

# Multiagent decision-making and control

## Dynamic games

Maryam Kamgarpour

Professor of Engineering (IGM, STI), EPFL

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## Course topics

- 1 Static games
- 2 Zero-sum games
- 3 Potential games
- 4 Extensive form games
- 5 Randomized strategies in extensive form games
- 6 Dynamic games, dynamic programming for games
- 7 Dynamic games, linear quadratic games
- 8 Convex games, Nash equilibria characterization
- 9 Convex games, Nash equilibria computation
- 10 Auctions
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- 13 Final project presentations

## Admin matter

- Timeline: project update: April 16, 13:15-14:00, 10%
- Template for presentation was posted on last week's Moodle

### Dynamic game (first zero-sum setting for simplicity)

There exists a **state** that evolves at each stage

$$x_{k+1} = f(x_k, u_k, v_k).$$

The **outcome** of the game can be expressed as

$$\sum_{k=1}^K g_k(x_k, u_k, v_k).$$

- player 1 minimizer, player 2 maximizer

Last time, we motivated and defined subgame perfect equilibrium.

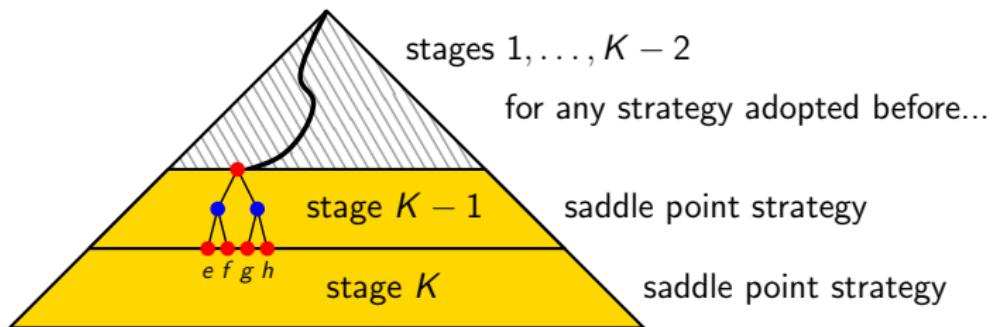
Today's goals:

- more intuition into subgame perfect equilibrium
- computation for specific class of dynamic games: linear quadratic games

# Backward induction to compute subgame perfect equilibria

## Subgame-perfect Nash Equilibrium

A strategy is a **subgame perfect** equilibrium if it represents a NE of every subgame of the original game.



At every stage, we have a static **simultaneous game**

Stage game at time  $K$

$$V_K(x) = \underbrace{\inf_{u \in U} \sup_{v \in V} g_K(x, u, v)}_{\text{equilibrium for } g_K(x, u, v)}$$

## Backward induction in 2-player zero-sum setting

**STEP  $K$ :** Consider all the infinite subgames rooted in  $x_K$ :

(Notice the abuse of notation: P1 node / state)

$$x_{K+1} = f(x_K, u_K, v_K)$$

with outcome

$$g_K(x_K, u_K, v_K)$$

Determine  $\gamma_K^*, \sigma_K^*$  (functions of  $x_K$ ) such that

$$g_K(x_K, \gamma_K^*(x_K), \sigma_K(x_K)) \leq g_K(x_K, \gamma_K^*(x_K), \sigma_K^*(x_K)) \leq g_K(x_K, \gamma_K(x_K), \sigma_K^*(x_K))$$

## Backward induction in 2-player zero-sum setting continued

**Value function**  $V_K(x_K)$ : value of the subgame rooted in  $x_K$ , that is

$$V_K(x_K) = g_K(x_K, \gamma_K^*(x_K), \sigma_K^*(x_K))$$

**STEP  $K - 1$** : Consider all the infinite subgames rooted in  $x_{K-1}$

$$x_K = f(x_{K-1}, u_{K-1}, v_{K-1})$$

$\kappa-1$

with outcome

$$\sum_{k=K-1}^K g_k(x_k, u_k, v_k)$$

which we rewrite as

$$g_{K-1}(x_{K-1}, u_{K-1}, v_{K-1}) + V_K(x_K)$$

and therefore

$$g_{K-1}(x_{K-1}, u_{K-1}, v_{K-1}) + V_K(f(x_{K-1}, u_{K-1}, v_{K-1}))$$

$\kappa-7$

## Backward induction

$$\overbrace{\quad}^{\text{J}_{K-1}(x_{K-1}, u_{K-1}, v_{K-1})} \\ g_{K-1}(x_{K-1}, u_{K-1}, v_{K-1}) + V_K(f(x_{K-1}, u_{K-1}, v_{K-1}))$$

Determine  $\gamma_{K-1}^*, \sigma_{K-1}^*$  (functions of  $x_{K-1}$ ) that are saddle-points for

$$g_{K-1}(x_{K-1}, \gamma_{K-1}^*(x_{K-1}), \sigma_{K-1}^*(x_{K-1})) + V_K(f(x_{K-1}, \gamma_{K-1}^*(x_{K-1}), \sigma_{K-1}^*(x_{K-1})))$$

and so on, backward until **stage 1**.

$$\overbrace{\quad}^{\text{J}_{K-1}(x_{K-1}, \gamma_{K-1}^*(x_{K-1}), \sigma_{K-1}^*(x_{K-1}))} \leq \overbrace{\quad}^{\text{J}_{K-1}(x_{K-1}, \gamma_{K-1}^*(x_{K-1}), \sigma(x_{K-1}))} \leq \overbrace{\quad}^{\text{J}_{K-1}(x_{K-1}, \gamma_{K-1}^*(x_{K-1}), \sigma^*(x_{K-1}))}$$
$$\forall \sigma_{K-1} : X \rightarrow V \quad \forall \gamma_{K-1} : X \rightarrow U$$

## Dynamic games with $N$ players, Nash equilibrium

We can generalize what we saw for two players in last lecture to  $N$  players

- Dynamics  $x_{k+1} = f(x_k, u_k^1, \dots, u_k^N), x_k \in X$
- Player  $i$ 's input set:  $U^i$ —can be time and state dependent, namely:  $U_k^i(x)$
- Player  $i$ 's cost function:  $\sum_{k=1}^K g_k^i(x_k, u_k^1, \dots, u_k^N)$  at  $k = K$
- State-feedback policy:  $\pi_k^i : X \rightarrow U^i, \pi_k^i(x_k) = u_k^i$  find equilibrium
- Open-loop policy:  $\pi_k^i : X \rightarrow U^i, \pi_k^i(x_1) = u_k^i$

$\left\{ \begin{array}{l} g^i(x, u^1, u^2, \dots, u^N) \\ K \end{array} \right\}_{i=1}^N$

Finding subgame perfect equilibrium by backward induction:

Set  $V_{K+1}^i(x) = 0, i \in \{1, 2, \dots, N\}$ . For  $k = K, K-1, \dots, 1$ ,

- find a Nash equilibrium policy at stage  $k$ :  $\{\pi_k^{*,i}(x)\}_{i=1}^N$
- compute  $V_k^i(x)$  corresponding to the above policies,  $i \in \{1, 2, \dots, N\}$

## An important extension: infinite horizon

Let us present it for simplicity in notation in single-player setting

player's cost:  $\lim_{K \rightarrow \infty} \sum_{k=1}^K g(x_k, u_k)$

ensure convergence of the sum, one approach is geometrically discounting costs

- infinite horizon discounted cost

$$\sum_{k=1}^{\infty} \alpha^k g(x_k, u_k)$$

►  $\alpha \in [0, 1)$  and  $\exists M > 0$  such that  $|g(x, u)| \leq M$  for all  $x \in X, u \in U$

$$\Rightarrow \sum_{k=1}^{\infty} \alpha^k g(x_k, u_k) < \infty$$

$$\leq \sum_{k=1}^{\infty} \alpha^k M = \frac{M}{1-\alpha}$$

- Bellman equation

$$V^*(x) = \min_{u \in U} \{g(x, u) + \alpha V^*(f(x, u))\}, \quad \forall x \in X$$

- Optimal stationary policy

$$\pi^*(x) = \arg \min_{u \in U} g(x, u) + \alpha V^*(f(x, u)), \quad \forall x \in X$$

## Computation of subgame perfect equilibrium policies

### Dynamic game (2-player zero-sum)

There exists a **state** that evolves at each stage

$$x_{k+1} = f(x_k, u_k, v_k).$$

The **outcome** of the game can be expressed as

$$\sum_{k=1}^K g_k(x_k, u_k, v_k).$$

Finding the NE strategy for a dynamic game corresponds to solving an optimization problem for every stage.

**These problems are in general difficult to solve.**

One special case:

- **Linear** state update  $f$
- **Quadratic** cost function  $g$ .

## One-player LQR

Consider the one-player case first.

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### Update equation

$$x_{k+1} = Ax_k + Bu_k, \quad x \in \mathbb{R}^n, u \in \mathbb{R}^m$$

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$$\sum_{k=0}^{K-1} \left( x_k^T Q x_k + u_k^T R u_k \right) + x_K^T S x_K,$$

$R, Q$  are symmetric and  $R \succ 0, Q \succeq 0$

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$R, Q$  are symmetric and  $R \succ 0, Q \succeq 0$

**Value function** (minimum cost to go, starting from  $x$  at time  $k$ )

$$V_k(x) = \min_{u_k, \dots, u_{K-1}} \sum_{s=k}^{K-1} (x_s^T Q x_s + u_s^T R u_s) + x_K^T S x_K$$

$V_0(x_0)$  is the value of the game.

## One-player LQR

$$x^T S x$$

Key ideas in the derivation of the NE feedback control law.

- 1  $V_K(x) = x^T Q x$  (quadratic function)
- 2 We will show that  $V_k(x)$  is also quadratic:  $V_k(x) = x^T P_k x$
- 3  $P_k$  can be found recursively, working backward from  $K$
- 4 The (NE)  $u_k$  is a function of  $P_k$  and can be found easily because  $P_k$  is positive definite.

We proceed by induction at stage  $k$ , where the value function is

$$V_k(x) = \min_u x^T Q x + u^T R u + V_{k+1}(Ax + Bu)$$

optimal input (since single player)

Induction recall

$$V_k(x) = \min_u x^T Q x + u^T R u + V_{k+1}(f(x, u))$$

We proceed by induction, assuming that  $V_{k+1}(x) = x^T P_{k+1} x$ . Then  $V_k(x)$  becomes

$$\begin{aligned} V_k(x) &= x^T Q x + \min_u u^T R u + (Ax + Bu)^T P_{k+1} (Ax + Bu) = \\ &= x^T Q x + \min_u u^T R u + x^T A^T P_{k+1} A x + 2u^T B^T P_{k+1} A x + u^T B^T P_{k+1} B u \\ &= x^T Q x + \min_u u^T (R + B^T P_{k+1} B) u + x^T A^T P_{k+1} A x + 2u^T B^T P_{k+1} A x \end{aligned}$$

To find the minimizer, we notice that  $R + B^T P_{k+1} B \succ 0$ . Hence, this is a strongly convex objective in  $u \in \mathbb{R}^m$  and by setting the gradient with respect to  $u$  to zero, we can find the optimizer.

$$(R + B^T P_{k+1} B)u + B^T P_{k+1} A x = 0$$

positive  
definite

which gives the optimal feedback control

$$u^* = -(R + B^T P_{k+1} B)^{-1} B^T P_{k+1} A x$$

$\Leftrightarrow$   
all eigen  
values  
strictly  $> 0$

$\Rightarrow$  invertible &  
function is strongly convex

## Induction

Now we need to check that  $V_k(x)$  is also quadratic in  $x$ , i.e.  $V_k(x) = x^T P_k x$ , and to find how to compute  $P_k$ .

We plug the minimizer  $u^*$  into  $V_k(x)$ , and obtain the expression

$$\begin{aligned} V_k(x) = & x^T Q x + x^T A P_{k+1} B (R + B^T P_{k+1} B)^{-1} (R + B^T P_{k+1} B) \cdot \\ & \cdot (R + B^T P_{k+1} B)^{-1} B^T P_{k+1} A x + x^T A^T P_{k+1} A x \\ & - 2x^T A P_{k+1} B (R + B^T P_{k+1} B)^{-1} B^T P_{k+1} A x. \end{aligned}$$

Just collecting the different terms we get  $V_k(x) = x^T P_k x$  where  $P_k$  is defined as

$$P_k = Q + A^T P_{k+1} A - A^T P_{k+1} B (R + B^T P_{k+1} B)^{-1} B^T P_{k+1} A$$

which completes the proof.

## One-player LQR

**Optimal feedback policy is linear:**

- Value function  $V_k(x) = x^T P_k x, P_k \succeq 0$

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- Subgame-perfect NE input is given by the linear state feedback

$$u_k = \Gamma_k x_k$$

where for all  $k = 0, \dots, K-1$  we define

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- For  $k = K, \dots, 1$ ,

$$P_{k-1} = Q + A^T P_k A - A^T P_k B (R + B^T P_k B)^{-1} B^T P_k A$$

starting from  $P_K = S$ .

## Comments on one-player LQR

Symmetry and positive semi-definitess of  $P_k$

Also this can be verified by induction.

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### Symmetry and positive semi-definiteness of $P_k$

Also this can be verified by induction.

$K \rightarrow \infty$

If  $P_0$  converges to some  $\bar{P}$  when  $K \rightarrow +\infty$ , then  $\bar{P}$  can be evaluated via a **discrete Algebraic Riccati Equation**:

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

### Exercise

How quickly does  $P_k$  converge to  $\bar{P}$  in a simple example, and what kind of performance is given by  $\bar{P}$

## Comments on one-player LQR

### Time-varying $A, B, Q, R$

The entire derivation (for finite horizons) works also in the case of time-varying system parameters (for example, linearization of a non-linear system along the optimal trajectory).

## Comments on one-player LQR

### Time-varying $A, B, Q, R$

The entire derivation (for finite horizons) works also in the case of time-varying system parameters (for example, linearization of a non-linear system along the optimal trajectory).

### Alternative approach in finite horizon

If there are state and input constraints, the Riccati equation above will not hold. We can use numerical computation approaches to solve the following

$$\min_{u_0, \dots, u_{K-1}} \sum_{k=0}^{K-1} \left( x_k^T Q x_k + u_k^T R u_k \right) + x_K^T S x_K$$

subject to  $x_{k+1} = Ax_k + Bu_k \quad \text{for } k = 0, \dots, K-1$

$$x_k \in \mathcal{X}_k$$

$$u_k \in \mathcal{U}_k$$

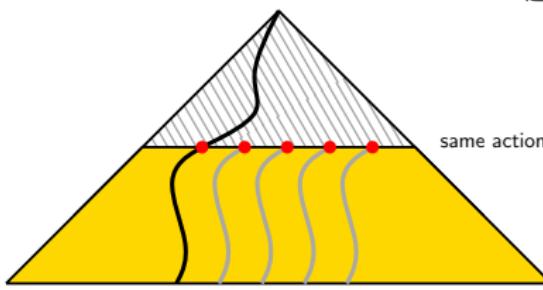
## Open-loop NE strategy

By solving the optimization **in one shot** (no DP), we get

$$u_0, u_1, \dots, u_{K-1} \in \mathbb{R}^m$$

instead of a state feedback

$$u_0(x), u_1(x), \dots, u_{K-1}(x)$$



with  
LQR  
approach  
we found  
optimal policy  
to be linear  
in state  $x$

$$u_{1c} = \Gamma_{1c} x_{1c}$$

$$\Gamma_{1c} \in \mathbb{R}^{m \times n}$$

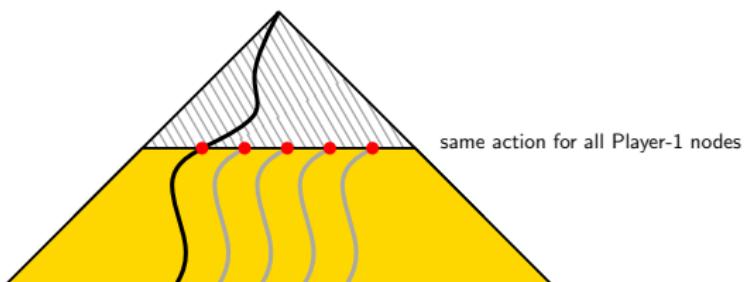
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This is an **open-loop** (= non-subgame-perfect) NE strategy!

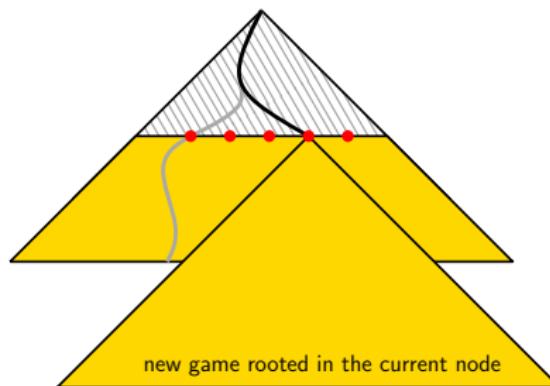
What to do if we get to a node of the tree which does not belong to the NE trajectory?

## Receding horizon

### Receding horizon

Re-calculate a NE strategy from the new starting point (i.e., for the subtree rooted in the current node).

For example: Model Predictive Control (MPC)



- Computationally not as efficient as explicit **backward induction**
- Optimization has to be solved **in real time**
- Still **better than solving the entire tree**

## Two-player LQR

Two controllers, with their own objective.

### Climate control

Player 1 goal: low humidity (byproduct: high temperature)

Player 2 goal: low temperature

### Multi-robot control

Both players want to create a formation that achieves optimal coverage of an area.

### Platoon of trucks

Fuel saving + safety objectives for all trucks.

Competitive (different companies) or collaborative (1-player LQR)

## Two-player LQR

State update equation for  $k = 0, \dots, K - 1$

$$x_{k+1} = Ax_k + B_1u_k + B_2v_k$$

### Non-zero sum game setup

$$J_1(u_1, \dots, u_{K-1}, v_1, \dots, v_{K-1}) = \sum_{k=0}^{K-1} \left( x_k^T Q_1 x_k + u_k^T R_1 u_k \right) + x_K^T S_1 x_K$$

$$J_2(u_1, \dots, u_{K-1}, v_1, \dots, v_{K-1}) = \sum_{k=0}^{K-1} \left( x_k^T Q_2 x_k + v_k^T R_2 v_k \right) + x_K^T S_2 x_K$$

We try to apply backward induction to find a sub-game perfect NE.

## Two-player LQR

cost to go for each player

Let us define the value of the game at state  $x$  in stage  $k$  as

$$\begin{array}{l} \text{Player 1} \nearrow \\ V_{1k}(x) = \min_{u_k, \dots, u_{K-1}} \sum_{s=k}^{K-1} (x_s^T Q_1 x_s + u_s^T R_1 u_s) + x_K^T S_1 x_K \end{array}$$
$$\begin{array}{l} \text{Player 2} \nearrow \\ V_{2k}(x) = \min_{u_k, \dots, u_{K-1}} \sum_{s=k}^{K-1} (x_s^T Q_2 x_s + v_s^T R_2 v_s) + x_K^T S_2 x_K \end{array}$$

## Two-player LQR

Let us define the value of the game at state  $x$  in stage  $k$  as

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$$V_{2k}(x) = \min_{u_k, \dots, u_{K-1}} \sum_{s=k}^{K-1} (x_s^T Q_2 x_s + v_s^T R_2 v_s) + x_K^T S_2 x_K$$

**STAGE  $K$ :** For  $k = K$  (last stage) we have the quadratic forms

$$V_{1K}(x) = x^T S_1 x$$

$$V_{2K}(x) = x^T S_2 x$$

## Two-player LQR

As before, we conjecture that the value function is quadratic for all  $k$ .

$$V_{1k}(x) = x^T P_{1k} x$$

$$V_{2k}(x) = x^T P_{2k} x$$

If this is true, then it is enough to find the Nash equilibrium of the **static** game at a generic stage  $k$ , and iterate backwards.

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**Stage  $k$  game:** two coupled problems

$$\begin{aligned} J_1 &= x_k^T Q_1 x_k + u_k^T R_1 u_k + V_{1,k+1}(x_{k+1}) \\ &= x_k^T Q_1 x_k + \textcolor{red}{u_k^T R_1 u_k} + V_{1,k+1}(Ax_k + B_1 \textcolor{red}{u_k} + B_2 \textcolor{blue}{v_k}) \\ J_2 &= x_k^T Q_2 x_k + v_k^T R_2 v_k + V_{2,k+1}(x_{k+1}) \\ &= x_k^T Q_2 x_k + \textcolor{blue}{v_k^T R_2 v_k} + V_{2,k+1}(Ax_k + B_1 \textcolor{red}{u_k} + B_2 \textcolor{blue}{v_k}) \end{aligned}$$

## Two-player LQR

$$\left( Ax_k + B_1 \bar{u}_k + B_2 \bar{v}_k \right) \stackrel{T}{\overbrace{P_{k+1}}} \left( Ax_k + B_1 u_k + B_2 v_k \right)$$

$$J_1 = x_k^T Q_1 x_k + \color{red}{u_k^T R_1 u_k} + V_{1,k+1}(Ax_k + B_1 \color{red}{u_k} + B_2 \color{blue}{v_k})$$

$$J_2 = x_k^T Q_2 x_k + \color{blue}{v_k^T R_2 v_k} + V_{2,k+1}(Ax_k + B_1 \color{red}{u_k} + B_2 \color{blue}{v_k})$$

For each player, we construct the **best response strategy**.

### Best response strategies

$$\hat{u}_k(v_k) = - \left( R_1 + B_1^T P_{1,k+1} B_1 \right)^{-1} B_1^T P_{1,k+1} (Ax_k + B_2 v_k)$$

$$\hat{v}_k(u_k) = - \left( R_2 + B_2^T P_{2,k+1} B_2 \right)^{-1} B_2^T P_{2,k+1} (Ax_k + B_1 u_k)$$

$$\left. \begin{array}{l} \frac{\partial J_1}{\partial u_1} = 0 \\ \frac{\partial J_2}{\partial u_2} = 0 \end{array} \right\}$$

$$\left. \begin{array}{l} u_k \\ v_k \end{array} \right\} = \left[ \begin{array}{l} c_1 \\ c_2 \end{array} \right]_k$$

## One-stage Nash equilibrium

Given the two best responses, the NE strategy  $(u_k^*, v_k^*)$  satisfies

$$\hat{u}_k(v_k^*) = u_k^*$$

$$\hat{v}_k(u_k^*) = v_k^*$$

that is

$$u_k^* = - \left( R_1 + B_1^T P_{1,k+1} B_1 \right)^{-1} B_1^T P_{1,k+1} (Ax_k + B_2 v_k^*)$$

$$v_k^* = - \left( R_2 + B_2^T P_{2,k+1} B_2 \right)^{-1} B_2^T P_{2,k+1} (Ax_k + B_1 u_k^*)$$

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### NE feedback

The NE strategy is a linear feedback of the state  $x_k$

$$u_k^* = H_{1k} x_k, \quad v_k^* = H_{2k} x_k$$

that satisfies the best-response coupled conditions above.

## Value of the single-stage game

Given the NE strategy

$$u_k^* = H_{1k}x_k, \quad v_k^* = H_{2k}x_k.$$

we have the following **quadratic** value of the single-stage game.

*k*th stage subgame value

$$V_{1k} = x_k^T P_{1k} x_k, \quad V_{2k} = x_k^T P_{2k} x_k$$

where

$$P_{1k} = Q_1 + H_{1k}^T R_1 H_{1k} + (A + B_1 H_{1k} + B_2 H_{2k})^T \textcolor{red}{P}_{1,k+1} (A + B_1 H_{1k} + B_2 H_{2k})$$

$$P_{2k} = Q_2 + H_{2k}^T R_2 H_{2k} + (A + B_1 H_{1k} + B_2 H_{2k})^T \textcolor{red}{P}_{2,k+1} (A + B_1 H_{1k} + B_2 H_{2k})$$

## From single stage to multi stage

- The value function is **quadratic**:  $V_{1k} = x_k^T P_{1k} x_k$ ,  $V_{2k} = x_k^T P_{2k} x_k$ 
  - ▶ we can use iterate backward on the stages

## From single stage to multi stage

- The value function is **quadratic**:  $V_{1k} = x_k^T P_{1k} x_k$ ,  $V_{2k} = x_k^T P_{2k} x_k$ 
  - ▶ we can use iterate backward on the stages
- Iterative computation via **two coupled Riccati equations**
  - ▶ how are they coupled?

$$P_{1k} = Q_1 + H_{1k}^T R_1 H_{1k} + (A + B_1 H_{1k} + B_2 H_{2k})^T P_{1,k+1} (A + B_1 H_{1k} + B_2 H_{2k})$$

$$P_{2k} = Q_2 + H_{2k}^T R_2 H_{2k} + (A + B_1 H_{1k} + B_2 H_{2k})^T P_{2,k+1} (A + B_1 H_{1k} + B_2 H_{2k})$$

$$P_{1K} = S_1$$

$$P_{2K} = S_2$$

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$$P_{1K} = S_1$$

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- The NE control  $u_k^*, v_k^*$  can be computed from  $P_{ik}$ 
  - ▶ System of linear equations (or explicit form)

## Summary and further reading

- We can find subgame perfect equilibria of dynamic feedback games using backward induction
- Computation:
  - ▶ at each stage, need to find a Nash equilibrium for every state  $x \in X$ : generally difficult
  - ▶ tractable for certain classes of games, such as linear quadratic games
- in linear quadratic games, there exists a linear state-feedback policy Nash equilibrium
- Reading: Chapter 17 of Hespanha



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