

HW 7: A 10.1 abc, 10.14, 11.5, 11.8 bd, 11.26

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10.1)

(a) Let $\begin{bmatrix} 1 & 1 \\ 0 & 0.95 \end{bmatrix} = A$ and $\begin{bmatrix} 0 \\ 0.1 \end{bmatrix} = b$

$$s(t+1) = A s(t) + b u(t)$$

$$s(0) = \vec{0} \quad s(1) = b u(0) \quad s(2) = A b u(0) + b u(1)$$

$$s(3) = A^2 b u(0) + A b u(1) + b u(2)$$

$$s(4) = A^3 b u(0) + A^2 b u(1) + A b u(2) + b u(3) \dots$$

$$s(N) = A^{N-1} b u(0) + A^{N-2} b u(1) + \dots + A b u(N-2) + b u(N-1)$$

$$= \begin{bmatrix} A^{N-1} b & A^{N-2} b & A^{N-3} b & \dots & A b & b \end{bmatrix} \begin{bmatrix} u(0) \\ u(1) \\ \vdots \\ u(N-1) \end{bmatrix} = \begin{bmatrix} 10 \\ 0 \end{bmatrix}$$

Let $[u(0); u(1); u(2) \dots; u(N-1)] = u$.

$$\begin{bmatrix} A^{N-1} b & A^{N-2} b & \dots & A b & b \end{bmatrix} \cdot u = \begin{bmatrix} 10 \\ 0 \end{bmatrix}$$

and we want to minimize

$$E = \sum_{t=0}^{N-1} u(t)^2 = \|u\|^2$$

If $C = \begin{bmatrix} A^{N-1} b & A^{N-2} b & A^{N-3} b & \dots & A b & b \end{bmatrix}$ and $d = \begin{bmatrix} 10 \\ 0 \end{bmatrix}$,

we are trying to minimize $\|x\|^2$ subject to $Cx = d$.

(b) & (c) on matlab next page. \rightarrow

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% 10.1b

N = 30;

A = [1 1; 0 0.95];
b = [0; 0.1];

C = zeros(2, N);

bi = b;
for i = N:-1:1
    C(:,i) = bi;
    bi = A * bi;
end

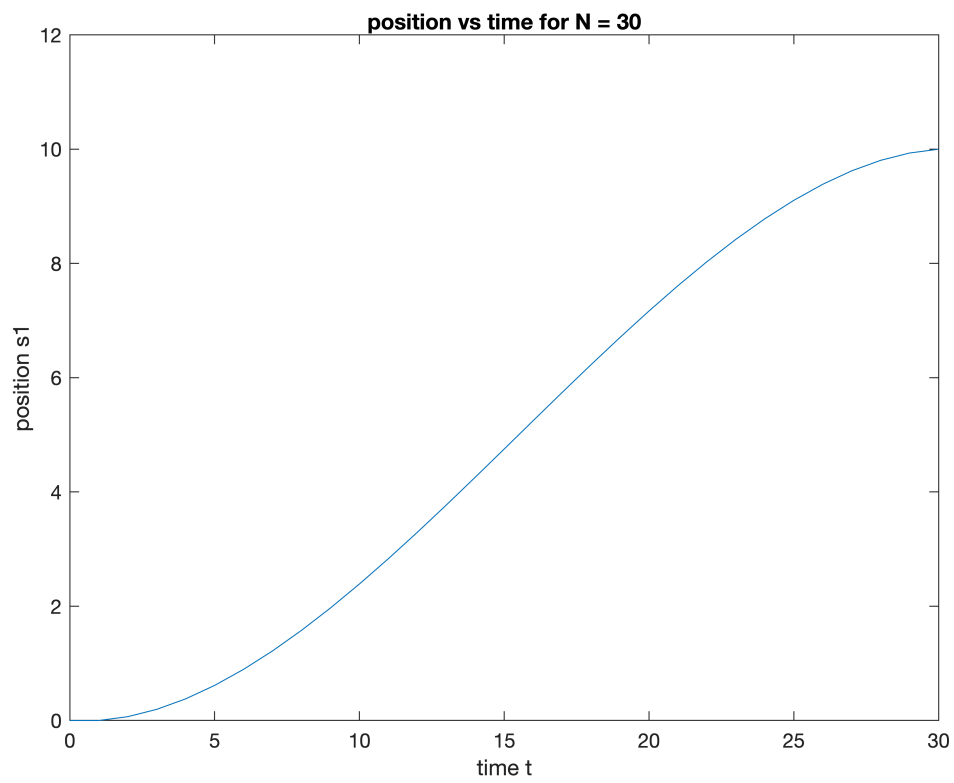
d = [10; 0];

[Q, R] = qr(C', 0);
u = Q * (R' \ d);

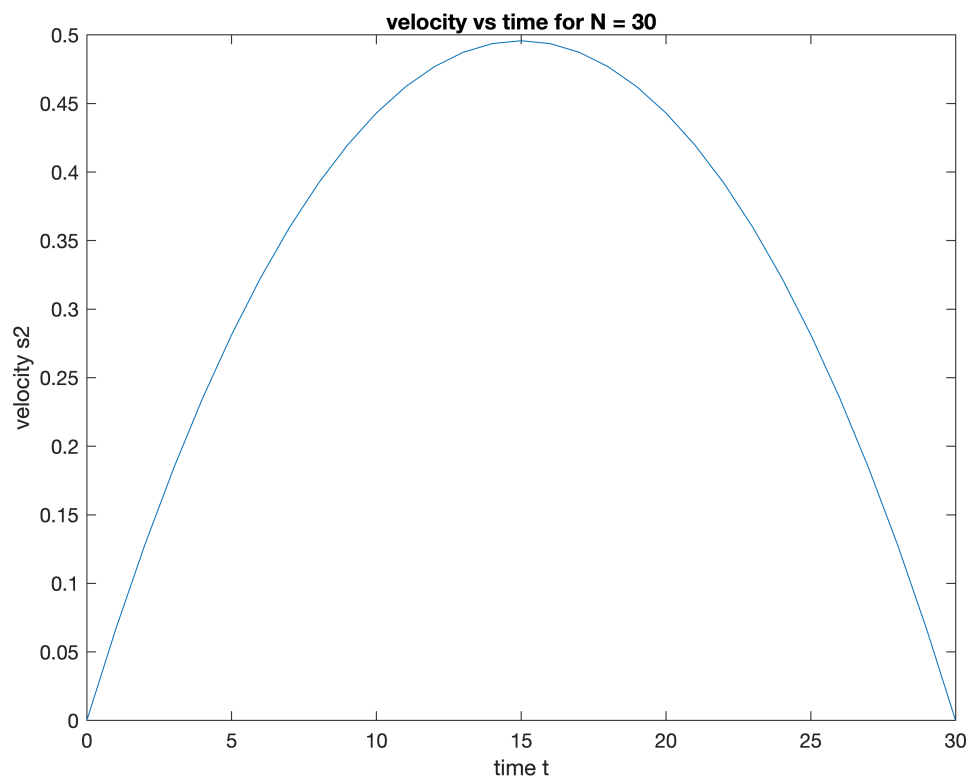
s = zeros(2, N);
for i = 1:N
    s(:,i + 1) = A * s(:,i) + b * u(i);
end

plot(0:N, s(1,:));
xlabel('time t');
ylabel('position s1');
title('position vs time for N = 30');

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plot(0:N, s(2,:));  
xlabel('time t');  
ylabel('velocity s2');  
title('velocity vs time for N = 30');
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% 10.1c
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E = zeros(28, 1);
for N = 2:29
    A = [1 1; 0 0.95];
    b = [0; 0.1];

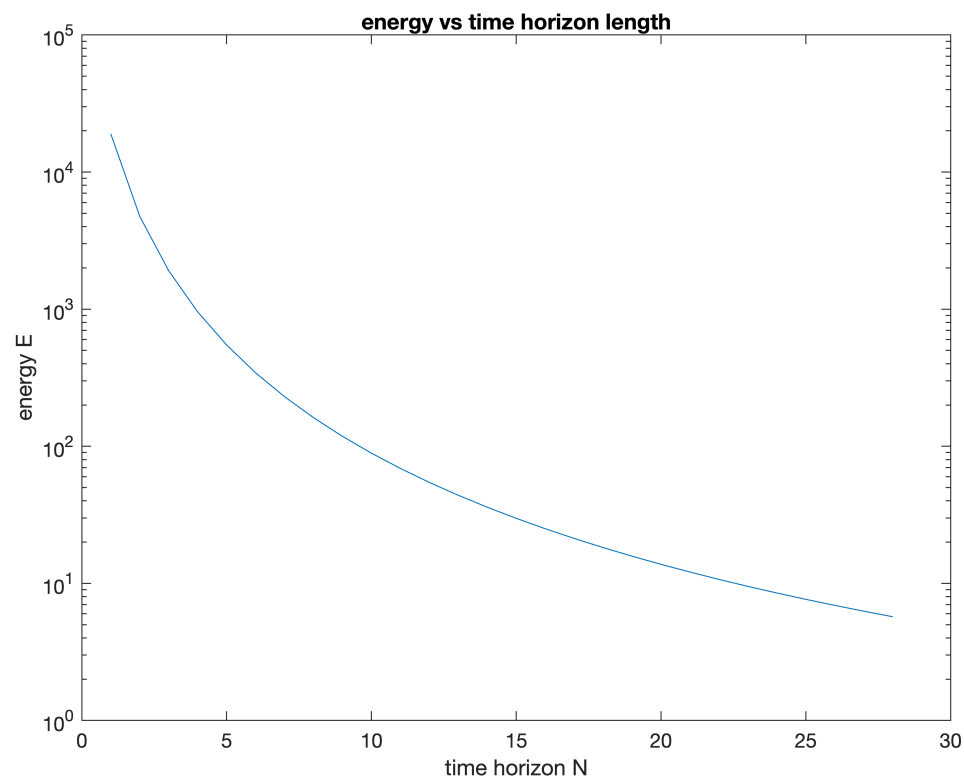
    C = zeros(2, N);

    bi = b;
    for i = N:-1:1
        C(:,i) = bi;
        bi = A * bi;
    end

    d = [10; 0];

    [Q, R] = qr(C', 0);
    u = Q * (R' \ d);
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    E(N - 1) = norm(u)^2;  
end  
  
semilogy(1:28, E);  
xlabel('time horizon N');  
ylabel('energy E');  
title('energy vs time horizon length');
```



10.14) A : $m \times n$ matrix with linearly \perp columns.

$$\hat{x}^{(i)} = \text{solution to } \begin{cases} \text{minimize } \|Ax\|^2 \\ \text{s.t. } e_i^T x = -1 \end{cases}$$

a) Prove
$$\hat{x}^{(i)} = \frac{-1}{e_i^T (A^T A)^{-1} e_i} (A^T A)^{-1} e_i$$

Constrained least squares formulation:

$$\text{minimize } \|Ax - b\|^2 \quad \text{s.t. } Cx = d$$

$$\text{Solution is } \begin{bmatrix} A^T A & C^T \\ C & 0 \end{bmatrix} \begin{bmatrix} x \\ z \end{bmatrix} = \begin{bmatrix} A^T b \\ d \end{bmatrix}$$

if a z exists

In our case $b = \vec{0}$, $C = e_i^T$ and $A = A$, $d = -1$.

$$A^T A x + e_i z = A^T \vec{0} = \vec{0}$$

$$\left(\begin{array}{l} e_i^T x = -1 \rightarrow \text{subject to condition.} \\ x = (A^T A)^{-1} \cdot (-e_i z) \end{array} \right.$$

$\xrightarrow{\quad} A \text{ has lin } \perp \text{ cols.}$

$$e_i^T (A^T A)^{-1} \cdot (-e_i z) = -1$$

$$e_i^T (A^T A)^{-1} e_i \cdot z = 1$$

$$\text{constat} \rightarrow z = \frac{1}{e_i^T (A^T A)^{-1} e_i}$$

plug back into eq. 1:

$$x = \frac{-1}{e_i^T (A^T A)^{-1} e_i} (A^T A)^{-1} e_i$$

10.14)

$$b) \quad A^T A = (QR)^T QR \\ = R^T Q^T Q R$$

$$1) \quad A = QR : \underline{2mn^2} \text{ flops.}$$

$$2) \quad (A^T A)^{-1} = R^{-1} R^{-T}$$

$$R^{-T} \Rightarrow R^T M = I \quad \text{col. by col. } n^3$$

$$N = R^{-1} M \Rightarrow R N = M \quad \text{col. by col. } n^3$$

$$N = (A^T A)^{-1}$$

$$\underline{2n^3 \text{ ops}}$$

$$4) \quad \hat{x}^{(i)} = \frac{1}{e_i^T N e_i} N e_i$$

$O(n^2)$ $O(n^2)$

5) Once we find N in $O(2n^3 + mn^2)$

each $\hat{x}^{(i)}$ takes $O(1)$ to calculate.

$$\hat{x}^{(i)} \quad \text{for } i \in \{1, \dots, N\}$$

takes

$$O(2n^3 + 2mn^2)$$

11.5)

(a) Is $A = \frac{1}{\|a\|^2} a a^T$ positive semi-definite?
 (b)

$$y^T A y = \frac{1}{\|a\|^2} y^T a a^T y = \frac{1}{\|a\|^2} \|a^T y\|^2$$

$$y^T a a^T y = (a^T y)^T (a^T y)$$

for any vector y , and nonzero vector a ,

$$\|a^T y\| \geq 0 \quad \text{and} \quad \frac{1}{\|a\|^2} > 0.$$

equality occurs when $y = \vec{0}$. If $y \neq \vec{0}$, then $\|a^T y\| > 0$.

Thus, A is positive semi-definite.

and ~~also positive definite~~ not positive definite b/c $a^T y = 0$ if a, y orthogonal.

Is $B = I - A$ positive semi-definite or positive definite?

$$y^T (B) y = y^T (I - A) y = y^T y - y^T A y$$

Now, for all y , $y^T A y \geq 0$ from previous section.

$$y^T y - y^T \frac{1}{\|a\|^2} a a^T y = y^T y - \frac{1}{\|a\|^2} y^T a a^T y$$

$$= y^T y - \frac{1}{\|a\|^2} (a^T y)^2 = \|y\|^2 - \frac{1}{\|a\|^2} (a^T y)^2 \geq 0$$

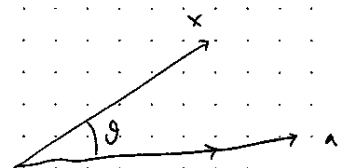
$$= \|y\|^2 \left(1 - \frac{1}{\|a\|^2 \|y\|^2} (a^T y)^2 \right)$$

$$= \|y\|^2 (1 - \cos^2 \theta)$$

$$= \|y\|^2 \sin^2 \theta \geq 0$$

Thus, B is positive semi-definite.

not positive definite ($\theta = 0$)



11.8)

b)

$$A = \begin{bmatrix} 1 & a & 0 \\ a & 1 & a \\ 0 & a & 1 \end{bmatrix} = \begin{bmatrix} R_{11} & & \\ R_{12} & R_{22} & \\ R_{13} & R_{23} & R_{33} \end{bmatrix} \begin{bmatrix} R_{11} & R_{12} & R_{13} \\ R_{22} & R_{23} & \\ R_{33} & & \end{bmatrix}$$

$$= \begin{bmatrix} 1 & 0 & 0 \\ R_{12} & R_{22} & 0 \\ R_{13} & R_{23} & R_{33} \end{bmatrix} \begin{bmatrix} 1 & a & 0 \\ 0 & R_{22} & R_{23} \\ 0 & 0 & R_{33} \end{bmatrix}$$

$$R_{12} + 0 \cdot R_{22} = a \rightarrow R_{12} = a$$

$$R_{13} + 0 \cdot 0 = 0 \rightarrow R_{13} = 0$$

A is positive definite

$$\boxed{|a| \leq 1}$$

$$= \begin{bmatrix} 1 & 0 & 0 \\ a & R_{22} & 0 \\ 0 & R_{23} & R_{33} \end{bmatrix} \begin{bmatrix} 1 & a & 0 \\ 0 & R_{22} & R_{23} \\ 0 & 0 & R_{33} \end{bmatrix}$$

$$\xrightarrow{2 \times 2 \text{ block}} \begin{bmatrix} 1 & a \\ a & 1 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ a & \sqrt{1-a^2} \end{bmatrix} \begin{bmatrix} 1 & a \\ 0 & \sqrt{1-a^2} \end{bmatrix}$$

$$(d) \begin{bmatrix} 1 & 0 & a \\ 0 & 1 & 0 \\ a & 0 & 1 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ a & 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 & a \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

factorable for all a

$$a \in \mathbb{R}$$

$$\begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

$$\boxed{|a| \leq \frac{\sqrt{2}}{2}}$$

11.26)

$$a^2 + R_{22}^2 = 1 \rightarrow R_{22} = \pm \sqrt{1-a^2}$$

$$0 + R_{22} \cdot R_{23} + 0 = a \rightarrow R_{23} = \frac{a}{\pm \sqrt{1-a^2}}$$

$$R_{23}^2 + R_{33}^2 = 1 \rightarrow R_{33} = \pm \sqrt{1 - \frac{a^2}{1-a^2}} = \pm \sqrt{\frac{1-2a^2}{1-a^2}}$$

$$(d) \begin{bmatrix} 1 & 0 & a \\ 0 & 1 & 0 \\ a & 0 & 1 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \pm 1 & 0 \\ a & 0 & \pm \sqrt{1-a^2} \end{bmatrix} \begin{bmatrix} 1 & 0 & a \\ 0 & \pm 1 & 0 \\ 0 & 0 & \pm \sqrt{1-a^2} \end{bmatrix}$$

$$\boxed{|a| \leq 1}$$

$$\sqrt{1} \Rightarrow \pm 1$$

11.26) (a) $A = \begin{bmatrix} B & -C^T \\ C & D \end{bmatrix} = \begin{bmatrix} R_{11}^T R_{11} & R_{11}^T R_{12} \\ -R_{12}^T R_{11} & -R_{12}^T R_{12} + R_{22}^T R_{22} \end{bmatrix}$

B is PD so $B = R_{11}^T R_{11}$ is possible.

$$C = -R_{12}^T R_{11}$$

since R_{11} has positive diagonal elements,

thus, since R_{11} is U.T. \rightarrow invertible

$$-R_{12}^T = C R_{11}^{-T}$$

$$\text{and } R_{12} = (-C R_{11}^{-T})^T$$

$$D = -R_{12}^T R_{12} + R_{22}^T R_{22} \quad \dots \text{ we want to prove that } R_{22} \text{ is upper triangular}$$

$$R_{11}^T R_{11} + R_{12}^T R_{12} = R_{22}^T R_{22}$$

positive definite positive semidefinite form:

$$a^T R_{22}^T R_{22} a = \|(R_{22} a)\|^2 \geq 0 \quad \text{for all } a.$$

PD + PSD = PD so R_{22} exists and is U.T.

(b) Step 1: $B = R_{11}^T R_{11} \rightarrow R_{11}$ takes $\boxed{\frac{1}{3}n^3}$ by Cholesky.

Step 2: $C = -R_{12}^T R_{11} \quad R_{11} \bar{X} = \bar{y}$ takes $O(N^2)$ to solve.

\hookrightarrow N columns $\Rightarrow \boxed{\cancel{N^3}}$ mn^2 since \bar{X} has m columns.

Step 3: $D \pm R_{12}^T R_{11} = R_{22}^T R_{22} \rightarrow$ Cholesky's $= \frac{1}{3}m^3$

\downarrow $(n \times m)^T (n \times m) \Rightarrow 2m^2 n$

$$\boxed{2mn^2 + \frac{1}{3}n^3 + \cancel{\frac{1}{3}n^3} + \frac{1}{3}m^3} \leftarrow \text{only cubic terms.}$$