67678 - Introduction to Control with Learning **Spring 2024**

Linear Dynamical Systems - Summary

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1 Mathematical Tools

1.1 Completing The Square

Lemma 1.1 (Completing the Square (scalars))
To complete the square for a quadratic equation of the form

$$ax^2 + bx + c = 0,$$

we can rewrite it as

$$a(x+d)^2 + e = 0,$$

where

$$d = \frac{b}{2a} \quad \text{and} \quad e = c - \frac{b^2}{4a}.$$

Proof.

$$\begin{aligned}
ax^2 + bx + c = 0 \quad &\rightarrow \quad x^2 + \frac{b}{a}x + \frac{c}{a} = 0 \quad \rightarrow \quad x^2 + \frac{b}{a}x = -\frac{c}{a} \quad \rightarrow \\
x^2 + \frac{b}{a}x + \left(\frac{b}{2a}\right)^2 = -\frac{c}{a} + \left(\frac{b}{2a}\right)^2 \quad &\rightarrow \quad \left(x + \frac{b}{2a}\right)^2 = \frac{b^2}{4a^2} - \frac{c}{a} \quad \rightarrow \quad \left(x + \frac{b}{2a}\right)^2 = \frac{b^2 - 4ac}{4a^2} \quad \rightarrow \\
a\left(x + \frac{b}{2a}\right)^2 = a\left(\frac{b^2 - 4ac}{4a^2}\right) \quad &\rightarrow \quad a\left(x + \frac{b}{2a}\right)^2 = \frac{b^2 - 4ac}{4a} \quad \rightarrow \quad a\left(x + \frac{b}{2a}\right)^2 + c - \frac{b^2}{4a} = 0
\end{aligned}$$

□

Lemma 1.2 (Completing the Square for Quadratic Forms)
Given a quadratic form $x^T Ax + b^T x + c$, where A is a symmetric positive definite matrix, b is a vector, and c is a scalar, the expression can be completed to a perfect square as follows:

$$x^T Ax + b^T x + c = (x + A^{-1}b/2)^T A(x + A^{-1}b/2) + c - \frac{1}{4}b^T A^{-1}b$$

2 The Shortest Path Problem

Definition 2.1 (The Shortest Path Problem)
Given a directed graph $G = (V, E)$, each edge in the graph has a cost a^t_{ij} where i is the outgoing node, j is the node to which the edge is connected, and $t \in \{0, \dots, N+1\}$ refers to the time. We adopt the convention that no edge implies an infinite cost $a^t_{ij} = \infty$.
The objective is to minimize the cumulative cost on a path from the source node $S_0 = S$ to the terminal node $S_{N+1} = T$. Formally, we aim to solve the optimization

$$J^* = \min_{\{n_i \in \mathcal{S}_i\}_{i=0}^{N+1}} \sum_{t=0}^{N} a^t_{n_t, n_{t+1}}. \tag{2.1}$$

Definition 2.2 (Cost-to-Go Function)
We define $J_k(i)$ as the cost-to-go function corresponding to the minimal cost from time k until the end when starting at node i. Formally, for $k = 0, \dots, N$, define

$$J_k(i) = \min_{\{n_j \in \mathcal{S}_j | j=k+1,\dots,N, n_k = i\}} \sum_{j=k}^{N} a^j_{n_t, n_{t+1}}, \quad \forall i \in \mathcal{S}_k. \tag{2.2}$$

Algorithm 1: Dynamic Programming Solution for the Shortest Path Problem (Cost-to-Go)

Input: Cost matrix a^t_{ij} and nodes $\mathcal{S}_0, \mathcal{S}_1, \dots, \mathcal{S}_{N+1}$
Output: Cost-to-go functions $J_k(i)$
Initialize $J_N(i) = a^N_{iT}$;
for $k = N-1, \dots, 0$ **do**
  for $i \in \mathcal{S}_k$ **do**
    $J_k(i) = \min_{j \in \mathcal{S}_{k+1}} \left[a^k_{ij} + J_{k+1}(j)\right]$
  end
end

Definition 2.3 (Cost-to-Arrive Function)
We define $J_{N-k}(j)$ as the cost-to-arrive function corresponding to the minimal cost from time 1 until time k when arriving at node j. Formally, for $k = 0, \dots, N$, define

$$J_{N-k}(j) = \min_{\{n_i \in \mathcal{S}_i | i=1,\dots,k-1, n_k = j\}} \sum_{i=1}^{k} a^i_{n_{i-1}, n_i}, \quad \forall j \in \mathcal{S}_k. \tag{2.3}$$

Algorithm 2: Forward Algorithm for the Shortest Path Problem (Cost-to-Arrive)

Input: Cost matrix a^t_{ij} and nodes $\mathcal{S}_0, \mathcal{S}_1, \dots, \mathcal{S}_{N+1}$
Output: Cost-to-arrive functions $J_{N-k}(j)$
Initialize $J_N(j) = a^0_{sj}, \forall j \in \mathcal{S}_1$;
for $k = 1, \dots, N$ **do**
  for $j \in \mathcal{S}_{N-k+1}$ **do**
    $J_k(j) = \min_{i \in \mathcal{S}_{N-k}} \left[a^{N-k}_{ij} + J_{k+1}(i)\right]$
  end
end

3 Markov Decision Processes (MDPs)

Definition 3.1 (MDP)
An MDP is defined by the following elements:

1. *The state at time k is x_k and takes values in the set $\mathcal{S}_k$.*
2. *The action at time k is u_k and takes values from $\mathcal{U}_k$.*
3. *The disturbance at time k is w_k and takes values from $\mathcal{W}_k$.*
4. *A dynamical system is given by the function*
$$x_{k+1} = f_k(x_k, u_k, w_k), \quad k = 0, \ldots, N-1. \tag{3.1}$$
5. *The probabilistic law of the disturbance random variable w_k is characterized by $P_{W_k}(\cdot|x_k, u_k)$ conditioned on the state x_k and the action u_k.*
6. *A cost function $g_k : \mathcal{S}_k \times \mathcal{U}_k \to \mathbb{R}$.*

The cost over a horizon N is

$$S_\pi(x_0) = \mathbb{E}[g_N(x_N) + \sum_{k=0}^{N-1} g_k(x_k, u_k)], \tag{3.2}$$

where $g_N(\cdot)$ is the terminal cost.

Definition 3.2 (History-dependent policy)
A history-dependent policy is defined by a sequence of functions:

$$\mu_k : \mathcal{S}_1 \times \cdots \times \mathcal{S}_k \times \mathcal{U}_1 \times \cdots \mathcal{U}_{k-1} \to \mathcal{U}_k, \tag{3.3}$$

such that $u_k = \mu_k(x_1, x_2, \ldots, x_k, u_1, \ldots, u_{k-1})$.

Definition 3.3 (Markovian policy)
A Markovian policy is defined by a sequence of functions:

$$\mu_k : \mathcal{S}_k \to \mathcal{U}_k, \tag{3.4}$$

such that $u_k = \mu_k(x_k)$.

Remark 3.1 (The Markov property)
We defined the dynamical system using a deterministic function $f_k(\cdot)$.
Equivalently, we could describe the evolution with the conditional probability

$$P_k(x_{k+1}|x_k, u_k) = P_s^u(s') \tag{3.5}$$

In particular, we assume that the new state conditioned on the current state and action is not affected by the past. Formally, we assume the Markov chain induced from

$$P(x_{k+1}|x_1, \ldots, x_k, u_1, \ldots, u_k) = P_k(x_{k+1}|x_k, u_k). \tag{3.6}$$

The MDP described above is called fully observable since the actions depend directly on the state. We will later encounter partially observable MDP where only a noisy version of the state is available to the controller.

4 Linear Systems

Definition 4.1 (Linear System)
A linear system is given by

$$x_{t+1} = Ax_t, \quad t = 0, 1, \dots \tag{4.1}$$

with some initial state x_0.

- $x_t \in \mathbb{R}^n$ *is the state vector.*
- $A \in \mathbb{R}^{n \times n}$ *is the state-transition matrix.*

Lemma 4.1 (State and Decoupling in Linear Systems)
Given a diagonalizable matrix $A = TDT^{-1}$, the state at time t in a linear system is

$$x_t = TD^tT^{-1}x_0. \tag{4.2}$$

By defining a new state $z_t = T^{-1}x_t$, we have

$$z_t = D^t z_0, \tag{4.3}$$

indicating that the states are decoupled, with each entry of z_t depending only on the corresponding entry of z_0.

Remark 4.1
Since the eigenvalues of real matrices may be complex, we have

$$\lambda = a + ib = re^{i\theta} \to \lambda^t = r^t e^{it\theta}(e^{i\theta} = \cos\theta + i\sin\theta).$$

As we increase t, the magnitude of $e^{it\theta}$ is clearly unchanged. However, the length of r determines whether it converges to zero, oscillates, or blows up.

Definition 4.2 (Stable System)
A system A is stable if all of its eigenvalues have magnitude smaller than 1, i.e., $r < 1$.

5 Linear Systems with Control

Definition 5.1 (Linear System with Control)
A linear system with control is given by

$$x_{t+1} = Ax_t + Bu_t, \quad t \geq 0, \quad x_0 \in \mathbb{R}^n, \tag{5.1}$$

where we added:

- $u_t \in \mathbb{R}^m$ *is the control signal (action).*
- $B \in \mathbb{R}^{n \times m}$ *is the control matrix.*

Definition 5.2 (State-feedback controller)
A controller (policy) is defined by a sequence of mappings $\mu_t : \mathbb{R}^n \to \mathbb{R}^m$ *for* $t = 0, 1, \dots, N$ *such that* $u_t = \mu_t(x_t)$.

Definition 5.3 (State-Feedback, Time-Invariant, Linear Controller)
A state-feedback, time-invariant, linear controller is any mapping of the form

$$u_t = -Kx_t.$$

Definition 5.4 (Closed-Loop Matrix)
The matrix $A_K = A - BK$ *is called the closed-loop matrix of the system* A. *I.H.T -*

$$x_{t+1} = A_K x_t = (A - BK)x_t = Ax_t + B(-Kx_t) = Ax_t + Bu_t$$

Definition 5.5 (Controllability)
The pair (A, B) *is controllable if the system can reach any* $\xi \in \mathbb{R}^n$ *from any initial state* $x_0 \in \mathbb{R}^n$ *at some finite time.*

Lemma 5.1 (Controllability Matrix)
A pair (A, B) *is controllable if and only if the controllability matrix*

$$C \triangleq \begin{bmatrix} B & AB & \cdots & A^{n-1}B \end{bmatrix}$$

has $rank(C) = n$.

Lemma 5.2 (Poles Placement in Controllable System)
Controllability implies that we can choose the eigenvalues (poles) of $A - BK$ *arbitrarily.*

6 The Linear Quadratic Regulator (LQR)

Definition 6.1 (The LQR problem)
For the linear model in (20), find a controller that minimizes

$$J_N(u^N) = \sum_{i=0}^{N}[x_i^T Q x_i + u_i^T R u_i] + x_{N+1}^T Q_f x_{N+1},$$

where $u^N \triangleq u_0, u_1, \ldots, u_{N-1}$, *and*

1. $Q, Q_f \succeq 0$ *are state weights*
2. $R \succ 0$ *is the input/action/control weight.*

Lemma 6.1 (LQR matrix formulation)

$$\begin{bmatrix} x_0 \\ \vdots \\ x_N \end{bmatrix} = \begin{bmatrix} 0 & 0 & \cdots & 0 \\ B & 0 & \cdots & 0 \\ AB & B & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ A^{N-1}B & A^{N-2}B & \cdots & B \end{bmatrix} \begin{bmatrix} u_0 \\ \vdots \\ u_{N-1} \end{bmatrix} + \begin{bmatrix} I \\ A \\ \vdots \\ A^N \end{bmatrix} x_0$$

The matrices above can be written in short as $x = Gu + Hx_0$.

Lemma 6.2 (LQR Closed-Form Solution)
The optimal control input $\mathbf{u}$ *that minimizes the cost function* $\mathbf{u}^T\mathbf{u} + \mathbf{x}^T\mathbf{x}$ *can be achieved with*

$$\mathbf{u} = -(I + G^T G)^{-1} G^T H x_0.$$

Proof.

$$\begin{aligned}
\min_{\mathbf{u}} \mathbf{x}^T\mathbf{x} + \mathbf{u}^T\mathbf{u} &= \min_{\mathbf{u}} (G\mathbf{u} + Hx_0)^T (G\mathbf{u} + Hx_0) + \mathbf{u}^T\mathbf{u} \\
&= \min_{\mathbf{u}} \left[\mathbf{u}^T G^T G\mathbf{u} + 2x_0^T H^T G\mathbf{u} + x_0^T H^T H x_0 + \mathbf{u}^T\mathbf{u}\right] \\
&= \min_{\mathbf{u}} \left[\mathbf{u}^T (I + G^T G)\mathbf{u} + 2x_0^T H^T G\mathbf{u} + x_0^T H^T H x_0\right] \\
&= \min_{\mathbf{u}} \left[(\mathbf{u} + (I + G^T G)^{-1} G^T H x_0)^T (I + G^T G)(\mathbf{u} + (I + G^T G)^{-1} G^T H x_0)\right. \\
&\quad \left. - x_0^T H^T G (I + G^T G)^{-1} G^T H x_0 + x_0^T H^T H x_0\right] \\
&= \min_{\mathbf{u}} \left[(\mathbf{u} + (I + G^T G)^{-1} G^T H x_0)^T (I + G^T G)(\mathbf{u} + (I + G^T G)^{-1} G^T H x_0)\right] \\
&\quad + x_0^T H^T (I - G(I + G^T G)^{-1} G^T) H x_0 \\
&= x_0^T H^T (I - G(I + G^T G)^{-1} G^T) H x_0 \\
&= x_0^T H^T (I + GG^T)^{-1} H x_0,
\end{aligned}$$

where the optimal control input is

$$\mathbf{u} = -(I + G^T G)^{-1} G^T H x_0.$$

□

Remark 6.1
This solution is the optimal solution. However, it is not efficient since we should compute the inverse of $I + GG^T$ *that grows linearly with* N, *i.e.,* $O(N^3)$ *computations.*

Definition 6.2 (Cost-to-Go Function)
The cost-to-go function (Value-function) is defined as

$$V_t(z) = \min_{u_t, u_{t+1}, \ldots, u_{N-1}} \left[\sum_{i=t}^{N-1} (x_i^T Q x_i + u_i^T R u_i) + x_N^T Q_f x_N\right]$$

for $x_t = z$.

Theorem 6.1 (Properties of the Value Function)
The value function satisfies the following properties.

1. $V_t(z)$ *is a quadratic function (of the variable* z*).*
   That is, we can write $V_t(z) = z^T P_t z$ *with some* $P_t \succeq 0$*.*
2. *The optimal controller* u_t *is given by*
$$u_t = -(R + B^T P_{t+1} B)^{-1} B^T P_{t+1} A x_t.$$
3. *The sequence* P_t *can be computed recursively with*
$$P_t = \begin{cases} Q_f & t = N \\ Q + A^T P_{t+1} A - A^T P_{t+1} B (R + B^T P_{t+1} B)^{-1} B^T P_{t+1} A & t < N. \end{cases}$$

Note that we can compute P_t and K_t offline prior to the control.
(Tools used in the proof - completion of the square, induction.)

Definition 6.3 (Stabilizability)
The pair (A, B) *is stabilizable if*
$$\exists K \in \mathbb{R}^{m \times n} : \rho(A - BK) < 1,$$
where $\rho(A - BK)$ *denotes the spectral radius of* $A - BK$*, i.e., the largest absolute value of its eigenvalues.*

An equivalent characterization of stabilizability is
$$\nexists (x, \lambda) \text{ s.t. } xA = \lambda x \ \wedge \ |\lambda| \geq 1 \ \wedge \ xB = 0.$$

In other words, we can control the unstable modes.
If we want $J^*(x_0) < \infty$ for all x_0, a necessary and sufficient condition is that of stabilizability.

7 Kalman Filter

Definition 7.1 (Kalman Filter State Space)

$$\begin{aligned} x_{i+1} &= Fx_i + Gw_i \\ y_i &= Hx_i + v_i \end{aligned} \tag{7.1}$$

where:

- x_{i+1} *is the state vector at time* $i+1$,
- x_i *is the state vector at time* i,
- y_i *is the measurement vector at time* i,
- w_i *is the process noise (zero mean, uncorrelated),*
- v_i *is the measurement noise (zero mean, uncorrelated).*

Definition 7.2 (Kalman Filter Covariance Matrix)
Formally, the following covariance matrix describes the model:

$$\mathbb{E}\left[\begin{pmatrix} w_i \\ v_i \\ x_0 \end{pmatrix} \begin{pmatrix} w_j^* & v_j^* & x_0^* & 1 \end{pmatrix}\right] = \left(\begin{matrix} \begin{pmatrix} Q & S \\ S^* & R \end{pmatrix}\delta_{ij} & 0 & 0 \\ 0 & \Pi_0 & 0 \end{matrix}\right), \tag{7.2}$$

where $\begin{pmatrix} Q & S \\ S^* & R \end{pmatrix}$ *and* Π_0 *are positive semidefinite matrices and* δ_{ij} *equals 1 if* $i = j$ *and is zero otherwise. Note that* w_i *is uncorrelated as a process over time but its coordinates at a fixed time can be correlated via* Q.

Markings:

- P_i - The error covariance matrix at time i
$$P_i \triangleq (x_i - \hat{x}_i)(x_i - \hat{x}_i)^T \tag{7.3}$$
- $R_{e,i}$ - The covariance of the innovation (or residual) at time i
$$R_{e,i} \triangleq HP_iH^* + R \tag{7.4}$$
- $K_{p,i}$ - The optimal Kalman gain at time i
$$K_{p,i} \triangleq (FP_iH^* + GS){R_{e,i}}^{-1} \tag{7.5}$$

Kalman Filter Optimality

We suggest the following predictor:

$$\hat{x}_{i+1|i} = F\hat{x}_{i|i-1} + K_{p,i}(y_i - H\hat{x}_{i|i-1}) \tag{7.6}$$

Lemma 7.1

$$\tilde{x}_{i+1} = (F - K_{p,i}H)\tilde{x}_i + (G - K_{p,i})\begin{pmatrix} w_i \\ v_i \end{pmatrix}. \tag{7.7}$$

Proof.

$$\begin{aligned} \tilde{x}_{i+1} &= x_{i+1} - \hat{x}_{i+1|i} \\ &= (Fx_i + Gw_i) - (F\hat{x}_i + K_{p,i}(y_i - H\hat{x}_i)) \\ &= Fx_i + Gw_i - F\hat{x}_i - K_{p,i}(Hx_i + v_i - H\hat{x}_i) \\ &= Fx_i + Gw_i - F\hat{x}_i - K_{p,i}Hx_i - K_{p,i}v_i + K_{p,i}H\hat{x}_i \\ &= Fx_i - F\hat{x}_i - K_{p,i}Hx_i + K_{p,i}H\hat{x}_i + Gw_i - K_{p_i}v_i \\ &= (F - K_{p,i}H)(x_i - \hat{x}_i) + Gw_i - K_{p,i}v_i \\ &= (F - K_{p,i}H)\tilde{x}_i + Gw_i - K_{p,i}v_i. \end{aligned}$$

□

Lemma 7.2
For $j < i$, the recursion can be evolved as

$$\begin{aligned}\tilde{x}_i &= (F - K_{p,i-1}H)\tilde{x}_{i-1} + (G - K_{p,i-1})\begin{pmatrix} w_{i-1} \\ v_{i-1} \end{pmatrix} \\ &= \dots \\ &= \phi_p(i,j)\tilde{x}_j + \xi_i(j),\end{aligned}$$

where

$$\begin{aligned}\phi_p(i,j) &= \prod_{k=j}^{i-1}(F - K_{p,k}H), \\ \xi_i(j) &= \sum_{k=j}^{i-1}\phi_p(i,k+1)(Gw_k - K_{p,k}v_k).\end{aligned}$$