



Information Retrieval

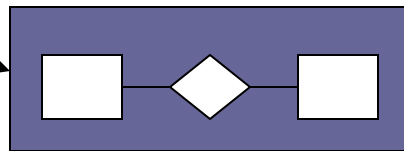
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Data sources

Information

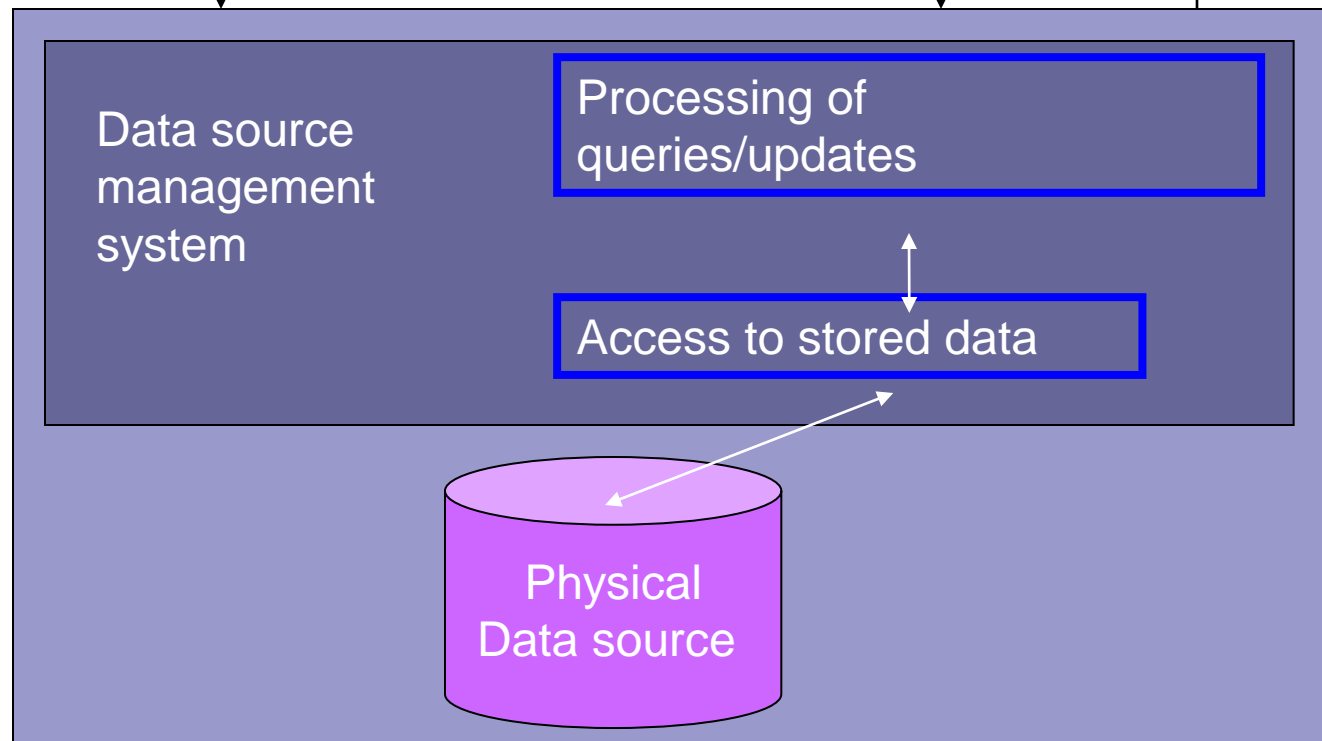


Model

Queries

Answer

Data source system



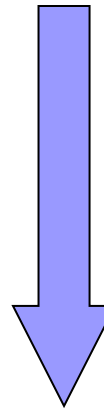
Storing and accessing textual information

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

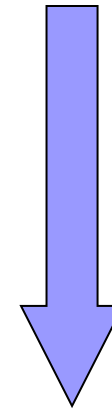
Storing textual information

- Text (IR)
- Semi-structured data
- Data models (DB)
- Rules + Facts (KB)

structure



precision



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

Inverted file

WORD	HITS	LINK
...
adrenergic	32	
...
cloning	53	
...
receptor	22	
...

Postings file

DOC#	LINK
...	...
1	
5	
...	...
1	
2	
5	
...	...

Document file

DOCUMENTS
Doc1
Doc2
...



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 document-query-pairs (ranking)



IR - conceptual models

Classic information retrieval

- Boolean model
- Vector model
- Probabilistic model



IR - conceptual models - Summary

Boolean

Vector

Probabilistic

D

Q

F

R



IR - conceptual models - Summary

Boolean

D

Q

F

R

Boolean model

Document representation

	adrenergic	cloning	receptor		
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)

Queries are translated to disjunctive normal form (DNF)

DNF: disjunction of conjunctions of terms with or without 'not'

Boolean model

DNF or not DNF?

1. $(A \text{ and } B) \text{ or } (C \text{ and } D)$
2. $(A \text{ and } B \text{ and } C) \text{ or } (A \text{ and } D) \text{ or } (E \text{ and } F)$
3. $(A \text{ or } B) \text{ and } (C \text{ or } D)$
4. $(A \text{ and not } B) \text{ or } (C \text{ and } D)$
5. $(A \text{ and not } B) \text{ or not}(A \text{ and } B)$
6. $(\text{not not } A \text{ and } B)$
7. $A \text{ and } B$
8. $A \text{ or } B$
9. A
10. $\text{not } A$
11. $\text{not not } A$

Boolean model

Queries : boolean (and, or, not)

Q1: cloning and (adrenergic or receptor)

Queries are translated to disjunctive normal form (DNF)

DNF: disjunction of conjunctions of terms with or without 'not'

Rules: not not A \rightarrow A

not(A and B) \rightarrow not A or not B

not(A or B) \rightarrow not A and not B

(A or B) and C \rightarrow (A and C) or (B and C)

A and (B or C) \rightarrow (A and B) or (A and C)

(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)

Boolean model

Q1: cloning and (adrenergic or receptor)

--> (cloning and adrenergic) or (cloning and receptor)

DNF is completed

+ translated to same representation as documents

(cloning and adrenergic) or (cloning and receptor)

--> (cloning and adrenergic and receptor)

or (cloning and adrenergic and not receptor)

or (cloning and receptor and adrenergic)

or (cloning and receptor and not adrenergic)

--> (1 1 1) or (1 1 0) or (1 1 1) or (0 1 1)

--> (1 1 1) or (1 1 0) or (0 1 1)

Boolean model

	adrenergic	cloning	receptor	
Doc1	yes	yes	no	--> (1 1 0)
Doc2	no	yes	no	--> (0 1 0)

Q1: cloning and (adrenergic or receptor)

--> (1 1 0) or (1 1 1) or (0 1 1)

Result: Doc1

Q2: cloning and not adrenergic

--> (0 1 0) or (0 1 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

Boolean model

	adrenergic	cloning	receptor		
Doc1	yes	yes	no	-->	(1 1 0)
Doc2	no	yes	no	-->	(0 1 0)

Q3: adrenergic and receptor

--> (1 0 1) or (1 1 1)

Result: empty

IR - conceptual models - Summary

Vector simplified / Vector

D

Q

F

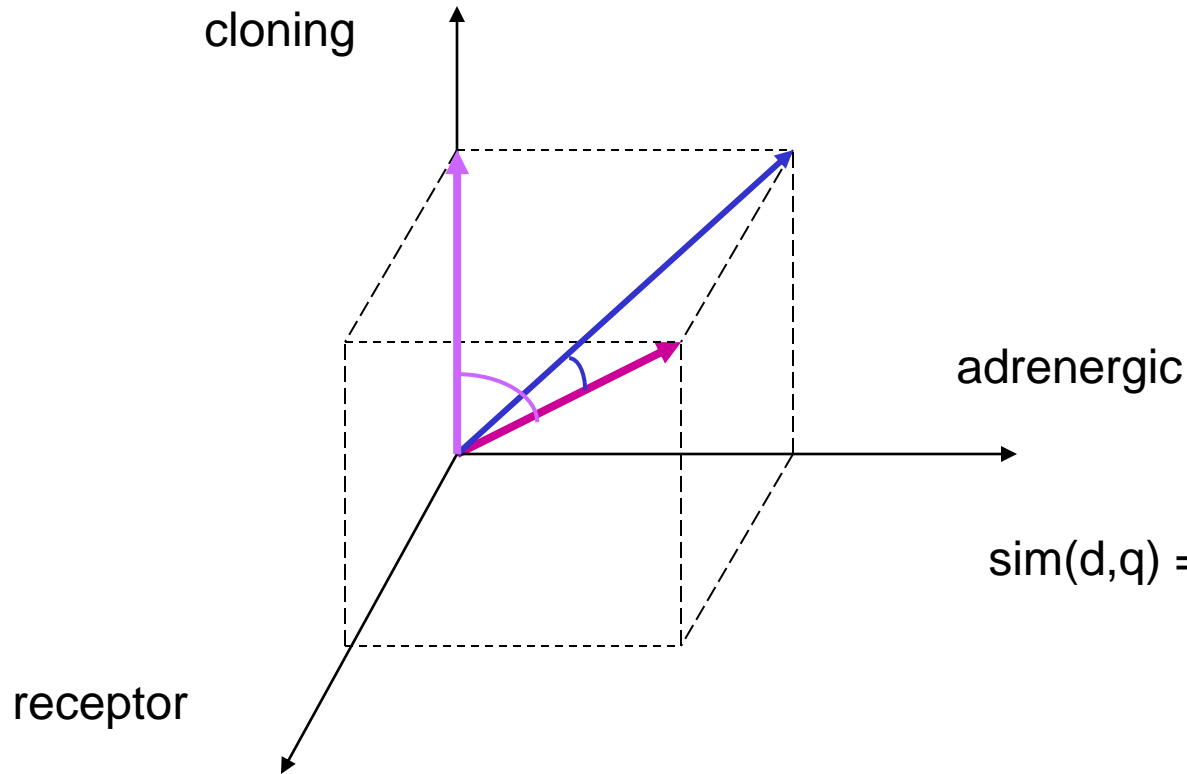
R

Vector model (simplified)

Doc1 (1,1,0)

Doc2 (0,1,0)

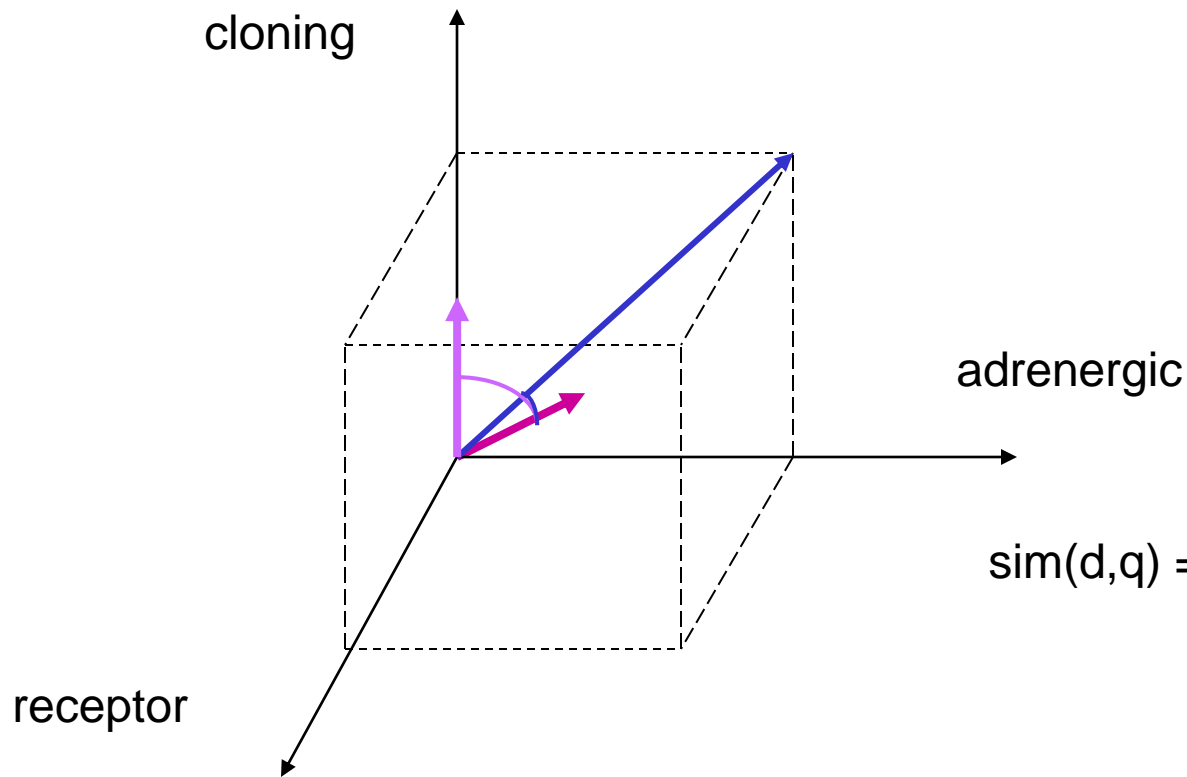
Q (1,1,1)



Vector model

- Introduce weights in document vectors
(e.g. Doc3 (0, 0.5, 0))
- Weights represent importance of the term for describing the document contents
- Weights are positive real numbers
- Term does not occur \rightarrow weight = 0

Vector model



Doc1 (1,1,0)

Doc3 (0,0.5,0)

Q4 (0.5,0.5,0.5)

$$\text{sim}(d,q) = \frac{d \cdot q}{|d| \times |q|}$$

Vector model

- How to define weights? tf-idf

$d_j (w_{1,j}, \dots, w_{t,j})$

$w_{i,j}$ = weight for term k_i in document d_j

$$= f_{i,j} \times \text{idf}_i$$

Vector model

- How to define weights? **tf-idf**

term frequency $\text{freq}_{i,j}$: how often does term k_i occur in document d_j ?

normalized term frequency:

$$f_{i,j} = \text{freq}_{i,j} / \max_l \text{freq}_{l,j}$$

Vector model

Example:

	Doc1	Doc2
K1: adrenergic	5	0
K2: cloning	0	10
K3: receptor	20	2

$f_{reqi,j}$

Vector model

Example:

	Doc1	Doc2
K1: adrenergic	5/20	0/10
K2: cloning	0/20	10/10
K3: receptor	20/20	2/10

$\text{freq}_{i,j} \rightarrow f_{i,j}$

Vector model

- How to define weights? tf-idf

document frequency : in how many documents does term k_i occur?

N = total number of documents

n_i = number of documents in which k_i occurs

inverse document frequency idf_i : $\log_2 (N / n_i)$

Vector model

Example:

	Doc1	Doc2	idfi
K1: adrenergic	5/20	0/10	1
K2: cloning	0/20	10/10	1
K3: receptor	20/20	2/10	0

$$\log_2 (2/1) = \log_2 2 = 1; \log_2 (2/2) = \log_2 1 = 0$$

Vector model

Example:

	Doc1	Doc2	idfi
K1: adrenergic	5/20	0/10	1
K2: cloning	0/20	10/10	1
K3: receptor	20/20	2/10	0
	(0.25,0,0)	(0,1,0)	

Vector model

- How to define weights for query?

recommendation:

$$q = (w_{1,q}, \dots, w_{t,q})$$

$w_{i,q}$ = weight for term k_i in q

$$= (0.5 + 0.5 f_{i,q}) \times \text{idf}_i$$

Vector model

■ Advantages

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

Disadvantage

- assumption of mutually independent terms?



IR - conceptual models - Summary

Probabilistic

D

Q

F

R

Probabilistic model

weights are binary ($w_{i,j} = 0$ or $w_{i,j} = 1$)

R: the set of relevant documents for query q

R_c : the set of non-relevant documents for q

$P(R|d_j)$: probability that d_j is relevant to q

$P(R_c|d_j)$: probability that d_j is not relevant to q

$$\text{sim}(d_j, q) = P(R|d_j) / P(R_c|d_j)$$

Probabilistic model

$$\text{sim}(d_j, q) = P(R|d_j) / P(Rc|d_j)$$

(Bayes' rule, independence of index terms,
take logarithms, $P(k_i|R) + P(\text{not } k_i|R) = 1$)

$$\text{--> SIM}(d_j, q) ==$$

$$\text{SUM}_{i=1}^t w_{i,q} \times w_{i,j} \times$$

$$(\log(P(k_i|R) / (1 - P(k_i|R)))) +$$

$$\log((1 - P(k_i|Rc)) / P(k_i|Rc))$$

Probabilistic model

- How to compute $P(k_i|R)$ and $P(k_i|R_c)$?
 - initially: $P(k_i|R) = 0.5$ and $P(k_i|R_c) = n_i/N$
with $N =$ number of documents and
 $n_i =$ number of documents containing k_i
 - Repeat: retrieve documents and rank them
 V : subset of documents (e.g. r best ranked)
 V_i : subset of V , elements contain k_i
$$P(k_i|R) = |V_i| / |V|$$

and
$$P(k_i|R_c) = (n_i - |V_i|) / (N - |V|)$$

Probabilistic model

- Advantages:

- ranking of documents with respect to probability of being relevant

- Disadvantages:

- initial guess about relevance
- all weights are binary
- independence assumption?

IR - measures

Precision =

$$\frac{\text{number of found relevant documents}}{\text{total number of found documents}}$$

Recall =

$$\frac{\text{number of found relevant documents}}{\text{total number of relevant documents}}$$



IR – measures (visual)



Literature

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