

Column-positivity of random labeled networks is resilient and scalable

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joint work with Raphaël Jungers (Université Catholique de Louvain)

Workshop on
Resilient Control of Infrastructure Networks



POLITECNICO
DI TORINO

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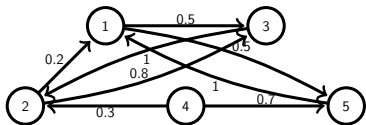
Motivation: discrete-time consensus systems

n agents, x_0 vector of their initial opinions. A = stochastic matrix.

$$\begin{cases} x_{k+1} = Ax_k \\ x_0 \in \mathbb{R}_{\geq 0}^n \end{cases}$$

At **each time** agent i updates her opinion by averaging on the opinions of her neighbours with weights $A[i, :]$.

$$A = \begin{pmatrix} 0 & 0 & 0.5 & 0 & 0.5 \\ 0.2 & 0 & 0.8 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0.3 & 0 & 0 & 0.7 \\ 1 & 0 & 0 & 0 & 0 \end{pmatrix}$$



Consensus: If $\lim_{k \rightarrow \infty} x_k = (a, a, \dots, a)^T$ for some $a \in \mathbb{R}$.

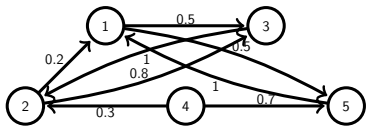
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$$A^4 = \begin{pmatrix} 0.25 & 0.65 & 0.5 & 0 & 0.5 \\ 0.2 & 0.64 & 0.21 & 0 & 0.13 \\ 0.26 & 1 & 0.64 & 0 & 0 \\ 0.42 & 0.38 & 0.19 & 0 & 0 \\ 1 & 0 & 0.65 & 0 & 0.25 \end{pmatrix}$$



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The system **converges to consensus** independently on x_0 iff A^k has an **entrywise positive column** for some $k \in \mathbb{N}$ (equiv. the graph associated to A has a globally reachable node).

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$$\mathcal{M} = \underbrace{\{M_1, \dots, M_m\}}_{\text{stochastic}} \quad \begin{cases} x_{k+1} = M_{i_k} x_k & M_{i_k} \in \mathcal{M} \\ x_0 \in \mathbb{R}_{\geq 0}^n \end{cases}$$

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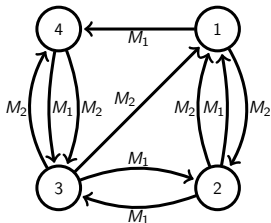
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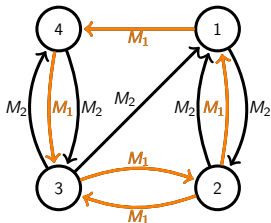
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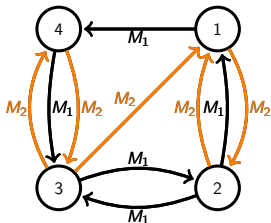
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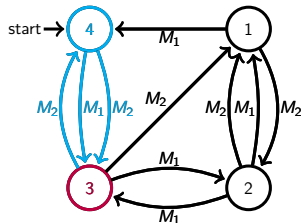
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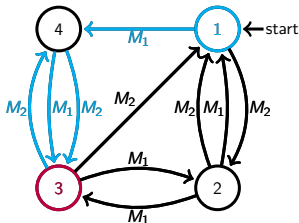
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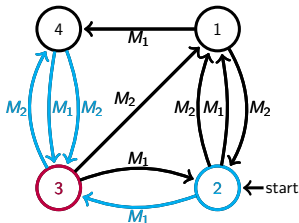
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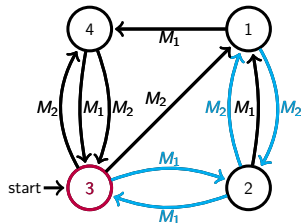
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YES iff there exists a finite product $M_{j_1} \cdot \dots \cdot M_{j_l}$ of matrices in \mathcal{M} that has an **entrywise positive column**.

Equivalently: iff there exists a vertex that is reachable from any vertex by a path labeled by M_{j_1}, \dots, M_{j_l} .

→ the length of the shortest positive-column product **influences** the **rate of convergence** to consensus

Column-positivity and pc-index

$$\mathcal{M} = \left\{ M_1 = \begin{pmatrix} 0 & 0 & 0 & 1 \\ 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{pmatrix}, M_2 = \begin{pmatrix} 0 & 1 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 \end{pmatrix} \right\}, M_1 M_2 M_2 M_1 = \begin{pmatrix} 0 & 0 & 1 & 1 \\ 1 & 1 & 1 & 1 \\ 1 & 0 & 1 & 0 \\ 1 & 1 & 1 & 0 \end{pmatrix} > 0$$

A set \mathcal{M} of nonnegative matrices is **column-positive** if it admits a product with an entrywise positive column. The length of the shortest of these products is called its **pc-index** $[pc(\mathcal{M})]$.

Equivalently the labeled directed graph induced by \mathcal{M} admits a sequence of labels $l = l_1, \dots, l_s$ and a vertex and that is **reachable** from any other vertex by following a path labeled by l .

Randomized generation of the matrices: $\mathcal{B}_m(n, \rho)$

$m = \#$ of matrices, $n =$ matrix size

$$\begin{pmatrix} \mathbf{1} \\ \phantom{\mathbf{1}} \end{pmatrix}, \quad \begin{cases} = 1 & \text{with probability } \rho = \rho(n) \\ = 0 & \text{with probability } 1 - \rho \end{cases}$$

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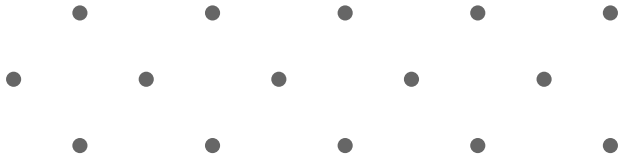
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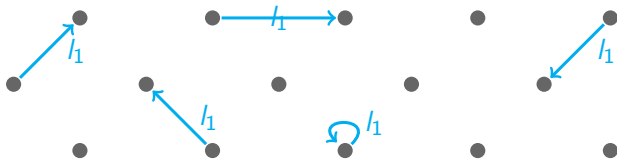
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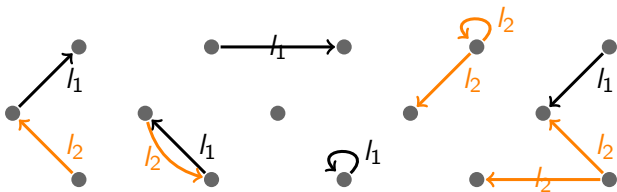
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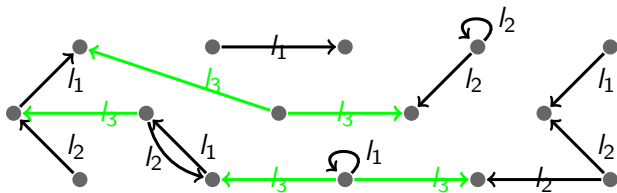
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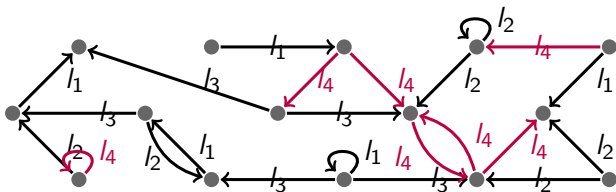
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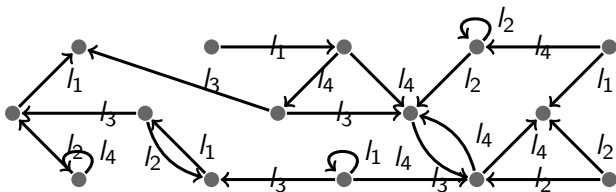
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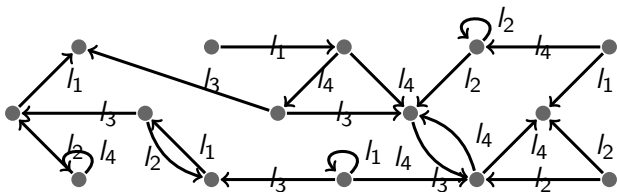
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What is the **probability** that $\mathcal{B}_m(n, p)$ is column-positive as $n \rightarrow \infty$?
 What is its **expected pc-index**?

Sharp threshold for column-positivity

Theorem. [C., Jungers '18] Let $m \geq 2$, $c \in \mathbb{R}$, $\hat{\mathbf{p}} = (\log \mathbf{n} + \mathbf{c})/\mathbf{n}$. For any $p(n) \in [0, 1]$, as $n \rightarrow \infty$ it holds that:

$$\mathbb{P}(\mathcal{B}_m(n, p) \text{ is column-positive}) \longrightarrow \begin{cases} 1 & \text{if } \lim_{n \rightarrow \infty} \frac{p}{\hat{p}} > 1 \\ 0 & \text{if } \lim_{n \rightarrow \infty} \frac{p}{\hat{p}} < 1 \end{cases}$$

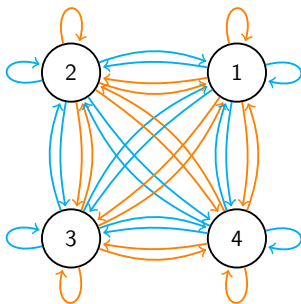
- * $\lim_{n \rightarrow \infty} \mathbb{P}(\mathcal{B}_m(n, \hat{p}) \text{ is column-positive}) \leq 1 - (1 - e^{-e^{-c}})^m$
- * $\lim_{n \rightarrow \infty} \mathbb{P}(\mathcal{B}_m(n, \hat{p}) \text{ is column-positive}) \geq 1 - (1 - e^{-2e^{-c}})^m m e^{-2e^{-c}} (1 - e^{-2e^{-c}})^{m-1}$

Moreover, if $\lim_{n \rightarrow \infty} p/\hat{p} > 1$:

$$\mathbb{P}(\mathcal{B}_m(n, p) \text{ is column-positive}) \geq 1 - n^{-1} - O(ne^{-np}) - O(n^{-2}) .$$

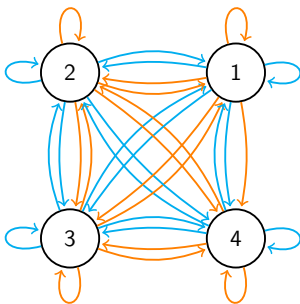
Why resilience?

Complete labeled graph where each edge has probability $1 - p$ to **break**:



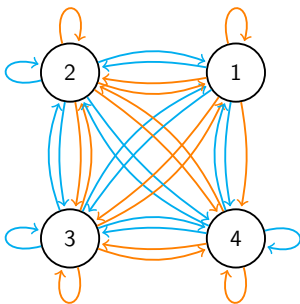
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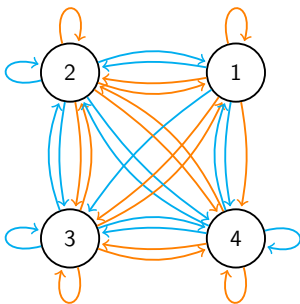
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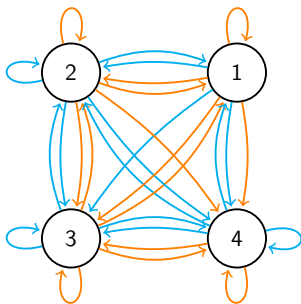
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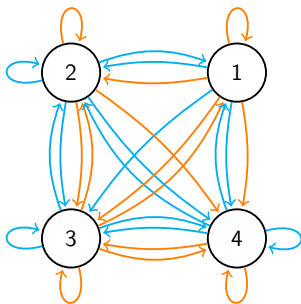
Why resilience?

Complete labeled graph where each edge has probability $1 - p$ to **break**:



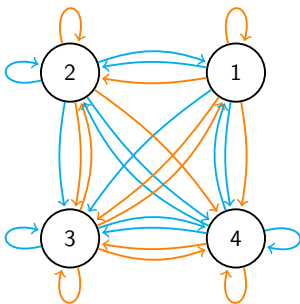
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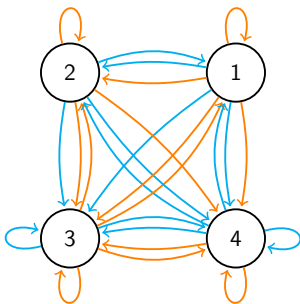
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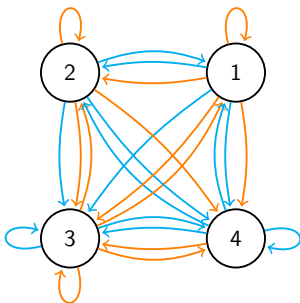
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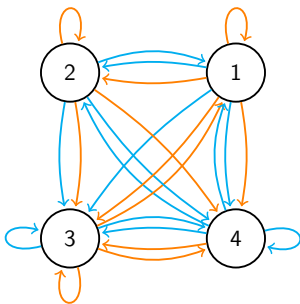
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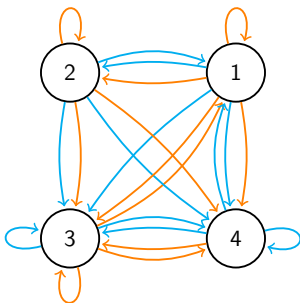
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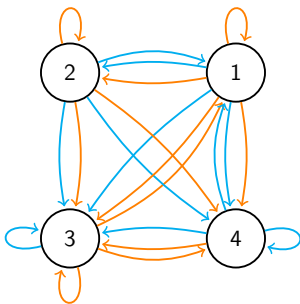
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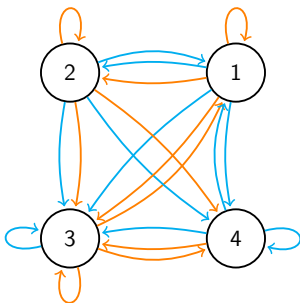
Why resilience?

Complete labeled graph where each edge has probability $1 - p$ to **break**:



Why resilience?

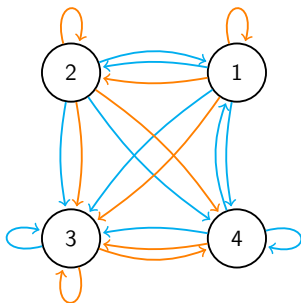
Complete labeled graph where each edge has probability $1 - p$ to **break**:



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Complete labeled graph where each edge has probability $1 - p$ to **break**:

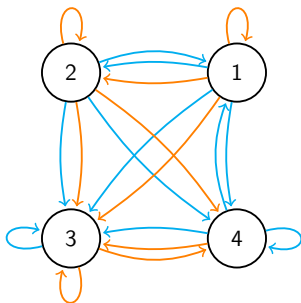
Does there still exist a node reachable from everywhere by the same sequence of labels?



Why resilience?

Complete labeled graph where each edge has probability $1 - p$ to **break**:

Does there still exist a node reachable from everywhere by the same sequence of labels?



YES when $p > (\log n + c)/n$ (with high probability).
In these terms the network is **resilient** with respect to the **column-positivity property**.

pc-index and scalability

Theorem. [C., Jungers '18] Let $m \geq 2$, $c \in \mathbb{R}$, $\hat{p} = (\log n + c)/n$. Then

* If $\lim_{n \rightarrow \infty} p/\hat{p} > 1$: $\lim_{n \rightarrow \infty} \mathbb{P}\left(\text{pc}(\mathcal{B}_m(n, p)) = O(n \log n)\right) = 1$

* If $\lim_{n \rightarrow \infty} p/\hat{p} = 1$:
 $\lim_{n \rightarrow \infty} \mathbb{P}\left(\text{pc}(\mathcal{B}_m(n, p)) = O(n \log^3 n) \mid \mathcal{B}_m(n, p) \text{ has no zero rows}\right) = 1$

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The **length** of the shortest positive-column product of $\mathcal{B}_m(p)$ is **scaling well** with respect to n with high probability.

↪ The convergence rate to consensus of the consensus system whose matrices are generated by $\mathcal{B}_m(p)$ is **scaling well** with respect to n .

Sketch of the proofs

- 1. Case $\lim_{n \rightarrow \infty} p/\hat{p} > 1$:** We prove that $\mathcal{B}_m(n, p) \geq \bar{\mathcal{P}}_m(n)$ whp, where $\bar{\mathcal{P}}_m(n)$ is a set of m permutation matrices with a positive entry added.
 - Perfect matchings on random bipartite graphs;
 - Prove that if $\bar{\mathcal{P}}_m(n)$ is uniformly distributed, then it is column-positive and with pc-index of $O(n \log n)$ with high probability;
 - Few technical lemmas to connect the distributions of $\mathcal{B}_m(n, p)$ and $\bar{\mathcal{P}}_m(n)$.
- 2. Case $\lim_{n \rightarrow \infty} p/\hat{p} < 1$:** each matrix of $\mathcal{B}_m(n, p)$ has a zero row whp.
- 3. Case $p \sim \hat{p} = (\log n + c)/n$:**
 - Similarly as case 1., but $\bar{\mathcal{P}}_m(n)$ is replaced by a set of $\{0, 1\}$ -matrices with exactly one 1 in every row (synchronizing automaton);
 - Results on random synchronizing automata [Nicaud 2014].

Thank you!