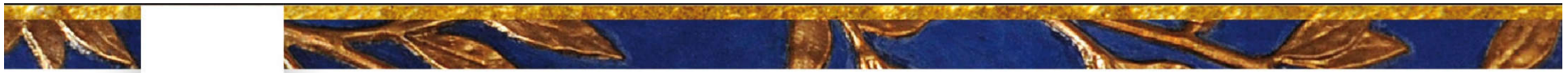

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Natural Computation Methods in Machine Learning (NCML)

Lecture 7: Reinforcement Learning

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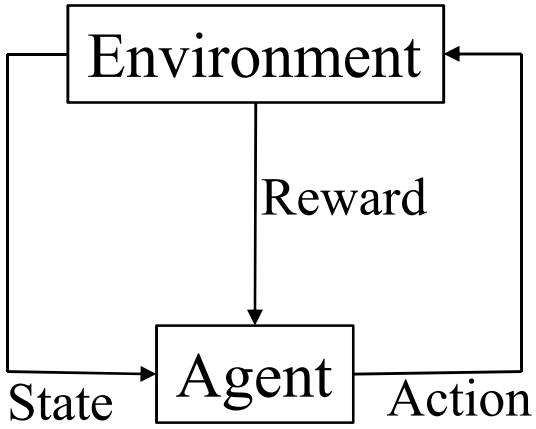
Reinforcement Learning (RL)

- Put the neural networks (ANNs) aside for a while
  - RL is not about ANNs, it is a field in its own right
  - (ANNs are often used in RL, though)
- Learning by interaction with an environment, to maximize som long-term scalar value
  - (or to minimize a cost)
  - Learning by trial-and-error
- Applicable to a very large set of real world problems
- Strongly related to Markov Decision Processes and Dynamic Programming



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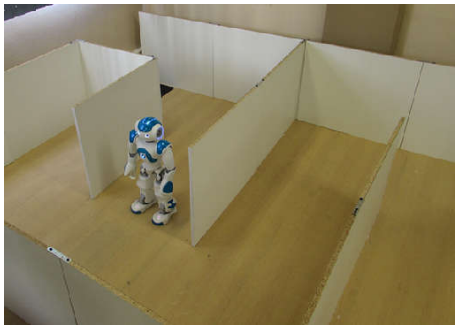
Reinforcement Learning (RL)

Application examples

- Board games
  - Checkers (1959), Tic-Tac-Toe (1961), Backgammon (1992), Go (2015) ...
- Robot navigation (maze solving in general)
- Pole balancing (control of unstable systems)
- Scheduling (elevators, schools, airline crews, ...)
- Traffic control (cars, trains, network routing, ...)

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MENACE

Machine Educable Noughts and Crosses Engine

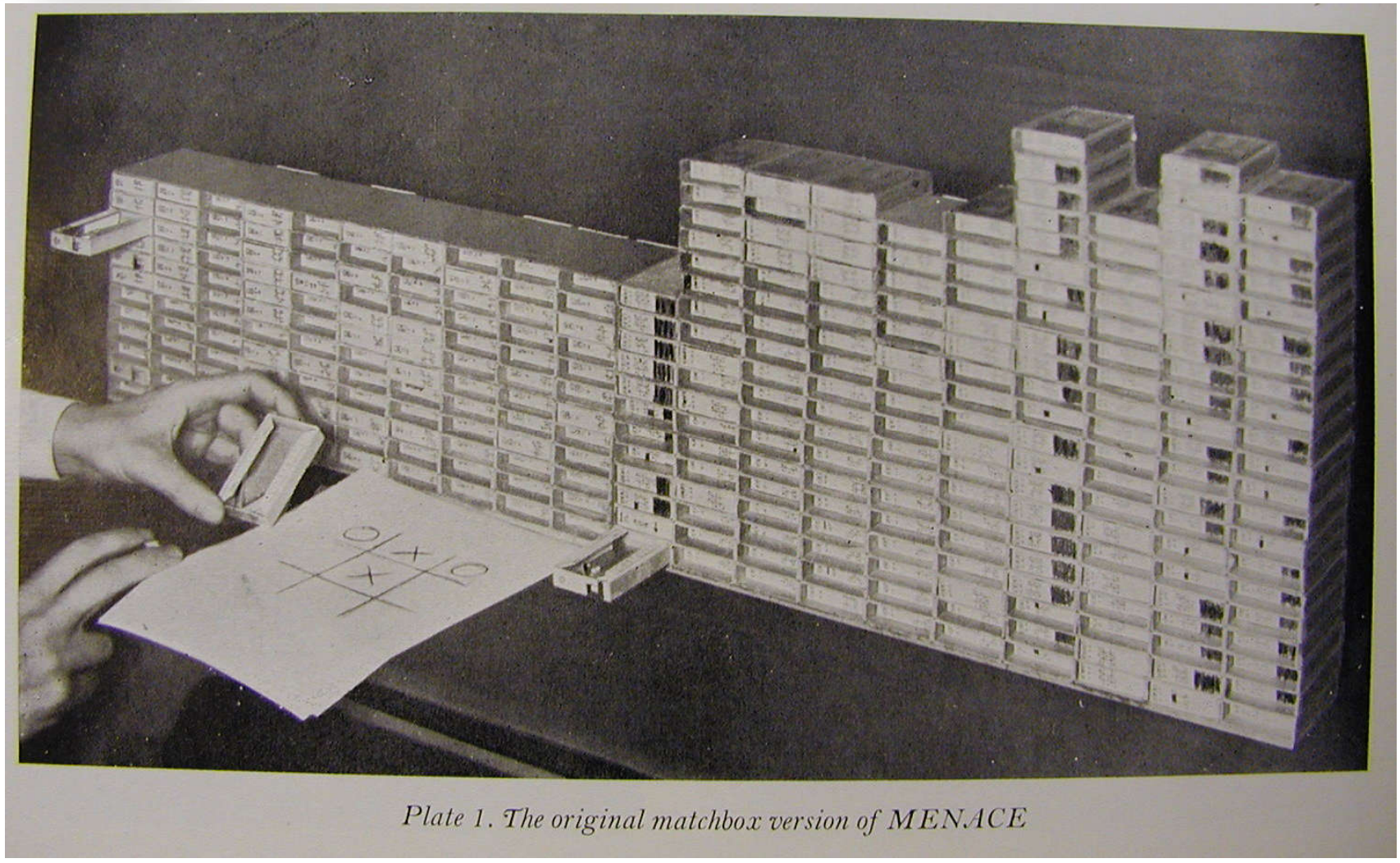

Plate 1. The original matchbox version of MENACE

Donald Michie, 1961

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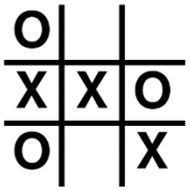
MENACE

Machine Educable Noughts and Crosses Engine

- Learns to play Tic-Tac-Toe (perfectly)
- The game board has at most $3^9 = 19683$ states
  - only 304, if we remove illegal and symmetric states
- One matchbox for each board position (state)
- Fill each box with a random number of coloured beads
  - 9 colours, corresponding to the 9 possible moves (actions)



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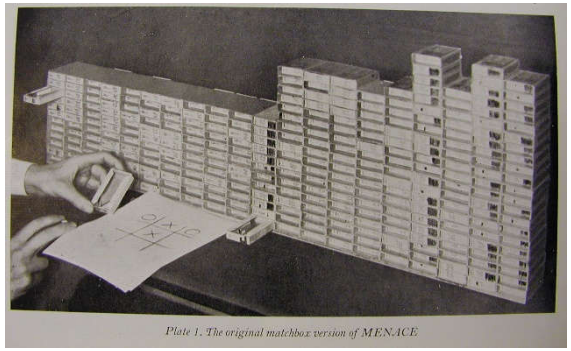
Plate 1. The original matchbox version of MENACE

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MENACE

How it works

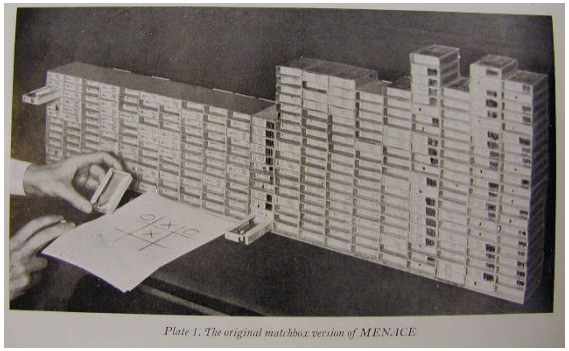

Plate 1. The original matchbox version of MENACE

- Given a board position (state)
  - Select the corresponding box
  - Draw random bead from the box
  - Colour decides position (the action)
  - Make the move and leave the bead outside the box
- When game ends
  - If MENACE won, put each bead back in its box + one more of same colour
  - If it lost, throw away the drawn beads
  - If the game was a draw, reset (put each bead back)
- It took about 150 games for MENACE to learn the optimal strategy, when playing against D. Michie

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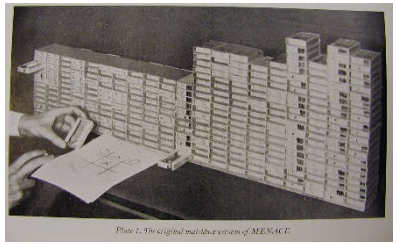

MENACE

Some notes

- All beads of a certain colour may be removed from a box!
  - That move will never be selected again
  - Neither would you, if you lost that many games ...
- A box may be emptied completely!
  - MENACE will refuse to play, if coming to that state
  - So would you, if you lost that many games ...
- That empty box may represent the very first state!
  - MENACE will refuse to play at all
  - So would you, if you lost that many games ...
- Game rules can be (and was) given as a prior
  - In initialization, make sure illegal moves have no beads
  - The machine can focus, not on *how* to play, but how to play *well*
- How to play against the machine? (on what level)

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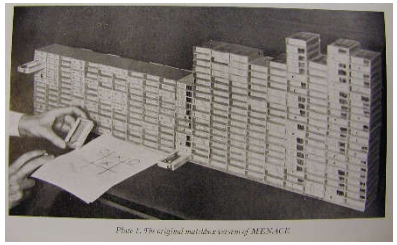

MENACE

Some notes

- MENACE gets no feedback until the game ends
  - Feedback depends on a sequence of moves
  - Difficult to decide which moves in the sequence were the most significant for the result
  - A credit assignment problem! (here, a temporal one)
  - Here, all moves in sequence are blamed/credited
- Are all moves blamed/credited by the same amount?
  - Not necessarily, depends on how boxes are seeded
  - Boxes representing late game states should have fewer beads of each colour

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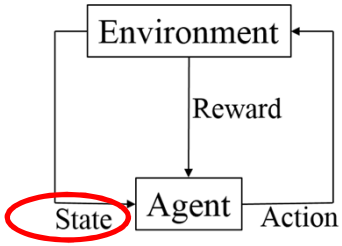

RL concepts and issues

State

- The State is a description of the environment's state
  - In MENACE, the board position
- Usually not a complete description of the environment, ...
  - Think of it as a vector of sensor values to a robot
- but must contain enough information for the agent to solve its task!
  - If not, the mapping (state→action) is no longer a function! (many-to-many instead of many-to-one)
    - Very common reason for experiment failures

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RL concepts and issues

Reward (reinforcement signal, grade)

- The reward is quality measure of the environment's state
  - Only indirectly, that of the agent's
    - The environment may have been affected by other things as well – e.g. random events or other agents
    - The agent's state may be incomplete
    - It does not say which actions in sequence to blame (or which other actions would have been better)
- This, very noisy, feedback is what we try to maximize (in the long run)
- Tip: Don't assume that negative rewards must be bad and positive rewards must be good!
  - To the agent, the reward is just a scalar to be maximized
  - That maximum may very well be negative (or zero)

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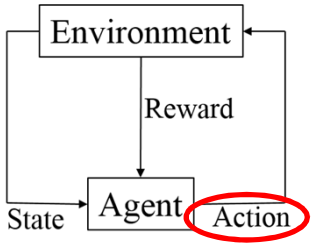

RL concepts and issues

Action

- Actions affect the environment and, indirectly, the next state/reward
  - The environment may be affected by other things as well
- Actions can be discrete or continuous
  - discrete: finite number of possible actions per state
    - as in MENACE
    - The agent selects an action, i.e. it is a classifier
  - continuous: infinite number of possible actions
    - for example, controlling the steering wheel of a car
    - The agent is a continuous function approximator
- For now, we will assume that they are discrete

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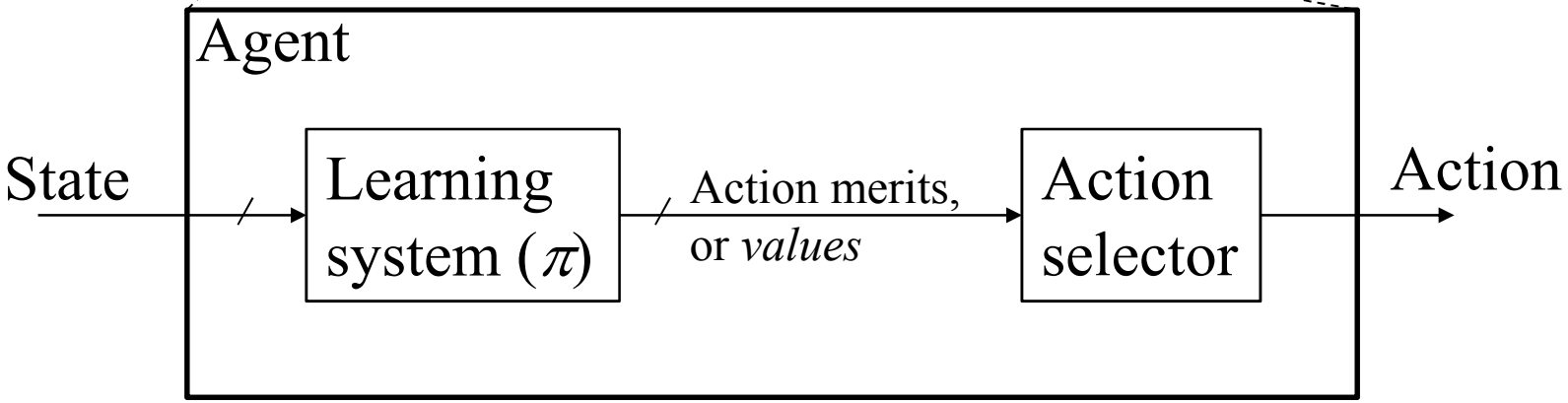
RL concepts and issues

The Agent



- Action selection must be stochastic!
  - The reward does not say which other actions, than the ones selected, would have been better
  - The agent must *explore*, to find better solutions
  - To explore = to sometimes select actions which (at that time) seem to be sub-optimal

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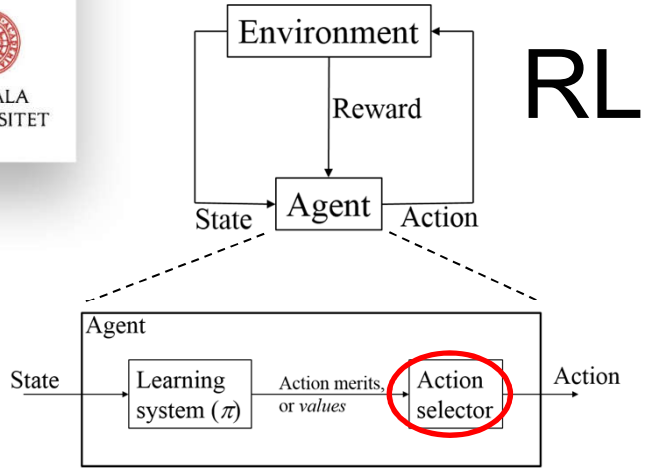

RL concepts and issues

Action Selection

- Epsilon-greedy (ε-greedy) action selection
  - With probability ε, select a random action
    - i.e. ignore the merit values from the learning system
  - Otherwise be *greedy*
    - *Greedy selection* is to choose the action which is currently believed to be the best (has highest merit value)
- Bolzmann selection (roulette-wheel sampling)
  - Select stochastically, proportionally to merit value
  - MENACE does this, in effect

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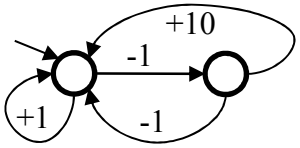
RL concepts and issues

Delayed v.s. Immediate RL

- Rewards should be associated with a sequence of actions (*delayed* RL), not just the latest one (*immediate* RL)
  - MENACE implements delayed RL, since it blames/credits all moves
- Also problems where rewards are payed after every action, may require delayed RL!
  - Simple example:



What's the optimal strategy here?
Is this strategy discoverable by immediate RL?

  - Real world example: Traffic control
  - Better to think of rewards as always being payed out
    - It's just that they are sometimes 0

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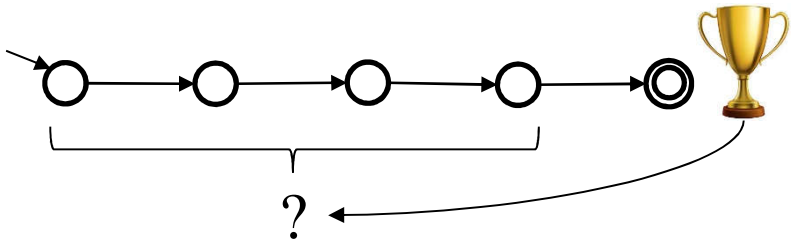
RL concepts and issues

The Temporal Credit Assignment problem

- In delayed RL, how to decide which actions in a sequence to give credit/blame for the result



- Common solution: Blame late decisions more than earlier ones
  - as MENACE does, if the boxes are seeded properly
  - not necessarily the best way, but easy to automate (and we usually don't know enough about the problem to be more clever)

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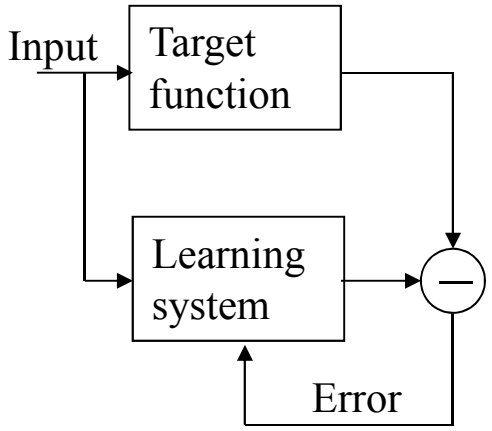
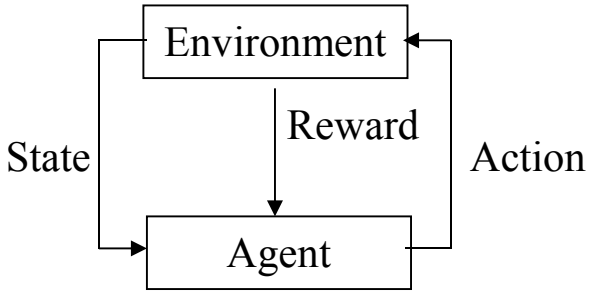
Comparison to supervised learning

Supervised Learning (SL)



- SL <u>imitates</u>
  - and can therefore never exceed the performance of its 'teacher'
- SL does not (usually) interact
- Feedback is specific and instructive
  - it says exactly what we want from the outputs

Reinforcement Learning (RL)



- RL <u>explores</u>
  - and therefore can outperform its 'teacher'
- RL <u>interacts</u>
- Feedback in RL is noisy, indirect and non-specific
  - It does not say which other actions would have been better

The two can be combined!

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More RL concepts

Goal, Value, and Policy

- The goal is to maximize the long-term reward
  - but we will soon reformulate this
- Sum of (expected) future rewards? (the *Return)*

$$R_t = E\left(\sum_{k=0}^{h} r_{t+k}\right)$$

- The Return has a *finite horizon* (h)
  - would like to have infinite horizon ($h{=}\infty$)
  - but that would make the sum infinite
    - not good since we try to maximize it
- Solution: Maximize a discounted sum instead

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More RL concepts

Goal, Value, and Policy

- Define the *Value* at time t, as a discounted sum of expected future rewards:

$$V_t = E\left(\sum_{k=0}^{\infty} \gamma^k r_{t+k}\right)$$

- γ is a *discount factor*, $0 \leq \gamma < 1$
  - side effect: decides short/long sightedness
  - Rule of thumb: The agent looks $\frac{1}{1-\gamma}$ time steps ahead
- Geometric sum ➔ finite (as long as $\gamma < 1$)
- Continuous variants exists
  - An integral instead of a sum

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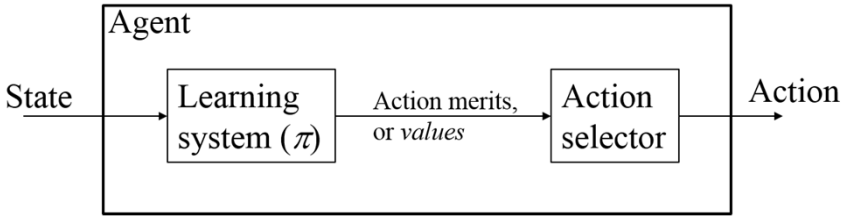
More RL concepts

Goal, Value, and Policy

- A *policy* is a function π from states to actions
  - i.e. it is the learning system in the agent



- The goal (reformulated) is to find an optimal policy, π^*, which for each state selects the action which maximizes V
  - This is a Markov Decision Problem, usually solved by some form of Dynamic Programming
  - RL (in this form) can be seen as a generalization of Dynamic Programming

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Challenges

- Implement MENACE as a table of values, and try to make it learn by playing against itself!
  - Nowadays, this should work even if you don't remove illegal/symmetric states
- How many matchboxes would we need if we wanted MENACE to play Connect Four instead?
- Does a reinforcement learning problem have to have an end state? (as in a board game)