# Overview of Natural Language Processing Part II \& ACS L90 <br> Lecture 2: Morphology 

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Some yinkish dripners blorked quastofically into the nindin with the pidibs

$\ldots$. dripn + ER + S blork + ED quastofical + LY into the nindin with the pidib $+S$

Lecture 2: Morphology

1. Morphology
2. Relevant NLP tasks
3. Finite state techniques
4. Byte-pair encoding

## Morphology

## Morpheme

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- suffix (units), prefix (incomplete), infix, circumfix

Root: nucleus of the word that affixes attach too.


Infix
Tagalog (Philippines)


Circumfix: occur on both sides

## Dutch collectives



Source: J Hana \& A Feldman. ESSLLI 2013: Computational Morphology.
http://ufal.mff.cuni.cz/~hana/teaching/2013-esslli/ 2 of 2

## Inflection and derivation

Inflection creates new forms of the same word

- e.g. bring, brought, brings, bringing
- generally fully productive (modulo irregular forms)
- tends to affect only its syntactic function

Derivation creates new words

- e.g. logic, logical, illogical, illogicality, logician, etc.
- generally semi-productive: e.g., escapee, textee, ?dropee, ?snoree, *cricketee (* and ?)
- tends to be more irregular; the meaning is more idiosyncratic and less compositional.
- tends to affect the meaning of the word, and may change part-of-speech


## Internal structure: ambiguity

Structural ambiguity


Capable of being unlocked.
Not capable of being locked.

Can cross word boundaries


More about beautiful dancer: Larson (1998).

Stem: word without its inflectional affixes $=$ roots + all derivational affixes.

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Lexeme: the set of all forms related by inflection (but not derivation). \{bookshops, bookshopped, bookshopping, ...\}

Lemma: the canonical/base/dictionary/citation form of a lexeme chosen by convention.
bookshop (cf. the stem-bookshopp)

## Phonaestheme

slither, slide, slip etc have somewhat similar meanings; but sl- is not a morpheme.

Etymology: slith, slid and slip are historically related. See
www.etymonline.com/word/slide

## Phonaestheme

a pattern of sounds systematically paired with a certain meaning in a language

- cl-: related to a closing motion of a single object, such as clam, clamp, clap, clasp, clench, cling, clip, clop, clutch.
- gl-: related to light, as in glance, glare, glass, gleam, glimmer, glint, glisten, glitter, gloaming, gloom, gloss, glow.


## Compound and multiword expression (1)

2015


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2016


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2017


## Compound and multiword expression (1)

2019


## Compound and multiword expression (2)

## Root: nucleus of the word that affixes attach too.

Compounds contain more than one root.
(1) a. youthquake
b. post-truth
c. railway
d. sunset

Multiword expression: combinations of two or more words that exhibit syntactic and semantic idiosyncratic behavior.
(2) a. climate emergency
b. computer science
c. random variable

## Different types of multiword expressions

## Fixed

(Syntactically) flexible
by and large
put on the clothes
put the clothes on
Non-compositional Semi-compositional Compositional

| kick the bucket | spill the beans <br> (reveal the secret) | strong tea |
| :--- | :--- | :--- |

## Multiword expression and grammatical errors

(3) a. At this moment Carole was living with her husband but they didn't love each other any more.
$\rightarrow$ At the moment
b. It is a dream becames true and was really unexpected for me!
$\rightarrow$ dream come true
c. They go together in groups, then they prepare power point presentations and at least they present it in front of the other pupils and teachers.
$\rightarrow$ finally
d. By the other side, I have never climbed a mountain but I always wanted to do it.
$\rightarrow$ On the other hand
e. I tried to take it on my stride but I couldn't.
$\rightarrow$ take it in my stride
f. However, I told my teacher that I am willing to give a hand next time.
$\rightarrow$ lend a hand

## Code－mixed languages

## Code－switching

a speaker alternates between two or more languages in the context of a single conversation or situation．

## Cantonese－English（widely used in Hong Kong）

The English word＂sure＂／＂cute＂is mixed into an otherwise Cantonese sentence．

- 我唔sure
- cu唔cute啊


## Text normalization

- Not using any punctuation at all

Eh speak english mi malay not tt good (Eh, speak English! My Ma-lay is not that good.)

- Using spell-ing/punctuation for emphasis goooooood Sunday morning !!!!!! (Good Sunday morning!)
- Using phonetic spelling dat iz enuf (That is enough)
- Dropping vowel i hv cm to c my luv. (I have come to see my love.)
- Introducing local flavor yar lor where u go juz now (yes, where did you go just now?)
- Dropping verb I hv 2 go. Dinner w parents. (I have to go. Have dinner with parents.)

Examples are from Aw et al. (2005). https://www.aclweb.org/anthology/P06-2005.pdf More: noisy-text.github.io/norm-shared-task.html

Relevant NLP Tasks

## Form transformation



## Computational tasks

natural language expression
word
saw

TAGGING $\rightarrow$ contextualized word saw @ J saw M

SEGMENTATION $\rightarrow \begin{gathered}\text { word } \\ \text { meaningful }\end{gathered}$

GENERATION $\leftarrow$
word
saw
representation $\mathcal{R}$

> lexeme $\{$ see, saw $\}$
contextualized tag $\langle$ see, verb. PAST〉
morphemes (subwords)
mean+ing+ful
abstract word $\langle$ see, VERB.PAST〉

## Segmentation

antidisestablishmentarianism $\Rightarrow$ anti- dis- e- stabl -ish -ment -arian -ism antidisestablishmentarianism
anti dis establish ment arian ism
en.wikipedia.org/wiki/Antidisestablishmentarianism WWW. etymonline.com/word/antidisestablishmentarianism

## important for some application, e.g. bioinformatics

## Word segmentation

Goal
－The written systems for some languages，e．g．Japanese and Chinese contain no word delimiters such as spaces．
－There is a need to develop algorithms that are able to automatically divide a string into its component words．

Example
解放大道路面积水问题
解放／大道／路面／积水／问题
解／放大／道路／面积／水／问题

## Finite State Techniques

## Language Is An Inherently Temporal Phenomenon

Orders matter!

- talk-ed $\neq{ }^{*}$ ed-talk
- re-write $\neq{ }^{*}$ write-re
- un-kind-ly $\neq$ *kind-un-ly


## Language Is An Inherently Temporal Phenomenon

Orders matter!

- talk-ed $\neq$ *ed-talk
- re-write $\neq{ }^{*}$ write-re
- un-kind-ly $\neq{ }^{*}$ kind-un-ly



## Turing machine



## Finite-state automata



- Circles are states of the automaton.
- Arrows are called transitions.
- The automaton changes states by following transitions.
- The double circle indicates that this state is an accepting state. The automaton accepts the string if it ends in an accepting state.


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- Form Transformation: agumenting transitions

$$
\text { input } \rightarrow \text { input:output }
$$

## Finite state transducer

- cakes $\rightarrow$ cake\#s
- boxes $\rightarrow$ box\#s


Analysing boxes
OUTPUT

| INPUT | $b$ | $o$ | $x$ | $e$ | $s$ |
| :--- | :--- | :--- | :--- | :--- | :--- |



Analysing boxes
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| INPUT | $b$ | $o$ | $x$ | $e$ | $s$ |
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## Analysing boxes

| OUTPUT | b |  |  |  |  |
| ---: | :--- | :--- | :--- | :--- | :--- |
| INPUT | b | o | x | e | s |
|  |  |  |  |  |  |



## Analysing boxes

| OUTPUT | b |  |  |  |  |
| ---: | :--- | :--- | :--- | :--- | :--- |
|  | b | o |  |  |  |



Analysing boxes

| OUTPUT | b | o |  |  |  |
| ---: | :--- | :--- | :--- | :--- | :--- |
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Analysing boxes

| OUTPUT | b | o | x |  |  |
| :--- | :--- | :--- | :--- | :--- | :--- |
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## Analysing boxes

| OUTPUT | b | o | x | $\#$ |  |
| ---: | :--- | :--- | :--- | :--- | :--- |
| INPUT | b | o | x | e | s |



## Analysing boxes

| OUTPUT | b | o | x | $\#$ | s |
| ---: | :---: | :---: | :---: | :---: | :---: |
| INPUT | b | o | x | e | s |



## Finite-state machine



- A symbolic system that can recognize or transform forms.


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- Partial grammars for text preprocessing, tokenization, named entity recognition etc.


## Cross－lingual variants

－English morphology is essentially concatenative cf．duplication in Chinese，e．g．

高 兴 $\rightarrow$| 高 高 兴 兴 |
| :--- |
| happy |

## Cross-lingual variants

- English morphology is essentially concatenative cf. duplication in Chinese, e.g.

- The phones making up a morpheme don't have to be contiguous, e.g. in Hebrew

| Root | Pattern | PoS | Phonological <br> Form | Gloss |
| :--- | :--- | :--- | :--- | :--- |
| $k t b$ | CaCaC | $v$ | katav | 'wrote' |
| ktb | hiCCiC | v | hixtiv | 'dictated' |
| ktb | miCCaC | n | mixtav | 'a letter' |
| ktb | CCaC | n | ktav | 'writing, alphabet' |
| om E. Bender's tutorial (faculty. washington.edu/ebender/papers/100things.pdf) |  |  |  |  |

## Byte-Pair Encoding

## Form transformation



Q Are there some magical algorithms that are able to automatically induce useful representations from data?

## Subword tokenisation

Isn't it just one symbol?


## Subword tokenisation

Isn't it just one symbol?


Phonaestheme: It is difficult to hard-code the knowledge

- cl-: related to a closing motion of a single object, such as clam, clamp, clap, clasp, clench, cling, clip, clop, clutch.


## Byte-Pair Encoding (BPE)

BPE was initially developed as an algorithm to compress texts, and then used by OpenAl for tokenization when pretraining the GPT model.

- Start from a small base vocabulary, e.g. 256 ASCII code.
- Add new tokens to the vocabulary until the desired vocabulary size is reached by learning merges, which are rules to merge two elements of the existing vocabulary together into a new one.
- At each step, the BPE algorithm search for the most frequent pair, namely two consecutive tokens, of existing tokens.
from https://huggingface.co/learn/nlp-course/chapter6/5?fw=pt


## Example

("hug", 10), ("pug", 5), ("pun", 12), ("bun", 4), ("hugs", 5)
on whiteboard

## Readings

## Required

- Ann's lecture notes. https://www.cl.cam.ac.uk/teaching/1920/NLP/materials.html
- E. Bender. 100 Things You Always Wanted to Know about Linguistics But Were Afraid to Ask. NAACL-HLT 2012 tutorial. faculty.washington.edu/ebender/papers/100things.pdf Please read Numbers \#7-\#27.


## Optional

* J. Hana \& A. Feldman. Computational Morphology. ESSLLI 2013 course. ufal.mff.cuni.cz/~hana/teaching/2013-esslli/
* M. Mohri. Finite-State Transducers in Language and Speech Processing. CL 1997 paper. www.aclweb.org/anthology/J97-2003/

