Intelligent Agents
Web-Mining Agents

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Acknowledgements

- Some slides have been taken from lecture material provided by researchers on the web. We hope this material is indicated appropriately. Thank you all.

Organization

- Intelligent agents: Two lectures (WMA) + project
- Lecture part I: Agents‘ reasoning and reasoning in agents
  - Wednesdays 14:00-15:30 in IFIS 2035
  - Modus: Inverted Classroom
    - Summary, discussion, questions, examples
    - Except for first lecture on October 20,which is a classical lecture on-site
  - Slides and videos (partly from last semester) available in advance
    - prepare yourself with this material
  - Lecturer: Özgür Özçep

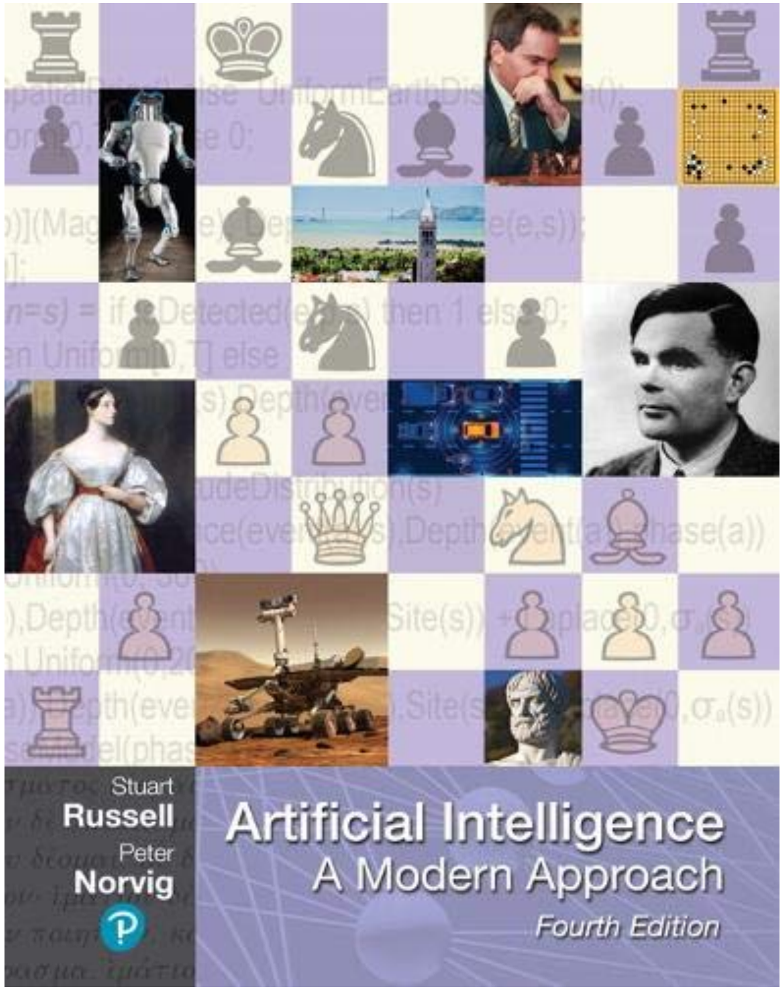
Organization (continued)

- Lecture part II: Intelligent agents for Information Retrieval
  - Thursdays 14:15-15:45 in IFIS 2035
  - Modus: Classical lecture on-site
  - Slides and videos (partly from last semester) available in advance
  - Lecturer: Ralf Möller
- Project
  - Fridays: 12:15-13:45, in IFIS 2035
  - Start: 29 October
  - Tutors: Bender/Luttermann
- More details: Moodle: https://moodle.uni-luebeck.de/course/view.php?id=7037#section-0

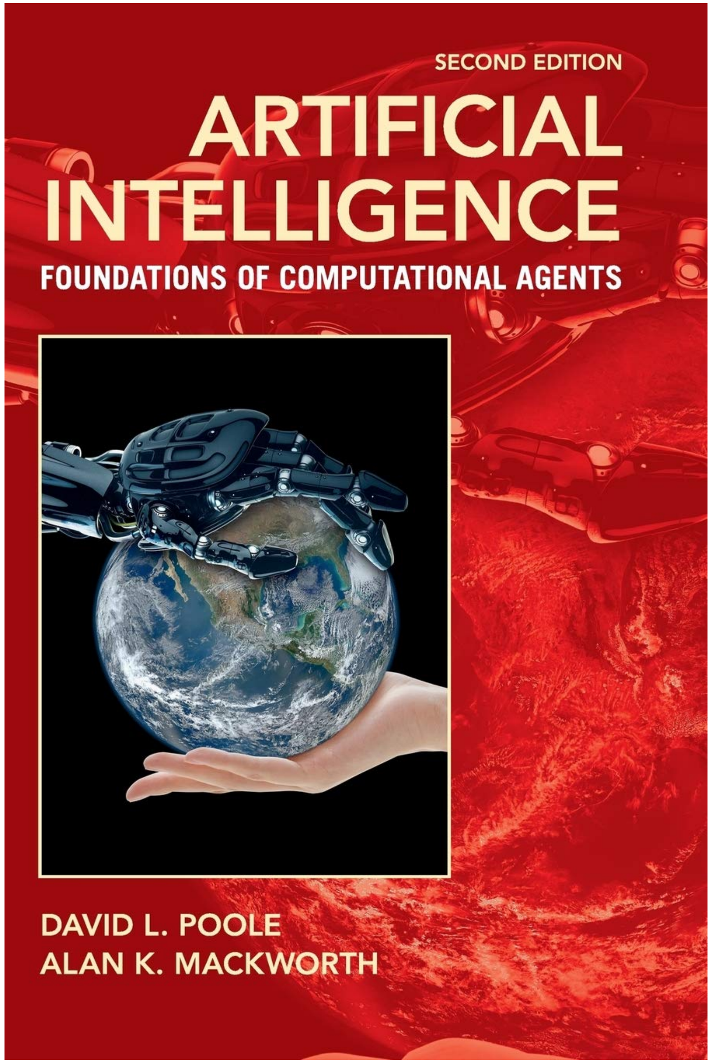
Artificial Intelligence and Intelligent Agents

- Artificial intelligence (AI) is the science of systematic synthesis and analysis of computational agents that act intelligently
  - Agents are central to AI (and vice versa)
  - Intelligent agent = computational agent that acts intelligently
  - Talking about AI w/o talking about agents misses the point (and vice versa)
- Need to technically define the notion of "acting intelligently"
- AI = Science of Intelligent Systems
  - Systems are called computational agents in AI, or agents for short

Literature

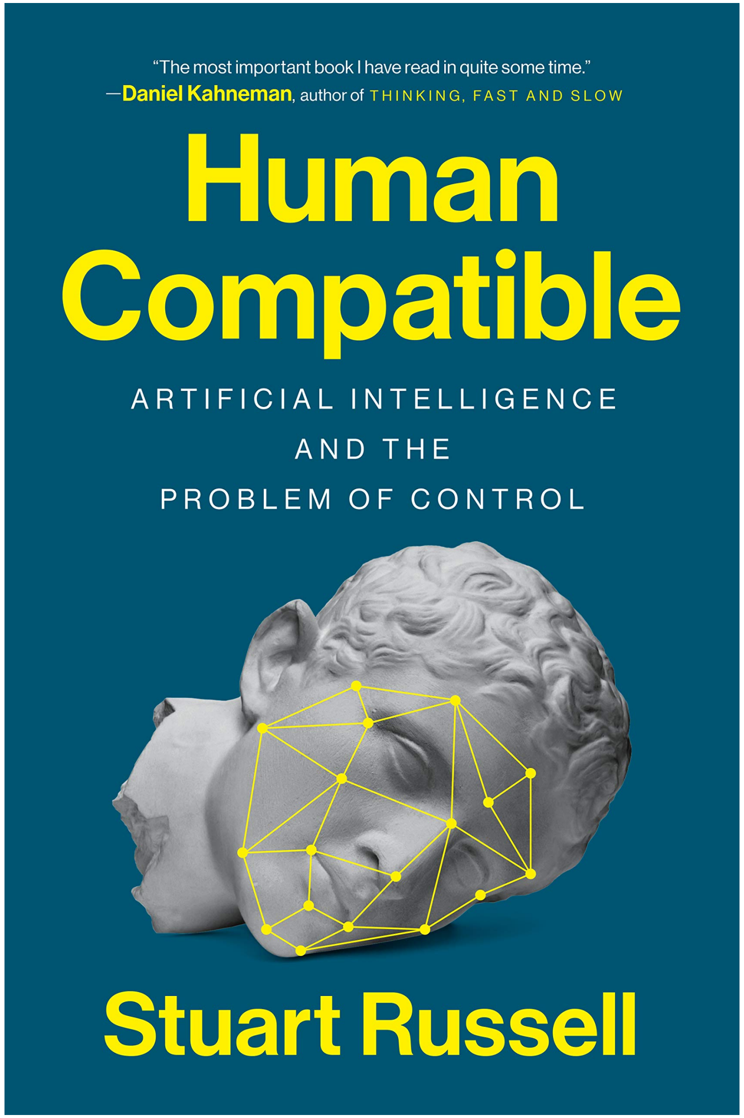


http://aima.cs.berkeley.edu
(AIMA, 1st edition 1995)

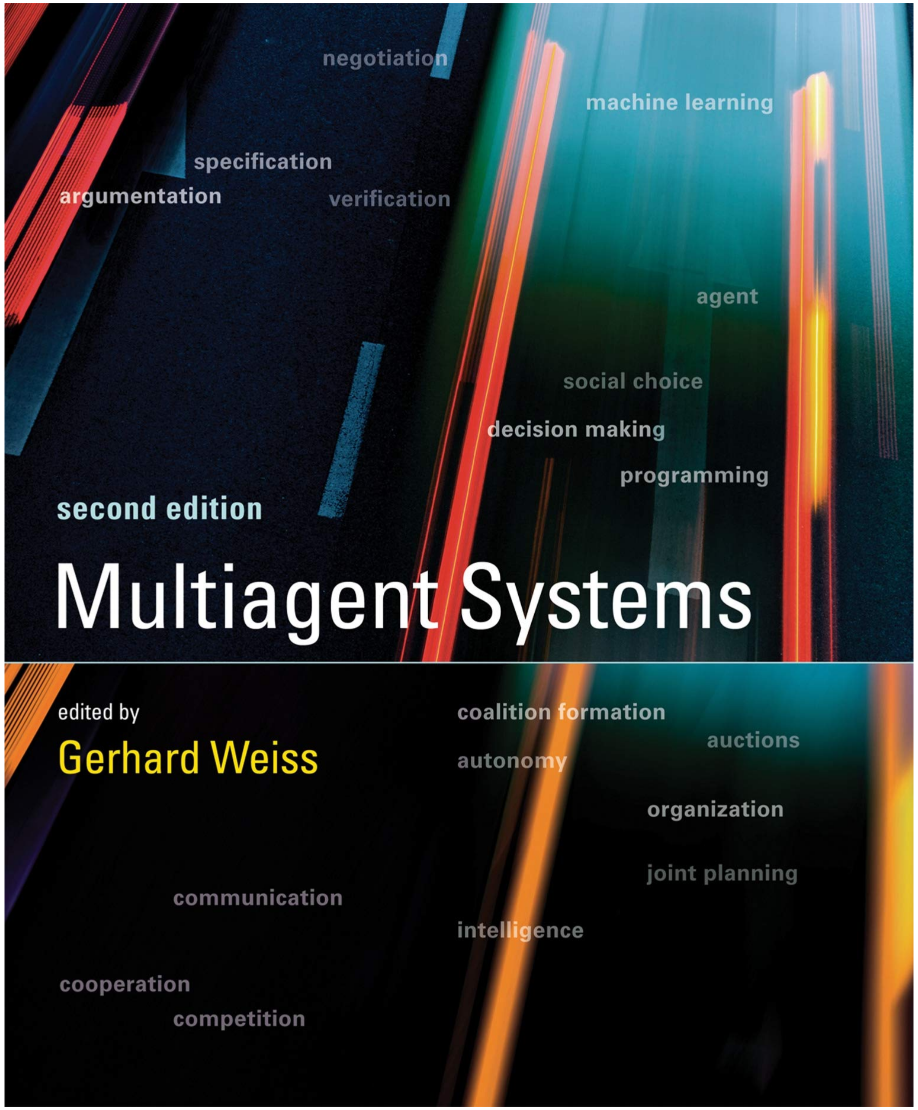


http://artint.info
(AIFCA, 1st edition 2010)

Literature

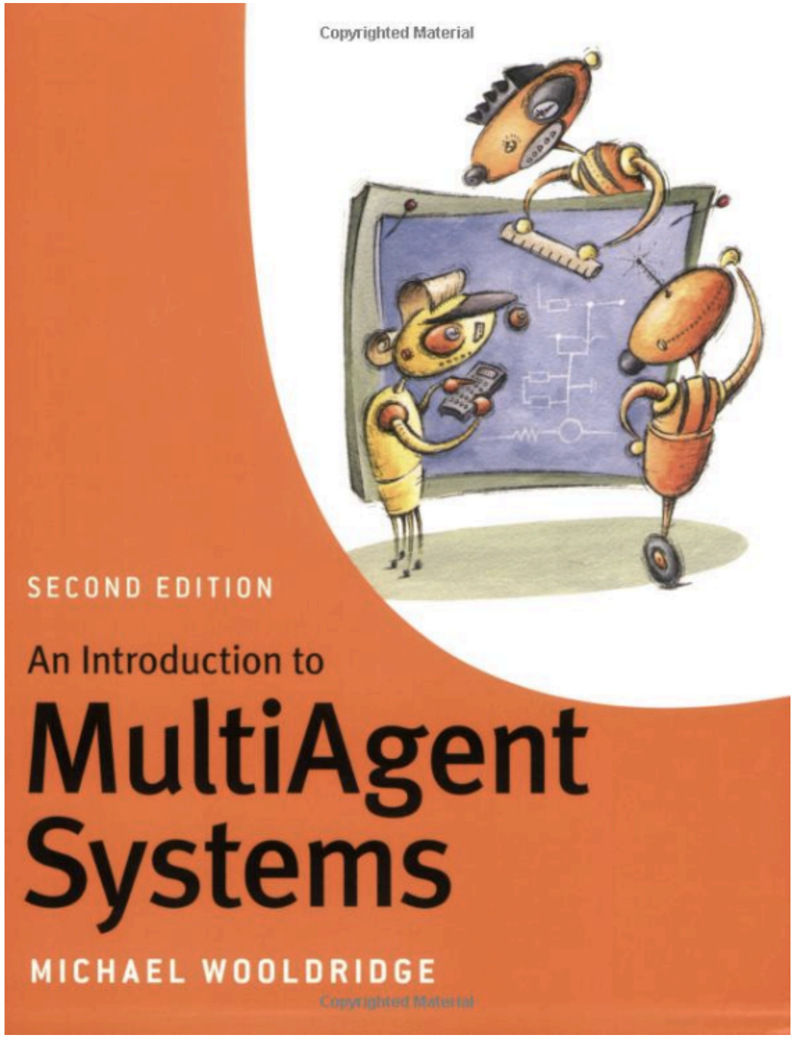


"The most important book I have read in quite some time."
—Daniel Kahneman, author of THINKING, FAST AND SLOW
Human Compatible
ARTIFICIAL INTELLIGENCE AND THE PROBLEM OF CONTROL
Stuart Russell



negotiation
machine learning
specification
argumentation
verification
agent
social choice
decision making
programming
second edition
Multiagent Systems
edited by
Gerhard Weiss
coalition formation
auctions
autonomy
organization
joint planning
communication
intelligence
cooperation
competition

Literature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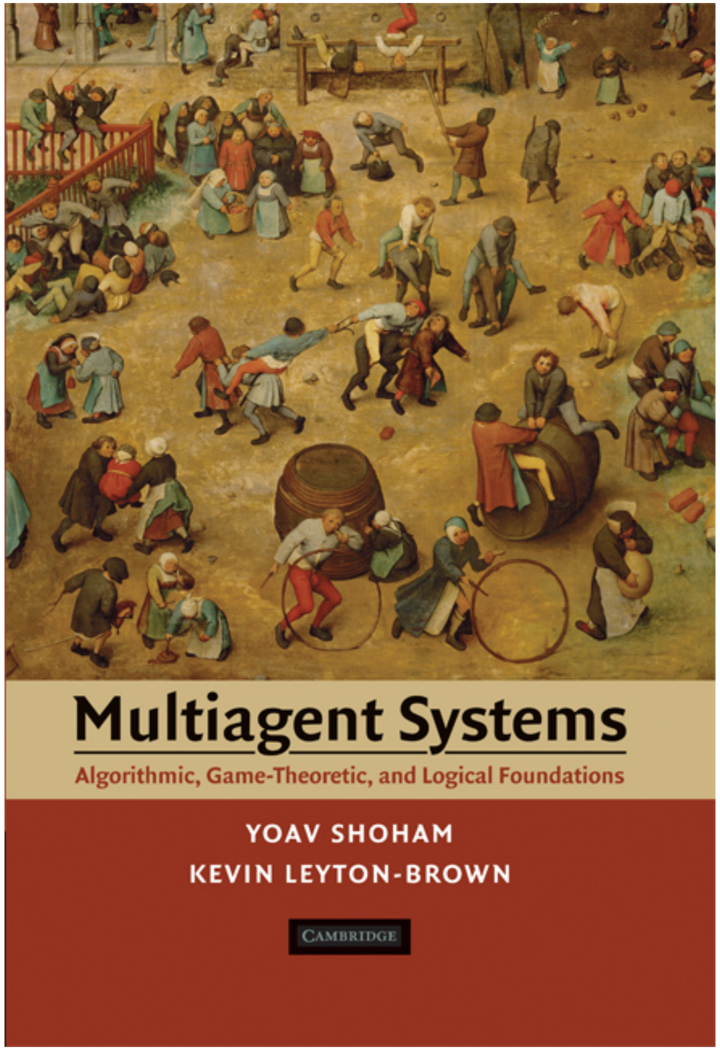
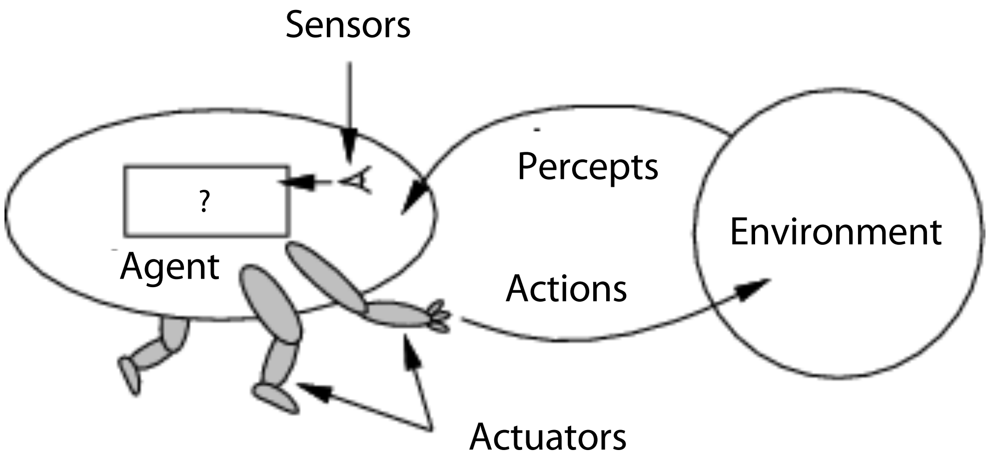
SECOND EDITION
An Introduction to
MultiAgent
Systems
MICHAEL WOOLDRIDGE


Multiagent Systems
Algorithmic, Game-Theoretic, and Logical Foundations
YOAV SHOHAM
KEVIN LEYTON-BROWN
CAMBRIDGE

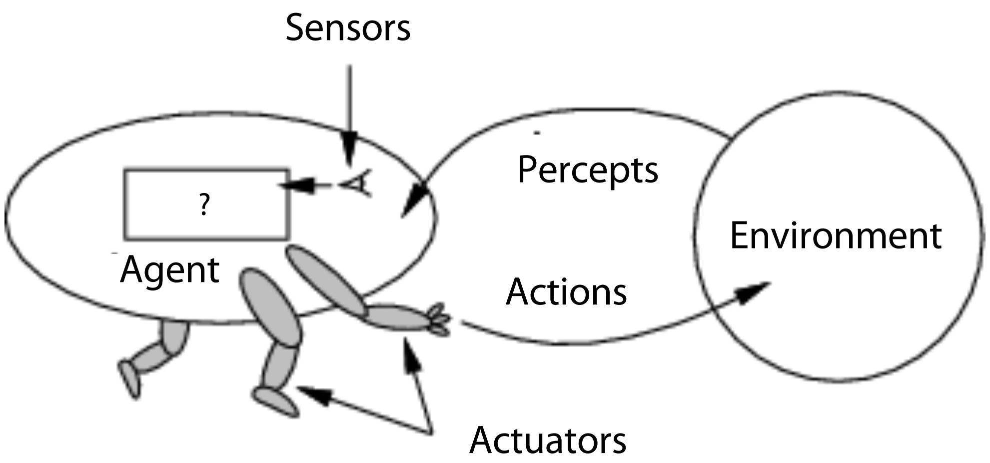
What is an Agent?

- Anything that can be viewed as perceiving its environment through sensors and acting upon that environment through actuators
[AIMA-Def]



  - Human agent
eyes, ears, and other
organs for sensors; hands, legs, mouth, and other body parts for actuators
  - Robotic agent
cameras and infrared range finders for sensors; various motors for actuators
  - Software agent
interfaces, data integration, interpretation, data manipulation/output

Abstractions: Agents and Environments



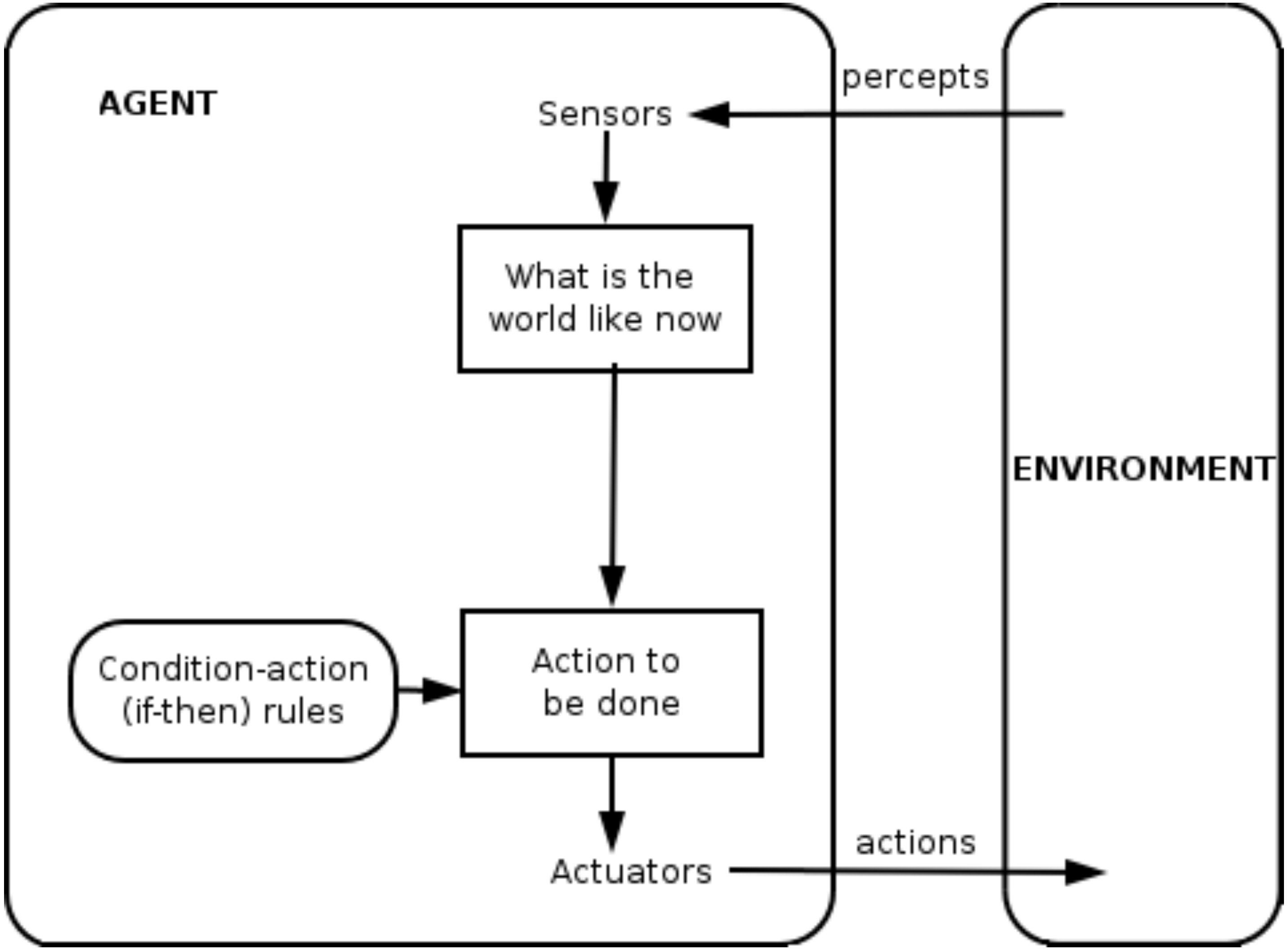
- The agent function maps from percept histories to actions:

$$[f: P^* \rightarrow A]$$

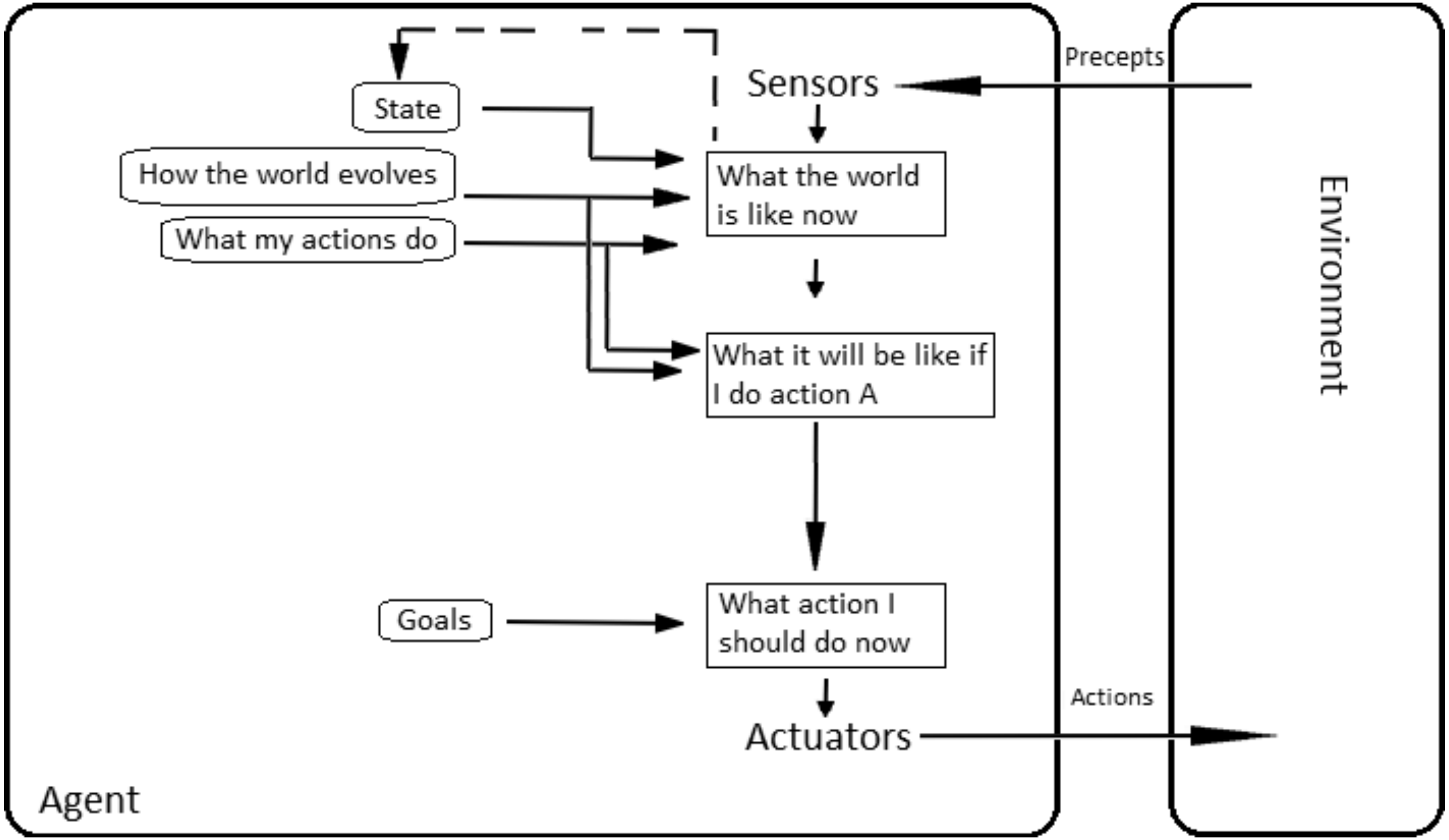
- The agent program runs on a physical architecture to produce f
- Agent = architecture + program

Really insist on functional behavior?

Reactive vs. Goal-based Agents



Reactive vs. *Goal-based* Agents



Balancing Reactive and Goal-Oriented Behavior

- We want our agents to be reactive, responding to changing conditions in an appropriate fashion (e.g., timely)
- We want our agents to systematically work towards long-term goals
- These two considerations can be at odds with one another
  - Designing an agent that can balance the two remains an open research problem
  - Achieve maximum freedom of action if there is no specific short-term goal (e.g., keep batteries charged)

Social Ability

- The real world is a multi-agent environment: we cannot go around attempting to achieve goals without taking others into account
- Some goals can only be achieved with the cooperation of others
- Social ability in agents is the ability to interact with other agents (and possibly humans) via some kind of agent-communication language …
- ... with the goal to let other agents to make commitments (of others) or reinforcements (about its own behavior)
- Need to represent and reason about beliefs about other agents

Rational Agents

- Rational Agent: For each possible percept sequence, a rational agent
  - should select an action
  - that is expected to maximize its local performance measure,
  - given the evidence provided by the percept sequence and
  - whatever built-in knowledge the agent has
- Rational = Intelligent ?
  - There is more to intelligence than to meet rationality

Autonomous Agents

- Rationality is distinct from omniscience (all-knowing with infinite knowledge)
- Computing the best action usually intractable
- Rationality is bounded
- Agents can perform actions in order to modify future percepts so as to obtain useful information (information gathering, exploration)
- An agent is autonomous if its behavior is determined by its own "experience" (with ability to learn and adapt)
  - What matters for the "experience" is the
    - percept sequence (which the agents can determine), the
    - state representation, and the
    - "computational success" of computing the best action as well as learning and adapting for the future

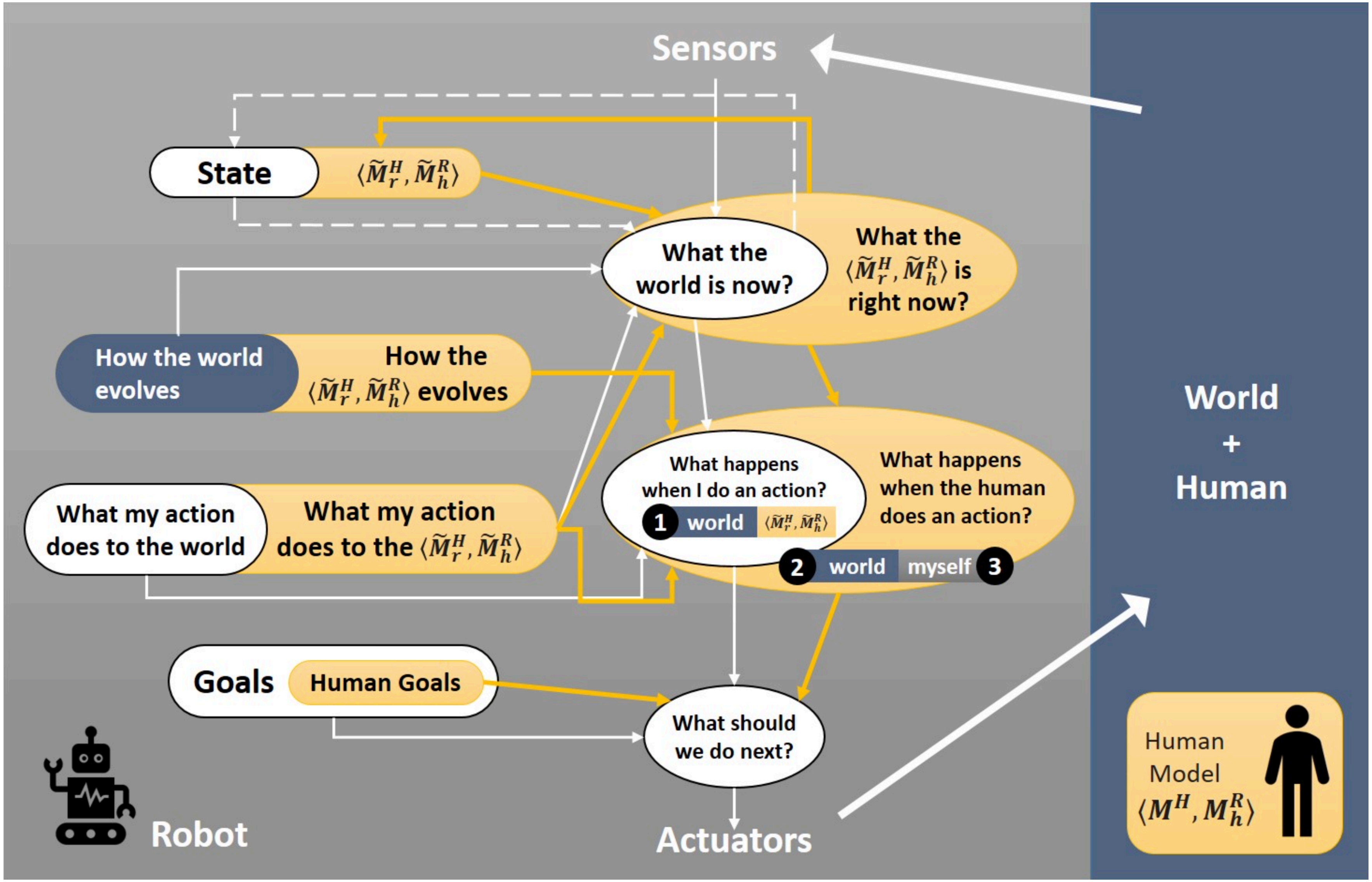
Human-compatible Behavior

- Agents act on behalf of humans, who specify the goals
- Agent should consider its initial goals to be uncertain (and to be challenged due to underspecification)
- Agent should be able to prove their behavior is beneficial to humans
- Artificial intelligence, agents, and ethics
  - Agents (and their designer) must act in an ethical way
    Developers should be able to prove …
    … that agents are able to prove
    … that they (the agents) act in an ethical way
  - Simple technology assessment is not enough
  - And yes, there are formal ethics, there is deontic logic, ...

Human-aware Behavior

- Agents interact with humans
- Selected actions must match human expectations
  – Maybe the presumably expected action might not be the best (for the human or the agent, or both)
- Selected actions that are assumed to not match human expectations must be explained

Agent Model vs. Human Model

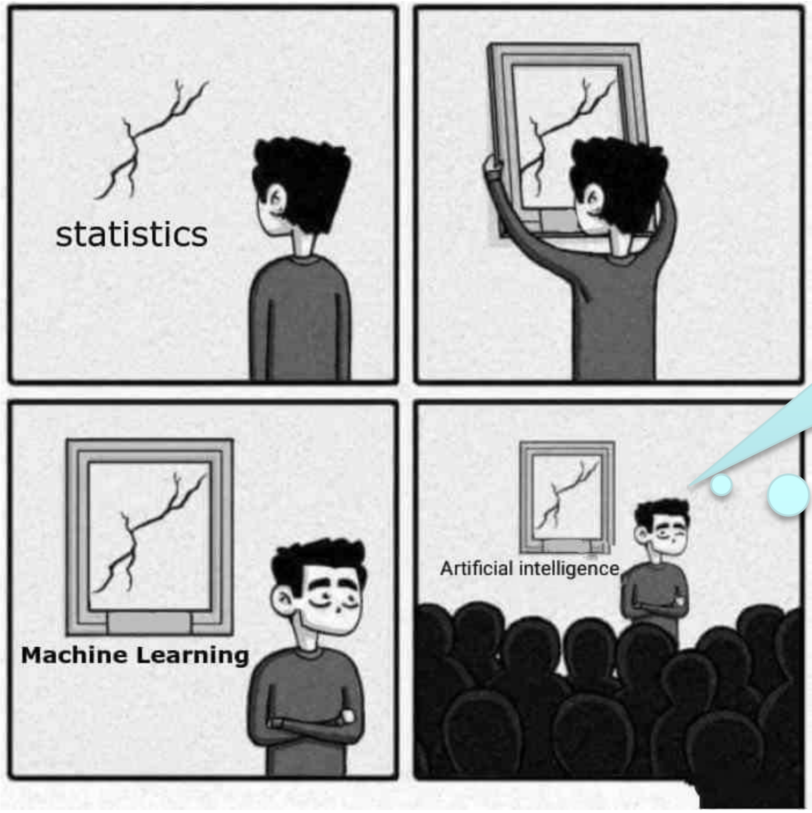


Learning Agents (Online)

- Ever extended percept sequence (incl. more or less explicitly encoded reinforcement feedback or rewards) is …
  - … sparse (no big data), but gives rise to model updates
  - … with the aim to better (faster) achieve goals
- We say: Agents learn (and we mean: while acting, or online)
  - Optimize a performance measure
- Setting up agents' online learning engines
  - Dedicated knowledge about online learning required
- Setting up an agent's initial model by exploiting data:
  - Dedicated knowledge of machine learning required
  - Also basically optimizing a performance measure

Machine Learning (ML): Offline

- Statistics vs. Data Science vs. Machine Learning

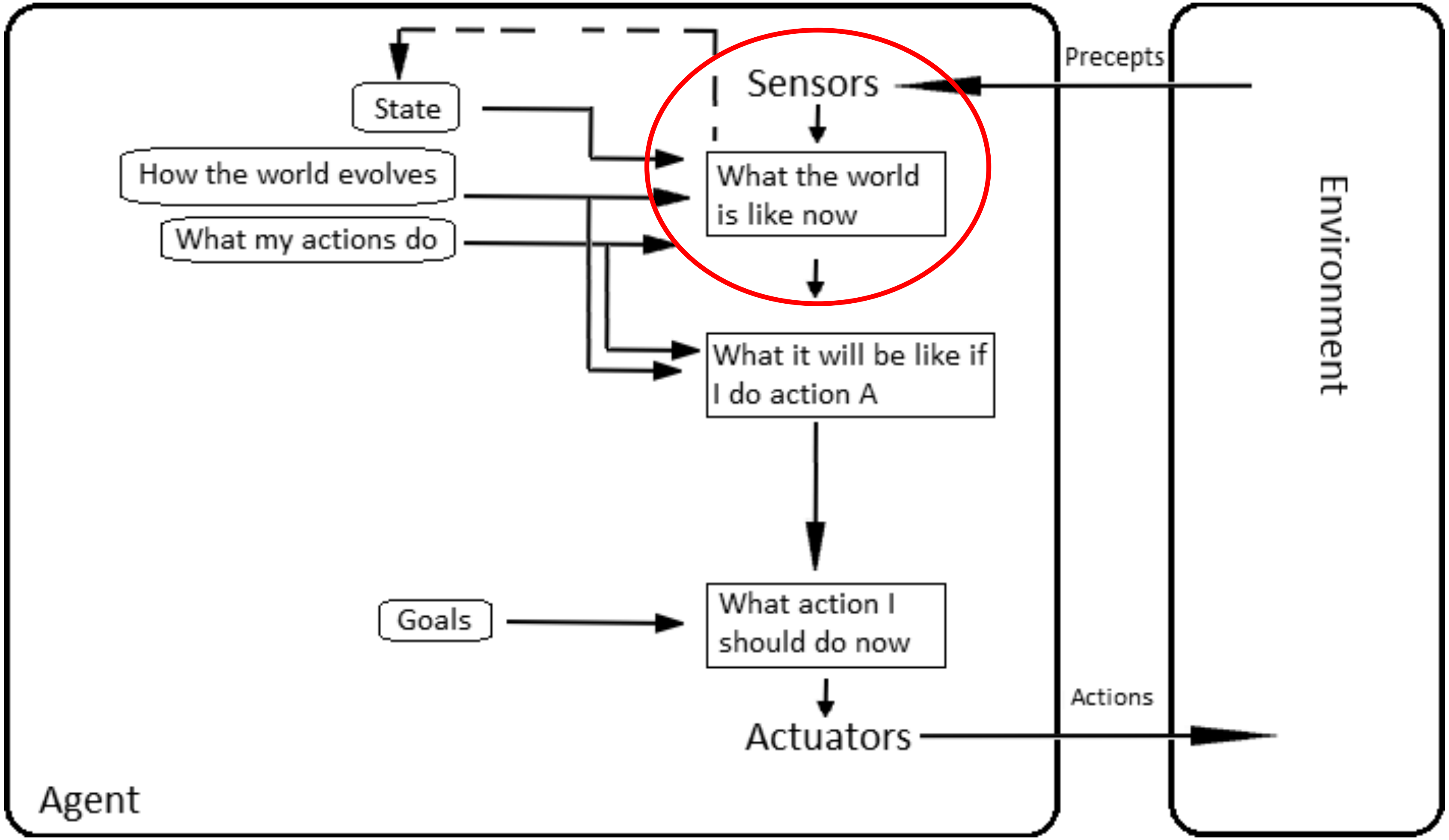


"When you're fundraising, it's AI. When you're hiring, it's ML. When you're implementing, it's logistic regression."

It is clear that claiming AI ***is*** machine learning or "contains" machine learning does not make much sense!

- Machine learning scales, but can only do so much
- All fields have evolved and still do evolve

Reactive vs. *Goal-based* Agents



Misunderstandings

- Applying ML to implement a function f some people say: "I have used ML technique X to create an AI"
- Unconsciously, AI is used as a synonym for agent, but … … mostly a very simple one
  - f: P → A
- Claiming that f is "an AI" is an indication of lack of understanding …
- … even if the last n percepts are considered
  - f: P × … × P → A
- One is lost w/o an understanding of intelligent agents
  - f: P* → A

Frame Agents

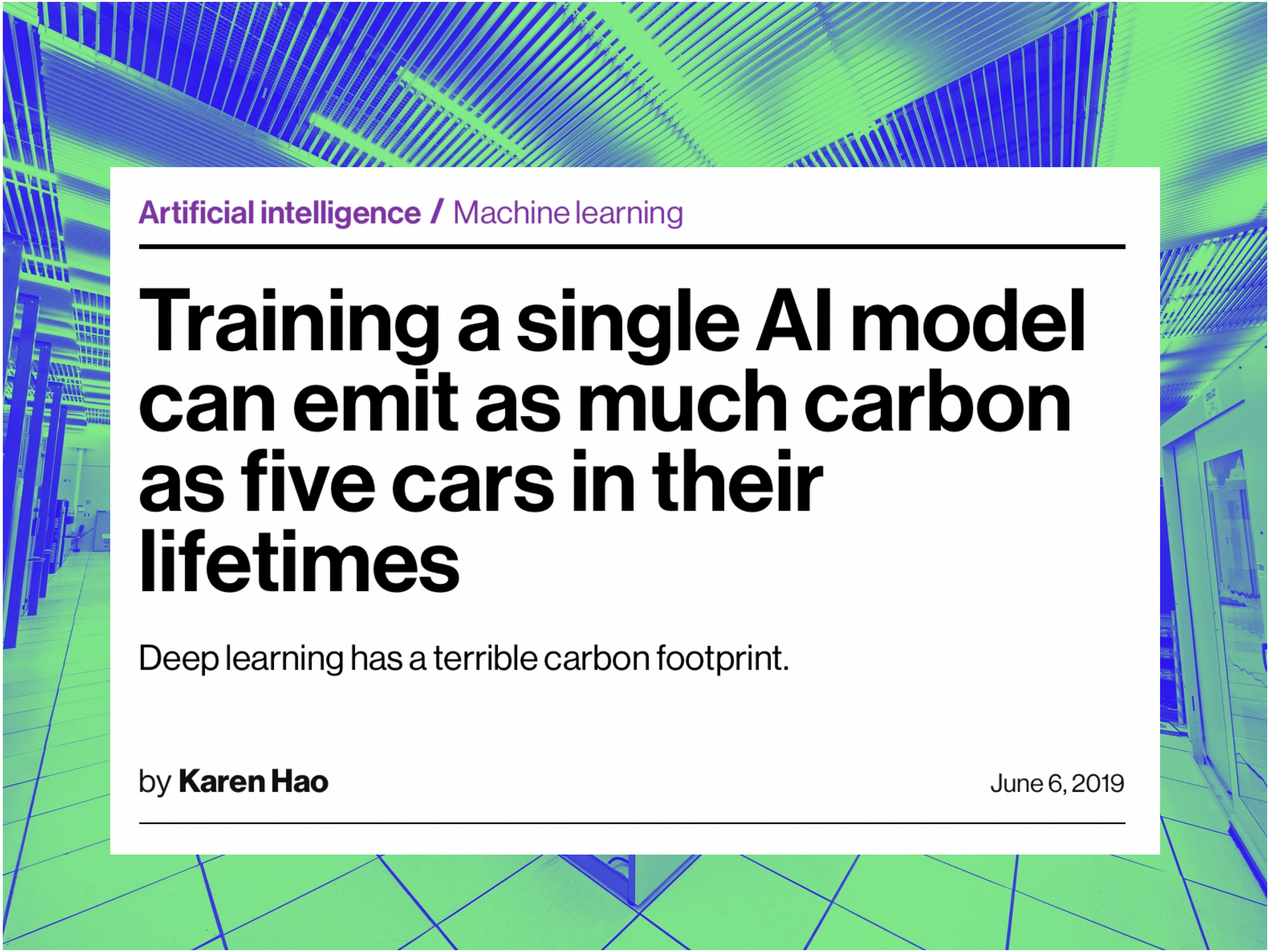
- Assume that machine learning techniques are used to build models at agent setup time
- Runtime behavior of agent always depends on last n elements of percept sequence only $f: P \times \ldots \times P \rightarrow A$
- No interaction w/ environment, no feedback
- Agent is fake (simply a frame around standard SW/HW)
  - Also holds when setup training data is camouflaged as initial percepts (but no actions towards goals are computed until training completed)
- Maybe even enlightening for practical applications, but agent idea …
- … does not show its full potential

Learning-based Software Development

- There is no need to deliberately
  conflate machine learning with agents and AI !
- No need to invent frame agents !
- Can build extremely cool SW/HW
  w/ machine learning techniques
  (e.g., for industrial image processing applications)

- → Probabilistic Differential Programming (CS5071-KP04)
- → Deep Learning Lab (CS5071-KP04)

- There are caveats, however:



Artificial intelligence / Machine learning

Training a single AI model can emit as much carbon as five cars in their lifetimes

Deep learning has a terrible carbon footprint.

by **Karen Hao**

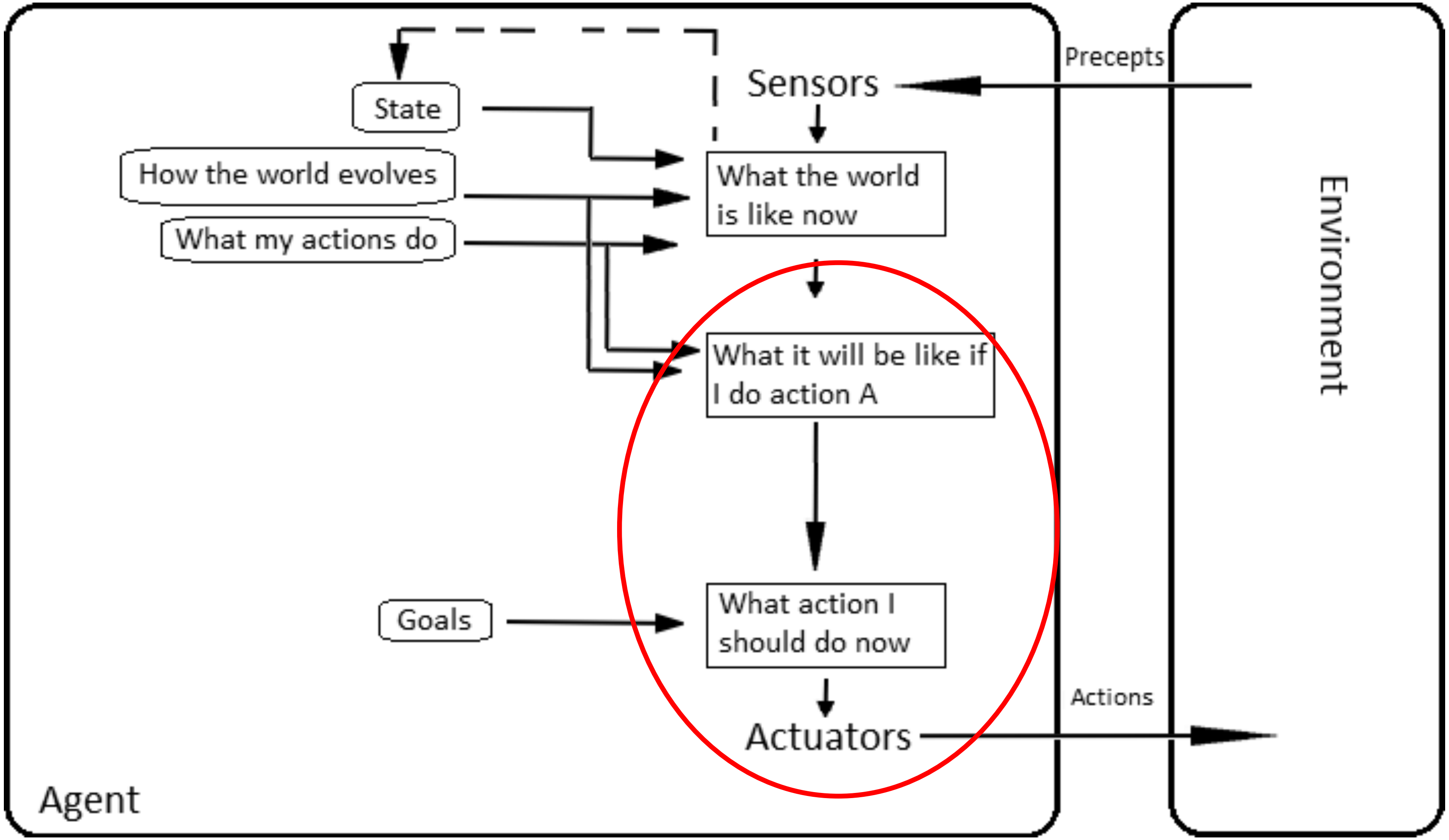
June 6, 2019

Back to the Future: Human-guided Learning

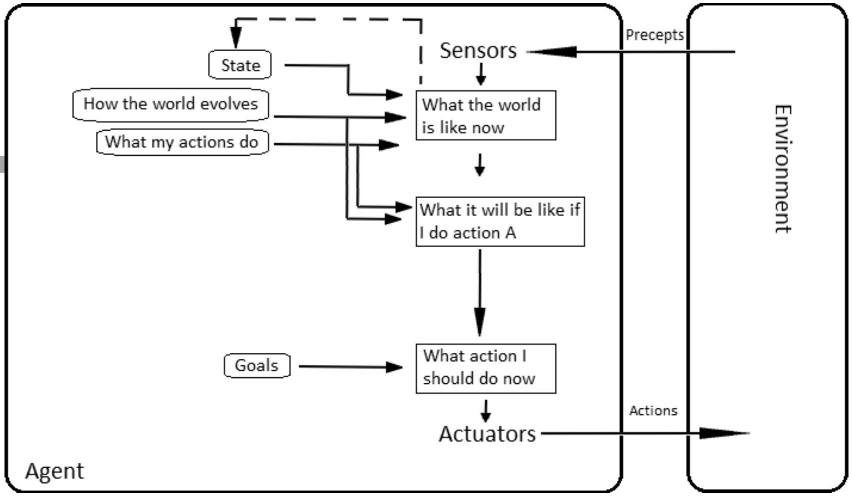
- Develop machine learning techniques that achieve good performace w/o too much training material
- Exploit human capabilities
- Artificial agents and human agents cooperate
- Machine learning becomes agent online learning
  - Motivation for studying agents!
  - Machine learning cannot go w/o agents in the future

- Agents allow for more or less learning (incl. no learning)
- Next: Proper agent with no learning

Proper Agent: An Example



Proper Agent: An Example



Given:

- Current state of the environment
- Description of goal state
- Set of action descriptions

→ Find sequence of actions (a plan) for transforming current state into goal state

→ Select first action, and hope that plan can be completed

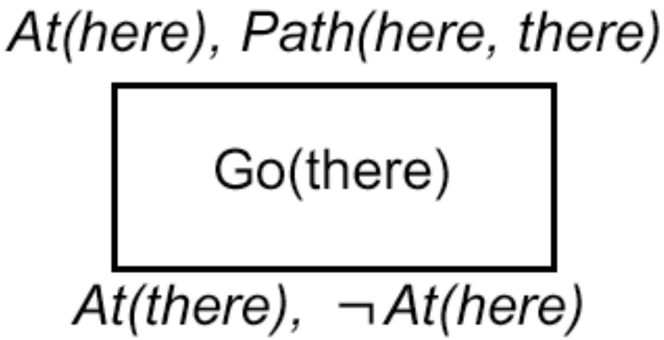
STRIPS Formalism

- States modeled as set of ground atoms (database)
  - Current state as well as goal state
  - Example: Blocks World
    - On_Table(A), On_Table(B), On_Table(C)
    - On_Block(C, B), On_Block(B, A)

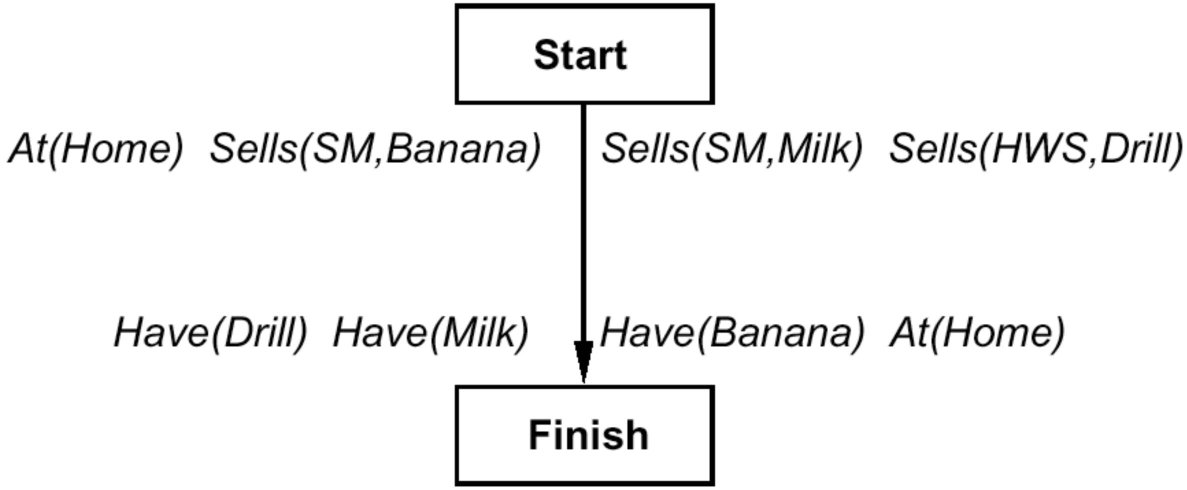
STRIPS = Stanford Research Institute Problem Solver (1971)

STRIPS Planning Operators

$$Op(\text{Action: } Go(there),\ \text{Precond: } At(here) \land Path(here, there),\ \text{Effect: } At(there) \land \neg At(here))$$



Complete Plan



Aktionen:

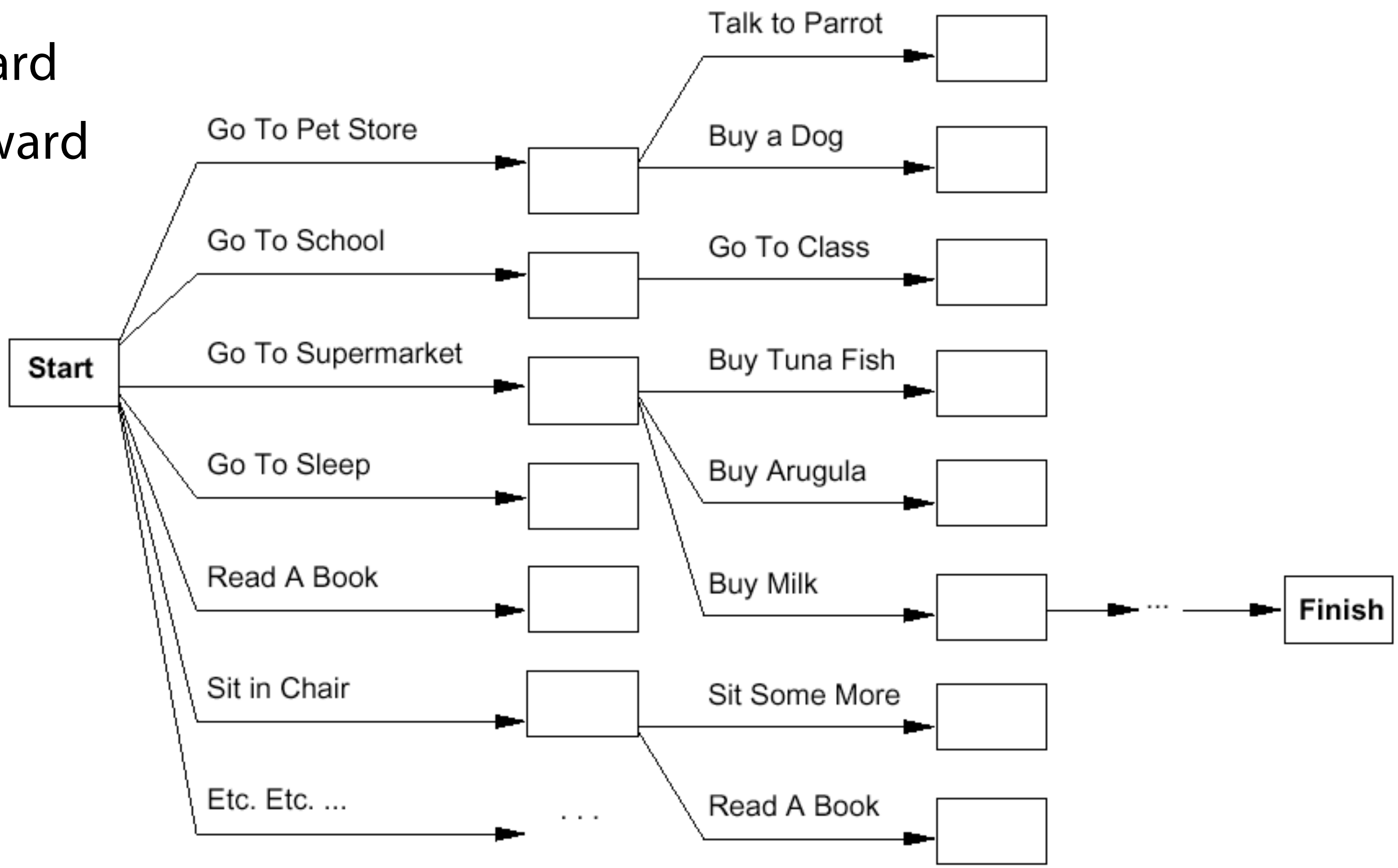
Op (Action: *go(there)*,
Precond: *At(here)*,
Effect: $At(there) \wedge \neg At(here)$)

Op (Action: *buy(x)*,
Precond: $At(store) \wedge Sells(store,x)$,
Effect: *Have(x)*)

there, here, x, store are variables

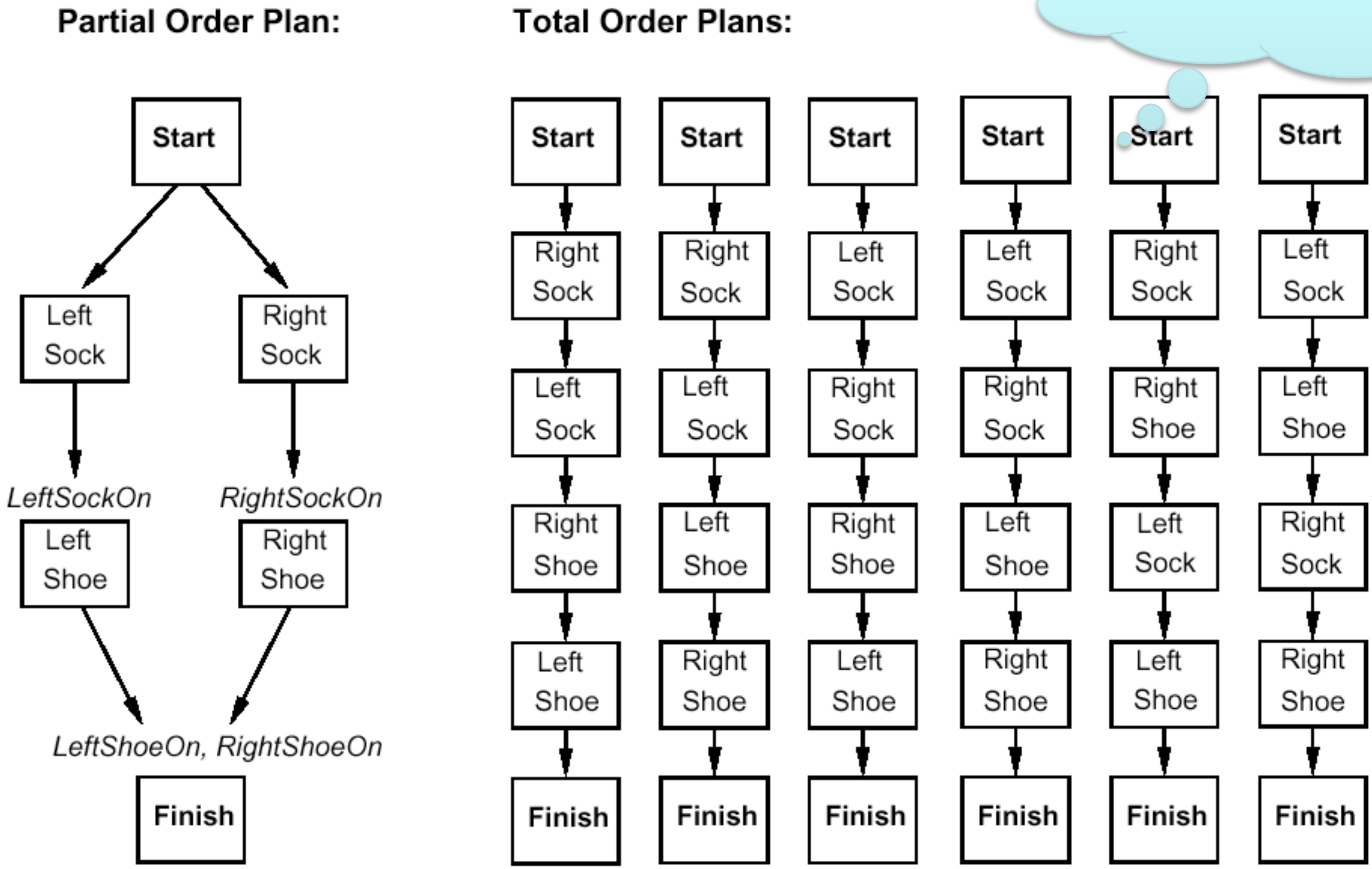
Planning as Search

- Forward
- Backward



Plan = (Linear) sequence of Actions?

Apply principle of Least Commitment



Representation of Partial-Order Plans

- Plan step = STRIPS Operator
- Plan consists of
  - Plan step with partial order (<),
    where $S_i < S_j$ iff S_i is to be executed before S_j
  - Set of variable assignments $x = t$,
    where x is a variable and t is a constant or variable
  - Set of causal relations:
    $S_i \rightarrow^c S_j$ means S_i creates the precondition c of S_j (entails $S_i < S_j$)

- Solutions to planning problems …
  … must satisfy certain conditions

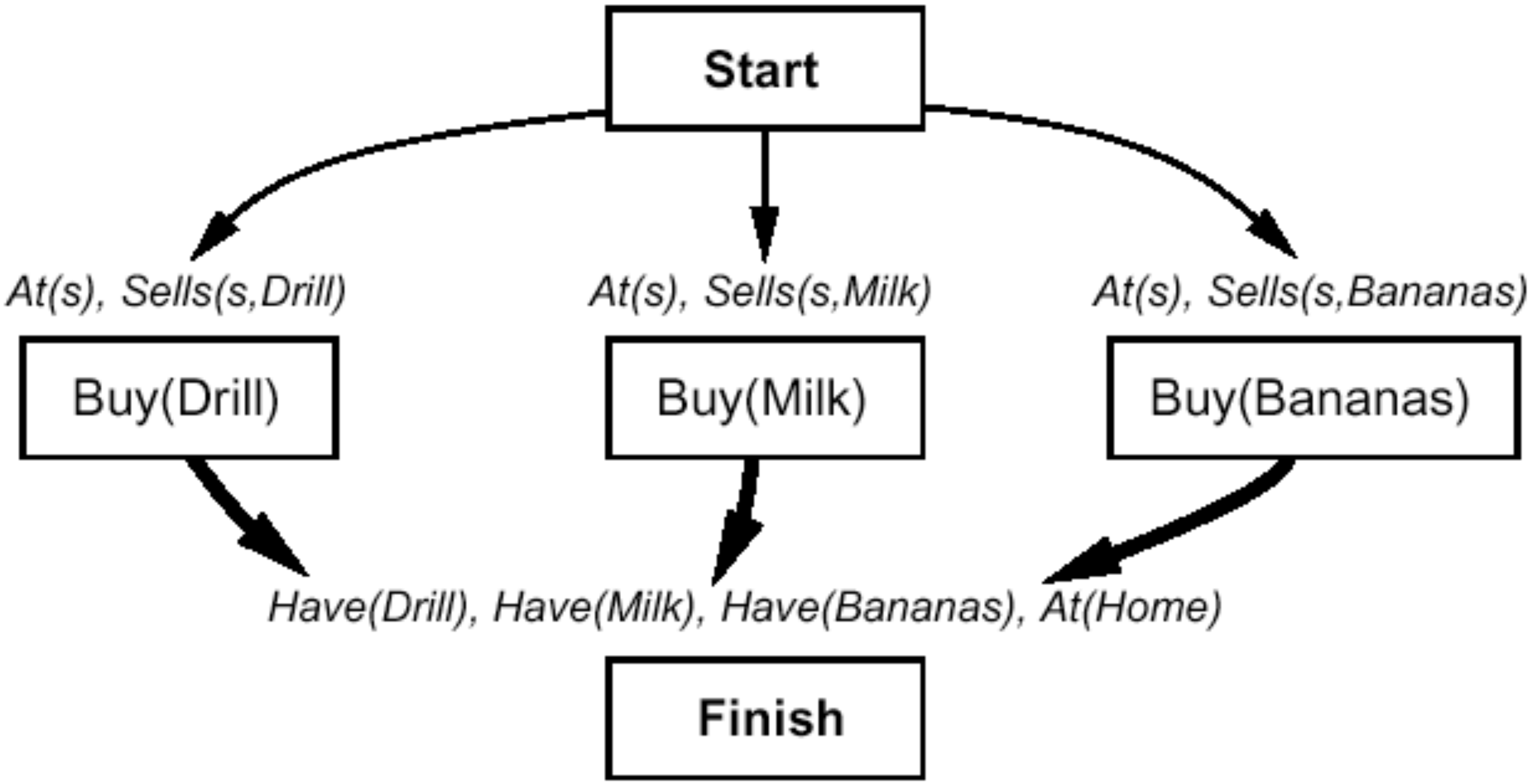
STRIPS = Stanford Research Institute Problem Solver (1971)

Completeness and Consistency

- Complete plan
  - Every precondition of a step is fulfilled
  - $\forall S_j$ with $c \in Precond(S_j)$,
    - $\exists S_i$ s.t. $S_i < S_j$ and $c \in Effects(S_i)$, and
    - for every linearization it holds that:
      - $\forall S_k$ with $S_i < S_k < S_j$, $\neg c \notin Effects(S_k)$
- Consistent plan
  - If $S_i < S_j$, then $S_j \not< S_i$ and
  - If $x = A$, then $x \neq B$ for different A and B for variable x (Unique Names Assumption)
- Solution of the planning problem: complete and consistent plan

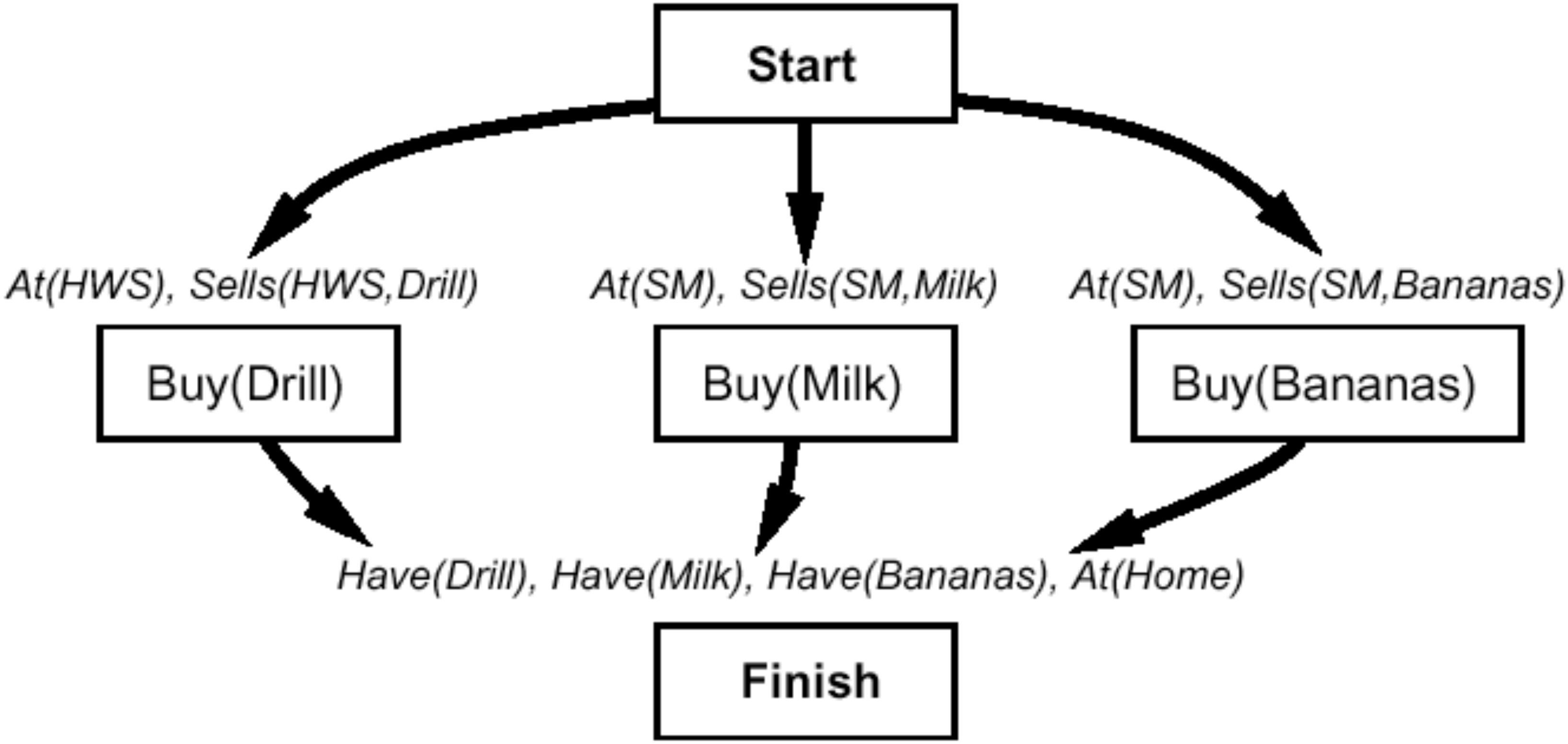
Plan Refinement (1)

- Backward planning



Thin arrows = <
Fat arrows = causal relation + <

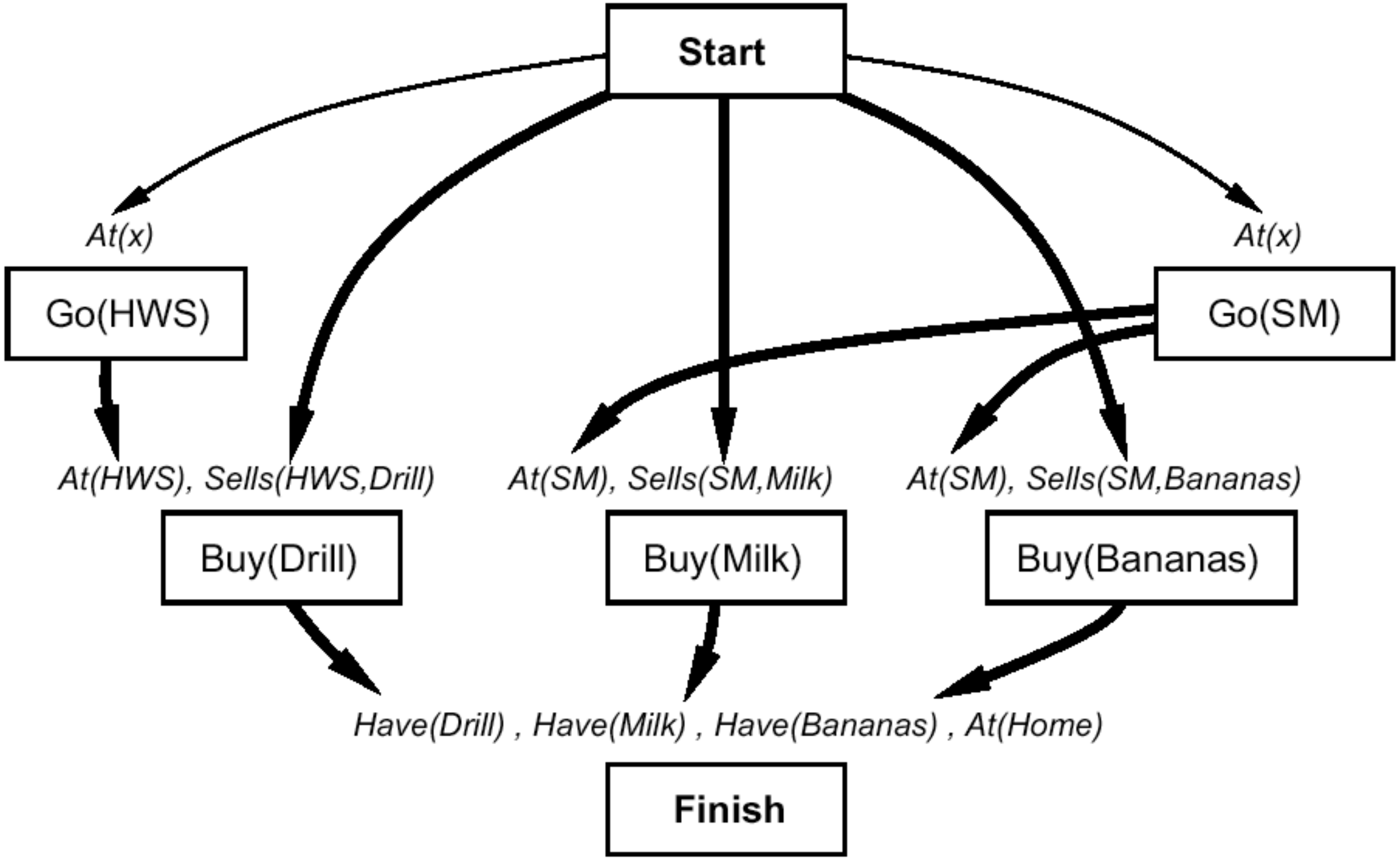
Plan Refinement (1)



. . . after variable instantiation

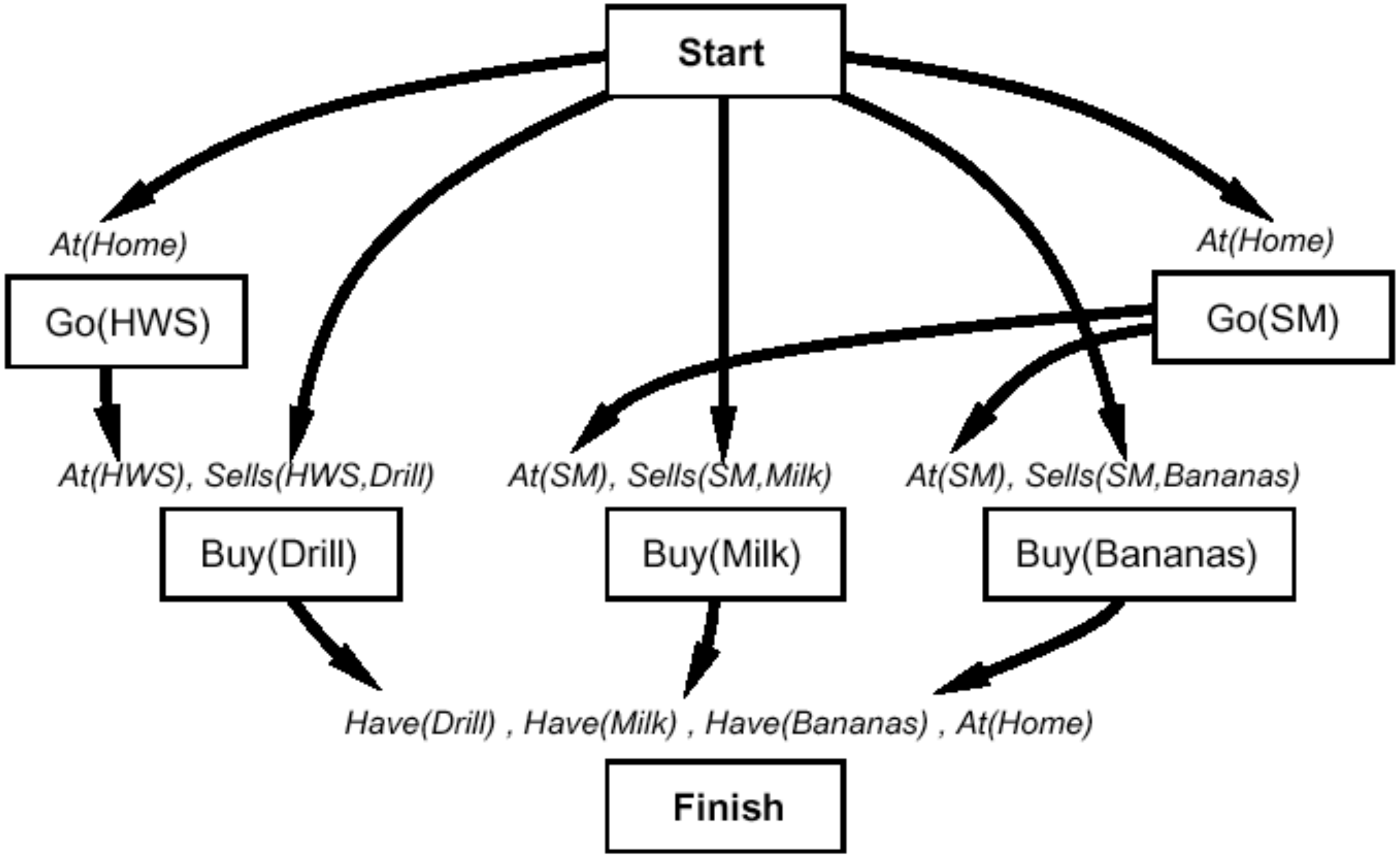
Plan Refinement (2)

- ... buy at the right store



Plan Refinement (3)

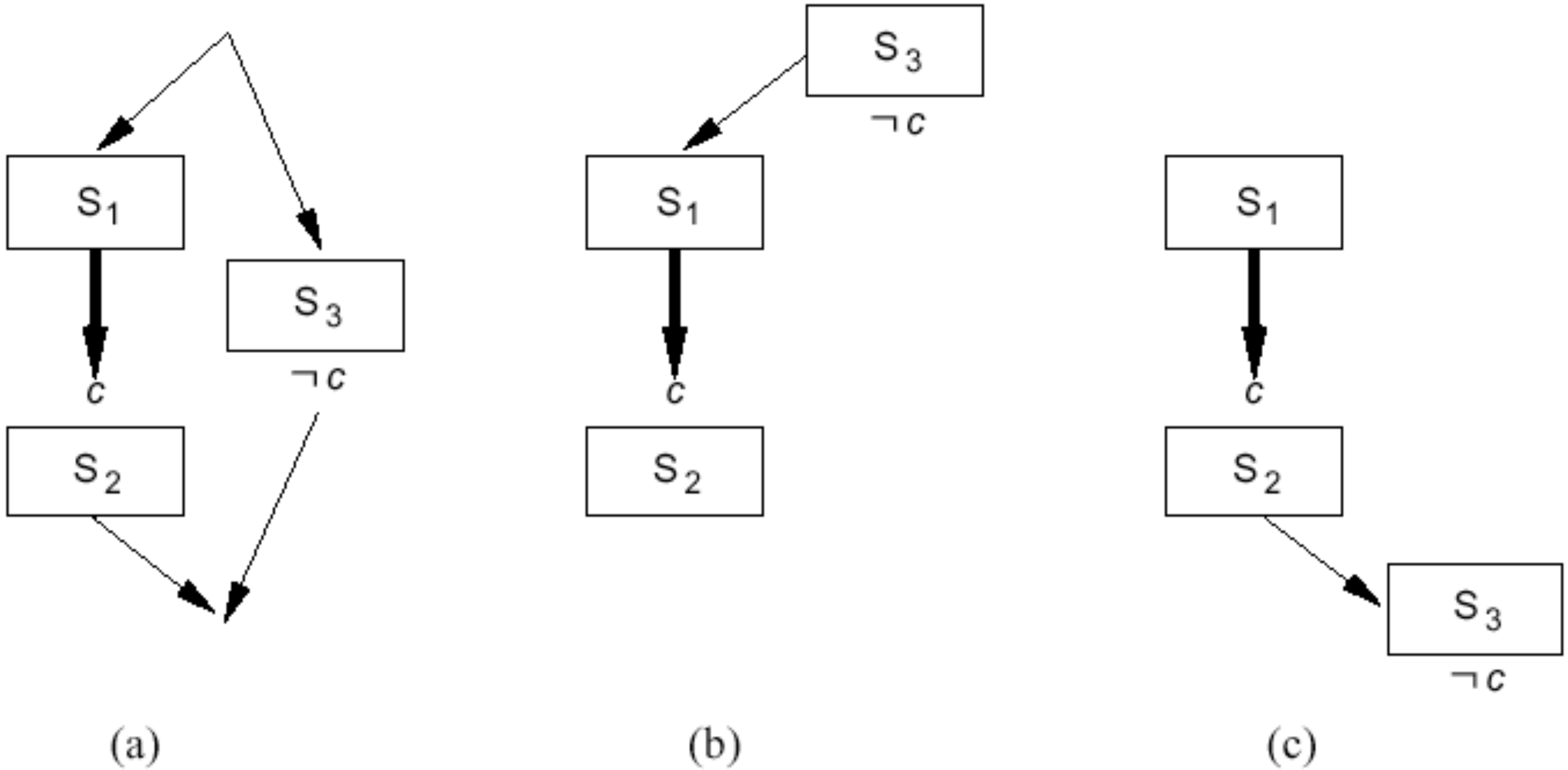
- ... but you must get there



Plan Refinement (3)

- Note:
  Up to now no search, but simple „backward chaining“
- Now:
  Conflict! After go(HWS) is executed, At(Home) no longer holds (similarly for go(SM))

Protection of Causal Relations



Protection of Causal Relations

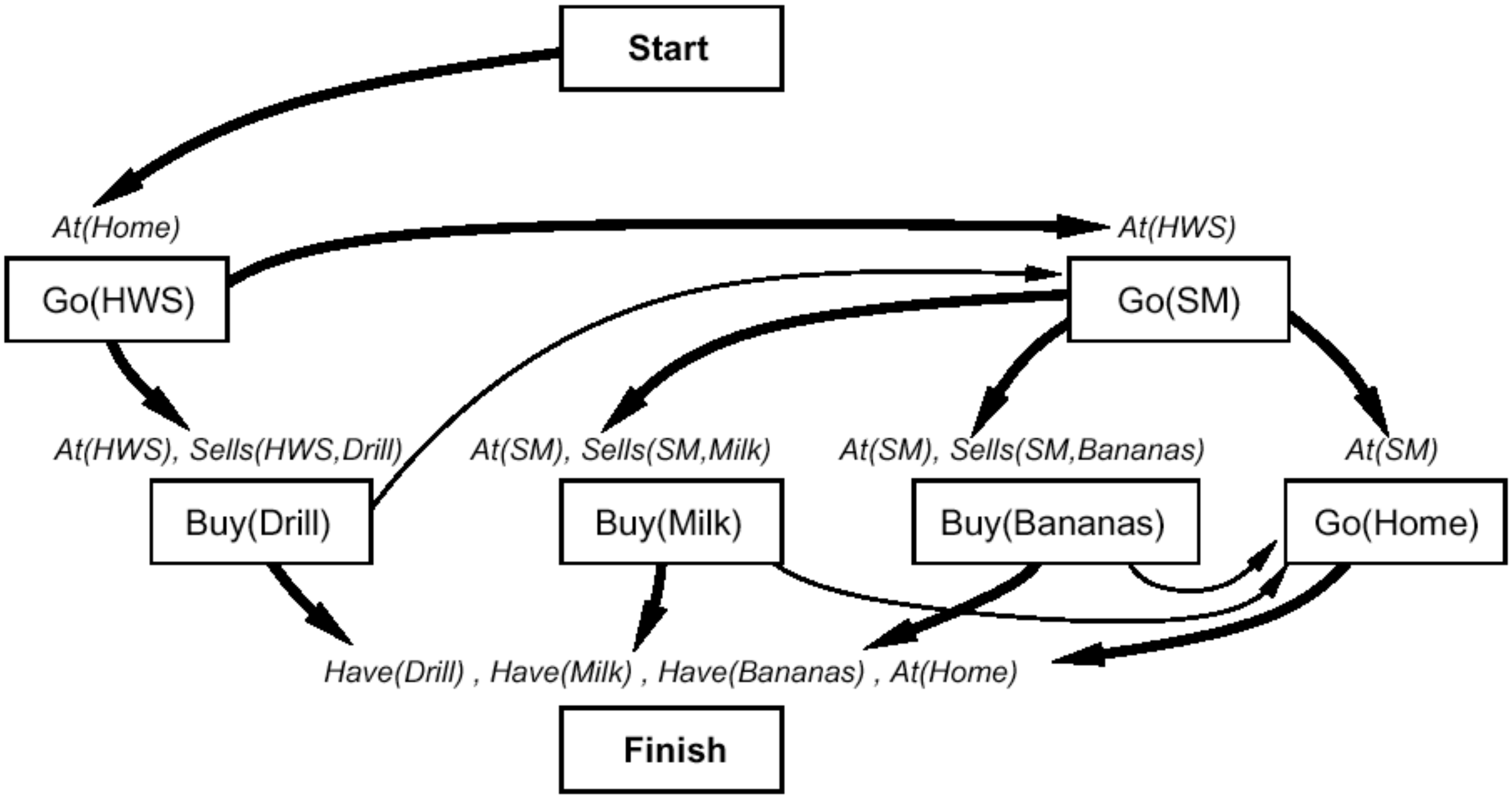
- Conflict:
  - S3 “threatens“ causal relation between S1 and S2
- Conflict resolution:
  - Promotion: Put threat before causal relation
  - Demotion: Put threat after causal relation

=> Dedicated lectures on causality in next lectures

Another Plan Refinement …

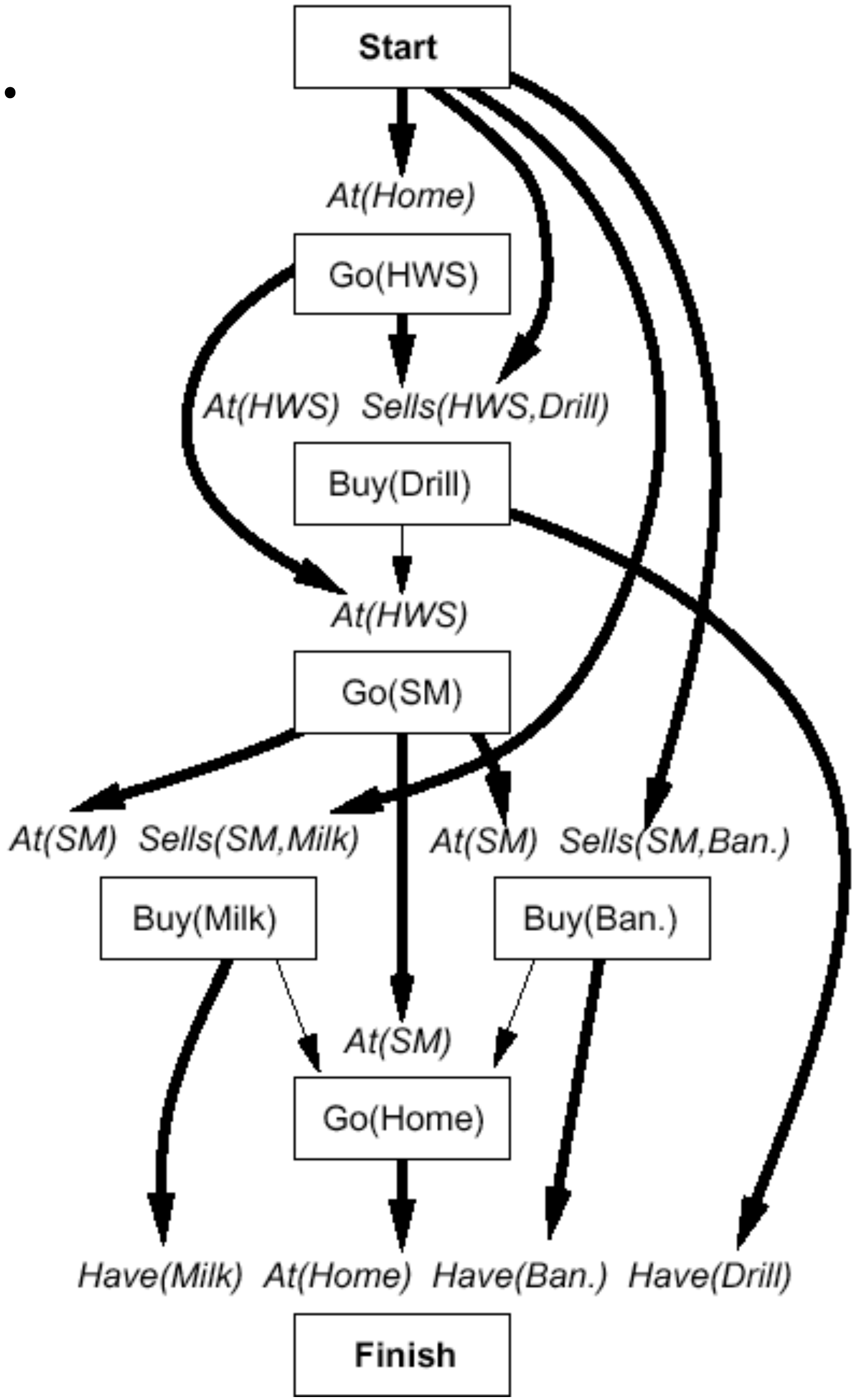
- Assumption: Cannot resolve conflict by protection
- Made a wrong step during plan refinement
- Alternative
  - Select x = HWS (with causal relation) while instantiating At(x) in go(SM)

Another Plan Refinement …



The Complete Solution …

- … with all links
- Computation by POP Algorithm
  - Complete
  - … and correct
- Additionally, not considered here, correct treatment of variables



Last Century Planning Systems (Last Decade!)

- UCPOP (Weld, UW)
  (http://www.cs.washington.edu/ai/ucpop.html)
- Sensory Graphplan (Weld, Blum, and Furst: UW)
  (http://aiweb.cs.washington.edu/ai/sgp.html)
- IPP (Köhler and Nebel: Univ. Freiburg)
  (https://idw-online.de/de/news5468)
- Prodigy: Planning and Learning (Veloso: CMU)
  (http://www-2.cs.cmu.edu/afs/cs.cmu.edu/project/prodigy/Web/prodigy-home.html)

- All systems have found interesting applications

Planning is an Active Field of Research

- More powerful successors
  - Systems learn how to plan fast for specific problem instances
  - Can deal with uncertainty
    - About state estimation
    - About effects of actions
- Very powerful problem solvers can be set up …
  - w/ less effort/knowledge than with mathematical optimization theory and respective tools

→Automated Planning and Acting (CS5072-KP04)

(https://www.ifis.uni-luebeck.de/index.php?id=dski-aktuell-ss20&L=2)

Back to Intelligent Agents / Acting Intelligently

- Rational agents that:
  - Act autonomously and are persistent
  - Achieve goals surprisingly fast
    (despite bounded rationality)
  - Learn how to behave in a clever way
    (even learn computational strategies)
- Can adapt their goals
  to anticipate humans needs and expectations
  - Human compatibility, human awareness
- Can learn new models online to
  - Keep high performance over time
  - Support human-guided machine learning

Outlook for Part I

- Causality
- Games, Cooperation, Mechanism Design
- Multiagent Logic