Safe Policy Improvement with Baseline Bootstrapping

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Problem setting

Batch setting

- Fixed dataset, no direct interaction with the environment.
- Access to the behavioural policy, called baseline.
- Objective: improve the baseline with high probability.
- Commonly encountered in real world applications.

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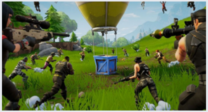

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Long trajectories

Contributions

Novel batch RL algorithm: SPIBB

- SPIBB comes with reliability guarantees in finite MDPs.
- SPIBB is as computationally efficient as classic RL.

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Finite MDPs benchmark

Extensive benchmark of existing algorithms.

Empirical analysis on random MDPs and baselines.

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In nite MDPs benchmark

- Model-free SPIBB for use with function approximation.
- First deep RL algorithm reliable in the batch setting.

Robust Markov Decision Processes

[Iyengar, 2005, Nilim and El Ghaoui, 2005]

- True environment $M = \langle X, A, P, R, \rangle$ is unknown.
- Maximum Likelihood Estimation (MLE) MDP built from counts: $\widehat{M} = \langle X, A, \widehat{P}, \widehat{R}, \rangle$.
- Robust MDP set $(\widehat{M}, e)$: $M \in (\widehat{M}, e)$ with probability at least 1 .
- Error function $e(x, a)$ derived from concentration bounds.

Existing algorithms

[Petrik et al., 2016]: SPI by robust baseline regret minimization

Robust MDPs considers the maxmin of the value over ,

! favors over-conservative policies.

They also consider the maxmin of the value improvement,

! NP-hard problem.

RaMDP hacks the reward to account for uncertainty:

$$\tilde{R}(x;a) \quad \hat{R}(x;a) \quad \sqrt{\frac{\text{adj}}{N_D(x;a)}};$$

! not theoretically grounded.

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[Thomas, 2015]: High-Con dence Policy Improvement

HCPI searches for the best regularization hyperparameter to allow safe policy improvement.

Safe Policy Improvement with Baseline Bootstrapping

Safe Policy Improvement with Baseline Bootstrapping (SPIBB)

- Tractable approximate solution to the robust policy improvement formulation.
- SPIBB allows policy update only with suf cient evidence.
- Suf cient evidence = state-action count that exceeds some threshold hyperparameter $N_{\wedge}$.

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SPIBB algorithm

Construction of the bootstrapped set:

$$B = f (x;a) 2 X \quad A \quad ; N_D(x;a) < N \quad g.$$

Optimization over a constrained policy set:

$$_{spibb} = \text{argmax}_{\ 2 \quad b} \ (\ ; \widehat{M});$$

$$_b = f \quad ; \quad \text{s.t.} \quad (ajx) = \quad _b(ajx) \text{ if } (x;a) 2 \ B \ g:$$

SPIBB policy iteration

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Policy improvement step example

Q-value	Baseline policy	Bootstrapping	SPIBB policy update
$Q^{(i)}_{\widehat{M}}(x, a_1) = 1$	$\pi_b(a_1 \vert x) = 0.1$	$(x, a_1) \in \mathfrak{B}$	
$Q^{(i)}_{\widehat{M}}(x, a_2) = 2$	$\pi_b(a_2 \vert x) = 0.4$	$(x, a_2) \notin \mathfrak{B}$	
$Q^{(i)}_{\widehat{M}}(x, a_3) = 3$	$\pi_b(a_3 \vert x) = 0.3$	$(x, a_3) \notin \mathfrak{B}$	
$Q^{(i)}_{\widehat{M}}(x, a_4) = 4$	$\pi_b(a_4 \vert x) = 0.2$	$(x, a_4) \in \mathfrak{B}$	

SPIBB policy iteration

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$Q^{(i)}_{bM}(x;a_1) = 1$	$_b(a_1 \mid x) = 0.1$	$(x;a_1) \in B$	$^{(i+1)}(a_1 \mid x) = 0.1$
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$Q^{(i)}_{\pi_b \widehat{M}}(x, a_3) = 3$	$\pi_b(a_3 \mid x) = 0.3$	$(x, a_3) \notin \mathcal{B}$	$\pi^{(i+1)}(a_3 \mid x) = 0.7$
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Theoretical analysis

Theorem (Convergence)

Policy iteration converges to a policy π_{spibb} that is Π_b-optimal in the MLE MDP $\widehat{M}$.

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Theorem (Safe policy improvement)

With high probability 1 :

$$(\ _{spibb}; M\ ) \quad (\ _{b}; M\ ) \quad (\ _{spibb}; \widehat{M}) \quad (\ _{b}; \widehat{M}) \quad \frac{4V_{max}}{1} \sqrt{\frac{2}{N_{\wedge}} \log \frac{2|X||A|\ 2^{|X|}}{}}$$

Model-free formulation

SPIBB algorithm

It may be formulated in a model-free manner by setting the targets:

$$y_j^{(i)} = r_j + \gamma \sum_{a' | (x'_j, a') \in \mathfrak{B}} \pi_b(a'|x'_j) Q^{(i)}(x'_j, a') + \gamma \left(\sum_{a' | (x'_j, a') \notin \mathfrak{B}} \pi_b(a'|x'_j) \right) \max_{a' | (x'_j, a') \notin \mathfrak{B}} Q^{(i)}(x'_j, a').$$

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Theorem (Model-free formulation equivalence)

In finite MDPs, the model-free formulation admits a unique fixed point that coincides with the Q-value of π_{spibb}.

25-state stochastic gridworld – mean

25-state stochastic gridworld – 1%-CVaR

Random MDPs, random baseline – 1%-CVaR

Gridworld – RaMDP hyperparameter sensitivity

Gridworld – SPIBB hyperparameter sensitivity

Helicopter domain (continuous task)

Helicopter domain - benchmark (improved results)

Vanilla DQN is off the chart

mean = 0.22,

10%-CVaR = -1 (minimal score).

Conclusion

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Follow-up work

- Factored SPIBB [Simão and Spaan, 2019a].
- Structure learning coupled [Simão and Spaan, 2019b].
- Soft SPIBB [Nadjahi et al., 2019].

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Still to do

- Improve the pseudo-count/error estimates.
- Investigate an online SPIBB inspired algorithm.

Thanks for your attention (POSTER #101)

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