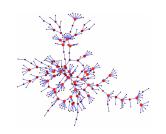
FRTN30 Network Dynamics Lecture 2 Algebraic graph theory, network centrality



Giacomo Como Lund, March 20, 2024

Connected components

Let $\mathcal{G} = (\mathcal{V}, \mathcal{E}, W)$ be a graph. Recall:

- $ightharpoonup j \in \mathcal{V}$ is reachable from $i \in \mathcal{V}$ if there exists a path from i to j
- ▶ by convection, every $i \in V$ reachable from itself (length-0 path)
- $lackbox{} j \in \mathcal{V}$ globally reachable if reachable from every $i \in \mathcal{V}$
- $ightharpoonup \mathcal{G}$ strongly connected if every node is globally reachable

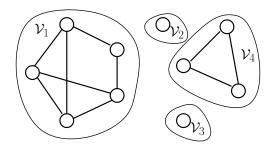
Connected components: largest nodes subsets $V_h \subseteq V$ such that if $i, j \in V_h$ then i reachable from j and j reachable from i

▶ Connected components are equivalence classes w.r.t. relation $v \sim w$ if v is reachable from w and w is reachable from v

$$\mathcal{V} = \bigcup_{1 \leq h \leq c_{\mathcal{G}}} \mathcal{V}_h \qquad \mathcal{V}_h \cap \mathcal{V}_k = \emptyset, \quad h \neq k$$

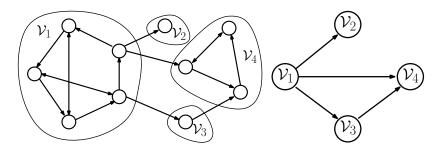
- ▶ $c_{\mathcal{G}} = \#\{\text{connected components of } \mathcal{G}\}$
- $ightharpoonup \mathcal{G}$ strongly connected $\Leftrightarrow c_{\mathcal{G}} = 1$

Connected components



In an undirected graph connected components are "islands"

Condensation graph



- ▶ condensation graph $\mathcal{H}_{\mathcal{G}}$: obtained by collapsing connected components \mathcal{V}_h into single nodes v_h and adding a directed link (v_h, v_k) whenever there exists at least one link in \mathcal{G} from some node $i \in \mathcal{V}_h$ to some node $j \in \mathcal{V}_k$
- $\blacktriangleright \mathcal{H}_{\mathcal{G}}$ is circuit-free (DAG)
- $ightharpoonup \mathcal{G}$ contains globally reachable node $\Leftrightarrow \mathcal{H}_{\mathcal{G}}$ has just one sink
- $ightharpoonup \mathcal{G}$ undirected $\Longrightarrow \mathcal{H}_{\mathcal{G}}$ has no links (only isolated nodes)

Normalized weight matrix and Laplacian of a graph

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

- $\triangleright W = \text{weight matrix}$
- $\triangleright w = W1$ out-degree vector
- $\triangleright D = diag(w)$
- ▶ normalized weight matrix¹

$$P = D^{-1}W$$

P row-stochastic, i.e., nonnegative and such that P1 = 1

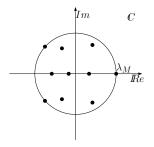
► Laplacian matrix

$$L = D - W$$

- -L 'Metzler' (nonnegative out of diagonal), $L\mathbb{1}=0$
- \blacktriangleright geometric properties of $\mathcal{G} \longleftrightarrow$ spectral properties of P and L

 $^{^1}$ We assume that $w_i > 0$ for every $i \in \mathcal{V}$ with no loss of generality

Perron-Frobenius Theorem

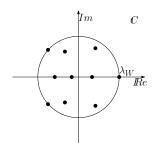


Let M be a nonnegative square matrix. Then, there exist a nonnegative real eigenvalue $\lambda_M \geq 0$ and non-negative right and left eigenvectors $x \neq 0$ and $y \neq 0$ such that:

- \blacktriangleright $Mx = \lambda_M x$, $M'y = \lambda_M y$
- ▶ every eigenvalue λ of M is such that $|\lambda| \leq \lambda_M$.

 λ_M dominant eigenvalue, x and y dominant eigenvectors

Perron-Frobenius applied to graphs

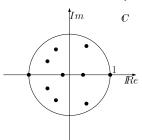


Proposition

 $\mathcal{G}=(\mathcal{V},\mathcal{E},W)$ graph s.t. w>0. Then, there exist positive real eigenvalue $\lambda_W\geq 0$ and dominant right and left eigenvectors

$$x = \lambda_W^{-1} W x \ge 0 \,, \qquad y = \lambda_W^{-1} W' y \ge 0 \label{eq:section_eq}$$

Perron-Frobenius applied to graphs (cont'd)

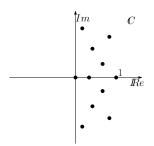


Proposition

$$\mathcal{G} = (\mathcal{V}, \mathcal{E}, W)$$
 graph s.t. $w > 0$, $P = \operatorname{diag}(w)^{-1}W$. Then,

- (i) dominant eigenvalue $\lambda_P = 1$;
- (ii) there exists invariant distribution $\pi \geq 0$ s.t. $1'\pi = 1$, $P'\pi = \pi$;
- (iii) $\mathcal G$ balanced $\Leftrightarrow w$ eigenvector of P' with eigenvalue 1 ;
- (iv) \mathcal{G} regular $\Rightarrow \mathbb{1}$ eigenvector of P' with eigenvalue 1;
- (v) \mathcal{G} is strongly connected $\Rightarrow \lambda_P = 1$ simple and $\pi = P'\pi > 0$;
- (vi) $\mathcal G$ strongly connected and aperiodic \Rightarrow any eigenvalue $\lambda \neq 1$ of P is such that $|\lambda| < 1$;
- (vii) \mathcal{G} is bipartite $\Rightarrow -1$ eigenvalue of P.

Perron-Frobenius applied to graphs (cont'd)

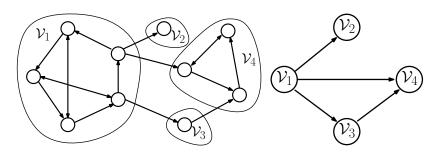


Proposition

 $\mathcal{G} = (\mathcal{V}, \mathcal{E}, W)$ graph, Laplacian L = diag(w) - W. Then,

- (i) 0 eigenvalue of L and L', all other eigenv. λ have $\mathbb{R}e(\lambda)>0$
- (ii) \overline{y} is in the kernel of $L' \Leftrightarrow \overline{y} = D^{-1}y$ for some y s.t. P'y = y;
- (iii) there exists Laplace-invariant distribution $\overline{\pi} \geq 0$ such that $\mathbb{1}'\overline{\pi} = 1$ and $L'\overline{\pi} = 0$;
- (iv) 1 in the kernel of $L' \Leftrightarrow \mathcal{G}$ balanced;
- (v) \mathcal{G} is strongly connected, \Rightarrow 0 is simple eigenv. of L and $\overline{\pi} > 0$.

Perron-Frobenius applied to graphs (cont'd)



Proposition

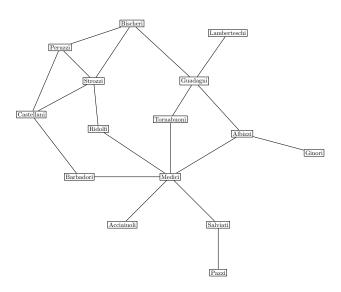
 $\mathcal{G} = (\mathcal{V}, \mathcal{E}, W)$ graph, $\mathcal{H}_{\mathcal{G}}$ condensation graph,

 $\mathit{s}_{\mathcal{G}} = \mathsf{number} \ \mathsf{of} \ \mathsf{sinks} \ \mathsf{in} \ \mathcal{H}_{\mathcal{G}}. \ \mathsf{Then},$

 $\mathit{s}_{\mathcal{G}} = \mathsf{multip.}$ of 1 as eigenv. of $\mathit{P} = \#$ extremal invariant distributions

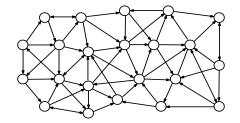
 $s_{\mathcal{G}}=$ multip. of 0 as eigenv. of L=# extremal Lap.-inv. distributions

Network centrality



What is the most central node?

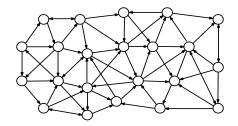
Network centrality



Most central node in $\mathcal{G} = (\mathcal{V}, \mathcal{E}, W)$?

 \triangleright z_i network centrality of node i

Degree centrality

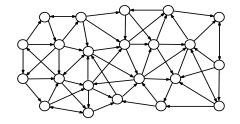


Most central node in G = (V, E, W)?

- $ightharpoonup z_i$ network centrality of node i
- ▶ first attempt: $z_i \propto w_i^-$ in-degree centrality

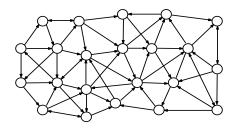
E.g., number of citations of an article, of followers on Twitter

Eigenvector centrality



- $ightharpoonup z_i$ network centrality of node i
- lacktriangle a more refined notion: $z_i \propto \sum_j W_{ji} z_j$

Eigenvector centrality

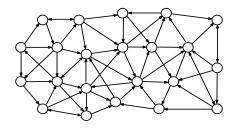


- \triangleright z_i network centrality of node i
- lacktriangle a more refined notion: $z_i \propto \sum_j W_{ji} z_j$

$$z_i = \frac{1}{\lambda} \sum_j W_{ji} z_j$$
 $\lambda z = W' z$

with $\lambda = \lambda_W$: eigenvector centrality

Eigenvector centrality



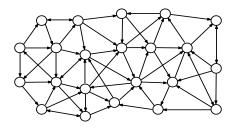
- \triangleright z_i network centrality of node i
- ▶ a more refined notion: $z_i \propto \sum_j W_{ji} z_j$

$$z_i = \frac{1}{\lambda} \sum_j W_{ji} z_j$$
 $\lambda z = W' z$

with $\lambda = \lambda_W$: eigenvector centrality

ightharpoonup drawback: node j contributes proportional to its out-degree w_j

Invariant distribution centrality

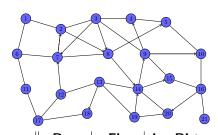


▶ a fix: normalize by out-degree

$$z_i \propto \sum_j \frac{1}{w_j} W_{ji} z_j = \sum_j P_{ji} z_j$$

- ▶ invariant distribution centrality: $z = P'z = \pi$
- ▶ Recall: in balanced networks $\pi_i \propto w_i$, not in general

Degree vs eigenvector vs invariant distribution centralities

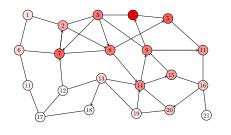


	Deg	Eig	Inv.Dist.
1	0.0345	0.0348	0.0313
2	0.0517	0.0581	0.0451
3	0.0517	0.0664	0.0613
4	0.0517	0.0689	0.0680
5	0.0517	0.0680	0.0869
6	0.0517	0.0430	0.0490

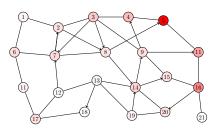
7	0.0690	0.0678	0.0514
8	0.0517	0.0661	0.0444
9	0.0517	0.0659	0.0491
10	0.0517	0.0627	0.0761
11	0.0345	0.0226	0.0324
12	0.0345	0.0215	0.0240
13	0.0517	0.0399	0.0317
14	0.0690	0.0640	0.0548
15	0.0517	0.0613	0.0464
16	0.0517	0.0484	0.0817
17	0.0517	0.0225	0.0481
18	0.0345	0.0215	0.0240
19	0.0345	0.0307	0.0300
20	0.0517	0.0492	0.0441
21	0.0172	0.0166	0.0204

Degree vs eigenvector vs invariant distribution centralities

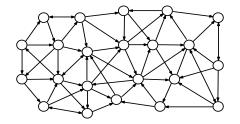
Eigenvector centrality



Invariant distribution centrality

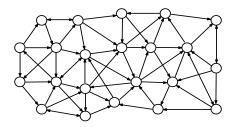


Drawback of eigenvector and invariant distribution



- ▶ single sink node gets all centrality
- ▶ single sink connected component gets all centrality
- even if strongly connected, incentive to "cluster"

Katz centrality

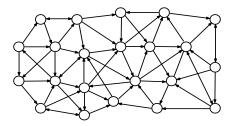


▶ Fix: convex comb. of intrinsic centrality and network centrality

$$z^{(\beta)} = \left(\frac{1-\beta}{\lambda_W}\right) W' z^{(\beta)} + \beta \mu$$

Katz centrality:
$$z^{(\beta)} = (I - \lambda_W^{-1}(1 - \beta)W')^{-1}\beta\mu$$

Bonacich centrality



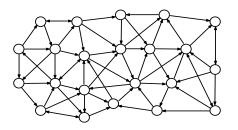
▶ Fix: convex combination of intrinsic and network centrality

$$z^{(\beta)} = (1 - \beta)P'z^{(\beta)} + \beta\mu$$

Bonacich centrality: $z^{(\beta)} = (I - (1 - \beta)P')^{-1} \beta \mu$

▶ PageRank (Google): $\mu = n^{-1}\mathbb{1}$, $\beta \sim 0.15$

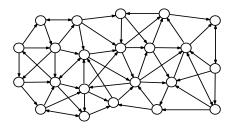
Bonacich centrality: an interpretation



$$z^{(\beta)} = (1 - \beta)P'z^{(\beta)} + \beta\mu$$

$$z^{(\beta)} = (I - (1 - \beta)P')^{-1} \beta \mu = \beta \sum_{k=0}^{+\infty} (1 - \beta)^k (P')^k \mu$$
$$= \beta \mu + \beta (1 - \beta)P' \mu + \beta (1 - \beta)^2 (P^2)' \mu + \dots$$

Eigenvector centrality: an interpretation



$$z^{(\beta)} = \frac{1 - \beta}{\lambda_W} W' z^{(\beta)} + \beta \mu$$

$$z^{(\beta)} = (I - \lambda_W^{-1}(1 - \beta)W')^{-1} \beta \mu = \beta \sum_{k=0}^{+\infty} \left(\frac{1 - \beta}{\lambda_W}\right)^k (W')^k \mu$$
$$= \beta \mu + \beta \frac{1 - \beta}{\lambda_W} W' \mu + \beta \left(\frac{1 - \beta}{\lambda_W}\right)^2 (W^2)' \mu + \dots$$

Eigenvector, inv. dist., Katz, and Bonacich centralities

Eigenvector centrality	Invariant distribution	
$z = \frac{1}{\lambda_W} W' z$	z = P'z	
Katz centrality	Bonacich centrality	
$z = \frac{1 - \beta}{\lambda_W} W' z + \beta \mu$	$z = (1 - \beta)P'z + \beta\mu$	

Application: a model for production networks

Economy with n sectors producing homogeneous goods.

For each sector k = 1, ..., n

- $\triangleright y_k = \text{total production}$
- $ightharpoonup c_k = consumption$
- $\triangleright p_k = \text{unit price}$
- $\triangleright w = \text{unit cost of labor}$
- $\triangleright s_k = \text{revenue}$
- $\blacktriangleright \pi_k = \text{profit}$
- $ightharpoonup I_k =$ employed labor
- $ightharpoonup z_{ik} = \text{quantity of product } j \text{ used}$

$$s_k = p_k y_k$$

$$\pi_k = s_k - \sum_{j} p_j z_{jk} - w l_k$$

A model for production networks (cont'd)

Cobb-Douglas production functions

$$y_k = a_k I_k^{\beta} \prod_j z_{jk}^{\alpha G_{jk}}$$

and consumer utility function

$$U=\prod_k c_k^{\mu_k}$$

where

 $a_k > 0$ efficiency of sector k $G_{jk} \geq 0$ effectiveness of product j in production of k $\mu_k \geq 0$ consumer preference weight

$$\sum_{j} G_{jk} = 1 \qquad \sum_{k} \mu_{k} = 1$$

A model for production networks (cont'd)

Assumptions:

▶ market for goods clears

$$y_k = \sum_j z_{kj} + c_k$$

▶ market for labor clears

$$\sum_{l} l_k = 1$$

▶ budget constraint

$$\sum_{k} p_k c_k \leq w + \sum_{k} \pi_k$$

Walrasian Equilibrium

tuple (y, c, p, l, z) satisfying assumptions and s.t.

- \blacktriangleright employed labor l_k and intermediate products z_{jk} maximize profit π_k given the prices p_k
- ightharpoonup consumptions $(c_k)_k$ maximize consumer utility U given everything else

Walrasian Equilibrium

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Theorem[Acemoglu ea.,'12] If $\alpha + \beta = 1$, at Walrasian Equilibrium

- ▶ no profits $\pi_k = 0$
- ▶ $\log U = (1 \alpha)^{-1} v' \log a + Constant$ where

$$a = efficiency vector$$

$$v = \beta (I - (1 - \beta)G)^{-1}\mu$$
 Bonacich centrality

Constant depends on μ , G, α only