# Information Retrieval

# Lecture 2: Retrieval models

Computer Science Tripos Part II

UNIVERSITY OF CAMBRIDGE

Simone Teufel

Natural Language and Information Processing (NLIP) Group

sht25@cl.cam.ac.uk

## Today



- Definition of the information retrieval problem
- Query languages and retrieval models
  - Boolean model
  - Vector space model
- Logical model of a document/a term
  - Term weighting
  - Term stemming

## Information Retrieval: the task



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

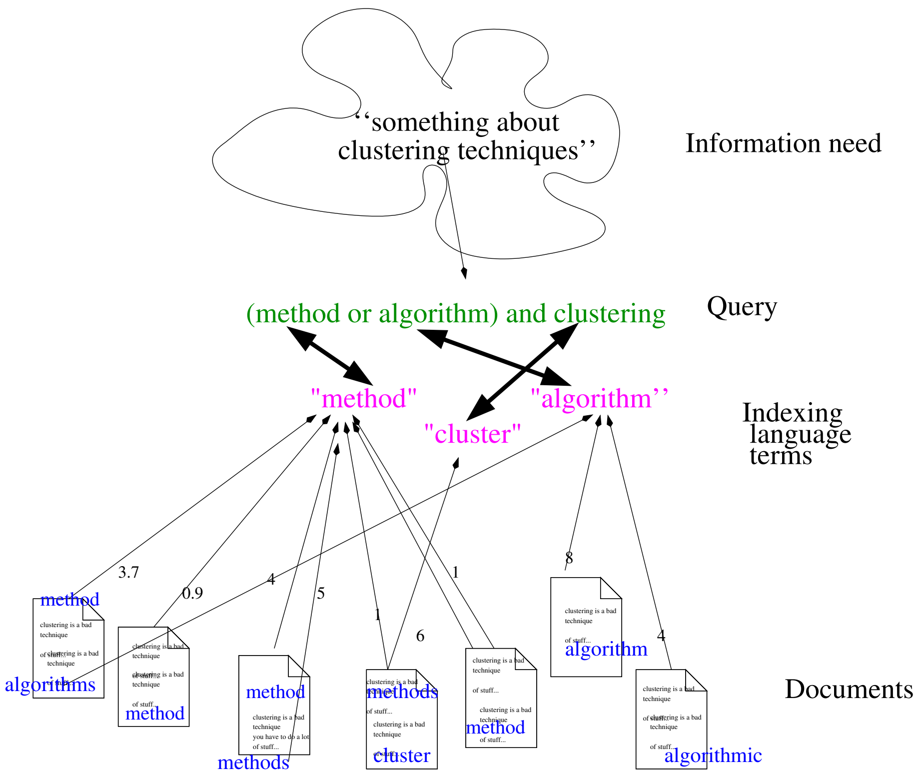
- Given: a large, static document collection
- Given: an information need (reformulated as a keyword-based query)
- Task: find all and only documents that are relevant to this query

### 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)?

## Query and document representation





## 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 $\rightarrow$ 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 |
| ... | |

# Free indexing languages



- 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 |
| was | 2 | 2 | 16 |

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

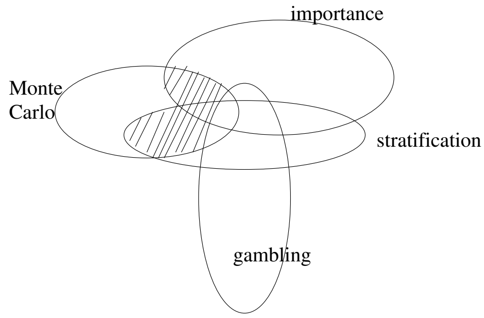
# Information Retrieval systems: Methods



- 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

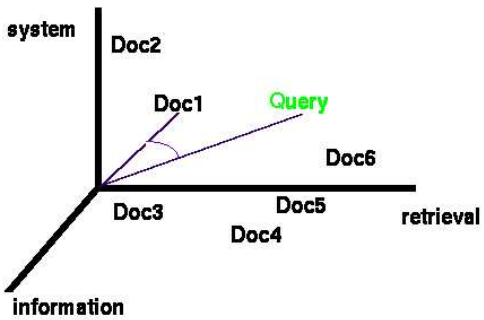



- Set theoretic interpretation of connectors AND OR BUT
- Often in use for bibliographic search engines (library)
- Problem 1: Expert knowledge necessary to create high-precision queries
- Problem 2: Binary relevance definition → unranked result lists (frustrating, time consuming)



# 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 | $\leftrightarrow$ | 0 |
| term$_2$ | 0 | 1 | 3 | ... | 1 | $\leftrightarrow$ | 1 |
| term$_3$ | 0 | 1 | 0 | ... | 2 | $\leftrightarrow$ | 0 |
| | ... | ... | ... | ... | ... | $\leftrightarrow$ | ... |
| term$_N$ | 4 | 7 | 0 | ... | 5 | $\leftrightarrow$ | 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')

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

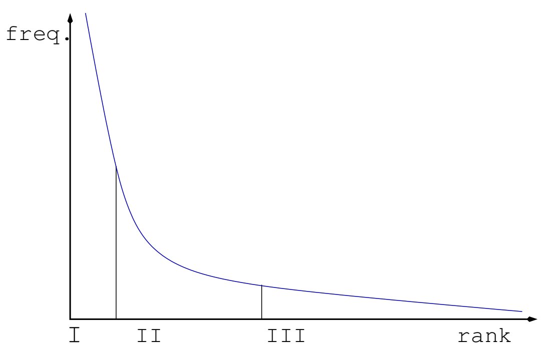


# Term importance and frequency

Zipf's law: the rank of a word is reciprocally proportional to its frequency:

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

(with $1.5 < \theta < 2$ for most languages)
($word_i$ being the $i$th most frequent word of the language)




- Zone I: High frequency words tend to be functional words ("the", "of")
- Zone III: Low frequency words tend to be typos, or unimportant words (too specific) ("Uni7ed", "super-noninteresting", "87-year-old", "0.07685")
- Zone II: Mid-frequency words are the best indicators of what the document is about

# 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 · 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 $D_{454}$)

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

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

$\rightarrow$ 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 23

- 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 24

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

CONNECT<br>CONNECTED<br>CONNECTING<br>CONNECTION<br>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
- Treats Sand — sander and wand — wander the same (does not conflate either, though sand/sander arguably could be conflated)
- 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 $\rightarrow \epsilon$ ($\epsilon$ 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 | → $\epsilon$ | cats | → cat |

#### Step 1b

| | | | | |
|---|---|---|---|---|
| (m>0) | EED | → EE | feed | → feed |
| | | | agreed | → agree |
| (*v*) | ED | → $\epsilon$ | plastered | → plaster |
| | | | bled | → bled |
| (*v*) | ING | → $\epsilon$ | 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 → | $\epsilon$ | 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 → | $\epsilon$ | hopeful | → hope |
| (m>0) | NESS → | $\epsilon$ | 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