Einführung in Web und Data Science

Community Analysis

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Today's lecture

- Social Network Analysis
- Anchor text
- Link analysis for ranking
  - PageRank and variants
  - Hyperlink-Induced Topic Search (HITS)

Acknowledgements

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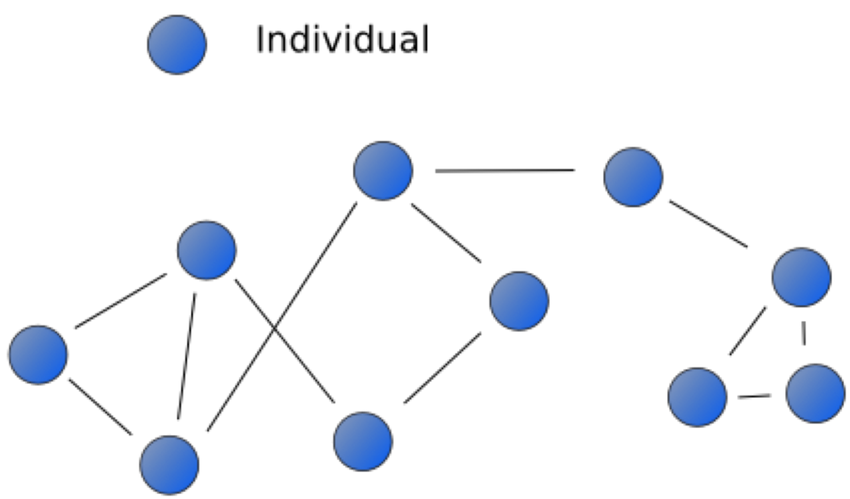
  - CS276A, Stanford Univ.,
    Text Information Retrieval, Mining, and Exploitation
  - Chr. Manning, P. Raghavan, H. Schütze

- Thanks also to other lecturers who provided their teaching material on the web

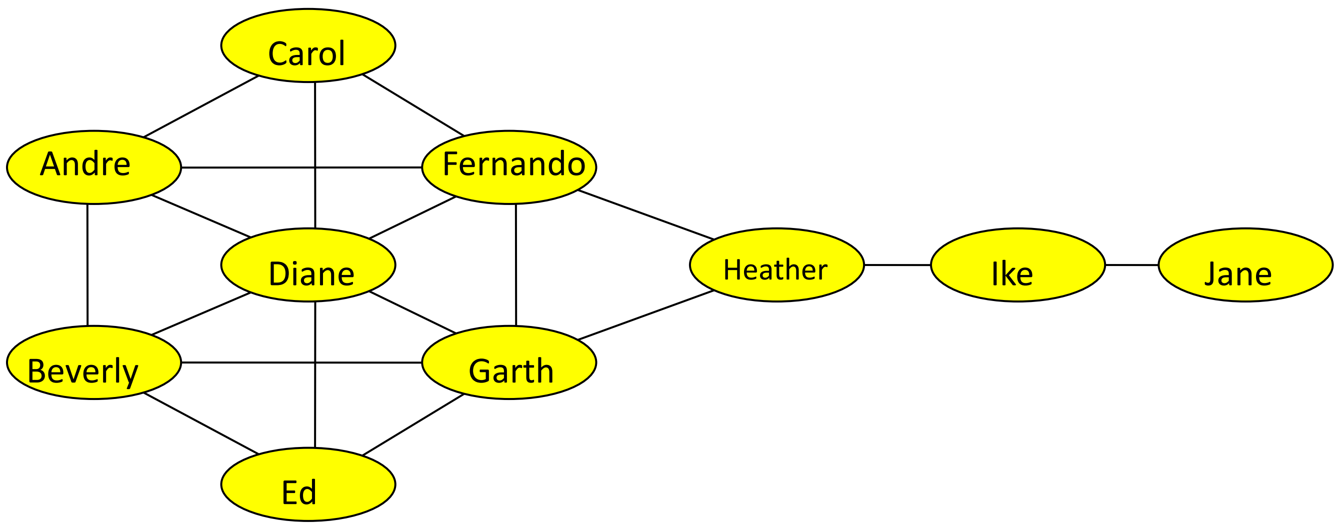
Social Network Analysis (SNA)

- Mapping and measuring of relationships and flows between people, groups, organizations, computers or other information/knowledge processing entities.

- The nodes in the network are the people and groups while the links show relationships or flows between the nodes.



Kite Network



- Who is the Connecter or Hub in the Network?
- Who has control over what flows in the Network?
- Who has best visibility of what is happening in the Network?
- Who are peripheral players? Are they Important?

Measures

1. Degree Centrality:

The number of direct connections a node has. What really matters is where those connections lead to and how they connect the otherwise unconnected.

$$C_D(n_i) = d(n_i) \qquad C'_D(n_i) = \frac{d(n_i)}{g-1}$$

2. Betweenness Centrality:

A node with high betweenness has great influence over what flows in the network indicating important links and single points of failure.

$$C_B(n_i) = \sum_{j<k} g_{jk}(n_i) / g_{jk} \qquad C'_B(n_i) = \frac{C_B(n_i)}{(g-1)(g-2)/2}$$

3. Closeness Centrality:

The measure of closeness of a node to everyone else.

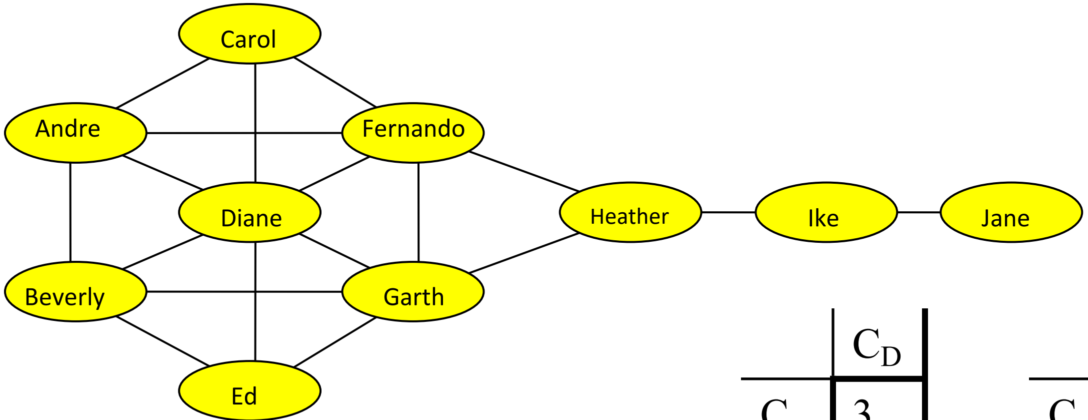
Determined by the sum of the length of the shortest paths between the node and all other nodes in the graph.

$$C_C(n_i) = \left[\sum_{j=1}^{g} d(n_i, n_j)\right]^{-1} \qquad C'_C(n_i) = \frac{g-1}{\sum_{j=1}^{g} d(n_i, n_j)} = (g-1)C_C(n_i)$$

Legend

- g = size of graph (number of nodes)
- $d(.)$ = (in)degree
- g_{jk} = number of minimal paths between nodes j and k
- $g_{jk}(n)$ = number of minimal paths between nodes j and k that contain n
- $(g-1)(g-2)/2$ = number of potential paths without node n
  $\Sigma_{x=1}^{u} x = (u+1)u/2$ für $u=(g-2)$
- $d(.,.)$= distance between two nodes

Example: Kite-Network



$$C_B(n_i) = \sum_{j<k} g_{jk}(n_i)/g_{jk}$$

$$C_C(n_i) = \left[\sum_{j=1}^{g} d(n_i, n_j)\right]^{-1}$$

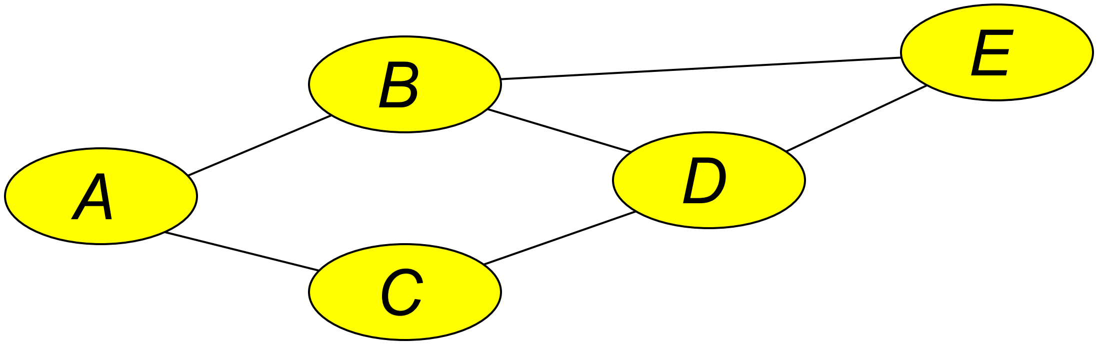
$$C_D(n_i) = d(n_i)$$

	C_D
C	3
A	4
F	5
D	6
B	4
G	5
E	3
H	3
I	2
J	1

	C	A	F	D	B	G	E	H	I	J
C	0	1	1	1	0	0	0	0	0	0
A	1	0	1	1	1	0	0	0	0	0
F	1	1	0	1	0	1	0	1	0	0
D	1	1	1	0	1	1	1	0	0	0
B	0	1	0	1	0	1	1	0	0	0
G	0	0	1	1	1	0	1	1	0	0
E	0	0	0	1	1	1	0	0	0	0
H	0	0	1	0	0	1	0	0	1	0
I	0	0	0	0	0	0	0	1	0	1
J	0	0	0	0	0	0	0	0	1	0

Example

$$C_B(n_i) = \sum_{j<k} g_{jk}(n_i)/g_{jk} \qquad C_C(n_i) = \left[\sum_{j=1}^{g} d(n_i, n_j)\right]^{-1} \qquad C_D(n_i) = d(n_i)$$



	A	B	C	D	E
A	0	1	1	0	0
B	1	0	0	1	1
C	1	0	0	1	0
D	0	1	1	0	1
E	0	1	0	1	0

Adjacency

	C_B	C_C	C_D
A	1	1/6	2
B	3	1/5	3
C	1	1/6	2
D	3	1/5	3
E	0	1/6	2

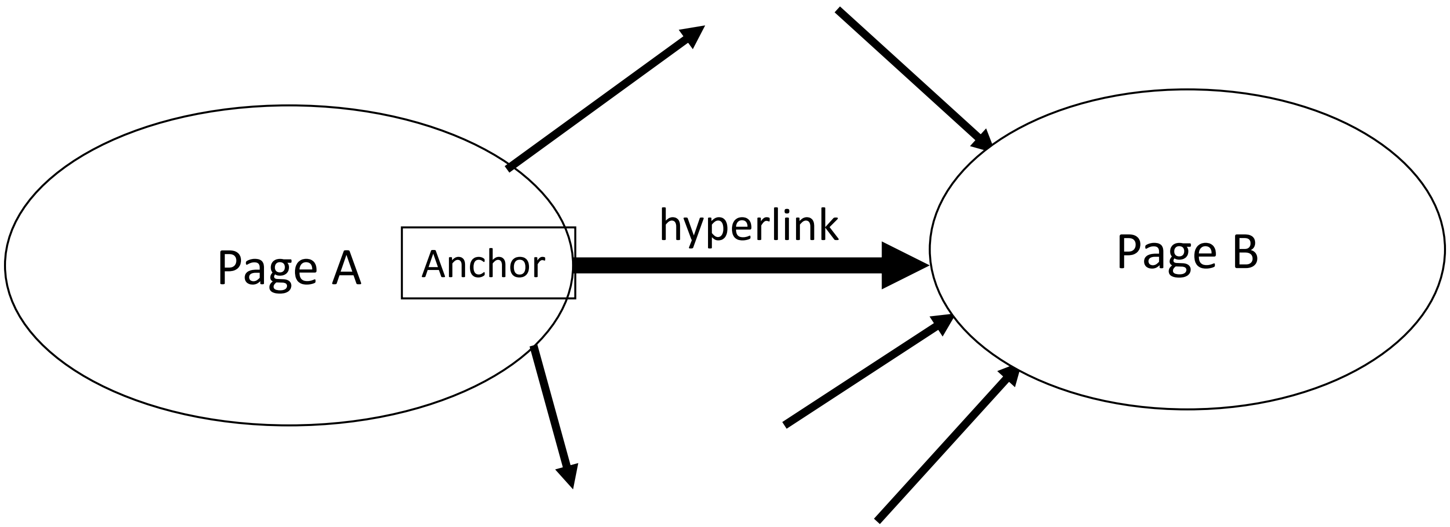
	A	B	C	D	E
A	0	1	1	2	2
B	1	0	2	1	1
C	1	2	0	1	2
D	2	1	1	0	1
E	2	1	2	1	0

Distance

	A	B	C	D	E
A	0	A	A	BC	B
B	B	0	AD	B	B
C	C	AD	0	C	D
D	BC	D	D	0	D
E	B	E	D	E	0

Paths

The Web as a Directed Graph

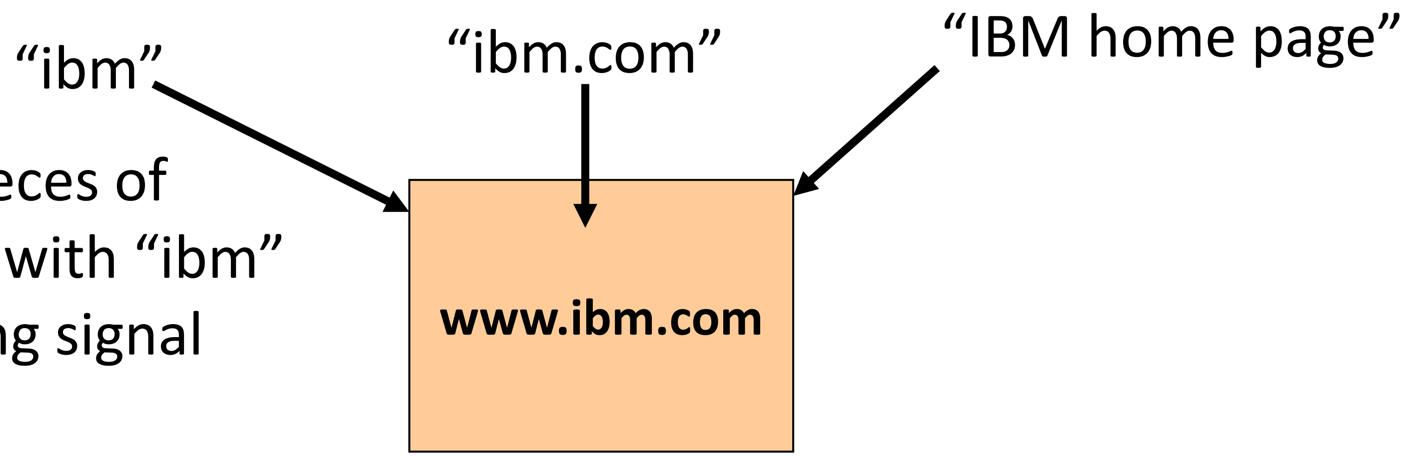


Assumption 1: A hyperlink between pages denotes author perceived relevance (quality signal)

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

Anchor Text

- 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.)

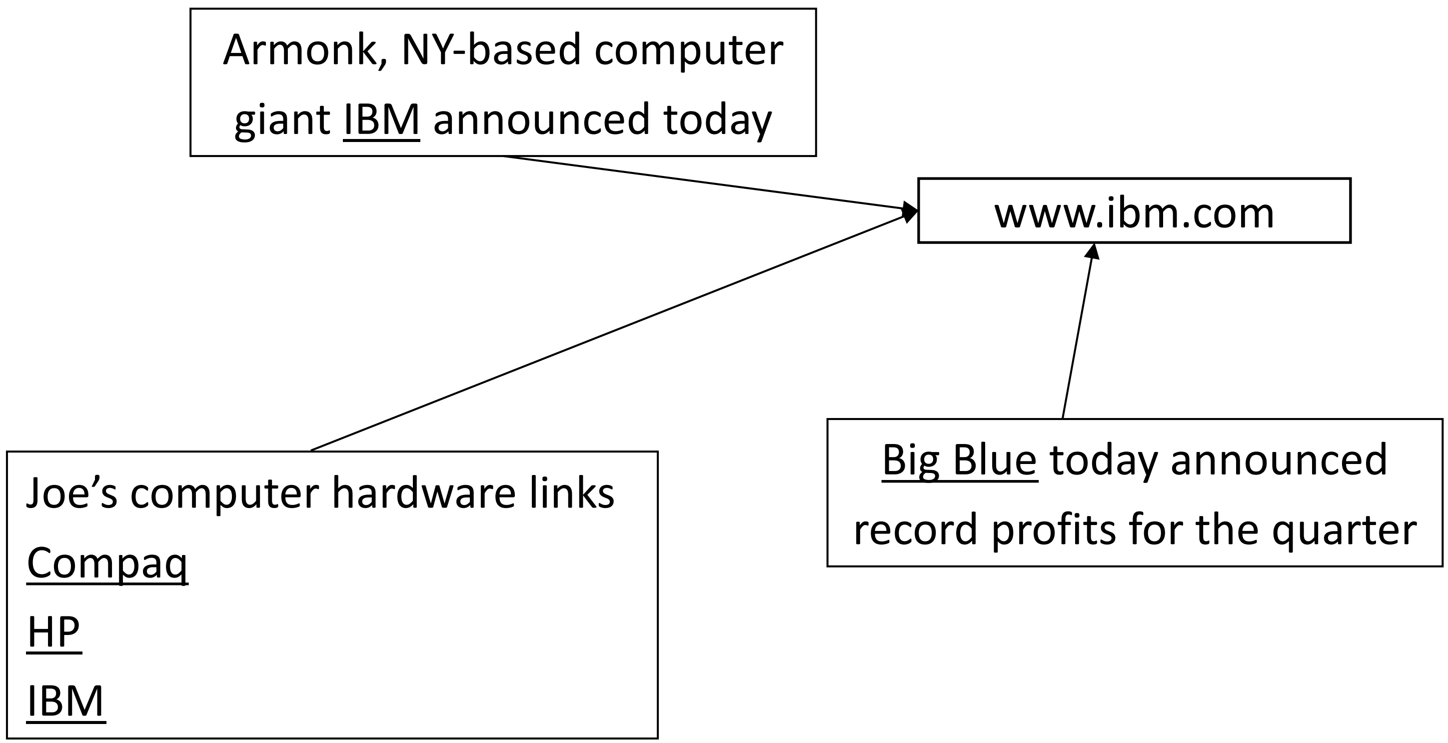


A million pieces of anchor text with “ibm” send a strong signal

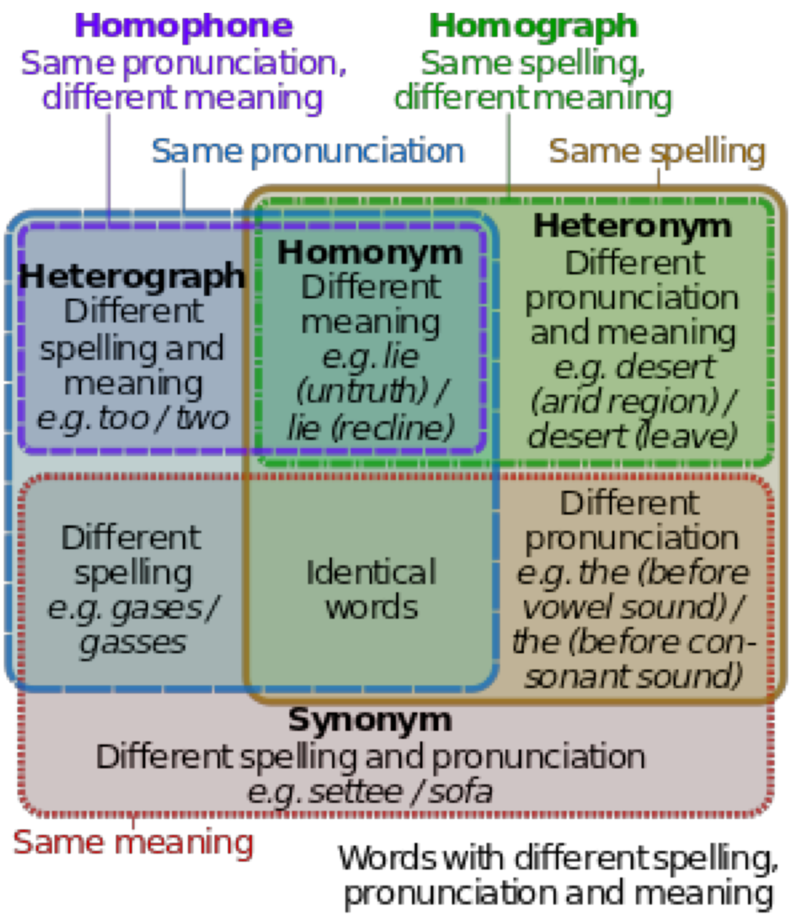
Oliver A. McBryan. GENVL and WWWW: Tools for Taming the Web. Research explained at First International Conference on the World Wide Web. CERN, Geneva (Switzerland), May 25-26-27 **1994**
(WWWW=World Wide Web Worm, first serach engine for the web)

Indexing anchor text

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



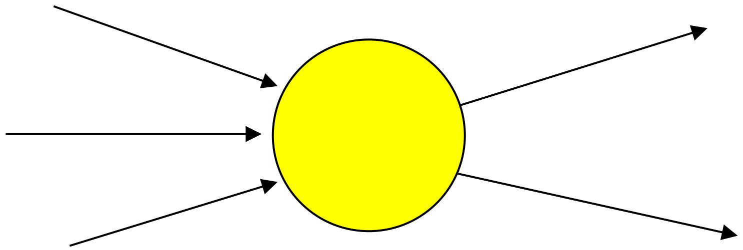
The Web as a Resource for NLP



[Wikipedia]

The Web as a Resource for Ranking

- First generation: using link counts as simple measures of popularity.
- Two basic suggestions:
  - <u>Undirected popularity:</u>
    - Each page gets a score = the number of in-links plus the number of out-links (3+2=5).
  - <u>Directed popularity:</u>
    - Score of a page = number of its in-links (3).



Query processing

- First retrieve all pages matching the text query (say ***venture capital***).
- Order these by their link popularity (either variant on the previous page).

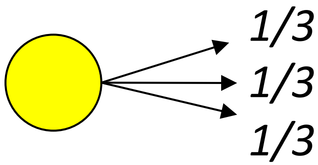
Spamming simple popularity

- *Exercise*: How do you spam each of the following heuristics so your page gets a high score?
- Each page gets a score = the number of in-links plus the number of out-links.
- Score of a page = number of its in-links.

"Search Engine Optimization"

PageRank scoring

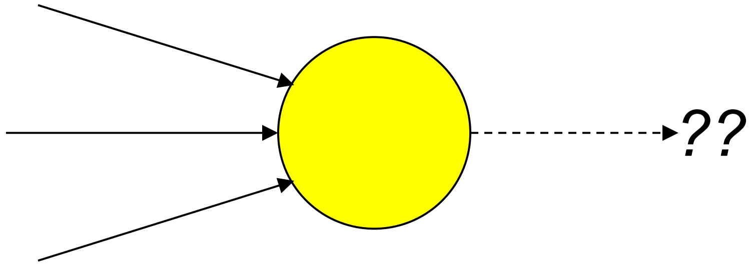
- Imagine a browser doing a random walk on web pages:
  - Start at a random page



  - At each step, go out of the current page along one of the links on that page, equiprobably
- 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.



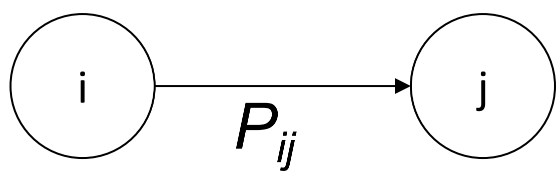
Teleporting / damping

- 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.
- There is a long-term rate at which any page is visited.
  - How do we compute this visit rate?

Markov chains

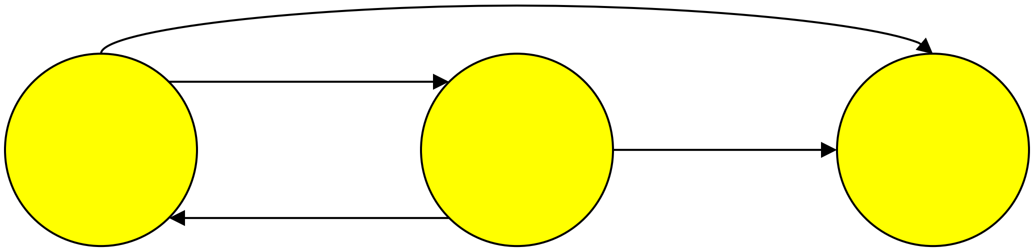
- A Markov chain consists of n <u>states</u>, plus an $n \times n$ <u>transition matrix</u> **P**.
- At each step, we are in exactly one of the states.
- For $1 \leq i,j \leq n$, the matrix entry P_{ij} tells us the relative frequency of j being the next state, given we are currently in state i.

$P_{ii}>0$ is OK.



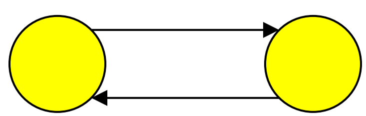
Markov chains

- Clearly, for all i, $\sum_{j=1}^{n} P_{ij} = 1.$
- 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 (reducibility)
  - returns to states occur at irregular times (aperiodicity)
  - For any start state, after a finite transient time T_0, the probability of being in any state at a fixed time $T>T_0$ is nonzero. (positive recurrence)



Not ergodic (even/odd).

Ergodic Markov chains

- 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.

State vectors

- A (row) vector (state vector) **x** = (x_1, … x_n) tells us where the walk is at any point.
- E.g., (000…1…000) means we're in state i.

1 i n

More generally, the vector **x** = (x_1, … x_n) means the walk is in state i with relative frequency x_i.

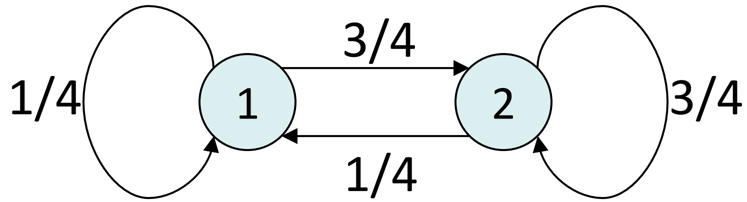
$$\sum_{i=1}^{n} x_i = 1.$$

Change in state vector

- If the state vector is
  x = $(x_1, \ldots x_n)$ at this step,
  what is it at the next step?
- Recall that row *i* of the transition matrix **P** tells us where we go next from state *i*
- So from **x**, our next state is distributed as **xP**.

Steady state example

- The steady state looks like a vector of probabilities $\mathbf{a} = (a_1, \ldots a_n)$:
  - a_i is the relative frequency that we are in state i.

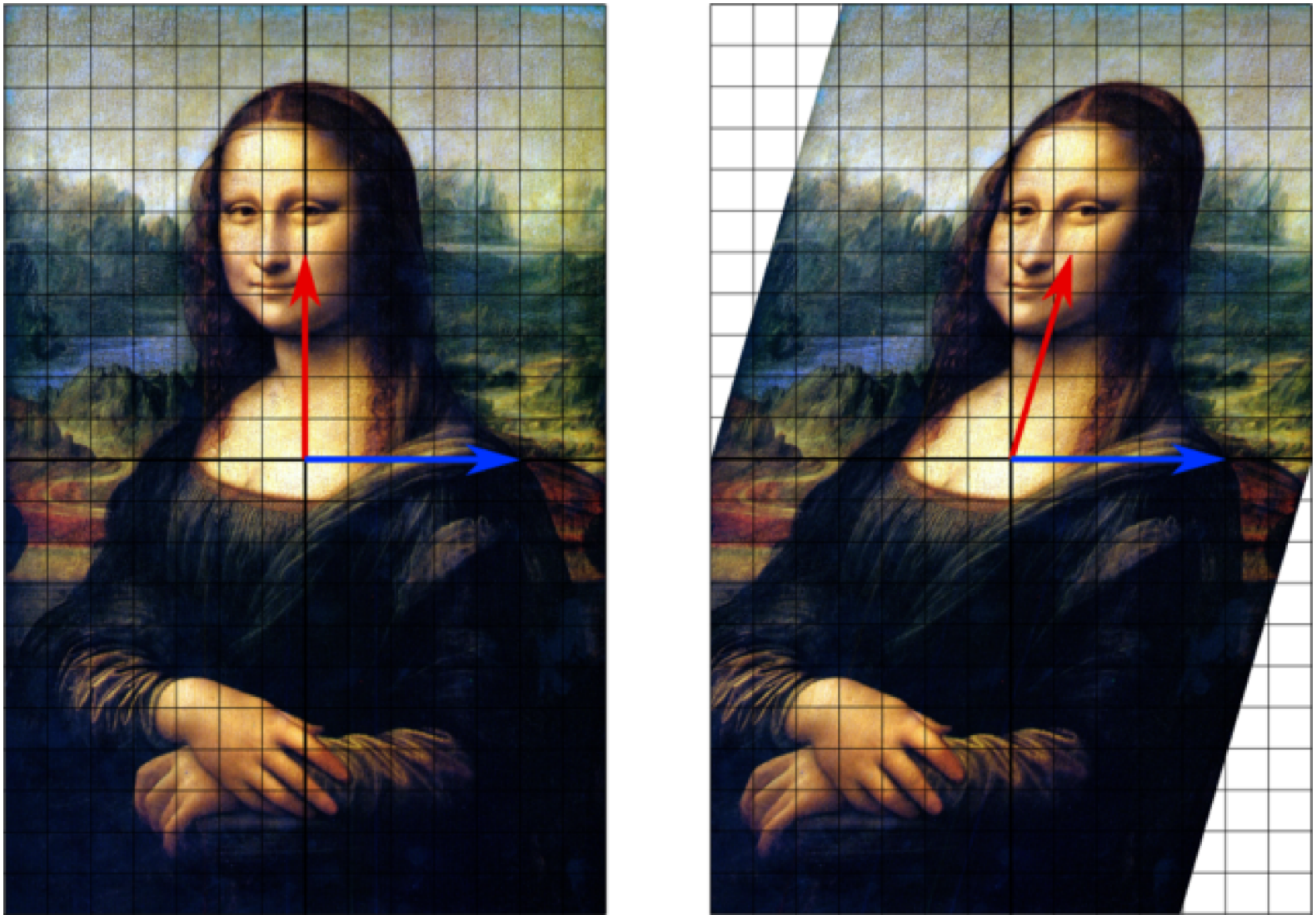


For this example, a_1=1/4 and a_2=3/4.

How do we compute this vector?

- Let **a** = (a_1, … a_n) denote the row vector of steady-state rates.
- If we our current position is described by **a**, then the next step is distributed as **aP**.
- But **a** is the steady state, so **a**=**aP**.
- Solving this matrix equation gives us **a**.
  - So **a** is the (left) eigenvector for **P**.
  - (Corresponds to the "principal" eigenvector of **P** with the largest eigenvalue)
  - Transition matrices always have largest eigenvalue 1.

Eigenvectors and Eigenvalues $Mx = \lambda x$



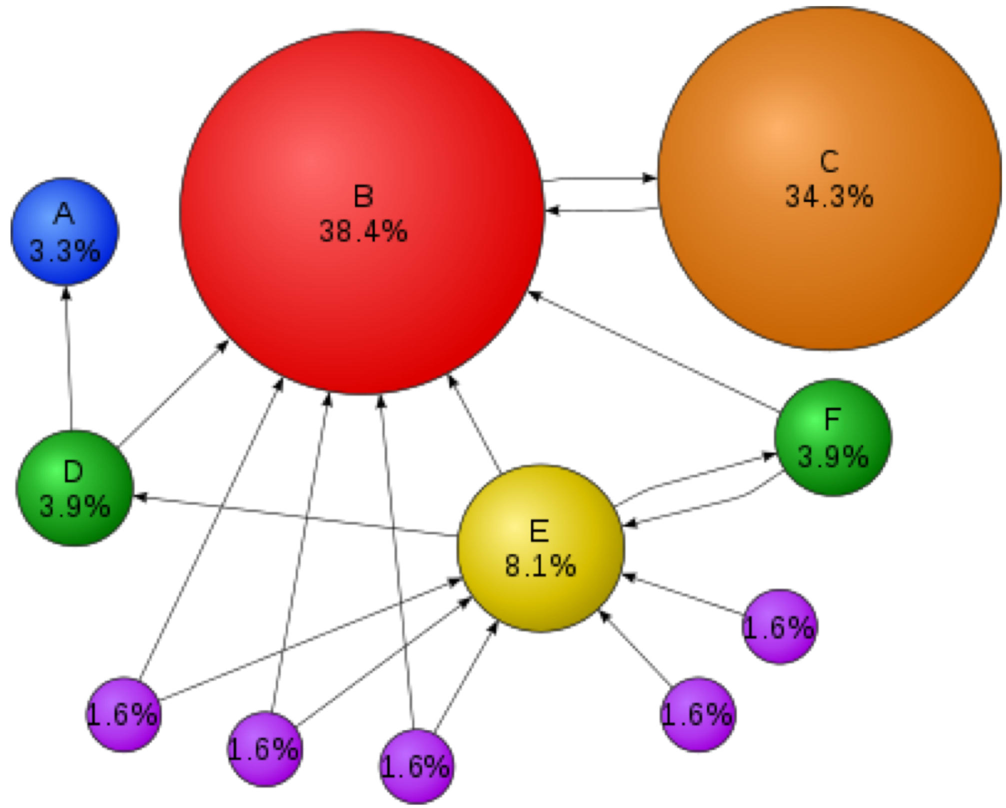
[Wikipedia]

One way of computing a

- Recall, regardless of where we start, we eventually reach the steady state **a**.
- Start with any distribution (say **x**=(*10…0*)).
- After one step, we're at **xP**;
- after two steps at $\mathbf{xP}^2$, then $\mathbf{xP}^3$ and so on.
- "Eventually" means for "large" k, $\mathbf{xP}^k = \mathbf{a}$.
- Algorithm: multiply **x** by increasing powers of **P** until the product looks stable.

Google PageRank

- Instead of rates, Google uses a logarithmic scale
- Links are weighted according to the importance of the source node
  - Page C has a higher PageRank than Page E, even though there are fewer links to C; the one link to C comes from an important page and hence is of high value.



PageRank Summary

- Preprocessing:
  - Given graph of links, build matrix **P**
  - From it compute **a**
  - The entry a_i is a number between 0 and 1: the pagerank of page i.
- Query processing:
  - Retrieve pages meeting query
  - Rank them by their pagerank
  - Order is query-*independent*
- PageRank is used in Google,
  but also many other clever heuristics

PageRank: Issues and Variants

- How realistic is the random surfer model?
  - What if we modeled the back button?
  - Surfer behavior sharply skewed towards short paths
  - Search engines, bookmarks & directories make jumps non-random
- Biased Surfer Models
  - Weight edge traversal probabilities based on match with topic/query (non-uniform edge selection)
  - Bias jumps to pages on topic (e.g., based on personal bookmarks & categories of interest)

Hyperlink-Induced Topic Search (HITS)

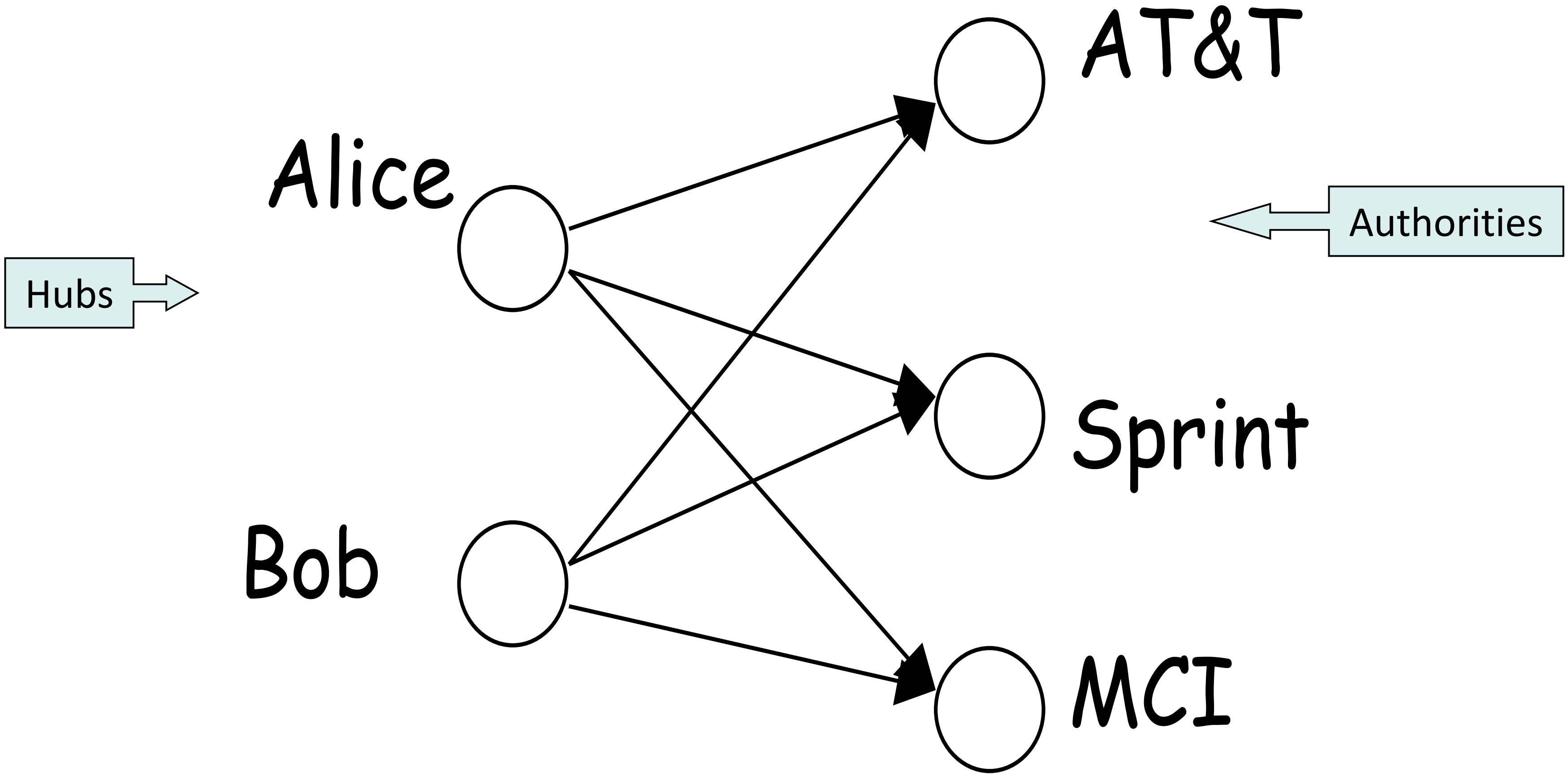
- In response to a query, instead of an ordered list of pages each meeting the query, find two sets of inter-related pages:
  - Hub pages are good lists of links on a subject
    - e.g., “Bob’s list of cancer-related links.”
  - Authority pages occur recurrently on good hubs for the subject
- Best suited for “broad topic” queries rather than for page-finding queries
- Gets at a broader slice of common opinion

Jon M. Kleinberg, Hubs, Authorities, and Communities,
ACM Computing Surveys 31(4), December **1999**

Hubs and Authorities

- Thus, a good hub page for a topic *points* to many authoritative pages for that topic
- A good authority page for a topic is *pointed* to by many good hubs for that topic
- Circular definition - will turn this into an iterative computation

The hope



Long distance telephone companies

High-level scheme

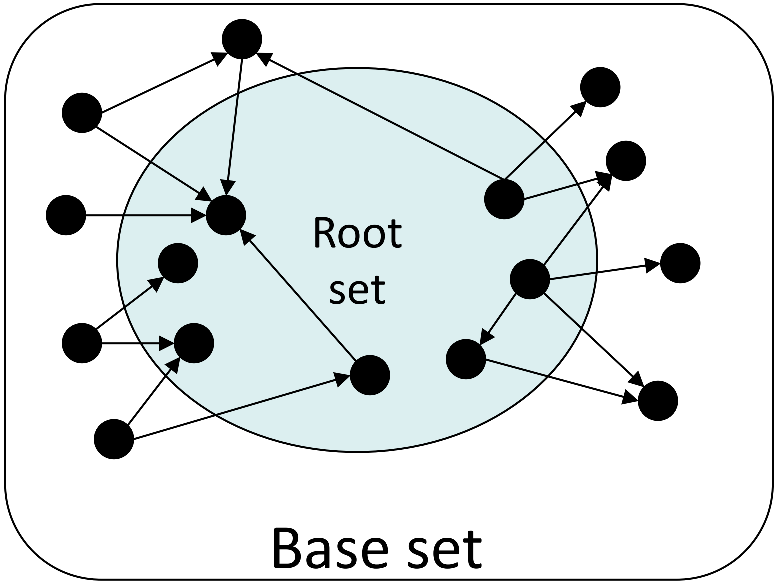
- Extract from the web a base set of pages that *could* be good hubs or authorities
- From these, identify a small set of top hub and authority pages;

  →iterative algorithm

Base set

- Given text query (say ***browser***), use a text index to get all pages containing ***browser***
  - Call this the root set of pages
- Add in any page that either
  - points to a page in the root set, or
  - is pointed to by a page in the root set
- Call this the base set

Visualization



Assembling the base set

- Root set typically 200-1000 nodes
- Base set may have up to 5000 nodes
- How do you find the base set nodes?
  - Follow out-links by parsing root set pages
  - Get in-links (and out-links) from a connectivity server
  - Actually, suffices to text-index strings of the form **href="URL"** to get in-links to URL

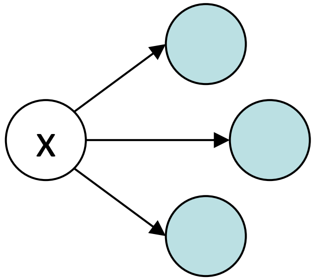
Distilling hubs and authorities

- Compute, for each page *x* in the base set, a hub score *h(x)* and an authority score *a(x)*
- Initialize: for all x, $h(x) \leftarrow 1$; $a(x) \leftarrow 1$;
- Iteratively update all *h(x), a(x)*;
- After iterations
  - output pages with highest *h()* scores as top hubs
  - highest *a()* scores as top authorities

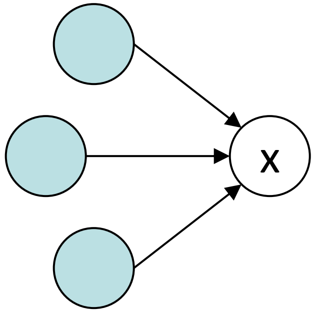
Iterative update

- Repeat the following updates, for all *x*:

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



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



Scaling

- To prevent the *h()* and *a()* values from getting too big, can scale down after each iteration
- Scaling factor doesn't really matter:
  - we only care about the *relative* values of the scores

How many iterations?

- Claim: relative values of scores will converge after a few iterations:
  - In fact, suitably scaled, *h()* and *a()* scores settle into a steady state!
- We only require the relative orders of the *h()* and *a()* scores - not their absolute values
- In practice, ~5 iterations get you close to stability

Things to note

- Pulled together good pages regardless of language of page content
- Use *only* link analysis <u>after</u> base set assembled
  - Iterative scoring is query-independent
- Iterative computation <u>after</u> text index retrieval - significant overhead