
Intelligent 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

- **Module Intelligent Agents (CS4514-KP12):**
 - Agents, Mechanism, and Collaboration (lecture)
 - Agent Perception (Language and Vision) (lecture)
 - Agent Planning, Causality, and Reinforcement Learning (lecture)
 - Project
- Mode of all lectures: classically, on site, with integrated exercises
- Lecture slides and videos partly available from last term, but new material produced on the run
- Today: overview of the general idea
- More details in [Moodle](https://moodle.uni-luebeck.de/course/view.php?id=8294) (<https://moodle.uni-luebeck.de/course/view.php?id=8294>)

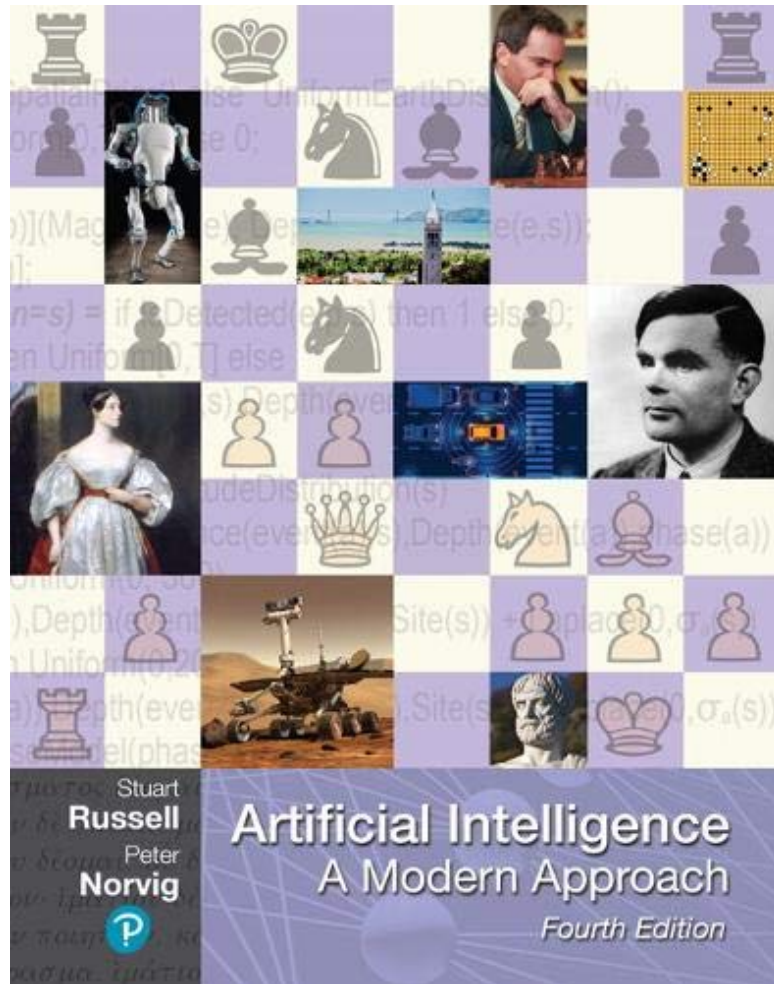
Organization

- **Agents, Mechanisms, and Collaboration**
 - Wednesdays, 14:15 - 15:45 Uhr, IFIS Seminarraum 2035,
 - Start: 19.10.2022
 - Lecturer: Özgür Özcep
- **Agent Perception (Language and Vision)**
 - Thursdays 14:15 - 15:45 Uhr, IFIS Seminarraum 2035
 - Start: 20.10.2022
 - Lecturer: Ralf Möller
- **Agent Planning, Causality, and Reinforcement Learning**
 - Fridays, 10:15 - 11:45 Uhr, IFIS Besprechungsraum 2032
 - Start: 21.10.2022
 - Lecturers: Mattis Hartwig & Ralf Möller
- **Project**
 - Fridays, 12:15 - 13:45 Uhr, IFIS Seminarraum 2035
 - Start: 21.10.2022

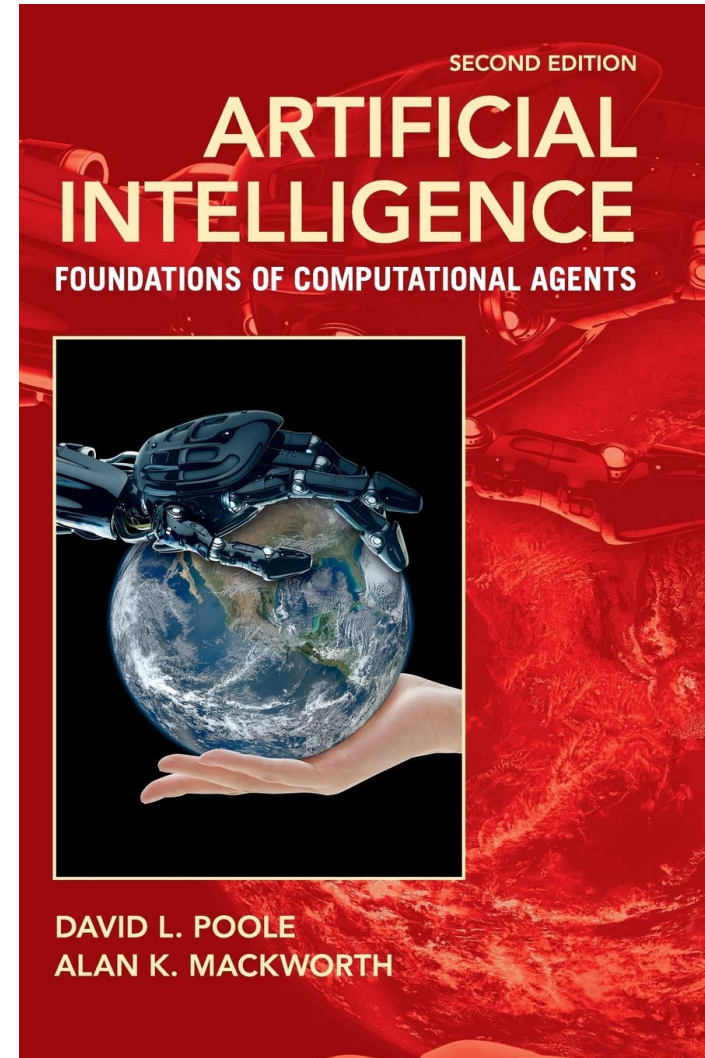
Artificial Intelligence and Intelligent Agents

- 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”
- Systems are called computational agents in AI, or agents for short

Literature

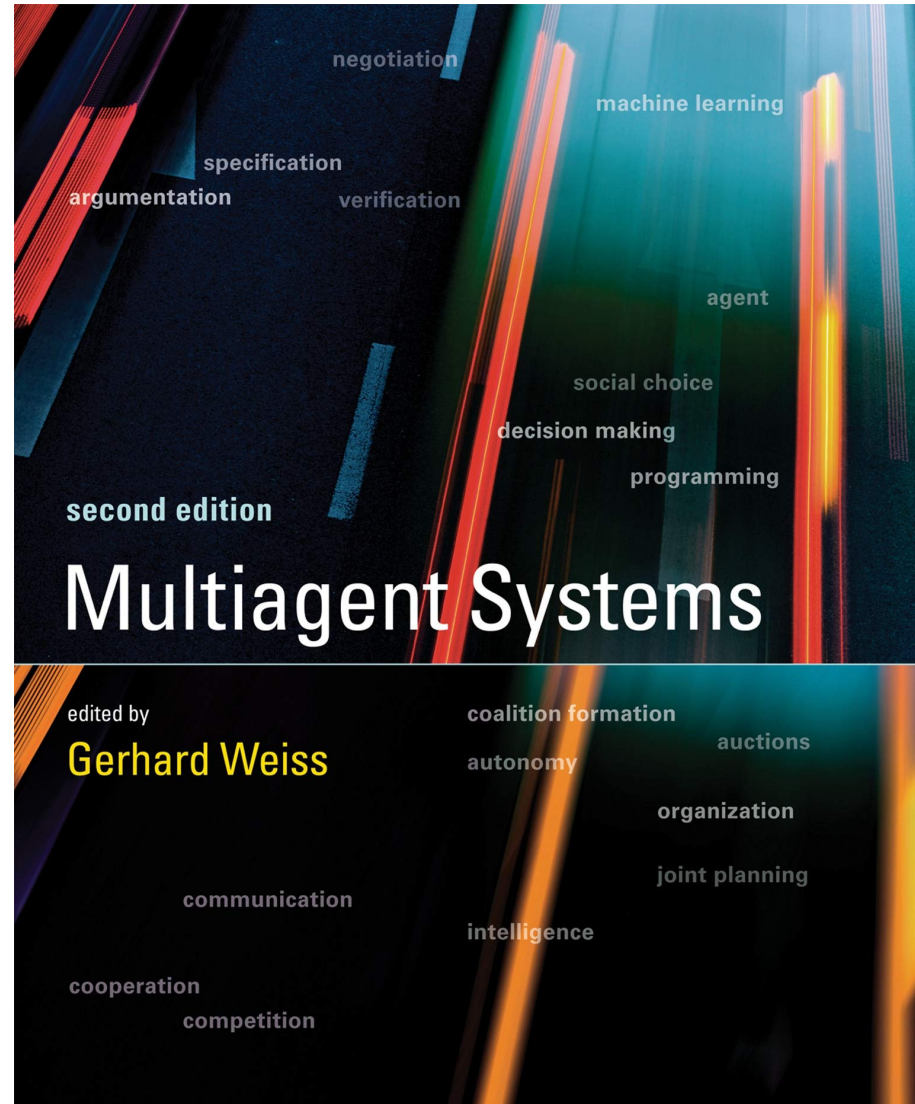
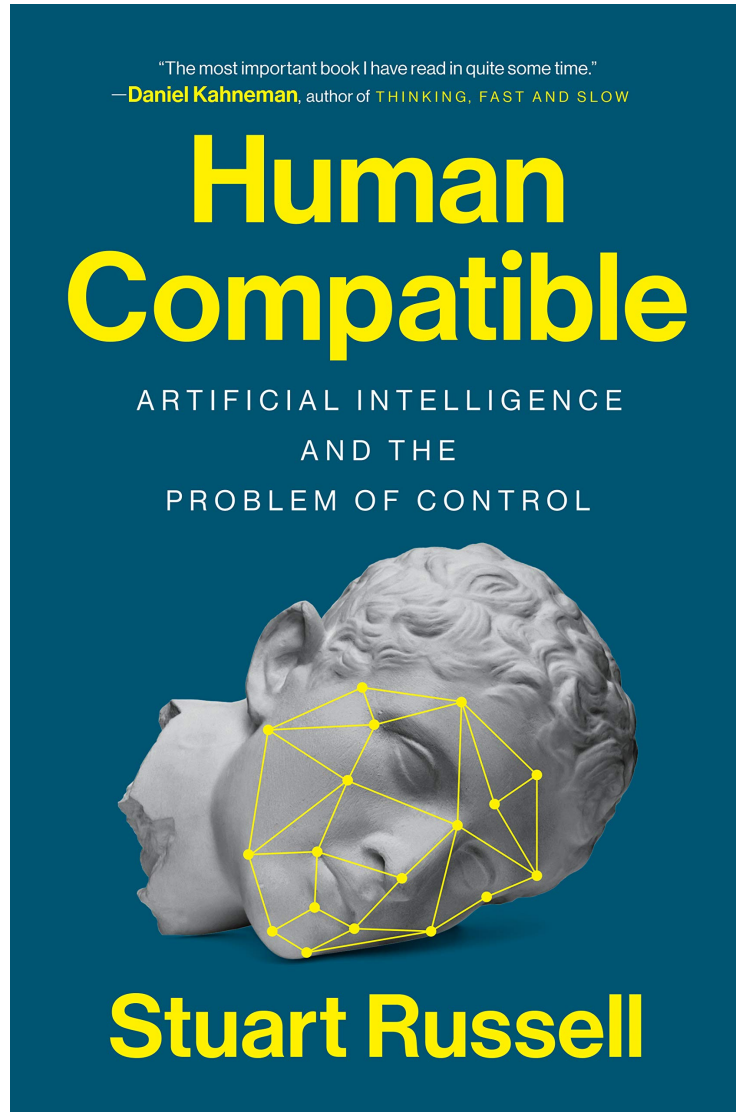


<http://aima.cs.berkeley.edu>
(AIMA, 1st edition 1995)

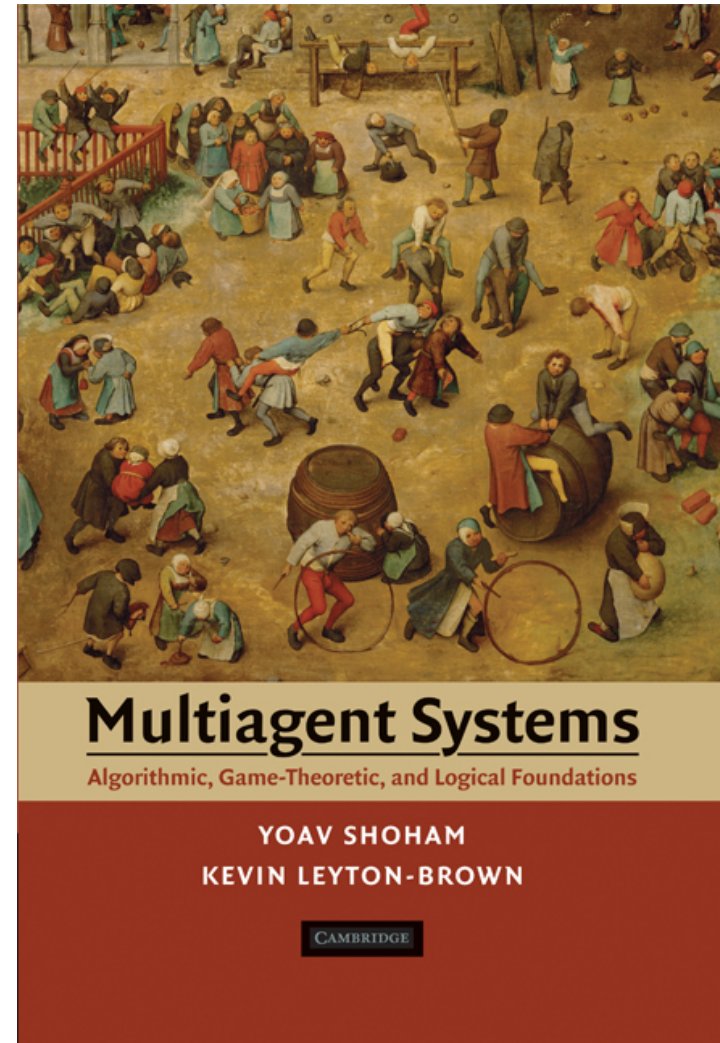
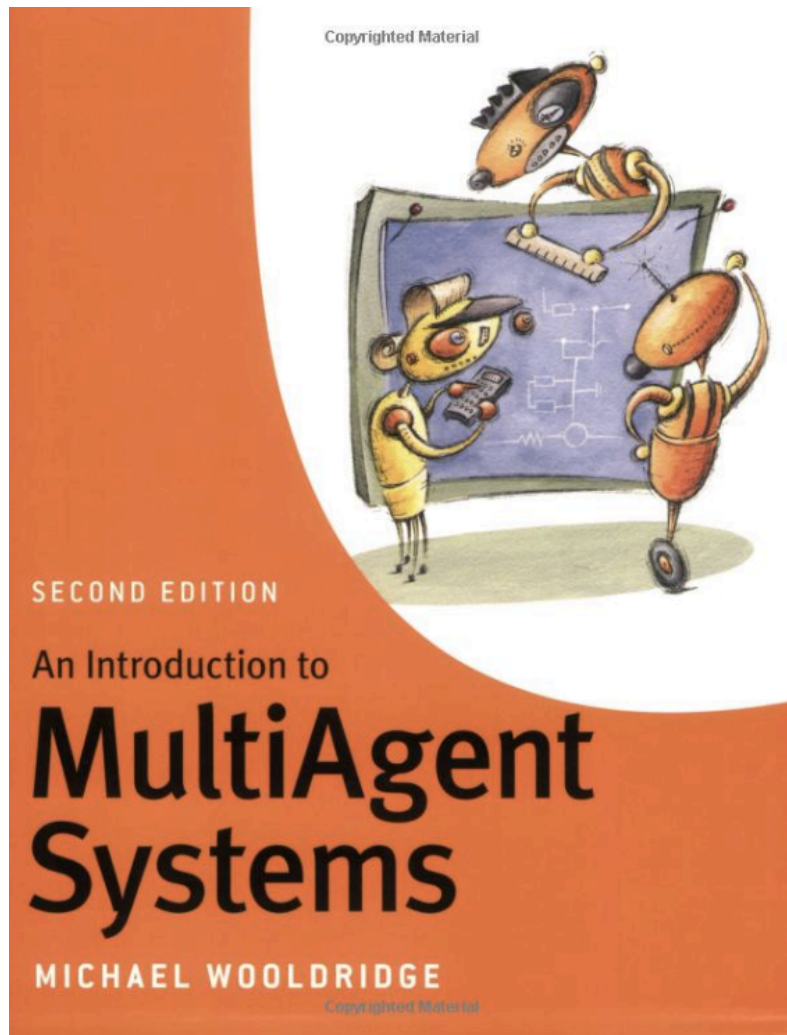


<http://artint.info>
(AIFCA, 1st edition 2010)

Literature



Literature



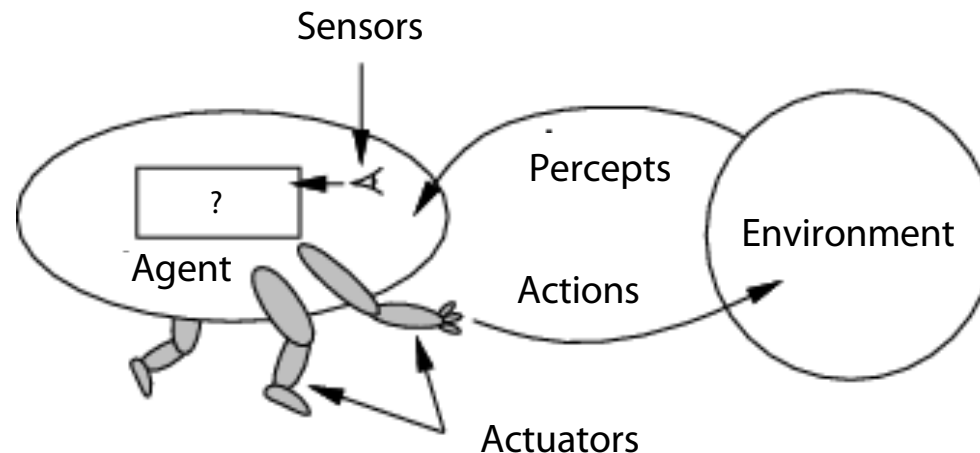
Literature



What is an Agent?

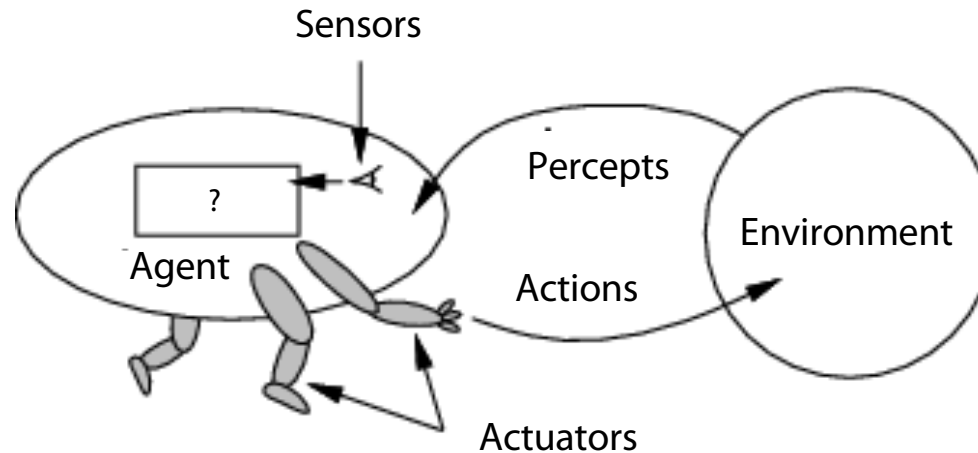
- Anything that can be viewed as **perceiving** its **environment** through **sensors** and **acting** upon that environment through **actuators**

[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



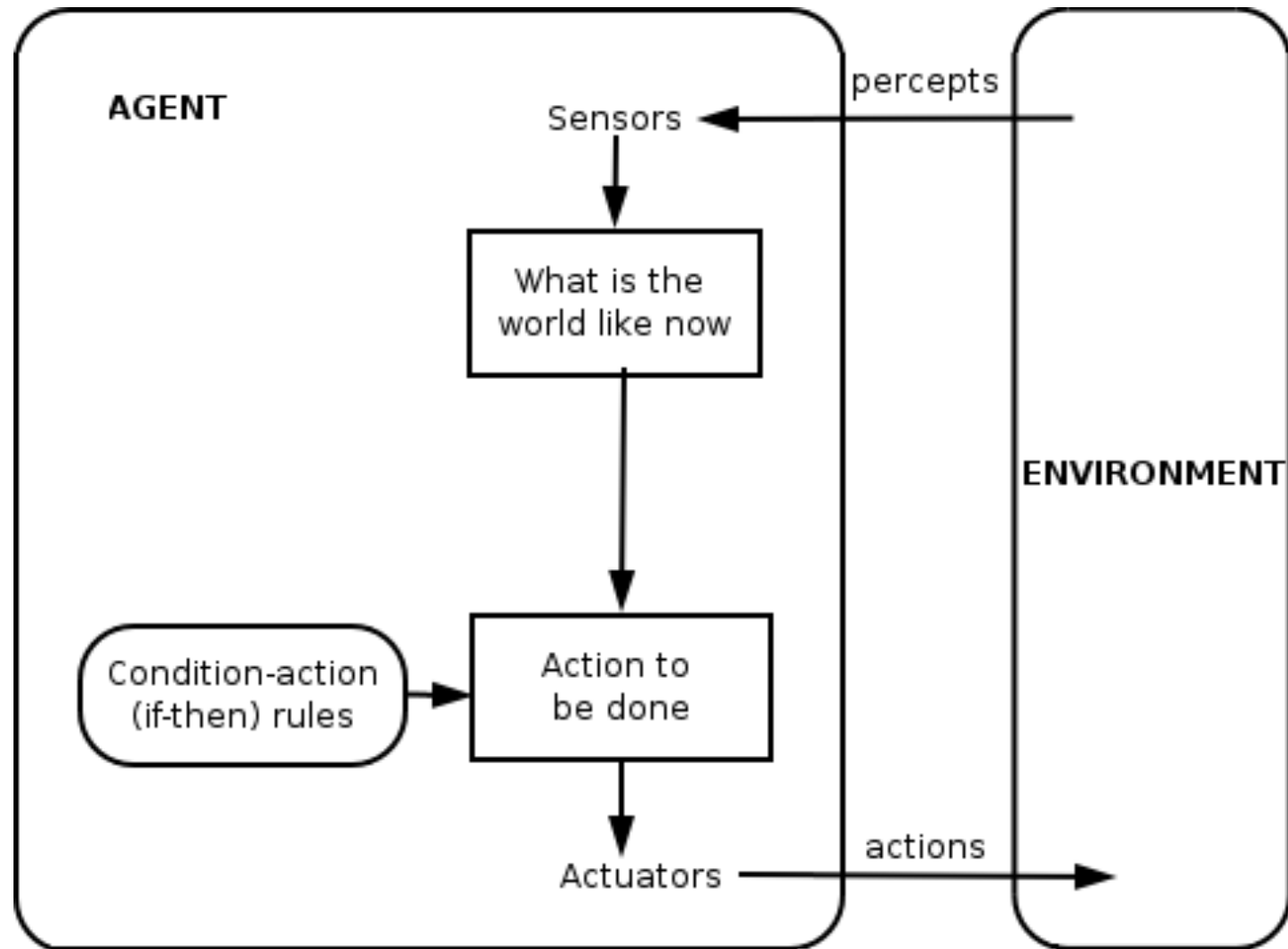
- The **agent function** maps from percept histories to actions:

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

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

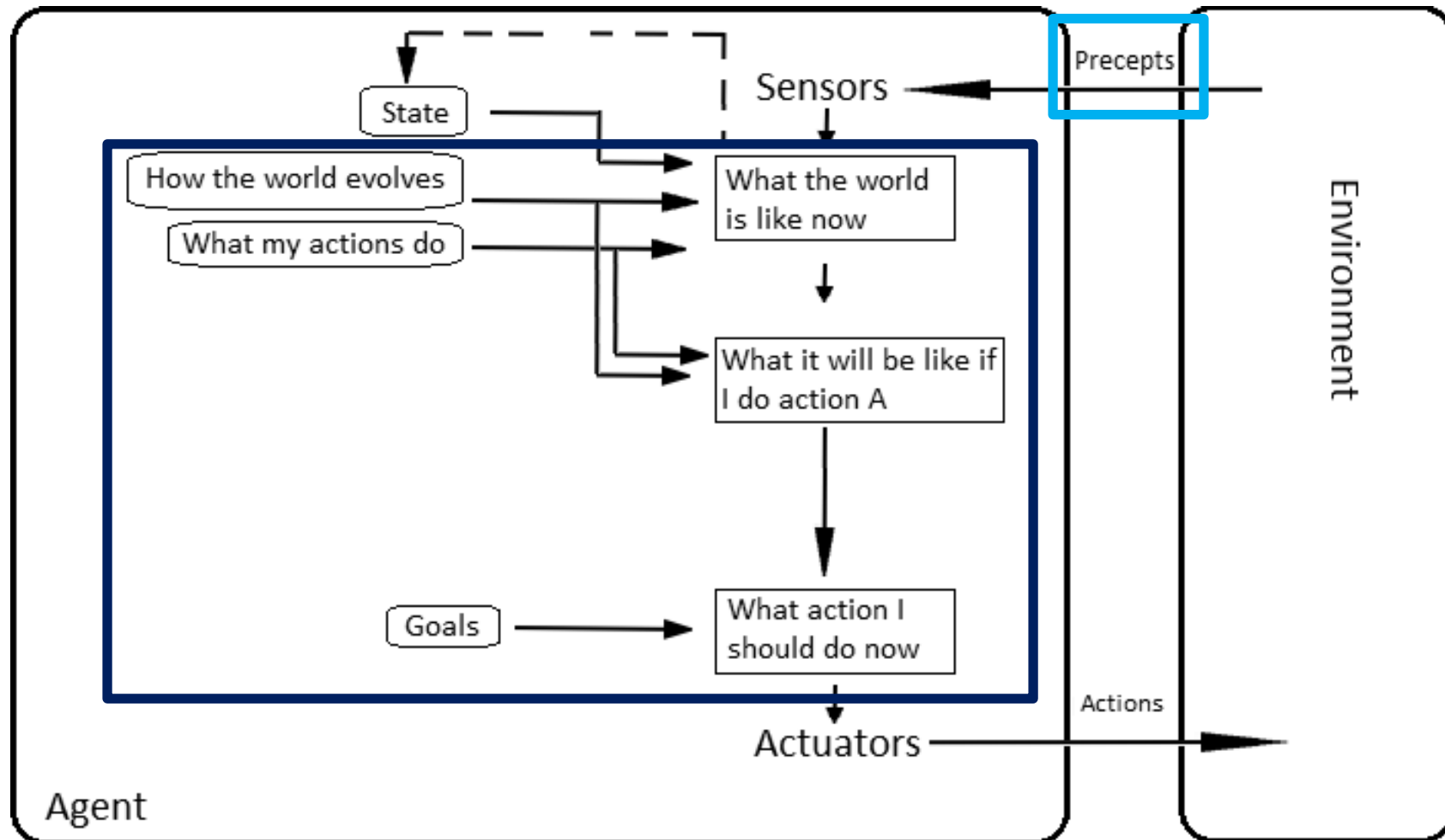
Really insist on functional behavior?

Reactive vs. Goal-based Agents



Reactive vs. *Goal-based* Agents

Agent Perception (Language and Vision)



Agent Planning, Causality, Reinforcement Learning



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 try achieving 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** ...
 - > **Agent Perception (Language and Vision)**
- ... 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**
 - > **Agents, Mechanism, and Collaboration**

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

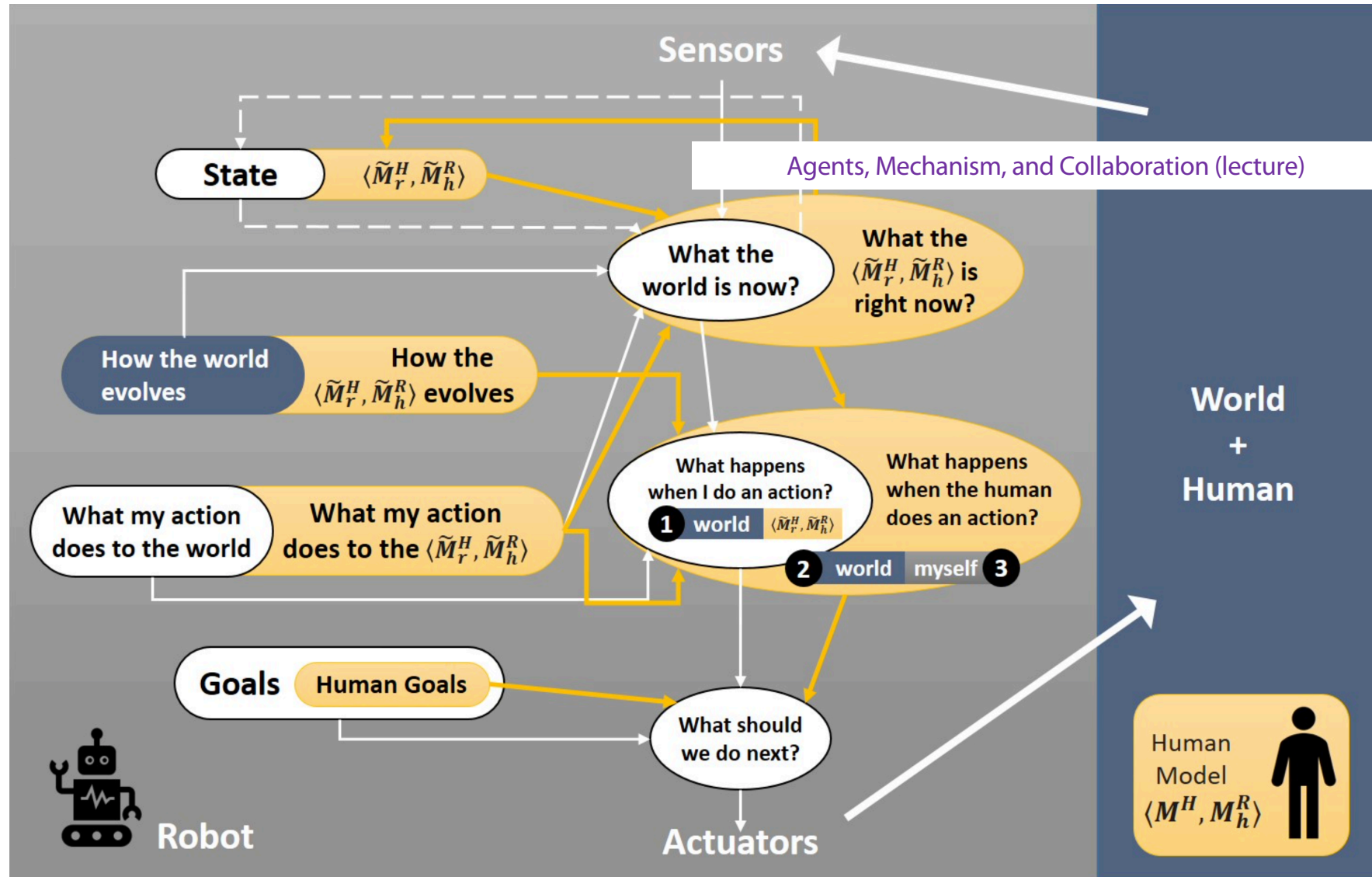
Human-compatible Behavior

- Agents **act on behalf** of humans, whose goals the agents have to fulfill (this is the single goal of agents)
- Agent should consider its initial **goals to be uncertain**
- 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**

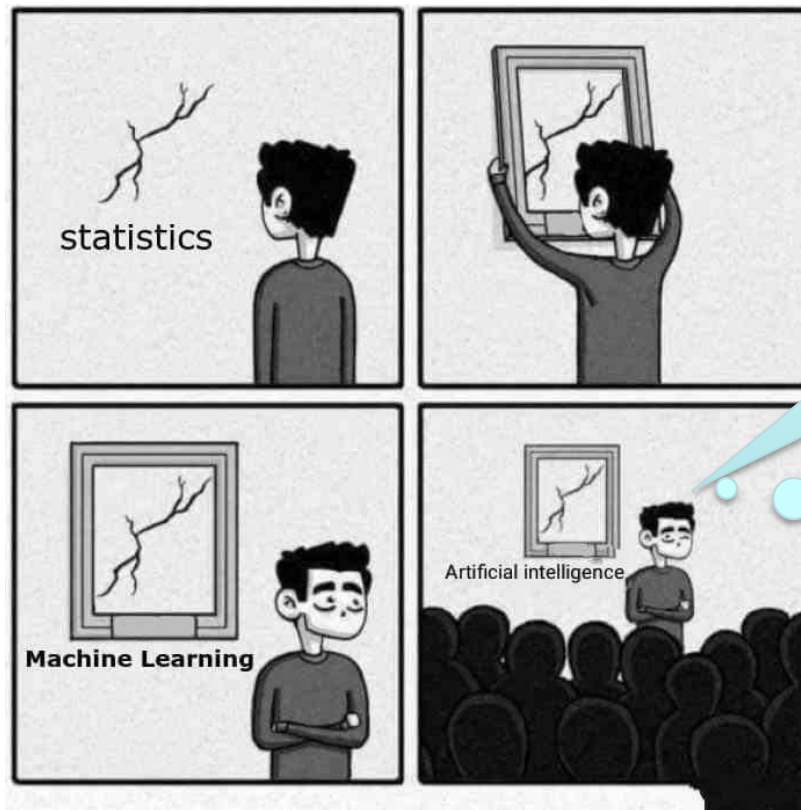
Agent Model vs. Human Model



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

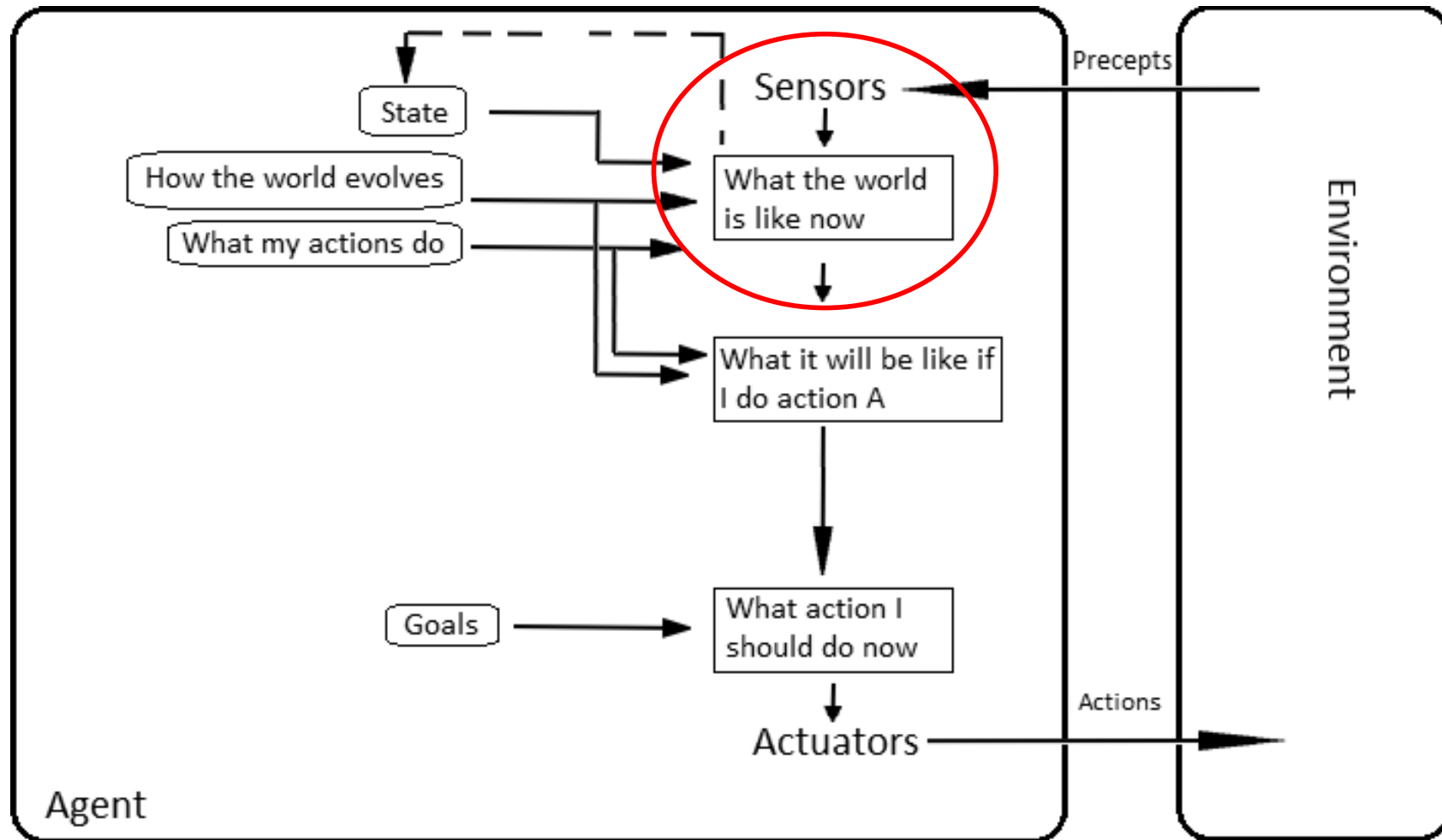


“When you’re fundraising, it’s AI. When you’re hiring, it’s ML. When you’re implementing, it’s logistic regression.”

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
 - $f: P \rightarrow A$
- Claiming that f is “an AI” is an indication of lack of understanding ...
- ... even if the last n percepts are considered
 - $f: P \times \dots \times P \rightarrow A$
- One is lost w/o an understanding of intelligent agents
 - $f: P^* \rightarrow A$

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 $f: P \times \dots \times P \rightarrow A$
- 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.

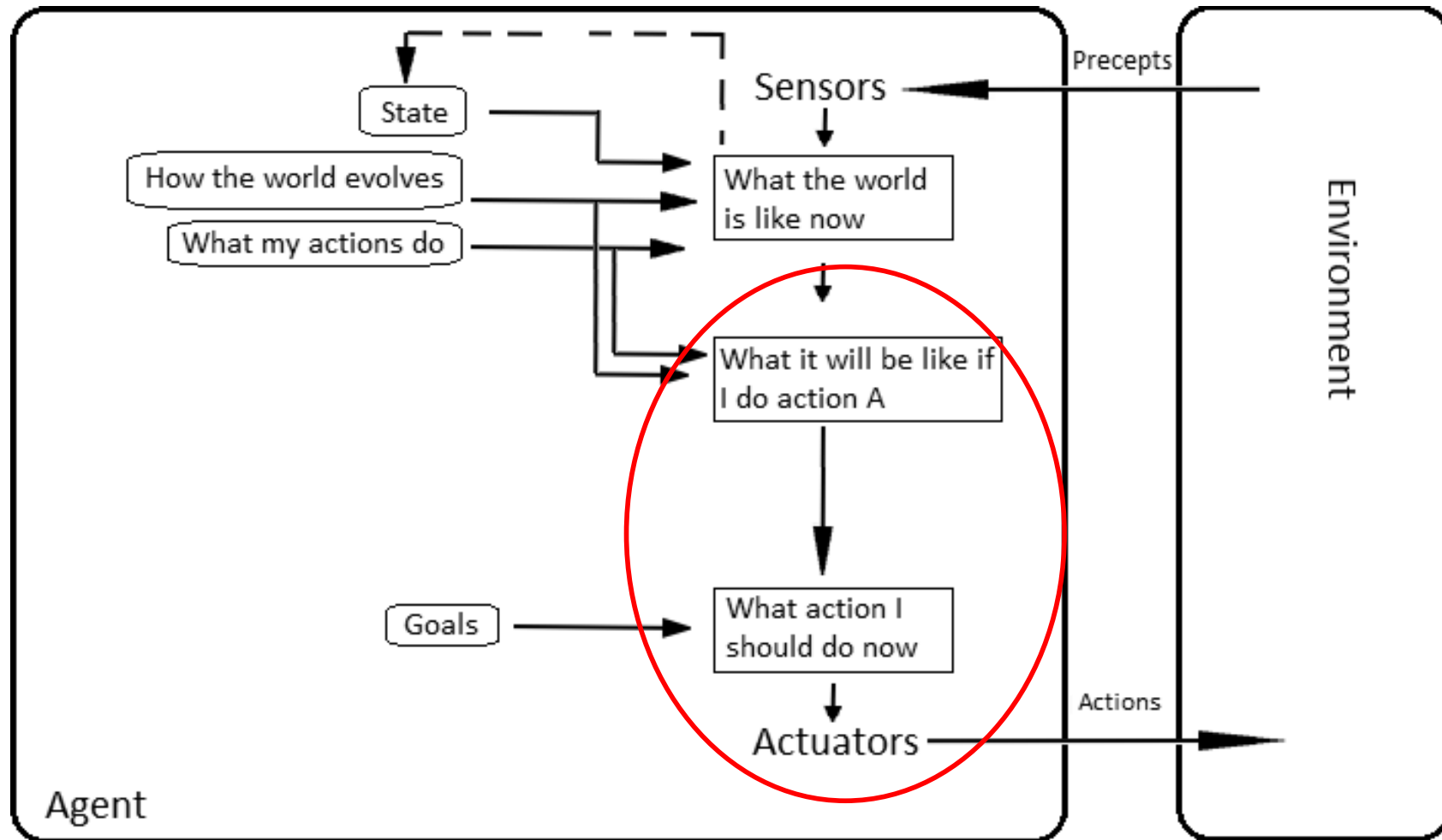
by **Karen Hao**

June 6, 2019

Back to the Future: Human-guided Learning

- Develop machine learning techniques that achieve good performance 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

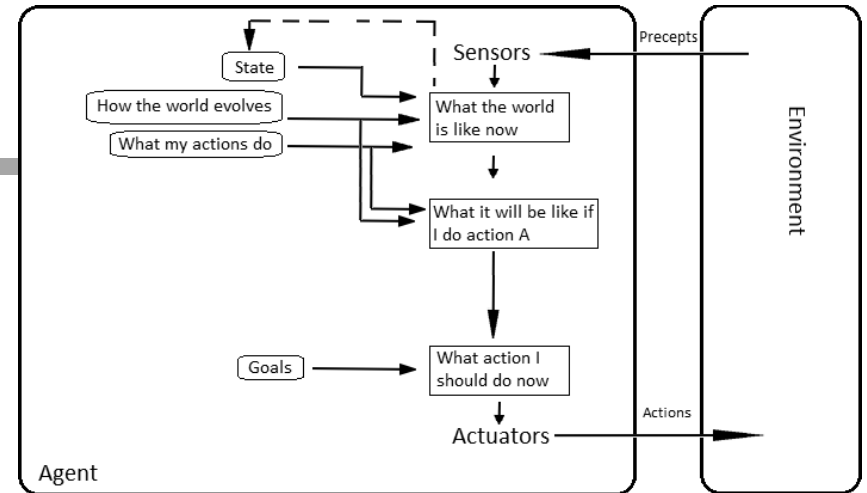
Proper Agent: An Example



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
 - $\text{On_Table}(A), \text{On_Table}(B), \text{On_Table}(C)$
 - $\text{On_Block}(C, B), \text{On_Block}(B, A)$
- Historical & name convention note
 - Nowadays STRIPS = representation language FOL
 - Part of PDDL (planning domain definition language)
 - Originally, STRIPS also denoted (linear, non-complete) hill-climbing style algorithm
 - We consider a different algorithm here based on partial order plans

STRIPS Planning Operators

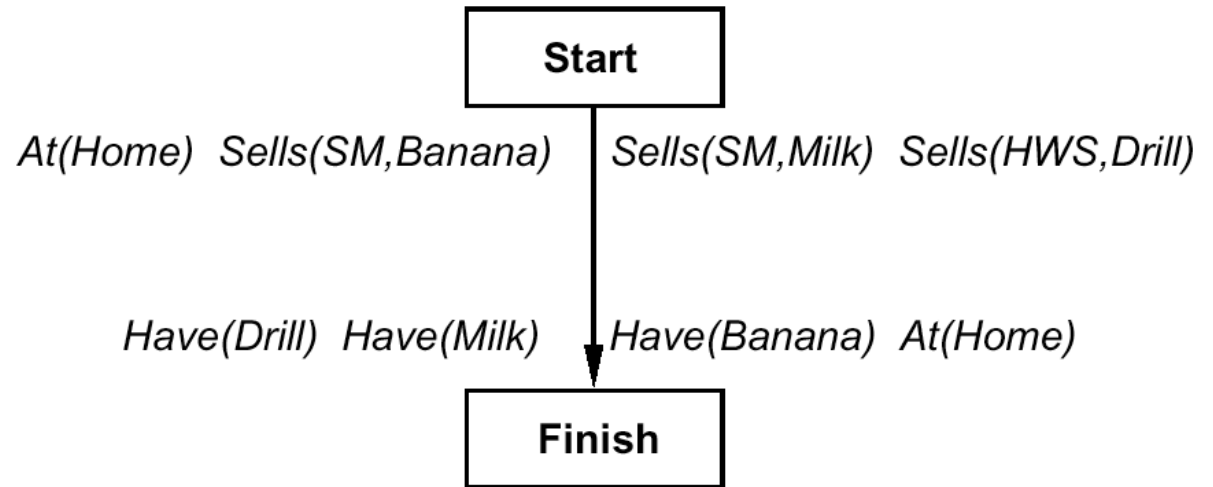
Op(Action: *Go(there)*,
Precond: *At(there) ∧ Path(there, there)*,
Effect: *At(there) ∧ ¬At(there)*)

At(there), Path(there, there)

Go(there)

At(there), ¬At(there)

Initial Plan



Action(Type)s:

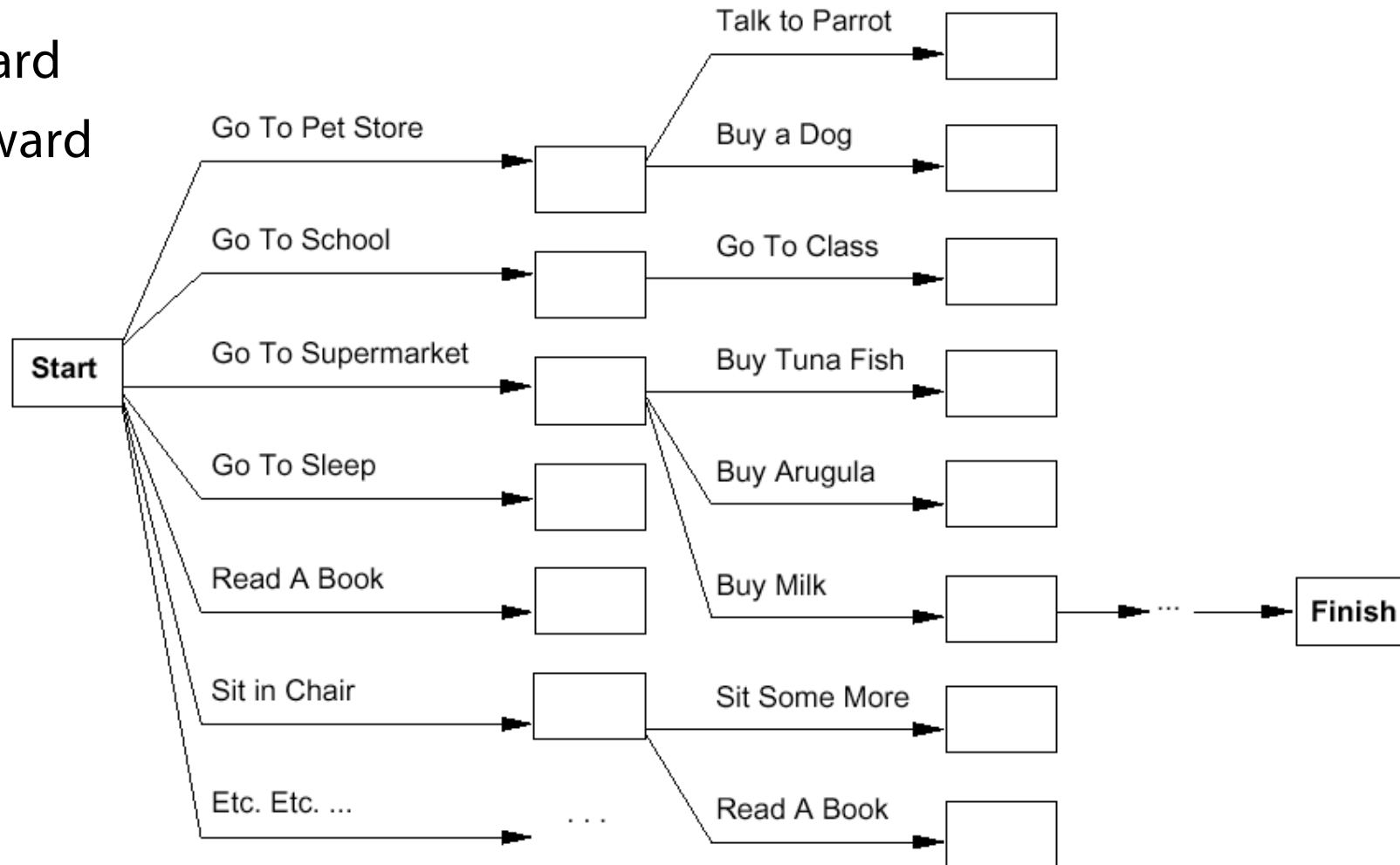
Op (Action: *go(there)*,
Precond: *At(there)*,
Effect: *At(here) ∧ ¬At(there)*)

Op (Action: *buy(x)*,
Precond: *At(store) ∧ Sells(store,x)*,
Effect: *Have(x)*)

there, here, x, store are variables

Planning as („Lifted“) Search

- Forward
- Backward



Classical Search

vs.

Planning



Problem solving by search

- Problem = single state space
- Program search algorithm

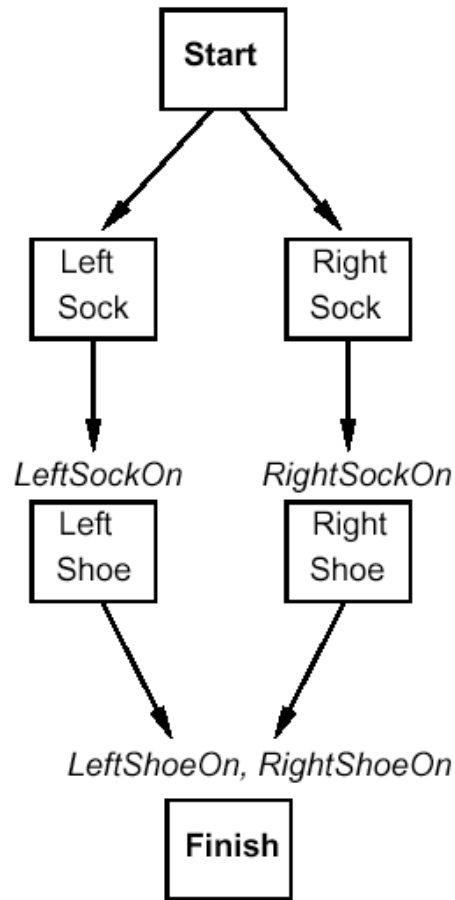
Problem solving by planning

- Specify problem declaratively
- Solve by general planning algorithm
- E.g.: instead of go-to-SM1, go-to-HW rather go(place)

Plan = (Linear) sequence of Actions?

Apply principle of Least Commitment

Partial Order Plan:



Total Order Plans:



Representation of Partial-Order Plans

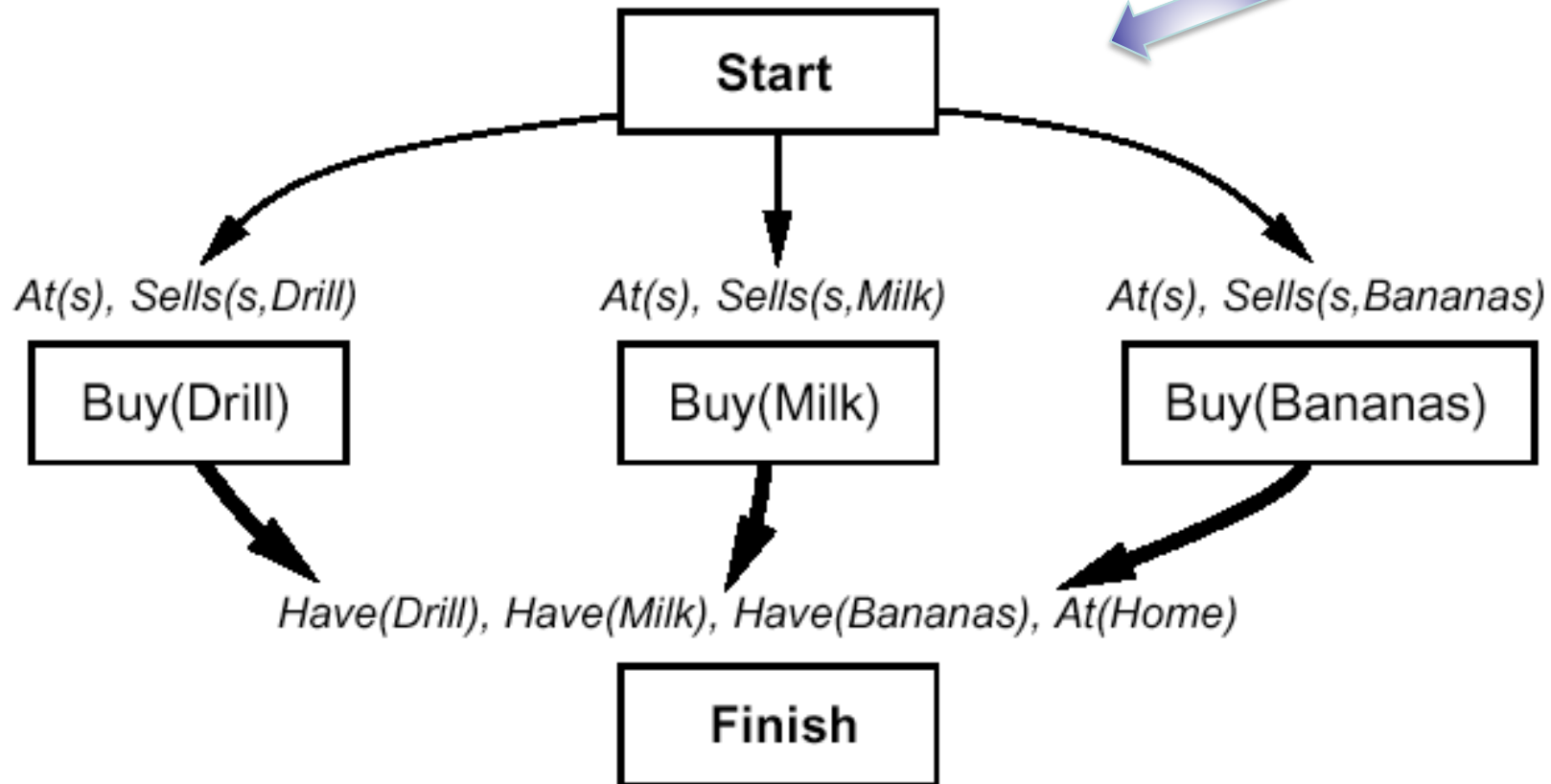
- Plan step = STRIPS Operator
- Plan consists of
 - Plan steps with partial order ($<$),
where $S_i < S_j$ iff S_i is to be executed before S_j
 - Set of variable assignments $x = t$,
where x is a variable and t is a constant or variable
 - Set of causal relations:
 $S_i \rightarrow^c S_j$ means S_i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

Completeness and Consistency

- **Complete** plan
 - Every precondition of a step is fulfilled
 - $\forall S_j$ with $c \in \text{Precond}(S_j)$,
 - $\exists S_i$ s.t. $S_i < S_j$ and $c \in \text{Effects}(S_i)$, and
 - for every linearization it holds that:
 - $\forall S_k$ with $S_i < S_k < S_j$, $\neg c \notin \text{Effects}(S_k)$
- **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)

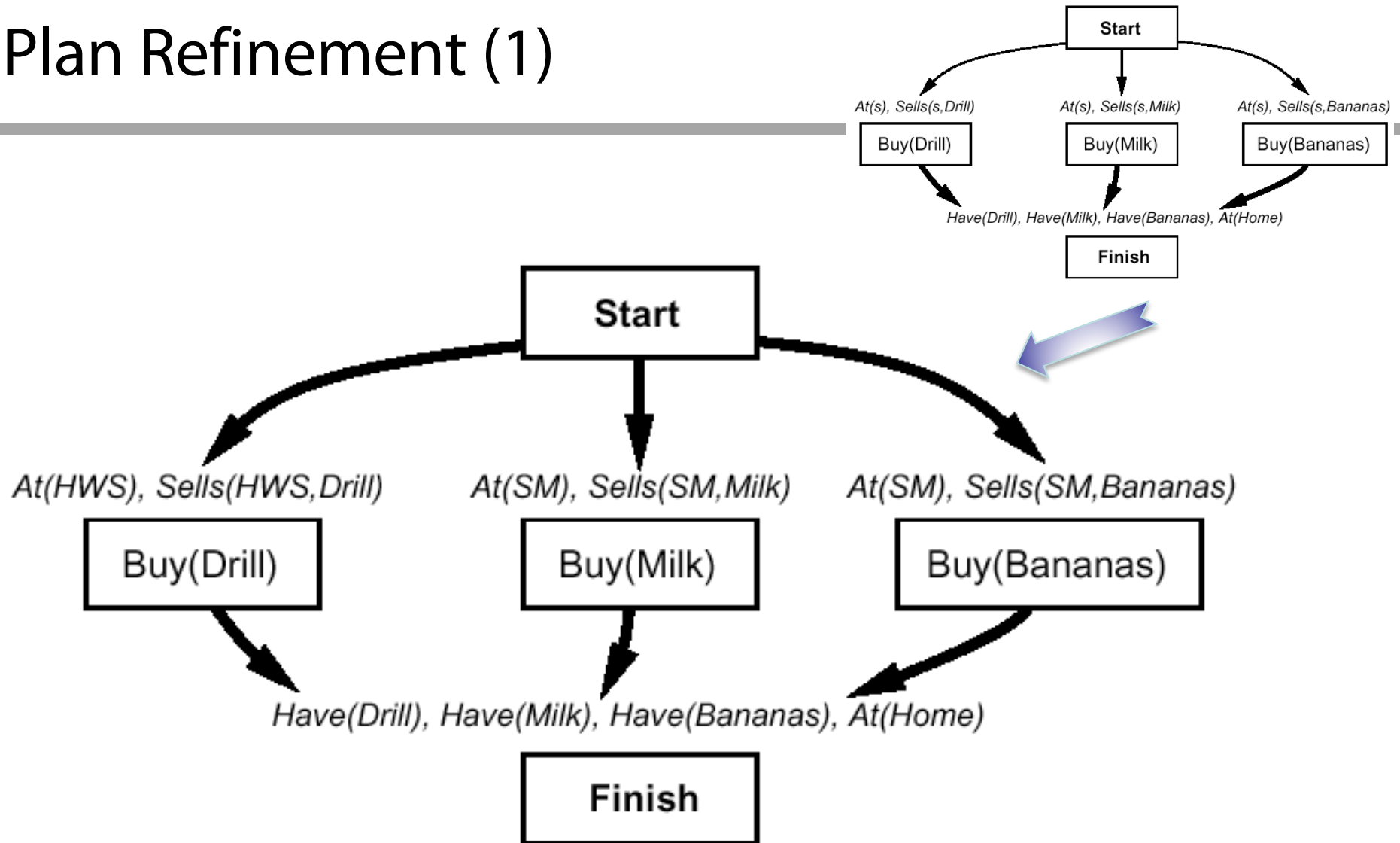
- Backward planning



Thin arrows = <

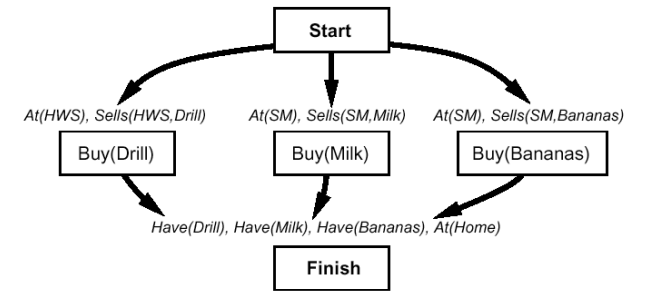
Fat arrows = causal relation + <

Plan Refinement (1)

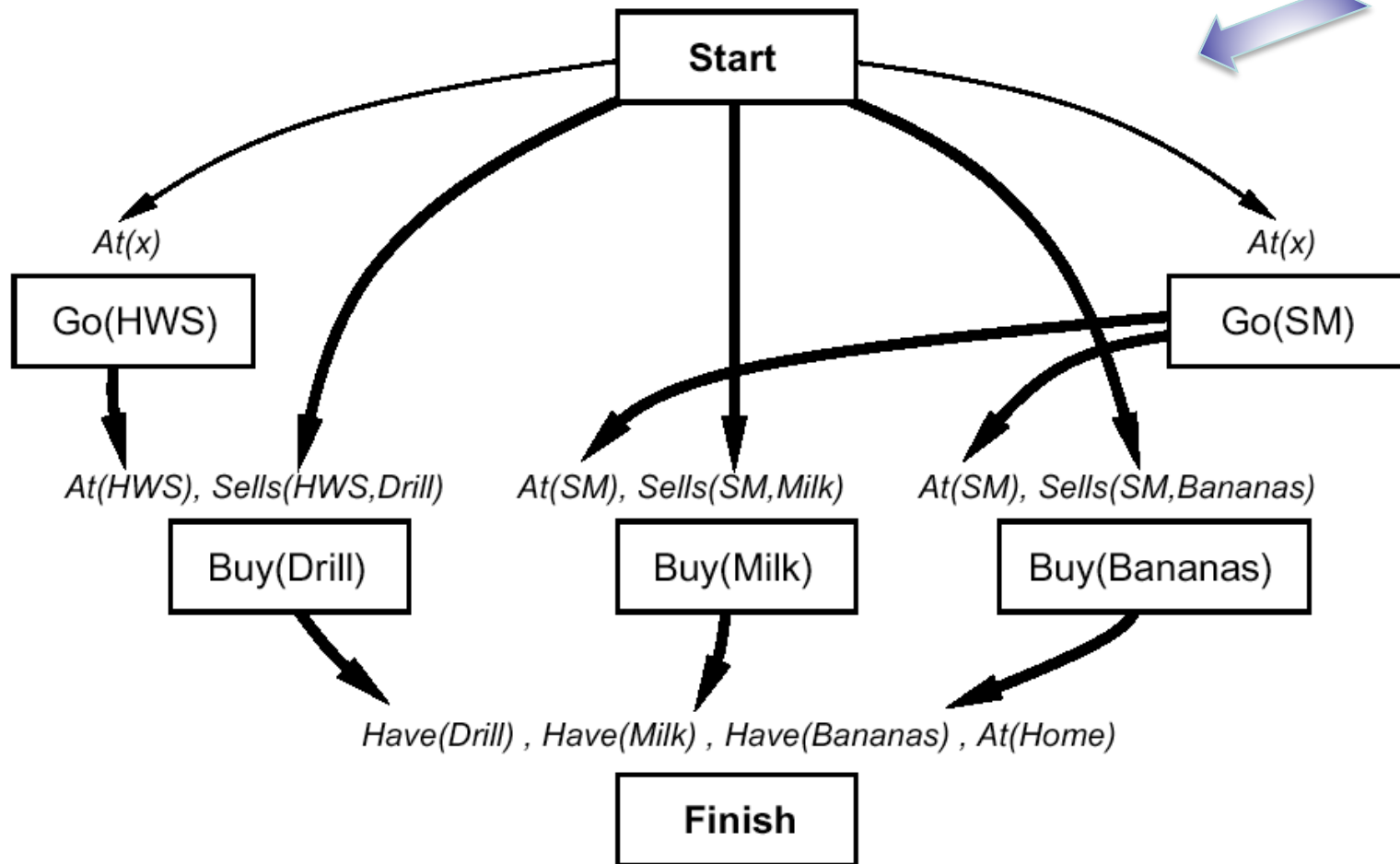


... after variable instantiation

Plan Refinement (2)

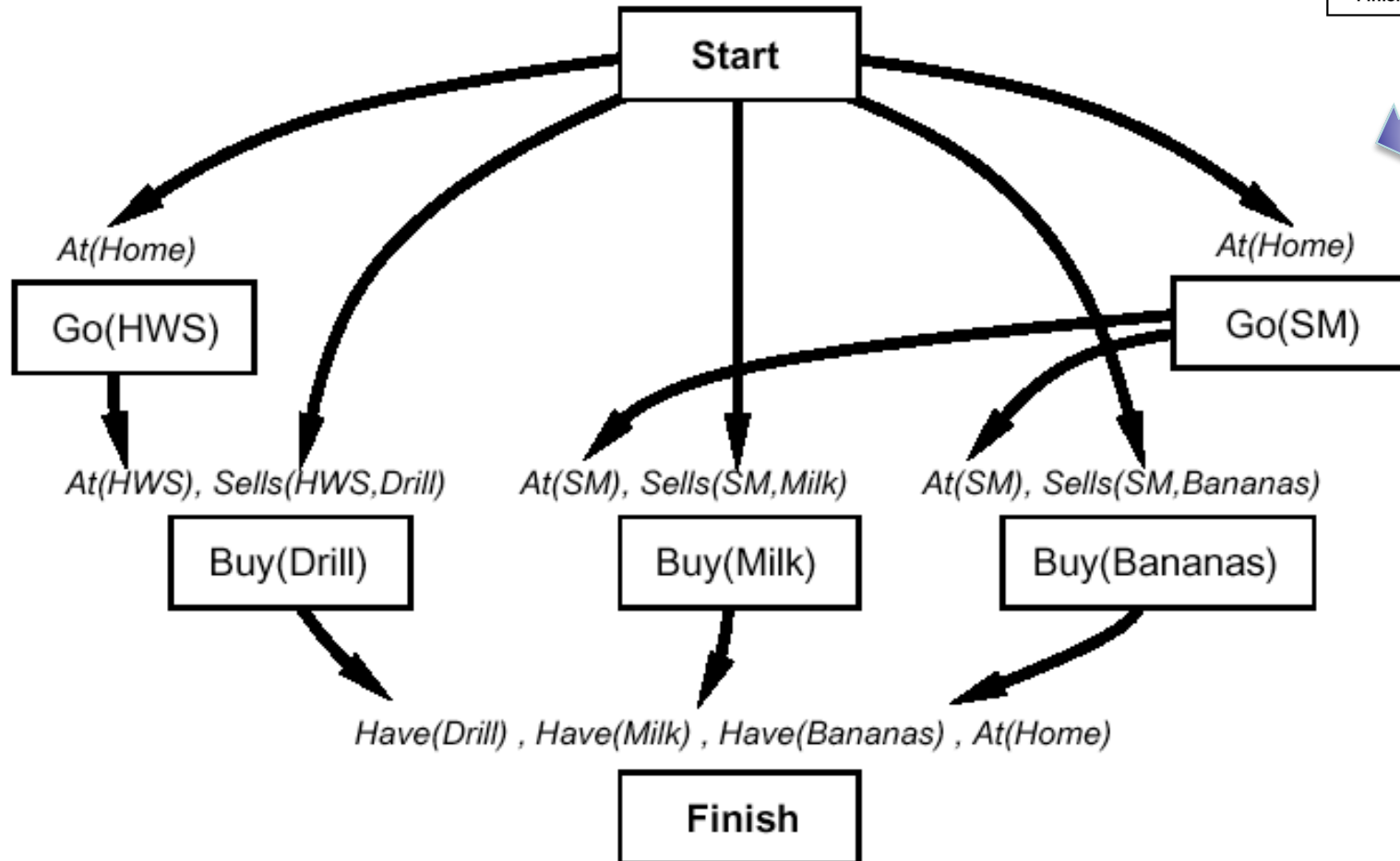
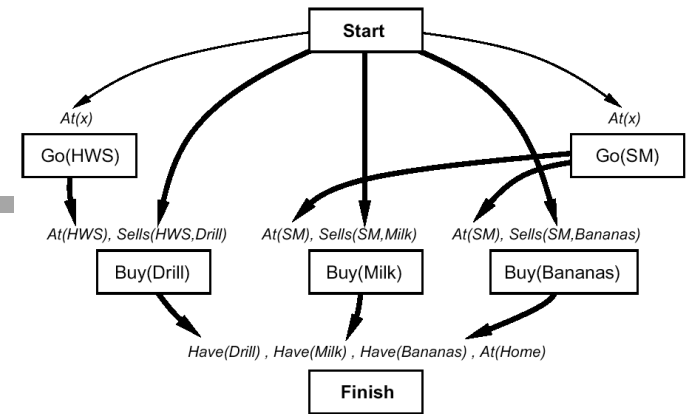


- ... buy at the right store



Plan Refinement (3)

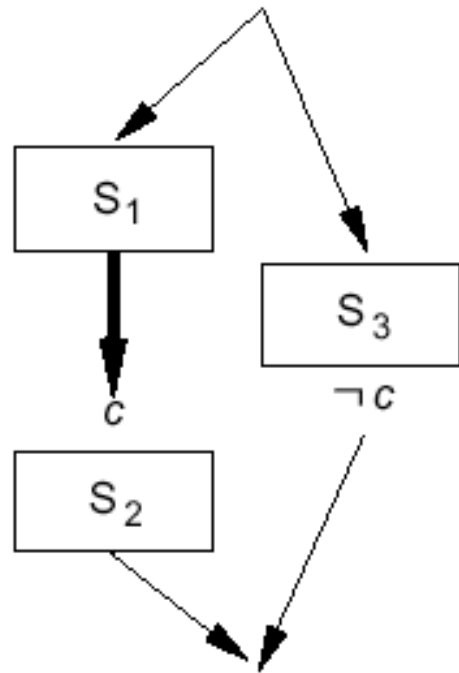
- ... but you must get there



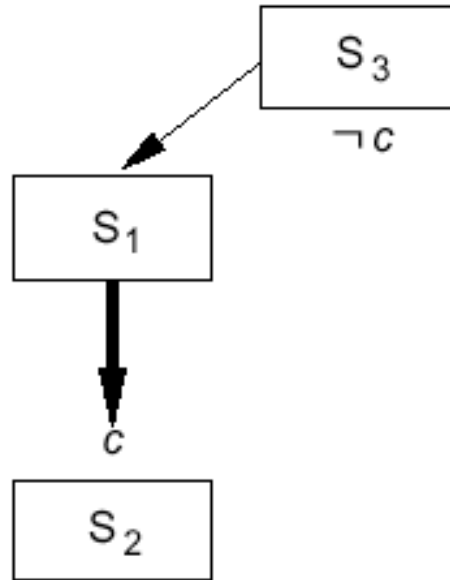
Plan Refinement (3)

- 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)`)

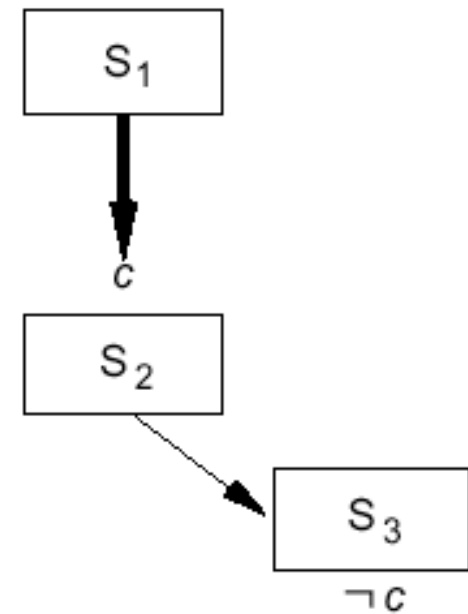
Protection of Causal Relations



(a)



(b)



(c)

Protection of Causal Relations

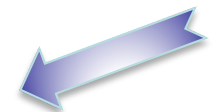
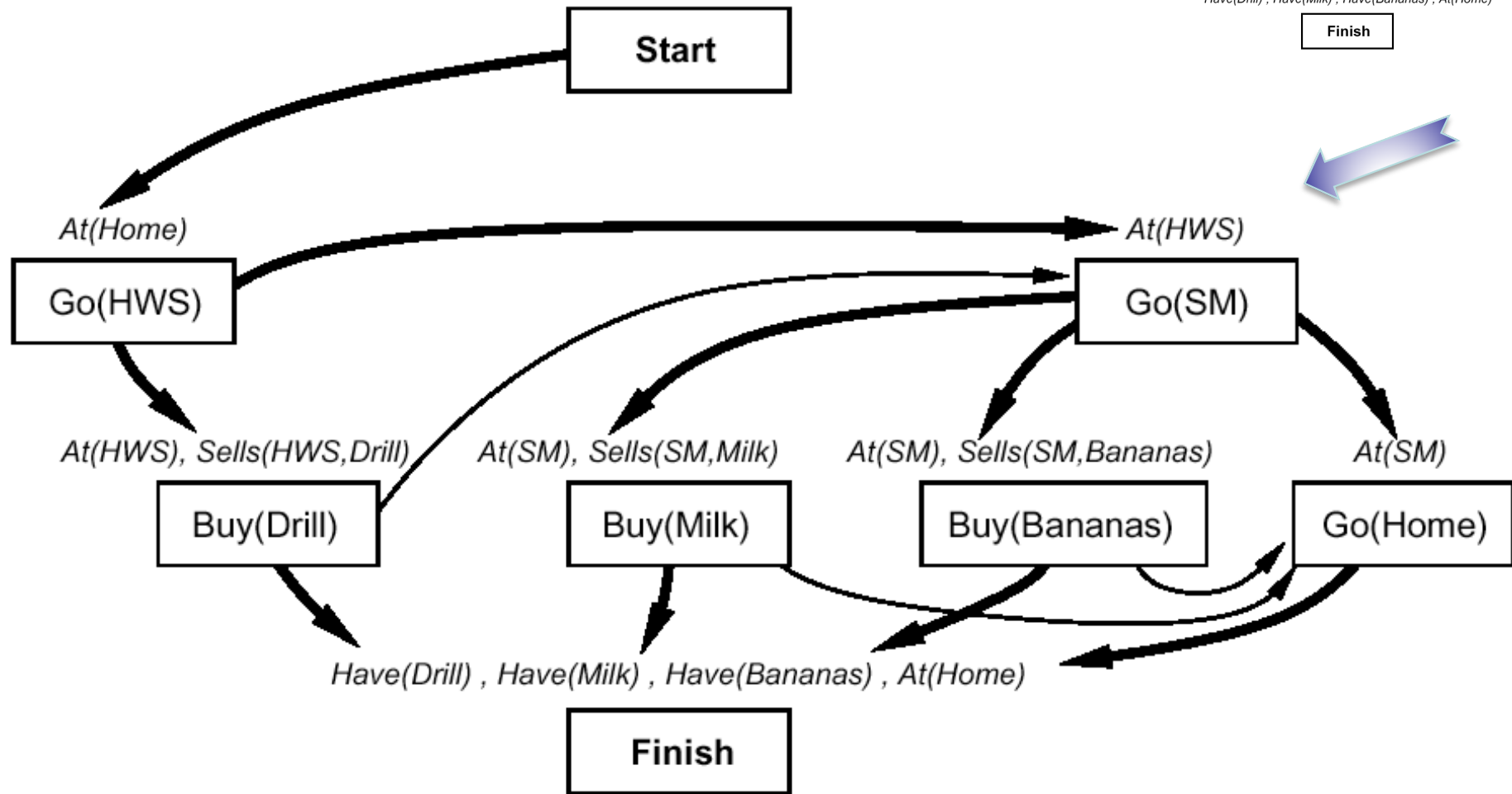
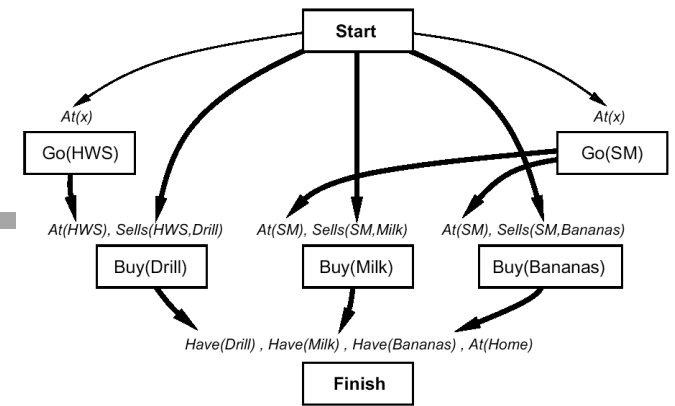
- Conflict:
 - S3 “threatens” causal relation between S1 and S2
- Conflict resolution:
 - Promotion: Put threat before causal relation (b)
 - Demotion: Put threat after causal relation (c)

=> Dedicated lectures on causality in part
Agent Planning, Causality, and Reinforcement Learning

Another Plan Refinement ...

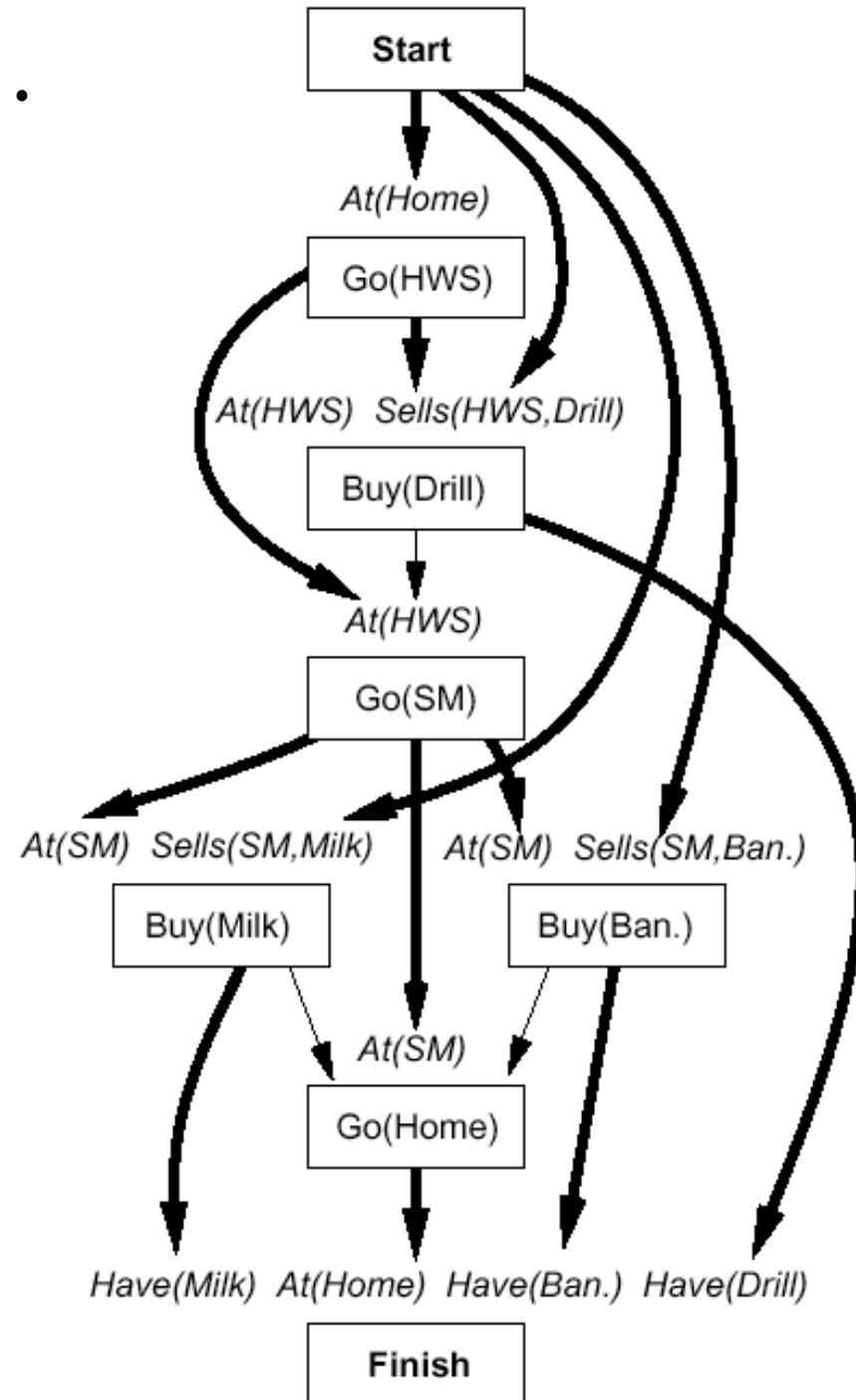
- Assumption: Cannot resolve conflict by protection
- Made a wrong step during plan refinement
- Alternative
 - Select $x = \text{HWS}$ (with causal relation) while instantiating $\text{At}(x)$ in $\text{go}(SM)$

Another Plan Refinement ...



The Complete Solution ...

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



function POP(*initial, goal, operators*) **returns** *plan*

plan \leftarrow MAKE-MINIMAL-PLAN(*initial, goal*)

loop do

if SOLUTION?(*plan*) **then return** *plan*

S_{need}, c \leftarrow SELECT-SUBGOAL(*plan*)

 CHOOSE-OPERATOR(*plan, operators, S_{need}, c*)

 RESOLVE-THREATS(*plan*)

end

function SELECT-SUBGOAL(*plan*) **returns** *S_{need}, c*

 pick a plan step *S_{need}* from STEPS(*plan*)

 with a precondition *c* that has not been achieved

return *S_{need}, c*

procedure CHOOSE-OPERATOR($plan, operators, S_{need}, c$)

choose a step S_{add} from $operators$ or $STEPS(plan)$ that has c as an effect

if there is no such step **then fail**

add the causal link $S_{add} \xrightarrow{c} S_{need}$ to $LINKS(plan)$

add the ordering constraint $S_{add} \prec S_{need}$ to $ORDERINGS(plan)$

if S_{add} is a newly added step from $operators$ **then**

 add S_{add} to $STEPS(plan)$

 add $Start \prec S_{add} \prec Finish$ to $ORDERINGS(plan)$

procedure RESOLVE-THREATS($plan$)

for each S_{threat} that threatens a link $S_i \xrightarrow{c} S_j$ in $LINKS(plan)$ **do**

choose either

Promotion: Add $S_{threat} \prec S_i$ to $ORDERINGS(plan)$

Demotion: Add $S_j \prec S_{threat}$ to $ORDERINGS(plan)$

if not CONSISTENT($plan$) **then fail**

end

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
- Lecture **Agent Planning, Causality, and Reinforcement Learning** of this module
- (→ Automated Planning and Acting (CS5072-KP04)

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



Round-Up

- 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