Introduction to

Information Retrieval

This lecture

- Improving results
  - For high recall. E.g., searching for *aircraft* doesn't match with *plane;* nor *thermodynamic* with *heat*
- Options for improving results…
  - Global methods
    - Query expansion
      - Thesauri
      - Automatic thesaurus generation
  - Local methods
    - <u>Relevance feedback</u>
    - Pseudo relevance feedback

Relevance Feedback

- Relevance feedback: user feedback on relevance of docs in an initial set of results
- Basic procedure:
  - User issues a (short, simple) query
  - System returns initial set of retrieval results
  - The user marks some results as relevant or non-relevant.
  - The system computes a better representation of the information need based on feedback.
  - System displays revised results
- Relevance feedback can go through one or more iterations.

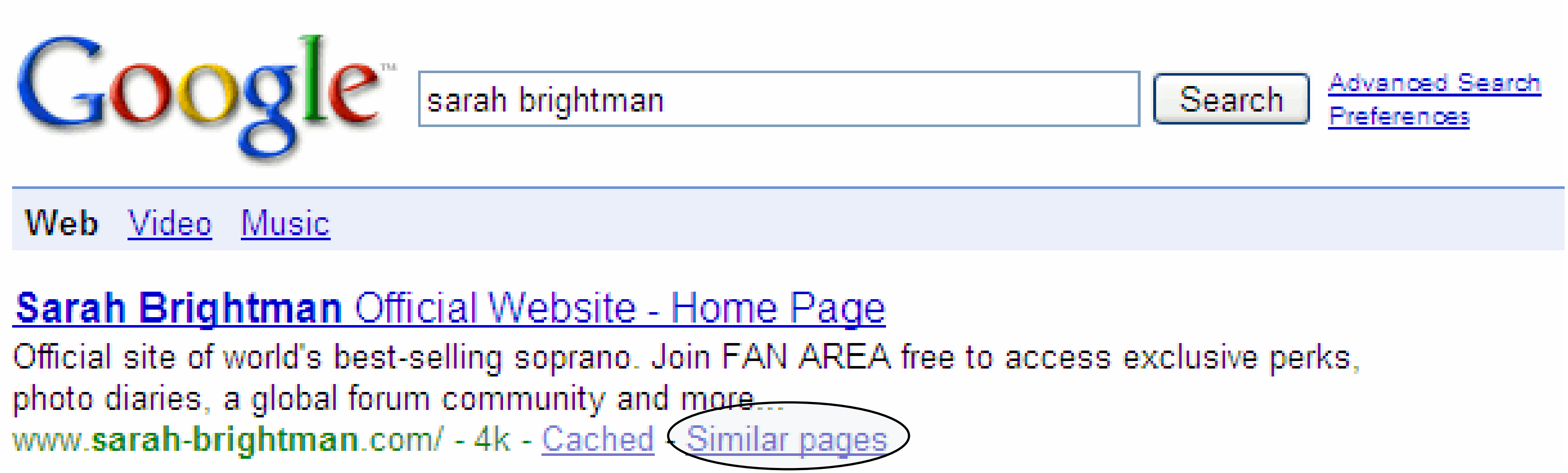
Relevance Feedback

- Idea: it may be difficult to formulate a good query when you don’t know the collection well, so iterate

Relevance feedback

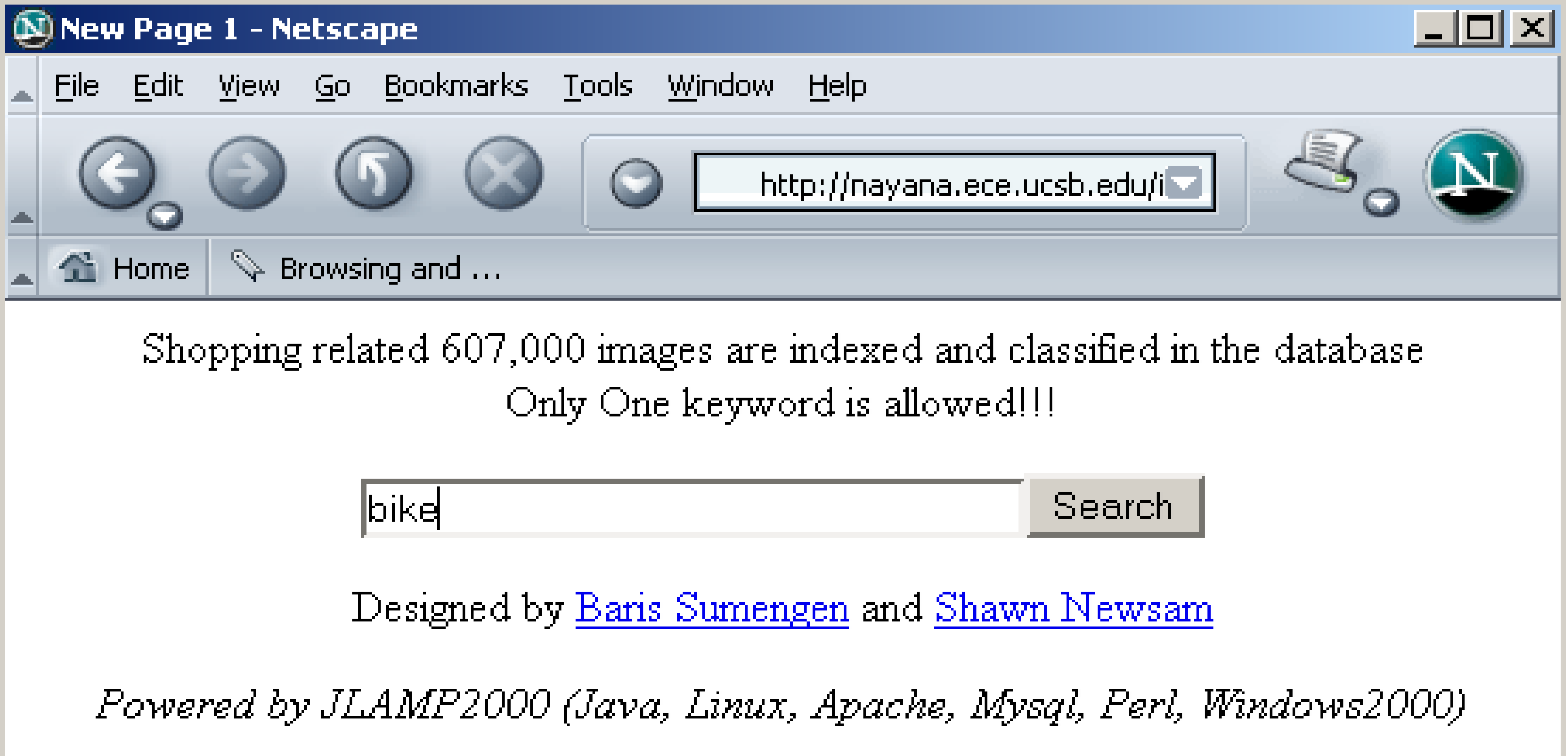
- A*d hoc retrieval:* refer to regular retrieval without relevance feedback.
- Examples of relevance feedback that highlight different aspects.

Similar pages

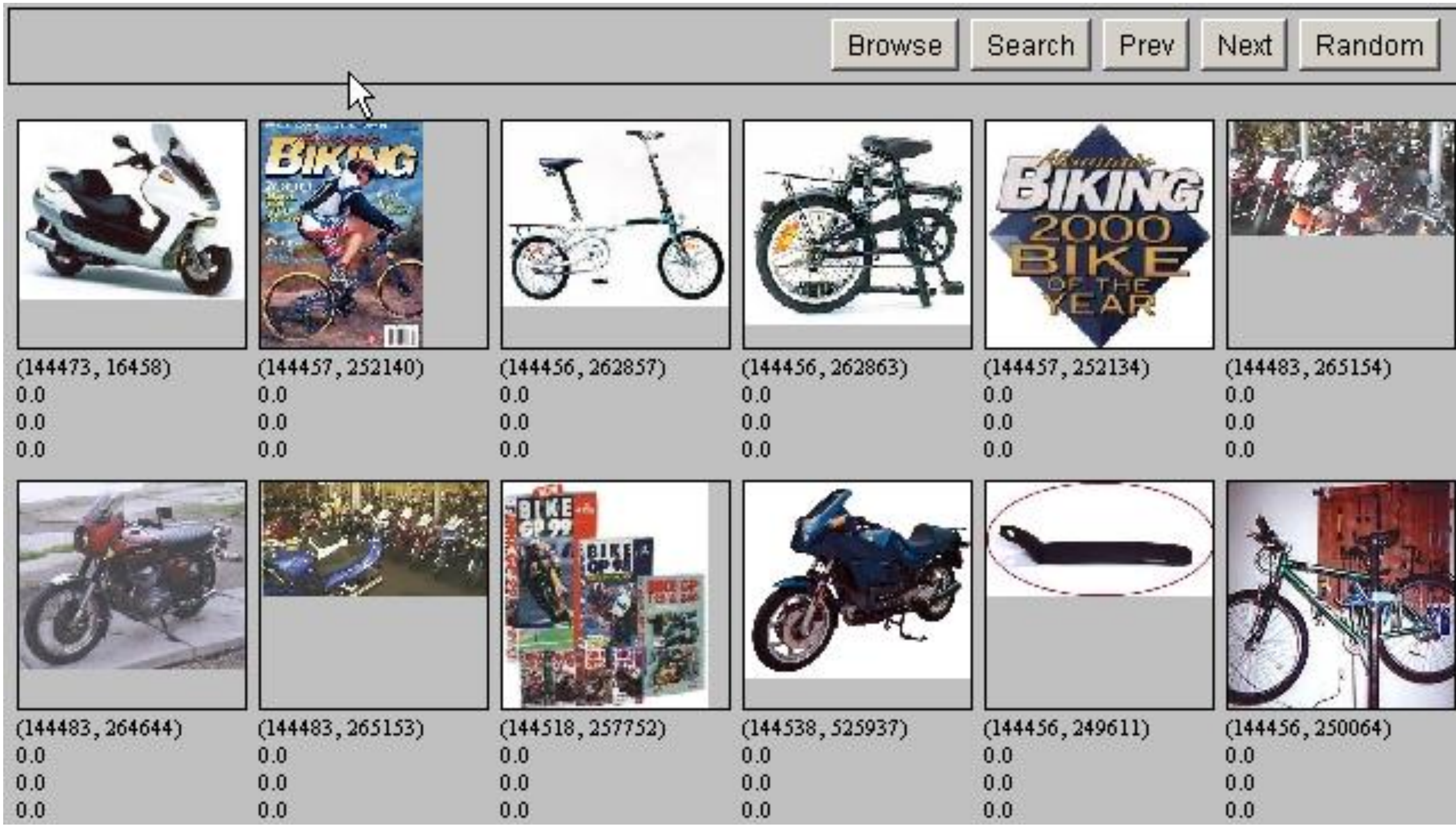


Relevance Feedback: Example

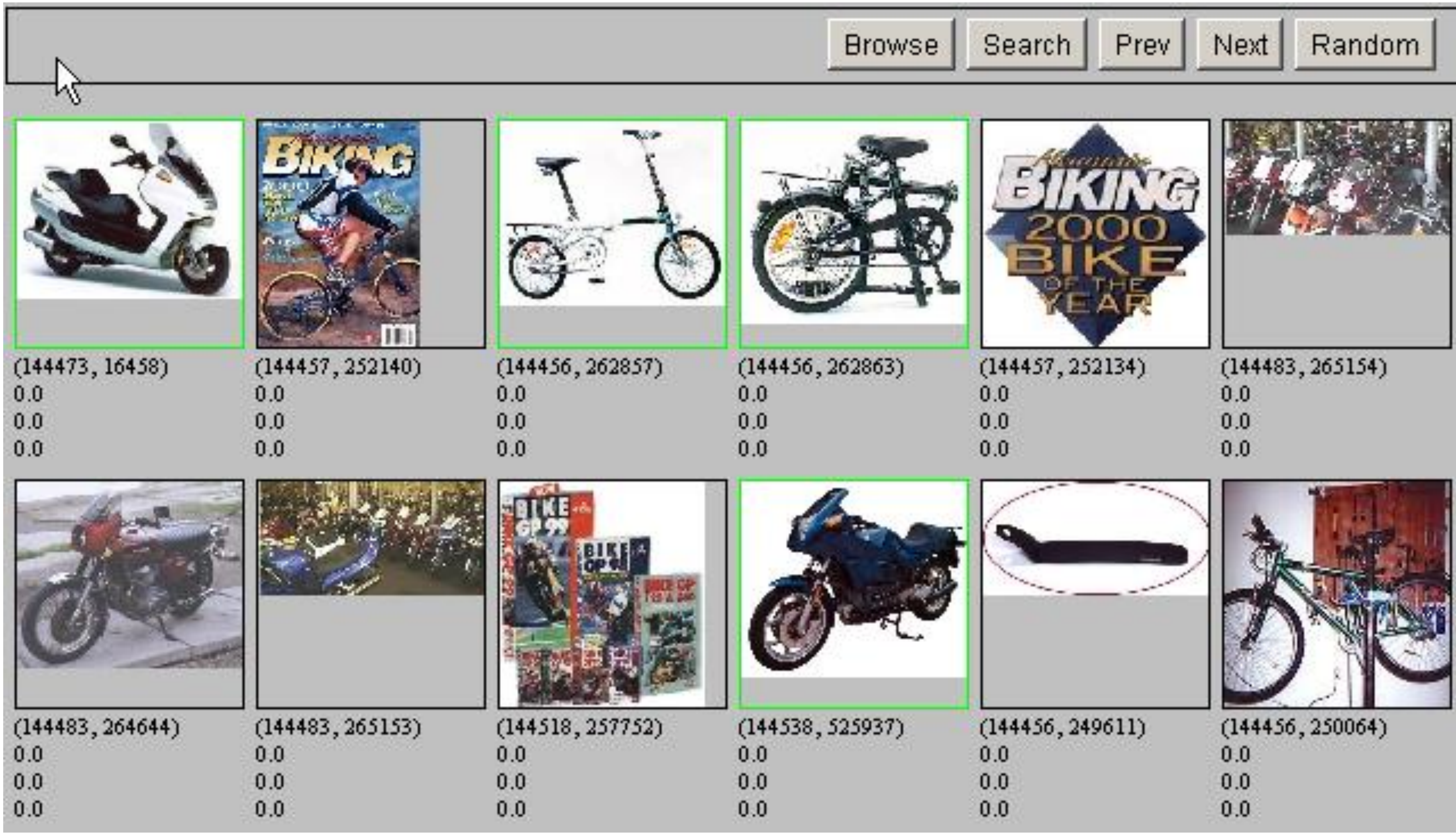
- Image search engine
  http://nayana.ece.ucsb.edu/imsearch/imsearch.html



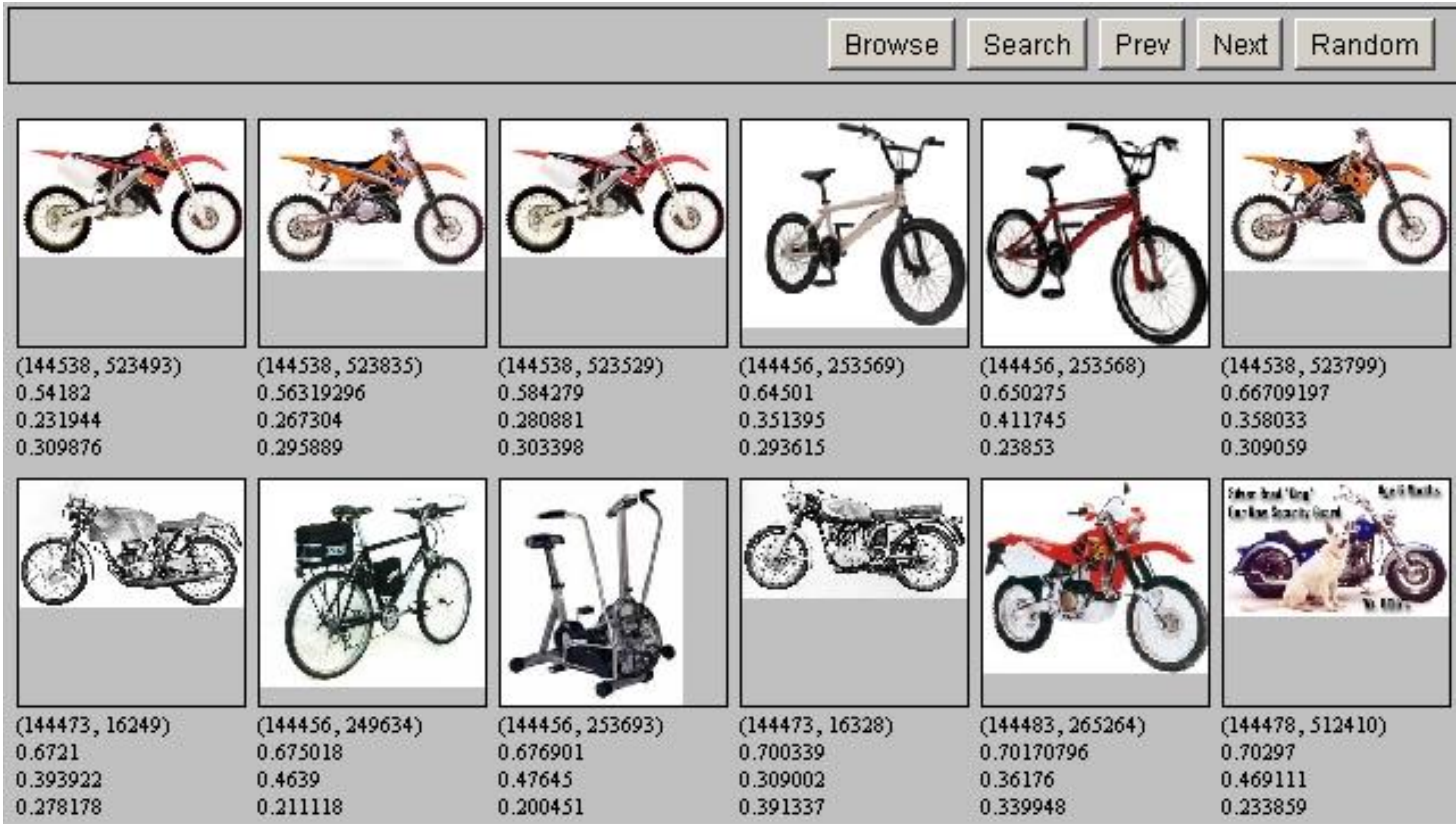
Results for Initial Query



Relevance Feedback



Results after Relevance Feedback



Initial query/results

- Initial query: *New space satellite applications*
  + 1. 0.539, 08/13/91, NASA Hasn't Scrapped Imaging Spectrometer
  + 2. 0.533, 07/09/91, NASA Scratches Environment Gear From Satellite Plan
  3. 0.528, 04/04/90, Science Panel Backs NASA Satellite Plan, But Urges Launches of Smaller Probes
  4. 0.526, 09/09/91, A NASA Satellite Project Accomplishes Incredible Feat: Staying Within Budget
  5. 0.525, 07/24/90, Scientist Who Exposed Global Warming Proposes Satellites for Climate Research
  6. 0.524, 08/22/90, Report Provides Support for the Critics Of Using Big Satellites to Study Climate
  7. 0.516, 04/13/87, Arianespace Receives Satellite Launch Pact From Telesat Canada
  + 8. 0.509, 12/02/87, Telecommunications Tale of Two Companies
- User then marks relevant documents with "+".

Expanded query after relevance feedback

- 2.074 new
- 30.816 satellite
- 5.991 nasa
- 4.196 launch
- 3.516 instrument
- 3.004 bundespost
- 2.790 rocket
- 2.003 broadcast
- 0.836 oil
- 15.106 space
- 5.660 application
- 5.196 eos
- 3.972 aster
- 3.446 arianespace
- 2.806 ss
- 2.053 scientist
- 1.172 earth
- 0.646 measure

Results for expanded query

2 1. 0.513, 07/09/91, NASA Scratches Environment Gear From Satellite Plan

1 2. 0.500, 08/13/91, NASA Hasn't Scrapped Imaging Spectrometer

3. 0.493, 08/07/89, When the Pentagon Launches a Secret Satellite, Space Sleuths Do Some Spy Work of Their Own

4. 0.493, 07/31/89, NASA Uses 'Warm' Superconductors For Fast Circuit

8 5. 0.492, 12/02/87, Telecommunications Tale of Two Companies

6. 0.491, 07/09/91, Soviets May Adapt Parts of SS-20 Missile For Commercial Use

7. 0.490, 07/12/88, Gaping Gap: Pentagon Lags in Race To Match the Soviets In Rocket Launchers

8. 0.490, 06/14/90, Rescue of Satellite By Space Agency To Cost $90 Million

Key concept: Centroid

- The centroid is the center of mass of a set of points
- Recall that we represent documents as points in a high-dimensional space
- Definition: Centroid

$$\vec{\mu}(C) = \frac{1}{|C|} \sum_{d \in C} \vec{d}$$

where C is a set of documents.

Rocchio Algorithm

- The Rocchio algorithm uses the vector space model to pick a relevance feedback query
- Rocchio seeks the query $\vec{q}_{opt}$ that maximizes

$$\vec{q}_{opt} = \arg\max_{\vec{q}} [\cos(\vec{q}, \vec{\mu}(C_r)) - \cos(\vec{q}, \vec{\mu}(C_{nr}))]$$

- Tries to separate docs marked relevant and non-relevant

$$\vec{q}_{opt} = \frac{1}{|C_r|} \sum_{\vec{d}_j \in C_r} \vec{d}_j - \frac{1}{|C_{nr}|} \sum_{\vec{d}_j \notin C_r} \vec{d}_j$$

- Problem: we don't know the truly relevant docs

Rocchio 1971 Algorithm (SMART)

- Used in practice:

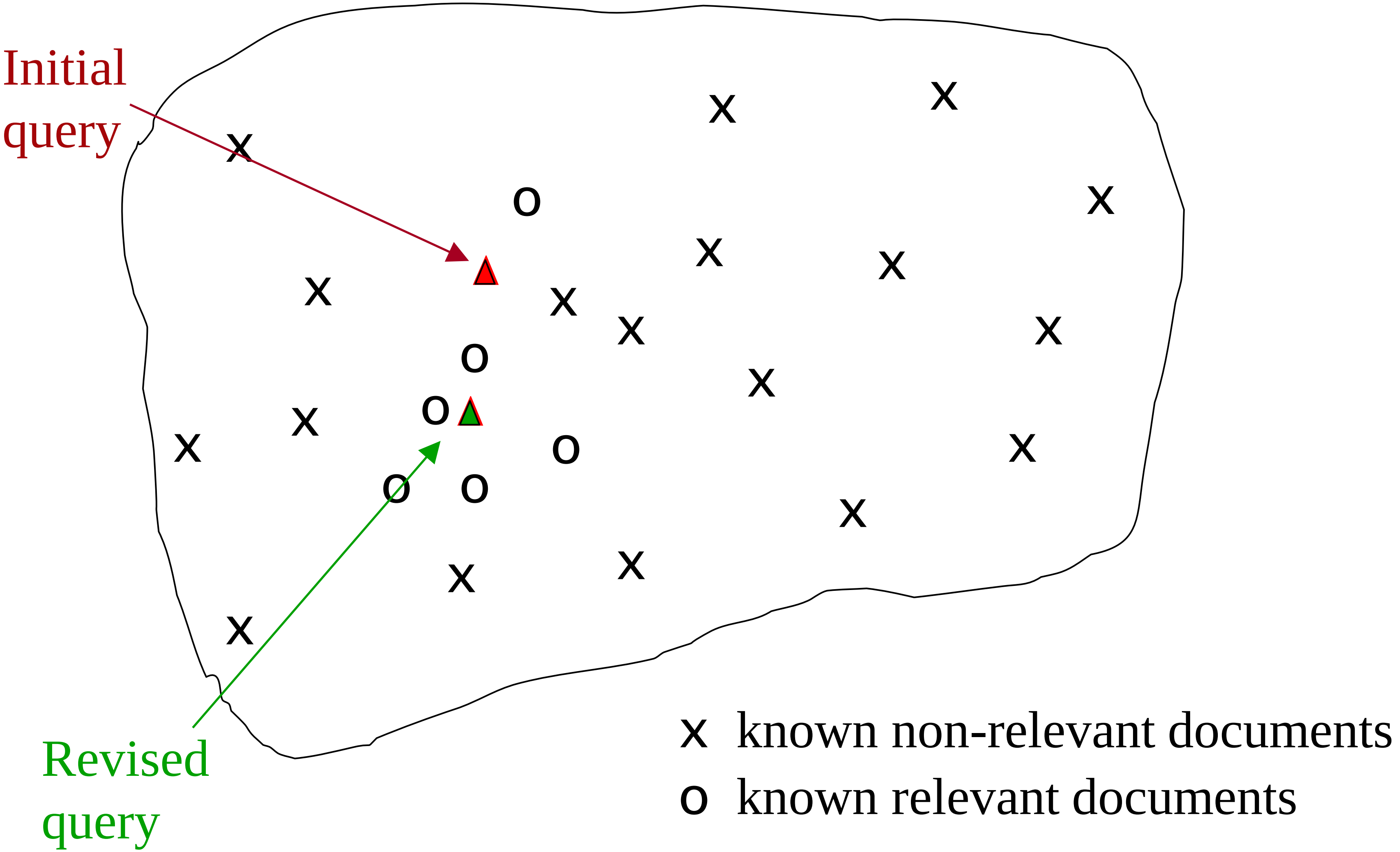
$$\vec{q}_m = \alpha \vec{q}_0 + \beta \frac{1}{|D_r|} \sum_{\vec{d}_j \in D_r} \vec{d}_j - \gamma \frac{1}{|D_{nr}|} \sum_{\vec{d}_j \in D_{nr}} \vec{d}_j$$

- D_r = set of known relevant doc vectors
- D_{nr} = set of known irrelevant doc vectors
  - Different from C_r and C_{nr} !
- q_m = modified query vector; q_0 = original query vector; α,β,γ: weights (hand-chosen or set empirically)
- New query moves toward relevant documents and away from irrelevant documents

Subtleties to note

- Tradeoff α vs. β/γ : If we have a lot of judged documents, we want a higher β/γ.
- Some weights in query vector can go negative
  - Negative term weights are ignored (set to 0)

Relevance feedback on initial query

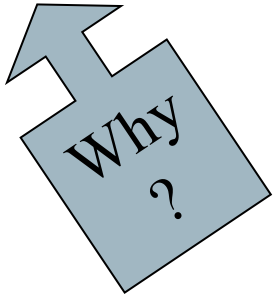


Relevance Feedback in vector spaces

- We can modify the query based on relevance feedback and apply standard vector space model.
- Use only the docs that were marked.
- Relevance feedback can improve recall and precision
- Relevance feedback is most useful for increasing *recall* in situations where recall is important

Positive vs Negative Feedback

- Positive feedback is more valuable than negative feedback (so, set $\gamma < \beta$; e.g. $\gamma = 0.25$, $\beta = 0.75$).
- Many systems only allow positive feedback (γ=0).



Success depends on assumptions

- A1: User has sufficient knowledge for initial query.
- A2: Relevance prototypes are “well-behaved”.
  - Term distribution in relevant documents will be similar
  - Term distribution in non-relevant documents will be different from those in relevant documents
    - Either: All relevant documents are tightly clustered around a single prototype.
    - Or: There are different prototypes, but they have significant vocabulary overlap.
    - Similarities between relevant and irrelevant documents are small

Violation of A1

- User does not have sufficient initial knowledge.
- Examples:
  - Misspellings (Brittany Speers).
  - Cross-language information retrieval (Khana).
  - Mismatch of searcher's vocabulary vs. collection vocabulary
    - Cosmonaut/astronaut

Violation of A2

- There are several relevance prototypes. Multimodal
- Examples:
  - Subsets if docs using diff. vocabulary (Burma/Myanmar)
  - Contradictory government policies
  - Query where answer set is highly disjunctive (Pop stars that worked at Burger King)
- Good editorial content can address problem
  - Report on contradictory government policies

Relevance Feedback: Problems

- Users are often reluctant to provide explicit feedback
- Long queries are inefficient for typical IR engine.
  - Long response times for user.
  - High cost for retrieval system.
  - Partial solution:
    - Only reweight certain prominent terms
      - Perhaps top 20 by term frequency

Why?

Evaluation of relevance feedback strategies

- Use q_0 and compute precision and recall graph
- Use q_m and compute precision recall graph
  - Assess on all documents in the collection
    - Spectacular improvements, but … it's cheating!
    - Partly due to known relevant documents ranked higher
    - Must evaluate with respect to documents not seen by user
  - Use documents in residual collection (set of documents minus those assessed relevant)
    - Measures usually then lower than for original query
    - But a more realistic evaluation
    - Relative performance can be validly compared
- Empirically, one round of relevance feedback is often very useful. Two rounds is sometimes marginally useful.

Evaluation of relevance feedback

- Second method – assess only the docs *not* rated by the user in the first round
  - Could make relevance feedback look worse than it really is
  - Can still assess relative performance of algorithms
- Most satisfactory – use two collections each with their own relevance assessments
  - q_0 and user feedback from first collection
  - q_m run on second collection and measured

Relevance Feedback on the Web

- Some search engines offer a similar/related pages feature (this is a trivial form of relevance feedback)
  - Google (link-based)
  - Altavista
  - Stanford WebBase
- But some don't because it's hard to explain to average user:
  - Alltheweb
  - bing
  - Yahoo

$\alpha/\beta/\gamma$??

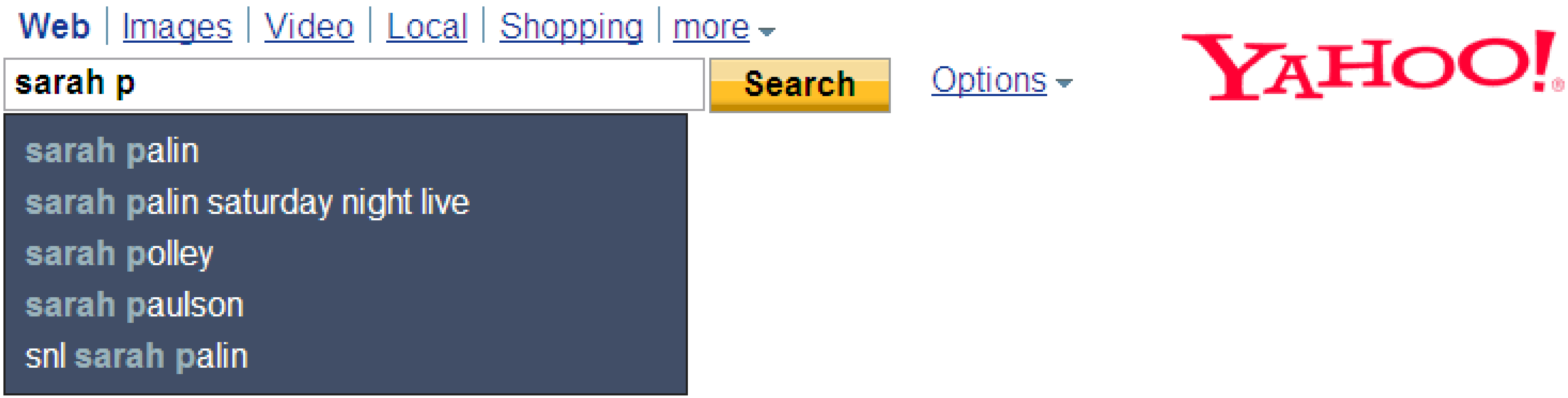
Pseudo relevance feedback

- Pseudo-relevance feedback automates the “manual” part of true relevance feedback.
- Pseudo-relevance algorithm:
  - Retrieve a ranked list of hits for the user’s query
  - Assume that the top k documents are relevant.
  - Do relevance feedback (e.g., Rocchio)
- Works very well on average
- But can go horribly wrong for some queries.
- Several iterations can cause query drift.
- Why?

Query Expansion

- In relevance feedback, users give additional input (relevant/non-relevant) on documents, which is used to reweight terms in the documents
- In query expansion, users give additional input (good/bad search term) on words or phrases

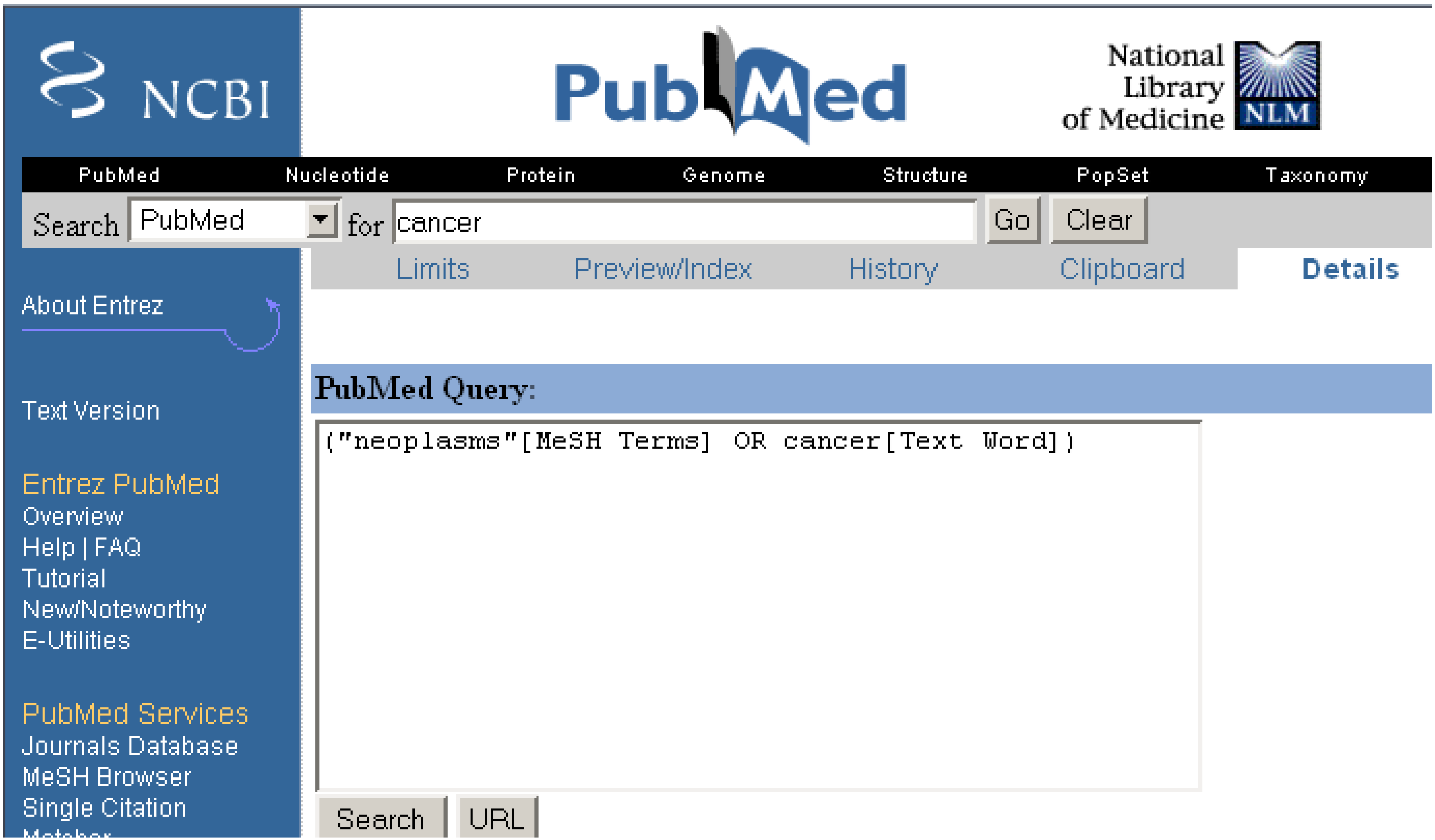
Query assist



How do we augment the user query?

- Manual thesaurus
  - E.g. MedLine: physician, syn: doc, doctor, MD, medico
  - Can be query rather than just synonyms
- Global Analysis: (static; of all documents in collection)
  - Automatically derived thesaurus
    - (word co-occurrence statistics)
- Local Analysis: (dynamic)
  - Analysis of documents in result set

Example of manual thesaurus



Thesaurus-based query expansion

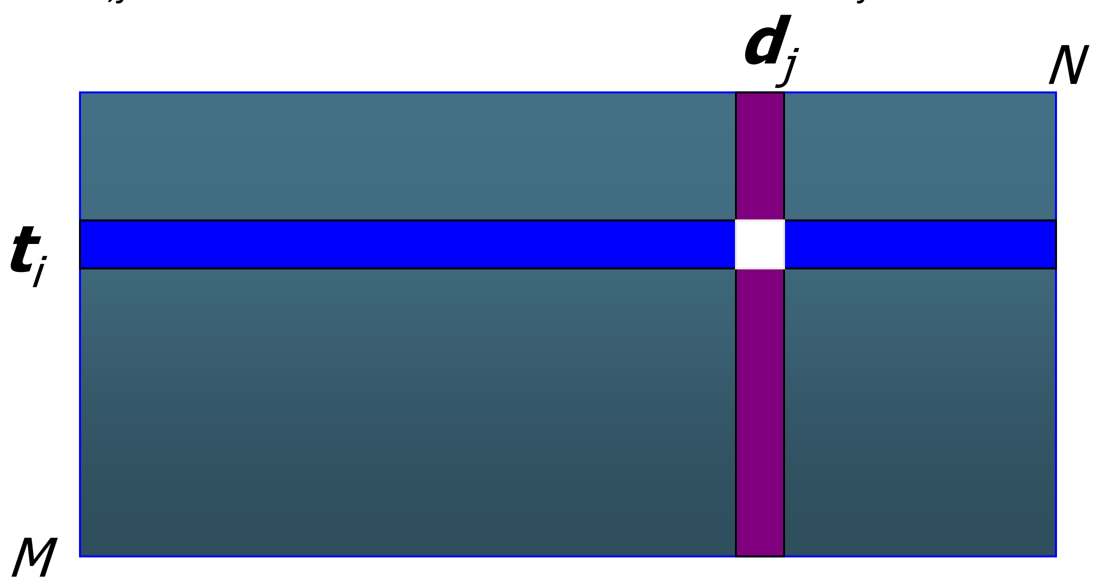
- For each term, *t*, in a query, expand the query with synonyms and related words of *t* from the thesaurus
  - feline → feline cat
- Widely used in many science/engineering fields
- May significantly decrease precision, particularly with ambiguous terms.
  - “interest rate” → “interest rate fascinate evaluate”
- There is a high cost of manually producing a thesaurus
  - And for updating it for scientific changes

Automatic Thesaurus Generation

- Attempt to generate a thesaurus automatically by analyzing the collection of documents
- Fundamental notion: similarity between two words
- Definition 1: Two words are similar if they co-occur with similar words.
- Definition 2: Two words are similar if they occur in a given grammatical relation with the same words.
- You can harvest, peel, eat, prepare, etc. apples and pears, so apples and pears must be similar.
- Co-occurrence based is more robust, grammatical relations are more accurate. Why?

Co-occurrence Thesaurus

- Simplest way to compute one is based on term-term similarities in $C = AA^T$ where A is term-document matrix.
- $w_{i,j}$ = (normalized) weight for (t_i,$\boldsymbol{d}_j$)



- For each t_i, pick terms with high values in C

Automatic Thesaurus Generation Example

word	ten nearest neighbors
absolutely	absurd whatsoever totally exactly nothing
bottomed	dip copper drops topped slide trimmed slig
captivating	shimmer stunningly superbly plucky witty
doghouse	dog porch crawling beside downstairs gazec
Makeup	repellent lotion glossy sunscreen Skin gel p
mediating	reconciliation negotiate cease conciliation p
keeping	hoping bring wiping could some would othe
lithographs	drawings Picasso Dali sculptures Gauguin
pathogens	toxins bacteria organisms bacterial parasite
senses	grasp psyche truly clumsy naive innate awl

Automatic Thesaurus Generation Discussion

- Quality of associations is usually a problem.
- Term ambiguity may introduce irrelevant statistically correlated terms.
  - "Apple computer" → "Apple red fruit computer"
- Problems:
  - False positives: Words deemed similar that are not
  - False negatives: Words deemed dissimilar that are similar

Indirect relevance feedback

- On the web, DirectHit (www.directhit.com) introduced a form of indirect relevance feedback.
- DirectHit ranked documents higher that users look at more often.
  - Clicked on links are assumed likely to be relevant
    - Assuming the displayed summaries are good, etc.
- Globally: Not necessarily user or query specific.
  - This is the general area of ***clickstream mining***
- Today – handled as part of machine-learned ranking