Information Retrieval

Advanced methods

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Synonymy

- In most collections, the same concept may be referred to using **different words**
- This issue, known as **synonymy**, has an impact on the **recall** of most information retrieval systems
- For example, you would want a search for **aircraft** to also match the word **airplane**

Query expansion (1/2)

- Idea: we augment the query with keywords synonyms.

User Query: “car”

Expanded Query: “car cars automobile automobiles auto”

Query expansion (2/2)

- Idea: we augment the query with keywords synonyms and related terms.
- A variety of automatic or semi-automatic query expansion techniques have been developed
  - goal is to improve effectiveness by matching related terms
  - semi-automatic techniques require user interaction to select best expansion terms
- Query suggestion is a related technique
  - alternative queries, not necessarily more terms

Related terms

- Where to find terms related to a query, in order to expand it?
  - Controlled vocabularies
    - **Wordnet**
  - Text collection
    - **Co-occuring** terms
    - Terms from relevant documents
    - Terms from retrieved documents
    - Terms in an adjacent **window** (of relevant or retrieved documents)

Thesaurus query expansion

- Automatic expansion based on general controlled vocabulary (thesaurus) is **not much effective**
  - It does not take **context** into account:

Query: “tropical fish tanks”

Expanded query: “tropical fish tanks aquariums”

Query: “armor for tanks”

Expanded query: “armor for tanks aquariums”

Co-occurence query expansion

- Instead of using a thesaurus, related keyword can be extracted from text collections.
- Different measures of **co-occurrence** can be used to find related keywords:
  - Dice's coefficient
  - Mutual information
  - Expected mutual information
  - Pearson's Chi-squared (χ^2)
- Measure are based on entire documents or smaller parts of documents (sentences, paragraphs, windows.). We will consider entire documents now, for simplicity.

Dice's coefficient 1/2

- Suppose we want to find words related to "fish"
- How to measure the "relatedness" of a second term to the word fish?
- A measure of co-occurrence:

$$\frac{\text{How many times they appear } \textbf{together}}{\text{How many times they appear } \textbf{singularly}}$$

- Idea: the higher this score, the more related should be the two words!

Dice's coefficient 2/2

- Term association measure used since the earliest studies of **term similarity** and **automatic thesaurus construction** in the 1960s and 1970s.
- Given two words **a** and **b**, it is formally defined as:

$$2n_{ab}/(n_a + n_b)$$

- $\mathbf{n_a}$ is the number of documents containing word **a**.
- $\mathbf{n_b}$ is the number of documents containing word **b**.
- $\mathbf{n_{ab}}$ is the number of documents containing **both** words **a** and **b**.

Mutual information

- It has been used in a number of studies of word collocation.
- Similar to Dice, based on probabilities.
- For two words a and b, it is defined as

$$log \frac{P(a,b)}{P(a)P(b)}$$

- **P(a)** is the probability that word **a** occurs in a text window.
- **P(b)** is the probability that word **b** occurs in a text window.
- **P(a, b)** is the probability that a and b occur in the same text window.

Mutual information: problem

- A problem with mutual information is that it tends to favor low-frequency terms.
- For example:
  - Consider two words **a** and **b**:
    - $\mathbf{n_a} = \mathbf{n_b} = 10$
    - co-occur **half the time** ($n_{ab} = 5$).
    - Mutual information for these two terms is $\mathbf{5 \cdot 10^{-2}}$.
  - Consider two words **c** and **d**:
    - $\mathbf{n_c} = \mathbf{n_d} = 1000$
    - co-occur **half the time** ($n_{cd} = 500$).
    - Mutual information for these two terms is $\mathbf{5 \cdot 10^{-4}}$.
- Both pairs co-occur half of the time they occur. However they have different mutual information: 0.05 vs 0.0005

Expected mutual information

- The *expected mutual information* addresses the **low-frequency problem** by weighting the mutual information value using the probability P(a,b).
- We are primarily interested in the case where both terms occur, giving the formula:

$$P(a,b) \cdot log \frac{P(a,b)}{P(a)P(b)}$$

Pearson's Chi-squared (χ^2)

- This measure
  - compares the number of co-occurrences of two words with the expected number of co-occurrences if the two words were independent
  - normalizes this comparison by the expected number.

$$\frac{(n_{ab} - N \cdot \frac{n_a}{N} \cdot \frac{n_b}{N})^2}{N \cdot \frac{n_a}{N} \cdot \frac{n_b}{N}}$$

- $N \cdot \frac{n_a}{N} \cdot \frac{n_b}{N}$ is the expected number of co-occurrences if the two terms occur independently.

Query expansion example

- Using a **TREC news collection** the four co-occurrence measures are applied on a document level
- Top-5 related words are shown.
- Word for which we are searching related terms is

fish

Query expansion results

Dice's coefficient	Mutual information	Expected mutual information	Pearson's Chi-squared
species	zoologico	water	arslq
wildlife	zapanta	species	happyman
fishery	wrint	wildlife	outerlimit
water	wpfmc	fishery	sportk
fisherman	wighout	sea	lingcod

- Mutual information favors very rare words (sometimes mistyped words!).
- Chi-squared also capture unusual words.
- Dice's coefficient and expected mutual information are more suitable for IR query expansion.

Query expansion with relevance feedback (RF)

- Relevance feedback is a query expansion and refinement technique based on **user feedback**.
- General idea:
  1. The user issues a (short, simple) query.
  2. The system returns an initial set of results.
  3. The user marks some returned documents as relevant (or non relevant).
  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.

RF example (1/2)

Query: *New space satellite applications*		
Rank	Document Title	User Feedback
1	**NASA Hasn’t Scrapped Imaging Spectrometer**	**YES**
2	**NASA Scratches Environment Gear From Satellite Plan**	**YES**
3	Science Panel Backs NASA Satellite Plan, But Urges Launches of Smaller Probes	NO
4	A NASA Satellite Project Accomplishes Incredible Feat: Staying Within Budget	NO
5	Scientist Who Exposed Global Warming Proposes Satellites for Climate Research	NO
6	Report Provides Support for the Critics Of Using Big Satellites to Study Climate	NO
7	Arianespace Receives Satellite Launch Pact From Telesat Canada	NO
8	**Telecommunications Tale of Two Companies**	**YES**

RF example (2/2)

Query: *New space satellite applications*

Documents relevant
from the user feedback

#1	**NASA Hasn't Scrapped Imaging Spectrometer**
#2	**NASA Scratches Environment Gear From Satellite Plan**
#8	**Telecommunications Tale of Two Companies**

Recurring keywords in
relevant documents

new, space, satellite,
application,
**nasa, eos, launch,
aster, instrument,
arianespace,
bundespost, ss,
rocket, scientist,
broadcast, earth,
oil, measure**

Expanded query: *new space satellite application* ***nasa eos launch aster instrument arianespace bundespost ss rocket scientist broadcast earth oil measure***

Pseudo RF

- *Pseudo relevance feedback*, also known as *blind relevance feedback*, provide a method for **automatic** relevance feedback.
- It automates the manual part of RF, so that the user gets improved retrieval performance **without an extended interaction**.
- The method involves the following:
  1. normal retrieval to find an initial set of most relevant documents
  2. assume that the top **k** ranked documents are **relevant**
  3. compute RF as before under this assumption.

Machine Learning and IR: Why?

- Suppose we want to consider (**combining**) at the same time:
  - term frequency in the document body
  - term frequency in the document title
  - document length
  - document popularity (e.g. PageRank)
- ...as “features” to estimate the relevance, how we should **weight** each feature?
- A **learning to rank** model learn the weights from a training set of features and relevance judgements.

Machine Learning and IR

- Idea: using machine learning (ML) to build a classifier that classify documents into **relevant and non-relevant classes**
- Although ML has been around for a long time, this good idea has been researched only recently
  - **Limited training data**: it was very hard to gather test collection queries and relevance judgments that are representative of real user needs
  - Traditional ranking functions in IR used a very **small number of features**:
    - Term frequency
    - Inverse document frequency
    - Document length

Learning to rank

- In the last 10 years things have changed:
- Modern systems – especially on the Web – use a **great number of features**
  - Log frequency of query word in anchor text
  - Query word color on page
  - # of images on page
  - # of (out) links on page
  - PageRank of page
  - URL length
  - URL contains query terms
  - Page edit recency
  - Page length
  - ...
- Lot of **training data** is available from huge query logs that are collected from user interactions

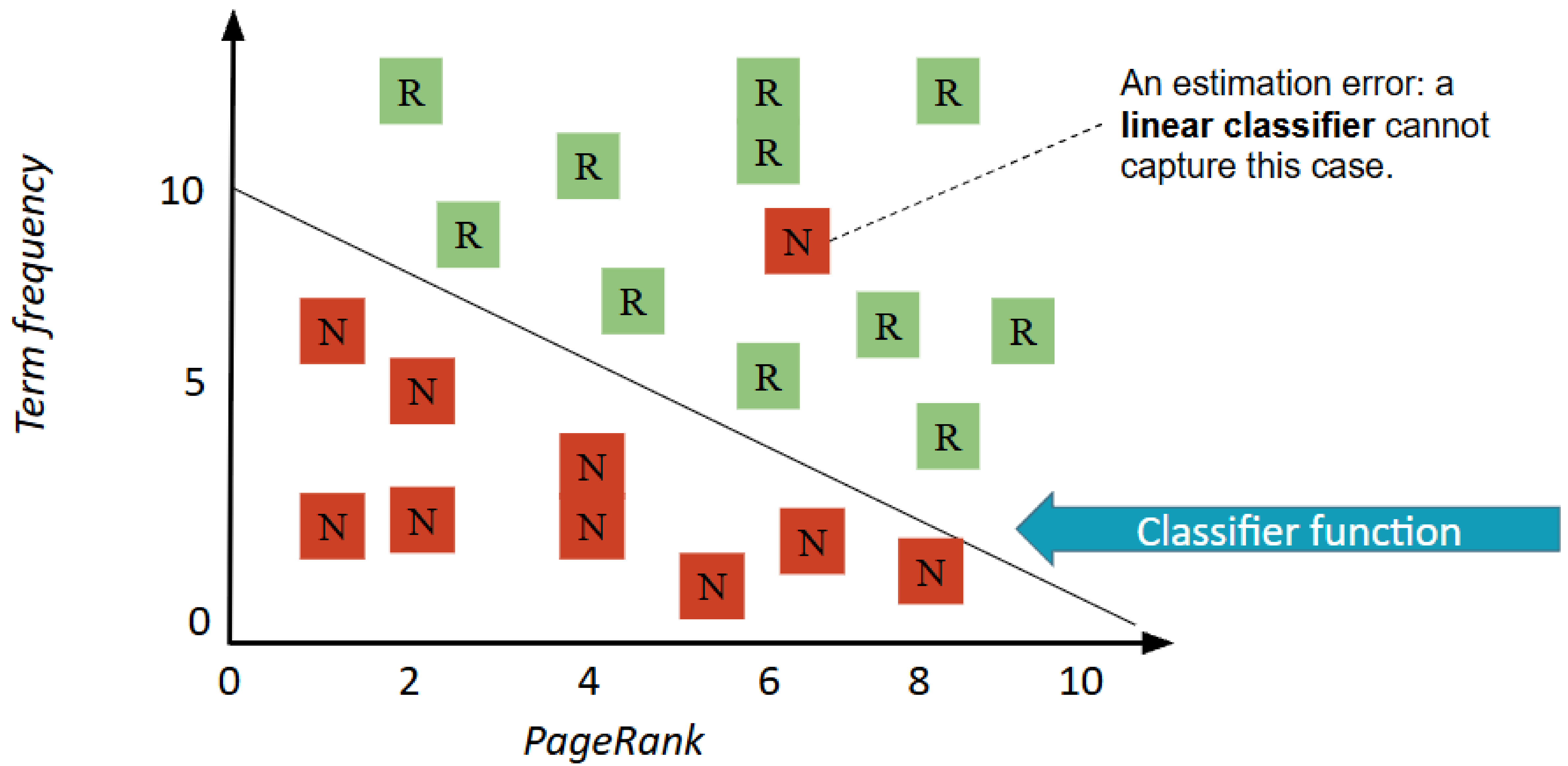
Example: features

- Suppose we are considering two features in each document:
  - Term frequency ***tf***: how many times the query terms are found in the document
  - Pagerank ***pr***: popularity of the document
- Training set is made of (tf,pr) vectors each with a correspondent relevance judgment
- A learning to rank model given the document features as input (tf,pr), should output the estimated relevance.

Example: training data

Query: "*fish tank price*"		INPUT		OUTPUT
Training sample	**Doc ID**	**Term frequency**	**PageRank**	**judgement**
001	37	11	3	1 (relevant)
002	37	0	8	0 (nonrelevant)
003	238	8	2	1 (relevant)
004	238	1	2	0 (nonrelevant)
005	1741	5	6	1 (relevant)
006	2094	18	1	1 (relevant)
007	3191	3	2	0 (nonrelevant)

Example: classifier



- The learned **weights** are the **coefficients** of a linear function.
- The function represent the learned model that **separates** relevant (output 1) from non relevant (output 0) documents based on the two input variables.

Relevance feedback and learning

- RF is a simple example of using supervised machine learning in information retrieval: **training data** (i.e. the identified relevant and non-relevant documents) is used to improve the system's performance.
- In the last example we have used the relevance judgements of a test collection to train a classifier: this is called **offline learning.**
- Using relevance feedback to tune the classifier weights and improve its accuracy is an example of **online learning**.

References

[Christopher D. Manning, Prabhakar Raghavan and Hinrich Schütze](#)

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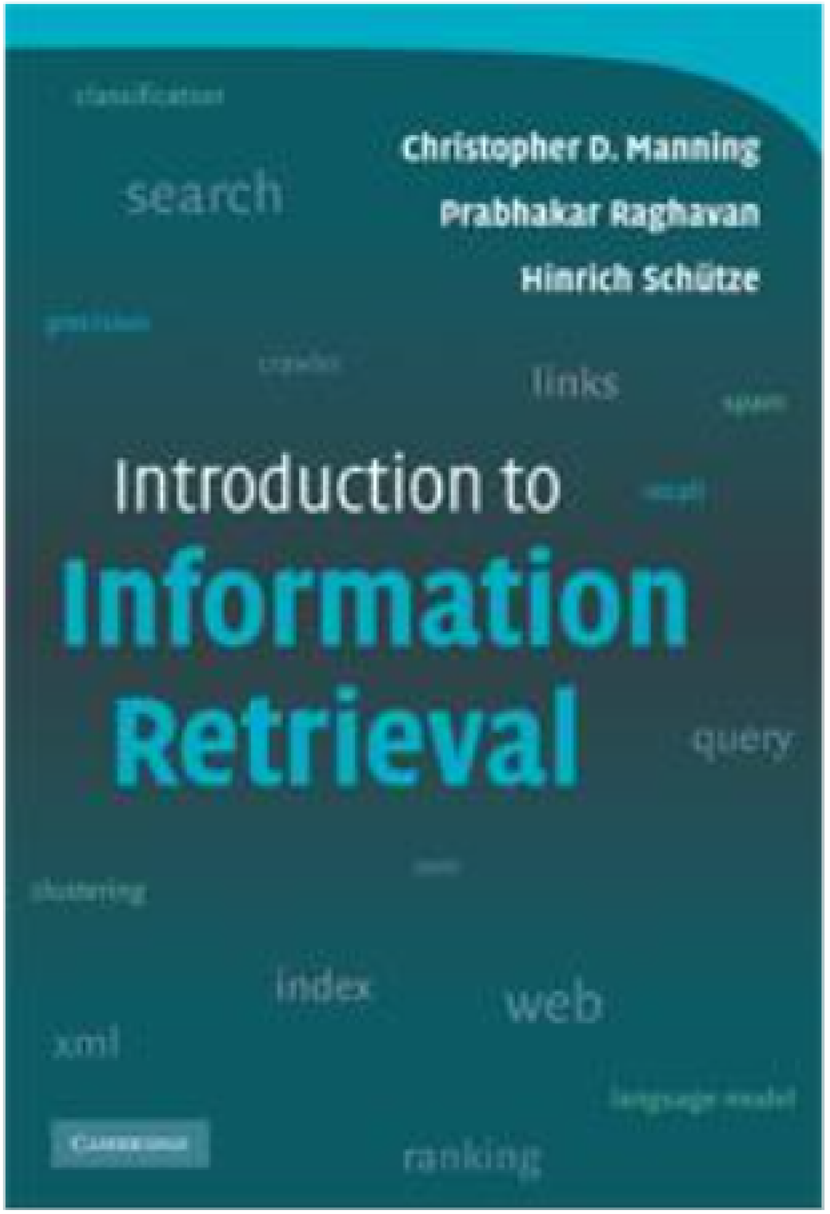

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