Part-of-Speech Tagging and Formal Grammars

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CS 421: Natural Language Processing

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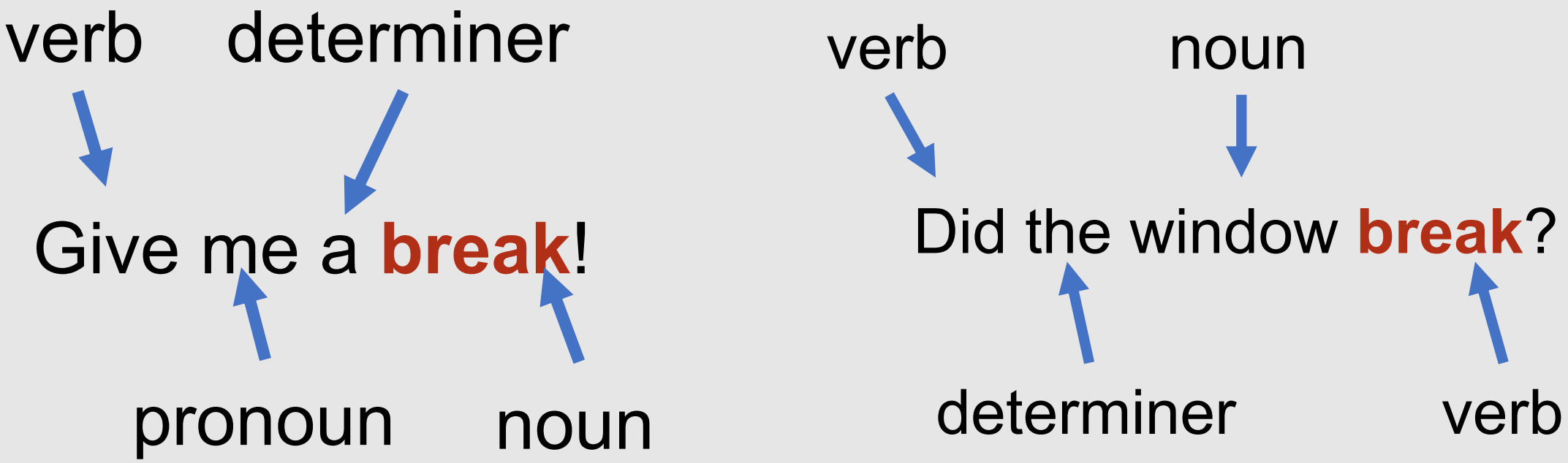
Many slides adapted from Jurafsky and Martin (https://web.stanford.edu/~jurafsky/slp3/) and UNT's NLP course (http://www.cse.unt.edu/~tarau/teaching/NLP/nlp.html).

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*

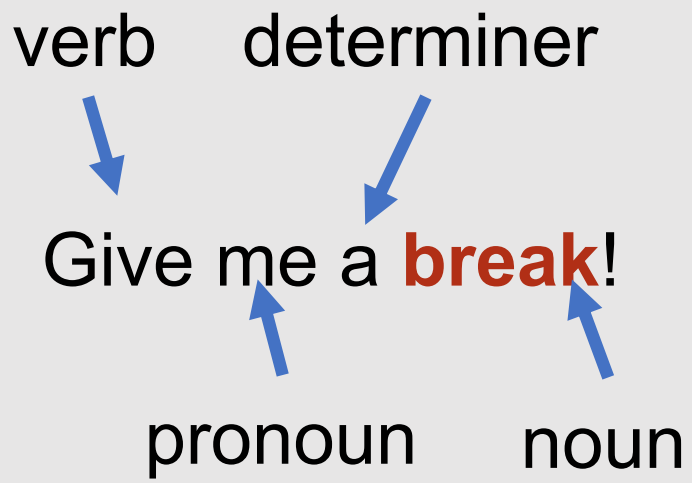
Closed Class

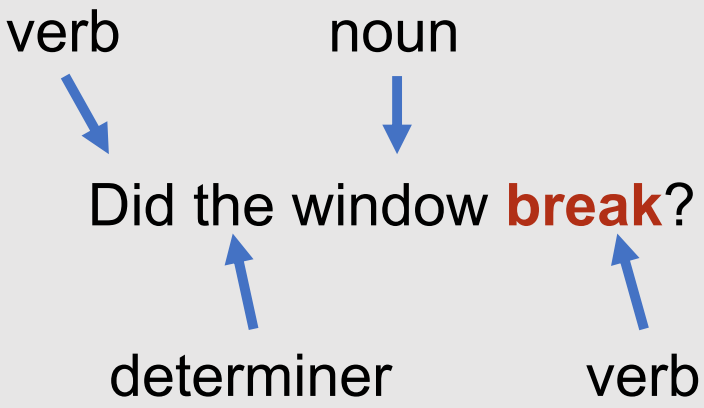
- **Determiners** — *the* *some*
- **Conjunctions** — *and* *or*
- **Pronouns** — *he* *its*
- **Prepositions** — *to* *with*
- **Interjections** — *Ow* *Eh*

… *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





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

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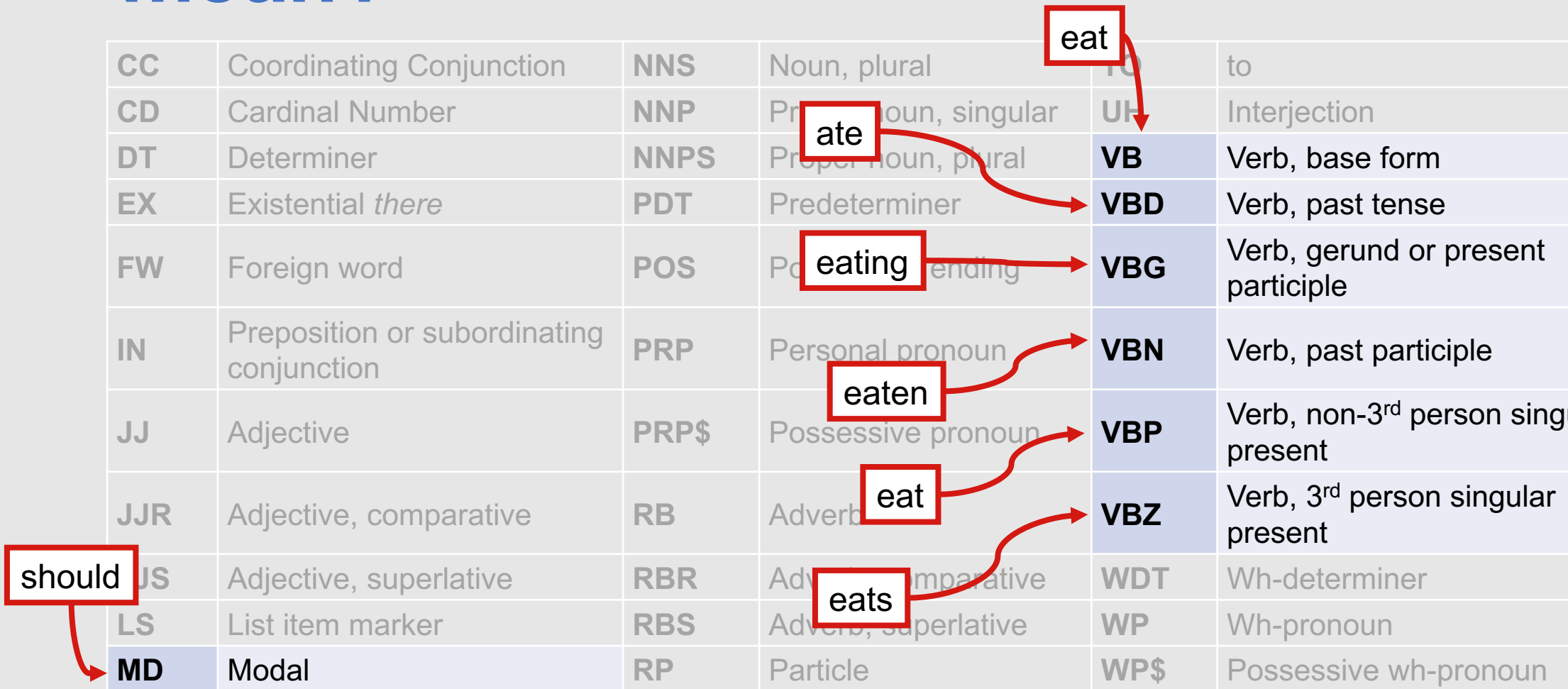

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calmly

calmer

calmest

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

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Closed Class

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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

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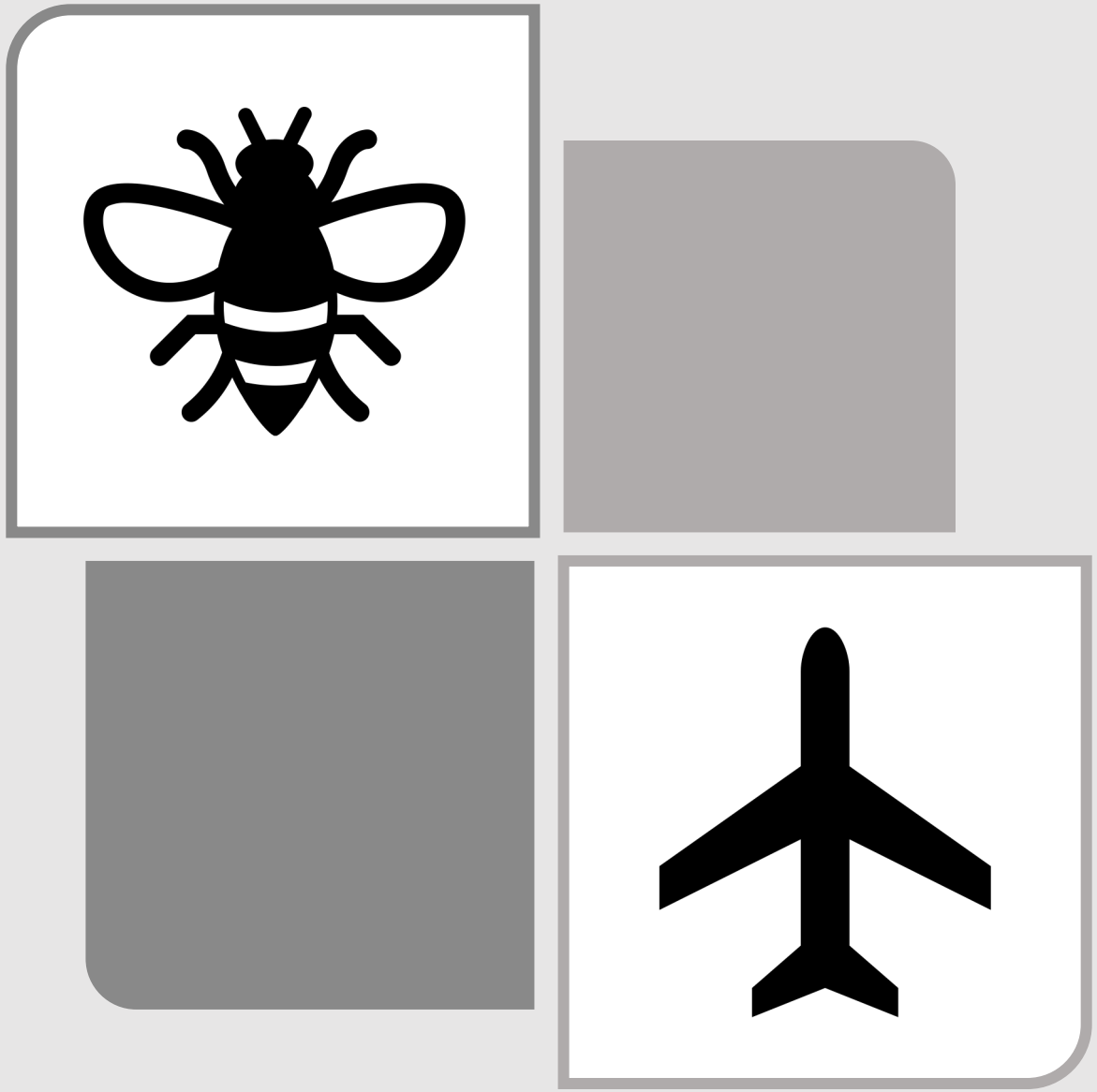
In-Class Exercise

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~~		

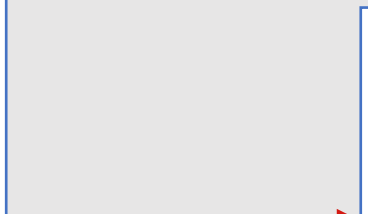
ENGTWOL

- **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

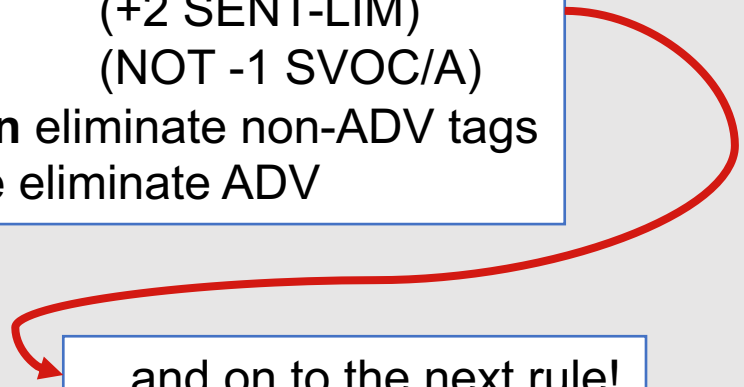
ENGTWOL

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**



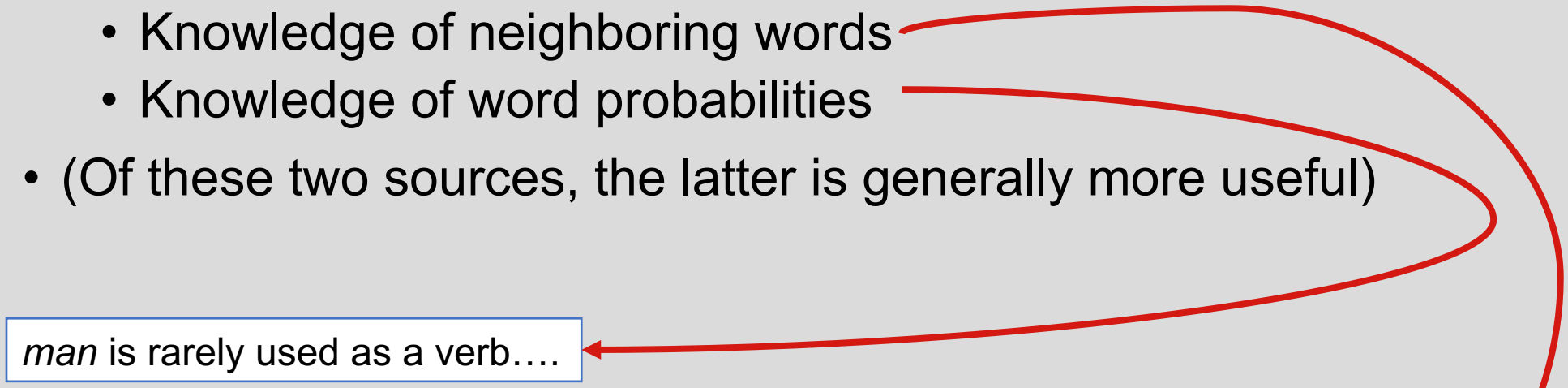
Given input: "that"
If
(+1 A/ADV/QUANT)
(+2 SENT-LIM)
(NOT -1 SVOC/A)
Then eliminate non-ADV tags
Else eliminate ADV



…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)



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!

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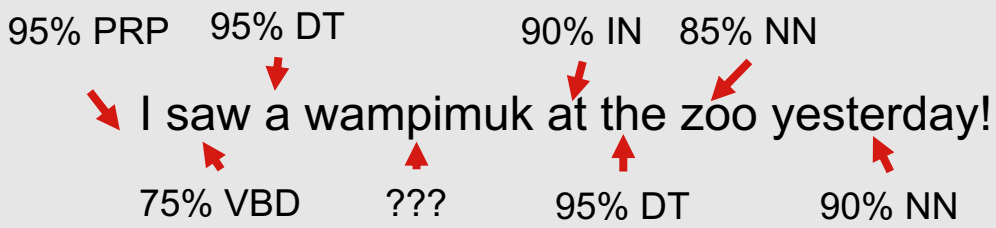

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I	saw	a	wampimuk	at	the	zoo	yesterday
PRP	VBD	DT	NN	IN	DT	NN	NN

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"

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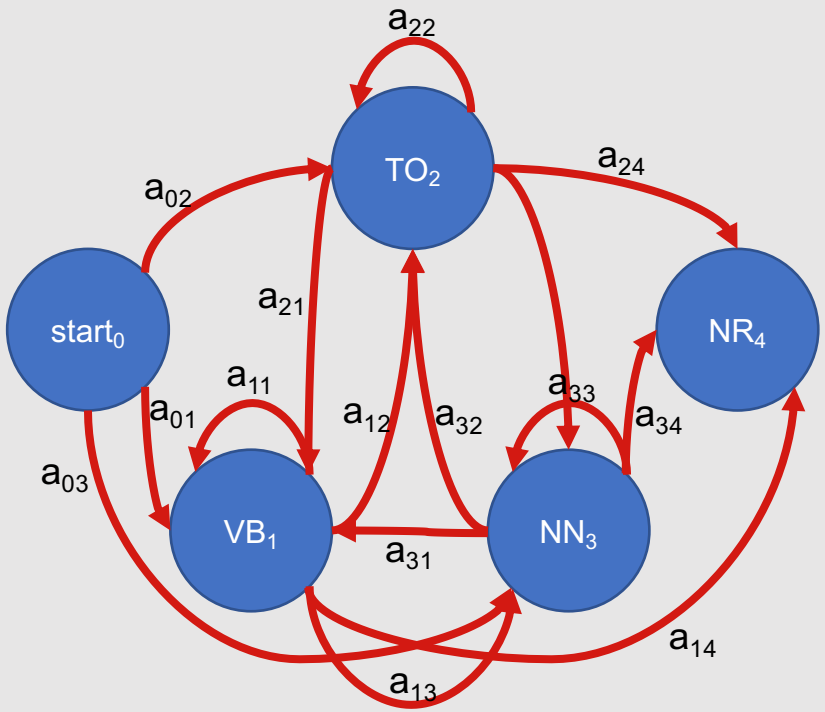
We can thus create the following Markov chain:



Example: Bigram HMM Tagger

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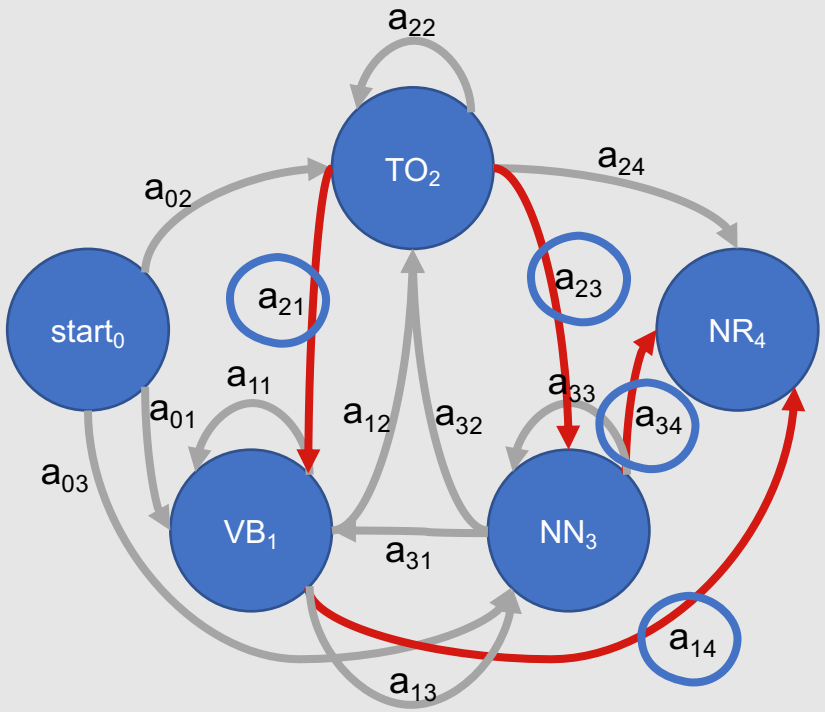
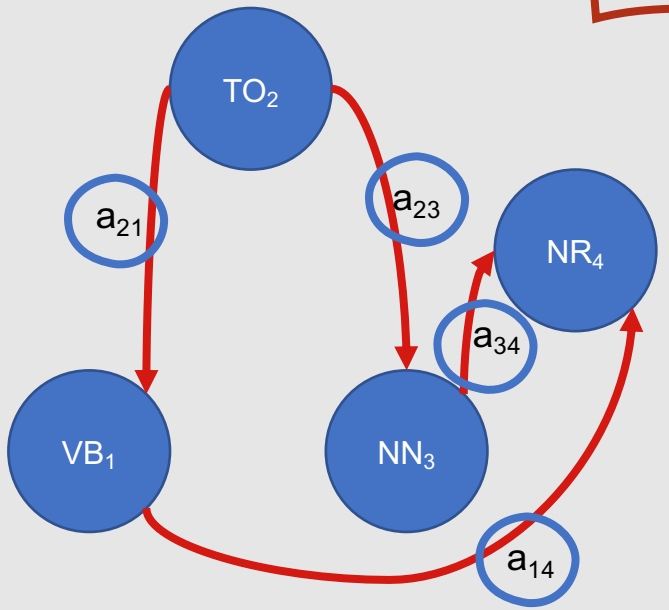
NNP	VBZ	VBN	TO	NN	NR

The specific transition probabilities we are interested in are:



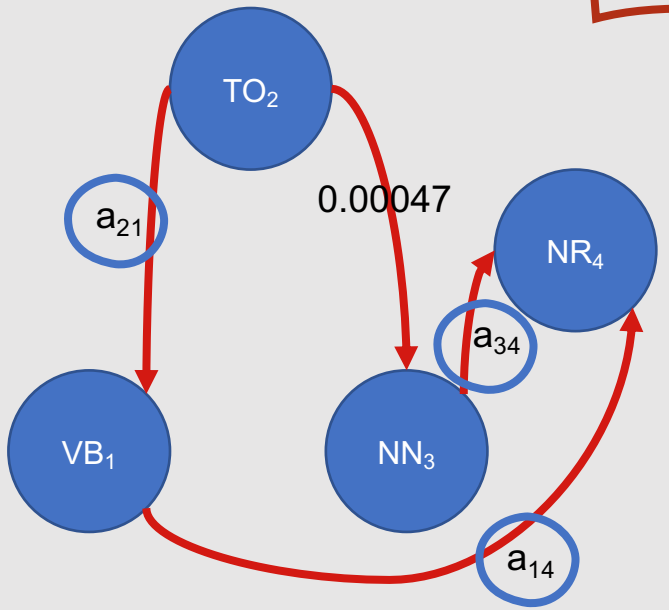
Secretariat	is	expected	to	race	tomorrow
NNP	VBZ	VBN	TO	VB	NR
NNP	VBZ	VBN	TO	NN	NR



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

Example: Bigram HMM Tagger

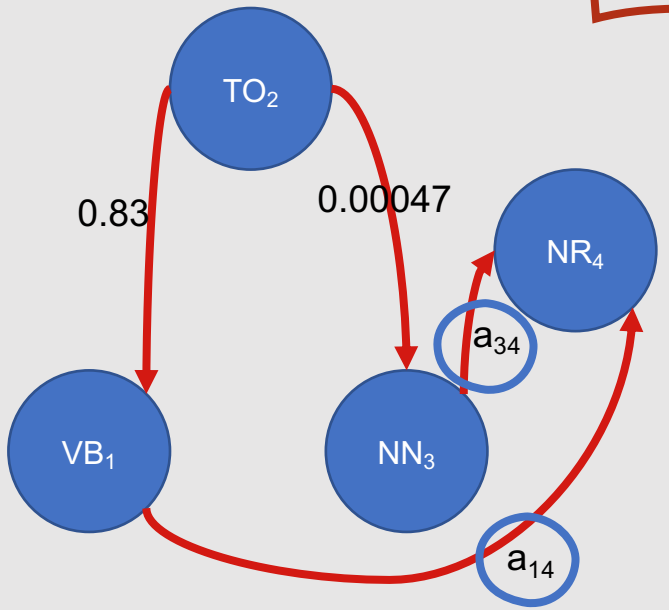
Secretariat	is	expected	to	race	tomorrow
NNP	VBZ	VBN	TO	VB	NR
NNP	VBZ	VBN	TO	NN	NR



- 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

Example: Bigram HMM Tagger

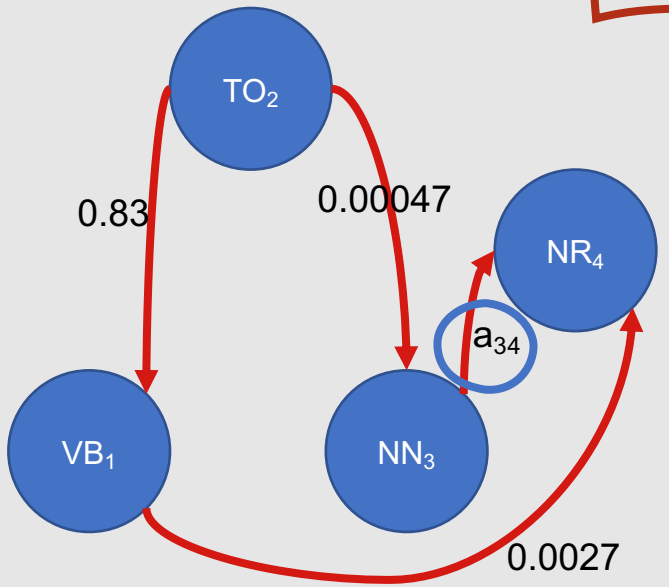
Secretariat	is	expected	to	race	tomorrow
NNP	VBZ	VBN	TO	VB	NR
NNP	VBZ	VBN	TO	NN	NR



- 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

Example: Bigram HMM Tagger

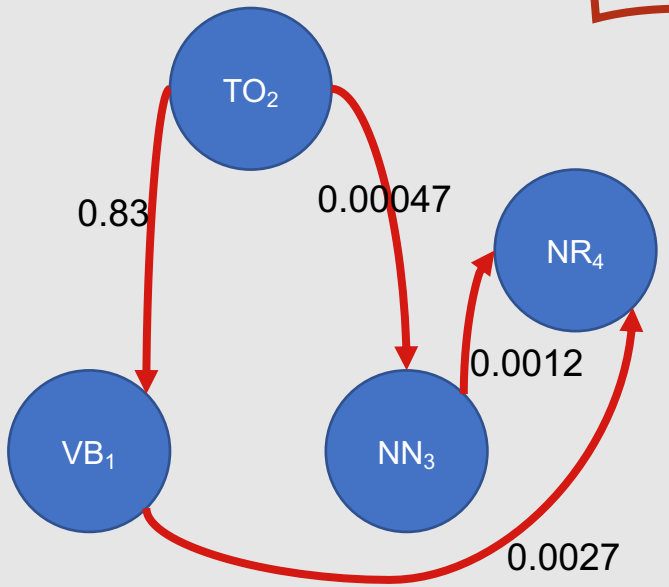
Secretariat	is	expected	to	race	tomorrow
NNP	VBZ	VBN	TO	VB	NR
NNP	VBZ	VBN	TO	NN	NR



- 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

Example: Bigram HMM Tagger

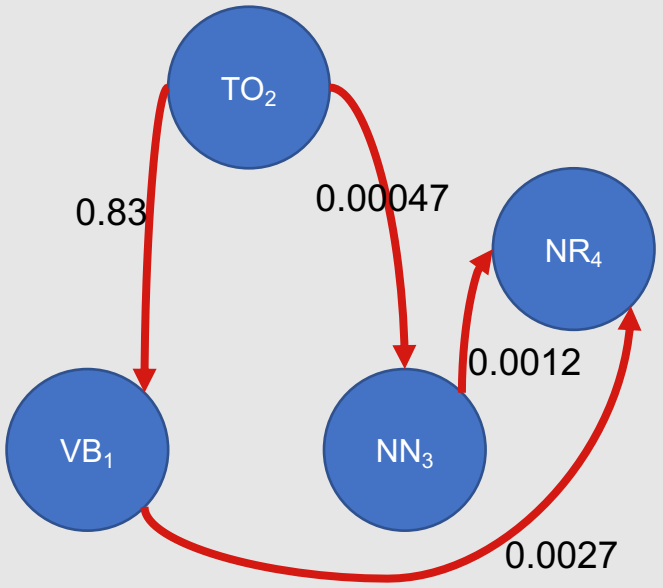
Secretariat	is	expected	to	race	tomorrow
NNP	VBZ	VBN	TO	VB	NR
NNP	VBZ	VBN	TO	NN	NR



- 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



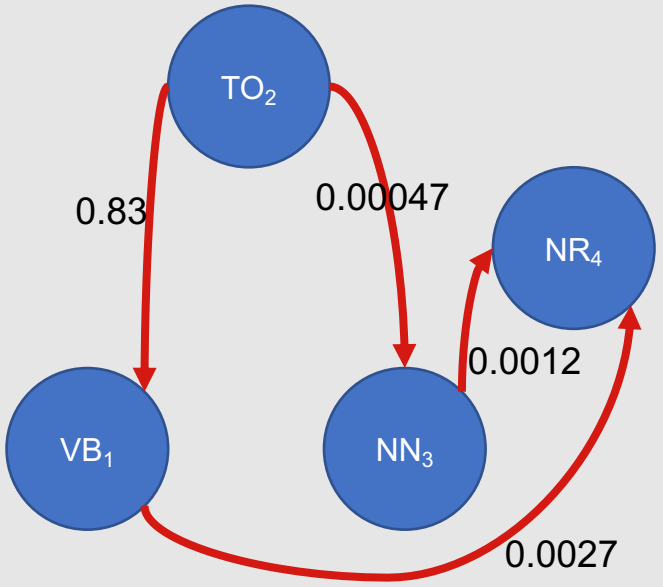
	race
VB	
NN	

- 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

Example: Bigram HMM Tagger

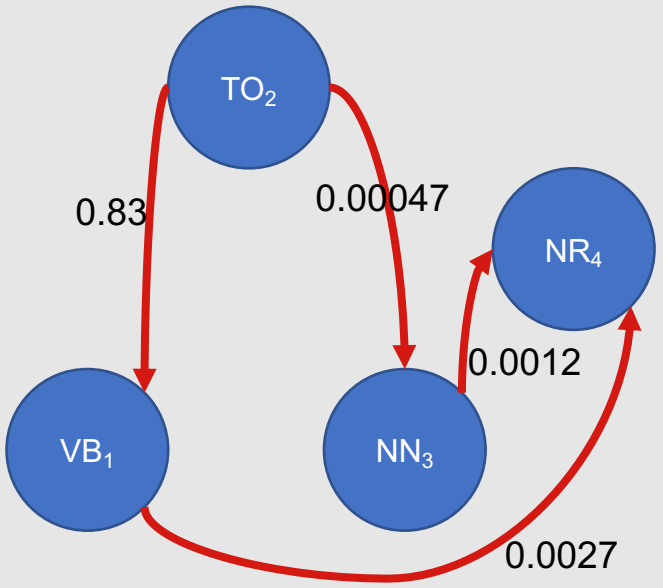
Secretariat	is	expected	to	race	tomorrow
NNP	VBZ	VBN	TO	VB	NR
NNP	VBZ	VBN	TO	NN	NR



	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

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

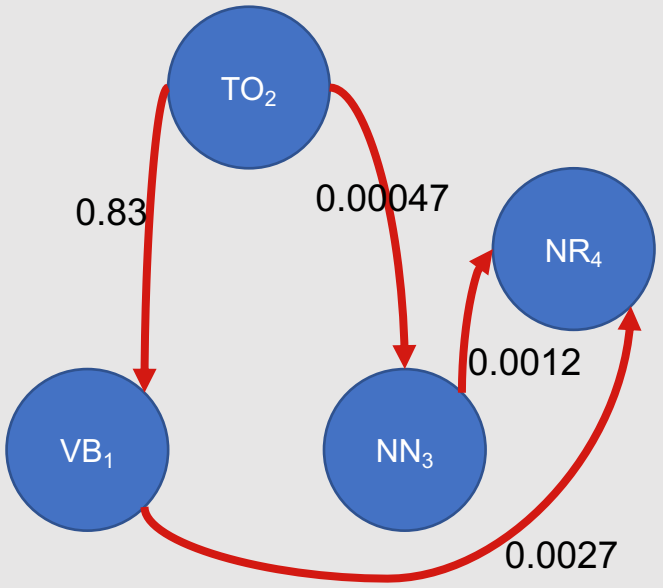


	race
VB	0.00012
NN	0.00057

- 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



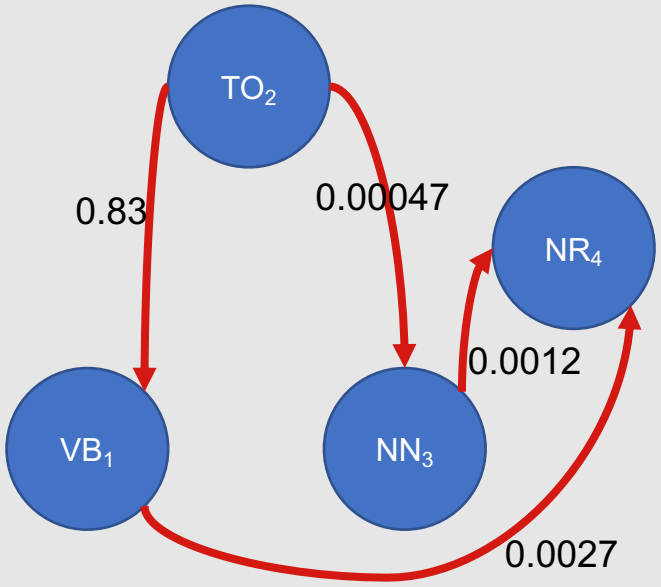
	race
VB	0.00012
NN	0.00057

- 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

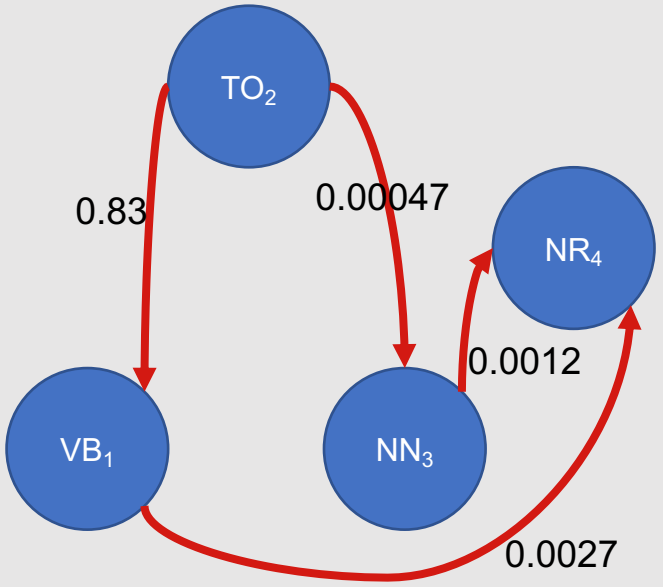
Secretariat	is	expected	to	race	tomorrow
NNP	VBZ	VBN	**TO**	**VB**	**NR**
NNP	VBZ	VBN	TO	NN	NR



	race
VB	0.00012
NN	0.00057

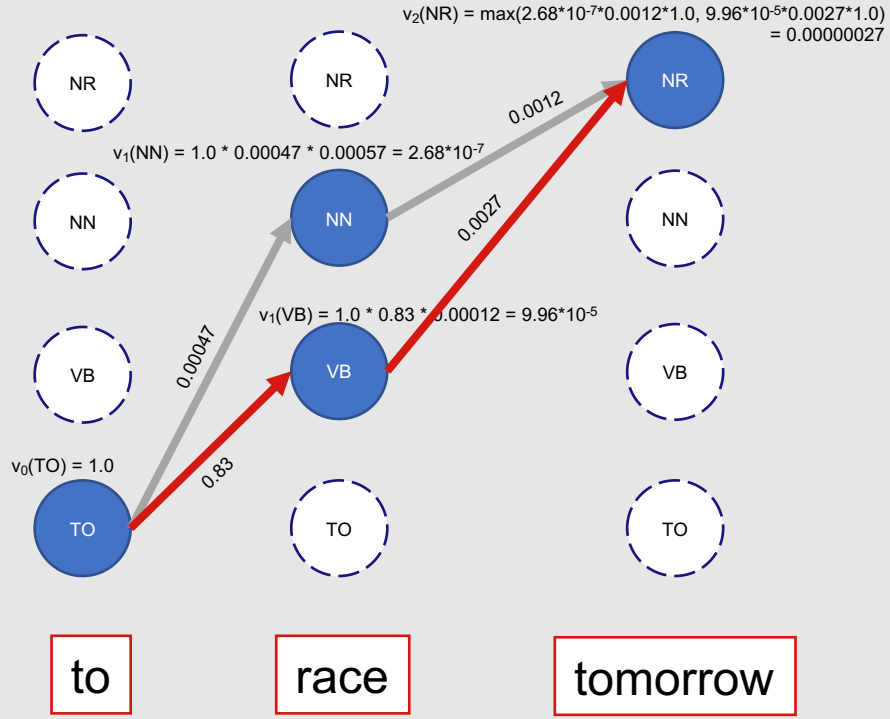
- Now, to decide how to tag "race," we can consider our two possible sequences:
  - to (TO) race (VB) tomorrow (NR)
  - to (TO) race (NN) tomorrow (NR)
- We will select the tag that maximizes the probability:
  - $P(t_i|TO)P(NR|t_i)P(race|t_i)$
- We determine that:
  - **$P(VB|TO)P(NR|VB)P(race|VB) =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

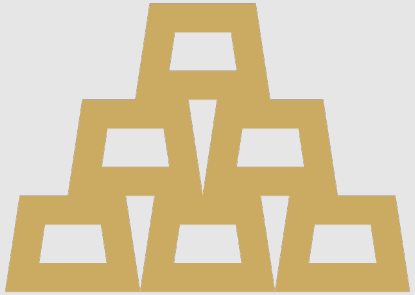
- There are advantages and disadvantages to all of these different POS tagging approaches
- Generally, both here and in other NLP problems, **rule-based approaches are faster and may work better for limited, well-defined domains**, whereas **statistical approaches are slower and may generalize better 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