Information Retrieval and Organisation

Dell Zhang

Birkbeck, University of London

Relevance Feedback and Query Expansion

Motivation

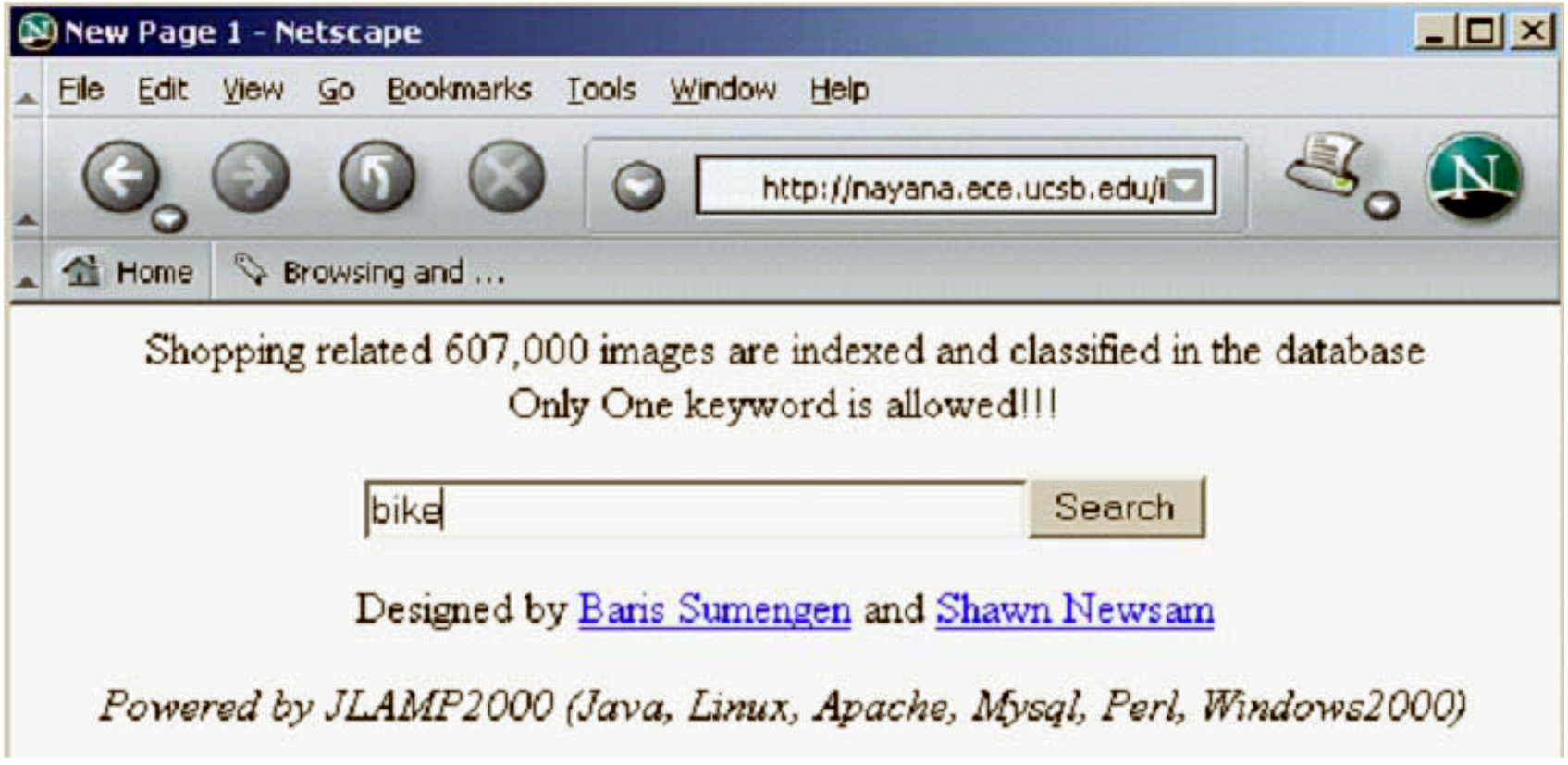
- How to improve the recall of a search (without compromising precision too much)?
  - "aircraft" in query doesn't match with "plane" in document
  - "heat" in query doesn't match with "thermodynamics" in document
- Two general approaches for increasing recall through query reformulation:
  - Local methods (query-dependent): e.g., relevance feedback
  - Global methods (query-independent): e.g., query expansion

Relevance Feedback

- Basic idea:
  - The user issues a (short, simple) query
  - The system returns an initial set of retrieval results
  - The user marks some returned documents as relevant or not relevant
  - The system computes a better representation of the information need based on the user feedback
  - The system displays a revised set of retrieval results
  - This can go through one or more iterations
  - We will use the term *ad hoc retrieval* to refer to regular retrieval without relevance feedback.

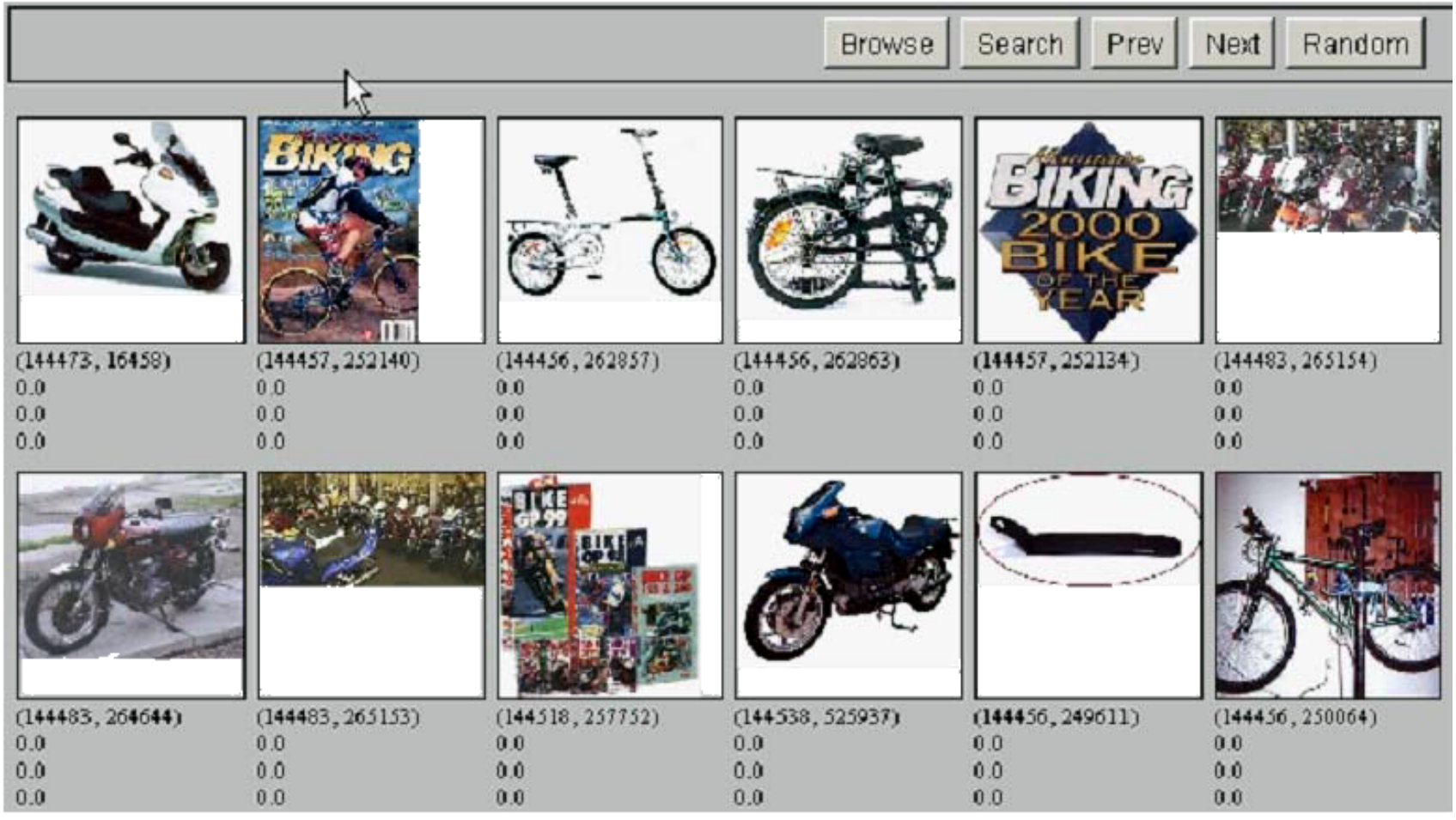
Relevance Feedback

- Example: Content based Image Retrieval (CBIR)



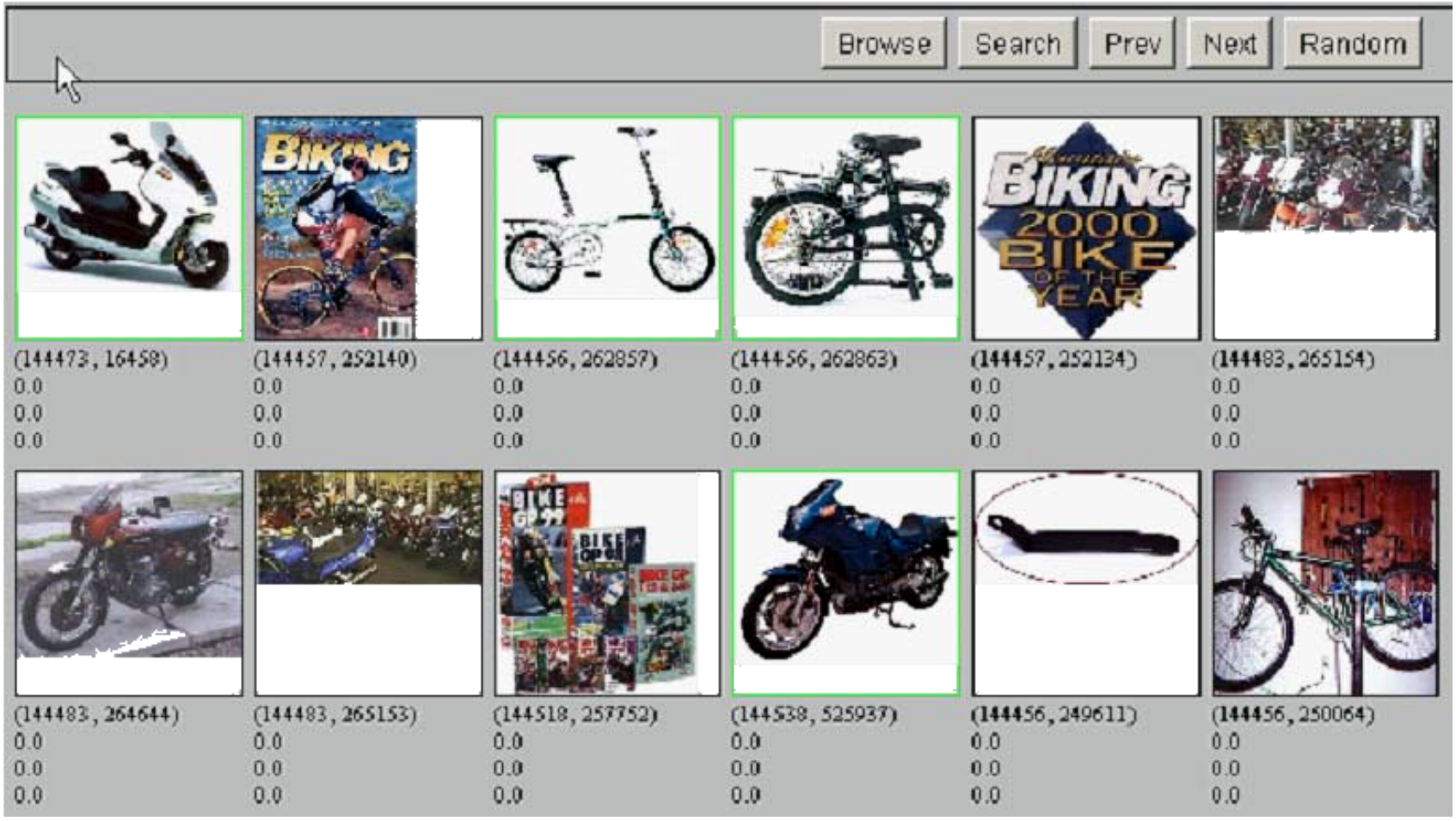
Relevance Feedback

- Results for Initial Query



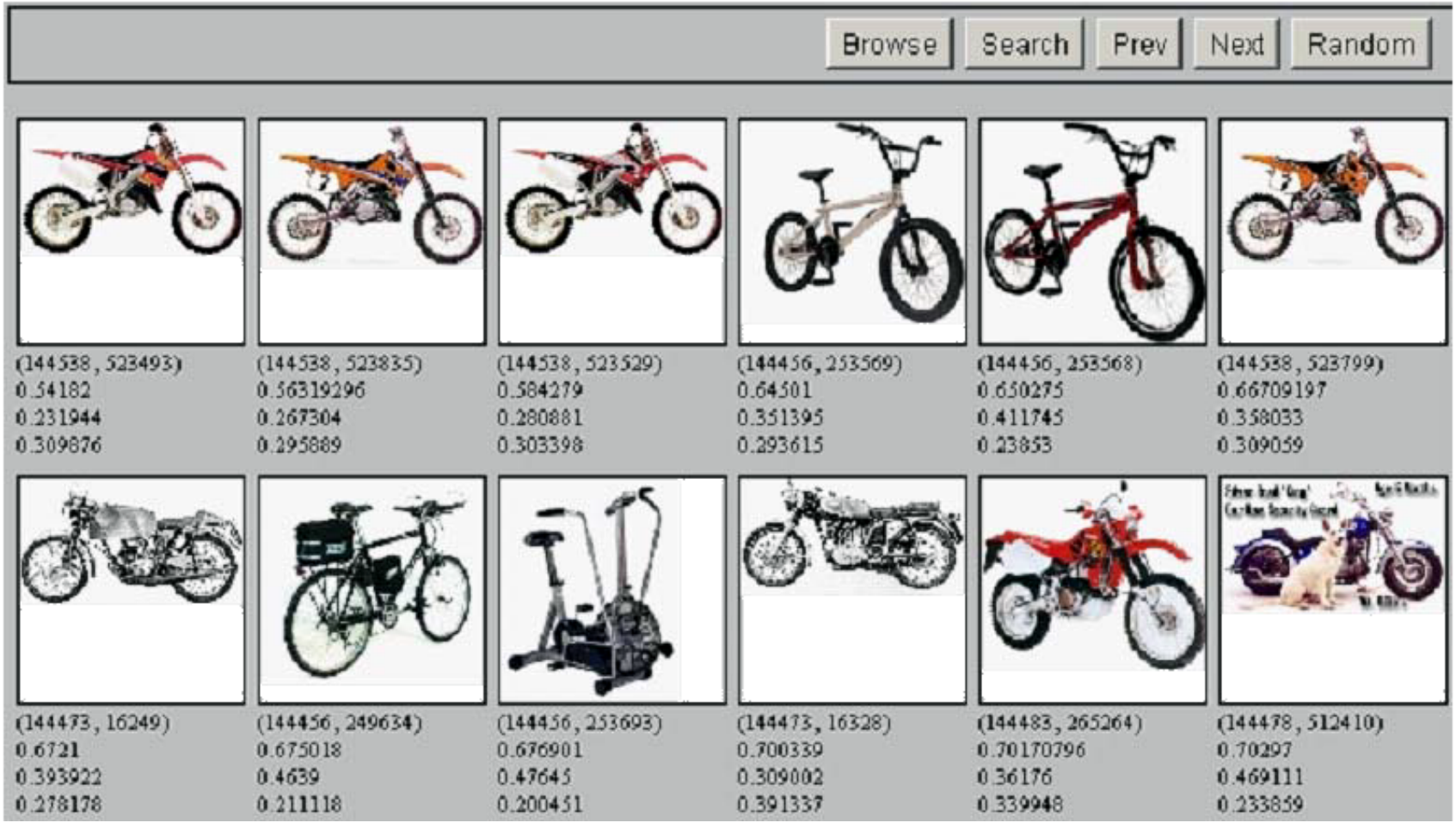
Relevance Feedback

- User Feedback: Select What is Relevant



Relevance Feedback

- Results After Relevance Feedback

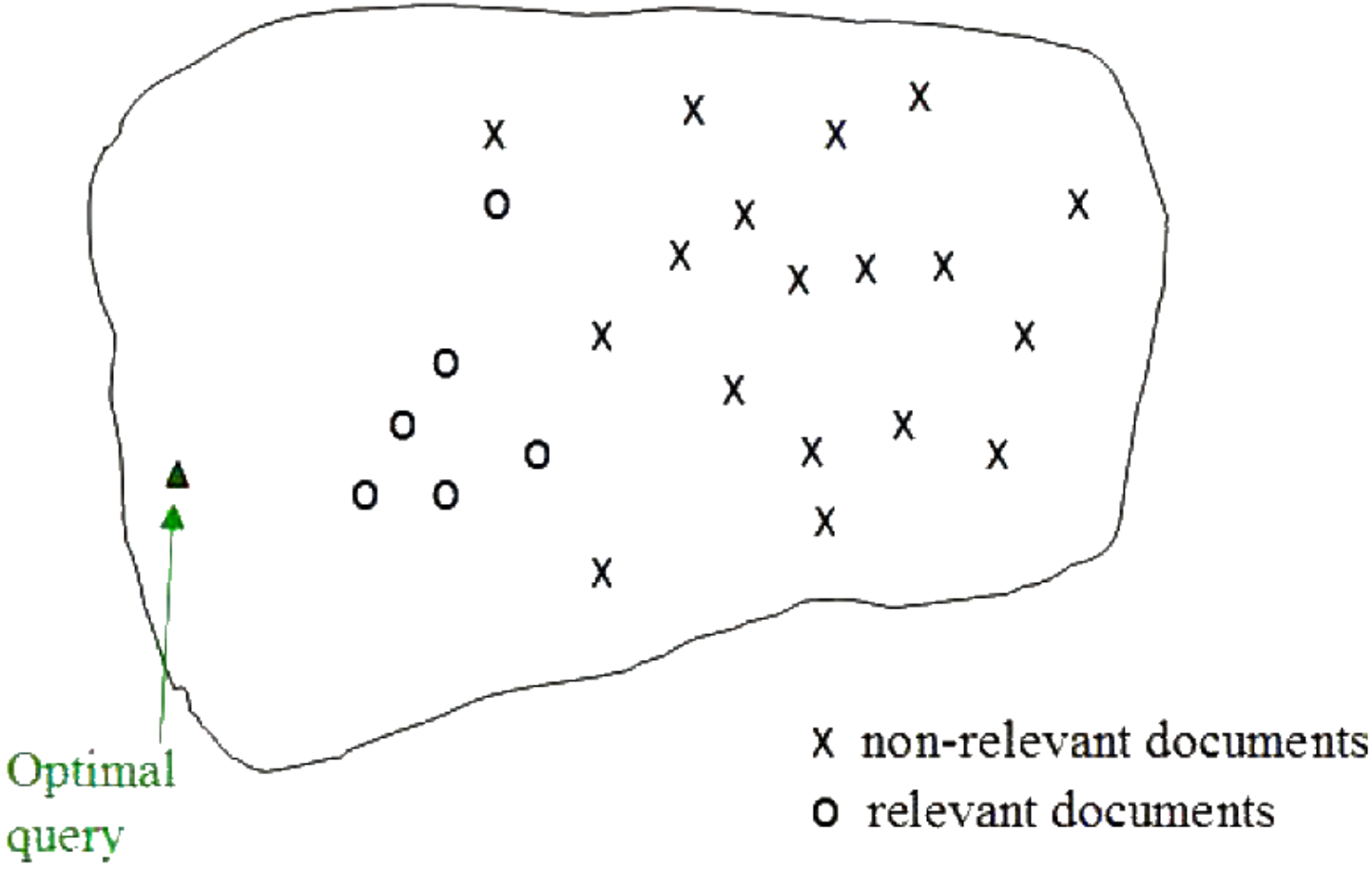


The Rocchio Algorithm

- The classic algorithm for implementing relevance feedback
- Incorporates relevance feedback information into the Vector Space Model
- It does so by "fiddling around" with the query vector $\vec{q}$: given a set of relevant documents and a set of non-relevant documents
  - It tries to maximize the similarity of $\vec{q}$ with the relevant documents
  - It tries to minimize the similarity of $\vec{q}$ with the non-relevant documents

Illustration

- The Rocchio algorithm tries to find the optimal position of the query vector:



Formal Definition

- Given a set D_r of relevant docs and a set D_{nr} of non-relevant docs, Rocchio chooses the query $\vec{q}_{opt}$ that satisfies

$$\vec{q}_{opt} = \max_{\vec{q}}[\text{sim}(\vec{q}, D_r) - \text{sim}(\vec{q}, D_{nr})]$$

  where $\text{sim}(\vec{q}, D)$ is the (avg) cosine measure
- Closely related to maximum separation between relevant and nonrelevant docs
- This optimal query vector is:

$$\vec{q}_{opt} = \frac{1}{|D_r|} \sum_{\vec{d}_j \in D_r} \vec{d}_j - \frac{1}{|D_{nr}|} \sum_{\vec{d}_j \in D_{nr}} \vec{d}_j$$

Centroids

- $\frac{1}{|D|} \sum_{d \in D} \vec{v}(d)$ is called a *centroid*
- The centroid is the centre of mass of a set of points
- Recall that we represent documents as points in a high-dimensional space.

Any Problem?

- So now we can do a perfect modification of the query vector?
- Unfortunately, that's not quite true ...
- This would work if we had the full sets of relevant and non-relevant documents
  - However, the full set of relevant documents is not known
  - Actually, that's what we want to find ...
- So, how's Rocchio's algorithm used in practice?

Rocchio 1971 Algorithm (SMART)

- Used in practice:

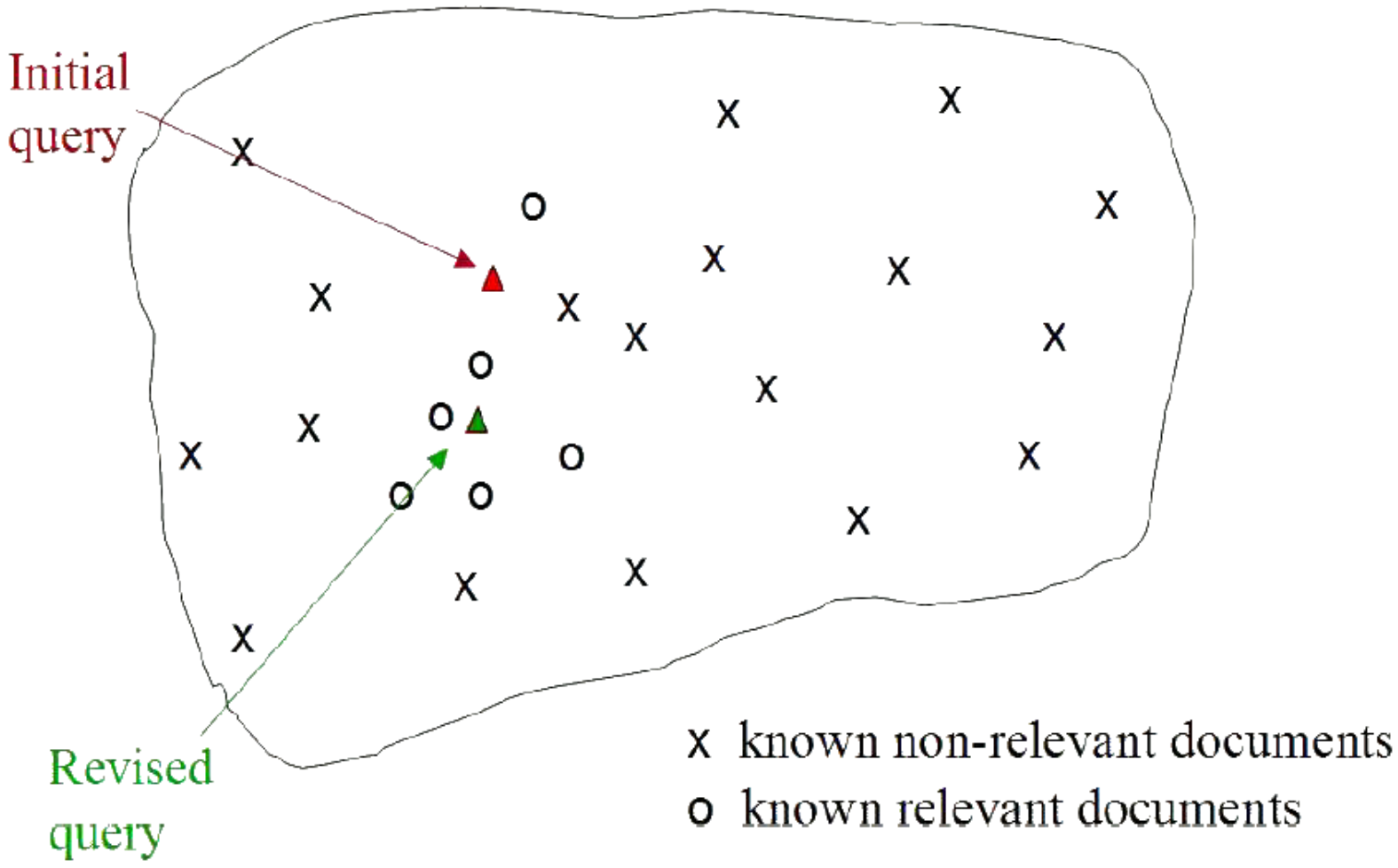
$$\vec{q}_m = \alpha \vec{q}_0 + \beta \frac{1}{|D_r|} \sum_{\vec{d}_j \in D_r} \vec{d}_j - \gamma \frac{1}{|D_{nr}|} \sum_{\vec{d}_j \in D_{nr}} \vec{d}_j$$

  - q_m: modified query vector;
  - q_0: original query vector;
  - D_r and D_{nr}: sets of known relevant and nonrelevant documents respectively;
  - α, β, and γ: weights attached to each term.
  - Negative term weights are ignored.

Rocchio 1971 Algorithm (SMART)

- New query (slowly) moves
  - towards relevant documents
  - away from nonrelevant documents
- Tradeoff α vs. β/γ:
  - If we have a lot of judged documents, we want a higher β/γ.

Illustration



Probabilistic Relevance Feedback

- Rather than rewriting the query in a vector space, we could build a *classifier*
- A classifier determines which classification an entity belongs to (e.g. classifying a document as relevant or non-relevant)
  - One way of doing this is with a Naive Bayes probabilistic model
  - We can estimate the probability of a term t appearing in a document, depending on whether it is relevant or not
  - We'll come back to this when discussing the probabilistic approach to IR

When Does Relevance Feedback Work?

- User has to have sufficient knowledge to be able to make an initial query, otherwise we'll be way off target.
- There can be various reasons why initial query may fail (leading to the result that no relevant documents are found):
  - Misspellings
  - Queries and documents are in different languages
  - Mismatch of user's and system's vocabulary: e.g. astronaut vs. cosmonaut

When Does Relevance Feedback Work?

- Relevance prototypes are well-behaved, i.e.
  - Term distribution in relevant documents will be similar to that in the documents marked by the users (relevant documents in one cluster)
  - Term distribution in all non-relevant documents will be different
- Problematic cases:
  - Subsets of the documents using different vocabulary, e.g., Burma vs Myanmar
  - Answer set is inherently disjunctive: e.g. irrational prime numbers
  - Instances of a general concept, which often are a disjunction of more specific concepts, e.g. felines (cat, tiger, etc.)

Relevance Feedback: Evaluation

- Relevance feedback can give very substantial gains in retrieval performance
- Empirically, one round of relevance feedback is often very useful, while two (or more) rounds are marginally useful
- At least five judged documents are recommended (otherwise process is unstable)

Relevance Feedback: Evaluation

- Straightforward evaluation strategy:
  - Start with an initial query q_0 and compute a precision-recall graph
  - After getting feedback, compute the modified query q_m, again compute a precision-recall graph
- This results in spectacular gains: on the order of 50% in Mean Average Precision (MAP)
  - Unfortunately, this is cheating ...
  - Gains are partly due to known relevant documents (judged by the user) now ranked higher

Relevance Feedback: Evaluation

- Alternatives:
  - Evaluate performance on *residual collection*, that is the collection without documents judged by user. However, now modified query may often seem to perform worse, as many relevant documents found by IR system don't count ...
  - Use two collections: one for initial query, and the other for comparative evaluation.
  - Do user studies: probably the best (and fairest) evaluation method.

Relevance Feedback on the Web

- Relevance feedback has been little used in web search
  - Exception: Excite web search engine
    - Initially provided full relevance feedback
    - However, the feature was in time dropped, due to lack of use
- What are the reasons for this?
  - Most users would like to complete their search in a single interaction
  - Relevance feedback is hard to explain to the average user (no incentive to give feedback)
  - Web search users are rarely concerned with increasing recall

Pseudo Relevance Feedback

- The technique of *pseudo relevance feedback* (aka *blind relevance feedback*), automates the manual part of relevance feedback
  - Use normal retrieval to find an initial set of most relevant documents
  - Assume that the top-k ranked documents are relevant, use these as relevance feedback
- This automatic technique mostly works
- However, it can lead to *query drift*:
  - Example: query is about `copper mines` and the top documents are mostly about mines in Chile, then pseudo relevance feedback may retrieve mainly documents on Chile.

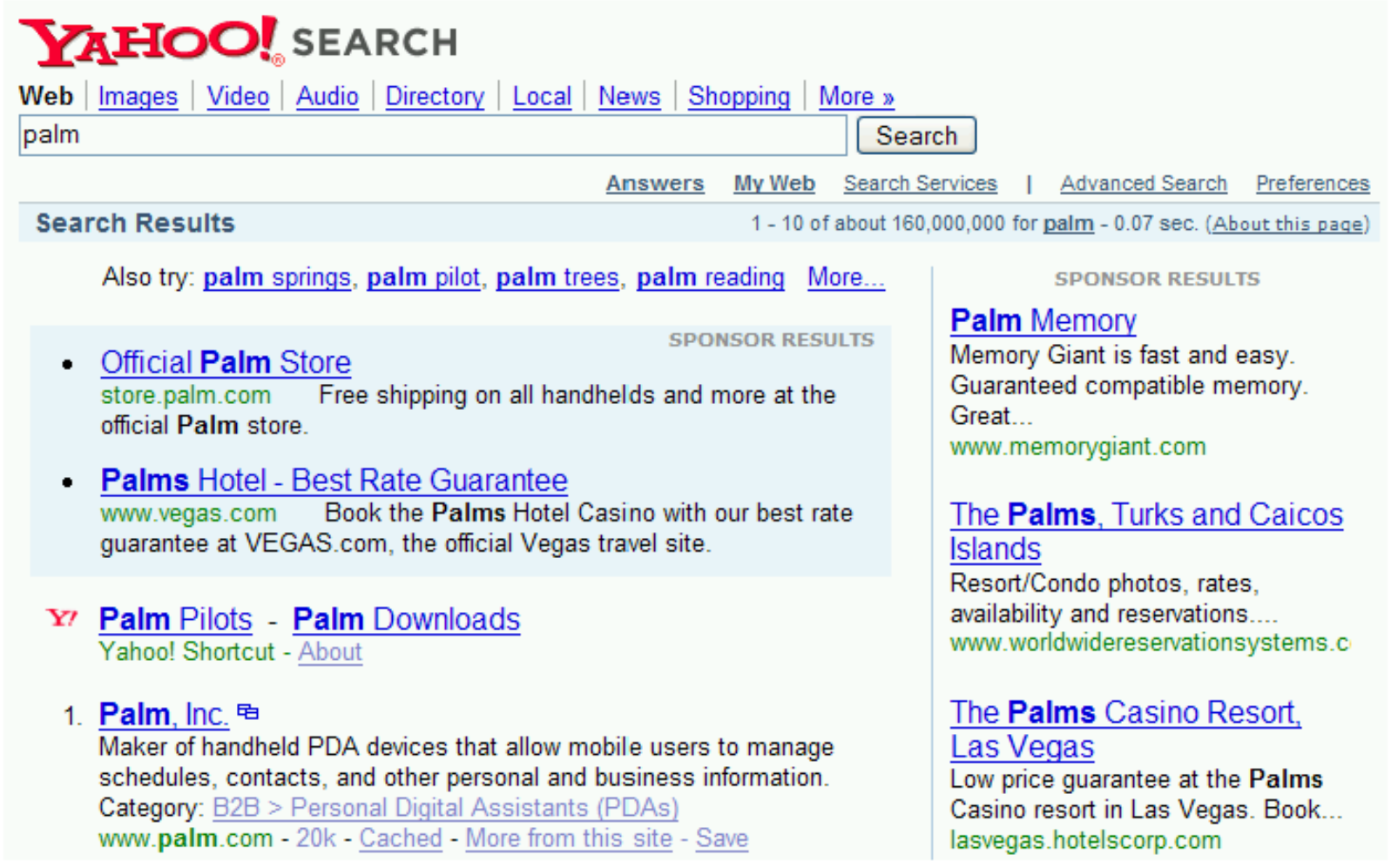
Indirect Relevance Feedback

- The technique of *indirect relevance feedback* (aka *implicit relevance feedback*) uses indirect sources of evidence
- Usually less reliable than explicit feedback, but more useful than pseudo relevance feedback
- Ideal for high volume systems like web search engines:
  - Clicks on links are assumed to indicate that the page is more likely to be relevant
  - Click-rates can be gathered globally for *clickstream mining*

Query Expansion

- In (global) query expansion, the query is modified based on some global resource, i.e. a resource that is not query-dependent.
- Main information we use: (near-)synonymy
  - A publication or database that collects (near-)synonyms is called a *thesaurus*.
  - We will look at two types of thesauri: manually created and automatically created.

Query Expansion: Example



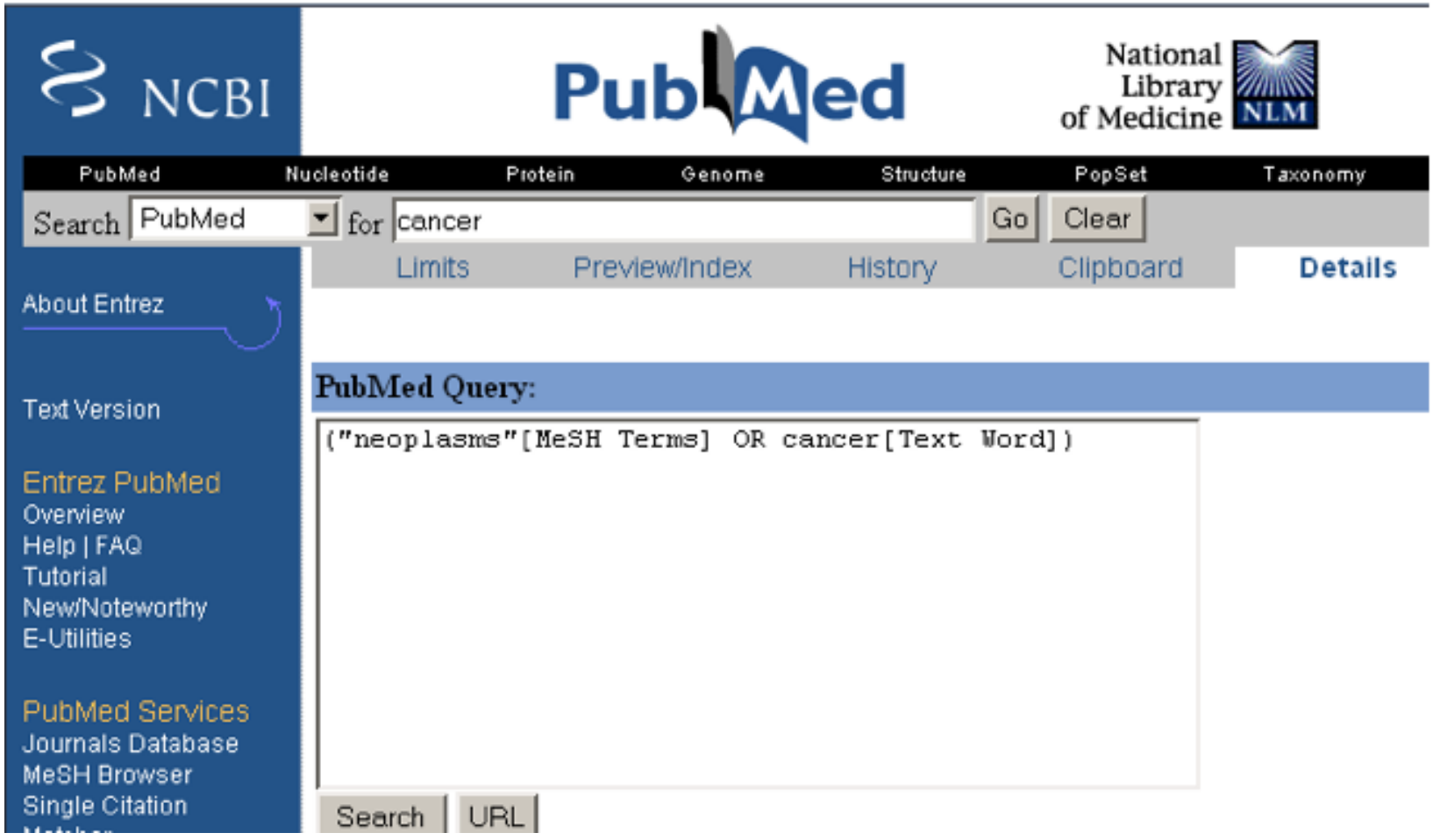
Thesaurus-based Query Expansion

- For each term t in the query, expand the query with the words semantically related with t in the thesaurus.
  - Example: `hospital` $\rightarrow$ `medical`
- Generally increases recall
- But can decrease precision, particularly with ambiguous terms:
  - `interest rate` $\rightarrow$ `interest rate fascinate evaluate`

Manual Thesaurus

- Maintained by publishers (e.g. PubMed)
- Widely used in specialized search engines for science and engineering
- It's very expensive to create a manual thesaurus and maintain it over time
- Roughly equivalent to annotation with a *controlled vocabulary*.

Manual Thesaurus: Example



Automatic Thesaurus

- It is possible to generate a thesaurus automatically by analysing the distribution of words in documents or by mining query logs
  - 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 oranges, so apples and oranges must be similar.
  - The former is more robust, while the latter is more accurate.

Automatic Thesaurus: Example

Word	Nearest Neighbours
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

Summary

- Users can give feedback
  - on documents: more common in relevance feedback
  - on words or phrases: more common in query expansion
- Relevance feedback can also be thought of as a type of query expansion, as we add terms to the query
  - The terms added in relevance feedback are based on "local" information in the result list.
  - The terms added in query expansion are based on "global" information that is not query-specific.

Summary

- Relevance feedback has been shown to be very effective at improving relevance of results
  - Its successful use requires queries for which the set of relevant documents is medium to large
  - Full relevance feedback often onerous for users; its implementation not very efficient in most IR systems
- Query expansion is often used in web-based or highly specialized IR systems
  - Less successful than relevance feedback, though may be as good as pseudo-relevance feedback
  - Easier to understand for users