Web Search
Information Retrieval

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Outline

Information Retrieval, Search

Problem

How to index Web content so as to answer (keyword-based) queries efficiently?

Context: set of text documents

- d_1 The jaguar is a New World mammal of the Felidae family.
- d_2 Jaguar has designed four new engines.
- d_3 For Jaguar, Atari was keen to use a 68K family device.
- d_4 The Jacksonville Jaguars are a professional US football team.
- d_5 Mac OS X Jaguar is available at a price of US $199 for Apple's new "family pack".
- d_6 One such ruling family to incorporate the jaguar into their name is Jaguar Paw.
- d_7 It is a big cat.

Text Preprocessing

Initial text preprocessing steps

- Number of optional steps
- Highly depends on the application
- Highly depends on the document language (illustrated with English)

Language Identification

How to find the language used in a document?

- Meta-information about the document: often not reliable!
- Unambiguous scripts or letters: not very common!

  한글
  カタカナ
  ދިވެހި
  Għarbi
  þorn

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  Respectively: Korean Hangul, Japanese Katakana, Maldivian Dhivehi, Maltese, Icelandic
- Extension of this: frequent characters, or, better, frequent k-grams
- Use standard machine learning techniques (classifiers)

Tokenization

Principle

Separate text into tokens (words)

Not so easy!

- In some languages (Chinese, Japanese), words not separated by whitespace
- Deal consistently with acronyms, elisions, numbers, units, URLs, emails, etc.
- Compound words: *hostname*, *host-name* and *host name*. Break into two tokens or regroup them as one token? In any case, lexicon and linguistic analysis needed! Even more so in other languages as German.

Usually, remove punctuation and normalize case at this point

Tokenization: Example

d_1 the$_1$ jaguar$_2$ is$_3$ a$_4$ new$_5$ world$_6$ mammal$_7$ of$_8$ the$_9$ felidae$_{10}$ family$_{11}$

d_2 jaguar$_1$ has$_2$ designed$_3$ four$_4$ new$_5$ engines$_6$

d_3 for$_1$ jaguar$_2$ atari$_3$ was$_4$ keen$_5$ to$_6$ use$_7$ a$_8$ 68k$_9$ family$_{10}$ device$_{11}$

d_4 the$_1$ jacksonville$_2$ jaguars$_3$ are$_4$ a$_5$ professional$_6$ us$_7$ football$_8$ team$_9$

d_5 mac$_1$ os$_2$ x$_3$ jaguar$_4$ is$_5$ available$_6$ at$_7$ a$_8$ price$_9$ of$_{10}$ us$_{11}$ \$199$_{12}$ for$_{13}$ apple's$_{14}$ new$_{15}$ family$_{16}$ pack$_{17}$

d_6 one$_1$ such$_2$ ruling$_3$ family$_4$ to$_5$ incorporate$_6$ the$_7$ jaguar$_8$ into$_9$ their$_{10}$ name$_{11}$ is$_{12}$ jaguar$_{13}$ paw$_{14}$

d_7 it$_1$ is$_2$ a$_3$ big$_4$ cat$_5$

Normalization (slide from [Manning et al., 2008])

- Need to “normalize” terms in indexed text as well as query terms into the same form.
- Example: We want to match *U.S.A.* and *USA*
- We most commonly implicitly define equivalence classes of terms.
- Alternatively: do asymmetric expansion
  - window → window, windows
  - windows → Windows, windows
  - Windows (no expansion)
- More powerful, but less efficient

Exercise

Why don’t you want to put *window*, *Window*, *windows*, and *Windows* in the same equivalence class?

Normalization: Other Languages (slide from [Manning et al., 2008])

- Accents: résumé vs. resume (simple omission of accent)
- Umlauts: Universität vs. Universitaet (substitution with special letter sequence "ae")
- Most important criterion: How are users likely to write their queries for these words?
- Even in languages that standardly have accents, users often do not type them. (Polish?)
- Normalization and language detection interact.
- *PETER WILL NICHT MIT.* $\rightarrow$ MIT $=$ mit
- *He got his PhD from MIT.* $\rightarrow$ MIT $\neq$ mit

Stemming

Principle

Merge different forms of the same word, or of closely related words, into a single stem

- Not in all applications!
- Useful for retrieving documents containing *geese* when searching for *goose*
- Various degrees of stemming
- Possibility of building different indexes, with different stemming

Stemming schemes (1/2)

Morphological stemming (lemmatization).

- Remove bound morphemes from words:
  - plural markers
  - gender markers
  - tense or mood inflections
  - etc.
- Can be linguistically very complex, cf:
  Les poules du couvent couvent.
  [The hens of the monastery brood.]
- In English, somewhat easy:
  - Remove final -s, -'s, -ed, -ing, -er, -est
  - Take care of semiregular forms (e.g., -y/-ies)
  - Take care of irregular forms (mouse/mice)
- But still some ambiguities: cf stocking

Stemming schemes (1/2)

Lexical stemming.

- Merge lexically related terms of various parts of speech, such as *policy*, *politics*, *political* or *politician*
- For English, Porter's stemming [Porter, 1980]; stem *university* and *universal* to *univers*: not perfect!
- Possibility of coupling this with lexicons to merge (near-)synonyms

Phonetic stemming.

- Merge phonetically related words: search proper names with different spellings!
- For English, Soundex [US National Archives and Records Administration, 2007] stems *Robert* and *Rupert* to *R163*. Very coarse!

Stemming Example

d_1 the$_1$ jaguar$_2$ be$_3$ a$_4$ new$_5$ world$_6$ mammal$_7$ of$_8$ the$_9$ felidae$_{10}$ family$_{11}$

d_2 jaguar$_1$ have$_2$ design$_3$ four$_4$ new$_5$ engine$_6$

d_3 for$_1$ jaguar$_2$ atari$_3$ be$_4$ keen$_5$ to$_6$ use$_7$ a$_8$ 68k$_9$ family$_{10}$ device$_{11}$

d_4 the$_1$ jacksonville$_2$ jaguar$_3$ be$_4$ a$_5$ professional$_6$ us$_7$ football$_8$ team$_9$

d_5 mac$_1$ os$_2$ x$_3$ jaguar$_4$ be$_5$ available$_6$ at$_7$ a$_8$ price$_9$ of$_{10}$ us$_{11}$ \$199$_{12}$ for$_{13}$ apple$_{14}$ new$_{15}$ family$_{16}$ pack$_{17}$

d_6 one$_1$ such$_2$ rule$_3$ family$_4$ to$_5$ incorporate$_6$ the$_7$ jaguar$_8$ into$_9$ their$_{10}$ name$_{11}$ be$_{12}$ jaguar$_{13}$ paw$_{14}$

d_7 it$_1$ be$_2$ a$_3$ big$_4$ cat$_5$

Stop Word Removal

Principle

Remove uninformative words from documents, in particular to lower the cost of storing the index

determiners: *a*, *the*, *this*, etc.

function verbs: *be*, *have*, *make*, etc.

conjunctions: *that*, *and*, etc.

etc.

Stop Word Removal Example

d_1 jaguar$_2$ new$_5$ world$_6$ mammal$_7$ felidae$_{10}$ family$_{11}$

d_2 jaguar$_1$ design$_3$ four$_4$ new$_5$ engine$_6$

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d_7 big$_4$ cat$_5$

Inverted Index

After all preprocessing, construction of an inverted index:

- Index of all terms, with the list of documents where this term occurs
- Small scale: disk storage, with memory mapping (cf. `mmap`) techniques; secondary index for offset of each term in main index
- Large scale: distributed on a cluster of machines; hashing gives the machine responsible for a given term
- Updating the index costly, so only batch operations (not one-by-one addition of term occurrences)

Inverted Index Example

family	d_1, d_3, d_5, d_6
football	d_4
jaguar	$d_1, d_2, d_3, d_4, d_5, d_6$
new	d_1, d_2, d_5
rule	d_6
us	d_4, d_5
world	d_1
...	

Storing positions in the index

- phrase queries, NEAR operator: need to keep position information in the index
- just add it in the document list!

family	$d_1/11$, $d_3/10$, $d_5/16$, $d_6/4$
football	$d_4/8$
jaguar	$d_1/2$, $d_2/1$, $d_3/2$, $d_4/3$, $d_5/4$, $d_6/8+13$
new	$d_1/5$, $d_2/5$, $d_5/15$
rule	$d_6/3$
us	$d_4/7$, $d_5/11$
world	$d_1/6$
...	

TF-IDF Weighting

- Some term occurrences have more weight than others:
  - Terms occurring frequently in a given document: more relevant
  - Terms occurring rarely in the document collection as a whole: more informative
- Add Term Frequency—Inverse Document Frequency weighting to occurrences;

$$\mathrm{tfidf}(t,d) = \frac{n_{t,d}}{\sum_{t'} n_{t',d}} \cdot \log \frac{|D|}{\left|\left\{d' \in D \,\middle|\, n_{t,d'} > 0\right\}\right|}$$

$n_{t,d}$	number of occurrences of t in d
D	set of all documents

- Store documents (along with weight) in decreasing weight order in the index

TF-IDF Weighting Example

family	$d_1/11/.13,\ d_3/10/.13,\ d_6/4/.08,\ d_5/16/.07$
football	$d_4/8/.47$
jaguar	$d_1/2/.04,\ d_2/1/.04,\ d_3/2/.04,\ d_4/3/.04,\ d_6/8+13/.04,\ d_5/4/.02$
new	$d_2/5/.24,\ d_1/5/.20,\ d_5/15/.10$
rule	$d_6/3/.28$
us	$d_4/7/.30,\ d_5/11/.15$
world	$d_1/6/.47$

...

Answering Boolean Queries

- Single keyword query: just consult the index and return the documents in index order.
- Boolean multi-keyword query

  (*jaguar* AND *new* AND NOT *family*) OR *cat*

  Same way! Retrieve document lists from all keywords and apply adequate set operations:

AND	intersection
OR	union
AND NOT	difference

- Global score: some function of the individual weight (e.g., addition for conjunctive queries)
- Position queries: consult the index, and filter by appropriate condition

Answering Top-k Queries

$$t_1 \text{ AND } \dots \text{ AND } t_n$$

$$t_1 \text{ OR } \dots \text{ OR } t_n$$

Problem

Find the top-k results (for some given k) to the query, without retrieving all documents matching it.

Notations:

- $s(t, d)$ weight of t in d (e.g., tfidf)
- $g(s_1, \dots, s_n)$ monotonous function that computes the global score (e.g., addition)

Fagin's Threshold Algorithm [Fagin et al., 2001]

(with an additional direct index giving $s(t, d)$)

1. Let R be the empty list and $m = +\infty$.
2. For each $1 \leq i \leq n$:
   1. Retrieve the document $d^{(i)}$ containing term t_i that has the next largest $s(t_i, d^{(i)})$.
   2. Compute its global score $g_{d^{(i)}} = g(s(t_1, d^{(i)}), \ldots, s(t_n, d^{(i)}))$ by retrieving all $s(t_j, d^{(i)})$ with $j \neq i$.
   3. If R contains less than k documents, or if $g_{d^{(i)}}$ is greater than the minimum of the score of documents in R, add $d^{(i)}$ to R (and remove the worst element in R if it is full).
3. Let $m = g(s(t_1, d^{(1)}), s(t_2, d^{(2)}), \ldots, s(t_n, d^{(n)}))$.
4. If R contains k documents, and the minimum of the score of the documents in R is greater than or equal to m, return R.
5. Redo step 2.

Fagin's No Random Access Algorithm [Fagin et al., 2001]

(no additional direct index needed)

1. Let R be the empty list and $m = +\infty$.
2. For each document d, maintain $W(d)$ as its worst possible score, and $B(d)$ as its best possible score.
3. At the beginning, $W(d) = 0$ and $B(d) = g(s(t_1, d^(1)) \ldots s(t_n, d^(n))$.
4. Then, access the next best document for each token, in a round-robin way (t_1, $t_2 \ldots t_n$, then t_1 again, etc.)
5. Update the $W(d)$ and $B(d)$ lists each time, and maintain R as the list of k documents with best $W(d)$ scores (solve ties with $B(d)$), and m as the minimum value for $W(d)$ in R.
6. Stop when R contains at least k documents, and all documents outside of R verify $B(d) \leq m$.

k-gram indexes for spelling correction (slide from [Manning et al., 2008])

- Problem: able to deal with incorrectly spelled terms in documents, or variants in spelling
- Enumerate all *k*-grams in the query term
- Use the *k*-gram index to retrieve "correct" words that match query term *k*-grams
- Threshold by number of matching *k*-grams
- E.g., only vocabulary terms that differ by at most 3 *k*-grams
- Example: bigram index, misspelled word *bordroom*
- Bigrams: *bo, or, rd, dr, ro, oo, om*

k-gram indexes for spelling correction: *bordroom*

BO → aboard → about → boardroom → border

OR → border → lord → morbid → sordid

RD → aboard → ardent → boardroom → border

Example with trigrams (slide from [Manning et al., 2008])

- Issue: Fixed number of k-grams that differ does not work for words of differing length.
- Suppose the correct word is NOVEMBER
- Trigrams: *nov*, *ove*, *vem*, *emb, mbe, ber*
- And the query term is DECEMBER
- Trigrams: *dec*, *ece*, *cem*, *emb, mbe, ber*
- So 3 trigrams overlap (out of 6 in each term)
- How can we turn this into a normalized measure of overlap?

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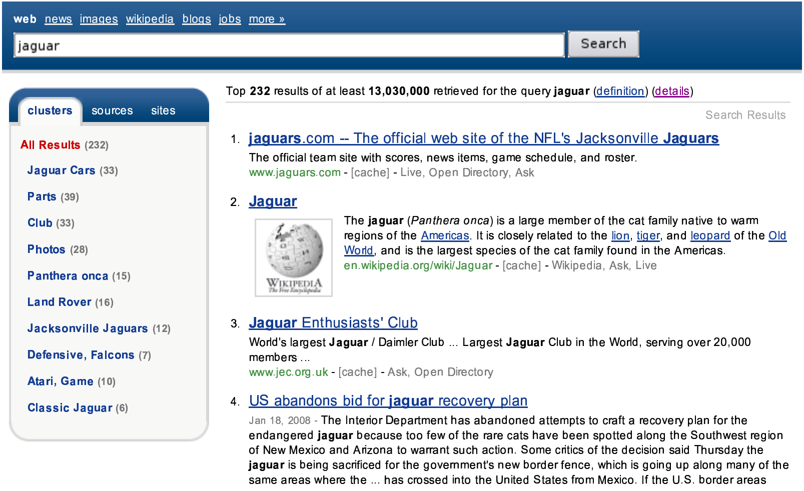
- So 3 trigrams overlap (out of 6 in each term)
- How can we turn this into a normalized measure of overlap?
  $\rightarrow$ Use Jaccard coefficent!

Context-sensitive spelling correction (slide from [Manning et al., 2008])

- *an asteroid that fell form the sky*
- How can we correct *form* here?
- One idea: hit-based spelling correction
  - Retrieve "correct" terms close to each query term
  - for *flew form munich*: *flea* for *flew*, *from* for *form*, *munch* for *munich*
  - Now try all possible resulting phrases as queries with one word "fixed" at a time
  - Try query *"flea form munich"*
  - Try query *"flew from munich"*
  - Try query *"flew form munch"*
  - The correct query *"flew from munich"* has the most hits.
- The "hit-based" algorithm we just outlined is not very efficient.
- More efficient alternative: look at "collection" of queries, not documents

Outline

Clustering Example



Cosine Similarity of Documents

- Document Vector Space model:

terms	dimensions
documents	vectors
coordinates	weights

  (The projection of document d along coordinate t is the weight of t in d, say $\mathrm{tfidf}(\mathrm{t}, \mathrm{d})$)

- Similarity between documents d and d': cosine of these two vectors

$$\cos(d, d') = \frac{d \cdot d'}{\|d\| \times \|d'\|}$$

$d \cdot d'$	scalar product of d and d'
$\|d\|$	norm of vector d

- $\cos(d, d) = 1$
- $\cos(d, d') = 0$ if d and d' are orthogonal (do not share any common term)

Agglomerative Clustering of Documents

1. Initially, each document forms its own cluster.
2. The similarity between two clusters is defined as the maximal similarity between elements of each cluster.
3. Find the two clusters whose mutual similarity is highest. If it is lower than a given threshold, end the clustering. Otherwise, regroup these clusters. Repeat.

Remark

Many other more refined algorithms for clustering exist.

Outline

Indexing HTML

- HTML: text + meta-information + structure
- Possibly: separate index for meta-information (title, keywords)
- Increase weight of structurally emphasized content in index
- Tree structure can also be queried with XPath or XQuery, but not very useful on the Web as a whole, because of tag soup and lack of consistency.

Indexing Multimedia Content

- Basic approach: index text from context of the media
  - surrounding text
  - text in or around the links pointing to the content
  - filenames
  - associated subtitles (hearing-impaired track on TV)
- Elaborate approach: index and search the media itself, with the help of speech recognition and sound, image, and video analysis. Mostly still experimental!
  - TrackID, Shazam: identify a song played on the radio.
  - Musipedia: look for a partition by whistling a tune, `http://www.musipedia.org/`
  - Image search from a similar image, `http://bigimbaz.inrialpes.fr/`
  - Google Audio Indexing, `http://labs.google.com/gaudi`

→ Athens course TPT17: Multimedia Indexing and Retrieval!

Outline

Precision and Recall

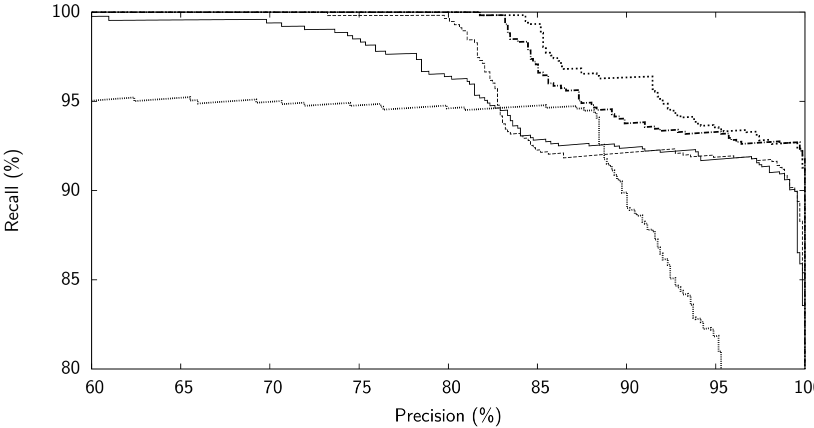
- Quality of search engines results evaluated with precision and recall

$$\text{precision} = \frac{\text{nb of correct results returned}}{\text{total nb of results}}$$

$$\text{recall} = \frac{\text{nb of correct results returned}}{\text{total nb of correct results}}$$

- "Correctness" usually given by human assessment
- Precision can be evaluated relatively reliably, much more difficult for recall! (Why?)
- Human judgment quite subjective! Agreement between human evaluators rarely go over 80%

Precision-Recall Curve



- Computed with the precision-at-k, recall-at-k for the k top results
- Area under the curve: quality of a method
- Usually, interpolate to force the decreasing of the curve

Outline

Conclusion

What you should remember

- The inverted index model, associated tools and techniques
- Main ideas behind Fagin's TA and NRA
- The document vector space model

Software

- Most DBMS have text indexing capabilities (e.g., MySQL's `FULLTEXT` indexes)
- Apache Lucene, free software library for information retrieval

To go further

- A good textbook [Manning et al., 2008]. Available online, along with slides!
- A very influential paper on top-k algorithms: [Fagin et al., 2001]

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