- A function of a vector
 - A function $f(x_1, \ldots, x_n)$ of variables x_1, \ldots, x_n can be regarded as a function f(x) of a vector $\mathbf{x} = \begin{bmatrix} x_1 \\ \vdots \\ x \end{bmatrix}$.
 - Partial derivative of f with respective to x is defined as

$$rac{\partial f}{\partial oldsymbol{x}} = egin{bmatrix} rac{\partial f}{\partial x_1} \ dots \ rac{\partial f}{\partial x_m} \end{bmatrix},$$

which is equal to the gradient of f, $\nabla f(x)$.

- A vector-valued function of a vector
 - A vector-valued function of a vector

$$egin{aligned} oldsymbol{f}(oldsymbol{x}) &= egin{aligned} f_1(oldsymbol{x}) \ dots \ f_m(oldsymbol{x}) \end{aligned}$$

- Partial derivative of f with respective to x is defined as

$$egin{aligned} rac{\partial oldsymbol{f}^T}{\partial oldsymbol{x}} &= \left[rac{\partial f_1}{\partial oldsymbol{x}} & \dots & rac{\partial f_m}{\partial oldsymbol{x}}
ight] = egin{bmatrix} rac{\partial f_1}{\partial x_1} & \dots & rac{\partial f_m}{\partial x_1} \ dots & & dots \ rac{\partial f_1}{\partial x_n} & \dots & rac{\partial f_m}{\partial x_n} \end{bmatrix} \end{aligned}$$

Second order derivative of a function of a vector

$$\frac{\partial}{\partial \boldsymbol{x}} \left(\frac{\partial f}{\partial \boldsymbol{x}} \right)^{T} = \frac{\partial}{\partial \boldsymbol{x}} \begin{bmatrix} \frac{\partial f}{\partial x_{1}} & \dots & \frac{\partial f}{\partial x_{n}} \end{bmatrix} = \begin{bmatrix} \frac{\partial^{2} f}{\partial x_{1}^{2}} & \dots & \frac{\partial^{2} f}{\partial x_{1} \partial x_{n}} \\ \vdots & & \vdots \\ \frac{\partial^{2} f}{\partial x_{n} \partial x_{1}} & \dots & \frac{\partial^{2} f}{\partial x_{n}^{2}} \end{bmatrix}$$

This matrix is called Hesse matrix.

If
$$\frac{\partial^2 f}{\partial x_i \partial x_j}$$
 is continuous, then $\frac{\partial^2 f}{\partial x_i \partial x_j} = \frac{\partial^2 f}{\partial x_j \partial x_i}$ and the Hesse matrix is a symmetrical matrix.

Examples - $f(m{x}) = m{a}^Tm{x} = m{x}^Tm{a} = \sum_{i=1}^n a_i x_i, \; m{a} = \begin{bmatrix} a_1 \\ \vdots \\ a_n \end{bmatrix}$ $\frac{\partial f}{\partial \boldsymbol{x}} = \frac{\partial}{\partial \boldsymbol{x}} \boldsymbol{a}^T \boldsymbol{x} = \frac{\partial}{\partial \boldsymbol{x}} \boldsymbol{x}^T \boldsymbol{a} = \frac{\partial}{\partial \boldsymbol{x}} \sum_{i=1}^n a_i x_i = \begin{vmatrix} a_1 \\ \vdots \\ a_i \end{vmatrix} = \boldsymbol{a}$ $\mathbf{f}(\mathbf{x}) = A\mathbf{x} = \begin{bmatrix} \sum_{j=1}^{n} a_{1j} x_j \\ \vdots \\ \sum_{j=1}^{n} a_{mj} x_j \end{bmatrix}, A = \begin{bmatrix} a_{11} & \dots & a_{1n} \\ \vdots & & \vdots \\ a_{m1} & \dots & a_{mn} \end{bmatrix} \in \mathbb{R}^{m \times n}$ $\frac{\partial \boldsymbol{f}^T}{\partial \boldsymbol{x}} = \frac{\partial}{\partial \boldsymbol{x}} (A\boldsymbol{x})^T = \frac{\partial}{\partial \boldsymbol{x}} \left[\sum_{j=1}^n a_{1j} x_j \dots \sum_{j=1}^n a_{mj} x_j \right]$ $= \begin{vmatrix} a_{11} & \dots & a_{m1} \\ \vdots & & \vdots \\ a_{1m} & a \end{vmatrix} = A^T$

Examples

Examples
$$-f(\boldsymbol{x}) = \boldsymbol{x}^T A \boldsymbol{x} = \sum_{i=1}^n \sum_{j=1}^n a_{ij} x_i x_j, \ A = \begin{bmatrix} a_{11} & \dots & a_{1n} \\ \vdots & & \vdots \\ a_{n1} & \dots & a_{nn} \end{bmatrix} \in \mathbb{R}^{n \times n}$$

$$\frac{\partial f}{\partial \boldsymbol{x}} = \frac{\partial}{\partial \boldsymbol{x}} \boldsymbol{x}^T A \boldsymbol{x} = \begin{bmatrix} \sum_{j=1}^n a_{1j} x_j + \sum_{i=1}^n a_{i1} x_i \\ \vdots \\ \sum_{j=1}^n a_{nj} x_j + \sum_{i=1}^n a_{in} x_i \end{bmatrix}$$

$$= \begin{bmatrix} \sum_{j=1}^{n} a_{1j} x_{j} \\ \vdots \\ \sum_{j=1}^{n} a_{nj} x_{j} \end{bmatrix} + \begin{bmatrix} \sum_{i=1}^{n} a_{i1} x_{i} \\ \vdots \\ \sum_{i=1}^{n} a_{in} x_{i} \end{bmatrix}$$

$$= \begin{bmatrix} a_{11} & \dots & a_{1n} \\ \vdots & & \vdots \\ a_{n1} & \dots & a_{nn} \end{bmatrix} \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix} + \begin{bmatrix} a_{11} & \dots & a_{n1} \\ \vdots & & \vdots \\ a_{1n} & \dots & a_{nn} \end{bmatrix} \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix} = A\boldsymbol{x} + A^T \boldsymbol{x}$$

$$= \frac{\partial}{\partial \boldsymbol{x}} \boldsymbol{x}^T (A\boldsymbol{x}) + \frac{\partial}{\partial \boldsymbol{x}} (\boldsymbol{x}^T A) \boldsymbol{x} = (A\boldsymbol{x}) + (\boldsymbol{x}^T A)^T = A\boldsymbol{x} + A^T \boldsymbol{x}$$
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$$\frac{\partial}{\partial \boldsymbol{x}} \left(\frac{\partial f}{\partial \boldsymbol{x}} \right)^T = \frac{\partial}{\partial \boldsymbol{x}} \left(A \boldsymbol{x} + A^T \boldsymbol{x} \right)^T = \frac{\partial}{\partial \boldsymbol{x}} \left(\boldsymbol{x}^T A^T + \boldsymbol{x}^T A \right) = A^T + A$$

When
$$A$$
 is symmetrical ($A^T = A$), $\frac{\partial}{\partial \boldsymbol{x}} \left(\frac{\partial f}{\partial \boldsymbol{x}} \right)^T = 2A$.

• Let us look at how matrices are used in system control.

- System models
 - Motion of an object is described by Newton's equation of motion:

 $f = m \frac{d^2x}{dt^2},$

where x is the position of the object, m is its mass, f is the force acting on the object, and t represents time.

When we define two variables

$$x_1 = x, \ x_2 = \frac{dx}{dt},$$

then the above second order differential equation is converted to a set of two first order differential equations:

$$\frac{dx_1}{dt} = x_2, \quad \frac{dx_2}{dt} = \frac{f}{m}.$$

The set of equations

$$\frac{dx_1}{dt} = x_2, \quad \frac{dx_2}{dt} = \frac{f}{m}$$

can be represented as

$$\begin{bmatrix} \frac{dx_1}{dt} \\ \frac{dx_2}{dt} \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \begin{bmatrix} 0 \\ \frac{1}{m} \end{bmatrix} f.$$

In general a linear dynamical system can be represented as

$$\frac{d}{dt}\boldsymbol{x} = A\boldsymbol{x} + B\boldsymbol{u}.$$

 $m{u}$ is an input vector which, in the above example, is f, and $m{x}$ is called a state vector.

- Discrete time model
 - Let us consider discrete time:

$$k = 0, 1, 2, \dots$$

The actual interval T between two time instances k and k+1 depends on the system.

Let the value of state x at discrete time k be denoted as x_k . Then we have $x_k = x(kT)$.

The derivative of x(t) with respective t is approximated as

$$\frac{d}{dt}\boldsymbol{x}(t) \simeq \frac{\boldsymbol{x}((k+1)T) - \boldsymbol{x}(kT)}{T} = \frac{\boldsymbol{x}_{k+1} - \boldsymbol{x}_k}{T}.$$

This is called forward Euler approximation(前進オイラー近似).

Equation representing a discrete time system

Using the forward Euler approximation, we can approximate the equation

$$\frac{d}{dt}\boldsymbol{x}(t) = A\boldsymbol{x}(t) + B\boldsymbol{u}(t).$$

as

$$\frac{\boldsymbol{x}_{k+1} - \boldsymbol{x}_k}{T} \simeq A\boldsymbol{x}_k + B\boldsymbol{u}_k,$$

or

$$\boldsymbol{x}_{k+1} \simeq (AT+I)\boldsymbol{x}_k + BT\boldsymbol{u}_k.$$

Therefore in discrete time, a linear dynamical system can be represented in the form of

$$\boldsymbol{x}_{k+1} = F\boldsymbol{x}_k + G\boldsymbol{u}_k,$$

which is a difference equation(差分方程式).

 The above discussion is based on Euler approximation and therefore is not exact.

If we want to derive an exact discrete-time representation of a linear dynamical system from its continuous-time representation, then we have to start with the solution of the

continuous-time differential equation $\frac{d}{dt}\mathbf{x}(t) = A\mathbf{x}(t) + B\mathbf{u}(t)$.

The solution is

$$\boldsymbol{x}(t) = e^{At}\boldsymbol{x}(0) + \int_0^t e^{A(t-\tau)}B\boldsymbol{u}(\tau)d\tau,$$

where

$$e^{At} = I + At + \frac{1}{2!}A^2t^2 + \frac{1}{3!}A^3t^3 + \dots$$

Then we have

$$\begin{aligned} \boldsymbol{x}_{k+1} &= \boldsymbol{x}((k+1)T) \\ &= e^{A(k+1)T}\boldsymbol{x}(0) + \int_0^{(k+1)T} e^{A((k+1)T-\tau)}B\boldsymbol{u}(\tau)d\tau \\ &= e^{AT}e^{AkT}\boldsymbol{x}(0) + \int_0^{kT} e^{AT}e^{A(kT-\tau)}B\boldsymbol{u}(\tau)d\tau \\ &+ \int_{kT}^{(k+1)T} e^{A((k+1)T-\tau)}B\boldsymbol{u}(\tau)d\tau \\ &= e^{AT}\left(e^{AkT}\boldsymbol{x}(0) + \int_0^{kT} e^{A(kT-\tau)}B\boldsymbol{u}(\tau)d\tau\right) \\ &+ \int_{kT}^{(k+1)T} e^{A((k+1)T-\tau)}B\boldsymbol{u}(\tau)d\tau \end{aligned}$$

$$= e^{AT}\boldsymbol{x}_k + \int_{kT}^{(k+1)T} e^{A((k+1)T-\tau)}B\boldsymbol{u}(\tau)d\tau$$

When u(t) is constant for $kT \le t \le (k+1)T$, then we denote its value by u_k and obtain

$$m{x}_{k+1} = e^{AT}m{x}_k + \int_{kT}^{(k+1)T} e^{A((k+1)T- au)} B d au m{u}_k$$
 $= e^{AT}m{x}_k + \left(\int_0^T e^{As} B ds
ight) m{u}_k$ and derive $F = e^{AT}$ and $G = \int_0^T e^{As} B ds$.

Since

$$e^{At} = I + At + \frac{1}{2!}A^2t^2 + \frac{1}{3!}A^3t^3 + \dots$$

we have

$$F = e^{AT} = I + AT + \frac{1}{2!}A^2T^2 + \frac{1}{3!}A^3T^3 + \dots,$$

$$G = \int_0^T e^{As}Bds = \int_0^T \left(I + As + \frac{1}{2!}A^2s^2 + \frac{1}{3!}A^3s^3 + \dots\right)Bds$$

$$= \left(IT + \frac{1}{2}AT^2 + \frac{1}{3!}A^2T^3 + \frac{1}{4!}A^3T^4 + \dots\right)B.$$

If we truncate the above series at the first order term of T, then

$$F \simeq I + AT$$
, $G \simeq BT$,

which are equal to those derived on page 159.

Reachability

- Let us consider a discrete-time linear dynamical system. If, for any destination state x_D , there is a sequence of inputs u_0, u_1, \ldots, u_N such that the state transitions from $\mathbf{0}$ to x_D in a finite time N, the system is said to be reachable (可到達).

$$egin{aligned} m{x}_0 &= m{0}, \ m{x}_1 &= F m{x}_0 + G m{u}_0 = G m{u}_0, \ m{x}_2 &= F m{x}_1 + G m{u}_1 = F G m{u}_0 + G m{u}_1, \ m{x}_3 &= F m{x}_2 + G m{u}_2 = F (F G m{u}_0 + G m{u}_1) + G m{u}_2 \ &= F^2 G m{u}_0 + F G m{u}_1 + G m{u}_2, \ &\vdots \ m{x}_{N+1} &= F^N G m{u}_0 + F^{N-1} G m{u}_1 + \dots + G m{u}_N. \end{aligned}$$

So the question is if there are a finite N and a vector

$$oldsymbol{U}_N = egin{bmatrix} oldsymbol{u}_0 \ oldsymbol{u}_1 \ dots \ oldsymbol{u}_N \end{bmatrix}$$

such that

$$m{x}_D = m{x}_{N+1} = egin{bmatrix} F^N G & F^{N-1} G & \cdots & G \end{bmatrix} m{U}_N,$$
 for any $m{x}_D$.

Such U_N exists when the mapping represented by $\begin{bmatrix} F^NG & F^{N-1}G & \cdots & G \end{bmatrix}$ is a surjection, i.e., the matrix has a row full rank.

Suppose that the dimension of state vector x is n and that the dimension of the input vector u is p.

Then $F \in \mathbb{R}^{n \times n}$ and $G \in \mathbb{R}^{n \times p}$, and therefore

$$\begin{bmatrix} F^N G & F^{N-1} G & \cdots & G \end{bmatrix} \in \mathbb{R}^{n \times (N+1)p}.$$

So the system is reachable when all the n row vectors of $\begin{bmatrix} F^NG & F^{N-1}G & \cdots & G \end{bmatrix}$ are linearly independent with each other.

The matrix $\begin{bmatrix} F^NG & F^{N-1}G & \cdots & G \end{bmatrix}$ is called a reachability matrix.

We just need consider N such that $(N+1)p \ge n$.

- Examples

$$\begin{bmatrix} x_{1,k+1} \\ x_{2,k+1} \end{bmatrix} = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x_{1,k} \\ x_{2,k} \end{bmatrix} + \begin{bmatrix} 0 \\ 1 \end{bmatrix} u_k$$

$$F = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix}, G = \begin{bmatrix} 0 \\ 1 \end{bmatrix}, n = 2, p = 1.$$

The minimum N that satisfies $(N+1)p \ge n$ is 1.

The reachability matrix is $\begin{bmatrix} FG & G \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 1 & 1 \end{bmatrix}$, which is

of row full rank, and therefore the system is reachable.

For
$$m{x}_D = egin{bmatrix} x_{D,1} \\ x_{D,2} \end{bmatrix}$$
 , from the relation $m{x}_D = egin{bmatrix} FG & G \end{bmatrix} egin{bmatrix} u_0 \\ u_1 \end{bmatrix}$,

we can derive the appropriate input sequence as

$$u_0 = x_{D,1}, u_1 = x_{D,2} - x_{D,1}.$$

$$\begin{bmatrix} x_{1,k+1} \\ x_{2,k+1} \end{bmatrix} = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x_{1,k} \\ x_{2,k} \end{bmatrix} + \begin{bmatrix} 1 \\ 0 \end{bmatrix} u_k$$

$$F = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix}, G = \begin{bmatrix} 1 \\ 0 \end{bmatrix}, n = 2, p = 1.$$

The minimum N that satisfies $(N+1)p \ge n$ is 1.

The reachability matrix is $\begin{bmatrix} FG & G \end{bmatrix} = \begin{bmatrix} 1 & 1 \\ 0 & 0 \end{bmatrix}$, which is

NOT of row full rank, and therefore the system is NOT reachable.

- Output equation
 - Let y be the output vector from the system. The output is measurement of the states (mixtures of the states) and is represented by

$$y_k = Hx_k$$
.

- Observability
 - Suppose we have a sequence of inputs $u_0, u_1, \ldots, u_{N-1}$ and the derived sequence of outputs y_0, y_1, \ldots, y_N from the system in response to the inputs. Can we know the initial state x_0 from the input and output sequences? If we can, we say the system is observable (可観測).

$$egin{aligned} m{x}_0 &= m{x}_0, \ m{y}_0 &= H m{x}_0, \\ m{x}_1 &= F m{x}_0 + G m{u}_0, \ m{y}_1 &= H F m{x}_0 + H G m{u}_0, \\ m{x}_2 &= F m{x}_1 + G m{u}_1 = F^2 m{x}_0 + F G m{u}_0 + G m{u}_1, \\ m{y}_2 &= H F^2 m{x}_0 + H F G m{u}_0 + H G m{u}_1, \\ m{x}_3 &= F m{x}_2 + G m{u}_2 = F^3 m{x}_0 + F^2 G m{u}_0 + F G m{u}_1 + G m{u}_2, \\ m{y}_3 &= H F^3 m{x}_0 + H F^2 G m{u}_0 + H F G m{u}_1 + H G m{u}_2, \\ &\vdots \\ m{x}_N &= F^N m{x}_0 + F^{N-1} G m{u}_0 + \dots + G m{u}_{N-1}. \\ m{y}_N &= H F^N m{x}_0 + H F^{N-1} G m{u}_0 + \dots + H G m{u}_{N-1}. \end{bmatrix}$$

 The relationships between the initial states and the input and output sequences are

$$egin{aligned} oldsymbol{y}_0 &= H oldsymbol{x}_0, \ oldsymbol{y}_1 - H G oldsymbol{u}_0 &= H F oldsymbol{x}_0, \ oldsymbol{y}_2 - H F G oldsymbol{u}_0 - H G oldsymbol{u}_1 &= H F^2 oldsymbol{x}_0, \ &dots \ oldsymbol{y}_N - H F^{N-1} G oldsymbol{u}_0 - \cdots - H G oldsymbol{u}_{N-1} &= H F^N oldsymbol{x}_0. \end{aligned}$$

These are expressed as

$$\begin{bmatrix} \mathbf{y}_0 \\ \mathbf{y}_1 - HG\mathbf{u}_0 \\ \vdots \\ \mathbf{y}_N - HF^{N-1}G\mathbf{u}_0 - \dots - HG\mathbf{u}_{N-1} \end{bmatrix} = \begin{bmatrix} H \\ HF \\ \vdots \\ HF^N \end{bmatrix} \mathbf{x}_0.$$

From the equation

$$\begin{bmatrix} \mathbf{y}_0 \\ \mathbf{y}_1 - HG\mathbf{u}_0 \\ \vdots \\ \mathbf{y}_N - HF^{N-1}G\mathbf{u}_0 - \dots - HG\mathbf{u}_{N-1} \end{bmatrix} = \begin{bmatrix} H \\ HF \\ \vdots \\ HF^N \end{bmatrix} \mathbf{x}_0,$$

we know we can uniquely determine x_0 when the matrix

$$egin{bmatrix} H \ HF \ dots \ HF^N \end{bmatrix}$$

represents an injection, i.e., the matrix has a column full rank.

Suppose the dimension of output vector y is q. Then $H \in \mathbb{R}^{q \times n}$, and therefore

$$\begin{bmatrix} H \\ HF \\ \vdots \\ HF^N \end{bmatrix} \in \mathbb{R}^{(N+1)q \times n}.$$

So the system is observable when all the n column vectors

of
$$\begin{bmatrix} H \\ HF \\ \vdots \\ HF^N \end{bmatrix}$$
 are linearly independent with each other. The matrix
$$\begin{bmatrix} H \\ HF \\ \vdots \\ HF^N \end{bmatrix}$$
 is called an observability matrix. We just need consider N such that $(N+1)q \geq n$.

The matrix
$$\begin{bmatrix} H \\ HF \\ \vdots \\ HF^N \end{bmatrix}$$
 is called an observability matrix

We just need consider N such that $(N+1)q \ge n$.

- Examples

•
$$\begin{bmatrix} x_{1,k+1} \\ x_{2,k+1} \end{bmatrix} = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x_{1,k} \\ x_{2,k} \end{bmatrix} + \begin{bmatrix} 0 \\ 1 \end{bmatrix} u_k, \ y_k = \begin{bmatrix} 1 & 0 \end{bmatrix} \begin{bmatrix} x_{1,k} \\ x_{2,k} \end{bmatrix}$$

$$F = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix}, \ H = \begin{bmatrix} 1 & 0 \end{bmatrix}, \ n = 2, \ q = 1.$$

The minimum N that satisfies $(N+1)q \ge n$ is 1.

The observability matrix is $\begin{bmatrix} H \\ HF \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 1 & 1 \end{bmatrix}$, which is of full column rank, and therefore the system is observable.

$$F = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix}, H = \begin{bmatrix} 0 & 1 \end{bmatrix}.$$

The observability matrix is $\begin{bmatrix} H \\ HF \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 0 & 1 \end{bmatrix}$, which is

NOT of full column rank, and therefore the system is NOT observable.