Transfer Learning in Gridworld Navigation: From Small Worlds to Larger Challenges using DQN

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1 Motivation

With models geting larger and larger the topic of transferlearning is getting bigger than ever before. Thats why we want to investigate the use of transferlearning for ML Agents. Its an exploratory research we want to do.

2 Related Topics

We would use DQN agents wich are known from the lecture and want to investigate using transfer learning [1] on them. It also have been used in some RL tasks already [2].

3 Idea

With multiple experiments we want to determine if transfer learning could be useful in DQNs. We also want to explore different approches (few shot learning, only fine tuning a few layers, ...) for that with full and limited observations of the enviroment to determine how useful which approach is.

4 Experiments

We want to investigate the effect of transfer learning on RL Agents, in our case DQN agents. We want to investigate approaches where the agents are using limited observations that stay the same in the first and the final enviroment, but we also want to investigate approches where the agents knows the states they are in. For the final enviromant that means that we have to deal with more states and therefore our network input have to be bigger. We want to investigate how well and fast a network adappts to the new enviroment and coming with it a new first layer of the appropriate size for the enviroment. Another potential approach could be training only the first or last or eny other given layers in the few shot training. Our baseline is a from scratch training with the same net in the large enviroment and we want to evaluate num. of frames or episodes till a performance threshold is surpassed.

Environments & Metrics
Enviroment: Small and large Gridworlds, maybe other envs as well.

Metrics: Num. of frames or episodes, cumulated episode reward, the resulting learning curve, mean final reward

Experimental Scope We plan to run 20 seedss per experiment and per Model. For one run of transfer learning we get one of the 20 DQN Agents who are trained on the small enviroment and train them in a few shot learning on the large enviroment. So that results in 20 models we learn in the small enviroment with different seeds and than training every one of them per experiment in few shot learning on the large enviroment. We also want to do that for a hand full of approaches: full vs

limited observations, few shot learning the full net vs just parts or single layers of it. The baseline we have to train for 20 seeds in the large enviroment.

Estimated Computational Load We would run all 20 runs with different seeds in sequance, so per experiment like that we would suggest a time of 8-20h on a GPU. The DQN could have a maximum size of about 2Gb. But multiple experiments could independently from each other be trained on seperate GPUs.

5 Timeline

- Research: 2-4 Days
- Implementation: 5 Days
- Experiments: 7 Days (incl. the time we need to fix stuff in our implementation we recognize while running the experiments)
- Analysis: 2 Days
- Reporting: 4 Days

References

[1] Fuzhen Zhuang, Zhiyuan Qi, Keyu Duan, Dongbo Xi, Yongchun Zhu, Hengshu Zhu, Hui Xiong, and Qing He. A comprehensive survey on transfer learning. *Proceedings of the IEEE*, 109(1):43–76, 2021.

[2] Matthia Sabatelli and Pierre Geurts. On the transferability of deep-q networks, 2021.