

LSTD with Random Projections

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Setting: RL in *high-dimensional spaces* — the number of features is bigger than the number of samples.

Problem: *Overfitting* and poor *prediction* performance.

Solutions

- **Regularization:** adding ℓ_1 and ℓ_2 regularizations to value-function approximation algorithms.
- **Random projections:** **this work.**

LSTD: A RL alg. for learning the value function of a given policy.

Algorithm – LSTD-RP: LSTD in a *low-dim* space generated by a **random projection** from the *high-dim* space.

- We present the LSTD-RP algorithm and discuss its computational complexity.

less expensive than performing LSTD in the high-dim space.

- We provide finite-sample performance bounds for LSTD-RP.
 - **Markov design:** performance on the training samples.
 - **Random design:** generalization over the entire state space

*avoid overfitting – better prediction: smaller **estimation error** and not much larger **approximation error**.*

- **Uniqueness** of the LSTD-RP solution.
 - When the *model-based* LSTD solution in *high-dim* exists,
 - How many *samples* are needed in order for LSTD-RP (*low-dim* random space) to have a unique solution w.h.p.?

*LSTD-RP is more **stable** and needs **less samples** to have a unique solution, compared to LSTD in the high-dim space.*

- We show how the error of LSTD-RP is propagated through the iterations of LSPI and present a bound for LSPI-RP.