PageRank

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Background

Search engine

Searches for information on World Wide Web based on keywords

Programmed to rank sites based on popularity, relevance

Three functions:

Crawling

Indexing

Searching

Source: Brin and Page, 1998

History

Archie (1990) - first search engine

Hosted an index of directory listings (no contents)

WebCrawler and Lycos (1994)
Able to search words of webpage

AskJeeves (1997)

Natural language search engine, ranked links by popularity

Yahoo! (pre-Google)
Searchable directory

The problem

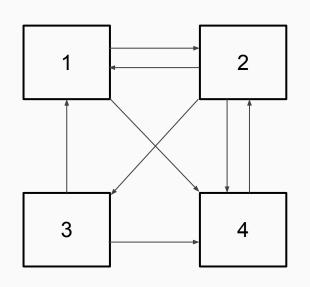
Text-based ranking systems of old search engines were easily manipulated Ex: Searching "Internet" pre-Google

"Any evaluation strategy which counts replicable features of web pages is prone to manipulation" (Page)

"Pages [were] engineered to manipulate search engine ranking functions" (Page)

Source: Brin and Page, 1998

The Internet as a directed graph



Nodes = pages, edges = links

Backlinks: hyperlinks from a page to another page i.e. edges directed towards nodes

Pages with many backlinks considered relevant



Linear algebra tutorial

Definitions and properties

Coefficient Matrix: An m x n matrix, **A**, containing only the coefficients of a linear system

Linear Independence: The columns of the matrix, \mathbf{A} , are linearly independent if and only if the equation $\mathbf{A}\mathbf{x} = 0$ has the trivial solution

Column-Stochastic Matrix: A square matrix, **A**, where every entry is non-negative $[\mathbf{A}_{ij} \ge 0]$, the entries in each column sum to 1 [for j=1 to n, $\sum \mathbf{A}_{ij} = 1$], and has an $\lambda = 1$

Eigenvalue: a scalar, λ , such that $\mathbf{A}\mathbf{x} = \lambda \mathbf{x}$, holds for some nonzero vector \mathbf{x}

Eigenvector: a nonzero vector \mathbf{x} of an $n \times n$ matrix, \mathbf{A} , such that $\mathbf{A}\mathbf{x} = \lambda \mathbf{x}$. Any nonzero multiple of an eigenvector is also an eigenvector.

Eigenspace: The null space of $(A - \lambda)I$

Source: Aerostudents, Bryan & Leise, 2006

Definitions and properties

Markov chain: A collection of random variables $\{X_t\}$ (t > 0) with the property that given the present, the future is conditionally independent of the past. i.e.

$$P(X_{t} = j \mid X_{t-1} = i_{t-1}, X_{t-2} = i_{t-2}, ..., X_{0} = i_{0}) = P(X_{t} = j \mid X_{t-1} = i_{t-1})$$

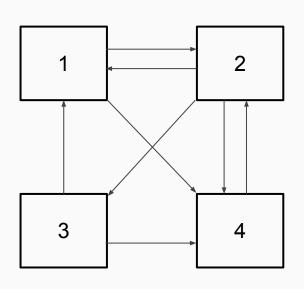
Column-Stochastic Matrix: A square matrix, **A**, where every entry is non-negative $[\mathbf{A}_{ij} \ge 0]$, the entries in each column sum to 1 [for j=1 to n, $\sum \mathbf{A}_{ij} = 1$], and has an $\lambda = 1$

Random walk: A random process consisting of a sequence of discrete steps of a fixed length; an example of a Markov chain.

Source: Weisstein, Eric

PageRank basics & simple example

Example: web is n = 4 pages (1/6)



 $x_k = \#$ of backlinks to page k

In this example:

$$x_1 = 2$$

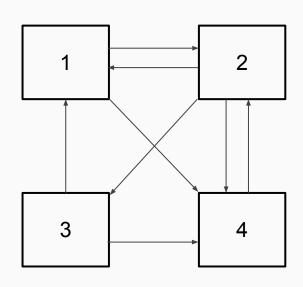
$$x_2 = 2$$

$$x_3 = 1$$
 [least important]

$$x_4 = 3$$
 [most important]

```
i = page i = backlink from page A to B
```

Example: web is n = 4 pages (2/6)



 $x_k = \#$ of backlinks to page k

In this example:

$$x_1 = 2$$

$$x_2 = 2$$

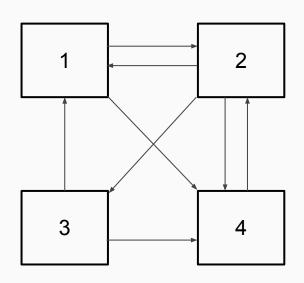
$$x_3 = 1$$
 [least important]

$$x_A = 3$$
 [most important]

PROBLEM:

- Are all links equal?
- What if a page has a large number of links?

Example: web is n = 4 pages (3/6)



ANSWER:

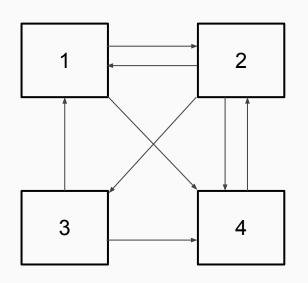
- Each page j gets a total vote of 1, that is weighted by page j's score, and divided evenly by its outgoing links
- x_k = ∑x_j / n_j
 x_j = page score of page j
 n_i = # of links out of page j

In this example:

$$x_1 = x_2/3 + x_3/2$$

 $x_2 = x_1/2 + x_2/3$
 $x_3 = x_2/3$
 $x_4 = x_1/2 + x_3/3 + x_3/2$

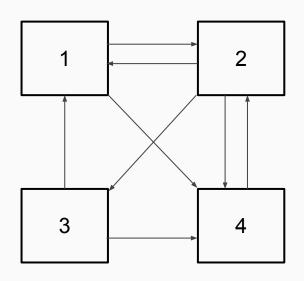
Example: web is n = 4 pages (4/6)



METHOD 1: We can rewrite as the link matrix, **A**, of coefficients and the unique, nonnegative eigenvector, **x**, with eigenvalues of 1.

Let
$$\mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix}$$
 s.t. $\mathbf{x} = \mathbf{A}\mathbf{x}$ and $\mathbf{A} = \begin{bmatrix} 0 & \frac{1}{3} & \frac{1}{2} & 0 \\ \frac{1}{2} & 0 & 0 & 1 \\ 0 & \frac{1}{3} & 0 & 0 \\ \frac{1}{2} & \frac{1}{3} & \frac{1}{2} & 0 \end{bmatrix}$ with λ 's = 1

Example: web is n = 4 pages (5/6)



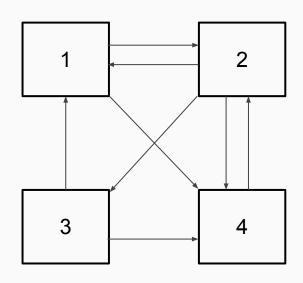
METHOD 1: We can rewrite as the link matrix, **A**, of coefficients and the unique, nonnegative eigenvector, **x**, with eigenvalues of 1.

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By setting $\mathbf{A}\mathbf{x} = \lambda \mathbf{x}$ or $(\mathbf{A} - \lambda \mathbf{I})\mathbf{x} = \mathbf{0}$, we find that

$$\mathbf{x} = \begin{bmatrix} 2/3 \\ 4/3 \\ 4/9 \\ 1 \end{bmatrix} = \begin{bmatrix} 0.194 \\ 0.387 \\ 0.129 \\ 0.290 \end{bmatrix}$$
 s.t. $\mathbf{\Sigma} \mathbf{x} = 1$ & dim $[\mathbf{V}_{1}(\mathbf{A})] = 1$

Example: web is n = 4 pages (6/6)



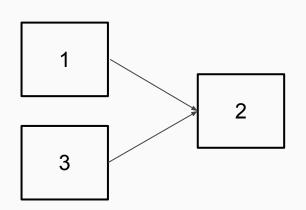
METHOD 2: This can be seen as a random walk. **A** is the transition matrix, **x** is the vector of stationary probabilities, and x is the vector of initial probabilities ($\frac{1}{4}$).

Let
$$\mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix}$$
 $\mathbf{x} = \begin{bmatrix} \frac{1}{4} \\ \frac{1}{4} \\ \frac{1}{4} \\ \frac{1}{4} \end{bmatrix}$ and $\mathbf{A} = \begin{bmatrix} 0 & \frac{1}{3} & \frac{1}{2} & 0 \\ \frac{1}{2} & 0 & 0 & 1 \\ 0 & \frac{1}{3} & 0 & 0 \\ \frac{1}{2} & \frac{1}{3} & \frac{1}{2} & 0 \end{bmatrix}$

To solve $\mathbf{A}^{\infty}x$, we solve for the stationary distribution through $\mathbf{x}^{\mathsf{T}}=\mathbf{x}^{\mathsf{T}}\mathbf{A}$.

Issues & complex example

Issues with simple model - dangling node (1/2)



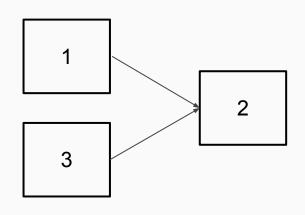
Using prior method, the calculated rank of every page is zero

Obviously not true, since page 2 is most important

Page 2 is called a dangling node



Issues with simple model - dangling node (2/2)



i = page i = backlink from page A to B

Using prior method, the calculated rank of every page is zero

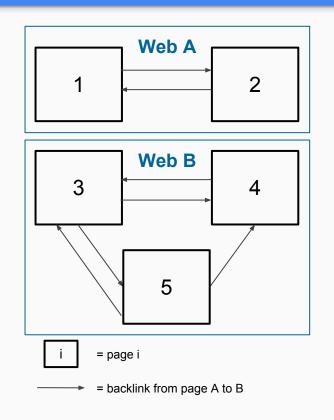
Obviously not true, since page 2 is most important

Page 2 is called a dangling node

Dangling nodes

- A is column-substochastic
 - Entries in each column sum to less than or equal to 1 [for j=1 to n, $\sum \mathbf{A}_{ij} \le 1$]
 - \circ $\lambda \leq 1$

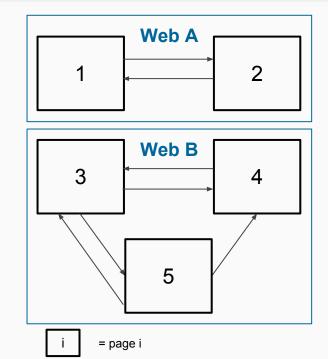
Issues with simple model - disconnected graphs (1/2)



We let
$$\mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix}$$
 s.t. $\mathbf{A}\mathbf{x} = \lambda \mathbf{x}$ $\mathbf{A} = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & \frac{1}{2} \\ 0 & 0 & \frac{1}{2} & 0 & \frac{1}{2} \\ 0 & 0 & \frac{1}{6} & 0 & 0 \end{bmatrix}$ with λ 's = 1

Webs A and B are disconnected graphs with non-unique rankings

Issues with simple model - disconnected graphs (2/2)



= backlink from page A to B

We let

$$\mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \end{bmatrix}$$
 s.t. $\mathbf{A}\mathbf{x} = \lambda \mathbf{x}$ $\mathbf{A} = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & \frac{1}{2} \\ 0 & 0 & \frac{1}{2} & 0 & \frac{1}{2} \\ 0 & 0 & \frac{1}{2} & 0 & 0 \end{bmatrix}$ with λ 's = 1

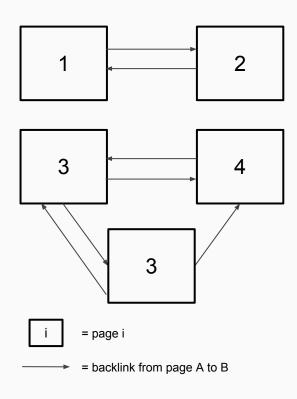
Webs A and B are **disconnected graphs** with **non-unique rankings** By setting $\mathbf{A}\mathbf{x} = \lambda \mathbf{x}$ or $(\mathbf{A} - \lambda \mathbf{I})\mathbf{x} = \mathbf{0}$, we find there are **2** eigenvectors

$$\mathbf{x}_{1} = \begin{bmatrix} 1 \\ 1 \\ 0 \\ 0 \\ 0 \end{bmatrix} \quad \begin{cases} & \mathbf{x}_{2} = \begin{bmatrix} 0 \\ 0 \\ 2 \\ 1.5 \\ 1 \end{cases}$$

Non-unique rankings

• $dim[V_1(A)] > r$, where r = # of sub-webs

PageRank modification (1/2)

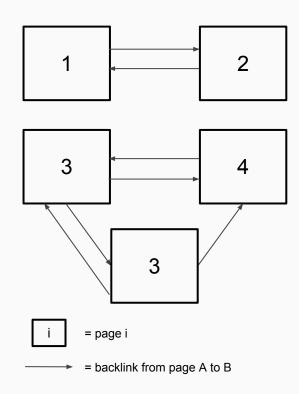


Consider model as "random surfer" instead of "random walk"

- Surfer will often follow links from one page to another (represented by matrix A from before)
- A small m% of the time, surfer will choose an arbitrary page
 - *m* called the **damping factor**

New transition matrix is still positive, column-stochastic

PageRank modification (2/2)



Consider model as "random surfer" instead of "random walk"

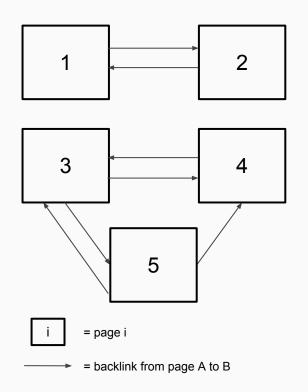
- Surfer will often follow links from one page to another (represented by matrix A from before)
- A small m% of the time, surfer will choose an arbitrary page
 - o m called the damping factor

New transition matrix is still positive, column-stochastic

$$\mathbf{M} = (1 - m)\mathbf{A} + m\mathbf{S}$$

- $m \in [0,1]$ (Google reportedly uses m = 0.15)
 - o m is called the **damping factor**
- $S = n \times n$ matrix with all entries 1/n

Comparing PageRank scores from matrix A and matrix M (5x5)

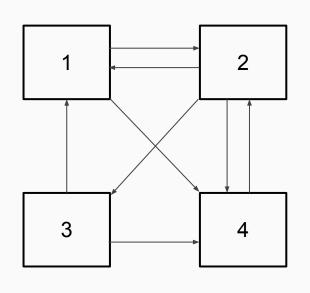


Matrix A:

Matrix M:

$$\begin{bmatrix}
0.03 & 0.88 & 0.03 & 0.03 & 0.03 \\
0.88 & 0.03 & 0.03 & 0.03 & 0.03 \\
0.03 & 0.03 & 0.03 & 0.88 & 0.455 \\
0.03 & 0.03 & 0.455 & 0.03 & 0.455 \\
0.03 & 0.03 & 0.455 & 0.03 & 0.03
\end{bmatrix}$$
 $x = \begin{bmatrix} 0.2 \\ 0.2 \\ 0.2 \\ 0.26 \\ 0.2 \\ 0.14 \end{bmatrix}$

Comparing PageRank scores from matrix A and matrix M (4x4)



Matrix A:

$$\left[
\begin{array}{cccccc}
0 & \frac{1}{3} & \frac{1}{2} & 0 \\
\frac{1}{2} & 0 & 0 & 1 \\
0 & \frac{1}{3} & 0 & 0 \\
\frac{1}{2} & \frac{1}{3} & \frac{1}{2} & 0
\end{array}
\right]$$

 $x = \begin{vmatrix} 0.194 \\ 0.387 \end{vmatrix}$

0.129 0.290

Matrix M:

Note the rankings are the same in a connected web

Is the modification appropriate?

Must test for **column-stochasticity**, **existence** and **uniqueness**

- Is M column-stochastic?
- Existence: does every column-stochastic matrix have 1 as an eigenvalue?
- Uniqueness: is $V_1(\mathbf{M})$ one-dimensional?

Perron-Frobenius Theorem: a real square matrix has a unique largest eigenvalue, with the corresponding eigenvector having only positive or negative entries

Source: Wikipedia

Computation

Numerical analysis of PageRank (1/2)

In real life, matrix M may be a billion-dimensional matrix

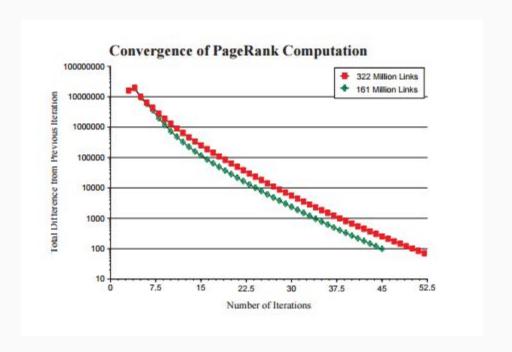
Computing an eigenvector requires iteration

Power Method Convergence Theorem

• Let x_0 represent the initial vector. The sequence x_0 , Mx_0 , M^2x_0 , ..., M^kx_0 converges to the eigenvector x

Source: Tanase and Radu, 2009

Numerical analysis of PageRank (2/2)



Source: Brin & Page, 1998

Python functions

```
def getM(A,m,n):
    S = ones((n,n))/n
    return (1-m)*A + m*S

def powerMethod(A,x0,k):
    for i in range(0,k):
        x0 = dot(A,x0)
    return x0
```

getM: computes M matrix

powerMethod: given initial vector \mathbf{x}_0 , number of iterations k, and matrix **A**, $\mathbf{A}^k \mathbf{x}_0$ is calculated

Implications and future

How to get a high PageRank?

Control a site that has many affiliates referring back it E.g. NYT's home page

Create something that other sites will use, and have a link back E.g. "Powered by ..."

Beware of risky methods

Ex: RapGenius, December 2013

Source: Rogers

Implications

```
Google created to test PageRank
```

"25 billion dollar eigenvector"

64% of market share, valued at ~\$500B (as of July 2015)

Outside applications

Ecological modeling

Network modeling

Recommendation systems

Currently, PageRank is one of many algorithms (N=200+) used by Google to filter search results

Sources: Comscore, 2015

About us

Varun Kumar



Marco Groenendaal



Source: LinkedIn

Appendix

Sources

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R. Tanase and R. Radu, Lecture #3: PageRank Algorithm - The Mathematics of Google Search. http://www.math.cornell.edu/~mec/Winter2009/RalucaRemus/Lecture3/lecture3.html, (accessed October 2, 2015).

A little bit of humor

Web Page	PageRank (average is 1.0)
Download Netscape Software	11589.00
http://www.w3.org/	10717.70
Welcome to Netscape	8673.51
Point: It's What You're Searching For	7930.92
Web-Counter Home Page	7254.97
The Blue Ribbon Campaign for Online Free Speech	7010.39
CERN Welcome	6562.49
Yahoo!	6561.80
Welcome to Netscape	6203.47
Wusage 4.1: A Usage Statistics System For Web Servers	5963.27
The World Wide Web Consortium (W3C)	5672.21
Lycos, Inc. Home Page	4683.31
Starting Point	4501.98
Welcome to Magellan!	3866.82
Oracle Corporation	3587.63

Table 1: Top 15 Page Ranks: July 1996

Source: Brin and Page, 1998