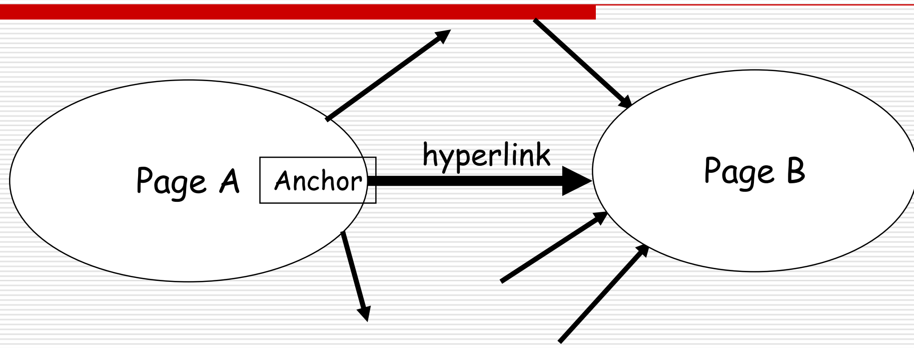
# Web Search Engines



# Web Search before Google

- Web Search Engines (WSEs) of the first generation (up to 1998)
  - Identified relevance with topic-relateness
  - Based on keywords inserted by web page creators (META tags)
  - Preprocessing (HTML tags removal, …), the only difference with standard text search
- Problems
  - Web pages are multimedia items and their relevance determined by non-testual content
  - Many Web pages, often use evocative (as opposed to descriptive) language

## The Web as a Directed Graph




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

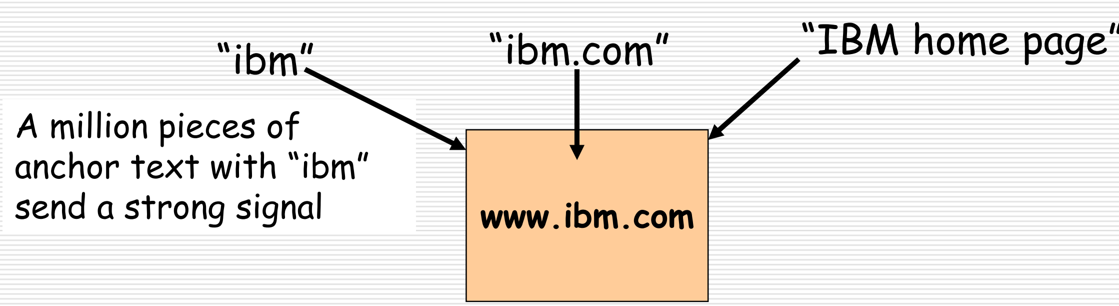
**Assumption 2:** The anchor of the hyperlink describes the target page (textual context)



## Anchor Text

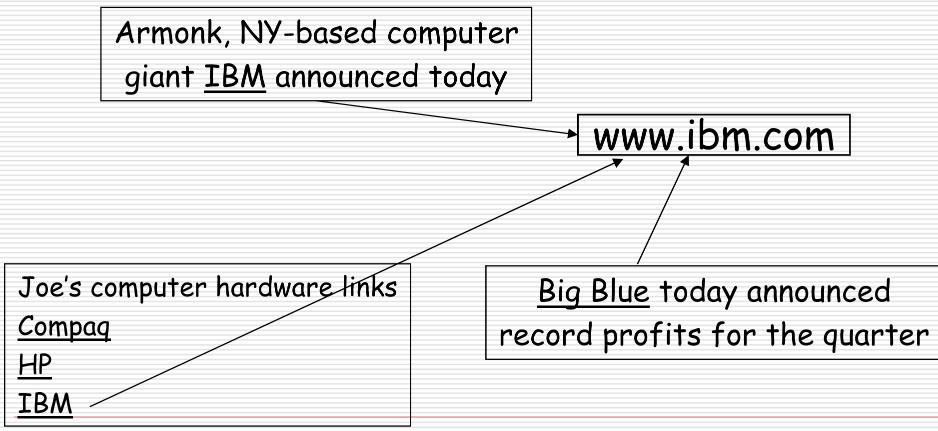
### *WWW Worm* - McBryan [Mcbr94]

- For ***ibm*** how to distinguish between:
  - IBM's home page (mostly graphical)
  - IBM's copyright page (high term freq. for 'ibm')
  - Rival's spam page (arbitrarily high term freq.)



# Indexing anchor text

- When indexing a document *D*, include anchor text from links pointing to *D*.






# Indexing anchor text

- Can sometimes have unexpected side effects, e.g. derogatory phrases
- Can index anchor text with less weight.

- Other applications
  - Weighting/filtering links in the graph
    - HITS [Chak98], Hilltop [Bhar01]
  - Generating page descriptions from anchor text [Amit98, Amit00]

# Web Search after Google

- Web Search Engines (WSEs) of the second generation (from 1998 onwards)
  - Identify relevance with topic-relateness and authoritativeness
    - Independent by the particular format of the Web site
    - Relevance computation is more selective
- This has been possible by the development of Link-based Ranking Schemes algorithms which compute authoritativeness exploiting the hyperlink structure of the Web
- The Web can be seen as a network of recommendations, a social network. Social networks analysis has been applied in many contexts in the past, including epidemiology, espionage and scientific production



# Spam Web Sites

- Spam Web Sites (SWSs) are Web pages designed to manipulate WSE ranking schemes, generally for commercial purposes
  - First Generation WSEs
    - Including deceptive self-description in the HTML META tag
    - Including "invisible words" (i.e. displayed in the same color as the background) or words typeset in tiny fonts, in order to deceive tfidf-based ranking schemes
  - Second Generation WSEs
    - LRSs would seem to be more robust, since SWSs are not authoritative, but naive LRSs may be fooled by artificially conferring authority onto SWSs
    - Adversarial IR to outwit companies specialized in promoting the rank of their customer (adaptive "enemies")

# LRSs and Bibliometrics

- LRSs leverage on the body of literature within bibliometrics, the 80-years-old science of the quantitative analysis of scientific literature
- Bibliometrics studies the quality of scientific papers, journals, etc., in terms of their impact factors (IFs), i.e. a measure of the impact that it has had, obtained through a quantitative analysis of the bibliographic citations to it
- Many results are directly applicable by observing that a hyperlink from page $p_i$ to page $p_j$ can be seen as a bibliographic reference to paper $p_j$ included in the bibliography of paper $p_i$



# Link-based Ranking Systems (LRSs)

- LRSs rank a “base set” BS of Web pages
- Depending on what BS is, we have:
  - Query Dependent LRSs rank a set of Web pages that have previously been identified as being topic-related with the query
    - Based on both topic-relatedness and authoritativeness
    - Must be computed on-line
    - Best known algorithm: HITS[Kleinberg98] (Clever WSE)
  - Query Independent LRSs, in principle, rank the entire Web
    - Only based on authoritativeness
    - Can be computed off-line
    - At query time, it must be merged in some way with a query-dependent ranking based on topic-relatedness
    - Best known algorithm: PageRank[Brin&Page98] (Google WSE)

# LRSs

- Preliminary steps to all LRSs are
  1. Identification of BS (necessary for QD LRSs only)
  2. The generation of the hyperlink graph G=<P,E>
- In Step 1, HITS obtains a base set BS of pages (loosely) topic-related to the query in the following way:
  - The query is fed to a standard text search system, and BS is initiated to a 'root set' consisting of the k top-ranked pages
  - All the pages pointing to pages in BS, and all the pages pointed to pages of BS, are added to BS
- Step 2 is obtained by considering all pages in BS as nodes in P, and all hyperlinks between pages of BS as edges in E, after discarding
  - 'nepotistic' hyperlinks (internal to the Web site)
  - 'duplicate' hyperlinks (only one link for any pair $<p_i,p_j>$)
  - 'self-loops' (links from $p_i$ to $p_i$)



# Adjacency Matrix

- The input to any LRS is thus a $|BS| \times |BS|$ adjacency matrix W such that
  W[i,j]=1 iif there is a hyperlink from page $p_i$ to $p_j$
- The output of any LRS is a vector $a=[a_1,..,a_{|BS|}]$ where $a_i$ is the authoritativeness of page $p_i$
- Backward Neighbors, $B(i)=\{p_j \mid W[j,i]=1\}$
- Forward Neighbors, $F(i)=\{p_j \mid W[i,j]=1\}$

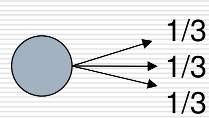
# The InDegree Algorithm

- The InDegree algorithm [Marchiori97], consists in identifying the authoritativeness $a_i$ of a page $p_i$ with the in-degree of $p_i$, i.e. $|B(i)|$
- It corresponds to ranking Web pages according to their 'popularity' ('visibility')
- In matric notation $a = W^T \cdot 1$
- Main weakness: only the quantity of backward links, and not their quality, matters
- It can fooled easily by SWSs. To promote a page $p_s$, they only need to set up lots of dummy pages $p_1,..p_k$, containing pointers to $p_s$
- Not used in any current-day WSE



# Pagerank scoring

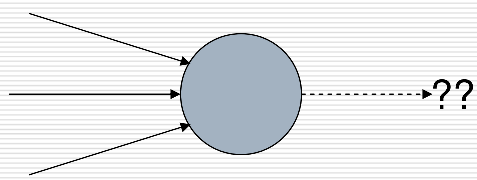
- Imagine a browser doing a random walk on web pages:
  - Start at a random page
  - At each step, go out of the current page along one of the links on that page, equiprobably




- "In the steady state" each page has a long-term visit rate - use this as the page's score.

# Not quite enough

- The web is full of dead-ends.
  - Random walk can get stuck in dead-ends.
  - Makes no sense to talk about long-term visit rates.






# Teleporting

- At a dead end, jump to a random web page.

- At any non-dead end, with probability 10%, jump to a random web page.
  - With remaining probability (90%), go out on a random link.
  - 10% - a parameter.

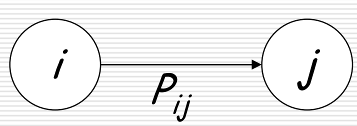
# Result of teleporting

- Now cannot get stuck locally.
- There is a long-term rate at which any page is visited
- How do we compute this visit rate?



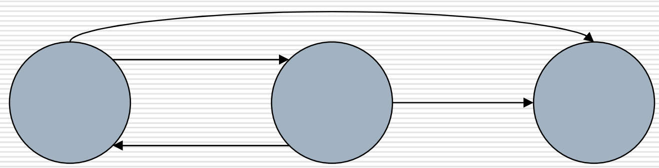
# Markov chains

- A Markov chain consists of *n* states, plus an *n*×*n* transition probability matrix **P**.
- At each step, we are in exactly one of the states.
- For $1 \leq i,j \leq n$, the matrix entry $P_{ij}$ tells us the probability of *j* being the next state, given we are currently in state *i*.



# Markov chains

- Clearly, for all i, $\sum_j P_{ij} = 1$
- Markov chains are abstractions of random walks.
- *Exercise*: represent the teleporting random walk from 3 slides ago as a Markov chain, for this case:





# Ergodic Markov chains

- A Markov chain is ergodic if
  - you have a path from any state to any other
  - you can be in any state at every time step, with non-zero probability.
- For any ergodic Markov chain, there is a unique long-term visit rate for each state.
  - *Steady-state distribution.*
- Over a long time-period, we visit each state in proportion to this rate.
- It doesn't matter where we start.