

Plan

- 1 Definiteness of quadratic forms
- 2 Non-negative matrices and Markov chains

Review: A $n \times n$ matrix

— eigenvectors and eigen values

— diagonalization of A

— how to compute

* A^m when m is big

* Markov chains

A diagonalizable if

- i) there are n eigen values
- ii) there are n lin. indep. eigenvectors

In that case: $P^{-1}AP = D$

$$D = \begin{pmatrix} \lambda_1 & & 0 \\ & \ddots & \\ 0 & & \lambda_n \end{pmatrix}, P = (\underline{v}_1 \dots \underline{v}_n)$$

① Definiteness of quadratic forms

Functions in n variables:

$f(x_1, x_2, \dots, x_n) =$ some fractional expression

$$\underline{x} = \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{pmatrix} : f(\underline{x}) = f(x_1, \dots, x_n)$$

Ex: $f(x_1, x_2, x_3, x_4) = \underbrace{1}_{\text{poly. deg 3}} + \underbrace{x_1}_{\text{deg 0}} + \underbrace{x_4}_{\text{deg 1}} + \underbrace{x_2 x_3}_{\text{deg 2}} - \underbrace{x_1 x_4}_{\text{deg 2}} + \underbrace{x_4^3}_{\text{deg 3}}$

Defn: A quadratic form in n variables is a polynomial function $f(x_1, \dots, x_n)$ where each term has degree two.

Ex: $n=1$ $f(x) = ax^2 + bx + c$
quadratic fn.

$f(x) = ax^2$
quadratic form

x^2, y^2 : Squares
 xy : mixed terms

Ex $f(x,y) = ax^2 + bxy + cy^2$
 $n=2$

Ex: $f(x,y) = \underline{x^2 + 4xy - y^2}$

$$f'_x = 2x + 4y = 0$$

$$f'_y = 4x - 2y = 0$$

Notice: For all quadratic forms, we have:

i) $(x,y) = (0,0)$ is a stationary pt ✓

ii) $f(0,0) = 0$ ✓

What kind of stat. pt
 is this? max? min?
 Saddle pt?

Matrix form:

Ex: $(x \ y) \cdot \begin{pmatrix} 1 & 2 \\ 2 & -1 \end{pmatrix} \cdot \begin{pmatrix} x \\ y \end{pmatrix} = \underline{\underline{x^T \cdot A \cdot x}}$, $\underline{x} = \begin{pmatrix} x \\ y \end{pmatrix}$

$$\begin{pmatrix} x+2y & 2x-y \end{pmatrix} \cdot \begin{pmatrix} x \\ y \end{pmatrix} = (x+2y) \cdot x + (2x-y) \cdot y$$

$$= 1x^2 + 2 \cdot yx + 2x \cdot y + (-1)y^2$$

$$= x^2 + 4xy - y^2$$

$(1,1) \rightarrow x^2$ terms
 $(1,2), (2,1) \rightarrow xy$ terms
 $(2,2) \rightarrow y^2$ terms

Fact:

Any quadratic form $f(x_1, \dots, x_n)$ can be written as

$$f(\underline{x}) = \underline{x}^T \cdot A \cdot \underline{x}, \quad \underline{x} = \begin{pmatrix} x_1 \\ \vdots \\ x_n \end{pmatrix}$$

for a unique symmetric $n \times n$ matrix A .

Ex: $f(x,y,z) = \underline{x^2} + \overset{3+5}{6}xy - \overset{-1+6-7}{2}yz + \underline{y^2} - \underline{3z^2}$

$\underline{x} = \begin{pmatrix} x \\ y \\ z \end{pmatrix}$: $f(\underline{x}) = (x \ y \ z) \cdot \begin{pmatrix} 1 & 3 & 0 \\ 3 & 1 & -1 \\ 0 & -1 & -3 \end{pmatrix} \cdot \begin{pmatrix} x \\ y \\ z \end{pmatrix} \Rightarrow A = \begin{pmatrix} 1 & 3 & 0 \\ 3 & 1 & -1 \\ 0 & -1 & -3 \end{pmatrix}$

yz : pos (2,3)
 (3,2)

symmetric matrix of f

Defn: Let $f(x_1, \dots, x_n)$ be a quadratic form

defn =
definite

We say that:

i) f positive defn.

if $f(x_1, \dots, x_n) > 0$
for all $(x_1, \dots, x_n) \neq (0, \dots, 0)$



$(0, 0, \dots, 0)$ unique
global min
for f



ii) f negative defn.

if $f(x_1, \dots, x_n) < 0$
for all $(x_1, \dots, x_n) \neq (0, \dots, 0)$



$(0, 0, \dots, 0)$ unique
global max for f

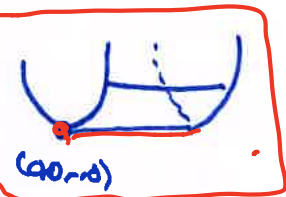


iii) f positive semidefn.

if $f(x_1, \dots, x_n) \geq 0$ for
all $(x_1, \dots, x_n)$



$(0, 0, \dots, 0)$
global min for f

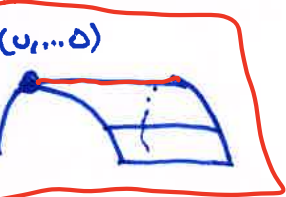


iv) f negative semidefn.

if $f(x_1, \dots, x_n) \leq 0$
for all $(x_1, \dots, x_n)$



$(0, 0, \dots, 0)$
global max for f



v) f indefinite if

$f(x_1, \dots, x_n)$ can take
both positive and
negative values



$(0, 0, \dots, 0)$
saddle pt. for f

$\Uparrow$
neither positive nor
negative semidefn.

pos. semidefn.	neg. semidefn.	<u>indefinite</u>
pos. defn.	neg. defn.	

Methods for determining the definiteness (classify)

$f(x_1, \dots, x_n)$ quadratic form $\iff$ A $n \times n$ symmetric matrix $f(x) = x^T A x$

(A) Let $\lambda_1, \lambda_2, \dots, \lambda_n$ be the eigenvalues of A .

Result:

A or f is:

$$\lambda_1, \lambda_2, \dots, \lambda_n > 0$$



positive defn.

$$\lambda_1, \lambda_2, \dots, \lambda_n \geq 0$$



positive semidefn.

$$\lambda_1, \lambda_2, \dots, \lambda_n < 0$$



negative defn.

$$\lambda_1, \lambda_2, \dots, \lambda_n \leq 0$$



negative semidefn.

all other cases



indefinite

(there are pos.

and neg. eigenvalues)

Ex: $f = x^2 + y^2 + 3z^2$

$$\rightarrow A = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 3 \end{pmatrix}$$

$$\begin{aligned} \lambda_1 &= 1 \\ \lambda_2 &= 1 \\ \lambda_3 &= 3 \\ \text{pos. defn.} \end{aligned}$$

$f(x, y, z) > 0$ when
 $(x, y, z) \neq (0, 0, 0)$

$f(x, y, z) = x^2 - y^2 + 3z^2$

$f(1, 0, 0) = 1 > 0$

$f(0, 1, 0) = -1 < 0$

$$A = \begin{pmatrix} 1 & 0 & 0 \\ 0 & -1 & 0 \\ 0 & 0 & 3 \end{pmatrix}$$

$$\begin{aligned} \text{indefn.} \\ \lambda_1, \lambda_3 > 0 \\ \lambda_2 < 0 \end{aligned}$$

$$x^2 - y^2 = 0 \quad x = \pm y$$

$$A = \begin{pmatrix} 0 & 2 \\ 2 & 0 \end{pmatrix}$$

$$\begin{aligned} \lambda_1 &= 2 \\ \lambda_2 &= -2 \end{aligned}$$

indefn.

$f(x, y) = 4xy$

$= 4 \cdot \left(\frac{u+v}{\sqrt{2}} \right) \left(\frac{u-v}{\sqrt{2}} \right)$

$= 2(u^2 - v^2) = \underbrace{2u^2}_{\lambda_1=2} - \underbrace{2v^2}_{\lambda_2=-2}$

Since A is always symmetric, we can diagonalize; that is

$$f(x, y) = \lambda_1 u^2 + \lambda_2 v^2 + \dots + \lambda_n u_n^2$$

where $u_1, \dots, u_n$ are new variables

(B) Principal minors: Minors where we pick the same rows as columns.

A
n x n
symm.
matrix

Ex: $A = \begin{pmatrix} 1 & 3 & 0 \\ 3 & 1 & 1 \\ 0 & 1 & 3 \end{pmatrix}$

2-minors:

principal
2-minors
of A

$$\begin{cases} M_{12,12} = \begin{vmatrix} 1 & 3 \\ 3 & 1 \end{vmatrix} = -8 \\ M_{23,23} = \begin{vmatrix} 1 & 1 \\ 1 & 3 \end{vmatrix} = 2 \\ M_{13,13} = \begin{vmatrix} 1 & 0 \\ 0 & 3 \end{vmatrix} = 3 \end{cases}$$

leading
principal
2-minor
of A

9 2-minors
(9 = 3 · 3)

Defn: A principal r-minor of A is an r-minor of the form $M_{I,I}$ with $I = \{1, 2, \dots, r\}$.
We write Δ_r for principal r-minors.

A leading principal-minor of A is
 $\Delta_r = M_{\{1,2,\dots,r\},\{1,2,\dots,r\}} = M_{I,I}$ with $I = \{1, 2, \dots, r\}$

Result: A n x n symmetric matrix $\Leftrightarrow f(x_1, \dots, x_n)$ quadr. form

$$\begin{aligned} D_1, D_2, \dots, D_n > 0 &\Leftrightarrow A \text{ pos. defn.} \\ D_1 < 0, D_2 > 0, D_3 < 0, \dots &\Leftrightarrow A \text{ neg. defn.} \end{aligned}$$

$$\begin{aligned} &\Updownarrow \\ (-1)^i \cdot D_i &> 0 \\ \text{for } i &= 1, 2, \dots, n. \end{aligned}$$

Ex: $f(x_1, x_2) = x^2 + 3y^2 + z^2 - xy$ ✓

$$A = \begin{pmatrix} 1 & -1/2 & 0 \\ -1/2 & 3 & 0 \\ 0 & 0 & 1 \end{pmatrix}$$

$$\begin{aligned} D_1 &= 1 > 0 \\ D_2 &= 3 - (-1/2)^2 = 11/4 > 0 \\ D_3 &= +1 \cdot D_2 = 11/4 > 0 \end{aligned}$$

positive defn
since $D_1, D_2, D_3 > 0$

Ex: $f = -x^2 - y^2 - 3z^2$

neg. defn.

$$\lambda_1 = D_1 = -1$$

$$\lambda_1 \lambda_2 = D_2 = +1 = (-1) \cdot (-1)$$

$$\lambda_1 \lambda_2 \lambda_3 = D_3 = -3 = (-1)(-1)(-3)$$

$$A = \begin{pmatrix} -1 & 0 & 0 \\ 0 & -1 & 0 \\ 0 & 0 & -3 \end{pmatrix} \quad \begin{array}{l} \lambda_1 = -1 \\ \lambda_2 = -1 \\ \lambda_3 = -3 \end{array}$$

negative defn.

Result: A nnn symmetric matrix $\leftrightarrow f(x_1, \dots, x_n)$ qu. form

$\Delta_1, \Delta_2, \dots, \Delta_n \geq 0$ for all
principal minors

$\Leftrightarrow$ positive ^{semi-}defn.

$$\Delta_1 \leq 0, \Delta_2 \geq 0, \dots$$

for all principal minors

$\Rightarrow$ negative ^{semi-}defn

$\Uparrow$
 $(-1)^i \Delta_i \geq 0$ for $i=1, 2, \dots, n$

Ex: $f = 2x^2 + 8y^2 - 8xy + z^2$

positive semidefn ✓

$$A = \begin{pmatrix} 2 & -4 & 0 \\ -4 & 8 & 0 \\ 0 & 0 & 1 \end{pmatrix}$$

$$\begin{array}{l} D_1 = 2 \checkmark \\ D_2 = 0 \checkmark \\ D_3 = 0 \checkmark \end{array}$$

$D_i \geq 0$
for all i

$$\begin{array}{l} \Delta_1 = 2, 8, 1 \geq 0 \\ \Delta_2 = 0, 8, 2 \geq 0 \\ \Delta_3 = 0 \geq 0 \end{array}$$

$$\Delta_1: M_{11}=2 \quad M_{22}=8 \quad M_{33}=1$$

$$\Delta_2: M_{12}=0 \quad M_{23}=8 \quad M_{13}=2$$

$$\Delta_3: M_{123,123} = 1 \cdot 1 = 0$$

Ⓒ Reduced rank criterion

A
n x n
symm.

$$|A| = 0 = D_n$$

$$\text{rk } A < n$$

A n x n symm.
matrix

$$r = \text{rk}(A) < n$$

RRC:

$$D_1, D_2, \dots, D_r > 0 \Rightarrow A \text{ pos. semi-defn.}$$

$$D_1 < 0, D_2 > 0, \dots,$$

$$(-1)^r \cdot D_r > 0 \Rightarrow A \text{ neg. semi-defn.}$$

Remember: $\text{rk } A = r < n$ means that
 $D_{r+1}, D_{r+2}, \dots, D_n = 0$

Ex: $f(x, y, z) = x^2 + y^2 + z^2 - 2xz$

$$A = \begin{pmatrix} 1 & 0 & -1 \\ 0 & 1 & 0 \\ -1 & 0 & 1 \end{pmatrix} \rightarrow \begin{pmatrix} 1 & 0 & -1 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{pmatrix} \quad \text{rk } A = 2 < 3$$

rk A = 2: r = 2

$D_1 = 1 > 0$
 $D_2 = 1 > 0$ RED $\Rightarrow$ positive semi-defn.

$(D_3 = 0$
Since $\text{rk } A = 2)$

$$\begin{array}{l} D_1 = 1 \\ D_2 = 1 \\ D_3 = +1 \cdot (-1) = 0 \end{array} \quad \begin{array}{l} \Delta_1 = 1, 1, 1 \\ \Delta_2 = 1, 1, 0 \\ \Delta_3 = 0 \end{array}$$

$\Delta_i \geq 0$
 $\Downarrow$
pos. semi-defn.

Plan:

- ① Definiteness of quadratic forms: More examples
- ② Non-negative matrices and Markov chains.

① Examples: Definiteness

a) $f = x^2 + 4xy + 8xz + 3y^2 - 2yz + 2z^2$

$$A = \begin{pmatrix} 1 & 2 & 4 \\ 2 & 3 & -1 \\ 4 & -1 & 2 \end{pmatrix}$$

$$D_1 = 1 > 0$$

$$D_2 = 3 - 4 = -1 < 0$$

A indefinite

A pos. semidef. $\Delta_i \geq 0$

A neg. ——— $\begin{cases} \Delta_1 \leq 0, \\ \Delta_2 \geq 0, \\ \Delta_3 \leq 0 \end{cases}$

$\Delta_2, \Delta_4, \dots < 0$
 $\Downarrow$
 indefinite

b) $f = 2x^2 + y^2 + 2z^2 + w^2 + 2xz - 2yw$

$$A = \begin{pmatrix} 2 & 0 & 1 & 0 \\ 0 & 1 & 0 & -1 \\ 1 & 0 & 2 & 0 \\ 0 & -1 & 0 & 1 \end{pmatrix}$$

$$D_1 = 2 > 0$$

$$D_2 = 2 > 0$$

$$D_3 = 1 \cdot (4 - 1) = 3 > 0$$

$$D_4 = |A| = 0$$

RRC:

1) $\text{rk } A = 3 < n = 4$

2) $D_1, D_2, D_3 > 0$

$\Downarrow$ RRC

A pos. semidefinite

c) $f = 2xw - 2yz$

$$A = \begin{pmatrix} 0 & 1 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 0 & 0 & -1 & 0 \\ 0 & 0 & 0 & -1 \end{pmatrix}$$

$$D_1 = 0 \geq 0$$

$$D_2 = 0 \geq 0$$

$$D_3 = 0 \geq 0$$

$$D_4 = -1 \cdot (-1 \cdot 1) = 1 \geq 0$$

$$\Delta_1 = 0, 0, 0, 0 \geq 0$$

$$\Delta_2 = 0, \begin{vmatrix} 0 & -1 \\ -1 & 0 \end{vmatrix} = 0 - 1 = -1 < 0$$

Δ_2

$\Downarrow$

A indefinite

② Non-negative matrices and Markov chains

Defn: $A = \begin{pmatrix} a_{11} & a_{12} & \dots & a_{1n} \\ \vdots & \vdots & & \vdots \\ a_{m1} & a_{m2} & \dots & a_{mn} \end{pmatrix}$
 $n \times n$
 matrix

A is positive if $a_{ij} > 0$ for all i, j , and write $A > 0$

A is non-negative if $a_{ij} \geq 0$ for all i, j , and write $A \geq 0$

Markov chains:

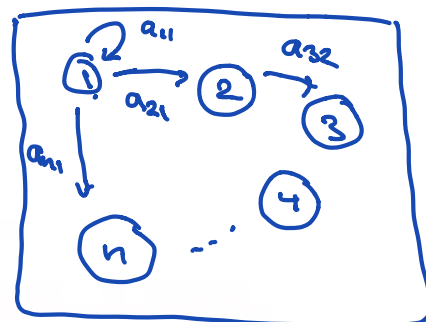
State vector:

$$\underline{v} = \begin{pmatrix} v_1 \\ v_2 \\ \vdots \\ v_n \end{pmatrix} \quad \begin{array}{l} v_1, \dots, v_n \geq 0 \\ v_1 + v_2 + \dots + v_n = 1 \end{array}$$

Transition matrix:

$$A = \begin{pmatrix} a_{11} & \dots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{n1} & \dots & a_{nn} \end{pmatrix} \quad \begin{array}{l} a_{ij} \geq 0 \text{ for all } i, j \\ a_{i1} + a_{i2} + \dots + a_{in} = 1 \text{ for all } i \\ \text{(each column has sum = 1)} \end{array}$$

Defn: The Markov chain is regular if you can get from any node to any other node in a finite no. of steps.



Dynamic equation:

$$\underline{v}_{t+1} = A \cdot \underline{v}_t$$

If $A > 0$ (all $a_{ij} > 0$) then it is regular.

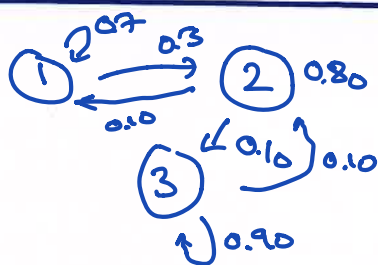
Thm:

Let us consider a regular Markov chain.

- Then:
- ① $\lambda = 1$ is an eigenvalue of A with multiplicity 1; all other eigenvalues have $|\lambda| < 1$.
 - ② there is a unique eigenvector $\underline{v}$ of A with eigenvalue $\lambda = 1$ that is a state vector.
 - ③ For any starting state $\underline{v}_0$, we have

$$\lim_{t \rightarrow \infty} A^t \cdot \underline{v}_0 = \underline{v}$$
 This $\underline{v}$ is ^{$\underline{v}_t$} called the equilibrium state.

$\lambda = 1$ dominant eigenvalue

Example:regular

$$A = \begin{pmatrix} 0.7 & 0.10 & 0 \\ 0.3 & 0.80 & 0.10 \\ 0 & 0.10 & 0.90 \end{pmatrix}$$

$$A^2 > 0 \quad (\text{no zeros})$$

Background:Positive matrices : $A > 0$ Markov chain
with $A > 0$:special case
with $\lambda_A = 1$ Theorem: (Perron)

If $A > 0$, then there is a dominant
eigenvalue $\lambda_A > 0$ of multiplicity 1
such that

- i) any other eigenvalue λ satisfies $|\lambda| < \lambda_A$
- ii) there is a unique vector $\underline{v}_A$ that is an
eigenvector of A with eigenvalue λ_A , such that
 $\underline{v}_A > 0$ and with $\sum = 1$.
- iii) $\text{lowest col. sum} \leq \lambda_A \leq \text{highest col. sum}$

Thm (Frobenius) $A \geq 0$ non-negative matrixIf A is irreducible, then A
has a dominant eigenvalue $\lambda_A > 0$ such that

- i) $|\lambda| \leq \lambda_A$ for all eigenvalues λ of A
- ii) there is a unique state vector $\underline{v}_A$
that is an eigenvector of A with
eigenvalue λ_A
- iii) $\text{lowest col. sum} \leq \lambda_A \leq \text{highest col. sum}$

 A irreducible means

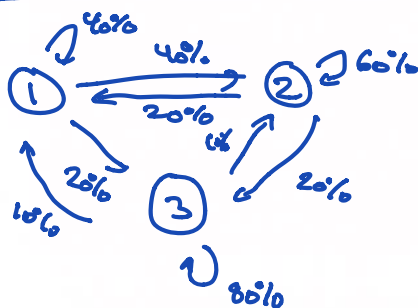
that there is a sequence

$$i \rightarrow i_1 \rightarrow i_2 \rightarrow \dots \rightarrow i_k \rightarrow j$$

$$\text{with } \begin{cases} a_{ii} \neq 0 \\ a_{i_1 i_2} \neq 0 \\ \vdots \\ a_{i_k j} \neq 0 \end{cases}$$

for any (i, j)

Example: Markov chain



$$A = \begin{pmatrix} 0.4 & 0.2 & 0.1 \\ 0.4 & 0.6 & 0.1 \\ 0.2 & 0.2 & 0.8 \end{pmatrix}$$

regular Markov chain

$$\underline{v}_0 = \begin{pmatrix} 20 \\ 40 \\ 20 \end{pmatrix} : \lim_{m \rightarrow \infty} A^m \underline{u}_0$$

Using theory:

$\lambda = 1$: dominant eigenvalue

$$\underline{E}_1: \begin{pmatrix} -0.6 & 0.2 & 0.1 \\ 0.4 & -0.4 & 0.1 \\ 0.2 & 0.2 & -0.2 \end{pmatrix} \begin{matrix} \cdot 10 \\ \cdot 10 \\ \cdot 10 \end{matrix} \rightarrow \begin{pmatrix} 2 & -2 \\ 4 & -4 \\ -6 & 2 \end{pmatrix} \begin{matrix} \cdot 2 \\ \cdot 2 \\ \cdot 3 \end{matrix}$$

$$\rightarrow \begin{pmatrix} 2 & -2 \\ 0 & -8 \\ 0 & 8 \end{pmatrix} \begin{matrix} \cdot 1 \\ \cdot 1 \\ \cdot 1 \end{matrix}$$

$$\underline{v}_1 = \begin{pmatrix} 32/8 \\ 52/8 \\ z \end{pmatrix} = \frac{z}{8} \cdot \begin{pmatrix} 3 \\ 5 \\ 8 \end{pmatrix}$$

Base: $\underline{v}_1 = \begin{pmatrix} 3 \\ 5 \\ 8 \end{pmatrix}$

$$2x + 2y - 2z = 0 \Rightarrow x = -y + z$$

$$-8y + 5z = 0 \Rightarrow 8y = 5z \\ y = \frac{5z}{8}$$

z free

$$\rightarrow x = -\frac{5z}{8} + z = \frac{3z}{8}$$

$$\boxed{\frac{3z}{8} + \frac{5z}{8} + z = 1} \quad | \cdot 8$$

$$3z + 5z + 8z = 8$$

$$16z = 8$$

$$z = 8/16 = 1/2$$

Eq. state:

$$\underline{v} = \underline{\underline{\left(\frac{3}{16}, \frac{5}{16}, \frac{1}{2} \right)}}$$

$$\underline{E}_1: \begin{pmatrix} 3 \\ 5 \\ 8 \end{pmatrix} t$$

$$3 + 5 + 8 = 16 \Rightarrow t = \frac{1}{16}$$

$$\Rightarrow \underline{v} = \underline{\underline{\left(\frac{3}{16}, \frac{5}{16}, \frac{1}{2} \right)}}$$

Remark: Regular Markov chains

The precise definition is as follows:

A Markov chain matrix A is called regular if there is an integer s such that you can get from any node to any other node in exactly s steps.

This means:

A regular $\iff A^s$ is a positive matrix for some integer $s \geq 1$ (i.e. all entries in A^s are positive)

$A > 0$ positive matrix $\Rightarrow$ regular Markov chain
(all $a_{ij} > 0$)

Ex: $A = \begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix}$



is not regular

$$A = \begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix}$$

$$A^2 = \begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix} \cdot \begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix} = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} = I$$

$$A^3 = A^2 \cdot A = I \cdot A = A = \begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix}$$

$$A^4 = A^2 \cdot A^2 = I \cdot I = I = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}$$

you can get from any node to any other node,
but there is no integer s so that you can get
from any node to any other node in exactly s steps
($1 \rightarrow 2, 2 \rightarrow 1$: odd no. steps $1 \rightarrow 1, 2 \rightarrow 2$: even no. steps)