Part-of-Speech Tagging and Formal Grammars

Natalie Parde, Ph.D.

Department of Computer Science

University of Illinois at Chicago

CS 421: Natural Language Processing

Fall 2019

Many slides adapted from Jurafsky and Martin (https://web.stanford.edu/~jurafsky/slp3/), UNT's NLP course (http://www.cse.unt.edu/~tarau/teaching/NLP/nlp.html), and UIUC's NLP course (https://courses.grainger.illinois.edu/cs447/fa2019/).

What is part-of-speech (POS) tagging?

The process of automatically assigning grammatical word classes to individual tokens in text.

verb determiner

Give me a **break**!

pronoun noun

verb noun

Did the window **break**?

determiner verb

POS Tagging

What are parts of speech?

- Traditional (broad) categories:
  - noun
  - verb
  - adjective
  - adverb
  - preposition
  - article
  - interjection
  - pronoun
  - conjunction
- Sometimes also referred to as **lexical categories**, **word classes**, **morphological classes**, or **lexical tags**

Parts of Speech

Noun

- People, places, or things
- Doctor, mountain, cellphone….

Verb

- Actions or states
- Eat, sleep, be….

Adjective

- Descriptive attributes
- Purple, triangular, windy….

Adverb

- Modifies other words by answering *how*, *in what way*, *when*, *where*, and *to what extent* questions
- Gently, quite, quickly….

Parts of Speech

Pronoun

- Refers to nouns mentioned elsewhere
- he, she, you….

Preposition

- Describes relationship between noun/pronoun and other word in clause
- on, above, to….

Article

- Indicates specificity
- a, an, the….

Interjection

- Exclamations
- oh, yikes, ah….

Conjunction

- Coordinates words in the same clause or connects multiple clauses/sentences
- and, but, if….

Why is POS tagging useful?

- First step of many downstream NLP tasks!
  - Speech synthesis
  - Constituency parsing
  - Dependency parsing
  - Information extraction
  - Machine translation

Open and Closed Classes

Each POS type falls into one of two larger classes:

- Open
- Closed

Open class:

- New members can be created at any time
- In English:
  - Nouns, verbs, adjectives, and adverbs
- Many (but not all!) languages have these four classes

Closed class:

- A small, fixed membership …new members cannot be created spontaneously
- Usually function words
- In English:
  - Prepositions, pronouns, auxiliaries (may, can, been, etc.)

Open and Closed Classes

- Broader POS classes often have smaller subclasses
  - Noun:
    - Proper (Illinois)
    - Common (state)
  - Verb:
    - Main (tweet)
    - Modal (had)
- Some subclasses of a part of speech might be open, while others are closed

Open Class

Nouns

Proper

IBM
Italy

Common

cat / cats
snow

Verbs

Main

see
registered

Modal

can
had

Adjectives *old older oldest*

Adverbs *slowly*

… more

Closed Class

Determiners *the some*

Conjunctions *and or*

Pronouns *he its*

Prepositions *to with*

Interjections *Ow Eh*

… more

POS Tagging

- Can be very challenging!
- Words often have more than one valid part of speech tag
  - Today's faculty meeting went really **well**! = adverb
  - Do you think the undergrads are **well**? = adjective
  - **Well**, did you see the latest response to your email? = interjection
  - Jurafsky and Martin's book is a **well** of information. = noun
  - Laughter began to **well** up inside her at, as always, a highly inconvenient time. = verb

verb determiner

Give me a **break**!

pronoun noun

verb noun

Did the window **break**?

determiner verb

POS Tagging

- Goal: Determine the *best* POS tag for a particular instance of a word.

POS Tagsets

In order to determine which POS tag to assign to a word, we first need to decide which **tagset** we will use

Tagset: A finite set of POS tags, where each tag defines a distinct grammatical role

Can range from very coarse to very fine

Penn Treebank Tagset

- **Most common POS tagset**
- 36 POS tags + 12 other tags (punctuation and currency)
- Used when developing the Penn Treebank, a **corpus** created at the University of Pennsylvania containing more than 4.5 million words of American English
- Link to documentation: https://catalog.ldc.upenn.edu/docs/LDC95T7/cl93.html

Penn Treebank Tagset

CC	Coordinating Conjunction	**NNS**	Noun, plural	**TO**	to
CD	Cardinal Number	**NNP**	Proper noun, singular	**UH**	Interjection
DT	Determiner	**NNPS**	Proper noun, plural	**VB**	Verb, base form
EX	Existential *there*	**PDT**	Predeterminer	**VBD**	Verb, past tense
FW	Foreign word	**POS**	Possessive ending	**VBG**	Verb, gerund or present participle
IN	Preposition or subordinating conjunction	**PRP**	Personal pronoun	**VBN**	Verb, past participle
JJ	Adjective	**PRP$**	Possessive pronoun	**VBP**	Verb, non-3rd person singular present
JJR	Adjective, comparative	**RB**	Adverb	**VBZ**	Verb, 3rd person singular present
JJS	Adjective, superlative	**RBR**	Adverb, comparative	**WDT**	Wh-determiner
LS	List item marker	**RBS**	Adverb, superlative	**WP**	Wh-pronoun
MD	Modal	**RP**	Particle	**WP$**	Possessive wh-pronoun
NN	Noun, singular or mass	**SYM**	Symbol	**WRB**	Wh-adverb

What do some of these distinctions mean?

cities

Chicago

Chicagos

city

CC	Coordinating Conjunction	**NNS**	Noun, plural	TO	to
CD	Cardinal Number	**NNP**	Proper noun, singular	UH	Interjection
DT	Determiner	**NNPS**	Proper noun, plural	VB	Verb, base form
EX	Existential *there*	PDT	Predeterminer	VBD	Verb, past tense
FW	Foreign word	POS	Possessive ending	VBG	Verb, gerund or present participle
IN	Preposition or subordinating conjunction	PRP	Personal pronoun	VBN	Verb, past participle
JJ	Adjective	PRP$	Possessive pronoun	VBP	Verb, non-3rd person singular present
JJR	Adjective, comparative	RB	Adverb	VBZ	Verb, 3rd person singular present
JJS	Adjective, superlative	RBR	Adverb, comparative	WDT	Wh-determiner
LS	List item marker	RBS	Adverb, superlative	WP	Wh-pronoun
MD	Modal	RP	Particle	WP$	Possessive wh-pronoun
NN	Noun, singular or mass	SYM	Symbol	WRB	Wh-adverb

What do some of these distinctions mean?

CC	Coordinating Conjunction	**NNS**	Noun, plural	**TO**	to
CD	Cardinal Number	**NNP**	Proper noun, singular	**UH**	Interjection
DT	Determiner	**NNPS**	Proper noun, plural	**VB**	Verb, base form
EX	Existential *there*	**PDT**	Predeterminer	**VBD**	Verb, past tense
FW	Foreign word	**POS**	Possessive ending	**VBG**	Verb, gerund or present participle
IN	Preposition or subordinating conjunction	**PRP**	Personal pronoun	**VBN**	Verb, past participle
JJ	Adjective	**PRP$**	Possessive pronoun	**VBP**	Verb, non-3rd person singular present
JJR	Adjective, comparative	**RB**	Adverb	**VBZ**	Verb, 3rd person singular present
JJS	Adjective, superlative	**RBR**	Adverb, comparative	**WDT**	Wh-determiner
LS	List item marker	**RBS**	Adverb, superlative	**WP**	Wh-pronoun
MD	Modal	**RP**	Particle	**WP$**	Possessive wh-pronoun
NN	Noun, singular or mass	**SYM**	Symbol	**WRB**	Wh-adverb

eat ate eating eaten eat eats should

What do some of these distinctions mean?

CC	Coordinating Conjunction	NNS	Noun, plural	TO	to
CD	Cardinal Number	NNP	Proper noun, singular	UH	Interjection
DT	Determiner	NNPS	Proper noun, plural	VB	Verb, base form
EX	Existential *there*	PDT	Predeterminer	VBD	Verb, past tense
FW	Foreign word	POS	Possessive ending	VBG	Verb, gerund or present participle
IN	Preposition or subordinating conjunction	PRP	Personal pronoun	VBN	Verb, past participle
JJ	**Adjective**	PRP$	Possessive pronoun	VBP	Verb, non-3rd person singular present
JJR	**Adjective, comparative**	RB	Adverb	VBZ	Verb, 3rd person singular present
JJS	**Adjective, superlative**	RBR	Adverb, comparative	WDT	Wh-determiner
LS	List item marker	RBS	Adverb, superlative	WP	Wh-pronoun
MD	Modal	RP	Particle	WP$	Possessive wh-pronoun
NN	Noun, singular or mass	SYM	Symbol	WRB	Wh-adverb

weird

weirder

weirdest

What do some of these distinctions mean?

CC	Coordinating Conjunction	NNS	Noun, plural	TO	to
CD	Cardinal Number	NNP	Proper noun, singular	UH	Interjection
DT	Determiner	NNPS	Proper noun, plural	VB	Verb, base form
EX	Existential *there*	PDT	Predeterminer	VBD	Verb, past tense
FW	Foreign word	POS	Possessive ending	VBG	Verb, gerund or present participle
IN	Preposition or subordinating conjunction	PRP	Personal pronoun	VBN	Verb, past participle
JJ	Adjective	PRP$	Possessive pronoun	VBP	Verb, non-3rd person singular present
JJR	Adjective, comparative	**RB**	**Adverb**	VBZ	Verb, 3rd person singular present
JJS	Adjective, superlative	**RBR**	**Adverb, comparative**	WDT	Wh-determiner
LS	List item marker	**RBS**	**Adverb, superlative**	WP	Wh-pronoun
MD	Modal	RP	Particle	WP$	Possessive wh-pronoun
NN	Noun, singular or mass	SYM	Symbol	WRB	Wh-adverb

calmly

calmer

calmest

As a general (but not perfect!) rule….

CC	Coordinating Conjunction	**NNS**	Noun, plural	**TO**	to
CD	Cardinal Number	**NNP**	Proper noun, singular	**UH**	Interjection
DT	Determiner	**NNPS**	Proper noun, plural	**VB**	Verb, base form
EX	Existential *there*	**PDT**	Predeterminer	**VBD**	Verb, past tense
FW	Foreign word	**POS**	Possessive ending	**VBG**	Ve[illegible]d or present pa[illegible]
IN	Preposition or subordinating conjunction	**PRP**	Personal pronoun	**VBN**	Verb, past participle
JJ	Adjective	**PRP$**	Possessive pronoun	**VBP**	Verb, non-3rd person singular present
JJR	Adjective, comparative	**RB**	Adverb	**VBZ**	Verb, 3rd person singular present
JJS	Adjective, superlative	**RBR**	Adverb, comparative	**WDT**	Wh-determiner
LS	List item marker	**RBS**	Adverb, superlative	**WP**	Wh-pronoun
MD	Modal	**RP**	Particle	**WP$**	Possessive wh-pronoun
NN	Noun, singular or mass	**SYM**	Symbol	**WRB**	Wh-adverb

Closed Class

As a general (but not perfect!) rule….

CC	Coordinating Conjunction	**NNS**	**Noun, plural**	TO	to
CD	Cardinal Number	**NNP**	**Proper noun, singular**	UH	Interjection
DT	Determiner	**NNPS**	**Proper noun, plural**	**VB**	**Verb, base form**
EX	Existential *there*	PDT	Predeterminer	**VBD**	**Verb, past tense**
FW	**Foreign word**	POS	Possessive	**VBG**	**Verb, gerund or present participle**
IN	Preposition or subordinating conjunction	PRP	Personal pronoun	**VBN**	**Verb, past participle**
JJ	**Adjective**	PRP$	Possessive pronoun	**VBP**	**Verb, non-3rd person singular present**
JJR	**Adjective, comparative**	**RB**	**Adverb**	**VBZ**	**Verb, 3rd person singular present**
JJS	**Adjective, superlative**	**RBR**	**Adverb, comparative**	WDT	Wh-determiner
LS	List item marker	**RBS**	**Adverb, superlative**	WP	Wh-pronoun
MD	Modal	RP	Particle	WP$	Possessive wh-pronoun
NN	**Noun, singular or mass**	SYM	Symbol	WRB	Wh-adverb

Open Class

Other Popular POS Tagsets

Brown Corpus

- ~1 million words of American English text
- 82 (!) POS tags

C5 Tagset

- 61 POS tags

C7 Tagset

- 146 (!!) POS tags

In-Class Exercise

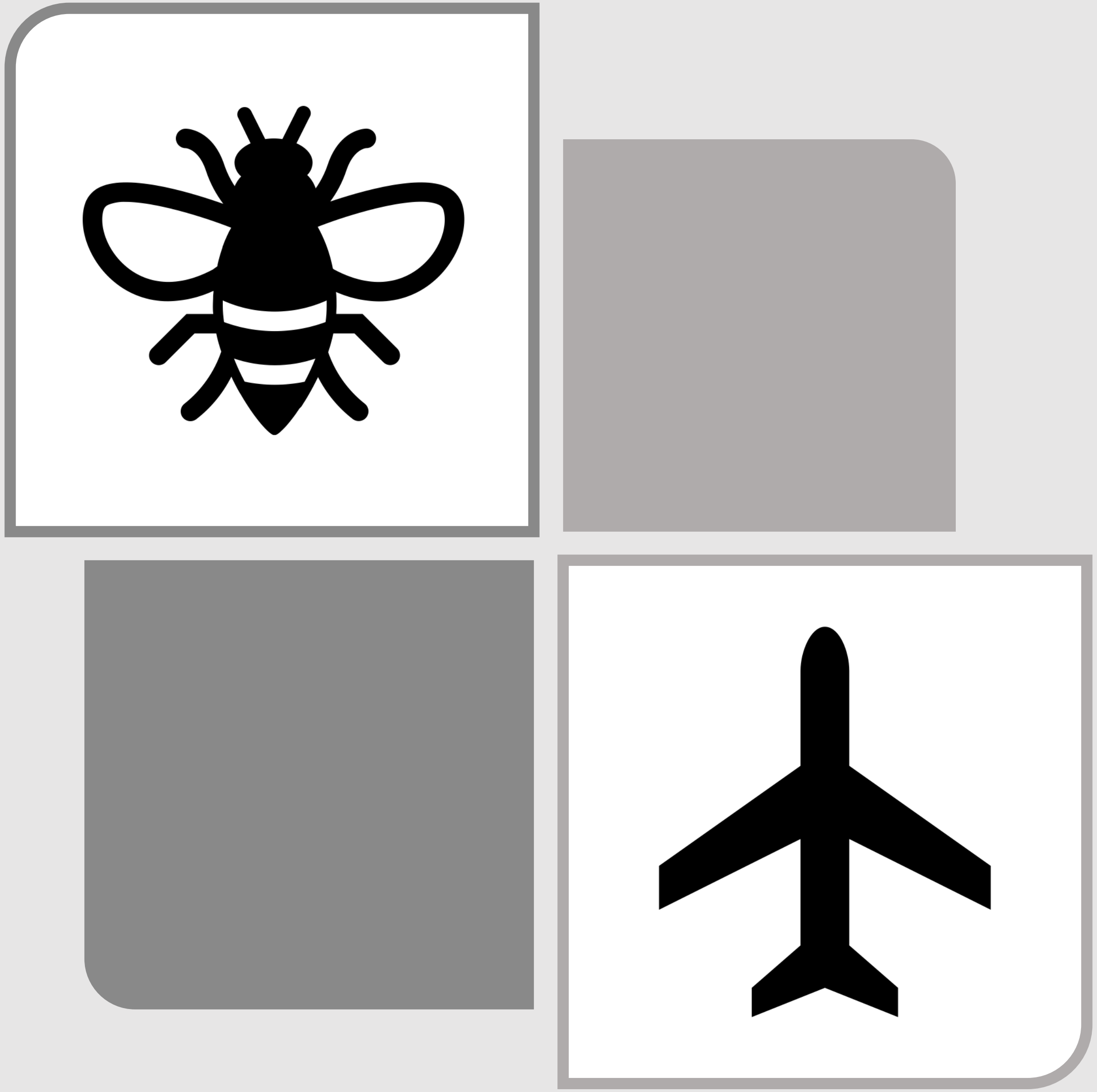
- Assign Penn Treebank POS tags to the following sentence:
  - **Time flies like an arrow; fruit flies like a banana.**

https://www.google.com/search?q=timer

CC	Coordinating Conjunction	**NNS**	Noun, plural	**TO**	to
CD	Cardinal Number	**NNP**	Proper noun, singular	**UH**	Interjection
DT	Determiner	**NNPS**	Proper noun, plural	**VB**	Verb, base form
EX	Existential *there*	**PDT**	Predeterminer	**VBD**	Verb, past tense
FW	Foreign word	**POS**	Possessive ending	**VBG**	Verb, gerund or present participle
IN	Preposition or subordinating conjunction	**PRP**	Personal pronoun	**VBN**	Verb, past participle
JJ	Adjective	**PRP$**	Possessive pronoun	**VBP**	Verb, non-3rd person singular present
JJR	Adjective, comparative	**RB**	Adverb	**VBZ**	Verb, 3rd person singular present
JJS	Adjective, superlative	**RBR**	Adverb, comparative	**WDT**	Wh-determiner
LS	List item marker	**RBS**	Adverb, superlative	**WP**	Wh-pronoun
MD	Modal	**RP**	Particle	**WP$**	Possessive wh-pronoun
NN	Noun, singular or mass	**SYM**	Symbol	**WRB**	Wh-adverb

In-Class Exercise

Time	flies	like	an	arrow	fruit	flies	like	a	banana



Ambiguity is a big issue for POS taggers!

- Many words have multiple senses
  - **time** = noun, verb
  - **flies** = noun, verb
  - **like** = verb, preposition

Just how ambiguous is natural language?

- Brown Corpus: Approximately 11% of word types have multiple valid part of speech labels
- These tend to be very common words!
  - We think **that** the faculty meeting will only last two more hours. = IN
  - Was **that** the 32nd Piazza post today? = DT
  - You can't eat **that** many donuts every time the clock strikes midnight! = RB
- Overall, ~40% of word tokens are instances of ambiguous word types

Despite this, modern POS taggers still work quite well.

- Accuracy > 97%
- Simple baseline can achieve ~90%
  - Tag every word with its most frequent tag
  - Tag unknown words as nouns

How do POS taggers work?

- Several ways to predict POS tags:
  - Rule-based
  - Statistical
    - HMMs
    - Maximum Entropy Markov Models (MEMMs)
  - Transformation-based

Rule-Based POS Tagging

- Start with a dictionary, and assign all possible tags to the words in that dictionary
- Manually design rules to selectively remove invalid tags
- Keep the remaining correct tag for each word

Example Rule-Based Approach

Start with a dictionary!

- she
  - PRP
- promised
  - VBN, VBD
- to
  - TO
- back
  - VB, JJ, RB, NN
- the
  - DT
- bill
  - NN, VB

(Add all words in the selected language)

Example Rule-Based Approach

Assign every possible tag to each word in the sequence

she	promised	to	back	the	bill
PRP	VBN	TO	VB	DT	NN
	VBD		JJ		VB
			RB		
			NN		

Example Rule-Based Approach

Write rules to eliminate invalid tags

Eliminate VBN if VBD is an option when VBN|VBD follows “<start> PRP”

she	promised	to	back	the	bill
PRP	~~VBN~~	TO	VB	DT	NN
	VBD		JJ		VB
			RB		
			NN		

Example Rule-Based Approach

Keep the remaining correct tag for each word

she	promised	to	back	the	bill
PRP	~~VBN~~	TO	VB	DT	NN
	VBD		~~JJ~~		~~VB~~
			~~RB~~		
			~~NN~~		

ENGTWOL

- **ENG**lish **TWO L**evel analysis
- A simple 😉 collection of 1000+ manually designed rules for English POS tagging
- **Stage 1:** Run the input sequence through an FST morphological analyzer to get all possible parts of speech
- **Stage 2:** Apply negative constraints

ENGTWOL

Example: *Pavlov had shown that salivation….*

Pavlov	**PAVLOV N NOM SG PROPER**
had	**HAVE V PAST VFIN SVO**
	HAVE PCP2 SVO
shown	**SHOW PCP2 SVOO SVO SV**
that	ADV
	PRON DEM SG
	DET CENTRAL DEM SG
	CS
salivation	**N NOM SG**

Given input: "that"
If
(+1 A/ADV/QUANT)
(+2 SENT-LIM)
(NOT -1 SVOC/A)
Then eliminate non-ADV tags
Else eliminate ADV

…and on to the next rule!

Statistical POS Tagging

- What are the main sources of information?
  - Knowledge of neighboring words
  - Knowledge of word probabilities
- (Of these two sources, the latter is generally more useful)

man is rarely used as a verb….

Bill	saw	that	man	yesterday
NNP	NN	DT	NN	NN
VB	VBD	IN	VB	

Other POS Tagging Features

- Statistical POS taggers can do surprisingly well just looking at a word by itself!
  - Word
    - “the” is likely DT
  - Uppercase or lowercase first letter?
    - Uppercase first letter is more likely to be NNP(S)
  - Prefixes
    - Words starting with “un” may be JJ
  - Suffixes
    - Words ending in “ly” may be RB
  - Word shape
    - A digit sequence and a character sequence separated by a hyphen (e.g., 12-year) may be JJ

Statistical POS Tagging

- Predicts POS tags based on the probabilities of those tags occurring
- Those probabilities can be based on various sources of information (such as the example features in the previous slide)
- Doing this requires a **training corpus**
  - No probabilities associated with words not in the corpus!
- This training corpus should be different from the **test corpus**

Baseline POS Tagger

- The simple baseline mentioned previously would be one example of a statistical POS tagger:
  - Using a training corpus, determine the most frequent tag for each word
  - Assign POS tags to new words based on those frequencies
  - Assign NN to new words for which there is no information from the training corpus

I saw a wampimuk at the zoo yesterday!

Baseline POS Tagger

- The simple baseline mentioned previously would be one example of a statistical POS tagger:
  - Using a training corpus, determine the most frequent tag for each word
  - Assign POS tags to new words based on those frequencies
  - Assign NN to new words for which there is no information from the training corpus

95% PRP 95% DT 90% IN 85% NN

I saw a wampimuk at the zoo yesterday!

75% VBD ??? 95% DT 90% NN

Baseline POS Tagger

- The simple baseline mentioned previously would be one example of a statistical POS tagger:
  - Using a training corpus, determine the most frequent tag for each word
  - Assign POS tags to new words based on those frequencies
  - Assign NN to new words for which there is no information from the training corpus

I	saw	a	wampimuk	at	the	zoo	yesterday
PRP	VBD	DT	NN	IN	DT	NN	NN

Baseline POS Tagger

- As previously mentioned, this approach works reasonably well
  - Approximately 90% accuracy
- However, we can do much better!
- One way to improve upon our results is to use **HMMs**

HMM POS Tagger

- Selects the most likely tag sequence for a sequence of observed words, maximizing the following formula:
  - P(word | tag) * P(tag | previous *n* tags)
- More formally, letting $T = \{t_1, t_2, \ldots, t_n\}$ and $W = \{w_1, w_2, \ldots, w_n\}$, find the most probable sequence of tags *T* underlying the observed words *W*

What do we mean by “previous *n* tags”?

- In NLP, a sequence of items (characters, words, etc.) of length *n* is commonly referred to as an *n*-gram.
- Special cases of *n*-grams:
  - Unigram (*n*=1)
  - Bigram (*n*=2)
  - Trigram (*n*=3)
- After that, usually just called e.g., 4-gram, 5-gram, etc.
- Much more about *n*-grams later this semester!
- For our example here, we’ll assume *n*=1 and create a bigram HMM tagger, meaning we’re only looking at a word/tag given the word/tag immediately preceding it

Bigram HMM Tagger

- To determine the tag t_i for a single word w_i:
  - $t_i = \underset{t_j \in \{t_0, t_1, \ldots, t_{t-1}\}}{\operatorname{argmax}} P(t_j | t_{i-1}) P(w_i | t_j)$
- This means we need to be able to compute two probabilities:
  - The probability that the tag is t_j given that the previous tag is t_{i-1}
    - $P(t_j | t_{i-1})$
  - The probability that the word is w_i given that the tag is t_j
    - $P(w_i | t_j)$
- We can compute both of these from corpora like the Penn Treebank or the Brown Corpus
- Then, we can find the most optimal sequence of tags using the Viterbi algorithm!

Example: Bigram HMM Tagger

Secretariat	is	expected	to	race	tomorrow
NNP	VBZ	VBN	TO	VB	NR
NNP	VBZ	VBN	TO	NN	NR

- Given two possible sequences of tags for the following sentence, what is the best way to tag the word “race”?
- We’ll use the 87-tag Brown Corpus tagset here
  - Contains a specific tag for the infinitive use of “to”
  - Labels “tomorrow” as NR (adverbial noun) rather than NN (singular common noun)

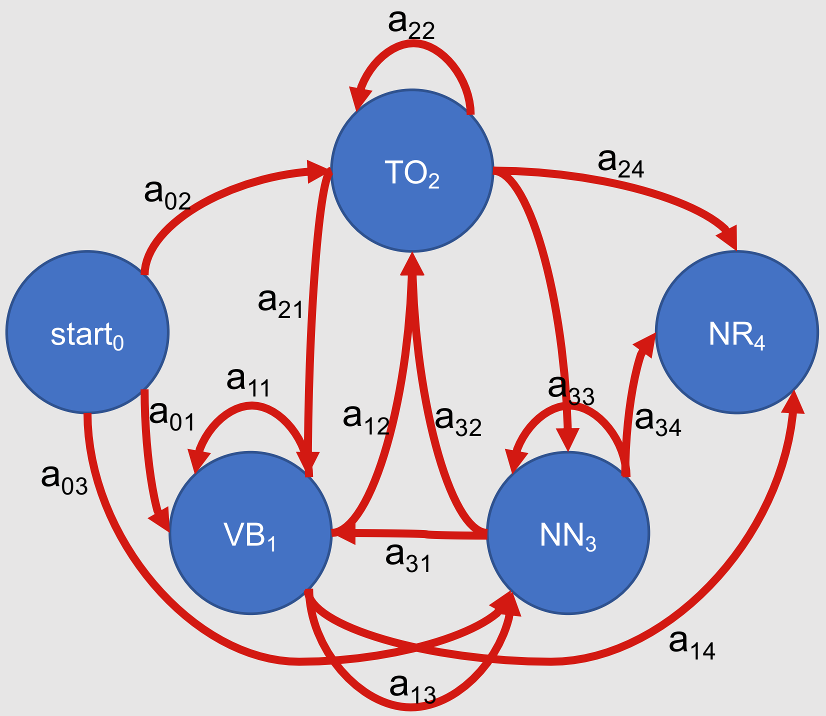
Secretariat	is	expected	to	race	tomorrow
NNP	VBZ	VBN	TO	VB	NR
NNP	VBZ	VBN	TO	NN	NR

- Since we're creating a bigram HMM tagger and focusing on the word "race," we only need to be concerned with the subsequence "to race tomorrow"

Example: Bigram HMM Tagger

We can thus create the following Markov chain:

Secretariat	is	expected	to	race	tomorrow
NNP	VBZ	VBN	TO	VB	NR
NNP	VBZ	VBN	TO	NN	NR

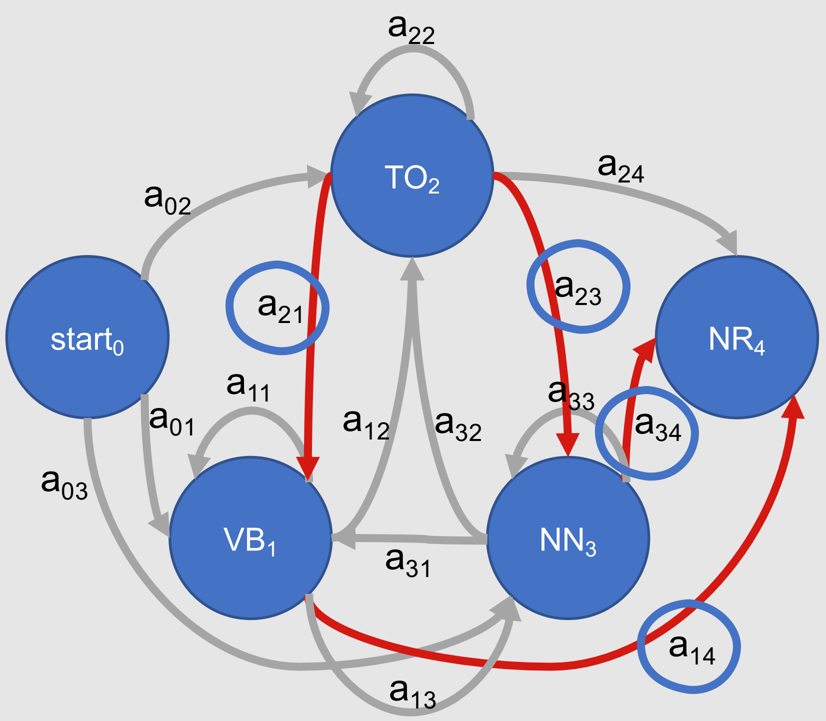


Example: Bigram HMM Tagger

Example: Bigram HMM Tagger

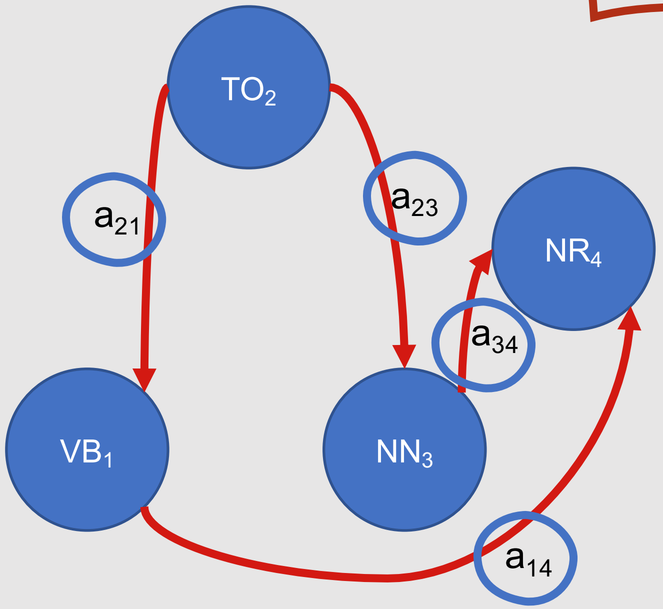
Secretariat	is	expected	to	race	tomorrow
NNP	VBZ	VBN	TO	VB	NR
NNP	VBZ	VBN	TO	NN	NR

The specific transition probabilities we are interested in are:



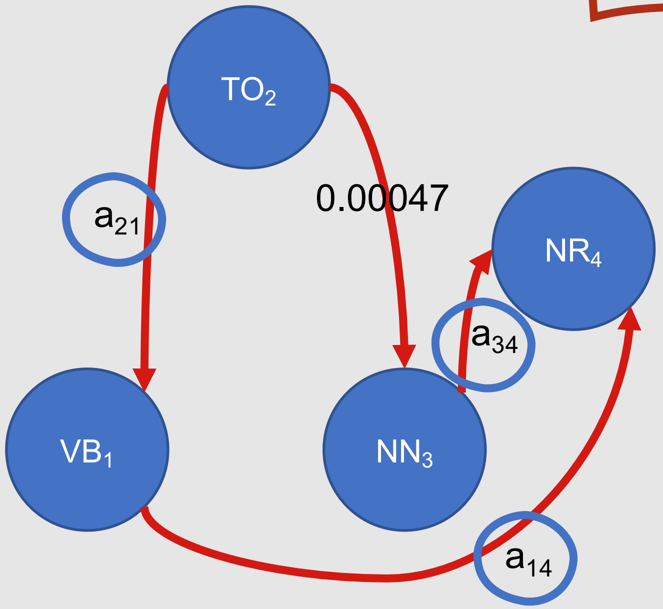
Example: Bigram HMM Tagger

Secretariat	is	expected	to	race	tomorrow
NNP	VBZ	VBN	TO	VB	NR
NNP	VBZ	VBN	TO	NN	NR



- We can compute the transition probabilities for a_{21}, a_{23}, a_{34}, and a_{14} using frequency counts from the Brown Corpus
- $P(t_i|t_{i-1}) = \frac{c(t_{i-1}t_i)}{c(t_{i-1})}$

Secretariat	is	expected	to	race	tomorrow
NNP	VBZ	VBN	TO	VB	NR
NNP	VBZ	VBN	TO	NN	NR

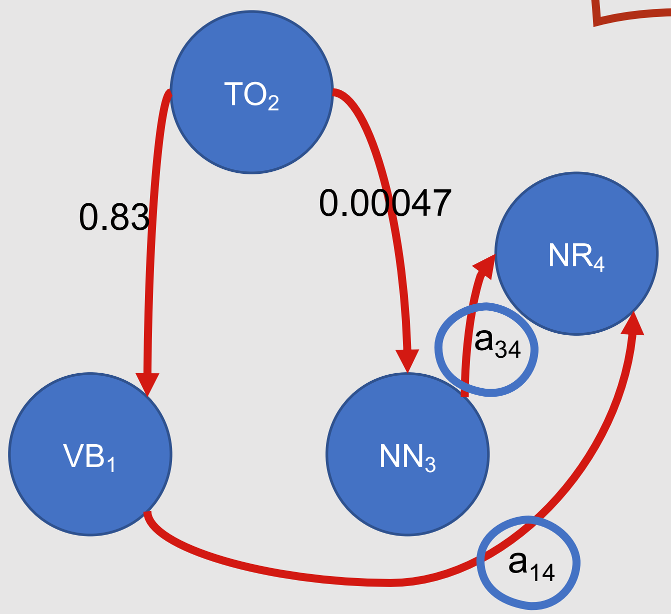


- We can compute the transition probabilities for a_{21}, a_{23}, a_{34}, and a_{14} using frequency counts from the Brown Corpus
- $P(t_i|t_{i-1}) = \frac{c(t_{i-1}t_i)}{c(t_{i-1})}$
- So, P(NN|TO) = C(TO NN) / C(TO) = 0.00047

Example: Bigram HMM Tagger

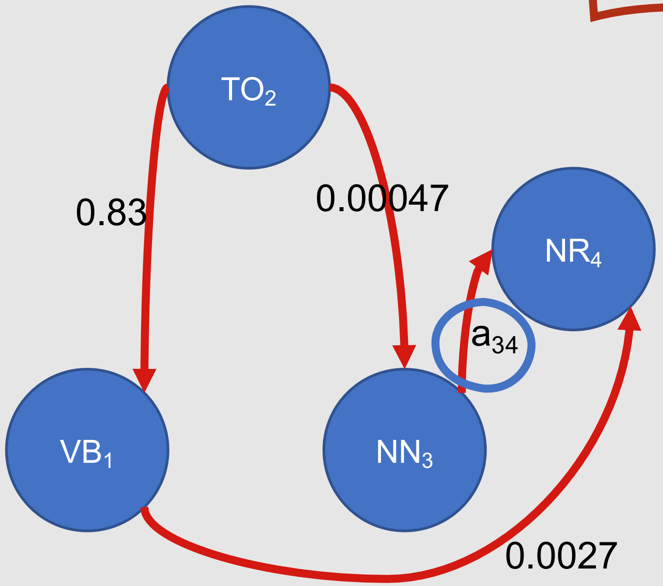
Example: Bigram HMM Tagger

Secretariat	is	expected	to	race	tomorrow
NNP	VBZ	VBN	TO	VB	NR
NNP	VBZ	VBN	TO	NN	NR



- We can compute the transition probabilities for a_{21}, a_{23}, a_{34}, and a_{14} using frequency counts from the Brown Corpus
- $P(t_i|t_{i-1}) = \frac{c(t_{i-1}t_i)}{c(t_{i-1})}$
- So, P(NN|TO) = C(TO NN) / C(TO) = 0.00047
- Likewise, P(VB|TO) = C(TO VB) / C(TO) = 0.83

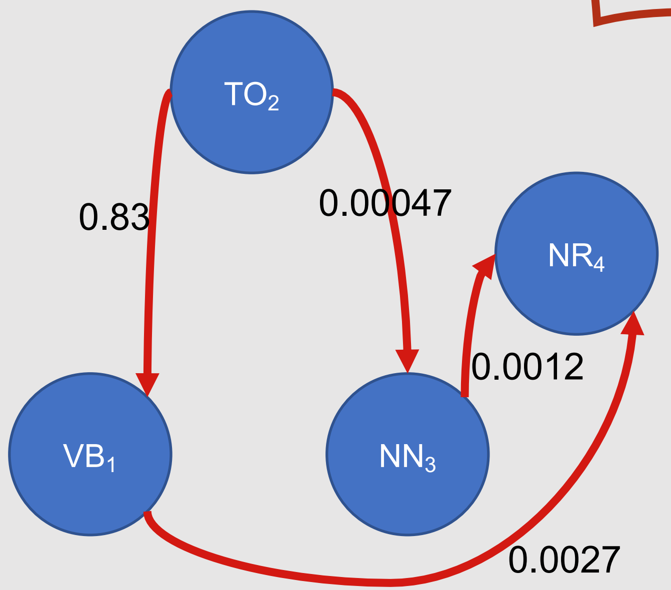
Secretariat	is	expected	to	race	tomorrow
NNP	VBZ	VBN	TO	VB	NR
NNP	VBZ	VBN	TO	NN	NR



- We can compute the transition probabilities for a_{21}, a_{23}, a_{34}, and a_{14} using frequency counts from the Brown Corpus
- $P(t_i|t_{i-1}) = \frac{c(t_{i-1}t_i)}{c(t_{i-1})}$
- So, P(NN|TO) = C(TO NN) / C(TO) = 0.00047
- Likewise, P(VB|TO) = C(TO VB) / C(TO) = 0.83
- P(NR|VB) = C(VB NR) / C(VB) = 0.0027

Example: Bigram HMM Tagger

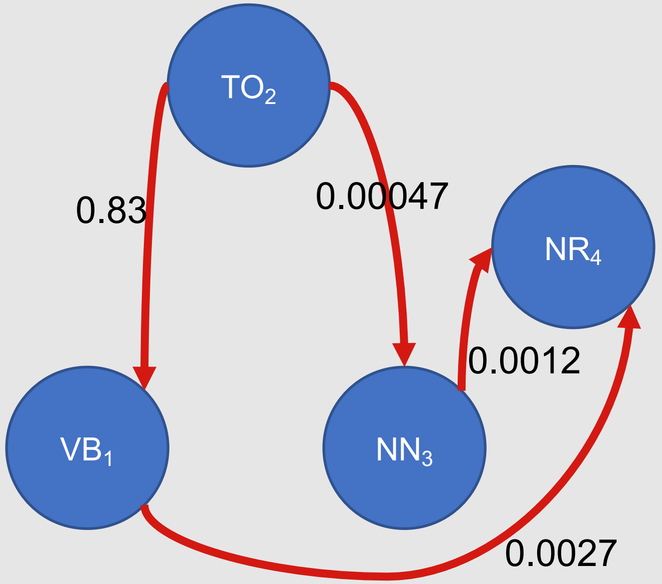
Secretariat	is	expected	to	race	tomorrow
NNP	VBZ	VBN	TO	VB	NR
NNP	VBZ	VBN	TO	NN	NR



- We can compute the transition probabilities for a_{21}, a_{23}, a_{34}, and a_{14} using frequency counts from the Brown Corpus
- $P(t_i|t_{i-1}) = \frac{c(t_{i-1}t_i)}{c(t_{i-1})}$
- So, P(NN|TO) = C(TO NN) / C(TO) = 0.00047
- Likewise, P(VB|TO) = C(TO VB) / C(TO) = 0.83
- P(NR|VB) = C(VB NR) / C(VB) = 0.0027
- Finally, P(NR|NN) = C(NN NR) / C(NN) = 0.0012

Example: Bigram HMM Tagger

Secretariat	is	expected	to	race	tomorrow
NNP	VBZ	VBN	TO	VB	NR
NNP	VBZ	VBN	TO	NN	NR

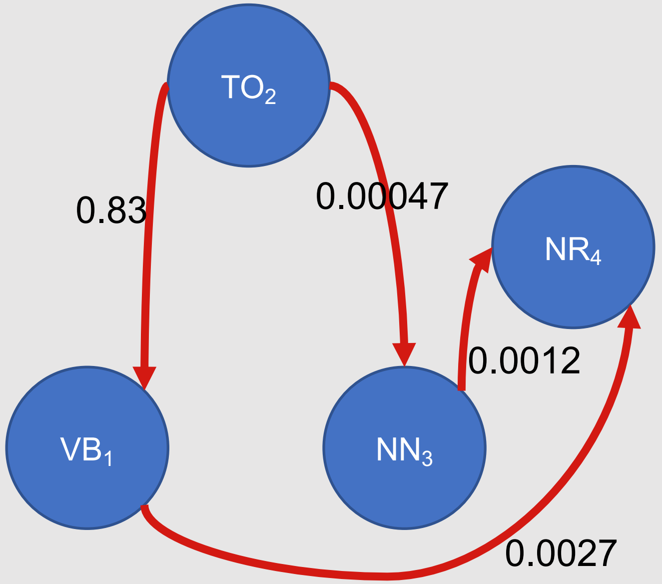


	race
VB	
NN	

- We have our transition probabilities …what now?
- Observation likelihoods!
- We can also compute these using frequency counts from the Brown Corpus
- $P(w_i|t_i) = \frac{c(w_i,t_i)}{c(t_i)}$
- Since we're trying to decide the best tag for "race," we need to compute both P(race|VB) and P(race|NN)

Example: Bigram HMM Tagger

Secretariat	is	expected	to	race	tomorrow
NNP	VBZ	VBN	TO	VB	NR
NNP	VBZ	VBN	TO	NN	NR

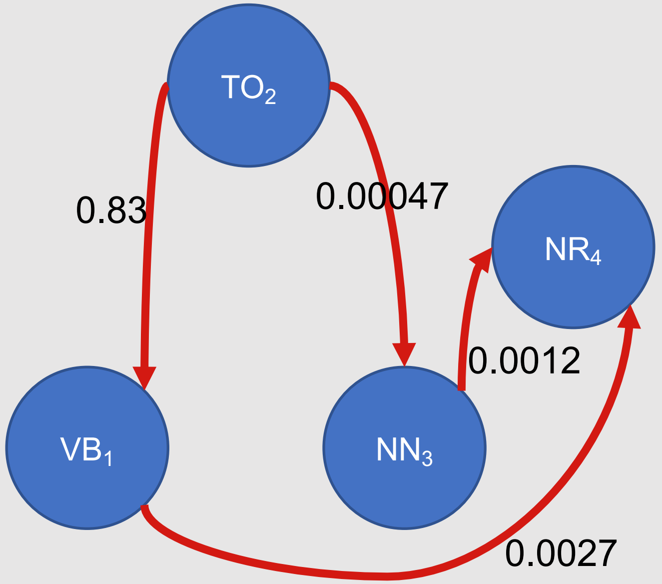


	race
VB	0.00012
NN	

- We have our transition probabilities …what now?
- Observation likelihoods!
- We can also compute these using frequency counts from the Brown Corpus
- $P(w_i|t_i) = \frac{c(w_i,t_i)}{c(t_i)}$
- Since we're trying to decide the best tag for "race," we need to compute both P(race|VB) and P(race|NN)
- P(race|VB) = C(race, VB) / C(VB) = 0.00012

Example: Bigram HMM Tagger

Secretariat	is	expected	to	race	tomorrow
NNP	VBZ	VBN	TO	VB	NR
NNP	VBZ	VBN	TO	NN	NR

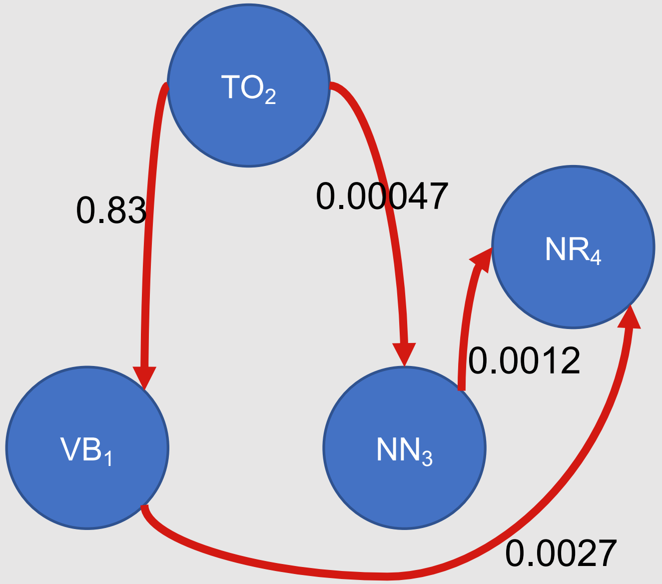


	race
VB	0.00012
NN	0.00057

- We have our transition probabilities …what now?
- Observation likelihoods!
- We can also compute these using frequency counts from the Brown Corpus
- $P(w_i|t_i) = \frac{c(w_i,t_i)}{c(t_i)}$
- Since we're trying to decide the best tag for "race," we need to compute both P(race|VB) and P(race|NN)
- P(race|VB) = C(race, VB) / C(VB) = 0.00012
- P(race|NN) = C(race, NN) / C(NN) = 0.00057

Example: Bigram HMM Tagger

Secretariat	is	expected	to	race	tomorrow
NNP	VBZ	VBN	TO	VB	NR
NNP	VBZ	VBN	TO	NN	NR



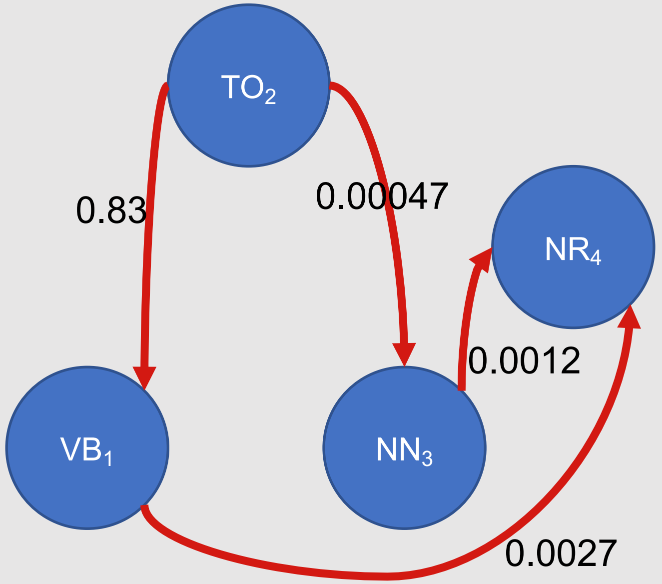
	race
VB	0.00012
NN	0.00057

- Now, to decide how to tag "race," we can consider our two possible sequences:
  - to (TO) race (VB) tomorrow (NR)
  - to (TO) race (NN) tomorrow (NR)
- We will select the tag that maximizes the probability:
  - $P(t_i|TO)P(NR|t_i)P(race|t_i)$
- We determine that:
  - P(VB|TO)P(NR|VB)P(race|VB) = 0.83 * 0.0027 * 0.00012 = 0.00000027
  - P(NN|TO)P(NR|NN)P(race|NN) = 0.00047 * 0.0012 * 0.00057 = 0.00000000032

Example: Bigram HMM Tagger

Example: Bigram HMM Tagger

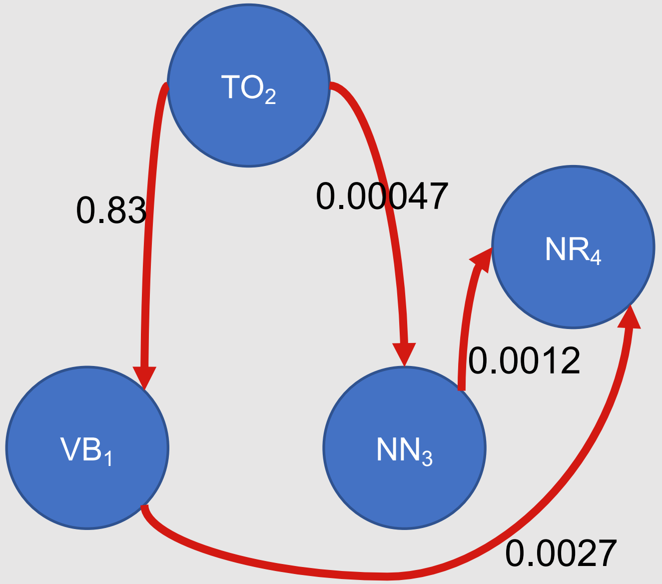
Secretariat	is	expected	to	race	tomorrow
NNP	VBZ	VBN	**TO**	**VB**	**NR**
NNP	VBZ	VBN	TO	NN	NR



	race
VB	0.00012
NN	0.00057

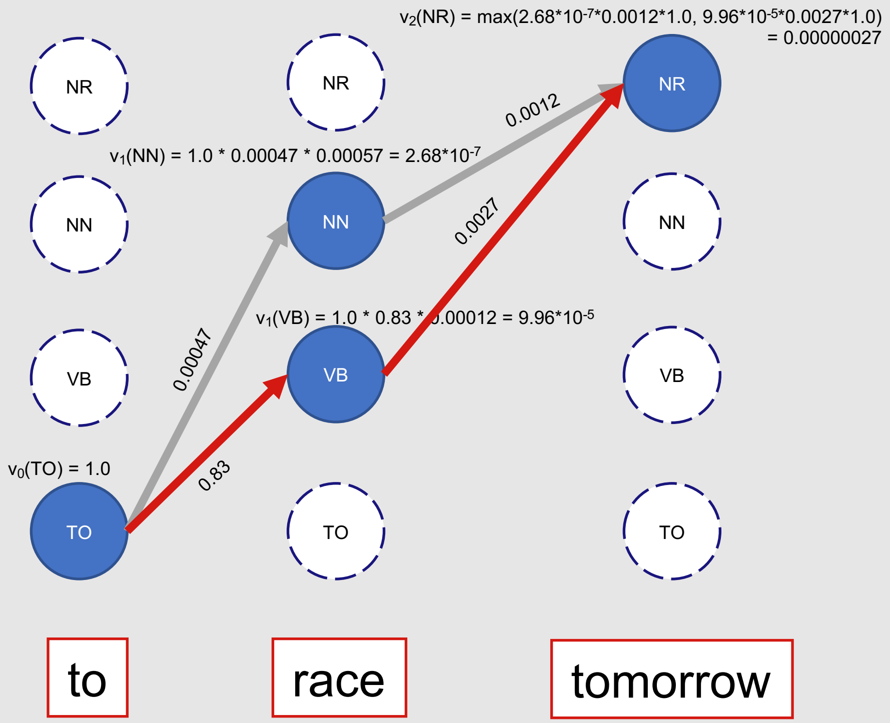
- Now, to decide how to tag "race," we can consider our two possible sequences:
  - to (TO) race (VB) tomorrow (NR)
  - to (TO) race (NN) tomorrow (NR)
- We will select the tag that maximizes the probability:
  - $P(t_i|TO)P(NR|t_i)P(race|t_i)$
- We determine that:
  - **P(VB|TO)P(NR|VB)P(race|VB) = 0.83 * 0.0027 * 0.00012 = 0.00000027**
    - Optimal sequence!
  - P(NN|TO)P(NR|NN)P(race|NN) = 0.00047 * 0.0012 * 0.00057 = 0.00000000032

Secretariat	is	expected	to	race	tomorrow
NNP	VBZ	VBN	**TO**	**VB**	**NR**
NNP	VBZ	VBN	TO	NN	NR



	race
VB	0.00012
NN	0.00057

- Visualized in a Viterbi trellis, this would look like:



Example: Bigram HMM Tagger

What if we used greater values of *n*?

- For example, a trigram HMM tagger instead of a bigram HMM tagger?
- Generally, more context → more accurate predictions
- However, greater values of *n* also require more computational work …you need to determine whether the trade-off is worth it

Transformation-Based Tagging

- **Brill Tagging**
- Instance of **transformation-based learning (TBL)** approach to machine learning
- **Combination of rule-based and statistical** POS tagging **methodologies**
  - Rules are used to specify which tags should be used in different environments
  - These rules are induced automatically from a training corpus
- Input:
  - Training corpus
  - Dictionary (with most frequent tags) constructed from the training corpus

Transformation-Based Tagging

- Basic Idea
  - **Set the most probable tag** for each word as a start value
  - **Change tags according to rules** in a specific order
    - For example, “if w_1 is a determiner and w_2 is a verb, than change the tag for w_2 to noun”
- **Learn these rules from a tagged corpus**
  - From start value, examine every possible transformation
  - Select the one that results in the most improved tagging (see example above)
  - Re-tag data according to this rule
  - Repeat previous two steps until stopping criterion is met
- Thus, **rules can make errors that are corrected by later rules**

Example Rule

- Start: Tagger labels every word with its most likely tag
  - P(NN|race) = 0.98
  - P(VB|race) = 0.02

Secretariat	is	expected	to	race	tomorrow
NNP	VBZ	VBN	TO	NN	NR

- New rule learned: Change NN to VB when previous tag is TO
- Re-tag data according to this rule

Secretariat	is	expected	to	race	tomorrow
NNP	VBZ	VBN	TO	VB	NR

In theory, there are endless rules that could be learned!

- In practice, this would be problematic
- Instead, Brill created a small set of templates to which all rules had to adhere
  - Change tag a to tag b when the preceding (following) word is tagged z.
  - Change tag a to tag b when the word two before (after) is tagged z.
  - Change tag a to tag b when one of the two preceding (following) words is tagged z.
  - Change tag a to tag b when one of the three preceding (following) words is tagged z.
  - Change tag a to tag b when the preceding word is tagged z and the following word is tagged w.
  - Change tag a to tag b when the preceding (following) word is tagged z and the word two before (after) is tagged w.

Types of POS Taggers

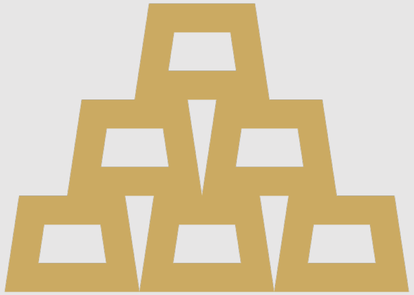
- There are advantages and disadvantages to all of these different POS tagging approaches
- Generally, both here and in other NLP problems, **rule-based approaches are faster and may work better for limited, well-defined domains**, whereas **statistical approaches are slower and may generalize better across broader domains**
  - HMM-based taggers can easily be trained on new languages, whereas rule-based taggers would have to be completely rewritten
- Statistical POS taggers are much more common in modern applications

How can POS taggers handle unknown words?

- New words are constantly being added to languages
- Thus, it is quite likely that a POS tagger will encounter words not found in its training corpus
- One approach, already mentioned as part of a baseline method: **Assume that unknown words are nouns**
- Another approach: **Assume that unknown words have a probability distribution similar to other words occurring only once in the training corpus**, and make an (informed) random choice
- Finally, a third approach: **Use morphological information** to choose the POS tag (for example, words ending with "ed" tend to be tagged VBN)

How are POS taggers evaluated?

- POS taggers are typically learned using (or rules are written based on) a training set
  - **Training Set:** A large collection of text that has been manually labeled with POS tags by human annotators
- The taggers are then used to predict POS tags for the text in a separate test set
  - **Test Set:** A collection of text that has also been manually labeled by human annotators, but that was not used to train the model
- These predictions on the test set are compared with the actual labels assigned to those words by human annotators
  - Labels from human annotators are often referred to as the **gold standard**



Evaluation Metrics

- Common metrics for POS taggers are:
  - Accuracy
  - Precision (of the words predicted to be NN, how many were labeled as NN by humans?)
  - Recall (of the words labeled NN by humans, how many were predicted to be NN by the POS tagger?)
  - F-Measure (combination of precision and recall)

Comparison

- The scores computed for these metrics should be compared to alternative POS tagging methods, to place the values in context
  - Is this a good accuracy score, or just a so-so one?
- It's good to compare to both a lower-bound baseline and an upper-bound ceiling
  - Baseline: What should your POS tagger definitely perform better than?
    - Most Frequent Class
  - Ceiling: What is the highest possible value for this task?
    - Human Agreement

What factors can impact performance?

- Many factors can lead to your results being higher or lower than expected!
- Some common factors:
  - The size of the training dataset
  - The specific characteristics of your tag set
  - The difference between your training and test corpora
  - The number of unknown words in your test corpus

Summary: Part-of-Speech Tagging

- POS tagging is the process of automatically assigning grammatical word classes (parts of speech) to individual tokens
- The most common POS tagset is the Penn Treebank tagset
- Ambiguity is common in natural language, and is a major issue that POS taggers must address
- POS taggers can be rule-based, statistical, or transformation-based
- Statistical approaches for POS tagging often utilize HMMs
- POS taggers are generally evaluated based on their performance on a test set according to a variety of metrics

What are formal grammars?

- Combination of:
  - A **set of rules** that describe how a language can be structured
  - A **lexicon** that defines the words and symbols that belong to the language

So far, we've dealt with NLP tasks focused on individual words.

Part-of-Speech Tagging

- What grammatical role does this word fill?

Text Preprocessing

- Is this a word?
- Does this word belong to the language in question?

Formal grammars instead function at the sentence level.

- What are the constituents in this sentence?
  - **Constituent:** A group of words that behaves as a single unit or phrase
- What are the **grammatical relations** between these constituents?
- Which words are **dependent** upon one another?

Although the models we've seen that focus on words model sentences as sequences, **formal grammars model sentences as recursive generating processes**.

How do they do this?

- Usually, a tree structure

It's all about finding the right balance!

- When constructing formal grammars, we want to strike a balance between:
  - **Capturing all of the sentence structures that are valid** for a given language
  - **Avoiding the sentence structures that are invalid**
- As usual, this is easier said than done!

Two terms to be aware of….

- **Grammar Formalisms:** A precise way to define and describe the structure of independent sentences.
  - There are many different grammar formalisms (you can learn much more about these in linguistics courses!)
- **Specific Grammars:** Implementations (according a specific formalism) for a particular language
  - English, Swedish, Arabic, etc.
- Analogy:
  - **Grammar Formalisms = Linguists' Programming Languages**
  - **Specific Grammars = Linguists' Programs**

English Grammar

Overgeneration:

Love NLP class my so much that don't care about being it 9:30 a.m. at!

Did get the you email guy that that from class said he forward to you would?

Well, there just happened.

English:

I love my NLP class so much that I don't even care about it being at 9:30 a.m.!

Did you get the email that that guy from class said he would forward to you?

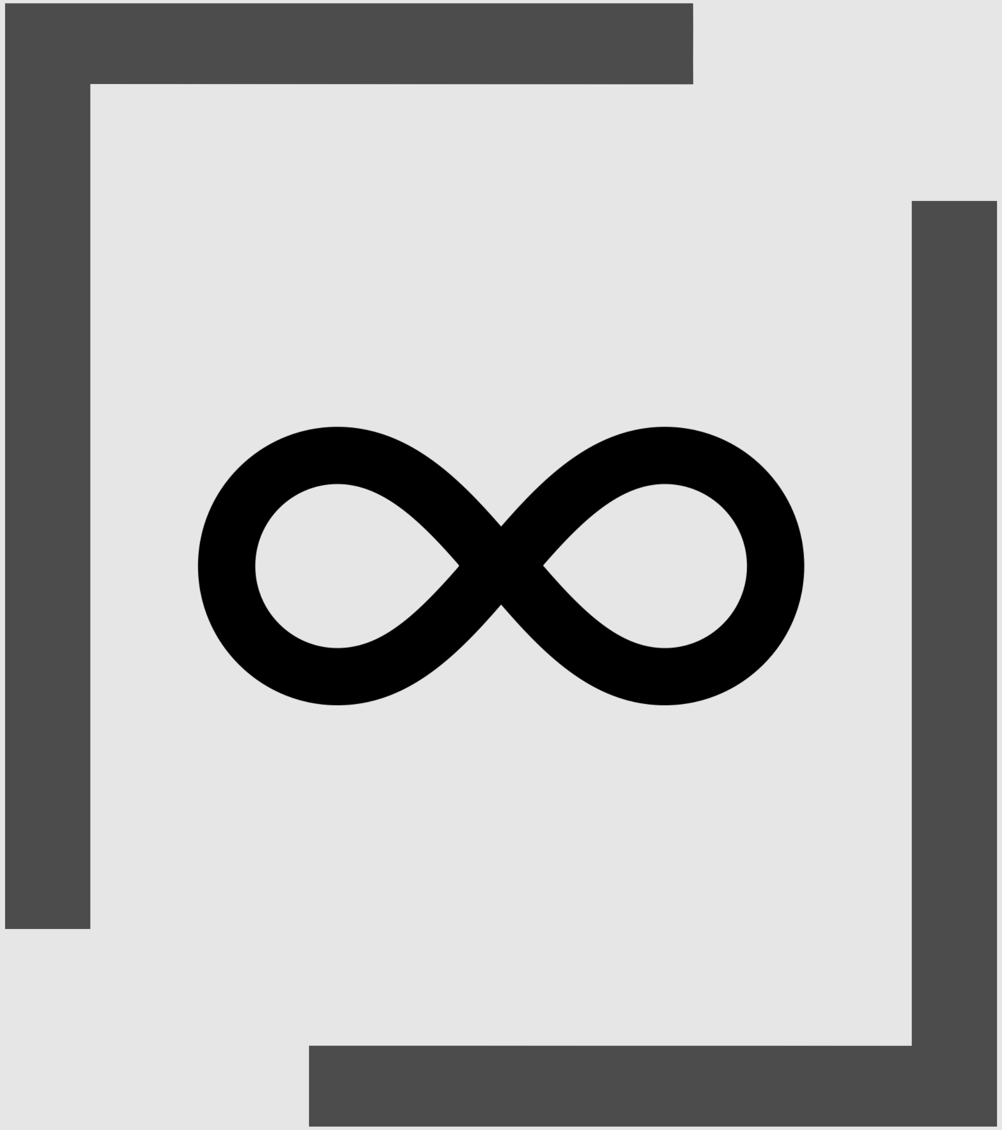
Well, that just happened.

Undergeneration:

I love my class!

Did you get his email?

What happened?



Is it possible to define a grammar that generates all English sentences?

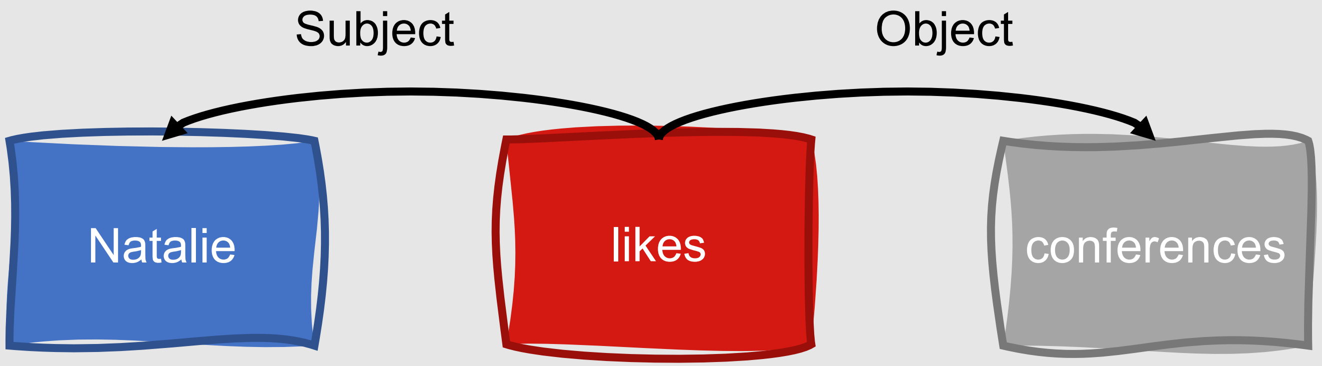
- Tricky question!
- The number of possible English sentences is infinite
- Our grammar needs to be finite

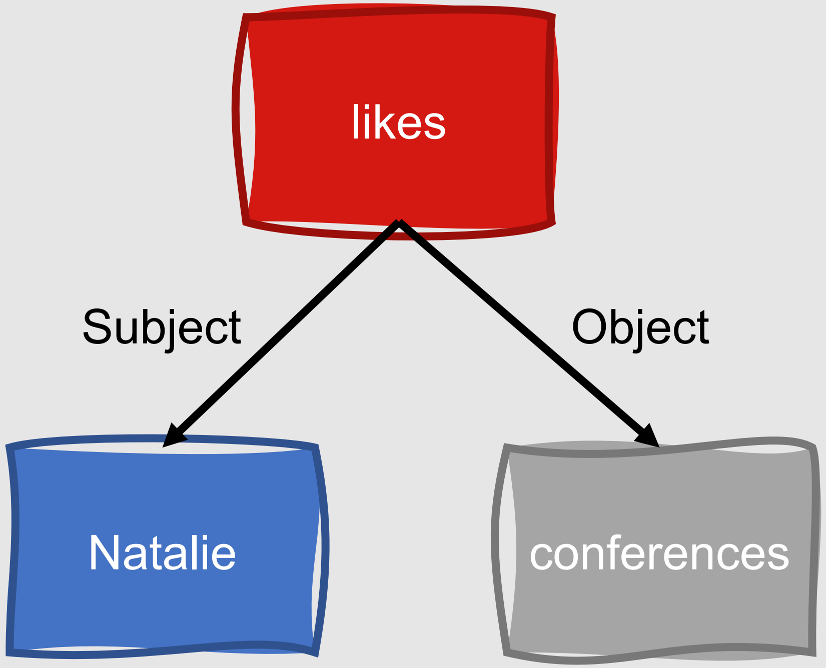
Basic English Sentence Structure

Natalie	likes	conferences
Noun (Subject)	Verb (Head)	Noun (Object)

In NLP, there are many different ways to represent a sentence!

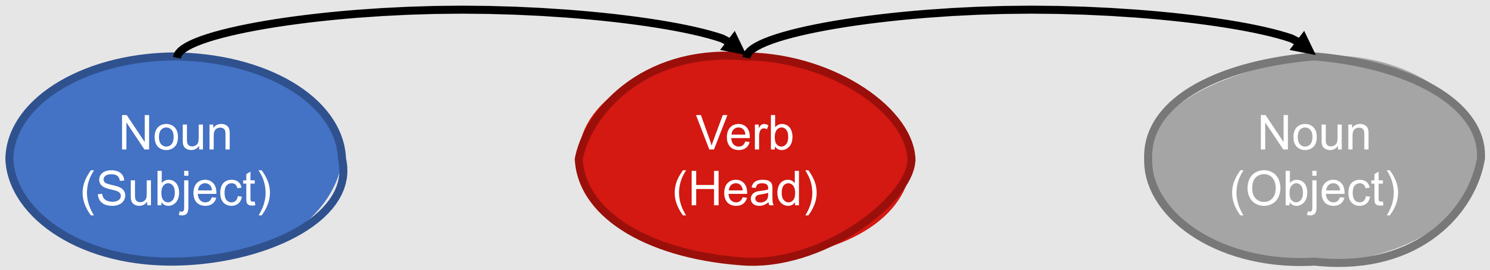
As a dependency graph:





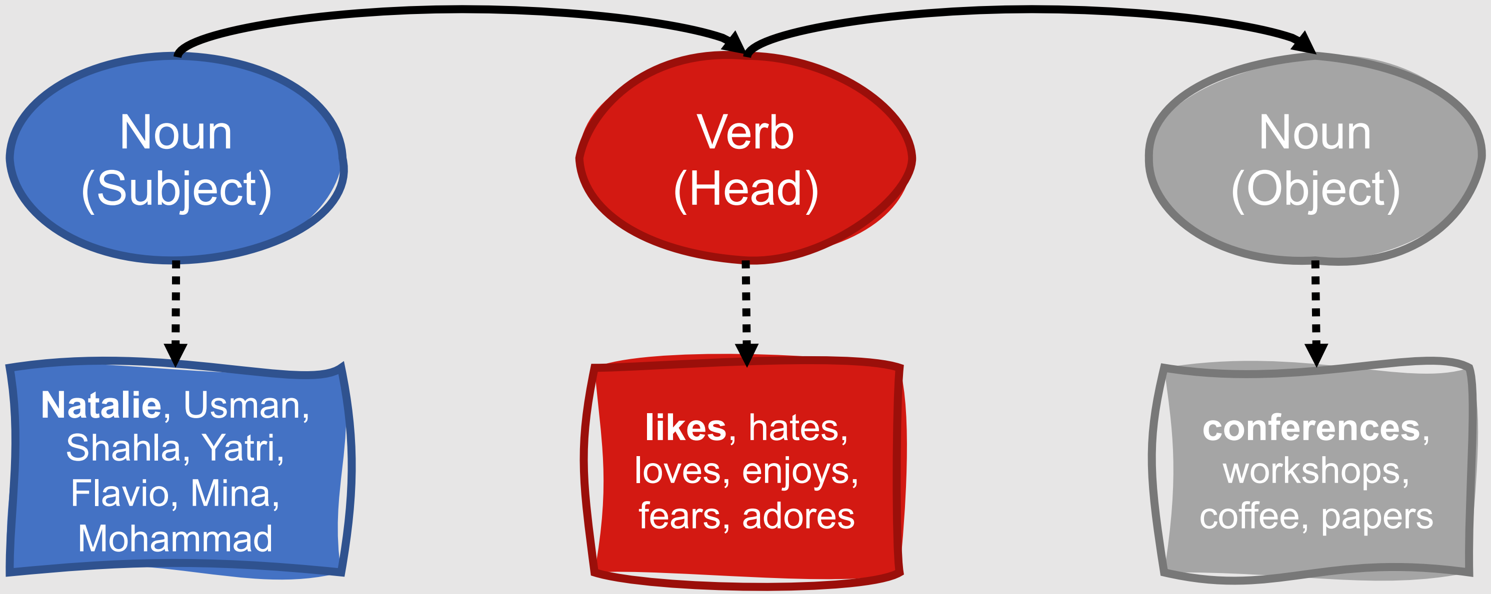
In NLP, there are many different ways to represent a sentence!

As a finite state automaton:



In NLP, there are many different ways to represent a sentence!

As a hidden Markov model:



Different types of words accept different types of **arguments**.

Natalie likes conferences. 🙂

Natalie likes conferences me. 🤨

Natalie drinks conferences. 🤨

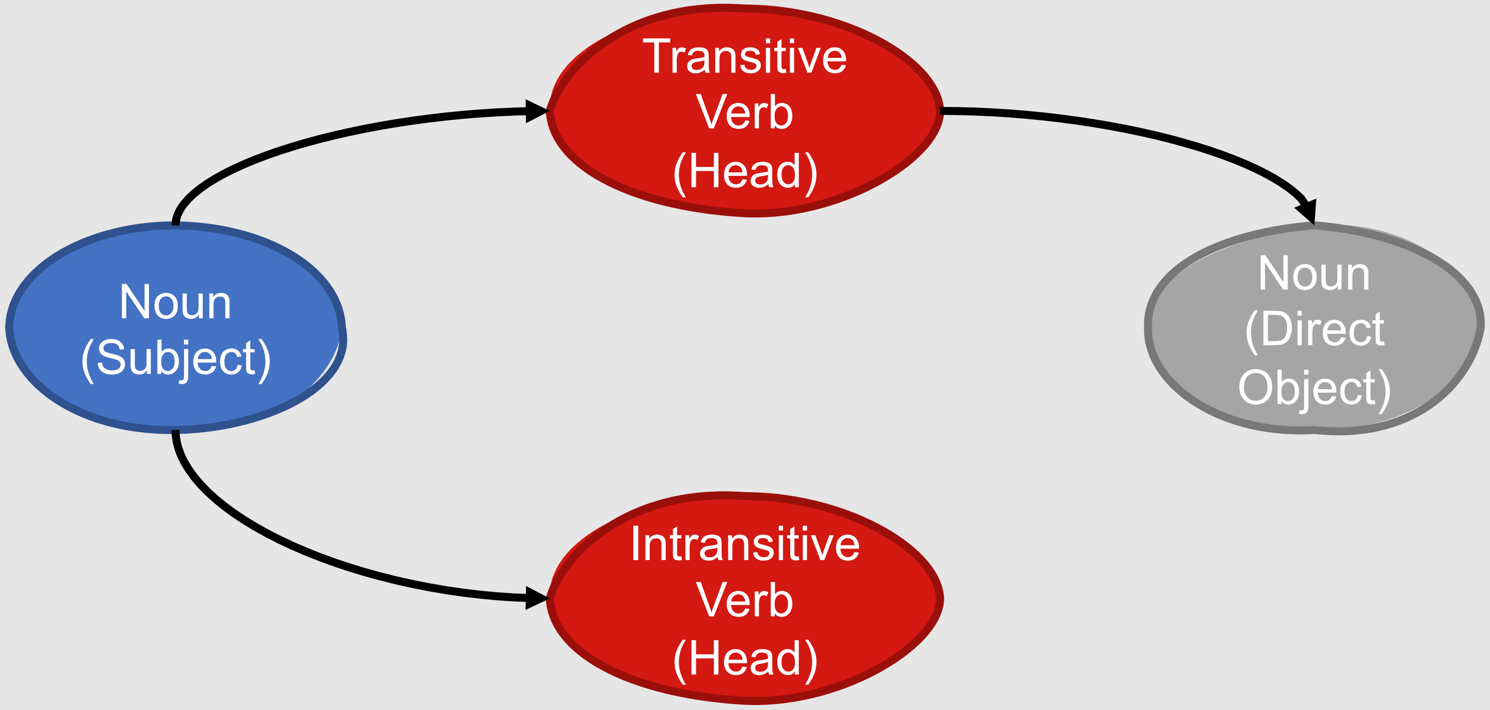
Some more terms to be aware of….

- **Subcategorization:** Syntactic constraints on the set of arguments that a group of words will accept.
  - **Intransitive verbs** accept only subjects
    - Sleep, arrive
  - **Transitive verbs** accept a subject and a direct object
    - Eat, drink
  - **Ditransitive verbs** accept a subject, a direct object, and an indirect object
    - Give, make

Some more terms to be aware of….

- **Selectional Preference:** Semantic constraints on the set of arguments that a group of words will accept.
  - The object of "drink" should be edible.
    - Natalie drinks conferences. 🤨
    - Natalie drinks tea. 🙂☕

Updating our FSA to incorporate some subcategorization rules….

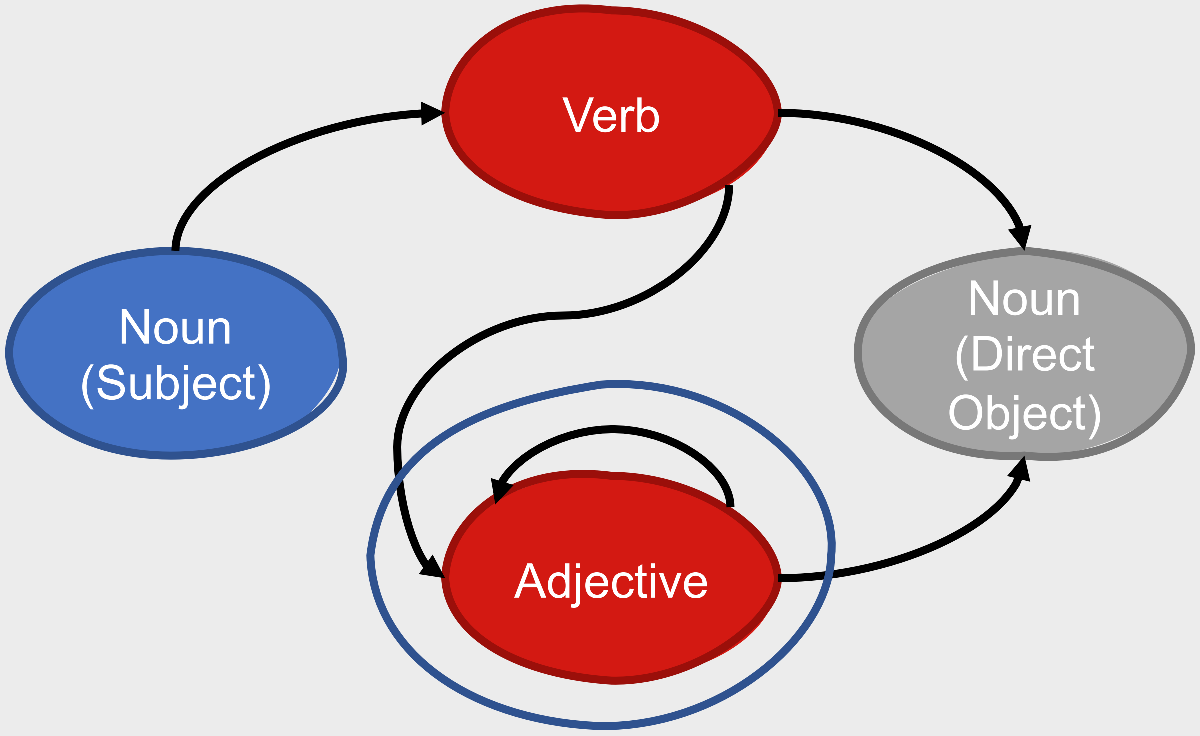


One of the reasons why the number of possible English sentences is infinite?

- Language is recursive!
- In theory, we can have unlimited modifiers (adjectives and adverbs)
  - Natalie likes conferences.
  - Natalie likes academic conferences.
  - Natalie likes busy academic conferences.

We can easily model simple cases of recursion.

- Natalie likes conferences.
- Natalie likes academic conferences.
- Natalie likes busy academic conferences.



However, recursion in sentences can also be more complex.

Natalie likes conferences.

Natalie likes conferences **in Europe**.

Natalie likes conferences **in Europe in the summer**.

Still, can't we just make complex FSAs?

- FSAs can model recursion, but they can't model hierarchical structure
- In complex sentences, you must also handle **attachment ambiguity**

Natalie likes conferences in either Europe or Asia.

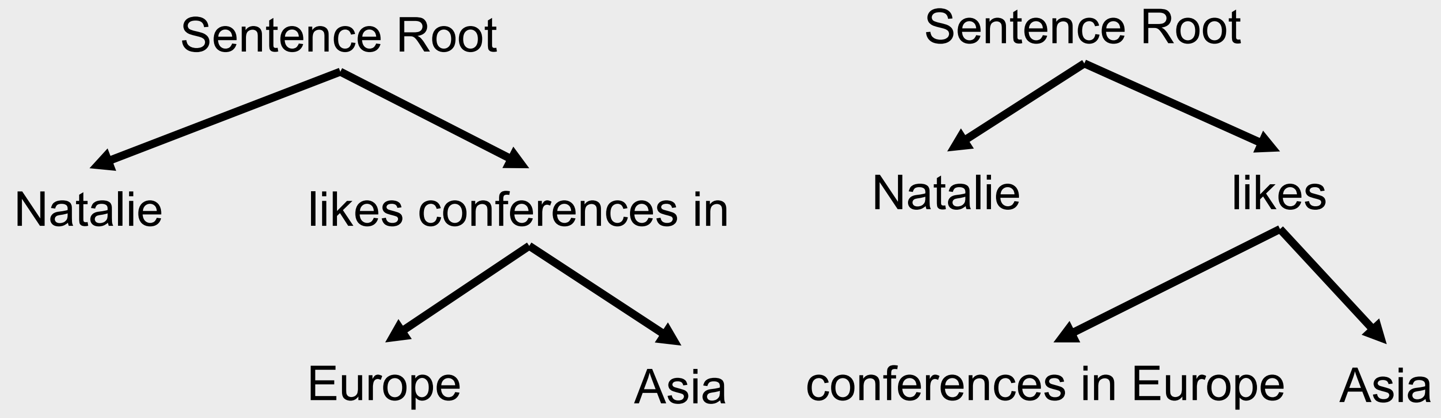
Natalie **likes conferences in** Europe **or** Asia.

Natalie **likes** conferences in Europe **or** Asia.

Natalie likes two things: Asia, or conferences in Europe.

Sentences Form a Hierarchy

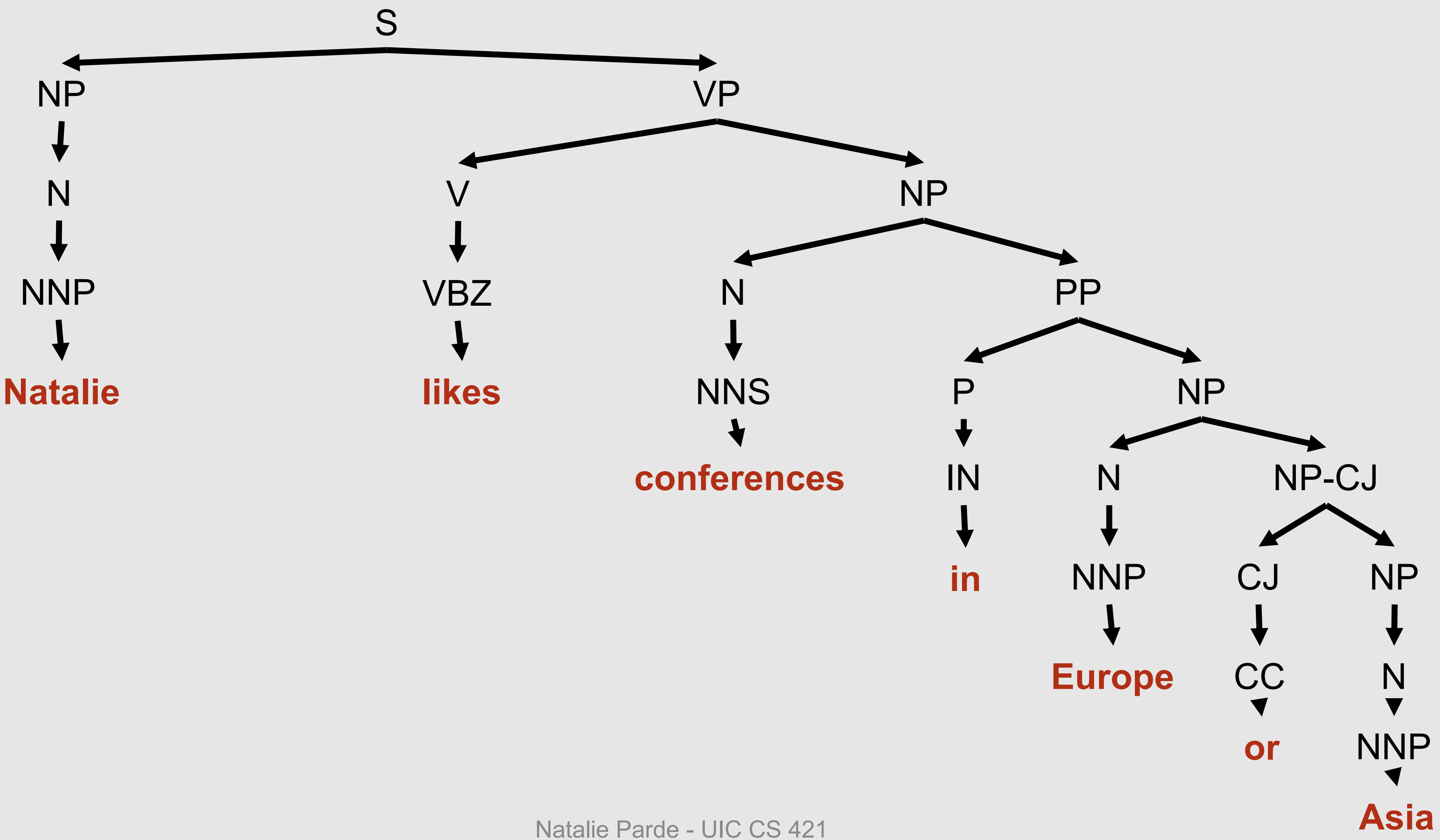
- A sentence consists of words that can be grouped into phrases (constituents)
- Sentence structure defines dependencies between these constituents



We can use trees to model this hierarchy.

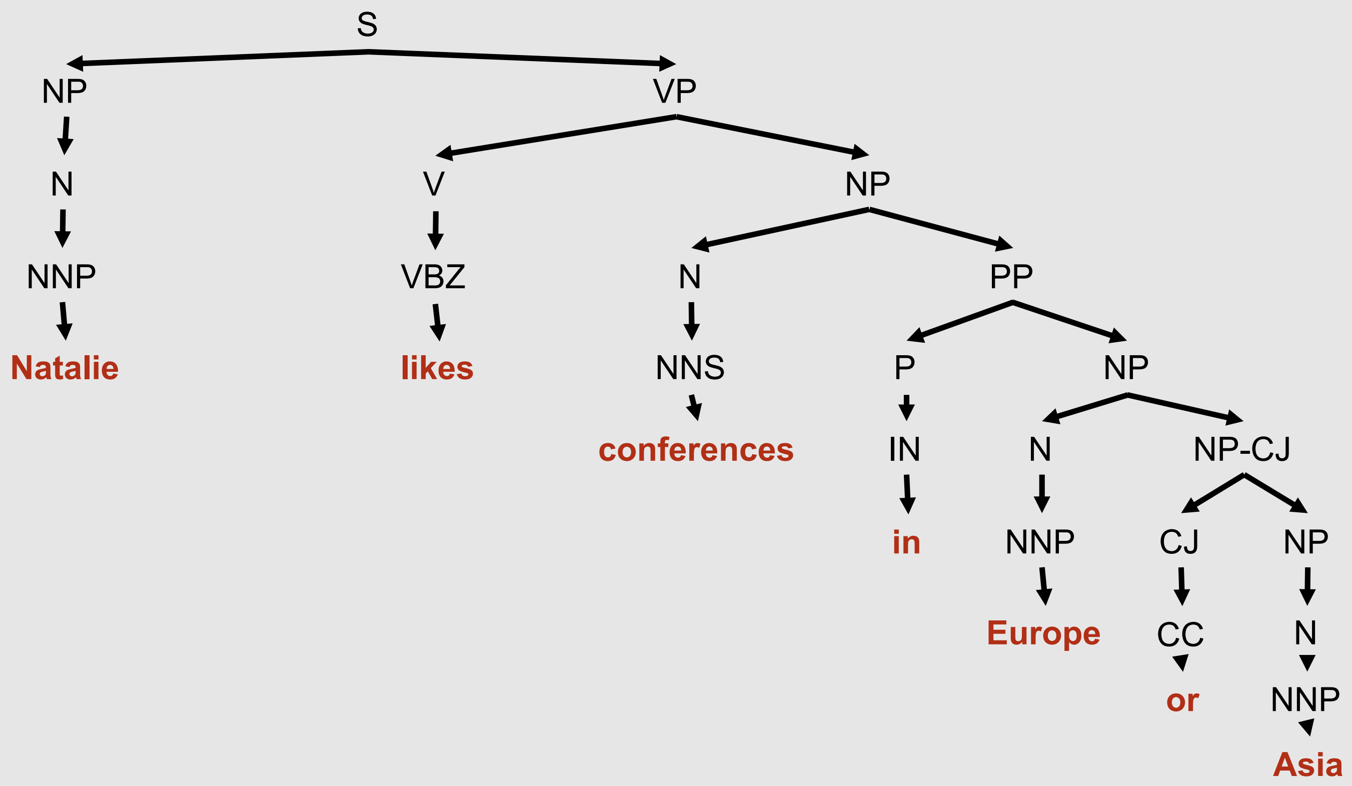
- Formal trees will usually have **internal (non-terminal) nodes** and **outer (terminal) leaves**
- **Nodes: Elements of sentence structure**
  - Constituent type
  - POS type
- **Leaves: Surface wordforms**
- The nodes and leaves are connected to one another by **branches**

What does this look like?



Trees can grow to be quite complex!

However, they can be reduced to simple subtrees defining underlying syntactic constituents



The grammars used in these hierarchical trees are called context-free grammars.

- **Context-Free Grammar (CFG):** A mathematical system for modeling constituent structure in natural language.
- Also called **Phrase-Structure Grammars**
- CFGs can describe all regular languages
- Why is it called context-free?
  - A subtree can be replaced by a production rule independent of the greater context (other nodes in the hierarchy) in which it occurs.

CFGs are defined by productions that indicate what strings they can generate.

- **Production:** Basically, the rules we've been talking about so far …productions express the allowable combinations of symbols (POS types) that can form a constituent
- Productions can be **hierarchically embedded**
  - Noun Phrase (NP) → Determiner Nominal
  - Nominal → Noun | Nominal Noun

Strong vs. Weak Generative Capacity

Formal Language Theory:

- Defines language as sets of strings
- Is only concerned with generating these strings (**weak generative capacity**)

Formal/Theoretical (Linguistic) Syntax:

- Defines language as sets of strings with (hidden) structure
- Is also concerned with generating the right structures (**strong generative capacity**)

More Information About Constituents

- **Constituent:** A group of words that behaves as a single unit.
  - Noun Phrase: the woman, the woman with red hair, the last conference of the year
  - Prepositional Phrase: with red hair, of the year
  - Verb Phrase: drinks tea, likes going to conferences
- Phrases contain **heads** and **dependents**
  - **Heads:** the **woman** with red hair, the last **conference** of the year
  - **Dependents:** **the** woman **with red hair**, **the last** conference **of the year**

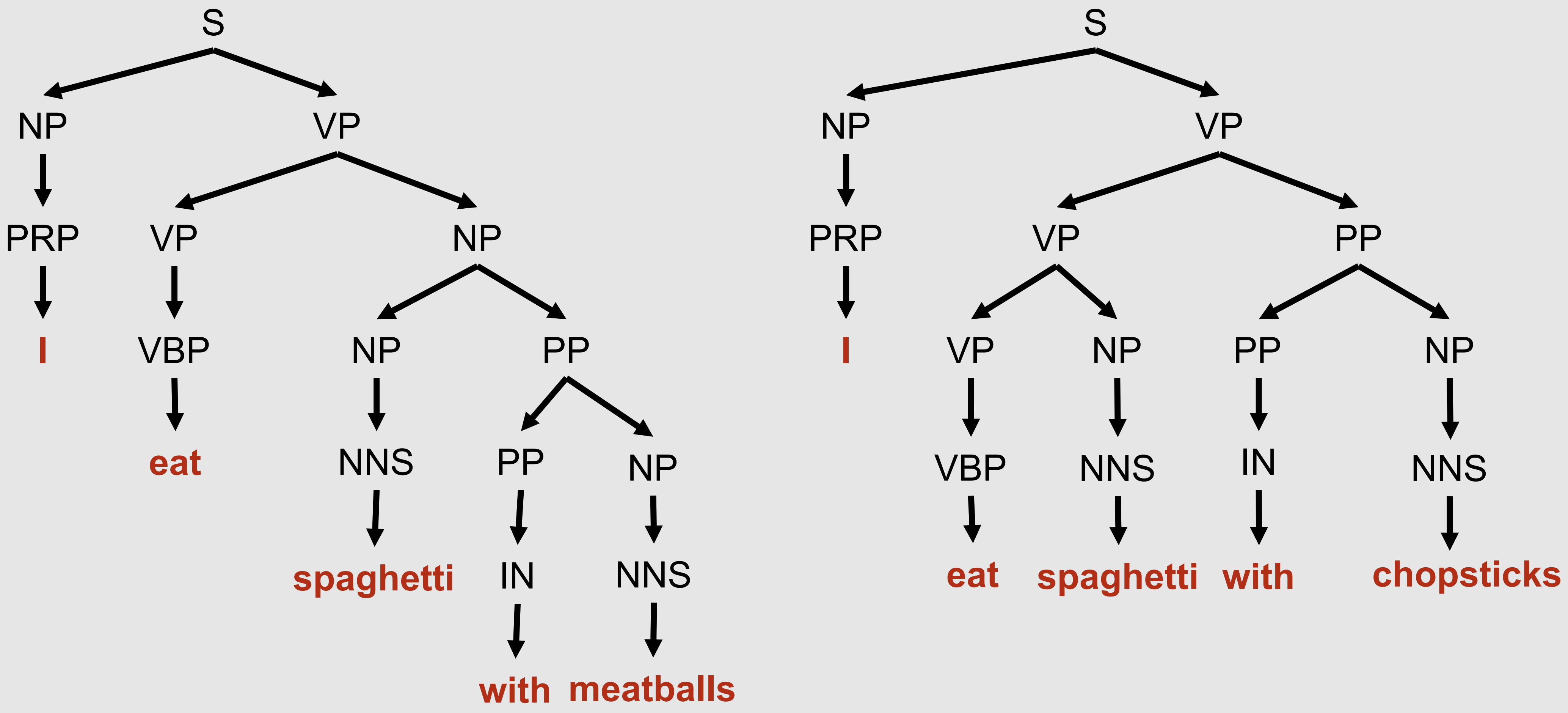
A Little More About Dependents

- Dependents can be arguments or adjuncts
- Arguments are obligatory
  - Must be present
  - Natalie likes **conferences**. 🙂
  - Natalie likes. 🤨
- Adjuncts are optional
  - Natalie drinks tea. 🙂
  - Natalie drinks. 🙂

Properties of Constituents

- **One constituent can be substituted with another** in the context of the greater sentence
  - **The woman with red hair** rolled her eyes and lightning immediately struck his house.
  - **The unicorn** rolled her eyes and lightning immediately struck his house.
- **A constituent can move around** within the context of the sentence
  - **The woman with red hair** rolled her eyes and lightning immediately struck his house.
  - Lightning immediately struck his house, and **the woman with red hair** rolled her eyes.
- **A constituent can be used to answer a question** about the sentence
  - Who rolled her eyes? **The woman with red hair**.

The structure of constituents in a tree corresponds to their meaning.



In-Class Exercise

- Draw a constituent tree for one (or both!) of these sentences:
  - **Time flies like an arrow.**
  - **Fruit flies like a banana.**

https://www.google.com/search?q=timer

Production Rules	
S ! NP VP	PP ! P NP
NP ! DET N	PP ! P
NP ! N	P ! like
NP ! N N	V ! flies | like
VP ! VP PP	DET ! a | an
VP ! V NP	N ! time | fruit | flies | arrow | banana
VP ! V	

Solutions?

Time flies like an arrow.

Fruit flies like a banana.

S

S

NP VP PP N V P DET time flies like an arrow fruit a banana

Formal Definition

- A CFG is a 4-tuple $\langle N, \Sigma, R, S \rangle$ consisting of:
  - A set of non-terminal nodes ***N***
    - ***N*** = {S, NP, VP, PP, N, V, …}
  - A set of terminal nodes (leaves) Σ
    - Σ = {time, flies, like, an, arrow, …}
  - A set of rules ***R***
  - A start symbol ***S*** ∈ ***N***

Which sentences are grammatically correct?

- Any sentences for which the CFG can construct a tree (all words in the sentence must be reachable as leaf nodes) are accepted by the CFG.

What about really complex sentences?

The mouse ate the corn. 🙂

The mouse **that the snake ate** ate the corn. 😕

The mouse **that the snake that the hawk ate ate** ate the corn. 🤯

CFGs and Center Embedding

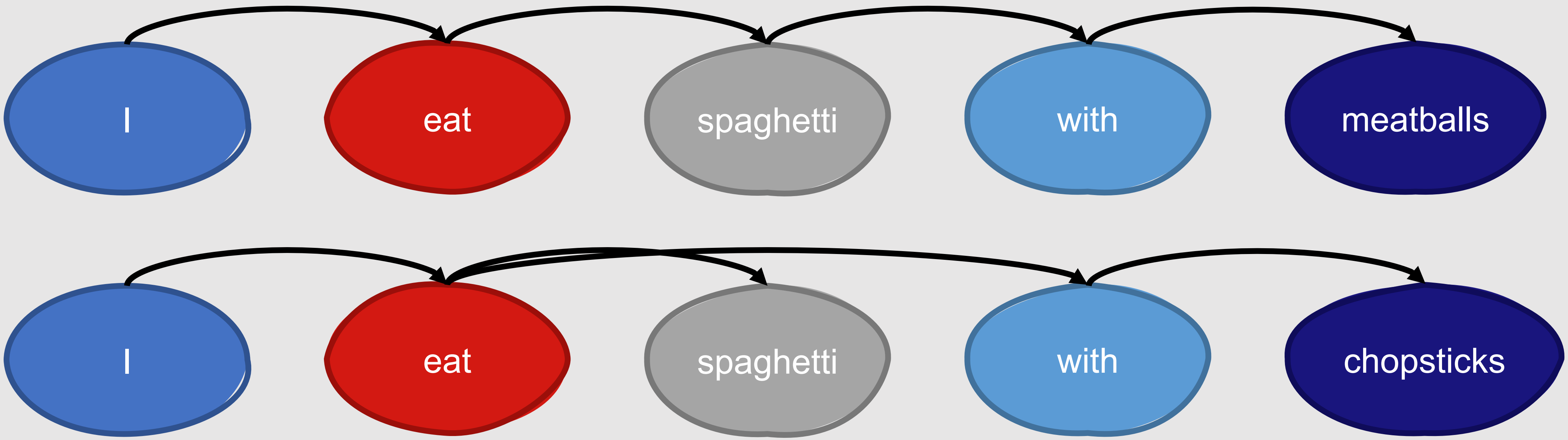
- Formally, these sentences are all grammatical, because they can be generated by the CFG that is required for the first sentence:
  - S → NP VP
  - NP → NP RelClause
  - RelClause → that NP ate
- However, very few humans would consider the last sentence to be grammatically correct!

CFGs and Center Embedding

- **CFGs are unable to capture bounded recursion** (e.g., embedding only one relative clause)
- So, linguists acknowledge that formal grammaticality is not perfectly equivalent to human perception of grammaticality
  - They additionally consider human grammatical knowledge, as well as processing and memory limitations
- In the context of this class, we'll just assume that if something is accepted by a CFG, it is grammatically correct

Dependency Grammars

- Dependency grammars describe the structure of a sentence as a directed acyclic graph
  - Nodes = words
  - Edges = dependencies



Relationship between Dependency Grammar and CFGs

- CFGs:
  - Is this sentence in the language?
- Dependency Grammars:
  - What is the semantic structure that would generate this sentence?
- If a CFG tree is translated into a dependency grammar, the resulting acyclic graph will have no crossing edges

Typical CFG Constituents (English)

- Noun phrases (NPs)
  - Simple:
    - **She** sleeps. (**pronoun**)
    - **Natalie** sleeps. (**proper noun**)
    - **A person** sleeps. (**determiner** + **common noun**)
  - Complex:
    - **A professorial** **person** sleeps. (**determiner** + **adjective** + **common noun**)
    - **The person at the lectern** sleeps. (**noun phrase (determiner + common noun)** + **prepositional phrase**)
    - **The person who teaches NLP** sleeps. (**noun phrase (determiner + common noun)** + **relative clause**)

Typical CFG Constituents (English)

- Visualized as production rules:
  - NP → Pronoun
  - NP → Proper Noun
  - NP → Determiner Common Noun
  - NP → Determiner Adjective Common Noun
  - NP → NP PP
  - NP → NP RelClause

  - Pronoun → {she}
  - Determiner → {a}
  - Proper Noun → {Natalie}
  - Common Noun → {person}
  - Adjective → {professorial}

Typical CFG Constituents (English)

- Adjective Phrases (AdjP) and Prepositional Phrases (PP)
  - AdjP → Adjective
  - AdjP → Adverb AdjP
  - Adj → {professorial}
  - Adv → {very}
    - A very professorial person sleeps.
  - PP → Preposition NP
  - Preposition → {at}

Typical CFG Constituents (English)

- Verb Phrases (VPs)
  - She **drinks**. (**verb**)
  - She **drinks** **tea**. (**verb** + **noun phrase**)
  - She **drinks tea** **from a mug**. (**verb phrase** + **prepositional phrase**)
- Visualized as production rules:
  - VP $\rightarrow$ V
  - VP $\rightarrow$ V NP
  - VP $\rightarrow$ V NP PP
  - VP $\rightarrow$ VP PP
  - V $\rightarrow$ {drinks}

Typical CFG Constituents (English)

- We can also capture subcategorization this way!
  - She **drinks**. (**verb**)
  - She **drinks** **tea**. (**verb** + **noun phrase**)
  - She **gives** **him** **tea**. (**verb phrase** + **noun phrase** + **noun phrase**)
- Visualized as production rules:
  - $VP \rightarrow V_{intransitive}$
  - $VP \rightarrow V_{transitive}\ NP$
  - $VP \rightarrow V_{ditransitive}\ NP\ NP$
  - $V_{intransitive} \rightarrow \{drinks, sleeps\}$
  - $V_{transitive} \rightarrow \{drinks\}$
  - $V_{ditransitive} \rightarrow \{gives\}$

Typical CFG Constituents (English)

- Production rules can also recursively include sentences
  - She drinks tea. (noun phrase + verb phrase)
  - Sometimes, she drinks tea. (adverbial phrase + sentence)
  - In England, she drinks tea. (prepositional phrase + sentence)
- Visualized as production rules:
  - $S \rightarrow NP\ VP$
  - $S \rightarrow AdvP\ S$
  - $S \rightarrow PP\ S$

To comprehensively cover English grammar, more complex production rules are necessary.

- She drinks tea. 🙂
- I drinks tea. 🤨
- They drinks tea. 🤨

- To avoid situations like the above, the simpler $S \rightarrow NP\ VP$ could be expanded to:
  - $S \rightarrow NP_{3sg}\ VP_{3sg}$
  - $S \rightarrow NP_{1sg}\ VP_{1sg}$
  - $S \rightarrow NP_{3pl}\ VP_{3pl}$

CFG Covering English Verb Tenses

- Present Tense: She drinks tea.
- Simple Past Tense: She drank tea.
- Past Perfect Tense: She has drunk tea.
- Future Perfect Tense: She will have drunk tea.
- Passive: The tea was drunk by her.
- Progressive: She will be drinking tea.

- $VP \rightarrow V_{have}\ VP_{pastPart}$
- $VP \rightarrow V_{be}\ VP_{pass}$
- $VP_{pastPart} \rightarrow V_{pastPart}\ NP$
- $VP_{pass} \rightarrow V_{pastPart}\ PP$
- $V_{have} \rightarrow \{has\}$
- $V_{pastPart} \rightarrow \{drunk\}$
- etc.…

Multiple sentences or clauses can be coordinated with one another via conjunction.

- **She drinks tea** and **he drinks coffee**.
- **Natalie** and **her mom** drink tea.
- She **drinks tea** and **eats cake**.

- S → S conj S
- NP → NP conj NP
- VP → VP conj VP

Relative Clauses

- **Relative clauses modify a noun phrase** by adding extra information
  - She had **a poodle that drank my tea**.
- Importantly, relative clauses do not have their own noun phrase!
  - Instead, it is understood that the NP is filled by the NP that the relative clause is modifying
    - She had a poodle **that** drank my tea. → that = a poodle
- There are two types of relative clauses
  - Subject: She had a poodle **that drank my tea**.
    - We cannot drop the relative pronoun
  - Object: I'd really been enjoying the tea **that her poodle drank**.
    - We can drop the relative pronoun and the sentence still works

The only things remaining are questions!

Yes/No Questions

- Auxiliary + Subject + Verb Phrase
  - Does she drink tea?
- YesNoQ → Aux NP VP

Wh-Questions

- Subject wh-questions contain a wh-word, an auxiliary, and a verb phrase
  - Who has drunk the tea?
- Object wh-questions contain a wh-word, an auxiliary, a noun phrase and a verb phrase
  - What does Natalie drink?

CFGs and dependency grammars for regular languages can be highly complex!

However, they facilitate automated syntactic and semantic parsing
…two essential tools for NLP systems

Summary: Formal Grammars

- **Formal grammars define how a language is syntactically and semantically structured**
  - CFGs represent syntactic structure
  - Dependency grammars represent semantic structure
- They contain **constituents**, which are groups of words that function as a single unit
- There are many ways to represent formal grammars, but the most common ways are **trees** (CFGs) and **directed acyclic graphs** (dependency grammars)
- Formal grammars can generate any sentences belonging to their language using (potentially recursive) combinations of **production rules**