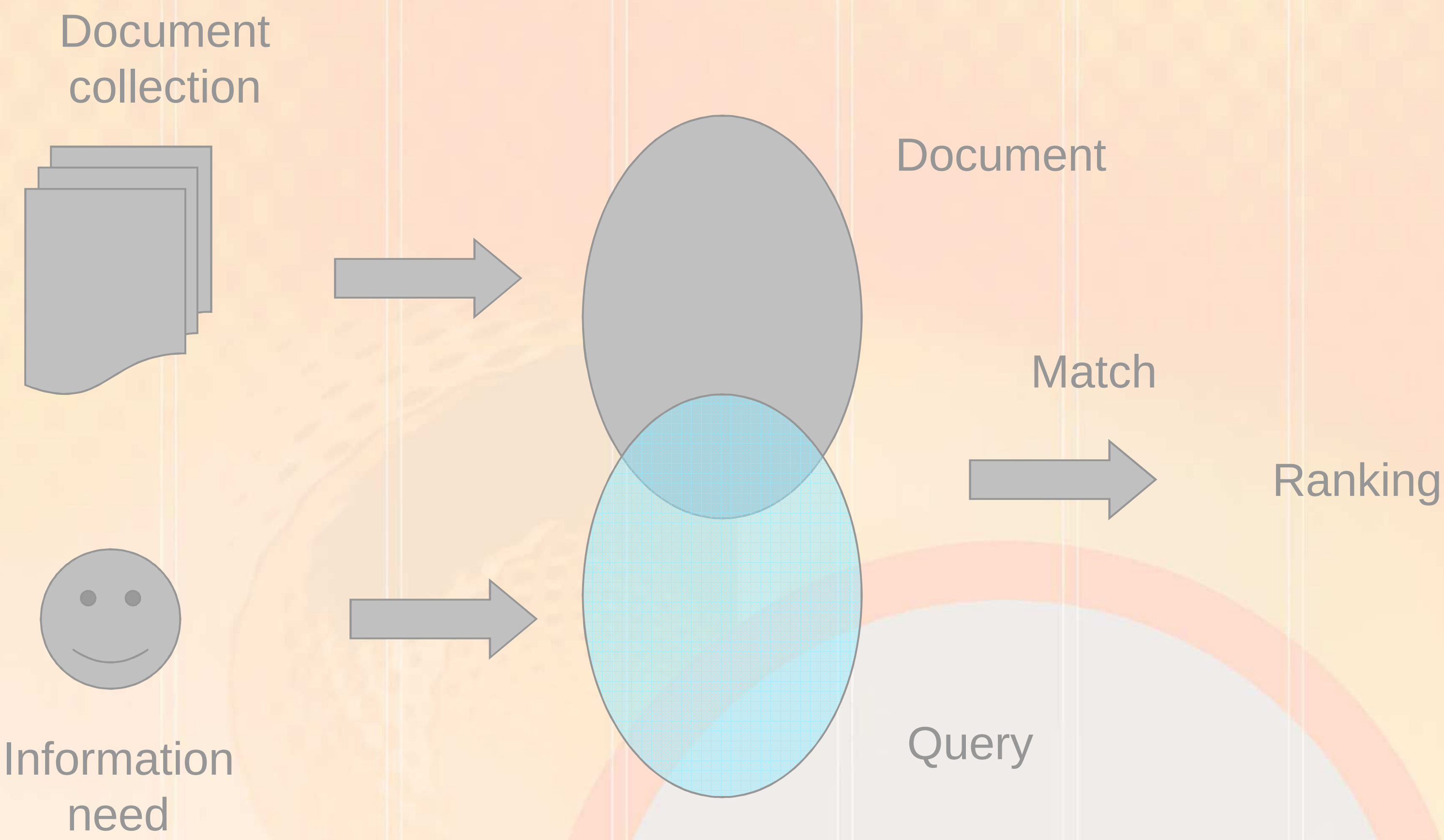
Language Technology I

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*

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 represen-tative 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

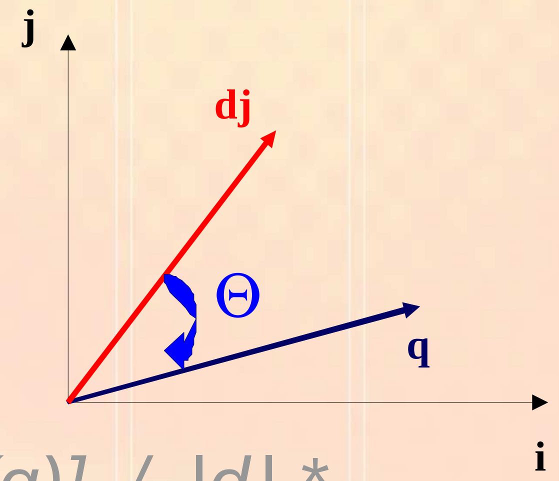
((text $\vee$ information) $\wedge$ retrieval $\wedge$ $\neg$theory)

- *"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

Vector Space Model



$vec(d_j) = (w_{1j}, w_{2j}, \ldots, w_{tj})$
$vec(q) = (w_{1q}, w_{2q}, \ldots, w_{tq})$
$Sim(q,d_j) = \cos(\Theta)$
$= [vec(d_j) \otimes vec(q)] \;/\; |d_j| * |q|$
$= [\Sigma\, w_{ij} * w_{iq}] \;/\; |d_j| * |q|$

- w_{ij} *is term's i weight in document j*
- Cosine is a normalized dot product
- Since $w_{ij} > 0$ and $w_{iq} > 0$, $0 \leq sim(q,d_j) \leq 1$
- A document is retrieved even if it matches the query terms only partially

Term Weighting

- Higher weight = greater impact on cosine
- Want to give more weight to the more "important" or useful terms
- What is an important term?
  - *If we see it in a query, then its presence in a document means that the document is relevant to the query.*
  - *How can we model this?*

Weights in the Vector Model

- $Sim(q,dj) = [\Sigma w_{ij} * w_{iq}] / |d_j| * |q|$
- How do we compute the weights w_{ij} and w_{iq}?
- A good weight must take into account two effects:
  - quantification of intra-document contents (similarity)
    - *tf* factor, the *term frequency* within a document
  - quantification of inter-documents separation (dissimilarity)
    - *idf* factor, the *inverse document frequency*
- $wij = tf(i,j) * idf(i)$

TF and IDF Factors

- Let:
  - N *be the total number of docs in the collection*
  - n_i *be the number of docs which contain* k_i
  - freq(i,j) *raw frequency of* k_i *within* d_j

- A normalized *tf* factor is given by

$$f(i,j) = freq(i,j) / max(freq(l,j))$$

  - *the maximum is computed over all terms which occur within the document* d_j

- The *idf* factor is computed as

$$idf(i) = log (N / n_i)$$

  - *the* log *is used to make the values of* tf *and* idf *comparable.*

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.*

Precision and Recall

- *Precision*
  - *The ability to retrieve top-ranked documents that are mostly relevant.*
- *Recall*
  - *The ability of the search to find* ***all*** *of the relevant items in the corpus.*

Determining Recall is Difficult

- *Total number of relevant items is sometimes not available:*
  - *Sample across the database and perform relevance judgment on these items.*
  - *Apply different retrieval algorithms to the same database for the same query. The aggregate of relevant items is taken as the total relevant set.*

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:*
  - β *= 1: Equally weight precision and recall (E=F).*
  - β *> 1: Weight recall more.*
  - β *< 1: Weight precision more.*