



THE UNIVERSITY OF  
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DEPARTMENT OF STATISTICS

## Master's Thesis Presentation

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“Low-Rank Reinforcement Learning for Robust Value Estimation”

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### Abstract

Offline deep reinforcement learning (RL) must learn reliable value functions from a fixed, imperfect dataset, where distribution shift induces extrapolation error and noisy Bellman targets compound through bootstrapping. While conservative methods such as CQL mitigate out-of-distribution (OOD) overestimation by penalizing large Q-values, they frequently become over-pessimistic—shrinking in-distribution values, requiring careful penalty tuning, and limiting expressiveness.

This thesis introduces Structured Value-based Reinforcement Learning (SVRL) and Uncertainty-Aware Low-Rank Q Estimation (UALQE), two complementary approaches that inject a low-rank inductive bias into value learning. At each update, we view the batch-wise next-state/policy action cross-product as a partially observed matrix and apply soft-impute re-construction to exploit shared structure across state-action pairs. We operationalize this reconstruction through T-matrix replacement that denoises TD targets via reconstructed diagonals. UALQE replaces random masking with uncertainty-guided masking (via an ensemble/EDAC-style diversification), concentrating reconstruction on the most error-prone entries.

An SVD tracker reveals that SVRL/UALQE stabilizes the spectrum of learned Q-matrices: unlike SAC's rank-one collapse and CQL's capped but over-compressed spectra, our methods preserve a compact yet multi-modal structure (moderate  $\sigma_1$ , elevated approximate rank), with dominant singular vectors exhibiting coherent, non-uniform patterns. Across standard D4RL continuous-control tasks, SVRL attains the most consistent gains, and UALQE reliably outperforms random masking. These results show that structural low-rank reconstruction, paired with uncertainty-

aware selection, provides a practical alternative to uniformly pessimistic objectives, mitigating over/under-estimation while improving stability and return under distribution shift.