AA203 Optimal and Learning-based Control

Lecture 11

Introduction to Model Predictive Control

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Outline of the next two lectures

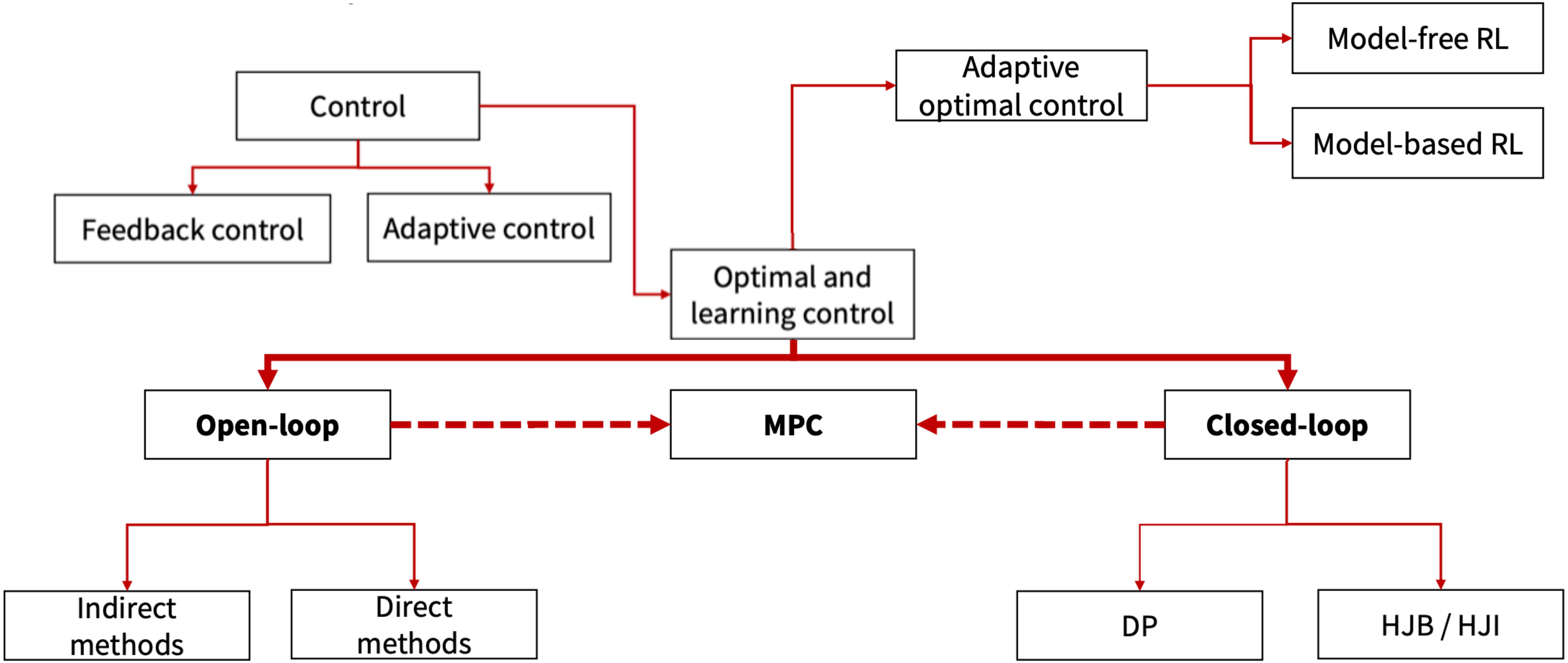
MPC: Basic setting and key ideas

Main design choices:
- Persistent feasibility
- Stability

Implementation aspects of MPC

Further reading:
- F. Borrelli, A. Bemporad, M. Morari. *Predictive Control for Linear and Hybrid Systems*, 2017.
- J. B. Rawlings, D. Q. Mayne, M. M. Diehl. *Model Predictive Control: Theory, Computation, and Design,* 2017.

Roadmap


Control
Feedback control
Adaptive control
Optimal and learning control
Adaptive optimal control
Model-free RL
Model-based RL
Open-loop
MPC
Closed-loop
Indirect methods
Direct methods
DP
HJB / HJI

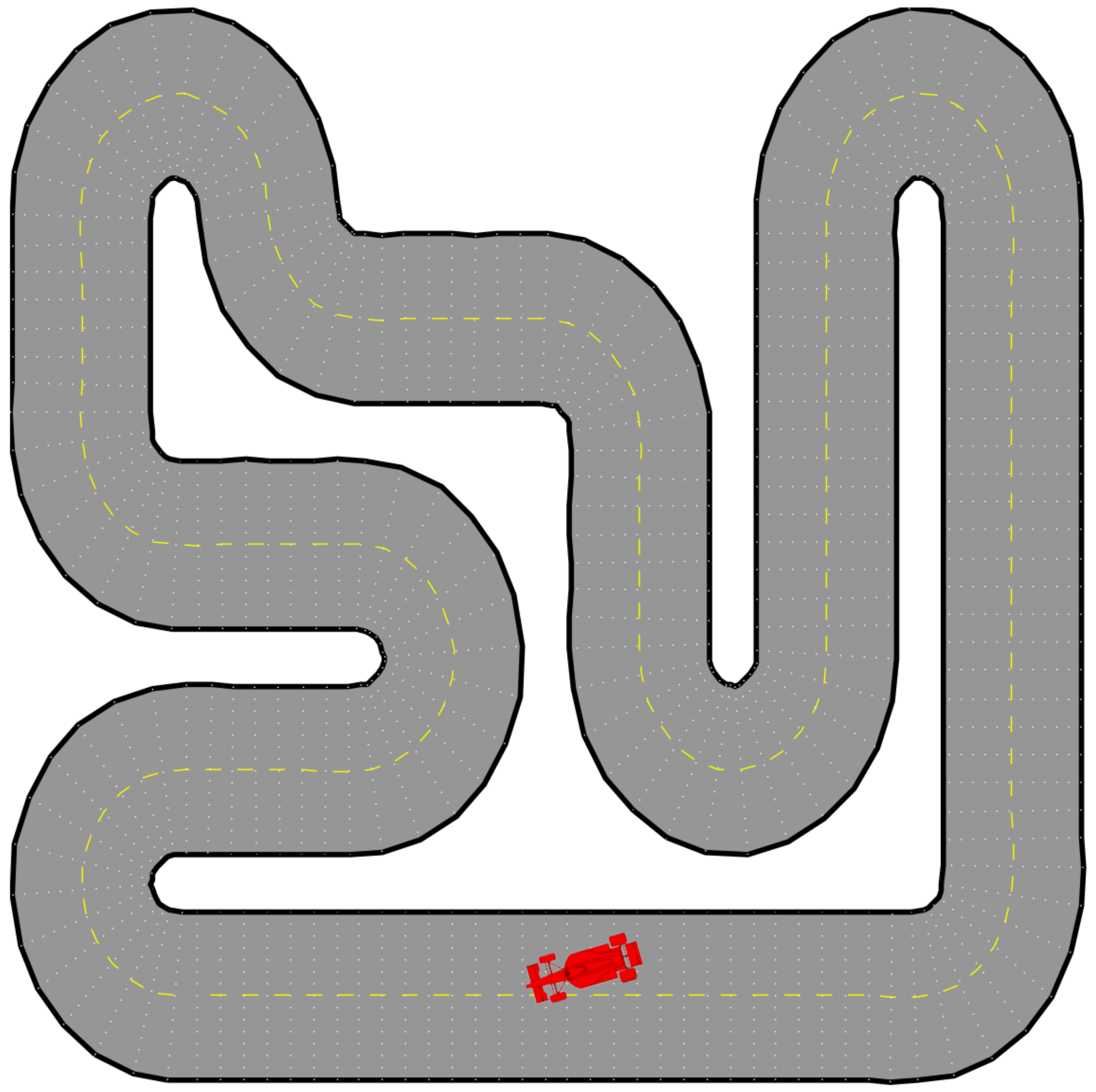
Model Predictive Control (MPC)

Let's consider the problem of controlling a F1 such that:

Objective: Minimize lap time

Constraints:
- Avoid other cars
- Stay on road
- Don't skid
- Limited acceleration

An intuitive approach would be to use formulate this as an optimization problem and resort to open-loop approaches to compute a full trajectory



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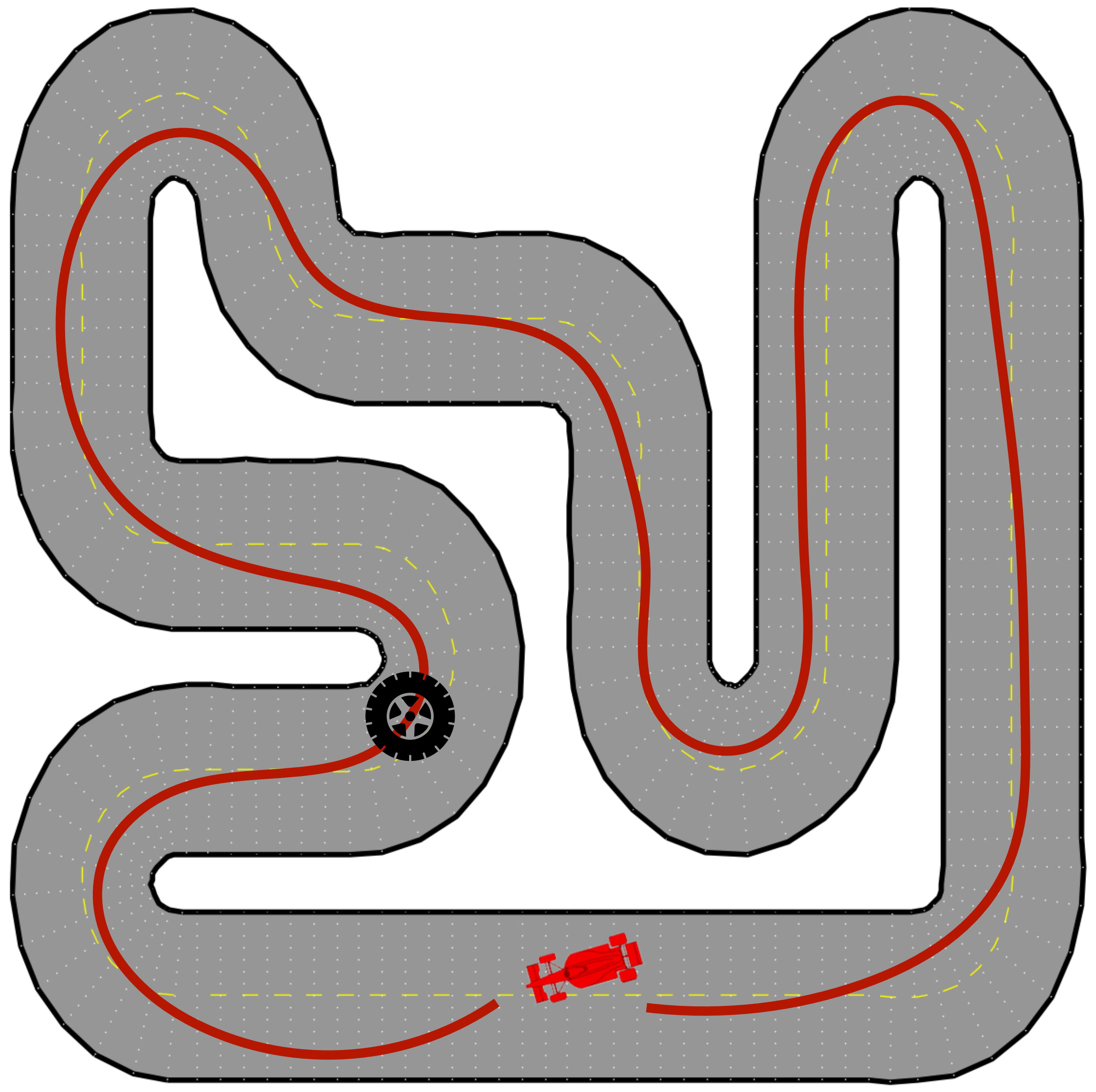


An intuitive approach would be to use formulate this as an optimization problem and resort to open-loop approaches to compute a full trajectory

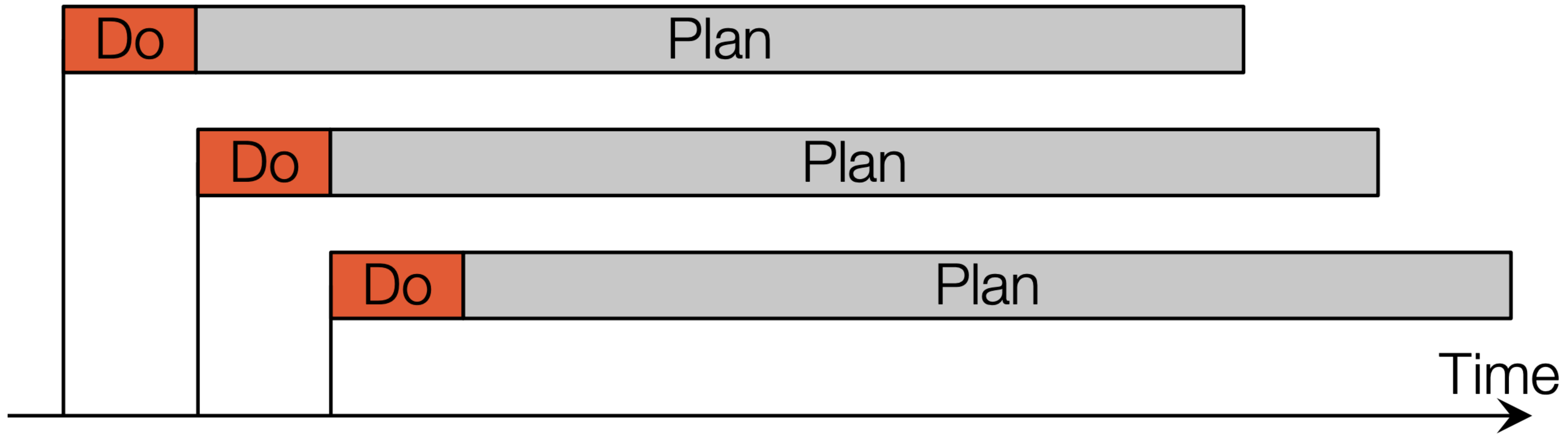
What if something unexpected happens (e.g., unseen obstacle)?

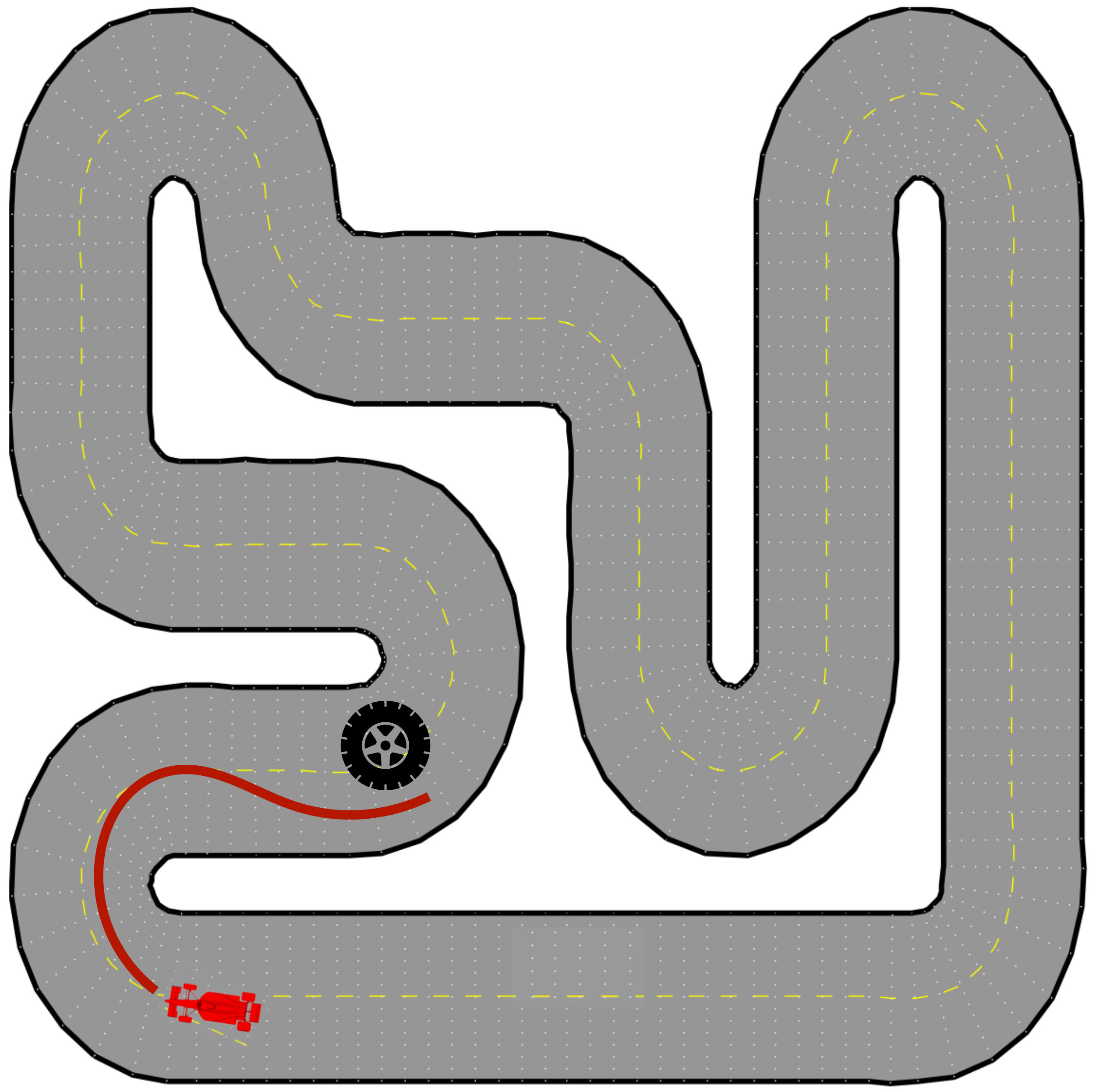
Model Predictive Control (MPC)

Model predictive control (or, more broadly, receding horizon control) entails solving finite-time optimal control problems in a receding horizon fashion

Specifically, given a model of the system:

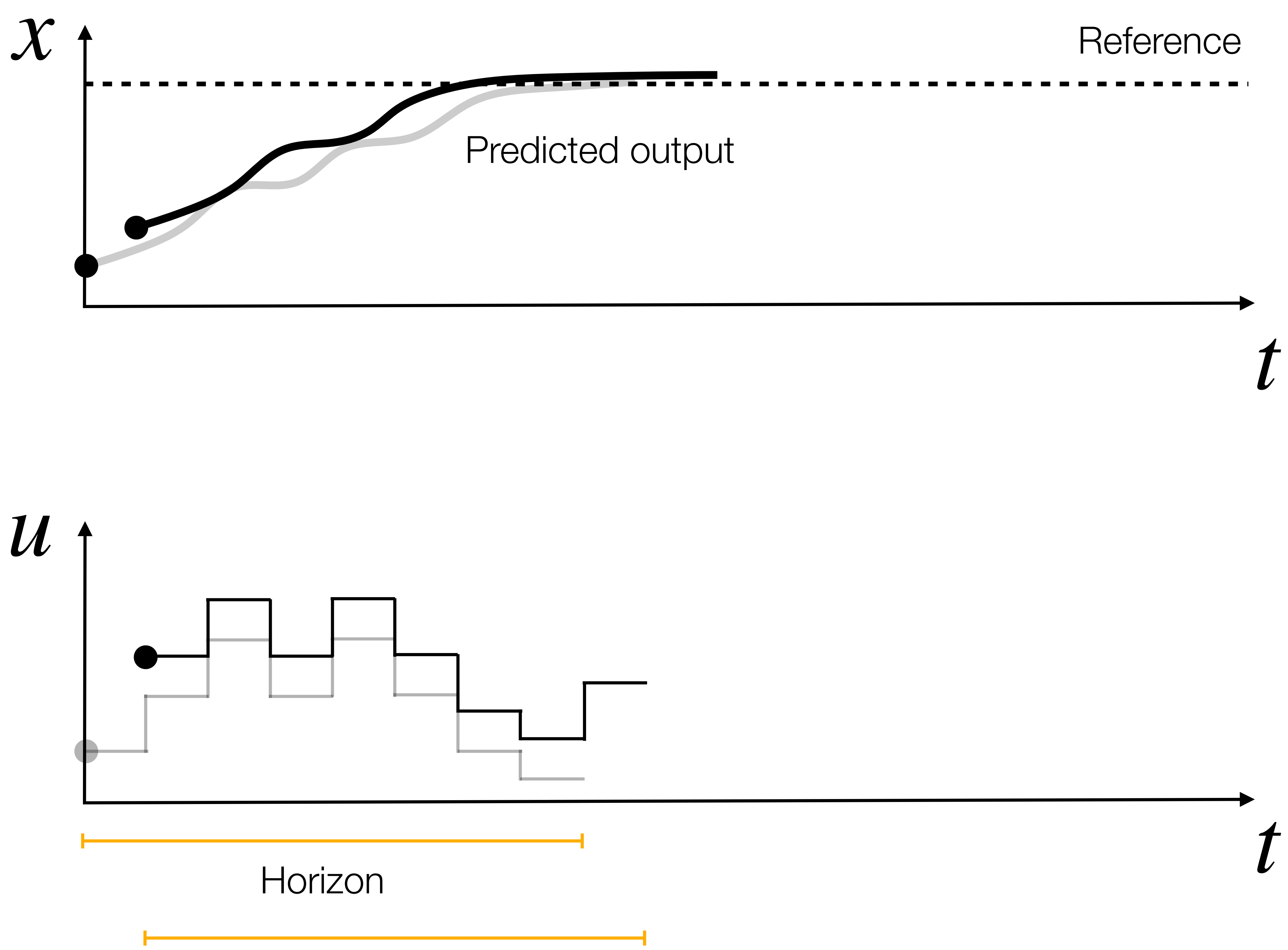
- Obtain a state measurement
- Generate a plan by solving a finite-time open-loop problem for a pre-specified planning horizon
- Execute the first control action
- Repeat





Receding horizon introduces **feedback**

Model Predictive Control (MPC)

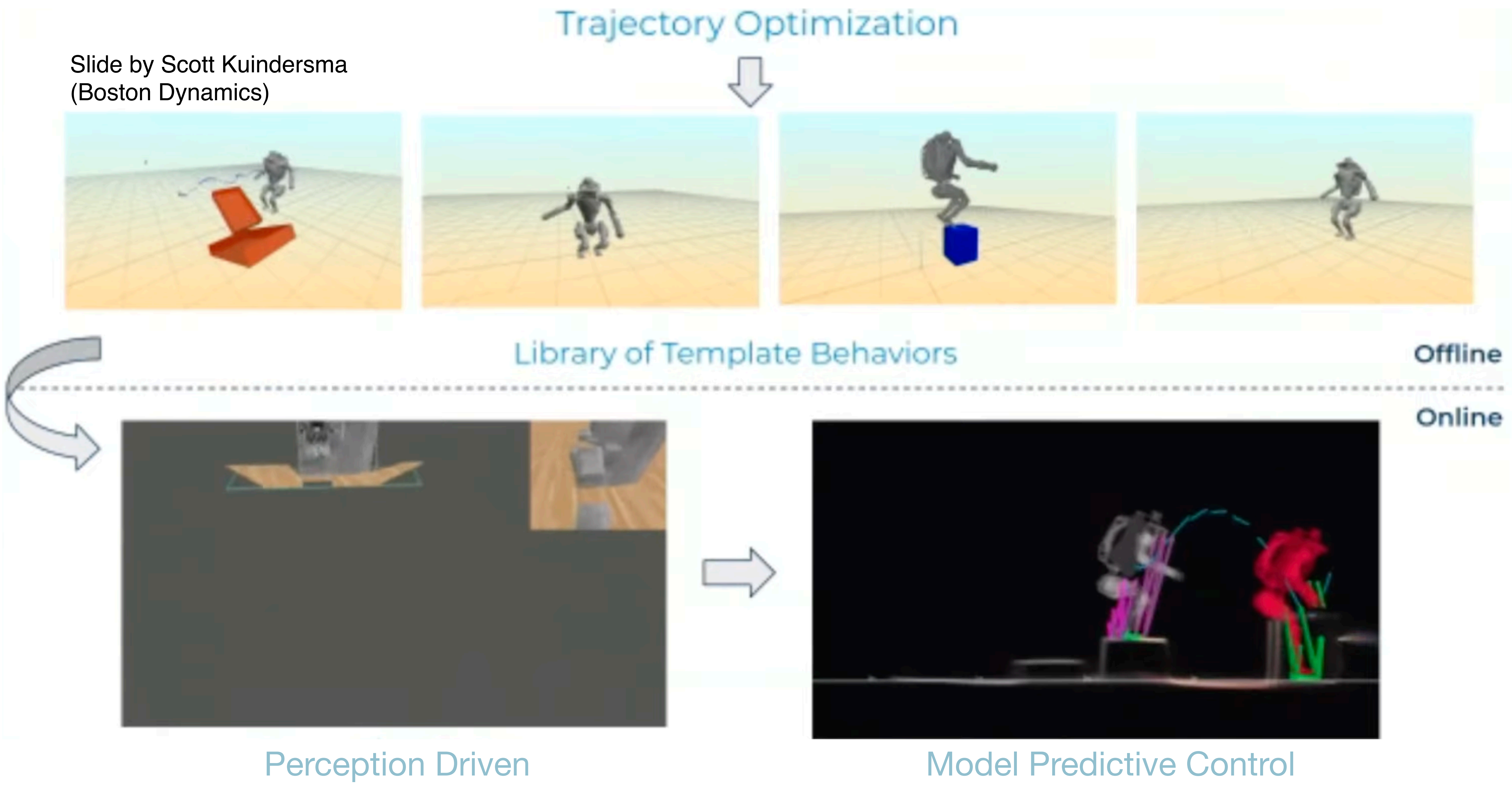


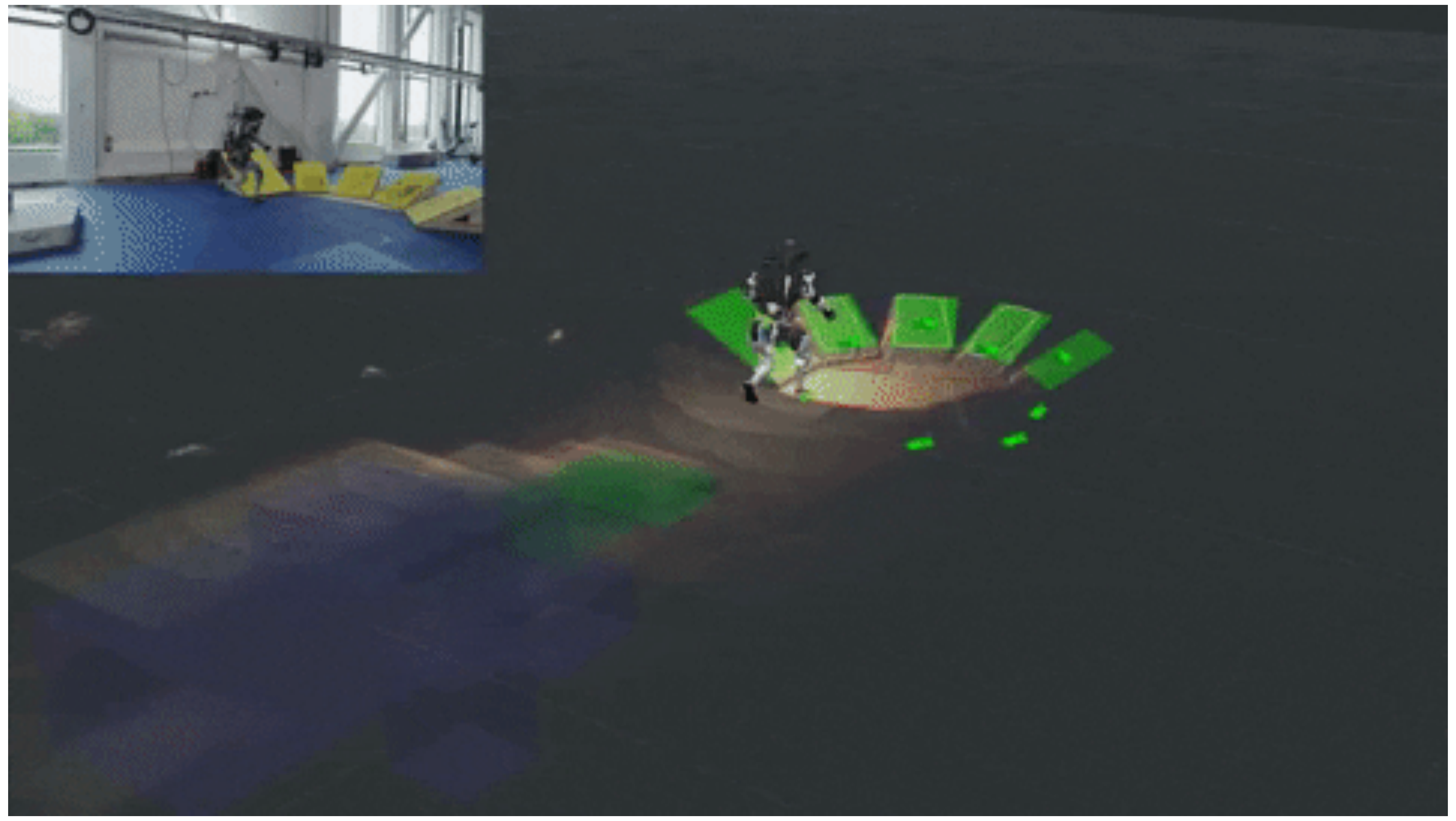
Key steps:

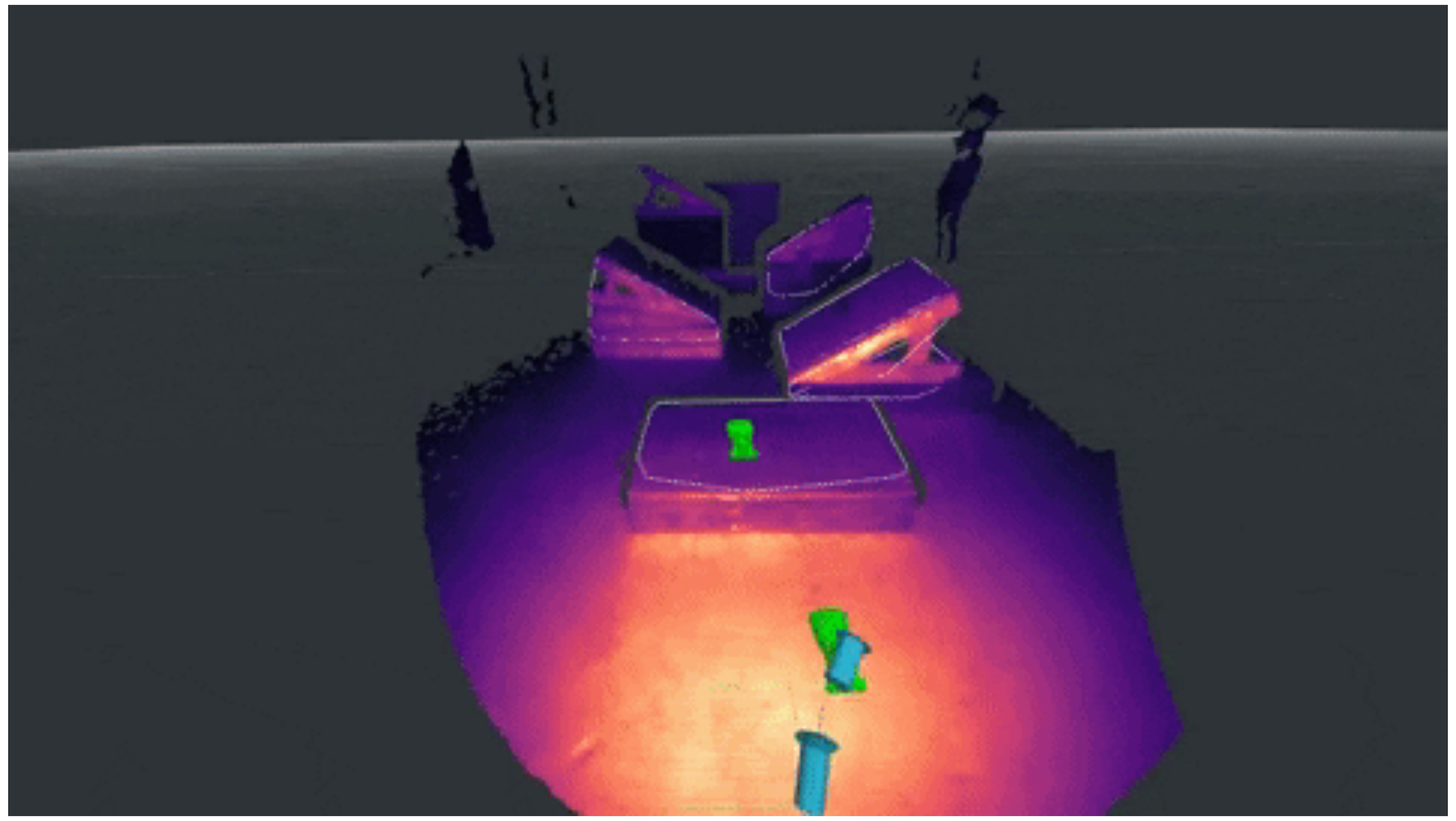
- At each sampling time t, solve an open-loop optimal control problem over a finite horizon
- Apply optimal input signal during the following sampling interval $[t, t+1)$
- At the next time step $t+1$, solve new optimal control problem based on new measurements of the state over a shifted horizon

MPC in the wild

Slide by Scott Kuindersma
(Boston Dynamics)







Basic formulation - Linear System

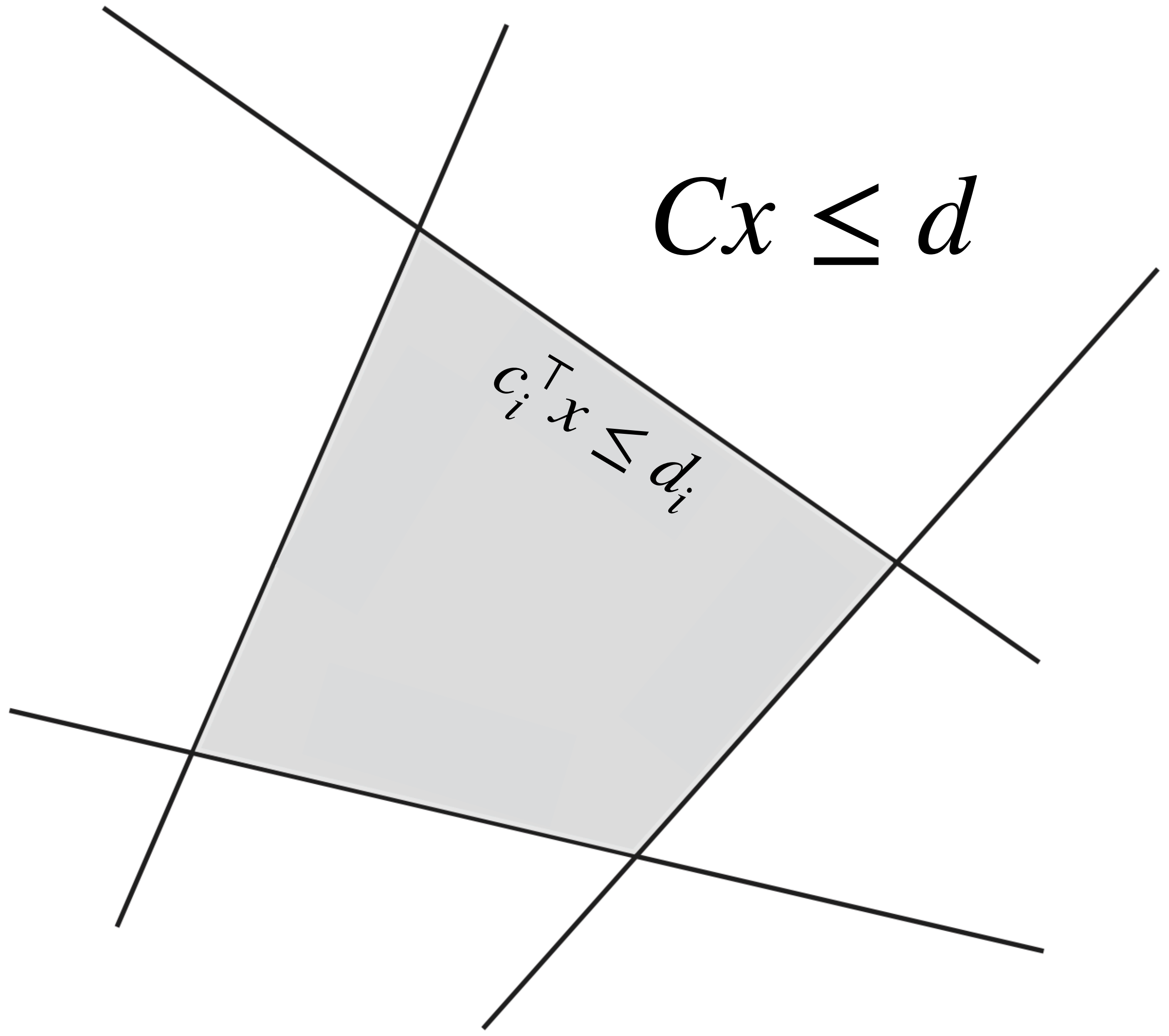
- Consider the problem of regulating to the origin the discrete-time linear time-invariant system

$$\mathbf{x}(t+1) = A\mathbf{x}(t) + B\mathbf{u}(t), \quad \mathbf{x}(t) \in \mathbb{R}^n, \quad \mathbf{u}(t) \in \mathbb{R}^m$$

Subject to constraints

$$\mathbf{x}(t) \in X, \quad \mathbf{u}(t) \in U, \quad t \geq 0$$

Where the sets X and U are *polyhedra*



- Historical note: MPC was originally developed in the context of chemical plant control

Notation

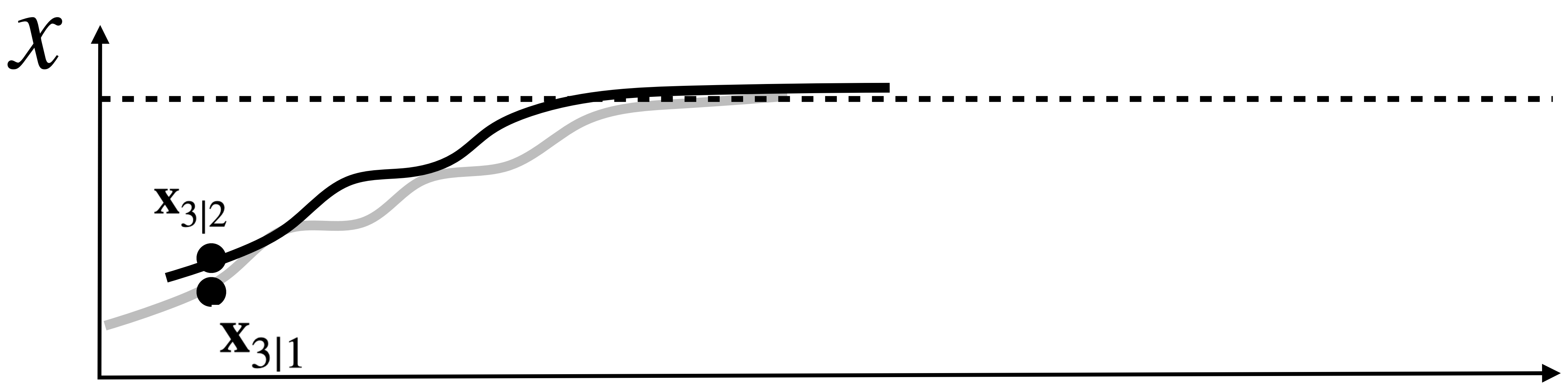
- $x(t)$ is the state of the system at time t
- $\mathbf{x}_{t+k|t}$ is the state of the model at time $t + k$, predicted at time t obtained by starting from the current state $x_{t|t} = x(t)$ and applying to the system model

$$x_{t+1|t} = Ax_{t|t} + Bu_{t|t},$$

the input sequence $u_{t|t}, \ldots, u_{t+k-1|t}$

- $\mathbf{u}_{t+k|t}$ to denote the input u at time $t + k$ computed at time t

Note: $\mathbf{x}_{3|1} \neq \mathbf{x}_{3|2}$



Notation

Let $U^*_{t\to t+N|t} := \left\{u^*_{t|t}, u^*_{t+1|t}, \ldots, u^*_{t+N-1|t}\right\}$ be the optimal solution to the short-term problem. The first element of $U^*_{t\to t+N|t}$ is applied to the system

$$u(t) = u^*_{t|t}(x(t)).$$

The optimization problem is then repeated at time $t+1$ based on the new state $x_{t+1|t+1} = x(t+1)$

Thus, we define the receding horizon control law as

$$\pi_t(\mathbf{x}(t)) := \mathbf{u}^*_{t|t}(\mathbf{x}(t))$$

Which results in the following closed-loop systems:

$$x(t+1) = Ax(t) + B\pi_t(x(t)) := \mathbf{f}_{\text{cl}}(x(t), t)$$

(Preview: a central question will be to characterize the behavior of the closed-loop system)

Basic formulation - OCP

Assume that a full measurement of the state $x(t)$ is available at the current time t

The finite-time optimal control problem solved at each stage is

$$J_t^*(x(t)) = \min_{u_{t|t},\ldots,u_{t+N-1|t}} l_T\left(x_{t+N|t}\right) + \sum_{k=0}^{N-1} l\left(x_{t+k|t}, u_{t+k|t}\right)$$

$$\begin{aligned} \text{s.t} \quad & x_{t+k+1|t} = Ax_{t+k|t} + Bu_{t+k|t}, \quad k = 0,\ldots,N-1 \\ & x_{t+k|t} \in X, \quad k = 0,\ldots,N-1 \\ & u_{t+k|t} \in U, \quad k = 0,\ldots,N-1 \\ & x_{t+N|t} \in X_f \\ & x_{t|t} = x(t) \end{aligned}$$

Why add a terminal cost and terminal constraints if what I really care about is the long-horizon problem?

l_T and X_f are key design decisions

Goal: Ensure that the short-horizon problem models the long-horizon problem

- l_T approximates the “tail” of the cost
- X_f approximates the “tail” of the constraints

Simplifying the notation: time-invariant systems

Note that the system, the constraints, and the cost function are time-invariant, hence, to simplify the notation, we can let (i) remove $|t$ and (ii) set $t = 0$, in the finite-time optimal control problem, namely

$$J_0^*(x(t)) = \min_{u_{0,\ldots,u_{N-1}}} l_T\left(x_N\right) + \sum_{k=0}^{N-1} l\left(x_k, u_k\right)$$

$$\begin{aligned}
\text{s.t} \quad & x_{k+1} = Ax_k + Bu_k, \quad k = 0,\ldots,N-1 \\
& x_k \in X, \quad k = 0,\ldots,N-1 \\
& u_k \in U, \quad k = 0,\ldots,N-1 \\
& x_N \in X_f \\
& x_0 = x(t)
\end{aligned}$$

- Denote the optimal solution to the short-term problem $U_0^*(x(t)) = \left\{u_0^*, \ldots, u_{N-1}^*\right\}$
- With the new notation, the closed-loop system becomes

$$x(t+1) = Ax(t) + B\pi(x(t)) := \mathbf{f}_{\text{cl}}(x(t))$$

Typical cost function

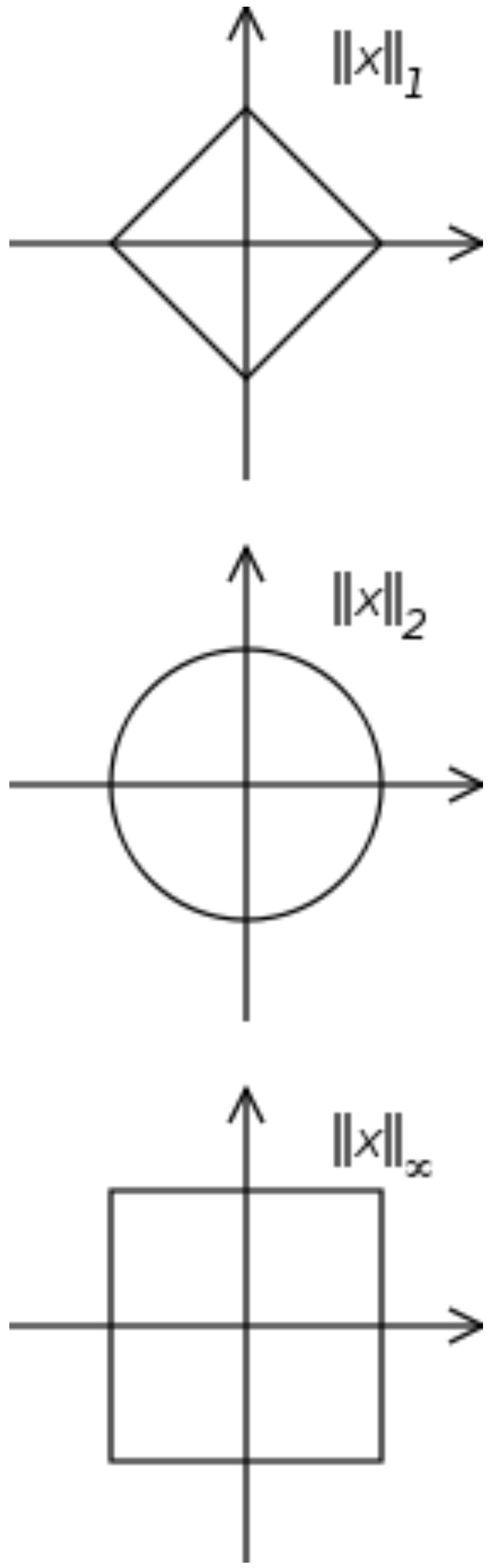
- 2-norm (i.e., constrained LQR)

$$l_T\left(x_N\right) = x_N^{\mathrm{T}} P x_N, \quad c\left(x_k, u_k\right) = x_k^{\mathrm{T}} Q x_k + u_k^{\mathrm{T}} R u_k, \quad P \succcurlyeq 0, Q \succcurlyeq 0, R \succ 0$$

- 1-norm

$$l_T\left(x_N\right) = \| P x_N \|_p \quad l\left(x_k, u_k\right) = \| Q x_k \|_p + \| R u_k \|_p, \quad p = 1 \text{ or } \infty$$

where P, Q, R are full column ranks



Online model predictive control (MPC v0)

repeat

measure the state $x(t)$ at time instant t

obtain $U_0^*(x(t))$ by solving finite-time optimal control problem

if $U_0^*(x(t)) = \emptyset$ **then** 'problem infeasible' **stop** ✗

apply the first element u_0^* of $U_0^*(x(t))$ to the system

wait for the new sampling time $t + 1$

MPC Features

Pros:

- Any model
  - Linear
  - Nonlinear
  - Single/Multivariable
  - Constraints
- Any objective
  - Sum of squared errors
  - Sum of absolute errors
  - Economic objective
  - Minimum time

Cons:

- Computationally demanding (important when embedding controller on hardware)
- May or may not be feasible
- May or may not be stable

Example: Loss of feasibility

Consider the double-integrator

$$x(t+1) = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} x(t) + \begin{bmatrix} 0 \\ 1 \end{bmatrix} u(t)$$

Consider a receding horizon controller that solves the optimization problem $J_0^*(x(t)) = \min_{u_{0,\ldots,u_{N-1}}} l_T\left(x_N\right) + \sum_{k=0}^{N-1} l\left(x_k, u_k\right),$

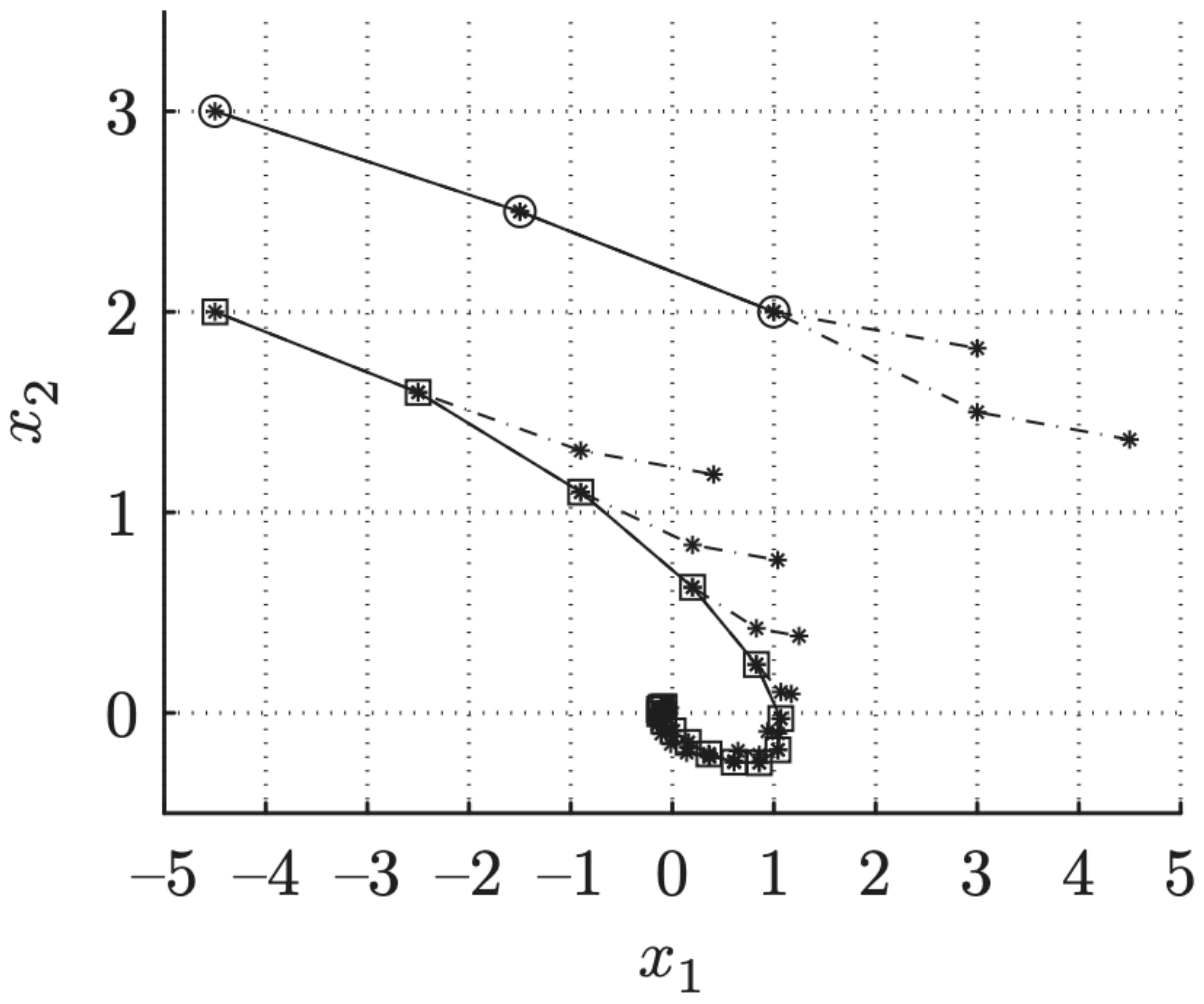
with $l_T\left(x_N\right) = x_N^\top P x_N, \quad l\left(x_k, u_k\right) = x_k^\top Q x_k + u_k^\top R u_k, \; N = 3, \quad P = Q = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, \quad R = 10, \quad X_f = \mathbb{R}^2$

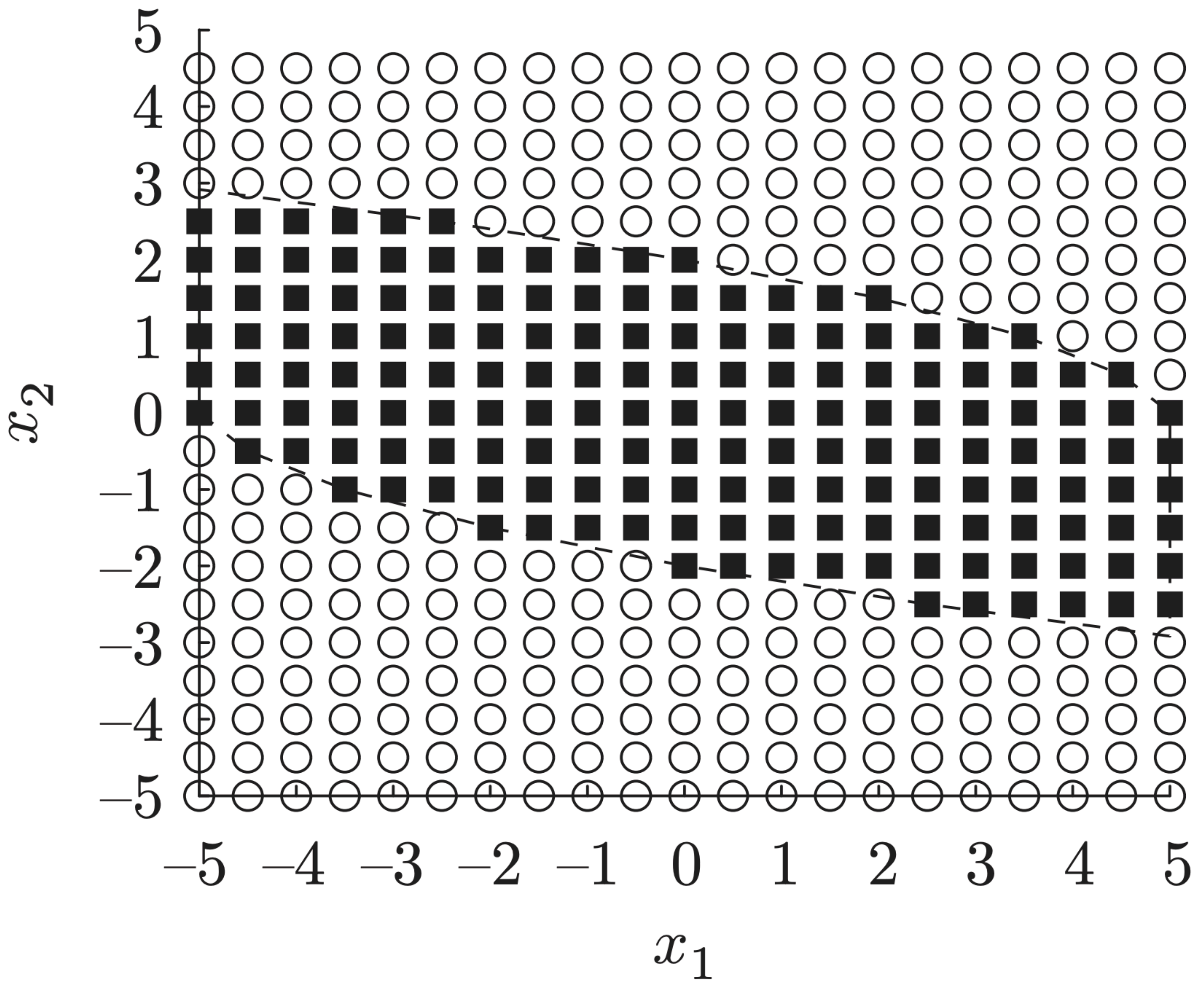
Subject to input and state constraints

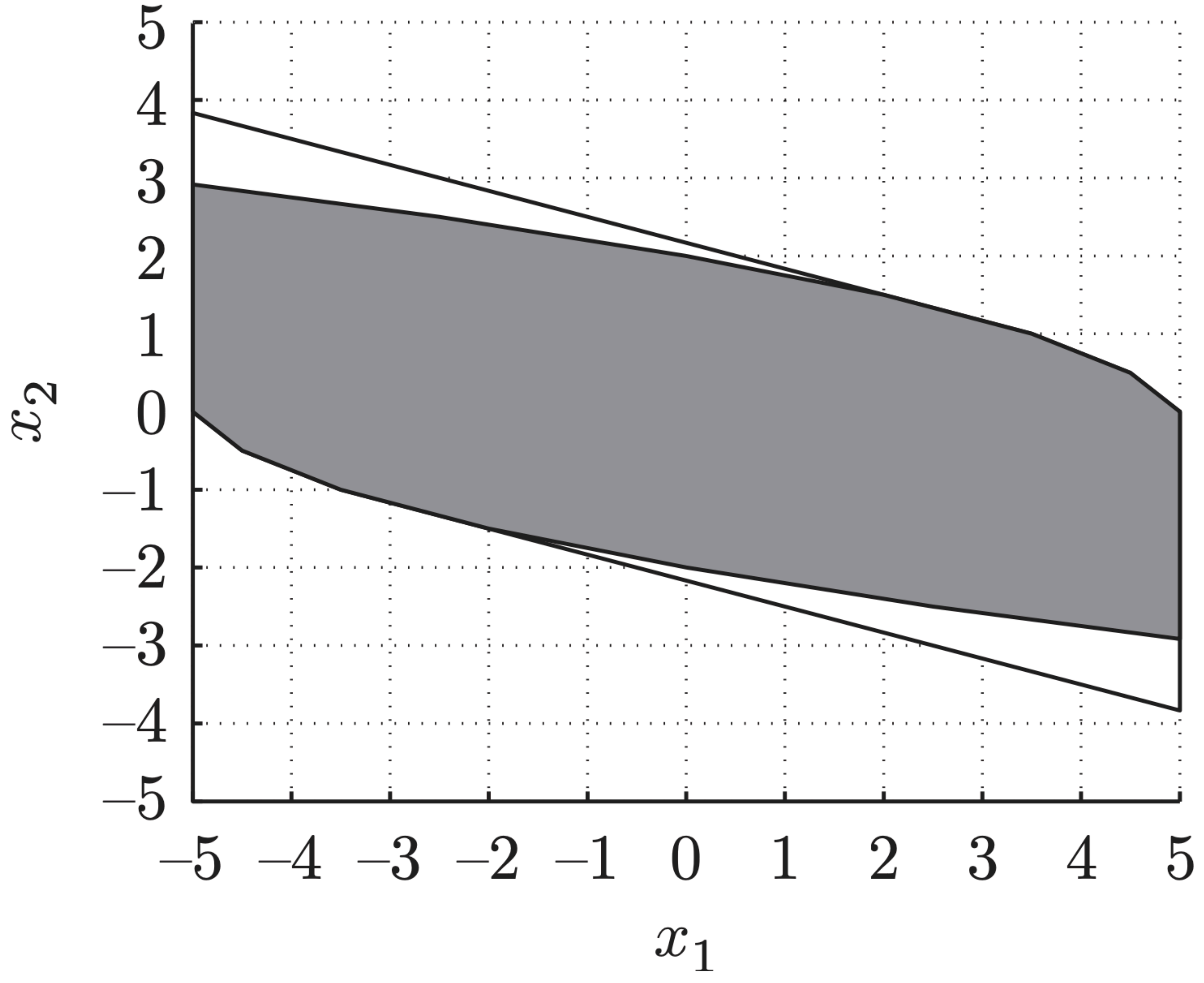
$$-0.5 \leq u(k) \leq 0.5, \quad k = 0,\ldots,3$$

$$\begin{bmatrix} -5 \\ -5 \end{bmatrix} \leq x(t) \leq \begin{bmatrix} 5 \\ 5 \end{bmatrix}, \quad k = 0,\ldots,3$$

Example: Loss of feasibility







Example: Dependency on parameters

Consider the double-integrator

$$x(t+1) = \begin{bmatrix} 2 & 1 \\ 0 & 0.5 \end{bmatrix} x(t) + \begin{bmatrix} 1 \\ 0 \end{bmatrix} u(t)$$

Consider a receding horizon controller that solves the optimization problem $J_0^*(x(t)) = \min_{u_{0,\ldots,u_{N-1}}} l_T\left(x_N\right) + \sum_{k=0}^{N-1} l\left(x_k, u_k\right),$

with $l_T\left(x_N\right) = x_N^\top P x_N, \quad l\left(x_k, u_k\right) = x_k^\top Q x_k + u_k^\top R u_k, \qquad Q = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, \quad X_f = \mathbb{R}^2, P = 0$

Subject to input and state constraints

$$-1 \leq u(k) \leq 1, \quad k = 0,\ldots,N-1$$

$$\begin{bmatrix} -10 \\ -10 \end{bmatrix} \leq x(t) \leq \begin{bmatrix} 10 \\ 10 \end{bmatrix}, \quad k = 0,\ldots,N-1$$

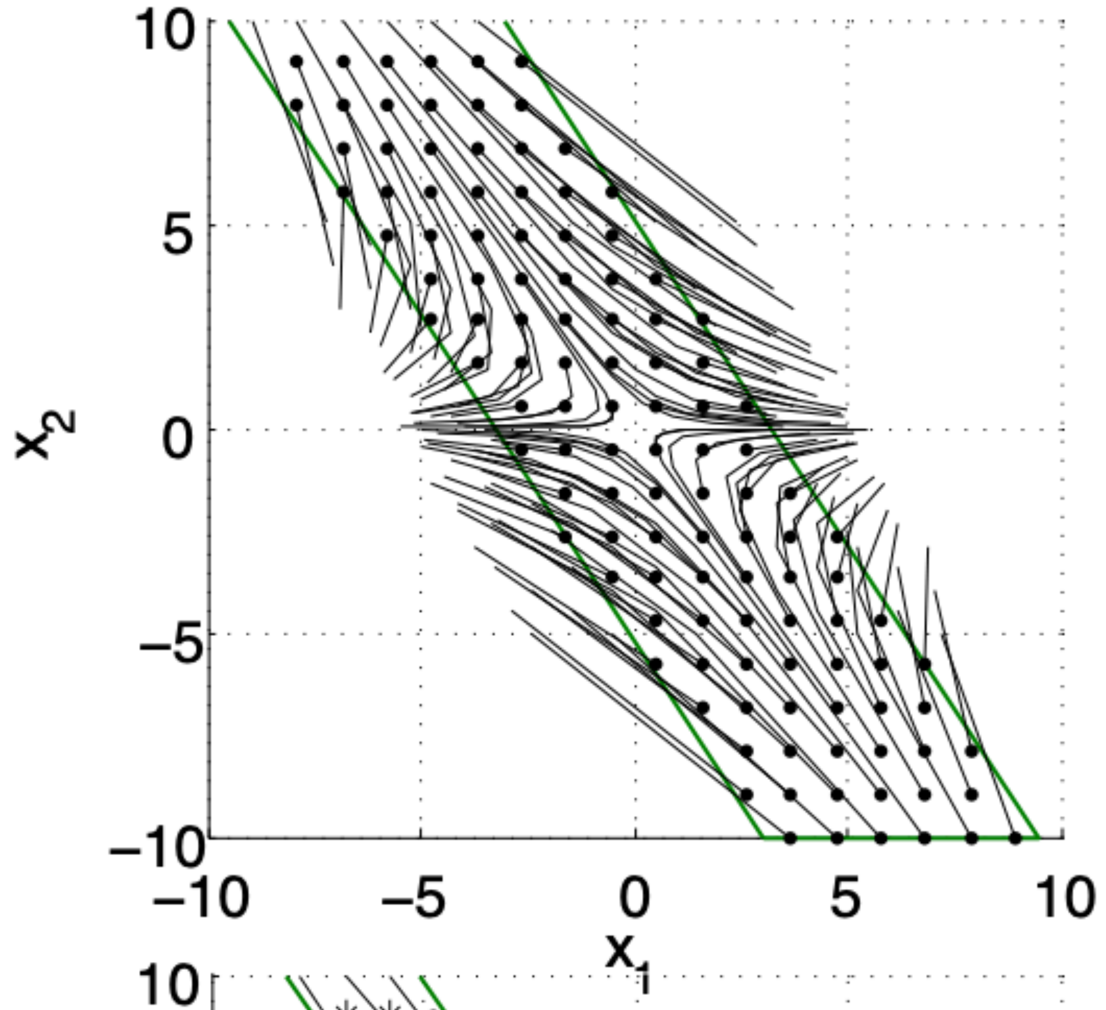
Example: Dependency on parameters

1. $R = 10,\ N = 2$: all trajectories unstable.
2. $R = 2,\ N = 3$: some trajectories stable.
3. $R = 1,\ N = 4$: more stable trajectories.

* Initial points with convergent trajectories

○ Initial points that diverge

①



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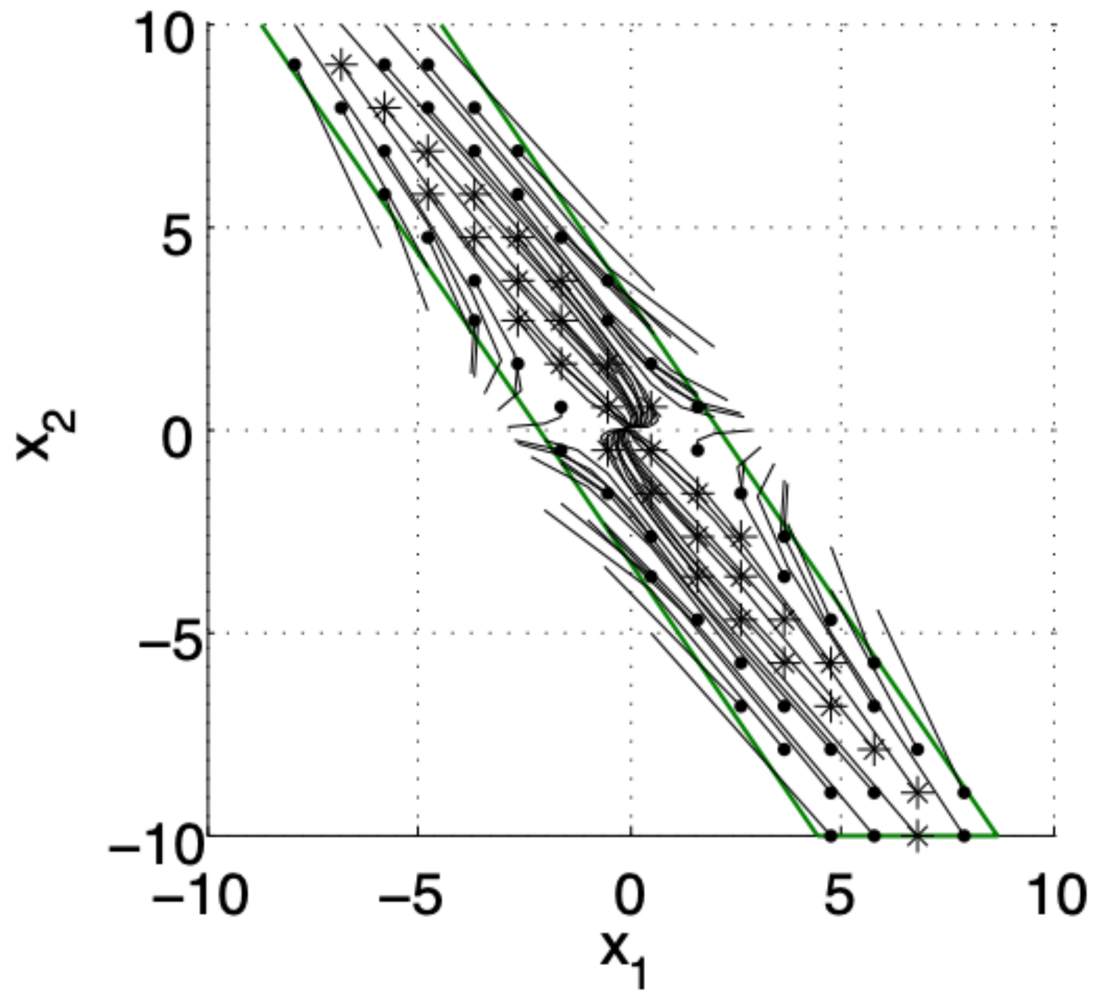

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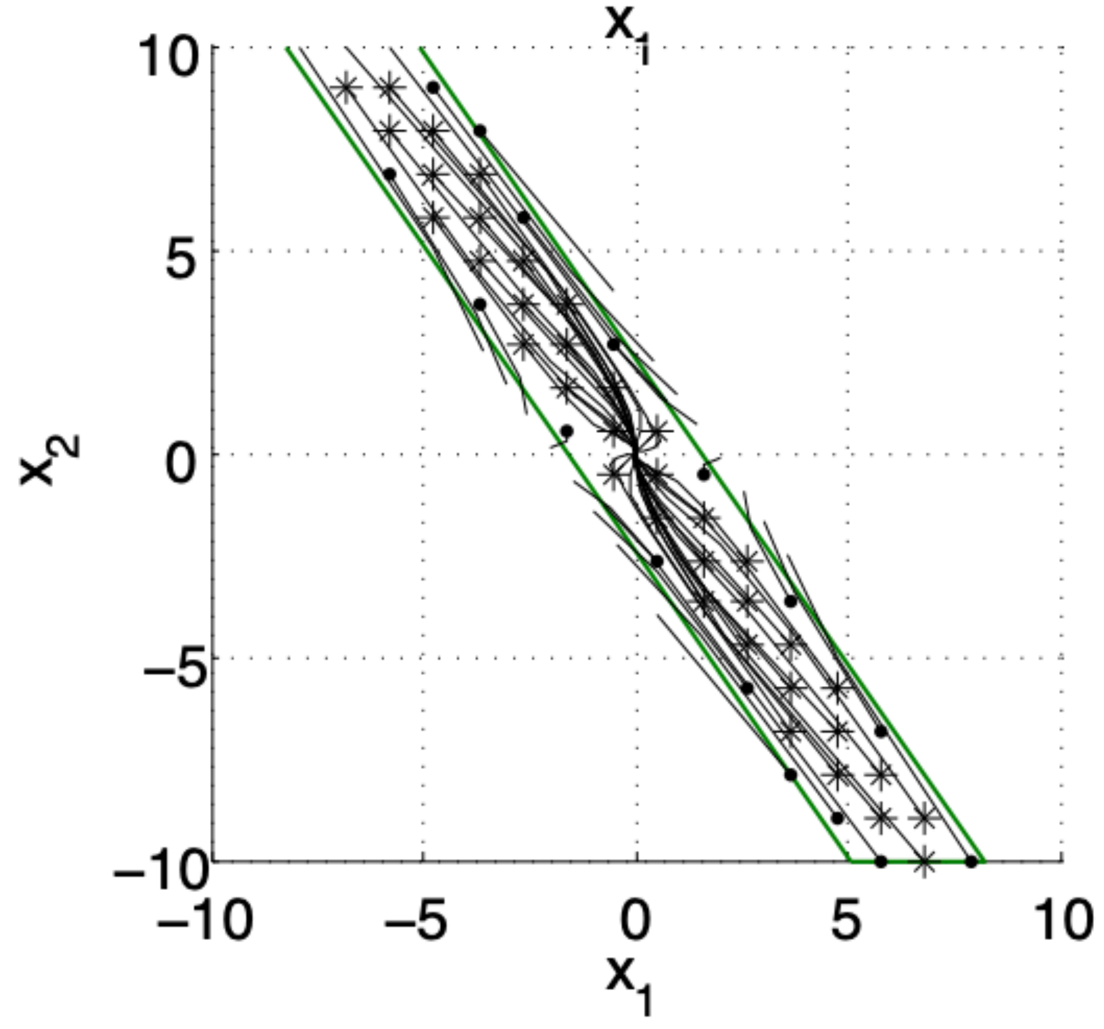

Take-away:

Parameters for receding horizon control influences the behavior of the resulting closed-loop trajectories in a complex manner

Main implementation issues

1. The controller may lead us into a situation where after a few steps the finite-time optimal control problem is infeasible → **persistent feasibility** issue

2. Even if the feasibility problem does not occur, the generated control inputs may not lead to trajectories that converge to the origin (i.e., closed-loop system is unstable) → **stability** *issue*

Key question: how do we guarantee that such a "short-sighted" strategy leads to effective long-term behavior?

One could consider two distinct approaches for doing this:

- Analyze closed-loop behavior directly → generally very difficult
- Derive conditions on
  - terminal function l_T so that closed-loop stability is guaranteed
  - terminal constraint set X_f so that persistent feasibility is guaranteed

Outline of the next two lectures

MPC: Basic setting and key ideas

Main design choices:
- Persistent feasibility
- Stability

Implementation aspects of MPC

Further reading:
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Addressing persistent feasibility

Goal: design MPC controller so that feasibility for all future times is guaranteed

Approach: leverage tools from *invariant set theory*

$$J_0^*(x(t)) = \min_{u_{0,\ldots,u_{N-1}}} l_T\left(x_N\right) + \sum_{k=0}^{N-1} l\left(x_k, u_k\right)$$

$$\text{s.t} \quad x_{k+1} = Ax_k + Bu_k, \quad k = 0,\ldots,N-1$$
$$x_k \in X, \quad k = 0,\ldots,N-1$$
$$u_k \in U, \quad k = 0,\ldots,N-1$$
$$x_N \in X_f$$
$$x_0 = x(t)$$

Def: Set of feasible initial states

$X_0 := \left\{x_0 \in X \mid \exists \left(u_0, \ldots, u_{N-1}\right) \text{ such that } x_k \in X, u_k \in U, k = 0,\ldots,N-1, x_N \in X_f \text{ where } x_{k+1} = Ax_k + Bu_k, k = 0,\ldots,N-1\right\}$

A control input can be found only if $x(0) \in X_0$

Controllable sets

For the autonomous system $x(t+1) = \phi(x(t))$ with constraints $x(t) \in X, u(t) \in U$, the one-step controllable set to set S is defined as

$$\text{Pre}(S) := \left\{X \in \mathbb{R}^n : \phi(X) \in S\right\}$$

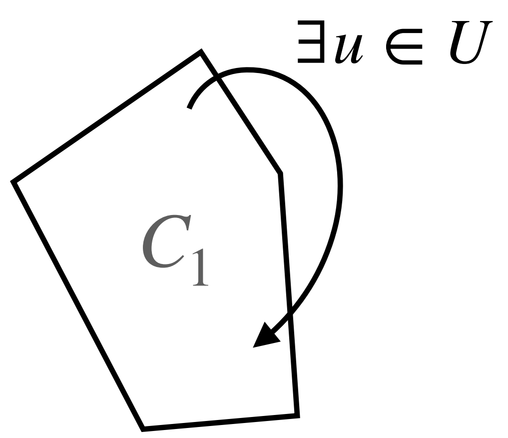
For the system $\mathbf{x}(t+1) = \phi(x(t), u(t))$ with constraints $x(t) \in X, u(t) \in U$, the one-step controllable set to set S is defined as

$$\text{Pre}(S) := \left\{x \in \mathbb{R}^n : \exists u \in U \text{ such that } \phi(X, U) \in S\right\}$$

Control invariant sets

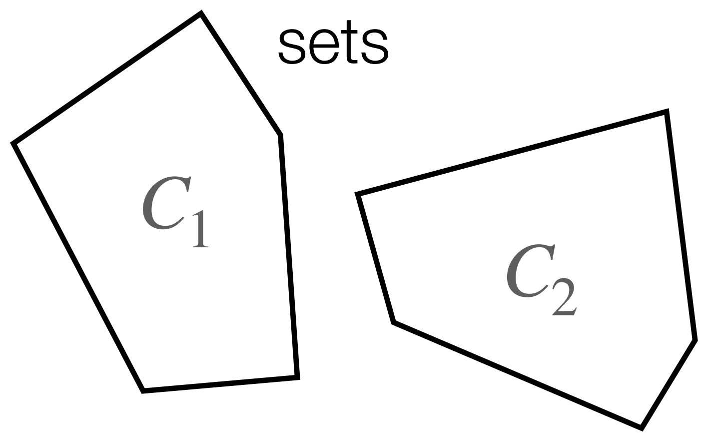
A set $C \subseteq X$ is said to be a **control invariant set** for the system $x(t+1) = \phi(x(t), u(t))$ with constraints $x(t) \in X, u(t) \in U$, if:

$$x(t) \in C \Rightarrow \exists u \in U \text{ such that } \phi(x(t), u(t)) \in C \text{ for all } t$$



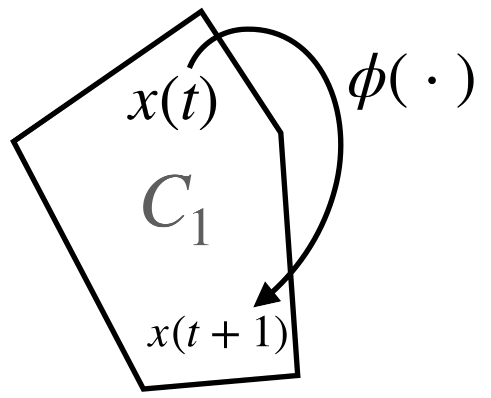
The set $C_\infty \subseteq X$ is said to be the **maximal control invariant set** for the system $x(t+1) = \phi(x(t), u(t))$ with constraints $x(t) \in X, u(t) \in U$, if it is control invariant and contains all control invariant sets contained in X

Consider the union of two control invariant sets



Let's define the equivalent for autonomous systems:

- a set $A \subseteq X$ is said to be a **positive invariant set** for the system $x(t+1) = \phi(x(t))$ if $x(t) \in A \Rightarrow \phi(x(t)) \in A$
- the **maximal positive invariant set** contains all other positive invariant sets



Note on implementation: these sets can be computed by using the MPT toolbox (multi-parametric toolbox) https://www.mpt3.org/

Persistent feasibility lemma

Define the "truncated" feasibility set:

$X_1 := \left\{ x_1 \in X \mid \exists \left(u_1, \ldots, u_{N-1}\right) \text{ such that } x_k \in X, u_k \in U, k = 1,\ldots, N-1 \; x_N \in X_f \text{ where } x_{k+1} = Ax_k + Bu_k, k = 1,\ldots, N-1 \right\}$

Feasibility lemma:

If set X_1 is a control invariant set for system $x(t+1) = Ax(t) + Bu(t), \quad x(t) \in X, \quad u(t) \in U, \quad t \geq 0$, then the MPC law is persistently feasible

Persistent feasibility lemma

Proof:

1. Consider the preimage of X_1, $\text{Pre}\left(X_1\right) = \left\{x \in \mathbb{R}^n : \exists u \in U \text{ such that } Ax + Bu \in X_1\right\}$
2. Since X_1 is control invariant, it means that $\forall x \in X_1, \exists u \in U$ such that $Ax + Bu \in X_1$
3. Thus $X_1 \subseteq \text{Pre}\left(X_1\right) \cap X$
4. One can write $X_0 = \left\{x_0 \in X \mid \exists u_0 \in U \text{ such that } Ax_0 + Bu_0 \in X_1\right\} = \text{Pre}\left(X_1\right) \cap X$
5. Thus, $X_1 \subseteq X_0$
6. Pick some $x_0 \in X_0$. Let U_0^* be the solution to the finite-time optimization problem, and u_0^* be the first control.

   Let $x_1 = Ax_0 + Bu_0^*$
7. Since U_0^* is clearly feasible, one has $x_1 \in X_1$. Since $X_1 \subseteq X_0$, one has $x_1 \in X_0$
8. Hence the next optimization problem is feasible!

Practical significance

- For $N = 1$, we can set $X_f = X_1$. If we choose the terminal set to be control invariant, then MPC will be persistently feasible *independent* of chosen control objectives and parameters
- Designer can choose the parameters to affect performance (e.g., stability)

- How to extend this result to N > 1?

Persistent feasibility theorem

Feasibility theorem:
If set X_f is a control invariant set for system $x(t+1) = Ax(t) + Bu(t), \quad x(t) \in X, \quad u(t) \in U, \quad t \geq 0$, then the MPC law is persistently feasible

Proof:
1. Define the "truncated" feasibility set:
$$X_{N-1} := \left\{ x_{N-1} \in X \mid \exists u_{N-1} \text{ such that } x_{N-1} \in X, u_{N-1} \in U \, x_N \in X_f \text{ where } x_N = Ax_{N-1} + Bu_{N-1} \right\}$$
2. Due to the terminal constraint, we know that $Ax_{N-1} + Bu_{N-1} = x_N \in X_f$
3. Since X_f is a control invariant set, there exists a $u \in U$ such that $x^+ = Ax_N + Bu_N \in X_f$
4. The above is exactly the requirement to belong to set X_{N-1}
5. Thus, $Ax_{N-1} + Bu_{N-1} = x_N \in X_{N-1}$
6. We have just proved that X_{N-1} is control invariant
7. Repeating this argument, one can recursively show that $X_{N-2}, X_{N-3}, \ldots, X_1$ are control invariant
8. The persistent feasibility lemma then applies

Practical aspects of persistent feasibility

- The terminal set X_f is introduced *artificially* for the sole purpose of leading to a *sufficient condition* for persistent feasibility
- We want it to be large so that it does not compromise closed-loop performance
- Though it is simplest to choose $X_f = \{0\}$, this is generally undesirable
- We'll discuss better choices in the next lecture

Next time

- Stability of MPC
- Explicit MPC
- Practical considerations