



# PageRank: An Eigenvector Problem

Minh Tran • Komlan Wussin • Tony Nielsen





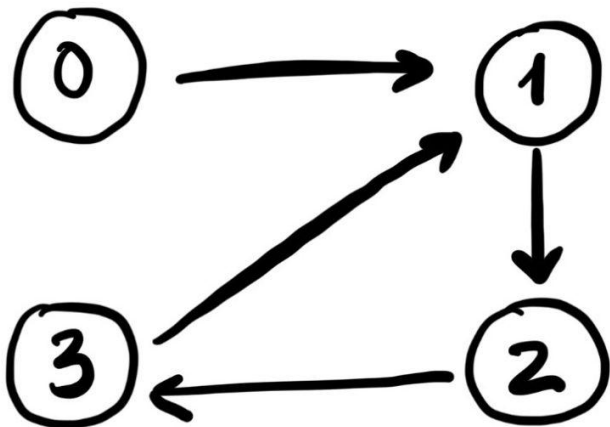
## What is the PageRank algorithm?

- **Larry Page & Sergey Brin (1998)**
- Determine a page's **importance** based on link structure
- A page is important if other **important pages linked** to it
- The secret sauce of the world's **most powerful** search engine
- I.e. Forbes, academic pages, etc.

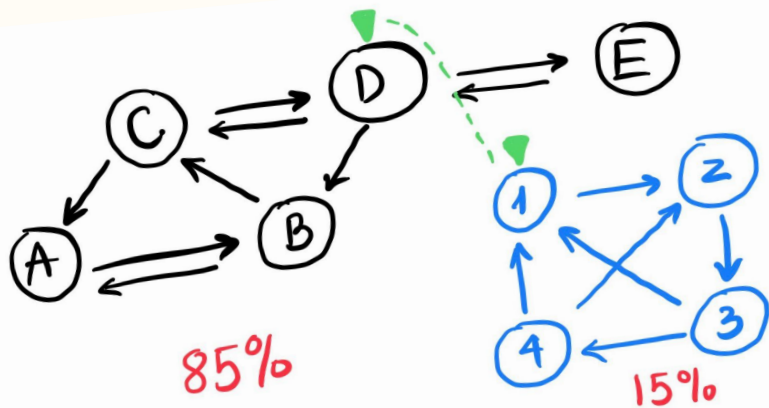
# The Web as a Directed Graph

Nodes = **pages** | Edges = **links** | Adjacency Matrix: column = **outgoing**, row = **incoming**

Out-degree: **# of outgoing link**



|   | 0 | 1 | 2 | 3 |
|---|---|---|---|---|
| 0 | 0 | 0 | 0 | 0 |
| 1 | 1 | 0 | 0 | 1 |
| 2 | 0 | 1 | 0 | 0 |
| 3 | 0 | 0 | 1 | 0 |

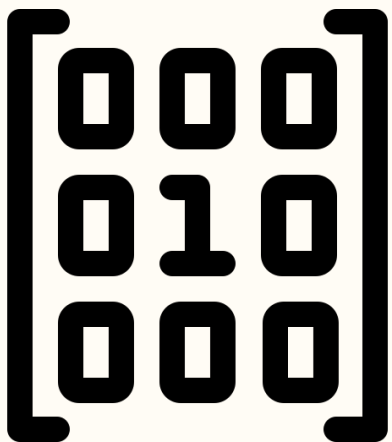


## Random Surfer Model

**Damping factor:** typically 0.85

- 85% follow links
- 15% hop to random pages
- More on this later ...

# The PageRank Equation



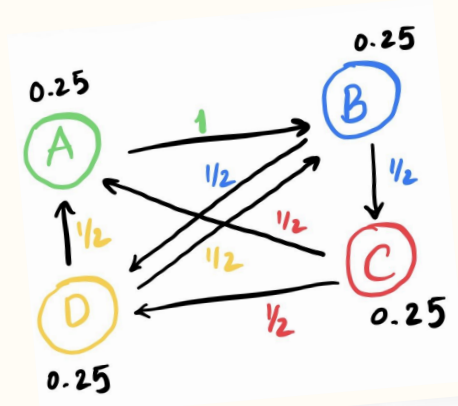
Transition Matrix



Google Matrix



PageRank Vector

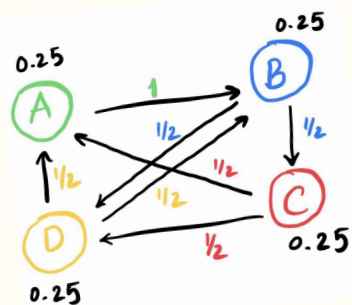


|      | OUT |     |     |     |
|------|-----|-----|-----|-----|
|      | A   | B   | C   | D   |
| IN A | 0   | 0   | 1/2 | 1/2 |
| B    | 1   | 0   | 0   | 1/2 |
| C    | 0   | 1/2 | 0   | 0   |
| D    | 0   | 1/2 | 1/2 | 0   |

## Transition Matrix M

$$M_{ij} = 1 / d_j$$

- Page j links to page i
- Column-stochastic (sums to 1)
- $d_j > 0$ : out-degree of page j



|      | OUT |     |     |     |
|------|-----|-----|-----|-----|
|      | A   | B   | C   | D   |
| IN A | 0   | 0   | 1/2 | 1/2 |
| B    | 1   | 0   | 0   | 1/2 |
| C    | 0   | 1/2 | 0   | 0   |
| D    | 0   | 1/2 | 1/2 | 0   |

For each entry:  $G_{ij} = \alpha M + \frac{1-\alpha}{n}$

$G_{11} = 0.85(0) + \frac{1-0.85}{4}$

$$G = \begin{bmatrix} 0.0375 & 0.0375 & 0.4625 & 0.4625 \\ 0.8875 & 0.0375 & 0.0375 & 0.0375 \\ 0.0375 & 0.4625 & 0.0375 & 0.0375 \\ 0.0375 & 0.4625 & 0.4625 & 0.0375 \end{bmatrix}$$

# Google Matrix G

$$G = \alpha M + (1-\alpha)/n (ee^T)$$

- $\alpha$  - damping factor : 0.85
- 2nd term:
  - Damping adjustment or teleportation
  - Uniform probability

$$(1-\alpha)/n (ee^T)$$

- Handle dead ends
  - Stuck = sum < 1
- Closed-circle traps
  - Spam farming
- Connection & Speed
  - Not fully connected
  - Huge computing time
- Humanizing the algorithm
  - 85% following links
  - 15% reset

# PageRank as an Eigenvector Problem

$$R_{k+1} \lambda = G \times R_k$$

- Power iteration

- $\dots(G(G(G \times R)))$

- $\lim_{n \rightarrow \infty} G^n R = R$

- Eigenvalue  $\lambda = 1$

- $R$ : rank scores = probabilities sums to 1

→  $\lambda$  forced to be 1

- Self-consistent

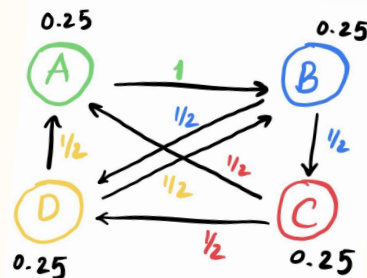
- Stable ranking system

$$G = \begin{bmatrix} 0.0375 & 0.0375 & 0.4625 & 0.4625 \\ 0.8875 & 0.0375 & 0.0375 & 0.4625 \\ 0.0375 & 0.4625 & 0.0375 & 0.0375 \\ 0.0375 & 0.4625 & 0.4625 & 0.0375 \end{bmatrix} \times \begin{matrix} R_0 \\ \downarrow \\ \begin{bmatrix} 0.25 \\ 0.25 \\ 0.25 \\ 0.25 \end{bmatrix} \end{matrix}$$

$$R_1 \approx \begin{bmatrix} +0.25 \\ +0.36 \\ +0.14 \\ +0.25 \end{bmatrix}$$


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# Python Demonstration

<https://github.com/minhtran021999/PageRank-Project.git>

**PAGE RANK YOU FOR  
YOUR ATTENTION!**

**The End.**