



Shortest Paths: Shortest Path Betweenness

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- Again assume that communication (workflows etc.) happen along shortest paths only. Let

$$\delta_{ab}(v) = \frac{\sigma_{ab}(v)}{\sigma_{ab}}$$

with σ_{ab} : total number of shortest paths between nodes a and b.

Interpretation. Probability that v is involved in a communication between a and b



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Shortest Paths: Shortest Path Between Centrality

- Again assume that communication is represented by a graph $G = (V, E)$. Let σ_{ab} be the shortest path between a and b . Let σ_{ab} be the shortest path between a and b .

Vertex stress centrality of node x . Number of shortest paths between a and b that pass through x . Straightforward version for σ_{ab} .

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respect capacity constraints: $0 \leq f(e) \leq m(e)$

$\forall v \in V \setminus \{s, t\}: \sum_{e \in \text{In-Edges of } v} f(e) = \sum_{e \in \text{Out-Edges of } v} f(e)$

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- Again assume that communication cost is proportional to the length of the path. The flow f is a function $f: E \rightarrow \mathbb{R}$.
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- Again not a flow $f: E \rightarrow \mathbb{R}$
- shortest path σ_{ab} $\log(|V|)$ distance

$$\sum_{v \in V} \sum_{a \neq v} \sum_{b \neq v} \sum_{e \in E} \frac{1}{|E|} \sum_{(s,t) \in P} \dots$$

with σ total number of shortest paths $q(\sigma) = \sum_{(s,t) \in P} \frac{1}{|E|}$

Interpretation: $f(s,t)$ is the "vitality" of (s,t)

$$c(x) = q(x) - q(\dots)$$

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$\text{flow}(i) :=$ number of units that slide through i in this set up, averaged over all s and t .

$\text{max-flow between } s \text{ and } t \text{ is:}$
 limit edge capacity to one

$\text{mf}(i) :=$ maximum possible flow through i over all possible solutions to the s - t -maximum flow problem over all s and t .

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Shortest Paths: Shortest Path Ret eowatra

$\sum_j A_{ij} = k_i$, the degree of node i .
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Shortest Paths: Shortest Path Problem

$\sum_j A_{ij} f_j = k_i$, the degree of v_i is k_i .
 The Laplacian matrix $L = D - A$ is symmetric and positive semi-definite.

$$\sum_j A_{ij} (V_i - V_j) = \delta_{is} - \delta_{it} \implies (D - A) \cdot V = s$$

This is the Laplacian system. The matrix D is the degree matrix, and A is the adjacency matrix. The vector s represents the source and sink nodes.

The flow conservation constraint is:

$$\sum_{e \in \{Out-Edges\ of\ v}} \tilde{f}(e) = \sum_{e \in \{In-Edges\ of\ v}} \tilde{f}(e)$$

For the source node s , the net flow is 1, and for the sink node t , the net flow is -1.

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Shortest Paths: Shortest Path Return

$\sum_j A_{ij} f_j = k_i$, then k_i is the net number of times through i on a random walk starting at s and ending at t .

$\sum_i A_{ij} f_j = k_i$ is not invertible, but because $\sum_i A_{ij} = 0$, we can remove the v -th row and column, since $V_{v,v} = 1$.

$(D_v - A_v)$ is invertible, and $(D_v - A_v)^{-1}$ is the matrix of expected return times $V_i^{(st)}$.

The maximum flow problem is solved by finding the shortest path from s to t .

The return time $V_i^{(st)}$ is given by:

$$V_i^{(st)} = \frac{1}{2} \sum_j A_{ij} |V_i^{(st)}(e) - V_j^{(st)}(e)|$$

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Shortest Paths: Shortest Path Retention

$\sum_j A_{ij} = k_i$, the degree of node i .

net number of times the particle goes through i , on its journey (averaged over a large number of trials)

$b_i = \frac{1}{n-1} \sum_j A_{ij} |V_i^{(f)}(e) - V_j^{(f)}(e)|$ [5]

If i is node j in next step at time t , then $V_i^{(f)}(t) = I_{ij}(t) + V_j^{(f)}(t)$.

If i is not node j in next step, then $V_i^{(f)}(t) = V_j^{(f)}(t)$.

$M = A D^{-1}$

Shortest Paths: Shortest Path Retention

$\sum_j A_{ij} = k_i$, the degree of node i .

net number of times the particle goes through i , on its journey (averaged over a large number of trials)

$b_i = \frac{1}{n-1} \sum_j A_{ij} |V_i^{(f)}(e) - V_j^{(f)}(e)|$ [5]

If i is node j in next step at time t , then $V_i^{(f)}(t) = I_{ij}(t) + V_j^{(f)}(t)$.

If i is not node j in next step, then $V_i^{(f)}(t) = V_j^{(f)}(t)$.

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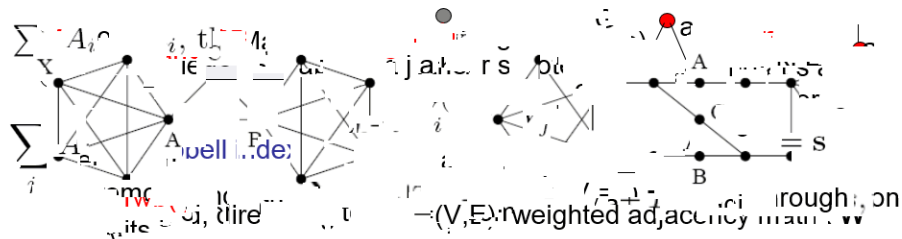
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Centrality $s(v)$ of node v is proportional to sum of centralities $s(w)$ of nodes w (multiplied with corresp. edge weights).

Let centrality vector of the nodes is thus an eigenvector of W : $s = Ws$

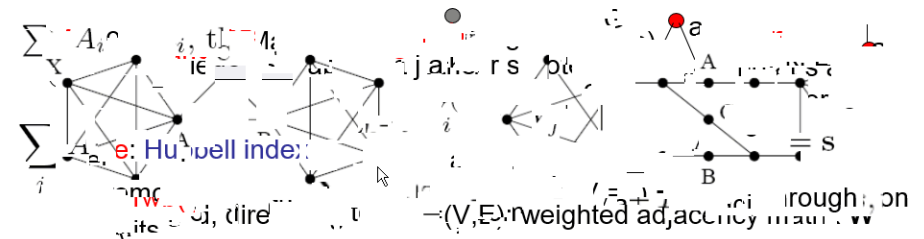
If in node j , in solving, introduce a centrality $s(j)$ from edge e from j to i .

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$s = (I - W)^{-1} E$

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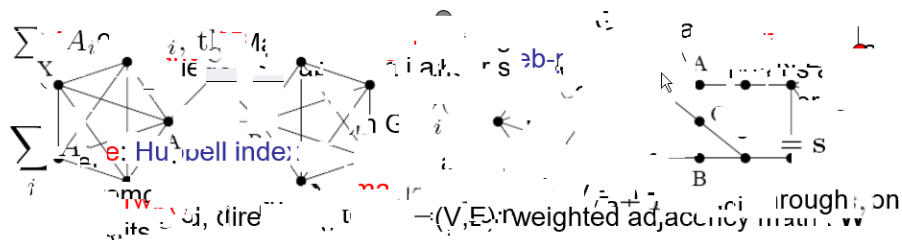
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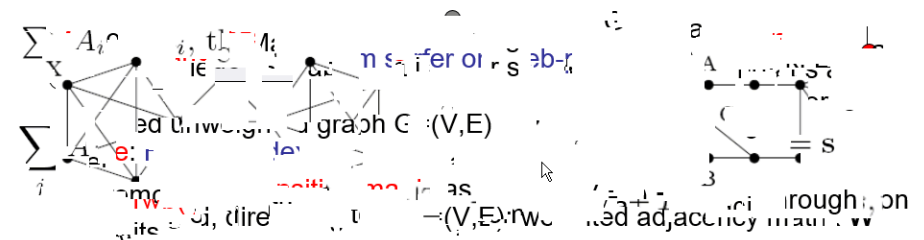
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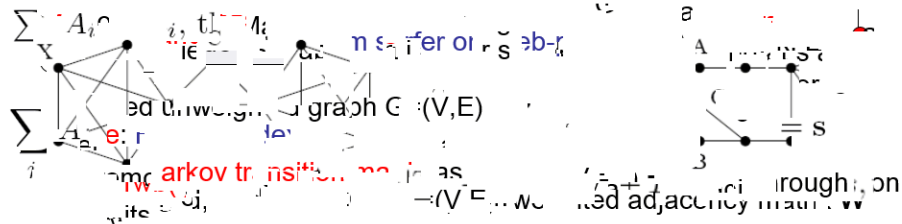
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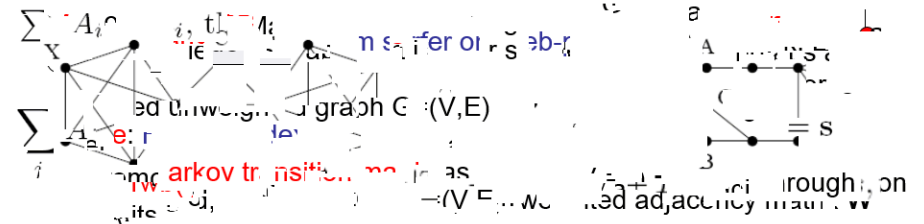
Let s be the vector of centralities. Then $s = Ws$ where W is the adjacency matrix.

If $(i,j) \in E$, $t_{ij} = \begin{cases} 0 & \text{if } (i,j) \notin E \\ 1 & \text{if } (i,j) \in E \end{cases}$. Introduce a "centrality" s as a solution to $s = E + Ws$.

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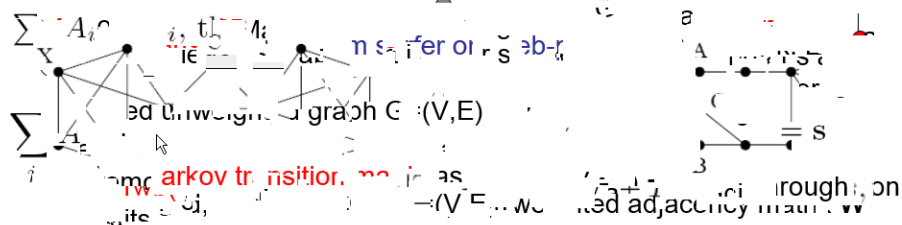
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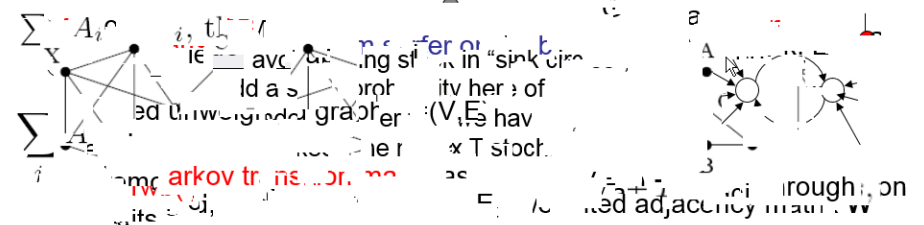
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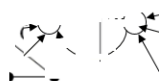
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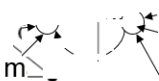
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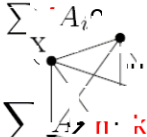
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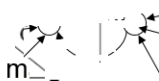
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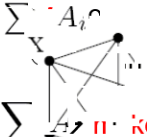
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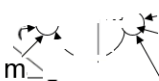
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... can we find a unique stationary distribution π ? (if G is irreducible and positively recurrent)

$\sum_{i \in V} \pi_i = 1$

$\pi_i = \frac{1}{n}$ (completely stochastic choice)

$\pi_i = \frac{deg(i)}{\sum_{v \in V} deg(v)}$

$\pi_j = \frac{deg(j)}{\sum_{v \in V} deg(v)}$

If $\pi_j = \frac{deg(j)}{\sum_{v \in V} deg(v)}$ then $\sum_{i \in V} \pi_i A_{ij} = \sum_{i \in V} \frac{deg(i) A_{ij}}{\sum_{v \in V} deg(v)} = \frac{\sum_{i \in V} A_{ij}}{\sum_{v \in V} deg(v)} = \frac{deg(j)}{\sum_{v \in V} deg(v)} = \pi_j$

In-W is $\pi_j = \frac{deg(j)}{\sum_{v \in V} deg(v)}$

net flow through vertex j is 0 if the sum of the ...

$\sum_{i \in V} A_{ij} c_j = d c_i + \sum_{j \in V} P_{ij} c_j$

... the solution a ...

$c_i^{(k+1)} = d c_i + \sum_{j \in V} P_{ij} c_j^{(k)}$

$a_{ij} = \frac{c_j}{\sum_{v \in V} c_v} = \frac{c_j}{\sum_{v \in V} \deg(v)}$

I-W is ...

ne flow through vertex i is ...

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I-W is ...

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