Introduction to Information Retrieval
http://informationretrieval.org

IIR 11: Probabilistic Information Retrieval

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Overview

Outline

1 **Recap**

2 Probabilistic Approach to IR

3 Basic Probability Theory

4 Probability Ranking Principle

5 Appraisal&Extensions

Relevance feedback: Basic idea

- The user issues a (short, simple) query.
- The search engine returns a set of documents.
- User marks some docs as relevant, some as nonrelevant.
- Search engine computes a new representation of the information need – should be better than the initial query.
- Search engine runs new query and returns new results.
- New results have (hopefully) better recall.
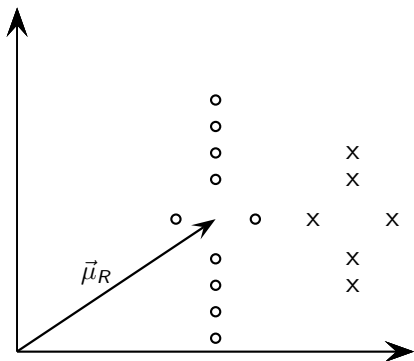
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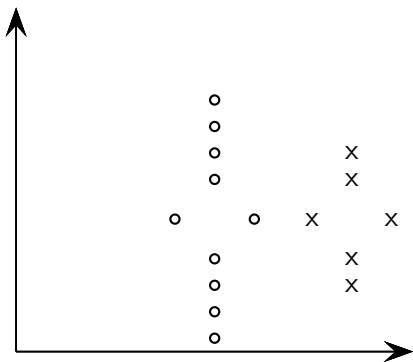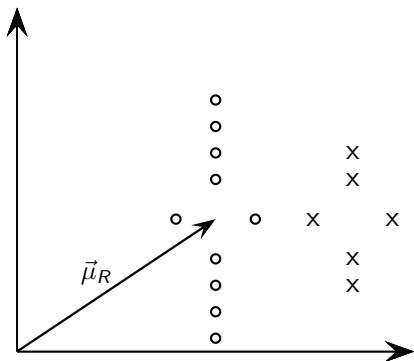
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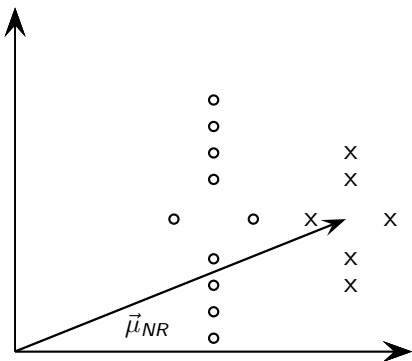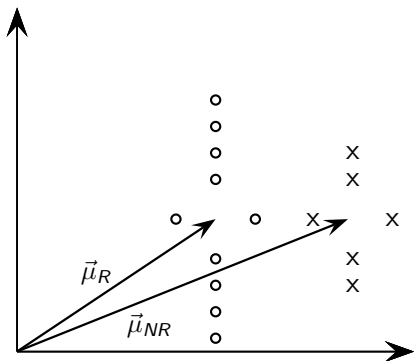
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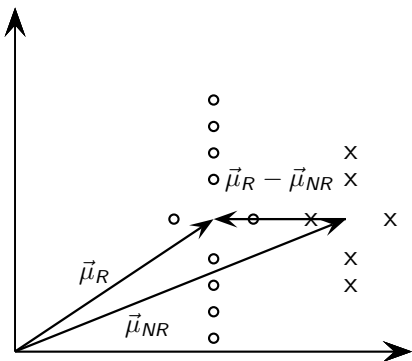
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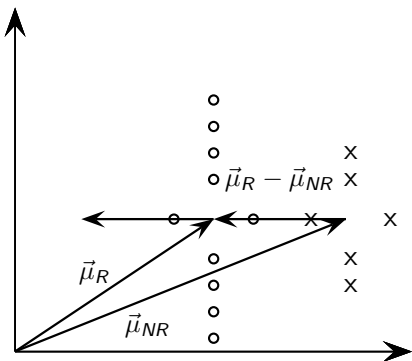
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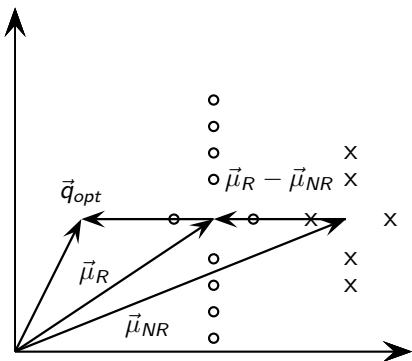
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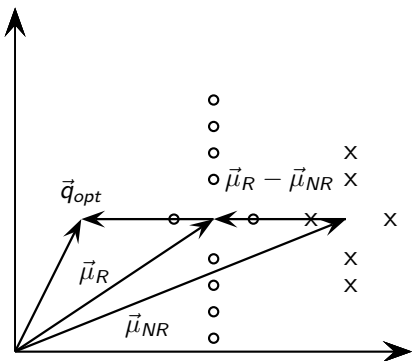
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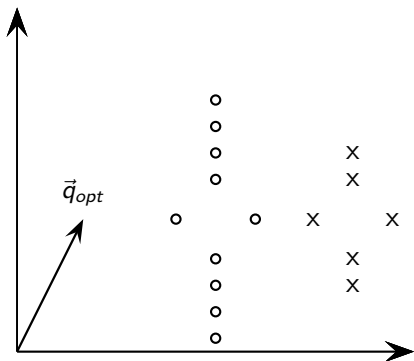
Types of query expansion

- Manual thesaurus (maintained by editors, e.g., PubMed)
- Automatically derived thesaurus (e.g., based on co-occurrence statistics)
- Query-equivalence based on query log mining (common on the web as in the "palm" example)

Query expansion at search engines

- Main source of query expansion at search engines: query logs
- Example 1: After issuing the query [herbs], users frequently search for [herbal remedies].
  - → "herbal remedies" is potential expansion of "herb".
- Example 2: Users searching for [flower pix] frequently click on the URL photobucket.com/flower. Users searching for [flower clipart] frequently click on the same URL.
  - → "flower clipart" and "flower pix" are potential expansions of each other.

Take-away today

- Probabilistically grounded approach to IR
- Probability Ranking Principle
- Models: BIM, BM25
- Assumptions these models make

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- Given some known relevant and nonrelevant documents, we compute weights for non-query terms that indicate how likely they will occur in relevant documents
- Today: develop a probabilistic approach for relevance feedback and also a general probabilistic model for IR

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- Probability theory provides a principled foundation for such reasoning under uncertainty
  - Probabilistic models exploit this foundation to estimate how likely it is that a document is relevant to a query

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- Bayesian networks for text retrieval
- Language model approach to IR
  - Important recent work, will be covered in the next lecture
- Probabilistic methods are one of the oldest but also one of the currently hottest topics in IR

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- Vector space model
  - The vector space model is also a formally defined model that supports ranking.
  - Why would we want to look for an alternative to the vector space model?

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- Vector space model: rank documents according to similarity to query.
- The notion of similarity does not translate directly into an assessment of "is the document a good document to give to the user or not?"
- The most similar document can be highly relevant or completely nonrelevant.
- Probability theory is arguably a cleaner formalization of what we really want an IR system to do: give relevant documents to the user.

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- Partition rule: if B can be divided into an exhaustive set of disjoint subcases, then $P(B)$ is the sum of the probabilities of the subcases. A special case of this rule gives:

$$P(B) = P(AB) + P(\overline{A}B)$$

Basic Probability Theory

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Bayes' Rule for inverting conditional probabilities:

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)} = \left[\frac{P(B|A)}{\sum_{X \in \{A, \overline{A}\}} P(B|X)P(X)} \right] P(A)$$

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Odds of an event provide a kind of multiplier for how probabilities change:

$$\text{Odds:} \qquad O(A) = \frac{P(A)}{P(\overline{A})} = \frac{P(A)}{1 - P(A)}$$

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- Probabilistic ranking orders documents decreasingly by their estimated probability of relevance w.r.t. query: $P(R = 1|d, q)$
- Assume that the relevance of each document is independent of the relevance of other documents

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- PRP in full
  - If [the IR] system's response to each [query] is a ranking of the documents [...] in order of decreasing probability of relevance to the [query], where the probabilities are estimated as accurately as possible on the basis of whatever data have been made available to the system for this purpose, the overall effectiveness of the system to its user will be the best that is obtainable on the basis of those data

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  - Different documents may have the same vector representation
- 'Independence': no association between terms (not true, but practically works - 'naive' assumption of Naive Bayes models)

Binary incidence matrix

	Anthony and Cleopatra	Julius Caesar	The Tempest	Hamlet	Othello	Macbeth	...
ANTHONY	1	1	0	0	0	1	
BRUTUS	1	1	0	1	0	0	
CAESAR	1	1	0	1	1	1	
CALPURNIA	0	1	0	0	0	0	
CLEOPATRA	1	0	0	0	0	0	
MERCY	1	0	1	1	1	1	
WORSER	1	0	1	1	1	0	
...							

Each document is represented as a binary vector $\in \{0, 1\}^{|V|}$.

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- Next: how exactly we can do this

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P(R = 1|\vec{x}, \vec{q}) &= \frac{P(\vec{x}|R = 1, \vec{q})P(R = 1|\vec{q})}{P(\vec{x}|\vec{q})} \\
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- Use statistics about the document collection to estimate these probabilities

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$$
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Deriving a Ranking Function for Query Terms (1)

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- Given a query q, ranking documents by $P(R = 1|d, q)$ is modeled under BIM as ranking them by $P(R = 1|\vec{x}, \vec{q})$

- Easier: rank documents by their odds of relevance (gives same ranking)

$$O(R|\vec{x}, \vec{q}) = \frac{P(R = 1|\vec{x}, \vec{q})}{P(R = 0|\vec{x}, \vec{q})} = \frac{\frac{P(R=1|\vec{q})P(\vec{x}|R=1,\vec{q})}{P(\vec{x}|\vec{q})}}{\frac{P(R=0|\vec{q})P(\vec{x}|R=0,\vec{q})}{P(\vec{x}|\vec{q})}}$$

$$= \frac{P(R = 1|\vec{q})}{P(R = 0|\vec{q})} \cdot \frac{P(\vec{x}|R = 1, \vec{q})}{P(\vec{x}|R = 0, \vec{q})}$$

- $\frac{P(R=1|\vec{q})}{P(R=0|\vec{q})}$ is a constant for a given query - can be ignored

Deriving a Ranking Function for Query Terms (2)

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It is at this point that we make the Naive Bayes conditional independence assumption that the presence or absence of a word in a document is independent of the presence or absence of any other word (given the query):

$$\frac{P(\vec{x}|R=1,\vec{q})}{P(\vec{x}|R=0,\vec{q})} = \prod_{t=1}^{M} \frac{P(x_t|R=1,\vec{q})}{P(x_t|R=0,\vec{q})}$$

So:

$$O(R|\vec{x},\vec{q}) = O(R|\vec{q}) \cdot \prod_{t=1}^{M} \frac{P(x_t|R=1,\vec{q})}{P(x_t|R=0,\vec{q})}$$

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- Let $u_t = P(x_t = 1 | R = 0, \vec{q})$ be the probability of a term appearing in a nonrelevant document
- Can be displayed as contingency table:

document		relevant ($R = 1$)	nonrelevant ($R = 0$)
Term present	$x_t = 1$	p_t	u_t
Term absent	$x_t = 0$	$1 - p_t$	$1 - u_t$

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Additional simplifying assumption: terms not occurring in the query are equally likely to occur in relevant and nonrelevant documents

- If $q_t = 0$, then $p_t = u_t$

Now we need only to consider terms in the products that appear in the query:

$$O(R|\vec{x}, \vec{q}) = O(R|\vec{q}) \cdot \prod_{t: x_t = q_t = 1} \frac{p_t}{u_t} \cdot \prod_{t: x_t = 0, q_t = 1} \frac{1 - p_t}{1 - u_t}$$

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- The left product is over query terms found in the document and the right product is over query terms not found in the document

Deriving a Ranking Function for Query Terms

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Including the query terms found in the document into the right product, but simultaneously dividing by them in the left product, gives:

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- $\rightarrow$ The only quantity that needs to be estimated to rank documents w.r.t a query is the left product
- Hence the Retrieval Status Value (RSV) in this model:

$$RSV_d = \log \prod_{t:x_t=q_t=1} \frac{p_t(1-u_t)}{u_t(1-p_t)} = \sum_{t:x_t=q_t=1} \log \frac{p_t(1-u_t)}{u_t(1-p_t)}$$

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Equivalent: rank documents using the log odds ratios for the terms in the query c_t:

$$c_t = \log \frac{p_t(1 - u_t)}{u_t(1 - p_t)} = \log \frac{p_t}{(1 - p_t)} - \log \frac{u_t}{1 - u_t}$$

- The odds ratio is the ratio of two odds: (i) the odds of the term appearing if the document is relevant ($p_t/(1 - p_t)$), and (ii) the odds of the term appearing if the document is nonrelevant ($u_t/(1 - u_t)$)

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- So BIM and vector space model are identical on an operational level . . .
- . . . except that the term weights are different.
- In particular: we can use the same data structures (inverted index etc) for the two models.

How to compute probability estimates

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For each term t in a query, estimate c_t in the whole collection using a contingency table of counts of documents in the collection, where df_t is the number of documents that contain term t:

	documents	relevant	nonrelevant	Total
Term present	$x_t = 1$	s	$\mathrm{df}_t - s$	df_t
Term absent	$x_t = 0$	$S - s$	$(N - \mathrm{df}_t) - (S - s)$	$N - \mathrm{df}_t$
	Total	S	$N - S$	N

$$p_t = s/S$$

$$u_t = (\mathrm{df}_t - s)/(N - S)$$

$$c_t = K(N, \mathrm{df}_t, S, s) = \log \frac{s/(S - s)}{(\mathrm{df}_t - s)/((N - \mathrm{df}_t) - (S - s))}$$

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- For example, use $S - s + 0.5$ in formula for $S - s$

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- Doc1: Obama rejects allegations about his own bad health
- Doc2: The plan is to visit Obama
- Doc3: Obama raises concerns with US health plan reforms

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Estimate the probability that the above documents are relevant to the query. Use a contingency table. These are the only three documents in the collection

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- The above approximation cannot easily be extended to relevant documents

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- This is the basis of probabilistic approaches to relevance feedback weighting in a feedback loop
- The exercise we just did was a probabilistic relevance feedback exercise since we were assuming the availability of relevance judgments.

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- Combining this method with the earlier approximation for u_t, the document ranking is determined simply by which query terms occur in documents scaled by their idf weighting
- For short documents (titles or abstracts) in one-pass retrieval situations, this estimate can be quite satisfactory

Outline

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- Next: how to add term frequency and length normalization to the probabilistic model.

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- BM25 is one of the most widely used and robust retrieval models

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Okapi BM25 basic weighting

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- Improve idf term [log N/df] by factoring in term frequency and document length.

$$RSV_d = \sum_{t \in q} \log \left[\frac{N}{\mathrm{df}_t} \right] \cdot \frac{(k_1 + 1)\mathrm{tf}_{td}}{k_1((1 - b) + b \times (L_d/L_{\mathrm{ave}})) + \mathrm{tf}_{td}}$$

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- b: tuning parameter controlling the scaling by document length

Exercise

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- Interpret BM25 weighting formula for $k_1 = 0$
- Interpret BM25 weighting formula for $k_1 = 1$ and $b = 0$
- Interpret BM25 weighting formula for $k_1 \mapsto \infty$ and $b = 0$
- Interpret BM25 weighting formula for $k_1 \mapsto \infty$ and $b = 1$

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- For long queries, use similar weighting for query terms

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- k_3: tuning parameter controlling term frequency scaling of the query

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- No length normalization of queries (because retrieval is being done with respect to a single fixed query)

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- tf_{tq}: term frequency in the query q
- k_3: tuning parameter controlling term frequency scaling of the query
- No length normalization of queries (because retrieval is being done with respect to a single fixed query)
- The above tuning parameters should ideally be set to optimize performance on a development test collection. In the absence of such optimization, experiments have shown reasonable values are to set k_1 and k_3 to a value between 1.2 and 2 and $b = 0.75$

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- I want something basic and simple $\rightarrow$ use vector space with tf-idf weighting.
- I want to use a state-of-the-art ranking model with excellent performance $\rightarrow$ use language models or BM25 with tuned parameters
- In between: BM25 or language models with no or just one tuned parameter

Take-away today

- Probabilistically grounded approach to IR
- Probability Ranking Principle
- Models: BIM, BM25
- Assumptions these models make

Resources

- Chapter 11 of IIR
- Resources at http://cislmu.org