

Off-Policy Deep Reinforcement Learning for Optimal Sepsis Treatment

Imran Ahmed and Aniruddh Raghu



Problem outline and goal

- Treatment policies for septic patients are suboptimal
 - Patients react variably to interventions
 - No universally agreed-upon treatment exists
- **Goal** - use observational data to discover treatment policies that improve chances of patient survival
- **Baseline** - mortality under physician treatment policy (13.7%)



Cohort

- MIMIC-III cohort - patients fulfilling Sepsis-3 criteria
 - Suspicion of infection
 - Evidence of organ dysfunction (SOFA score > 2)
- Include data from up to 24h preceding diagnosis
 - Time period around diagnosis is critical
- Outcome of interest - in-hospital mortality

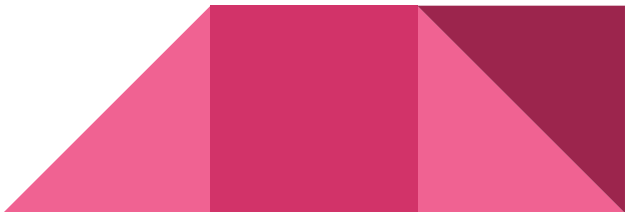


Methods

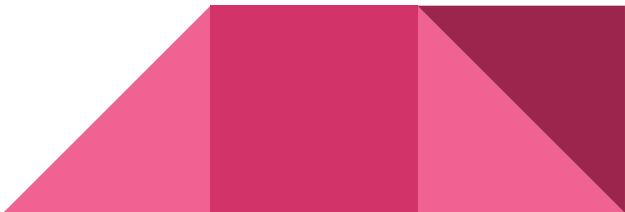
- Formulation - continuous state-space Markov Decision Process (MDP)
 - **State** - continuous vector of patient's physiological measurements + vital signs
 - **Actions** - discretized over doses of vasopressors and IV fluids
 - **Rewards** - depend on model:
 - Sparse: at terminal timesteps, depending on outcome
 - Clinically-guided: also at intermediate timesteps

$$r(s_t, s_{t+1}) = C_0 1(s_{t+1}^{SOFA} = s_t^{SOFA} \ \& \ s_{t+1}^{SOFA} > 0) + C_1 (s_{t+1}^{SOFA} - s_t^{SOFA}) + C_2 \tanh(s_{t+1}^{Lactate} - s_t^{Lactate})$$

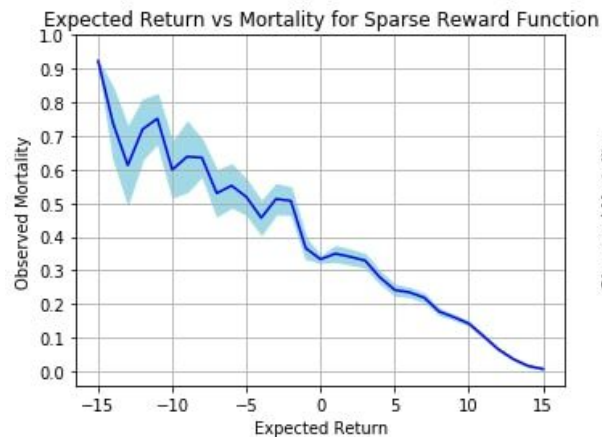
- Finding optimal policy
 - Q-learning to find treatment policy that maximises expected **return** R (discounted sum of rewards)



Evaluation methodology

- Off-policy evaluation is hard!
 - Use Doubly-Robust Value Estimator (Jiang and Li, 2015)
 - Accurately assess quality of learned policy using observational data from clinician actions
 - Associate value estimate with mortality
 - Learn mapping between value estimates and mortality from observational data
 - Find value estimate of the learned policy
 - Use mapping to estimate expected mortality
 - Qualitative policy evaluation
- 

Results



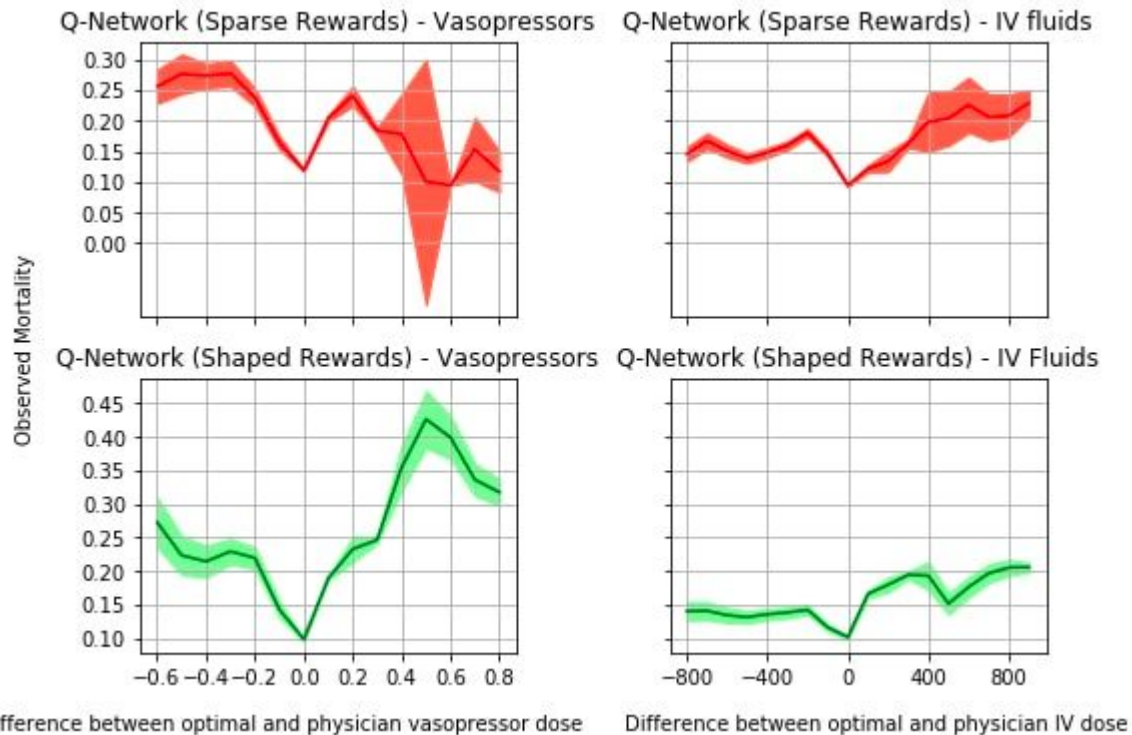
Policy	Expected Return	Estimated Mortality
Physician Sparse	11.17	$11.9 \pm 0.5\%$
Physician Shaped	11.04	$11.4 \pm 0.6\%$
Dueling DDQN Sparse	10.16	$12.8 \pm 0.5\%$
Dueling DDQN Shaped	13.3	$3.71 \pm 0.6\%$

Discussion and Future Work

- Learned improved treatment policies
 - Better than baseline
- Expected mortality is reduced
 - Our estimates are optimistic, but show promise
- Future work
 - Clinical insights into learned policies
 - Temporal aspects - recurrent Q networks, POMDPs



Other results



Other results

