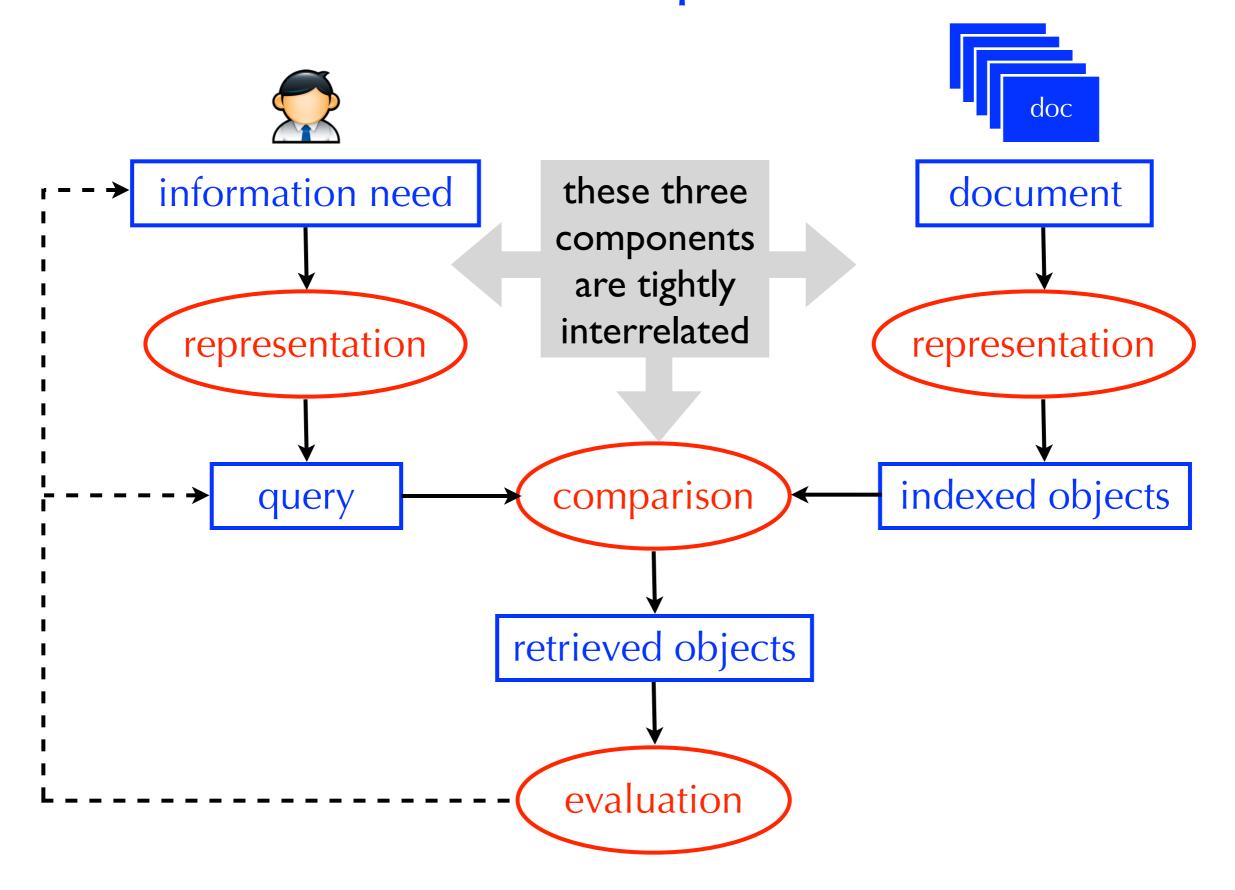
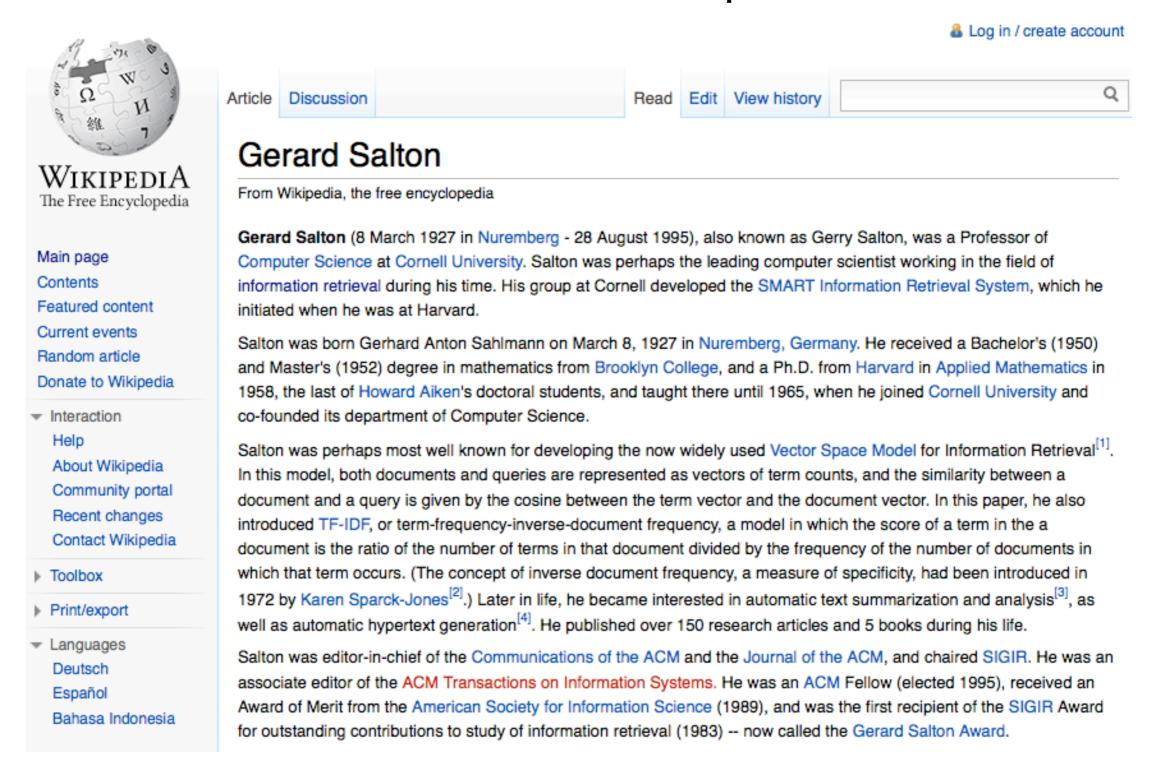
Jaime Arguello

INLS 509: Information Retrieval

jarguell@email.unc.edu



How should this document be represented?



Elements of a Document Representation

- Document attributes (metadata)
 - source, publication date, language, length, etc.
- Controlled vocabulary index terms
- Free-text index terms
 - terms selected from the document text itself
 - may also include text from <u>outside</u> the document (e.g., anchor text)
 - lots of room for creativity!

Elements of a Document Representation



controlledvocabulary index terms

Categories: 1927 births I 1995 deaths I American computer scientists I Computer pioneers I Harvard University alumni I Harvard University faculty I Cornell University faculty I Fellows of the Association for Computing Machinery I Guggenheim Fellows

Elements of a Document Representation



Text Processing

gerard salton 8 march 1978 in nuremberg 28 august 1995 also know as gerry salton was professor of computer science at cornell university salton was perhaps the leading computer scientist working in the field of information retrieval during his time his group at cornell developed the smart information retrieval system which he initiated when he was at harvard

- Our goal is to describe content using content
- After mark-up removal, down-casing, and tokenization, what we have is a sequence of terms
- What are the most descriptive words?

Salton was editor-in-chief of the Communications of the ACM and the Journal of the ACM, and chaired SIGIR. He was an associate editor of the ACM Transactions on Information Systems. He was an ACM Fellow (elected 1996), received an Award of Meltr from the American Society for Information Science (1998), and was the first recipient of the SIGIR Award for outstanding contributions to study of information retrieval (1983) — now called the Gerard Salton Award.

Term-Frequencies top 20

rank	term	freq.	rank	term	freq.
ı	the	34	11	as	9
2	of	29	12	he	9
3	a	20	13	vector	8
4	in	20	14	an	8
5	and	19	15	S	7
6	salton	18	16	term	7
7	model	15	17	for	7
8	was	12	18	automatic	7
9	information	11	19	paper	6
10	retrieval	10	20	gerard	6

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9	information	11	19	paper	6
10	retrieval	10	20	gerard	6

IMDB Corpus term-frequencies

rank	term	frequency	rank	term	frequency
l	the	1586358	11	year	250151
2	a	854437	12	he	242508
3	and	822091	13	movie	241551
4	to	804137	14	her	240448
5	of	657059	15	artist	236286
6	in	472059	16	character	234754
7	is	395968	17	cast	234202
8	i	390282	18	plot	234189
9	his	328877	19	for	207319
10	with	253153	20	that	197723

Stopwords

- A stopword is a term that is discarded from the document representation
- Typically the <u>same</u> set of stopwords is used in processing all documents in the collection
- Stopwords are typically function words: determiners (a, the), prepositions (on, above), conjunctions (and, but)
- May also be corpus-specific: "plot" in the IMDB corpus
- Assumption: stopwords are unimportant because they are frequent in <u>every</u> document

Lemur Stopword List

first 60 (sorted alphabetically)

a	all	amongst	anywhere	become	besides
about	almost	an	apart	becomes	between
above	alone	and	are	becoming	beyond
according	along	another	around	been	both
across	already	any	as	before	but
after	also	anybody	at	beforehand	by
afterwards	although	anyhow	av	behind	can
again	always	anyone	be	being	can
against	am	anything	became	below	cannot
albeit	among	anyway	because	beside	canst

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Term-Frequencies after stopword removal

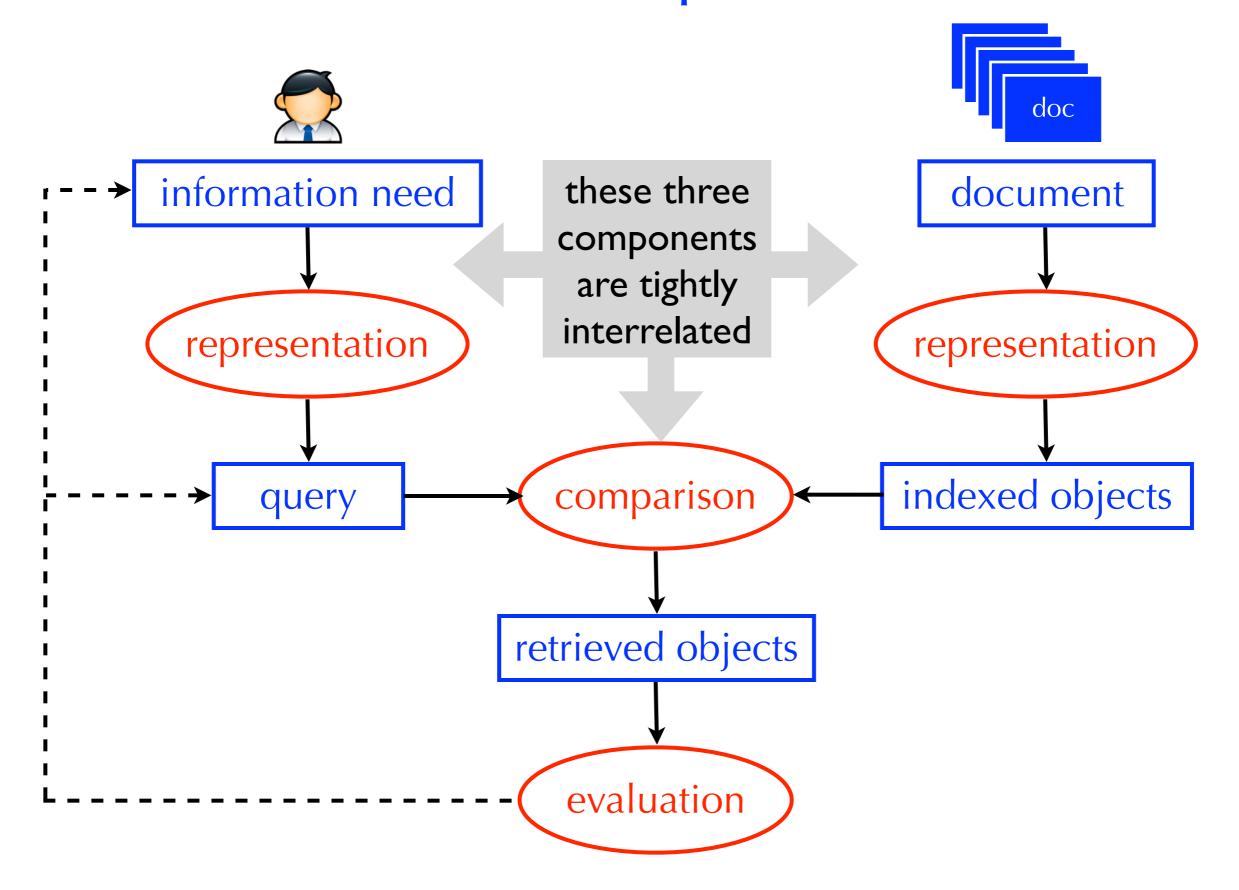
<u>rank</u>	term	freq.	rank	term	freq.
I	salton	18	11	paper	6
2	model	15	12	document	6
3	information	11	13	acm	6
4	retrieval	10	14	1975	4
5	vector	8	15	frequency	4
6	S	7	16	science	4
7	term	7	17	cornell	4
8	automatic	7	18	award	3
9	gerard	6	19	0	3
10	space	6	20	8	3

Creating a Stopword List

- Sort vocabulary based on frequency in the corpus
- Examine the most frequent words
- Examine a query-log to see which frequent terms may be important
- 38% of unique AOL queries contain at least one stopword (may or may not be important - more later)
- 0.025% of unique AOL queries are nothing but stopwords
 - longest: i want something else to get me through this (third eye blind lyrics)

Trends in Stopword Removal

- The earliest systems used stopword lists of 200-300 terms
- To improve efficiency and effectiveness
- Very frequent terms were problematic for early retrieval models (e.g, OR operations in ranked boolean)
- Web search engines generally do not remove stopwords
- The latest trend is to index stopwords and (possibly) ignore them at query-time if they seem unimportant
- Newer retrieval models are better at handling very frequent terms (later lecture)



AOL Query-Log Examples

stopword removal

wrong lyrics

am i wrong lyrics

i was wrong lyrics

wrong again lyrics

where did i go wrong lyrics

wrong lyrics

got me wrong lyrics

what went wrong lyrics

change

be the change you want in others

how can i change me

change

where is my change

i want my change

never change

buy house

who will buy my house

buy a house

buy my house

buy house

we buy house

how to buy a house

calculate bmi

calculate bmi

calculate my bmi

how to calculate your bmi

how to calculate bmi

Morphology

• the study and description of word formation (as inflection, derivation, and compounding) in language

Merriam-Webster Dictionary

Morphology

- Inflectional morphology: changes to a word that encode its grammatical usage (e.g., tense, number, person)
 - say vs. said, cat vs. cats, see vs. sees
- Derivational morphology: changes to a word to make a new word with related meaning
 - organize, organization, organizational
- Compounding: combining words to form new ones
 - shipwreck, outbound, beefsteak
 - more common in other languages (e.g., german)
 - lebensversicherungsgesellschaftangestellter

Morphological Analysis in information retrieval

- Basic question: words occur in different forms. Do we want to treat different forms as different index terms?
- Conflation: treating different (inflectional and derivational) variants <u>as the same index term</u>

in information retrieval

 Conflation: treating different (inflectional and derivational) variants <u>as the same index term</u>

image	images	imaging	imag* (root form)
df=6	df=4	df=3	df=6
1,4	1,4	1,4	1, 12
10, 1	10, 5	10, 5	10, 11
15, 2	16, 1	16, 1	15, 2
16, 1	68, I		16, 3
33, 5			33, 5
68 , 7			68 , 8

docid, term frequency

Morphological Analysis in information retrieval

- What are we trying to achieve by conflating morphological variants?
- Goal: help the system ignore <u>unimportant</u> variations of language usage



Morphological Analysis in information retrieval

repairing computer

Q

Guide to Computer Troubleshooting and Repair - PC ... Q

www.daileyint.com/hmdpc/manual.htm - Cached

PC's are actually much easier to **repair** these days than in the early 90's when I wrote my original guide for technicians I was training. The number of discrete ...

Online Computer Training Courses - For all beginners and experts ... www.beyourownit.com/ - Cached

Want to learn about **computers**? You've found the right place! On this website, you'll be able to find everything from simple **computer repair** articles and **computer ..**

Repairing basic computer hard ware problem (system disk failure ...

www.instructables.com/.../Repairing-basic-computer-hard-ware-and... - Cached May 10, 2008 – THIS GUIDE IS NOT YET FINISHED, I WILL ADD MORE INFORMATION WHEN I GET A CHANCE.If you need any help with fixing a computer ...

Computer-Repair Technicians

www.collegeboard.com > ... > Majors & Careers Central > Profiles - Cached
Computer-repair technicians maintain and repair computers, scanners, printers, monitors, and other computer equipment. Learn more about this career at ...

Computer repair NYC | Laptop repair ny | PC repair NY |

ifixny.com/ - Cached

Computer repair ny. Data recovery nyc. We offers a full range of computer fix and technical support with free diagnostics and estimates, also iPhone BlackBerry ...

in information retrieval

 The query "computer repairs" will match all combinations of:

computers
computing
computation
computational

and

repairs
repaired
repairing
repairable

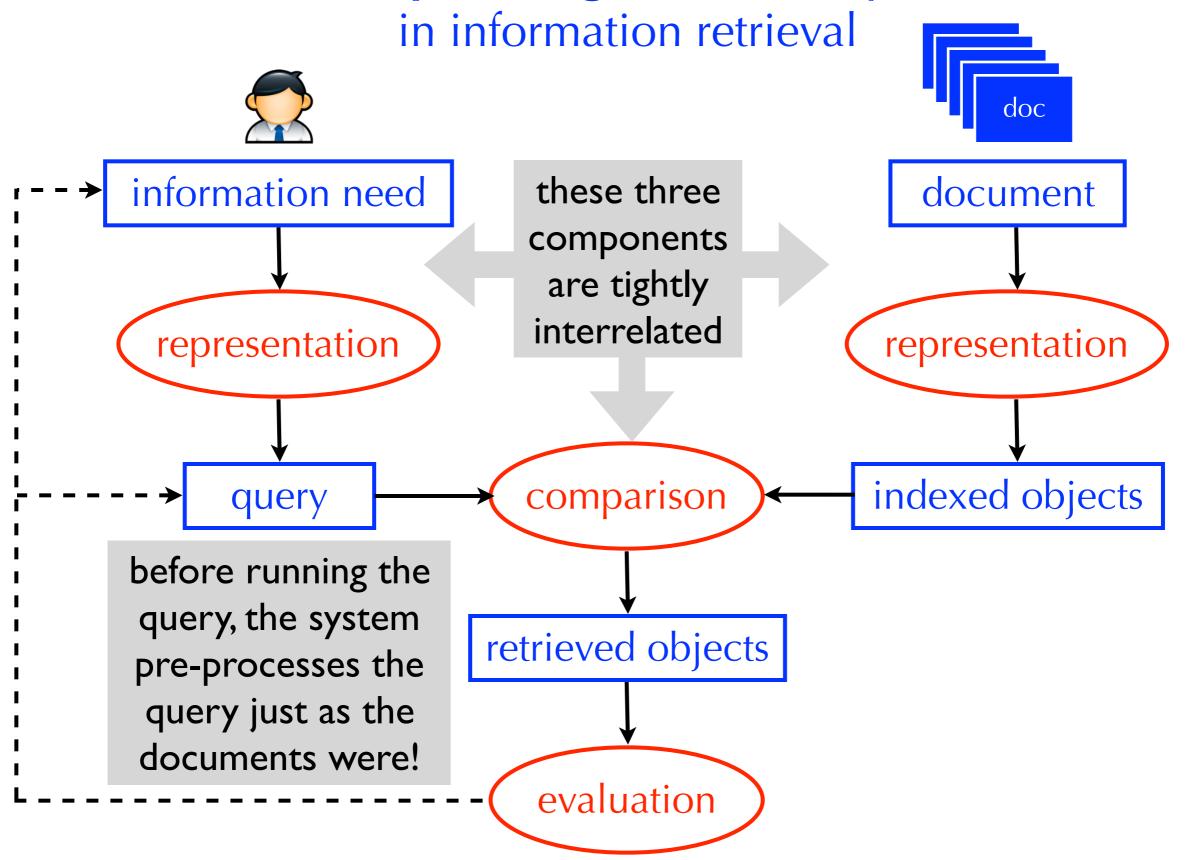
in information retrieval

- In English, conflating morphological variants is usually done using a stemmer
- Stemming: automatic suffix-stripping
- English word variations occur at the end of a word
- root/stem + suffix
 - repair + s/ed/ing/able
- A stemmer conflates different variations by reducing them to a common root/stem

in information retrieval

- In some cases, whatever is left after suffix-stripping is not even a word (e.g., comput)
- Is this a problem?

```
computers repairs
computing repaired
computation repairing
computational repairable
::
```



the porter stemmer (porter '80)

- A long list of rules that are applied in sequence
 - apply the rule that removes the longest suffix
 - check to see that the stem is likely to be a root (replac+ement vs. c+ement)
- Fast, effective, and, therefore, <u>very</u> popular

Martin Porter's Home Page

No doubt you came here out of idle curiosity from the <u>Porter Stemming Algorithm</u> page. Before you hastily return, you are welcome to look at the following.

This (jerkily) spinning can is the work of <u>Philip Holmes</u> <u>Esquire</u>, ingenious graphic designer and inventor of visual puns. I could never have thought up anything so clever. (Apologies to the Dr Pepper people!)



the porter stemmer (porter '80)

• Example step (1 of 5)

Step 1a:

- Replace sses by ss (e.g., stresses \rightarrow stress).
- Delete s if the preceding word part contains a vowel not immediately before the s (e.g., gaps \rightarrow gap but gas \rightarrow gas).
- Replace *ied* or *ies* by *i* if preceded by more than one letter, otherwise by ie (e.g., ties \rightarrow tie, cries \rightarrow cri).
- If suffix is us or ss do nothing (e.g., stress \rightarrow stress).

Step 1b:

- Replace *eed*, *eedly* by *ee* if it is in the part of the word after the first non-vowel following a vowel (e.g., agreed \rightarrow agree, feed \rightarrow feed).
- Delete *ed*, *edly*, *ing*, *ingly* if the preceding word part contains a vowel, and then if the word ends in *at*, *bl*, or *iz* add *e* (e.g., fished → fish, pirating → pirate), or if the word ends with a double letter that is not *ll*, *ss* or *zz*, remove the last letter (e.g., falling→ fall, dripping → drip), or if the word is short, add *e* (e.g., hoping → hope).
- Whew!

the porter stemmer (porter '80)

Original Text

gerard salton 8 march 1978 in nuremberg 28 august 1995 also know as gerry salton was professor of computer science at cornell university salton was perhaps the leading computer scientist working in the field of information retrieval during his time his group at cornell developed the smart information retrieval system which he initiated when he was at harvard

Stemmed Text

gerard salton 8 march 1978 in nuremberg 28 august 1995 also know as gerri salton wa professor of comput scienc at cornel univers salton wa perhap the lead comput scientist work in the field of inform retriev dure hi time hi group at cornel develop the smart inform retriev system which he initi when he wa at harvard

the porter stemmer (porter '80)

 false positives: two words conflated to the same root when they shouldn't have been

> organization/organ generalization/generic numerical/numerous policy/police university/universe addition/additive negligible/negligent execute/executive past/paste ignore/ignorant special/specialized head/heading

the porter stemmer (porter '80)

 false negatives: two words <u>not</u> conflated to the same root word when they should have been

```
european/europe
cylinder/cylindrical
matrices/matrix
urgency/urgent
create/creation
analysis/analyses
useful/usefully
noise/noisy
decompose/decomposition
sparse/sparsity
resolve/resolution
triangle/triangular
```

AOL Query-log Examples

stemmed queries

russian translat

russian translations russian translator russian translation russian translate

secret

secret

secretions

secrets

secretion

stock for sale

stockings for sale stocking for sale stocks for sale

smokei mountain nation park

smokey mountains national park smokey mountain national park smokey mountains national parks

cat fenc

cat fencing cat fences cat fence

strawberri plant

strawberry planting strawberry plants strawberries planting

AOL Query-log Examples

stopped + stemmed queries

bui comput

buy a computer
buying a computer
we buy computers
how to buy a computer
buying computers

rid raccoon

get rid of raccoons
how to get rid of raccoons
how to get rid of a raccoon
what to use to get rid of raccoons
how do i get rid of a raccoon

auto repair

auto repairables
how to auto repairs
auto repair do it yourself
do it yourself auto repair
auto repair .com
do it yourself auto repairs
auto repair

water diet

the water diet
the all water diet
water and diet
water diet
water diet
water diets

AOL Query-log Examples

stopped + stemmed queries

planet orbit sun

why is there only one planet in each orbit around the sun why do the planets orbit the sun planets that orbit the sun

plant shade

plants for shade plants that do well in shade plants that like shade plants shade planting in the shade

univers

universalism
universism
other universe
university
our universe
across the universe
the universe within
universities

Morphological Analysis

evaluation results

- Stemming
 - English: 0-5% improvements
 - Finnish: 30% improvement
 - Spanish: 10% improvement
- Compound Splitting
 - German: 15% improvements
 - Swedish: 25% improvement

(Hollink et al., 2004)

Morphology Across Languages European Parliament Corpus

- Number of unique terms (remember, these are translations of the same text):
 - English: 150,725
 - Spanish: 213,486
 - Portuguese: 219,121
 - Danish: 367,282
 - Finnish: 709,049
 - German: 401,929

To Stem or Not To Stem

users care more about recall

users care more about precision

?

To Stem or Not To Stem

users care more about recall

users care more about precision

Yes

Maybe

Big Picture

- Text-processing requires making decisions about what to store in the index
- Two big decisions: stopword-removal and stemming
- My own recommendation (take it, leave it, question it)
 - remove stopwords only if you have to (don't have enough disk-space)
 - off-load the job to query-processing (removing stopwords from the query)
 - stem depending on the importance of recall and the size of the collection

What about homonyms?

(words that are spelled the same, but have different meaning)

Words often have multiple senses

- bank (noun)
 - 1. the rising ground bordering a lake, river, or sea
 - 2. a mound, pile, or ridge above the surrounding level
 - 3. a steep slope (as in "bank of a hill")
 - 4. an establishment for the custody, loan, exchange, and issue of money
 - 5. a supply of something held in reserve
 - 6. the lateral inward tilt of a vehicle (as an airplane) when turning

(Merriam-Webster Dictionary)

 Given a word in a particular context, automatically predict its correct sense from a finite set (bank 1-6)?

"I stopped by the bank to deposit some cash."

An establishment for the custody, loan, and exchange of money

"I stopped by the food bank to donate some food."

A supply of something held in reserve

- An active area of research since the 1950's
- How would you do this?

 Predict the sense whose definition contains terms that co-occur often with those in the surrounding context "I stopped by the bank to deposit some cash."

An establishment for the custody, loan, and exchange of money

, 1
mutual
information
from IMDB
corpus

money	raise	2.686
debt	money	2.578
<u>dollars</u>	money	2.567
money	cash	2.546
buy	money	2.471
money	gambling	2.436
money	pay	2.427
money	bank	2.387
insurance	money	2.117
money	paid	2.018

in information retrieval

- 1. Expand the indexed vocabulary so that each sense of a word is a <u>different</u> index term
- 2. Automatically predict the correct sense for each word in the collection (e.g, bank¹, bank², ..., bank⁶)
 - lots of context (i.e., surrounding text)
- 3. Index the collection as usual
- 4. At query-time, predict the correct word sense in the query (e.g., "drive-through bank4 carrboro")
 - more difficult, not much context
- 5. Retrieve documents as usual

Does it improve (average) retrieval effectiveness?

Not much. Why not?

- Not really a problem for long-queries (other query terms disambiguate the ambiguous ones)
- In theory, could improve performance for short queries
- However, these are precisely the queries for which disambiguation is the most difficult (not much context)

• There is another reason. What is it?

in information retrieval

united bank union bank california union bank tyra banks show star bank republic bank pnc bank people bank outer banks north carolina outer banks no online banking bank america national bank texas commerce bank

national bank south carolina national bank oneida national bank omaha national bank marin national bank alaska national bank merchants bank loans bank account hotels outer banks no hotels outer banks guaranty bank freedom bank farmers merchants bank

• Wait for it..., Wait for it...

in information retrieval

 Word senses also (more or less) follow Zipf's law: a few are very frequent and most a rare

united bank
union bank california
union bank
tyra banks show
star bank
republic bank
pnc bank
pnc bank
outer banks north carolina
outer banks nc
online banking bank america
national bank texas
commerce bank

national bank south carolina
national bank oneida
national bank omaha
national bank marin
national bank alaska
national bank
merchants bank
loans bank account
hotels outer banks nc
hotels outer banks
guaranty bank
freedom bank
farmers merchants bank

in information retrieval

No. of	Size	Most	common
senses	of set	sense	(%)
2	3145	92	{50}
3	1697	85	{33}
4	1046	79	{25}
5	640	72	{20}
6	448	68	{17}
7	275	63	{14}
8	200	60	{13}
9	141	60	{11}
10	93	53	{10}

Table 10. Percentage of occurrences accounted for by the most common sense of a word.

The figures in brackets (shown for comparison) is the percentage that would result if senses occurred is equal amounts. Measurements made on the SEMCOR corpus.

(Sanderson, 1996)