

# Random Walks

Paolo Ferragina

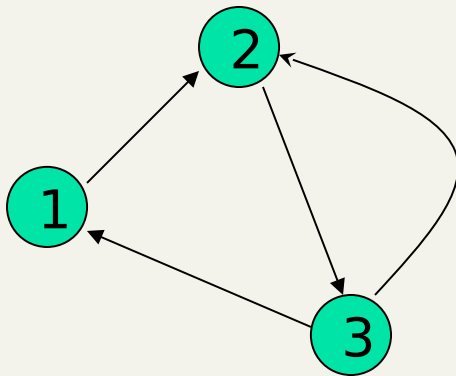
Dipartimento di Informatica

Università di Pisa

# Definitions

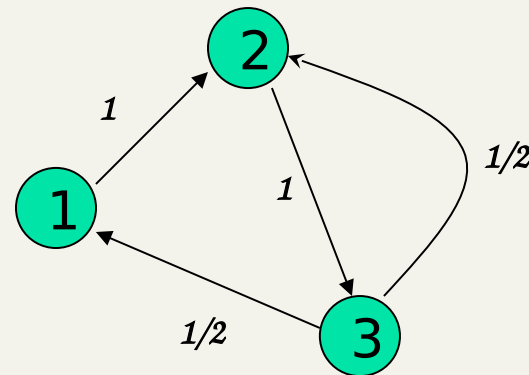
0	1	0
0	0	1
1	1	0

**Adjacency matrix  $A$**



0	1	0
0	0	1
1/2	1/2	0

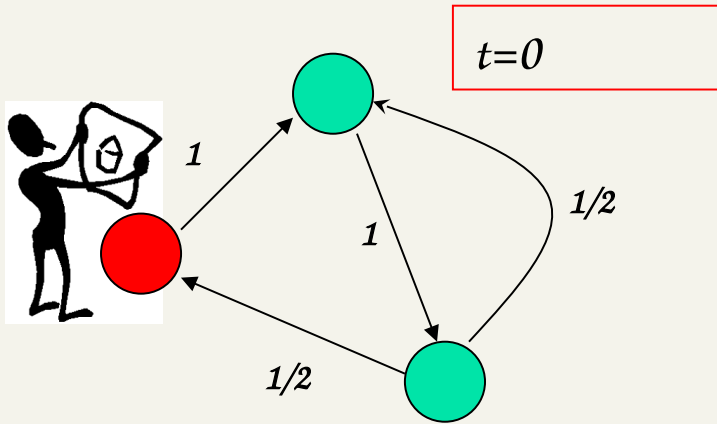
*Transition matrix  $P$*



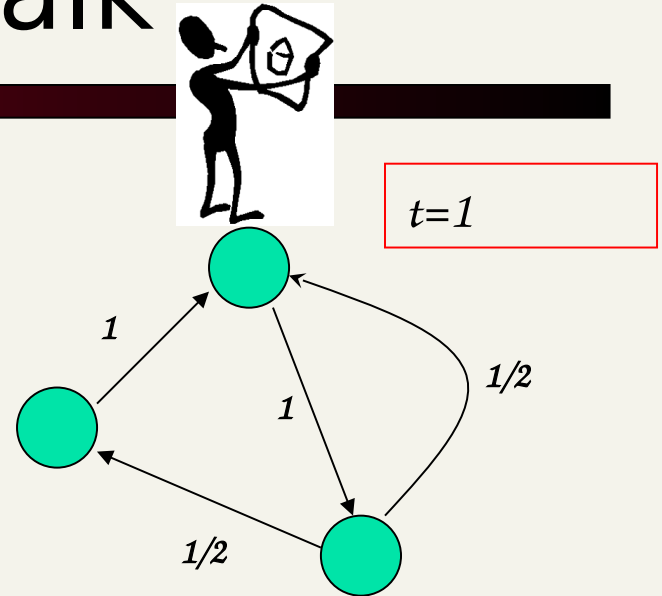
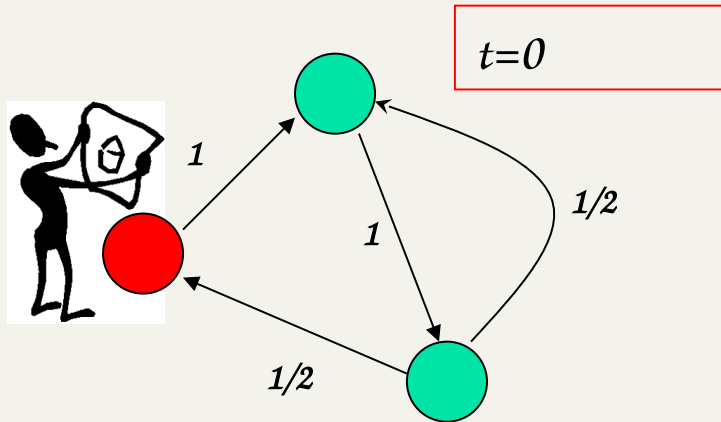
Any edge  
weighting  
is possible

# What is a random walk

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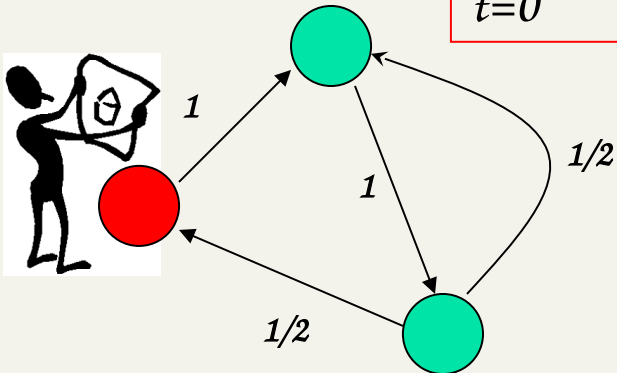
# What is a random walk



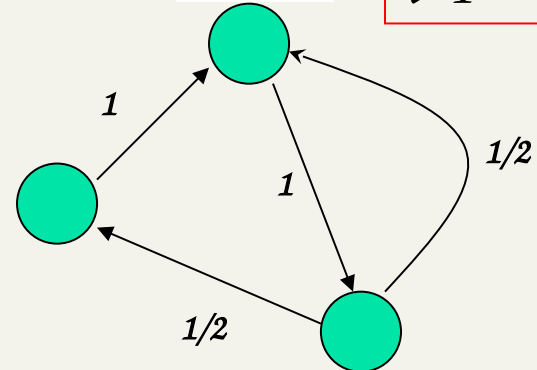
# What is a random walk



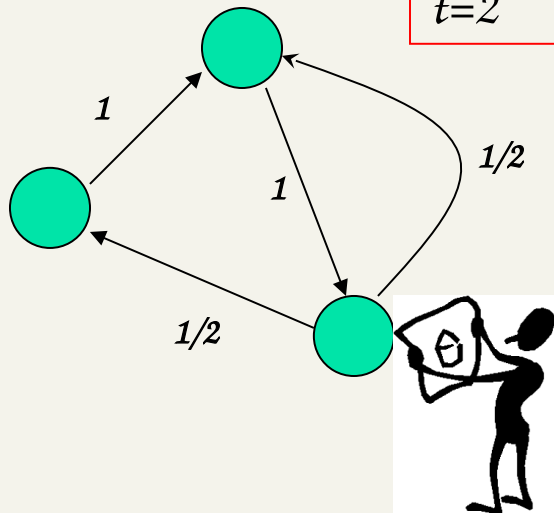
$t=0$



$t=1$



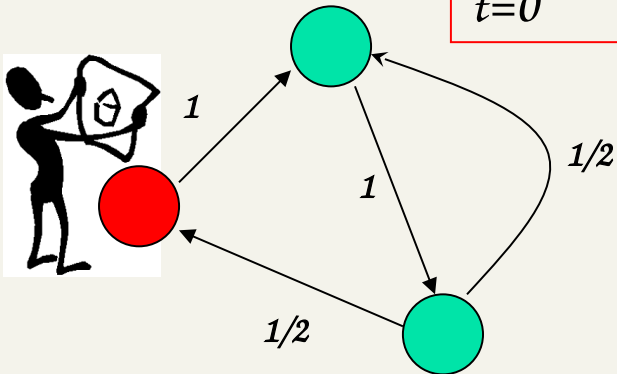
$t=2$



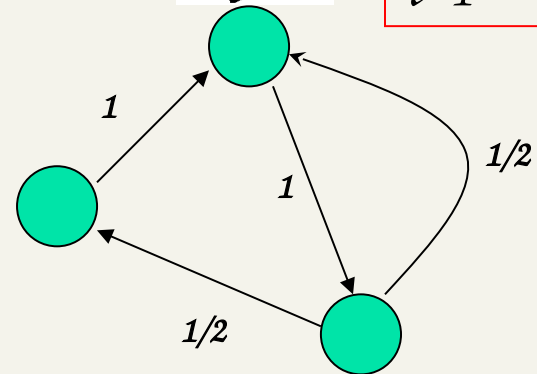
# What is a random walk



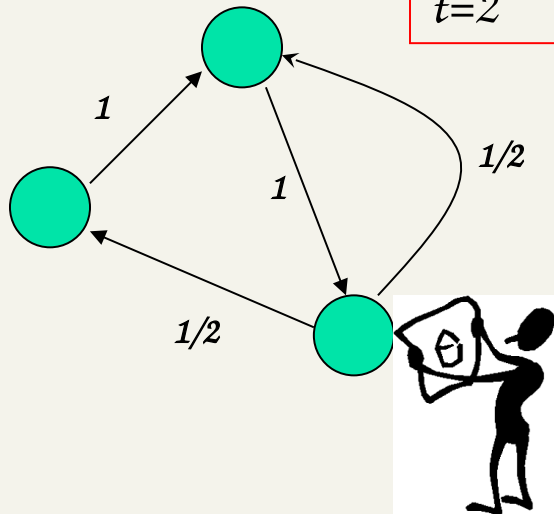
$t=0$



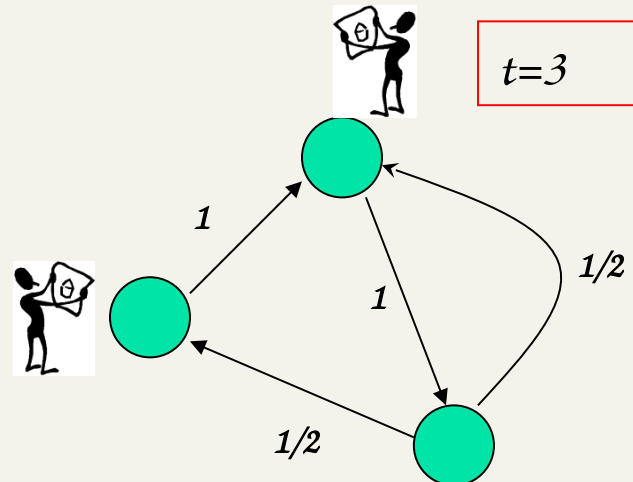
$t=1$



$t=2$



$t=3$



# Probability Distributions

- $x_t(i)$  = probability that surfer is at node  $i$  at time  $t$
- $x_{t+1}(i) = \sum_j (\text{Probability of being at node } j) * \Pr(j \rightarrow i)$   
 $= \sum_j x_t(j) * P(j, i) = x_t * P$

0	0	1
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$x_t$

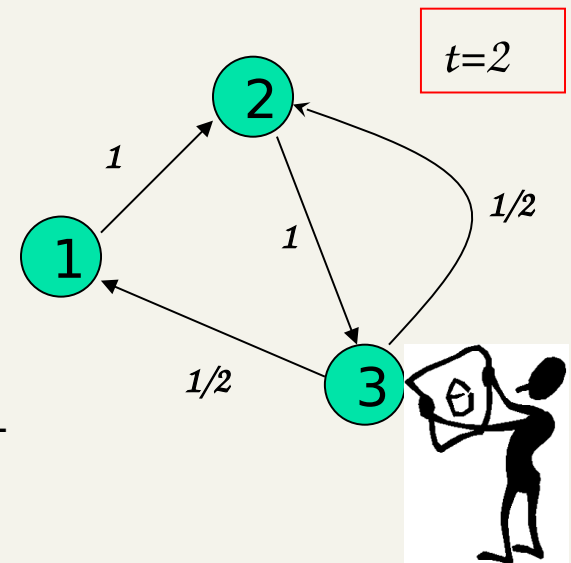
0	1	0
0	0	1
1/2	1/2	0

*Transition matrix  $P$*

=

1/2	1/2	0
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$x_{t+1}$



# Probability Distributions

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Recall that:

- $x_t(i)$  = probability that surfer is at node  $i$  at time  $t$
- $x_{t+1}(i) = \sum_j (\text{Probability of being at node } j) * \Pr(j \rightarrow i)$   
 $= \sum_j x_t(j) * P(j, i) = x_t * P$

We can write:

- $x_{t+1} = x_t * P = (x_{t-1} * P) * P = (x_{t-2} * P) * P * P = \dots = x_0 P^{t+1}$
- What happens when the surfer keeps walking for a long time? **Called Stationary distribution**



# Stationary Distribution

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- The stationary distribution at a node is related to the **amount of time a random walker spends** visiting that node.
- It is when the distribution does not change:  
 $x_{T+1} = x_T \rightarrow x_T P = 1 * x_T$  *(left eigenvector, with eigenvalue 1)*
- For “well-behaved” graphs this does not depend on the start distribution  $x_0$

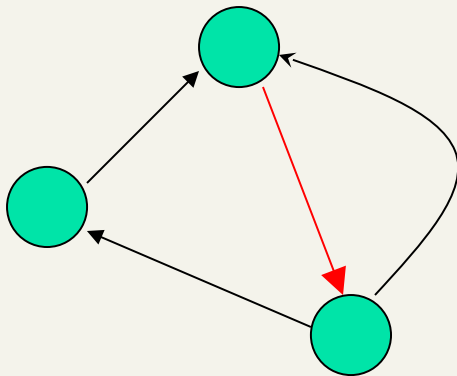
# Interesting questions

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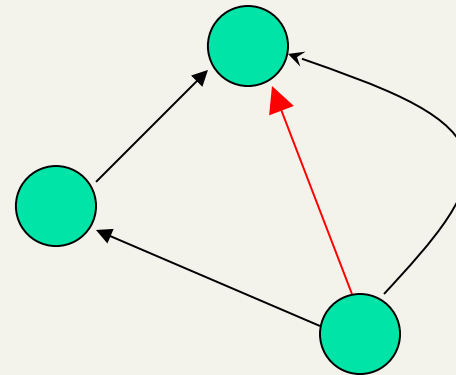
- Does a stationary distribution always exist? Is it unique?
  - Yes, if the graph is “well-behaved”, namely the markov chain is irreducible and aperiodic.
- How fast will the random surfer approach this stationary distribution?
  - Mixing Time!

# Well behaved graphs

- **Irreducible:** There is a path from every node to every other node ( $\rightarrow$  it is an SCC).



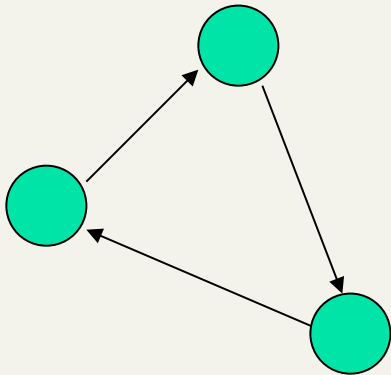
*Irreducible*



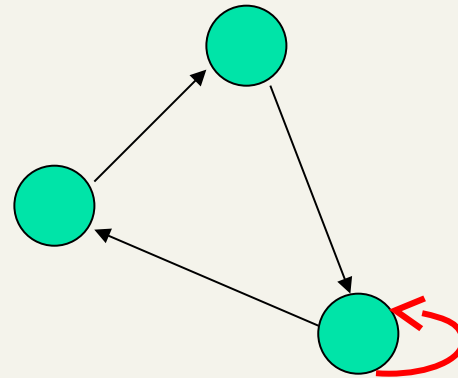
*Not irreducible*

# Well behaved graphs

- **Aperiodic**: The GCD of all cycle lengths is  $1$ . The GCD is also called period.



*Periodicity is 3*

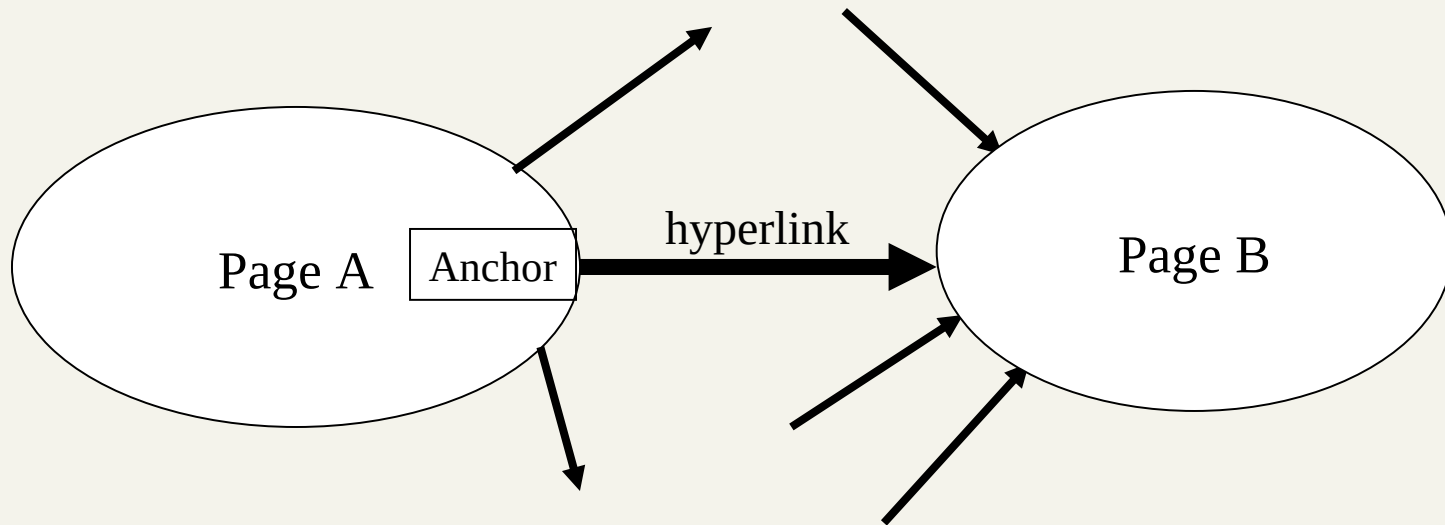


*Aperiodic*

# Ranking

Link-based Ranking  
(2<sup>o</sup> generation)

# The Web as a Directed Graph

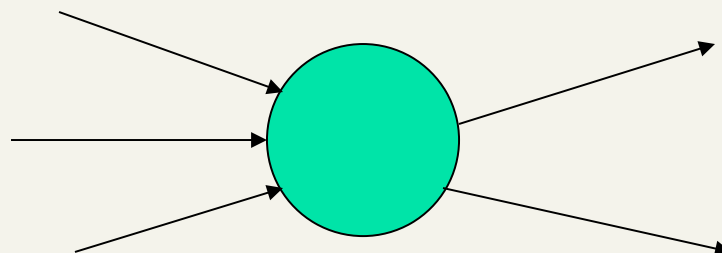


**Assumption 1:** A hyperlink between pages denotes author perceived relevance (quality signal)

**Assumption 2:** The text in the anchor of the hyperlink describes the target page (textual context)

# Query-independent ordering

- First generation: using link counts as simple measures of popularity.
  - Undirected popularity:
    - Each page gets a score given by the number of in-links plus the number of out-links (es.  $3+2=5$ ).
  - Directed popularity:
    - Score of a page = number of its in-links (es. 3).



Easy to SPAM

# Second generation:

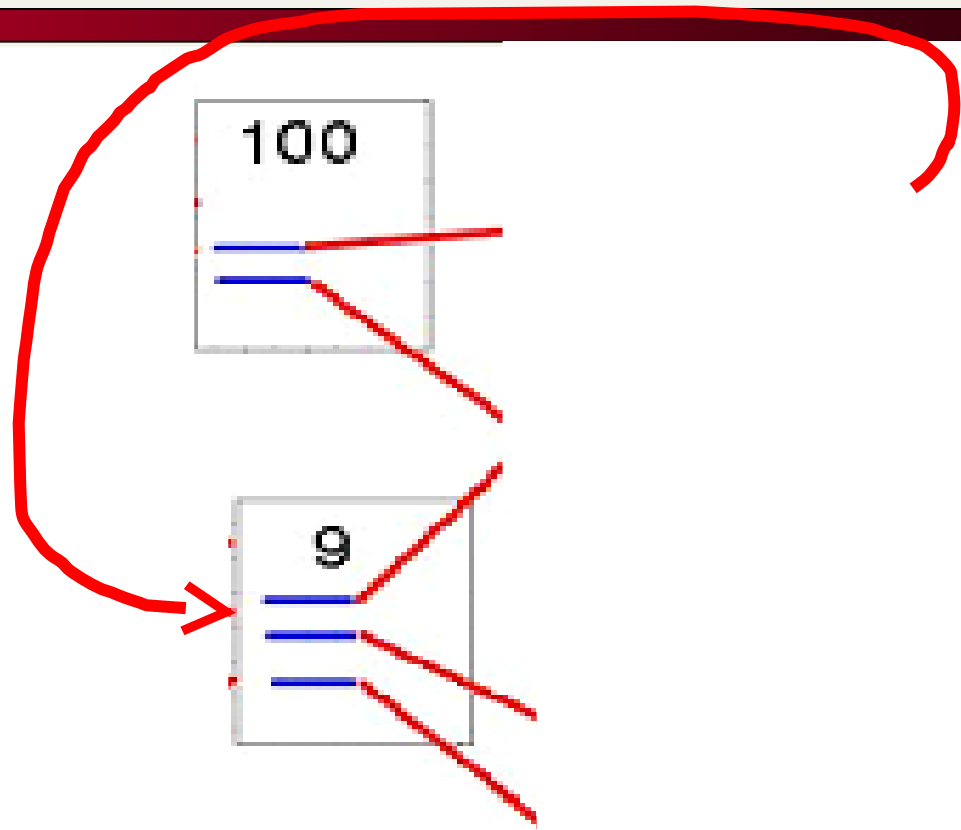
## PageRank

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- *Each link has its own importance!!*
- *PageRank* is
  - independent of the query
  - many interpretations...



# The (classic) PageRank

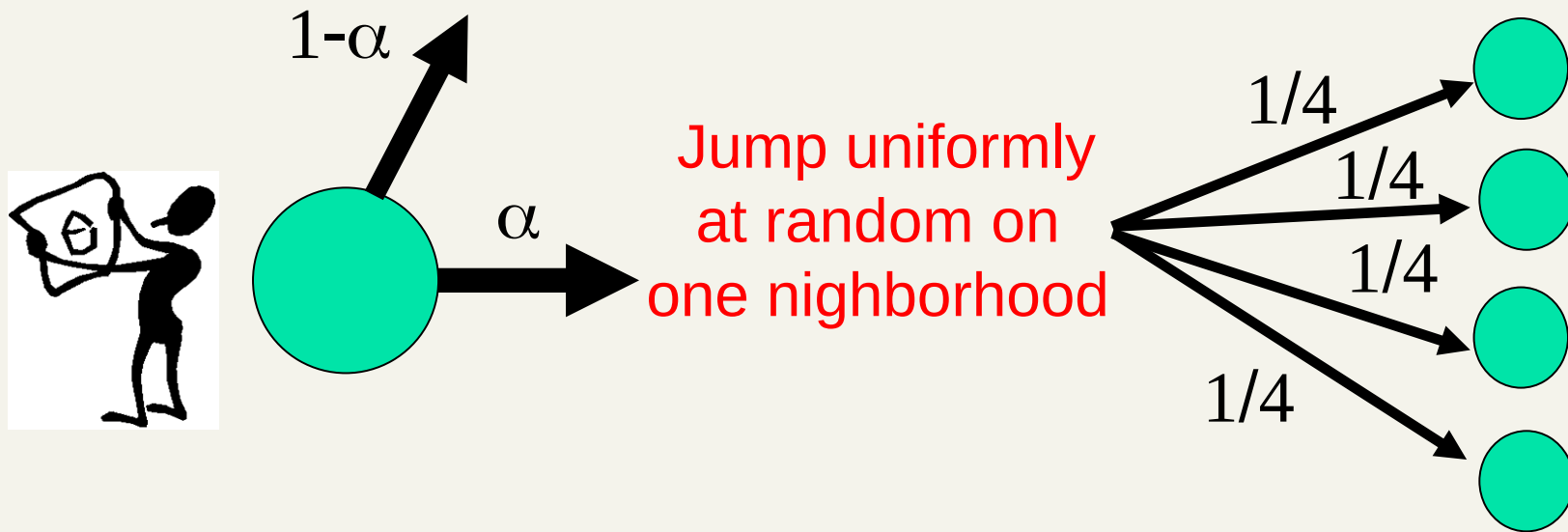


If we make  
these values  
flow,  
Do they  
stabilize?

- Various interpretations: linear system of equations with billion variables and billion constraints
- Random walks

# PageRank, as a Random Walk on the Web Graph

Jump uniformly at random at any page (node) in the Web



PageRank of a node is the «frequency of visit» that node by assuming an infinite random walk

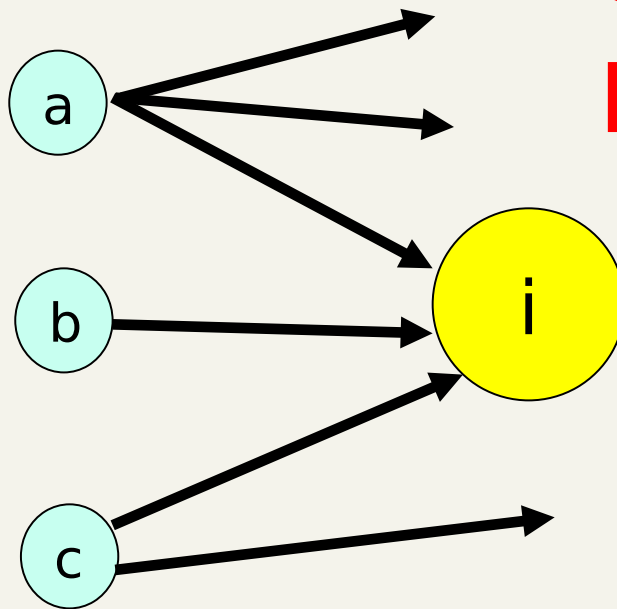
A «measure of centrality» of a node in a (directed) graph

# PageRank, as a Linear System of Equations

$$r(i) = \alpha \cdot \sum_{j \in B(i)} \frac{r(j)}{\#out(j)} + (1 - \alpha) \cdot \frac{1}{N}$$

$$\alpha = 0.85$$

$$N = \# \text{ nodes in graph}$$

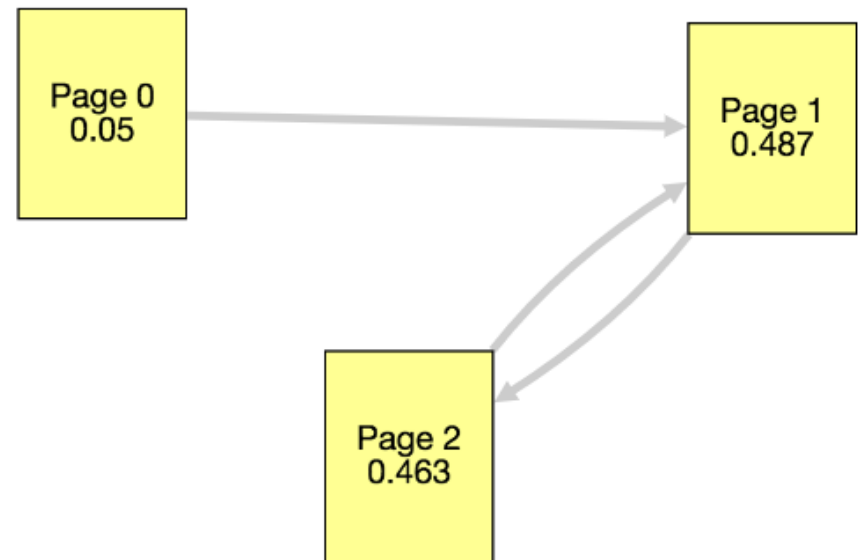
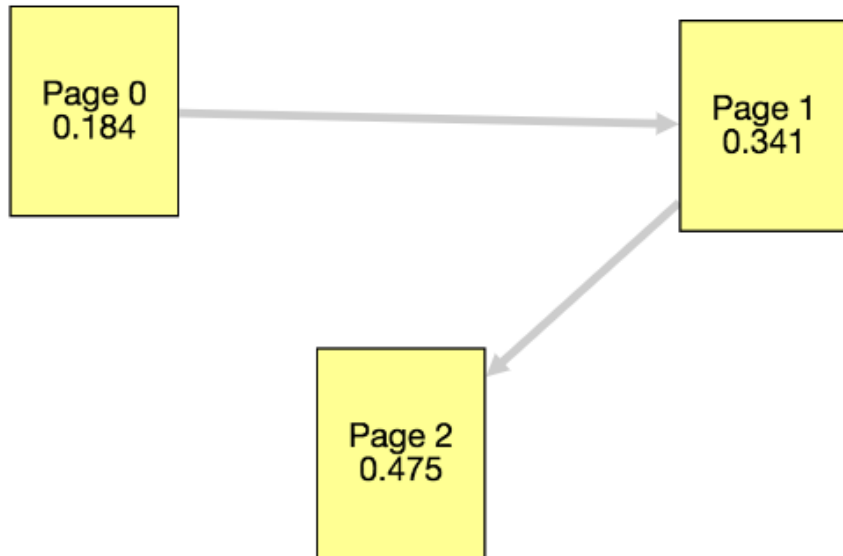


$$r(i) = \alpha \left( r(a) / 3 + r(b) / 1 + r(c) / 2 \right) + (1 - \alpha) / N$$

It is «related» to the eigenvalues of the matrix describing the linear system of equations

# Hands-on test

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<http://bit.ly/2iwHH3e>

<http://faculty.chemeketa.edu/ascholer/cs160/WebApps/PageRank/>

# Pagerank: use in Search Engines

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- Preprocessing:
  - Given graph, build  $P$
  - Compute  $\mathbf{r} = [\mathbf{1/N}, \dots, \mathbf{1/N}] * \mathbf{P}^t$  for  $t=0, 1, \dots$
  - $r[i]$  is the pagerank of page  $i$

*We are interested in the relative order*

- Query processing:
  - Retrieve pages containing query terms
  - Rank them by their Pagerank

*The final order is query-independent*

# Nowadays

Relevance is a not well defined mathematical concept, which is actually not even depending on the single user because its needs may change over time too

For every page we compute a series of **features**:

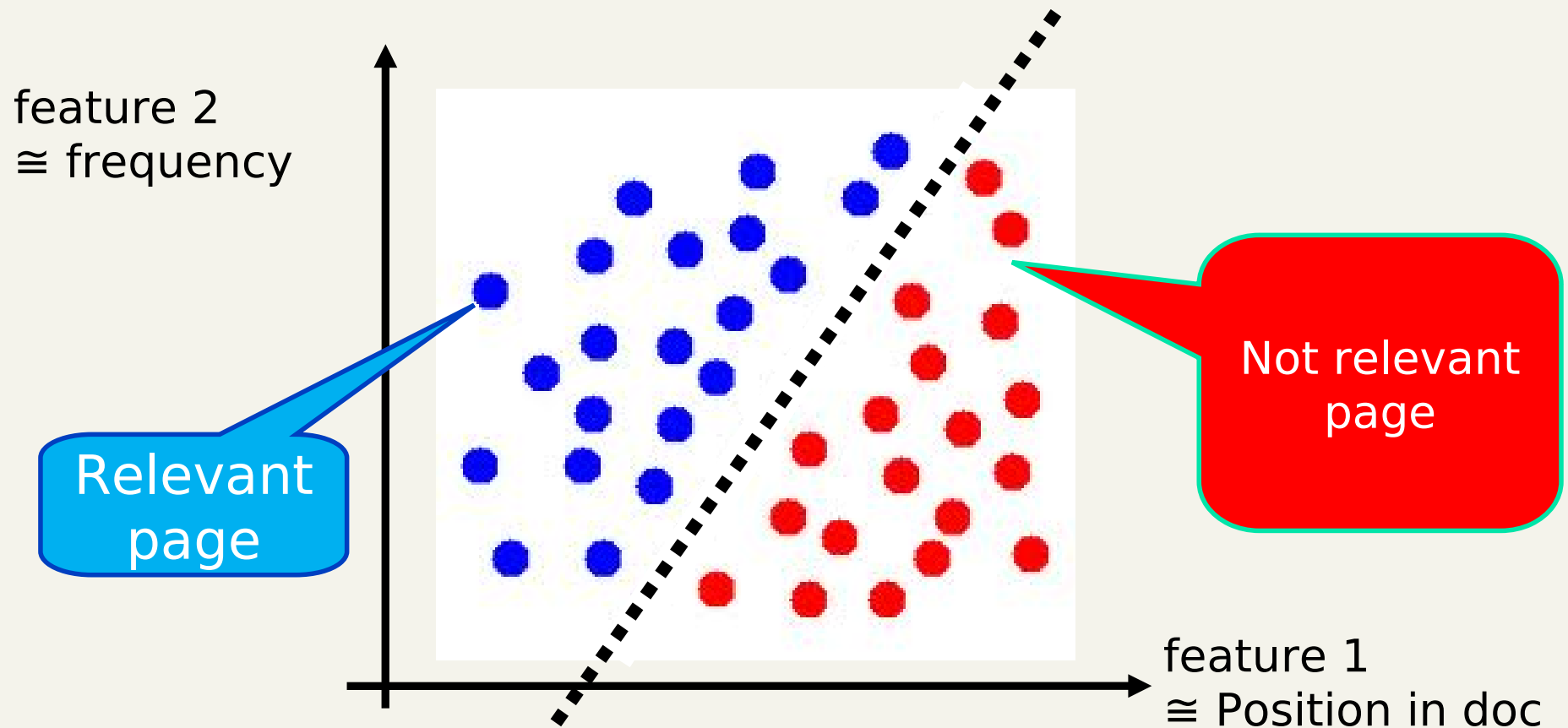
- TF-IDF of tokens
- PageRank
- Their proximity in the page
- Their occurrence in URL
- Their occurrence in the title
- ...

**there are > 200 «features» ...**

The screenshot shows a Google search for "torre pisa". The search bar at the top contains "torre pisa" with a microphone icon and a search button. Below the search bar are tabs for "Tutti", "Immagini", "Maps", "Notizie", "Video", "Altro", "Impostazioni", and "Strumenti". The search results show "Circa 3.860.000 risultati (0,83 secondi)". The first result is "Torre di Pisa - Wikipedia" with a link to the Wikipedia page. Below it is "TORRE DI PISA" from "www.torrepisa.com/torre-di-pisa/" with a description of the tower's location and history. The third result is "La Torre di Pisa pende e ruota - Il Sole 24 ORE" with a link to an article. The fourth result is "Torre Pendente: storia e curiosità sulla torre che pende e che mai cadrà" from "www.tuscanypeople.com". The fifth result is "Vi racconto la torre di Pisa - Didatticarte" with a link to a blog post. On the right side of the search results is a knowledge panel for "Torre di Pisa" with a star rating of 4.5, 5,317 reviews, and a link to the Google Maps page. The panel includes a map of the tower's location in Pisa, a photo of the tower, and a description: "La torre di Pisa è il campanile della cattedrale di Santa Maria Assunta, nella celeberrima piazza del Duomo di cui è il monumento più famoso per via della caratteristica pendenza, simbolo della città e fra i simboli iconici d'Italia. Wikipedia". It also lists the address "Piazza del Duomo, 56126 Pisa PI", the height "57 m", the construction start date "agosto 1173", the opening hours "Oggi aperto · 10-18", and the architectural style "Architettura romanica". There is a link to "Suggerisci una modifica" at the bottom.

# Computing the Ranking

Strong use of **AI e Machine Learning**



# Personalized Pagerank

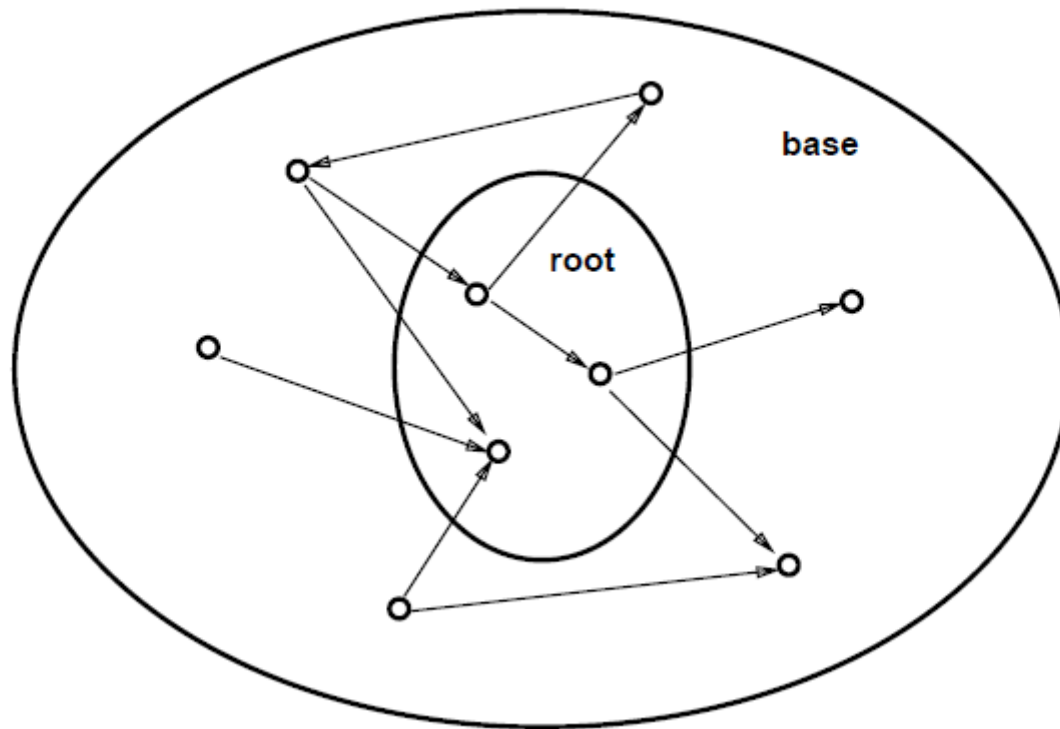
- Bias the random jump substituting the **uniform** jump to **all** nodes with the jump to **one** specific node (second term is  $(1-\alpha)$  only for that node, the others are 0)
- ... or uniform jump to **some** set **S** of preferred nodes (second term is  $(1-\alpha)/|S|$  only for that set of nodes, the others are 0)
- Possibly not a uniform jump (change  $1/\text{\#out}(j)$  with the proper weight of the edge  $(j,i)$ )

$$r(i) = \alpha \cdot \sum_{j \in B(i)} \frac{r(j)}{\text{\#out}(j)} + (1 - \alpha) \cdot \frac{1}{N}$$



# HITS: Hypertext Induced Topic Search

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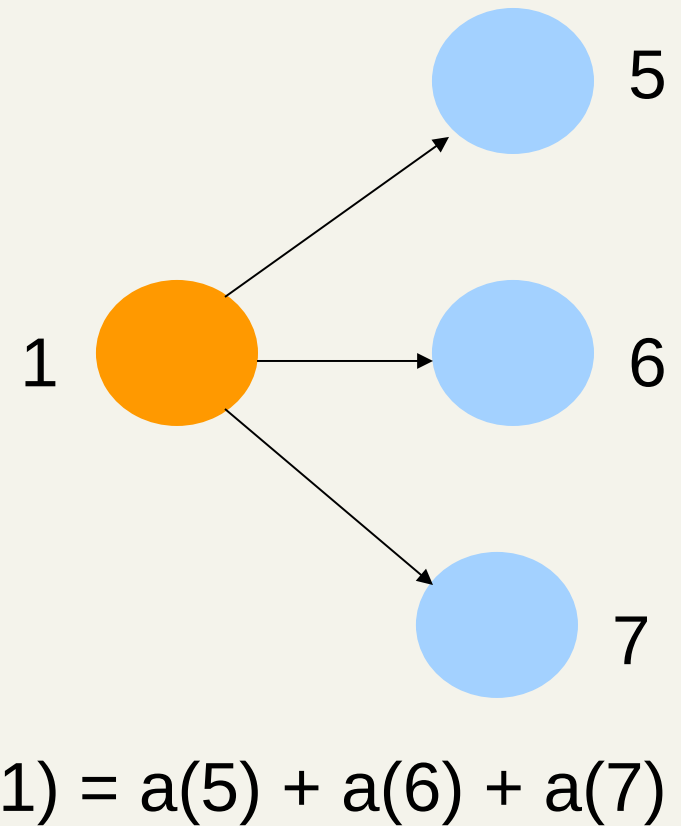
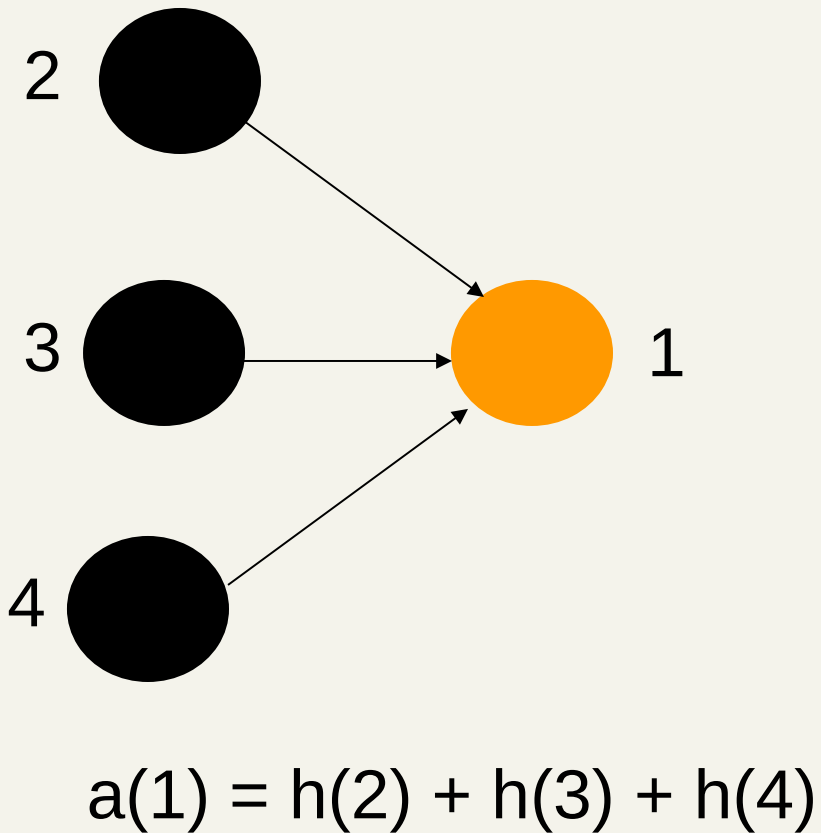
# Calculating HITS

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- *It is query-dependent*
- Produces two scores per page:
  - **Authority score:** a *good authority* page for a topic is *pointed* to by many good hubs for that topic.
  - **Hub score:** A *good hub* page for a topic *points* to many authoritative pages for that topic.

# Authority and Hub scores

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# HITS: Link Analysis Computation

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$$\left. \begin{array}{l} a = A^T h \\ h = Aa \end{array} \right\} \Rightarrow \begin{array}{l} a = A^T Aa \\ h = AA^T h \end{array}$$

Where

a: Vector of Authority's scores

h: Vector of Hub's scores.

A: Adjacency matrix in which  $a_{i,j} = 1$  if  $i \rightarrow j$

Symmetric  
matrices

Thus,  $h$  is an eigenvector of  $AA^t$   
 $a$  is an eigenvector of  $A^tA$

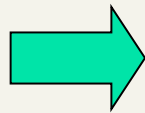
# Weighting links

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Weight more if the query occurs in the neighborhood of the link (e.g. anchor text).

$$h(x) \leftarrow \sum_{x \sqcap y} a(y)$$

$$a(x) \leftarrow \sum_{y \sqcap x} h(y)$$



$$h(x) = \sum_{x \sqcap y} w(x, y) \cdot a(y)$$

$$a(x) = \sum_{y \sqcap x} w(x, y) \cdot h(y)$$

# Summarization via Random Walks

Paolo Ferragina

# The key simple idea

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Rank (and select) sentences by saliency score of their constituting words ***w*** , computed as:

- **TF-IDF** for  $weight(w)$

$$saliency(S_i) = \sum_{w \in S_i} \frac{weight(w)}{|S_i|}$$

- **Centrality over proper graphs:**  
PageRank, HITS, or other measures

# TextRank

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- The key issue is how the GRAPH is built
  - **Nodes** = terms or sentences
  - **Edges** = similarity relation between nodes

$$\textit{Similarity}(S_i, S_j) = \frac{|S_i \cap S_j|}{\log |S_i| + \log |S_j|}$$

- Use **PageRank** over weighted graph (directed by S's position) and compute the score of the nodes



# Lexical PageRank (LexRank)

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- The main difference with TextRank resides in the way they compute **edge weights**:
  - **Cosine similarity** via Tf-Idf between sentences, so it is not pure content overlap (binary)
  - Edges are **pruned** if weight < threshold
- Scoring of **nodes** via **weighed HITS** to ensure a mutual reinforcement between words and sentences

- 1) Do exist more sophisticated construction of graphs
- 2) What about multi-topic documents?