The Role of Information Scent in On-line Browsing:

Extensions of the ACT-R Utility and Concept Formation Mechanisms

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User Interface Research Area

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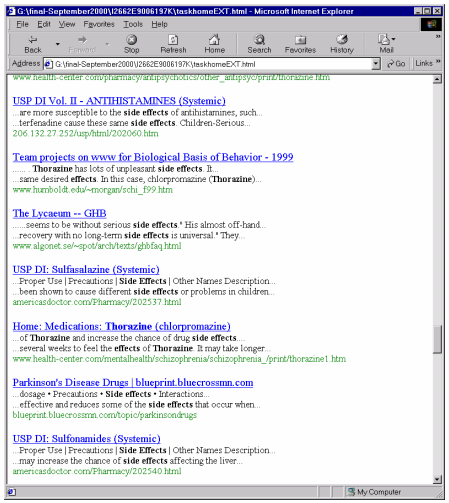
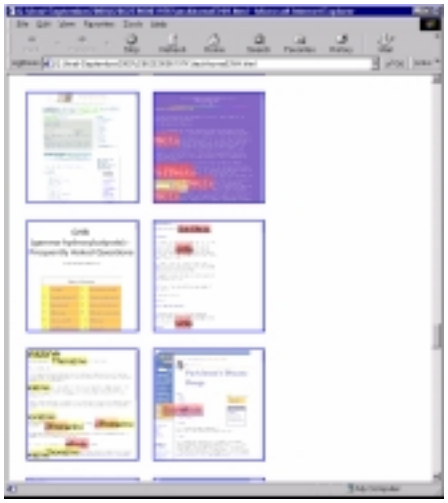
Information Scent

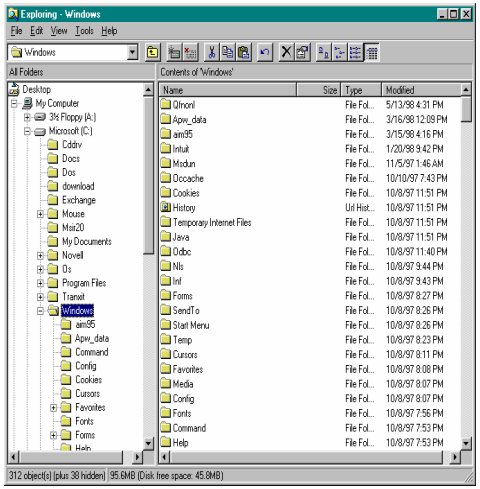


(a)



(b)

(c)



(d)

Browsing often requires that we use visual or textual cues to direct our actions.

These local (proximal) cues are called *information scent*.

The *theory of information scent* is a psychological theory

Used to develop new user interface designs and new Web site evaluation tools

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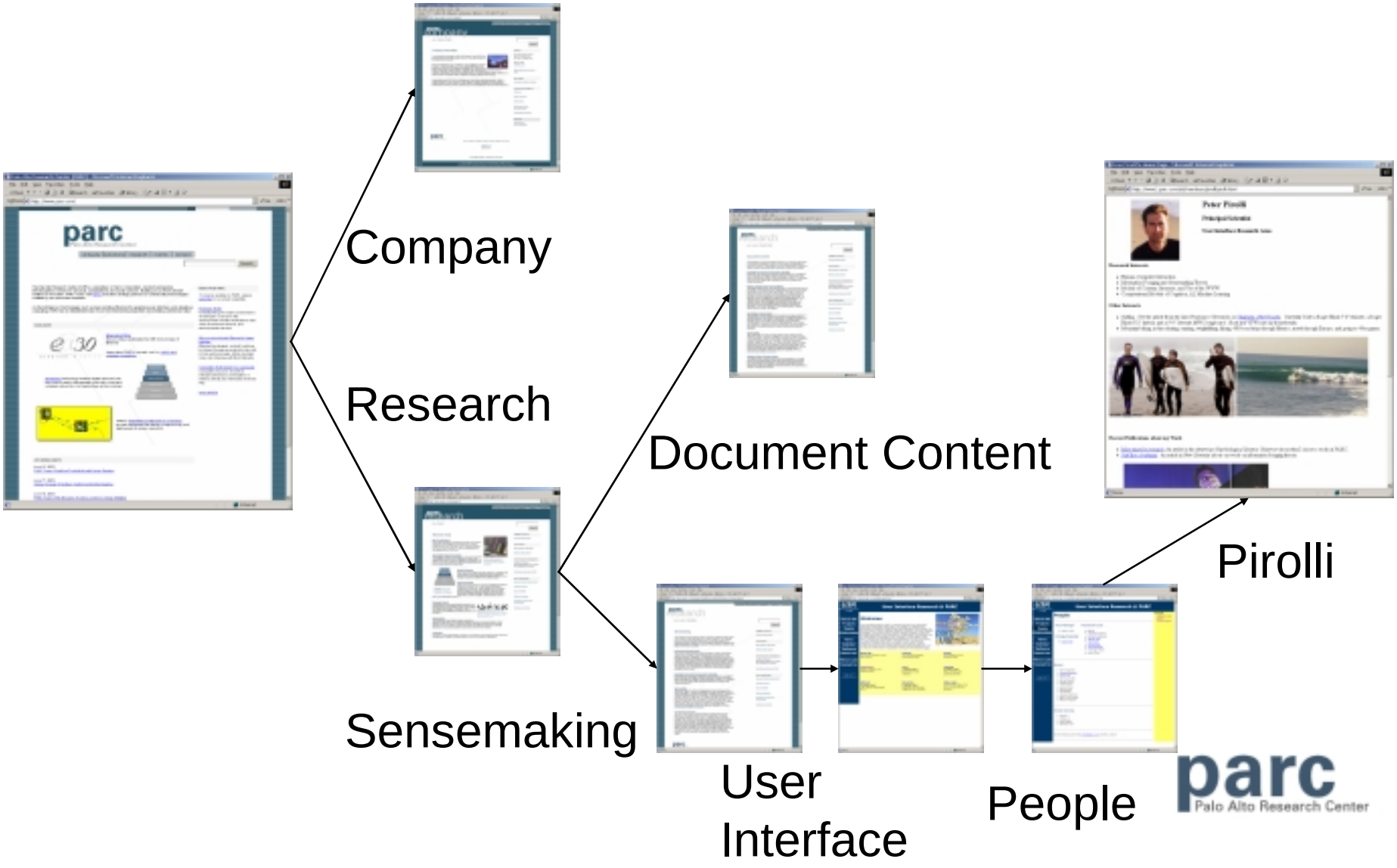
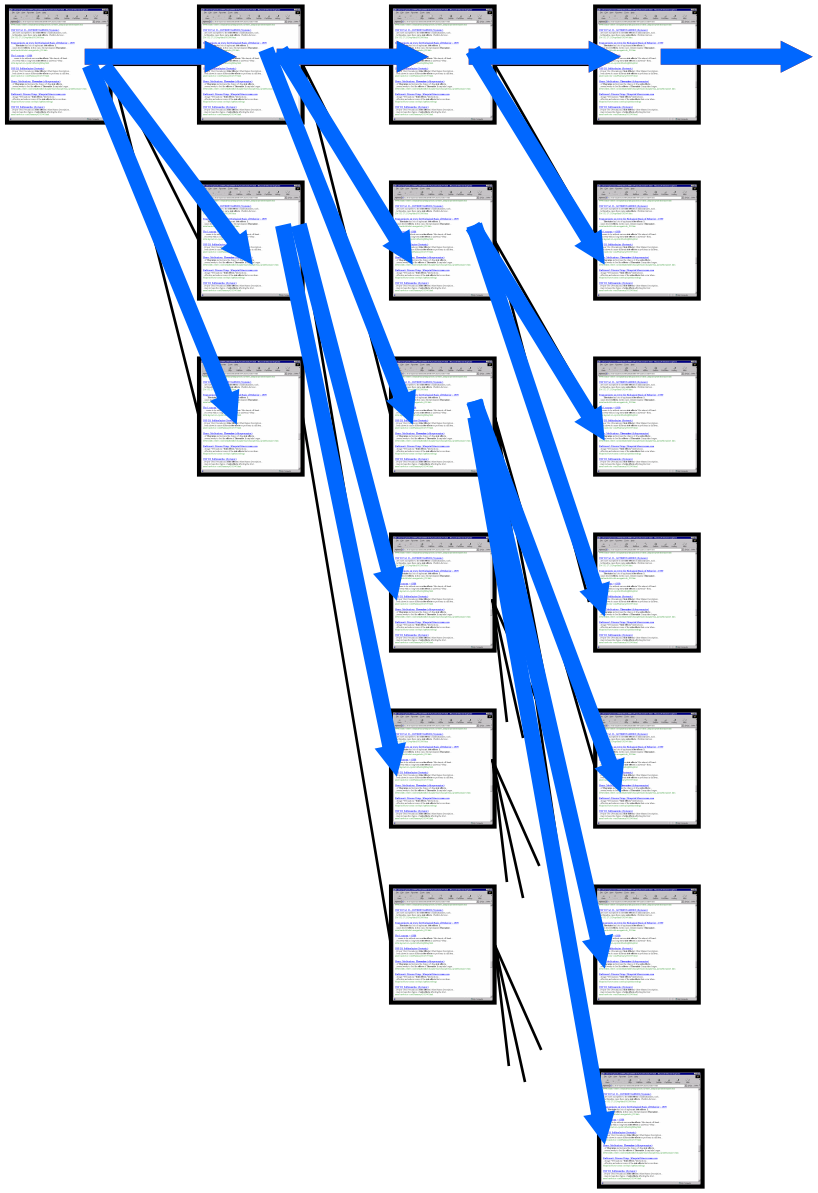
Overview

- Why information scent is important
- SNIF-ACT Model of Navigation
  - Where to go next (navigational choices)?
  - When to stop (leaving a Web site)?
- InfoCLASS Model of topic category formation
  - What categories of topics are where (learning about the information environment)

Example: Looking for Pirolli's Personal Page on the PARC Site



Hierarchical Navigation Spaces



Strong Information Scent
= Navigation Cost
Linear in Depth

Weak Information Scent
= Navigation Cost
Exponential in Depth

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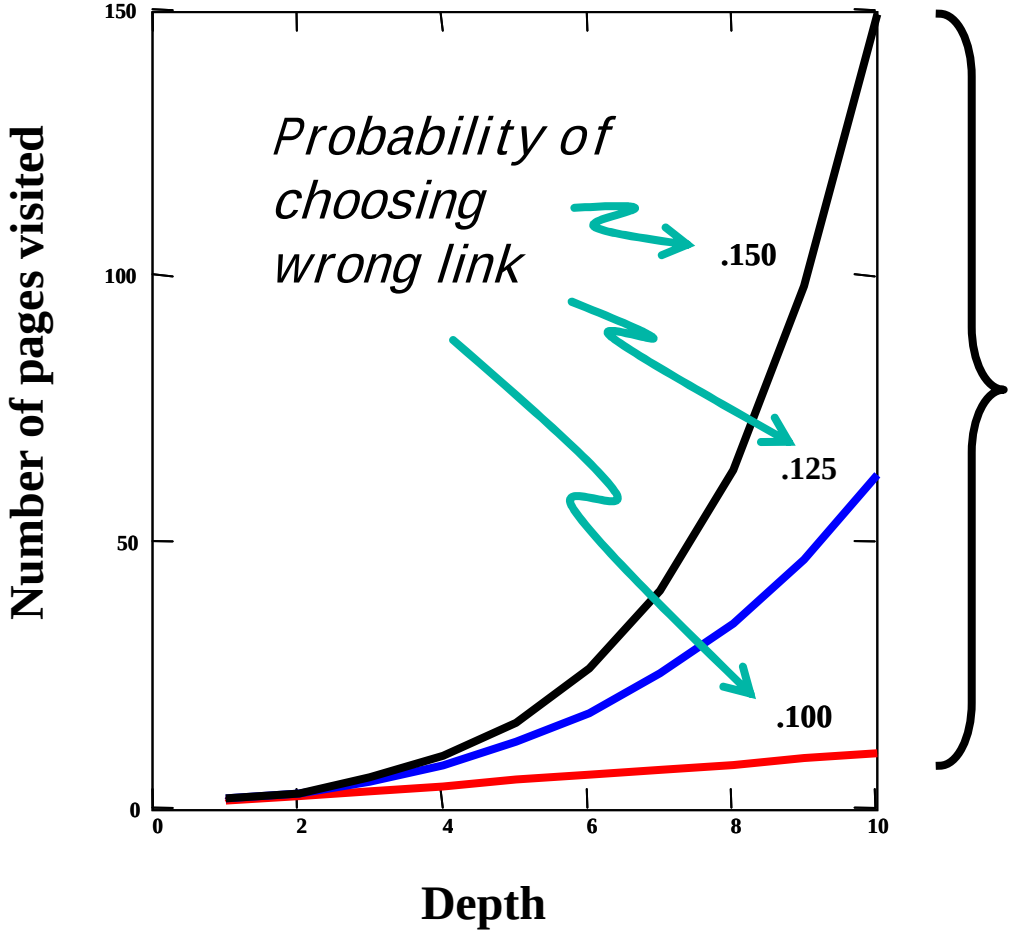
Navigation Costs as Function of Information Scent



Probabilities within range of empirical values in Woodruff et al. (2002)

Notes: Average branching factor = 10
Depth = 10

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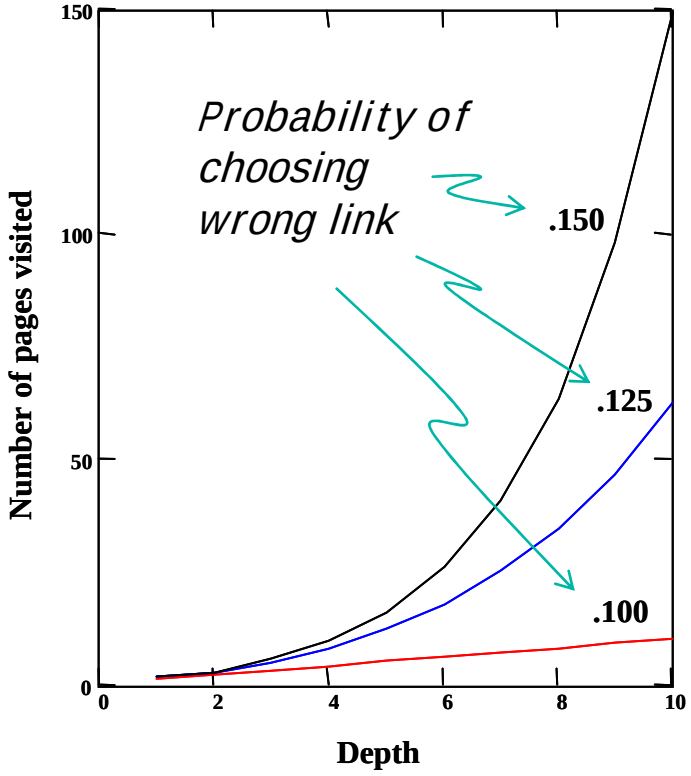
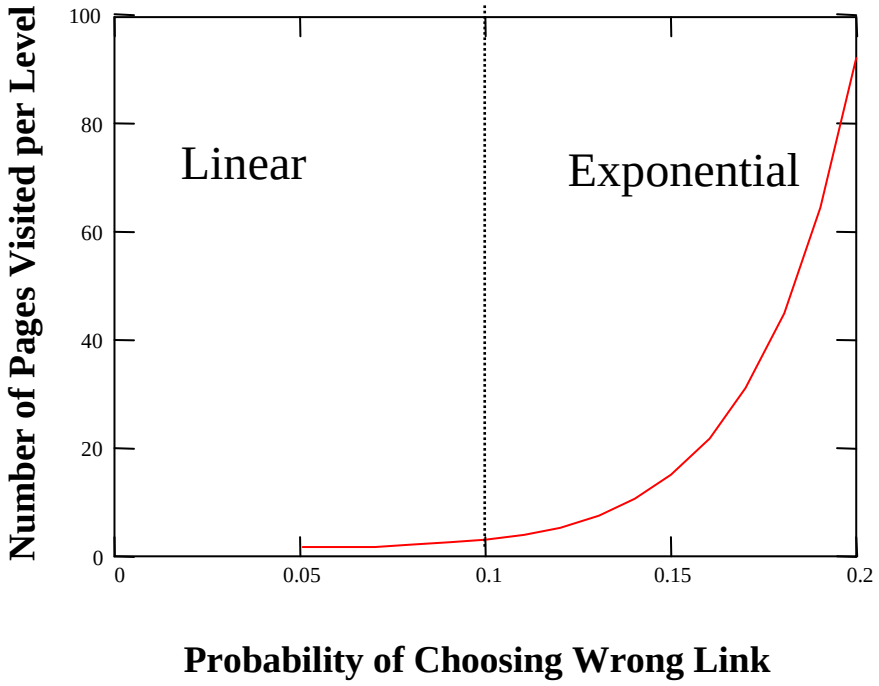
Phase Transition in Navigation Costs as Function of Information Scent





Notes: Average branching factor = 10
Depth = 10

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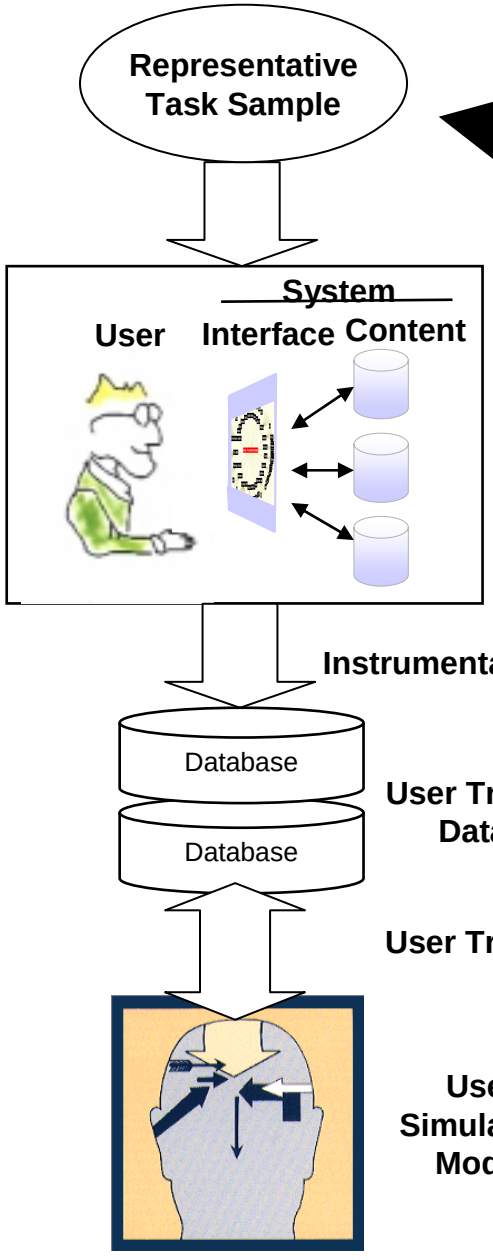
WWW Studies



Survey of user tasks (N = 2188). Develop *ecologically valid* tasks for study in experiments.

Experiments

Develop instrumentation to record user trace data.

Analyze data. Develop cognitive model. Validate against user trace data.

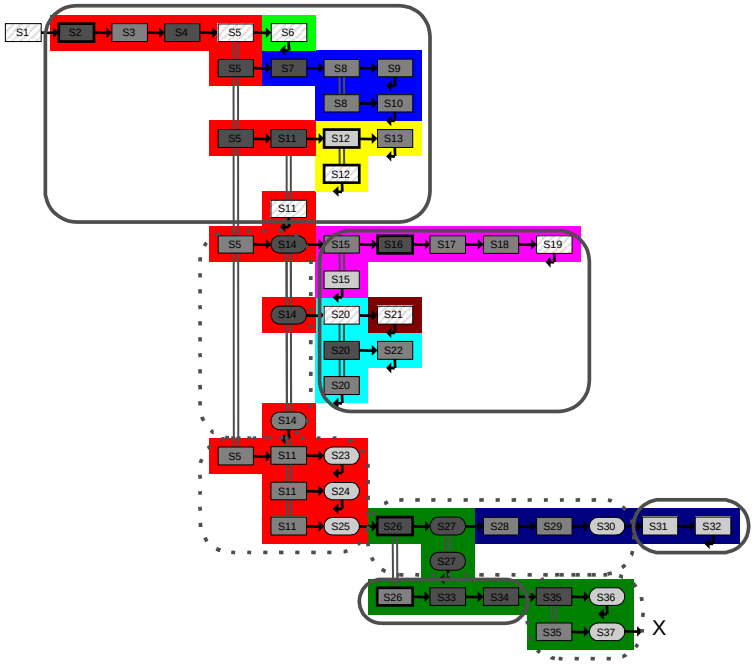
WWW Experiment & Model

- 12 Stanford University students
- 6 tasks
- 2 tasks analyzed and modeled for 4 participants
- Example tasks
  - Find specific movie posters for your new living room
  - Find dates for a performance by a comedy troupe

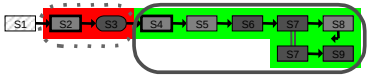
Pirolli, P. & Fu, W. (2003). SNIF-ACT: A model of information foraging on the World Wide Web. Proceedings of the Conference on User Modeling.

Web Behavior Graphs (WBGs)

Find a poster for the movie "Antz"



Find the tour schedule of the "Second City Comedy Troupe"



- Links providing better information scent yield more direct navigation
- People abandon Web sites when information scent diminishes

Card, S., Pirolli, P., Van Der Wege, M., Morrison, J., Reeder, R., Schraedley, P., & Boshart, J. (2001). ***CHI Proceedings***

SNIF-ACT

- Scent-based Navigation and Information Foraging in the ACT theory
- Declarative knowledge
  - User goal (e.g. Find the poster for “Antz”)
  - Perceived aspects of Web page & browser
  - Large spreading activation network representing word associations
- Procedural knowledge
  - Productions representing basic Web browsing actions
- Utility: Information Scent
  - Mutual relevance between link text and user goal

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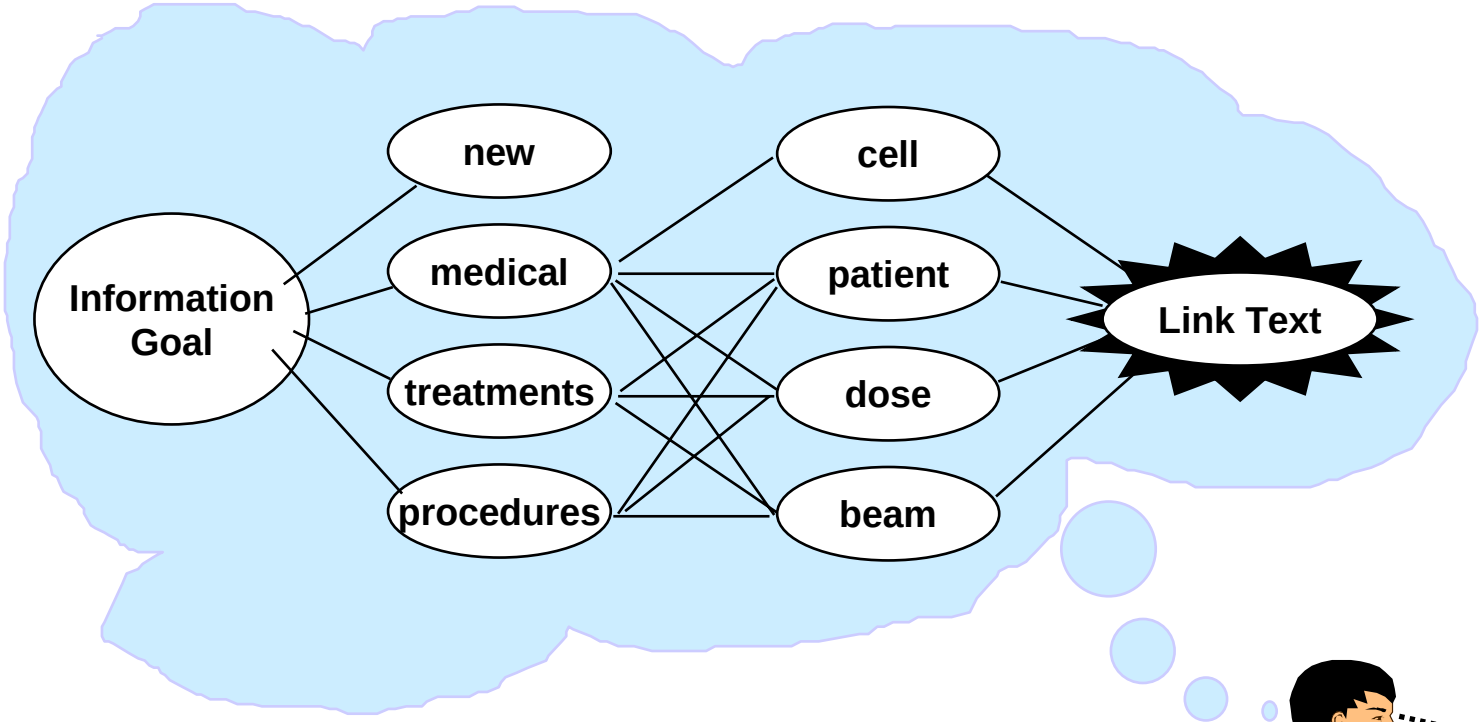
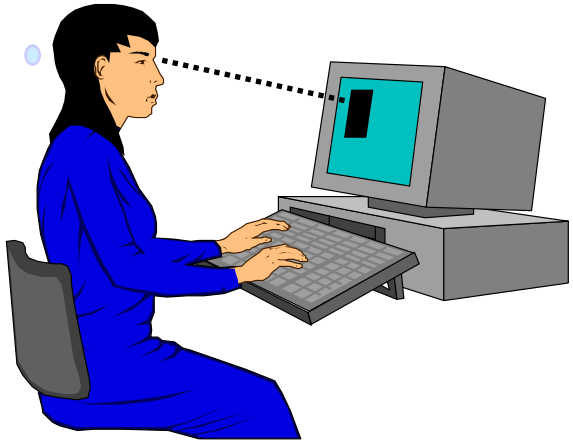
Cognitive Model of Information Scent





- *Spreading activation*
  - Activation reflects likelihood of relevance given past history and current context

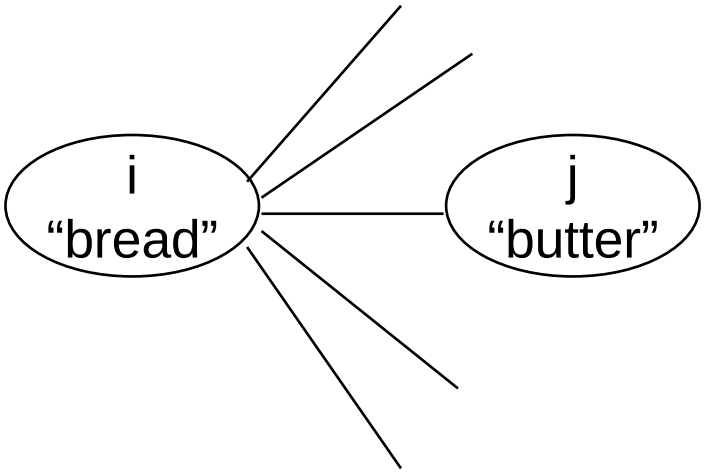
Spreading activation

Activation of node i

$$A_i = B_i + \Sigma W_j S_{ji}$$

Base-level activation

Activation spread from linked nodes j



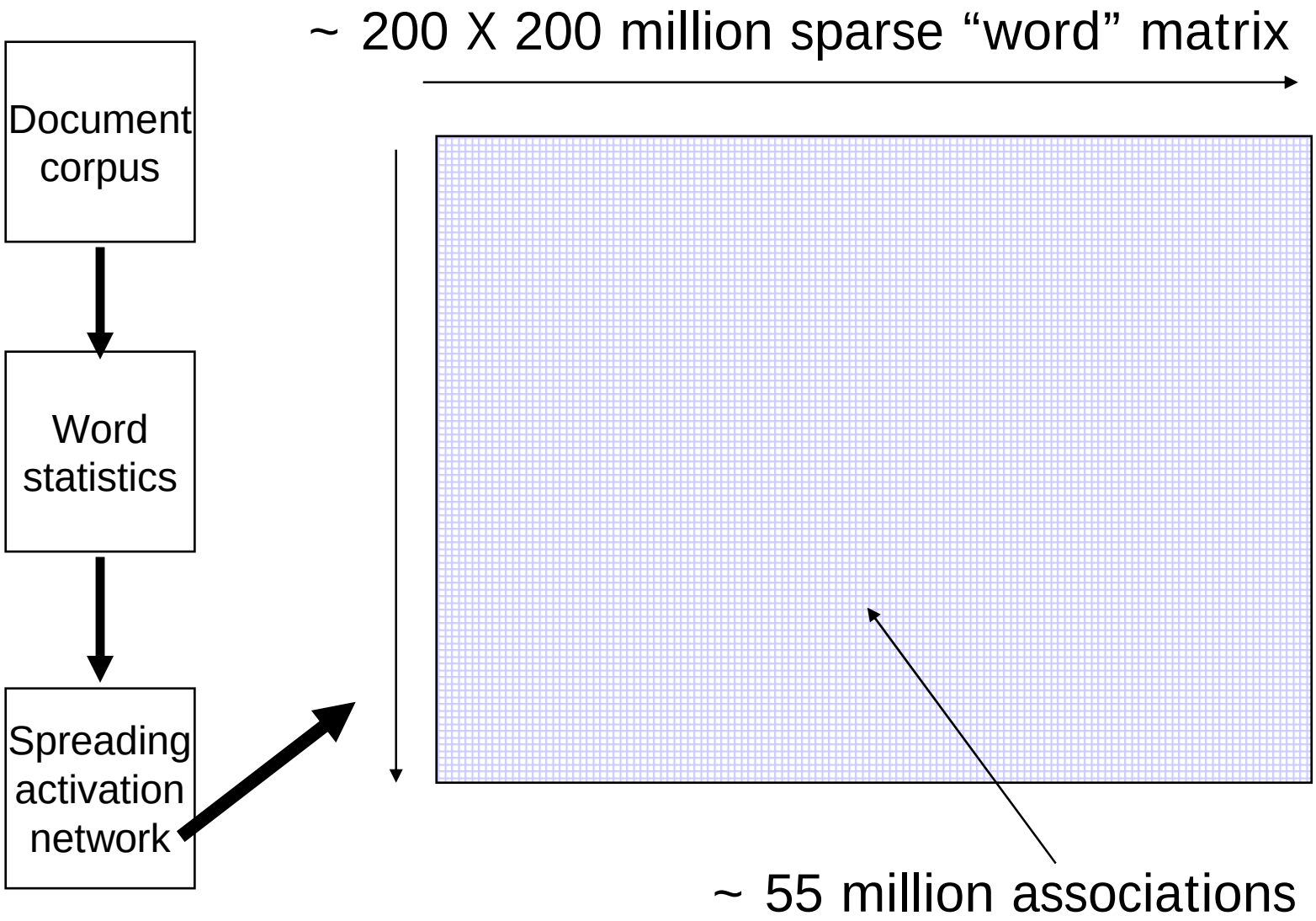
Base-level reflects log odds of occurrence

$$B_i = \ln\left(\frac{\Pr(i)}{\Pr(\text{not } i)}\ \psi\right)$$

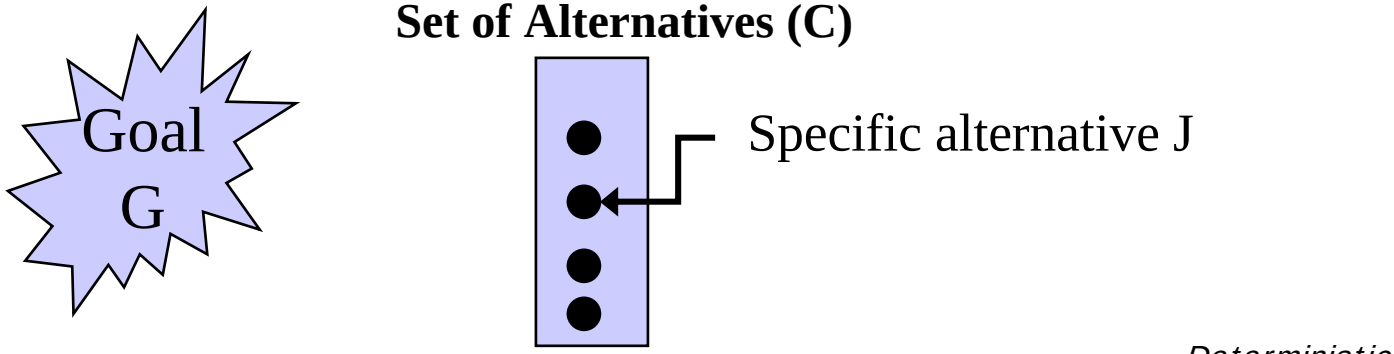
Strength of link spread reflects log likelihood odds of cooccurrance

$$S_{ji} = \ln\left(\frac{\Pr(j|i)}{\Pr(j|\text{not } i)}\ \psi\right)$$

spreading activation networks



Information Scent:
Random Utility Model based on Activation



Utility of alternative J, out of set C, in context of goal G:

$$U_{J|G} = V_{J|G} + \varepsilon_{J|G}$$

Deterministic

Stochastic

Deterministic utility is based on activation:

$$V_{J|G} = \sum_{i \in G} A_i$$

Summed activation from scent cues to goal

Probability of choosing alternative J:

$$\Pr(J \mid G, C) = \frac{e^{\mu V_{J|Q}}}{\sum_{K \in C} e^{\mu V_{K|Q}}}$$

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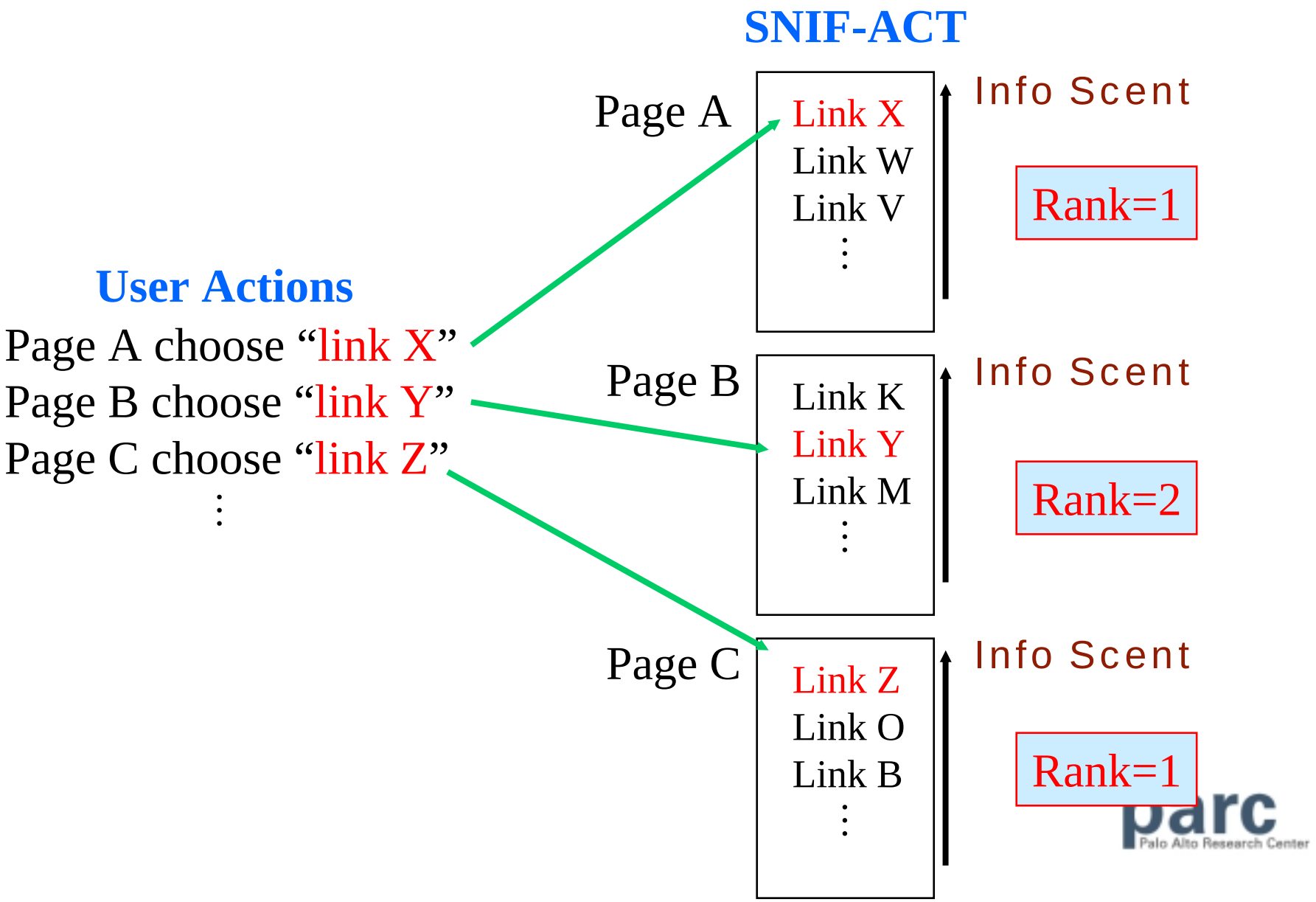
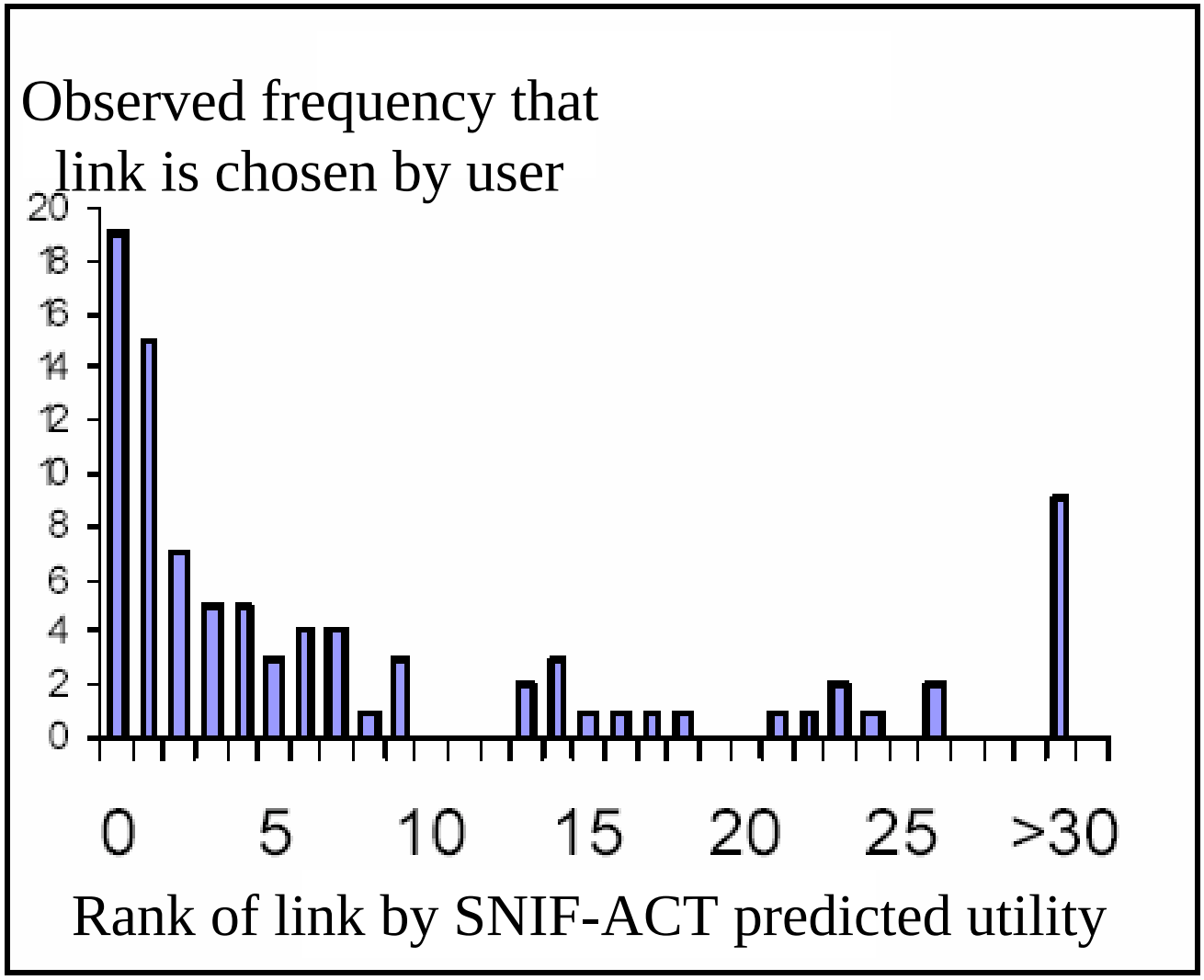
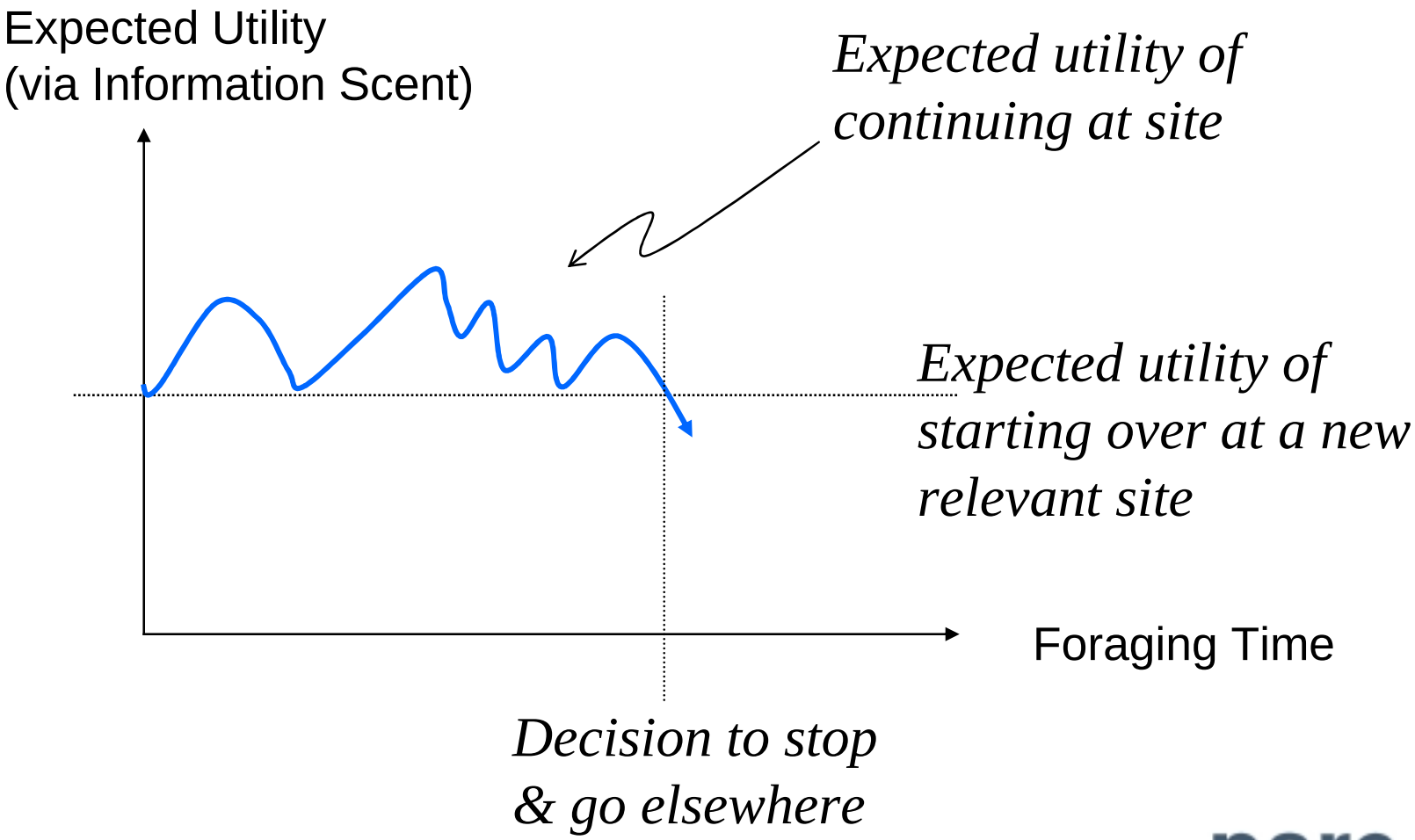
Evaluation:Link-following actions



Observed vs Predicted Link Choice



Theory: Decision to Leave Web Site



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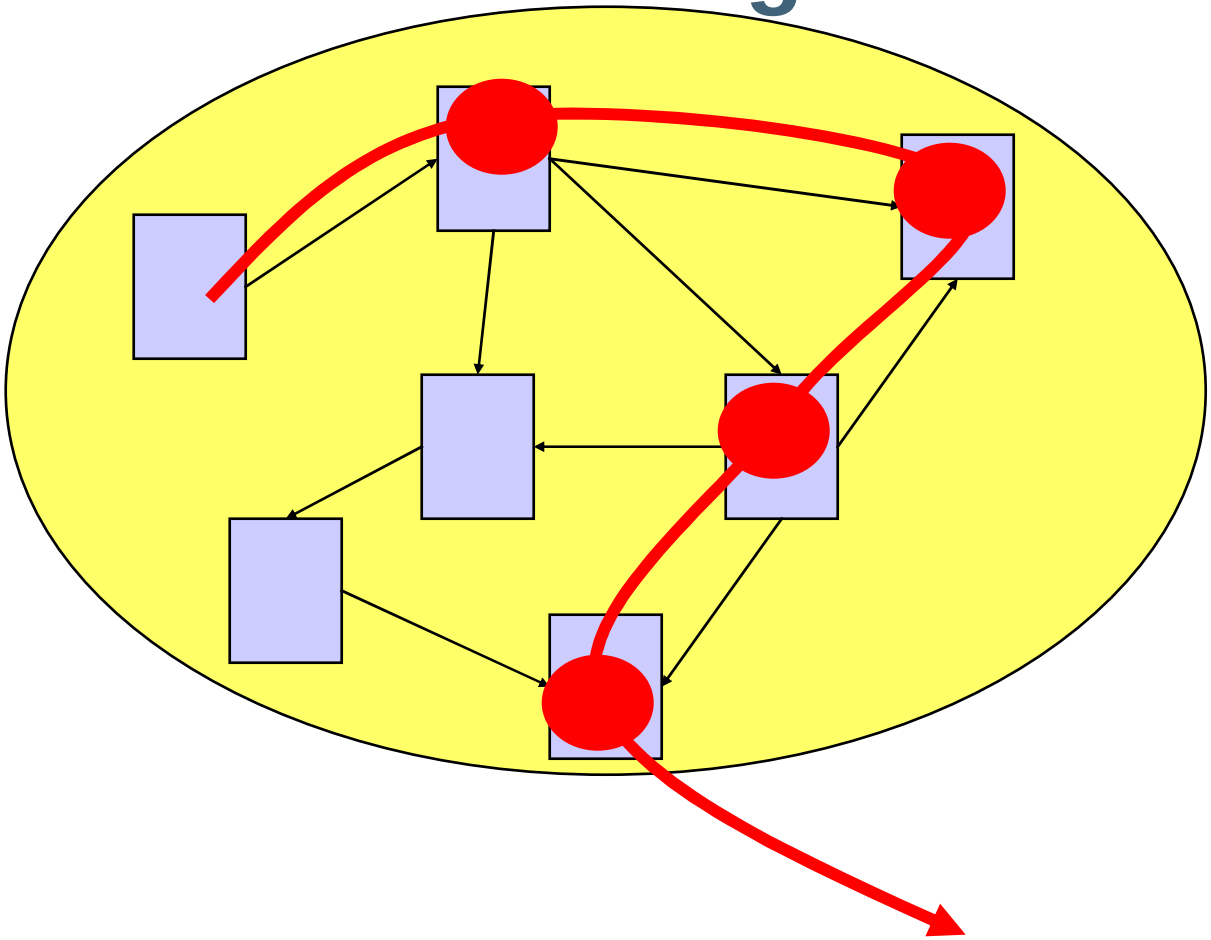
Data: Sequences of Moves Just Prior to Leaving a Site



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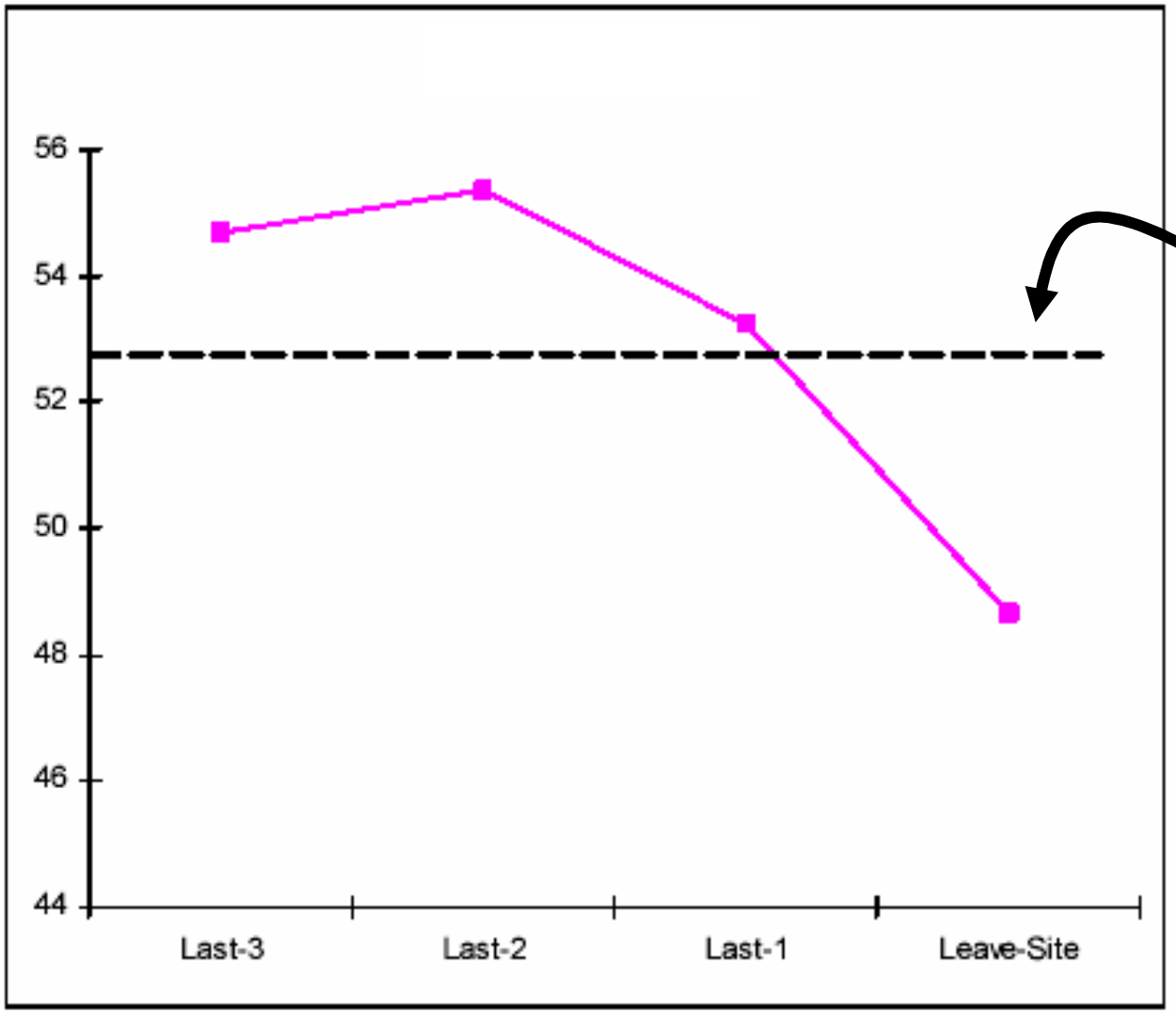
Match of SNIF-ACT to User Data

SNIF-ACT Predicted utility of next link



SNIF-ACT Average utility of new site

User Move Before Leaving Site

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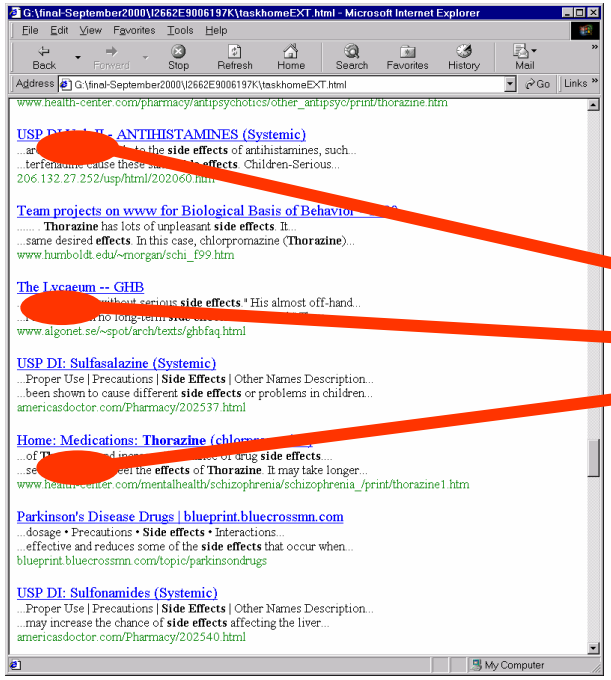
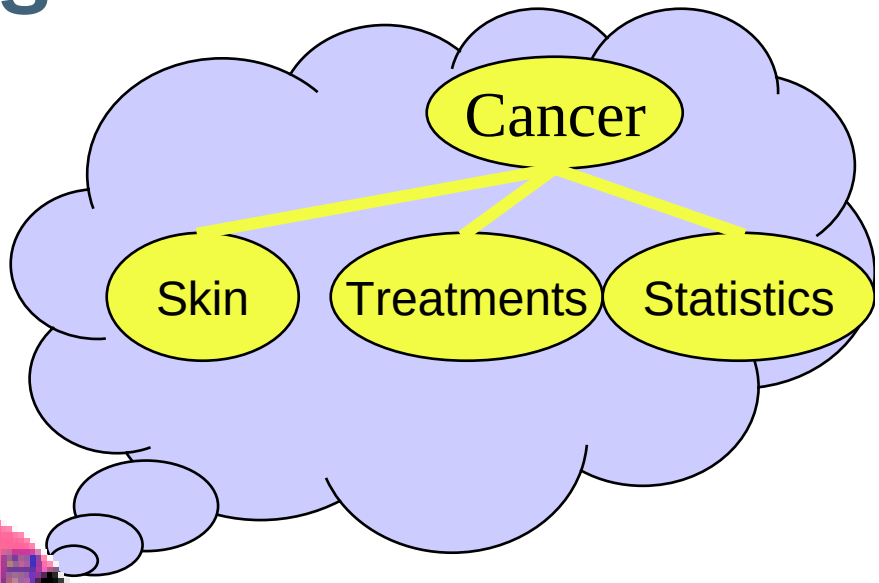
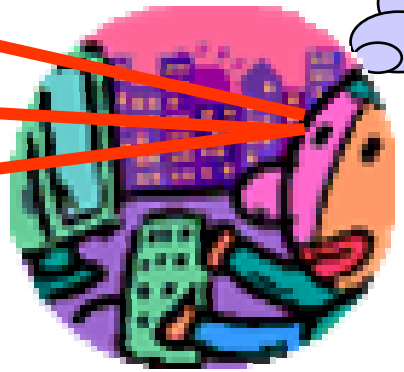
Forming Concepts about Information Sources

Standard Web Site Search Engine







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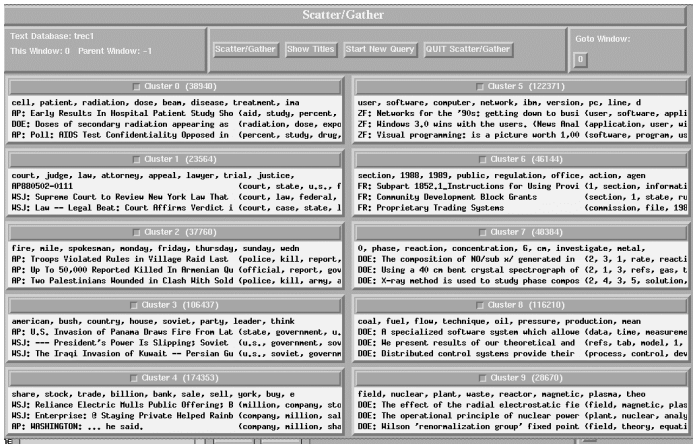
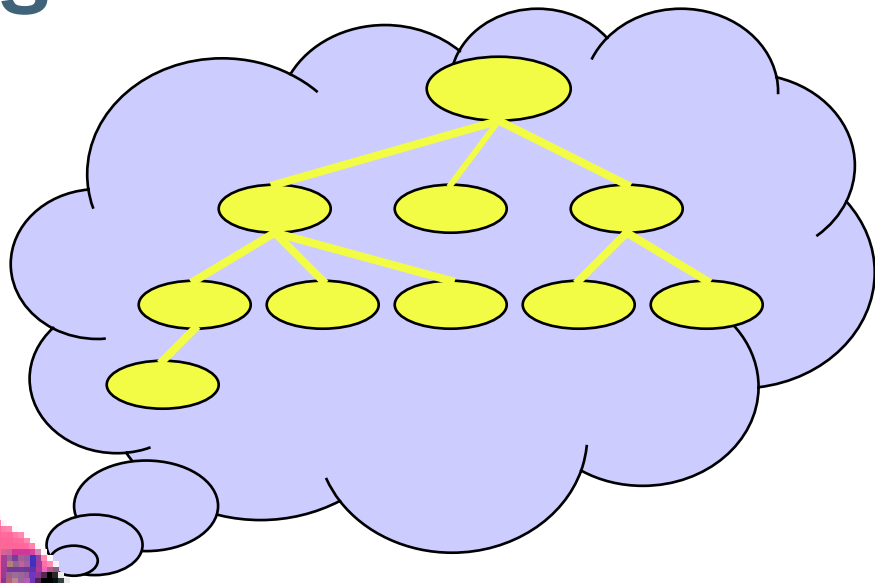
Forming Concepts about Information Sources

Scatter/Gather
Document Clustering Browser





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Browser Study

- Browsers
  - Scatter-Gather (*N* = 8)
  - Standard Similarity Search Engine (*N* = 8)
- 12 Tasks (TREC)
  - E.g., Find documents on new medical procedures for cancer

Pirolli, P., Hearst, M., Schank, P., & Diehl, C. (1996). Scatter-Gather browsing communicates the topic structure of a very large text collection. *Proceedings of the 'CHI '96 Conference*.

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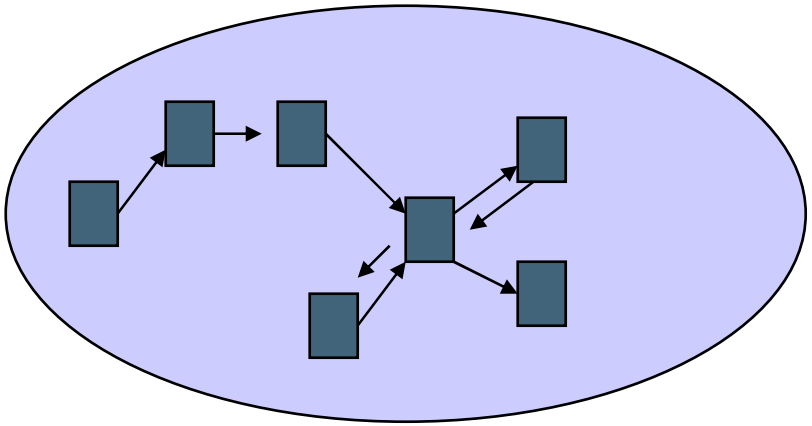
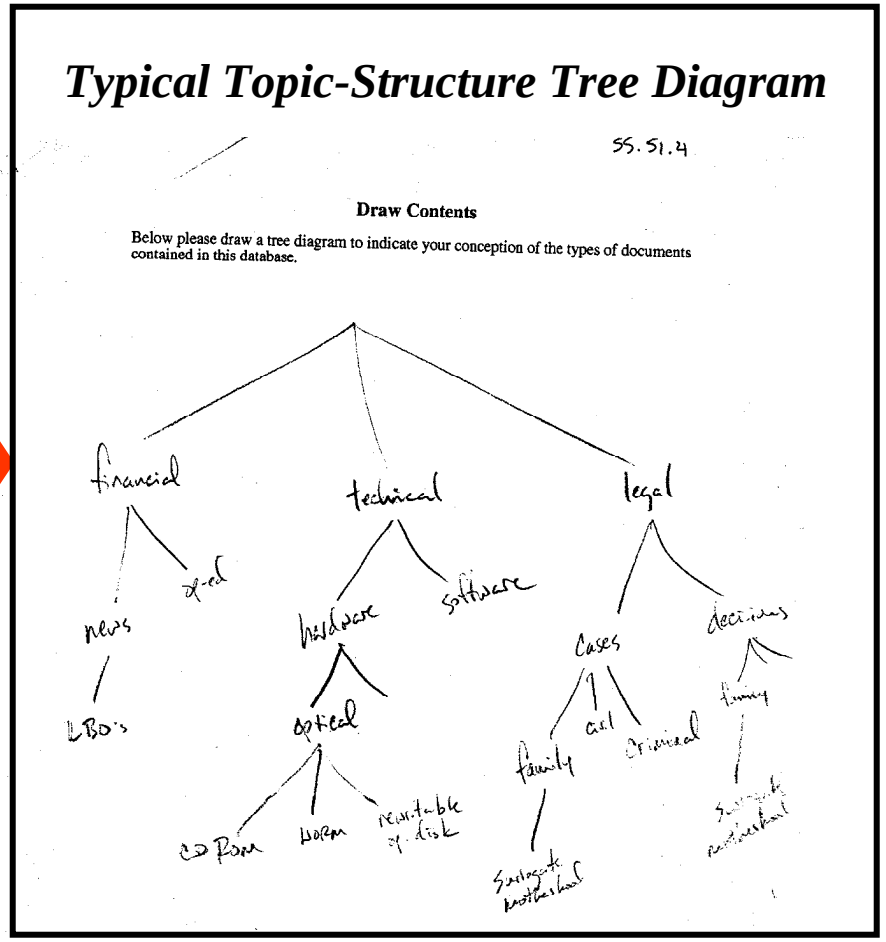
Inferred Topic Structure

Browse documents





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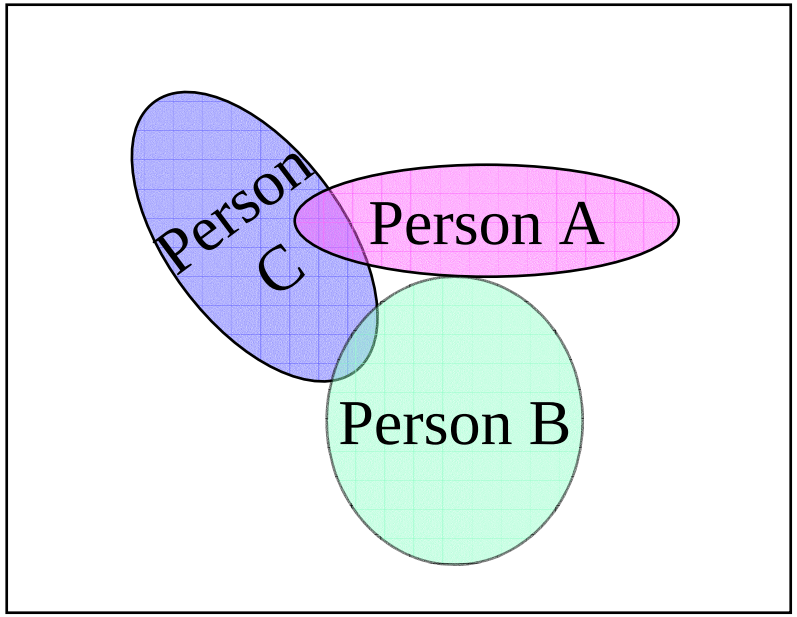
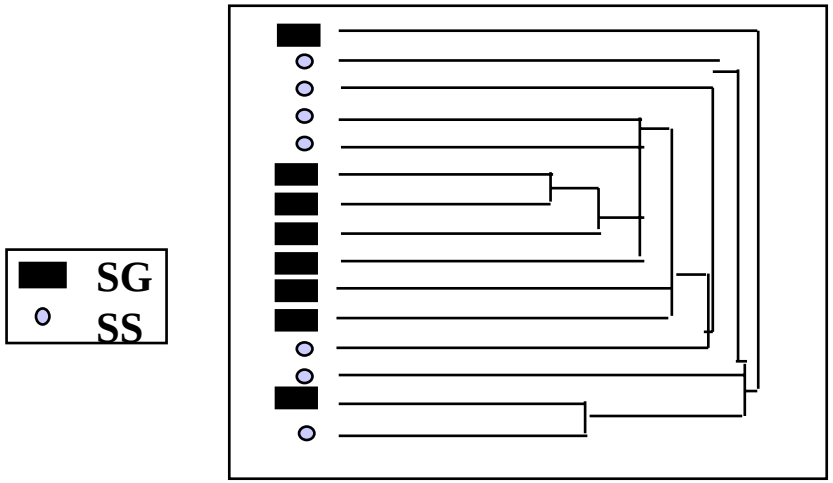
Coherence of Mental Topics Among Users



Hierarchical clustering of users based on similarity of topic trees



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InfoCLASS

- Information Category Learning by Adaptation to Scent Stimuli
  - Rational Analysis Model of Human Category Learning (Anderson, 1991, 1991)
- Assumes
  - Topics are mental categories
  - Mental categories are probabilistic collections of concepts
  - Links, thumbnails, citations provide information scent cues that evoke mental concepts

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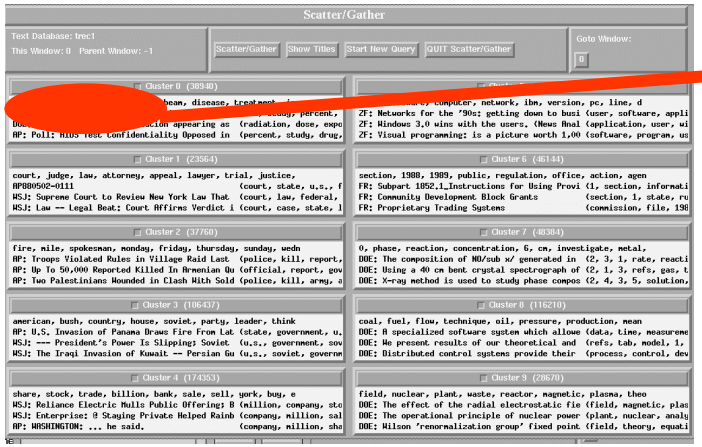
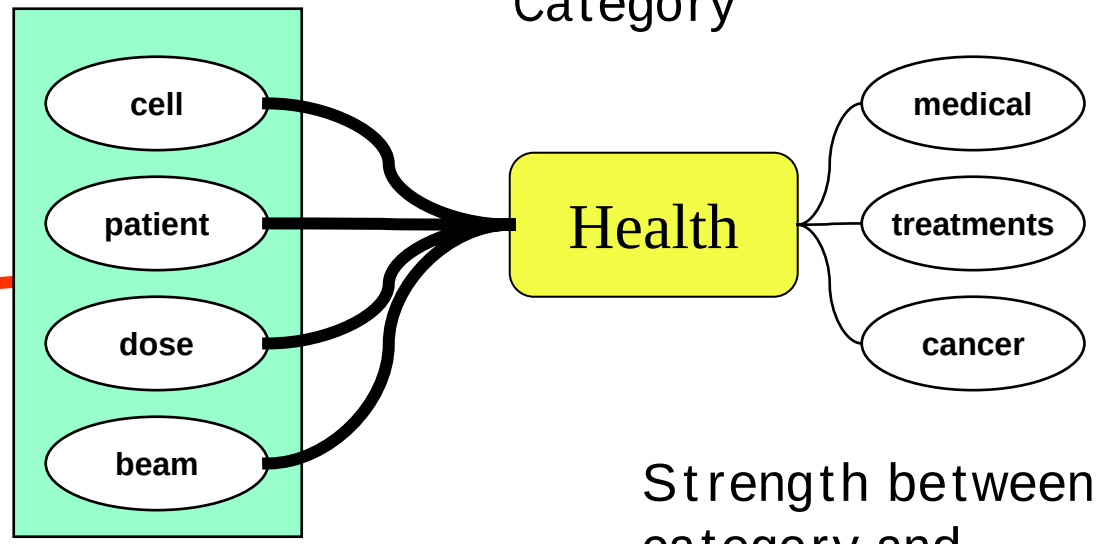
Evoking Categories and Inferences





Strength between observed UI features (words) and category reflects log odds

Strength between category and inferred features reflects log odds

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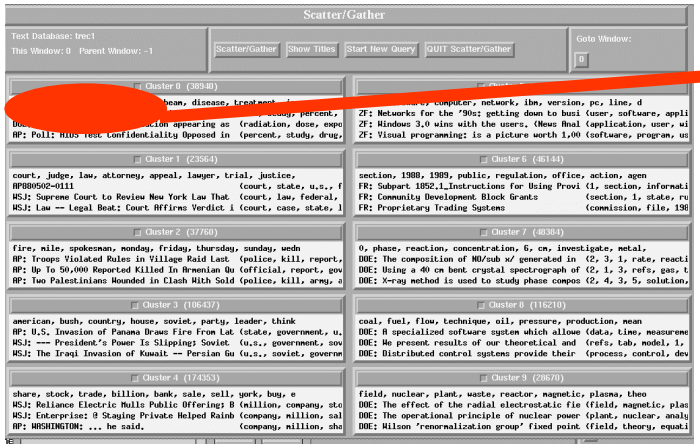
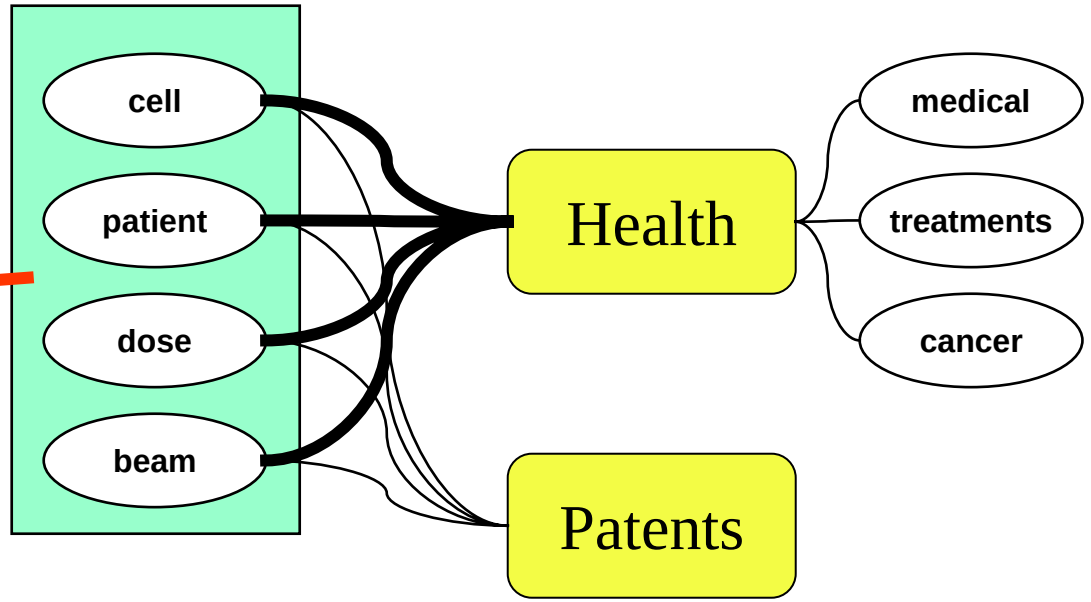
Cues correspond to existing mental topics: Choose most activated (highest odds)





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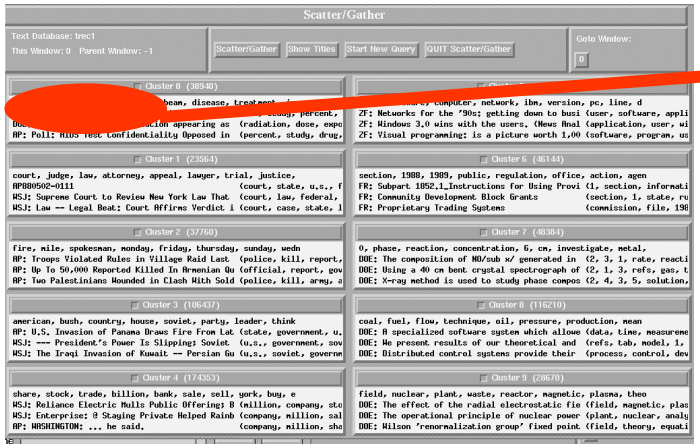
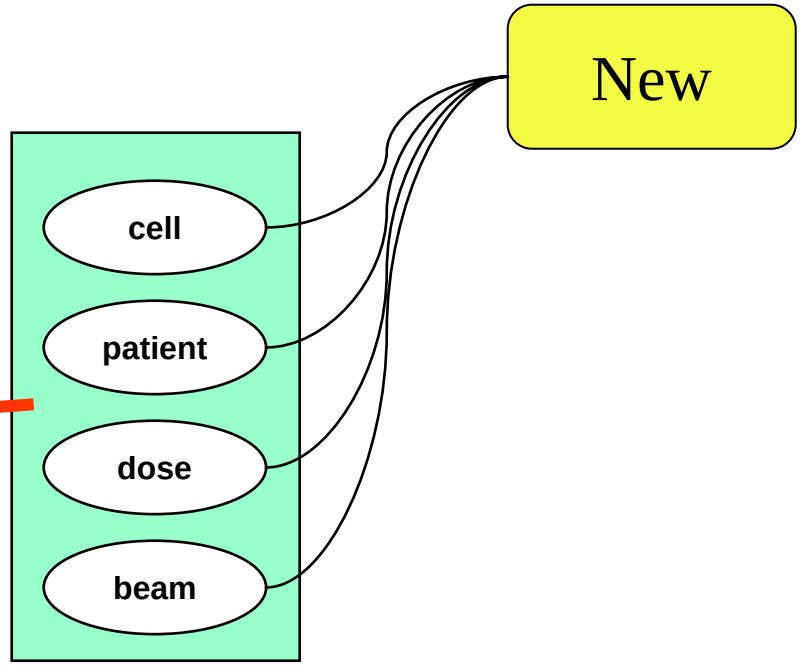
Otherwise create new category





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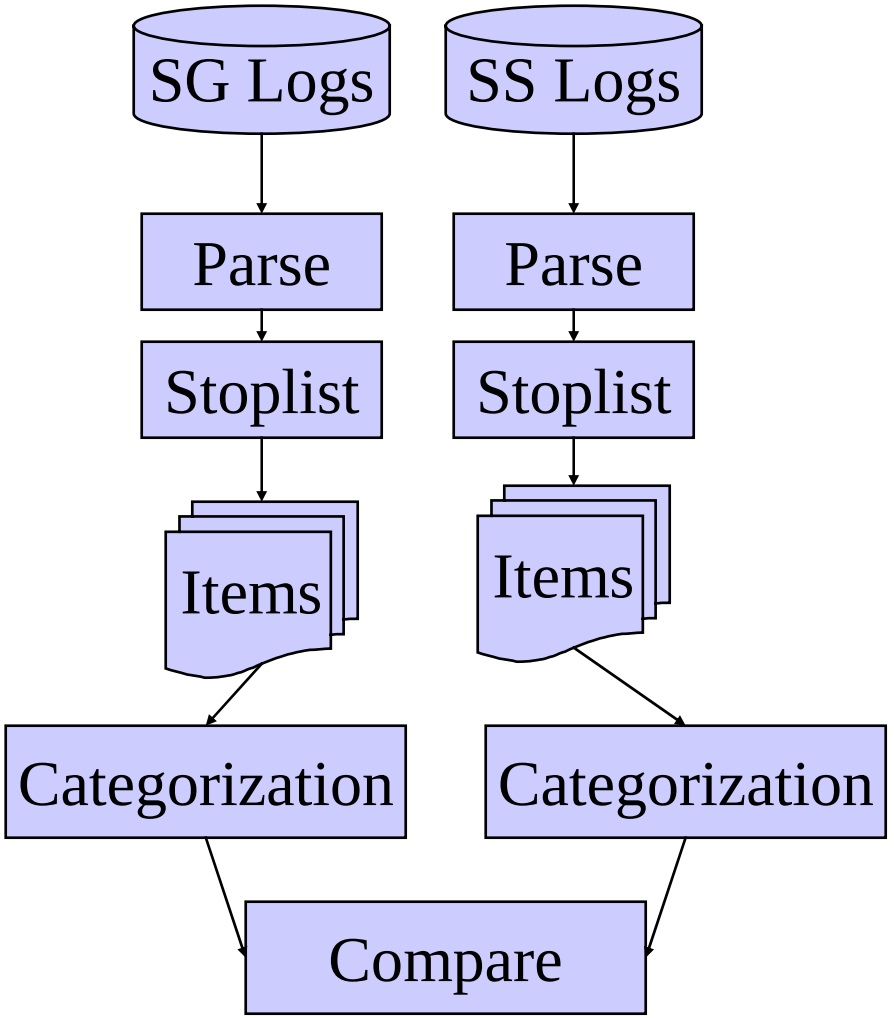
InfoCLASS Simulation

- Scatter/Gather (SG): expose to *cluster summaries* from user logs
- Standard Search (SS) Expose to *search result lists* from user logs
- Evaluate ADA (category coherence) for the two groups of users



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Simulation Performance

	Items		Categories	
	SG	SS	SG	SS
1	330	464	59	28
2	470	767	149	39
3	526	1926	142	33
4	579	1481	101	28
5	770	1331	120	28
6	420	565	152	45
7	370	963	151	16
8	507	1486	124	14
	496	1123	125	29

Scatter-Gather (SG) simulations develop more categories than Standard Search (SS).

Same trend as Pirolli et al (1996) comparison of SG vs SS users.

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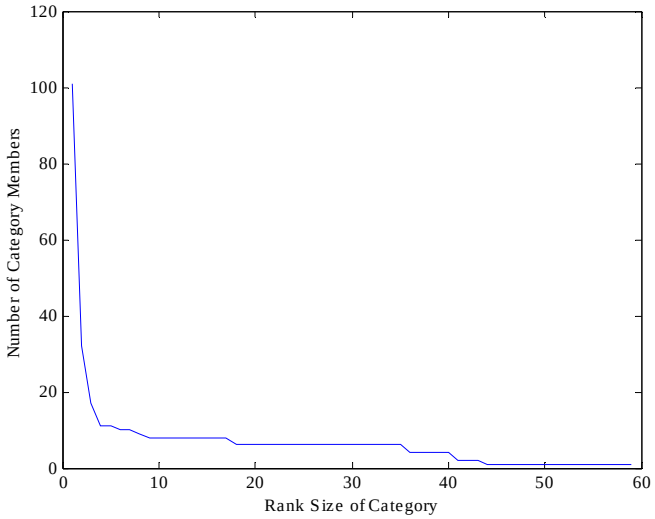
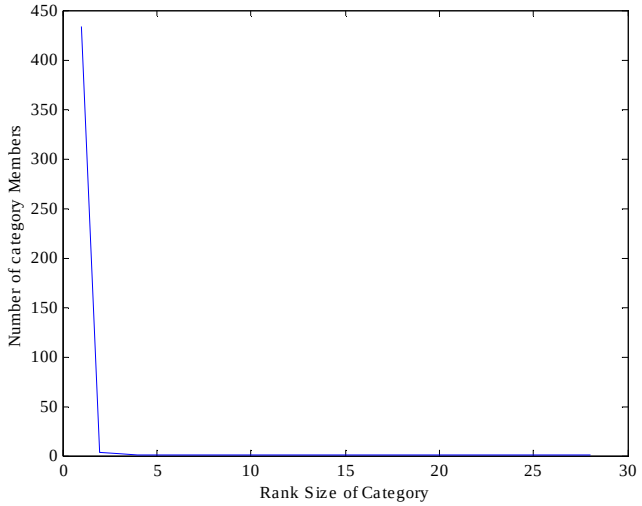
Category structure and coherence

Scatter/Gather User 1



Similarity Search User 1



	ADA
SG	.949
SS	1.292

x 10^{-6} bits

Scatter-Gather simulations exhibit greater category coherence (less divergence).

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Summary

- Importance
  - Quality of information scent can effect qualitative changes in navigation costs (linear to exponential)
  - Browsers can differ in the how they communicate the topic structure of a collection of information
- SNIF-ACT model of navigation
  - Navigation & when to stop
- InfoClass
  - Model of formation of mental categories of topic structure
- Applications
  - New UIs (ScentTrails, Relevance Enhanced Thumbnails, …)
  - Web Site Evaluation tools (Bloodhound, Lumberjack)

BACKUP SLIDES

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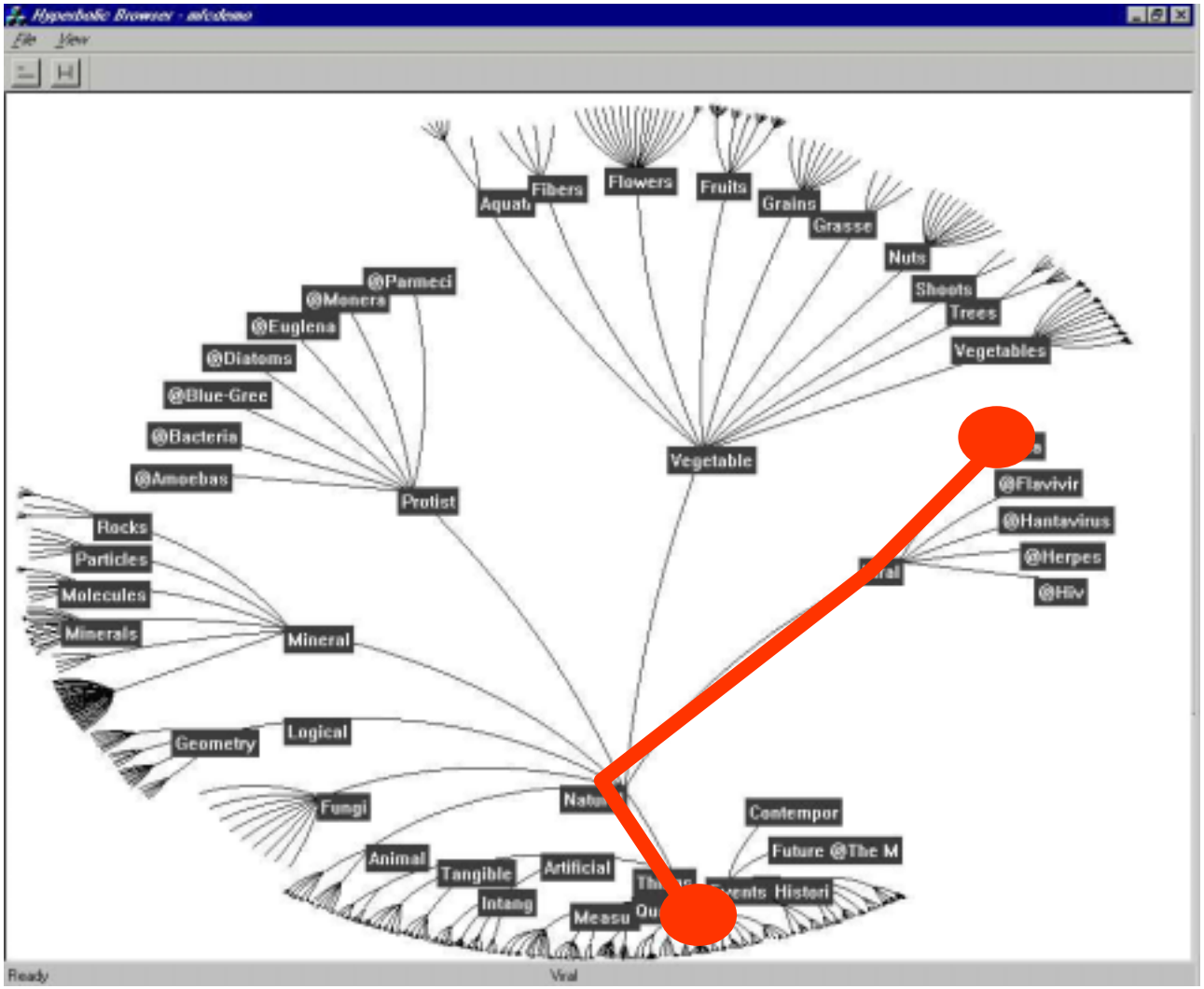
Eye Movements:
High Information Scent
(Pirolli, Card, & Van Der Wege, 2003, TOCHI)



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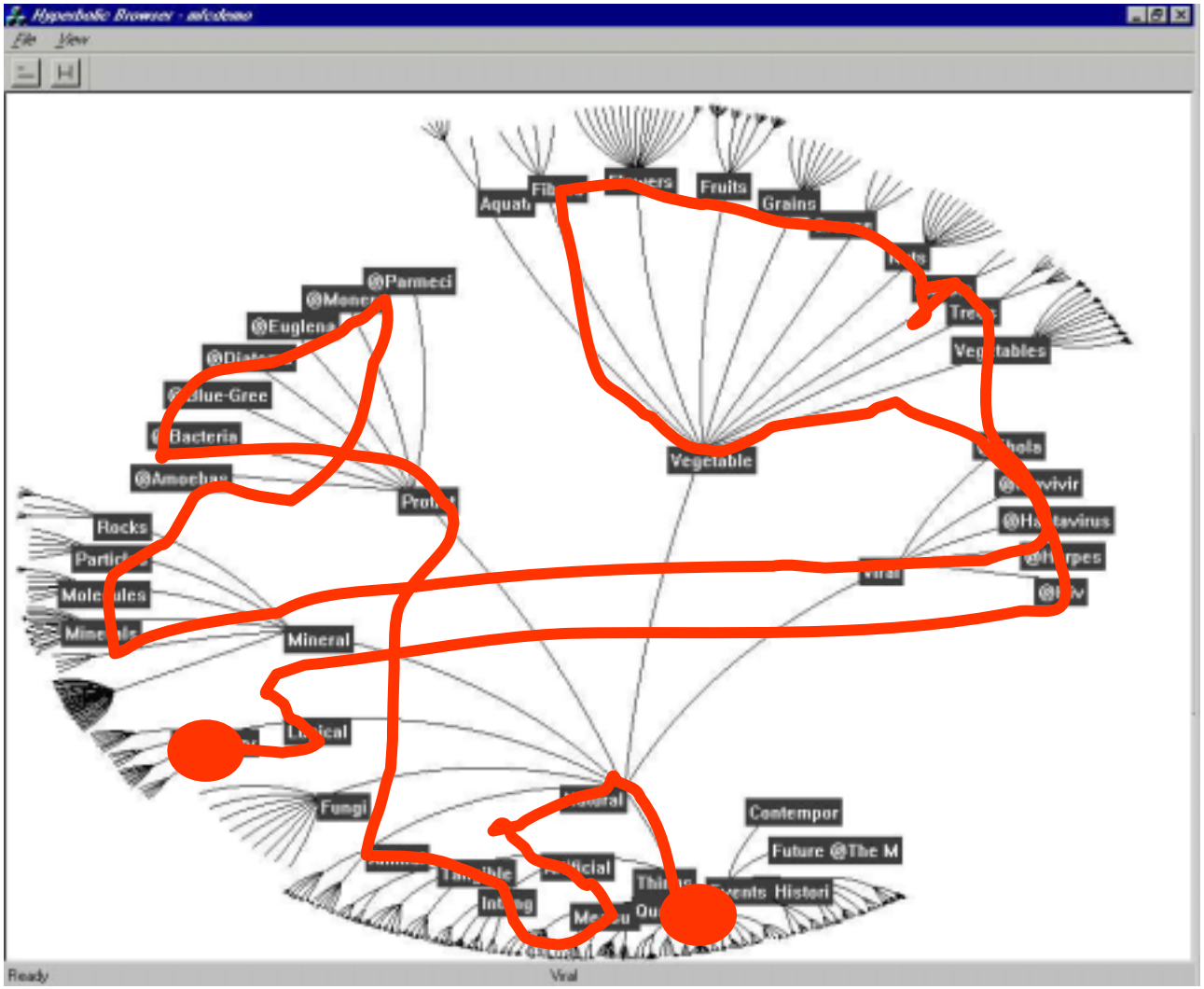
Eye Movements:
Low Information Scent

(Pirolli, Card, & Van Der Wege, 2003, TOCHI)



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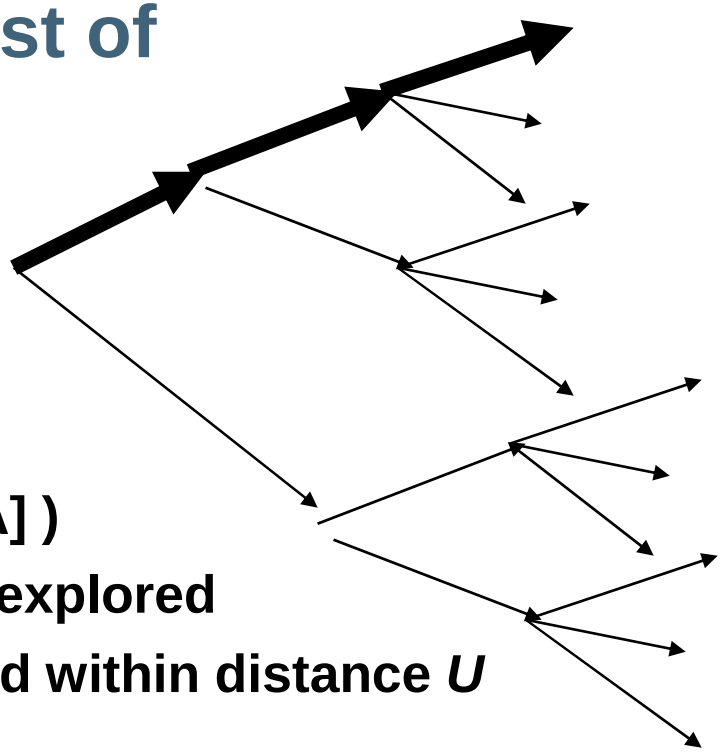
Information Scent and the Cost of Navigation

(based on Hogg & Huberman, 1987)



D = depth of search hierarchy

z = average branching factor

$(1-q)$ = prob. of false alarm (Pr[FA])

$\mu(q, z)$ = qz =average no. branches explored

$A(U, q, z)$ = average no. nodes explored within distance U

$= (1-\mu(q, z)^{U+1})/(1-\mu(q, z))$

$N(D, z, q)$ = average no. nodes examined before desired goal found

$$= \left[\frac{(z-1)q}{2}\right] \sum_{s=1}^{D-1} A(s-1, q, z)$$

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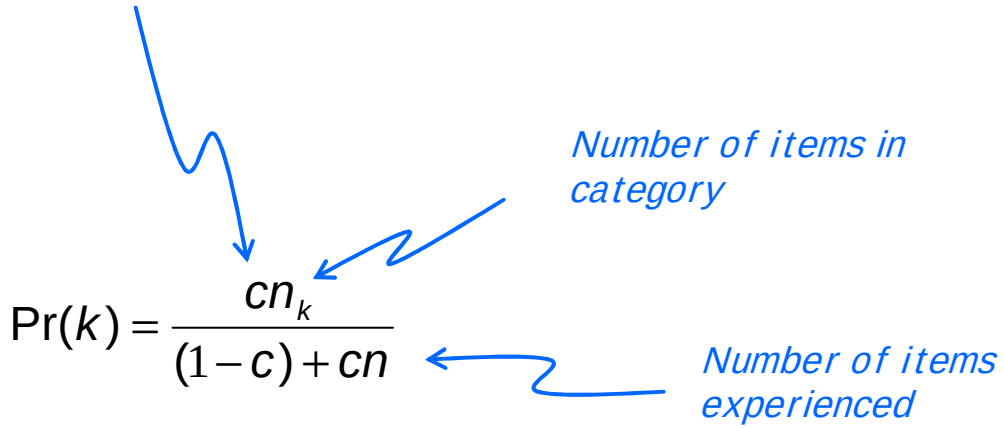
Prototype Formation

- If there are no existing categories, then create a new category (k_{New}) and assign instance P to the category, otherwise
- Determine the prob that the instance comes from a new category, $\Pr(k_{New}|P)$, and compare that to the existing category with the highest probability of including the instance, $\Pr(k_{Max}|P)$
  - Assign P to k_{New} if $\Pr(k_{New}|P) > \Pr(k_{Max}|P)$, else
  - Assign P to k_{Max}

Coupling Parameter (c)



$$\Pr(k) = \frac{cn_k}{(1-c)+cn}$$

$$\Pr(k_{New}) = \frac{1-c}{(1-c)+cn}$$

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Categorization Model

	w_1	w_2	....	w_N	
Item =	[2	0	1	0	0] Series of multinomial trials

	w_1	w_2		w_N	
Category =	[.5	.1	.4	.1	.1] Vector of probabilities

$$\Pr(p_1, p_2, \ldots p_n \mid \alpha_1, \alpha_2, \ldots \alpha_n) = \frac{1}{Z(\alpha_1, \alpha_2, \ldots \alpha)} \prod_i p_i^{\alpha_i - 1}$$ Dirichlet

$$\sum_i p_i = 1$$

Expected value $$\mathbf{E}[p_i] = \frac{\alpha_i}{\alpha_0}$$

$$\alpha_0 = \sum_i \alpha_i$$

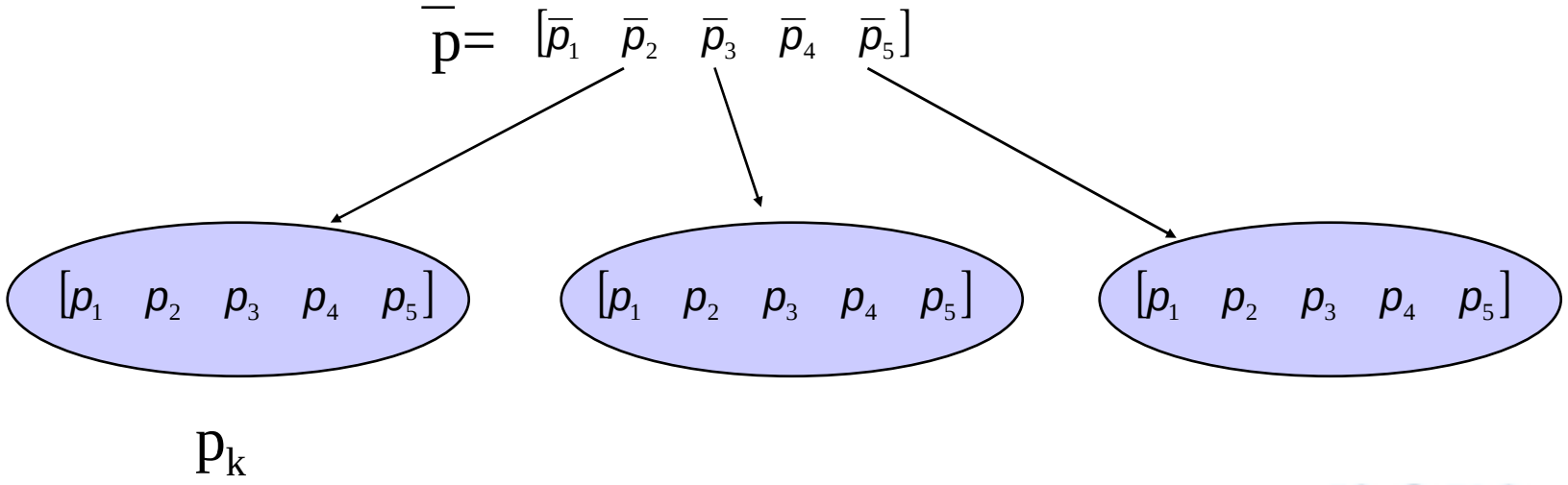
Noninformative prior $$\alpha_i = 1$$

Posterior distribution $$\mathbf{E}[p_i] = \frac{\alpha_i + n_i}{\alpha_0 + \sum_j n_j}$$

Average Divergence from Average Entropy

$$D(p \,||\, q) = \sum_x p(x) \log\left(\frac{p(x)}{q(w)}\right)$$

$$ADA = \frac{\sum_{k=1}^{K} D(\mathbf{p}_k \,||\, \bar{\mathbf{p}})}{K}$$



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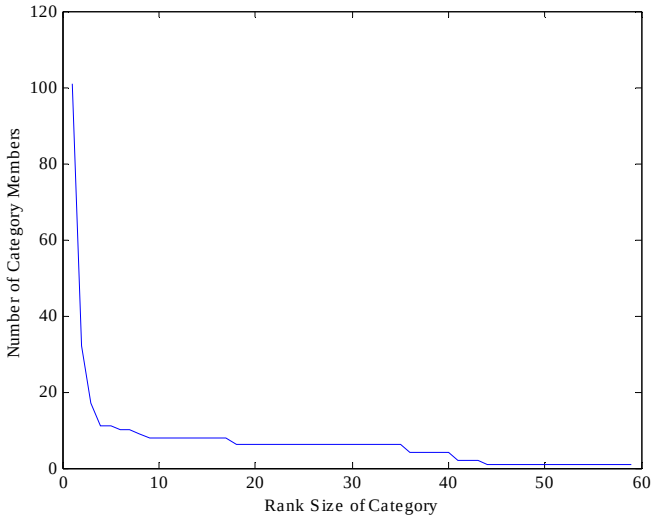
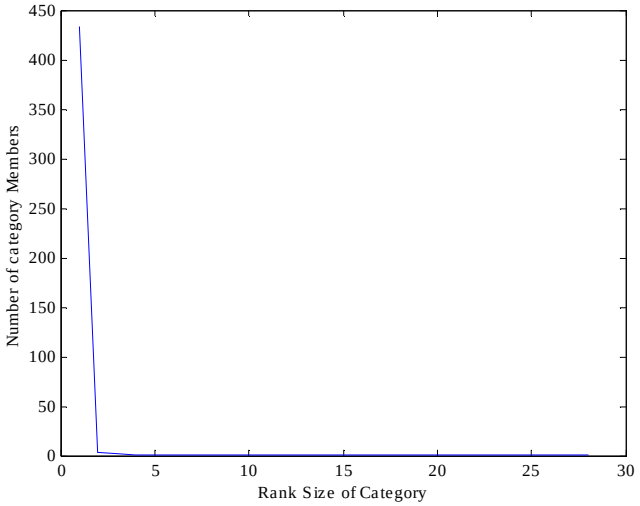
Category structure and coherence

Scatter/Gather User 1



Similarity Search User 1



	ADA
SG	.949
SS	1.292

x 10^{-6} bits

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