A Regret Minimization Approach to Iterative Learning Control

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Wide-angle Perspective

- Learn an (adaptive) policy
- + given an approximate model
- + subject to changing, <u>unknown</u> perturbations
- + in a *handful* of <u>episodes</u>





+Arises in real-world applications

+ Sandboxed setup for sim2real, meta-learning, policy transfer

Problem Setting

Episode 1 of T Learner has a model f(x,u)Timestep 1 of H Play action u_h $x_{h+1} = f(x_h, u_h) + w_h$ Suffer $c(x_h, u_h)$ Episodic $Cost_t = \sum_h c_h(x_h, u_h)$

Compare:

Iterative LQR > no perturbations Iterative LQG > Gaussian perturbations Model Predictive Control > One-shot Iterative Learning Control > Same setup (here)

> Unknown, Nonstationary Perturbations

(*arbitrary*, no dist. assumption) (changes every *step*, every *episode*)

Objective: *Planning Regret*



Main Result

For time-varying linear dynamical system Subject to arbitrary perturbation An efficient gradient-based algorithm

$$\frac{1}{TH} \left(\sum_{t=1}^{T} Cost_t(Alg) - \min_{U_{1:H}^*} \sum_{t=1}^{T} \min_{\pi_t^*} Cost_t(U_{1:H}^* + \pi_t^*) \right) \leq \frac{1}{\sqrt{T}} + \frac{1}{\sqrt{H}}$$
Inter-episodic learning
Best Overall Open-Loop Plan
Intra-episodic learning
Instance-optimal Adaptation

Preview: Nested Online Convex Opt.

Biconvex $f_{t,h}(x, y)$.

Episode 1 of T Timestep 1 of H Choose parameter x, yUpdate $y = y - \eta_y \nabla_y f_{t,h}(x, y)$ Update $x = x - \eta_x \nabla_x f_{t,h}(x, y)$ $\frac{1}{TH} \left(\sum_{t=1}^T \sum_{h=1}^H f_{t,h}(x_t, y_{t,h}) - \min_{x^*} \sum_{t=1}^T \min_{y_t^*} \sum_{h=1}^H f_{t,h}(x^*, y_t^*) \right) \leq \frac{R_x}{\sqrt{T}} + \frac{R_y}{\sqrt{H}}$

Captures Initialization-based Meta Learning:

x, y share the same space and choose x + y



Experiment 1: Quadcopter in Wind

