Web Structure Mining

- The Web Graph
  - properties, visualization, etc.
- Using Graph Information for Ranking
  - Hubs and Authorities
  - PageRank
- Using Graph Information for Hypertext Classification
  - Absorbing Features from Neighboring Pages
  - Hyperlink Ensembles

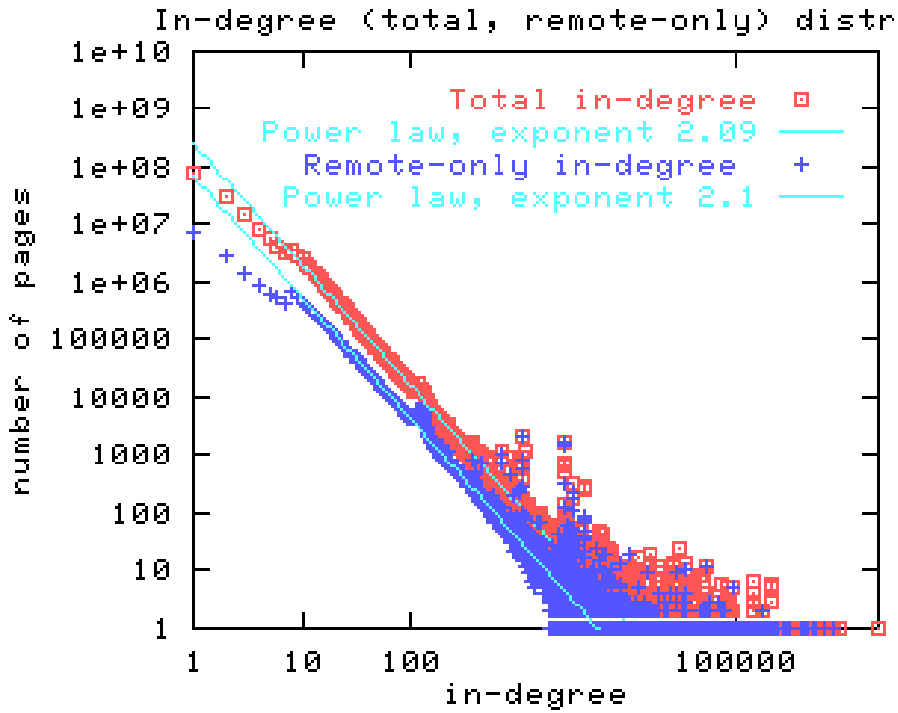
The Web is a Graph

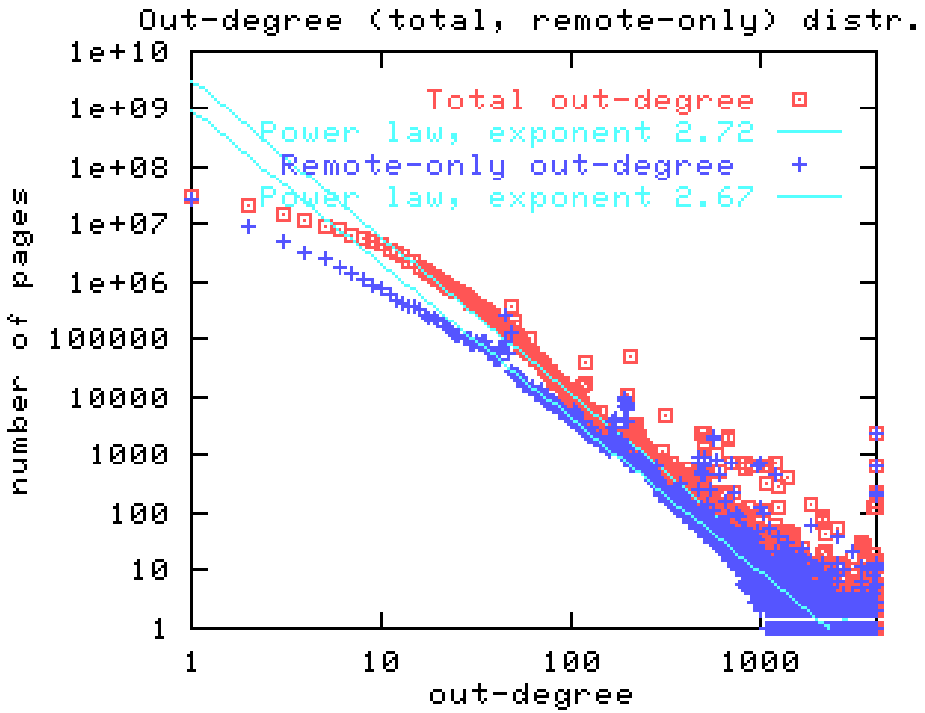
- pages are nodes, hyperlinks are edges
- Interesting Questions:
  - What is the distribution of in- and out-degrees?
  - How is its connectivity structure?
  - What is the diameter of the Web?
- Connectivity server (Bharat et al. 98)
  - Inverted index enriched with efficient data structures for hyperlink information (in-links and out-links)
- Detailed analysis of graph structure (Broder et al. 00)
  - Using an Altavista crawl (May 1999) with 203 million URLs and 1466 million links (all of which fit in 9.5 GB of storage)
  - Breadth-first search that reaches 100M nodes took about 4 minutes (on an improved version of the Connectivity Server)

In-Degree and Out-Degree

- Power law of in(out) degree:

  the probability that a node has in(out)-degree i is proportional to $1/i^x$ for some $x > 1$.

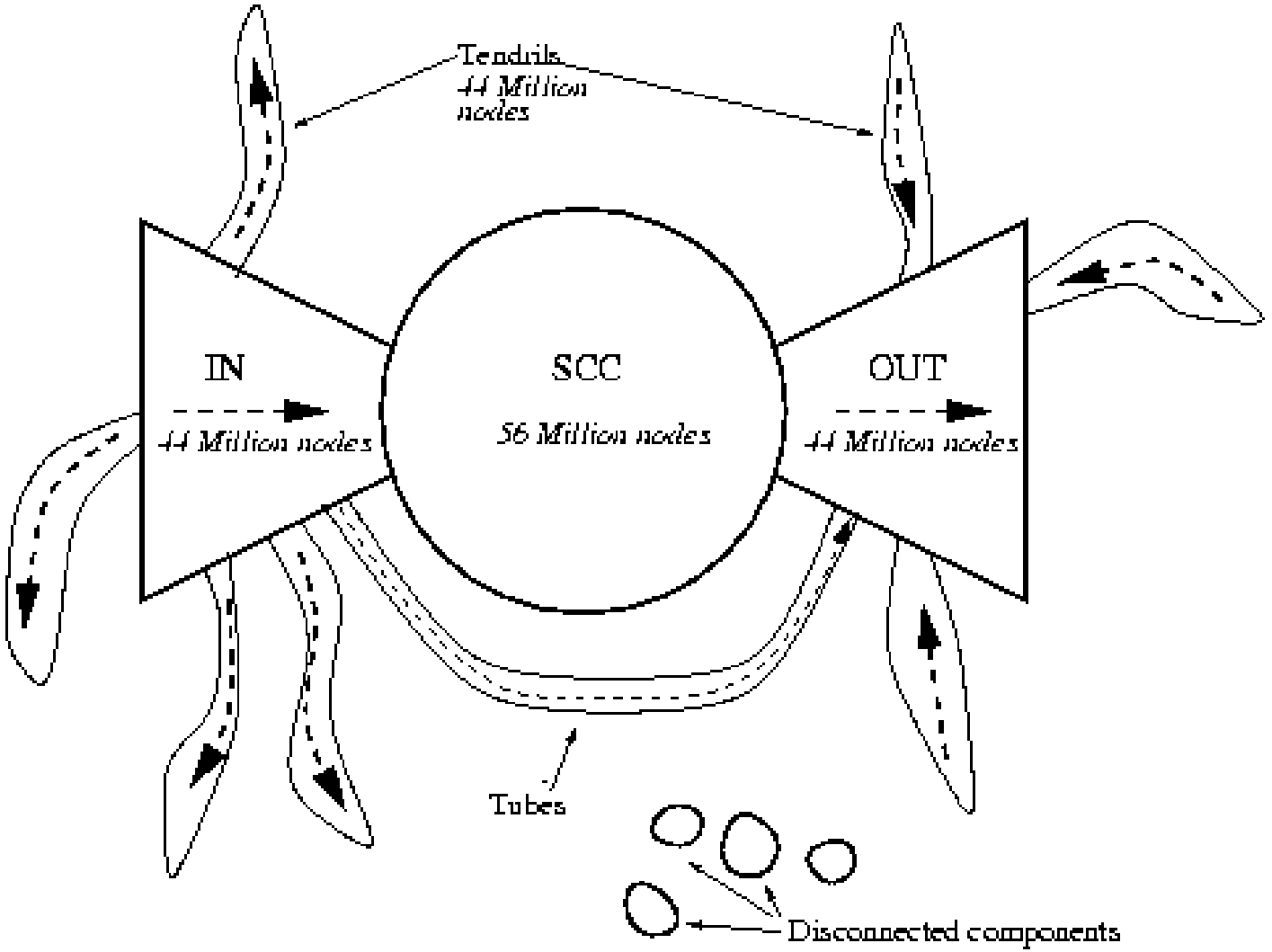




Connectivity

- Weakly connected components:
  - links are considered to be undirected
  - about 90% form a single component
- Strongly connected components:
  - only directed links
  - about 28% form a strongly connected core set of pages
  - number of strongly connected components also follows power law
- Diameter:
  - diameter of strongly connected core is > 27
  - diameter of the entire graph is > 500
  - probability that a path between two randomly selected pages exists is 0.24

Structure of the Web

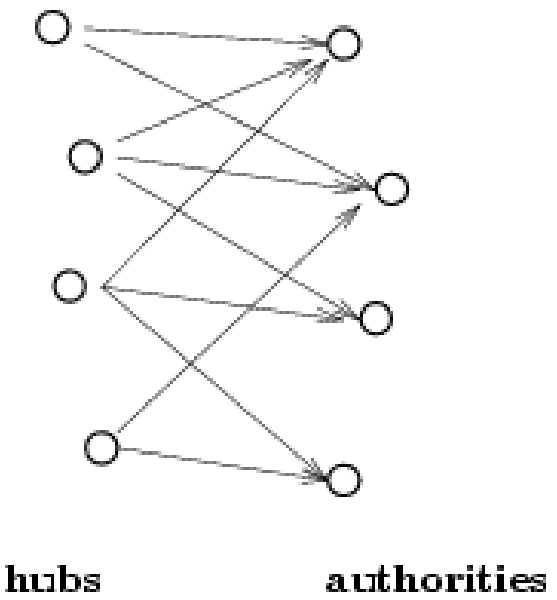


Finding relevant pages

- Search engines:
  - consult inverted index
  - return pages that match some or all query terms
- Problem:
  - query results are often too large to be inspected by user
- Need:
  - sorting according to relevance
- Limitations of Text-based approaches:
  - query terms may occur on non-relevant pages as well (maybe more frequently or more prominently)
  - query terms may not occur on a relevant page
  - queries as "short documents" do not provide good similarity scores
  - November 1997: (Brin & Page)
    only one of four top search engines finds itself!

Hubs & Authorities

- Authorities:
  - Pages that contain a lot of information about the query topic
- Hubs:
  - Pages that contain a large number of links to pages that contain information about the topic
- Mutual reinforcement:
  - A good *hub* points to many good *authorities*
  - A good *authority* is pointed to by many good *hubs*



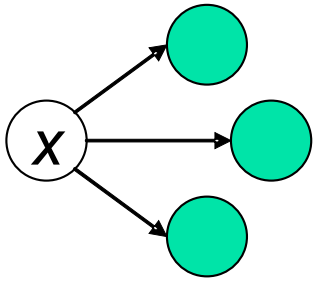
Using Graph Structure to Determine Relevance

- simple approach:
  - sort query results according to number of in-links
  - *Problem:* universally popular pages would be considered to be highly authorative for all search terms they contain
- HITS: Algorithm for identifying good hub and authority pages for a query
  - each page is associated with a *hub score* and an *authority score*
  - scores are computed based on graph structure of the Web
  - mutual reinforcement of hubs and authorities is exploited with an *iterative algorithm*

Hub and Authority Scores

- Hub Scores h(p):
  - hub scores are updated with the sum of all authority weights of pages it points to

$$h(x) = \sum_{(x,y) \in E} a(y)$$



- Authority Scores a(p):
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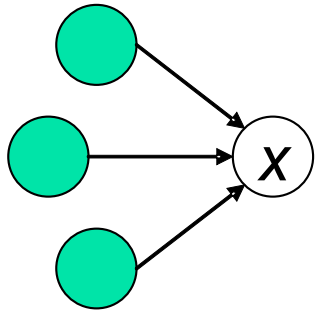
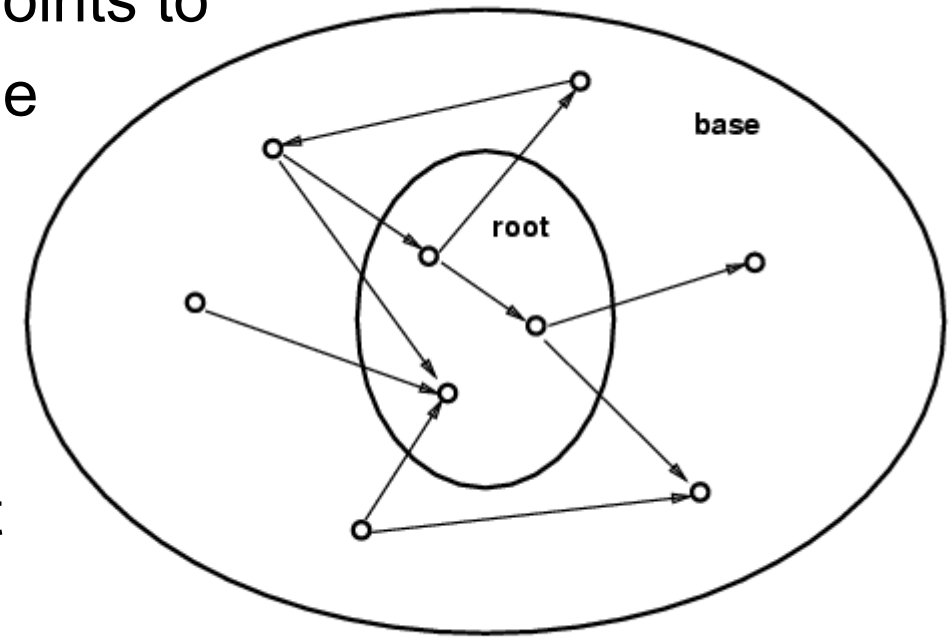
$$a(x) = \sum_{(y,x) \in E} h(y)$$



- Iterative Computation:
  - normalize weights
  - repeat update
  - convergence can be proven

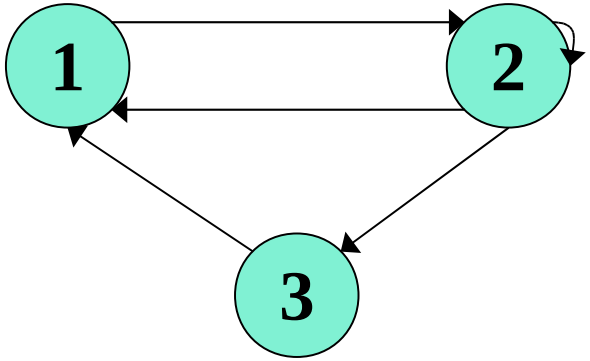
HITS: Hyperlink Induced Topic Search (Kleinberg, 1997)

- collect the *root set*
  - first t hits from a conventional search engine (typically $t = 200$)
- construct a *base set*
  - include all pages the root set points to
  - include pages that point into the root set ($< d$ for each page in the root set, typically $d = 50$)
  - size ~ 1000 - 5000
- construct a *focused subgraph*
  - graph structure of the base set
  - delete *intrinsic* links (i.e., links between pages in same domain)
- iteratively compute hub and authority scores



HITS algorithm: Linear Algebra Version

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

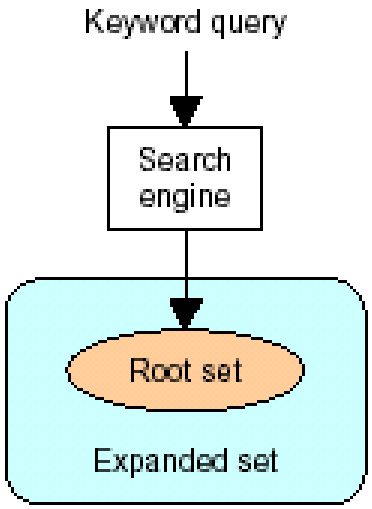


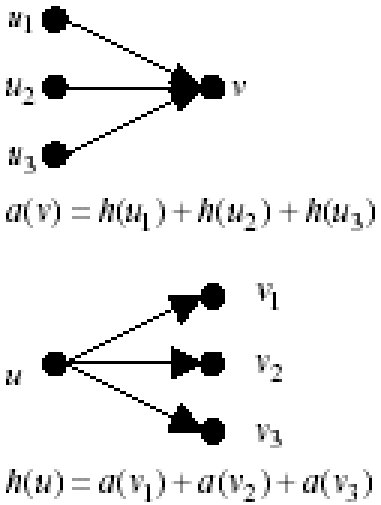
	1	2	3
1	0	1	0
2	1	1	1
3	1	0	0

- Rewrite update formulas with matrices: $\vec{a} = E^T \vec{h}$ and $\vec{h} = E \vec{a}$
  - Thus $\vec{a} = E^T E \vec{a}$ and $\vec{h} = E E^T \vec{h}$

$\rightarrow$ $\vec{a}$ and $\vec{h}$ are eigenvectors of the matrices $E^T E$ and $E E^T$

HITS algorithm: Linear Algebra Version





$\vec{a} \leftarrow (1, \ldots, 1)^T$, $\vec{h} \leftarrow (1, \ldots, 1)^T$
while $\vec{h}$ and $\vec{a}$ change 'significantly' do
  $\vec{h} \leftarrow E\vec{a}$
  $\ell_h \leftarrow \|\vec{h}\|_1$
  $\vec{h} \leftarrow \vec{h}/\ell_h$
  $\vec{a} \leftarrow E^T\vec{h}_0 = E^T E\vec{a}_0$
  $\ell_a \leftarrow \|\vec{a}\|_1$
  $\vec{a} \leftarrow \vec{a}/\ell_a$
end while

||h|| and ||a|| are L_1 vector norms
E is the neighborhood matrix
a converges to the principal eigenvector of E^TE
h converges to the principal eigenvector of EE^T

Convergence of HITS

- The iterative algorithm is a particular, known algorithm for computing eigenvectors: the *power iteration* method.
  - This is known to converge
- How many iterations are needed?
  - relative values of scores will converge after a few iterations
  - We only require the relative orders of the hubs and authority scores - not their absolute values.
  - In practice, ~5 iterations get you close to stability.

Problems

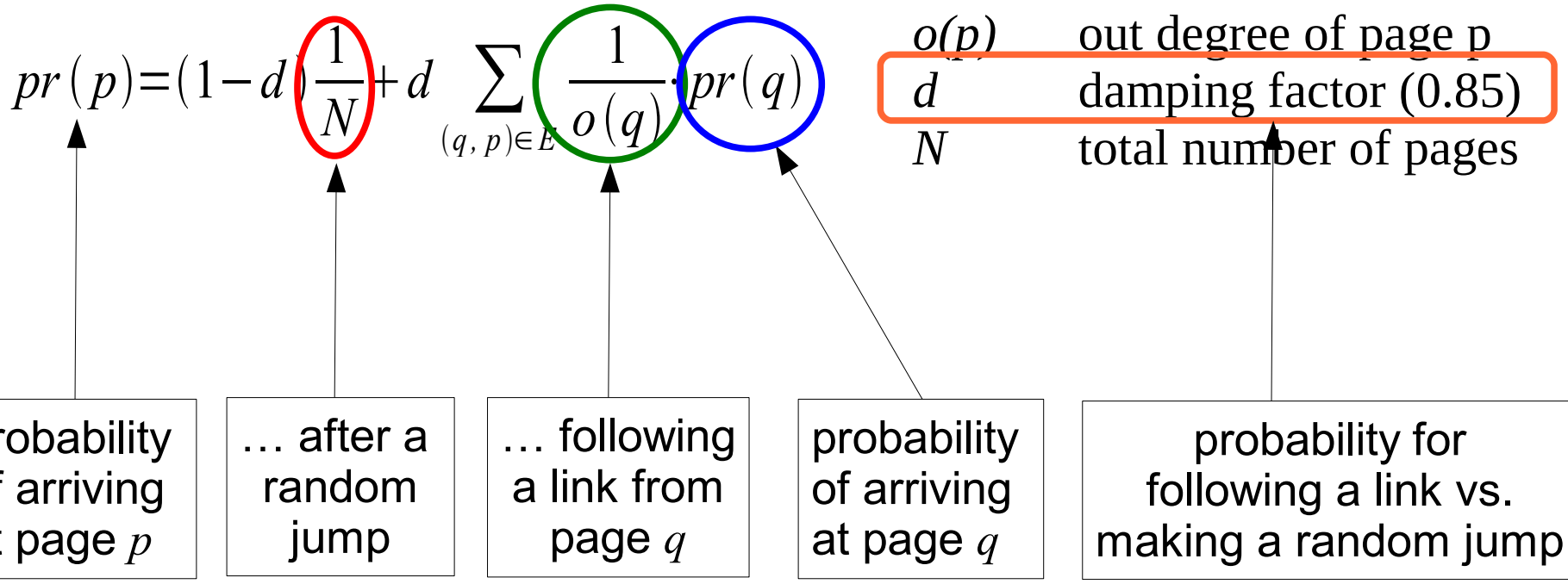
- Efficiency
  - construction of graph has to be performed on-line
- Irrelevant links
  - Advertisements
  - Automatically generated links
- Mutually reinforcing relationship between hosts
  - multiple documents on one site pointing to document D at another drives up their hub scores and the authority score of D
- Topic Drift
  - documents in base set may be too general (e.g. Jaguar -> car)

Improvements (Bharat & Henzinger 98)

- Improved Connectivity Analysis:
  - normalize score by number of links between different hosts
  - *authority weights:*
    - weight a link with $1/k$ if there are k documents from the same site pointing to the authority
  - *hub weights:*
    - weight a link with $1/k$ if the hub points to k documents on the same host
- Relevance Weights:
  - compute a pseudo-document of first 1000 words of each document in root set
  - only include documents in base set that have a minimum similarity to the pseudo-document
  - weight propagation is weighted by relevance weight

Page Rank (Brin & Page, 1998)

- Idea: model of a random surfer
  - clicks on one of the outgoing links at random
  - or jump to a random page on the Web
- PageRank $pr(p)$:



Page Rank (Brin & Page, 1998)

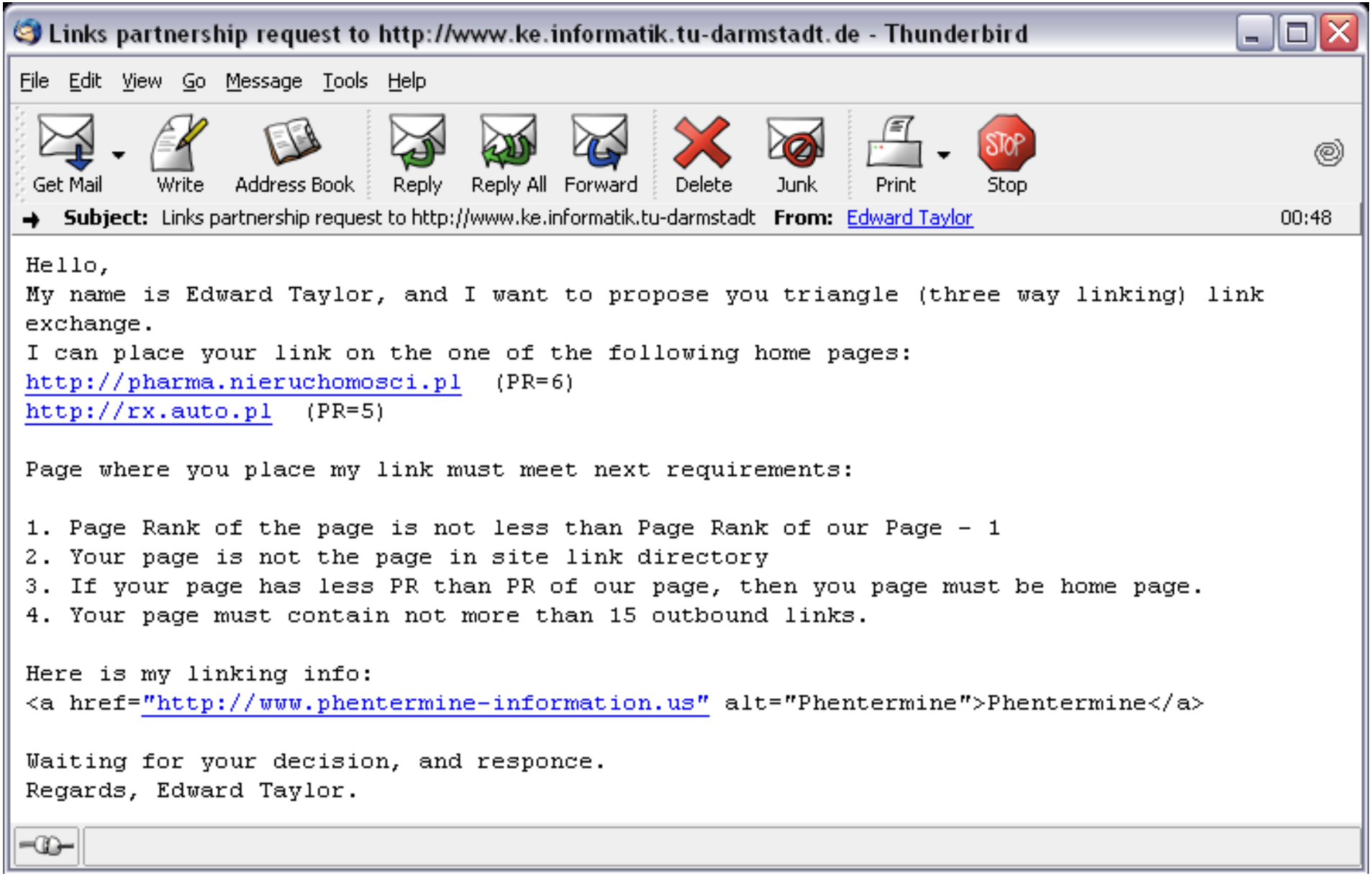
- Idea: model of a random surfer
  - clicks on one of the outgoing links at random
  - or jump to a random page on the Web
- PageRank $pr(p)$:

$$pr(p) = (1-d)\frac{1}{N} + d \sum_{(q,p)\in E} \frac{pr(q)}{o(q)}$$

$o(p)$	out degree of page p
d	damping factor (0.85)
N	total number of pages

- page rank prefers pages that have
  - a large in-degree
  - predecessors with a large page rank
  - predecessors with a small out-degree
- page rank is a probability distribution over pages

Link Spam



Google (status ~ 1998)

- Design goal: High precision in relevance sorting
- Ranking is based on combination of several factors
  - PageRank weights
    - iterative PageRank computations
    - off-line, for 26 million pages in several hours
  - matches in anchor texts
  - proximity information
  - assigns different weights to different types of hits
    - font size, font face, URL, title, ...
- Tuning the weights for the combiner is a "black art"
  - earlier versions used feedback of "trusted" users

PageRank vs HITS

- PageRank advantage over HITS
  - Query-time cost is low
    - HITS: computes an eigenvector for every query
  - Less susceptible to localized link-spam
- HITS advantage over PageRank
  - HITS ranking is sensitive to query
  - HITS has notion of hubs and authorities
- Topic-sensitive PageRanking
  - Attempt to make PageRanking query sensitive
  - Basic idea: Tele-Portation (random jump) is topic-sensitive

Google Games

- Google Whacking
  - try to find 2 English dictionary words that return a single hit
  - example: “masterfully incubatory” (http://www.googlewhack.com)
- Google Fight
  - try 2 keywords / phrases and see which one gets more hits
  - real applications: e.g., spelling correction
- BananaSlug (http://bananaslug.com/)
  - add random keywords to your query to get unexpected results

Google Bombs

- increasing a page's importance by adding links from different sites to it (e.g., in blogs)
- possibly connected with spurious information
- examples:
  - “talentless hack”
  - “miserable failure”
  - “völlige Inkompetenz”
  - “jämmerlicher Waschlappen”
  - “Experiment Kohlkopf”
  - u.v.m.
- most of them no longer work

A quick word about Googlebombs

Thursday, January 25, 2007 at 4:16 PM

Co-written with Ryan Moulton and Kendra Carattini

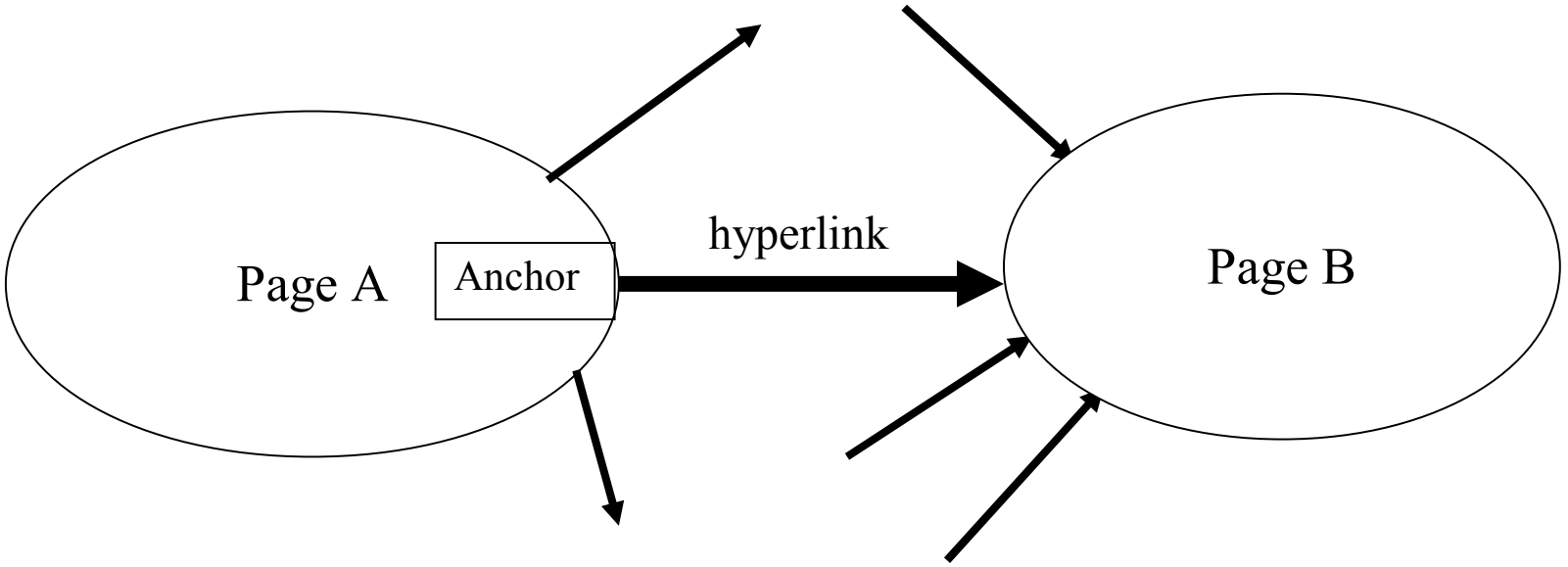
We wanted to give a quick update about "Googlebombs." By improving our analysis of the link structure of the web, Google has begun minimizing the impact of many Googlebombs. Now we will typically return commentary, discussions, and articles about the Googlebombs instead. The actual scale of this change is pretty small (there are under a hundred well-known Googlebombs), but if you'd like to get more details about this topic, read on.

First off, let's back up and give some background. Unless you read all about search engines all day, you might wonder "What is a Googlebomb?" Technically, a "Googlebomb" (sometimes called a "linkbomb" since they're not specific to Google) refers to a prank where people attempt to cause someone else's site to rank for an obscure or meaningless query. Googlebombs very rarely happen for common queries, because the lack of any relevant results for that phrase is part of why a Googlebomb can work. One of the earliest Googlebombs was for the phrase "talentless hack," for example.

People have asked about how we feel about Googlebombs, and we have talked about them in

http://googlewebmastercentral.blogspot.com/2007/01/quick-word-about-googlebombs.html

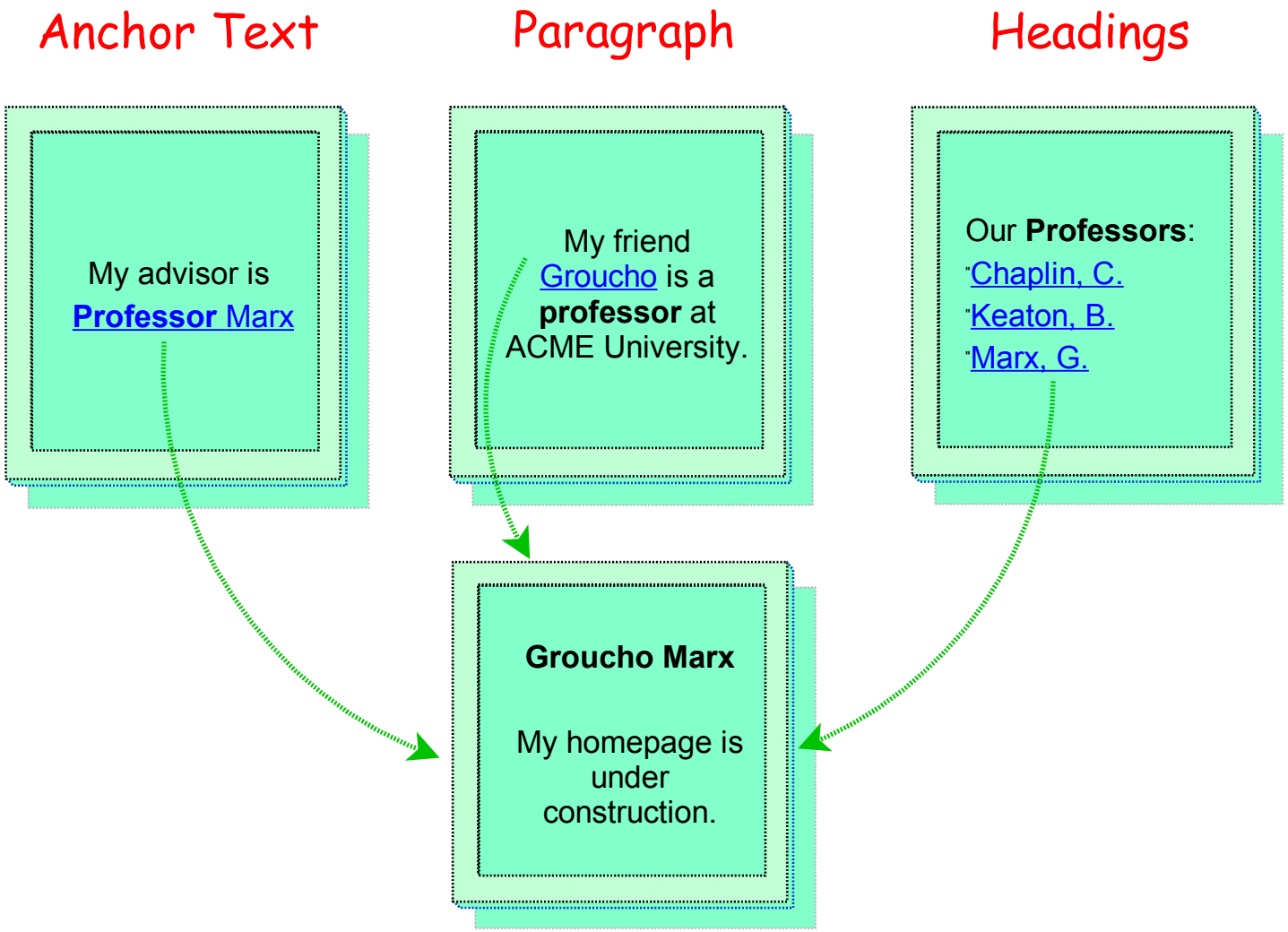
Hyperlinks Provide Important Information



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)

Hypertext Classification



Using Text vs. Links for Classification

- Text on WWW Pages may be
  - non-existent (images)
  - sparse
  - in an unknown language
  - misleading (false keywords)
  - irrelevant
- Links to WWW Pages provide
  - richer vocabulary (multiple authors)
  - redundancy
  - diversity through independent assessment of content
  - focus on important issues
  - multiple view points
  - multiple languages

Exploiting Hyperlink Structure

- Merging the Features:
  - join text of documents with (parts of) the text of the documents pointing to it
  - e.g., WWW Worm (McBryan 1994) indexes anchor text with the page it refers to
  - Chakrabarti et al. 1998 investigated this approach for hypertext classification (merging of full texts)
  - results got worse
- Use of Meta-Information: (Chakrabarti et al. 1998)
  - use *classification* of in-coming pages
  - iterative EM-like algorithm to converge to class assignments
  - produced somewhat better results
- Use of ILP (Craven & Slattery 1998, 2001)
  - represent Web graph in first-order logic
  - features of pages can be accessed via `link_to/2` relation

Labeling hypertext graphs: Scenario

- Snapshot of the Web graph $G = (D,E)$
  - Vertices D (Web Pages)
  - Edges E (URLs between pages)
- Set of topics C
  - Each page belongs to one of the topics
- Small subset of nodes D_k labeled
  - i.e., the topic is only known for a few pages
- Task: Predict the labels for some or all nodes in $D - D_k$
  - using the labels from the training set D_k
  - AND the information provided by the edges E

Absorbing features from neighboring pages

- Simple approach:
  - use supervised or semi-supervised learning: train on D_k and use the learned classifier for labeling the documents in $D - D_k$
- Disadvantage:
  - A page may have little text on it to train or apply a text classifier
- but it may reference other pages
  - Often second-level pages have usable quantities of text
- Question: How to use these features ?

Absorbing features

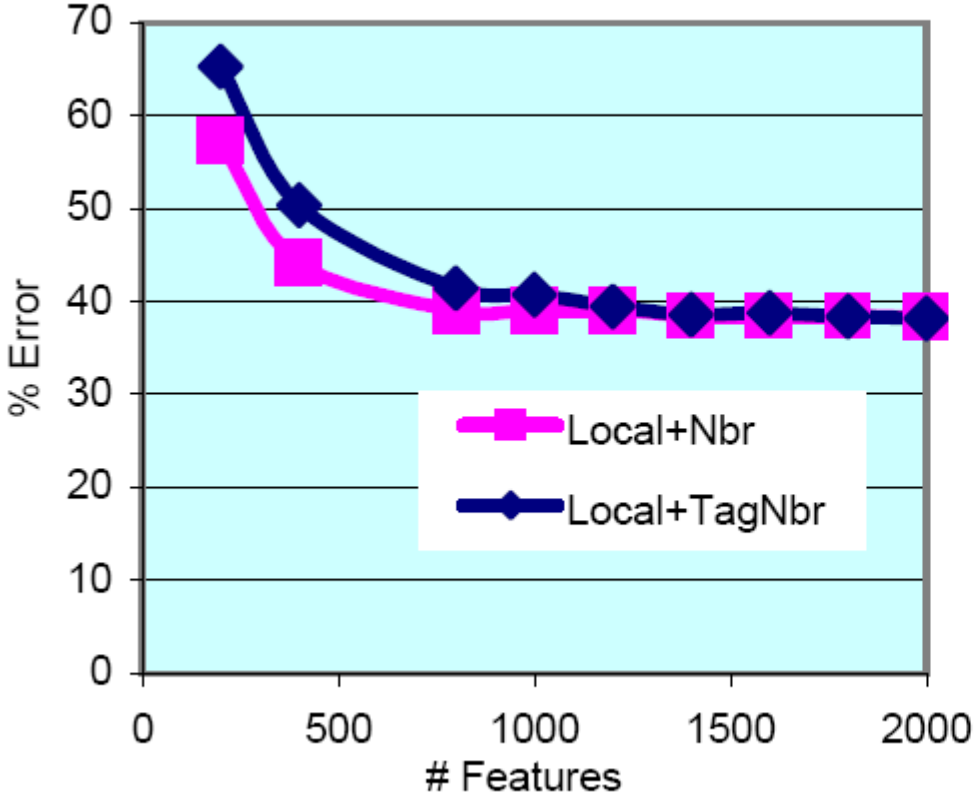
First simple idea:

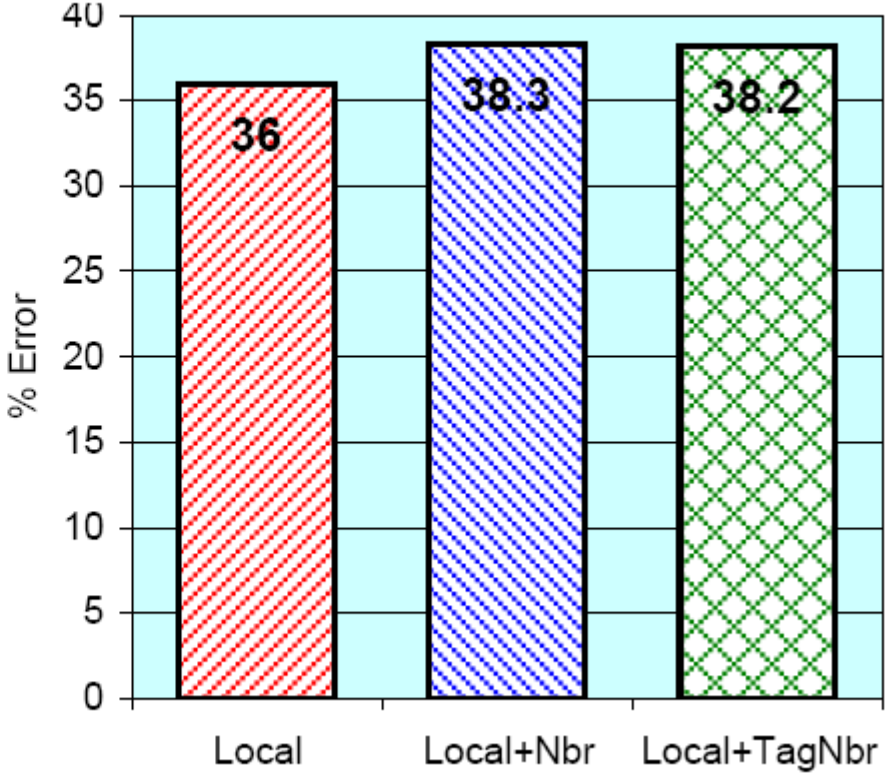
- add features of all neighboring pages $\mathbf{d}_i$ to a page $\mathbf{d}$
  - neighboring could be restricted to predecessors (or successors)
  - features of are $\mathbf{d}_i$ absorbed by $\mathbf{d}$
- essentially this corresponds to concatenating the text of all neighboring pages of a document $\mathbf{d}$ to a new document $\overline{\mathbf{d}}$
  - $\overline{\mathbf{d}} = \mathbf{d} + \sum_{(\mathbf{d}, \mathbf{d}_i) \in E} \mathbf{d}_i + \sum_{(\mathbf{d}_i, \mathbf{d}) \in E} \mathbf{d}_i$

Second idea:

- Maybe it is good to keep the absorbed features separate from the original features
  - e.g., by prefixing them with a special character

Results





Local: Only text of the page
Nbr: Merge text of page with text of all predecessor and successor pages
TagNbr: Maintain 3 separate sets of features:
text of predecessors, local text, text of successors

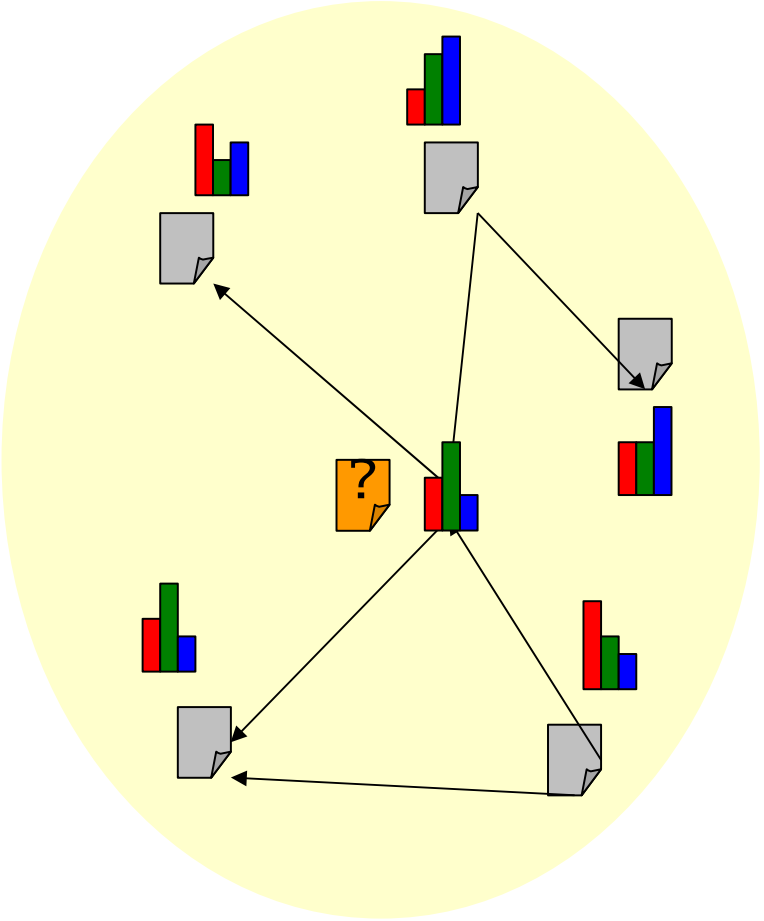
Results are Error Rates of naïve Bayes Classifier on Patent Classification Task

Absorbing features

- Indiscriminate absorption of neighborhood text does not help
  - At times even deteriorates accuracy
- Reason: Implicit assumption:
  - Topic of a page **d** is likely to be the same as the topic of a page cited by **d**.
  - Not always true
  - Topic may be “related” but not “same”
- Distribution of topics of the pages cited could be quite distorted compared to the totality of contents available from the page itself
- E.g.: university page with little textual content
  - Points to “how to get to our campus” or “recent sports prowess"

Using Class Information as Features

- Text-only model:
  - estimate $p(c|\mathbf{d})$
- Using neighbors' text:
  - estimate $p(c|\mathbf{d}, \bigcup \mathbf{d}_i)$
- Using class distribution of neigbors
  - estimate $p(c|\mathbf{d}, c(\mathbf{d}_1), \ldots, c(\mathbf{d}_n))$

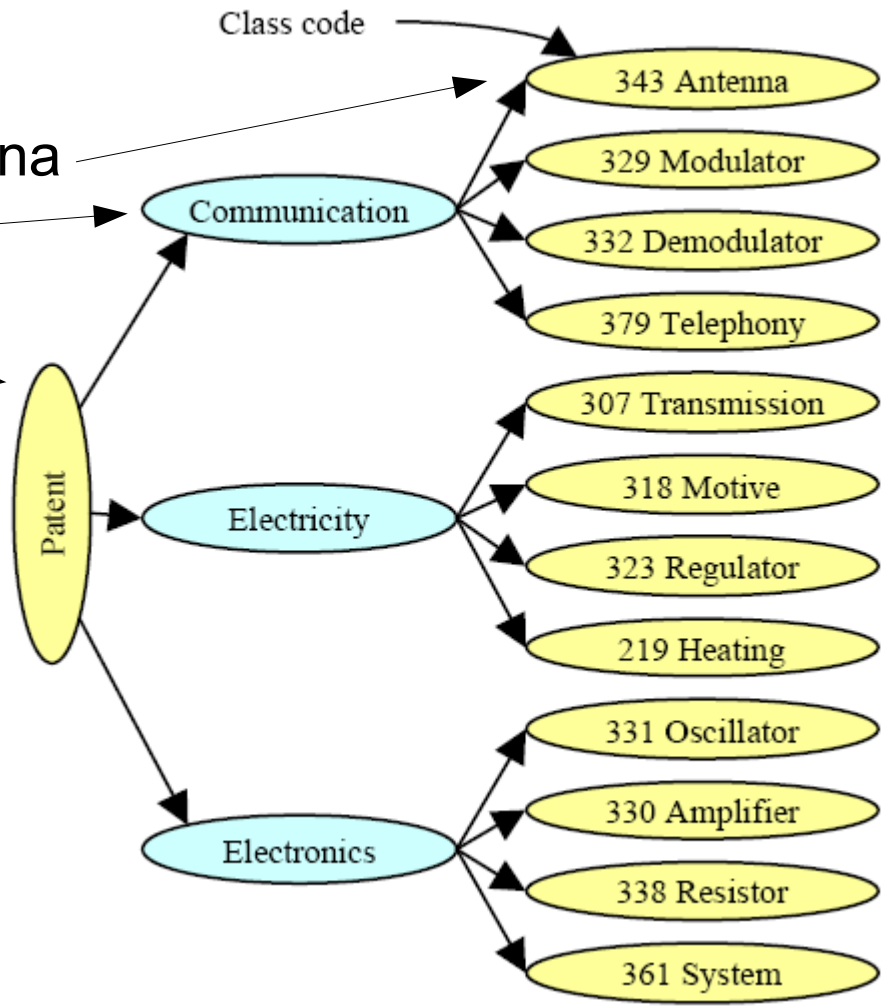


Absorbing link-derived features
(Chakrabarti, Dom, Indyk, 1998)

- Classes as Features:
  - The classes of hyper-linked neighbors are a better representation of hyperlinks.
  - E.g.:
    - use the fact that **d** points to a page about athletics to raise our belief that **d** is a university homepage,
    - learn to systematically reduce the attention we pay to the fact that a page links to the Netscape download site.
- In many applications, class labels are from a is-a hierarchy.
  - evidence at the detailed topic level may be too noisy
  - coarsening the topic helps collect more reliable data on the dependence between the class of the homepage and the link-derived feature.

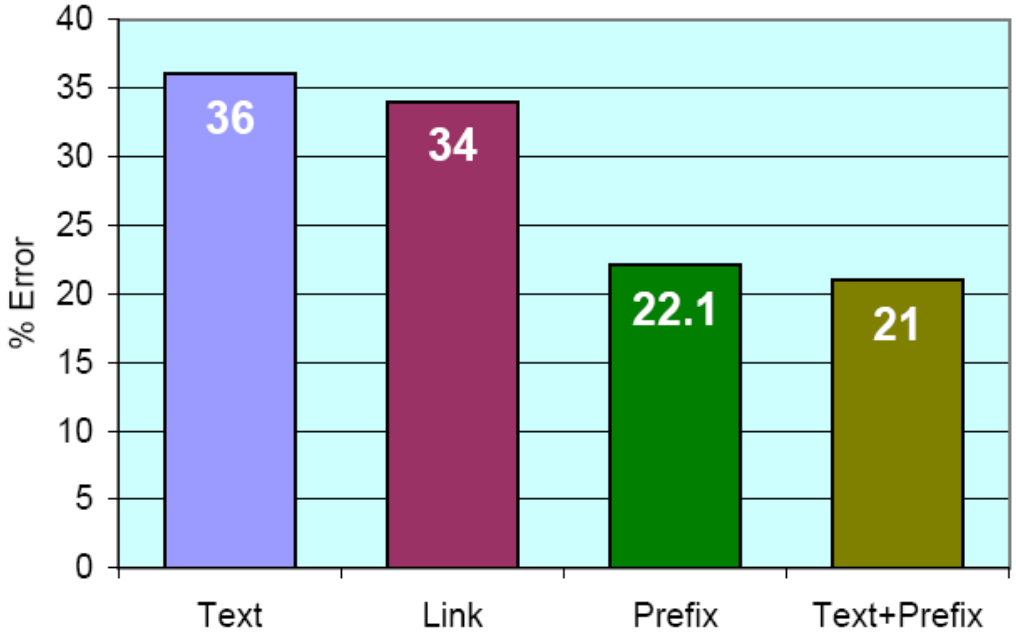
Absorbing link-derived features

- Add all prefixes of the class path to the feature pool:
  - Patent/Communication/343 Antenna
  - Patent/Communication
  - Patent
- Do feature selection to get rid of noise features
- Experiment
  - Corpus of US patents
  - Two level topic hierarchy
    - three first-level classes,
    - each has four children.
  - Each leaf topic has 800 documents,



Link-Derived Features: Results

- Experiment with
  - **Text** : only the Text on the page
  - **Link**: only all classes of neighboring pages
  - **Prefix:** classes of neighboring pages plus their prefixes
  - **Text+Prefix:** Text plus classes plus prefixes



Using prefix-encoded link features in conjunction with text can significantly reduce classification error

Absorbing link-derived features: Limitation

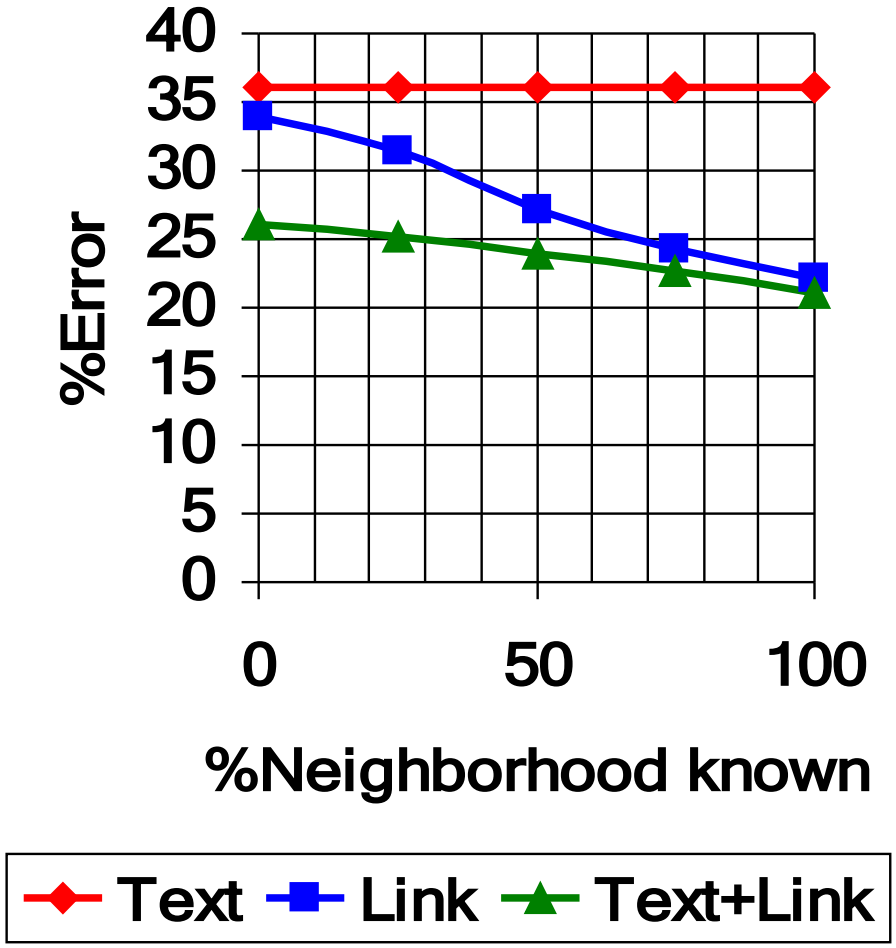
- only a small subset is labeled ($|D^k| << |D|$)
  - How can we use classes as features if we don't know (most of) them?

- Simple iterative algorithm:

  - Start with a labeling of reasonable quality
    - Maybe using a text classifier
  - Do
    - Refine the labeling using a coupled distribution of text and labels of neighbors,
  - Until the labeling stabilizes.

Results

- 9600 patents from 12 classes marked by USPTO
- Patents have text and cite other patents
- Expand test patent to include neighborhood
- 'Forget' fraction of neighbors' classes



Problems

- Features of predecessor pages should be kept separately
  - Absorbing features merges the entire text from all predecessor pages into a single pot
- Redundancy provided by multiple predecessors should be exploited
  - Approaches based on logical representations can (in principle) keep features separately, but focus on single discriminators
- Not the entire text of a predecessor page is relevant
  - each page is predecessor of several pages, in the worst case each belongs to a potentially different class -> each case should be represented differently
- Not all pages have relevant meta-information

Hyperlink Ensembles

I. Discard page text
II. Represent each link to a page as a separate example
   - use only part of the text (otherwise all links of the same page have identical representations, but may point to different targets)
III. Encode as Set-Valued Features:
   - **ANCHOR**: All words between <A HREF...> and </A>
   - **HEADING**: All words occurring in Headings that structurally precede the link
   - **PARAGRAPH**: All words of the paragraph that contains the link
IV. Ensemble formation:
   - one training example for each hyperlink
   - one ensemble of predictions for each page (one prediction originating from each predecessor)
   - combine predictions for each predecessor to a single prediction for the target page

Comparison to Full-Text Classifier

- Setup:
  - Ripper as base learner
  - WebKB, 1050 pages, 5803 links, 7 classes
- Results
  - full text uses about 20,000 features
  - the link classifier uses about 8,000 features
  - feature suset selection (using information gain) helps to improve the performance
  - link-based classifier are better anyways

Links (Weight,All)	82,67
Links (Weight, A&H)	85.14
Full Text	70.67
Text (50% features)	73.90
Text (10% features)	74.19
Text (5% features)	74,76
Text (1% features)	71,33
Text (0.1% features)	54.67

Feature Sets / Voting Schemes

- anchor text and headings are more important than text in paragraph around the link
- use of confidences is important for combining

	Vote	Weight	Max
Default	51.81	51.81	51.81
Anchor	67.52	74.19	74.76
Headings	60.48	72.95	72.95
Paragraph	63.05	66.95	66.29
Anchor & Hdgs.	74.48	85.14	86.57
Anchor & Par.	68.00	73.90	74.67
Headings & Par.	70.48	81.14	81.33
All	74.19	82.67	83.24

Gain through Ensemble

- comparison between accuracy on *predicting links* without (left) and with (right) combining predictions
- redundancy is exploited
- pages with more incoming links are classified more reliably

	Links	Weight
Default	36.67	36.67
Anchor	57.92	75.37
Headings	43.34	70.77
Paragraph	53.40	66.33
Anchor & Hdgs.	62.49	86.25
Anchor & Par.	58.40	73.46
Headings & Par.	58.50	80.30
All	57.99	79.44

Hyperlink Ensembles: Results

- using link and HTML structure can outperform text classifiers
  - anchor text and section headings are good complimentary features
  - weighting is important for combining predictors
  - successful exploitation of the redundancy provided by multiple links to a page
- later work has shown that the reason for the good performance is primarily absorbing a neighborhood of the text of the preceding page
  - not so much the ensemble effect from combining multiple predictions