Introduction to Information Retrieval

http://informationretrieval.org

IIR 1: Boolean Retrieval

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2014-04-09

Take-away

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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

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

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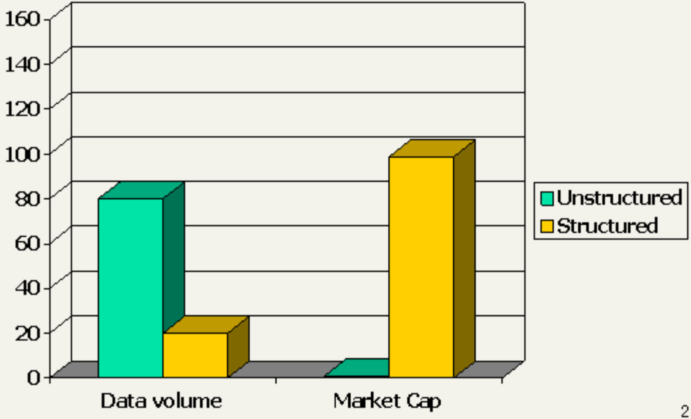
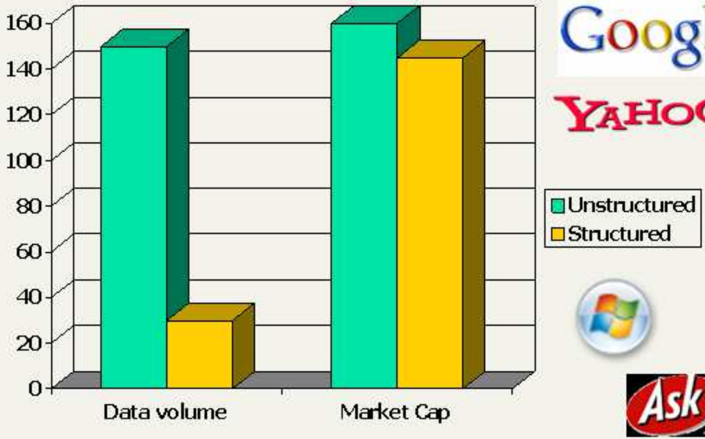
Unstructured (text) vs. structured (database) data in 1996



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



Google

YAHOO!

Ask

Boolean retrieval

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  - Simple Boolean retrieval returns matching documents in no particular order.
  - Google (and most well designed Boolean engines) rank the result set – they rank good hits (according to some estimator of relevance) higher than bad hits.

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Unstructured data in 1650: Shakespeare

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  - Slow (for large collections)
  - 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 vectors and result of bitwise operations

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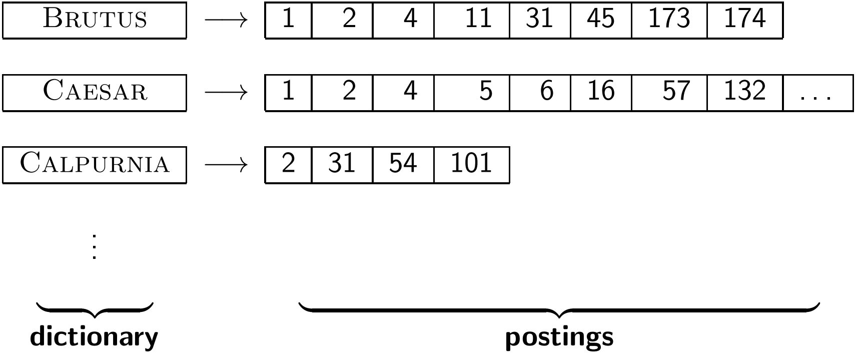
- But the matrix has no more than one billion 1s.
    - Matrix is extremely sparse.
- What is a better representations?
    - We only record the 1s.

Inverted Index

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



BRUTUS ⟶ 1 | 2 | 4 | 11 | 31 | 45 | 173 | 174

CAESAR ⟶ 1 | 2 | 4 | 5 | 6 | 16 | 57 | 132 | ...

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⋮

dictionary

postings

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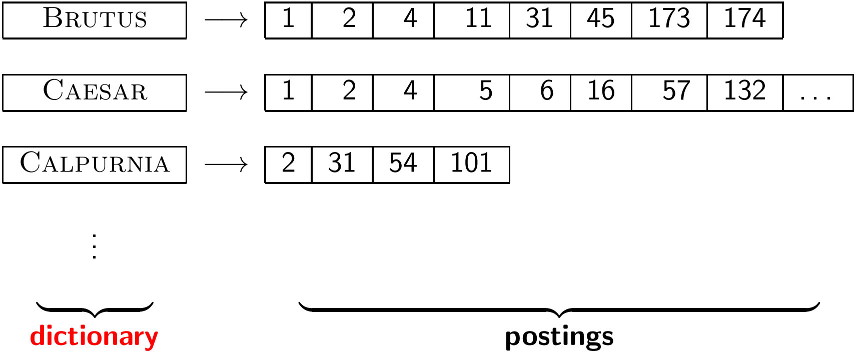

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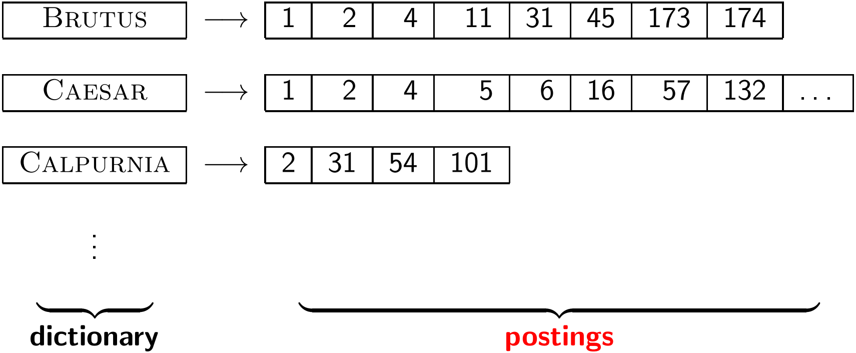

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$\underbrace{\qquad\qquad}_{\text{dictionary}}$ $\underbrace{\qquad\qquad\qquad\qquad\qquad\qquad}_{\text{postings}}$

Inverted index construction

1. Collect the documents to be indexed:
   Friends, Romans, countrymen. So let it be with Caesar . . .
2. Tokenize the text, turning each document into a list of tokens:
   Friends Romans countrymen So . . .
3. Do linguistic preprocessing, producing a list of normalized tokens, which are the indexing terms: friend roman countryman 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

⟹

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
killed	1
me	1
so	2
let	2
it	2
be	2
with	2
caesar	2
the	2
noble	2
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ambitious	2
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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
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told	2
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with	2

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ambitious	1	→	2
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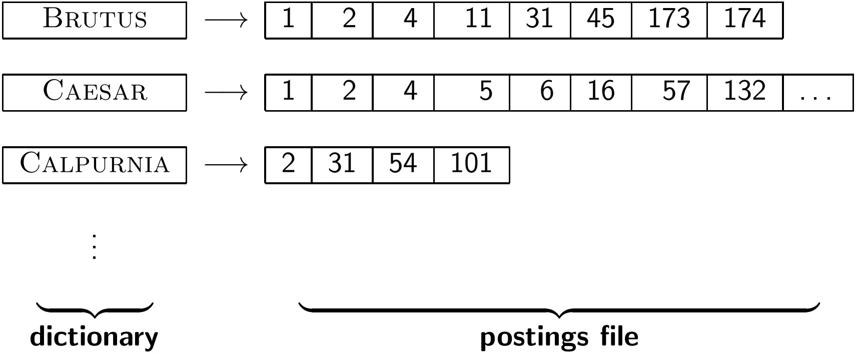
enact	1	→	1
hath	1	→	2
i	1	→	1
i'	1	→	1
it	1	→	2
julius	1	→	1
killed	1	→	1
let	1	→	2
me	1	→	1
noble	1	→	2
so	1	→	2
the	2	→	1 → 2
told	1	→	2
you	1	→	2
was	2	→	1 → 2
with	1	→	2

Split the result into dictionary and postings file



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- 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?

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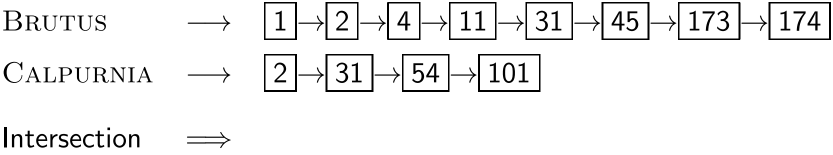
    5. Intersect the two postings lists
    6. Return intersection to user

Intersecting two postings lists

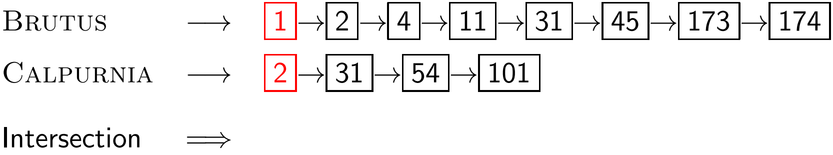


BRUTUS $\longrightarrow$ $\boxed{1}\to\boxed{2}\to\boxed{4}\to\boxed{11}\to\boxed{31}\to\boxed{45}\to\boxed{173}\to\boxed{174}$

CALPURNIA $\longrightarrow$ $\boxed{2}\to\boxed{31}\to\boxed{54}\to\boxed{101}$

Intersection $\Longrightarrow$

Intersecting two postings lists



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Intersection ⟹

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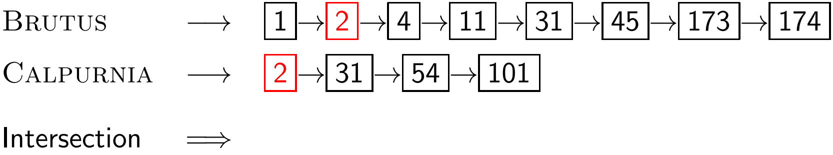

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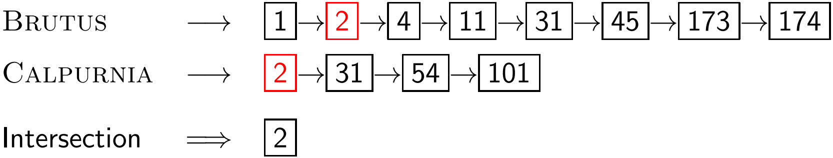

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Intersection ⟹ 2

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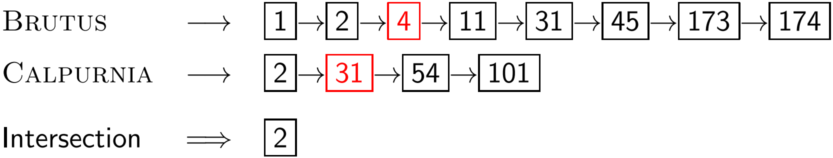

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Intersecting two postings lists

$$\textsc{Brutus} \longrightarrow \boxed{1} \to \boxed{2} \to \boxed{4} \to \boxed{11} \to \boxed{31} \to \boxed{45} \to \boxed{173} \to \boxed{174}$$

$$\textsc{Calpurnia} \longrightarrow \boxed{2} \to \boxed{31} \to \boxed{54} \to \boxed{101}$$

$$\text{Intersection} \Longrightarrow \boxed{2}$$

Intersecting two postings lists

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Intersection $\Longrightarrow$ $\boxed{2}$

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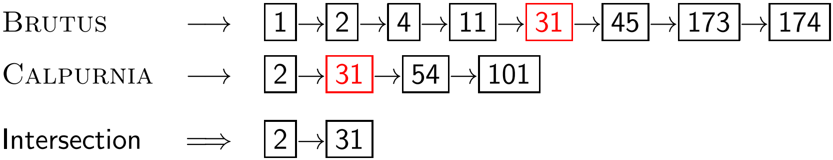

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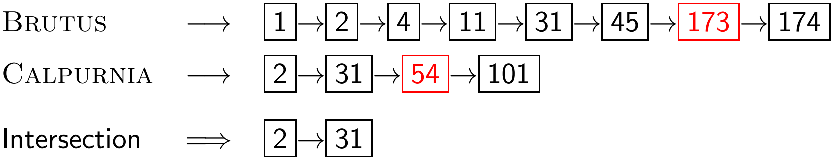

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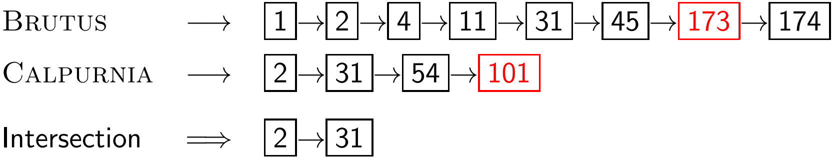

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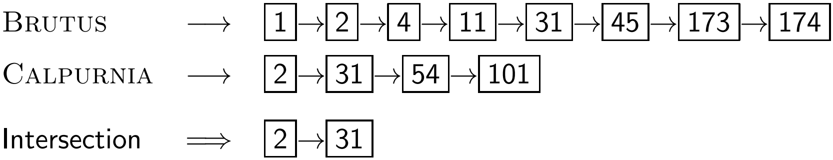

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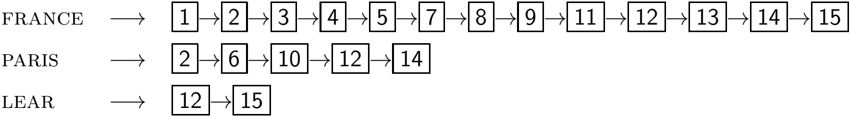
- This is linear in the length of the postings lists.
- Note: This only works if postings lists are sorted.

Intersecting two postings lists

```
$\textsc{Intersect}(p_1, p_2)$
    $answer \leftarrow \langle\ \rangle$
    while $p_1 \neq \textsc{nil}$ and $p_2 \neq \textsc{nil}$
    do if $docID(p_1) = docID(p_2)$
          then $\textsc{Add}(answer, docID(p_1))$
               $p_1 \leftarrow next(p_1)$
               $p_2 \leftarrow next(p_2)$
          else if $docID(p_1) < docID(p_2)$
                 then $p_1 \leftarrow next(p_1)$
                 else $p_2 \leftarrow next(p_2)$
    return $answer$
```

Query processing: Exercise



FRANCE $\longrightarrow \boxed{1} \to \boxed{2} \to \boxed{3} \to \boxed{4} \to \boxed{5} \to \boxed{7} \to \boxed{8} \to \boxed{9} \to \boxed{11} \to \boxed{12} \to \boxed{13} \to \boxed{14} \to \boxed{15}$

PARIS $\longrightarrow \boxed{2} \to \boxed{6} \to \boxed{10} \to \boxed{12} \to \boxed{14}$

LEAR $\longrightarrow \boxed{12} \to \boxed{15}$

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

Boolean retrieval model: Assessment

- The Boolean retrieval model can answer any query that is a Boolean expression.

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

Commercially successful Boolean retrieval: Westlaw

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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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- 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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- Example query: Brutus AND Calpurnia AND Caesar
- What is the best order for processing this query?

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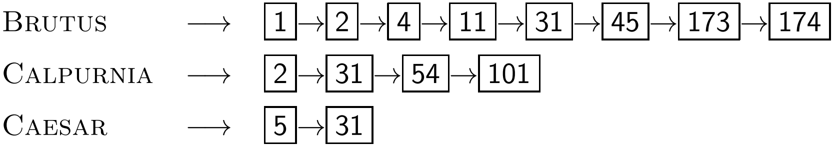

Brutus ⟶ 1 → 2 → 4 → 11 → 31 → 45 → 173 → 174

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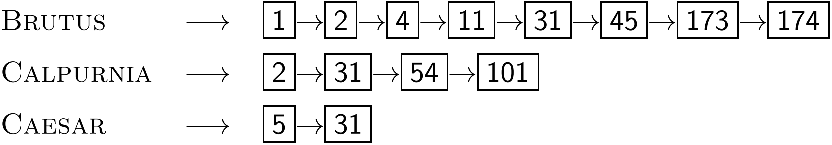
Query optimization

- 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($\langle t_1, \ldots, t_n \rangle$)
    terms ← SORTBYINCREASINGFREQUENCY($\langle t_1, \ldots, t_n \rangle$)
    result ← postings(first(terms))
    terms ← rest(terms)
    while terms $\neq$ NIL and result $\neq$ 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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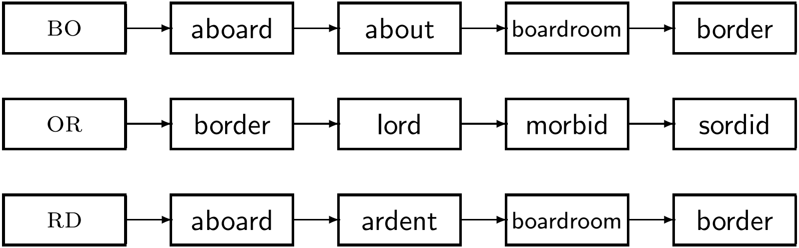
- In what follows: teasers for most chapters – to give you a sense of what will be covered.

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

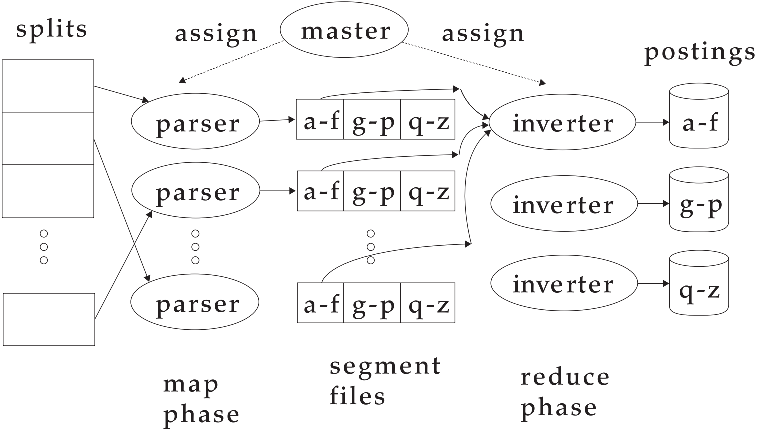


BO → aboard → about → boardroom → border

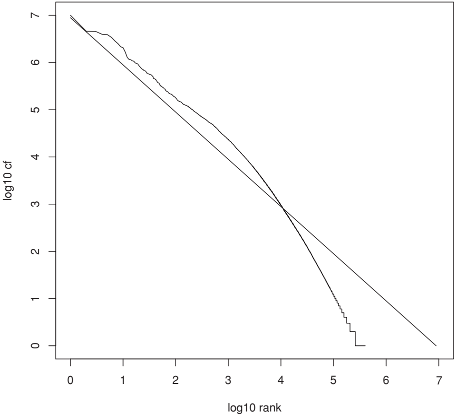
OR → border → lord → morbid → sordid

RD → aboard → ardent → boardroom → border

IIR 04: Index construction



IIR 05: Index compression

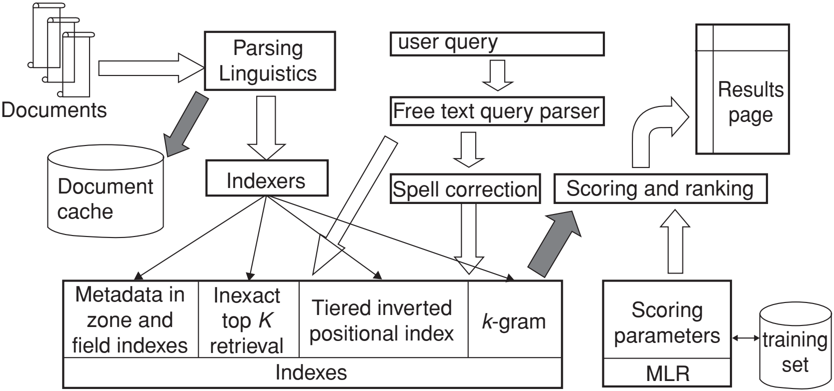


Zipf's law

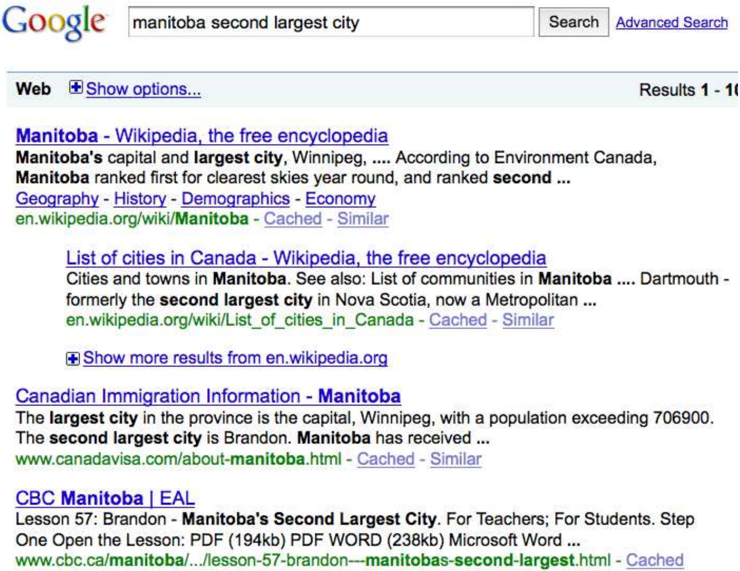
IIR 06: Scoring, term weighting and the vector space model

- 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



Manitoba - Wikipedia, the free encyclopedia
Manitoba's capital and **largest city**, Winnipeg, ... According to Environment Canada, **Manitoba** ranked first for clearest skies year round, and ranked **second** ...
Geography - History - Demographics - Economy
en.wikipedia.org/wiki/**Manitoba** - Cached - Similar

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Cities and towns in **Manitoba**. See also: List of communities in **Manitoba** .... Dartmouth - formerly the **second largest city** in Nova Scotia, now a Metropolitan ...
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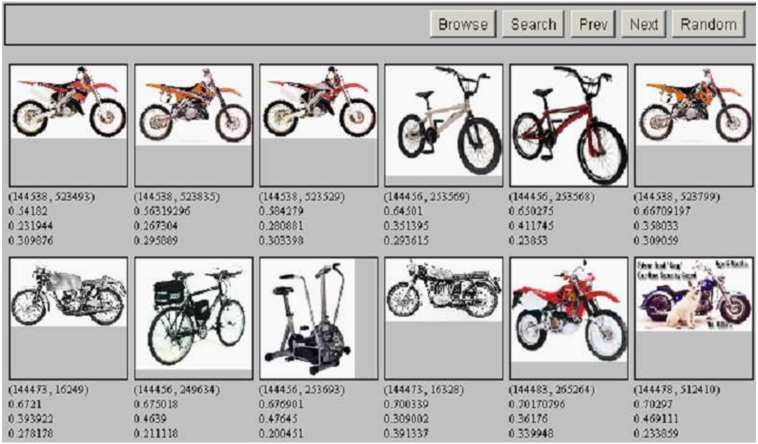
Canadian Immigration Information - **Manitoba**
The **largest city** in the province is the capital, Winnipeg, with a population exceeding 706900. The **second largest city** is Brandon. **Manitoba** has received ...
www.canadavisa.com/about-**manitoba**.html - Cached - Similar

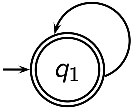
CBC **Manitoba** | EAL
Lesson 57: Brandon - **Manitoba's Second Largest City**. For Teachers; For Students. Step One Open the Lesson: PDF (194kb) PDF WORD (238kb) Microsoft Word ...
www.cbc.ca/**manitoba**/.../lesson-57-brandon---**manitobas-second-largest**.html - Cached

IIR 09: Relevance feedback & query expansion



(144538 , 523493) 0.54182 0.231944 0.309876	(144538 , 523835) 0.56319296 0.267304 0.295889	(144538 , 523529) 0.584279 0.280881 0.303398	(144456 , 253569) 0.64501 0.351395 0.293615	(144456 , 253568) 0.650275 0.411745 0.23853	(144538 , 523799) 0.66709197 0.358033 0.309059
(144473 , 16249) 0.6721 0.393922 0.278178	(144456 , 249634) 0.675018 0.4639 0.211118	(144456 , 253693) 0.676901 0.47645 0.200451	(144473 , 16328) 0.700339 0.309002 0.391337	(144483 , 265264) 0.70170796 0.36176 0.339948	(144478 , 512410) 0.70297 0.469111 0.233859

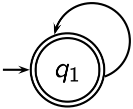
IIR 12: Language models



w	$P(w\|q_1)$	w	$P(w\|q_1)$
STOP	0.2	toad	0.01
the	0.2	said	0.03
a	0.1	likes	0.02
frog	0.01	that	0.04
		...	...

This is a one-state probabilistic finite-state automaton – a unigram language model – and the state emission distribution for its one state q_1.

IIR 12: Language models



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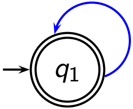

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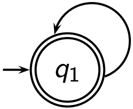

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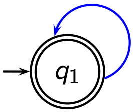

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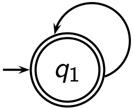

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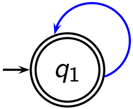

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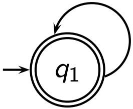
IIR 12: Language models



w	$P(w\|q_1)$	w	$P(w\|q_1)$
STOP	0.2	toad	0.01
the	0.2	said	0.03
a	0.1	likes	0.02
frog	0.01	that	0.04
		...	...

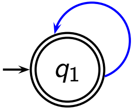
This is a one-state probabilistic finite-state automaton – a unigram language model – and the state emission distribution for its one state q_1.

STOP is not a word, but a special symbol indicating that the automaton stops.

frog said that

$P(\text{string}) = 0.01 \cdot 0.03 \cdot 0.04$

IIR 12: Language models



w	$P(w\|q_1)$	w	$P(w\|q_1)$
STOP	0.2	toad	0.01
the	0.2	said	0.03
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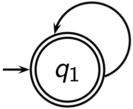
IIR 12: Language models



w	$P(w\|q_1)$	w	$P(w\|q_1)$
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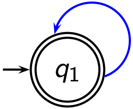
$P(\text{string}) = 0.01 \cdot 0.03 \cdot 0.04 \cdot 0.01$

IIR 12: Language models



w	$P(w\|q_1)$	w	$P(w\|q_1)$
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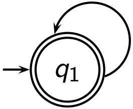
$P(\text{string}) = 0.01 \cdot 0.03 \cdot 0.04 \cdot 0.01$

IIR 12: Language models



w	$P(w \mid q_1)$	w	$P(w \mid q_1)$
STOP	0.2	toad	0.01
the	0.2	said	0.03
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frog	0.01	that	0.04
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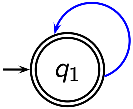
IIR 12: Language models



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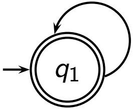
IIR 12: Language models



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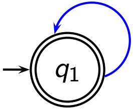
IIR 12: Language models



w	$P(w\|q_1)$	w	$P(w\|q_1)$
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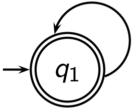
$P(\text{string}) = 0.01 \cdot 0.03 \cdot 0.04 \cdot 0.01 \cdot 0.02 \cdot 0.01$

IIR 12: Language models



w	$P(w\|q_1)$	w	$P(w\|q_1)$
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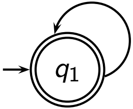
IIR 12: Language models



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STOP is not a word, but a special symbol indicating that the automaton stops.

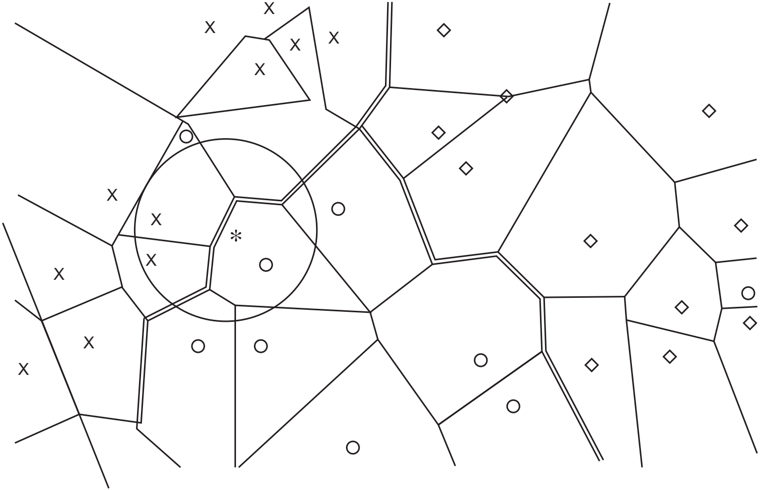
frog said that toad likes frog STOP

$P(\text{string}) = 0.01 \cdot 0.03 \cdot 0.04 \cdot 0.01 \cdot 0.02 \cdot 0.01 \cdot 0.2$
$= 0.0000000000048$

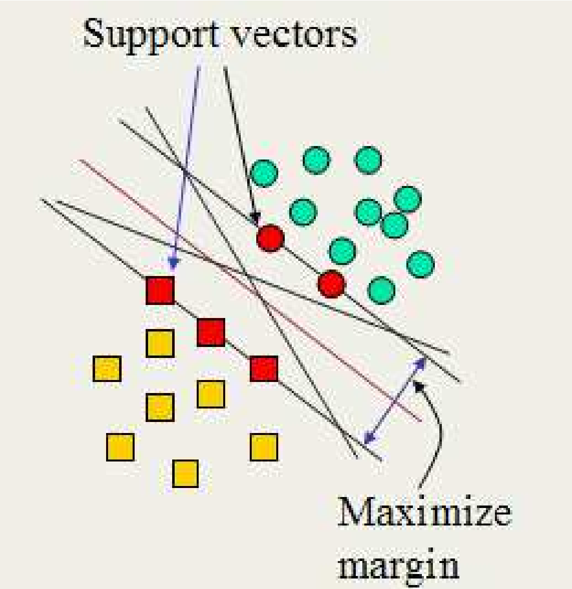
IIR 13: Text classification & Naive Bayes

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

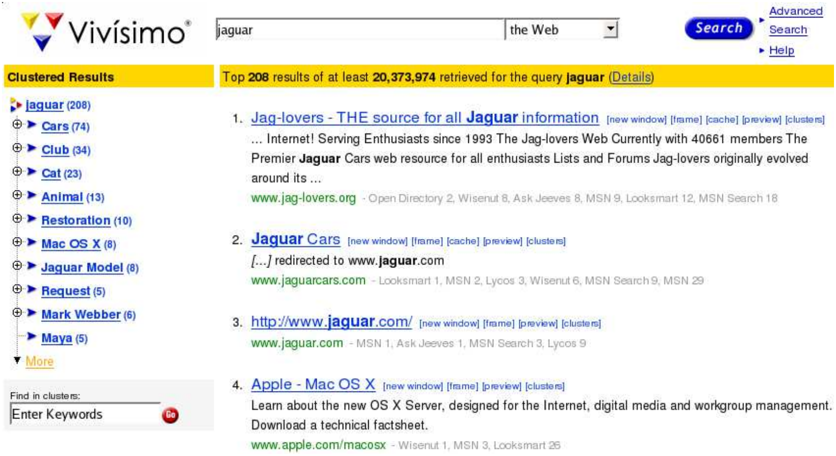
IIR 14: Vector classification



IIR 15: Support vector machines



IIR 16: Flat clustering



Clustered Results

- jaguar (208)
  - Cars (74)
  - Club (34)
  - Cat (23)
  - Animal (13)
  - Restoration (10)
  - Mac OS X (8)
  - Jaguar Model (8)
  - Request (5)
  - Mark Webber (6)
  - Maya (5)
- More

Find in clusters:

Enter Keywords Go

Top **208** results of at least **20,373,974** retrieved for the query **jaguar** (Details)

1. Jag-lovers - THE source for all **Jaguar** information [new window] [frame] [cache] [preview] [clusters]
   ... Internet! Serving Enthusiasts since 1993 The Jag-lovers Web Currently with 40661 members The Premier **Jaguar** Cars web resource for all enthusiasts Lists and Forums Jag-lovers originally evolved around its ...
   www.jag-lovers.org - Open Directory 2, Wisenut 8, Ask Jeeves 8, MSN 9, Looksmart 12, MSN Search 18

2. **Jaguar** Cars [new window] [frame] [cache] [preview] [clusters]
   [...] redirected to www.**jaguar**.com
   www.jaguarcars.com - Looksmart 1, MSN 2, Lycos 3, Wisenut 6, MSN Search 9, MSN 29

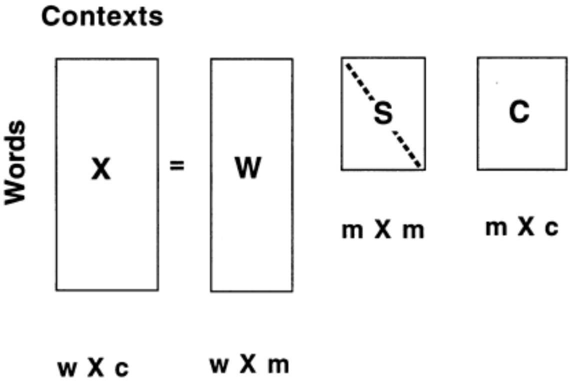
3. http://www.**jaguar**.com/ [new window] [frame] [preview] [clusters]
   www.jaguar.com - MSN 1, Ask Jeeves 1, MSN Search 3, Lycos 9

4. Apple - Mac OS X [new window] [frame] [preview] [clusters]
   Learn about the new OS X Server, designed for the Internet, digital media and workgroup management. Download a technical factsheet.
   www.apple.com/macosx - Wisenut 1, MSN 3, Looksmart 26

IIR 17: Hierarchical clustering

http://news.google.com

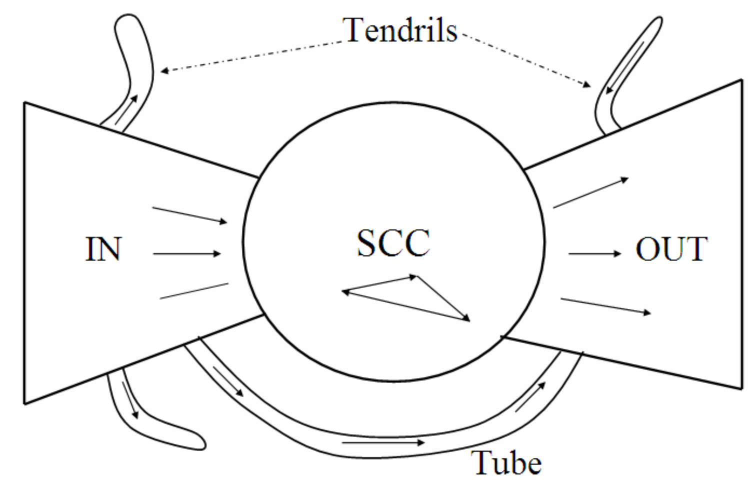
IIR 18: Latent Semantic Indexing



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 21: Link analysis / PageRank



Take-away

- 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://cislmu.org
  - course schedule
  - information retrieval links
  - Shakespeare search engine