

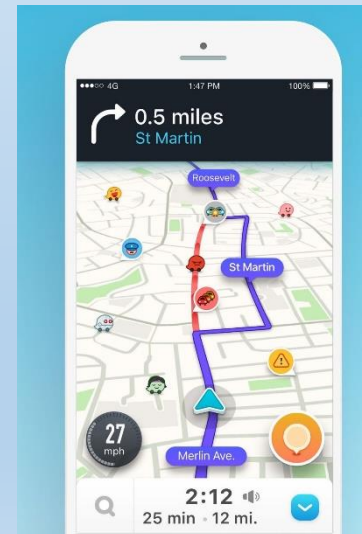
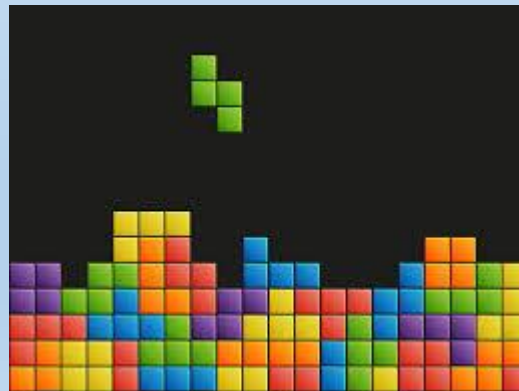
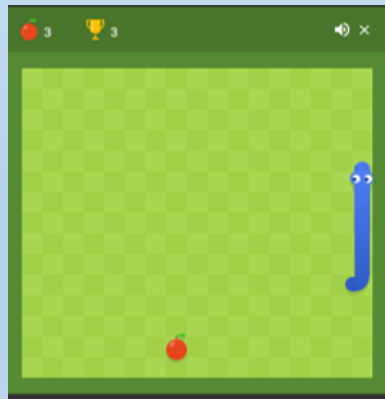
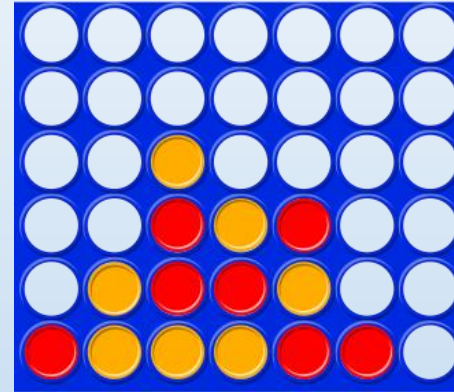
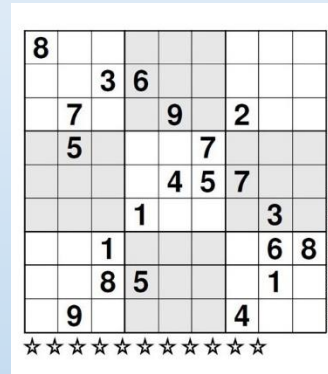
# The three fundamental mechanisms of AI: Search, Optimisation, Learning

Hugues Bersini

IRIDIA-CODE

ULB

Use indifferently different techniques for the same problems





- $A^*$  = **search**
- Genetic Algorithm = **optimisation**
- Q-Learning = **learning**

How to differentiate them:

- CPU Time and Memory
- Algorithm Complexity
- Ease to integrate Human Expertise

# Multiple ways to mix or to hybridize them

- Make AI becoming a software tool box
  - For instance:
    - Learn the right heuristic for A\*
    - Improve the optimisation algorithm for the learning phase of Neural Nets
    - Learn the best parameters of a Genetic Algorithm
    - Combine them: Optimisation + Neural Nets
- + Classical problem solving algorithms not originally coming from and with AI

# Not immune to fashion

- Neural Nets many successive deaths and resurrections: 50', 80', 2000'
  - Connectionims, NN, Deep Learning
- Fuzzy Sets in the 80'
- Complexity Theory: Chaos, Multi-Agents
- The Deep Learning current fashion

# First Example: the 15 puzzle game

1	2	3
4	5	6
7	8	

(a)

5	8	1
	3	7
4	2	6

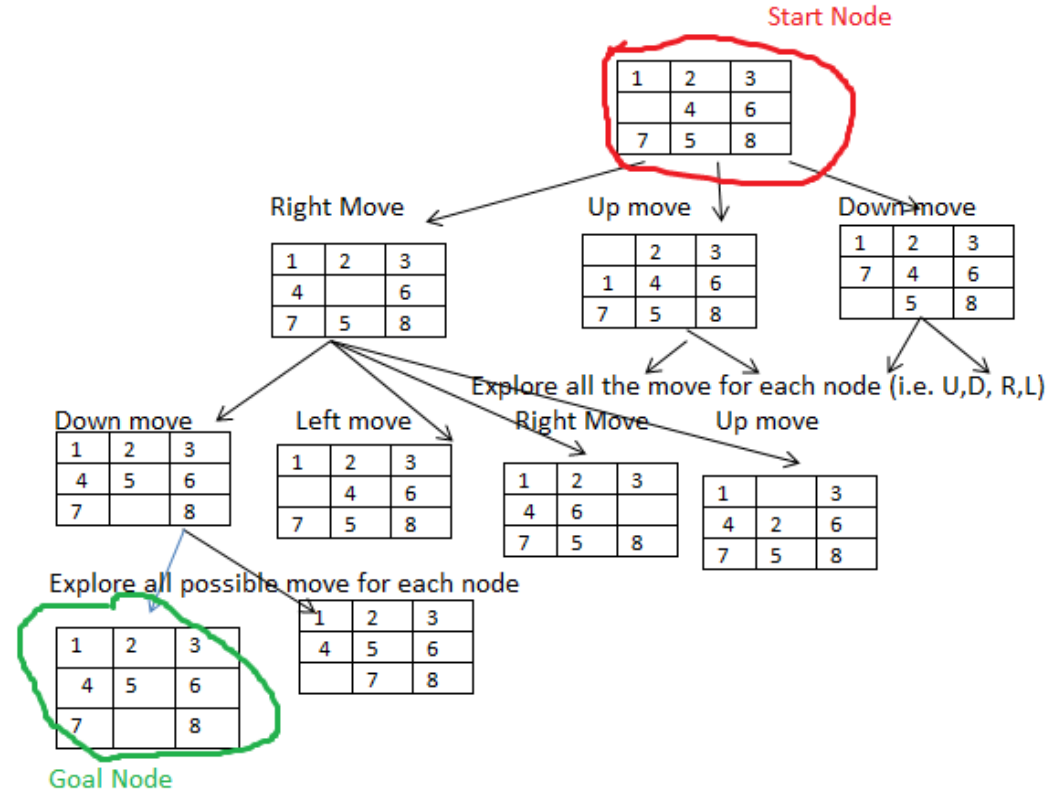
(b)

1	2	3
4	5	6
8	7	

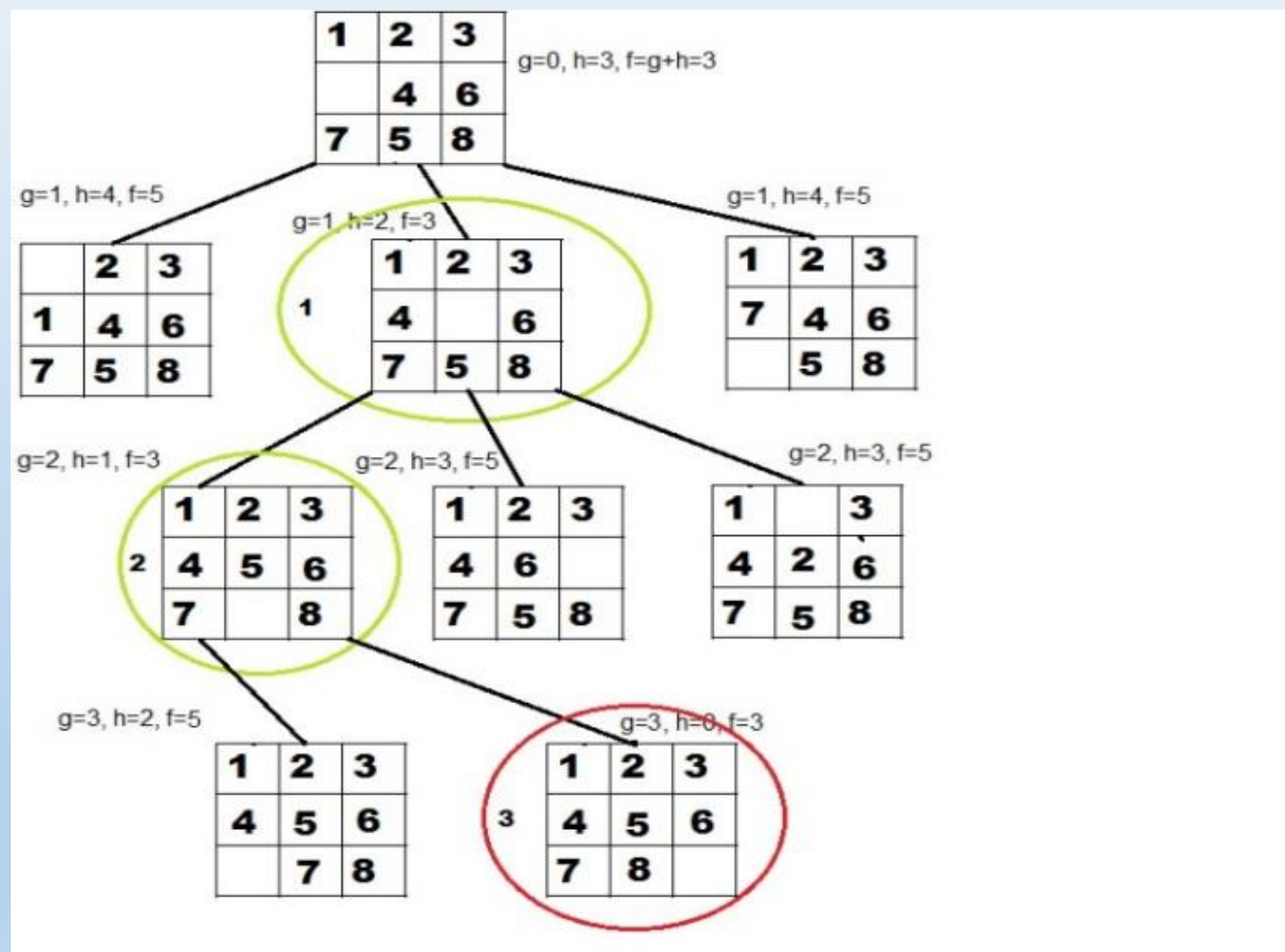
(c)

# Breath First

### Breath First Search to solve Eight puzzle problem

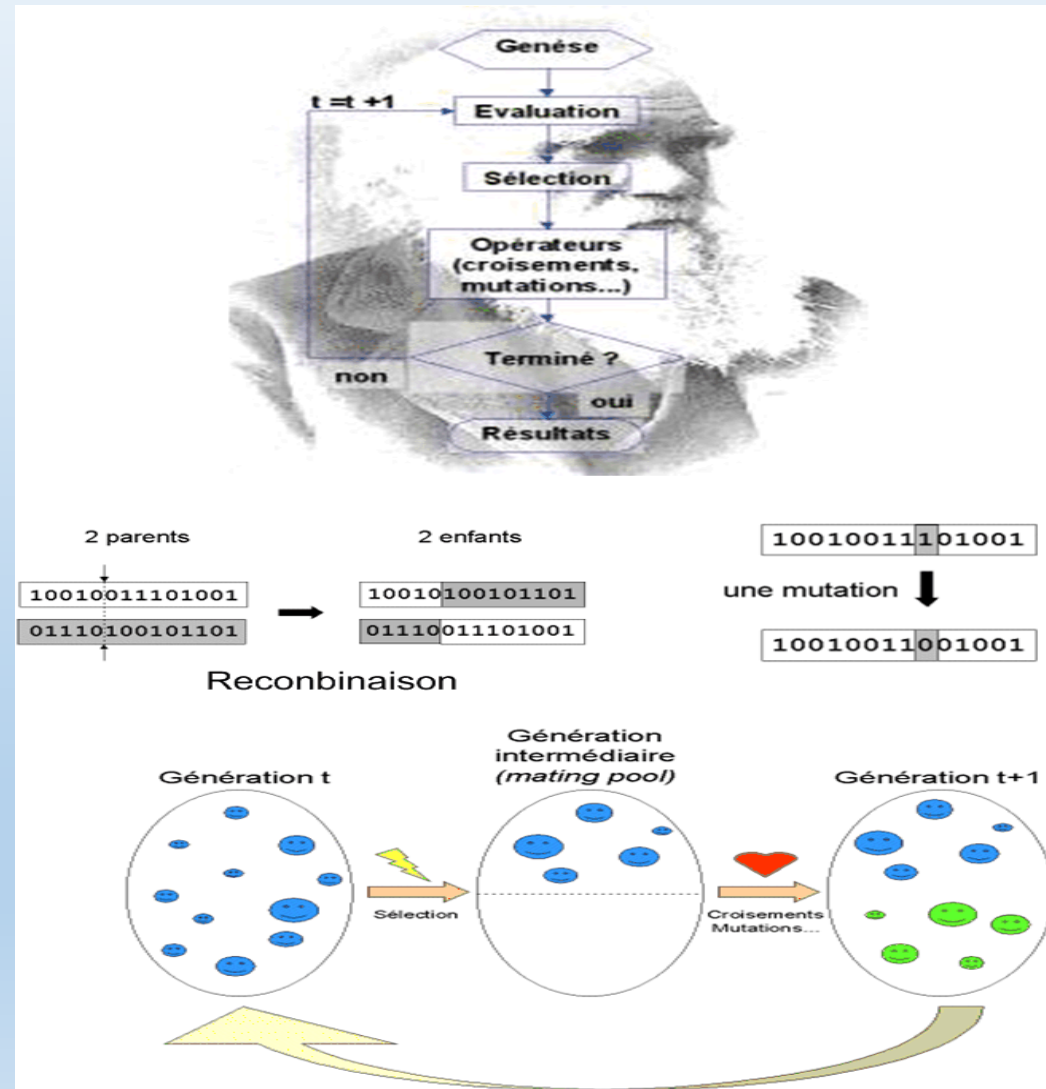


A\*





# Genetic Algorithms



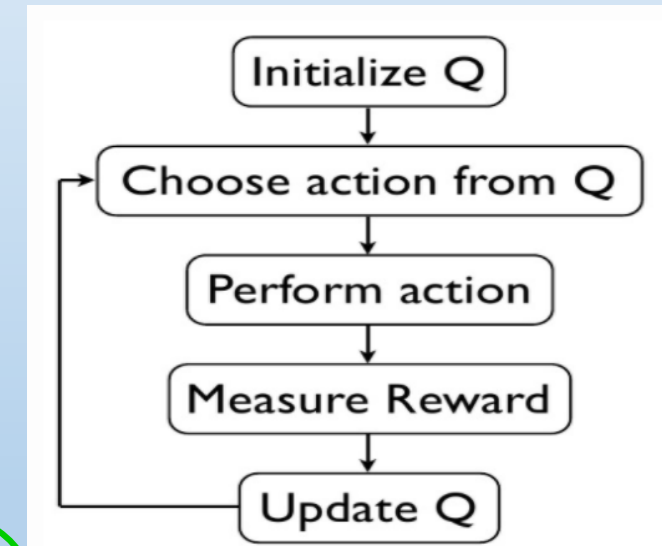
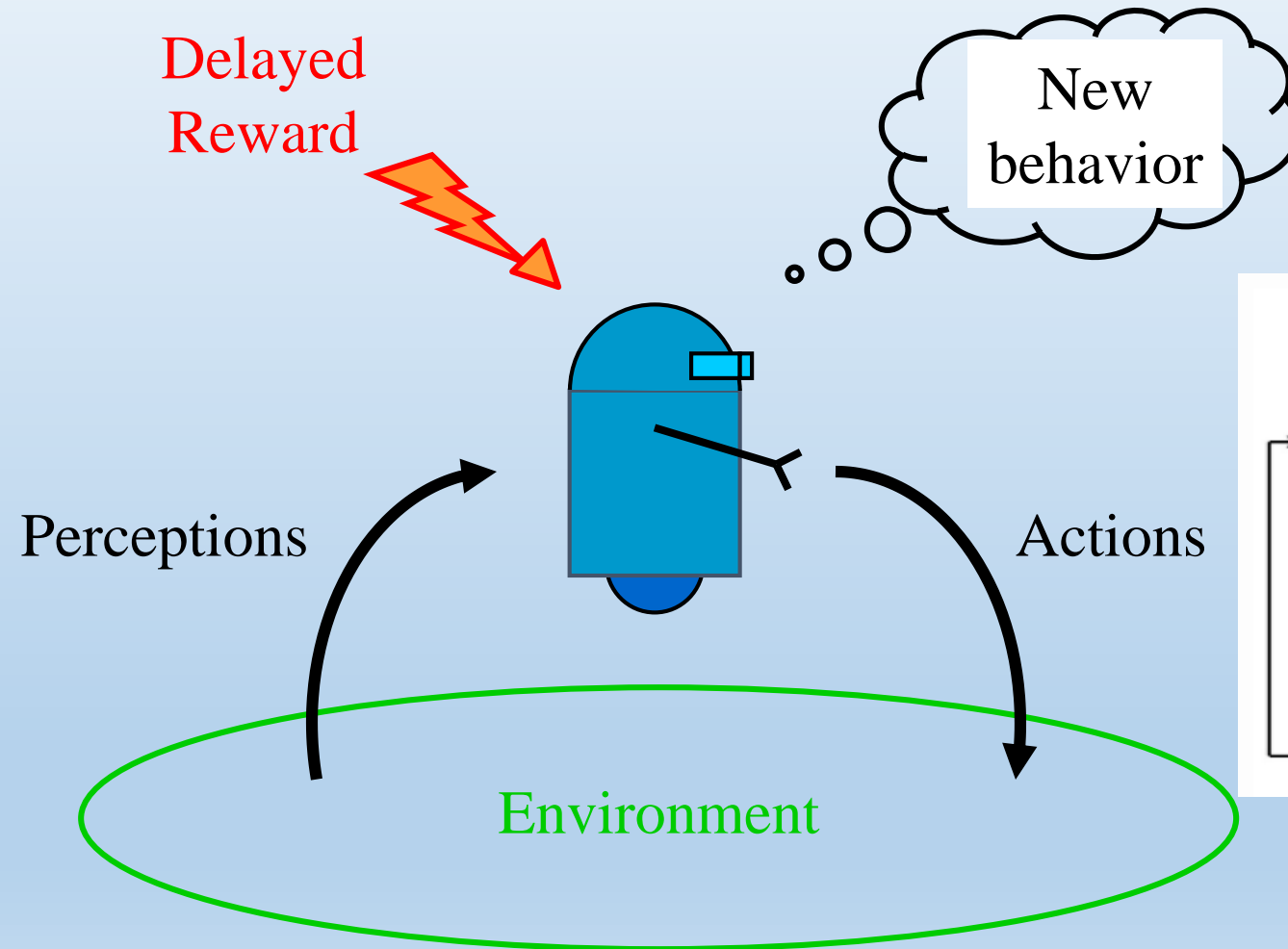
[1,3,4,2,3,1] et [1,4,3,3]  
pour donner [1,3,4,3,3] et [1,3,2,3,1]

*Fitness = Individual size: nbr of moves + nbr of bad positions at the end of the sequence of moves*

# Drawbacks and Discussions

- Disappear the notion of states and trees that guide the search
- Possibility of very long sequences or sequences composed of cycles.
- In  $A^*$ , possibility of backtracking, very guided construction of moves
- It's very possible that after a very long CPU time, solution will be found
- Many AI users choose to favour CPU time instead of Cognitive time
- But this CPU time saving still makes a lot of sense and honors and gives tribute to human intelligence

# Q-Learning



$$\underbrace{NewQ(s, a)}_{\text{New Q value for that state and that action}} = \underbrace{Q(s, a)}_{\text{Current Q value}} + \underbrace{\alpha}_{\text{Learning Rate}} [\underbrace{R(s, a)}_{\text{Reward for taking that action at that state}} + \underbrace{\gamma}_{\text{Discount rate}} \underbrace{\max Q'(s', a')}_{\text{Maximum expected future reward given the new } s' \text{ and all possible actions at that new state}} - Q(s, a)]$$

The state is each possible configuration

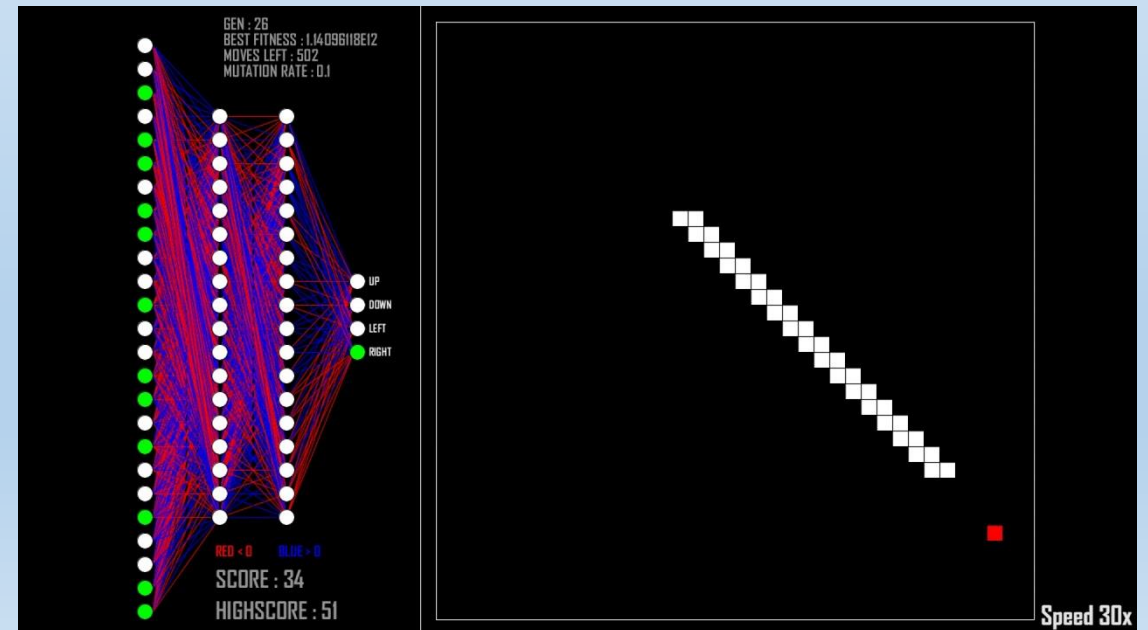
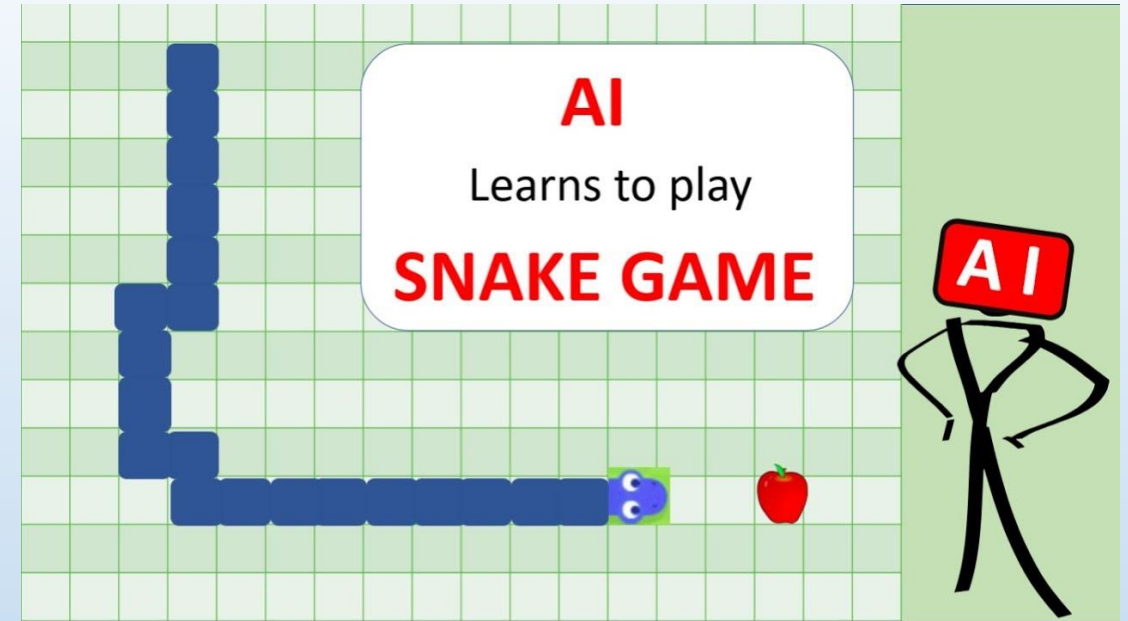
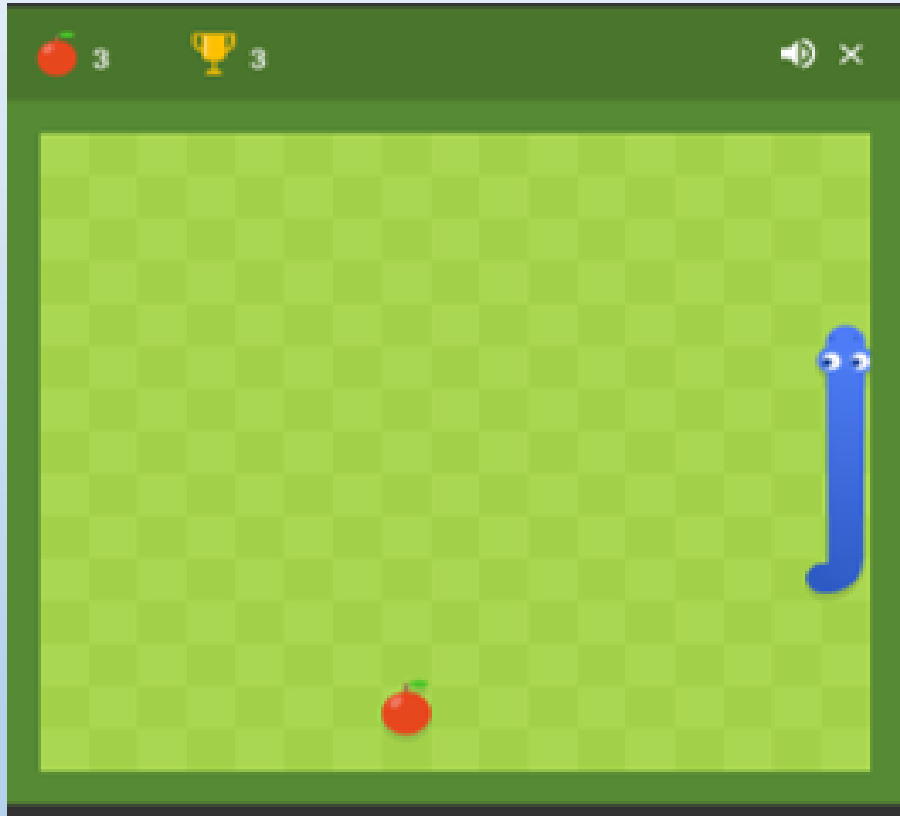
The actions are all possible moves from that state

# Drawbacks and discussions

- The notion of state is well preserved
- The best sequence of moves will be even found for each initial configuration (each initial state)
- Learning to compensate for the need for an intermediary evolution of the state
- The only possible feedback is at the end like with GA
- But even so, it could be possible to run an inverted  $A^*$  (called also dynamic programming) to accelerate the search.
- But still a learning of the best  $A^*$  heuristic might still be an interesting idea.

Snake and Tetris

# Snake: A\* or Q-Learning

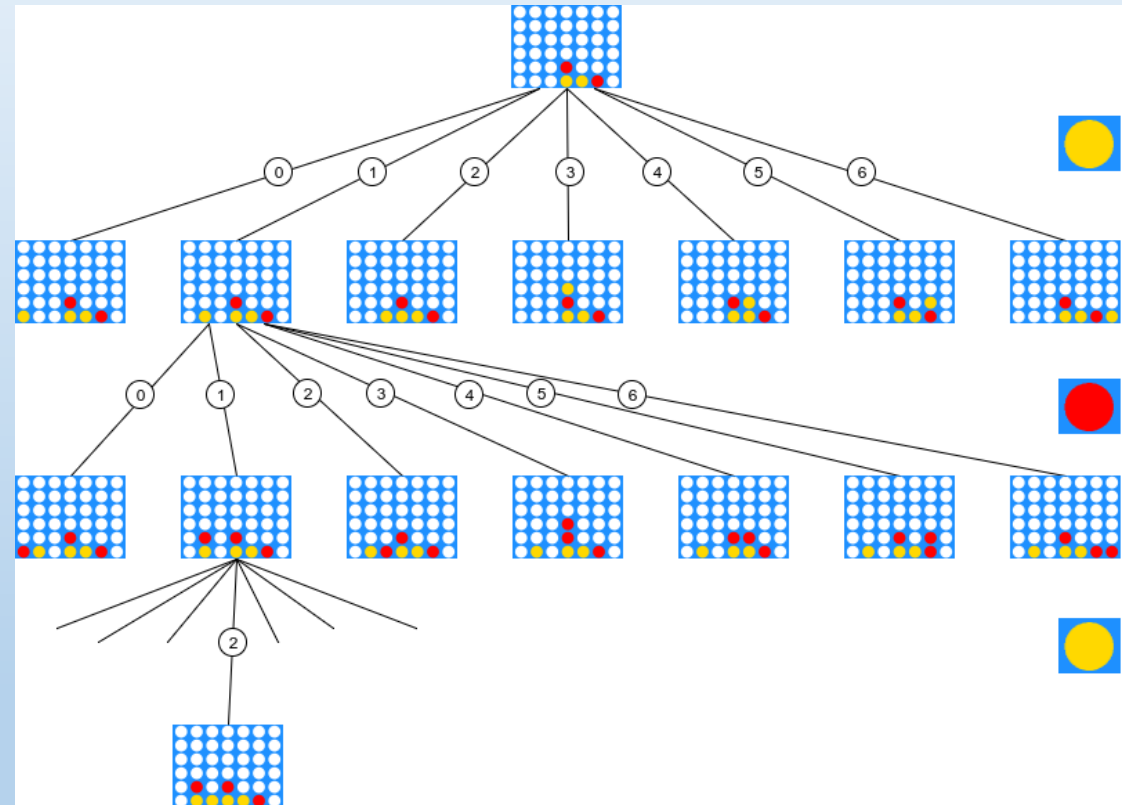
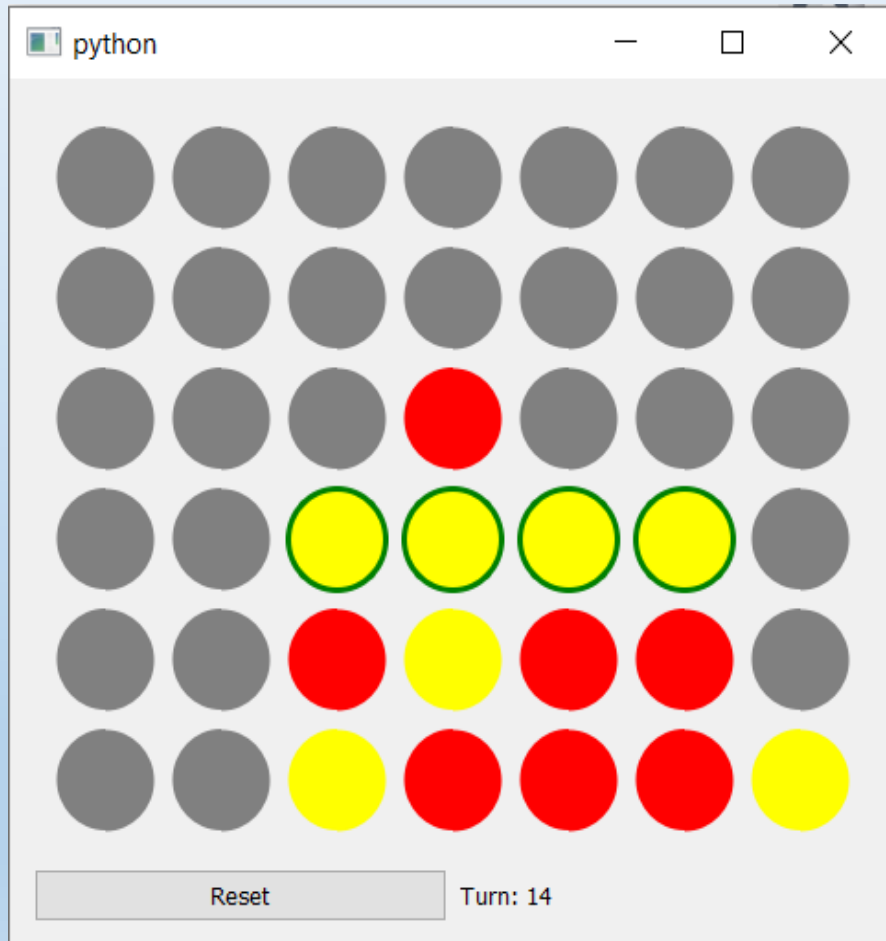




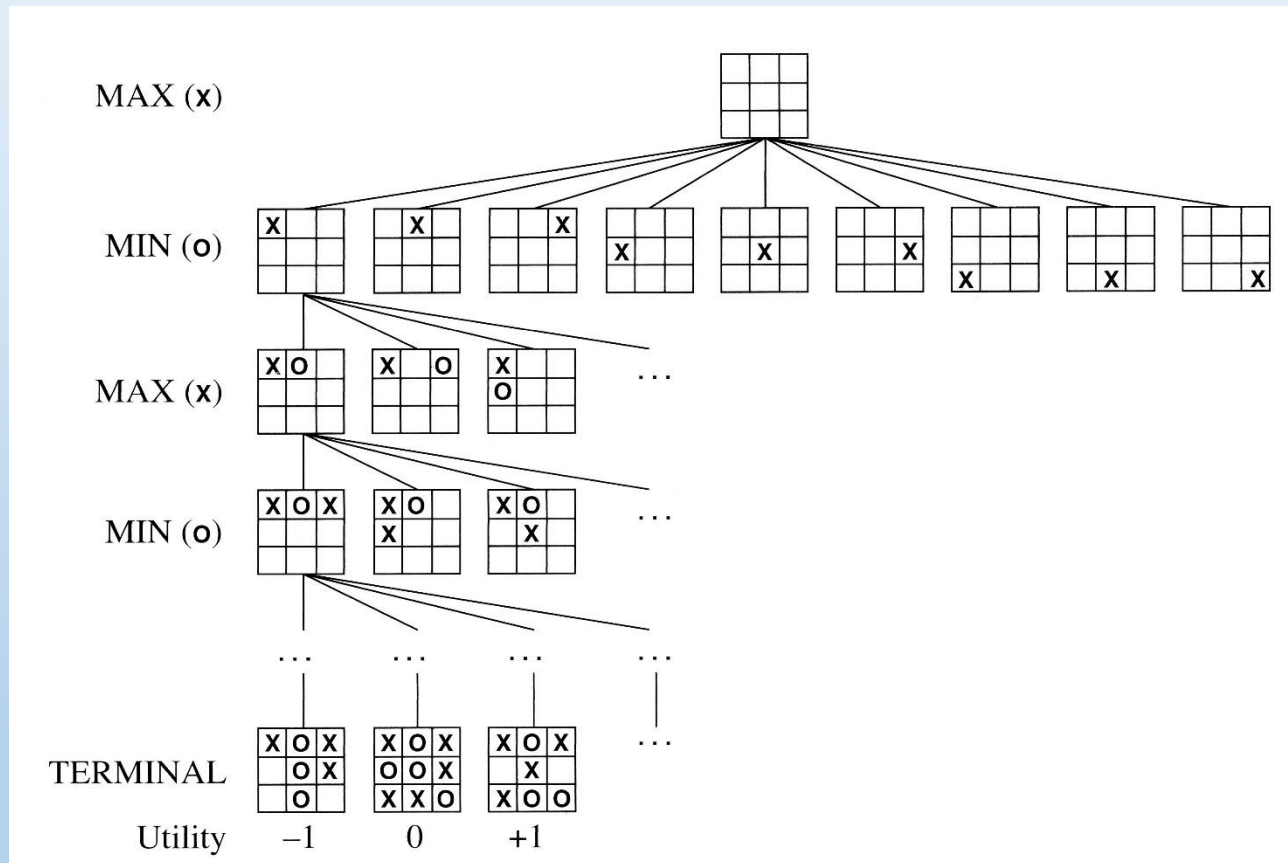
- The states can be defined relatively to the snake head, to limit the size.
- The four actions are easy to define
- The snake moves independently of the actions. Hard to draw the search tree.
- A\* becomes very problematic since no final state really exists.
- Much easier to use reinforcement or a cost function to evaluate the performance of the snake and thus the player.
- -> Reinforcement Learning or NN + GA are classical ways to find the best player.

Connect-4 and two players game.

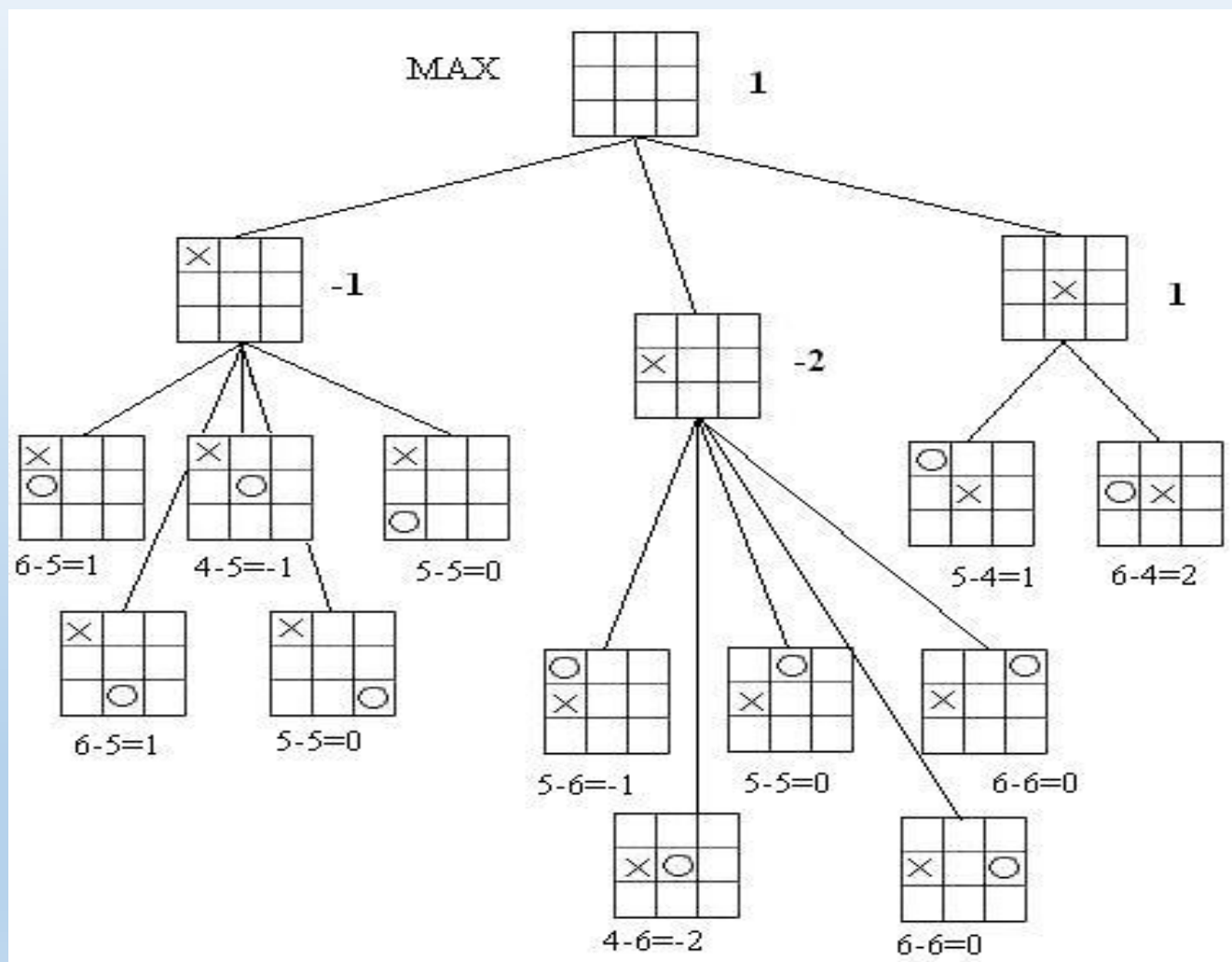
# Connect-4



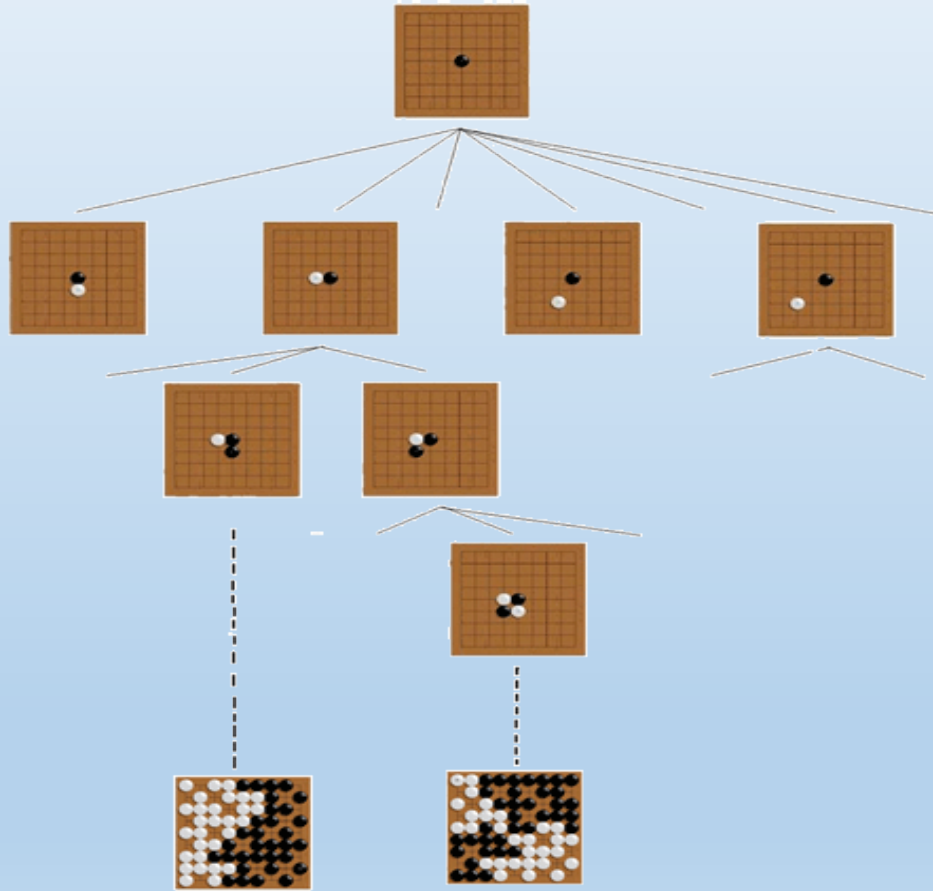
# The Min-Max Strategy for the Tic-Tac-Toe



# With heuristics

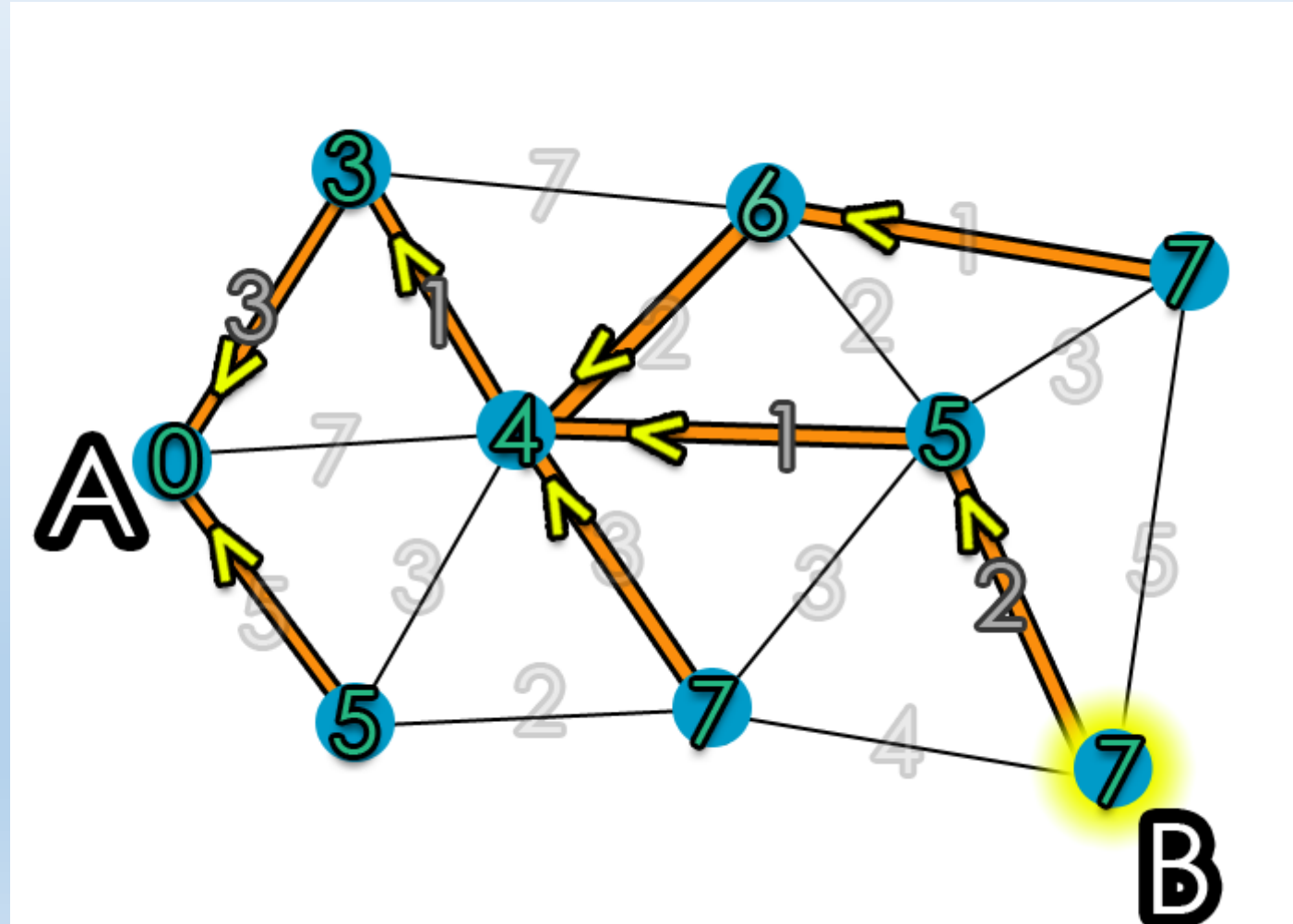


# Learning the heuristics



**Learning by statistics.  
Playing randomly and  
computing the number of lost games  
vs the number of winning games.**

Discovering the shortest path: Dijkstra or A\*







# Dijkstra's Rules

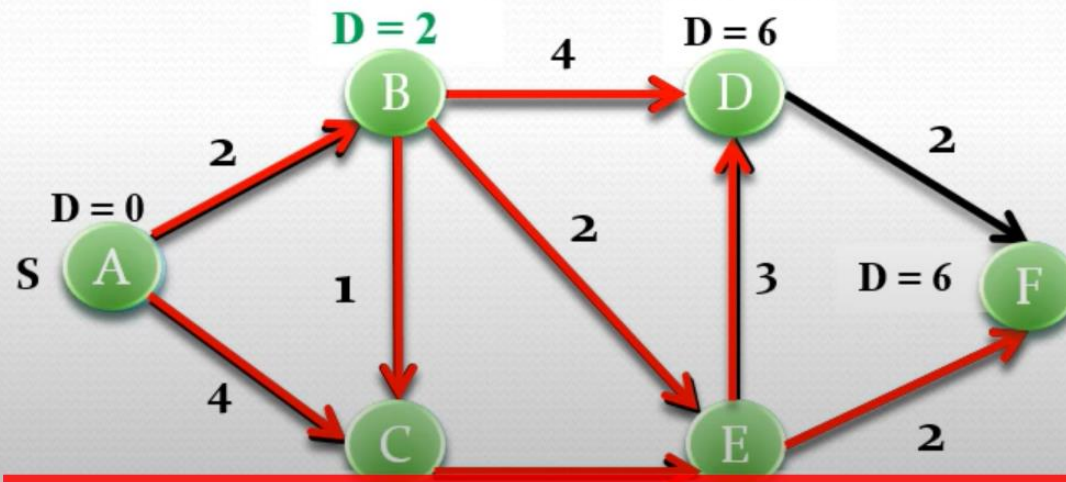
**Rule 1:** Make sure there is no negative edges. Set distance to source vertex as zero and set all other distances to infinity.

**Rule 2:** Relax all vertices adjacent to the current vertex.

**Rule 3:** Choose the closest vertex as next current vertex.

**Rule 4:** Repeat Rule2 and Rule 3 until the queue or reach the destination.

*If  $(D[C] + D[AdjEdge]) < D[Adj]$  {Update Adj's D with new shortest path}*



Q <= V	A	B	C	D	E	F
A	0 <sup>A</sup>	2 <sup>A</sup>	4 <sup>A</sup>	∞ <sup>A</sup>	∞ <sup>A</sup>	∞ <sup>A</sup>
B	0 <sup>A</sup>	2 <sup>A</sup>	3 <sup>B</sup>	6 <sup>B</sup>	4 <sup>B</sup>	∞ <sup>A</sup>
C	0 <sup>A</sup>	2 <sup>A</sup>	3 <sup>B</sup>	6 <sup>B</sup>	4 <sup>B</sup>	∞ <sup>A</sup>
E				6 <sup>B</sup>	4 <sup>B</sup>	6 <sup>F</sup>



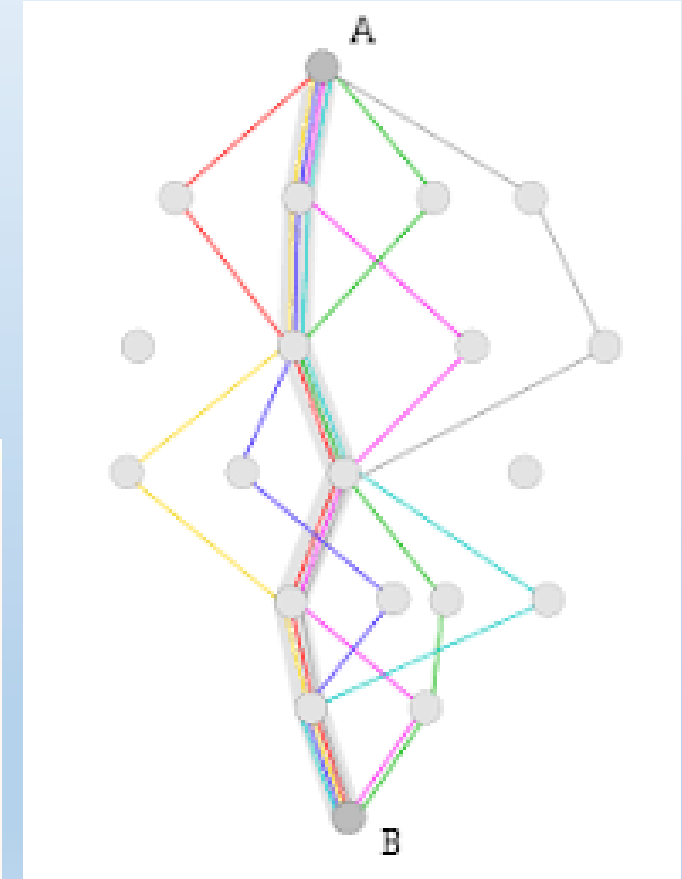
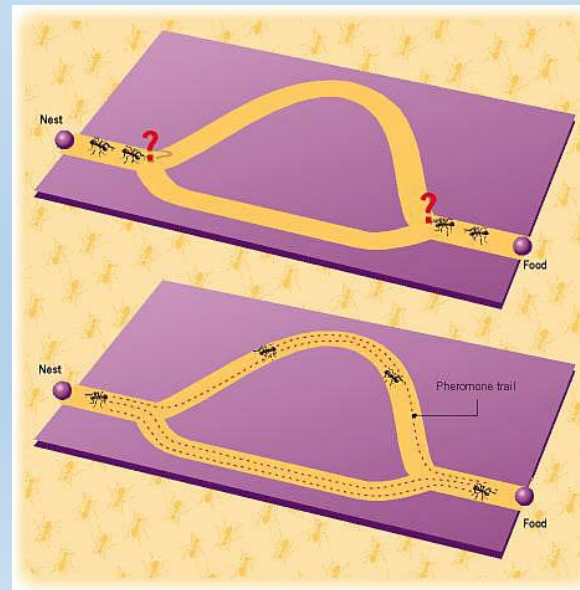
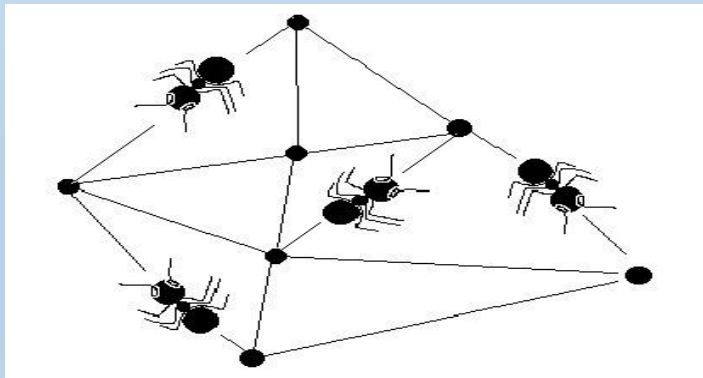
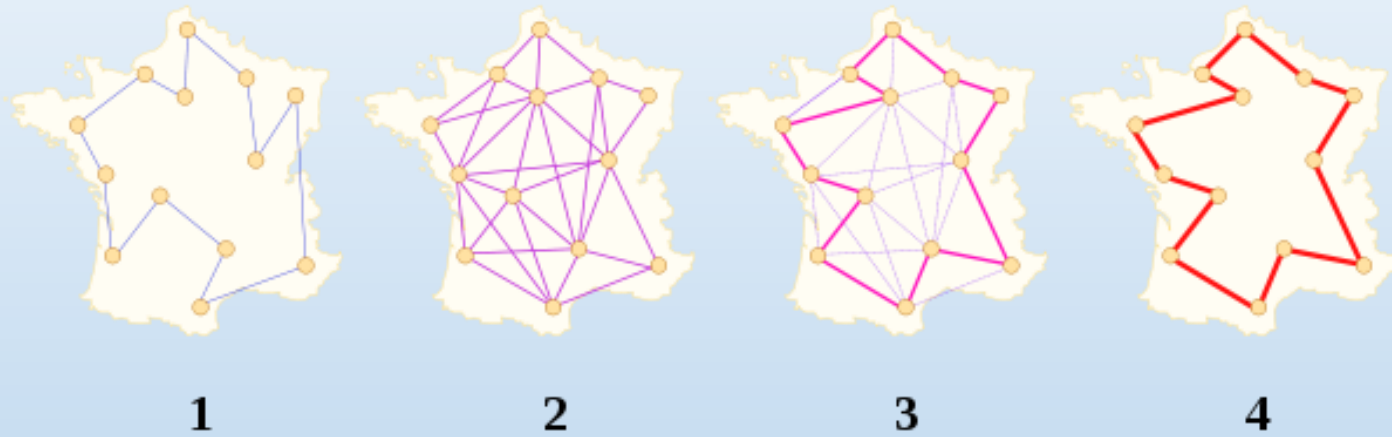
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# GA and ACO for shortest path



# Distinguishing a cat from a dog: NN and DL

