

Lecture 9

Information retrieval

Recap and today's topics

- Last lecture
 - web search overview
 - pagerank
- Today
 - more sophisticated link analysis
 - using links + content

Pagerank recap

- Pagerank computation
 - Random walk on the web graph
 - Teleport operation to get unstuck from dead ends
- ⇒ Steady state visit rate for each web page
- Call this its pagerank score
 - computed from an eigenvector computation (linear system solution)

Pagerank recap

- Pagerank usage
 - Get pages matching text query
 - Return them in order of pagerank scores
- This order is query-independent
- Can combine arithmetically with text-based scores
- Pagerank is a global property
 - Your pagerank score depends on "everybody" else
- Harder to spam than simple popularity counting

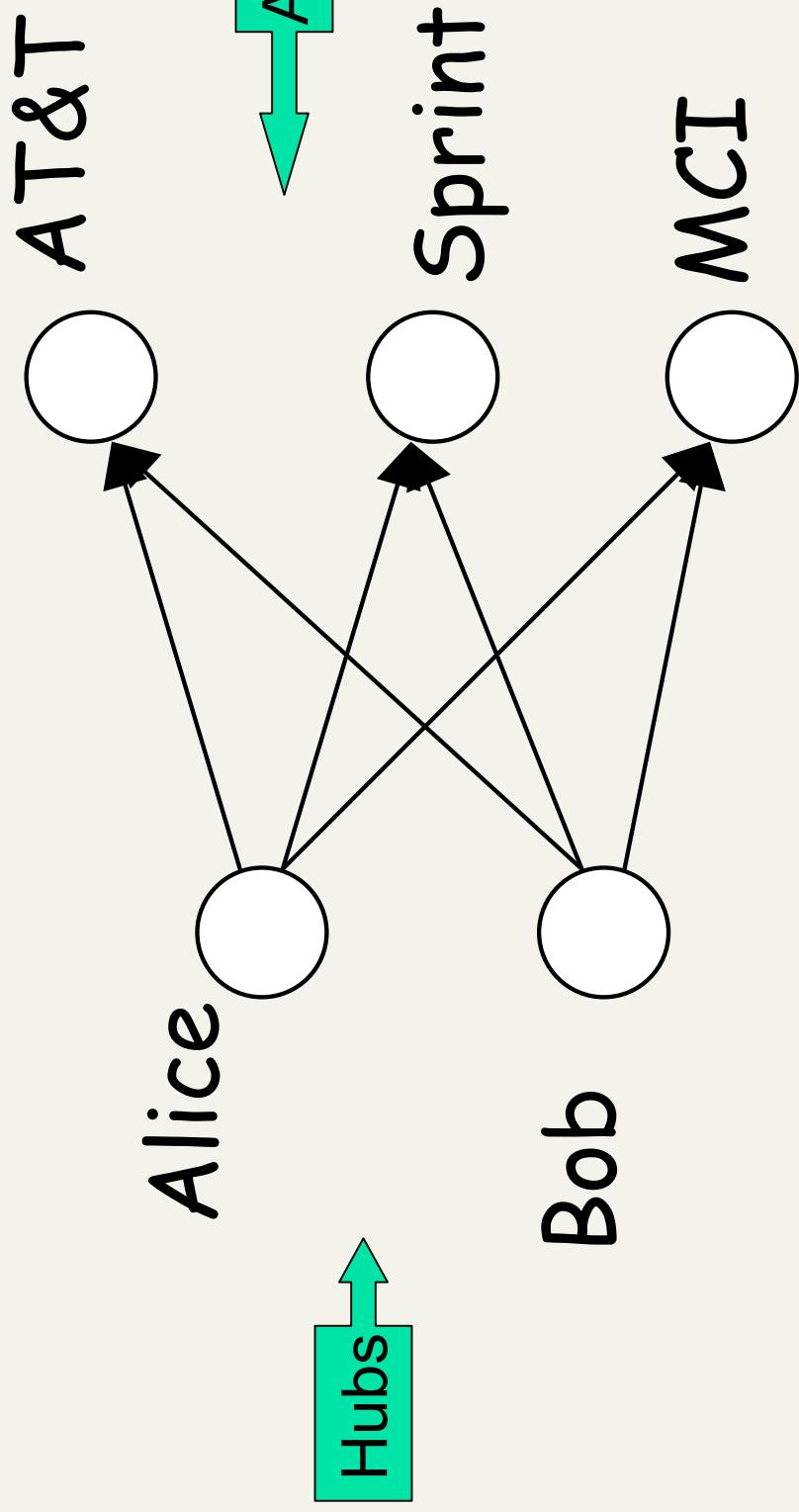
Hyperlink-Induced Topic Search (HITS) – Klein

- 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*.

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

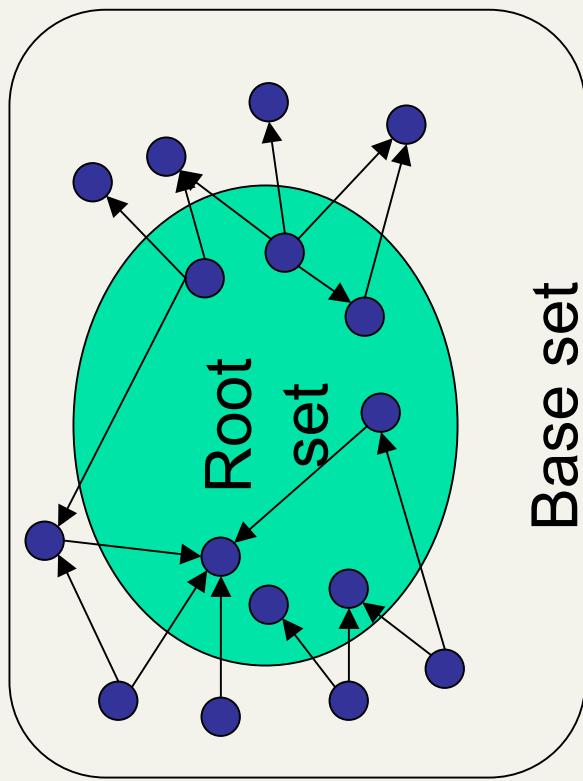
High-level scheme

- 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.)

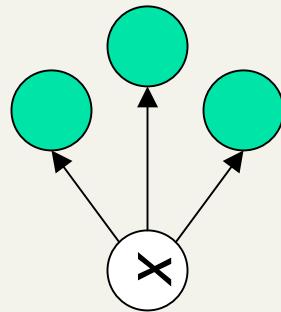
Distilling hubs and authorities

- Compute, for each page x in the base set, a hub score $h(x)$ and an authority score $a(x)$.
- Initialize: for all x , $h(x) \leftarrow 1$; $a(x) \leftarrow 1$.

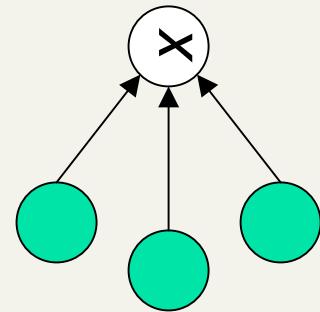
- Iteratively update all $h(x)$, $a(x)$.
- After iterations
 - output pages with highest $h\theta$ scores as top hubs
 - highest $a\theta$ scores as top authorities.

Iterative update

- Repeat the following updates, for all x :



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



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

Scaling

- To prevent the $h\theta$ and $a\theta$ 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, $h\theta$ and $a\theta$ scores settle into a steady state!
 - proof of this comes later.
- We only require the relative orders of the $h\theta$ and $a\theta$ scores - not their absolute values.
- In practice, ~5 iterations get you close to stability.

Japan Elementary Schools

Hubs

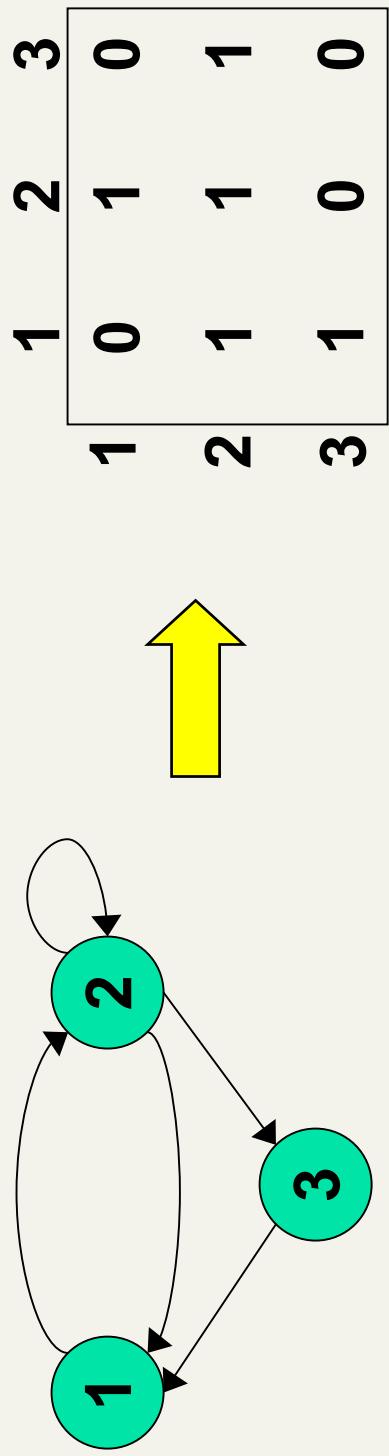
Authorities

Things to note

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

Proof of convergence

- $n \times n$ adjacency matrix A:
 - each of the n pages in the base set has a row and column in the matrix.
 - Entry $A_{ij} = 1$ if page i links to page j , else = 0.



Hub/authority vectors

- View the hub scores $h(\theta)$ and the authority scores $a(\theta)$ as vectors with n components.
- Recall the iterative updates

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

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

Rewrite in matrix form

- $h = Aa$.
- $a = A^t h$.

Recall A^t
is the
transpose
of A .

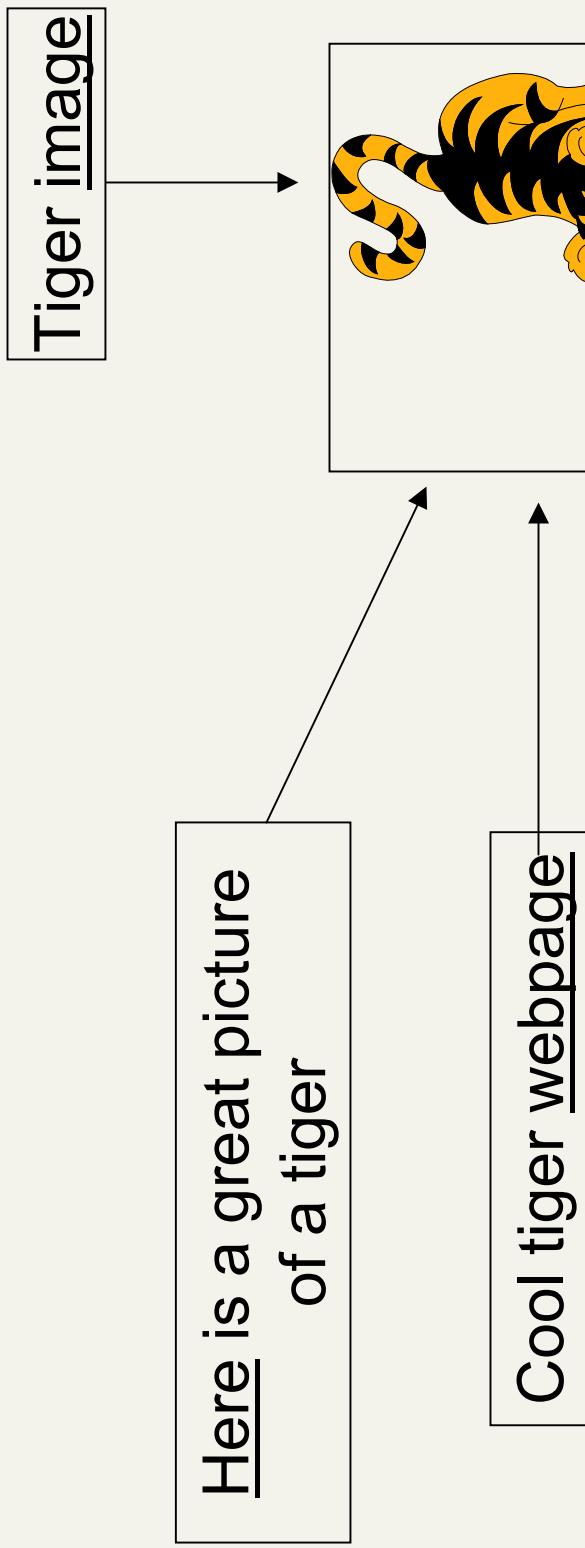
Substituting, $h = AA^t h$ and $a = A^t A a$.

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

Tag/position heuristics

- Increase weights of terms
 - in titles
 - in tags
- near the beginning of the doc, its chapters and sections

Anchor text (first used *Www Worm* - McBryan [Mcbr94])



The text in the vicinity of a hyperlink is descriptive of the page it points to.

TWO USES OF ANCHOR TEXT

- When indexing a page, also index the anchor text of links pointing to it.
- Retrieve a page when query matches its anchor text.
- To weight links in the hubs/authories algorithm.
- Anchor text usually taken to be a window of 6-8 words around a link anchor.

Indexing anchor text

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

Armonk, NY-based computer giant IBM announced today

www.ibm.com

Joe's computer hardware links
Compaq
HP
IBM

Big Blue today announced record profits for the quarter

Indexing anchor text

- Can sometimes have unexpected side effects
 - *e.g., evil empire.*
- Can index anchor text with less weight.

Weighting links

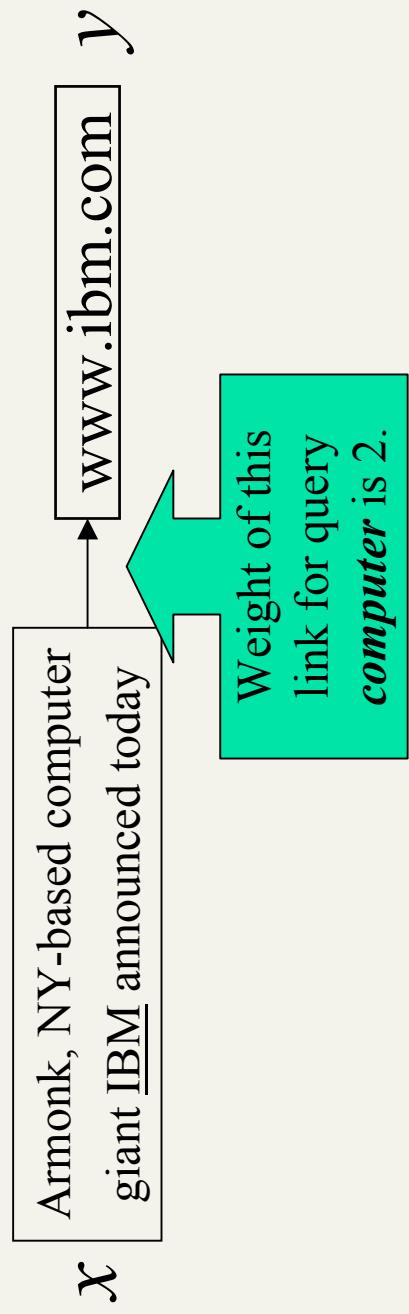
- In hub/authority link analysis, can match anchor text to query, then weight link.

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

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

Weighting links

- What is $w(x,y)$?
- Should increase with the number of query terms in anchor text.
- E.g.: $1 + \text{number of query terms.}$



Weighted hub/authority computation

- Recall basic algorithm:
 - Iteratively update all $h(x), a(x)$:
 - After iteration, output pages with
 - highest $h\theta$ scores as top hubs
 - highest $a\theta$ scores as top authorities.
 - Now use weights in iteration.
 - Raises scores of pages with "heavy" links.

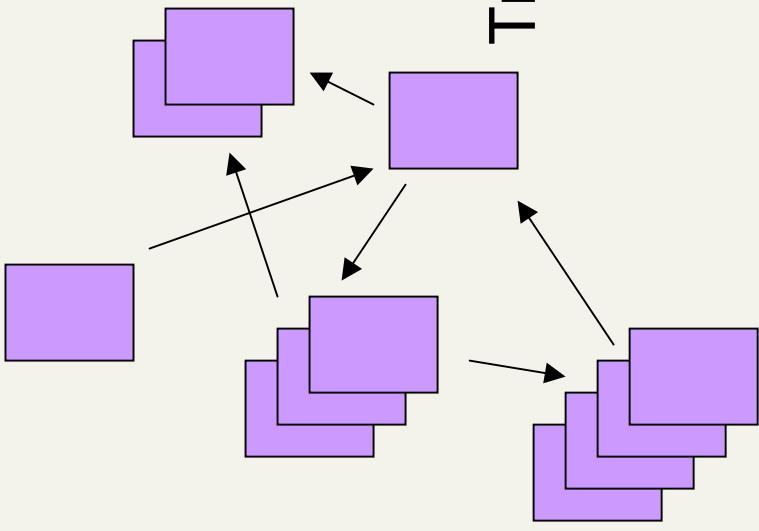
Do we still have convergence
of scores? To what?

Anchor Text

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

Web sites, not pages

- Lots of pages in a site give varying aspects of information on the same topic.



Treat portions of web-sites as a single entity for score computations.

Link neighborhoods

- Links on a page tend to point to the same topics as neighboring links.
- Break pages down into *pagelets* (say separate by tags)
 - compute a hub/authority score for each pagelet.

Link neighborhoods – example

Ron Fagin's links

- Logic links
 - Moshe Vardi's logic page
 - International logic symposium
 - Paper on modal logic
-
- My favorite football team
 - The 49ers
 - Why the Raiders suck
 - Steve's homepage
 - The NFL homepage

Comparison

HITS & Variants	
PageRank	Pros <ul style="list-style-type: none">▪ Hard to spam▪ Computes quality signal for <u>all</u> pages Cons <ul style="list-style-type: none">▪ Non-trivial to compute▪ Not query specific▪ Doesn't work on small graphs <p>Proven to be effective for general purpose ranking</p>
	Pros <ul style="list-style-type: none">▪ Easy to compute, real-time execution is hard [Bhar98b, Stato0]▪ Query specific▪ Works on small graphs Cons <ul style="list-style-type: none">▪ Local graph structure can be manufactured (spam!)▪ Provides a signal <u>only</u> when there's direct connectivity (e.g., home pages) <p>Well suited for supervised directory construction</p>

Topic Specific Pagerank [Havel02]

- Conceptually, we use a random surfer who teleports, with say 10% probability, using the following rule:
 - Selects a category (say, one of the 16 top level ODP categories) based on a query & user - specific distribution over the categories
 - Teleport to a page uniformly at random within the chosen category
- Sounds hard to implement: can't compute PageRank at query time!

Topic Specific Pagerank [Havel02]

- Implementation
 - offline: Compute pagerank distributions wrt to *individual* categories

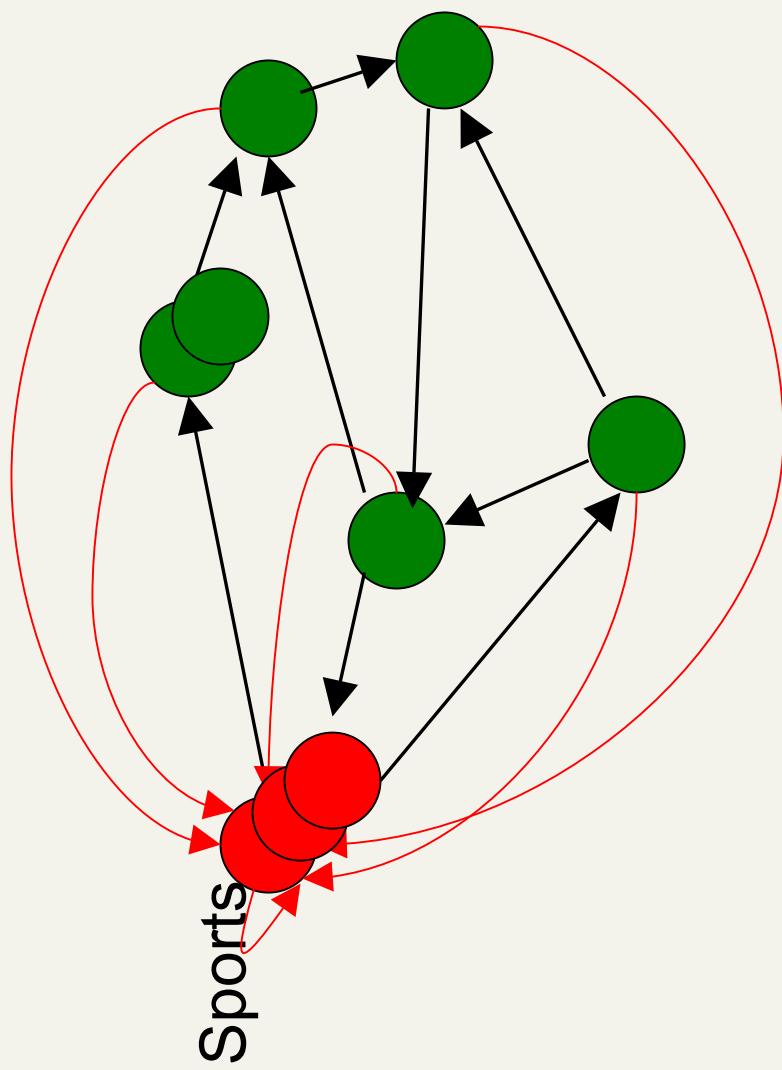
Query independent model as before
Each page has multiple pagerank scores – one for each ODP category, with teleportation only to that category
 - online: Distribution of weights over categories computed by query context classification

Generate a dynamic pagerank score for each page – weighted sum of category-specific pageranks

Influencing PageRank ("Personalization")

- Input:
 - Web graph W
 - influence vector v
 - $v : (\text{page} \rightarrow \text{degree of influence})$
- Output:
 - Rank vector $r : (\text{page} \rightarrow \text{page importance wrt } v)$
 - $r = PR(W, v)$

Non-uniform Teleportation



Teleport with 10% probability to a Sports page

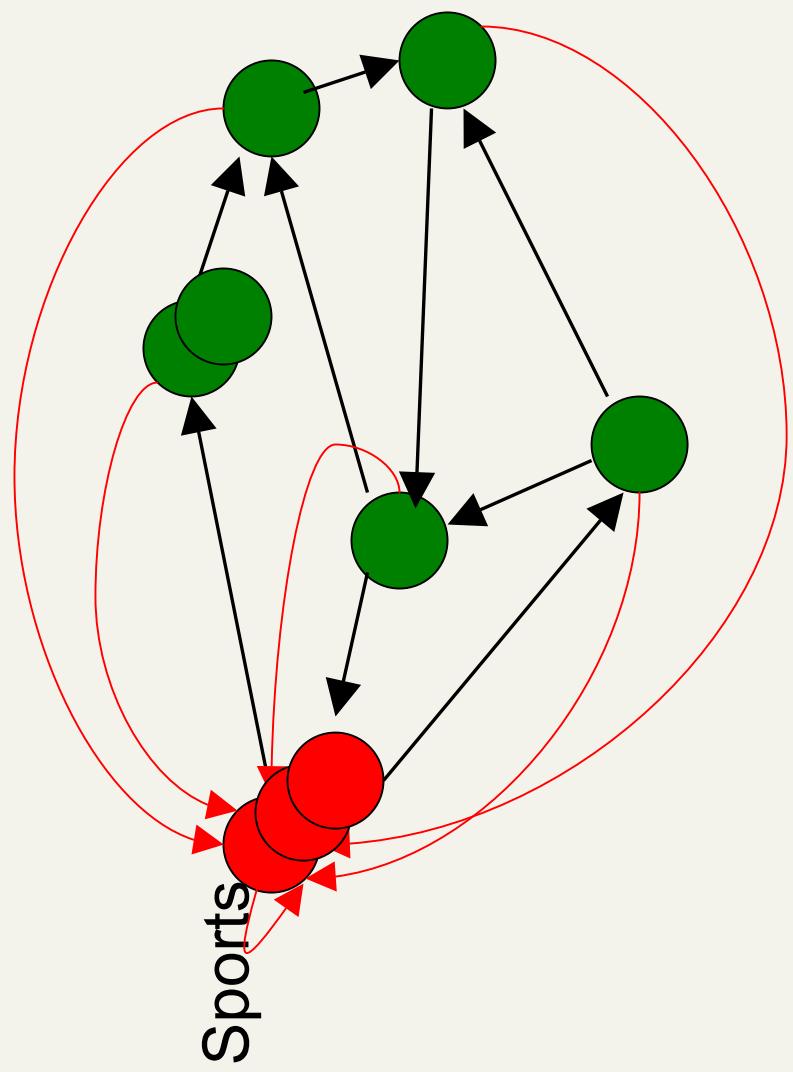
Interpretation of Composite Score

- For a set of personalization vectors $\{v_j\}$

$$\sum_j [w_j \cdot PR(W, v_j)] = PR(W, \sum_j [w_j \cdot v_j])$$

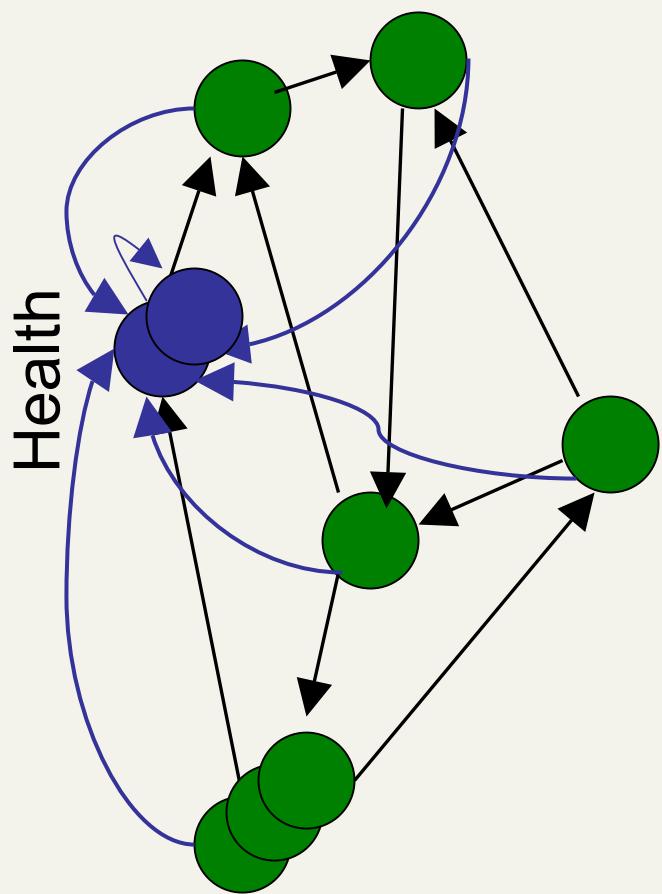
- Weighted sum of rank vectors itself forms a valid rank vector, because $PR()$ is linear wrt v_j

Interpretation



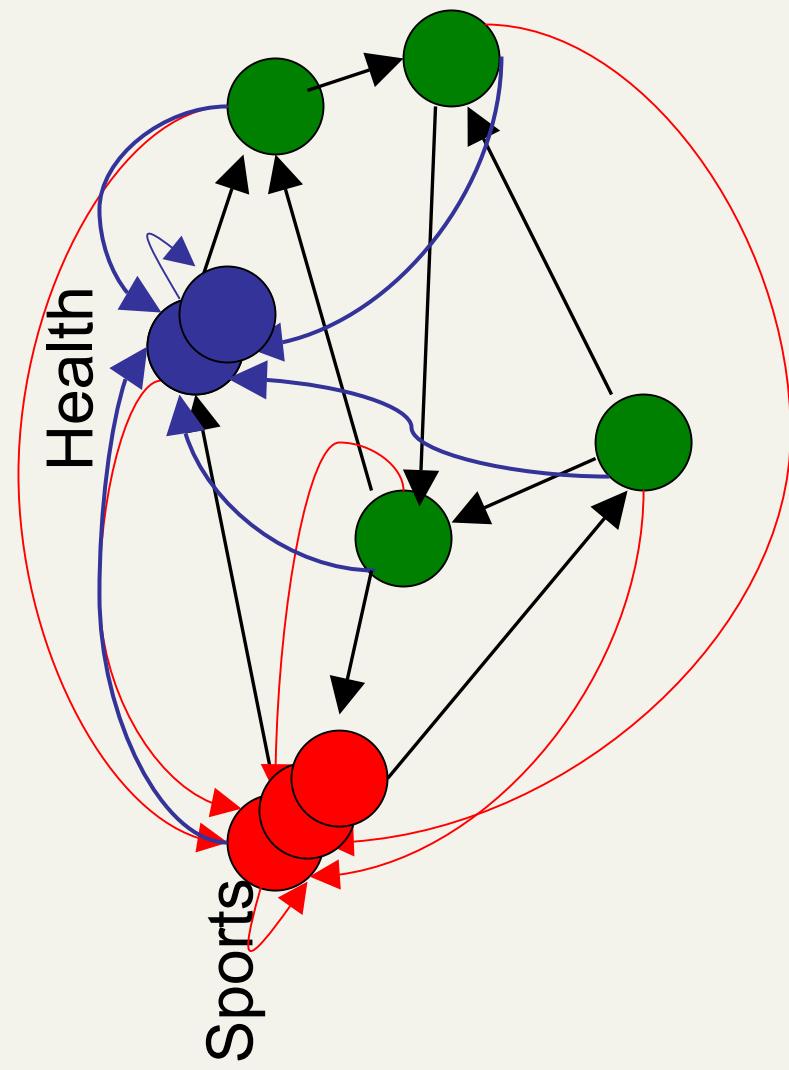
10% Sports teleportation

Interpretation



10% Health teleportation

Interpretation



$pr = (0.9 PR_{\text{sports}} + 0.1 PR_{\text{health}})$ gives you:
9% sports teleportation, 1% health teleportation

Web vs. hypertext search

- The WWW is full of free-spirited opinion, annotation, authority conferral
- Most other forms of hypertext are far more structured
 - enterprise intranets are regimented and templated
 - very little free-form community formation
 - web-derived link ranking doesn't quite work

Next up

- Behavior-based ranking
- Crawling
- Spam detection
- Mirror detection
- Web search infrastructure