Optimal Control Theory and Linear Quadratic Regulators

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CS 6789: Foundations of Reinforcement Learning

Today

- Summarize:
  - TRPO/PPO

- This week: LQRs
  - The model + planning + SDP formulations
  - convex parameterization and LQR w/ adversarial disturbances and cost functions

TRPO:

$$\max_{\pi_\theta} V^{\pi_\theta}(\rho)$$

s.t., $KL\left(\mathrm{Pr}^{\pi_{\theta_0}} || \mathrm{Pr}^{\pi_\theta}\right) \leq \delta$

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We have a closed form solution:

$$\theta = \theta_0 + \sqrt{\frac{\delta}{(\nabla V^{\pi_{\theta_0}})^\top F_{\theta_0}^{-1} \nabla V^{\pi_{\theta_0}}}} \cdot F_{\theta_0}^{-1} \nabla V^{\pi_{\theta_0}}$$

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- Self-normalized step-size (Learning rate is adaptive)
- Solve with CG

PPO

- To find the next policy π_{t+1}, use objective:

$$\max_{\theta} \quad E_{s\sim d^{\pi_t}} E_{a\sim \pi^{\theta}(\cdot|s)} A^{\pi_t}(s,a)$$

$$\text{subject to} \quad \sup_{s} \left\| \pi^{\theta}(\cdot\,|\,s) - \pi_t(\cdot\,|\,s) \right\|_{\mathrm{TV}} \le \delta,$$

This is like the CPI greedy policy chooser.

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- We can do multiple gradient steps by rewriting the objective function using importance weighting using a clip function:

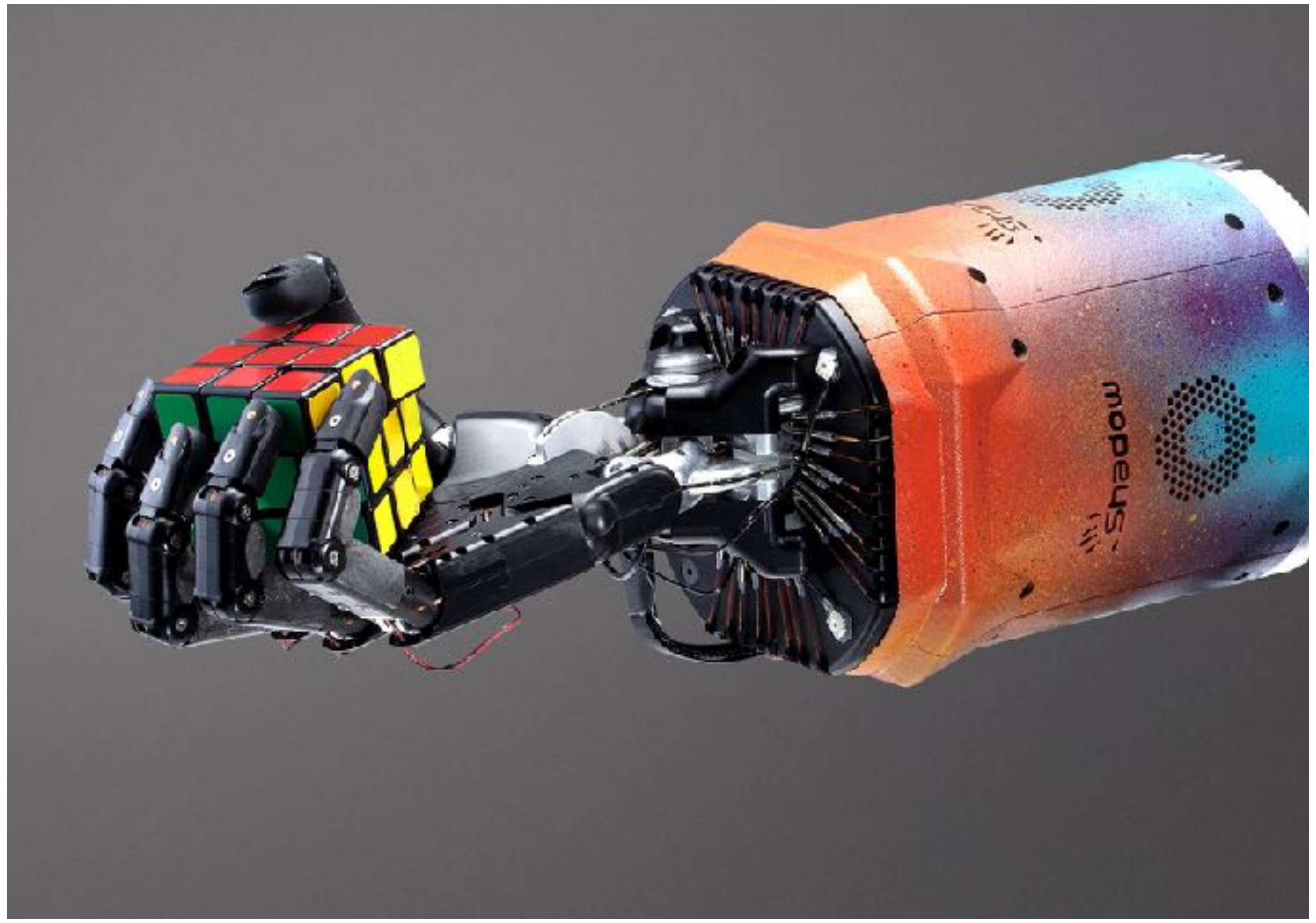
$$\max_{\theta} \; E_{s\sim d^{\pi_t}} E_{a\sim\pi_t(\cdot|s)} \left[\mathrm{clip}\left(\frac{\pi^{\theta}(a\,|\,s)}{\pi_t(a\,|\,s)}, 1-\epsilon, 1+\epsilon \right) A^{\pi_t}(s,a) \right]$$

Clip: when the ratio is outside of $[1-\epsilon, 1+\epsilon]$, we get gradient zero

Today

Robotics and Controls

Dexterous Robotic Hand Manipulation
OpenAI, 2019



Optimal Control

- a dynamical system is described as
  $x_{t+1} = f_t(x_t, u_t, w_t)$
  where f_t maps a state $x_t \in R^d$, a control (the action) $u_t \in R^k$, and a disturbance w_t, to the next state $x_{t+1} \in R^d$, starting from an initial state x_0.

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- The objective is to find the control policy π which minimizes the long term cost,

  minimize $\quad E_\pi\left[\sum_{t=0}^{H-1} c_t(x_t, u_t)\right]$

  such that $\quad x_{t+1} = f_t(x_t, u_t, w_t)$

  where H is the time horizon (which can be finite or infinite) and where w_t is either statistical or constrained in some way.

Linearization Approach

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- In practice, this is often solved by considering the linearized control (sub-)problem where the dynamics are approximated by
  $x_{t+1} = A_t x_t + B_t u_t + w_t,$
  with the matrices A_t and B_t are derivatives of the dynamics f (around some trajectory) and where the costs are approximated by a quadratic function in x_t and u_t.

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- This approach does not capture global information.

The LQR Model

The Linear Quadratic Regulator (LQR)

(finite horizon case)

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- The finite horizon LQR problem is given by

minimize $\quad E\left[x_H^\top Q x_H + \sum_{t=0}^{H-1} (x_t^\top Q x_t + u_t^\top R u_t)\right]$

such that $\quad x_{t+1} = A_t x_t + B_t u_t + w_t\,, \quad x_0 \sim D,\ w_t \sim N(0,\sigma^2 I)\,,$

where initial state $x_0 \sim D$ is randomly distributed according D;
the disturbance $w_t \in R^d$ is multi-variate normal, with covariance $\sigma^2 I$;
$A_t \in R^{d\times d}$ and $B_t \in R^{d\times k}$ are referred to as system (or transition) matrices;
$Q \in R^{d\times d}$ and $R \in R^{k\times k}$ are psd matrices that parameterize the quadratic costs.

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- Note that this model is a finite horizon MDP, where the $S = R^d$ and $A = R^k$.

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where A and B are time homogenous.

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(discounting doesn't necessarily make costs finite)
- Note that we can have 'unbounded' average cost.

Bellman Optimality:

Value Iteration and the Ricatti Equations

Same defs (but for costs)

- define the value function $V_h^\pi : R^d \to R$ as

$$V_h^\pi(x) = E\Big[x_H^\top Q x_H + \sum_{t=h}^{H-1} (x_t^\top Q x_t + u_t^\top R u_t) \;\Big|\; \pi, x_h = x\Big],$$

- and the state-action value $Q_h^\pi : R^d \times R^k \to R$ as:

$$Q_h^\pi(x, u) = E\Big[x_H^\top Q x_H + \sum_{t=h}^{H-1} (x_t^\top Q x_t + u_t^\top R u_t) \;\Big|\; \pi, x_h = x, u_h = u\Big],$$

Value Iteration and the Ricatti Equations

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Theorem: (for the finite horizon case, with time homogenous $A_t = A, B_t = B$)

The optimal policy is a linear controller specified by:

$$\pi^\star(x_t) = -K_t^\star x_t \text{ where } K_t^\star = (B^\top P_{t+1} B + R)^{-1} B^\top P_{t+1} A$$

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where P_t can be computed iteratively, in a backwards manner, using the following algebraic Ricatti equations, where for $t \in [H]$,

$$\begin{aligned} P_t &= A^\top P_{t+1} A + Q - A^\top P_{t+1} B (B^\top P_{t+1} B + R)^{-1} B^\top P_{t+1} A \\ &= A^\top P_{t+1} A + Q - (K_{t+1}^\star)^\top (B^\top P_{t+1} B + R) K_{t+1}^\star \end{aligned}$$

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Furthermore, for $t \in [H]$, we have that:

$$V_t^\star(x) = x^\top P_t x + \sigma^2 \sum_{h=t+1}^{H} \mathrm{Trace}(P_h)$$

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- Bellman equations ⇒ there is an optimal policy which is deterministic + only a function of x_t and t.
- Define $V_H(x) = x^\top P_H x$, where $P_H := Q$
- Due to that $x_H = Ax + Bu + w_{H-1}$, we have:

$$Q^\star_{H-1}(x,u) = E\Big[(Ax + Bu + w_{H-1})^\top P_H (Ax + Bu + w_{H-1})\Big] + x^\top Q x + u^\top R u$$

$$= (Ax + Bu)^\top P_H (Ax + Bu) + \sigma^2 \text{Trace}(P_H) + x^\top Q x + u^\top R u$$

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- This is a quadratic function of u. Solving for the optimal control at x, gives:

$$\pi^\star_{H-1}(x) = -(B^\top P_H B + R)^{-1} B^\top P_H A x = -K^\star_{H-1} x,$$

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$$
\begin{aligned}
V^\star_{H-1}(x) &= Q^\star_{H-1}(x, -K^\star_{H-1}x) \\
&= x^\top (A - BK)^\top P_H (A - BK)x + x^\top Q x + x^\top K^\top R K x + \sigma^2 \text{Trace}(P_H)
\end{aligned}
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- Continuing

$$\begin{aligned}
V^\star_{H-1}(x) - \sigma^2 \mathrm{Trace}(P_H) &= x^\top \Big((A - BK)^\top P_H (A - BK) + Q + K^\top RK \Big) x \\
&= x^\top \Big(AP_H A + Q - 2K^\top B^\top P_H A + K^\top (B^\top P_H B + R)K \Big) x \\
&= x^\top \Big(AP_H A + Q - 2K^\top (B^\top P_H B + R)K + K^\top (B^\top P_H B + R)K \Big) x \\
&= x^\top \Big(AP_H A + Q - K^\top (B^\top P_H B + R)K \Big) x \\
&= x^\top P_{H-1} x\,.
\end{aligned}$$

where the fourth step uses our expression for $K = K^\star_{H-1}$.

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- This implies that:

$$Q^\star_{H-2}(x,u) = E[V^\star_{H-1}(Ax+Bu+w_{H-2})] + x^\top Qx + u^\top Ru$$
$$= (Ax+Bu)^\top P_{H-1}(Ax+Bu) + \sigma^2\Big(\text{Trace}(P_{H-1}) + \text{Trace}(Q)\Big) + x^\top Qx + u^\top Ru\,.$$

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- The remainder of the proof follows from a recursive argument, which can be verified along identical lines to the $t = H-1$ case.

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(Note that P is a positive definite matrix).

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We have that P is unique and that the optimal average cost is $\sigma^2 \mathrm{Trace}(P)$.

Semidefinite Programs to find P

The Dual SDP:

- The dual optimization problem is:

$$\begin{aligned} &\text{minimize} \quad \text{Trace}\left(\Sigma \cdot \begin{bmatrix} Q & 0 \\ 0 & R \end{bmatrix}\right) \\ &\text{subject to} \quad \Sigma_{xx} = (A \quad B)\Sigma(A \quad B)^\top + \sigma^2 I, \quad \Sigma \succeq 0 \end{aligned}$$

where the optimization variable is Σ, a $(d+k) \times (d+k)$ matrix, with the block structure:

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- This SDP has a unique solution, say $\Sigma^\star$. The optimal gain matrix is then given by: $K^\star = -\Sigma^\star_{ux}(\Sigma^\star_{xx})^{-1}$

The Primal SDP:

(for the infinite horizon LQR)

- The primal optimization problem is given as:

$$\text{maximize} \quad \sigma^2 \mathrm{Trace}(P)$$

$$\text{subject to} \quad \begin{bmatrix} A^T P A + Q - P & A^\top P B \\ B^T P A & B^\top P B + R \end{bmatrix} \succeq 0, \quad P \succeq 0$$

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- This SDP has a unique solution, $P^\star$, which implies:
  - $P^\star$ satisfies the Ricatti equations.
  - The optimal average cost of the infinite horizon LQR is $\sigma^2 \text{Trace}(P^\star)$
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- Proof idea: Following from the Ricatti equation,
  we have the relaxation that for all matrices K, the matrix P must satisfy:

$$P \succeq A^T PA + Q - A^T PB(B^T PB + R)^{-1} B^T PA$$