Supplementary Material

Anonymous Author(s)
Affiliation
Address
email

1 Multi-agent Indoor Navigation Benchmark

We publish the dataset, the code and the documentation on our website: https://main-dataset.github.io/. It is our priority to protect the privacy of third parties. We bear all responsibility in case of violation of rights. We bear all responsibility in case of violation of rights, etc, and the confirmation of data license.

Data License. The Multi-agent Indoor Navigation Benchmark is published under CC BY-NC-SA 4.0 license, which allows everyone to use its dataset for non-commercial research purpose.

Dataset Documentation We publish our dataset documentation on our website: https://main-dataset.github.io/

Code Accessment. The code for training and testing models in our paper is released on our Github repository: https://github.com/ZhuFengdaaa/MAIN.

Data Format. The format of our dataset is follow the data format of Habitat Challenge [3]. Thus a lot of methods and implementations could be easily adapted to our benchmark.

Limitations. A major limitation is training efficiency. Even though we implement a asynchronous-synchronous pipeline to speed up the data sampling, it still cost a 8-GPU device to run 36 hours to train a model. We are actively searching for solutions.

2 Open-source Codebase

Our benchmark project is a complex system which is built on various codebases. Some of them is for environment while others are training code, as shown in Tab. 1.

Codebase	Link
habitat-sim [3]	https://github.com/facebookresearch/habitat-sim
habitat-lab	https://github.com/facebookresearch/habitat-lab
multiON [5]	https://github.com/saimwani/multiON
PPO-PyTorch [4]	https://github.com/nikhilbarhate99/PPO-PyTorch
SMAC [2]	https://github.com/oxwhirl/smac
UPDeT [1]	https://github.com/hhhusiyi-monash/UPDeT
MAPPO [6]	https://github.com/zoeyuchao/mappo

Table 1: The codebase used in our benchmark.

References

[1] S. Hu, F. Zhu, X. Chang, and X. Liang. Updet: Universal multi-agent rl via policy decoupling with transformers. In *ICLR 2021: The Ninth International Conference on Learning Representations*, 2021.

[2] M. Samvelyan, T. Rashid, C. S. De Witt, G. Farquhar, N. Nardelli, T. G. Rudner, C.-M. Hung, P. H. Torr, J. Foerster, and S. Whiteson. The starcraft multi-agent challenge. *arXiv preprint arXiv:1902.04043*, 2019.

[3] M. Savva, A. Kadian, O. Maksymets, Y. Zhao, E. Wijmans, B. Jain, J. Straub, J. Liu, V. Koltun, J. Malik, et al. Habitat: A platform for embodied ai research. In *Proceedings of the IEEE International Conference on Computer Vision*, pages 9339–9347, 2019.

[4] J. Schulman, F. Wolski, P. Dhariwal, A. Radford, and O. Klimov. Proximal policy optimization algorithms. *arXiv preprint arXiv:1707.06347*, 2017.

[5] S. Wani, S. Patel, U. Jain, A. X. Chang, and M. Savva. Multion: Benchmarking semantic map memory using multi-object navigation. In *Advances in Neural Information Processing Systems*, volume 33, pages 9700–9712, 2020.

[6] C. Yu, A. Velu, E. Vinitsky, Y. Wang, A. M. Bayen, and Y. Wu. The surprising effectiveness of MAPPO in cooperative, multi-agent games. *CoRR*, abs/2103.01955, 2021.