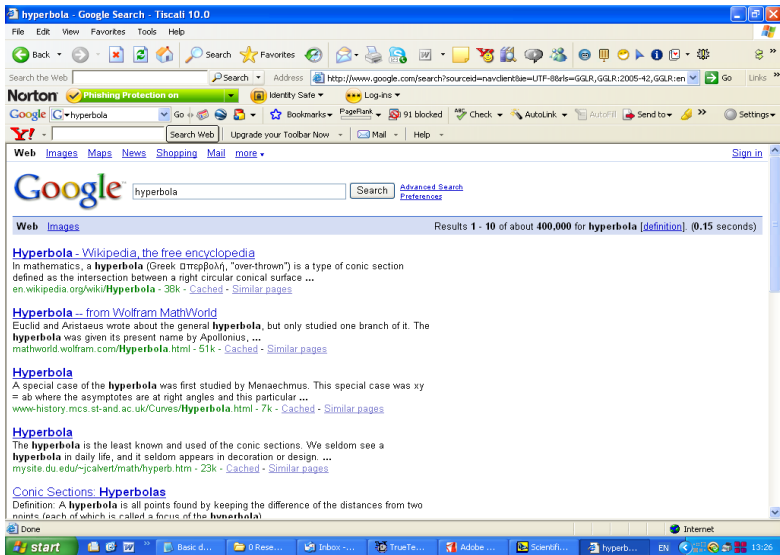


Google: An Application of Linear Algebra

(The mathematics of a great success)

Peter Butkovic



madonna - Google Search - Tiscali 10.0

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Madonna's official web site and fan club, featuring news, photos, concert tickets, merchandise, and more.
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[Madonna \(entertainer\) - Wikipedia, the free encyclopedia](#)
Madonna Louise Ciccone Ritchie (born August 16, 1958), known as **Madonna**, is an American pop singer-songwriter, record producer, and actress. ...
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Soundtrack: Die Another Day. The remarkable, hyper-ambitious Material Girl who never stops re-inventing... Visit IMDb for Photos, Filmography, Discussions, ...
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 [Madonna's Ford Field date set for Nov. 18](#) - 5 Aug 2008
The date confirms information reported this week by the Free Press and hinted at by **Madonna** during a weekend film screening in Traverse City. ...
[Detroit Free Press - 687 related articles >](#)
[Justin Timberlake's 'specific' Madonna - China Daily - 12 related articles >](#)

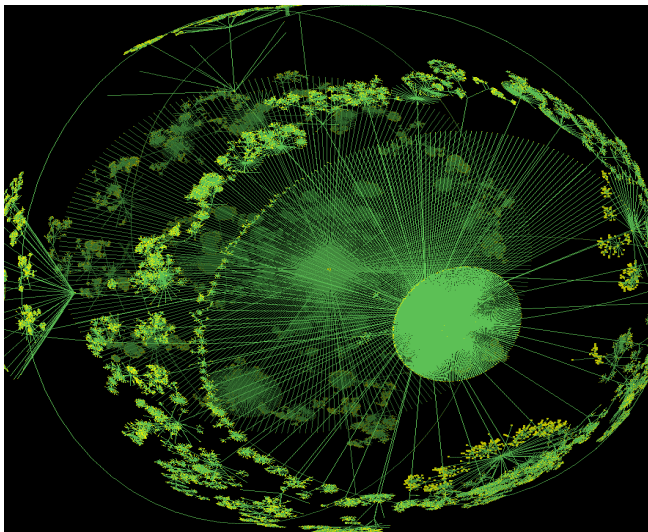
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Modelling the Universe, explaining reality, exploring the unknown.

A warm welcome to the School of Mathematics

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- [Extremal Combinatorics Workshop](#): 15-16 September 2008
- [LMS/EPSCRC short instructional course: Algebraic groups and related topics](#): 15-19 September 2008
- NEW! [Postgraduate Scholarships](#) available
- [Centre for Mathematical Modeling and Chemical Engineering](#) - a result of collaborations between the School of Mathematics and Chemical Engineering

School Intranet

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POSTGRADUATE STUDY

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Today's featured article

The **history of timekeeping devices** begins thousands of years ago with the invention of the **sexagesimal system of time measurement** in approximately 2000 BC, in **Sumer**. The **Ancient Egyptians** divided the day into two 12-hour periods and used large **obelisks** to track the movement of the Sun. They also developed **water clocks**, which were probably first used in the **Precinct of Amun-Re**, and later outside Egypt as well. Other ancient timekeeping devices include the **candle clock**, used in China, Japan, England, and Iraq; the **timestick**, used in India and Tibet, as well as some parts of Europe; and the **hourglass**, which functioned similarly to a water clock. The first clock with an **escapement**, which transferred rotational energy into discrete motions, appeared in China in the 8th century, and **Muslim engineers** invented **weight-driven clocks** in the 11th century. Mechanical

In the news

- President Sidi Ould Cheikh Abdallahi (*pictured*) of Mauritania is deposed in a **military coup d'état**.
- Eleven mountaineers from international expeditions **die while descending K2**, the second-highest mountain on Earth.
- An **attack** on a police post near Kashgar in the Xinjiang Uyghur Autonomous Region of China leaves 16 officers dead and 16 others injured.
- Over 160 people die in a **stampede** at a Hindu temple in Naina Devi, Himachal Pradesh, India.
- The International Olympic Committee and Chinese organizers announce that some **Internet restrictions** have been lifted for media covering the Beijing Games.
- A **total solar eclipse** is visible from northern Canada.

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- Google (\sim googol $= 10^{100}$)

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- Founders of Google: Larry Page and Sergey Brin

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- Founders of Google: Larry Page and Sergey Brin
- 1995: Research students at Stanford
- 1996: Started a student project on search engines
- 1998: Google incorporates as a company (initial investment: \$1.1million) and files patent for PageRank

- 2000: Selling advertisements began

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- 2008: Google uses 450,000 servers in 25 locations around the world to index > 8 billion websites

KEY IDEAS

- Each webpage is assigned a measure of importance ...
PageRank

KEY IDEAS

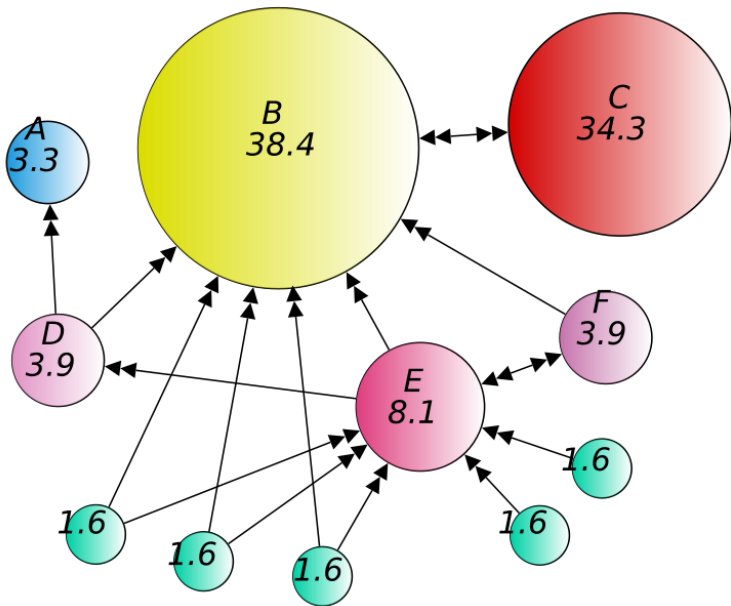
- Each webpage is assigned a measure of importance ...
PageRank
- A hyperlink is a "recommendation": A webpage is important if other webpages point to it (via hyperlinks)

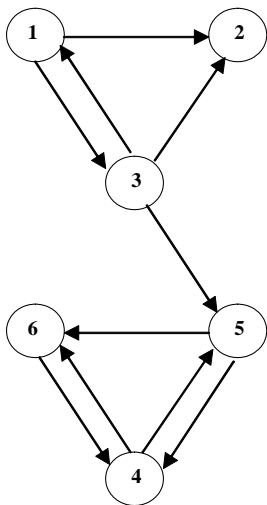
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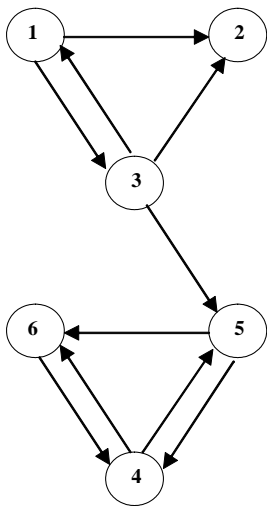
- Each webpage is assigned a measure of importance ...
PageRank
- A hyperlink is a "recommendation": A webpage is important if other webpages point to it (via hyperlinks)
- The PageRank of the recommender matters (the higher the better)
- The generosity of the recommender matters (the higher the worse)





- $r(P_1) = \frac{1}{3}r(P_3)$

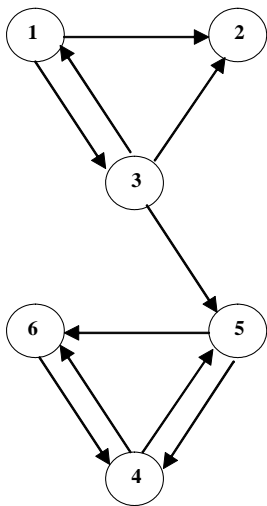
Node 2 - *dangling*



- $r(P_1) = \frac{1}{3}r(P_3)$

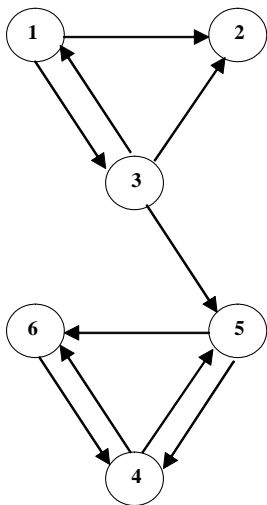
- $r(P_2) = \frac{1}{2}r(P_1) + \frac{1}{3}r(P_3)$

Node 2 - *dangling*



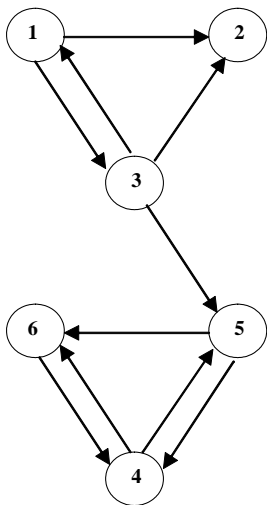
- $r(P_1) = \frac{1}{3}r(P_3)$
- $r(P_2) = \frac{1}{2}r(P_1) + \frac{1}{3}r(P_3)$
- $r(P_3) = \frac{1}{2}r(P_1)$

Node 2 - *dangling*



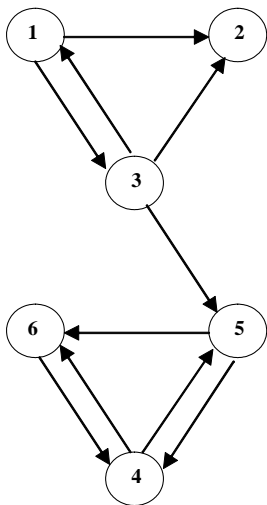
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- $r(P_3) = \frac{1}{2}r(P_1)$
- $r(P_4) = \frac{1}{2}r(P_5) + r(P_6)$

Node 2 - *dangling*



- $r(P_1) = \frac{1}{3}r(P_3)$
- $r(P_2) = \frac{1}{2}r(P_1) + \frac{1}{3}r(P_3)$
- $r(P_3) = \frac{1}{2}r(P_1)$
- $r(P_4) = \frac{1}{2}r(P_5) + r(P_6)$
- $r(P_5) = \frac{1}{3}r(P_3) + \frac{1}{2}r(P_4)$

Node 2 - *dangling*



- $r(P_1) = \frac{1}{3}r(P_3)$
- $r(P_2) = \frac{1}{2}r(P_1) + \frac{1}{3}r(P_3)$
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- $r(P_4) = \frac{1}{2}r(P_5) + r(P_6)$
- $r(P_5) = \frac{1}{3}r(P_3) + \frac{1}{2}r(P_4)$
- $r(P_6) = \frac{1}{2}r(P_4) + \frac{1}{2}r(P_5)$

Node 2 - *dangling*

- $r_0 = \left(\frac{1}{n}, \frac{1}{n}, \dots\right)$

- $r_0 = \left(\frac{1}{n}, \frac{1}{n}, \dots\right)$
- $r_0 \longrightarrow r_1$

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- $r_1 \longrightarrow r_2$

- $r_0 = \left(\frac{1}{n}, \frac{1}{n}, \dots\right)$
- $r_0 \longrightarrow r_1$
- $r_1 \longrightarrow r_2$
- ...

- $r_0 = \left(\frac{1}{n}, \frac{1}{n}, \dots\right)$
- $r_0 \longrightarrow r_1$
- $r_1 \longrightarrow r_2$
- ...
- $r_k \longrightarrow r_{k+1}$

- $r_0 = \left(\frac{1}{n}, \frac{1}{n}, \dots\right)$

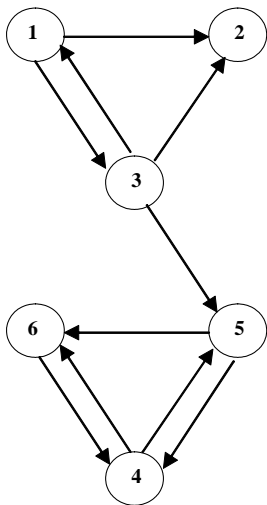
- $r_0 \longrightarrow r_1$

- $r_1 \longrightarrow r_2$

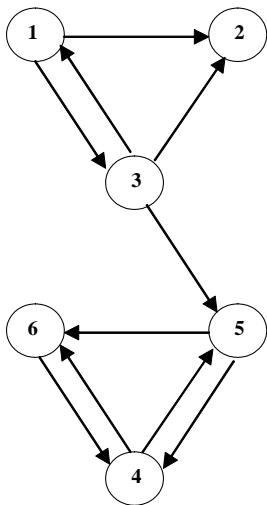
- \dots

- $r_k \longrightarrow r_{k+1}$

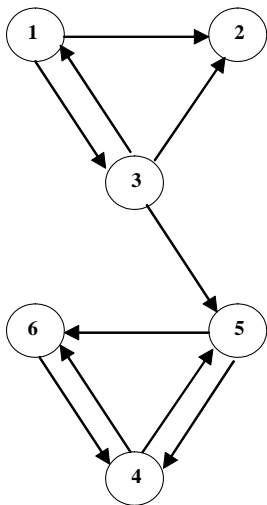
- \dots



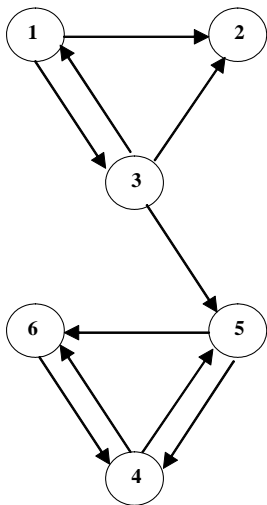
- $r_0 = (\frac{1}{6}, \frac{1}{6}, \frac{1}{6}, \frac{1}{6}, \frac{1}{6}, \frac{1}{6})$



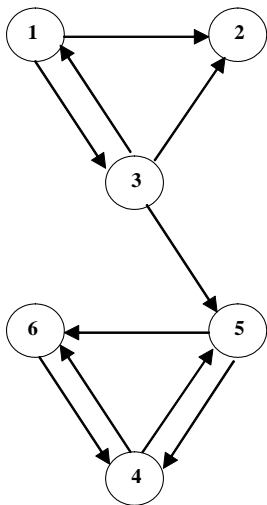
- $r_0 = (\frac{1}{6}, \frac{1}{6}, \frac{1}{6}, \frac{1}{6}, \frac{1}{6}, \frac{1}{6})$
- $r_1(P_1) = \frac{1}{3}r_0(P_3) = \frac{1}{18}$



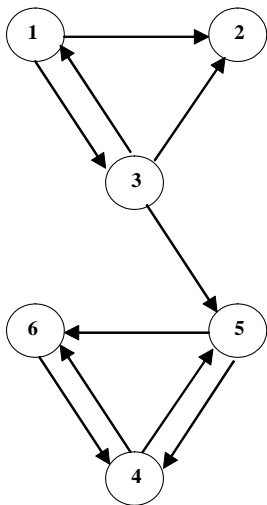
- $r_0 = (\frac{1}{6}, \frac{1}{6}, \frac{1}{6}, \frac{1}{6}, \frac{1}{6}, \frac{1}{6})$
- $r_1(P_1) = \frac{1}{3}r_0(P_3) = \frac{1}{18}$
- $r_1(P_2) = \frac{1}{2}r_0(P_1) + \frac{1}{3}r_0(P_3) = \frac{5}{36}$



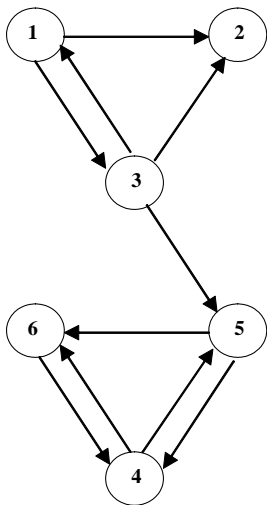
- $r_0 = (\frac{1}{6}, \frac{1}{6}, \frac{1}{6}, \frac{1}{6}, \frac{1}{6}, \frac{1}{6})$
- $r_1(P_1) = \frac{1}{3}r_0(P_3) = \frac{1}{18}$
- $r_1(P_2) = \frac{1}{2}r_0(P_1) + \frac{1}{3}r_0(P_3) = \frac{5}{36}$
- $r_1(P_3) = \frac{1}{2}r_0(P_1) = \frac{1}{12}$



- $r_0 = (\frac{1}{6}, \frac{1}{6}, \frac{1}{6}, \frac{1}{6}, \frac{1}{6}, \frac{1}{6})$
- $r_1(P_1) = \frac{1}{3}r_0(P_3) = \frac{1}{18}$
- $r_1(P_2) = \frac{1}{2}r_0(P_1) + \frac{1}{3}r_0(P_3) = \frac{5}{36}$
- $r_1(P_3) = \frac{1}{2}r_0(P_1) = \frac{1}{12}$
- $r_1(P_4) = \frac{1}{2}r_0(P_5) + r_0(P_6) = \frac{1}{4}$



- $r_0 = \left(\frac{1}{6}, \frac{1}{6}, \frac{1}{6}, \frac{1}{6}, \frac{1}{6}, \frac{1}{6}\right)$
- $r_1(P_1) = \frac{1}{3}r_0(P_3) = \frac{1}{18}$
- $r_1(P_2) = \frac{1}{2}r_0(P_1) + \frac{1}{3}r_0(P_3) = \frac{5}{36}$
- $r_1(P_3) = \frac{1}{2}r_0(P_1) = \frac{1}{12}$
- $r_1(P_4) = \frac{1}{2}r_0(P_5) + r_0(P_6) = \frac{1}{4}$
- $r_1(P_5) = \frac{1}{3}r_0(P_3) + \frac{1}{2}r_0(P_4) = \frac{5}{36}$



- $r_0 = \left(\frac{1}{6}, \frac{1}{6}, \frac{1}{6}, \frac{1}{6}, \frac{1}{6}, \frac{1}{6}\right)$
- $r_1(P_1) = \frac{1}{3}r_0(P_3) = \frac{1}{18}$
- $r_1(P_2) = \frac{1}{2}r_0(P_1) + \frac{1}{3}r_0(P_3) = \frac{5}{36}$
- $r_1(P_3) = \frac{1}{2}r_0(P_1) = \frac{1}{12}$
- $r_1(P_4) = \frac{1}{2}r_0(P_5) + r_0(P_6) = \frac{1}{4}$
- $r_1(P_5) = \frac{1}{3}r_0(P_3) + \frac{1}{2}r_0(P_4) = \frac{5}{36}$
- $r_1(P_6) = \frac{1}{2}r_0(P_4) + \frac{1}{2}r_0(P_5) = \frac{1}{6}$

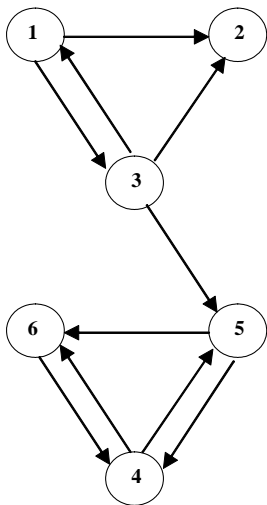
	r_0	r_1
P_1	$1/6$	$1/18$
P_2	$1/6$	$5/36$
P_3	$1/6$	$1/12$
P_4	$1/6$	$1/4$
P_5	$1/6$	$5/36$
P_6	$1/6$	$1/6$

	r_0	r_1	rank
P_1	$1/6$	$1/18$	6
P_2	$1/6$	$5/36$	3 – 4
P_3	$1/6$	$1/12$	5
P_4	$1/6$	$1/4$	1
P_5	$1/6$	$5/36$	3 – 4
P_6	$1/6$	$1/6$	2

	r_0	r_1	rank	r_2
P_1	$1/6$	$1/18$	6	$1/36$
P_2	$1/6$	$5/36$	$3 - 4$	$1/18$
P_3	$1/6$	$1/12$	5	$1/36$
P_4	$1/6$	$1/4$	1	$17/72$
P_5	$1/6$	$5/36$	$3 - 4$	$11/72$
P_6	$1/6$	$1/6$	2	$14/72$

	r_0	r_1	rank	r_2	rank
P_1	$1/6$	$1/18$	6	$1/36$	$5 - 6$
P_2	$1/6$	$5/36$	$3 - 4$	$1/18$	4
P_3	$1/6$	$1/12$	5	$1/36$	$5 - 6$
P_4	$1/6$	$1/4$	1	$17/72$	1
P_5	$1/6$	$5/36$	$3 - 4$	$11/72$	3
P_6	$1/6$	$1/6$	2	$14/72$	2

	r_0	r_1	rank	r_2	rank
P_1	$1/6$	$1/18$	6	$1/36$	$5 - 6$
P_2	$1/6$	$5/36$	$3 - 4$	$1/18$	4
P_3	$1/6$	$1/12$	5	$1/36$	$5 - 6$
P_4	$1/6$	$1/4$	1	$17/72$	1
P_5	$1/6$	$5/36$	$3 - 4$	$11/72$	3
P_6	$1/6$	$1/6$	2	$14/72$	2



Hyperlink matrix H :

	P_1	P_2	P_3	P_4	P_5	P_6
P_1	0	$\frac{1}{2}$	$\frac{1}{2}$	0	0	0
P_2	0	0	0	0	0	0
P_3	$\frac{1}{3}$	$\frac{1}{3}$	0	0	$\frac{1}{3}$	0
P_4	0	0	0	0	$\frac{1}{2}$	$\frac{1}{2}$
P_5	0	0	0	$\frac{1}{2}$	0	$\frac{1}{2}$
P_6	0	0	0	1	0	0

Stochastic matrix: Every row is ≥ 0 and sums to 1.

H could be a stochastic matrix if it was not for the rows corresponding to the dangling nodes

$$\bullet \underbrace{\left(\frac{1}{6}, \frac{1}{6}, \frac{1}{6}, \frac{1}{6}, \frac{1}{6}, \frac{1}{6} \right)}_{r_0} \cdot \begin{pmatrix} 0 & \frac{1}{2} & \frac{1}{2} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ \frac{1}{3} & \frac{1}{3} & 0 & 0 & \frac{1}{3} & 0 \\ 0 & 0 & 0 & 0 & \frac{1}{2} & \frac{1}{2} \\ 0 & 0 & 0 & \frac{1}{2} & 0 & \frac{1}{2} \\ 0 & 0 & 0 & 1 & 0 & 0 \end{pmatrix} \\
 = \underbrace{\left(\frac{1}{18}, \frac{5}{36}, \frac{1}{12}, \frac{1}{4}, \frac{5}{36}, \frac{1}{6} \right)}_{r_1}$$

$$\bullet \underbrace{\left(\frac{1}{6}, \frac{1}{6}, \frac{1}{6}, \frac{1}{6}, \frac{1}{6}, \frac{1}{6} \right)}_{r_0} \cdot \begin{pmatrix} 0 & \frac{1}{2} & \frac{1}{2} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ \frac{1}{3} & \frac{1}{3} & 0 & 0 & \frac{1}{3} & 0 \\ 0 & 0 & 0 & 0 & \frac{1}{2} & \frac{1}{2} \\ 0 & 0 & 0 & \frac{1}{2} & 0 & \frac{1}{2} \\ 0 & 0 & 0 & 1 & 0 & 0 \end{pmatrix} \\
 = \underbrace{\left(\frac{1}{18}, \frac{5}{36}, \frac{1}{12}, \frac{1}{4}, \frac{5}{36}, \frac{1}{6} \right)}_{r_1}$$

•

$$r_1 = r_0 \cdot H$$

- $$\underbrace{\left(\frac{1}{6}, \frac{1}{6}, \frac{1}{6}, \frac{1}{6}, \frac{1}{6}, \frac{1}{6}\right)}_{r_0} \cdot \begin{pmatrix} 0 & \frac{1}{2} & \frac{1}{2} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ \frac{1}{3} & \frac{1}{3} & 0 & 0 & \frac{1}{3} & 0 \\ 0 & 0 & 0 & 0 & \frac{1}{2} & \frac{1}{2} \\ 0 & 0 & 0 & \frac{1}{2} & 0 & \frac{1}{2} \\ 0 & 0 & 0 & 1 & 0 & 0 \end{pmatrix}$$

$$= \underbrace{\left(\frac{1}{18}, \frac{5}{36}, \frac{1}{12}, \frac{1}{4}, \frac{5}{36}, \frac{1}{6}\right)}_{r_1}$$

-

$$r_1 = r_0 \cdot H$$

- Similarly:

$$r_2 = r_1 \cdot H = (r_0 \cdot H) \cdot H = r_0 \cdot H^2$$



$$r_3 = r_2 \cdot H = \dots = r_0 \cdot H^3$$



$$r_3 = r_2 \cdot H = \dots = r_0 \cdot H^3$$

- In general:

$$r_k = r_{k-1} \cdot H = \dots = r_0 \cdot H^k$$



$$r_3 = r_2 \cdot H = \dots = r_0 \cdot H^3$$

- In general:

$$r_k = r_{k-1} \cdot H = \dots = r_0 \cdot H^k$$

- ... "Power Method"

QUESTIONS

- Will this power method converge? If not what conditions must be satisfied?

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- If it converges, will it do so to a vector meaningful for page ranking?

QUESTIONS

- Will this power method converge? If not what conditions must be satisfied?
- If it converges, will it do so to a vector meaningful for page ranking?
- Does the convergence depend on the starting vector?

QUESTIONS

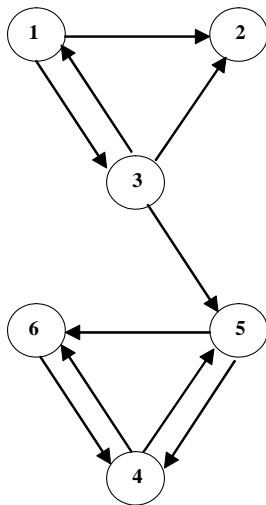
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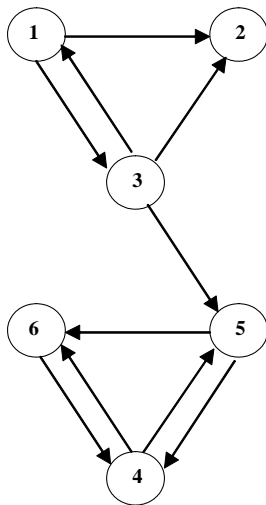
Rank sink pages



	r_0	r_1	...	r_{13}
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P_3	1/6	1/12	...	0
P_4	1/6	1/4	...	2/3
P_5	1/6	5/36	...	1/3
P_6	1/6	1/6	...	1/5

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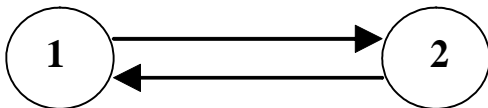
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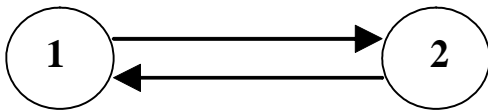
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- Nodes 4,5,6 are a *link farm*.

- Another problem: *Cycles*

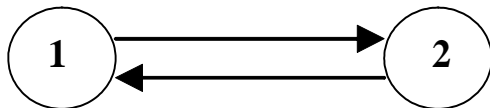


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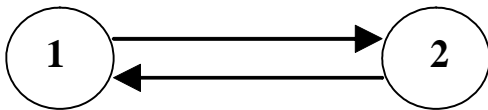
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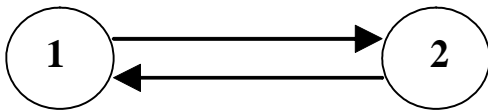
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- Flip-flop \rightarrow no convergence

Elements of the Markov chains theory:

- If H is a stochastic matrix and x_0 a stochastic vector then the sequence

$$\{x_0, x_1 = x_0 H, x_2 = x_1 H, x_3 = x_2 H, \dots\}$$

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- H is called the *transition probability matrix*.

Theorem (Markov, 1906)

*If H is a **positive** transition probability matrix of a Markov chain then this chain converges to a unique positive vector (called stationary vector) independently of the starting vector.*

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The new matrix is S .

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$$H \rightarrow S = \begin{pmatrix} 0 & \frac{1}{2} & \frac{1}{2} & 0 & 0 & 0 \\ \frac{1}{6} & \frac{1}{6} & \frac{1}{6} & \frac{1}{6} & \frac{1}{6} & \frac{1}{6} \\ \frac{1}{3} & \frac{1}{3} & 0 & 0 & \frac{1}{3} & 0 \\ 0 & 0 & 0 & 0 & \frac{1}{2} & \frac{1}{2} \\ 0 & 0 & 0 & \frac{1}{2} & 0 & \frac{1}{2} \\ 0 & 0 & 0 & 1 & 0 & 0 \end{pmatrix}$$

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- S is stochastic! (But not yet positive)

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- and $\alpha \in (0, 1)$ controls the proportion of the time RS follows the *hyperlinks* as opposed to *teleportation*

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- Hence any Markov chain with G is guaranteed to converge to a unique positive vector, independently of the starting vector.
- Actually used $\alpha \approx .85$

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- $G = 0.9S + 0.1E = \frac{1}{60} \begin{pmatrix} 1 & 28 & 28 & 1 & 1 & 1 \\ 10 & 10 & 10 & 10 & 10 & 10 \\ 19 & 19 & 1 & 1 & 19 & 1 \\ 1 & 1 & 1 & 1 & 28 & 28 \\ 1 & 1 & 1 & 28 & 1 & 28 \\ 1 & 1 & 1 & 55 & 1 & 1 \end{pmatrix}$

- Google's PageRank vector is the stationary vector of G which is

$$(.03721, .05396, .04151, .3751, .206, .2802)$$

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- The importance ranking therefore is: $P_4, P_6, P_5, P_2, P_3, P_1$.

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- The stationary point of any Markov chain with transition matrix G is an eigenvector of G corresponding to the eigenvalue 1

Perron-Frobenius theory of Linear Algebra solves the eigenvector-eigenvalue problem for non-negative matrices.

Theorem (Perron, 1912)

If G is a positive, stochastic matrix then $\lambda = 1$ is an eigenvalue of G and G has a unique positive eigenvector (up to multiples).

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- CONCLUSION: The power method with Google matrix is *very* fast!

THANK YOU

Next session in this room at 12.00:
"Careers, degrees and mathematics"