

# First-Order Methods for Wasserstein Distributionally Robust MDPs

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*What is this paper about?*

- Solving distributionally robust Markov Decision Processes (MDP)
- Distributional robustness with Wasserstein distance
- Goal: improve convergence rate of Value Iteration algorithms

- Main idea: adapt First-Order Methods<sup>1</sup> (FOMs) for DR-MDP
- Challenges:
  - Adapt FOMs to a dynamically changing setting
  - Develop tractable proximal updates for interesting metrics/decision sets

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<sup>1</sup>Mirror Descent, Mirror Prox, Primal-Dual Algorithms, etc.

## Main complexity results

Consider an MDP with  $S/A/N$  states/actions/observed kernels.

Complexity of our algorithm:

$$O(N A^{2.5} S^{3.5} \log(\epsilon^{-1}) \epsilon^{-1.5}). \quad (1)$$

Note: complexity of classical Value Iteration:

$$O(N^{3.5} A^{3.5} S^{4.5} \log^2(\epsilon^{-1})). \quad (2)$$

$\Rightarrow$  improvement of  $\Omega(N^{2.5} AS)$  ...

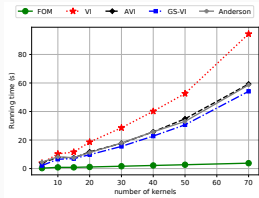
... at the price of a worst-dependence in  $\epsilon^{-1}$ .

Comparing our algorithms with other methods:

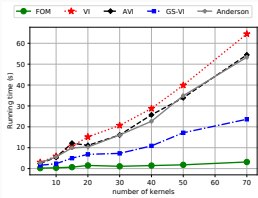
- Three MDP instances (two real, one random).
- Other algorithms<sup>2</sup>: Value Iteration (VI), Gauss-Seidel VI, Accelerated VI, Anderson VI.
- We compare running times to return  $\epsilon$ -optimal policy, when  $S, N$  grow larger.

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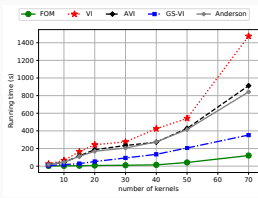
<sup>2</sup>Puterman (1994), Geist and Scherrer (2018), Goyal and G.-C. (2019)



(a) Forest.

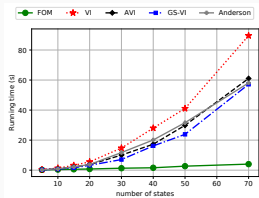


(b) Machine.

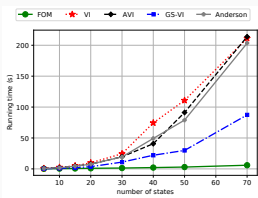


(c) Garnet.

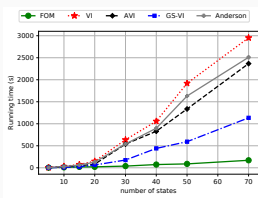
Figure 1: Running times of various algorithms (vs. number of kernels  $N$ ).



(a) Forest.



(b) Machine.



(c) Garnet.

Figure 2: Running times of various algorithms (vs. number of states  $S$ ).

# Conclusion

Our contributions.

- We present the first algorithm adapting FOM to *Distributionally Robust MDP*.
- In terms of state/action, we improve complexity to  $O(NA^{2.5}S^{3.5})$  from previous  $O(N^{3.5}A^{3.5}S^{4.5})$ .
- Empirically, significant speedups on both random and structured MDP instances, even for small  $N, S, A$ .

In the paper:

- More details on Wasserstein setup,
- Details on convergence rate/complexity,
- Detailed simulation setup.