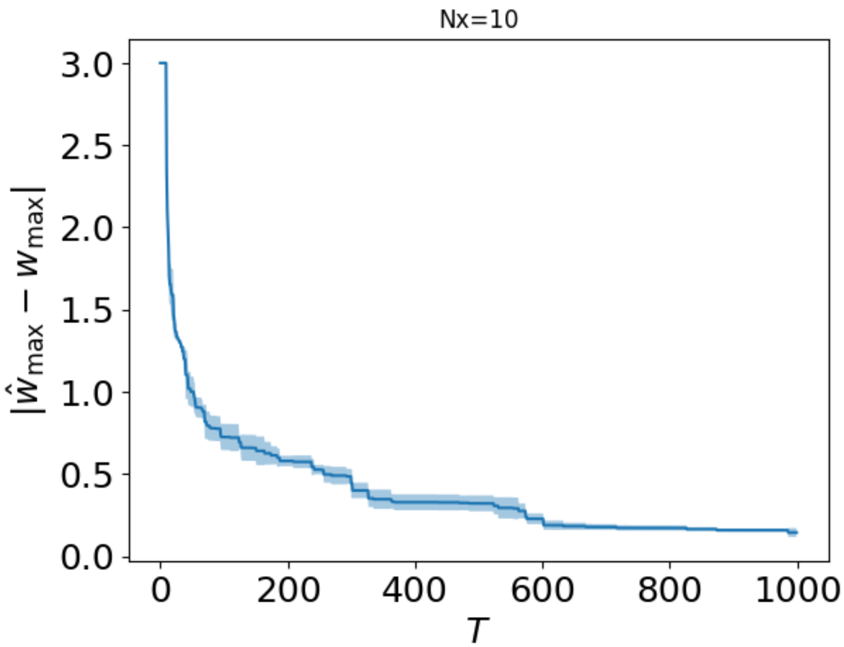

Figure 1: **Our ongoing work on learning $w_{\max}$ when a sharp bound is unknown.** This is a preliminary result of the convergence of $\hat{w}_{\max}$ estimated by our new algorithm, which tries to resolve the requirement of knowing a sharp bound of $w_{\max}$. **Experiment setting:** consider a linear autonomous systems $x_{t+1} = Ax_t + w_t$, where $A \in \mathbb{R}^{10\times 10}$, its each entry is generated i.i.d. from Unif$[0, 1]$, then rescale A to make it stable. The norm of A used for this figure is $\|A\|_2 = 0.83$. The disturbances w_t are generated i.i.d from $N(0, I_{10})$ truncated to $[-3, 3]^{10}$. **Algorithm:** Given data $\{x_0\}_{t=1}^{T}$, compute the Chebyshev estimate (Cramer, 1964; Rider, 1957) of A by: $\hat{A}_{\text{cheb}} = \arg\min_A \max_{0\leq t\leq T-1} \|x_{t+1} - Ax_t\|_\infty$. Then, estimate $w_{\max}$ by the $\hat{A}_{\text{cheb}} = \max_{0\leq t\leq T-1} \|x_{t+1} - Ax_t\|_\infty$. **Observation:** The estimation error of $w_{\max}$ quickly decreases to close to 0. This is promising since we can apply the estimated $\hat{w}_{\max}$ to SM. With proper two-time-scale updates and analysis, we expect that SM is able to converge even without knowing a sharp bound $w_{\max}$. The non-asymptotic analysis is heavily based on the novel proof techniques developed in Appendix D.3. However, the two-time-scale updates involves more complicated analysis, which is our ongoing work.