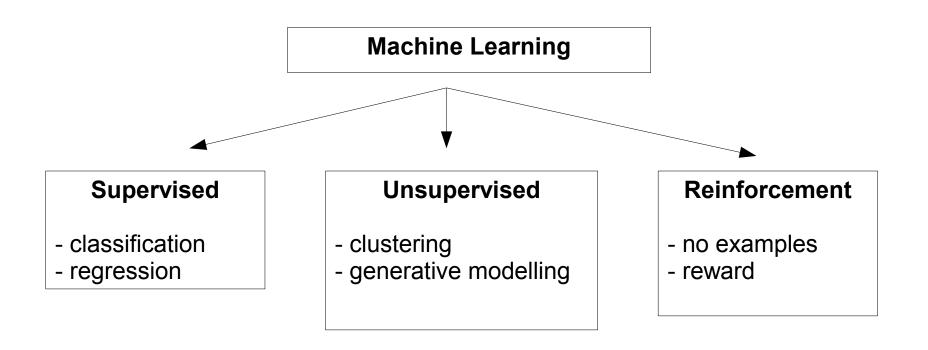
Reinforcement Learning

on an example

Overview



https://deepmind.com/research/publications/playing-atari-deep-reinforcement-learning/

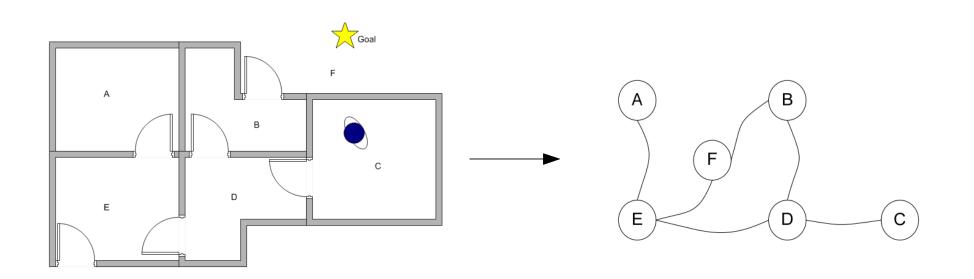
Theory Q-Learning:

- exploration vs. exploitation dilemma : example K-Armed-Bandit Problem
- Markov-Decision-Process:
 - s0 : Initial state
 - A(s): all possible actions from state s
 - P(s'|s,a): probability to get from state s to s'
 - R(s,a,s'): reward from state s to s'

- Q-Learning:

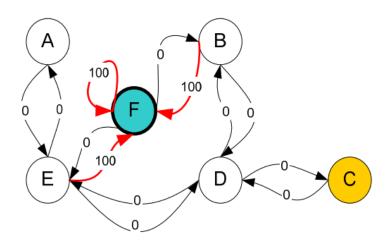
- find best policy π(s) to get best reward
- model free, no Information about P(s'|s,a)
- Agent learns the value of state action pairs (Q-values)
- update function: $Q(s,a) = Q(s,a) + \alpha(R(s) + \gamma maxQ(s',a') Q(s,a))$
 - Q(s,a): old Q-value or 0 (not defined)
 - α : 0→1 learning rate
 - R(s): reward
 - γ : 0→1 discount factor, near 0 no reward in future, near 1 high reward
 - maxQ(s',a'): maximum Q-value from state s' is next action a'

Q-Learning on an example



Andre Betz

6



Q Learning

Given: State diagram with a goal state (represented by matrix R)

Find: Minimum path from any initial state to the goal state (represented by matrix Q)

Q Learning Algorithm goes as follow

- 1. Set parameter γ , and environment reward matrix **R**
- 2. Initialize matrix **Q** as zero matrix
- 3. For each episode:
 - A. Select random initial state
 - B. Do while not reach goal state
 - a. Select one among all possible actions for the current state
 - b. Using this possible action, *consider* to go to the next state
 - c. Get maximum Q value of this next state based on all possible actions
 - d. Compute

 $\mathbf{Q}(state, action) = \mathbf{R}(state, action) + \gamma \cdot Max[\mathbf{Q}(next \ state, \ all \ actions)]$

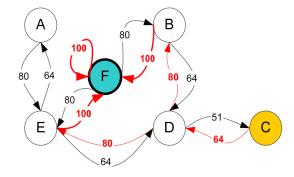
e. Set the next state as the current state End Do

End For

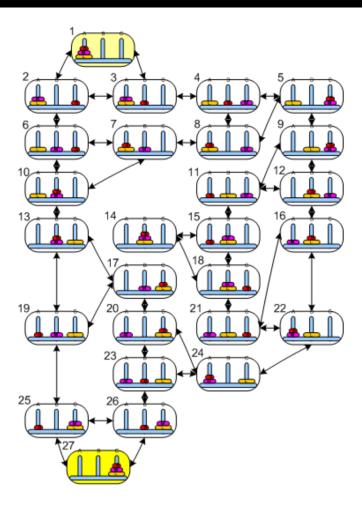
By random selection, we select to go to F as our action

$$\mathbf{Q}(state, action) = \mathbf{R}(state, action) + \gamma \cdot Max \big[\mathbf{Q}(next \ state, all \ actions) \big]$$

$$\mathbf{Q}(B, F) = \mathbf{R}(B, F) + 0.8 \cdot Max \big\{ \mathbf{Q}(F, B), \mathbf{Q}(F, E), \mathbf{Q}(F, F) \big\} = 100 + 0.8 \cdot 0 = 100$$



Towers of Hanoi



```
- setRMatrix();
- hanoiGame.setLambda(lambda);
- for ( int i = 0; i < rounds; i++ ) {
        String res = hanoiGame.learn();
        System.out.print(".");
        // System.out.print(res);
    }
- System.out.print(hanoiGame.bestMoves());</pre>
```

R-Matrix:

```
100
100
100
```

Q-Matrix:

0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	1	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	1	0	0	0	0	3	0	0	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	3	0	1	0	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	1	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	1	0	0	0	0	0	3	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	3	3	0	0	0	0	0	12	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	3	0	0	6	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	3	0	3	0	0	0	0	12	0 12	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	6 0	0	0	0	0	0 1	0	0	3	25 0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	3	0	0	1	0	0	0	3	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	6	0	0	0	0	0	0	0	0	6	0	25	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	12	0	0	0	0	0	25	12	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	6	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	12	0	0	0	12	0	0	0	0	0	0	0	50	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	12	0	0	0	0	0	25	12	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	12	0	3	0	0	0	6	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	12	0	0	0	0	6	0	0	12	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	12	0	0	0	12	0	50	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	12	0	6	25	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	25	0	0	0	0	0	0	50	100
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	25	0	50	0	100
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Ablauf: