

Advanced Topics in Control: Distributed Systems and Control

Lecture 4: Discrete-Time Averaging

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rowpixel

Brief review

1. elements of graphs, types of graphs
2. neighbours, subgraphs, paths, cycles
3. globally reachable node, directed spanning tree
4. strongly connected, aperiodic, condensation
5. adjacency matrix (degree, path, connectivity)
6. equivalent definition for irreducibility
7. equivalent definition for aperiodicity

Clarification

1. “If \exists directed path $i \rightarrow j$, then \exists simple directed path $i \rightarrow j$ with length $\leq n - 1$.” only holds for the case when $i \neq j$.
2. “ $(A^k)_{ij} > 0 \Rightarrow \exists$ directed path $i \rightarrow j$ with length k ”.

Here the path is not necessarily simple and can pass through j for multiple times.

Equivalent definition for aperiodicity

Consider a directed graph G .

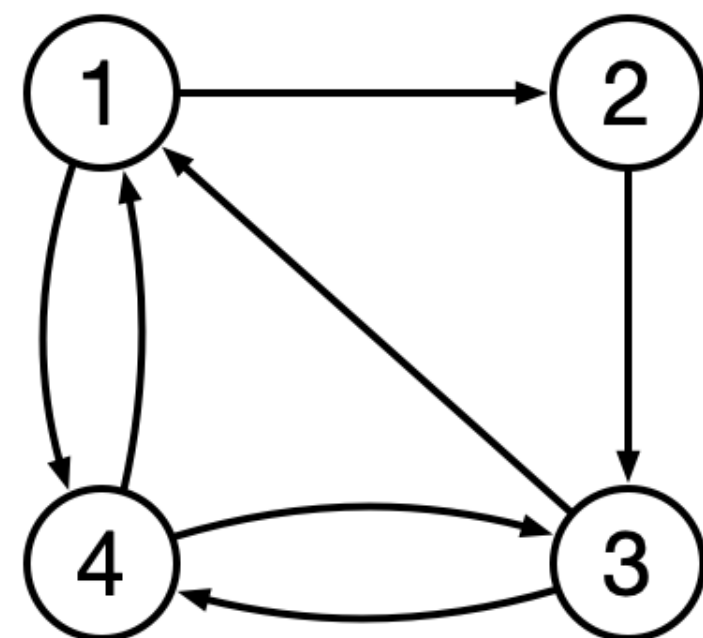
Definition: \exists directed path $i \rightarrow i$ with length $k \Rightarrow k$ is *a recurrence time* of node i .

period of node i : the greatest common divisor of all its recurrence times.

Theorem 1: (1) All nodes belonging to the same strongly-connected component of G have the same period;
(2) If G is strongly connected, then

G is aperiodic \Leftrightarrow The period of each node is 1.

E.g.



- Node 1: recurrence times 2 (1-4-1), 3 (1-2-3-1), 4 (1-2-3-4-1), 5 (1-2-3-1-4-1), ... \Rightarrow period = 1
- Node 2: recurrence times 3 (2-3-1-2), 4 (2-3-4-1-2), 5 (2-3-1-4-1-2), 6 (2-3-1-2-3-1-2) ... \Rightarrow period = 1
- Node 3: recurrence times 2 (3-4-3), 3 (3-1-2-3), 4 (3-4-1-4-3), 5 (3-1-2-3-4-3), ... \Rightarrow period = 1
- Node 4: recurrence times 2 (4-1-4), 3 (4-3-1-4), 5 (4-1-4-3-4), 5 (4-1-2-3-1-4), ... \Rightarrow period = 1

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Application:

Corollary 2: Consider a strongly connected digraph G with non-negative link weights. If $\exists k \in \mathbb{N}$ s.t. the i -th column of A^k is entry-wise positive. then A is primitive.

Corollary 2: Consider a strongly connected digraph G with non-negative link weights. If $\exists k \in \mathbb{N}$ s.t. the i -th column of A^k is entry-wise positive. then A is aperiodic.

Algebraic graph theory II: network structure \rightarrow behavior of discrete-time averaging

“Behavior”: 1) converge? 2) consensus? 3) consensus value

Discrete-time averaging algorithm

$$x(t+1) = Ax(t), \text{ where } A \text{ is row-stochastic.}$$

In this lecture, we always assume A to be row-stochastic.

Example 1: converge? consensus?

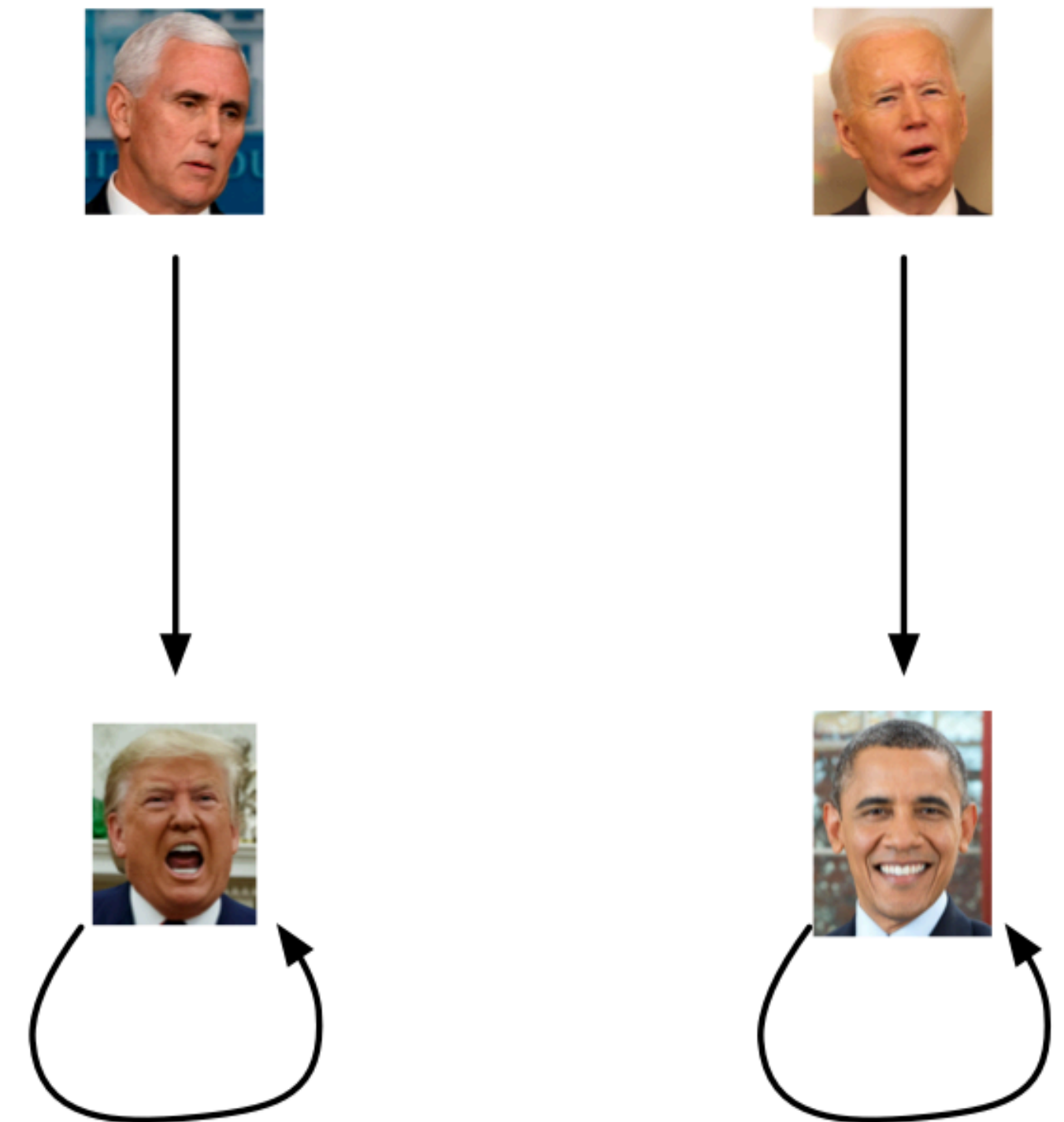
Pence's opinion (1) = Trump's opinion (0)

Trump's opinion (1) = Trump's opinion (0)

Biden's opinion (1) = Obama's opinion (0)

Obama's opinion (1) = Obama's opinion (0)

It converges. Consensus \Leftrightarrow Obama's opinion (0) = Trump's opinion (0).



Algebraic graph theory II: network structure \rightarrow behavior of discrete-time averaging


“Behaviour”: 1) converge? 2) consensus? 3) consensus value

Discrete-time averaging algorithm

$$x(t+1) = Ax(t), \text{ where } A \text{ is row-stochastic.}$$

In this lecture, we always assume A to be row-stochastic.

Example 2: converge? consensus?


$$\Rightarrow [A] = \begin{bmatrix} 0 & 1 & 0 \\ 1 & 0 & 1 \\ 0 & 1 & 0 \end{bmatrix} \text{ e.g. } A = \begin{bmatrix} 0 & 1 & 0 \\ 0.3 & 0 & 0.7 \\ 0 & 1 & 0 \end{bmatrix}$$

Algebraic graph theory II: network structure \rightarrow behavior of discrete-time averaging


“Behavior”: 1) converge? 2) consensus? 3) consensus value

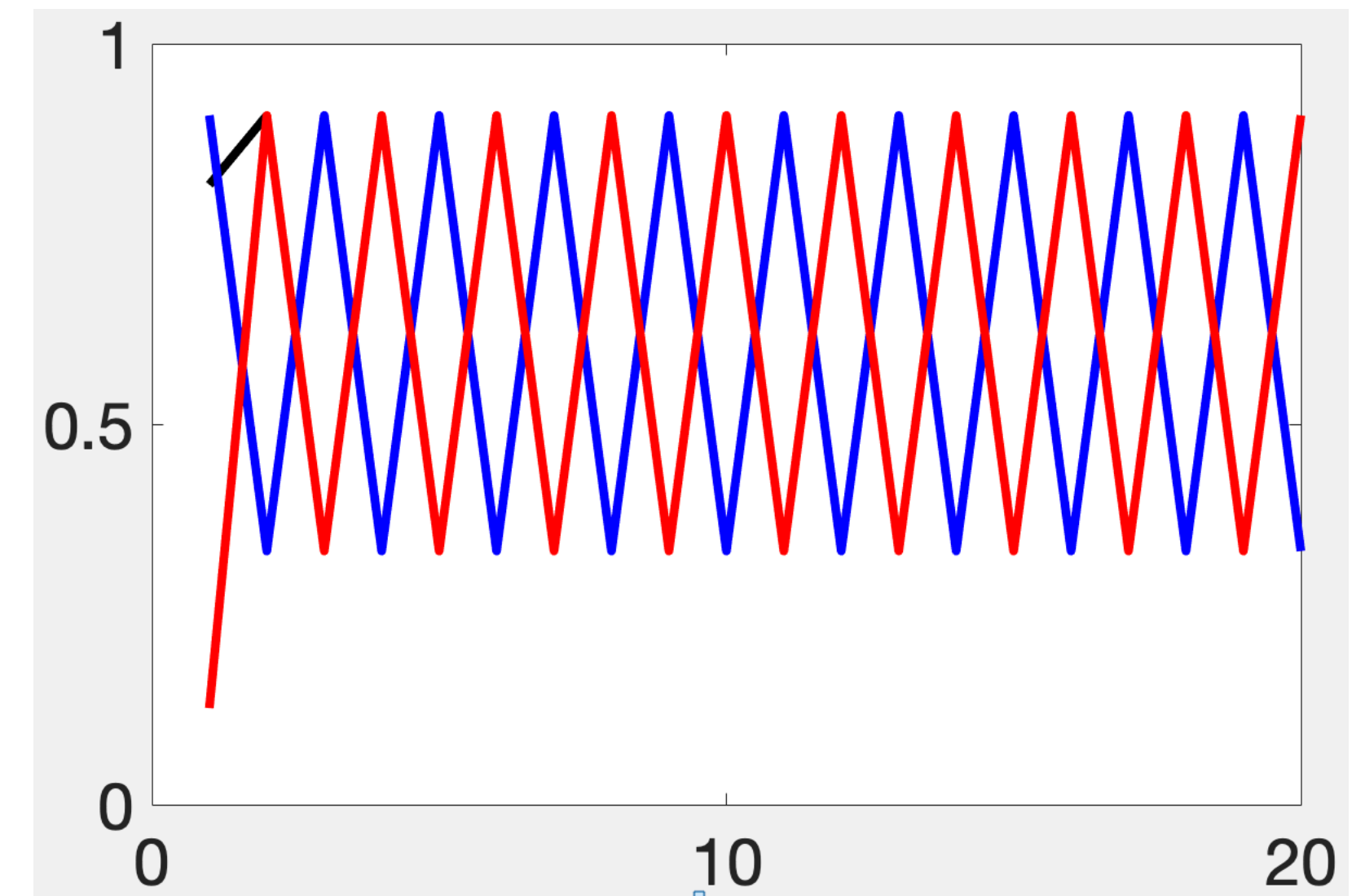
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Algebraic graph theory II: network structure \rightarrow behavior of discrete-time averaging

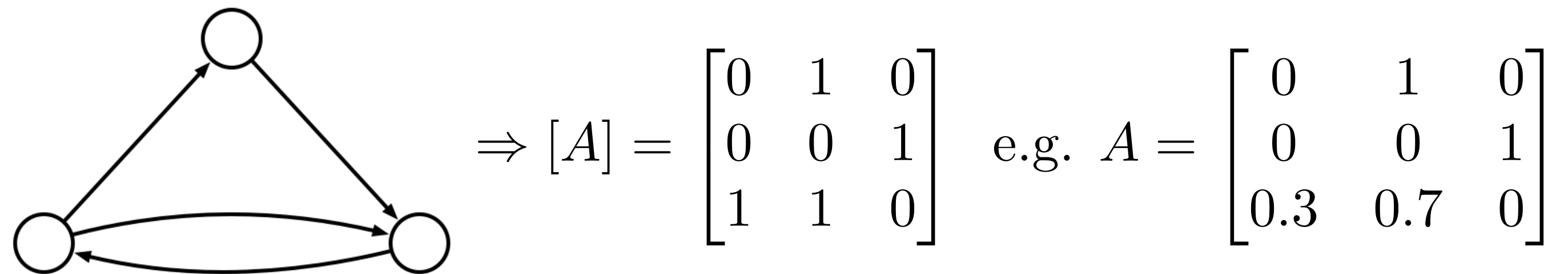
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Algebraic graph theory II: network structure \rightarrow behavior of discrete-time averaging

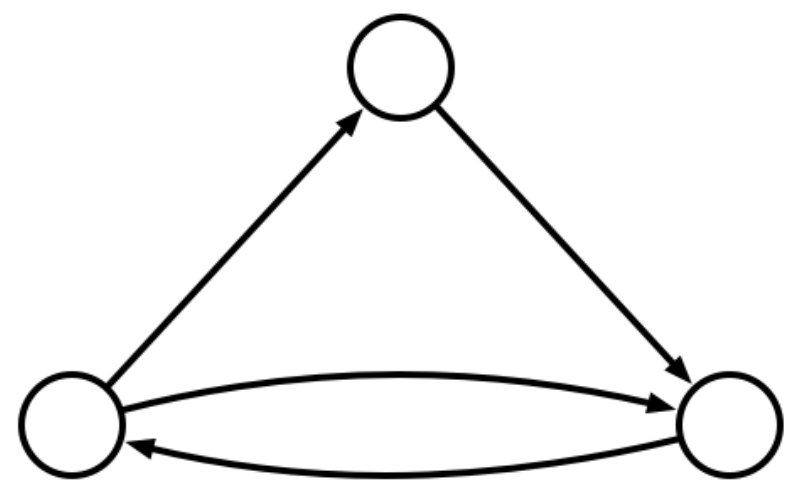
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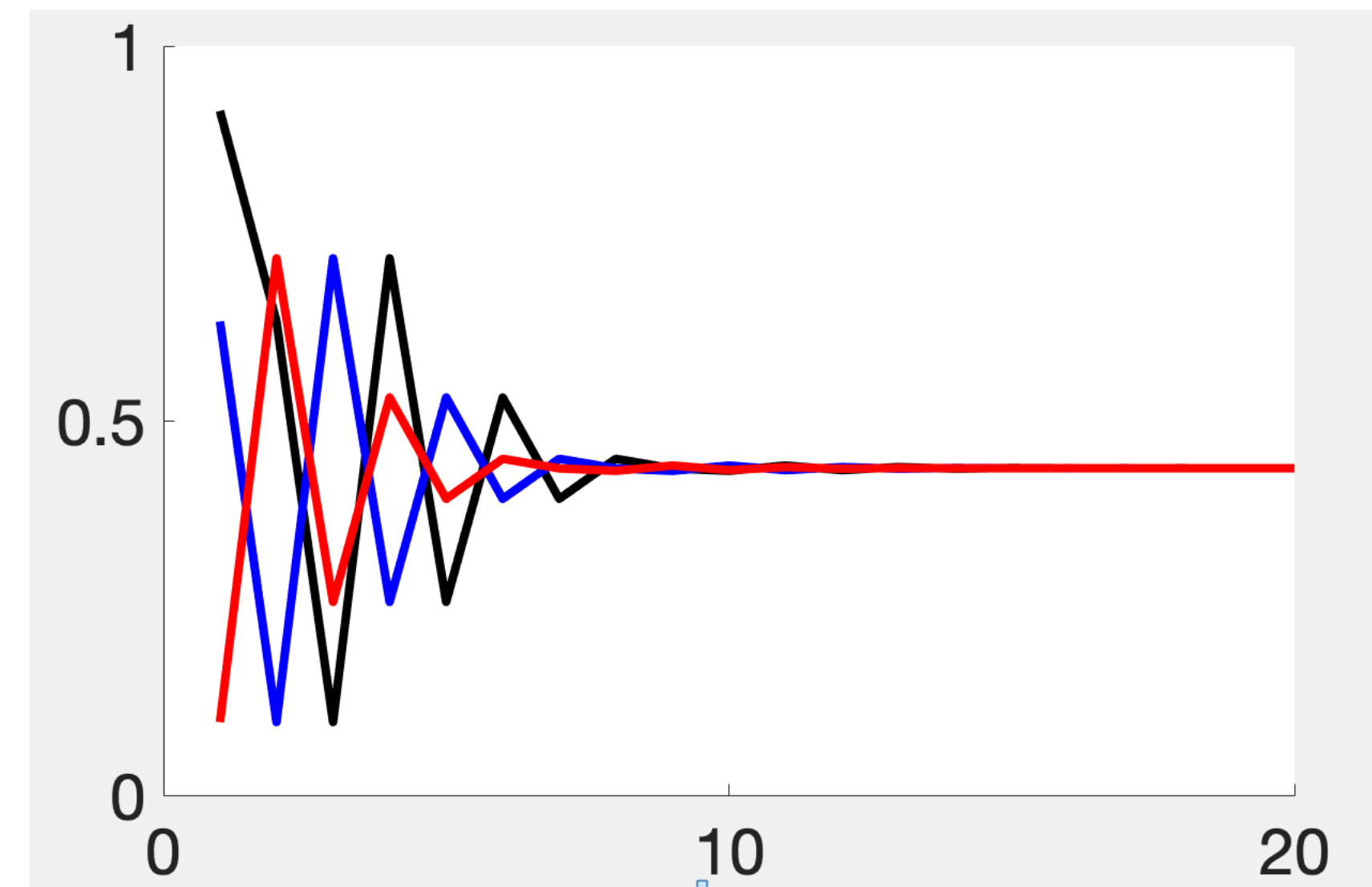
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$$\text{e.g. } A = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0.3 & 0.7 & 0 \end{bmatrix}$$



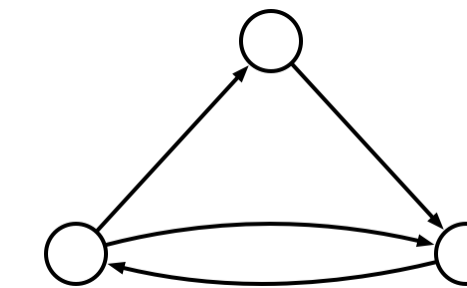
Example 2



not converge

strongly connected, periodic

Example 3



converge to consensus

strongly connected, aperiodic

Theorem 2.13 in the textbook

A is non-negative

$\rho(A)$ is a simple eigenvalue

$|\mu| < \rho(A), \forall \text{ other } \mu \in \text{spec}(A)$

\Rightarrow

$A/\rho(A)$ is semi-convergent &
 $\lim_{t \rightarrow \infty} A^t / \rho(A)^t = v w^\top$

where

$Av = \rho(A)v$

$w^\top A = \rho(A)w^\top$

$v \geq 0, w \geq 0, w^\top v = 1$

\Uparrow

$\rho(A)$ is a simple eigenvalue

$|\mu| < \rho(A), \forall \text{ other } \mu \in \text{spec}(A)$

$v = 1_n, w > 0$ (unique up to rescaling)

Perron-Frobenius theorem

A is primitive

A is row-stochastic

\Leftrightarrow

Algebraic graph theory

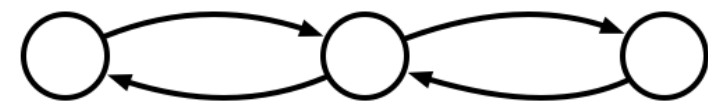
G is strongly-connected
& aperiodic

\Leftrightarrow

Suppose G is strongly connected.

The discrete-time averaging algorithm converges to consensus. \Leftrightarrow The digraph G is aperiodic.

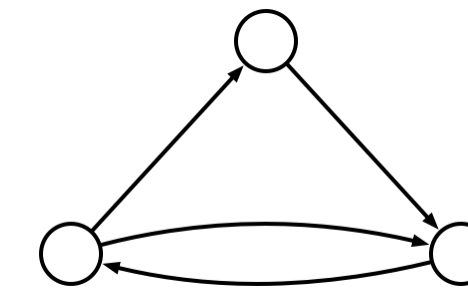
Example 2



not converge

strongly connected, periodic

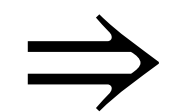
Example 3



converge to consensus

strongly connected, aperiodic

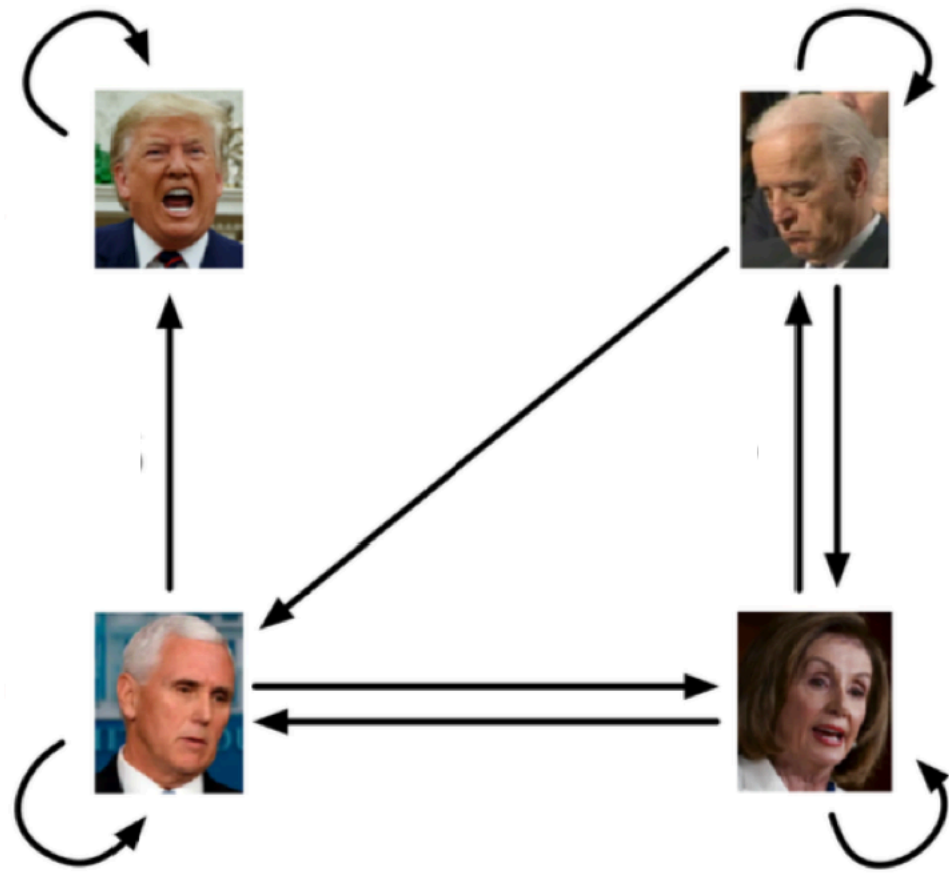
$$A \text{ is primitive} \Rightarrow x(\infty) = (w^\top x(0)) \mathbf{1}_n = \left(\sum_{i=1}^n w_i x_i(0) \right) \mathbf{1}_n$$



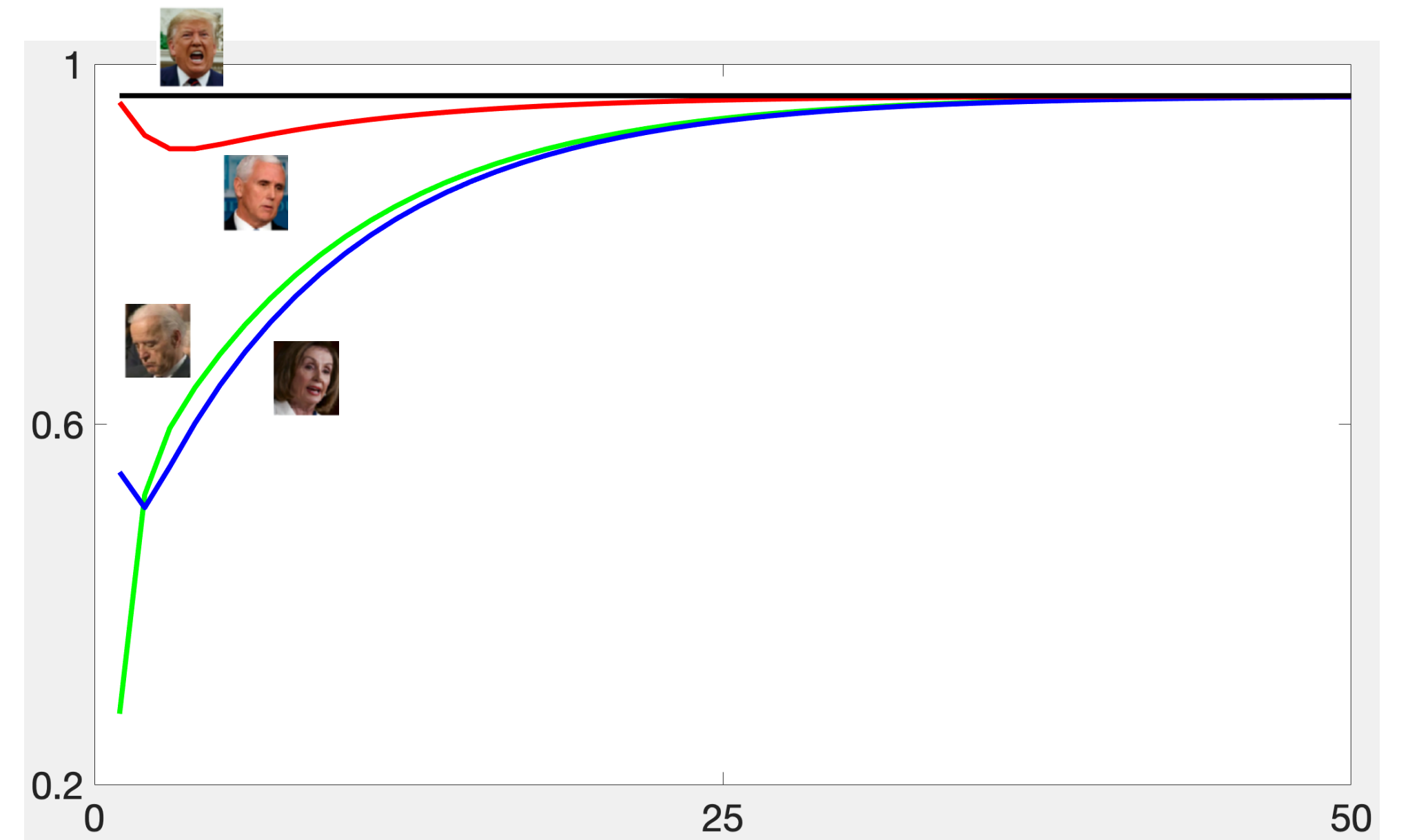
DeGroot opinion dynamics model: social power ~ eigenvector centrality.

A is primitive $\Leftrightarrow x(t)$ converges to consensus?

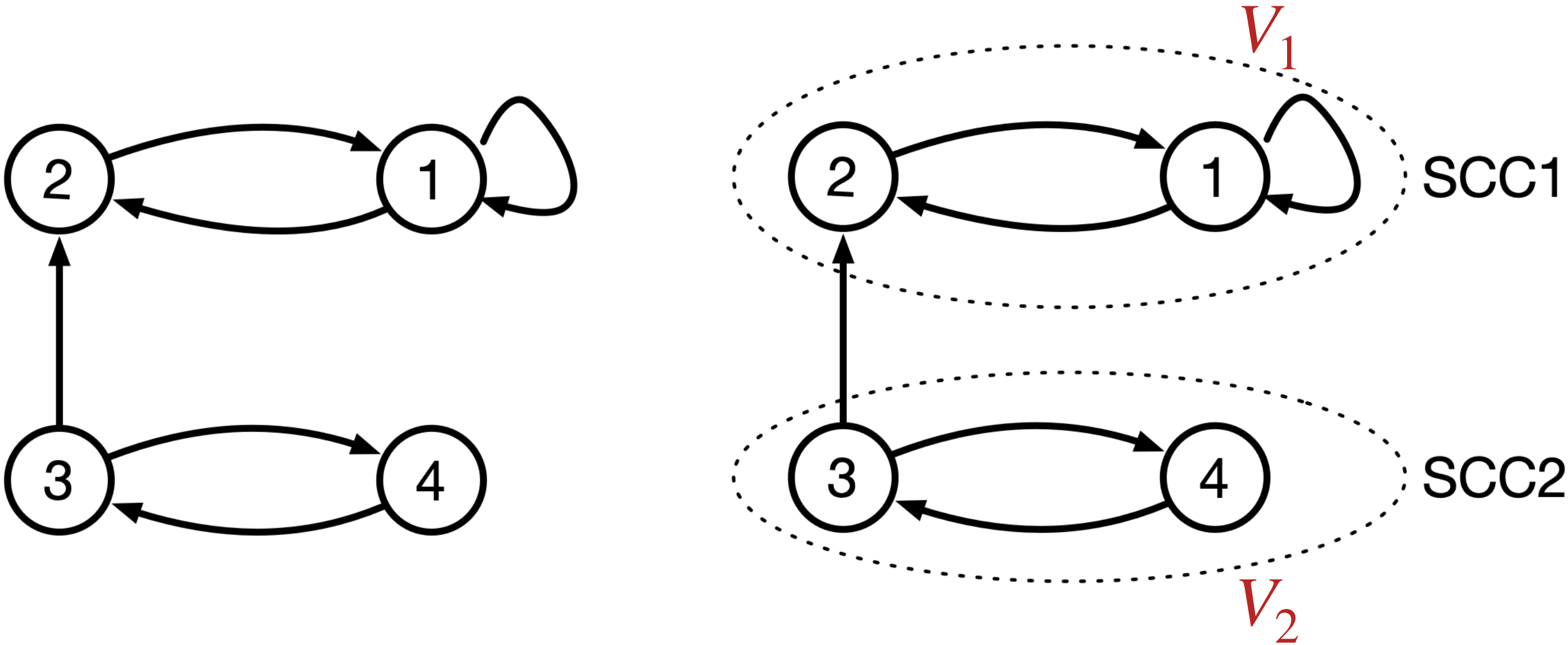
“ \Leftarrow ” does not hold.



$$A = \begin{bmatrix} 0.4 & 0.4 & 0.2 & 0 \\ 0.3 & 0.6 & 0.1 & 0 \\ 0 & 0.1 & 0.3 & 0.6 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$



Example 4: converge? consensus?

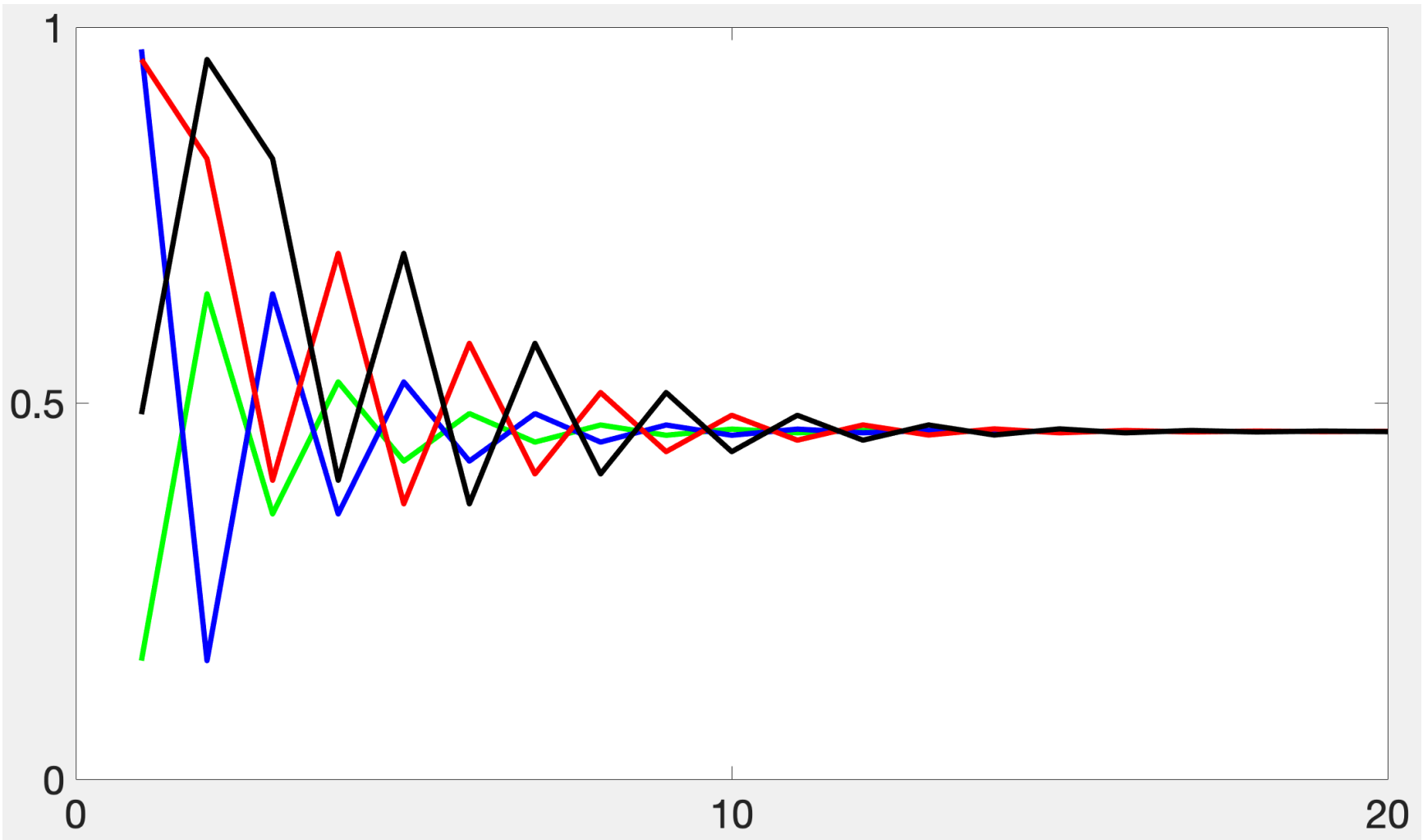


$$[A] = \begin{bmatrix} 1 & 1 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 1 \\ 0 & 0 & 1 & 0 \end{bmatrix}$$

Labels around the matrix: A_{11} above the first column, $A_{12} = 0$ above the second column, $A_{21} \neq 0$ below the first column, and A_{22} below the second column. A dashed red line separates the first two columns from the last two.

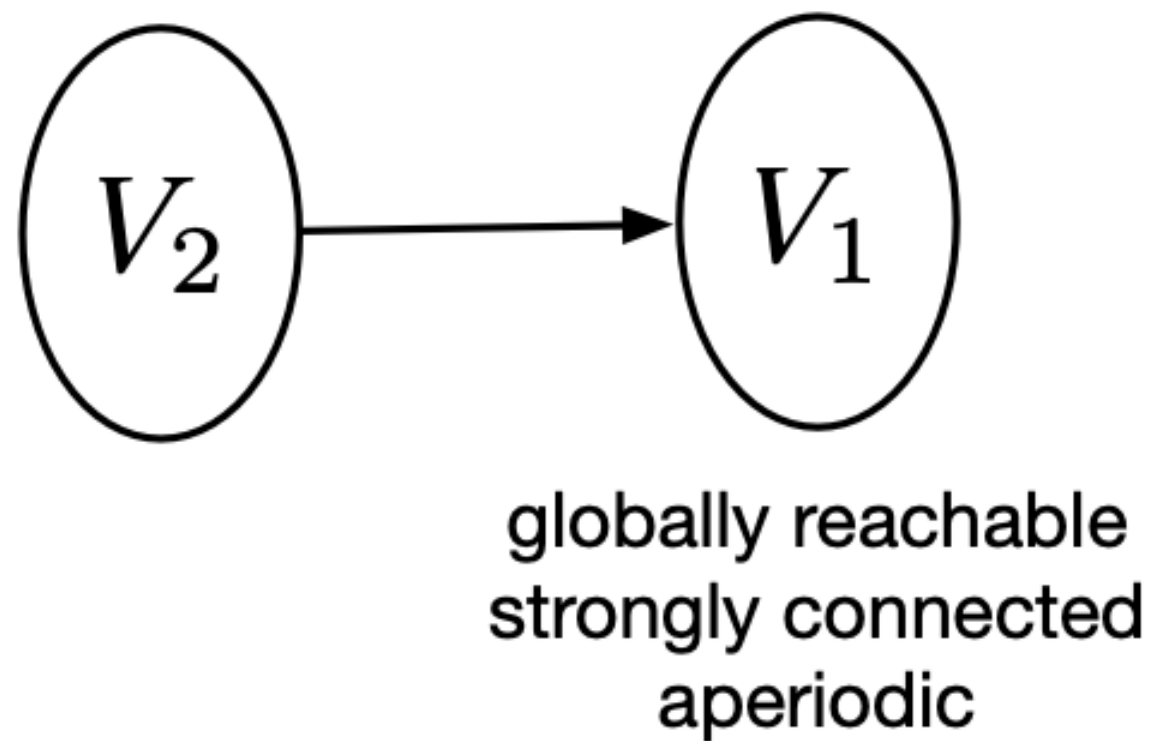
e.g.

$$A = \begin{bmatrix} 0.4 & 0.6 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 0 & 0.7 & 0 & 0.3 \\ 0 & 0 & 1 & 0 \end{bmatrix}$$



- 1. \exists globally reachable node
- 2. The SCC containing the globally reachable node is aperiodic.

Example 4 in general



1. \exists globally reachable node
2. The SCC containing the globally reachable node is aperiodic.

$$A = \begin{bmatrix} A_{11} & 0 \\ A_{21} & A_{22} \end{bmatrix}$$

$$x(t+1) = Ax(t) \Leftrightarrow \begin{bmatrix} x^{(1)}(t+1) \\ x^{(2)}(t+1) \end{bmatrix} = \begin{bmatrix} A_{11} & 0 \\ A_{21} & A_{22} \end{bmatrix} \begin{bmatrix} x^{(1)}(t) \\ x^{(2)}(t) \end{bmatrix} \Leftrightarrow \begin{cases} x^{(1)}(t+1) = A_{11}x^{(1)}(t) \\ x^{(2)}(t+1) = A_{21}x^{(1)}(t) + A_{22}x^{(2)}(t) \end{cases}$$

(1) $x^{(1)}(t+1) = A_{11}x^{(1)}(t)$, where A_{11} is row-stochastic and primitive $\Rightarrow x^{(1)}(t) \rightarrow \left(w^{(1)\top} x^{(1)}(0) \right) 1_{n_1}$

(2) What about $x^{(2)}(t+1) = A_{21}x^{(1)}(t) + A_{22}x^{(2)}(t)$?

(2) What about $x^{(2)}(t+1) = A_{21}x^{(1)}(t) + A_{22}x^{(2)}(t)$?

1) **Suppose A is semi-convergent.** $\Rightarrow \lim_{t \rightarrow \infty} x(t) = x^*$ exists. $\Rightarrow x^{*(2)} = A_{21}x^{*(1)} + A_{22}x^{*(2)}$

2) **If $\rho(A_{22}) < 1$, then** $(I - A_{22})x^{*(2)} = A_{21}x^{*(1)} \Rightarrow x^{*(2)} = (I - A_{22})^{-1}A_{21}x^{*(1)} = \left(w^{(1)\top}x^{(1)}(0)\right)(I - A_{22})^{-1}A_{21}1_{n_1}$

3) Since A is row-stochastic, $A_{21}1_{n_1} + A_{22}1_{n_2} = 1_{n_2} \Rightarrow (I - A_{22})^{-1}A_{21}1_{n_1} = 1_{n_2} \Rightarrow x^{*(2)} = \left(w^{(1)\top}x^{(1)}(0)\right)1_{n_2}$

$$\Rightarrow x^* = \begin{bmatrix} w^{(1)\top} & 0 \end{bmatrix} \begin{bmatrix} x^{(1)}(0) \\ x^{(2)}(0) \end{bmatrix} 1_n$$

Moreover, $\rho(A_{22}) < 1 \Rightarrow A$ is semi-convergent. (Why?)

Row-substochastic matrix: A non-negative matrix $A \in \mathbb{R}^{n \times n}$ is said to be row-substochastic if its row-sums are at most one, with at least one row-sum being strictly less than one.

► Any row-substochastic matrix A that has at least one row-sum equal to one, satisfies:

$$\min_i (A1_n)_i < \max_i (A1_n)_i$$

$$\rho(A_{22}) < 1 ?$$

Lemma 3 (The. 4.11 in textbook): Consider a non-negative matrix A associated with a directed weighted graph G .

$$(i) \min_i (A \mathbf{1}_n)_i \leq \rho(A) \leq \max_i (A \mathbf{1}_n)_i$$

(ii) If $\min_i (A \mathbf{1}_n)_i < \max_i (A \mathbf{1}_n)_i$, i.e, A is row-substochastic then the following two statements are equivalent.

(a) $\forall i$ such that $(A \mathbf{1}_n)_i = \max_k (A \mathbf{1}_n)_k$, \exists a directed path from i to some j such that $(A \mathbf{1}_n)_j < \max_k (A \mathbf{1}_n)_k$;

(b) $\rho(A) < \max_k (A \mathbf{1}_n)_k$.

1) $\exists j$ s.t. $(A_{22} \mathbf{1}_{n_2})_j < 1$, i.e., A_{22} is row-substochastic!

2) $\max_k (A_{22} \mathbf{1}_{n_2})_k \leq 1$

3) $\forall i$ such that $(A_{22} \mathbf{1}_{n_2})_i = 1$, \exists directed path from i to at least one such j in 1).

}

Lemma 3

\Rightarrow

$$\rho(A_{22}) < 1$$

Theorem 4 (Thm. 5.1 in textbook)

Theorem 5.1 (Consensus for row-stochastic matrices with a globally-reachable aperiodic strongly-connected component). *Let A be a row-stochastic matrix and let G be its associated digraph. The following statements are equivalent:*

- (A1) *the eigenvalue 1 is simple and all other eigenvalues μ satisfy $|\mu| < 1$;*
- (A2) *A is semi-convergent and $\lim_{k \rightarrow \infty} A^k = \mathbf{1}_n w^\top$, where $w \in \mathbb{R}^n$ satisfies $w \geq 0$, $\mathbf{1}_n^\top w = 1$, and $w^\top A = w^\top$;
and*
- (A3) *G contains a globally reachable node and the subgraph of globally reachable nodes is aperiodic.*

If any, and therefore all, of the previous conditions are satisfied, then the matrix A is said to be indecomposable and

- (i) *$w \geq 0$ is the left dominant eigenvector of A and $w_i > 0$ if and only if node i is globally reachable;*
- (ii) *the solution to the averaging model (5.1) $x(k+1) = Ax(k)$ satisfies*

$$\lim_{k \rightarrow \infty} x(k) = (w^\top x(0)) \mathbf{1}_n;$$

- (iii) *if additionally A is doubly-stochastic, then $w = \frac{1}{n} \mathbf{1}_n$ (since $A^\top \mathbf{1}_n = \mathbf{1}_n$ and $\frac{1}{n} \mathbf{1}_n^\top \mathbf{1}_n = 1$) so that*

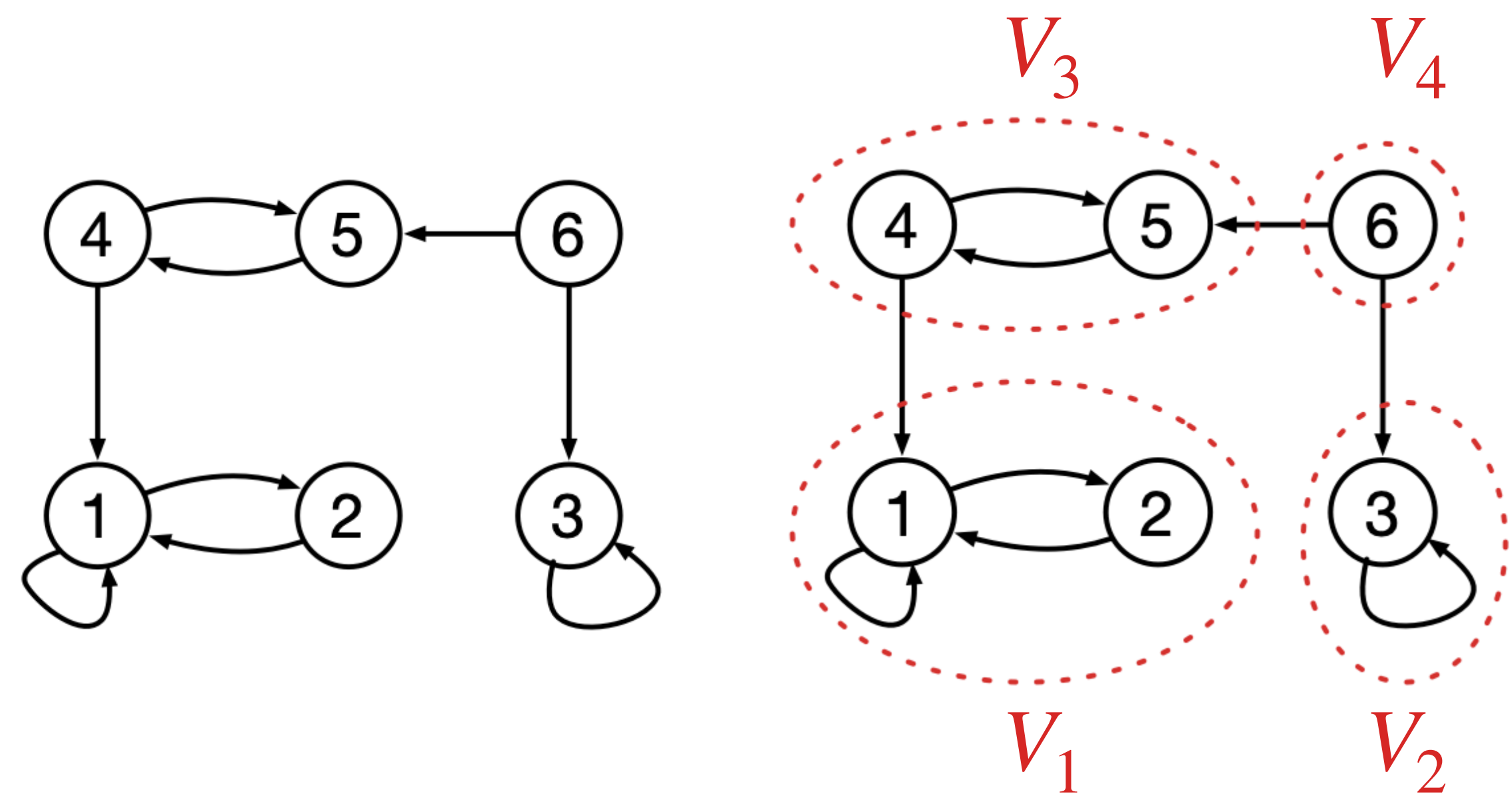
$$\lim_{k \rightarrow \infty} x(k) = \frac{\mathbf{1}_n^\top x(0)}{n} \mathbf{1}_n = \text{average}(x(0)) \mathbf{1}_n.$$

$(A3) \Rightarrow (A1)$: We have already proved it. (Why?)

$(A1) \Rightarrow (A2)$: By applying Theorem 2.13 in textbook.

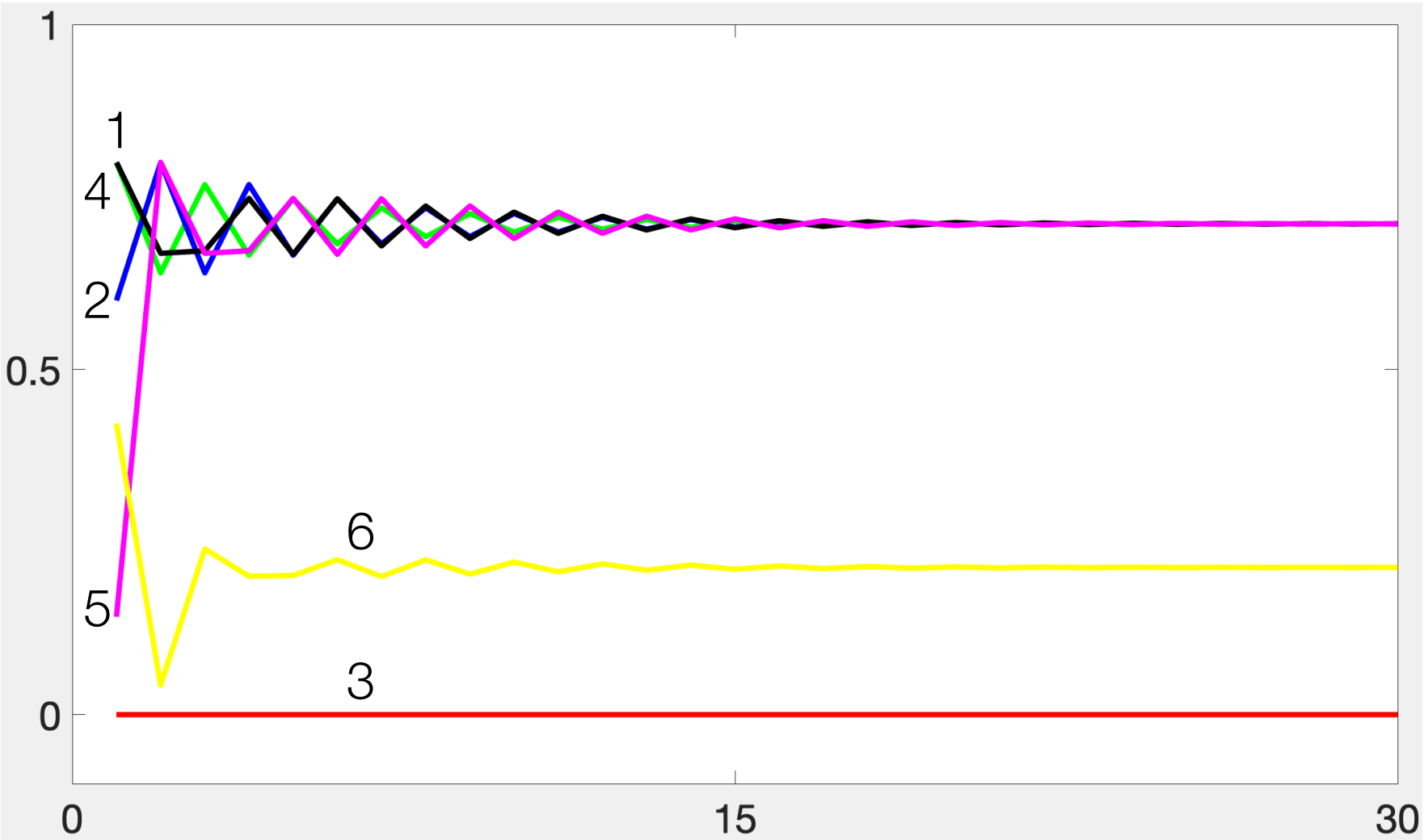
$(A2) \Rightarrow (A3)$:

Example 5: What if \nexists globally reachable node?



$$[A] = \begin{bmatrix} 1 & 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 & 1 & 0 \end{bmatrix}$$

- 1) $C(G)$ has multiple sinks;
- 2) Each sink in $C(G)$ is an aperiodic SCC in G ;



Theorem 5 (Thm. 5.2 in textbook)

Theorem 5.2 (Convergence for row-stochastic matrices with multiple aperiodic sinks). *Let A be a row-stochastic matrix, G be its associated digraph, and $n_s \geq 2$ be the number of sinks in the condensation digraph $C(G)$. The following statements are equivalent:*

- (A1) *the eigenvalue 1 is semi-simple with multiplicity n_s and all other eigenvalues μ satisfy $|\mu| < 1$,*
- (A2) *A is semi-convergent, and*
- (A3) *each sink of $C(G)$, regarded as a subgraph of G , is aperiodic.*

If any, and therefore all, of the previous conditions are satisfied, then

- (i) *the left eigenvectors $w^p \in \mathbb{R}^n$, $p \in \{1, \dots, n_s\}$, of A corresponding to the eigenvalue 1 can be selected to satisfy: $w^p \geq 0$, $\mathbf{1}_n^\top w^p = 1$, and $w_i^p > 0$ if and only if node i belongs to sink p ,*
- (ii) *the solution to the averaging model $x(k+1) = Ax(k)$ with initial condition $x(0)$ satisfies*

$$\lim_{k \rightarrow \infty} x_i(k) = \begin{cases} (w^p)^\top x(0), & \text{if node } i \text{ belongs to sink } p, \\ \sum_{p=1}^{n_s} z_{i,p} ((w^p)^\top x(0)), & \text{otherwise,} \end{cases}$$

where $z_{i,p}$, $p \in \{1, \dots, n_s\}$, are convex combination coefficients and $z_{i,p} > 0$ if and only if there exists a directed path from node i to the sink p .

(A3) \Rightarrow (A1): Lemma 3 $\Rightarrow \rho(\tilde{A}) < 1$

(A1) \Rightarrow (A2): By Jordan decomposition

(A2) \Rightarrow (A3):

1) A is semi-convergent $\Rightarrow A_{ii}$ is semi-convergent $\Rightarrow |\mu| < \rho(A_{ii}), \forall \text{ other } \mu \in \text{spec}(A)$ } $\xRightarrow{\text{Thm. 2.13}} A_{ii}^t \rightarrow 1_{n_i} w^{(i)\top}$
2) A_{ii} is row-stochastic & irreducible $\Rightarrow v^{(i)} = 1_{n_i}, w^{(i)} > 0, \rho(A_{ii}) = 1$

\Rightarrow Every node has period 1 \Rightarrow The digraph associated with A_{ii} is aperiodic.

Theorem 5 (ii)

Centrality Measures/Scores

It is of great interest for network science applications to determine the relative importance of a node in a graph!

Various measures for centrality based on adjacency matrix: Degree centrality, Eigenvector centrality, Katz centrality, PageRank centrality (we review the first two, for more please check Ch. 5 of Prof. Bullo's lecture notes)

1. **Degree centrality:** For a weighted digraph G , the degree centrality of node i , $c_{\text{degree}}(i)$, is the in-degree of node i :

$$c_{\text{degree}}(i) = \sum_{j=1}^n a_{ji}$$

2. **Eigenvector centrality:** For a weighted digraph G with globally reachable nodes, the eigenvector centrality vector c_{ev} is defined as the left dominant eigenvector (associated with the dominant eigenvalue) of the adjacency matrix.

Eigenvector centrality satisfies:

$$A^{\top} c_{\text{ev}} = \rho(A) c_{\text{ev}} \quad \Leftrightarrow \quad c_{\text{ev}}(i) = \frac{1}{\rho(A)} \sum_{j=1}^n a_{ji} c_{\text{ev}}(j)$$

Centrality Measures/Scores: An example

1. **Degree centrality:** the most important node is the one with the largest in-degree, i.e., nodes {5,7}.

2. **Eigenvector centrality:**

Eigenvalues of the adjacency matrix:

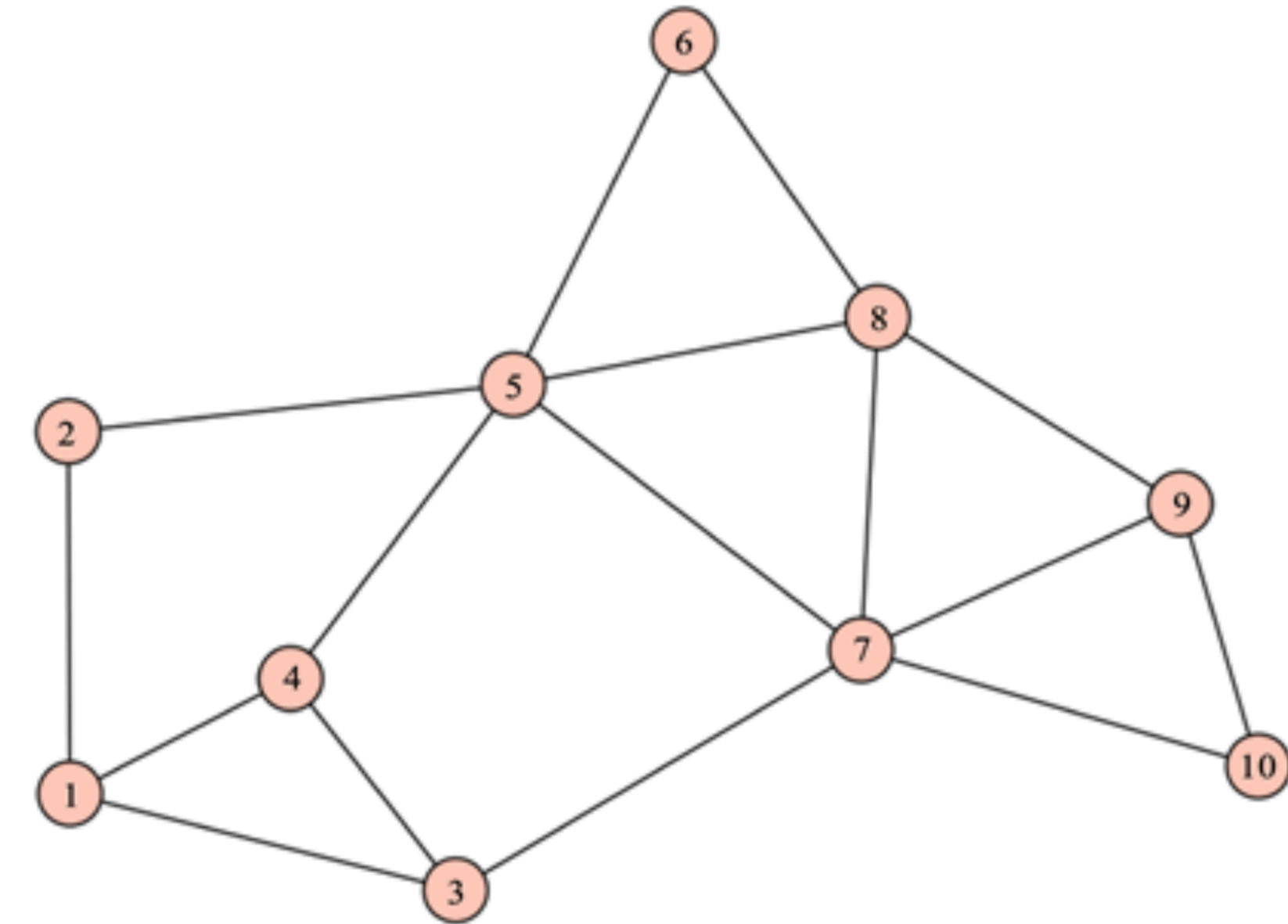
$\{-2.46, -1.93, -1.54, -0.66, -0.47, -0.33, 0.37, 1.39, 2.11, 3.53\}$

The greatest eigenvalue = 3.53

Eigenvector associated with the greatest eigenvalue:

$v = \{0.19, 0.18, 0.26, 0.25, 0.44, 0.24, 0.46, 0.41, 0.31, 0.22\} = c_{ev}$

The most important node is node 7.



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

Summary

