Tokenization and sentence segmentation

Text processing: tokenization

What is Tokenization?

Tokenization is the process of segmenting a string of characters into words.

Depending on the application in hand, you might have to perform *sentence segmentation* as well.

Sentence Segmentation

The problem of deciding where the sentences begin and end.

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For each "."

- Decides EndOfSentence/NotEndOfSentence

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For each “.”

- Decides EndOfSentence/NotEndOfSentence
- Classifiers can be: hand-written rules, regular expressions, or machine learning

Sentence Segmentation: Decision Tree Example

Decision Tree: Is this word the end-of-sentence (E-O-S)?

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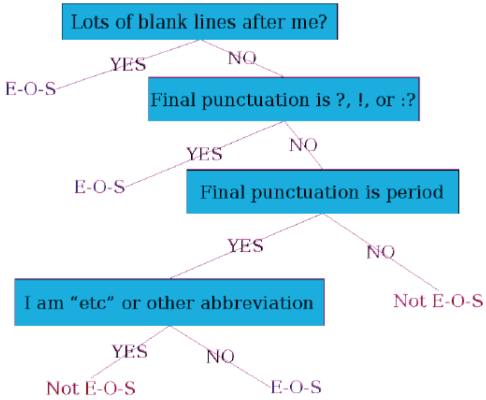

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Basic Idea

Usually works top-down, by choosing a variable at each step that best splits the set of items.
Popular algorithms: ID3, C4.5, CART

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- Support Vector Machines
- Logistic regression
- Neural Networks

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I have a can opener; but I can't open these cans.

Word Token

- An occurrence of a word
- For the above sentence, 11 word tokens.

Word Type

- A different realization of a word
- For the above sentence, 10 word types.

Tokenization in practice

- NLTK Toolkit (Python)
- Stanford CoreNLP (Java)
- Unix Commands

Word Tokenization

Issues in Tokenization

- Finland's $\rightarrow$ Finland Finlands Finland's ?
- What're, I'm, shouldn't $\rightarrow$ What are, I am, should not ?
- San Francisco $\rightarrow$ one token or two?
- m.p.h. $\rightarrow$??

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For information retrieval, use the same convention for documents and queries

Handling Hyphenation

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End-of-Line Hyphen

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Sententially Determined Hyphenation

Mainly to prevent incorrect parsing of the phrase. Some possible usages:

- Noun modified by an 'ed'-verb: *case-based, hand-delivered*
- Entire expression as a modifier in a noun group: *three-to-five-year direct marketing plan*

Language Specific Issues: French and German

French

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German

Noun coumpounds are not segmented

- Lebensversicherungsgesellschaftsangestellter
- 'life insurance company employee'
- Compound splitter required for German information retrieval

Language Specific Issues: Chinese and Japanese

No space between words

莎拉波娃现在居住在美国东南部的佛罗里达。

莎拉波娃 现在 居住 在 美国 东南部 的 佛罗里达

Sharapova now lives in US southeastern Florida

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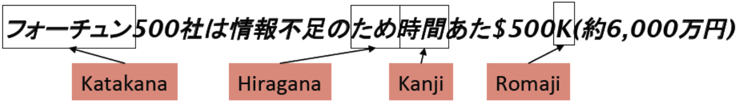
Japanese: further complications with multiple alphabets intermingled.



सत्यम्ब्रूयात्प्रियम्ब्रूयान्नब्रूयात्सत्यमप्रियम्प्रियञ्चनानृतम्ब्रूयादेषधर्मःसनातनः

satyaṃbrūyātpriyaṃbrūyānnabrūyātsatyamapriyaṃpriyaṃcanānṛtambrūyād-eṣadharmaḥsanātanaḥ.

"One should tell the truth, one should say kind words; one should neither tell harsh truths, nor flattering lies; this is a rule for all times."

Segmented Text:

satyam brūyāt priyam brūyāt na brūyāt satyam apriyam priyam ca na anṛtam brūyāt eṣaḥ dharmaḥ sanātanaḥ.

Longest Words

Max	Language (non scientific)
431	**Sanskrit** *(Longest)*
173	Greek
136	Afrikaans
85	Māori
79	German
74	Turkish
64	Icelandic
56	Hungarian
54	Spanish
49	Dutch
46	Malay
45	English

44	Romanian
42	Georgian
41	Czech
39	Bulgarian
39	Lithuanian
36	Kazakh
33	Norwegian
32	Tagalog
32	Polish
30	Serbian
30	Montenegrin
30	Italian
30	Croatian

Word Tokenization in Chinese or Sanskrit

Also called ‘**Word Segmentation**’.

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Greedy Algorithm for Chinese

Maximum Matching (Greedy Algorithm)

- Start a pointer at the beginning of the string
- Find the largest word in dictionary that matches the string starting at pointer
- Move the pointer over the word in string

Think of the cases when word segmentation would be required for English Text.

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Finding constituent words in a compound hashtags: #ThankYouSachin, #musicmonday etc.

Text normalization

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Indexed text and query terms must have the same form.

- U.S.A. and USA should be matched
- We implicitly define equivalence classes of terms

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- Possible exceptions (Task dependent):
  - Upper case in mid sentence, may point to named entities (e.g. General Motors)
  - For MT and inforamtion extraction, some cases might be helpful (*US* vs. *us*)

Lemmatization

- Reduce inflections or variant forms to base form:
  - am, are, is $\rightarrow$ be
  - car, cars, car's, cars' $\rightarrow$ car
- Have to find the correct dictionary headword form

Note: the lemma (output of lemmatization) is a dictionary word

To find the correct lemma for a given word, we use Morphology

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Morphemes are divided into two categories

- Stems: The core meaning bearing units
- Affixes: Bits and pieces adhering to stems to change their meanings and grammatical functions

Both stems and affixes depend on the language

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  - Infix: '*n*' in '*vindati*' (he knows), as contrasted with *vid* (to know).

Stemming

- Reducing terms to their stems, used in information retrieval

Note: A stem is not necessarily a dictionary word (unlike a lemma)

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  - *automate(s), automatic, automation* all reduced to *automat*

for example compressed and compression are both accepted as equivalent to compress.

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The most commonly used algorithm for stemming in English: Porter's algorithm

Basically, a set of if-then-else rules to convert a given word to its "stem"

Porter's algorithm

Step 1a

- sses $\rightarrow$ ss (caresses $\rightarrow$ caress)
- ies $\rightarrow$ i (ponies $\rightarrow$ poni)
- ss $\rightarrow$ ss (caress $\rightarrow$ caress)
- s $\rightarrow$ ϕ (cats $\rightarrow$ cat)

Read the rules as:

If a word ends with “sses”, remove “es” and retain “ss”
Else if the word ends with “ies”, remove “es” and retain “i”
Else if the word ends with “ss”, retain “ss”
Else if the word ends with “s”, remove “s”

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Step 1b

- (*v*)ing $\rightarrow$ ϕ (walking $\rightarrow$ walk, king $\rightarrow$

If the word has a vowel and ends with "ing", remove the "ing"

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Step 1b

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- (*v*)ed $\rightarrow$ ϕ (played $\rightarrow$ play)

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Porter's algorithm

Step 2

- ational $\rightarrow$ ate (relational $\rightarrow$ relate)
- izer $\rightarrow$ ize (digitizer $\rightarrow$ digitize)
- ator $\rightarrow$ ate (operator $\rightarrow$ operate)

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Step 3

- al $\rightarrow$ ϕ (revival $\rightarrow$ reviv)
- able $\rightarrow$ ϕ (adjustable $\rightarrow$ adjust)
- ate $\rightarrow$ ϕ (activate $\rightarrow$ activ)