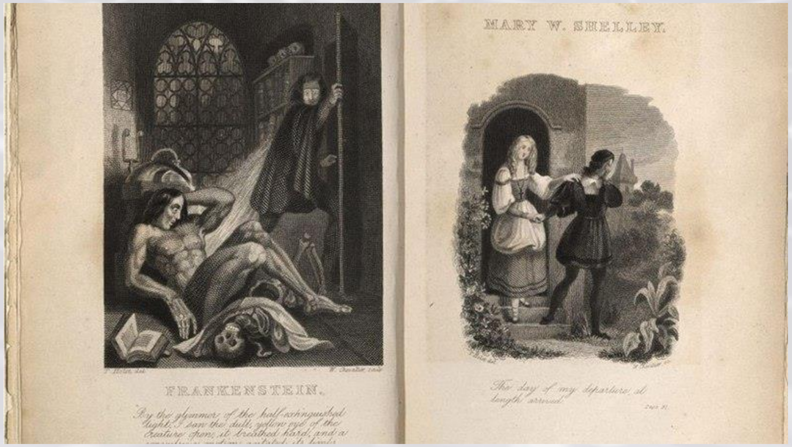
“Perfect rationality” – a good starting point for AI.

A Brief History of AI

Themes of AI & "Dangerous knowledge" in culture.

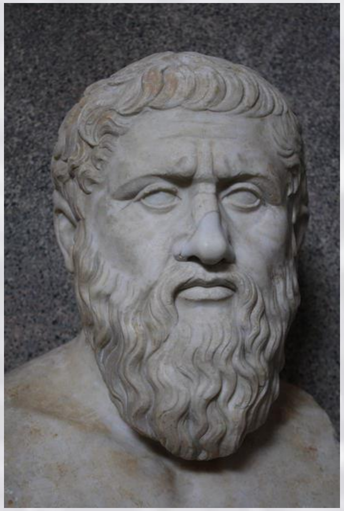






MARY W. SHELLEY.
FRANKENSTEIN.
By the glimmer of the half-extinguished light, I saw the dull, yellow eye of the creature open; it breathed hard, and a
The day of my departure at length arrived.

A Brief History of AI

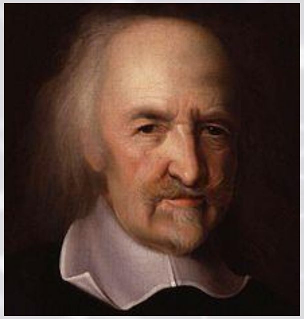


What is the nature of knowledge, where does it come from?

(**Epistemology**) Plato – Meno dialogue & *a priori* knowledge.

Induction vs. Deduction (Reasoning)

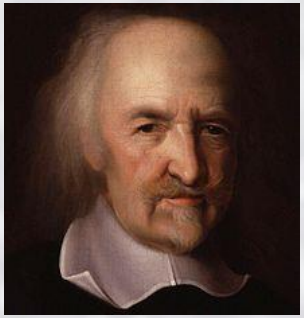
Q's: (*)Can we simply learn a huge list of inference rules?
(*) Does a look-up table constitute intelligence?
(*) How to proceed from knowledge to action?



Hobbes: "Reasoning is like numerical computation" (1651, Leviathan)
Leonardo: Designs for mechanical calculator (15C);
IBM built a replica in 1968

Leibniz: "Step Reckoner" – could perform all 4 arithmetic operations (1694)
Also conceived of a computational machine operating on concepts!

A Brief History of AI



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Pascal: “Pascaline” (1652): Arithmetic / Mechanical Calculator

Descartes: *Cogito* (Meditations, 1641)

Rationalists – Dualism: Part of Mind/Spirit outside body & external world

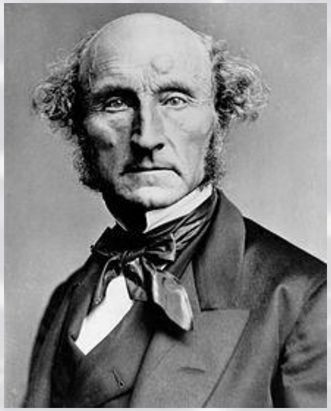
Materialism: Brain constitutes mind

Sources and Nature of Knowledge

Empiricism: Bacon (16C), Locke, Hume

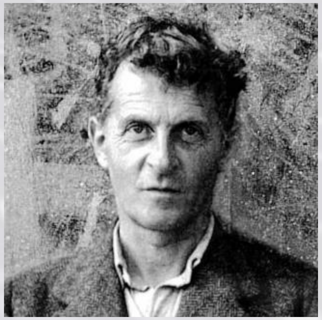
Inductive Reasoning: General rules acquired by repeated exposure/association. (can we prove induction?)

Paradoxes of Induction: Black Swan



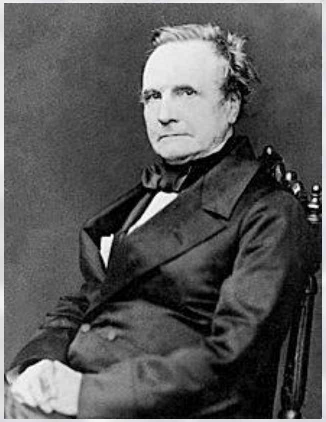
Utilitarianism: Mill (19C) – Ethics: maximize/quantify utility

Phenomenology: Husserl -> Heidegger: attempts to square subjective experiences with rationalism.



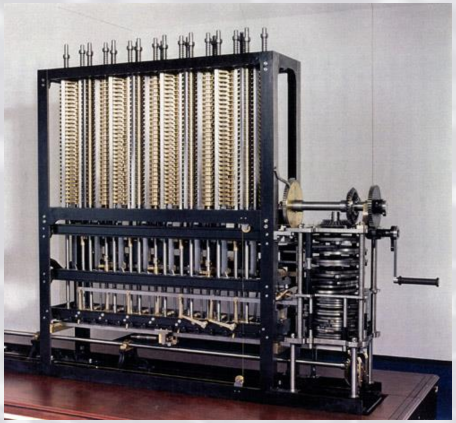
Logical Positivism (20C): Russell -> Wittgenstein -> Carnap – (Verificationism) only meaningful problems are those solvable by logical analysis (against metaphysics).

A Brief History of AI



C. Babbage: Difference Engine (1820s) – computes polynomial coefficients from Newton's Difference (classical interpolation).

Analytical Engine (AE, 1837): Proposed general-purpose computer; integrating loops, memory, logic unit (Turing-complete machine).

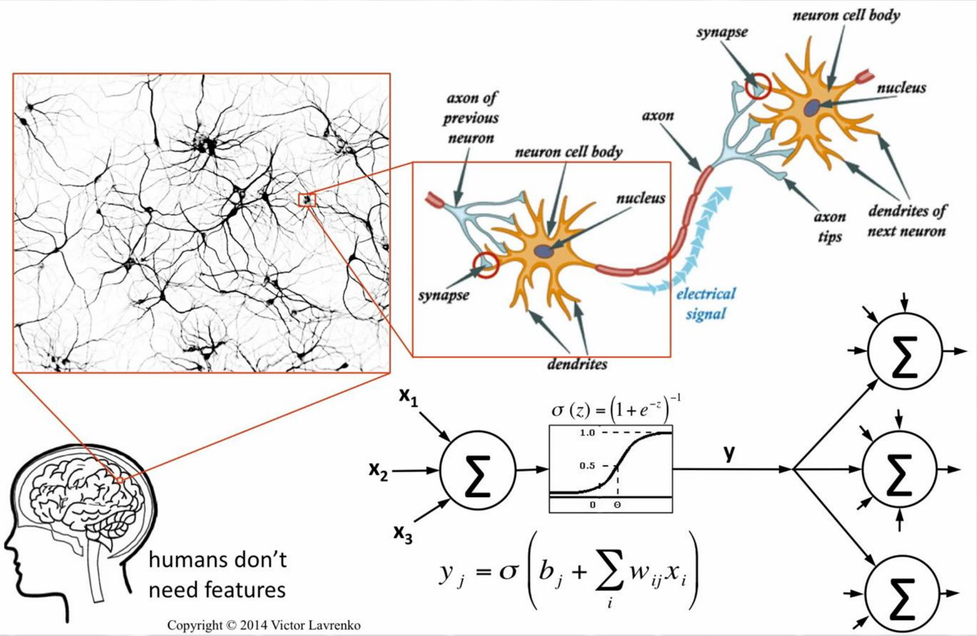


Ada Lovelace: (first "programmer"?) Wrote programs for AE; speculated about creative ability of AI (chess/music).

Leonardo: Designs for mechanical calculator (15C);

"[The Analytical Engine] might act upon other things besides number, were objects found whose mutual fundamental relations could be expressed by those of the abstract science of operations, and which should be also susceptible of adaptations to the action of the operating notation and mechanism of the engine...Supposing, for instance, that the fundamental relations of pitched sounds in the science of harmony and of musical composition were susceptible of such expression and adaptations, the engine might compose elaborate and scientific pieces of music of any degree of complexity or extent." – Ada Lovelace

Gestation 1943-1955



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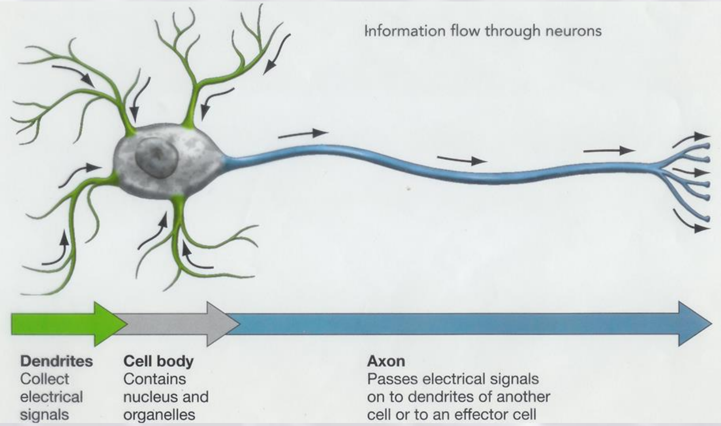
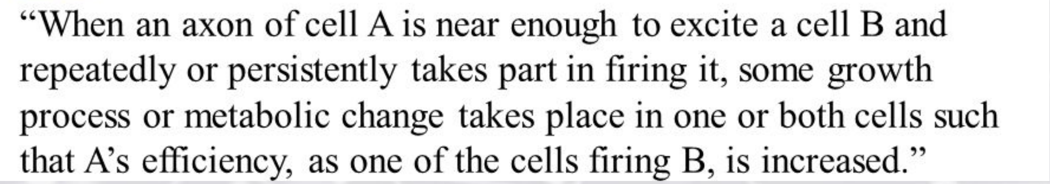


Dendrites
Collect electrical signals

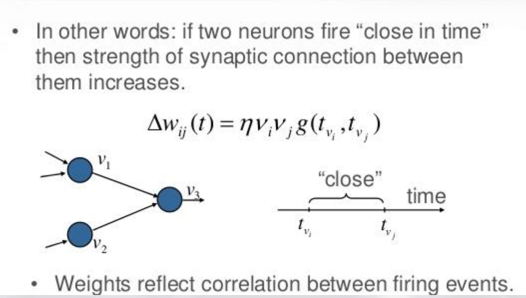
Cell body
Contains nucleus and organelles

Axon
Passes electrical signals on to dendrites of another cell or to an effector cell

Hebb's Postulate



"When an axon of cell A is near enough to excite a 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 other words: if two neurons fire "close in time" then strength of synaptic connection between them increases.

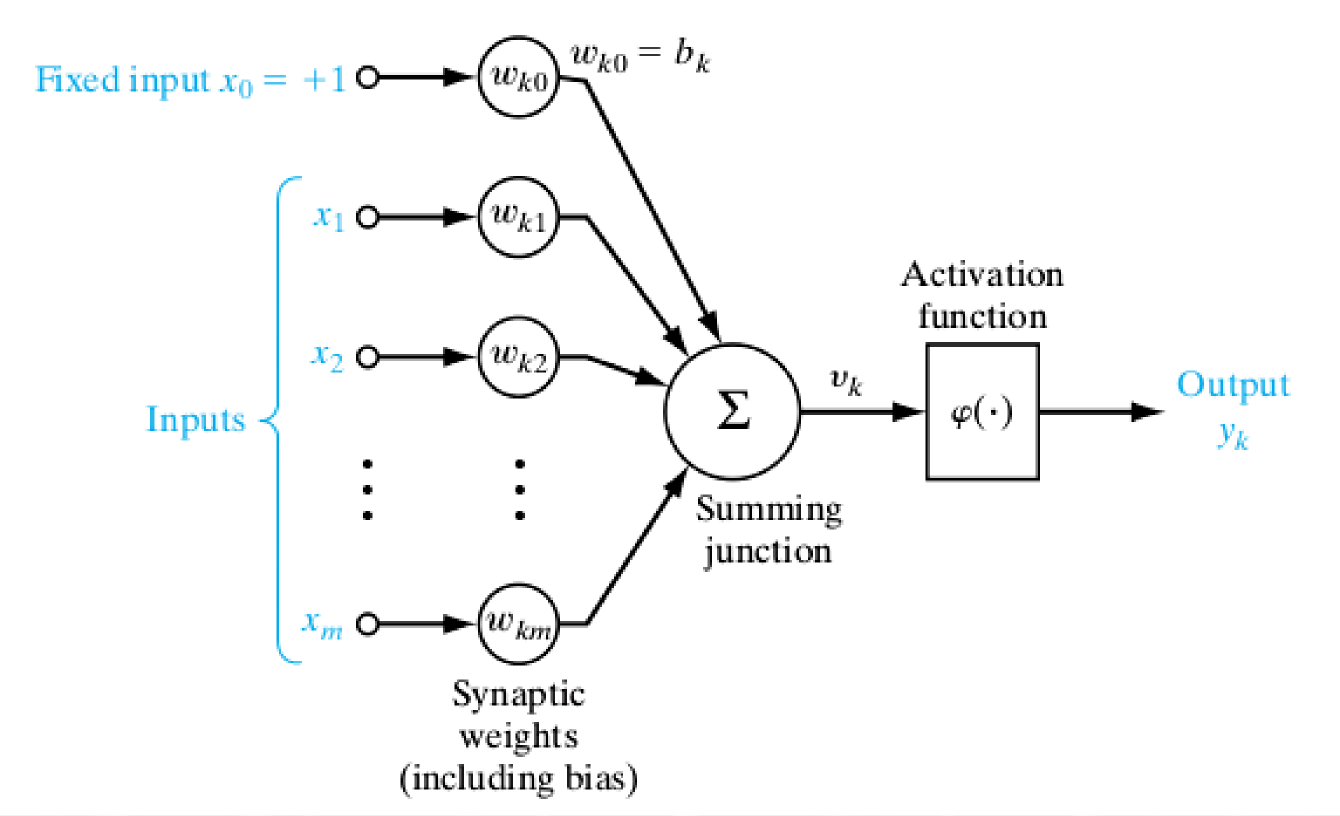
$$\Delta w_{ij}(t) = \eta v_i v_j g(t_{v_i}, t_{v_j})$$

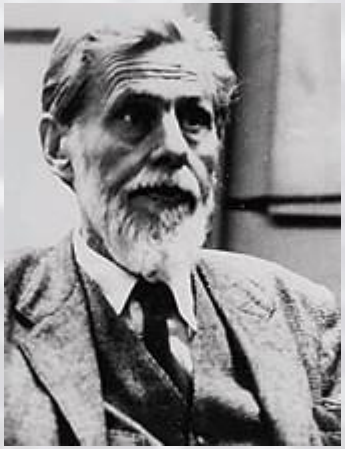
v_1
v_3
v_2
"close"
time
t_{v_i}
t_{v_j}

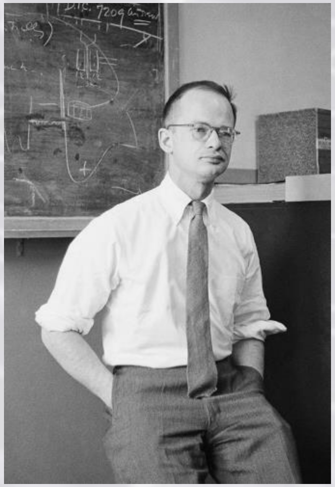
- Weights reflect correlation between firing events.

Gestation 1943-1955

McCulloch & Pitts Neuron Model (1943)







Gestation

(1956) Dartmouth Workshop on AI

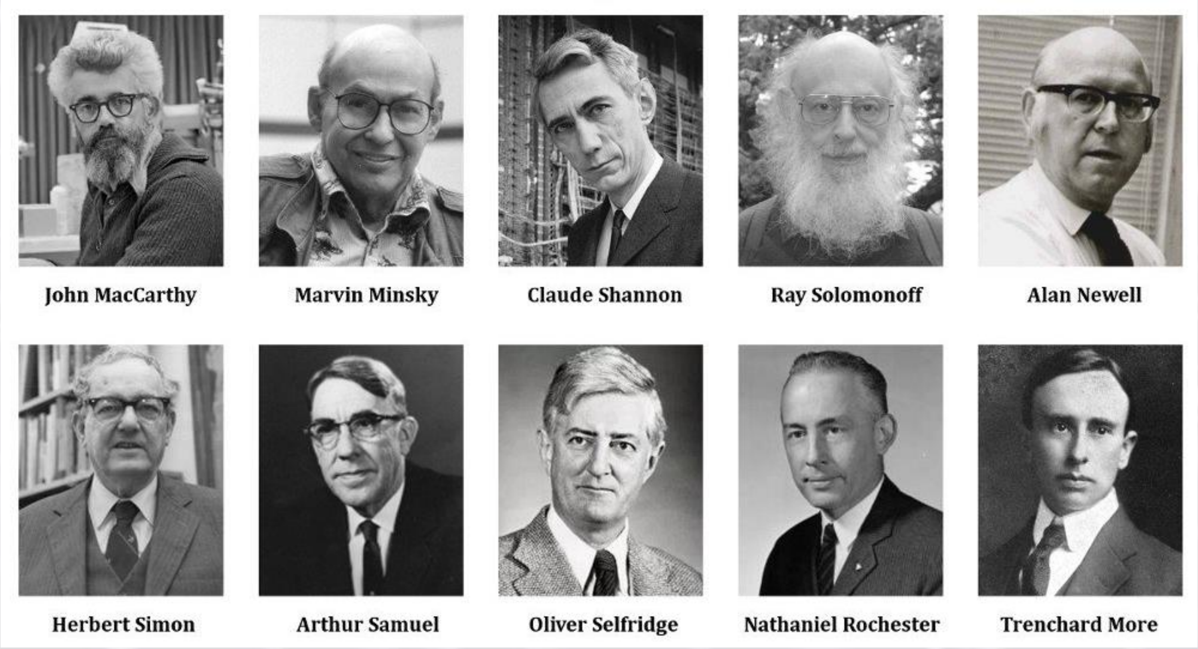
John McCarthy: Founded Stanford AI Lab, invented Lisp, Advice Taker program

Alan Newell: RAND/CMU, received Turing award

Claude Shannon: Founder of information theory

Herbert Simon: CMU, received Nobel prize in Economics, Turing award

Marvin Minsky: initiated MIT AI Lab, built SNARC (early NN machine)



Gestation

(*) The Dartmouth Workshop charter:

"We propose a 2 month, 10 man study of artificial intelligence be carried out … The study is to proceed on the basis of the conjecture that every aspect of learning or any other feature of intelligence can in principle be so precisely described that a machine can be made to simulate it. An attempt will be made to find out how to make machines that use language, form abstractions and concepts, solve kinds of problems now reserved for humans, and improve themselves. We think that a significant advanced can be made in one or more of these problems if a carefully selected group of scientists work on it together for a summer."

(*) A more tempered perspective: I.J. Good in 1965
(British mathematician who worked with Turing at Bletchley Park):

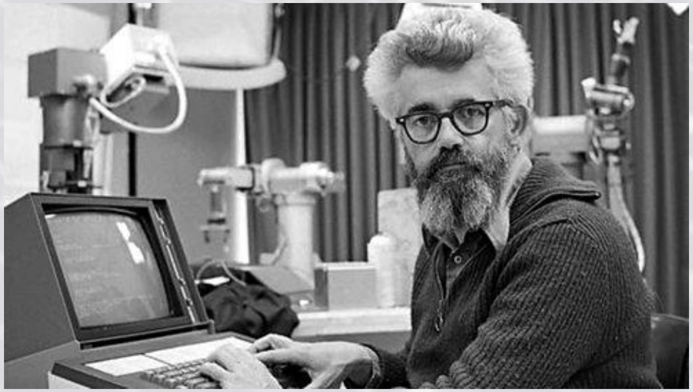
"Let an ultra-intelligent machine be defined as a machine that can far surpass all the intellectual activities of any man however clever. Since the design of machines is one of these intellectual activities, an ultra- intelligent machine could design even better machines; there would unquestionably be an "intelligence explosion," and the intelligence of man would be left far behind. Thus the first ultra-intelligent machine is the last invention that man need ever make, provided that the machine is docile enough to tell us how to keep it under control."

1952-1969
Early Enthusiasm/Great Expectations

(*) For the two decades following the Dartmouth workshop, AI research was largely dominated by the workshop participants and their immediate colleagues.

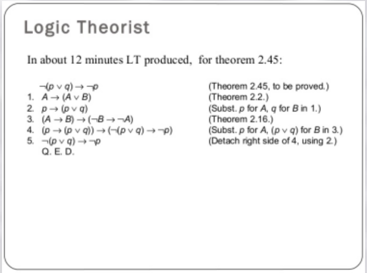
(*) John McCarthy referred to this era as the "Look, Ma, no hands!" era of AI research.; during these days researchers built systems designed to refute claims of the form "No machine could ever do X!"

(*) Such skeptical claims were common at the time. To counter them, the AI researchers created small systems that achieved X in a "**microworld**" (a well-defined, limited domain that enabled a pared-down version of the performance to be demonstrated), thus providing a proof of concept and showing that X could, in principle, be done by a machine.



1952-1969
Early Enthusiasm/Great Expectations

(*) LT: **Logic Theorist** (1956) designed by Allen Newell and Herbert Simon, dubbed the "first AI program", it was deliberately engineered to mimic the problem solving skills of humans. In total it successfully proved 38 of the first 52 theorems from Russell/Whitehead's *Principia*.



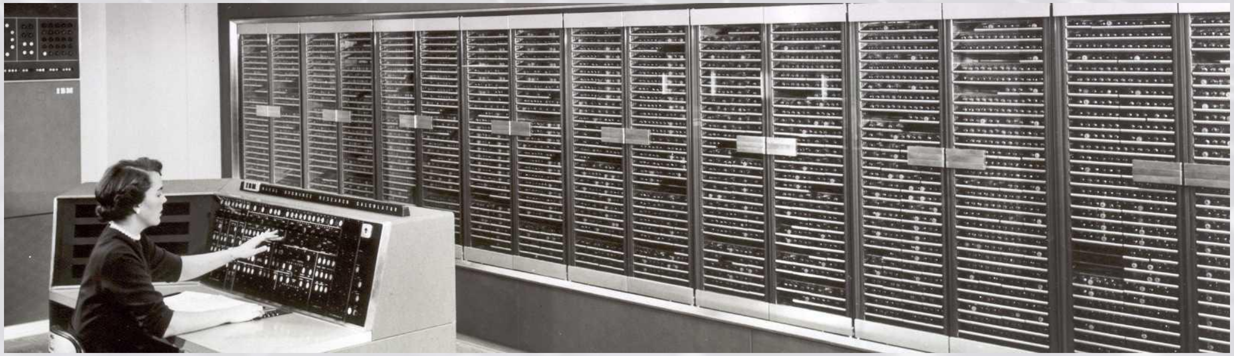
Logic Theorist

In about 12 minutes LT produced, for theorem 2.45:

	$\neg(p \vee q) \rightarrow \neg p$	(Theorem 2.45, to be proved.)
1.	$A \rightarrow (A \vee B)$	(Theorem 2.2.)
2.	$p \rightarrow (p \vee q)$	(Subst. p for A, q for B in 1.)
3.	$(A \rightarrow B) \rightarrow (\neg B \rightarrow \neg A)$	(Theorem 2.16.)
4.	$(p \rightarrow (p \vee q)) \rightarrow (\neg(p \vee q) \rightarrow \neg p)$	(Subst. p for A, $(p \vee q)$ for B in 3.)
5.	$\neg(p \vee q) \rightarrow \neg p$	(Detach right side of 4, using 2.)
	Q. E. D.	

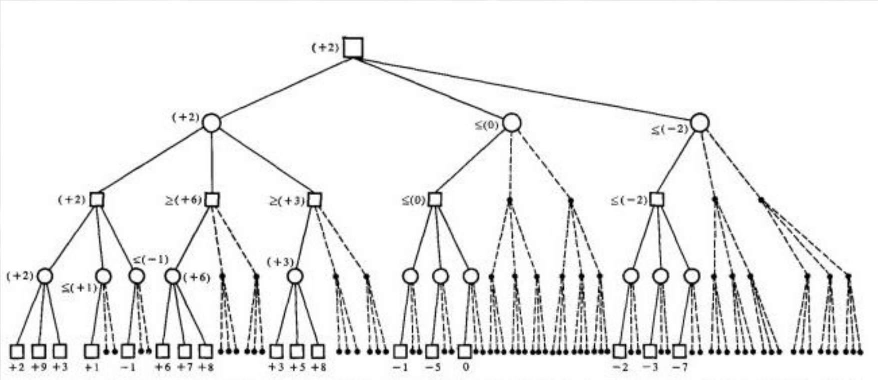
(*) GPS: **General Problem Solver** (1959), also developed by Newell And Simon; used a separate knowledge representation module – intended as a universal solver machine (any problems expressed as WFFs could be solved, in principle) – limited due to combinatorial explosion.

(*) **Geometry Theorem Prover** (IBM, 1959)

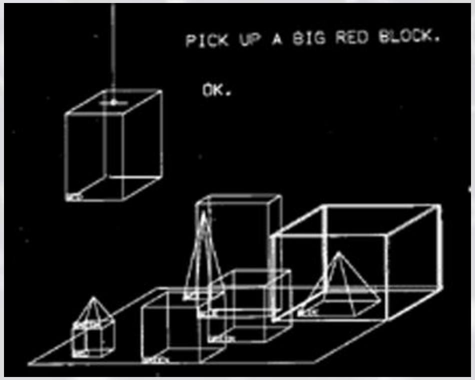


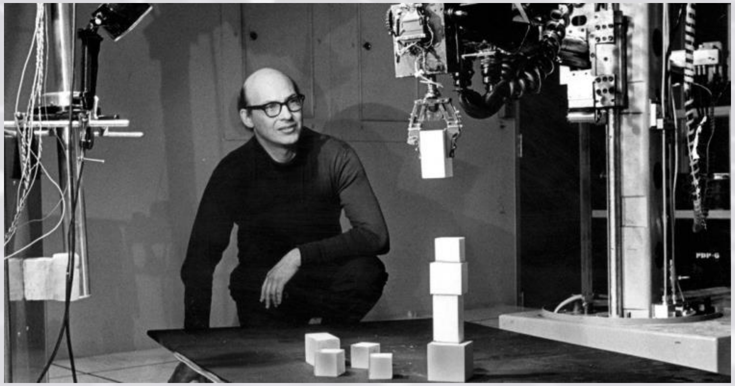
1952-1969
Early Enthusiasm/Great Expectations

(*) **Arthur Samuel** (IBM, Stanford) was an early pioneer in AI (first to coin term "machine learning"); began seminal work on **AI checkers** program in 1959, invents **alpha-beta pruning** and **minimax** algorithms (among others).



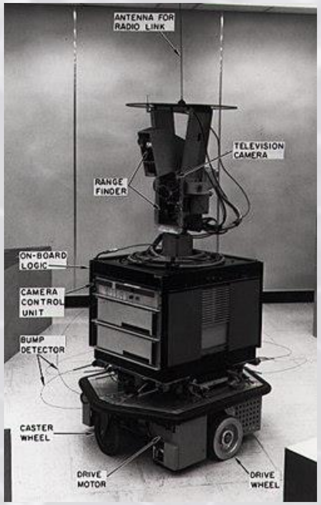
(*) Minsky supervised students in microworld problems (e.g. *blockworld*)





1952-1969
Early Enthusiasm/Great Expectations

(*) **Shakey the Robot**, developed at Stanford, (so named because of its tendency to tremble during operation) demonstrated how logical reasoning could be integrated with perception an used to plan and control physical activity. It was the first general-purpose mobile robot to be able to reason about its actions; project combined research in robotics, computer vision and NLP. As notable for one of the first applications of the **A* algorithm**.



https://www.youtube.com/watch?v=7bsEN8mwUB8

(*) The **ELIZA** (MIT, 1964-1966) program showed how a computer could impersonate a Rogerian psychotherapist. ELIZA simulated conversation by using a pattern maching and substitution methodology that gives the illusion of understanding (note that ELIZA is incapable of learning new patterns of speech/words through interaction alone).

Demo: http://www.manifestation.com/neurotoys/eliza.php3

1952-1969
Early Enthusiasm/Great Expectations

(*) Following a number of early successes of applied AI in these microworld domains, enthusiasm was high for AI to solve the "big problems" (e.g. computer vision, NLP, etc.); H. Simon declared (1957): "There are now in the world machines that think, that learn and that create."

(*) However, the methods that produces these early successes often proved difficult to extend to a wider variety of problems or to harder problem instances.

(*) One reason for this is the "**combinatorial explosion**" of possibilities that must be explored by methods that rely on something like exhaustive search. (note that the inception of **computational complexity** as a formal discipline only began in the mid 1960s)

(*) For instance: to prove a theorem using 5-lines and a deductive system containing 5 axioms, one could simply enumerate the 3,125 possible combinations; proving a 50-line proof by contrast requires ~**8.9 x 10^{34} possible sequences (!)** – which is computationally infeasible for even the fastest supercomputers.

1966-1973: AI Winter

(*) During the U.S.-Soviet space race, the U.S. government funded research in **machine translation**. At the time, researchers believed (naively) that NLP (in addition to computer vision) would be solved in a matter of a few years.

(*) After nearly a decade of funding research in machine translation, researchers discovered that they were still a long way from "solving" the problem. A famous mistranslation encapsulated this difficulty:

"*the spirit is willing, but the flesh is weak*" (originally in Russian) was translated: "*the vodka is good but the meat is rotten*"! (in 1966 all funding was halted for this project)

(*) Note that to overcome **the combinatorial explosion** in AI, one needs algorithms that **exploit structure in the target domain** and take advantage of **prior knowledge** by using **heuristic search**, planning, and flexible abstract representations – capabilities that were poorly developed by early AI systems.

(*) The performance of these early systems also suffered because of the poor methods for handling uncertainty, reliance on brittle and ungrounded symbolic representations, **data scarcity**, and severe **hardware limitations** of memory capacity and processor speed.

1966-1973: AI Winter

(*) **Rosenblatt** (1962) proved that the **perceptron learning rule** converges to correct weights in a finite number of steps, provided the training examples are linearly separable.

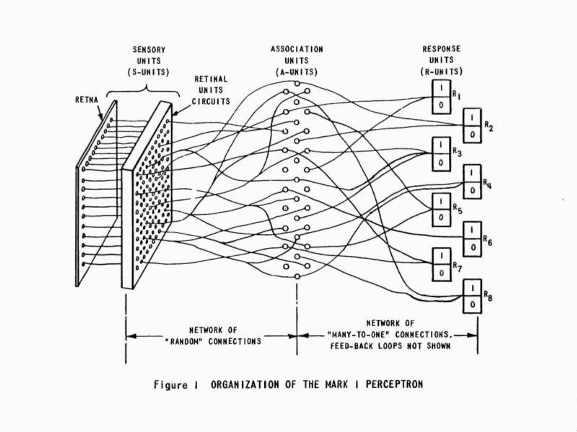
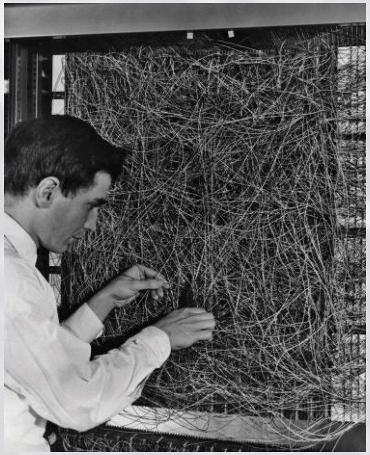
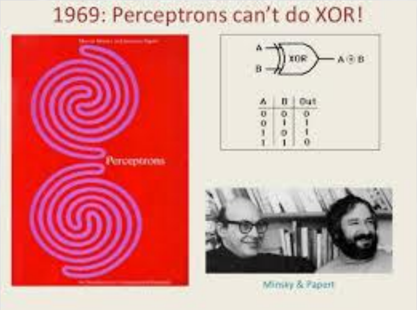

SENSORY UNITS (S-UNITS)
RETINAL UNITS CIRCUITS
ASSOCIATION UNITS (A-UNITS)
RESPONSE UNITS (R-UNITS)
RETNA
R1
R2
R3
R4
R5
R6
R7
R8
1
0
NETWORK OF "RANDOM" CONNECTIONS
NETWORK OF "MANY-TO-ONE" CONNECTIONS. FEED-BACK LOOPS NOT SHOWN

Figure I ORGANIZATION OF THE MARK I PERCEPTRON



(*) **Minsky and Papert** (1969) proved that perceptrons cannot represent non-linearly separable target functions.

(*) Later it was shown that by using continuous activation functions (rather than thresholds), a fully connected network with a single hidden layer can in principle represent any function (UAT (1989): **universal approximation theorem**). The well-known **backpropagation algorithm** (essential to deep learning) algorithm was later "rediscovered" by **Hinton** et al.



1969: Perceptrons can't do XOR!

A	B	Out
0	0	0
0	1	1
1	0	1
1	1	0

Minsky & Papert

$$
\begin{aligned}
y_i &= f(x_i) \\
&= f(\sum_j w_{ij}\, y_j) \\
E &= \sum_\alpha \left(y_i{}^{(\alpha)} - t_i{}^{(\alpha)}\right)^2 \\
\delta_i^{(\alpha)} &= \frac{\partial E}{\partial x_i^{(\alpha)}} \\
&= \frac{\partial E}{\partial y_i^{(\alpha)}} \frac{\partial y_i^{(\alpha)}}{\partial x_i^{(\alpha)}} \\
&= 2\left(y_i{}^{(\alpha)} - t_i{}^{(\alpha)}\right)\ f'(x_i^{(\alpha)}) \\
\frac{\partial E}{\partial w_{ij}} &= \sum_\alpha \delta_i^{(\alpha)}\ \frac{\partial x_i{}^{(\alpha)}}{\partial w_{ij}} \\
&= \sum_\alpha \delta_i^{(\alpha)}\ y_j{}^{(\alpha)}
\end{aligned}
$$

AI in the 1980s: Expert Systems

(*) The ensuing years saw a great proliferation of **expert systems** (rule-based programs that made simple inferences from a knowledge based of facts, elicited from human domain experts and painstakingly hand-coded in a formal language).

(*) Hundreds of these expert systems were built; however, the smaller systems provided little benefit, and the larger ones proved expensive to develop, validate, and keep updated, and were generally cumbersome to use.

(*) At this point, a critic could justifiably bemoan: "*the history of AI research to date, consisting always of very limited success in particular areas, followed immediately by failure to reach the broader goals at which these initial successes seem at first to hint*"; AI became something of an unwanted epithet at this time.

1990s-2000s: Resurgence of AI

(*) By the early 1990s, a second AI winter began to thaw. Optimism was rekindled by the introduction of new techniques, which seemed to offer alternatives to the traditional logicist paradigm (often referred to as *Good Old-Fashioned AI* (GOFAI)) which had reached its apogee in the 1980s.

(*) In particular, two newly popular techniques: **Neural Networks *(NNs)*** and **Genetic Algorithms** (GAs), promised to overcome some of the shortcomings of the GOFAI approach.

(*) The resurgence of AI in the 1990s was also prompted especially by the rediscovery of the backpropagation algorithm, the UAT for NNS, a proliferation of data (due in part to the widespread use of the internet), and new develops processing techniques.

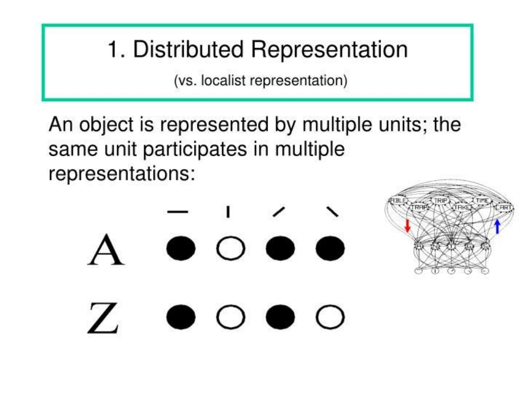
1990s-2000s: Resurgence of AI

(*) These new techniques (NNs and GAs) boasted a more *organic* performance on the whole.

(*)NNs for instance exhibited a useful, “graceful degradation” property and they could learn from experience – thereby finding natural ways to generalize from examples by discovering hidden statistical patterns in their input.

(*) NNs were also seen as more biologically-plausible models (cf. *GOFAI*); the brain-like qualities of NNs contrasted favorably with the rigid and brittle performance of traditional, rule-based GOFAI systems.

(*) The philosophy of **connectionism** gained traction in cognitive science / neuroscience, which further supported modeling with NNs. Connectionism emphasizes the importance of massively parallel sub-symbolic processing .

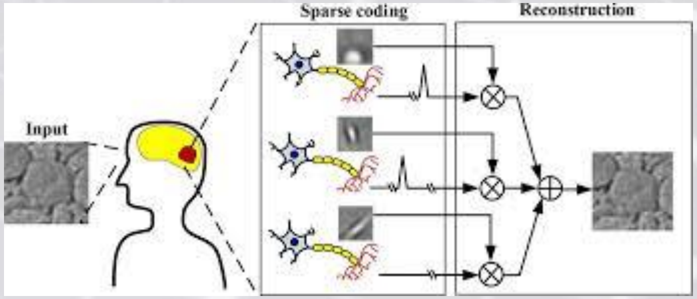


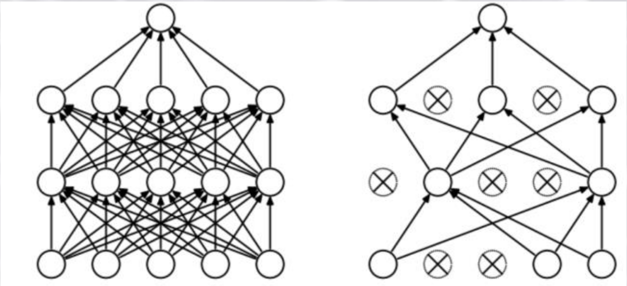
1. Distributed Representation

(vs. localist representation)

An object is represented by multiple units; the same unit participates in multiple representations:

	—	I	/	\
A	●	○	●	●
Z	●	○	●	○





(a) Standard Neural Net

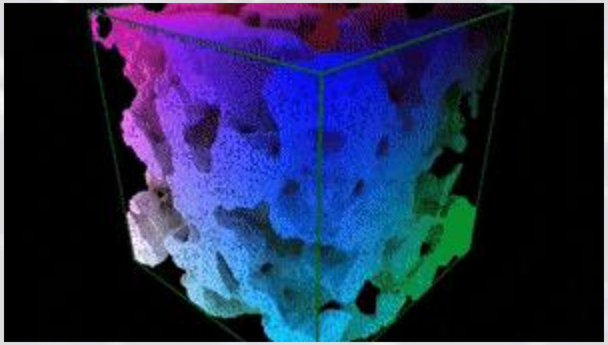
(b) After applying dropout.

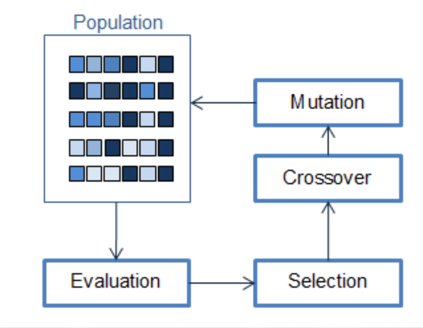
1990s-2000s: Resurgence of AI

(*) In evolution-based models (e.g. GAs), a population of candidate solutions (which can be data structures or programs) is maintained, and new candidate solutions are generated randomly by mutating or recombining variants in the existing population.

(*) Periodically, the population is pruned by applying a selection criterion (a *fitness function*) that allows only the better candidates to survive into the next generation and thereby combine their "genetic material" with other "fit" subjects.

(*) When it works, this kind of algorithm can produce efficient solutions to a very wide range of problems – solutions that may be strikingly novel and unintuitive, often looking more like natural structures than anything that a human engineer would design. Furthermore, this can happen without much need for direct human input (beyond the specification of the problem/learning parameters).





Holland

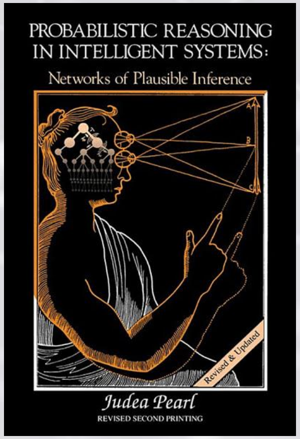
1990s-2000s: Resurgence of AI

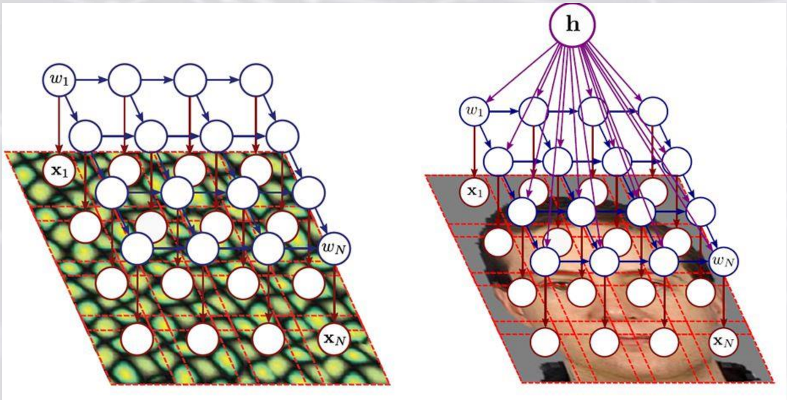
(*) Behind many of the new state-of-the-art techniques in AI lies a set of mathematically well-specified tradeoffs. The ideal one is that of a **Bayesian agent**, one that makes probabilistically optimal use of available information.

(*) This ideal is, however, unattainable because it is too computationally demanding to be implemented in any physical computer. Accordingly, *one can view* ***AI as a quest to find shortcuts****: ways of tractably approximating the Bayesian ideal by sacrificing some optimality while preserving enough to get high performance*.

(*) In 1988 Judea Pearl published a highly influential book on **probabilistic graphical models** (e.g. *Bayesian nets*). Bayesian networks provide a concise way of representing probabilistic and conditional independence relations that hold in some particular domain. Exploiting these independence relations is essential to overcoming the combinatorial explosion (graphical models have led to improvements in Monte Carlo approximation techniques, deep learning, and causal models, among other domains).

Pearl



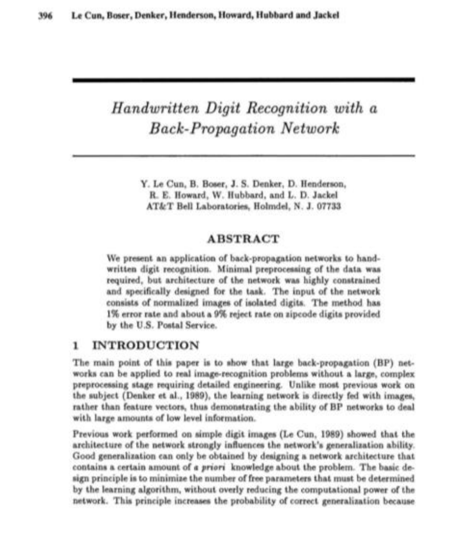


1990s-2000s: Resurgence of AI

(*) An important benchmark in the history of AI that helped usher in the recent, "deep learning" phenomenon, was **Yann LeCun** (Facebook) et al.'s seminal 1990 paper, for which researchers applied a convolutional neural network (CNN) to perform handwritten digit recognition.

(*) Remarkably, this technique, which has been extraordinarily influential for subsequent deep learning and computer vision approaches, achieved a **1% error rate** (on par with human error). This approach was later adopted by the US post office to automate mail sorting (using handwritten zip codes).

LeCun



396 Le Cun, Boser, Denker, Henderson, Howard, Hubbard and Jackel

Handwritten Digit Recognition with a Back-Propagation Network

Y. Le Cun, B. Boser, J. S. Denker, D. Henderson,
R. E. Howard, W. Hubbard, and L. D. Jackel
AT&T Bell Laboratories, Holmdel, N. J. 07733

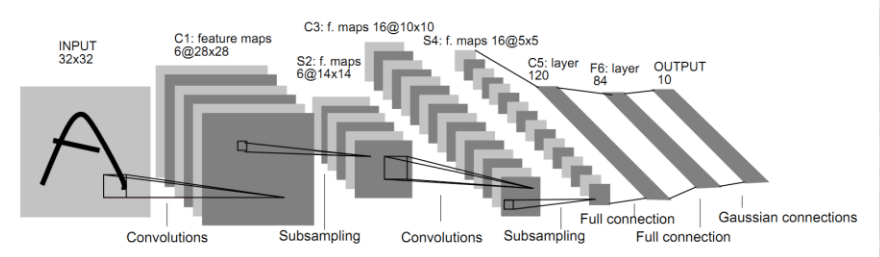
ABSTRACT

We present an application of back-propagation networks to handwritten digit recognition. Minimal preprocessing of the data was required, but architecture of the network was highly constrained and specifically designed for the task. The input of the network consists of normalized images of isolated digits. The method has 1% error rate and about a 9% reject rate on zipcode digits provided by the U.S. Postal Service.

1 INTRODUCTION

The main point of this paper is to show that large back-propagation (BP) networks can be applied to real image-recognition problems without a large, complex preprocessing stage requiring detailed engineering. Unlike most previous work on the subject (Denker et al., 1989), the learning network is directly fed with images, rather than feature vectors, thus demonstrating the ability of BP networks to deal with large amounts of low level information.

Previous work performed on simple digit images (Le Cun, 1989) showed that the architecture of the network strongly influences the network's generalization ability. Good generalization can only be obtained by designing a network architecture that contains a certain amount of *a priori* knowledge about the problem. The basic design principle is to minimize the number of free parameters that must be determined by the learning algorithm, without overly reducing the computational power of the network. This principle increases the probability of correct generalization because



http://papers.nips.cc/paper/293-handwritten-digit-recognition-with-a-back-propagation-network.pdf

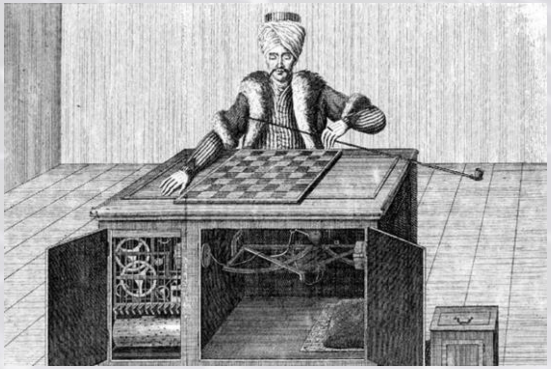
1990s-2000s: Resurgence of AI

(*) In 1997 **Deep Blue** (IBM), a chess-playing computer defeated the world champion, Garry Kasparov by a final score of 4-2. (Note that Kasparov accused IBM of cheating and demanded a rematch, IBM refused).

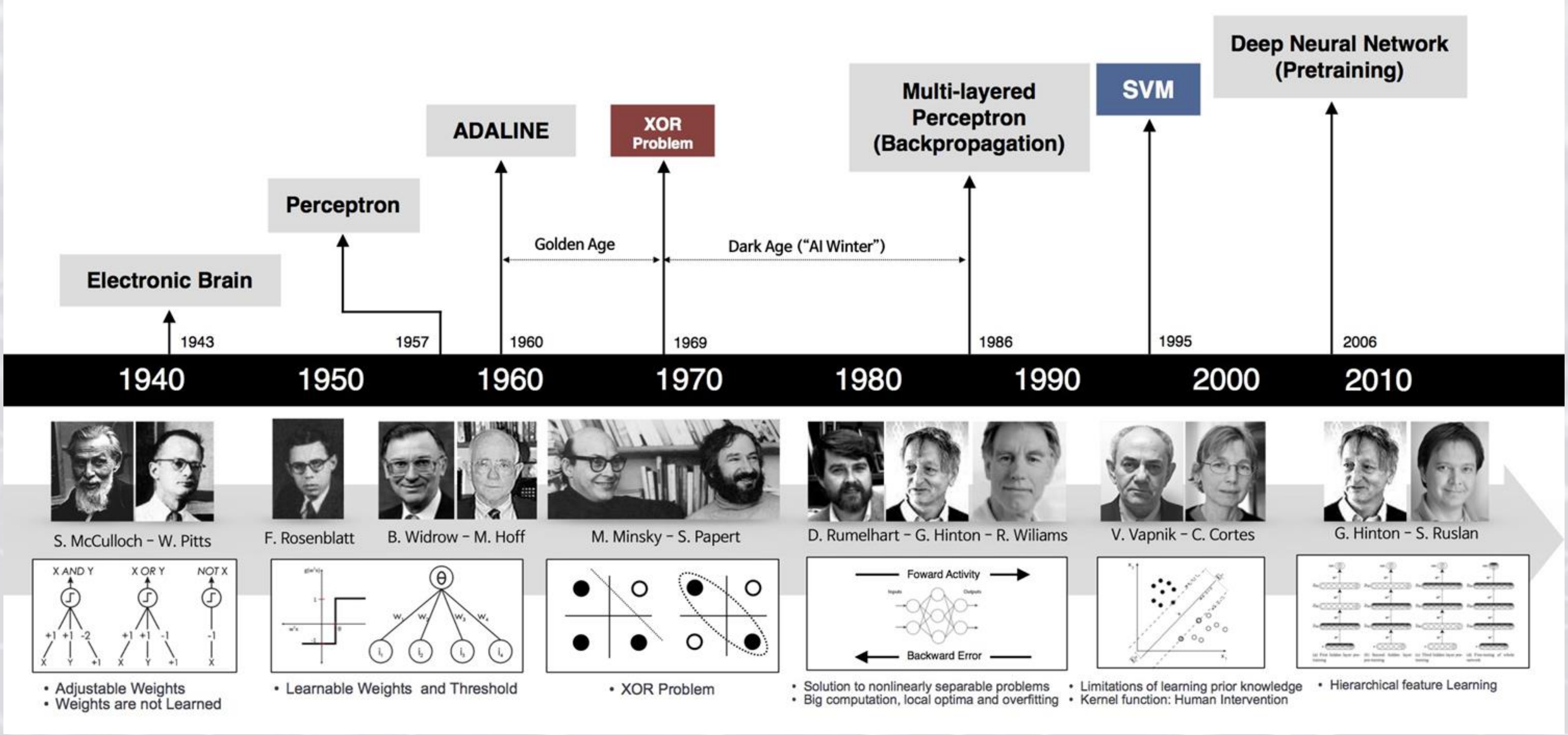
(*) Deep Blue employed custom VLSI chips to execute alpha-beta pruning search in parallel; notably Deep Blue is an example of GOFAI rather than deep learning – which is to say it used a relatively naïve (by contemporary standards), brute force approach.

(*) These issues aside, Deep Blue's victory had a significant impact on capturing the imaginations of both the public (and industry) regarding AI and its future potential.

(*) Notably, it was once thought (in the early days of AI) that the invention of master-level chess AI systems would presuppose the invention of AGI (artificial general intelligence) – clearly this is not the case, as we still await the invention of AGI (John McCarthy once lamented: "As soon as it works, no one calls it AI anymore.")

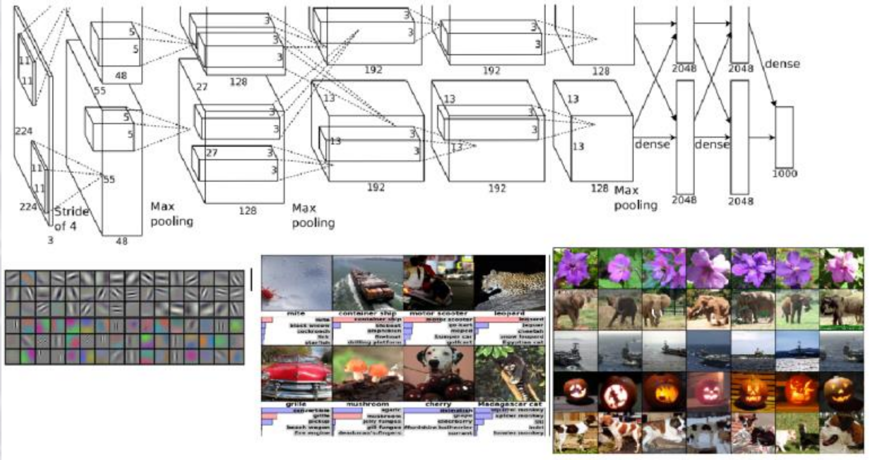


2010s and Beyond


Electronic Brain
Perceptron
ADALINE
XOR Problem
Multi-layered Perceptron (Backpropagation)
SVM
Deep Neural Network (Pretraining)
Golden Age
Dark Age ("AI Winter")
1943
1957
1960
1969
1986
1995
2006
1940
1950
1960
1970
1980
1990
2000
2010
S. McCulloch - W. Pitts
F. Rosenblatt
B. Widrow - M. Hoff
M. Minsky - S. Papert
D. Rumelhart - G. Hinton - R. Wiliams
V. Vapnik - C. Cortes
G. Hinton - S. Ruslan
X AND Y
X OR Y
NOT X
Foward Activity
Backward Error
• Adjustable Weights
• Weights are not Learned
• Learnable Weights and Threshold
• XOR Problem
• Solution to nonlinearly separable problems
• Big computation, local optima and overfitting
• Limitations of learning prior knowledge
• Kernel function: Human Intervention
• Hierarchical feature Learning

2010s and Beyond

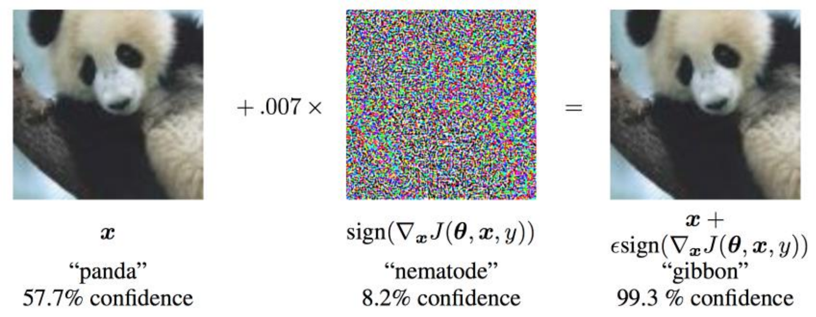
(*) **AlexNet** (2012), Alex Krizhevsky et al.: A new benchmark for deep learning, achieved top-5 error rate of 15% on ImageNet challenge (23k categories).



Krizhevsky

Goodfellow

(*) **Adversarial Learning and GANs** (2014), Goodfellow et al.



$+ .007 \times$
$=$
$\boldsymbol{x}$
"panda"
57.7% confidence
$\text{sign}(\nabla_{\boldsymbol{x}} J(\boldsymbol{\theta}, \boldsymbol{x}, y))$
"nematode"
8.2% confidence
$\boldsymbol{x} + \epsilon\text{sign}(\nabla_{\boldsymbol{x}} J(\boldsymbol{\theta}, \boldsymbol{x}, y))$
"gibbon"
99.3 % confidence

2010s and Beyond

(*) **IBM Watson** (2011)

https://www.techrepublic.com/article/ibm-watson-the-inside-story-of-how-the-jeopardy-winning-supercomputer-was-born-and-what-it-wants-to-do-next/

(*) **DeepMind** (2014): Playing Atari (at super-human levels) using Deep Reinforcement Learning

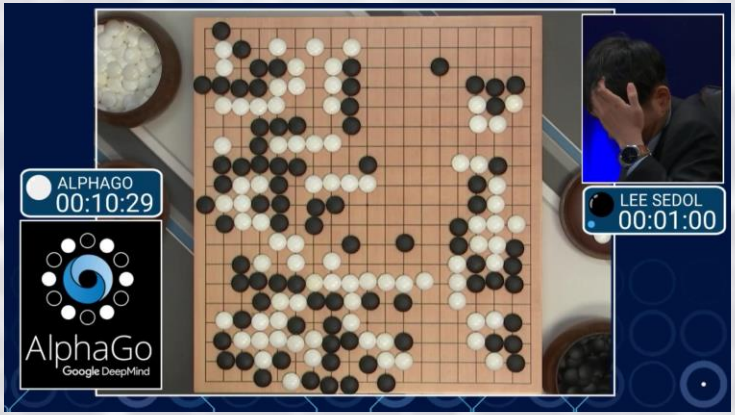
https://www.youtube.com/watch?v=V1eYniJ0Rnk

Hassabis

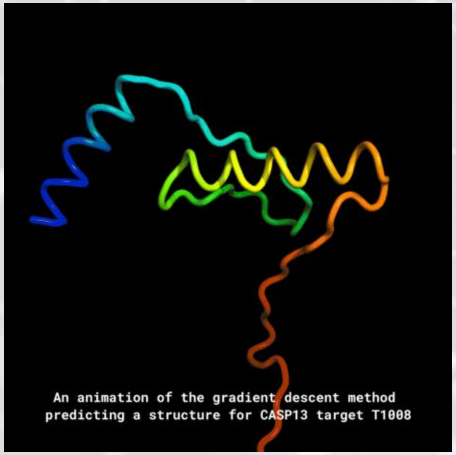
DeepMind

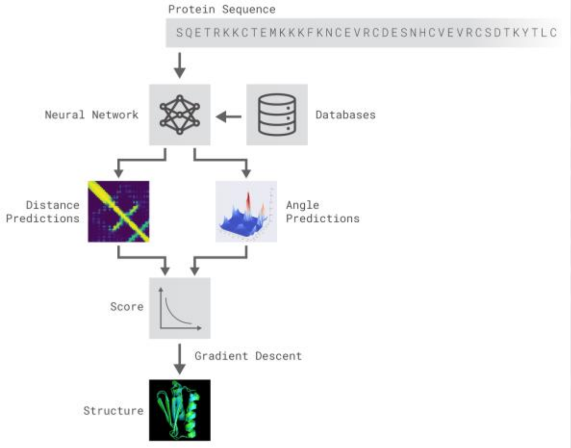
2010s and Beyond

(*) **DeepMind AlphaGo** (2015) https://deepmind.com/documents/119/agz_unformatted_nature.pdf



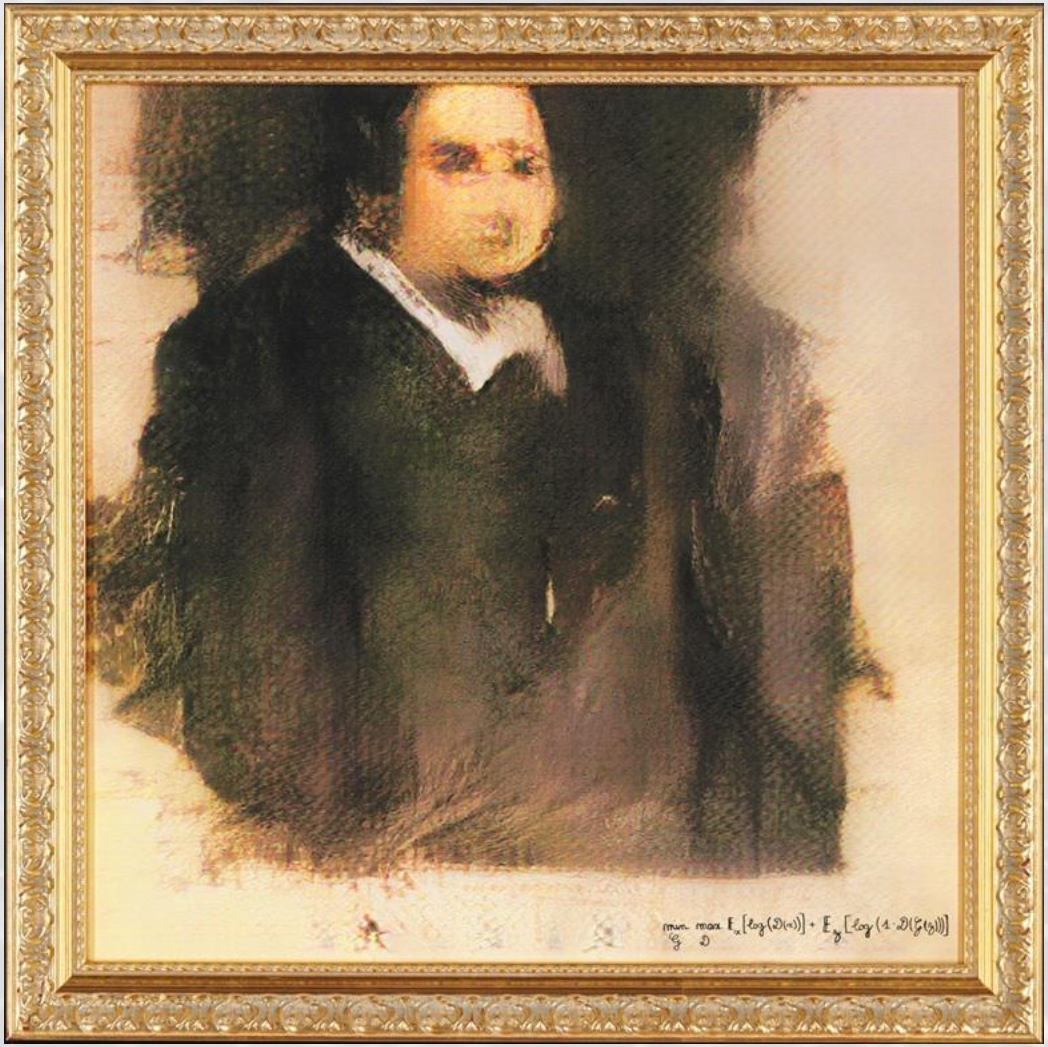
(*) AlphaFold (2018)


An animation of the gradient descent method
predicting a structure for CASP13 target T1008



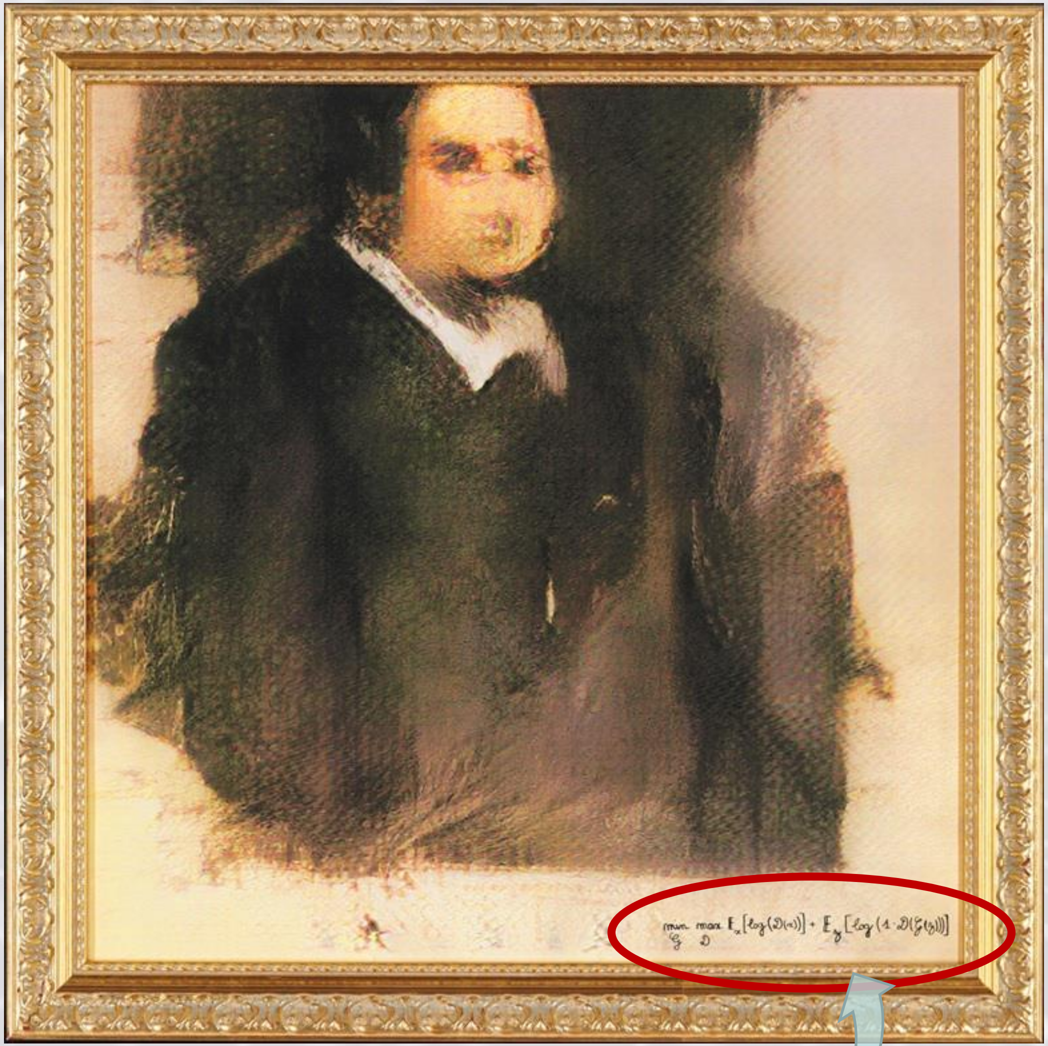
https://deepmind.com/blog/alphafold/

2010s and Beyond: AI & Creativity



(*) In 2018, this painting sold for $432,000 at a Christie’s auction.

2010s and Beyond: AI & Creativity



(*) In 2018, this painting sold for $432,000 at a Christie's auction.
It was created by an AI program

2010s and Beyond: AI & Creativity

(*) **Google DeepDream** (2015)

https://www.youtube.com/watch?v=dbQh1I_uvjo&t=1s

(*) **AI-Generated Music: AIVA Technologies** (2018)

https://soundcloud.com/user-95265362/sets/genesis

(*) **AI-Generated Opera** (NIPS, 2018)

https://nips2018creativity.github.io/doc/legend_of_wrong_mountain.pdf

(*) **Improvised Robotic Design with Found Objects** (NIPS, 2018)

https://nips2018creativity.github.io/doc/improvised_robotic_design.pdf

AI: The Future

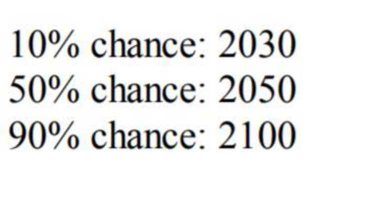
Final Considerations:

(*) Is human-level AGI (artificial general intelligence) possible?

(*) Is deep learning the answer? (or is it still a “microworld”?)

(*) Supervised vs. unsupervised learning: it turns out that more/”better” data might trump effectiveness of an algorithm! Need to consider the “knowledge bottleneck” – automate the learning process, bootstrap new patterns.

(*) “The first ultra-intelligent machine is the last invention that man need ever make”



10% chance: 2030
50% chance: 2050
90% chance: 2100

Polling results for researchers in AI when asked about arrival date of HMLI (human-level machine intelligence) and its potentnail impact

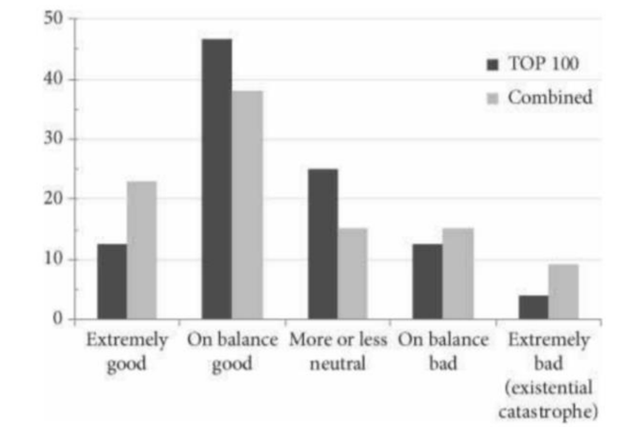
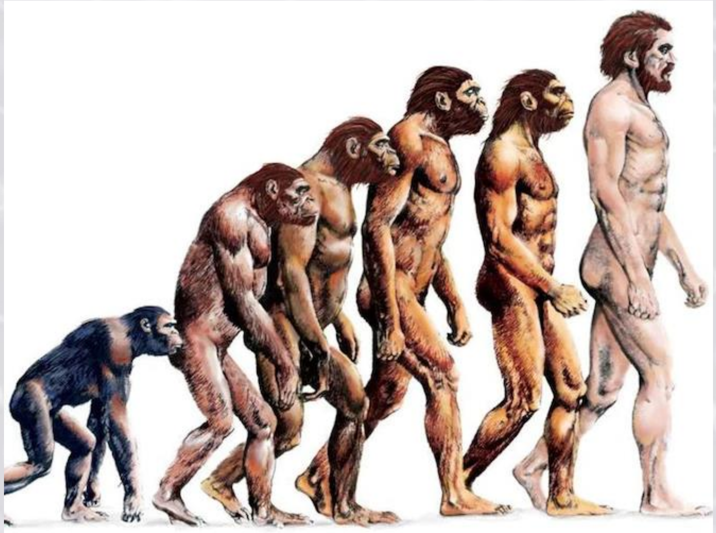


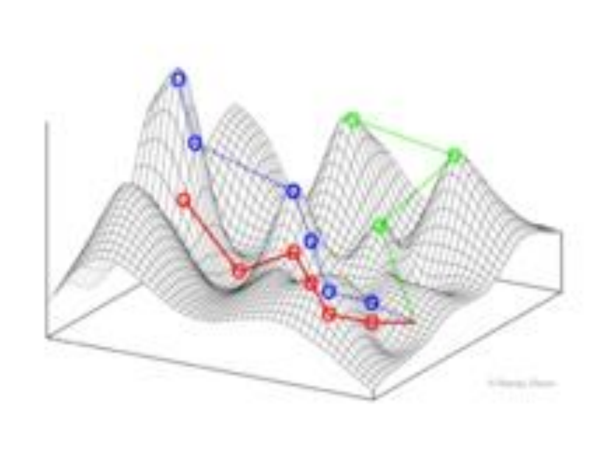
Figure 2 Overall long-term impact of HLMI.[83]

Can we use evolution to re-discover intelligence?

(*) We know that blind evolutionary processes can produce human-level general intelligence, since they have already done so at least once!

(*) Q: It stands to reason that evolutionary processes **with foresight** – that is, genetic programs designed and guided by an intelligent human programmer – can achieve a similar outcome with far greater efficiency.





Can we use evolution to re-discover intelligence?

A back-of-the-envelope approximation for the complexity of "inventing" intelligence with foresight:

(*) One can argue that the key insights for AI are embodied in the structure of the **nervous system**, which came into existence less than a billion years ago.

(*) Evolutionary algorithms require not only variations to select among but also a fitness function to evaluate variants, and this is typically the most computationally expensive component. A fitness function for the evolution of AI plausibly requires simulation of neural development, learning and cognition to evaluate fitness.

(*) We can make a crude estimate of the number of neurons in biological organisms that we might need to simulate to mimic evolution's fitness function.

(*) If, for instance, we consider that the honeybee brain consists of ~10^6 neurons, a fruit fly, ~10^5, and ants ~250k, then erring on the side of conservative, there are approximately 10^{19} insects on Earth, there would be roughly a total of 10^{24} insect neurons.

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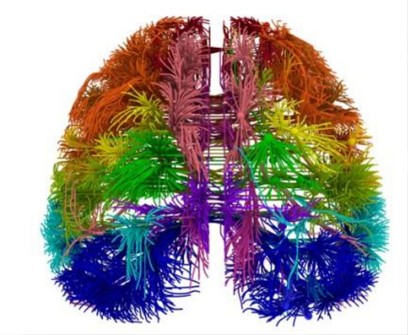
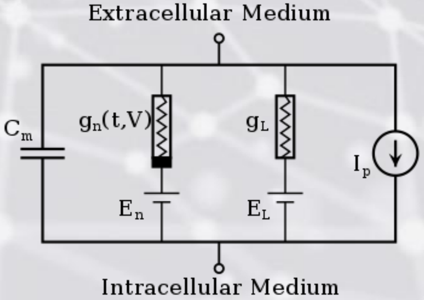
(*) This figure can further be augmented an additional order of magnitude when we consider aquatic life, birds, reptiles, mammals, etc., to reach **10^{25}**.

(*) The computational cost of simulating one neuron depends on the level of detail that one includes in the simulation. Extremely simple neural models use ~1k floating-point operations per second (FLOPS) to simulate on neuron in real-time.

(*) A more electrophysiologically realistic *Hodgkin-Huxley model* uses 1.2 million FLOPS.





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A back-of-the-envelope approximation for the complexity of "inventing" intelligence with foresight:

(*) A more electrophysiologically realistic *Hodgkin-Huxley model* uses 1.2 million FLOPS.

(*) A more detailed, multi-compartmental model would add another three or four orders of magnitude (while higher-level models that abstract systems of neurons might subtract two or three orders of magnitude).

(*) If we were to simulate 10^{25} neurons over a billion years of evolution (longer than the existence of nervous systems as we know them), and we allow our computers to run for one year, these figures would give us a requirement in the range of **10^{31}-10^{44} FLOPS**.

(*) Contemporary super computers provide only roughly 10^{18} FLOPS, which means this brute force search would on the surface require well over a trillion years to execute!