Syntactic Parsing

Natalie Parde

UIC CS 421

We’ve learned all about the general building blocks of NLP.

- How can we use these tools to make sense of language?
- Popular category of tasks: syntactic parsing
  - Useful for grammar checking and miscellaneous information extraction tasks
- **Syntactic parsing:** The process of automatically recognizing and assigning syntactic (grammatical) roles to the constituents within sentences

This Week's Topics

Tuesday

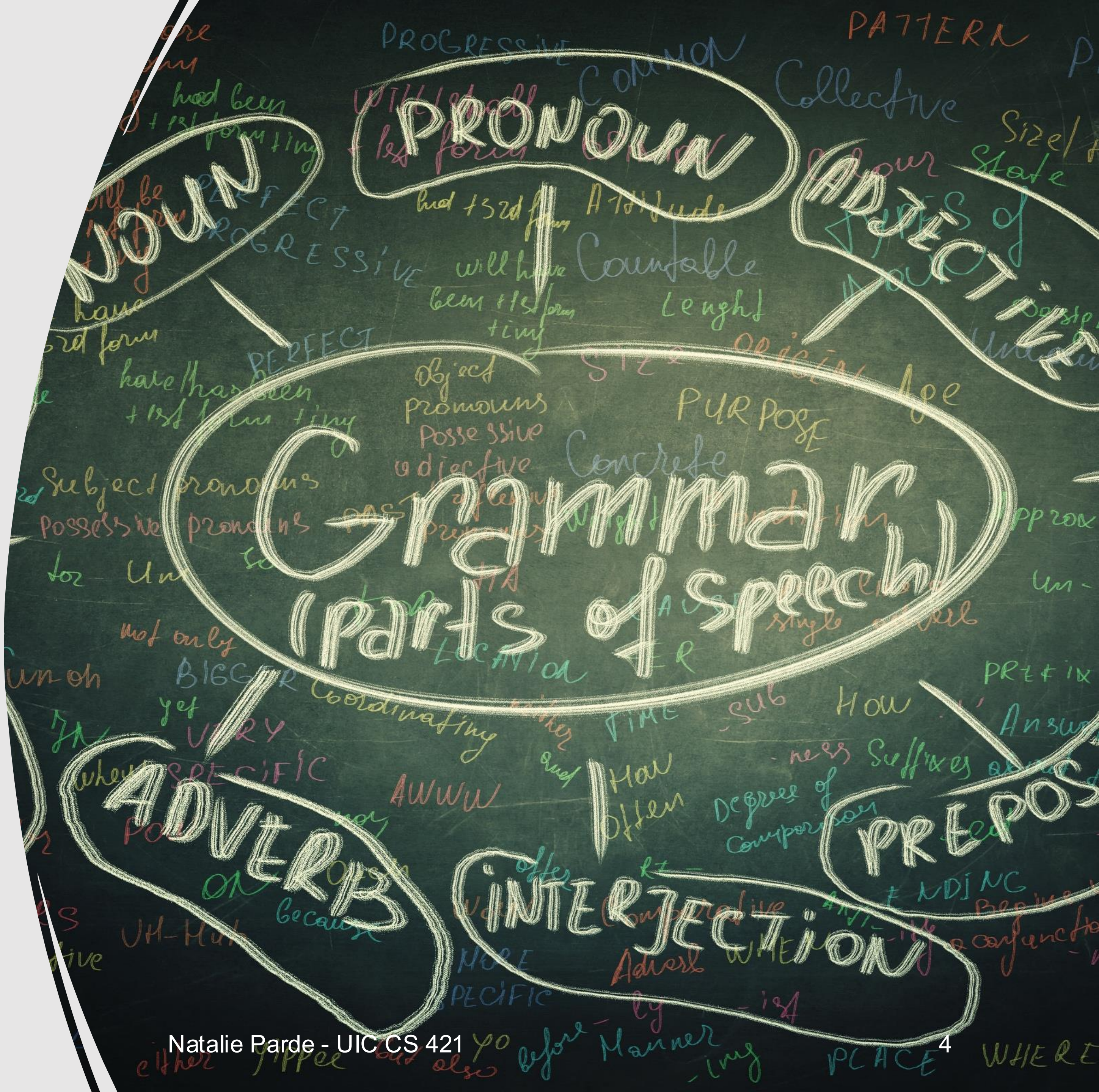
- Parts of Speech
- POS Tagging
- Context-Free Grammars
- Hierarchical Parsing

Thursday

- Dynamic Programming Parsing Algorithms
- Probabilistic CKY
- Lexicalized Grammars

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

- The process of automatically assigning grammatical word classes to individual tokens in text.
- Sometimes also referred to as **lexical categories**, **word classes**, or **morphological classes**
- Early step for many pipelined NLP tasks
- Avenue for interpretable linguistic analysis



- 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
- Our goal in those cases is to determine the *best* POS tag for a particular instance of a word.

POS Tagging

POS Tag Categories

Each POS type falls into one of two larger classes:

- Open
- Closed

Open class:

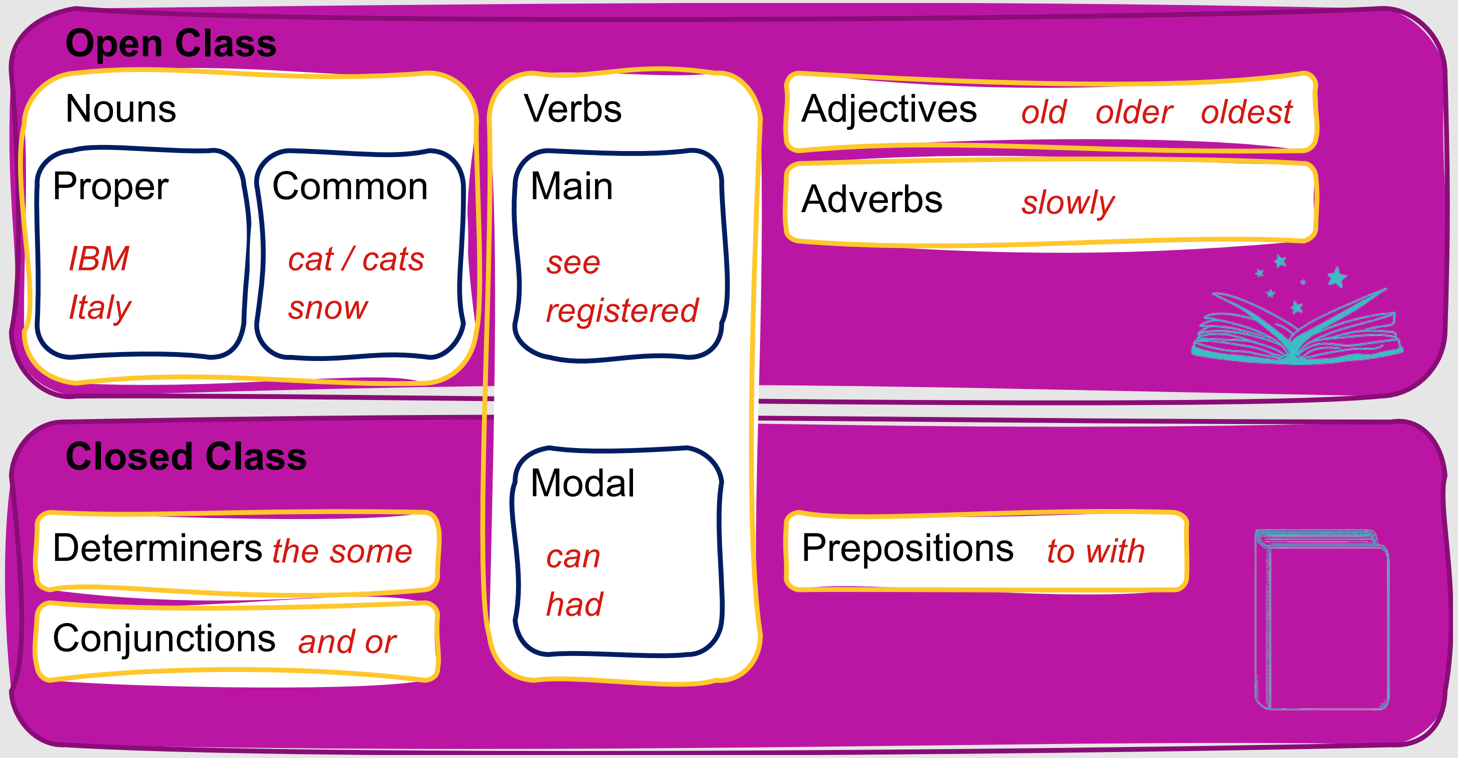
- New members can be created at any time
- In English:
  - Nouns, verbs, adjectives, and adverbs
- Many (but not all!) languages have these four classes

Closed class:

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

Finer-Grained POS Classes

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



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POS Tagsets

When determining 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

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DT	Determiner	**NNPS**	Proper noun, plural	**VB**	Verb, base form
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What do some of these distinctions mean?

cities

Chicago

Chicagos

city

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eat

ate

eating

eaten

eat

eats

should

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weird

weirder

weirdest

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calmly

calmer

calmest

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Closed Class

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Open Class

Other Popular POS Tagsets

Brown Corpus

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

C5 Tagset

- Text from the British National Corpus
- 61 POS tags

C7 Tagset

- Text from the British National Corpus
- 146 (!!) POS tags

So …how can we assign POS tags?

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Time	flies	like	an	arrow;	fruit	flies	like	a	banana

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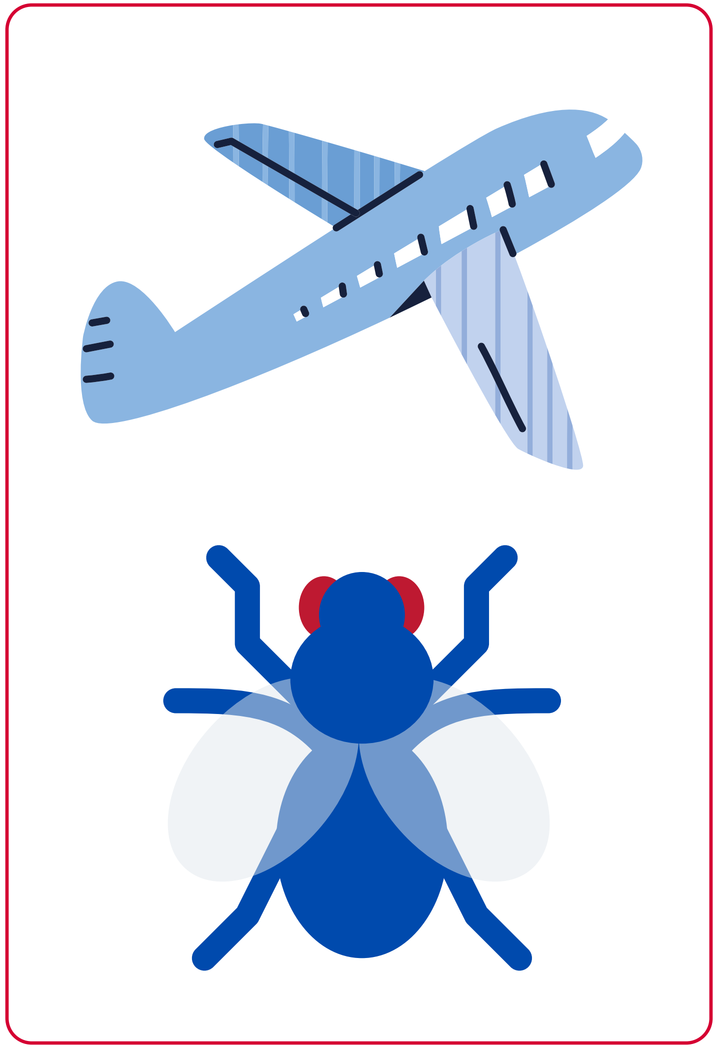
Ambiguity is a big issue for POS taggers!

- Many words have multiple senses
  - **time** = noun, verb
  - **flies** = noun, verb
  - **like** = verb, preposition
- Brown Corpus: Approximately 11% of word types have multiple valid part of speech labels, and many words with multiple valid POS labels are very common words
- Overall, ~40% of word *tokens* are instances of ambiguous word *types*



How do POS taggers work?

- Numerous ways to predict POS tags:
  - Rule-based (historical)
  - Statistical
    - HMMs (more recent)
    - Neural sequence modeling (most recent)

Rule-Based POS Tagging

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

Example Rule-Based Approach

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

Example Rule-Based Approach

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

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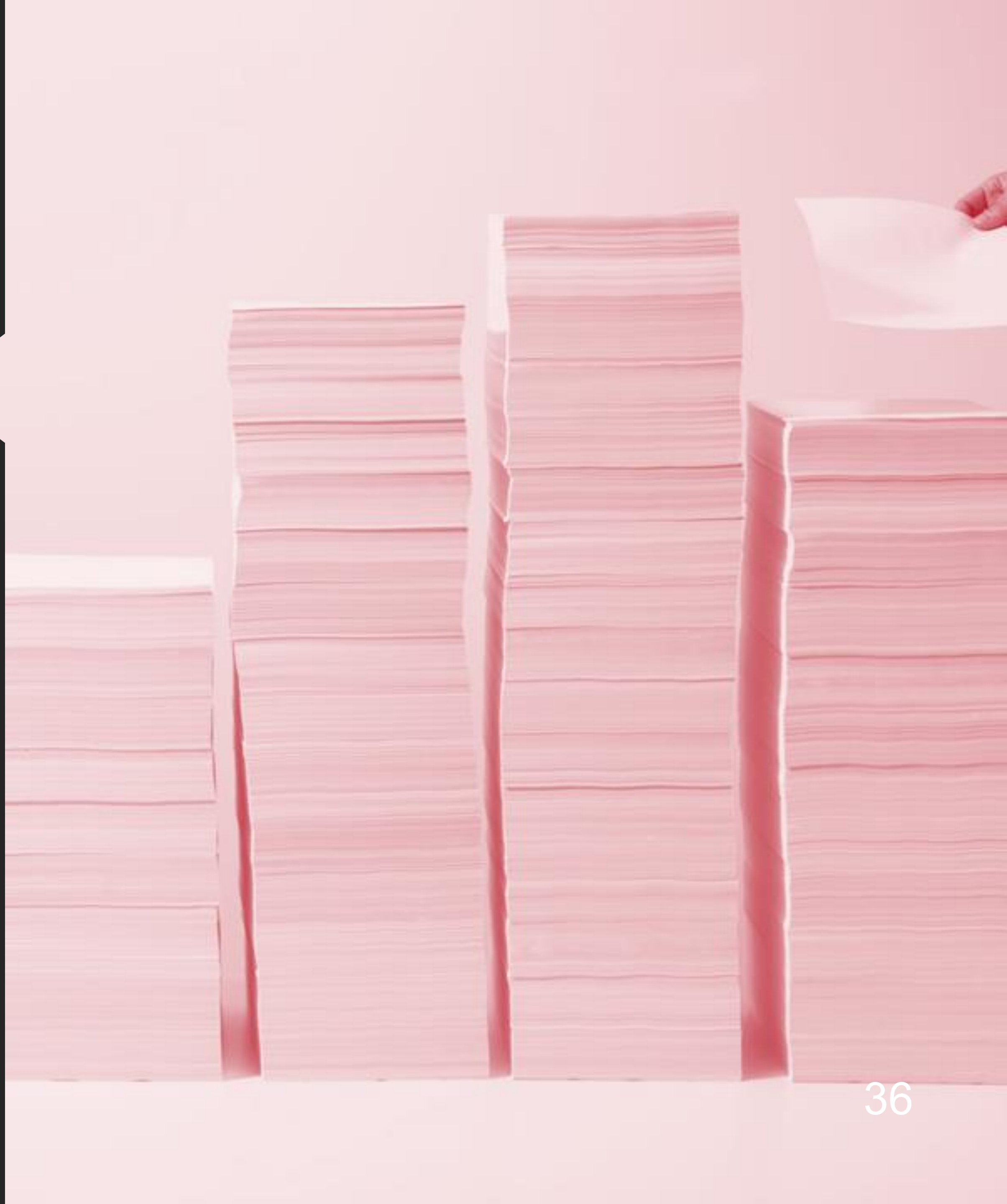
			~~RB~~		
			~~NN~~		

Statistical POS Tagging

- **Statistical POS Tagging:** POS taggers that make decisions based on learned knowledge of POS tag distribution in a training corpus
  - *the* is usually tagged as DT
  - Words with uppercase letters are more likely to be tagged NNP or NNPS
  - Words starting with the prefix *un-* may be tagged JJ
  - Words ending with the suffix *–ly* may be tagged RB



Example 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!

Example 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
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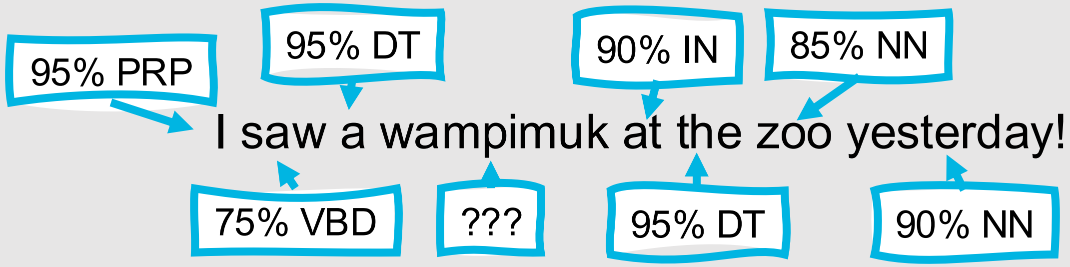

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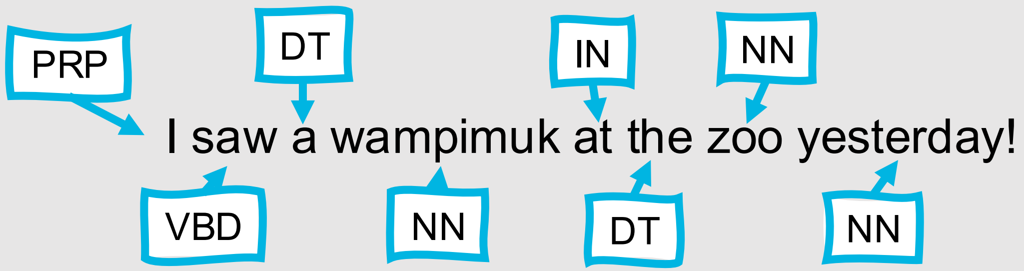


Experiments show that this approach achieves ~90% accuracy!

Bigram HMM POS Tagger

- We can improve upon the previous approach using HMMs
- 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

Superman	is	expected	to	fly	tomorrow
NNP	VBZ	VBN	TO	VB	NR
NNP	VBZ	VBN	TO	NN	NR

Proper noun, singular

Verb, 3rd person singular present

Verb, past participle

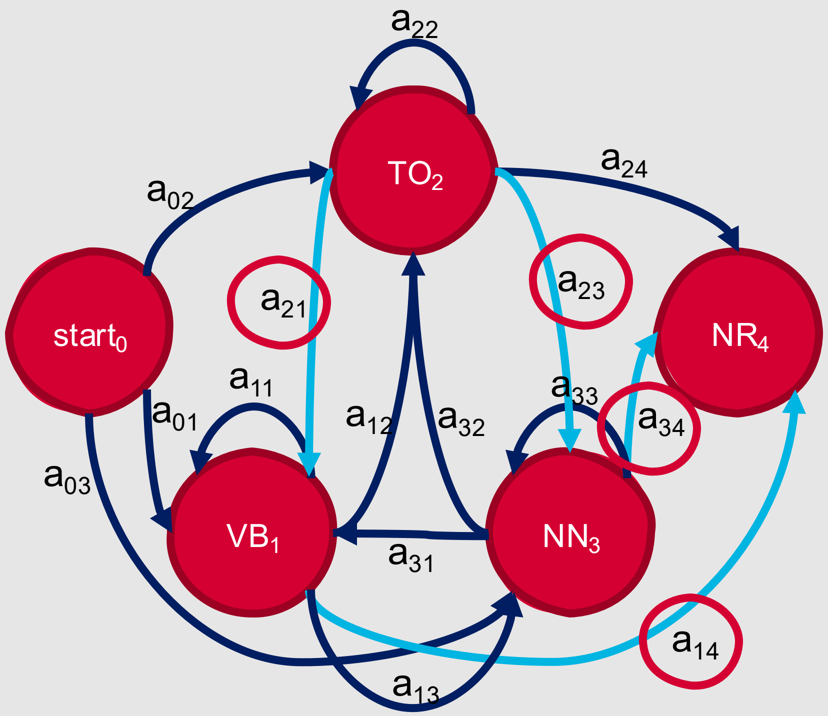
Infinitive to

Adverbial noun

- Given two possible sequences of tags from the Brown Corpus tagset for the following sentence, what is the best way to tag the word “fly”?

The specific transition probabilities we are interested in are:

Superman	is	expected	to	fly	tomorrow
NNP	VBZ	VBN	TO	VB	NR
NNP	VBZ	VBN	TO	NN	NR



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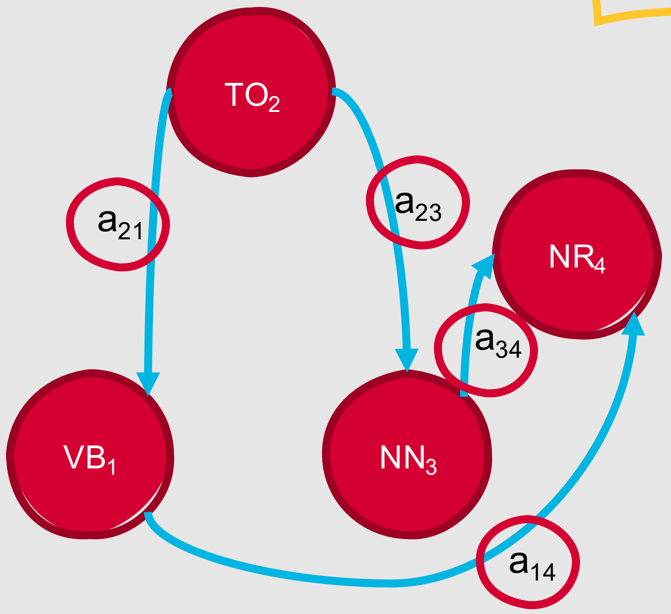

- We can estimate the transition probabilities for a_{21}, a_{23}, a_{34}, and a_{14} using frequency counts from the Brown Corpus
- $P(t_i|t_{i-1}) = \frac{c(t_{i-1}t_i)}{c(t_{i-1})}$

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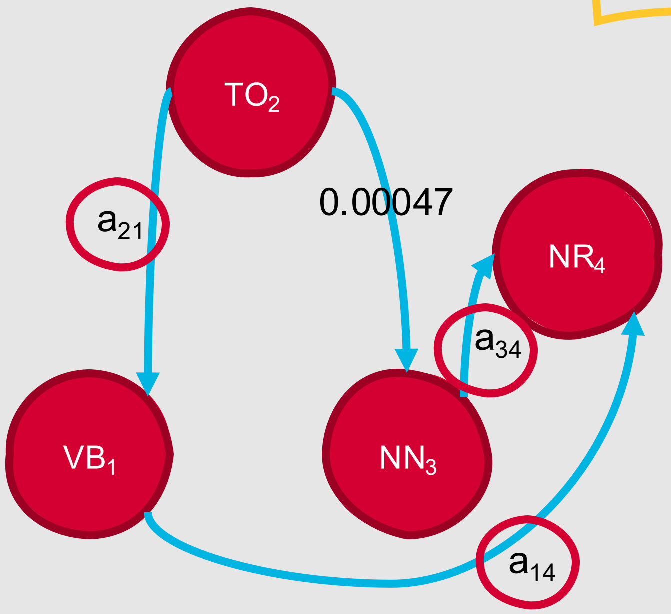

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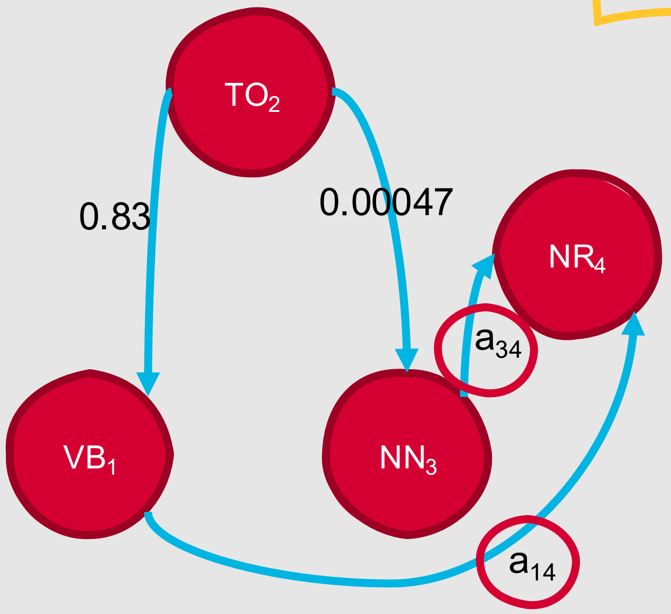

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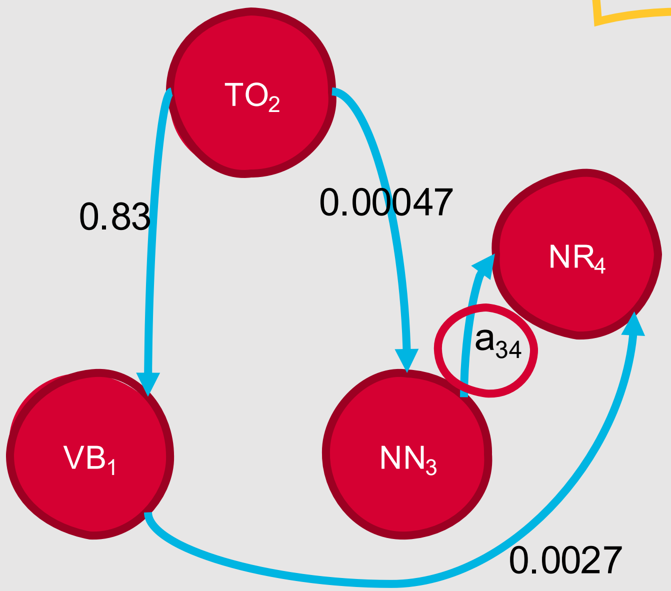

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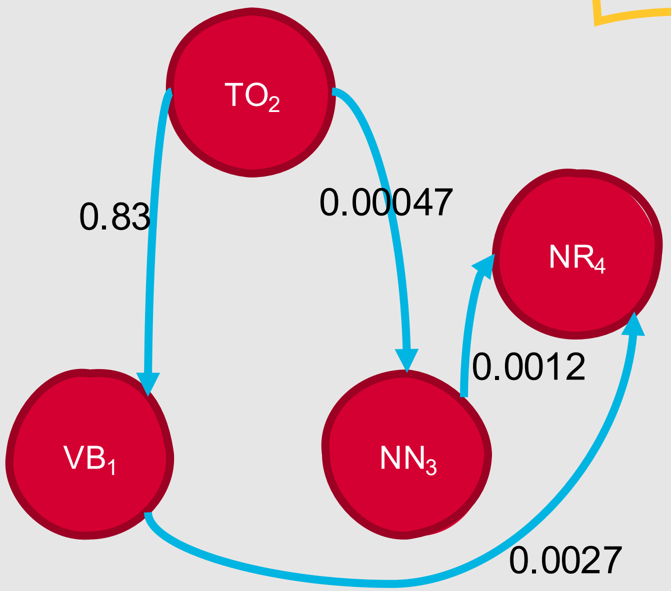
- P(NR|VB) = C(VB NR) / C(VB) = 0.0027

Example: Bigram HMM Tagger

Superman	is	expected	to	fly	tomorrow
NNP	VBZ	VBN	TO	VB	NR
NNP	VBZ	VBN	TO	NN	NR



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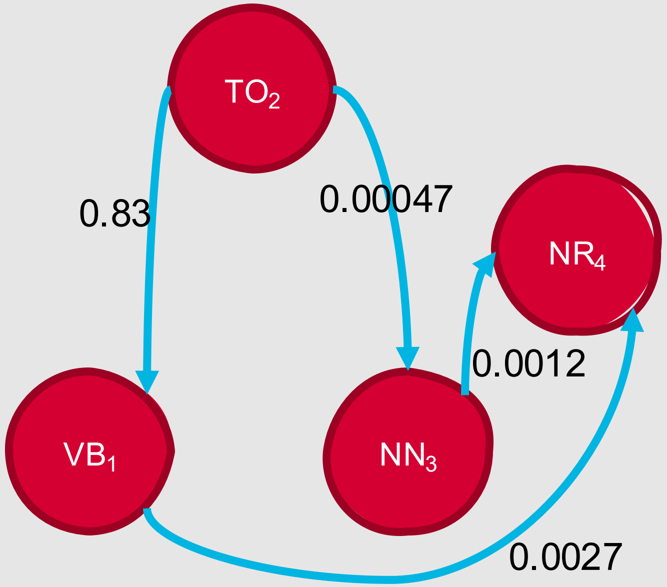
- $P(t_i|t_{i-1}) = \frac{c(t_{i-1}t_i)}{c(t_{i-1})}$
- So, P(NN|TO) = C(TO NN) / C(TO) = 0.00047
- Likewise, P(VB|TO) = C(TO VB) / C(TO) = 0.83
- P(NR|VB) = C(VB NR) / C(VB) = 0.0027
- Finally, P(NR|NN) = C(NN NR) / C(NN) = 0.0012

Example: Bigram HMM Tagger

Superman	is	expected	to	fly	tomorrow
NNP	VBZ	VBN	TO	VB	NR
NNP	VBZ	VBN	TO	NN	NR



	fly
VB	
NN	

- We have our transition probabilities …what now?
- Observation likelihoods!
- We can also estimate 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 "fly," we need to compute both P(fly|VB) and P(fly|NN)

Example: Bigram HMM Tagger

Example: Bigram HMM Tagger

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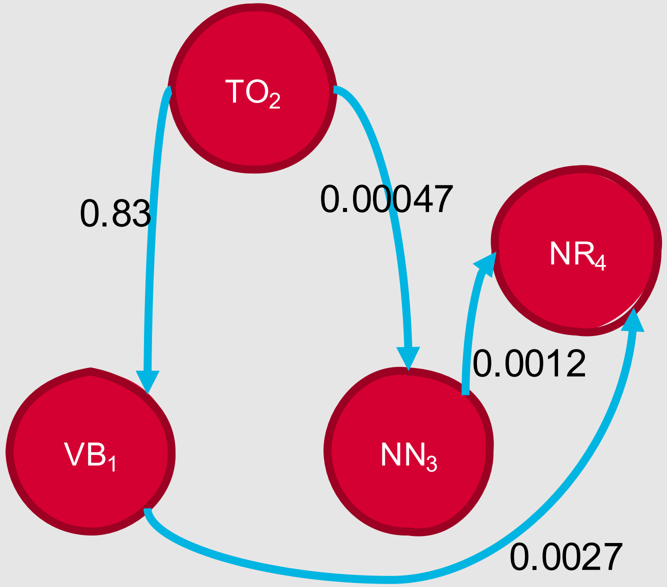

	fly
VB	0.00012
NN	0.00057

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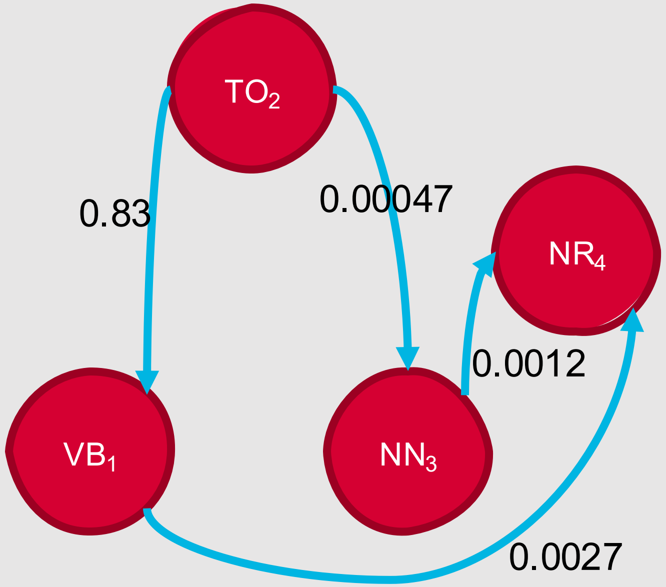
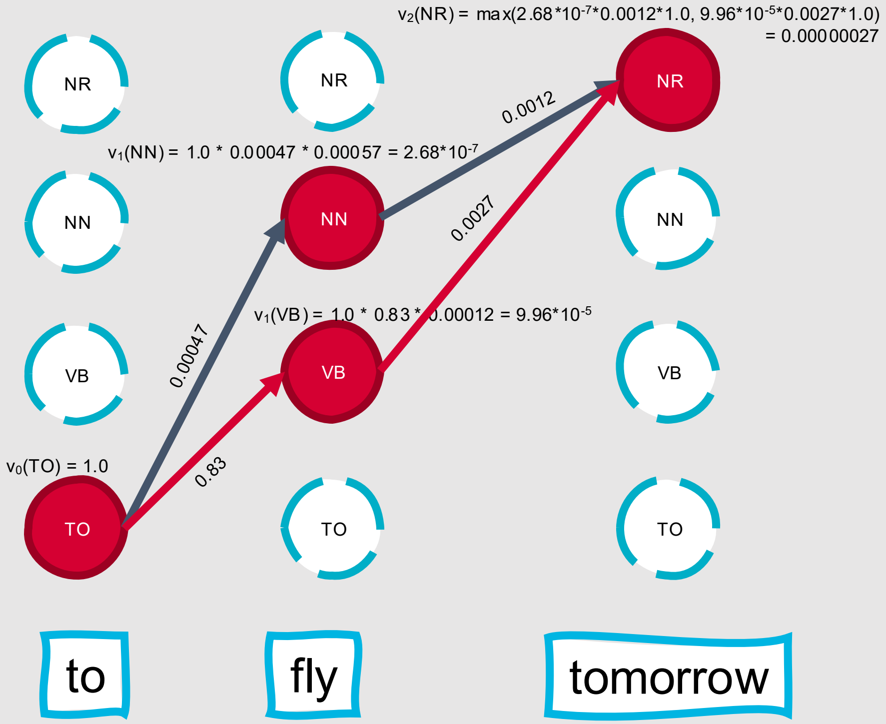
- We can also estimate these using frequency counts from the Brown Corpus
- $P(w_i|t_i) = \frac{c(w_i,t_i)}{c(t_i)}$
- Since we're trying to decide the best tag for "fly," we need to compute both P(fly|VB) and P(fly|NN)
- P(fly|VB) = C(fly, VB) / C(VB) = 0.00012
- P(fly|NN) = C(fly, NN) / C(NN) = 0.00057

Superman	is	expected	to	fly	tomorrow
NNP	VBZ	VBN	**TO**	**VB**	**NR**
NNP	VBZ	VBN	TO	NN	NR



	fly
VB	0.00012
NN	0.00057

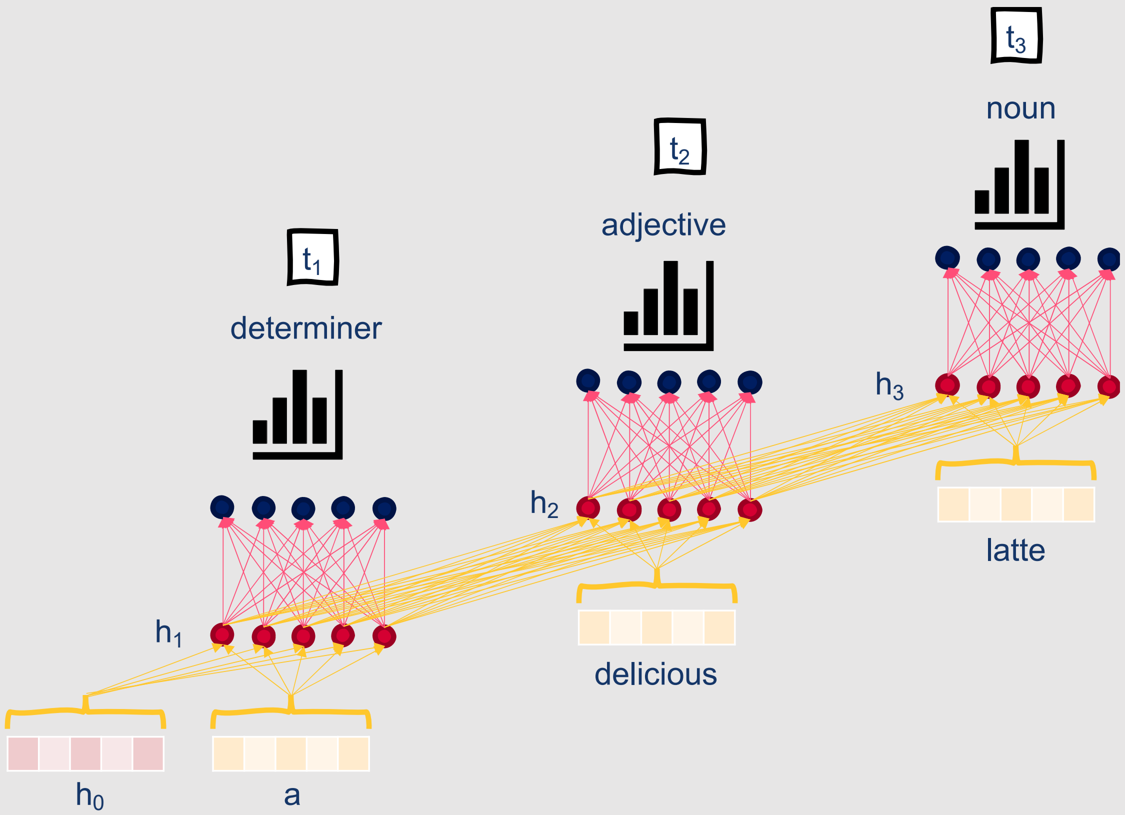
- We then decode the best sequence using Viterbi probabilities



Example: Bigram HMM Tagger

Neural Sequence Modeling

- Current best specialized POS tagging model
- Use a sequence processing architecture
    - Recurrent neural networks
    - Transformers
- Predict a label for each item in the input sequence
    - If using a subword vocabulary, you will need to merge the labels predicted for all subwords in a word



How can POS taggers handle unknown words?

- New words are continually added to language, so it is likely that a POS tagger will encounter words not found in its training corpus
- Easy baseline approach: **Assume that unknown words are nouns**
- More sophisticated 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
- Even more sophisticated approach: **Use morphological information** to choose the POS tag (for example, words ending with "ed" tend to be tagged VBN)

Comparing POS Taggers

- Standard NLP metrics are often calculated (precision, recall, and F1)
- 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

This Week's Topics

Tuesday

- Parts of Speech
- POS Tagging
- Context-Free Grammars
- Hierarchical Parsing

Thursday

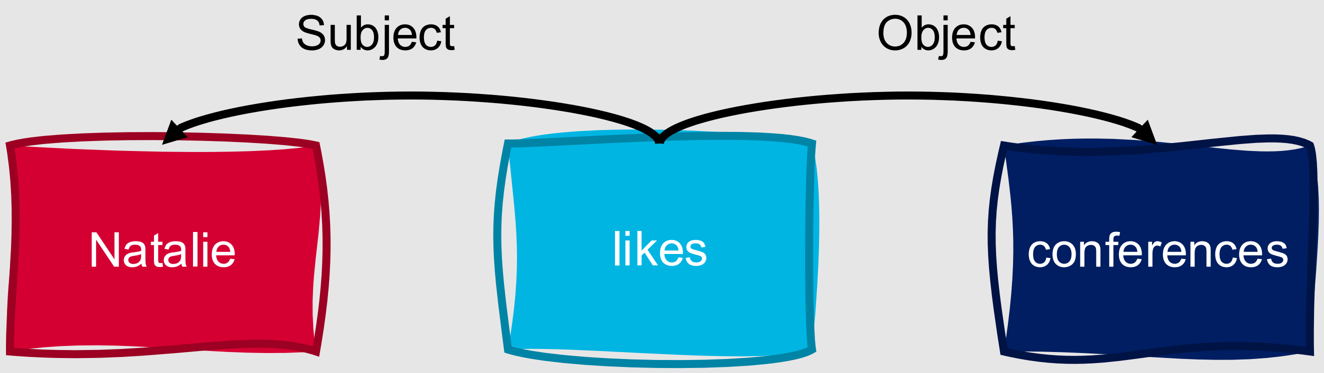
- Dynamic Programming Parsing Algorithms
- Probabilistic CKY
- Lexicalized Grammars

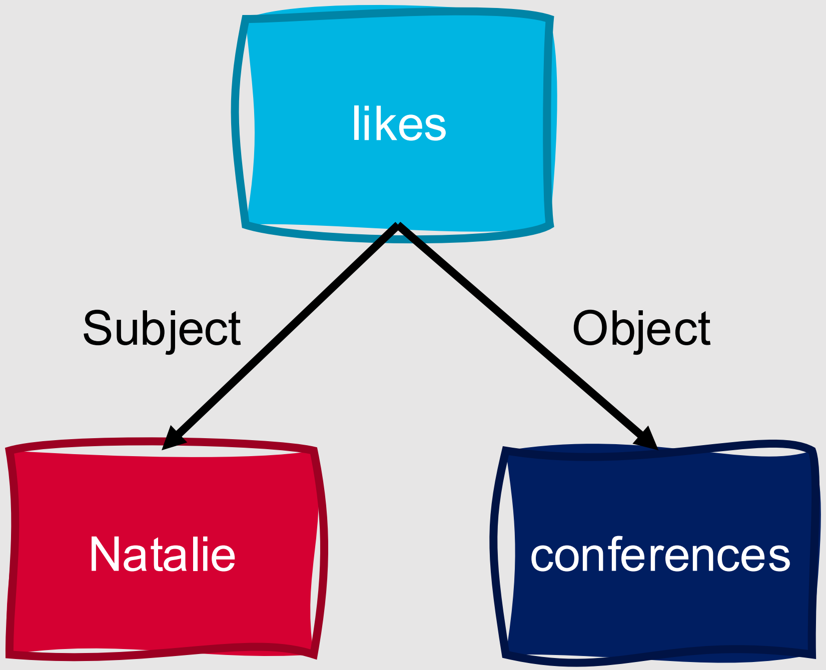
POS tags are one way to formalize language structure.

- Constituency grammars are another!
- Constituency grammars define language using a lexicon and a set of rules to break sentences into hierarchical parts
- They provide the necessary structure to answer important questions:
  - What are the **constituents** (groups of words that behave as a single unit or phrase) in this sentence?
  - What are the **grammatical relations** between these constituents?
  - Which words are **dependent** upon one another?
- **Constituency grammars model sentences as recursive generating processes**

Visually, we can represent grammars in many ways.

As dependency graphs:





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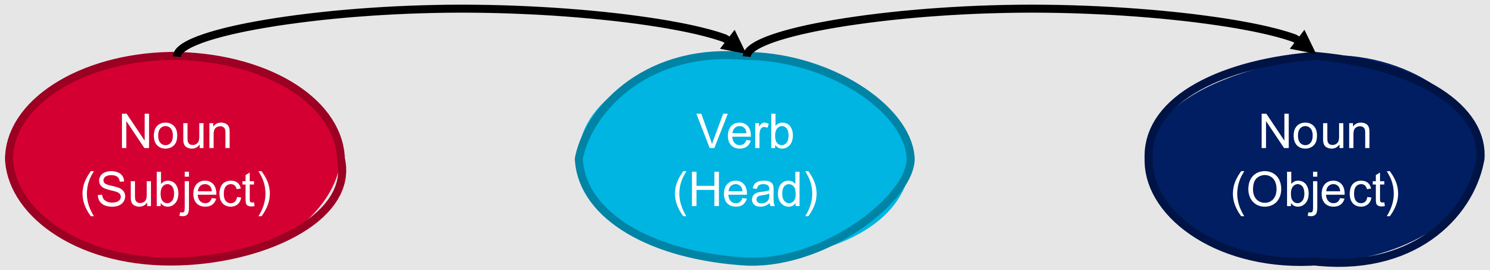
As finite state automata:



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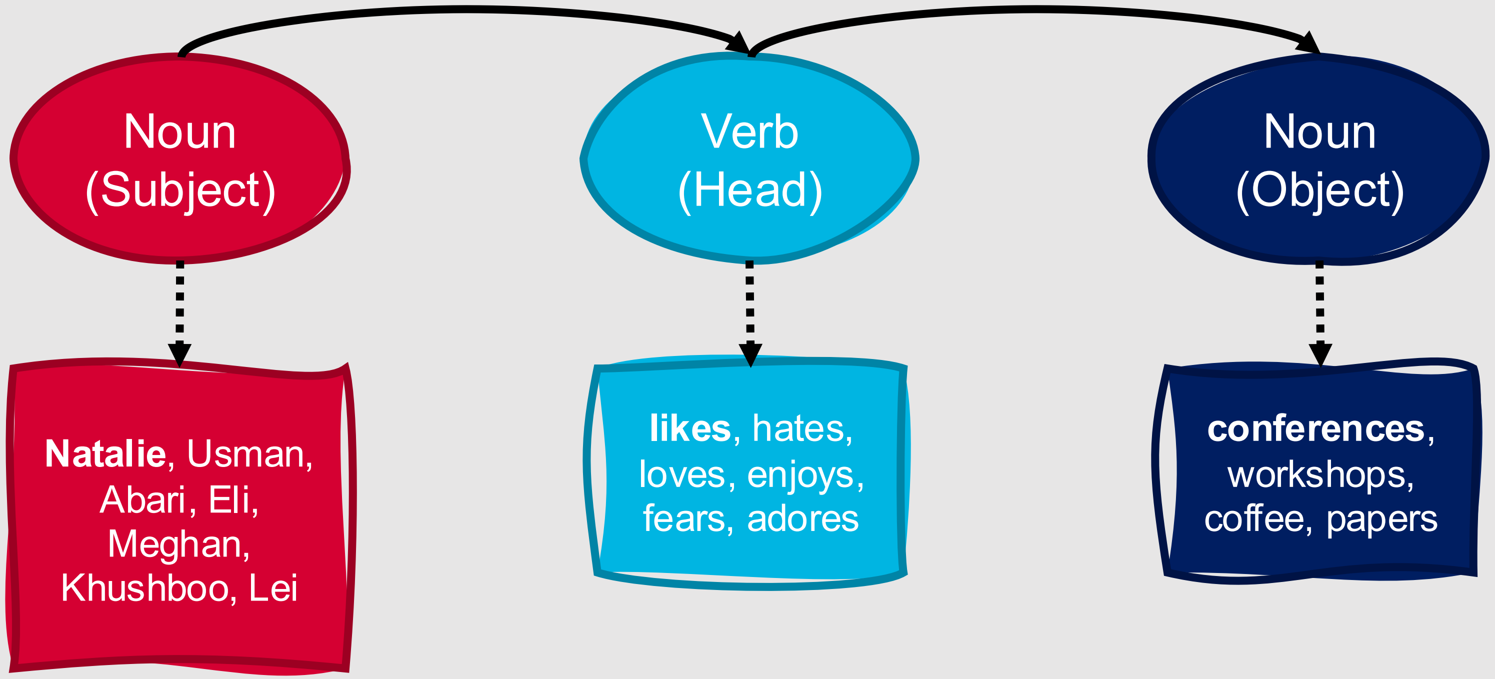
As hidden Markov models:

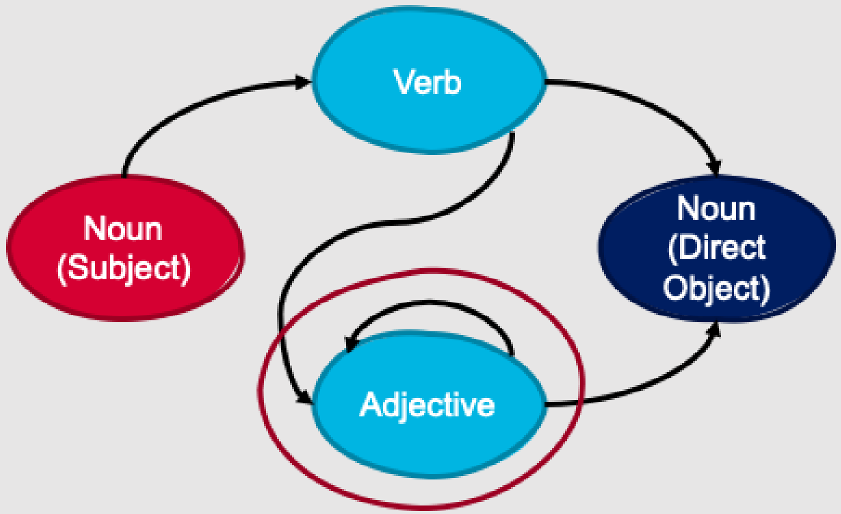


One of the reasons why the number of possible English sentences is infinite?

- 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.

Modeling Complex Recursion

- FSAs can model recursion, but they can't model hierarchical structure or handle issues like **attachment ambiguity**

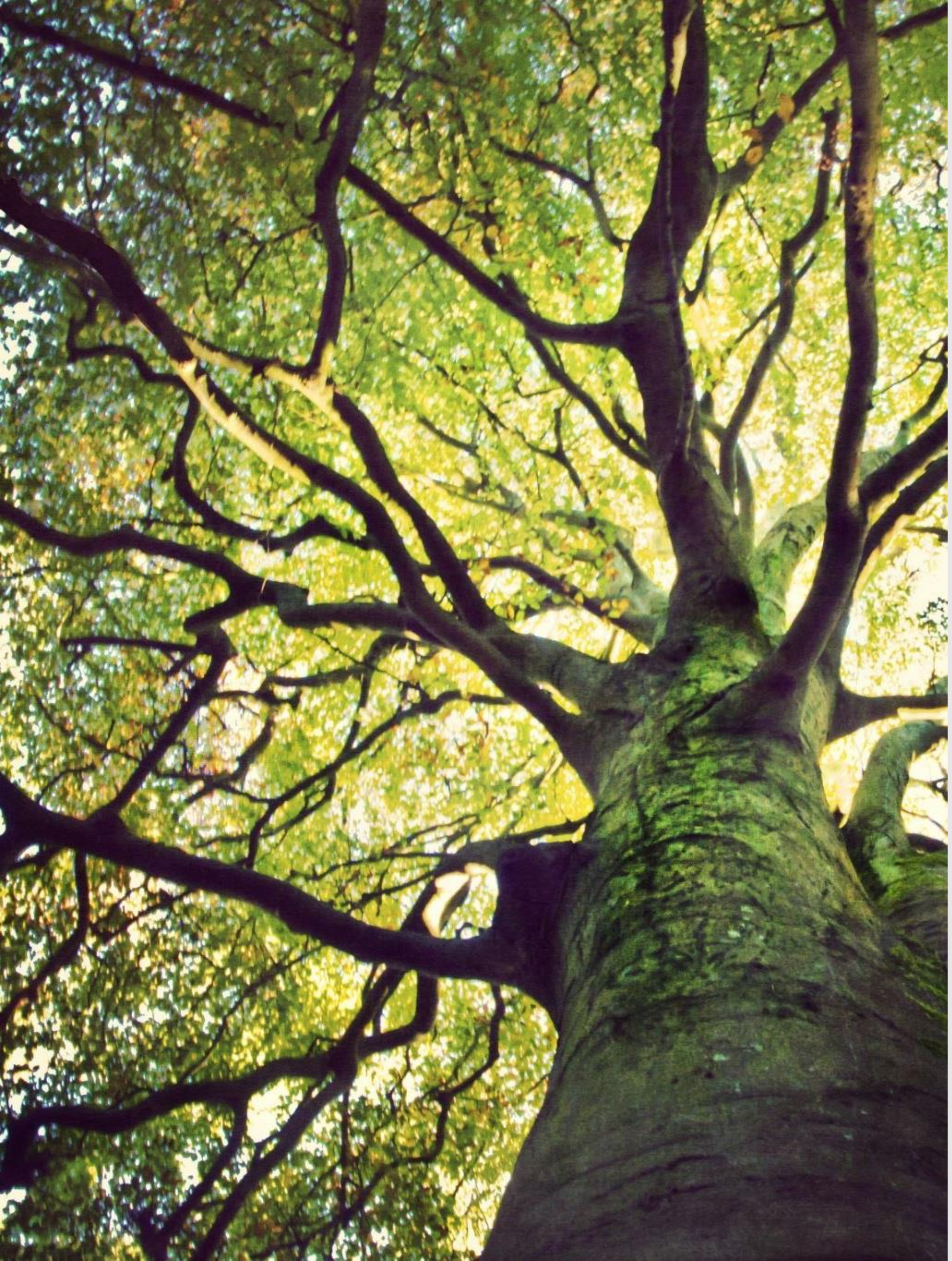


Natalie likes conferences in either Europe or Asia.

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

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

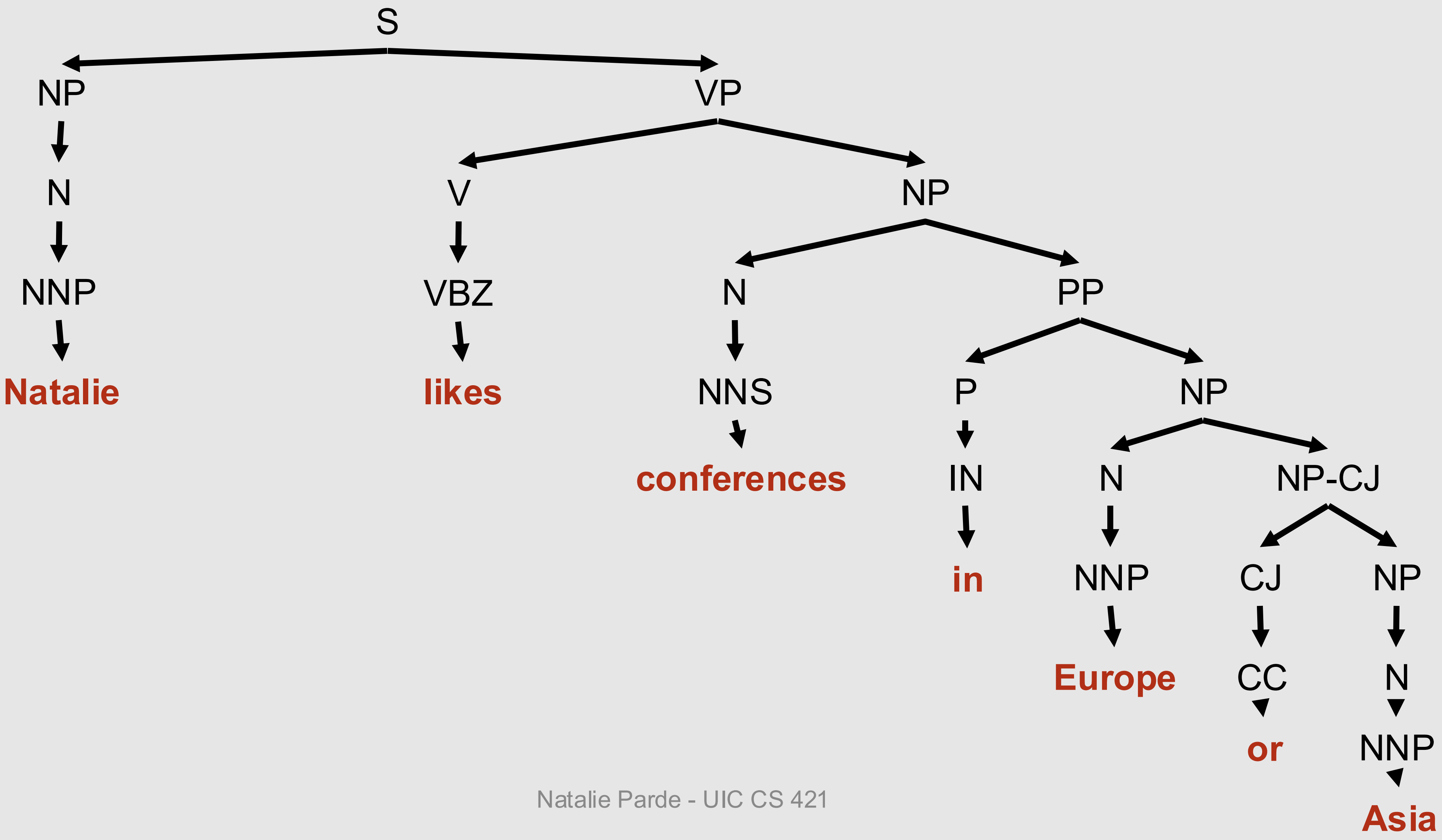
Natalie likes two things: Asia, or conferences in Europe.



Hierarchical trees to the rescue!

- Words in a sentence can be grouped into phrases (**constituents**) using a hierarchical structure
- 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?



We use context-free grammars to structure these hierarchical trees.

- **Context-Free Grammar (CFG):** A system to define constituent structure in regular languages, defined by productions that indicate which strings can be generated.
  - **Production:** Rules expressing the allowable combinations of symbols (e.g., POS types) that can form a constituent
  - Productions can be **hierarchically embedded**
    - Noun Phrase (NP) → Determiner Nominal
    - Nominal → Noun | Nominal Noun
- 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.
- Also called **Phrase-Structure Grammars**

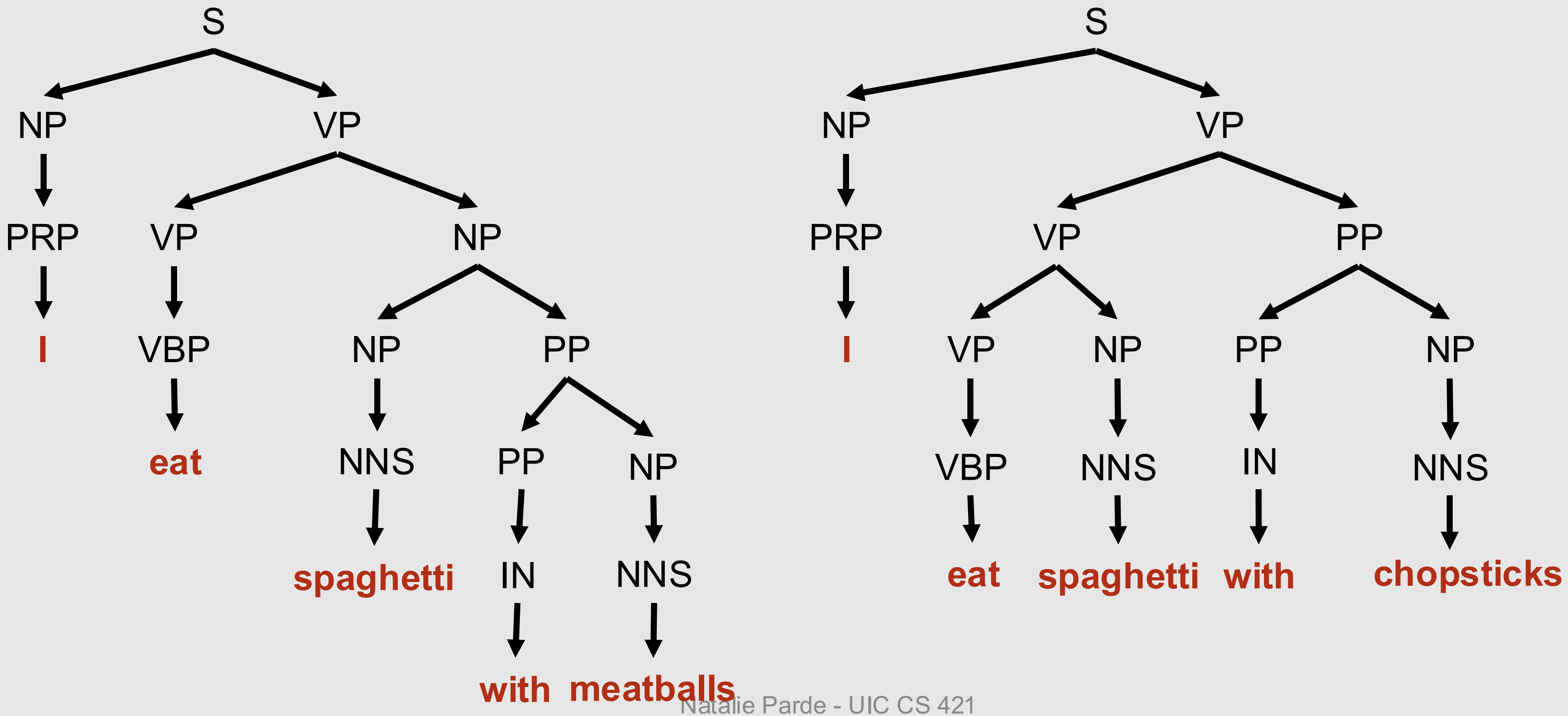
Formal Definition

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

Production rules determine how constituents can be combined.

- **Constituent:** A group of words that behaves as a single unit.
  - **Constituents can be substituted with one another** in the context of the greater sentence
  - **A constituent can move around** within the context of the sentence
  - **A constituent can be used to answer a question** about the sentence
- Constituents contain **heads** and **dependents**
  - **Head:** The most informative word in the constituent
  - **Dependent:** The other word that contributes to the overall meaning
- Dependents can be arguments or adjuncts
  - Arguments are **obligatory**
  - Adjuncts are **optional**

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



Typical CFG Constituents (English)

Noun phrases (NPs)

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

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)

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 → V
  - VP → V NP
  - VP → V NP PP
  - VP → VP PP
  - V → {drinks}

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 → $V_{intransitive}$
  - VP → $V_{transitive}$ NP
  - VP → $V_{ditransitive}$ NP NP
  - $V_{intransitive}$ → {drinks, talks}
  - $V_{transitive}$ → {drinks}
  - $V_{ditransitive}$ → {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 → NP VP
  - S → AdvP S
  - S → PP S
- They can include coordinating conjunctions:
  - **She drinks tea** and **he drinks coffee**.
  - **Natalie** and **her mom** drink tea.
  - She **drinks tea** and **eats cake**.
  - Production Rules:
    - S → S conj S
    - NP → NP conj NP
    - VP → VP conj VP
- They can use relative clauses to add extra information to noun phrases:
  - Subject: She had a poodle **that drank my tea**.
    - We cannot drop the relative pronoun and keep the same meaning
  - Object: I'd really been enjoying the tea **that her poodle drank**.
    - We can drop the relative pronoun and the sentence still works

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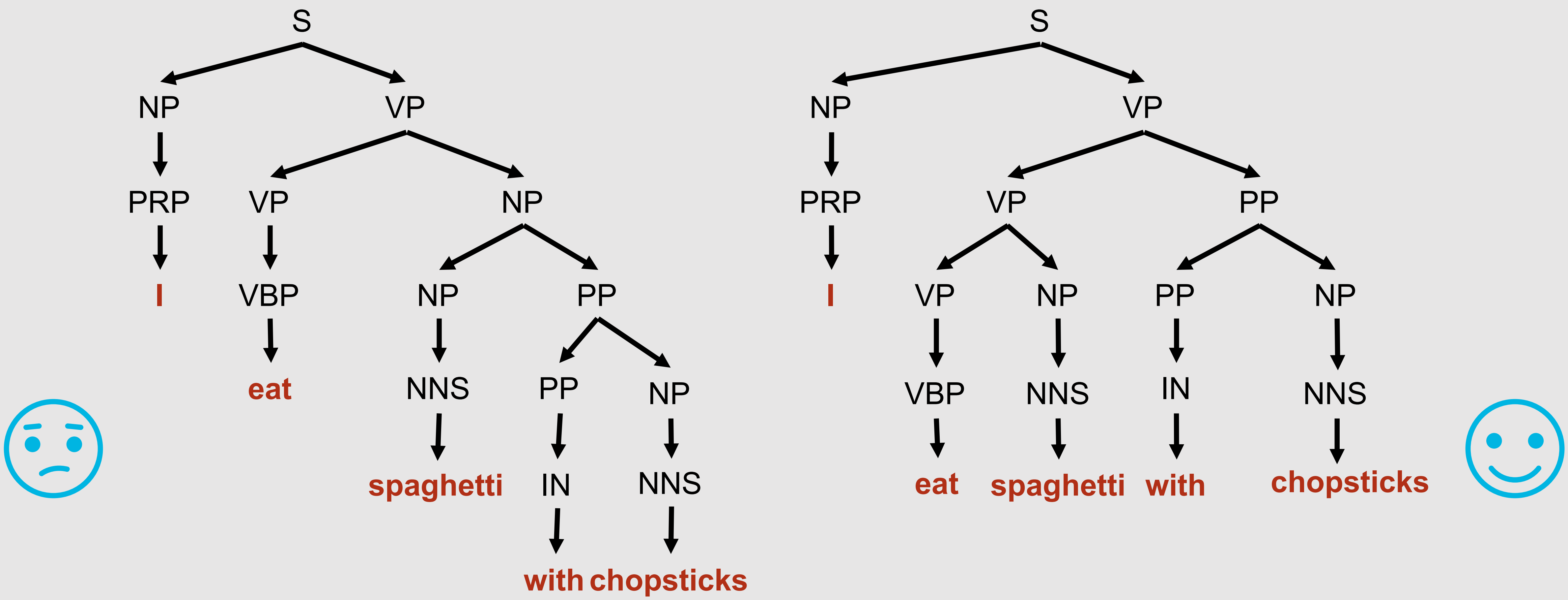

Remember, language is ambiguous!

Input sentences may have many possible parses

There are also many ways to generate parse trees.

Top-Down Parsing:	Bottom-Up Parsing:
Goal-driven Builds parse tree from the start symbol down to the terminal nodes	Data-driven Builds parse tree from the terminal nodes up to the start symbol

Top-Down Parsing

- Assume that the input can be derived by the designated start symbol ***S***
- Find the tops of all trees that can start with ***S***
  - Look for all production rules with ***S*** on the left-hand side
- Find the tops of all trees that can start with those constituents
- (Repeat recursively until terminal nodes are reached)
- Trees whose leaves fail to match all words in the input sentence can be rejected, leaving behind trees that represent successful parses

Top-Down Parsing: Example

Input Sentence:

Book that flight.

Grammar:

S → NP VP
S → Aux NP VP
S → VP
NP → Pronoun
NP → Proper-Noun
NP → Det Nominal
Nominal → Noun
Nominal → Nominal Noun
Nominal → Nominal PP
VP → Verb
VP → Verb NP
VP → Verb NP PP
VP → Verb PP
VP → VP PP
PP → Preposition NP

Lexicon:

Det → that | this | a
Noun → book | flight | meal | money
Verb → book | include | prefer
Pronoun → I | she | me
Proper-Noun → Houston | NWA
Aux → does
Preposition → from | to | on | near | through

Top-Down Parsing: Example

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S S S

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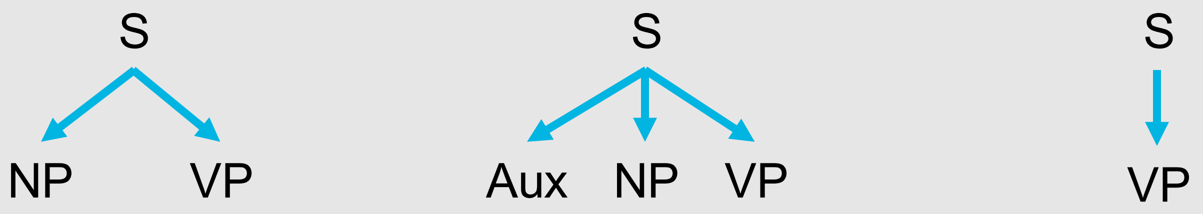

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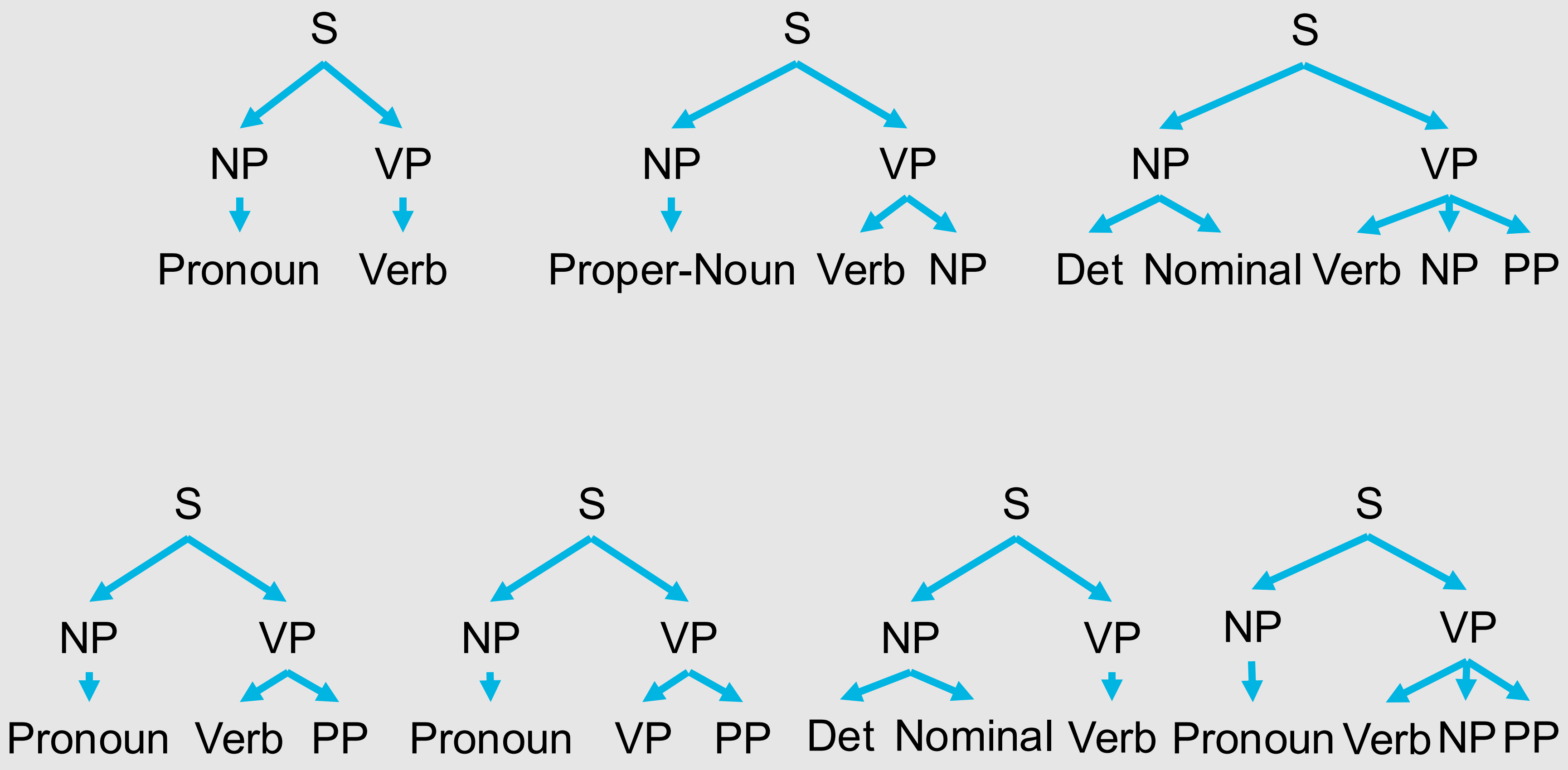

…and many more!

Top-Down Parsing: Example

Book that flight.

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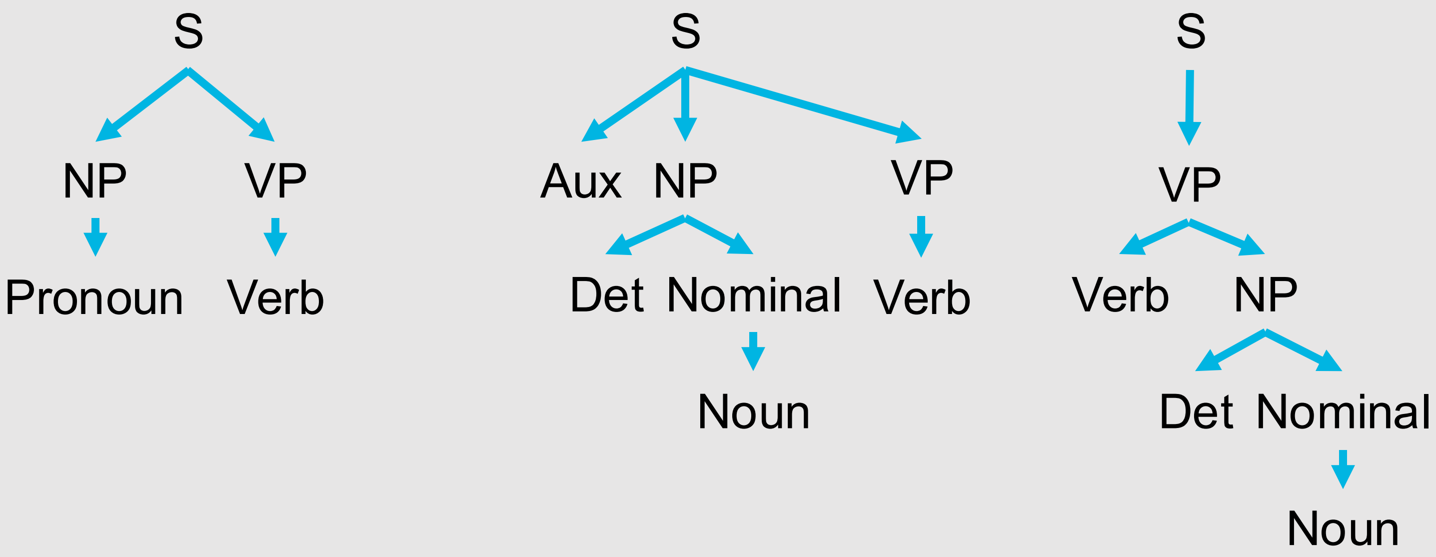

…and many, many more not shown!

Top-Down Parsing: Example

Book that flight.

S → NP VP
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S → VP
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NP → Det Nominal
Nominal → Noun
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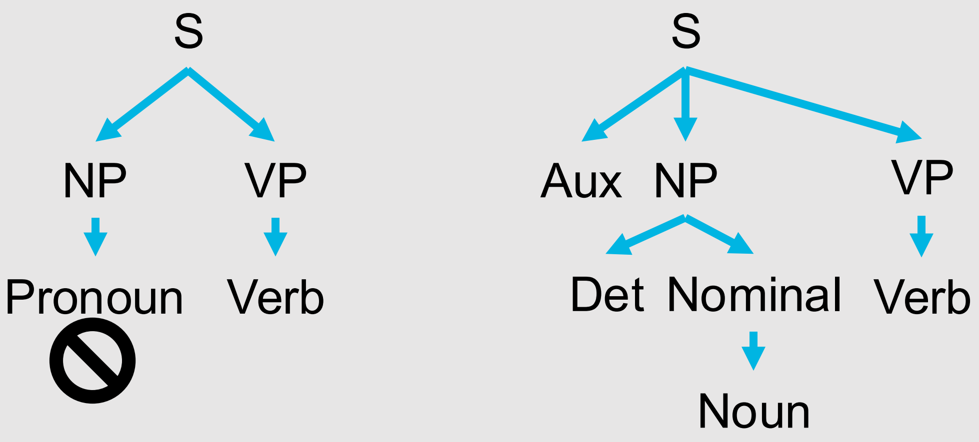
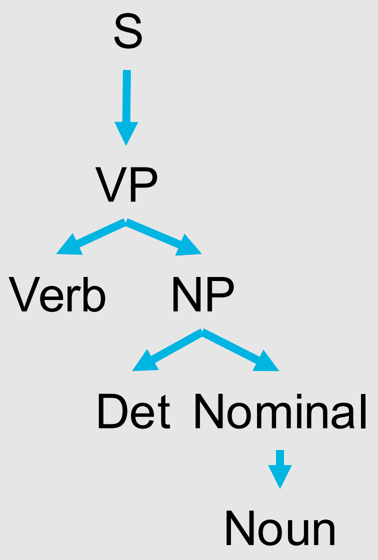
PP → Preposition NP





Det → that | this | a
Noun → book | flight | meal | money
Verb → **book** | include | prefer
Pronoun → I | she | me
Proper-Noun → Houston | NWA
Aux → does
Preposition → from | to | on | near | through

…and many, many more not shown!

Top-Down Parsing: Example

Book that flight.

S → NP VP
S → Aux NP VP
S → VP
NP → Pronoun
NP → Proper-Noun
NP → Det Nominal
Nominal → Noun
Nominal → Nominal Noun
Nominal → Nominal PP
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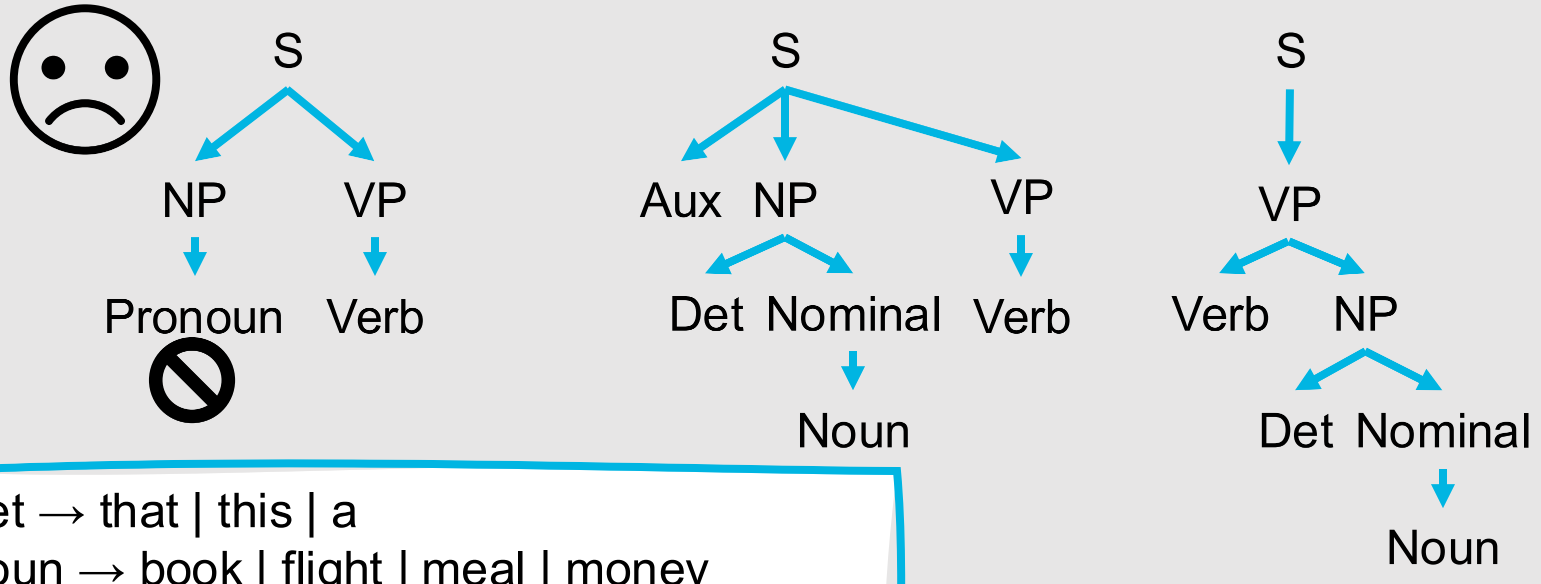

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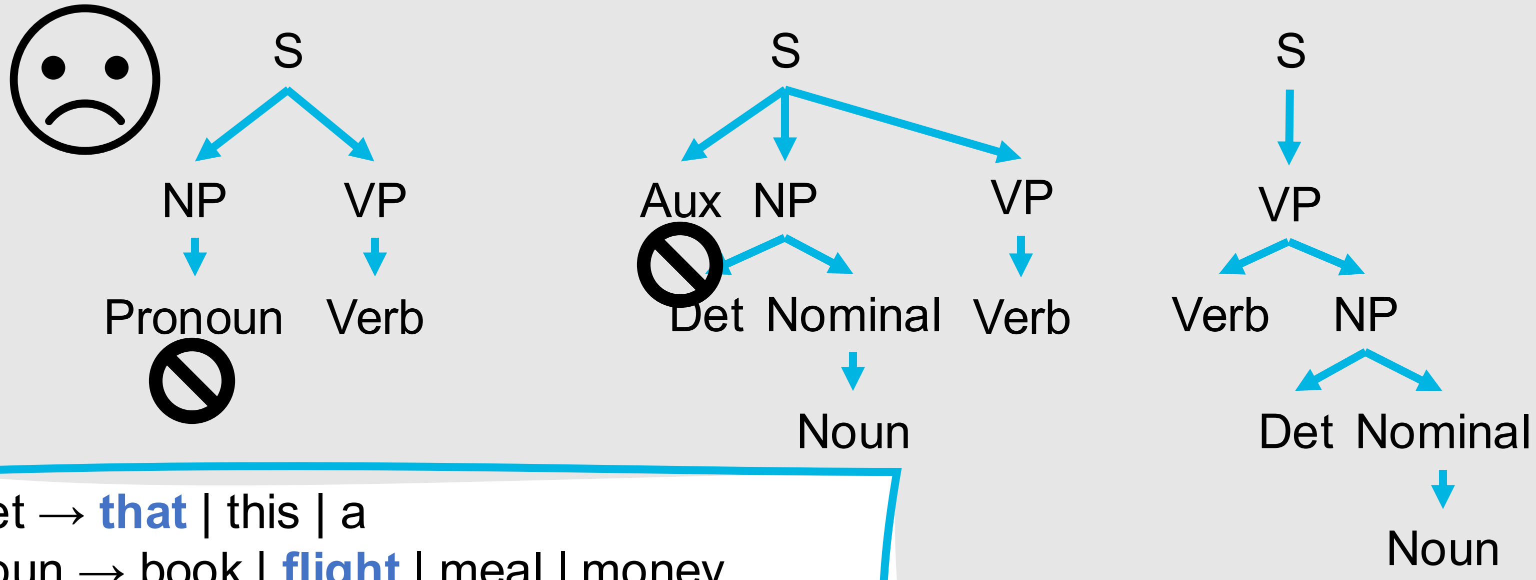

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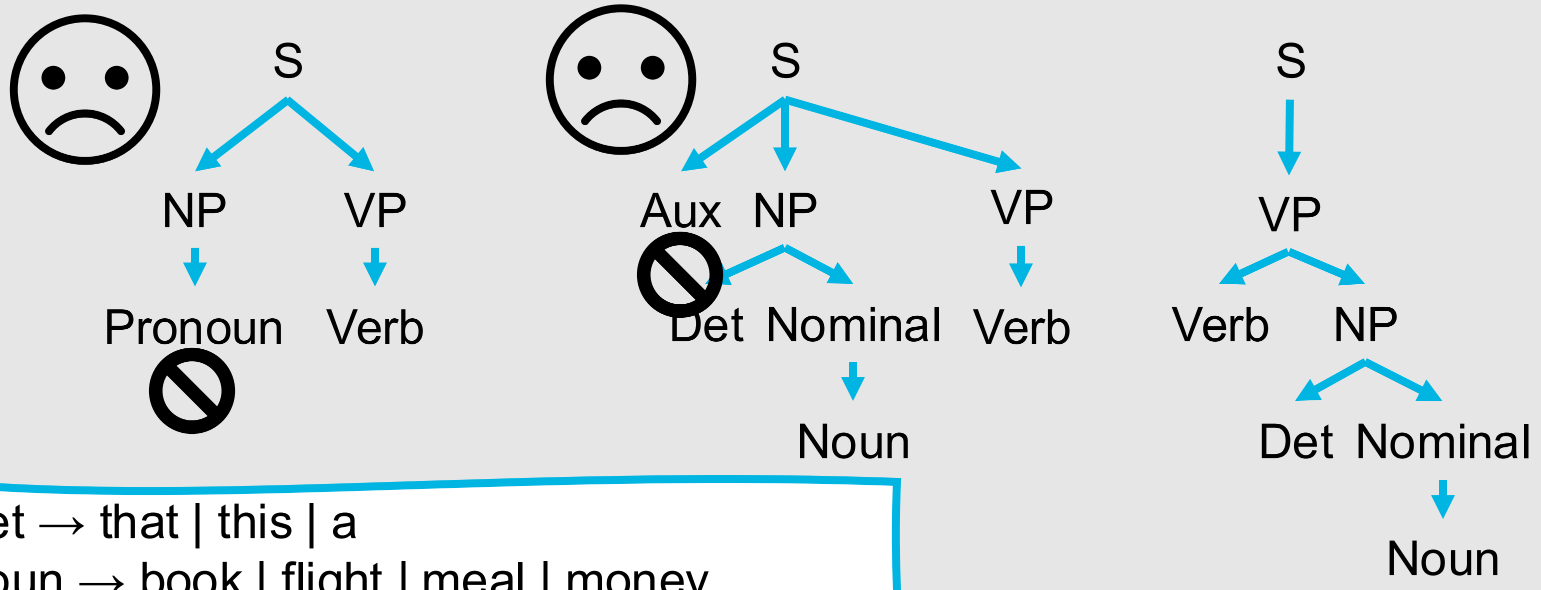

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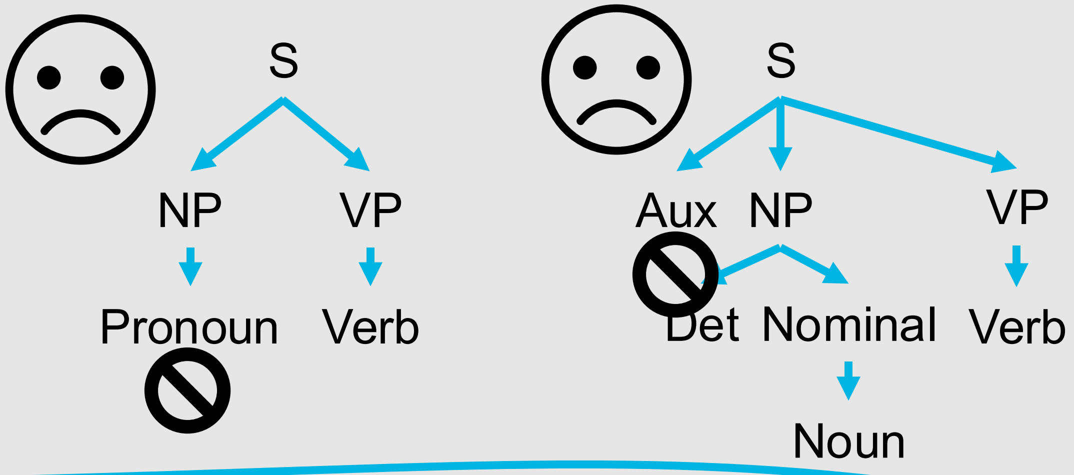

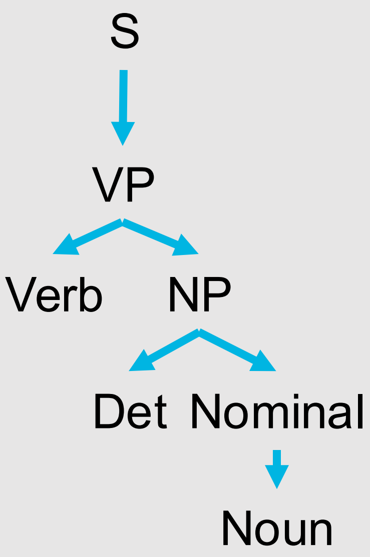

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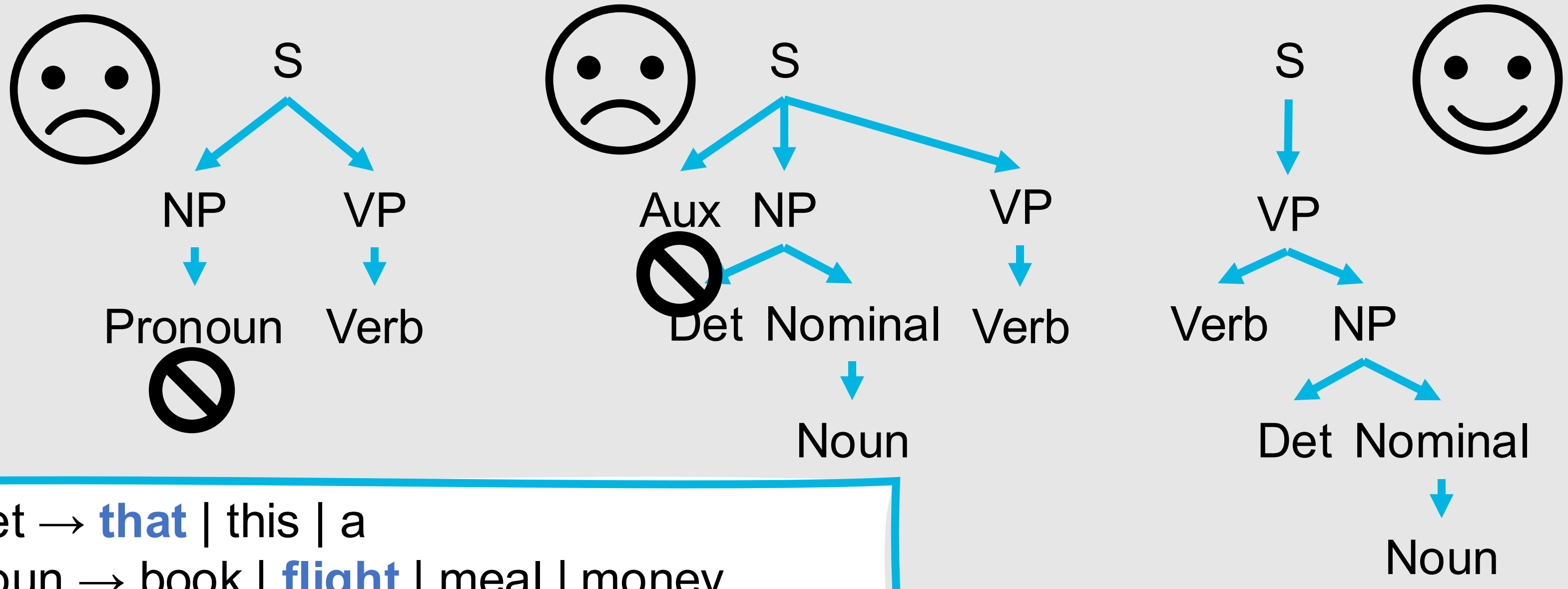

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Bottom-Up Parsing

- Used in the earliest known parsing algorithm
- Starts with the words in the input sentence, and tries to build trees from those words up by applying rules from the grammar one at a time
  - Looks for places in the in-progress parse where the righthand side of a production rule might fit
- Success = parser builds a tree rooted in the start symbol ***S*** that covers all of the input words

Bottom-Up Parsing: Example

Input Sentence:

Book that flight.

Grammar:

S → NP VP
S → Aux NP VP
S → VP
NP → Pronoun
NP → Proper-Noun
NP → Det Nominal
Nominal → Noun
Nominal → Nominal Noun
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VP → Verb NP
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Lexicon:

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Preposition → from | to | on | near | through

Noun	Det	Noun
↓	↓	↓
book	that	flight

Verb	Det	Noun
↓	↓	↓
book	that	flight

Bottom-Up Parsing: Example

Book that flight.

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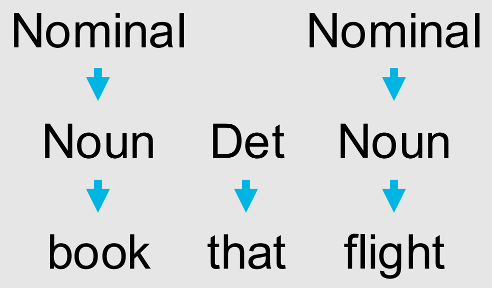

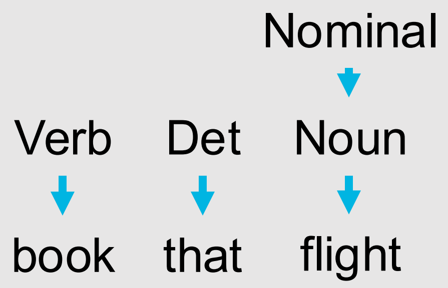

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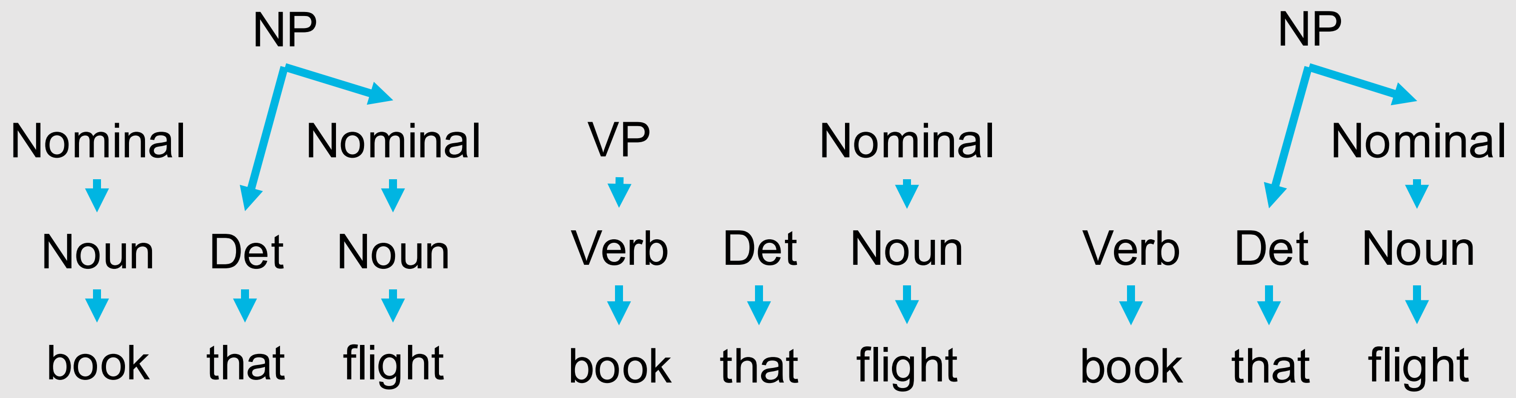

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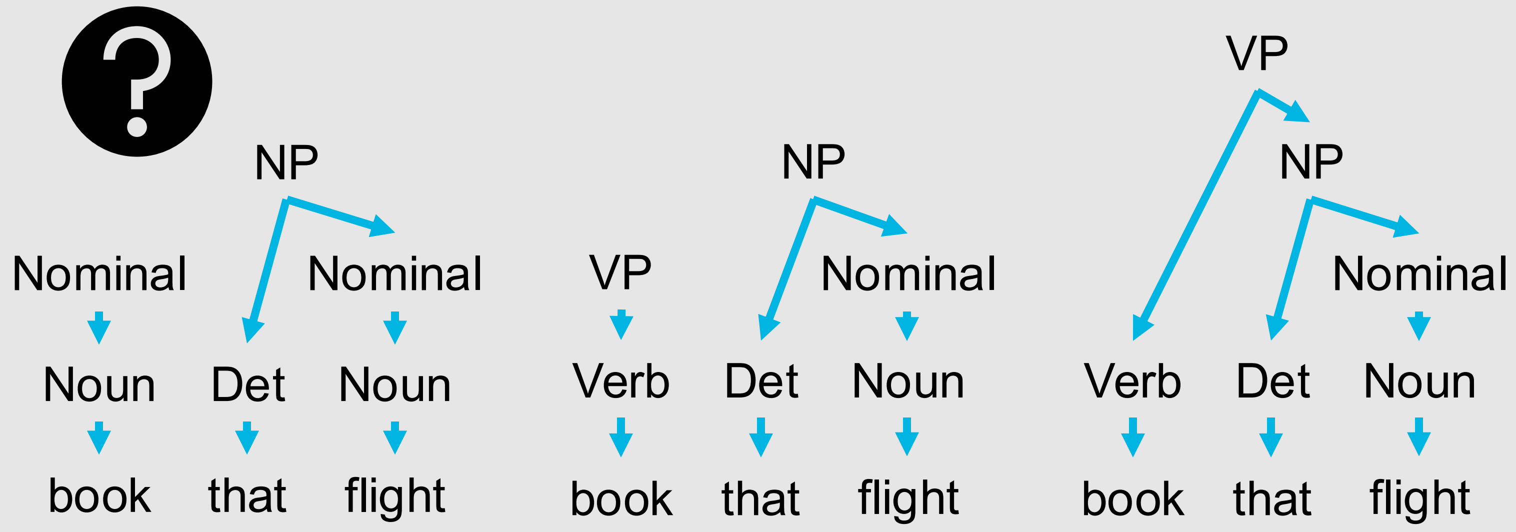

Bottom-Up Parsing: Example

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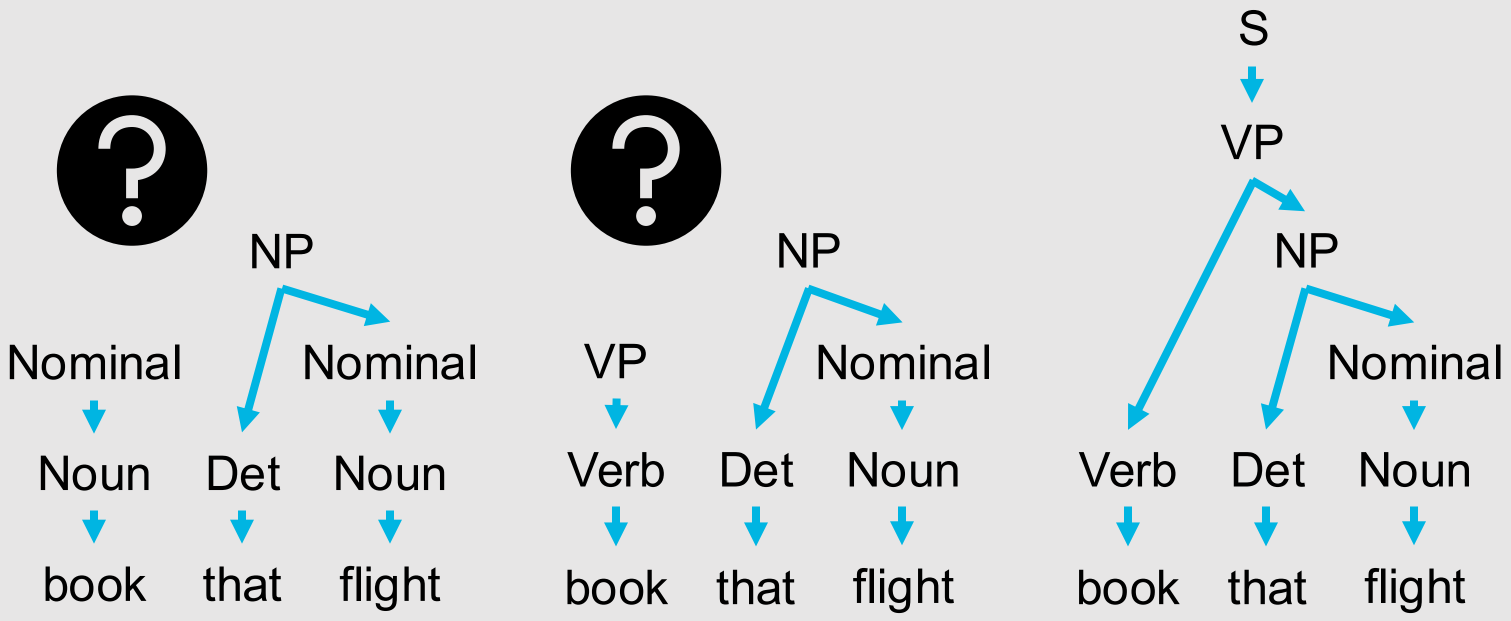

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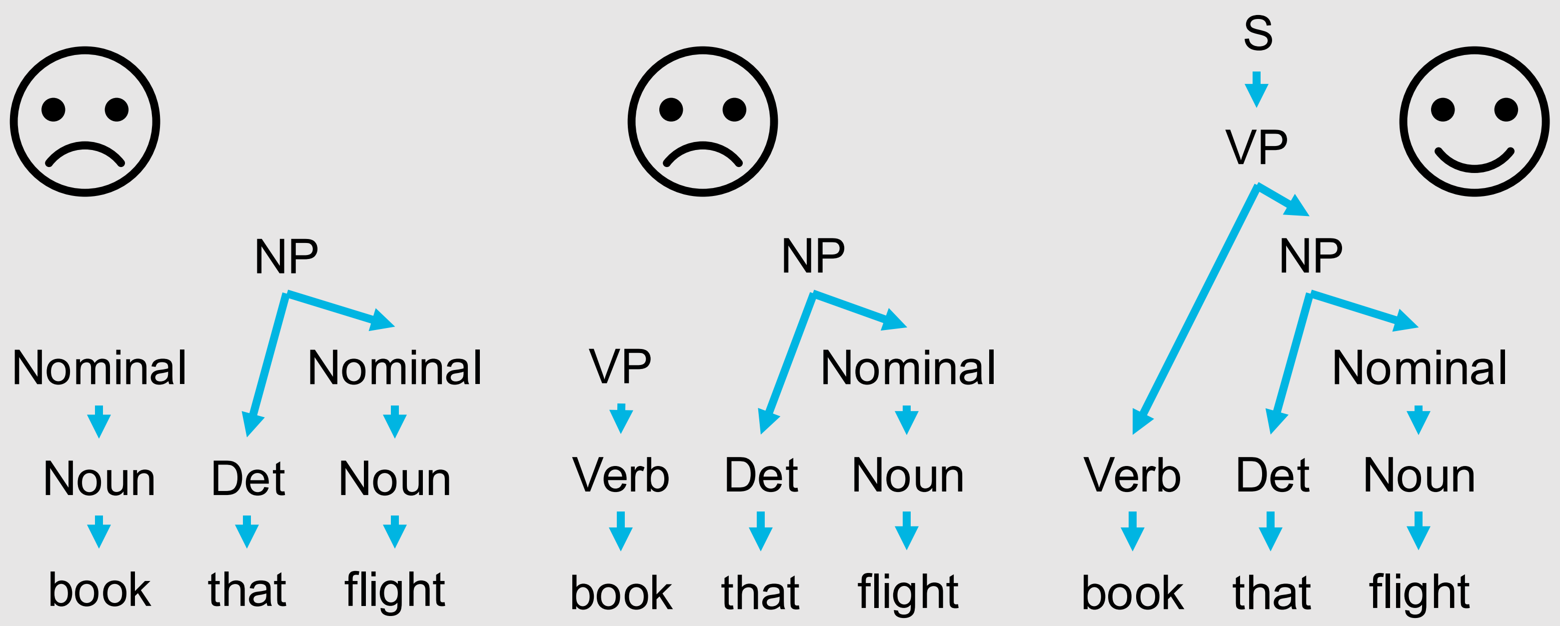


Top-Down vs. Bottom-Up Parsing

Top-Down Parsing

- Pros:
  - Never wastes time exploring invalid trees
- Cons:
  - Spends considerable effort on trees that are not consistent with the input

Bottom-Up Parsing

- Pros:
  - Never suggests trees that are inconsistent with the input
- Cons:
  - Generates many trees and subtrees that cannot result in a valid sentence (according to production rules specified by the grammar)

Summary: Part-of-Speech Tagging and Constituency Grammars

- **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
- **Constituency grammars** describe a language's syntactic structure
- **Constituents**, a core component of constituency grammars, are groups of words that function as a single unit
- Constituency grammars can generate any sentences belonging to their language using (potentially recursive) combinations of **production rules**
- **Constituency parsing** is a way to automatically describe the structure of an input sentence according to a constituency grammar
- Constituency parsing can be performed using either a **top-down** or a **bottom-up approach**

This Week's Topics

Parts of Speech
POS Tagging
Context-Free Grammars
Hierarchical Parsing

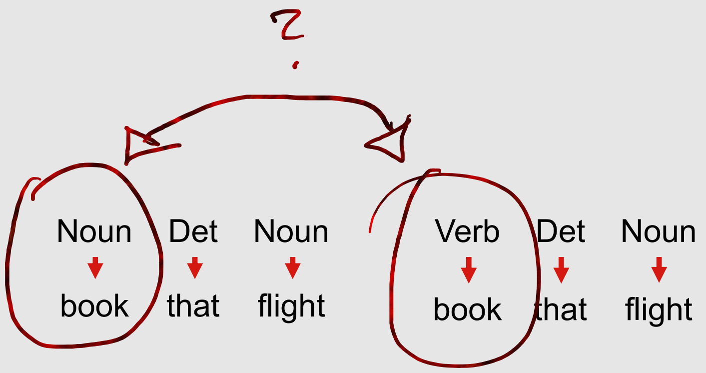
Tuesday

Thursday

Dynamic Programming Parsing Algorithms
Probabilistic CKY
Lexicalized Grammars

Many forms of ambiguity can arise during syntactic parsing!

- **Structural Ambiguity:** Grammar allows for more than one possible parse for a given sentence
  - **Attachment Ambiguity:** Constituent can be attached to a parse tree at more than one place
    - I eat spaghetti *with chopsticks.*
  - **Coordination Ambiguity:** Different sets of phrases can be conjoined by a conjunction
    - I grabbed a muffin from the table marked “nut-free scones *and* muffins,” hoping I’d parsed the sign correctly.
- **Local Ambiguity:** Word may be interpreted multiple ways



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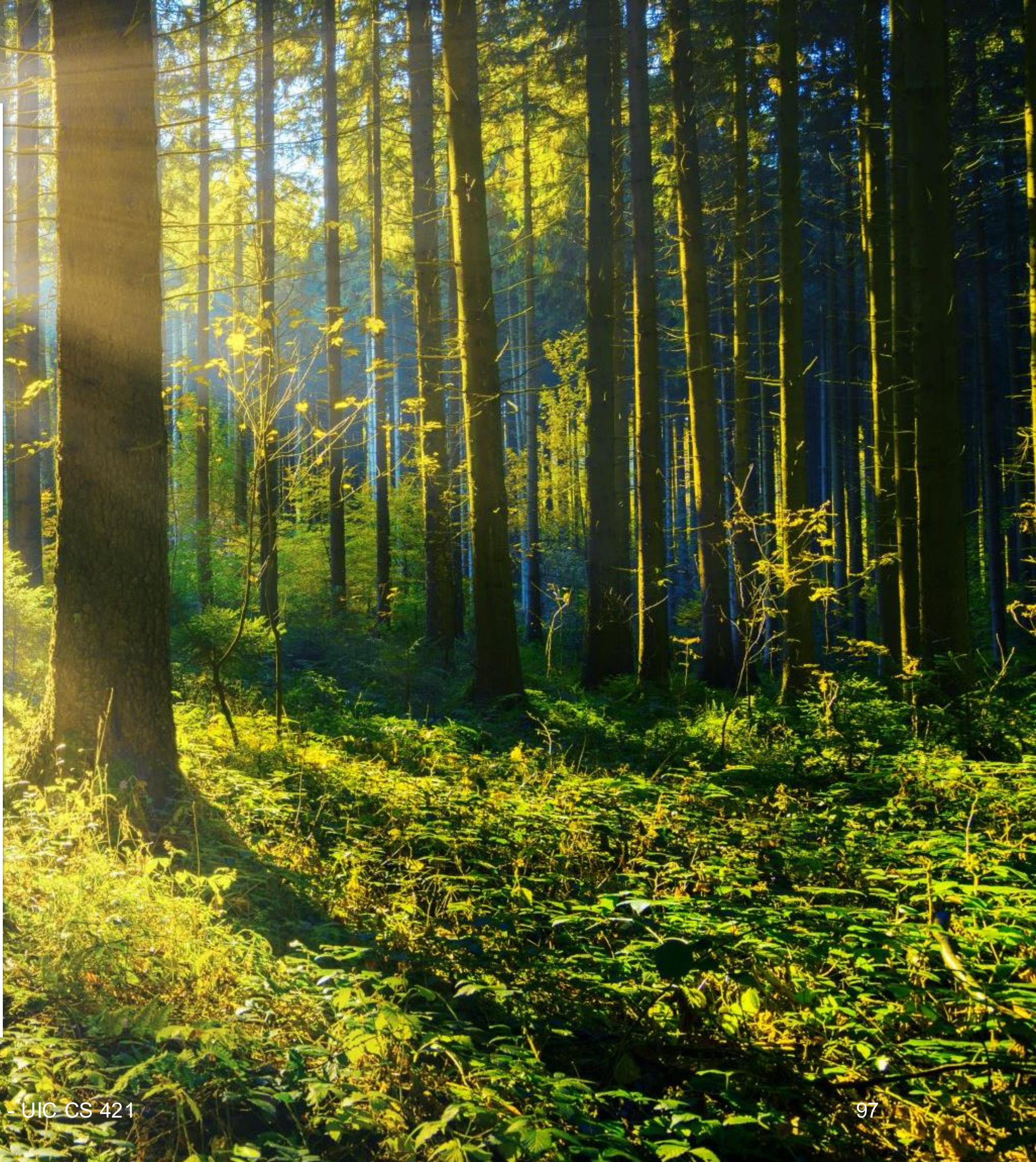
- Verb → **book** | include | prefer
- Pronoun → I | she | me
- Proper-Noun → Houston | NWA
- Aux → does
- Preposition → from | to | on | near | through

This ambiguity can create complex search spaces.

- **Backtracking** approaches systematically explore one state at a time
  - When they arrive at trees inconsistent with the input, they return to an unexplored alternative
  - However, in doing so, they tend to discard valid subtrees …this means that time-consuming work needs to be repeated
- More efficient approach?
  - **Dynamic programming**



Dynamic Programming Parsing Methods

- Widely used methods:
  - Cocke-Kasami-Younger (**CKY**) algorithm
    - Bottom-up approach
  - **Earley** algorithm
    - Top-down approach

CKY Algorithm

- One of the earliest recognition and parsing algorithms
- Standard version can only recognize CFGs in **Chomsky Normal Form** (CNF)
  - Grammars are restricted to production rules of the form:
    - A → B C
    - A → w
  - This means that the righthand side of each rule must expand to either two non-terminals or a single terminal
  - Any CFG can be converted to a corresponding CNF grammar that accepts exactly the same set of strings as the original grammar!

How does this conversion work?

- Avoid production rules that mix terminals and non-terminals on the righthand side: **Introduce a dummy non-terminal that covers only the original terminal**
  - INF-VP → to VP could be replaced with INF-VP → TO VP and TO → to
- Avoid unit productions (single non-terminal on the righthand side): **Replace the non-terminals with the non-unit production rules to which they eventually lead**
  - A → B and B → w could be replaced with A → w
- Avoid production rules with more than two non-terminals on the righthand side: **Introduce new non-terminals that spread longer sequences over multiple rules**
  - A → B C D could be replaced with A → B X1 and X1 → C D

Original	CNF
S → NP VP	S → NP VP
S → AdjP NP VP	S → X1 VP
	X1 → AdjP NP
S → VP	S → book | include | prefer

CKY Algorithm

- With the grammar in CNF, each non-terminal node above the POS level of the parse tree will have exactly two children
- Thus, a two-dimensional matrix can encode the tree structure
- Each cell [*i*,*j*] contains a set of non-terminals that represent all constituents spanning positions *i* through *j* of the input
  - Cell that represents the entire input resides in position [0,*n*]

CKY Algorithm

- Non-terminal entries: For each constituent [*i*,*j*], there is a position, *k*, where the constituent can be split into two parts such that $i < k < j$
  - [*i*,*k*] must lie to the left of [*i*,*j*] somewhere along row *i*, and [*k*,*j*] must lie beneath it along column *j*
- To fill in the parse table, we proceed in a bottom-up fashion so when we fill a cell [*i*,*j*], the cells containing the parts that could contribute to this entry have already been filled

CKY Algorithm: Example

Det → that | this | a | the
Noun → book | flight | meal | money
Verb → book | include | prefer
Preposition → from | to | on | near | through

S → NP VP
S → book | include | prefer
S → Verb NP
NP → I | she | me
NP → Chicago | Dallas
NP → Det Nominal
Nominal → book | flight | meal | money
Nominal → Nominal Noun
Nominal → Nominal PP
VP → book | include | prefer
VP → Verb NP
VP → Verb PP
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PP → Preposition NP

	0 - Book	1 - the	2 - flight	3 - through	4 - Chicago
0					
1					
2					
3					
4					

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	0 - Book	1 - the	2 - flight	3 - through	4 - Chicago
0	Noun, Verb, S, Nominal, VP				
1					
2					
3					
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2			Noun, Nominal		
3				Prep.	
4					

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3				Prep.	
4					NP

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	0 - Book	1 - the	2 - flight	3 - through	4 - Chicago
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2			Noun, Nominal		
3				Prep.	
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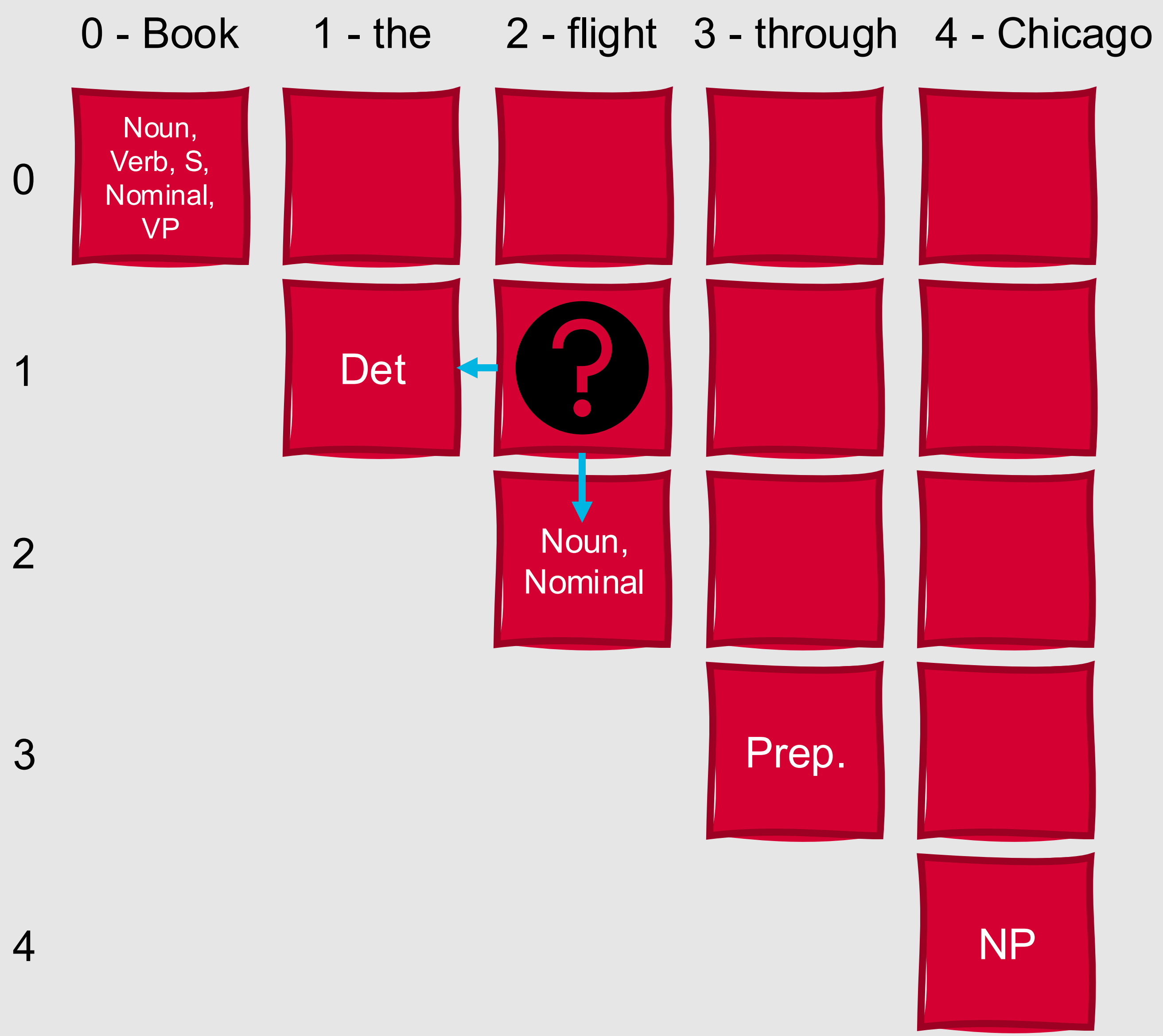

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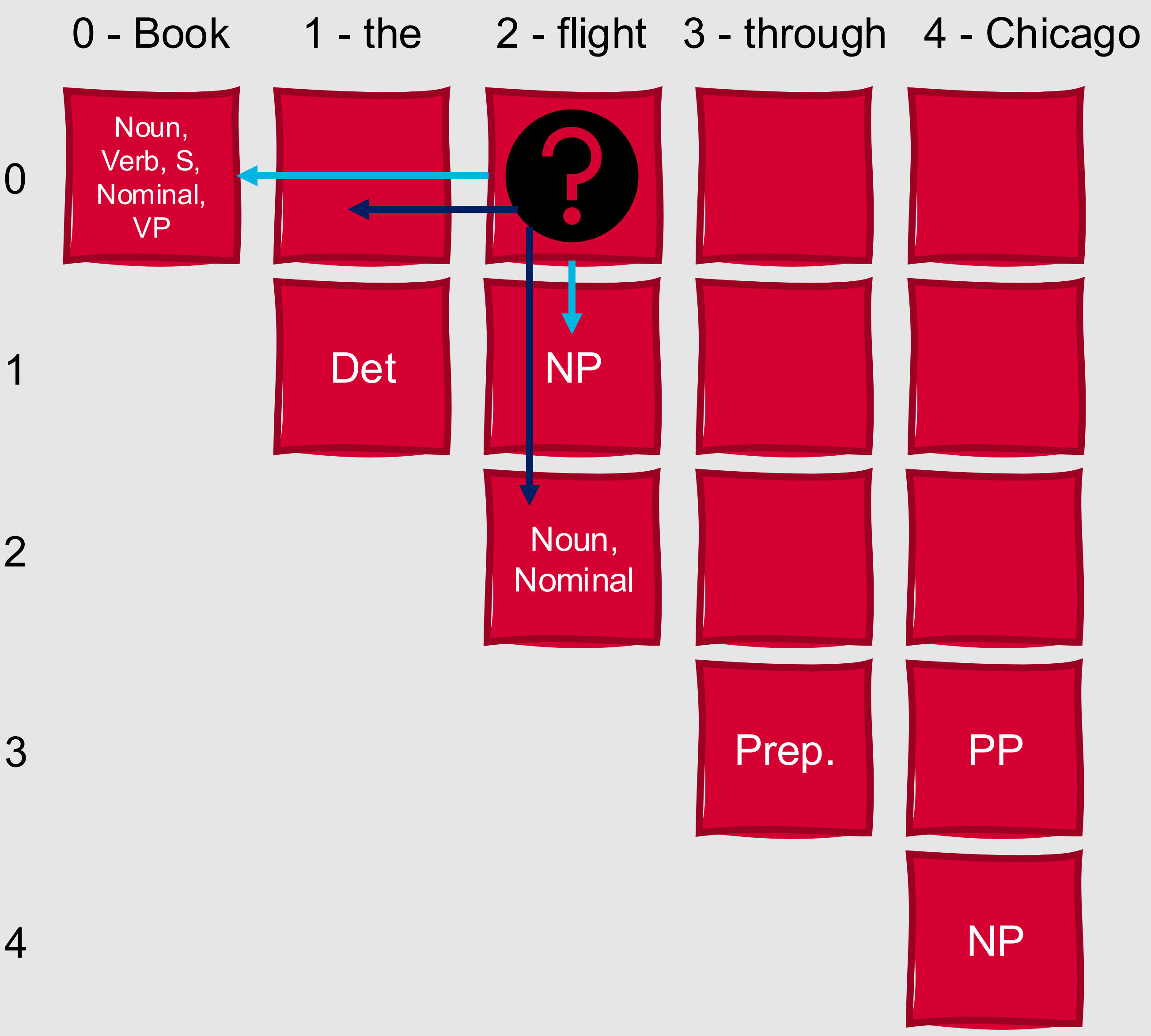
VP → Verb NP
VP → Verb PP
VP → VP PP
PP → Preposition NP



CKY Algorithm: Example

Det → that | this | a | the
Noun → book | flight | meal | money
Verb → book | include | prefer
Preposition → from | to | on | near | through

S → NP VP
S → book | include | prefer
S → Verb NP
NP → I | she | me
NP → Chicago | Dallas
NP → Det Nominal
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	0 - Book	1 - the	2 - flight	3 - through	4 - Chicago
0	Noun, Verb, S, Nominal, VP		S, VP		
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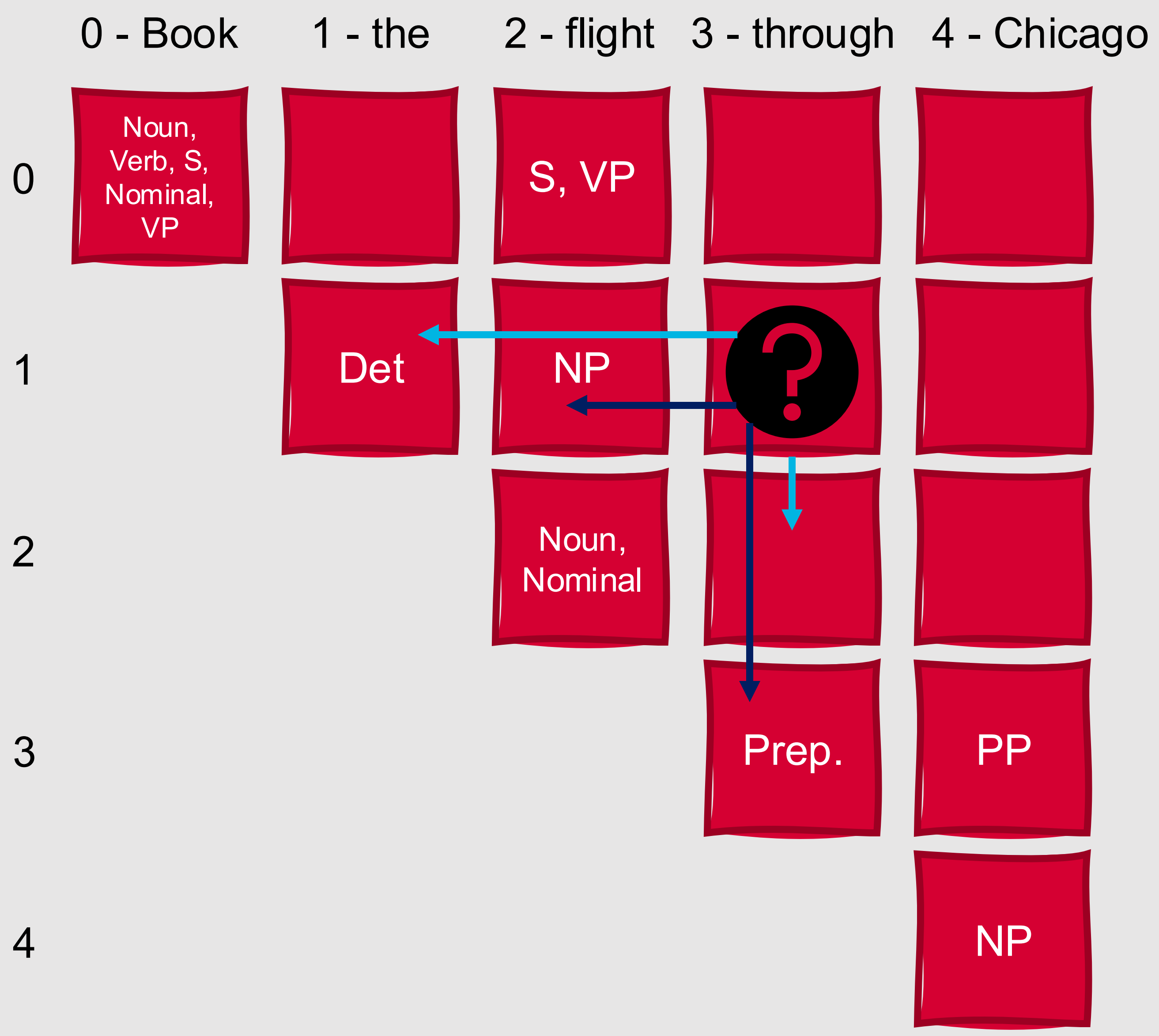

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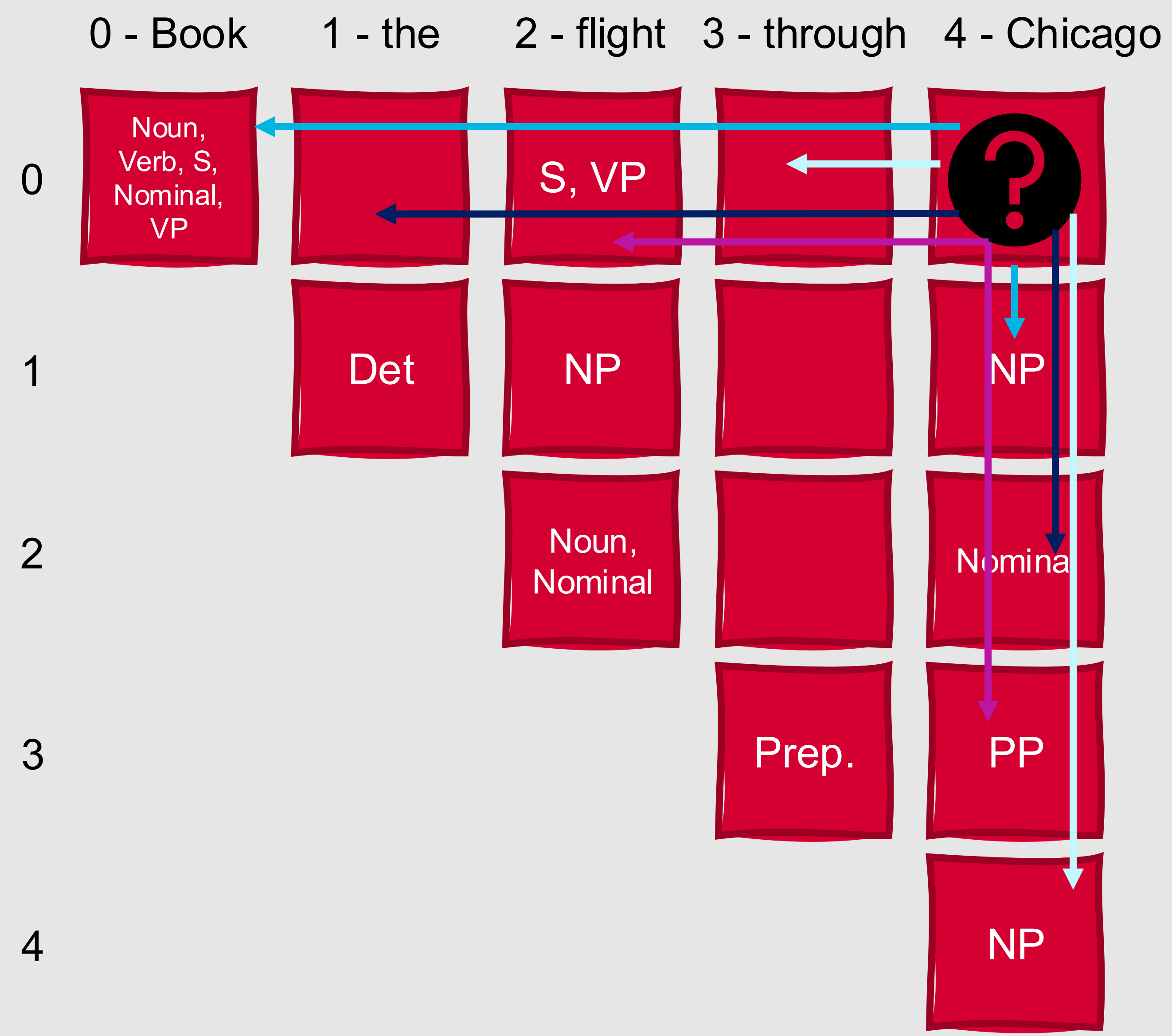
3				Prep.	PP
4					NP

CKY Algorithm: Example



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	0 - Book	1 - the	2 - flight	3 - through	4 - Chicago
0	Noun, Verb, S, Nominal, VP		S, VP		S, VP_1, VP_2
1		Det	NP		NP
2			Noun, Nominal		Nominal
3				Prep.	PP
4					NP

If we arrive at VP in multiple ways, each way is an alternative parse (VP_1, VP_2, …, VP_n).

CKY Algorithm

- In the previous example, we **recognized** a valid that this sentence was valid according to our grammar by finding an S in cell [0,n]
- To return all possible parses, we need to also pair each non-terminal with pointers to the table entries from which it was derived
- Then, we can choose a non-terminal and recursively retrieve its component constituents from the table
- Complexity of this algorithm:
  - Time complexity: $O(n^3)$
  - Space complexity: $O(n^2)$

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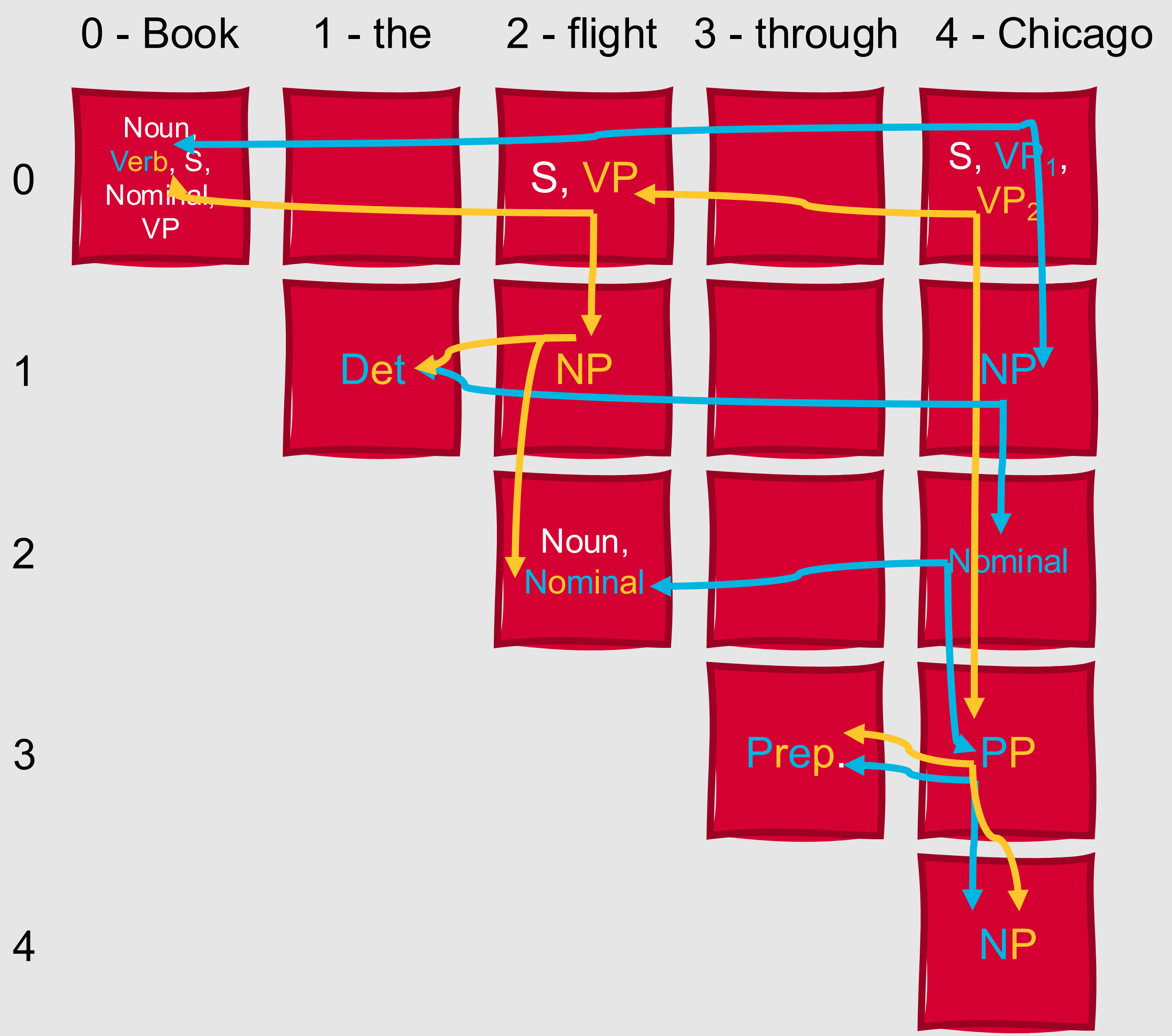


Top-Down Dynamic Parsing Approach?

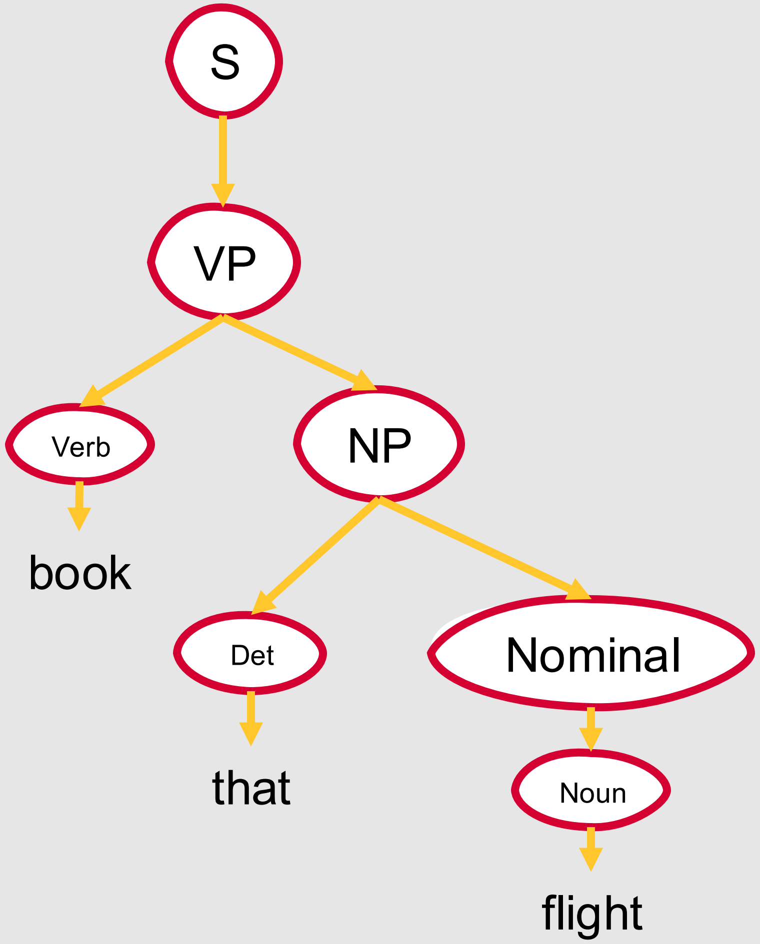
- **Earley** algorithm
- Table entries contain three types of information:
  - A single grammar rule
  - Information about the progress made in completing that rule
    - A • within the righthand side of a state's grammar rule indicates the progress made towards recognizing it
  - The position of the in-progress rule with respect to the input
    - Represented by two numbers, indicating (1) where the state begins, and (2) where its dot lies

Earley Algorithm

- An Earley parser moves through sets of states in a chart in order
- At each step, one of three operators is applied to each state depending on its status
  - Predictor
  - Scanner
  - Completer
- States can be added to the chart, but are never removed
- The algorithm never backtracks
- The presence of $S \rightarrow \alpha \bullet, [0,n]$ indicates a successful parse

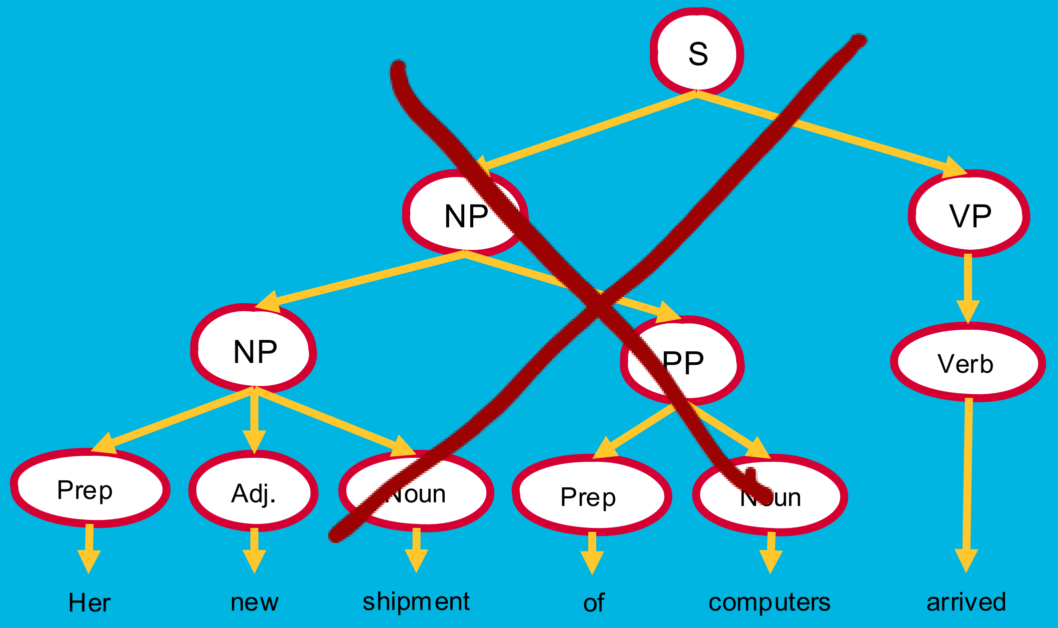
Example Earley Parse

Chart	State	Rule	Start, End	Added By (Backward Pointer)
0	S0	$\gamma \rightarrow \bullet$ S	0, 0	Start State
0	S1	S → • NP VP	0, 0	Predictor
0	S2	S → • VP	0, 0	Predictor
0	S3	NP → • Det Nominal	0, 0	Predictor
0	S4	VP → • Verb	0, 0	Predictor
0	S5	VP → • Verb NP	0, 0	Predictor
1	S6	Verb → book •	0, 1	Scanner
1	S7	VP → Verb •	0, 1	Completer
1	S8	VP → Verb • NP	0, 1	Completer
1	S9	S → VP •	0, 1	Completer
1	S10	NP → • Det Nominal	1, 1	Predictor
2	S11	Det → that •	1, 2	Scanner
2	S12	NP → Det • Nominal	1, 2	Completer
2	S13	Nominal → • Noun	2, 2	Predictor
3	S14	Noun → flight •	2, 3	Scanner
3	S15	Nominal → Noun •	2, 3	Completer (S14)
3	S16	NP → Det Nominal •	1, 3	Completer (S11, S15)
3	S17	VP → Verb NP •	0, 3	Completer (S6, S16)
3	S18	S → VP •	0, 3	Completer (S17)



Partial Parsing

- Full parse trees can be complex and time-consuming to build
- Many NLP tasks don't require full hierarchical parses



[Her new shipment]$_{NP}$ [of]$_{PP}$ [computers]$_{NP}$ [arrived]$_{VP}$

How is partial parsing ("chunking") performed?

Segmentation: Identify the non-overlapping, fundamental phrases

[Her new order] [of] [computers] [arrived]

Labeling: Assign labels to those phrases

$[\text{Her new order}]_{NP}$ $[\text{of}]_{PP}$ $[\text{computers}]_{NP}$ $[\text{arrived}]_{VP}$

Labeling Text Segments

- Often framed as a sequence labeling task that performs **IOB tagging**
  - **I:** Tokens **inside** a span
  - **O:** Tokens **outside** any span
  - **B:** Tokens **beginning** a span

Task: IOB Tagging (All Constituent Types)

B_NP I_NP B_NP

Her new order of computers arrived.

I_NP B_PP B_VP

Task: IOB Tagging (Noun Phrases)

B_NP I_NP B_NP

Her new order of computers arrived.

I_NP O O

We typically evaluate chunking systems using standard NLP performance metrics, including precision, recall, and F1.

This Week's Topics

Tuesday

- Parts of Speech
- POS Tagging
- Context-Free Grammars
- Hierarchical Parsing

Thursday

- Dynamic Programming Parsing Algorithms
- Probabilistic CKY
- Lexicalized Grammars

CKY and Earley parsers can produce multiple parse trees …which parse is best?

- **Probabilistic Context-Free Grammars:** Can help determine which parse out of multiple valid parses should be selected, based on how likely the parse tree is to occur in a large corpus
- Same core components as regular CFGs:
  - A set of non-terminals, N
  - A set of terminal symbols, Σ
  - A set of rules or productions, R
  - A designated start symbol, S
- However, R is augmented with a probability, [p], learned from a corpus
- The sum of all probabilities for a given non-terminal is 1.0
- For example, if the following three expansions for S were possible, they might have the probabilities:
  - S → NP VP [0.80]
  - S → Aux NP VP [0.15]
  - S → VP [0.05]

Probabilistic Context-Free Grammars

- The probability of sentence S having a parse tree T is the product of the individual probabilities associated with its constituent rules
  - $P(T,S) = \prod_{i=1}^{n} P(\beta_i|A_i)$
- To disambiguate between multiple valid parses, we find the parse tree T that results in the highest probability for the sentence S
  - $\hat{T}(S) = \underset{T\ s.t.\ S=\text{yield}(T)}{\text{argmax}} P(T)$
- We can compute the probabilities for our parse trees by extending the parsing algorithms we already have
- Probabilities are typically learned from a labeled corpus:
  - $P(\alpha \rightarrow \beta|\alpha) = \frac{Count(\alpha\rightarrow\beta)}{\sum_{\gamma} Count(\alpha\rightarrow\gamma)} = \frac{Count(\alpha\rightarrow\beta)}{Count(\alpha)}$

Case Example: Probabilistic CKY

The price includes a computer

Production Rule	Probability
S → NP VP	0.80
NP → Det N	0.30
VP → V NP	0.20
V → includes	0.05
Det → the	0.40
Det → a	0.40
N → price	0.01
N → computer	0.02

Still assume grammar is in Chomsky normal form!

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	0 - The	1 - price	2 - includes	3 - a	4 - computer
0	Det (0.40)				
1		N (0.01)			
2					
3					
4					

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	0 - The	1 - price	2 - includes	3 - a	4 - computer
0	Det (0.40)	NP (0.3 * 0.4 * 0.01 = 0.0012)			
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3				Det (0.40)	NP (0.3 * 0.4 * 0.02 = 0.0024)
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0	Det (0.40)	NP (0.3 * 0.4 * 0.01 = 0.0012)	☹		
1		N (0.01)	☹	☹	
2			V (0.05)	☹	VP (0.2 * 0.05 * 0.0024 = 0.000024)
3				Det (0.40)	NP (0.3 * 0.4 * 0.02 = 0.0024)
4					N (0.02)

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Case Example: Probabilistic CKY

The price includes a computer

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Challenges Associated with PCFGs

- PCFGs solve many issues associated with resolving ambiguities, but they still have:
  - **Poor independence assumptions** (can lead to issues modeling **structural dependencies** in the parse tree)
  - **Lack of lexical conditioning**, which may allow **lexical dependency issues** (e.g., preposition attachment) to arise
- How can we address these lingering limitations?
  - **Lexicalized grammars**

This Week's Topics

Parts of Speech
POS Tagging
Context-Free Grammars
Hierarchical Parsing

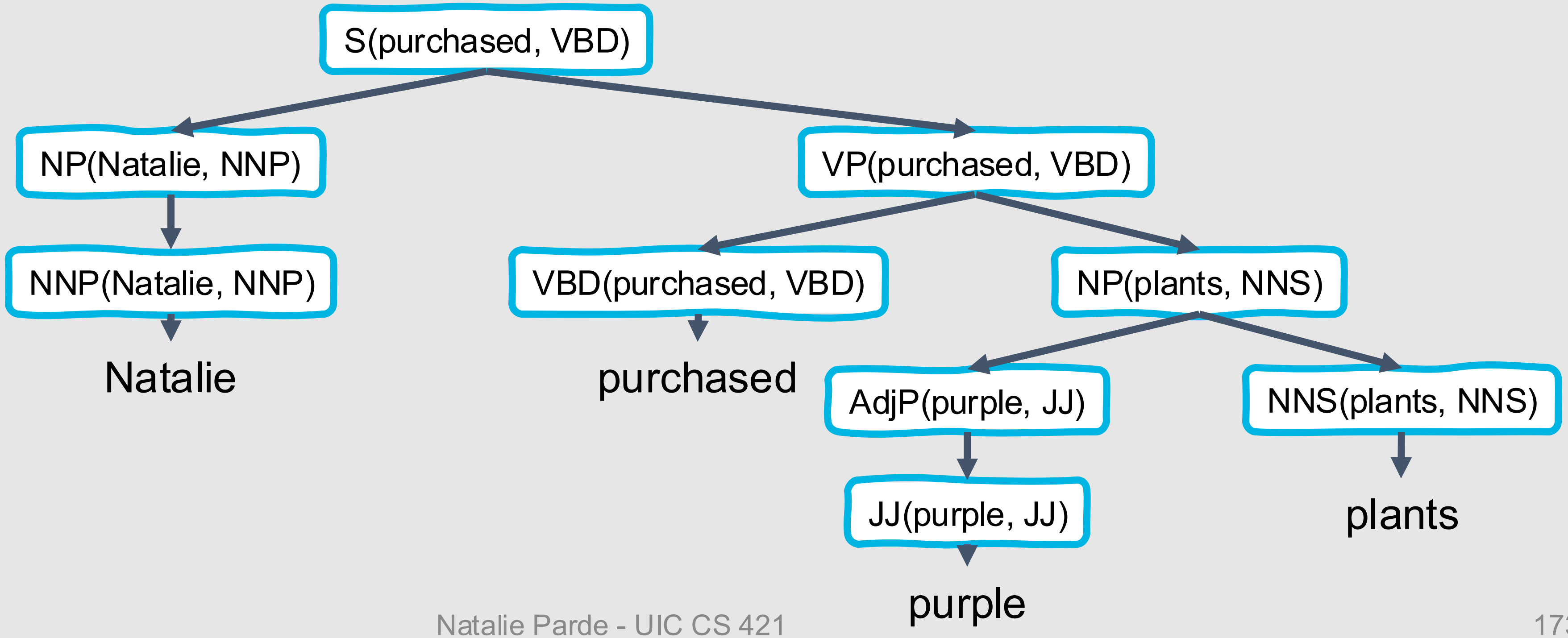
Tuesday

Thursday

Dynamic Programming Parsing Algorithms
Probabilistic CKY
Lexicalized Grammars

Lexicalized Parsers

- Non-terminals specify lexical heads and associated POS tags
  - NP(plants, NNS) → AdjP(purple, JJ) NNS(plants, NNS)



Lexicalized Production Rules

- Lexicalized rules thus are more complex:
  - $LHS \rightarrow L_n \; L_{n-1} \dots L_1 \; H \; R_1 \dots R_{n-1} \; R_n$

Non-terminal LHS
NP(plants, NNS)

Non-terminal left of head
AdjP(purple, JJ)

Head
NNS(plants, NNS)

Non-terminal right of head
PP(under, P)

P_L: Probability for generating dependents on the left

P_H: Probability for generating heads

P_R: Probability for generating dependents on the right

The Collins Parser

- Each constituent has a head word
- Tree structure thus captures:
  - P(head | parent)
  - P(left modifiers | head)
  - P(right modifiers | head)
- Can be viewed as a head-driven generative parsing model

Combinatory Categorial Grammars (CCGs)

- *Heavily* lexicalized way to group words from a lexicon into categories and define rules indicating how those categories may be combined
- CCG categories include:
  - **Atomic elements**
    - $\mathcal{A} \subseteq \mathcal{C}$, where $\mathcal{A}$ is a set of atomic elements, and $\mathcal{C}$ is the set of categories for the grammar
    - Simple noun phrases
  - **Single-argument functions**
    - (X/Y), (X\Y) $\in \mathcal{C}$, if $\mathrm{X}, \mathrm{Y} \in \mathcal{C}$
      - (X/Y): Seeks a constituent of type Y to the right, and returns X
      - (X\Y): Seeks a constituent of type Y to the left, and returns X
    - Verb phrases, more complex noun phrases, etc.

CCG Lexica and Rules

- CCG lexica assign CCG categories to words
  - Chicago: NP
    - **Atomic category**
  - cancel: (S\NP)/NP
    - **Functional category**
    - Seeks an NP to the right, returning (S\NP), which seeks an NP to the left, returning S
- CCG rules specify how functions and their arguments may be combined
  - **Forward function application:** Applies the function to its argument on the right, resulting in the specified category
    - $X/Y \; Y \Rightarrow X$
  - **Backward function application:** Applies the function to its argument on the left, resulting in the specified category
    - $Y \; X\backslash Y \Rightarrow X$
  - A coordination rule can also be applied
    - $X \; CONJ \; X \Rightarrow X$

Syntactic Parsing and LLMs

- LLMs have changed how we use syntactic parsers
  - Likelier to be used as a **tool** rather than as a component of an NLP pipeline
  - Offer a lens for **interpreting** what LLMs encode
  - Provide reliable fallback measures for low-resource or **safety-critical** tasks

Parsing as a Diagnostic Tool

- Parsing is often used as a probe to understand LLMs
- Example use cases:
  - Determine whether syntax trees are embedded in word representation space (Hewitt and Manning, 2019)
  - Understand how LLMs encode syntax at different levels of linguistic hierarchy (Starace et al., 2023)

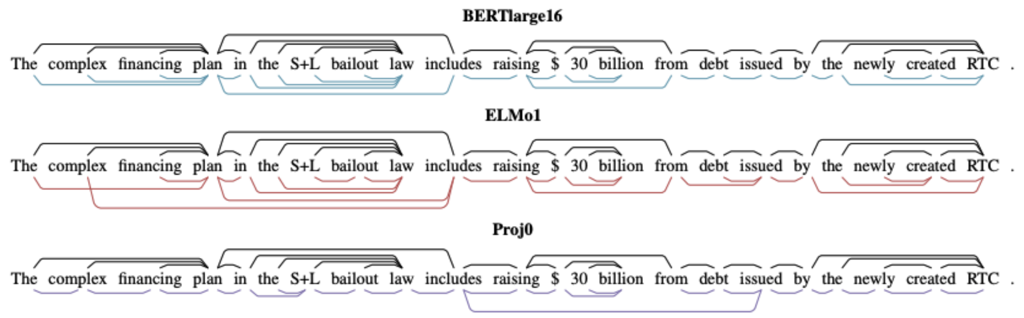


Figure 2: Minimum spanning trees resultant from predicted squared distances on BERTLARGE16 and ELMO1 compared to the best baseline, PROJ0. Black edges are the gold parse, above each sentence; blue are BERTLARGE16, red are ELMO1, and purple are PROJ0.

John Hewitt and Christopher D. Manning. 2019. A Structural Probe for Finding Syntax in Word Representations. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pages 4129–4138, Minneapolis, Minnesota. Association for Computational Linguistics.

Giulio Starace, Konstantinos Papakostas, Rochelle Choenni, Apostolos Panagiotopoulos, Matteo Rosati, Alina Leidinger, and Ekaterina Shutova. 2023. Probing LLMs for Joint Encoding of Linguistic Categories. In *Findings of the Association for Computational Linguistics: EMNLP 2023*, pages 7158–7179, Singapore. Association for Computational Linguistics.

How can we use syntactic parsers and LLMs jointly?

Incorporate syntactic parsing-based scoring into LLM decoding to support controllable, interpretable generation

Develop syntax-aware prompting techniques or add syntactic constraints to prompts to improve performance at structured tasks (e.g., information extraction)

We now know how to build parsers (in many different ways)! How can we evaluate them?

- **PARSEVAL measures:** Seek to determine how close a predicted parse is to a gold standard parse for the same text, based on its individual constituents
  - Constituent is correct if it matches a constituent in the gold standard in terms of its:
    - Starting point
    - Ending point
    - Non-terminal symbol

Once constituent correctness is defined….

- We can apply the same metrics we use for other NLP problems!
  - $\text{Recall} = \dfrac{\text{\# correct constituents in predicted parse}}{\text{\# constituents in gold standard parse}}$
  - $\text{Precision} = \dfrac{\text{\# correct constituents in predicted parse}}{\text{\# constituents in predicted parse}}$

Summary: Constituency Parsing

The **CKY algorithm** and **Earley algorithm** are popular dynamic programming approaches to parsing that work in a bottom-up and top-down manner, respectively

We can select the best parse for a sentence using **probabilistic context-free grammars**

The **CKY algorithm** can be updated to incorporate these probabilities for use with PCFG parsing

An alternative parsing paradigm uses **lexicalized grammar frameworks**

We can evaluate parsers using standard NLP metrics applied based on the number of **correctly identified constituents** in a predicted parse