THE UNIVERSITY of EDINBURGH

Text Technologies for Data Science

INFR11145

Preprocessing

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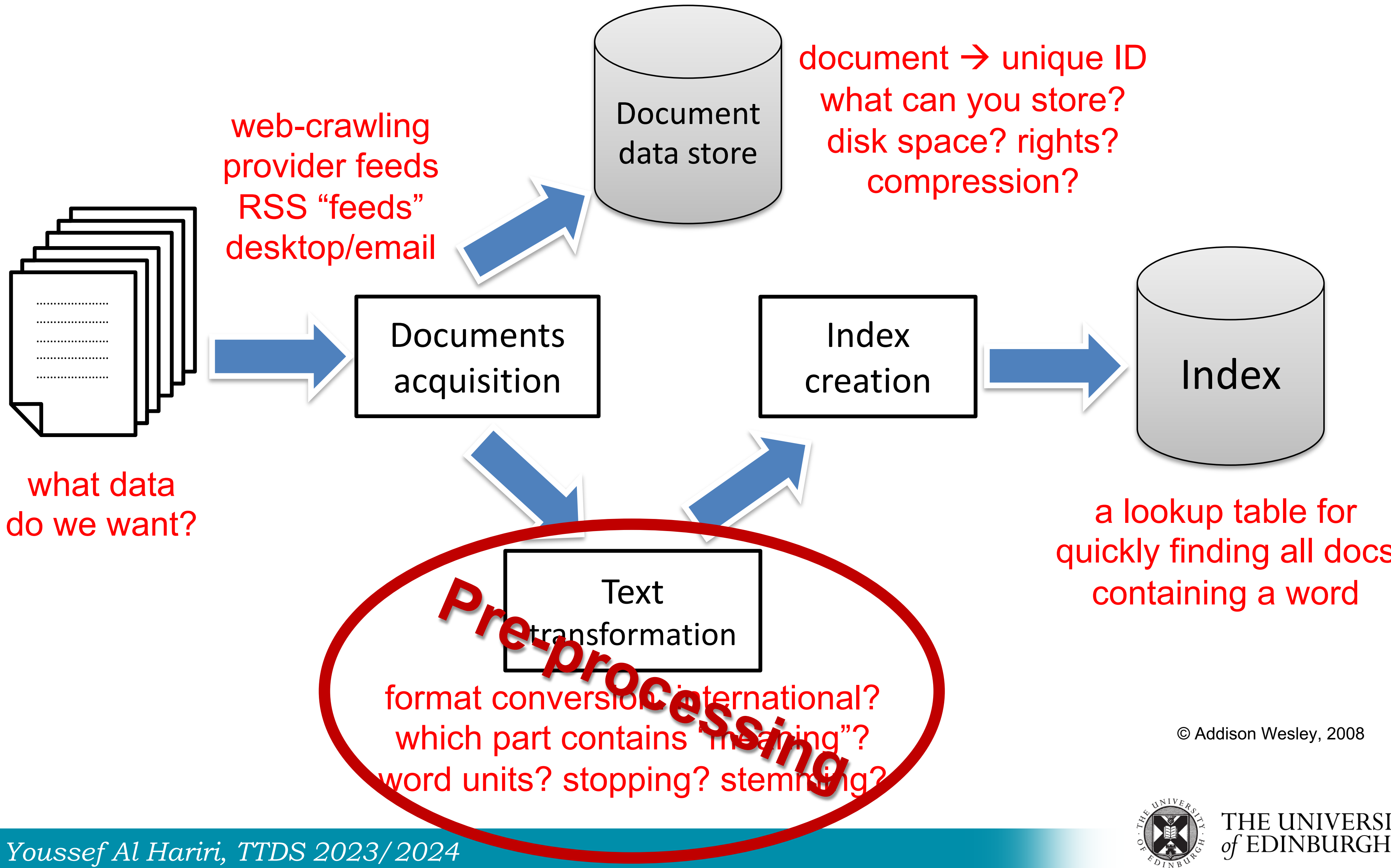
Lecture Objectives

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

Indexing Process



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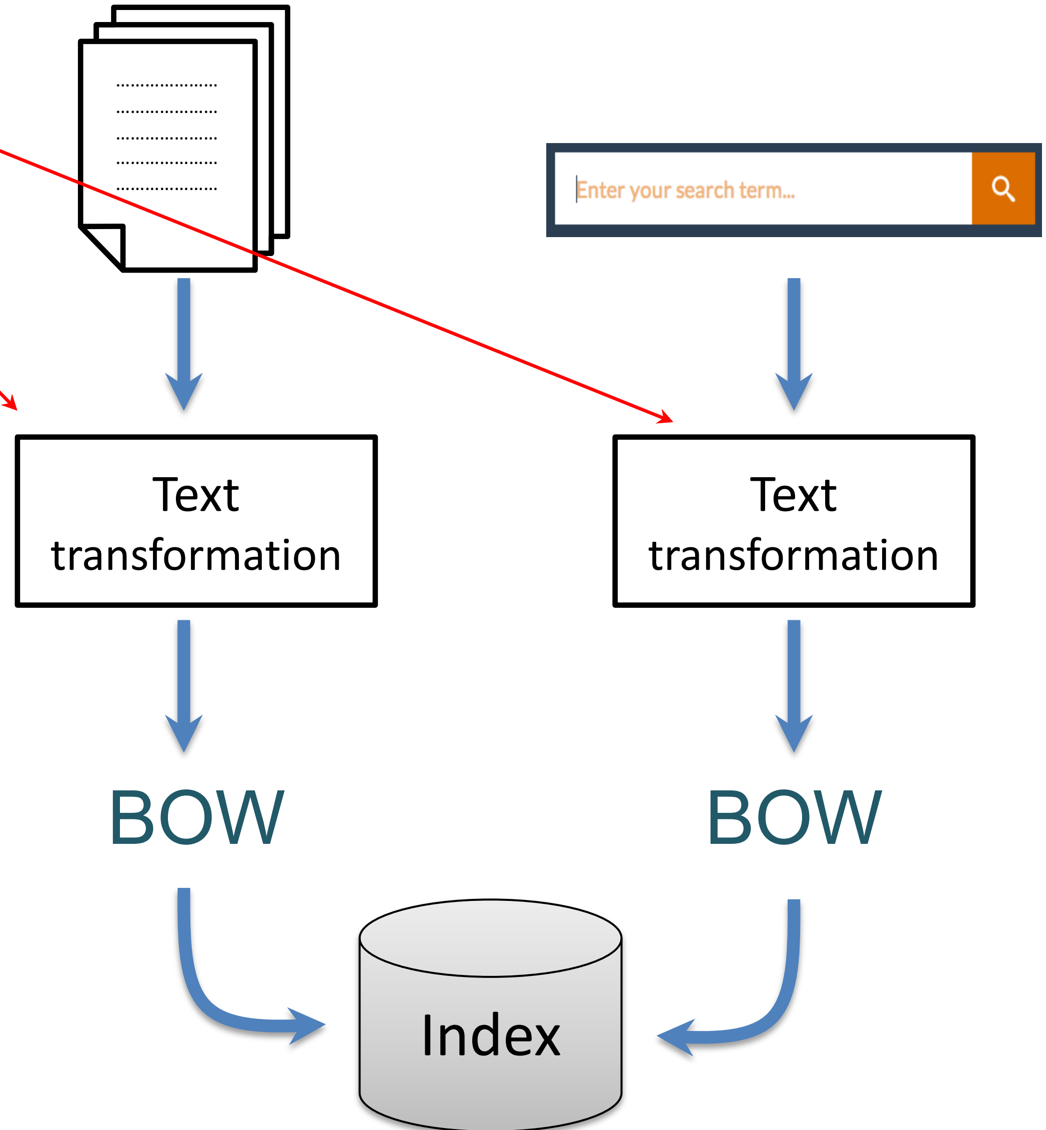
Preprocessing



Find the best text transformation technique (preprocessing) that will lead to better match between different forms of words in document and query

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 optimal form of the term to be indexed to achieve the best retrieval performance

Tokenisation

- Input: "***Friends, Romans; and Countrymen!***"
- Output: Tokens
  - *Friends*
  - *Romans*
  - *and*
  - *Countrymen*
- Sentence → tokenization (splitting) → tokens
- A **token** is an **instance** 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 further processing

Issues in Tokenisation

- "*Finland's*" capital $\rightarrow$ *Finland*? *Finlands*? *Finland's*?
- Hewlett-Packard $\rightarrow$ 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

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 ***l'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

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)

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

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: كُتُبٍ → كتب

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)

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**	هؤلاء **أبناء** بيتر
The **children** behaved well	**الأبناء** تصرفوا جيدا
Her **children** are cute	**أبناءها** لطاف
My **children** are funny	**أبنائي** ظرفاء
We have to save our **children**	علينا أن نحمي **أبناءنا**
Patents and **children** are happy	الآباء **والأبناء** سعداء
He loves his **children**	هو يحب **أبناءه**
His **children** loves him	**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

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* → *i* (reply → repli)
  - *ies* → *i* (replies → repli)
  - *ement* → null (replacement → replac)

Stemmed words are misspelled!!

- repli, replac, suppli, inform retriev, anim
- These are not <u>words</u> anymore, these are <u>terms</u>
- 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. replac → replace, replaces, replaced, replacing, replacer, replacers, replacement, replacements.

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
  - tokeni**s**ation vs. tokeni**z**ation
  - Television vs. TV
- Synonyms
  - car vs. vehicle
  - UK vs. Britain
- Solution → Query expansion …

Asymmetric Expansion

- Maintains relations between unnormalised tokens
- An alternative to equivalence classing
- An example of where this may be useful
  - query: *window* search: *window, windows*
  - query: *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

↓

exampl sentenc pre process appli text inform retriev includ token stop word remov stem

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

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*

Next lecture

- Indexing:
  How to build an index!

- Assignment 1 announcement:
  - Build indexing components
  - Today: build your pre-processing module!
  - Next time: build the index