

LING/C SC/PSYC 438/538

Lecture 29

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Gentle Reminder

- Please fill out the class survey!

Today's Topics

- 538 Presentations contd.
- Homework 14 Review

Homework 14 Review

- g26.prolog:

1. dt(dt(a)) --> [a].
2. dt(dt(the)) --> [the].
3. vbd(vbd(see+ed)) --> [saw].
4. nn(nn(Noun)) --> [Noun]
, {member(Noun, [man, boy, telescope])}.
5. in(in(with)) --> [with].
6. np(np(DT, NN)) --> dt(DT), nn(NN).
7. pp(pp(IN, NP)) --> in(IN), np(NP).
8. vp(vp(VBD, NP, PP)) --> vbd(VBD),
np(NP), pp(PP).
9. s(s(NP, VP)) --> np(NP), vp(VP).

- Important to know:

- Prepositional Phrase (PP) is an adjunct
- Adjuncts are optional
- the boy saw the man (with a telescope)
- rule #8 has counterpart without PP:
- vp(vp(VBD, NP)) --> vbd(VBD), np(NP).

- Example:

```
swipl
```

```
?- [hw14].
```

```
true.
```

```
?- s(Parse, [the, boy, saw, the, man], []).
```

```
Parse = s(np(dt(the), nn(boy)), vp(vbd(see+ed),  
np(dt(the), nn(man)))) ;
```

```
false.
```

Homework 14 Review

- hw14.prolog:

1. `dt(dt(a)) --> [a].`
2. `dt(dt(the)) --> [the].`
3. `vbd(vbd(see+ed)) --> [saw].`
4. `nn(nn(Noun)) --> [Noun
, {member(Noun, [man, boy, telescope])}].`
5. `in(in(with)) --> [with].`
6. `np(np(DT, NN)) --> dt(DT), nn(NN).`
7. `np(np(DT, NN, PP)) --> dt(DT), nn(NN), pp(PP).`
8. `pp(pp(IN, NP)) --> in(IN), np(NP).`
9. `vp(vp(VBD, NP)) --> vbd(VBD), np(NP).`
10. `vp(vp(VBD, NP, PP)) --> vbd(VBD), np(NP), pp(PP).`
11. `s(s(NP, VP)) --> np(NP), vp(VP).`

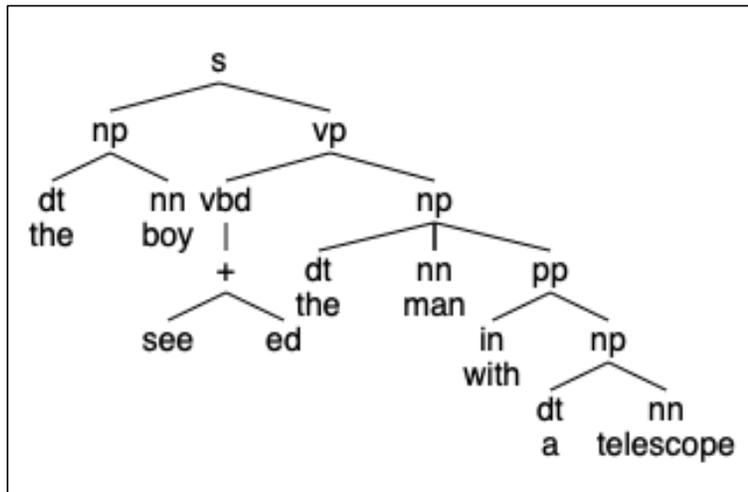
- **Important to know:**

- rule #6 has counterpart **with** a PP, rule #7:
- `np(np(DT, NN, PP)) --> dt(DT),
nn(NN), pp(PP).`

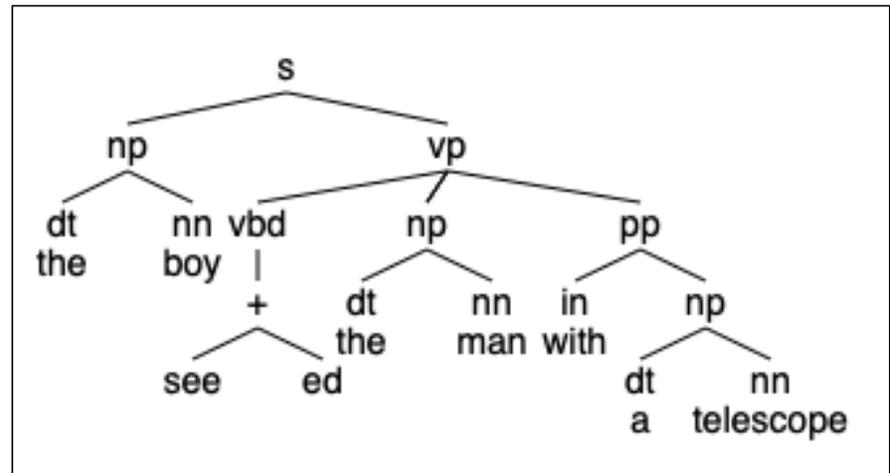
Homework 14 Review

- Example:
- ?–
s(Parse, [the, boy, saw, the, man, with, a, telescope], [])
▪
- Parse = s(np(dt(the), nn(boy)), vp(vbd(see+ed), np(dt(the), nn(man), pp(in(with), np(dt(a), nn(telescope)))))) ;
- Parse = s(np(dt(the), nn(boy)), vp(vbd(see+ed), np(dt(the), nn(man)), pp(in(with), np(dt(a), nn(telescope)))))) ;
- **false.**

Homework 14 Review



```
s(np(dt(the), nn(boy)),
  vp(vbd(see+ed), np(dt(the),
    nn(man), pp(in(with), np(dt(a),
      nn(telescope))))))
```



```
s(np(dt(the), nn(boy)),
  vp(vbd(see+ed), np(dt(the),
    nn(man)), pp(in(with), np(dt(a),
      nn(telescope)))))
```

Homework 14 Review

- Is ChatGPT right about this?
- No.
 - *with* (instrument) modifies VP
 - *with* (possession) modifies NP

 **You**
a boy saw the man with a telescope. Is this sentence ambiguous?

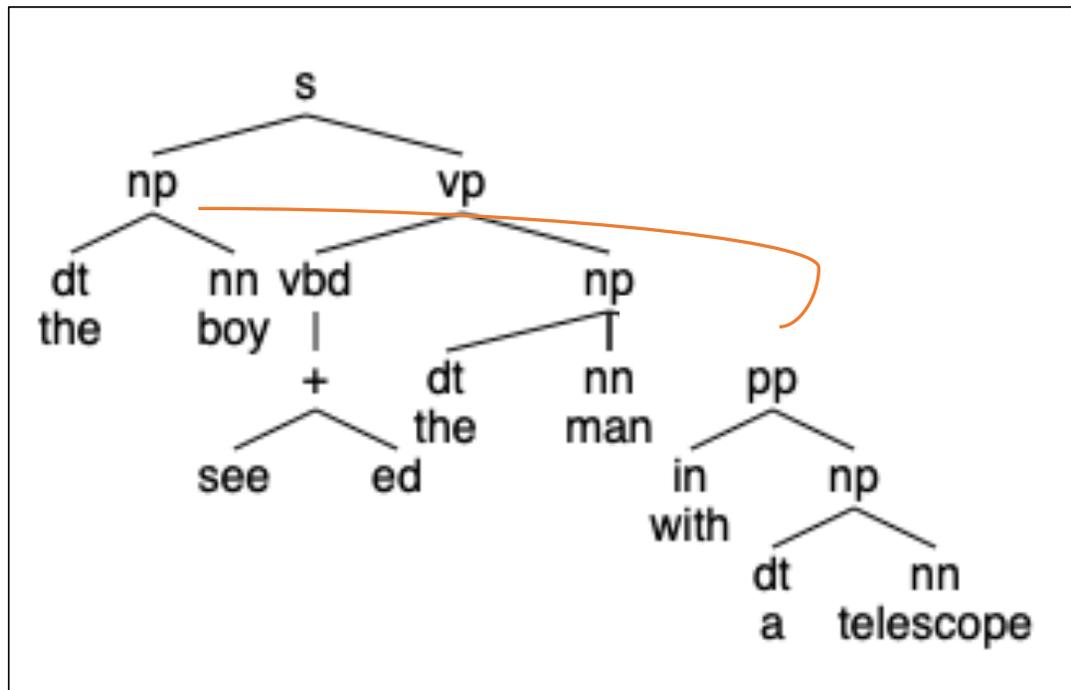
 **ChatGPT**
Yes, the sentence "A boy saw the man with a telescope" is ambiguous because it could be interpreted in two different ways:

1. The boy saw a man who had a telescope.
2. The boy, who had a telescope, saw a man.

In the first interpretation, the man is the one with the telescope, and in the second interpretation, the boy is the one with the telescope. The placement of the prepositional phrase "with a telescope" creates this ambiguity.

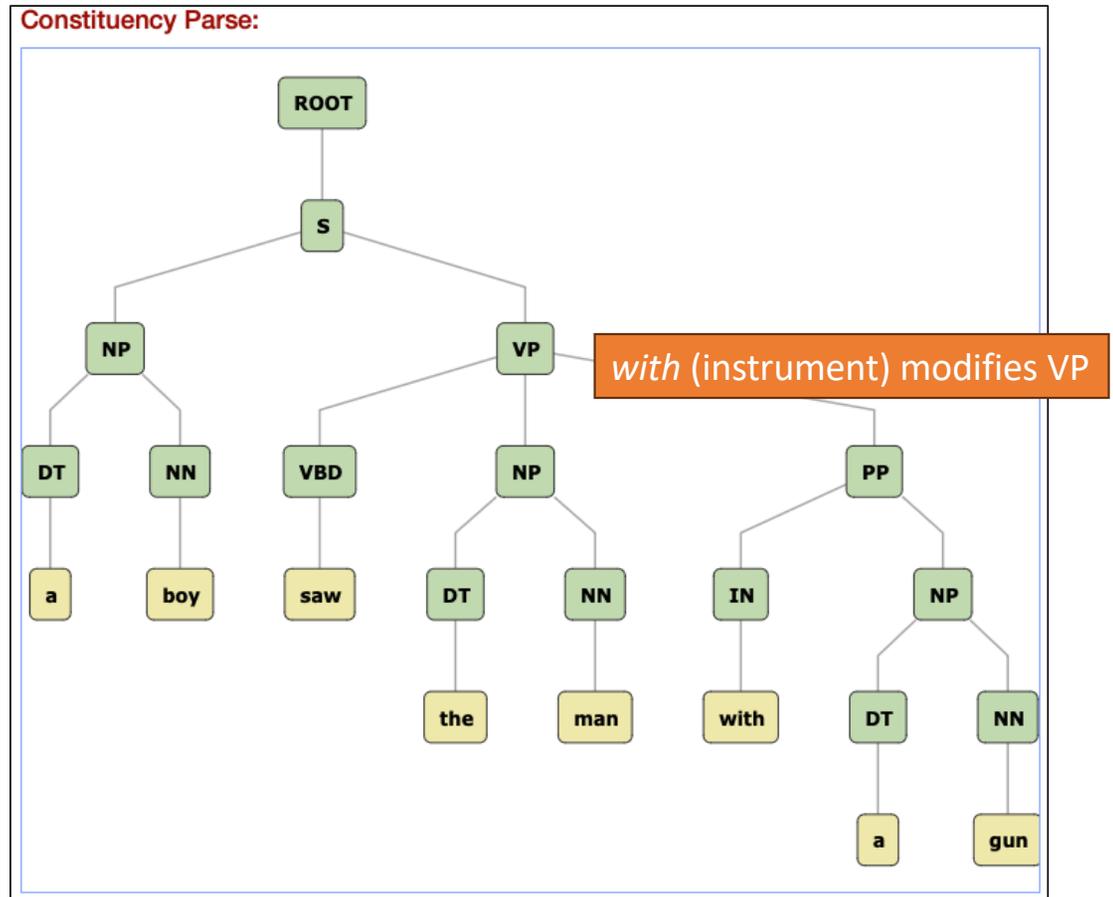
   

Homework 14 Review



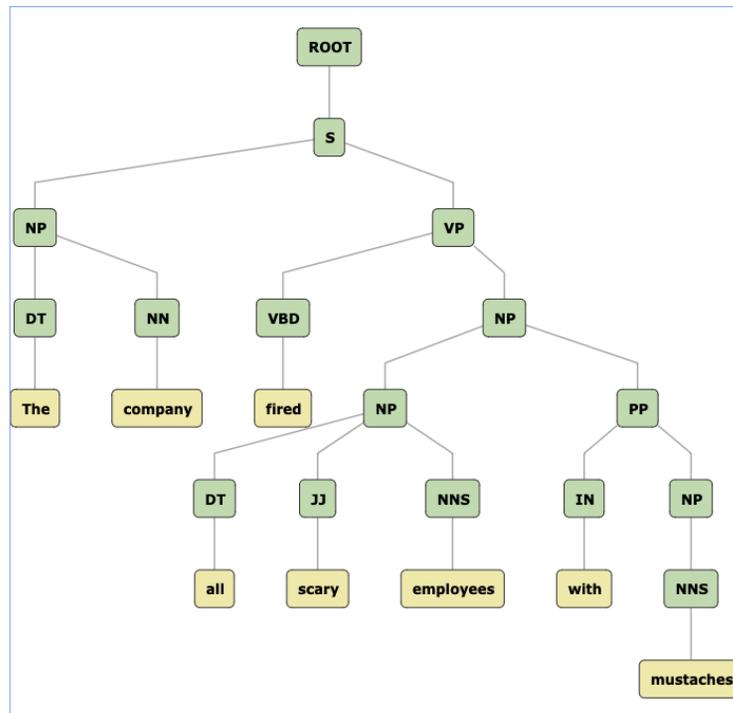
Not possible!
tree structure
would have
crossing

Homework 14 Review



Homework 14 Review

Constituency Parse:



 Stanza 1.6.0 (updated October 2023)

– Text to annotate –

The company fired all scary employees with mustaches

– Annotations –

parts-of-speech × named entities × lemmas × constituency parse ×

Part-of-Speech (XPOS):

DT NN VBD DT JJ NNS IN NNS
1 The company fired all scary employees with mustaches

Lemmas:

the company fire all scary employee with mustach
1 The company fired all scary employees with mustaches

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