Advanced Topics in Deep Reinforcement Learning

RL Algorithms

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Generalist algorithms

What makes up an RL algorithm?

Interaction
Paradigm

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Data Acquisition

Exploration

Policy

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Interaction Paradigm

Interaction Backup

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Models

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Policy Updating

- Objective functions
- Optimizers
- Losses
- Hyperparameters

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Policy Search (without value baseline)

Offline RL

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Policy Search (without value baseline)

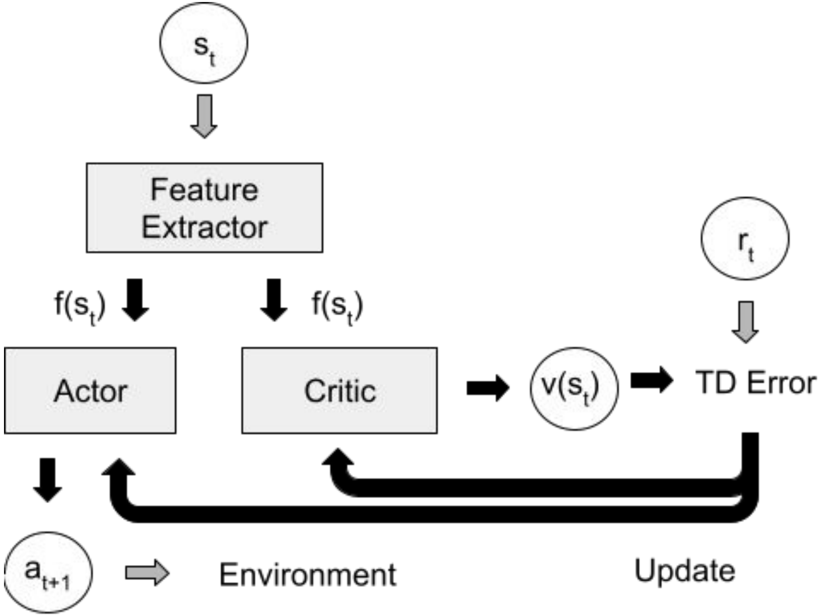
Policy Search with baseline

Off-policy online RL

Offline RL

Model-Free On-Policy Learning

- State of the art: Policy Gradient with value baselines
- Actor-critic architectures learn policy and baseline jointly



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  - Parallel rollouts for efficiency
  - Limiting policy updates, e.g. via clipping in PPO [Schulman et al. 2017]
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- Example Algorithms: PPO, TRPO, A2C/A3C, Impala

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- But: experience sharing makes training harder to implement, this may not be worth it [De Witt et al. 2020]

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Note: Off-policy MARL exists, is just less common

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- Important ideas:
  - Buffer sampling strategies
  - Exploration beyond epsilon-greedy
  - Regular parameter resets [Nikishin et al. 2022]
  - Better representations, e.g. via self-prediction [Schwarzer et al. 2021]
  - Distributional RL [Bellemare et al. 2023]
  - Architecture choices for Q-networks
  - Alternative Losses [Farebrother et al. 2024]

Off-Policy Example: SOTA DQNs

- Rainbow DQN [Hessel et al. 2017, Obando-Ceron & Castro 2021]
  - Noisy Nets
  - Distributional policy
  - Prioritized Replay
  - Target Network
  - Dueling Architecture
  - Multi-step learning

Off-Policy Example: SOTA DQNs

- Rainbow DQN [Hessel et al. 2017, Obando-Ceron & Castro 2021]
- Updates in recent years: BBF [Schwarzer et al. 2023]
  - Target network
  - Prioritized replay
  - Self-predictive representations
  - High replay ratio
  - Periodic parameter resets
  - Larger networks
  - Weight decay

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How do we judge a state of the art algorithm?

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  - Supervised learning [Chen et al. 2021]
- Big challenge: how to evaluate a policy?
  - Access to online evaluation is assumed (potentially not realistic)
  - We have to estimate policy quality, e.g. via errors [Zitovsky et al. 2023]

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- Models are usually learned with supervised learning
- Probably best model-based algorithm currently: Dreamer V3 [Hafner et al. 2023]

My Understanding of RL Algorithms

- ❑ I know the elements of RL algorithms
- ❑ I can describe at least one algorithm per domain
- ❑ I know at least one important idea per domain

- ❑ I know the important ideas for each domain
- ❑ I understand why they are important research directions
- ❑ I can explain where the combination of some ideas can work

- ❑ I understand the basic idea of most algorithms
- ❑ I theorize where one algorithm could be better than another
- ❑ I can propose an algorithm given a problem setting

Examples for Seminar Session Ideas

- Applying algorithms to our settings (aka creating baselines)
- Investigating differences between methods
- Applying an algorithm to a domain it’s not usually used in (e.g. offline DQN)
- Thinking about why a certain direction of algorithm research might (not) work for one of our settings (e.g. highly parallel evaluations or model-based RL)
- Suggesting a change to a common algorithm that would make sense for us
- …