

Web Structure & Content (not a theory talk)

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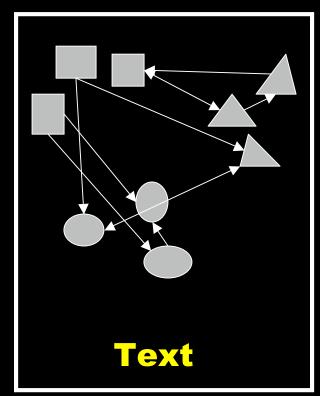
Exploiting the Web's text and link cues

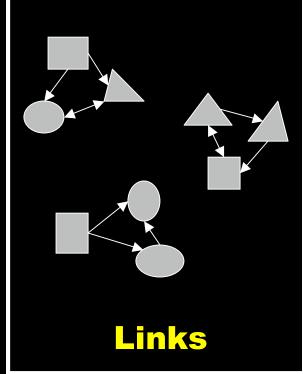
- Pages close in word vector space tend to be related
 - Cluster hypothesis (van Rijsbergen 1979)
 - The WebCrawler (Pinkerton 1994)
 - The whole first generation of search engines
- Pages that link to each other tend to be related
 - Link-cluster conjecture (Menczer 1997)
 - Many formulations: Gibson & al 1998, Bharat & Henzinger 1998, Chakrabarti & al 1998, Dean & Henzinger 1999, Davison 2000, etc
 - Link eigenvalue analysis: HITS, hubs and authorities
 - (Kleinberg & al 1998 segg. @ Almaden etc.)
 - Google's PageRank analysis
 - (Brin & Page 1998)
 - The whole second generation of search engines

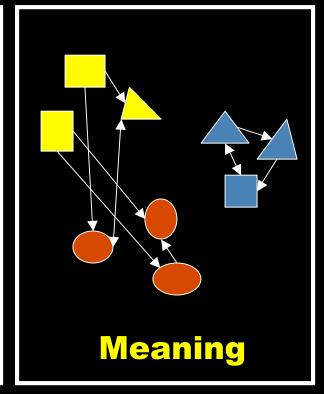


Three topologies

What about the *relationship* between lexical / link cues and page meaning?









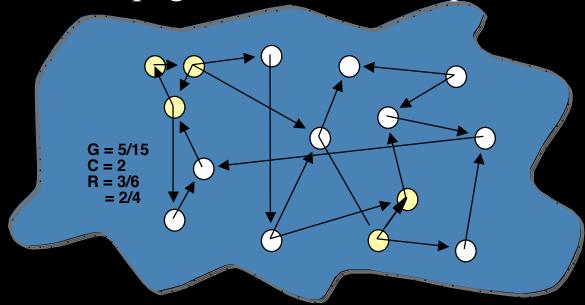
Talk outline

- The topologies of the Web
- Correlations, distributions, projections
- Power laws and Web growth models
- Navigating optimal paths
- Semantic maps (?)



The "link-cluster" conjecture

- Connection between semantic topology (relevance) and linkage topology (hypertext)
 - $-G = Pr[rel(p)] \sim fraction of relevant pages (generality)$
 - -R = Pr[rel(p) | rel(q) AND link(q,p)]
- Related nodes are clustered if R > G
 - Necessary and sufficient condition for a random crawler to find pages related to start points

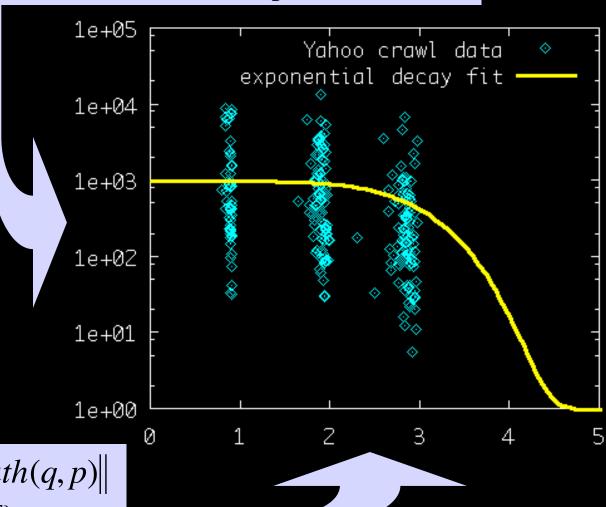




$$\frac{R(q, \square)}{G(q)} = \frac{\Pr[rel(p)|rel(q)\square|path(q, p)||\square|]}{\Pr[rel(p)]}$$

Link-cluster conjecture

Preservation of semantics (meaning) across links

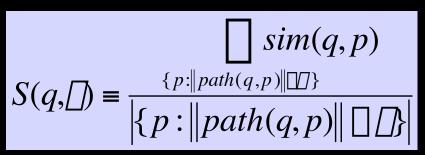


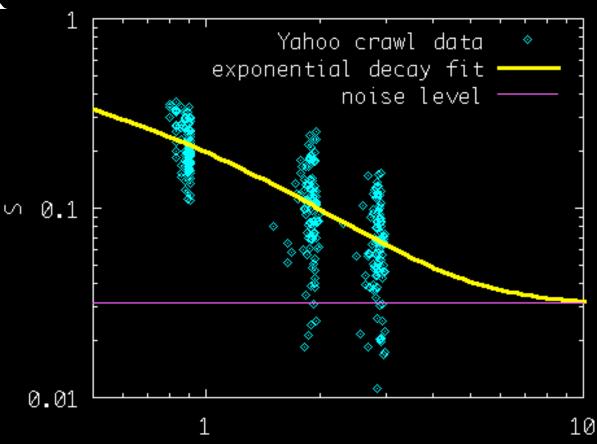
$$L(q, \square) = \frac{\left\| path(q, p) \right\|}{\left\| \{p : \left\| path(q, p) \right\| \square \right\} \right\|}$$



The "link-content" conjecture

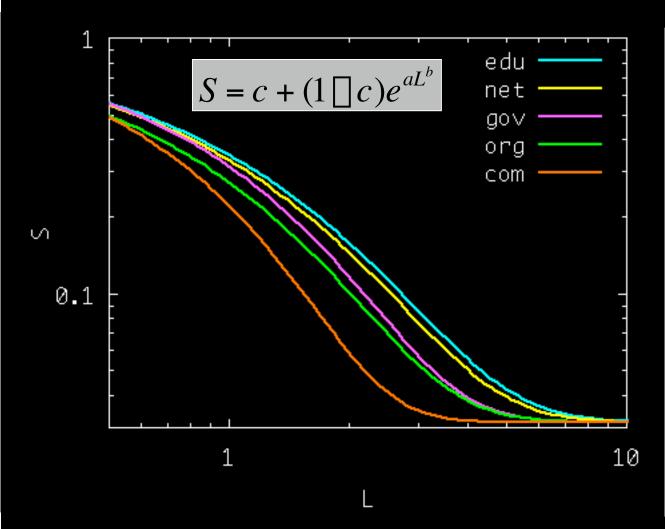
- Correlation of lexical and linkage topology
- L([]): average link distance
- S([]: average similarity to start (topic) page from pages up to distance []
- Correlation $\Box(\mathbf{L},\mathbf{S}) = -0.76$

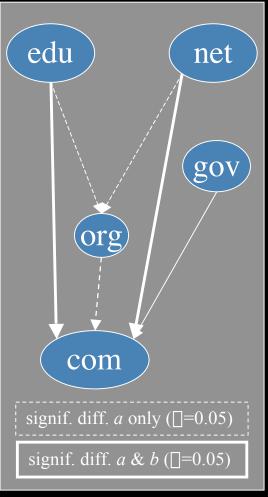






Heterogeneity of lexical-linkage correlation



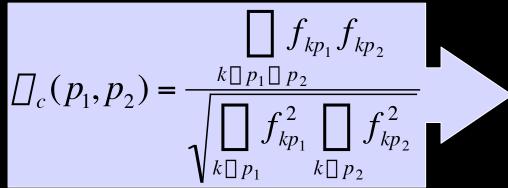




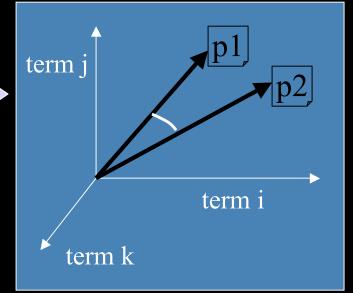
Mapping the relationship between topologies

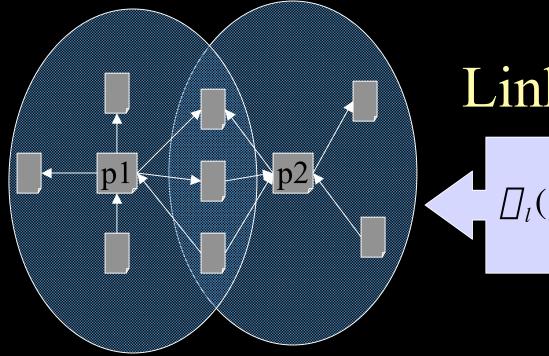
- Any pair of pages rather than linked pages from crawl
- Data: Open Directory Project (dmoz.org)
 - RDF Snapshot: 2002-02-14 04:01:50 GMT
 - After cleanup: 896,233 URLs in 97,614 topics
 - After sampling: 150,000 URLs in 47,174 topics
 - 10,000 from each of 15 top-level branches
- Need 'similarity' or 'proximity' metric for each topology, given a pair of pages:
 - Content: textual/lexical (cosine) similarity
 - Link: co-citation/bibliographic coupling
 - Semantic: relatedness inferred from manual classification





Content similarity





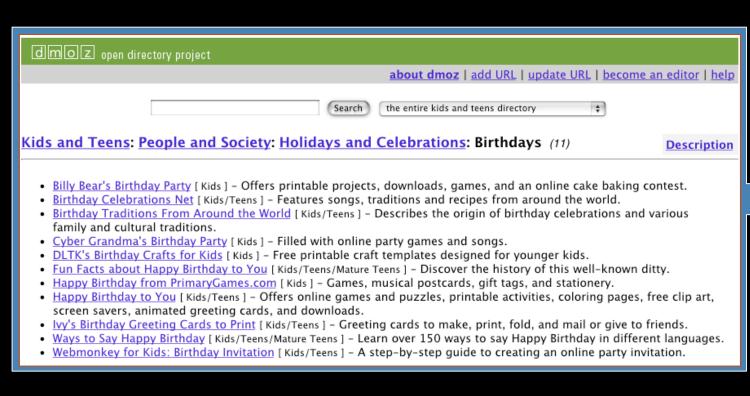
Link similarity

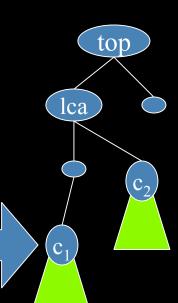


Semantic similarity

$$\prod_{s} (c_1, c_2) = \frac{2 \log \Pr[lca(c_1, c_2)]}{\log \Pr[c_1] + \log \Pr[c_2]}$$

- Information-theoretic measure based on classification tree (Lin 1998)
- Classic path distance in special case of balanced tree

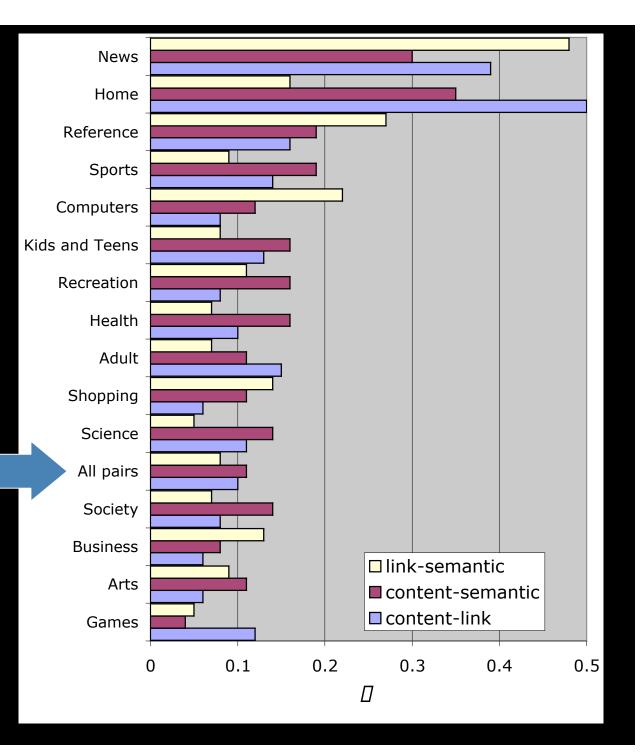






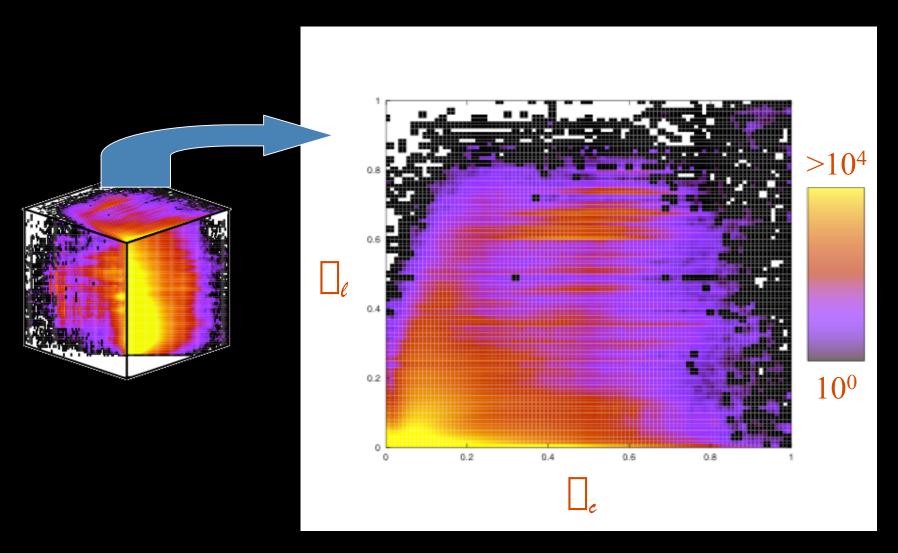
Correlations between similarities

3.84 x 10⁹ pairs





Joint distribution cube

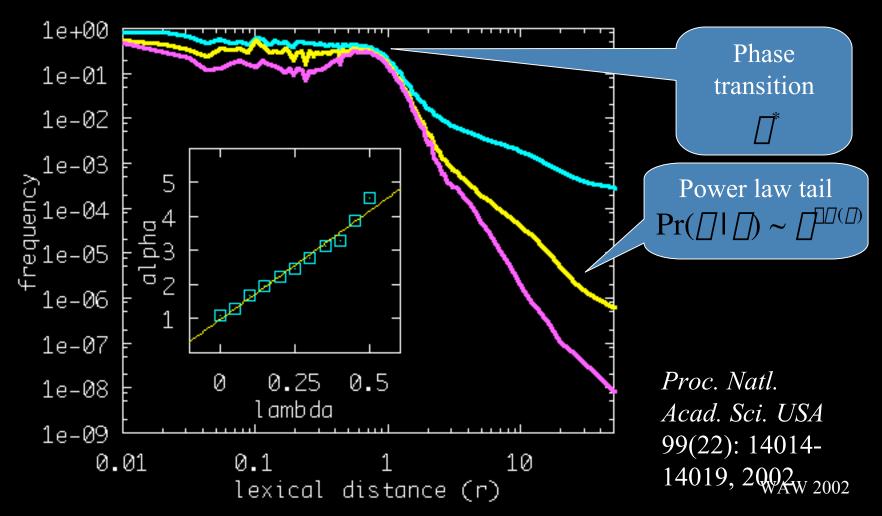




Link probability vs lexical distance

$$r = \frac{1}{\Box_{c}} \Box 1$$

$$\Pr(\Box \Box) = \frac{|(p,q): r = \Box \Box \Box_{l} > \Box}{|(p,q): r = \Box}$$





Web growth models

- Preferential attachment "BA"
 - At each step t add page p_t
 - Create m new links from p_t to $p_{i < t}$ (Barabasi & Albert 1999, de Solla Price 1976)

Modified BA

(Bianconi & Barabasi 2001, Adamic & Huberman 2000)



Mixture

(Pennock & al. 2002,

$$Pr(i) \quad \Box \cdot k(i) + (1 \Box \Box) \cdot c$$

Cooper & Frieze 2001, Dorogovtsev & al 2000)

Web copying

$$Pr(i) \quad \square \cdot Pr(j \quad \square \quad i) + (1 \quad \square \quad \square) \cdot$$

(Kleinberg, Kumar & al 1999, 2000)

Mixture with Euclidean distance in graphs $i = \arg\min([r_{it} + g_i))$ (Fabrikant, Koutsoupias & Papadimitriou 2002)

$$i = \operatorname{argmin}(\mathcal{D}_{it} + g_i)$$



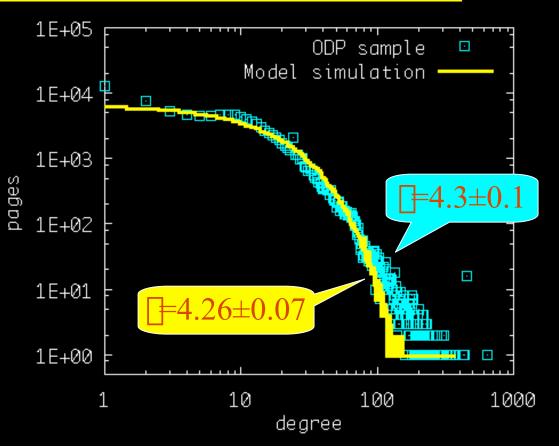
Local content-based growth model

$$\Pr(p_t \ \square \ p_{i < t}) = \frac{k(i)}{mt} \quad \text{if } r(p_i, p_t) < \square^*$$

$$\exists c[r(p_i, p_t)]^{\square \square} \quad \text{otherwise}$$

- Similar to preferential attachment (BA)
- At each step t add page p_t
- Create m new links from p_t to existing pages
- Use degree (k) info only for nearby pages

(popularity/importance of similar/related pages)





Efficient crawling algorithms?

- <u>Theory</u>: since the Web is a small world network, or has a scale free degree distribution, there exist short paths between any two pages:
 - − ~ log N (Barabasi & Albert 1999)
 - $\sim \log N / \log \log N$ (Bollobas 2001)
- Practice: can't find them!
 - Greedy algorithms based on location in geographical small world networks: ~ poly(N) (Kleinberg 2000)
 - Greedy algorithms based on degree in power law networks: ~ N (Adamic, Huberman et al 2001)



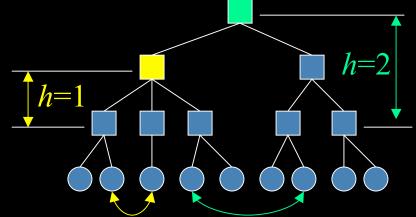
Exception # 1

- Geographical networks (Kleinberg 2000)
 - Local links to all lattice neighbors
 - Long-range link probability distribution: power law $Pr \sim r^{-\square}$
 - r: lattice (Manhattan) distance
 - []: constant clustering exponent

$$t \sim \log^2 N \square \square = D$$



Exception # 2



- Hierarchical networks (Kleinberg 2002, Watts & al. 2002)
 - Nodes are classified at the leaves of tree
 - Link probability distribution: exponential tail $Pr \sim e^{-h}$
 - h: tree distance (height of lowest common ancestor)

$$t \sim \log^{\square} N, \square \geq 1$$

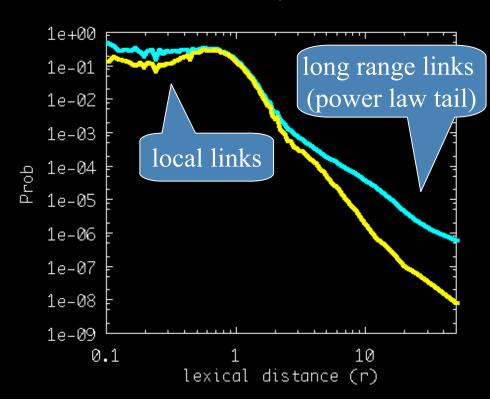


Is the Web one of these exceptions?

Geographical model

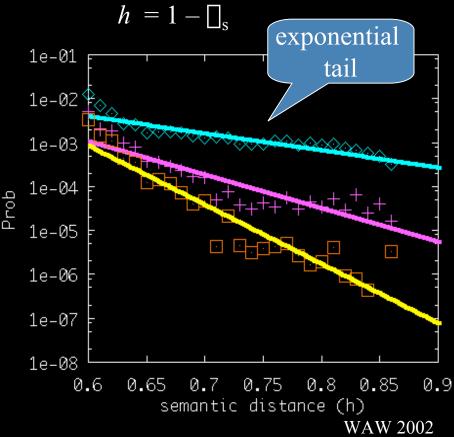
 Replace lattice distance by lexical distance

$$r = (1 / \square_{\rm c}) - 1$$



Hierarchical model

 Replace tree distance by semantic distance

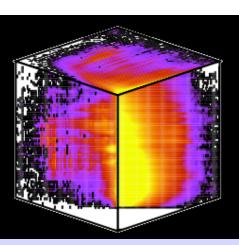




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Semantic maps: define "local" Precision and Recall

$$\prod_s(p,q)$$

$$P(s_c, s_l) = \frac{\{p, q: [l_c = s_c, [l_l = s_l]\}\}}{|\{p, q: [l_c = s_c, [l_l = s_l]\}|\}|}$$

$$\prod_s(p,q)$$

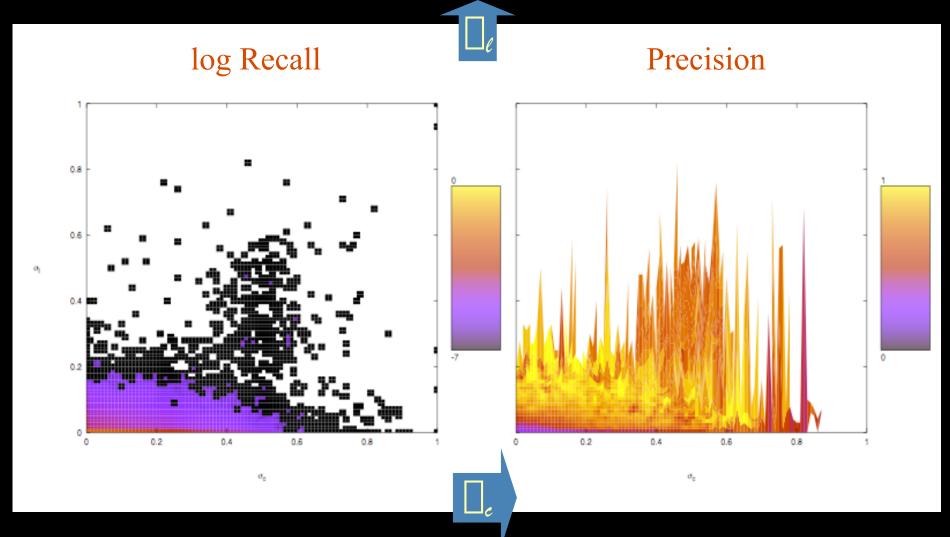
$$R(s_c, s_l) = \frac{\{p, q: \square_c = s_c, \square_l = s_l\}}{\square_s(p, q)}$$

Averaging semantic similarity

Summing semantic similarity

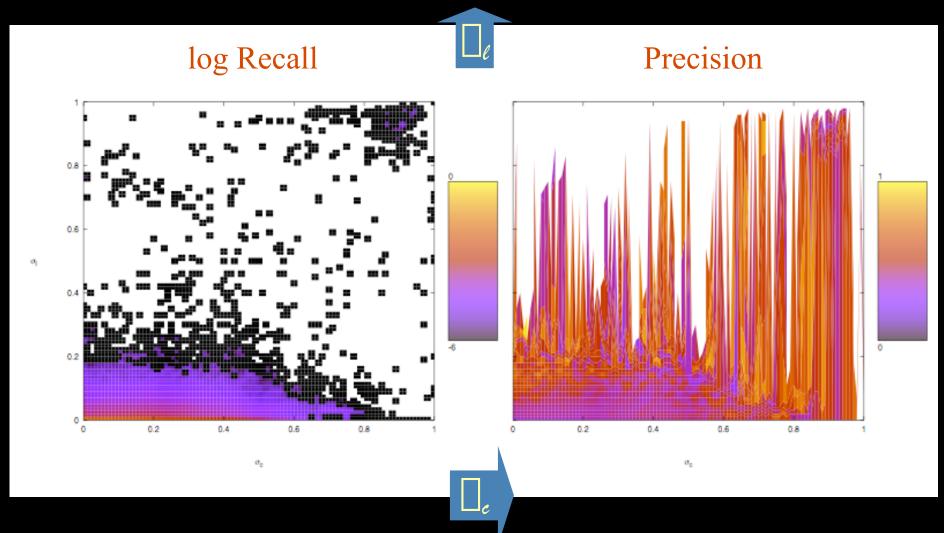


Semantic maps: Business



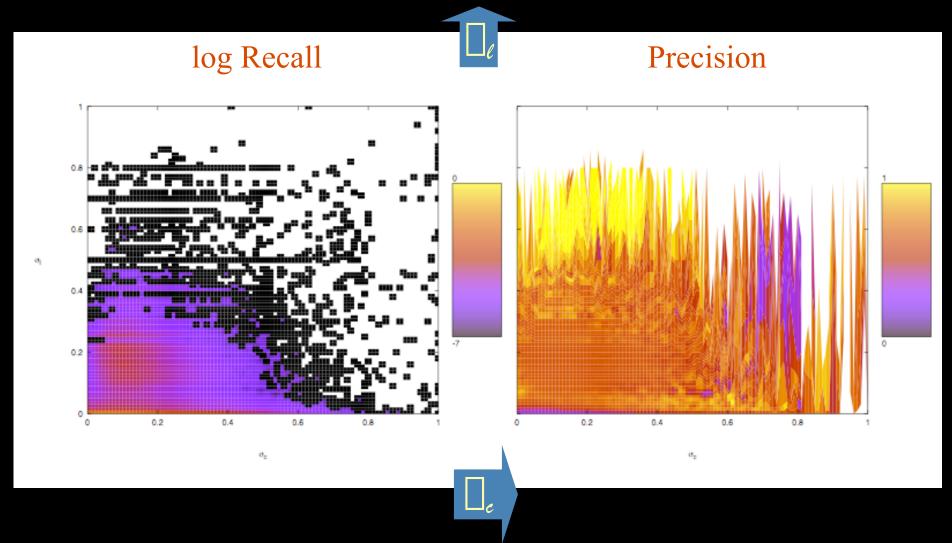


Semantic maps: Adult



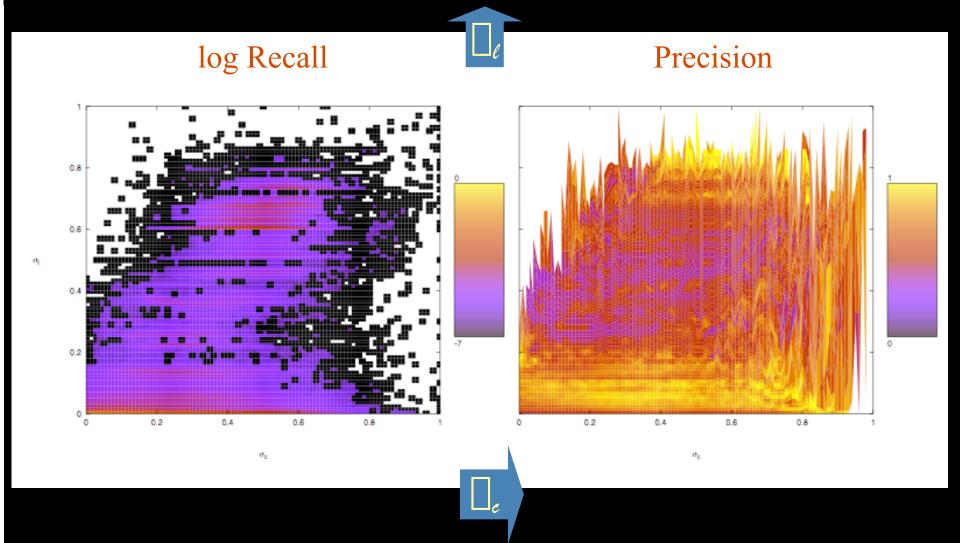


Semantic maps: Computers



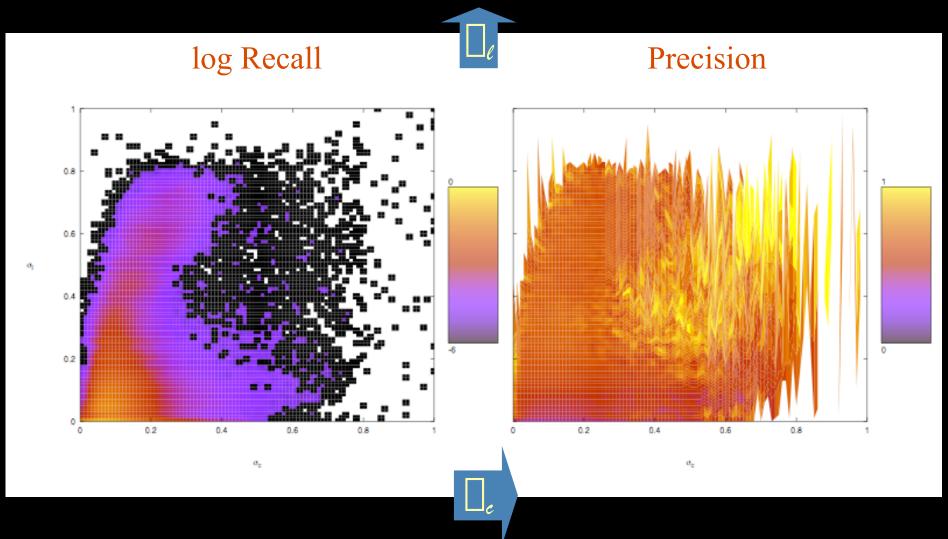


Semantic maps: Home



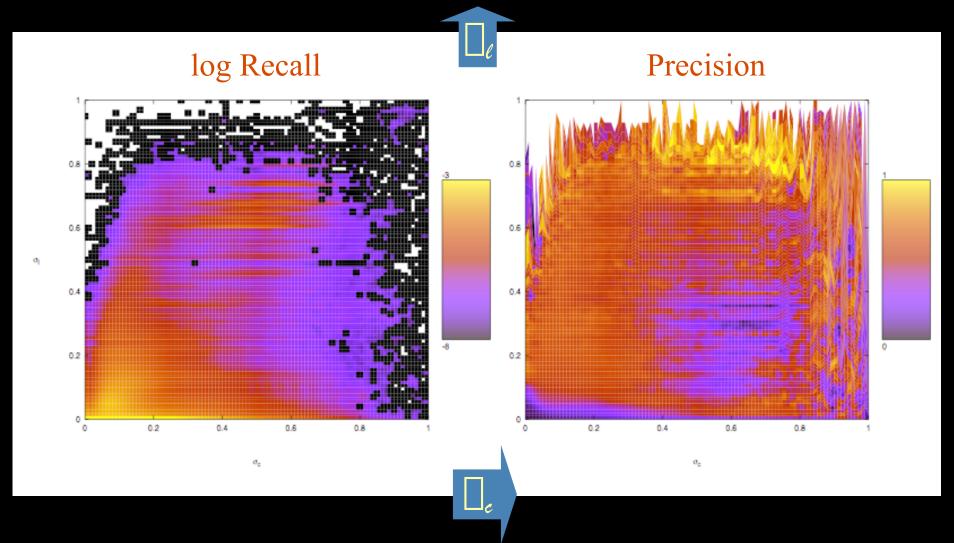


Semantic maps: News





Semantic maps: all pairs





So what?

- Interpret performance of search engines
- Understand "ranking optimization"
 - vs filtering
 - vs combinations
- Topical signatures for topical/community portals
- Design "better" (and more scalable) crawlers
 - Topic driven
 - Query driven
 - User/community/peer driven
- Competitive intelligence, security applications



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- Questions?

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