Introduction to Information Retrieval

http://informationretrieval.org

IIR 1: Boolean Retrieval

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Take-away

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- Administrativa

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- Boolean Retrieval: Design and data structures of a simple information retrieval system

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- Boolean Retrieval: Design and data structures of a simple information retrieval system
- What topics will be covered in this class?

Outline

Definition of *information retrieval*

Information retrieval (IR) is finding material (usually documents) of an unstructured nature (usually text) that satisfies an information need from within large collections (usually stored on computers).

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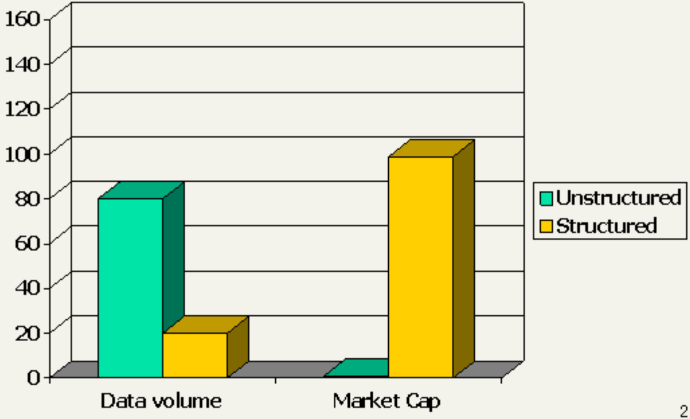
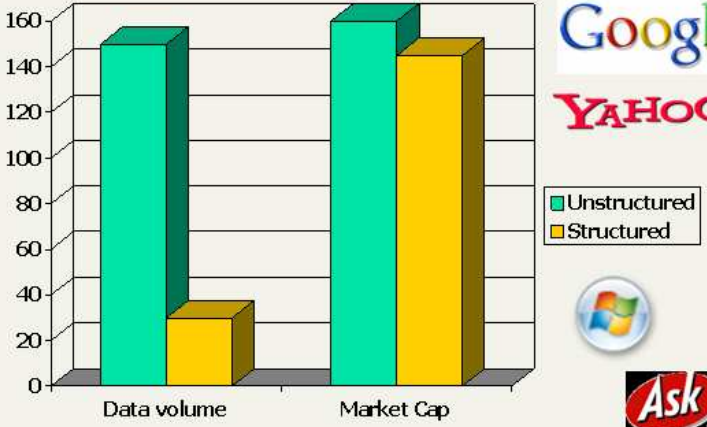
Unstructured (text) vs. structured (database) data in 1996



Unstructured (text) vs. structured (database) data in 2006



Boolean retrieval

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Does Google use the Boolean model?

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Unstructured data in 1650: Shakespeare

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  - grep is line-oriented, IR is document-oriented
  - "NOT CALPURNIA" is non-trivial
  - Other operations (e.g., find the word ROMANS near COUNTRYMAN) not feasible

Term-document incidence matrix

	Anthony and Cleopatra	Julius Caesar	The Tempest	Hamlet	Othello	Macbeth	. . .
ANTHONY	1	1	0	0	0	1	
BRUTUS	1	1	0	1	0	0	
CAESAR	1	1	0	1	1	1	
CALPURNIA	0	1	0	0	0	0	
CLEOPATRA	1	0	0	0	0	0	
MERCY	1	0	1	1	1	1	
WORSER	1	0	1	1	1	0	
. . .							

Entry is 1 if term occurs. Example: CALPURNIA occurs in *Julius Caesar*.
Entry is 0 if term doesn't occur. Example: CALPURNIA doesn't occur in *The tempest*.

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Incidence vectors

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- To answer the query BRUTUS AND CAESAR AND NOT CALPURNIA:
  - Take the vectors for BRUTUS, CAESAR, and CALPURNIA
  - Complement the vector of CALPURNIA
  - Do a (bitwise) AND on the three vectors
  - 110100 AND 110111 AND 101111 = 100100

0/1 vector for Brutus

	Anthony and Cleopatra	Julius Caesar	The Tempest	Hamlet	Othello	Macbeth	...
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Brutus	1	1	0	1	0	0	
Caesar	1	1	0	1	1	1	
Calpurnia	0	1	0	0	0	0	
Cleopatra	1	0	0	0	0	0	
mercy	1	0	1	1	1	1	
worser	1	0	1	1	1	0	
...							
result:	1	0	0	1	0	0	

Answers to query

Anthony and Cleopatra, Act III, Scene ii

Agrippa [Aside to Domitius Enobarbus]: Why, Enobarbus,
When Antony found Julius Caesar dead,
He cried almost to roaring; and he wept
When at Philippi he found Brutus slain.

Hamlet, Act III, Scene ii

Lord Polonius: I did enact Julius Caesar: I was killed i' the Capitol; Brutus killed me.

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- (Notice that we are making a term/token distinction.)

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- But the matrix has no more than one billion 1s.
  - Matrix is extremely sparse.
- What is a better representations?
  - We only record the 1s.

Inverted Index

For each term *t*, we store a list of all documents that contain *t*.

BRUTUS	$\longrightarrow$	1, 2, 4, 11, 31, 45, 173, 174
CAESAR	$\longrightarrow$	1, 2, 4, 5, 6, 16, 57, 132, ...
CALPURNIA	$\longrightarrow$	2, 31, 54, 101
⋮		
dictionary		**postings**

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dictionary **postings**

Inverted index construction

1. Collect the documents to be indexed:
   $\boxed{\text{Friends, Romans, countrymen.}}$ $\boxed{\text{So let it be with Caesar}}$ ...
2. Tokenize the text, turning each document into a list of tokens:
   $\boxed{\text{Friends}}$ $\boxed{\text{Romans}}$ $\boxed{\text{countrymen}}$ $\boxed{\text{So}}$ ...
3. Do linguistic preprocessing, producing a list of normalized tokens, which are the indexing terms: $\boxed{\text{friend}}$ $\boxed{\text{roman}}$ $\boxed{\text{countryman}}$ $\boxed{\text{so}}$ ...
4. Index the documents that each term occurs in by creating an inverted index, consisting of a dictionary and postings.

Tokenization and preprocessing

Doc 1. I did enact Julius Caesar: I was killed i' the Capitol; Brutus killed me.
Doc 2. So let it be with Caesar. The noble Brutus hath told you Caesar was ambitious:

$\Longrightarrow$

Doc 1. i did enact julius caesar i was killed i' the capitol brutus killed me
Doc 2. so let it be with caesar the noble brutus hath told you caesar was ambitious

Generate postings

Doc 1. i did enact julius caesar i was killed i' the capitol brutus killed me
Doc 2. so let it be with caesar the noble brutus hath told you caesar was ambitious

$\Longrightarrow$

term	**docID**
i	1
did	1
enact	1
julius	1
caesar	1
i	1
was	1
killed	1
i'	1
the	1
capitol	1
brutus	1
killed	1
me	1
so	2
let	2
it	2
be	2
with	2
caesar	2
the	2
noble	2
brutus	2
hath	2
told	2
you	2
caesar	2
was	2
ambitious	2

Sort postings

term	docID
i	1
did	1
enact	1
julius	1
caesar	1
i	1
was	1
killed	1
i'	1
the	1
capitol	1
brutus	1
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me	1
so	2
let	2
it	2
be	2
with	2
caesar	2
the	2
noble	2
brutus	2
hath	2
told	2
you	2
caesar	2
was	2
ambitious	2

$\Longrightarrow$

term	docID
ambitious	2
be	2
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brutus	2
capitol	1
caesar	1
caesar	2
caesar	2
did	1
enact	1
hath	1
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i'	1
it	2
julius	1
killed	1
killed	1
let	2
me	1
noble	2
so	2
the	1
the	2
told	2
you	2
was	1
was	2
with	2

Create postings lists, determine document frequency

term	docID
ambitious	2
be	2
brutus	1
brutus	2
capitol	1
caesar	1
caesar	2
caesar	2
did	1
enact	1
hath	1
i	1
i	1
i'	1
it	2
julius	1
killed	1
killed	1
let	2
me	1
noble	2
so	2
the	1
the	2
told	2
you	2
was	1
was	2
with	2

$\Longrightarrow$

term	doc. freq.	→	postings lists
ambitious	1	→	2
be	1	→	2
brutus	2	→	1 → 2
capitol	1	→	1
caesar	2	→	1 → 2
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enact	1	→	1
hath	1	→	2
i	1	→	1
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it	1	→	2
julius	1	→	1
killed	1	→	1
let	1	→	2
me	1	→	1
noble	1	→	2
so	1	→	2
the	2	→	1 → 2
told	1	→	2
you	1	→	2
was	2	→	1 → 2
with	1	→	2

Split the result into dictionary and postings file

BRUTUS	⟶	1	2	4	11	31	45	173	174	
CAESAR	⟶	1	2	4	5	6	16	57	132	...
CALPURNIA	⟶	2	31	54	101					
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dictionary **postings file**

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- Index construction: how can we create inverted indexes for large collections?
- How much space do we need for dictionary and index?
- Index compression: how can we efficiently store and process indexes for large collections?
- Ranked retrieval: what does the inverted index look like when we want the "best" answer?

Outline

1. Introduction
2. Inverted index
3. Processing Boolean queries
4. Query optimization
5. Course overview

Simple conjunctive query (two terms)

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  4. Retrieve its postings list from the postings file
  5. Intersect the two postings lists

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  5. Intersect the two postings lists
  6. Return intersection to user

Intersecting two postings lists

$$\text{B}\textsc{rutus} \longrightarrow \boxed{1} \rightarrow \boxed{2} \rightarrow \boxed{4} \rightarrow \boxed{11} \rightarrow \boxed{31} \rightarrow \boxed{45} \rightarrow \boxed{173} \rightarrow \boxed{174}$$

$$\text{C}\textsc{alpurnia} \longrightarrow \boxed{2} \rightarrow \boxed{31} \rightarrow \boxed{54} \rightarrow \boxed{101}$$

Intersection $\Longrightarrow$

Intersecting two postings lists

BRUTUS	$\longrightarrow$	$\boxed{1} \to \boxed{2} \to \boxed{4} \to \boxed{11} \to \boxed{31} \to \boxed{45} \to \boxed{173} \to \boxed{174}$
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- This is linear in the length of the postings lists.
- Note: This only works if postings lists are sorted.

Intersecting two postings lists

```
INTERSECT(p1, p2)
  answer ← ⟨ ⟩
  while p1 ≠ NIL and p2 ≠ NIL
  do if docID(p1) = docID(p2)
       then ADD(answer, docID(p1))
            p1 ← next(p1)
            p2 ← next(p2)
       else if docID(p1) < docID(p2)
              then p1 ← next(p1)
              else p2 ← next(p2)
  return answer
```

Query processing: Exercise

FRANCE ⟶ 1 → 2 → 3 → 4 → 5 → 7 → 8 → 9 → 11 → 12 → 13 → 14 → 15

PARIS ⟶ 2 → 6 → 10 → 12 → 14

LEAR ⟶ 12 → 15

Compute hit list for ((paris AND NOT france) OR lear)

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  - Boolean queries are queries that use AND, OR and NOT to join query terms.
  - Views each document as a set of terms.
  - Is precise: Document matches condition or not.

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- Many search systems you use are also Boolean: spotlight, email, intranet etc.

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- . . . although ranked retrieval has been available since 1992.

Westlaw: Example queries

Information need: Information on the legal theories involved in preventing the disclosure of trade secrets by employees formerly employed by a competing company

Query: "trade secret" /s disclos! /s prevent /s employe!

Westlaw: Example queries

Information need: Requirements for disabled people to be able to access a workplace

Query: disab! /p access! /s work-site work-place (employment /3 place)

Westlaw: Example queries

Information need: Cases about a host's responsibility for drunk guests

Query: host! /p (responsib! liab!) /p (intoxicat! drunk!) /p guest

Westlaw: Comments

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- Space is disjunction, not conjunction! (This was the default in search pre-Google.)
- Long, precise queries: incrementally developed, not like web search
- Why professional searchers often like Boolean search: precision, transparency, control
- When are Boolean queries the best way of searching? Depends on: information need, searcher, document collection, . . .

Outline

1. Introduction
2. Inverted index
3. Processing Boolean queries
4. Query optimization
5. Course overview

Query optimization

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- For each of the terms, get its postings list, then AND them together
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- What is the best order for processing this query?

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BRUTUS	⟶	1 → 2 → 4 → 11 → 31 → 45 → 173 → 174
CALPURNIA	⟶	2 → 31 → 54 → 101
CAESAR	⟶	5 → 31

Query optimization

- Example query: Brutus AND Calpurnia AND Caesar
- Simple and effective optimization: Process in order of increasing frequency
- Start with the shortest postings list, then keep cutting further
- In this example, first Caesar, then Calpurnia, then Brutus

Brutus ⟶ 1 → 2 → 4 → 11 → 31 → 45 → 173 → 174

Calpurnia ⟶ 2 → 31 → 54 → 101

Caesar ⟶ 5 → 31

Optimized intersection algorithm for conjunctive queries

```
INTERSECT(⟨t_1, ..., t_n⟩)
    terms ← SORTBYINCREASINGFREQUENCY(⟨t_1, ..., t_n⟩)
    result ← postings(first(terms))
    terms ← rest(terms)
    while terms ≠ NIL and result ≠ NIL
    do result ← INTERSECT(result, postings(first(terms)))
        terms ← rest(terms)
    return result
```

More general optimization

- Example query: (MADDING OR CROWD) AND (IGNOBLE OR STRIFE)

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- Example query: (MADDING OR CROWD) AND (IGNOBLE OR STRIFE)
- Get frequencies for all terms
- Estimate the size of each OR by the sum of its frequencies (conservative)
- Process in increasing order of OR sizes

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- In what follows: teasers for most chapters – to give you a sense of what will be covered.

IIR 02: The term vocabulary and postings lists

- Phrase queries: "STANFORD UNIVERSITY"
- Proximity queries: GATES NEAR MICROSOFT
- We need an index that captures position information for phrase queries and proximity queries.

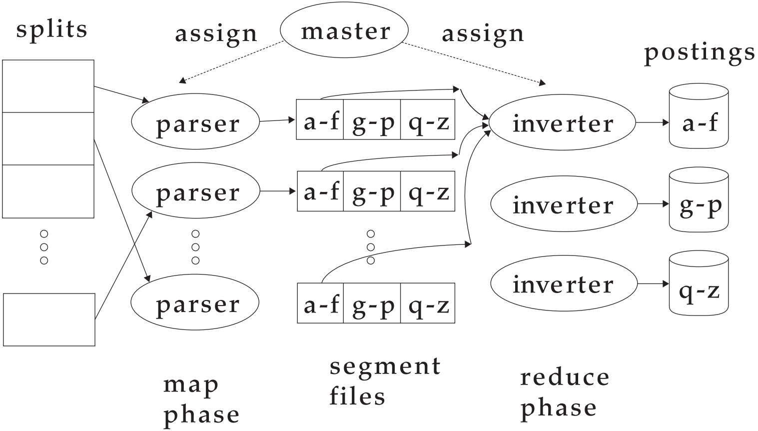
IIR 03: Dictionaries and tolerant retrieval

BO → aboard → about → boardroom → border

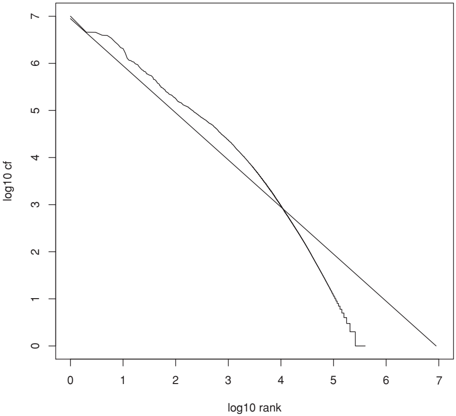
OR → border → lord → morbid → sordid

RD → aboard → ardent → boardroom → border

IIR 04: Index construction



IIR 05: Index compression

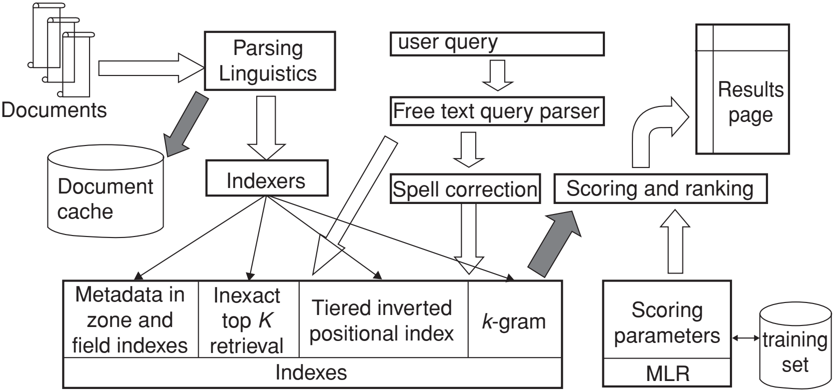


Zipf's law

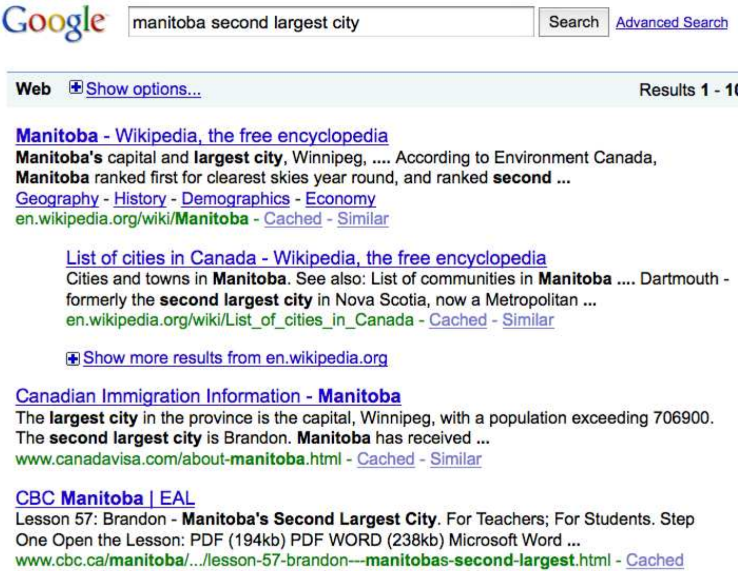
IIR 06: Scoring, term weighting and the vector space model

- Ranking search results
  - Boolean queries only give inclusion or exclusion of documents.
  - For ranked retrieval, we measure the proximity between the query and each document.
  - One formalism for doing this: the vector space model
- Key challenge in ranked retrieval: evidence accumulation for a term in a document
  - 1 vs. 0 occurence of a query term in the document
  - 3 vs. 2 occurences of a query term in the document
  - Usually: more is better
  - But by how much?
  - Need a scoring function that translates frequency into score or weight

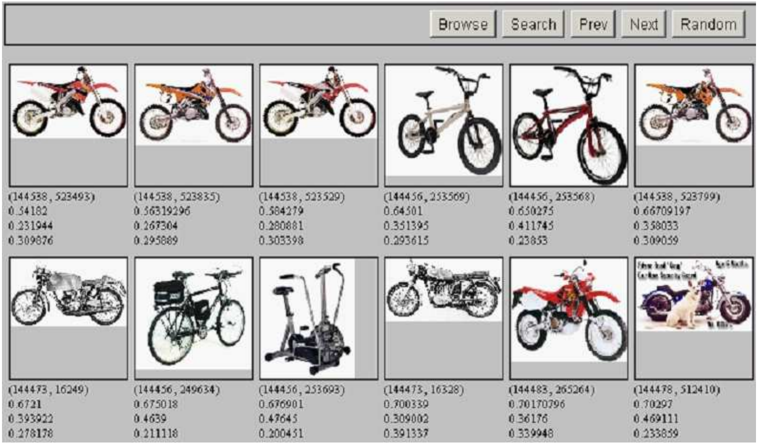
IIR 07: Scoring in a complete search system



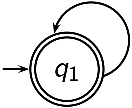
IIR 08: Evaluation and dynamic summaries



IIR 09: Relevance feedback & query expansion



IIR 12: Language models



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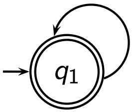

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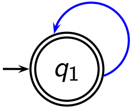

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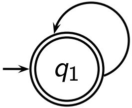

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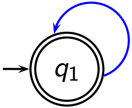

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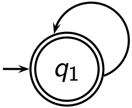

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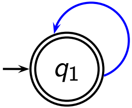

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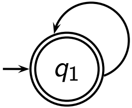

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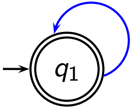

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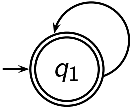

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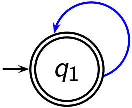

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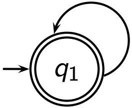

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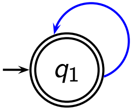

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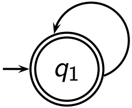

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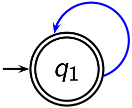

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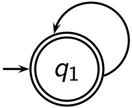

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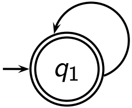

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$= 0.0000000000048$

IIR 13: Text classification & Naive Bayes

- Text classification = assigning documents automatically to predefined classes
- Examples:
  - Language (English vs. French)
  - Adult content
  - Region

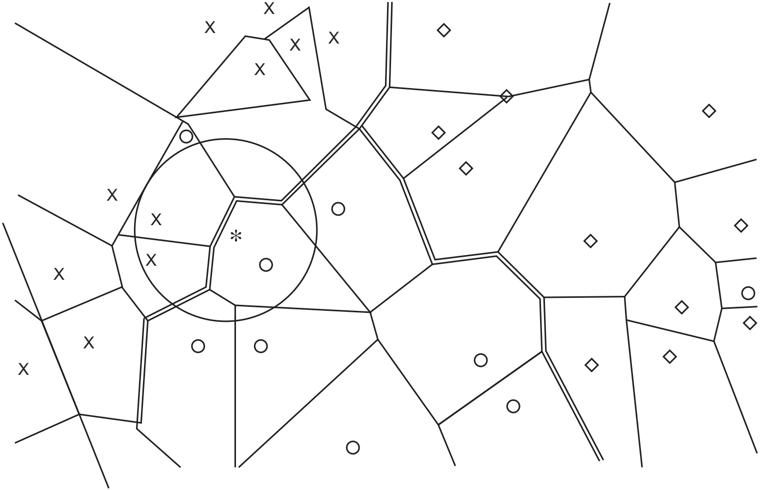
IIR 11: Probabilistic information retrieval

IIR 11: Probabilistic information retrieval

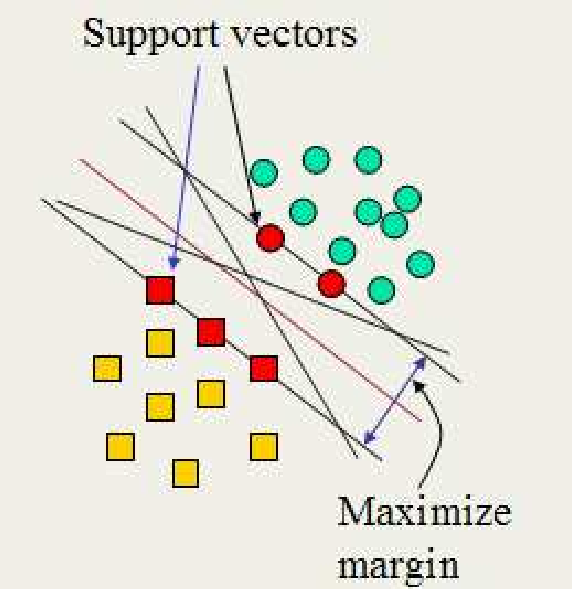
	document	relevant ($R = 1$)	nonrelevant ($R = 0$)
Term present	$x_t = 1$	p_t	u_t
Term absent	$x_t = 0$	$1 - p_t$	$1 - u_t$

$$O(R|\vec{q},\vec{x}) = O(R|\vec{q}) \cdot \prod_{t:x_t=q_t=1} \frac{p_t}{u_t} \cdot \prod_{t:x_t=0,q_t=1} \frac{1-p_t}{1-u_t} \qquad (1)$$

IIR 14: Vector classification



IIR 15: Support vector machines

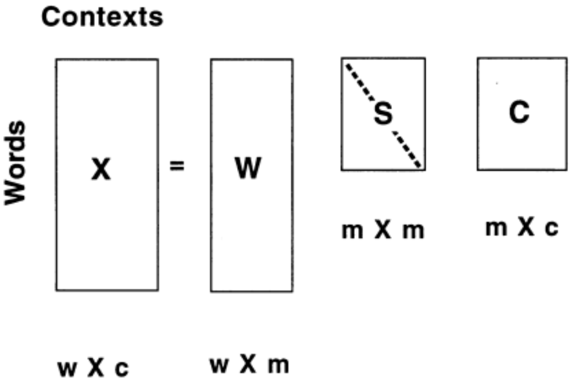


IIR 16: Flat clustering

IIR 17: Hierarchical clustering

http://news.google.com

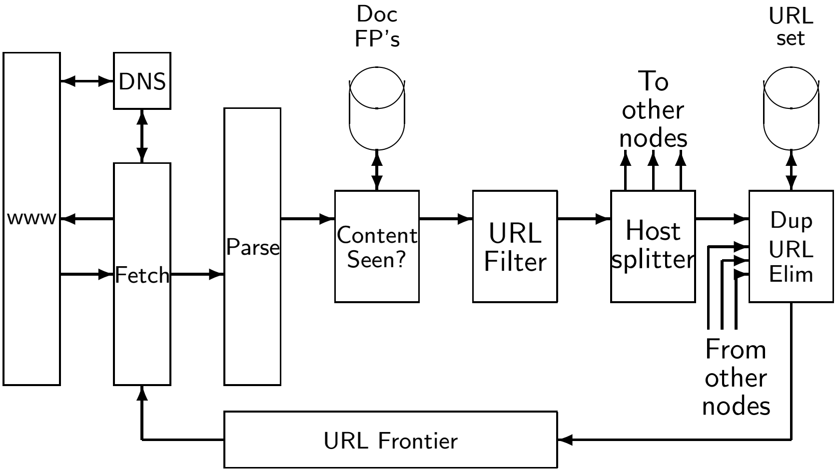
IIR 18: Latent Semantic Indexing



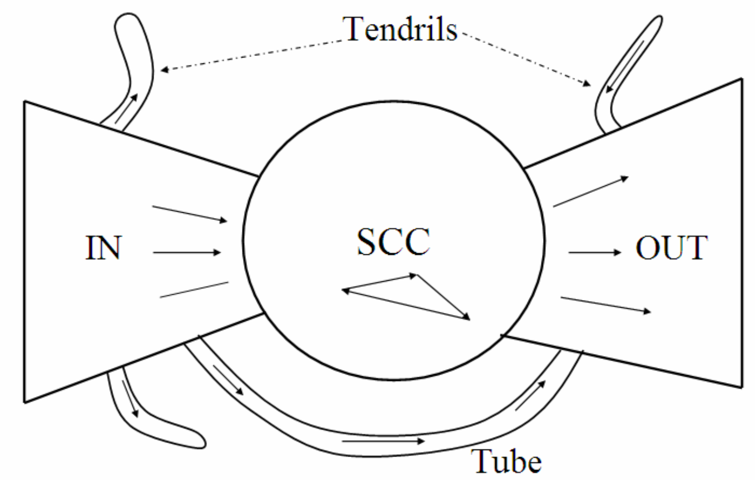
IIR 19: The web and its challenges

- Unusual and diverse documents
- Unusual and diverse users and information needs
- Beyond terms and text: exploit link analysis, user data
- How do web search engines work?
- How can we make them better?

IIR 20: Crawling



IIR 21: Link analysis / PageRank



Take-away

- Administrativa
- Boolean Retrieval: Design and data structures of a simple information retrieval system
- What topics will be covered in this class?

Resources

- Chapter 1 of IIR
- http://ifnlp.org/ir
  - course schedule
  - administrativa
  - information retrieval links
  - Shakespeare search engine