Lecture

Organic Computing II

Summer term 2020

Chapter 6: Learning

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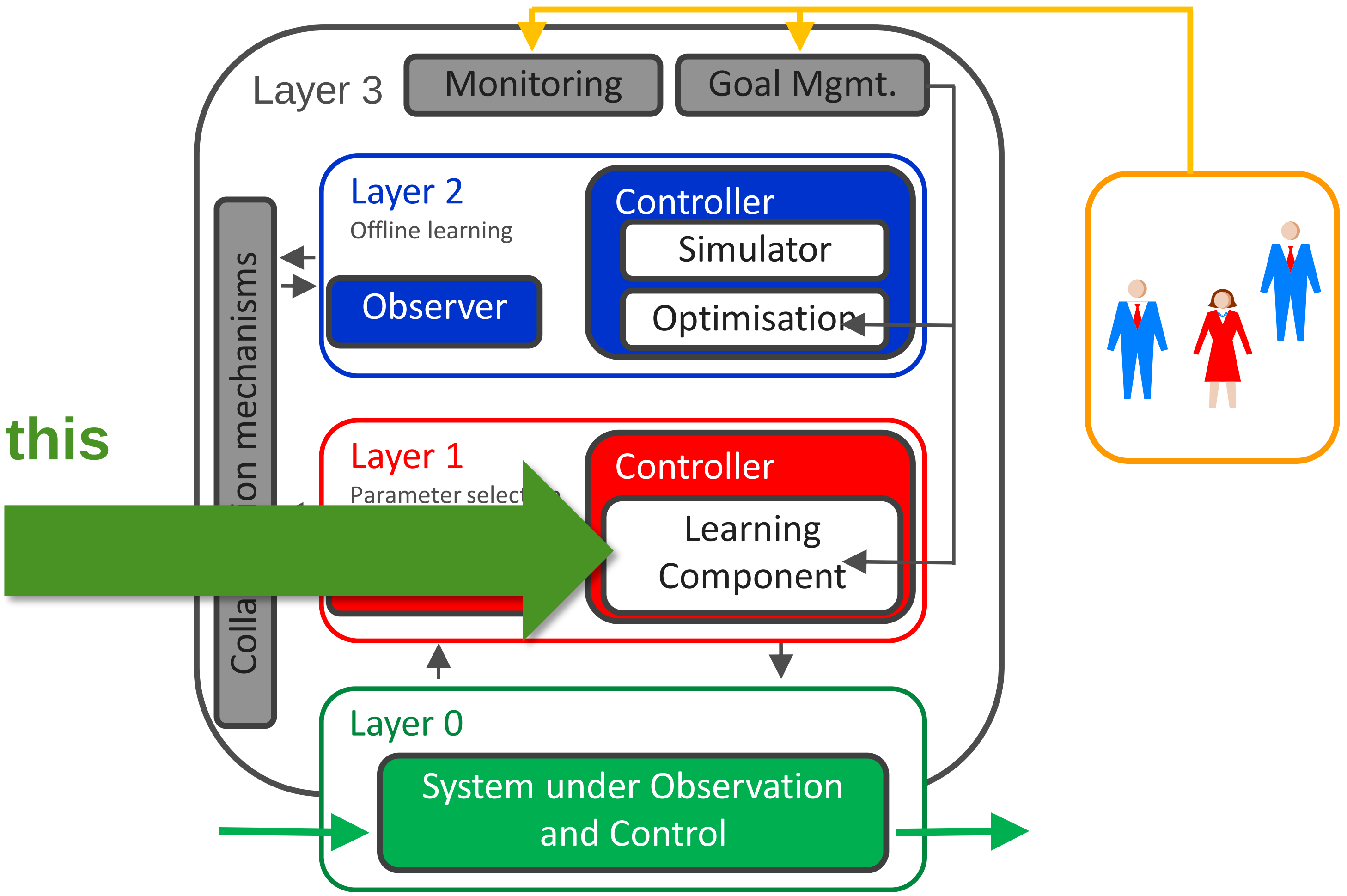
Focus of this chapter

Focus of this Lecture!



Agenda

Content

- Motivation
- Extended Classifier System
- XCS-O/C
- Artificial Neural Networks
- Conclusion and further readings

Goals

Students should be able to:

- Explain what machine 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.
- Explain basic Feed-Forward ANNs and how backpropagation works

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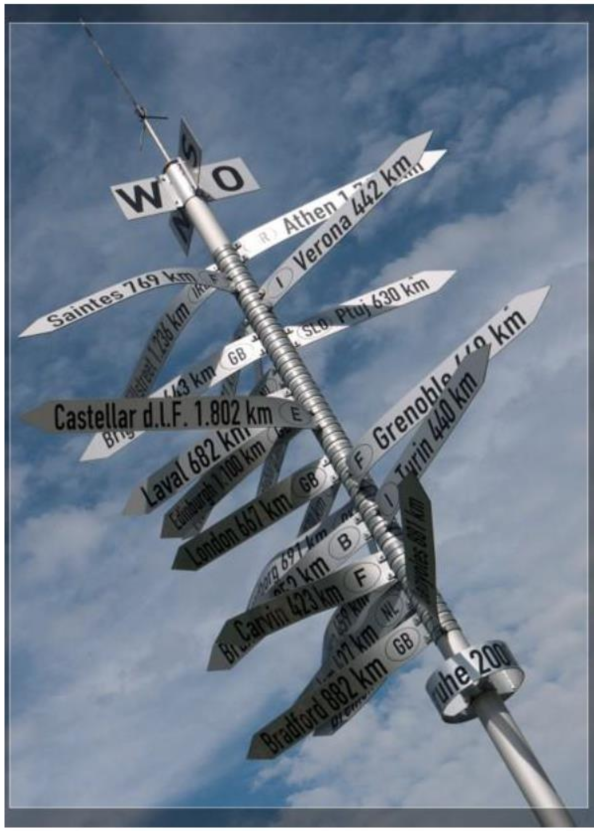
- **Motivation**
- Extended Classifier System
- XCS-O/C
- Artificial Neural Networks
- Conclusion and further readings



Learning in organic systems

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).

Motivation

- Machine learning techniques seem to be a promising approach for continuous self-improvement in Organic Computing 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 of the environments and/or the system itself are desirable.

Motivation (2)

- Machine learning is used when:
  - human expertise does not exist (navigating on Mars)
  - humans are unable to explain their expertise (speech recognition)
  - solution changes in time (routing on a computer network)
  - solution needs to be adapted to particular cases (user biometrics)
  - human learning is not feasible (map protein sequences to secondary structures)
  - …

- The slides for the introduction part to Machine Learning are mainly based on the book:

Alpaydin, E. (2004). Introduction to machine learning. MIT press.

Definition of learning (2)

- Common definition:

  "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."

- *Example:*
  - consider a program that learns playing checker
  - task *T*: play checker
  - performance measure *P*: percentage of the games won
  - experience *E*: play against itself

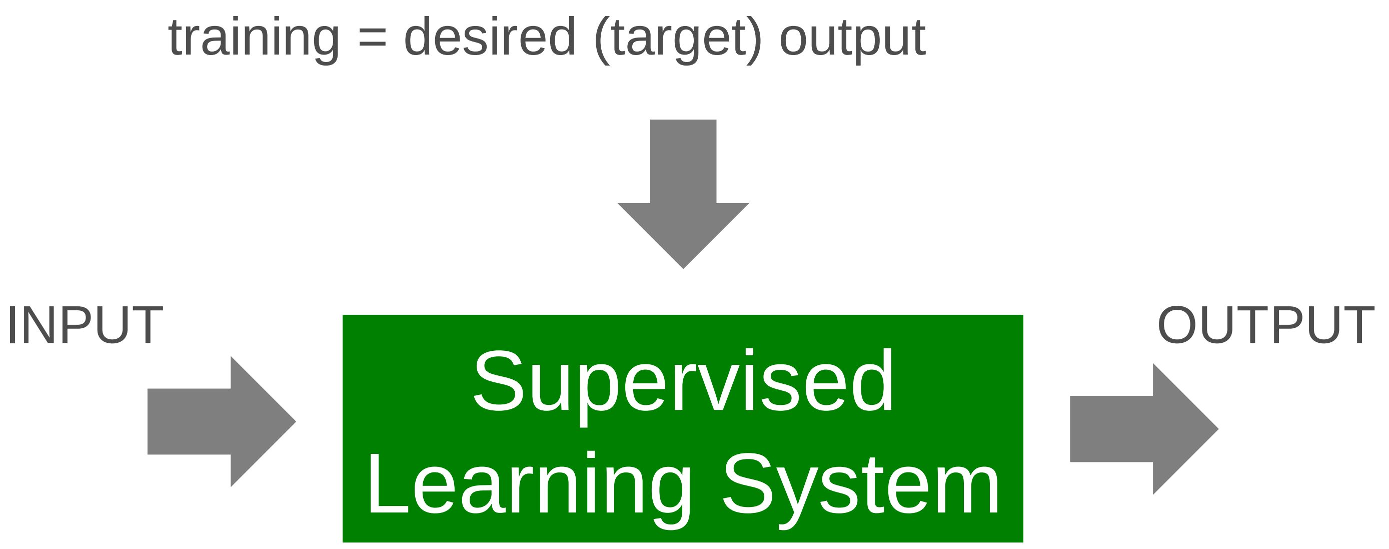
The inductive learning problem

- consider a given set of examples (training set)
- make accurate predictions about future examples (validation set)
- with the goal of predicting concrete values for unknown feature sets, the learning problem can be mapped to learning a function

  $f(X) = Y$, whereas X is an input example and Y the desired output

Supervised Learning

Supervised Learning


training = desired (target) output
INPUT
Supervised Learning System
OUTPUT

error = (target output – actual system output)

Supervised vs. unsupervised inductive learning

- Supervised learning means that the training set of (X, Y) is provided (by a ``supervisor’’ or ``teacher’’)
- Unsupervised learning means only the input data X and feedback on the prediction performance are provided
- Example supervised learning: Face recognition
  - x: Bitmap picture of person's face
  - *f*(x): Name of the person
- Example unsupervised learning: Customer segmentation
  - x: Customer’s buying habits, address, age,…
  - *f*(x): Customer class

Expected learning results

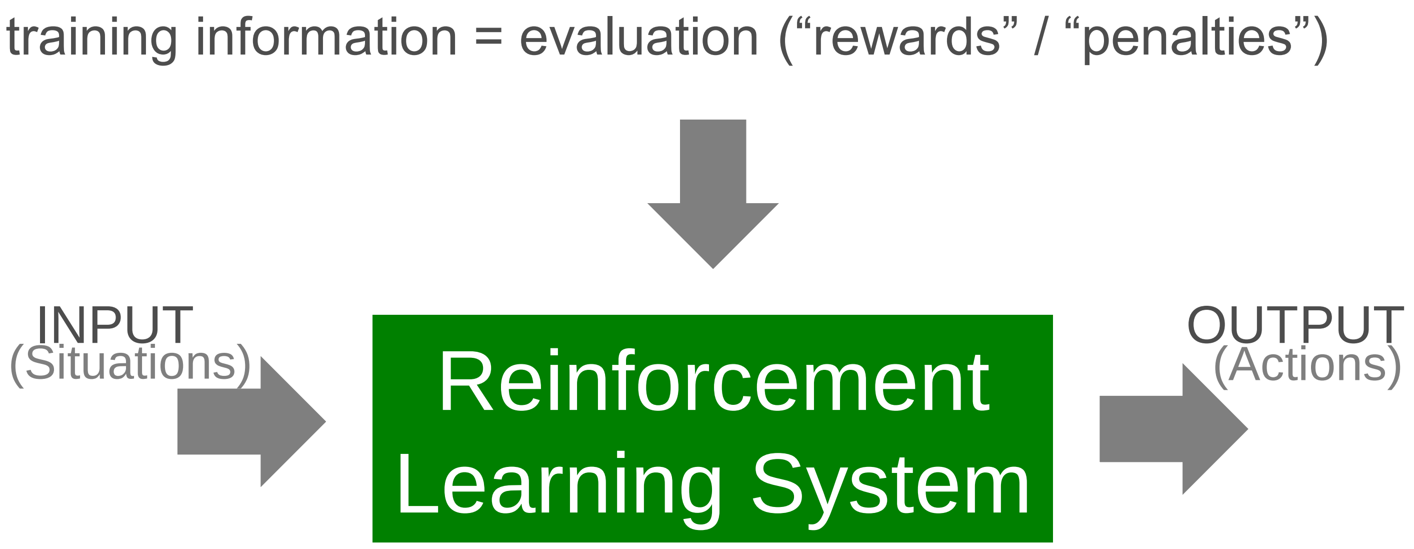
Supervised learning

1. Prediction of future cases:
   Use the learned model (or *hypothesis*) to predict the output for future input
2. Knowledge extraction:
   The hypothesis is easy to understand
3. Compression:
   The hypothesis is simpler than the data it explains
4. Outlier detection:
   Exceptions that are not covered by the hypothesis (e.g. fraud)

Unsupervised learning

1. Clustering of data
2. Density estimation of data
   ➞ gain insights into the organisation of data

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

Reinforcement Learning

- 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

Reinforcement learning

- Learning based on feedback
  - feedback tells the system how well it performs (**not** what it should be doing)
  - no supervised output; but a delayed “reward”

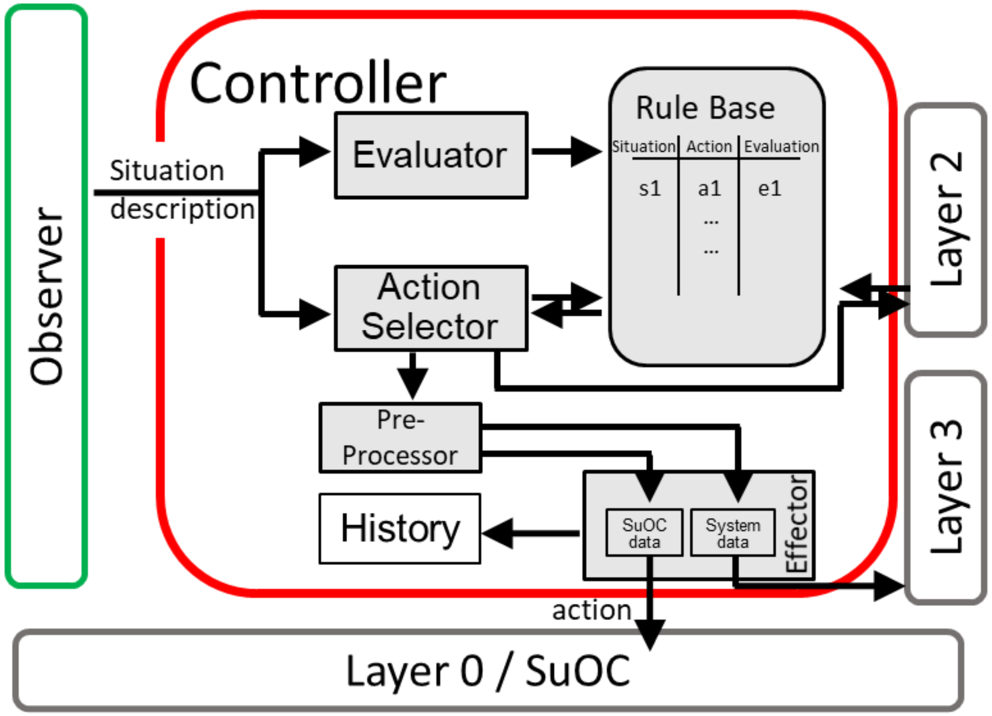
- Aspects:
  - credit assignment problem
  - game playing
  - robot in a maze
  - multiple agents, partial observability, ...

This is exactly what we will have to cope with in most OC applications!

Recap: Layer 1 Controller

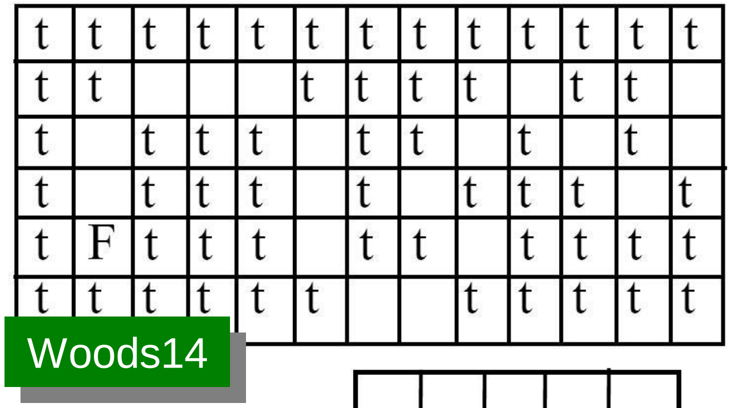
Observer/Controller

- 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.

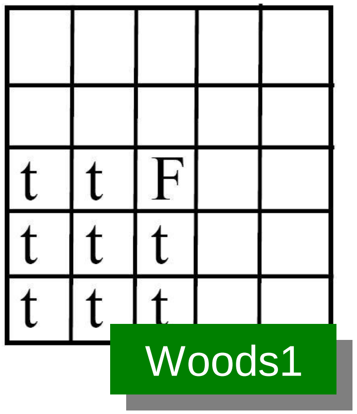


Example: 'Woods' scenario / Maze

- 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 empty cell.
- Walks around, looking for food
- In each step, agent can go to one of the eight neighboring cells (empty and food cells only).



t	t	t	t	t	t	t	t	t	t	t	t	t
t	t				t	t	t	t		t	t	
t		t	t	t		t	t		t		t	
t		t	t	t		t		t	t	t		t
t	F	t	t	t		t	t		t	t	t	t
t	t	t	t	t	t			t	t	t	t	t



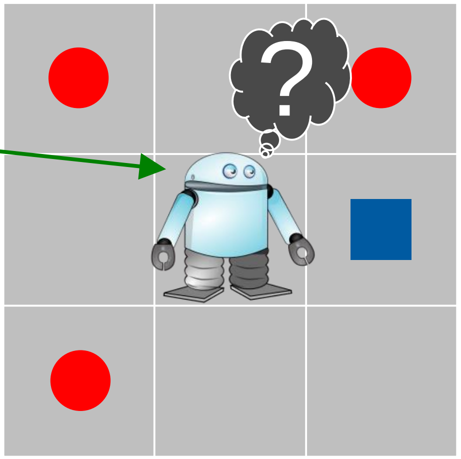
t	t	F		
t	t	t		
t	t	t		

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 upon this perception, it has to decide where to go next.
  - Reward is paid once the food is found.

Agent
- Observation: 8 cells
- Status



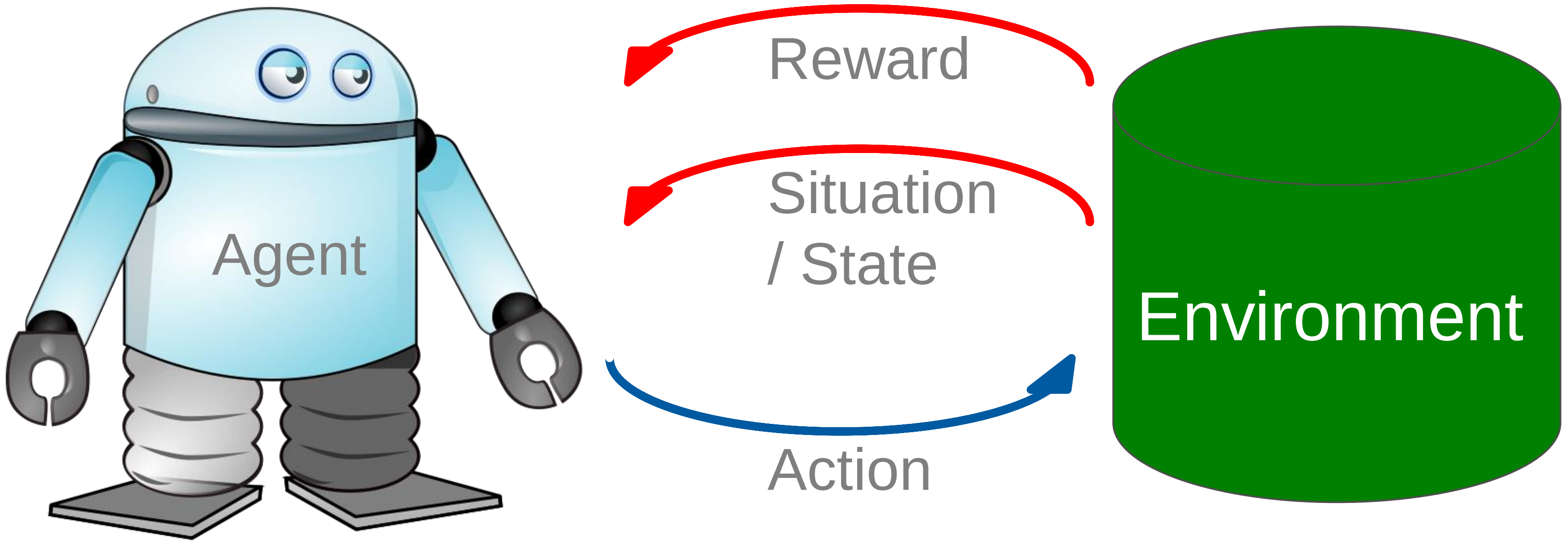
● Obstacle

■ Previous cell

Where to go?

Agent model

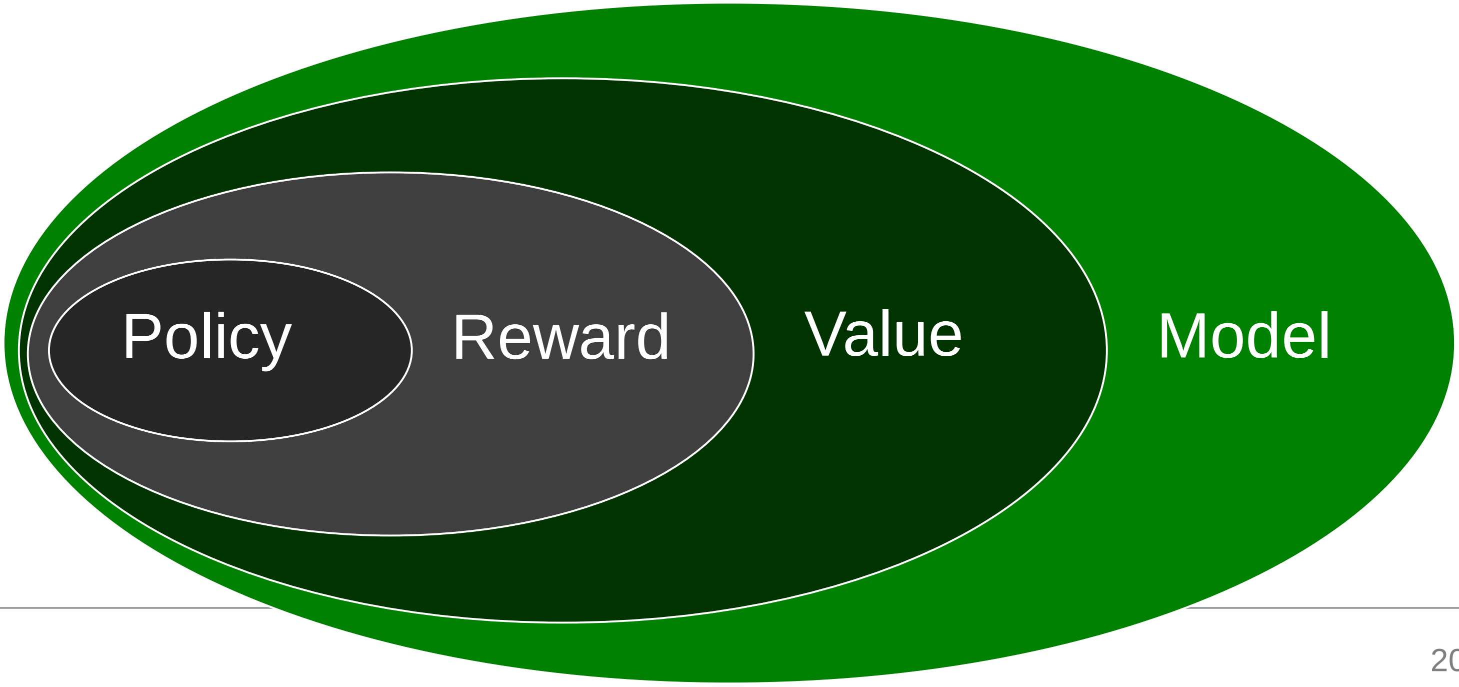
- The complete agent
  - Chronologically situated
  - Constant learning and planning
  - Affects the environment
  - Environment is stochastic and uncertain



Elements of Reinforcement Learning

Elements

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



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 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:

$$
\begin{aligned}
a_t^* &= \arg max_a\, Q_t(a) \\
a_t &= a_t^* \Rightarrow exploitation \\
a_t &\neq a_t^* \Rightarrow exploration
\end{aligned}
$$

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

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- **Extended Classifier System**
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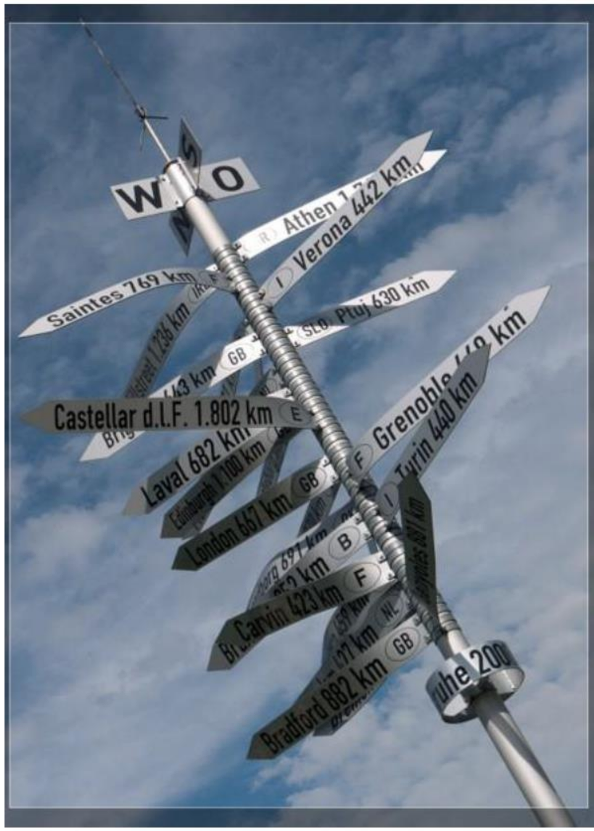


Names to remember in LCS research

- 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.

Initial approach by Holland

- Initially system
  - Holland designed a 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

XCS in brief

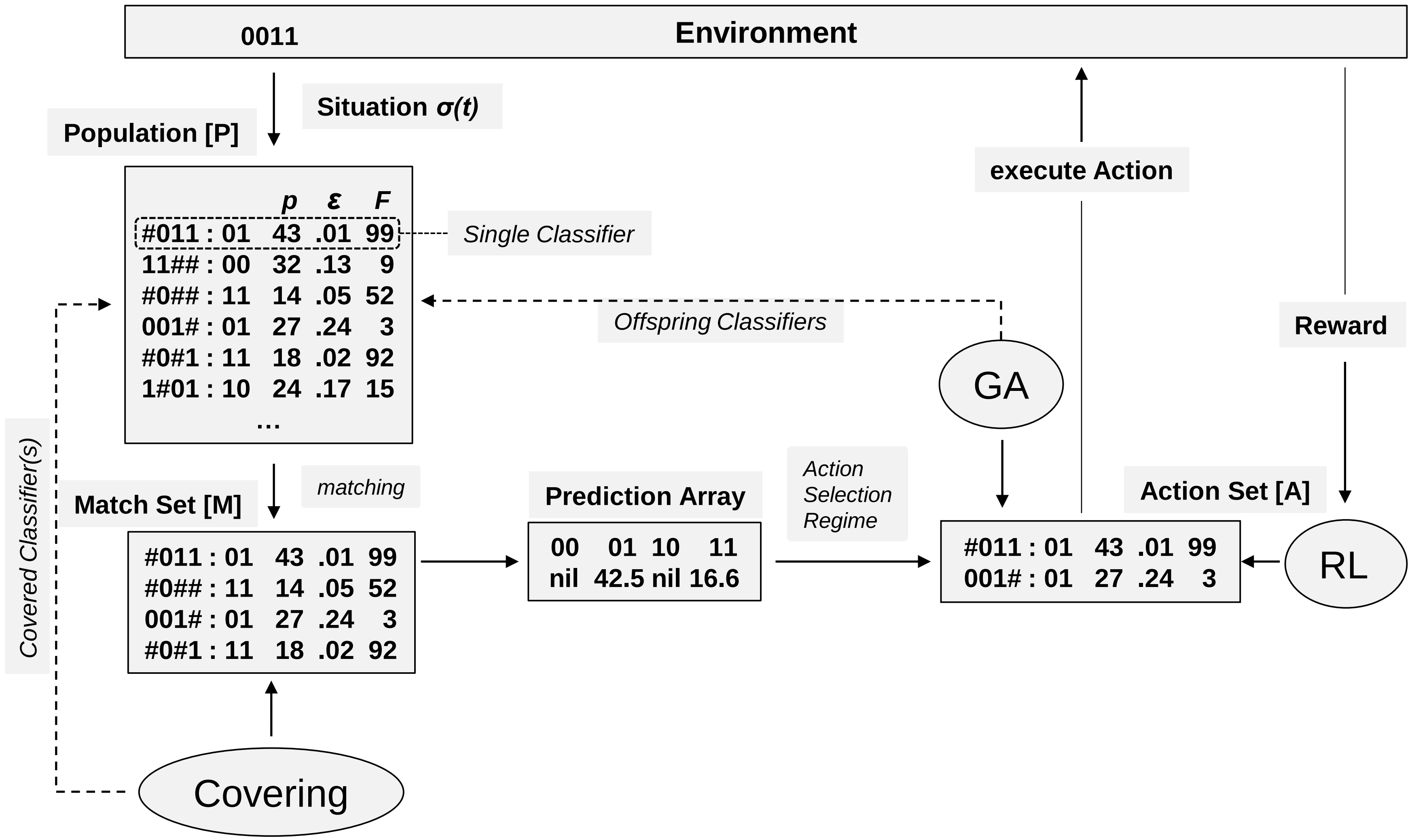
The Extended Classifier System (XCS) by Wilson

- 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.

Strength vs. accuracy

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

- What is the difference of 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"

- 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 $X \times A \rightarrow P$, by means of 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.

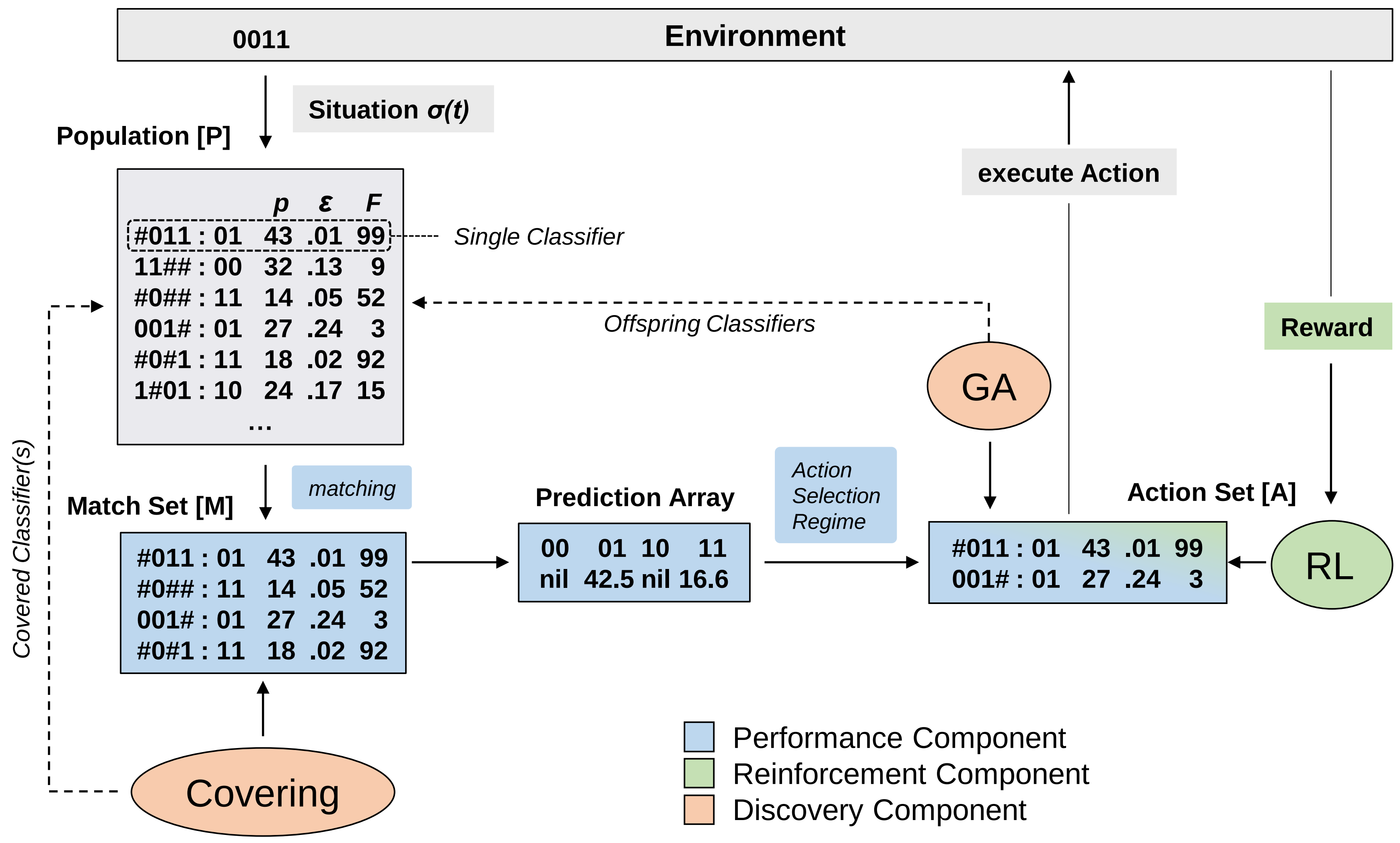
- Thus, accurate classifiers are more likely to reproduce and will eventually take over the environmental niche.

XCS‘ algorithmic structure

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)



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 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 $\sigma(t)$

XCS‘ algorithmic structure (3)

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 (4)

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 by means of the modified delta rule (Widrow-Hoff delta rule) in combination with the moyenne adaptiv modifee (MAM) technique.

XCS‘ algorithmic structure (5)

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 predefined initial values (typically 10.0, 0.0 and 0.01).

XCS‘ algorithmic structure (6)

Genetic Algorithm:

- One of the most essential part 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 (7)

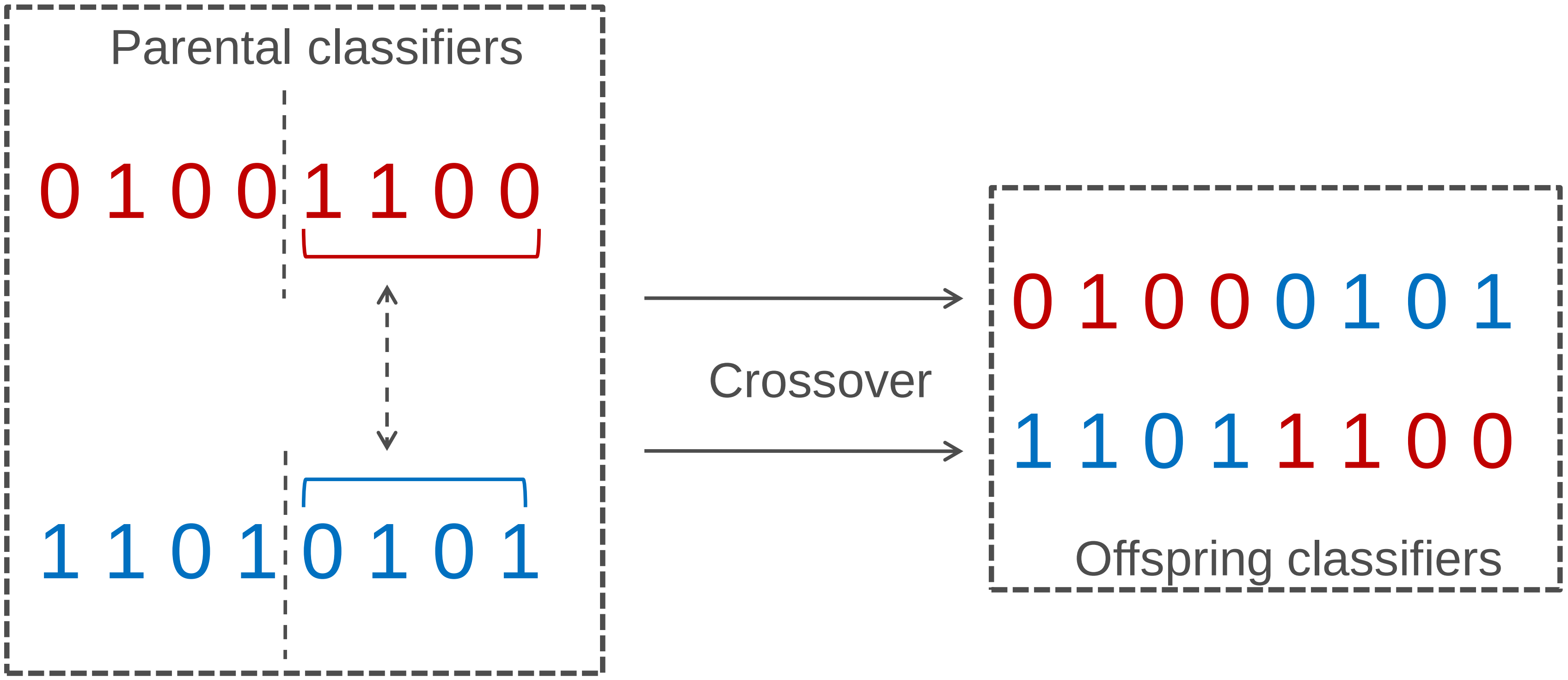
Genetic operators

- 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 $\{0,1,\#\}$.

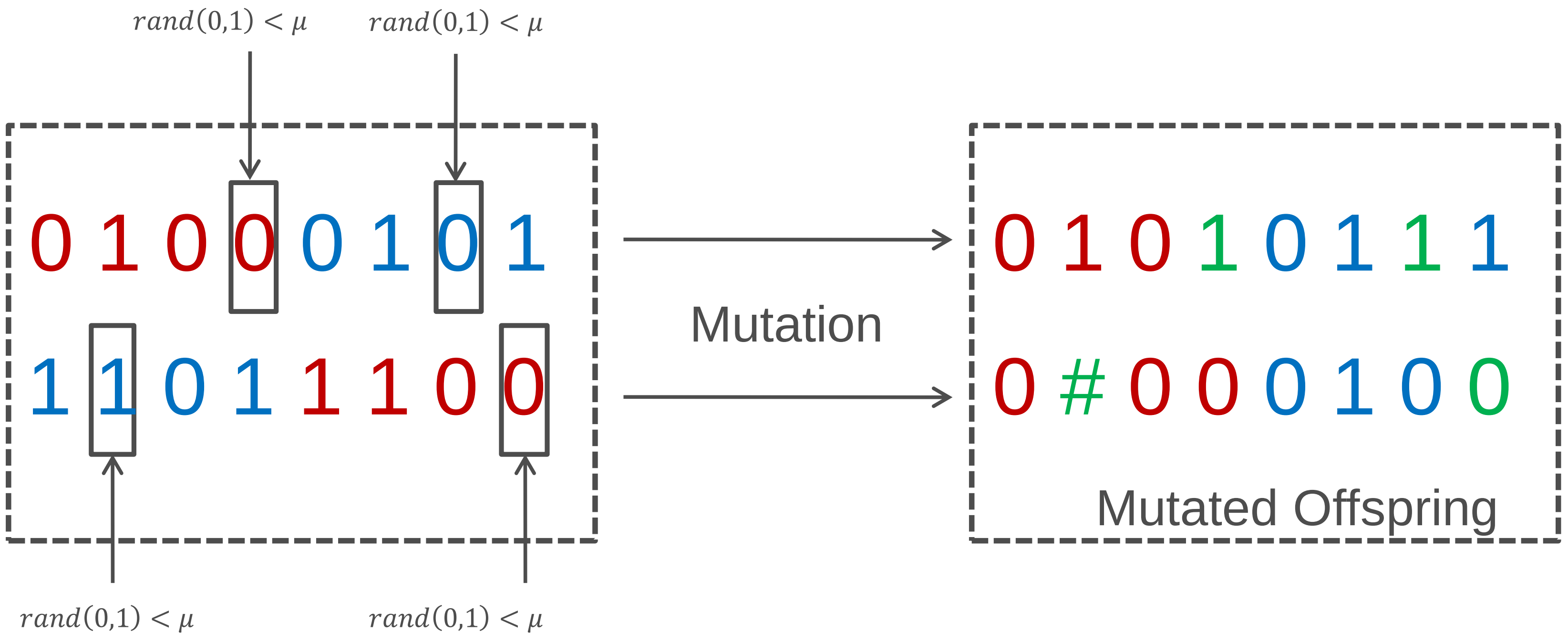
XCS‘ algorithmic structure (8)

One-point crossover:

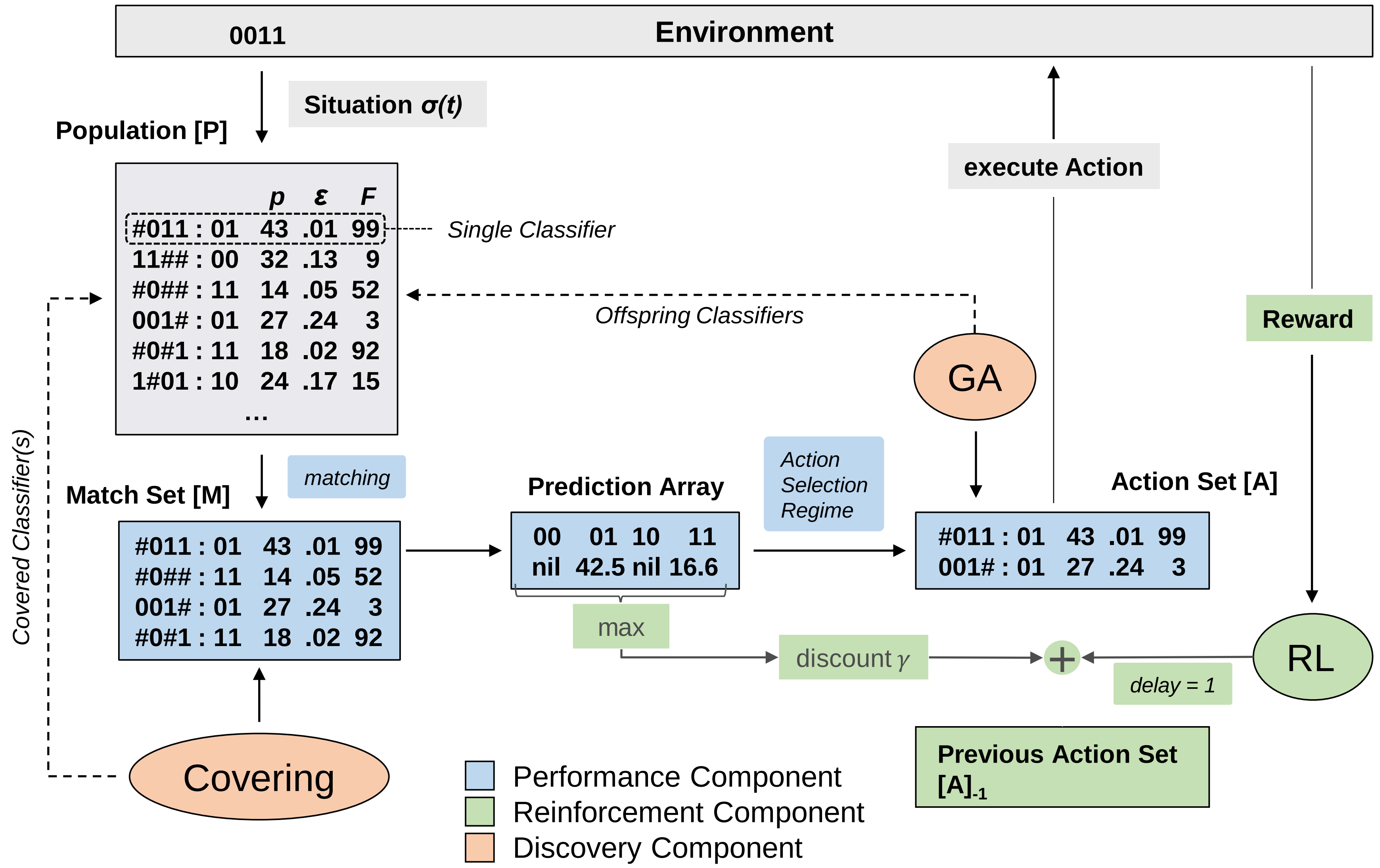


XCS‘ algorithmic structure (9)

Mutation:



Multi-step problems



Credit assignment: single- vs. 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 (may be 0).
- This delay allows to retrieve “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 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.

From binary to real-valued problem domains

- 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 $\vec{x}_t = (x_1 \dots x_n) \in X \subseteq \mathbb{R}^n$.
- 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.

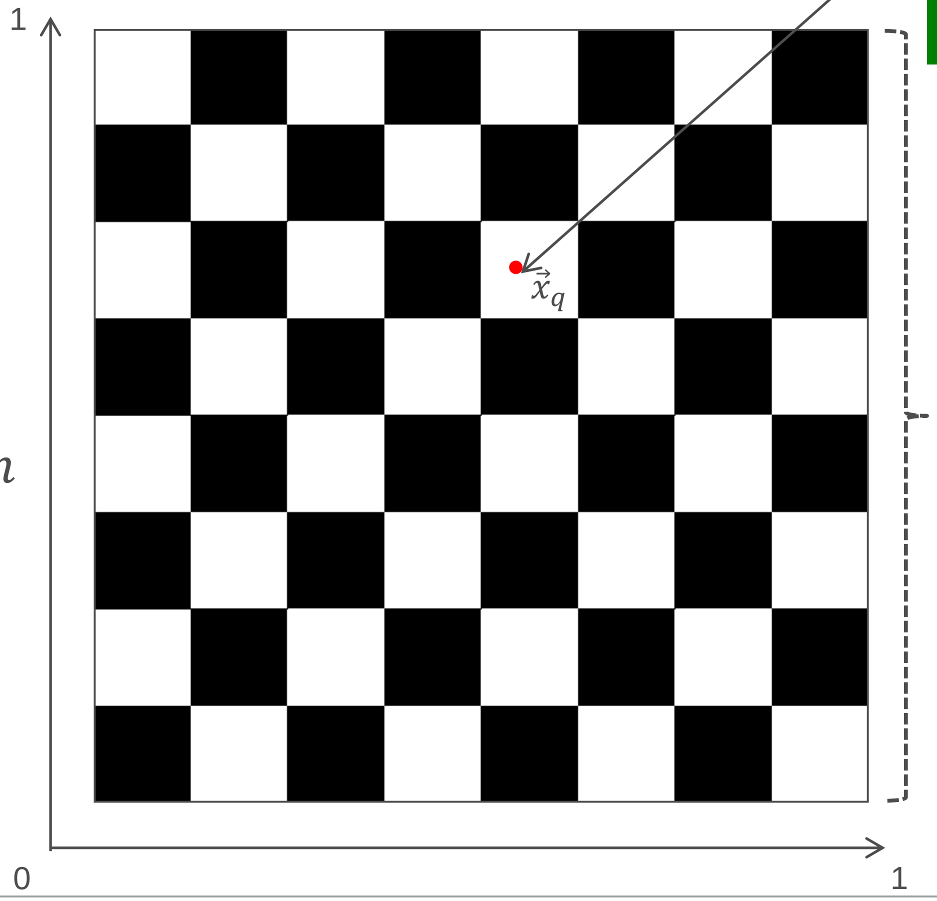
A `real toy problem‘: the checkerboard problem

Checkerboard Problem - CBP(2,8)

cf. [Stone2003]

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

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



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

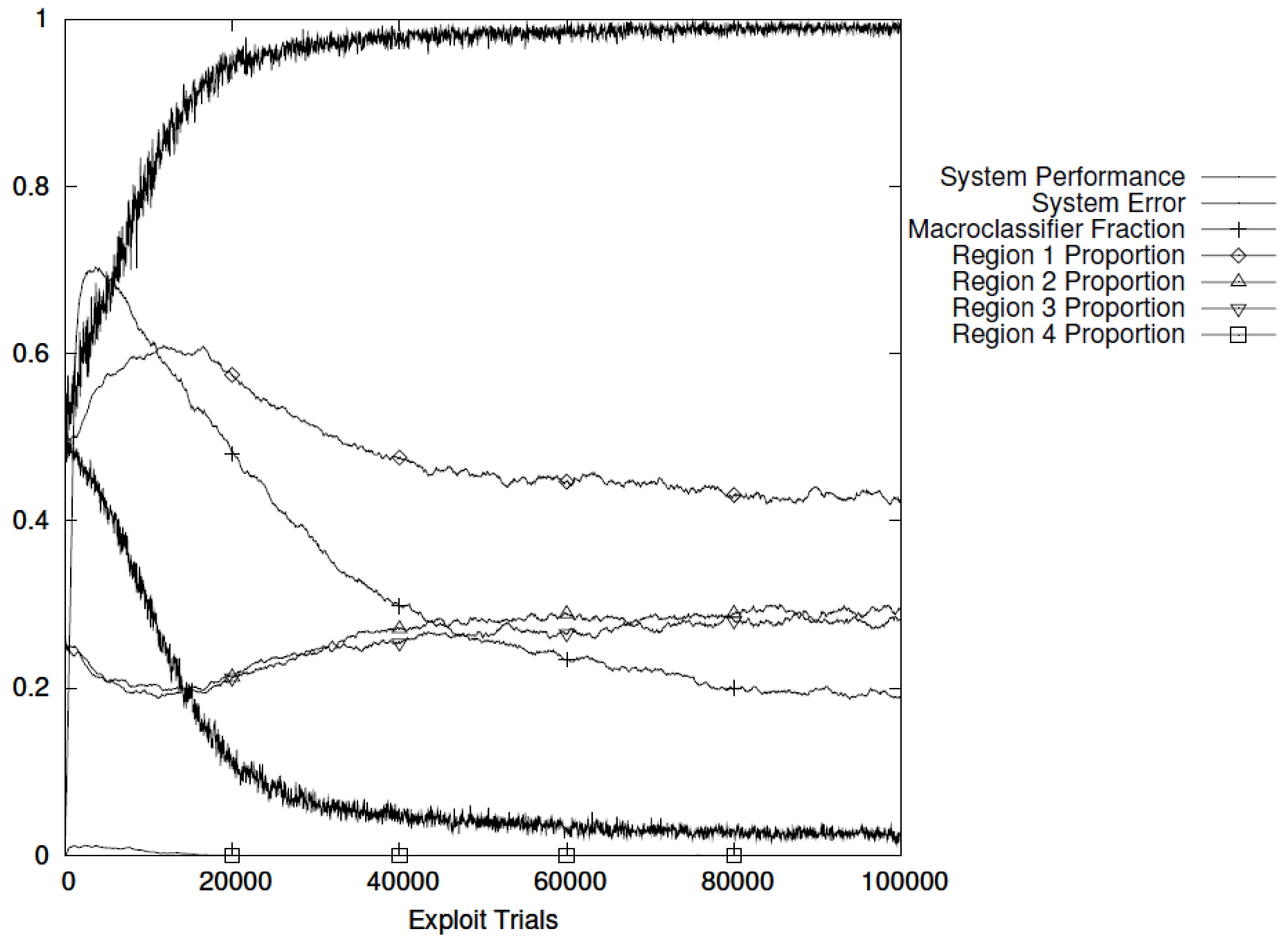
8 divisions $n_d = 8$ for each dimension with alternate field colours (black/white)

XCS at CBP

- 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 wrong guess

Single-step or multi-step problem?

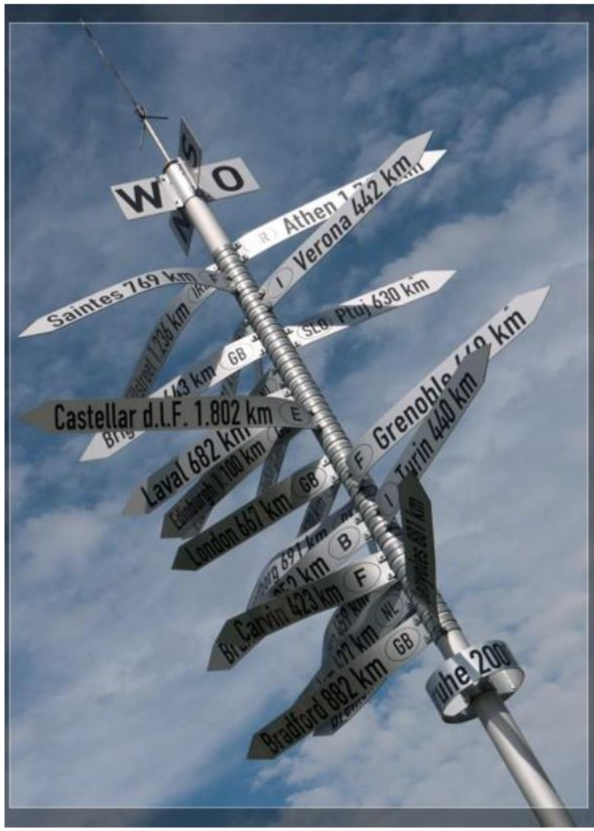
XCSR results on CBP(3,3)



cf. [Stone2003]

Agenda

- Motivation
- Extended Classifier System
- **XCS-O/C**
- Artificial Neural Networks
- Conclusion and further readings

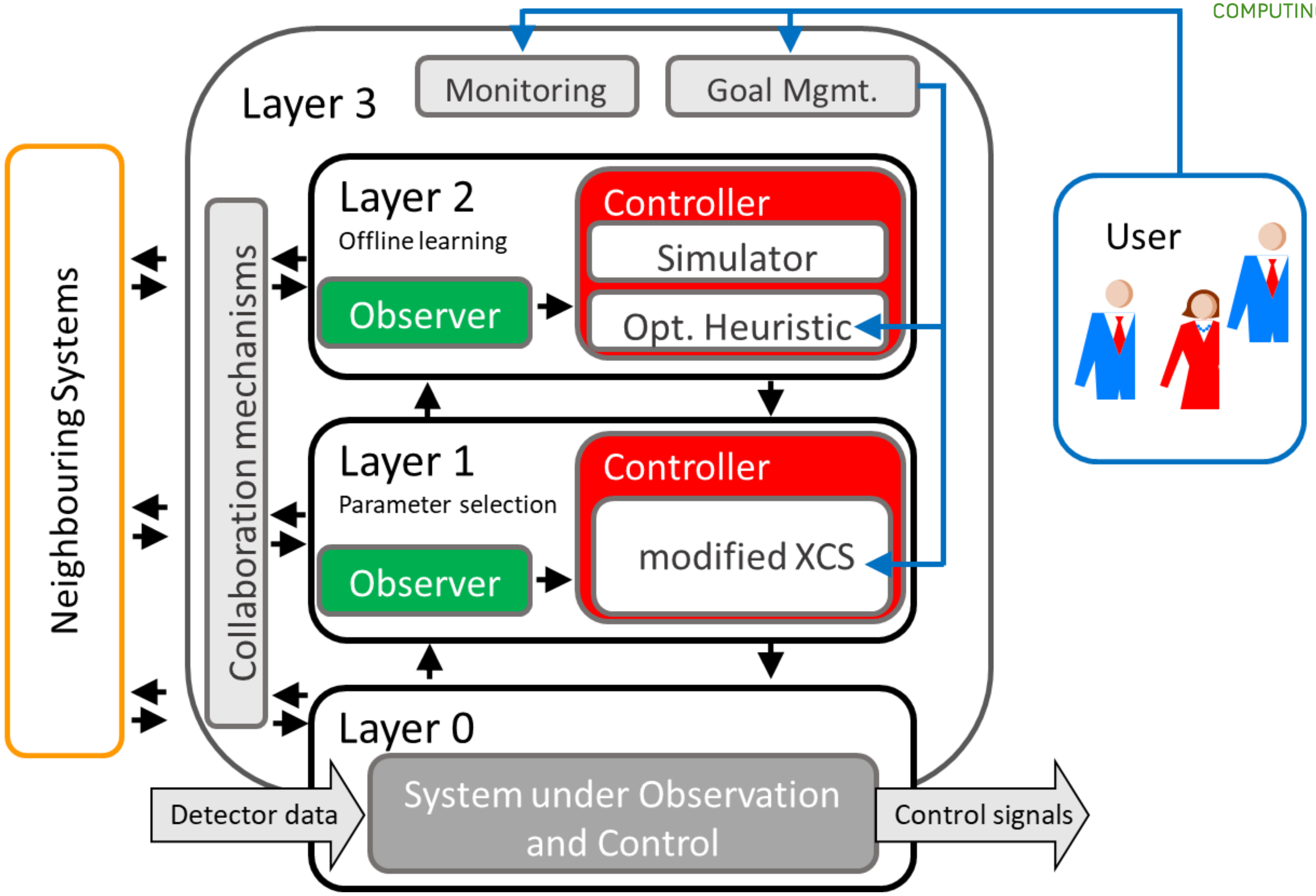


Learning in organic systems

Modifications needed

- Exploring configuration space online using GA can be dangerous!
  - System will try suboptimal (or even bad) solutions.
  - Example: 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.

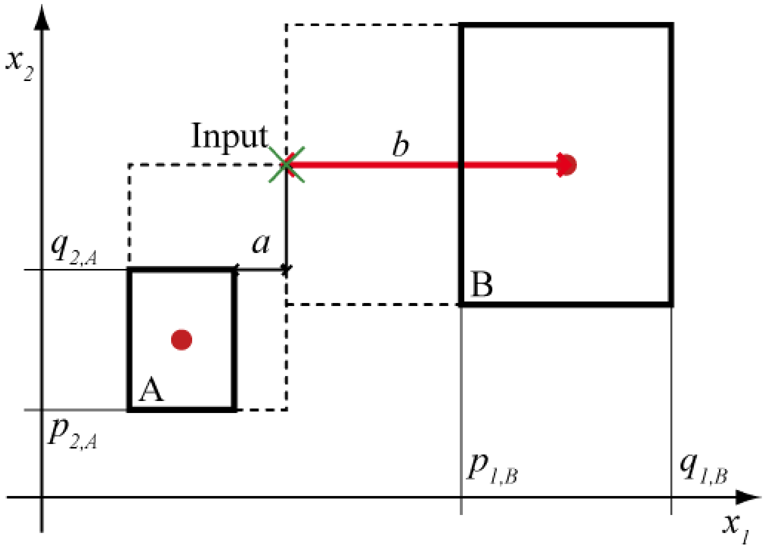
Multi-level observer/controller framework

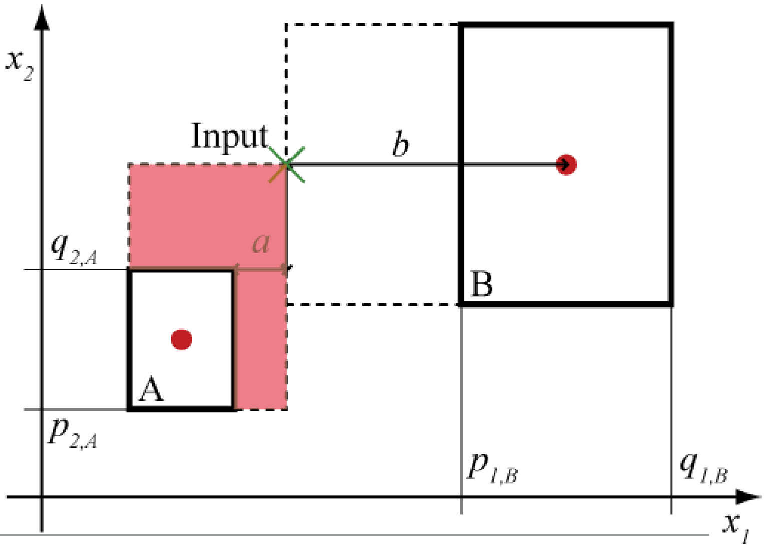


Modifications: covering

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:

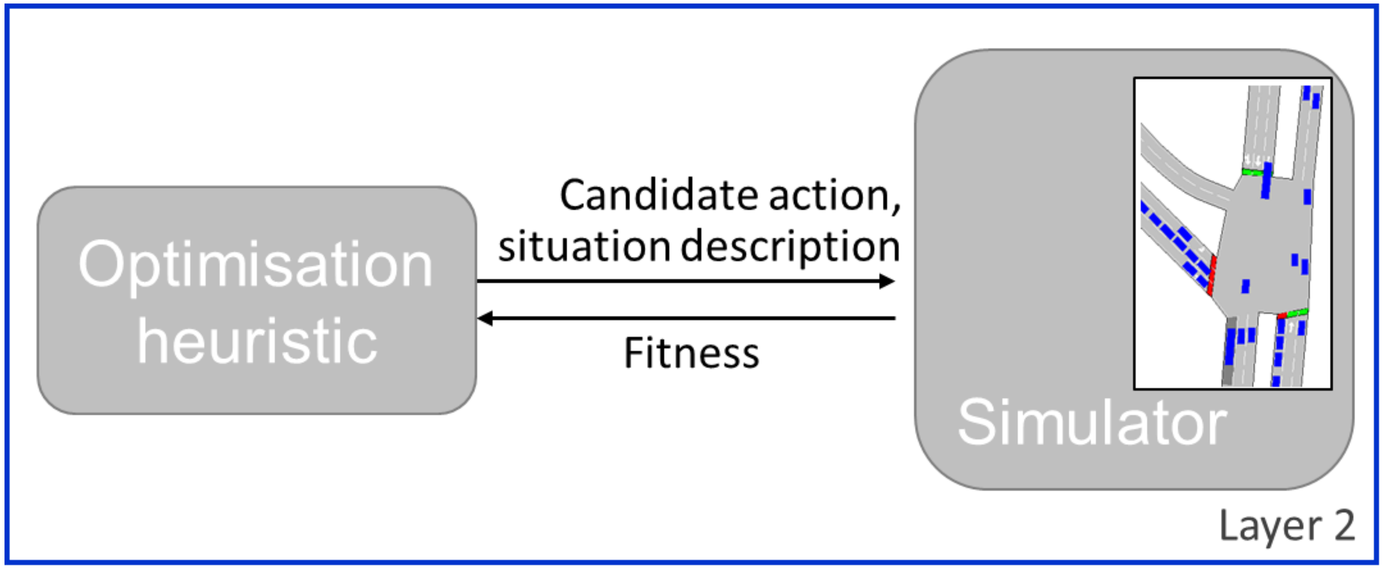
- Covering at Layer 1 solves only a part of the problem.
- Building of match set: trade-off between “use only matching solutions” and competition needed for learning.
- What to do with an empty population?

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.
- Process is repeated until stop criterion is reached.

Modifications: rule generation (3)

Novel rule

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

Process is activated:

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

Further modifications

Modifications:

- Representation
  - Use classifiers as 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)

Alternative optimisation techniques

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…

Hardware solutions

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 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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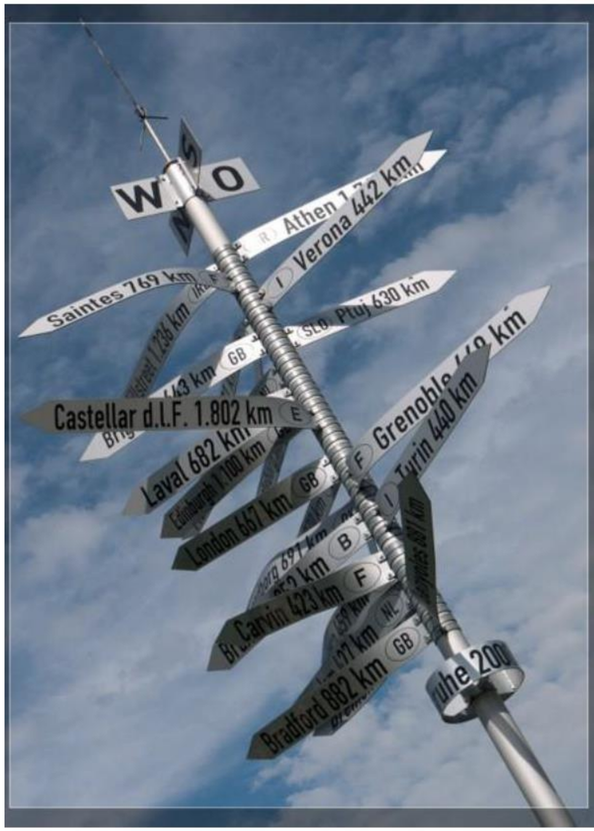
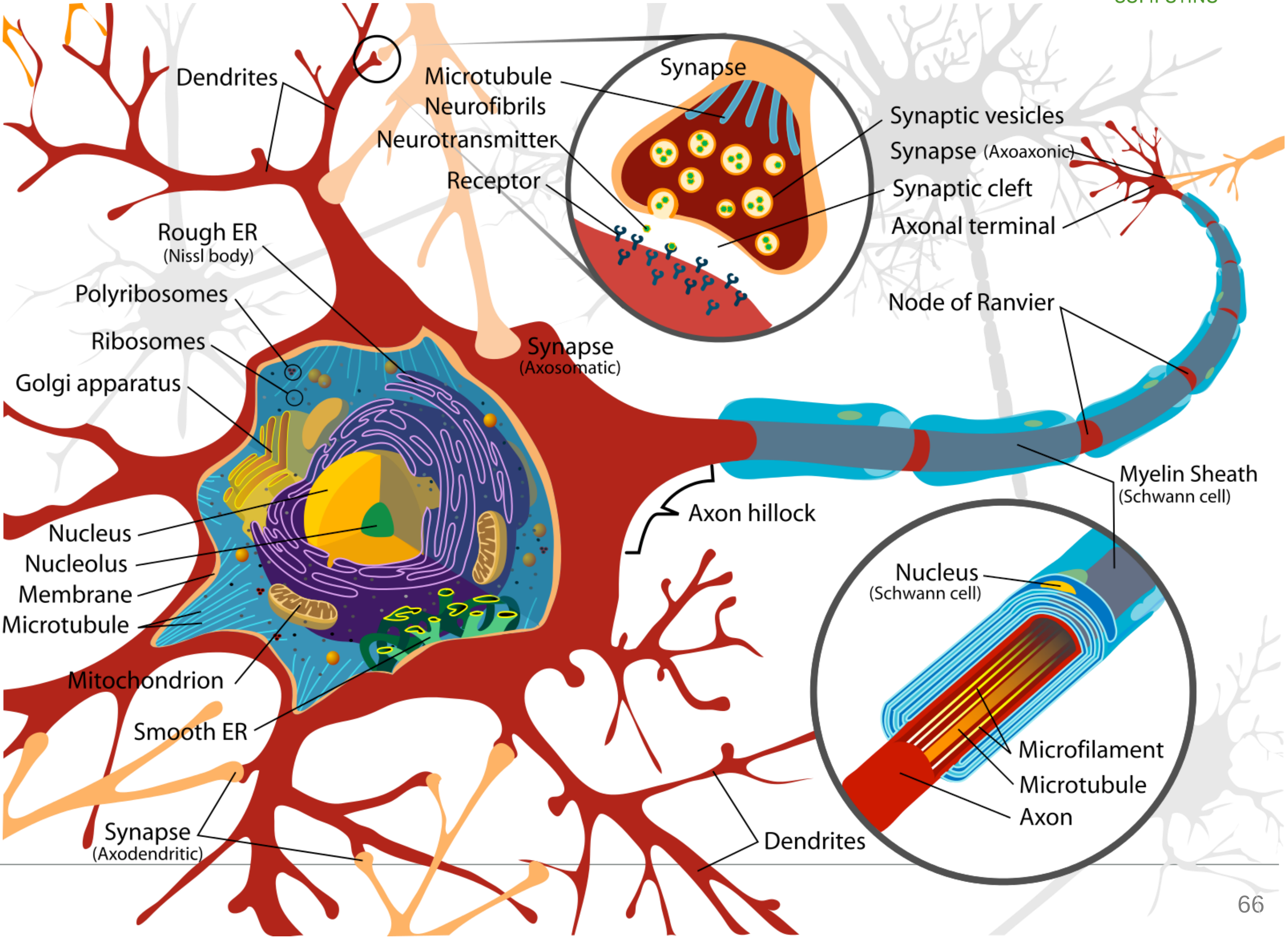
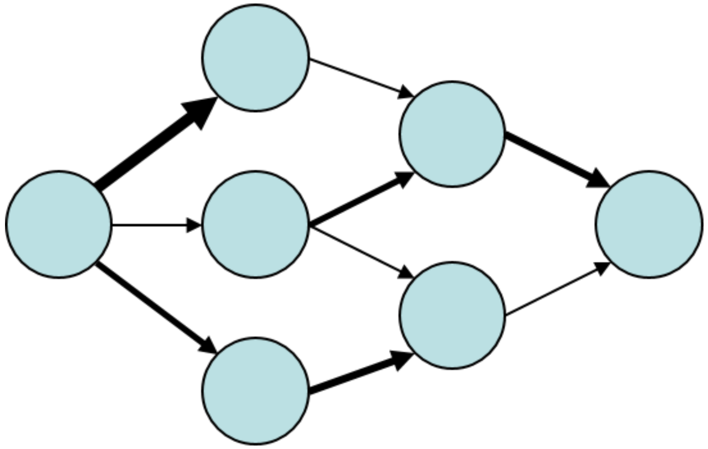


Neural networks in nature



Artificial neural networks

- a set of simple processing elements (neurons)
- each neuron
  - may receive multiple inputs
  - provides an output
- input and output values are mediated by weighted connections
- the connected neurons form a directed graph, the network



What are ANNs used for?

Function approximation!

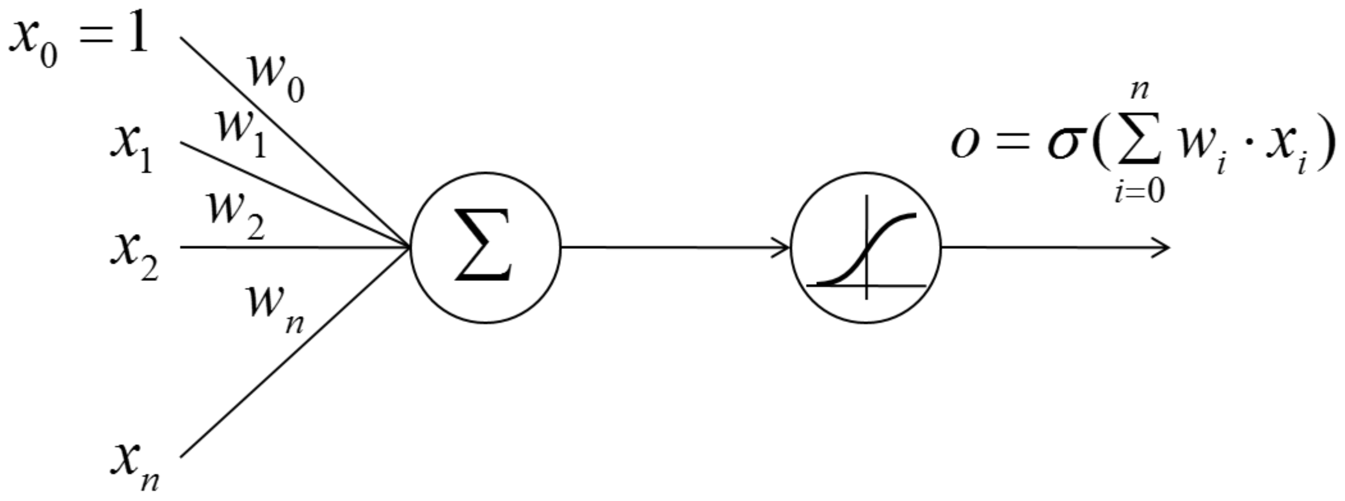
(i.e. supervised learning)

How can functions be approximated using ANNs?

- altering the network’s weights ⇒ calculations of the network are altered
- thus: adjust the weights so that the network maps certain inputs to certain outputs
- this process is referred to as training
- training relies on a set of examples, i.e. a set of inputs along with desired outputs

Neuron structure

1. Calculate weighted sum of inputs.
2. Apply activation function σ.
3. Provide output.

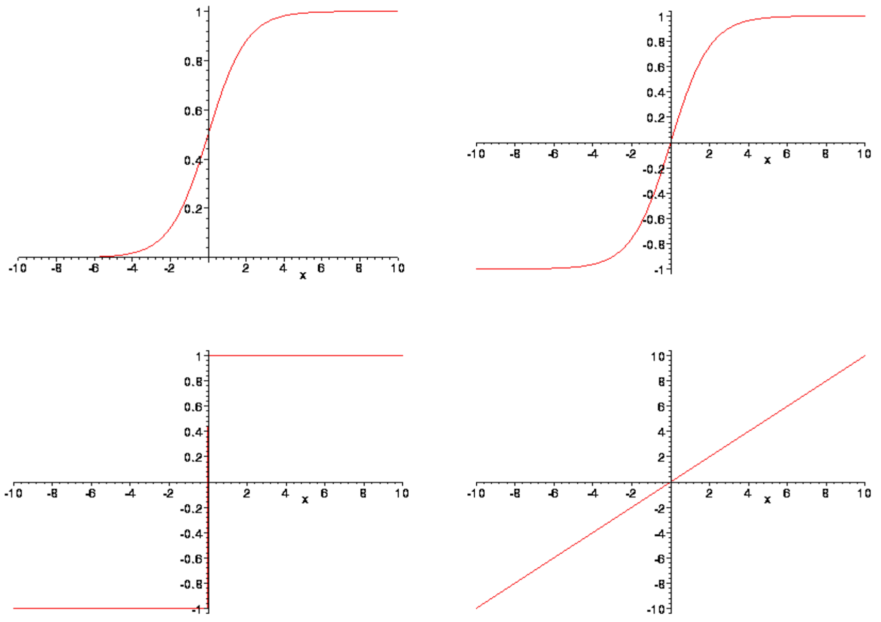


Activation functions

- map net input value to neuron output
- many possibilities (linear, nonlinear, …)
- choice can influence necessary training

Typical activation functions

- logistic function (aka sigmoid)
- hyperbolic tangent function
- step function
- Identity function

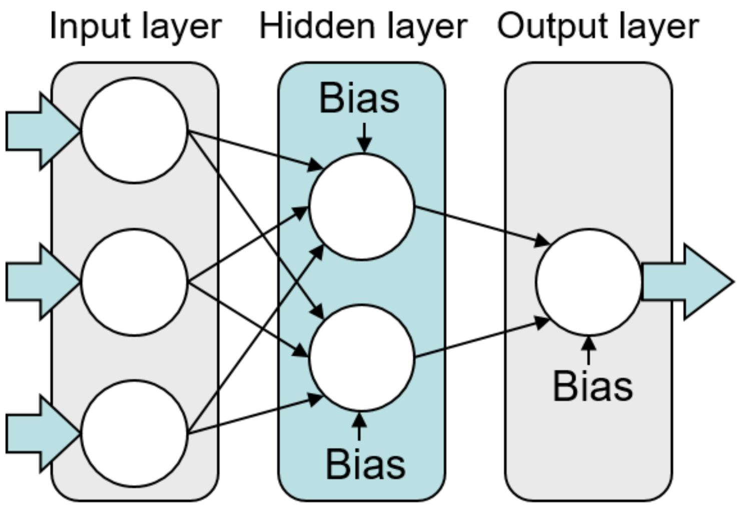


Topologies

- feed-forward
- convolutional
- recurrent
- …

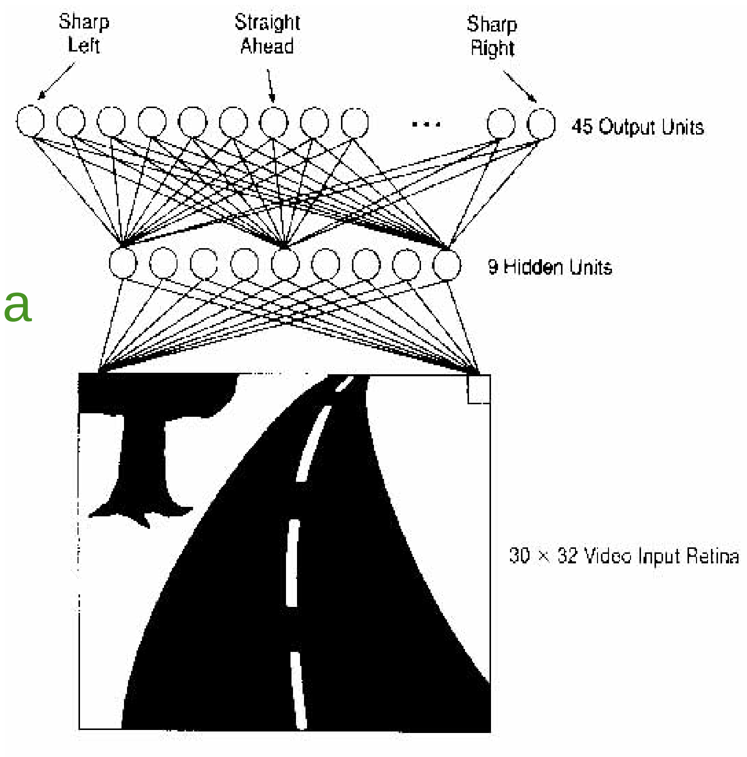
Multilayer feed-forward networks

- special case of feed-forward networks
- each layer fully connected to the next one
- no other connections



Example: ALVINN

- ALVINN: **A**utonomous **L**and **V**ehicle **I**n a **N**eural **N**etwork
- learn to steer a vehicle driving at reasonable speed on a public highway
- steering decisions based on images from a forward pointing camera
- training by watching a human driver
- ALVINN is able to drive at speeds of around 100 km/h and for distances of 150 km after only 5 minutes of training



Pomerleau, D. A. (1993). Knowledge-based training of artificial neural networks for autonomous robot driving. In Robot learning (pp. 19-43). Springer US.

Training

- Goal: Find weights such that input generates desired output!
- Idea: Minimize error of prediction!

  ⇒ Optimization problem!
- Several options to solve this, e.g.
  - gradient descent (e.g. backpropagation)
  - evolutionary algorithms

Prediction error

e.g. mean squared error

$$\frac{1}{n}\sum_{i=1}^{n}(y_{true} - y)^2$$

Backpropagation algorithm

- idea:
  - compute the network's prediction
  - calculate the prediction's error
  - adjust the network, layer by layer, starting from the output layer
- use gradient of error measure for weight updates

  ⇒ error measure must be differentiable
- Note: Prediction is part of error measure ⇒ Activation function must be differentiable as well!

$$\Delta w_{ij} = -\eta \frac{\partial E}{\partial w_{ij}}$$

Drop the derivatives! Neuroevolution!

- Why not use evolutionary optimization instead of gradient descent for weight update?
- Why not evolve the network's structure as well?

Neuroevolution for network weights

- represent network weights as an individual of a population
- fitness measure for an individual: How well does a network with the individual's weights perform on the data?
- perform the usual GA operations on these individuals, e.g.
  - definitely mutation and selection
  - perhaps crossover
- result: network weights
- This works surprisingly well!
  - often less computationally intensive on (really) large networks
  - often the same or better performance as other optimization methods

Neuroevolution for network structure

- represent network structure as an individual of a population
- fitness measure for an individual: How well does a network with the individuals's structure perform on the data?
  - to calculate fitness: Have to train the network (using some optimization like backpropagation or another GA)
  - usually computationally intensive
- perform the usual GA operations on these individuals (mutation, crossover, selection, …)
- result: network structure

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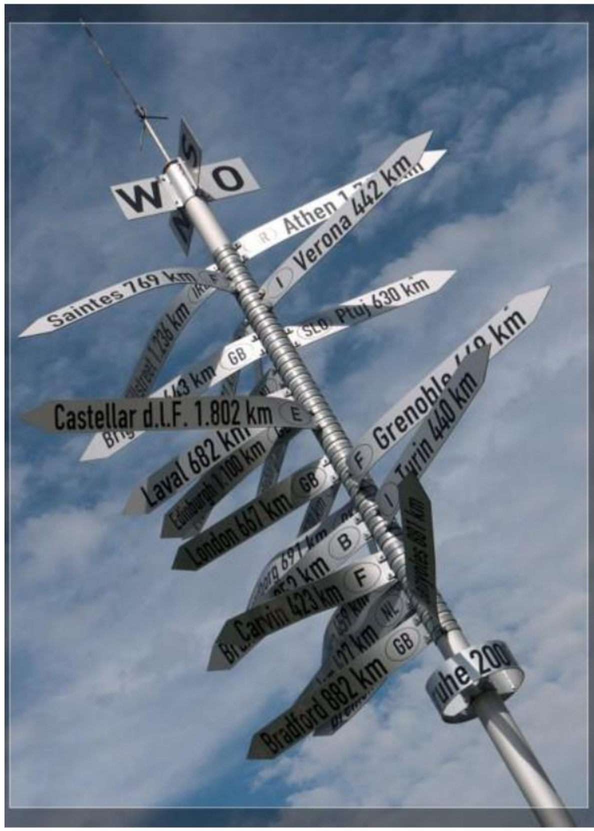

Conclusion

This chapter:

- Introduced to the concepts of machine 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 machine 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.

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End of chapter

Questions ...?