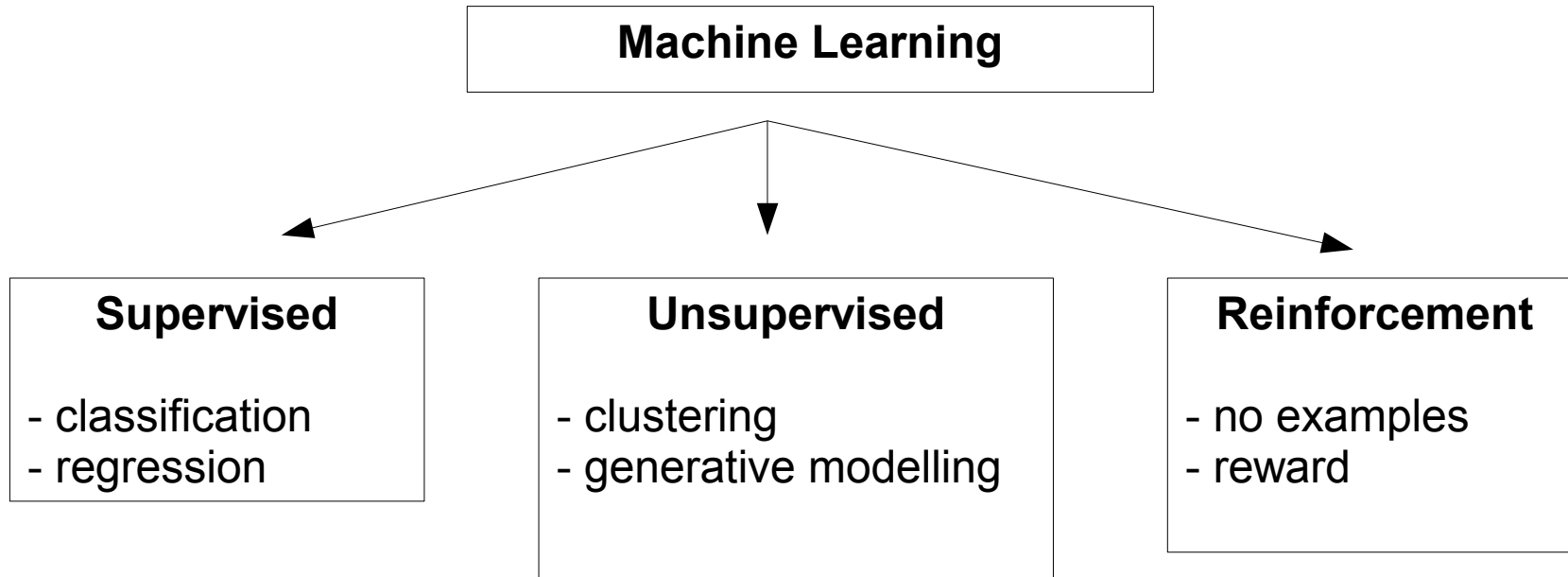


Reinforcement Learning

on an example

Overview

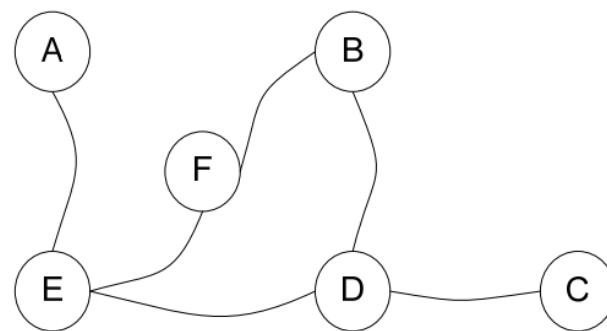
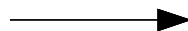
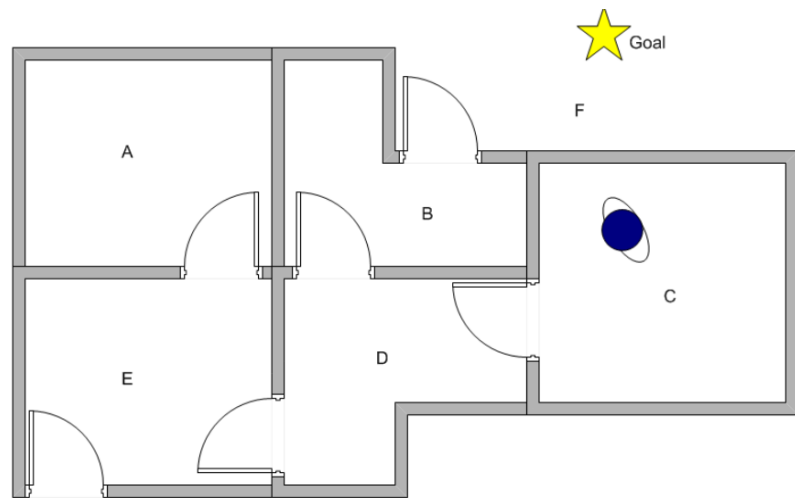


<https://deepmind.com/research/publications/playing-atari-deep-reinforcement-learning/>

Theory Q-Learning:

- **exploration vs. exploitation dilemma** : example K-Armed-Bandit Problem
- **Markov-Decision-Process:**
 - s_0 : 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 $\pi(s)$ 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:** $Q(s,a) = Q(s,a) + \alpha(R(s) + \gamma \max_{a'} Q(s',a') - Q(s,a))$
 - $Q(s,a)$: old Q-value or 0 (not defined)
 - α : $0 \rightarrow 1$ learning rate
 - $R(s)$: reward
 - γ : $0 \rightarrow 1$ discount factor, near 0 no reward in future, near 1 high reward
 - $\max Q(s',a')$: maximum Q-value from state s' is next action a'

Q-Learning on an example



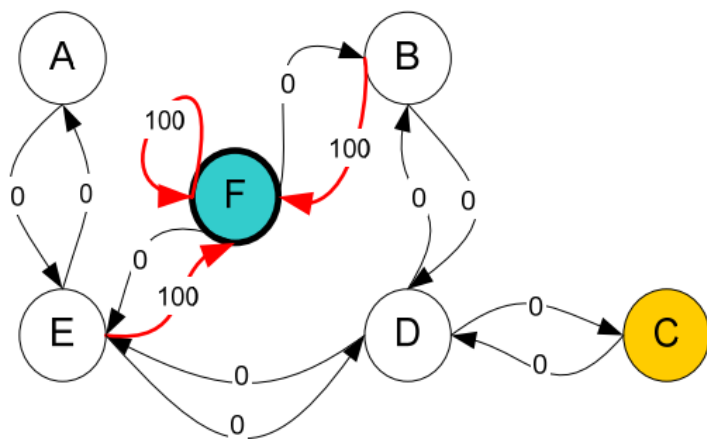
Q Learning

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
$$Q(\text{state}, \text{action}) = R(\text{state}, \text{action}) + \gamma \cdot \text{Max}[Q(\text{next state}, \text{all actions})]$$
 - e. Set the next state as the current stateEnd Do
- End For




$\mathbf{R} =$

<i>state \ action</i>	<i>A</i>	<i>B</i>	<i>C</i>	<i>D</i>	<i>E</i>	<i>F</i>
<i>A</i>	–	–	–	–	0	–
<i>B</i>	–	–	–	0	–	100
<i>C</i>	–	–	–	0	–	–
<i>D</i>	–	0	0	–	0	–
<i>E</i>	0	–	–	0	–	100
<i>F</i>	–	0	–	–	0	100

$$\mathbf{Q} = \begin{matrix} & A & B & C & D & E & F \\ \begin{matrix} A \\ B \\ C \\ D \\ E \\ F \end{matrix} & \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \end{matrix}$$

$$\mathbf{R} = \begin{matrix} \text{state} \backslash \text{action} & A & B & C & D & E & F \\ \begin{matrix} A \\ B \\ C \\ D \\ E \\ F \end{matrix} & \begin{bmatrix} - & - & - & - & 0 & - \\ - & - & - & 0 & - & 100 \\ - & - & - & 0 & - & - \\ - & 0 & 0 & - & 0 & - \\ 0 & - & - & 0 & - & 100 \\ - & 0 & - & - & 0 & 100 \end{bmatrix} \end{matrix}$$

$\mathbf{Q}(B, F)$





$$\mathbf{Q} = \begin{matrix} & A & B & C & D & E & F \\ \begin{matrix} A \\ B \\ C \\ D \\ E \\ F \end{matrix} & \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 100 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \end{matrix}$$

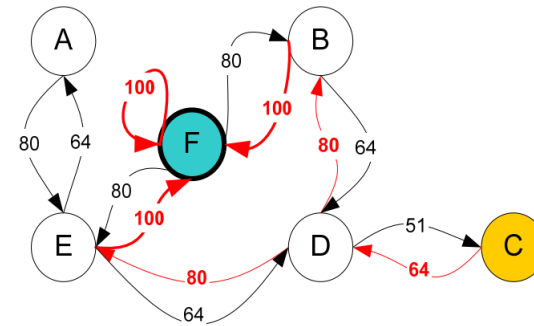
By random selection, we select to go to F as our action

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

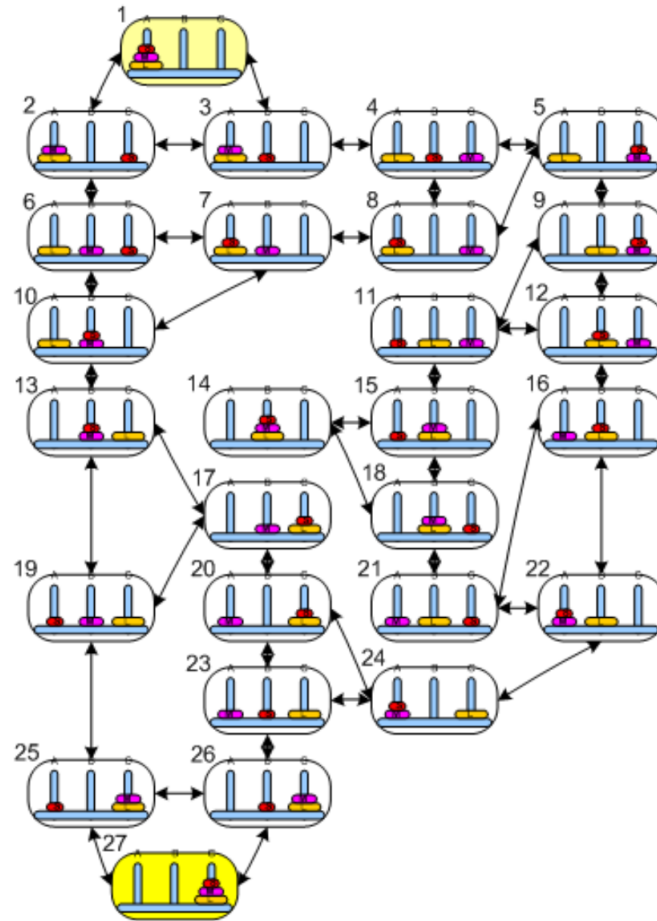
$$\mathbf{Q}(B, F) = \mathbf{R}(B, F) + 0.8 \cdot \text{Max}\{\mathbf{Q}(F, B), \mathbf{Q}(F, E), \mathbf{Q}(F, F)\} = 100 + 0.8 \cdot 0 = 100$$

Q =

<i>state \ action</i>	<i>A</i>	<i>B</i>	<i>C</i>	<i>D</i>	<i>E</i>	<i>F</i>
<i>A</i>	—	—	—	—	400	—
<i>B</i>	—	—	—	320	—	500
<i>C</i>	—	—	—	320	—	—
<i>D</i>	—	400	256	—	400	—
<i>E</i>	320	—	—	320	—	500
<i>F</i>	—	400	—	—	400	500



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());

<https://github.com/sky4walk/HanoiTowersSolver>

R-Matrix:

[illegible]

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	3	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	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	1	3	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	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	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	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	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	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	3	0	3	0	0	0	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	12	0	25	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	3	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	6	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	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	12	0	0	0	12	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	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	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	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	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	25	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	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

Ablauf:

1)

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2)

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19)

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27)

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		--+--
