

# Statistical Natural Language Processing

Tokenization, normalization, segmentation

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# Tokenization – a solved problem?

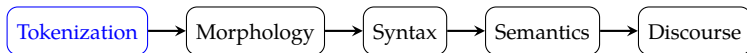
- Typically, we (in NLP/CL/IR/...) process text as a sequence of tokens
- Tokens are word-like units
- A related task is *sentence segmentation*
- Tokenization is a language dependent task, where it becomes more challenging in some languages
- Tokenization is often regarded as trivial, and a mostly solved task

# Classical NLP pipeline

- *Tokenization*  
Sentences, (normalized) words, stems / lemmas
- *Lexical / morphological processing*  
POS tags, morphological features, stems / lemmas, named entities
- *Parsing*  
Constituency / dependency trees
- *Semantic processing*  
word-senses, logical forms
- *Discourse*  
Co-reference resolution, discourse representation

We do not always use a pipeline, not all steps are necessary for all applications

# Tokenization in the classical NLP pipeline



- Tokenization is the first in the pipeline
- Even for end-to-end approaches, tokenization is often considered given (needs to be done in advance)
- Errors propagate!

# But, can't we just tokenize based on spaces?

...and get rid of the punctuation

Some examples from English:

- \$10 billion
- rock 'n' roll
- he's
- can't
- O'Reilly
- 5-year-old
- B-52
- C++
- C4.5
- 29.05.2017
- 134.2.129.121
- sfs.uni-tuebingen.de
- New York-based
- wake him up

## Gets more interesting in other languages

- Chinese: 猫占领了婴儿床  
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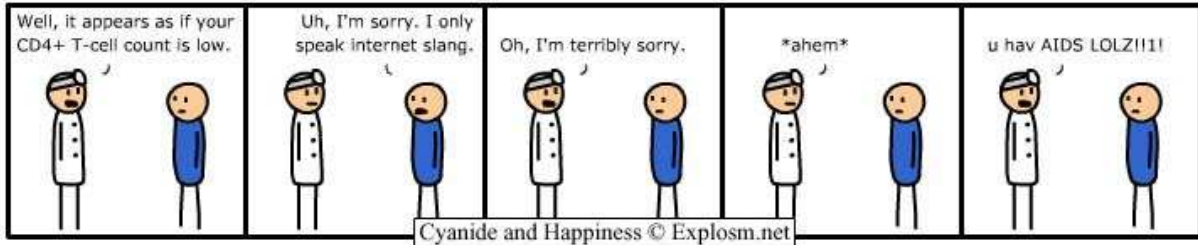
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'You were (evidentially) one of those who we may not be able to convert to an Istanbulite'
- Even more interesting when we need to process 'mixed' text with *code-switching*

## Specialized and non-standard text

- More difficult for non-standard text
  - Many specialized terms use a mixture of letters, numbers, punctuation
  - Frequent misspelling, omitting space (e.g., after sentence final punctuation)

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- Non-standard text can be
  - Spoken language
  - Old(er) samples of text (e.g., historical records)
  - Specialized domains, e.g., bio-medical texts
  - Informal communication, e.g., social media



# Normalization

*Normalization* is a related task that often interacts with tokenization.

- For most applications (e.g., IR) we want to treat the following the same
  - Linguistics – linguistics
  - color – colour
  - lower case – lowercase – lower-case
  - Tübingen – Tuebingen – Tubingen
  - seee – see
  - flm – film
  - Different date/time formats, phone numbers
- Most downstream tasks require the ‘normalized’ forms of the words

# So, what is a token?

- One token or multiple?
  - John's
  - New York
  - German: *im* (*in* + *dem*)
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- Answer is language and application dependent
- Tokenization decisions are often arbitrary
- Consistency is important



# Rule based tokenization

## Regular expressions and finite-state automata

- The ‘easy’ solution to the tokenization is rule-based
- Using regular expressions,
  - we can define regular expressions for allowed tokens
  - split after match, disregard/discard the remaining parts
- For example,
  - All alphabetic characters, *word*, `[a-z]+`
  - Capitalization, *John*, `[A-Z]?[a-z]+`
  - Abbreviations, *Prof.*, `[A-Z]?[a-z]+[.]?`
  - Numbers too, *123*, `[A-Z]?[a-z]+[.]?|[0-9]+`
  - Numbers with decimal parts `[A-Z]?[a-z]+[.]?|[0-9.]+`
  - ...
- Result is typically imprecise, difficult to maintain

# Splitting sentences

- Another relevant task is *sentence tokenization*
- For most applications, we need sentence boundaries
- Sentence-final markers, `[. ! ?]` are useful
- But the dot `'.'` is ambiguous: can either be end-of- sentence or abbreviation marker, or both
  - The U.N. is the largest intergovernmental organisation.
  - I had the impression he'll be ambassador to the U.N.
- Again, heuristics along with a list of abbreviations is possible

# Problems with rule-based approaches

- Rule-based approaches are (still) common in practice, however
  - it is difficult to build a rule set that works well in practice
  - it is difficult to maintain
  - it is not domain or language general: needs re-implementation, re-adjustment for every case

# Machine learning for word / sentence tokenization

- Another approach is to use machine learning
- Label each character in the text with
  - I inside a token
  - O outside tokens
  - B beginning of a token,  
alternatively to combine word/sentence tokenization
  - T beginning of a token
  - S beginning of a sentence
- How do we create the training data?
- What are the features for the ML?

# I/O/B tokenization: an example

The U.N. is the largest intergovernmental  
BIIOBIIIOBIOBIIIOBIIIIIOBIIIIIIIIIIIIIIIO  
organisation. I had the impression he'll be  
BIIIIIIIIIIIOOBIOBIIIOBIIIIIIIIIOBIBIIIOBIO  
ambassador to the U.N.  
BIIIIIIIIIIIOBIOBIIIOBIIIO

# I/O/B tokenization example

with sentence boundary markers

The U.N. is the largest intergovernmental  
 SIIOTIIIIOTIOTIIOTIIIIIIOTIIIIIIIIIIIIIIIO  
 organisation. I had the impression he'll be  
 TIIIIIIIIIIIOOSOTIIOTIIOTIIIIIIIIIIOTITIIOTIO  
 ambassador to the U.N.  
 TIIIIIIIIIIOTIOTIIOTIIIO

# Features for tokenization

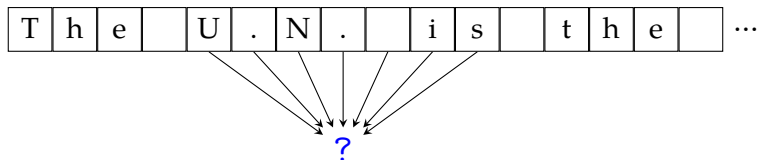
T	h	e		U	.	N	.		i	s		t	h	e	
---	---	---	--	---	---	---	---	--	---	---	--	---	---	---	--

 ...

?

- We predict label of each character

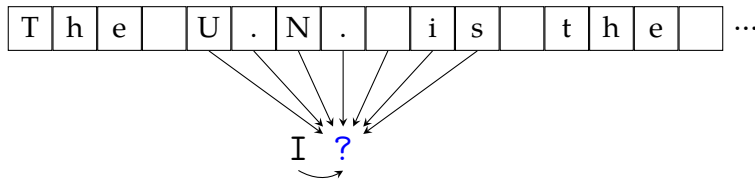
## Features for tokenization



- We predict label of each character
- Typical features are the other characters around the target
- Choice of features and the machine learning method vary



## Features for tokenization



- We predict label of each character
- Typical features are the other characters around the target
- Choice of features and the machine learning method vary
- Using the previous prediction is also useful

# Segmentation

- Segmentation is a related problem in many areas of computational linguistics
  - In some languages, the word boundaries are not marked  
猫占领了婴儿床 → 猫 占领 了 婴儿床
  - We often want to split words into their morphemes  
Lebensversicherungsgesellschaftsangestellter →  
Leben+s+versicherung+s+gesellschaft+s+angestellter
  - In spoken language there are no reliable word boundaries

# Supervised segmentation

- I/O/B tokenization is applicable to segmentation as well
- Often produces good accuracy
- The main drawback is the need for labeled data
- Some unsupervised methods with reasonable accuracy also exist
- In some cases, unsupervised methods are useful and favorable

## A simple 'unsupervised' approach

- Using a lexicon, segment at maximum matching lexical item
  - Serves as a good baseline, but fails in examples like  
theman  
where maximum match suggests segmentation 'them an'
  - The out-of-vocabulary words are problematic
- One can use already known boundaries as signal for supervision
  - Known to work especially well for sentence segmentation, (e.g., using cues .?!)

# Unsupervised segmentation

- Two main approaches
  - Learn a compact lexicon that maximizes the likelihood of the data

$$P(s) = \prod_{i=1}^n P(w_i)$$

$$P(w) = \begin{cases} (1 - \alpha)f(w) & \text{if } w \text{ is known} \\ \alpha \prod_{i=1}^m P(a_i) & \text{if } w \text{ is unknown} \end{cases}$$

- Segment at points where predictability (entropy) is low
 

The general idea: the predictability within words is high, predictability between words is low

# Summary

- Tokenization is an important part of an NLP application
- Tokens are word-like units that are
  - linguistically meaningful
  - useful in NLP applications
- Tokenization is often treated as trivial, has many difficulties of its own
- White spaces help, but does not solve the tokenization problem completely
- Segmentation is tokenization of input where there are no boundary markers
- Solutions include rule-based (regex) or machine learning approaches

Next

Wed POS tagging / morphological processing

# Some extra: modeling segmentation by children

NLP can be 'sciency', too

- An interesting application of unsupervised segmentation methods is modeling child language acquisition
- How children learn languages has been one of the central topics in linguistics and cognitive science
- Computational models allow us to
  - test hypotheses
  - create explicit models
  - make predictions



# The puzzle to solve

ljuuzuibutsjhiuljuuz  
ljuuztbzjubhbjompwfljuuz  
xibutuibu  
ljuuz  
epzpvxbounpsfnjmlipofz  
ljuuzljuuzephbjf  
opnjxibuepftbljuuztbz  
xibuepftbljuuztbz  
ephhjfebh  
ephhbjf  
opnjxibuepftuifebhbjftbz  
xibuepftuifebhbjftbz  
mjuumfcbczcjsejf  
cbczcjsejf  
zpvepoumjlfuibupof  
plbznppnzublfuijtpvu  
dpx  
uifdpxtbztnppnp  
xibuepftuifdpxtbzopnj

# The puzzle to solve

ljuuzuibutsjhiuljuuz  
ljuuztbzjubhbjompwfljuuz  
xibutuibu  
ljuuz  
epzpvxbounpsfnjmlipofz  
ljuuzljuuzephjhj  
opnjxibuepftbljuuztbz  
xibuepftbljuuztbz  
ephhjfe  
ephhj  
opnjxibuepftuife  
xibuepftuife  
mjuumfcbczcjsej  
cbczcjsej  
zpvepoumjlfuibupof  
plbznpnnzublfuijtpvu  
dpx  
uifdpxtbztnppnp  
xibuepftuifdpxtbzopnj

- No clear boundary markers
- No lexical knowledge

## How do children segment? – a bit of psycholinguistics

Children very early in life (8-months) seem to be sensitive to statistical regularities between syllables (Saffran, Aslin, and Newport 1996)

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Training: bidakupadotigolabubidakugolabupadoti...

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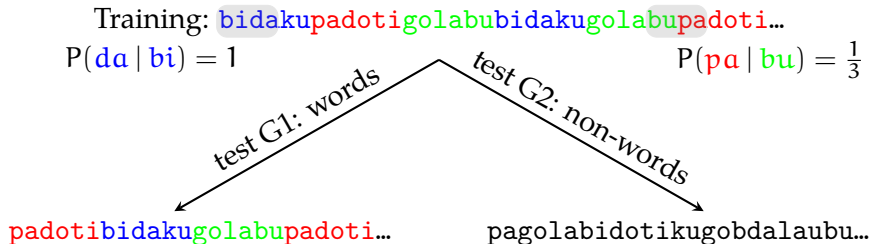
Training: **bi**da**ku**pa**do**ti**go**la**bu**bi**da**ku**go**la**bu**pa**do**ti...

$$P(\text{da} \mid \text{bi}) = 1$$

$$P(\text{pa} \mid \text{bu}) = \frac{1}{3}$$

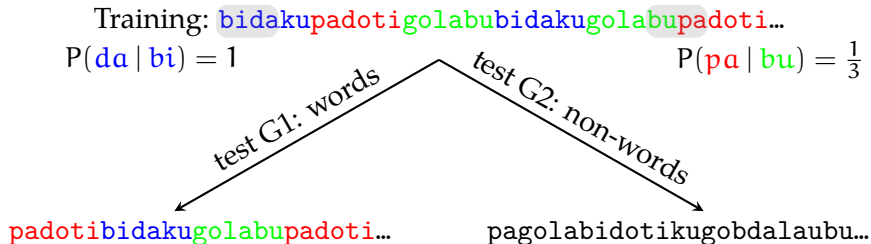
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Children showed preference towards the 'words' that are used in the training phase.

# Predictability

*Predictability within units is high, predictability between units is low.*



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Given a sequence  $lr$ , where  $l$  and  $r$  are sequences of phonemes:

- If  $l$  help us predict  $r$ ,  $lr$  is likely to be part of a word
- If observing  $r$  after  $l$  is surprising it is likely that there is a boundary between  $l$  and  $r$

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The strategy dates back to 1950s (Harris 1955), where he used a measure called *successor variety* (SV):

*The morpheme boundaries are at the locations where there is a high variety of possible phonemes that follow the initial segment.*

# How to calculate the measures

# I z D & t 6 k I t i #

## How to calculate the measures

#	I	z	D	&	t	6	k	I	t	i	#
P:	0.40										

$$P(z|\#I) = 0.40$$

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#	I	z	D	&	t	6	k	I	t	i	#
P:	0.40	0.22									

$$P(D|Iz) = 0.22$$

## How to calculate the measures

#	I	z	D	&	t	6	k	I	t	i	#
P:	0.40	0.22	0.46								

$$P(\&|zD) = 0.46$$

## How to calculate the measures

#	I	z	D	&	t	6	k	I	t	i	#
P:	0.40	0.22	0.46	0.99							

$$P(t|D\&) = 0.99$$

## How to calculate the measures

#	I	z	D	&	t	6	k	I	t	i	#
P:	0.40	0.22	0.46	0.99	0.03						

$$P(6|\&t) = 0.03$$



## How to calculate the measures

#	I	z	D	&	t	6	k	I	t	i	#
P:	0.40	0.22	0.46	0.99	0.03	0.04					

$$P(k|t6) = 0.04$$

## How to calculate the measures

#	I	z	D	&	t	6	k	I	t	i	#
P:	0.40	0.22	0.46	0.99	0.03	0.04	0.30				

$$P(I|6k) = 0.30$$

## How to calculate the measures

#	I	z	D	&	t	6	k	I	t	i	#
P:	0.40	0.22	0.46	0.99	0.03	0.04	0.30	0.48			

$$P(t|kI) = 0.48$$

## How to calculate the measures

#	I	z	D	&	t	6	k	I	t	i	#
P:	0.40	0.22	0.46	0.99	0.03	0.04	0.30	0.48	0.10		

$$P(i|It) = 0.10$$

Calculations are done on a corpus of child-directed English

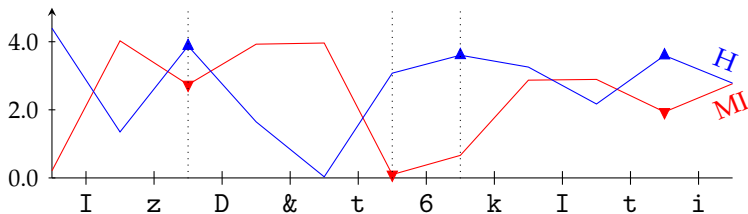
## An unsupervised method

- An obvious way to segment the sequence is using a threshold value. However, the choice of threshold is difficult in an unsupervised system.

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However, the choice of threshold is difficult in an unsupervised system.

A simple unsupervised method: segment at peaks/valleys.



# Segmentation puzzle: a solution

ljuuz uibut sjhiu ljuuz  
ljuuz tbz ju bhhjo mpwf ljuuz  
xibut uibu  
ljuuz  
ep zpv xbou npsf njml ipofz  
ljuuz ljuuz ephhjf  
opnj xibu epft b ljuuz tbz  
xibu epft b ljuuz tbz  
ephhjf eph  
ephhjf  
opnj xibu epft uif ephhjf tbz  
xibu epft uif ephhjf tbz  
mjuumf cbcz cjsejf  
cbcz cjsejf  
zpv epou mjlf uibu pof  
plbz npnnz ublf uijt pvu  
dpx  
uif dpx tbzt npp npp  
xibu epft uif dpx tbz opnj

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ljuuz uibut sjhiu ljuuz  
ljuuz tbz ju bhbjo mpwf ljuuz  
xibut uibu  
ljuuz  
ep zpv xbou npsf njml ipofz  
ljuuz ljuuz ephhj  
opnj xibu epft b ljuuz tbz  
xibu epft b ljuuz tbz  
ephhj eph  
ephhj  
opnj xibu epft uif ephhj tbz  
xibu epft uif ephhj tbz  
mjuumf cbcz cjsej  
cbcz cjsej  
zpv epou mjlf uibu pof  
plbz npnnz ublf uijt pvu  
dpx  
uif dpx tbzt npp npp  
xibu epft uif dpx tbz opnj

ljuuz uibu tsjhiuljuuz  
ljuuz tbz jubhbjompwfljuuz  
xibu tuibu  
ljuuz  
ep zpvxbounpsfnjml pof z  
ljuuz ljuuz ephhj  
opnj xibu ep ftb ljuuz tbz  
xibu ep ftb ljuuz tbz  
ephhj eph  
ephhj  
opnj xibu epft uif ephhj tbz  
xibu ep ft uif ephhj tbz  
mjuumfcbczcjsej  
cbczcjsej  
zpv epoumj lf uibu pof  
plbznpnnzublfui jtpvu  
dpx  
uif dpx tbz tnppnpp  
xibu epft uif dpx tbz opnj



# Segmentation puzzle: a solution

kitty thats right kitty  
kitty say it again love kitty  
whats that  
kitty  
do you want more milk honey  
kitty kitty doggie  
nomi what does a kitty say  
what does a kitty say  
doggie dog  
doggie  
nomi what does the doggie say  
what does the doggie say  
little baby birdie  
baby birdie  
you dont like that one  
okay mommy take this out  
cow  
the cow says moo moo  
what does the cow say nomi

kitty that srightkitty  
kitty say itagainlovekitty  
what s that  
kitty  
do youwantmoremilkh one y  
kitty kitty doggie  
nomi what do esa kitty say  
what do esa kitty say  
doggie dog  
doggie  
nomi what does the doggie say  
what do es the doggie say  
littlebabybirdie  
babybirdie  
you dontli ke that one  
okaymommytaketh isout  
cow  
the cow say smoomoo  
what does the cow say nomi

## Additional reading, references, credits

- Textbook reference: Jurafsky and Martin (2009, chapter 2 of the 3rd edition draft) sections 2.1–2.3 (inclusive)
- The Chinese word segmentation example is from Ma and Hinrichs (2015)
- Other segmentation examples are from Çöltekin (2011), where there is also a good amount of introductory information on segmentation

# Additional reading, references, credits (cont.)



Çöltekin, Çağrı (2011). “Catching Words in a Stream of Speech: Computational simulations of segmenting transcribed child-directed speech”. PhD thesis. University of Groningen. URL: <http://irs.ub.rug.nl/ppn/33913190X>.



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