

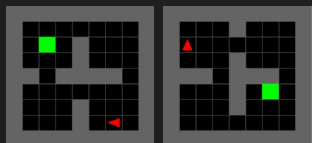
# Zero-Shot Generalization in Offline Reinforcement Learning with WSAC-N

Maxime Museur (M.D.I.Museur@student.tudelft.nl)

Supervisors: Dr. Matthijs Spaan, Max Weltevrede

## (1) Introduction

- Offline reinforcement learning (RL) = RL where agent cannot perform actions in environment, only has access to **static dataset**.
- Recent work has shown that offline RL does **not generalize as well** as behavioral cloning (BC). [1]
- We aim to:
  - Compare generalization abilities between WSAC-N and baseline BC
  - Investigate effect of dataset **size** and **quality** on generalization
- Environment from [2] (see figure 1)



## (3) Generalization

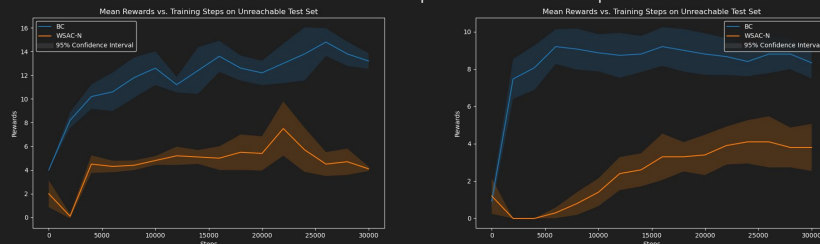
- **Zero-shot** generalization [5]
- **Test sets** from [2]:
  - **Reachable** = unseen agent location and direction, seen topology and goal location
  - **Unreachable** = unseen agent location, direction, topology, seen goal location

## References

- [1] Qingfei Yu, Ishita Mediratta, Minqi Jiang, and Roberto Raileanu. The generalization gap in offline reinforcement learning, 2024.
- [2] Max Weltevrede, Matthijs T. J. Spaan, and Wendelin Böhm. The role of diverse replay for generalization in reinforcement learning, 2023.
- [3] Gaom An, Seungyong Moon, Jang-Hyun Kim, and Hyun Oh Song. Uncertainty-based offline reinforcement learning with diversified ensemble, 2021.
- [4] Kimin Lee, Michael Laskin, Aravind Srinivas, and Pieter Abbeel. Sunrise: A simple unified framework for ensemble learning in deep reinforcement learning, 2021.
- [5] Robert Kirk, Amy Zhang, Edward Grefenstette, and Tim Rocktäschel. A survey of zero-shot generalisation in deep reinforcement learning. Journal of Artificial Intelligence Research, 76:201-264, January 2023. ISSN 1076-9757. doi: 10.1613/jair.14174.

## (4) Experiments & Conclusions

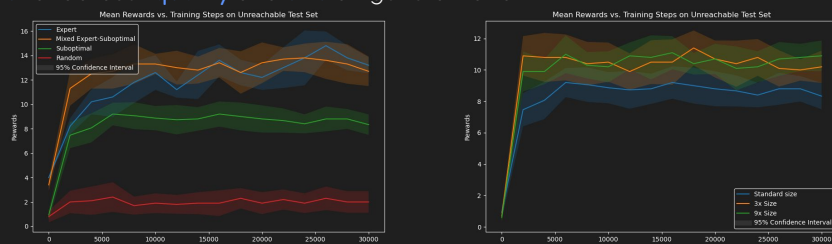
a) **Generalization** of WSAC-N and BC with expert and non-expert datasets as training



Mean rewards over various training steps, using expert datasets (left) and suboptimal datasets (right) for training and testing on the unreachable test set.

**Conclusion: BC generalizes better than WSAC-N with both expert and non-expert datasets.**

b) **Effect** of dataset **quality** and **size** on generalization



Mean rewards over training steps, using varying dataset quality as training (left) and varying dataset size as training (right) while testing on the unreachable test set.

**Conclusion: Quality of data generally has a positive impact on generalization, and dataset size has negligible impact on generalization.**

## (2) Method

- Propose and implement **WSAC-N**
- = **SAC-N** [3] weighted with **weights** from SUNRISE DQN [4] to downweight actions with high variance
- **Generate datasets** with varying quality of policies: expert, mixed suboptimal-expert, suboptimal, random
- Compare generalization of **WSAC-N** with baseline **BC**
- Compare effect of dataset size and quality on generalization