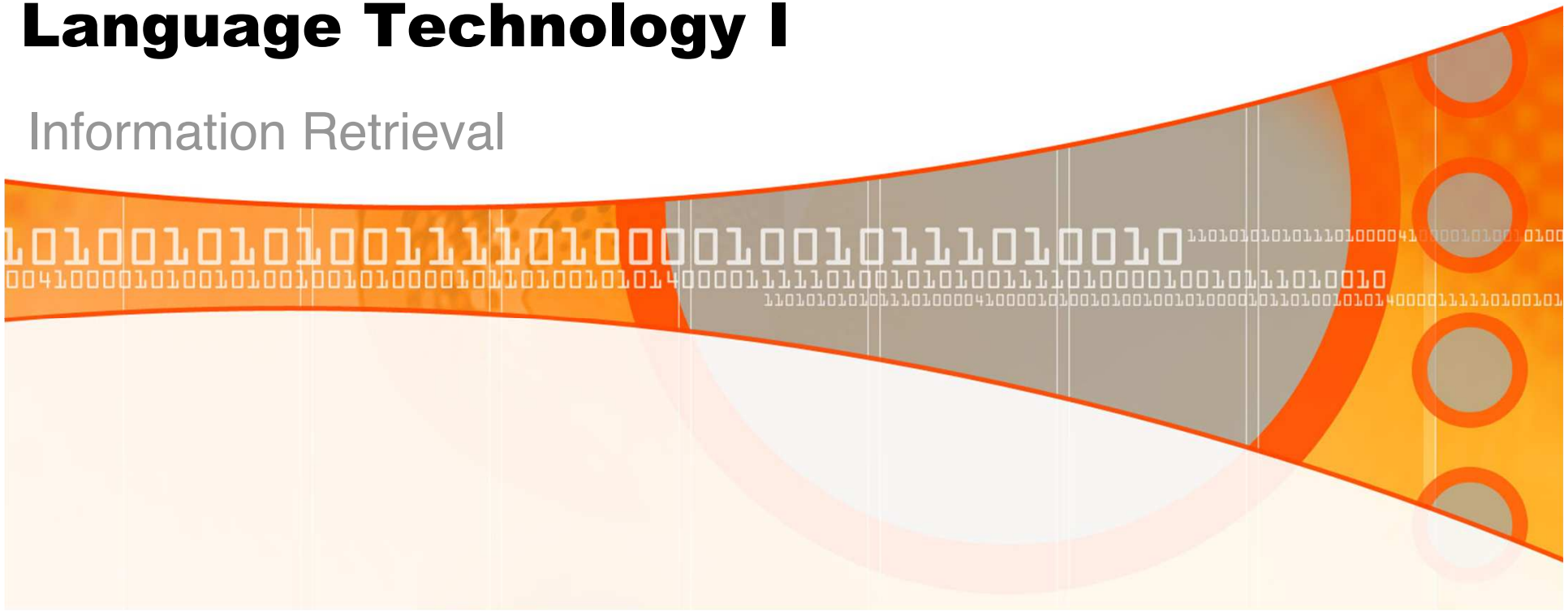
Language Technology I

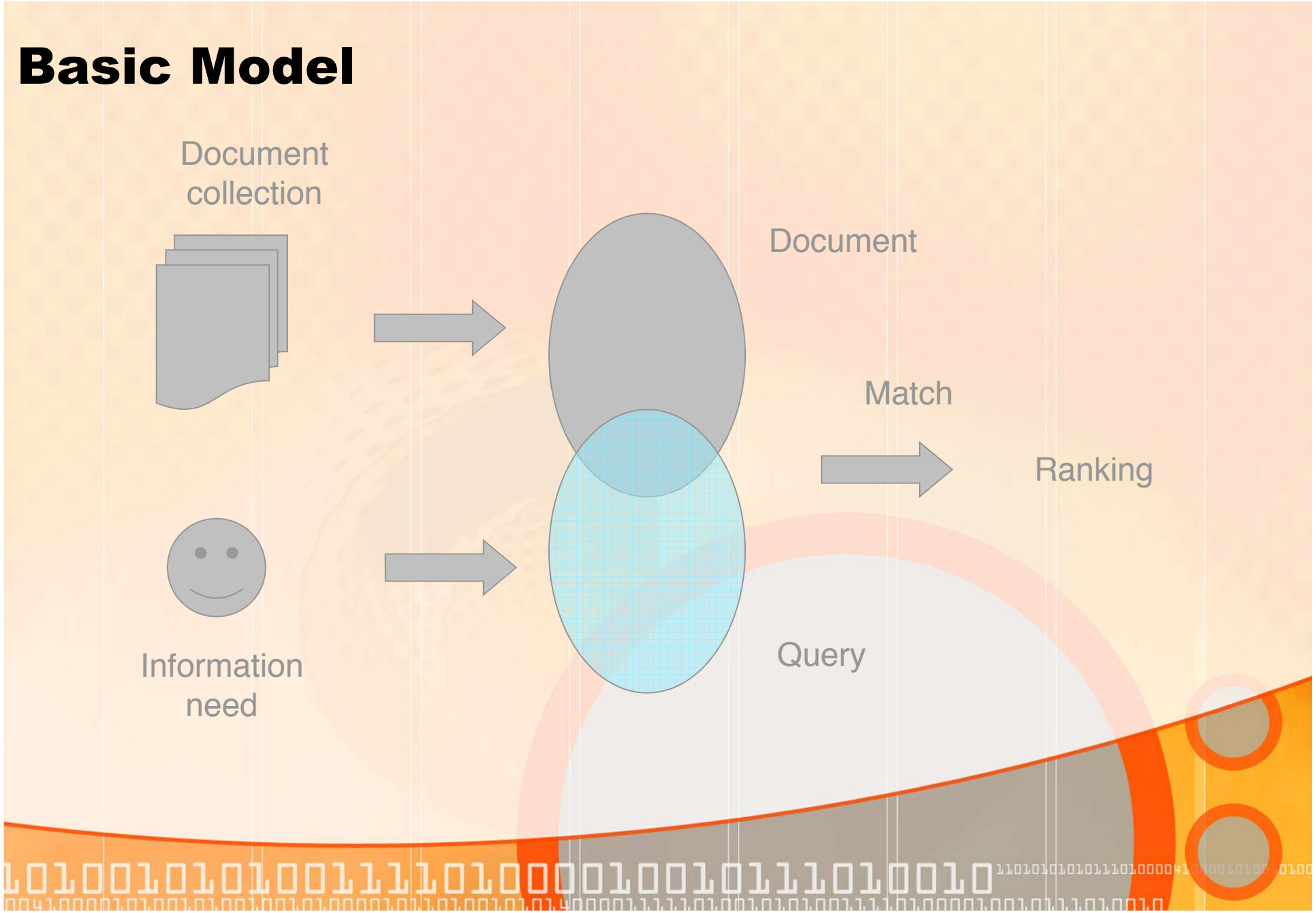
Information Retrieval



Information Retrieval

- Traditional information retrieval is basically text search
  - *A collection of text documents*
  - *Documents are generally high-quality and designed to convey information*
  - *Documents are assumed to have no structure beyond words*
- Searches are generally based on meaningful phrases
- The goal is to find the document(s) that best match the search phrase, according to a search model

Basic Model


Document collection
Document
Match
Ranking
Information need
Query

Terminology

- Document
  - *Unit of text indexed in the system*
  - *Result of the retrieval*
- IR systems usually adopt index terms to process queries
- Index term:
  - *a keyword or group of selected words*
  - *any word (more general)*
- An inverted index is built for the chosen index terms
  - *D0 = "it is what it is", D1 = "what is it" and D2 = "it is a banana“*
  - *"a": {D2}*
  - *"banana": {D2}*
  - *"is": {D0, D1, D2}*
  - *"it": {D0, D1, D2}*
  - *"what": {D0, D1}*
- Query
  - *User‘s information need as a set of terms*

Relevance

- Relevance is a subjective judgment and may include:
  - Being on the proper subject.
  - Being timely (recent information).
  - Being authoritative (from a trusted source).
  - Satisfying the goals of the user and his/her intended use of the information (*information need*).

Keyword Search

- Simplest notion of relevance is that the query string appears verbatim in the document.
- Slightly less strict notion is that the words in the query appear frequently in the document, in any order (*bag of words*).
  - Documents have to be *about* the query terms

Problems with Keywords

- 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)

IR models

- An IR model is characterized by three parameters:
  - *representations for documents and queries*
  - *matching strategies for assessing the relevance of documents to a user query*
  - *methods for ranking query output*
- Classic models
  - *Boolean*
  - *Vector space*
  - *Probabilistic*

Set Theoretic
- *Boolean model*
- *Fuzzy model*
- *Extended boolean model*

Algebraic
- *Vector space model*
- *Generalized vector model*
- *Latent semantic index*
- *Neural networks model*

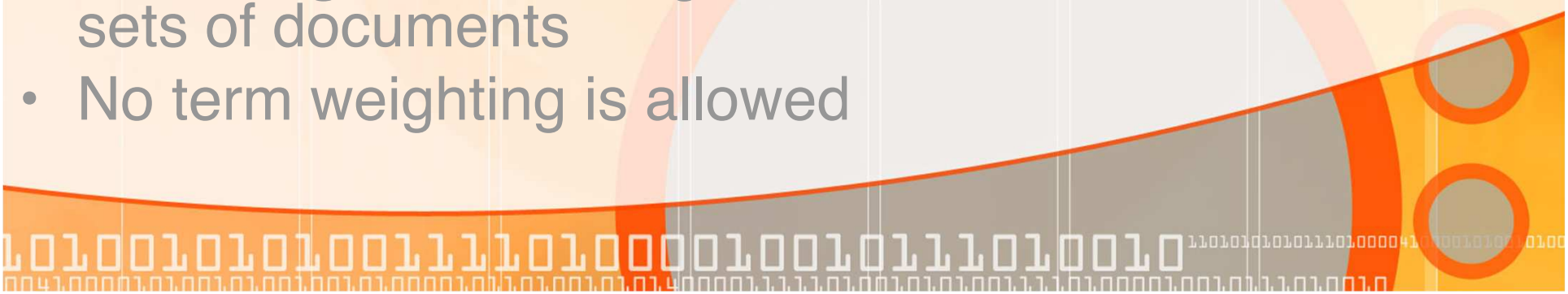
Probabilistic
- *Probabilistic model*
- *Inference network*
- *Belief network*

IR models – basic concepts

- Each document represented by a set of representative keywords or index terms
- An index term is a document word useful for remembering the document main themes
- Traditionally, index terms were nouns because nouns have meaning by themselves
- Not all terms are equally useful for representing the document contents: less frequent terms allow identifying a narrower set of documents
- The *importance* of the index terms is represented by weights associated to them

Boolean Model

- Based on set theory and Boolean algebra
  - *Documents are sets of terms*
  - *Queries are Boolean expressions on terms*
- **D:** set of words (indexing terms) present in a document
  - *each term is either present (1) or absent (0)*
- **Q:** A boolean expression
  - *terms are index terms*
  - *operators are AND, OR, and NOT*
- **Matching:** Boolean algebra over sets of terms and sets of documents
- No term weighting is allowed



Boolean Model - Example

Terms:

Index vocabular = {Corsica, Sardinia, Beach, flat, mountains}

Documents:

document d1 = {Sardinia, Beach, flat}
document d2 = {Corsica, Beach, flat}
document d3 = {Corsica, mountains}

Queries:	Yields:
Corsica	{d2, d3}
flat	{d1, d2}
flat and Corsica	{d2}
flat or Corsica	{d1, d2, d3}
flat and not Corsica	{d1}

Boolean Model example

$((text \vee information) \wedge retrieval \wedge \neg theory)$

- *"Information Retrieval"* X
- *"Information Theory"*
- *"Modern Information Retrieval: Theory and Practice"*
- *"Text Compression"*

Boolean Model Disadvantages

- Similarity function is boolean
  - *Exact-match only, no partial matches*
  - *Retrieved documents not ranked*
- All terms are equally important
  - *Boolean operator usage has much more influence than a critical word*
- Query language is expressive but complicated

Issues for Vector Space Model

- How to determine important words in a document?
  - Word sense?
  - Word n-grams (and phrases, idioms,…) → terms
- How to determine the degree of importance of a term within a document and within the entire collection?
- How to determine the degree of similarity between a document and the query?
- In the case of the web, what is a collection and what are the effects of links, formatting information, etc.?

The Vector-Space Model

- Assume *t* distinct terms remain after preprocessing; call them index terms or the vocabulary.
- These "orthogonal" terms form a vector space.

  Dimension = *t* = |vocabulary|

- Each term, *i*, in a document or query, *j*, is given a real-valued weight, $w_{ij.}$
- Both documents and queries are expressed as t-dimensional vectors:

  $d_j = (w_{1j}, w_{2j}, \ldots, w_{tj})$

Document Collection

- A collection of *n* documents can be represented in the vector space model by a term-document matrix.
- An entry in the matrix corresponds to the "weight" of a term in the document; zero means the term has no significance in the document or it simply doesn't exist in the document.

$$\begin{array}{c|cccc} & T_1 & T_2 & .... & T_t \\ D_1 & w_{11} & w_{21} & \dots & w_{t1} \\ D_2 & w_{12} & w_{22} & \dots & w_{t2} \\ \vdots & \vdots & \vdots & & \vdots \\ \vdots & \vdots & \vdots & & \vdots \\ D_n & w_{1n} & w_{2n} & \dots & w_{tn} \end{array}$$

Term Weights: Term Frequency

- More frequent terms in a document are more important, i.e. more indicative of the topic.

  f_{ij} = frequency of term *i* in document *j*

- May want to normalize *term frequency* (*tf*) across the entire corpus:

  $tf_{ij} = f_{ij} / max\{f_{ij}\}$

Term Weights: Inverse Document Frequency

- Terms that appear in many *different* documents are *less* indicative of overall topic.

  df_i = document frequency of term i

  = number of documents containing term i

  idf_i = inverse document frequency of term i,

  $= \log_2(N/ df_i)$

  (N: total number of documents)
- An indication of a term's *discrimination* power.
- Log used to dampen the effect relative to *tf*.

TF-IDF Weighting

- A typical combined term importance indicator is *tf-idf weighting*:

$$w_{ij} = tf_{ij}\, idf_i = tf_{ij} \log_2 (N/ df_i)$$

- A term occurring frequently in the document but rarely in the rest of the collection is given high weight.
- Many other ways of determining term weights have been proposed.
- Experimentally, *tf-idf* has been found to work well.

Computing TF-IDF - An Example

Given a document containing terms with given frequencies:

A(3), B(2), C(1)

Assume collection contains 10,000 documents and document frequencies of these terms are:

A(50), B(1300), C(250)

Then:

A: tf = 3/3; idf = log(10000/50) = 5.3; tf-idf = 5.3

B: tf = 2/3; idf = log(10000/1300) = 2.0; tf-idf = 1.3

C: tf = 1/3; idf = log(10000/250) = 3.7; tf-idf = 1.2

Similarity Measure

- A similarity measure is a function that computes the *degree of similarity* between two vectors.

- Using a similarity measure between the query and each document:
  - It is possible to rank the retrieved documents in the order of presumed relevance.
  - It is possible to enforce a certain threshold so that the size of the retrieved set can be controlled.

Similarity Measure - Inner Product

- Similarity between vectors for the document $\boldsymbol{d}_i$ and query $\boldsymbol{q}$ can be computed as the vector inner product:

$$\text{sim}(\boldsymbol{d}_j, \boldsymbol{q}) = \boldsymbol{d}_j \bullet \boldsymbol{q} = \sum_{i=1}^{t} w_{ij} \cdot w_{iq}$$

where w_{ij} is the weight of term i in document j and w_{iq} is the weight of term i in the query

- For binary vectors, the inner product is the number of matched query terms in the document (size of intersection).
- For weighted term vectors, it is the sum of the products of the weights of the matched terms.

Properties of Inner Product

- Favors long documents with a large number of unique terms.
- Measures how many terms matched but not how many terms are *not* matched.

Inner Product -- Examples

Binary:

	retrieval	database	architecture	computer	text	management	information
– D =	1,	1,	1,	0,	1,	1,	0
– Q =	1,	0 ,	1,	0,	0,	1,	1

Size of vector = size of vocabulary = 7
0 means corresponding term not found in document or query

sim(D, Q) = 3

Weighted:

$D_1 = 2T_1 + 3T_2 + 5T_3 \qquad D_2 = 3T_1 + 7T_2 + 1T_3$

$Q = 0T_1 + 0T_2 + 2T_3$

$\text{sim}(D_1 , Q) = 2*0 + 3*0 + 5*2 = 10$

$\text{sim}(D_2 , Q) = 3*0 + 7*0 + 1*2 = 2$

Comments on Vector Space Models

- Simple, mathematically based approach.
- Considers both local (*tf*) and global (*idf*) word occurrence frequencies.
- Provides partial matching and ranked results.
- Tends to work quite well in practice despite obvious weaknesses.
- Allows efficient implementation for large document collections.

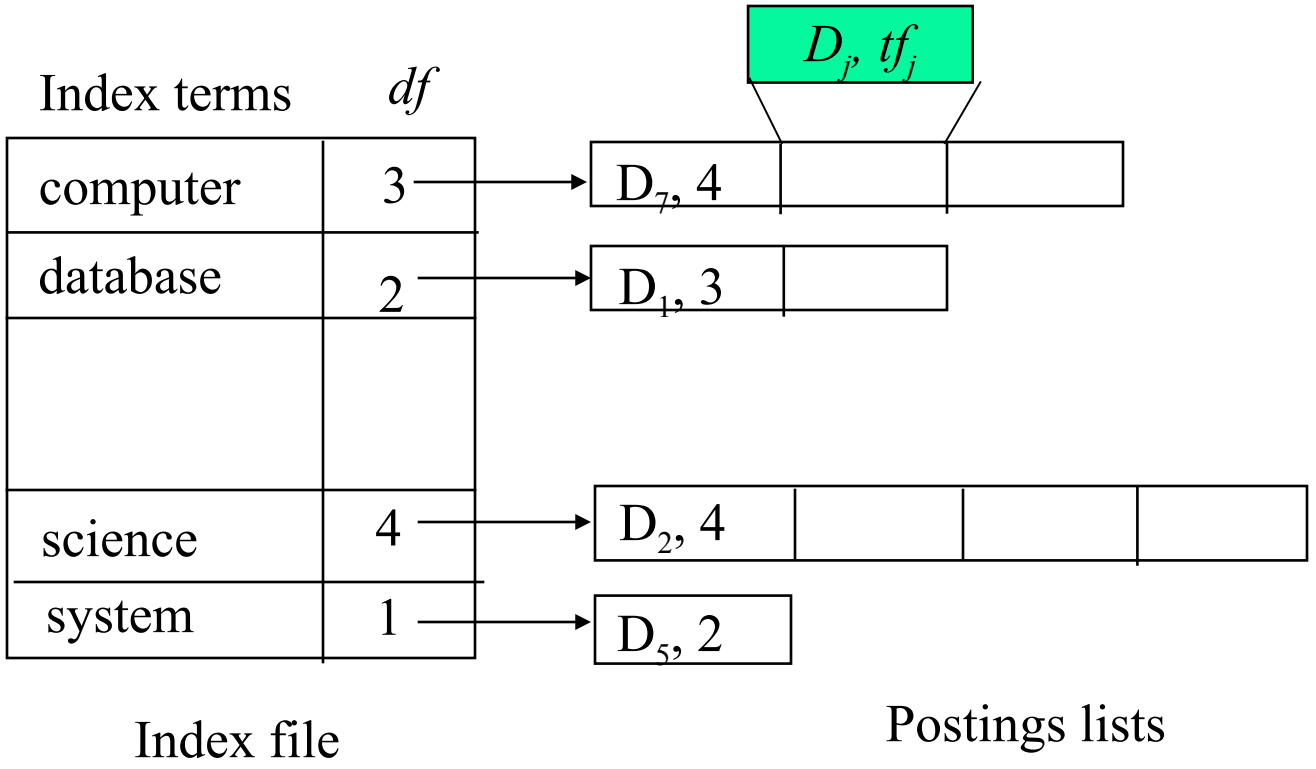
Sparse Vectors

- Vocabulary and therefore dimensionality of vectors can be very large, ~10^4 .
- However, most documents and queries do not contain most words, so vectors are sparse (i.e. most entries are 0).
- Need efficient methods for storing and computing with sparse vectors.

Implementation Based on Inverted Files

- In practice, document vectors are not stored directly; an inverted organization provides much better efficiency.
- The keyword-to-document index can be implemented as a hash table, a sorted array, or a tree-based data structure (trie, B-tree).
- Critical issue is logarithmic or constant-time access to token information.

Inverted Index

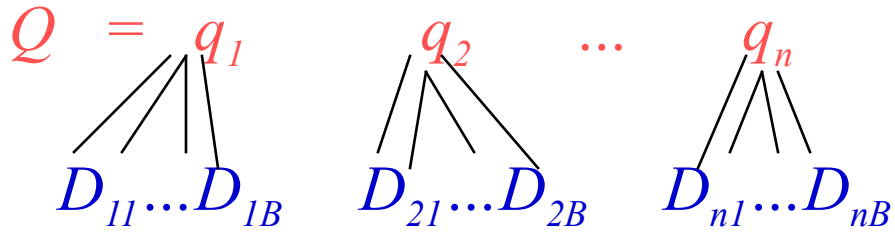


Retrieval with an Inverted Index

- Tokens that are not in both the query and the document do not effect cosine similarity.
  - Product of token weights is zero and does not contribute to the dot product.
- Usually the query is fairly short, and therefore its vector is *extremely* sparse.
- Use inverted index to find the limited set of documents that contain at least one of the query words.

Inverted Query Retrieval Efficiency

- Assume that, on average, a query word appears in *B* documents:



- Then retrieval time is O(|*Q*| *B*), which is typically, **much** better than naïve retrieval that examines all *N* documents, O(|*V*| *N*), because |*Q*| << |*V*| and *B* << *N*.

Vector Space Model, Summarized

- The best term-weighting schemes tf-idf weights:

$$w_{ij} = f(i,j) * log(N/n_i)$$

- For the query term weights, a suggestion is

$$w_{iq} = (0.5 + [0.5 * freq(i,q) / max(freq(l,q)]) * log(N / n_i)$$

- This model is very good in practice:
  - tf-idf works well with general collections
  - Simple and fast to compute
  - Vector model is usually as good as the known ranking alternatives

Pros & Cons of Vector Model

- Advantages:
  - term-weighting improves quality of the answer set
  - partial matching allows retrieval of docs that approximate the query conditions
  - cosine ranking formula sorts documents according to degree of similarity to the query
- Disadvantages:
  - assumes independence of index terms; not clear if this is a good or bad assumption

Comparison of Classic Models

- **Boolean model** does not provide for partial matches and is considered to be the weakest classic model
- Some experiments indicate that the **vector model** outperforms the third alternative, the **probabilistic model**, in general
  - Recent IR research has focused on improving probabilistic models – but these haven't made their way to Web search
- Generally we use a variation of the vector model in most text search systems

Why evaluate IR systems?

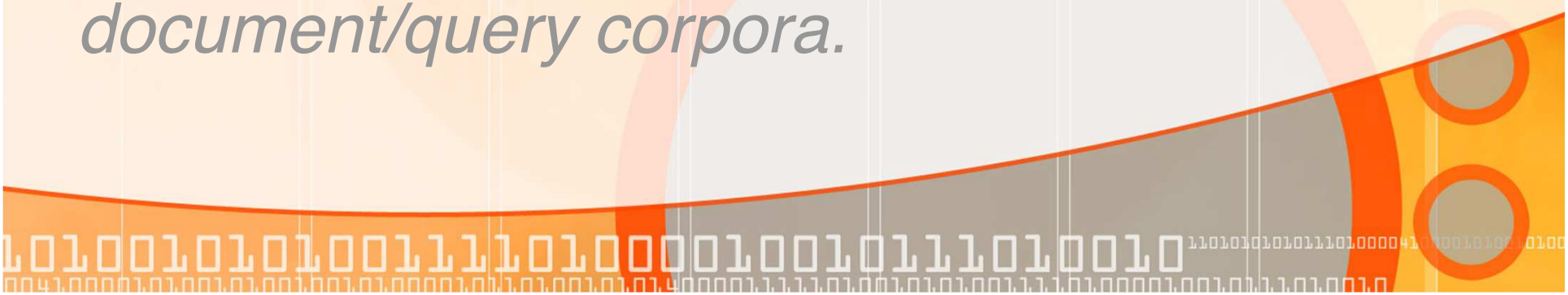
- *There are many retrieval models/ algorithms/ systems, which one is the best?*
- *What is the best component for:*
  - *Ranking function (dot-product, cosine, …)*
  - *Term selection (stopword removal, stemming…)*
  - *Term weighting (TF, TF-IDF,…)*
- *How far down the ranked list will a user need to look to find some/all relevant documents?*

Difficulties in Evaluating IR Systems

- *Effectiveness is related to the* **relevancy** *of retrieved items.*
- *Relevancy is not typically binary but continuous.*
- *Even if relevancy is binary, it can be a difficult judgment to make.*
- *Relevancy, from a human standpoint, is:*
  - *Subjective: Depends upon a specific user's judgment.*
  - *Situational: Relates to user's current needs.*
  - *Cognitive: Depends on human perception and behavior.*
  - *Dynamic: Changes over time.*

Human Labeled Corpora (Gold Standard)

- *Start with a corpus of documents.*
- *Collect a set of queries for this corpus.*
- *Have one or more human experts exhaustively label the relevant documents for each query.*
- *Typically assumes binary relevance judgments.*
- *Requires considerable human effort for large document/query corpora.*



What to Evaluate?

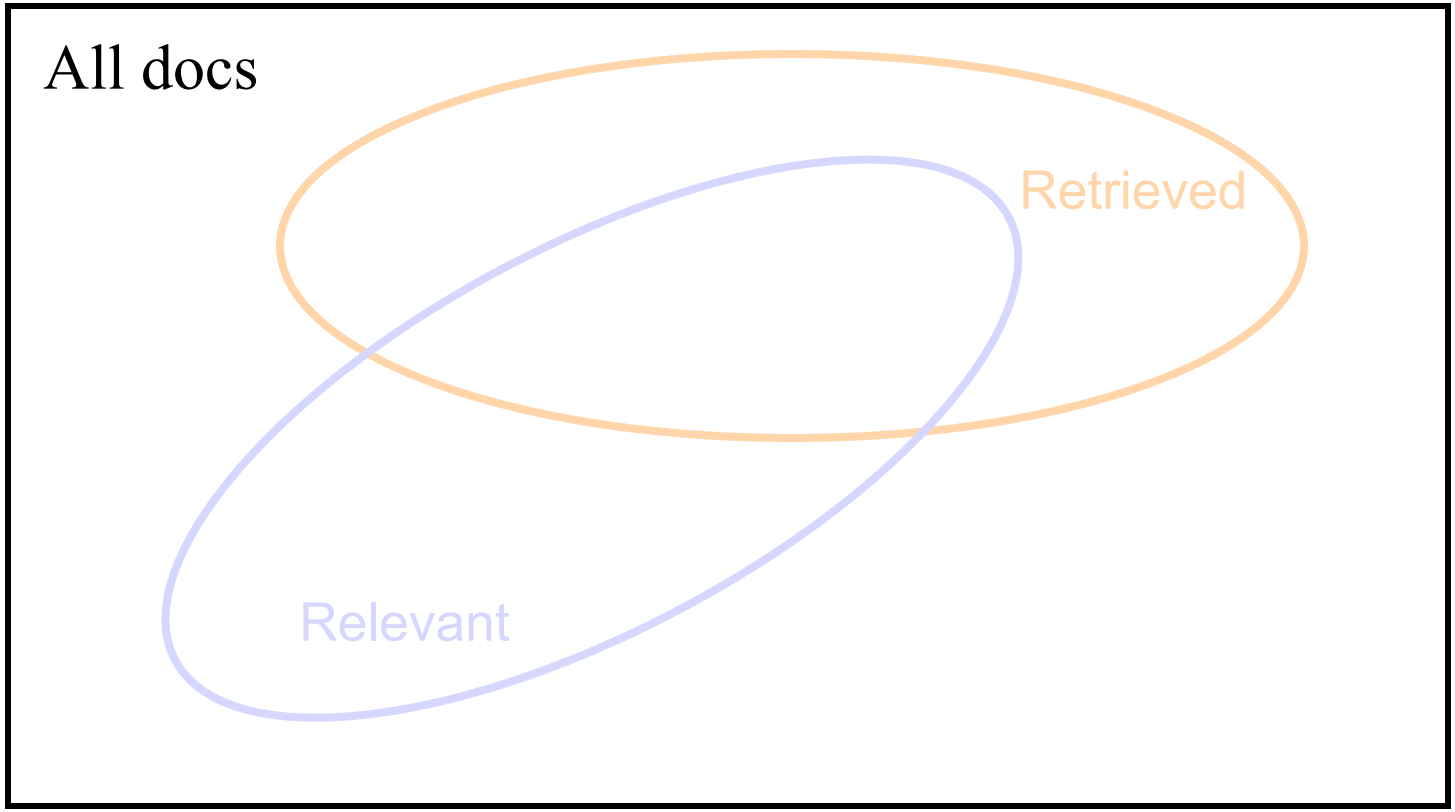
What can be measured that reflects users' ability to use system? (Cleverdon 66)

- Coverage of Information
- Form of Presentation
- Effort required/Ease of Use
- Time and Space Efficiency

effectiveness

- Recall
  - proportion of relevant material actually retrieved
- Precision
  - proportion of retrieved material actually relevant

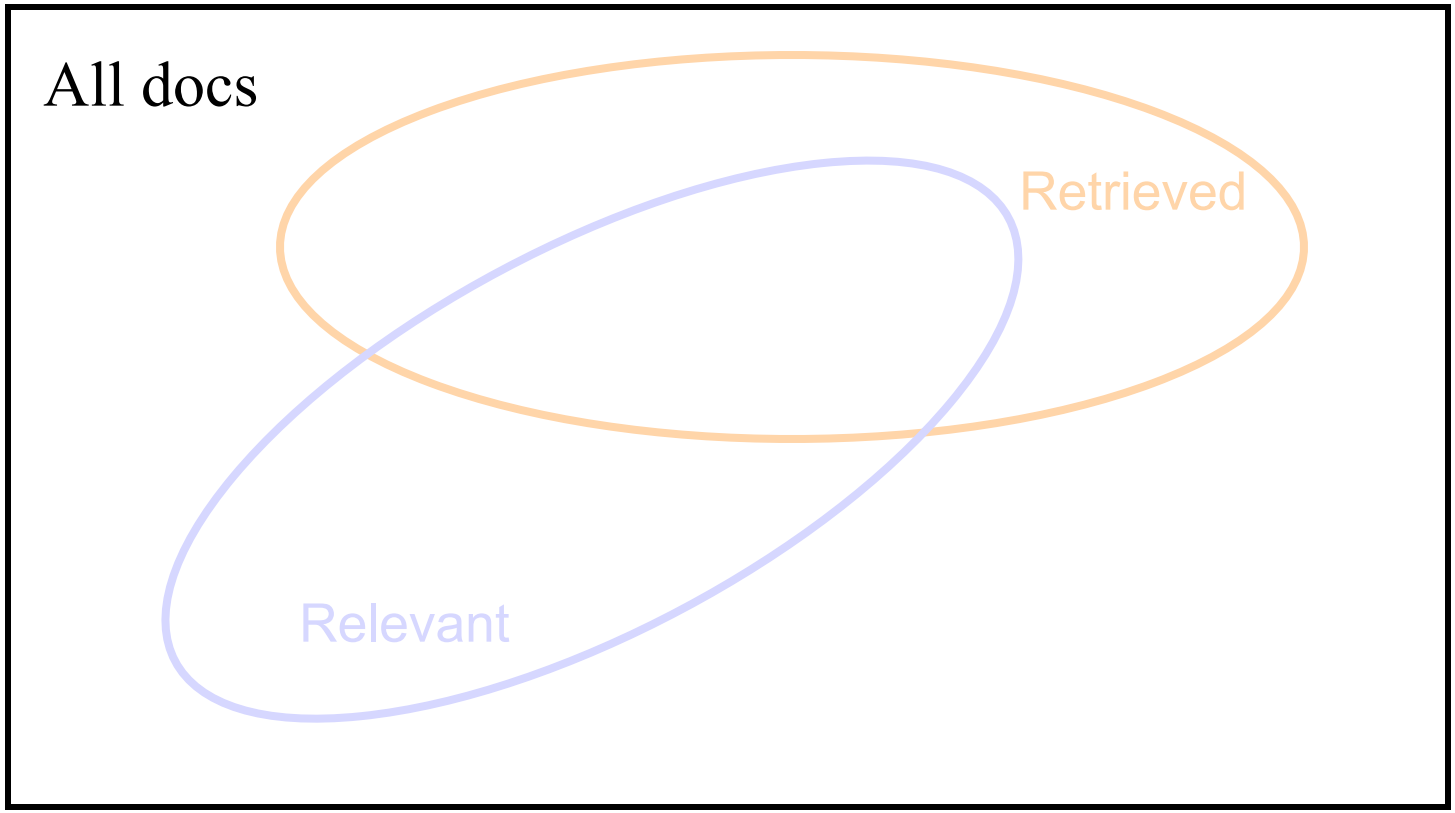
Relevant vs. Retrieved



Precision vs. Recall

$$\text{Precision} = \frac{|\,\text{RelRetrieved}\,|}{|\,\text{Retrieved}\,|}$$

$$\text{Recall} = \frac{|\,\text{RelRetrieved}\,|}{|\,\text{Rel in Collection}\,|}$$

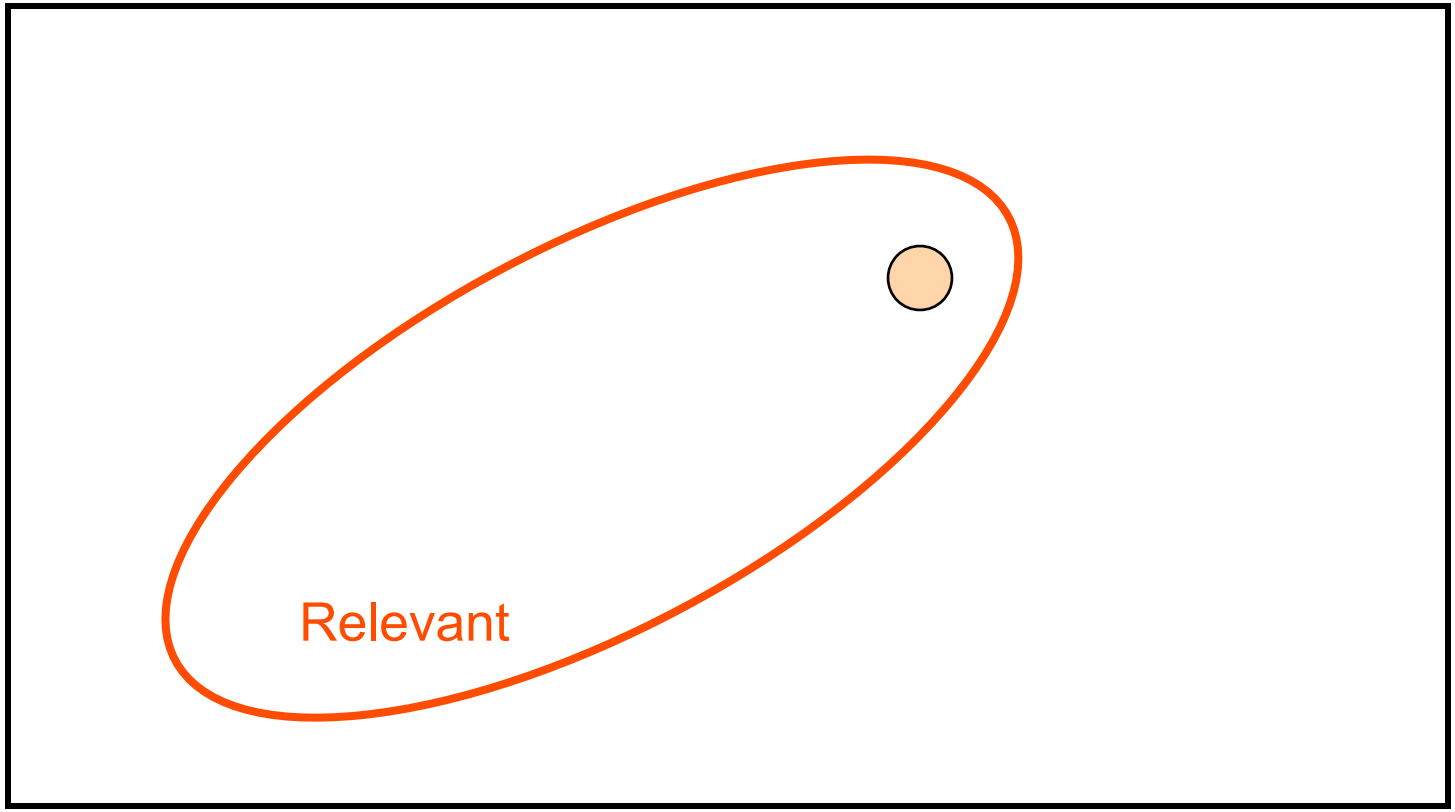


Why Precision and Recall?

Get as much good stuff while at the same time getting as little junk as possible.

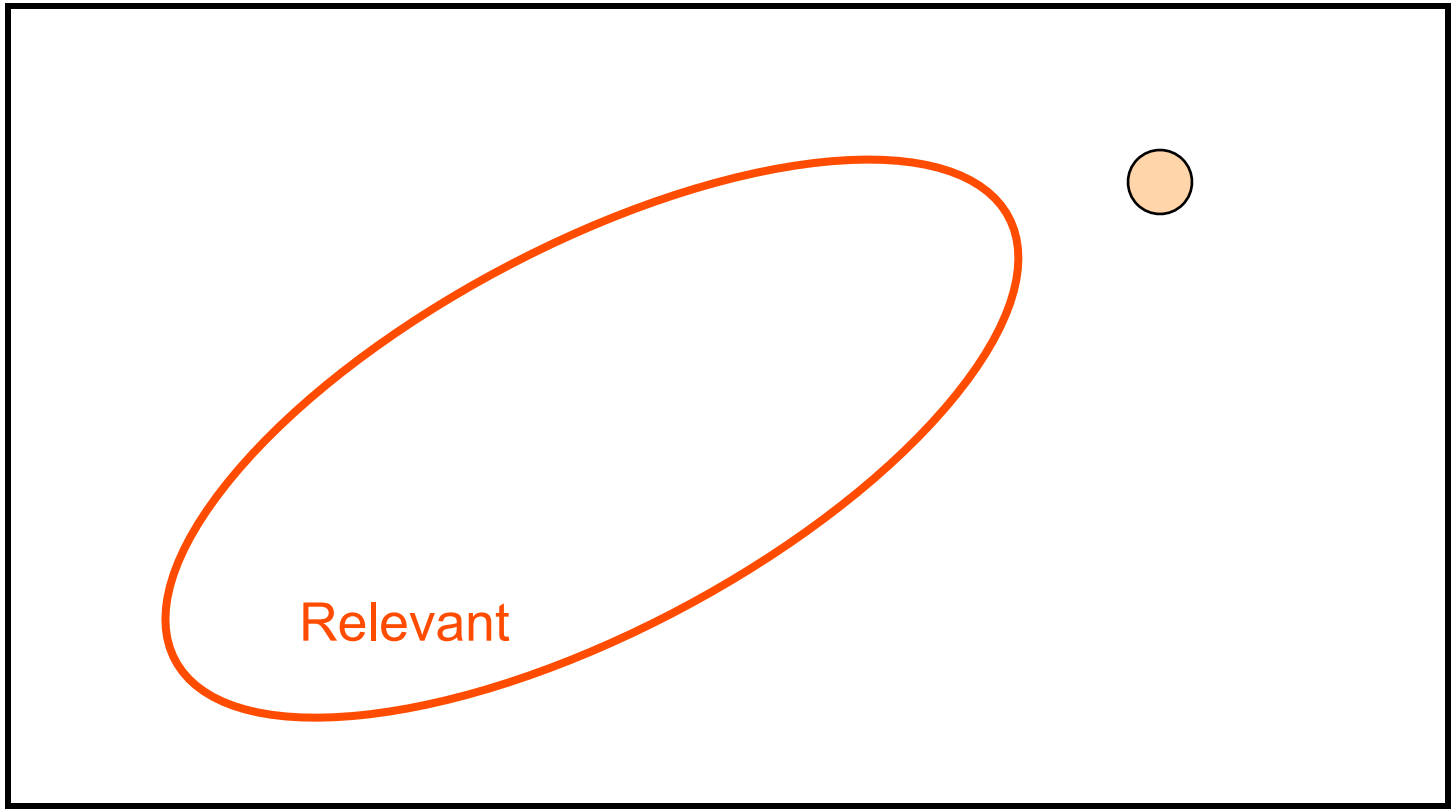
Retrieved vs. Relevant Documents

Very high precision, very low recall



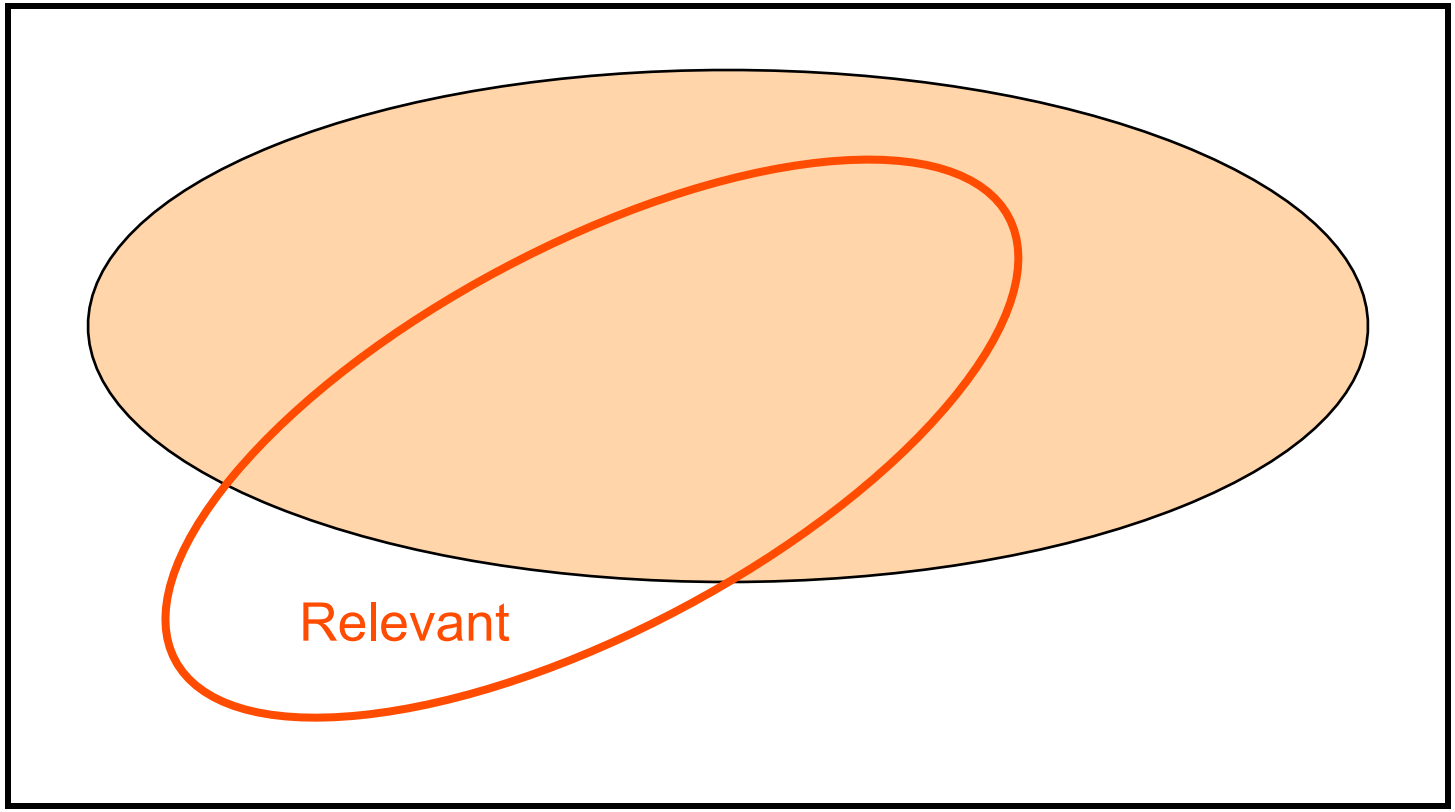
Retrieved vs. Relevant Documents

Very low precision, very low recall (0 in fact)



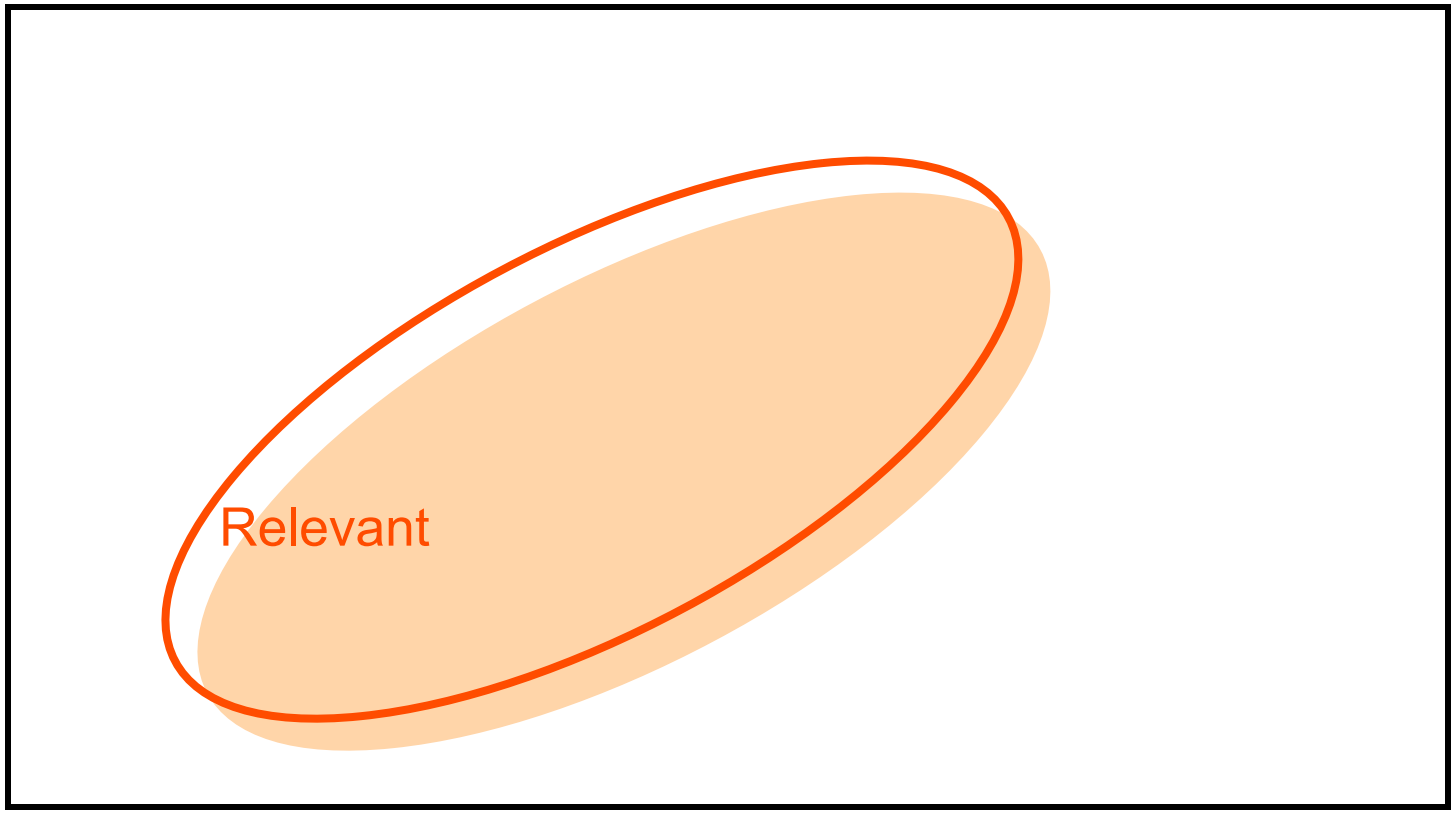
Retrieved vs. Relevant Documents

High recall, but low precision



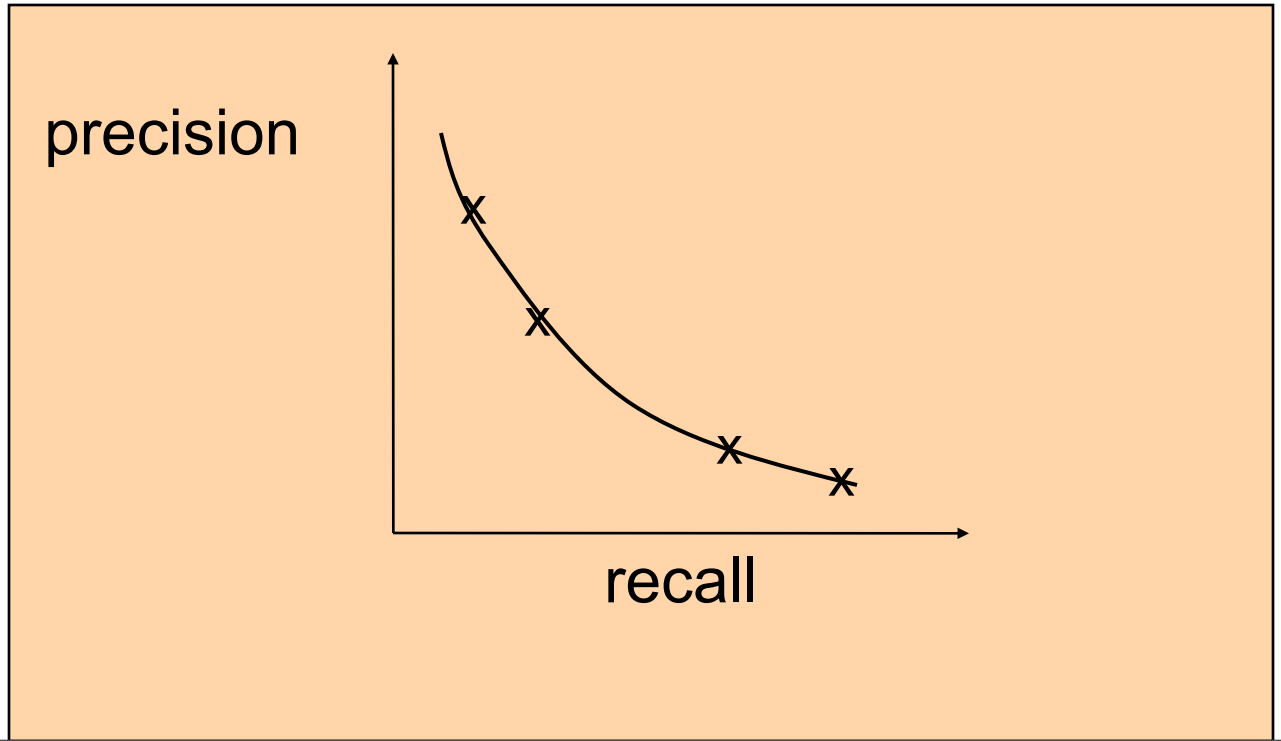
Retrieved vs. Relevant Documents

High precision, high recall (at last!)



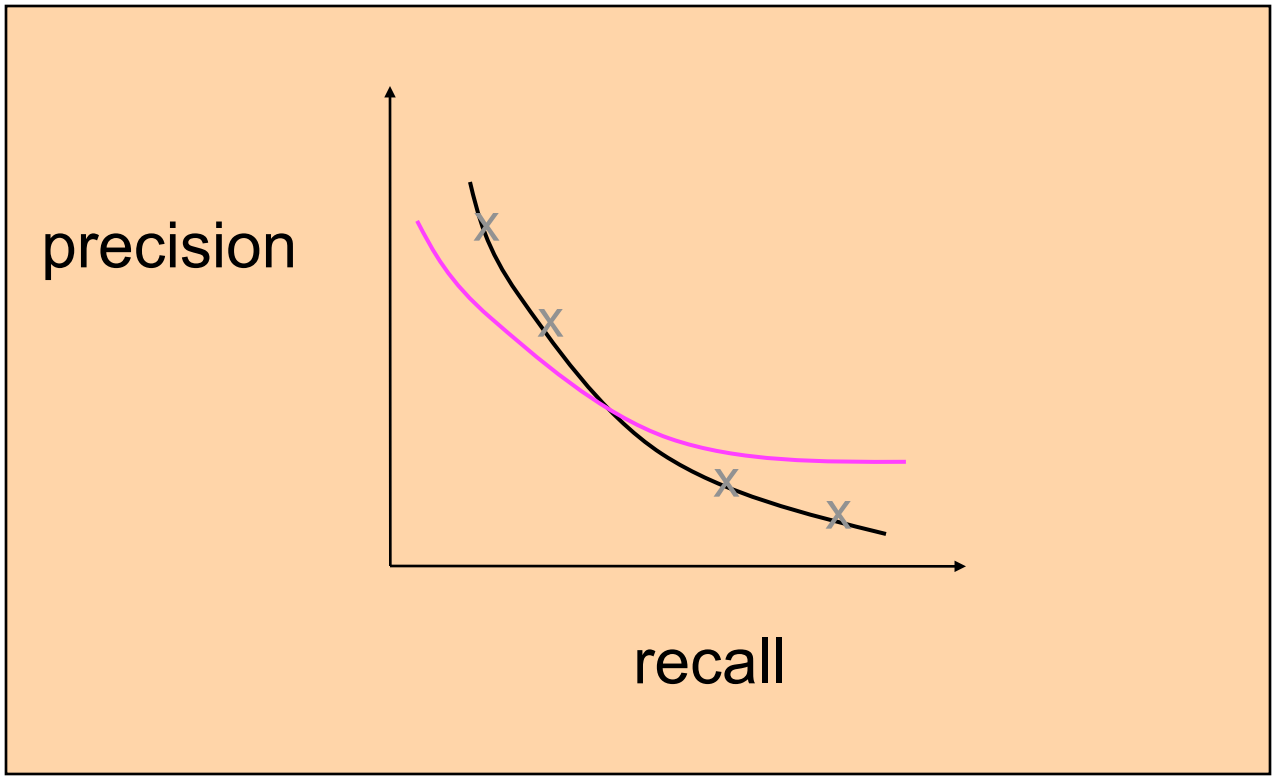
Precision/Recall Curves

- There is a tradeoff between Precision and Recall
- So measure Precision at different levels of Recall
- Note: this is an AVERAGE over MANY queries

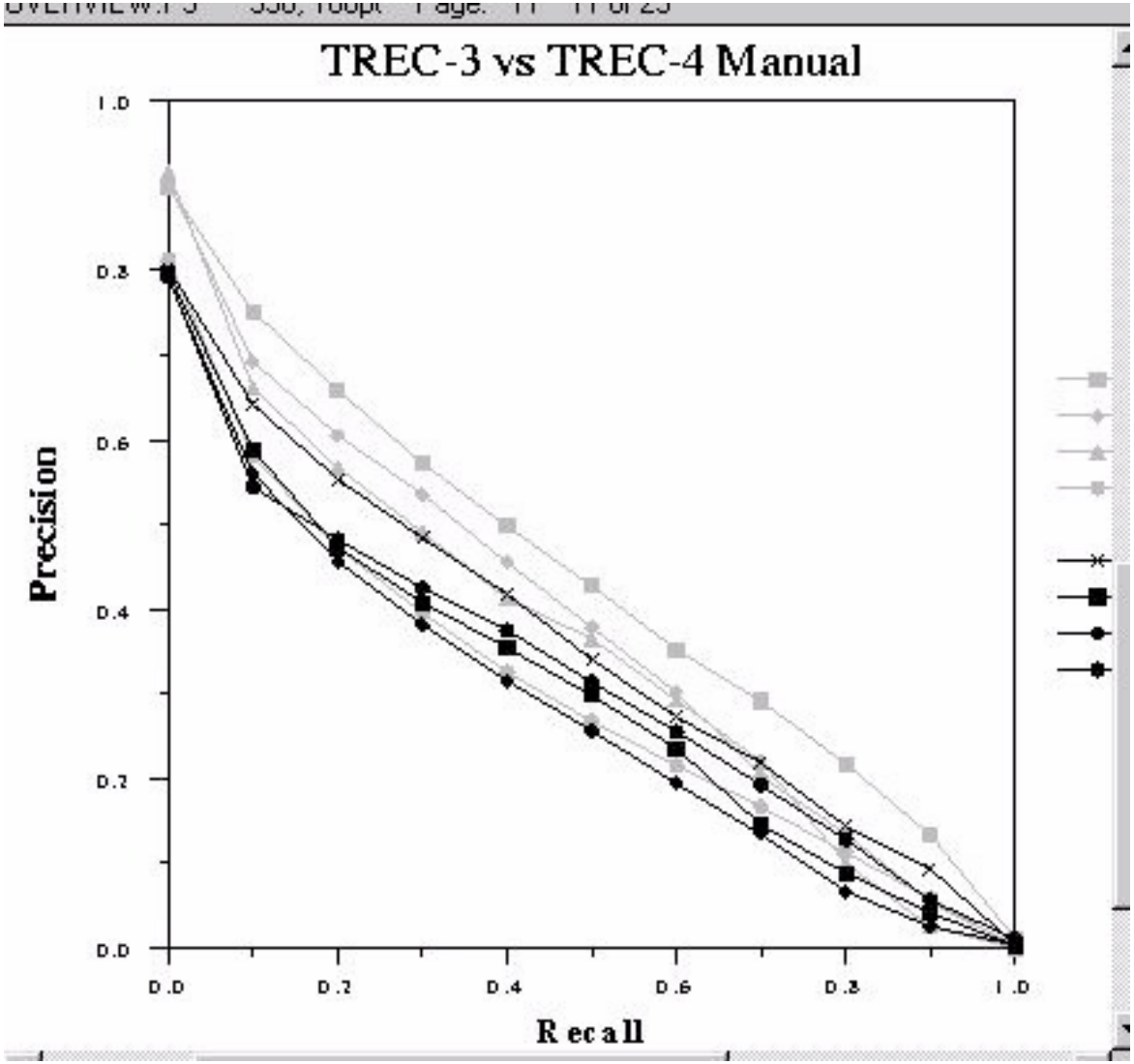


Precision/Recall Curves

- Difficult to determine which of these two hypothetical results is better:



Precision/Recall Curves



Document Cutoff Levels

- Another way to evaluate:
  - Fix the number of documents retrieved at several levels:
    - top 5
    - top 10
    - top 20
    - top 50
    - top 100
    - top 500
  - Measure precision at each of these levels
  - Take (weighted) average over results
- This is a way to focus on how well the system ranks the first k documents.

Problems with Precision/Recall

- Can't know true recall value
  - except in small collections
- Precision/Recall are related
  - A combined measure sometimes more appropriate
- Assumes batch mode
  - Interactive IR is important and has different criteria for successful searches
- Assumes a strict rank ordering matters.

Relation to Contingency Table

	Doc is Relevant	Doc is NOT relevant
Doc is retrieved	a	b
Doc is NOT retrieved	c	d

- Accuracy: (a+d) / (a+b+c+d)
- Precision: a/(a+b)
- Recall: ?
- Why don't we use Accuracy for IR?
  - (Assuming a large collection)
  - Most docs aren't relevant
  - Most docs aren't retrieved
  - Inflates the accuracy value

F-Measure

- One measure of performance that takes into account both recall and precision.
- Harmonic mean of recall and precision:

$$F = \frac{2PR}{P+R} = \frac{2}{\frac{1}{R}+\frac{1}{P}}$$

- Compared to arithmetic mean, both need to be high for harmonic mean to be high.

E Measure (parameterized F Measure)

- A variant of F measure that allows weighting emphasis on precision over recall:

$$E = \frac{(1+\beta^2)PR}{\beta^2 P + R} = \frac{(1+\beta^2)}{\frac{\beta^2}{R}+\frac{1}{P}}$$

- Value of β controls trade-off:
  - $\beta = 1$: Equally weight precision and recall (E=F).
  - $\beta > 1$: Weight recall more.
  - $\beta < 1$: Weight precision more.