Schütze: Relevance feedback & Query expansion

Introduction to Information Retrieval
http://informationretrieval.org

IIR 9: Relevance Feedback & Query Expansion

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2014-05-14
Overview

1. Recap
2. Motivation
3. Relevance feedback: Basics
4. Relevance feedback: Details
5. Query expansion
Outline

1 Recap
2 Motivation
3 Relevance feedback: Basics
4 Relevance feedback: Details
5 Query expansion
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.
This curve is typical of performance levels for the TREC benchmark.
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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.
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- 70% chance of getting the first document right (roughly)
- 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.
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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.
Google dynamic summaries for [vegetarian diet running]

No Meat Athlete | Vegetarian Running and Fitness
www.nomeatathlete.com/
Vegetarian Running and Fitness. ... (Oh, and did I mention Rich did it all on a plant-based diet?) In this episode of No Meat Athlete Radio, Doug and I had the ...
Vegetarian Recipes for Athletes - Vegetarian Shirts - How to Run Long - About

Running on a vegetarian diet – Top tips | Freedom2Train Blog
www.freedom2train.com/blog/?p=4
Nov 8, 2012 – In this article we look to tackle the issues faced by long distance runners on a vegetarian diet. By its very nature, a vegetarian diet can lead to ...

HowStuffWorks "5 Nutrition Tips for Vegetarian Runners"
www.howstuffworks.com/.../running/.../5-nutrition-tips-for-vegetarian-r...
Even without meat, you can get enough fuel to keep on running. Stockbyte/Thinkstock ...
Unfortunately, a vegetarian diet is not a panacea for runners. It could, for ...

Nutrition Guide for Vegetarian and Vegan Runners - The Running Bug
therunningbug.co.uk/.../nutrition-guide-for-vegetarian-and-vegan-runn... 
Feb 28, 2012 – The Running Bug’s guide to nutrition for vegetarian and vegan ...
different types of vegetarian diet ranging from lacto-ovo-vegetarians who eat ...

Vegetarian Runner
www.vegetarianrunner.com/
Vegetarian Runner - A resource center for vegetarianism and running and how to make sure you have proper nutrition as an athlete with a vegetarian diet.
Take-away today
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- **Interactive relevance feedback**: improve initial retrieval results by telling the IR system which docs are relevant / nonrelevant
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- **Query expansion**: improve retrieval results by adding synonyms / related terms to the query
Take-away today

- **Interactive relevance feedback**: improve initial retrieval results by telling the IR system which docs are relevant / nonrelevant
- **Best known relevance feedback method**: Rocchio feedback
- **Query expansion**: improve retrieval results by adding synonyms / related terms to the query
  - **Sources for related terms**: Manual thesauri, automatic thesauri, query logs
How can we improve recall in search?

- Main topic today: two ways of improving recall: relevance feedback and query expansion

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- We want to change this:
  - Return relevant documents even if there is no term match with the (original) query
Recall
Loose definition of recall in this lecture: “increasing the number of relevant documents returned to user”
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This may actually decrease recall on some measures, e.g., when expanding “jaguar” to “jaguar AND panthera”
Recall

- Loose definition of recall in this lecture: “increasing the number of relevant documents returned to user”
- This may actually decrease recall on some measures, e.g., when expanding “jaguar” to “jaguar AND panthera”
  - …which eliminates some relevant documents, but increases relevant documents returned on top pages
Options for improving recall
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- Local: Do a “local”, on-demand analysis for a user query
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- Global: Do a global analysis once (e.g., of collection) to produce thesaurus
  - Use thesaurus for query expansion
  - Part 2
Google used to expose query expansion in UI

- \textit{flights} -flight
- \textit{dogs} -dog

no longer available:

http://searchenginewatch.com/article/2277383/Google-Kill
Relevance feedback: Basic idea
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Relevance feedback: Basic idea

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Relevance feedback: Basic idea

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- Search engine runs new query and returns new results.
- New results have (hopefully) better recall.
- We will use the term ad hoc retrieval to refer to regular retrieval without relevance feedback.
Relevance feedback: Examples

- We will now look at three different examples of relevance feedback that highlight different aspects of the process.
Relevance Feedback: Example 1

Shopping related 607,000 images are indexed and classified in the database
Only One keyword is allowed!!!

bike

Search

Designed by Baris Sumengen and Shawn Newsam

Powered by JLAMP2000 (Java, Linux, Apache, Mysql, Perl, Windows2000)
Results for initial query
User feedback: Select what is relevant
Results after relevance feedback
Vector space example: query “canine” (1)

source: Fernando Díaz
Similarity of docs to query “canine”

source:
Fernando Díaz
User feedback: Select relevant documents
User feedback: Select relevant documents

source: Fernando Díaz
Results after relevance feedback
Results after relevance feedback

source: Fernando Díaz
Example 3: A real (non-image) example
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Initial query: [new space satellite applications]
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Results for initial query: \((r = \text{rank})\)

\[
\begin{array}{cccc}
\text{r} & \text{rank} & \text{Story Title} \\
1 & 0.539 & NASA Hasn’t Scrapped Imaging Spectrometer \\
2 & 0.533 & NASA Scratches Environment Gear From Satellite Plan \\
3 & 0.528 & Science Panel Backs NASA Satellite Plan, But Urges Launches of Smaller Probes \\
4 & 0.526 & A NASA Satellite Project Accomplishes Incredible Feat: Staying Within Budget \\
5 & 0.525 & Scientist Who Exposed Global Warming Proposes Satellites for Climate Research \\
6 & 0.524 & Report Provides Support for the Critics Of Using Big Satellites to Study Climate \\
7 & 0.516 & Arianespace Receives Satellite Launch Pact From Telesat Canada \\
8 & 0.509 & Telecommunications Tale of Two Companies \\
\end{array}
\]
Example 3: A real (non-image) example

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\end{array}
\]

User then marks relevant documents with “+”.
Example 3: A real (non-image) example

Initial query: [new space satellite applications]

Results for initial query: ($r = \text{rank}$)

<table>
<thead>
<tr>
<th>$r$</th>
<th>1</th>
<th>0.539</th>
<th>NASA Hasn’t Scrapped Imaging Spectrometer</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>2</td>
<td>0.533</td>
<td>NASA Scratches Environment Gear From Satellite Plan</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>0.528</td>
<td>Science Panel Backs NASA Satellite Plan, But Urges Launches of Smaller Probes</td>
</tr>
<tr>
<td></td>
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<tr>
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<td>8</td>
<td>0.509</td>
<td>Telecommunications Tale of Two Companies</td>
</tr>
</tbody>
</table>

User then marks relevant documents with “+”. 
Expanded query after relevance feedback

<table>
<thead>
<tr>
<th>Term</th>
<th>TF-IDF Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>new</td>
<td>2.074</td>
</tr>
<tr>
<td>satellite</td>
<td>30.816</td>
</tr>
<tr>
<td>nasa</td>
<td>5.991</td>
</tr>
<tr>
<td>launch</td>
<td>4.196</td>
</tr>
<tr>
<td>instrument</td>
<td>3.516</td>
</tr>
<tr>
<td>bundespost</td>
<td>3.004</td>
</tr>
<tr>
<td>rocket</td>
<td>2.790</td>
</tr>
<tr>
<td>broadcast</td>
<td>2.003</td>
</tr>
<tr>
<td>oil</td>
<td>0.836</td>
</tr>
<tr>
<td>space</td>
<td>15.106</td>
</tr>
<tr>
<td>application</td>
<td>5.660</td>
</tr>
<tr>
<td>eos</td>
<td>5.196</td>
</tr>
<tr>
<td>aster</td>
<td>3.972</td>
</tr>
<tr>
<td>arianespace</td>
<td>3.446</td>
</tr>
<tr>
<td>ss</td>
<td>2.806</td>
</tr>
<tr>
<td>scientist</td>
<td>2.053</td>
</tr>
<tr>
<td>earth</td>
<td>1.172</td>
</tr>
<tr>
<td>measure</td>
<td>0.646</td>
</tr>
</tbody>
</table>

Compare to original query: [new space satellite applications]
### Results for expanded query (old ranks in parens)

<table>
<thead>
<tr>
<th>r</th>
<th>1 (2)</th>
<th>0.513</th>
<th>NASA Scratches Environment Gear From Satellite Plan</th>
</tr>
</thead>
<tbody>
<tr>
<td>r</td>
<td>2 (1)</td>
<td>0.500</td>
<td>NASA Hasn’t Scrapped Imaging Spectrometer</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>0.493</td>
<td>When the Pentagon Launches a Secret Satellite,</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Space Sleuths Do Some Spy Work of Their Own</td>
</tr>
<tr>
<td>r</td>
<td>4</td>
<td>0.493</td>
<td>NASA Uses ‘Warm’ Superconductors For Fast Circuit</td>
</tr>
<tr>
<td>r</td>
<td>5 (8)</td>
<td>0.492</td>
<td>Telecommunications Tale of Two Companies</td>
</tr>
<tr>
<td>r</td>
<td>6</td>
<td>0.491</td>
<td>Soviets May Adapt Parts of SS-20 Missile For Com-</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>mercial Use</td>
</tr>
<tr>
<td></td>
<td>7</td>
<td>0.490</td>
<td>Gaping Gap: Pentagon Lags in Race To Match the</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Soviets In Rocket Launchers</td>
</tr>
<tr>
<td></td>
<td>8</td>
<td>0.490</td>
<td>Rescue of Satellite By Space Agency To Cost $90</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Million</td>
</tr>
</tbody>
</table>
Key concept for relevance feedback: Centroid
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- The centroid is the center of mass of a set of points.
Key concept for relevance feedback: Centroid

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- Recall that we represent documents as points in a high-dimensional space.
Key concept for relevance feedback: Centroid

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- Thus: we can compute centroids of documents.
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 document \( d \).
Centroid: Examples
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Rocchio algorithm
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- The Rocchio algorithm implements relevance feedback in the vector space model.
Rocchio algorithm

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- Rocchio chooses the query $\tilde{q}_{opt}$ that maximizes

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

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

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- Intent: $\tilde{q}_{opt}$ is the vector that separates relevant and nonrelevant docs maximally.
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$D_r$: set of relevant docs; $D_{nr}$: set of nonrelevant docs

- Intent: $\vec{q}_{opt}$ is the vector that separates relevant and nonrelevant docs maximally.
- Making some additional assumptions, we can rewrite $\vec{q}_{opt}$ as:

$$
\vec{q}_{opt} = \mu(D_r) + [\mu(D_r) - \mu(D_{nr})]
$$
Rocchio algorithm
Rocchio algorithm

- The optimal query vector is:

\[
\tilde{q}_{opt} = \mu(D_r) + [\mu(D_r) - \mu(D_{nr})]
\]

\[
= \frac{1}{|D_r|} \sum_{\tilde{d}_j \in D_r} \tilde{d}_j + \left[ \frac{1}{|D_r|} \sum_{\tilde{d}_j \in D_r} \tilde{d}_j - \frac{1}{|D_{nr}|} \sum_{\tilde{d}_j \in D_{nr}} \tilde{d}_j \right]
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Rocchio algorithm

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\]

- We move the centroid of the relevant documents by the difference between the two centroids.
Exercise: Compute Rocchio vector

circles: relevant documents, Xs: nonrelevant documents
compute: $\vec{q}_{opt} = \mu(D_r) + [\mu(D_r) - \mu(D_{nr})]$
Rocchio illustrated
Rocchio illustrated

\( \mu_R \): centroid of relevant documents
Rocchio illustrated

\[ \vec{\mu}_R \] does not separate relevant/nonrelevant.
Rocchio illustrated

\[ \vec{\mu}_{NR} \text{: centroid of nonrelevant documents} \]
Rocchio illustrated

\[ \vec{\mu}_R \]

\[ \vec{\mu}_{NR} \]
Rocchio illustrated

\[ \vec{\mu}_R - \vec{\mu}_{NR} : \text{difference vector} \]
Rocchio illustrated

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

\[ \vec{q}_{opt} \]

\[ \vec{\mu}_R - \vec{\mu}_{NR} \]

\[ \ldots \text{to get } \vec{q}_{opt} \]
Rocchio illustrated

\[ \vec{q}_{opt} \] separates relevant/nonrelevant perfectly.
Rocchio illustrated

\( \tilde{q}_{opt} \) separates relevant/nonrelevant perfectly.
Terminology
So far, we have used the name Rocchio for the theoretically better motivated original version of Rocchio.
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The implementation that is actually used in most cases is the SMART implementation – this SMART version of Rocchio is what we will refer to from now on.
Rocchio 1971 algorithm (SMART)
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- Used in practice:

\[
\tilde{q}_m = \alpha \tilde{q}_0 + \beta \mu(D_r) - \gamma \mu(D_{nr})
\]

\[
= \alpha \tilde{q}_0 + \beta \frac{1}{|D_r|} \sum_{\tilde{d}_j \in D_r} \tilde{d}_j - \gamma \frac{1}{|D_{nr}|} \sum_{\tilde{d}_j \in D_{nr}} \tilde{d}_j
\]

$q_m$: modified query vector; $q_0$: original query vector; $D_r$ and $D_{nr}$: sets of known relevant and nonrelevant documents respectively; $\alpha$, $\beta$, and $\gamma$: weights
Rocchio 1971 algorithm (SMART)

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- New query moves towards relevant documents and away from nonrelevant documents.

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- \( q_m \): modified query vector; \( q_0 \): original query vector; \( D_r \) and \( D_{nr} \): sets of known relevant and nonrelevant documents respectively; \( \alpha, \beta, \text{and} \gamma \): weights

- New query moves towards relevant documents and away from nonrelevant documents.

- Tradeoff \( \alpha \) vs. \( \beta/\gamma \): If we have a lot of judged documents, we want a higher \( \beta/\gamma \).
Rocchio 1971 algorithm (SMART)

- Used in practice:

\[
\tilde{q}_m = \alpha \tilde{q}_0 + \beta \mu(D_r) - \gamma \mu(D_{nr})
\]

\[
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$q_m$: modified query vector; $q_0$: original query vector; $D_r$ and $D_{nr}$: sets of known relevant and nonrelevant documents respectively; $\alpha$, $\beta$, and $\gamma$: weights

- New query moves towards relevant documents and away from nonrelevant documents.

- Tradeoff $\alpha$ vs. $\beta/\gamma$: If we have a lot of judged documents, we want a higher $\beta/\gamma$.

- Set negative term weights to 0.
Rocchio 1971 algorithm (SMART)

- Used in practice:

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Positive vs. negative relevance feedback
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- For example, set $\beta = 0.75$, $\gamma = 0.25$ to give higher weight to positive feedback.
- Many systems only allow positive feedback.
Relevance feedback: Assumptions
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- Relevance feedback on tobacco docs will not help with finding docs on developing countries.
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Empirically, one round of relevance feedback is often very useful. Two rounds are marginally useful.
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- 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 relevance feedback is the “best use” of the user’s time.
Exercise

- Do search engines use relevance feedback?
- Why?
Relevance feedback: Problems
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  - Long queries are expensive to process.
- Users are reluctant to provide explicit feedback.
- It’s often hard to understand why a particular document was retrieved after applying relevance feedback.
- The search engine Excite had full relevance feedback at one point, but abandoned it later.
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  - If you do several iterations of pseudo-relevance feedback, then you will get query drift for a large proportion of queries.
Pseudo-relevance feedback at TREC4
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- Cornell SMART system
Pseudo-relevance feedback at TREC4

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- Results show number of relevant documents out of top 100 for 50 queries (so total number of documents is 5000):

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- The pseudo-relevance feedback method used added only 20 terms to the query. (Rocchio will add many more.)
- This demonstrates that pseudo-relevance feedback is effective on average.
Query expansion: Example
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![Yahoo Search Result for "palm"](image)

**Official Palm Store**
store.palm.com  Free shipping on all handhelds and more at the official Palm store.

**Palms Hotel - Best Rate Guarantee**
www.vegas.com  Book the Palms Hotel Casino with our best rate guarantee at VEGAS.com, the official Vegas travel site.

**Palm Pilots - Palm Downloads**
Yahoo! Shortcut - About

1. **Palm, Inc.**
Makers of handheld PDA devices that allow mobile users to manage schedules, contacts, and other personal and business information.
Category: B2B > Personal Digital Assistants (PDAs)
www.palm.com  20k - Cached - More from this site - Save
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- Main information we use: (near-)synonymy
“Global” resources used for query expansion
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- Query-equivalence based on query log mining (common on the web as in the “palm” example)
Thesaurus-based query expansion
For each term $t$ in the query, expand the query with words the thesaurus lists as semantically related with $t$. 
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- It’s very expensive to create a manual thesaurus and to maintain it over time.
Example for manual thesaurus: PubMed
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PubMed Query:

("neoplasms"[MeSH Terms] OR cancer[Text Word])
Automatic thesaurus generation
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- Co-occurrence is more robust, grammatical relations are more accurate.
Co-occurrence-based thesaurus: Examples
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<thead>
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<th>Nearest neighbors</th>
</tr>
</thead>
<tbody>
<tr>
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<td>absurd whatsoever totally exactly nothing</td>
</tr>
<tr>
<td>bottomed</td>
<td>dip copper drops topped slide trimmed</td>
</tr>
<tr>
<td>captivating</td>
<td>shimmer stunningly superbly plucky witty</td>
</tr>
<tr>
<td>doghouse</td>
<td>dog porch crawling beside downstairs</td>
</tr>
<tr>
<td>makeup</td>
<td>repellent lotion glossy sunscreen skin gel</td>
</tr>
<tr>
<td>mediating</td>
<td>reconciliation negotiate case conciliation</td>
</tr>
<tr>
<td>keeping</td>
<td>hoping bring wiping could some would</td>
</tr>
<tr>
<td>lithographs</td>
<td>drawings Picasso Dali sculptures Gauguin</td>
</tr>
<tr>
<td>pathogens</td>
<td>toxins bacteria organisms bacterial parasite</td>
</tr>
<tr>
<td>senses</td>
<td>grasp psyche truly clumsy naive innate</td>
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WordSpace demo on web
Query expansion at search engines
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  - “flower clipart” and “flower pix” are potential expansions of each other.
Interactive relevance feedback: improve initial retrieval results by telling the IR system which docs are relevant / nonrelevant

Best known relevance feedback method: Rocchio feedback

Query expansion: improve retrieval results by adding synonyms / related terms to the query

Sources for related terms: Manual thesauri, automatic thesauri, query logs
Resources

- Chapter 9 of IIR
- Resources at http://cislmu.org
  - Salton and Buckley 1990 (original relevance feedback paper)
  - Spink, Jansen, Ozmultu 2000: Relevance feedback at Excite
  - Justin Bieber: related searches fail
  - Word Space
  - Schütze 1998: Automatic word sense discrimination (describes a simple method for automatic thesaurus generation)