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.

Challenges Involved

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For each "."

- Decides EndOfSentence/NotEndOfSentence

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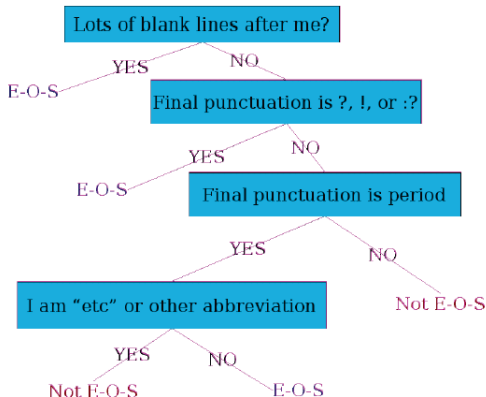### Approach: build a binary classifier

For each "."

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

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

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

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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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The questions in the decision tree can be thought of as features, that could be exploited by any other classifier:

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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.

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

Word Tokenization

Word Tokenization

Issues in Tokenization

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

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

Hyphens can be

Handling Hyphenation

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End-of-Line Hyphen

Used for splitting whole words into part for text justification.
This paper describes MIMIC, an adaptive mixed initia-tive spoken dialogue system that provides movie show-time information.

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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

l'ensemble: want to match with un ensemble

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German

Noun coumpounds are not segmented

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

No space between words

莎拉波娃现在居住在美国东南部的佛罗里达。

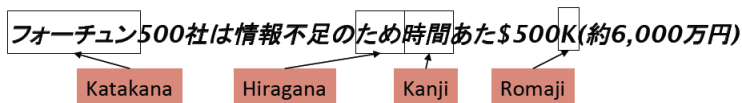| 莎拉波娃	现在	居住	在	美国	东南部	的	佛罗里达
Sharapova now		lives in		US	southeastern		Florida

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Japanese: further complications with multiple alphabets intermingled.

フォーチュン500社は情報不足のため時間あた$500K(約6,000万円)

| Katakana | Hiragana | Kanji | Romaji |

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."

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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

Longest Words

Compound word composed of 431 letters, from the Varadāmbikā Pariṇaya Campū by Tirumalāmba

निरन्तरान्धकारिता-दिगन्तर-कन्दलदमन्द-सुधारस-बिन्दु-सान्द्रतर-घनाघन-वृन्द-सन्देहकर-स्यन्दमान-मकरन्द-बिन्दु-बन्धुरतर-माकन्द-तरु-कुल-तल्प-कल्प-मृदुल-सिकता-जाल-जटिल-मूल-तल-मरुवक-मिलदलघु-लघु-लय-कलित-रमणीय-पानीय-शालिका-बालिका-करार-विन्द-गलन्तिका-गलदेला-लवङ्ग-पाटल-घनसार-कस्तूरिकातिसौरभ-मेदुर-लघुतर-मधुर-शीतलतर-सलिलधारा-निराकरिष्णु-तदीय-विमल-विलोचन-मयूख-रेखापसारित-पिपासायास-पथिक-लोकान्

Also called '**Word Segmentation**'.

Word Tokenization in Chinese or Sanskrit

Also called '**Word Segmentation**'.

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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Think of the cases when word segmentation would be required for English Text.
Finding constituent words in a compound hashtags: #ThankYouSachin, #musicmonday etc.

1

General assumption behind the design

Sentences from Classical Sanskrit may be generated by a regular relation R of the Kleene closure W^* of a regular set W of *words* over a finite alphabet Σ.

---

[1] http://sanskrit.inria.fr

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Analysis of a sentence

A candidate sentence w is analyzed by inverting relation R to produce a finite sequence $w_1, w_2, ...w_n$ of word forms, together with a proof that $w \in R(w_1 \cdot w_2... \cdot w_n)$.

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Sentence: सत्यम्ब्रूयात्प्रियम्ब्रूयान्नब्रूयात्सत्यमप्रियम्प्रियञ्चनानृतम्ब्रूयादेषधर्मःसनातनः

✓Undo   (120 Solutions)

satyambrūyātpriyambrūyānnabrūyātsatyam a priyampriyañcanānṛtambrūyādeṣadharmaḥsan ā tanaḥ

satyam	brūyāt	priyam	brūyāt	na brūyāt	satyam	a	priyam	priyam	cana	ṛtam	brūyāt	eṣa	dharmas	sanātanas
✓	✓	✓	✓✗	✓ ✓	✓✗	✓✗ ✓	✓	✓✗	✓ ✓	✓ ✓	✓✗

brūyām ✓✗

sati | ama ✓✗ ✓✗

satī ✓✗

ca na ✓✗ ✓✗

an ✓

sana ✓✗ | tanas

sanā ✓✗ | nas ✓✗

san ata ✓✗ ✓✗

sa na ✓✗ ✓✗

āta ✓✗

a ✓✗

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Indexed text and query terms must have the same form.

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- We implicitly define equivalence classes of terms

- Reduce all letters to lower case

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- Possible exceptions (Task dependent):
    - Upper case in mid sentence, may point to named entities (e.g. General Motors)

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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*)

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

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

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Stemming

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- Crude chopping of affixes
  - ▶ language dependent
  - ▶ *automate(s), automatic, automation* all reduced to *automat*

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

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)

Porter's algorithm

Step 1a

- sses → ss (caresses → caress)
- ies → i (ponies → poni)
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Step 1b

- (*v*)ing → ϕ (walking → walk, king →

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Step 1b

- (*v*)ing → ϕ (walking → walk, king → king)
- (*v*)ed → ϕ (played → play)

Porter's algorithm

Step 2

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

Porter's algorithm

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- ational → ate (relational → relate)
- izer → ize (digitizer → digitize)
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Step 3

- al → φ (revival → reviv)
- able → φ (adjustable → adjust)
- ate → φ (activate → activ)