Machine Intelligence 1

1.1 Introduction

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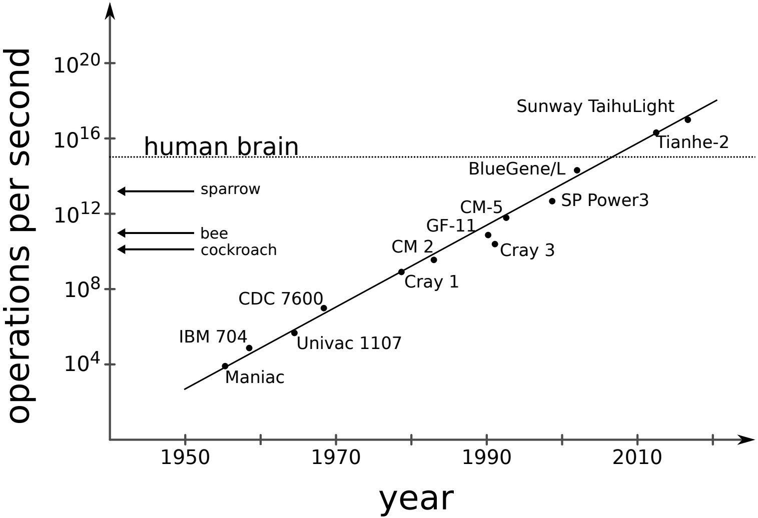
Moore's law


operations per second
10^{20}
10^{16}
10^{12}
10^{8}
10^{4}
human brain
sparrow
bee
cockroach
Sunway TaihuLight
Tianhe-2
BlueGene/L
SP Power3
CM-5
GF-11
Cray 3
CM 2
Cray 1
CDC 7600
IBM 704
Univac 1107
Maniac
1950
1970
1990
2010
year

Brains vs. machines

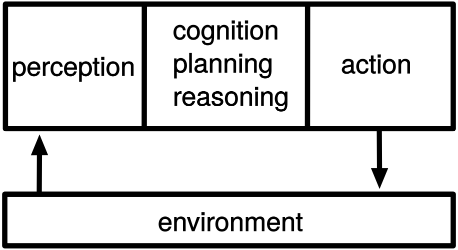
Brains are good where machines are bad:

- pattern recognition (images,audio, touch, multimodal data, but also abstract patterns)
- communication (language, speech)
- categorization and classification
- model building, inference and prediction
- control (robots, plants, software agents)

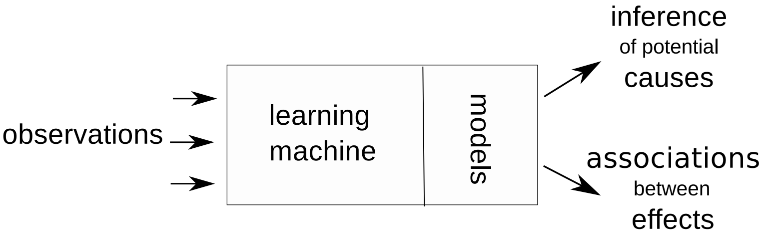
Machines are good where brains are bad:

- calculus
- chess
- manipulating symbols/strings

Machine intelligence: embedded agents

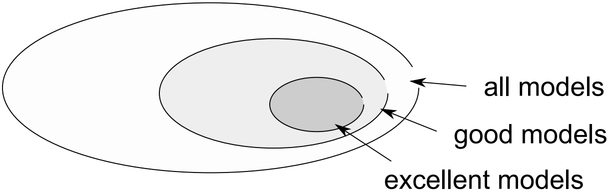


Learning to predict



- inductive learning: learning from examples

Learning as model selection



Learning as model selection

data representation

↓

model class

↓

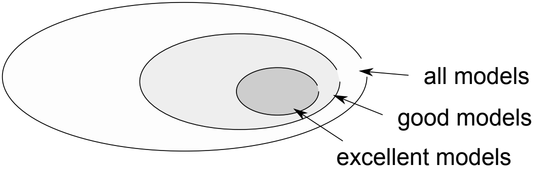
performance measure

↓

optimization

↓

validation



Supervised learning: "learning with a teacher"

Observations:

- series of observations: $\underline{\mathbf{x}}^{(1)}, \underline{\mathbf{x}}^{(2)}, \dots, \underline{\mathbf{x}}^{(p)}$
- corresponding labels/targets: $y^{(1)}, y^{(2)}, \dots, y^{(p)}$

Goal:

- predict the label/target of new (previously unseen) observation

Application:

- classification
- regression

Unsupervised learning: "self-organization"

Observations:

- series of observations: $\underline{\mathbf{x}}^{(1)}, \underline{\mathbf{x}}^{(2)}, \ldots, \underline{\mathbf{x}}^{(p)}$

Goal:

- build a *useful* representation of observations $\underline{\mathbf{x}}$
- extract relevant structure of observations $\underline{\mathbf{x}}$

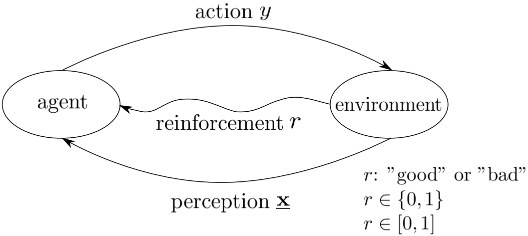
Application:

- dimensionality reduction
- clustering
- categorization
- source separation

Reinforcement learning: "learning behavior"

Observations:

- series of visited states: $\underline{\mathbf{x}}^{(1)}, \underline{\mathbf{x}}^{(2)}, \ldots, \underline{\mathbf{x}}^{(p)}$
- series of executed actions: $y^{(1)}, y^{(2)}, \ldots, y^{(p)}$
- series of experienced rewards: $r^{(1)}, r^{(2)}, \ldots, r^{(p)}$



Goal:

- find for every state $\underline{\mathbf{x}}$ the action y that maximizes future reward

Learning paradigms

- phenomenological characterization of learning paradigms
- not at all based on mathematical principles (e.g. same inductive learning approaches for "supervised" and "unsupervised" problems)

Overview over MI1: supervised methods (1)

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Artificial neural networks

- Connectionist neurons
- Multilayer perceptrons & radial basis function networks
- Learning, generalization, regularization
- Deep convolutional neural networks
- Recurrent neural networks

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Learning theory and support vector machines

- Statistical learning theory
- Support vector machines (SVMs) & the kernel trick
- Learning and generalization with SVMs

Overview over MI1: supervised methods (2)

Probabilistic methods

- Uncertainty and inference
- Bayesian networks
- Bayesian inference and neural networks

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Reinforcement learning

- Markov decision processes
- Policy evaluation
- Policy improvement
- Exploration and exploitation
- Approximate RL and deep end-to-end learning

Overview over MI2: unsupervised methods

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Dimension reduction

- Principal component analysis
- Independent component analysis

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Stochastic optimization

- Simulated annealing / mean field annealing

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Clustering and embedding

- k-means & pairwise clustering
- Self-organizing maps

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Probability density estimation

- Parametric & nonparametric density estimation
- Maximum likelihood estimation

Textbooks for Machine Intelligence I

- Bertsekas: *Dynamic Programming and Optimal Control*, Vol. 1&2, Athena Scientific, 4rd Ed., 2012 & 2017*.
- Bishop: *Pattern Recognition and Machine Learning*, Springer-Verlag, 2006.
- Cowell, Dawid, Lauritzen & Spiegelhalter: *Probabilistic Networks and Expert Systems*, Springer Verlag, 1999*.
- Duda, Hart & Stock: *Pattern Classification*, Wiley, 2000.
- Goodfellow, Bengio & Courville: *Deep Learning*, MIT Press, 2016*.
- Haykin: *Neural Networks*, Prentice Hall, 1998.
- Jordan (Editor): *Learning in Graphical Models*, MIT Press, 1999*.
- Schölkopf & Smola: *Learning with Kernels*, MIT Press 2002.
- Sutton & Barto: *Reinforcement Learning: an Introduction*. MIT Press, 1998.
- Russel & Norvig: *Artificial Intelligence*, Prentice Hall, 2003, Chapters 13 und 14.
- Vapnik: *Statistical Learning Theory*, Wiley, 1998*.
- Wiering & van Otterlo (Editors): *Reinforcement Learning: State-of-the-Art*, Springer, 2012*.

* advanced readings

Advanced reading for MI1 chapters (1)

1. Artificial Neural Networks
   - 1.1 **Introduction and General Comments:** Haykin, Ch. 1
   - 1.2 **Connectionist Neurons:** Haykin, Chs. 1.3, 1.4
   - 1.3 **Multilayer Perceptrons:** Haykin, Ch. 4; Bishop, Chs. 5.1-5.5; Duda et al., Ch. 6.1-6.5
   - 1.4 **Learning and Generalization:** Haykin, Ch. 4; Bishop, Ch. 3.2; Duda et al., Ch. 6.8, 6.9
   - 1.5 **Deep learning:** Goodfellow et al., Chs. 7-9
   - 1.6 **Recurrent networks:** Haykin, Chs. 13-15; Goodfellow et al., Ch. 10;
   - 1.7 **Radial Basis Function Networks:** Haykin, Ch. 5

2. Learning Theory and Support Vector Machines
   - 2.1 **Elements of Statistical Learning Theory:** Haykin, Ch. 2.14; Schölkopf & Smola, Ch. 5
   - 2.2 **Support Vector Machines:** Haykin, Ch. 6; Bishop, Ch. 7.1; Schölkopf & Smola, Chs. 2, 7, 10.5, and - more advanced but useful - Ch. 13

Advanced reading for MI1 chapters (2)

3. Probabilistic Methods
   - 3.1 **Bayesian Inference:** Russel & Norvik, Ch. 13
   - 3.2 **Graphical Models and Bayesian Networks:** Bishop, Ch. 8; Russel & Norvik, Ch. 14, and - advanced but complete with all proofs - Cowell et al., Chs. 3-6
   - 3.3 **Artificial Neural Networks and the Generative Model Approach:** Bishop, Chs. 3.4, 3.5; Duda et al., Chs. 3.3-3.5

4. Reinforcement Learning
   - 4.1 **Evaluation:** Sutton & Barto, Chs. 3-7; Bertsekas, Vol 1; Haykin, Ch. 12
   - 4.2 **Improvement:** Sutton & Barto: Ch. 6.5; Haykin, Ch. 12
     Exploration: Sutton & Barto, Ch. 2; Wiering & van Otterlo: Ch 6
     Approximation: Sutton & Barto, Ch. 8; Bertsekas, Vol. 2, Ch. 6; Wiering & van Otterlo, Ch. 3

End of Section 1.1

the following slides contain

OPTIONAL MATERIAL

Artificial **Intelligence** (from Russel & Norvig)

Motivating question

"How is it possible for a slow, tiny brain, whether biological or electronic, to perceive, understand, predict, and manipulate a world far larger and more complicated than itself?"

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- strategies/activities we would call "intelligent" if done by a person to make decisions, solve problems, learn ($\rightarrow$ homo sapiens).
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$\rightarrow$ **Extraction** and **representation** of knowledge; **reasoning** (inference)

AI: From Hanoi to ELIZA, ACT-R and ANNs

GOAL: build agents that think/act rational/like (successful) humans.

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A list of Problems / Challenges

- simple decision making (sensor fusion)
- simple problem solving (Tower of Hanoi, means-ends analysis)
- chatterbots (ELIZA, Help systems), intelligent tutoring ($\rightarrow$ CogSci)
- chess (Deep Blue), video game adversaries
- shift to technology industry: smartphones, SIRI, google, translation
- DARPA Challenge, Google driverless car, Jeopardy! (Watson)

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leading-edge definition of AI

- "AI research is that which computing scientists do not know how to do cost-effectively today". (Wikipedia)

Machine Learning

Definition: Learning

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- important part of many AI systems ($\rightarrow$ extraction of knowledge)
- data driven, adaptive systems
- programming & deduction vs. learning & self-organization
- symbolic approaches vs. sub-symbolic approaches
  biologically inspired learning rules
  (knowledge bases & reasoning vs. easy & robust learning rules, Hebb)
- Many problems involve uncertainty $\rightarrow$ Probability & Decision theory

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$\rightarrow$ Extract, analyse, and use principles of neural information processing to build intelligent "machines".

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Main Topics

- Learning / prediction & generalization of statistical relationships
- Statistical inference in graphical models
- Finding structure in high dimensional data sets

Influences from biology

2 Perspectives: engineering $\leftrightarrow$ reverse engineering of biological systems

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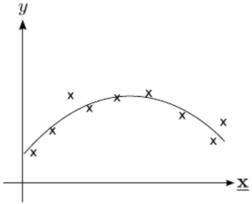
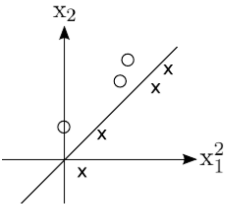
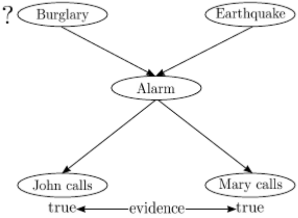
Design Principles from Biology

- simple, but highly optimized hardware (echolocation in bats, sound localization in barn owls, ultra fast face recognition)
- Plasticity (synaptic strength, lifelong renewal of cells in the olfactory system) drifting environments,
- Adaptation in sensory systems
- Graceful degradation

Illustration of MI1 paradigms

Regression	Classification	Inference
		
predict value y given $\underline{\mathbf{x}}$	predict label y given $\underline{\mathbf{x}}$	predict p(Burglary) given evidence

Artificial Neural Networks (ANNs)

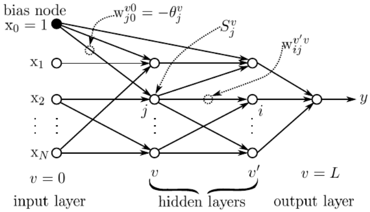
ANNs are ...

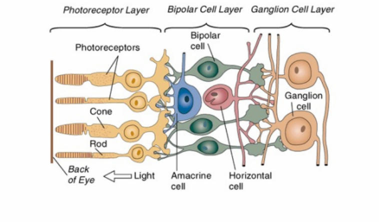
- ... useful for Regression and Classification
- ... brain *inspired* model architectures (McCulloch & Pitts, 1943)
- ... built from simple elements ($\rightarrow$ connectionist neurons)
- ...... with low precision & robustness ($\rightarrow$ binary, noisy)
- ... massively parallel systems ($\rightarrow$ "networks")

Consequences

- Distributed representation of information
- No clear separation between "data" and "program"

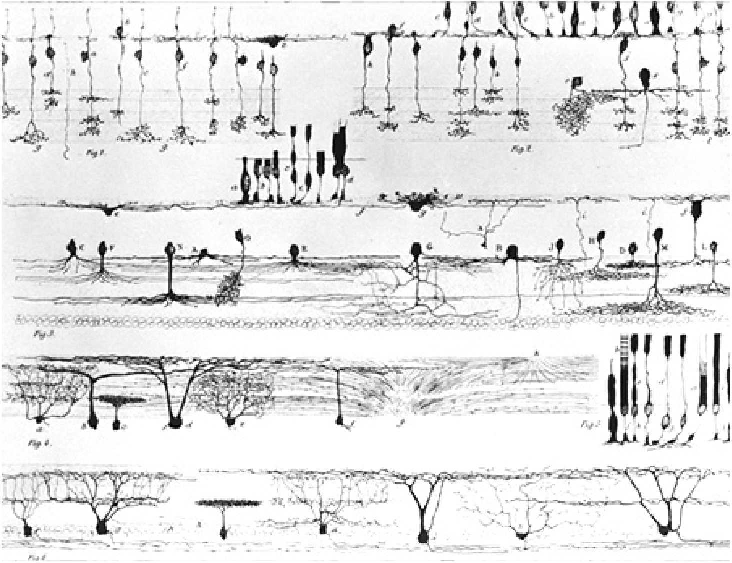
ANNs & brain style computation



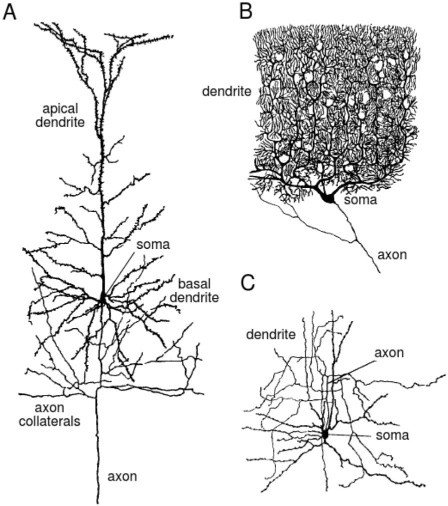


Source: Adapted from Dowling, J. E., and Boycott, B. B. *Proceedings of the Royal Society of London, B.*, 1966, *166*, 80–111

Retinal cells (Ramon y Cajal)



Excitatory cortical cells



from Dayan & Abbott (2001)