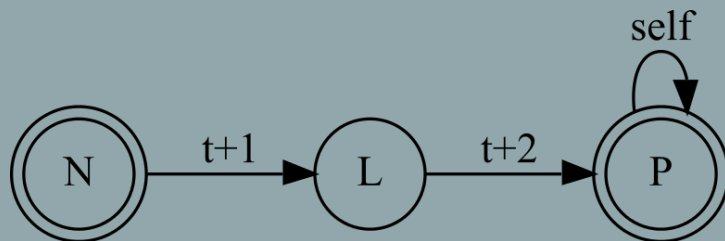


LING-362

Introduction to Natural Language Processing

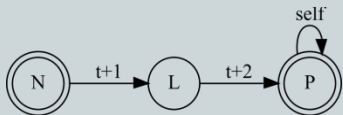
Syntactic parsing III



Review - CKY

• Tokens at the top of the table

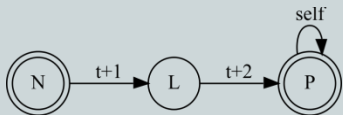
The	boys	shop	daily



Dynamic programming – CKY

- Check bottom of column for possible categories for each token

The	boys	shop	daily
DT			

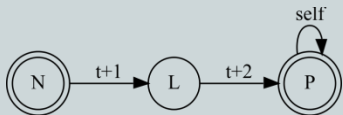


Dynamic programming – CKY

◎ Check intersections in higher rows:

- Is this a possible segmentation?
- Only binary branching grammars allowed (Chomsky Normal Form – **CNF**)

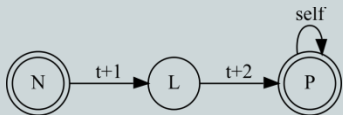
The	boys	shop	daily
DT			
	NNS		



Dynamic programming – CKY

◎ Unambiguous – no problem

The	boys	shop	daily
DT	NP		
	NNS		

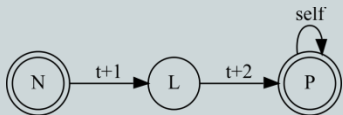


Dynamic programming – CKY

- For ambiguous cases, we must keep track of what goes with what

The	boys	shop	daily
DT	NP		S S
	NNS	NP	
		VBP NN	VP
			RB NN

Derivation
does not
terminate!



Choosing the right parse

- ◎ All an algorithm like CKY does for us so far is check for **possible** positions to **split into phrases**
 - Useful in many contexts (CKY can be applied to Chinese word segmentation! Qian & Liu 2012)
 - Genome mapping (see Poptsova 2014)
 - ...
- ◎ How can we decide which parse is right?

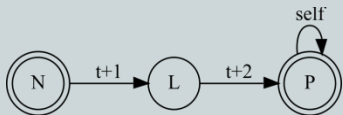


From CFGs to PCFGs

- ◉ We can amend our definition to include probabilities – a **Probabilistic CFG**:

$G \equiv$

- | | |
|----------|--|
| N | Set of non-terminal symbols |
| Σ | Set of terminal symbols (not in N !) |
| R | Set of rules of the form $A \rightarrow \beta$ [p]
where $A \in N$, $\beta \in (\Sigma \cup N)^*$
and p is the probability $P(\beta A)$ |
| S | The designated start symbol |

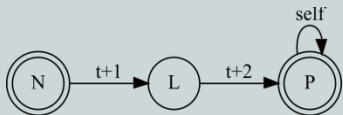


From CFGs to PCFGs

⦿ Probabilities?

- We can treat the proportion of each decomposition of each category as its probability
 - NP > DT NN: 35%
 - NP > NNS: 20%
 - NP > PRP: 20%
 - NP > DT JJ NN: 10%
 - ...

100%



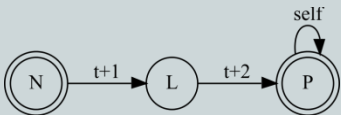
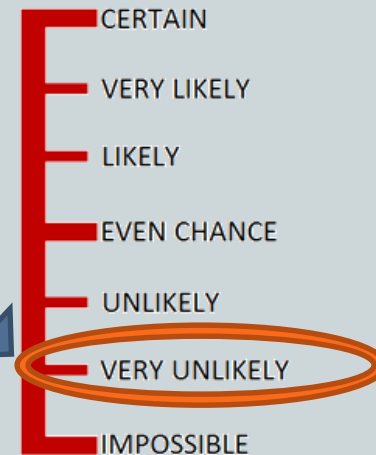
This sounds like a great idea!

◎ Even if we have lots of spurious generations in our data, the parser will **never** choose them!

- Sure, these constituents are licensed by the grammar:

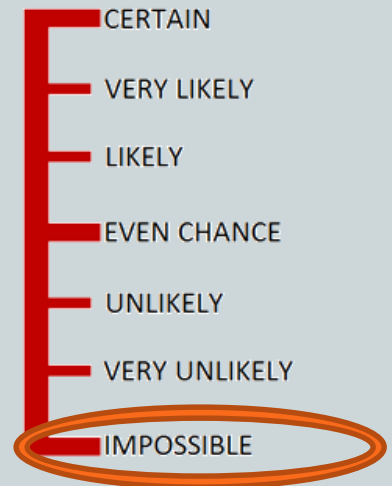
- (ADVP (NP (NNS finishes))))
- (NP (DT the) (NP (NNS finishes)))

- But they are very unlikely
- This is good news, right?

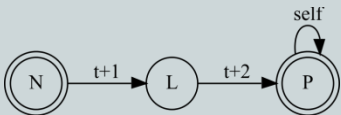


..parser will **never** choose them?

- ◎ The problem with ‘very unlikely’ in CFG is that it effectively means **never**
- ◎ Consider legitimate ambiguities:
 - PP attachment:
 - I [saw [the man with the telescope]]
 - I [saw [the man] [with the telescope]]
 - PCFG level view:
 - $VP > V\ NP$ 65%
 - $VP > V\ NP\ PP$ 35%



➤ Incapable of **ever** getting high attachment! ☹



Structural and lexical dependencies

- ◉ Which rules we apply depends on:
 - Lexical information (some verbs often have a high attached instrument and some prepositions mark these, e.g. *break X with Y*)
 - Non-terminal, structural context: pronoun NPs are much more likely as subjects than objects
- ◉ How can we get these into our grammar



Band-aid 1

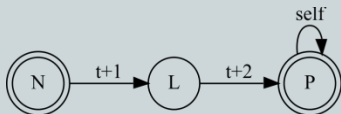
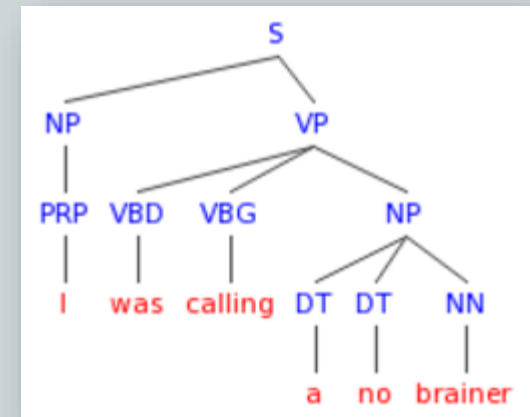
- We can annotate each internal node with its parent: (Johnson 1998)

(S

(NP (PRP I))

(VP (VBD was) (VBG calling)

(NP (DT a) (DT no) (NN brainer))))



Band-aid 1

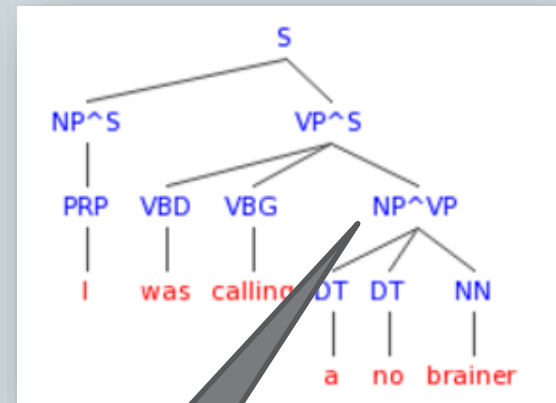
- We can annotate each internal node with its parent: (Johnson 1998)

(S

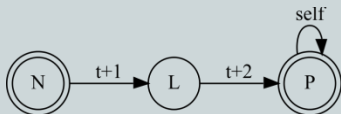
(NP^S (PRP I))

(VP^S (VBD was) (VBG calling)

(NP^VP (DT a) (DT no) (NN brainer))))



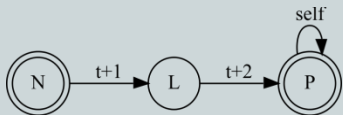
Parent Annotation



Pros and cons

⊙ Adding parent information effectively causes **label splitting**

- Leads to data sparseness: less examples of each label
 - Some splits are useful, others are harmful – how can we tell?
-
- Initial attempts at choosing the right cases to split required a lot of manual work
 - But paid off for English: 72% -> 86% accuracy (Klein & Manning 2003)



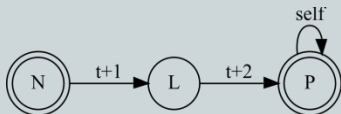
Why choose ourselves?

- ◎ Petrov et al. (2006) devised the **split and merge** algorithm
 - Automatically testing splitting of categories (88.4%)
 - Automatically merging categories (89.5%)
 - Best result with smoothing (90.2%)
 - State of the art into the 2010s, when neural networks and distributional semantics were added



Excursus: cognitive implications

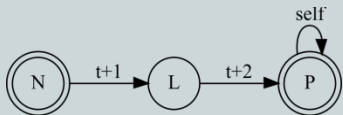
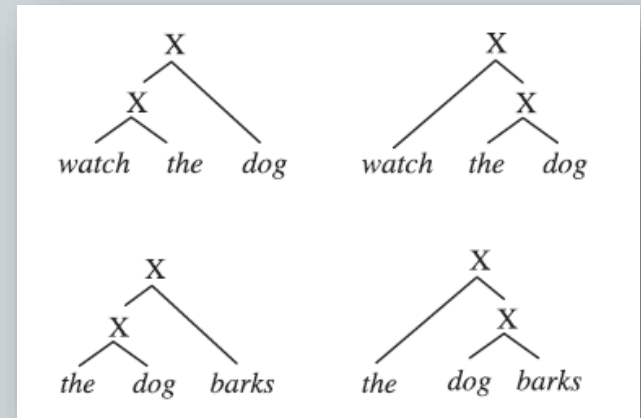
- ◎ It is very clear that we know more than CFGs
 - Lexicalized effects in processing, garden path sentences
 - Humans not bogged down by massive ambiguity options, unless lexical items collude with syntax
 - *I saw the man with the telescope*
 - *The cop chased the criminal with the fast car*



Excursus: cognitive implications

◉ What tree depths are we tracking?

- According to Bod (2009), allowing a language acquisition simulation to condition on **depth 4** trees is optimal
- Learning based on PTB and CHILDES (MacWhinney 2000)
- Computers reproduce children's errors! 😊



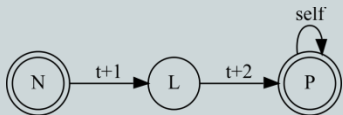
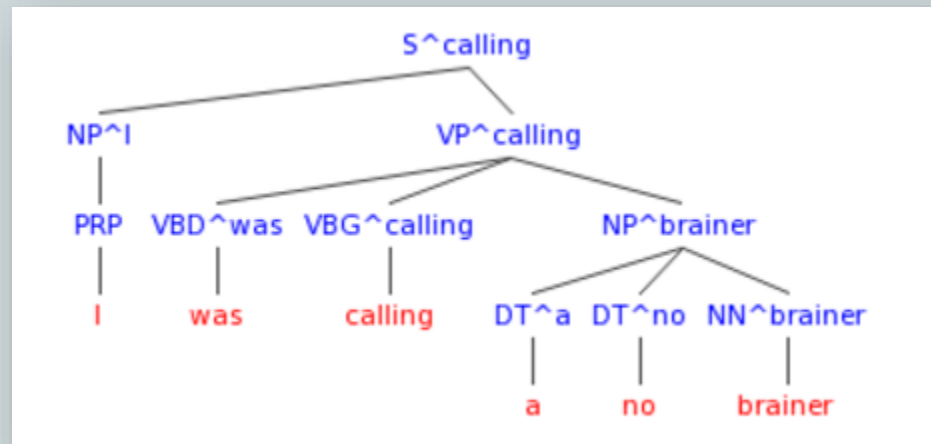
Band-aid 2

- ◉ Even label splitting doesn't help with **lexical** probabilities
 - Does it matter for PP attachment that the preposition is *with*?
 - Does it matter whether the verb is *chased* or *saw*?



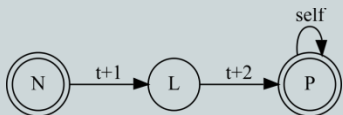
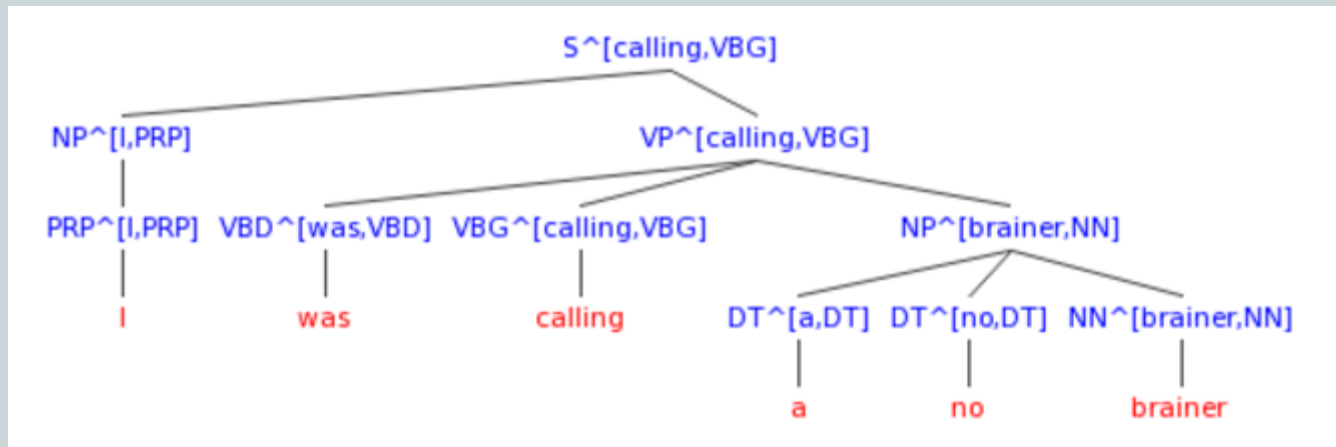
Lexicalized grammars

- An easy way to bring in lexical information is to annotate each node with its lexical head (**head percolation**)



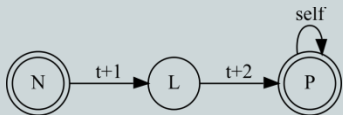
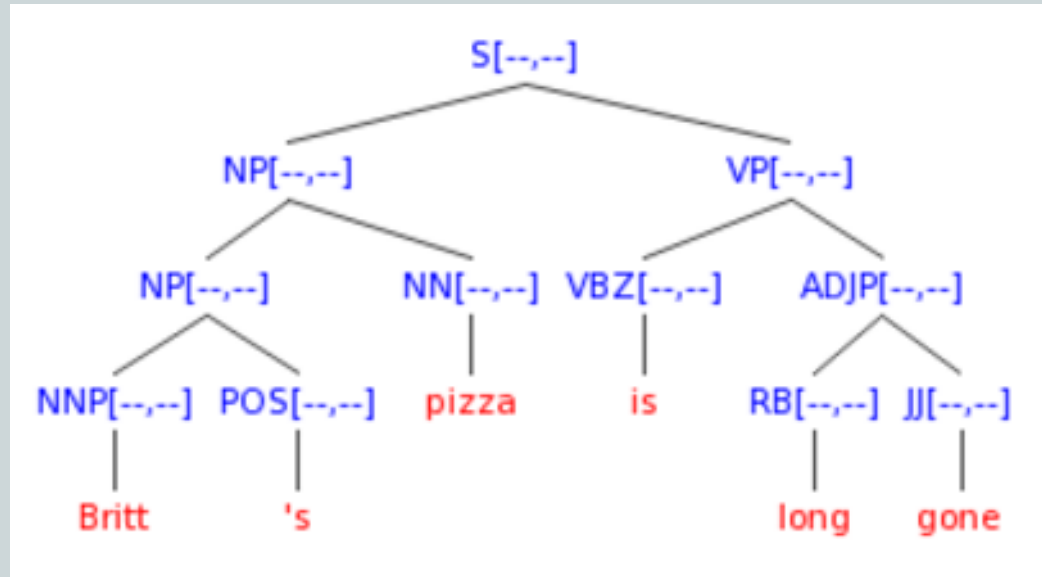
Lexicalized grammars

- In practice, most lexicalized parsers work on percolated head+POS annotation
- State of the art choice when data is limited/no large word embeddings available



Quick exercise

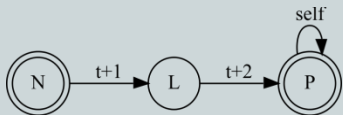
◉ What needs to percolate where?



Data sparseness

- ⊙ A major problem with the lexicalized approach is sparseness
- ⊙ We hardly get probabilities for rules like this:

VP[calling,VBG] > VBD[was,VBD] VBG[calling,VBG] NP[brainer,NN]



Generation probabilities

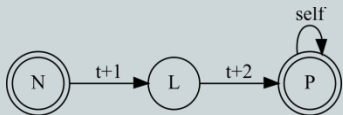
◎ Instead of considering the full rule:

- $VP[calling,VBG] > VBD[was,VBD] VBG[calling,VBG] NP[brainer,NN]$

◎ We can pretend that the head gets generated first:

- $VP[calling,VBG] > VBG[calling,VBG]$

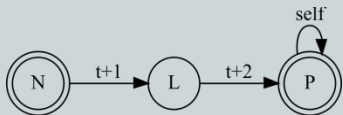
◎ This part is still trivial but...



Generation probabilities

◎ Imagine we now consider each additional RHS component separately:

- What is the chance that VBG[calling,VBG] has NP[brainer,NN] to the right?
- $P(\text{NP}[\text{brainer,NN}] \mid \text{VBG}[\text{calling,VBG}])$
- Maybe also not so common – but more so than an entire rule

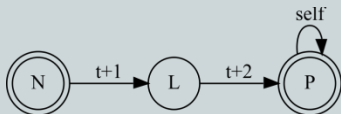


Generation probabilities

- ◉ We repeat this for all possible RHS members to the right of the head
- ◉ And do the same on the left

VP[calling,VBG] > VBG[calling,VBG]

VBD[was,VBD] ? \leftarrow VBG[calling,VBG] \rightarrow ? NP[brainer,NN]



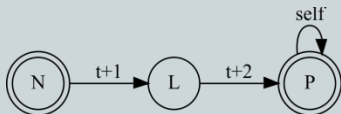
Generation probabilities

◉ What if there are two options?

- calling > was calling NP_{brainer}
- calling > was calling #

◉ We need to consider 'end of the line' as an item for probability estimation

- Add 'fake' RHS member "STOP"
- Estimate probability of stopping generation



Implementation: Collins Parser

- ◎ The Collins parser implements this approach:
 - Estimate probability for lexicalized decomposition rules
 - Separately calculate probability of adding potential RHS constituent until STOP symbol is generated



In Python

- ⦿ There are many parsers out there
- ⦿ Many developers use the **Stanford Parser**
 - Written in Java
 - A Python ‘wrapper’ exists
 - But you can really run any Java tool from your code!



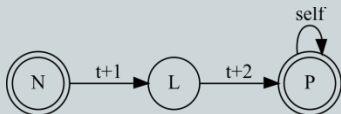
Calling the command line

```
import subprocess
```

```
command_params = ["java", "-mx2048m", "-cp" ,"*;",  
"edu.stanford.nlp.parser.lexparser.LexicalizedParser" ,...]
```

```
proc = subprocess.Popen(command_params)  
(stdout, stderr) = proc.communicate()
```

your parse is now in stdout



In Python

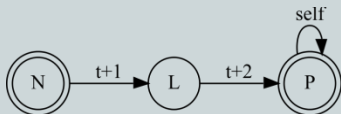
◎ Another option is spacy

- pip install spacy
- python -m spacy.en.download (takes long!)

◎ See <https://spacy.io/> for a tutorial!

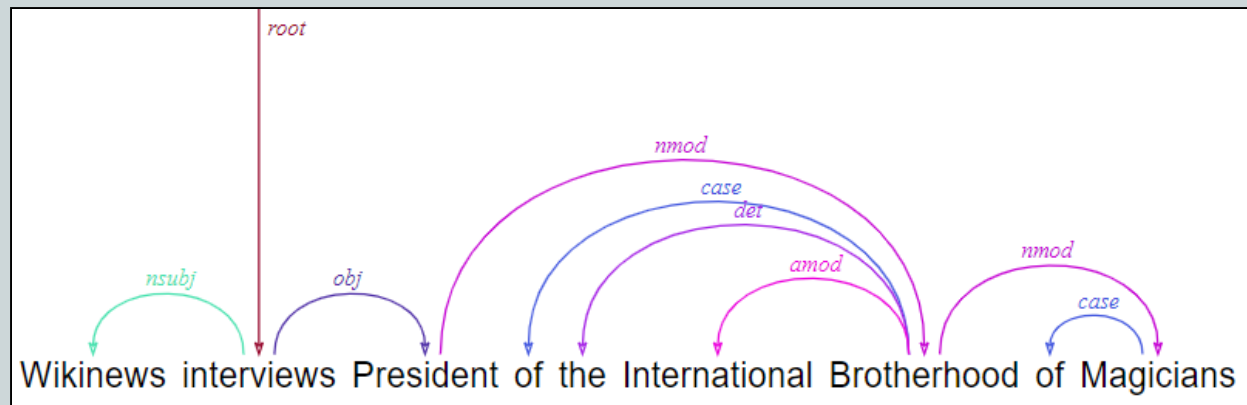
◎ For latest SOTA constituent parsers (not user friendly):

- http://nlpprogress.com/english/constituency_parsing.html



In Python

- And many applications use **dependency parses** either instead of or in tandem with constituents



- Not covered in this course -> see LING-367 and more advanced classes

