

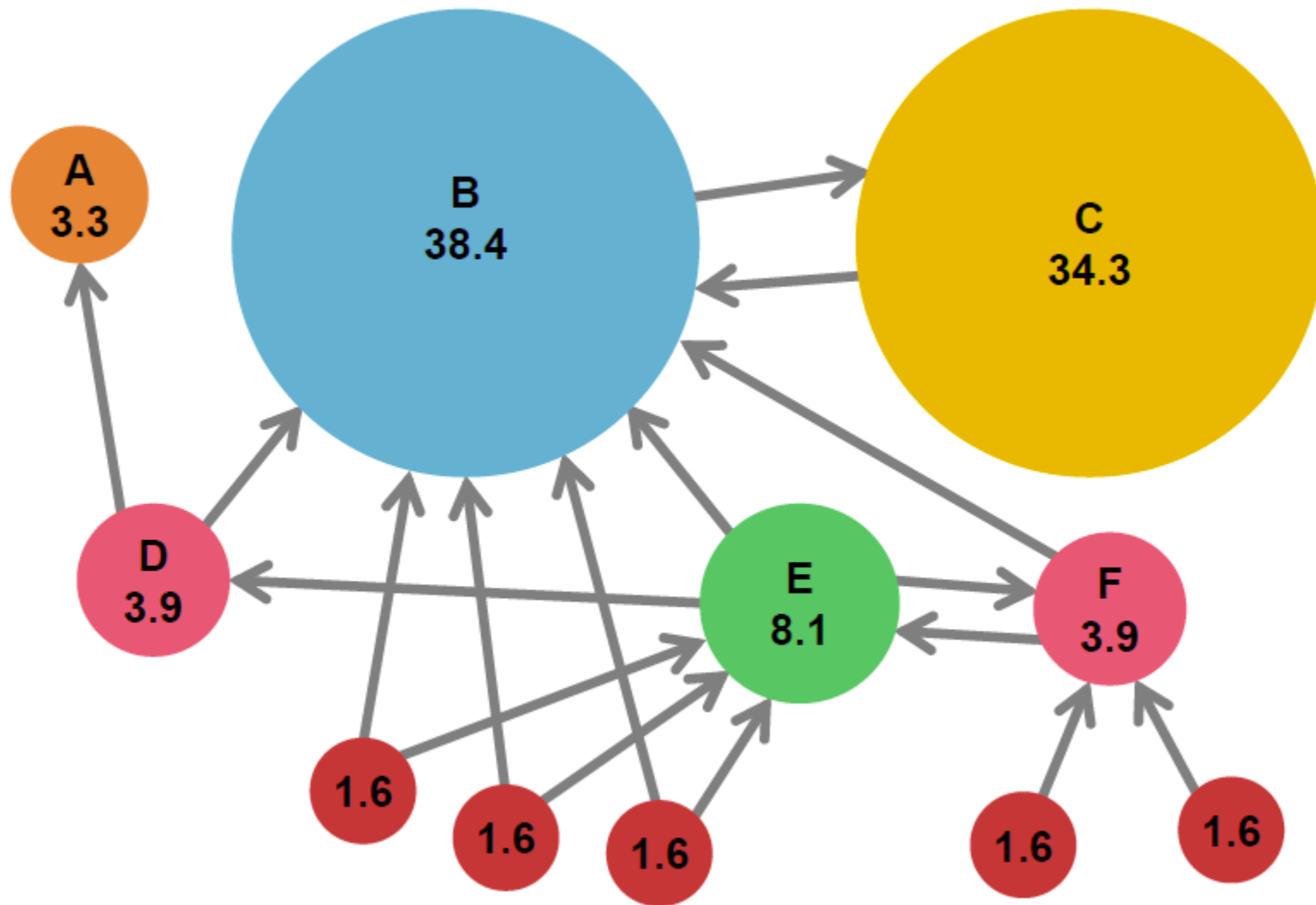
# PAGERANK & HITS

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# PAGERANK SCORES



# THE „FLOW“ MODEL

A page is important if it is pointed to by other important pages

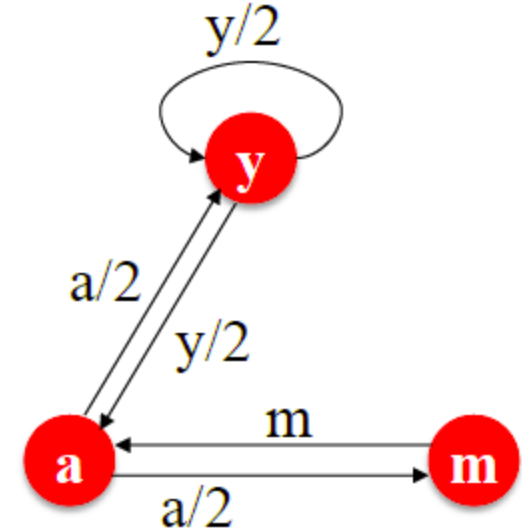
Define a “rank”  $r_j$  for page  $j$

$$r_j = \sum_{i \rightarrow j} \frac{r_i}{d_i}$$

$d_i$  ... out-degree of node  $i$

**Additional constraint forces uniqueness:**

- $r_y + r_a + r_m = 1$
- **Solution:**  $r_y = \frac{2}{5}$ ,  $r_a = \frac{2}{5}$ ,  $r_m = \frac{1}{5}$



“Flow” equations:

$$r_y = r_y/2 + r_a/2$$

$$r_a = r_y/2 + r_m$$

$$r_m = r_a/2$$

# PAGERANK: MATRIX FORMULATION

**Rank vector  $r$ :** vector with an entry per page

- $r_i$  is the importance score of page  $i$
- $\sum_i r_i = 1$

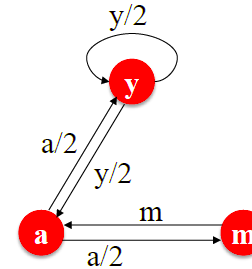
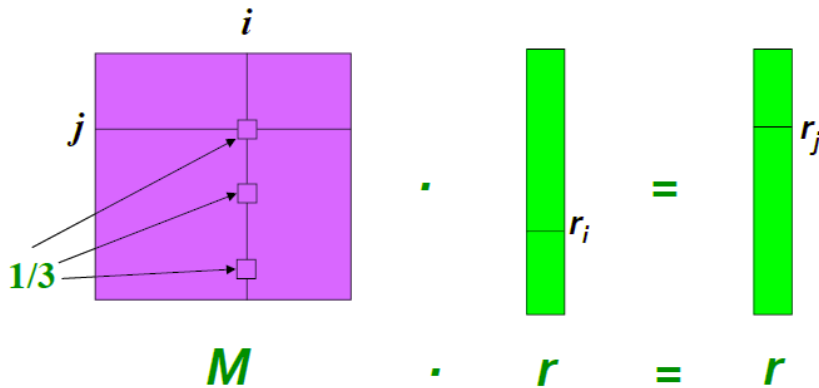
The flow equations can be written

$$r = M \cdot r$$

- Flow equation in the matrix form

$$M \cdot r = r$$

- Suppose page  $i$  links to 3 pages, including  $j$



“Flow” equations:

$$r_y = r_y/2 + r_a/2$$

$$r_a = r_y/2 + r_m$$

$$r_m = r_a/2$$

$$r_y + r_a + r_m = 1$$

$$\text{Solution: } r_y = \frac{2}{5}, r_a = \frac{2}{5}, r_m = \frac{1}{5}$$

$$r_j = \sum_{i \rightarrow j} \frac{r_i}{d_i}$$

$d_i$  ... out-degree of node  $i$

$M$  is a column stochastic matrix

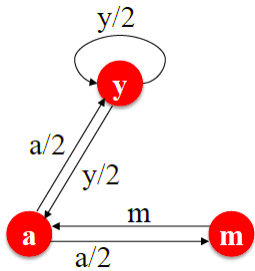
- Columns sum to 1

**NOTE:**  $x$  is an eigenvector with the corresponding eigenvalue  $\lambda$  if:

$$Ax = \lambda x$$

So the rank vector  $r$  is an eigenvector of the stochastic web matrix  $M$

# POWER ITERATION METHOD



“Flow” equations:

$$r_y = r_y/2 + r_a/2$$

$$r_a = r_y/2 + r_m$$

$$r_m = r_a/2$$

	y	a	m
y	1/2	1/2	0
a	1/2	0	1
m	0	1/2	0

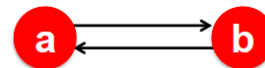
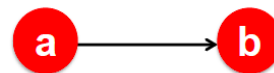
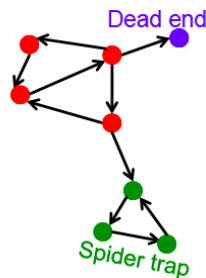
## Power Iteration:

- Set  $r_j = 1/N$
- 1:  $r'_j = \sum_{i \rightarrow j} \frac{r_i}{d_i}$
- 2:  $r = r'$
- Goto 1

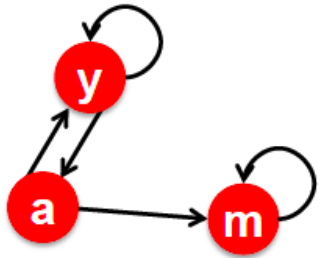
$$\begin{pmatrix} r_y \\ r_a \\ r_m \end{pmatrix} = \begin{pmatrix} 1/3 & 1/3 & 5/12 & 9/24 & & 6/15 \\ 1/3 & 3/6 & 1/3 & 11/24 & \dots & 6/15 \\ 1/3 & 1/6 & 3/12 & 1/6 & & 3/15 \end{pmatrix}$$

Iteration 0, 1, 2, ...

## 2 problems:



# SPIDER TRAPS AND TELEPORTS



	y	a	m
y	1/2	1/2	0
a	1/2	0	0
m	0	1/2	1

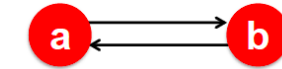
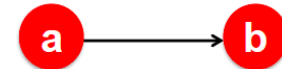
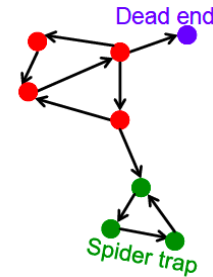
m is a spider trap

$$r_y = r_y/2 + r_a/2$$

$$r_a = r_y/2$$

$$r_m = r_a/2 + r_m$$

2 problems:



$$\begin{bmatrix} r_y \\ r_a \\ r_m \end{bmatrix} = \begin{bmatrix} 1/3 & 2/6 & 3/12 & 5/24 & & 0 \\ 1/3 & 1/6 & 2/12 & 3/24 & \dots & 0 \\ 1/3 & 3/6 & 7/12 & 16/24 & & 1 \end{bmatrix}$$

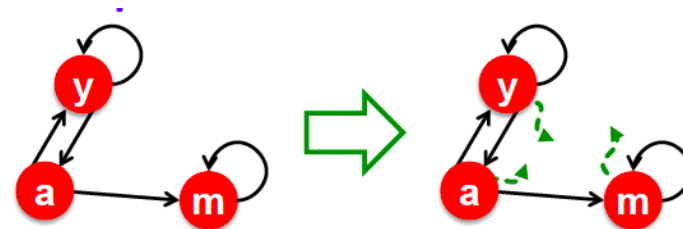
Iteration 0, 1, 2, ...

All the PageRank score gets "trapped" in node m.

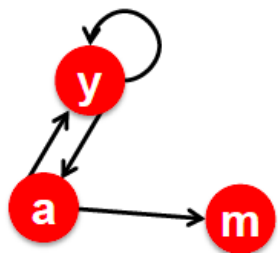
Surfer will teleport out of spider trap

With prob.  $\beta$ , follow a link at random

With prob.  $1-\beta$ , jump to some random page



# DEAD ENDS: ALWAYS TELEPORT!



	y	a	m
y	$\frac{1}{2}$	$\frac{1}{2}$	0
a	$\frac{1}{2}$	0	0
m	0	$\frac{1}{2}$	0

$$r_y = r_y/2 + r_a/2$$

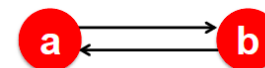
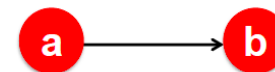
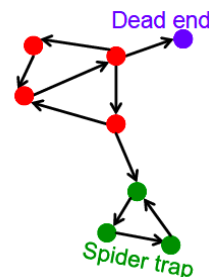
$$r_a = r_y/2$$

$$r_m = r_a/2$$

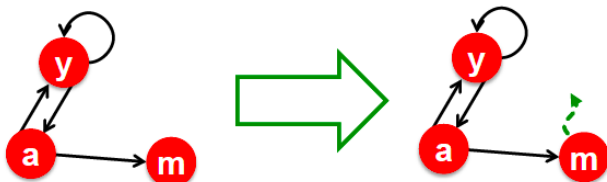
$$\begin{pmatrix} r_y \\ r_a \\ r_m \end{pmatrix} = \begin{pmatrix} 1/3 & 2/6 & 3/12 & 5/24 & \dots & 0 \\ 1/3 & 1/6 & 2/12 & 3/24 & \dots & 0 \\ 1/3 & 1/6 & 1/12 & 2/24 & \dots & 0 \end{pmatrix}$$

Iteration 0, 1, 2, ...

2 problems:



**Teleports:** Follow random teleport links with probability 1.0 from dead-ends

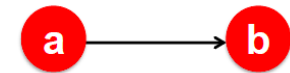
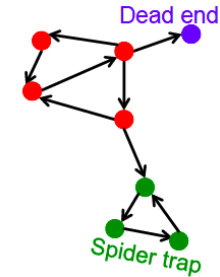


	y	a	m
y	$\frac{1}{2}$	$\frac{1}{2}$	$\frac{1}{3}$
a	$\frac{1}{2}$	0	$\frac{1}{3}$
m	0	$\frac{1}{2}$	$\frac{1}{3}$

# RANDOM TELEPORTS

## Dead-ends are a problem

- The matrix is not column stochastic so our initial assumptions are not met



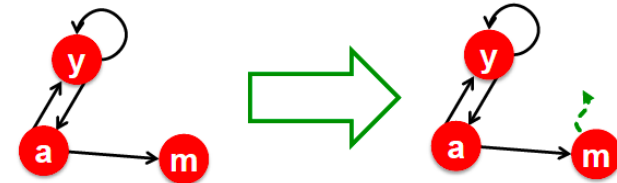
## At each step, random surfer has two options:

- With probability  $\beta$ , follow a link at random
- With probability  $1-\beta$ , jump to some random page

- **PageRank equation** [Brin-Page, 98]

$$r_j = \sum_{i \rightarrow j} \beta \frac{r_i}{d_i} + (1 - \beta) \frac{1}{N}$$

$d_i, \dots$  out-degree of node  $i$



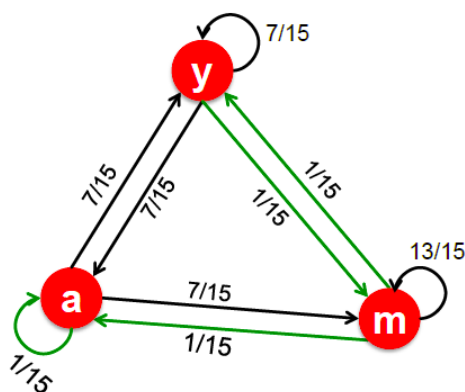
## The Google Matrix $A$ :

$$A = \beta M + (1 - \beta) \left[ \frac{1}{N} \right]_{N \times N}$$

$[1/N]_{N \times N} \dots N$  by  $N$  matrix where all entries are  $1/N$



# COMPUTING PAGERANK & REARRANGING THE EQUATION



$$\begin{matrix}
 \mathbf{M} & & \mathbf{[1/N]_{N \times N}} \\
 0.8 \begin{bmatrix} 1/2 & 1/2 & 0 \\ 1/2 & 0 & 0 \\ 0 & 1/2 & 1 \end{bmatrix} & + & 0.2 \begin{bmatrix} 1/3 & 1/3 & 1/3 \\ 1/3 & 1/3 & 1/3 \\ 1/3 & 1/3 & 1/3 \end{bmatrix} \\
 & & \mathbf{A} \\
 \begin{matrix} y & 7/15 & 7/15 & 1/15 \\ a & 7/15 & 1/15 & 1/15 \\ m & 1/15 & 7/15 & 13/15 \end{matrix}
 \end{matrix}$$

$$\mathbf{A} = \beta \cdot \mathbf{M} + (1-\beta) \mathbf{[1/N]_{N \times N}}$$

$$\mathbf{A} = 0.8 \begin{bmatrix} 1/2 & 1/2 & 0 \\ 1/2 & 0 & 0 \\ 0 & 1/2 & 1 \end{bmatrix} + 0.2 \begin{bmatrix} 1/3 & 1/3 & 1/3 \\ 1/3 & 1/3 & 1/3 \\ 1/3 & 1/3 & 1/3 \end{bmatrix}$$

$$= \begin{bmatrix} 7/15 & 7/15 & 1/15 \\ 7/15 & 1/15 & 1/15 \\ 1/15 & 7/15 & 13/15 \end{bmatrix}$$

y	=	1/3	0.33	0.24	0.26	...	7/33
a		1/3	0.20	0.20	0.18	...	5/33
m		1/3	0.46	0.52	0.56	...	21/33

Matrix **A** has  $N^2$  entries

We just rearranged the **PageRank equation**

$$\mathbf{r} = \beta \mathbf{M} \cdot \mathbf{r} + \left[ \frac{\mathbf{1} - \beta}{N} \right]_N$$

- where  $\mathbf{[(1-\beta)/N]_N}$  is a vector with all  $N$  entries  $(1-\beta)/N$

$\mathbf{M}$  is a **sparse matrix!** (with no dead-ends)

- **Input: Graph  $G$  and parameter  $\beta$** 
  - Directed graph  $G$  (can have **spider traps** and **dead ends**)
  - Parameter  $\beta$
- **Output: PageRank vector  $r^{new}$**

- **Set:**  $r_j^{old} = \frac{1}{N}$
- **repeat until convergence:**  $\sum_j |r_j^{new} - r_j^{old}| > \epsilon$ 
  - $\forall j: r_j^{new} = \sum_{i \rightarrow j} \beta \frac{r_i^{old}}{d_i}$   
 $r_j^{new} = 0$  if in-degree of  $j$  is 0
  - **Now re-insert the leaked PageRank:**  
 $\forall j: r_j^{new} = r_j^{new} + \frac{1-S}{N}$  where:  $S = \sum_j r_j^{new}$
  - $r^{old} = r^{new}$

If the graph has no dead-ends then the amount of leaked PageRank is  $1-\beta$ . But since we have dead-ends the amount of leaked PageRank may be larger. We have to explicitly account for it by computing  $S$ .

# TOPIC SPECIFIC PAGERANK

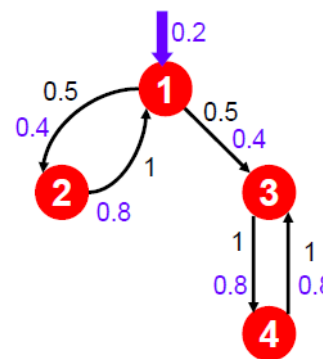
To make this work all we need is to update the teleportation part of the PageRank formulation:

$$A_{ij} = \begin{cases} \beta M_{ij} + (1 - \beta)/|S| & \text{if } i \in S \\ \beta M_{ij} + 0 & \text{otherwise} \end{cases}$$

▪  $A$  is a stochastic matrix!

We weighted all pages in the teleport set  $S$  equally

▪ Could also assign different weights to pages!



Suppose  $S = \{1\}$ ,  $\beta = 0.8$

Node	Iteration				
	0	1	2	...	stable
1	0.25	0.4	0.28		0.294
2	0.25	0.1	0.16		0.118
3	0.25	0.3	0.32		0.327
4	0.25	0.2	0.24		0.261

$S = \{1, 2, 3, 4\}$ ,  $\beta = 0.8$ :

$r = [0.13, 0.10, 0.39, 0.36]$

$S = \{1, 2, 3\}$ ,  $\beta = 0.8$ :

$r = [0.17, 0.13, 0.38, 0.30]$

$S = \{1, 2\}$ ,  $\beta = 0.8$ :

$r = [0.26, 0.20, 0.29, 0.23]$

$S = \{1\}$ ,  $\beta = 0.8$ :

$r = [0.29, 0.11, 0.32, 0.26]$

$S = \{1\}$ ,  $\beta = 0.9$ :

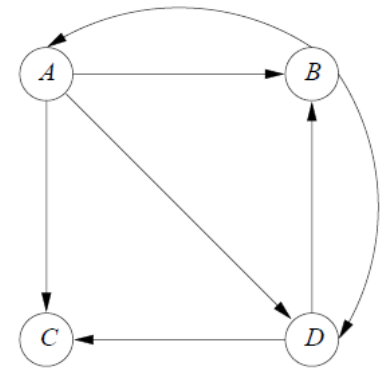
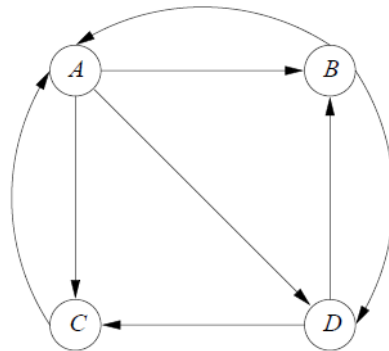
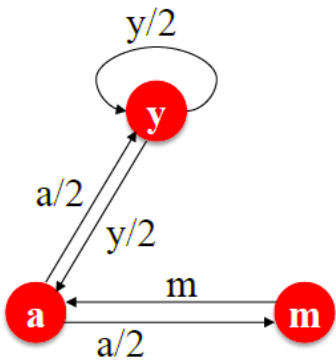
$r = [0.17, 0.07, 0.40, 0.36]$

$S = \{1\}$ ,  $\beta = 0.8$ :

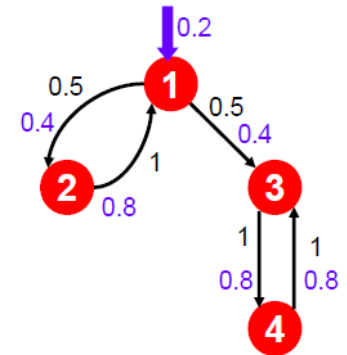
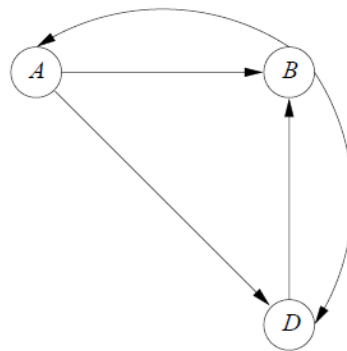
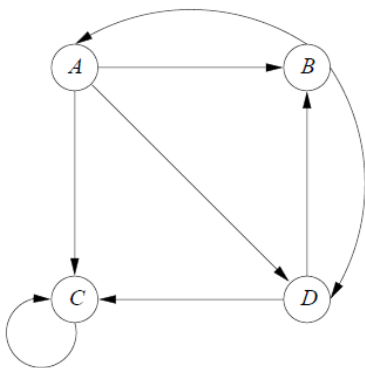
$r = [0.29, 0.11, 0.32, 0.26]$

$S = \{1\}$ ,  $\beta = 0.7$ :

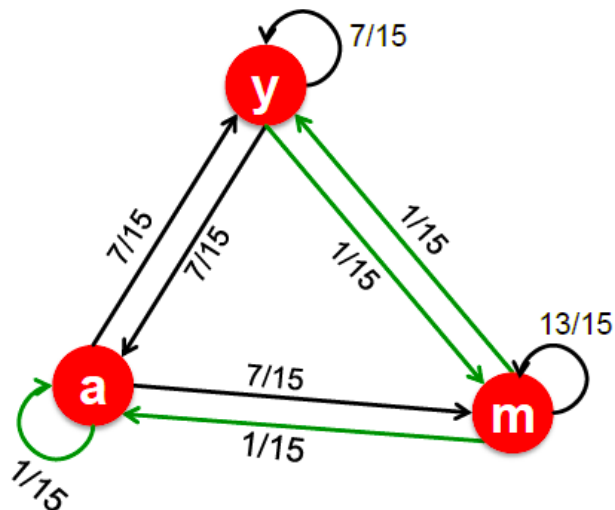
$r = [0.39, 0.14, 0.27, 0.19]$



# Exercises



# EXERCISE I



$$0.8 \begin{matrix} \mathbf{M} \\ \begin{bmatrix} 1/2 & 1/2 & 0 \\ 1/2 & 0 & 0 \\ 0 & 1/2 & 1 \end{bmatrix} \end{matrix} + 0.2 \begin{matrix} \mathbf{[1/N]}_{N \times N} \\ \begin{bmatrix} 1/3 & 1/3 & 1/3 \\ 1/3 & 1/3 & 1/3 \\ 1/3 & 1/3 & 1/3 \end{bmatrix} \end{matrix}$$

$$\mathbf{A} = \begin{matrix} y \\ a \\ m \end{matrix} \begin{bmatrix} 7/15 & 7/15 & 1/15 \\ 7/15 & 1/15 & 1/15 \\ 1/15 & 7/15 & 13/15 \end{bmatrix}$$

$$\begin{matrix} y \\ a \\ m \end{matrix} = \begin{matrix} 1/3 & 0.33 & 0.24 & 0.26 & & 7/33 \\ 1/3 & 0.20 & 0.20 & 0.18 & \dots & 5/33 \\ 1/3 & 0.46 & 0.52 & 0.56 & & 21/33 \end{matrix}$$

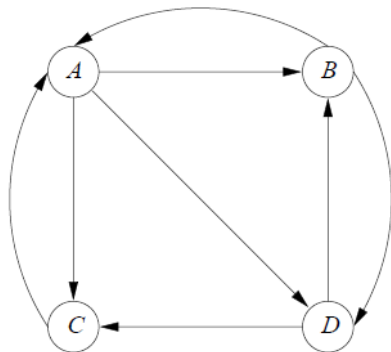
$$A = \beta M + (1 - \beta) \left[ \frac{1}{N} \right]_{N \times N}$$

$[1/N]_{N \times N} \dots N$  by  $N$  matrix  
where all entries are  $1/N$

$$r = \beta M \cdot r + \left[ \frac{1-\beta}{N} \right]_N$$

since  $\sum r_i = 1$

# EXERCISE 2



$$M = \begin{bmatrix} 0 & 1/2 & 1 & 0 \\ 1/3 & 0 & 0 & 1/2 \\ 1/3 & 0 & 0 & 1/2 \\ 1/3 & 1/2 & 0 & 0 \end{bmatrix}$$

$$\begin{bmatrix} 1/4 \\ 1/4 \\ 1/4 \\ 1/4 \end{bmatrix}, \begin{bmatrix} 9/24 \\ 5/24 \\ 5/24 \\ 5/24 \end{bmatrix}, \begin{bmatrix} 15/48 \\ 11/48 \\ 11/48 \\ 11/48 \end{bmatrix}, \begin{bmatrix} 11/32 \\ 7/32 \\ 7/32 \\ 7/32 \end{bmatrix}, \dots, \begin{bmatrix} 3/9 \\ 2/9 \\ 2/9 \\ 2/9 \end{bmatrix}$$

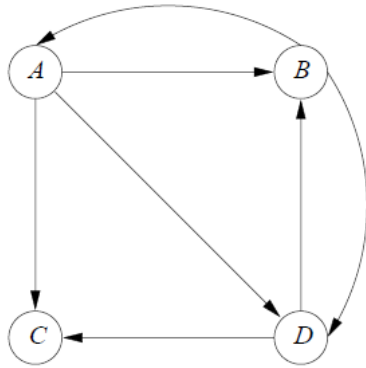
$$A = \beta M + (1 - \beta) \left[ \frac{1}{N} \right]_{N \times N}$$

$[1/N]_{N \times N}$ ...N by N matrix  
where all entries are 1/N

$$r = \beta M \cdot r + \left[ \frac{1-\beta}{N} \right]_N$$

since  $\sum r_i = 1$

# EXERCISE 3



$$M = \begin{bmatrix} 0 & 1/2 & 0 & 0 \\ 1/3 & 0 & 0 & 1/2 \\ 1/3 & 0 & 0 & 1/2 \\ 1/3 & 1/2 & 0 & 0 \end{bmatrix}$$

$$\begin{bmatrix} 1/4 \\ 1/4 \\ 1/4 \\ 1/4 \end{bmatrix}, \begin{bmatrix} 3/24 \\ 5/24 \\ 5/24 \\ 5/24 \end{bmatrix}, \begin{bmatrix} 5/48 \\ 7/48 \\ 7/48 \\ 7/48 \end{bmatrix}, \begin{bmatrix} 21/288 \\ 31/288 \\ 31/288 \\ 31/288 \end{bmatrix}, \dots, \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

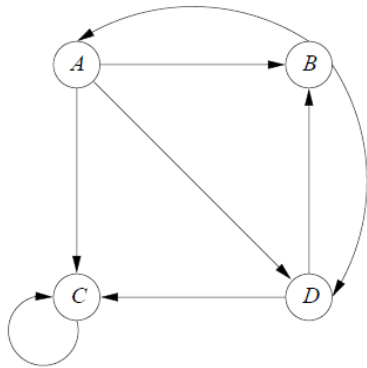
$$A = \beta M + (1 - \beta) \left[ \frac{1}{N} \right]_{N \times N}$$

$[1/N]_{N \times N}$ ...N by N matrix  
where all entries are 1/N

$$r = \beta M \cdot r + \left[ \frac{1-\beta}{N} \right]_N$$

since  $\sum r_i = 1$

# EXERCISE 4



$$M = \begin{bmatrix} 0 & 1/2 & 0 & 0 \\ 1/3 & 0 & 0 & 1/2 \\ 1/3 & 0 & 1 & 1/2 \\ 1/3 & 1/2 & 0 & 0 \end{bmatrix}$$

$$\begin{bmatrix} 1/4 \\ 1/4 \\ 1/4 \\ 1/4 \end{bmatrix}, \begin{bmatrix} 3/24 \\ 5/24 \\ 11/24 \\ 5/24 \end{bmatrix}, \begin{bmatrix} 5/48 \\ 7/48 \\ 29/48 \\ 7/48 \end{bmatrix}, \begin{bmatrix} 21/288 \\ 31/288 \\ 205/288 \\ 31/288 \end{bmatrix}, \dots, \begin{bmatrix} 0 \\ 0 \\ 1 \\ 0 \end{bmatrix}$$

$$A = \beta M + (1 - \beta) \left[ \frac{1}{N} \right]_{N \times N}$$

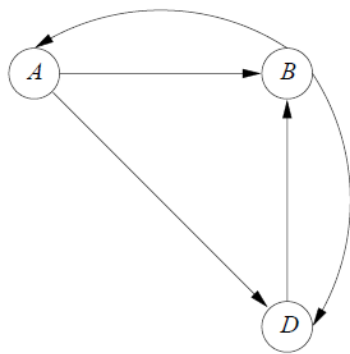
$[1/N]_{N \times N} \dots N$  by  $N$  matrix  
where all entries are  $1/N$

$$r = \beta M \cdot r + \left[ \frac{1-\beta}{N} \right]_N$$

since  $\sum r_i = 1$



# EXERCISE 5



$$M = \begin{bmatrix} 0 & 1/2 & 0 \\ 1/2 & 0 & 1 \\ 1/2 & 1/2 & 0 \end{bmatrix}$$

$$\begin{bmatrix} 1/3 \\ 1/3 \\ 1/3 \end{bmatrix}, \begin{bmatrix} 1/6 \\ 3/6 \\ 2/6 \end{bmatrix}, \begin{bmatrix} 3/12 \\ 5/12 \\ 4/12 \end{bmatrix}, \begin{bmatrix} 5/24 \\ 11/24 \\ 8/24 \end{bmatrix}, \dots, \begin{bmatrix} 2/9 \\ 4/9 \\ 3/9 \end{bmatrix}$$

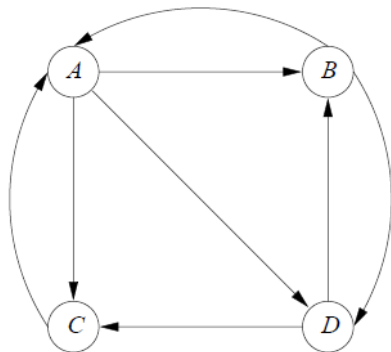
$$A = \beta M + (1 - \beta) \left[ \frac{1}{N} \right]_{N \times N}$$

$[1/N]_{N \times N}$ ...N by N matrix  
where all entries are 1/N

$$r = \beta M \cdot r + \left[ \frac{1-\beta}{N} \right]_N$$

since  $\sum r_i = 1$

# EXERCISE 6

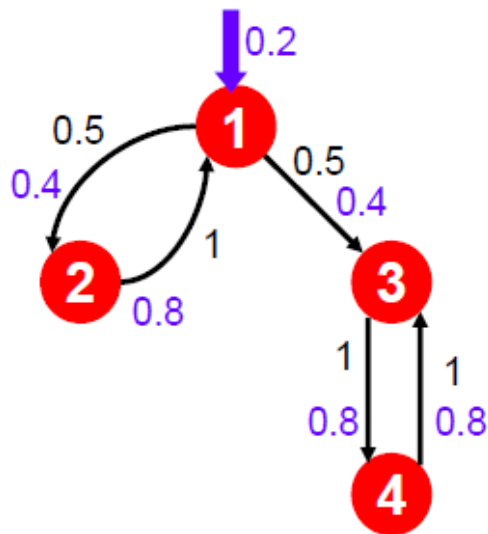


$$\beta M = \begin{bmatrix} 0 & 2/5 & 4/5 & 0 \\ 4/15 & 0 & 0 & 2/5 \\ 4/15 & 0 & 0 & 2/5 \\ 4/15 & 2/5 & 0 & 0 \end{bmatrix}$$

$$\mathbf{v}' = \begin{bmatrix} 0 & 2/5 & 4/5 & 0 \\ 4/15 & 0 & 0 & 2/5 \\ 4/15 & 0 & 0 & 2/5 \\ 4/15 & 2/5 & 0 & 0 \end{bmatrix} \mathbf{v} + \begin{bmatrix} 0 \\ 1/10 \\ 0 \\ 1/10 \end{bmatrix}$$

$$\begin{bmatrix} 0/2 \\ 1/2 \\ 0/2 \\ 1/2 \end{bmatrix}, \begin{bmatrix} 2/10 \\ 3/10 \\ 2/10 \\ 3/10 \end{bmatrix}, \begin{bmatrix} 42/150 \\ 41/150 \\ 26/150 \\ 41/150 \end{bmatrix}, \begin{bmatrix} 62/250 \\ 71/250 \\ 46/250 \\ 71/250 \end{bmatrix}, \dots, \begin{bmatrix} 54/210 \\ 59/210 \\ 38/210 \\ 59/210 \end{bmatrix}$$

# TOPIC-SPECIFIC PAGE RANK



Suppose  $S = \{1\}$ ,  $\beta = 0.8$

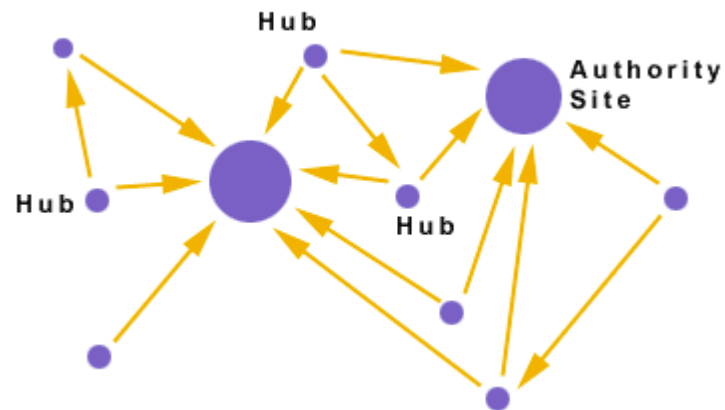
Node	Iteration				
	0	1	2	...	stable
1	0.25	0.4	0.28		0.294
2	0.25	0.1	0.16		0.118
3	0.25	0.3	0.32		0.327
4	0.25	0.2	0.24		0.261

beta=0.8		0.9	0.7
S={1,2,3,4}	S={1,2,3}	S={1,2}	S={1}
0.13	0.17	0.26	0.29
0.1	0.13	0.2	0.11
0.39	0.38	0.29	0.32
0.36	0.3	0.23	0.26

$S=\{1,2,3,4\}$ ,  $\beta=0.8$ :  
 $r=[0.13, 0.10, 0.39, 0.36]$   
 $S=\{1\}$ ,  $\beta=0.9$ :  
 $r=[0.17, 0.07, 0.40, 0.36]$   
 $S=\{1,2,3\}$ ,  $\beta=0.8$ :  
 $r=[0.17, 0.13, 0.38, 0.30]$   
 $S=\{1,2\}$ ,  $\beta=0.8$ :  
 $r=[0.26, 0.20, 0.29, 0.23]$   
 $S=\{1\}$ ,  $\beta=0.8$ :  
 $r=[0.29, 0.11, 0.32, 0.26]$   
 $S=\{1\}$ ,  $\beta=0.7$ :  
 $r=[0.39, 0.14, 0.27, 0.19]$   
 $S=\{1\}$ ,  $\beta=0.8$ :  
 $r=[0.29, 0.11, 0.32, 0.26]$

## Avtoritete

- ugledne spletne strani (npr. spletne strani univerz in vladnih organov)
- vsebujejo koristne informacije



## Vozlišča

- spletne strani s povezavami do avtoritet  
oz. spletnih strani s koristnimi informacijami

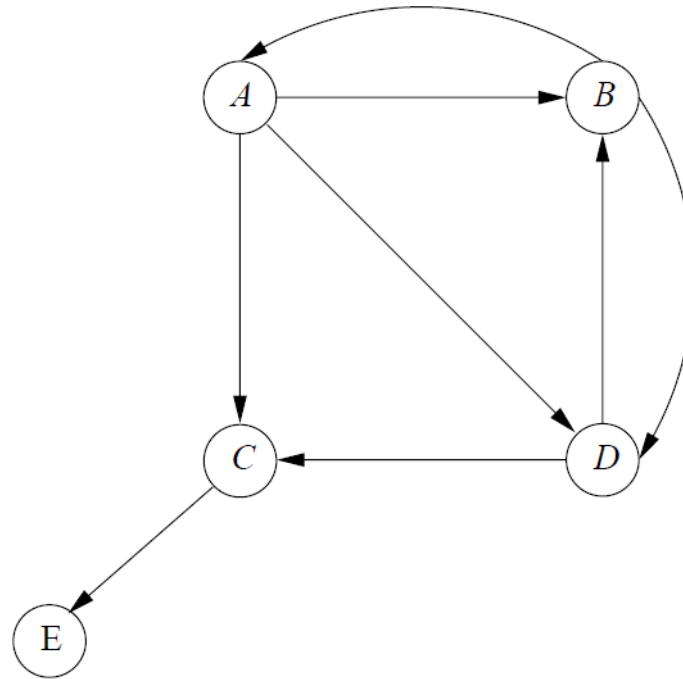


Figure 5.18: Sample data used for HITS examples

$$L = \begin{bmatrix} 0 & 1 & 1 & 1 & 0 \\ 1 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \\ 0 & 1 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix} \quad L^T = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 1 & 0 \\ 1 & 0 & 0 & 1 & 0 \\ 1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \end{bmatrix}$$

Repeat until convergence (or use fixed number of iterations):

1. Compute  $\mathbf{a} = L^T \mathbf{h}$ .
2. Scale so the largest component is 1.
3. Compute  $\mathbf{h} = L \mathbf{a}$ .
4. Scale again so the largest component is 1.

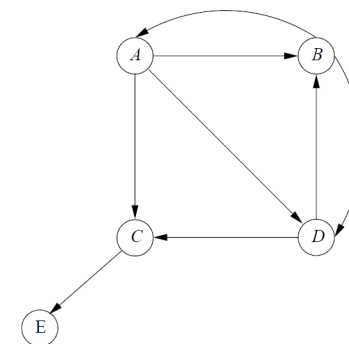


Figure 5.18: Sample data used for HITS examples

$$L = \begin{bmatrix} 0 & 1 & 1 & 1 & 0 \\ 1 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \\ 0 & 1 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix} \quad L^T = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 1 & 0 \\ 1 & 0 & 0 & 1 & 0 \\ 1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \end{bmatrix}$$

$$\begin{matrix} \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \\ 1 \end{bmatrix} & \begin{bmatrix} 1 \\ 2 \\ 2 \\ 2 \\ 1 \end{bmatrix} & \begin{bmatrix} 1/2 \\ 1 \\ 1 \\ 1 \\ 1/2 \end{bmatrix} & \begin{bmatrix} 3 \\ 3/2 \\ 1/2 \\ 2 \\ 0 \end{bmatrix} & \begin{bmatrix} 1 \\ 1/2 \\ 1/6 \\ 2/3 \\ 0 \end{bmatrix} \\ \mathbf{h} & L^T \mathbf{h} & \mathbf{a} & L \mathbf{a} & \mathbf{h} \end{matrix}$$

$$\begin{matrix} \begin{bmatrix} 1/2 \\ 5/3 \\ 5/3 \\ 3/2 \\ 1/6 \end{bmatrix} & \begin{bmatrix} 3/10 \\ 1 \\ 1 \\ 9/10 \\ 1/10 \end{bmatrix} & \begin{bmatrix} 29/10 \\ 6/5 \\ 1/10 \\ 2 \\ 0 \end{bmatrix} & \begin{bmatrix} 1 \\ 12/29 \\ 1/29 \\ 20/29 \\ 0 \end{bmatrix} \\ L^T \mathbf{h} & \mathbf{a} & L \mathbf{a} & \mathbf{h} \end{matrix}$$

$$\sum_i \left( \bar{h}_i^{(t)} - h_i^{(t-1)} \right)^2 < \varepsilon$$

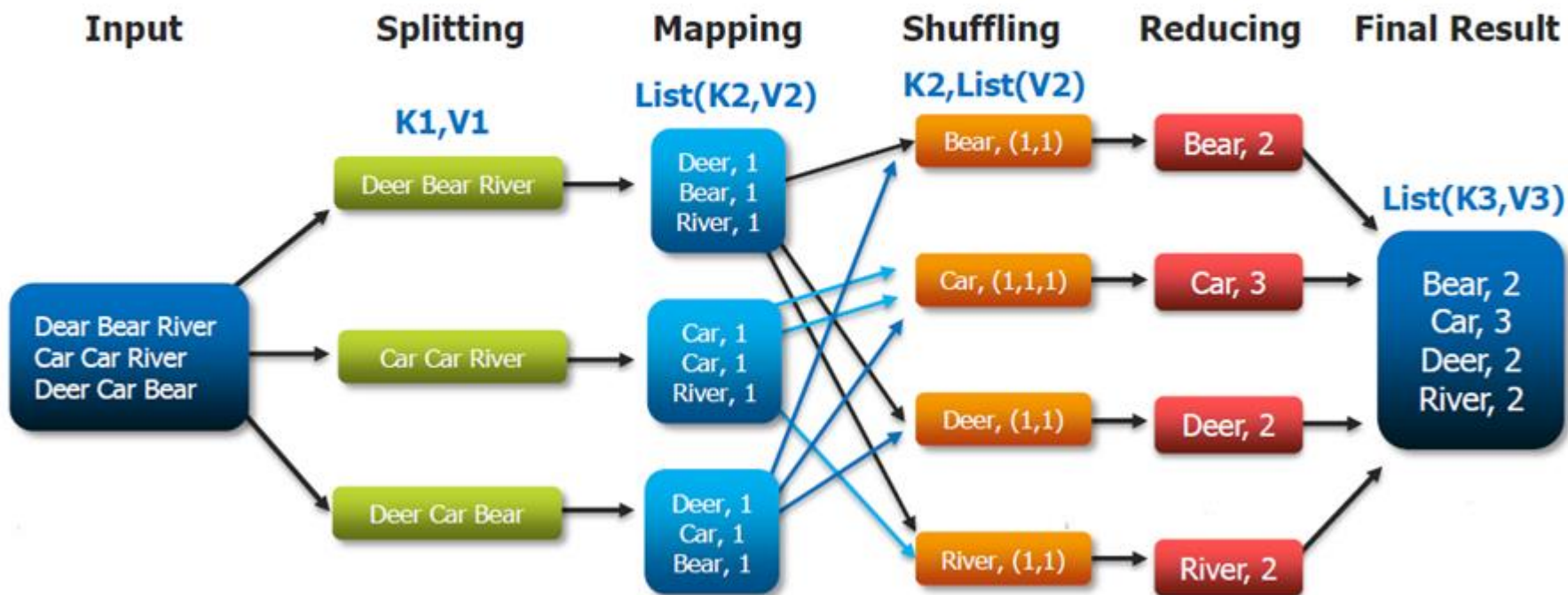
$$\sum_i \left( a_i^{(t)} - a_i^{(t-1)} \right)^2 < \varepsilon$$

# HITS SIMULATION

SUM :  $\times$   $\checkmark$   $f_x$   $=\$H2*\$A\$9+\$I2*\$A\$10+\$J2*\$A\$11+\$K2*\$A\$12+\$L2*\$A\$13$

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	
1		L						L <sup>T</sup>										
2		0	1	1	1	0		0	1	0	0	0						
3		1	0	0	1	0		1	0	0	1	0						
4		0	0	0	0	1		1	0	0	1	0						
5		0	1	1	0	0		1	1	0	0	0						
6		0	0	0	0	0		0	0	1	0	0						
7																		
8	h	LTh	a	La	h	LTh	a	La	h	LTh	a	La	h	LTh	a	La	h	
9	1.000	=H2*A\$9	0.500	3.000	1.000	0.500	0.300	2.900	1.000	0.414	0.245	2.837	1.000	0.381	0.224	2.810	1.000	
10	1.000	2.000	1.000	1.500	0.500	1.667	1.000	1.200	0.414	1.690	1.000	1.082	0.381	1.705	1.000	1.034	0.368	
11	1.000	2.000	1.000	0.500	0.167	1.667	1.000	0.100	0.034	1.690	1.000	0.020	0.007	1.705	1.000	0.004	0.002	
12	1.000	2.000	1.000	2.000	0.667	1.500	0.900	2.000	0.690	1.414	0.837	2.000	0.705	1.381	0.810	2.000	0.712	
13	1.000	1.000	0.500	0.000	0.000	0.167	0.100	0.000	0.000	0.034	0.020	0.000	0.000	0.007	0.004	0.000	0.000	
14																		
15					0.00000		0.20000		0.00000		0.05510		0.00000		0.02127		0.00000	
16					0.50000		0.00000		0.08621		0.00000		0.03250		0.00000		0.01343	
17					0.83333		0.00000		0.13218		0.00000		0.02729		0.00000		0.00569	
18					0.33333		0.10000		-0.02299		0.06327		-0.01538		0.02661		-0.00668	
19					1.00000		0.40000		0.00000		0.07959		0.00000		0.01619		0.00000	

## The Overall MapReduce Word Count Process



source: <https://wikis.nyu.edu/display/NYUHPC/Tutorials>



## STEP 1: obtain key-value pairs for $L$ and $L^T$

```
L =          # key-value pairs for L-matrix  
LT =         # key-value pairs for transpose of L-matrix
```

## STEP 2: start with $h$ (hubbiness) vector of all 1's

```
h =          # initial hubbiness vector
```

## STEP 3: compute vectors $h$ (hubbiness) and $a$ (authority) iteratively in mutual recursion

```
for _ in range(NUM_ITERATIONS):  
    a =          # compute a = LTh  
    a_max =      # obtain maximum value in a  
    a =          # scale a so the largest component is 1  
  
    h =          # compute h = La  
    h_max =      # obtain maximum value in h  
    h =          # scale h so the largest component is 1
```

## STEP 4: List the nodes with the highest/lowest hubbiness/authority score

## STANFORD COMPUTER SCIENCE COURSE CS246: MINING MASSIVE DATASETS: BOOK

- Mining of Massive Datasets book by Jure Leskovec, Anand Rajaraman, and Jeff Ullman.  
<http://www.mmds.org/>

## STANFORD COMPUTER SCIENCE COURSE CS246: MINING MASSIVE DATASETS: HANDOUTS

- Page, Lawrence, Sergey Brin, Rajeev Motwani, and Terry Winograd. "The pagerank citation ranking: Bring order to the web." In Stanford Digital Libraries Working Paper. 1998.

