Knowledge Representation and Reasoning

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People involved

Lectures:

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Practicals and tutorials:

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Start practical: See blackboard/website

Course outline

Website: http://www.cs.ru.nl/∼peterl/teaching/KeR

(1) Lectures:

- Theory of knowledge representation and reasoning; core of this formed by:
  - AI-style logics and probability theory
  - Nowadays you can even combine logic and probability theory

(2) Tutorials: do exercises

(3) Practical:

- Learn some programming in Prolog (the AI logic programming language)
- Develop reasoning systems in AIlog

Topics

- Refresh your memory on formal logic
  - this week: read “Logic and Resolution” (available on blackboard and website) – no lectures on 8th September!
  - 12th September: revision lecture on logic
  - 19th September: logic exercises
- Week 26th September: programming in Prolog and AILog
- Knowledge representation formalisms
- Model-based reasoning
- Reasoning with uncertainty
- Decision making

Learning aims of the course

- Obtain insight into the development of knowledge systems, the use of problem solving methods, forms of knowledge representation, and model-based reasoning
- Gain knowledge about logical expressiveness of forms of knowledge representation and the use of probability theory in reasoning with uncertainty
- Being able to develop reasoning programs using Prolog and AILog
- Being able to understand core AI research as reflected in ECAI, IJCAI, AAAI

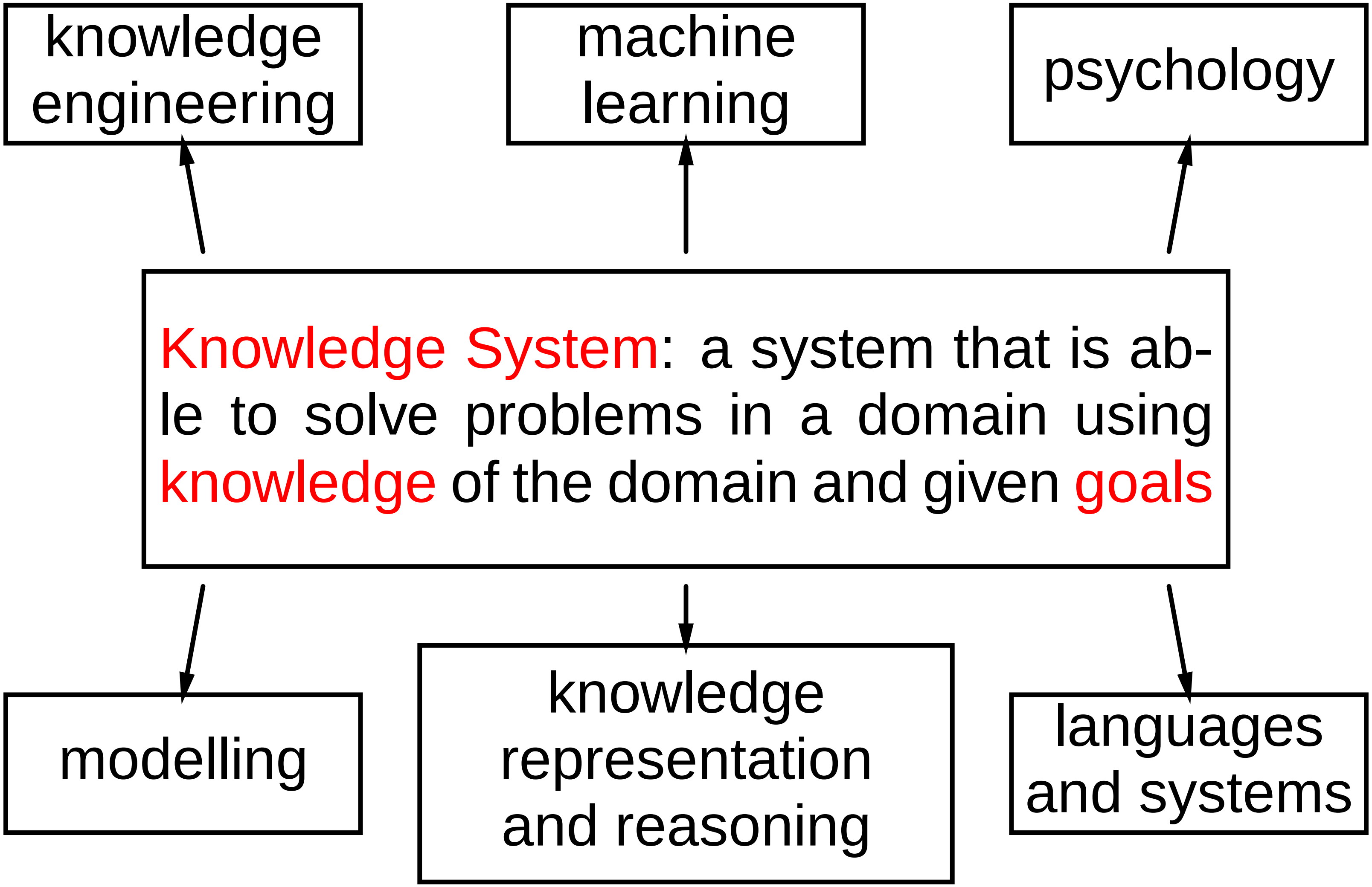
Reading and study material

- Slides and exercises
- Summarising lecture notes
- Practical manual
- Some material can be found in:
  S. Russell and P. Norvig, Artificial Intelligence: A Modern Approach, 2003 or 2009:
  - Part III Knowledge and Reasoning
    8 First-Order Logic
    9 Inference in First-Order Logic
    10 Knowledge Representation
  - Part V Uncertain Knowledge and Reasoning
    13 Uncertainty
    14 Probabilistic Reasoning

Further reading

- R.J. Brachman and H.J. Levesque, Readings in Knowledge Representation, Morgan Kaufmann, San Mateo, CA, 1985:
  - good collection of early KR papers
- F. van Harmelen, V. Lifschitz, and B. Poter, Handbook of Knowledge Representation, Elsevier, Amsterdam, 2008:
  - state of the art handbook on KR
- D. Poole, Artificial Intelligence: Foundations of Computational Agents, Cambridge University Press, 2010
  - nice systematic and coherent approach to AI using logical and probabilistic reasoning (freely accessible)

Knowledge systems



Early knowledge systems

- Expert system: use of a *large* collection of symbolic expert knowledge to solve problems:
  - E.A. Feigenbaum, B.G. Buchanan, J. Lederberg – Heuristic DENDRAL (1965): contains knowledge from organic chemistry
  - E.H. Shortliffe: MYCIN (1974–1979) – diagnostics of infectious diseases
  - H.E. Pople, J.D. Myers: Internist-1 (1973-1982) – diagnosis in the big area of internal medicine
  - D. Lenat: Cyc (1984-) – representation of common sense knowledge

Modern knowledge systems

- Use of more sophisticated logical methods:
  - abductive reasoning (cause-effect reasoning and explaining observations), e.g., used in abductive diagnosis
  - use of functional models of behaviour, e.g., in consistency-based diagnosis
- Use of probabilistic and decision-theoretic methods:
  - Bayesian networks (to reason with uncertain knowledge)
  - augmented by decision theory (to allow making decision about appropriate actions)

Knowledge: Implicit versus explicit

Two hypotheses:

(1) Human reasoning is hard to capture, and, thus, intricate implicit methods, such as neural networks, capture human reasoning best;

(2) Human reasoning can be captured, although possibly incompletely. However, explicit representation is necessary for getting a grip on that knowledge (e.g., to be able to explain recommendations)

Choice: explicit knowledge

Knowledge representation hypothesis

Brian Smith (1982):

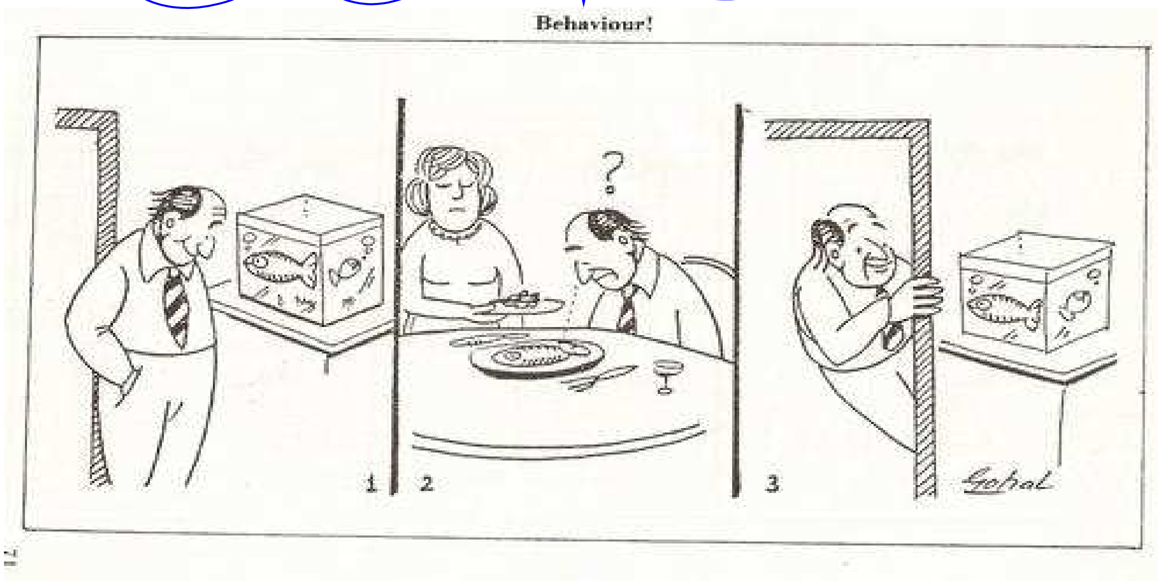
Any mechanically embodied intelligent process will be comprised of structural ingredients that

(a) we as external observers naturally take to represent a propositional account of the knowledge that the overall process exhibits;

(b) independent of such external semantical attribution, play a formal but causal and essential role in engendering the behaviour that manifests that knowledge

Knowledge representation hypothesis

Forall x (Fish(x) and InAquarium(x) and ...



Observers

Formal knowledge representation

- Logic was originally developed as a language for mathematical reasoning
- Goal of knowledge representation different: represent semantic content of psychologically plausible memory models
- Need for semantics shared by most researchers in knowledge representation
- In time logic has become the dominant language as probability theory for uncertainty reasoning

Natural kinds

- Mathematical definitions: exact and complete. Example triangle: shape defined by three points that are not on a straight line and that are connected by lines

- Natural kinds: objects in the real word. 'Definitions' of objects are often approximate and incomplete

  Example:

  $\forall x(\text{Human}(x) \rightarrow \text{Animal}(x))$
  $\forall x(\text{Human}(x) \rightarrow (\text{walks}(x) = \text{upright} \wedge \cdots \wedge \cdots))$

Role of representation system

- To manage beliefs expressed in the language
- More than just implementation of a (logical, probabilistic) calculus
- The symbolic representation cause the system to behave in a particular fashion

Thus,

> Any language with sufficient expressive power can be used

Language requirements

Levesque & Brachman (A fundamental tradeoff in knowledge representation and reasoning)

Emphasis on:

- What is represented $\equiv$ content $\Rightarrow$ knowledge level (rather than symbol level)
- Statements must be interpreted in relationship to other statements (otherwise no knowledge)
- This implies: language should have a truth theory
- Not a single language, but spectrum of languages (from simple, computationally tractable, to complex, computationally intractable)

Truth theory

- Knowledge base KB: what we know about the world
- Question: is the truth of statement φ implied by KB (note φ need not be included in KB)
- Notation:

$$\text{KB} \models \varphi$$

- In the form of inference $=$ reasoning:

$$\text{KB} \vdash \varphi$$

or,

$$\vdash \text{KB} \rightarrow \varphi$$

(KB $\rightarrow \varphi$ is a theorem) if we use logic, but many logics and other languages are still possible

Logics for knowledge representation

- First-order logic:
  - satisfiability: undecidable
  - when it is known that KB is unsatisfiable, then KB $\models \perp$ is decidable
- (Finite) propositional logic:
  - decidable, but NP complete
  - propositional Horn logic: model checking in polynomial time

    Horn formula: $(A_1 \wedge \cdots \wedge A_n) \rightarrow B$, with A_i and B positive literals

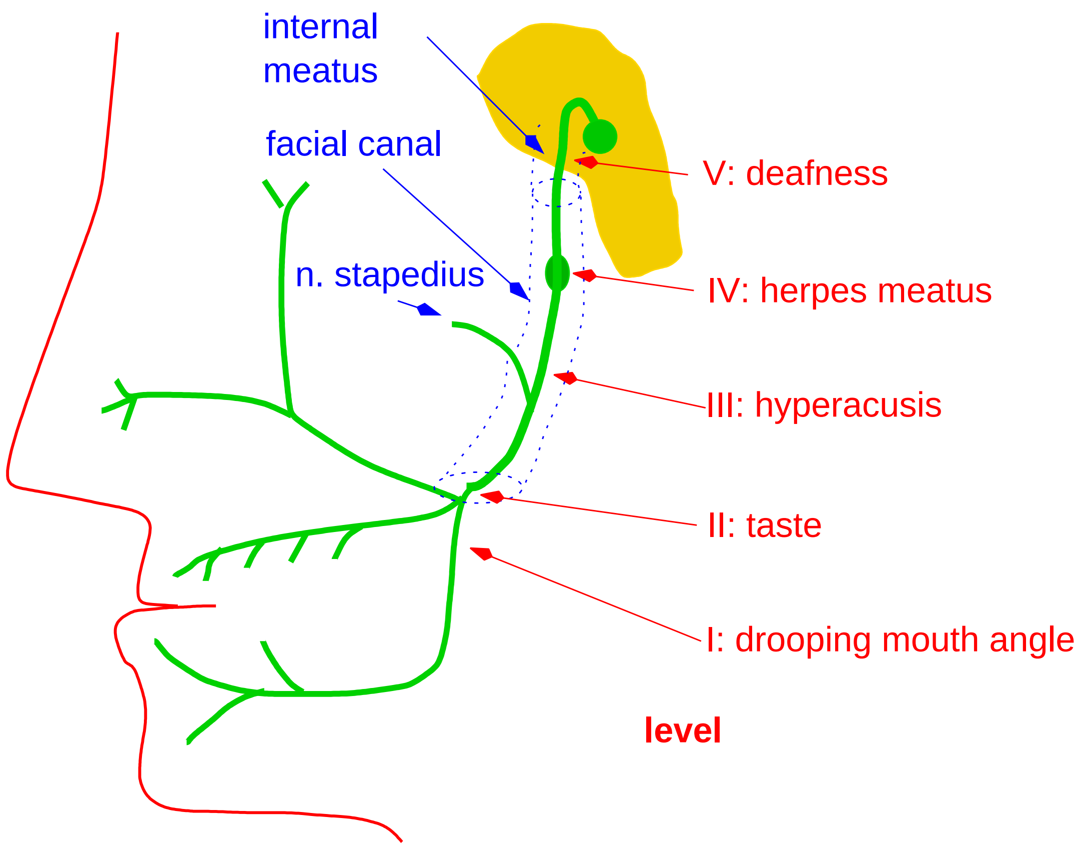
$\Rightarrow$ tradeoff between expressive power and computational complexity

Prolog

- Logical (programming) language with some restrictions, but based on first-order predicate logic
- One of the typical AI programming languages (other Lisp)
- Close relationship with knowledge representation and reasoning: AILog

```
in_mind([h,o,l,i,d,a,y]).
start :- write('Guess first letter'), read(X),
         in_mind([X|T]), write('OK. '), guess(T).
guess([]) :- write('The word is '), in_mind(W), write(W),!
guess(L)  :- repeat, write('Next letter'), read(X),
             ((L=[X|T1], write('OK. '), guess(T1));
             (write('Fail. Try again!'), guess(L))).
```

Model-based reasoning



- Explicit representation of structure and function of systems ($=$ model)
- Reasoning with this model to solve problems (e.g. diagnosis)

Reasoning with uncertainty

- Early: uncertainty attached to rule-based reasoning (ako uncertain reasoning with logical implications)
- 1990s: introduction of Bayesian/belief networks (causal networks with attached probability distributions)
- 1990s: extension to decision networks/influence diagrams (decision making under uncertainty)
- Recent: probabilistic logics (logic and probability theory integrated in an AI fashion)

Thus, after 30 years back to the early problem, which is now well understood

Examples 1: Pacemaker programming

display patient information

show settings

display histograms, counters, holters

provide treatment advice

enter patient data

change settings, perform tests

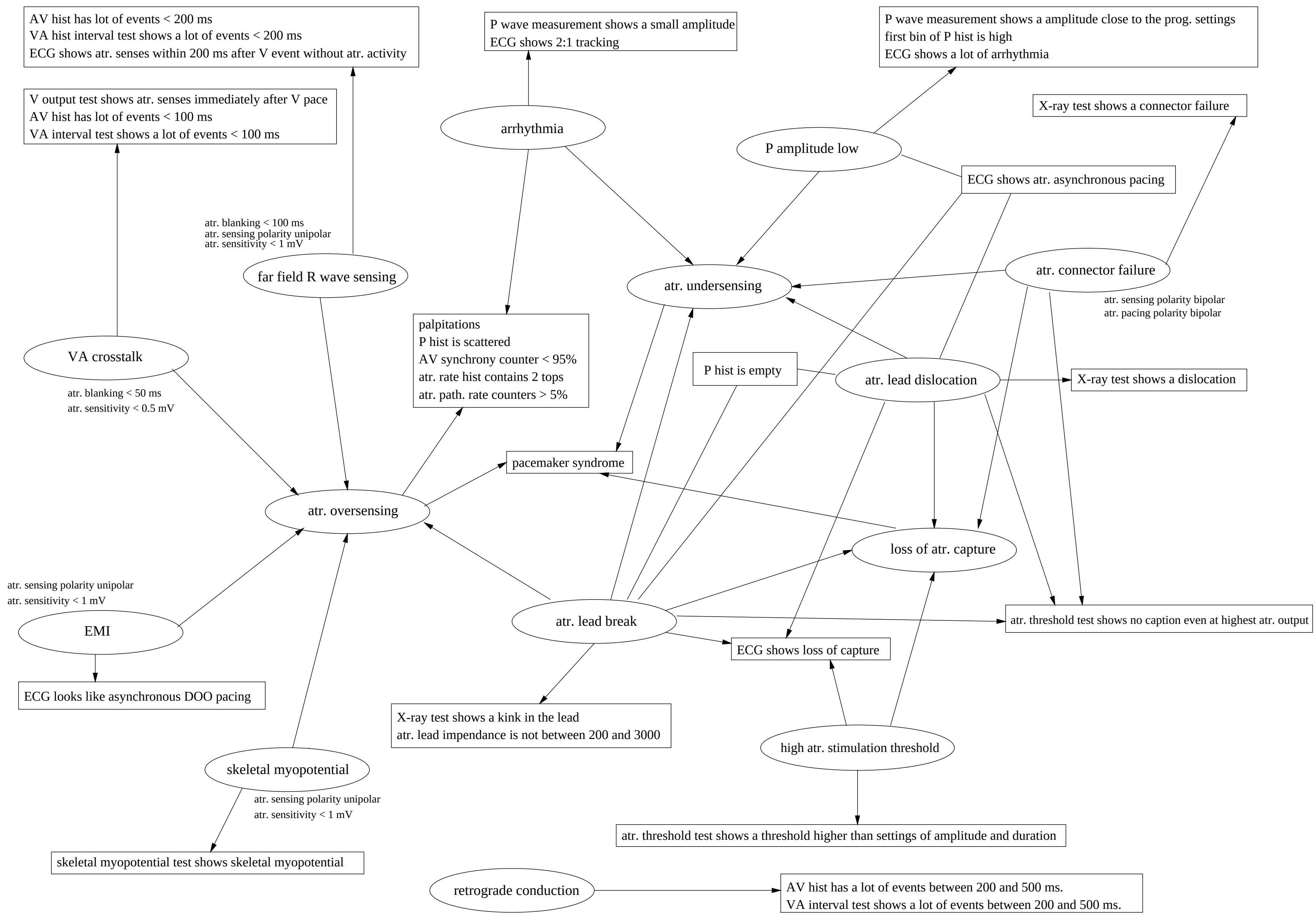
diagnostics

settings

reprogrammed settings

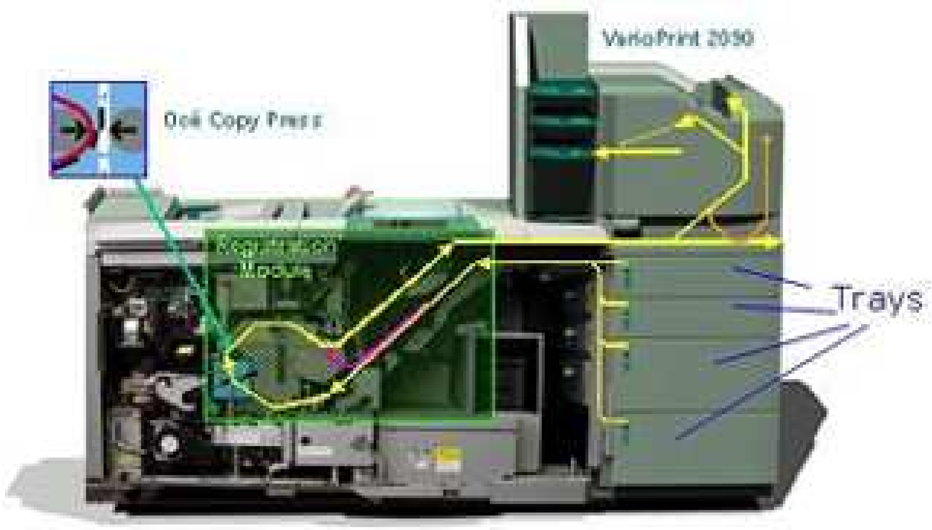
tests

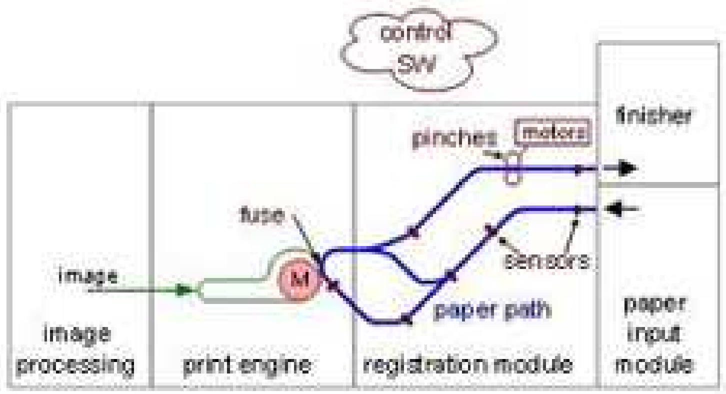
Examples 1: Causal pacemaker model



Examples 2: Smart production printers

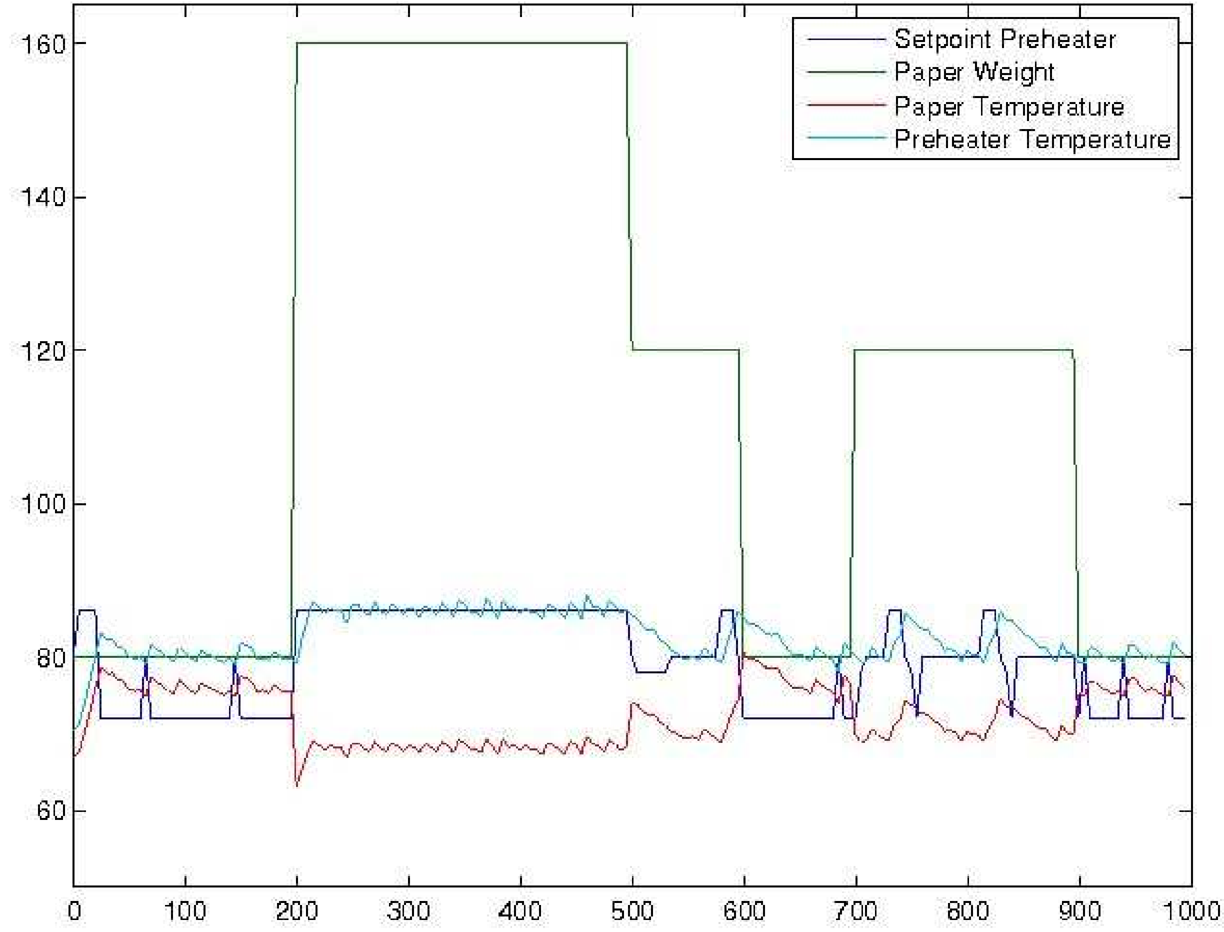
- project with Océ and Embedded Systems Institute
- model-based reasoning about behaviour of printers/copiers
- interpretation of sensor information
- adaptation to changing environment





Examples 2: Adaptive control

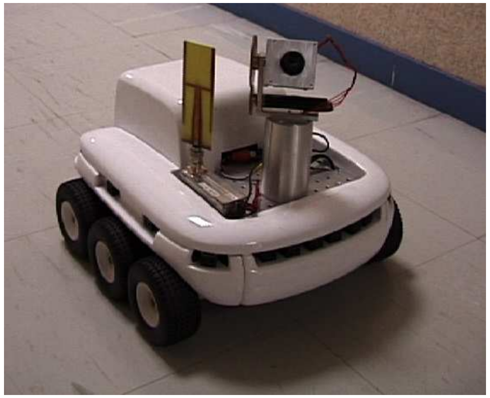
Avoid that paper temperature becomes lower than 66°C with 99% certainty:

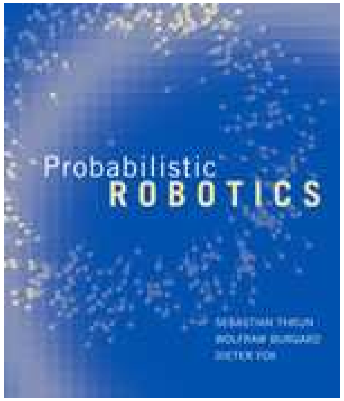


Research at CAI

- Cognitive robotics
- Theoretical models of human reasoning
- Brain-computer interfaces
- Brain reading

Cognitive robotics





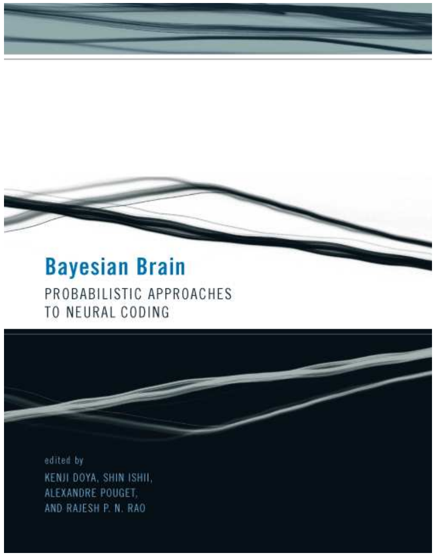
- Robots perceive an incomplete image of the world using sensors that are inherently unreliable
- Given this partial observability, we need algorithms to:
  - Estimate the true state of the world
  - perform planning in order to reach goals
- Relies on probability theory and decision theory

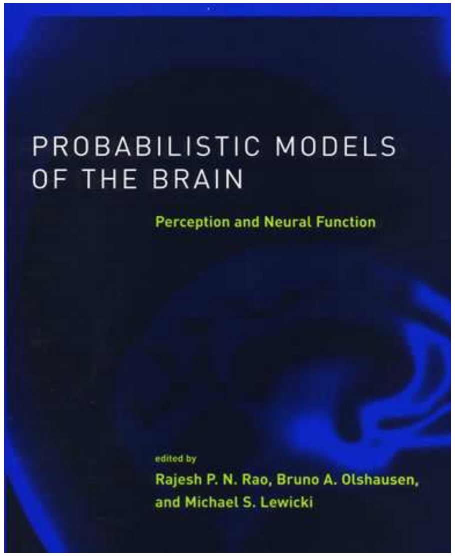
Models of human reasoning

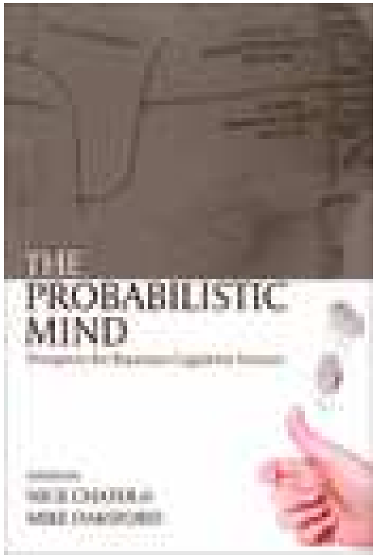
- Helmholtz proposed that perception is unconscious inference.
- That is, our percepts are our best guess as to what is in the world, given both sensory data and prior experience
- This hypothesis can be formulated in terms of probability theory

Models of human reasoning

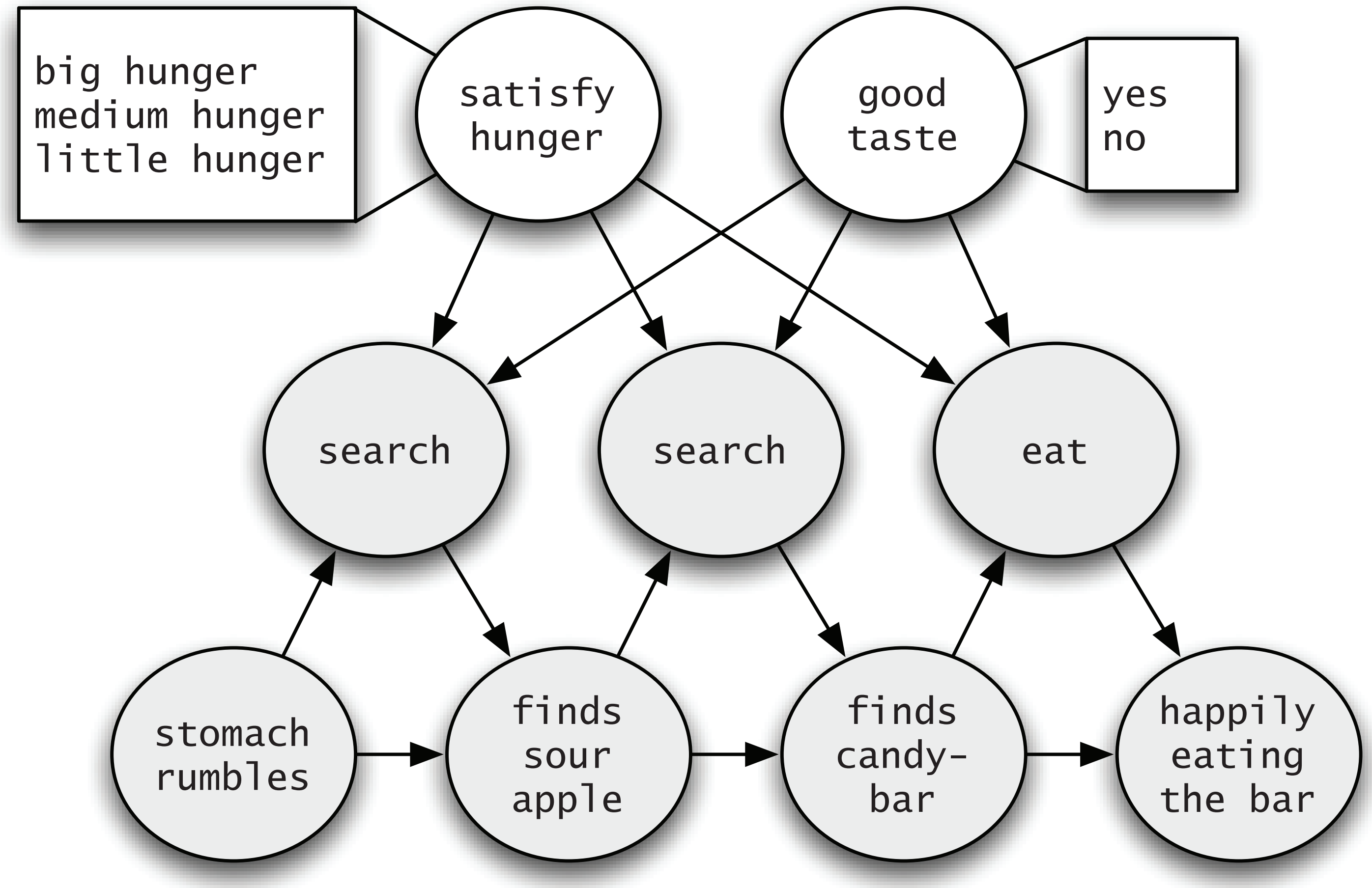
- Probabilistic theories of human brain function and cognition are dominant



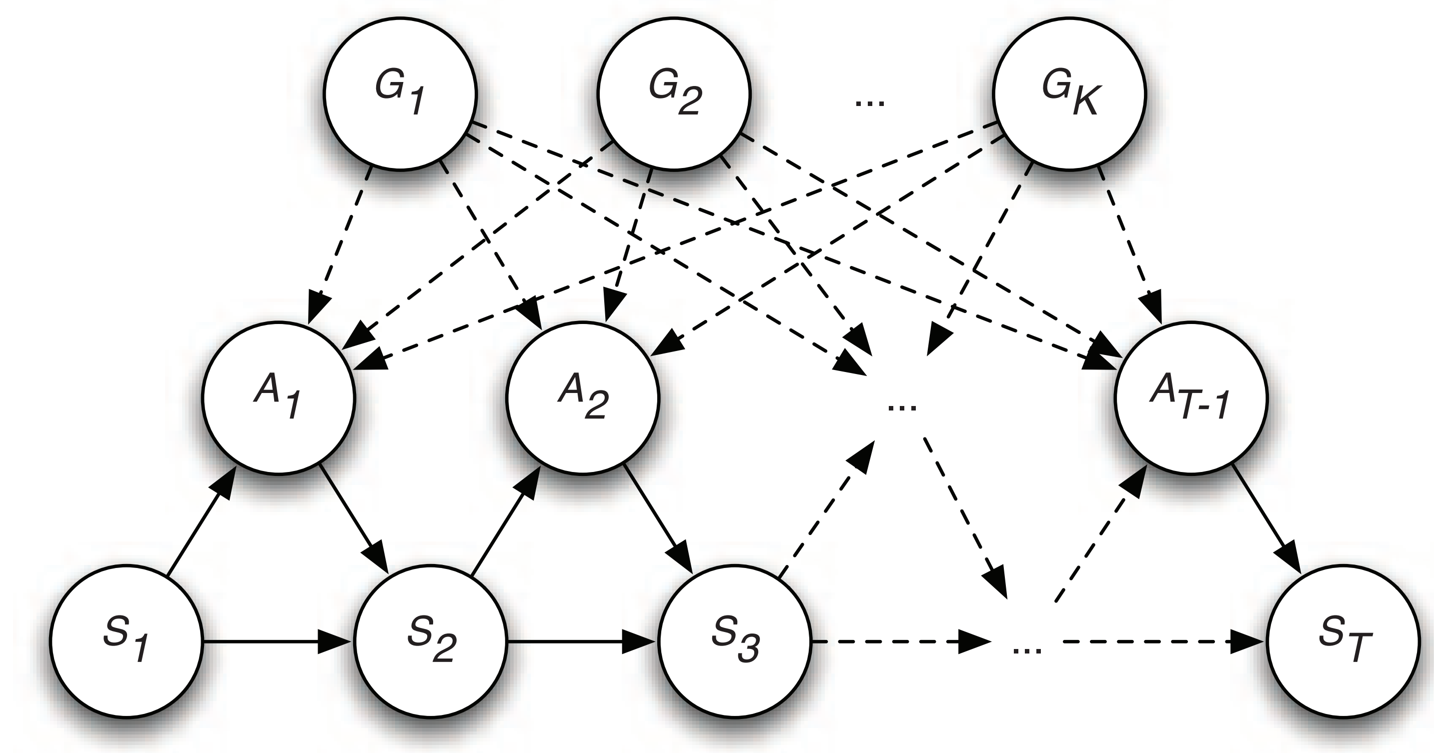




Example: Goal inference

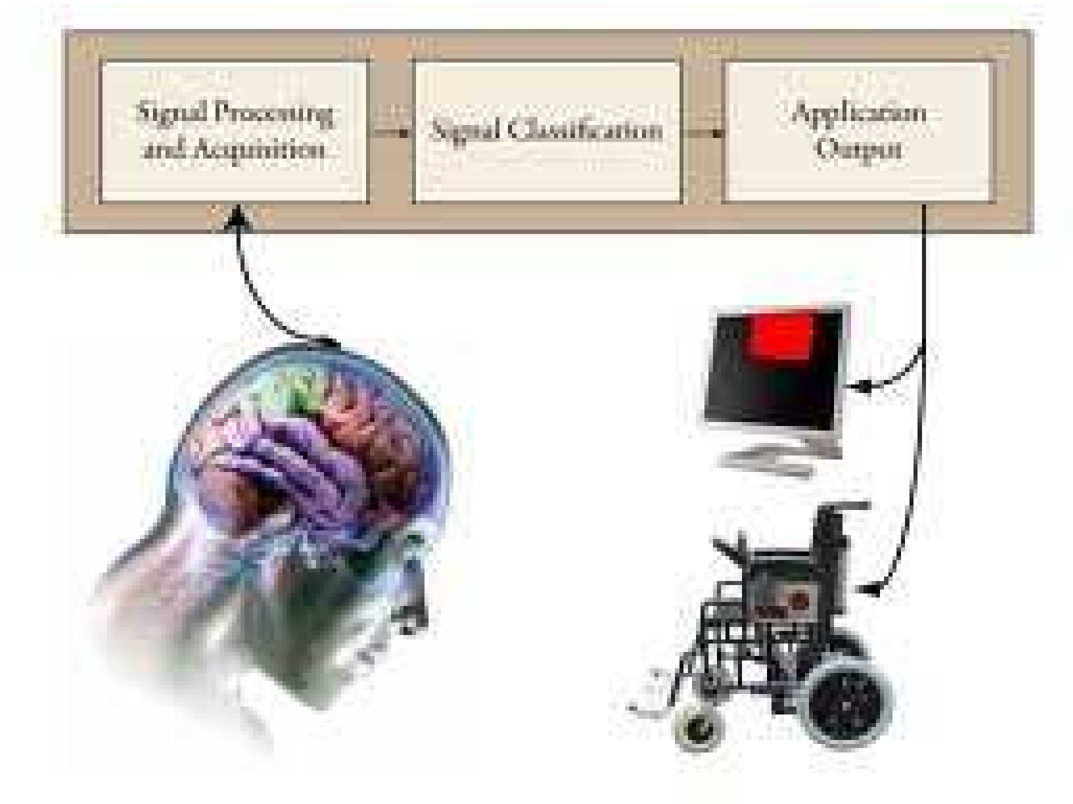


Example: Goal inference



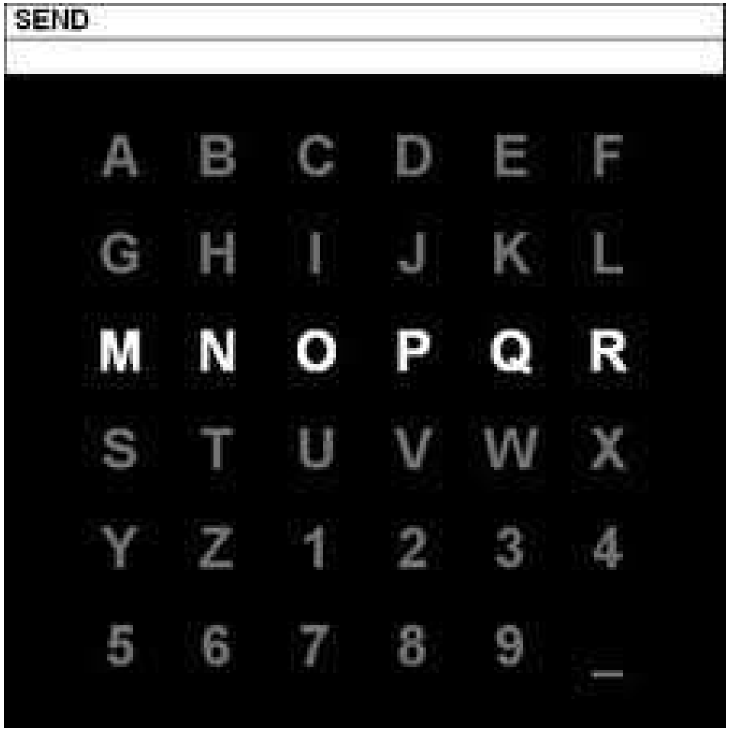
- Formal models of abstract reasoning
- Formulated as inference in probabilistic networks
- Complexity analysis of these models informs human cognition

Brain-computer interfaces



- BCIs allow brain-based communication and control
- Requires new algorithmic developments

Example



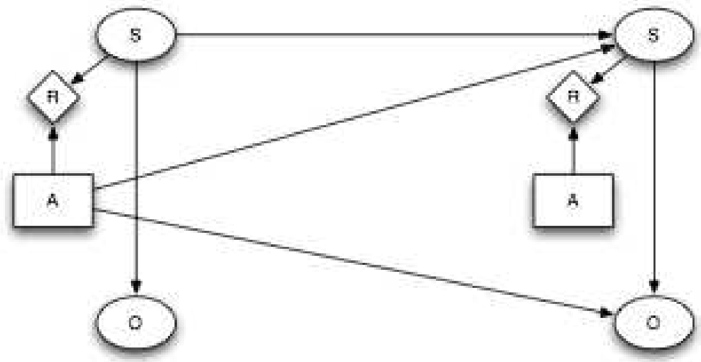
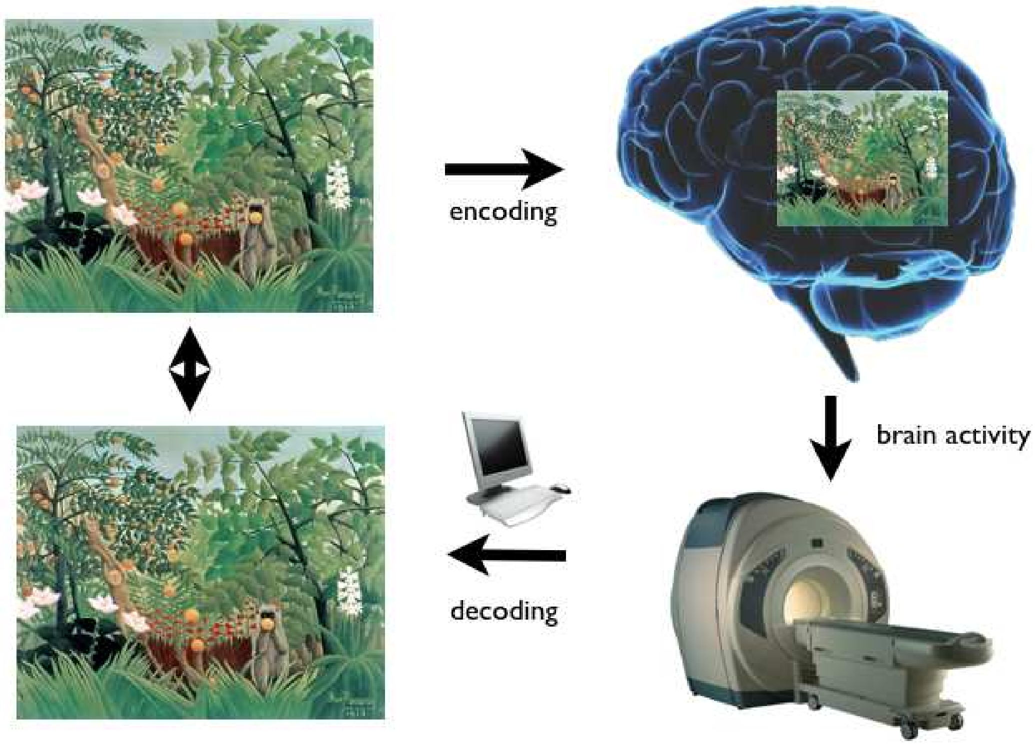


Figure 1: Adaptive flashing POMDP.

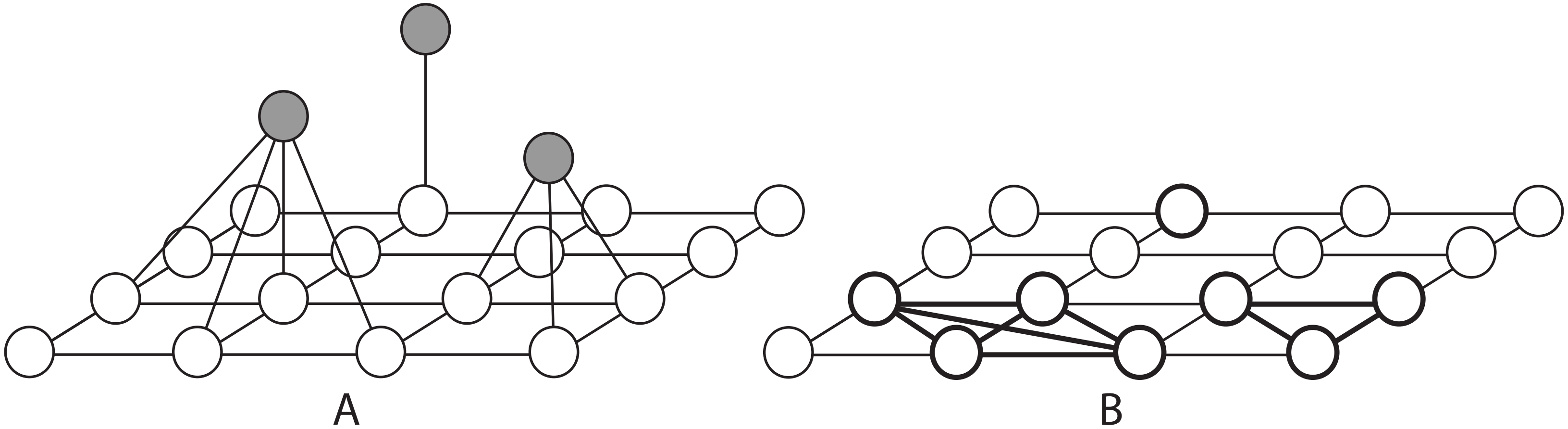
- Optimal experimental design for P300 spellers
- Based on partially-observable Markov decision processes

Brain reading



- It is possible to decode mental states from brain data
- New ways of analyzing the brain increases our understanding
- This relies on sophisticated probabilistic machine learning algorithms

Example



- Reconstruction of perceived images from BOLD data
- Probabilistic inference in Markov random fields

Conclusions

- Knowledge representation and reasoning defines the very core of AI
- Logic, probability theory and decision theory form its theoretical foundations
- The basis for building intelligent agents and applications
- Concepts form the basis of modern theories on human knowledge representation and reasoning and their complexity