



# Storing and accessing textual information

- How is the information stored?
   high level
- How is the information retrieved?



# Storing textual information -Text - Information Retrieval

- search using words
- conceptual models: boolean, vector, probabilistic, ...
- file model:
   flat file, inverted file, ...



#### IR – File model: inverted files

- Controlled vocabulary
- Stop list
- Stemming

#### IR - formal characterization

Information retrieval model: (D,Q,F,R)

- D is a set of document representations
- Q is a set of queries
- F is a framework for modeling document representations, queries and their relationships
- R associates a real number to documentquery-pairs (ranking)

#### IR - conceptual models

Classic information retrieval

- Boolean model
- Vector model
- Probabilistic model

Boolean model        Document representation        adrenergic      cloning      receptor        Doc1      yes      yes      no     >      (1 1 0)        Doc2      no      yes      no     >      (0 1 0)						
Document representationadrenergiccloningreceptorDoc1yesyesno>(1 1 0)Doc2noyesno>(0 1 0)	Воо	lean moc	lel			
adrenergic cloning receptor Doc1 yes yes no> (1 1 0) Doc2 no yes no> (0 1 0)	Docum	nent representati	on			
Doc1        yes        yes        no       >        (1 1 0)          Doc2        no        yes        no       >        (0 1 0)		adrenergic	cloning	receptor		
Doc2 no yes no> (0 1 0)	Doc1	yes	yes	no	>	(1 1 0)
	Doc2	no	yes	no	>	(0 1 0)

## Boolean model

Queries : boolean (and, or, not)

Q1: cloning and (adrenergic or receptor)

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Queries are translated to disjunctive normal form (DNF)
DNF: disjunction of conjunctions of terms with or without 'not'
Rules: not not A --> A
         not(A and B) --> not A or not B
         not(A or B) --> not A and not B
          (A or B) and C --> (A and C) or (B and C)
         À and (B or C) --> (A and B) or (A and C)
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- (A and B) or C  $\rightarrow$  (A or C) and (B or C) A or (B and C)  $\rightarrow$  (A or B) and (A or C)



adrenergic Doc1 yes Doc2 no Q1: cloning and (adren > (1 1 0) or (1 1	cloning ves	receptor					
Doc1        yes          Doc2        no          Q1: cloning and (adrem         > (1 1 0) or (1 1	ves	20					
Doc2 no Q1: cloning and (adreu > (1 1 0) or (1 1	,	10 -	>	(1 1 0)			
Q1: cloning and (adren > (1 1 0) or (1 1	yes	no -	>	(0 1 0)			
> (1 1 0) or (1 1	Q1: cloning and (adrenergic or receptor)						
<b>OO O O O O O O O O </b>	> (1 1 0) or (1 1 1) or (0 1 1)			Result: Doc1			
Q2: cloning and not ac	renergic						
> (0 1 0) or (0 1	Result: Doc2						

#### Boolean model

Advantages

- based on intuitive and simple formal model (set theory and boolean algebra)
- Disadvantages
- binary decisions
- words are relevant or not
- document is relevant or not,
- no notion of partial match









#### Vector model

How to define weights? tf-idf

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term frequency freqi,j: how often does term ki occur in document dj? normalized term frequency: fi,j = freqi,j / maxi freqi,j

#### Vector model

How to define weights? tf-idf document frequency : in how many documents does term ki occur?

N = total number of documents ni = number of documents in which ki occurs inverse document frequency idfi: log (N / ni)

#### Vector model

• How to define weights for query? recommendation:

q= (w1,q, ..., wt,j)

 $w_{i,q}$  = weight for term ki in q = (0.5 + 0.5 fi,q) x idfi

#### Vector model

- Advantages
- term weighting improves retrieval performance
- partial matching
- ranking according to similarity

Disadvantage

- assumption of mutually independent terms?
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# Probabilistic model

weights are binary (wi,j = 0 or wi,j = 1) R: the set of relevant documents for query q Rc: the set of non-relevant documents for q P(Rldj): probability that dj is relevant to q P(Rcldj): probability that dj is not relevant to q

 $sim(d_j,q) = P(Rld_j) / P(Rcld_j)$ 

#### Probabilistic model

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\begin{split} & sim(dj,q) = P(Rldj) \ \textit{I} \ P(Rcldj) \\ & (Bayes' rule, independence of index terms, take logarithms, P(ki|R) + P(not ki|R) = 1) \\ & --> SIM(dj,q) == \\ & SUM \stackrel{t}{_{i=1}} \ wi,q \ x \ w_{i,j} \ x \\ & (log(P(ki|R) \ \textit{I} \ (1-P(ki|R))) + \\ & log((1-P(ki|Rc)) \ \textit{I} \ P(ki|Rc))) \end{split}
```

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#### Probabilistic model

- How to compute P(kilR) and P(kilRc)?
- initially: P(kilR) = 0.5 and P(kilRc) = ni/N
  Repeat: retrieve documents and rank them
- V: subset of documents (e.g. r best ranked)
- Vi: subset of V, elements contain ki

P(ki|R) = |Vi| / |V|and P(ki|Rc) = (ni-|Vi|) /(N-|V|)

#### Probabilistic model

- Advantages:
- ranking of documents with respect to probability of being relevant
- Disadvantages:
- initial guess about relevance
- all weights are binary
- independence assumption?

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### Literature

Baeza-Yates, R., Ribeiro-Neto, B., *Modern Information Retrieval*, Addison-Wesley, 1999.

# IR - measures

#### Precision =

number of found relevant documents total number of found documents

Recall =

number of found relevant documents total number of relevant documents