Search Engines

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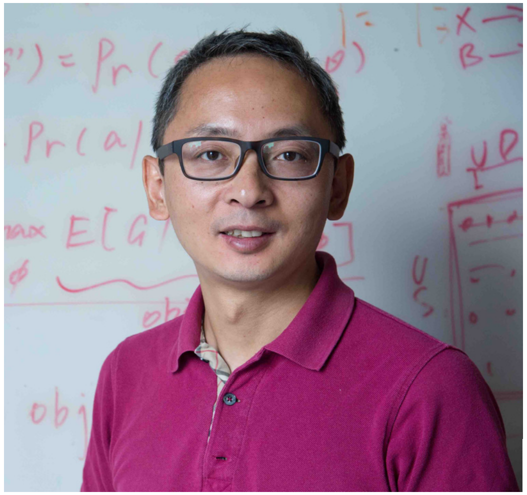
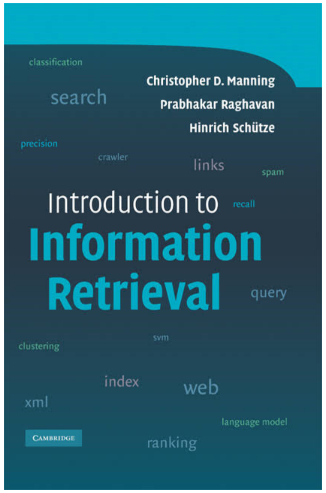
Acknowledgement and References



- Dr. Jun Wang is the Chair Professor of Data Science and Founding Director of MSc Web Science and Big Data Analytics, Dept. of Computer Science, University College London (UCL)
- Most of slides in this lecture is based on Jun's Information Retrieval and Data Mining (IRDM) course at UCL

- Referred text book:

  Christopher D. Manning, Prabhakar Raghavan, Hinrich Schütze. Introduction to Information Retrieval. Cambridge University Press. ISBN: 0521865719. 2008.



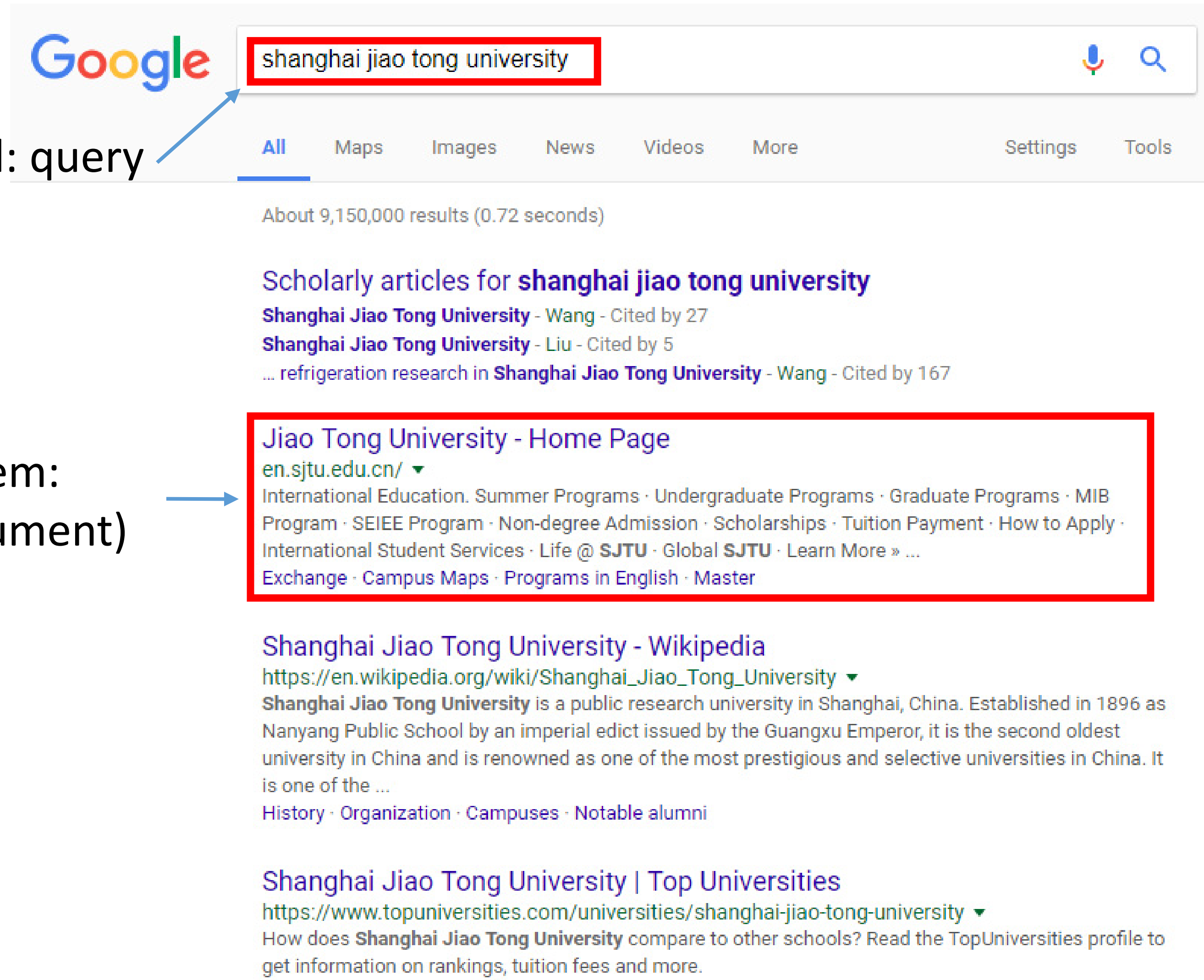
Information Retrieval

- Information retrieval (IR) is the activity of obtaining information items relevant to an information need from a collection of information items.

Web Search is the Typical Scenario of IR

Information need: query

Information item:
Webpage (or document)



Other IR Scenarios

- Library Book Retrieval System
  - Information need: a book title, or an author name etc.
  - Information item: the book to seek for
- Recommender Systems
  - Information need: a user in a certain context (without query)
  - Information item: a move (music, product etc.) she would likes
- Search Advertising
  - Information need: a user with query keywords
  - Information item: a text ad she would click

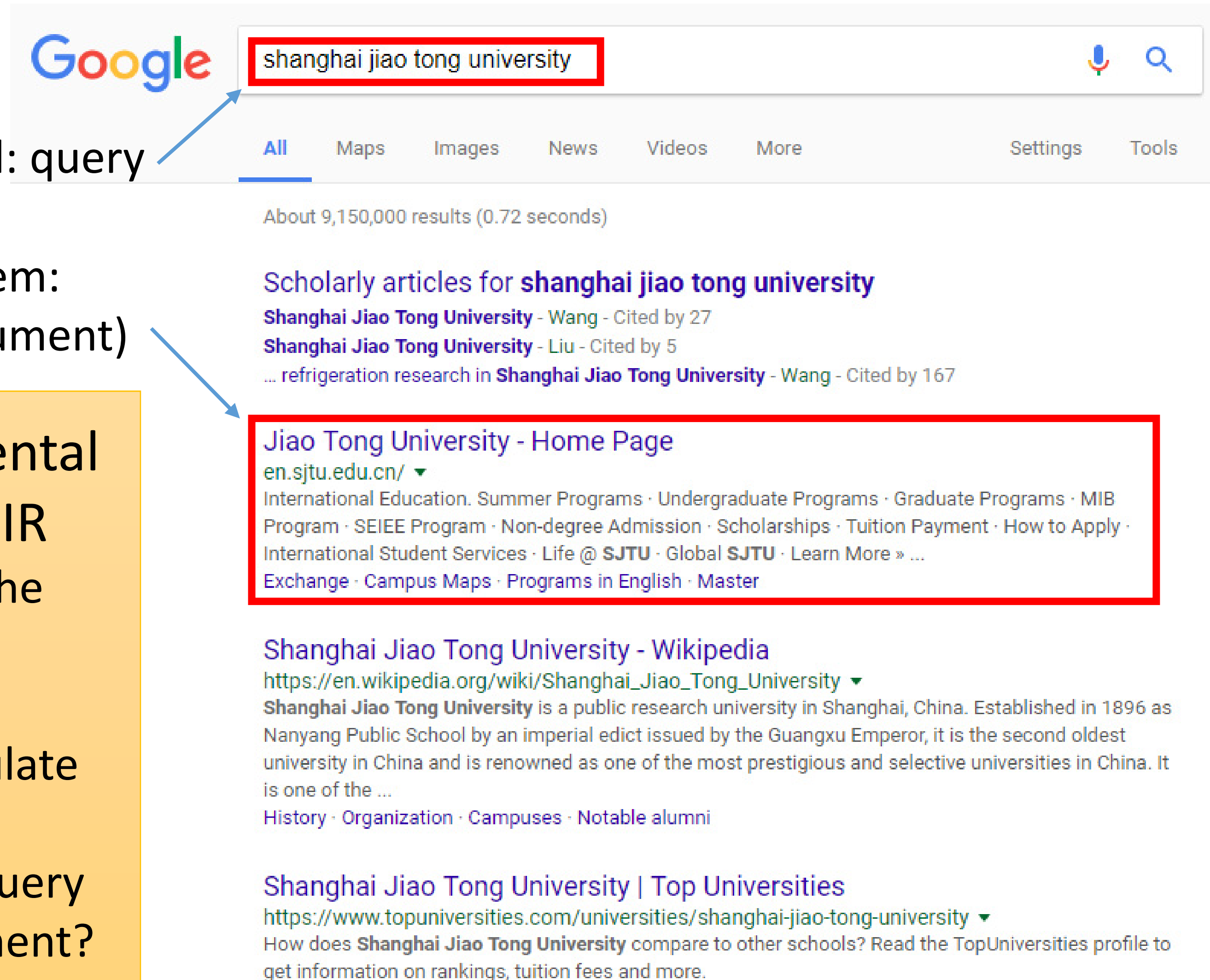
Prof. Stephen Robertson

- Emeritus professor of University College London and City University London
- The pioneer of information retrieval
- The proposer of
  - Probabilistic Ranking Principle (1977)
  - BM25 (1980s)
  - Worked in Chengdu National Library in 1976!

We Focus on Web Search Engines

Information need: query

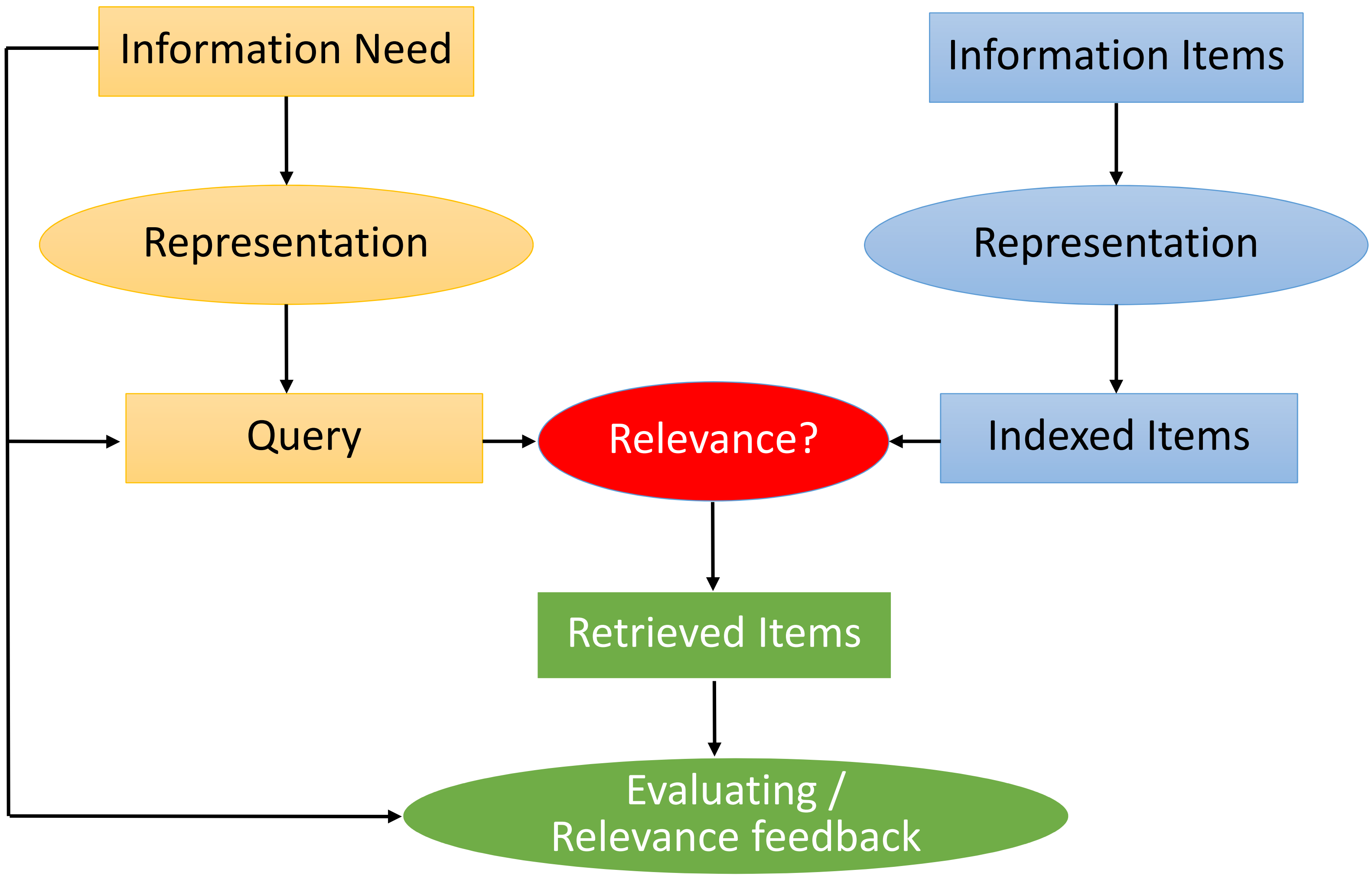
Information item: Webpage (or document)



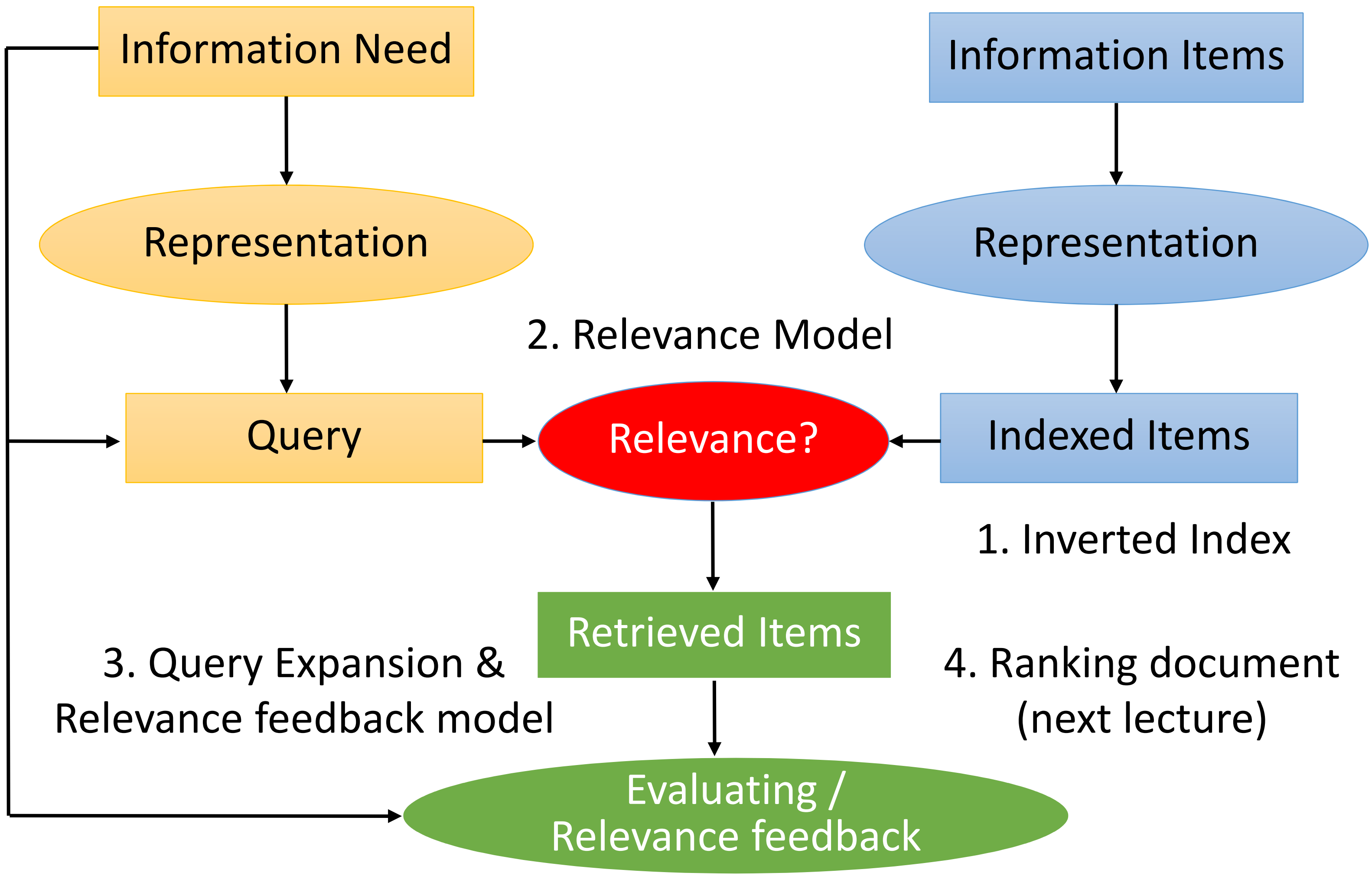
Two fundamental problems for IR

- How to get the candidate documents?
- How to calculate relevance between a query and a document?

Overview Diagram of Information Retrieval



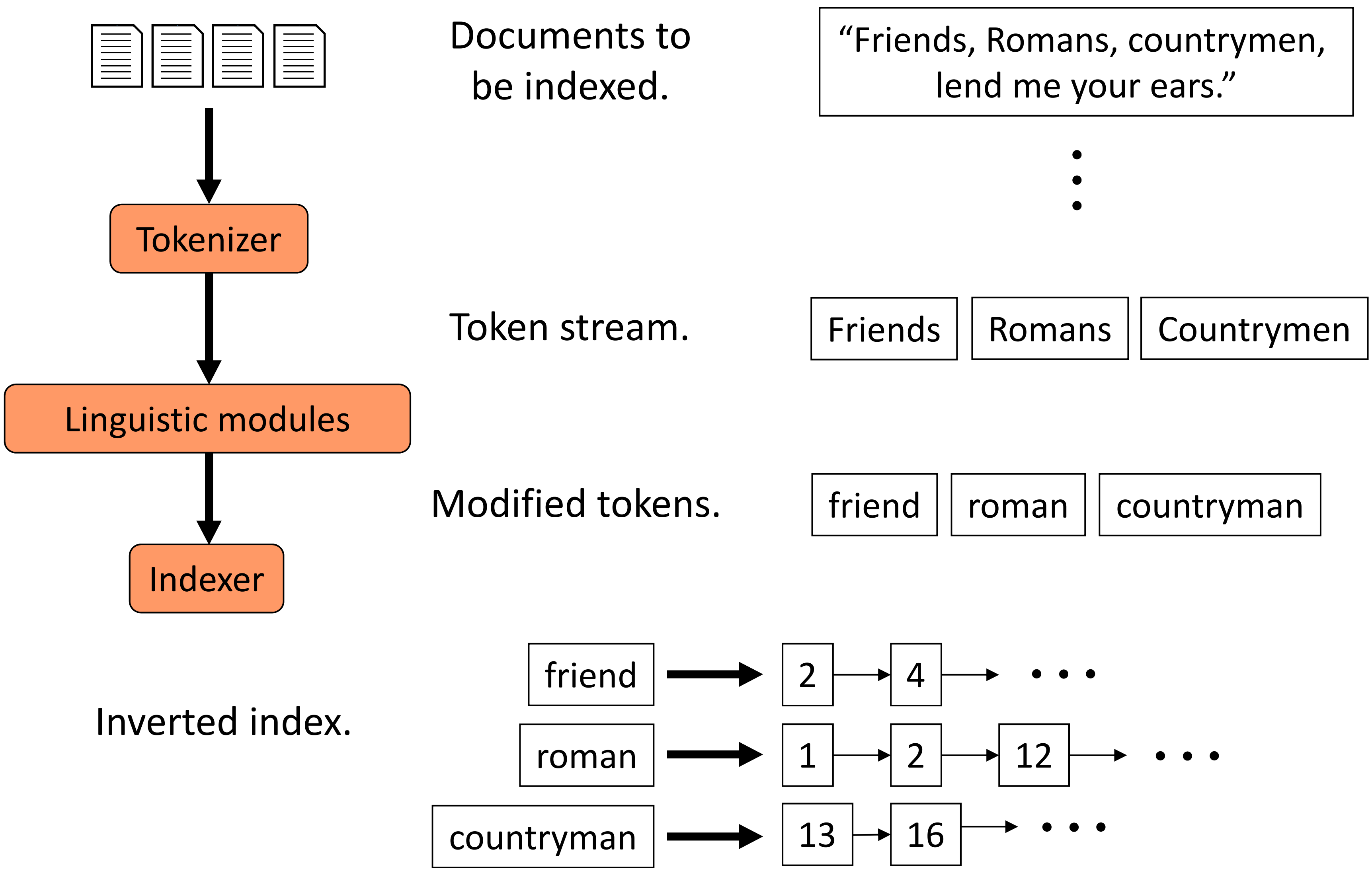
Overview Diagram of Information Retrieval



Content of This Lecture

- Inverted Index for Search Engine
- Relevance Models
- Query Expansion and Relevance Feedback

Overall Indexing Pipeline



Tokenization

- Tokenization is the task of chopping a character sequence into the smallest units, called tokens
- It seems very easy: - Chop on whilespace and ignore punctuation characters
  - Input: *Friends, Romans, countrymen. So let . . .*
  - Output: *Friends Romans countrymen So let . . .*
- But, there are many tricky cases
  - Example *O'Neill → neill, oneill, or O neill*
  - How about *aren't , co-education, the While House*
- Need to do the exact same tokenization of document and query terms
  - Guarantee that a sequence of characters in a text will match the same sequence typed in a query
- Tokenization of other languages
  - E.g., Chinese (word segmentation)

Normalization with Linguistic Models

- Normalize terms in indexed text and query terms into the same form
- Words can appear in different forms
- Need some way to recognize common concept
  - Examples:

  how to match ***U.S.A*** and ***USA*** → remove punctuation

  walking vs. walks → stemming

  Retrieval vs. retrieval → case folding

Normalization: Case Folding

- Reduce all letters to lower case
  - ***Retrieval → retrieval***
  - ***ETHICS → ethics***
  - ***MIT → mit***
- Possible exceptions: capitalized words in mid-sentence
- It is often best to lowercase everything since users will use lowercase regardless of correct capitalization

Normalization: Stemming

- Stemming is a technique to reduce morphological variants of search terms
- Stem: portion of a word which is left after the removal of its affixes
  - *walk ← walked, walker, walking, walks*
  - *be ← am, are, is*
  - *cut ← cutting*
  - *destroy ← destruction*
- Significantly reduce the number of the index terms
- Increase recall while harming precision

Porter Algorithm for Stemming

- One of the most common stemming algorithms in English
  - Conventions plus five phases of reductions
  - Phases are applied sequentially
  - Each phase consists of a set of commands
- A few rules in phase 1 (apply sequentially)

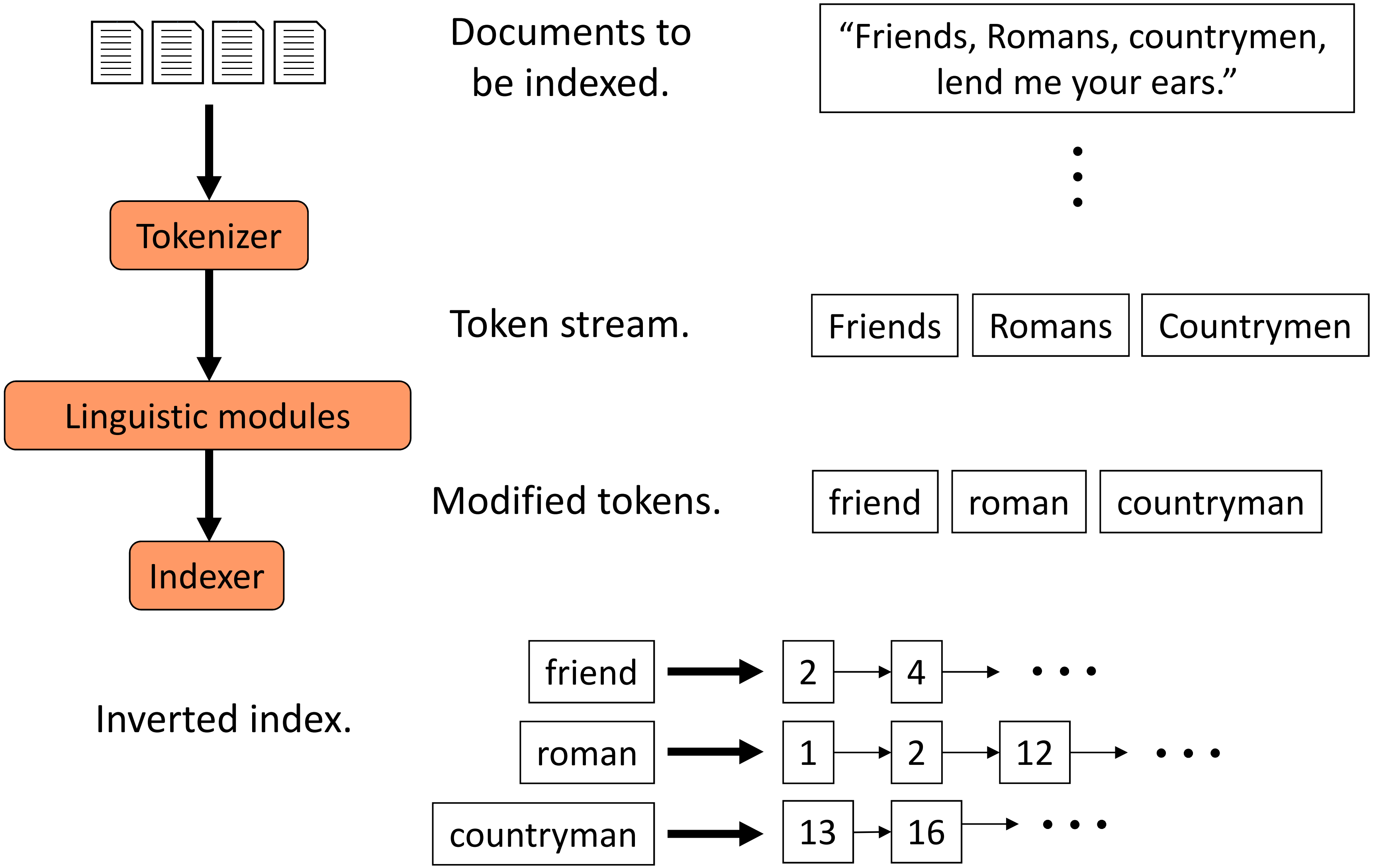
Rule	**Example**
SSES → SS	caresses → caress
IES →	Ponies → poni
SS→SS	caress → caress
S→	cats→ cat

https://tartarus.org/martin/PorterStemmer/

Normalization: Stop Words

- Drop some extremely common words from the vocabulary because they are of little value in helping selecting documents
  - examples*:* *"the", "a", "by", "will" ...*
- Take the most frequent terms (by *collection frequency*) to construct the stop word list
  - e.g., remove word that appears in more than 5% of documents
- Perhaps remove numbers and dates. However, these might be very useful
- Produce a considerable reduction of the index terms. Results: smaller index files and faster search
- Most web search engines index stop words

Overall Indexing Pipeline



Indexing the Documents

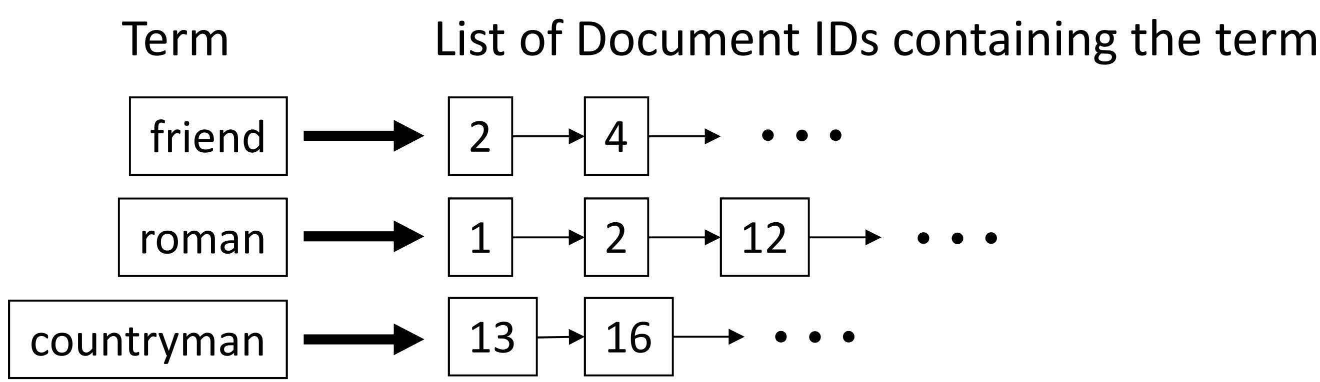
- Key Problem: given a query, how to obtain the candidates from the massive number of documents
- Solution: indexing the documents for IR
- The difficulties in IR
  - Indexing “titles”, “abstract”, etc. only does not support content-based retrieval; document contents are, in most case, unstructured.
  - Cannot predict the terms that people will use in queries - every word in a document is a potential search term
- A solution: index all terms in the documents
  - Full text indexing

Data Access

- Scan the entire document collection
  - Typically used in early retrieval systems
  - Still popular today, e.g., grep command in Linux - “slow”; need real-time process
  - Practical for “small” collections
- Index (query) terms for direct access
  - An index associates each of the keys (normally terms) with one or more documents
  - “Fast”; practical for “large” collection
- Hybrid approaches - Use small index and then scan a subset of collection

Inverted Index

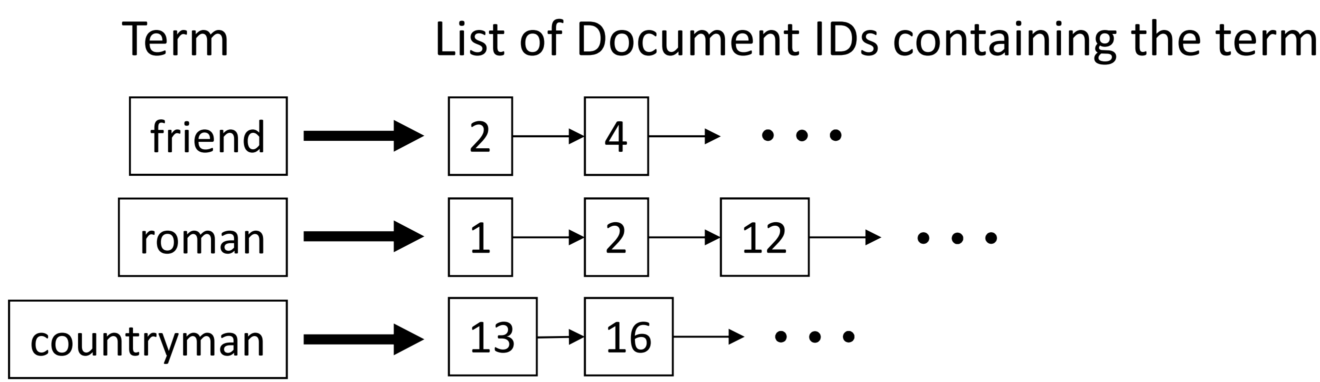
- Inverted index is the most common indexing technique
- Collection organized by terms (words). One record per term, listing locations (doc. IDs) where term occurs. May have more information.
- During retrieval, traverse lists for each query term



Called posting list

Inverted Index

- Different terms have vastly different sizes of posting lists
  - E.g. on Google, ‘information’ has 2,990M documents, while ‘bayesian’ has 17M
- We need variable-size postings lists
  - On disk, a continuous run of postings is normal and best
  - In memory, can use linked lists or variable length arrays
    - Some tradeoffs in size/ease of insertion



Called posting list, sorted by IDs (why?)

Steps of Building Inverted Index

Document 1

I did enact Julius
Caesar I was
killed
i' the Capitol;
Brutus killed me.

Document 2

So let it be with
Caesar. The noble
Brutus hath told
you Caesar was
ambitious.

Term	docID
I	1
did	1
enact	1
julius	1
caesar	1
I	1
was	1
killed	1
i'	1
the	1
capitol	1
brutus	1
killed	1
me	1
so	2
let	2
it	2
be	2
with	2
caesar	2
the	2
noble	2
brutus	2
hath	2
told	2
you	2
caesar	2
was	2
ambitious	2

- Step 1: extract the sequence of (modified term, document ID) pairs.

Steps of Building Inverted Index

Document 1

I did enact Julius Caesar I was killed i' the Capitol; Brutus killed me.

Document 2

So let it be with Caesar. The noble Brutus hath told you Caesar was ambitious.

- Step 1: extract the sequence of (modified term, document ID) pairs.
- Step 2: sort by terms and then docID
  - Core indexing step

Term	docID
I	1
did	1
enact	1
julius	1
caesar	1
I	1
was	1
killed	1
i'	1
the	1
capitol	1
brutus	1
killed	1
me	1
so	2
let	2
it	2
be	2
with	2
caesar	2
the	2
noble	2
brutus	2
hath	2
told	2
you	2
caesar	2
was	2
ambitious	2

→

Term	docID
ambitious	2
be	2
brutus	1
brutus	2
capitol	1
caesar	1
caesar	2
caesar	2
did	1
enact	1
hath	1
I	1
I	1
i'	1
it	2
julius	1
killed	1
killed	1
let	2
me	1
noble	2
so	2
the	1
the	2
told	2
you	2
was	1
was	2
with	2

Steps of Building Inverted Index

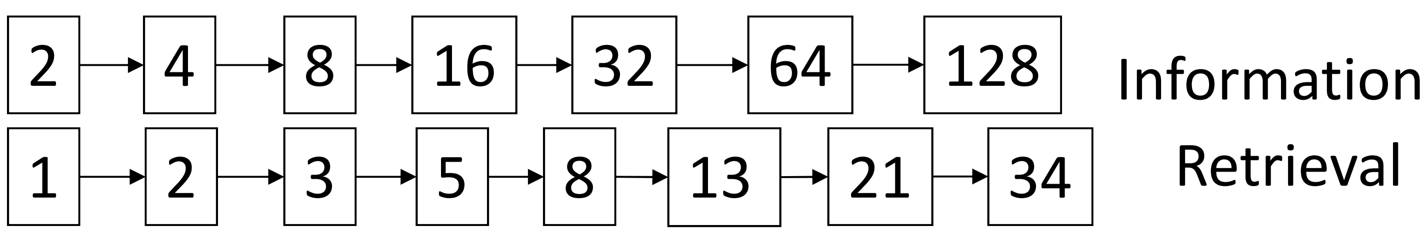
- Multiple term entries in a single document are merged.
- Split into Dictionary and Postings
- Document frequency information is added.

Term	docID
ambitious	2
be	2
brutus	1
brutus	2
capitol	1
caesar	1
caesar	2
caesar	2
did	1
enact	1
hath	1
I	1
I	1
i'	1
it	2
julius	1
killed	1
killed	1
let	2
me	1
noble	2
so	2
the	1
the	2
told	2
you	2
was	1
was	2
with	2

term	doc. freq.	→	postings lists
ambitious	1	→	2
be	1	→	2
brutus	2	→	1 → 2
capitol	1	→	1
caesar	2	→	1 → 2
did	1	→	1
enact	1	→	1
hath	1	→	2
i	1	→	1
i'	1	→	1
it	1	→	2
julius	1	→	1
killed	1	→	1
let	1	→	2
me	1	→	1
noble	1	→	2
so	1	→	2
the	2	→	1 → 2
told	1	→	2
you	1	→	2
was	2	→	1 → 2
with	1	→	2

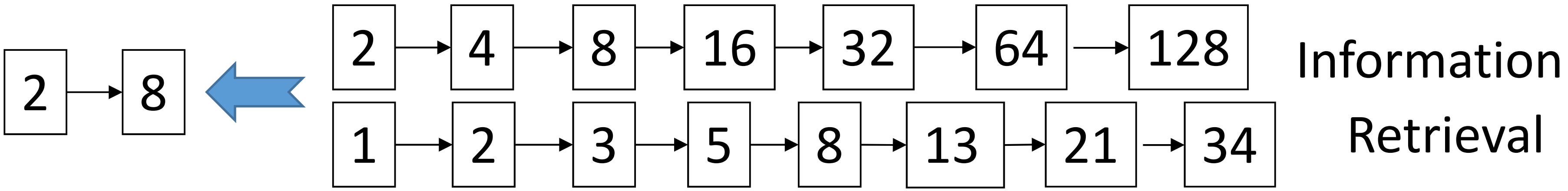
Query Processing: AND

- Consider processing the query:
  ‘Information’ AND ‘Retrieval’
  - Locate ‘Information’ in the dictionary;
    - Retrieve its postings.
  - Locate ‘Retrieval’ in the dictionary;
    - Retrieve its postings.
  - “Merge” the two postings:



Merging the Posting Lists

- Walk through the two postings simultaneously, in time linear in the total number of postings entries



  - If list lengths are *x* and *y*, merge takes *O*(*x*+*y*) operations.
  - <u>Crucial</u>: postings sorted by docID.

Phrase Queries

- Want to be able to answer queries such as "Shanghai Jiao Tong University" – as a phrase
  - Note that it is different from search Shanghai AND Jiao AND Tong AND University (why?)
- Thus the sentence "I went to Xi'an Jiao Tong University from Shanghai" is not a match.
  - The concept of phrase queries has proven easily understood by users
  - Many more queries are *implicit phrase queries*
- For this purpose, it no longer suffices to store only <*term*: *docs*> entries

Positional Indexes

- In the postings, store for each term the position(s) in which tokens of it appear:

<term, number of docs containing term;
doc1: position1, position2 … ;
doc2: position1, position2 … ;
…>

Positional Index Example

<***be***: 993427;

1: 7, 18, 33, 72, 86, 231;

2: 3, 149;

4: 17, 191, 291, 430, 434;

5: 363, 367, …>

Which of docs 1,2,4,5 **could** contain "***to be or not to be***"?

- For phrase queries, we use a merge algorithm recursively at the document level
- But we now need to deal with more than just equality

Processing a Phrase Query

- Extract inverted index entries for each distinct term: ***to, be, or, not.***
- Merge their *doc:position* lists to enumerate all positions with "***to be or not to be".***
    - ***to***:
        - *2*:1,17,74,222,551; *4*:8,16,190,429,433; *7*:13,23,191; ...
    - ***be***:
        - *1*:17,19; *4*:17,191,291,430,434; *5*:14,19,101; ...
    - ***Or:***
        - 3:34,71; *4*:31,341,510; 8:31,420,551; ...

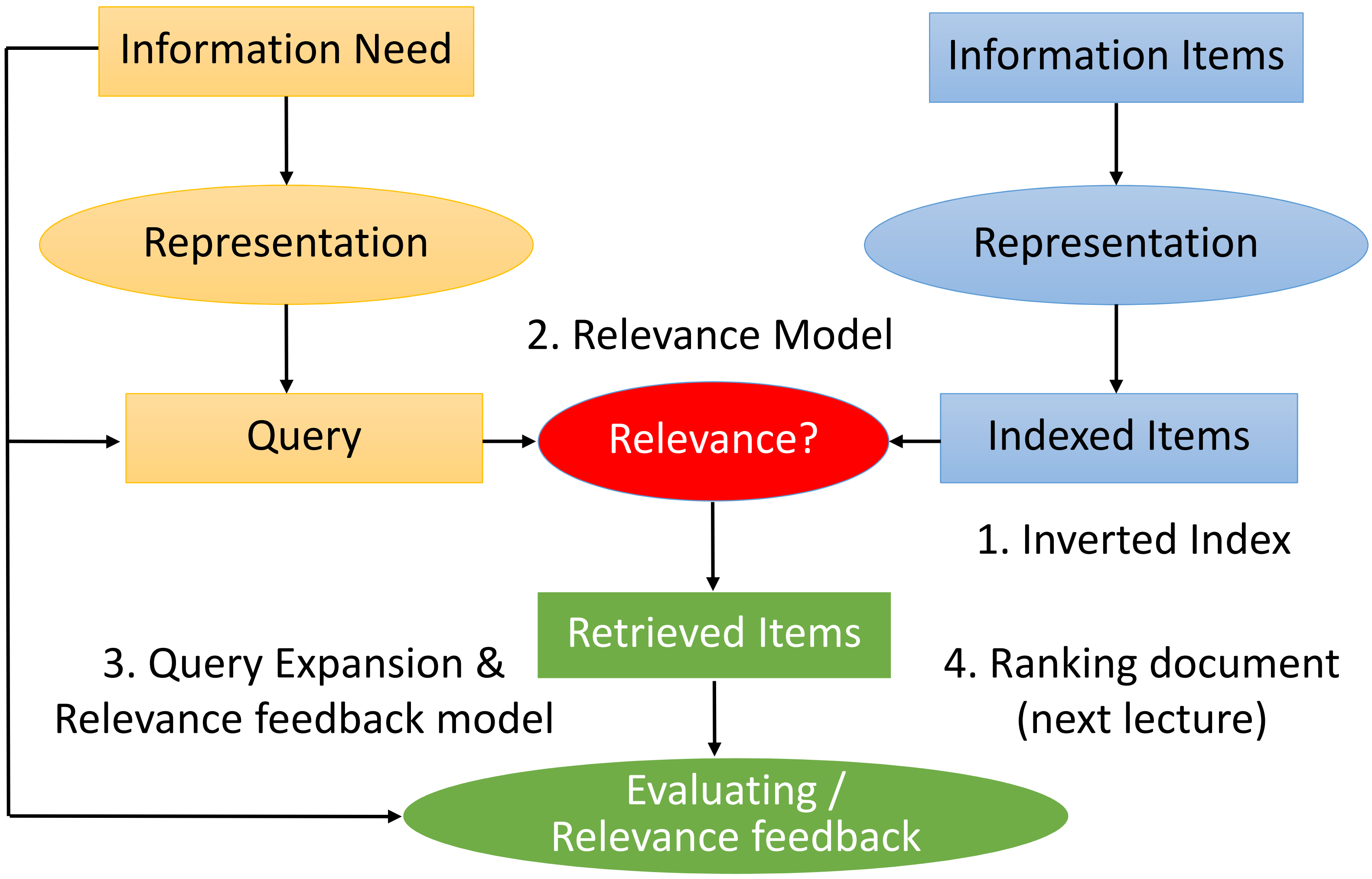
Content of This Lecture

- Inverted Index for Search Engine

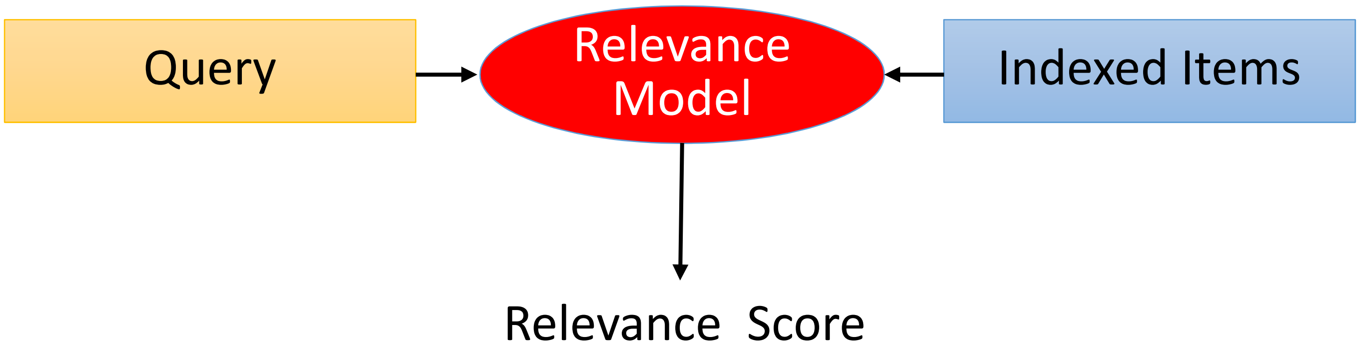
- Relevance Models

- Query Expansion and Relevance Feedback

Overview Diagram of Information Retrieval



Relevance Model



- Estimate the relevance between a query and a document
- Relevance is the "correspondence" between information needs (queries) and information items (documents, webpages, images etc.)
- But, the exact meaning of relevance depends on applications:
  - = usefulness
  - = aboutness
  - = interestingness
  - = ?
- Predicting relevance is the central goal of IR

Representation of Information Need/Items

- We consider textual queries and documents
  - Boolean:
    - “(information AND retrieval) OR (machine AND learning)”
  - Free text: “movie matrix review”

- A bag-of-words representation
  - the item (query or document) is the “bag”
  - the bag contains word tokens
  - word order is ignored

REVIEW

Bag-of-Words Representation for Text

- A sequence of words/tokens that represents semantic meanings of human

```
Text mining, also referred
to as text data mining,
roughly equivalent to text
analytics, is the process
of deriving high-quality
information from text.
```

Bag-of-Words Format:

```
{
    text: 4;
    mining: 2;
    also: 1;
    referred: 1;
    to: 2;
    as: 1;
    data: 1;
    roughly: 1;
    equivalent: 1;
    analytics: 1;
    is: 1;
    the: 1;
    process: 1;
    of: 1;
    deriving: 1;
    high-quality: 1;
    information: 1;
    from: 1;
}
```

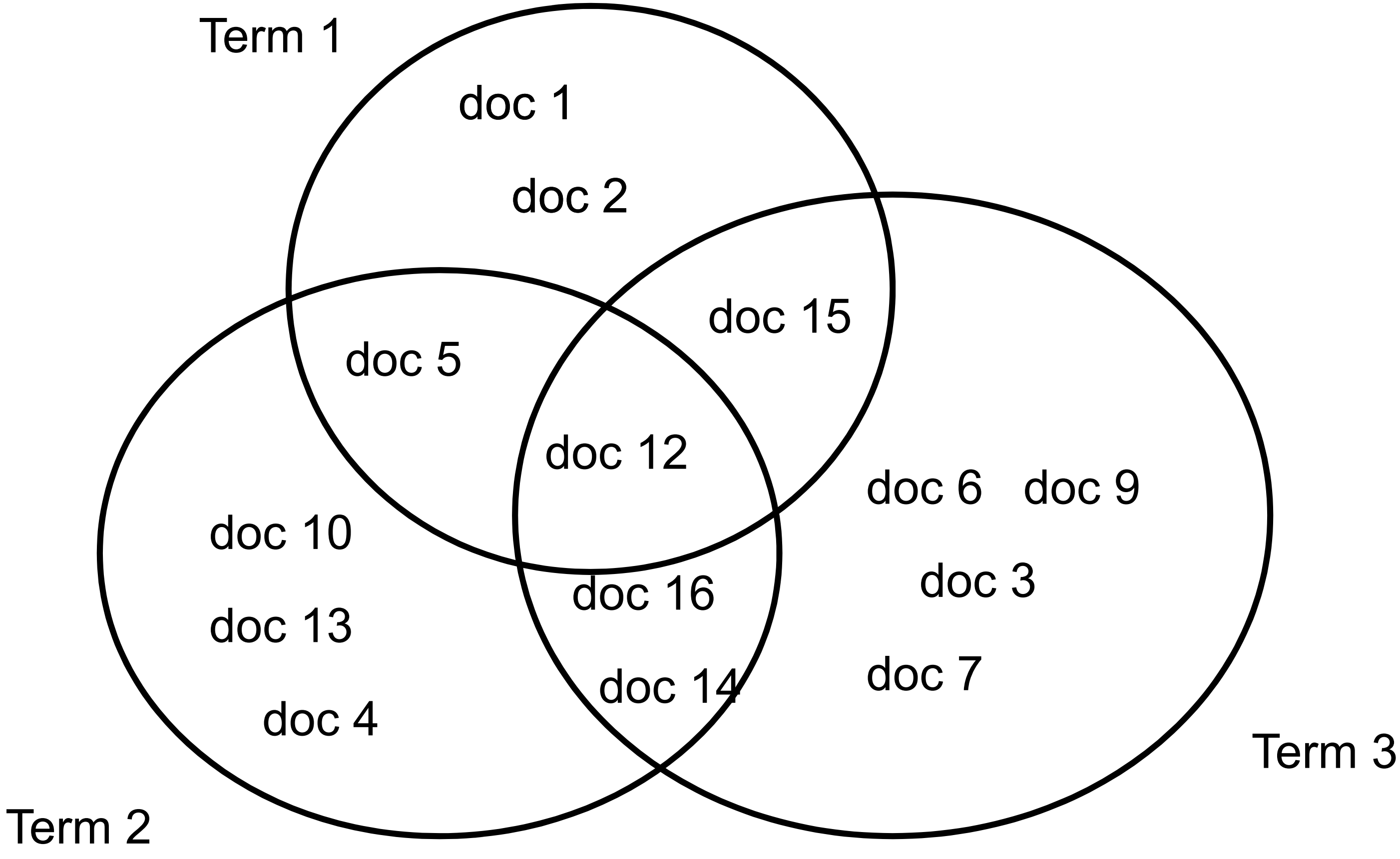
Boolean Retrieval

- The simplest Exact Match model
  - Retrieve documents iff they satisfy a Boolean expression
  - Query specifies precise relevance criteria
  - Documents returned in no particular order
- Document: A bag of words
- Query: A Boolean expression
- Operators:
  - Logical operators: AND, OR, AND NOT
  - Proximity operators: number of intervening words between two query terms, etc.
  - String matching operators: Wild-card

Boolean Retrieval

- Boolean logic:

Query: term 1 AND term 2 AND NOT term 3
retrieve doc 5



Boolean Retrieval: Summary

- Advantages
  - Works great if you know exactly what you want
  - Structured queries
  - Simple to program
  - Complete expressiveness
- Disadvantages
  - Artificial language – unintuitive, misunderstood
  - Either too precise or too loose (the size of the output)
  - Unordered output: have to examine all of the results

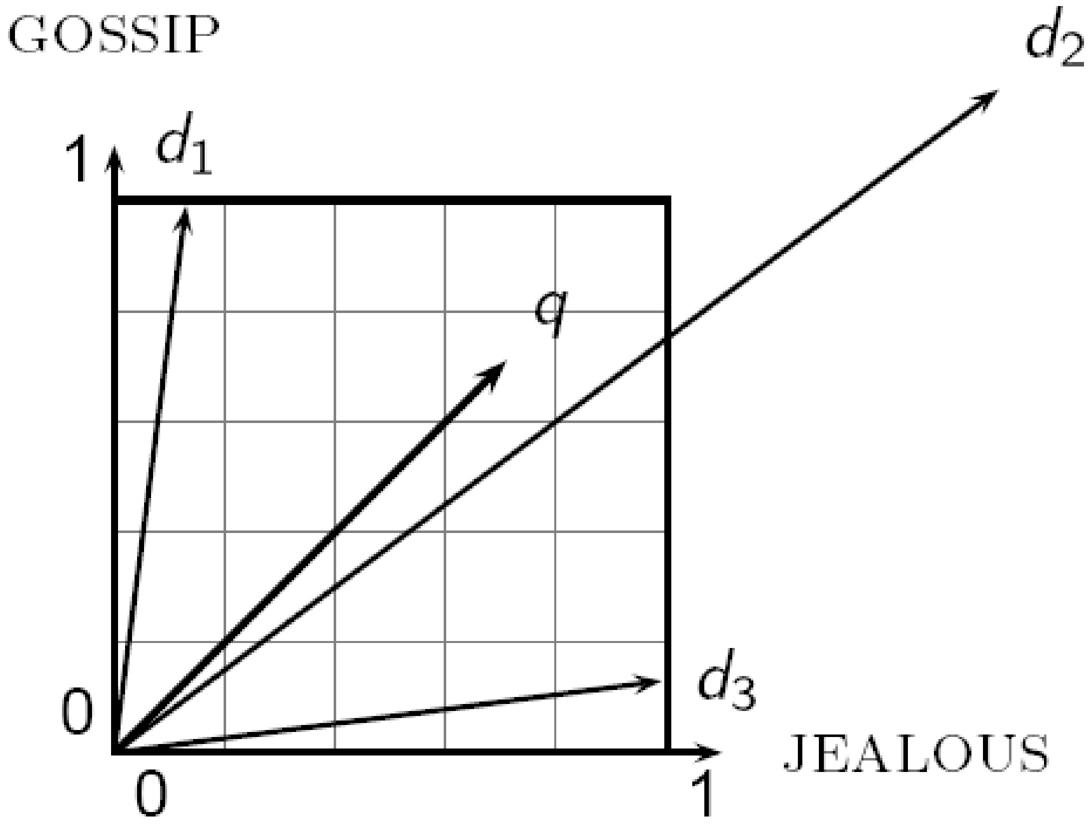
Vector Space Model

- Regarding queries and documents as vectors
  - We have a $|V|$-dimensional vector space, where $|V|$ is the vocabulary size
  - Terms are axes of the space
  - Queries and documents are points or vectors in this space
- Very high-dimensional: tens of millions of dimensions when you apply this to a web search engine
- These are very sparse vectors - most entries are zero (as mentioned in inverted index part)

Formalizing Vector Space Proximity

- We need to come up with a distance between two points
  - (= distance between the end points of the two vectors)
- Euclidean distance?
- Euclidean distance is a bad idea . . .
- . . . because Euclidean distance is large for vectors of different lengths.

Why Distance is a Bad Idea



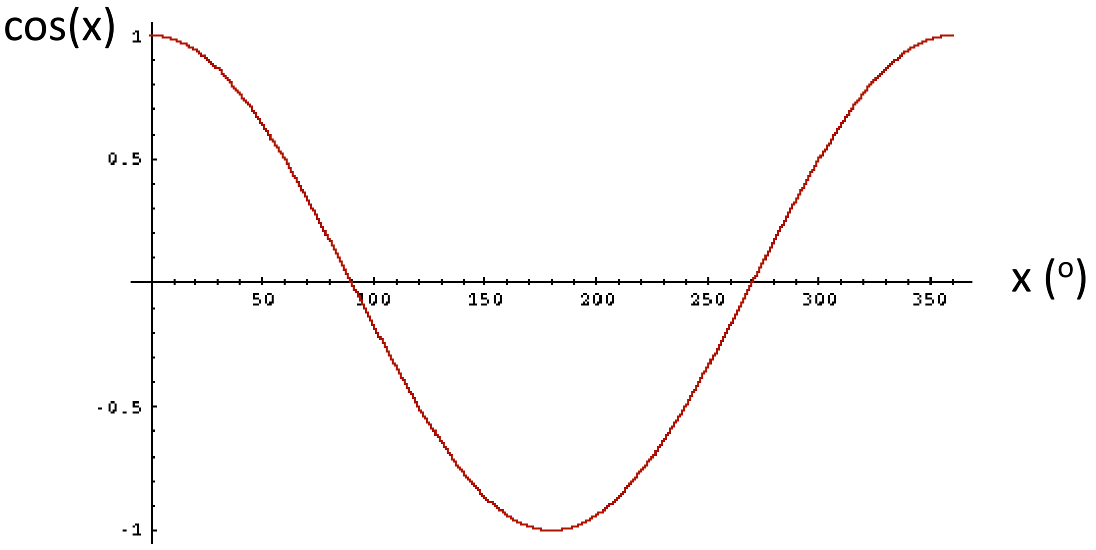
- The Euclidean distance between q and d_2 is large even though the distribution of terms in the query q and the distribution of terms in the document d_2 are very similar.

Use Angle instead of Distance

- Thought experiment: take a document *d* and append it to itself. Call this document *d*′.
- “Semantically” *d* and *d*′ have the same content
- The Euclidean distance between the two documents can be quite large
- The angle between the two documents is 0, corresponding to maximal similarity
- Key idea: Rank documents according to angle with query.

Cosine Similarity

- The following two notions are equivalent.
  - Rank documents in <u>increasing</u> order of the angle between query and document
  - Rank documents in <u>decreasing</u> order of cosine (query, document)
- Cosine is a monotonically decreasing function for the interval [0^o, 180^o]



Cosine(query, document)

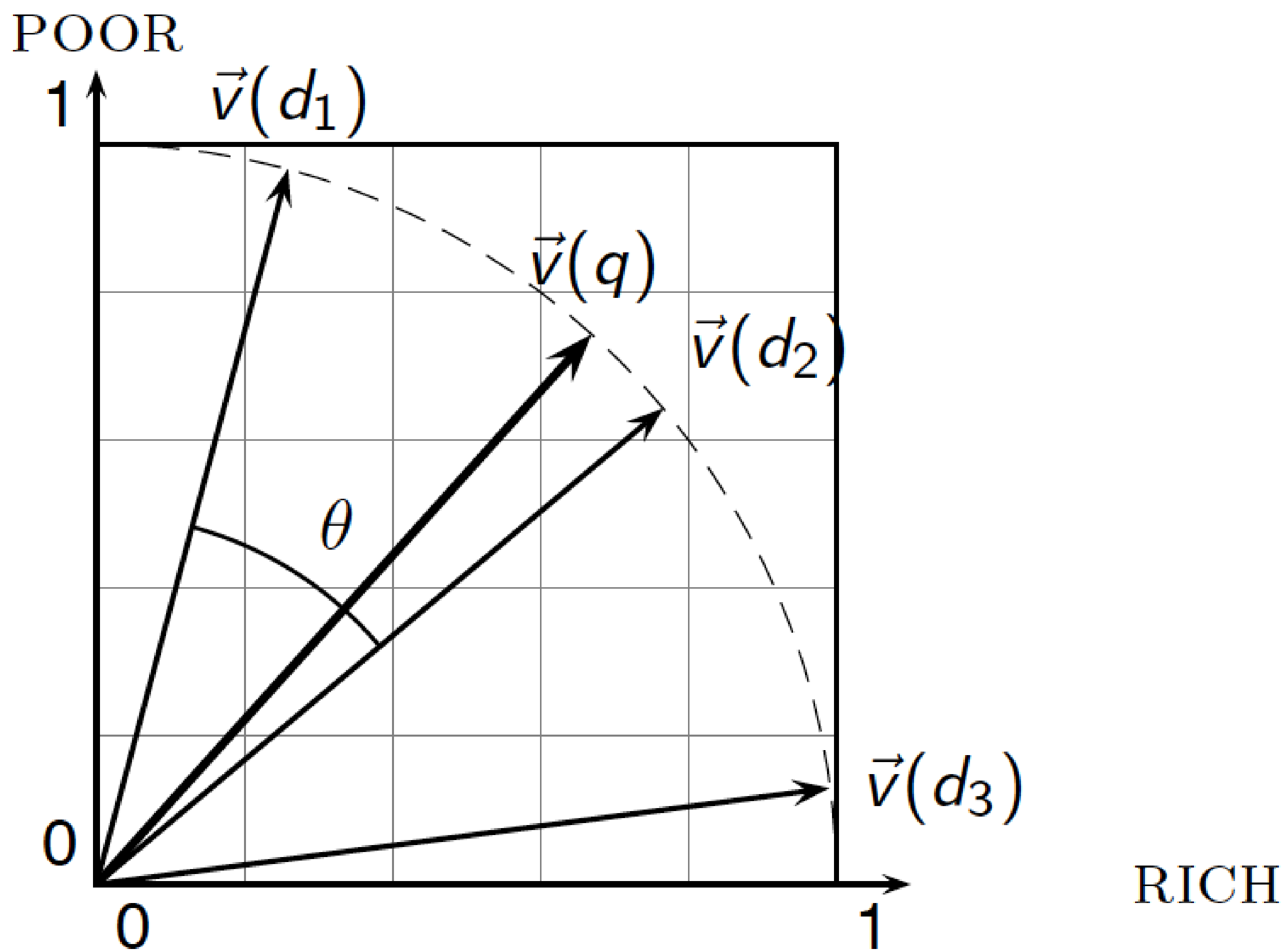
- q_i is the weight of term *i* in the query
- d_i is the weight of term *i* in the document

- cos(*q,d*) is the cosine similarity of *q* and *d* … or,
- equivalently, the cosine of the angle between *q* and *d*.

$$\cos(q,d) = \frac{q}{\|q\|} \cdot \frac{d}{\|d\|} = \frac{q \cdot d}{\|q\| \cdot \|d\|} = \frac{\sum_i^{|V|} q_i d_i}{\sqrt{\sum_i^{|V|} q_i^2}\sqrt{\sum_i^{|V|} d_i^2}}$$

Unit Vectors

Cosine Similarity Illustrated



TF·IDF Term Weighting

- q_i *and* d_i are can be beyond just binary values nor term frequency values
- TF·IDF term weighting
  - $TF_{i,d}$: term frequency of term *i* in the document
  - IDF_i : inverse document frequency of term *i* in the document set

$$IDF_i = \log_{10} \frac{N}{n_i} \qquad TFIDF_{i,d} = TF_{i,d} \log_{10} \frac{N}{n_i}$$

$$\text{score}(q, d) = \sum_{i \in q \cap d} TFIDF_{i,d}$$

- TF·IDF term weighting has many variants
  - TF: $1+\log_{10}(\text{TF})$, bool etc.
  - IDF: $\log_{10}[(N-n_i+0.5)/(n_i+0.5)]$

Okapi BM25 Term Weighting

- Consider document length in words $|d|$
- BM (Best Match) 25 Term weighting
  - $TF_{i,d}$: term frequency of term *i* in the document
  - IDF_i : inverse document frequency of term *i* in the document set
  - $\bar{d}$: average document word length in the document set
  - k_1 and b: constant parameters

$$BM25_{i,d} = \frac{TF_{i,d} \cdot (k_1 + 1)}{TF_{i,d} + k_1 \cdot \left(1 - b + b \cdot |d|/\bar{d}\right)} \cdot IDF_i$$

$$\mathrm{score}(q, d) = \sum_{i \in q \cap d} BM25_{i,d}$$

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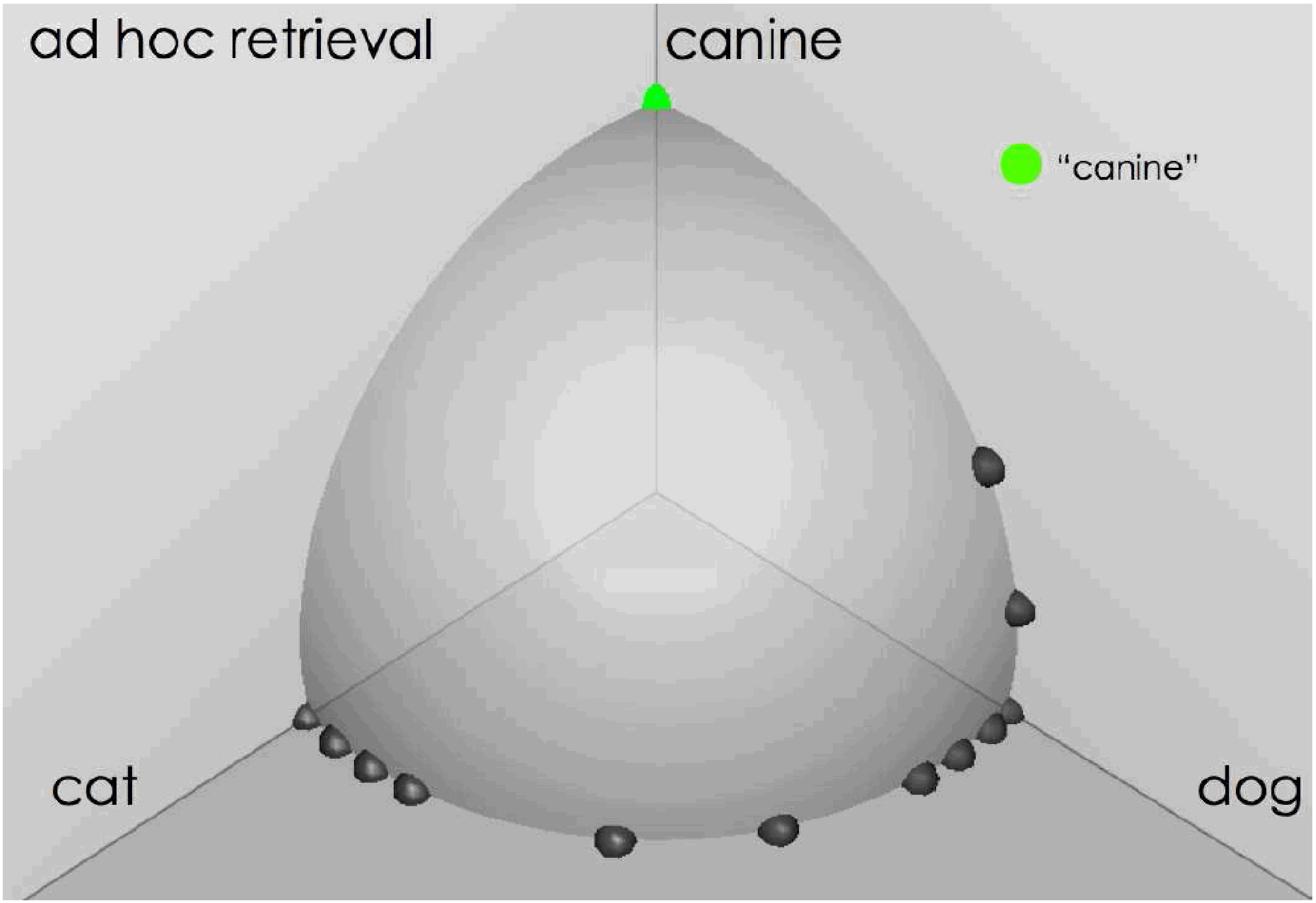
- Query Expansion and Relevance Feedback

Relevance Feedback

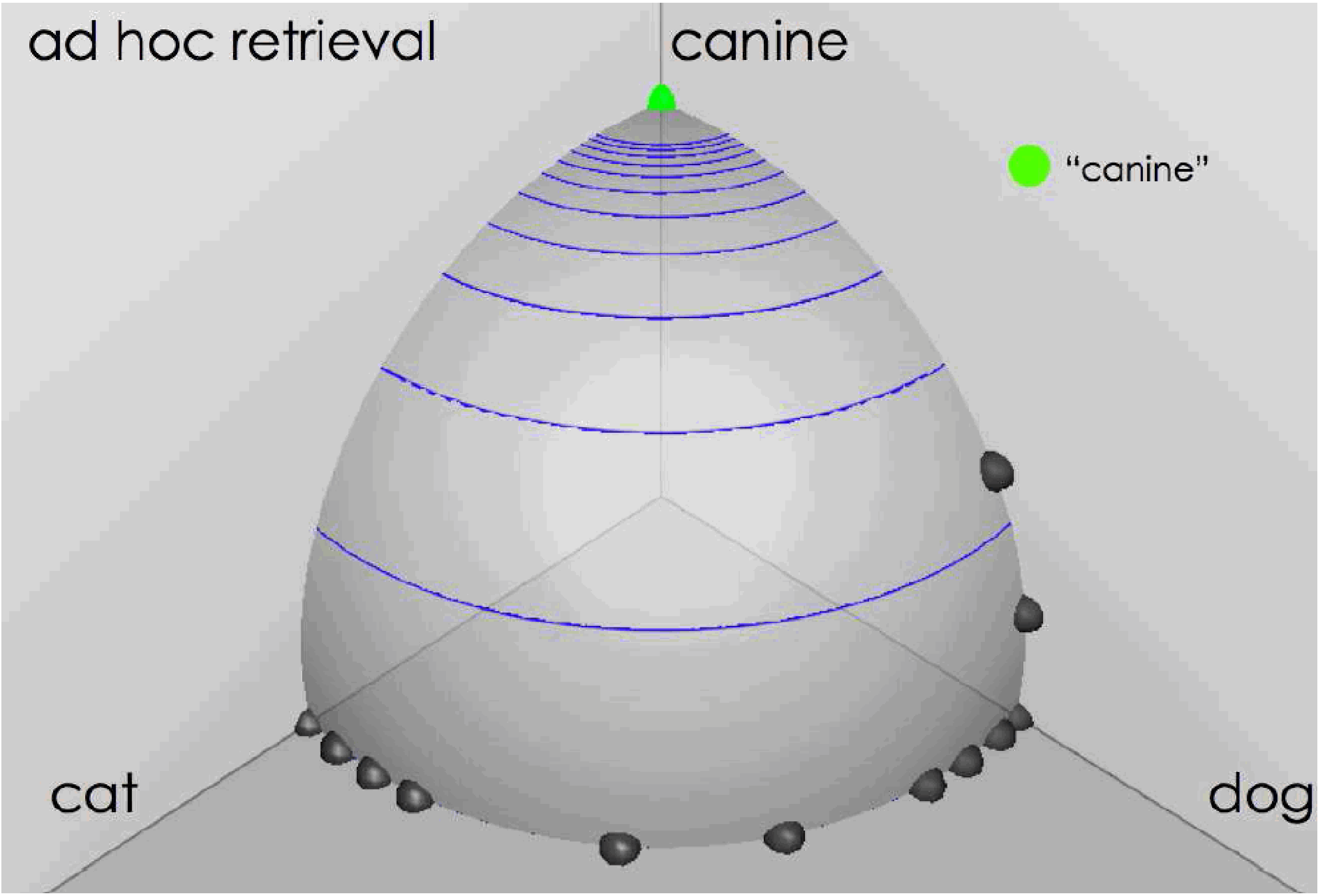
- Relevance feedback: user feedback on relevance of docs in initial set of results
  - User issues a (short, simple) query
  - The user marks some results as relevant or non-relevant.
  - The system computes a better representation of the information need based on feedback.
  - Relevance feedback can go through one or more iterations.
- Idea: it may be difficult to formulate a good query when you don't know the collection well, so iterate

Ad hoc results for query *canine*



source: Fernando Diaz

Ad hoc results for query *canine*



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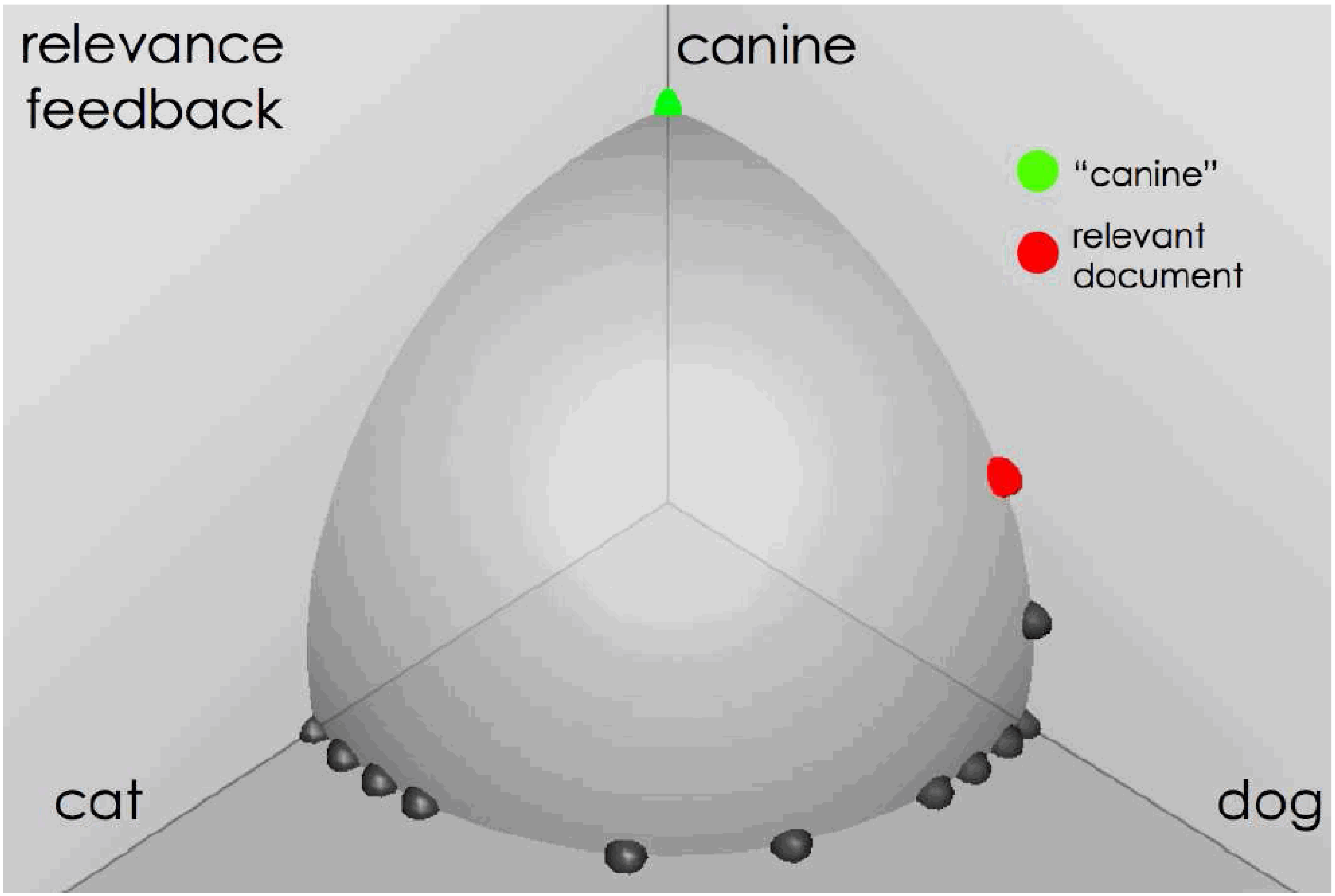

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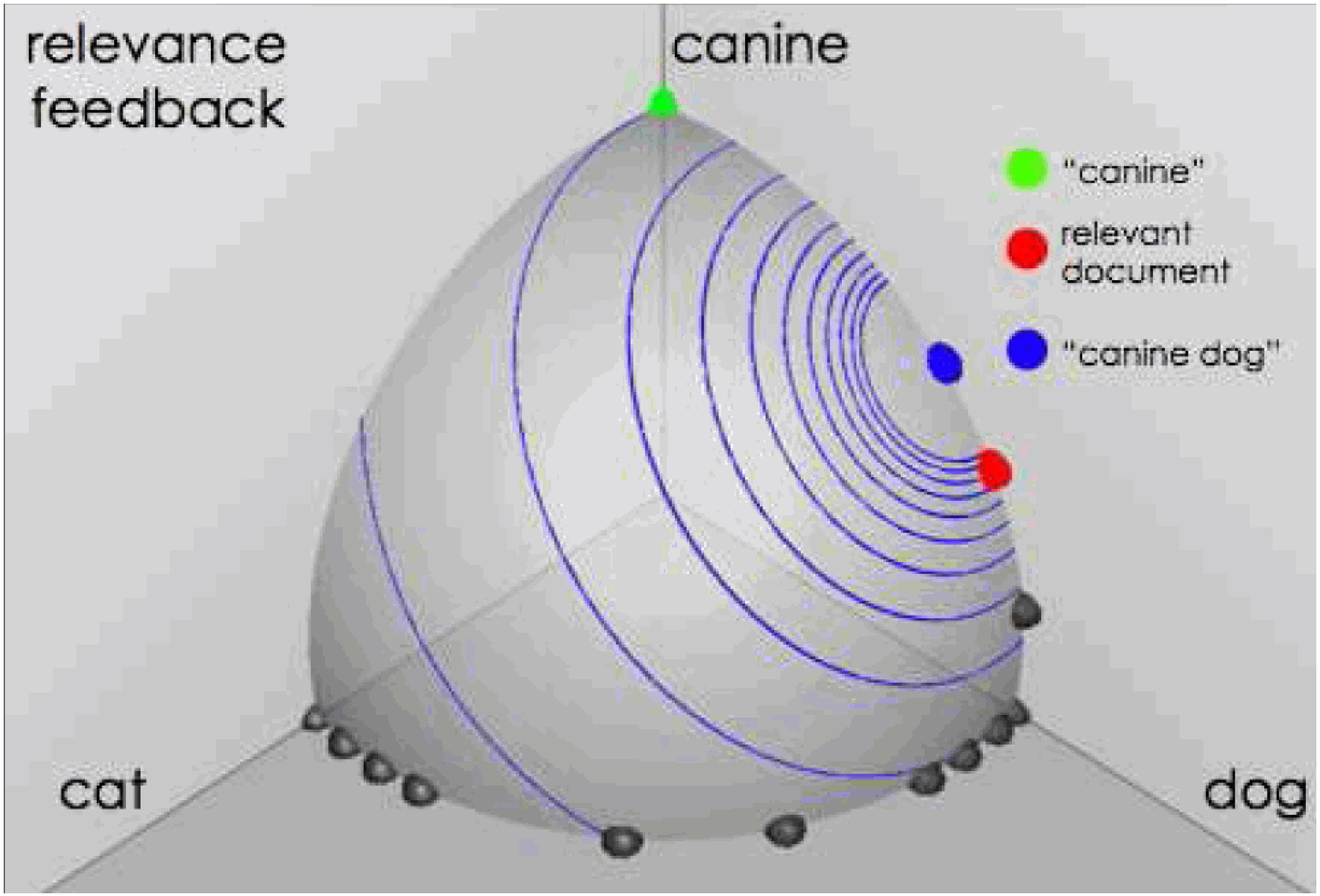
Ad hoc results for query *canine*



source: Fernando Diaz

A Real (non-Image) Example

Initial query: [new space satellite applications]

Results for initial query:

fb	rank	relevance	document
+	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

User then marks relevant documents with "+".

Query Expansion by Relevance Feedback

- Expanded query

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

Compared to the original query: [new space satellite applications]

Results for Expanded Query

Initial query: [new space satellite applications]

Results for expanded query:

fb	rank	relevance	document
*	1	0.513	NASA Scratches Environment Gear From Satellite Plan
*	2	0.500	NASA Hasn't Scrapped Imaging Spectrometer
	3	0.493	When the Pentagon Launches a Secret Satellite, Space Sleuths Do Some Spy Work of Their Own
	4	0.493	NASA Uses 'Warm' Superconductors For Fast Circuit
*	5	0.492	Telecommunications Tale of Two Companies
	6	0.491	Soviets May Adapt Parts of SS-20 Missile for Commercial Use
	7	0.490	Gaping Gap: Pentagon Lags in Race To Match the Soviets In Rocket Launchers
	8	0.490	Rescue of Satellite By Space Agency To Cost $90 Million

Such "user feedback – query expansion – reranking" process can iterate multiple times

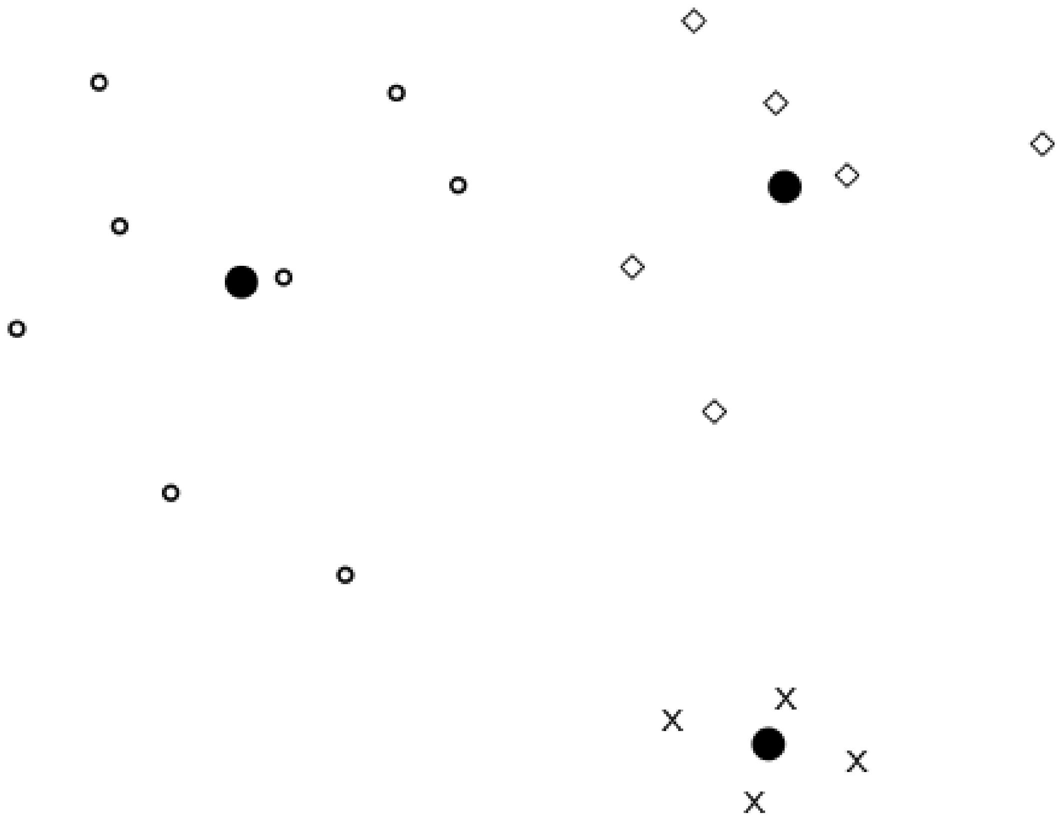
Key Concept: Centroid

- The centroid is the center of mass of a set of points
- Suppose that we represent documents as points in a high-dimensional space using terms
- Definition: Centroid

$$\mu(C) = \frac{1}{|C|} \sum_{d \in C} d$$

where C is a set of documents.

Centroid: Example



Rocchio Algorithm

- The Rocchio algorithm uses the vector space to pick a relevance feedback query
- Rocchio seeks the query q_{opt} that maximizes the similarity margin between the two clusters of docs

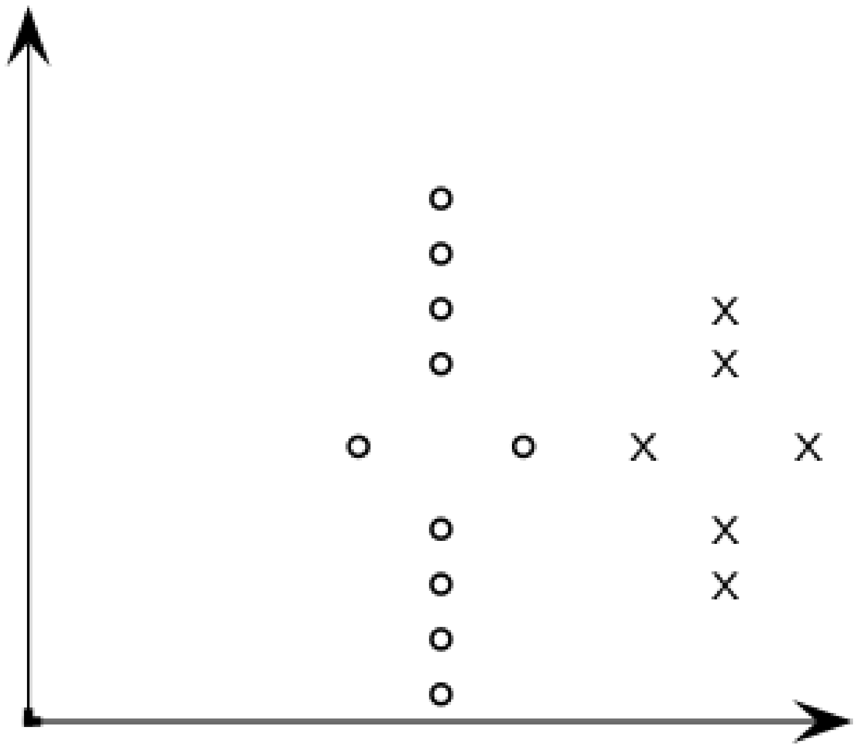
$$q_{\text{opt}} = \arg\max_{q} \Big\{ \cos(q, \mu(C_r)) - \cos(q, \mu(C_n)) \Big\}$$

- Implementation: try to separate docs marked relevant and non-relevant

$$q_{\text{opt}} = a \cdot q_0 + b \cdot \frac{1}{|C_r|} \sum_{d \in C_r} d - c \cdot \frac{1}{|C_n|} \sum_{d \in C_n} d$$

J. J. Rocchio, Relevance feedback in information retrieval In The SMART Retrieval System: Experiments in Automatic Document Processing (1971)

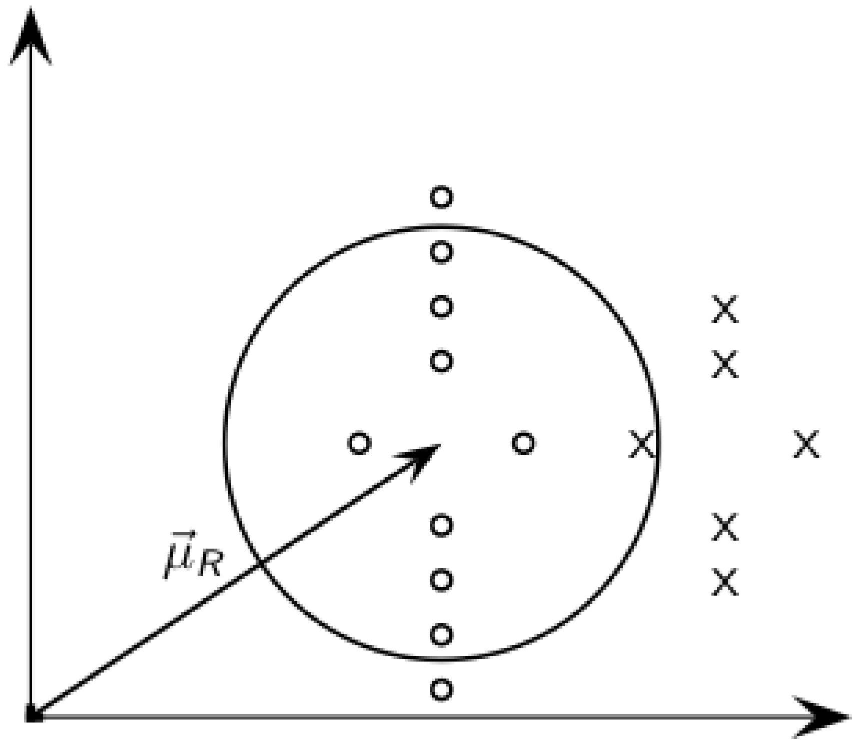
Ricchio Example



x non-relevant documents

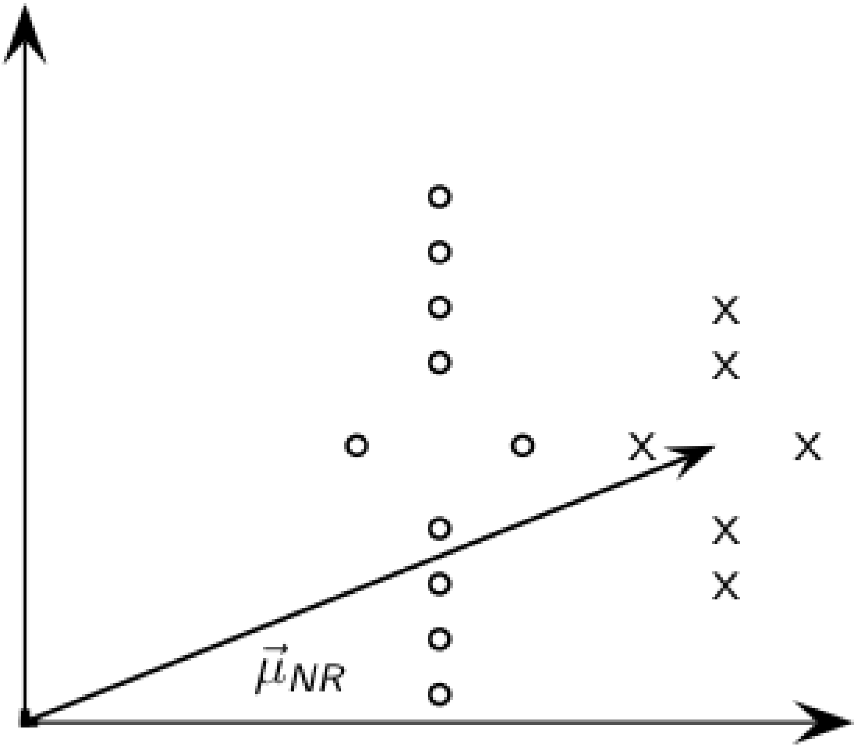
o relevant documents

Ricchio Example

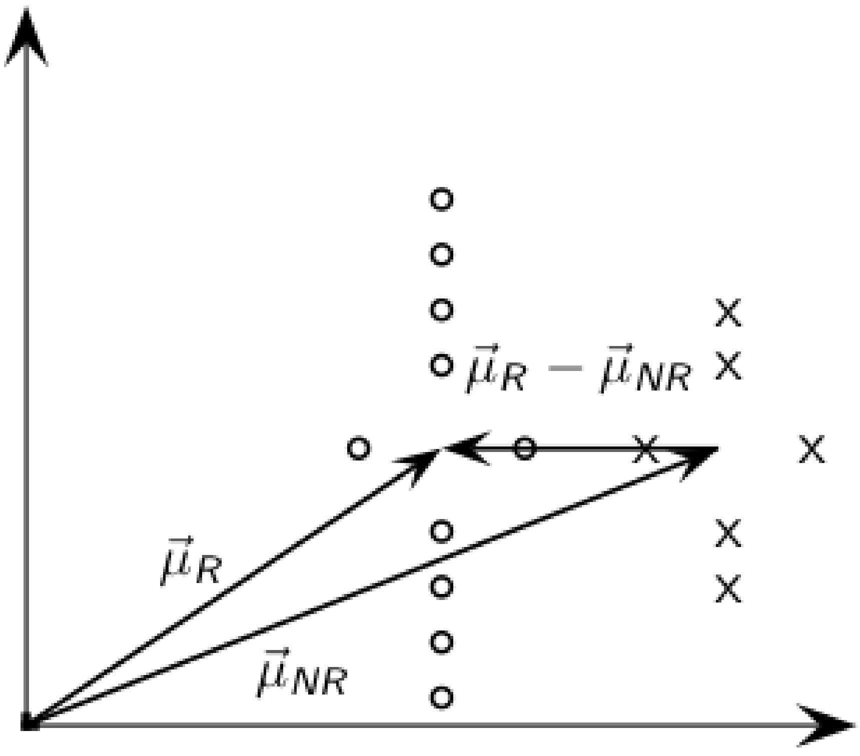


μ_R cannot separate relevant/non-relevant documents

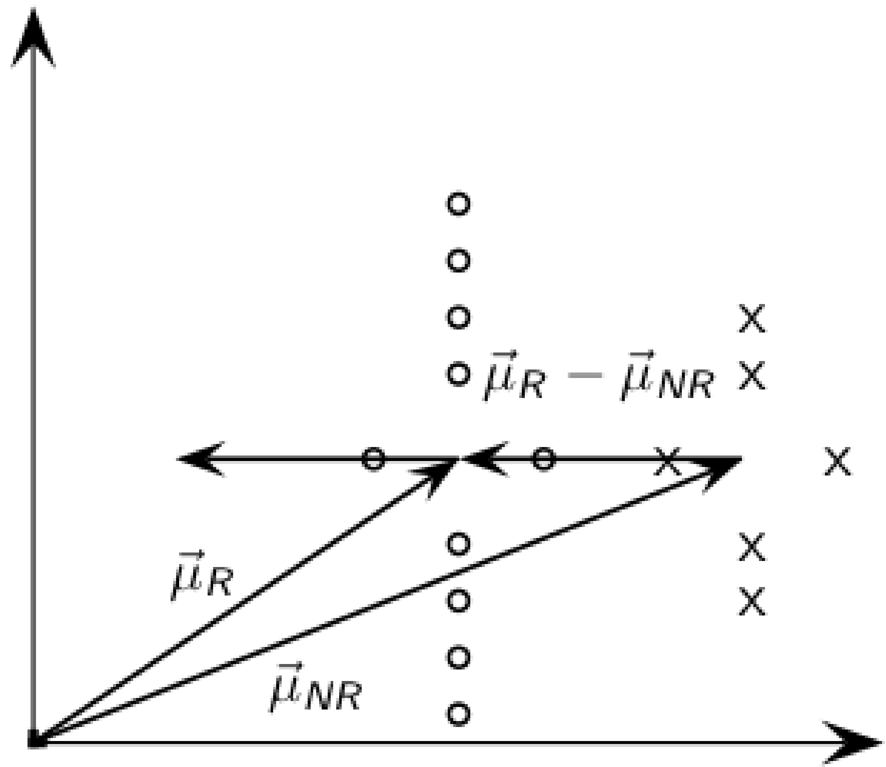
Ricchio Example



Ricchio Example

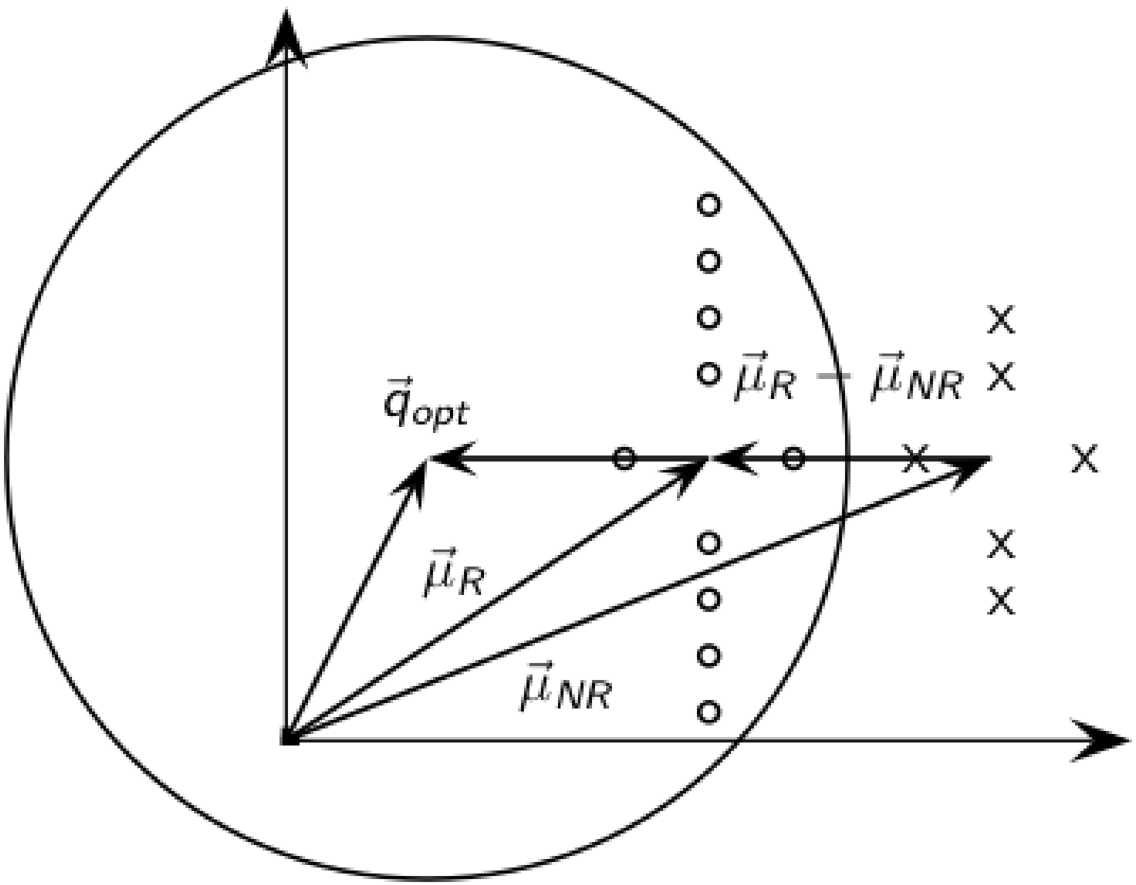


Ricchio Example



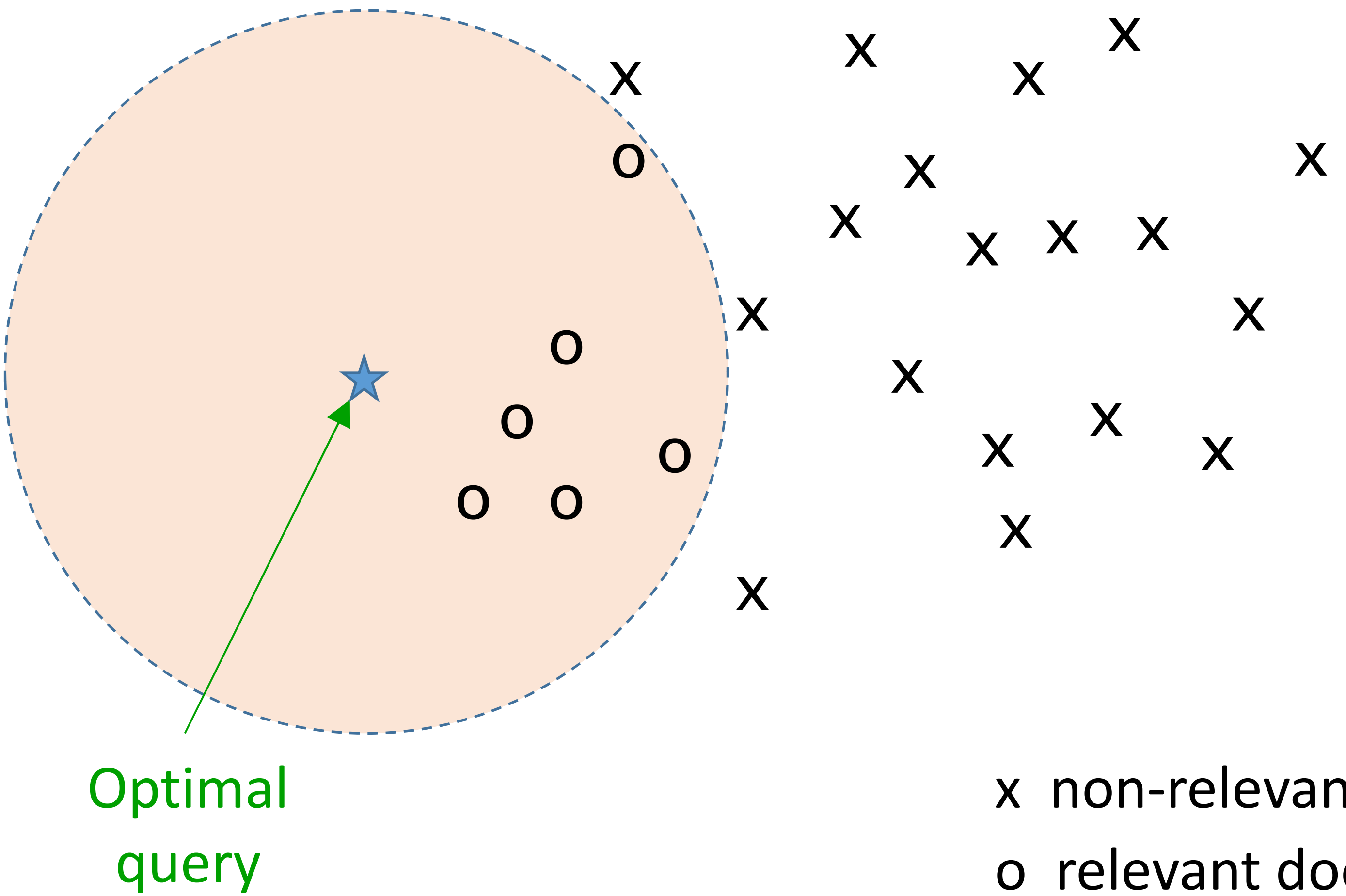
$$q_{\text{opt}} = \mu_R + \alpha(\mu_R - \mu_{NR})$$

Ricchio Example



q_{opt} could separate relevant / nonrelevant perfectly.

The Theoretically Best Query



x non-relevant documents

o relevant documents

Further on Relevance Feedback

- Probabilistic relevance feedback
  - There is a probability for each doc to be relevant to a query $P(r=1|q,d)$
    - Could be used to weight each document and search term
  - Robertson and Spärck-Jones (RSJ) Model
- Pseudo relevance feedback
  - There is no users' rating on the relevance of retrieved documents
  - Regarding the top-N retrieved documents as relevant ones to update the query

Prob. Ranking Principle: https://nlp.stanford.edu/IR-book/html/htmledition/the-probability-ranking-principle-1.html