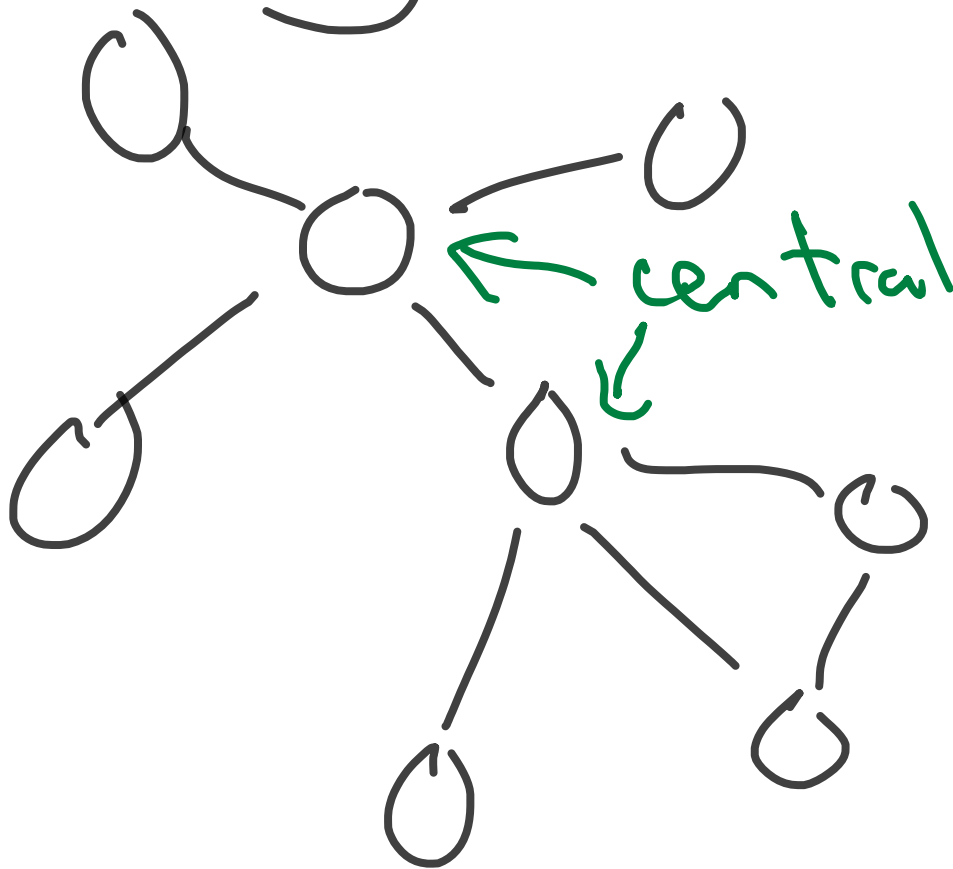


April 11, 2019

# Centrality in networks Ranking



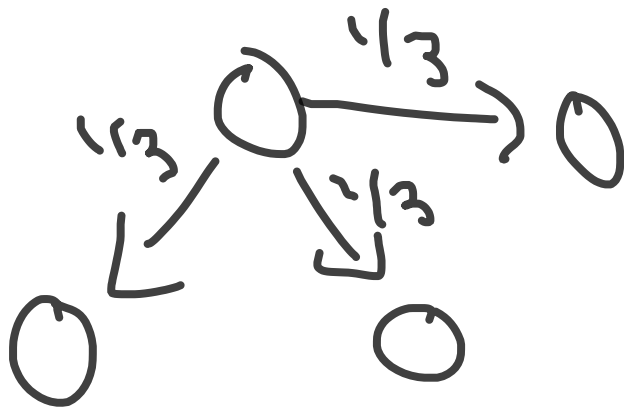
- Page Rank
  - HITS
  - Eigenvector
  - Katz
- } web
- } sociology

# Page Rank (Page et al. 98)

(Assume directed, strongly connected graph)

Stochastic process:

- start at some node
- With prob  $\alpha$ , follow an outgoing edge at random



- With prob.  $1 - \alpha$ , "teleport" to a random node
- telep. vector  $v$

this is a Markov chain  
steady state? (stationary dist)

$$\alpha P x + (1-\alpha)v = x$$



$$P_{ji} = \text{Prob}(i \rightarrow j)$$

Since  $\mathbf{1}^T x = 1$  at steady state,

$$\alpha P x + (1-\alpha)v \mathbf{1}^T x = x$$

$$(\alpha P + (1-\alpha)v \mathbf{1}^T) x = x$$

Markov chain matrix

Alternatively, linear system

$$(I - \alpha P)x = (1 - \alpha)v$$

How to compute  $x$ ?

$$x = \alpha P x + (1 - \alpha)v$$

$$x^{(k+1)} = \alpha P x^{(k)} + (1 - \alpha)v$$

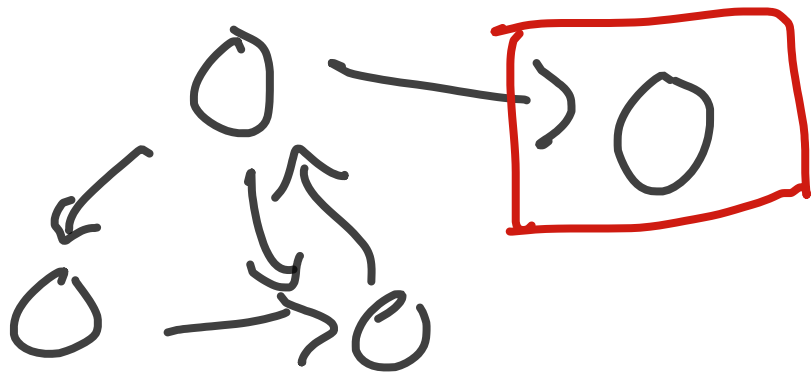
$$x - x^{(k+1)} = \alpha P (x - x^{(k)})$$

$$\begin{aligned} \|x - x^{(k+1)}\|_1 &= \|\alpha P (x - x^{(k)})\|_1 \\ &\leq \alpha \|P\|_1 \|x - x^{(k)}\|_1 \\ &= \alpha \|x - x^{(k)}\|_1 \\ &\leq \alpha^k (\|x - x^{(0)}\|_1) \\ &\leq 2\alpha^k \end{aligned}$$

Exponential decay in error!

Problem when not strongly conn?

"sink nodes"



nowhere to go

if we land at one of these,  
could just follow  $v$

Theorem: equivalent to rescaling  
iterates at each step

$$x^{(k+1)} = \alpha P x^{(k)} + (1-\alpha)v$$

$$x^{(k+1)} = x^{(k+1)} / \|x^{(k)}\|,$$

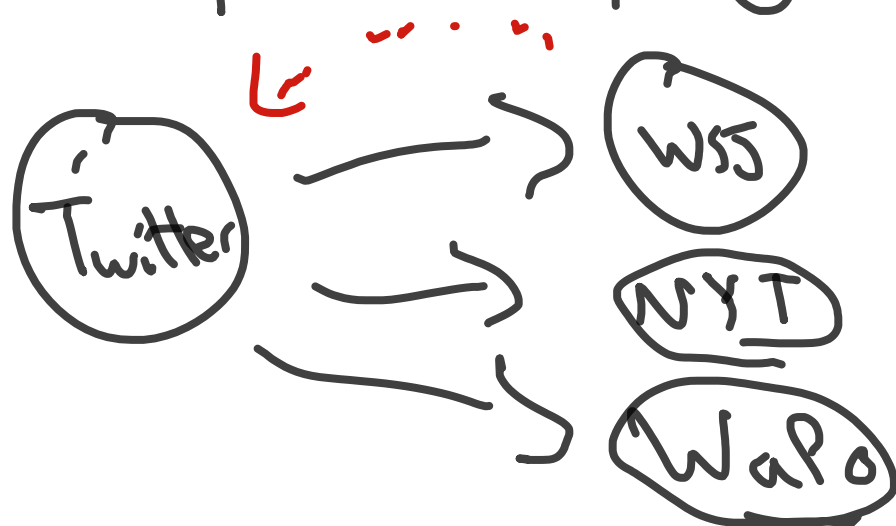
HITS (J. Kleinberg 98)

hubs & authorities

Main idea: web sites have  
"hub" and "authority" scores

hubs point to many good  
authorities

authorities are pointed to  
by many good hubs



$h_0, a_0$  initial hub and auth

$$h_1(i) = \sum_{(i,j)} a_0(j)$$

$$h_1 = A a_0$$

$$a_1(j) = \sum_{(i,j)} h_1(i) \quad a_1 = A^T h_1$$

$$h_2 = A a_1 = A A^T h_1 = A A^T A a_0$$

$$a_2 = A^T h_2 = A^T A A^T A a_0 = (A^T A)^2 a_0$$

$$h_k = (A A^T)^{k-1} \cdot A a_0$$

$$a_k = (A^T A)^k a_0$$

$$h_k \leftarrow \frac{h_k}{\|h_k\|_2}$$

$$a_k \leftarrow \frac{a_k}{\|a_k\|_2}$$

Running power method on  
 $AA^T (h_k)$  or  $A^T A (a_k)$

$\Rightarrow$  converge to the  
principal eigenvector  
(assuming its unique)

$$A = U \Sigma V^T$$

$$AA^T = U \Sigma^2 U^T \text{ (eigen decomp)}$$

$\Rightarrow h_k$  converges to  $u_1$



(first left singular vector)

$$A^T A = V \Sigma^2 V^T$$

$\Rightarrow a_k$  converges to  $v_1$   
(first right singular vector)

We could have initialized  
 $a_0$  as nonnegative

$u_1, v_1$  are both nonnegative  
(can be made nonnegative)

(uniqueness of singular vectors  
up to sign)

# Eigenvector centrality (Bonacich 1972)

Assume node  $i$  has some  
"power" or "influence"  $v_i$

Power is proportional to  
sum of your neighbors' power

$$v_i \approx \gamma \sum_{(i,j)} v_j$$

↑  
proportionality  
constant  $> 0$

$$\Leftrightarrow \frac{1}{\gamma} v_i \approx \sum_{j=1}^n A_{ij} v_j$$

$$\approx [Av];$$

$$\Leftrightarrow \frac{1}{r}v \approx Av$$

Eigenvalue problem!

This could hold for any  
eigenpair  $(\frac{1}{r}, v)$ ,  $\frac{1}{r} > 0$

Assume  $v > 0$

if graph is strongly conn.,  
then we can find  
such an eigenpair  
and its unique

# Theorem (Perron-Frobenius)

Let  $A$  be the adj. matrix of a strongly conn. graph

Then there exists  $\lambda > 0$  such that

①  $Av = \lambda v$

②  $\lambda > 0$  is an eigenvalue of largest magnitude of  $A$

③ the eigenspace of  $\lambda$  is one-dimensional

④  $v$  is the only nonneg.

eigenvector of  $A$   
(up to scaling)

①+②  $\Rightarrow$  which eigenvector  
(largest real eigenval)

③+④  $\Rightarrow$  uniqueness

if the graph is not  
 $k$ -partite, then  $|\hat{\lambda}| < 1$   
 $\hat{\lambda}$  is any other eigenvalue

$\Rightarrow$  can use simple power  
method to compute

# Katz centrality (Katz 1953)

node  $i$  is important  
if there are many paths  
to node  $i$

shorter paths more important  
than longer ones

Katz: weight paths of  
length  $l$  by  $\beta^l$

Katz score of node  $i$

$$K_i = \sum_{l=1}^{\infty} \sum_{j=1, j \neq i}^n \beta^l \cdot \# \text{ paths from } j \text{ to } i \text{ of length } l$$

length  $l$ )

$$K_i = \sum_{l=1}^{\infty} \sum_{j=1}^i A_{ji}^l$$

$$(I - M)^{-1} = \sum_{l=0}^{\infty} M^l \quad (M^0 = I)$$

$$K = [(I - BA^T)^{-1} - I] \mathbf{1}$$

need  $\beta$  small enough to conv.

$$\beta < \|A^T\|_2^{-1} = \sigma_1^{-1}$$

$$\Rightarrow \|BA\|_2 < 1$$

