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Lecture
“Intelligent Systems“

Chapter 11: Reinforcement Learning

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Agenda

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Content

- Motivation
- Reinforcement learning
- Extended Classifier System
- Strength vs. accuracy
- Algorithmic structure of XCS
- Credit assignment
- Real-world applicability
- XCS-O/C
- Example application
- Variants
- Conclusion and further readings

Goals

Students should be able to:

- Explain what reinforcement learning is and why it is needed in organic systems.
- Compare basic concepts such as supervised vs. reinforcement learning or exploration vs. exploitation.
- Outline an XCS and explain the main loop with all components.
- Discuss the necessary modifications to XCS for OC.

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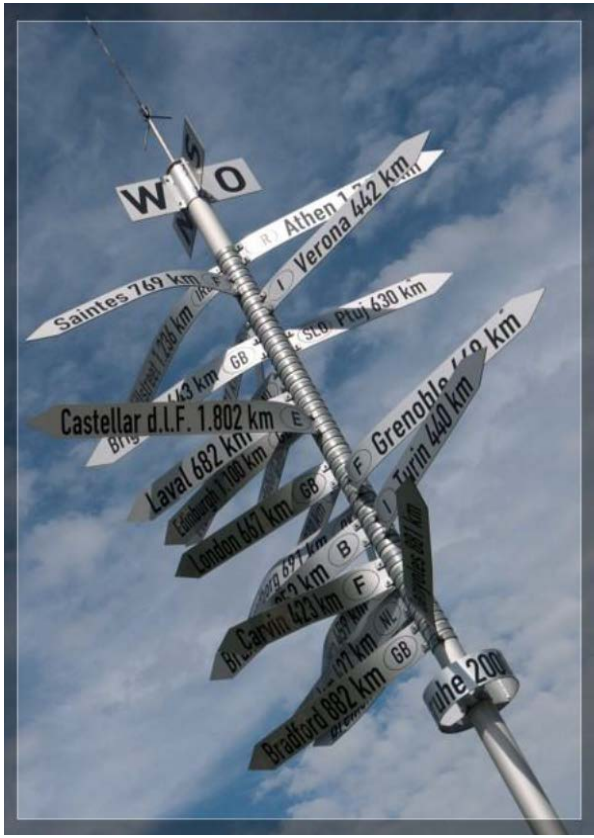

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- Machine learning techniques seem to be a promising approach for continuous self-improvement in intelligent systems.
  → How can computers be programmed so that problem-solving capabilities are built up by specifying "what is to be done" rather than "how to do it"? (Holland, 1975).
- Major issues:
  - How can the system react to unforeseen situations?
  - How can the system automatically improve its performance (if possible) at runtime?
  - How can knowledge (and expected behaviour) be encoded in a human-comprehensible manner?
  - Overall: flexible and autonomous reaction to changes in the environments and/or the system itself are desirable.

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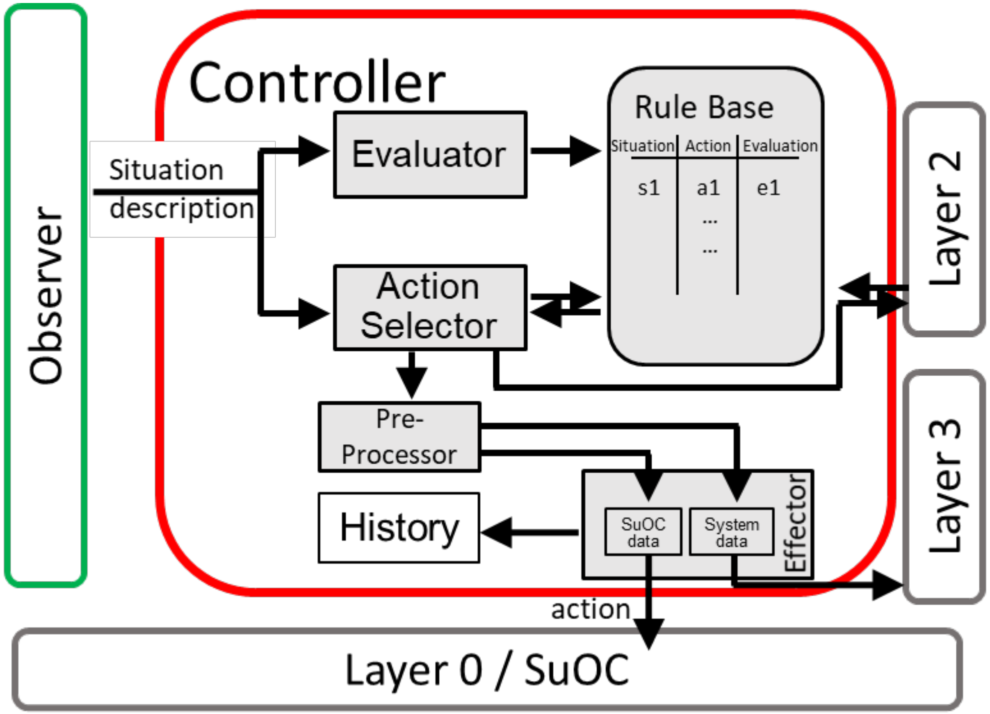
Observer/Controller

- Controller has to learn from feedback.
- Basic concept: rule-based system
- Learning is done by „book-keeping“ attributes, i.e. evaluation parameters.
- These are modified depending on the observed success.



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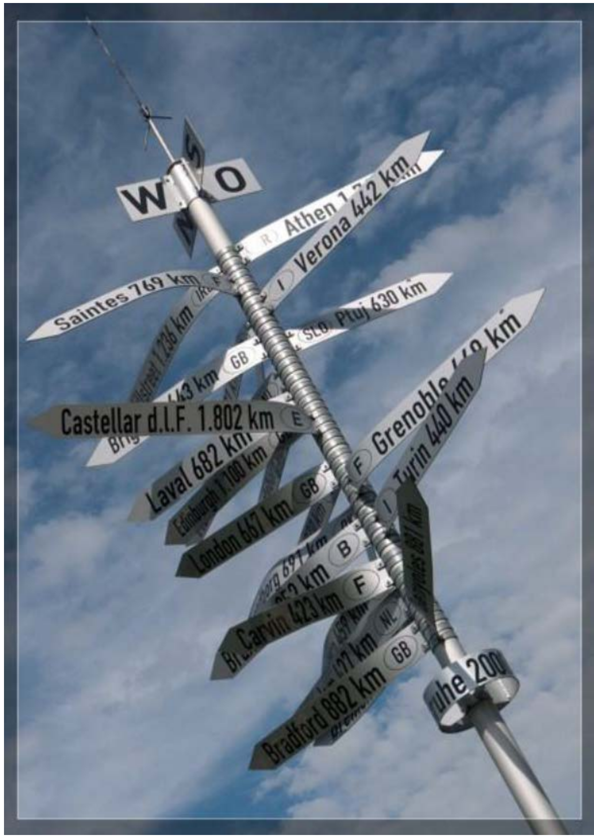


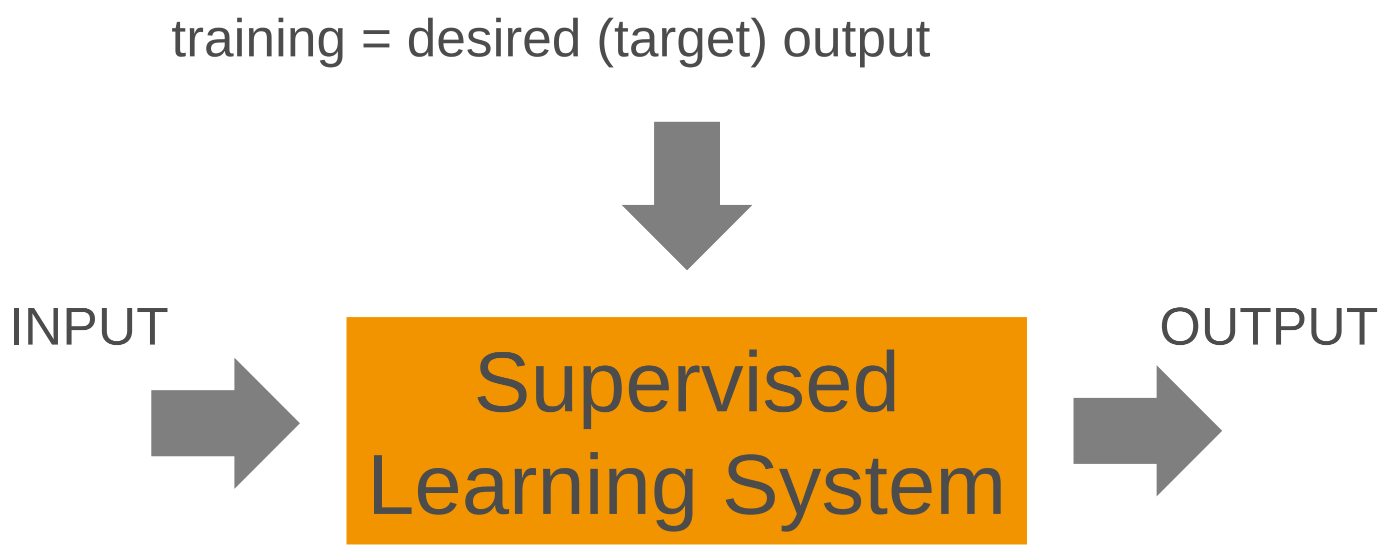
A common definition for "**Machine Learning**" (by Mitchell):

A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E.

→ *Increase the system performance by taking experiences with the same problem instance into account!*

- What is Reinforcement Learning?
  - German: “Bestärkendes Lernen“
  - Learning from interaction
  - Goal-oriented learning
  - Learning **by/from/during** interaction with an external environment
  - Learning “what to do“ (how to map situations to actions) to maximise a numeric reward

Supervised Learning



error = (target output – actual system output)

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Reinforcement Learning

training information = evaluation (“rewards” / “penalties”)

INPUT
(Situations)

Reinforcement Learning System

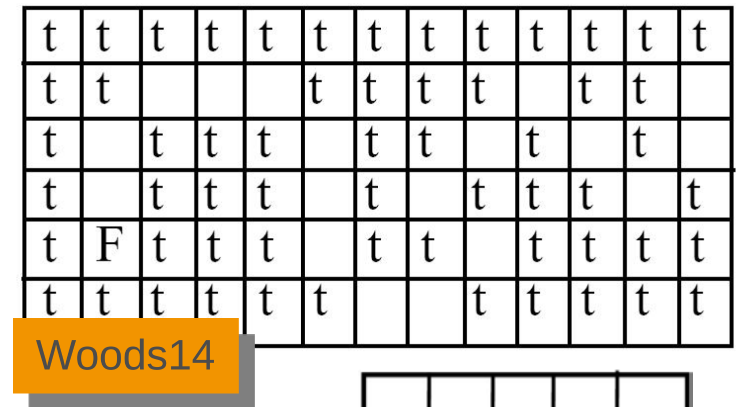
OUTPUT
(Actions)

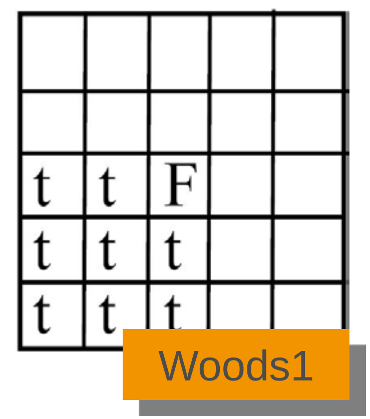
Goal: achieve as much reward as possible!

- Act “successfully“ in the environment
- Implication: maximise the sequence of rewards R_t

Example: 'Woods' scenario / Maze

- Example of an Animat problem
- Basis: rectangular toroidal regular (n x m)-grid
- Each grid cell may contain a tree (t), food (F), or it may be empty.
- Food and trees fixed per instance
- Animat/agent/robot is initially randomly placed on an empty cell.
- Walks around, looking for food
- In each step, the agent can go to one
  of the eight neighbouring cells
  (empty and food cells only).



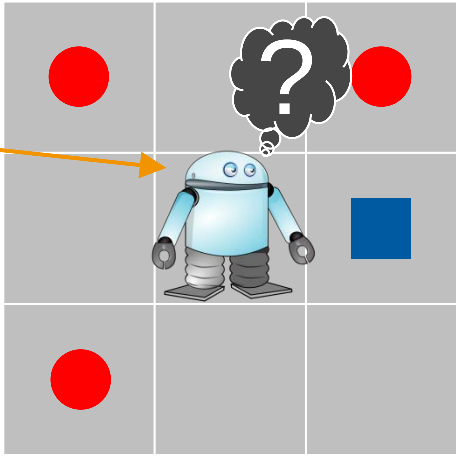


Woods1: optimal average number of steps to reach food: 1.7 steps (Bull & Hurst, "ZCS redux")

Example: ‘Woods’ and the underlying problem

- Question: Can we build an agent that can efficiently find food “in the Woods” without global knowledge?
- One idea to build such an agent:
  - Suppose the agent can “see” the eight surrounding cells.
  - Based on this perception, it has to decide where to go next.
  - Reward is paid once the food is found.

Agent
- Observation: 8 cells
- Status

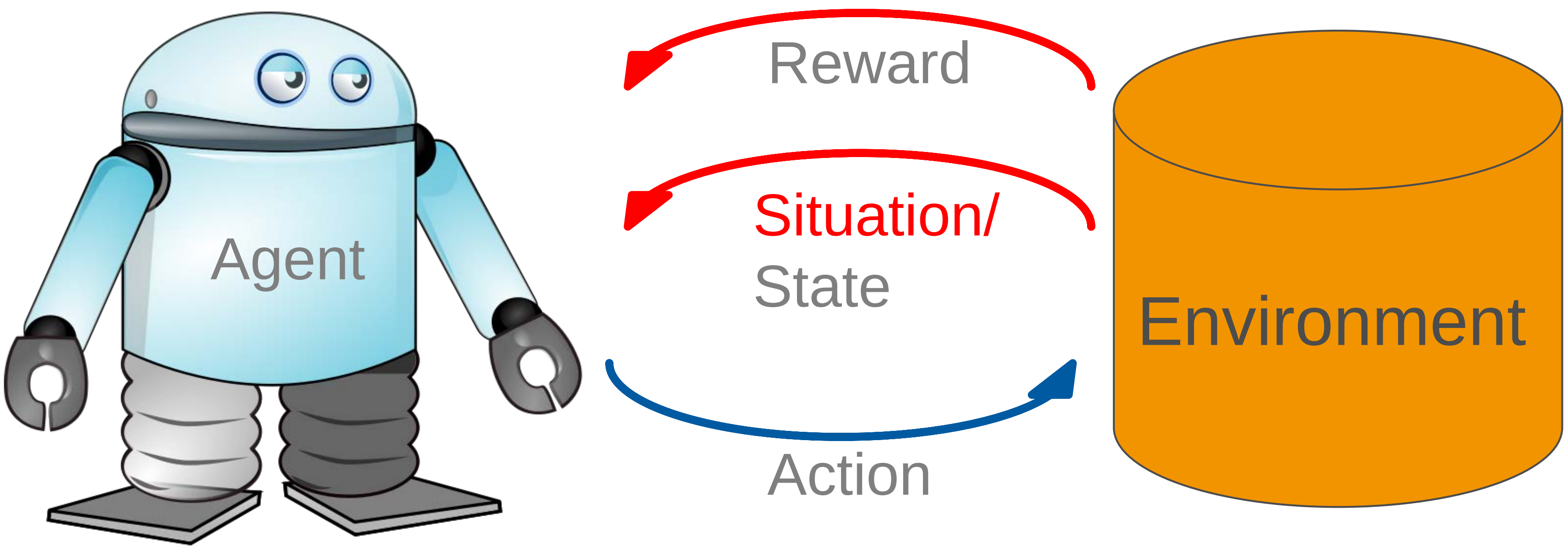


Obstacle

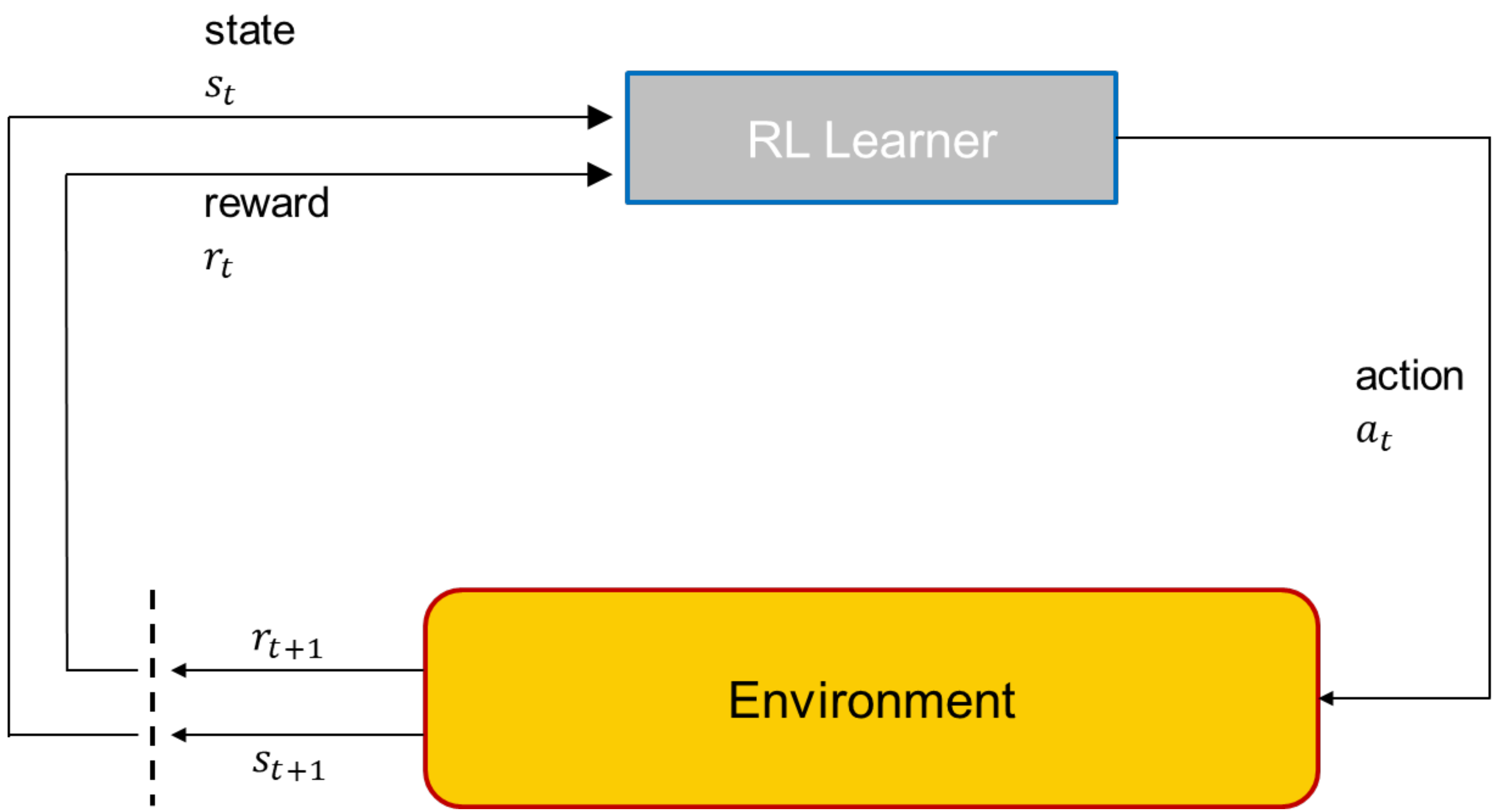
Previous cell

Where to go?

- The complete agent
  - Chronologically situated
  - Constant learning and planning
  - Affects the environment
  - Environment is stochastic and uncertain



Reinforcement Learning model



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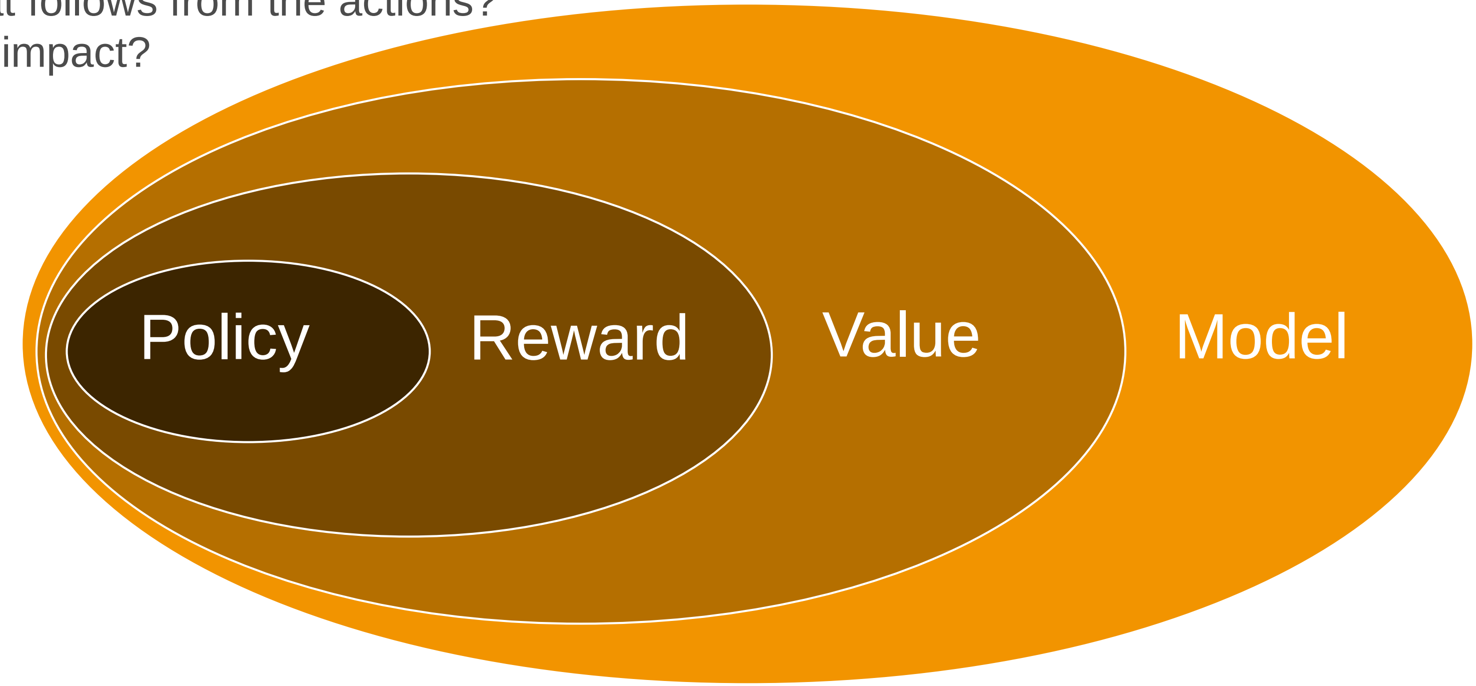
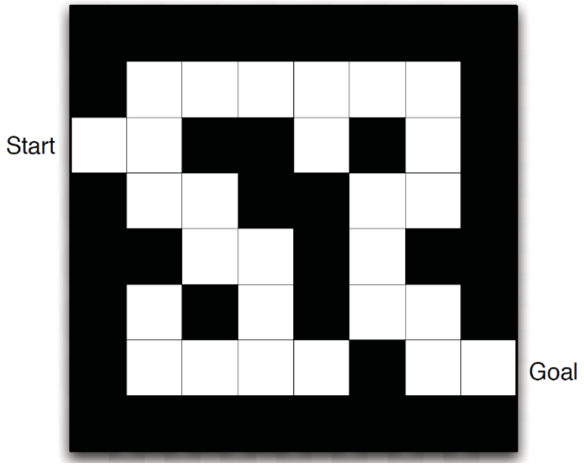
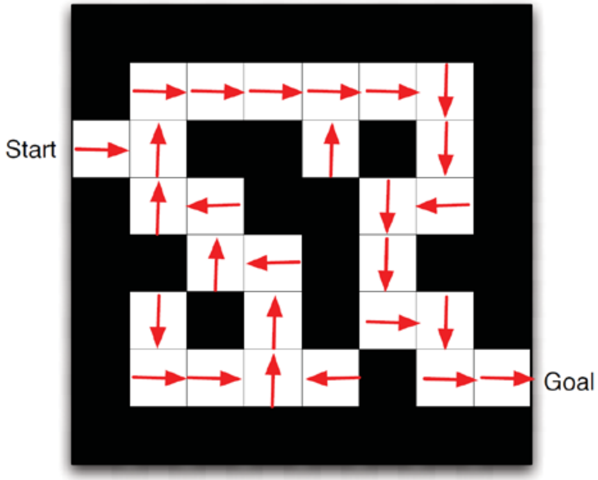
Elements

- Policy: What to do in a particular situation?
- Reward: What is good or bad behaviour (experience)?
- Value: What is good action due to the expected reward?
- Model: What follows from the actions?
  What is the impact?







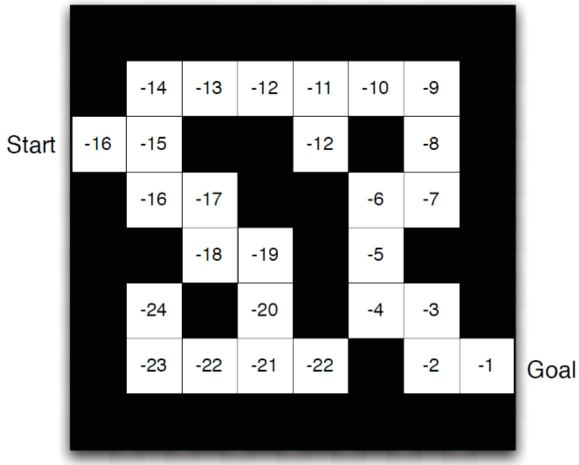
MAZE example

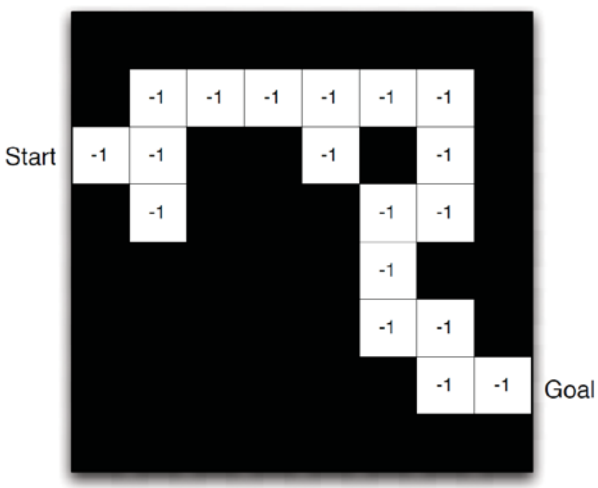
- Rewards: -1 per time step
- Actions: N, E, S, W (north, east, south, west)
- States: Agent‘s location

Policy

- Arrows represent policies
- One policy $\pi(s)$ for each state s

Elements of Reinforcement Learning (3)





Value function:

- Numbers represent value $v(s)$ of each state s
- One policy $\pi(s)$ for each state s

Model

- Grid layout represents a transition model
- Numbers represent immediate reward from each state s (same for all a)
- Agent may have an internal model of the environment
- Rewards: How much reward from each state?

Exploration vs. exploitation

Exploration:
A process of visiting entirely new regions of a search space.

vs.

Exploitation:
A process of visiting regions of a search space based on previously visited points (neighbourhood).

To be successful, a search algorithm needs to find a good balance between exploration and exploitation.

- Exploration is important in the early stages:
  - seek good patterns
  - spread out through the search space
  - avoid local optima
- Exploitation is important in later stages:
  - exploit good patterns
  - focus on good areas of the search space
  - refine to global optimum

Exploration vs. exploitation (2)

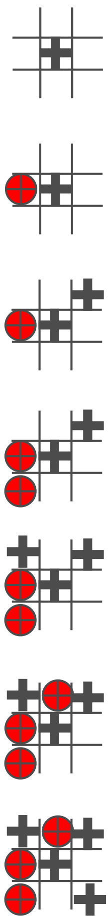
The Exploration/Exploitation Problem: Formalisation

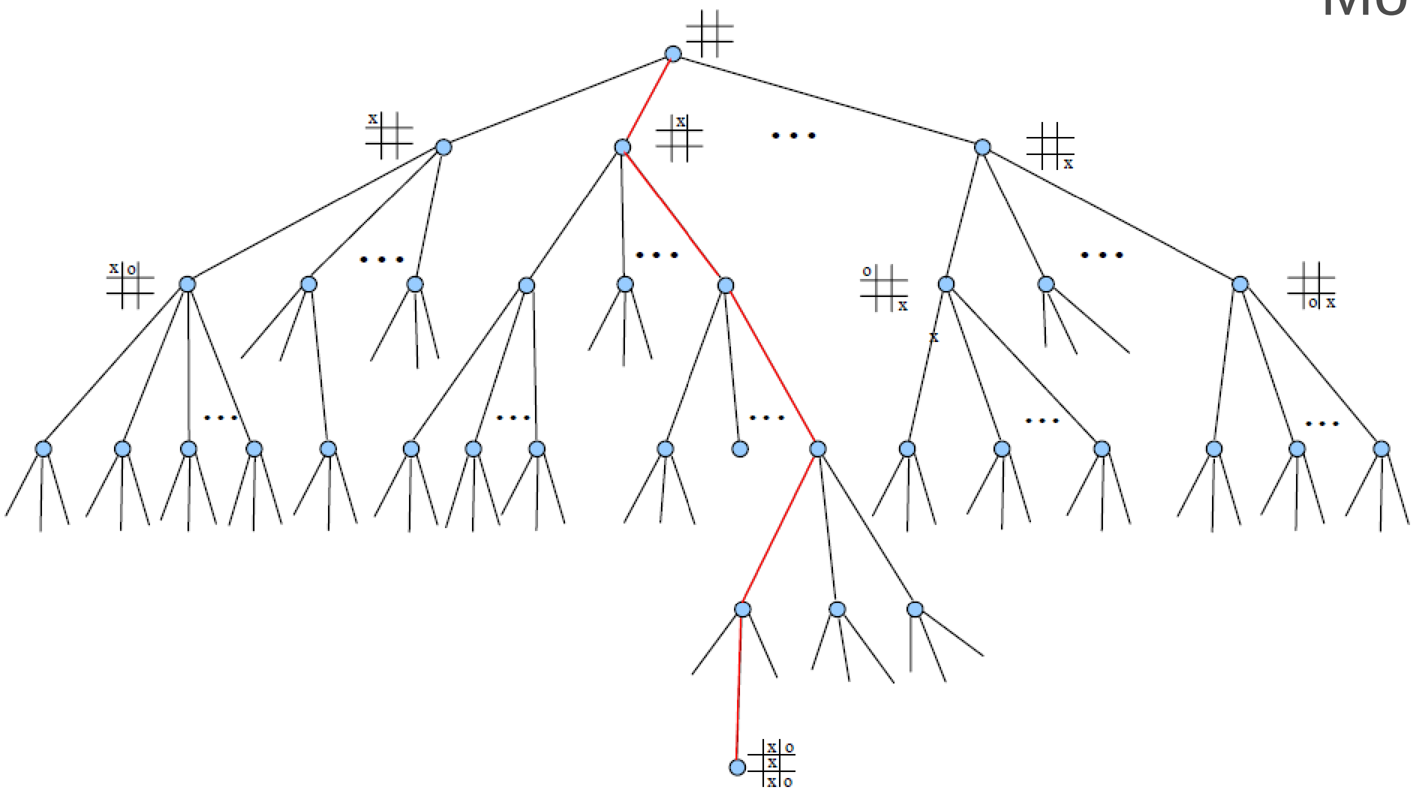
- Suppose values are estimated:
  $Q_t(a) \approx Q^*(a)$; **estimation of action values**
- The greedy-action for time t is:

$$a_t^* = \arg max_a\, Q_t(a)$$
$$a_t = a_t^* \Rightarrow exploitation$$
$$a_t \neq a_t^* \Rightarrow exploration$$

- Insights:
  - You cannot explore all the time, but also not exploit all the time.
  - Exploration should never be stopped, but it should be reduced.

Example: Tic-Tac-Toe



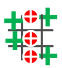


Move by:

- X
- O
- X
- O
- X

Example: Tic-Tac-Toe (2)

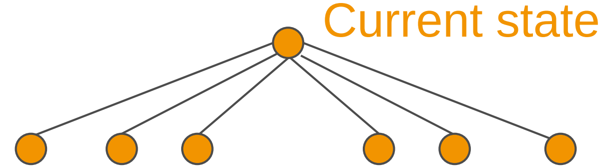
Step 1: Create a table with one entry per state

State	p(x)	comment
	0.5	
	0.5	
⋮	⋮	
	1.0	Game won!
⋮	⋮	
	0.0	Game lost!

p(x) = (estimated) probability to win

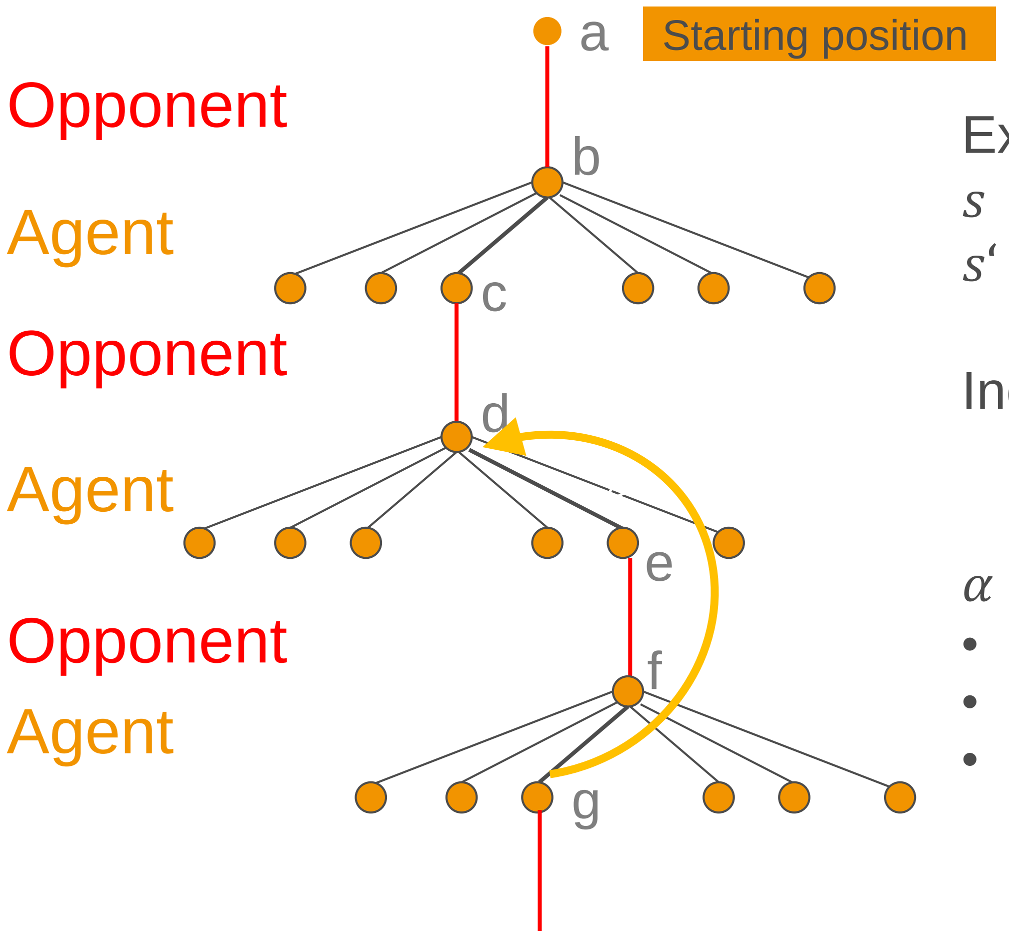
Step 2: Play a lot of games!

- For each move, look ahead one step.



- Choose move with the highest p(x): greedy.
- With a certain probability (e.g. 10%), choose a random move (an exploring move).

Example: Tic-Tac-Toe (3)



Exploring move:

s - State before the greedy move

s' - State after the greedy move

Increment $p(s)$ to $p(s')$:

$$p(s) \leftarrow p(s) + \alpha\, [p(s') - p(s)]$$

α is the learning rate

- A small positive value
- E.g.: 0.1
- Defines the rate of adaptation

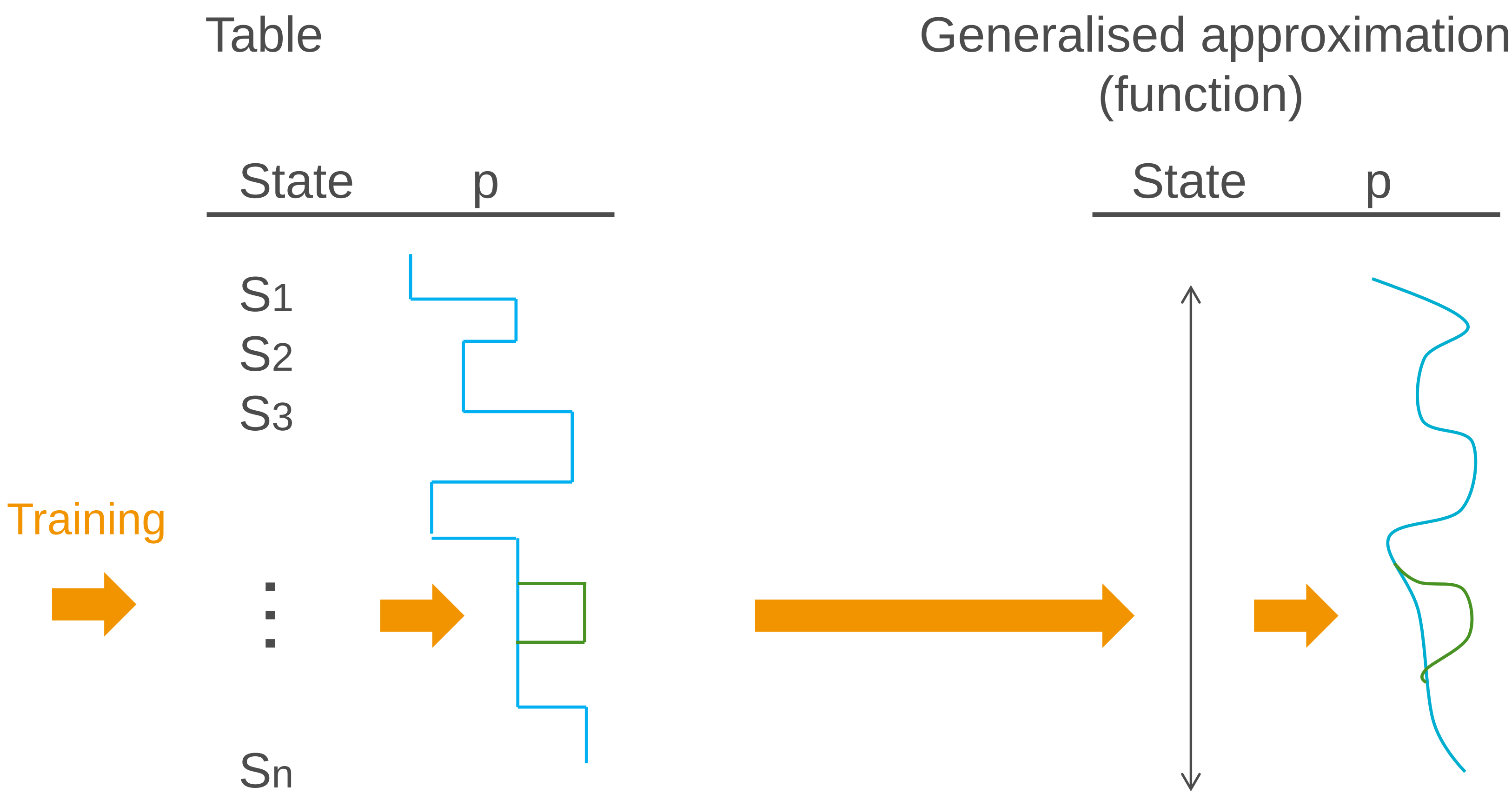
Example: Tic-Tac-Toe (4)

Improvements for the Tic-Tac-Toe player

- Take notice of symmetries!
  - Representation / Generalisation?
  - How can it fail?
- Random moves
  - Why do we need random moves?
    → Exploration vs. exploitation!
  - What about the 10%?
- Can we learn from random moves?
- Can we learn offline?
  - Pre-learning by playing against oneself?
  - Domain knowledge of experts?
  - Using the learned models of the opponent?
- …

Example: Tic-Tac-Toe (5)

A generalisation of the knowledge



Tic-Tac-Toe

→ Obviously, a simple example. But why?

- Finite, small number of states
- Deterministic (look-ahead of one)
- All states are recognisable
- Direct evaluation of move possible
- No noise when observing the state, etc.
- …

Complex learning tasks:

- Sparse and imbalanced data
  - E.g. due to non-uniform distributions and class imbalances
- Non-stationary environments
  - May exhibit severe changes in the target concepts.
  - Also called *concept drift*.
- Necessity of exploration boundaries
  - Unrestricted or unknown feature spaces
  - Continuous or large discrete action spaces
  - Legal constraints
    → Trial-and-error must be avoided!
- Complexity of underlying problem space
  - Functions mapping inputs to certain outputs regarding are complex.
  - E.g. due to their dimensionality, continuity, obliqueness and curvature.
- Knowledge and expected behaviour must be represented in a human-comprehensible manner (e.g. as rules).

Q-Learning

Example of a simple Reinforcement Learning technique

- Q-Learning, Watkins in 1989
- Q stands for "Quality"
- One of the early breakthroughs in reinforcement learning
- An off-policy temporal-difference learning algorithm
- Maintains a list of Q-values for all state-action pairs
- Defined as:

$$Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \alpha \left[R_{t+1} + \gamma \max_a Q(S_{t+1}, a) - Q(S_t, A_t) \right]$$

S_t: State of time t A_t: Action at time t

$Q(S_t, A_t)$: Estimated value of applying A_t in S_t

α: Learning rate γ: Discount factor

R_{t+1}: Reward at time t+1

Q-Learning (2)

Algorithm:

Q-learning (off-policy TD control) for estimating $\pi \approx \pi_*$

Initialize $Q(s,a)$, for all $s \in \mathcal{S}, a \in \mathcal{A}(s)$, arbitrarily, and $Q(\textit{terminal-state}, \cdot) = 0$
Repeat (for each episode):
    Initialize S
    Repeat (for each step of episode):
        Choose A from S using policy derived from Q (e.g., ϵ-greedy)
        Take action A, observe R, S'
        $Q(S,A) \leftarrow Q(S,A) + \alpha\big[R + \gamma \max_a Q(S',a) - Q(S,A)\big]$
        $S \leftarrow S'$
    until S is terminal

Q-Learning (3)

- What are the major drawbacks of the Q-learning technique?

- Or in other words: Why is it seldom applicable to real-world problems in intelligent systems?

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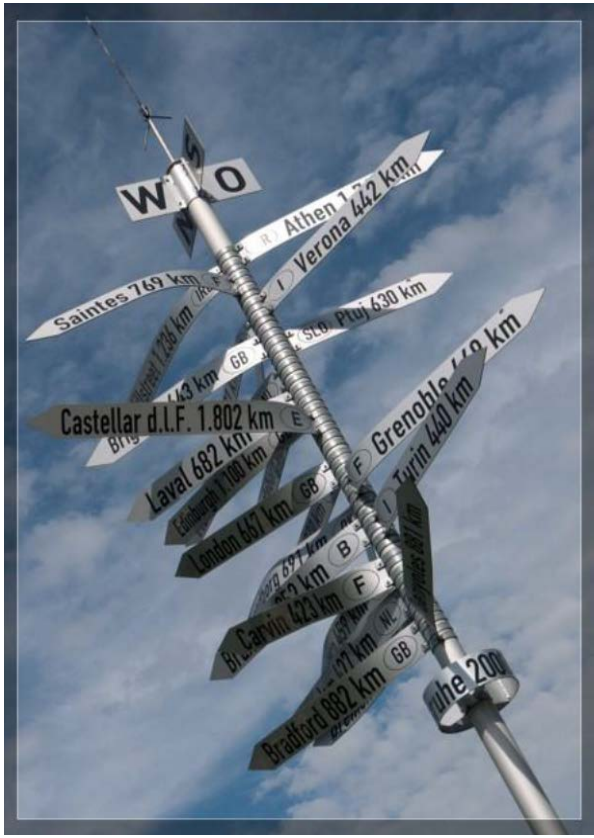


Names to remember in LCS research

- Initial Learning Classifier System (LCS) was introduced by John H. Holland in 1975.
- He was (and still is) interested in complex adaptive systems.
- How can computers be programmed so that problem-solving capabilities are built up by specifying “what is to be done” rather than “how to do it”? (Holland, 1975)
- An important development in LCS was done by Stewart W. Wilson in 1995.
- Based on the initial approach by Holland, Wilson proposed a simplified and more efficient classifier system called Extended Classifier System (XCS).
- XCS is today one of the most studied classifier systems.
- Many extensions have been proposed.

The initial approach by Holland

- Initially system
  - Holland designed the first system in 1978.
  - System is called CS1.
- System contains
  - Set of classifiers (condition/action)-pairs
    → Not called "rule" since they compete (classifier is a "may rule")!
  - Input interface to receive state from the environment
  - Output interface to apply actions to the environment
  - Internal message list as an internal "workspace" for I/O
  - Evolutionary process (genetic algorithm) to generate new classifiers

The Extended Classifier System (XCS) by Wilson

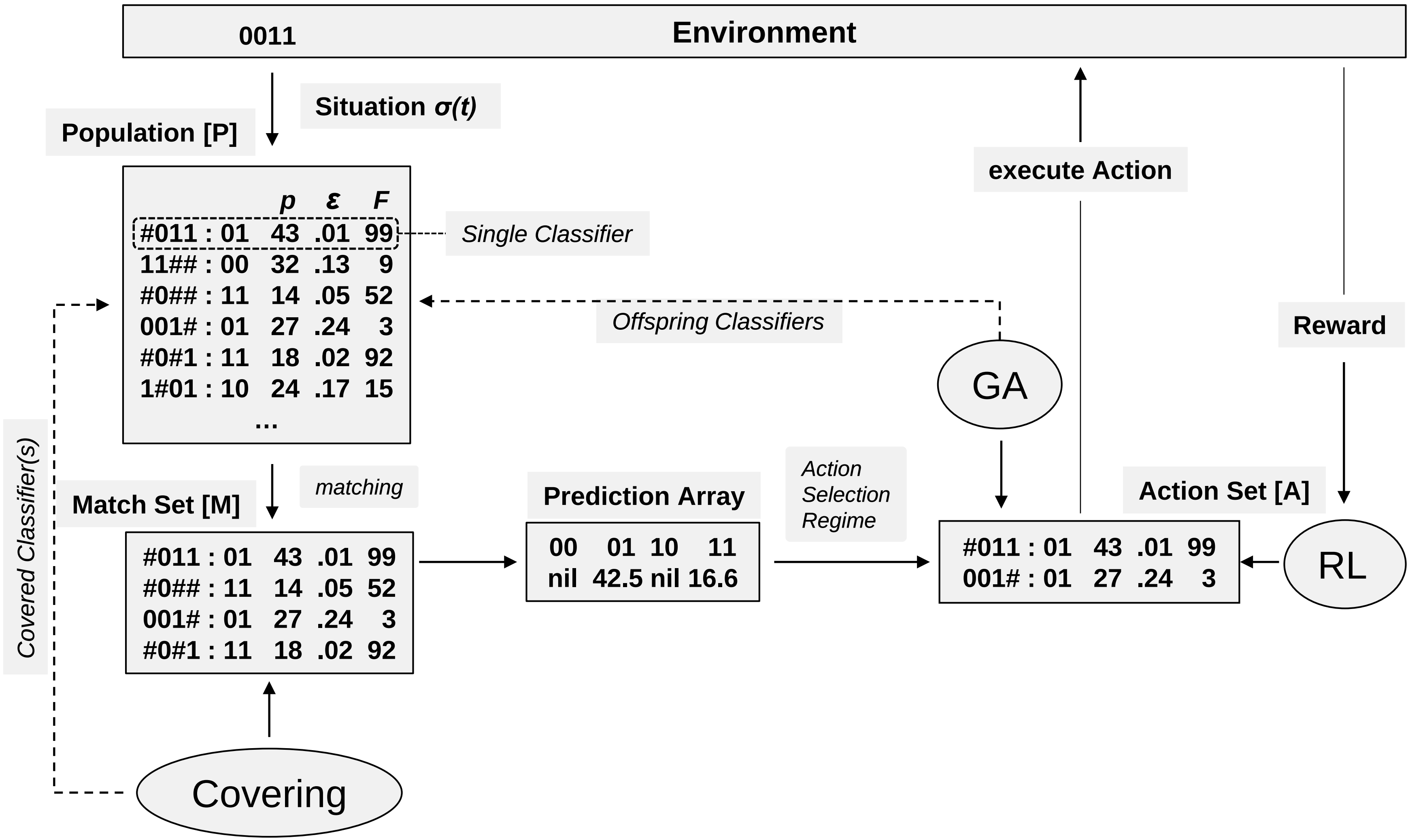
- XCS is a rule-based (online) learning system.
- It can be used for pure classification as well as for regression problems.
- It is a derivative of the overall class of *Learning Classifier Systems (LCS)*, initially proposed by Holland in 1978 (CS-1)
- Wilson in 1994 simplified Hollands CS-1 to the so-called *Zeroth-Classifier System (ZCS).*
- In 1995 Wilson presented the *Extended Classifier System (XCS).*
- Initially designed for binary problems, Wilson further extended XCS toward the ability to cope with real-valued inputs (XCSR) in 2001.

Why “Classifier” system?

- XCS stores rules (termed `classifiers‘) in a limited set of max. N classifiers called population $[P]$.

- A single classifier cl is comprised of:
  - A condition C that defines a subspace of the input space X
  - An action a that determines a reaction executed on the environment (e.g. `0‘ and `1‘ for `turn left‘ or `turn right‘)
  - A predicted payoff scalar p which is an estimate of the expected reward when the action a of this classifier is selected for execution
  - An absolute error of the payoff prediction ϵ
  - A measure of accuracy termed fitness F which is some sort of inverse function of ϵ
  - Some more so-called “book-keeping” parameters (e.g. experience)

One cycle through XCS



A single iteration through the main loop

1. At each timestep t, XCS retrieves a situation $\sigma(t)$ from the observed environment.

2. XCS scans $[P]$ for matching classifiers and builds a so-called match set $[M]$.

3. Among all matching classifiers, the `prediction array' PA calculates the most promising action a.

4. All classifiers from $[M]$ with the selected action a, from another subset $[A]$ called the action set.

5. The selected action a_{exec} is actualised on the environment which in turn delivers a so-called payoff or reward r.

6. r is used to updated and refine all classifiers in $[A]$ since these particular classifiers advocated the same action as the one executed.

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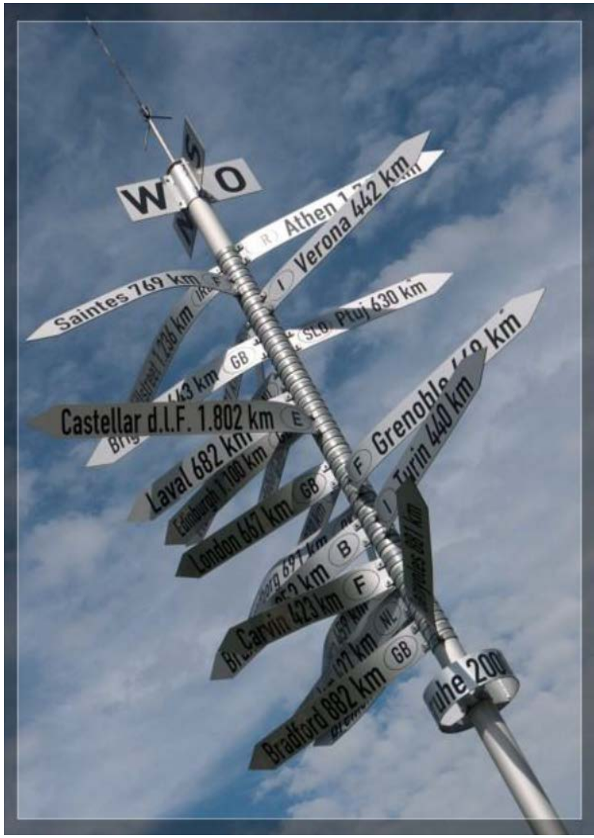

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Why such a triple ranking by p, ε, and F?

- What is the difference between a classifier's strength and its accuracy?
  - Strength = predicted payoff p
  - Accuracy = Fitness (inverse of prediction error ϵ)
- Is a classifier predicting a high payoff also an accurate one?
  - When a classifier predicts a high payoff, this does not necessarily mean that its prediction is correct!
- Is it beneficial to know low performing (regarding p) but highly accurate (F) classifiers?
  - Yes, indeed!
  - The system has an indicator which action delivers low payoff and thus will decide more likely against this action.

Wilson's "Generalisation Hypothesis"

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- Wilson hypothesised that XCS constructs classifiers that are maximally general and accurate at the same time.
- Thus, XCS attempts to construct a map/approximation of the underlying payoff-landscape, that is $X \times A \rightarrow P$, using single classifiers:
  - X is the input space (possible input)
  - A is the action space (possible outputs)
  - P is the payoff space (possible rewards)
- This map/approximation shall be:
  - *Complete*, in the sense that the entire payoff landscape is covered.
  - *Compact,* in terms of the # physical classifiers (macro-classifiers).
  - *Accurate*, *since* the system error shall be as minimal as possible (of course).
  - *Maximally general*, *since* the shape of a classifier (determined by its condition) shall be large enough to cover the environmental niche within X but specific enough to remain accurate.

Wilson’s “Generalisation Hypothesis” (2)

- The separation of strength and accuracy combined with the incorporated `niche‘ genetic algorithm exerts evolutionary pressure toward the aforementioned properties.
- The GA favours accurate (high fitness) classifiers within the environmental niche.
- Thus, accurate classifiers are more likely to reproduce and will eventually take over the environmental niche.

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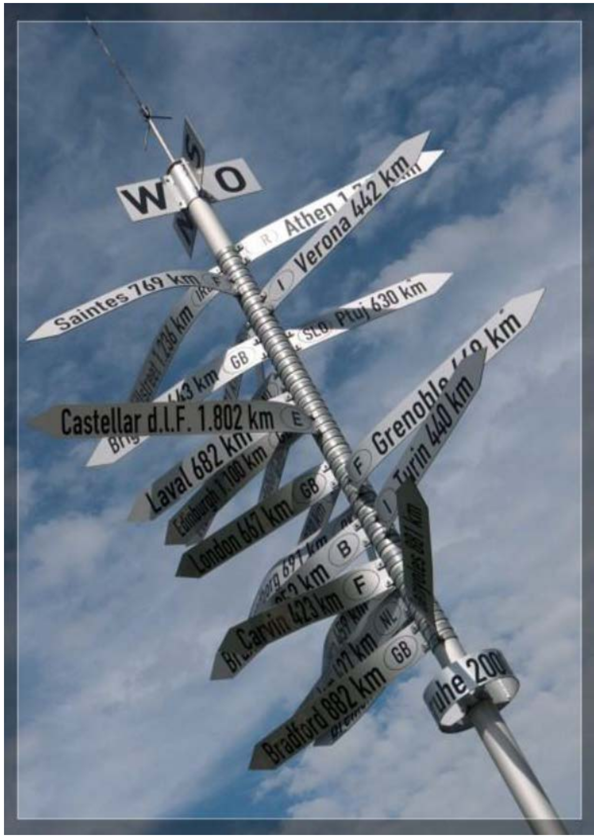
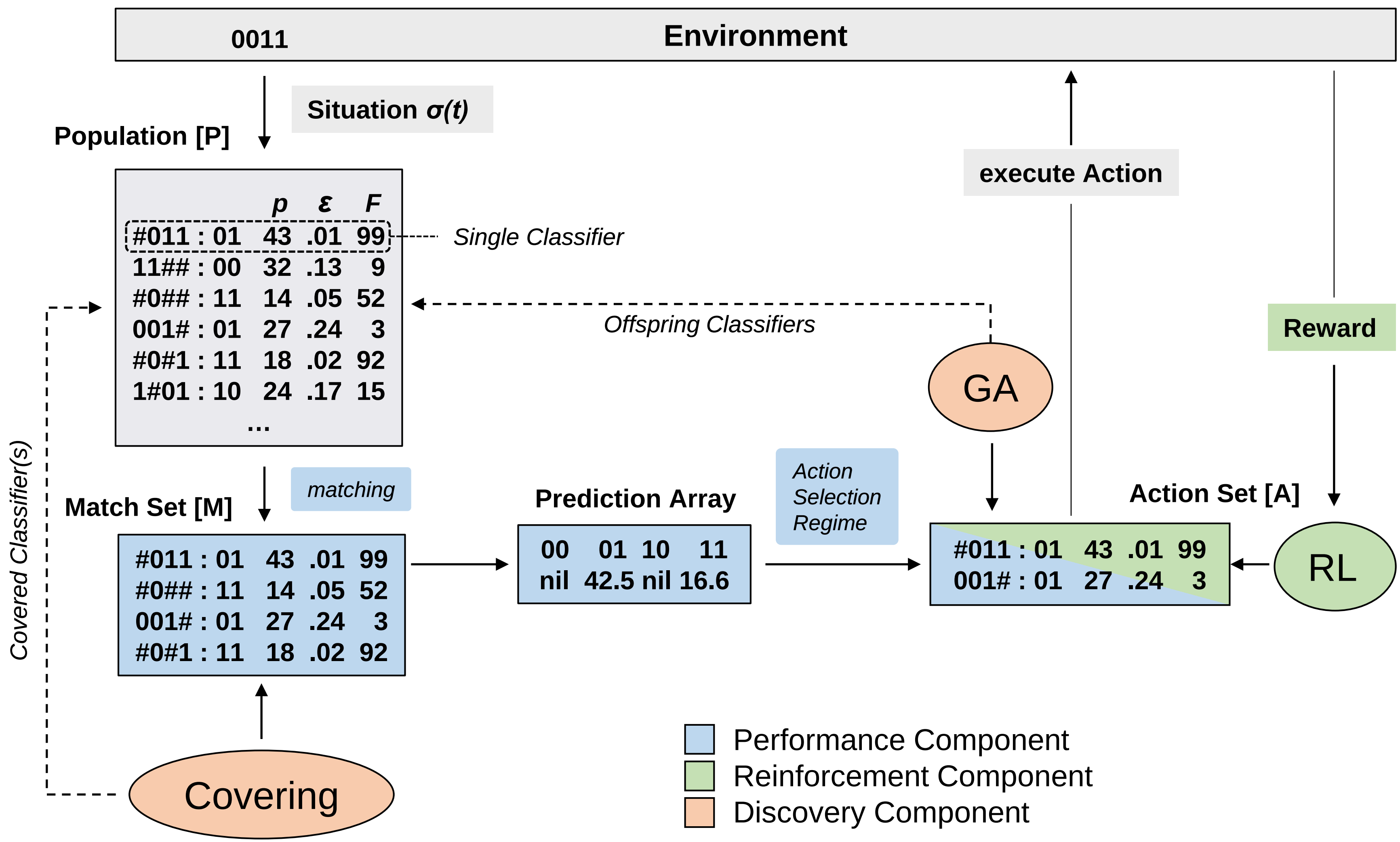


XCS` three main components

- Performance component
  - Matching, Payoff Prediction, Action Selection
- Reinforcement component
  - Attribute update, deferred credit assignment
- Discovery component
  - Covering of non-explored niches, refinement of poorly explored niches

XCS` algorithmic structure (2)



Matching

- At each time step t XCS retrieves a binary string on length n
- This string is denoted as $\sigma(t) \in \{0,1\}^n$
- Example for $n = 6$ and $t = 1$: $\sigma(1) = 011001$
- Each classifier maintains a condition or schema C.
- The conditions are encoded ternary, i.e. $C \in \{0,1,\#\}^n$.
- The # symbol serves as a wildcard or `don't care' operator.
- Examples of conditions: (is matching $\sigma(1)$?)
  - 0#1001 (yes)
  - #01001 (no)
  - 011##1 (yes)

Matching is the process of scanning the entire population [P] for classifiers with a condition that fits the situation $\sigma(t)$

The system prediction

- The system prediction $P(a)$ is a fitness-weighted sum of predictions of all classifiers advocating action a

$$P(a) = \frac{\sum_{cl \in [M] | cl.a = a} cl.F * cl.p}{\sum_{cl \in [M] | cl.a = a} cl.F}$$

- Especially at this place, the separation of strength and accuracy plays a major role!

- For each possible action $a \in A$ there exists one entry within the PA.
  → There may be several classifiers supporting the same action.

XCS` algorithmic structure (5)

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Update rules:

- $\epsilon_j = \epsilon_j + \beta\left(\left|P - p_j\right| - \epsilon_j\right)$
- $p_j = p_j + \beta(P - p_j)$
- $F_j = F_j + \beta\left(k_j' - F_j\right),\ k_j' = \frac{k_j}{\sum_{cl_i \in [A]} cl_i.k},\ k_j = \alpha\left(\frac{\epsilon_j}{\epsilon_0}\right)^{-v}$

- β is the learning rate (typically set to 0.2)
- α (often set to 0.1) and ν (usually set to 5) control how strong accuracy decreases when the error is higher than ϵ_0
- ϵ_0 defines the targeted error level of the system
- In single-step problems: P is set to the reward r_{imm}
- Classifier attributes are updated using the modified delta rule (Widrow-Hoff delta rule) in combination with the moyenne adaptiv modifee (MAM) technique.

Covering

- Covering is the process of generating a novel classifier that matches the current input whenever:
  - Match set $[M]$ is empty (i.e. no matching cl in [P]).
  - $[M]$ is poor, i.e. average fitness below a certain threshold.
  - $[M]$ contains less then θ_{mna} distinct actions.
- The condition of the covered classifier cl_{cov} is set to the current input.
- Additionally, each bit is replaced by a # (for generalisation purposes) with probability $P_{\#}$.
- Values for p, ϵ and F are set to predefine initial values (typically 10.0, 0.0 and 0.01).

XCS` algorithmic structure (7)

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Genetic Algorithm:

- One of the most essential parts of XCS is the incorporated niche Genetic Algorithm (GA).

- It is triggered when the average time of all classifiers in $[A]$ since the last GA invocation is greater than θ_{GA} (often set to 50).

- The GA selects two parents from [A] with a probability proportional to their fitness values (roulette-wheel selection).
  - The higher a classifier‘s fitness, the higher the selection chance.

- The selected parents are copied to generate two offspring classifiers cl_{off}.

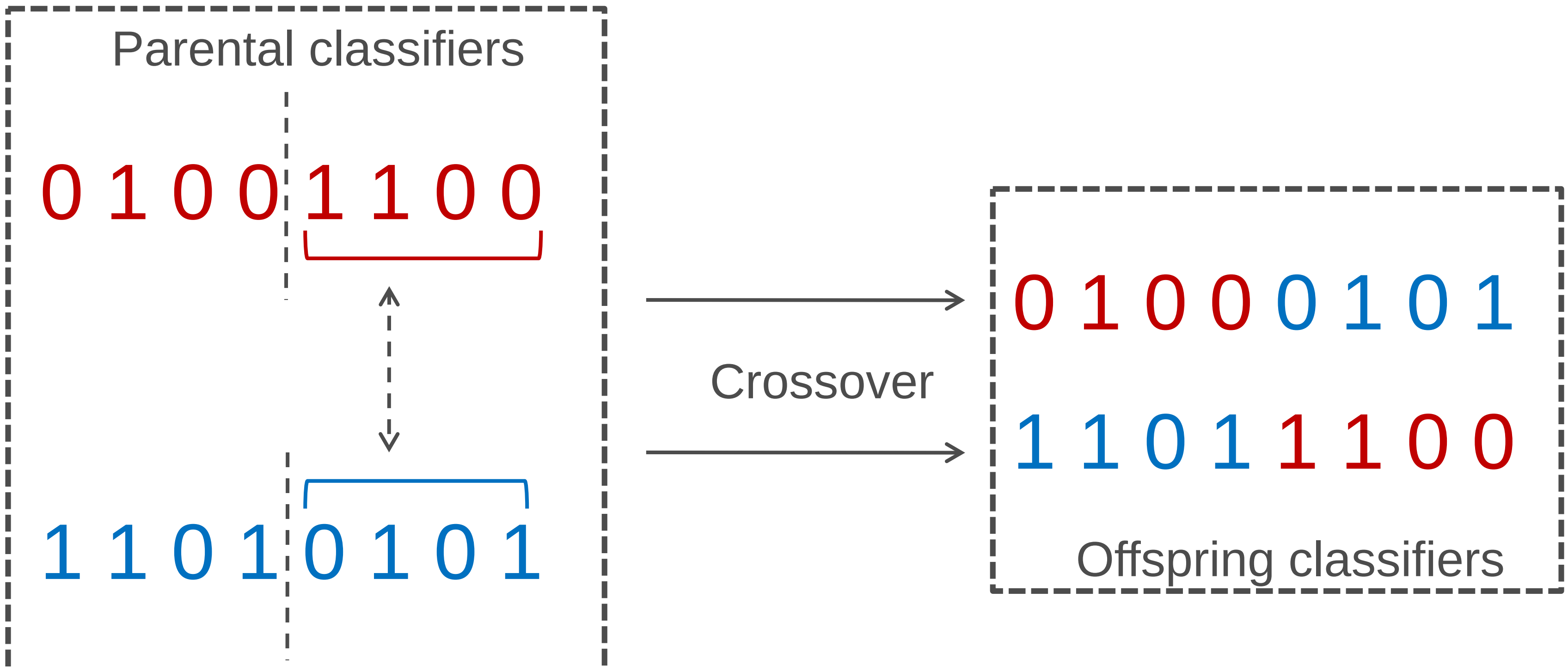
XCS` algorithmic structure (8)

Genetic operators

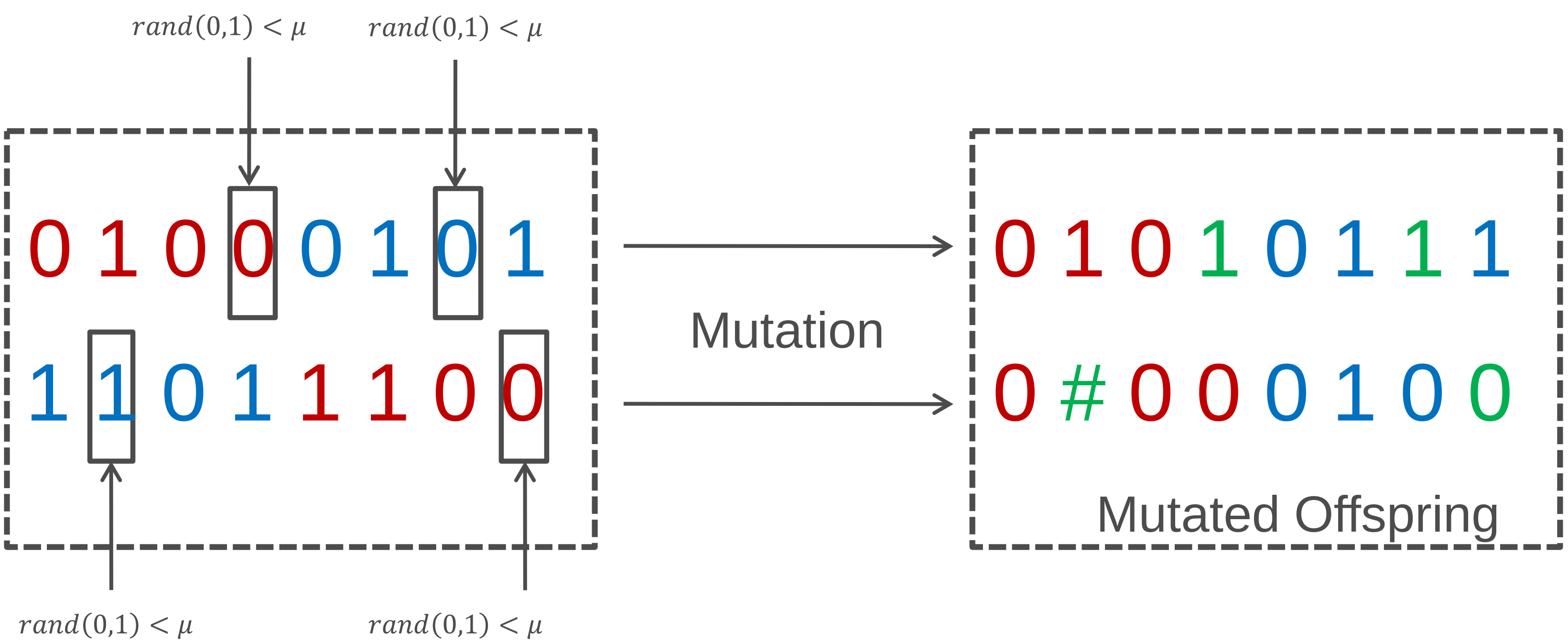
- The conditions of both cl_{off} are crossed (crossover operator):
  - One-point crossover: Each offspring classifier's condition is split at a certain point and switched with the other offspring classifier.
  - n-point crossover: more than one point is determined for switching.
  - Uniform crossover: Each value is switched with probability $P_\chi = 0.8$.

- Afterward, each bit is flipped with probability $P_\mu = 0.04$ to one of the other allowed alleles, that is $\{0,1,\#\}$.

One-point crossover:



Mutation:


$rand(0,1) < \mu$
$rand(0,1) < \mu$
0 1 0 0 0 1 0 1
1 1 0 1 1 1 0 0
$rand(0,1) < \mu$
$rand(0,1) < \mu$
Mutation
0 1 0 1 0 1 1 1
0 # 0 0 0 1 0 0
Mutated Offspring

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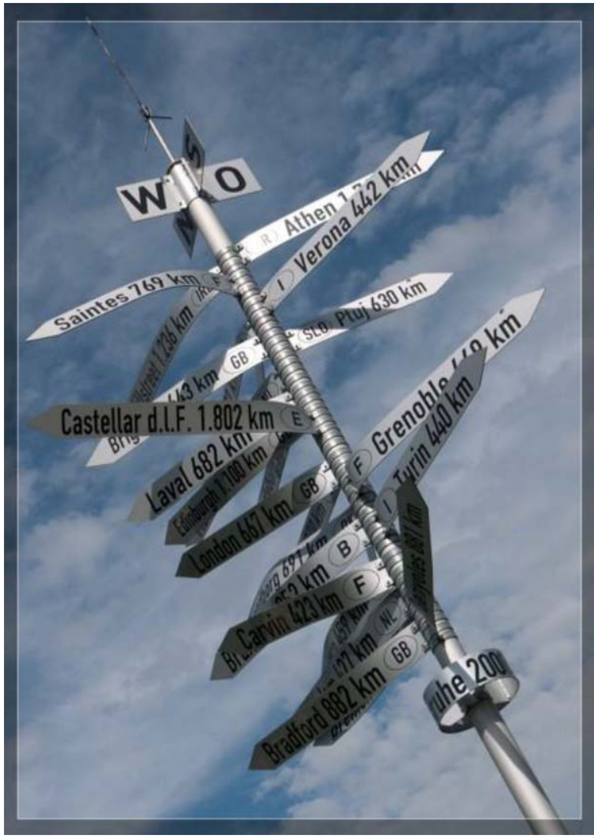
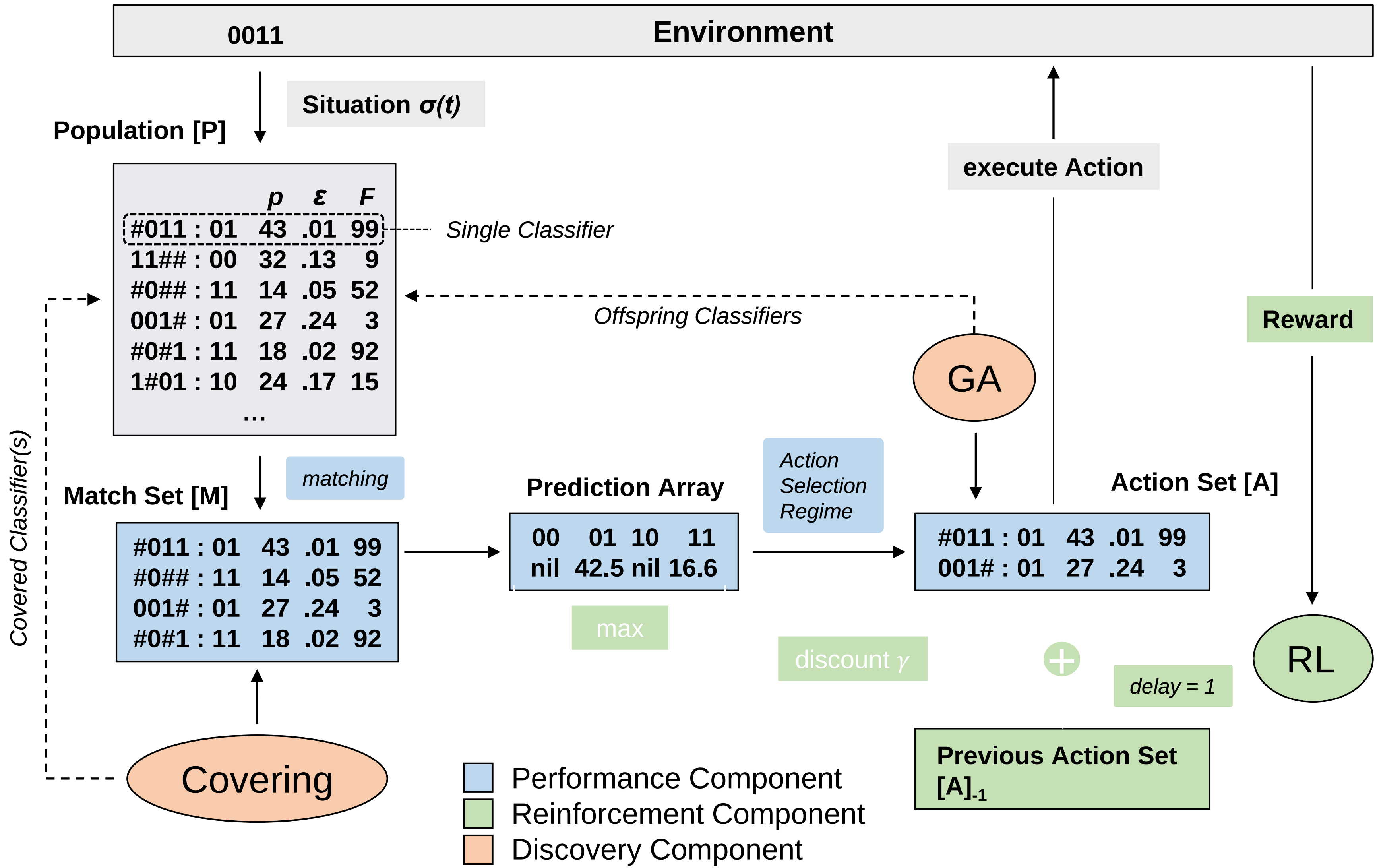


Multi-step problems



Credit assignment

- r may or may not be retrieved in each step.
- Update of classifier attributes is performed on the action set of the previous time step $t - 1$ ($[A]_{-1}$).
- The maximum system prediction $P(a)$ from the PA is discounted by a factor γ (usually $\gamma = 0.95$).
- Additionally, the reward from the previous time-step is added in (maybe 0).
- This delay allows retrieving “information from the future“.

Distinguish:

- In single-step environments $P = r_{imm}$.
- In multi-step problems $P = r_{t-1} + \gamma * \max P(a)$.

Single- vs. multi-step problems

Real-world problems

- E.g.: traffic control
- There is no ‘end‘ of the process!
- Hence: there is no reward!
- However, we can handle the control problem as a single-step problem.
  - Activate XCS in discrete cycles.
  - Perform observation and adaptation loop.
  - Use utility function: (i) to estimate success, (ii) to analyse conditions.

- For the remainder of this lecture, we only consider single-step problems with immediate reward.

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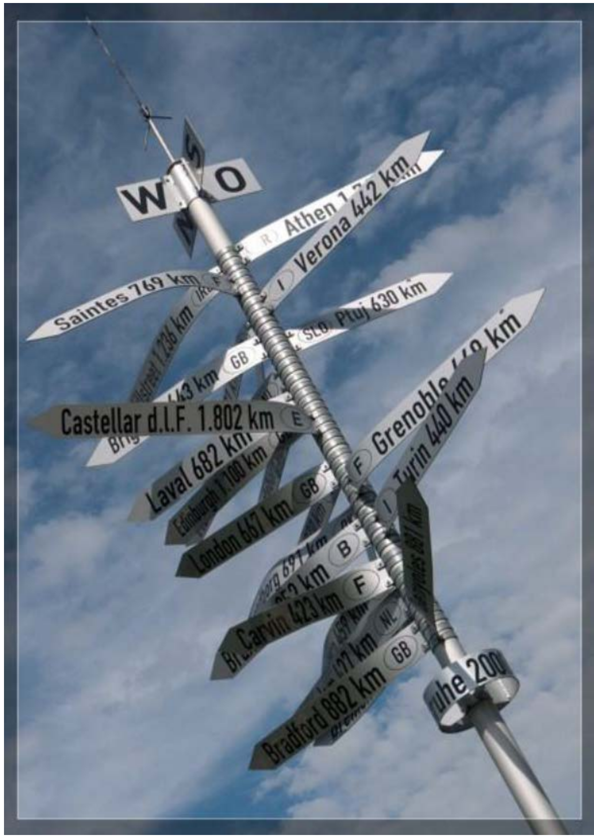

- Wilson proposed changes to conventional XCS to allow for real-valued input (cf. [Wilson2000]).

- To accomplish this, some changes were necessary regarding the internal calculations:
  - Representation of the condition
  - Matching
  - Covering
  - GA (Crossover, Mutation)

- The extended system is called XCSR in literature.

Representation of the condition part

The condition part C:

- The situation $\sigma(t)$ is now represented as an n-dimensional input/feature vector.
- The input vector is defined as $\vec{x}_t = (x_1 \ldots x_n) \in X \subseteq \mathbb{R}^n$.
- Thus: a binary string is not appropriate anymore!

- For each dimension x_i a so-called interval predicate has to be defined.
- An interval predicate is a tuple (l_i, u_i) representing:
  - a lower l_i and
  - an upper bound u_i .
- The geometric interpretation of a condition for real-valued inputs is that of hyper-rectangles.
- Accordingly, this condition representation is called hyper-rectangular representation.

XCS` algorithmic structure: matching

- In the following, we assume that the input space X is normalised to the standard interval: [0,1].

- Thus, for an $n = 2$ dimensional problem space a classifier's condition C may look like:

$$cl.C \ = \ [(0.30, 0.70), (0.55, 0.95)]$$

- E.g.: This condition would match the input
  $\sigma(t) =$ (0.4, 0.75)

- In general, a classifier matches the current input if and only if

$$\forall i: \quad l_i \leq x_i < u_i \quad i = 1 \ldots n$$

XCS` algorithmic structure: covering

- When covering occurs the newly generated classifier is initialised with predefined initial values as before.

- The condition is set to the current situation

$$\sigma(t) = (x_1 \dots x_n)$$

- Additionally, to provide interval predicates

$$(l_i, u_i),\ i\ =\ 1 \dots n$$

  - $l_i = x_i - rand(r_0)$
  - $u_i = x_i + rand(r_0)$
  - $rand(r_0)$ delivers a uniformly distributed random number between 0 and r_0.
  - r_0 is a predefined default spread.

XCS` algorithmic structure: genetic operators

- Crossover is actualised as in standard XCS
  - It can be distinguished whether it is allowed to cross in-between a certain interval predicate or only between the interval predicates

- When an allele is selected for mutation its current value is updated according to the following rule:
  - $l_i \pm rand(m_0)$
  - $u_i \pm rand(m_0)$
  - m_0 is a predefined mutation value to extend or shrink the current interval.

- The alleles to mutate are selected probabilistically as in standard XCS.

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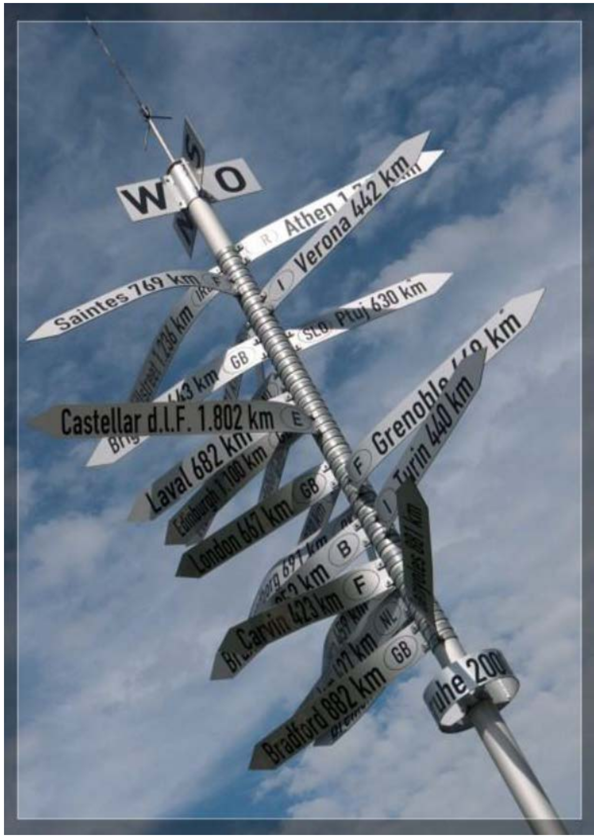

Modifications needed

- Exploring configuration space online using GA can be dangerous!
  - System will try suboptimal (or even bad) solutions.
  - Example: the system could set all traffic lights to green.
  - We cannot allow failures!
- Learning requires experience!
  - What to do in case of missing knowledge?
  - How to avoid failures if the action is unknown (i.e. bad/good)?
- Approach:
  1. Provide “sandbox” for trying novel behaviour.
  2. Use action that works under ‘similar’ conditions.

Multi-level observer/controller framework

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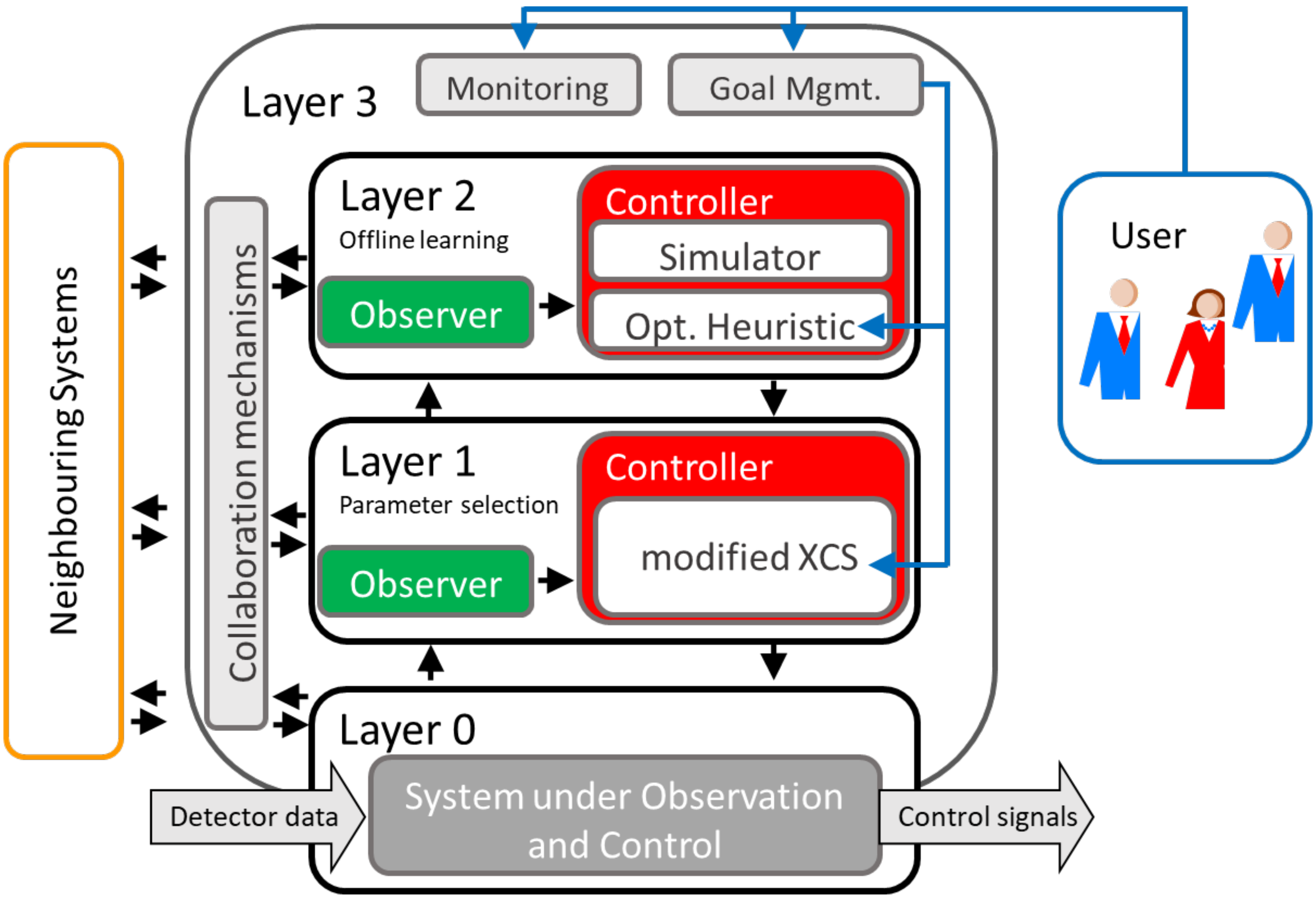
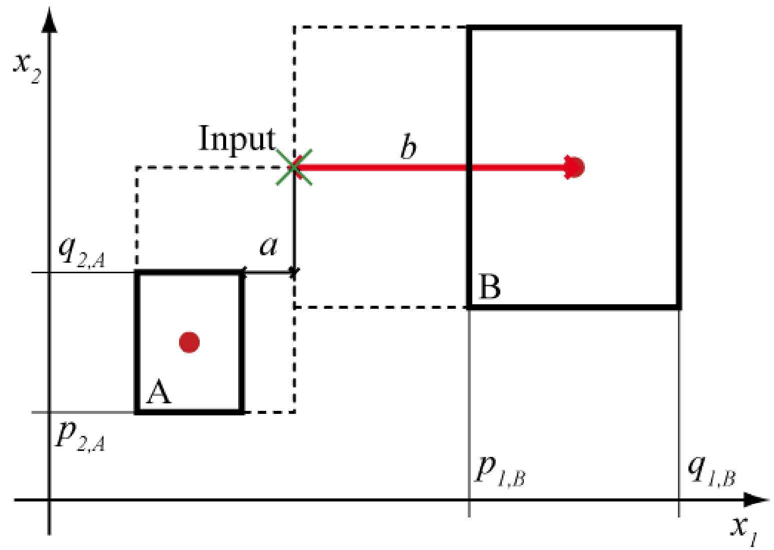
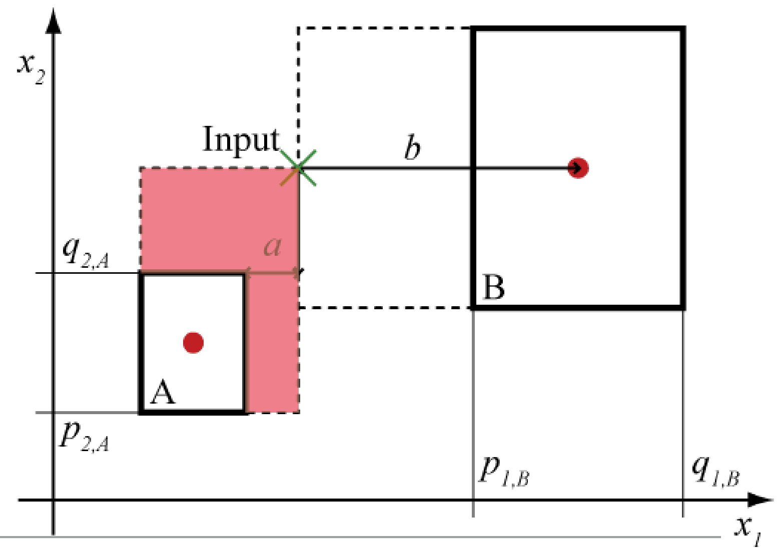


Covering

- Original XCS: covering creates new classifier for the current situation randomly.
- OC: application-specific widening of existing classifiers.
  - Select “closest” classifier.
  - Copy classifier.
  - Widen condition until matching.
- Trade-off between “use only tested solutions” and quick reaction time.
- Additionally: threshold used to trigger rule generation at Layer 2.





Modifications: rule generation

Idea:

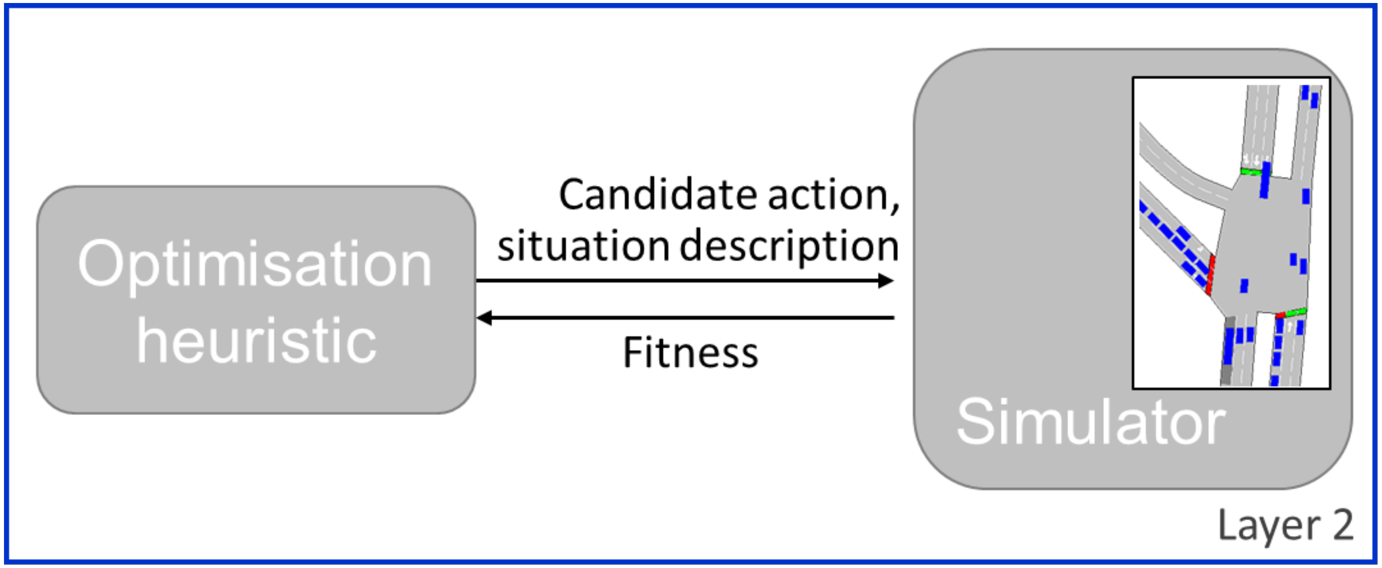
- Covering at Layer 1 solves only a part of the problem.
- Building of match set: trade-off between “use only matching solutions” and competition needed for learning.
- What to do with an empty population?

Approach:

- Generation of new rules is done in a separate component.
- Learning is done offline in a simulator (Layer 2).
- Offline means: takes some time…
  → In the meantime, Layer 1 reacts with covering.

Modifications: rule generation (2)

- Generation of candidate actions.
- Quality of action is tested using simulations.
- Simulator is configured using observed conditions (situation).



- Fitness is measured.
- The process is repeated until a stop criterion is reached.

Modifications: rule generation (3)

Novel rule

- Build as follows:
  - Condition: situation description, widened using a standard interval.
  - Action: parameter set as a result of the optimisation process.
  - Prediction: measured in simulation.
    → I.e. utility as observed for the best action.
  - Fitness: an average of all classifiers in population
  - Error: zero
- Added to rule base of Layer 1

The process is activated:

- If match set is empty.
- If the fitness of rules in match set is below a certain threshold.
- Periodically.

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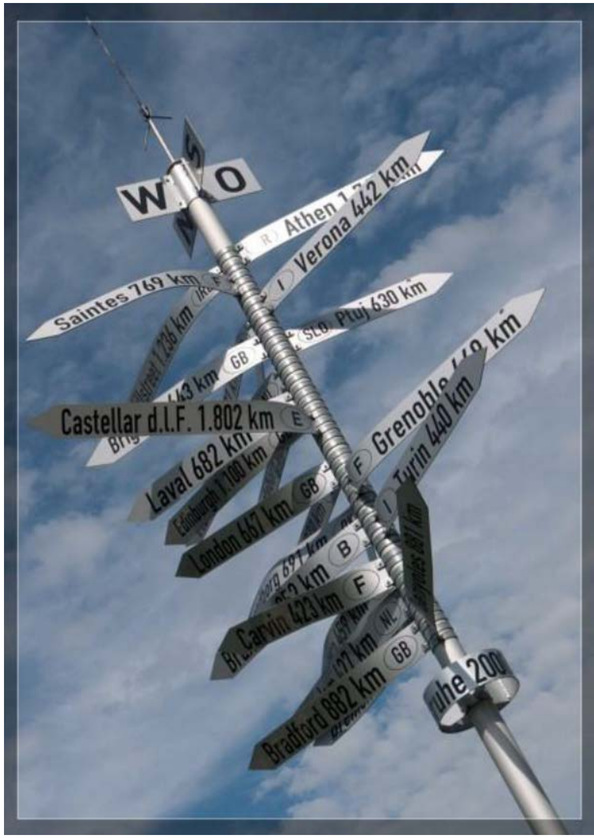

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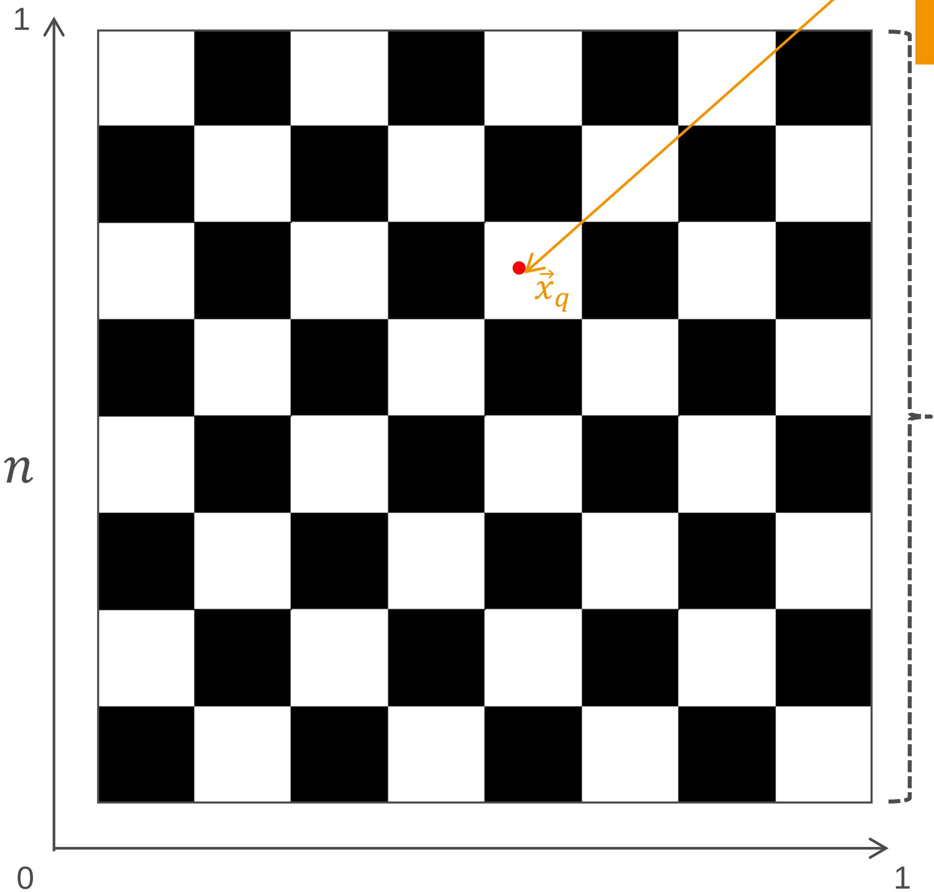
The task of XCS-R:
Of which colour is the field encompassing the query point $\vec{x}_q$?

Checkerboard Problem - CBP(2,8)

cf. [Stone2003]

2 dimensions
$n = 2$
each within $[0,1]$

$\vec{x}_q \in \mathbb{R}^n$
$x_i \in [0,1], i = 1 \dots n$



8 divisions $n_d = 8$ for each dimension with alternate field colours (black/white)

- A CBP(2,8) situation $\sigma(t)$ represents coordinates.
  - E.g.: $\vec{x}_q = (0.25, 0.79)$
- Possible actions are \`black‘ and \`white‘, respectively \`0‘ and \`1‘, thus $A \coloneqq \{0,1\}$
- Reward is 1000 for correct guess and 0 for the wrong guess

Single-step or multi-step problem?

XCSR results on CBP (3,3)

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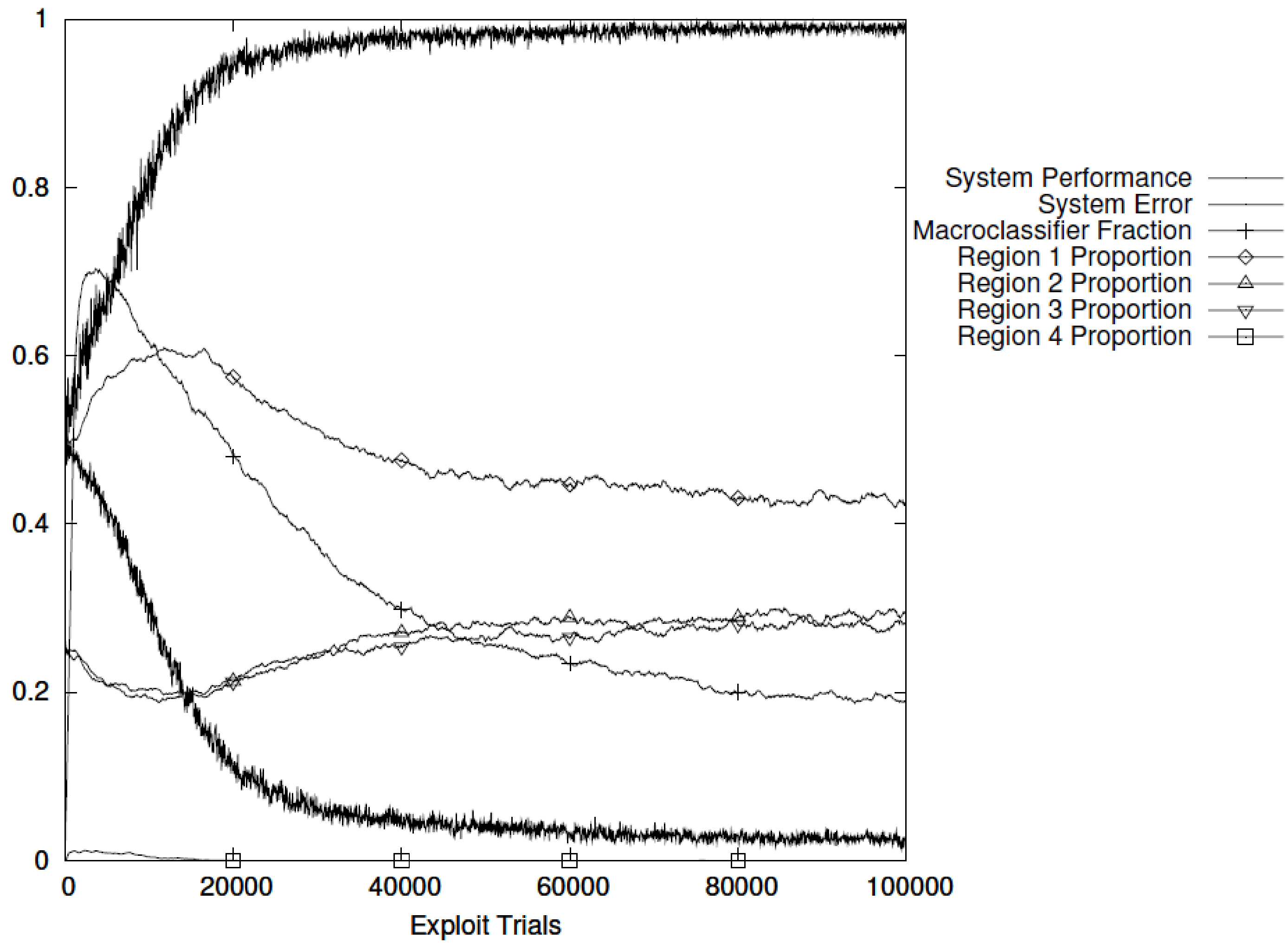

cf. [Stone2003]

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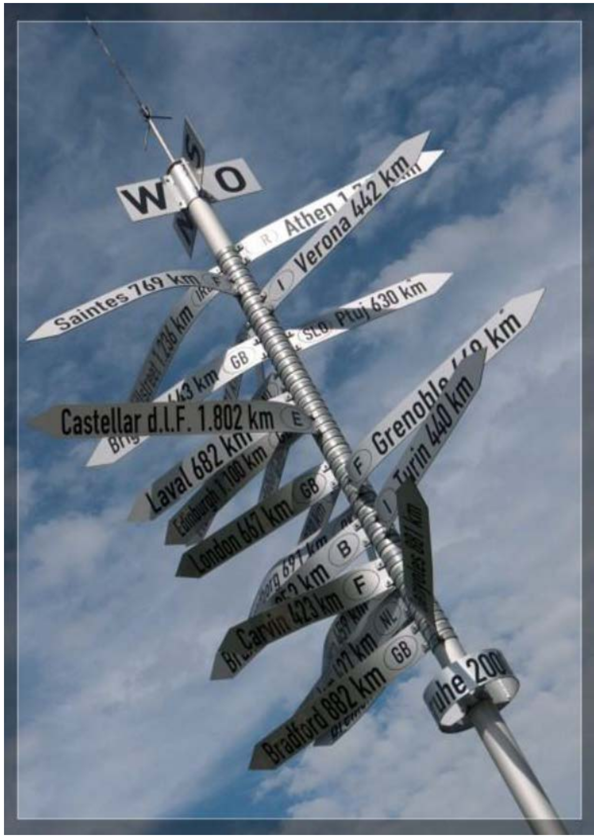

Further modifications

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Modifications:

- Representation
  - Use classifiers as a basis for interpolation
  - Avoids knowledge gaps
- Generalisation
  - More sophisticated rule combination concepts
  - Recombination of partly matching classifiers
- Involve user
  - Combine, e.g., with active learning concept.
  - Proactive knowledge generation
- Second-order optimisation
  - XCS comes with several parameters
  - Adapt them at runtime (i.e. customisation)

XCS makes use of a Genetic Algorithm

- Is part of the research domain of Evolutionary Computing
- There are alternatives!
- Requirements:
  - Find “good enough“ solutions
  - Come up with preliminary result quite fast
- Possible methods and techniques:
  - If available: approximation functions or mathematical functions
  - Swarm-based optimisation heuristics, e.g. Particle Swarm Optimisation
  - OC-based, e.g. Role-based imitation algorithm by Cakar et al.
  - Mimicking physical processes, e.g. simulated annealing
  - An many more…

Everything in software…?

- Concepts for hardware solutions investigated in the context of OC
- Groups at Munich and Tübingen
- Result: Learning Classifier Table
  - Initial training and rule generation in software
  - Logic at runtime at FPGA
  - Scope in hardware: perform the main loop for action selection and modify evaluation parameters

Further issues and challenges

- Besides the hyper-rectangular condition structure, alternative geometric shapes have been proposed
  - Hyper-spherical or Hyper-ellipsoidal representation
  - Weaken the negative effect of high prediction errors in the corners of rectangles
- There are situations at which XCS is hardly able to learn
  - *Covering challenge*: Covering-Deletion Cycle
  - *Schema challenge*: from over-specification and over-generalisation to maximal general/specific and accurate subspaces
  - *Detrimental forgetting* of rarely sampled niches

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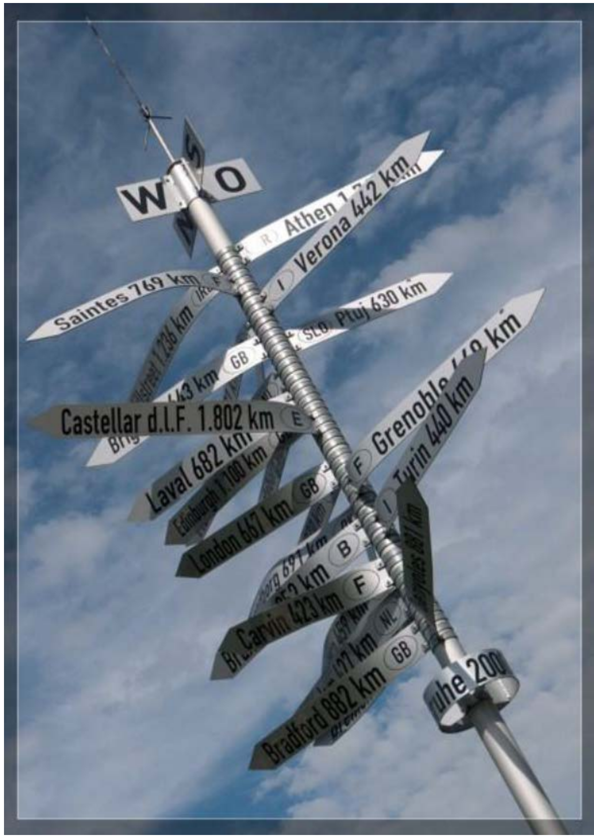

Conclusion

This chapter:

- Explained the concept of reinforcement learning.
- Discussed the challenges of learning control strategies in organic systems.
- Presented the Extended Classifier System and its modifications for usage in organic systems.
- Compared concepts such as strength vs. accuracy, exploration vs. exploitation, etc.
- Highlighted how credit assignment is realised and summarised the corresponding challenges for real-world problems.

By now, students should be able to:

- Explain how learning is done in organic systems.
- Summarise the ideas of reinforcement learning in technical applications.
- Outline the structure and process of XCS and its variants.
- Highlight the tasks of the major components and their impact on the learning process.
- Explain how what credit assignment is and how it is realised in OC.
- Discuss the major concepts and customisations used in organic systems.

Beyond this chapter

Reinforcement Learning is a large field

- Check the “Autonomous Learning” lecture in the upcoming term

LCSs are used due to their explainability and generalisation capabilities

- Current trend is to combine e.g. Q-learner with artificial neural networks (solves generalisation, but not explanation problem)

Current activities concerning utilisation in intelligent systems

- Proactive knowledge generation
- Combination with other knowledge sources such as humans
- Transfer of knowledge between similar systems

➡ Just ask if you‘re interested in a topic for a thesis / project work / HiWi position

References

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- Any questions …?