## Learning Model Predictive Control

AIM: The objective of Learning MPC is to design a reference-free iterative control strategy, able to learn from previous iterations.

An infinite horizon optimal control problem can be approximated as a finite horizon optimal control problem for MPC formulation:

$$\min_{\substack{U_k \\ V_k \\ \text{s.t.}}} \sum_{i=0}^{\infty} (h(x_k, u_k)) \\
\text{s.t.} \quad \sum_{i=0}^{N_p-1} \left( h(x_k, u_k) + \boxed{Q^{j-1}(x_{N_p|k})} \right) \\
\text{s.t.} \quad \sum_{i=0}^{N_p-1} \left( h(x_k, u_k) + \boxed{Q^{j-1}(x_{N_p|k})} \right) \\
\text{s.t.} \quad \sum_{i=0}^{N_p-1} \left( h(x_k, u_k) + \boxed{Q^{j-1}(x_{N_p|k})} \right) \\
\text{s.t.} \quad \sum_{i=0}^{N_p-1} \left( h(x_k, u_k) + \boxed{Q^{j-1}(x_{N_p|k})} \right) \\
\text{s.t.} \quad \sum_{i=0}^{N_p-1} \left( h(x_k, u_k) + \boxed{Q^{j-1}(x_{N_p|k})} \right) \\
\text{s.t.} \quad \sum_{i=0}^{N_p-1} \left( h(x_k, u_k) + \boxed{Q^{j-1}(x_{N_p|k})} \right) \\
\text{s.t.} \quad \sum_{i=0}^{N_p-1} \left( h(x_k, u_k) + \boxed{Q^{j-1}(x_{N_p|k})} \right) \\
\text{s.t.} \quad \sum_{i=0}^{N_p-1} \left( h(x_k, u_k) + \boxed{Q^{j-1}(x_{N_p|k})} \right) \\
\text{s.t.} \quad \sum_{i=0}^{N_p-1} \left( h(x_k, u_k) + \boxed{Q^{j-1}(x_{N_p|k})} \right) \\
\text{s.t.} \quad \sum_{i=0}^{N_p-1} \left( h(x_k, u_k) + \boxed{Q^{j-1}(x_{N_p|k})} \right) \\
\text{s.t.} \quad \sum_{i=0}^{N_p-1} \left( h(x_k, u_k) + \boxed{Q^{j-1}(x_{N_p|k})} \right) \\
\text{s.t.} \quad \sum_{i=0}^{N_p-1} \left( h(x_k, u_k) + \boxed{Q^{j-1}(x_{N_p|k})} \right) \\
\text{s.t.} \quad \sum_{i=0}^{N_p-1} \left( h(x_k, u_k) + \boxed{Q^{j-1}(x_{N_p|k})} \right) \\
\text{s.t.} \quad \sum_{i=0}^{N_p-1} \left( h(x_k, u_k) + \boxed{Q^{j-1}(x_{N_p|k})} \right) \\
\text{s.t.} \quad \sum_{i=0}^{N_p-1} \left( h(x_k, u_k) + \boxed{Q^{j-1}(x_{N_p|k})} \right) \\
\text{s.t.} \quad \sum_{i=0}^{N_p-1} \left( h(x_k, u_k) + \boxed{Q^{j-1}(x_{N_p|k})} \right) \\
\text{s.t.} \quad \sum_{i=0}^{N_p-1} \left( h(x_k, u_k) + \boxed{Q^{j-1}(x_{N_p|k})} \right) \\
\text{s.t.} \quad \sum_{i=0}^{N_p-1} \left( h(x_k, u_k) + \boxed{Q^{j-1}(x_{N_p|k})} \right) \\
\text{s.t.} \quad \sum_{i=0}^{N_p-1} \left( h(x_k, u_k) + \boxed{Q^{j-1}(x_{N_p|k})} \right) \\
\text{s.t.} \quad \sum_{i=0}^{N_p-1} \left( h(x_k, u_k) + \boxed{Q^{j-1}(x_{N_p|k})} \right) \\
\text{s.t.} \quad \sum_{i=0}^{N_p-1} \left( h(x_k, u_k) + \boxed{Q^{j-1}(x_{N_p|k})} \right) \\
\text{s.t.} \quad \sum_{i=0}^{N_p-1} \left( h(x_k, u_k) + \boxed{Q^{j-1}(x_{N_p|k})} \right) \\
\text{s.t.} \quad \sum_{i=0}^{N_p-1} \left( h(x_k, u_k) + \boxed{Q^{j-1}(x_{N_p|k})} \right) \\
\text{s.t.} \quad \sum_{i=0}^{N_p-1} \left( h(x_k, u_k) + \boxed{Q^{j-1}(x_{N_p|k})} \right) \\
\text{s.t.} \quad \sum_{i=0}^{N_p-1} \left( h(x_k, u_k) + \boxed{Q^{j-1}(x_{N_p|k}} \right) \\
\text{s.t.} \quad \sum_{i=0}^{N_p-1} \left( h(x_k, u_k) + \boxed{Q^{j-1}(x_{N_p|k}} \right) \\
\text{s.t.} \quad \sum_{i=0}^{N_p-1} \left( h(x_k, u_k) + \boxed{Q^{j-1}(x_{N_p|k}} \right) \\
\text{s.t.} \quad \sum_{i=0}^{N_p-1} \left( h(x_k, u_k) + \boxed{Q^{j-1}(x_{N_p})} \right) \\
\text{s.t.} \quad \sum_{i=0}^{N_p-1} \left( h(x_$$

where:  $SS^{j-1}$  terminal constraint (Safe Set)

 $Q^{j-1}$  terminal cost function (Iteration Cost)

Assumption: There exists a initial feasible trajectory  $x^0$ , which starts from the initial state  $x_0$  and converging to the final goal  $x_f$ .

## Safe Set

Terminal constraint is needed to ensure:

- ► Recursive feasibility
- Iterative feasibility

It is defined the Safe Set SS at j-th iteration, as the set of all the successful trajectories performed in the first j iterations:

$$SS^{j} = \left\{ \bigcup_{i \in M^{j}} \bigcup_{t=0}^{\infty} x_{t}^{j} \right\}$$
 (2)

where:  $M^{j}$  set of trajectories of successful iterations

Particular case: Linear System For linear systems it is possible to relax the Safe Set to its convex hull, defined Convex Set:

$$CS^{j} = Conv(SS^{j}) \tag{3}$$

## **Iteration Cost**

Terminal cost is needed to ensure:

- Asymptotical stability
- Performance improvement

It is defined the Iteration cost:

$$Q^{j}(x) = \begin{cases} \min_{(i,t) \in F^{j}(x)} & J^{i}_{t \to \infty}(x) & \text{if } x \in SS^{j} \\ +\infty, & \text{if } x \notin SS^{j} \end{cases}$$
(4)

where:  $J_{t\to\infty}^i(x)=\sum_{i=0}^\infty \left(h(x_{i|k}^j,u_{i|k}^i)\right)$  terminal cost (cost-to-go)

Particular case: Linear System For linear systems it is possible to relax the iteration cost, to its convex function:

$$P^{j}(x) = \begin{cases} p^{j}(x) & \text{if } x \in SS^{j} \\ +\infty, & \text{if } x \notin SS^{j} \end{cases}$$
 (5)

which is a LP:

$$p^{j}(x) = \min_{\lambda_{t}^{j} \geqslant 0} \sum_{k=0}^{j} \sum_{t=0}^{t_{j}} \left( \lambda_{t}^{k} J_{t \to \infty}^{i}(x) \right)$$
s.t.  $x_{k+1} = Ax_{k} + Bu_{k}, \quad x_{0} = x_{s}$ 

$$x_{k} \in X_{c}$$

$$u_{k} \in U_{c}$$

$$(6)$$