Multimedia Information Retrieval and Technology

Lecture 10 Kappa Measure and Relevance Feedback

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Recap：Measuring relevance

To measure IR effectiveness, we need a test collection consisting of **Three elements**:

1. A benchmark document collection

   Must be representative

2. A benchmark suite of information needs, expressible as queries

   Again, representative

3. An assessment of either Relevant or Nonrelevant judgments for each query-document pair.

   How?

Kappa Measure

Measure how much agreement/disagreement between judges there is on relevance judgment.

Kappa statistic is a common measure for agreement between judges.

Kappa Measure: Example

Number of docs	Judge 1	Judge 2
300	Relevant	Relevant
70	Nonrelevant	Nonrelevant
20	Relevant	Nonrelevant
10	Nonrelevant	Relevant

Kappa Measure: Example

Kappa = [P(A) – P(E)] / [1 – P(E)]

$P(A)$:proportion of the times judges agreed
= (300+70)/400 = 0.925

$P(E)$: the proportion of the times the judges would be expected to agree by chance.

Chance Agreement

There are choices in how P(E) is estimated:

- if we simply say we are making a two-class decision and assume nothing more, then the expected chance agreement rate is 0.5;

- With the given class distribution, usually *marginal statistics* is used to calculated P(E).

$$P(E) = P(nonrelevant)^2 + P(relevant)^2$$

pools the marginal distribution across judges.

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Marginal Statistics

		Judge 2 Relevance		
		Yes	No	Total
Judge 1	Yes	300	20	320
Relevance	No	10	70	80
	Total	310	90	400

For a contingency table, as above, a *marginal statistic* is formed by summing a row or column.

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Kappa Measure: Example

Kappa measure

- Designed for categorical judgments
- Corrects for chance agreement P(E)

Kappa = [P(A) – P(E)] / [1 – P(E)]

Kappa = 0 is they agree only at the rate given by chance, 1 for total agreement(two judges always agree).

Kappa Measure: Example

P(nonrelevant) = (10+20+70+70)/800 = 0.2125

P(relevant) = (10+20+300+300)/800 = 0.7878

Probability that two judges agreed by chance:

P(E) = ?

Kappa ?

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Kappa Example

Kappa > 0.8: good agreement;

0.67 < Kappa < 0.8: acceptable;

Kappa < 0.67: need redesign relevance assessment methodology;

Depends on purpose of study

For >2 judges: an average pairwise kappa value.

Relevance Feedback and Query Expansion

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Improving Recall

Options for improving recall:

- Local methods: Do a "local" on-demand analysis for a user query.

  Main local method: **relevance feedback**;

- Global methods: Do a global analysis for the collection to produce **thesaurus**

  Use thesaurus for **query expansion.**

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Relevance feedback

The idea of ***relevance feedback*** **(RF)** is to involve the user in the retrieval process so as to improve the final result set.

The basic procedure is:

1. The user issues a (short, simple) query.
2. The system returns an initial set of retrieval results.
3. The user marks some returned documents as relevant or nonrelevant.
4. The system computes a better representation of the information need based on the user feedback.
5. The system displays a revised set of retrieval results.

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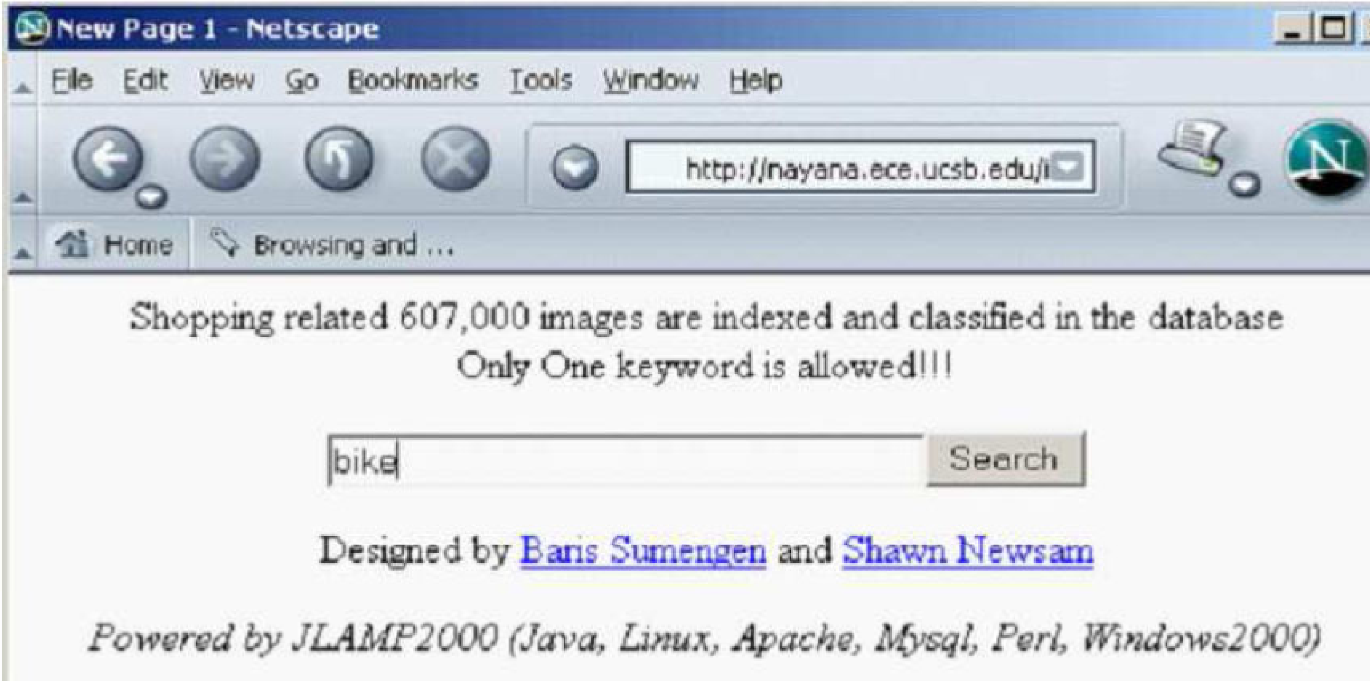

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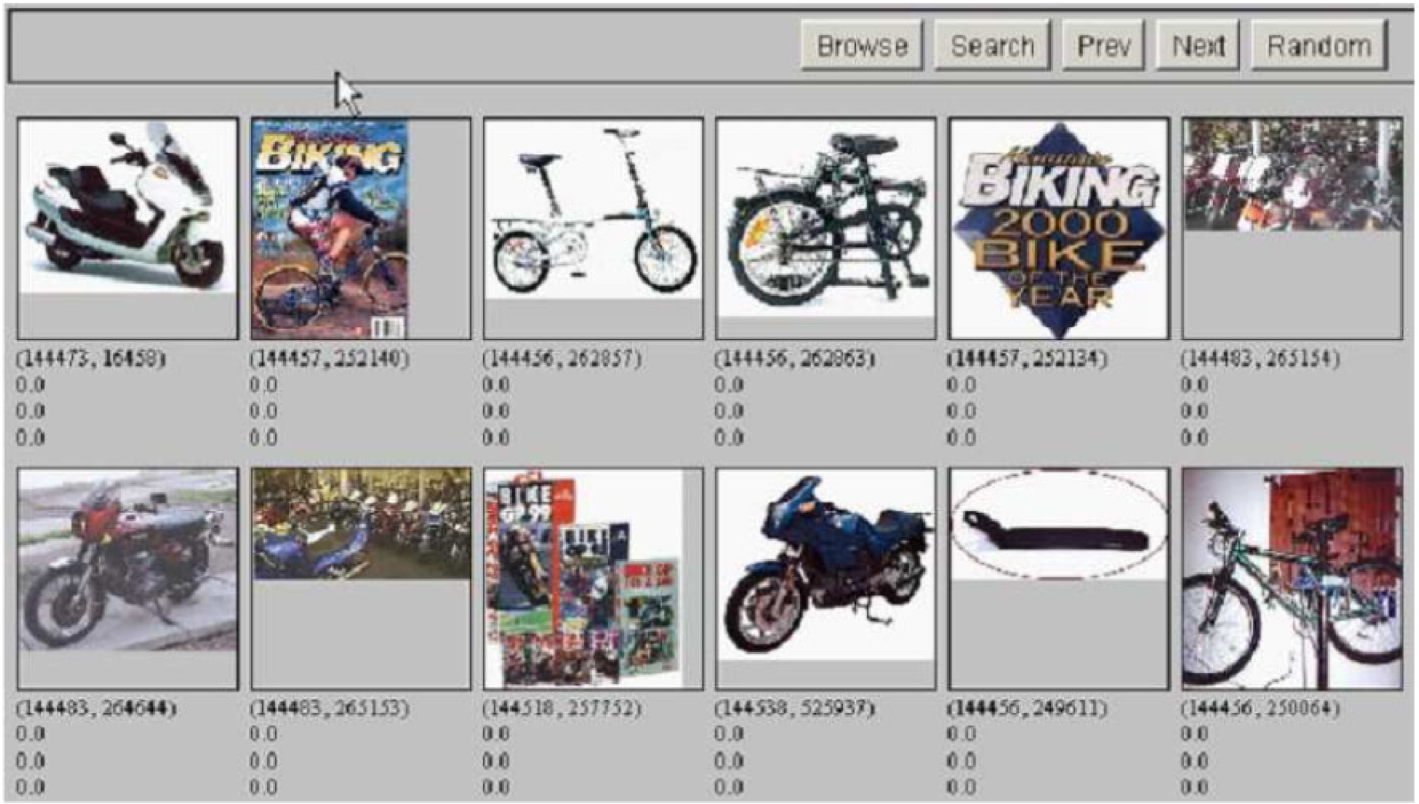
Results for initial query



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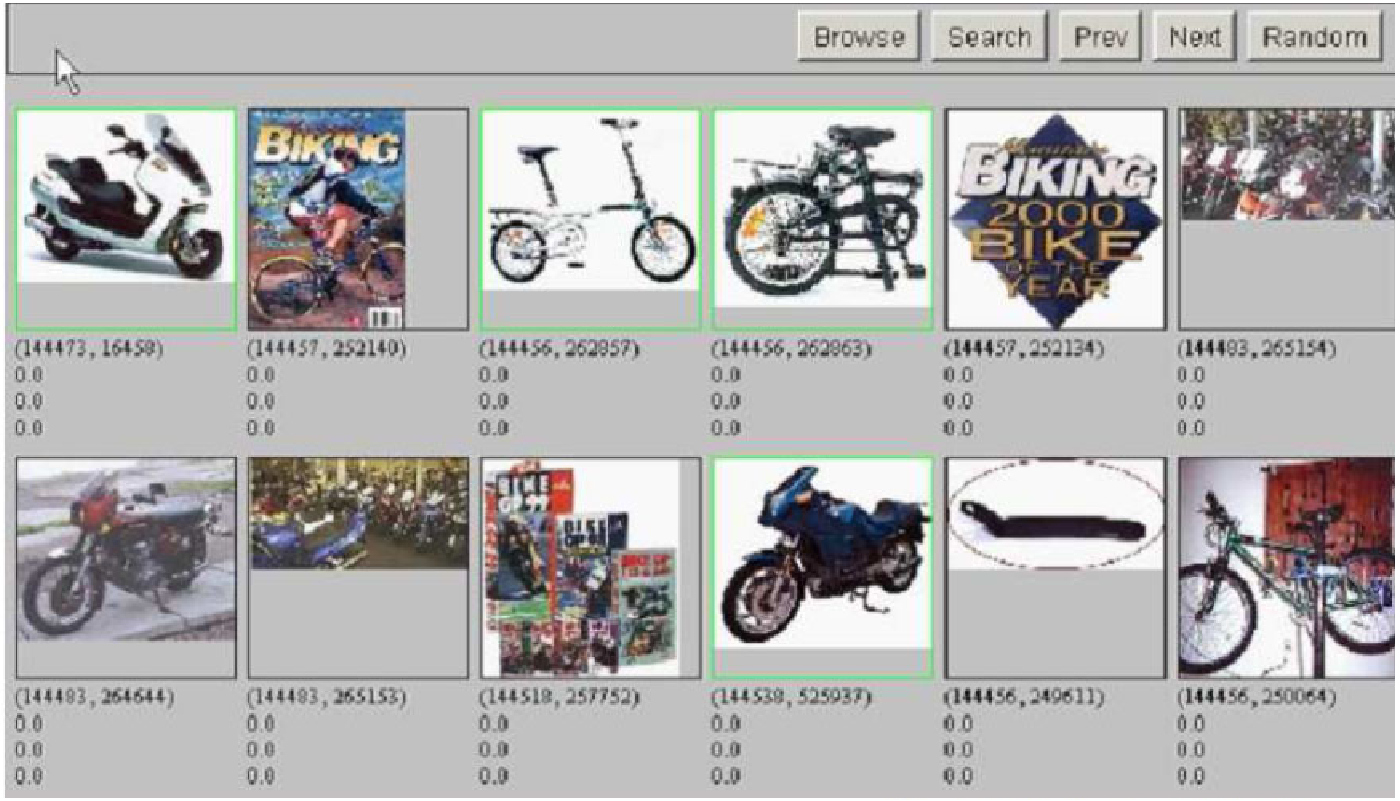
Select what is relevant



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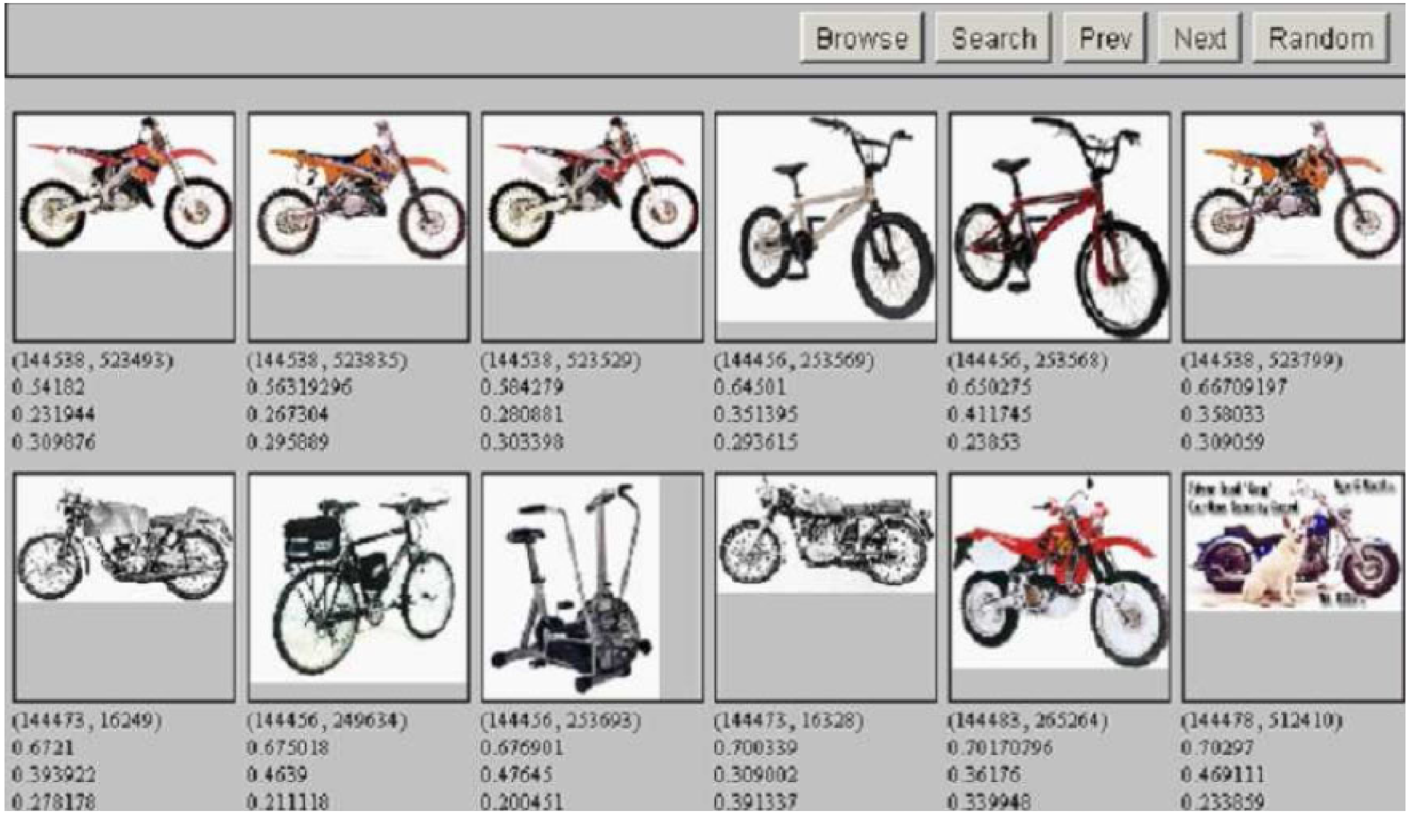
Results after relevance feedback



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Relevance feedback

Image search provides a good example of relevance feedback.

This is a domain where a user can easily have difficulty formulating what they want in words, but can easily indicate relevant or nonrelevant.

The underlying theory

Relevance feedback: refine a query with user's input.

To refine a query, firstly we need to know how to define the best query.

The optimal query vector will maximizes similarity with relevant documents while minimizing similarity with non-relevant documents.

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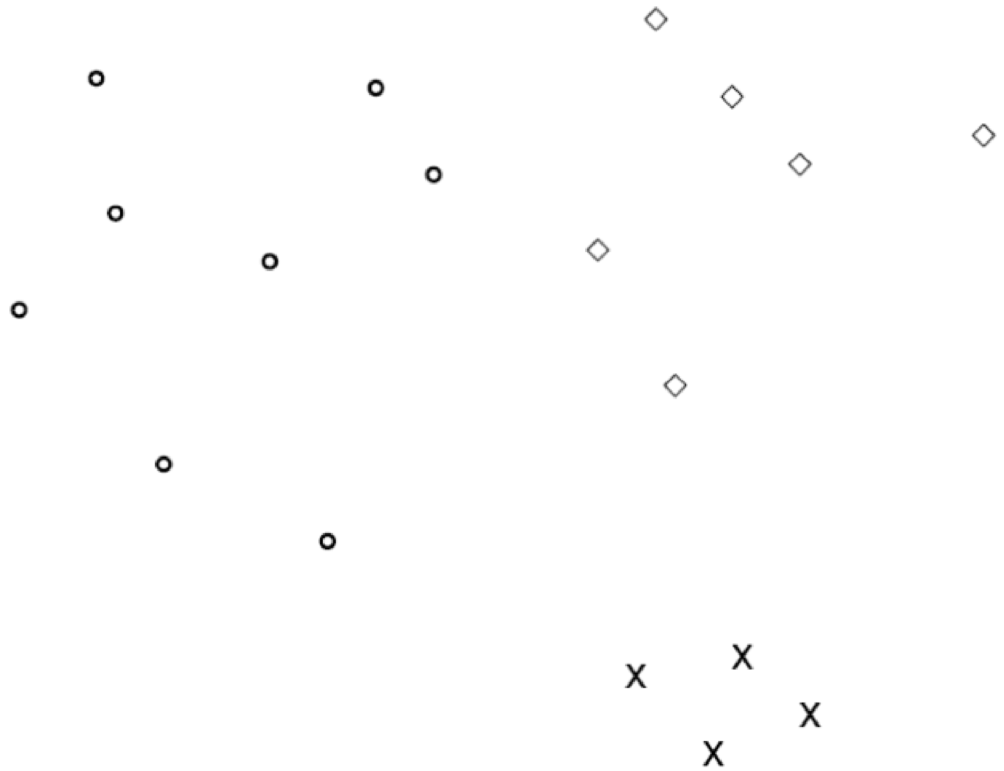
Key concept for relevance feedback: Centroid

- The centroid is the center of mass of a set of points.
- Recall that we represent documents as points in a high-dimensional space.
- Thus: we can compute centroids of documents.
- Definition:

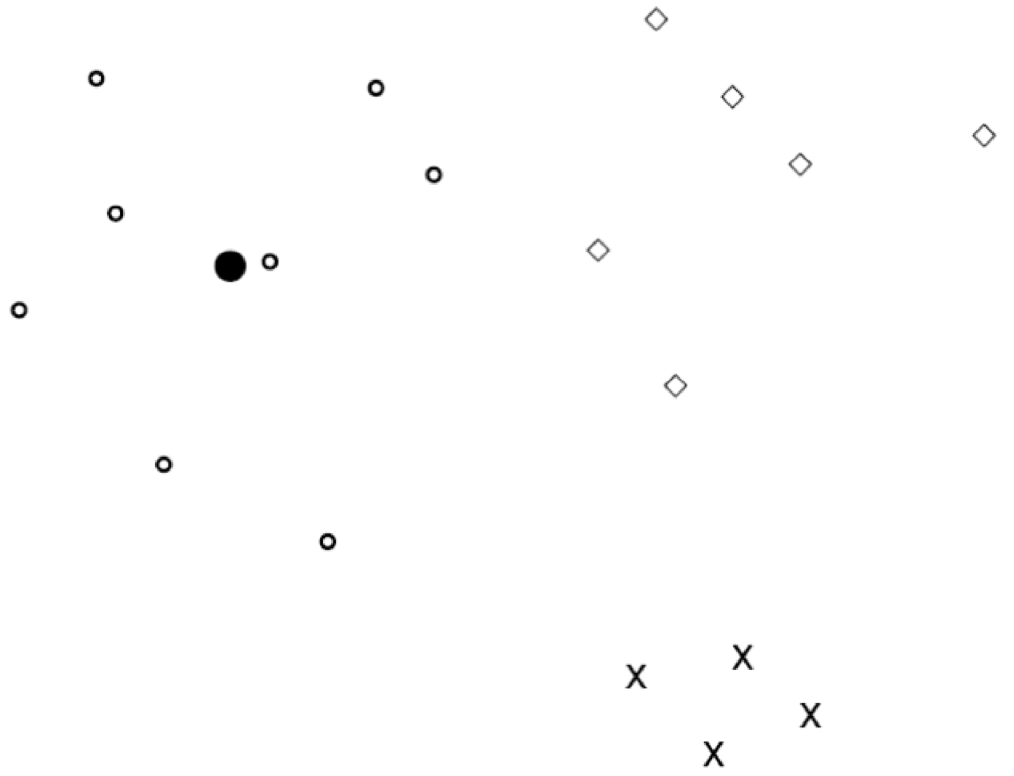
$$\vec{\mu}(D) = \frac{1}{|D|} \sum_{d \in D} \vec{v}(d)$$

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

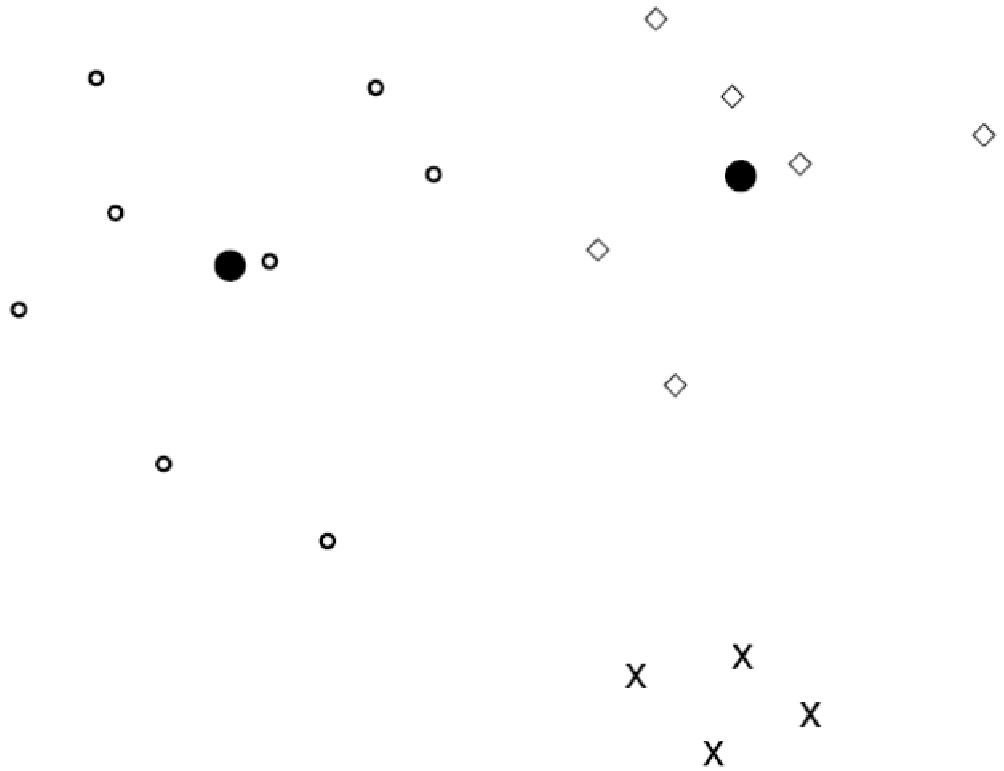
Centroid: Examples



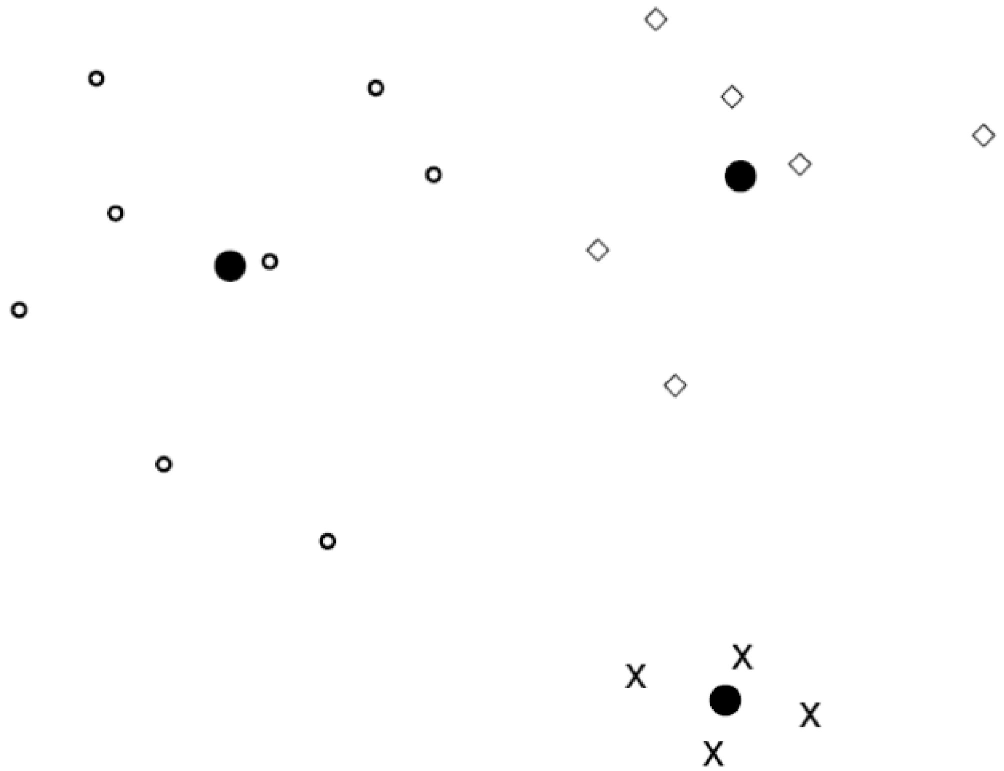
Centroid: Examples



Centroid: Examples



Centroid: Examples



Rocchio algorithm

- The Rocchio algorithm implements relevance feedback in the vector space model.
- Rocchio chooses the query $\vec{q}_{opt}$ that maximizes

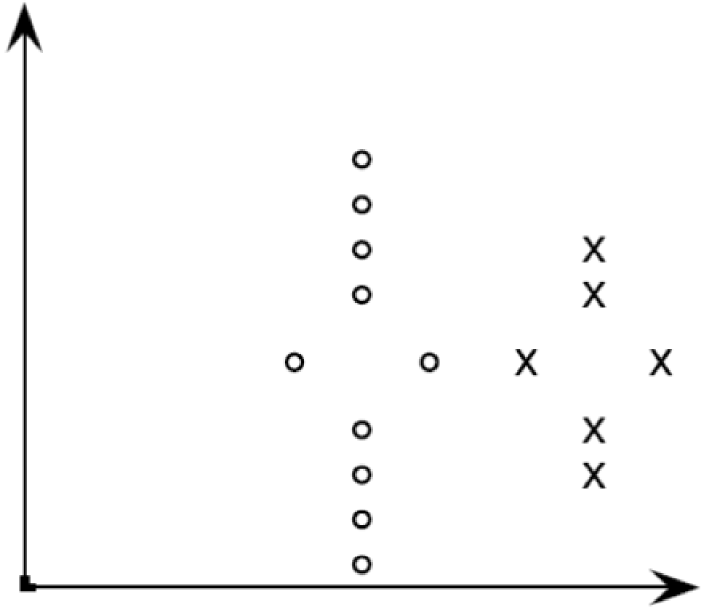
$$\vec{q}_{opt} = \arg\max_{\vec{q}} [\text{sim}(\vec{q}, D_r) - \text{sim}(\vec{q}, D_{nr})]$$

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

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

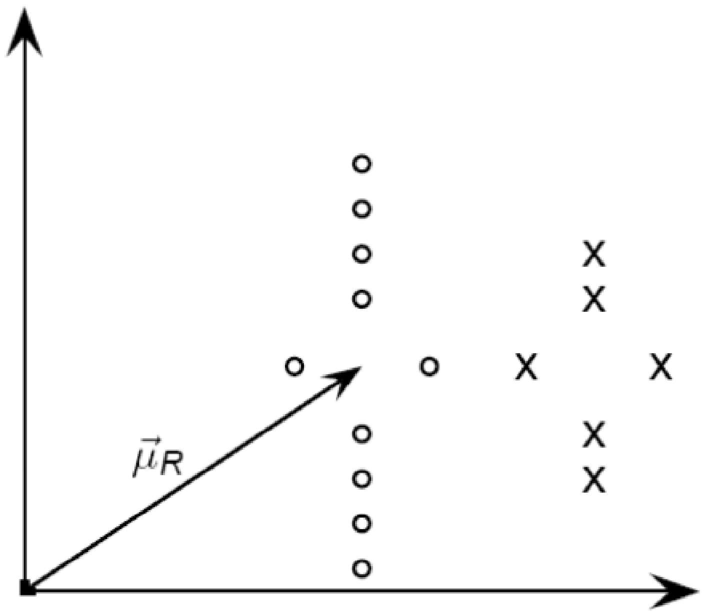
D_r: set of relevant docs; D_{nr}: set of nonrelevant docs

Rocchio illustrated



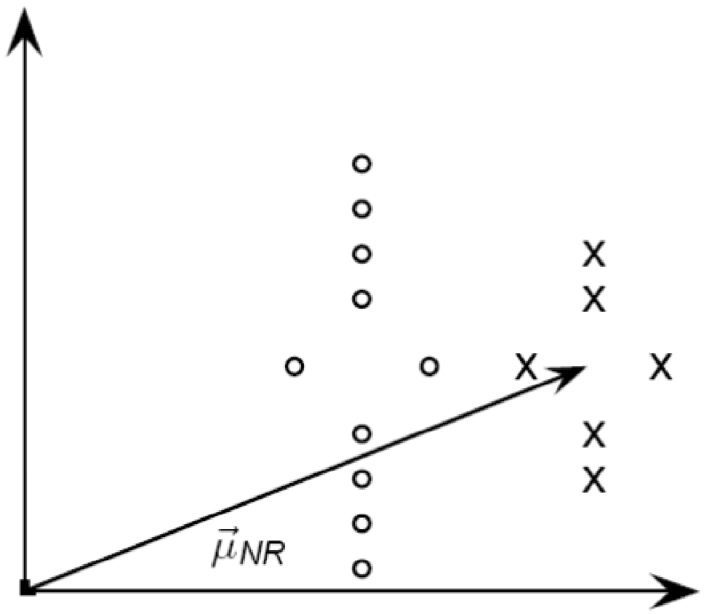
circles: relevant documents, Xs: nonrelevant documents

Rocchio illustrated



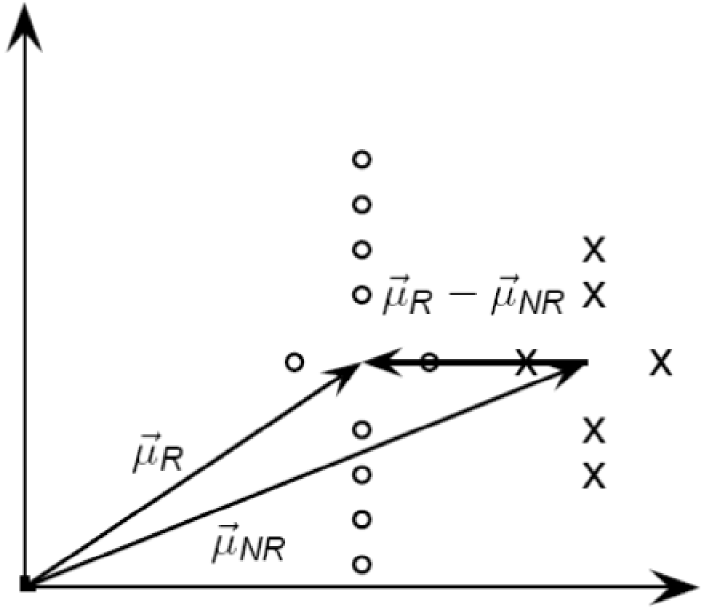
$\vec{\mu}_R$: centroid of relevant documents

Rocchio illustrated



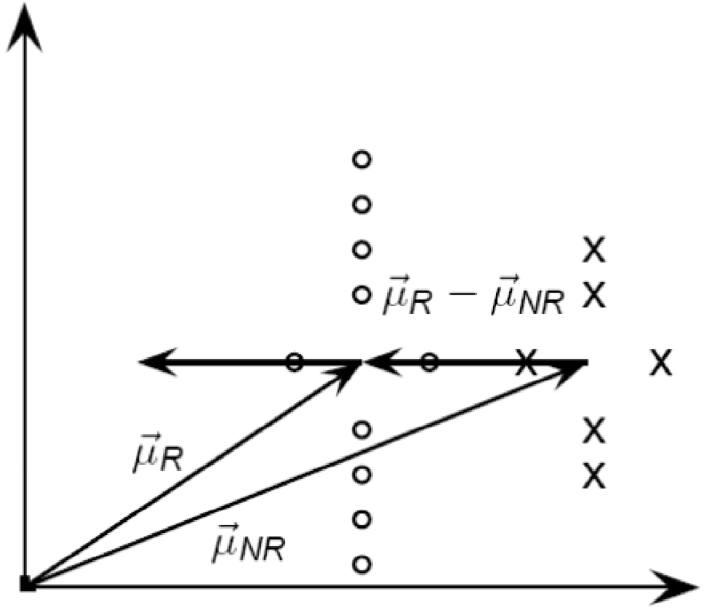
$\vec{\mu}_{NR}$: centroid of nonrelevant documents

Rocchio illustrated



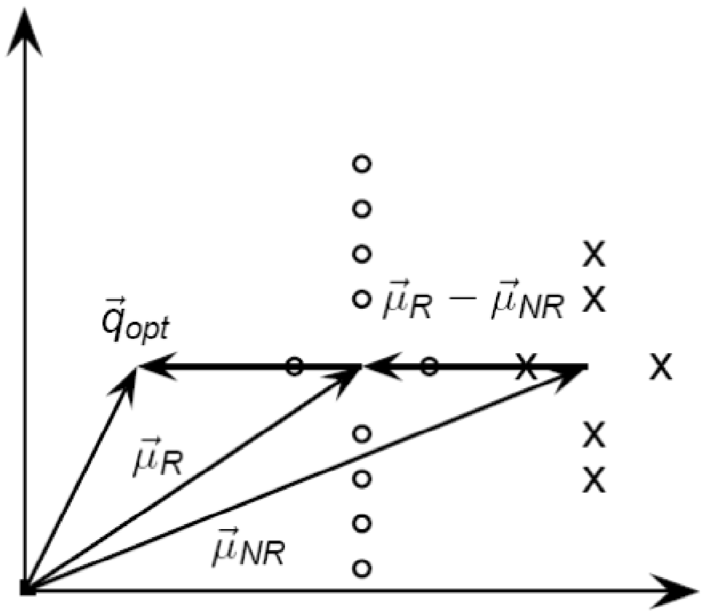
$\vec{\mu}_R - \vec{\mu}_{NR}$: difference vector

Rocchio illustrated



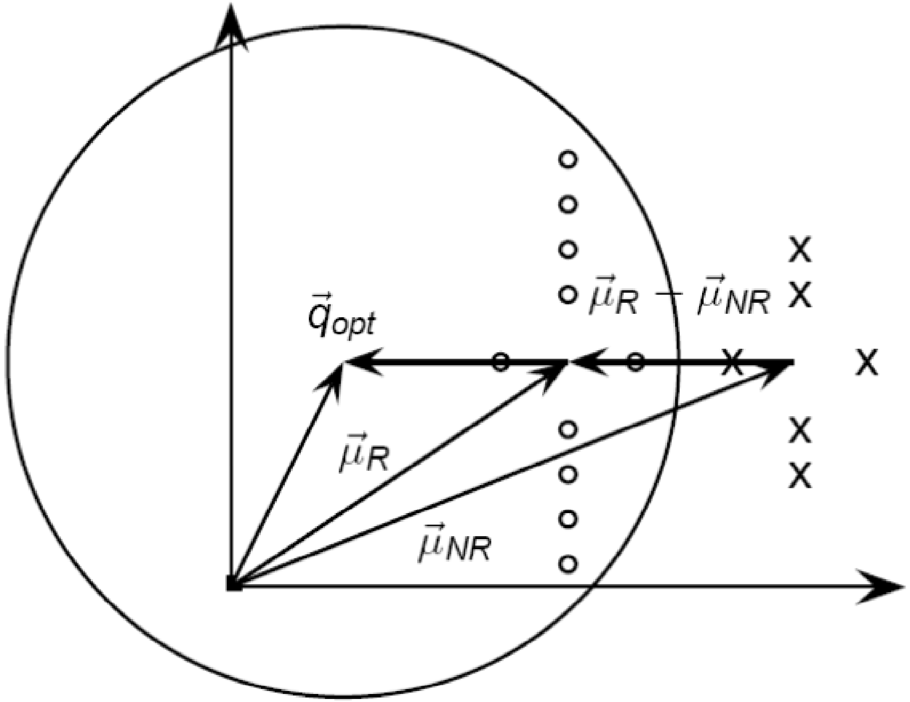
Add difference vector to $\vec{\mu}_R$ ...

Rocchio illustrated



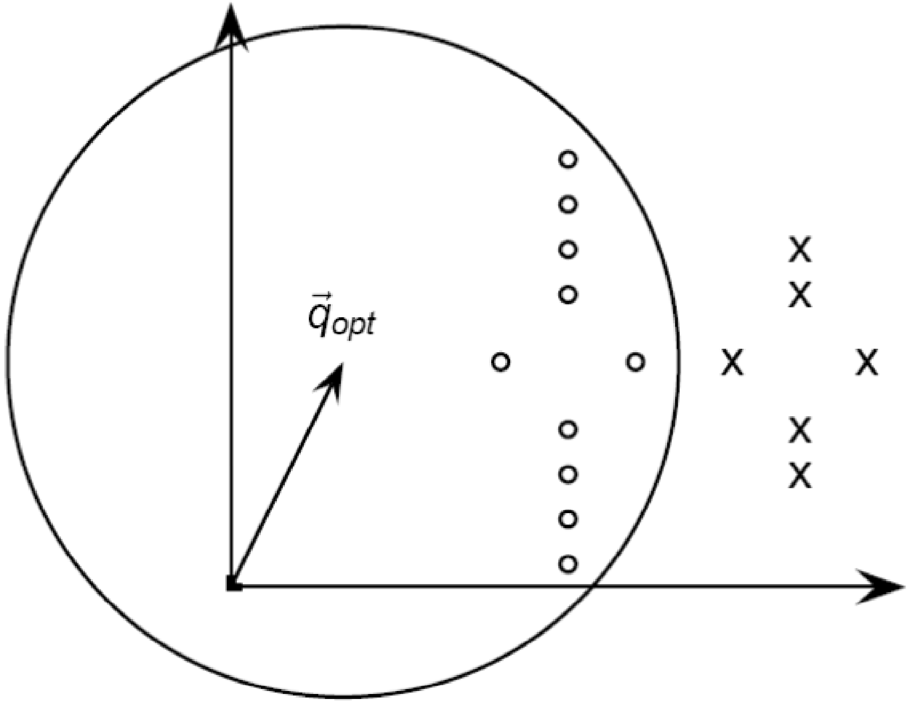
...to get $\vec{q}_{opt}$

Rocchio illustrated



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

Rocchio illustrated



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

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
- New query moves towards relevant documents and away from nonrelevant documents.
- Tradeoff α vs. β/γ: If we have a lot of judged documents, we want a higher β/γ.
- Set negative term weights to 0.
- "Negative weight" for a term doesn't make sense in the vector space model.

Exercise II

Suppose that a user's initial query is cheap CDs cheap DVDs extremely cheap CDs. The user examines two documents, *d*1 and *d*2. She judges *d*1, with the content *CDs cheap software cheap CDs* relevant and *d*2 with content *cheap thrills DVDs* nonrelevant. Assume that we are using direct term frequency (with no scaling and no document frequency). There is no need to length-normalize vectors. Using Rocchio relevance feedback, what would the revised query vector be after relevance feedback? Assume $\alpha = 1$, $\beta = 0.75$, $\gamma = 0.25$.

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