Hochschule Karlsruhe
Technik und Wirtschaft
UNIVERSITY OF APPLIED SCIENCES

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AI Labor - Sommersemester 2020

Reinforcement **L**earning
Einführung

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Karlsruhe, 29. Mai 2020

Frederik Martin

Software Entwickler

seit 2014

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Data Scientist

seit 2017

Reinforcement Learning

Quelle: https://www.youtube.com/watch?v=x4O8pojMF0w, OpenAI

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Meilensteine im Reinforcement Learning

1950's	Optimal control, dynamic programming
1970-80's	Temporal difference learning
1989	Q-Learning
1992	TD Gammon
2013	Playing atari with deep reinforcement learning
2016	AlphaGo vs. Lee Sedol
2019	AlphaStar & OpenAI Five beat professionals in Starcraft and Dota 2

1 2

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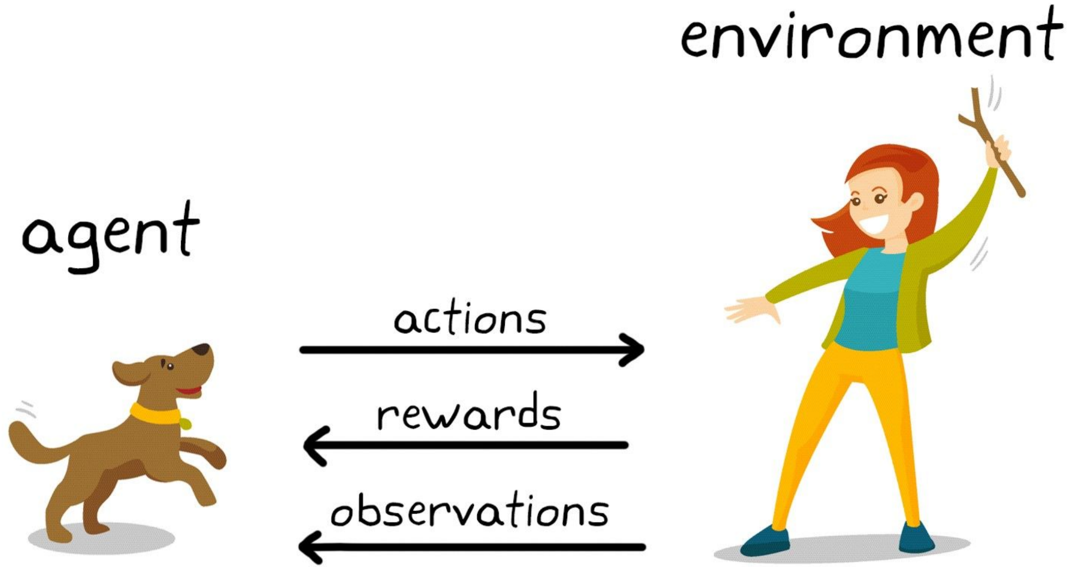
Reinforcement Learning

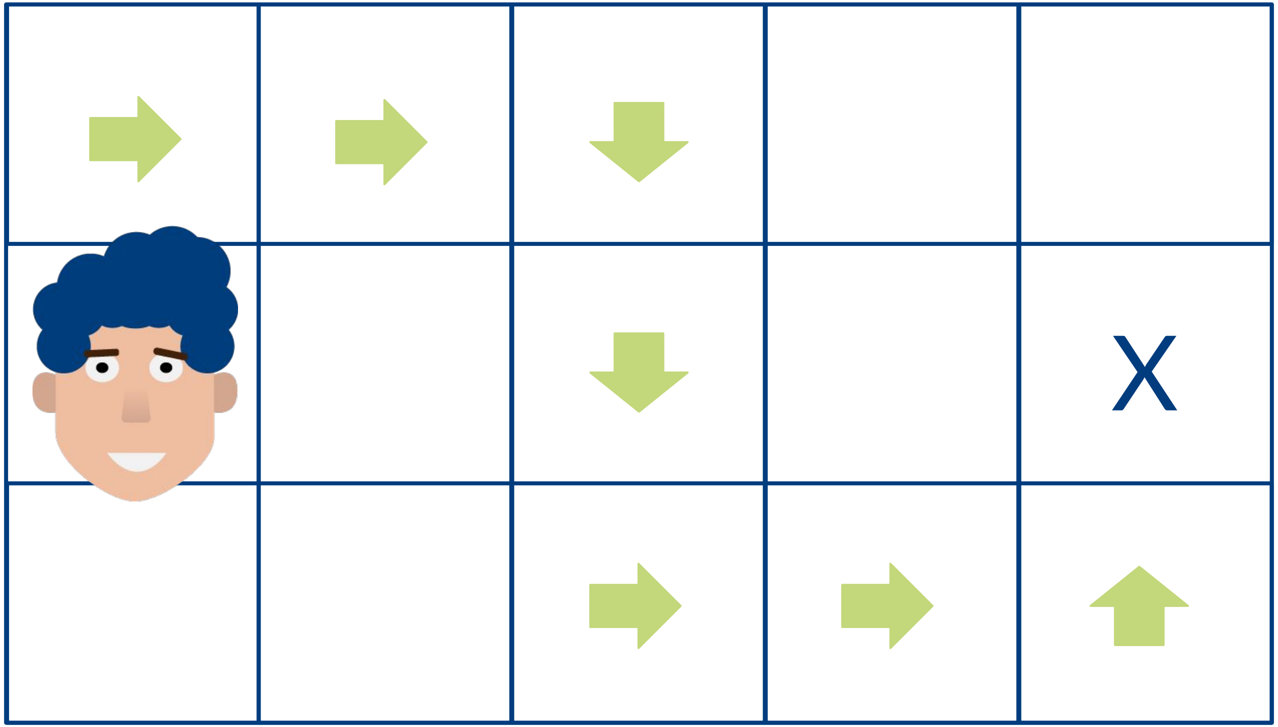
- **Theorie**
  - Problemstellung & Lösungsansatz
  - Monte Carlo Methoden
  - Temporal-Difference Methoden
  - Q-Learning
- **Praxis**
  - CliffWalking mit Q-Learning (Aufgabe 1)
  - CartPole Gym mit Q-Learning (Aufgabe 2)

Reinforcement Learning



https://www.technik-und-wissen.ch/detail/drei-dinge-die-sie-ueber-reinforcement-learning-wissen-sollten.html

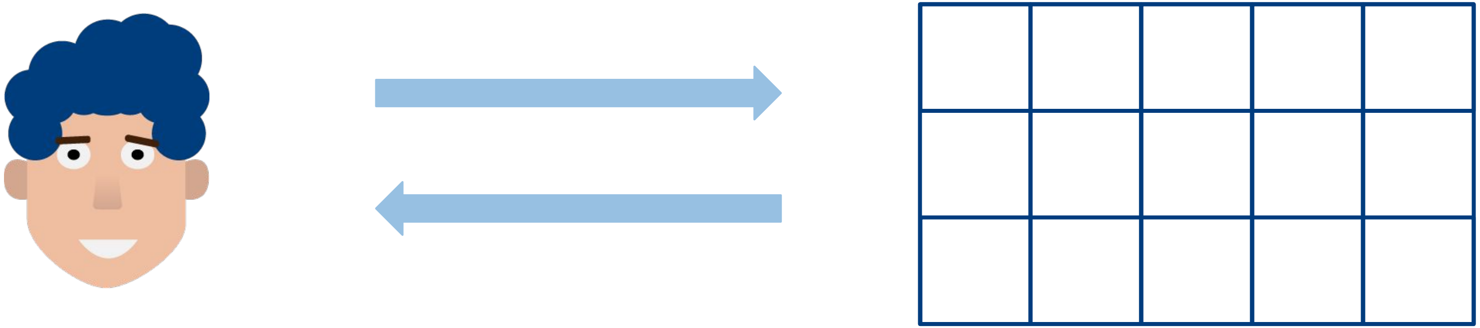
Setting



Grundbegriffe

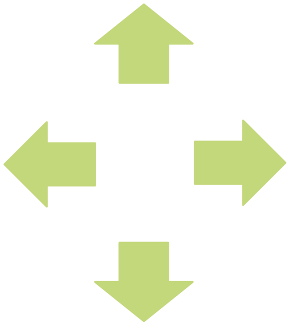
Agent

Environment



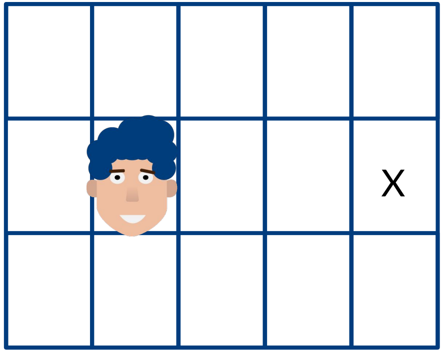
Grundbegriffe

Actions



$$a_t \in \mathcal{A}$$

States



$$s_t \in \mathcal{S}$$

Rewards

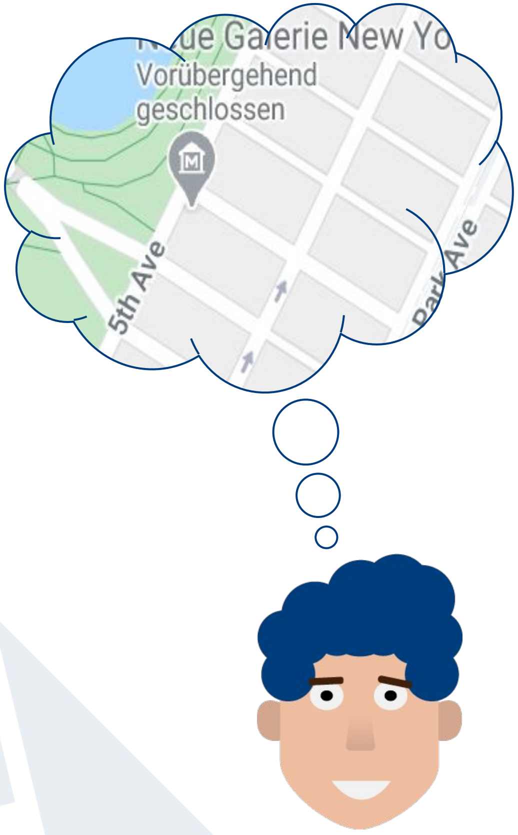
-1	-1	-1	-1	-1
-1	-1	-1	-1	0
-1	-1	-1	-1	-1

$$r_t \in \mathcal{R}$$

Return

$$\underbrace{G_t}_{\text{Return}} = \underbrace{R_{t+1}}_{\text{Rewards}} + \underbrace{\gamma}_{\text{Discount factor}} \underbrace{R_{t+2}}_{\text{Rewards}} + \ldots = \sum_{k=0}^{\infty} \gamma^k R_{t+k+1}$$

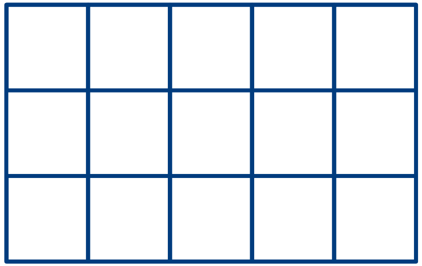
Interaktion zwischen Agent und Umwelt

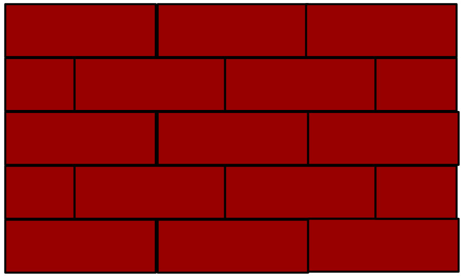


State_t

Action_t

State_{t+1}, Reward_t





$$\text{State}_{t+1} = P(\text{State}_t, \text{Action}_t)$$

$$\text{Reward}_t = R(\text{State}_t)$$

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Transition probabilities P(s,a)

https://unsplash.com/photos/TvJAmcTuJG8

https://unsplash.com/photos/T1L9Q5g7eIQ

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Transition probabilities P(s,a)

tatsächlicher Zustandsübergang

Action des Agenten

		←	→	↑	↓
←	1	80%	0%	10%	10%
→	2	0%	80%	10%	10%
↑	3	10%	10%	80%	0%
↓	4	10%	10%	0%	80%

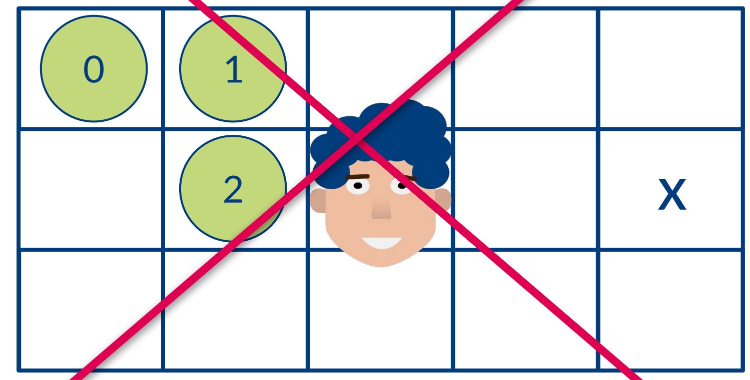
Markov Decision Process (MDP)

Formale Beschreibung der Interaktion im RL

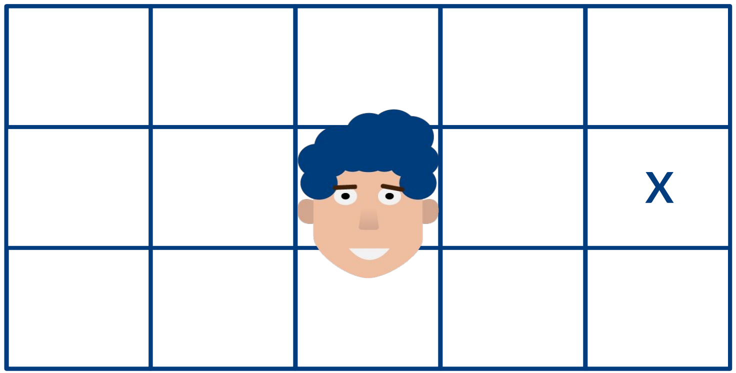
• S	Set von States
• A	Set von Aktionen
• $R(s,a)$	Reward Funktion
• $P(s,a)$	Transition Probabilities
• γ	Discount Factor

Markov Decision Process (MDP)

~~Wissen über vorherige Aktionen~~



Unwissenheit über Vergangenheit



Der Übergang in den nächsten Zustand *s'* hängt nur von aktuellem Zustand *s* und Aktion *a* ab.

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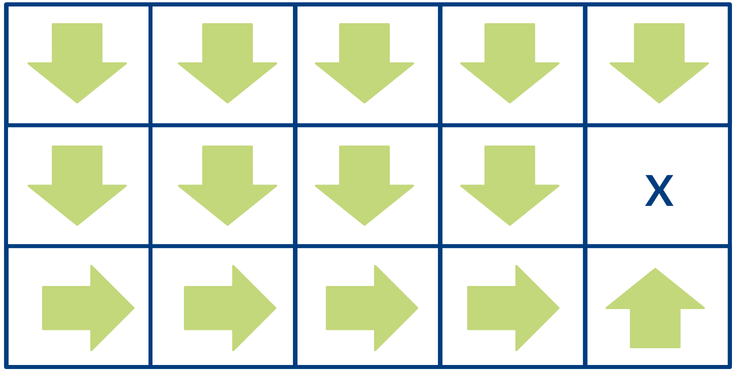
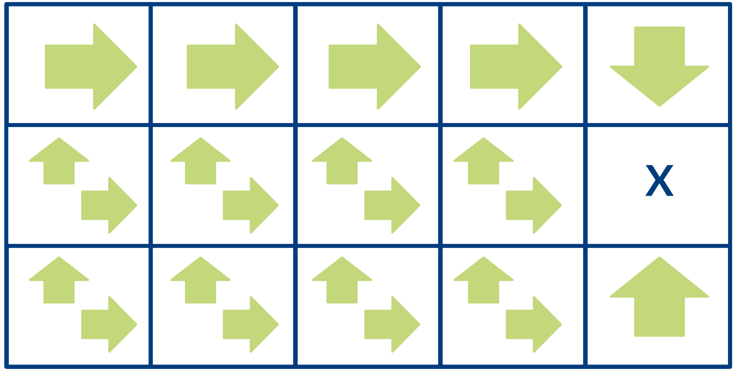
Policy π

Deterministische Policy



Stochastische Policy

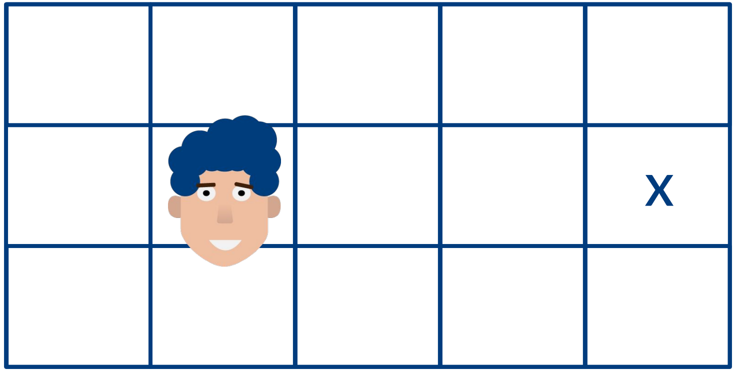


Policies definieren das Verhalten eines Agenten gegeben einem State.

State-value function

Können wir mit diesen Infos den Wert des Zustands bestimmen?

State *s*



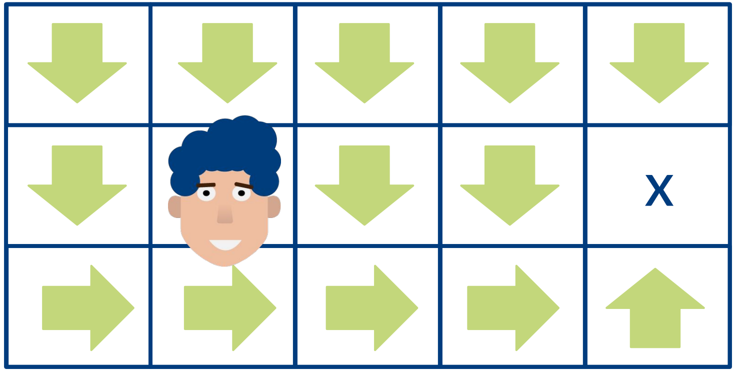
Rewards

-1	-1	-1	-1	-1
-1	-1	-1	-1	0
-1	-1	-1	-1	-1

State-value function

-1	-1	-1	-1	-1
-1	-1	-1	-1	0
-1	-1	-1	-1	-1

State *s* und Policy *π*



State-value function $v_{\pi}(s)$

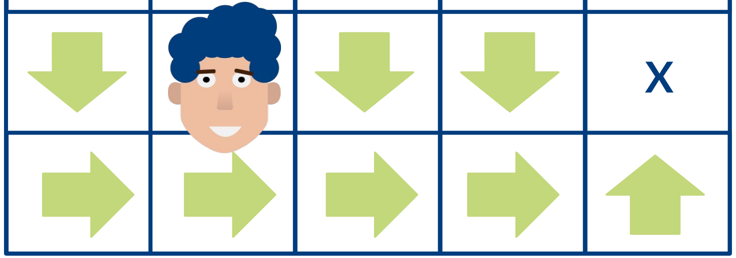
-7	-6	-5	-4	-1
-6	-5	-4	-3	x
-5	-4	-3	-2	-1

$$v_\pi(s) = \mathbb{E}_\pi[G_t | S_t = s] = R_{t+1} + \mathbb{E}_\pi[G_{t+1} | S_{t+1} = s']$$

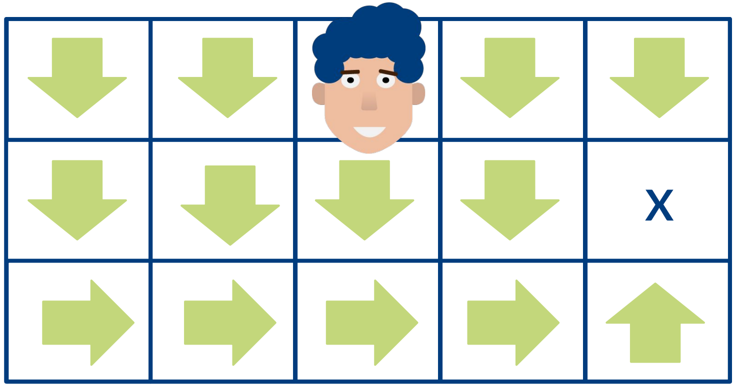
State-value function

Welcher Zustand ist besser?

State 1



State 2



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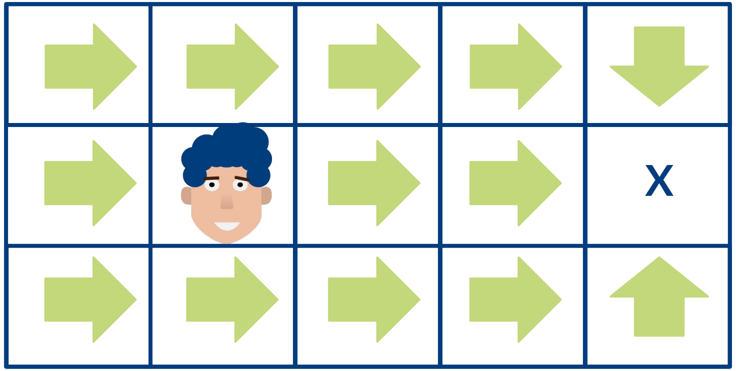
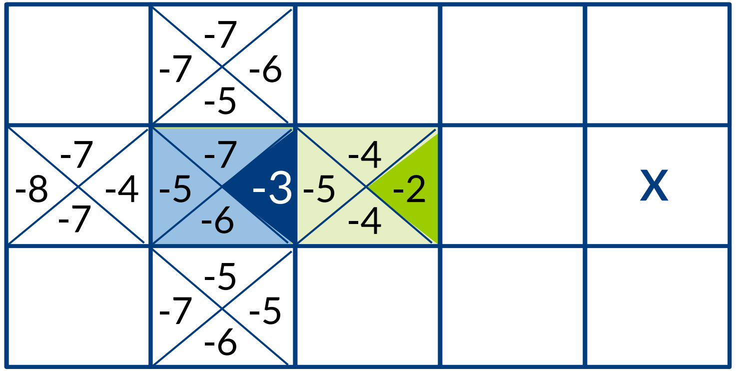
Action-value function $q_\pi(s,a)$

State s und Policy π



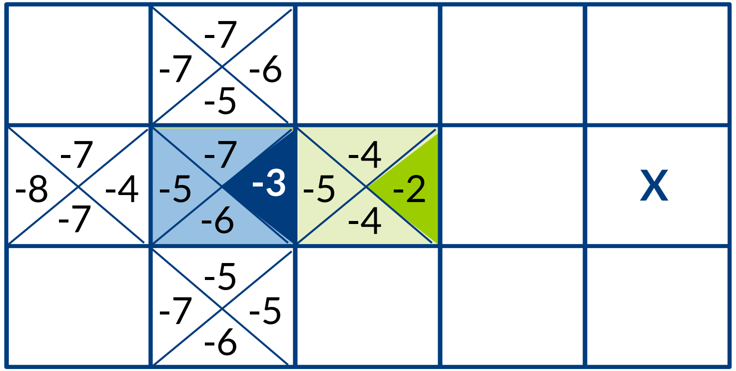
Action-value function $q_\pi(s,a)$



$$q_\pi(s,a) = \mathbb{E}_\pi[G_t | S_t = s, A_t = a]$$
$$= R_{t+1} + \mathbb{E}_\pi[G_{t+1} | S_{t+1} = s', A_{t+1} = a'_\pi]$$

Action-value function $q_\pi(s,a)$

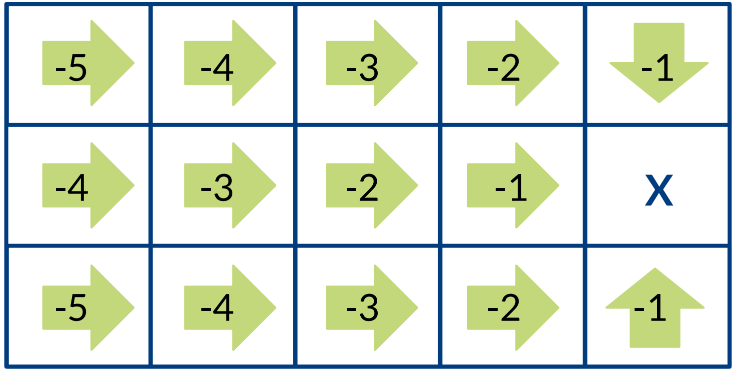
Action-value function $q_\pi(s,a)$

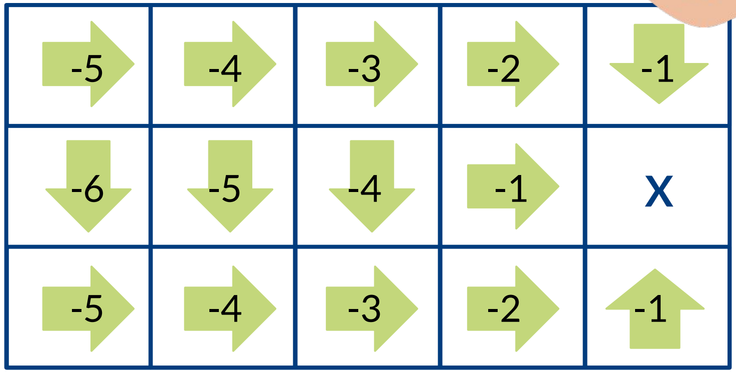


Q-Table

	→	←	↑	↓
S_{12}	-6	-7	-7	-5
S_{21}	-4	-8	-7	-7
S_{22}	-3	-5	-7	-6
S_{23}	-2	-5	-4	-4
S_{32}	-5	-7	-5	-6

Optimal Policies π*





Optimale Policy ist besser alle andere Policies:

$$\pi^* \geq \pi, \forall \pi$$

Was bedeutet besser?

$$\pi \geq \pi', \text{if } v_\pi(s) \geq v_{\pi'}(s), \forall s$$

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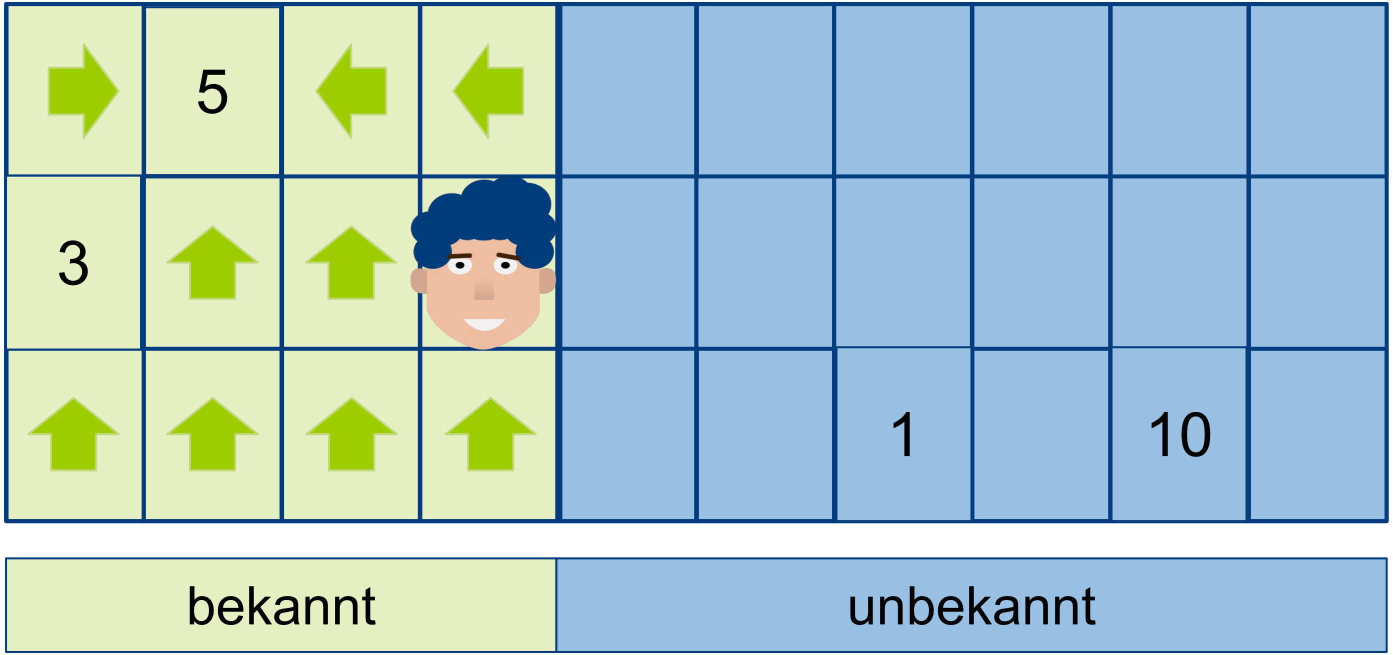
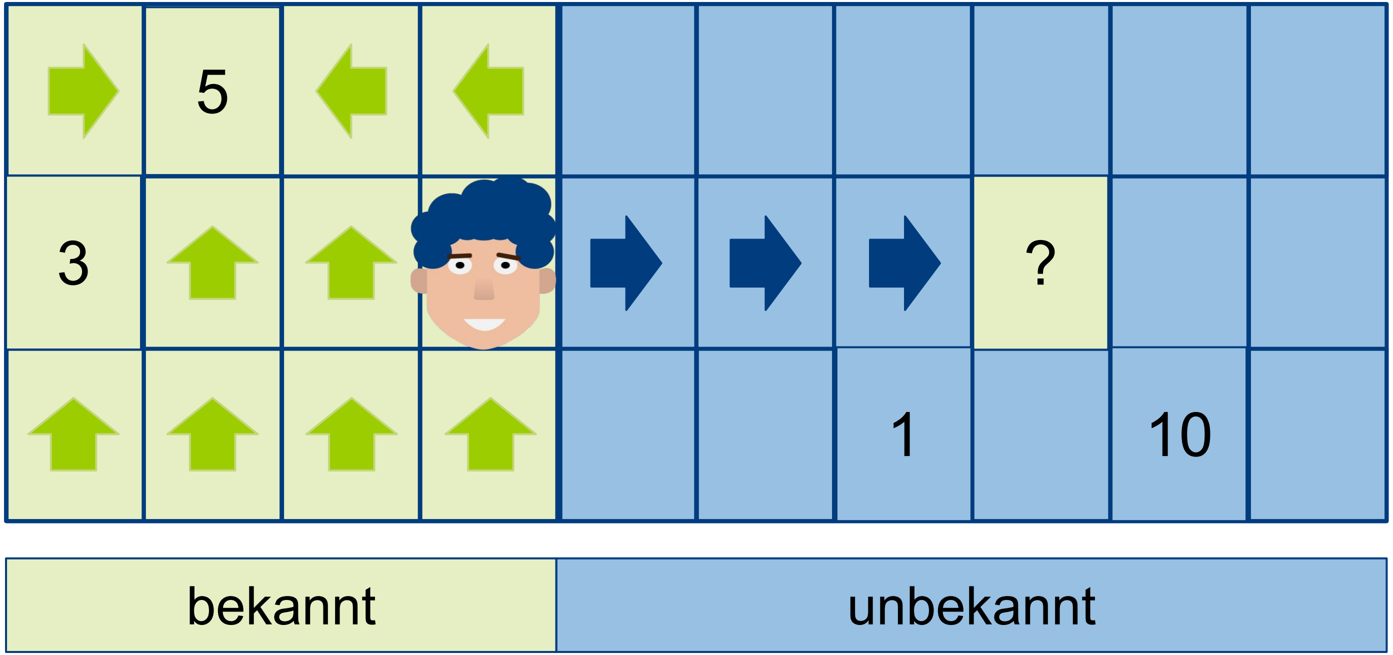
Exploitation

Maximierung des Rewards gg. bekannter Information

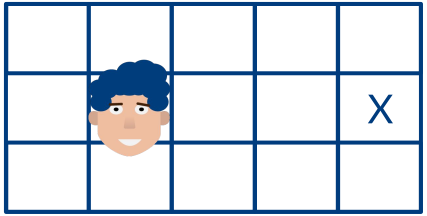


Exploration

Erschließung neuer, unbekannter Bereiche



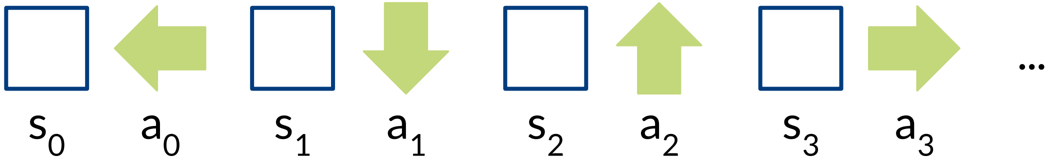
Monte Carlo Methods



Random Policy π

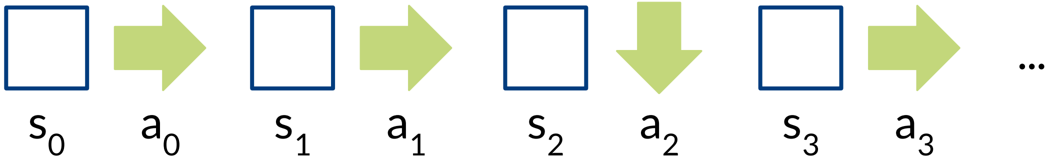
Episode 1

Score:
-4



Episode 2

Score:
-7



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Monte Carlo Prediction

Policy Evaluation		**Policy Improvement**
sammeln von Episoden mit π + update der Q-Table	← →	$\pi' \leftarrow \epsilon\text{-}greedy(Q)$ $\pi \leftarrow \pi'$

$$Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \alpha(\underbrace{G_t}_{\text{alternative Schätzung}} - \underbrace{Q(S_t, A_t)}_{\text{aktuelle Schätzung}})$$

Control Problem: Estimate the optimal policy

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Temporal-Difference Methods

Monte Carlo Control

$$Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \alpha(\underbrace{G_t}_{\text{alternative Schätzung}} - \underbrace{Q(S_t, A_t)}_{\text{aktuelle Schätzung}})$$

Temporal-Difference Control

$$Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \alpha(\underbrace{R_{t+1} + \gamma Q(S_{t+1}, A_{t+1})}_{\text{alternative Schätzung}} - \underbrace{Q(S_t, A_t)}_{\text{aktuelle Schätzung}})$$

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Q-Learning

Off-Policy TD-Control

TD Update

$$Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \alpha(R_{t+1} + \underline{\gamma Q(S_{t+1}, A_{t+1})} - Q(S_t, A_t))$$

alternative Schätzung

Q-Learning Update

$$Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \alpha(R_{t+1} + \underline{\gamma max_a Q(S_{t+1}, a)} - Q(S_t, A_t))$$

alternative Schätzung

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Q-Learning

Off-Policy TD-Control

Initialize $Q(s, a), \forall s \in \mathcal{S}, a \in \mathcal{A}(s)$, arbitrarily, and $Q(\textit{terminal-state}, \cdot) = 0$
Repeat (for each episode):
    Initialize S
    Repeat (for each step of episode):
        Choose A from S using policy derived from Q (e.g., ϵ-greedy)
        Take action A, observe R, S'
        $Q(S, A) \leftarrow Q(S, A) + \alpha\big[R + \gamma \max_a Q(S', a) - Q(S, A)\big]$
        $S \leftarrow S'$;
    until S is terminal

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Aufgaben

OpenAI Gym

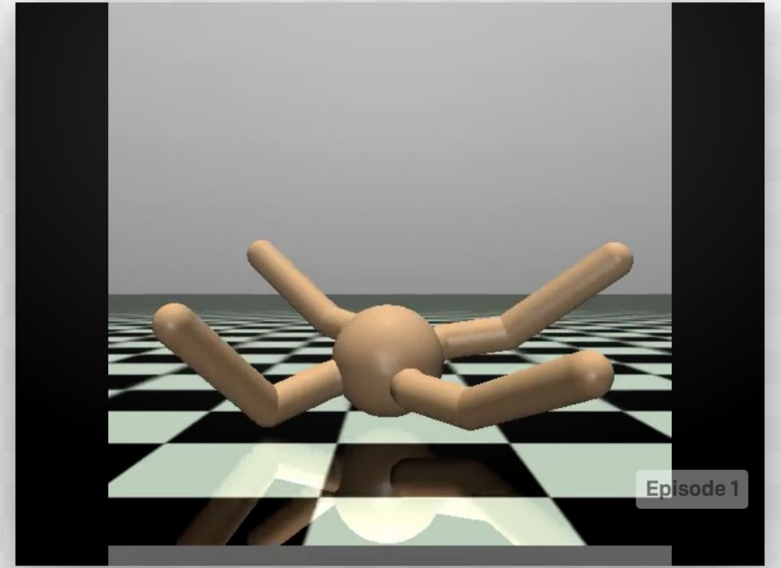
Gym

Gym is a toolkit for developing and comparing reinforcement learning algorithms. It supports teaching agents everything from walking to playing games like Pong or Pinball.

View documentation ›

View on GitHub ›

RandomAgent on LunarLander-v2



RandomAgent on Ant-v2

https://gym.openai.com/

OpenAI Gym

```python
import gym

env = gym.make('CartPole-v0')
for i_episode in range(20):
    observation = env.reset()
    for t in range(100):
        env.render()
        action = env.action_space.sample()
        observation, reward, done, info = env.step(action)
        if done:
            print("Episode finished after {} timesteps".format(t+1))
            break
env.close()
```

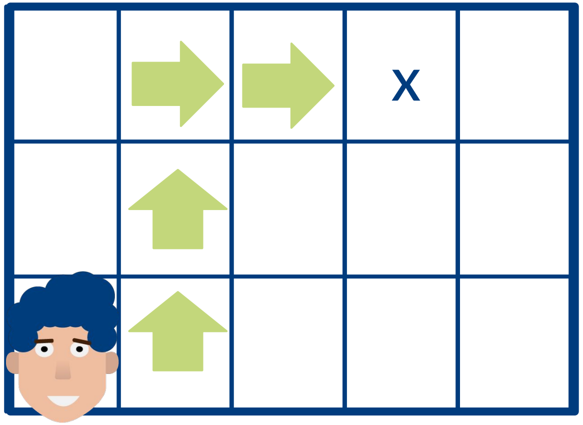
https://gym.openai.com/

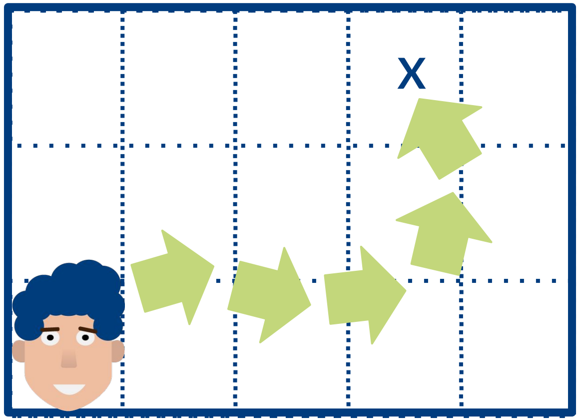
Aufgabe 1: CliffWalking mit Q-Learning

- **Jupyter Lab Notebook**

Zustands- und Aktionsräume

Wie unterscheiden sich diese beiden Environments?





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Aufgabe 2: CartPole Gym mit Q-Learning

- **Jupyter Lab Notebook**

colab

Google Colab

- In GCP gehosteter Jupyter Notebook Service
- Kollaborative Arbeit (ähnlich GDoc) möglich
- Frei nutzbar (inklusive GPU/TPU!)
  - → Ressourcen sind limitiert
  - → GPU/TPU Runtime sparsam nutzen!
- Notebooks und Daten liegen im Google Drive


#TFDevSummit
Making the most of Colab

Literatur

- Kostenlose "Standard"-Lektüre für den Einstieg in RL:
  Reinforcement Learning: An Introduction (Sutton and Barto), siehe
  http://incompleteideas.net/book/RLbook2018.pdf
- Ausführlich und gut erklärter Einstieg in RL (Video-Lektionen):
  UCL Course on RL (David Silver, Google DeepMind), siehe
  https://www.davidsilver.uk/teaching/
- *Algorithms in Reinforcement Learning* von Csaba Szepesvári, siehe
  https://sites.ualberta.ca/~szepesva/papers/RLAlgsInMDPs.pdf
- Blog mit Videos zum Einstieg in RL und Q-Learning, DQN und vieles mehr:
  Reinforcement Learning – Introducing Goal Oriented Intelligence, siehe
  https://deeplizard.com/learn/video/nyjbcRQ-uQ8

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Feedback

https://forms.gle/zDjawTGbbs1Z8ryXA

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Vielen Dank

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