

Increasing Information for Model Predictive Control with Semi-Markov Decision Processes

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How and when should data be collected along the system trajectory for Gaussian Process-Based Model Predictive Control?

Background

Markov Decision Process (MDP)

$$P(dx_0 du_0 dx_1 \dots) = P_{X_0}(dx_0) \pi(du_0 | dx_0) \mathcal{P}(dx_1 | dx_0, du_0) \dots$$

\mathcal{P} : transition Kernel

$u \in \mathcal{U}$: control

$x \in \mathcal{X}$: state

Gaussian Process (GP) Model Predictive Control (MPC)

Dynamics model (GP)

$$\hat{\mathcal{P}}_{\mathcal{D}}(\cdot, (x, u)) \sim \mathcal{N}(\mu(x, u), \Sigma((x, u), (x, u)) | \mathcal{D})$$

Cost function

$$J^{\pi} = \mathbb{E}^{\pi} \left[\sum_{k=0}^T c(X_k, U_k) \right]$$

Model Predictive Control with Cross-Entropy Method (CEM)

$$\pi^{\text{MPC}}(x) = u_0^*$$

$$s.t. \quad (u_0^*, \dots, u_{T^{\text{MPC}}}^*) = \arg \min_{(u_0, \dots, u_{T^{\text{MPC}}})} \mathbb{E}^{(u_0, \dots, u_{T^{\text{MPC}}})} \left[\sum_{k=0}^{T^{\text{MPC}}} c(X_k, u_k) | X_0 = x \right]$$

Objective

Collect minimal $\mathcal{D} = (x_k, u_k)_{k=1}^n$ **such that** $\hat{\mathcal{P}}_{\mathcal{D}} \simeq \mathcal{P}$ **from evolving dynamical system**

State-of-the-art strategy: **Expected Information Gain (EIG)** on the optimal trajectory $H_T^* = (X_0^*, U_0^*, \dots, U_{T-1}^*, X_T^*)$ (under π^*)

$$\text{EIG}_n(x, u) = \mathcal{H}[\hat{H}_T^* | \mathcal{D}_n] - \mathbb{E}_{P_{X_{n+1}} | \mathcal{D}_n, X_n = x, U_n = u} [\mathcal{H}[\hat{H}_T^* | \mathcal{D}_n, X_n = x, U_n = u, X_{n+1}]]$$

Dataset update: $\mathcal{D}_{n+1} = \mathcal{D}_n \cup (x^*, u^*)$ $(x^*, u^*) = \arg \max_{x, u} \text{EIG}(x, u)$

Select point which minimises the uncertainty (entropy) \mathcal{H} on the optimal trajectory

By symmetry of EIG, the entropy of X_{t+1} (more tractable) is considered:

$$\text{EIG}_n(x, u) = \mathcal{H}[X_{n+1} | \mathcal{D}_n, X_n = x, U_n = u] - \mathbb{E}_{P_{\hat{H}_T^*} | \mathcal{D}_n} \left[\mathcal{H}[X_{n+1} | \mathcal{D}_n, X_n = x, U_n = u, \hat{H}_T^*] \right]$$

Question

How to **extend the EIG criterion** to avoid **information redundancy**?

Contribution

Introduction of **temporal abstraction** with Semi-markov Decision Process (options framework)

Temporally extended actions (options)

Interdecision time $\longrightarrow t \in \{1, \dots, t_{\max}\}$

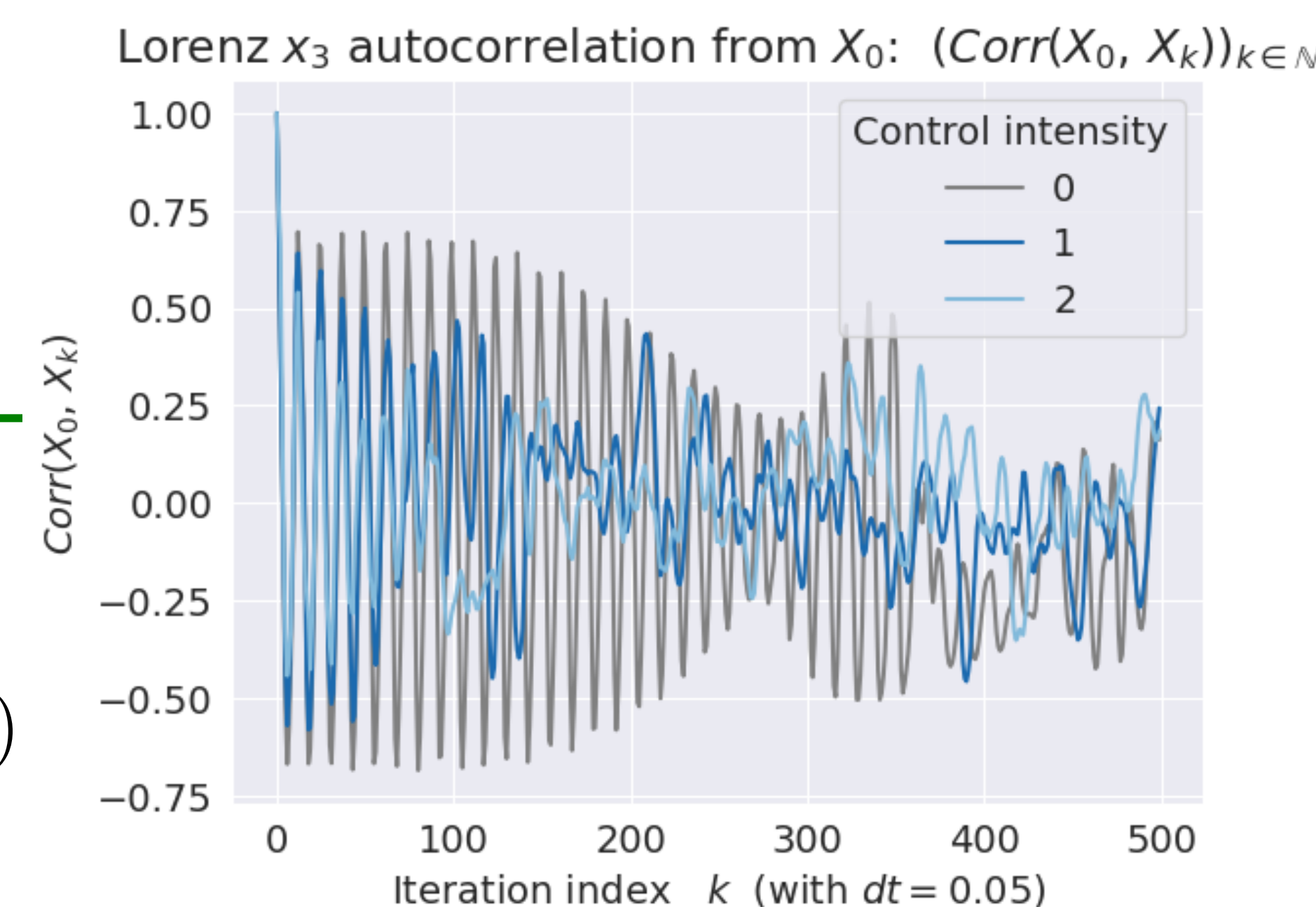
New temporally-extended transition $\mathcal{P}^{\text{SMDP}}(dx' | (x, (u, t))) = P(X_{k+t} | X_k = x, U_{k:k+t-1} = u)$

No system interaction for a duration of length t

Look-ahead (non-causal) information criterion

$$\text{EIG}^{\text{SM}}(x, (u, t)) = \mathcal{H}[X_{\kappa_n+t+1} | \mathcal{D}_n, X_{\kappa_n} = x, U_{\kappa_n:\kappa_n+t} = u, \kappa_n] - \mathbb{E}_{P_{\hat{H}_T^*} | \mathcal{D}_n} \left[\mathcal{H}[X_{\kappa_n+t+1} | \mathcal{D}_n, X_{\kappa_n} = x, U_{\kappa_n:\kappa_n+t} = u, \hat{H}_T^*, \kappa_n] \right]$$

Dataset update: $\mathcal{D}_{n+1} = \mathcal{D}_n \cup (x^*, u^*)$ $(x^*, u^*) = \arg \max_{x, u, t} \text{EIG}^{\text{SM}}(x, (u, t))$

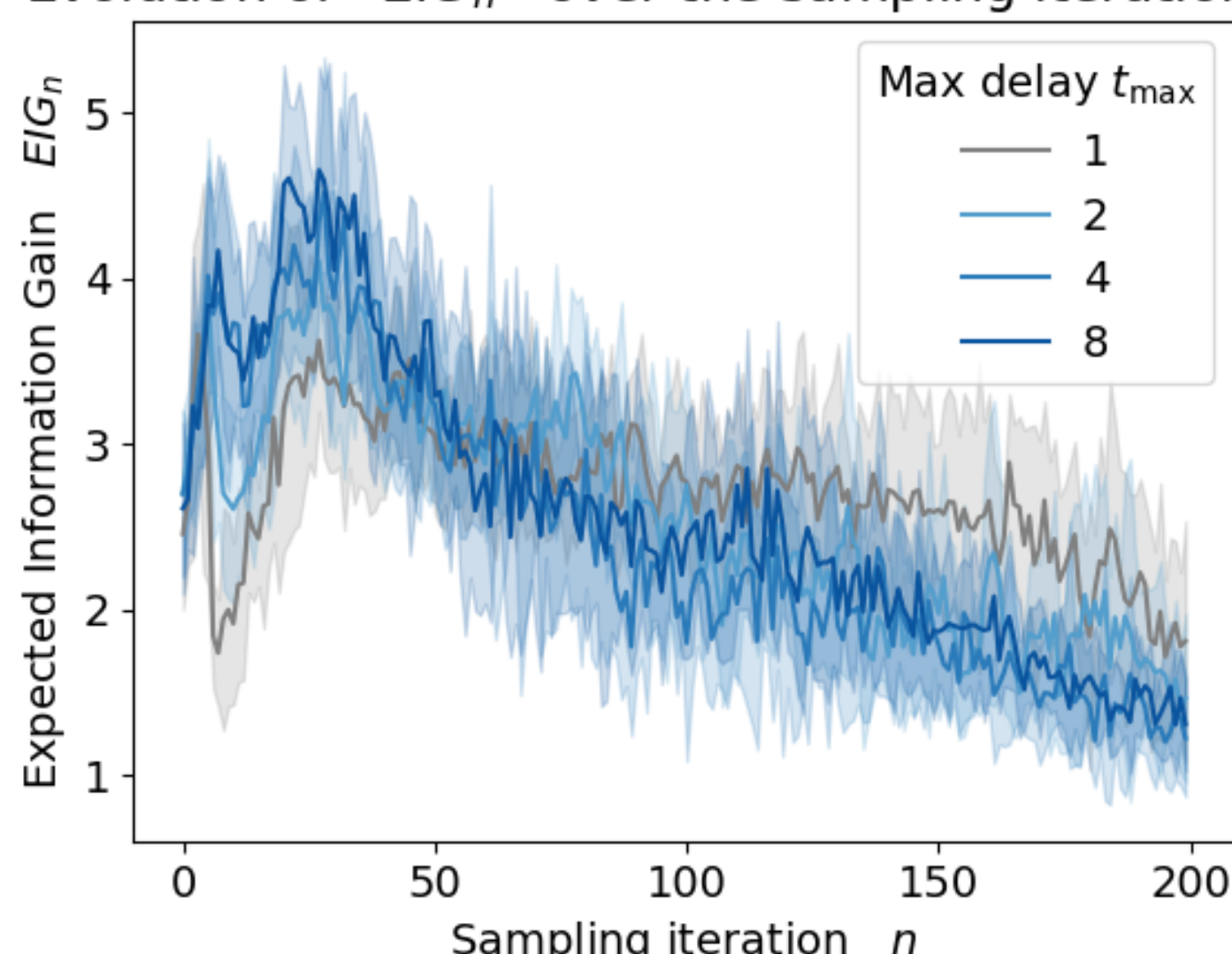


Results

Experiment on the Lorenz system:

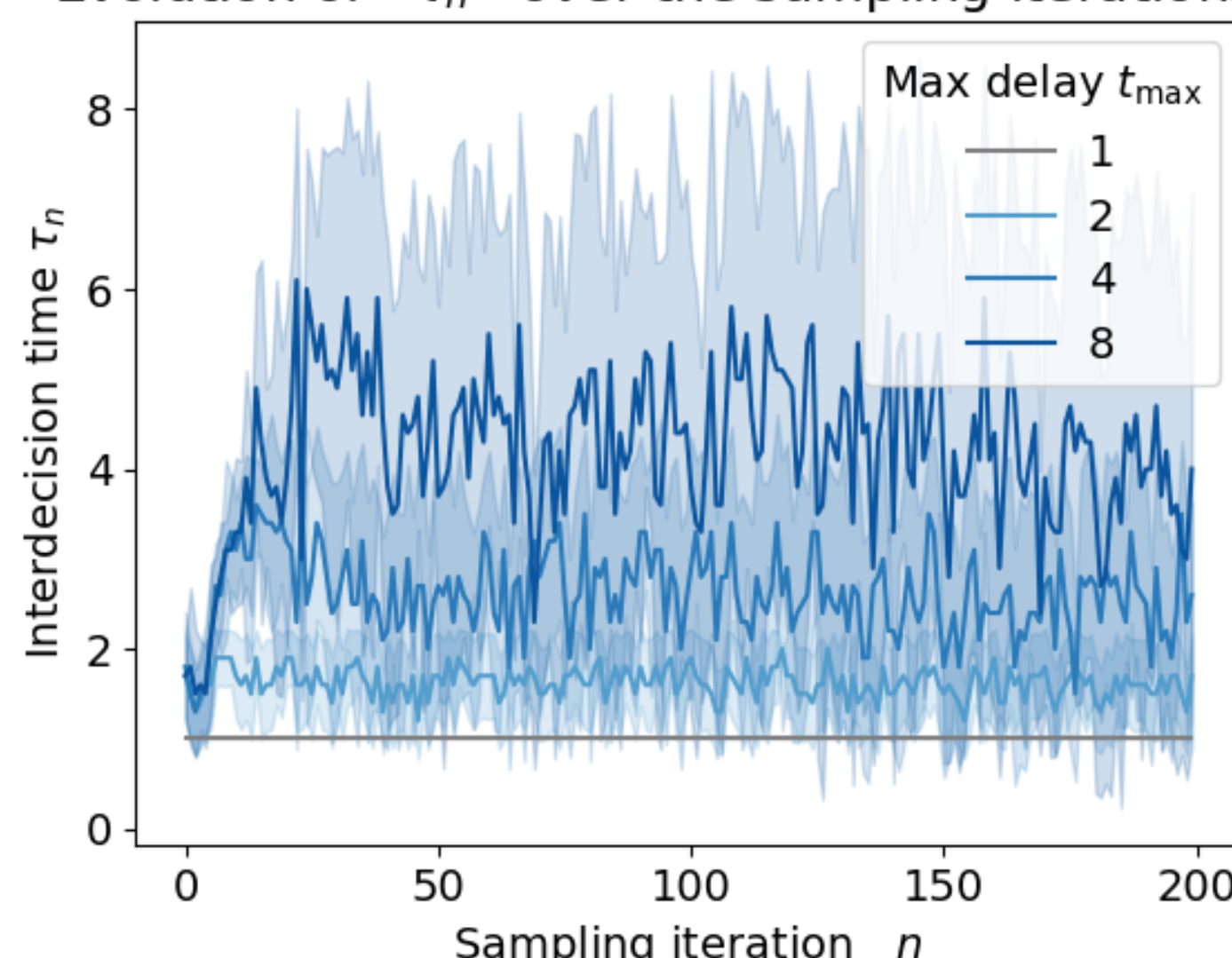
- max inter-decision time: $t_{\max} = 8$
- sampling budget: $n = 200$

Evolution of EIG_n over the sampling iterations n



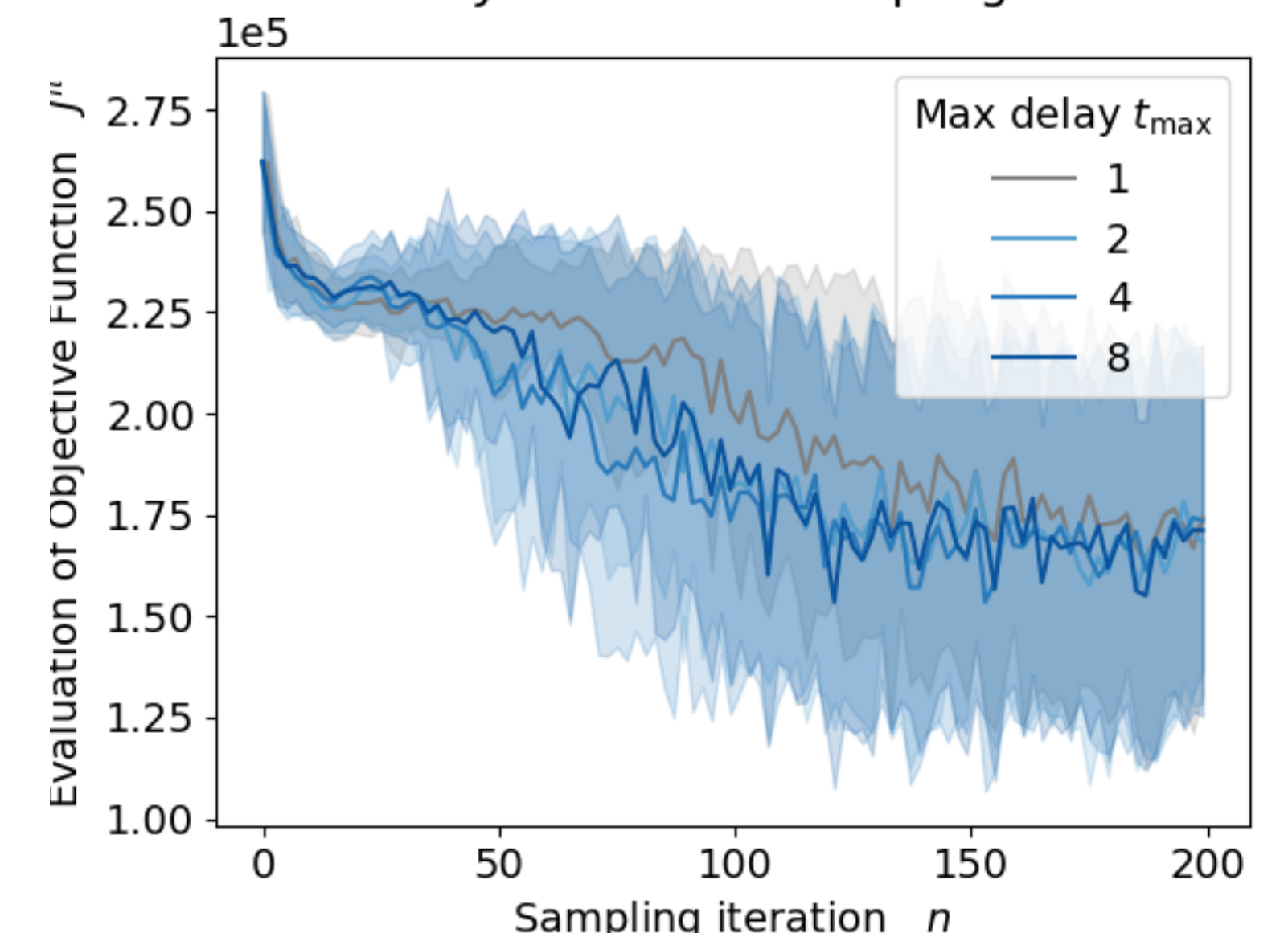
✓ Temporal abstraction increases EIG

Evolution of τ_n over the sampling iterations n



✓ Semi-markov interdecision time $t > 1$

Evolution of J^{π} over the sampling iterations n



✓ Improved MPC