Reinforcement learning II

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April 22, 2020

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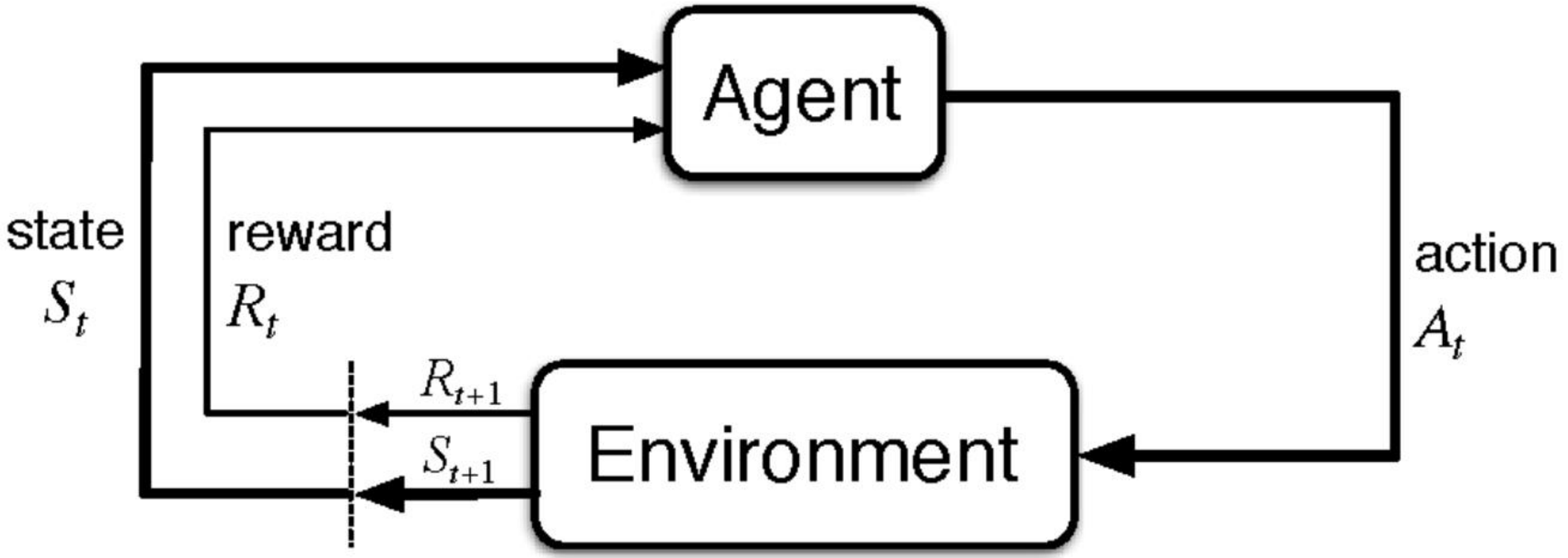
Recap: Reinforcement Learning



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- Feedback in form of Rewards
- Learn to act so as to maximize sum of expected rewards.
- In `kuimaze` package, `env.step(action)` is the method.

[1] Scheme from [2]

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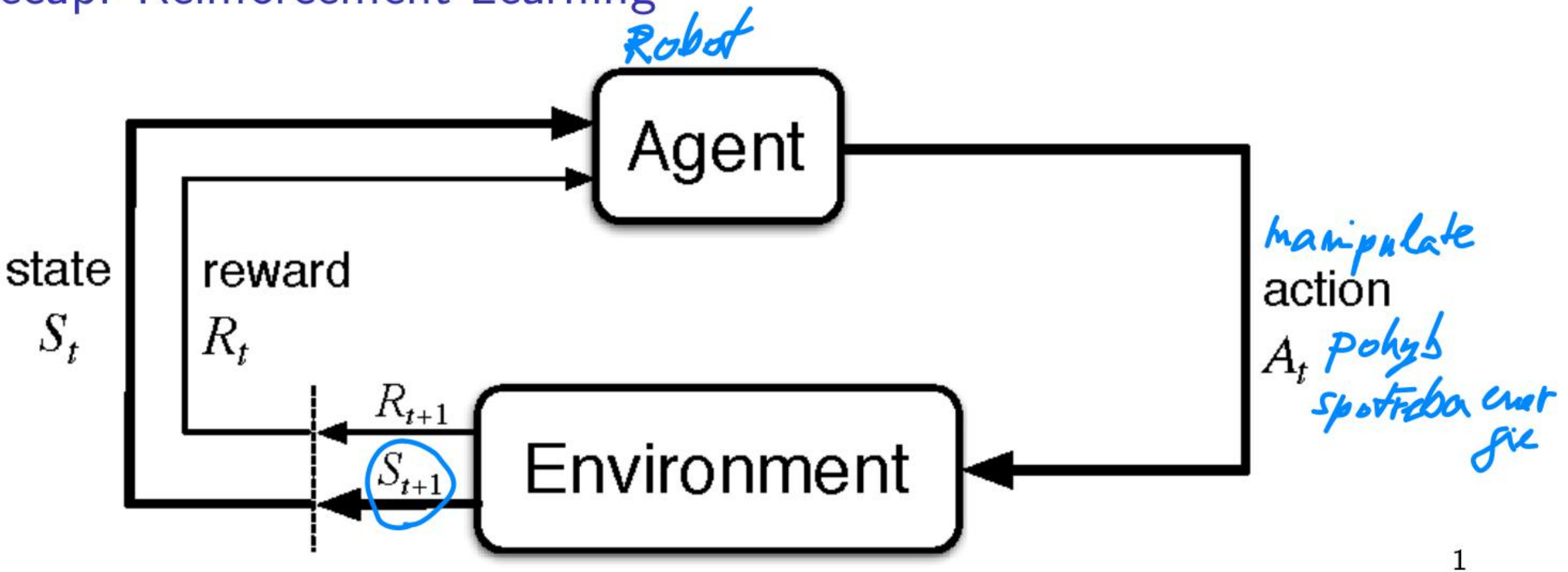

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Learning to control flippers

http://cyber.felk.cvut.cz/vras/

- What are the states?
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- Simulator to reality gap.

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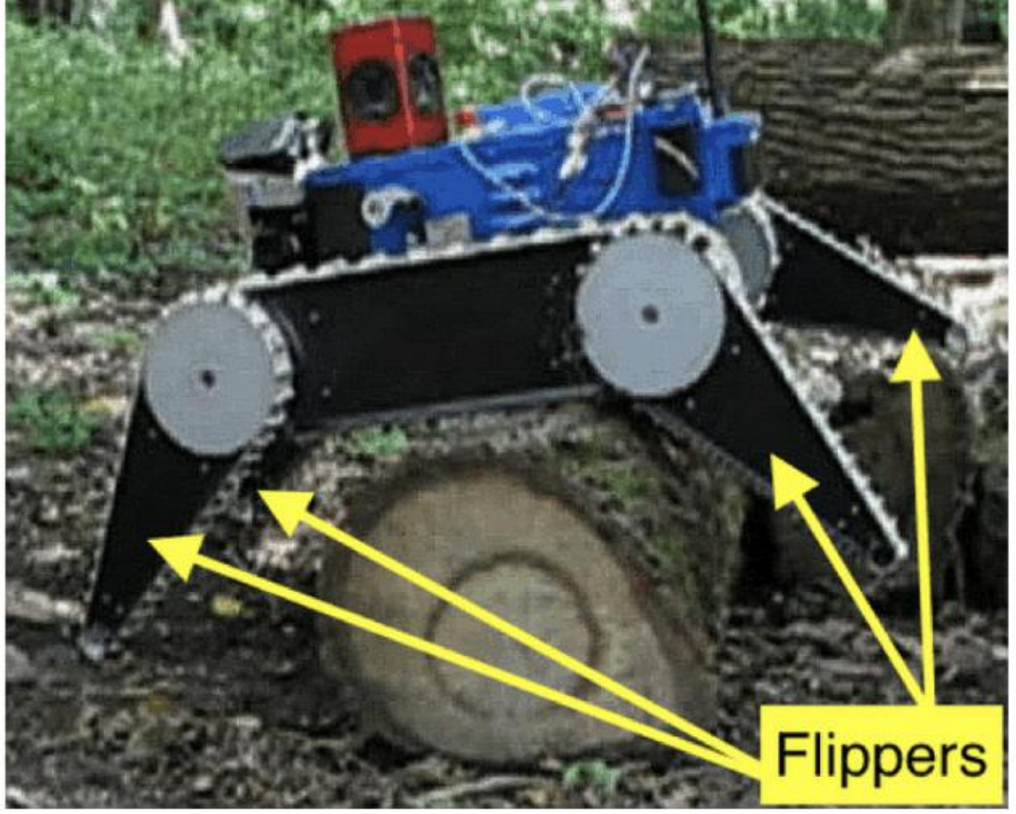
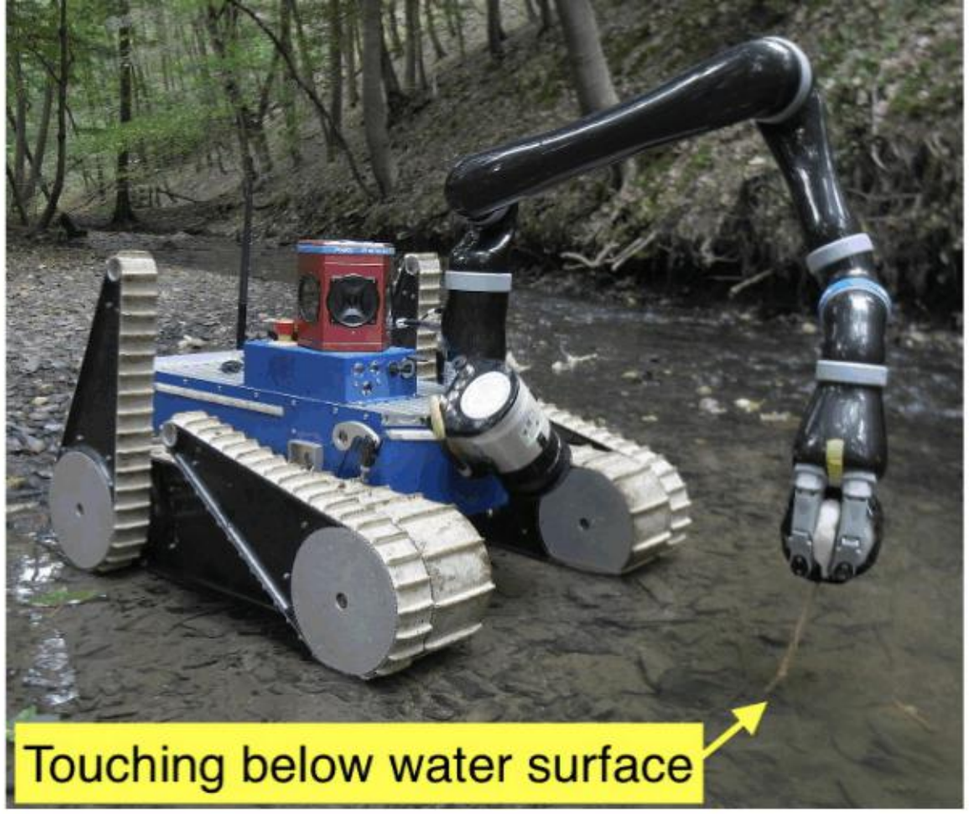
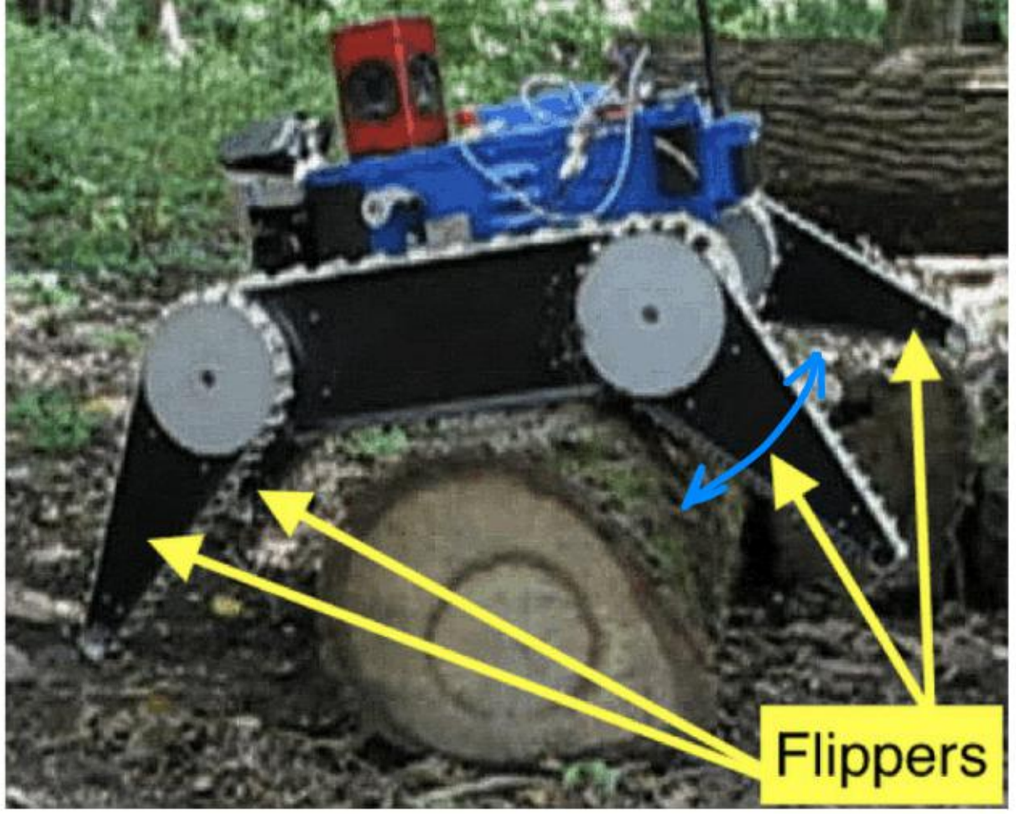
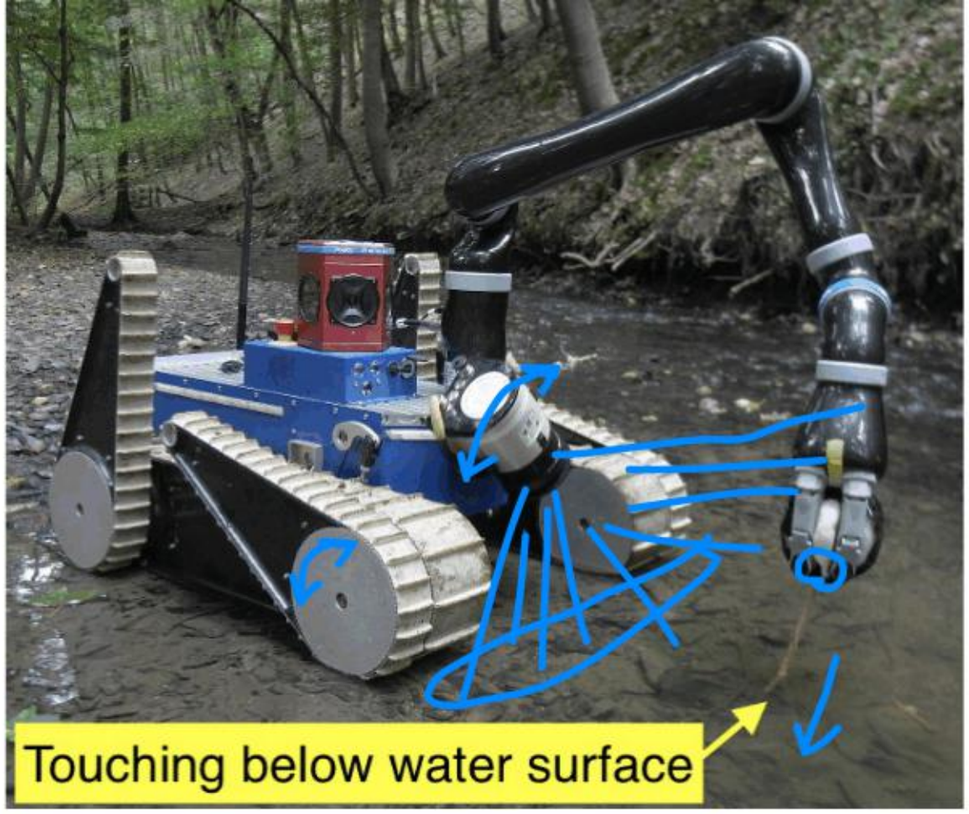




- Construction: $2\times$ main tracks, $4\times$ subtracks (flippers), differential break
  great stability and climbing capability
- Sensor suite: SICK LMS-151 range finder, Ladybug omnicam, Xsens MTi-G IMU
  3D sensing and localization
- Control inputs: Velocity vector, $4\times$**flipper angle**, $4\times$ **flipper stiffness**, differential break (0/1)
  difficult to control all of them manually!





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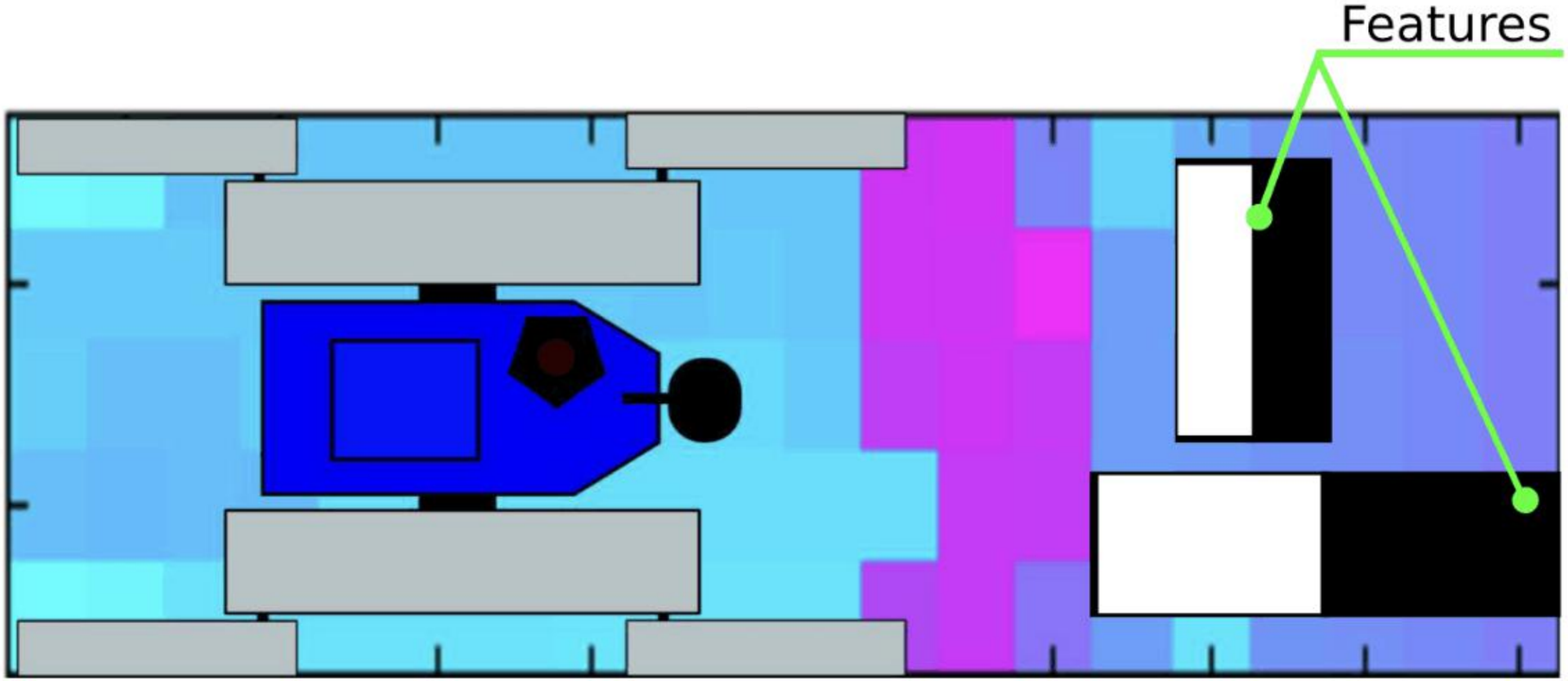
State $\mathbf{s} \in \mathcal{S} \subset \mathbb{R}^n$ concatenates:

- Proprioceptive measurements: roll, pitch, torques, velocity, acceleration.

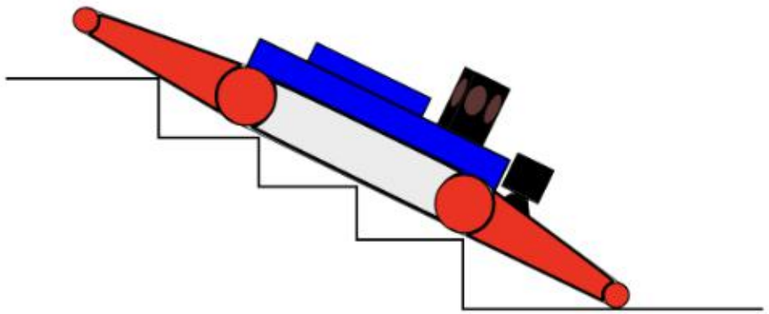
- Local exteroceptive measurements.

features on digital elevation map with fixed size.

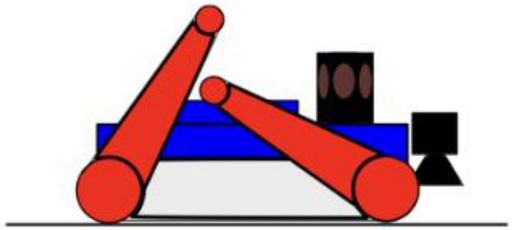


Instead of $\mathbf{a} \in \mathcal{A} \subset \mathbb{R}^8$ we consider only 5 configurations[2]:

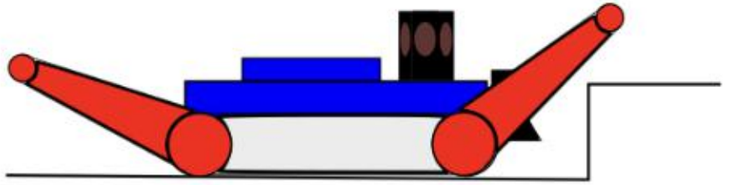
$$\mathcal{A} = \{\text{I-shape}, \text{V-shape}, \text{L-shape}, \text{U-shape soft}, \text{U-shape hard}\}$$



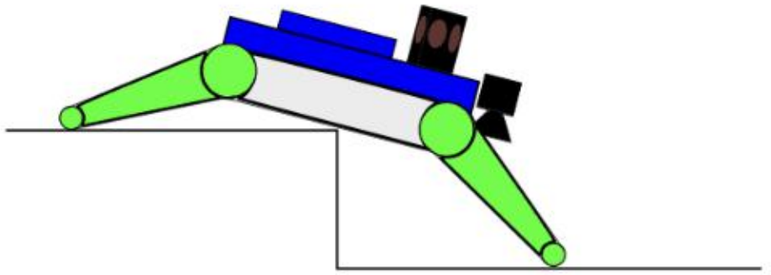
I-shape
(Maximizes traction)



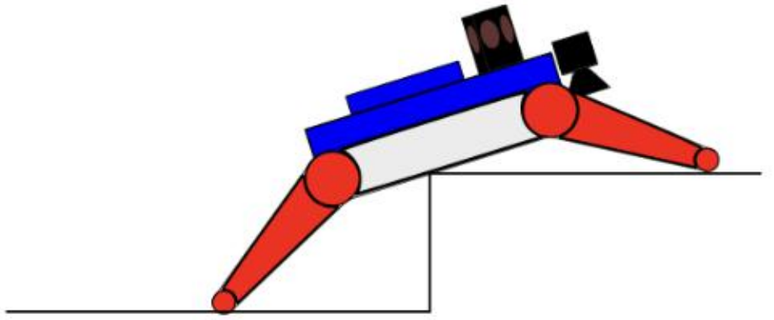
V-shape
(Provides observability)



L-shape
(Forward approach)



U-shape soft
(Smooth climbing down)



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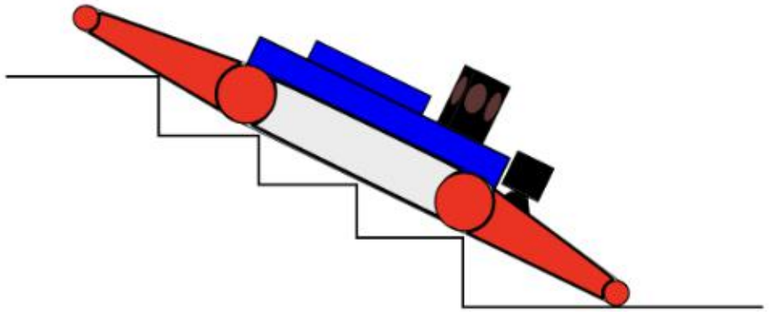

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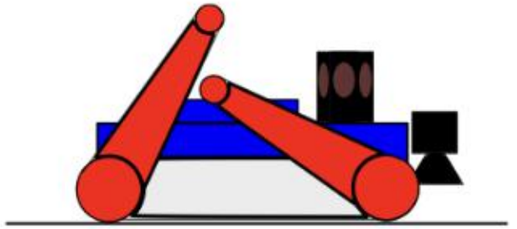

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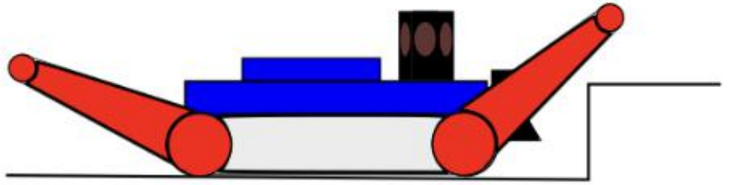

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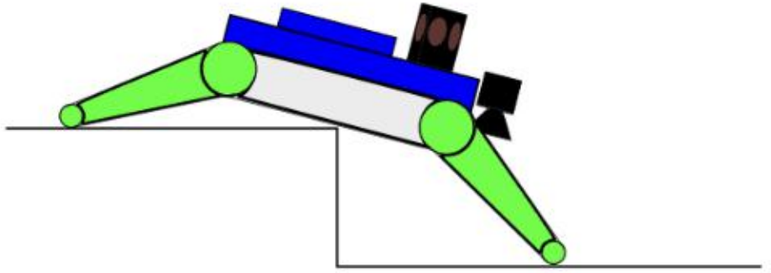

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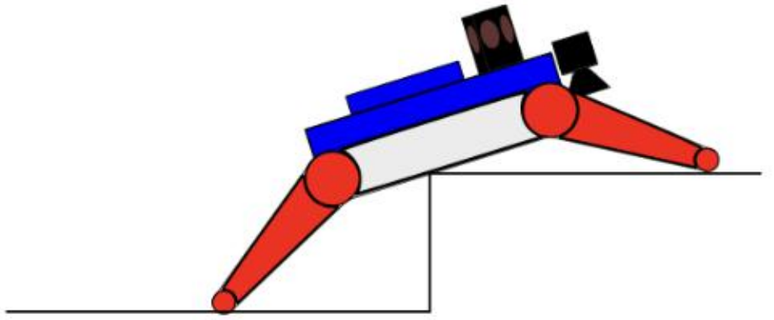

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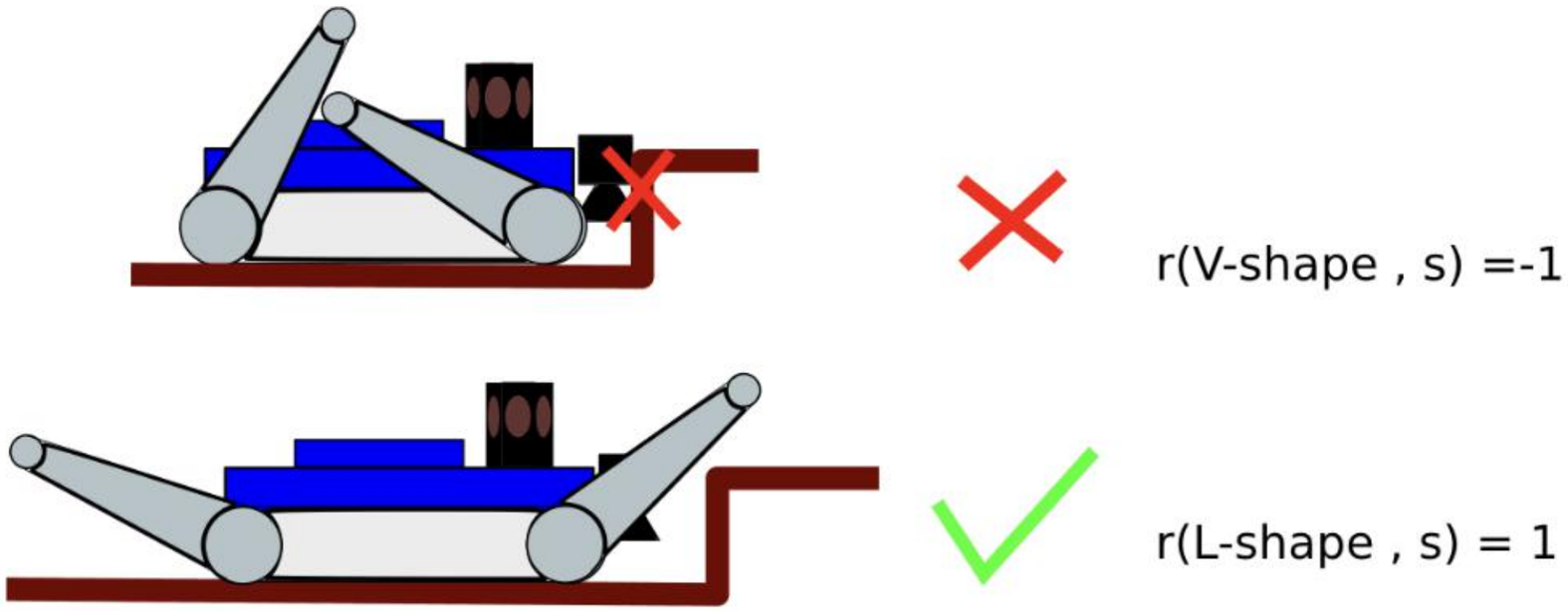

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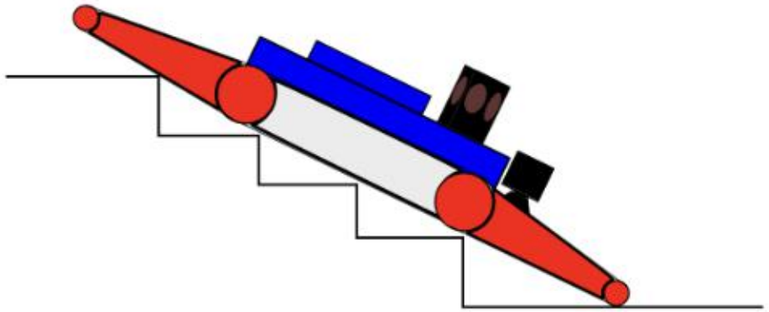

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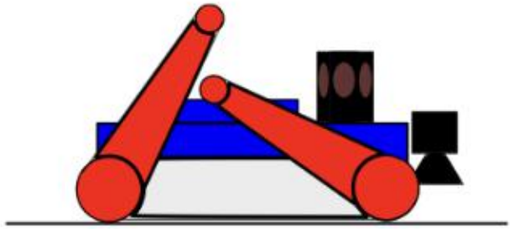

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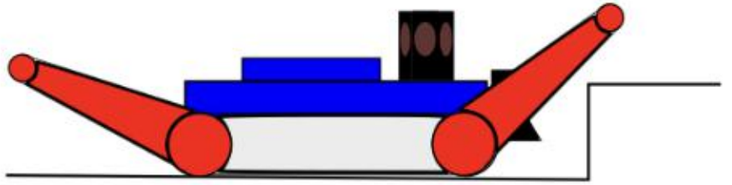

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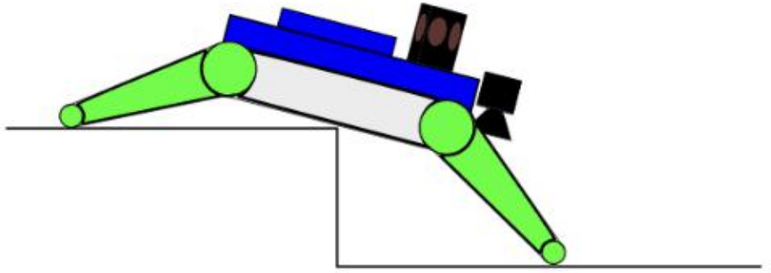

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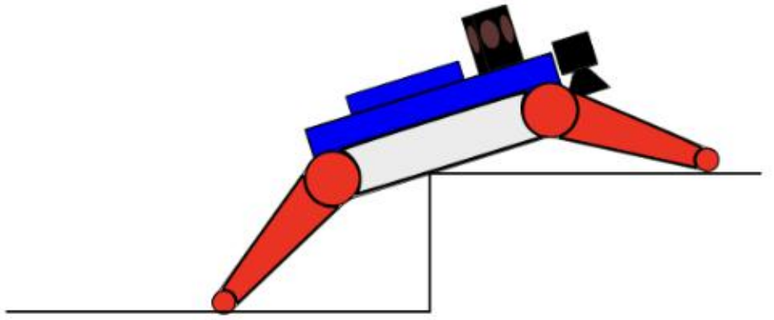

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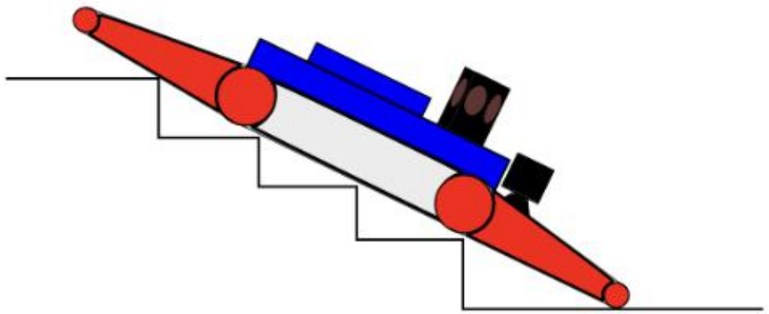

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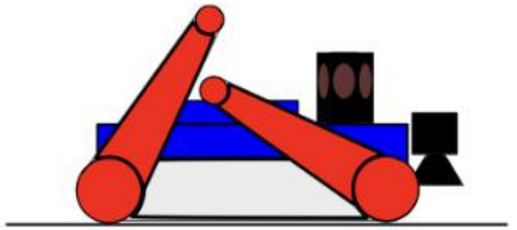

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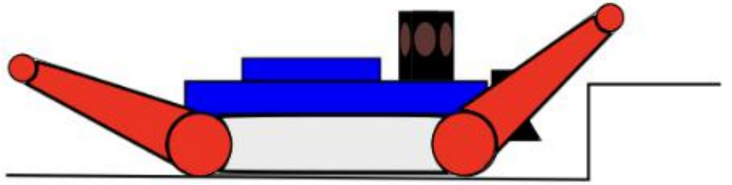

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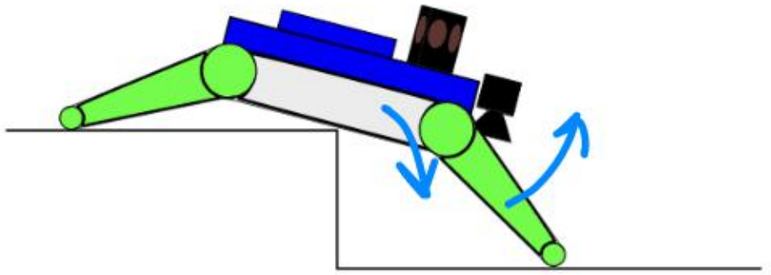

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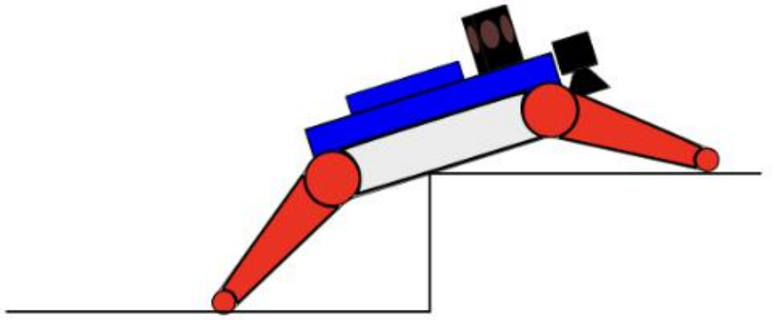

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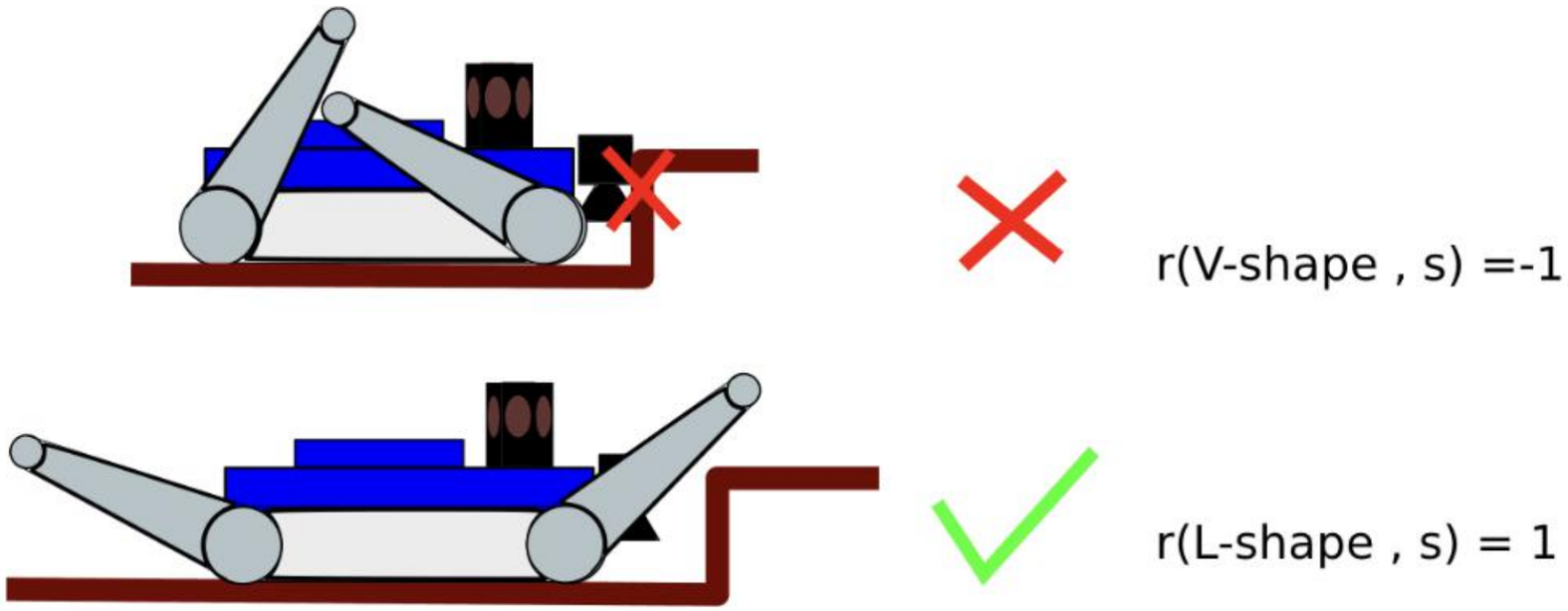

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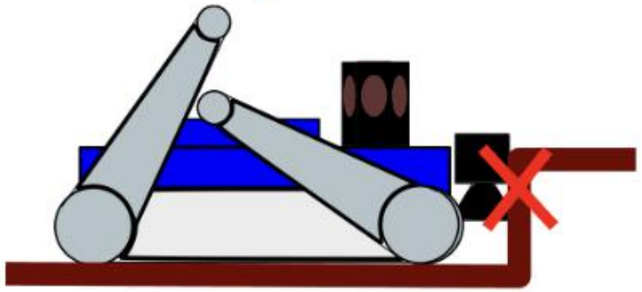
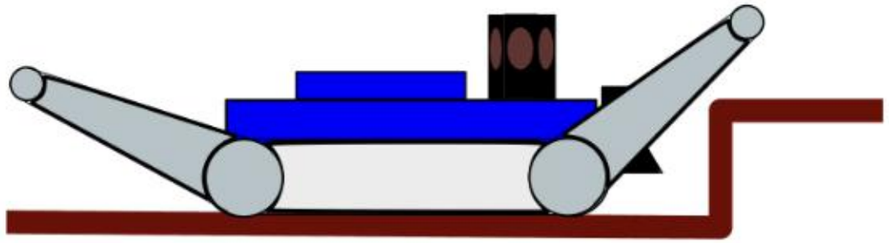
Reward shaping



r(V-shape , s) =-1



r(L-shape , s) = 1

From off-line (MDPs) to on-line (RL)

Markov decision process – MDPs. Off-line search, we know:

- A set of states $s \in \mathcal{S}$ (map)
- A set of actions per state. $a \in \mathcal{A}$
- A transition model $p(s'|s, a)$ (robot)
- A reward function $r(s, a, s')$ (map, robot)

Looking for the optimal policy $\pi(s)$. We can plan/search before the robot enters the environment.

On-line problem:

- Transition p and reward r functions not known.
- Agent/robot must act and learn from experience.

(Transition) Model-based learning

The main idea: Do something and:

- Learn an approximate model from experiences.
- Solve as if the model were correct.

Learning MDP model:

- Try s, a, observe s', count s, a, s'.
- Normalize to get and estimate of $p(s'|s, a)$
- Discover each $r(s, a, s')$ when experienced.

Solve the learned MDP.

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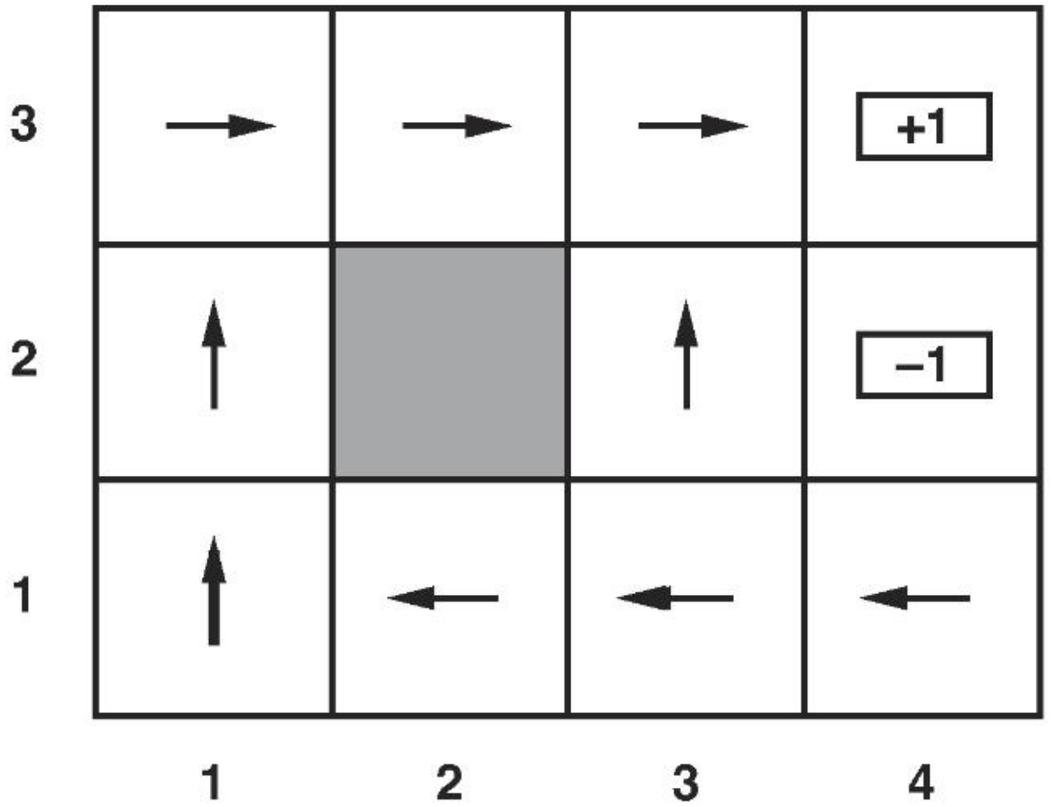
- Move around, observe
- And learn on the way.
- **Goal:** learn the state value $v(s)$ or (better) q-value $q(s, a)$ functions.



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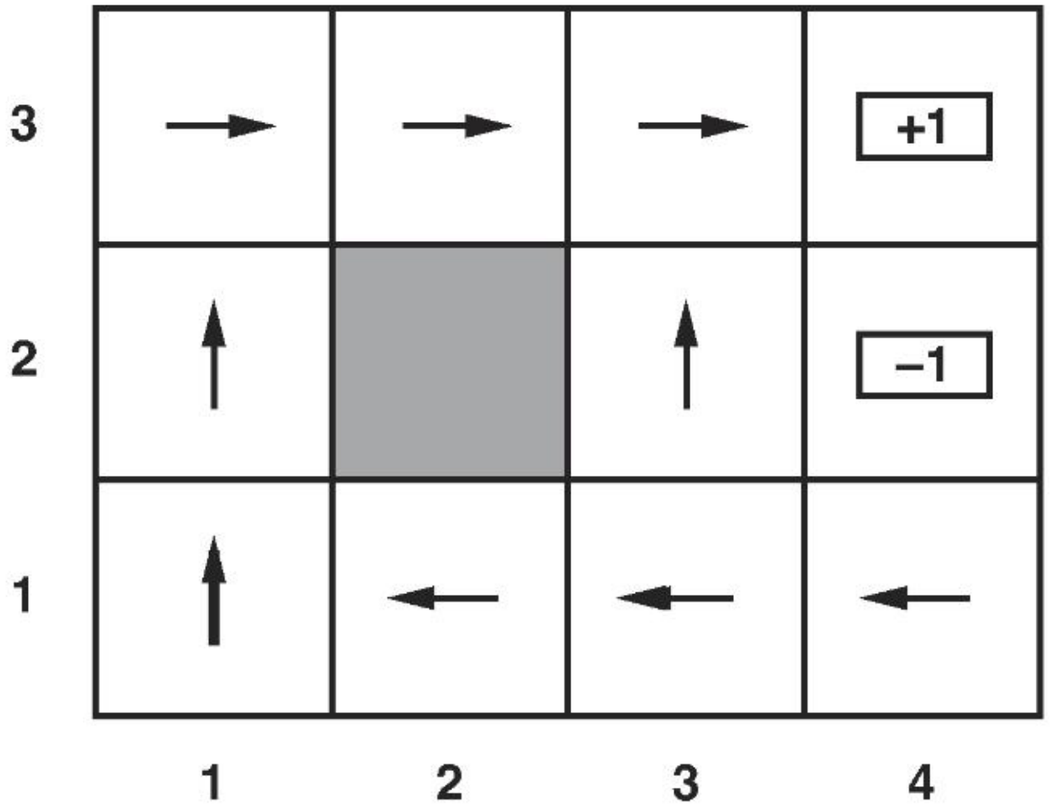

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Recap: $V-$ and $Q-$ values, converged ...

$\gamma = 1$, rewards $-1, +10, -10$, and no confusion - deterministic robot

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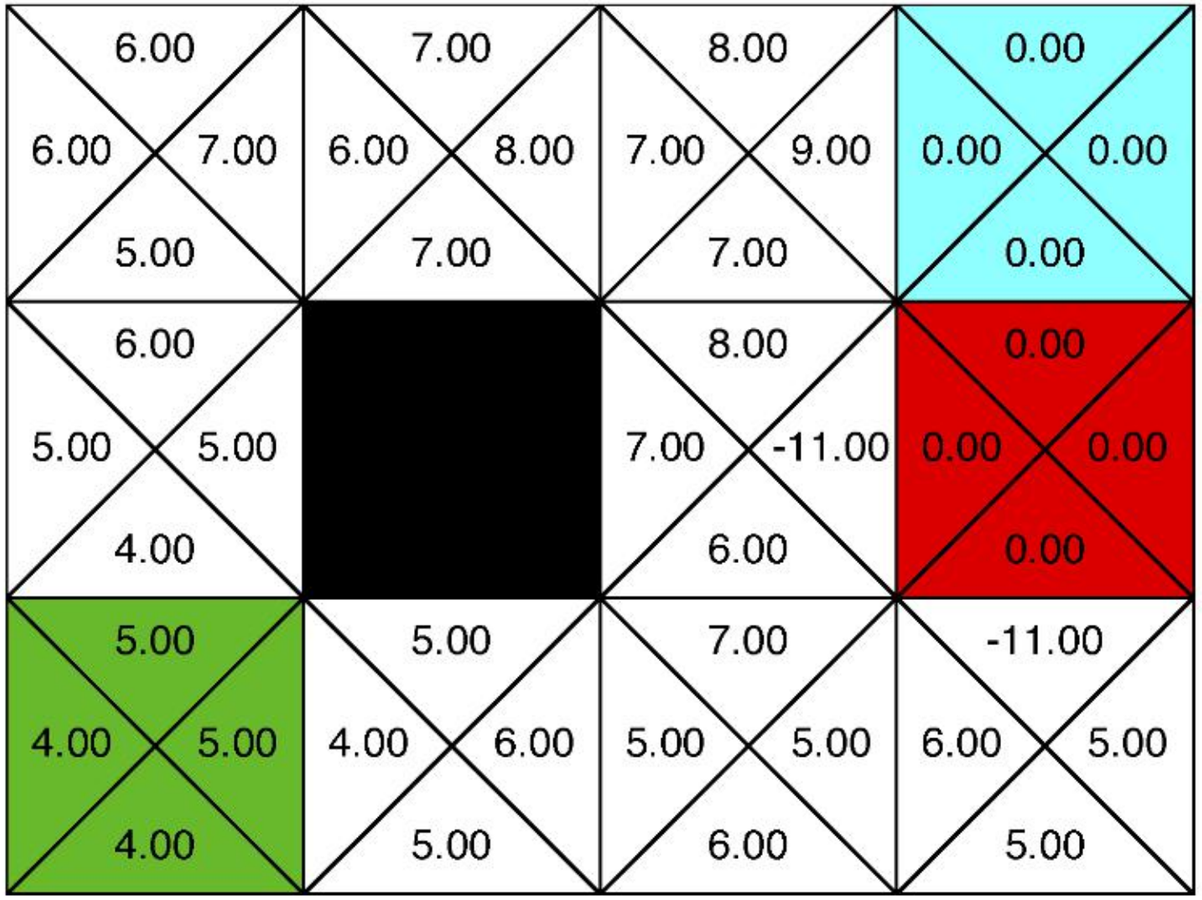

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\begin{aligned}
V(S_t) &= R_{t+1} + V(S_{t+1}) \\
Q(S_t, A_t) &= R_{t+1} + \max_a Q(S_{t+1}, a)
\end{aligned}
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Model-free TD learning, updating after each transition

- Observe, experience environment through learning episodes, collecting:

$$S_t, A_t, R_{t+1}, S_{t+1}, A_{t+1}, R_{t+2}, \ldots$$

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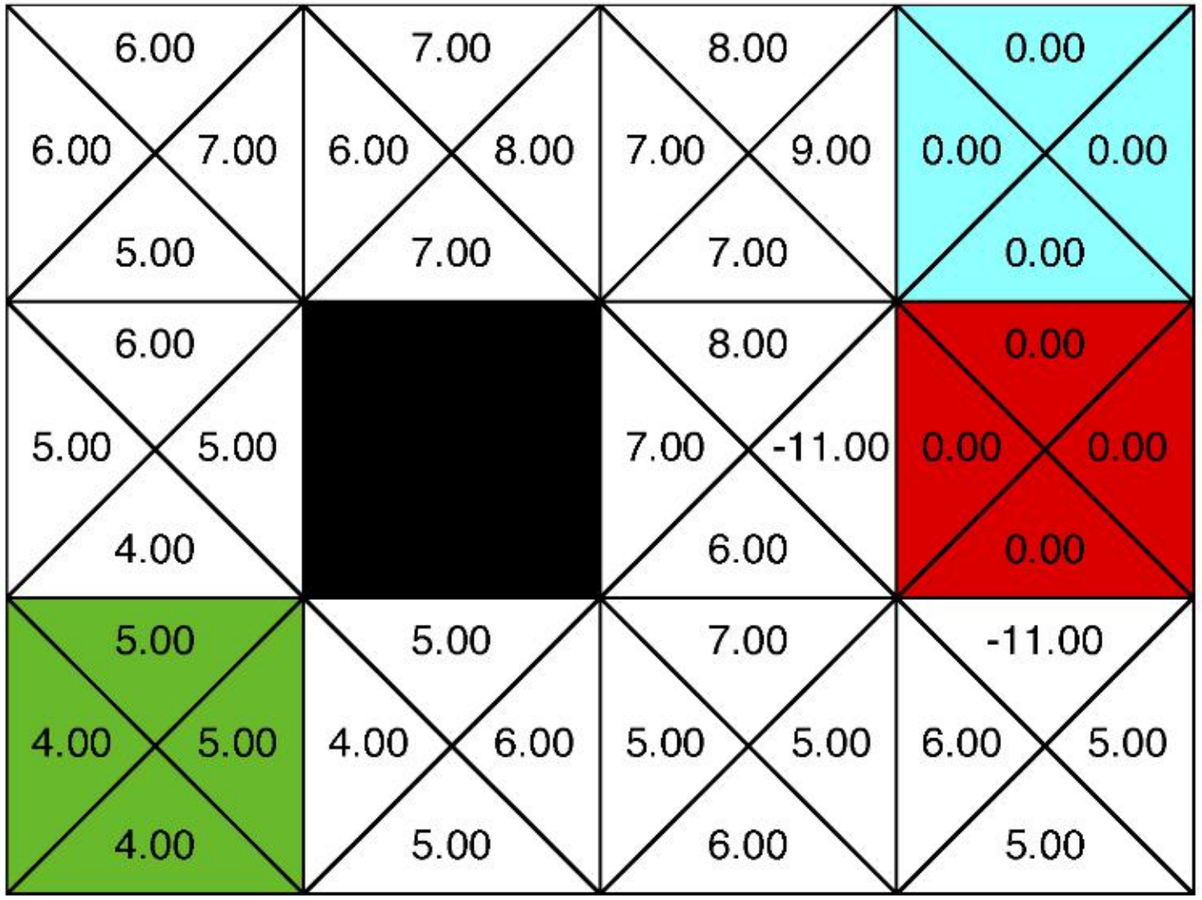

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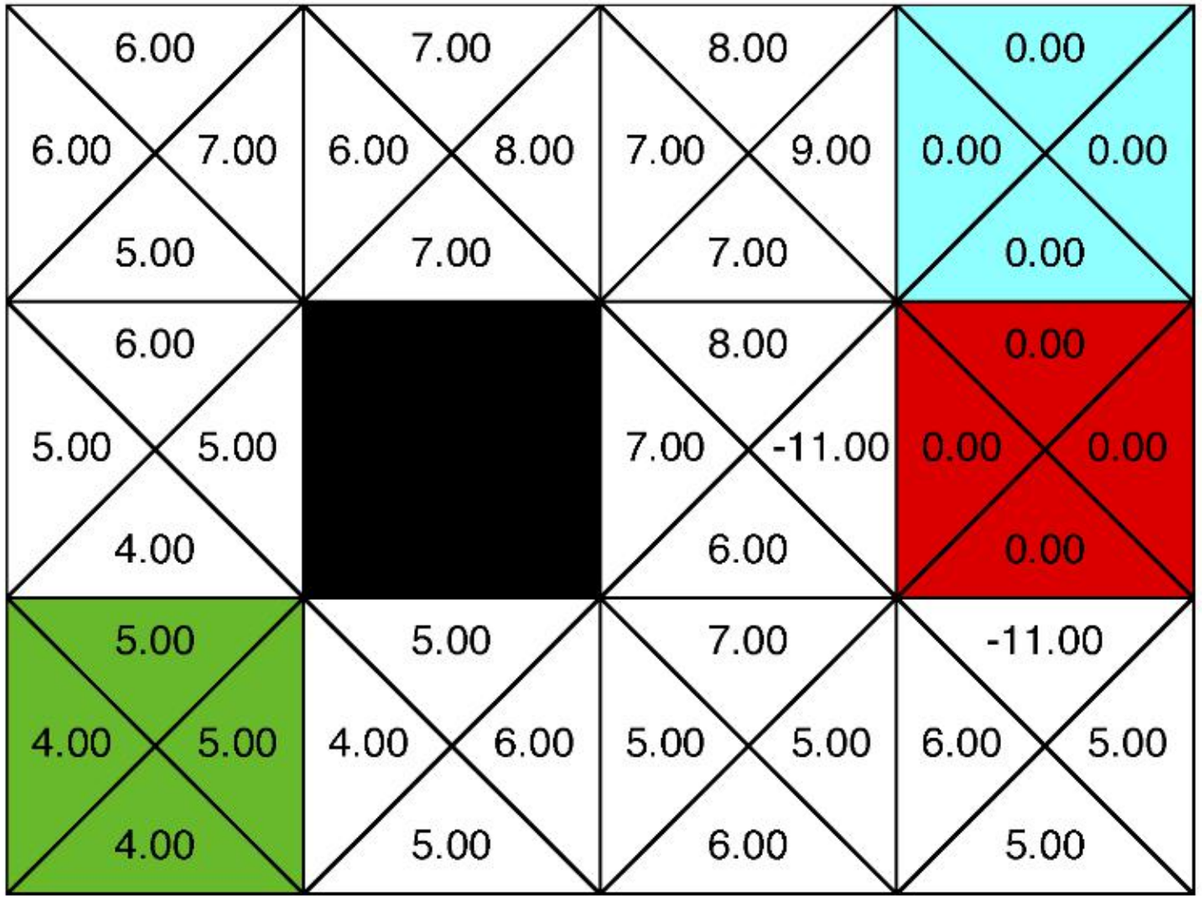

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Model-free TD learning, updating after each transition

temporal difference

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Recap: Bellman optimality equations for $v(s)$ and $q(s, a)$

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v(s) &= \max_a \sum_{s'} p(s'|s, a) \left[r(s, a, s') + \gamma \, v(s') \right] \\
&= \max_a q(s, a)
\end{aligned}
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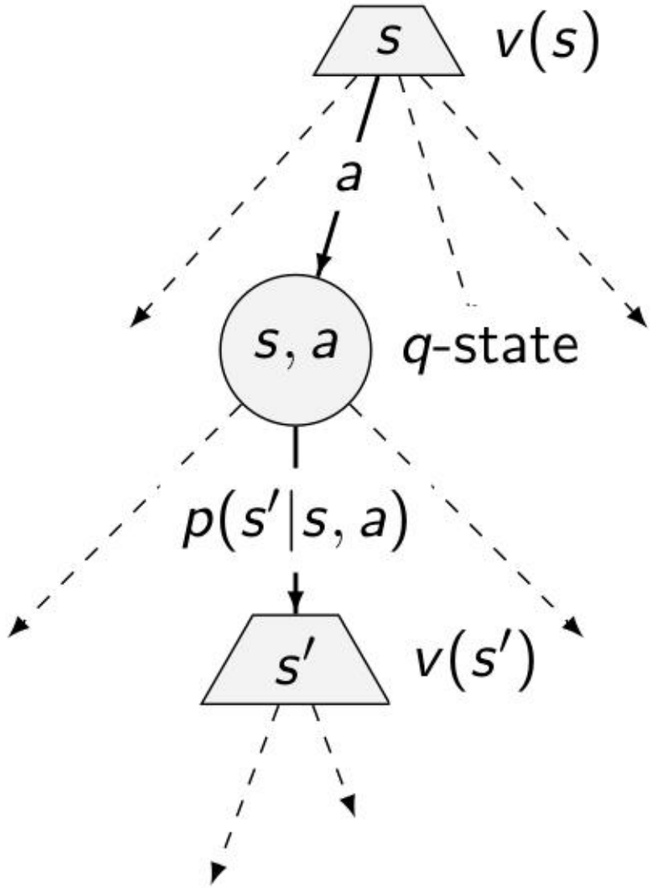

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v(s) &= \max_a \sum_{s'} p(s'|s, a) \left[r(s, a, s') + \gamma \, v(s') \right] \\
&= \max_a q(s, a)
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The value of a q-state (s, a):

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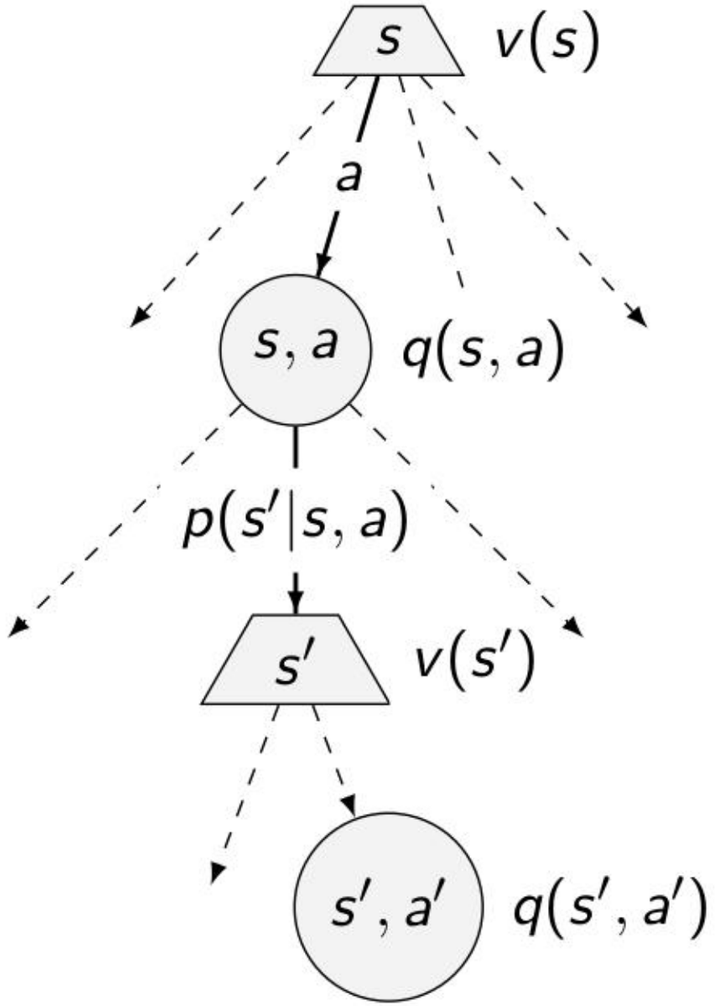

Recap: Bellman optimality equations for $v(s)$ and $q(s, a)$

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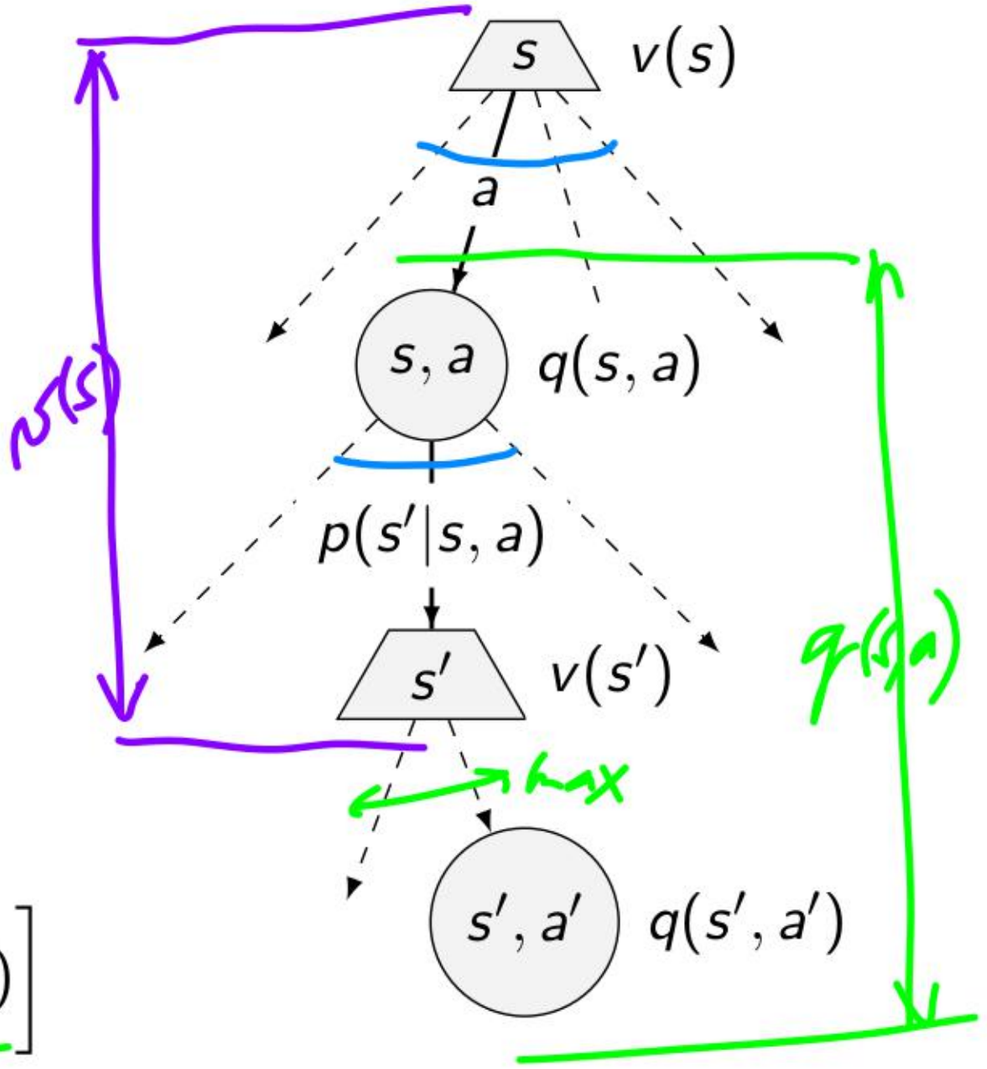

Q-learning

Learn Q values as the robot/agent goes (temporal difference). If some Q quantity not known, initialize.

- time t, at S_t
- take $A_t \in \mathcal{A}(S_t)$, observe R_{t+1}, S_{t+1}
- compute trial/sample estimate at time t
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In each step Q approximates the optimal q^* function.

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In each step Q approximates the optimal q^* function.

Q-learning: algorithm

step size $0 < \alpha \leq 1$
initialize $Q(s, a)$ for all $s \in \mathcal{S}, a \in \mathcal{S}(s)$
repeat episodes:
    initialize S
    for for each step of episode: **do**
        choose A from S
        take action A, observe R, S'
        $Q(S, A) \leftarrow Q(S, A) + \alpha\big[R + \gamma \max_a Q(S', a) - Q(S, A)\big]$
        $S \leftarrow S'$
    end for until S is terminal
until Time is up, ...

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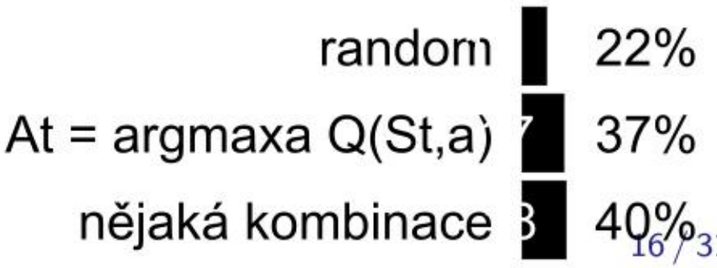

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. . . A_t derived from Q

What about keeping optimality, taking max?

$$A_t = \arg\max_a Q(S_t, a)$$

see the demo run of `rl_agents.py`.

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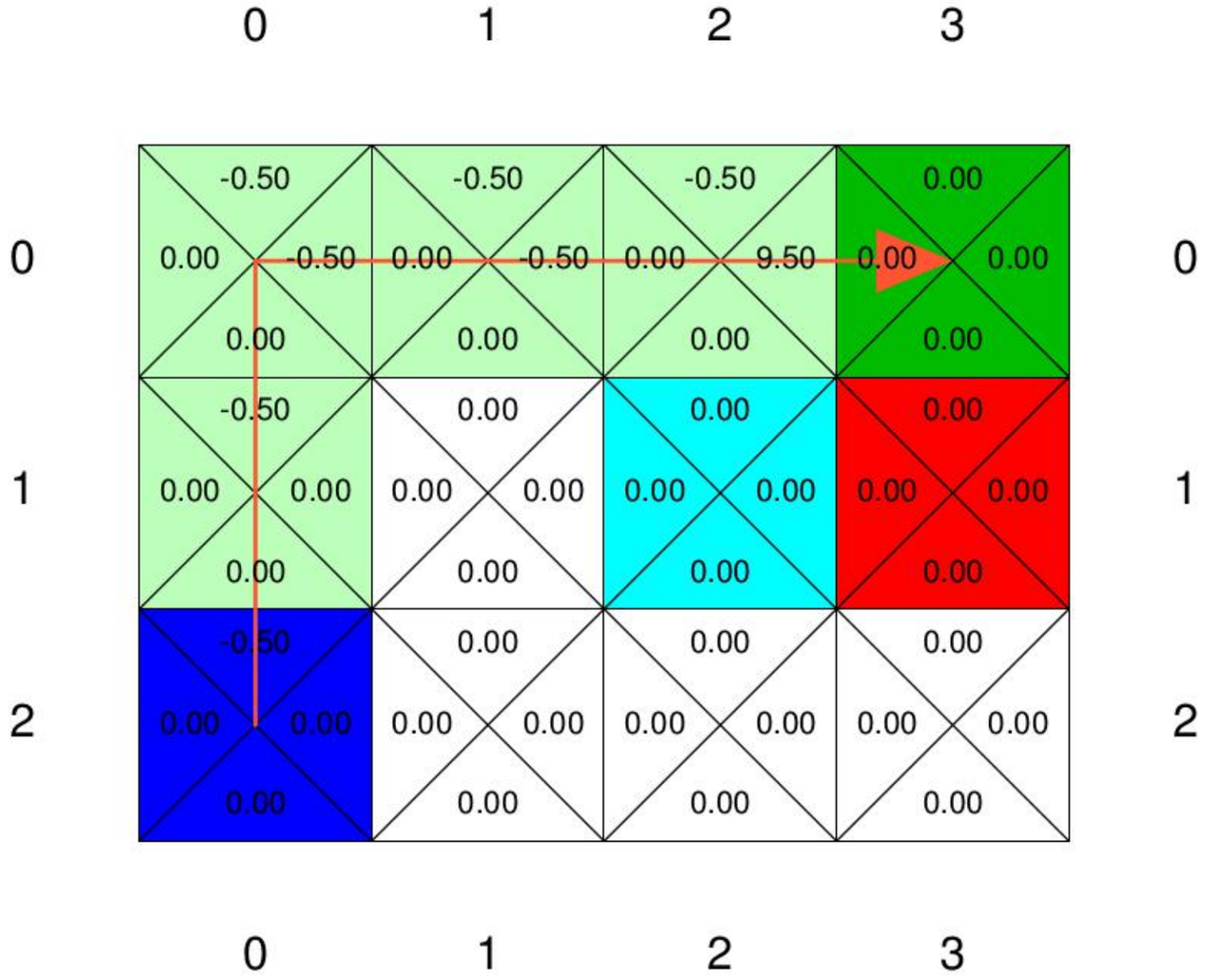
Two good goal states



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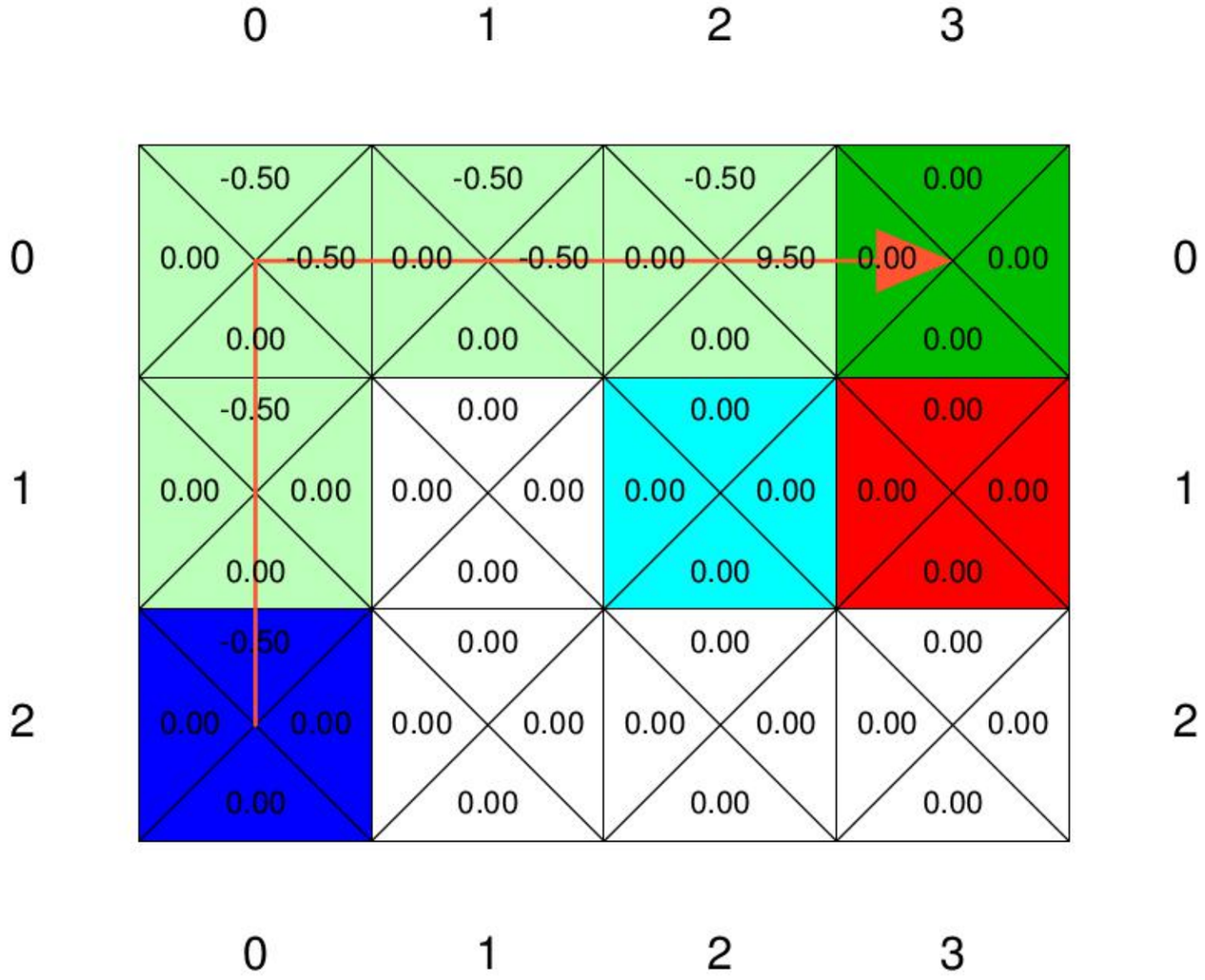

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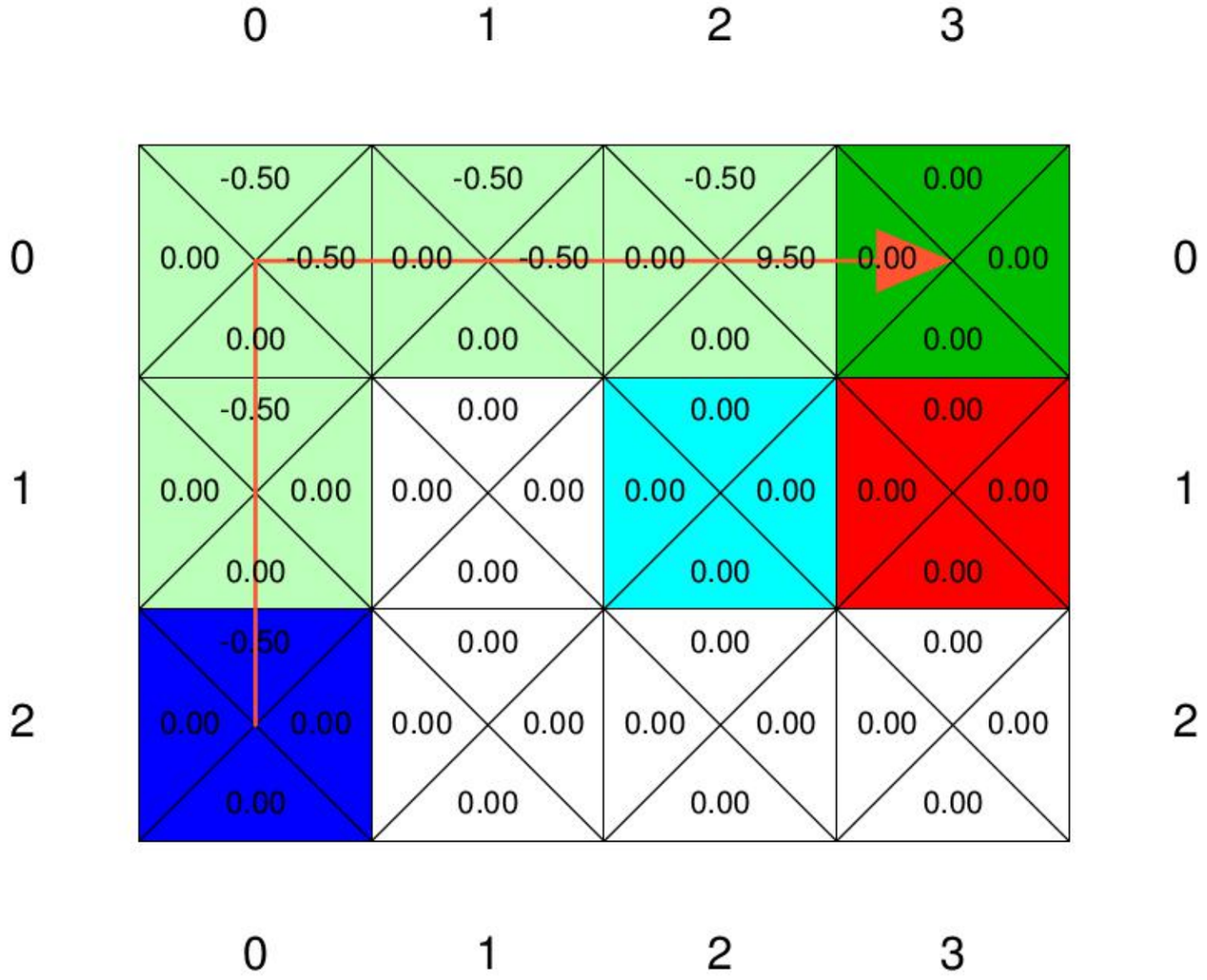

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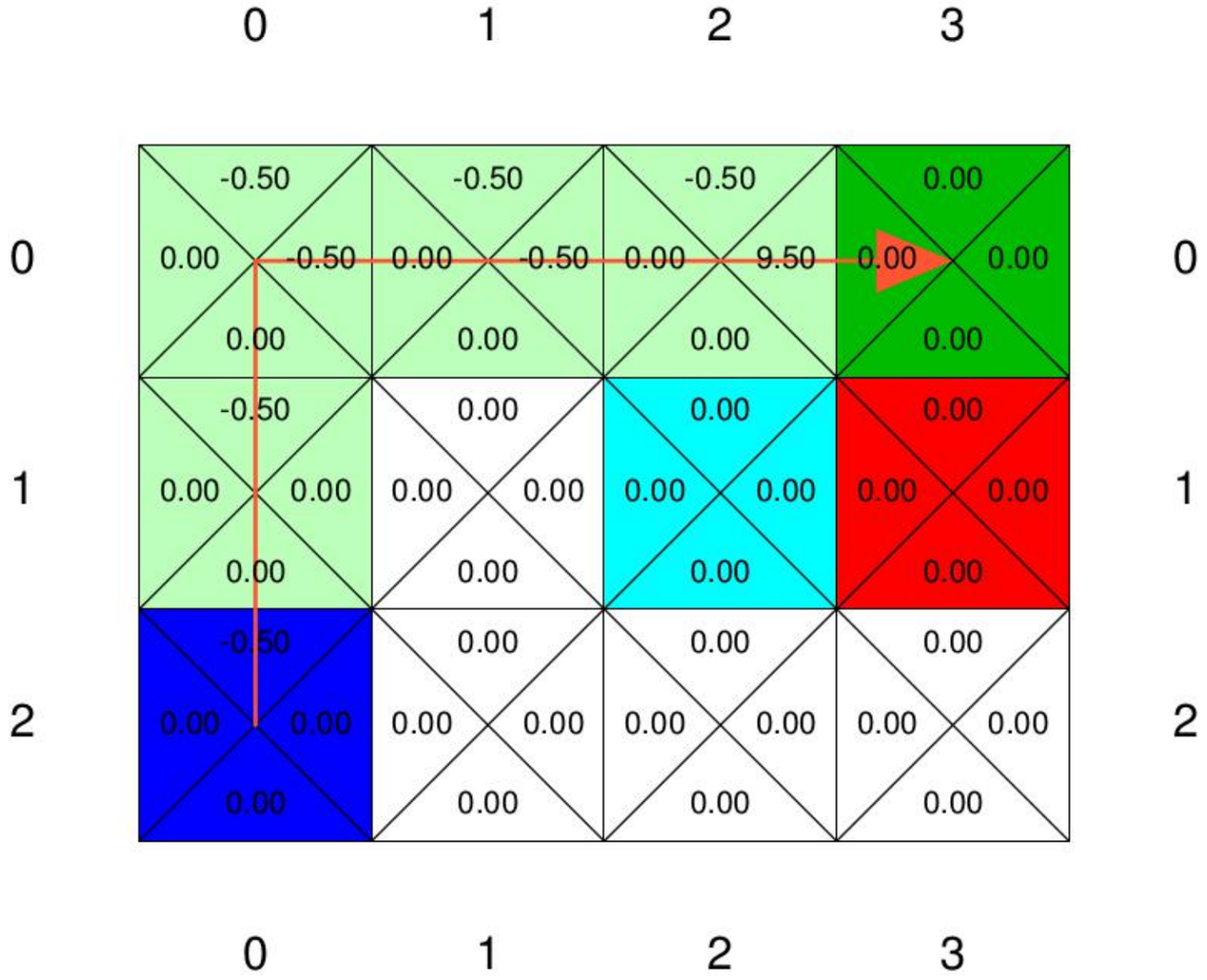

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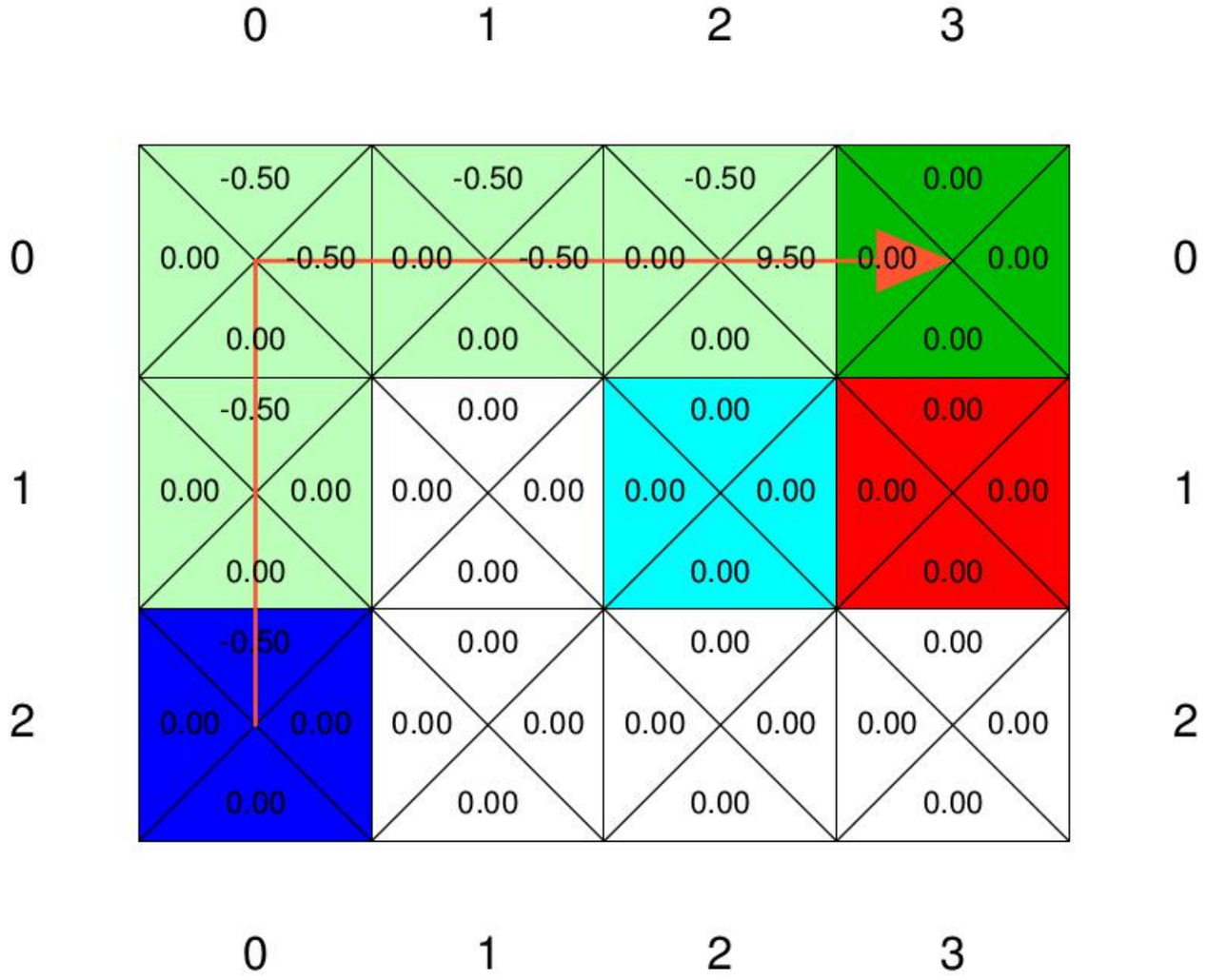

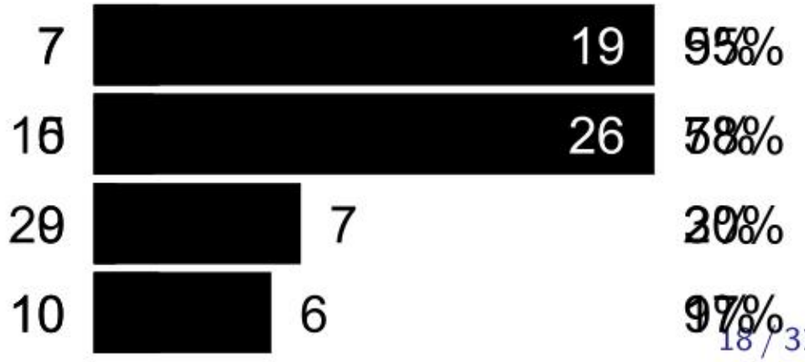

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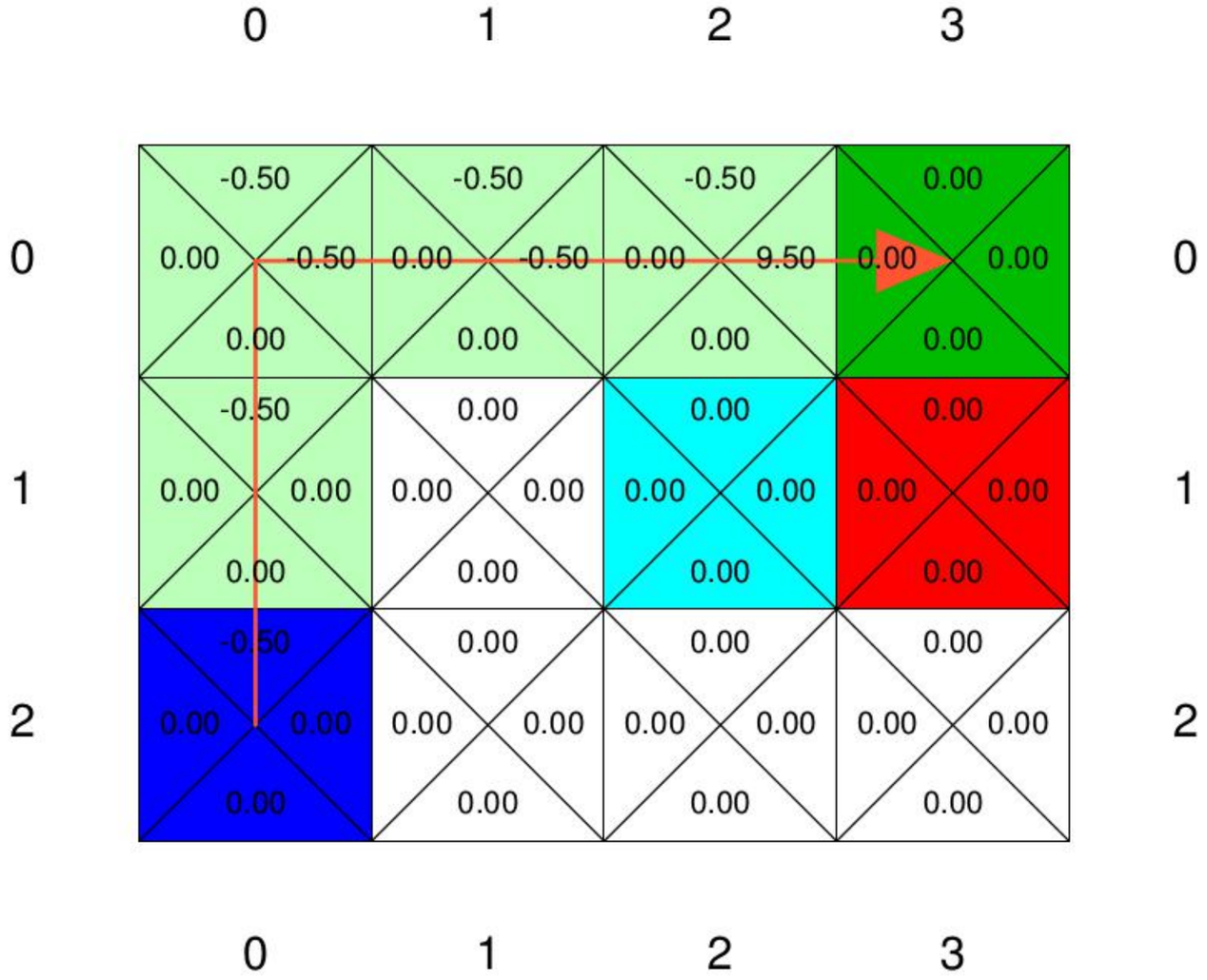

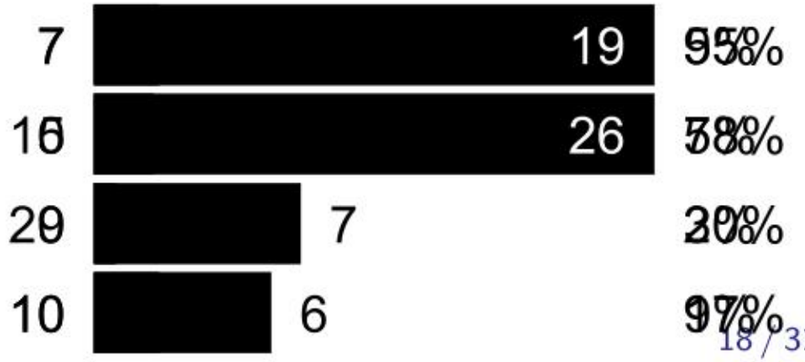

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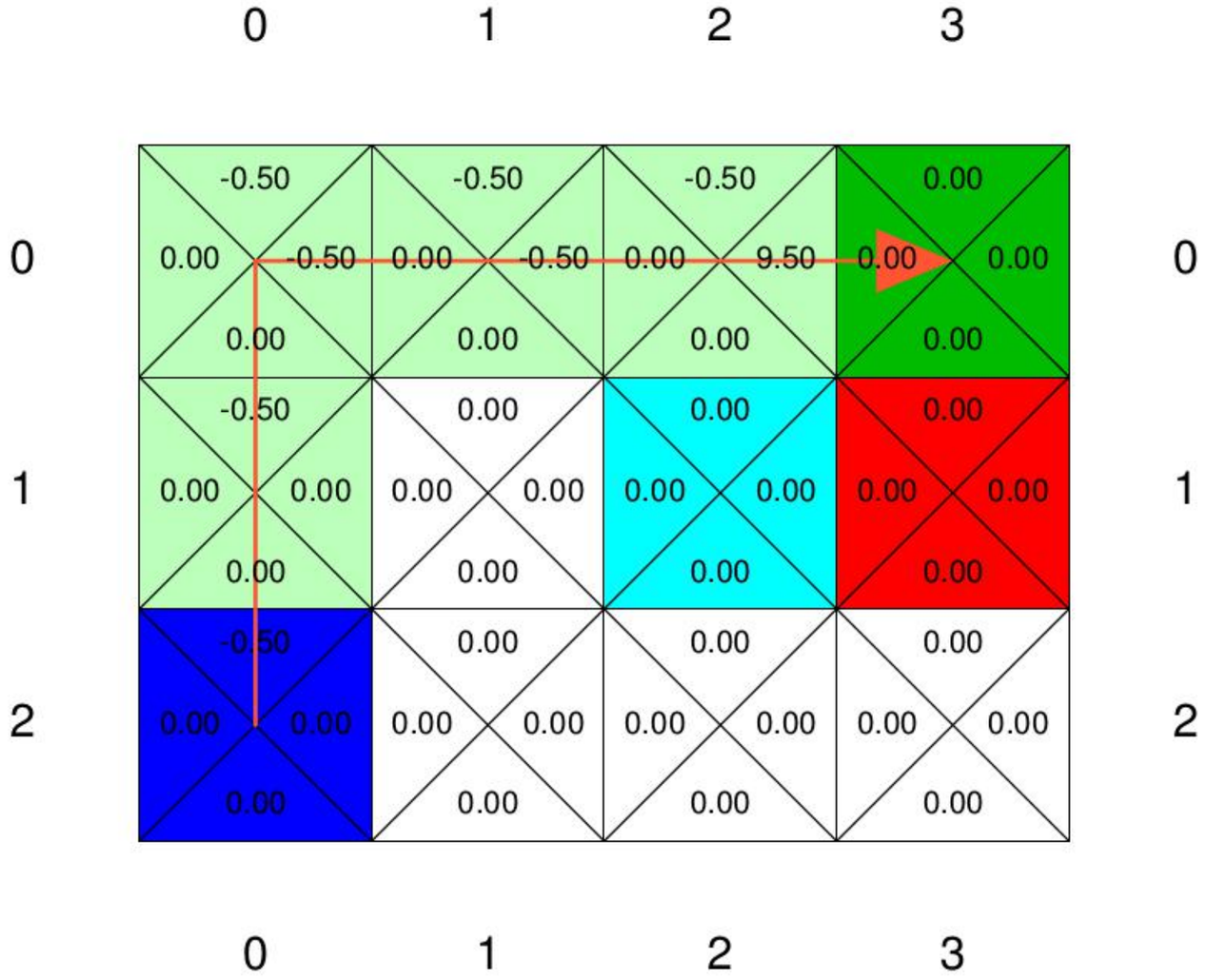
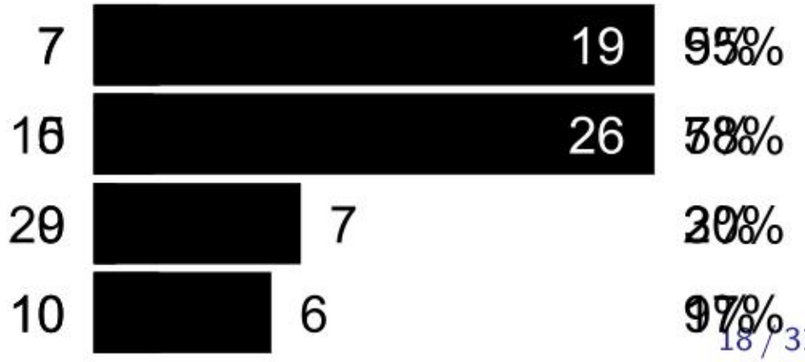
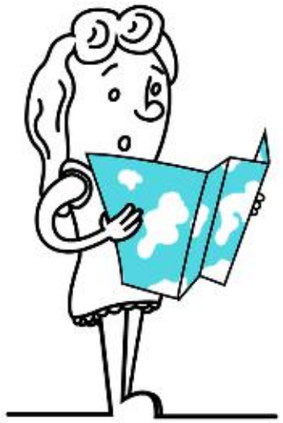
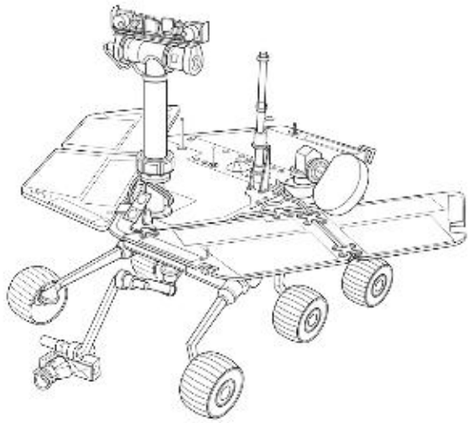
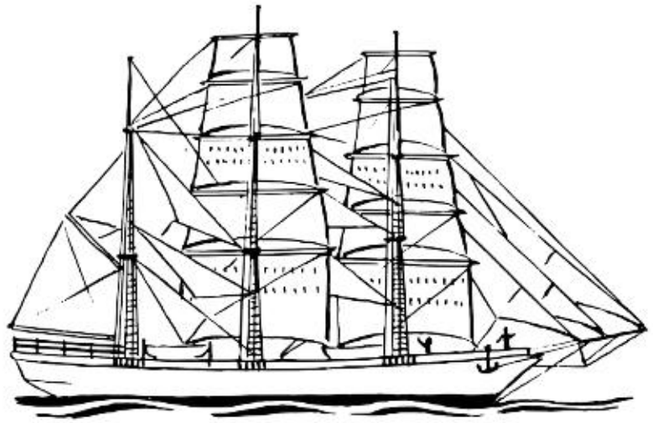




Exploration vs Exploitation







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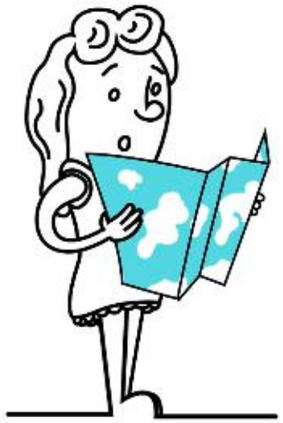

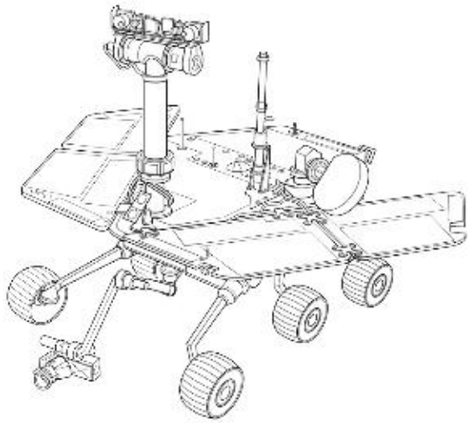

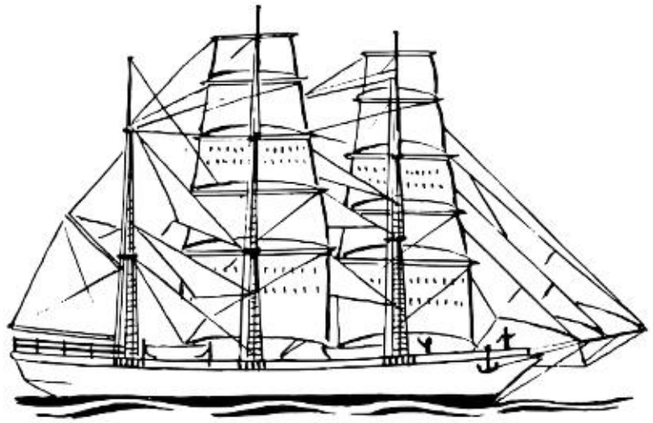

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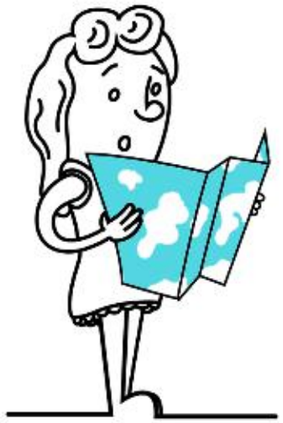

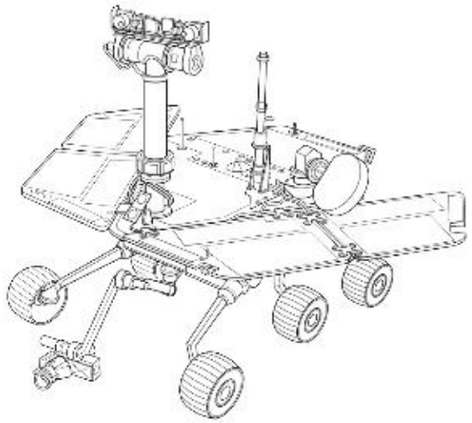

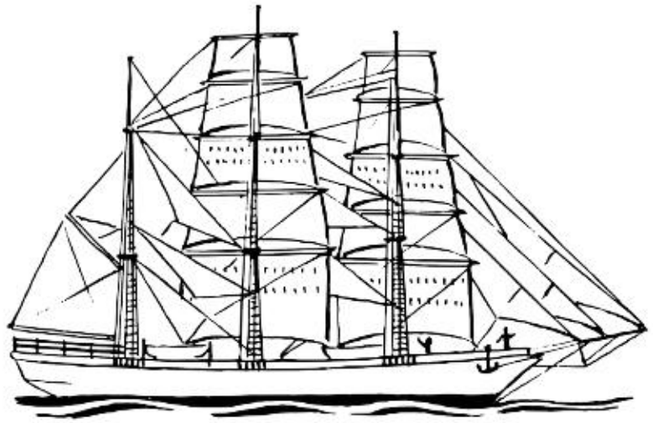

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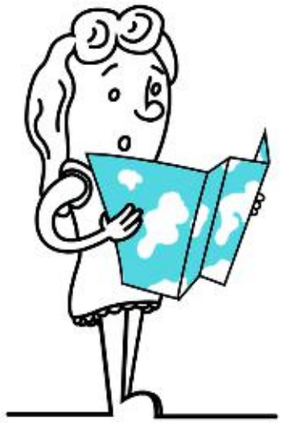

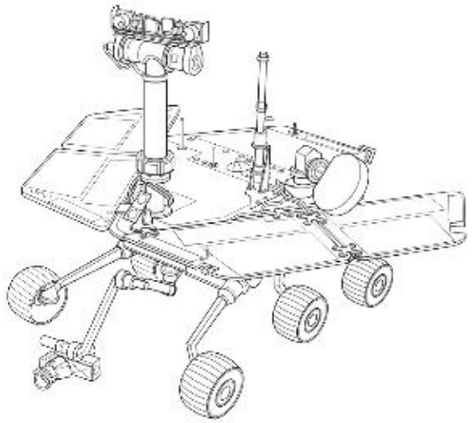

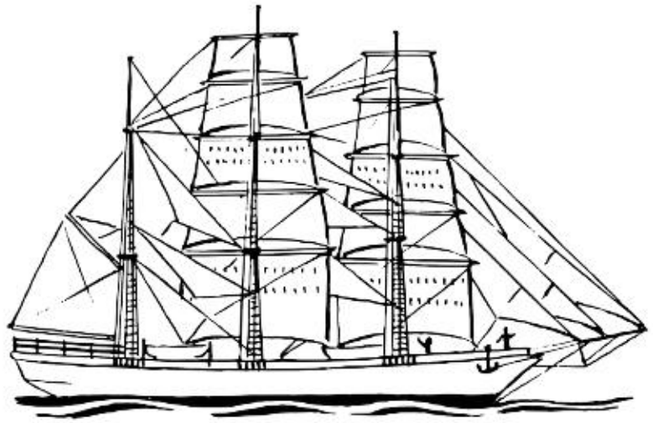

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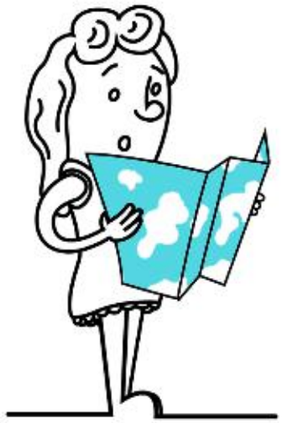

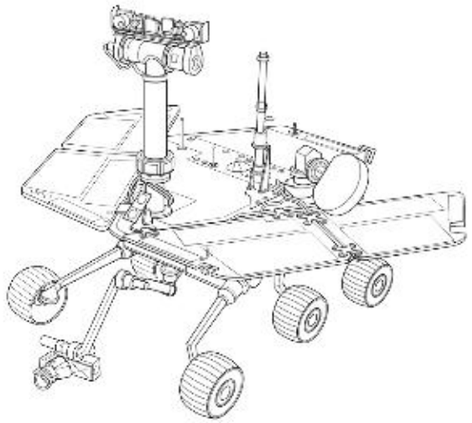

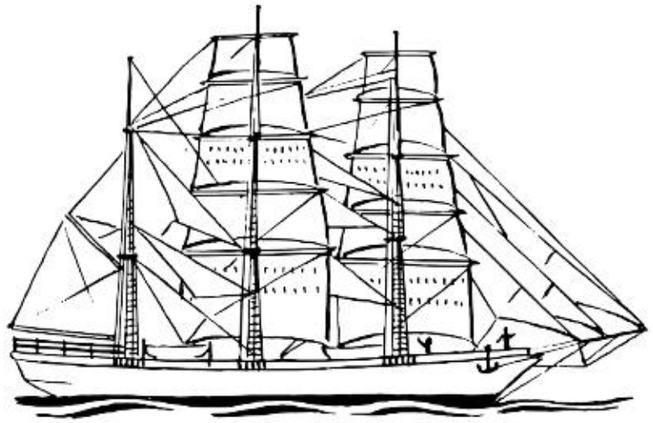

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How to explore?

Random (ϵ-greedy):

- Flip a coin every step.
- With probability ϵ, act randomly.
- With probability $1 - \epsilon$, use the policy.

Problems with randomness?

- Keeps exploring forever.
- Should we keep ϵ fixed (over learning)?
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How to explore?

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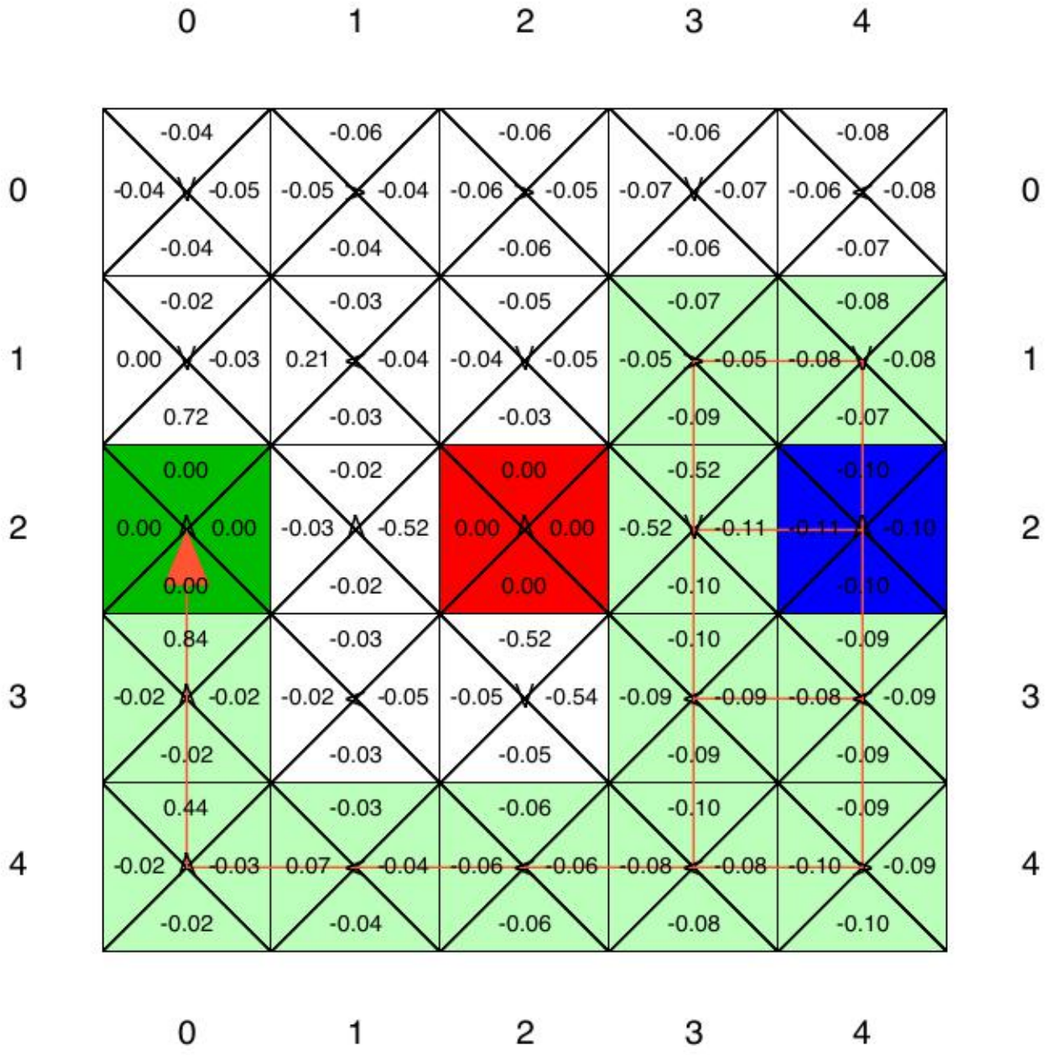
How to evaluate result, when to stop learning?



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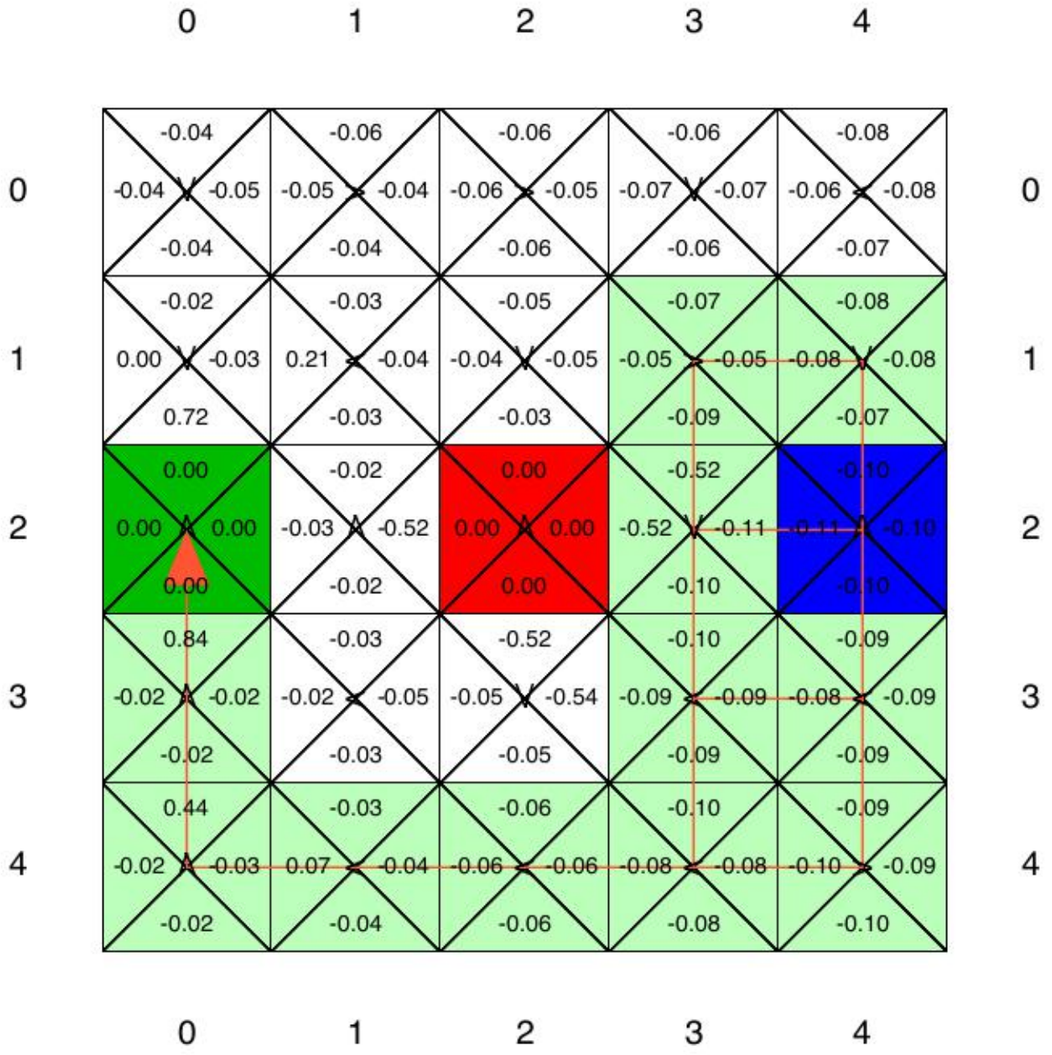

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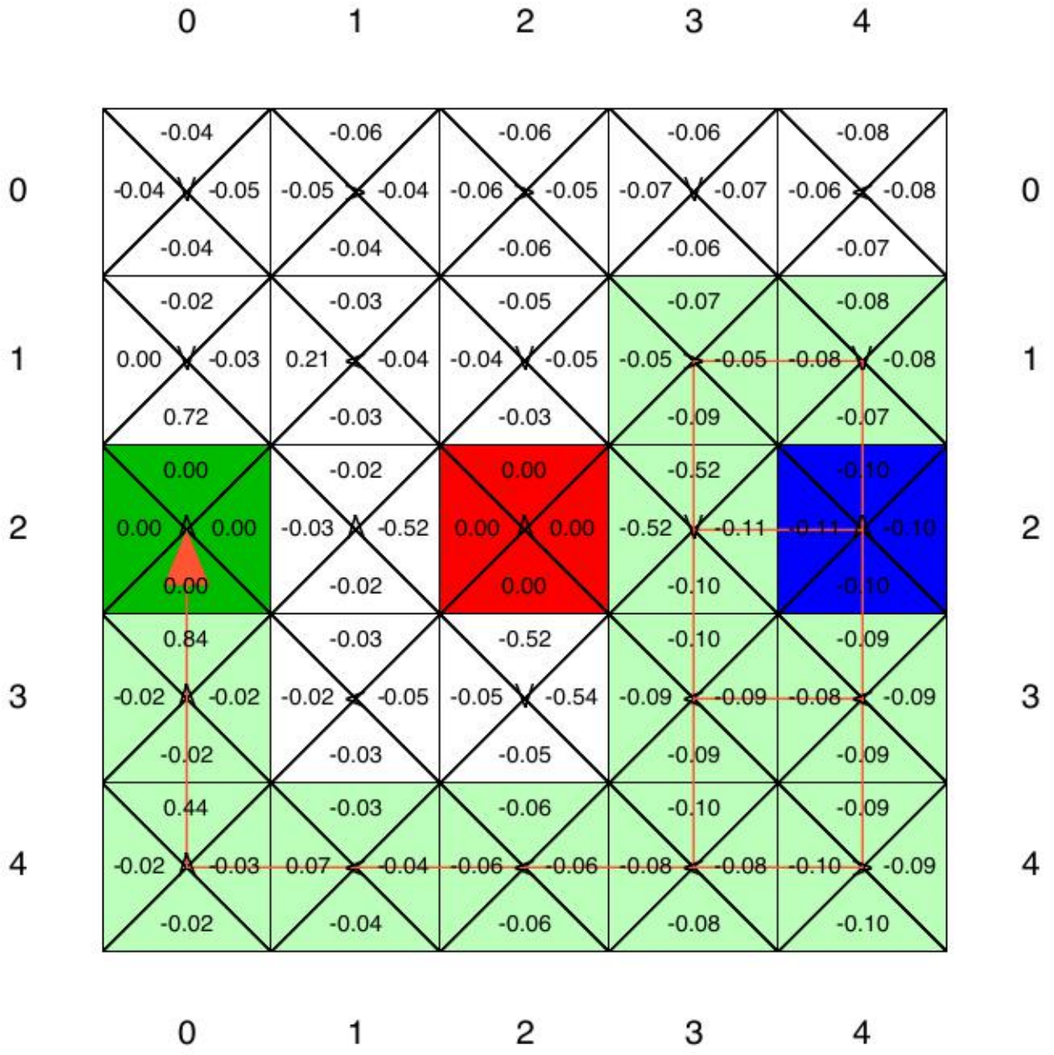

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Exploration function $f(u, n)$

- Regular trial/sample estimate: trial $= R_{t+1} + \gamma \max_a Q(S_{t+1}, a)$
- If (S_t, a) not yet tried, then perhaps too pesimistic.
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where $f(u, n)$

$$\begin{aligned} f(u, n) &= R^+ \text{ if } n < N_e \\ &= u \text{ otherwise} \end{aligned}$$

where

- R^+ is an optimistic estimate of the best possible reward obtainable in any state
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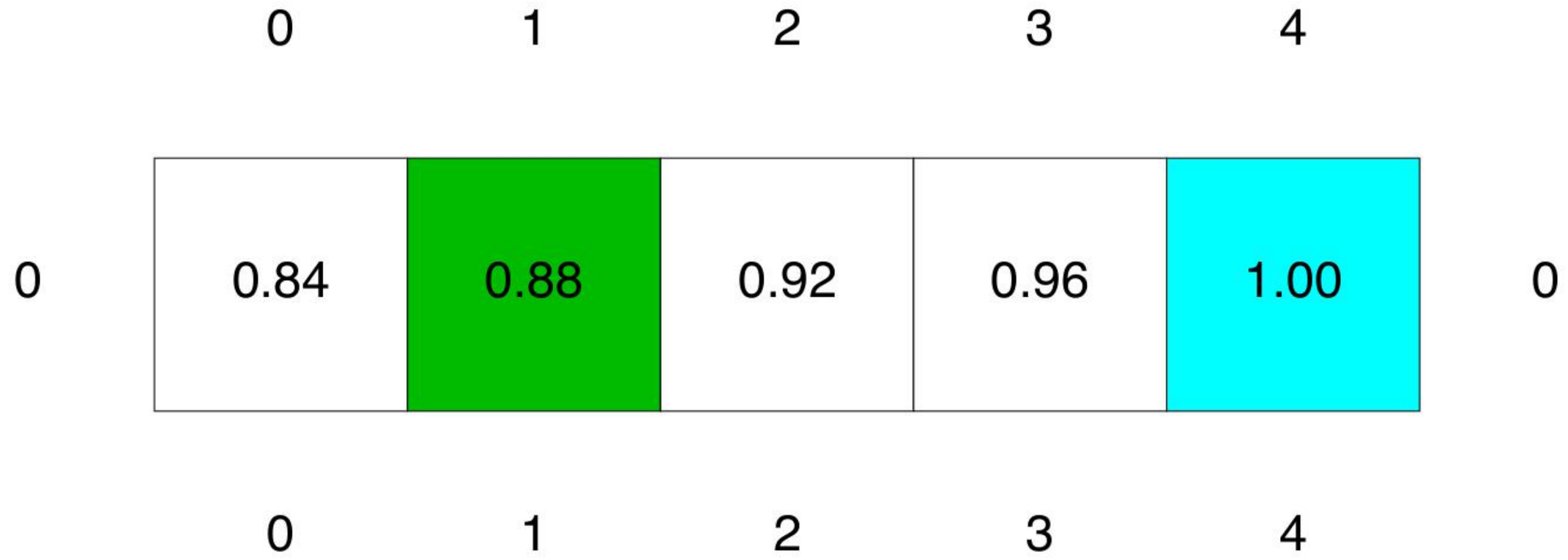
Going beyond tables - generalizing across states



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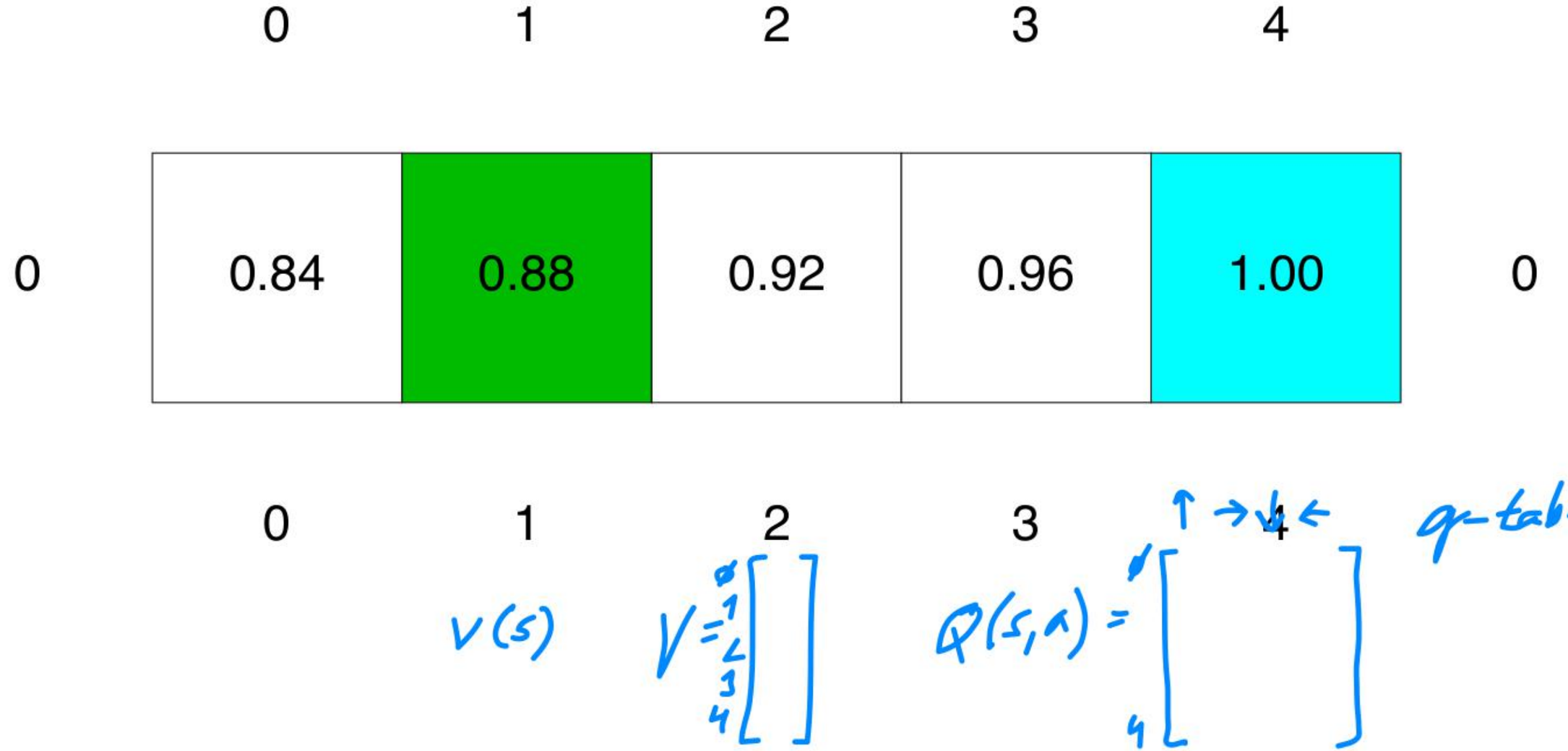
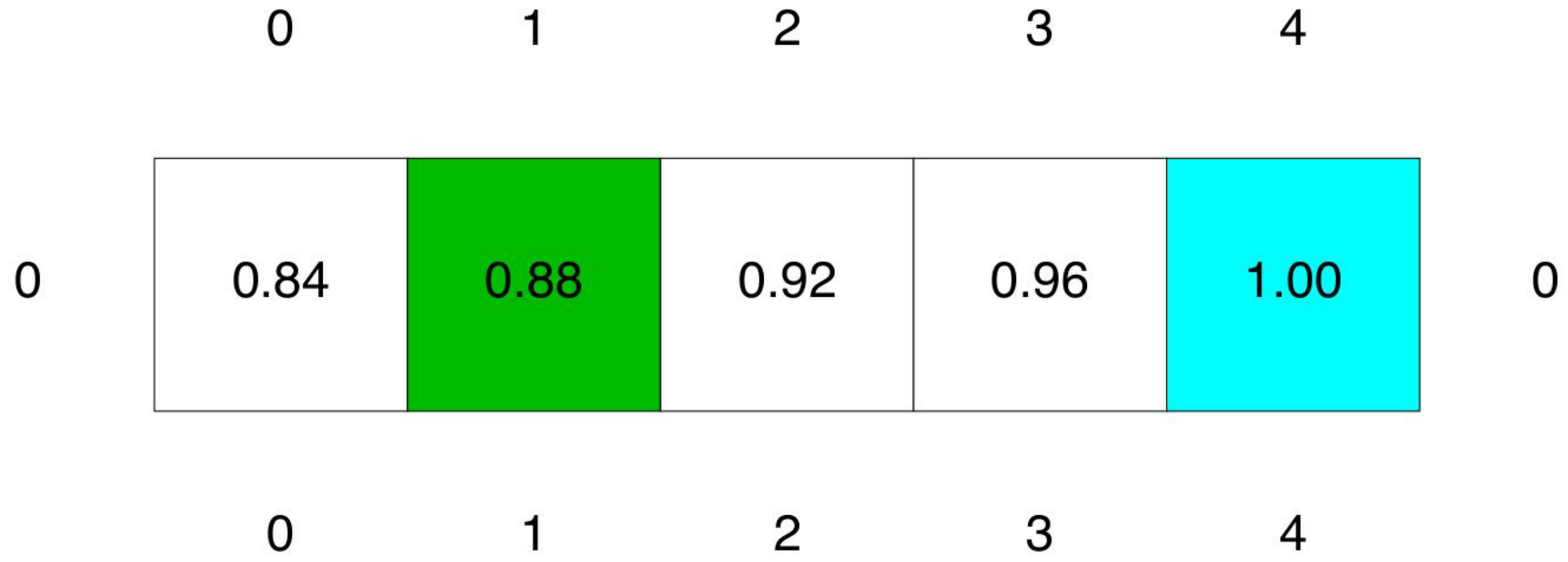


Going beyond tables - generalizing across states

	0	1	2	3	4	
0	0.84	0.80	0.76	0.72	0.68	0
1	0.88	0.84	0.80	0.76	0.72	1
2	0.92	0.88	0.84	0.80	0.76	2
3	0.96	0.92	0.88	0.84	0.80	3
4	1.00	0.96	0.92	0.88	0.84	4
	0	1	2	3	4	

v(s) not as table but as an approximation function



$$\hat{v}(s, \mathbf{w}) = w_0 + w_1 s$$

What are w_0, w_1 equal to?

Instead of the complete table, only 2 parameters to learn $\mathbf{w} = [w_0, w_1]^\top$

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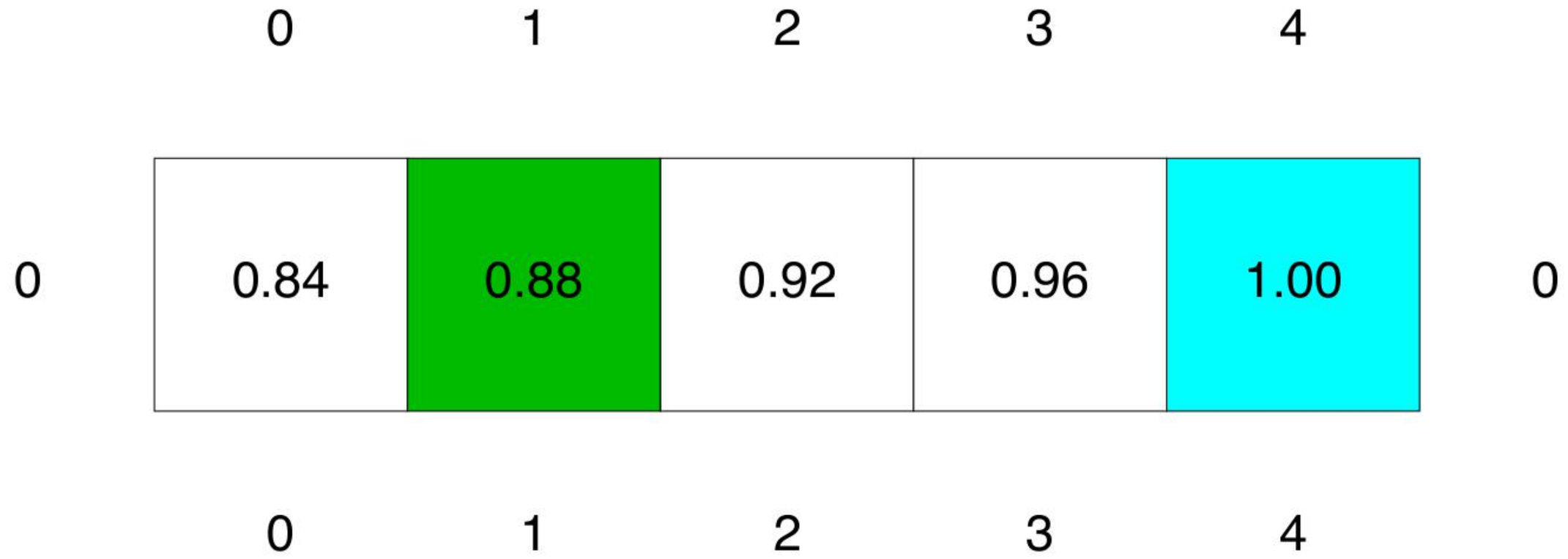

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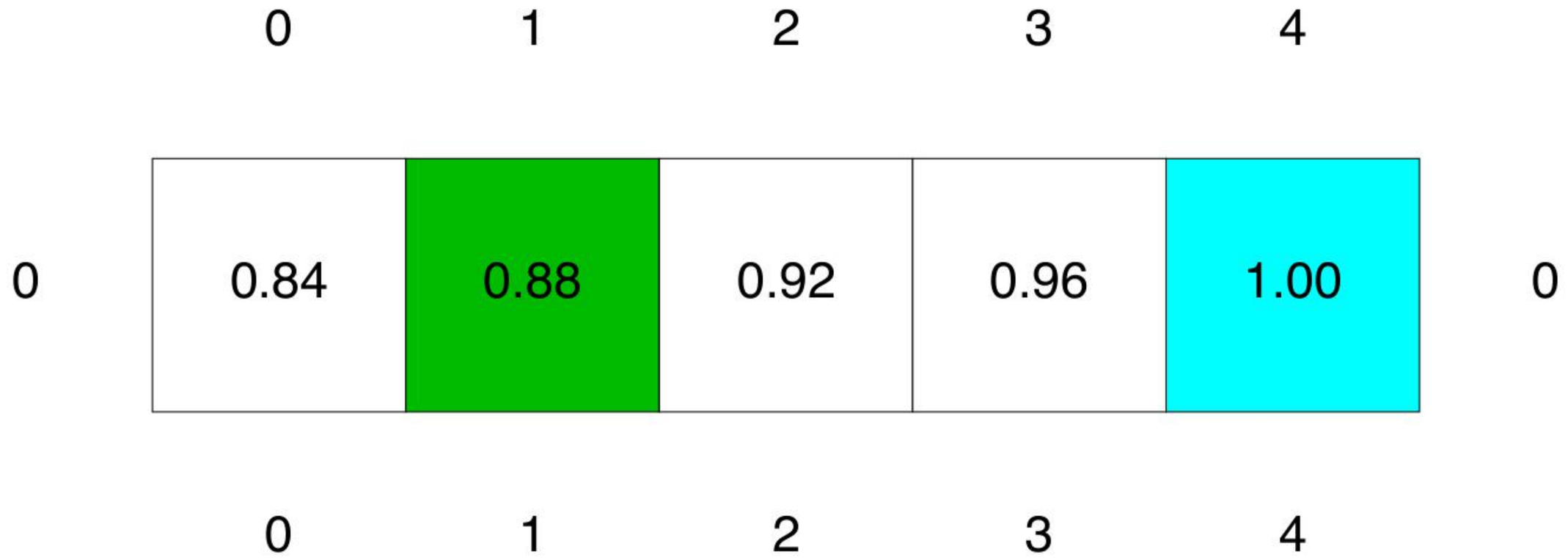

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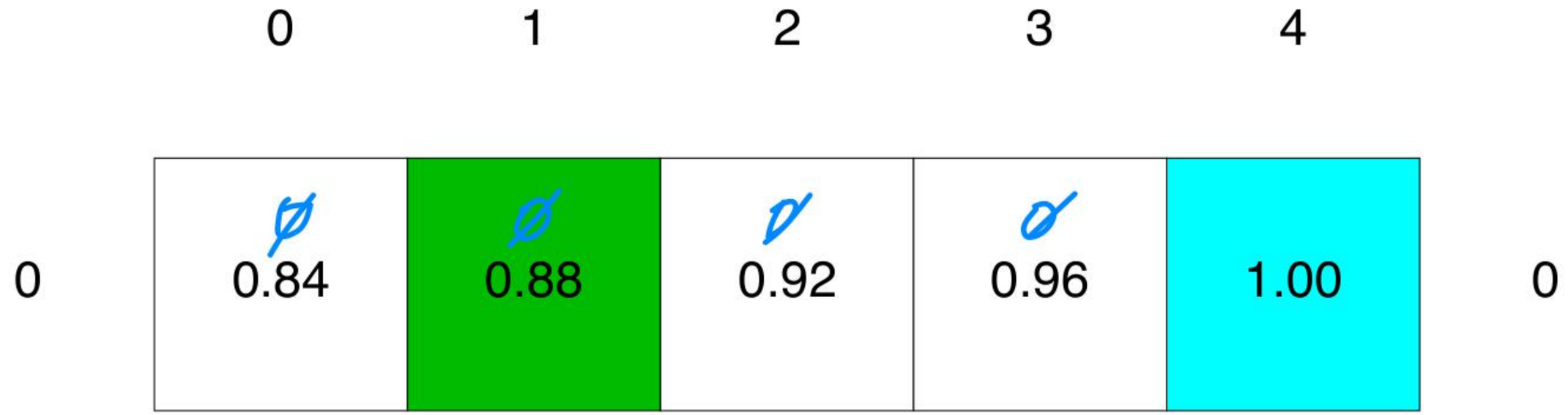

$s = [\ 0 \quad 1 \quad 2 \quad 3 \quad 4\ ]$

5 → 2

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