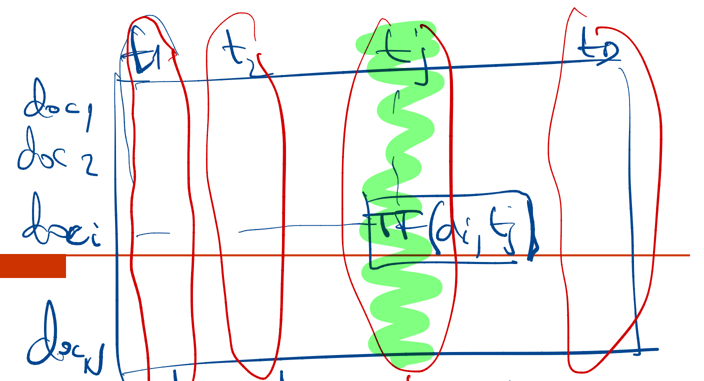
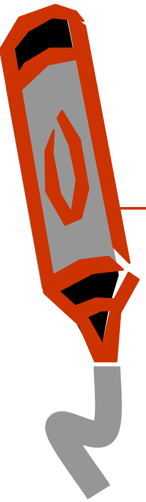
indexing



- inverted list = DT matrix listed by column (not by row = doc) = term

inv list(tj) = { (doc_d, TF(tj, d)), (doc_g, TF(tj, g)), ... (doc_z, TF(tj, z)) }

- inverted index engineering
- what to index? terms = words?, bigrams?, stopwords? NLP? positions?
- stemming: friend / friends / friendship / friendliness / ? (same stem root)
- how often words appear?



• how fast vocabulary grows?

1st word → new 100%
2nd word → new 99.9%?
1000th word → new 20%?

set of unique terms = **vocabulary**

collect. size = 1000,000,000 word → new 0.0001%

- File organizations or *indexes* are used to increase performance of system
  - Will talk about how to store indexes later

- Text *indexing* is the process of deciding what will be used to represent a given document

- These *index terms* are then used to build indexes for the documents

- The *retrieval model* described how the indexed terms are incorporated into a model
  - Relationship between retrieval model and indexing model

manual vs automatic

Manual vs. Automatic Indexing

- Manual or human indexing:
  - – Indexers decide which keywords to assign to document based on *controlled vocabulary*
    - e.g. MEDLINE, MeSH, LC subject headings, Yahoo
  - – Significant cost

- Automatic indexing:
  - – Indexing program decides which words, phrases or other features to use *from text of document*
  - – Indexing speeds range widely

- Indri (CIIR research system) indexes approximately 10GB/hour

terminology

- *Index language*
  - Language used to describe documents and queries
- *Exhaustivity*
  - Number of different topics indexed, completeness
- *Specificity*
  - Level of accuracy of indexing
- *Pre-coordinate indexing*
  - Combinations of index terms (e.g. phrases) used as indexing label
  - E.g., author lists key phrases of a paper
- *Post-coordinate indexing*
  - Combinations generated at search time
  - Most common and the focus of this course

library of Congress headings

A -- GENERAL WORKS
B -- PHILOSOPHY. PSYCHOLOGY. RELIGION
C -- AUXILIARY SCIENCES OF HISTORY
D -- HISTORY: GENERAL AND OLD WORLD
E -- HISTORY: AMERICA
F -- HISTORY: AMERICA
G -- GEOGRAPHY. ANTHROPOLOGY. RECREATION
H -- SOCIAL SCIENCES
J -- POLITICAL SCIENCE
K -- LAW
L -- EDUCATION
M -- MUSIC AND BOOKS ON MUSIC
N -- FINE ARTS
P -- LANGUAGE AND LITERATURE
Q -- SCIENCE
R -- MEDICINE
S -- AGRICULTURE
T -- TECHNOLOGY
U -- MILITARY SCIENCE
V -- NAVAL SCIENCE
Z -- BIBLIOGRAPHY. LIBRARY SCIENCE. INFORMATION RESOURCES (GENERAL)

where is computer science ?

- Subclass Q
- Subclass QA
- Subclass QB
- Subclass QC
- Subclass QD
- Subclass QE
- Subclass QH
- Subclass QK
- Subclass QL
- Subclass QM
- Subclass QP
- Subclass QR Microbiology

Subclass Q

Q1-390	Science (General)
Q1-295	General
Q300-390	Cybernetics
Q350-390	Information theory

Subclass QA

QA1-939	Mathematics
QA1-43	General
QA47-59	Tables
QA71-90	Instruments and machines
QA75-76.95	Calculating machines
QA75.5-76.95	Electronic computers. Computer science
QA76.75-76.765	Computer software
QA101-(145)	Elementary mathematics. Arithmetic
QA150-272.5	Algebra
QA273-280	Probabilities. Mathematical statistics
QA299.6-433	Analysis
QA440-699	Geometry. Trigonometry. Topology
QA801-939	Analytic mechanics

manual vs automatic indexing

	Manual	**Automatic**
Controlled Vocabulary	Current indexing practice	Text categorization “Intelligent” IR
Free Text	Current indexing practice	Text search engines “Statistical” IR

manual vs automatic indexing

- Experimental evidence is that retrieval effectiveness using automatic indexing can be at least as effective as manual indexing with controlled vocabularies
  - original results were from the Cranfield experiments in the 60s
  - considered counter-intuitive
  - other results since then have supported this conclusion
  - broadly accepted at this point

- Experiments have also shown that using *both* manual and automatic indexing improves performance
  - "combination of evidence"

basic automatic indexing

- Parse documents to recognize structure
  - e.g. title, date, other fields
  - clear advantage to XML
- Scan for word tokens
  - numbers, special characters, hyphenation, capitalization, etc.
  - languages like Chinese need *segmentation*
  - record positional information for *proximity* operators
- Stopword removal
  - based on short list of common words such as “the”, “and”, “or”
  - saves storage overhead of very long indexes
  - can be dangerous (e.g., “The Who”, “and-or gates”, “vitamin a”)

basic automatic indexing

- Stem words
  - morphological processing to group word variants such as plurals
  - better than string matching (e.g. comput*)
  - can make mistakes but generally preferred
  - not done by most Web search engines (why?)

- Weight words
  - want more “important” words to have higher weight
  - using frequency in documents and database
  - frequency data independent of retrieval model

- Optional
  - phrase indexing
  - thesaurus classes (probably will not discuss)
  - others...

basic indexing

- Parse and tokenize → parse data
- Remove stop words
- Stemming
- Weight terms (not HW2)

→ (simple) NLP analysis

words vs terms vs concepts

very costly

very useful

- Simple indexing is based on words or word stems
  - More complex indexing could include phrases or thesaurus classes
  - *Index term* is general name for word, phrase, or feature used for indexing

– topics
– classes
– types

- *Concept-based retrieval* often used to imply something beyond word indexing

medical: – body parts
– disease cat
– med. branch

- In virtually all systems, a *concept* is a name given to a set of recognition criteria or rules
  - similar to a thesaurus class

topic modeling (Hw8)

⇒ automatic clustering

- Words, phrases, synonyms, linguistic relations can all be evidence used to infer presence of the concept

- e.g. the concept "information retrieval" can be inferred based on the presence of the words "information", "retrieval", the phrase "information retrieval" and maybe the phrase "text retrieval" cost/benefit =?

index units:

– words

– bigrams, trigrams ---

– skipgrams/phrases

phrases

- Both statistical and syntactic methods have been used to identify “good” phrases

- Proven techniques include finding all word pairs that occur more than *n* times in the corpus or using a partof-speech tagger to identify simple noun phrases
  - 1,100,000 phrases extracted from all TREC data (more than 1,000,000 WSJ, AP, SJMS, FT, Ziff, CNN documents)
  - 3,700,000 phrases extracted from PTO 1996 data

- Phrases can have an impact on both effectiveness and efficiency
  - phrase indexing will speed up phrase queries
  - finding documents containing “Black Sea” better than finding documents containing both words
  - effectiveness not straightforward and depends on retrieval model

- e.g. for “information retrieval”, how much do individual words count?

top phrases on T R E C 2–8

these
bigrams

useful >>>

unigrams

65824 United States
61327 Article Type
33864 Los Angeles
18062 Hong Kong
17788 North Korea
17308 New York
15513 San Diego
15009 Orange County
12869 prime minister
12799 first time
12067 Soviet Union
10811 Russian Federation
9912 United Nations
8127 Southern California
7640 South Korea
7620 end recording
7524 European Union
7436 South Africa
7362 San Francisco
7086 news conference
6792 City Council
6348 Middle East
6157 peace process
5955 human rights
5837 White House
5778 long time
5776 Armed Forces
5636 Santa Ana
5619 Foreign Ministry
5527 Bosnia-Herzegovina
5458 words indistinct
5452 international community
5443 vice president
5247 Security Council
5098 North Korean
5023 Long Beach
4981 Central Committee
4872 economic development
4808 President Bush
4652 press conference
4602 first half
4565 second half
4495 nuclear weapons
4448 UN Security Council
4426 South Korean
4219 first quarter
4166 Los Angeles County
4107 State Duma
4085 State Council
3969 market economy
3941 World War II

phrases from 50 T R E C queries

14	international criminal activity	
9	international criminal	
1436	criminal activity	
84	hubble telescope	
188	passenger vehicle	
9086	civil war	
255	hydroelectric project	
5261	detailed description	
183	rap music	
1449	negative effect	→ sentiment analysis
8081	young people	
297	radio wave	
26	radio tower	
404	car phone	
135	brain cancer	

5	theft of trade secret
1324	trade secret
573	sources of information
530	trade journal
334	business meet
506	patent office
1870	trade show
26	competitor's product
63	growing plant
41	magnetic levitate
38	commercial harvest
58	highway accident

information extraction

- Special recognizers for specific concepts
  - people, organizations, places, dates, monetary amounts, products, …

• “Meta” terms such as #COMPANY, #PERSON can be added to indexing

• e.g., a query could include a restriction like “…the document must specify the location of the companies involved…”

• Could potentially customize indexing by adding more recognizers
  - difficult to build
  - problems with accuracy
  - adds considerable overhead

• Key component of question answering systems
  - To find concepts of the right type (e.g., people for “who” questions)

indexing example

- **Original text:**
  John Davenport, ~~52 years old, was~~ appointed chief executive officer ~~of this~~ international telecommunications concern~~'s~~ ~~U.S.~~ subsidiary, Cable ~~&~~ Wireless North America ~~Inc.~~ ~~Mr.~~ Davenport, ~~who~~ succeeds John Zrno, ~~is~~ currently general manager ~~of the~~ group's operations ~~in~~ Bermuda.
- **One indexing result:**
  john davenport appoint chief executive officer international telecommunication concern subsidiary cable wireless north america davenport succeed john zrno current general manager group operation bermuda

basic HW2

N.E.R tags → very useful

very costly

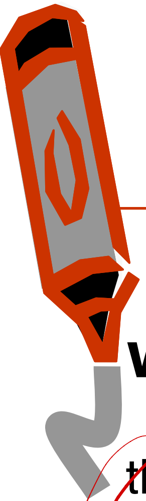
(cost/benefit?)

- **Another possibility:**
  John_Davenport #person 52 years_old #age appoint chief_executive_officer international telecommunication concern #USA subsidiary Cable_&_Wireless_North_America #company Davenport #person succeed John_Zrno #person general_manager group operation Bermuda #foreigncountry

NLP tags

stopwords

- Remove non-content-bearing words
  - Function words that do not convey much meaning
- Can be as few as one word
  - What might that be?
- Can be several hundreds
  - Surprising(?) examples from Inquery at UMass (of 418)
  - Halves, exclude, exception, everywhere, sang, saw, see, smote, slew, year, cos, ff, double, down
- Need to be careful of words in phrases
  - Library of Congress, Smoky the Bear
- Primarily an efficiency device, though sometimes helps with spurious matches



stopwords

Word	Occurrences	Percentage
the	8,543,794	6.8 ≃ 7%
of	3,893,790	3.1
to	3,364,653	2.7
and	3,320,687	2.6
in	2,311,785	1.8
is	1,559,147	1.2
for	1,313,561	1.0
that	1,066,503	0.8
said	1,027,713	0.8

Frequencies from 336,310 documents in the 1GB TREC Volume 3 Corpus
125,720,891 total word occurrences; 508,209 unique words

stopwords

a about above according across after afterwards again against albeit all almost alone along already also although always am among amongst an and another any anybody anyhow anyone anything anyway anywhere apart are around as at av be became because become becomes becoming been before beforehand behind being below beside besides between beyond both but by can cannot canst certain cf choose contrariwise cos could cu day do does doesn't doing dost doth double down dual during each either else elsewhere enough et etc even ever every everybody everyone everything everywhere except excepted excepting exception exclude excluding exclusive far farther farthest few ff first for formerly forth forward from front further furthermore furthest get go had halves hardly has hast hath have he hence henceforth her here hereabouts hereafter hereby herein hereto hereupon hers herself him himself hindmost his hither hitherto how however howsoever i ie if in inasmuch inc include included including indeed indoors inside insomuch instead into inward inwards is it its itself just kind kg km last latter latterly less lest let like little ltd many may maybe me meantime meanwhile might moreover most mostly more mr mrs ms much must my myself namely need neither never nevertheless next no nobody none nonetheless noone nope nor not nothing notwithstanding now nowadays nowhere of off often ok on once one only onto or other others otherwise ought our ours ourselves out outside over own per perhaps plenty provide quite rather really round said sake same sang save saw see seeing seem seemed seeming seems seen seldom selves sent several shalt she should shown sideways since slept slew slung slunk smote so some somebody somehow someone something sometime sometimes somewhat somewhere spake spat spoke spoken sprang sprung stave staves still such supposing than that the thee their them themselves then thence thenceforth there thereabout therabouts thereafter thereby therefore therein thereof thereon thereto thereupon these they this those thou though thrice through throughout thru thus thy thyself till to together too toward towards ugh unable under underneath unless unlike until up upon upward upwards us use used using very via vs want was we week well were what whatever whatsoever when whence whenever whensoever where whereabouts whereafter whereas whereat whereby wherefore wherefrom wherein whereinto whereof whereon wheresoever whereto whereunto whereupon wherever wherewith whether whew which whichever whichsoever while whilst whither who whoa whoever whole whom whomever whomsoever whose whosoever why will wilt with within without worse worst would wow ye yet year yippee you your yours yourself yourselves

stemming

- Stemming is commonly used in IR to conflate morphological variants

- Typical stemmer consists of collection of rules and/or dictionaries
    - simplest stemmer is “suffix s”
    - Porter stemmer is a collection of rules
    - KSTEM [Krovetz] uses lists of words plus rules for inflectional and derivational morphology
    - similar approach can be used in many languages
    - some languages are difficult, e.g. Arabic

- Small improvements in effectiveness and significant usability benefits
    - With huge document set such as the Web, less valuable

stemming

servomanipulator | servomanipulators servomanipulator
logic | logical logic logically logics logicals logicial logicially
login | login logins
microwire | microwires microwire
overpressurize | overpressurization overpressurized overpressurizations overpressurizing overpressurize
vidrio | vidrio
sakhuja | sakhuja
rockel | rockel
pantopon | pantopon
knead | kneaded kneads knead kneader kneading kneaders
linxi | linxi
rocket | rockets rocket rocketed rocketing rocketings rocketeer ?
hydroxytoluene | hydroxytoluene
ripup | ripup

Porter stemmer

- Based on a measure of vowel-consonant sequences
  - measure m for a stem is [C](VC)m[V] where C is a sequence of consonants and V is a sequence of vowels (inc. y), [] = optional
  - m=0 (tree, by), m=1 (trouble,oats, trees, ivy), m=2 (troubles, private)
- Algorithm is based on a set of condition action rules
  - old suffix → new suffix
  - rules are divided into steps and are examined in sequence
- Longest match in a step is the one used
  - e.g. Step 1a: sses → ss *(caresses → caress)*
    ies i *(ponies → poni)*
    s NULL *(cats → cat)*
  - e.g. Step 1b: if m>0 eed → ee *(agreed → agree)*
    if *v*ed → NULL *(plastered → plaster but bled → bled)*
    then at → ate (*conflat(ed) → conflate)*
- Many implementations available
  - http://www.tartarus.org/~martin/PorterStemmer/
- Good average recall and precision

stemming example

- **Original text:**

Document will describe marketing strategies carried out by U.S. companies for their agricultural chemicals, report predictions for market share of such chemicals, or report market statistics for agrochemicals, pesticide, herbicide, fungicide, insecticide, fertilizer, predicted sales, market share, stimulate demand, price cut, volume of sales

- **Porter Stemmer:**

market strateg carr compan agricultur chemic report predict market share chemic report market statist agrochem pesticid herbicid fungicid insecticid fertil predict sale stimul demand price cut volum sale

- **KSTEM:**

marketing strategy carry company agriculture chemical report prediction market share chemical report market statistic agrochemic pesticide herbicide fungicide insecticide fertilizer predict sale stimulate demand price cut volume sale

stemming issues

- Lack of domain-specificity and context can lead to occasional serious retrieval failures
- Stemmers are often difficult to understand and modify
- Sometimes too aggressive in conflation
  - e.g. "policy"/"police", "execute"/"executive", "university"/"universe", "organization"/"organ" are conflated by Porter
- Miss good conflations
  - e.g. "European"/"Europe", "matrices"/"matrix", "machine"/"machinery" are not conflated by Porter
- Produce stems that are not words and are often difficult for a user to interpret
  - e.g. with Porter, "iteration" produces "iter" and "general" produces "gener"
- Corpus analysis can be used to improve a stemmer or replace it

corpus-based stemming

- Hypothesis: Word variants that should be conflated will co-occur in documents (text windows) in the corpus

- Modify equivalence classes generated by a stemmer or other "aggressive" techniques such as initial n-grams
  - more aggressive classes mean less conflations missed

- New equivalence classes are clusters formed using (modified) EMIM scores between pairs of word variants

- Can be used for other languages

equivalence classes

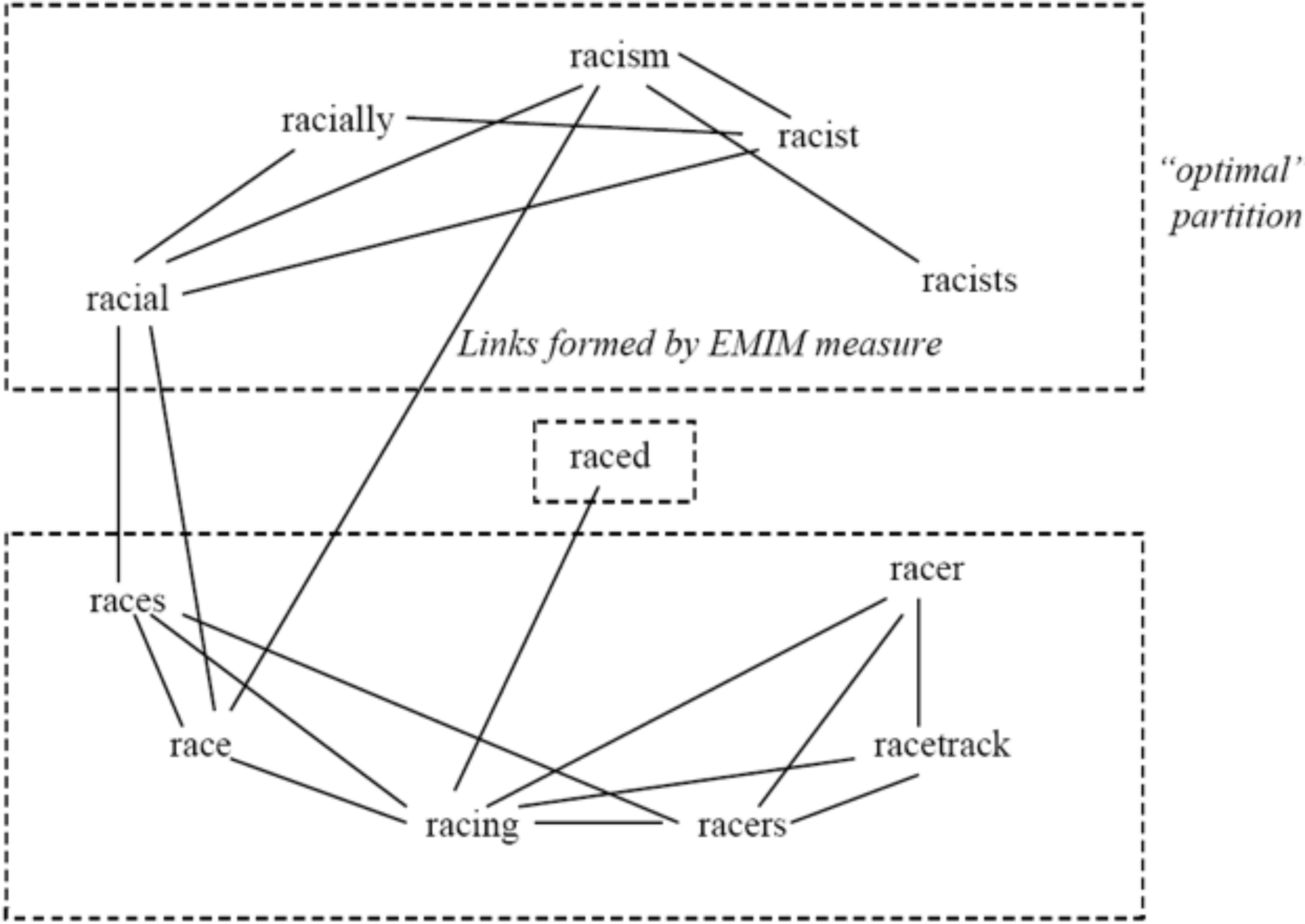
Some Porter Classes for a WSJ Database

abandon abandoned abandoning abandonment abandonments abandons
abate abated abatement abatements abates abating
abrasion abrasions abrasive abrasively abrasiveness abrasives
absorb absorbable absorbables absorbed absorbencies absorbency absorbent
absorbents absorber absorbers absorbing absorbs
abusable abuse abused abuser abusers abuses abusing abusive abusively
access accessed accessibility accessible accessing accession

Classes refined through corpus analysis (singleton classes omitted)

abandonment abandonments
abated abatements abatement
abrasive abrasives
absorbable absorbables
absorbencies absorbency absorbent
absorber absorbers
abuse abusing abuses abusive abusers abuser abused
accessibility accessible

partitions



racism
racially
racist
racists
racial
Links formed by EMIM measure
"optimal" partition
raced
racer
races
race
racetrack
racing
racers

corpus-based stemming

- Clustering technique used has an impact

- Both Porter and KSTEM stemmers are improved slightly by this technique (max. of 4% avg. precision on WSJ)

- N-gram stemmer gives same performance as improved “linguistic” stemmers

- N-gram stemmer gives same performance as baseline Spanish linguistic stemmer

- Suggests advantage to this technique for
  - building new stemmers
  - building stemmers for new languages

feature selection/weighting

- Basic Issue: Which terms should be used to index (describe) a document?

- Different focus than retrieval model, but related

- Sometimes seen as *term weighting*

- Some approaches
  - TF·IDF
  - Term Discrimination model
  - 2-Poisson model
  - Clumping model
  - Language models

index models

- What makes a term good for indexing?
  - Trying to represent “key” concepts in a document

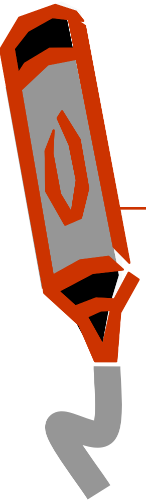
- What makes an index term good for a query?

tf weights

- Standard weighting approach for many IR systems
  - many different variations of exactly how it is calculated

- TF component - the more often a term occurs in a document, the more important it is in describing that document
  - normalized term frequency
  - normalization can be based on maximum term frequency or could include a document length component
  - often includes some correction for estimation using small samples
  - some bias towards numbers between 0.4-1.0 to represent fact that a single occurrence of a term is important
  - logarithms used to smooth numbers for large collections
  - e.g. where c is a constant such as 0.4, *tf* is the term frequency in the document, and *max_tf* is the maximum term frequency in any document

$$c+(1-c)\frac{\log(tf+0.5)}{\log(\max\_tf+1.0)}$$



tf = term frequency

² raw tf (called tf) = count of 'term' in document

² robinsontf (okpitf): $okpitf = \frac{tf}{tf + :5 + 1{:}5\frac{doclen}{avgdoclen}}$

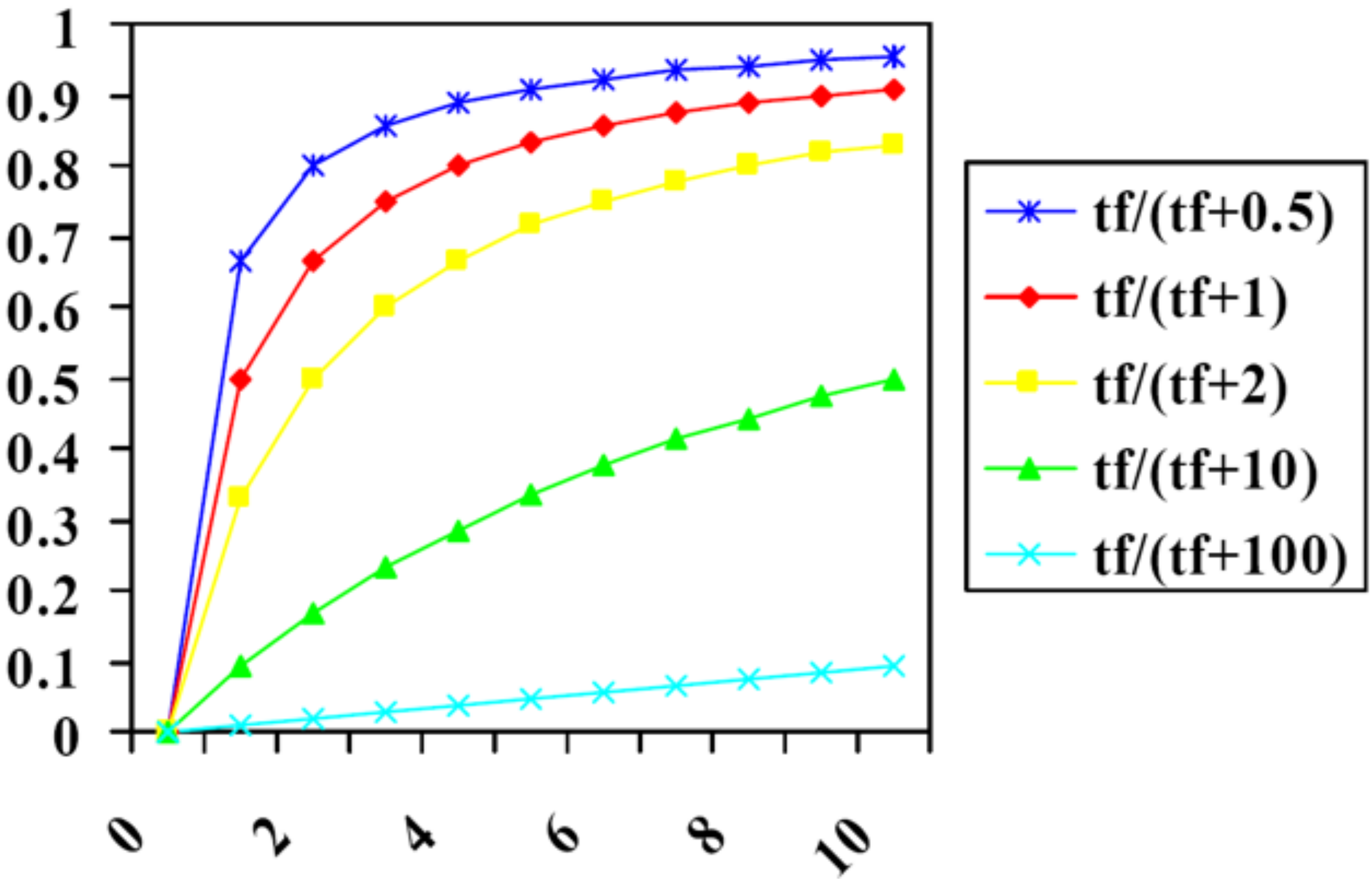
– Based on a set of simple criteria loosely connected to the 2–Poisson model

– Basic formula is tf/(k+tf) where k is a constant (approx. 1–2)

– Document length introduced as a verbosity factor

² many variants

Robertson tf



IDF weights

- Invers Document Frequency
- used to weight terms based on frequency in the corpus (or language)
- ¯xed, it can be precomputed for every term
- $IDF(t) = \log(\frac{N}{N_t})$ where

$N =$ # of docs

$N_t =$ # of docs containing term t

tf–idf

- in fact tf*idf
- the weight on every term is tf(t,d)*idf(t)

Often : $IDF = \log(N/df) + 1$ where N is the number of documents in the collection, df is the number of documents the term occurs in

$IDF = -\log p$, wher p is the term probability

sometimes normalized when in TF.IDF combination

e.g. for INQUERY: $\frac{\log(\frac{N+0.5}{df})}{\log(N+1.0)}$

- T F and IDF combined using multiplication
- No satisfactory model behind these combinations

term discrimination model

- Proposed by Salton in 1975

- Based on vector space model
  - documents and queries are vectors in an n-dimensional space for n terms

- Compute *discrimination value* of a term
  - degree to which use of the term will help to distinguish documents

- Compare average similarity of documents both with and without an index term

term discrimination model

- Compute average similarity or "density" of document space

$$AVGSIM = K \sum_{i=1}^{n} \sum_{\substack{j=1 \\ i \neq j}}^{n} similar(D_i, D_j)$$

  - *AVGSIM* is the density
  - where K is a normalizing constant (e.g., 1/n(n-1))
  - *similar()* is a similarity function such as cosine correlation
- Can be computed more efficiently using an average document or *centroid*
  - frequencies in the centroid vector are average of frequencies in document vectors

$$AVGSIM = K \sum_{i=1}^{n} similar(\overline{D}, D_i)$$

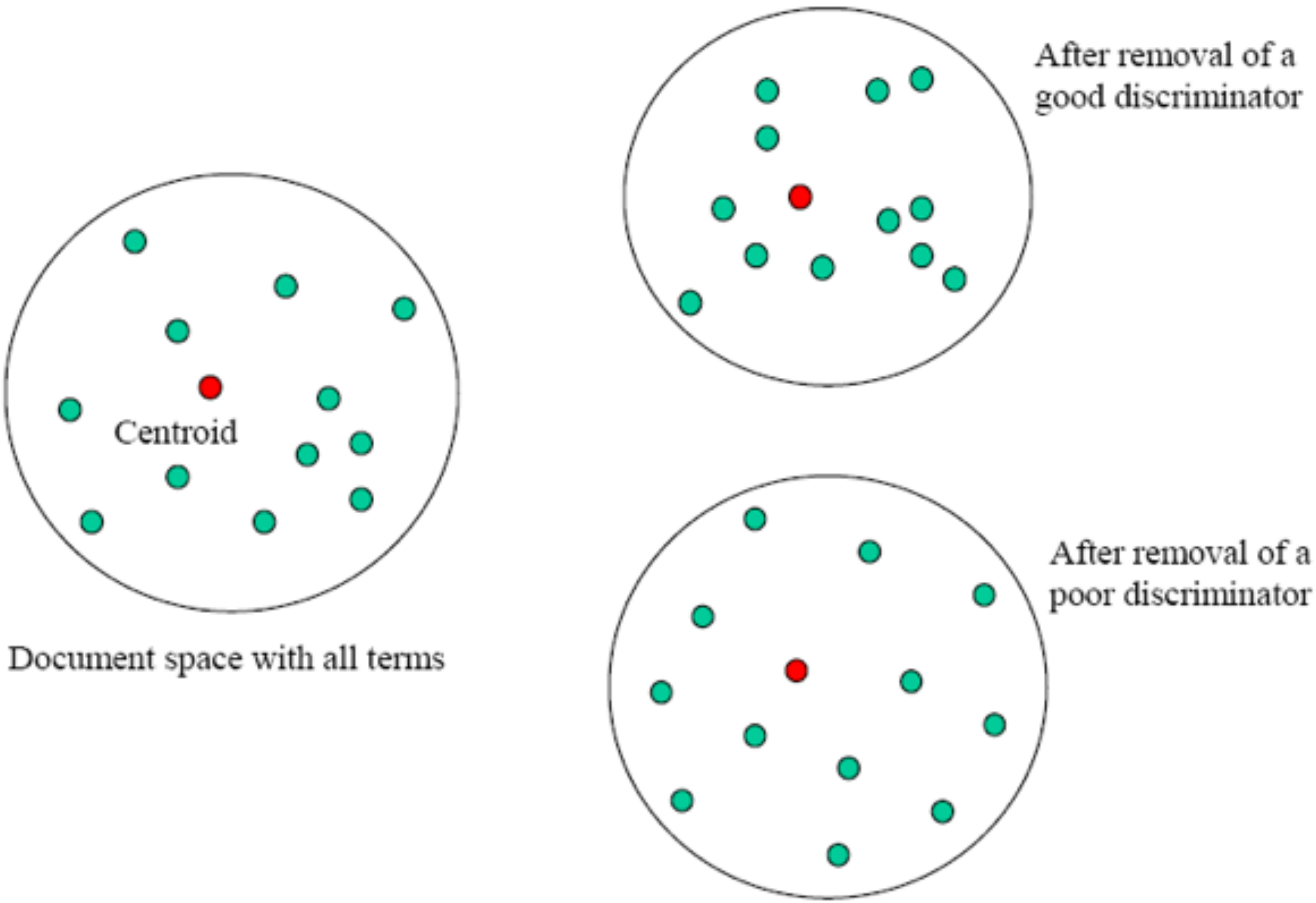
term discrimination model

- Let *(AVGSIM)*$_k$ be density with term k removed from documents
- Discrimination value for term k is

$$DISCVALUE_k = (AVGSIM)_k - AVGSIM$$

- Good discriminators have positive *DISCVALUE*$_k$
  - introduction of term decreases the density (moves some docs away)
  - tend to be medium frequency
- Indifferent discriminators have *DISCVALUE* near zero
  - introduction of term has no effect
  - tend to be low frequency
- Poor discriminators have negative *DISCVALUE*
  - introduction of term increases the density (moves all docs closer)
  - tend to be high frequency
- Obvious criticism is that discrimination of *relevant* and *nonrelevant* documents is the important factor

term discrimination model



term discrimination model

Cranfield 424	MED 450	Time 425
	Best Discriminators	
panel	marrow	Buddhist
flutter	Amyloidosis	Diem
jet	Lymphostasis	Lao
cone	Hepatitis	Arab
separate	Hela	Viet
shell	antigan	Kurd
yaw	chromosome	Wilson
nozzle	irradiate	Baath
transit	tumor	Park
degree	virus	Nenni
	Worst Discriminators	
equate	clinic	work
theo	children	lead
bound	act	Red
effect	high	minister
solution	develop	nation
method	treat	party
press	increase	commune
result	result	U.S.
number	cell	govern
flow	patient	new

summary

- Index model identifies how to represent documents
  - Manual
  - Automatic
- Typically consider content-based indexing
  - Using features that occur within the document
- Identifying features used to represent documents
  - Words, phrases, concepts, …
- Normalizing them if needed
  - Stopping, stemming, …
- Assigning a weight (significance) to them
  - TF·IDF, discrimination value
- Some decisions determined by retrieval model
  - E.g., language modeling incorporates "weighting" directly