Acting in the Face of Uncertainty Pessimism in Model-Based Reinforcement Learning

1. Introduction

- Model-Based RL (MBRL) creates a model of the environment to generate policies.
- Challenges in MBRL: inaccurate world models in underexplored regions of the training set can lead to suboptimal decisions.
- Pessimism aims to address this issue by disincentivizing actions leading to out-ofdistribution (OOD) states.
- **Research question: How does incorporating** pessimism in the planning loop affect agent performance?

2. Model Architecture



- The world model uses a representation, dynamics and reward network to plan.
- The agent uses a Monte Carlo tree search with the world model to chose actions.

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- uncertainty can be quantified.





3. Pessimism Approaches Pessimism requires the quantification of the uncertainty in the world models predictions. Investigated Techniques: Lower Confidence Bound (LCB), Ensembles, Monte Carlo (MC) Dropout **LCB** [1] penalizes actions based on the counts of state-action pairs in the training set. A penalty can be enacted, or the planning can be constrained to only actions above a threshold. **Ensembles** [2] combine the results of multiple diverse neural networks to quantify uncertainty. MC Dropout [3] uses dropout at model inference time to perform stochastic forward passes from which

Results



Epsilon

- distributions.

- optimisation.

References

[1] Rashidinejad, P., Zhu, B., Ma, C., Jiao, J., & Russell, S. (2023). Bridging Offline Reinforcement Learning and Imitation Learning: A Tale of Pessimism http://arxiv.org/abs/2103.12021 [2] An, G., Moon, S., Kim, J.-H., & Song, H. O. (2021). Uncertainty-Based Offline Reinforcement Learning with Diversified Q-Ensemble https://doi.org/10.48550/arXiv.2110.01548 [3] Wu, Y., Zhai, S., Srivastava, N., Susskind, J., Zhang, J., Salakhutdinov, R., & Goh, H. (2021). Uncertainty Weighted Actor-Critic for Offline Reinforcement Learning https://doi.org/10.48550/arXiv.2105.08140

5. Conclusion

Ensembles provide the highest performance gains over the widest range of data

LCB shows variable improvement. It is only effective with near-optimal datasets MC Dropout generally not effective, but it

may benefit from increased model size.

Future Work

Apply methods in more complex

environments.

Methods for automatic penalty coefficient

Investigate MC dropout with larger models or uncertainty decomposition.