# COM3110/4115/6115: Text Processing

## *Information Retrieval: Term Manipulation*

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# Overview

- Definition of the information retrieval problem
- Approaches to document indexing
  - manual approaches
  - automatic approaches
- Automated retrieval models
  - boolean model
  - ranked retrieval methods (e.g. vector space model)
- **Term manipulation:**
  - **stemming, stopwords, term weighting**
- Evaluation

# What counts as a term?

Common to just use the **words**, but pre-process them for generalisation

- **Tokenisation**: split words from punctuation (get rid of punctuation)

  e.g. word-based. → word based    three issues: → three issues

- **Capitalisation**: normalise all words to lower (or upper) case

  e.g. Cat and cat should be seen as the same term, but should we conflate Turkey and turkey?

- **Lemmatisation**: conflate different inflected forms of a word to their basic form (singular, present tense, 1st person):

  e.g. cats, cat → cat    have, has, had → have    worried, worries → worry

- **Stemming**: conflate morphological variants by chopping their affix:

| | | |
|---|---|---|
| CONNECT | WORRY | GALL |
| CONNECTED | WORRIED | GALLING |
| CONNECTING | WORRIES | GALLED |
| CONNECTION | WORRYING | GALLEY |
| CONNECTIONS | WORRYINGLY | GALLERY |

# What counts as a term? (ctd)

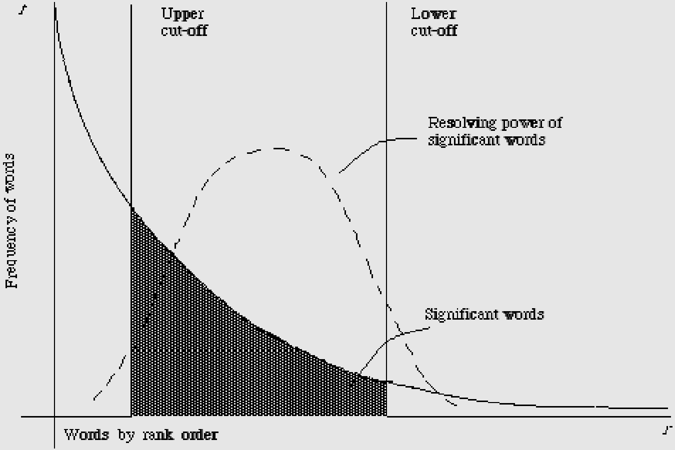
- **Normalisation**: heuristics to conflate variants due to spelling, hyphenation, spaces, etc.
  - e.g. USA and U.S.A. and U S A → USA
  - e.g. chequebook and cheque book → cheque book
  - e.g. word-sense and word sense → word-sense

- **Single vs. multi-word terms**
  - e.g. recognise phrases, e.g. Sheffield University
    - ◇ Multi-word indexing, e.g. bigram indexing, each bigram is a term in the index: pease porridge in the pot

| |
|---|
| pease porridge |
| porridge in |
| in the |
| the pot |

    - ◇ Issue: index increase in size due to large number of possible phrases, esp. for larger n-grams

# Word Frequency and Term Usefulness




- The most and least frequent terms are not the most useful for retrieval
- (Figure from van Rijsbergen (1979) *Information Retrieval* `http://www.dcs.gla.ac.uk/Keith/Preface.html`)

# Stop words

- Use **Stop list** removal to exclude “non-content” words
- Usually most frequent (and least useful for retrieval)

| | | |
|---|---|---|
| a | always | both |
| about | am | being |
| above | among | co |
| across | amongst | could |

  - ◇ greatly reduces the size of the inverted index
  - ◇ but what if we want to search for *phrases* that include these terms?
    - Kings of Leon
    - Let it be
    - To be or not to be
    - Flights to London

# Term Weighting

What do we use for the inverted index?

- binary weights - 0/1: whether or not term is present in document
  - But documents with multiple occurrences of query keyword may be more relevant
- Frequency of term in document: like the examples we have seen
  - But what if the term is also frequent in collection?
  - Common terms: not very useful for discriminating relevant documents
- Frequency in document vs in collection: weight terms highly if
  - They are **frequent** in relevant documents ... *but*
  - They are **infrequent** in collection as a whole

# Term Weighting (ctd)

- Key concepts:

| | | |
|---|---|---|
| document collection | $D$ | collection (set) of documents |
| size of collection | $\|D\|$ | total number of documents in collection |
| term freq | $tf_{w,d}$ | number of times $w$ occurs in document $d$ |
| collection freq | $cf_w$ | number of times $w$ occurs in collection |
| document freq | $df_w$ | number of documents containing $w$ |

# Term Weighting (ctd)

The informativeness of terms

- Idea that *less common* terms are *more useful* to finding relevant docs:

  i.e. these terms are more *informative*

- Is this idea best addressed using *document frequency* or *collection frequency*?

- Consider following counts (from New York Times data, $|D| = 10000$):

| Word | $cf_w$ | $df_w$ |
|---|---|---|
| insurance | 10440 | 3997 |
| try | 10422 | 8760 |

  ◇ term *insurance* semantically focussed, term *try* very general

  - document frequency reflects this difference
  - collection frequency fails to distinguish them (i.e. very similar counts)

# Term Weighting (ctd)

- Informativeness is inversely related to (document) frequency

  i.e. *less common* terms are *more useful* to finding relevant documents

  *more common* terms are *less useful* to finding relevant documents

- Compute metric such as: $\frac{|D|}{df_w}$
  - ◇ Value reduces as $df_w$ gets larger, tending to 1 as $df_w$ approaches $|D|$

    e.g. $\frac{10000}{3997} = 2.5$ (insurance) $\frac{10000}{8760} = 1.14$ (try)

  - ◇ Value very large for small $df_w$ — over-weights such cases

    e.g. $\frac{10000}{350} = \mathbf{28.6}$ (mischief)

- To moderate this, take *log*: **Inverse document frequency** (idf)

$$idf_{w,D} = log \frac{|D|}{df_w}$$

$log \frac{10000}{3997} = 0.398$ (insurance) $log \frac{10000}{8760} = 0.057$ (try) $log \frac{10000}{350} = 1.456$ (mischief)

# Term Weighting (ctd)

- **BUT** Not all terms describe a document equally well
- Putting it all together: **tf.idf**
  - Terms which are frequent in a document are better:

$$tf_{w,d} = freq_{w,d}$$

  - Terms that are rare in the document collection are better:

$$idf_{w,D} = log \frac{|D|}{df_w}$$

  - Combine the two to give **tf.idf** term weighting:

$$tf.idf_{w,d,D} = tf_{w,d} \cdot idf_{w,D}$$

- Most commonly used method for term weighting. Used in other fields too (e.g. summarisation)

# Term Weighting (ctd)

tf.idf example:

| Term | $tf$ | $df$ | $\|D\|$ | $idf$ | $tf.idf$ |
|---|---|---|---|---|---|
| the | 312 | 28,799 | 30,000 | 0.018 | 5.54 |
| in | 179 | 26,452 | 30,000 | 0.055 | 9.78 |
| general | 136 | 179 | 30,000 | 2.224 | 302.50 |
| fact | 131 | 231 | 30,000 | 2.114 | 276.87 |
| explosives | 63 | 98 | 30,000 | 2.486 | 156.61 |
| nations | 45 | 142 | 30,000 | 2.325 | 104.62 |
| haven | 37 | 227 | 30,000 | 2.121 | 78.48 |

For term the:

$$idf(the) = \log_{10}\left(\frac{30,000}{28,799}\right) = 0.018$$

$$tf.idf(the) = 312 \cdot 0.018 = 5.54$$

# Putting things together

Example: Vector Space Model, tf.idf term weighting, cosine similarity

- tf.idf values for words in two documents $D_1$ and $D_2$, and in a query Q "hunter gatherer Scandinavia":

| | Q | $D_1$ | $D_2$ |
|---|---|---|---|
| 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 |
| $\sqrt{\sum_{i=1}^{n} x_i^2}$ | 41.9 | 622.9 | 467.5 |

(i.e. length of vector)

- $$sim(\vec{q}, \vec{d}) = cos(\vec{q}, \vec{d}) = \frac{\sum_{i=1}^{n} q_i d_i}{\sqrt{\sum_{i=1}^{n} q_i^2}\sqrt{\sum_{i=1}^{n} d_i^2}}$$

# Putting things together (ctd)

- $$sim(\vec{q},\vec{d}) = cos(\vec{q},\vec{d}) = \frac{\sum_{i=1}^{n} q_i d_i}{\sqrt{\sum_{i=1}^{n} q_i^2}\sqrt{\sum_{i=1}^{n} d_i^2}}$$

$$\begin{aligned} cos(Q,D_1) &= \frac{(19.2 * 56.4) + (34.5 * 122.4) + \cdots + (0 * 0) + (0 * 344.2)}{41.9 * 622.9} \\ &= \frac{5305.68}{26071.72} \\ &= 0.20 \end{aligned}$$

$$\begin{aligned} cos(Q,D_2) &= \frac{(19.2 * 112.2) + (34.5 * 0) + \cdots + (0.0 * 452.2) + (0.0 * 0.0)}{41.9 * 467.5} \\ &= \frac{2583.8}{19570.0} \\ &= 0.13 \end{aligned}$$

- so document $D_1$ is more similar to Q than $D_2$

# Summary

- Term manipulation
  - Pre-processing
    - tokenisation, stemming, stop word removal ...
- Term weighting
  - Binary
  - Term frequency
  - TF.IDF