```
rules = {
   RegularExpression["(\\w+)(ss)(es)"] :> "$1$2",
   RegularExpression["(\\w+)(sh)(es)"] :> "$1$2",
   RegularExpression["(\\w+)(ies)"] :> "$1" ~~ "y",
   RegularExpression["(\\w+)(ss)"] :> "$1$2",
   RegularExpression["(\\w+)(us)"] :> "$1$2",
   RegularExpression["(\\w+)(s)"] :> "$1"
  };
```

COMP90042 LECTURE 1B

PREPROCESSING

DEFINITIONS

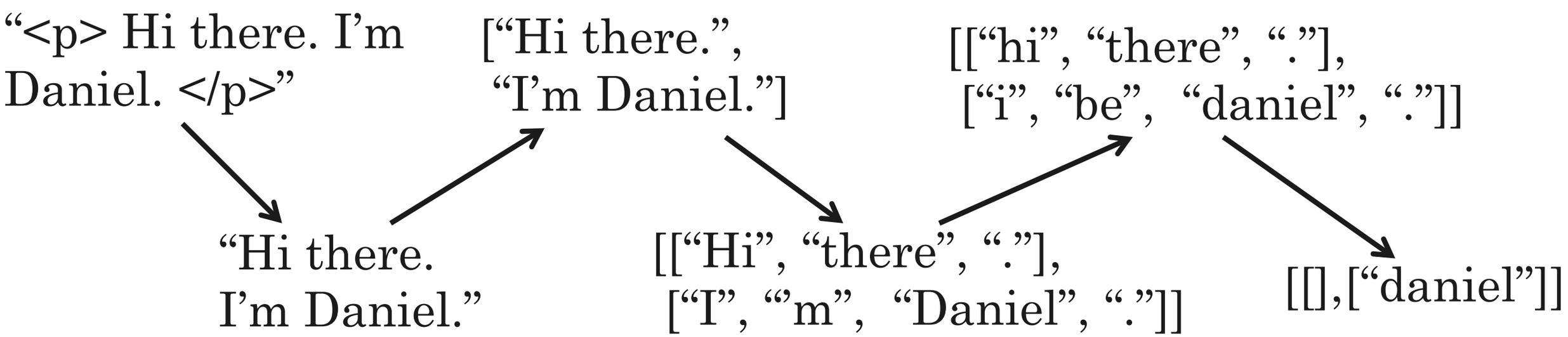
- Words
  - Sequence of characters with a meaning and/or function
- Sentences
  - "The student is enrolled at the University of Melbourne."
- Word token: each instance of "the" in the sentence above.
- Word type: the distinct word "the".
  - Lexicon: a group of word **types**.
- Document: one or more sentences.
- Corpus: a collection of documents.

DEFINITIONS

- Most NLP applications have documents as inputs:
  - "This movie is so great!!! U should definitely watch it in the theater! Best sci-fi eva!" → 
  - "Eu estive em Melbourne no ano passado." → "I was in Melbourne last year."
- **Key point:** language is *compositional*. As humans, we can break these documents into individual components. To understand language, a computer should do the same.
- **Preprocessing** is the first step.

TEXT NORMALISATION

- Remove unwanted formatting (e.g. HTML)
- Segment structure (e.g. sentences)
- Tokenise words
- Normalise words
- Remove unwanted words



SENTENCE SEGMENTATION

- Naïve approach: break on sentence punctuation ([.?!])
  - But periods are used for abbreviations! (U.S. dollar)
- Second try: use regex to require capital ([.?!] [A-Z])
  - But abbreviations often followed by names (Mr. Brown)
- Better yet: have lexicons
  - But difficult to enumerate all names and abbreviations
- State-of-the-art uses machine learning, not rules

TOKENISATION: ENGLISH

- Naïve approach: separate out alphabetic strings (\w+)
- Abbreviations (*U.S.A.*)
- Hyphens (*merry-go-round vs. well-respected* vs. *yes-but*)
- Numbers (*1,000,00.01*)
- Dates (3/1/2016)
- Clitics (*n't* in *can't*)
- Internet language (http://www.google.com, #RefugeesWelcome, :-))
- Multiword units (New Zealand)

TOKENISATION: CHINESE

- Some Asian languages are written without spaces between words
- In Chinese, words often correspond to more than one character

墨大	的	学生	与众不同
Unimelb	's	student(s) (are)	special

TOKENISATION: CHINESE

- Standard approach assumes an existing vocabulary
- MaxMatch algorithm
  - Greedily match longest word in the vocabulary

V = {墨,大,的,学,生,与,众,不,同, 墨大,学生,不同,与众不同}

墨大的学生与众不同

match 墨大, match 的, match 学生, match与众不同,
move to 的 move to 学 move to 与 done

TOKENISATION: CHINESE

- But how do we know what the vocabulary is
- And doesn't always work

去买新西兰花

去 买 新西兰 花
go buy New Zealand flowers

去 买 新 西兰花
go buy new broccoli

WORD NORMALISATION

- Lower casing (Australia -> australia)
- Removing morphology
- Correcting spelling
- Expanding abbreviations

INFLECTIONAL MORPHOLOGY

- Inflectional morphology creates grammatical variants
- English inflects nouns, verbs, and adjectives
  - Nouns: *number* of the noun (*-s*)
  - Verbs: *number* of the subject *(-s*), the *aspect* (*-ing*) of the action and the *tense (-ed*) of the action
  - Adjectives: *comparatives* (*-er*) and *superlatives* (*-est*)
- Many languages have much richer inflectional morphology than English
  - E.g. French inflects nouns for gender (*un chat*, *une chatte*)

LEMMATISATION

- Lemmatisation means removing any inflection to reach the uninflected form, the *lemma*
  - *speaking* → *speak*
- In English, there are irregularities that prevent a trivial solution:
  - *poked* → *poke* (not pok)
  - *stopping* → *stop* (not *stopp*)
  - *watches* → *watch* (not *watche*)
  - was → be (not *wa*)
- A lexicon of lemmas needed for accurate lemmatisation

DERIVATIONAL MORPHOLOGY

- Derivational morphology creates distinct words
- English derivational *suffixes* often change the lexical category, e.g.
  - *-ly* (*personal* → *personally*)
  - *-ise* (*final* → *finalise*)
  - *-er* (*write* → *writer*)
- English derivational *prefixes* often change the meaning without changing the lexical category
  - *write* → *rewrite*
  - *healthy* → *unhealthy*

STEMMING

- Stemming strips off all suffixes, leaving a *stem*
  - *E.g. automate, automatic, automation* → *automat*
  - Often not an actual lexical item
- Even less lexical sparsity than lemmatisation
- Popular in information retrieval

THE PORTER STEMMER

- Most popular stemmer for English
- Applies rewrite rules in stages
  - First strip inflectional suffixes,
    - E.g. *-ies* → *-i*
  - Then derivational suffixes, from right to left
    - E.g *-isation* → *-ise; -ise* →

FIXING SPELLING ERRORS

- Why fix them?
  - Spelling errors create new, rare types
  - Disrupt various kinds of linguistic analysis
  - Very common in internet corpora
  - In web search, particularly important in queries
- How?
  - String distance (Levenshtein, etc.)
  - Modelling of error types (phonetic, typing etc.)
  - Use an *n*-gram language model

OTHER WORD NORMALISATION

- Normalising spelling variations
  - Normalize → Normalise (or vice versa)
  - U r so coool! → *you are so cool*
- Expanding abbreviations
  - US, U.S. → United States
  - imho → in my humble opinion

STOP WORDS

- Definition: a list of words to be removed from the document
  - Typical in bag-of-word (BOW) representations
  - Not appropriate when sequence is important
- How to choose them?
  - All *closed-class* or *function* words
    - E.g. *the, a, of, for, he, …*
  - Any high frequency words

A FINAL WORD

- Preprocessing unavoidable in text analysis
- Can have a major effect on downstream applications
- Exact steps may vary depending on corpus, task
- Simple rule-based systems work well, but rarely perfectly

FURTHER READING

- J&M3 Ch 2. on Normalisation (includes a review of regex and Levenshtien distance)
- (Optional) details on the Porter Stemmer algorithm (http://snowball.tartarus.org/algorithms/porter/stemmer.html)