

# A Theory of the Learnable 1984

L. G. VALIANT

PAC Adaptive Control of Linear Systems

1997

Claude-Nicolas Fiechter  
Department of Computer Science  
University of Pittsburgh  
Pittsburgh, PA 15260  
fiechter@cs.pitt.edu

## On the Sample Complexity of the Linear Quadratic Regulator 2019

Sarah Dean<sup>‡</sup>, Horia Mania<sup>‡</sup>, Nikolai Matni<sup>†</sup>, Benjamin Recht<sup>‡</sup>, and Stephen Tu<sup>‡</sup>

<sup>‡</sup> University of California, Berkeley

<sup>†</sup> California Institute of Technology

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- consider discounted LQR problem with disturbance

$$\min_u E \left[ \sum_{t=0}^{\infty} \gamma^t \cdot (x_t^T Q x_t + u_t^T R u_t) \right], \quad x \in \mathbb{R}^n, \quad u \in \mathbb{R}^m, \quad \gamma \in (0, 1)$$

$$\text{s.t. } x_t^+ = A x_t + B u_t + w_t \quad \text{where } w_t \sim \mathcal{N}(0, \sigma^2 I) \text{ iid}$$

recall: solution is  $u = \pi^*(x) = -K^* x$  if  $(A, B)$  controllable &  $(A, \sqrt{Q})$  observable

$$\text{where } K^* = \gamma (\gamma B^T P^* B + R)^{-1} B^T P^* A,$$

$$P^* = A^T (\gamma P^* - \gamma^2 P^* B (\gamma B^T P^* B + R)^{-1} B^T P^*) A + Q$$

- we will consider 2 classes of learning algorithms:

1°. Fiechter 1997 : PAC learnability

2°. Dean et al 2019 : high-dimensional statistics

1°. idea: use linear regression to estimate  $A$  &  $B$  then use  $\pi$  to compute  $\pi$

1'. let  $\Theta = [B \ A]^T \in \mathbb{R}^{(n+m) \times n}$ ,  $\varphi = \begin{bmatrix} u \\ x \end{bmatrix} \in \mathbb{R}^{n+m}$ ,  $y^T = x$

1°. let  $\Theta = [B \ A]^T \in \mathbb{R}^{(n+m) \times n}$ ,  $\varphi = \begin{bmatrix} u \\ x \end{bmatrix} \in \mathbb{R}^{n+m}$ ,  $y^T = x$

so that  $x^+ = Ax + Bu + w \Leftrightarrow y = \varphi^T \Theta + w$

1°. given trajectory data  $x: [0, T] \rightarrow \mathbb{R}^n$ ,  $u: [0, T] \rightarrow \mathbb{R}^m$

create data matrices  $Y_T = \begin{bmatrix} y_1 \\ \vdots \\ y_T \end{bmatrix}$ ,  $\Phi_T = \begin{bmatrix} \varphi_1^T \\ \vdots \\ \varphi_T^T \end{bmatrix}$ ,  $W_T = \begin{bmatrix} w_1^T \\ \vdots \\ w_T^T \end{bmatrix}$

so that  $Y_T = \Phi_T \cdot \Theta + W_T$  measured,  $\hat{Y}_T = \Phi_T \cdot \hat{\Theta}$  predicted

1°. solve  $\min_{\hat{\Theta}} \|Y_T - \hat{Y}_T\|$  to obtain  $\hat{\Theta} = (\Phi_T^T \Phi_T)^{-1} \Phi_T^T Y_T$ ,

the minimum-variance estimate of  $\Theta$ :  $\text{Cov}[\hat{\Theta}_i, \hat{\Theta}_j] = \sigma^2 P_T$  where

the matrix  $P_T = (\Phi_T^T \Phi_T)^{-1} = \left[ \sum_{t=1}^T \varphi_t \varphi_t^T \right]^{-1}$  is dispersion,  $\hat{\Theta} = [\hat{\Theta}_1, \dots, \hat{\Theta}_n]$

14. show that this is a probably approximately correct (PAC) algorithm:

$$\forall \delta, \varepsilon > 0: P\left(\forall x: \frac{|v^{\hat{\pi}}(x) - v^{\pi^*}(x)|}{1 + \|x\|^2} \leq \varepsilon\right) \geq 1 - \delta$$

• error in  $\hat{A}, \hat{B}$  inversely proportional to  $\lambda = \min \text{spec } P_T^{-1}$

• for large  $T$ ,  $\lambda$  increases linearly with  $T$

• error  $v^{\hat{\pi}} - v^{\pi^*}$  bounded by  $T$

2°. begins similarly to (1°), but with "batches" of data

$$\{(x_t^l, u_t^l) : l \in \{1, \dots, N\}, t \in [0, T]\}$$

2°. the least-squares data is

$$Y = \begin{bmatrix} y_1^1 \\ \vdots \\ y_T^N \end{bmatrix} \quad \Phi = \begin{bmatrix} (\varphi_1^1)^T \\ \vdots \\ (\varphi_T^N)^T \end{bmatrix} \quad W = \begin{bmatrix} (w_1^1)^T \\ \vdots \\ (w_T^N)^T \end{bmatrix} \quad \left. \vphantom{\begin{bmatrix} y_1^1 \\ \vdots \\ y_T^N \end{bmatrix}} \right\} \text{only use final sample!}$$

but the equation remains  $Y = \Phi \cdot \Theta + W$

2°. show that least-squares estimate together with

2<sup>2</sup>. show that least-squares estimate together with SLS LQR controller achieves error bound

$$P \left( \frac{\hat{v}^{\pi} - v^{\pi^*}}{v^{\pi^*}} \leq O \left( C_{LQR} \sqrt{\frac{(n+m) \log(1/\delta)}{N}} \right) \right) \geq 1 - \delta$$

where  $C_{LQR}$  depends on  $T, A, B, Q, R, \sigma_u^2, \sigma_w^2$ :

$$C_{LQR} \propto \sigma_w \left( \underbrace{\frac{1}{\sqrt{\lambda_G}} + \frac{\|K^*\|_2}{\sigma_u}}_{\text{eigval of controllability grammians}} \right) \underbrace{\|zI - (A - BK^*)\|_{\infty}}_{\text{xfer func from disturbance to state}}$$

2<sup>3</sup>. importantly, controller is robust; also consider FIR implementation, other performance criteria