TU Clausthal
Clausthal University of Technology

Multiagent Systems I

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Clausthal University of Technology
SS 2012

Time: Monday, Tuesday: 10–12
Place: 201 Am Regenbogen (lecture), (labs)
Labs: From 30. April on, IfI R301.

Website

`http://studip.tu-clausthal.de/`

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Lecture: Prof. Dix, T. Behrens, M. Köster
Labs: T. Behrens, M. Köster
Schein: Lab work

About this Lecture

This course gives a first introduction to multi-agent systems for Bachelor students. Emphasis is put on applications and programming MAS, not on theory.
Only the first two weeks are in class, the rest are labs where students are programming a team to compete in our newest agent contest scenario. Students are grouped into teams and implement agent teams for solving a task on our agent contest platform. We consider BDI as a basic framework for developing agents using JAVA.

My thanks go to Tristan, Michael, Federico and our students who prepared the lab work and also some of the slides of this course.

References

- Mike Wooldridge (2002).
  An Introduction to Multi Agent Systems.
  John Wiley & Sons.

- Stuart Russel and Peter Norvig (2010).
  Artificial Intelligence.
  Third Edition.
  Pearson.

Lecture Overview

1. Week: 1. Introduction,
   2.1 Reactive Agents

2. Week: 2.2 BDI, 3. Searching

3. Week: 4. Agent Contest Scenario

4.-15. Week: Labs.

Outline

1. Introduction

Content of this Chapter:

We are setting the stage for a precise discussion of *agency*. From **informal concepts** to (more or less) *mathematical definitions*.

1. *MAS* versus **Distributed AI (DAI)**,
2. *Environment* of agents,
3. *Agents* and other frameworks,
4. *Runs* as characteristic behaviour,
5. *state-based* versus *standard* agents.

1.1 Why Agents?

Three Important Questions

(Q1) What is a (software) agent?

(Q2) If some program P is not an agent, how can it be transformed into an agent?

(Q3) If (Q1) is clear, what kind of Software Infrastructure is needed for the interaction of agents? What services are necessary?

Definition 1.1 (Distributed AI (DAI))

The area investigating systems, where several *autonomous acting entities work together* to reach a given goal.

The entities are called *Agents*, the area *Multiagent Systems*.

AAMAS: several conferences joined in 2002 to form *the main annual event*. Bologna (2002), Melbourne (2003), New York (2004), Utrecht (2005), Hakodate (2006), Hawaii (2007), Lisbon (2008), Budapest (2009), Toronto (2010), Taiwan (2011).

Example 1.2 (RoboCup)

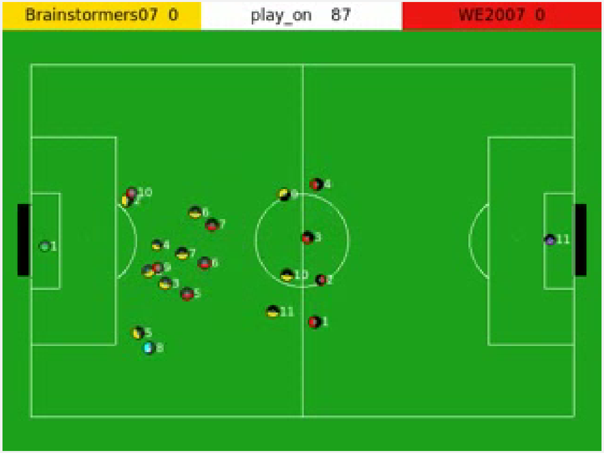


Figure : 2D-Simulation league: RoboCup 2007 Final

Example 1.3 (RoboCup)

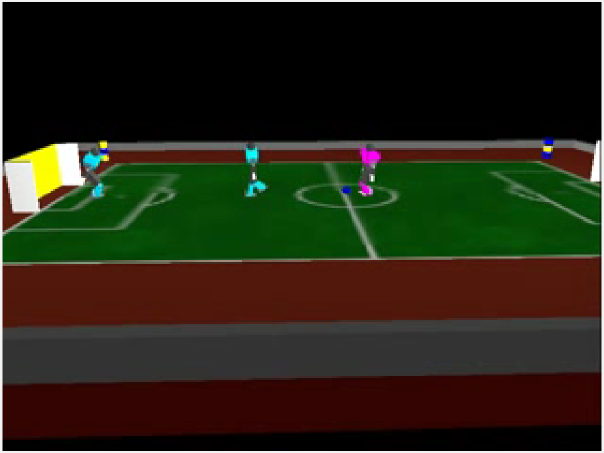


Figure : 3D-Simulation league: RoboCup 2007 Final

Example 1.4 (RoboCup)

Figure : Small size league

Example 1.5 (RoboCup)

Figure : Middle size league

Example 1.6 (RoboCup)

Figure : Standard platform

Example 1.7 (RoboCup)

Figure : Humanoid league

Example 1.8 (RoboCup)

Figure : Rescue league

Example 1.9 (Grand Challenge 2004)

Grand Challenge: Organised by DARPA since 2004.
First try: **Huge Failure**.

Figure : Grand Challenge 2004

- Prize money: 1 million Dollars
- Race course: 241 km in the Mojave desert
- 10 hours pure driving time
- More than 100 registered participants, 15 of them were chosen
- **No one reached the end of the course**
- **The favourite** “Sandstorm” of Carnegie Mellon in Pittsburgh **managed 5%** of the distance

Example 1.10 (Grand Challenge 2005)

Second try: **Big Success**:
Stanley (Sebastian Thrun) won in 2005.

Figure : VW Touareg coached by Stanford University

- Prize money: 2 million Dollars
- Race course: 212,76 km in the Mojave desert
- 10 hours pure driving time
- 195 registered participants, 23 were qualified
- **5 teams** reached the end of the course (**4 teams in time**)
- **Stanley** finished the race in 6 hours and 53 minutes (30,7 km/h)
- **Sandstorm** achieved the second place

Example 1.11 (Urban Challenge)

Urban Challenge: Organised by DARPA in 2007.

Figure : Urban Challenge 2007

- No straight-line course but real streets covered with buildings.
- 60 miles
- Prize money: 3,5 million Dollars
- **Tartan Racing** won, **Stanford Racing Team** second, **VictorTango** third place.
- Some teams like **Stanford Racing Team** and **VictorTango** as well as **Tartan Racing** were sponsored by **DARPA** with 1 million Dollar beforehand.

Example 1.12 (CLIMA Contest: Gold Mining)

First try: A simple grid where agents are supposed to collect gold. Different roles of agents: scouts, collectors.

- `http://multiagentcontest.org`

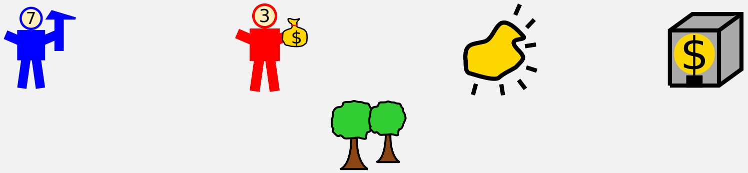


Figure : Gold mining elements

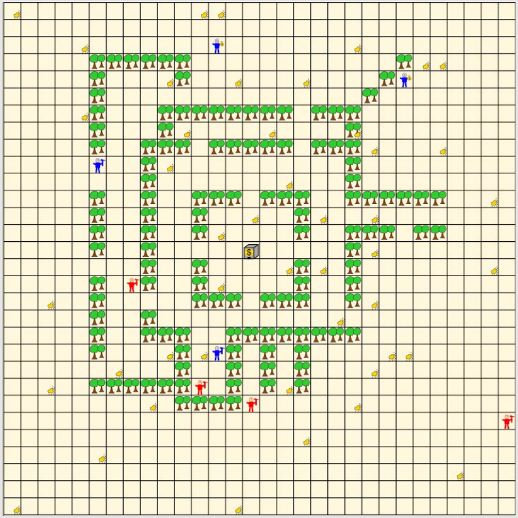


Figure : Gold Mining 2006: CLIMABot (blue) vs. brazil (red)

Example 1.13 (Agent Contest: Chasing Cows)

Second try: Push cows in a corral.

- `http://multiagentcontest.org`

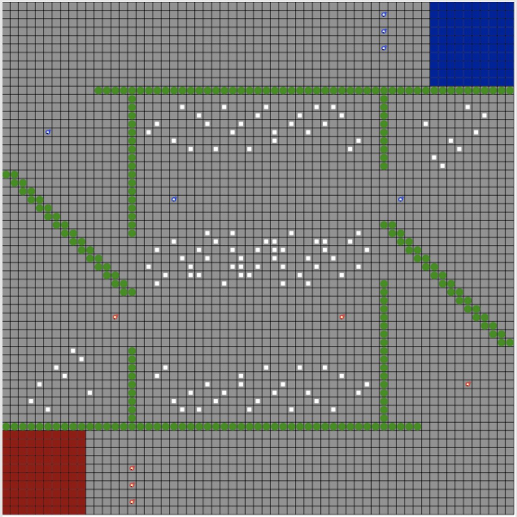


Figure : Chasing Cows 2008

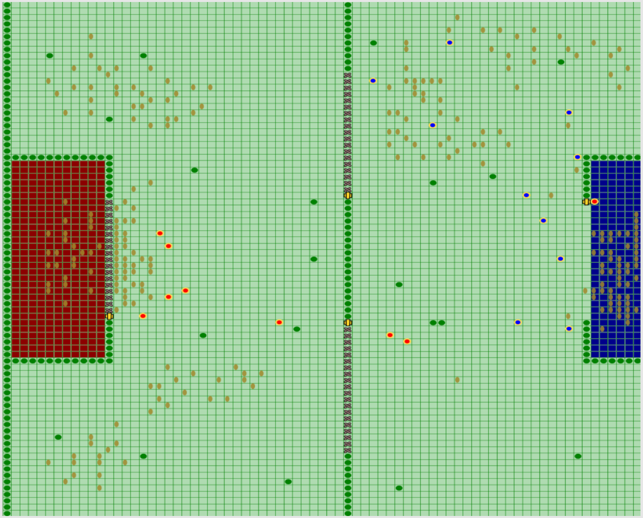


Figure : Chasing Cows 2009

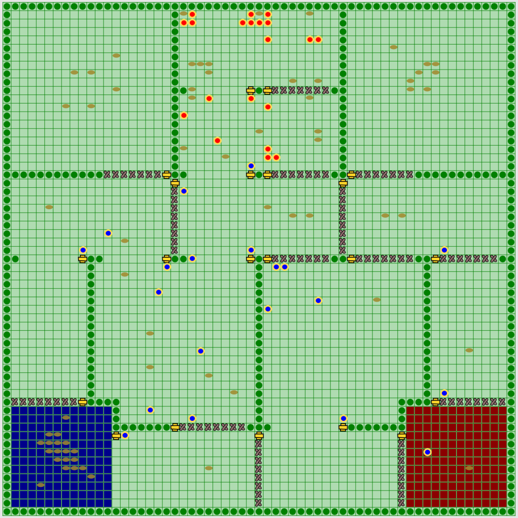


Figure : Chasing Cows 2010

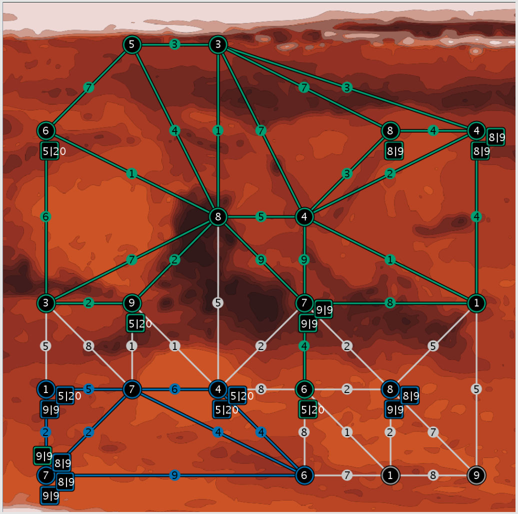


Figure : Mars Scenario 2011

Agents: Why do we need them?

Information systems are **distributed**, **open**, **heterogenous**.
We therefore need *intelligent, interactive agents*, that *act autonomously*.

(Software) Agent: Programs that are implemented on a platform and have **sensors** and **effectors** to read from and make changes to the environment, respectively.

Intelligent: Performance measures, to evaluate the success. **Rational** vs. **omniscient**, **decision making**

Interactive: with other agents (software or humans) by observing the environment. Coordination: **Cooperation** vs. **Competition**

MAS versus Classical DAI

MAS: Several Agents coordinate their knowledge and actions (semantics describes this).

DAI: Particular problem is divided into smaller problems (nodes). These nodes have common knowledge. **The solution method is given.**

Attention:

Today DAI is used synonymously with MAS.

AI	DAI
Agent	**Multiple** Agents
Intelligence: Property of a **single** Agent	Intelligence: Property of several Agents
Cognitive Processes of a **single** Agent	Social Processes of several Agents

10 Desiderata

1. *Agents are for everyone!* We need a method to agentise given programs.
2. Take into account that **data is stored in a wide variety of data structures, and data is manipulated by an existing corpus of algorithms.**
3. A theory of agents must *not* depend upon the set of actions that the agent performs. Rather, **the set of actions that the agent performs must be a *parameter* that is taken into account in the semantics.**

10 Desiderata

4. **Every (software) agent should execute actions based on some *clearly articulated* decision policy.** A declarative framework for articulating decision policies of agents is imperative.

5. Any agent construction framework must allow agents to reason:
   - **Reasoning about its beliefs** about other agents.
   - **Reasoning about uncertainty** in its beliefs about the world and about its beliefs about other agents.
   - **Reasoning about time**.

These capabilities should be viewed as *extensions* to a core agent action language.

10 Desiderata

6. **Any infrastructure to support multiagent interactions *must* provide security.**

7. While the efficiency of the code underlying a software agent cannot be guaranteed (as it will vary from one application to another), **guarantees are needed that provide information on the performance of an agent relative to an oracle that supports calls to underlying software code.**

10 Desiderata

8. We must identify efficiently computable fragments of the general hierarchy of languages alluded to above, and our implementations must take advantage of the specific structure of such language fragments.
9. A critical point is reliability—there is no point in a highly efficient implementation, if all agents deployed in the implementation come to a grinding halt when the agent "infrastructure" crashes.

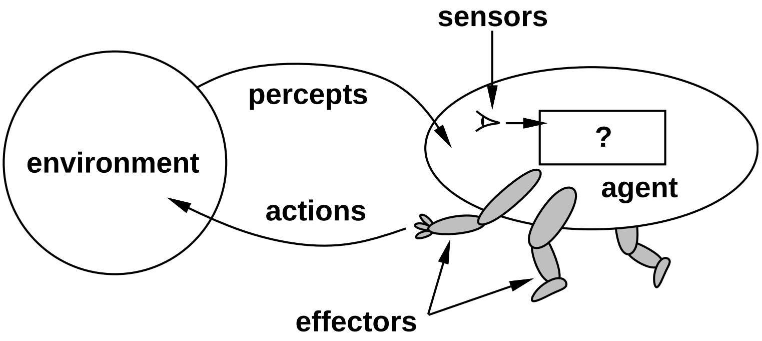
10 Desiderata

10. The only way of testing the applicability of any theory is to build a software system based on the theory, to deploy a set of applications based on the theory, and to report on experiments based on those applications.

1.2 Intelligent Agents

Definition 1.14 (Agent a)

An *agent* a is anything that can be viewed as **perceiving** its environment through **sensor** and **acting** upon that environment through **effectors**.



Definition 1.15 (Rational, Omniscient Agent)

A *rational agent* is one that does the *right thing* (**Performance measure** determines how successful an agent is).

A *omniscient agent* knows the actual outcome of his actions and can act accordingly.

Attention:

A rational agent is in general not omniscient!

Question

What is the right thing and what does it depend on?

1. Performance measure (as objective as possible).
2. Percept sequence (everything the agent has received so far).
3. The agent's knowledge about the environment.
4. How the agent can act.

Definition 1.16 (Ideal Rational Agent)

For each possible percept-sequence an *ideal rational agent* should do whatever action is expected to maximize its performance measure (based on the evidence provided by the percepts and built-in knowledge).

Mappings:

$$\text{set of percept sequences} \mapsto \text{set of actions}$$

can be used to describe agents in a mathematical way.

Hint:

Internally an agent is

agent = architecture + program

AI is engaged in designing agent programs

Agent Type	**Perform. Measure**	**Environment**	**Actuators**	**Sensors**
Medical diagnosis system	Healthy patient, minimize costs	Patient, hospital, staff	Display questions, tests, diagnoses, treatments	Entry of symptoms, findings, patient's answers
Satellite image analysis system	Correct image categorization	Downlink from orbiting satellite	Display categorization of scene	Color pixel arrays
Part-picking robot	Percentage of parts in correct bins	Conveyor belt with parts; bins	Jointed arm and hand	Camera, joint angle sensors
Interactive English tutor	Maximize student's score on test	Set of students, testing agency	Display exercises, suggestions, corrections	Keyboard entry

Table : Examples of agents types and their **PEAS** descriptions.

Question:

How do environment properties influence agent design?

Definition 1.17 (Environment Properties)

Accessible/Inaccessible: If not completely accessible, one needs internal states.

Deterministic/Indeterministic: An inaccessible environment might seem indeterministic, even if it is not.

Episodic/Nonepisodic: Percept-Action-Sequences are independent from each other. Closed episodes.

Static/Dynamic: While the agent is thinking, the world is the same/changing. **Semi-dynamic**: The world does not change, but the performance measure.

Discrete/Continous: Density of observations and actions. Relevant: Level of granularity.

Environment	Accessible	Deterministic	Episodic	Static	Discrete
Chess with a clock	Yes	Yes	No	Semi	Yes
Chess without a clock	Yes	Yes	No	Yes	Yes
Poker	No	No	No	Yes	Yes
Backgammon	Yes	No	No	Yes	Yes
Taxi driving	No	No	No	No	No
Medical diagnosis system	No	No	No	No	No
Image-analysis system	Yes	Yes	Yes	Semi	No
Part-picking robot	No	No	Yes	No	No
Refinery controller	No	No	No	No	No
Interactive English tutor	No	No	No	No	Yes

xbiff, software demons are agents (not intelligent).

Definition 1.18 (Intelligent Agent)

An *intelligent agent* is an agent with the following properties:

1. *Autonomous*: Operates without direct intervention of others, has some kind of control over its actions and internal state.
2. *Reactive*: Reaction to changes in the environment at certain times to reach its goals.
3. *Pro-active*: Taking the initiative, being goal-directed.
4. *Social*: Interaction with others to reach the goals.

Pro-active alone is not sufficient (C-Programs): The environment can change during execution.

Socialisation: coordination, communication, (negotiation) skills.

Difficulty: right balance between pro-active and reactive!

Agents vs. Object Orientation I

Objects have

1. a state (encapsulated): control over internal state
2. message passing capabilities

Java: private and public methods.

- Objects have control over their state, but **not over their behaviour**.
- An object can not prevent others to use its public methods.

Agents vs. Object Orientation II

Agents call other agents and request them to execute actions.

- Objects do it for free, agents do it for money.
- No analoga to **reactive**, **pro-active**, **social** in OO.
- MAS are multi-threaded or even multi-processed: each agent has a control thread or is a new process. (In OO only the system as a whole possesses one.)

A Simple Agent Program

```
**function** SKELETON-AGENT(*percept*) **returns** action
    **static**: *memory*, the agent's memory of the world

    $memory \leftarrow$ UPDATE-MEMORY($memory, percept$)
    $action \leftarrow$ CHOOSE-BEST-ACTION($memory$)
    $memory \leftarrow$ UPDATE-MEMORY($memory, action$)
    **return** *action*
```

In Theory Everything is Trivial

```
function TABLE-DRIVEN-AGENT(percept) returns action
    static: percepts, a sequence, initially empty
            table, a table, indexed by percept sequences, initially fully specified

    append percept to the end of percepts
    action ← LOOKUP(percepts, table)
    return action
```

Example 1.19 (Agent: Taxi Driver)

PEAS description of the task environment for an automated taxi:

Performance Measure: Safe, fast, legal, maximize profits

Environment: Roads, other traffic, pedestrians, customers

Actuators: Steering, accelerator, brake, signal, horn

Sensors: Cameras, sonar, GPS, odometer, engine sensors

Example 1.20 (Agent: Taxi Driver)

1. **Production rules:** If the driver in front hits the breaks, then hit the breaks too.

```
function SIMPLE-REFLEX-AGENT(percept) returns action
    static: rules, a set of condition-action rules

    state $\leftarrow$ INTERPRET-INPUT(percept)
    rule $\leftarrow$ RULE-MATCH(state, rules)
    action $\leftarrow$ RULE-ACTION[rule]
    return action
```

Agents as Intentional Systems

Intentions: Agents are endowed with **mental states**.

Matthias took his umbrella because he **believed** it was going to rain.
Kjeld attended the MAS course because he **wanted** to learn about agents.

An *intentional system* describes entities whose behaviour can be predicted by the method of attributing beliefs, desires and rational acumen.

1.3 Formal Description

A First Mathematical Description

At first, we want to keep everything as simple as possible.

Agents and environments

An agent is situated in an environment and can perform actions

$$A := \{a_1, \ldots, a_n\} \qquad \text{(set of actions)}$$

and change the state of the environment

$$S := \{s_1, s_2, \ldots, s_n\} \qquad \text{(set of states).}$$

How does the environment (the state s) develop when an action a is executed?

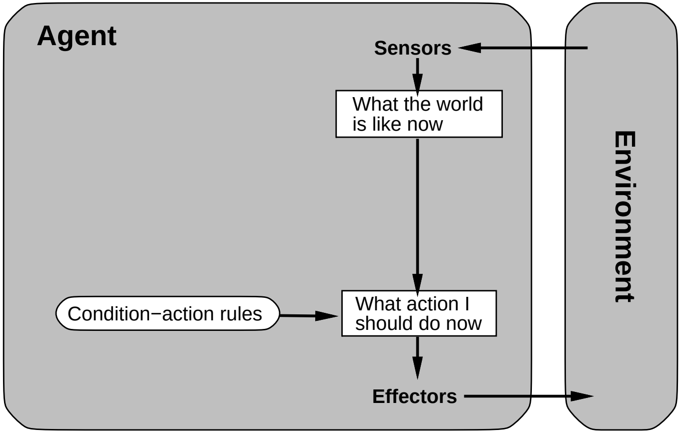
We describe this with a function

$$\mathbf{env} : \mathbf{S} \times \mathbf{A} \longrightarrow \mathbf{2}^{\mathbf{S}}.$$

This includes non-deterministic environments.

How do we describe agents?

We could take a function $\mathbf{action} : \mathbf{S} \longrightarrow \mathbf{A}$.



Question:

How can we describe an agent, now?

Definition 1.21 (Purely Reactive Agent)

An agent is called purely reactive, if its function is given by

$$\mathbf{action} : \mathbf{S} \longrightarrow \mathbf{A}.$$

This is too weak!

Take the whole history (of the environment) into account:

$\mathbf{s_0} \rightarrow_{\mathbf{a_0}} \mathbf{s_1} \rightarrow_{\mathbf{a_1}} \ldots \mathbf{s_n} \rightarrow_{\mathbf{a_n}} \ldots.$

The same should be done for $\mathbf{env}$!

This leads to agents that take the **whole sequence of states** into account, i.e.

$$\mathbf{action} : \mathbf{S}^{*} \longrightarrow \mathbf{A}.$$

We also want to consider the actions **performed by an agent**. This requires the notion of a run (next slide).

We define the run of an agent in an environment as a *sequence of interleaved states and actions*:

Definition 1.22 (Run r, $R = R^{act} \cup R^{state}$)

A run r over $\mathbf{A}$ and $\mathbf{S}$ is a finite sequence

$$\mathbf{r} : \mathbf{s_0} \rightarrow_{\mathbf{a_0}} \mathbf{s_1} \rightarrow_{\mathbf{a_1}} \ldots \mathbf{s_n} \rightarrow_{\mathbf{a_n}} \ldots$$

Such a sequence may end with a state $\mathbf{s_n}$ or with an action $\mathbf{a_n}$: we denote by R^{act} the set of **runs ending with an action** and by R^{state} the set of **runs ending with a state**.

Definition 1.23 (Environment, 2. version)

An **environment** Env is a triple $\langle \mathrm{S}, \mathrm{s}_0, \tau \rangle$ consisting of

1. the set S of states,
2. the initial state $\mathrm{s}_0 \in \mathrm{S}$,
3. a function $\tau : \mathrm{R}^{act} \longrightarrow 2^{\mathrm{S}}$, which describes how the environment changes when an action is performed (given the whole history).

Definition 1.24 (Agent $\mathfrak{a}$)

An agent $\mathfrak{a}$ is determined by a function

$$\mathbf{action} : \mathrm{R}^{state} \longrightarrow \mathbf{A},$$

describing which action the agent performs, given its current history.

Important:

An agent system is then a pair $\mathfrak{a} = \langle \mathbf{action}, Env \rangle$ consisting of an agent and an environment.
We denote by $\mathrm{R}(\mathfrak{a}, Env)$ the set of runs of agent $\mathfrak{a}$ in environment Env.

Definition 1.25 (Characteristic Behaviour)

The characteristic behaviour of an agent $\mathfrak{a}$ in an environment Env is the set $\mathcal{R}$ of all possible runs $\mathbf{r} : \mathbf{s_0} \rightarrow_{a_0} \mathbf{s_1} \rightarrow_{a_1} \dots \mathbf{s_n} \rightarrow_{a_n} \dots$ with:

1. for all n: $\mathbf{a_n} = \mathbf{action}(\langle \mathbf{s_0}, \mathbf{a_0} \dots, \mathbf{a_{n-1}}, \mathbf{s_n} \rangle)$,
2. for all $n > 0$: $\mathbf{s_n} \in \boldsymbol{\tau}(\mathbf{s_0}, a_0, \mathbf{s_1}, a_1, \dots, \mathbf{s_{n-1}}, a_{n-1})$.

For deterministic $\boldsymbol{\tau}$, the relation “$\in$” can be replaced by “=”.

Important:

The formalization of the characteristic behaviour is dependent of the concrete agent type. Later we will introduce further behaviours (and corresponding agent designs).

Equivalence

Two agents $\mathfrak{a}$, $\mathfrak{b}$ are called **behaviourally equivalent wrt. environment** Env, if $\mathrm{R}(\mathfrak{a}, Env) = \mathrm{R}(\mathfrak{b}, Env)$.
Two agents $\mathfrak{a}$, $\mathfrak{b}$ are called behaviourally equivalent, if they are behaviourally equivalent wrt. all possible environments Env.

So far so good, but...

What is the problem with all these agents and this framework in general?

Problem

All agents have perfect information about the environment!

(Of course, it can also be seen as feature!)

We need more realistic agents!

Note

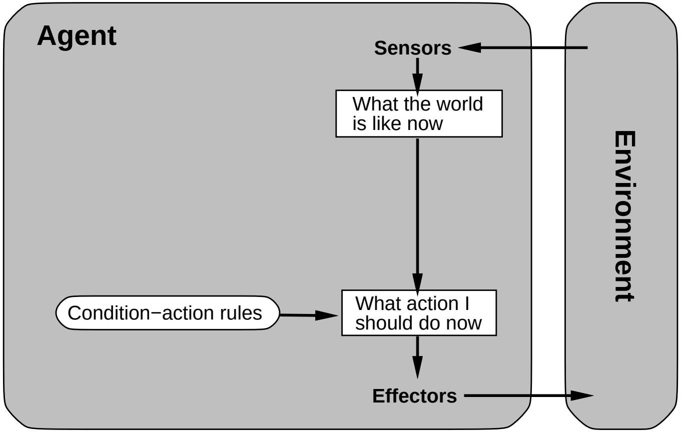
In general, agents only have incomplete/uncertain information about the environment!

We extend our framework by perceptions:

Definition 1.26 (Actions, Percepts, States)

$\mathbf{A} := \{\mathbf{a}_1, \mathbf{a}_2, \dots, \mathbf{a}_n\}$ is the set of *actions*.
$\mathbf{P} := \{\mathbf{p}_1, \mathbf{p}_2, \dots, \mathbf{p}_m\}$ is the set of percepts.
$\mathbf{S} := \{\mathbf{s}_1, \mathbf{s}_2, \dots, \mathbf{s}_l\}$ is the set of *states*

Sensors don’t need to provide perfect information!



Question

How can agent programs be designed?

There are four types of agent programs:

- Simple **reflex agents**
- **Agents that keep track of the world**
- Goal-based agents
- Utility-based agents

First Try

We consider a purely reactive agent and just replace states by perceptions.

Definition 1.27 (Simple Reflex Agent)

An agent is called *simple reflex agent*, if its function is given by

$$\mathbf{action} : \mathbf{P} \longrightarrow \mathbf{A}.$$

A Very Simple Reflex Agent

```
**function** SIMPLE-REFLEX-AGENT(*percept*) **returns** *action*
    **static**: *rules*, a set of condition-action rules

    $state \leftarrow$ INTERPRET-INPUT(*percept*)
    $rule \leftarrow$ RULE-MATCH(*state*, *rules*)
    $action \leftarrow$ RULE-ACTION[*rule*]
    **return** *action*
```

A Simple Reflex Agent with Memory

```
function REFLEX-AGENT-WITH-STATE(percept) returns action
    static: state, a description of the current world state
            rules, a set of condition-action rules

    state ← UPDATE-STATE(state, percept)
    rule ← RULE-MATCH(state, rules)
    action ← RULE-ACTION[rule]
    state ← UPDATE-STATE(state, action)
    return action
```

As before, let us now consider sequences of percepts:

Definition 1.28 (Standard Agent $\mathfrak{a}$)

$$\mathrm{action} : \mathbf{P}^* \longrightarrow A$$

together with

$$\mathrm{see} : \mathbf{S} \longrightarrow \mathbf{P}.$$

An agent is thus a pair $\langle \mathrm{see}, \mathrm{action} \rangle$.

Definition 1.29 (Indistinguishable)

Two different states s, s' are *indistinguishable* for an agent **a**, if $\mathrm{see}(s) = \mathrm{see}(s')$.

The relation “indistinguishable” on $\mathrm{S} \times \mathrm{S}$ is an **equivalence** relation.

What does $|\sim| = |\mathrm{S}|$ mean?

And what $|\sim| = 1$?

As mentioned before, the characteristic behaviour has to match with the agent design!

Definition 1.30 (Characteristic Behaviour)

The characteristic behaviour of a standard agent $\langle \mathbf{see}, \mathbf{action} \rangle$ in an environment Env is the set of all finite sequences

$$\mathbf{p_0} \rightarrow_{a_0} \mathbf{p_1} \rightarrow_{a_1} \ldots \mathbf{p_n} \rightarrow_{a_n} \ldots \quad \text{where}$$

$\mathbf{p_0} = \mathbf{see}(\mathbf{s_0})$,
$\mathbf{a_i} = \mathbf{action}(\langle \mathbf{p_0}, \ldots, \mathbf{p_i} \rangle)$,
$\mathbf{p_i} = \mathbf{see}(\mathbf{s_i})$, where $\mathbf{s_i} \in \boldsymbol{\tau}(\mathbf{s_0}, a_0, \mathbf{s_1}, a_1, \ldots, \mathbf{s_{i-1}}, a_{i-1})$.

Such a sequence, even if deterministic from the agent’s viewpoint, may cover different environmental behaviours (runs):
$\mathbf{s_0} \rightarrow_{a_0} \mathbf{s_1} \rightarrow_{a_1} \ldots \mathbf{s_n} \rightarrow_{a_n} \ldots$

Instead of using the whole history, resp. $\mathbf{P}^*$, one can also use **internal states** $\mathbf{I} := \{\mathbf{i}_1, \mathbf{i}_2, \ldots, \mathbf{i}_n, \mathbf{i}_{n+1}, \ldots\}$.

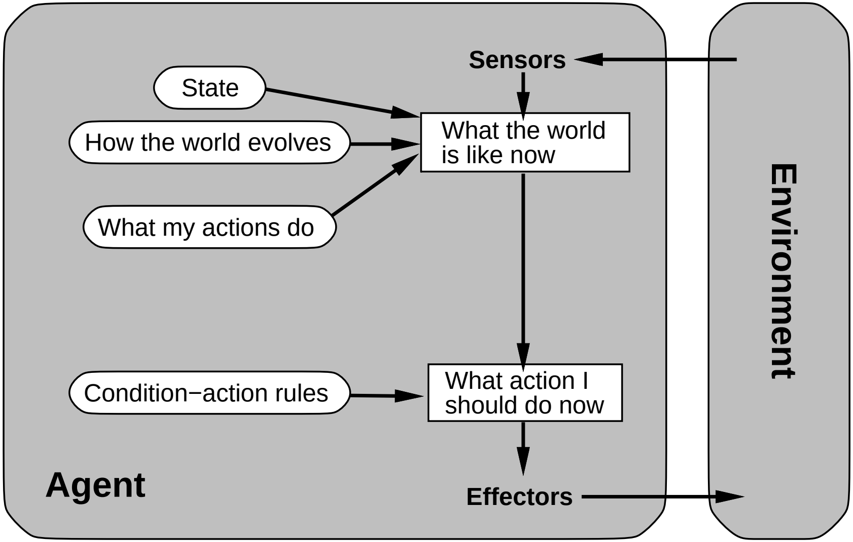
Definition 1.31 (State-based Agent a_{state})

A *state-based* agent a_{state} is given by a function $\mathbf{action} : I \longrightarrow A$ together with

$$\mathbf{see} : \mathbf{S} \longrightarrow \mathbf{P},$$

and $$\mathbf{next} : \mathbf{I} \times \mathbf{P} \longrightarrow \mathbf{I}.$$

Here $\mathbf{next}(\mathbf{i}, \mathbf{p})$ is the successor state of $\mathbf{i}$ if $\mathbf{p}$ is observed.


Sensors
State
How the world evolves
What the world is like now
What my actions do
Condition−action rules
What action I should do now
Agent
Effectors
Environment

Definition 1.32 (Characteristic Behaviour)

The characteristic behaviour of a state-based agent $\mathfrak{a}_{state}$ in an environment Env is the set of all finite sequences

$$(\mathbf{i}_0, \mathbf{p_0}) \rightarrow_{a_0} (\mathbf{i}_1, \mathbf{p_1}) \rightarrow_{a_1} \ldots \rightarrow_{a_{n-1}} (\mathbf{i}_n, \mathbf{p_n}), \ldots$$

with

$\mathbf{p_0} = \mathbf{see}(\mathbf{s_0})$,
$\mathbf{p_i} = \mathbf{see}(\mathbf{s_i})$, where $\mathbf{s_i} \in \boldsymbol{\tau}(\mathbf{s_0}, a_0, \mathbf{s_1}, a_1, \ldots, \mathbf{s_{i-1}}, a_{i-1})$,
$\mathbf{a_n} = \mathbf{action}(\mathbf{i_{n+1}})$,
$\mathbf{next}(\mathbf{i_n}, \mathbf{p_n}) = \mathbf{i_{n+1}}$.

Sequence covers the runs $\mathbf{r} : \mathbf{s_0} \rightarrow_{\mathbf{a_0}} \mathbf{s_1} \rightarrow_{\mathbf{a_1}} \ldots$ where

$\mathbf{a_j} = \mathbf{action}(\mathbf{i_{j+1}})$,
$\mathbf{s_j} \in \boldsymbol{\tau}(\mathbf{s_0}, a_0, \mathbf{s_1}, a_1, \ldots, \mathbf{s_{j-1}}, a_{j-1})$,
$\mathbf{p_j} = \mathbf{see}(\mathbf{s_j})$

Are state-based agents more expressive than standard agents? How to measure?

Definition 1.33 (Env. Behaviour of a_{state})

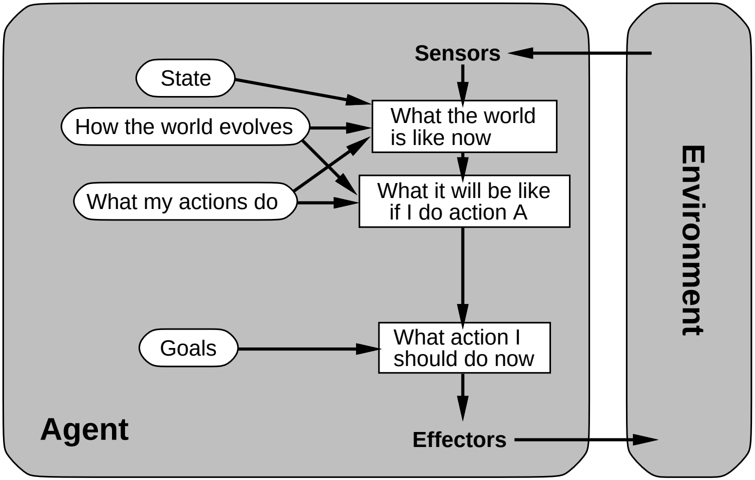
The *environmental behaviour* of an agent a_{state} is the set of possible runs covered by the characteristic behaviour of the agent.

Theorem 1.34 (Equivalence)

Standard agents and state-based agents are equivalent with respect to their environmental behaviour.

More precisely: For each state-based agent $\mathfrak{a}_{state}$ *and* $\mathbf{next}$ *storage function there exists a standard agent* $\mathfrak{a}$ *which has the same environmental behaviour, and vice versa.*

Goal based agents


Sensors
State
How the world evolves
What my actions do
What the world is like now
What it will be like if I do action A
Goals
What action I should do now
Agent
Effectors
Environment

This leads to **Planning**.

2. Basic Architectures

Content of this Chapter:

We are presenting two very basic architectures: a simple subsumption architecture, and an important paradigm of agent programming: The BDI-framework. While this is a very general framework, several programming languages can be seen as implementations of BDI.

1. We present a simple model for a subsumption architecture.
2. We discuss the agent control loop of BDI through several stages.
3. We introduce means-end reasoning.

2.1 Reactive Agents

Idea:

Intelligent behaviour is Interaction of the agents with their environment.

It emerges through splitting in simpler interactions.

Subsumption-Architectures:

- Decision making is realized through **goal-directed behaviours**: each behaviour is an individual action.
  nonsymbolic implementation.
- Many behaviours can be applied **concurrently**. How to select between them?
  Implementation through Subsumption-Hierarchies, Layers.
  Upper layers represent abstract behaviour.

Formal Model:

- see: Close relation between observation and action: **no transformation of the input**.
- action: Set of behaviours and a relation.

$$Beh := \{\langle \mathbf{c}, \mathbf{a}\rangle : \mathbf{c} \subseteq \mathbf{P}, \mathbf{a} \in \mathbf{A}\}.$$

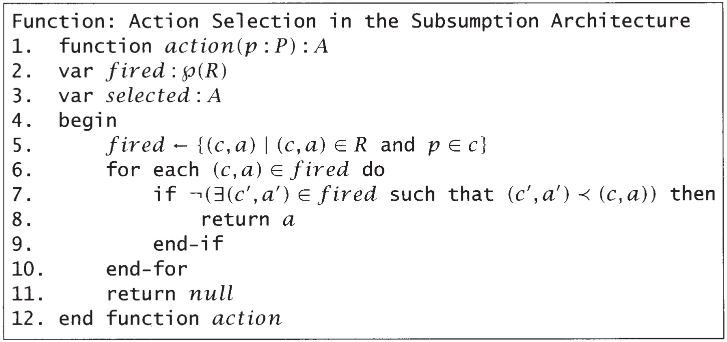
$\langle \mathbf{c}, \mathbf{a}\rangle$ “fires” if $\mathrm{see}(\mathbf{s}) \in \mathbf{c}$

$$\prec \subseteq Ag_{rules} \times Ag_{rules}$$

is called inhibition-relation, $Ag_{rules} \subseteq Beh$.
We require $\prec$ to be a total ordering.

$\mathbf{b_1} \prec \mathbf{b_2}$ means: b_1 inhibits b_2,

$\mathrm{b_1}$ has priority over $\mathbf{b_2}$.



```
Function: Action Selection in the Subsumption Architecture
1.  function $action(p : P) : A$
2.  var $fired : \wp(R)$
3.  var $selected : A$
4.  begin
5.      $fired \leftarrow \{(c,a) \mid (c,a) \in R$ and $p \in c\}$
6.      for each $(c,a) \in fired$ do
7.          if $\neg(\exists (c',a') \in fired$ such that $(c',a') \prec (c,a))$ then
8.              return $a$
9.          end-if
10.     end-for
11.     return $null$
12. end function $action$
```

Figure 5.1 Action Selection in the subsumption architecture.

Example 2.1 (Exploring a Planet)

A distant planet (asteroid) is assumed to contain gold. Samples should be brought to a spaceship landed on the planet. It is not known where the gold is. Several autonomous vehicles are available. Due to the topography of the planet there is no connection between the vehicles.

Gradient Field

The spaceship sends off radio signals: **gradient field**.

Low Level Behaviour: (1) **If** detect an obstacle **then** change direction.

2. Layer: (2) **If** Samples on board **and** at base **then** drop off.
(3) **If** Samples on board **and** not at base **then** follow gradient field.

3. Layer: (4) **If** Samples found **then** pick them up.

4. Layer: (5) **If** true **then** take a random walk.

With the following ordering

$$(1) \prec (2) \prec (3) \prec (4) \prec (5).$$

Assumptions

Under which assumptions (on the distribution of the gold) does this work perfectly?

Coordination

Vehicles can communicate indirectly with each other:

- they put off, and
- pick up

radioactive samples that can be sensed.

Low Level Behaviour:

(1) **If** detect an obstacle **then** change direction.

2. Layer:

(2) **If** Samples on board **and** at base **then** drop off.
(3) **If** Samples on board **and** not at base **then** drop off two radioactive crumbs and follow gradient field.

3. Layer:

(4) **If** Samples found **then** pick them up.
(5) **If** radioactive crumbs found **then** take one and follow the gradient field (away from the spaceship).

4. Layer:

(6) **If** true **then** take a random walk.

With the ordering $(1) \prec (2) \prec (3) \prec (4) \prec (5) \prec (6)$.

Pro: Simple, economic, efficient, robust, elegant.

Contra:

- Without knowledge about the environment agents need to know about the own local environment.
- Decisions only based on local information.
- How about bringing in **learning**?
- Relation between agents, environment and behaviours is not clear.
- Agents with ≤ 10 behaviours are doable. But the more layers the more complicated to understand what is going on.

2.2 BDI-Agents

What is BDI?

BDI is based on the assumption that the mind, that is the mental state, of agents consists of:

- beliefs: what the agent believes to be true about the world (information).
- desires: which state(s) of the world the agents wants to establish (motivation).
- intentions: what the agent actually intends to do and how to do it (deliberation).

The world of an agent is the other agents, the environment, and the agent itself.

Where does it come from?

BDI builds on three subfields of artificial intelligence:

- **rational agents**,
- **planning**, and
- **decision theory**.

What is it good for?

BDI allows for

- **means-end reasoning**,
- **weighing of competing possibilities**,
- the **interaction** between these two forms of reasoning, and addresses the problem of **resource-boundedness**.

Means-end reasoning

- comes from the subfield of AI that deals with **planning**
- **Given**: an initial state, a set of goal states (ends), and a description of actions (means or capabilities)
- **Goal**: find a sequence of actions (plan) that leads from the goal state to the final state

Means-end reasoning (2)

Example:

- initial state: I am at home, I have a picture, I have nails, I have no frame and no tools.
- goal state: the picture is framed and hangs on the wall
- plan: 1. go to DIY store, 2. acquire a frame and a hammer, 3. go home, 4. frame the picture, 5. use hammer and nails to hang the picture on the wall

Weighing of competing possibilities

- comes from decision theory
- competing possibilities are taken as given
- weigh the possibilities and decide for one of them, that is select an option based on the agent's utility function which takes into account beliefs (what the agent knows) and desires (what the agent wants)

Weighing of competing possibilities (2)

Example:

- desire: have a meal
- possibility 1: go to Mensa
- possibility 2: go to a fancy restaurant
- beliefs: I am low on funds
- decision: go to Mensa

Resource-Boundedness

- Agents are resource bounded, that is
- they are unable to perform arbitrarily large computations in the available time.

Necessity of BDI

Important characteristics of real-time applications:

1. **The environment is nondeterministic**, i.e. in each state of the environment can evolve in several ways.
2. **The system is nondeterministic**, i.e. in each state there are potentially several different actions to perform.
3. The system can have **several different objectives at the same time**.
4. The actions/procedures that achieve the objectives best are **dependent on the state of the environment** and are **independent of the internal state of the system**.
5. The environment can only be **sensed locally**.
6. The rate at which computations and actions can be carried out is **within reasonable bound to the rate at which the environment evolves**.

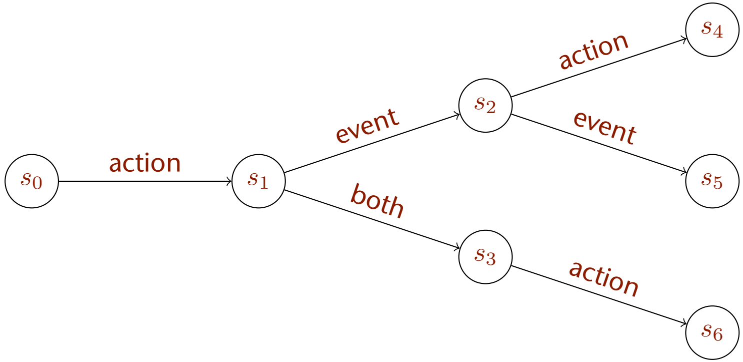
Necessity of BDI II

Nondeterminism of the environment (1) and of the system (2) imply a formal model:

Branching Tree Structure

- Each node is a certain state of the world,
- each transition represents a primitive action made by the system, a primitive event occurring in the environment, or both,
- each branch represents an alternative execution path,
- choice nodes are manifestations of the system’s nondeterminism, and
- chance nodes are manifestations of the environments nondeterminism.

Branching Tree Structure Example


$$\begin{tikzcd}
 & & & s_4 \\
 & & s_2 \arrow[ur, "action"] \arrow[dr, "event"] & \\
s_0 \arrow[r, "action"] & s_1 \arrow[ur, "event"] \arrow[dr, "both"] & & s_5 \\
 & & s_3 \arrow[dr, "action"] & \\
 & & & s_6
\end{tikzcd}$$

nodes transitions an exemplary path choice nodes chance nodes

Selection Function

The branching tree structure requires a **selection function**, that selects appropriate actions to execute from the various available options.

How should the selection function look like? What should be the right data-structures?

Necessity of BDI III

Characteristics 4 (best action dependent on environment-state and independent of internal system-state), 1 (environment-nondeterminism), and 5 (local sensing) imply that it is necessary that **there is some component of the system that can represent the information about the state of the world**.

$\leadsto$ Beliefs!

Necessity of BDI IV

Characteristics 3 (several parallel objectives) and 5 (local sensing) imply that it is necessary that **the system also has information about the objectives to be accomplished**.

$\leadsto$ Desires!

Necessity of BDI V

Idea: reconsider the choice of action at each step.

Dilemma: this is potentially too expensive and the chosen action might possibly be invalid when selected.

Assumption: it is possible to limit the frequency of reconsideration and achieve a balance between too much and not enough reconsideration. Remember characteristic 6 (rate of computations and actions is reasonable).

Implication: it is necessary to include a component of the system that represents the currently chosen course of action.

$\leadsto$ Intentions!

Basic Data-Structures (Practice)

- Set of beliefs: Usually stored in a belief-base.
  Example:
  - *I am a student of computer-science.*
  - *I am in my third semester.*
- Set of goals: Usually stored in a goal-base.
  Example:
  - *I want to graduate in computer science.*
- Set of plans: Recipes of how to reach the goals. Usually somehow structured, e.g. nested actions, and stored in a **plan-base**.

Basic Data-Structures (Practice) II

Example:

1. *Become a bachelor of science.*
   - *Attend some lectures.*
   - *Succeed in a lot of exams.*
   - *Earn a living.*
2. *Become a master of science.*
   - *Attend more lectures.*
   - *Succeed in even more exams.*
   - *Earn a living.*

Basic Data-Structures (Practice) III

Usually the mental attitudes are based on a *knowledge representation language*, e.g. Prolog.

- **Beliefs**: `studies(me,computer_science).` `semester(me,3).`
- **Goals**: `graduate(me,computer_science).`
- **Plan**: `[attend(info1),attend(l_algebra),...]`

Agent Control Loop v1

```
while true do
    observe the world;
    update the internal world model;
    deliberate about what intention to achieve
    next;
    use means-ends reasoning to get a plan for
    the intention;
    execute the plan;
end while
```

$\rightsquigarrow$ very high-level

We have to answer three questions

1. Deliberation: How to deliberate? That is carefully considering and weighing options.
2. Planning: Once committed to something, how to reach the goal?
3. Replanning: What if during execution of the plan, things are running out of control and the original plan fails?

Agent Control Loop v2

```
Set<Belief> beliefs = initBeliefBase();
while( true ) {
    Percept percept = getNextPercept();
    beliefs = beliefRevision(beliefs,percept);
    Set<Intention> intentions =
    deliberation(beliefs);
    Plan plan = generatePlan(beliefs,intentions);
    execute(plan);
}
```

What is the problem here?

The philosophy behind

- Intentions are the most important things.
- Beliefs and intentions generate desires.
- Desires can be **inconsistent** with each other.
- Intentions are **recomputed** based on the current intentions, desires and beliefs.
- Intentions should **persist**, normally.
- Beliefs are constantly updated and thus **generate** new desires.
- From time to time intentions need to be re-examined.

BDI-Agent Control Loop v3

```
Set<Belief> beliefs = initBeliefBase();
Set<Intention> intentions = initIntentionBase();
while( true ) {
    Percept percept = getNextPercept();
    beliefs = beliefRevision(beliefs,percept);
    Set<Desire> desires =
    findOptions(beliefs,intentions);
    intentions = filter(beliefs,desires,intentions);
    Plan plan = generatePlan(beliefs,intentions);
    execute(plan);
}
```

Observation

Deliberation has been split into two components:

1. Generate options (desires).
2. Filter the right intentions.

Intentions can be represented as a stacks (i.e. priorities are available).

Observation

An agent has commitments both to

- ends: the wishes to bring about, and
- means: the mechanism to achieve a certain state of affairs.

$\leadsto$ means-end reasoning.

What is wrong with our current control loop?

It is overcommitted to both means and ends. No way to replan if something goes wrong.

BDI-Agent Control Loop v4

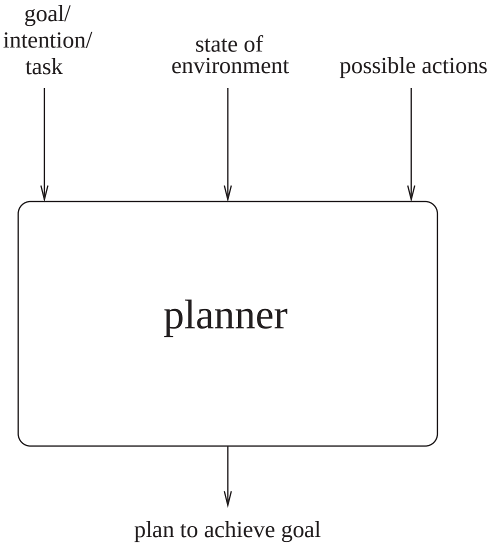
```
Set<Belief> beliefs = initBeliefBase();
Set<Intention> intentions = initIntentionBase();
while( true ) {
    Percept percept = getNextPercept();
    beliefs = beliefRevision(beliefs,percept);
    Set<Desire> desires = findOptions(beliefs,intentions);
    intentions = filter(beliefs,desires,intentions);
    Plan plan = generatePlan(beliefs,intentions);
    while( !plan.isEmpty() ) {
        Action head = plan.removeFirst();
        execute(head);
        percept = getNextPercept();
        beliefs = beliefRevision(beliefs,percept);
        if( !sound(plan,intentions,beliefs) ) {
            plan = generatePlan(beliefs,intentions);
        }
    }
}
```

What is a plan?

Plan

A plan π is a list of primitive actions. They lead, by applying them successively, from the initial state to the goal state.

What is a planner?



What is wrong with our control loop?

It is still overcommitted to intentions.

BDI-Agent Control Loop v5

```
Set<Belief> beliefs = initBeliefBase();
Set<Intention> intentions = initIntentionBase();
while( true ) {
    Percept percept = getNextPercept();
    beliefs = beliefRevision(beliefs,percept);
    Set<Desire> desires = findOptions(beliefs,intentions);
    intentions = filter(beliefs,desires,intentions);
    Plan plan = generatePlan(beliefs,intentions);
    while( !(plan.isEmpty() || succeeded(intentions,beliefs) ||
    impossible(intentions,beliefs) ) {
        Action head = plan.removeFirst();
        execute(head);
        percept = getNextPercept();
        beliefs = beliefRevision(beliefs,percept);
        if( !sound(plan,intentions,beliefs) ) {
            plan = generatePlan(beliefs,intentions);
        }
    }
}
```

What is wrong with our control loop?

It is still limited in the way the agent can reconsider its intentions.

BDI-Agent Control Loop v6

```
Set<Belief> beliefs = initBeliefBase();
Set<Intention> intentions = initIntentionBase();
while( true ) {
    Percept percept = getNextPercept();
    beliefs = beliefRevision(beliefs,percept);
    Set<Desire> desires = findOptions(beliefs,intentions);
    intentions = filter(beliefs,desires,intentions);
    Plan plan = generatePlan(beliefs,intentions);
    while( !(plan.isEmpty() || succeeded(intentions,beliefs) ||
    impossible(intentions,beliefs) ) {
        Action head = plan.removeFirst();
        execute(head);
        percept = getNextPercept();
        beliefs = beliefRevision(beliefs,percept);
        desires = findOptions(beliefs,intentions);
        intentions = filter(beliefs,desires,intentions);
        if( !sound(plan,intentions,beliefs) ) {
            plan = generatePlan(beliefs,intentions);
        }
    }
}
```

Problems

But reconsidering intentions is **costly**.

Pro-active vs. reactive

Extreme: *stubborn agents*, *unsure agents*.

What is better?

Depends on the environment.

Let γ the **rate of world change**.

1. γ small: stubbornness pays off.
2. γ big: unsureness pays off.

What to do?
Meta-level control

BDI-Agent Control Loop v7

```
Set<Belief> beliefs = initBeliefBase();
Set<Intention> intentions = initIntentionBase();
while( true ) {
    Percept percept = getNextPercept();
    beliefs = beliefRevision(beliefs,percept);
    Set<Desire> desires = findOptions(beliefs,intentions);
    intentions = filter(beliefs,desires,intentions);
    Plan plan = generatePlan(beliefs,intentions);
    while( !(plan.isEmpty() || succeeded(intentions,beliefs) ||
    impossible(intentions,beliefs) ) {
        Action head = plan.removeFirst();
        execute(head);
        percept = getNextPercept();
        beliefs = beliefRevision(beliefs,percept);
        if( reconsider(I,B) ) {
            desires = findOptions(beliefs,intentions);
            intentions = filter(beliefs,desires,intentions);
        }
        if( !sound(plan,intentions,beliefs) ) {
            plan = generatePlan(beliefs,intentions);
        }
    }
}
```

3. Searching

Content of this chapter:

Searching: Search Algorithms are perhaps the most basic notion of AI. Almost any problem can be formulated as a search problem.

3.1 Problem Formulation

We distinguish four types:

1. **1-state-problems:** Actions are completely described. Complete information through sensors to determine the actual state.
2. **Multiple-state-problems:** Actions are completely described, but the initial state is not certain.
3. **Contingency-problems:** Sometimes the result is not a fixed sequence, so the complete tree must be considered.
4. **Exploration-problems:** Not even the effect of each action is known. You have to *search in the world* instead of **searching in the abstract model**.

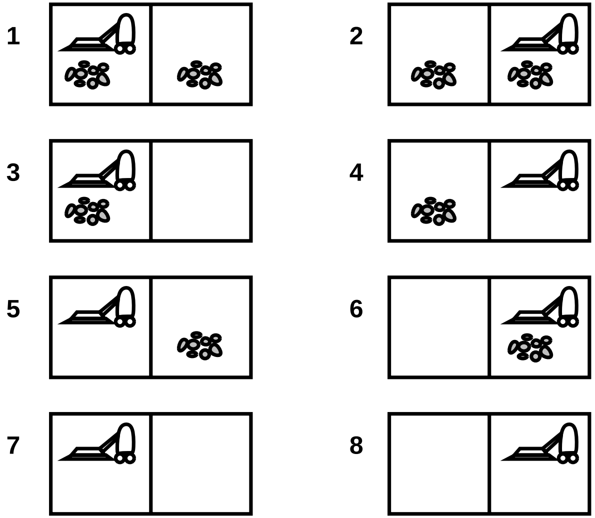


Table : The vacuum world.

Definition 3.1 (1-state-problem)

A 1-state-problem consists of:

- a set of **states** (incl. the *initial state*)
- a set of n **actions** (*operators*), which – applied to a state – leads to an other state:

  $$\text{Operator}_i\text{: States} \to \text{States}, \;\; i = 1, \ldots, n$$

  We use a function **Successor-Fn**: $\mathbf{S} \to 2^{\mathbf{A} \times \mathbf{S}}$. It assigns each state a set of pairs $\langle a, s \rangle$: the set of possible actions and the state it leads to.
- a set of **goal states** or a *goal test*, which – applied on a state – determines if it is a goal-state or not.
- a **cost function** g, which assesses every path in the state space (set of reachable states) and is usually additive.

Definition 3.2 (State Space)

The state space of a problem is the set of all reachable states (from the initial state). It forms a directed graph with the states as nodes and the arcs the actions leading from one state to another.

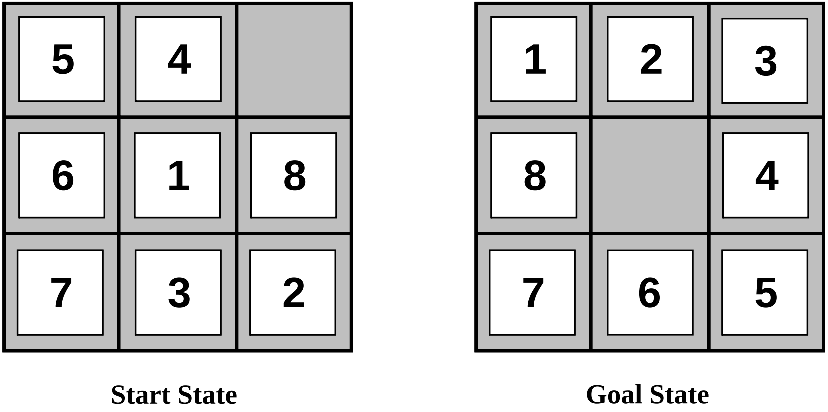


Table : The 8-puzzle.

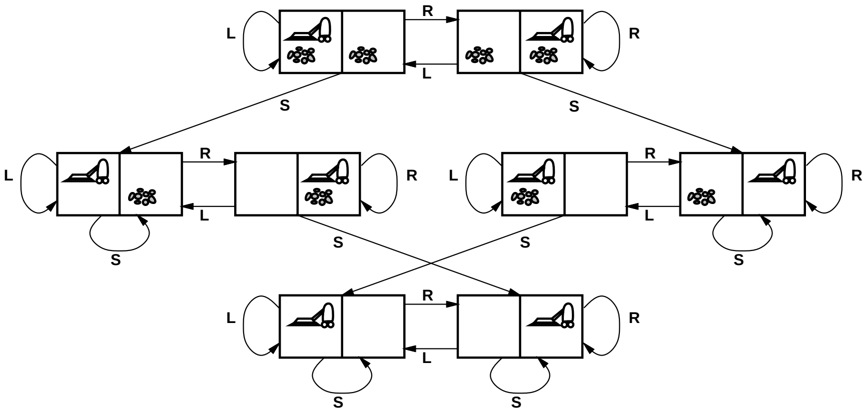


Table : State Space for Vacuum world.

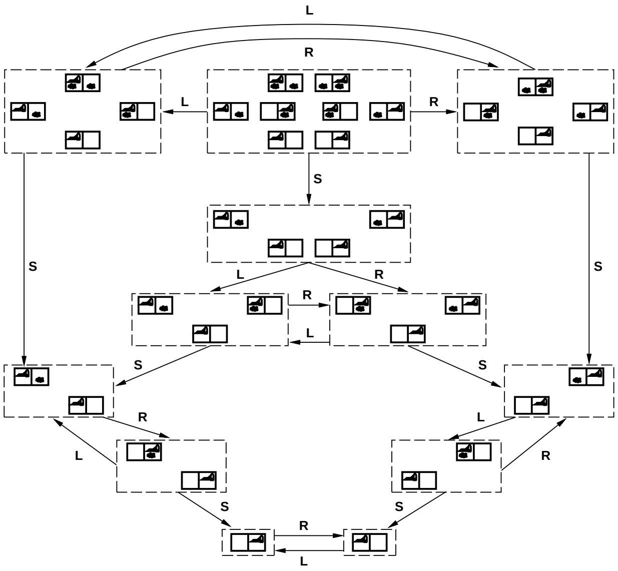
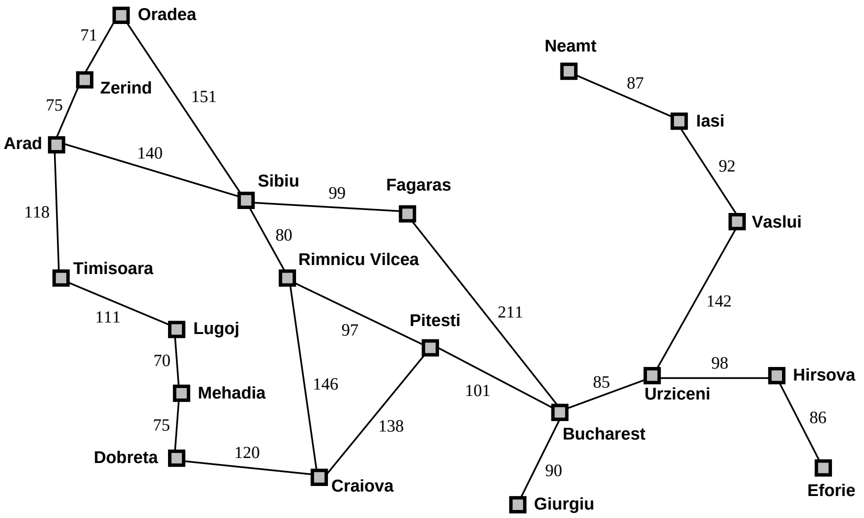


Table : Belief Space for Vacuum world without sensors.

3.2 Uninformed search

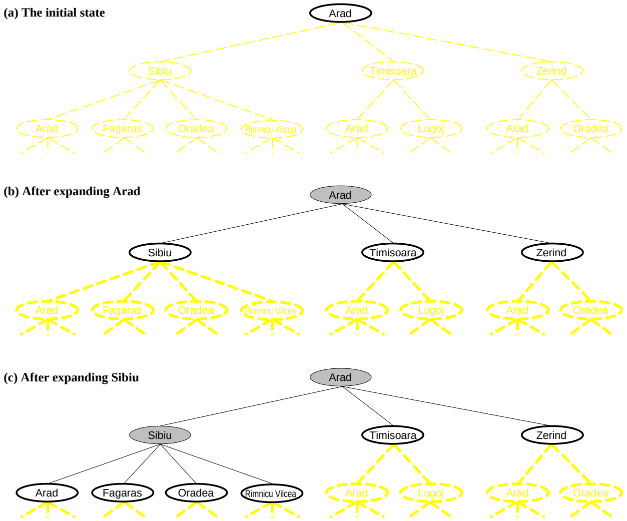


Choose, test, expand | RBFS

Table : Map of Romania

Principle: Choose, test, expand.

Search-tree



Map of Romania

Tree Search

```
function TREE-SEARCH( $problem$, $strategy$ ) returns a solution, or failure
  initialize the search tree using the initial state of $problem$
  loop do
      if there are no candidates for expansion then return failure
      choose a leaf node for expansion according to $strategy$
      if the node contains a goal state then return the corresponding solution
      else expand the node and add the resulting nodes to the search tree
```

Table : Tree Search.

Important:

State-space versus **search-tree**:

The search-tree is countably infinite in contrast to the finite state-space.

- a node is **a bookkeeping data structure** with respect to the problem instance and with respect to an algorithm;
- a **state** is a **snapshot** of the world.

Definition 3.3 (Datatype Node)

The datatype node is defined by state ($\in \mathbf{S}$), parent (a node), action (also called operator) which **generated** this node, path-costs (the costs to reach the node) and depth (distance from the root).

▸ Tree-Search

Important:

The recursive dependency between node and parent is important. If the depth is left out then a special node $root$ has to be introduced.

Conversely the $root$ can be defined by the depth: $root$ is its own parent with depth 0.

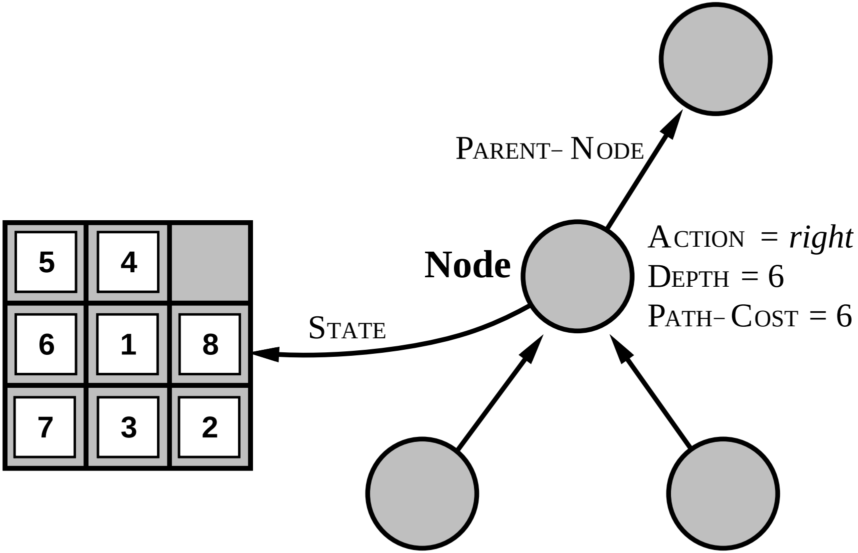


Figure : Illustration of a node in the 8-puzzle.

Instantiating Tree-SEARCH

Design-decision: Queue

Tree-SEARCH generates nodes. Among them are those that **are-to-be-expanded** later on. Rather than describing them as a set, we use a queue instead.
The fringe is the set of generated nodes that have not yet been expanded.

Here are a few functions operating on queues:

Make-Queue(Elements)	**Remove-First(Queue)**
Empty?(Queue)	**Insert(Element,Queue)**
First(Queue)	**Insert-All(Elements,Queue)**

```
function TREE-SEARCH( problem, fringe) returns a solution, or failure

  fringe ← INSERT(MAKE-NODE(INITIAL-STATE[problem]), fringe)
  loop do
      if EMPTY?(fringe) then return failure
      node ← REMOVE-FIRST(fringe)
      if GOAL-TEST[problem] applied to STATE[node] succeeds
          then return SOLUTION(node)
      fringe ← INSERT-ALL(EXPAND(node, problem), fringe)
```

```
function EXPAND( node, problem) returns a set of nodes

  successors ← the empty set
  for each ⟨action, result⟩ in SUCCESSOR-FN[problem](STATE[node]) do
      s ← a new NODE
      STATE[s] ← result
      PARENT-NODE[s] ← node
      ACTION[s] ← action
      PATH-COST[s] ← PATH-COST[node] + STEP-COST(node, action, s)
      DEPTH[s] ← DEPTH[node] + 1
      add s to successors
  return successors
```

▸ Datatype Node

▸ Graph-Search

Table : Tree-Search

Question:

Which are interesting requirements of search-strategies?

- **completeness**
- **time-complexity**
- **space complexity**
- **optimality (w.r.t. path-costs)**

We distinguish:

Uninformed vs. *informed* search.

Definition 3.4 (Completeness, optimality)

A search strategy is called

- complete, if it finds a solution, provided there exists one at all.
- optimal, if whenever it produces an output, this output is an optimal solution, i.e. one with the smallest path costs among all solutions.

Is any optimal strategy also complete? Vice versa?

Breadth-first search: *“nodes with the smallest depth are expanded first”*,

Make-Queue : add new nodes at the end: FIFO

Complete? Yes.
Optimal? Yes, if all operators are equally expensive.

Constant branching-factor b: for a solution at depth d we have generated[1] (in the worst case)

$$b + b^2 + \ldots + b^d + (b^{d+1} - b)\text{-many nodes.}$$

Space complexity = Time Complexity

[1] Note this is different from “expanded”.

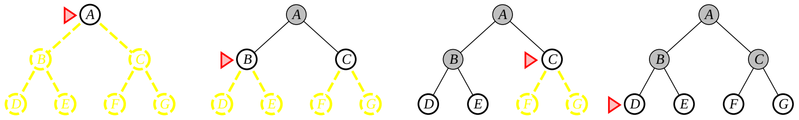


Figure : Illustration of Breadth-First Search.

Depth	Nodes	Time	Memory
0	1	1 millisecond	100 bytes
2	111	.1 seconds	11 kilobytes
4	11,111	11 seconds	1 megabyte
6	10^6	18 minutes	111 megabytes
8	10^8	31 hours	11 gigabytes
10	10^{10}	128 days	1 terabyte
12	10^{12}	35 years	111 terabytes
14	10^{14}	3500 years	11,111 terabytes

Table : Time versus Memory.

Uniform-Cost-Search: *"Nodes n with lowest path-costs $g(n)$ are expanded first"*

Make-Queue : new nodes are compared to those in the queue according to their path costs and are inserted accordingly

Complete? Yes, if each operator increases the path-costs by a minimum of $\delta > 0$ (see below).

Worst case space/time complexity: $O(b^{1+\lfloor\frac{C^*}{\delta}\rfloor})$, where C^* is the cost of the optimal solution and each action costs at least δ

If all operators have the same costs (in particular if $g(n) = \text{depth}(n)$ holds):

Uniform-cost search

Uniform-cost search=**Breadth-first search**.

Theorem 3.5 (Optimality of Uniform-cost search)

If $\exists \delta > 0 : \ g(succ(n)) \geq g(n) + \delta$ *then: Uniform-cost search is* optimal.

How to avoid repeated states?

- Can we avoid infinite trees by checking for loops?
- Compare number of states with number of paths in the search tree.

State space vs. Search tree

Rectangular grid: How many different states are reachable within a path of length d?

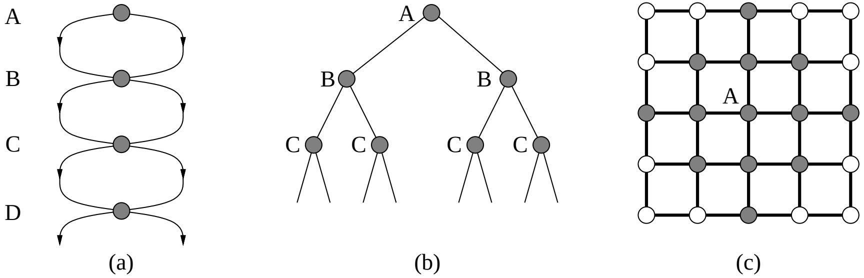


Table : State space versus Search tree: exponential blow-up.

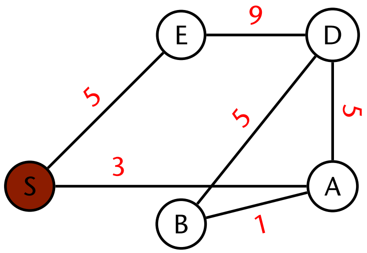
Graph-Search= Tree-Search+ Loop-checking

▸ Tree-Search

```
function GRAPH-SEARCH($problem$, $fringe$) returns a solution, or failure

    $closed$ ← an empty set
    $fringe$ ← INSERT(MAKE-NODE(INITIAL-STATE[$problem$]), $fringe$)
    loop do
        if EMPTY?($fringe$) then return failure
        $node$ ← REMOVE-FIRST($fringe$)
        if GOAL-TEST[$problem$](STATE[$node$]) then return SOLUTION($node$)
        if STATE[$node$] is not in $closed$ then
            add STATE[$node$] to $closed$
            $fringe$ ← INSERT-ALL(EXPAND($node$, $problem$), $fringe$)
```

Dijkstra's Algorithm



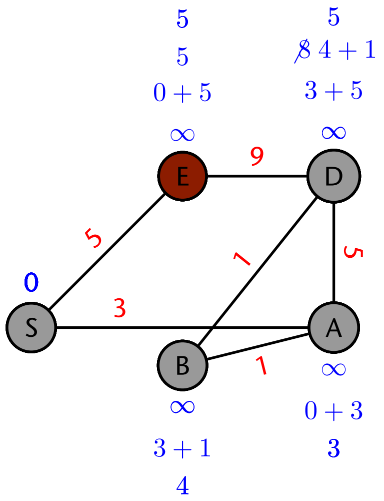
Given

Graph, Source node in the graph.

Problem

Find the path with lowest cost between source and all other nodes.

Concept



1. Initial distance value
2. Mark all nodes as unvisited
   Set initial node as current
3. Consider all unvisited neighbors and calculate their distance
4. After considering all neighbors of the current node, mark it as visited.
5. All nodes visited? $\rightsquigarrow$ finish. Otherwise:
   current node := unvisited node with the smallest distance
6. Step 3.

Complexity

Worst-Case Performance:

- Dijkstra's original algorithm does not use a min-priority queue: $O(|V|^2)$.
- With a min-priority queue implemented by a Fibonacci heap: $O(|E| + |V| log|V|)$.

4. MASSim & The Multi-Agent Programming Contest

Content of this Chapter:

This chapter is about the programming part of the lecture. We

- introduce the Multi-Agent Contest 2011 scenario *Agents on Mars*;
- describe the *structure of the agents*: properties, roles, actions, percepts;
- motivate how to *program* and run agents.

4.1 Introduction

Multi-Agent Programming Contest 2011

`http://www.multiagentcontest.org/`

- annual competition, started in 2005
- Aims to stimulate research in the area of MAS development and programming by:
  1. identifying key problems,
  2. collecting suitable benchmarks, and
  3. gathering test cases which require and enforce coordinated action.
- participants include researchers from around the world and developers of the most well known multi-agent programming platforms.

What is MASSim?

- a platform for testing and comparing MAS
- discrete, step-based simulations of environments
- teams of agents compete against each other
- supports different pluggable scenarios
- client-server architecture
- platform used for the Multi Agent Programming Contest

4.2 The Scenario

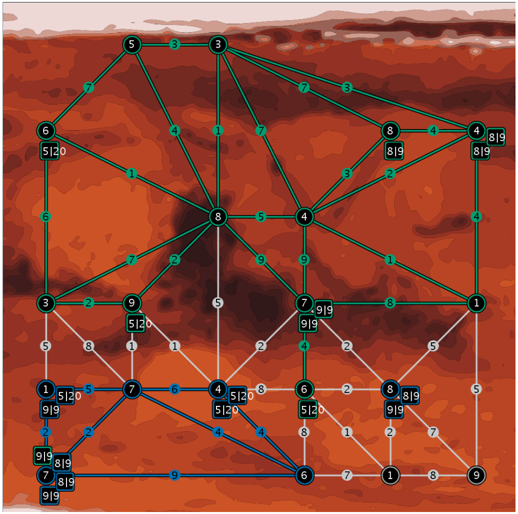
The 2011 Scenario: Mars

In the year 2033 mankind finally populates Mars. While in the beginning the settlers received food and water from transport ships sent from earth shortly afterwards —because of the outer space pirates— sending these ships became too dangerous and expensive. Also, there were rumors going around that somebody actually found water on Mars below the surface. Soon the settlers started to develop autonomous intelligent agents, so-called All Terrain Planetary Vehicles (ATPV), to search for water wells. The World Emperor —enervated by the pirates — decided to strengthen the search for water wells by paying money for certain achievements.

The Mars Scenario - The tasks of the agents

- find the best water wells,
- occupy the best zones of Mars,
- sabotage the rivals,
- defend from sabotages, and
- earn money through different *achievements*, such as:
  - inspect certain percentages of the maps,
  - build zones worth at least some value,
  - successfully attack a number of opponent agents,
  - etc.

The Mars Map



The Mars Map

- the map is represented by a graph
- numbers on each edge indicate the cost of traversing that edge
- numbers on each node is the score that the node will earn when part of a zone
- the visualization shows the zones conquered
- agents must find out characteristics of the map by exploring and executing specific actions

Conquering zones

To dominate parts of the map, agents must stand on specific nodes of the map.

- The algorithm for determining map domination depends on the locations of all the agents.
- The objective is to *isolate* parts of the map from the opponent agents!
- Agents should choose zones strategically to maximize the score.
- *Coordination is required!*: an agent can not build a zone on its own; at least two agents are needed.

Conquering zones - The algorithm

Consist of three steps:

1. A node with agents belongs to the team that has the majority (at least half) of the agents in that node.
2. Nodes that are neighbors of occupied nodes belong to the team that controls most of those neighbors node.
3. The previous two step may draw a frontier that *isolates* a part of the graph from all the agents of the other teams: if that is case, the team also dominates nodes inside that frontier.

Building zones - Example

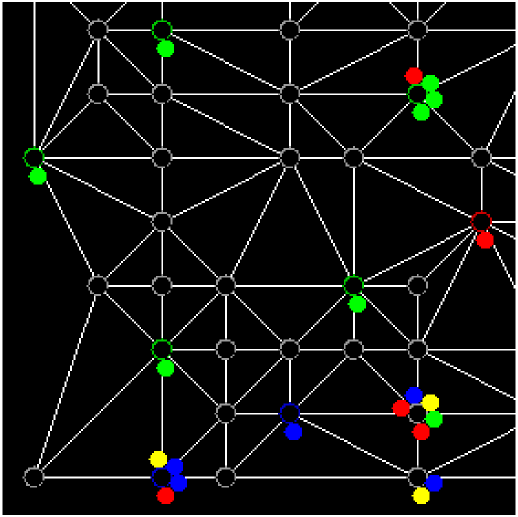


Figure : Step 1.

Building zones - Example (2)

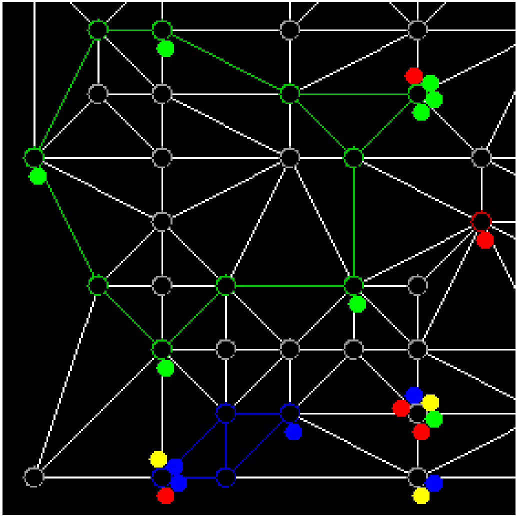


Figure : Step 2.

Building zones - Example (3)

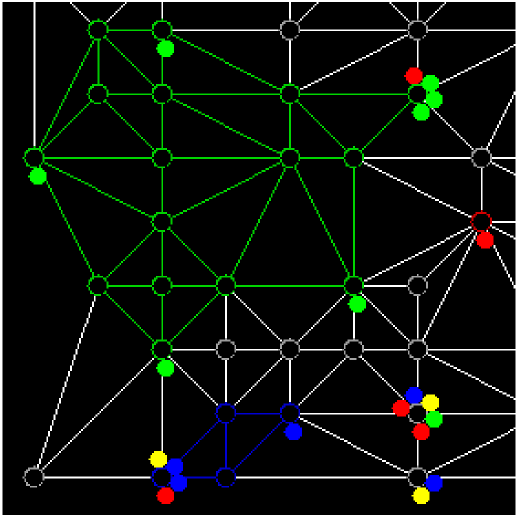


Figure : Step 3.

Building zones - Example (4)

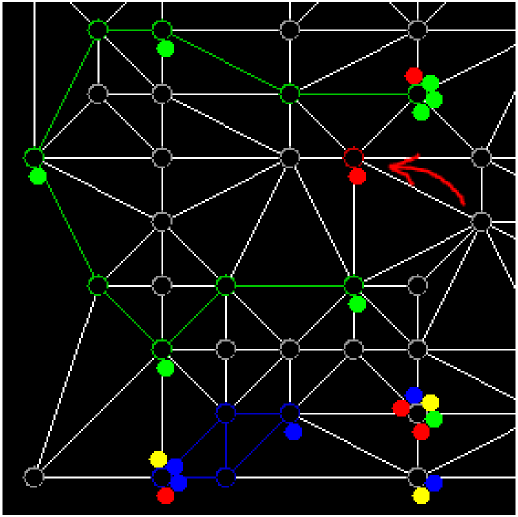


Figure : Breaking a frontier.

Attributes of an agent

Agents have the following numerical attributes:

- energy: consumed by performing actions.
- health: decreased when attacked.
- strength: used when attacking.
- visibility range: how far the the agents can perceive.

These attributes can vary during the simulation.

Available actions

The following actions are available to agents, depending on the agent's role:

- skip: no action is performed.
- recharge: part of the energy is restored.
- goto: move to a neighbor node.
- attack: decrease health of an opponent agent.
- parry: defend oneself against possible attacks.
- repair: Restore the health of another teammate.

Available actions (2)

- probe: Find out the value of the current node.
- survey: Find out costs of edges connected to current node.
- inspect: Find out current attributes of other agents in the range.
- buy: Exchange achievement points for improvements in one attribute’s (maximum) value.

Roles

The agents are heterogeneous!

Each agent assumes one of these roles:

- Explorer
- Repairer
- Saboteur
- Sentinel
- Inspector

There are two agents of each kind in every team.

The Explorer

It can: skip, goto, probe, survey, buy, recharge.

Attributes:

- Energy (maximum): 12
- Health (maximum): 4
- Strength: 0
- Visibility range: 2

The Repairer

It can: skip, goto, parry, survey, buy, repair, recharge.

Attributes:

- Energy (maximum): 8
- Health (maximum): 6
- Strength: 0
- Visibility range: 1

Roles: The Saboteur

It can: skip, goto, parry, attack, survey, buy, recharge.

Attributes:

- Energy (maximum): 7
- Health (maximum): 3
- Strength: 4
- Visibility range: 1

Roles: The Sentinel

It can: skip, goto, parry, survey, buy, recharge.

Attributes:

- Energy (maximum): 10
- Health (maximum): 1
- Strength: 0
- Visibility range: 3

Roles: The Inspector

It can: skip, goto, inspect, survey, buy recharge.

Attributes:

- Energy (maximum): 8
- Health (maximum): 6
- Strength: 0
- Visibility range: 1

Disabled agents

When an agent's health reaches 0, the agent is disabled:

- it does not count for zones building.
- only goto, repair, skip, and recharge can be executed.
- the recharging rate is lower.

Disabled agents don't count for zones! Disabling an opponent agent may help in building your own zones or destroying the opponents'.

Achievements

When a team reaches a milestone, its money (a.k.a. achievement points) is increased.

Possible achievements are:

- having zones with fixed values, e.g. 10, 20, etc.
- fixed numbers of probed vertices, e.g. 5, 10, etc.
- fixed numbers of surveyed edges, e.g. 10, 20, etc.
- fixed numbers of inspected vehicles, e.g. 5, 10, etc.
- fixed numbers of successful attacks, e.g. 5, 10, etc. or
- fixed numbers of successful parries, e.g. 5, 10. etc.

Perceptions

In every simulation step, agents perceive:

- state of the simulation: the current step,
- state of the team: the current scores and money,
- state of the agent: its internals as described previously,
- visible vertices: identifier and dominating team,
- visible edges: its vertices’ identifiers,
- visible agents: its identifier, vertex, team.

Perceptions (2)

Some elements are only perceived after an specific action. These elements are:

- probed agents: its identifier and its value,
- surveyed edges: its vertices' identifiers and weight, and
- inspected agents: its identifier, vertex, team and internals.

Score

A step score is calculated on every step, summing up the zones' scores and the current money.

The final score for the team is the sum of these step scores:

$$\mathtt{score} = \sum_{s=1}^{\mathtt{steps}} (\mathtt{zones}_s + \mathtt{money}_s)$$

Only probed nodes contribute fully to the zone's score! (otherwise just 1).

4.3 Programming and running the agents

Starting the MASSim Server

Download and uncompress the MAPC 2011 Package from
`http://www.multiagentcontest.org/`

You can start the MASSim server by invoking this:

```
$ ./startServer.sh
```

You will then be prompted to choose a simulation.

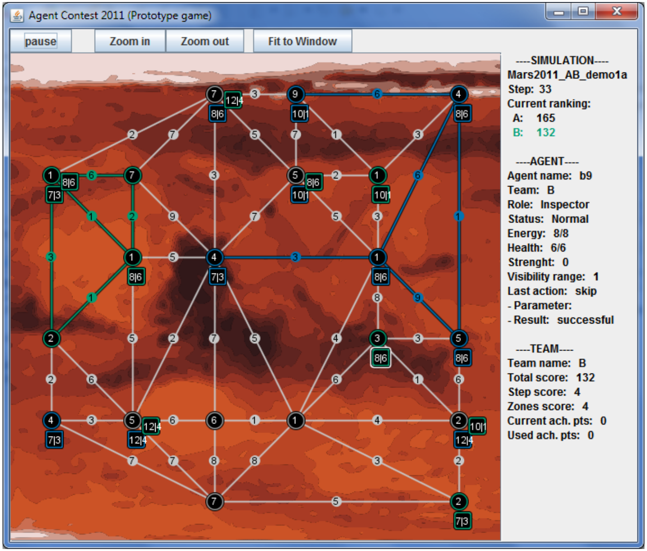
The monitor

You can start the monitor to observe the simulation:

```
$ ./startMarsMonitor.sh
```

Click on nodes or agent to see more information about the element.

Bear in mind that the monitor shows more information than what agents perceive!



----SIMULATION----
Mars2011_AB_demo1a
Step: 33
Current ranking:
A: 165
B: 132

----AGENT----
Agent name: b9
Team: B
Role: Inspector
Status: Normal
Energy: 8/8
Health: 6/6
Strenght: 0
Visibility range: 1
Last action: skip
- Parameter:
- Result: successful

----TEAM----
Team name: B
Total score: 132
Step score: 4
Zones score: 4
Current ach. pts: 0
Used ach. pts: 0

Figure : The monitor application

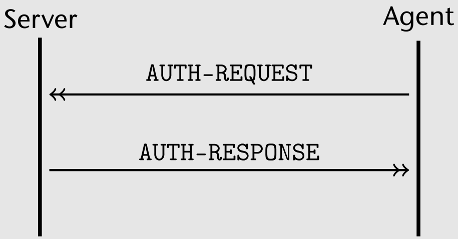
Connections to the server

Agents run independently from the server. They communicate with the server by exchanging XML messages via a socket connection.

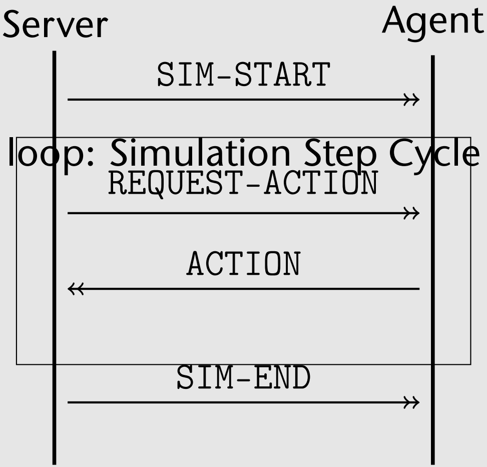
The connection is supposed to remain established (or resumed if lost) during the duration of a tournament, which consists of three phases:

1. the initial phase,
2. the simulation phase, and
3. the final phase.

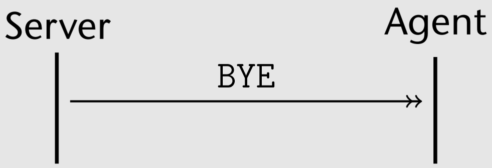
The initial phase



The simulation-phase



Final phase



Simulation state transition

During the simulation step cycle, the state transition is as follows:

1. collect all actions from the agents,
2. let each action fail with a specific probability,
3. execute all remaining attack and parry actions,
4. determine disabled agents,
5. execute all remaining actions,
6. prepare percepts,
7. deliver the percepts.

The environment interface

To facilitate managing the connection to the server, our agents make use of EISMASSim.

- EISMASSim is based on EIS, which is a proposed standard for agent-environment interaction.
- It maps the communication between the MASSim-server and agents, that is sending and receiving XML-messages, to Java-method-calls and call-backs.
- It automatically establishes and maintains connections to a specified MASSim-server.

Running the dummy agents

In the software package we have included a single agent-configuration. It sets up two teams A and B. Each team has 10 agents.

In order to run the dummy agents, navigate to the `javaagents/scripts` directory and execute

```
    $ ./startAgents.sh
```

You will then be asked to select a configuration.

Creating your own agents

In order to create and use your own agents you are required to perform these steps:

1. create a new agent-class that inherits from `massim.javaagents.Agent`,
2. implement a constructor and a couple of required methods,
3. incorporate your new agent-class into the `javaagentsconfig.xml` and, if necessary, adapt the `eismassimconfig.xml`-file,
4. make sure that your new agent-class is in the class-path, and
5. execute.

Creating your own agents 2

The abstract agent class already implements some useful data structures and methods for implementing BDI agents, including those for storing goals and beliefs.

The `step`-method is automatically called by the interpreter that executes all agents. It is supposed to return an action, which will then be executed automatically. The `step`-method is the place where you are supposed to add your agent's intelligence.

Refer to `javaagents.pdf` and `eismassim.pdf`, included with the documentation of the MASSim package, to see the full listings of available methods, percepts and actions.