# LG 467 Computers in Linguistics

## [1-2021] Topic 5: POS tagging

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### We can count frequencies of individual items with FreqDist:

import nltk

f = open('text1.txt')
txt = f.read()
f.close()

tokens = nltk.word\_tokenize(txt)
freq = nltk.FreqDist(tokens)

freq.most\_common(15)
freq.plot()
freq.plot(cumulative = True)

Code 6.2

# take multiple parameters plus a docstring:

def ttr(lst, digits): accepts one list and digits to round.""" result = len(set(lst))/len(lst) return round(result, digits)

ttr(text1, 3) ttr(text2, 4) help(ttr)

You can define your own functions to automate tasks. Functions can

Code 6.11

```
"""Compute type-token ratio on a list of strings,
```

Language is not random. Things pattern together.

- We can ask what the next word might be given context
- Simple and efficient way of modeling context is using n-grams
- N-grams are units of n sequences
  - Characters: 'custard'
    - (cus, ust, sta, tar, ard)
  - (c, u, s, t, a, r, d) (cu, us, st, ta, ar, rd) • Words: 'He is eating fried rice'

• (he, is, eating, fried, rice) (he is, is eating, eating fried, fried rice)



N-grams to model language data

- "Turn in your  $\_$   $\rightarrow p(\_$  ["turn in your")
  - decide on a useful context size (2, 3, 4, or ?)
  - previous n words

save analyses not of individual words but of words given the



## Bigram counts from the Berkeley Restaurant Project:

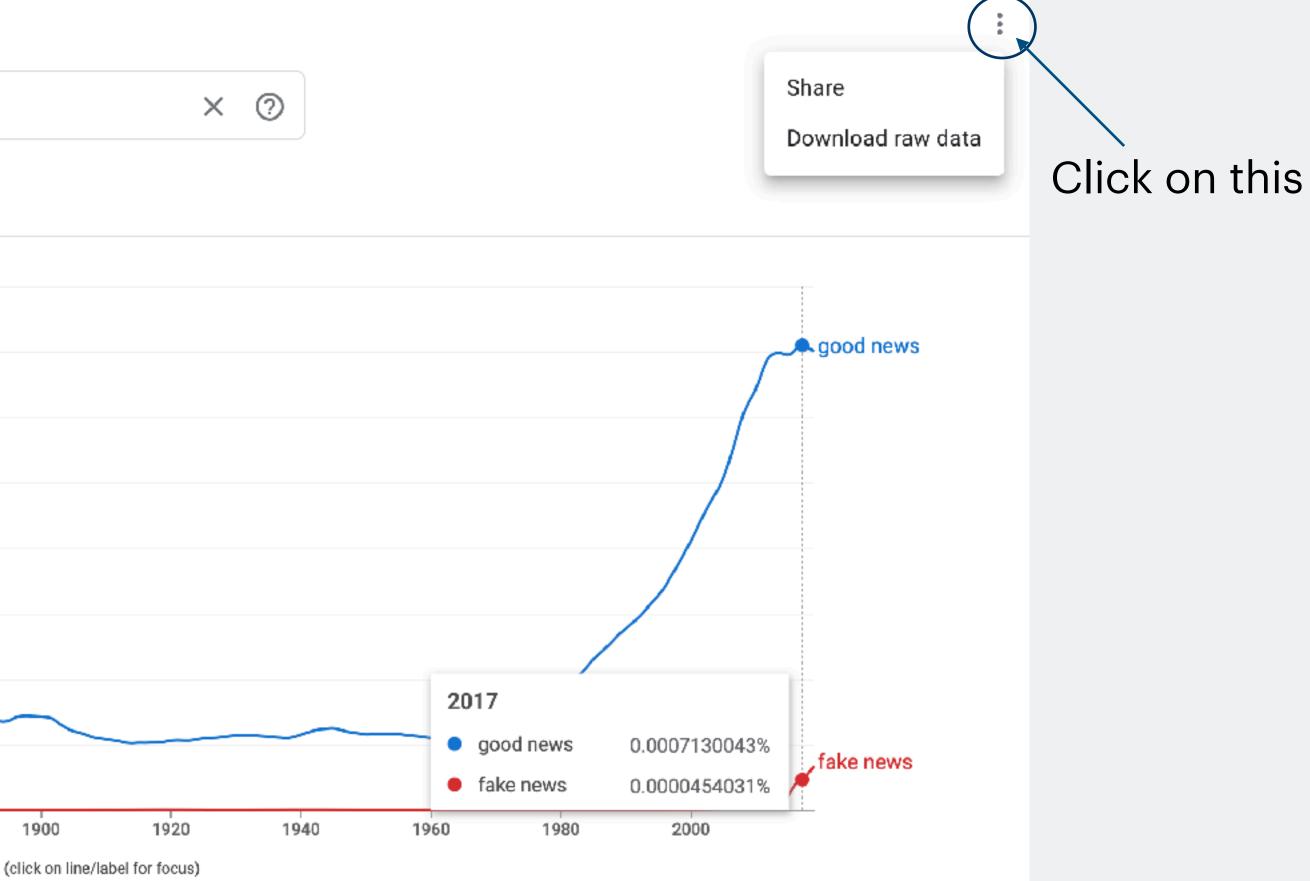
	i	want	to	eat	chinese	food	lunch	spend
i	5	827	0	9	0	0	0	2
want	2	0	608	1	6	6	5	1
to	2	0	4	686	2	0	6	211
eat	0	0	2	0	16	2	42	0
chinese	1	0	0	0	0	82	1	0
food	15	0	15	0	1	4	0	0
lunch	2	0	0	0	0	1	0	0
spend	1	0	1	0	0	0	0	0

Source: Figure 3.1 in Jurafsky & Martin [chapter 3]



## Check out: Google N-grams and Google Books ngram viewer

	Google Books Ngram Viewer
	Q good news,fake news
	1800 - 2019 - English (2019) - Case-Insensitive Smoothing -
	0.000800% -
Toggle to change	0.000700% -
	0.000600% -
	0.000500% -
	0.000400% -
	0.000300% -
	0.000200% -
	0.000100% -
	0.000000%
	(cli



We can generate bigram (or any n-gram) counts with NLTK:

import nltk nltk.bigrams(text1)

list(nltk.bigrams(text1))

nltk.ngrams(text1, 2) list(nltk.ngrams(text1, 2))

bigrams = list(nltk.ngrams(text1, 2)) bicount = FreqDist(bigrams)

Code 6.12

# **Beneath the surface**

Our token n-gram models represent transitions between observed characters/words

• We can call them Visible Markov Models (VMMs)

For things that are overt, we are also interested in the probabilities of hidden categories

• We will need Hidden Markov Models (HMMs)



# **Beneath the surface**

Did I hear hidden categories? What did you mean?

- We may not be interested in a phrase like 'awesome news'
- Instead, we might want to know the likelihood of adjectives followed by nouns (ADJ + NOUN)
- How can we look at categories that are not in the data explicitly?



# Parts of speech (POS)

has been around for two millennia

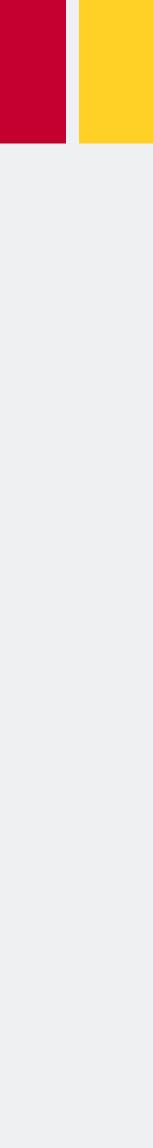
• part of speech, word classes, POS, POS tags

C. BCE):

- noun, verb, pronoun, preposition, adverb, conjunction, participle, article
- These categories are relevant for NLP today.

The idea that words can be classified into grammatical categories

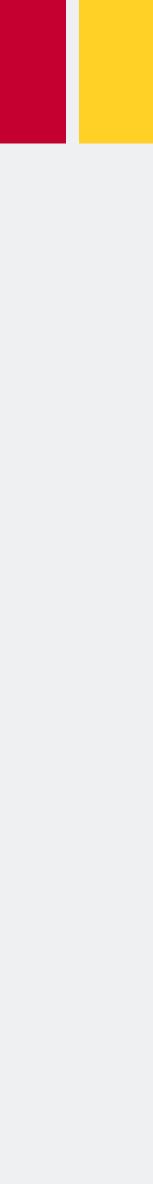
8 parts of speech attributed to Dionysius Thrax of Alexandria (c. 1st



# Parts of speech (POS)

Parts of speech are defined based on:

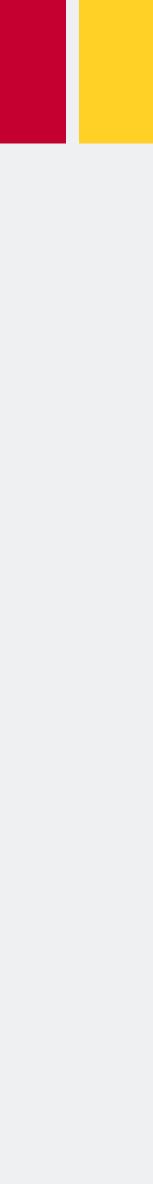
- grammatical relationship with their neighboring words
- Morphological properties about their affixes (-ness, -able, -ed)



# **Two classes of English words**

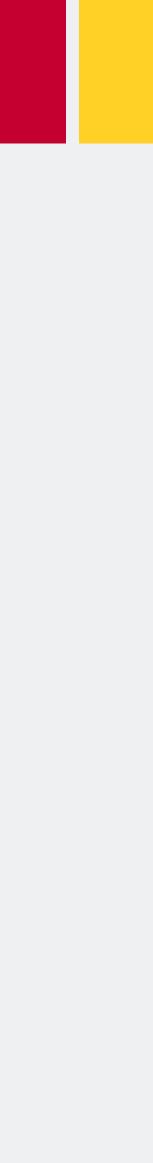
1. Closed class words

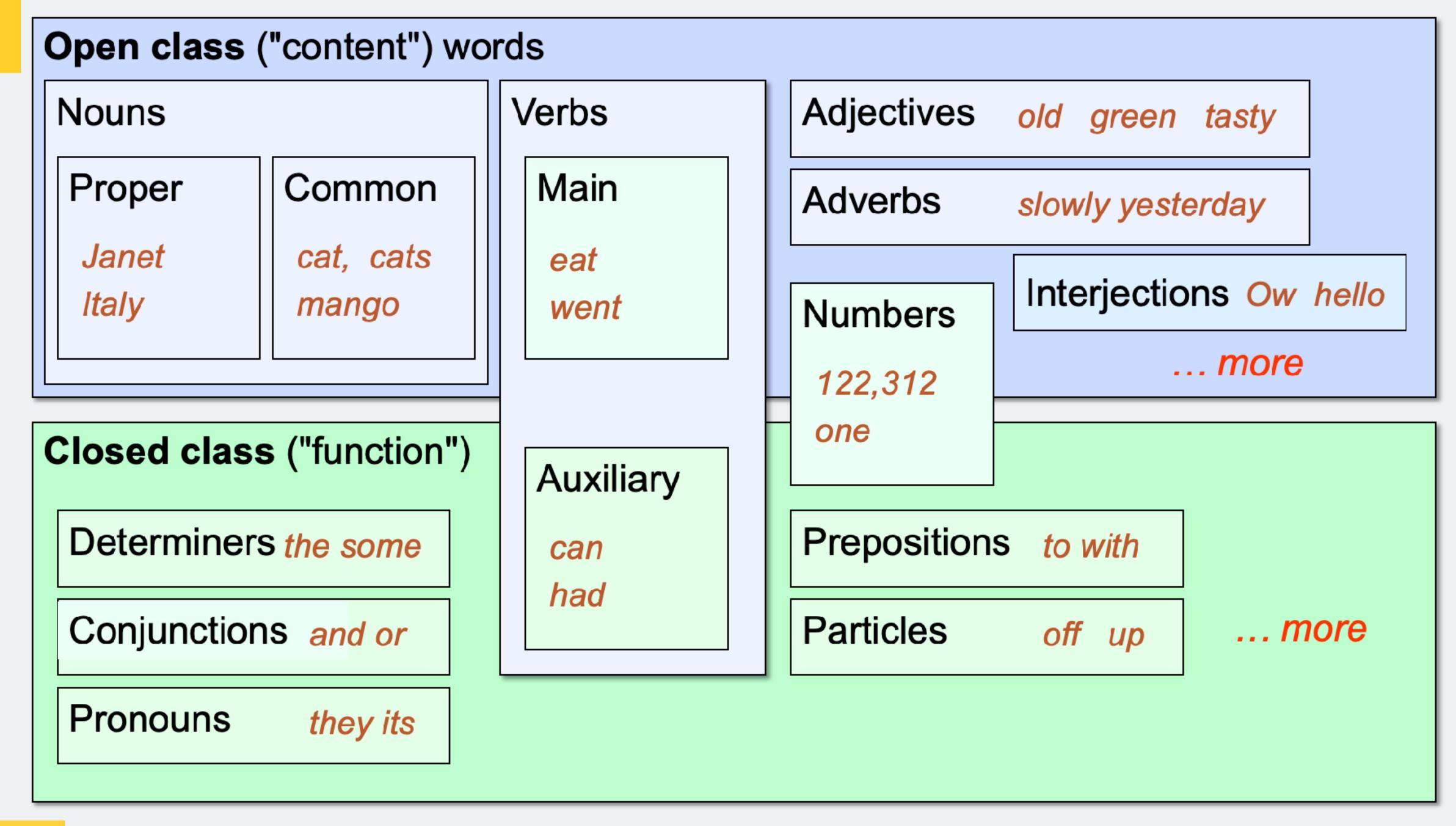
- Relatively fixed membership
- Usually function words:
  - determiners: this, that, a, an, the
  - pronouns: she, I, me, them, her, our, who, whose
  - prepositions: on, under, over, at, with, ...
  - conjunctions: and, but, while, because, that, ...
  - particles: go <u>over</u>, turn in, ...



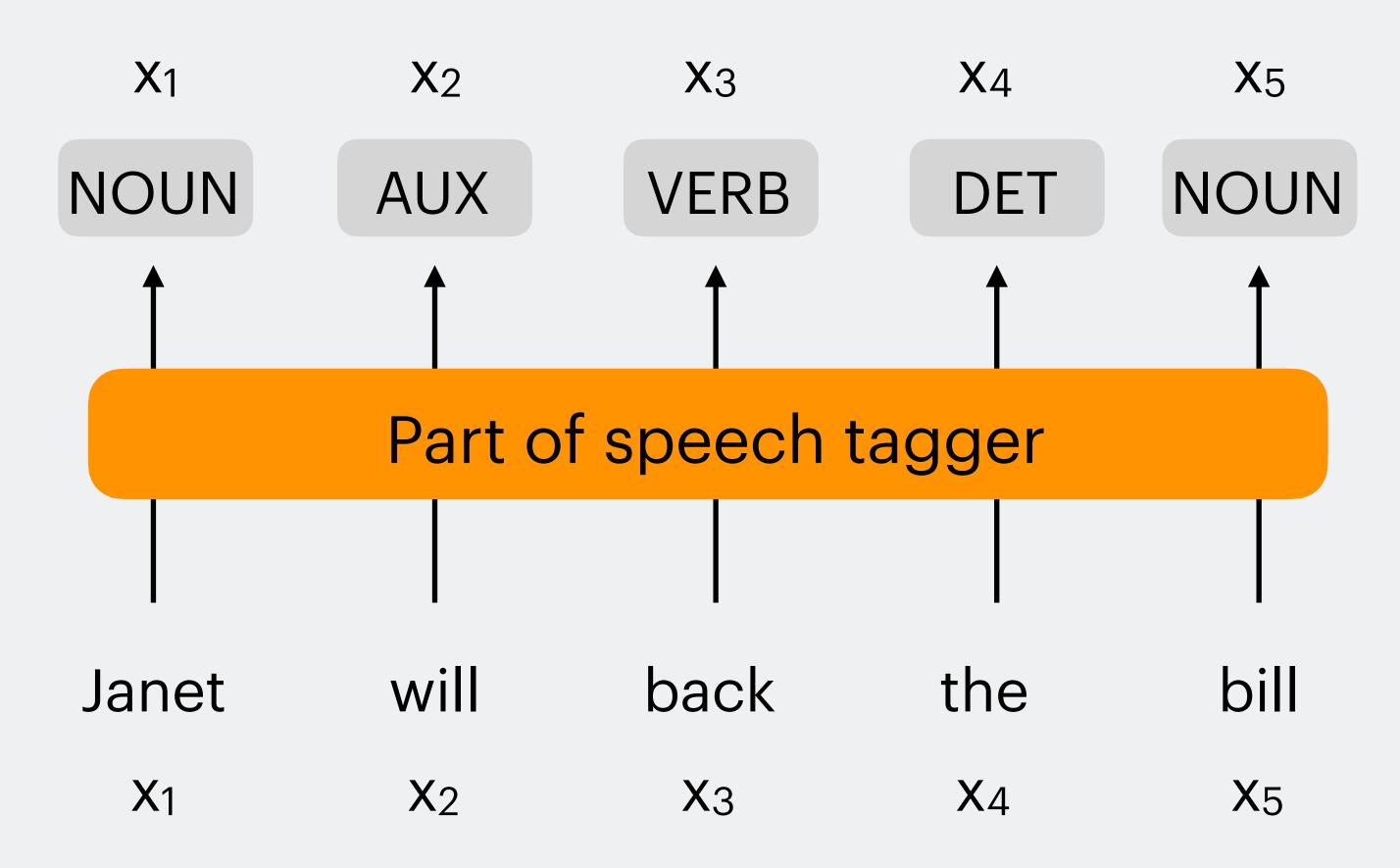
# **Two classes of English words**

- 2. Open class words
  - Usually content words: Nouns, Verbs, Adjectives, Adverbs
    - Plus interjections: oh, ouch, uh-huh, yes, no, hello
  - New nouns and verbs like iPhone, facebook, mansplain, google

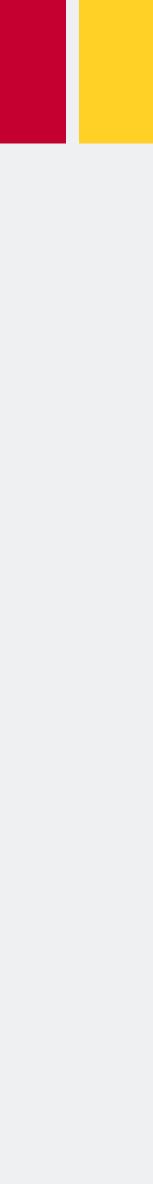




## POS tagging = assigning a part of speech to each word in a text



# **POS** tagging



Tagging is a disambiguation task

- Words often have more than one POS
- The goal is to find the correct tag for the situation
- Case 1: 'book' Case 2: 'tired'
  - He <u>tired</u> me out • <u>Book</u> a flight
  - Whose <u>book</u> is it? • I'm just <u>tired</u>

# **POS** tagging

- Case 3: 'that'
  - Hand me <u>that</u> book
  - I think <u>that</u> you liked





## Though tagging is challenging, the accuracy of POS tagging algorithms is extremely high (97% or higher)

55-67% of word tokens in running text are ambiguous!

Types:	
Unambiguous	(1 tag)
Ambiguous	(2+ tags)
Tokens:	
Unambiguous	(1 tag)
Ambiguous	(2+ tags)

# **POS** tagging

WS	SJ	Bro	wn
44,432	(86%)	45,799	(85%)
7,025	(14%)	8,050	(15%)
577,421	(45%)	384,349	(33%)
711,780	(55%)	786,646	(67%)

Source: Figure 8.4 in Jurafsky & Martin [chapter 8]



# **Tagsets for English**

### Common in the US:

- Penn Treebank Tagset (PTB)
- Brown Tagset

Common in the UK:

• CLAWS 5 (or C5)

45 tags 87 tags

61 tags

CLAWS = Constituent Likelihood Automatic Word-tagging System (for BNC)



# Penn Treebank Tags

Tag	Description	Example	Tag	Description	Example	Tag	Description	Examp
CC	coord. conj.	and, but, or	NNP	proper noun, sing.	IBM	TO	"to"	to
CD	cardinal number	one, two	NNPS	proper noun, plu.	Carolinas	UH	interjection	ah, oop
DT	determiner	a, the	NNS	noun, plural	llamas	VB	verb base	eat
EX	existential 'there'	there	PDT	predeterminer	all, both	VBD	verb past tense	ate
FW	foreign word	mea culpa	POS	possessive ending	's	VBG	verb gerund	eating
IN	preposition/	of, in, by	PRP	personal pronoun	I, you, he	VBN	verb past partici-	eaten
	subordin-conj						ple	
JJ	adjective	yellow	PRP\$	possess. pronoun	your, one's	VBP	verb non-3sg-pr	eat
JJR	comparative adj	bigger	RB	adverb	quickly	VBZ	verb 3sg pres	eats
JJS	superlative adj	wildest	RBR	comparative adv	faster	WDT	wh-determ.	which,
LS	list item marker	1, 2, One	RBS	superlaty. adv	fastest	WP	wh-pronoun	what, v
MD	modal	can, should	RP	particle	up, off	WP\$	wh-possess.	whose
NN	sing or mass noun	llama	SYM	symbol	+,%, &	WRB	wh-adverb	how, w

Source: Figure 8.2 in Jurafsky & Martin [chapter 8]





- Try tagging the following sentences with the PTB tags:
- grand/ The/ 1. jury/ of/ number/ a/
- preliminary/ findings/ Although/ 2. were/ than/ a/ reported/ more/ year/ ago/ ,/ the/ latest/ results/ in/ today/ 's/ appear/ New/ England/ Journal/ Medicine/ of/

## Practice

commented/ on/ topics/ other/



## Practice

Try tagging the following sentences with the PTB tags:

- grand/JJ The/DT 1. number/NN of/IN a/DT
- Although/IN preliminary/JJ findings/NNS 2. were/VBD reported/VBN more/RBR than/IN a/DT year/NN ago/IN ,/, the/DT latest/JJS results/NNS appear/VBP in/IN today/NN 's/POS New/NNP England/NNP Journal/NNP of/IN Medicine/NNP ./.

- jury/NN commented/VBD on/IN other/JJ topics/NNS ./.



# **Universal Dependencies Tagset**

	Tag	Description	Example	
	ADJ	Adjective: noun modifiers describing properties	red, young, awesome	
Class	ADV	Adverb: verb modifiers of time, place, manner	very, slowly, home, yesterday	
	NOUN	words for persons, places, things, etc.	algorithm, cat, mango, beauty	
Open	VERB	words for actions and processes	draw, provide, go	
Ō	PROPN	Proper noun: name of a person, organization, place, etc	Regina, IBM, Colorado	
	INTJ	Interjection: exclamation, greeting, yes/no response, etc.	oh, um, yes, hello	
	ADP	Adposition (Preposition/Postposition): marks a noun's spacial, temporal, or other relation	in, on, by under	
rds	AUX	Auxiliary: helping verb marking tense, aspect, mood, etc.,	can, may, should, are	
Words	CCONJ	Coordinating Conjunction: joins two phrases/clauses	and, or, but	
	DET	Determiner: marks noun phrase properties	a, an, the, this	
Class	NUM	Numeral	one, two, first, second	
Closed	PART	Particle: a preposition-like form used together with a verb	up, down, on, off, in, out, at, by	
Jo	PRON	Pronoun: a shorthand for referring to an entity or event	she, who, I, others	
	SCONJ	Subordinating Conjunction: joins a main clause with a subordinate clause such as a sentential complement	that, which	
u.	PUNCT	Punctuation	;,()	
Other	SYM	Symbols like \$ or emoji	\$, %	
	Χ	Other	asdf, qwfg	

Source: Figure 8.1 in Jurafsky & Martin [chapter 8]



# **Universal Dependencies Tagset for Thai**

Abbreviation	Part-of-Speech tag	Examples
ADJ	Adjective	ใหม่, พิเศษ , ก่อน
ADP	Adposition	แม้, ว่า, เมื่อ, ของ,
ADV	Adverb	ก่อน, ก็, เล็กน้อย,
AUX	Auxiliary	เป็น, ใช่, คือ, คล้า
CCONJ	Coordinating conjunction	แต่, และ, หรือ
DET	Determiner	ที่, นี้, ซึ่ง, ทั้ง <b>, ทุ</b> ก,
INTJ	Interjection	อุ้ย, โอ้ย
NOUN	Noun	กำมือ, พวก, สนา
NUM	Numeral	5,000, 103.7, 20
PART	Particle	มา ขึ้น ไม่ ได้ เข้า
PRON	Pronoun	<b>เรา, เขา, ต</b> ัวเอง, '
PROPN	Proper noun	โอบามา, แคปิตอ
PUNCT	Punctuation	(, ), ", ', :
SCONJ	Subordinating conjunction	หาก
VERB	Verb	เปิด, ให้, ใช้, เผชิ

น, มาก, สูง
ง, สำหรับ
I, เลย, สุด
้าย
, หลาย
าม, กีฬา, บัญชี
2004, หนึ่ง, ร้อย
ו
ใคร, เธอ
อลฮิล, จีโอพี, ไมเคิล
ชิญ, อ่าน

- Universal Dependencies (UD) is one of the tagsets in PyThaiNLP
- In PyThaiNLP, this tagset is known as Parallel Universal Dependencies (PUD)

Source: <u>PyThaiNLP</u>





# **POS tagging in NLTK**

# An off-the-shelf tagger is available for English:

from nltk import pos\_tag, word\_tokenize

- text = "John's big idea isn't all that bad." token = word\_tokenize(text)
- pos = pos\_tag(token)

print(pos)

### **Question**: What tagset is this?

Code 7.1

# **POS tagging in NLTK**

What can we do with pos? We can separate tags from tokens

from nltk import FreqDist

tok = [tok for (tok, tag) in pos] tag = [tag for (tok, tag) in pos]

# Then, you may choose to count FreqDist(tok) FreqDist(tag)

Code 7.2

# Our plan next week...

- Part-of-speech (POS) tagging
  - More tagging!
  - Please install SpaCy
    - Windows:
      - Use Anaconda Prompt to install (<u>Here</u>)
      - Follow the instructions on SpaCy (<u>Here</u>)
    - Mac:
      - Use Terminal

o install (<u>Here</u>) n SpaCy (<u>Here</u>)

