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Robust Physics-Informed Learning for Modeling and Optimal Control

Communication Info

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- (7) Offline reinforcement learning

Abstract

Physics-Informed Neural Networks (PINNs) are a promising tool to learn ODE/PDE models and solution operators from limited data, yet they may fail on stiff or multi-scale problems due to difficult optimization and poor conditioning [1]. We present a compact robust physics-informed viewpoint that improves training stability and generalization for both deterministic dynamics and uncertainty-affected models. Our approach builds on (i) known PINN failure-mode analyses and stabilization techniques such as loss reweighting and curriculum strategies [1], (ii) HJB-based optimal control learned via time-dependent finite-horizon formulations to avoid non-uniqueness in stationary infinite-horizon HJB equations [2], and (iii) pessimistic, distributionally robust principles inspired by offline RL to mitigate overestimation under model mismatch [3]. This perspective provides practical guidelines for designing more reliable physics-informed models for modeling and optimal control.

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References

- [1] Krishnapriyan A. S., Gholami A., Zhe S., et al., Characterizing possible failure modes in physics-informed neural networks, NeurIPS, 2021
- [2] Fotiadis F., Vamvoudakis K. G., A Physics-Informed Learning Framework to Solve the infinite-Horizon Optimal Control Problem, 2025
- [3] Powell W. B., From Reinforcement Learning to Optimal Control: A unified framework for sequential decisions, 2019.
- [4] Shi L., Chi Y., Distributionally Robust Model-Based Offline Reinforcement Learning, JMLR, 2024.
- [5] Pang G., Lu L., Karniadakis G. E., Fractional Physics-Informed Neural Networks, 2018.