Introduction to

Information Retrieval

CS276

Information Retrieval and Web Search

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Lecture 9: Query expansion

Recap of the last lecture

- Evaluating a search engine
  - Benchmarks
  - Precision and recall
- Results summaries

Recap: Unranked retrieval evaluation: Precision and Recall

- **Precision**: fraction of retrieved docs that are relevant = P(relevant|retrieved)
- **Recall**: fraction of relevant docs that are retrieved = P(retrieved|relevant)

	Relevant	Nonrelevant
Retrieved	tp	fp
Not Retrieved	fn	tn

- Precision P = tp/(tp + fp)
- Recall R = tp/(tp + fn)

Recap: A combined measure: *F*

- Combined measure that assesses precision/recall tradeoff is **F measure** (weighted harmonic mean):

$$F = \frac{1}{\alpha\frac{1}{P} + (1-\alpha)\frac{1}{R}} = \frac{(\beta^2+1)PR}{\beta^2 P + R}$$

- People usually use balanced F_1 measure
  - i.e., with $\beta = 1$ or $\alpha = ½$
- Harmonic mean is a conservative average
  - See CJ van Rijsbergen, *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
    - Relevance feedback
    - Pseudo relevance feedback

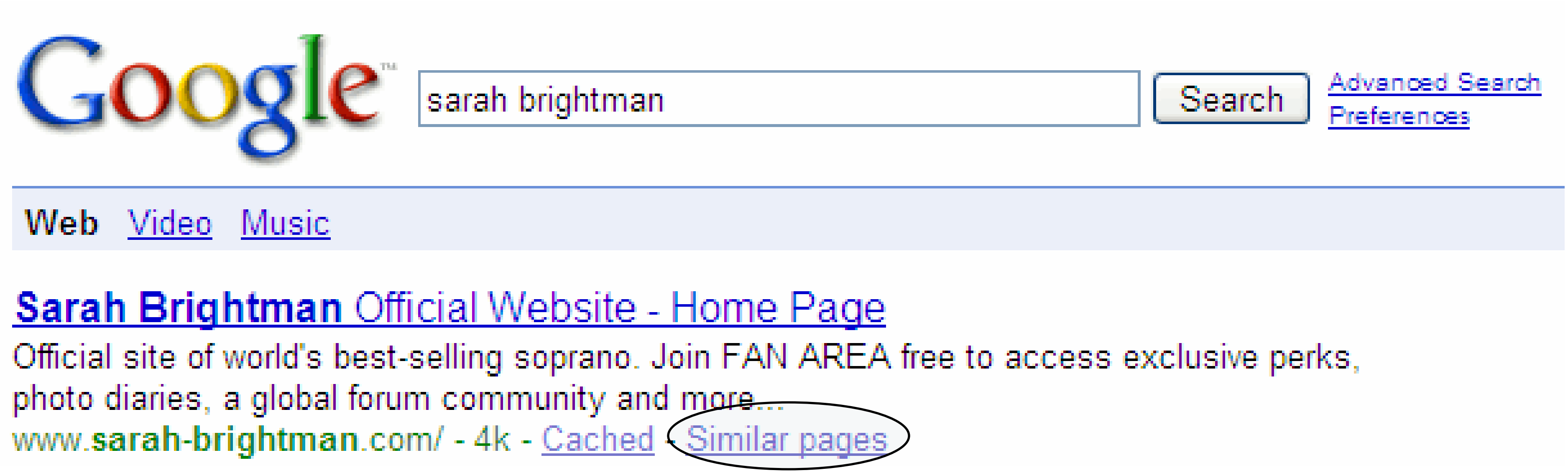
Relevance Feedback

- Relevance feedback: user feedback on relevance of docs in initial set of results
  - User issues a (short, simple) query
  - The user marks some results as relevant or non-relevant.
  - The system computes a better representation of the information need based on feedback.
  - Relevance feedback can go through one or more iterations.
- Idea: it may be difficult to formulate a good query when you don't know the collection well, so iterate

Relevance feedback

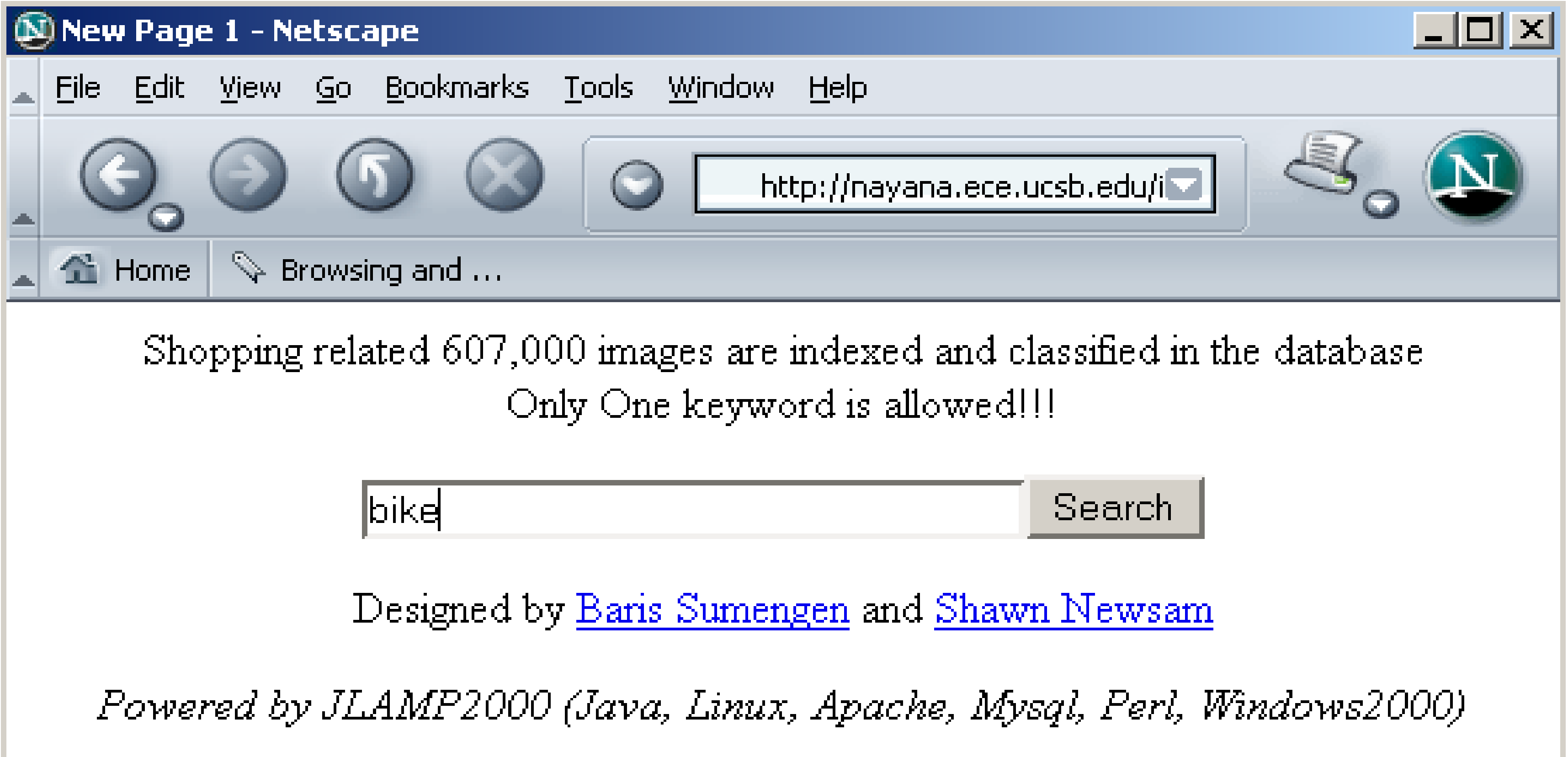
- We will use ***ad hoc retrieval*** **to refer to regular retrieval without relevance feedback.**
- We now look at four examples of relevance feedback that highlight different aspects.

Similar pages

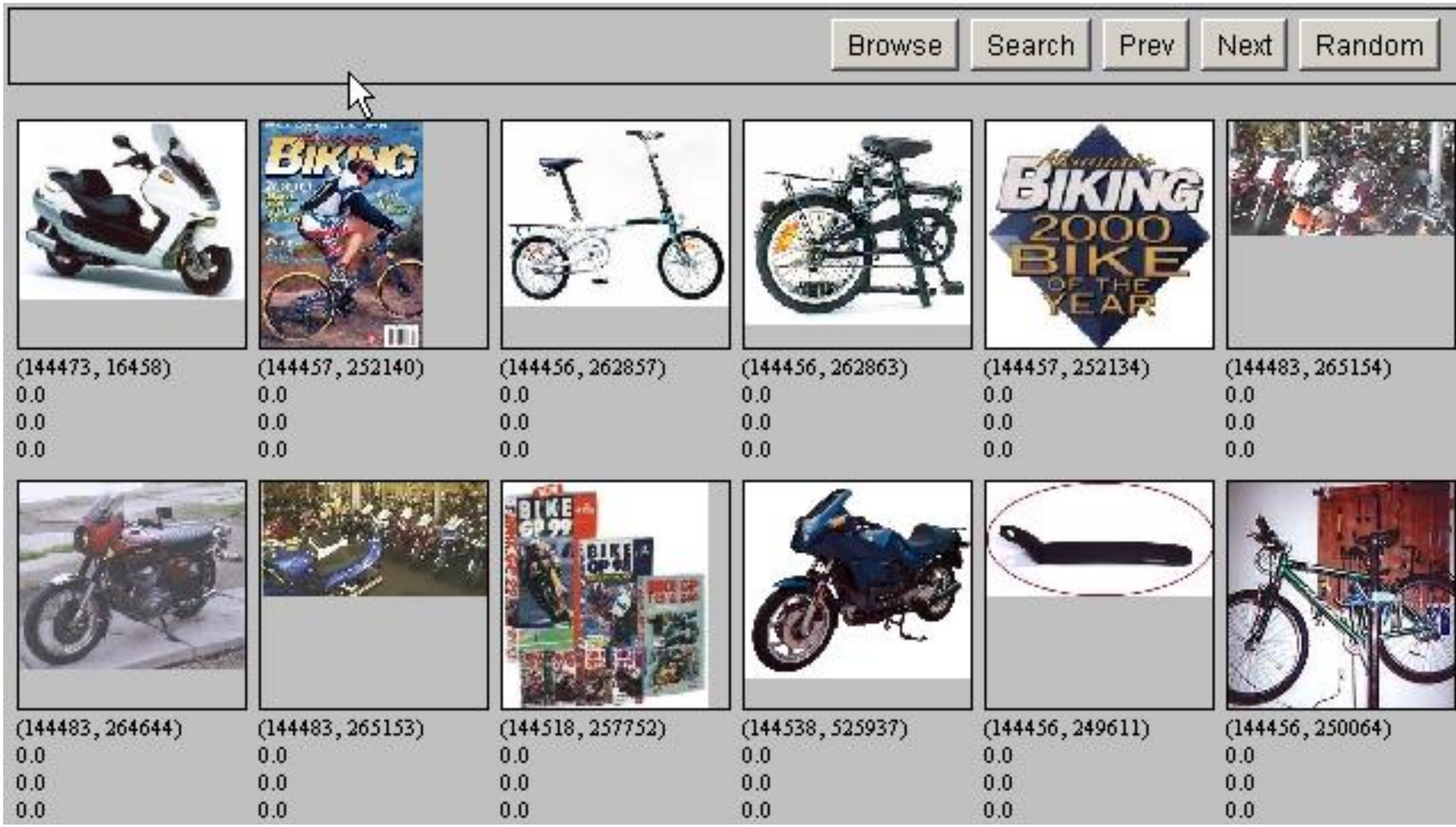


Relevance Feedback: Example

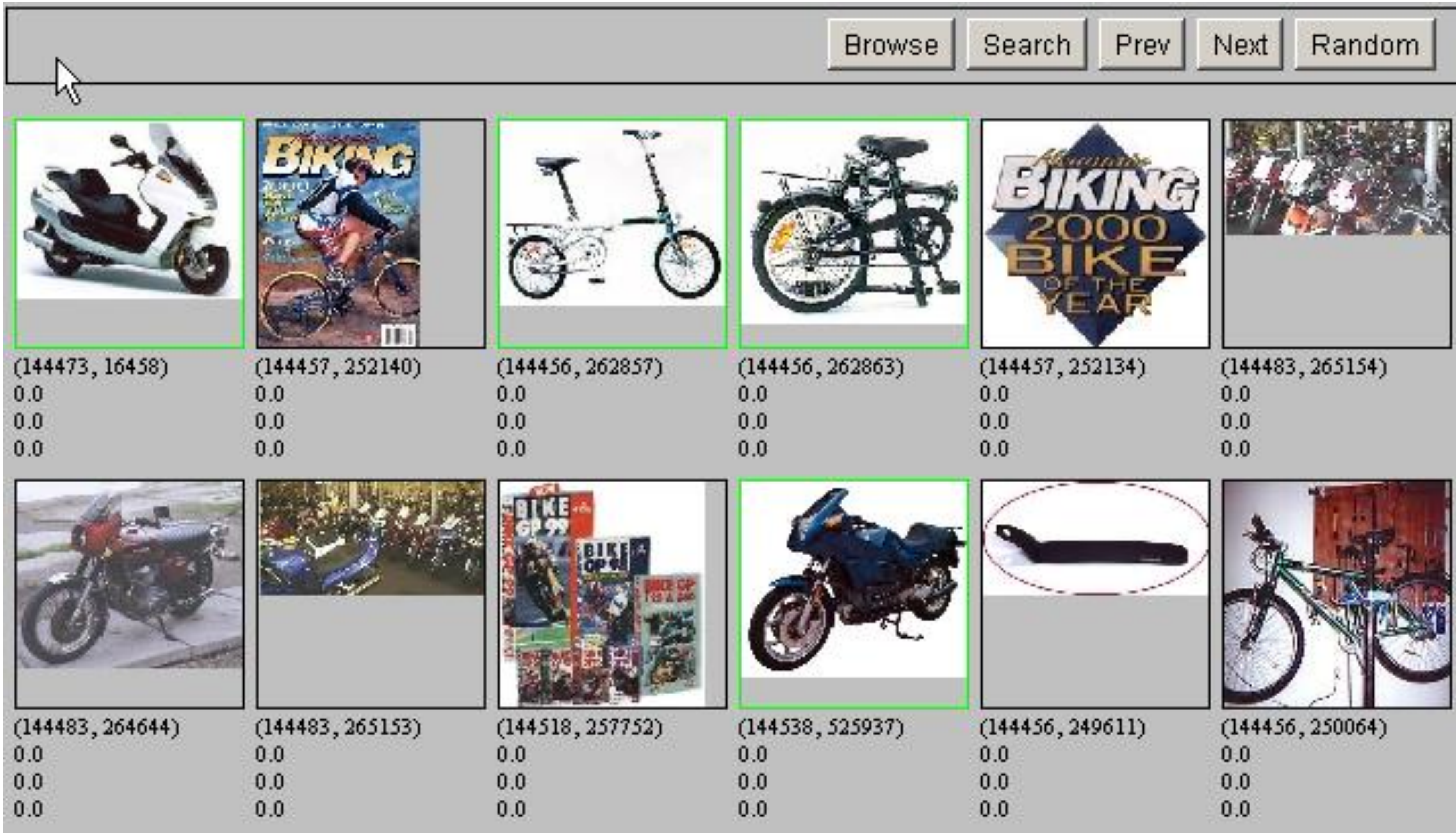
- Image search engine
  http://nayana.ece.ucsb.edu/imsearch/imsearch.html



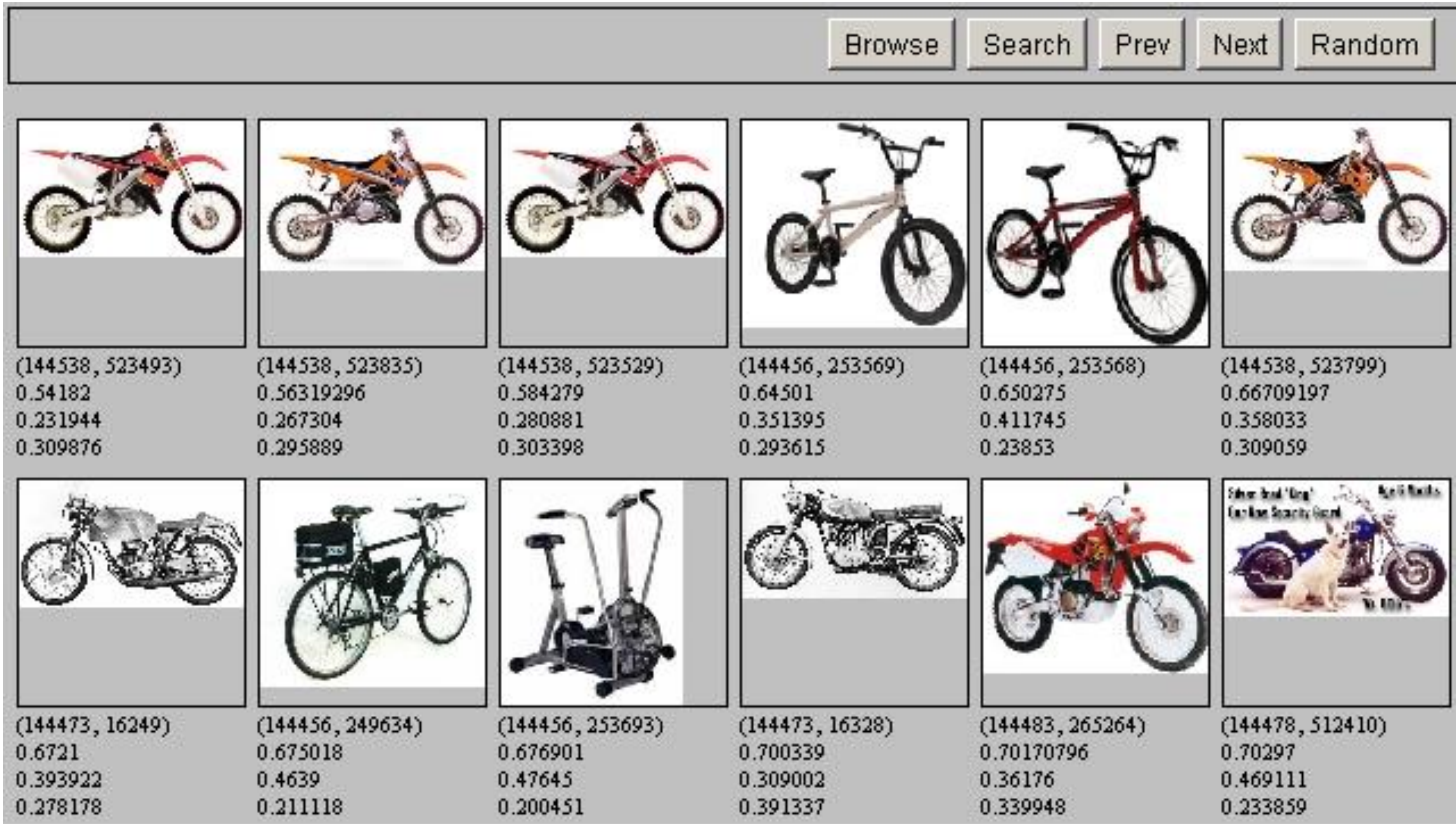
Results for Initial Query



Relevance Feedback

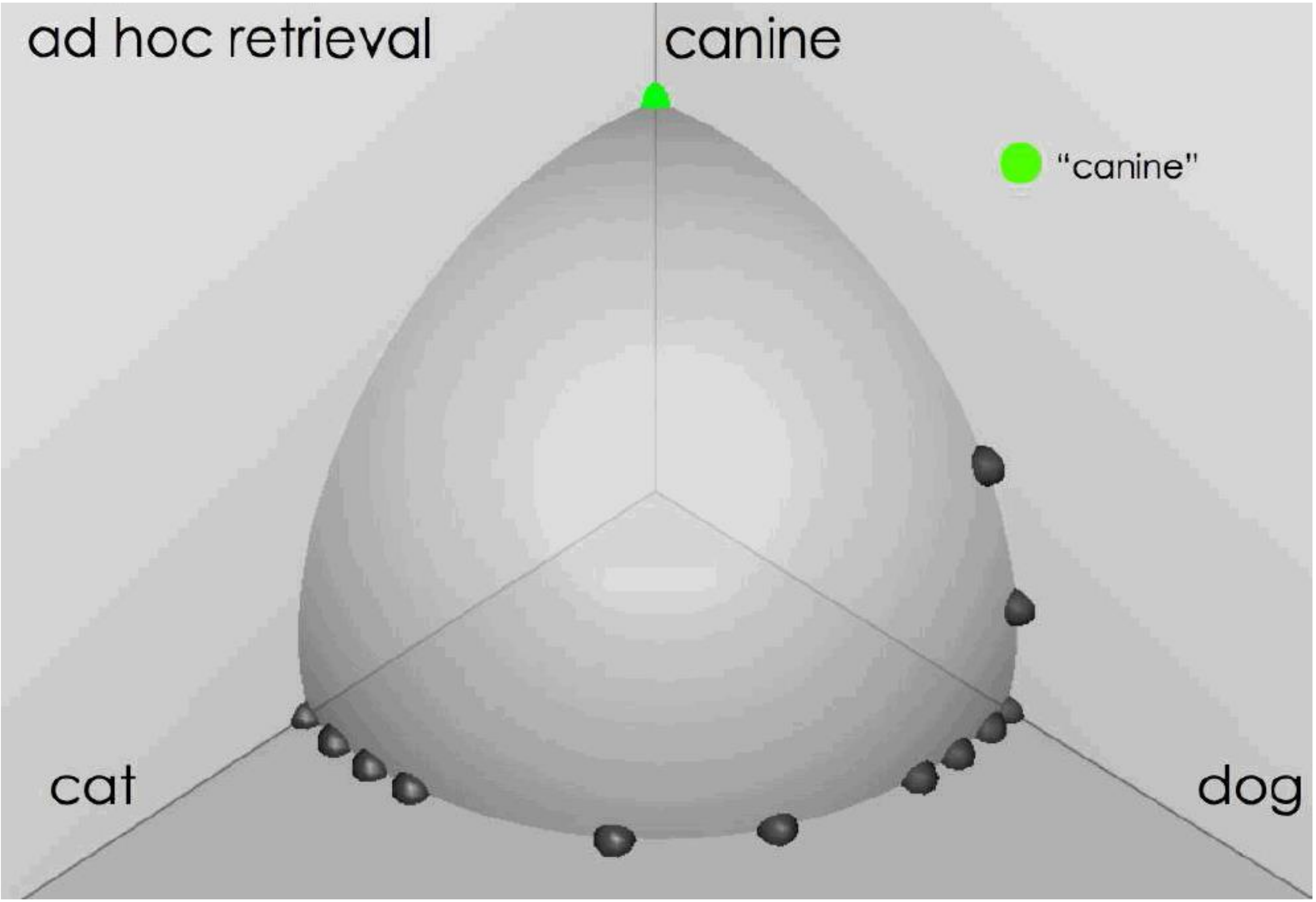


Results after Relevance Feedback



Ad hoc results for query *canine*

source: Fernando Diaz



Ad hoc results for query *canine*

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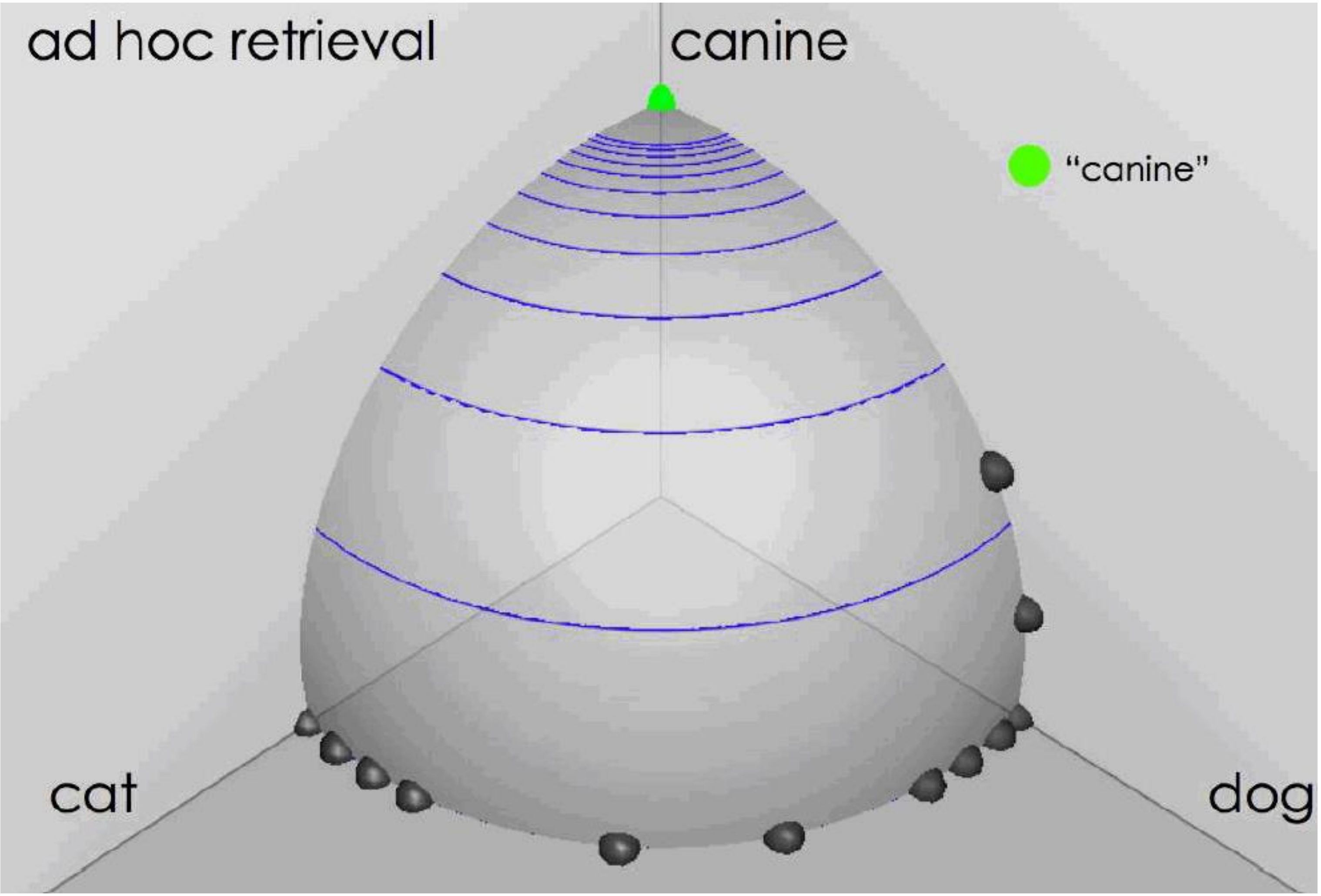
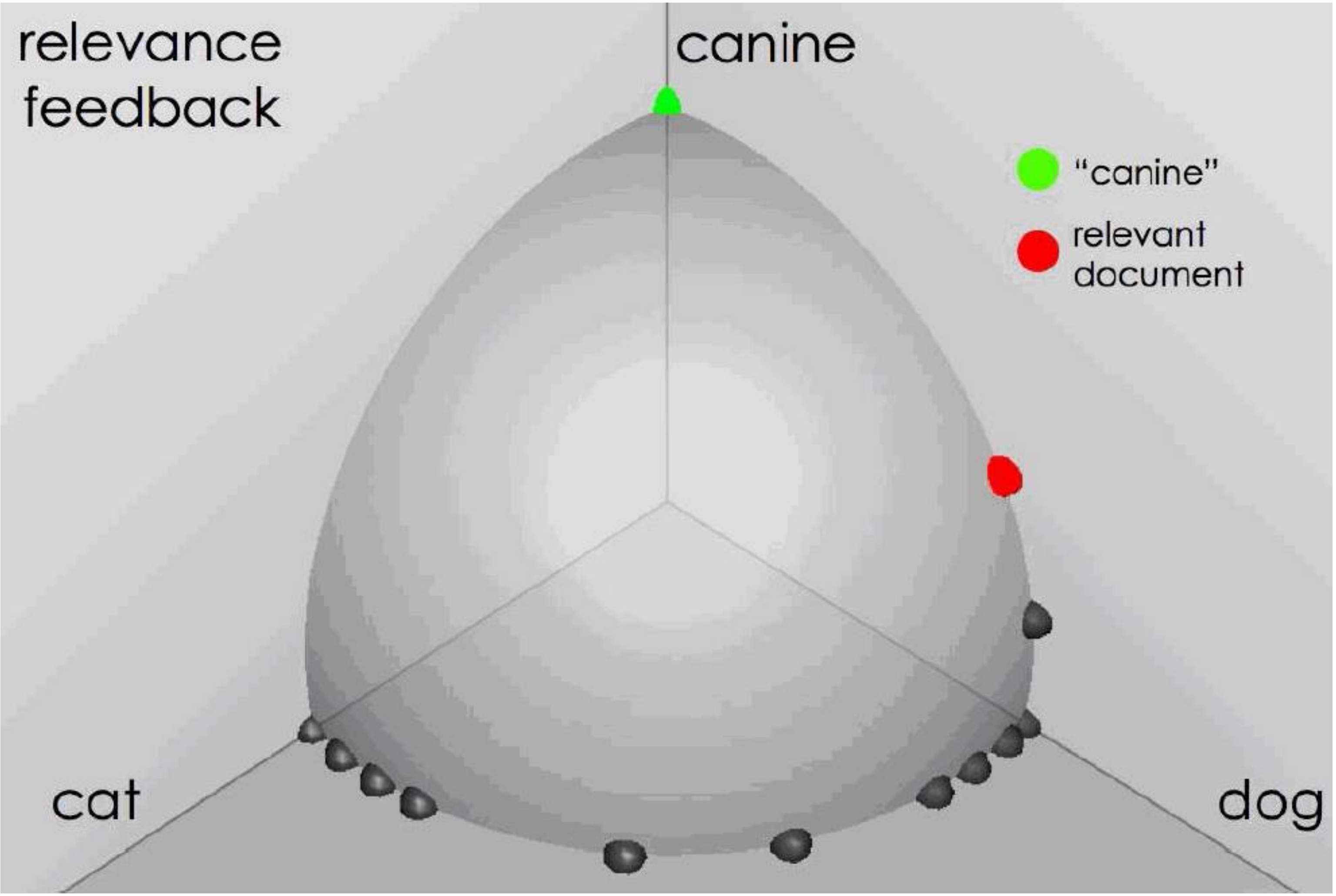


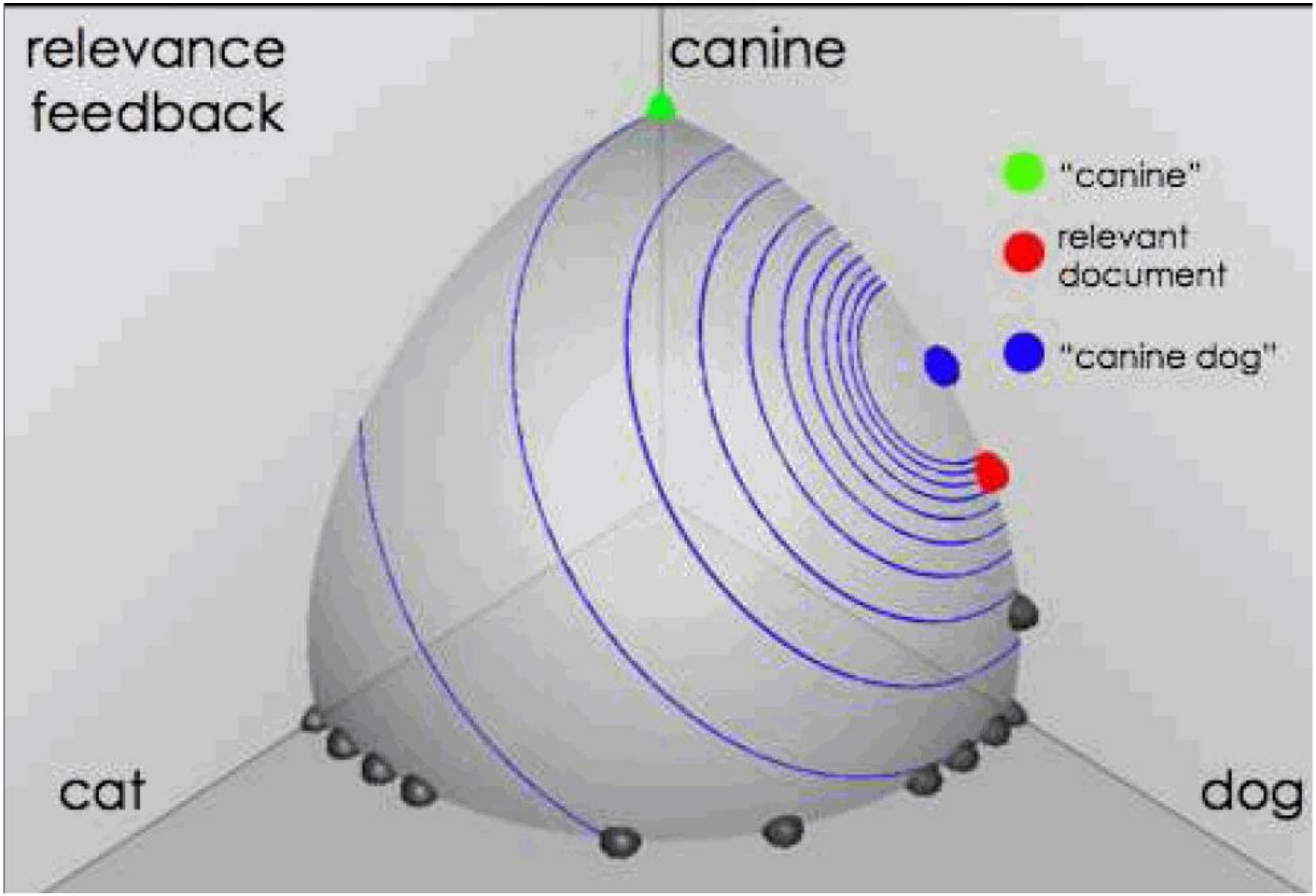
User feedback: Select what is relevant

source: Fernando Diaz



Results after relevance feedback

source: Fernando Diaz



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 15.106 space
- 30.816 satellite 5.660 application
- 5.991 nasa 5.196 eos
- 4.196 launch 3.972 aster
- 3.516 instrument 3.446 arianespace
- 3.004 bundespost 2.806 ss
- 2.790 rocket 2.053 scientist
- 2.003 broadcast 1.172 earth
- 0.836 oil 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 <u>centroid</u> 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

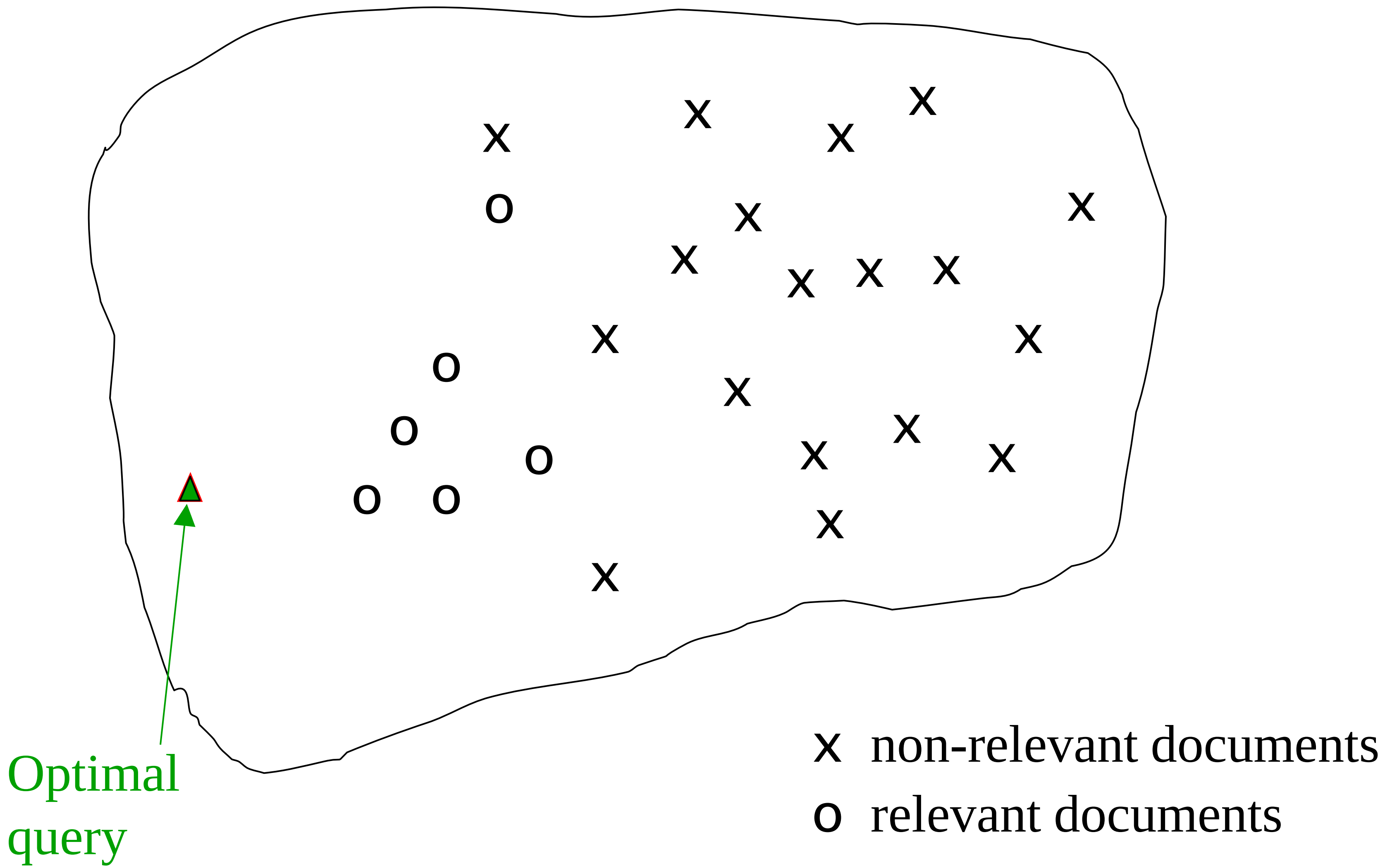
$$\vec{q}_{opt} = \arg\max_{\vec{q}} [\cos(\vec{q}, \vec{\mu}(C_r)) - \cos(\vec{q}, \vec{\mu}(C_{nr}))]$$

- 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

The Theoretically Best Query



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 <u>known</u> relevant doc vectors
- D_{nr} = set of <u>known</u> irrelevant doc vectors
  - Different from C_r and C_{nr}

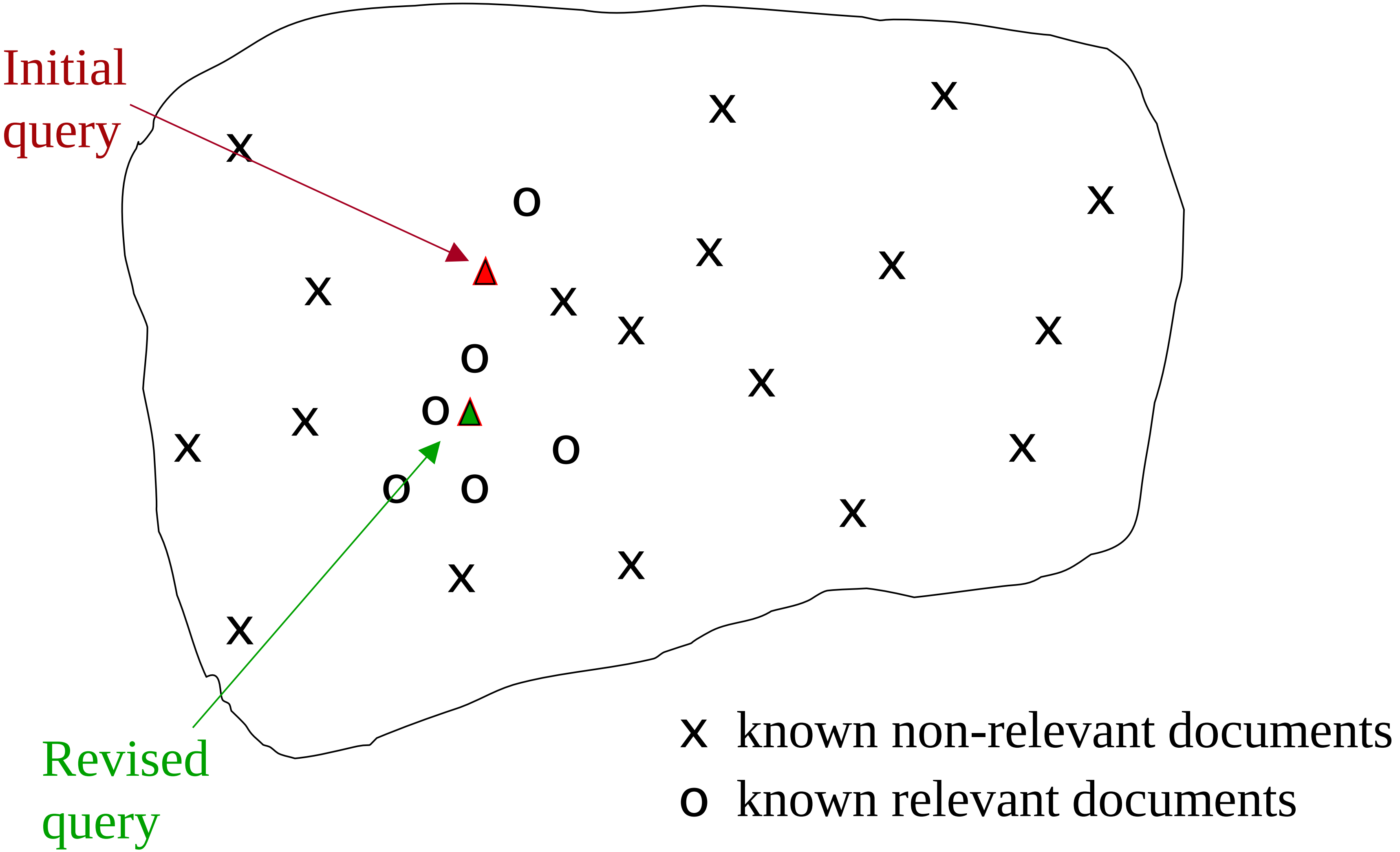
! Q = query, Cr = relevant documents Cnr = not relevant documents

- 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
  - Users can be expected to review results and to take time to iterate

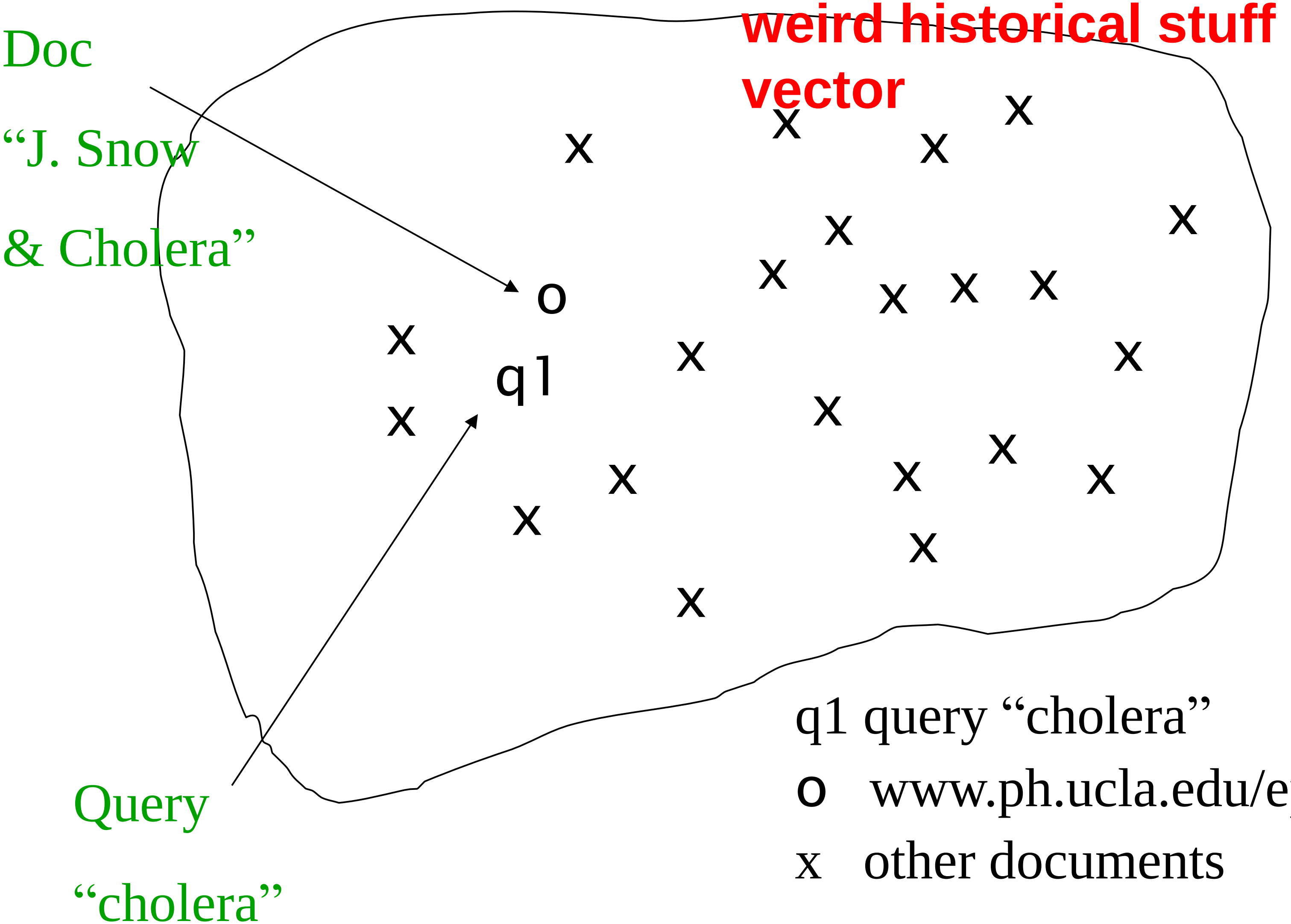
Positive vs Negative Feedback

- 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).

Why?

Aside: Vector Space can be Counterintuitive.

Snow document puts a lot of weird historical stuff into the vector



q1 query “cholera”

o   www.ph.ucla.edu/epi/snow.html

x   other documents

High-dimensional Vector Spaces

- The queries “cholera” and “john snow” are far from each other in vector space.
- How can the document “John Snow and Cholera” be close to both of them?
- Our intuitions for 2- and 3-dimensional space don't work in >10,000 dimensions.
- 3 dimensions: If a document is close to many queries, then some of these queries must be close to each other.
- Doesn't hold for a high-dimensional space.

Relevance Feedback: 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

Violation of A1

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

Violation of A2

- There are several relevance prototypes.
- Examples:
  - Burma/Myanmar
  - Contradictory government policies
  - Pop stars that worked at Burger King
- Often: instances of a general concept
- Good editorial content can address problem
  - Report on contradictory government policies

Relevance Feedback: Problems

- 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?

- Users are often unwilling to provide explicit feedback
- It’s often harder to understand why a particular document was retrieved after applying relevance feedback

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 (<u>set of documents minus those assessed relevant</u>)**
    - Measures usually then lower than for original query
    - But a more realistic evaluation
    - Relative performance can be validly compared
- Empirically, one round of relevant 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 relevant assessments**
  - Q_0 and user feedback from the first collection
  - Q_m run on the second collection and measured

Evaluation: Caveat

- **True evaluation of usefulness must compare to other methods taking the same amount of time.**
- **Alternative to relevance feedback: User revises and resubmits query.**
- Users may prefer revision/resubmission to having to judge relevance of documents.
- There is no clear evidence that relevant feedback is the "best use" of the user's time.

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

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

- **But some don't because it's hard to explain to average user:**
  - Alltheweb
  - bing
  - Yahoo
- Excite initially had true relevance feedback, but abandoned it due to lack of use.

Excite Relevance Feedback

Spink et al. 2000

- Only about 4% of query sessions from a user used relevance feedback option
  - **Expressed as "More like this" link next to each result**
- But about 70% of users only looked at the first page of results and didn't pursue things further
  - So 4% is about 1/8 of people extending search
- Relevance feedback improved results about 2/3 of the time

Pseudo relevance feedback

- **Pseudo-relevance feedback automates the "manual" part of true relevance feedback.**

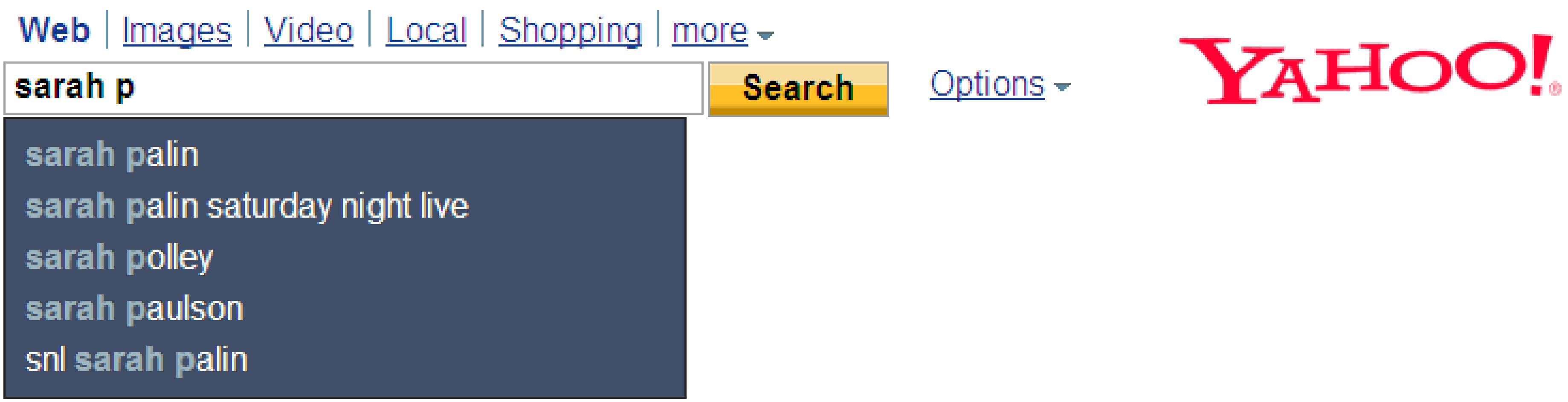
Pseudo relevance feedback

- **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 relevant 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

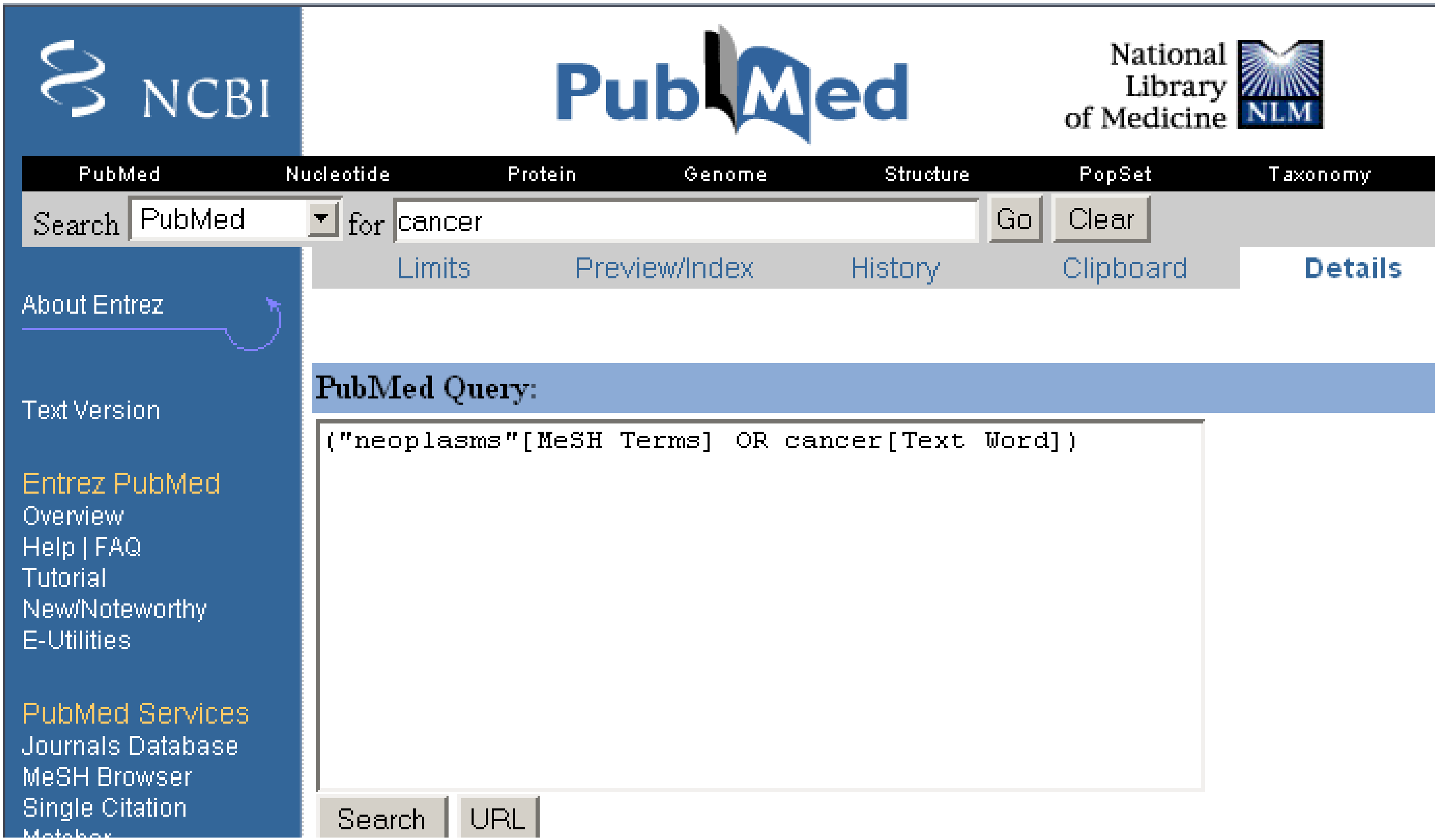


Would you expect such a feature to increase the query volume at a search engine?

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**
    - (co-occurrence statistics)
  - **Refinements based on query log mining**
    - Common on the web
- Local Analysis: (dynamic)
  - **Analysis of documents in result set**

Example of manual thesaurus



Thesaurus-based query expansion

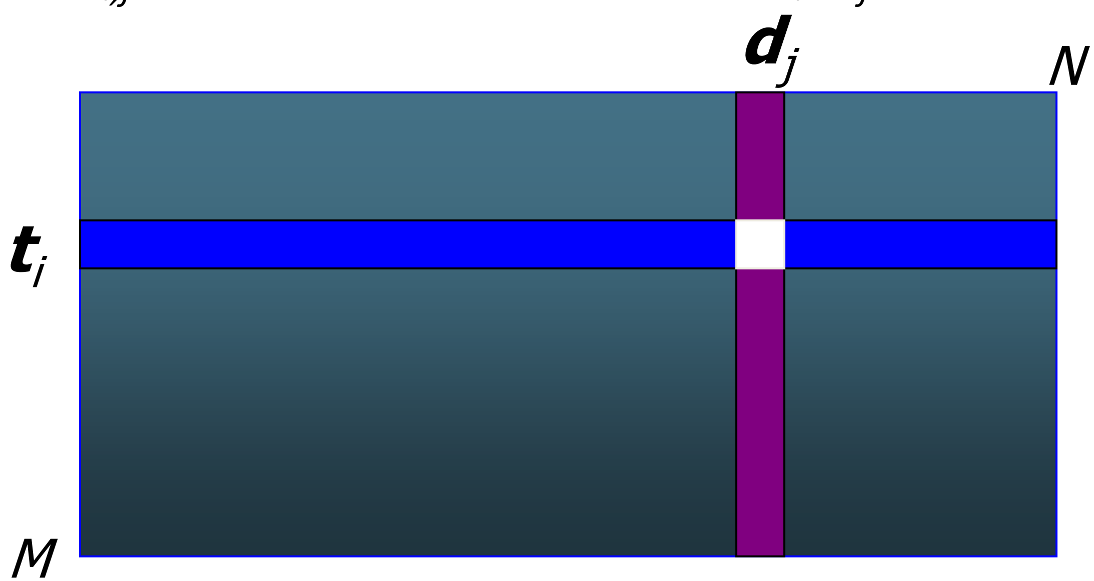
- **For each term, *t*, in a query, expand the query with synonyms and related words of *t* from the thesaurus**
  - feline → feline cat
- **May weight added terms less than original query terms.**
- Generally increases recall
- Widely used in many science/engineering fields
- **May significantly decrease 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, and grammatical relations are more accurate.

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

What does C contain if A is a term-doc incidence (0/1) matrix?

Automatic Thesaurus Generation Example

Word	Nearest neighbors
absolutely	absurd, whatsoever, totally, exactly, nothing
bottomed	dip, copper, drops, topped, slide, trimmed
captivating	shimmer, stunningly, superbly, plucky, witty
doghouse	dog, porch, crawling, beside, downstairs
makeup	repellent, lotion, glossy, sunscreen, skin, gel
mediating	reconciliation, negotiate, case, conciliation
keeping	hoping, bring, wiping, could, some, would
lithographs	drawings, Picasso, Dali, sculptures, Gauguin
pathogens	toxins, bacteria, organisms, bacterial, parasite
senses	grasp, psyche, truly, clumsy, naive, innate

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
- **Since terms are highly correlated anyway, expansion may not retrieve many additional documents.**

Indirect relevance feedback

- On the web, DirectHit introduced a form of indirect relevance feedback.
- DirectHit ranked documents higher, which 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

Resources

IIR Ch 9

MG Ch. 4.7

MIR Ch. 5.2 – 5.4