Introduction to Information Retrieval

http://informationretrieval.org

IIR 9: Relevance Feedback & Query Expansion

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Overview

Plan for this lecture

- First: Recap

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  - Use thesaurus for query expansion

Google example query:
~hospital -hospital -hospitals

Overview

1. Recap
2. Relevance feedback: Basics
3. Relevance feedback: Details
4. Global query expansion

Outline

Relevance

- We will evaluate the quality of an information retrieval system and, in particular, its ranking algorithm with respect to relevance.
- A document is relevant if it gives the user the information she was looking for.
- To evaluate relevance, we need an evaluation benchmark with three elements:
  - A benchmark document collection
  - A benchmark suite of queries
  - An assessment of the relevance of each query-document pair

Relevance: query vs. information need

- The notion of "relevance to the query" is very problematic.
- Information need i: You are looking for information on whether drinking red wine is more effective at reducing your risk of heart attacks than white wine.
- Query q: WINE AND RED AND WHITE AND HEART AND ATTACK
- Consider document d': *He then launched into the heart of his speech and attacked the wine industry lobby for downplaying the role of red and white wine in drunk driving.*
- d' is relevant to the query q, but d' is not relevant to the information need i.
- User happiness/satisfaction (i.e., how well our ranking algorithm works) can only be measured by relevance to information needs, not by relevance to queries.

Precision and recall

- Precision (P) is the fraction of retrieved documents that are relevant

$$\text{Precision} = \frac{\#(\text{relevant items retrieved})}{\#(\text{retrieved items})} = P(\text{relevant}|\text{retrieved})$$

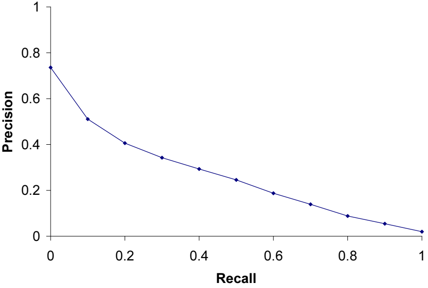
- Recall (R) is the fraction of relevant documents that are retrieved

$$\text{Recall} = \frac{\#(\text{relevant items retrieved})}{\#(\text{relevant items})} = P(\text{retrieved}|\text{relevant})$$

A combined measure: F

- F allows us to trade off precision against recall.
- Balanced F:
$$F_1 = \frac{2PR}{P + R}$$
- This is a kind of soft minimum of precision and recall.

Averaged 11-point precision/recall graph



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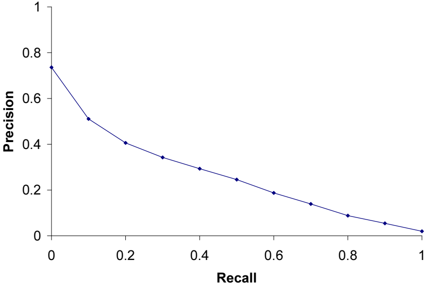

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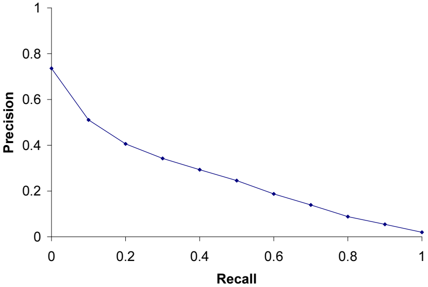

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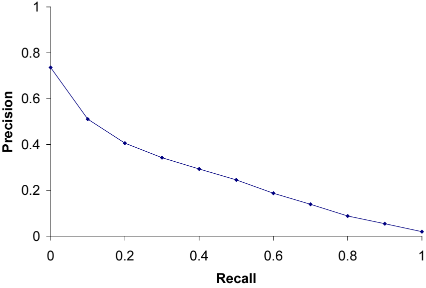

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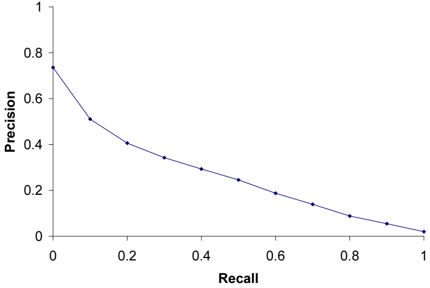

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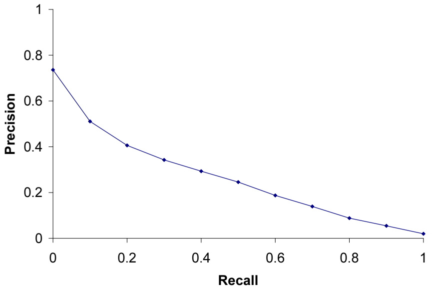

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- When we want to look at at least 50% of all relevant documents, then for each relevant document we find, we will have to look at about two nonrelevant documents.
- That's not very good.
- High-recall retrieval is an unsolved problem.

Outline

Relevance feedback: Basic idea

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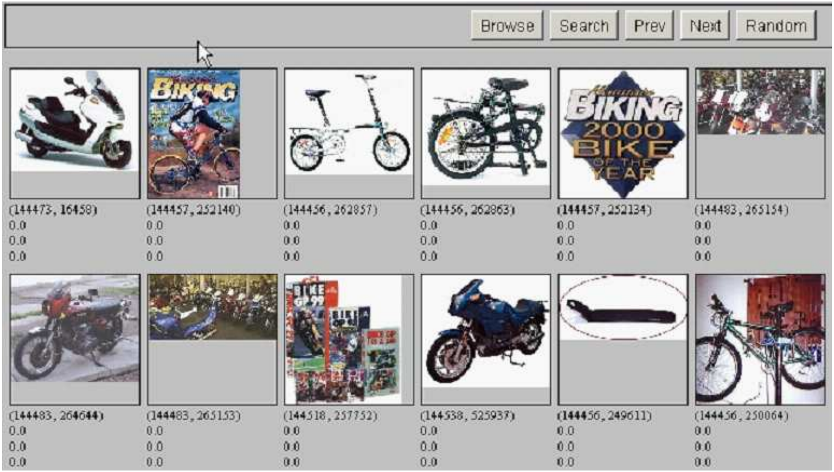
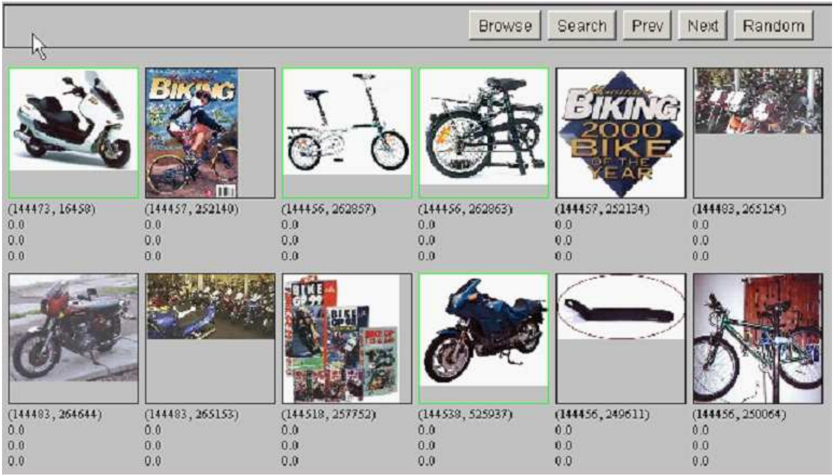
- We can iterate this.
- We will use the term *ad hoc retrieval* to refer to regular retrieval without relevance feedback.
- We will now look at three different examples of relevance feedback that highlight different aspects of the process.

Relevance Feedback: Example

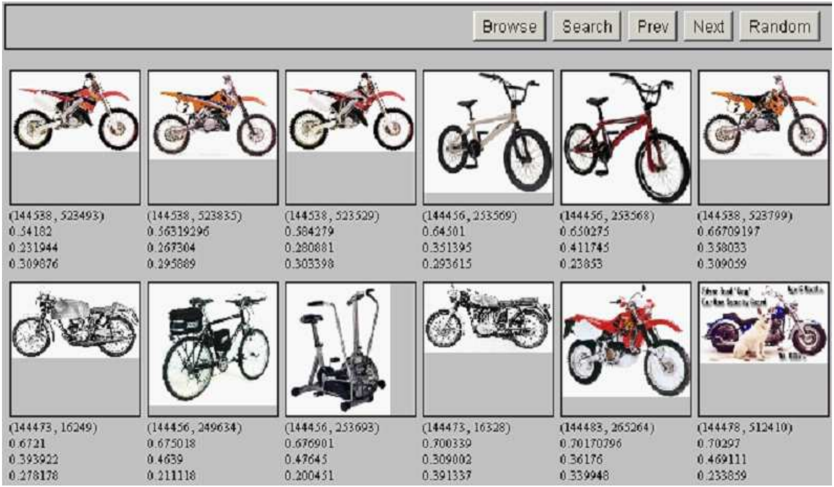
Results for initial query



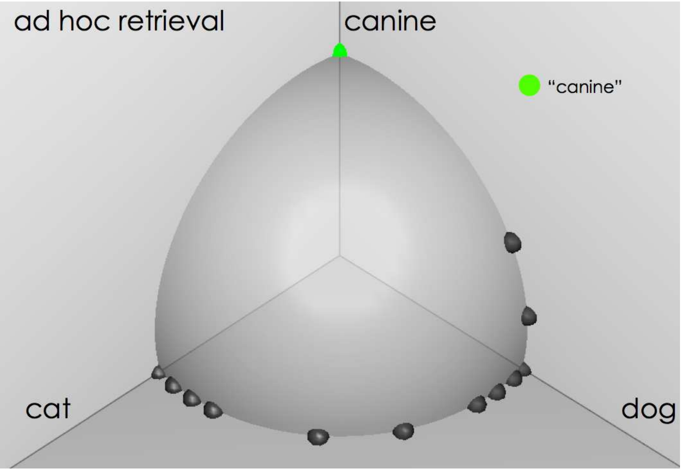
User feedback: Select what is relevant



Results after relevance feedback

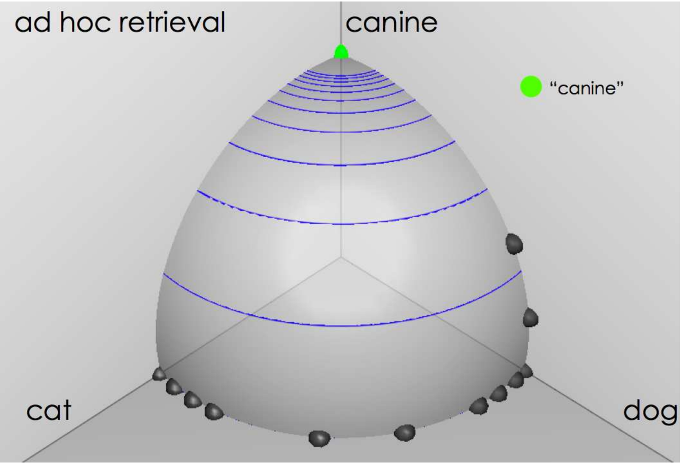


Ad hoc retrieval for query "canine" (1)



source:
Fernando Díaz

Ad hoc retrieval for query "canine" (2)



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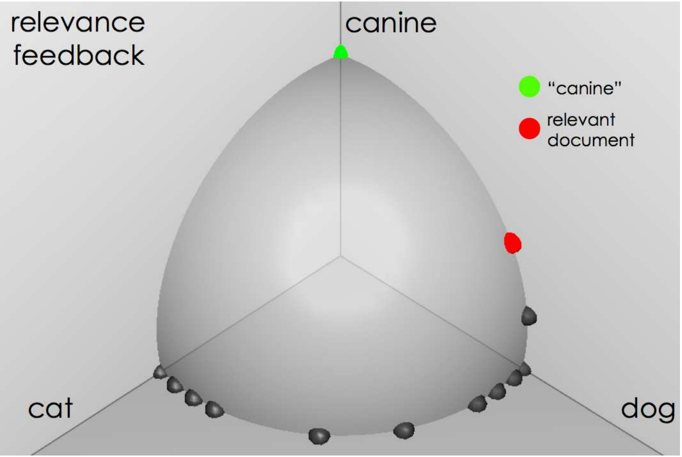

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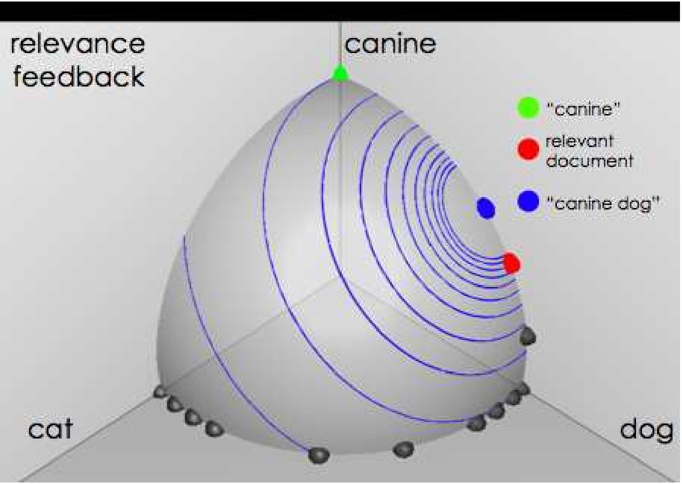

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Results for initial query

Initial query: New space satellite applications

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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
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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

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

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Key concept for relevance feedback: Centroid

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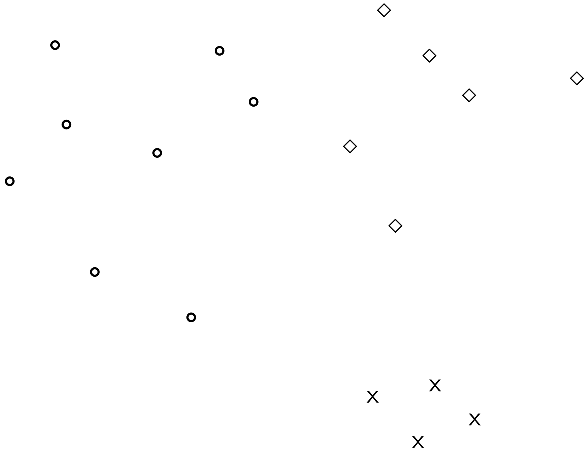
- Recall that we represent documents as points in a high-dimensional space.
- Thus: we can compute centroids of documents.
- Definition:

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

where D is a set of documents and $\vec{v}(d) = \vec{d}$ is the vector we use to represent the document d.

Centroid: Examples



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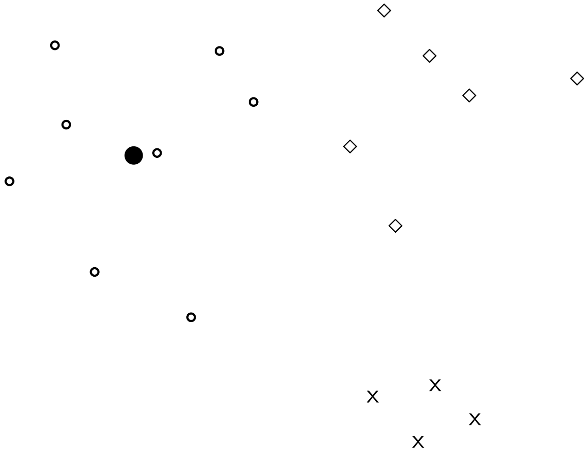

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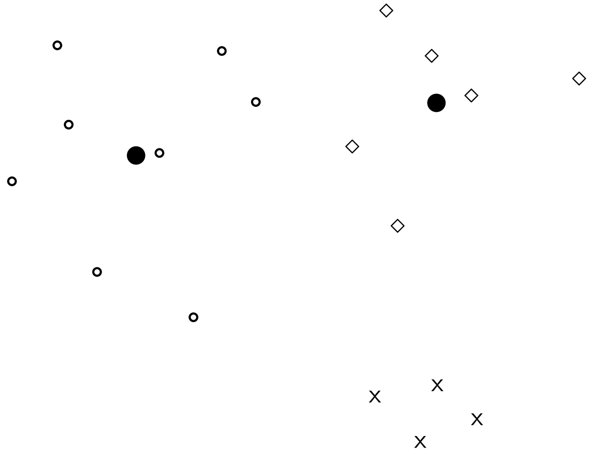

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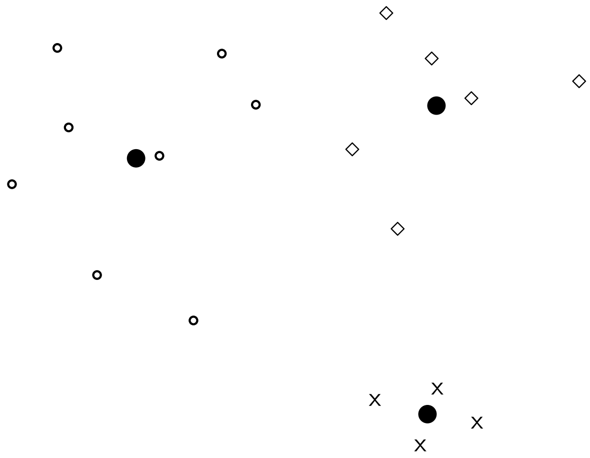

Rocchio algorithm

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- Closely related to maximum separation between relevant and nonrelevant docs
- This optimal query vector is:

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

D_r: set of relevant docs; D_{nr}: set of nonrelevant docs

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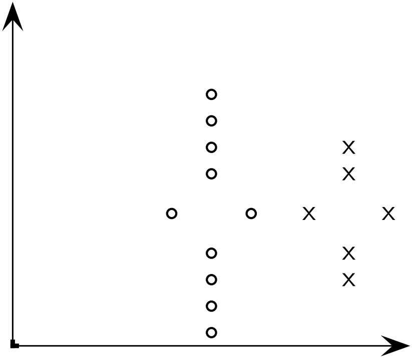
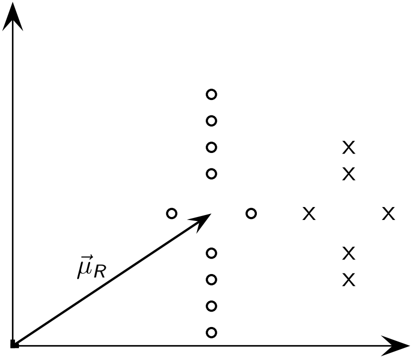
- We move the centroid of the relevant documents by the difference between the two centroids.
- We had to assume $|\vec{\mu}_r| = |\vec{\mu}_{nr}| = 1$ for this derivation.

Rocchio illustrated



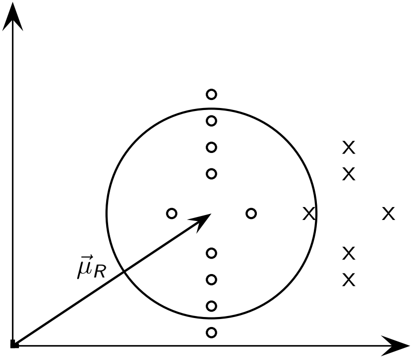
circles: relevant documents, Xs: nonrelevant documents

Rocchio illustrated



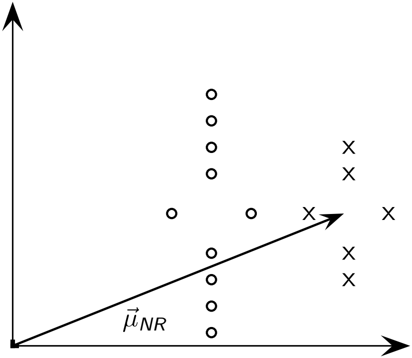
$\vec{\mu}_R$: centroid of relevant documents

Rocchio illustrated



$\vec{\mu}_R$ does not separate relevant/nonrelevant.

Rocchio illustrated



$\vec{\mu}_{NR}$: centroid of nonrelevant documents

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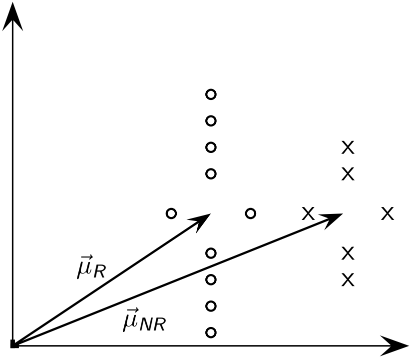

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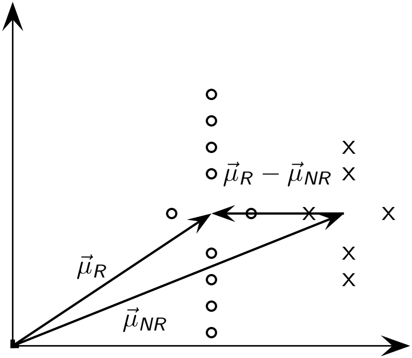
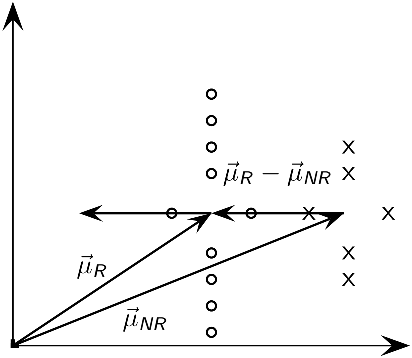


$\vec{\mu}_R - \vec{\mu}_{NR}$: difference vector

Rocchio illustrated



Add difference vector to $\vec{\mu}_R$ . . .

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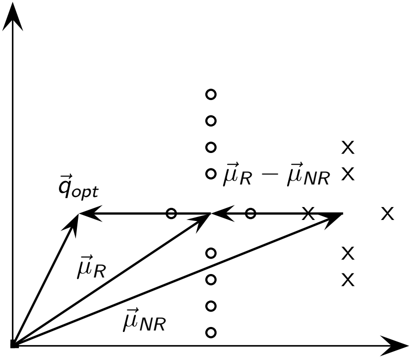
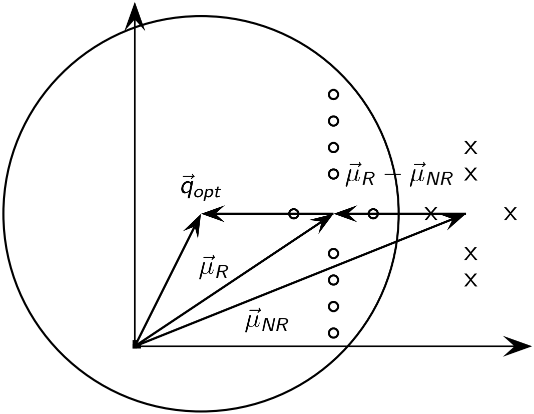


... to get $\vec{q}_{opt}$

Rocchio illustrated



$\vec{q}_{opt}$ separates relevant/nonrelevant perfectly.

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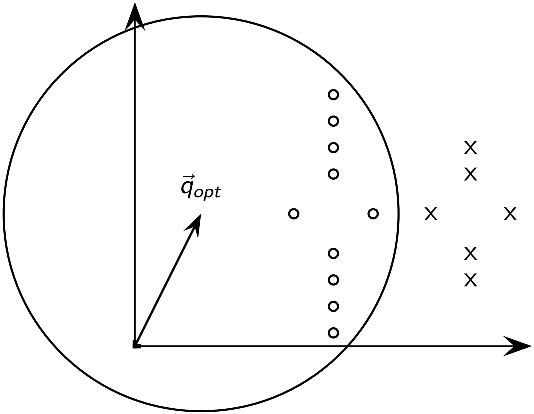

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Rocchio 1971 algorithm (SMART)

- Used in practice:

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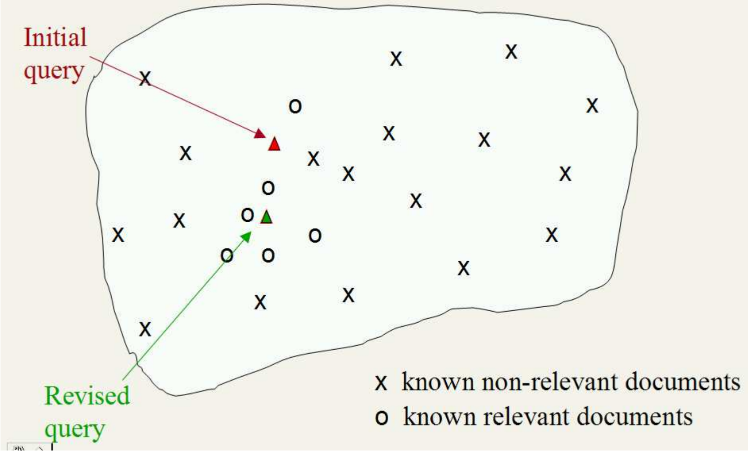
Rocchio relevance feedback illustrated



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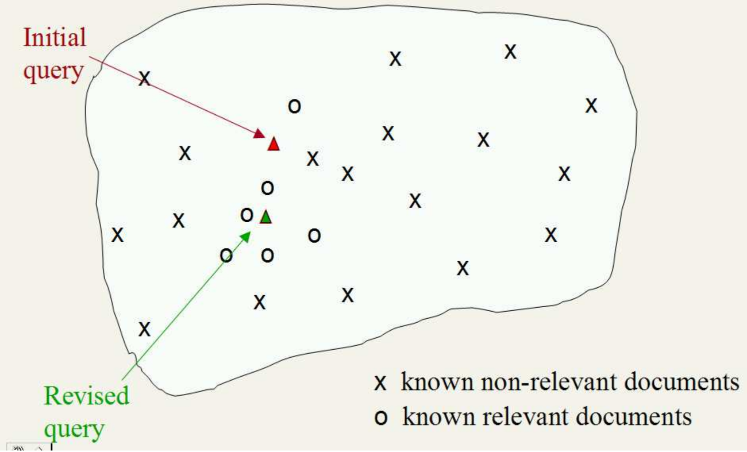

- Questions?

Positive vs. negative relevance feedback

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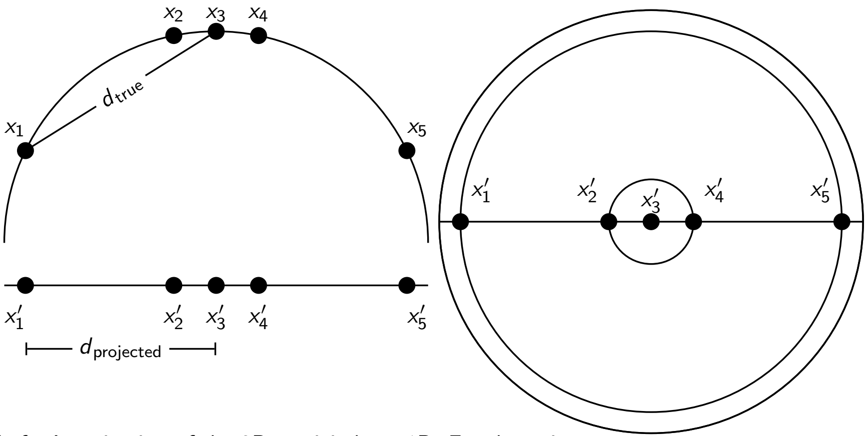
- Many systems only allow positive feedback.

Aside: 2D/3D graphs can be misleading



Left: A projection of the 2D semicircle to 1D. For the points x_1, x_2, x_3, x_4, x_5 at x coordinates $-0.9, -0.2, 0, 0.2, 0.9$ the distance $|x_2x_3| \approx 0.201$ only differs by 0.5% from $|x'_2x'_3| = 0.2$; but $|x_1x_3|/|x'_1x'_3| = d_{\text{true}}/d_{\text{projected}} \approx 1.06/0.9 \approx 1.18$ is an example of a large distortion (18%) when projecting a large area. *Right:* The corresponding projection of the 3D hemisphere to 2D.

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- Assumption A2: Relevant documents contain similar terms (so I can "hop" from one relevant document to a different one when giving relevance feedback).

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- Relevance feedback on tobacco docs will not help with finding docs on developing countries.

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- Users may prefer revision/resubmission to having to judge relevance of documents.
- There is no clear evidence that relevance feedback is the "best use" of the user's time.

Do search engines use relevance feedback?

“similar pages” at Google

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- Excite had full relevance feedback at one point, but abandoned it later.

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- We’ll revisit this issue in IIR 13.

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- This demonstrates that pseudo-relevance feedback is effective on average.

Outline

1. Recap
2. Relevance feedback: Basics
3. Relevance feedback: Details
4. Global query expansion

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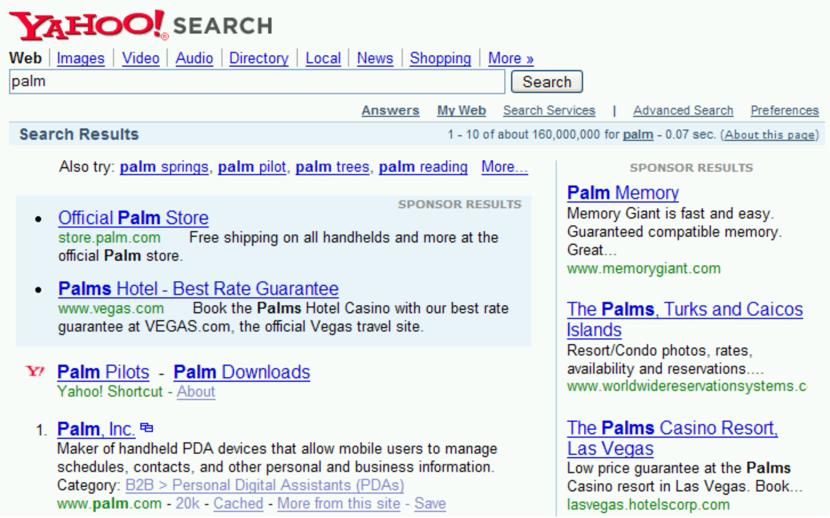
- We will look at two types of thesauri: manually created and automatically created.

"Global" query expansion: Example



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- Query-equivalence based on query log mining (common on the web as in the "palm" example)

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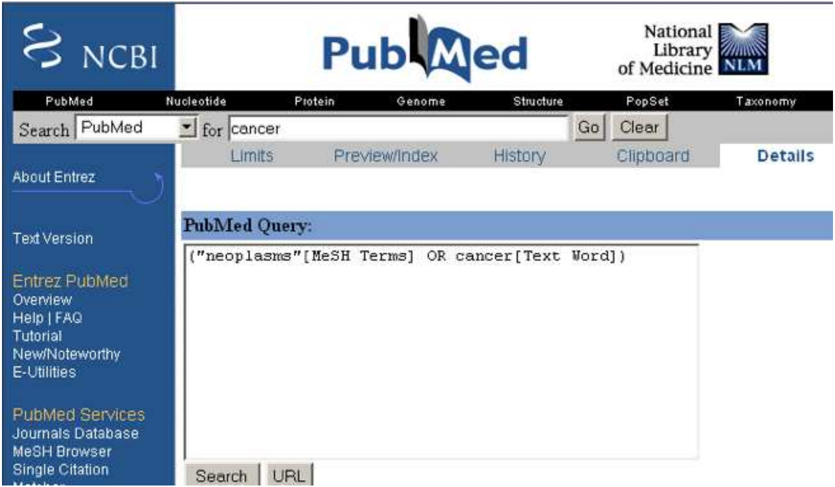
- A manual thesaurus is roughly equivalent to annotation with a *controlled vocabulary*.

Example for manual thesaurus: PubMed



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- Co-occurrence is more robust, grammatical relations are more accurate.

Co-occurence-based thesaurus: Examples

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

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- Log-based query modification (which is more complex than simple query expansion) is more common on the web than relevance feedback.

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- Chapter 9 of IIR
- Resources at `http://ifnlp.org/ir`
- Salton and Buckley 1990 (original relevance feedback paper)
- Spink, Jansen, Ozmultu 2000: Relevance feedback at Excite
- Schütze 1998: Automatic word sense discrimination (describes a simple method for automatic thesuarus generation)