Information Retrieval

Lecture 1: Introduction to concepts and problems

Computer Science Tripos Part II

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Information access in an ideal world

Question: "What was the historical development of Boolean algebra and set theory?"

Answer: "In 1854 George Boole published a seminal work *An investigation into the Laws of Thought, on Which are founded the Mathematical Theories of Logic and Probabilities.*"...

The user's information need is ideally met:

- Right type of response for information need
- Expected amount of information
- In perfect English, natural interaction
- And the information is of course correct!

Types of information needs

- Known-item search: Know that a certain item is there, want to refind it → want to find exactly that item (Boole's book)
- Precise information-seeking search → don't care where the information comes from, expect at least one document answering it ("when was Boole born?")
- Open-ended search ("topic search"): → do not know if a document exists; potentially, many exist ("has anybody implemented a probabilistic version of Boolean algebra?")

Two open-ended search problems

- Information scarcity problem (or needle-in-haystack problem): hard to find rare information
  - Lord Byron's first words? 3 years old? Long sentence to the nurse in perfect English?

> . . . when a servant had spilled an urn of hot coffee over his legs, he replied to the distressed inquiries of the lady of the house, 'Thank you, madam, the agony is somewhat abated.' (wasn't Lord Byron, but Lord Macaulay, though...)

- Information abundance problem (for more clear-cut information needs): redundancy of obvious information
  - What is toxoplasmosis?

A known-item search, in old-style library catalogue 5

"Boole's book"

- If I know title, author, year ("An investigation of the laws of thought, on which are founded the mathematical theories of logic and probabilities, George Boole, 1854")

  → Boole, G ... 1854 → Location: Betty & Gordon Moore Library Class-mark: QA9 .B65
- "Bool? Boole? on algebra??, 19th Century" → L paper catalogue

  as above
- "on algebra, 19th century, called '*Laws of Thought*"' → L subject index

  Algebra 347.9 → Shelves

A known-item search, in electronic library catalogue 6

"Boole's book"

Search	Query	Results
(full text)	"laws thought"	→ 10000 entries (truncated)
(title)	"laws thought"	→ 0 entries
(title)	"laws of thought"	→ 2 entries
(title)	"law of thought"	→ 0 entries
(title)	"algebra"	→ 623 entries
(full text)	"algebra"	→ 2474 entries
(Boolean)	"logic AND boole"	→ 9 entries

More searches (I)

Google

- “law” → Lawyers, legal services, law schools
- “laws” → Lists of laws, public and private laws, four spiritual laws

  → law and laws are different search terms on Google!
- Boole does not show up in the first 10 pages

Altavista has “wildcards”:

- law* → law, laws, lawyers, lawn, Lawndale, CA

More searches (II)

Google

- “law thought”
  - “Savannah NOW: Local News - Mother-in-law thought mechanic was a ...”

  → Unexpected other meanings of terms (here: multi-word term)

  → Grammatical function of term ignored (verb instead of noun)

  → Treatment of dash

  Rest: divorce, law as thought control, law and social thought, Scottish thought...
- “thought law”
  - “And you thought law enforcement was boring?”

  → Order of terms matters in Google (but capitalisation does not)

Factors in IR (I)

Syntax of query language:

- Capitalisation?
- Stemming?
- Wildcards?
- String search? (“laws of thought”)
- If there are more than one search terms:
  - Does the order of search terms matter?
  - Boolean operators available?
  - Implicit “AND” between terms?
  - Can I make a search term compulsory?
  - Proximity search? (Altavista’s NEAR: within 10 words of each other)

Factors in IR (II)

- Search Ground:
  - Which text representation is indexed? Abstract, title, full text?
  - Can I specify where I am searching?
- Interpreting the output:
  - Is the output ranked?
  - If more than one search term is used, is each term guaranteed to be there?

A better Google search for initial query: `(develop|history| historical) set theory (boole|boolean) algebra` 11

STEP II: Develop Course Objectives and Outcomes
STEP II: Develop Course Objectives and Outcomes COURSE ... partially ordered sets, lattices, Boolean algebras, semigroups ... and predicate logic 2. Set theory and its ...

06: Order, lattices, ordered algebraic structures
... History. ... especially on infinite sets is the study of Ordinals in Set Theory; ...

03E: Set theory
... do no better describing the history of Set ... propositions; 03E30: Axiomatics of classical set theory and its ... Other aspects of forcing and Boolean-valued models; ... Description: From Dave Rusin's "Known Math" collection.

Introduction to Algebra: History
... The next major development in the history of algebra ... Boole's original notation is no longer used, and ... uses the symbols of either set theory, or propositional ...

HiLight ... to a particular epoch in human history, that of ... Every historical position to achieve is like a ... Algebra Classical propositional logic and set theory are often ...

Selected course history
... Rosen). Basic set theory, discrete probability, combinatorics, Boolean algebra, graph theory. Fundamentals of Dynamical Systems. Elementary

MA003 MATHEMATICS FOR COMPUTING
... develop and use the concepts presented in the lectures. In particular emphasis will be put on parallel or similar systems such as set theory & Boolean algebra ...

Boolean algebra
... a new method of diagramming Boole's notation; this was ... When used in set theory, Boolean notation can demonstrate the ... indicating what is in each set alone, what ...

Graduate Courses
... Combinations, logic set theory, Boolean algebra, relations and functions, graph ... The historical evolution of non-Euclidean geometries ... History of Mathematics. ...

Barnes & Noble.com - Ones and Zeros: Understanding Boolean ...
... features include: a history of mathematical logic, an ... Electronic digital computers, Set theory, Design. Logic, Symbolic and mathematical, Circuits, Algebra, Boolean. ...

Results... after some reading and searching 12

Somewhere in document 4:

> ... Boolean algebra was formulated by the English mathematician George Boole in 1847 ...

Somewhere in document 8:

> Boolean algebra, an abstract mathematical system primarily used in computer science and in expressing the relationships between sets (groups of objects or concepts). The notational system was developed by the English mathematician George Boole c.1850 to permit an algebraic manipulation of logical statements.

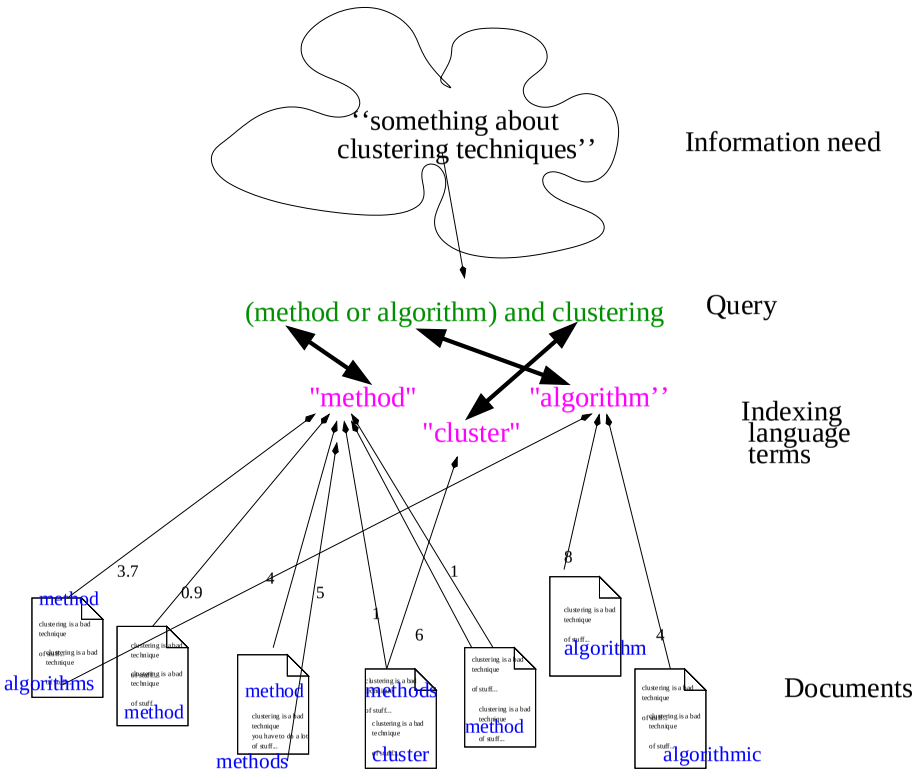
→ Searching requires knowledge about underlying model to be effective

Problem: given a query, find documents that are “relevant” to the query

- Given: a large, static document collection
- Given: an information need (reformulated as a keyword-based query)
- Task: find all and only documents that are relevant to this query

Issues in IR:

- How can I formulate the query? (Query type, query constructs)
- How does the system find the best-matching document? (Retrieval model)
- How are the results presented to me (unsorted list, ranked list, clusters)?



This course is about. . .

improving all the things the user does not want:

- to read irrelevant documents → Information Retrieval
- to read entire documents when information need can be satisfied with far shorter pieces of text:
  - with a phrase or extracted sentence → Question Answering
  - by some of the material in the document → Summarisation

→ Drive is towards access methods closer to natural language (NL)

- (to read similar documents (without being informed that these documents are similar) → clustering (cf. CSTIT MPhil course)

This course: topics

IR
- Lecture 2: Information retrieval models
- Lecture 3: IR evaluation methodology
- Lecture 4: Search engines and linkage algorithms

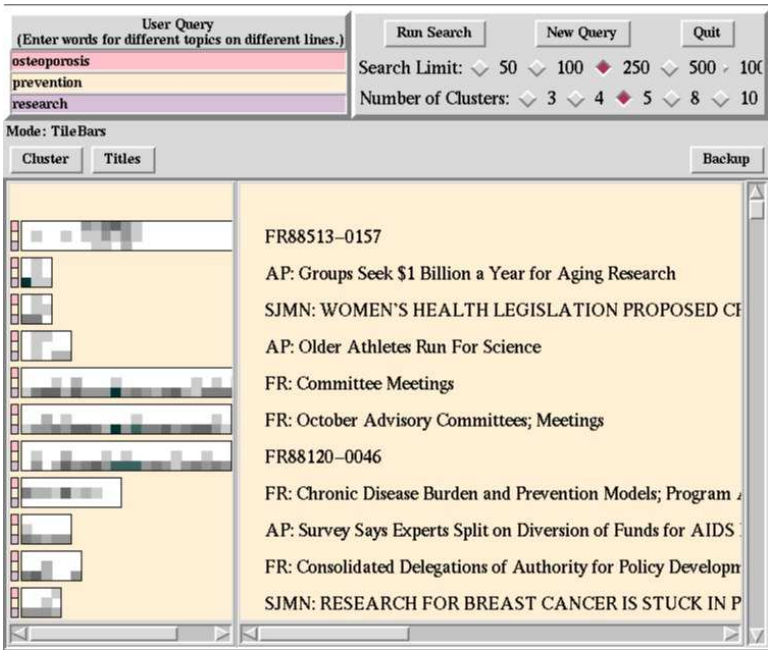
IE
- Lecture 5: Information extraction
- Lecture 6: Bootstrapping in information extraction

Lecture 7: Question answering

Lecture 8: Summarisation; outlook

Beyond IR: More fine-grained search (Hearst, 1993)

TileBars: Show distribution of query terms (e.g. “osteoporosis” “prevention” “research”) in segments of the document



Asking Questions

“What did George Boole invent?”

“And when?”

Solution One (the shortcut):

Ask google for the following exact strings:

```
"Boole invented"
"Boole developed"
"Boole invents"
"invented by Boole"
"invented by George Boole"
"developed by Boole"
"Boole discovered"
```

- Near-synonyms
- Passive/Active Voice variation

George Boole invented a mathematical tool for future computer-builders –an ”algebra of logic” that was used nearly a a hundred years later to link the process of human reason to the operations of machines.

George Boole invented a system for symbolic and logical reasoning, called Boolean Algebra, which became the basic design tool for computer design.

George Boole invented a bramch of mathematic colled Coolean Algebra which has been applied to the development of logic and electrical relays.

1854 AD, Boole invented Boolean algebra.

George Boole invented Boolean logic, which birthed discrete mathematics, which enabled the development of the transistor and ultimately the home computer, so essentially this one man is the reason our country is so fat, detached, sequestered, posh, and lazy and the reason we are all headed for a sublime Hell on Earth not unlike the environment depicted in the video ”Sober” by Tool.

Around the 1850s, the British mathematician George Boole invented a new form of mathematics, in which he represented logical expressions in a mathematical form now known as Boolean Algebra.

Boole invented ”Boolean algebra” (switching theory)

Boole invented the truth table to test the truth and validity of compound propositions.

Boole invented the first practical system of logic in algebraic form

While working here in UCC in 1854, Boole invented Boolean Algebra which has become the cornerstone of modern electronics and information technology.

George Boole invented propositional logic (1847).

In 1854, Boole invented Boolean algebra. George Boole invented the branch of mathematics known as Boolean algebra.

In the 19th century George Boole invented Boolean algebra as a theoretical study.

Later in the year 1850, Charles Boole invented binary codes, which uses only numbers 0 and 1.

In the 1850s, George Boole invented a mathematical system of symbolic logic that would later become the basis for modern computer design.

The English mathematician, George Boole, developed an algebra of logic, which has become the basis for computer database searches.

Boole developed an algebraic calculus to interpret whether composite assertions were true or false

Initially a schoolteacher in Lincolnshire and Yorkshire, England, Boole developed his ideas about symbolic logic without the benefit of a formal university training.

Boole developed ”The Mathematical Analysis of Logic.”

Boole developed the meaning of the logical operators.

By considering assertions to by true or false, Boole developed an algebraic calculus to interpret whether composite assertions were true or false in terms of how they composition was formed.

The first major advance came when George Boole developed an algebra of logic.

The Algebra of Logic was originally developed by Boole

Boolean algebra was developed by Boole.

The modern concept of abstract algebra was developed by Boole In the 1930’s Claude Shannon, an American mathematician who later worked for Bell Labs, noted that the algebra developed by Boole was the appropriate

The idea of a completely formalistic logic, however, was developed by Boole in the 19th century.

an internationally recognized system of logic invented by Boole

Algebra invented by Boole allows easy manipulation of symbols

Probabilistic logic, invented by Boole, is a technique for drawing inferences from uncertain propositions for which there are no independence assumptions.

This page defines 'boolean,' pertaining to the logical operations described in the algebra invented by George Boole

That little bit of computer logic was actually invented by George Boole, a British mathematician and logistician.

Boolean Logic, invented by George Boole, began the process for what are today's computational methods.

Shannon explained how the algebra invented by George Boole in the mid-1800s could be used to . . .

Boolean circuits are certain electric circuits that were invented by George Boole.

So are the bit and bytes that obey complex laws first invented by George Boole a hundred or so years ago.

Search engines use Boolean logic, which is a system of logic invented by George Boole, a nineteenth century mathematician.

Explain how Boole applied his new algebra to logic, and explain (according to Davis) how it was that Boole discovered the importance /validity of using the sets 1 and 0 by proceeding in accord with the Aristotelian "principle of contradiction" Bayes's work.

Boole discovered analogy of algebraic symbols and those of logic.

In 1854 George Boole "discovered pure mathematics "(Bertrand Russell's expression) this equivalence

How to recognise that...

- ... the following are not answers:
  - What Boole discovered in that meadow and worked out on paper two decades later was destined to become the mathematical linchpin that coupled the logical abstractions of software with the physical operations of electronic machines.
  - Lots of Rules and EXECs, developed by Boole SSEs and customers.
- ... the following might be answers, but more work is needed:
  - Boole invented this method back in the 18th century, so that human thought could be strictly analysed and evaluated.
  - It was invented by George Boole, a British mathematician in the 1840's.
  - Leibniz ... invented binary numbers in this case, but he didn't even invent propositional calculus; that was invented by Boole one hundred and fifty years later.
- ... the last sentence cancels our sought-for fact:
  - Many collegues in Algebra and Logic think that Boole developed either Boolean Algebra, or Boolean Rings. He did neither.

Information extraction

We implicitly used information extraction in the QA-“shortcut” solution.

But the string-based approach does not generalise to similar mentions, eg. “Boole was the inventor of”

Components of the task of information extraction:

1. Template Recognition:
   Find predefined relations in unrestricted text, for example inventors/invention patterns
2. Named Entity Recognition:
   Find entities of a certain semantic type in unrestricted text

   HERE: Find names, find dates, in all possible formulations, with robustness to typos and formatting
3. Coreference Resolution:
   Decide which strings refer to the same entities

IE templates

The INVENTOR relation/template has pre-determined slots and relationship between slots

- “To accomplish this, we’ll first learn about the concept of Boolean algebra - a system of logic designed by George Boole.”

  ```
  INVENTOR: George Boole
  INVENTED: Boolean algebra
  ```
- “Peirce developed what amounts to a semantics for three-valued logic.”

  ```
  INVENTOR: Peirce
  INVENTED: a semantics for three-valued logic
  ```
- Information need known beforehand → template
- Domain dependence (only talk about invention events)

Question Answering – deeper approaches

Necessary if:

- information need cannot be expressed with templates a priori
- no simple meaning–surface mapping and/or not enough data.

QA:

- Need to understand something about the question:
  - Grammatical function – who does what to whom?
  - What is the expected answer type?
- Need to understand something about the document:
  - Locate the expected answer type in the text
  - Not all necessary information locally available (e.g. pronouns)
- Need to produce an answer:
  - Answers are phrases, sentences, paragraphs, 50Byte strings
  - “Information packaging”, reversal of non-local effects

Summarisation

- The holy grail of NLP
- Methods working today are either very simple or very complicated
- The simple ones are robust but have many other disadvantages
  - Textual problems for all effects above the sentence-level
  - No guarantee of truth preservation
- The complicated ones are not robust
- Two recent tasks:
  - Multi-document summarisation
  - Incremental-time-line summarisation
- Evaluation is a major problem

- Each sentence is represented by a set of 'importance indicators' (features)
- These are combined in such a way to rank the sentences
- The N highest-ranking sentences are extracted and constitute the summary (here: black sentences)

		Importance indicators			
1	Algebra provides a generalization of arithmetic by using symbols, usually letters, to represent numbers.	0	1	3	1
2	For example, it is obviously true that 2 + 3 = 3 + 2	0	0	2	1
	...				
14	In about 1100, the Persian mathematician Omar Khayyam wrote a treatise on algebra based on Euclid's methods.	0	0	1	0
	...				
26	Boolean algebra is the algebra of sets and of logic.	1	0	1	1
27	It uses symbols to represent logical statements instead of words.	1	0	1	1
28	Boolean algebra was formulated by the English mathematician George Boole in 1847.	1	1	2	1

		Importance indicators			
29	Logic had previously been largely the province of philosophers, but in his book, The Mathematical Analysis of Logic, Boole reduced the whole of classical, Aristotelian logic to a set of algebraic equations.	0	0	0	1
30	Boole's original notation is no longer used, and modern Boolean algebra now uses the symbols of either set theory, or propositional calculus.	0	0	0	1
31	Boolean algebra is an uninterpreted system - it consists of rules for manipulating symbols, but does not specify how the symbols should be interpreted.	0	0	0	1
32	The symbols can be taken to represent sets and their relationships, in which case we obtain a Boolean algebra of sets.	0	1	3	0
33	Alternatively, the symbols can be interpreted in terms of logical propositions, or statements, their connectives, and their truth values.	0	0	0	1
34	This means that Boolean algebra has exactly the same structure as propositional calculus.	0	0	0	1
35	The most important application of Boolean algebra is in digital computing.	1	0	2	1
36	Computer chips are made up of transistors arranged in logic gates.	0	0	0	1
37	Each gate performs a simple logical operation.	0	0	0	1
38	For example, an AND gate produces a high voltage electrical pulse at the output r if and only if a high voltage pulse is received at both inputs p, q.	0	0	0	1
39	The computer processes the logical propositions in its program by processing electrical pulses - in the case of the AND gate, the proposition represented is p q r.	0	0	0	1
40	A high pulse is equivalent to a truth value of "true" or binary digit 1, while a low pulse is equivalent to a truth value of "false", or binary digit 0.	0	0	0	1
41	The design of a particular circuit or microchip is based on a set of logical statements.	0	0	0	1
42	These statements can be translated into the symbols of Boolean algebra.	0	0	0	1
43	The algebraic statements can then be simplified according to the rules of the algebra, and translated into a simpler circuit design.	0	3	1	1
44	An algebraic equation shows the relationship between two or more variables.	0	0	0	1
45	The equation below states that the area (a) of a circle equals p (pi, a constant) multiplied by the radius squared (r 2).	0	0	0	1

Summarisation by re-generation

Doc1
Born in Lincoln, England on November 2, 1815, George Boole was the son of a poor shoemaker. As a child, Boole was educated at a National Society primary school. He received very little formal education, but was determined to become self-educated.

Doc2
George was born in 1815 at 34 Silver Street, which is now occupied by Langleys, the Solicitors. He was the eldest son of John Boole, a shoemaker.

Doc3
Born in the English industrial town of Lincoln, Boole was lucky enough to have a father who passed along his own love of math.

Doc4
Boole was born of humble parents in 1815, the same year as the battle of Waterloo. It is doubtful he received early schooling in mathematics beyond that required for the most basic commerce. Unsatisfied with mathematics texts of the time, he set about reading the great masters, Gauss, Laplace, Leibnitz, and others.

Re-generation after clustering

Cluster 1:
Born in Lincoln, England on November 2, 1815, George Boole was the son of a poor shoemaker.
George was born in 1815 at 34 Silver Street, which is now occupied by Langleys, the Solicitors.

→ S1: “George Boole was born in 1815”.

Cluster 2:
Born in Lincoln, England on November 2, 1815, George Boole was the son of a poor shoemaker.
Born in the English industrial town of Lincoln, Boole was lucky enough to have a father who passed along his own love of math.

→ S1’: “George Boole was born in 1815 in Lincoln, England.”. (Aggregation (information packaging))

Cluster 3:
Boole was born of humble parents in 1815, the same year as the battle of Waterloo.
He was the eldest son of John Boole, a shoemaker.
Born in Lincoln, England on November 2, 1815, George Boole was the son of a poor shoemaker.

→ S2: “He was the son of a shoemaker”.

Cluster 4:
As a child, Boole was educated at a National Society primary school.
He received very little formal education, but was determined to become self-educated.

→ S3: “He received little schooling as a child.”

- Why searching is difficult: mapping from natural language to the underlying search model
- Query constructs: Search terms and how to combine them
- Retrieval models: Finding the best answer document
- Beyond Information Retrieval: Information extraction
  - Type of required information is known beforehand
  - Information need can be expressed by templates
- Question answering: domain-independent
- Summarisation: additional problem of text production

Information Retrieval

Lecture 2: Retrieval models

Computer Science Tripos Part II

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Today

- Indexing
- Query languages and retrieval models
  - Boolean model
  - Vector space model
- Logical model of a document/a term
  - Term weighting
  - Term stemming

Indexing

- Indexing: the task of finding terms that describe documents well
- Manual indexing by cataloguers, using fixed vocabularies (“thesauri”)
  - labour and training intensive
- Automatic indexing
  - Term manipulation (certain words count as the same term)
  - Term weighting (certain terms are more important than others)
  - Index terms can only be those words or phrases that occur in the text

Fixed indexing languages/vocabularies (“thesauri”)

- Large vocabularies (several thousand items)
- Examples: ACM – subfields of CS; Library of Congress Subject Headings
- Problems:
  - High effort in training in order to achieve consistency
  - Subject matters emerge → schemes change constantly
- Advantages:
  - High precision searches
  - Works well for valuable, closed collections like books in a library

Examples, fixed indexing languages

Medical Subject Headings (MeSH)

...	
Eye Diseases	C11
Asthenopia	C11.93
Conjunctival Diseases	C11.187
Conjunctival Neoplasms	C11.187.169
Conjunctivitis	C11.187.183
Conjunctivitis, Allergic	C11.187.183.200
Conjunctivitis, Bacterial	C11.187.183.220
Conjunctivitis, Inclusion	C11.187.183.220.250
Ophthalmia Neonatorum	C11.187.183.220.538
Trachoma	C11.187.183.220.889
Conjunctivitis, Viral	C11.187.183.240
Conjunctivitis, Acute Hemorrhagic	C11.187.183.240.216
Keratoconjunctivitis	C11.187.183.394
Keratoconjunctivitis, Infectious	C11.187.183.394.520
Keratoconjunctivitis Sicca	C11.187.183.394.550
Reiter’s Disease	C11.187.183.749
Pterygium	C11.187.781
Xerophthalmia	C11.187.810
...	

ACM Computing Classification System (1998)

B	Hardware
B.3	Memory structures
B.3.0	General
B.3.1	Semiconductor Memories (NEW) (was B.7.1)
	Dynamic memory (DRAM) (NEW)
	Read-only memory (ROM) (NEW)
	Static memory (SRAM) (NEW)
B.3.2	Design Styles (was D.4.2)
	Associative memories
	Cache memories
	Interleaved memories
	Mass storage (e.g., magnetic, optical, RAID)
	Primary memory
	Sequential-access memory
	Shared memory
	Virtual memory
B.3.3	Performance Analysis and Design Aids
	Formal models
	Simulation
	Worst-case analysis
B.3.4	Reliability, Testing, and Fault-Tolerance
	Diagnostics
	Error-checking
	Redundant design
	Test generation
...	

- No predefined set of index terms
- Instead: use natural language as indexing language
- Mappings words → meanings is not 1:1
  - Synonymy (n words : 1 meaning) sofa – couch
  - Polysemy (1 word : n meanings) bank – bank
- Do the terms get manipulated?
  - De-capitalised? Turkey – turkey
  - Stemmed? advice – advised
  - Stemmed and POS-tagged? can – can
- Use important phrases, instead of single words
  cheque book (rather than cheque and book)

Implementation of indexes: inverted files

Inverted files

Doc 1
Except Russia and Mexico no country had had the decency to come to the rescue of the government.

Doc 2
It was a dark and stormy night in the country manor. The time was past midnight.

Term	Doc no	Freq	Offset
a	2	1	2
and	1	1	2
and	2	1	4
come	1	1	11
country	1	1	5
country	2	1	9
dark	2	1	3
decency	1	1	9
except	1	1	0
government	1	1	17
had	1	2	6,7
in	2	1	7
it	2	1	0
manor	2	1	10
mexico	1	1	3
midnight	2	1	17
night	2	1	6
no	1	1	4
of	1	1	15
past	2	1	15
rescue	1	1	14
russia	1	1	1
stormy	2	1	5
the	1	2	8,13
the	2	2	8,12
time	2	1	14
to	1	2	10,12

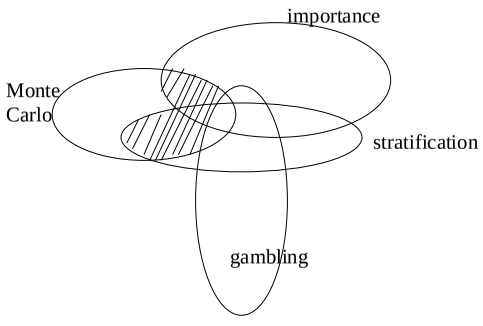
Information kept for each term:

- Document ID where this term occurs
- Frequency of occurrence of this term in each document
- Possibly: Offset of this term in document

- Boolean search
  - Binary decision: Document is relevant or not (no ranking)
  - Presence of term is necessary and sufficient for match
  - Boolean operators are set operations (AND, OR, NOT, BUT)
- Ranked algorithms
  - Ranking takes frequency of terms in document into account
  - Not all search terms necessarily present in document
  - Incarnations:
    - The vector space model (SMART, Salton et al, 1971)
    - The probabilistic model (OKAPI, Robertson/Spärck Jones, 1976)
    - Web search engines

The Boolean model

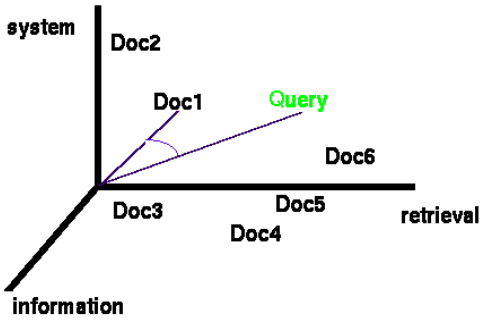

```
Monte Carlo AND (importance OR stratification) BUT gambling
```



- Set theoretic interpretation of connectors AND OR BUT
- Often in use for bibliographic search engines (library)
- Problem 1: Expert knowledge necessary to create high-precision queries
- Problem 2: Binary relevance definition → unranked result lists (frustrating, time consuming)

The Vector Space model

- A document is represented as a point in high-dimensional vector space
- Query is also represented in vector space
- Select document(s) with highest document–query similarity
- Document–query similarity is model for relevance → ranking



3-dimensional term vector space:

- Dimension 1: “information”
- Dimension 2: “retrieval”
- Dimension 3: “system”

Documents and queries in term feature space

	Doc_1	Doc_2	Doc_3	...	Doc_n		Q
term_1	14	6	1	...	0	↔	0
term_2	0	1	3	...	1	↔	1
term_3	0	1	0	...	2	↔	0
	...	...	...	...	...	↔	...
term_N	4	7	0	...	5	↔	1

Decisions to take:

1. Choose dimensionality of vector: what counts as a term?
2. Choose weights for each term/document mapping (cell)
   - presence or absence (binary)
   - term frequency in document
   - more complicated weight, eg. TF*IDF (cf. later in lecture)
3. Choose a proximity measure

Proximity measures

A proximity measure can be defined either by similarity or dissimilarity. Proximity measures are

- Symmetric ($\forall i, j : d(j, i) = d(i, j)$)
- Maximal/minimal for identity:
  - For similarity measures: $\forall i : d(i, i) = max_k d(i, k)$
  - For dissimilarity measures: $\forall i : d(i, i) = 0$
- A distance metric is a dissimilarity metric that satisfies the triangle inequality
$$\forall i, j, k : d(i, j) + d(i, k) \geq d(j, k)$$
- Distance metrics are non-negative: $\forall i, k : d(i, k) \geq 0$

Similarity measures, binary

X is the set of all terms occurring in document D_X, Y is the set of all terms occurring in document D_Y.

- Raw Overlap: $raw\_overlap(X, Y) = |X \cap Y|$
- Dice's coefficient: (normalisation by average size of the two original vectors)
$$dice(X, Y) = \frac{2|X \cap Y|}{|X| + |Y|}$$
- Jaccard's coefficient: (normalisation by size of combined vector – penalises small number of shared feature values)
$$jacc(X, Y) = \frac{|X \cap Y|}{|X \cup Y|}$$
- Overlap coefficient:
$$overlap\_coeff(X, Y) = \frac{|X \cap Y|}{min(|X|, |Y|)}$$
- Cosine: (normalisation by vector lengths)
$$cosine(X, Y) = \frac{|X \cap Y|}{\sqrt{|X|} \cdot \sqrt{|Y|}}$$

Similarity measures, weighted

Weighted versions of Dice's and Jaccard's coefficient exist, but are used rarely for IR:

- Vectors are extremely sparse
- Vectors are of very differing length

Cosine (or normalised inner product) is the measure of choice for IR

Document i is represented as a vectors of terms or lemmas ($\vec{w_i}$); t is the total number of index terms in system, $w_{i,j}$ is the weight associated with j th term of vector $\vec{w_i}$.

Vector length normalisation by the two vectors $|\vec{w_i}|$ and $|\vec{w_k}|$:

$$cos(\vec{w_i}, \vec{w_k}) = \frac{\vec{w_i}\vec{w_k}}{|\vec{w_i}| \cdot |\vec{w_k}|} = \frac{\Sigma_{j=1}^{d} w_{i,j} \cdot w_{k,j}}{\sqrt{\Sigma_{j=1}^{d} w_{i,j}^2} \cdot \sqrt{\Sigma_{j=1}^{d} w_{k,j}^2}}$$

Distance measures

- Euclidean distance: (how far apart in vector space)

$$euc(\vec{w_i}, \vec{w_k}) = \sqrt{\sum_{j=1}^{d} (w_{i,j} - w_{k,j})^2}$$

- Manhattan distance: (how far apart, measured in 'city blocks')

$$manh(\vec{w_i}, \vec{w_k}) = \sum_{j=1}^{d} |w_{i,j} - w_{k,j}|$$

Most frequent words in a large language sample, with frequencies:

Rank	English		German		Spanish		Italian		Dutch	
1	the	61,847	der	7,377,879	que	32,894	non	25,757	de	4,770
2	of	29,391	die	7,036,092	de	32,116	di	22,868	en	2,709
3	and	26,817	und	4,813,169	no	29,897	che	22,738	het / 't	2,469
4	a	21,626	in	3,768,565	a	22,313	è	18,624	van	2,259
5	in	18,214	den	2,717,150	la	21,127	e	17,600	ik	1,999
6	to	16,284	von	2,250,642	el	18,112	la	16,404	te	1,935
7	it	10,875	zu	1,992,268	es	16,620	il	14,765	dat	1,875
8	is	9,982	das	1,983,589	y	15,743	un	14,460	die	1,807
9	to	9,343	mit	1,878,243	en	15,303	a	13,915	in	1,639
10	was	9,236	sich	1,680,106	lo	14,010	per	10,501	een	1,637

Zipf's Law: The frequency rank of a word is reciprocally proportional to its frequency:

$$freq(word_i) = \frac{1}{i^\theta} freq(word_1)$$

($word_i$ is the ith most frequent word of the language); $1.5 < \theta < 2$ for most languages)

Zipf's law: Rank $\times$ Frequency $\sim$ Constant

English:			
Rank R	Word	Frequency f	$R \times f$
10	he	877	8770
20	but	410	8200
30	be	294	8820
800	friends	10	8000
1000	family	8	8000

German:			
Rank R	Word	Frequency f	$R \times f$
10	sich	1,680,106	16,801,060
100	immer	197,502	19,750,200
500	Mio	36,116	18,059,500
1,000	Medien	19,041	19,041,000
5,000	Miete	3,755	19,041,000
10,000	vorläufige	1.664	16,640,000

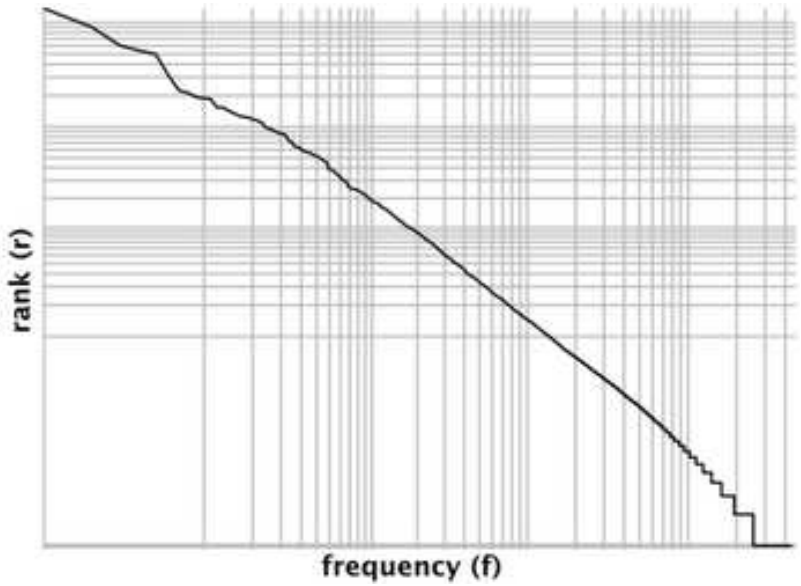
Text Coverage (tokens) with N most frequent items (types) 49

	German	English
1	3%	5%
10	40%	42%
100	60%	65%
1000	79%	90%
10000	92%	99%
100000	98%	

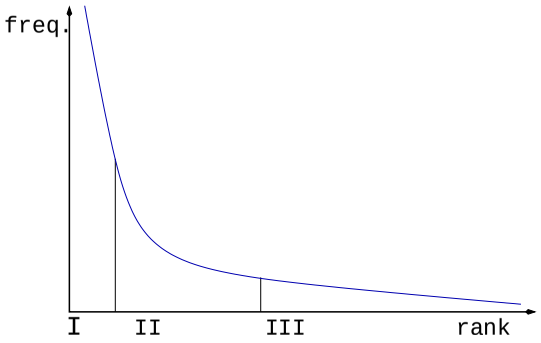
Other collections (allegedly) obeying Zipf's law 50

- Sizes of settlements
- Frequency of access to web pages
- Income distributions amongst top earning 3% individuals
- Korean family names
- Size of earth quakes
- Word senses per word
- Notes in musical performances
- . . .

Plotting a Zipfian distribution on a log-scale



Zipf's law and term importance



- Zone I: High frequency words tend to be function words. Top 135 vocabulary items account for 50% of words in the Brown corpus. These are not important for IR.
- Zone II: Mid-frequency words are the best indicators of what the document is about
- Zone III: Low frequency words tend to be typos or overly specific words (not important, for a different reason) ("Uni7ed", "super-noninteresting", "87-year-old", "0.07685")

Term Weighting: TF*IDF

Not all terms describe a document equally well:

- Terms which are frequent in a document are better $\rightarrow$ $tf_{w,d} = freq_{w,d}$ should be high
- Terms that are overall rare in the document collection are better
  $\rightarrow$ $idf_{w,D} = log\frac{|D|}{n_{w,D}}$ should be high
  $\rightarrow$
- TF*IDF formula: $tf * idf_{w,d,D} = tf_{w,d} \cdot idf_{w,D}$ should be high
- Improvement: Normalise $tf_{w,d}$ by term frequency of most frequent term in document: $tf_{norm,w,d} = \frac{freq_{w,d}}{max_{l \in d} freq_{l,d}}$
  - Normalised TF*IDF:
    $tf * idf_{norm,w,d,D} = tf_{norm,w,d} \cdot idf_{w,D}$

$tf_{w,d}$:	Term frequency of word w in document d
$n_{w,D}$:	Number of documents in document collection D which contain word w
$idf_{w,D}$:	Inverse document frequency of word w in document collection D
$tf * idf_{w,d,D}$:	TF*IDF weight of word w in document d in document collection D
$tf * idf_{norm,w,d,D}$:	Length-normalised TF*IDF weight of word w in document d in document collection D
$tf_{norm,w,d}$:	Normalised term frequency of word w in document d
$max_{l \in d} freq_{l,d}$:	Maximum term frequency of any word in document d

Example: TF*IDF

Document set: 30,000

Term	tf	$n_{w,D}$	TF*IDF
the	312	28,799	5.55
in	179	26,452	9.78
general	136	179	302.50
fact	131	231	276.87
explosives	63	98	156.61
nations	45	142	104.62
1	44	2,435	47.99
haven	37	227	78.48
2-year-old	1	4	3.88

IDF(“the”) = log ($\frac{30{,}000}{28{,}799}$) = 0.0178
TF*IDF(“the”) = 312 $\cdot$ 0.0178 = 5.55

Example: VSM (TF*IDF; cosine)

Query: `hunter gatherer Scandinavia`

	Q	D_{7655}	D_{454}
hunter	19.2	56.4	112.2
gatherer	34.5	122.4	0
Scandinavia	13.9	0	30.9
30,000	0	457.2	0
years	0	12.4	0
BC	0	200.2	0
prehistoric	0	45.3	0
deer	0	0	23.6
rifle	0	0	452.2
Mesolithic	0	344.2	0
barber	0	0	25.2
household	0	204.7	0
...	...	...	...

(Normally there would be many more terms in D_{7655} and D_{454})

$\cos(Q, D_{7655}) = \frac{19.2 \cdot 56.4 + 34.5 \cdot 122.4 + 13.9 \cdot 0}{\sqrt{19.2^2 + 34.5^2 + 13.9^2} \cdot \sqrt{56.4^2 + 122.4^2 + 457.2^2 + 12.4^2 + 200.2^2 + 45.3^2 + 344.2^2 + 204.7^2 + \ldots}} = .1933303426$

$\cos(Q, D_{454}) = \frac{19.2 \cdot 112.2 + 34.5 \cdot 0 + 13.9 \cdot 30.9}{\sqrt{19.2^2 + 34.5^2 + 13.9^2} \cdot \sqrt{112.2^2 + 30.9^2 + 23.6^2 + 452.2^2 + 25.2^2 + \ldots}} = .1318349238$

→ choose document D_{7655}

Self test VSM/ TF*IDF

- Build a document-term matrix for three (very!) short documents of your choice
- Weight by presence/absence (binary) and by TF*IDF (with estimated IDFs)
- Write a suitable query
- Calculate document–query similarity, using
  - cosine
  - inner product (i.e. cosine without normalisation)
- What effect does normalisation have?

Term Manipulation

- So far: each term is indexed and weighted only in string-equal form
- This misses many semantic similarities between morphologically related words ("whale" → "whaling", "whales")
- Automatic models of term identity
  - The same string between blanks or punctuation
  - The same prefix (eg. up to 6 characters)
  - The same stem (e.g. Porter stemmer)
  - The same linguistic lemma (sensitive to Parts-of-speech)
- Effect of term manipulation on retrieval result
  - changes the counts, reduces total number of terms
  - increases recall
  - might decrease precision, introduction of noise

Stemming: the Porter stemmer

M. Porter, "An algorithm for suffix stripping", Program 14(3):130-137, 1980

CONNECT
CONNECTED
CONNECTING
CONNECTION
CONNECTIONS

- Removal of suffixes without a stem dictionary, only with a suffix dictionary
- Terms with a common stem have similar meanings:
- Deals with inflectional and derivational morphology
- Conflates relate — relativity — relationship
- Sees no difference between sand — sander and wand — wander (does not conflate either)
- Root changes (deceive/deception, resume/resumption) aren't dealt with, but these are rare

Stemming: Representation of a word

[C] (VC){m}[V]

C	one or more adjacent consonants
V	one or more adjacent vowels
[ ]	optionality
( )	group operator
{x}	repetition x times
m	the "measure" of a word

shoe	$[sh]_C[oe]_V$	m=0
Mississippi	$[M]_C([i]_V[ss]_C)([i]_V[ss]_C)([i]_V[pp]_C)[i]_V$	m=3
ears	$([ea]_V[rs]_C)$	m=1

Notation: m is calculated on the word excluding the suffix of the rule under consideration (eg. In m=1 for 'element' in rule "(m $>$ 1) EMENT", so this rule would not trigger.)

Porter stemmer: rules and conditions

Rules in one block are run through in top-to-bottom order; when a condition is met, execute rule and jump to next block

Rules express criteria under which suffix may be removed from a word to leave a valid stem: (condition) S1 $\rightarrow$ S2

Possible conditions:

- constraining the measure:

  (m $>$ 1) EMENT $\rightarrow \epsilon$ (ϵ is the empty string)

  REPLACEMENT $\rightarrow$ REPLAC
- constraining the shape of the word piece:
  - *S – the stem ends with S
  - *v* – the stem contains a vowel
  - *d – the stem ends with a double consonant (e.g. -TT, -SS).
  - *o – the stem ends cvc, where the second c is not W, X or Y (e.g. -WIL, -HOP)
- expressions with AND, OR and NOT:
  - (m$>$1 AND (*S OR *T)) – a stem with m>1 ending in S or T

Porter stemmer: selected rules

SSES → SS
IES → I
SS → SS
S →
caresses → caress
cares → care

(m>0) EED → EE
feed → feed
agreed → agree
BUT: freed, succeed

(*v*) ED →
plastered → plaster
bled → bled

Porter stemmer: the algorithm

Step 1: plurals and past participles

Step 1a

SSES	→ SS	caresses	→ caress
IES	→ I	ponies	→ poni
		ties	→ ti
SS	→ SS	caress	→ caress
S	→ ϵ	cats	→ cat

Step 1b

(m>0)	EED	→ EE	feed	→ feed
			agreed	→ agree
(*v*)	ED	→ ϵ	plastered	→ plaster
			bled	→ bled
(*v*)	ING	→ ϵ	motoring	→ motor
			sing	→ sing

If rule 2 or 3 in Step 1b applied, then clean up:

AT	→ ATE	conflat(ed/ing)	→ conflate
BL	→ BLE	troubl(ed/ing)	→ trouble
IZ	→ IZE	siz(ed/ing)	→ size
(*d and not (*L or *S or *Z))	→ single letter	hopp(ed/ing)	→ hop
		hiss(ed/ing)	→ hiss
(m=1 and *o)	→ E	fil(ed/ing)	→file
		fail(ed/ing)	→ fail

Step 1c

(*v*)	Y	→ I	happy	→ happi
			sky	→ sky

Step 2: derivational morphology

(m>0)	ATIONAL	→ ATE	relational	→ relate
(m>0)	TIONAL	→ TION	conditional	→ condition
			rational	→ rational
(m>0)	ENCI	→ ENCE	valenci	→ valence
(m>0)	ANCI	→ ANCE	hesitanci	→ hesitance
(m>0)	IZER	→ IZE	digitizer	→ digitize
(m>0)	ABLI	→ ABLE	conformabli	→ conformable
(m>0)	ALLI	→ AL	radicalli	→ radical
(m>0)	ENTLI	→ ENT	differentli	→ different
(m>0)	ELI	→ E	vileli	→ vile
(m>0)	OUSLI	→ OUS	analogousli	→ analogous
(m>0)	IZATION	→ ISE	vietnamization	→ vietnamize
(m>0)	ISATION	→ ISE	vietnamization	→ vietnamize
(m>0)	ATION	→ ATE	predication	→ predicate
(m>0)	ATOR	→ ATE	operator	→ operate
(m>0)	ALISM	→ AL	feudalism	→ feudal
(m>0)	IVENESS	→ IVE	decisiveness	→ decisive
(m>0)	FULNESS	→ FUL	hopefulness	→ hopeful
(m>0)	OUSNESS	→ OUS	callousness	→ callous
(m>0)	ALITI	→ AL	formaliti	→ formal
(m>0)	IVITI	→ IVE	sensitiviti	→ sensitive
(m>0)	BILITI	→ BLE	sensibiliti	→ sensible

Step 3: more derivational morphology

(m>0)	ICATE →	IC	triplicate	→ triplic
(m>0)	ATIVE →	ϵ	formative	→ form
(m>0)	ALIZE →	AL	formalize	→ formal
(m>0)	ALISE →	AL	formalise	→ formal
(m>0)	ICITI →	IC	electriciti	→ electric
(m>0)	ICAL →	IC	electrical	→ electric
(m>0)	FUL →	ϵ	hopeful	→ hope
(m>0)	NESS →	ϵ	goodness	→ good

Step 4: even more derivational morphology

(m>1)	AL →	ϵ	revival	→ reviv
(m>1)	ANCE →	ϵ	allowance	→ allow
(m>1)	ENCE →	ϵ	inference	→ infer
(m>1)	ER →	ϵ	airliner	→ airlin
(m>1)	IC →	ϵ	gyroscopic	→ gyroscop
(m>1)	ABLE →	ϵ	adjustable	→ adjust
(m>1)	IBLE →	ϵ	defensible	→ defens
(m>1)	ANT →	ϵ	irritant	→ irrit
(m>1)	EMENT →	ϵ	replacement	→ replac
(m>1)	MENT →	ϵ	adjustment	→ adjust
(m>1)	ENT →	ϵ	dependent	→ depend
(m>1 and (*S or *T))	ION →	ϵ	adoption	→ adopt
(m>1)	OU →	ϵ	homologou	→ homolog
(m>1)	ISM →	ϵ	communism	→ commun
(m>1)	ATE →	ϵ	activate	→ activ
(m>1)	ITI →	ϵ	angulariti	→ angular
(m>1)	OUS →	ϵ	homologous	→ homolog
(m>1)	IVE →	ϵ	effective	→ effect
(m>1)	ISE →	ϵ	bowdlerize	→ bowdler
(m>1)	IZE →	ϵ	bowdlerize	→ bowdler

Step 5: cleaning up

Step 5a

(m>1)	E → ϵ	probate	→ probat
		rate	→ rate
(m=1 and not *o)	E → ϵ	cease	→ ceas

Step 5b

(m > 1 and *d and *L)	→ single letter	controll	→ control
		roll	→ roll

Self test Porter Stemmer

1. Show which stems *rationalisations, rational, rationalizing* result in, and which rules they use.
2. Explain why *sander* and *sand* do not get conflated.
3. What would you have to change if you wanted to conflate them?
4. Find five different examples of incorrect stemmings.
5. Can you find a word that gets reduced in every single step (of the 5)?
6. Exemplify the effect that stemming (eg. with Porter) has on the Vector Space Model, using your example from before.

- Indexing languages
- Retrieval models
- Term weighting
- Term stemming

Textbook (Baeza-Yates and Ribeiro-Neto):

- 2.5.2 Boolean model
- 6.3.3 Zipf's law
- 2.5.3 Vector space model, TF*IDF
- 7.2 Term manipulation, stemming

Information Retrieval

Lecture 3: Evaluation methodology

Computer Science Tripos Part II

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Today

1. General concepts in IR evaluation
2. The TREC competitions
3. IR evaluation metrics

Evaluation: difficulties

- IR system
  - in: a query
  - out: relevant documents
- Evaluation of IR systems
- Goal: predict future from past experience
- Reasons why IR evaluation is hard:
  - Large variation in human information needs and queries
  - The precise contributions of each component are hard to entangle:
    - Collection coverage
    - Document indexing
    - Query formulation
    - Matching algorithm

Evaluation: “the laboratory model” 71

- Test only “system parameters”
  - Index language devices for description and search
  - Methods of term choice for documents
  - Matching algorithm
  - Type of user interface
- Ignore environment variables
  - Properties of documents → use many documents
  - Properties of users → use many queries

What counts as acceptable test data? 72

- In 60s and 70s, very small test collections, arbitrarily different, one per project
  - in 60s: 35 queries on 82 documents
  - in 1990: still only 35 queries on 2000 documents
- not always kept test and training apart as so many environment factors were tested
- TREC-3: 742,000 documents; TREC Web-track: small snapshot of the web
- Large test collections are needed
  - to capture user variation
  - to support claims of statistical significance in results
  - to demonstrate that systems scale up → commercial credibility
- Practical difficulties in obtaining data; non-balanced nature of the collection

Today's test collections

A test collection consists of:

- Document set:
  - Large, in order to reflect diversity of subject matter, literary style, noise such as spelling errors
- Queries/Topics
  - short description of information need
  - TREC "topics": longer description detailing relevance criteria
  - "frozen" $\rightarrow$ reusable
- Relevance judgements
  - binary
  - done by same person who created the query

TREC

- Text REtrieval Conference
- Run by NIST (US National Institute of Standards and Technology)
- Marks a new phase in retrieval evaluation
  - common task and data set
  - many participants
  - continuity
- Large test collection: text, queries, relevance judgements
  - Queries devised and judged by information specialist (same person)
  - Relevance judgements done only for up to 1000 documents/query
- 2003 was 12th year
- 87 commercial and research groups participated in 2002

Sample TREC query

<num> Number: 508
<title> hair loss is a symptom of what diseases

<desc> Description:
Find diseases for which hair loss is a symptom.

<narr> Narrative:
A document is relevant if it positively connects the loss of head hair in humans with a specific disease. In this context, ”thinning hair” and ”hair loss” are synonymous. Loss of body and/or facial hair is irrelevant, as is hair loss caused by drug therapy.

TREC Relevance Judgements

Humans decide which document–query pairs are relevant.

Evaluation metrics

	Relevant	Non-relevant	Total
Retrieved	A	B	A+B
Not retrieved	C	D	C+D
Total	A+C	B+D	A+B+C+D

Recall: proportion of retrieved items amongst the relevant items ($\frac{A}{A+C}$)

Precision: proportion of relevant items amongst retrieved items ($\frac{A}{A+B}$)

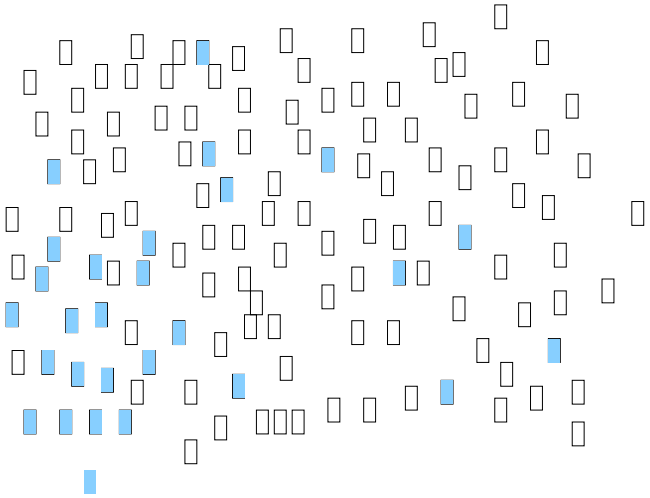
Accuracy: proportion of correctly classified items as relevant/irrelevant ($\frac{A+D}{A+B+C+D}$)

Recall: [0..1]; Precision: [0..1]; Accuracy: [0..1]

Accuracy is not a good measure for IR, as it conflates performance on relevant items (A) with performance on irrelevant (uninteresting) items (D)

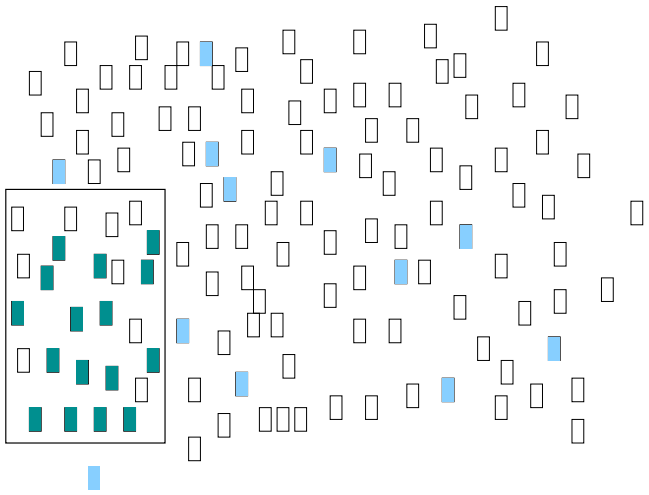
Recall and Precision

- All documents: A+B+C+D = 130
- Relevant documents for a given query: A+C = 28



Recall and Precision: System 1

- System 1 retrieves 25 items: $(A+B)_1 = 25$
- Relevant and retrieved items: $A_1 = 16$



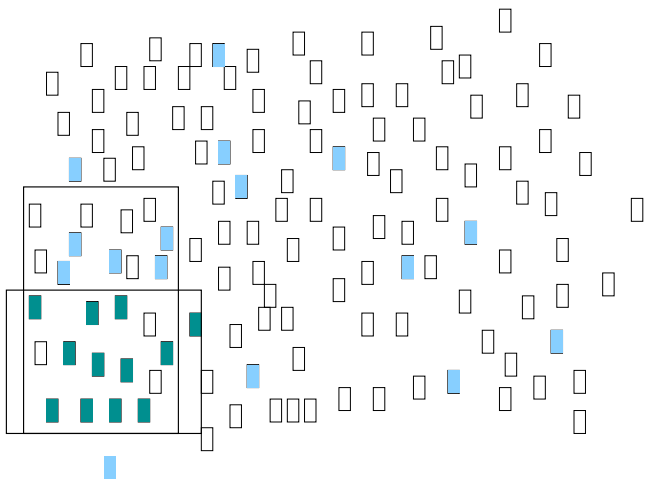
$$R_1 = \frac{A_1}{A+C} = \frac{16}{28} = .57$$

$$P_1 = \frac{A_1}{(A+B)_1} = \frac{16}{25} = .64$$

$$A_1 = \frac{A_1+D_1}{A+B+C+D} = \frac{16+93}{130} = .84$$

Recall and Precision: System 2

- System B retrieves set $(A+B)_2 = 15$ items
- $A_2 = 12$

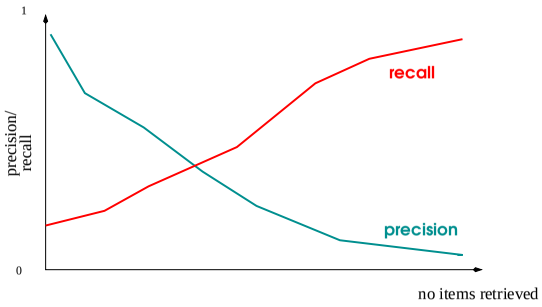


$$R_2 = \frac{12}{28} = .43$$

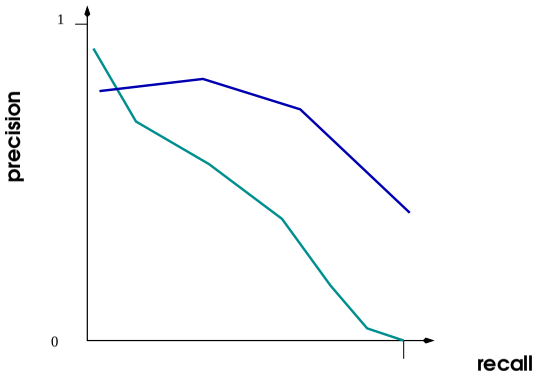
$$P_2 = \frac{12}{15} = .8$$

$$A_2 = \frac{12+99}{130} = .85$$

Recall-precision curve



- Plotting precision and recall (versus no. of documents retrieved) shows inverse relationship between precison and recall
- Precision/recall cross-over can be used as combined evaluation measure



- Plotting precision versus recall gives recall-precision curve
- Area under normalised recall-precision curve can be used as evaluation measure

Recall-criticality and precision-criticality

- Inverse relationship between precision and recall forces general systems to go for compromise between them
- But some tasks particularly need good precision whereas others need good recall:

Precision-critical task	Recall-critical task
Little time available	Time matters less
A small set of relevant documents answers the information need	One cannot afford to miss a single document
Potentially many documents might fill the information need (redundantly)	Need to see *each* relevant document
Example: web search for factual information	Example: patent search

Relevance Judgements and Subjectivity

- Relevance is subjective → Judgements differ across judges
- Relevance is situational → Judgements also differ across time (same judge!)
- Problem: Systems are not comparable if metrics compiled from different judges or at different times will differ
- Countermeasure, Part A: Use guidelines
  - Relevance defined independently of novelty
  - Then, relevance decisions are independent of each other
- Countermeasure, Part B: counteract natural variation by extensive sampling; large populations of users and information needs
- Then: Relative success measurements on systems stable across judges (but not necessarily absolute ones) (Voorhees, 2000)
- Okay if all you want to do is compare systems

The problem of determining recall

- Recall problem: for a collection of non-trivial size, it becomes impossible to inspect each document
- It would take 6500 hours to judge 800,000 documents for one query (30 sec/document)
- Pooling addresses this problem

Pooling

Pooling (Sparck Jones and van Rijsbergen, 1975)

- Pool is constructed by putting together top N retrieval results from a set of n systems (TREC: N = 100)
- Humans judge every document in this pool
- Documents outside the pool are automatically considered to be irrelevant
- There is overlap in returned documents: pool is smaller than theoretical maximum of $N \cdot n$ systems (around $\frac{1}{3}$ the maximum size)
- Pooling works best if the approaches used are very different
- Large increase in pool quality by manual runs which are recall-oriented, in order to supplement pools

F-measure

- Weighted harmonic mean of P and R (Rijsbergen 1979)

$$F_\alpha = \frac{PR}{(1-\alpha)P + \alpha R}$$

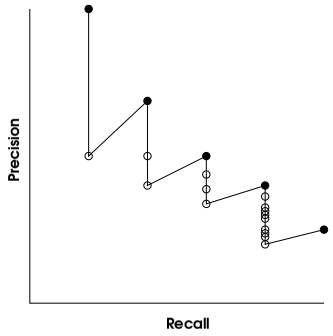
  - High α: Precision is more important
  - Low α: Recall is more important
- Most commonly used with α=0.5 $\rightarrow$

$$F_{0.5} = \frac{2PR}{P+R}$$

- Maximum value of $F_{0.5}$-measure (or F-measure for short) is a good indication of best P/R compromise
- F-measure is an approximation of cross-over point of precision and recall

Precision and recall in ranked IR engines

- With ranked list of return documents there are many P/R data points
- Sensible P/R data points are those after each new relevant document has been seen (black points)



Query 1			
Rank	Relev.	R	P
1	X	0.20	1.00
2		"	0.50
3	X	0.40	0.67
4		"	0.50
5		"	0.40
6	X	0.60	0.50
7		"	0.43
8		"	0.38
9		"	0.33
10	X	0.80	0.40
11		"	0.36
12		"	0.33
13		"	0.31
14		"	0.29
15		"	0.27
16		"	0.25
17		"	0.24
18		"	0.22
19		"	0.21
20	X	1.00	0.25

Summary IR measures

- Precision at a certain rank: P(100)
- Precision at a certain recall value: P(R=.2)
- Precision at last relevant document: P(last_relev)
- Recall at a fixed rank: R(100)
- Recall at a certain precison value: R(P=.1)

Summary IR measures over several queries

- Want to average over queries
- Problem: queries have differing number of relevant documents
- Cannot use one single cut-off level for all queries
  - This would not allow systems to achieve the theoretically possible maximal values in all conditions
  - Example: if a query has 10 relevant documents
    - If cutoff $>$ 10, $P < 1$ for all systems
    - If cutoff $<$ 10, $R < 1$ for all systems
- Therefore, more complicated joint measures are required

Mean Average Precision (MAP)

- Also called “average precision at seen relevant documents”
- Determine precision at each point when a new relevant document gets retrieved
- Use P=0 for each relevant document that was not retrieved
- Determine average for each query, then average over queries

$$MAP = \frac{1}{N} \sum_{j=1}^{N} \frac{1}{Q_j} \sum_{i=1}^{Q_j} P(doc_i)$$

with:

Q_j	number of relevant documents for query j
N	number of queries
$P(doc_i)$	precision at ith relevant document

Mean Average Precision: example

Query 1		
Rank	Relev.	$P(doc_i)$
1	X	1.00
2		
3	X	0.67
4		
5		
6	X	0.50
7		
8		
9		
10	X	0.40
11		
12		
13		
14		
15		
16		
17		
18		
19		
20	X	0.25
AVG:		0.564

Query 2		
Rank	Relev.	$P(doc_i)$
1	X	1.00
2		
3	X	0.67
4		
5		
6		
7		
8		
9		
10		
11		
12		
13		
14		
15	X	0.2
AVG:		0.623

- MAP favours systems which return relevant documents fast
- Precision-biased

$$MAP = \frac{0.564+0.623}{2} = 0.594$$

11 point average precision

$$P_{11\_pt} = \frac{1}{11} \sum_{j=0}^{10} \frac{1}{N} \sum_{i=1}^{N} \tilde{P}_i(r_j)$$

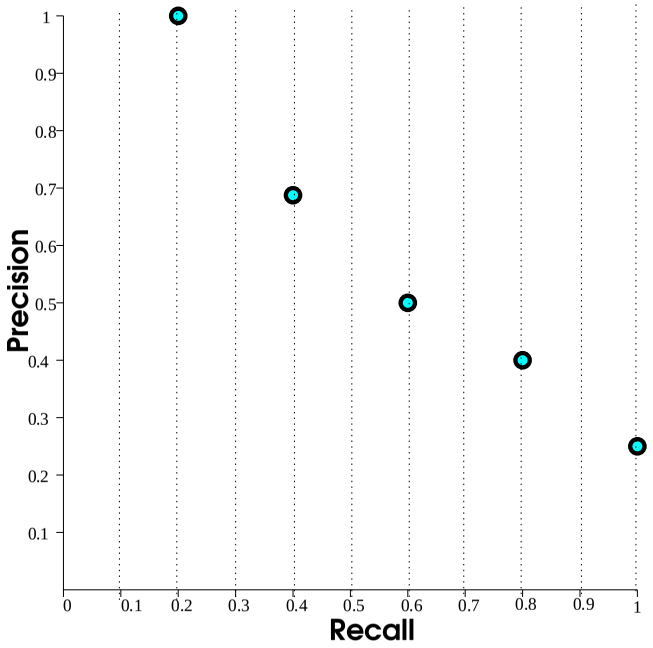
with $\tilde{P}_i(r_j)$ the precision at the jth recall point in the ith query (out of N queries)

- Define 11 standard recall points $r_j = \frac{j}{10}$: $r_0 = 0$, $r_1 = 0.1$ ... $r_{10} = 1$
- We need $\tilde{P}_i(r_j)$; i.e. the precision at our recall points
- $P_i(R = r)$ can be measured: the precision at each point when recall changes (because a new relevant document is retrieved)
- Problem: unless the number of relevant documents per query is divisible by 10, $\tilde{P}_i(r_j)$ does not coincide with a measurable data point r
- Solution: interpolation

$$\tilde{P}_i(r_j) = \begin{cases} max(r_j \leq r < r_{j+1}) P_i(R = r) & \text{if } P_i(R = r) \text{ exists} \\ \tilde{P}_i(r_{j+1}) & \text{otherwise} \end{cases}$$

- Note that $P(R = 1)$ can always be measured

11 point average precision: measured data points, Q1

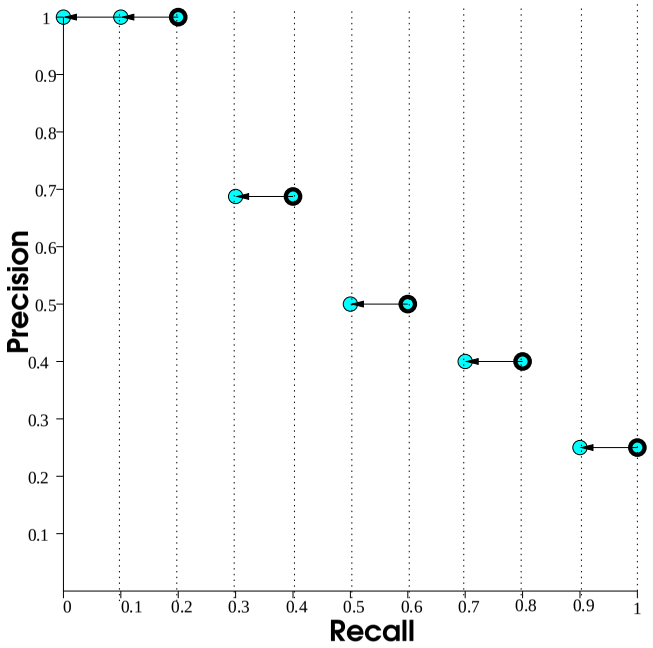


- Blue for Query 1
- Bold Circles measured

Query 1				
Rank	Relev.	R	P	
1	X	0.2	1.00	$\tilde{P}_1(r_2)$ = 1.00
2				
3	X	0.4	0.67	$\tilde{P}_1(r_4)$ = 0.67
4				
5				
6	X	0.6	0.50	$\tilde{P}_1(r_6)$ = 0.50
7				
8				
9				
10	X	0.8	0.40	$\tilde{P}_1(r_8)$= 0.40
11				
12				
13				
14				
15				
16				
17				
18				
19				
20	X	1.0	0.25	$\tilde{P}_1(r_{10})$ = 0.25

- Five r_js $(r_2, r_4, r_6, r_8, r_{10})$ coincide directly with datapoint

11 point average precision: interpolation, Q1



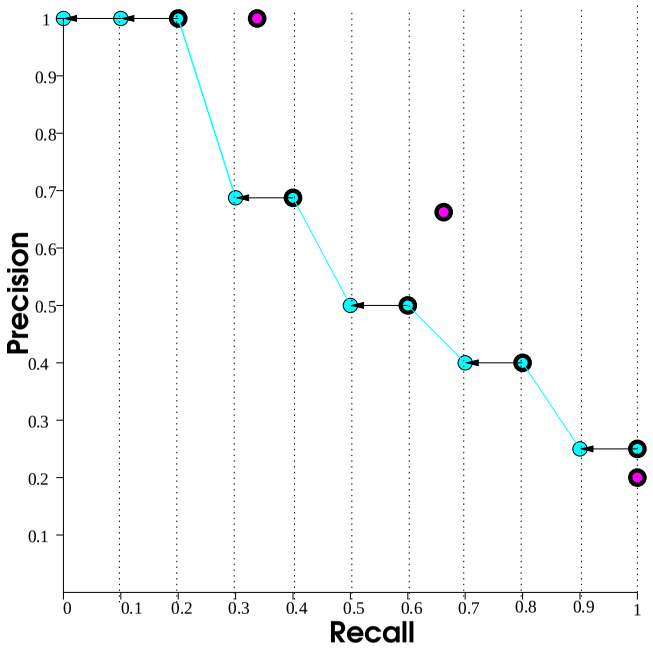
- **Blue: Query 1**
- Bold circles measured: **thin circles interpol**

Query 1				
Rank	Relev	R	P	
1	X	0.20	1.00	$\tilde{P}_1(r_2)$ = 1.00
2				
3	X	0.40	0.67	$\tilde{P}_1(r_4)$ = 0.67
4				
5				
6	X	0.60	0.50	$\tilde{P}_1(r_6)$ = 0.50
7				
8				
9				
10	X	0.80	0.40	$\tilde{P}_1(r_8)$= 0.40
11				
12				
13				
14				
15				
16				
17				
18				
19				
20	X	1.00	0.25	$\tilde{P}_1(r_{10})$ = 0.25

$\tilde{P}_1(r_0)$ = 1.00
$\tilde{P}_1(r_1)$ = 1.00
$\tilde{P}_1(r_3)$ = 0.67
$\tilde{P}_1(r_5)$ = 0.50
$\tilde{P}_1(r_7)$ = 0.40
$\tilde{P}_1(r_9)$ = 0.25

- The six other r_js (r_0, r_1, r_3, r_5, r_7, r_9) are interpolated.

11 point average precision: measured data points, Q2

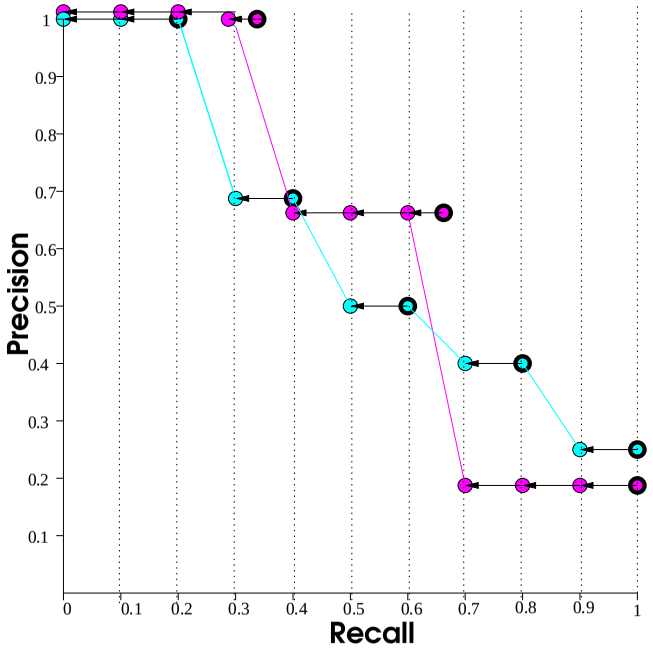


- Blue: Query 1; **Red: Query 2**
- **Bold circles measured**; thin circles interpol.

Query 2				
Rank	Relev.	R	P	
1	X	0.33	1.00	
2				
3	X	0.67	0.67	
4				
5				
6				
7				
8				
9				
10				
11				
12				
13				
14				
15	X	1.0	0.2	$\tilde{P}_2(r_{10})$ = 0.20

- Only r_{10} coincides with a measured data point

11 point average precision: interpolation, Q2



- Blue: Query 1; **Red: Query 2**
- Bold circles measured; **thin circles interpol.**

$\tilde{P}_2(r_0)$ = 1.00
$\tilde{P}_2(r_1)$ = 1.00
$\tilde{P}_2(r_2)$ = 1.00
$\tilde{P}_2(r_3)$ = 1.00

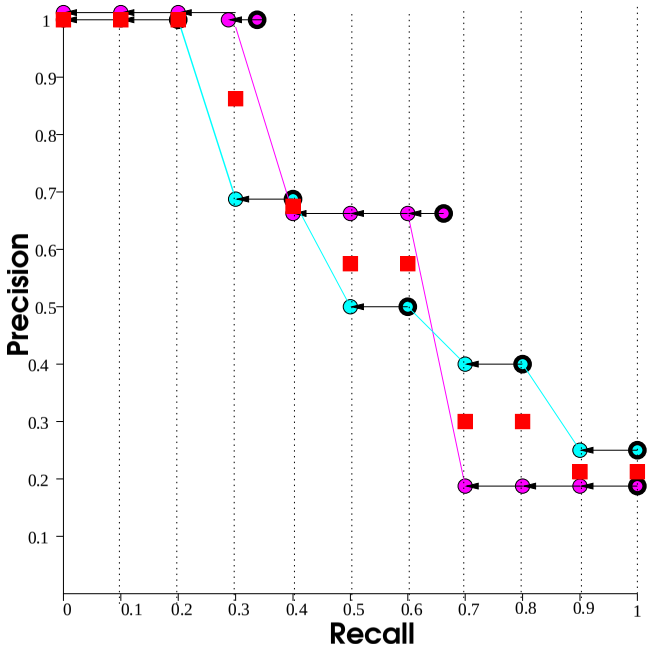
$\tilde{P}_2(r_4)$ = 0.67
$\tilde{P}_2(r_5)$ = 0.67
$\tilde{P}_2(r_6)$ = 0.67

$\tilde{P}_2(r_7)$ = 0.20
$\tilde{P}_2(r_8)$ = 0.20
$\tilde{P}_2(r_9)$ = 0.20

Query 2				
Rank	Relev.	R	P	
1	X	0.33	1.00	
2				
3	X	0.67	0.67	
4				
5				
6				
7				
8				
9				
10				
11				
12				
13				
14				
15	X	1.0	0.2	$\tilde{P}_2(r_{10})$ = 0.20

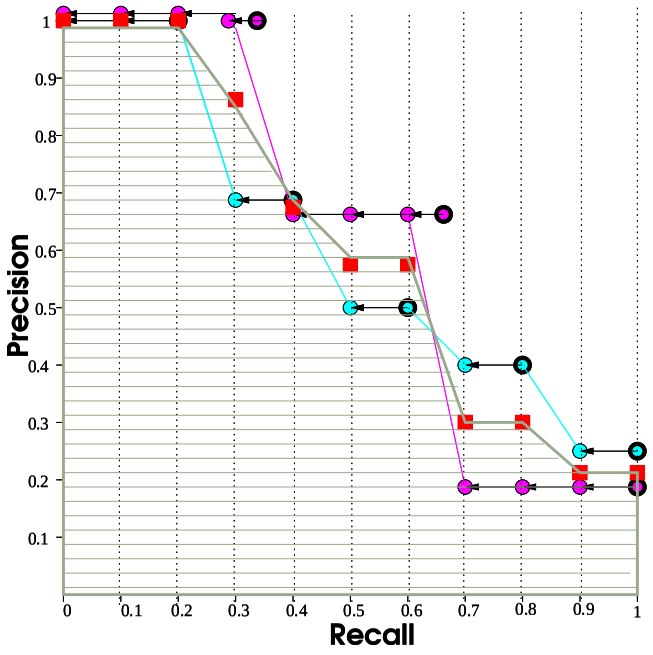
- 10 of the r_js are interpolated

11 point average precision: averaging



- Now average at each p_j
- over N (number of queries)
- $\rightarrow$ 11 averages

11 point average precision: area/result



- End result:
- 11 point average precision
- Approximation of area under prec. recall curve

11 point average precision: same example as a table

Query 1		
#		R
1	X	0.20
2		
3	X	0.40
4		
5		
6	X	0.60
7		
8		
9		
10	X	0.80
11		
12		
13		
14		
15		
16		
17		
18		
19		
20	X	1.00

$P_1(r_i)$		$\Sigma_{j=1}^{N} P_j(r_i)$		$P_2(r_i)$
$\tilde{P}_1(r_0)$ = 1.00	→	1.00	←	$\tilde{P}_2(r_0)$ = 1.00
$\tilde{P}_1(r_1)$ = 1.00	→	1.00	←	$\tilde{P}_2(r_1)$ = 1.00
$\tilde{P}_1(r_2) = P_1(R = .2)$ = 1.00	→	1.00	←	$\tilde{P}_2(r_2)$ = 1.00
$\tilde{P}_1(r_3)$ = 0.67	→	0.84	←	$\tilde{P}_2(r_3)$ = 1.00
$\tilde{P}_1(r_4) = P_1(R = .4)$ = 0.67	→	0.67		
			↖	$\tilde{P}_2(r_4)$ = 0.67
$\tilde{P}_1(r_5)$ = 0.50	→	0.59	←	$\tilde{P}_2(r_5)$ = 0.67
$\tilde{P}_1(r_6) = P_1(R = .6)$ = 0.50	→	0.59	←	$\tilde{P}_2(r_6)$ = 0.67
$\tilde{P}_1(r_7)$ = 0.40	→	0.30	←	$\tilde{P}_2(r_7)$ = 0.20
$\tilde{P}_1(r_8) = P_1(R = .8)$ = 0.40	→	0.30	←	$\tilde{P}_2(r_8)$ = 0.20
$\tilde{P}_1(r_9)$ = 0.25	→	0.23	←	$\tilde{P}_2(r_9)$ = 0.20
		0.23	←	$\tilde{P}_2(r_{10}) = P_2(R = 1.0)$ = 0.20
	↗	↓		
$\tilde{P}_1(r_{10}) = P_1(R = 1.0)$ = 0.25		$P_{11\text{-}pt}$ = 0.61		

Query 2		
R		#
0.33	X	1
		2
0.67	X	3
		4
		5
		6
		7
		8
		9
		10
		11
		12
		13
		14
1.00	X	15

$\tilde{P}_i(r_j)$ is (interpolated) precision of ith query, at jth recall point. $P_i(R = r_j)$ (black) are exactly measured precision values.

TREC: IR system performance, future

- TREC-7 and 8: P(30) between .40 and .45, using long queries and narratives (one team even for short queries); P(10) = .5 even with short queries, $>$ .5 with medium length queries
- Systems must have improved since TREC-4, 5, and 6 $\rightarrow$ manual performance (sanity check) remained on a plateau of around .6
- The best TREC-8 ad-hoc systems not stat. significantly different $\rightarrow$ plateau reached? Ad hoc track discontinued after TREC-8.
- New tasks: filtering, web, QA, genomics, interactive, novelty, robust, video, cross-lingual,. . .
- 2006 is TREC-15. Latest tasks: spam, terabyte, blog, web, legal

TREC tracks 1992-2002

TRACK	TREC													
	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005
Ad Hoc	18	24	26	23	28	31	42	41						
Routing	16	25	25	15	16	21								
Interactive			3	11	2	9	8	7	6	6	6			
Spanish			4	10	7									
Confusion				4	5									
Database Merging				3	3									
Filtering				4	7	10	12	14	15	19	21			
Chinese					9	12								
NLP					4	2								
Speech						13	10	10	3					
Cross-Language						13	9	13	16	10	9			
High Precision						5	4							
Very Large Corpus							7	6						
Query							2	5	6					
Question Answering								20	28	36	34	33	28	33
Web								17	23	30	23	27	28	
Video										12	19			
Novelty Detection											13	14	14	
Genomic												29	33	41
HARD												14	16	16
Robust												16	14	17
Terabyte													17	23
Enterprise														19
Spam														13
	22	31	33	36	38	51	56	66	68	87	93	93	103	117

Summary

- IR evaluation as currently performed (TREC) only covers one small part of the spectrum:
  - System performance in batch mode
  - Laboratory conditions; not directly involving real users
  - Precision and recall measured from large, fixed test collections
- However, this evaluation methodology is very stable and mature
  - Host of elaborate performance metrics available, e.g. MAP
  - Relevance problem solvable (in principle) by query sampling, guidelines, relative system comparisons
  - Recall problem solvable (in practice) by pooling methods
  - Provable that these methods produce stable evaluation results

- Teufel (2007): Chapter *An Overview of evaluation methods in TREC Ad-hoc Information Retrieval and TREC Question Answering*. In: L. Dybkjaer, H. Hemsen, W. Minker (Eds.) Evaluation of Text and Speech Systems. Springer, Dordrecht, The Netherlands.

Information Retrieval

Lecture 4: Search engines and linkage algorithms

Computer Science Tripos Part II

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Today

- Fixed document collections $\rightarrow$ World Wide Web:
  What are the differences?
- Linkage-based algorithms
  - PageRank (Brin and Page, 1998)
  - HITS (Kleinberg, 1998)

Differences closed-world/web: data on web is...

- Large-volume
  - Estimates of 80 billion pages for 2006 (1600 TB)
    (1TB = 1024 GB = 2^{40}B)
  - Google indexed 8 billion pages in 2004; coverage 15-20% of web
  - Size of the web is doubling every half a year (Lawrence and Giles, "Searching the world wide web", Science, 1998)
- Redundant (copied or dynamically generated)
- Unstructured/differently structured documents
- Heterogenous (length, quality, language, contents)
- Volatile/dynamic
  - 1 M new pages per day; average page changes every 2-3 weeks
  - 2-9% of indexed pages are invalid
- Hyperlinked

Differences closed-world/web: search algorithms

- Different syntactic features in query languages
  - Ranked with proximity, phrase units, order relevant, with or without stemming
- Different indexing (“web-crawling”)
  - Heuristic enterprise; not all pages are indexed (est. 15-20% (2005); 28-55% (1999) of web covered)
- Different heuristics used (in addition to standard IR measures)
  - Proximity and location of search terms (Google)
  - Length of URL (AltaVista)
  - Anchor text pointing to a page (Google)
  - Quality estimates based on link structure

Web Crawling

- At search time, browsers do not access full text
- Index is built off-line; crawlers/spiders find web pages
  - Start with popular URLs and recursively follow links
  - Send new/updated pages to server for indexing
  - Search strategy: breadth-first, depth-first, backlink count, estimated popularity
- Parallel crawling
  - Avoid visiting the same page more than once
  - Partition the web and explore each partition exhaustively
- Agreement `robots.txt`: directories off-limits for crawlers
- In 1998, Google processed 4 M pages/day (50 pages, 500 links per second); fastest crawlers today: 10 M pages/day
- In 1998, AltaVista used 20 processors with 130G RAM and 500 GB disk each for indexing.

Link structure as a quality measure

- Links contain valuable information: latent human judgement
- Idea: derive quality measure by counting links
- Cf. citation index in science: papers which are cited more are considered to be of higher quality
- Similarity to scientific citation network
  - Receiving a “backlink” is like being cited (practical caveat: on the web, there is no certainty about the number of backlinks)

Simple backlink counting

Suggestion: of all pages containing the search string, return the pages with the most backlinks

- Generalisation problem
  - Many pages are not sufficiently self-descriptive
  - Example: the term “car manufacturer” does not occur anywhere on Honda homepage
  - No endogenous information (ie. information found in the page itself, rather than elsewhere) will help
- Page quality not considered at all, only raw backlink number
  - Overall popular page (Yahoo, Amazon) would be wrongly considered an expert on every string it contains
  - A page pointed to by an important page is also important (even if it has only that one single backlink)
  - Possible to manipulate this measure

Additional problem: manipulatability

- Web links are not quite like scientific citations
  - Large variation in web pages: quality, purpose, number of links, length (scientific articles are more homogeneous)
    - No publishing/production costs associated with web sites
    - No quality check (cf. peer review in scientific articles)
    - No cost associated with links (cf. length restrictions in scientific articles)
  - Therefore, linking is gratuitous (replicable), whereas citing is not
  - Any quality evaluation strategy which counts replicable features of web pages is prone to manipulation
- Therefore, raw counting will work less well than it does in scientific area
- Must be more clever when using link structure: PageRank, HITS

PageRank (Brin and Page, 1998)

- L. Page et al: "The PageRank Citation Ranking: Bringing order to the web", Tech Report, Stanford Univ., 1998
- S. Brin, L. Page: "The anatomy of a large-scale Hypertextual Web Search Engine", WWW7/Computer Networks 30(1-7):107-117, 1998
- Goal: estimate overall relative importance of web pages
- Simulation of a random surfer
  - Given a random page, follows links for a while (randomly), with probability q — assumption: never go back on already traversed links
  - Gets bored after a while and jumps to the next random page, with probability $1 - q$
  - Surfs infinitely long
- PageRank is the number of visits to each page

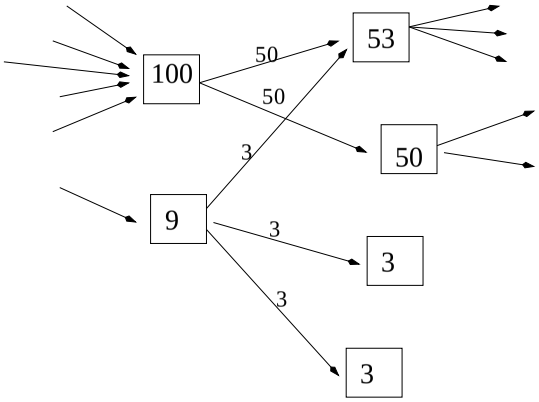
PageRank formula (simple case)

$$R(u) = (1-q) + q \sum_{v \in B_u} \frac{R(v)}{N_v}$$

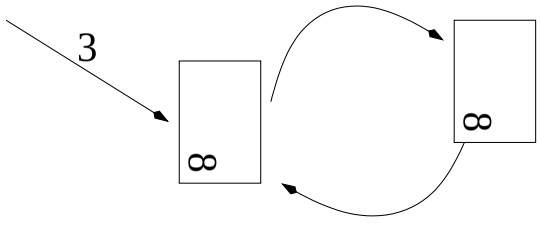
u	a web page
F_u	set of pages u points to ("Forward" set)
B_u	set of pages that point to u
$N_u = \lvert F_u \rvert$	number of pages u points to
q	probability of staying locally on page

This formula assumes that no PageRank gets lost in any iteration. In order for this to be the case, each page must have at least one outgoing link.

Simplified PageRank (q=1.0):

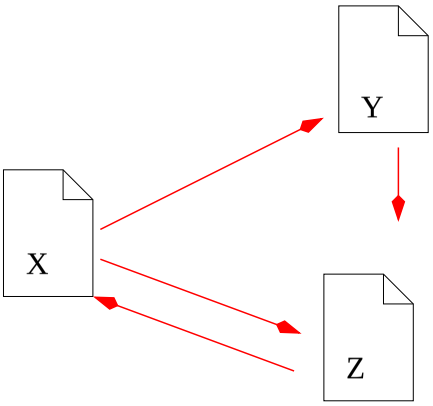


Rank sinks and rank sources



- The amount of pagerank in the web should be equal to N (so that the average page rank on the web is 1)
- Rank must stay constant in each step, but rank sinks lose infinitely much rank
- Rank also gets lost in each step for pages without onward links
- Solution: rank source $\vec{e}$ counteracts rank sinks
- $\vec{e}$ is the vector of the probability of random jumps of random surfer to a random page

An example: PageRank computation



$$R(u) = (1-q) + q \sum_{v \in B_u} \frac{R(v)}{N_v}$$

This assumes that all R(v)s are from the previous iteration.

Pagerank for the “mini-web” (q=.85)

Iteration	PR(X)	PR(Y)	PR(Z)	∑(PR(i))
1	1.00000	1.000000	1.00000	3.00000
2	1.00000	0.575000	1.06375	2.63875
3	1.05418	0.598029	1.10635	2.75857
4	1.09040	0.613420	1.13482	2.83865
5	1.11460	0.623706	1.15385	2.89216
6	1.13077	0.630581	1.16657	2.92793
7	1.14158	0.635175	1.17507	2.95183
8	1.14881	0.638245	1.18075	2.96781
9	1.15363	0.640292	1.18454	2.97846
	...	...	...	...
82	1.16336	0.64443	1.19219	2.99999
83	1.16336	0.64443	1.19219	3.00000

Iteration	PR(X)	PR(Y)	PR(Z)	∑(PR(i))
1	0.00000	0.00000	0.00000	0.00000
2	0.15000	0.21375	0.39543	0.75918
3	0.48612	0.35660	1.50243	1.50243
4	0.71075	0.45203	0.83633	1.99915
5	0.86088	0.51587	0.95436	2.33112
6	0.96121	0.55853	1.03325	2.55298
7	1.02826	0.58701	1.08597	2.70125
8	1.07307	0.60605	1.12120	2.80034
9	1.10302	0.61878	1.14475	2.86656
	...	...	...	...
86	1.16336	0.64443	1.19219	2.99999
87	1.16336	0.64443	1.19219	3.00000

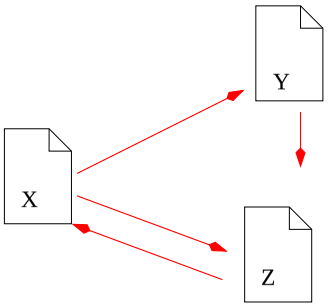
Matrix notation of PageRank, I

Idea, first part: represent the entire link structure as one matrix A; $\vec{r}$ is eigenvector of this matrix (and this is our PageRank vector!); we want to iterate something like $\vec{r} := A\vec{r}$, in order to get $\vec{r}$.

$$A_{uv} = \begin{cases} \frac{1}{N_v} & if\ \exists v \rightarrow u \\ 0 & otherwise \end{cases}$$

$$A = \begin{vmatrix} 0 & 0 & 1 \\ .5 & 0 & 0 \\ .5 & 1 & 0 \end{vmatrix}$$

Normalise so that each column adds to one!



But now we need to also take care of the “random jump” part of the equation. . .

Matrix notation of PageRank, II

Idea, second part: add “random jump” part of equation in as matrix

$\frac{1-q}{N}\mathbf{1}$

($\mathbf{1}$ is a matrix filled with all ones)

Together:

$$\vec{r} = c(qA + \frac{1-q}{N}\mathbf{1})\vec{r}$$

For simplicity sake, let’s call $B = qA + \frac{1-q}{N}\mathbf{1}$.

Now iteratively:

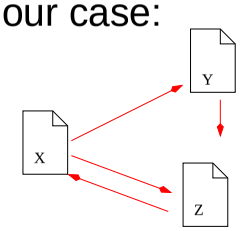
$\vec{r} := B\vec{r}$; normalise ($\vec{r}$); $\vec{r} := B\vec{r}$. . .

This will make $\vec{r}$ converge to the dominant eigenvector of B (independently of $\vec{r}$’s initial value), with eigenvalue c.

Pagerank, matrix algorithm

1. Initialise $\vec{r}$, A
2. Loop:
   - $\vec{r} = c(qA + \frac{1-q}{N}\mathbf{1})\vec{r}$
   - Stop criterion: $||\vec{r_{i+1}} - \vec{r_i}|| < N\epsilon$ ($||\vec{r_{i+1}} - \vec{r_i}||$ is page-wise "movement" in PageRank between two iterations)
   - This will result in a Page rank vector $\vec{r}$ whose average PageRank per page is 1: $||\vec{r}_{i+1}||_1 = N$

In our case:



$$A = \begin{vmatrix} 0 & 0 & 1 \\ .5 & 0 & 0 \\ .5 & 1 & 0 \end{vmatrix}$$

$$\vec{r_0} = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix};\ q = .85;\ B = qA + \frac{1-q}{N}\mathbf{1}$$

$$B = \begin{vmatrix} .050 & .050 & .900 \\ .475 & .050 & .050 \\ .475 & .900 & .050 \end{vmatrix}$$

Now iterate $\{\ \vec{r_n} = B\vec{r_{n-1}}$; normalise $\vec{r_n}\}$

Iterative matrix-based PageRank computation

$$B = \begin{vmatrix} .050 & .050 & .900 \\ .475 & .050 & .050 \\ .475 & .900 & .050 \end{vmatrix}$$

Iterate $\vec{r_n} = B\vec{r_{n-1}}$:

$$\vec{r_0} = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix};\ \vec{r_1} = \begin{bmatrix} 1.0000 \\ 0.5750 \\ 1.4250 \end{bmatrix};\ \vec{r_2} = \begin{bmatrix} 1.3613 \\ 0.5750 \\ 1.0637 \end{bmatrix};\ \vec{r_3} = \begin{bmatrix} 1.0542 \\ 0.7285 \\ 1.2173 \end{bmatrix};\ \vec{r_4} = \begin{bmatrix} 1.1847 \\ 0.5980 \\ 1.2173 \end{bmatrix};\ \vec{r_5} = \begin{bmatrix} 1.1847 \\ 0.6535 \\ 1.1618 \end{bmatrix};$$

$$\vec{r_6} = \begin{bmatrix} 1.1375 \\ 0.6535 \\ 1.2090 \end{bmatrix};\ \vec{r_7} = \begin{bmatrix} 1.1776 \\ 0.6335 \\ 1.1889 \end{bmatrix};\ \vec{r_8} = \begin{bmatrix} 1.1606 \\ 0.6505 \\ 1.1889 \end{bmatrix};\ \vec{r_9} = \begin{bmatrix} 1.1606 \\ 0.6432 \\ 1.1962 \end{bmatrix};\ \vec{r_{10}} = \begin{bmatrix} 1.1667 \\ 0.6432 \\ 1.1900 \end{bmatrix} \ldots$$

PageRank computation (practicalities)

- Space
  - Example: 75 M unique links on 25 M pages
  - Then: memory for PageRank 300MB
  - Link structures is compact (8B/link compressed)
- Time
  - Each iteration takes 6 minutes (for the 75 M links)
  - Whole process: 5 hours
  - Convergence after 52 iter. (322M links), 48 iter. (161M links)
  - Scaling factor linear in log n
- Pages without children removed during iteration
- Raw data can be obtained during web crawl; cost of computing PageRank is insignificant compared to the cost of building a full index

PageRank versus usage data

- Difference between linking behaviour (public) and actual usage data (web page access numbers from NLANR)
  - PageRank uses only public information; thus fewer privacy implications than usage data (pages that are accessed but not linked to)
  - PageRank produces a finer resolution compared to small usage sample
  - But: not all web users create links
- Propagation simulates word-of-mouth effects in complex network (ahead of time):
  - PageRank can change fast (one link on Yahoo)
    - Good pages often have only a few important backlinks (at first)
    - Those pages would not be found by simply back-link counting
  - Net traffic can change fast (one mention on the radio)

Summary PageRank

- Model of collaborative trust; users want information from “trusted” sources
- PageRank is immune to manipulation: it must convince an important site, or many unimportant ones, to point to it
  - Spamming PageRank costs real money – a good property for a search algorithm
  - Google’s business model: never sell PageRank (only advertising space)
- PageRank is a good predictor of optimal crawling order

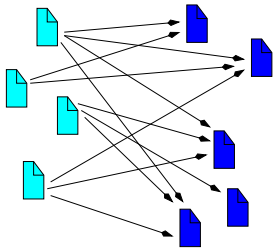
Top 15 PageRanks in July 1996

Download Netscape Software	11589.00
http://www.w3.org	10717.70
Welcome to Netscape	8673.51
Point: It’s what you’re searching for	7930.92
Web-Counter home page	7254.97
THe Blue Ribbon Campaign for Online Free Speech	7010.39
CERN Welcome	6562.49
Yahoo!	6561.80
Welcome to Netscape	6203.47
Wusage 4.1: A Usage Statistics System for Web Servers	5963.27
The World Wide Web consortium (W3C)	5672.21
Lycos, Inc. Home Page	4683.31
Starting Point	4501.98
Welcome to Magellan!	3866.62
Oracle Corporation	3587.63

Benefits for search with PageRank are greatest for underspecified queries

Hypertext Induced Topic Search (HITS) 125

- J. Kleinberg, “Authoritative sources in a hyperlinked environment”, ACM-SIAM 1998
- Goal: find authorities on a certain topic (relevance, popularity)
- Idea: There are hubs and authorities on the web, which exhibit a mutually reinforcing relationship
- Hubs: Recommendation pages with links to high-quality pages (authorities), e.g. compilations of favourite bookmarks, “useful links”
- Authorities: Pages that are recognised by others (particularly by hubs!) as experts on a certain topic

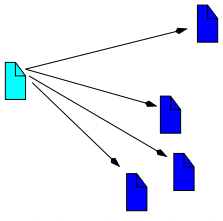


- Authorities are different from universally popular pages (high backlink count), which are not particular experts on that topic

HITS 126

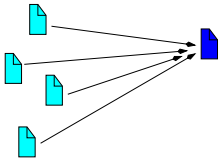
- Each page has two non-negative weights: an authority weight a and a hub weight h
- At each iteration, update the weights:
  - If a page points at many good authorities, it is probably a good hub:

$$h_p = \sum_{q:<p,q>\in A} a_q$$



  - If a page is pointed to by many good hubs, it is probably a good authority:

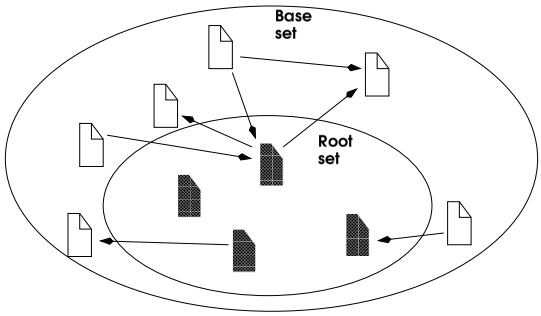
$$a_p = \sum_{q:<q,p>\in A} h_q$$



- Normalise weights after each iteration

HITS: Initialisation

- Start with the root set: set of web pages containing the query terms
- Create the base set: root set plus all pages pointing to the root set (cut-off if too many), and being pointed to by the root set
- The base set typically contains 1000-5000 documents



HITS: Algorithm

Given:

- a set $D = \{D_1 \ldots D_n\}$ of documents (base set)
- A, the linking matrix: edge $< i, j > \in A$ iff D_i points to D_j
- k, the number of desired iterations

Initialise: $\vec{a}$ = {1, 1,. . . , 1}; $\vec{h}$ = {1, 1, . . . , 1}

Iterate: for $c = 1 \ldots k$

- for $i = 1 \ldots n : a_p = \Sigma_{q:<q,p> \in A} h_q$
- for $i = 1 \ldots n : h_p = \Sigma_{q:<p,q> \in A} a_q$

Normalise $\vec{a}$ and $\vec{h}$: $\Sigma_{i \in D_i} a_i = \Sigma_{i \in D_i} h_i = 1$

HITS: Convergence

- Updates:

$$\vec{a} = A^T\vec{h} \qquad \vec{h} = A\vec{a}$$

- After the first iteration:

$$\vec{a}_1 = A^TA\vec{a}_0 = (A^TA)\vec{a}_0 \qquad \vec{h}_1 = AA^T\vec{h}_0 = (AA^T)\vec{h}_0$$

- After the second iteration:

$$\vec{a}_2 = (A^TA)^2\vec{a}_0 \qquad \vec{h}_2 = (AA^T)^2\vec{h}_0$$

- Convergence to
  - $\vec{a} \leftarrow$ dominant eigenvector(A^TA)
  - $\vec{h} \leftarrow$ dominant eigenvector(AA^T)

HITS: Example results

Authorities on “java”

0.328	`http://www.gamelan.com`	Gamelan
0.251	`http://java.sun.com`	JavaSoft home page
0.190	`http://www.digitalfocus.com/digital`	The Java Developer: How do I

Authorities on “censorship”

0.376	`http://www.eff.org`	EFF – The Electronic Frontier Fountation
0.344	`http://www.eff.org/blueribbon.html`	The Blue Ribbon Campaign for Online Free Speech
0.238	`http://www.cdt.org`	The Center for Democracy and Technology
0.235	`http://www.vtw.org`	Voters Telecommunication Watch
0.218	`http://www.aclu.org`	ACLU: American Civil Liberties Union

Authorities on “search engine”

0.346	`http://www.yahoo.com`	Yahoo
0.291	`http://www.excite.com`	Excite
0.239	`http://www.mckinley.com`	Welcome to Magellan
0.231	`http://www.lycos.com`	Lycos Home Page
0.231	`http://www.altavista.digital.com`	AltaVista: Main Page

- Both HITS and PageRank infer quality/“expert-ness” from link structure of the web
- Link structure contains latent human judgement
- Use different models of type of web pages
- Iterative algorithms
- Use of these weights for search (in different ways)
- Other differences between closed-world assumption (IR) and world wide web: data, indexing, query constructs, search heuristics

Information Retrieval

Lecture 5: Information Extraction

Computer Science Tripos Part II

UNIVERSITY OF CAMBRIDGE

Simone Teufel

Natural Language and Information Processing (NLIP) Group

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Information Extraction: the task

- Identify instances of a particular class of events or relationships in a natural language text
- Limited semantic range of events/relationships (domain-dependence)
- Extract the relevant arguments of the event or relationship into pre-existing “templates” (tabular data structures)
- MUC (Message Understanding Conference; NIST) 1986-97 competitive evaluation

History of IE

- 1980s and before: lexico-semantic patterns written by hand (FRUMP, satellite reports, patient discharge summaries...)
- 1987 First MUC (Message Understanding Conference); domain: naval sightings
- 1889 Second MUC; domain: naval sightings
- 1991 Third MUC; domain: terrorist acts
  - Winner (SRI) used partial parsing
- 1992 Fourth MUC; domain: terrorist acts
- 1993 Fifth MUC; domain: joint ventures/electronic circuit fabrication
  - Performance of best systems $\sim$ 40% R, 50% P (Humans in 60-80% range)
  - Lehnert et al.: first bootstrapping method

History of IE, ctd.

- 1995 Sixth MUC; domain: labour unit contract negotiations/changes in corporate executive management personnel
  - Encourage more portability and deeper understanding
  - Separate tasks into
    - NE: Named Entity
    - CO: Coreference
    - TE: Template Element
    - ST: Scenario Templates
- 1995: IE for summarisation (Radev and McKeown)
- 1998: Seventh MUC; domain: satellite rocket launch events
  - Mikheev et al., hybrid methods for NE
- 2003: CoNLL NE recognition task; similar training data to MUC

MUC setup

- Participants get a description of the scenario and a training corpus (a set of documents and the templates to be extracted from these)
- 1-6 months time to adapt systems to the new scenario
- NIST analysts manually fill templates of test corpus (“answer key”)
- Test corpus delivered; systems run at home
- Automatic comparison of system response with answer key
- Primary scores: precision and recall
- Participants present paper at conference in spring after competition
- Show system’s workings on predefined “walk through” example

Template example (MUC-3) 137

0	MESSAGE ID	TST1-MUC3-0080
1	TEMPLATE ID	1
2	DATE OF INCIDENT	03 APR 90
3	TYPE OF INCIDENT	KIDNAPPING
4	CATEGORY OF INCIDENT	TERRORIST ACT
5	PERPETRATOR: ID OF INDIV(S)	“THREE HEAVILY ARMED MEN”
6	PERPETRATOR: ID OF ORG(S)	“THE EXTRADITABLES”
7	PERPETRATOR: CONFIDENCE	CLAIMED OR ADMITTED: “THE EXTRADITABLES”
8	PHYSICAL TARGET: ID(S)	*
9	PHYSICAL TARGET: TOTAL NUM	*
10	PHYSICAL TARGET: TYPE(S)	*
11	HUMAN TARGET: ID(S)	“FEDERICO ESTRADA VELEZ” (“LIBERAL SENATOR”)
12	HUMAN TARGET: TOTAL NUM	1
13	HUMAN TARGET: TYPE(S)	GOVERNMENT OFFICIAL: “FEDERICO ESTRADA VELEZ”
14	TARGET: FOREIGN NATION(S)	–
15	INSTRUMENT: TYPE(S)	*
16	LOCATION OF INCIDENT	COLOMBIA: MEDELLIN (CITY)
17	EFFECT ON PHYSICAL TARGETS	*
18	EFFECT ON HUMAN TARGETS	*

Source Text (MUC-3) 138

TST-1-MUC3-0080

BOGOTA, 3 APR 90 (INRAVISION TELEVISION CADENA 1) - [REPORT] [JORGE ALONSO SIERRA VALENCIA] [TEXT] LIBERAL SENATOR FEDERICO ESTRADA VELEZ WAS KIDNAPPED ON 3 APRIL AT THE CORNER OF 60TH AND 48TH STREETS IN WESTERN MEDELLIN, ONLY 100 METERS FROM A METROPOLITAN POLICE CAI [IMMEDIATE ATTENTION CENTER]. THE ANTIOQUIA DEPARTMENT LIBERAL PARTY LEADER HAD LEFT HIS HOUSE WITHOUT ANY BODYGUARDS ONLY MINUTES EARLIER. AS WE WAITED FOR THE TRAFFIC LIGHT TO CHANGE, THREE HEAVILY ARMED MEN FORCED HIM TO GET OUT OF HIS CAR AND INTO A BLUE RENAULT.

HOURS LATER, THROUGH ANONYMOUS TELEPHONE CALLS TO THE METROPOLITAN POLICE AND TO THE MEDIA, THE EXTRADITABLES CLAIMED RESPONSIBILITY FOR THE KIDNAPPING. IN THE CALLS, THEY ANNOUNCED THAT THEY WILL RELEASE THE SENATOR WITH A NEW MESSAGE FOR THE NATIONAL GOVERNMENT. LAST WEEK, FEDERICO ESTRADA HAD REJECTED TALKS BETWEEN THE GOVERNMENT AND THE DRUG TRAFFICKERS.

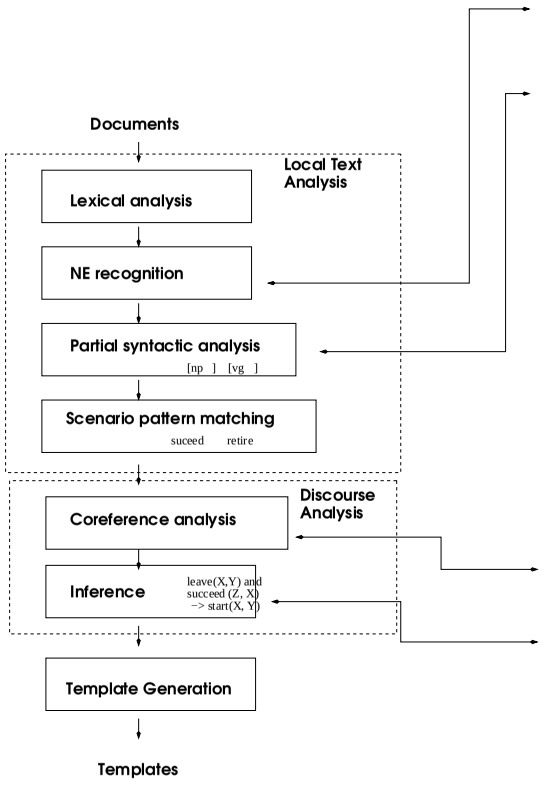
Text Example (MUC-5)

<DOC>
<DOCNO> 0592 </DOCNO>
<DD> NOVEMBER 24, 1989, FRIDAY </DD>
<SO>Copyright (c) 1989 Jiji Press Ltd.;</SO>
<TXT>
BRIDGESTONE SPORTS CO. SAID FRIDAY IT HAS SET UP A JOINT VENTURE IN TAIWAN WITH A LOCAL CONCERN AND A JAPANESE TRADING HOUSE TO PRODUCE GOLF CLUBS TO BE SHIPPED TO JAPAN.
THE JOINT VENTURE, BRIDGESTONE SPORTS TAIWAN CO., CAPITALIZED AT 20 MILLION NEW TAIWAN DOLLARS, WILL START PRODUCTION IN JANUARY 1990 WITH PRODUCTION OF 20,000 IRON AND ”METAL WOOD” CLUBS A MONTH. THE MONTHLY OUTPUT WILL BE LATER RAISED TO 55,000 UNITS, BRIDGESTON SPORTS OFFICIALS SAID.
THE NEW COMPANY, BASED IN KAOHSIUNG, SOUTHERN TAIWAN, IS OWNED 75 PCT BY BRIDGESTONE SPORTS, 15 PCT BY UNION PRECISION CASTING CO. OF TAIWAN AND THE REMAINDER BY TAGA CO., A COMPANY ACTIVE IN TRADING WITH TAIWAN, THE OFFICIALS SAID.
BRIDGESTONE SPORTS HAS SO FAR BEEN ENTRUSTING PRODUCTION OF GOLF CLUBS PARTS WITH UNION PRECISION CASTING AND OTHER TAIWAN COMPANIES.
WITH THE ESTABLISHMENT OF THE TAIWAN UNIT, THE JAPANESE SPORTS GOODS MAKER PLANS TO INCREASE PRODUCTION OF LUXURY CLUBS IN JAPAN.
</TXT>
</DOC>

Template Example (MUC-5)

<TEMPLATE-0592-1> :=
DOC NR: 0592
DOC DATE: 241189
DOCUMENT SOURCE: “Jiji Press Ltd.”
CONTENT: <TIE_UP_RELATIONSHIP-0592-1>
<TIE_UP_RELATIONSHIP-0592-1>:=
TIE-UP STATUS: EXISTING
ENTITY:<ENTITY-0592-1>
<ENTITY-0592-2>
<ENTITY-0592-3>
JOINT VENTURE CO:<ENTITY-0592-4>
OWNERSHIP: <OWNERSHIP-0592-1>
ACTIVITY:<ACTIVITY-0592-1>
<ENTITY-0592-1>:=
NAME: BRIDGESTONE SPORTS CO
ALIASES: “BRIDGESTONE SPORTS”
“BRIDGESTON SPORTS”
NATIONALITY: Japan (COUNTRY)
TYPE: COMPANY
ENTITY RELATIONSHIP:<ENTITY_RELATIONSHIP-0592-1>
<ENTITY-0592-2>:=
NAME: UNION PRECISION CASTING CO
ALIASES: “UNION PRECISION CASTING”
“BRIDGESTON SPORTS”
LOCATION: Taiwan (COUNTRY)
NATIONALITY: Taiwan (COUNTRY)
TYPE: COMPANY
ENTITY RELATIONSHIP:<ENTITY_RELATIONSHIP-0592-1>
<ENTITY-0592-3>:=
NAME: TAGA CO
NATIONALITY: Japan (COUNTRY)
TYPE: COMPANY
ENTITY RELATIONSHIP:<ENTITY_RELATIONSHIP-0592-1>
<ENTITY-0592-4>:=
NAME: BRIDGESTONE SPORTS TAIWAN CO
ALIASES: “UNION PRECISION CASTING”
“BRIDGESTON SPORTS”
LOCATION: “KAOHSIUNG” (UNKNOWN) Taiwan (COUNTRY)
TYPE: COMPANY
ENTITY RELATIONSHIP:<ENTITY_RELATIONSHIP-0592-1>
<INDUSTRY-0592-1>:=
INDUSTRY-TYPE: PRODUCTION
PRODUCT/SERVICE: (CODE 39 “20,000 IRON AND 'METAL WOOD”) ([CLUBS]”)
<ENTITY_RELATIONSHIP-0592-1>:=
ENTITY1: <ENTITY-0592-1
<ENTITY-0592-2
<ENTITY-0592-3
ENTITY2: <ENTITY-0592-4
REL OF ENTITY2 TO ENTITY1: CHILD
STATUS: CURRENT
<ACTIVITY-0592-1>:=
INDUSTRY: <INDUSTRY-0592-1>
ACTIVITY-SITE: (Taiwan (COUNTRY) <ENTITY-0592-4>)
START TIME: <TIME-0592-1>
<TIME-0592-1>:=
DURING: 0190
<OWNERSHIP-0592-1>:=
OWNED: <ENTITY-0592-4>
TOTAL-CAPITALIZATION: 20000000 TWD
OWNERSHIP-%: (<ENTITY-0592-3> 10)
(<ENTITY-0592-2> 15)
(<ENTITY-0592-1> 75)

NYU's IE system



Sam Schwartz retired as executive vice president of the famous hot dog manufacturer, Hupplewhite Inc. He will be succeeded by Harry Himmelfarb.

Sam Schwartz (person) retired as executive vice president of the famous hot dog manufacturer, Hupplewhite Inc (organisation). He will be succeeded by Harry Himmelfarb(person).

[np: e1 Sam Schwartz (person)] [vg retired] as [np: e2 executive vice president] of [np: e3 the famous hot dog manufacturer], [np:e4 Hupplewhite Inc (organisation)]. [np: e5 He] [vg will be succeeded] by [np: e6 Harry Himmelfarb(person)].

e1	type:person	name:"Sam Schwartz"
e2	type:position	value:"executive vice president"
e3	type:manufacturer	
e4	type:company	name: "Hupplewhite Inc."
e5	type:person	
e6	type:person	name: "Harry Himmelfarb"

e2	type:position	value:"executive vice president" company:e3
e3 = e4		
e7	leave-job	person:e1 position:e2
e8	succeed	person1:e6 person2:e5
e5 = e1		
e9	start-job	person:e6 position e2

EVENT:	leave job
PERSON:	Sam Schwartz
POSITION:	executive vice president
COMPANY:	Hupplewhite Inc.

EVENT:	start job
PERSON:	Harry Himmelfarb
POSITION:	executive vice president
COMPANY:	Hupplewhite Inc.

Named Entity recognition – as defined at MUC-6

- NE types:
  - ENAMEX (type= person, organisation, location)
  - TIMEX (type= time, date)
  - NUMEX (type= money, percent)
- Allowed to use gazetteers (fixed list containing names of a certain type, e.g. countries, last names, titles, state names, rivers...)
- ENAMEX is harder, more context dependent than TIMEX and NUMEX:
  - Is Granada a COMPANY or a LOCATION?
  - Is Washington a PERSON or a LOCATION?
  - Is Arthur Anderson a PERSON or an ORGANISATION?

Named Entity recognition – common approaches

- NE markup with subtypes:

  <ENAMEX TYPE='PERSON'>Flavel Donne</ENAMEX> is an analyst with <ENAMEX TYPE='ORGANIZATION'>General Trends</ENAMEX>, which has been based in <ENAMEX TYPE='LOCATION'>Little Spring</ENAMEX> since <TIMEX>July 1998</TIMEX>.

- Most systems use manually written regular expressions
  - Rules about mid initials, postfixes, titles
  - Gazetteers of common first names
  - Acronyms: Hewlett Packard Inc. → HP

PATTERN: "president of <company>" matches

executive vice president of Hupplewhite

Person names – evidence against gazetteers

- Gazetteer of full names impossible and not useful, as both first and last names can occur on their own
- Last name gazetteer impractical
  - Almost infinite set of name patterns possible: last names are productive (1.5M surnames in US alone)
  - Overlap with common nouns/verbs/adjectives
    - First 2 pages of Cambridge phone book include 237 names
    - Of those, 6 (2.5%) are common nouns: Abbey, Abbot, Acres, Afford, Airs, Alabaster
- First name gazetteer less impractical, but still not foolproof
  - First names can be surprising, eg. MUC-7 walk-through example: "Llennel Evangelista"
  - First names are productive, eg. Moonunit Zappa, Apple Paltrow . . .

Person Names – evidence against gazetteers

- – Overlap with common nouns:
  - River and Rain Phoenix, Moon Unit Zappa, Apple Paltrow
  - "Virtue names": Grace (134), Joy (390), Charity (480), Chastity (983), Constance, Destiny
  - "Month names": June, April, May
  - "Flower names": Rose, Daisy, Lily, Erica, Iris . . .
  - From US Social Security Administration's list of most popular girls' names in 1990, with rank:
    Amber (16), Crystal (41), Jordan (59), Jade (224), Summer (291), Ruby (300), Diamond (450), Infant (455), Precious (472), Genesis (528), Paris (573), Princess (771), Heaven (902), Baby (924) . . .
- Additional problem: non-English names alliterated into English; variant spellings
- Complicated name patterns with titles: Sammy Davis Jr,
  HRH The Prince of Wales, Dr. John T. Maxwell III

Name type ambiguity: more evidence against gazetteers

- Ambiguity of name types: *Columbia* (Org.) vs. (British) *Columbia* (Location) vs. *Columbia* (Space shuttle)
- Company names often use common nouns ("Next", "Boots", "Thinking Machines"...) and can occur in variations ("Peter Stuyvesant", "Stuyvesant')
- Coordination problems/ left boundary problems:
  - One or two entities in *China International Trust and Investment Corp invests $2m in...* ?
  - Unknown word at beginning of potential name: in or out?
    Suspended Ceilings Inc vs *Yesterday Ceilings Inc*
    Mason, Daily and Partners vs. *Unfortunately, Daily and Partners*
- Experiments show: simple gazetteers fine for locations (90%P/80%R) but not for person and organisations (80%P/50%R)

Mikheev et al. (1998): Cascading NE

- Staged combination of rule-based system with probabilistic partial matching
- Use machine learning to decide type of NE
- Use internal phrase structure of name
- Make high-precision decisions first
- Keep off decision about unsure items until all evidence has been seen
- Assume: one name type per discourse (article)
  - unless signalled by writer with additional context information

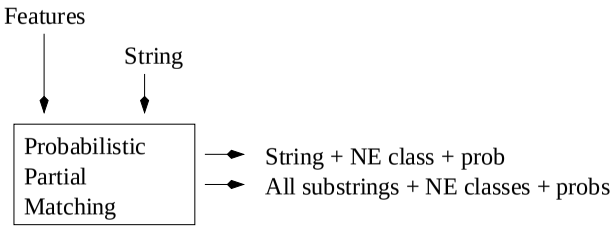
Mikheev et al. (1998): Examples of sure fire rules

Rule	Assign	Example
`(Xx+)+ (is|,) a? JJ* PROF`	PERS	Yuri Gromov, a former director
`(Xx+)+ is? a? JJ* REL`	PERS	John White is beloved brother
`(Xx+)+ himself`	PERS	White himself
`(Xx+)+, DD+ ,`	PERS	White, 33,
`share in (Xx+)+`	ORG	shares in Trinity Motors
`(Xx+)+ Inc.`	ORG	Hummingbird Inc.
`PROF (of|at|with) (Xx+)+`	ORG	director of Trinity Motors
`(Xx+)+ (region|area)`	LOC	Lower Beribidjan area

Mikheev et al. (1998): ML; External and internal evidence

External:

- Position in sentence (sentence initial)
- Word exists in lexicon in lowercase
- Word seen in lowercase in document



Internal:

- Contains any non-alpha characters
- Number of words it consists of
- Suffix, Prefix
- Adjectives ending in “an” or “ese” + whose root is in Gazetteer

Mikheev et al. (1998): Algorithm

1. Apply Grammar Rule Set 1 (“Sure fire” rules)
   → tag as definite NEs of given type
2. Use ML for variants (probabilistic partial match)
   - Generate all possible substrings of sure-fire tagged NEs:
     – *Adam Kluver Ltd* → *Adam Kluver*, *Adam Ltd*, *Kluver Ltd*
   - ME model gives probability for possible string and NE type
   - Tag all occurrences of NE in text (over prob. threshold) with type
3. Apply Grammar Rule Set 2 (Relaxed rules)
   - Mark anything that looks like a PERSON (using name grammar)
   - Resolve coordination, genitives, sentence initial capitalized modifiers
     – Coordinated or possessive name parts, or rest of sentence initial coordinated name seen on their own? If not, assume one name (*Murdoch’s News Corp, Daily, Bridge and Mason*)
4. Apply ML again (for new variants)
   - X and Y are of same type → resolved typo ‘‘`Un7ited States and Russia`’’
5. Apply specialised ME model to title (capitalisation, different syntax).

Mikheev et al – example text 151

MURDOCH SATELLITE CRASH UNDER FBI INVESTIGATION

London and Tomsk. The crash of Rupert Murdoch Inc's news satellite yesterday is now under investigation by Murdoch and by the Sibirian state police. Clarity J. White, vice president of Hot Start, the company which produced the satellite's ignition system, yesterday stated that her company considered human failure the most likely cause of the crash. Investigator Robin Black, 33, who investigates the crash for the FBI, recently arrived by train at the crash site in the Tomsk region. Neither White nor Black were available for comment today; Murdoch have announced a press conference for tomorrow.

Mikheev et al – potential NE hypotheses (all incorrect) 152

`LONDON and TOMSK`	Org
`Rupert Murdoch`	Person
`Murdoch`	Person
`Neither White`	Person
`Investigator Robin Black`	Person

Additional problem: `Black` and `White` have last names which overlap with adjectives and first names which overlap with common nouns (`Robin` and `Clarity`), thus they cannot be in a gazetteer.

Mikheev et al – After Step 1

MURDOCH SATELLITE CRASH UNDER FBI INVESTIGATION

London and Tomsk. The crash of Rupert Murdoch Inc(ORG)'s news satellite yesterday is now under investigation by Murdoch and by the Sibirian state police. Clarity J. White, vice president of Hot Start(ORG), the company which produced the satellite's ignition system, yesterday stated that her company considered human failure the most likely cause of the crash. Investigator Robin Black(PERSON), 33, who investigates the crash for the FBI, recently arrived by train at the crash site in the Tomsk(LOC) region. Neither White nor Black were available for comment today; Murdoch have announced a press conference for tomorrow.

Underlined instances: newly suggested in this round

- Sure fire rules applied
- But exact extend of name not known yet: Investigator Robin Black? Black?

Mikheev et al – After Step 2 (Partial Match)

MURDOCH SATELLITE CRASH UNDER INVESTIGATION

London and Tomsk(LOC?). The crash of Rupert Murdoch Inc(ORG?)'s news satellite yesterday is now under investigation by Murdoch(ORG?) and by the Sibirian state police. Clarity J. White, vice president of Hot Start(ORG?), the company which produced the satellite's ignition system, yesterday stated that her company considered human failure the most likely cause of the crash. Investigator Robin Black(PERSON?), 33, recently arrived by train at the crash site in the Tomsk(LOC?) region. Neither White nor Black(PERSON?) were available for comment today; Murdoch(ORG?) have announced a press conference for tomorrow.

Green instances: around from last round

- All instances from last round and their substrings are now hypothesized; they and their context are now subjected to ML

Mikheev et al – After Step 2 (Probabilistic Match) 155

MURDOCH SATELLITE CRASH UNDER INVESTIGATION

London and Tomsk(LOC$\surd$). The crash of Rupert Murdoch Inc(ORG$\surd$)'s news satellite yesterday is now under investigation by Murdoch(ORG$\surd$) and by the Sibirian state police. Clarity J. White, vice president of Hot Start(ORG$\surd$), the company which produced the satellite's ignition system, yesterday stated that her company considered human failure as the most likely cause of the crash. Investigator Robin Black(PERS$\surd$), 33, recently arrived by train at the crash site in the Tomsk(LOC$\surd$) region. Neither White nor Black(PERS$\surd$) were available for comment today; Murdoch(ORG$\surd$) have announced a press conference for tomorrow.

- ML has reconfirmed some instances (Robin Black) and discarded others (Investigator Robin Black)

Mikheev et al – After Step 3 156

MURDOCH SATELLITE CRASH UNDER INVESTIGATION

London and Tomsk(LOC). The crash of Rupert Murdoch Inc(ORG)'s news satellite yesterday is now under investigation by Murdoch(ORG) and by the Sibirian state police. Clarity J. White(PERS?), vice president of Hot Start(ORG), the company which produced the satellite's ignition system, yesterday stated that her company considered human failure as the most likely cause of the crash. Investigator Robin Black(PERS), 33, recently arrived by train at the crash site in the Tomsk(LOC) region. Neither White(PERS?) nor Black(PERS) were available for comment today; Murdoch(ORG) have announced a press conference for tomorrow.

- Relaxed rules: Mark everything as a possibility which roughly follows Name shape (blue, underlined)
- (plus confirmed NEs from last round in green)

Mikheev et al – After Step 4

MURDOCH SATELLITE CRASH UNDER INVESTIGATION

London(LOC$\surd$) and Tomsk(LOC). The crash of Rupert Murdoch Inc(ORG)'s news satellite yesterday is now under investigation by Murdoch(ORG) and by the Sibirian state police. Clarity J. White(PERS$\surd$), vice president of Hot Start(ORG), the company which produced the satellite's ignition system, yesterday stated that her company considered human failure as the most likely cause of the crash. Investigator Robin Black(PERS), 33, recently arrived by train at the crash site in the Tomsk(LOC) region. Neither White(PERS$\surd$) nor Black(PERS) were available for comment today; Murdoch(ORG) have announced a press conference for tomorrow.

- Some of these possibilities reconfirmed by ML, others discarded
- "London" found by X and Y rule.
- Missing step: different segmentation and ML for title; 'Murdoch' is found there.

Mikheev et al: Results in MUC-7

93.39% combined P and R – best and statistically different from next contender

		ORG		PERSON		LOC	
		R	P	R	P	R	P
1	Sure fire rules	42	98	40	99	36	96
2	Partial Match 1	75	98	80	99	69	93
3	Relaxed Rules	83	96	90	98	86	93
4	Partial Match 2	85	96	93	97	88	93
5	Title Assignment	91	95	95	97	95	93

- System design: Keep precision high at all stages, raise recall if possible
- Gazetteers improve performance, but system can determine persons and organizations reasonably well even without any gazetteer (ORG: P86/R85; PERSON: P90/R95), but not locations (P46/R59)

Summary of today

- IE consists of different tasks (as defined by MUC): NE, CO, TE, ST
- Today: NE
  - Principal problems with NE
  - NE with manual rules
  - Mikheev et al. (1998)
    - Use internal and external evidence
    - Cascaded design: commit in order of confidence/supportive evidence from text, not in text order!

Literature

- Mikheev, Moens and Grover (1998). Description of the LTG system. MUC-7 Proceedings.
- Mikheev, Moens and Grover (1999). Named Entity Recognition without Gazetteers. EACL'99
- R. Grishman (1997): Information Extraction: Techniques and challenges, in: Information Extraction, Springer Verlag, 1997.

Information Retrieval

Lecture 6: Information Extraction and Bootstrapping

Computer Science Tripos Part II

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Last time

- Range of problems that make named entity recognition (NE) hard
- Mikheev et al's (1998) cascading NE system
- NE is the simplest kind of IE task: no relations between entities must be determined
- NIST MUC conferences pose three kinds of harder IE tasks
- Today: more of the full task (scenario templates), and on learning

Lexico-semantic patterns

- “Flattened-out” semantic representations with lexemes directly hard-wired into them
- String-based matching with type of semantic category to be found directly expressed in lexical pattern
- Problem with all string-based mechanisms: generalisation to other strings with similar semantics, and to only those
- Do generalisation by hand...
  - <Perpetrator> (APPOSITION) {blows/blew/has blown} {himself/herself} up
  - <Perpetrator> detonates
  - {blown up/detonated} by <Perpetrator>
- Manual production of patterns is time-consuming, brittle, and not portable across domains

Learning of lexico-semantic patterns (Riloff 1993)

- UMASS participant system in MUC-4: AutoSlog
- Lexico-semantic patterns for MUC-3 took 1500 person hours to build → knowledge engineering bottleneck
- AutoSlog achieved 98% performance of manual system; AutoSlog dictionary took 5 person hours to build
- “Template mining:”
  - Use MUC training corpus (1500 texts + human answer keys; 50% non-relevant texts) to learn contexts
  - Have human check the resulting templates (30% - 70% retained)

Lexico-syntactic-semantic patterns (Riloff 1993)

- 389 Patterns (“concept nodes”) with enabling syntactic conditions, e.g. active or passive:
  - kidnap-passive: <VICTIM> expected to be subject
  - kidnap-active: <PERPETRATOR> expected to be subject
- Hard and soft constraints for fillers of slots
  - Hard constraints: selectional restrictions; soft constraints: semantic preferences
- Semantic lexicon with 5436 entries (including semantic features)

Heuristics for supervised template mining (Riloff 1993)

- Stylistic conventions: relationship between entity and event made explicit in first reference to the entity
- Find key word there which triggers the pattern: *kidnap, shot,*
- Heuristics to find these trigger words
- Given: filled template plus raw text. Algorithm:
  - Find first sentence that contains slot filler
  - Suggest good conceptual anchor point (trigger word)
  - Suggest a set of enabling conditions

“the diplomat was kidnapped” + VICTIM: the diplomat
Suggest: <SUBJECT> passive-verb + trigger=kidnap

System uses 13 “heuristics” (= syntactic patterns):

EXAMPLE	PATTERN
<victim> was murdered	<subject> passive-verb
<perpetrator> bombed	<subject> active-verb
<perpetrator> attempted to kill	<subject> verb infinitive
<victim> was victim	subject auxiliary <noun>
killed <victim>	passive-verb <dobj>
bombed <target>	active-verb <dobj>
to kill <victim>	infinitive <dobj>
threatened to attack <target>	verb infinitive <dobj>
killing <victim>	gerund <dobj>
fatality was <victim>	noun auxiliary <dobj>
bomb against <target>	noun prep <np>
killed with <instrument>	active-verb prep <np>
was aimed at <target>	passive-verb prep <np>

Riloff 1993: a good concept node

ID: DEV-MUC4-0657
Slot Filler: “public buildings”
Sentence: IN LA OROYA, JUNIN DEPARTMENT, IN THE CENTRAL PERUVIAN MOUNTAIN RANGE, PUBLIC BUILDINGS WERE BOMBED AND A CAR-BOMB WAS DETONATED.

CONCEPT NODE

Name:	target-subject-passive-verb-bombed
Trigger:	bombed
Variable slots:	(target (*S* 1))
Constraints:	(class phys-target *S*)
Constant slots:	(type bombing)
Enabling Conditions:	((passive))

Riloff 1993: another good concept node 169

ID: DEV-MUC4-0071
Slot Filler: “guerrillas
Sentence: THE SALVADORAN GUERRILLAS ON MAR_12_89, TODAY, THREATENED TO MURDER INDIVIDUALS INVOLVED IN THE MAR_19_88 PRESIDENTIAL ELECTIONS IF THEY DO NOT RESIGN FROM THEIR POSTS.

CONCEPT NODE	
Name:	perpetrator-subject-verb-infinitive-threatened-to-murder
Trigger:	murder
Variable slots:	(perpetrator (*S* 1))
Constraints:	(class perpetrator *S*)
Constant slots:	(type perpetrator)
Enabling Conditions:	((active) (trigger-preceded-by? ’to ’threatened))

Riloff 1993: a bad concept node 170

ID: DEV-MUC4-1192
Slot Filler: “gilberto molasco
Sentence: THEY TOOK 2-YEAR-OLD GILBERTO MOLASCO, SON OF PATRICIO RODRIGUEZ, AND 17-OLD ANDRES ALGUETA, SON OF EMIMESTO ARGUETA.

CONCEPT NODE	
Name:	victim-active-verb-dobj-took
Trigger:	took
Variable slots:	(victim (*DOBJ* 1))
Constraints:	(class victim *DOBJ*)
Constant slots:	(type kidnapping)
Enabling Conditions:	((active))

Riloff 1993: evaluation

System/Test Set	Recall	Prec	F-measure
MUC-4/TST3	46	56	50.5
AutoSlog/TST3	43	56	48.7
MUC-4/TST4	44	40	41.9
AutoSlog/TST4	39	45	41.8

- 5 hours of sifting through AutoSlog's patterns
- Porting to new domain in less than 10 hours of human interaction
- But: creation of training corpus ignored in this calculation

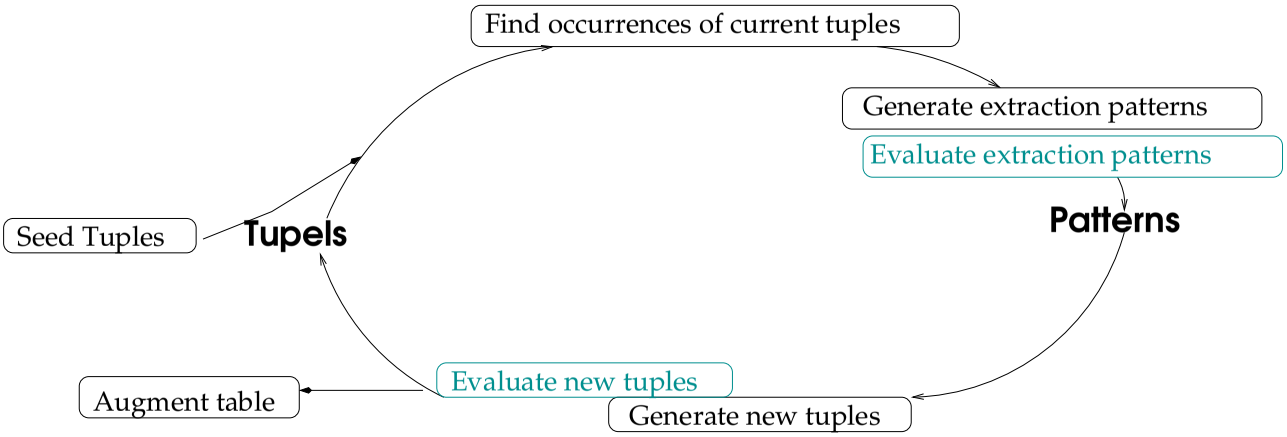
Agichtein, Gravano (2000): Snowball

- Find locations of headquarters of a company and the corresponding company name ($< o, l >$ tuples)

Organisation	Location of Headquarters
Microsoft	Redmond
Exxon	Irving
IBM	Armonk
Boeing	Seattle
Intel	Santa Clara

  "Computer servers at Microsoft's headquarters in Redmond"
- Use minimal human interaction (handful of positive examples)
  - no manually crafted patterns
  - no large annotated corpus (IMass system at MUC-6)
- Automatically learn extraction patterns
- Less important to find every occurrence of patterns; only need to fill table with confidence

Agichtein, Gravano (2000): Bootstrapping



Agichtein, Gravano (2000): Overall process

- Start from table containing some $< o, l >$ tuples (which must exist in document collection)
- Perform NE (advantage over prior system DIPRE (Brin 98))
- System searches for occurrences of the example $< o, l >$ tuples in documents
- System learns extraction patterns from these example contexts, e.g.:

<ORGANIZATION> 's headquarters in <LOCATION>
<LOCATION>-based <ORGANIZATION>

- Evaluate patterns; use best ones to find new $< o, l >$ tuples
- Evaluate new tuples, choose most reliable ones as new seed tuples
- Iteratively repeat the process

Agichtein, Gravano (2000): Context generalisation and patterns

A SNOWBALL pattern is a 5-tuple <left,tag1,middle,tag2,right>

left	Tag1	middle	Tag2	right
The	Irving	-based	Exxon Corporation	
<{<the, 0.2>},	LOCATION,	{<-,0.5> <based, 0.5>},	ORGANIZATION,	{} >

- Associate term weights as a function of frequency of term in context
- Normalize each vector so that norm is 1; then multipy with weights $W_{left}, W_{right}, W_{mid}$.
- Degree of match between two patterns $t_p =< l_p, t_1, m_p, t_2, r_p >$ and $t_s =< l_s, t'_1, m_s, t'_2, r_s >$:

$$match(t_p, t_s) = l_p l_s + m_p m_s + r_p r_s$$ (if tags match, 0 otherwise)

Agichtein, Gravano (2000): Pattern generation

- Similar contexts form a pattern
  - Cluster vectors using a clustering algorithm (minimum similarity threshold τ_{sim})
  - Vectors represented as cluster centroids $\bar{l_s}, \bar{m_s}, \bar{r_s}$
- Generalised Snowball pattern defined via centroids:

$$< \bar{l_s}, tag_1, \bar{m_s}, tag_2, \bar{r_s} >$$

- Remember for each Generalised Snowball pattern
  - All contexts it came from
  - The distances of contexts from centroid

Agichtein, Gravano (2000): Productivity/Reliability

- We want productive and reliable patterns
  - productive but not reliable:
    $< \{\}, ORGANIZATION, \{<",", 1>\}, LOCATION, \{\} >$

    "Intel, Santa Clara, announced that..."
    "Invest in Microsoft, New York-based analyst Jane Smith said..."
  - reliable but not productive:
    $< \{\}, ORGANIZATION, \{< whose, 0.1 >, < headquarter, 0.4 >, < is, 0.1 >< located, 0.3 >, < in, 0.09 >, < nearby, 0.01 >\}, LOCATION, \{\} >$

    "Exxon, whose headquarter is located in nearby Irving..."
- Eliminate patterns supported by less than $\tau_{sup} < o, l >$ tuples

Agichtein, Gravano (2000): Pattern reliability

- If P predicts tuple $t =< o, l >$ and there is already tuple $t' =< o, l' >$ with high confidence, then: if $l = l' \rightarrow P.positive$++, otherwise $P.negative$++ (uniqueness constraints: organization is key).
- Pattern reliability: $Conf(P) = \frac{P.positive}{P.positive + P.negative}$ (range [0..1])
- Example:
  $P_{43} =< \{\}, ORGANIZATION, \{<",", 1>\}, LOCATION, \{\} >$ matches
  1. Exxon, Irving, said... (CORRECT: in table)
  2. Intel, Santa Clara, cut prices (CORRECT: in table)
  3. invest in Microsoft, New York-based analyst (INCORRECT, contradicted by entry <Microsoft, Redmont>)
  4. found at ASDA, Irving. (????, unknown, no contradiction $\rightarrow$ disregard evidence)
- disregard unclear evidence such as 4.
- Thus, $Conf(P_{43}) = \frac{2}{2+1}$

Agichtein, Gravano (2000): Pattern confidence

- Consider productivity, not just reliability:

$$Conf_{RlogF}(P) = Conf(P) log_2(P.positive)$$

- Normalized $Conf_{RlogFNorm}(P)$:

$$Conf_{RlogFNorm}(P) = \frac{Conf_{RlogF}(P)}{max_{i \in \mathcal{P}} Conf(i)}$$

  (this brings $Conf_{RlogFNorm}(P)$ into range [0...1])

- $max_{i \in \mathcal{P}} Conf(i)$ is the largest confidence value seen with any pattern
- $Conf_{RlogFNorm}(P)$ is a rough estimate of the probability of pattern P producing a valid tuple (called $Conf(P)$ hereafter)

Agichtein, Gravano (2000): Tuple evaluation I

- Confidence of a tuple T is probability that at least one valid tuple is produced:

$$Conf(T) = 1 - \prod_{i=0}^{|P|} (1 - Conf(P_i) Match(C_i, P_i))$$

$P = \{P_i\}$ is the set of patterns that generated T
C_i is the context associated with an occurrence of T
$Match(C_i, P_i)$ is goodness of match between P_i and C_i

- Explanation: probability of every pattern matched incorrectly:

$$Prob(T \text{ is NOT valid}) = \prod_{i=0}^{|P|} (1 - P(i))$$

- Formula due to the assumption that for an extracted tuple T to be valid, it is sufficient that at least one pattern matched the “correct” text context of T.

Agichtein, Gravano (2000): Tuple evaluation II

- Then reset confidence of patterns:

$$Conf(P) = Conf_{new}(P)W_{updt} + Conf_{old}(P)(1 - W_{updt})$$

  W_{updt} controls learning rate: does system trust old or new occurrences more? Here: $W_{updt} = 0.5$

- Throw away tuples with confidence $< \tau_t$

Agichtein, Gravano (2000): Results

Conf	middle	right
1	<based, .53>, <in, .53>	<”,” ,.01>
.69	<””, .42>,<s, .42>,<headquarters, .42>,<in,.42>	
.61	<(,.93>	<),.12>

- Use training corpus to set parameters: $\tau_{sim}, \tau_t, \tau_{sup}$, I_{max}, W_{left}, W_{right}, W_{middle}
- Only input: 5 $< o, l >$ tuples
- Punctuation matters: performance decreases when punctuation is removed
- Recall b/w .78 and .87 ($\tau_{sup} > 5$); precision .90 ($\tau_{sup} >> 4$)
- High precision possible (.96 with τ_t = .8); remaining problems come from NE recognition
- Pattern evaluation step responsible for most improvement over DIPRE

Summary: IE and template matching, learning

- Possible to learn simple relations from positive examples (Snowball)
- Possible to learn more diverse relations from annotated training corpus (Riloff)
- Even modest performance can be useful
  - Later manual verification
  - In circumstances where there would be no time to review source documents, so incomplete extracted information is better than none

Summary: IE Performance

Current methods perform well if

- Information to be extracted is expressed directly (no complex inference is required)
- Information is predominantly expressed in a relatively small number of forms
- Information is expressed locally within the text

Difference between IE and QA (next time):

- IE is domain dependent, open-domain QA is not

- Ellen Riloff, Automatically constructing a dictionary for information extraction tasks. In Proc. 11th Ann. Conference of Artificial Intelligence, p 811-816, 1993
- Eugene Agichtein, Luis Gravano: Snowball: Extracting Relations from Large Plain-Text Collections, Proceedings of the Fifth ACM International Conference on Digital Libraries, 2000

Information Retrieval

Lecture 7: Question Answering

Computer Science Tripos Part II

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Question Answering: Task definition in TREC-QA

- QA Track since TREC-1999: Open-domain factual textual QA
- Task requirements (in comparison with IR):
  1. Input: NL questions, not keyword-based queries
  2. Output: answers, not documents
- Rules:
  - All runs completely automatic
  - Frozen systems once questions received; answers back to TREC within one week
  - Answers may be extracted or automatically generated from material in document collection only
  - The use of external resources (dictionaries, ontologies, WWW) is allowed
  - Each returned answer is checked manually by TREC-QA (no comparison to gold standard)

TREC QA: Example questions

TREC-8	How many calories are there in a Big Mac? Where is the Taj Mahal?
TREC-9	Who invented the paper clip? How much folic acid should an expectant mother take daily? Who is Colin Powell?
TREC-10	What is an atom? How much does the human adult female brain weigh? When did Hawaii become a state?

Questions in TREC

- Type of question: reason, definition, list of instances, context-sensitive to previous questions (TREC-10)
- Source of question: invented for evaluation (TREC-8); since TREC-9 mined from logs (Encarta, Excite)
  - → strong impact on task: more realistic questions are harder on assessors and systems, but more representative for training
- Type of answer string: 250 Bytes (TREC-8/9, since TREC-12); 50 Bytes (TREC-8–10); exact since TREC-11
- Guarantee of existence of answer: no longer given since TREC-10

Examples of answer strings

What river in the US is known as the Big Muddy?

System A:	the Mississippi
System B:	Known as Big Muddy, the Mississippi is the longest
System C:	as Big Muddy , the Mississippi is the longest
System D:	messed with . Known as Big Muddy , the Mississip
System E:	Mississippi is the longest river in the US
System F:	the Mississippi is the longest river in the US
System G:	the Mississippi is the longest river(Mississippi)
System H:	has brought the Mississippi to its lowest
System I:	ipes.In Life on the Mississippi,Mark Twain wrote t
System K:	Southeast;Mississippi;Mark Twain;officials began
System L:	Known; Mississippi; US,; Minnessota; Cult Mexico
System M:	Mud Island,; Mississippi; “The; history; Memphis

Decreasing quality of answers

Manual checking of answers

- Systems return [docid, answer-string] pairs; mean answer pool per question judged: 309 pairs
- Answers judged in the context of the associated document
- ”Objectively” wrong answers okay if document supports them
  - Taj Mahal
- Considerable disagreement in terms of absolute evaluation metrics
- But relative MRRs (rankings) across systems very stable

Labels

- Ambiguous answers are judged as “incorrect”:

  What is the capital of the Kosovo?

  250B answer:

  protestors called for intervention to end the “Albanian uprising”. At Vucitrn, 20 miles northwest of Pristina, five demonstrators were reported injured, apparently in clashes with police. Violent clashes were also repo

- Answers need to be supported by the document context → the second answer is “unsupported”:

  What is the name of the late Phillippine President Marco’s wife?

  - Ferdinand Marcos and his wife Imelda. . . → [supported]
  - Imelda Marcos really liked shoes. . . → [unsupported]

List task (TREC-10, since TREC-12)

- 25 questions: retrieve a given target number of instances of something
- Goal: force systems to assemble an answer from multiple strings
  - `Name 4 US cities that have a ‘‘Shubert’’ theater`
  - `What are 9 novels written by John Updike?`
  - `What are six names of navigational satellites?`
  - `Name 20 countries that produce coffee.`
- List should not be easily located in reference work
- Instances are guaranteed to exist in collection
- Multiple documents needed to reach target, though single documents might have more than one instance
- Since TREC-12: target number no longer given; task is to find all

MRR: Mean reciprocal rank

- Task is precision-oriented: only look at top 5 answers
- Score for individual question i is the reciprocal rank r_i where the first correct answer appeared (0 if no correct answer in top 5 returns).

$$RR_i = \frac{1}{r_i}$$

- Possible reciprocal ranks per question: [0, 0.2, 0.25, 0.33, 0.5, 1]
- Score of a run (MRR) is mean over n questions:

$$MRR = \frac{1}{n} \sum_{i=1}^{n} RR_i$$

Example: Mean reciprocal rank

162: What is the capital of Kosovo?

```
1 18 April, 1995, UK GMT Kosovo capital
2 Albanians say no to peace talks in Pr
3 0 miles west of Pristina, five demon
4 Kosovo is located in south and south
5 The provincial capital of the Kosovo
```

$\rightarrow RR_{162} = \frac{1}{3}$

23: Who invented the paper clip?

```
1 embrace Johan Vaaler, as the true invento
2 seems puzzling that it was not invented e
3 paper clip. Nobel invented many useful th
4 modern-shaped paper clip was patented in A
5 g Johan Valerand, leaping over Norway, in
```

$\rightarrow RR_{23} = 1$

2: What was the monetary value of the Nobel Peace Prize in 1989?

```
1 The Nobel poll is temporarily disabled. 1994 poll
2 perience and scientific reality, and applied to socie
3 Curies were awarded the Nobel Prize together with Beqc
4 the so-called beta-value. $40,000 more than expected
5 that is much greater than the variation in mean value
```

$\rightarrow RR_2 = 0$

$\rightarrow MRR = \frac{\frac{4}{3}}{3} = .444$

Other QA evaluation metrics used in TREC

- Average accuracy since 2003: only one answer per question allowed; accuracy is $\frac{\textit{Answers correct}}{\textit{Total Answers}}$
- Confidence-weighted score: systems submit one answer per question and order them according to the confidence they have in the answer (with their best answer first in the file)

$$\frac{1}{Q} \sum_{i=1}^{Q} \frac{\#\textit{correct in first } i}{i}$$

(Q being the number of questions). This evaluation metric (which is similar to Mean Average Precision) was to reward systems for their confidence in their answers, as answers high up in the file participate in many calculations.

Results

- In TREC-8, 9, 10 best systems returned MMR of .65–.70 for 50B answers, answering around 70–80% of all questions
- In 55% of the cases where answer was found in the first 5 answers, this answer was in rank 1
- Accuracy of best system in TREC-10's list task had an accuracy of .75
- The best confidence-weighted score in TREC-11 achieved was .856 (NIL-prec .578, NIL recall .804)
- TREC-12 (exact task): Best performance was an accuracy of .700

QA systems

- Overview of three QA systems:
- Cymphony system (TREC-8)
  - NE plus answer type detection
  - Shallow parsing to analyse structure of questions
- SMU (TREC-9)
  - Matching of logical form
  - Feedback loops
- Microsoft (TREC-10)
  - Answer redundancy and answer harvesting
  - Claim: "Large amounts of data make intelligent processing unnecessary."

Overall algorithm

- Question Processing
  - Shallow parse
  - Determine expected answer type
  - Question expansion
- Document Processing
  - Tokenise, POS-tag, NE-index
- Text Matcher (= Answer production)
  - Intersect search engine results with NE
  - Rank answers

Named entity recognition

- Over 80% of 200 TREC-8 questions ask for a named entity (NE)
- NE employed by most successful systems in TREC (Verhees and Tice, 2000)
- MUC NE types: person, organisation, location, time, date, money, percent
- Textract covers additional types:
  - frequency, duration, age
  - number, fraction, decimal, ordinal, math equation
  - weight, length, temperature, angle, area, capacity, speed, rate
  - address, email, phone, fax, telex, www
  - name (default proper name)
- Textract subclassifies known types:
  - organisation $\rightarrow$ company, government agency, school
  - person $\rightarrow$ military person, religious person

Expected answer type

Who won the 1998 Nobel Peace Prize?

Expected answer type:	PERSON
Key words:	won, 1998, Nobel, Peace, Prize

Why did David Koresh ask the FBI for a word processor?

Expected answer type:	REASON
Key words:	David, Koresh, ask, FBI, word, processor

Question Expansion:

Expected answer type:	[because | because of | due to | thanks to | since | in order to | to VP]
Key words:	[ask|asks|asked|asking, David, Koresh, FBI, word, processor]

FST rules for expected answer type

R1: Name NP(city | country | company) → CITY|COUNTRY|COMPANY

VG[name] NP[a country] that VG[is developing] NP[a magnetic levitation railway system]

R2: Name NP(person_w) → PERSON

VG[Name] NP[the first private citizen] VG[to fly] PP[in space]

("citizen" belongs to word class `person_w`).

R3: CATCH-ALL: proper noun

Name a film that has won the Golden Bear in the Berlin Film Festival.

Direct matching of question words

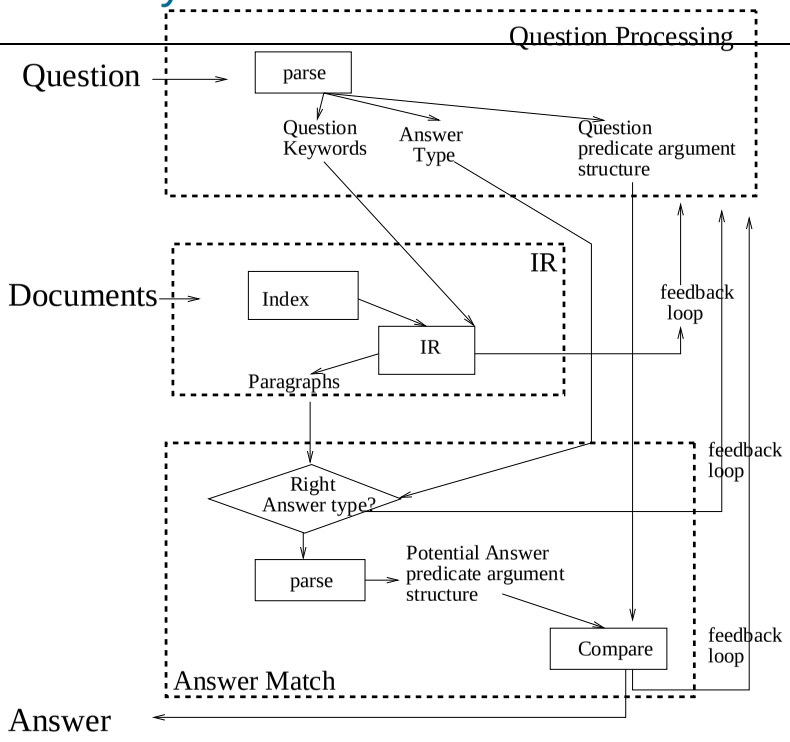
who/whom →	PERSON
when →	TIME/DATE
where/what place →	LOCATION
what time (of day) →	TIME
what day (of the week) →	DAY
what/which month →	MONTH
how often →	FREQUENCY
...	

This classification happens only if the previous rule-based classification did not return unambiguous results.

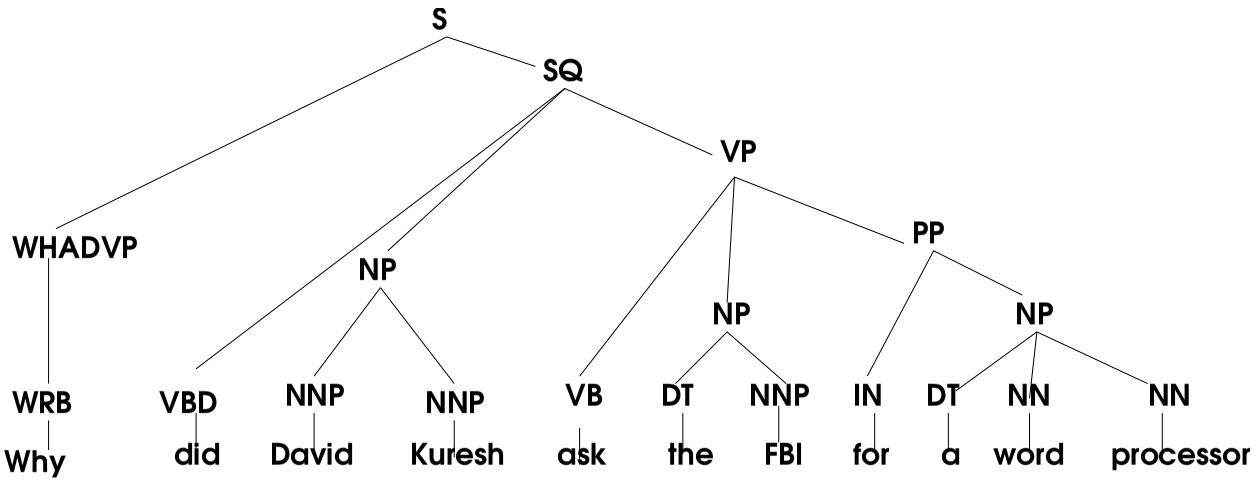
The Southern Methodist University (SMU) system (Harabagiu et al.)

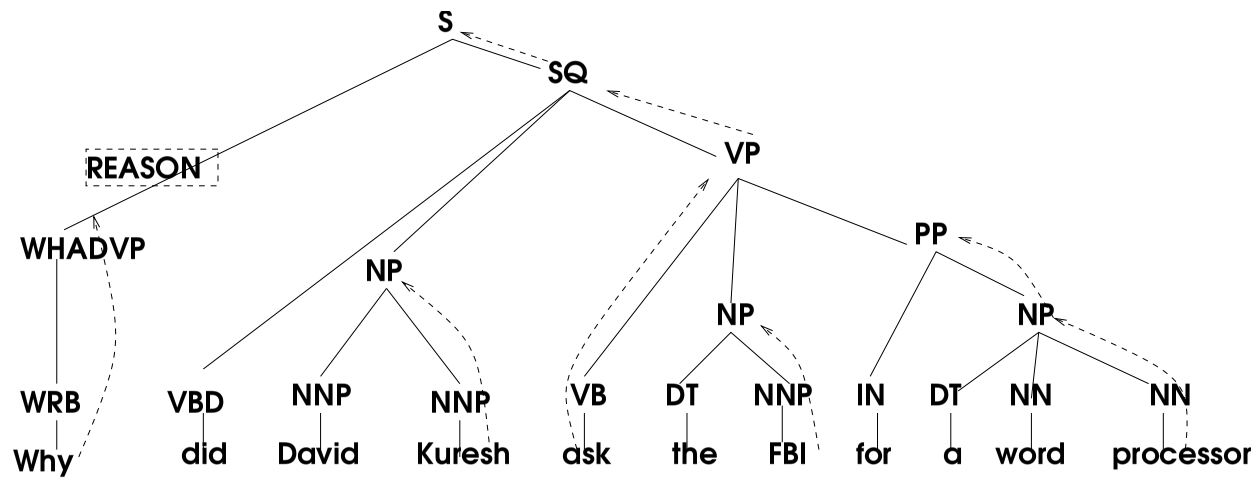
- Example of a deep processing system which has been extremely successful in TREC-QA (clear winner in most years)
- Machinery beyond answer type determination:
  1. Variants/feedback loops: morphological, lexical, syntactic, by reasoning
  2. Comparison between answer candidate and question on basis of logical form
- Deep processing serves to
  - capture semantics of open-domain questions
  - justify correctness of answers

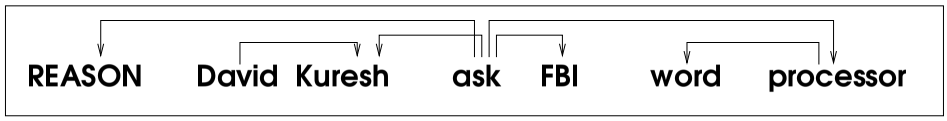
Overview of SMU system



SMU: Derivation of logical forms







SMU: Variants (“Feedback loops”) 208

- Morphological (+40%):
  - *Who invented the paper clip?* — Main verb “invent”, ANSWER-TYPE “who” (subject) → add keyword “inventor”
- Lexical (+52%; used in 129 questions):
  - *How far is the moon?* — “far” is an attribute of “distance”
  - *Who killed Martin Luther King?* — “killer” = “assassin”
- Semantic alternations and paraphrases, abductive reasoning (+8%; used in 175 questions)
  - *How hot does the inside of an active volcano get?*
  - Answer in “lava fragments belched out of the mountain were as hot as 300 degrees Fahrenheit”
  - Facts needed in abductive chain:
    - volcano IS-A mountain; lava PART-OF volcano
- Combination of loops increases results considerably (+76%)

At the other end of the spectrum: the Microsoft system

- Circumvent difficult NLP problems by using more data
- The web has 2 billion indexed pages
- Claim: deep reasoning is only necessary if search ground is restricted
- The larger the search ground, the greater the chance of finding answers with a simple relationship between question string and answer string:

Who killed Abraham Lincoln?

DOC 1	John Wilkes Booth is perhaps America's most infamous assassin. He is best known for having fired the bullet that ended Abraham Lincoln's life.	TREC
DOC 2	John Wilkes Booth killed Abraham Lincoln.	web

The Microsoft system: Methods

1. Question processing is minimal: reordering of words, removal of question words, morphological variations
2. Matching done by Web query (google):
   - Extract potential answer strings from top 100 summaries returned
3. Answer generation is simplistic:
   - Weight answer strings (frequency, fit of match) – learned from TREC-9
   - Shuffle together answer strings
   - Back-projection into TREC corpus: keywords + answers to traditional IR engine
4. Improvement: Expected answer type filter (24% improvement)
   - No full-fledged named entity recognition

Query string generation

Rewrite module outputs a set of 3-tupels:

- Search string
- Position in text where answer is expected with respect to query string : LEFT|RIGHT|NULL
- Confidence score (quality of template)

Who is the world's richest man married to?

[+is the world's richest man married to	LEFT	5]
[the +is world's richest man married to	LEFT	5]
[the world's +is richest man married to	RIGHT	5]
[the world's richest +is man married to	RIGHT	5]
[the world's richest man +is married to	RIGHT	5]
[the world's richest man married +is to	RIGHT	5]
[the world's richest man married to +is	RIGHT	5]
[world's richest man married	NULL	2]
[world's AND richest AND married	NULL	1]

String weighting

- Obtain 1-grams, 2-grams, 3-grams from google short summaries
- Score each n-gram n according to the weight r_q of query q that retrieved it
- Sum weights across all summaries containing the ngram n (this set is called S_n)

$$w_n = \sum_{n \in S_n} r_q$$

w_n: weight of ngram n
S_n: set of all retrieved summaries which contain n
r_q: rewrite weight of query q

Answer string generation

- Merge similar answers (ABC + BCD → ABCD)
  - Assemble longer answers from answer fragments
  - Weight of new n-gram is maximum of constituent weights
  - Greedy algorithm, starting from top-scoring candidate
  - Stop when no further ngram tiles can be detected
  - But: cannot cluster “redwoods” and “redwood trees”
- Back-projection of answer
  - Send keywords + answers to traditional IR engine indexed over TREC documents
  - Report matching documents back as “support”
- Always return NIL on 5th position

The Microsoft system: Examples

- Time sensitivity of questions:
  Q1202: Who is the Governor of Alaska? → system returns governor in 2001, but TREC expects governor in 1989.
- Success stories:

Question	Answer	TREC document
What is the birth-stone for June?	Pearl	for two weeks during June (the pearl is the birth-stone for those born in that month)
What is the rainiest place on Earth?	Mount Wailaleale	and even Pago Pago, noted for its prodigious showers, gets only about 196 inches annually (The titleholder, according to the National Geographic Society, is Mount Wailaleale in Hawaii, where about 460 inches of rain falls each year).

Microsoft system: Discussion

- Results: mid-range (.347 MRR, 49% no answer)
- Development time of less than a month
- Produced “exact strings” before TREC-11 demanded it: average returned length 14.6 bytes
- Does this system undermine of QA as a gauge for NL understanding?
  - If TREC wants to measure straight performance on factual question task, less NLP might be needed than previously thought
  - But if TREC wants to use QA as test bed for text understanding, it might now be forced to ask “harder” questions
- And still: the really good systems are still the ones that do deep NLP processing!

Summary

- Open domain, factual question answering
- TREC: Source of questions matters (web logs v. introspection)
- Mean reciprocal rank main evaluation measure
- MRR of best systems 0.68 - 0.58
- Best systems answer about 75% of questions in the first 5 guesses, and get the correct answer at position 1.5 on avg ($\frac{1}{.66}$)
- System technology
  - NE plus answer type detection (Cymphony)
  - Matching of logical form, Feedback loops (SMU)
  - Answer redundancy and answer harvesting (Microsoft)

- Teufel (2007): Chapter *An Overview of evaluation methods in TREC Ad-hoc Information Retrieval and TREC Question Answering*. In: L. Dybkjaer, H. Hemsen, W. Minker (Eds.) Evaluation of Text and Speech Systems. Springer, Dordrecht, The Netherlands.
- Ellen Voorhees (1999): The TREC-8 Question Answering Track Report, Proceedings of TREC
- R. Srihari and W. Li (1999): “Information-extraction supported question answering”, TREC-8 Proceedings
- S. Harabagiu et al (2001), “The role of lexico-semantic feedback in open-domain textual question-answering”, ACL-2001
- E. Brill et al (2001), “Data intensive question answering”, TREC-10 Proceedings

Information Retrieval

Lecture 8: Automatic Summarisation

Computer Science Tripos Part II

UNIVERSITY OF CAMBRIDGE

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Summarisation – an impossible task? 219

- Summarisation is intelligent and linguistically viable information compression
- Part of human activity in many different genres
  - TV guide: movie plot summaries
  - Blurb on back of book
  - Newsflashes
  - Subtitles
- Why do research in automatic summarisation?
  - Practical reasons: information compression needed in today's information world
  - Scientific reasons: summarisation is a test bed for current document understanding capabilities

Text Summarisation 220

- Compress the "most important" points of a text, express these main points in textual form
- Information reduction
- Different types of summaries
  - informative/indicative
    - informative: summary replaces full document v.
    - indicative: decision aid for question "should I read the full document?"
  - abstract/extract
    - abstract (generated text) v.
    - extract (verbatim text snippets)

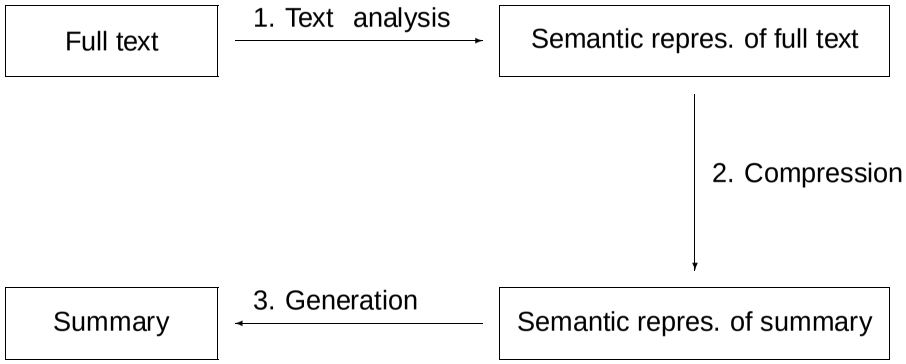
Properties of a good summary

- Considerably shorter than the input text
- Covers main points of input text
- Truth-preserving
- A good text in its own right (coherence...)
- Additional goals: flexibility (with respect to length, user, task)

Human abstracting

- Abstractors are employed at indexing/abstracting companies which produce abstract journals
- Need expert knowledge about summarising and about domain
- Several studies of human abstractors (Cremmins 1996, Endress-Niggemeyer 1995, Liddy 1991)
- Studies show that human abstractors
  - extract textual material, rework it (Cremmins, E-N)
  - only create new material from scratch when they have to, by generalisation and inference (Cremmins, E-N)
  - have a consistent building plan of a summary in their minds, but agree more on type of information to be put into summary than on the actual sentences (Liddy)
- But: Instructions for abstractors too abstract to be used for actual algorithms

Text summarisation: the deep model



Steps of the deep model:

1. Analysis of text into semantic representation
2. Manipulation (compression) of semantic representation
3. Text generation from semantic representation

How realistic is the deep model?

- Compression methods exist (step 2)
  - Summarisation model by Kintsch and van Dijk (1979), based on propositions and human memory restrictions
  - Reasoning theories, e.g. by Lehnert (1982)
- Natural and flexible text generation exists (step 3), working from semantic representation
  - McKeown et al.: Generation from basketball game statistics, weather reports
  - Moore and DiEugenio: Generation of tutor's explanations
- Bottleneck: text analysis (step 1)

Summarisation by fact extraction (Radev and McKeown 1998, CL)

Compress several descriptions about the same event from multiple news stories

MESSAGE: ID	**TST-REU-0001**
SECSOURCE: SOURCE	Reuters
SECSOURCE: DATE	March 3, 1996 11:30
PRIMSOURCE: SOURCE	
INCIDENT: DATE	March 3, 1996
INCIDENT: LOCATION	Jerusalem
INCIDENT: TYPE	Bombing
HUM TGT: NUMBER	"killed: 18" "wounded: 10"
PERP: ORGANIZATION ID	

MESSAGE: ID	**TST-REU-0002**
SECSOURCE: SOURCE	Reuters
SECSOURCE: DATE	March 4, 1996 07:20
PRIMSOURCE: SOURCE	Israel Radio
INCIDENT: DATE	March 4, 1996
INCIDENT: LOCATION	Tel Aviv
INCIDENT: TYPE	Bombing
HUM TGT: NUMBER	"killed: at least 10" "wounded: 30"
PERP: ORGANIZATION ID	

MESSAGE: ID	**TST-REU-0003**
SECSOURCE: SOURCE	Reuters
SECSOURCE: DATE	March 4, 1996 14:20
PRIMSOURCE: SOURCE	
INCIDENT: DATE	March 4, 1996
INCIDENT: LOCATION	Tel Aviv
INCIDENT: TYPE	Bombing
HUM TGT: NUMBER	"killed: at least 13" "wounded: more than 100"
PERP: ORGANIZATION ID	"Hamas"

MESSAGE: ID	**TST-REU-0004**
SECSOURCE: SOURCE	Reuters
SECSOURCE: DATE	March 4, 1996 14:30
PRIMSOURCE: SOURCE	
INCIDENT: DATE	March 4, 1996
INCIDENT: LOCATION	Tel Aviv
INCIDENT: TYPE	Bombing
HUM TGT: NUMBER	"killed: at least 12" "wounded: 105"
PERP: ORGANIZATION ID	"Hamas"

Summarisation by fact extraction (Radev and McKeown 1998, CL)

- Reason over templates
- New templates are generated by combining other templates
- The most important template, as determined by heuristics, is chosen for generation
- Rules:
  - Change of perspective: If the same source reports conflicting information over time, report both pieces of information
  - Contradiction: If two or more sources report conflicting information, choose the one that is reported by independent sources
  - Addition: If additional information is reported in a subsequent article, include the additional information

  - Refinement: Prefer more specific information over more general one (name of a terrorist group rather than the fact that it is Palestinian)
  - Agreement: Agreement between two sources is reported as it will heighten the reader's confidence in the reported fact
  - Superset/Generalization: If the same event is reported from different sources and all of them have incomplete information, report the combination of these pieces of information
  - Trend: If two or more messages reflect similar patterns over time, these can be reported in one statement (e.g. three consecutive bombings at the same location)
  - No Information: Report the lack of information from a certain source when this would be expected
- Output summary, deep-generated:

> Reuters reported that 18 people were killed in a Jerusalem bombing Sunday. The next day, a bomb in Tel Aviv killed at least 10 people and wounded 30 according to Israel Radio. Reuters reported that the radical Muslim group Hamas had claimed responsibility for the act.

- Problem: domain-specificity built into the templates

A domain-inspecific method: text extraction

- Split text in units (paragraphs or sentences or text tiles)
- Assign each unit a score of importance/"extractworthiness", using sentential and/or relational features
  - Sentential features of a unit can be calculated in isolation, e.g. number of TF/IDF words or location
  - Relational features of a unit are calculated in context of other units, e.g. unit with highest amount of shared terms
- Extract sentences with highest score verbatim as extract

External marking of “more important” material

- Text is globally structured (rhetorical sections, anecdotal/summary beginning in journalistic writing) – location feature
- Text is locally structured (paragraph structure; headlines and sub-headlines) – paragraph structure feature
- Important concepts/terms mark important prepositions – tf/idf feature
- Certain typographic regions are good places to find important concepts: captions, title, headlines – title feature
- Sentence length is important, but the experts argue; probably genre-dependent
- Phrases mark important sections (“in this paper”, “most important”) and less important sections (hedging by auxiliaries, adverbs) – cue phrase feature

Sentential features, I

1. Concept feature (Luhn, 1958)
   - Find concepts using *tf* (nowadays: *tf*idf*), sentence score = no of frequency concepts in sentence
2. Header feature (Baxendale, 1959)
   - Find concepts in title (variation: title and headlines), sentence score = no of title concepts in sentence
3. Location feature (Edmundson, 1969)
   - Divide text into n equal sections
   - sentences in section $1 \leq i \leq n$ get sentence score = $\frac{1}{i}$
   - Always used in combination

Sentential features, II

4. Paragraph feature
   - First sentence in paragraph gets a higher score than last one, and higher than sentences in the middle
   - Always used in combination
5. Cue phrases (Paice, 1991)
6. First-sentence-in-section feature
7. Sentence length
8. Occurrence of bonus or malus word (ADAM system, Zomora (1972))
9. Occurrence of a named entity (Kupiec et al., 1995)

Combination of sentential features: manually

- Combinations of features are more robust than single features
- Manual feature combination (Edmundson):

$$Score(S) = \alpha A + \beta B + ...\omega O$$

A, B,..O: feature scores
α, β, ω: manual weights

Combination of sentential features: machine learning

- Kupiec, Pedersen, Chen: A trainable document summariser, SIGIR 1995
- Create examples of sentences that are abstract-worthy, calculate their features, using 5 well-known features ($F_1 \ldots F_5$)
- Use Naive Bayesian classifier:

$$P(s \in S|F_1, \ldots, F_k) = \frac{P(F_1,\ldots,F_k|s\in S)P(s\in S)}{P(F_1,\ldots,F_k)} \approx \frac{P(s\in S)\prod_{j=1}^{k} P(F_j|s\in S)}{\prod_{j=1}^{k} P(F_j)}$$

$P(s \in S\|F_1, \ldots, F_k)$:	Probability that sentence s from the source text is included in summary S, given its feature values;
$P(s \in S)$:	Probability that a sentence s in the source text is included in summary S unconditionally; compression rate of the task (constant);
$P(F_j\| \, s \in S)$:	probability of feature-value pair occurring in a sentence which is in the summary;
$P(F_j)$:	probability that the feature-value pair F_j (j th feature-value pair out of k feature-value pairs) occurs unconditionally;

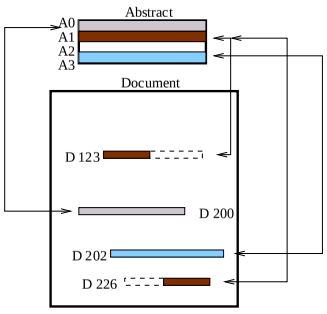
Finding the right gold standard

Subjective measures:

- Humans subjects select sentences (system developers?)

Looking for more objective measures:

- Earl: indexible sentences
- Kupiec et al: sentences with similarity to abstract sentences



Kupiec et al: gold standard

- Find best match for each abstract sentence by automatic similarity measure
- One example for a similarity measure is based on the longest common substring:

$$lcs(X,Y) = \frac{length(X) + length(Y) - edit_{i,d}(X,Y)}{2}$$

  (where $edit_{i,d}$ is the minimum number of deletions and insertions needed to transform X into Y).
- Possible similarity measures are the ratio of longest common substring to the maximum length of the two sentences, or the average.
- Reject sentences with similary $<$ .5; accept sentences with similarity $>$ 0.8, hand-judge sentences with medium similarity $.5 \leq X \leq .8$

Kupiec et al's evaluation

- Corpus of 85 articles in 21 journals
- Extract as many sentences as there are gold standards in the document $\rightarrow$ precision = recall
- Very high compression makes this task harder
- Results:

Feature	Individual	Cumulative
Cue Phrases	33%	33%
Location	29%	42%
Sentence Length	24%	44%
*tf*idf*	20%	42%
Capitalization + *tf*idf*	20%	42%
Baseline	24%	

Example of an extract (Microsoft's AutoSummarize) 237

Distributional Clustering of English Sentences
Distributional Similarity To cluster nouns n according to their conditional verb distributions pn, we need a measure of similarity between distributions.
We will take (1) as our basic clustering model.
In particular, the model we use in our experiments has noun clusters with cluster memberships determined by p(njc) and centroid distributions determined by p(vjc).
Given any similarity measure d(n;c) between nouns and cluster centroids, the average cluster distortion is
If we maximize the cluster membership entropy
Clustering Examples
Figure 1 shows the five words most similar to the each [sic] cluster centroid for the four clusters resulting from the first two cluster splits.
Model Evaluation
1990. Statistical mechanics and phrase transitions in clustering.

Source: "*Distributional Clustering of English Sentences*" by Pereira, Tishby and Lee, ACL 1993

What are extracts good for? 238

- Extraction is the basis of all robust and reliable summarisation technology widely deployed nowadays
- It can give readers a rough idea of what this text is about
- Information analysts work successfully with them
- Task-based evaluation results:
  - Tombros et al. (1998) show slight improvement in precision and recall and larger improvement in time for a human search task
  - Mani et al. (1999) slight loss in accuracy and large advantage in time saving (50% of the time needed) for a relevance decision task

Problems with extracts

- Unclear to reader why particular sentence was chosen
- Coherence (syntactic, local problems)
  - Dangling anaphora
  - Unconnected discourse markers
- Cohesion (semantic discontinuities, global)
  - Concepts and agents are not introduced
  - Succession of events does not seem coherent

Fixes for coherence problems

- E.g. dangling anaphora:
  - resolve anaphora
  - recognize anaphoric use (as opposed to expletive use (“it”, Paice and Husk 1987)), then either
    - exclude sentences with dangling anaphora
    - include previous sentence if it contains the referent (Johnson et al. 1993; also for definite NPs) – But: length!
- There are no fixes for cohesion

Strategies for summary evaluation

1. Subjective judgements:
   How much do subjects like this summary? How coherent, well-written, etc do they find it?
2. Comparison to “gold standard” (predefined right answer):
   In how far does this summary resemble the “right answer”?
3. Task-based evaluation:
   How well can humans perform a task if they are given this summary?
4. Usability evaluation (extrinsic):
   Does the recipient of the summary have to change it? How much?

Problems in Summarisation Evaluation

1. Subjective judgements
   - Subjects can be biased
   - How to make sure they understand the same thing under ”informativeness”, for instance
2. Comparison to “gold standard”
   - by sentence co-selection, surface string similarity or “information overlap”
   - Problematic: humans do not agree on what a good summary is
   - Doubt about existence of a “gold standard”
3. Task-based evaluation
   - Probably the best evaluation around
   - Hard to define the task/set up the experiment
   - Time-consuming and expensive to do experiment
   - For final, end-of-project evaluation, not for day-to-day evaluation

Summary

- Summarisation by deep methods and problems
- Summarisation by text extraction
  - Importance features
  - Kupiec et al.'s (1995) method and training material
  - Lexical chains
- Summarisation evaluation and its problems