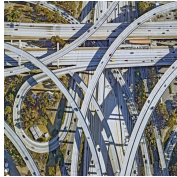


Centralities, perturbations, resilience in network models.

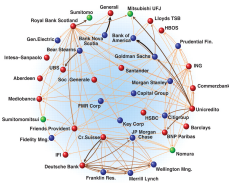
Fabio Fagnani,
DISMA Department of Mathematical Sciences
Politecnico di Torino

Kick off meeting Project of Excellence

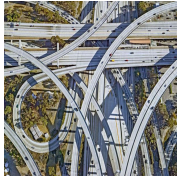
The behavior of complex infrastructures



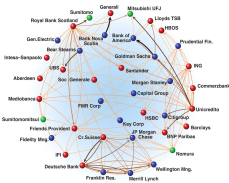
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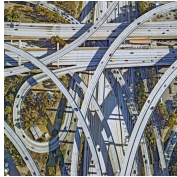
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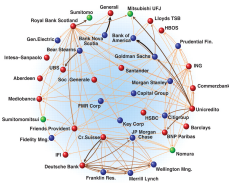
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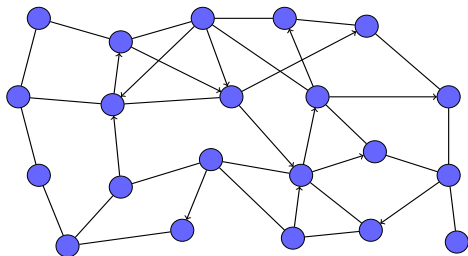


- ▶ Designed to work under 'normal' operative conditions.
- ▶ Local failures, exogeneous events.
- ▶ **Systemic risk**: spreading and amplification of the perturbation. The domino effect
- ▶ **Resilience**: the capacity of a system to absorb the effect of a perturbation.



The general picture

$\mathcal{G} = (\mathcal{V}, \mathcal{E})$ graph

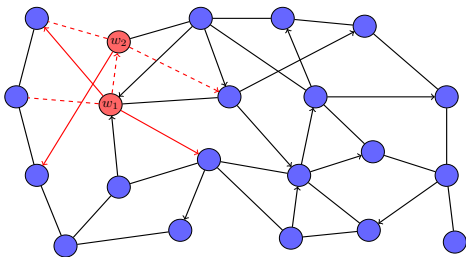


An 'object' attached to \mathcal{G} :

- ▶ A static vector $\pi \in \mathbb{R}^{\mathcal{V}}$
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Study the effect on the 'object' of perturbations on \mathcal{G} :

- ▶ The effect of a (local) **rewiring**. Optimization issues.
- ▶ **Resilience** to small/local perturbation.
- ▶ The **large scale** limit $n = |\mathcal{V}| \rightarrow +\infty$.

What is classical

- ▶ The effect of perturbations on graph connectivity.
- ▶ Results for families of random graphs.
- ▶ Percolation.

An example of ongoing research: Bonacich centrality

$\mathcal{G} = (\mathcal{V}, \mathcal{E})$ strongly connected graph, d_i out-degree of node i ,

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Generalization: any weight matrix W .



The computation of π

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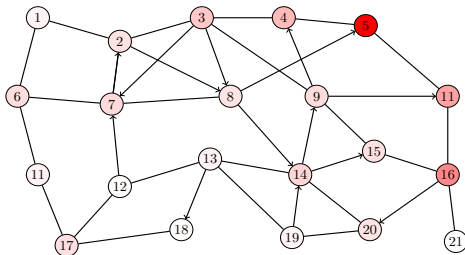
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The dynamics beyond π

Two dynamical systems connected to P :

- ▶ $x_i(t+1) = \sum_j P_{ij} x_j(t)$ *Averaging dynamics*
- ▶ $y_j(t+1) = \sum_j P_{ij} y_i(t)$ *Flow dynamics*

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▶ $\lim_{t \rightarrow +\infty} y(t) = \lim_{t \rightarrow +\infty} P'^t y(0) = \pi(\mathbb{1}'y(0))$

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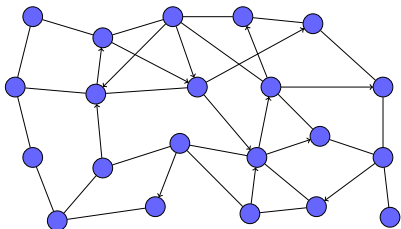
Some key issues:

- ▶ Behavior in large scale graphs $\mathcal{G} = (\mathcal{V}, \mathcal{E})$, $n = |\mathcal{V}| \rightarrow +\infty$
 - ▶ infer properties of π without explicit computation ($\|\pi\|_\infty \rightarrow 0$)
- ▶ Network engineering problems:
 - ▶ shaping π by local rewiring
 - ▶ centrality optimization
- ▶ Fundamental limitations to the effect of local perturbations. Resilience properties.

A general optimization problem

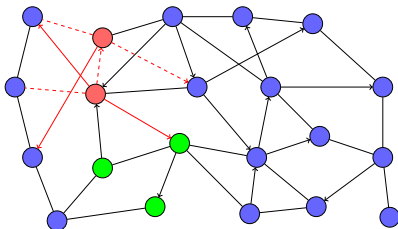
$$\mathcal{G} = (\mathcal{V}, \mathcal{E}) \rightarrow P$$

$$\pi = P' \pi \text{ centrality}$$



$$\tilde{\mathcal{G}} = (\mathcal{V}, \tilde{\mathcal{E}}) \rightarrow \tilde{P}$$

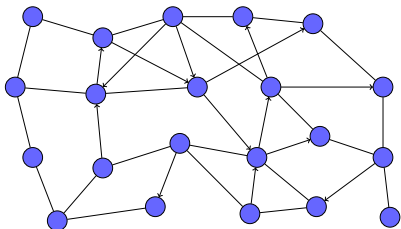
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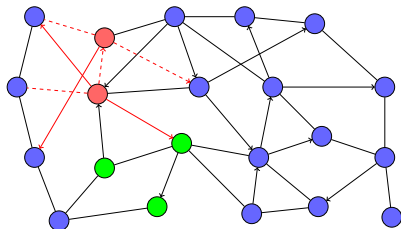
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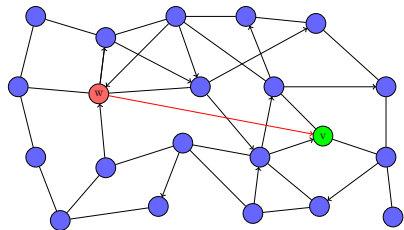
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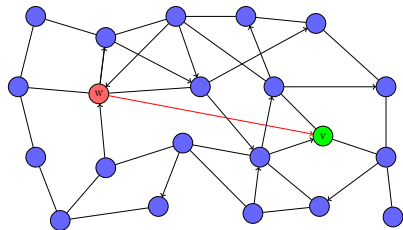
$\mathbf{G}_{\mathcal{G}}$ family of admissible perturbations of \mathcal{G} , $\mathcal{D} \subseteq \mathcal{V}$ target subset.

$$\text{Problem: } \operatorname{argmax}_{\tilde{\mathcal{G}} \in \mathbf{G}_{\mathcal{G}}} \tilde{\pi}(\mathcal{D})$$

The effect of adding an edge

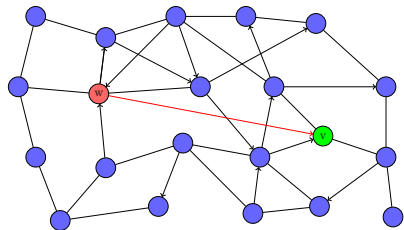


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The effect of adding an edge



- ▶ $\tilde{\pi}_v > \pi_v$
- ▶ $\operatorname{argmax}_{v \in \mathcal{V}} \tilde{\pi}_w = \operatorname{argmax}_{v: (v,w) \in \mathcal{E}} Z_{vw}$
- ▶ $Z_{ij} := \sum_{t=0}^{+\infty} [P_{ij}^t - \pi_j]$
Fundamental matrix

Fundamental limitations

P and \tilde{P} irreducible stochastic matrices on \mathcal{V}

- ▶ differing in a subset $\mathcal{W} \subseteq \mathcal{V}$ of rows.
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The result we are looking for:

Small perturbation in a large network has a small effect:

$$|\mathcal{W}| \ll n = |\mathcal{V}| \Rightarrow \pi - \tilde{\pi} \rightarrow 0$$

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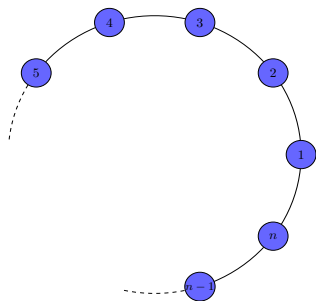
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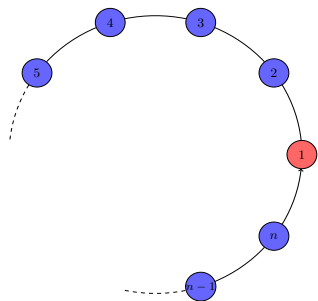
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- ▶ $\|\tilde{P} - P\|_p \geq \max\{|\tilde{P}_{ij} - P_{ij}|\}$ bounded away from 0 independently on the size n .

Example 1



$$P_{ii+1} = P_{ii-1} = 1/2,$$

$$\pi = P' \pi \text{ uniform}$$



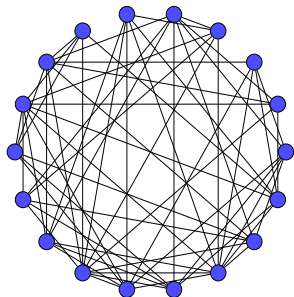
$$\tilde{P}_{1,2} = 1, \tilde{P}_{1,n} = 0$$

$$\tilde{\pi}_1 = 1/n, \tilde{\pi}_j = \frac{2(n-j+1)}{n^2} \quad j \geq 2$$

$$\|\pi - \tilde{\pi}\|_1 \asymp \text{Const.}$$

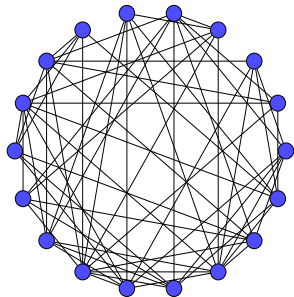
Example 2

$\mathcal{G} = ER(n, p)$ Erdos-Renyi
random graph with n nodes.

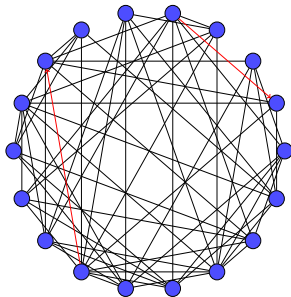


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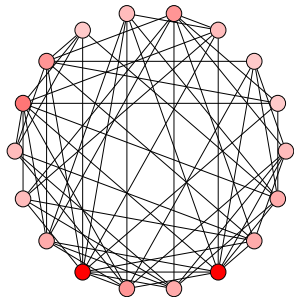


$\tilde{\mathcal{G}}$ is obtained from \mathcal{G} erasing two
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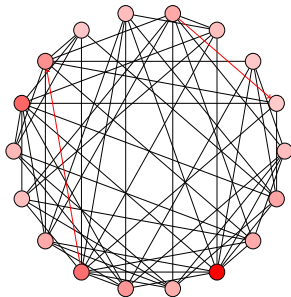


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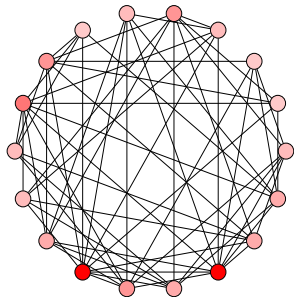
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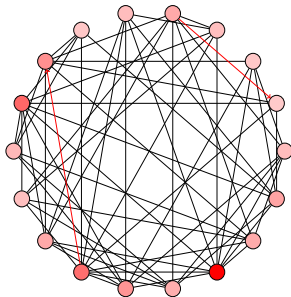
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Well connected graphs \Rightarrow Fast mixing \Rightarrow Resilience

Page rank centrality

\mathcal{G} web graph.

Page-rank centrality: $\pi_i^{pr} = \alpha\mu_i + (1 - \alpha) \sum_j P_{ji} \pi_j^{pr}$

μ_i intrinsic centrality of node i

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$$\|\tilde{\pi}^{pr} - \pi^{pr}\|_1 \leq \frac{8}{\log(1 - \alpha)} \pi^{pr}(\mathcal{W})$$

Any modification of the hyperlinks from a set \mathcal{W} of webpages, generates a perturbation of the page-rank centrality whose 1-norm is bounded by the original page-rank centrality of \mathcal{W} .

Production network

\mathcal{G} graph of production interactions. P_{ij} fraction of the goods used by firm i in its production coming from firm j .

$$\text{Profits: } \pi_i^{Pr} = \alpha \mu_i + (1 - \alpha) \sum_j P_{ji} \pi_j^{Pr}$$

Perturbations: price distortions, changes in the production topology, technological shifts.

Wrap up

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- ▶ Underlying dynamics are linear (averaging).

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Future directions: the effect of perturbations on more complex systems.

- ▶ flow dynamics in infrastructure networks;
- ▶ game theoretic models in financial and economic networks;
- ▶ opinion formation and evolution in social networks.