Basic Text Processing

Dr Muhammad Sarim

Contents

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Text Normalization

- Every NLP task requires text normalization.

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  2. Normalizing word formats.
  3. Segmenting sentences in running text.

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Can you count the words?

I do uh main- mainly business data processing.

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- Lemma: same stem, part of speech, rough word sense.
  cat and cats = same lemma.

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Seuss's cat in the hat is different from other cats!

- Lemma: same stem, part of speech, rough word sense.
  cat and cats = same lemma.
- Wordform: the full inflected surface form.
  cat and cats are different wordforms.

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  - 15 tokens (or 14)

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N = Number of tokens

V = vocabulary = set of types

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	Tokens = N	**Types = $|V|$**
Switchboard phone conversations	2.4 million	20 thousand
Shakespeare	884,000	31 thousand
Google N-grams	1 trillion	13 million

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- m.p.h., PhD. $\rightarrow$??

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- German noun compounds are not segmented
  - Lebensversicherungsgesellschaftsangestellter
    'life insurance company employee'
    German information retrieval needs compound splitter

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- Japanese has more complications, with multiple alphabets intermingled

Word Tokenization in Chinese

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- Chinese words are composed of characters
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- Standard baseline segmentation algorithm:
    - Maximum Matching (also known as Greedy Matching)

Maximum Matching: Word Segmentation Algorithm

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  4. Go to 2

Maximum Matching: Example

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- Modern probabilistic segmentation algorithms even better

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- Alternative: Asymmetric expansion:
  - Enter: window Search: window, windows
  - Enter: windows Search: Windows, windows, window
  - Enter: Windows Search: Windows
- Potentially more powerful, but less efficient

Case folding

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- For sentiment analysis, MT, Information extraction
  - Case is helpful

    US versus us is important

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  - Spanish quiero ('I want'), quieres ('you want') same lemma as querer 'want'

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Morphology

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  - Stems: The core meaning-bearing units
  - Affixes: Bits and pieces that adhere to stems
    Often with grammatical functions

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for example compressed and compression are both accepted as equivalent to compress.	→	for exampl compress and compress ar both accept as equival to compress

Porters Algorithm: The most common English stemmer

- Step 1a:

sses	$\rightarrow$	ss	caresses	$\rightarrow$	caress
ies	$\rightarrow$	i	ponies	$\rightarrow$	poni
ss	$\rightarrow$	ss	caress	$\rightarrow$	caress
s	$\rightarrow$	$\emptyset$	cats	$\rightarrow$	cat

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- Step 1b:

(*v*) ing	$\rightarrow$	$\emptyset$	walking	$\rightarrow$	walk
			sing	$\rightarrow$	sing
(*v*) ed	$\rightarrow$	$\emptyset$	plastered	$\rightarrow$	plaster

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- Step 2: (long stems)

ational	$\rightarrow$	ate	relational	$\rightarrow$	relate
izer	$\rightarrow$	ize	digitizer	$\rightarrow$	digitize
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- Step 3: (longer stems)

al	$\rightarrow$	$\emptyset$	revival	$\rightarrow$	reviv
able	$\rightarrow$	$\emptyset$	adjustable	$\rightarrow$	adjust
ate	$\rightarrow$	$\emptyset$	activate	$\rightarrow$	activ

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tr -sc 'A-Za-z' '\n' < mytext.txt | grep '[aeiou].*ing$' |
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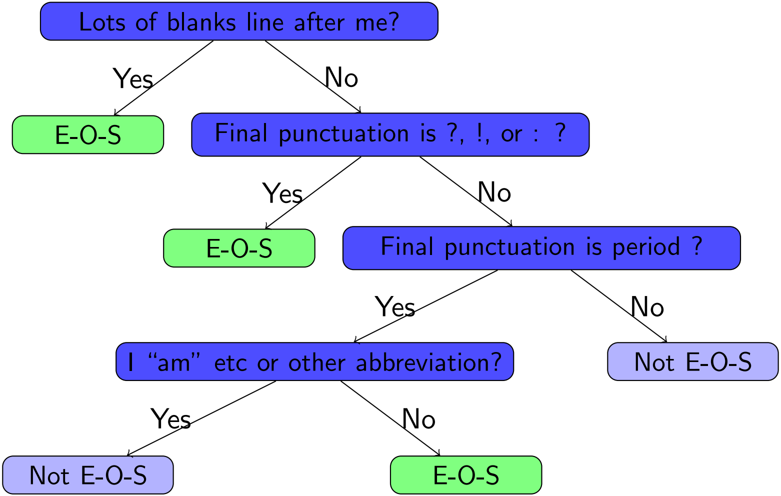
  - Decides End-Of-Sentence/Not-End-Of-Sentence
  - Classifiers: hand-written rules, regular expressions, or machine-learning

A Decision Tree for E-O-S



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  - Probability (word with "." occurs at E-O-S)

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    - For numeric features, its too hard to pick each threshold
  - Instead, structure usually learned by machine learning from a training corpus

Other Classifiers

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- As features that could be exploited by any kind of classifier

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- We can think of the questions in a decision tree
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  - etc.