Swarmrobotics Workshop

MAXQ-Q Learning with MDLe

1. Introduction

What this lecture is about …

- Reinforcement learning
  - Hierarchical reinforcement learning
  - MAXQQ learning Algorithm
- MAXQ-Q learning with MDLe
  - Integration into MDLe
  - Needed Additions in MDLe

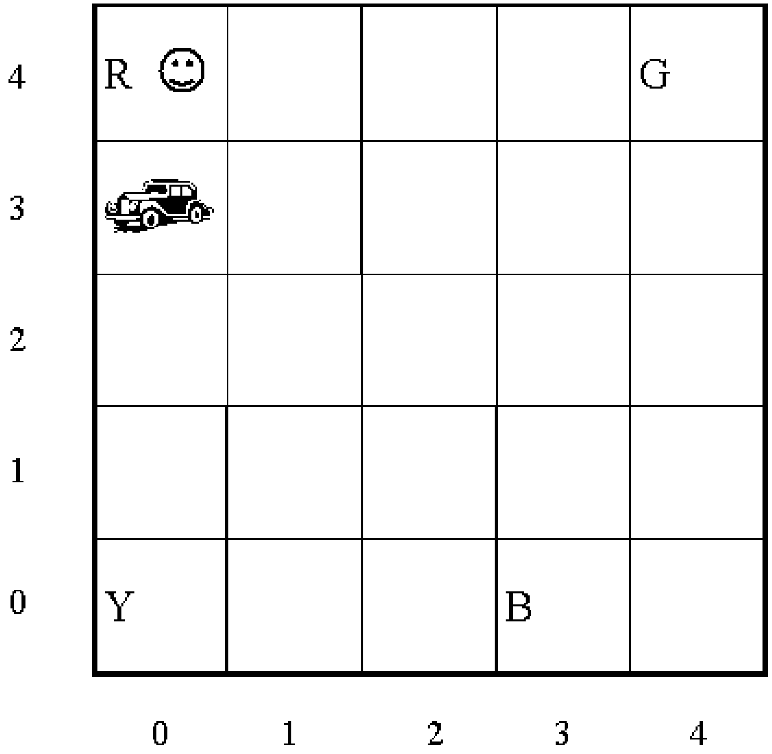
2. Reinforcement learning

Reinforcement Learning

- Agent learns a behaviour in a world
  - Unknown
  - Dynamic
  - Fully observable
- Learning through try and error
  - Looks at current state *s*
  - Performs action *a*
  - Looks at resulting state *s'* and receives reward *r*

2. Reinforcement learning

Example of Reinforcement Learning



- Actions
  - Movement(*N,E,S,W*)
  - *Pickup*
  - *Putdown*
- Rewards
  - Action *-1*
  - Successful *Putdown +20*
  - Unsuccessfull *Putdown -10*
  - Unsuccessfull *Pickup -10*

2. Reinforcement learning

Reinforcement Learning

- Exploration
  - Tries action and gets Reward/Penalty
  - Better action selection in future
- Exploitation
  - Tries to maximize reward
- Find an optimal policy
  - Optimal value function

2. Reinforcement learning

Optimal value function

4	7	6	5	4	3
3	8	7	6	5	4
2	9	8	7	6	5
1	10	7	6	5	4
0	11	6	5	4	3
	0	1	2	3	4

4	12	13	14	15	14
3	13	14	15	16	15
2	14	15	16	17	16
1	13	14	15	18	17
0	12	13	14	G	18
	0	1	2	3	4

- Passenger at location Y (0,0) Destination B (3,0)

2. Reinforcement learning

Drawbacks of Reinforcement Learning

- Many training iterations are needed
  - >100000 for complicated tasks
  - Solutions:
    - Hierarchical Reinforcement Learning
    - Model Based Reinforcement Learning
- State space grows exponentially with state variables
  - Bad scaling
- Learned knowledge can’t be transferred to similar tasks
  - Hierarchical Reinforcement Learning
  - MAXQ value function decomposition

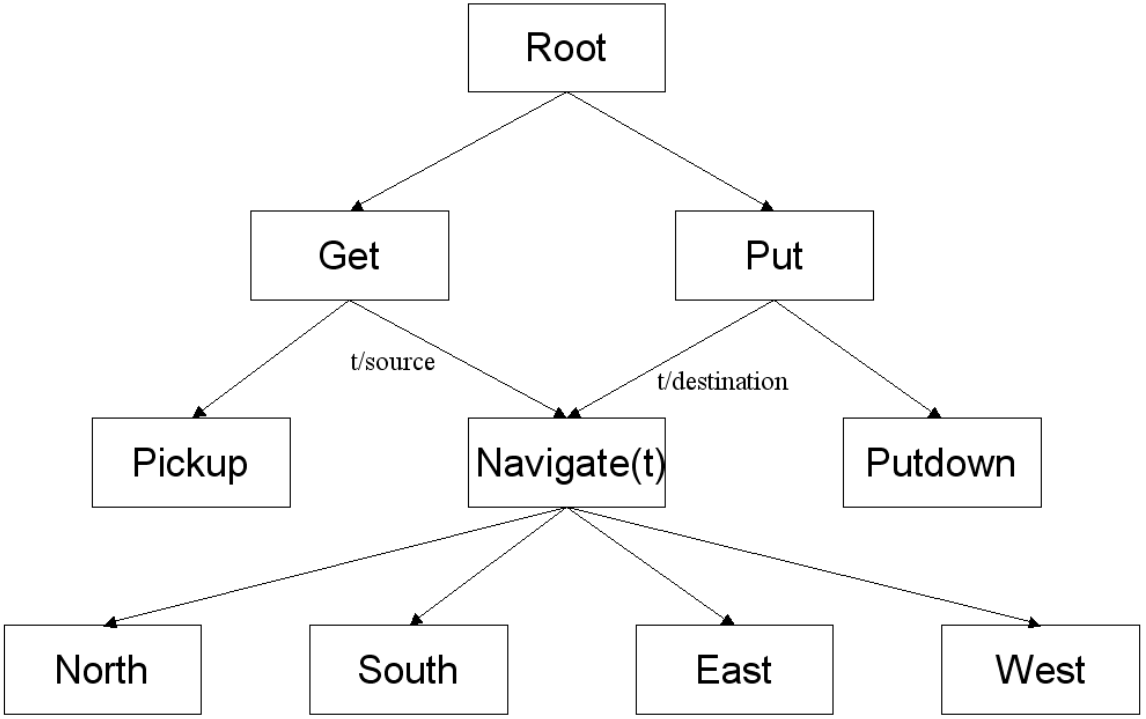
3. MAXQ

MAXQ learning

- Task decomposition
  - Discover and exploit hierarchical structure
  - Programmer defines hierarchy
- Value Function Decomposition
  - Value function of subtask + Completion function
- State Abstraction
  - Irrelevant variables
  - Funnel abstractions
  - Structural constraints

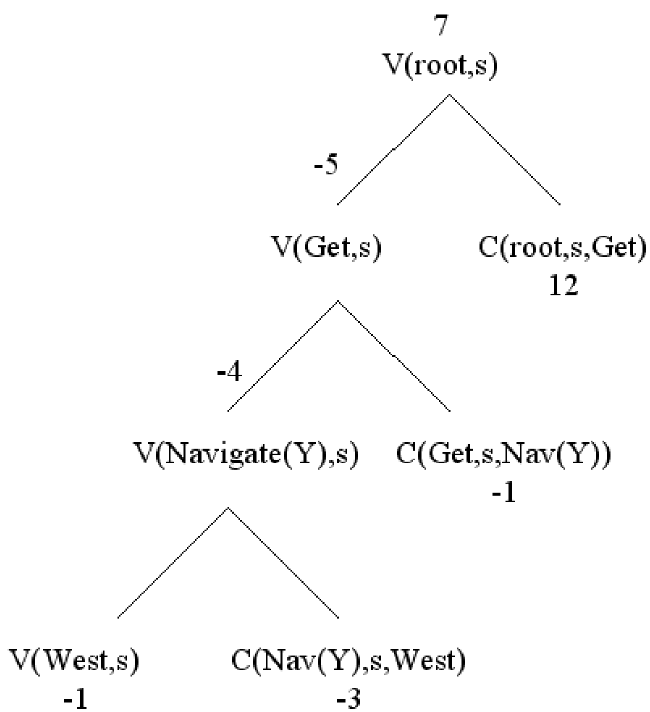
3. MAXQ

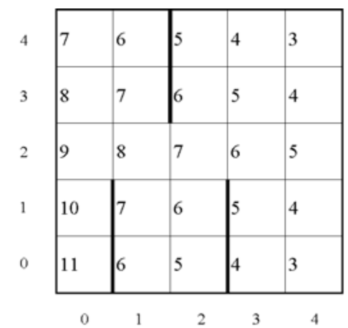
Task decomposition

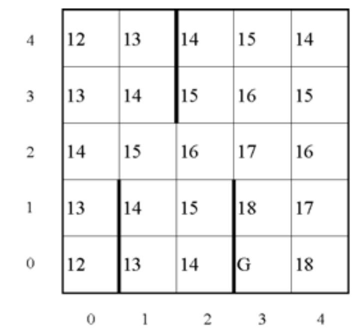


3. MAXQ

MAXQ value function decomposition







$$\begin{aligned} V(root, s) = V(west, s) &+ C(navigate(Y), s, west) \\ &+ C(get, s, navigate(Y)) \\ &+ C(root, s, get). \end{aligned}$$

3. MAXQ

MAXQQ learning

Function MAXQQ(state s, subtask p) **returns** float
Let *TotalReward* = 0
while *p* is not terminated **do**
Choose and execute action *a*
if *a* is primitive Observe one-step reward *r*
else *r* := MAXQQ(*s,a*), invokes subroutine *a* and returns total reward received during *a*
TotalReward := *TotalReward* + *r*
if *a* is a primitive

$$V(a,s) = (1-\alpha)V(a,s) + \alpha r$$

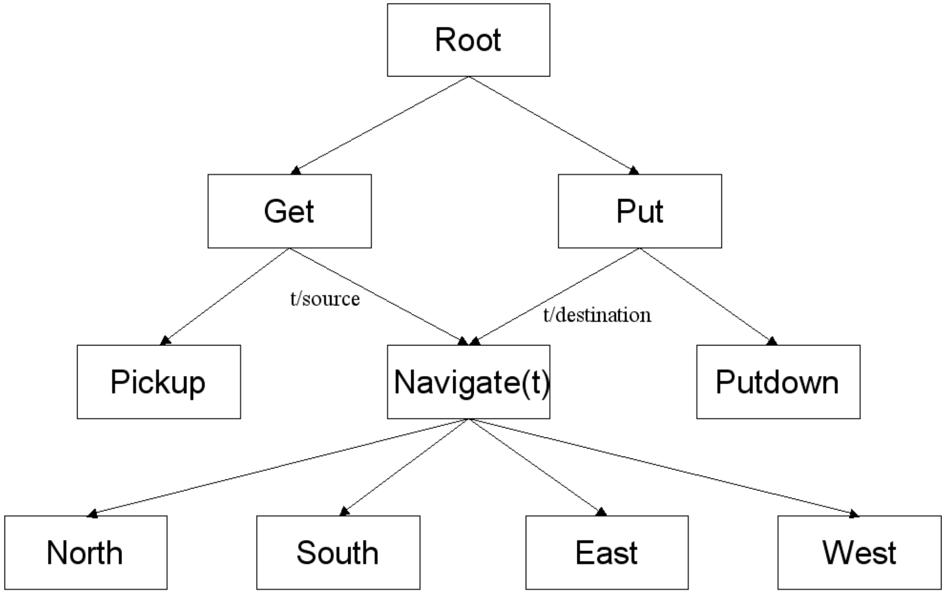
else *a* is a subroutine

$$C(p,a,s) := (1-\alpha)C(p,s,a) + \alpha \max_{a'}[V(a',s') + C(p,s',a')]$$

end // **while**
return *TotalReward*
end

3. MAXQ

MAXQQ learning

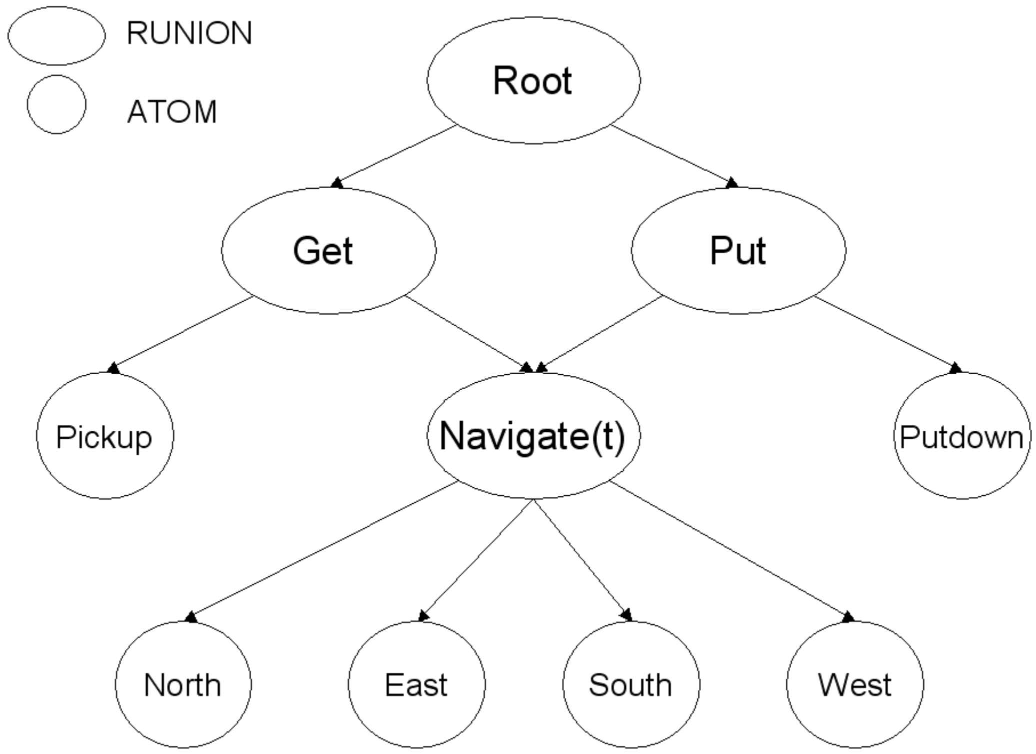


$$V(a,s) = (1-\alpha)V(a,s) + \alpha r$$

$$C(p,a,s) := (1-\alpha)C(p,s,a) + \alpha \max_{a'}[V(a',s') + C(p,s',a')]$$

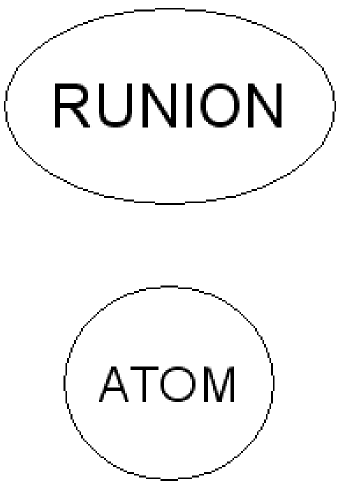
4. MAXQ with MDLe

Integration in MDLe



4. MAXQ with MDLe

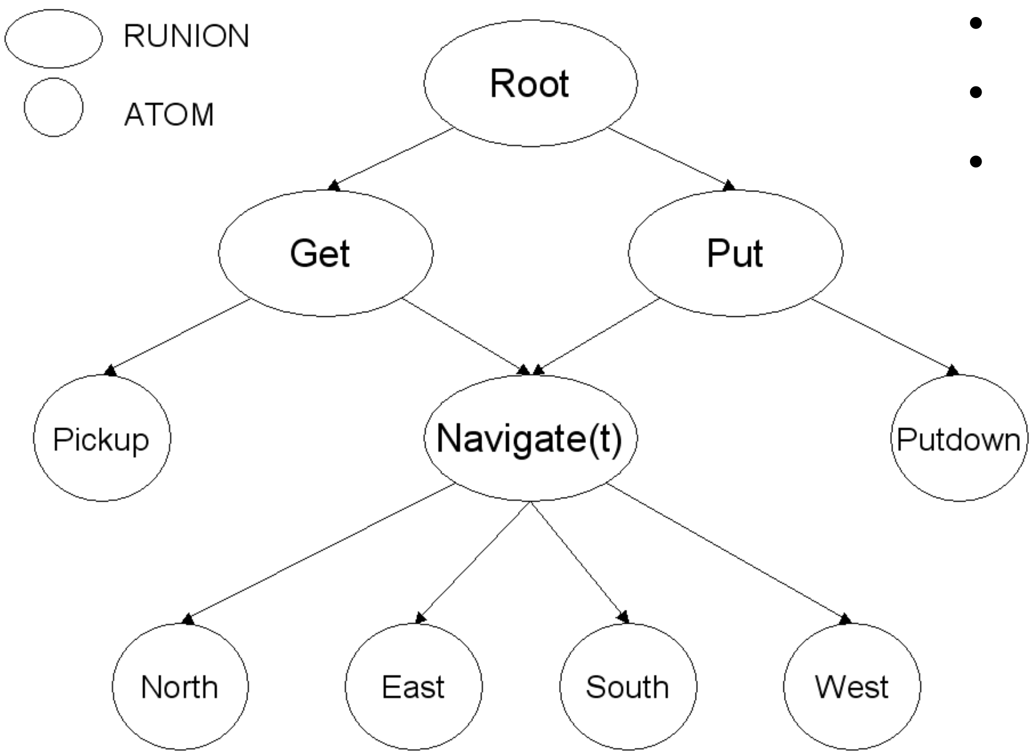
Implementation in MDLe



- RUNION
  - Goal State
  - Temperature (exploration vs exploitation)
  - C(p,s,a)
- ATOM
  - Reward
  - V(s)
  - V(a,s)

4. MAXQ with MDLe

Integration in MDLe



- Correct order of sequence
- Reward propagation
- State representation