

Text Technologies for Data Science INFR11145

Preprocessing

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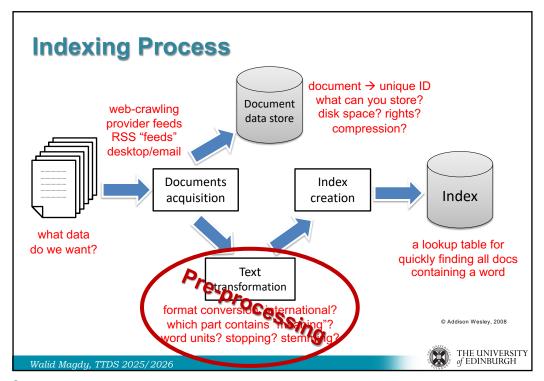
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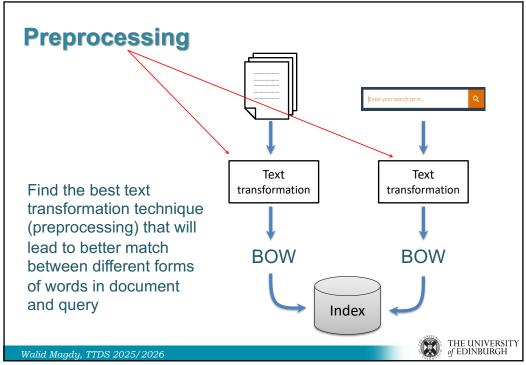
Lecture Objectives

- · Learn about and implement
- Standard text pre-processing steps:
 - Tokenisation
 - Stopping
 - Normalisation
 - Stemming



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Getting ready for indexing?

- BOW, what is a word?
- In IR, we refer to word-elements as "terms"
 - word "preprocessing"
 - part of a word "pre"
 - number / code "INFR11145"
- Pre-processing steps before indexing:
 - Tokenisation
 - Stopping
 - Stemming
- **Objective** → identify the <u>optimal form</u> of the term to be indexed to achieve the best retrieval performance

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Tokenisation

- Input: "Friends, Romans; and Countrymen!"
- Output: Tokens
 - Friends
 - Romans
 - and
 - Countrymen
- Sentence → <u>tokenization (splitting)</u> → tokens
- A token is an <u>instance</u> of a sequence of characters
- Typical technique: split at non-letter characters
- Each such token is now a candidate for an index entry (term), after <u>further processing</u>

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Issues in Tokenisation

- "Finland's" capital → Finland? Finlands? Finland's?
- Hewlett-Packard → one token or two?
 - state-of-the-art: break up hyphenated sequence.
 - co-education
 - lowercase, lower-case, lower case?
 - It can be effective to get the user to put in possible hyphens

Numbers?

- 3/20/91 vs. Mar. 20, 1991 vs. 20/3/91
- This course code is INFR11145
- (800) 234-2333



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Issues in Tokenisation

- URLs:
 - http://www.bbc.co.uk
 - http://www.bbc.co.uk/news/world-europe-41376577

Social Media

- · Black lives matter
- #Black lives matter
- #BlackLivesMatter
- #blacklivesmatter
- @blacklivesmatter
- San Francisco: one token or two?
 - How do you decide it is one token?



Tokenisation for different languages

- French → L'ensemble → one token or two?
 - L?L'?Le?
 - Want I'ensemble to match with un ensemble
 - Until at least 2003, it didn't on Google
- German → compounds
 - Lebensversicherungsgesellschaftsangestellter 'life insurance company employee'
 - German retrieval systems benefit greatly from a compound splitter module → Can give a 15% performance boost for German
- Chinese and Japanese → no spaces between words:
 - 莎拉波娃现在居住在美国东南部的佛罗里达
 - Tokenisation → Segmentation

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Tokenisation: common practice

- Just split at non-letter characters
- Add special cases if required
- Some applications have special setup
 - Social media: hashtags/mentions handled differently
 - URLs: no split, split at domain only, remove entirely!
 - Medical: protein & diseases names



Stopping (stop words removal)

- This is a very exciting lecture on the technologies of text
- **Stop words**: the most common words in collection → the, a, is, he, she, I, him, for, on, to, very, ...
- There are a lot of them ≈ 30-40% of text
- New stop words appear in specific domains
 - Tweets: RT → "RT @realDonalTrump Mexico will ..."
 - Patents: said, claim → "a said method that extracts"
- Stop words
 - influence on sentence structure
 - less influence on topic (aboutness)

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Stopping: always apply?

- Sometimes very important:
 - Phrase queries: "Let it be", "To be or not to be"
 - Relational queries:
 - flights to London from Edinburgh
 - flights from London to Edinburgh
- In Web search, trend is to keep them:
 - Good compression techniques means the space for including stop words in a system is very small
 - Good query optimization techniques mean you pay little at query time for including stop words.
 - Probabilistic retrieval models give them low weight.



Stopping: stop words

- Common practice in many applications
 → remove stop words
- There are common stop words list for each language
 - NLTK (python)
 - http://members.unine.ch/jacques.savoy/clef/index.html
- There are special stop words list for some applications
- How to create your list:
 - Sort all terms in a collection by frequency
 - Manually select the possible stop words from top N terms

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Normalisation

- Objective → make words with different surface forms look the same
- Document: "this is my CAR!!"
 Query: "car"
 should "car" match "CAR"?
- Sentence → tokenisation → tokens → normalisation
 → terms to be indexed
- Same tokenisation/normalisation steps should be applied to documents & queries



Case folding and equivalents

- "A" & "a" are different strings for computers
- Case folding: convert all letters to lower case
 - CAR, Car, caR → car
 - Windows → windows, should we do that?
- Diacritics/Accents removal
 - French: Château → chateau
 - German: Tüebingen → tuebingen
 - Arabic: کثب → کثب

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Equivalence Classes

- U.S.A. → USA
- Ph.D. → PhD
- 92.3 → 923? 92 3?
- multi-disciplinary → multidisplinary ← multi disciplinary
- The most important criteria:
 - · Be consistent between documents & queries
 - Try to follow users' most common behaviour



Stemming

- Search for: "play" should it match: "played", "playing", "player"?
- Many morphological variations of words
 - *inflectional* (plurals, tenses)
 - derivational (making verbs nouns etc.)
- In most cases, <u>aboutness</u> does not change
- Stemmers attempt to reduce morphological variations of words to a common stem
 - · usually involves removing suffixes (in English)
- Can be done at indexing time or as part of query processing (like stopwords)

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Stemming

- Usually, it achieves 5-10% improvement in retrieval effectiveness, e.g. English
- For highly inflected languages, it is more critical:
 - 30% improvement in Finnish IR
 - 50% improvement in Arabic IR

They are Peter's children
The children behaved well
Her children are cute
My children are funny
We have to save our children
Patents and children are happy
He loves his children
His children loves him

هؤلاء أبناء بيتر الأبناء تصرفوا جيدا أبناءها لطاف أبنائي ظرفاء علينا أن نحمي أبناءنا الآباء والأبناء سعداء هو يحب أبناءه أبناؤه يحبونه



Stemming

- Two basic types
 - · Dictionary-based: uses lists of related words
 - Algorithmic: uses program to determine related words
- Algorithmic stemmers
 - suffix-s: remove 's' endings assuming plural
 - e.g., cats → cat, lakes → lake, windows → window
 - Many false negatives: supplies → supplie
 - Some false positives: James → Jame



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Porter Stemmer

- Most common algorithm for stemming English
- Conventions + 5 phases of reductions
 - phases applied sequentially
 - each phase consists of a set of commands
 - sample convention:
 of the rules in a compound command, select the one that
 applies to the longest suffix.
- Example rules in Porter stemmer
 - sses → ss (processes → process)
 - $y \rightarrow i$ (reply \rightarrow repli)
 - $ies \rightarrow i$ (replies \rightarrow repli)
 - $ement \rightarrow null$ (replacement $\rightarrow replac$)



Stemmed words are misspelled!!

- repli, replac, suppli, inform retriev, anim
- These are not words anymore, these are terms
- These terms are not seen by the user, but just used by the IR system (search engine)
- These represent the optimal form for a better match between different surface forms of a term
 - e.g. replace → replace, replaces, replaced, replacing, replacer, replacers, replacement, replacements.

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Pre-processing: Common practice

- Tokenisation: split at non-letter characters
 - Basic regular expression
 - → process \w and neglect anything else
 - For tweets, you might want to keep "#" and "@"
- Remove stop words
 - find a common list, and filter these words out
- Apply case folding
 - One command in Perl or Python: lc(\$string)
- Apply Porter stemmer
 - Other stemmers are available, but Porter is the most famous with many implementations available in different programming languages



Limitations

- Irregular verbs:
 - saw → see
 - went → go
- Different spellings
 - · colour vs. color
 - tokenisation vs. tokenization
 - Television vs. TV
- Synonyms
 - · car vs. vehicle
 - UK vs. Britain
- Solution → Query expansion …

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Asymmetric Expansion

- Maintains relations between unnormalized tokens
- An alternative to equivalence classing
- An example of where this may be useful
 - query: window search: window, windowsquery: windows search: windows, Windows
 - query: Windows search: Windows
- Potentially more powerful, but less efficient
 - More vocabulary, longer query
- Can be less effective:
 - Inaccurate stats on terms ("car" ≠ "Car")



Summary

- Text pre-processing before IR:
 - Tokenisation → Stopping → Stemming

This is an example sentence of how the pre-processing is applied to text in information retrieval. It includes: Tokenization, Stop Words Removal, and Stemming

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Practical

Collection	Original		After Pre-processing	
	# words	File size	# words	File size
Bible	824,054	4.24 MB	358,112	2.05 MB
Wiki abstracts	78,137,597	472 MB	47,741,065	309 MB

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Resources

- Text book 1: Intro to IR, Chapter 2 → 2.2.4
- Text book 2: IR in Practice, chapter 4
- Lab 1 → Implement what learnt in these two lectures START NOW, support on PIAZZA
- Optional reading:
 if you think English pre-processing is hard!
 - Arabic Information Retrieval. Darwish & Magdy

