

EML 6934  
optimal estimation, Fall '09

①

1.1 (i) Let  $x, y \in S$ ,  $\Rightarrow x_1 - x_2 = 0$   
 $y_1 - y_2 = 0$

Consider  $z := x + y$  then  $z_1 - z_2 = (x_1 + y_1) - (x_2 + y_2) = 0$

consider  $z = \alpha x$ ,  $\alpha$  is a scalar. ~~Then~~ Then  $z_1 - z_2 = \alpha x_1 - \alpha x_2 = 0$

$\therefore S$  is closed under addition and scalar multiplication.

$\Rightarrow S$  is a vector space.

1.1 (ii) Let  $x, y \in S \Rightarrow x_2 - x_1 = 1, y_2 - y_1 = 1$

Consider  $z = \alpha x \Rightarrow z_2 - z_1 = \alpha(x_2 - x_1) = \alpha \neq 1$  unless  $\alpha = 1$

$\therefore S$  is not closed under scalar multiplication, so  $S$  is

not a vector space. [key: A subspace must contain the 0 vector!]

1.2 Let  $f$  and  $g$  be two real valued continuous functions defined in the interval  $[0, 1]$

To show closure under addition, we have to show

that the sum of two continuous functions is continuous.

To do so, start from the definition of a continuous function. A function  $\eta$  is continuous at a

point, say,  $x_0$ , if, for every  $\epsilon > 0$ , there exists  $\delta > 0$

such that  $|\eta(x) - \eta(x_0)| < \epsilon$  whenever  $|x - x_0| < \delta$ .

By using this definition, we can say the following about

$f$  and  $g$  at every point  $x_0 \in [0, 1]$  :

$\forall \epsilon > 0, \exists \delta_1, \delta_2 > 0$  so that  $|f(x) - f(x_0)| < \frac{\epsilon}{2}$  whenever  $|x - x_0| < \delta_1$  (2)

~~and~~ and  $|g(x) - g(x_0)| < \frac{\epsilon}{2}$  whenever  $|x - x_0| < \delta_2$

$$\begin{aligned} \Rightarrow |(f+g)(x) - (f+g)(x_0)| &= |f(x) + g(x) - f(x_0) - g(x_0)| \\ &\leq |f(x) - f(x_0)| + |g(x) - g(x_0)| \quad (\text{triangle inequality}) \\ &\leq \frac{\epsilon}{2} + \frac{\epsilon}{2} = \epsilon \quad \text{whenever } |x - x_0| < \min(\delta_1, \delta_2) \end{aligned}$$

$\Rightarrow f+g$  is a continuous function at  $x_0$ . The same argument can be repeated at every point  $x_0 \in [0, 1]$ , which shows  $f+g$  is continuous in the interval  $[0, 1]$ .

This shows closure under addition. A similar argument, which we are not going to repeat, proves closure under scalar multiplication.

Problem 2

$$Ax = \begin{bmatrix} 1 & 2 \\ 5 & 4 \\ 13 & 6 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} x_1 + 2x_2 \\ 5x_1 + 4x_2 \\ 13x_1 + 6x_2 \end{bmatrix} = \begin{bmatrix} 1 \\ 5 \\ 13 \end{bmatrix} x_1 + \begin{bmatrix} 2 \\ 4 \\ 6 \end{bmatrix} x_2$$

Problem 3 (1) if  $y_1, y_2 \in R(A)$ , there exist vectors  $x_1, x_2$  s.t.

$$y_1 = Ax_1, \quad y_2 = Ax_2$$

$$\Rightarrow y_1 + y_2 = Ax_1 + Ax_2 = A(x_1 + x_2) = Az, \quad z \stackrel{\Delta}{=} x_1 + x_2$$

$$\therefore y_1 + y_2 \in R(A)$$

$$\text{Similarly, } \alpha y_1 = \alpha Ax_1 = A(\alpha x_1) = Az \Rightarrow z = \alpha x_1$$

$$\Rightarrow \alpha y_1 \in R(A)$$

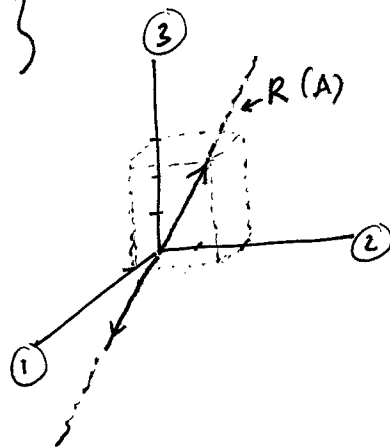
This shows  $R(A)$  is closed under addition and scalar multiplication, so it is a vector space.

(3)

$$R(A), A = \begin{bmatrix} 1 & 2 \\ 2 & 4 \\ 3 & 6 \end{bmatrix}$$

$$Ax = \begin{bmatrix} 1 & 2 \\ 2 & 4 \\ 3 & 6 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = x_1 \begin{bmatrix} 1 \\ 2 \\ 3 \end{bmatrix} + x_2 \begin{bmatrix} 2 \\ 4 \\ 6 \end{bmatrix} = (x_1 + 2x_2) \begin{bmatrix} 1 \\ 2 \\ 3 \end{bmatrix} \quad \text{so } Ax \text{ is a vector along } \begin{bmatrix} 1 \\ 2 \\ 3 \end{bmatrix}$$

$$\Rightarrow R(A) = \left\{ y \mid y = \alpha \begin{bmatrix} 1 \\ 2 \\ 3 \end{bmatrix}, \alpha \text{ any scalar} \right\}$$



3.2 Let  $x_1, x_2 \in N(A)$

$$\Rightarrow Ax_1 = 0, Ax_2 = 0$$

$$\text{Now, } A(x_1 + x_2) = Ax_1 + Ax_2 = 0$$

which shows  $x_1 + x_2 \in N(A)$

Similarly,  $\alpha x_1 \in N(A)$ , for every scalar  $\alpha$

$\Rightarrow N(A)$  is closed under addition and scalar multiplication.

and therefore a vector space.

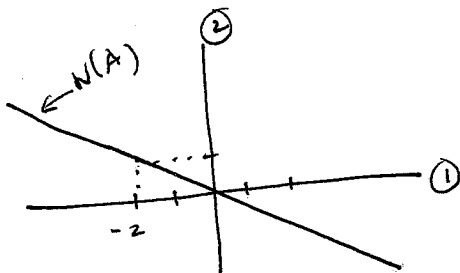
to find  $N\left(\begin{bmatrix} 1 & 2 \\ 2 & 4 \\ 3 & 6 \end{bmatrix}\right)$ , examine  $Ax = 0$

$$\begin{bmatrix} 1 & 2 \\ 2 & 4 \\ 3 & 6 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} \Rightarrow (x_1 + 2x_2) \begin{bmatrix} 1 \\ 2 \\ 3 \end{bmatrix} = 0 \Rightarrow x_1 + 2x_2 = 0$$

$$\Rightarrow x_1 = -2x_2$$

$$\Rightarrow x = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} -2 \\ 1 \end{bmatrix} x_2 \quad \text{for } x \text{ to be in } N(A)$$

$$\Rightarrow N(A) = \left\{ \alpha \begin{bmatrix} -2 \\ 1 \end{bmatrix}, \alpha \text{ any scalar} \right\}$$



Problem 4

$$\text{span}(L) = R(A) \quad \text{reason } \circ$$

(4)

$$Ax = \begin{bmatrix} a_1 & a_2 & \dots & a_n \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix}$$

$$= a_1 x_1 + a_2 x_2 + \dots + a_n x_n \quad (\text{using the useful fact from Problem 2})$$

$$= \sum_{i=1}^n x_i a_i$$

as  $x$  takes all possible values,  $Ax$  creates all the possible vectors in the set  $\text{span}(L) = \left\{ y \mid y = \sum_{i=1}^n x_i a_i \right\}$ ,

$$\text{where } L = \{ a_1, a_2, \dots, a_n \}$$

Problem 5 (5.1)  $S$  is a set of vectors,  $S^\perp = \{ y \mid y^T x = 0 \quad \forall x \in S \}$

$$\text{Let } y_1, y_2 \in S \Rightarrow y_1^T x = y_2^T x = 0 \quad \forall x \in S$$

$$\text{then } (y_1 + y_2)^T x = y_1^T x + y_2^T x = 0 + 0 = 0 \quad \forall x \in S$$

$$\Rightarrow y_1 + y_2 \in S^\perp$$

$$\text{Similarly, } (\alpha y_1)^T x = \alpha y_1^T x = 0 \quad \forall x \in S$$

$$\Rightarrow \alpha y_1 \in S^\perp \text{ as well, where } \alpha \text{ is any scalar.}$$

This shows that  $S^\perp$  is closed under addition and scalar multiplication, which shows  $S^\perp$  is a vector space. (Note that  $S$  need not be a vector space for  $S^\perp$  to be one).

(5.2) No, since the vector  $v = \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix} \in$  "x-y plane" and also "y-z plane"

$$\text{but } v^T v \neq 0$$

5.3

$$R(A)^\perp = \{x \mid x^T y = 0 \quad \forall y \in R(A)\}$$

$$= \{x \mid x^T (Az) = 0 \quad \forall z \in \mathbb{R}^n\}$$

(Assume, for concreteness, that  $A: \mathbb{R}^n \rightarrow \mathbb{R}^m$   
so  $x \in \mathbb{R}^m$ )

$$= \{x \mid z^T A^T x = 0 \quad \forall z \in \mathbb{R}^n\}$$

$$= \{x \mid A^T x = 0\}$$

(if  $z^T (A^T x) = 0 \quad \forall z$ , then  $A^T x$  must be the 0 vector,

~~because~~ we can pick  $z = A^T x$ , which gives us

$$\begin{aligned} (A^T x)^T (A^T x) = 0 &\Leftrightarrow y^T y = 0 \quad (y \triangleq A^T x) \Leftrightarrow y_1^2 + y_2^2 + \dots + y_n^2 = 0 \\ &\Leftrightarrow y_i = 0 \quad \forall i \Leftrightarrow A^T x = 0 \end{aligned}$$

$$= N(A) \quad \text{— Q.E.D.}$$

(or, think of it this way,

$$\text{if } x \in R(A)^\perp, \quad x \perp y \quad \forall y \in R(A) \Leftrightarrow x^T (Az) = 0 \quad \forall z \in \mathbb{R}^n$$

$$\Leftrightarrow z^T A^T x = 0 \quad \forall z \in \mathbb{R}^n$$

$$\Leftrightarrow A^T x = 0$$

by the arguments above

$$\Rightarrow x \in R(A)^\perp \Leftrightarrow A^T x = 0, \text{ which means } R(A)^\perp = N(A^T)$$

(Problem 5.3 contd.)

We have shown  $R(A)^\perp = N(A^T)$  — ①

to show  $N(A)^\perp = R(A^T)$ , take ' $\perp$ ' of both sides of ①,

$$\left( R(A)^\perp \right)^\perp = \left( N(A^T) \right)^\perp$$

$$\Leftrightarrow R(A) = N(A^T)^\perp$$

replace  $A$  by  $A^T$  to get

$$R(A^T) = N(A)^\perp \text{ — Q.E.D.}$$

Problem 6:  
6.1

$$Ax = \begin{bmatrix} 1 & 2 & 2 & 4 \\ 2 & 4 & 1 & 2 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix}$$

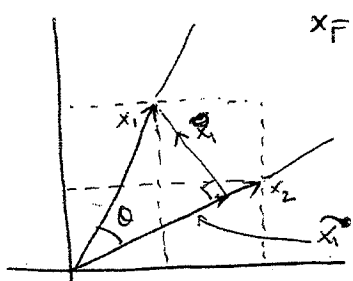
$$= \begin{bmatrix} 1 \\ 2 \end{bmatrix} x_1 + \begin{bmatrix} 2 \\ 4 \end{bmatrix} x_2 + \begin{bmatrix} 2 \\ 1 \end{bmatrix} x_3 + \begin{bmatrix} 4 \\ 2 \end{bmatrix} x_4 \text{ — ①}$$

$$= (x_1 + 2x_2) \begin{bmatrix} 1 \\ 2 \end{bmatrix} + \begin{bmatrix} 2 \\ 1 \end{bmatrix} (x_3 + 2x_4) \text{ — ②}$$

① shows, (we have seen it before) that  $R(A)$  is spanned by the four vectors that are the columns of  $A$ . This is true in general,  $R(A)$  is spanned by the columns of  $A$ . But in this example, not all the columns of  $A$  are linearly independent.

(problem 6 contd...) (2) shows that  $R(A)$  is spanned by  $\begin{bmatrix} 1 \\ 2 \end{bmatrix}$  and  $\begin{bmatrix} 2 \\ 1 \end{bmatrix}$ , which are linearly independent and hence form a basis. So, a basis of  $R(A)$  is  $\left\{ \begin{bmatrix} 1 \\ 2 \end{bmatrix}, \begin{bmatrix} 2 \\ 1 \end{bmatrix} \right\}$

6.2:



$$x_1 = \begin{bmatrix} 1 \\ 2 \end{bmatrix} \quad x_2 = \begin{bmatrix} 2 \\ 1 \end{bmatrix}$$

$$x_1 = x_1^o + \tilde{x}_1$$

$\tilde{x}_1 =$  projection of  $x_1$  onto  $x_2$

$$= \frac{(x_1^T x_2)}{\|x_2\|} \hat{x}_2$$

↑ unit vector along  $x_2$

$$= \frac{(x_1^T x_2)}{\|x_2\|^2} x_2$$

$$\left( \begin{aligned} \text{proj} &= \|x_1\| \cdot \|x_2\| \cos \theta = |x_1^T x_2| \\ \text{proj} &= \|x_1\| \cos \theta \end{aligned} \right)$$

$$\begin{aligned} \Rightarrow x_1^o &= x_1 - \tilde{x}_1 = x_1 - \frac{(x_1^T x_2)}{\|x_2\|^2} x_2 \\ &= \begin{bmatrix} 1 \\ 2 \end{bmatrix} - \frac{4}{(\sqrt{5})^2} \begin{bmatrix} 2 \\ 1 \end{bmatrix} = \begin{bmatrix} 1 - \frac{8}{5} \\ 2 - \frac{4}{5} \end{bmatrix} = \begin{bmatrix} -\frac{3}{5} \\ \frac{6}{5} \end{bmatrix} \end{aligned}$$

normalize:  $y_1 = \frac{x_1^o}{\|x_1^o\|} = \frac{1}{\sqrt{5}} \begin{bmatrix} -1 \\ 2 \end{bmatrix}$

$$y_2 = \frac{x_2}{\|x_2\|} = \frac{1}{\sqrt{5}} \begin{bmatrix} 2 \\ 1 \end{bmatrix}$$

6.3 Let  $x_1, x_2, \dots, x_n$  be a given basis of  $\mathbb{R}^n$ .

We "project  $x_1$  onto  $\text{span}\{x_2, \dots, x_n\}$  orthogonally,"

so  $x_1 = x_1^0 + \tilde{x}_1$  where  $\tilde{x}_1 \in \text{span}\{x_2, \dots, x_n\}$

and  $x_1^0 \perp \text{span}(x_2, \dots, x_n)$

Assign  $y_1 \triangleq \frac{x_1^0}{\|x_1^0\|}$

Now pick  $x_2$  and project it orthogonally onto  $\text{span}\{x_3, \dots, x_n\}$  so that  $x_2 = x_2^0 + \tilde{x}_2$ , where

$\tilde{x}_2 \in \text{span}\{x_3, \dots, x_n\}$  and  $x_2^0 \perp \text{span}\{x_3, \dots, x_n\}$

Note that  $x_2^0 \perp y_1$  by construction.

Now assign  $y_2 \triangleq \frac{x_2^0}{\|x_2^0\|}$

repeat this procedure till you are done with all

the  $n$ -vectors. By construction,  $y_i \perp y_j$   $i \neq j$

and  $\|y_i\| = 1$   $\forall i$ , and  $\{y_1, \dots, y_n\}$  span  $\mathbb{R}^n$ .

This is called the Gram-Schmidt procedure.

To do it numerically, you'll have to construct matrices called orthogonal projectors. You can read about them in Carl Meyer's book.

Problem 7: statement  $p \equiv$  "H is a full column <sup>rank</sup> matrix and P is a symmetric positive definite matrix."

statement  $q \equiv$  "H<sup>T</sup>PH is symmetric positive definite"

We have to show  $p \Rightarrow q$

ie, starting with p, we have to show  $x^T(H^T P H)x > 0 \quad \forall x \neq 0$

pick an arbitrary x, Now  $x^T(H^T P H)x = (Hx)^T P (Hx) \stackrel{\Delta}{=} J$

since P is sym pos. def.,  $J \geq 0$ , and  $J=0$  if and only if  $Hx=0$ , but that occurs if and only if  $x=0$ , since H is full column rank.

$\Rightarrow x^T(H^T P H)x > 0 \quad \forall x \neq 0 \Rightarrow H^T P H$  is positive definite

$(H^T P H)^T = H^T P^T H = H^T P H \Rightarrow$  it is symmetric. So we have  $p \Rightarrow q$ .

reverse: To show it is an if and only if statement, we have to show  $q \Rightarrow p$  as well.

That is, if "H<sup>T</sup>PH is symmetric +ve definite", then "H is a full column rank matrix and  $P=P^T > 0$ ". As you can see, it is asking quite a lot. In fact, this is ~~not~~ not true.

Counter example:  $H = \begin{bmatrix} 1 & 4 \\ 2 & 5 \\ 3 & 6 \end{bmatrix}$ ,  $P = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}$  H is full column rank, but P is not +ve definite so ~~p~~ this example violates "p".

evaluate  $H^T P H = \begin{bmatrix} 5 & 14 \\ 14 & 41 \end{bmatrix}$ , which is a symmetric +ve definite matrix (how do you verify?)

so, we have an example of "q, but not p", which shows that 'q  $\Rightarrow$  p' is false. Hence, the answer is no

Problem 8: decompose  $y$  as:  
 $y = y_1 + y_2$  where  $y_1 \in R(A)$ ,  $y_2 \in R(A)^\perp$

Since  $y_2 \in R(A)^\perp$  and  $R(A)^\perp = N(A^T)$ ,  
(by the orthogonal decomposition theorem)

$$\therefore y_2 \in N(A^T)$$

$$\Rightarrow A^T y_2 = 0$$

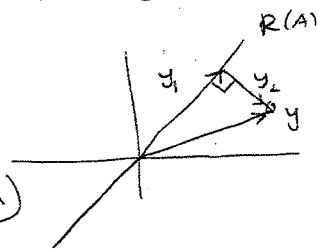
Now multiply both sides of the equation  $y = y_1 + y_2$  by  $A^T$ :

$$A^T y = A^T (y_1 + y_2) = A^T y_1 + A^T y_2 = A^T y_1$$

Since  $y_1 \in R(A)$ ,  $\exists$  a vector, call it  $x_0$  such that

$$Ax_0 = y_1$$

$$\Rightarrow A^T y = A^T (y_1) = A^T (Ax_0) = A^T A x_0$$



(problem 8 contd...)

there exists

therefore, ~~we have found~~ an  $x_0$  which satisfies ~~the~~ ~~is~~

$$A^T A x = A^T y, \quad (\text{given } y \text{ and } A)$$

$\Rightarrow$  Normal equations are always consistent.

Note: When people say " $Ax=y$  does not have a solution" or even "consider  $Ax=y$ ", ~~they don't mean~~ the equality between  $Ax$  and  $y$  is merely a convenient notation. The data given is  $A$  and  $y$ , and the problem is to find  $x$  such that  $Ax$  becomes equal to  $y$ . So " $Ax=y$ " does not in general mean  $\exists x$  and  $y$  such that  $Ax$  ~~is~~ is equal to  $y$ !

Problem 9:  $\|x\|_2 \stackrel{\Delta}{=} \sqrt{x_1^2 + \dots + x_n^2} = \sqrt{x^T x}$  (typo in the H.W.)

start with  $\|\alpha x - y\|_2^2 \geq 0$ ,  $\alpha \in \mathbb{R}$ , which is true since the  $2$ -norm of a vector is always non-negative.

$$\|\alpha x - y\|_2^2 \geq 0 \Leftrightarrow (\alpha x - y)^T (\alpha x - y) \geq 0 \Leftrightarrow \alpha^2 x^T x + y^T y \geq 2\alpha x^T y \quad \text{--- (1)}$$

$$\text{choose } \alpha = \frac{x^T y}{x^T x} \quad (\in \mathbb{R})$$

$$\therefore \alpha^2 x^T x + y^T y \geq 2\alpha x^T y \Rightarrow \frac{(x^T y)^2}{x^T x} + y^T y \geq 2 \frac{(x^T y)^2}{x^T x} \Rightarrow (x^T y)^2 \leq (y^T y)(x^T x)$$

$$\Rightarrow |x^T y| \leq \sqrt{y^T y} \cdot \sqrt{x^T x} = \|x\| \|y\|$$

Problem 10

1 and 2 are trivial.

to prove 3,

$$\|x+y\|^2 = (x+y)^T(x+y) = x^T x + y^T y + 2x^T y \quad (\because x^T y = y^T x)$$

by the CBS inequality,

$$x^T y \leq |x^T y| \leq \sqrt{(x^T x)(y^T y)}$$

$$\begin{aligned} \Rightarrow \|x+y\|^2 &\leq \|x\|_2^2 + \|y\|_2^2 + 2\sqrt{\|x\|_2^2 \|y\|_2^2} \\ &= \|x\|_2^2 + \|y\|_2^2 + 2\|x\|_2 \|y\|_2 \\ &= (\|x\|_2 + \|y\|_2)^2 \end{aligned}$$

$$\Rightarrow \|x+y\| \leq |\|x\| + \|y\|| = \|x\| + \|y\|$$

Alt solution to 9

$$(\alpha x + y)^T(\alpha x + y) \geq 0 \quad \forall \alpha \in \mathbb{R}$$

$$\Rightarrow \alpha^2 x^T x + 2\alpha x^T y + y^T y \geq 0$$

this is a quadratic (in  $\alpha$ ) inequality. For this to hold forall  $\alpha$ , no real roots of  $\alpha^2(x^T x) + \alpha(2x^T y) + y^T y = 0$  are

$$\text{possible, } \Leftrightarrow b^2 - 4ac \leq 0$$

$$\Leftrightarrow (2x^T y)^2 - 4(x^T x)(y^T y) \leq 0$$

$$\Leftrightarrow (x^T y)^2 \leq (x^T x)(y^T y) = \|x\|^2 \|y\|^2$$

$$\Rightarrow |x^T y| \leq \|x\| \|y\|$$

Problem 11

$$x(t) = e^{A(t-t_0)} x(t_0) + \int_{t_0}^t e^{A(t-\tau)} B u(\tau) d\tau$$

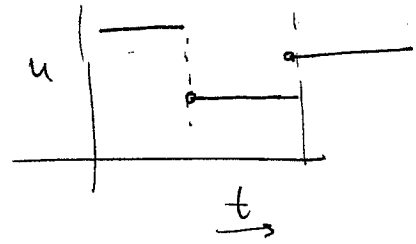
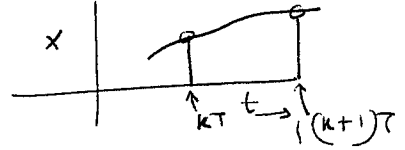
$$x_k := x(kT)$$

$$x_{k+1} := x((k+1)T), \quad u(t) = u_k \quad \text{for } kT \leq t < (k+1)T$$

so integrate between

$$t_0 = kT \quad \text{and} \quad t = (k+1)T$$

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



$$\Rightarrow x_{k+1} = e^{AT} x_k + \int_{kT}^{(k+1)T} e^{A(kT+T-\tau)} B u_k d\tau$$

define  $\eta = (k+1)T - \tau$

$$\Rightarrow d\eta = -d\tau, \quad \eta : T \rightarrow 0$$

as  $\tau : kT \rightarrow (k+1)T$

$$= e^{AT} x_k + \int_T^0 e^{A\eta} (-d\eta) B u_k$$

$$= e^{AT} x_k + \left( \int_0^T e^{A\eta} d\eta B \right) u_k$$

$$\Rightarrow \underline{A_d = e^{AT}}, \quad B_d = \left( \int_0^T e^{A\eta} d\eta \right) B$$

$$y(kT) = C x(kT)$$

$$\Rightarrow y_k = C x_k \Rightarrow \underline{C_d = C}$$

[ note that  $e^A, B, u$  etc are matrices and vectors, their order of multiplication cannot be changed ]