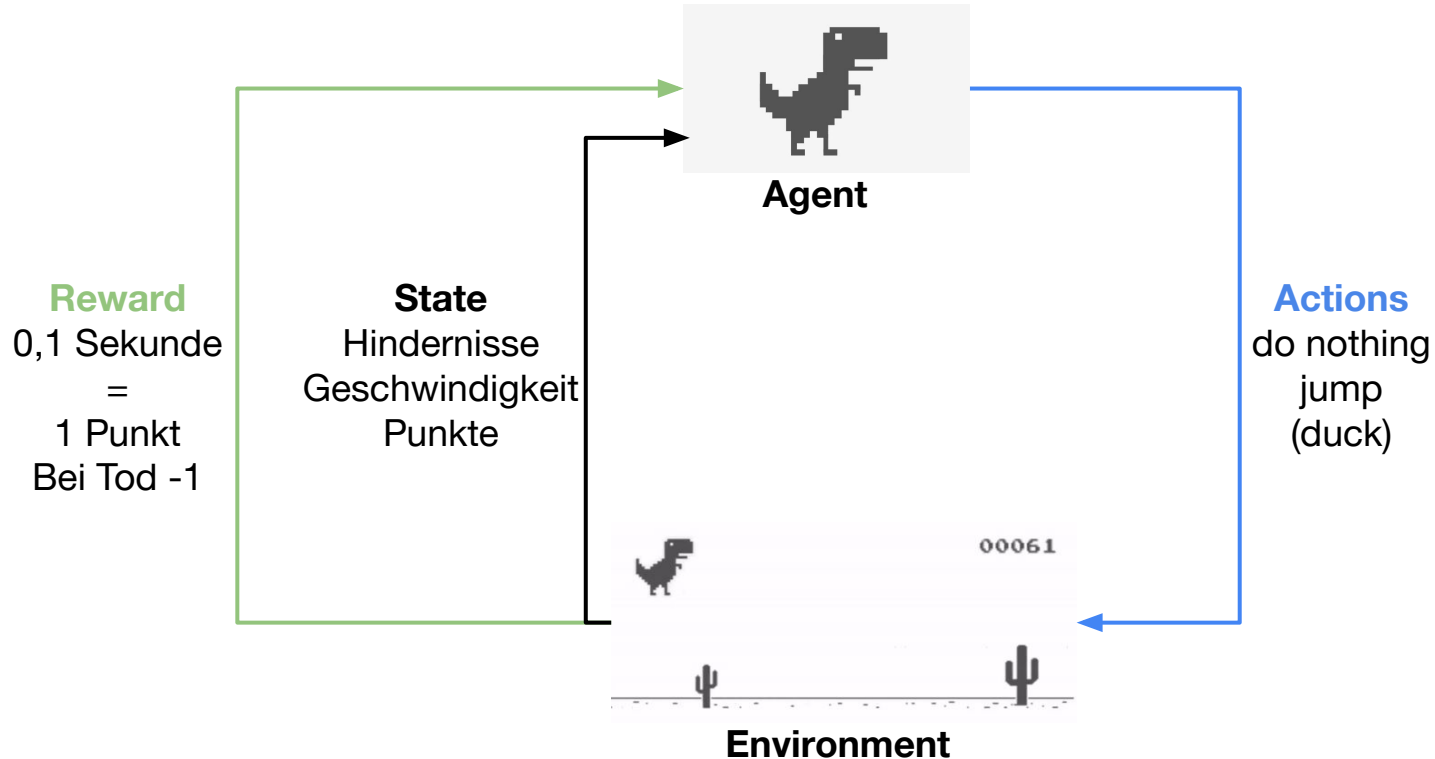


Reinforcement Learning für Chrome Dino Run



Chrome Dino Run



Unser Vorgehen

Setup

✗ keine Beschleunigung

✗ keine Vögel

→ nur 2 Aktionen

→ auto. Steuerung mit Selenium

Training

1. Baseline: Agent springt immer

2. DDQN (3 Varianten)

- Variante 1: Initial
- Variante 2: Prioritized Experience Replay
- Variante 3: Höhere Learning Rate

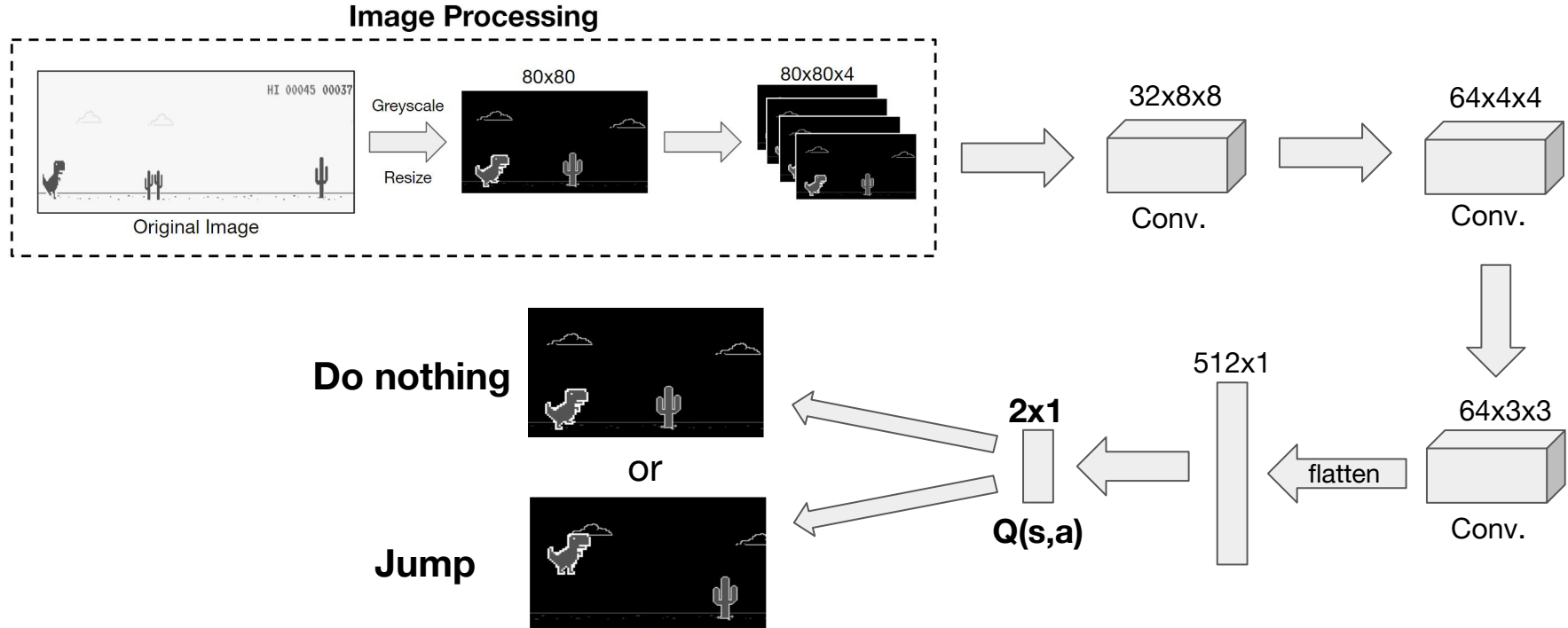
Test

20 Runden in einer neuen Environment

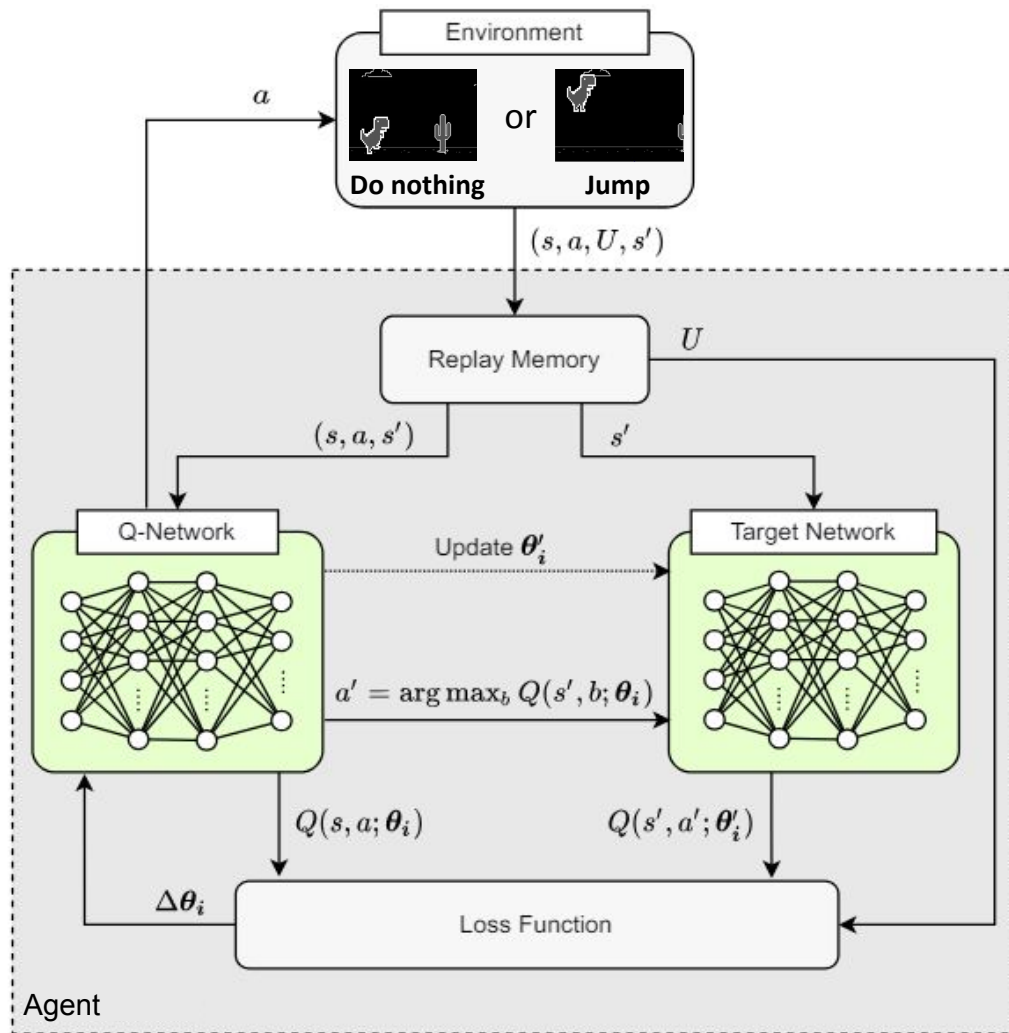
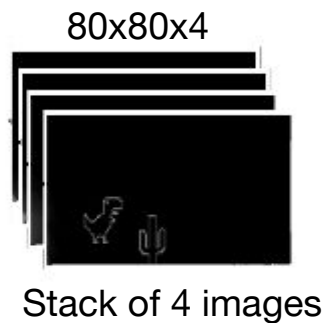
Messung von:

- Max. Score
- Avg. Score
- Median Score
- Standard Deviation

Deep Q Network (DQN) - Implementierung



Double Deep Q Network (DDQN) - Implementierung

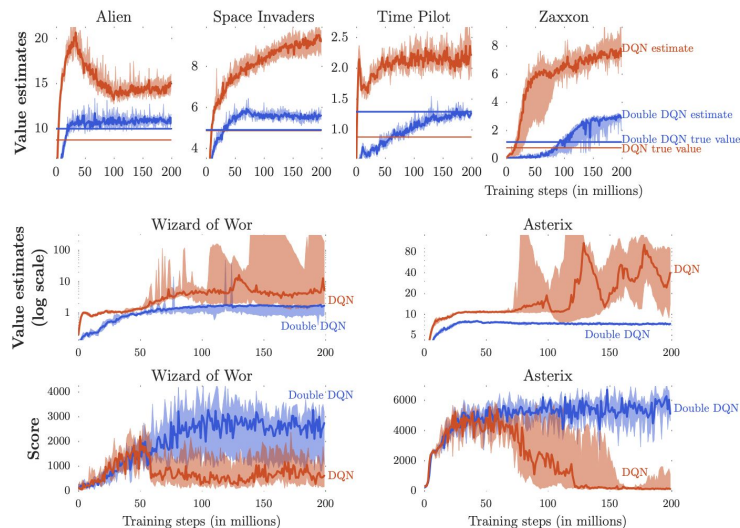


Double Deep Q Network (DDQN) - Warum?

- Overestimation Bias in Q-Learning
- Stabilität und Performance im Vergleich zu DQN
- Bereits auf anderen Spielen getestet
- Lerneffizienz

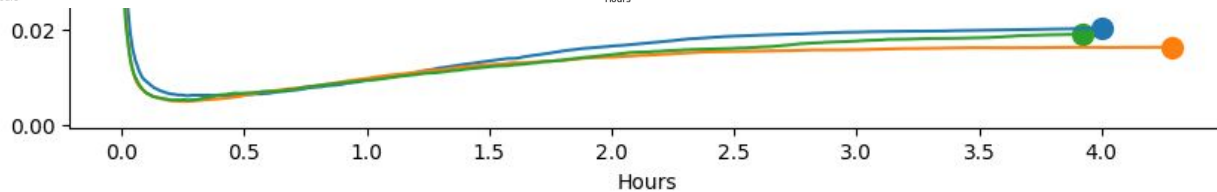
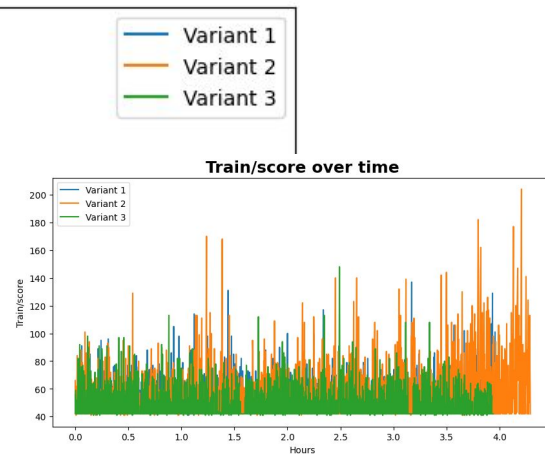
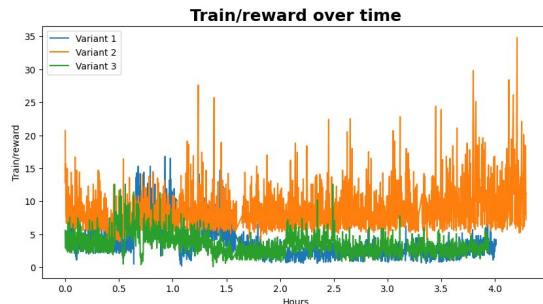
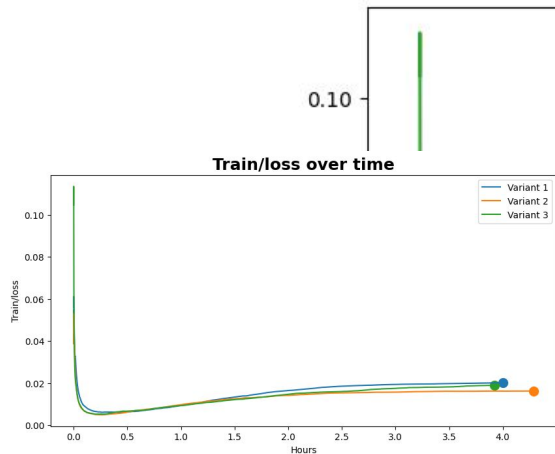
	DQN	Double DQN
Median	93.5%	114.7%
Mean	241.1%	330.3%

Table 1: Summary of normalized performance up to 5 minutes of play on 49 games. Results for DQN are from Mnih et al. (2015)



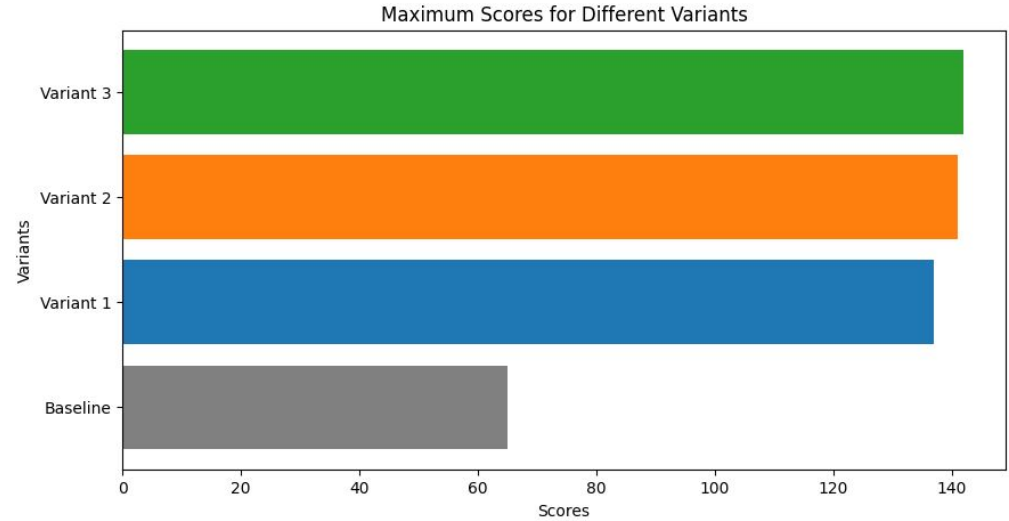
Trainings-Ergebnisse

Train/loss over time



Test-Ergebnisse

Method	Max. Score	Avg. Score	Std	Median Score
Human Expert	1399	922	324	850
Baseline	65	51	22	40
Variant 1	137	52	25	43
Variant 2	141	65	23	63
Variant 3	142	61	15	51



Fazit

- 3 Varianten getestet
- Aktuelle Modell-Leistung kommt nicht an Human-Expert ran
- Zukünftige Verbesserungen
 - Hardware-Upgrade
 - Algorithmische Anpassung
- Stufenweise Lernen
- Hyperparameter-Tuning



Live Demo

Quellen

- van Hasselt, H., Guez, A., & Silver, D. (2016). Deep Reinforcement Learning with Double Q-Learning. *Proceedings of the AAAI Conference on Artificial Intelligence*, 30(1). <https://doi.org/10.1609/aaai.v30i1.10295>
- Richard S. Sutton and Andrew G. Barto. 2018. Reinforcement Learning: An Introduction. A Bradford Book, Cambridge, MA, USA.