CS4442/9542b
Artificial Intelligence II
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Lecture 11

Natural Language Processing

Information Retrieval

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Outline

- Introduction to Information Retrieval (IR)
- Ad hoc information retrieval
  - Boolean Model
  - Vector Space Model
    - Cosine similarity measure
    - Choosing term weights
  - Performance evaluation methods
  - Improving IR system
    - Query expansion
    - Relevance feedback

Information Retrieval Intro

- **Then:** most digital information is stored in databases
  - Structured data storage
  - Supports efficient information extraction with queries
  - mostly used by corporations/governments
  - Majority of innovation is for structured data
- **Now:** most digital information is stored in unstructured text form (reports, email, web pages, discussion boards, blogs, legal information retrieval, etc.)
  - Estimates: 70%, 90% ?? All depends how you measure
  - Unstructured data, not in traditional databases
  - Used by companies/organizations/people
  - How extract information from unstructured text data?
  - Majority of innovation is for unstructured data

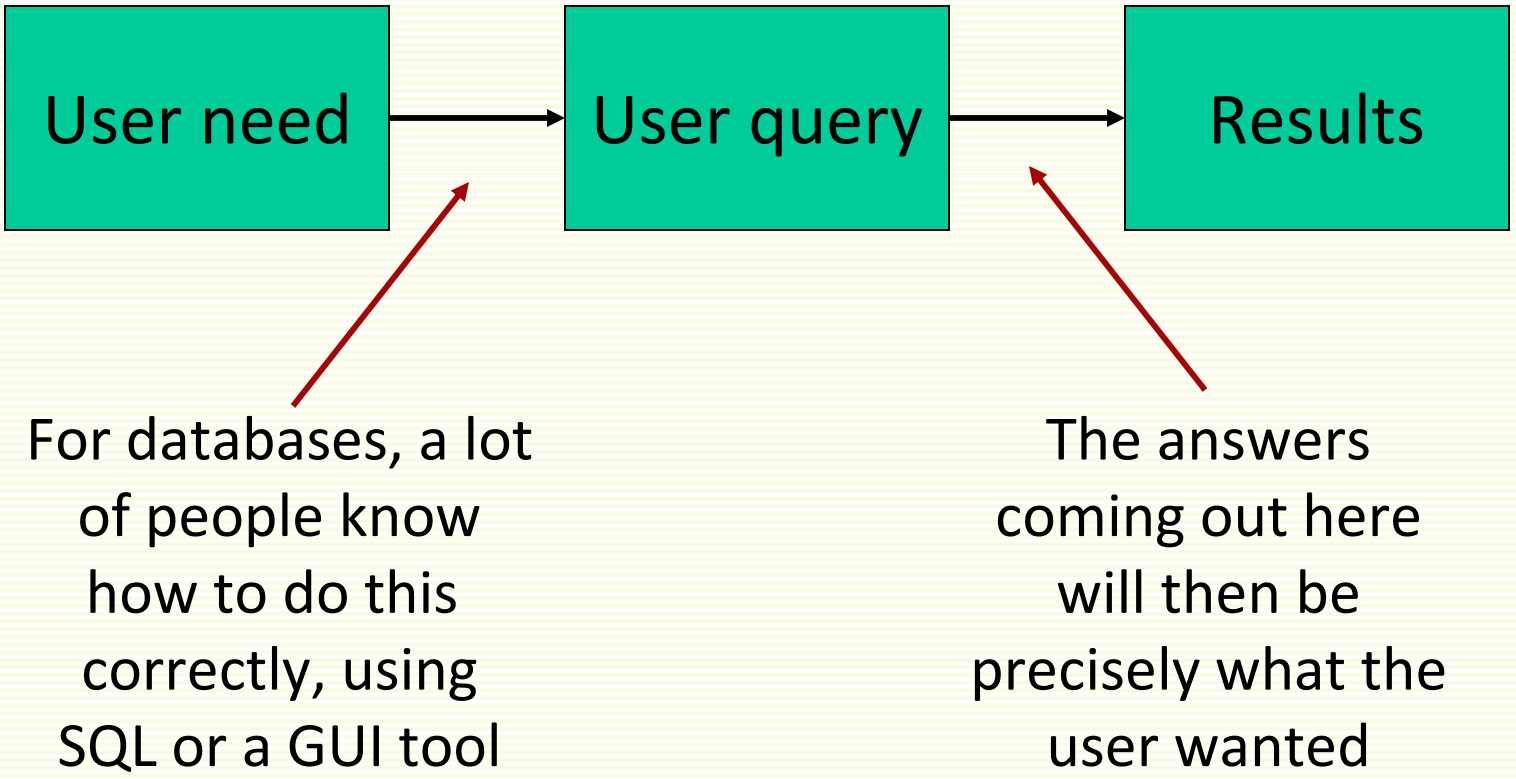
The Problem

- When people see text, they understand its meaning (by and large)
- When computers see text, they get only character strings (and perhaps HTML tags)
- We'd like computer agents to see meanings and be able to intelligently process text
- These desires have led to many proposals for structured, semantically marked up formats
- But often human beings still resolutely make use of text in human languages
- This problem isn’t likely to just go away

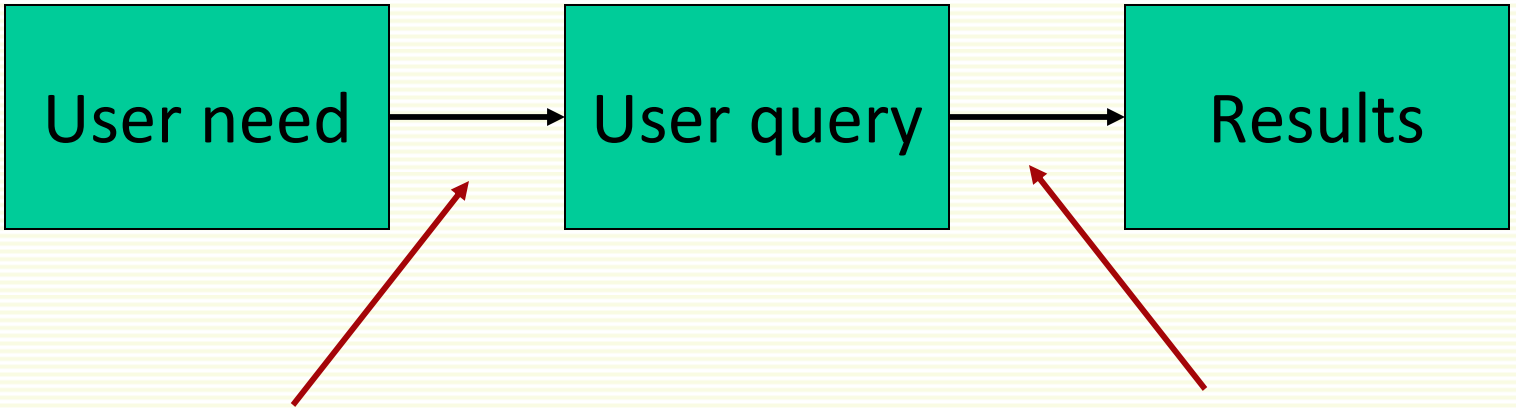
Information Retrieval

- IR deals with retrieving information from unstructured document repositories
- Traditionally
  - Text documents repositories
- More recently
  - Speech
  - Images
  - music
  - Video

Translating User Needs: Databases



Translating User Needs: Text Documents



For meanings in text, no IR-style query gives one exactly what one wants; it only hints at it

The answers coming out may be roughly what was wanted, or can be refined

Sometimes!

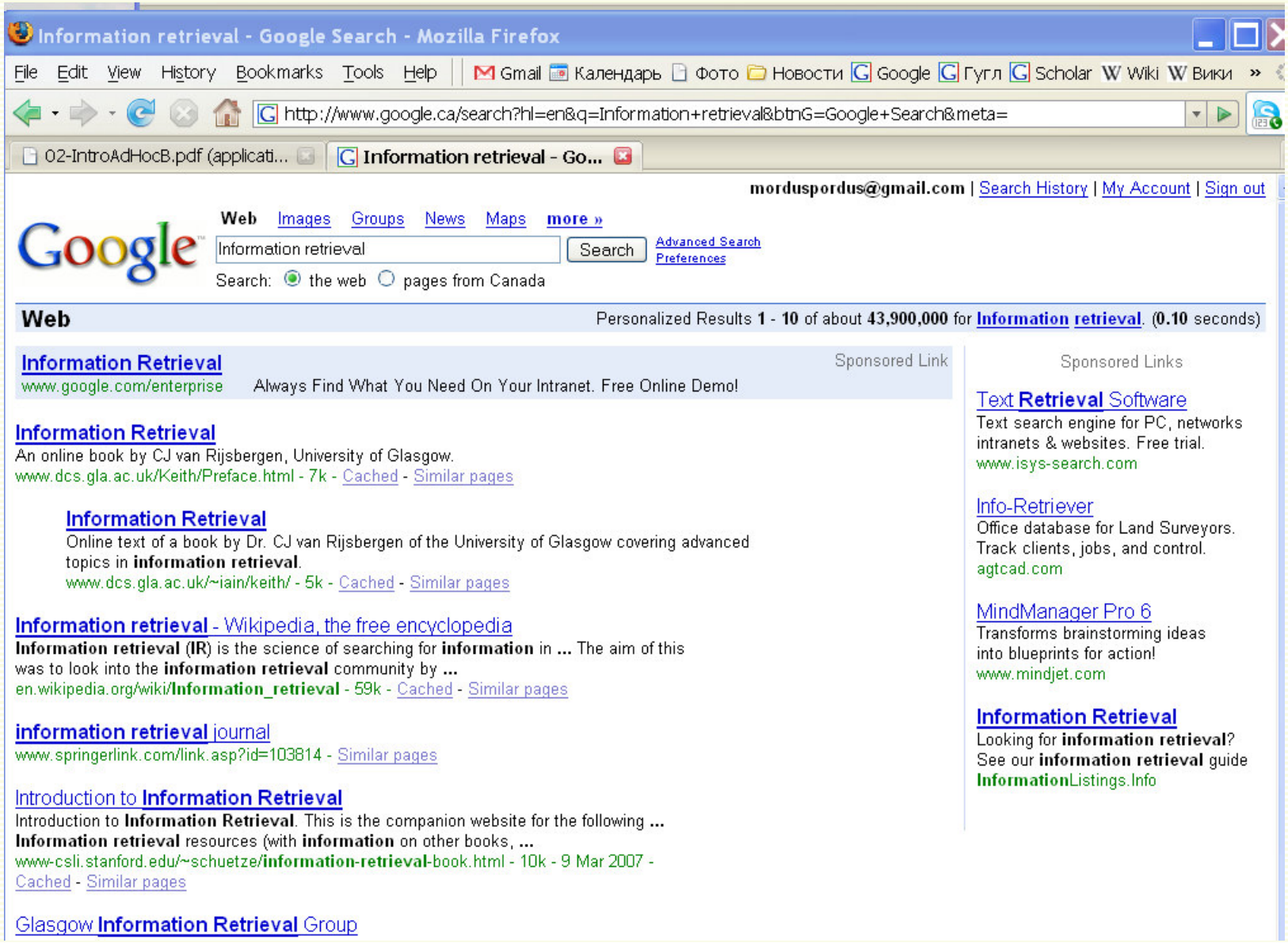
Major Types of Information Retrieval

- ad-hoc retrieval
  - user creates an "ad hoc" query which is usually not reused or saved
  - system returns a list of (hopefully) relevant documents
  - sometimes also called "archival" retrieval
  - no training data is available
- classification / categorization
  - training data is available
  - documents are classified in a pre-determined set of categories
  - Ex: Reuters (corporate news (CORP-NEWS), crude oil (CRUDE), …)
  - any of machine learning techniques can be used
- filtering / routing
  - special cases of categorization
  - 2 categories: relevant and not-relevant
  - filtering:
    - absolute assessment ($\mathbf{d}_1$ is relevant but $\mathbf{d}_2$ is not)
  - routing:
    - relative ranking of documents, such as $\mathbf{d}_1$, $\mathbf{d}_2$

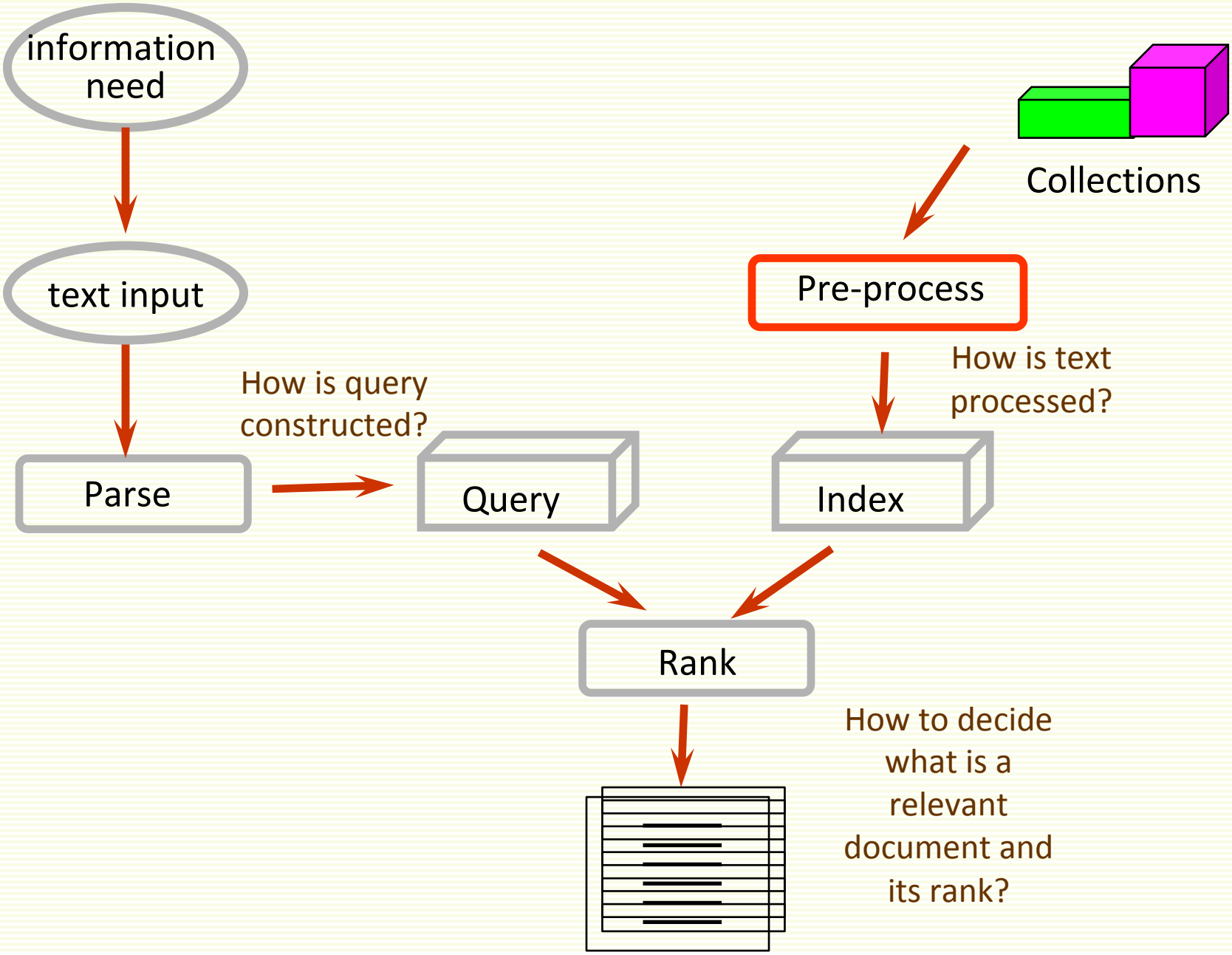
Different Types of Ad-Hoc Retrieval

- Web search
  - Massive collection (10^8-10^9) of documents
  - Query log analysis reveals population-based patterns
  - Typically high precision (most retrieved documents are relevant), low recall (not all relevant documents are retrieved)
- Commercial information providers (e.g. West, LexisNexis)
  - Large Collection (10^6-10^8) of documents
  - often high recall is essential (e.g. legal or patent search)
- Enterprise search (e.g. UWO, IBM)
  - Medium-sized to large collection (10^4-10^6) of documents
  - Opportunity to exploit domain knowledge
- Personal search (e.g. your PC)
  - Small collection (10^3-10^4) of documents
  - Good opportunity to learn a user model, do personalization

Example of ad-hoc IR



Information Retrieval Process



Relevance

- In what ways can a document be relevant to a query?
  - Answer precise question precisely
  - Partially answer question
  - Suggest a source for more information
  - Give background information
  - Remind the user of other knowledge
  - Others ...

Two Major Issues

- Indexing
  - How to represent a collection of documents to support fast search?
- Retrieval methods
  - How do we match a user query to indexed documents?

Indexing

- Most IR systems use **inverted index** to represent collection of texts
- Inverted Index = a data structure that lists for each word all documents in the collection that contain that word
- Sorted by document number

assassination	$\{d_1, d_4, d_{95}, d_5, d_{90}\ldots\}$
murder	$\{d_3, d_7, d_{95}\ldots\}$
Kennedy	$\{d_{24}, d_{33}, d_{44}\ldots\}$
conspiracy	$\{d_3, d_{55}, d_{90}, d_{98}\ldots\}$

- Inverted index is usually implemented as a dictionary which allows fast lookups based on word
  - B-trees, hash tables, etc are used to implement a dictionary

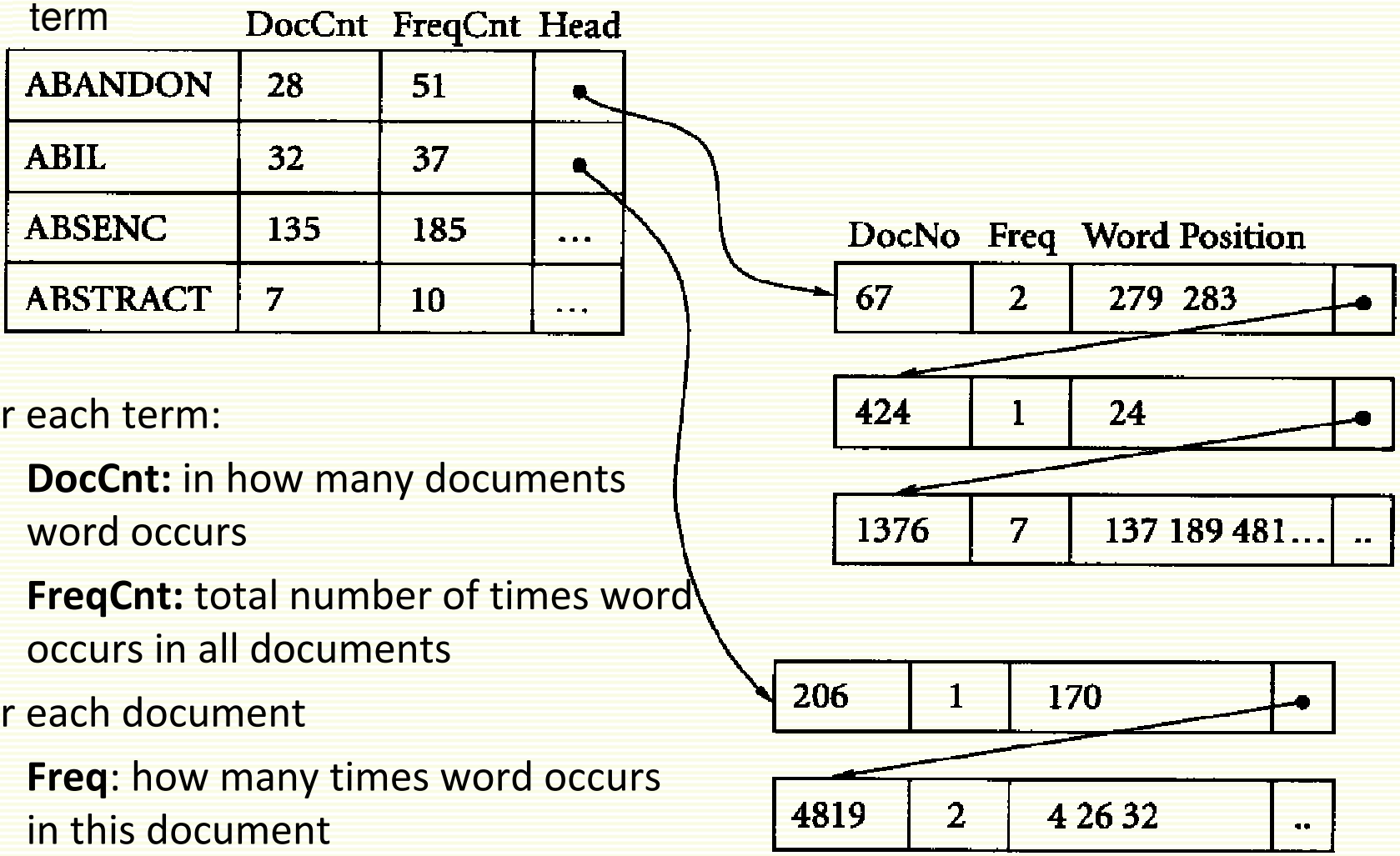
Indexing

- More sophisticated version of inverted index also contains position information, say byte offset from document start
  - Can search for phrases efficiently
  - Example: need to find "car insurance"
    - "car" in documents (d_1, offset 5), (d_7, offset 10), (d_9, offset 35)
    - "insurance" in documents (d_2, offset 3), (d_7, offset 11), (d_8, offset 7)
    - "car insurance" occurs in document d_7
  - Still rather primitive: "car insurance" ≠ "insurance for car"
  - Possible solution: can find frequent phrases (simply frequently occurring bigrams, trigrams, etc.) and index those too, in addition to words:

    car insurance $\{d_1, d_4, d_{95}, d_{155}, d_{190}\ldots\}$

    insurance for car $\{d_5, d_7, d_{95}, d_{99}\ldots\}$
- So we index words and word phrases
- Say "term" to refer to these indexed entities
  - However, sometimes just say "word", because it's simpler

Inverted Index Example



- For each term:
  - **DocCnt:** in how many documents word occurs
  - **FreqCnt:** total number of times word occurs in all documents
- For each document
  - **Freq**: how many times word occurs in this document
  - **WordPosition**: offset where these occurrences are found in document

Choosing Terms To Index

1. Controlled Vocabulary Indexing
   - A human expert selects a set of terms to index
   - This is done for libraries, web directories, etc
   - Pros
     - Usually “controlled” terms are unambiguous
   - Cons:
     - Expensive, need manual work
     - Controlled vocabularies can’t represent arbitrary detail
2. Free Text Indexing
   - Automatically select “good” terms to index
   - Some search engines do this
3. Full Text Indexing
   - Most search engines do this
   - Cons:
     - Many words are ambiguous
   - Pros:
     - Can represent arbitrary detail
     - Inexpensive and easy

Full Text Indexing

Are these terms useful?

Term	Tf	Term	Tf	Term	tf
the	78	up	8	pictures	6
to	35	for	7	red	6
i	31	have	7	digital	5
and	29	image	7	eye	5
a	19	like	7	not	5
camera	17	mode	7	on	5
is	17	much	7	or	5
in	12	software	7	shutter	5
with	11	very	7	sony	5
be	9	can	6	than	5
but	9	images	6	that	5
it	9	movies	6	after	4
of	9	my	6	also	4
this	9	no	6	: :	:

Can you tell what this document is about?

Full Text Indexing Design Issues

- To stem or not to stem
  - Stemming: *laughing, laughs, laugh* and *laughed* are stemmed to *laugh*
  - Problem: semantically different words like *gallery* and *gall* may both be truncated to *gall* making the stems unintelligible to
- Exclude/Include Stop words
  - Stop words make up about 50% of the text, excluding them makes representation more space efficient
  - But impossible to search for documents for phrases containing stop words
    - “to be or not to be”, “take over”
    - Most queries are unaffected, but could be very annoying sometimes

After Stemming and Stop Word Removal

Term	Tf	Term	Tf	Term	tf
camera	18	sony	5	lag	3
image	13	after	4	last	3
like	8	any	4	lcd	3
mode	8	auto	4	mavica	3
up	8	battery	4	record	3
buy	7	flash	4	reduce	3
movie	7	problem	4	size	3
picture	7	zoom	4	15	2
software	6	include	3	2mp	2
red	6	2100	3	8x10	2
digital	5	button	3	98	2
eye	5	down	3	automatic	2
look	5	feature	3	bag	2
shutter	5	focus	3	best	2

Problems with Index Terms

- May not retrieve relevant documents that include synonymous terms
  - “restaurant” vs. “café”
  - “PRC” vs. “China”
- May retrieve irrelevant documents that include ambiguous terms.
  - “bat” (baseball vs. mammal)
  - “Apple” (company vs. fruit)
  - “bit” (unit of data vs. act of eating)

Retrieval models

- We study 2 basic models:
  - boolean model
    - the oldest one, similar to what is used in database queries
  - vector-space model
    - most popular in IR
- Models vary on:
  - how they represent the query & the documents
  - how they calculate the relevance between the query and the documents

Boolean Model

- User gives a set of terms (keywords) that are likely to appear in relevant documents
  - *Ex: JFK Kennedy conspiracy assassination*
- Connects the terms in the query with Boolean operators (AND, OR, NOT)

```
AND(Kennedy, conspiracy, assassination)
```

- Can expand query using synonyms

```
AND (OR (Kennedy, JFK),
         (OR (conspiracy, plot),
              (OR (assassination, assassinated,
                   assassinate, murder, murdered, kill, killed)
              ) ))
```

- system returns set of documents that satisfy query **exactly**

Example

- Which of these documents will be returned for the following query :

  computer AND (*information* OR *document*) AND *retrieval*

document collection:

d_1: {*computer* √ , *software*, *information* √, *language*} ×

d_2: {*computer* √, *document* √, *retrieval* √, *library*} √

d_3: {*computer* √, *information* √, *filtering*, *retrieval* √} √

Implementation With Set Operators

- Assume that the inverted index contains:

  t1-list: {d1,d2,d3,d4} t2-list: {d1,d2} t3-list: {d1,d2,d3} t4-list: {d1}

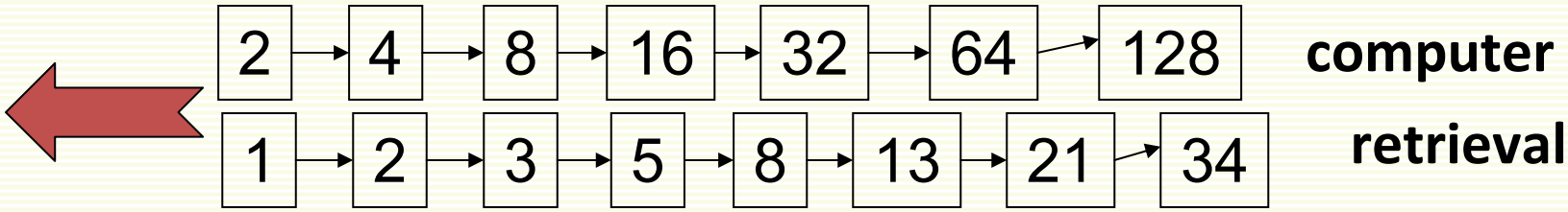
  - The query Q = (t1 AND t2) OR (t3 AND (NOT t4))
- We perform set operations:
  - to satisfy (t1 **AND** t2), we **intersect** the t1 and t2 lists
    - {d1,d2,d3,d4} ∩ {d1,d2} = {d1,d2}
  - to satisfy (t3 AND (**NOT** t4)), we **subtract** the t4 list from the t3 list
    - {d1,d2,d3} - {d1} = {d2,d3}
  - to satisfy (t1 AND t2) **OR** (t3 AND (NOT t4)), we take the **union** of the two sets of documents obtained for the parts.
    - {d1,d2} ∪ {d2,d3} = {d1,d2,d3}

Query processing: AND

- Consider processing the query:

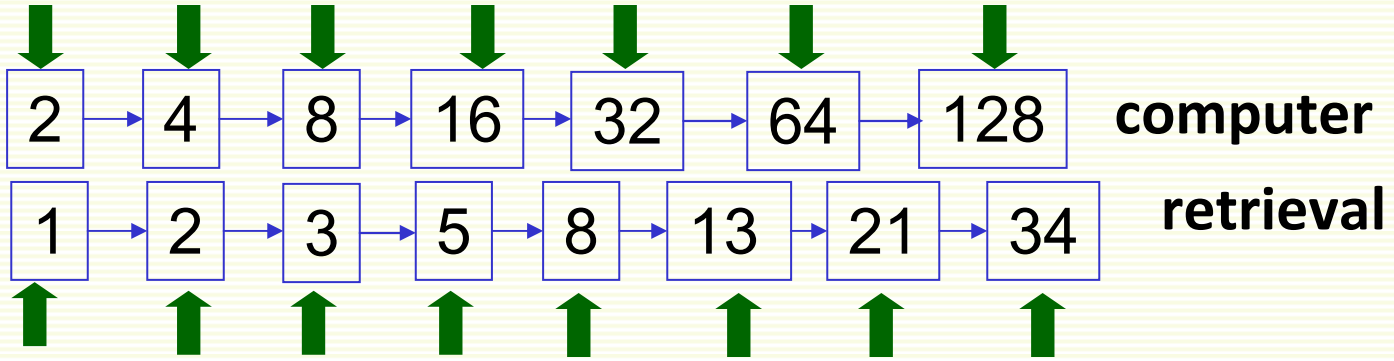
  computer AND r**etrieval**

  - Locate **computer** in the Inverted Index
    - retrieve its document list
  - Locate **retrieval** in the Inverted Index
    - Retrieve its postings.
  - "Merge" (intersect) the document sets):



The Merge

- Walk through two lists, in time linear in to the total number of entries



{2, 8 }

- If the list lengths are x and y, merge takes **O**(**x**+**y**) time
- Crucial: lists are sorted by document ID

Analysis of the Boolean Model

- advantages
  - queries are expressed with Boolean operators, i.e.semantics is clearly defined
  - results are easy to explain
  - usually computationally efficient
  - useful for expert users
- disadvantages
  - retrieval strategy is a binary decision (relevant or not)
  - difficult to *rank* documents in order of relevance
  - non-expert users have difficulty to express their need as Boolean expressions
  - "Feast of Famine" phenomena, people create quires that are either
    - **too strict**: few relevant documents are found
    - **too loose**: too many documents, most irrelevant, are found
    - Therefore most boolean searches on the web either return no documents or a huge set of documents

Ranked Retrieval Models

- Rather than a set of documents **exactly** satisfying a query expression, in ranked retrieval models, the system returns an ordering over the (top) documents in the collection with respect to a query
  - large set of retrieved documents is not a problem, just show top 10 ranked documents
- Free text queries: rather than a query language of operators and expressions, the user query is just one or more words in a human language
- In principle, there are two separate choices here, but in practice, ranked retrieval models have normally been associated with free text queries and vice versa

Vector-Space Model

- Documents and queries are represented by a “term vector”
  - each dimension corresponds to a term in the vocabulary
- Similarity between a document and a query is determined by a distance in vector space
- First system is “SMART” system
  - developed by G. Salton at Cornell 1960-1999
  - still used widely today

Gerard Salton

Term-Document Matrix

- the collection of documents is represented by a matrix of weights called a term-by-document matrix

	d_1	d_2	d_3	d_4	d_5	…
$term_1$	w_{11}	w_{12}	w_{13}	w_{14}	w_{15}	
$term_2$	w_{21}	w_{22}	w_{23}	w_{24}	w_{25}	
$term_3$	w_{31}	w_{32}	w_{33}	w_{34}	w_{35}	
…						
$term_N$	w_{n1}	w_{n2}	w_{n3}	w_{n4}	w_{n5}	

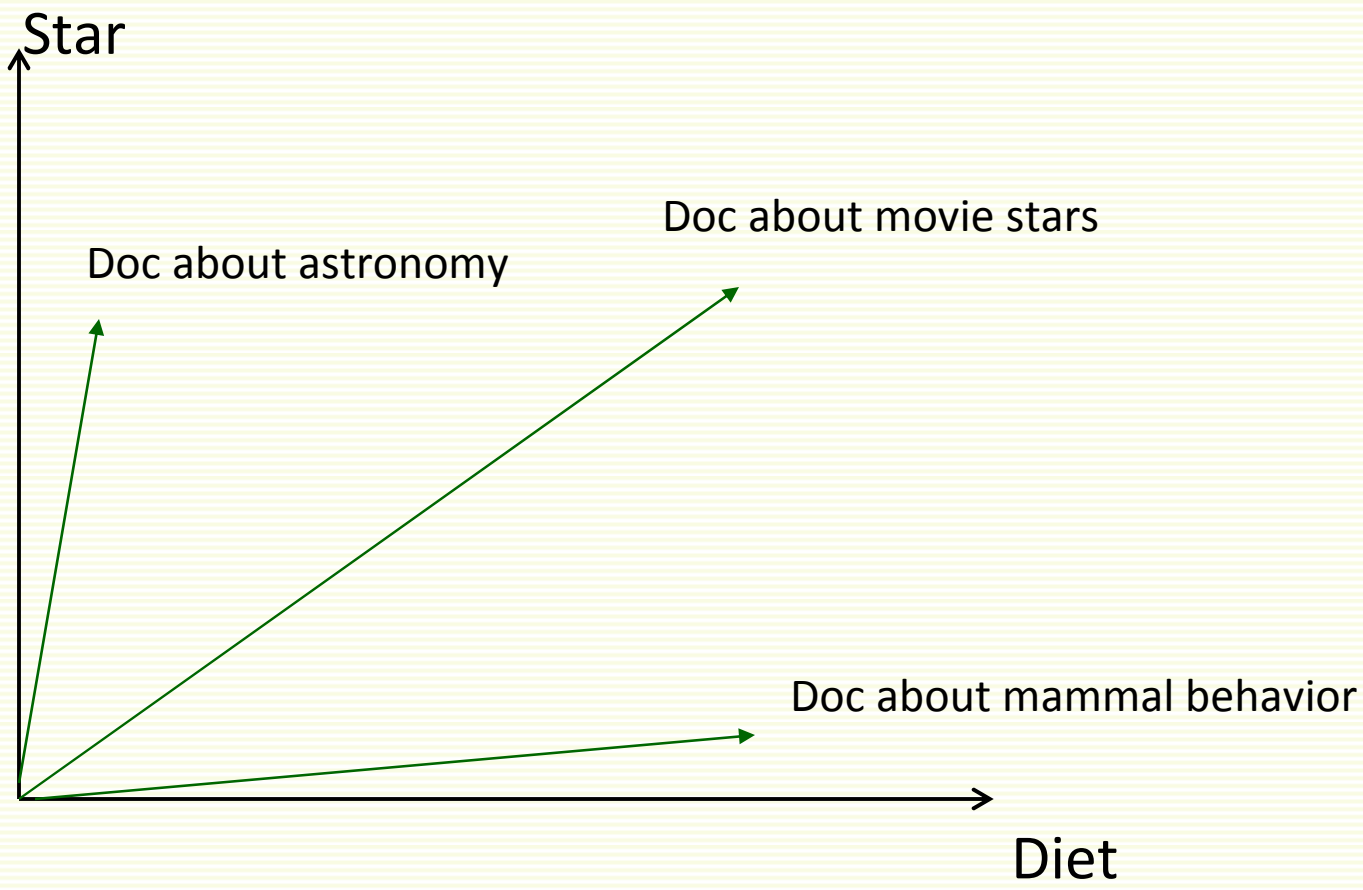
- 1 column = representation of one document
- 1 row = representation of one term across all documents
- cell $\mathbf{w_{ij}}$ = weight of term **i** in document **j**
  - simplest weight $\mathbf{w_{ij}}$ is the count of times term **i** occurred in document **j**
- matrix is sparse, i.e. most weights are 0

Term-document Count Matrix

- Consider number of occurrences of a term in a document:
  - each document is a count vector in $\mathbb{N}^{|V|}$: a column below

	Antony and Cleopatra	Julius Caesar	The Tempest	Hamlet	Othello	Macbeth
Antony	157	73	0	0	0	0
Brutus	4	157	0	1	0	0
Caesar	232	227	0	2	1	1
Calpurnia	0	10	0	0	0	0
Cleopatra	57	0	0	0	0	0
mercy	2	0	3	5	5	1
worser	2	0	1	1	1	0

Documents as Vectors



Bags of Words

- Even simpler representation is **bags of words**
  - The document is the "Bag"
  - "Bag" contains word tokens
  - A particular word may occur more than once in the bag
  - Stop words are usually ignored
    - "the","a","to",…
  - Word order is ignored

    "I see what I eat " = "I eat what I see"

Document 1

The quick brown fox jumped over the lazy dog's back.

Document 2

Now is the time for all good men to come to the aid of their party.

Indexed Term	Document 1	Document 2
aid	0	1
all	0	1
back	1	0
brown	1	0
come	0	1
dog	1	0
fox	1	0
good	0	1
jump	1	0
lazy	1	0
men	0	1
now	0	1
over	1	0
party	0	1
quick	1	0
their	0	1
time	0	1

Stop words: for, is, of, 's, the, to

Documents as Vectors

- Now we have a |V|-dimensional vector space
  - |V| is the number of terms
- Terms are axes of the space
- 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

Queries as vectors

- Key idea 1
  - represent queries also as vectors in the same vector space
- Key idea 2
  - Rank documents according to their proximity to the query in this space
- proximity = similarity of vectors
- proximity $\approx$ inverse of distance
- Recall: we do this because we want to get away from the "you're-either-in-or-out" Boolean model
- Instead: rank more relevant documents higher than less relevant documents

Query Representation

- A query can also be represented as a vector, like a document

$$\mathbf{q} = (0,0,0,1,0,\ldots 1,..0,1)$$

- Size of vector corresponding to query **q** is also the number of terms $|\mathbf{V}|$

Example

- The collection:
  - d_1 = {introduction knowledge in speech and language processing ambiguity models and algorithms language thought and understanding the state of the art and the near-term future some brief history summary}
  - d_2 = {hmms and speech recognition speech recognition architecture overview of the hidden markov models the Viterbi algorithm revisited advanced methods in decoding acoustic processing of speech computing acoustic probabilities training a speech recognizer waveform generation for speech synthesis human speech recognition summary}
  - d_3 = {language and complexity the chomsky hierarchy how to tell if a language isn't regular the pumping lemma are English and other languages regular languages ? is natural language context-free complexity and human processing summary}
- The query:

  Q = {speech language processing}

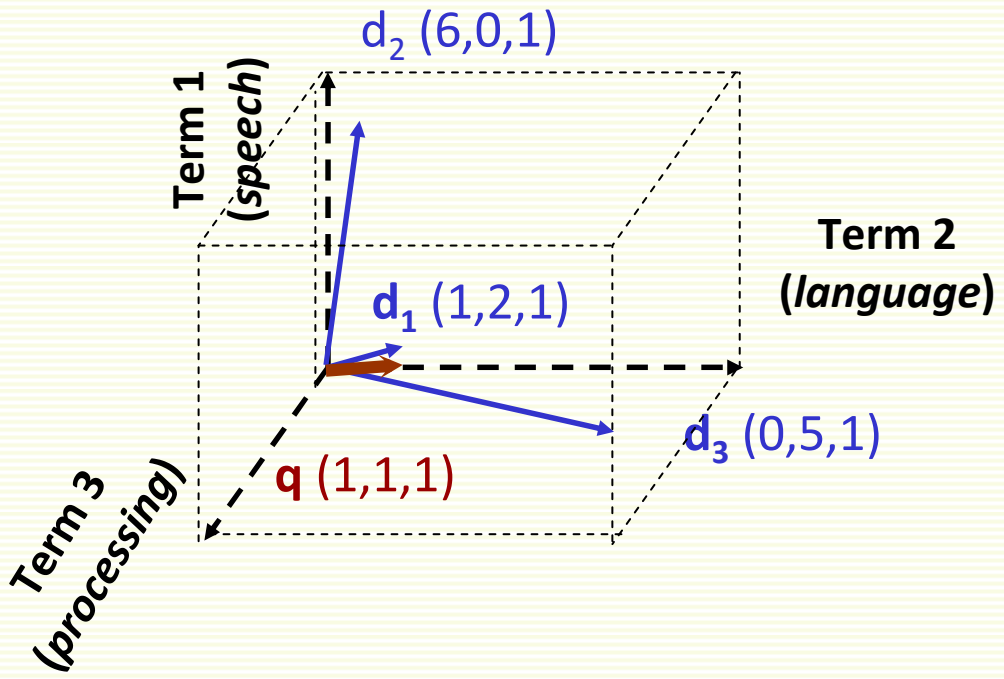
Example Continued

- The collection:
  - d_1 = {introduction knowledge in speech and language processing ambiguity models and algorithms language thought and understanding the state of the art and the near-term future some brief history summary}
  - d_2 = {hmms and speech recognition speech recognition architecture overview of the hidden markov models the viterbi algorithm revisited advanced methods in decoding acoustic processing of speech computing acoustic probabilities training a speech recognizer waveform generation for speech synthesis human speech recognition summary}
  - d_3 = {language and complexity the chomsky hierarchy how to tell if a language isn't regular the pumping lemma are English and other language regular language ? is natural language context-free complexity and human processing summary}
- The query:

  Q = {speech language processing}

Example Continued

	d_1	d_2	d_3	q
introduction	…	…	…	…
knowledge	…	…	…	…
…	…	…	…	…
speech	1	6	0	1
language	2	0	5	1
processing	1	1	1	1
…	…	…	…	…



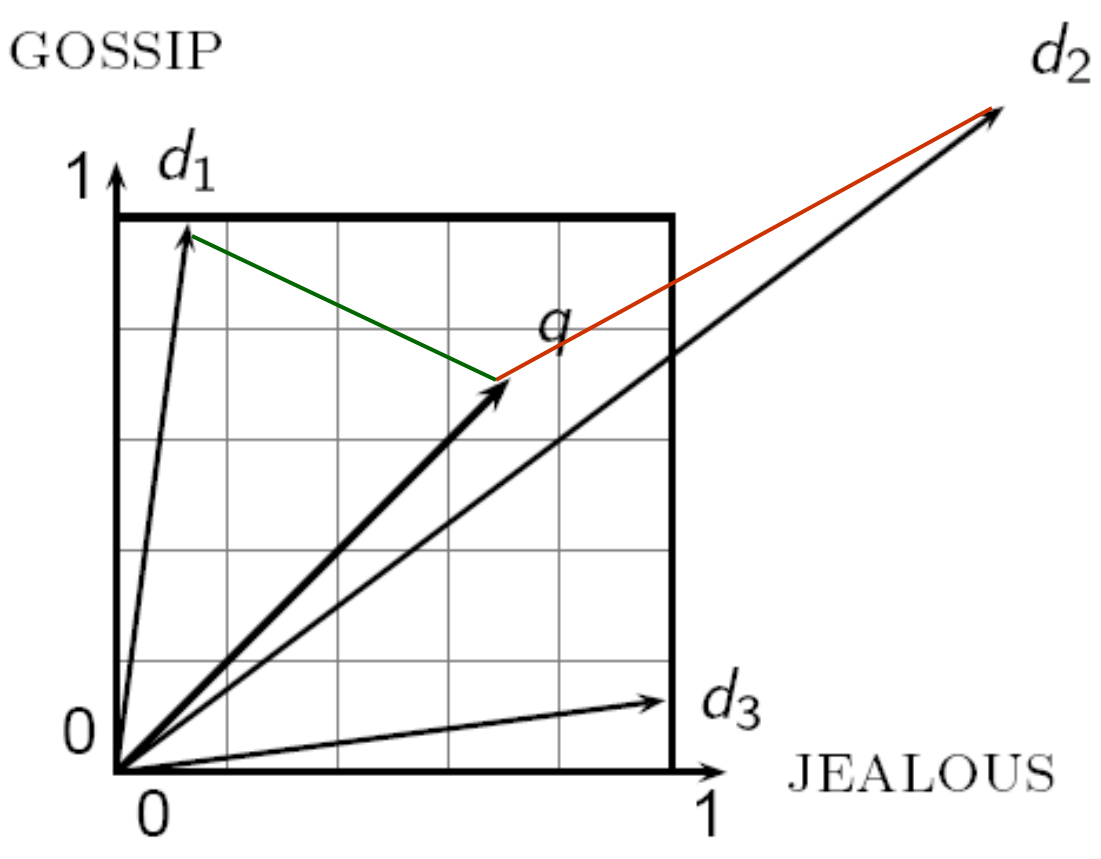
- using raw term frequencies for weights

Formalizing vector space proximity

- First idea: use standard Euclidean distance
  - does not work well
  - because Euclidean distance is large for vectors of different lengths
  - documents tend to vary in lengths widely

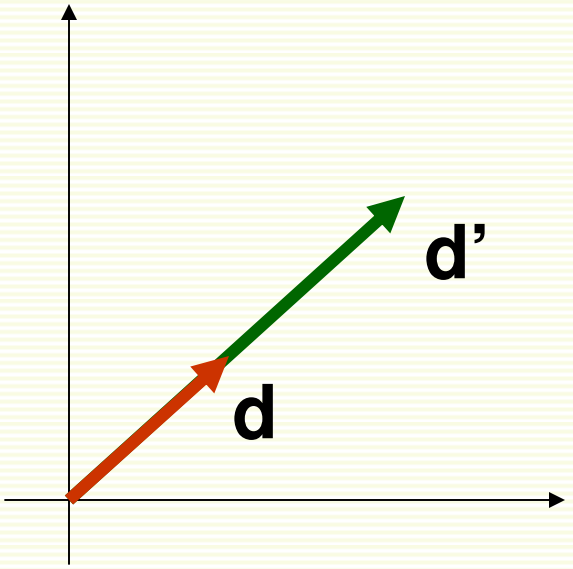
Why Eucledian Distance is a Bad Idea

- Euclidean distance between **q** and $\mathbf{d_2}$ is large even though the distribution of terms in the query **q** and the distribution of terms in the document $\mathbf{d_2}$ are very similar
- Query **q** is closes to $\mathbf{d_1}$ in terms of Eucledian distance



Use Angle Instead

- Thought experiment:
  - take a document **d** and append it to itself
  - call this document **d′**
- "Semantically" **d** and **d′** have the same content
  - **d** is a short document, **d'** is a long document
- 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

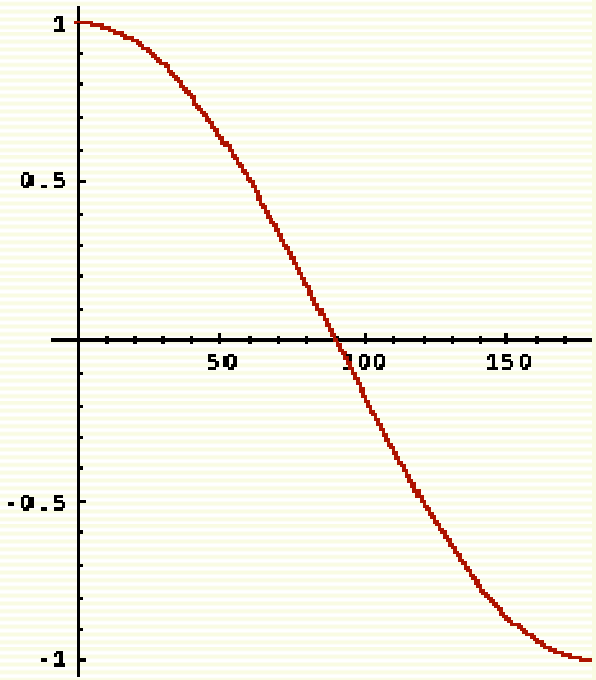


From Angles to Cosines

- The following two notions are equivalent.
  - rank documents in decreasing order of the angle between query and document
  - rank documents in increasing order of cosine(query,document)

- Cosine is a monotonically decreasing function for the interval [0^o, 180^o]

From Angles to Cosines



- Why cosines?
  - efficiency

Length Normalization

- A vector can be (length-) normalized by dividing each of its components by its length – for this we use the $\mathbf{L_2}$ norm:

$$\|\mathbf{x}\|_2 = \sqrt{\sum_i \mathbf{x}_i^2}$$

- Dividing a vector by its $\mathbf{L_2}$ norm makes it a unit (length) vector
- Effect on the two documents **d** and **d′** (**d** appended to itself) from earlier slide: they are identical after length-normalization
  - long and short documents now have comparable weights

Cosine(query,document)

Dot product

Unit vectors

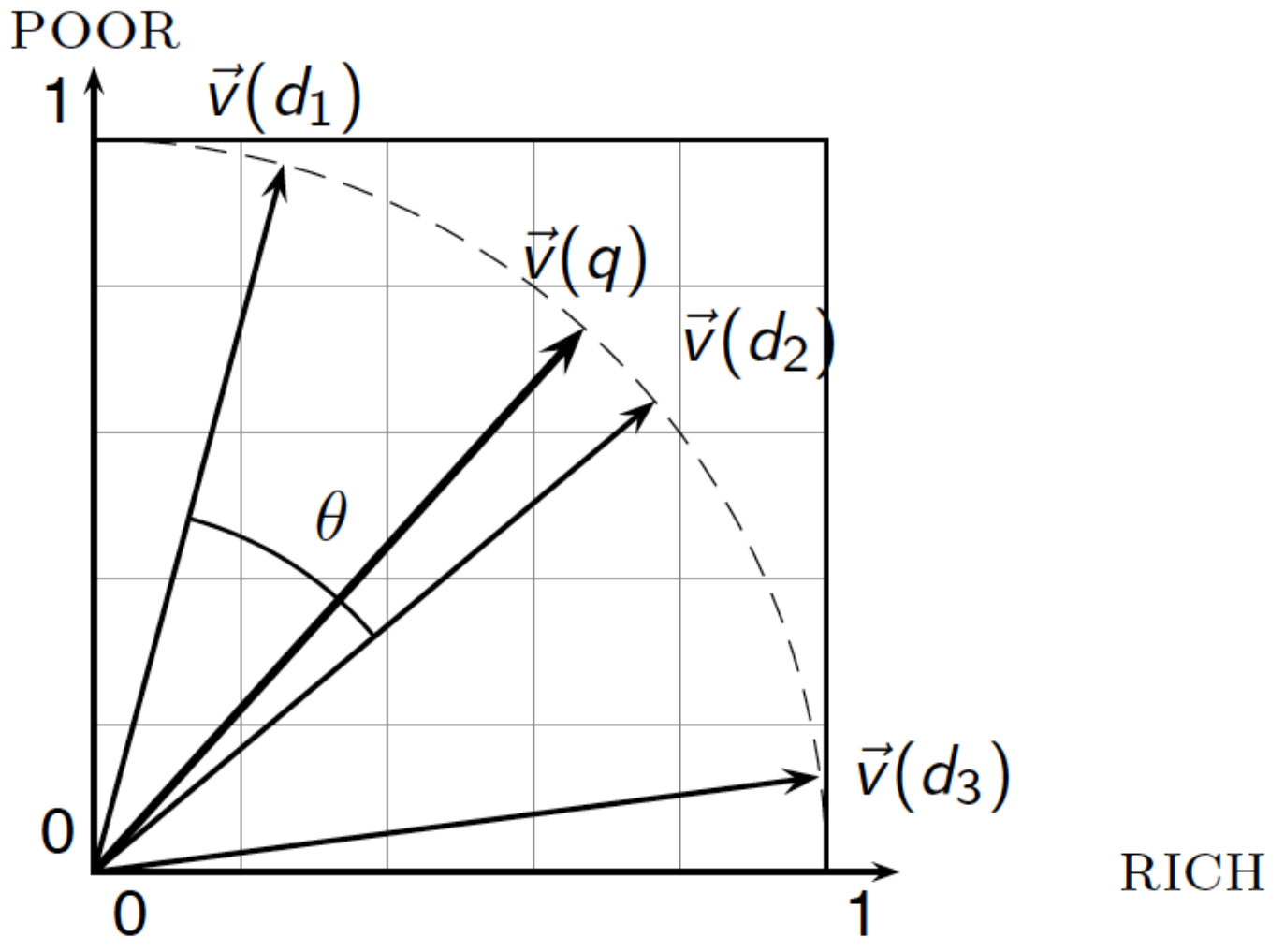
$$\cos(q,d) = \frac{q \cdot d}{|q||d|} = \frac{q}{|q|} \cdot \frac{d}{|d|} = \frac{\sum_{i=1}^{|V|} q_i d_i}{\sqrt{\sum_{i=1}^{|V|} q_i^2} \sqrt{\sum_{i=1}^{|V|} d_i^2}}$$

Cosine for Length-Normalized Vectors

- For length-normalized vectors, cosine similarity is simply the dot product (or scalar product):

$$\cos(\mathbf{q},\mathbf{d}) = \mathbf{q}\cdot\mathbf{d} = \sum_{i=1}^{|V|} q_i d_i$$

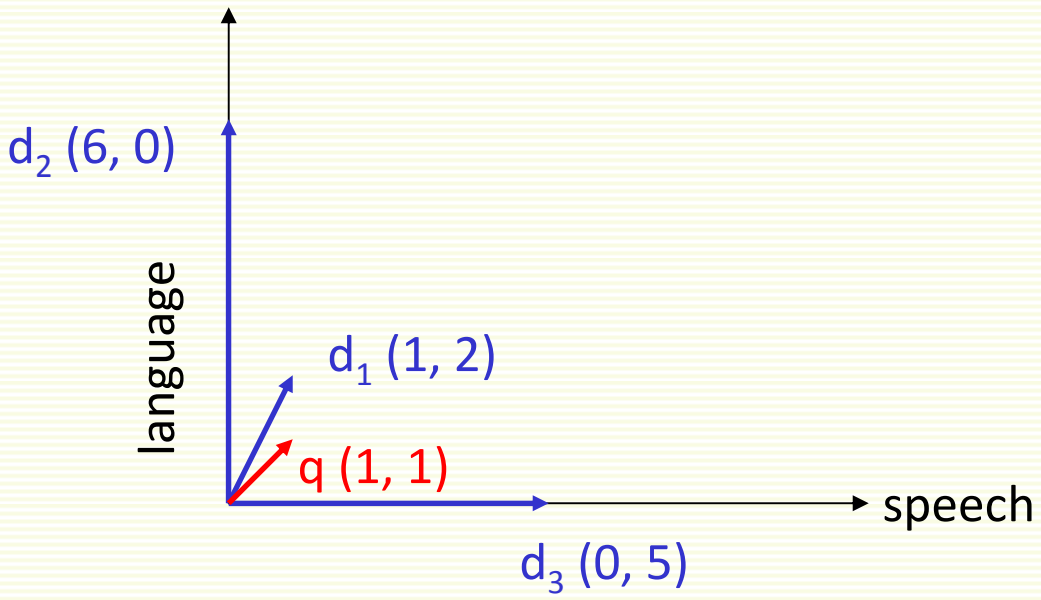
Cosine Similarity Illustrated



Example

Query = “speech language”

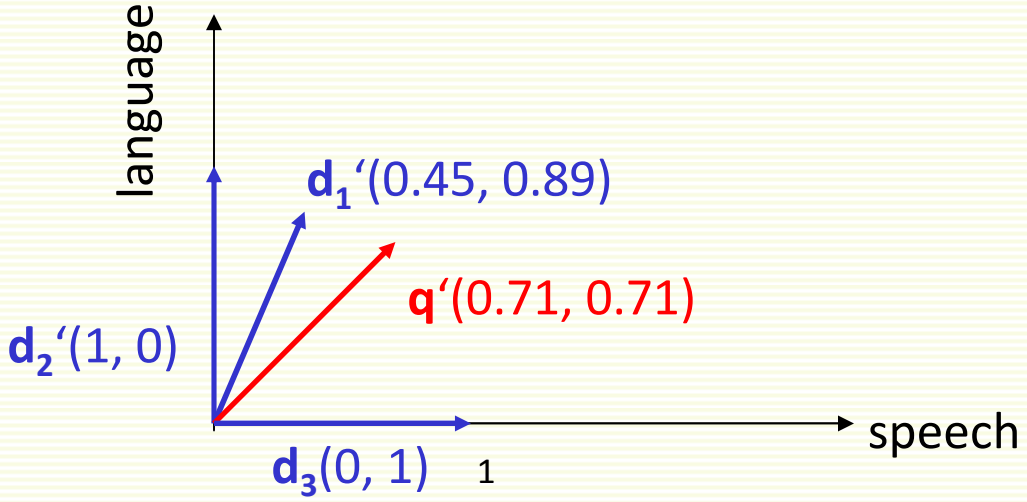
original representation:



Example: Normalized vectors

Query = "speech language"

after normalization:



q(1,1): $L = \sqrt{1^2 + 1^2} = 1.41$ $\Rightarrow$ normalized **q**' (0.71, 0.71)

$\mathbf{d_1}(1,2)$: $L = \sqrt{1^2 + 2^2} = 2.24$ $\Rightarrow$ normalized $\mathbf{d_1}'$ (0.45, 0.89)

$\mathbf{d_2}(6,0)$: $L = \sqrt{6^2 + 0^2} = 6$ $\Rightarrow$ normalized $\mathbf{d_2}'$ (1, 0)

$\mathbf{d_3}(0,5)$: $L = \sqrt{0^2 + 5^2} = 5$ $\Rightarrow$ normalized $\mathbf{d_3}'$ (0, 1)

Term frequency **tf**

- Are word counts or binarized counts (bag of word) the best representation for document vectors?
- Define the number of occurrences of a term **t** in a document is **d** term frequency $\mathbf{tf}_{td}$
- Want to use **tf** when computing query-document match scores. But how?
- Raw term frequency is not what we want:
  - document with 10 occurrences of term is more relevant than document with 1 occurrence of term
  - But not 10 times more relevant
- Relevance does not increase proportionally with term frequency

Log-frequency weighting

- The log frequency weight of term **t** in **d** is

$$w_{td} = \begin{cases} 1 + \log_{10} tf_{td}, & \text{if } tf_{td} > 0 \\ 0, & \text{otherwise} \end{cases}$$

- $0 \rightarrow 0$, $1 \rightarrow 1$, $2 \rightarrow 1.3$, $10 \rightarrow 2$, $1000 \rightarrow 4$, etc
  - document that has 10 times more occurrences of a term is only 2 times more important

Document Frequency

- Rare terms are more informative than frequent terms
  - recall stop words “the”, “in”, “from”…
- Consider a term in the query that is rare in the collection
  - e.g., *arachnocentric*
- Document containing this term is very likely to be relevant to the query *arachnocentric*
- Want a higher weight for rare terms like *arachnocentric*

Document Frequency

- Frequent terms are less informative than rare terms
- Consider a query term that is frequent in the collection
  - e.g., *high, increase, line*
- A document containing such a term is more likely to be relevant than a document that doesn't
- But it's not a sure indicator of relevance
- For frequent terms, we want positive weights for words like *high, increase, and line*
- But lower weights than for rare terms
- We use document frequency (**df**) to capture this

idf weight

- $\mathbf{df}_t$, the document frequency of **t** is the number of documents that contain **t**
  - $\mathbf{df}_t$ is an inverse measure of the informativeness of **t**
  - $\mathbf{df}_t \leq \mathbf{N}$, where **N** is the number of documents
- Define **idf** (inverse document frequency) of **t**

$$\mathbf{idf}_t = \mathbf{log}_{10}\,(\mathbf{N}/\mathbf{df}_t)$$

  - use log ($\mathbf{N}/\mathbf{df}_t$) instead of $\mathbf{N}/\mathbf{df}_t$ to "dampen" the effect of **idf**
  - the base of the log is of little importance

idf Example

- Suppose **N** = 1 million

term	df_t	idf_t
calpurnia	1	6
animal	100	4
sunday	1,000	3
fly	10,000	2
under	100,000	1
the	1,000,000	0

$$\mathbf{idf_t = \log_{10}(N/df_t)}$$

- There is one **idf** value for each term **t** in a collection

Effect of idf on ranking

- Question: Does **idf** have an effect on ranking for one-term queries, like
  - iPhone
- **idf** has no effect on ranking one term queries
  - **idf** affects the ranking of documents for queries with at least two terms
  - For the query capricious person, **idf** weighting makes occurrences of capricious count for much more in the final document ranking than occurrences of person

tf-idf weighting

- The **tf-idf** weight of a term is the product of its tf weight and its **idf** weight

$$w_{t,d} = (1 + \log tf_{t,d}) \times \log_{10}(N / df_t)$$

- Best known weighting scheme in information retrieval
  - Note: the "-" in tf-idf is a hyphen, not a minus sign!
  - Alternative names: tf.idf, tf x idf
- Increases with the number of occurrences within a document
- Increases with the rarity of the term in the collection

Analysis of the Vector Space Model

- advantages:
  - Simple and effective
  - term-weighting scheme improves retrieval performance
  - partial matching allows for retrieval of documents that approximate the query
  - cosine ranking allows for sorting the results
- disadvantages
  - no real theoretical basis for the assumption of a term space
  - Assumed independence between terms is not really true
- Note: In WWW search engines the weights may be calculated differently
  - use heuristics on where a term occurs in the document (ex, title)
  - notion of *hub* and *authority*

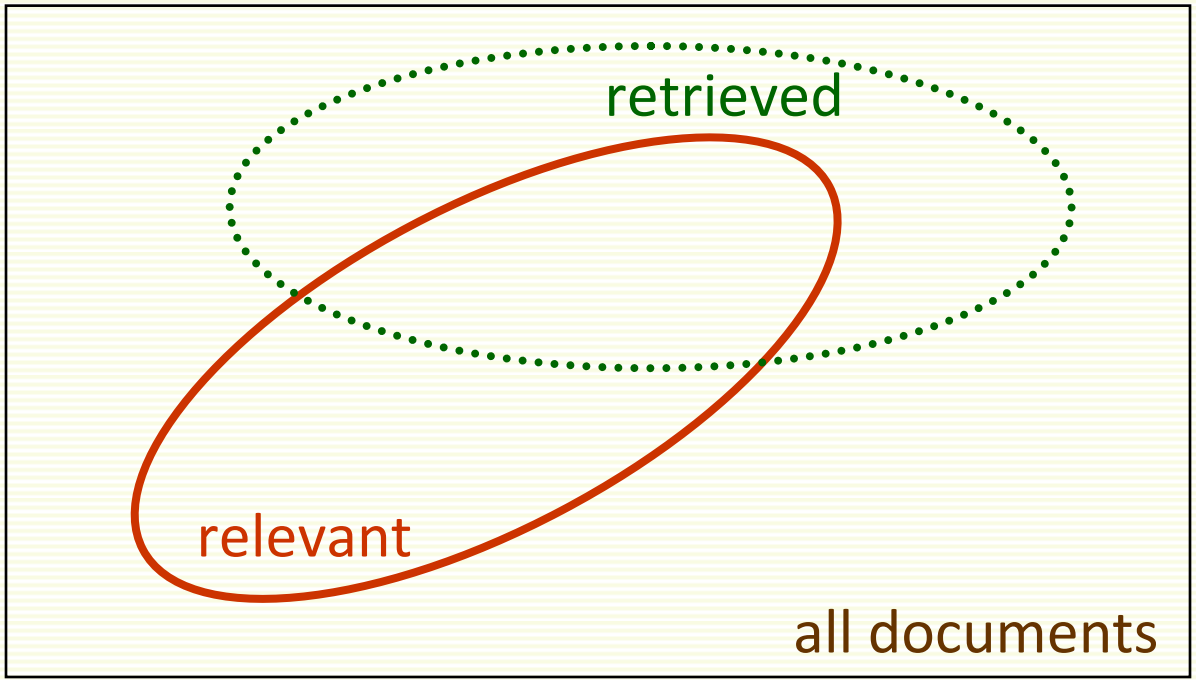
Evaluation

- Suppose have several retrieval methods
- Which one is the best?
  - for us, “best” = effectiveness, or the relevance of retrieved documents
  - other possible measures: ease of use, efficiency, nice interface, cost, etc.
- An **information need** is translated into a **query**
- Relevance is assessed relative to the **information need** *not* the **query**
- **Information need**: *I’m looking for information on whether drinking red wine is more effective at reducing your risk of heart attacks than white wine.*
- **Query**: ***wine red white heart attack effective***
- You evaluate whether the doc addresses the information need, not whether it has these words

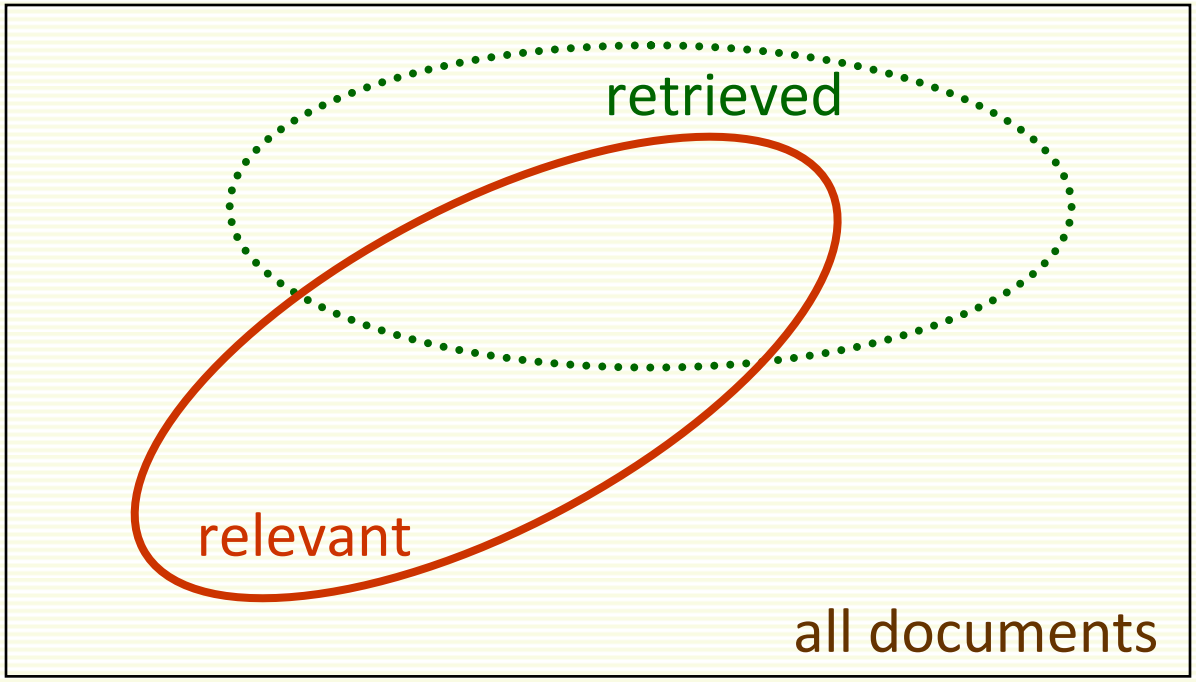
Evaluation

- To evaluate, we need
  - a benchmark document collection
  - a benchmark set of queries
  - a set of relevance query/document judgments
- To compare two (or more) methods
  - Each method is used to retrieve documents for a query
  - Results are compared using some measures
  - Common measures are based on **precision** and **recall**

Relevant vs. Retrieved



Precision vs. Recall



$$\text{Precision} = \frac{\text{number of relevant documents retrieved}}{\text{number of documents retrieved}} = \frac{|O \cap O|}{|O|}$$

$$\text{Recall} = \frac{\text{number of relevant documents retrieved}}{\text{number of relevant documents in collection}} = \frac{|O \cap O|}{|O|}$$

Evaluation: Example of P&R

- Relevant: d_3 d_5 d_9 d_{25} d_{39} d_{44} d_{56} d_{71} d_{123} d_{389}
- system1: d_{123} d_{84} d_{56}
  - Precision : ??
  - Recall : ??
- system2: d_{123} d_{84} d_{56} d_6 d_8 d_9
  - Precision : ??
  - Recall : ??

Evaluation: Example of P&R

- Relevant: d_3 d_5 d_9 d_{25} d_{39} d_{44} d_{56} d_{71} d_{123} d_{389}

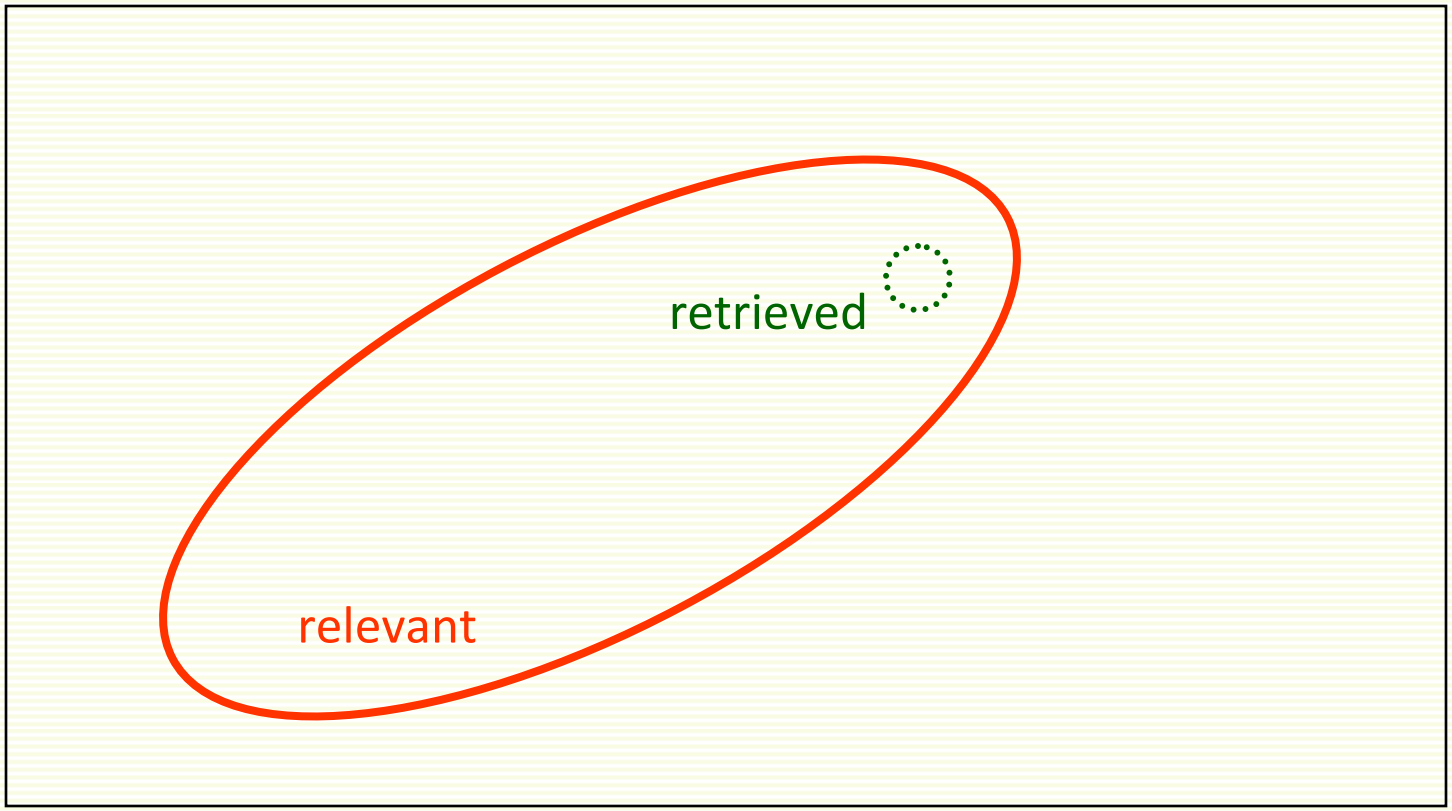
- system1: d_{123}√ d_{84}× d_{56}√
  - Precision: 66% (2/3)
  - Recall: 20% (2/10)
- system2: d_{123}√ d_{84}× d_{56}√ d_6× d_8× d_9√
  - Precision: 50% (3/6)
  - Recall: 30% (3/10)

Why Precision and Recall?

- Get as much good stuff (high recall) while at the same time getting as little junk as possible (high precision)

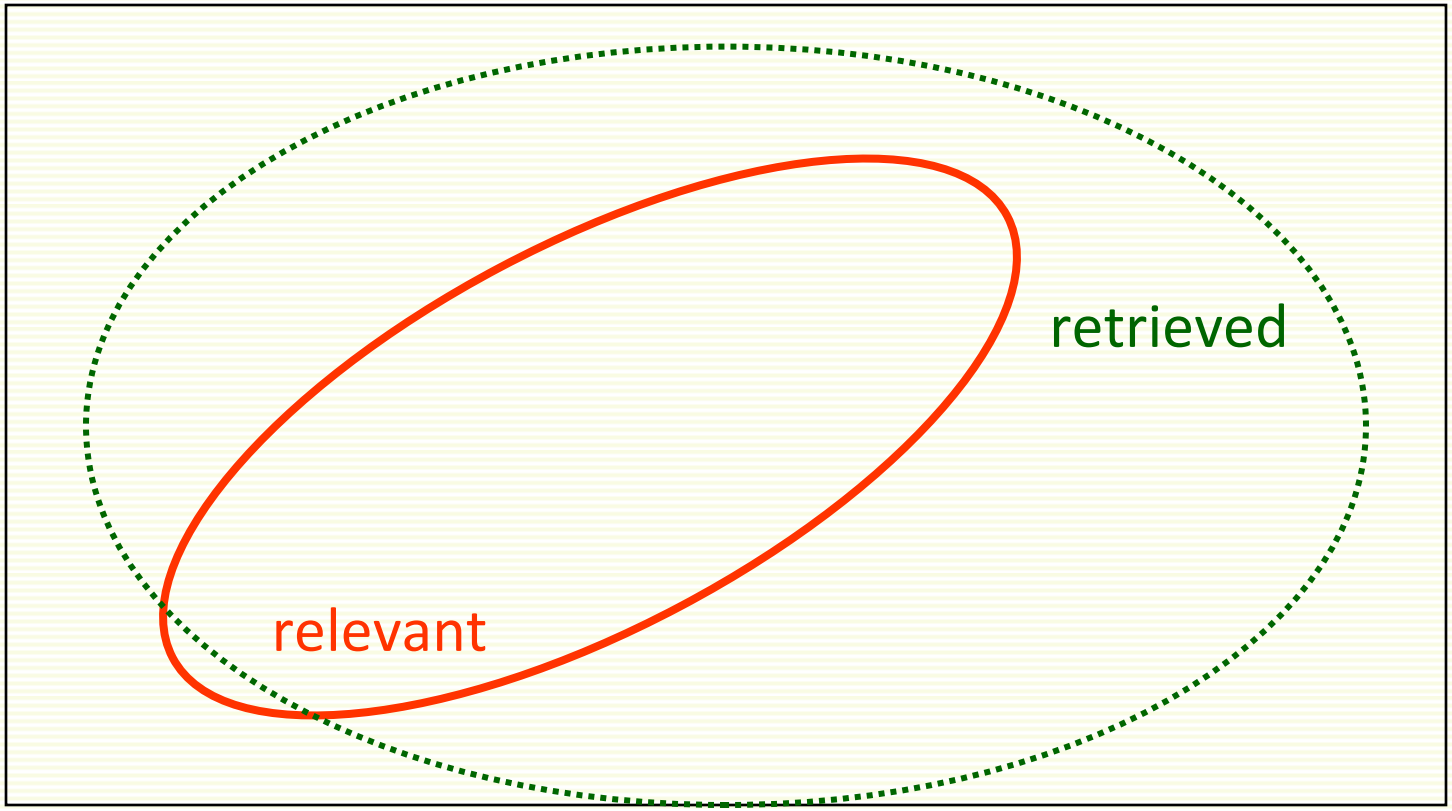
Retrieved vs. Relevant Documents

high precision, but low recall



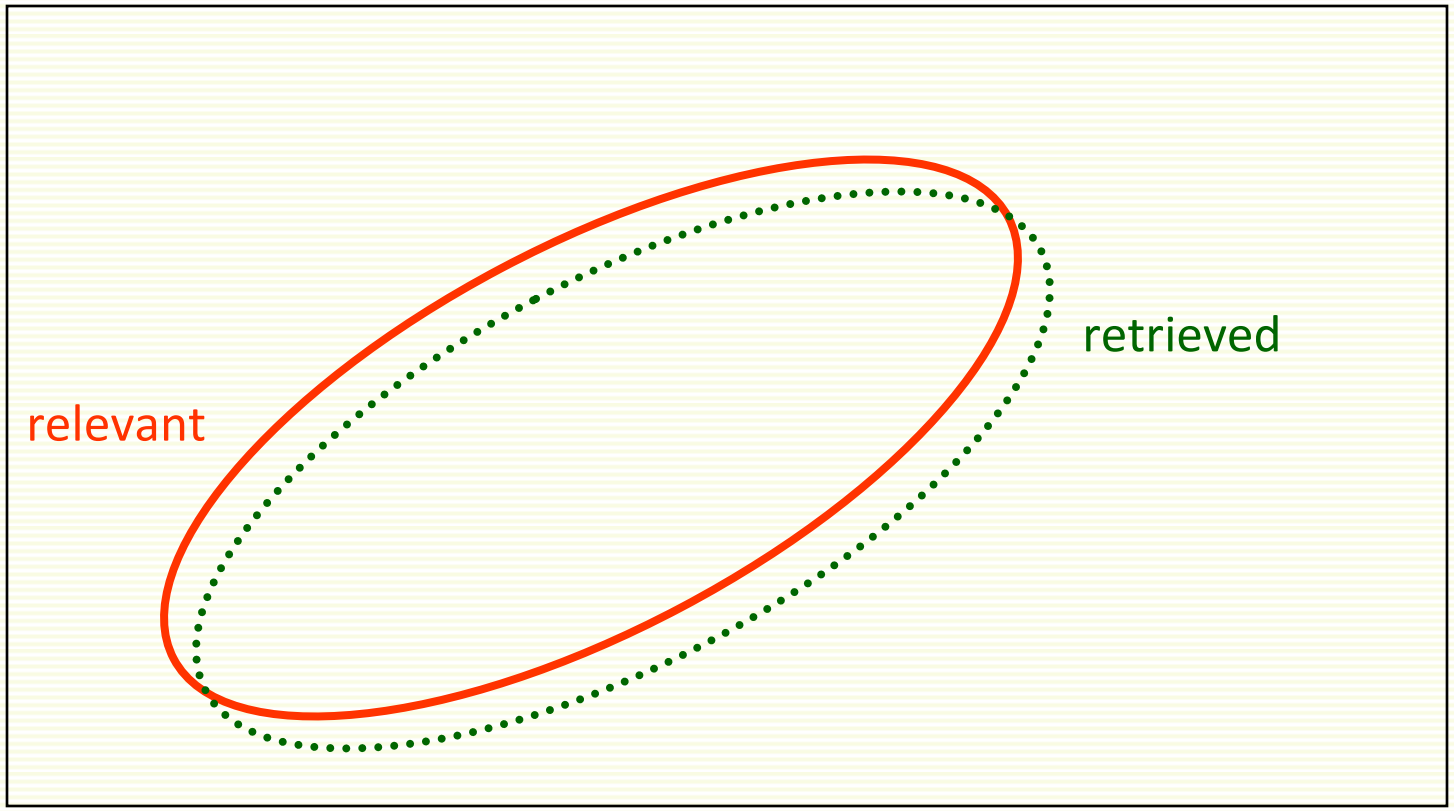
Retrieved vs. Relevant Documents

high recall, but low precision



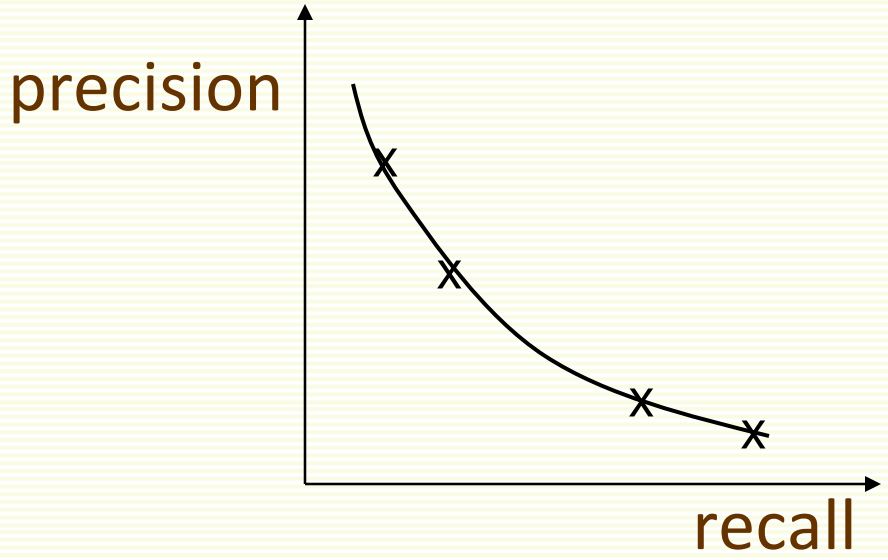
Retrieved vs. Relevant Documents

high precision, high recall (at last!)



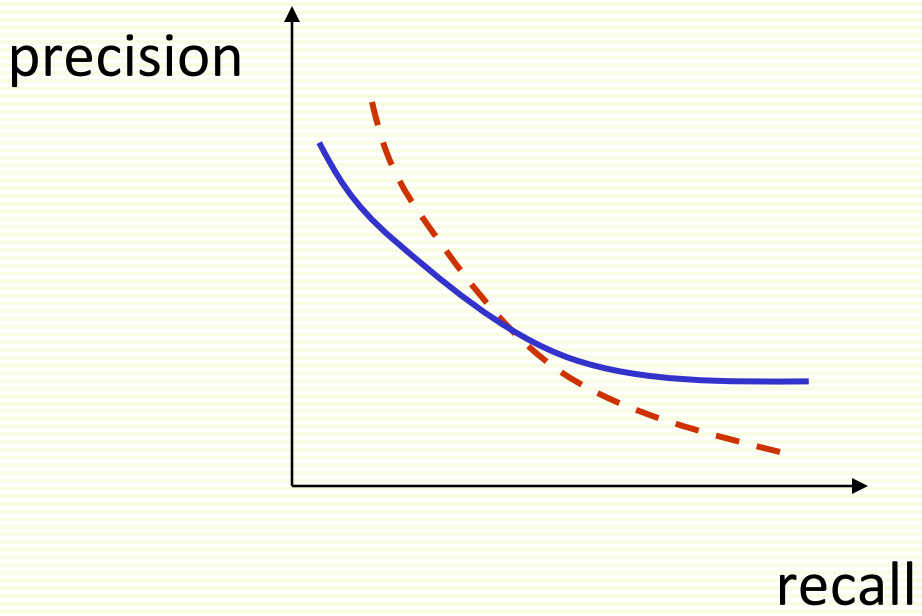
Precision/Recall Curves

- There is a tradeoff between Precision and Recall
  - easy to get either high precision or high recall, but not both
- So measure Precision at different levels of Recall
- Note: this is an AVERAGE over MANY queries



Precision/Recall Curves

- Difficult to determine which of these two hypothetical results is better:
  - Is blue method performing better than the red one?



Importance of Ranking

- IR systems typically output a ranked list of documents
- Should take "relevance" into account when measuring performance
- The three systems have same precision/recall rates, but the method in the first column is better since it ranks the relevant documents higher

system 1	*system 2*	*system 3*
d1 √	d10 ×	d6 ×
d2 √	d9 ×	d1 √
d3 √	d8 ×	d2 √
d4 √	d7 ×	d10 ×
d5 √	d6 ×	d9 ×
d6 ×	d1 √	d3 √
d7 ×	d2 √	d5 √
d8 ×	d3 √	d4 √
d9 ×	d4 √	d7 ×
d10 ×	d5 √	d8 ×

Cutoff

- Look at precision of the top 5 (or 10, … etc) ranked documents

	system 1	*system 2*	*system 3*
	d1 √	d10 ×	d6 ×
	d2 √	d9 ×	d1 √
	d3 √	d8 ×	d2 √
	d4 √	d7 ×	d10 ×
	d5 √	d6 ×	d9 ×
	d6 ×	d1 √	d3 √
	d7 ×	d2 √	d5 √
	d8 ×	d3 √	d4 √
	d9 ×	d4 √	d7 ×
	d10 ×	d5 √	d8 ×
precision at 5	1.0	0.0	0.4
precision at 10	0.5	0.5	0.5

- How to decide on the "cut off" threshold?
  - threshold 5 is informative in this example, threshold 10 is not informative

Uninterpolated Average Precision

- Instead of using a single "cut off", average precision at many "cut off" points, usually at points where a relevant document is found

For system 3:

- At cutoff **d1**: 2 retrieved, 1 relevant, precision ½
- At cutoff **d2**: 3 retrieved, 2 relevant, precision 2/3
- ……
- At cutoff **d4**: 8 retrieved, 5 relevant, precision 5/8
- **Average precision 0.5726**

	system 1	*system 2*	*system 3*
	d1 √	d10 ×	d6 ×
	d2 √	d9 ×	d1 √ 1/2
	d3 √	d8 ×	d2 √ 2/3
	d4 √	d7 ×	d10 ×
	d5 √	d6 ×	d9 ×
	d6 ×	d1 √	d3 √ 3/6
	d7 ×	d2 √	d5 √ 4/7
	d8 ×	d3 √	d4 √ 5/8
	d9 ×	d4 √	d7 ×
	d10 ×	d5 √	d8 ×
precision at 5	1.0	0.0	0.4
precision at 10	0.5	0.5	0.5
aver. precision	1.0	0.3544	0.5726

F-Measure

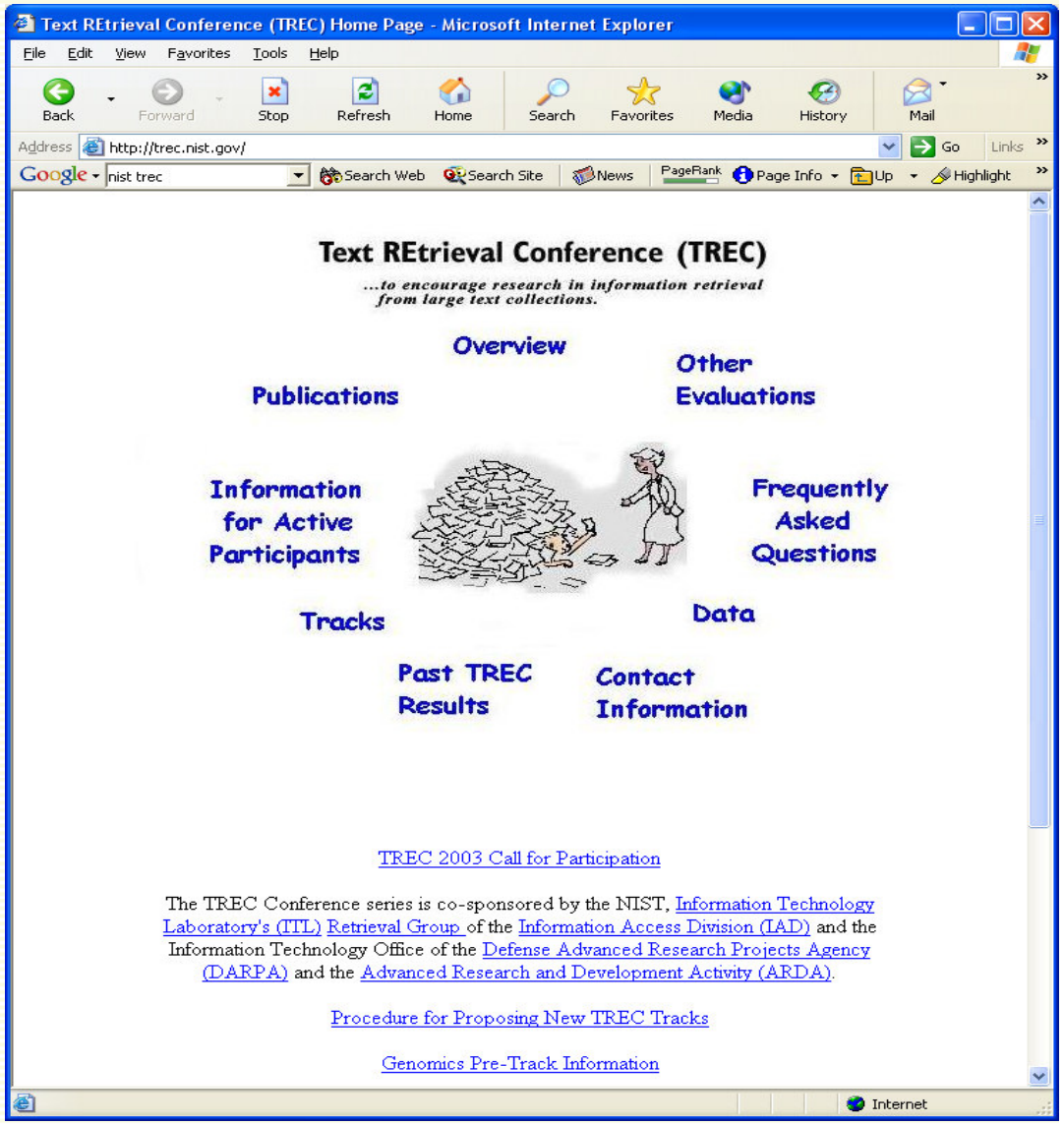
- Sometime only one pair of precision and recall is available
  - e.g., filtering task
- F-Measure

$$F = \frac{1}{\alpha \frac{1}{P} + (1-\alpha)\frac{1}{R}}$$

  - $\alpha > 0.5$: precision is more important
  - $\alpha < 0.5$: recall is more important
  - Usually $\alpha = 0.5$

Evaluation: TREC

- Text Retrieval Conference/competition
- Collection: about 3 Gigabytes > 1 million documents
  - Newswire & text news (AP, WSJ,…)
- Queries + relevance judgements
  - Queries devised and judged by annotators
- Participants
  - Various research and commercial group
- Tracks
  - Cross-lingual, filtering, genome, video, web, QA, etc.



IR System Improvements

- Most Queries are short
  - Web queries tend to be 2-3 keywords long
- The two big problems with short queries are:
  - Synonymy: poor recall results from missing documents that contain synonyms of search terms, but not the terms themselves
  - Polysemy/Homonymy: Poor precision results from search terms that have multiple meanings leading to the retrieval of non-relevant documents

Query Expansion

- Find a way to expand a user's query to automatically include relevant terms (that they should have included themselves), in an effort to improve recall
  - Use a dictionary/thesaurus
  - Use relevance feedback

Query Expansion

- Example:
  - query: seller of email solutions for cell phones
  - document: […] Giszmotron is a leading vendor of electronic messaging services for cellular devices […]

- But effect of polysemy on IR:
  - cell --> a prison room or a unit ?

  --> returning irrelevant documents

  --> decrease precision

- Effects of synonymy and hyponymy on IR

  --> missing relevant documents

  --> decrease recall

- Solution: let's expand the user query with related terms
  - often using a thesaurus to find related terms (synonyms, hyponyms)
  - new terms will have lower weights in the query
  - ex: expanded query: seller vendor phones device …
  - need to do WSD

Relevance Feedback

- Ask the user to identify a few documents which appear to be related to their information need
- Extract terms from those documents and add them to the original query
- Run the new query and present those results to the user
- Iterate (ask the user to identify relevant documents…extract terms… add them to the query…)
  - Typically converges quickly

Blind Feedback

- Assume that first few documents returned are most relevant rather than having users identify them
- Proceed as for relevance feedback
- Tends to improve recall at the expense of precision

Additional IR Issues

- In addition to improved relevance, can improve overall information retrieval with some other factors:
  - Eliminate duplicate documents
  - Provide good context
- For the web:
  - Eliminate multiple documents from one site
  - Clearly identify paid links

IR within NLP

- IR needs to process the large volumes of online text
- And (traditionally), NLP methods were not *robust* enough to work on thousands of real world texts.
- so IR:
  - not based on NLP tools (ex. syntactic/semantic analysis)
  - uses (mostly) simple (shallow) techniques
  - based mostly on word frequencies
- in IR, meaning of documents:
  - is the composition of meaning of individual words
  - ordering & constituency of words play are not taken into account
  - *bag of word* approach

I see what I eat.
I eat what I see.
} same meaning

Summary

- Information Retrieval is the process of returning documents from unstructured data collection to meet a user's information need based on a query
- Typical methods are BOW (bag of words) which rely on keyword indexing with little semantic processing
- Results can be improved by adding semantic information (such as thesauri) and by filtering and other post-hoc analysis.