

$$a \in \mathbb{R}^{n+1}$$

P1: $P(x) = a[1] + a[2]x + a[3]x^2 + \dots + a[n+1]x^n = 0$

(a) Given $P(x)$

Then companion matrix

$$A = \begin{bmatrix} -\frac{a_{n-1}}{a_n} & -\frac{a_{n-2}}{a_n} & \dots & -\frac{a_0}{a_n} \\ 1 & & & \\ & 1 & & \\ & & \ddots & \\ & & & 1 & 0 \end{bmatrix}$$

using Power iteration, we can find largest root

which is try to find its eigenvector by
then its eigenvalue is $x_{k+1} = A x_k$

$$x_{k+1} = \frac{A x_k}{\|A x_k\|_2}$$

(b) $B = A - \lambda I$, the largest in magnitude of the matrix B corresponds to the smallest eigenvalue of A , then apply the power method to B to obtain the v_k with the smallest eigenvalue λ_k

In Hw9, if vector b is in reverse order of a , then
eigenvalues of $A = \frac{1}{\text{eigenvalues of } B}$

$$b = [a_n \quad a_{n-1} \quad \dots \quad a_0]$$

companion matrix B is

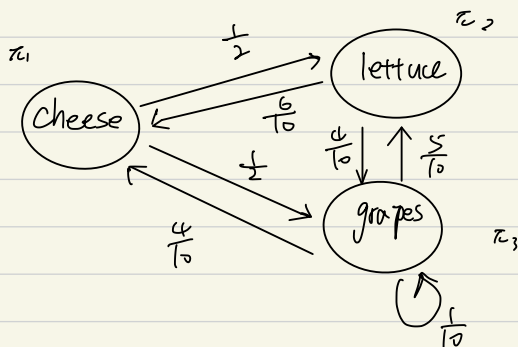
$$\begin{bmatrix} -\frac{a_1}{a_0} & -\frac{a_2}{a_0} & \dots & -\frac{a_n}{a_0} \\ 1 & & & \\ & 1 & & \\ & & \ddots & \\ & & & 1 & 0 \end{bmatrix}$$

Same in part (a)

$$x_{k+1} = \frac{B x_k}{\|B x_k\|_2}$$

and compute corresponding
min eigenvalue is $\frac{1}{x_{k+1}^T B x_{k+1}}$

P2.



(a)

$$\pi P = \pi$$

\Rightarrow

$$\begin{cases} \pi_1 = \frac{6}{10} \pi_2 + \frac{4}{10} \pi_3 \\ \pi_2 = \frac{1}{2} \pi_1 + \frac{1}{2} \pi_3 \\ \pi_3 = \frac{1}{10} \pi_3 + \frac{1}{2} \pi_1 + \frac{4}{10} \pi_2 \\ \pi_1 + \pi_2 + \pi_3 = 1 \end{cases}$$

$$P = \begin{bmatrix} 0 & \frac{6}{10} & \frac{4}{10} \\ \frac{1}{2} & 0 & \frac{5}{10} \\ \frac{1}{2} & \frac{4}{10} & \frac{1}{10} \end{bmatrix}$$

\Rightarrow

$$\begin{cases} \pi_1 = \frac{3}{5} \pi_2 + \frac{2}{5} \pi_3 \\ \pi_2 = \frac{1}{2} \pi_1 + \frac{1}{2} \pi_3 \\ \pi_3 = \frac{1}{2} \pi_1 + \frac{2}{5} \pi_2 + \frac{1}{10} \pi_3 \end{cases}$$

\Rightarrow

$$\begin{cases} \pi_1 = \frac{1}{3} \\ \pi_2 = \frac{1}{3} \\ \pi_3 = \frac{1}{3} \end{cases}$$

\therefore the long term average probability is $(\frac{1}{3}, \frac{1}{3}, \frac{1}{3})$ of eating cheese grapes or lettuce

(b) This answer $(\frac{1}{3}, \frac{1}{3}, \frac{1}{3})$ is the unique solution.

Because P is square non-negative and strongly connected graph, so it is irreducible, then the equilibrium distribution is unique.

Problem 3:

(a) $\pi = \left[\frac{1}{4}, \frac{1}{4}, \frac{1}{4}, \frac{1}{4} \right]^T$
rank-1 transition matrix $P \in \mathbb{R}^{4 \times 4}$

$$P = \begin{bmatrix} \frac{1}{4} & \frac{1}{4} & \frac{1}{4} & \frac{1}{4} \\ \frac{1}{4} & \frac{1}{4} & \frac{1}{4} & \frac{1}{4} \\ \frac{1}{4} & \frac{1}{4} & \frac{1}{4} & \frac{1}{4} \\ \frac{1}{4} & \frac{1}{4} & \frac{1}{4} & \frac{1}{4} \end{bmatrix}$$

$$\pi P = \pi \Rightarrow \pi = \begin{bmatrix} \frac{1}{4} \\ \frac{1}{4} \\ \frac{1}{4} \\ \frac{1}{4} \end{bmatrix}$$

(b) This example has unique solution,

Because P is square non-negative and strongly connected graph, so it is irreducible, then the equilibrium distribution is unique.

P4:

Given that A has full column rank and P is symmetric positive definite.

$$-1 < \text{eig}(I - P^{\frac{1}{2}} A' A P^{\frac{1}{2}}) < 1$$

$$\begin{aligned} \text{LHS : } -1 &< \text{eig}(I - P^{\frac{1}{2}} A' A P^{\frac{1}{2}}) \\ -1 &< 1 - \text{eig}(P^{\frac{1}{2}} A' A P^{\frac{1}{2}}) \end{aligned}$$

$$\text{eig}(P^{\frac{1}{2}} A' A P^{\frac{1}{2}}) < 2$$

$$2 - \text{eig}(P^{\frac{1}{2}} A' A P^{\frac{1}{2}}) > 0$$

$$\text{eig}(2I - P^{\frac{1}{2}} A' A P^{\frac{1}{2}}) > 0$$

$$2I - P^{\frac{1}{2}} A' A P^{\frac{1}{2}} \succ 0$$

$$P^{-\frac{1}{2}} (2I - P^{\frac{1}{2}} A' A P^{\frac{1}{2}}) P^{-\frac{1}{2}} \succ 0$$

$$2P^{-1} - A' A \succ 0$$

\therefore

$$2P^{-1} \succ A' A$$

Problem 5:

(a) If H is a (Hermitian) symmetric matrix that is diagonally dominant, then $|h_{ii}| \geq \sum_{j \neq i} |h_{ij}|$ for $i=1 \dots n$

Since $h_{ii} > 0$ and by Gershgorin disk theorem, the disk D doesn't contain the negative value since $h_{ii} - \underbrace{\sum_{j \neq i} |h_{ij}|}_{R: \text{radius of disk}} \geq 0$

\therefore the eigenvalue of H are nonnegative and symmetric matrix

$\therefore H \succeq 0$

(b) $D \triangleq \text{Diag}(|B| \mathbf{1}_n)$ $\begin{bmatrix} 1 & 2 & 3 \\ 2 & 3 & 4 \\ 3 & 4 & 4 \end{bmatrix} \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} =$

$= \text{Diag} \left(\begin{bmatrix} \sum |B_{1,j}| \\ \sum |B_{2,j}| \\ \vdots \\ \sum |B_{n,j}| \end{bmatrix} \right)$

and $D - B \Rightarrow \begin{bmatrix} \sum |B_{1,j}| - B_{11} & & \\ & \sum |B_{2,j}| - B_{22} & \\ & & \ddots \\ & & & \sum |B_{n,j}| - B_{nn} \end{bmatrix}$ test are entries of B

We notice that the matrix $[D - B]_{ii} = \sum_j |B_{ij}| - B_{ii} > \sum_{j \neq i} B_{ij}$

(Since $\sum_j |B_{ij}| > \sum_j B_{ij}$)

So $D - B$ is diagonally dominant

Therefore, based on part (a) $D - B$ is $n \times n$ Hermitian symmetric matrix and is diagonally dominant, then $D - B \succeq 0$

$\therefore D \triangleq \text{Diag}(|B| \mathbf{1}_n) \succeq B$

P6.

$$f(x) = \frac{1}{2} \|Ax - y\|_2^2 + \delta^2 \frac{1}{2} \|x\|_2^2$$

(a) gradient of this cost function.

$$\nabla f(x) = A'(Ax - y) + \delta^2 x$$

(b) $\forall x, z \in \mathbb{R}^N$

$$\begin{aligned} \|\nabla f(x) - \nabla f(z)\|_2 &= \|A'(Ax - y) + \delta^2 x - (A'(Az - y) + \delta^2 z)\|_2 \\ &= \|A'(Ax - y) - A'(Az - y) + \delta^2(x - z)\|_2 \\ &= \|A'A(x - z) + \delta^2(x - z)\|_2 \\ &= \|(A'A + \delta^2 I)(x - z)\|_2 \\ &\leq \|A'A + \delta^2 I\|_2 \|x - z\|_2 \end{aligned}$$

and notice that $\|A'A + \delta^2 I\|_2 \leq \|A'A\|_2 + \|\delta^2 I\|_2 = \|A'A\|_2 + \delta^2$

\therefore the upper bound is $\|A'A\|_2 + \delta^2$ (not singular values in expression)

(c) When $A = \begin{bmatrix} I_5 \\ I_5 I_5' \end{bmatrix}$ and $\delta = 2$

$$A'A = \begin{bmatrix} I_5 & I_5 I_5' \\ I_5 I_5' & I_5 I_5' \end{bmatrix} \begin{bmatrix} I_5 \\ I_5 I_5' \end{bmatrix} = I_5 + 5 I_5 I_5' = \begin{bmatrix} 1 & & & & \\ & 1 & & & \\ & & 1 & & \\ & & & 1 & \\ & & & & 1 \end{bmatrix} +$$

$$\therefore \|A'A\|_2 = \max \text{ column sum} = 1 + 25 = 26$$

$$\begin{bmatrix} 5 & 5 & 5 & 5 & 5 \\ 5 & 5 & 5 & 5 & 5 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 5 & 5 & 5 & 5 & 5 \end{bmatrix}$$

\therefore the upper bound is $26 + 2^2 = 30$

(d) $L = \|A'A + \delta^2 I\|_2 = 30$ which is exactly the same as upper bound

P7:

$$x_1 = -2 + i\sqrt{3}$$

$$p_1(x) = (x - (-2 + i\sqrt{3}))(x - (-2 - i\sqrt{3})) \\ = x^2 + 4x + 7$$

So the companion matrix is (corresponding x_1)

$$A = \begin{bmatrix} -4 & -7 \\ 1 & 0 \end{bmatrix}$$

eigenvalues of $A \oplus B$ are $\lambda_i(A) + \lambda_j(B)$

$$A \oplus B = A \otimes I_N + I_m \otimes B$$

$$= \begin{bmatrix} 6 & 0 & -25 & 0 \\ 0 & 6 & 0 & -25 \\ 2 & 0 & 0 & 0 \\ 0 & 2 & 0 & 0 \end{bmatrix}$$

$$x_2 = 5 - \sqrt{7}$$

$$p_2(x) = (x - (5 - \sqrt{7}))(x - (5 + \sqrt{7})) \\ = x^2 - (5 + \sqrt{7})x - (5 - \sqrt{7})x + (25 - 7) \\ = x^2 - 10x + 18$$

companion matrix of $p_2(x)$

$$B = \begin{bmatrix} 10 & -18 \\ 1 & 0 \end{bmatrix}$$

the eigenvalues of $A \otimes B$ are $\lambda_i(A) \cdot \lambda_j(B)$

$$A \otimes B$$

$$= \begin{bmatrix} -40 & 72 & -70 & 126 \\ -4 & 0 & -7 & 0 \\ 10 & -18 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

Now use Symbolic computation:

$$p_3 = x^4 - 12x^3 + 136x^2 - 600x + 2500$$

$$p_4 = x^4 + 40x^3 + 736x^2 + 5040x + 15876$$

P8:

$$x_1 = a + \sqrt{b}$$

$$\begin{aligned} P_1(x) &= (x - (a + \sqrt{b}))(x - (a - \sqrt{b})) \\ &= x^2 - (a - \sqrt{b})x - (a + \sqrt{b})x + (a^2 - b) \\ &= x^2 - 2ax + a^2 - b \end{aligned}$$

$$C_1 = [a^2 - b \quad -2a]$$

$$x_2 = c - \sqrt{d}$$

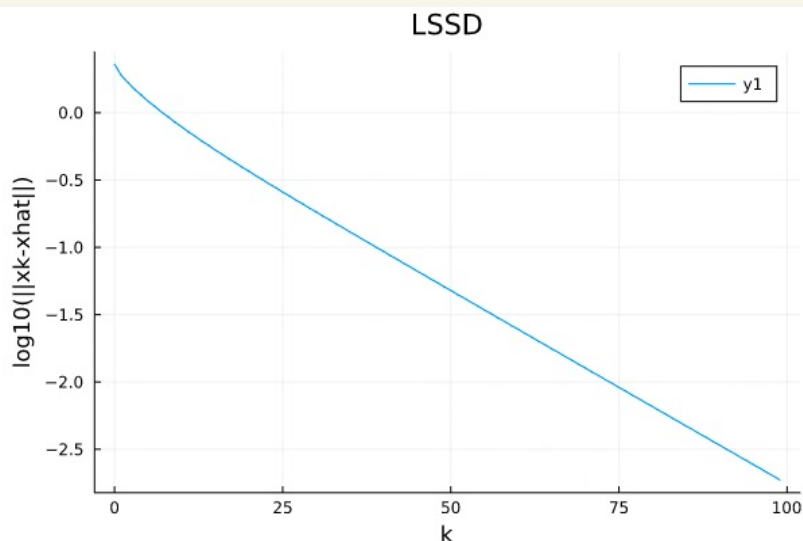
$$\begin{aligned} P_2(x) &= (x - (c - \sqrt{d}))(x - (c + \sqrt{d})) \\ &= x^2 - 2cx + c^2 - d \end{aligned}$$

$$C_2 = [c^2 - d \quad -2c]$$

Pg,

(b)

Out[170]:



In [170]:

```
1 using Random: seed!
2 using Plots
3 seed!(0) # seed random number generator
4 m = 100; n = 50; sigma = 0.1
5 A = randn(m, n); xtrue = rand(n)
6 b = A * xtrue + sigma * randn(m)
7
8 k=LinRange(0,99,100)
9 xhat = A \ b
10 y1=zeros(100)
11 for i=1:100
12     y1[i]=log10(norm(lssd(A,b,nIters=i)-xhat ))
13 end
14
15 plot(xlabel = "k")
16 plot!(ylabel = "log10(||xk-xhat||)")
17 plot!(k,y1)
18 plot!(title="LSSD")
```

(C)

```
21 function lssd(A, b ; x0=zeros(size(A,2)), nIters::Int=10)
22 |
23     x_current = x0
24     Ax = A * x_current
25     for _ in 1:nIters
26         gradient = A' * (Ax - b)
27         direction = - gradient
28         Ad = A * direction
29         Ad_norm = norm(Ad)
30
31         if(Ad_norm == 0)
32             return x_current
33         else
34             step = - direction' * gradient / (Ad_norm.^2)
35         end
36
37         x_current = x_current + step * direction
38         Ax = Ax + step * Ad
39     end
40
41     return x_current
42
43 end
```