

Deep Reinforcement Learning and Control

iLQR

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Optimal Control (Open Loop)

- The optimal control problem:

$$\min_{x,u} \sum_{t=0}^T c_t(x_t, u_t)$$

$$\text{s.t. } x_0 = \bar{x}_0$$

$$x_{t+1} = f(x_t, u_t) \quad t = 0, \dots, T-1$$

Optimal Control (Open Loop)

- The optimal control problem:

$$\begin{aligned} \min_{x,u} \quad & \sum_{t=0}^T c_t(x_t, u_t) \\ \text{s.t.} \quad & x_0 = \bar{x}_0 \end{aligned}$$

$$x_{t+1} = f(x_t, u_t) \quad t = 0, \dots, T-1$$

- Solution:
 - Sequence of controls u and resulting state sequence x
- In general non-convex optimization problem, can be solved with sequential convex programming (SCP): https://stanford.edu/class/ee364b/lectures/seq_slides.pdf

Optimal Control (Closed Loop a.k.a. MPC)

Given: \bar{x}_0

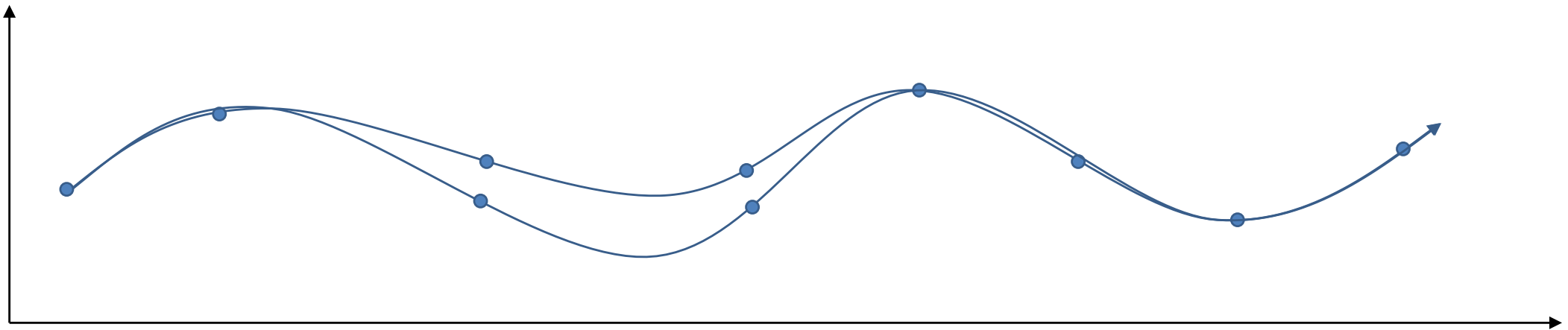
For $t = 0, 1, 2, \dots, T$

- Solve
$$\min_{x,u} \sum_{k=t}^T c_k(x_k, u_k)$$
s.t. $x_{k+1} = f(x_k, u_k), \quad \forall k \in \{t, t+1, \dots, T-1\}$
$$x_t = \bar{x}_t$$
- Execute u_t
- **Observe resulting state**, \bar{x}_{t+1}
- Initialize with solution from $t-1$ to solve fast at time t

Shooting methods vs collocation methods

Collocation Method: optimize over actions and state, with constraints

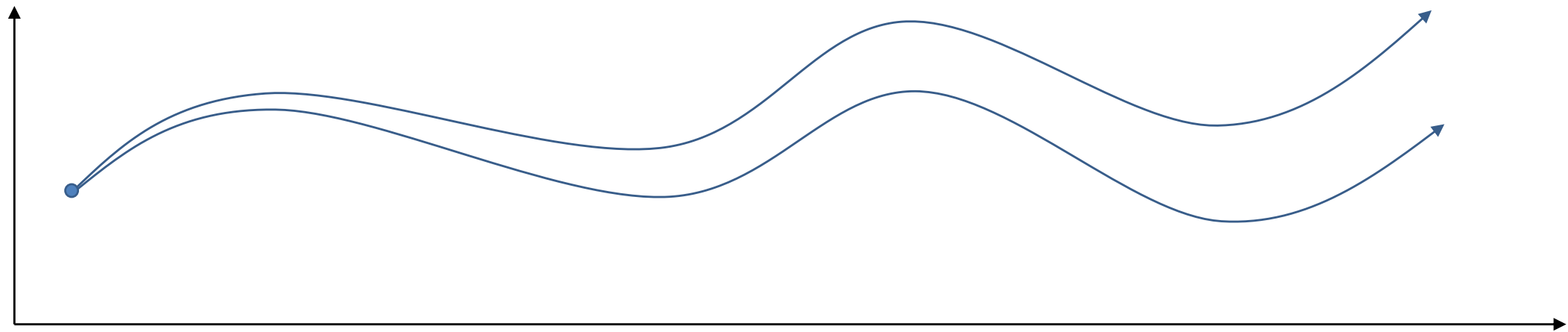
$$\min_{u_1, \dots, u_T, x_1, \dots, x_T} \sum_{t=1}^T c(x_t, u_t) \quad \text{s.t.} \quad x_t = f(x_{t-1}, u_{t-1})$$



Shooting methods vs collocation methods

Shooting Method: optimize over actions only

$$\min_{u_1, \dots, u_T} c(x_1, u_1) + c(f(x_1, u_1), u_2) + \dots + c(f(f(\dots)), u_T)$$



Indeed, x are not necessary since every u results (following the dynamics) in a state sequence x , for which in turn the cost can be computed

- Not clear how to initialize in a way that nudges towards a goal state

Bellman's Curse of Dimensionality

- n-dimensional state space
- Number of states grows exponentially in n (for fixed number of discretization levels per coordinate)
- In practice
 - Discretization is considered only computationally feasible up to 5 or 6 dimensional state spaces even when using
 - Variable resolution discretization
 - Highly optimized implementations

Linear case: LQR

- Very special case: Optimal Control for **Linear Dynamic** Systems and Quadratic Cost (a.k.a. LQ setting)
- Can solve continuous state-space optimal control problem **exactly**
- Running time: $O(Tn^3)$

$$\min_{\mathbf{u}_1, \dots, \mathbf{u}_T} c(\mathbf{x}_1, \mathbf{u}_1) + c(f(\mathbf{x}_1, \mathbf{u}_1), \mathbf{u}_2) + \dots + c(f(f(\dots)\dots), \mathbf{u}_T)$$

$$f(\mathbf{x}_t, \mathbf{u}_t) = \mathbf{F}_t \begin{bmatrix} \mathbf{x}_t \\ \mathbf{u}_t \end{bmatrix} + \mathbf{f}_t$$

linear

$$c(\mathbf{x}_t, \mathbf{u}_t) = \frac{1}{2} \begin{bmatrix} \mathbf{x}_t \\ \mathbf{u}_t \end{bmatrix}^T \mathbf{C}_t \begin{bmatrix} \mathbf{x}_t \\ \mathbf{u}_t \end{bmatrix} + \begin{bmatrix} \mathbf{x}_t \\ \mathbf{u}_t \end{bmatrix}^T \mathbf{c}_t$$

quadratic

Linear dynamics: Newtonian Dynamics



- $x_{t+1} = x_t + \Delta t \dot{x}_t + \Delta t^2 F_x$
- $y_{t+1} = y_t + \Delta t \dot{y}_t + \Delta t^2 F_y$
- $\dot{x}_{t+1} = \dot{x}_t + \Delta t F_x$
- $\dot{y}_{t+1} = \dot{y}_t + \Delta t F_y$

What is the state x ?

In most robotic tasks, state is hand engineered and includes:

- position and velocities of the robotic joints
- position and velocity of the object being manipulated

Those are both known: the robot knows its state and we perceive the state of the objects in the world. In tasks where we do not even want to bother with object state, we just concatenate the robotic state across multiple time steps to implicitly infer the interaction (collision with the object)

What is the cost $c(x_t, u_t)$

- $c(x_t, u_t) = \|x_t - x^*\| + \beta \|u_t\|$

x^* is the target state

- In the final time step, you can add a term with higher weight:

Final cost $c(x_T, u_T) = 2(\|x_T - x^*\| + \beta \|u_T\|)$

- For object manipulation, x^* includes not only desired pose of the end effector but also desired pose of the objects

Linear Quadratic Regulator (LQR)

$$\min_{\mathbf{u}_1, \dots, \mathbf{u}_T} c(\mathbf{x}_1, \mathbf{u}_1) + c(f(\mathbf{x}_1, \mathbf{u}_1), \mathbf{u}_2) + \dots + c(f(f(\dots)\dots), \mathbf{u}_T)$$

$$c(\mathbf{x}_t, \mathbf{u}_t) = \frac{1}{2} \begin{bmatrix} \mathbf{x}_t \\ \mathbf{u}_t \end{bmatrix}^T \mathbf{C}_t \begin{bmatrix} \mathbf{x}_t \\ \mathbf{u}_t \end{bmatrix} + \begin{bmatrix} \mathbf{x}_t \\ \mathbf{u}_t \end{bmatrix}^T \mathbf{c}_t$$

$$f(\mathbf{x}_t, \mathbf{u}_t) = \mathbf{F}_t \begin{bmatrix} \mathbf{x}_t \\ \mathbf{u}_t \end{bmatrix} + \mathbf{f}_t$$

Definitions:

$Q(x_t, u_t)$: **optimal** action value function, optimal cost-to-go at state x_t as a function of u_t assuming we act optimal past step t

$V(x_t)$: **optimal** state value function, optimal cost-to-go from state x_t

$$V(x_t) = \min_{u_t} Q(x_t, u_t)$$

x_0 : the initial state, **known and given**

Principle of Optimality

An optimal policy has the property that whatever the initial state and initial decision are, the remaining decisions must constitute an optimal policy with regard to the state resulting from the first decision. (See Bellman, 1957, Chap. III.3.)

Linear Quadratic Regulator (LQR)

$$\min_{\mathbf{u}_1, \dots, \mathbf{u}_T} c(\mathbf{x}_1, \mathbf{u}_1) + c(f(\mathbf{x}_1, \mathbf{u}_1), \mathbf{u}_2) + \dots + c(f(f(\dots)\dots), \mathbf{u}_T)$$

$$c(\mathbf{x}_t, \mathbf{u}_t) = \frac{1}{2} \begin{bmatrix} \mathbf{x}_t \\ \mathbf{u}_t \end{bmatrix}^T \mathbf{C}_t \begin{bmatrix} \mathbf{x}_t \\ \mathbf{u}_t \end{bmatrix} + \begin{bmatrix} \mathbf{x}_t \\ \mathbf{u}_t \end{bmatrix}^T \mathbf{c}_t$$

$$f(\mathbf{x}_t, \mathbf{u}_t) = \mathbf{F}_t \begin{bmatrix} \mathbf{x}_t \\ \mathbf{u}_t \end{bmatrix} + \mathbf{f}_t$$

Value iteration: backward propagation!

Start from u_T and work backwards

Linear Quadratic Regulator (LQR)

$$\min_{\mathbf{u}_1, \dots, \mathbf{u}_T} c(\mathbf{x}_1, \mathbf{u}_1) + c(f(\mathbf{x}_1, \mathbf{u}_1), \mathbf{u}_2) + \dots + \underbrace{c(f(f(\dots)), \mathbf{u}_T)}$$

$$c(\mathbf{x}_t, \mathbf{u}_t) = \frac{1}{2} \begin{bmatrix} \mathbf{x}_t \\ \mathbf{u}_t \end{bmatrix}^T \mathbf{C}_t \begin{bmatrix} \mathbf{x}_t \\ \mathbf{u}_t \end{bmatrix} + \begin{bmatrix} \mathbf{x}_t \\ \mathbf{u}_t \end{bmatrix}^T \mathbf{c}_t$$

only term that depends on \mathbf{u}_T

$$f(\mathbf{x}_t, \mathbf{u}_t) = \mathbf{F}_t \begin{bmatrix} \mathbf{x}_t \\ \mathbf{u}_t \end{bmatrix} + \mathbf{f}_t$$

Cost matrices

for the last time step:

$$\mathbf{C}_T = \begin{bmatrix} \mathbf{C}_{\mathbf{x}_T, \mathbf{x}_T} & \mathbf{C}_{\mathbf{x}_T, \mathbf{u}_T} \\ \mathbf{C}_{\mathbf{u}_T, \mathbf{x}_T} & \mathbf{C}_{\mathbf{u}_T, \mathbf{u}_T} \end{bmatrix}$$

$$\mathbf{c}_T = \begin{bmatrix} \mathbf{c}_{\mathbf{x}_T} \\ \mathbf{c}_{\mathbf{u}_T} \end{bmatrix}$$

Value iteration: backward propagation!

Start from u_T and work backwards

$$Q(\mathbf{x}_T, \mathbf{u}_T) = \text{const} + \frac{1}{2} \begin{bmatrix} \mathbf{x}_T \\ \mathbf{u}_T \end{bmatrix}^T \mathbf{C}_T \begin{bmatrix} \mathbf{x}_T \\ \mathbf{u}_T \end{bmatrix} + \begin{bmatrix} \mathbf{x}_T \\ \mathbf{u}_T \end{bmatrix}^T \mathbf{c}_T$$

Linear Quadratic Regulator (LQR)

$$\min_{\mathbf{u}_1, \dots, \mathbf{u}_T} c(\mathbf{x}_1, \mathbf{u}_1) + c(f(\mathbf{x}_1, \mathbf{u}_1), \mathbf{u}_2) + \dots + \underbrace{c(f(f(\dots)), \mathbf{u}_T)}$$

$$c(\mathbf{x}_t, \mathbf{u}_t) = \frac{1}{2} \begin{bmatrix} \mathbf{x}_t \\ \mathbf{u}_t \end{bmatrix}^T \mathbf{C}_t \begin{bmatrix} \mathbf{x}_t \\ \mathbf{u}_t \end{bmatrix} + \begin{bmatrix} \mathbf{x}_t \\ \mathbf{u}_t \end{bmatrix}^T \mathbf{c}_t$$

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$$\mathbf{c}_T = \begin{bmatrix} \mathbf{c}_{\mathbf{x}_T} \\ \mathbf{c}_{\mathbf{u}_T} \end{bmatrix}$$

Value iteration: backward propagation!

Start from \mathbf{u}_T and work backwards

$$Q(\mathbf{x}_T, \mathbf{u}_T) = \text{const} + \frac{1}{2} \begin{bmatrix} \mathbf{x}_T \\ \mathbf{u}_T \end{bmatrix}^T \mathbf{C}_T \begin{bmatrix} \mathbf{x}_T \\ \mathbf{u}_T \end{bmatrix} + \begin{bmatrix} \mathbf{x}_T \\ \mathbf{u}_T \end{bmatrix}^T \mathbf{c}_T$$

Set derivative to zero since we have a quadratic to find minimizing \mathbf{u}_T :

$$\nabla_{\mathbf{u}_T} Q(\mathbf{x}_T, \mathbf{u}_T) = \mathbf{C}_{\mathbf{u}_T, \mathbf{x}_T} \mathbf{x}_T + \mathbf{C}_{\mathbf{u}_T, \mathbf{u}_T} \mathbf{u}_T + \mathbf{c}_{\mathbf{u}_T}^T = 0$$

Linear Quadratic Regulator (LQR)

$$\min_{\mathbf{u}_1, \dots, \mathbf{u}_T} c(\mathbf{x}_1, \mathbf{u}_1) + c(f(\mathbf{x}_1, \mathbf{u}_1), \mathbf{u}_2) + \dots + \underbrace{c(f(f(\dots)), \mathbf{u}_T)}$$

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only term that depends on \mathbf{u}_T

$$f(\mathbf{x}_t, \mathbf{u}_t) = \mathbf{F}_t \begin{bmatrix} \mathbf{x}_t \\ \mathbf{u}_t \end{bmatrix} + \mathbf{f}_t$$

Cost matrices

for the last time step:

$$\mathbf{C}_T = \begin{bmatrix} \mathbf{C}_{\mathbf{x}_T, \mathbf{x}_T} & \mathbf{C}_{\mathbf{x}_T, \mathbf{u}_T} \\ \mathbf{C}_{\mathbf{u}_T, \mathbf{x}_T} & \mathbf{C}_{\mathbf{u}_T, \mathbf{u}_T} \end{bmatrix}$$

$$\mathbf{c}_T = \begin{bmatrix} \mathbf{c}_{\mathbf{x}_T} \\ \mathbf{c}_{\mathbf{u}_T} \end{bmatrix}$$

Value iteration: backward propagation!

Start from \mathbf{u}_T and work backwards

$$Q(\mathbf{x}_T, \mathbf{u}_T) = \text{const} + \frac{1}{2} \begin{bmatrix} \mathbf{x}_T \\ \mathbf{u}_T \end{bmatrix}^T \mathbf{C}_T \begin{bmatrix} \mathbf{x}_T \\ \mathbf{u}_T \end{bmatrix} + \begin{bmatrix} \mathbf{x}_T \\ \mathbf{u}_T \end{bmatrix}^T \mathbf{c}_T$$

Set derivative to zero since we have a quadratic to find minimizing \mathbf{u}_T :

$$\nabla_{\mathbf{u}_T} Q(\mathbf{x}_T, \mathbf{u}_T) = \mathbf{C}_{\mathbf{u}_T, \mathbf{x}_T} \mathbf{x}_T + \mathbf{C}_{\mathbf{u}_T, \mathbf{u}_T} \mathbf{u}_T + \mathbf{c}_{\mathbf{u}_T}^T = 0$$

$$\mathbf{u}_T = -\mathbf{C}_{\mathbf{u}_T, \mathbf{u}_T}^{-1} (\mathbf{C}_{\mathbf{u}_T, \mathbf{x}_T} \mathbf{x}_T + \mathbf{c}_{\mathbf{u}_T})$$

$$\mathbf{K}_T = -\mathbf{C}_{\mathbf{u}_T, \mathbf{u}_T}^{-1} \mathbf{C}_{\mathbf{u}_T, \mathbf{x}_T}$$

$$\mathbf{k}_T = -\mathbf{C}_{\mathbf{u}_T, \mathbf{u}_T}^{-1} \mathbf{c}_{\mathbf{u}_T}$$

$$\mathbf{u}_T = \mathbf{K}_T \mathbf{x}_T + \mathbf{k}_T$$

Linear Quadratic Regulator (LQR)

Remember: $V(x_t) = \min_{u_t} Q(x_t, u_t)$

Substituting the minimizer u_T into $Q(x_T, u_T)$ gives us $V(x_T)$!

Linear Quadratic Regulator (LQR)

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$$V(\mathbf{x}_T) = \text{const} + \frac{1}{2} \begin{bmatrix} \mathbf{x}_T \\ \mathbf{K}_T \mathbf{x}_T + \mathbf{k}_T \end{bmatrix}^T \mathbf{C}_T \begin{bmatrix} \mathbf{x}_T \\ \mathbf{K}_T \mathbf{x}_T + \mathbf{k}_T \end{bmatrix} + \begin{bmatrix} \mathbf{x}_T \\ \mathbf{K}_T \mathbf{x}_T + \mathbf{k}_T \end{bmatrix}^T \mathbf{c}_T$$

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$$V(\mathbf{x}_T) = \text{const} + \frac{1}{2} \begin{bmatrix} \mathbf{x}_T \\ \mathbf{K}_T \mathbf{x}_T + \mathbf{k}_T \end{bmatrix}^T \mathbf{C}_T \begin{bmatrix} \mathbf{x}_T \\ \mathbf{K}_T \mathbf{x}_T + \mathbf{k}_T \end{bmatrix} + \begin{bmatrix} \mathbf{x}_T \\ \mathbf{K}_T \mathbf{x}_T + \mathbf{k}_T \end{bmatrix}^T \mathbf{c}_T$$

$$V(\mathbf{x}_T) = \frac{1}{2} \mathbf{x}_T^T \mathbf{C}_{\mathbf{x}_T, \mathbf{x}_T} \mathbf{x}_T + \frac{1}{2} \mathbf{x}_T^T \mathbf{C}_{\mathbf{x}_T, \mathbf{u}_T} \mathbf{K}_T \mathbf{x}_T + \frac{1}{2} \mathbf{x}_T^T \mathbf{K}_T^T \mathbf{C}_{\mathbf{u}_T, \mathbf{x}_T} \mathbf{x}_T + \frac{1}{2} \mathbf{x}_T^T \mathbf{K}_T^T \mathbf{C}_{\mathbf{u}_T, \mathbf{u}_T} \mathbf{K}_T \mathbf{x}_T + \\ \mathbf{x}_T^T \mathbf{K}_T^T \mathbf{C}_{\mathbf{u}_T, \mathbf{u}_T} \mathbf{k}_T + \frac{1}{2} \mathbf{x}_T^T \mathbf{C}_{\mathbf{x}_T, \mathbf{u}_T} \mathbf{k}_T + \mathbf{x}_T^T \mathbf{c}_{\mathbf{x}_T} + \mathbf{x}_T^T \mathbf{K}_T^T \mathbf{c}_{\mathbf{u}_T} + \text{const}$$

Linear Quadratic Regulator (LQR)

Remember: $V(x_t) = \min_{u_t} Q(x_t, u_t)$

Substituting the minimizer u_T into $Q(x_T, u_T)$ gives us $V(x_T)$!

$$V(\mathbf{x}_T) = \text{const} + \frac{1}{2} \begin{bmatrix} \mathbf{x}_T \\ \mathbf{K}_T \mathbf{x}_T + \mathbf{k}_T \end{bmatrix}^T \mathbf{C}_T \begin{bmatrix} \mathbf{x}_T \\ \mathbf{K}_T \mathbf{x}_T + \mathbf{k}_T \end{bmatrix} + \begin{bmatrix} \mathbf{x}_T \\ \mathbf{K}_T \mathbf{x}_T + \mathbf{k}_T \end{bmatrix}^T \mathbf{c}_T$$

$$V(\mathbf{x}_T) = \frac{1}{2} \mathbf{x}_T^T \mathbf{C}_{\mathbf{x}_T, \mathbf{x}_T} \mathbf{x}_T + \frac{1}{2} \mathbf{x}_T^T \mathbf{C}_{\mathbf{x}_T, \mathbf{u}_T} \mathbf{K}_T \mathbf{x}_T + \frac{1}{2} \mathbf{x}_T^T \mathbf{K}_T^T \mathbf{C}_{\mathbf{u}_T, \mathbf{x}_T} \mathbf{x}_T + \frac{1}{2} \mathbf{x}_T^T \mathbf{K}_T^T \mathbf{C}_{\mathbf{u}_T, \mathbf{u}_T} \mathbf{K}_T \mathbf{x}_T + \\ \mathbf{x}_T^T \mathbf{K}_T^T \mathbf{C}_{\mathbf{u}_T, \mathbf{u}_T} \mathbf{k}_T + \frac{1}{2} \mathbf{x}_T^T \mathbf{C}_{\mathbf{x}_T, \mathbf{u}_T} \mathbf{k}_T + \mathbf{x}_T^T \mathbf{c}_{\mathbf{x}_T} + \mathbf{x}_T^T \mathbf{K}_T^T \mathbf{c}_{\mathbf{u}_T} + \text{const}$$

$$V(\mathbf{x}_T) = \text{const} + \frac{1}{2} \mathbf{x}_T^T \mathbf{V}_T \mathbf{x}_T + \mathbf{x}_T^T \mathbf{v}_T$$

$$\mathbf{V}_T = \mathbf{C}_{\mathbf{x}_T, \mathbf{x}_T} + \mathbf{C}_{\mathbf{x}_T, \mathbf{u}_T} \mathbf{K}_T + \mathbf{K}_T^T \mathbf{C}_{\mathbf{u}_T, \mathbf{x}_T} + \mathbf{K}_T^T \mathbf{C}_{\mathbf{u}_T, \mathbf{u}_T} \mathbf{K}_T$$

$$\mathbf{v}_T = \mathbf{c}_{\mathbf{x}_T} + \mathbf{C}_{\mathbf{x}_T, \mathbf{u}_T} \mathbf{k}_T + \mathbf{K}_T^T \mathbf{c}_{\mathbf{u}_T} + \mathbf{K}_T^T \mathbf{C}_{\mathbf{u}_T, \mathbf{u}_T} \mathbf{k}_T$$

Linear Quadratic Regulator (LQR)

Remember: $V(x_t) = \min_{u_t} Q(x_t, u_t)$

Substituting the minimizer u_T into $Q(x_T, u_T)$ gives us $V(x_T)$!

$$V(\mathbf{x}_T) = \text{const} + \frac{1}{2} \begin{bmatrix} \mathbf{x}_T \\ \mathbf{K}_T \mathbf{x}_T + \mathbf{k}_T \end{bmatrix}^T \mathbf{C}_T \begin{bmatrix} \mathbf{x}_T \\ \mathbf{K}_T \mathbf{x}_T + \mathbf{k}_T \end{bmatrix} + \begin{bmatrix} \mathbf{x}_T \\ \mathbf{K}_T \mathbf{x}_T + \mathbf{k}_T \end{bmatrix}^T \mathbf{c}_T$$

$$V(\mathbf{x}_T) = \frac{1}{2} \mathbf{x}_T^T \mathbf{C}_{\mathbf{x}_T, \mathbf{x}_T} \mathbf{x}_T + \frac{1}{2} \mathbf{x}_T^T \mathbf{C}_{\mathbf{x}_T, \mathbf{u}_T} \mathbf{K}_T \mathbf{x}_T + \frac{1}{2} \mathbf{x}_T^T \mathbf{K}_T^T \mathbf{C}_{\mathbf{u}_T, \mathbf{x}_T} \mathbf{x}_T + \frac{1}{2} \mathbf{x}_T^T \mathbf{K}_T^T \mathbf{C}_{\mathbf{u}_T, \mathbf{u}_T} \mathbf{K}_T \mathbf{x}_T + \\ \mathbf{x}_T^T \mathbf{K}_T^T \mathbf{C}_{\mathbf{u}_T, \mathbf{u}_T} \mathbf{k}_T + \frac{1}{2} \mathbf{x}_T^T \mathbf{C}_{\mathbf{x}_T, \mathbf{u}_T} \mathbf{k}_T + \mathbf{x}_T^T \mathbf{c}_{\mathbf{x}_T} + \mathbf{x}_T^T \mathbf{K}_T^T \mathbf{c}_{\mathbf{u}_T} + \text{const}$$

$$V(\mathbf{x}_T) = \text{const} + \frac{1}{2} \mathbf{x}_T^T \mathbf{V}_T \mathbf{x}_T + \mathbf{x}_T^T \mathbf{v}_T$$

optimal cost-to-go as a function of
the final state

$$\mathbf{V}_T = \mathbf{C}_{\mathbf{x}_T, \mathbf{x}_T} + \mathbf{C}_{\mathbf{x}_T, \mathbf{u}_T} \mathbf{K}_T + \mathbf{K}_T^T \mathbf{C}_{\mathbf{u}_T, \mathbf{x}_T} + \mathbf{K}_T^T \mathbf{C}_{\mathbf{u}_T, \mathbf{u}_T} \mathbf{K}_T$$

$$\mathbf{v}_T = \mathbf{c}_{\mathbf{x}_T} + \mathbf{C}_{\mathbf{x}_T, \mathbf{u}_T} \mathbf{k}_T + \mathbf{K}_T^T \mathbf{c}_{\mathbf{u}_T} + \mathbf{K}_T^T \mathbf{C}_{\mathbf{u}_T, \mathbf{u}_T} \mathbf{k}_T$$

Linear Quadratic Regulator (LQR)

We propagate the optimal value function backwards!!

cost at T-1

best cost-to-go

$$Q(\mathbf{x}_{T-1}, \mathbf{u}_{T-1}) = \text{const} + \frac{1}{2} \begin{bmatrix} \mathbf{x}_{T-1} \\ \mathbf{u}_{T-1} \end{bmatrix}^T \mathbf{C}_{T-1} \begin{bmatrix} \mathbf{x}_{T-1} \\ \mathbf{u}_{T-1} \end{bmatrix} + \begin{bmatrix} \mathbf{x}_{T-1} \\ \mathbf{u}_{T-1} \end{bmatrix}^T \mathbf{c}_{T-1} + V(f(\mathbf{x}_{T-1}, \mathbf{u}_{T-1}))$$

Linear Quadratic Regulator (LQR)

We propagate the optimal value function backwards!!

cost at T-1

best cost-to-go

$$Q(\mathbf{x}_{T-1}, \mathbf{u}_{T-1}) = \text{const} + \underbrace{\frac{1}{2} \begin{bmatrix} \mathbf{x}_{T-1} \\ \mathbf{u}_{T-1} \end{bmatrix}^T \mathbf{C}_{T-1} \begin{bmatrix} \mathbf{x}_{T-1} \\ \mathbf{u}_{T-1} \end{bmatrix} + \begin{bmatrix} \mathbf{x}_{T-1} \\ \mathbf{u}_{T-1} \end{bmatrix}^T \mathbf{c}_{T-1}}_{\text{cost at T-1}} + \underbrace{V(f(\mathbf{x}_{T-1}, \mathbf{u}_{T-1}))}_{\text{best cost-to-go}}$$
$$V(\mathbf{x}_T) = \text{const} + \frac{1}{2} \mathbf{x}_T^T \mathbf{V}_T \mathbf{x}_T + \mathbf{x}_T^T \mathbf{v}_T$$

Linear Quadratic Regulator (LQR)

We propagate the optimal value function backwards!!

cost at T-1

best cost-to-go

$$Q(\mathbf{x}_{T-1}, \mathbf{u}_{T-1}) = \text{const} + \underbrace{\frac{1}{2} \begin{bmatrix} \mathbf{x}_{T-1} \\ \mathbf{u}_{T-1} \end{bmatrix}^T \mathbf{C}_{T-1} \begin{bmatrix} \mathbf{x}_{T-1} \\ \mathbf{u}_{T-1} \end{bmatrix} + \begin{bmatrix} \mathbf{x}_{T-1} \\ \mathbf{u}_{T-1} \end{bmatrix}^T \mathbf{c}_{T-1}}_{\text{cost at T-1}} + \underbrace{V(f(\mathbf{x}_{T-1}, \mathbf{u}_{T-1}))}_{\text{best cost-to-go}}$$

$$q_*(s, a) = \underbrace{r(s, a)}_{\text{cost at T-1}} + \gamma \sum_{s' \in S} T(s'|s, a) \underbrace{v_*(s')}_{\text{best cost-to-go}}$$

$V(\mathbf{x}_T) = \text{const} + \frac{1}{2} \mathbf{x}_T^T \mathbf{V}_T \mathbf{x}_T + \mathbf{x}_T^T \mathbf{v}_T$

Linear Quadratic Regulator (LQR)

We propagate the optimal value function backwards!!

Immediate cost

best cost-to-go

$$Q(\mathbf{x}_{T-1}, \mathbf{u}_{T-1}) = \text{const} + \underbrace{\frac{1}{2} \begin{bmatrix} \mathbf{x}_{T-1} \\ \mathbf{u}_{T-1} \end{bmatrix}^T \mathbf{C}_{T-1} \begin{bmatrix} \mathbf{x}_{T-1} \\ \mathbf{u}_{T-1} \end{bmatrix} + \begin{bmatrix} \mathbf{x}_{T-1} \\ \mathbf{u}_{T-1} \end{bmatrix}^T \mathbf{c}_{T-1}}_{\text{Immediate cost}} + \underbrace{V(f(\mathbf{x}_{T-1}, \mathbf{u}_{T-1}))}_{\text{best cost-to-go}}$$

$$q_*(s, a) = \underbrace{r(s, a)}_{\text{Immediate cost}} + \gamma \sum_{s' \in S} T(s'|s, a) \underbrace{v_*(s')}_{\text{best cost-to-go}}$$

$V(\mathbf{x}_T) = \text{const} + \frac{1}{2} \mathbf{x}_T^T \mathbf{V}_T \mathbf{x}_T + \mathbf{x}_T^T \mathbf{v}_T$

We can eliminate \mathbf{x}_T by writing only in terms of quantities of $T-1$!

Linear Quadratic Regulator (LQR)

We propagate the optimal value function backwards!!

Immediate cost

best cost-to-go

$$Q(\mathbf{x}_{T-1}, \mathbf{u}_{T-1}) = \text{const} + \underbrace{\frac{1}{2} \begin{bmatrix} \mathbf{x}_{T-1} \\ \mathbf{u}_{T-1} \end{bmatrix}^T \mathbf{C}_{T-1} \begin{bmatrix} \mathbf{x}_{T-1} \\ \mathbf{u}_{T-1} \end{bmatrix} + \begin{bmatrix} \mathbf{x}_{T-1} \\ \mathbf{u}_{T-1} \end{bmatrix}^T \mathbf{c}_{T-1}}_{\text{Immediate cost}} + \underbrace{V(f(\mathbf{x}_{T-1}, \mathbf{u}_{T-1}))}_{\text{best cost-to-go}}$$

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We can eliminate \mathbf{x}_T by writing only in terms of quantities of $T-1$!

$$f(\mathbf{x}_{T-1}, \mathbf{u}_{T-1}) = \mathbf{x}_T = \mathbf{F}_{T-1} \begin{bmatrix} \mathbf{x}_{T-1} \\ \mathbf{u}_{T-1} \end{bmatrix} + \mathbf{f}_{T-1}$$

Linear Quadratic Regulator (LQR)

We propagate the optimal value function backwards!!

Immediate cost

best cost-to-go

$$Q(\mathbf{x}_{T-1}, \mathbf{u}_{T-1}) = \text{const} + \underbrace{\frac{1}{2} \begin{bmatrix} \mathbf{x}_{T-1} \\ \mathbf{u}_{T-1} \end{bmatrix}^T \mathbf{C}_{T-1} \begin{bmatrix} \mathbf{x}_{T-1} \\ \mathbf{u}_{T-1} \end{bmatrix} + \begin{bmatrix} \mathbf{x}_{T-1} \\ \mathbf{u}_{T-1} \end{bmatrix}^T \mathbf{c}_{T-1}}_{\text{Immediate cost}} + \underbrace{V(f(\mathbf{x}_{T-1}, \mathbf{u}_{T-1}))}_{\text{best cost-to-go}}$$

$$q_*(s, a) = \underbrace{r(s, a)}_{\text{Immediate cost}} + \gamma \sum_{s' \in S} T(s'|s, a) \underbrace{v_*(s')}_{\text{best cost-to-go}}$$

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$$V(\mathbf{x}_T) = \text{const} + \underbrace{\frac{1}{2} \begin{bmatrix} \mathbf{x}_{T-1} \\ \mathbf{u}_{T-1} \end{bmatrix}^T \mathbf{F}_{T-1}^T \mathbf{V}_T \mathbf{F}_{T-1} \begin{bmatrix} \mathbf{x}_{T-1} \\ \mathbf{u}_{T-1} \end{bmatrix}}_{\text{quadratic}} + \underbrace{\begin{bmatrix} \mathbf{x}_{T-1} \\ \mathbf{u}_{T-1} \end{bmatrix}^T \mathbf{F}_{T-1}^T \mathbf{V}_T \mathbf{f}_{T-1}}_{\text{linear}} + \underbrace{\begin{bmatrix} \mathbf{x}_{T-1} \\ \mathbf{u}_{T-1} \end{bmatrix}^T \mathbf{F}_{T-1}^T \mathbf{v}_T}_{\text{linear}}$$

Linear Quadratic Regulator (LQR)

We propagate the optimal value function backwards!!

Immediate cost

best cost-to-go

$$Q(\mathbf{x}_{T-1}, \mathbf{u}_{T-1}) = \text{const} + \underbrace{\frac{1}{2} \begin{bmatrix} \mathbf{x}_{T-1} \\ \mathbf{u}_{T-1} \end{bmatrix}^T \mathbf{C}_{T-1} \begin{bmatrix} \mathbf{x}_{T-1} \\ \mathbf{u}_{T-1} \end{bmatrix} + \begin{bmatrix} \mathbf{x}_{T-1} \\ \mathbf{u}_{T-1} \end{bmatrix}^T \mathbf{c}_{T-1}}_{\text{Immediate cost}} + \underbrace{V(f(\mathbf{x}_{T-1}, \mathbf{u}_{T-1}))}_{\text{best cost-to-go}}$$

$$q_*(s, a) = \underbrace{r(s, a)}_{\text{Immediate cost}} + \gamma \sum_{s' \in S} T(s'|s, a) \underbrace{v_*(s')}_{\text{best cost-to-go}}$$

$V(\mathbf{x}_T) = \text{const} + \frac{1}{2} \mathbf{x}_T^T \mathbf{V}_T \mathbf{x}_T + \mathbf{x}_T^T \mathbf{v}_T$

We can eliminate \mathbf{x}_T by writing only in terms of quantities of $T-1$!

$$f(\mathbf{x}_{T-1}, \mathbf{u}_{T-1}) = \mathbf{x}_T = \mathbf{F}_{T-1} \begin{bmatrix} \mathbf{x}_{T-1} \\ \mathbf{u}_{T-1} \end{bmatrix} + \mathbf{f}_{T-1}$$

$$V(\mathbf{x}_T) = \text{const} + \underbrace{\frac{1}{2} \begin{bmatrix} \mathbf{x}_{T-1} \\ \mathbf{u}_{T-1} \end{bmatrix}^T \mathbf{F}_{T-1}^T \mathbf{V}_T \mathbf{F}_{T-1} \begin{bmatrix} \mathbf{x}_{T-1} \\ \mathbf{u}_{T-1} \end{bmatrix}}_{\text{quadratic}} + \underbrace{\begin{bmatrix} \mathbf{x}_{T-1} \\ \mathbf{u}_{T-1} \end{bmatrix}^T \mathbf{F}_{T-1}^T \mathbf{V}_T \mathbf{f}_{T-1}}_{\text{linear}} + \underbrace{\begin{bmatrix} \mathbf{x}_{T-1} \\ \mathbf{u}_{T-1} \end{bmatrix}^T \mathbf{F}_{T-1}^T \mathbf{v}_T}_{\text{linear}}$$

We have written $V(x_T)$ only in terms of x_{T-1}, u_{T-1} !

Linear Quadratic Regulator (LQR)

We propagate the optimal value function backwards!!

Immediate cost

best cost-to-go

$$Q(\mathbf{x}_{T-1}, \mathbf{u}_{T-1}) = \text{const} + \frac{1}{2} \begin{bmatrix} \mathbf{x}_{T-1} \\ \mathbf{u}_{T-1} \end{bmatrix}^T \mathbf{C}_{T-1} \begin{bmatrix} \mathbf{x}_{T-1} \\ \mathbf{u}_{T-1} \end{bmatrix} + \begin{bmatrix} \mathbf{x}_{T-1} \\ \mathbf{u}_{T-1} \end{bmatrix}^T \mathbf{c}_{T-1} + V(f(\mathbf{x}_{T-1}, \mathbf{u}_{T-1}))$$



$$Q(\mathbf{x}_{T-1}, \mathbf{u}_{T-1}) = \text{const} + \frac{1}{2} \begin{bmatrix} \mathbf{x}_{T-1} \\ \mathbf{u}_{T-1} \end{bmatrix}^T \mathbf{Q}_{T-1} \begin{bmatrix} \mathbf{x}_{T-1} \\ \mathbf{u}_{T-1} \end{bmatrix} + \begin{bmatrix} \mathbf{x}_{T-1} \\ \mathbf{u}_{T-1} \end{bmatrix}^T \mathbf{q}_{T-1}$$

$$\mathbf{Q}_{T-1} = \mathbf{C}_{T-1} + \mathbf{F}_{T-1}^T \mathbf{V}_T \mathbf{F}_{T-1}$$

$$\mathbf{q}_{T-1} = \mathbf{c}_{T-1} + \mathbf{F}_{T-1}^T \mathbf{V}_T \mathbf{f}_{T-1} + \mathbf{F}_{T-1}^T \mathbf{v}_T$$

Linear Quadratic Regulator (LQR)

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Immediate cost

best cost-to-go

$$Q(\mathbf{x}_{T-1}, \mathbf{u}_{T-1}) = \text{const} + \frac{1}{2} \begin{bmatrix} \mathbf{x}_{T-1} \\ \mathbf{u}_{T-1} \end{bmatrix}^T \mathbf{C}_{T-1} \begin{bmatrix} \mathbf{x}_{T-1} \\ \mathbf{u}_{T-1} \end{bmatrix} + \begin{bmatrix} \mathbf{x}_{T-1} \\ \mathbf{u}_{T-1} \end{bmatrix}^T \mathbf{c}_{T-1} + V(f(\mathbf{x}_{T-1}, \mathbf{u}_{T-1}))$$



$$Q(\mathbf{x}_{T-1}, \mathbf{u}_{T-1}) = \text{const} + \frac{1}{2} \begin{bmatrix} \mathbf{x}_{T-1} \\ \mathbf{u}_{T-1} \end{bmatrix}^T \mathbf{Q}_{T-1} \begin{bmatrix} \mathbf{x}_{T-1} \\ \mathbf{u}_{T-1} \end{bmatrix} + \begin{bmatrix} \mathbf{x}_{T-1} \\ \mathbf{u}_{T-1} \end{bmatrix}^T \mathbf{q}_{T-1}$$

$$\mathbf{Q}_{T-1} = \mathbf{C}_{T-1} + \mathbf{F}_{T-1}^T \mathbf{V}_T \mathbf{F}_{T-1}$$

$$\mathbf{q}_{T-1} = \mathbf{c}_{T-1} + \mathbf{F}_{T-1}^T \mathbf{V}_T \mathbf{f}_{T-1} + \mathbf{F}_{T-1}^T \mathbf{v}_T$$

We have written optimal action value function $Q(x_{T-1}, u_{T-1})$ only in terms of x_{T-1}, u_{T-1} !

Linear Quadratic Regulator (LQR)

We propagate the optimal value function backwards!!

Immediate cost

best cost-to-go

$$Q(\mathbf{x}_{T-1}, \mathbf{u}_{T-1}) = \text{const} + \frac{1}{2} \begin{bmatrix} \mathbf{x}_{T-1} \\ \mathbf{u}_{T-1} \end{bmatrix}^T \mathbf{C}_{T-1} \begin{bmatrix} \mathbf{x}_{T-1} \\ \mathbf{u}_{T-1} \end{bmatrix} + \begin{bmatrix} \mathbf{x}_{T-1} \\ \mathbf{u}_{T-1} \end{bmatrix}^T \mathbf{c}_{T-1} + V(f(\mathbf{x}_{T-1}, \mathbf{u}_{T-1}))$$



$$Q(\mathbf{x}_{T-1}, \mathbf{u}_{T-1}) = \text{const} + \frac{1}{2} \begin{bmatrix} \mathbf{x}_{T-1} \\ \mathbf{u}_{T-1} \end{bmatrix}^T \mathbf{Q}_{T-1} \begin{bmatrix} \mathbf{x}_{T-1} \\ \mathbf{u}_{T-1} \end{bmatrix} + \begin{bmatrix} \mathbf{x}_{T-1} \\ \mathbf{u}_{T-1} \end{bmatrix}^T \mathbf{q}_{T-1}$$

$$\mathbf{Q}_{T-1} = \mathbf{C}_{T-1} + \mathbf{F}_{T-1}^T \mathbf{V}_T \mathbf{F}_{T-1}$$

$$\mathbf{q}_{T-1} = \mathbf{c}_{T-1} + \mathbf{F}_{T-1}^T \mathbf{V}_T \mathbf{f}_{T-1} + \mathbf{F}_{T-1}^T \mathbf{v}_T$$

We have written optimal action value function $Q(x_{T-1}, u_{T-1})$ only in terms of x_{T-1}, u_{T-1} !

Let's take derivative to find the minimizing $u_{\{T-1\}}$!

Linear Quadratic Regulator (LQR)

We propagate the optimal value function backwards!!

Immediate cost

best cost-to-go

$$Q(\mathbf{x}_{T-1}, \mathbf{u}_{T-1}) = \text{const} + \frac{1}{2} \begin{bmatrix} \mathbf{x}_{T-1} \\ \mathbf{u}_{T-1} \end{bmatrix}^T \mathbf{C}_{T-1} \begin{bmatrix} \mathbf{x}_{T-1} \\ \mathbf{u}_{T-1} \end{bmatrix} + \begin{bmatrix} \mathbf{x}_{T-1} \\ \mathbf{u}_{T-1} \end{bmatrix}^T \mathbf{c}_{T-1} + V(f(\mathbf{x}_{T-1}, \mathbf{u}_{T-1}))$$



$$Q(\mathbf{x}_{T-1}, \mathbf{u}_{T-1}) = \text{const} + \frac{1}{2} \begin{bmatrix} \mathbf{x}_{T-1} \\ \mathbf{u}_{T-1} \end{bmatrix}^T \mathbf{Q}_{T-1} \begin{bmatrix} \mathbf{x}_{T-1} \\ \mathbf{u}_{T-1} \end{bmatrix} + \begin{bmatrix} \mathbf{x}_{T-1} \\ \mathbf{u}_{T-1} \end{bmatrix}^T \mathbf{q}_{T-1}$$

$$\mathbf{Q}_{T-1} = \mathbf{C}_{T-1} + \mathbf{F}_{T-1}^T \mathbf{V}_T \mathbf{F}_{T-1}$$

$$\mathbf{q}_{T-1} = \mathbf{c}_{T-1} + \mathbf{F}_{T-1}^T \mathbf{V}_T \mathbf{f}_{T-1} + \mathbf{F}_{T-1}^T \mathbf{v}_T$$

We have written optimal action value function $Q(x_{T-1}, u_{T-1})$ only in terms of x_{T-1}, u_{T-1} !

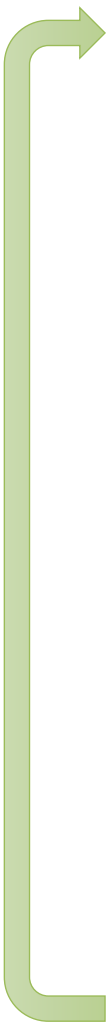
Let's take derivative to find the minimizing \mathbf{u}_{T-1} !

$$\nabla_{\mathbf{u}_{T-1}} Q(\mathbf{x}_{T-1}, \mathbf{u}_{T-1}) = \mathbf{Q}_{\mathbf{u}_{T-1}, \mathbf{x}_{T-1}} \mathbf{x}_{T-1} + \mathbf{Q}_{\mathbf{u}_{T-1}, \mathbf{u}_{T-1}} \mathbf{u}_{T-1} + \mathbf{q}_{\mathbf{u}_{T-1}}^T = 0$$

$$\mathbf{u}_{T-1} = \mathbf{K}_{T-1} \mathbf{x}_{T-1} + \mathbf{k}_{T-1} \quad \mathbf{K}_{T-1} = -\mathbf{Q}_{\mathbf{u}_{T-1}, \mathbf{u}_{T-1}}^{-1} \mathbf{Q}_{\mathbf{u}_{T-1}, \mathbf{x}_{T-1}} \quad \mathbf{k}_{T-1} = -\mathbf{Q}_{\mathbf{u}_{T-1}, \mathbf{u}_{T-1}}^{-1} \mathbf{q}_{\mathbf{u}_{T-1}}$$

Linear case: LQR

Backward recursion:



for $t = T$ to 1:

$$\mathbf{Q}_t = \mathbf{C}_t + \mathbf{F}_t^T \mathbf{V}_{t+1} \mathbf{F}_t$$

$$\mathbf{q}_t = \mathbf{c}_t + \mathbf{F}_t^T \mathbf{V}_{t+1} \mathbf{f}_t + \mathbf{F}_t^T \mathbf{v}_{t+1}$$

$$Q(\mathbf{x}_t, \mathbf{u}_t) = \text{const} + \frac{1}{2} \begin{bmatrix} \mathbf{x}_t \\ \mathbf{u}_t \end{bmatrix}^T \mathbf{Q}_t \begin{bmatrix} \mathbf{x}_t \\ \mathbf{u}_t \end{bmatrix} + \begin{bmatrix} \mathbf{x}_t \\ \mathbf{u}_t \end{bmatrix}^T \mathbf{q}_t$$

$$\mathbf{u}_t \leftarrow \arg \min_{\mathbf{u}_t} Q(\mathbf{x}_t, \mathbf{u}_t) = \mathbf{K}_t \mathbf{x}_t + \mathbf{k}_t$$

$$\mathbf{K}_t = -\mathbf{Q}_{\mathbf{u}_t, \mathbf{u}_t}^{-1} \mathbf{Q}_{\mathbf{u}_t, \mathbf{x}_t}$$

$$\mathbf{k}_t = -\mathbf{Q}_{\mathbf{u}_t, \mathbf{u}_t}^{-1} \mathbf{q}_{\mathbf{u}_t}$$

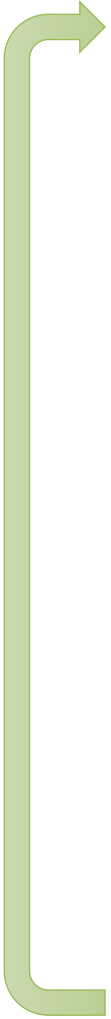
$$\mathbf{V}_t = \mathbf{Q}_{\mathbf{x}_t, \mathbf{x}_t} + \mathbf{Q}_{\mathbf{x}_t, \mathbf{u}_t} \mathbf{K}_t + \mathbf{K}_t^T \mathbf{Q}_{\mathbf{u}_t, \mathbf{x}_t} + \mathbf{K}_t^T \mathbf{Q}_{\mathbf{u}_t, \mathbf{u}_t} \mathbf{K}_t$$

$$\mathbf{v}_t = \mathbf{q}_{\mathbf{x}_t} + \mathbf{Q}_{\mathbf{x}_t, \mathbf{u}_t} \mathbf{k}_t + \mathbf{K}_t^T \mathbf{q}_{\mathbf{u}_t} + \mathbf{K}_t^T \mathbf{Q}_{\mathbf{u}_t, \mathbf{u}_t} \mathbf{k}_t$$

$$V(\mathbf{x}_t) = \text{const} + \frac{1}{2} \mathbf{x}_t^T \mathbf{V}_t \mathbf{x}_t + \mathbf{x}_t^T \mathbf{v}_t$$

Linear case: LQR

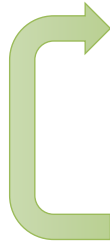
Backward recursion:



for $t = T$ to 1:

$$\mathbf{Q}_t = \mathbf{C}_t + \mathbf{F}_t^T \mathbf{V}_{t+1} \mathbf{F}_t$$
$$\mathbf{q}_t = \mathbf{c}_t + \mathbf{F}_t^T \mathbf{V}_{t+1} \mathbf{f}_t + \mathbf{F}_t^T \mathbf{v}_{t+1}$$
$$Q(\mathbf{x}_t, \mathbf{u}_t) = \text{const} + \frac{1}{2} \begin{bmatrix} \mathbf{x}_t \\ \mathbf{u}_t \end{bmatrix}^T \mathbf{Q}_t \begin{bmatrix} \mathbf{x}_t \\ \mathbf{u}_t \end{bmatrix} + \begin{bmatrix} \mathbf{x}_t \\ \mathbf{u}_t \end{bmatrix}^T \mathbf{q}_t$$
$$\mathbf{u}_t \leftarrow \arg \min_{\mathbf{u}_t} Q(\mathbf{x}_t, \mathbf{u}_t) = \mathbf{K}_t \mathbf{x}_t + \mathbf{k}_t$$
$$\mathbf{K}_t = -\mathbf{Q}_{\mathbf{u}_t, \mathbf{u}_t}^{-1} \mathbf{Q}_{\mathbf{u}_t, \mathbf{x}_t}$$
$$\mathbf{k}_t = -\mathbf{Q}_{\mathbf{u}_t, \mathbf{u}_t}^{-1} \mathbf{q}_{\mathbf{u}_t}$$
$$\mathbf{V}_t = \mathbf{Q}_{\mathbf{x}_t, \mathbf{x}_t} + \mathbf{Q}_{\mathbf{x}_t, \mathbf{u}_t} \mathbf{K}_t + \mathbf{K}_t^T \mathbf{Q}_{\mathbf{u}_t, \mathbf{x}_t} + \mathbf{K}_t^T \mathbf{Q}_{\mathbf{u}_t, \mathbf{u}_t} \mathbf{K}_t$$
$$\mathbf{v}_t = \mathbf{q}_{\mathbf{x}_t} + \mathbf{Q}_{\mathbf{x}_t, \mathbf{u}_t} \mathbf{k}_t + \mathbf{K}_t^T \mathbf{q}_{\mathbf{u}_t} + \mathbf{K}_t^T \mathbf{Q}_{\mathbf{u}_t, \mathbf{u}_t} \mathbf{k}_t$$
$$V(\mathbf{x}_t) = \text{const} + \frac{1}{2} \mathbf{x}_t^T \mathbf{V}_t \mathbf{x}_t + \mathbf{x}_t^T \mathbf{v}_t$$

Forward recursion:



for $t = 1$ to T :

$$\mathbf{u}_t = \mathbf{K}_t \mathbf{x}_t + \mathbf{k}_t$$
$$\mathbf{x}_{t+1} = f(\mathbf{x}_t, \mathbf{u}_t)$$

We know \mathbf{x}_0 !

Non-linear case: Use iterative approximations!

First order Taylor expansion for the dynamics around a trajectory $\hat{x}_t, \hat{u}_t, t = 1 \dots T$:

$$f(\mathbf{x}_t, \mathbf{u}_t) \approx f(\hat{\mathbf{x}}_t, \hat{\mathbf{u}}_t) + \nabla_{\mathbf{x}_t, \mathbf{u}_t} f(\hat{\mathbf{x}}_t, \hat{\mathbf{u}}_t) \begin{bmatrix} \mathbf{x}_t - \hat{\mathbf{x}}_t \\ \mathbf{u}_t - \hat{\mathbf{u}}_t \end{bmatrix}$$

Second order Taylor expansion for the cost around a trajectory $\hat{x}_t, \hat{u}_t, t = 1 \dots T$:

$$c(\mathbf{x}_t, \mathbf{u}_t) \approx c(\hat{\mathbf{x}}_t, \hat{\mathbf{u}}_t) + \nabla_{\mathbf{x}_t, \mathbf{u}_t} c(\hat{\mathbf{x}}_t, \hat{\mathbf{u}}_t) \begin{bmatrix} \mathbf{x}_t - \hat{\mathbf{x}}_t \\ \mathbf{u}_t - \hat{\mathbf{u}}_t \end{bmatrix} + \frac{1}{2} \begin{bmatrix} \mathbf{x}_t - \hat{\mathbf{x}}_t \\ \mathbf{u}_t - \hat{\mathbf{u}}_t \end{bmatrix}^T \nabla_{\mathbf{x}_t, \mathbf{u}_t}^2 c(\hat{\mathbf{x}}_t, \hat{\mathbf{u}}_t) \begin{bmatrix} \mathbf{x}_t - \hat{\mathbf{x}}_t \\ \mathbf{u}_t - \hat{\mathbf{u}}_t \end{bmatrix}$$

Non-linear case: Use iterative approximations!

First order Taylor expansion for the dynamics around a trajectory $\hat{x}_t, \hat{u}_t, t = 1 \dots T$:

$$f(\mathbf{x}_t, \mathbf{u}_t) \approx f(\hat{\mathbf{x}}_t, \hat{\mathbf{u}}_t) + \nabla_{\mathbf{x}_t, \mathbf{u}_t} f(\hat{\mathbf{x}}_t, \hat{\mathbf{u}}_t) \begin{bmatrix} \mathbf{x}_t - \hat{\mathbf{x}}_t \\ \mathbf{u}_t - \hat{\mathbf{u}}_t \end{bmatrix}$$

Second order Taylor expansion for the cost around a trajectory $\hat{x}_t, \hat{u}_t, t = 1 \dots T$:

$$c(\mathbf{x}_t, \mathbf{u}_t) \approx c(\hat{\mathbf{x}}_t, \hat{\mathbf{u}}_t) + \nabla_{\mathbf{x}_t, \mathbf{u}_t} c(\hat{\mathbf{x}}_t, \hat{\mathbf{u}}_t) \begin{bmatrix} \mathbf{x}_t - \hat{\mathbf{x}}_t \\ \mathbf{u}_t - \hat{\mathbf{u}}_t \end{bmatrix} + \frac{1}{2} \begin{bmatrix} \mathbf{x}_t - \hat{\mathbf{x}}_t \\ \mathbf{u}_t - \hat{\mathbf{u}}_t \end{bmatrix}^T \nabla_{\mathbf{x}_t, \mathbf{u}_t}^2 c(\hat{\mathbf{x}}_t, \hat{\mathbf{u}}_t) \begin{bmatrix} \mathbf{x}_t - \hat{\mathbf{x}}_t \\ \mathbf{u}_t - \hat{\mathbf{u}}_t \end{bmatrix}$$

Non-linear case: Use iterative approximations!

First order Taylor expansion for the dynamics around a trajectory $\hat{x}_t, \hat{u}_t, t = 1 \dots T$:

$$f(\mathbf{x}_t, \mathbf{u}_t) \approx f(\hat{\mathbf{x}}_t, \hat{\mathbf{u}}_t) + \nabla_{\mathbf{x}_t, \mathbf{u}_t} f(\hat{\mathbf{x}}_t, \hat{\mathbf{u}}_t) \begin{bmatrix} \mathbf{x}_t - \hat{\mathbf{x}}_t \\ \mathbf{u}_t - \hat{\mathbf{u}}_t \end{bmatrix}$$

Second order Taylor expansion for the cost around a trajectory $\hat{x}_t, \hat{u}_t, t = 1 \dots T$:

$$c(\mathbf{x}_t, \mathbf{u}_t) \approx c(\hat{\mathbf{x}}_t, \hat{\mathbf{u}}_t) + \nabla_{\mathbf{x}_t, \mathbf{u}_t} c(\hat{\mathbf{x}}_t, \hat{\mathbf{u}}_t) \begin{bmatrix} \mathbf{x}_t - \hat{\mathbf{x}}_t \\ \mathbf{u}_t - \hat{\mathbf{u}}_t \end{bmatrix} + \frac{1}{2} \begin{bmatrix} \mathbf{x}_t - \hat{\mathbf{x}}_t \\ \mathbf{u}_t - \hat{\mathbf{u}}_t \end{bmatrix}^T \nabla_{\mathbf{x}_t, \mathbf{u}_t}^2 c(\hat{\mathbf{x}}_t, \hat{\mathbf{u}}_t) \begin{bmatrix} \mathbf{x}_t - \hat{\mathbf{x}}_t \\ \mathbf{u}_t - \hat{\mathbf{u}}_t \end{bmatrix}$$

$$\bar{f}(\delta \mathbf{x}_t, \delta \mathbf{u}_t) = \underbrace{\mathbf{F}_t}_{\nabla_{\mathbf{x}_t, \mathbf{u}_t} f(\hat{\mathbf{x}}_t, \hat{\mathbf{u}}_t)} \begin{bmatrix} \delta \mathbf{x}_t \\ \delta \mathbf{u}_t \end{bmatrix}$$

$$\bar{c}(\delta \mathbf{x}_t, \delta \mathbf{u}_t) = \frac{1}{2} \begin{bmatrix} \delta \mathbf{x}_t \\ \delta \mathbf{u}_t \end{bmatrix}^T \underbrace{\mathbf{C}_t}_{\nabla_{\mathbf{x}_t, \mathbf{u}_t}^2 c(\hat{\mathbf{x}}_t, \hat{\mathbf{u}}_t)} \begin{bmatrix} \delta \mathbf{x}_t \\ \delta \mathbf{u}_t \end{bmatrix} + \begin{bmatrix} \delta \mathbf{x}_t \\ \delta \mathbf{u}_t \end{bmatrix}^T \underbrace{\mathbf{c}_t}_{\nabla_{\mathbf{x}_t, \mathbf{u}_t} c(\hat{\mathbf{x}}_t, \hat{\mathbf{u}}_t)}$$

$$\delta \mathbf{x}_t = \mathbf{x}_t - \hat{\mathbf{x}}_t$$

$$\delta \mathbf{u}_t = \mathbf{u}_t - \hat{\mathbf{u}}_t$$

Now we can run LQR with dynamics \bar{f} , cost \bar{c} , state $\delta \mathbf{x}_t$, and action $\delta \mathbf{u}_t$

Iterative LQR (i-LQR)

Initialization: Given \hat{x}_0 , pick a random control sequence $\hat{u}_0 \dots \hat{u}_T$ and obtain corresponding state sequence $\hat{x}_0 \dots \hat{x}_T$

until convergence:

$$\mathbf{F}_t = \nabla_{\mathbf{x}_t, \mathbf{u}_t} f(\hat{\mathbf{x}}_t, \hat{\mathbf{u}}_t) \quad \forall t$$

$$\mathbf{c}_t = \nabla_{\mathbf{x}_t, \mathbf{u}_t} c(\hat{\mathbf{x}}_t, \hat{\mathbf{u}}_t) \quad \forall t$$

$$\mathbf{C}_t = \nabla_{\mathbf{x}_t, \mathbf{u}_t}^2 c(\hat{\mathbf{x}}_t, \hat{\mathbf{u}}_t) \quad \forall t$$

Run LQR backward pass on state $\delta \mathbf{x}_t = \mathbf{x}_t - \hat{\mathbf{x}}_t$ and action $\delta \mathbf{u}_t = \mathbf{u}_t - \hat{\mathbf{u}}_t \quad \forall t$

Run forward pass with real nonlinear dynamics and $u_t = \hat{u}_t + K_t(x_t - \hat{x}_T) + k_t \quad \forall t$

Update $\hat{\mathbf{x}}_t$ and $\hat{\mathbf{u}}_t$ based on states and actions in forward pass $\forall t$

Iterative LQR (i-LQR)

Initialization: Given \hat{x}_0 , pick a random control sequence $\hat{u}_0 \dots \hat{u}_T$ and obtain corresponding state sequence $\hat{x}_0 \dots \hat{x}_T$

until convergence:

$$\mathbf{F}_t = \nabla_{\mathbf{x}_t, \mathbf{u}_t} f(\hat{\mathbf{x}}_t, \hat{\mathbf{u}}_t) \quad \forall t$$

$$\mathbf{c}_t = \nabla_{\mathbf{x}_t, \mathbf{u}_t} c(\hat{\mathbf{x}}_t, \hat{\mathbf{u}}_t) \quad \forall t$$

$$\mathbf{C}_t = \nabla_{\mathbf{x}_t, \mathbf{u}_t}^2 c(\hat{\mathbf{x}}_t, \hat{\mathbf{u}}_t) \quad \forall t$$

Run LQR backward pass on state $\delta \mathbf{x}_t = \mathbf{x}_t - \hat{\mathbf{x}}_t$ and action $\delta \mathbf{u}_t = \mathbf{u}_t - \hat{\mathbf{u}}_t \quad \forall t$

Run forward pass with real nonlinear dynamics and $u_t = \hat{u}_t + K_t(x_t - \hat{x}_T) + k_t \quad \forall t$

Update $\hat{\mathbf{x}}_t$ and $\hat{\mathbf{u}}_t$ based on states and actions in forward pass $\forall t$

Linear approximation around \hat{x}, \hat{u}

Find $\Delta u_t, t = 1 \dots T$ so

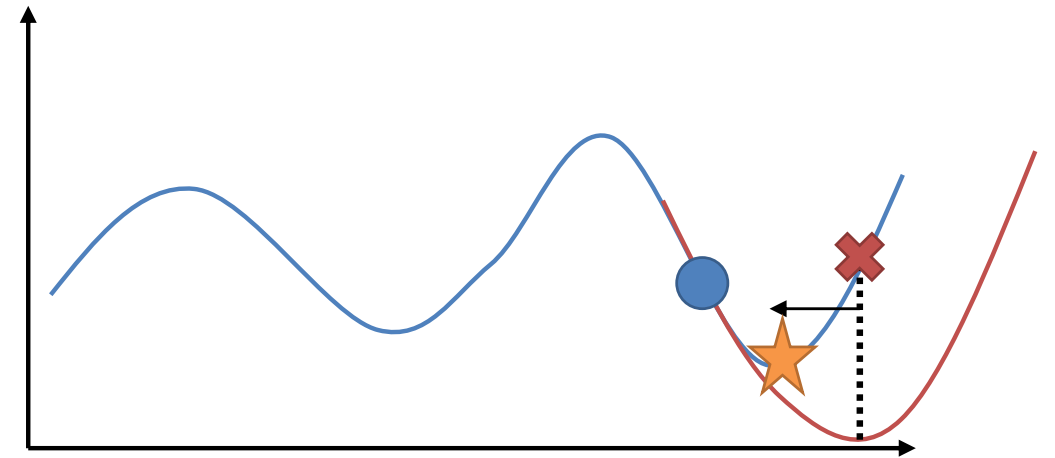
that $\hat{u}_t + \Delta u_t$ minimizes the linear approximation

Go to the $\hat{x}' = \hat{x} + \Delta x_t$ and $\hat{u}' = \hat{u} + \Delta u_t$

Nonlinear case: DDP/iterative LQR

The quadratic approximation is invalid too far away from the reference trajectory

$$\hat{\mathbf{x}} \leftarrow \arg \min_{\mathbf{x}} \frac{1}{2}(\mathbf{x} - \hat{\mathbf{x}})^T \mathbf{H}(\mathbf{x} - \hat{\mathbf{x}}) + \mathbf{g}^T(\mathbf{x} - \hat{\mathbf{x}})$$



Instead of finding the argmin i do a line search

until convergence:

$$\mathbf{F}_t = \nabla_{\mathbf{x}_t, \mathbf{u}_t} f(\hat{\mathbf{x}}_t, \hat{\mathbf{u}}_t)$$

$$\mathbf{c}_t = \nabla_{\mathbf{x}_t, \mathbf{u}_t} c(\hat{\mathbf{x}}_t, \hat{\mathbf{u}}_t)$$

$$\mathbf{C}_t = \nabla_{\mathbf{x}_t, \mathbf{u}_t}^2 c(\hat{\mathbf{x}}_t, \hat{\mathbf{u}}_t)$$

Run LQR backward pass on state $\delta \mathbf{x}_t = \mathbf{x}_t - \hat{\mathbf{x}}_t$ and action $\delta \mathbf{u}_t = \mathbf{u}_t - \hat{\mathbf{u}}_t$

Run forward pass with real nonlinear dynamics and $u_t = \hat{u}_t + K_t(x_t - \hat{x}_T) + \alpha k_t$

Update $\hat{\mathbf{x}}_t$ and $\hat{\mathbf{u}}_t$ based on states and actions in forward pass

line search for α

Nonlinear case: DDP/iterative LQR

- So far we have been planning (e.g. 100 steps) and then we close our eyes and hope our modeling was accurate enough..
- At convergence of iLQR and DDP, we end up with linearization around the (state, input) trajectory the algorithm converged to.
- In practice: the system could not be on this trajectory due to perturbations / initial state being off / dynamics model being off / ...
- Can we handle such noise better?

Model Predictive Control

- Yes! **If we close the loop! Model predictive control!**
- Solution: at time t when asked to generate control input u_t , we could re-solve the control problem using iLQR or DDP over the time steps t through T

every time step:

observe the state \mathbf{x}_t

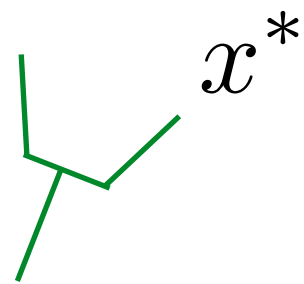
use iLQR to plan $\mathbf{u}_t, \dots, \mathbf{u}_T$ to minimize $\sum_{t'=t}^{t+T} c(\mathbf{x}_{t'}, \mathbf{u}_{t'})$

execute action \mathbf{u}_t , discard $\mathbf{u}_{t+1}, \dots, \mathbf{u}_{t+T}$

- Re-planning entire trajectory is often impractical \rightarrow in practice: replay over horizon H (receding horizon control)

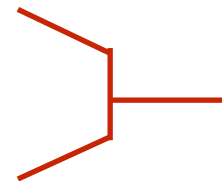
i-LQR: When it works

$$\text{Cost: } \|x_t - x^*\|$$



x^*

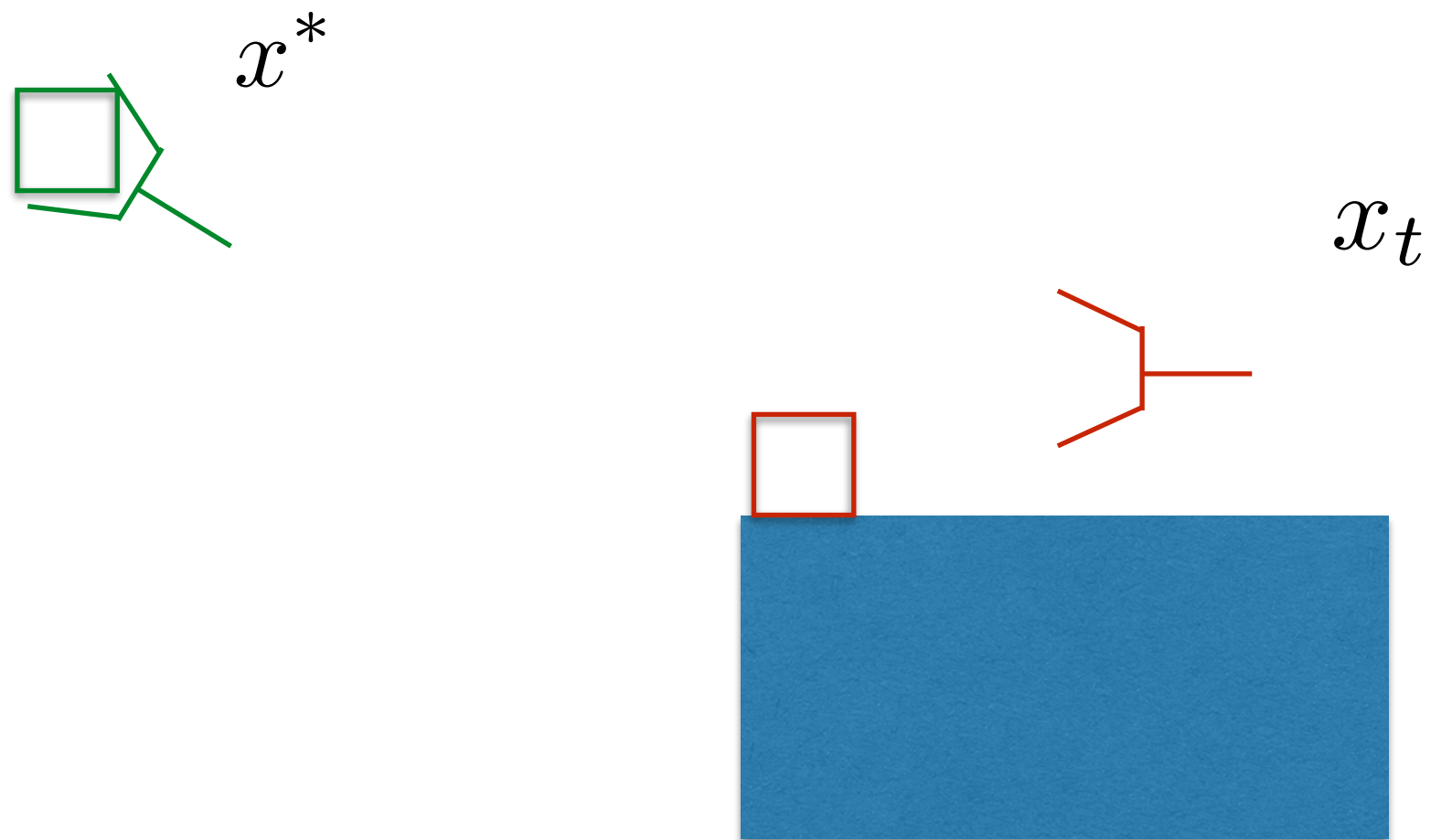
Direction for minimizing the cost



x_t

i-LQR: When it doesn't work

$$\text{Cost: } \|x_t - x^*\|$$



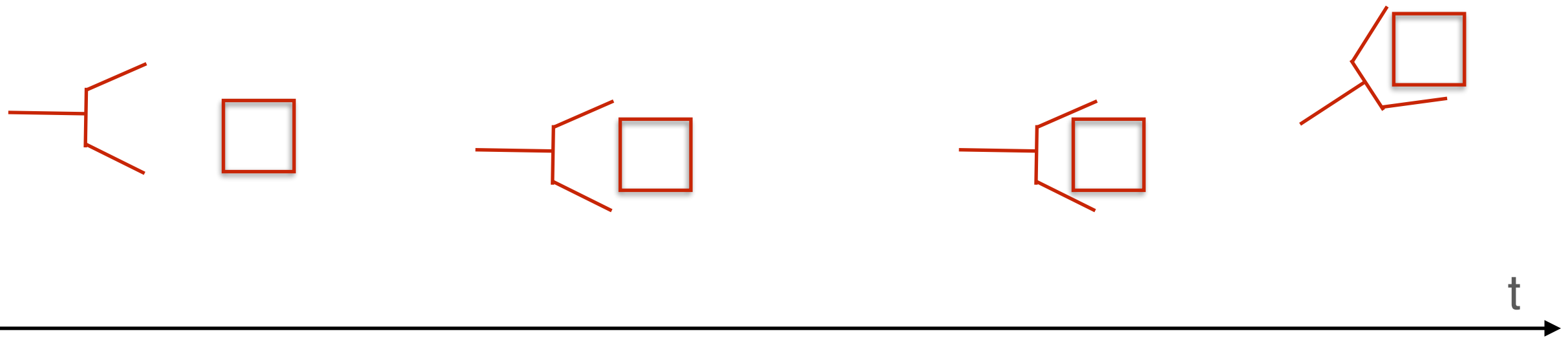
Due to discontinuities of contact, the local search fails! Solution?

Initialize using a human demonstration instead of random!

Time varying linear dynamics



reference trajectory $\hat{x}_t, \hat{u}_t, t = 1, \dots, T$



Time varying linear dynamics

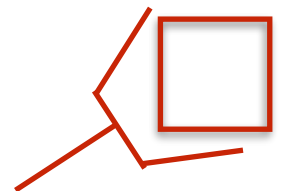
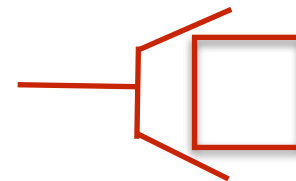
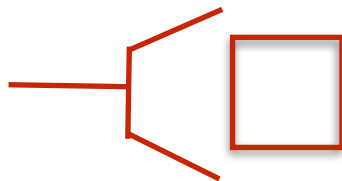
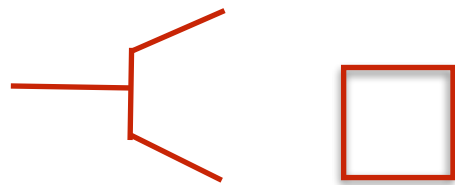


$$f(x_t, u_t) \approx \mathbf{A}_t x_t + \mathbf{B}_t u_t$$

$$\mathbf{A}_t = \frac{df}{dx_t} \quad \mathbf{B}_t = \frac{df}{du_t}$$

reference trajectory $\hat{x}_t, \hat{u}_t, t = 1, \dots, T$

learn time varying linear dynamics: $\mathbf{A}_t, \mathbf{B}_t$



t

Time varying linear dynamics

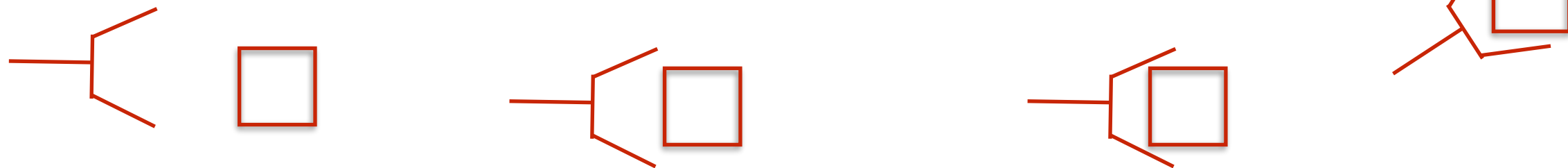


$$f(x_t, u_t) \approx \mathbf{A}_t x_t + \mathbf{B}_t u_t$$

$$\mathbf{A}_t = \frac{df}{dx_t} \quad \mathbf{B}_t = \frac{df}{du_t}$$

reference trajectory $\hat{x}_t, \hat{u}_t, t = 1, \dots, T$

learn time varying linear dynamics: $\mathbf{A}_t, \mathbf{B}_t$



t

How do I get the data to fit my linear dynamics at each time step?

We execute the controller u_t at state x_t to explore how the world works in the vicinity of the reference trajectory!

Discrete and Continuous version

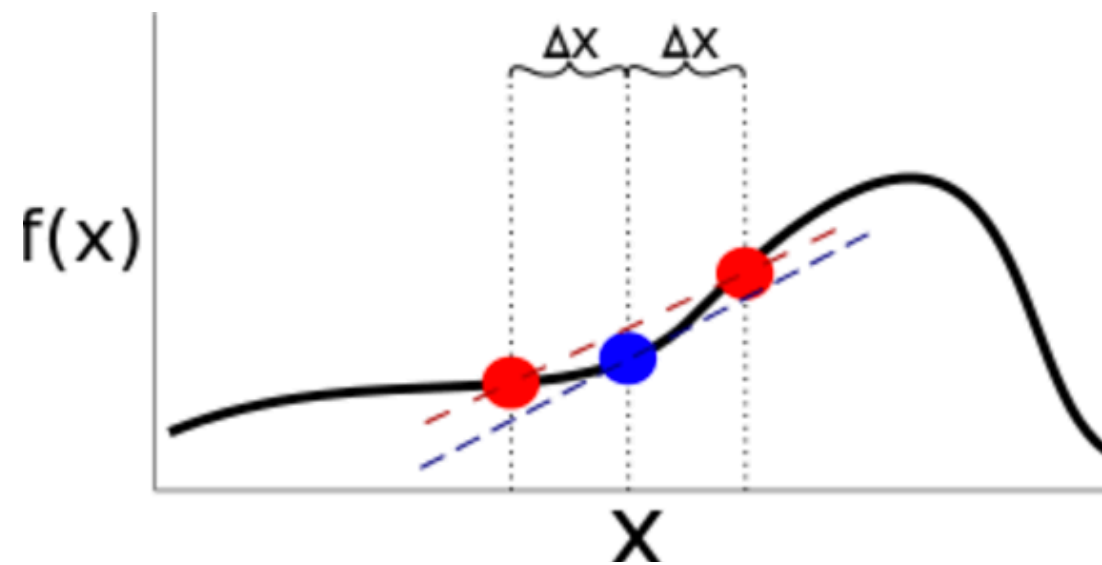
$$\mathbf{x}(t+1) = \mathbf{A}\mathbf{x}(t) + \mathbf{B}\mathbf{u}(t) + \mathbf{D}$$

$$\dot{\mathbf{x}} = \mathbf{A}\mathbf{x} + \mathbf{B}\mathbf{u}$$

Fitting Dynamics(1): Compute analytically derivatives of the “true” non-linear dynamics

- We may not have such analytic non linear dynamic equations available
- Very limiting: under modeling errors
- Complicated derivations

Fitting Dynamics(2): Finite Differences



$$\dot{\mathbf{x}} = \mathbf{A}\mathbf{x} + \mathbf{B}\mathbf{u}$$

$$\dot{f}(x) \approx \frac{f(x+\Delta x) - f(x-\Delta x)}{2\Delta x},$$

We need 2 samples per state dimension

Fitting Dynamics(3): Linear regression

$$\mathbf{x}(t+1) = \mathbf{A}\mathbf{x}(t) + \mathbf{B}\mathbf{u}(t) + \mathbf{D}$$

Use linear regression to fit A,B,D to samples $\{\mathbf{x}_i, \mathbf{u}_i, \mathbf{x}'_i\}$

Use GMM priors as described in the lecture

Bayesian Linear dynamics fitting

Fit a *Global* Gaussian Mixture Model using all samples (x_t, u_t, x_{t+1}) of all iterations and time steps. -> prior

Use current samples (from this iteration) and obtain Gaussian posterior for (x_t, u_t, x_{t+1}) , which you condition to obtain $p(x_{t+1}|x_t, u_t)$.

Such prior results in 4 to 8 times less samples needed, despite the fact that it is not accurate enough by itself.

$$\Sigma = \frac{\Phi + N\hat{\Sigma} + \frac{Nm}{N+m}(\hat{\mu} - \mu_0)(\hat{\mu} - \mu_0)^T}{N + n_0}$$
$$\mu = \frac{m\mu_0 + n_0\hat{\mu}}{m + n_0}.$$

Posterior of mean and covariance where $\hat{\mu}, \hat{\Sigma}$ are the empirical means and covariances and Φ, μ_0, n_0, m an inverse Wishart prior

Bayesian Linear dynamics fitting

Fit a *Global* Model of Dynamics by fitting a Neural Network using all samples (x_t, u_t, x_{t+1}) of all iterations and time steps, **and across multiple manipulation tasks->multi-task learning**.

Use model predictive control with iLQR for computing the policy at every time step.

State is the robotic arm configuration and cost depends on a desired end-effector pose. No object involved in the state.

$$\bar{f}([\mathbf{x}; \mathbf{u}]) \approx \bar{f}([\mathbf{x}_i; \mathbf{u}_i]) + \frac{d\bar{f}}{d[\mathbf{x}; \mathbf{u}]}^T ([\mathbf{x}; \mathbf{u}] - [\mathbf{x}_i; \mathbf{u}_i])$$

$$\bar{\mu} = \begin{bmatrix} [\mathbf{x}_i; \mathbf{u}_i] \\ \bar{f}([\mathbf{x}_i; \mathbf{u}_i]) \end{bmatrix}$$
$$\bar{\Sigma} = \begin{bmatrix} \bar{\Sigma}_{\mathbf{xu}, \mathbf{xu}} & \frac{d\bar{f}}{d[\mathbf{x}; \mathbf{u}]}^T \bar{\Sigma}_{\mathbf{xu}, \mathbf{xu}} \\ \bar{\Sigma}_{\mathbf{xu}, \mathbf{xu}} \frac{d\bar{f}}{d[\mathbf{x}; \mathbf{u}]} & \frac{d\bar{f}}{d[\mathbf{x}; \mathbf{u}]}^T \bar{\Sigma}_{\mathbf{xu}, \mathbf{xu}} \frac{d\bar{f}}{d[\mathbf{x}; \mathbf{u}]} + \bar{\Sigma}_{\mathbf{x}', \mathbf{x}'} \end{bmatrix}$$

Time varying linear dynamics

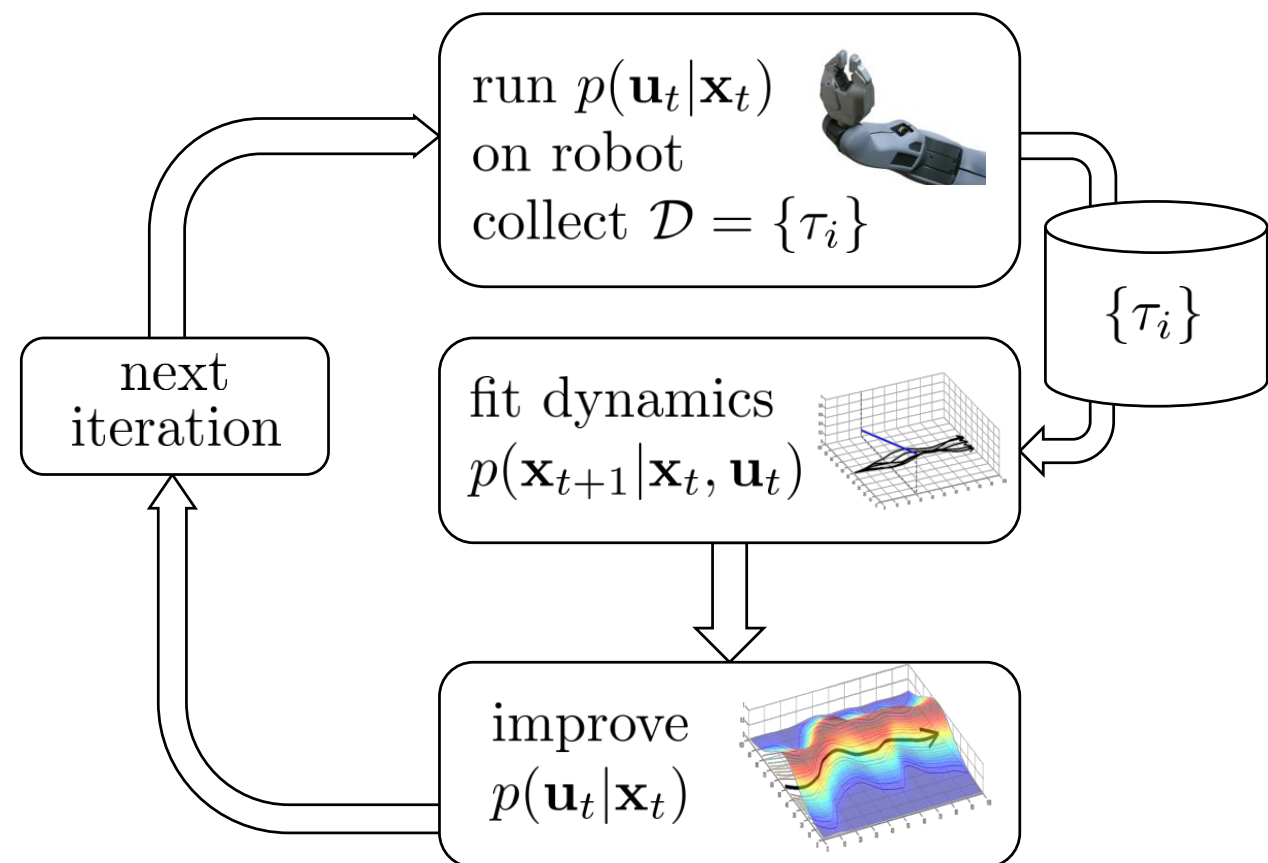
We iteratively fit dynamics and update the policy. Why such iteration is important?

So that the space (state, action distribution) our dynamics are estimated is similar to the one our policy visits (last lecture).

$$p(\mathbf{x}_{t+1}|\mathbf{x}_t, \mathbf{u}_t) = \mathcal{N}(f(\mathbf{x}_t, \mathbf{u}_t), \Sigma)$$

$$f(\mathbf{x}_t, \mathbf{u}_t) \approx \mathbf{A}_t \mathbf{x}_t + \mathbf{B}_t \mathbf{u}_t$$

$$\mathbf{A}_t = \frac{df}{d\mathbf{x}_t} \quad \mathbf{B}_t = \frac{df}{d\mathbf{u}_t}$$



Fitting time varying linear dynamics

- Can we further improve sample complexity? Right now each sample (x_t, u_t, x_{t+1}) contributes in one linear model fitting.
- Instead of linear regression use Bayesian linear regression!

$$p(\mathbf{x}_{t+1}|\mathbf{x}_t, \mathbf{u}_t) = \mathcal{N}(f(\mathbf{x}_t, \mathbf{u}_t), \Sigma)$$

$$f(\mathbf{x}_t, \mathbf{u}_t) \approx \mathbf{A}_t \mathbf{x}_t + \mathbf{B}_t \mathbf{u}_t$$

$$\mathbf{A}_t = \frac{df}{d\mathbf{x}_t} \quad \mathbf{B}_t = \frac{df}{d\mathbf{u}_t}$$

