Hochschule Karlsruhe
Technik und Wirtschaft
UNIVERSITY OF APPLIED SCIENCES

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AI Labor - Sommersemester 2020

Reinforcement **L**earning
Sprintwechsel

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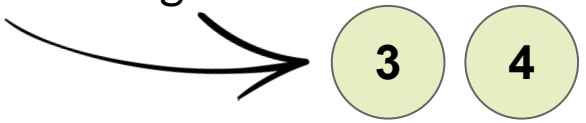
Reinforcement Learning

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



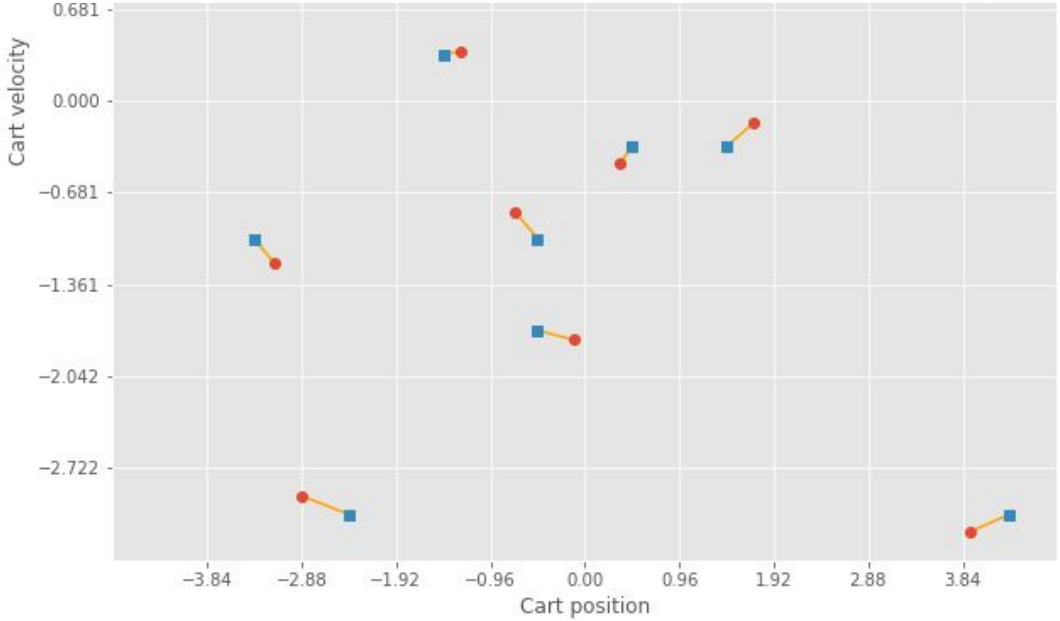
Reinforcement Learning

- **Theorie**
  - Deep Q-Network
  - Experience Replay
  - Target Model
  - Vorverarbeitung für Pixel-basierte Atari Games (Framestacking, etc.)

- **Praxis**
  - CartPole Gym mit Deep Q-Learning (Aufgabe 3)
  - Pong (Pixel-basiert) mit Deep Q-Learning (Aufgabe 4)

Was bisher geschah ...

Diskretisierung



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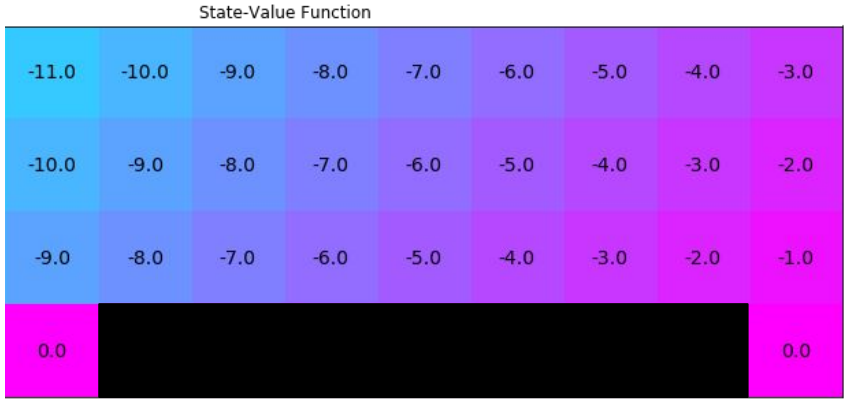
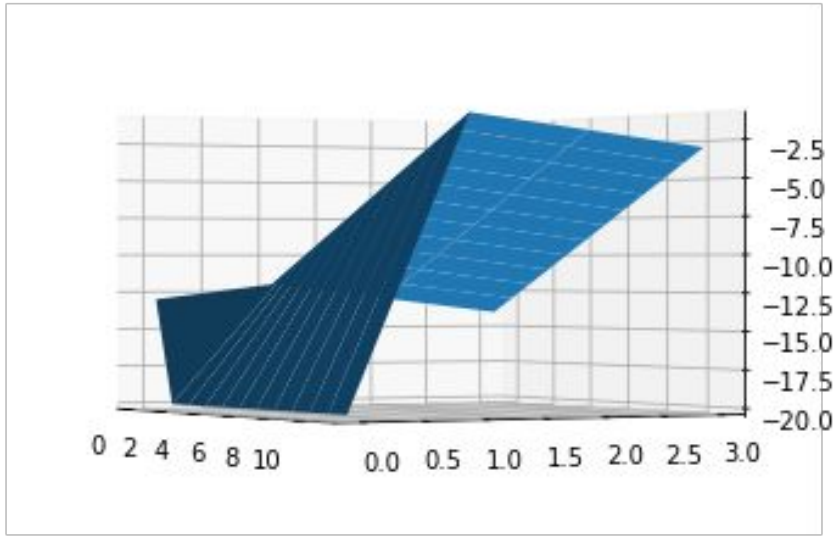
Funktionsapproximation

Beispiel Cliffwalking





$$\hat{v}(s,\theta) \approx v_\pi(s), \theta \in \mathbb{R}^d$$

Approximation — Value-Function — Gewichtsvektor

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Funktionsapproximation

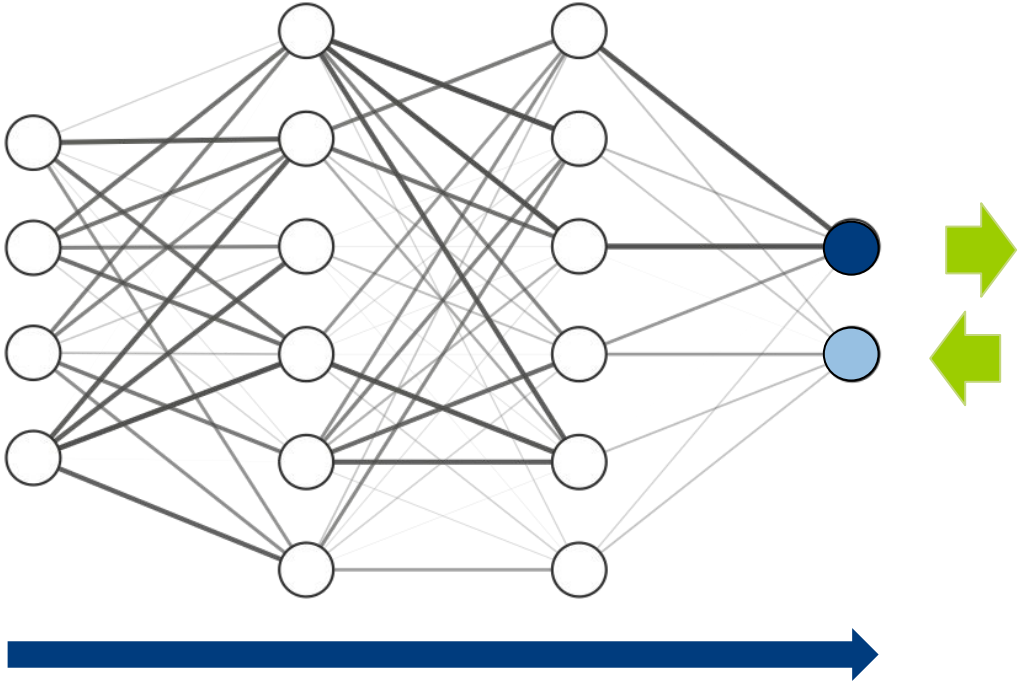
Beispiel CartPole: Forward-Pass

Cart Position

Cart Velocity

Pole Angle

Pole Velocity at Tip



Funktionsapproximation

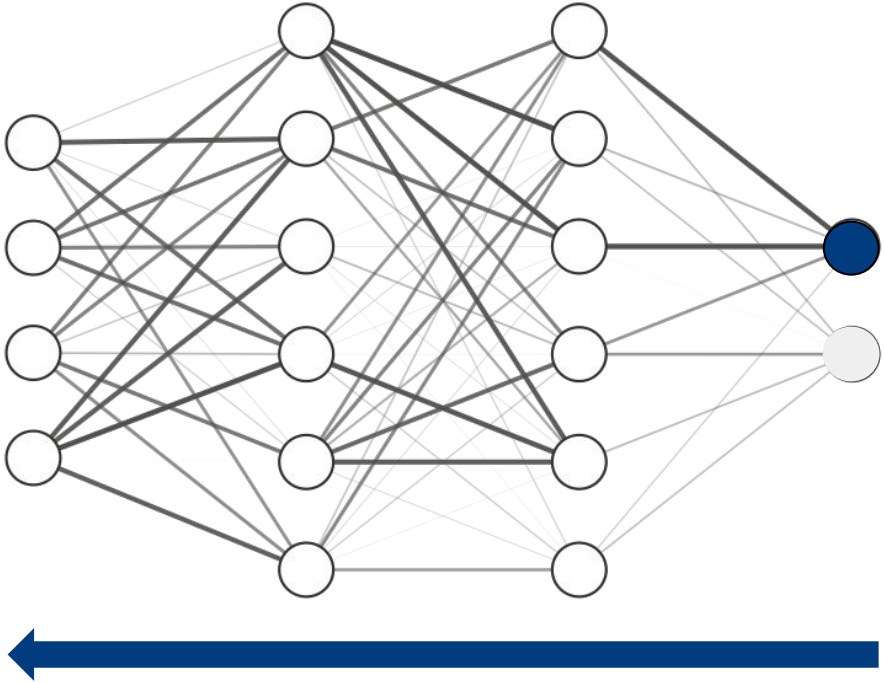
Beispiel CartPole: Backward-Pass

Cart Position

Cart Velocity

Pole Angle

Pole Velocity at Tip



Action: right selected

$$\begin{bmatrix} 1 \\ 0 \end{bmatrix}$$

Funktionsapproximation

Deep Q-Network

- Approximation der Q-Funktion mit NN
- Optimierung mit SGD
  - Minimierung des Abstands zwischen Schätzer und Target

$$L_i(\theta_i) = \mathbb{E}_{(s,a,r,s')\sim U(D)}[(y_i - \hat{q}(s, a, \theta_i))^2]$$

Loss L_i — **Weights** θ_i **in Iteration i**

Experience Replay $(s,a,r,s')\sim U(D)$

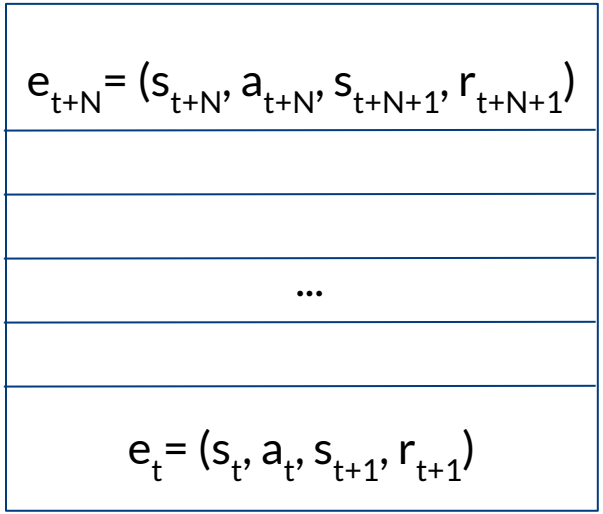
Target Q-Value y_i

approximierter Q-Value $\hat{q}(s, a, \theta_i)$

Mnih et al. (2015) - Human-level Control through Deep Reinforcement Learning

Experience Replay

- Problem
  - Starke Korrelation der States erschwert das Lernen
- Lösung
  - Letzte *N* Experiences werden in **Replay Memory** gespeichert
  - Random Uniform Sampling



Replay Memory

Target Network

- Kopie der eigentlichen Architektur mit fixen Gewichten
- Update alle *c* Iterationen

$$L_i(\theta_i) = \mathbb{E}_{(s,a,r,s')\sim U(D)}[(y_i - \hat{q}(s, a, \theta_i))^2]$$

Q-Network

$$r + \gamma \max_{a'} Q(s', a', \theta_i^-)$$

Target Network

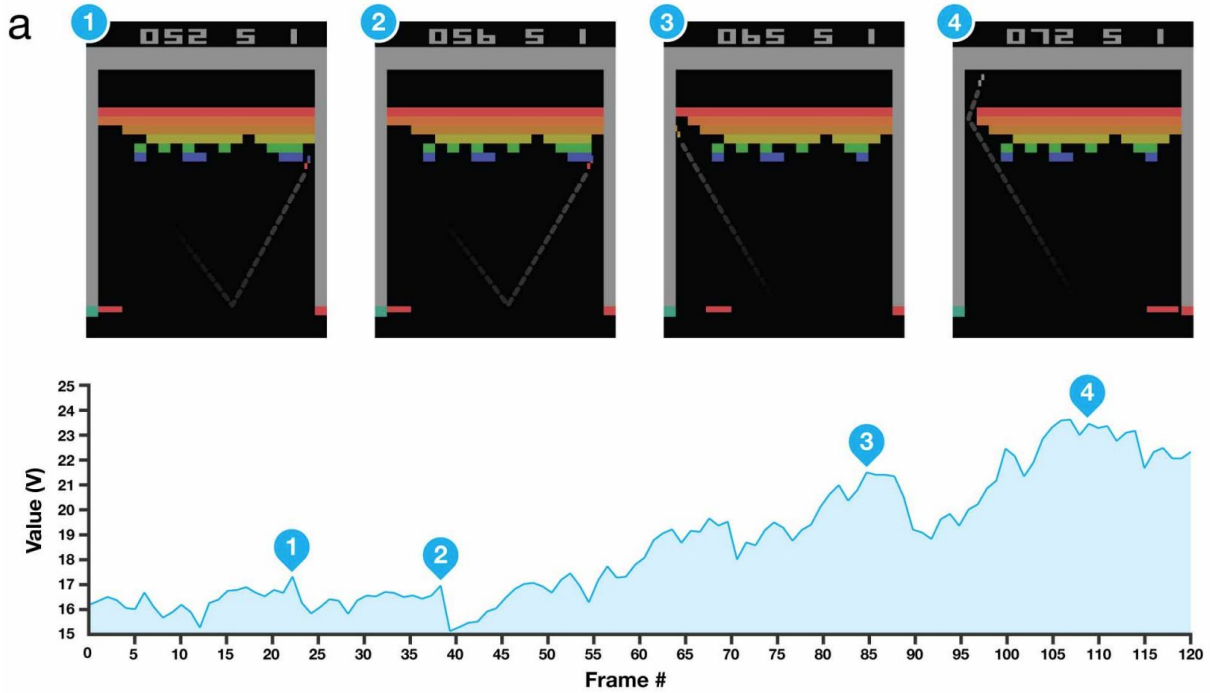
Mnih et al. (2015) - Human-level Control through Deep Reinforcement Learning

Aufgabe 3: CartPole Gym mit Deep Q-Learning

- **Jupyter Lab Notebook**

Deep Q-Network

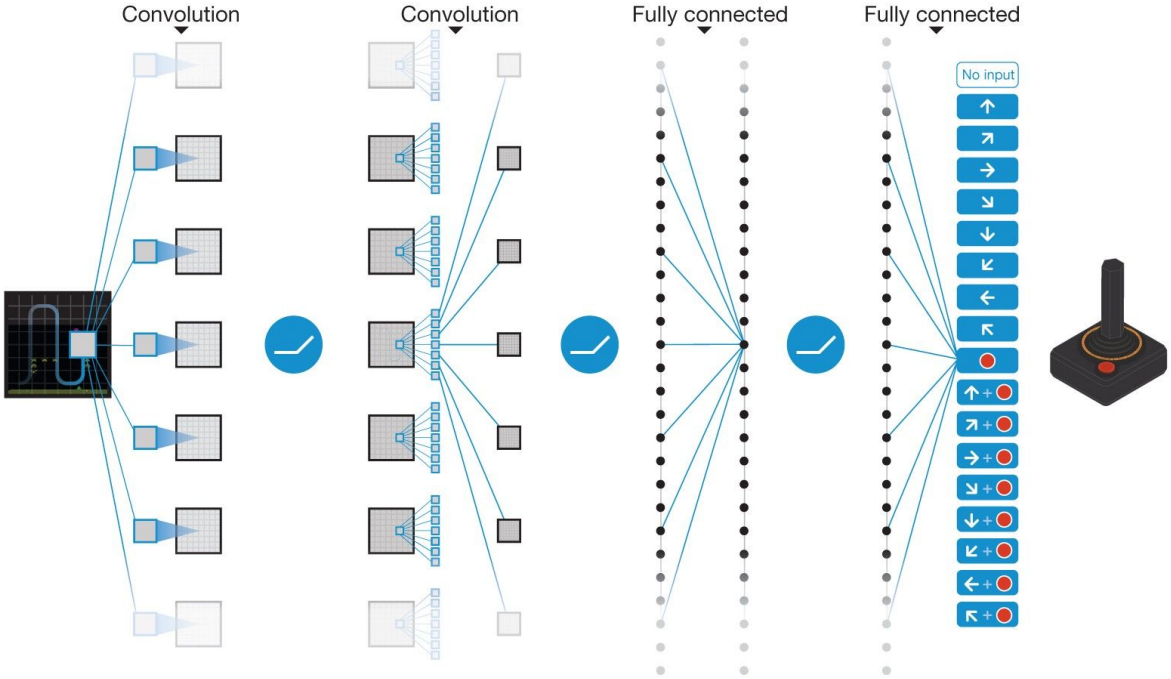
Pixel-basierte Atari Games



Mnih et al. (2015) - Human-level Control through Deep Reinforcement Learning

Deep Q-Network

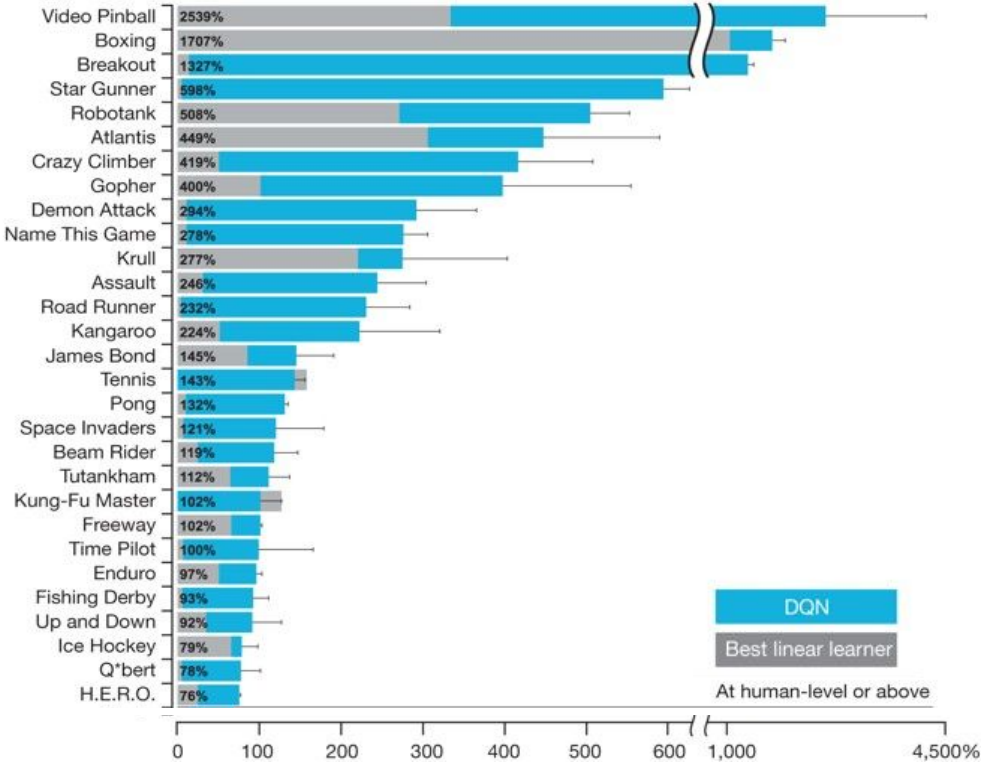
Pixel-basierte Atari Games



Mnih et al. (2015) - Human-level control through Deep Reinforcement Learning

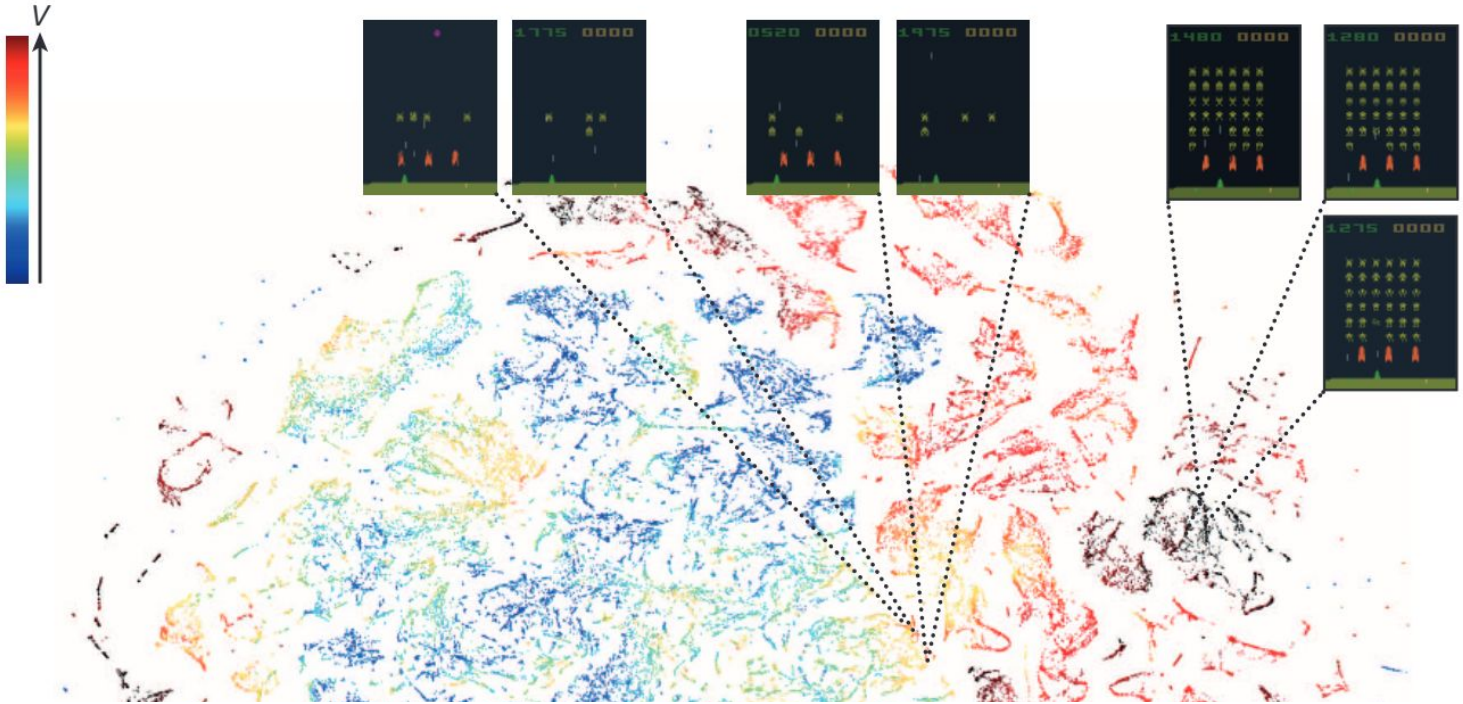
Deep Q-Network

Pixel-basierte Atari Games



Mnih et al. (2015) - Human-level control through Deep Reinforcement Learning

Deep Q-Network



Mnih et al. (2015) - Human-level control through Deep Reinforcement Learning

Deep Q-Network

Preprocessing Pixel-basierter Inputs

- **Warp Frame**
  - Konvertierung der Frames in Graufstufen
  - Downsampling auf 84x84 Pixel

- **Framestack**
  - Kombination von vier aufeinanderfolgenden Frames um Bewegungen nachvollziehen zu können
  - Auswahl der maximalen Helligkeitswerten
  - Ausführung der gewählten Aktion für Framestack

Deep Q-Network

Besonderheiten Pong / Atari

- **No-Ops after Reset**
  - Skippen der ersten 30 Steps
- **Fire Reset**
  - Automatisches Drücken der FIRE-Taste als erste Aktion
- **Episodic Life**
  - Verlust eines Lebens bedeutet das Ende der Episode
  - Game Over setzt die Environment komplett zurück
- **Reward Clipping**
  - Sieg: +1 Niederlage: -1 Sonst: 0

Deep Q-Learning

Algorithmus

Algorithm 1 Deep Q-learning with Experience Replay

Initialize replay memory $\mathcal{D}$ to capacity N
Initialize action-value function Q with random weights
for episode $= 1, M$ **do**
  Initialise sequence $s_1 = \{x_1\}$ and preprocessed sequenced $\phi_1 = \phi(s_1)$
  for $t = 1, T$ **do**
    With probability ϵ select a random action a_t
    otherwise select $a_t = \max_a Q^*(\phi(s_t), a; \theta)$
    Execute action a_t in emulator and observe reward r_t and image x_{t+1}
    Set $s_{t+1} = s_t, a_t, x_{t+1}$ and preprocess $\phi_{t+1} = \phi(s_{t+1})$
    Store transition $(\phi_t, a_t, r_t, \phi_{t+1})$ in $\mathcal{D}$
    Sample random minibatch of transitions $(\phi_j, a_j, r_j, \phi_{j+1})$ from $\mathcal{D}$
    Set $y_j = \begin{cases} r_j & \text{for terminal } \phi_{j+1} \\ r_j + \gamma \max_{a'} Q(\phi_{j+1}, a'; \theta) & \text{for non-terminal } \phi_{j+1} \end{cases}$
    Perform a gradient descent step on $(y_j - Q(\phi_j, a_j; \theta))^2$ according to equation 3
  end for
end for

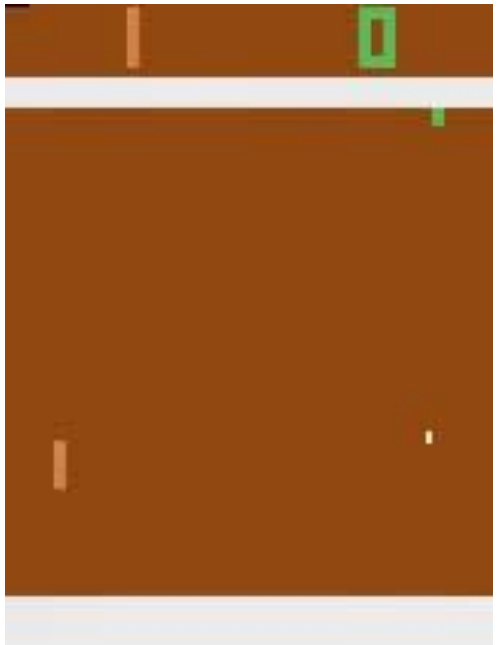
Erstes Paper (2013) ohne Target Network

$$\nabla_{\theta_i} L_i(\theta_i) = \mathbb{E}_{s,a \sim \rho(\cdot); s' \sim \mathcal{E}} \left[\left(r + \gamma \max_{a'} Q(s', a'; \theta_{i-1}) - Q(s, a; \theta_i) \right) \nabla_{\theta_i} Q(s, a; \theta_i) \right]. \quad (3)$$

Mnih et al. (2013) - Playing Atari with Deep Reinforcement Learning

Aufgabe 4: Pong mit Deep Q-Learning

- **Jupyter Lab Notebook**

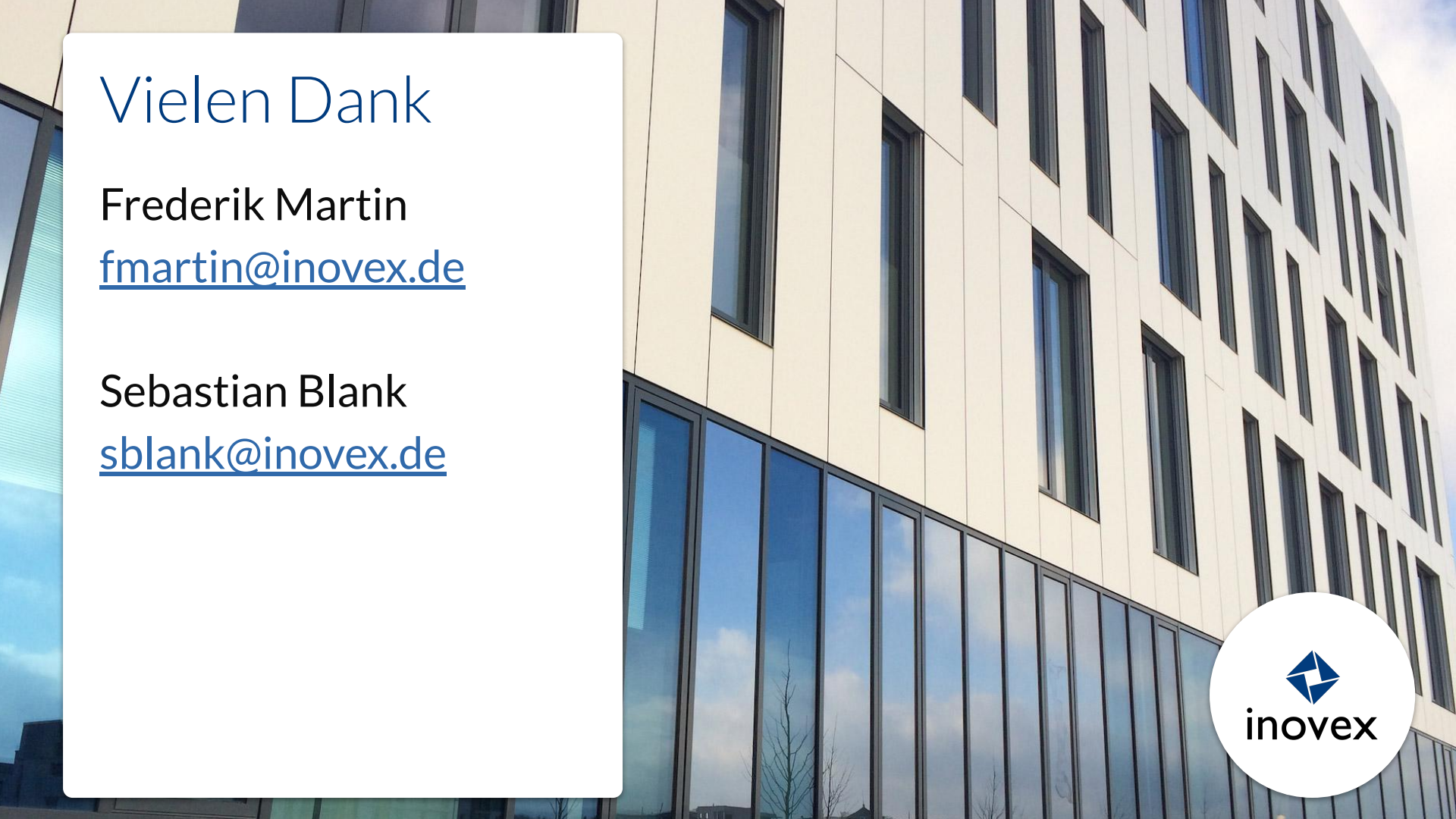


Literatur

- 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

Feedback

https://forms.gle/fPisrqSjqHJCCV8Q6



Vielen Dank

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