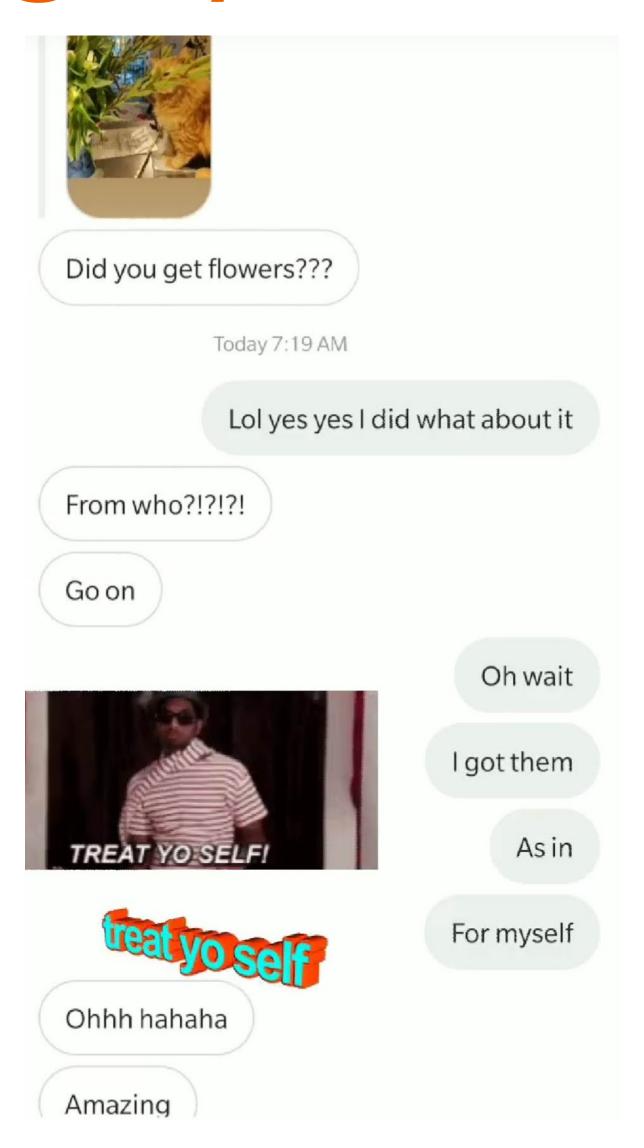
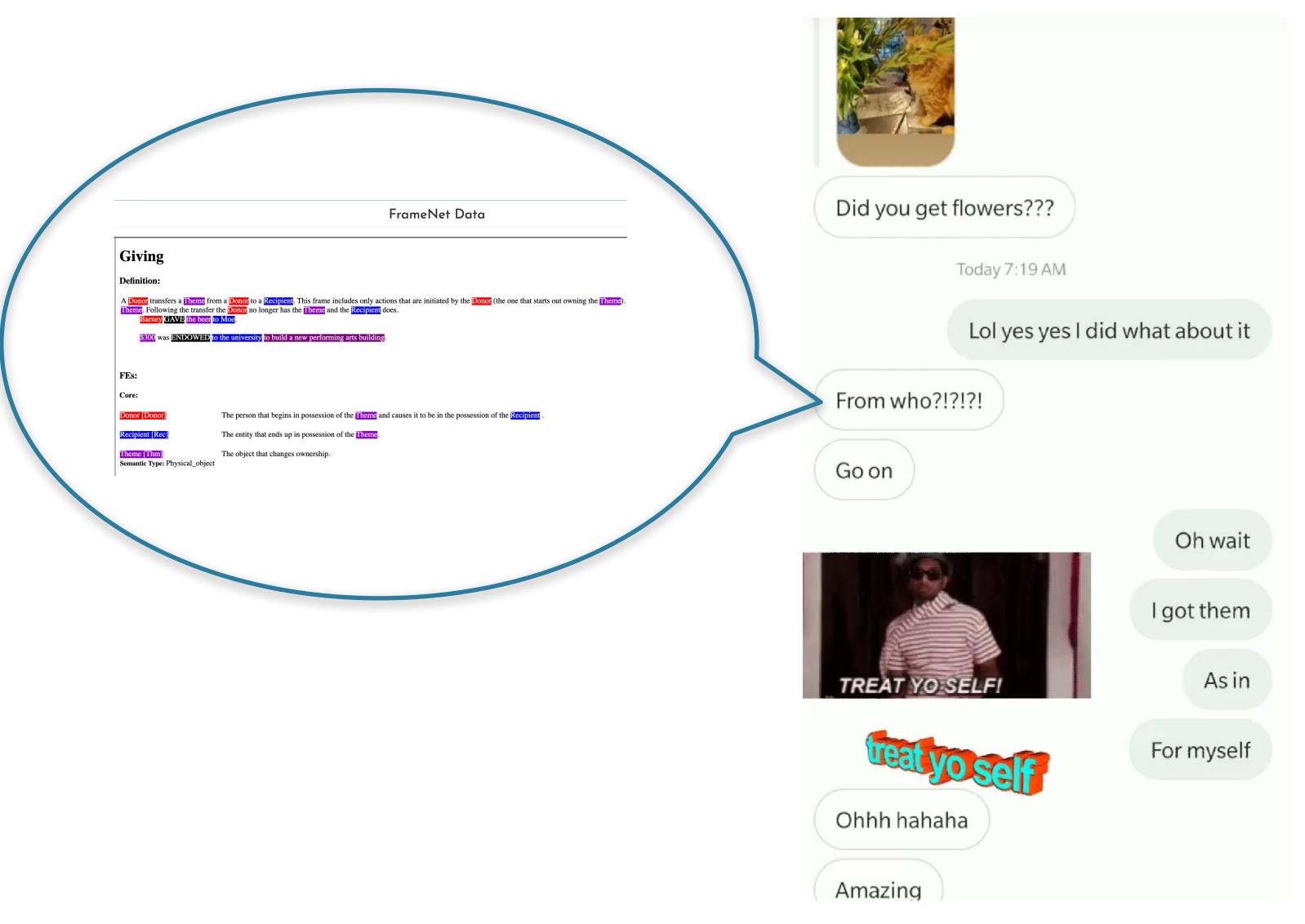
Discourse and Coreference

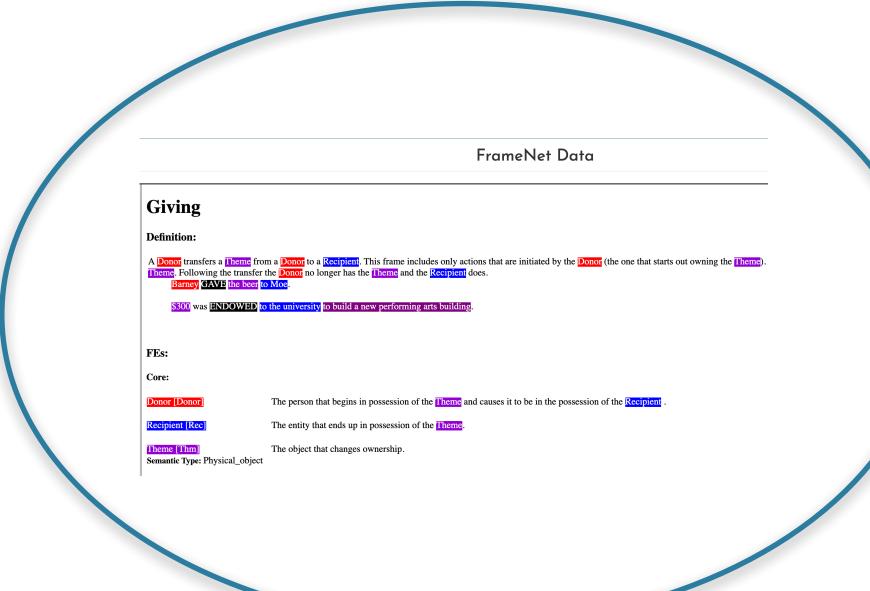
LING 571 — Deep Processing Methods in NLP Shane Steinert-Threlkeld

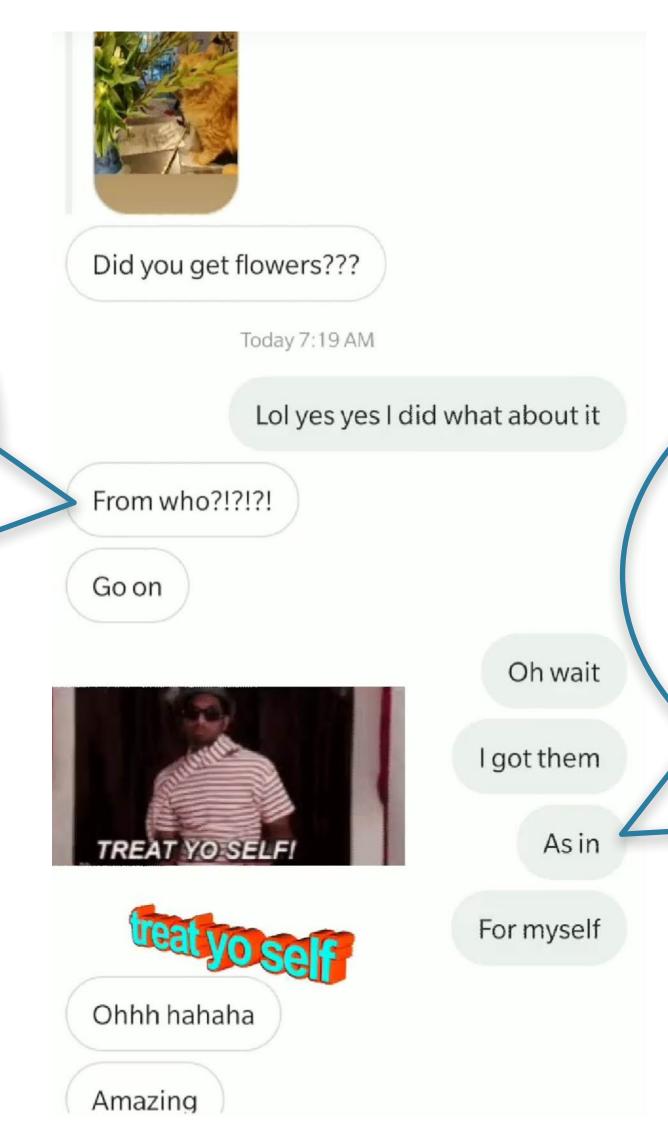
Announcements

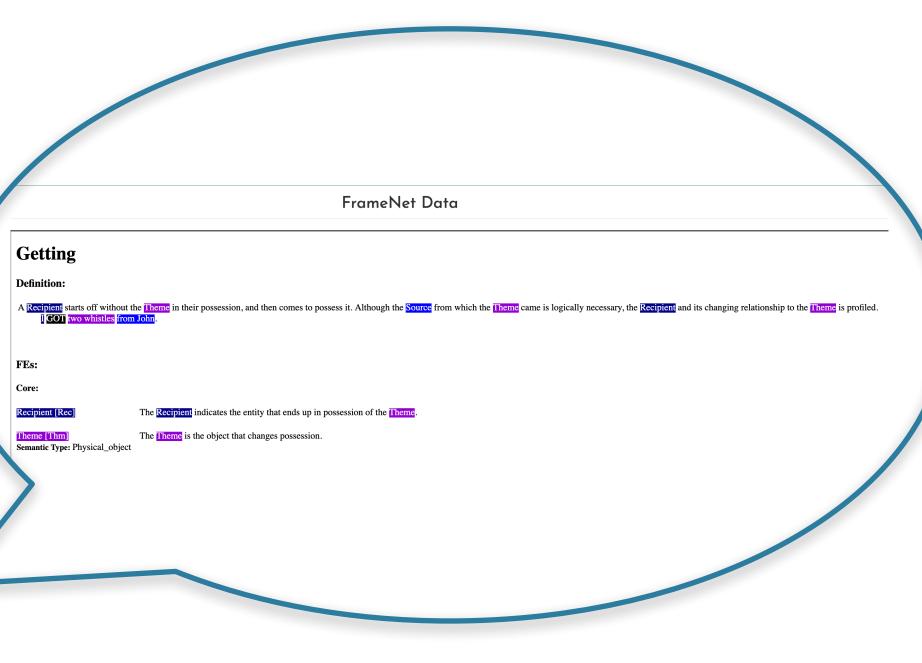
- No class next Wednesday (Nov 27)
- HW9 (last of the quarter (2):):
 - Due December 4
 - Content mostly covered on Monday











Roadmap

- Introduction to Discourse
- Coreference Resolution
 - Phenomena
 - Pronominal Anaphora Resolution
 - Hobbs' Algorithm

Introduction to Discourse

What is Discourse?

 Discourse is "a coherent structured group of sentences." (J&M p. *681)*

What is Discourse?

 Discourse is "a coherent structured group of sentences." (J&M p. 681)

- Discourse is language in situ
 - rather than synthetic, isolated sentences.
 - language use toward a goal

Different Parameters of Discourse

- Number of participants
 - Single author/voice → Monologue
 - Multiple participants → Dialogue

Different Parameters of Discourse

- Number of participants
 - Single author/voice → Monologue
 - Multiple participants → Dialogue
- Modality
 - Spoken vs. Written

Different Parameters of Discourse

Number of participants

- Single author/voice → Monologue
- Multiple participants → Dialogue

Modality

Spoken vs. Written

Goals

- Transactional (message passing) vs. Interactional (relations, attitudes)
- Cooperative task-oriented rational interaction

Understanding depends on context

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 - Word sense plant

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 - Intention Do you have the time?

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 - Referring expressions *it, that, the screen*

- Understanding depends on context
 - Word sense plant
 - Intention Do you have the time?
 - Referring expressions *it, that, the screen*
 - Domain restriction "All of the students read the announcement."

- Applications: Discourse in NLP
 - Question-Answering
 - Information Retrieval
 - Summarization
 - Dialogue / Conversational Al
 - Automatic Essay Grading

User: Where is A Bug's Life playing in Summit?

A Bug's Life is playing at the Summit Theater. System:

When is it playing there? User:

It's playing at 2PM, 5PM, and 8PM. System:

- Knowledge sources:
 - Domain Knowledge

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A Bug's Life is playing at the Summit Theater. System:

User: When is it playing there?

It's playing at 2PM, 5PM, and 8PM. System:

- Knowledge sources:
 - Domain Knowledge
 - Discourse Knowledge
 - World Knowledge

Where is A Bug's Life playing in Summit? User:

A Bug's Life is playing at the Summit Theater. System:

User: When is it playing there?

System: It's playing at 2PM, 5PM, and 8PM.

Not All Sentences Are Created Equal

• First Union Corp. is continuing to wrestle with severe problems.^[1] According to industry insiders at PW, their president, John R. Georgius, is planning to announce his retirement tomorrow.^[2]

Not All Sentences Are Created Equal

- First Union Corp. is continuing to wrestle with severe problems.^[1] According to industry insiders at PW, their president, John R. Georgius, is planning to announce his retirement tomorrow.^[2]
- Summary:
 - First Union President John R. Georgius is planning to announce his retirement tomorrow.

Not All Sentences Are Created Equal

- First Union Corp. is continuing to wrestle with severe problems.^[1] According to industry insiders at PW, their president, John R. Georgius, is planning to announce his retirement tomorrow.^[2]
- Summary:
 - First Union President John R. Georgius is planning to announce his retirement tomorrow.
- Inter-sentence coherence relations:
 - Second sentence: main concept (nucleus)
 - First sentence: background

John hid Bill's car keys. He was drunk.

John hid Bill's car keys. He was drunk. John hid Bill's car keys. He likes spinach

Why is this odd?

- Why is this odd?
 - No obvious relation between sentences

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 - statement explanation/cause

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 - Breaks our assumption as readers that information presented in discourse is relevant
- How is the first pair related?
 - statement explanation/cause
- Assumption: utterances should have meaningful connection
 - Establish through coherence relations

John hid Bill's car keys. He was drunk. John hid Bill's car keys. He likes spiech.

Assumption

- Segments of discourse should have meaningful connection.
- Establish through coherence relations

Discourse: Looking Ahead

Discourse: Looking Ahead

Coreference

Discourse: Looking Ahead

Coreference

Cohesion

Discourse: Looking Ahead

Coreference

Cohesion

Coherence

Discourse: Looking Ahead

Coreference

Cohesion

Coherence

Structure / Segmentation

Coreference Resolution

• referring expression: (refexp)

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 - An expression that picks out entity (*referent*) in some knowledge model

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 - Logue, a renowned speech therapist

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 - An expression that picks out entity (*referent*) in some knowledge model
 - Referring expressions used for the same entity corefer
 - Queen Elizabeth, her, the Queen
 - Logue, a renowned speech therapist
 - Entities in purple do not corefer to anything.

• Antecedent:

- An expression that introduces an item to the discourse for other items to refer back to
- Queen Elizabeth... her

- *Anaphora*: An expression that refers back to a previously introduced entity.
 - cataphora: Introduction of expression before referent:
 - "Even before she saw it, Dorothy had been thinking about..."

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*Not all anaphora is referential! e.g. "No dancer hurt their knee."

- Many forms:
 - Queen Elizabeth
 - she/her
 - the Queen
 - HRM
 - the British Monarch

Queen Elizabeth – she/her – the Queen – HRM – the British Monarch

"Correct" form depends on discourse context

Queen Elizabeth – she/her – the Queen – HRM – the British Monarch

- "Correct" form depends on discourse context
 - she, her presume prior mention or presence in the world

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 - the Queen presumes an Anglocentric geopolitical discourse context generally or the UK (or British Commonwealth) specifically

Queen Elizabeth – she/her – the Queen – HRM – the British Monarch

- "Correct" form depends on discourse context
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(...i.e. likely a different interpretation during a RPDR viewing party.)

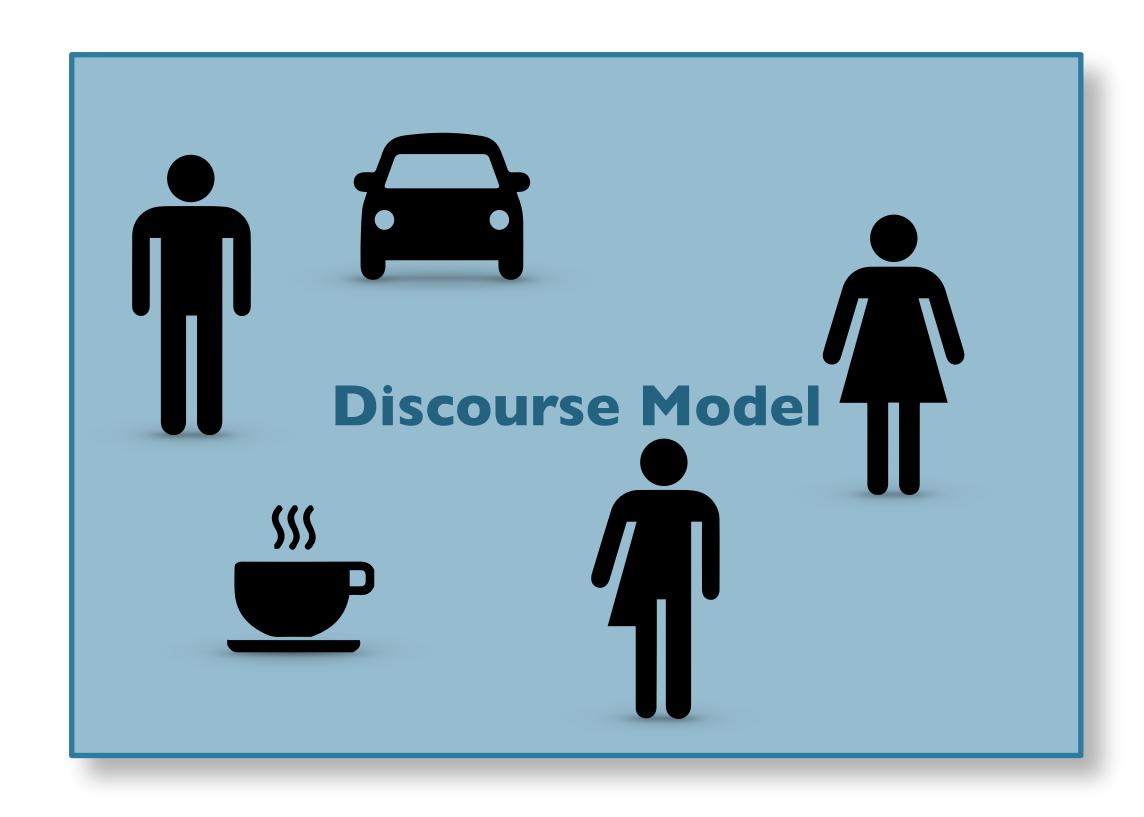
- Correct interpretation of reference requires Discourse Model
 - Entities referred to in the discourse
 - Relationships of these entities

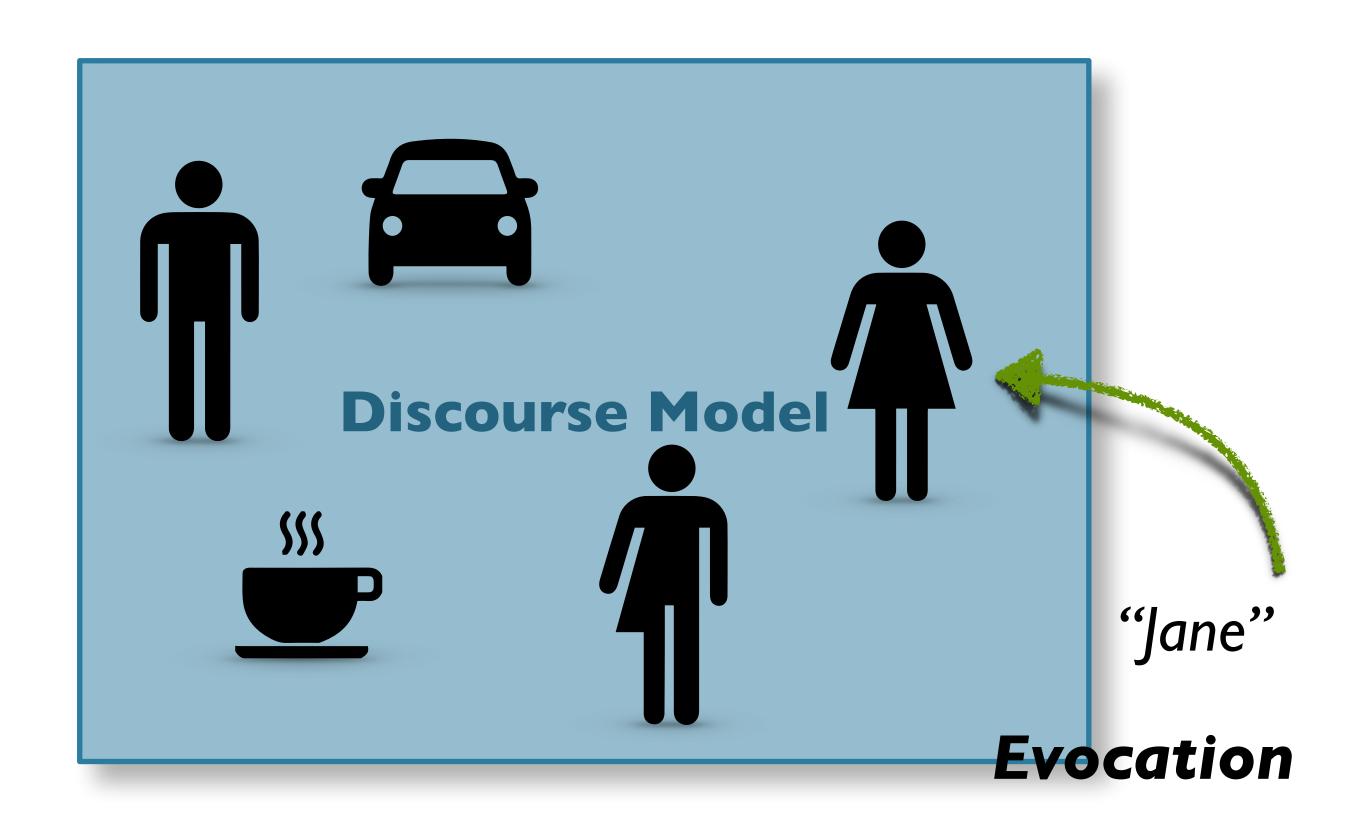
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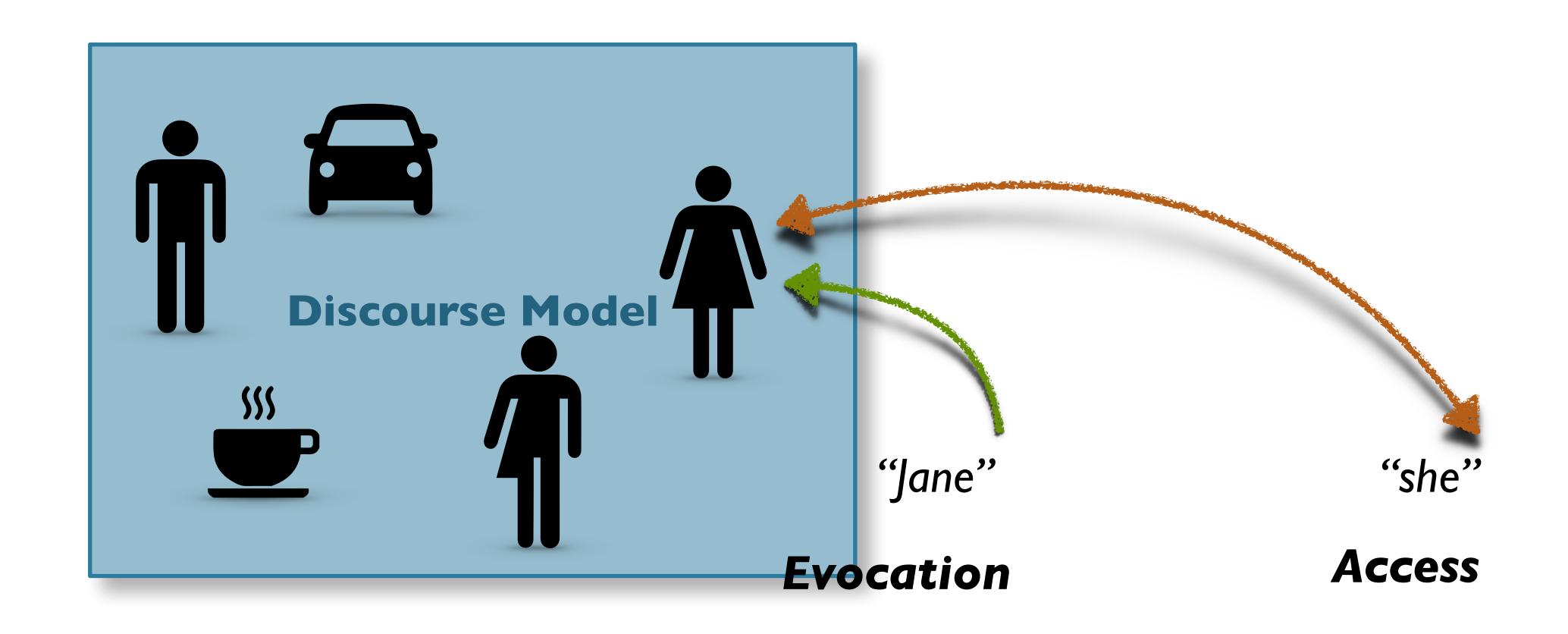
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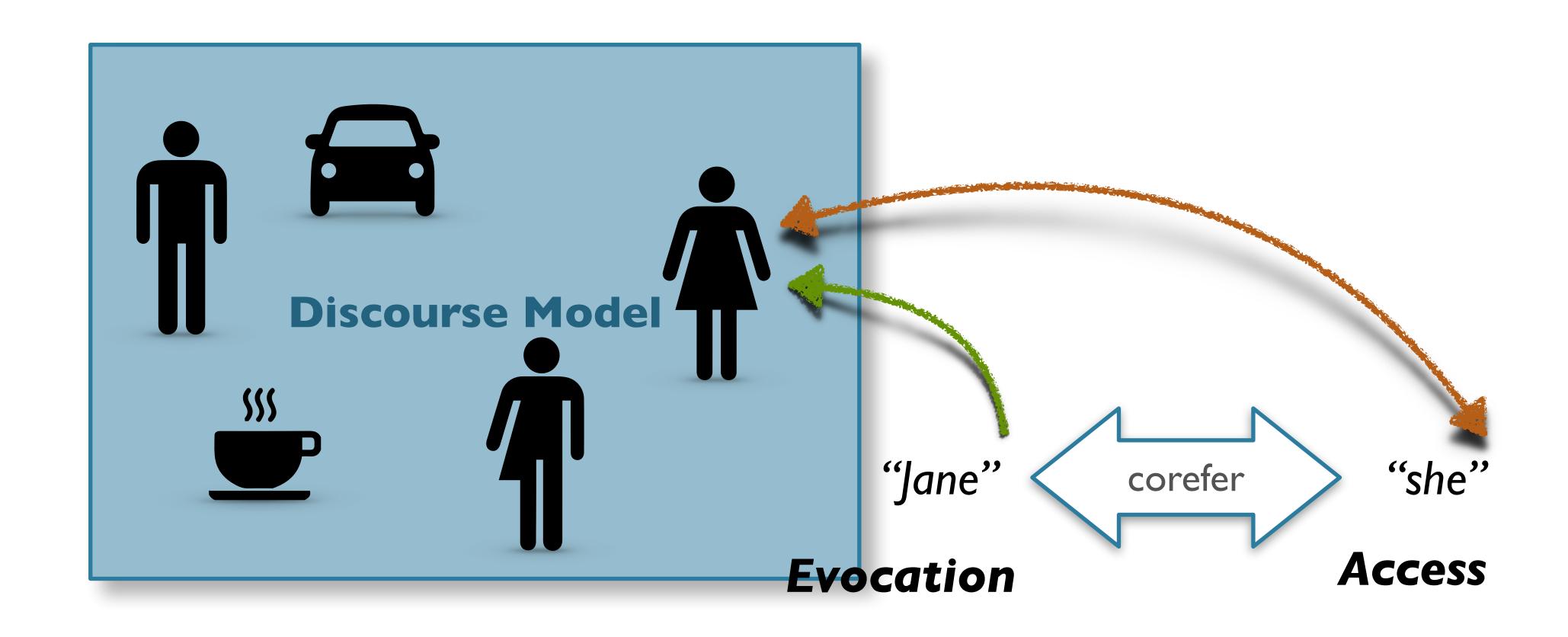
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 - Entities referred to in the discourse
 - Relationships of these entities
- Need way to construct, update model
 - First mention of entity evokes entity into model
 - ["introduces a discourse referent (dref)"]
 - Subsequent mentions access entity from the model.









Reference Tasks

Coreference resolution:

- Find all expressions referring to the same entity in a text.
- A set of coreferring expressions is a coreference chain.

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Pronominal anaphora resolution:

- Find antecedent for a single pronoun.
- Subtask of coreference resolution

Pronominal Anaphora Resolution

Reference Phenomena

Expression Type	Examples	Constraints
Indefinite NP	"a cat", "some geese"	Introduces new entity to context
Definite NP	"the dog"	Refers to entity identifiable by hearer in context
Pronouns	"he," "them," "they"	Refers to entity, must be "salient"
Demonstratives	"this," "that"	Refers to entity, sense of distance (literal/figurative)
Names	"Dr. Woodhouse," "IBM"	New or old entities

Reference Phenomena: Activation/Salience

a) John went to Erin's party, and parked next to a classic Ford Falcon.

Reference Phenomena: Activation/Salience

- a) John went to Erin's party, and parked next to a classic Ford Falcon.
- b) He went inside and talked to Erin for more than an hour.

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- d) ?? She also said that she bought it yesterday.
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- d) is problematic because the Falcon has lost its salience.
- e) is acceptable because the definite NP has a further range for salience.

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```
in focus >
it
```

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```
in focus > activated >
it
           this
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           this N
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```
in focus > activated >
                     familiar >
         this
                     that N
it
         that
         this N
```

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```
uniquely
in focus > activated > familiar > identifiable >
                    that N the N
it
         this
         that
         this N
```

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```
uniquely
in focus > activated > familiar > identifiable > referential >
                    that N the N indef. this N
it
         this
         that
         this N
```

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```
uniquely
                                                        type
in focus > activated > familiar > identifiable > referential > identifiable
                    that N the N indef. this N a N
it
         this
         that
         this N
```

- Accessibility scale: (Ariel, 2001)
 - More salient elements easier to call up, can be shorter
 - correlates with length: more accessible, shorter refexp

```
Full name+modifier
             ↓full name
     ↓long definite description
    $\prec$short definite description
            ↓last name
            ↓first name
  $\distal demonstrative+modifier
↓ proximate demonstrative+modifier
     $\distal demonstrative+NP$
  ↓proximate demonstrative+NP
    ↓distal demonstrative(-NP)
 ↓proximate demonstrative (-NP)
    $\draw{\text{stressed pronoun+gesture}}$
        ↓stressed pronoun
       ↓unstressed pronoun
        ↓cliticized pronoun
     ↓verbal person inflections
```

Complicating Factors

Inferrables

- refexp refers to inferentially related entity:
- I bought a car today, but a door had a dent, and the engine was noisy.
 - a door, the engine ∈ a car

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- I want to buy a Jaguar. They are very stylish.
- General group evoked by instance.

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 - a door, the engine ∈ a car

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- I want to buy a Jaguar. They are very stylish.
- General group evoked by instance.

Non-referential cases:

- It's raining. (Pleonasm)
- It was good that Frodo carried the ring. (Extraposition)

- Number:
 - Anjali has a Corvette. It is red. *They are red.

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- Person:
 - 2nd: you, y'all • 1st: *I, we* 3rd: he, she, it, they

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 - Anjali has a Corvette. *They are red. It is red.
- Person:
 - 2nd: you, y'all • 1st: /, we 3rd: he, she, it, they
- Gender:
 - Janae plays the guitar. She sounds great.
 - Janae plays the guitar. It sounds great.

- How to handle reflexive pronouns vs. nonreflexives
 - Aaron bought themself a new car.

Binding Theory

- How to handle reflexive pronouns vs. nonreflexives
 - Aaron bought themself a new car.
 - Aaron bought them a new car.

[them # Aaron]

- How to handle reflexive pronouns vs. nonreflexives
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 - Aaron bought them a new car. [them # Aaron]
 - Jen said that Imani bought herself a new car. [herself = Imani]

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 - Jen said that Imani bought her a new car. [her ≠ Imani]
 - He₁ said that he₂ bought Willie a new car. [He₁ ≠ Willie, he₂ ≠ Willie]
- Pronoun/Def. NP: can't corefer with subject of clause
 - Reflexives do corefer with subject of containing clause

Recency:

- Prefer closer antecedents.
- The doctor found an old map in the captain's chest. Jim found an even older map on the shelf. It described an island.

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• Grammatical role:

- Saliency hierarchy of roles
- e.g. Subj > Object > Ind. Object > Oblique > AdvP
 - Billy Bones went to the bar with Jim Hawkins.
 - Jim Hawkins went to the bar with Billy Bones.

He called for a glass of rum.

He called for a glass of rum.

Repeated Mention:

- Once entity is focused, likely to continue to be focused → more likely pronomialized.
 - Billy Bones had been thinking of a glass of rum. He hobbled over to the bar. Jim Hawkins went with him. He called for a glass of rum.

Repeated Mention:

- Once entity is focused, likely to continue to be focused → more likely pronomialized.
 - Billy Bones had been thinking of a glass of rum. He hobbled over to the bar. Jim Hawkins went with him. He called for a glass of rum.

• Parallelism:

- Prefer entity in same role.
- Silver went with Jim to the bar. Billy Bones went with him to the inn.

Verb Semantics

Some verbs semantically bias for one of their argument positions.

```
John telephoned Bill. He had lost the laptop.
```

John criticized Bill. He had lost the laptop.

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```
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John criticized Bill. He had lost the laptop.
```

Selectional Restrictions

- Other kinds of semantic knowledge
 - John parked his car in the garage after driving it around for hours.
 - Understood that a car has the ability to *drive* whereas garage does not.

Reference Resolution Approaches

- Common features:
 - Use of a "Discourse Model"
 - Referents evoked in discourse, available for reference
 - Structure indicating relative salience
 - Syntactic & Semantic Constraints
 - Syntactic & Semantic Preferences
- Differences:
 - Which constraints/preferences? How to combine? Rank?

Hobbs' Algorithm

Hobbs' Resolution Algorithm

• Requires:

- Syntactic parser
- Gender & number checker

• Input:

- Pronoun
- Parse of current and previous sentences

• Captures:

- Preferences: Recency, grammatical role
- Constraints: binding theory, gender, person, number

Hobbs Algorithm

- Summary:
 - English-centric, rule-based algorithm.
 - Exploits English features of:
 - Agreement
 - Right-branching
 - SVO order
 - Inter-sententially, exploits notions of recency.

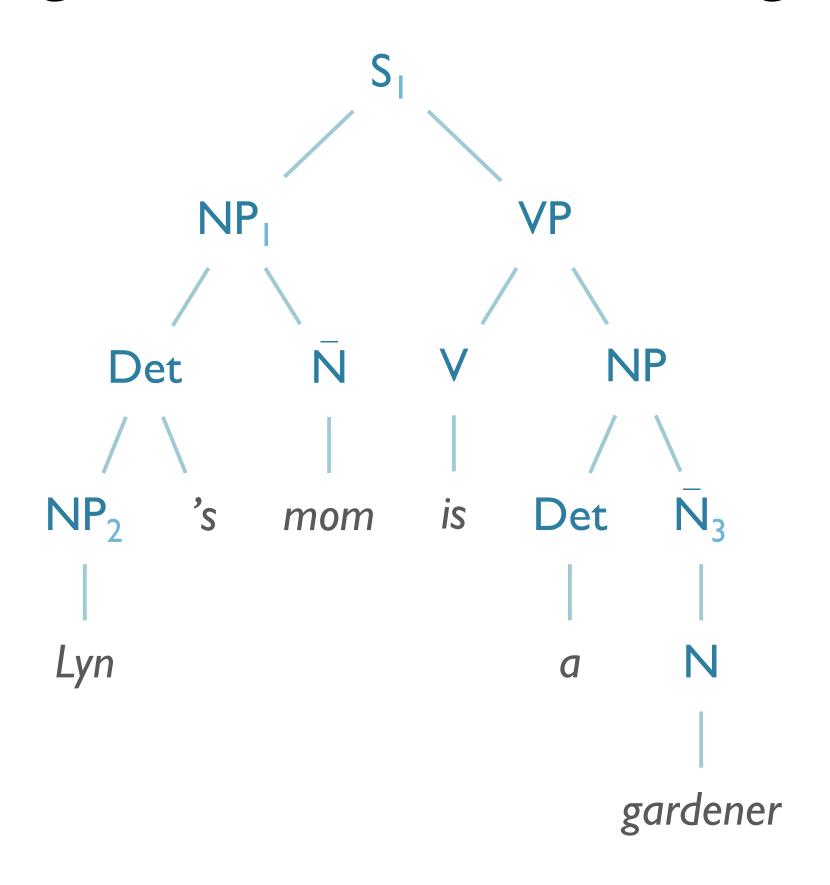
Hobbs Algorithm Detail (Hobbs, 1978)

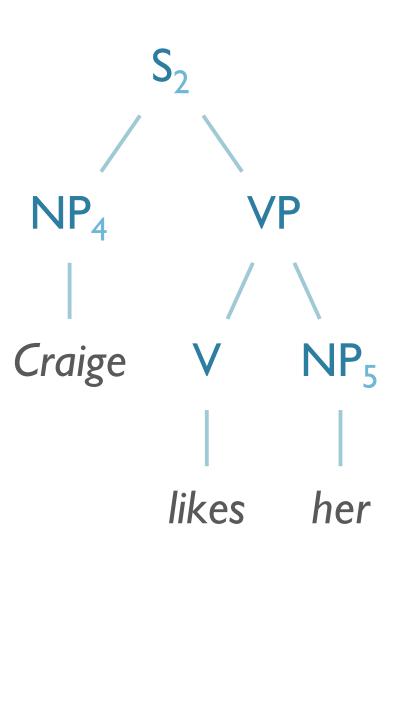
- 1. Begin at the noun phrase (NP) node immediately dominating the pronoun
- 2. Go up the tree to the first NP or sentence (S) node encountered. Call this node **X**, and call the path used to reach it *p*.
- 3. Traverse all branches below node \mathbf{X} to the left of path p in a left-to-right, breadth-first fashion. Propose as the antecedent any encountered NP node that has an NP or S node between it and \mathbf{X} .
- 4. If node **X** is the highest S node in the sentence, traverse the surface parse trees of previous sentences in the text in order of recency, the most recent first; each tree is traversed in a left-to-right, breadth-first manner, and when an NP node is encountered, it is proposed as antecedent. If X is not the highest S node in the sentence, continue to step 5.

Hobbs Algorithm Detail (Hobbs, 1978)

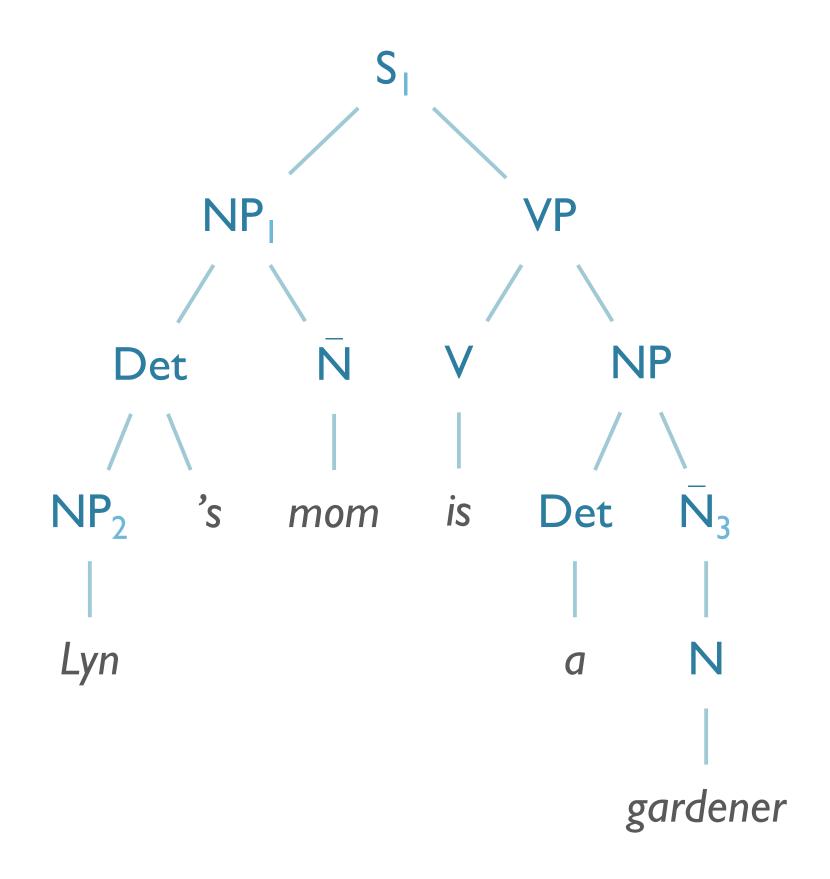
- 5. From node **X**, go up the tree to the first NP or S node encountered. Call this new node **X**, and call the path traversed to reach it *p*.
- 6. If **X** is an NP node and if the path *p* to **X** did not pass through the Nominal node that **X** immediately dominates, propose **X** as the antecedent.
- 7. Traverse all branches below node **X** to the *left* of path *p* in a left-to-right, breadth-first manner. Propose any NP node encountered as the antecedent.
- 8. If **X** is an S node, traverse all branches of node **X** to the *right* of path *p* in a left-to-right, breadth-first manner, but do not go below any NP or S node encountered. Propose any NP node encountered as the antecedent.
- 9. Go to step 4.

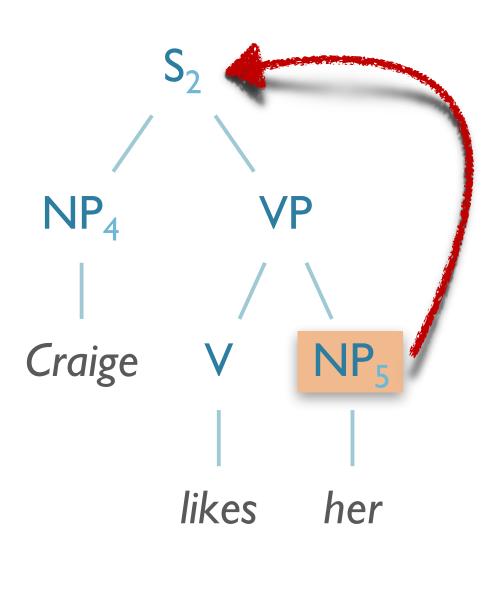
Lyn's mom is a gardener.



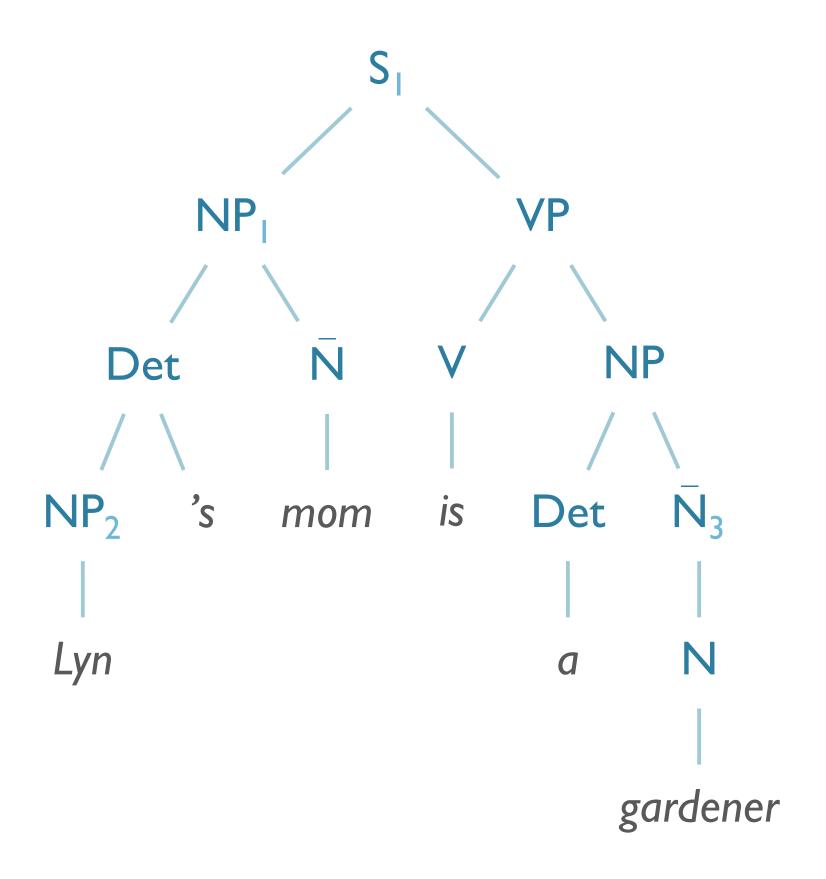


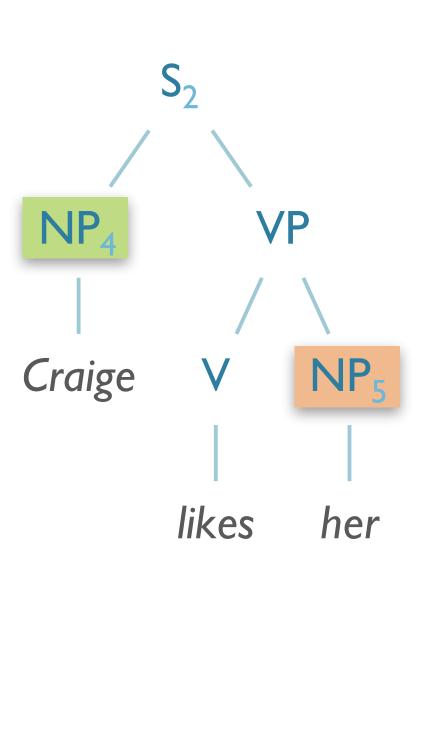
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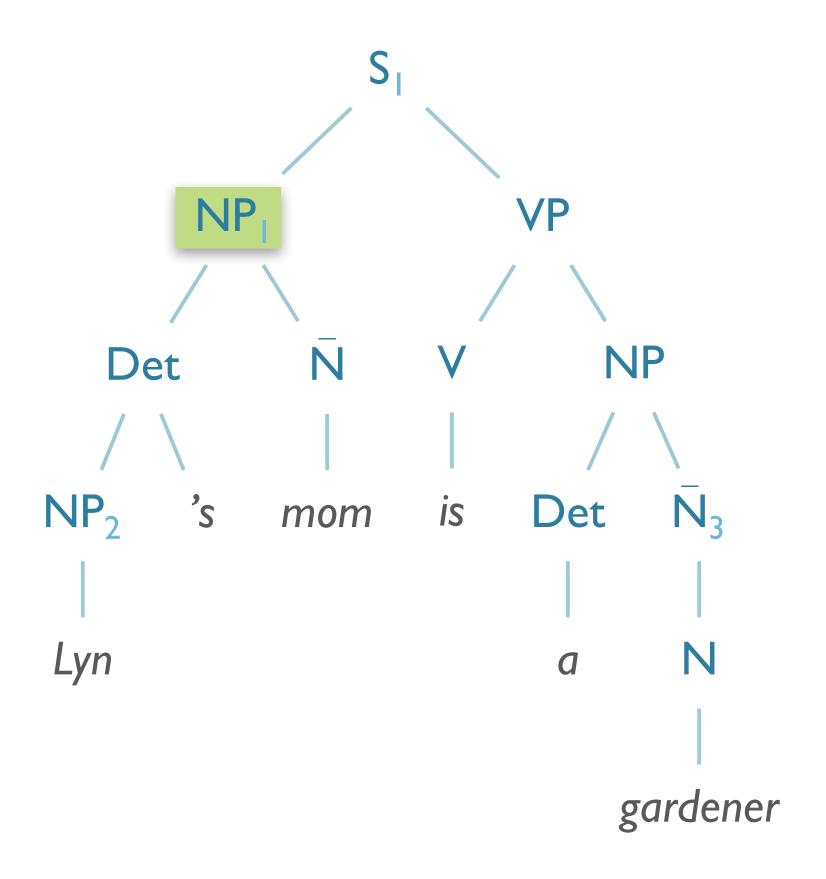


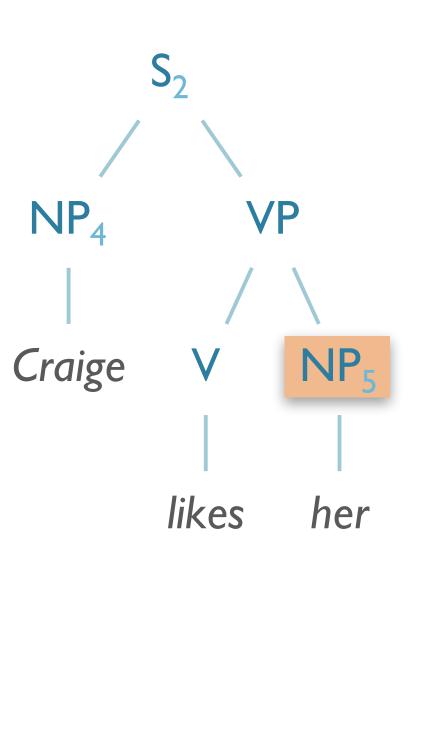
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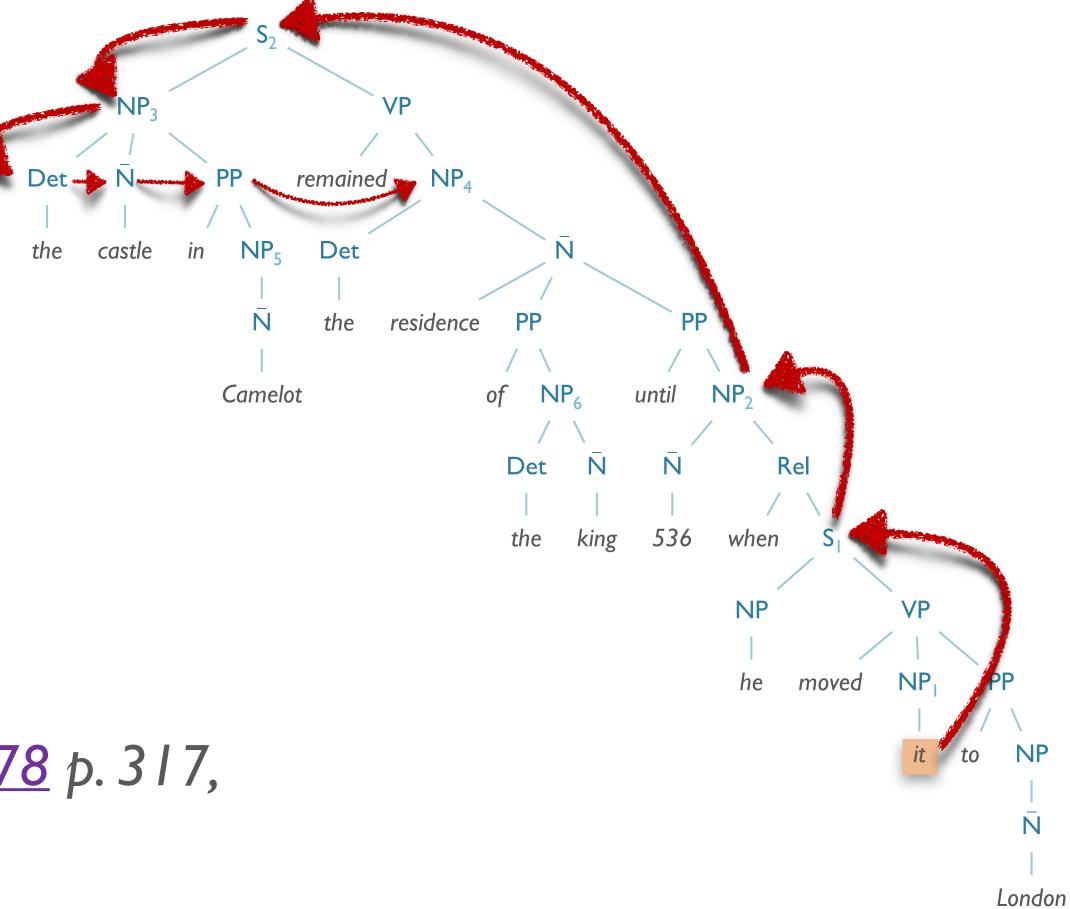




Another Hobbs Example

...the castle in Camelot remained the residence of the king until 536 when he

moved it to London.



for full walkthrough see <u>Hobbs</u>, <u>1978</u> p. 317, and the end of today's slides

Hobbs Algorithm

- Results: 88% Accuracy; 90% intrasentential
 - ...on perfect, manually parsed sentences
- Useful baseline for evaluating pronomial anaphora
- Issues:
- Parsing:
 - Not all languages have parsers
 - Parsers not always accurate
- Constraints/Preferences:
 - Captures: Binding theory, grammatical role, recency
 - But not: parallelism, repetition, verb semantics, selection

Hobbs Algorithm

- Other issue: does not implement world knowledge
 - The city council refused the women a permit because they feared violence.
 - The city council refused the women a permit because they advocated violence. (Winograd, 1972)*

*more on this later

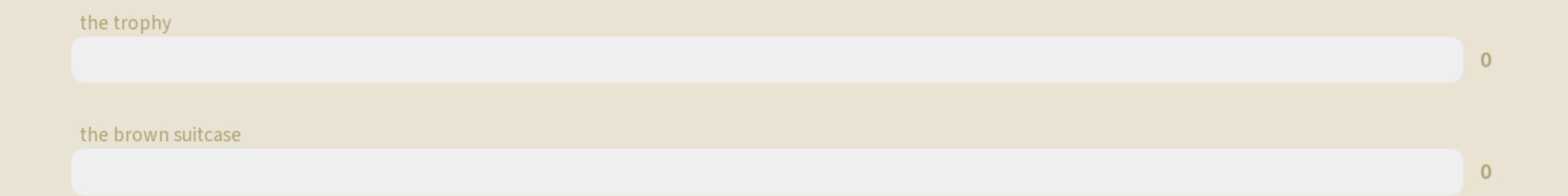
 Get this reading by knowledge of city councils and permitting, and reasons why permits would be refused.

Hobbs Algorithm: **A Parable**

- Was actually one of the first instances in NLP where a researcher tried an informed, if "naïve" baseline
 - ...found that (in 1972) no system he could build could beat it!
- "the naïve approach is quite good. Computationally speaking, it will be a long time before a semantically based algorithm is sophisticated enough to perform as well, and these results set a very high standard for any other approach to aim for.

"Yet there is every reason to pursue a semantically based approach. The naïve algorithm does not work. Any one can think of examples where it fails. In these cases it not only fails; it gives no indication that it has failed and offers no help in finding the real antecedent." — Hobbs (1978), Lingua, p. 345

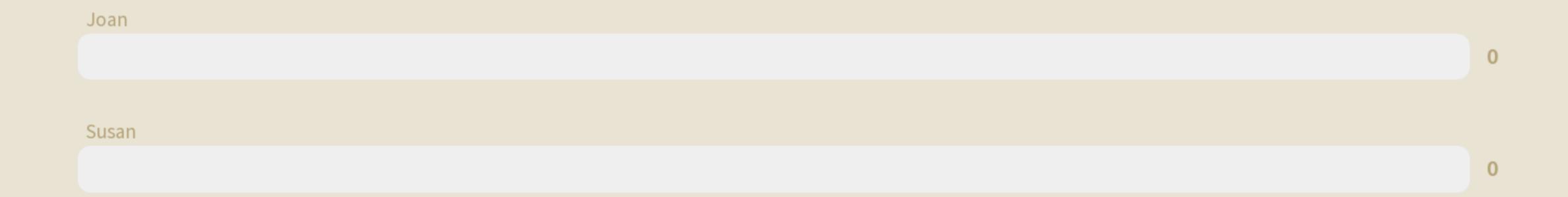
The trophy doesn't fit into the brown suitcase because it's too small. What's too small?





Joan made sure to thank Susan for all the help she had received. Who had received help?







The trophy doesn't fit into the brown suitcase because it's too large. What's too large?

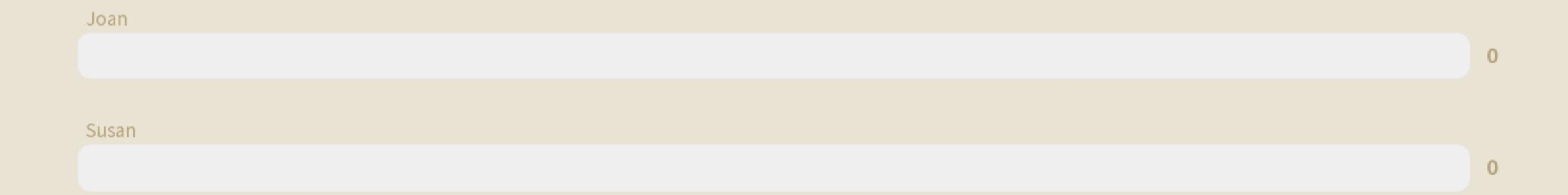


the trophy	
the brown suitcase	



Joan made sure to thank Susan for all the help she had given. Who had given help?





• The trophy doesn't fit into the brown suitcase because it's too [small/large]. What is too [small/large]?

- The trophy doesn't fit into the brown suitcase because it's too [small/large]. What is too [small/large]?
 - Answers:The suitcase/the trophy.

- The trophy doesn't fit into the brown suitcase because it's too [small/large]. What is too [small/large]?
 - Answers: The suitcase/the trophy.
- Joan made sure to thank Susan for all the help she had [given/received]. Who had [given/ received] help?

- The trophy doesn't fit into the brown suitcase because it's too [small/large]. What is too [small/large]?
 - Answers: The suitcase/the trophy.
- Joan made sure to thank Susan for all the help she had [given/received]. Who had [given/ received] help?
 - Answers: Susan/Joan.

- The trophy doesn't fit into the brown suitcase because it's too [small/large]. What is too [small/large]?
 - Answers: The suitcase/the trophy.
- Joan made sure to thank Susan for all the help she had [given/received]. Who had [given/ received] help?
 - Answers: Susan/Joan.
- Paul tried to call George on the phone, but he wasn't [successful/available]. Who was not [successful/available]?

- The trophy doesn't fit into the brown suitcase because it's too [small/large]. What is too [small/large]?
 - Answers: The suitcase/the trophy.
- Joan made sure to thank Susan for all the help she had [given/received]. Who had [given/ received] help?
 - Answers: Susan/Joan.
- Paul tried to call George on the phone, but he wasn't [successful/available]. Who was not [successful/available]?
 - Answers: Paul/George.

- The trophy doesn't fit into the brown suitcase because it's too [small/large]. What is too [small/large]?
 - Answers: The suitcase/the trophy.
- Joan made sure to thank Susan for all the help she had [given/received]. Who had [given/ received] help?
 - Answers: Susan/Joan.
- Paul tried to call George on the phone, but he wasn't [successful/available]. Who was not [successful/available]?
 - Answers: Paul/George.
- The lawyer asked the witness a question, but he was reluctant to [answer/repeat] it . Who was reluctant to [answer/repeat] the question?

- The trophy doesn't fit into the brown suitcase because it's too [small/large]. What is too [small/large]?
 - Answers:The suitcase/the trophy.
- Joan made sure to thank Susan for all the help she had [given/received]. Who had [given/received] help?
 - Answers: Susan/Joan.
- Paul tried to call George on the phone, but he wasn't [successful/available]. Who was not [successful/available]?
 - Answers: Paul/George.
- The lawyer asked the witness a question, but he was reluctant to [answer/repeat] it . Who was reluctant to [answer/repeat] the question?
 - Answers: The witness/the lawyer.

Winograd Schema Challenge

- Still hard!
 - WSC: used in a lot of early LM evals
 - Hand-designed
 - Very small
 - Probably "saturated"
 - Winogrande

DOI:10.1145/3474381

WinoGrande: An Adversarial Winograd Schema Challenge at Scale

By Keisuke Sakaguchi, Ronan Le Bras, Chandra Bhagavatula, and Yejin Choi

Abstract

Commonsense reasoning remains a major challenge in AI, and yet, recent progresses on benchmarks may seem to suggest otherwise. In particular, the recent neural language models have reported above 90% accuracy on the Winograd Schema Challenge (WSC),²² a commonsense benchmark originally designed to be unsolvable for statistical models that rely simply on word associations. This raises an important question—whether these models have truly acquired robust commonsense capabilities or they rely on spurious biases in the dataset that lead to an overestimation of the true capabilities of machine commonsense.

To investigate this question, we introduce WinoGrande, a large-scale dataset of 44k problems, inspired by the original WSC, but adjusted to improve both the scale and the hardness of the dataset. The key steps of the dataset construction consist of (1) large-scale crowdsourcing, followed by (2) systematic bias reduction using a novel AFLITE algorithm that generalizes human-detectable word associations to machine-detectable embedding associations. Our experiments demonstrate that state-of-the-art models achieve considerably lower accuracy (59.4%–79.1%) on WINOGRANDE compared to humans (94%), confirming that the high performance on the original WSC was inflated by spurious biases in the dataset.

WSC dataset where the models now achieve around 90% accuracy. This raises a curious question:

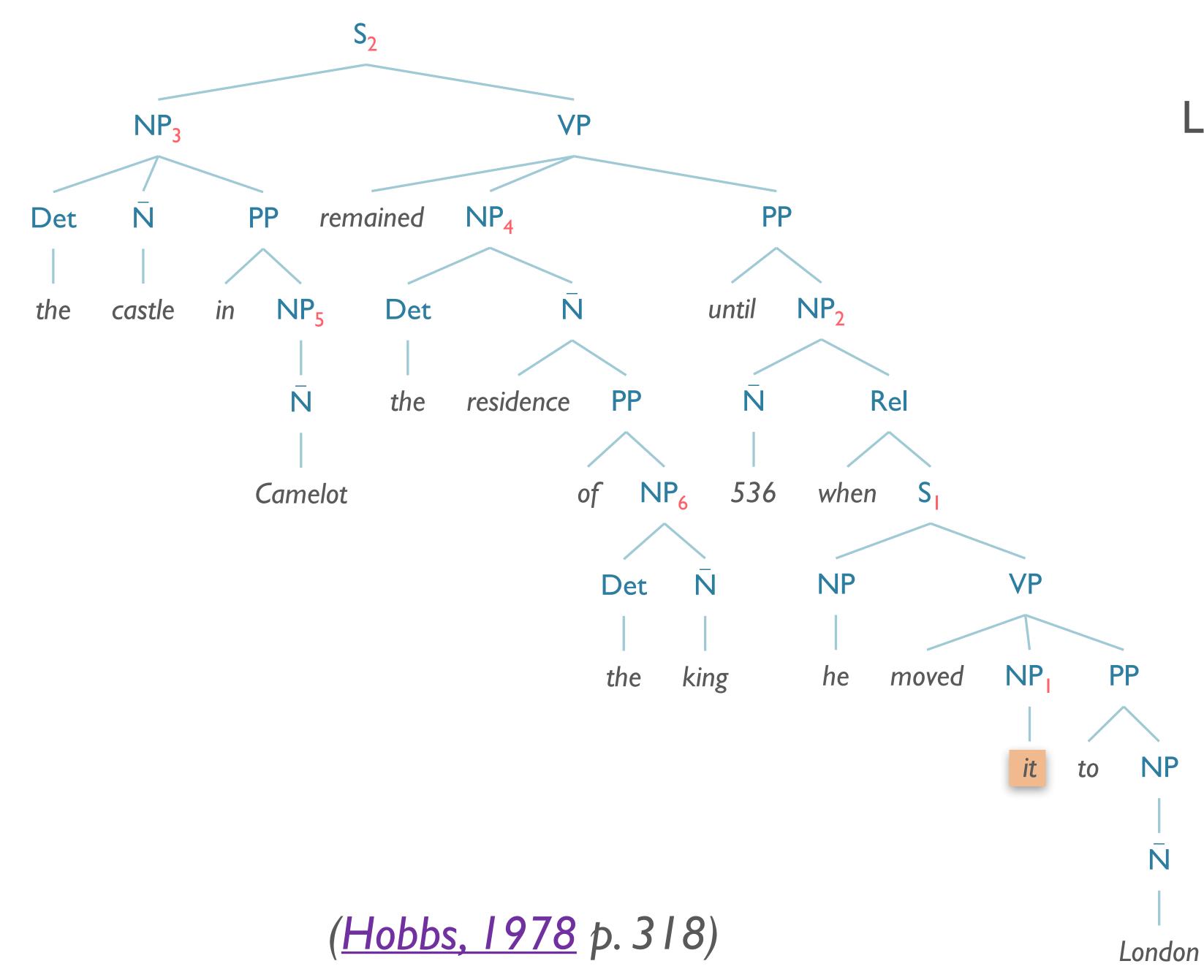
Have neural language models successfully acquired commonsense or are we overestimating the true capabilities of machine commonsense?

This question about the potential overestimation leads to another crucial question regarding potential unwanted biases that the large-scale neural language models might be exploiting, essentially solving the problems *right*, but for *wrong* reasons. Indeed, although WSC questions are carefully crafted by experts, recent studies have shown that they are nevertheless prone to incidental biases. Trichelair et al.³⁶ have reported *word-association* (13.5% of the cases, see Table 1 for examples) as well as other types of *dataset-specific* biases. Although such biases and annotation artifacts are not apparent for individual instances, they get introduced in the dataset as problems as authors subconsciously repeat similar problem-crafting strategies.

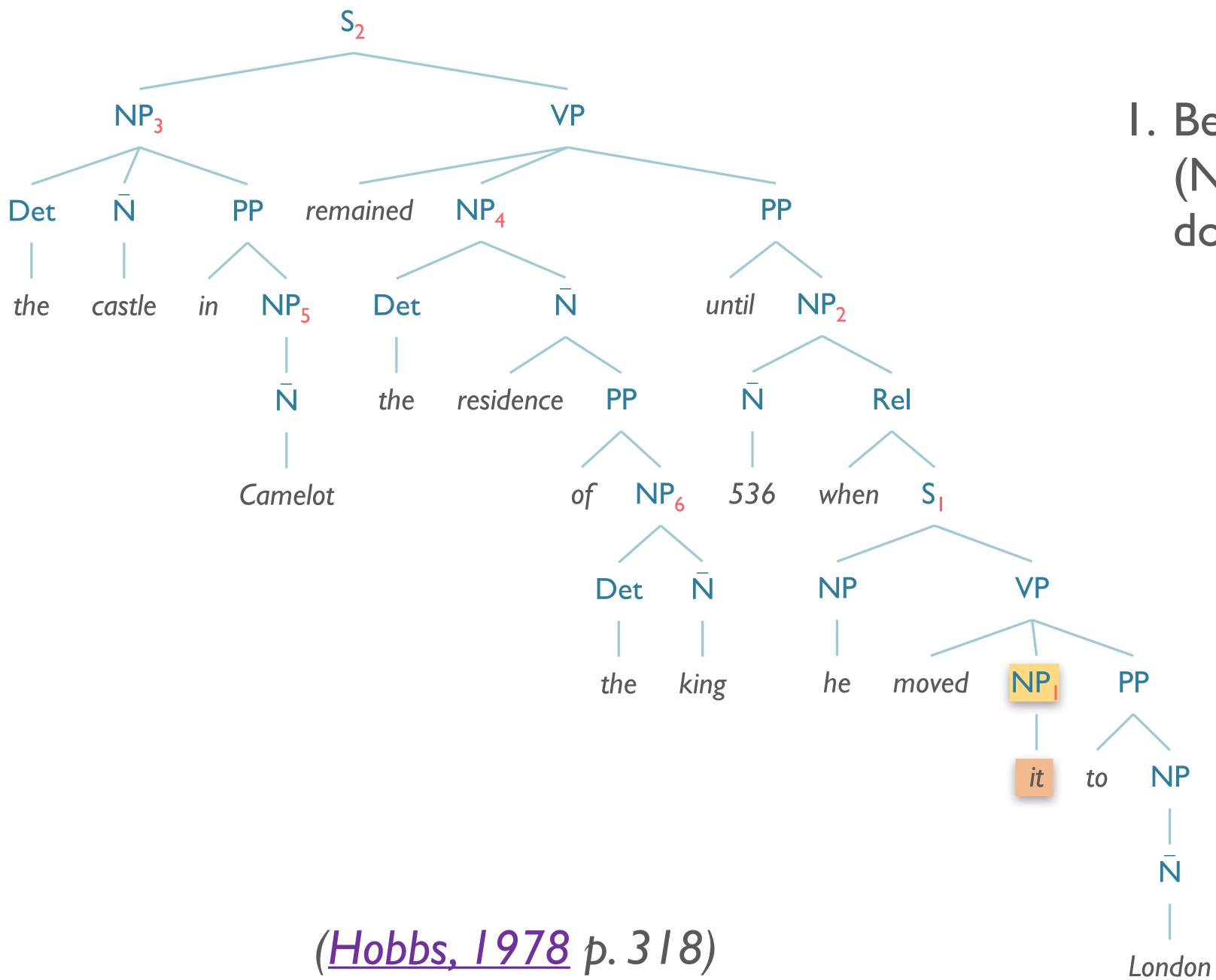
To investigate this question about the true estimation of the machine commonsense capabilities, we introduce **Wino-Grande**, a new dataset with 44k problems that are inspired by the original design of WSC, but modified to improve both the

Hobbs Algorithm Walkthrough

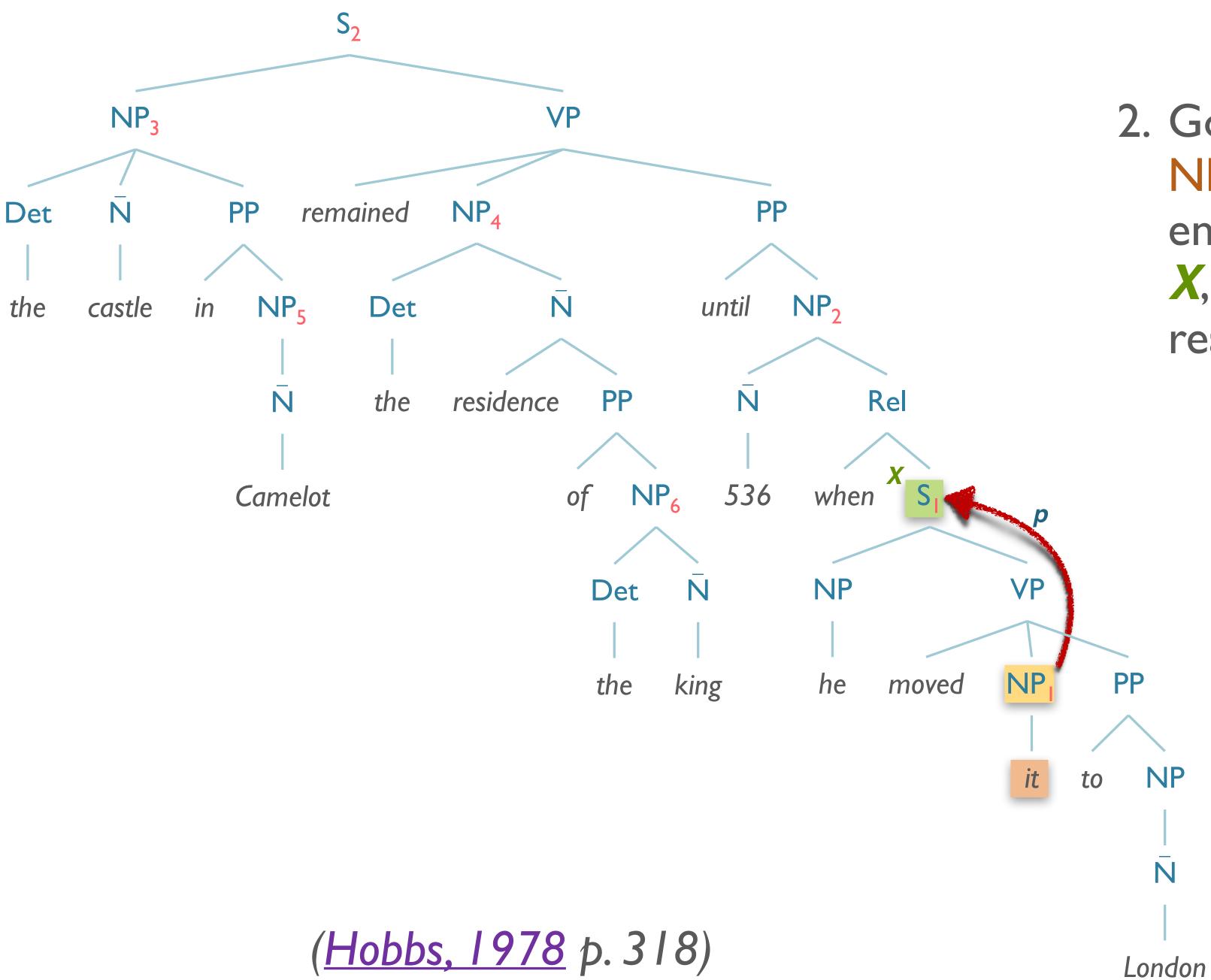
(h/t Ryan Georgi)



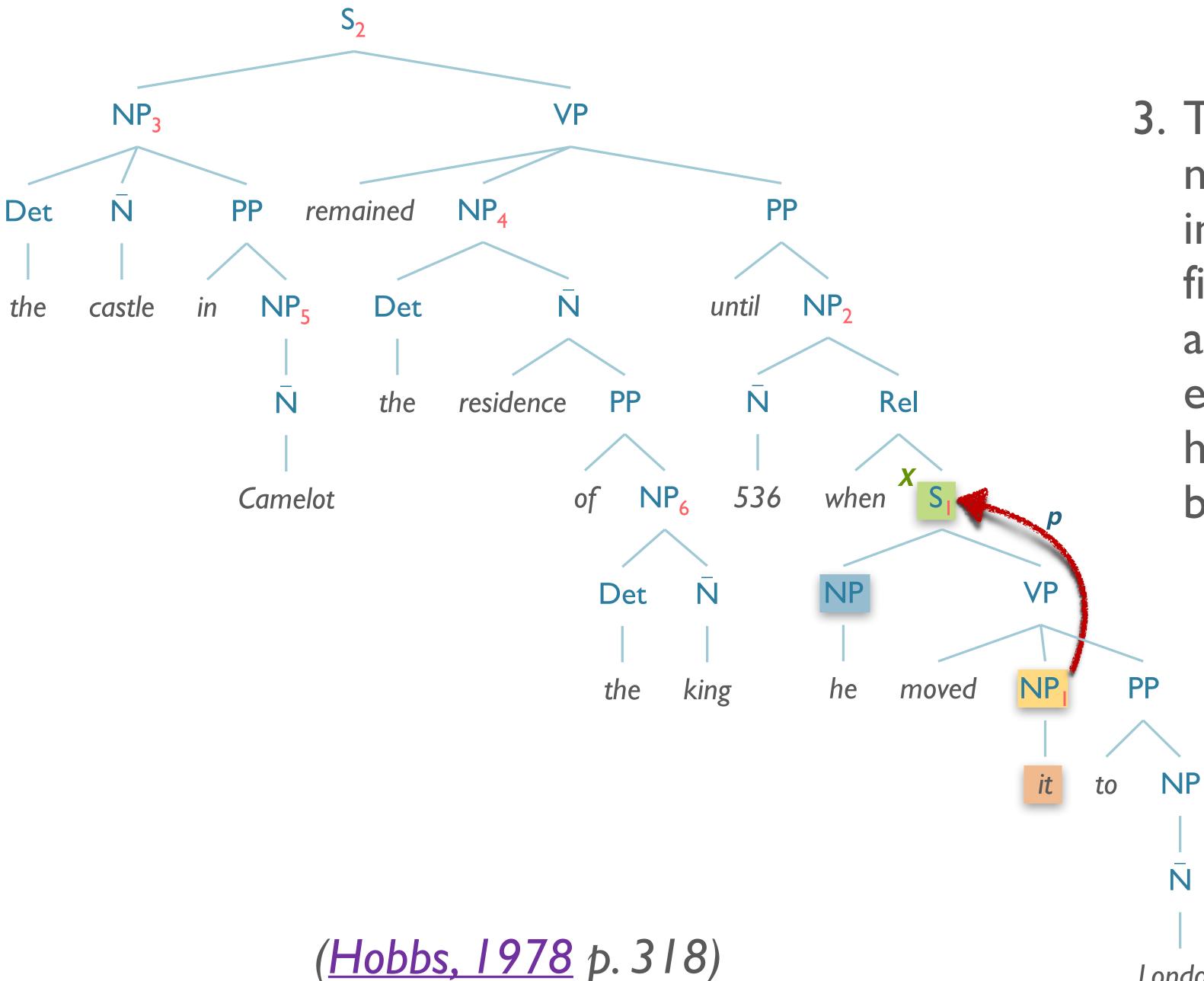
Let's figure out what the antecedent for "it" is



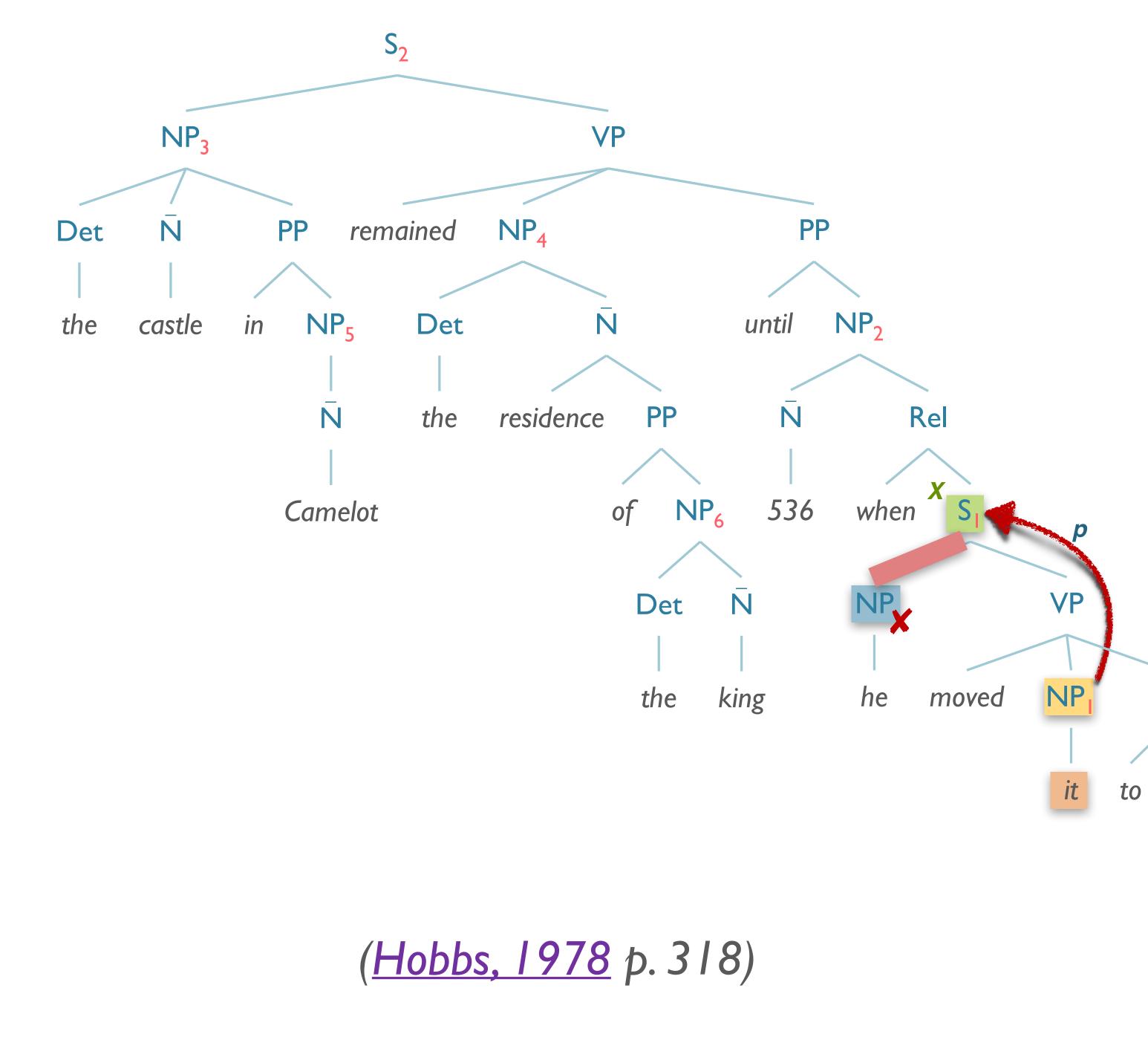
 Begin at the noun phrase (NP) node immediately dominating the pronoun



2. Go up the tree to the first NP or sentence (S) node encountered. Call this node X, and call the path used to reach it p.



3. Traverse all branches below node X to the left of path p in a left-to-right, breadth-first fashion. Propose as the antecedent any encountered NP node that has an NP or S node between it and X.

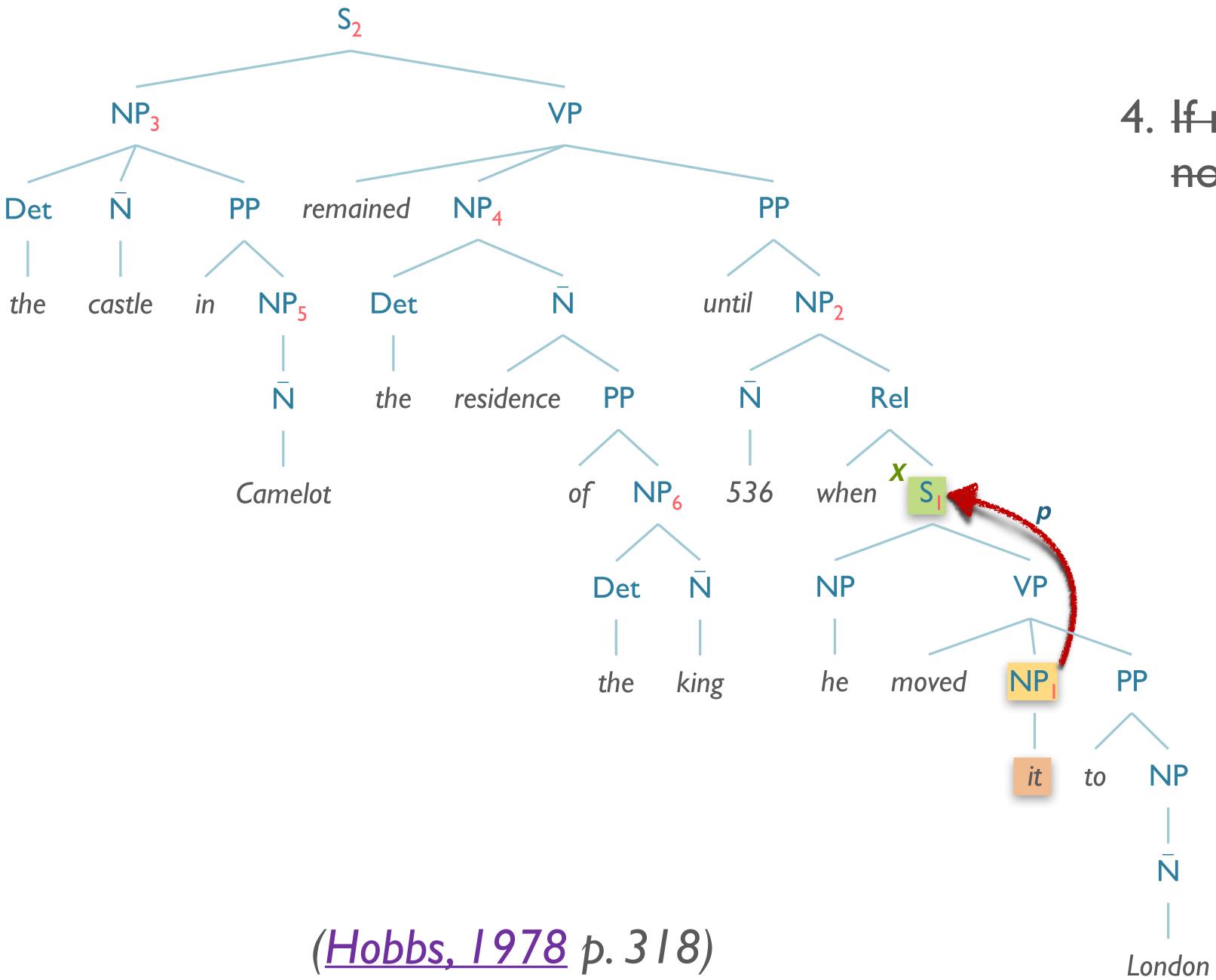


3. Traverse all branches below node X to the left of path p in a left-to-right, breadth-first fashion. Propose as the antecedent any encountered NP node that has an NP or S node between it and X.

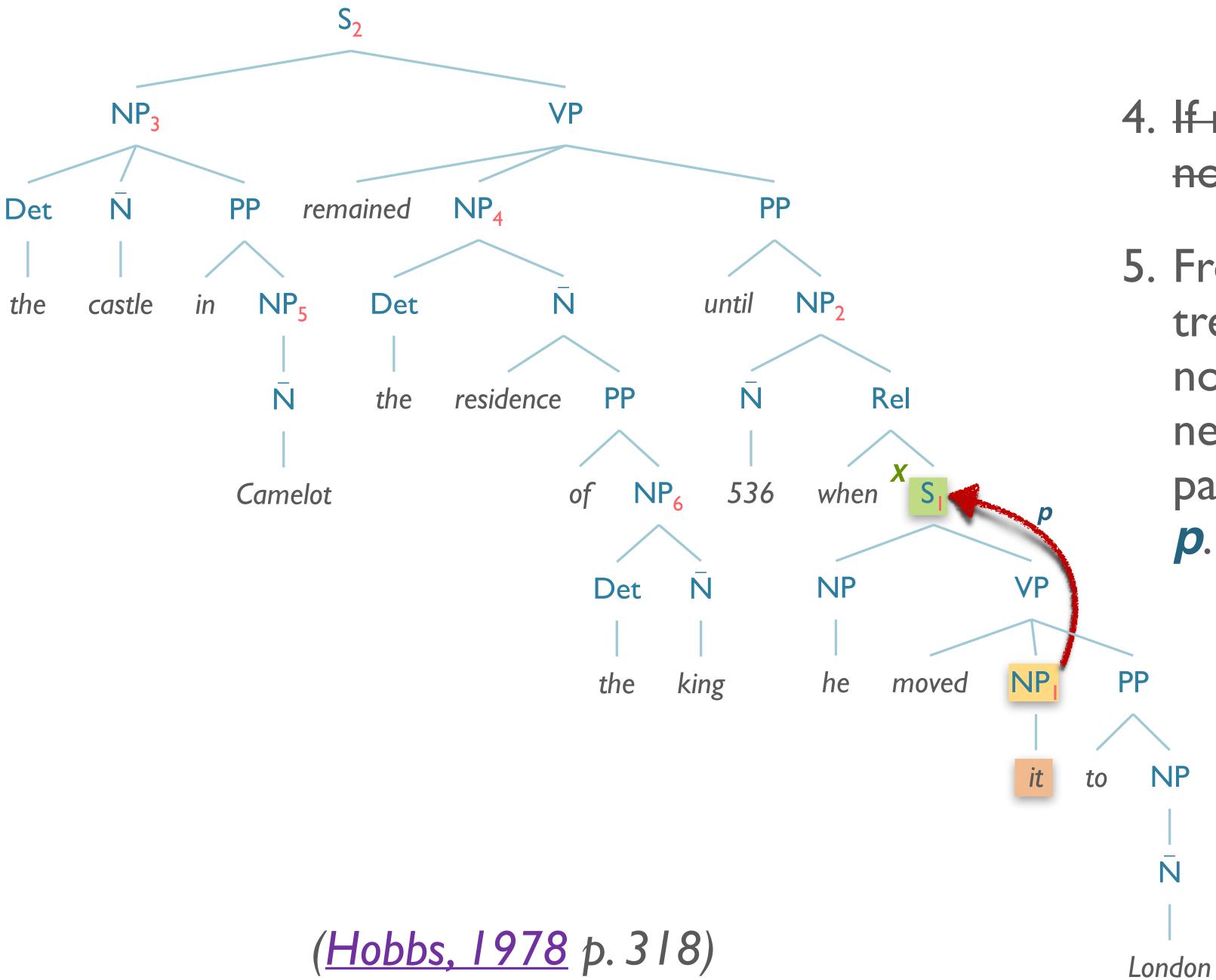
NP

London

No NP or S between "he" NP and X

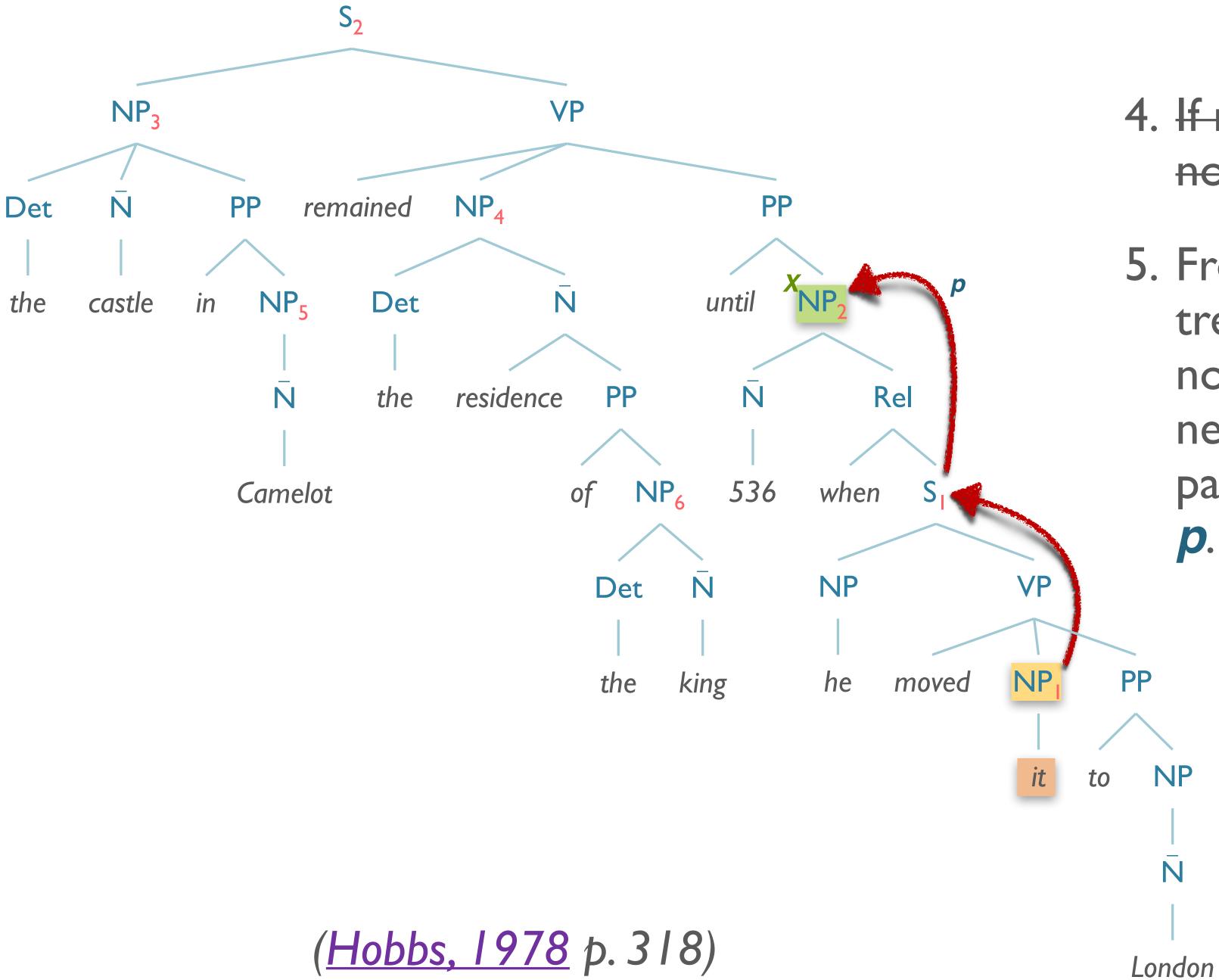


4. If node X is the highest S



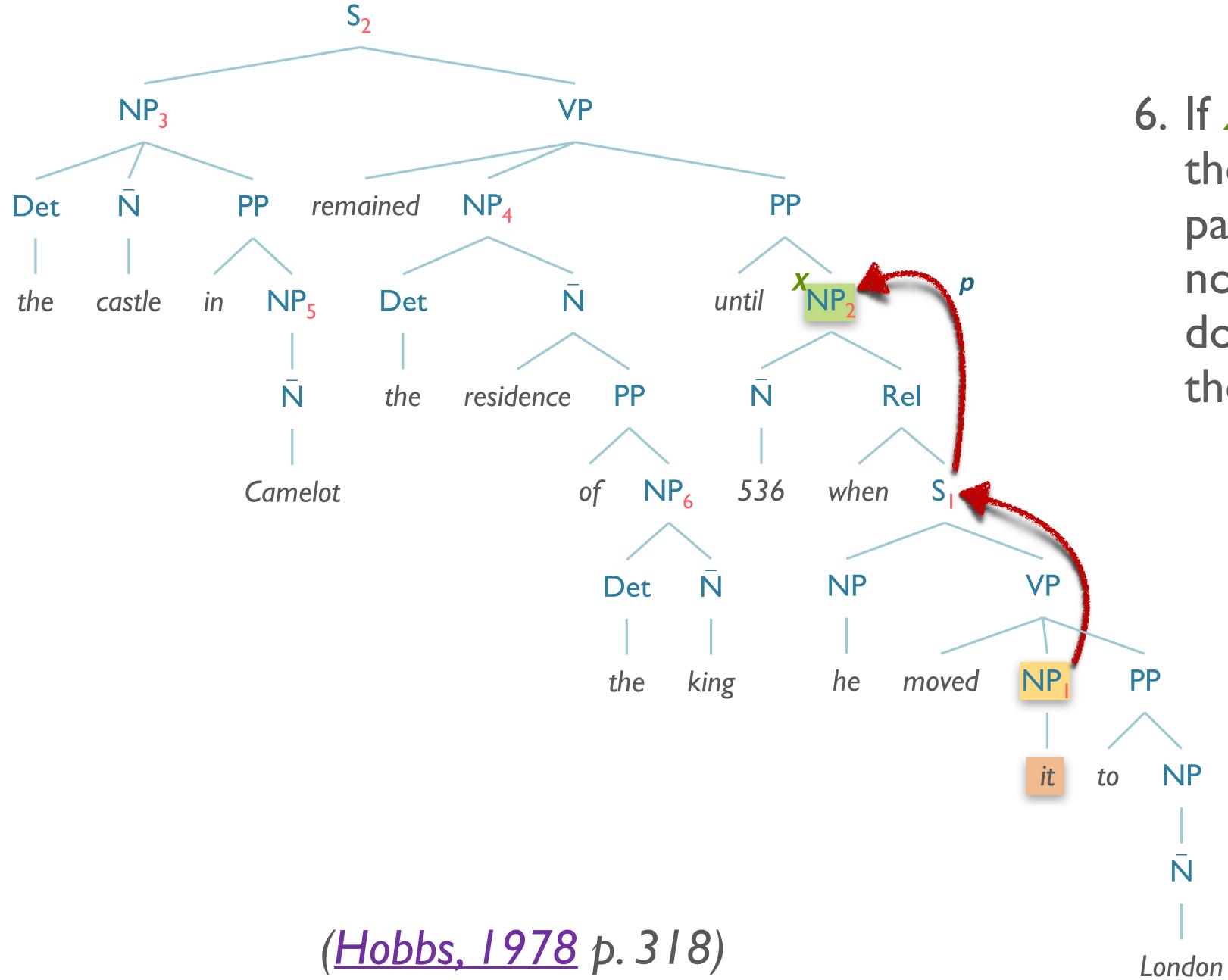
4. If node X is the highest S node in the sentence...

5. From node X, go up the tree to the first NP or S node encountered. Call this new node X, and call the path traversed to reach it p.

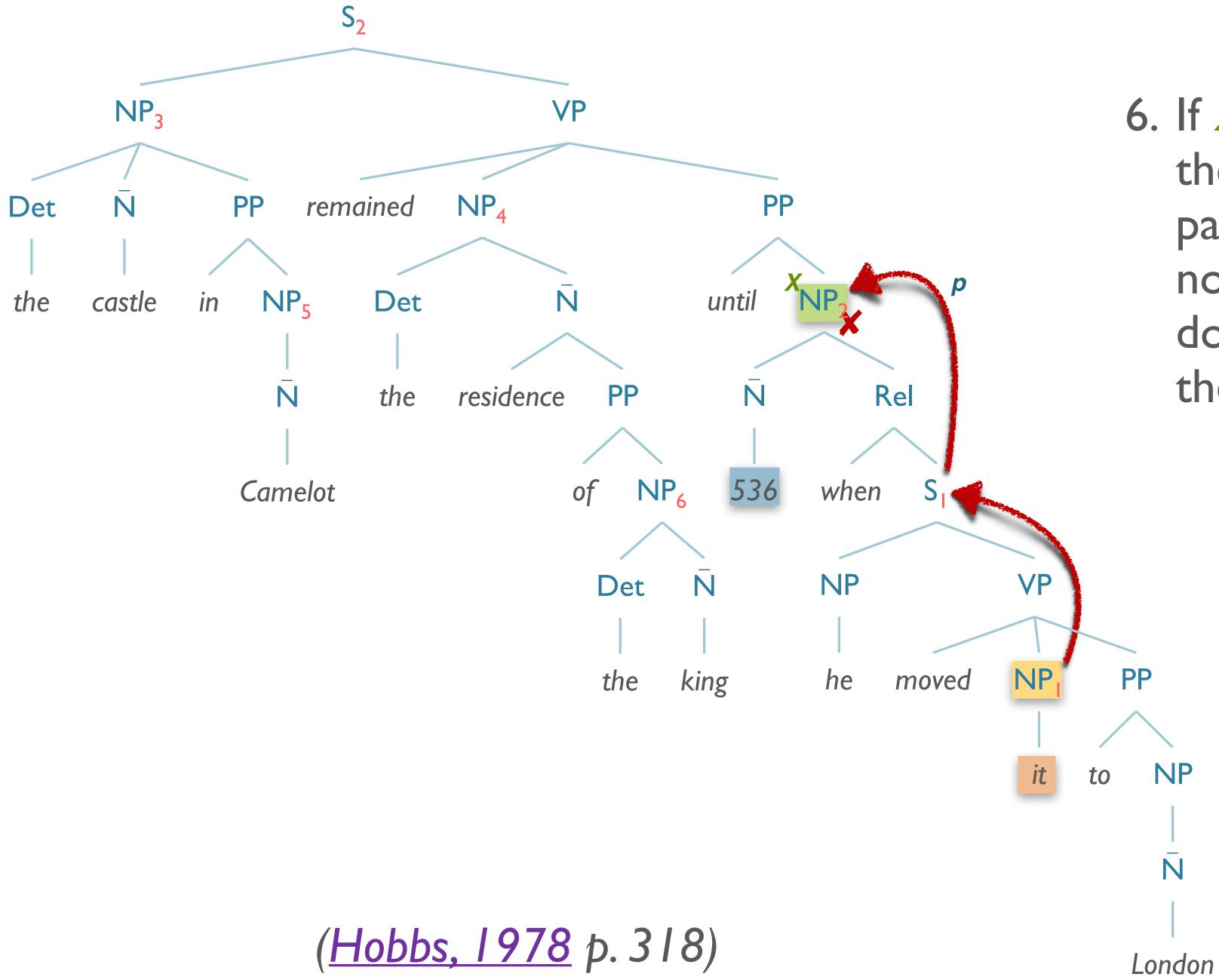


4. If node X is the highest S node in the sentence...

5. From node *X*, go up the tree to the first NP or S node encountered. Call this new node *X*, and call the path traversed to reach it *p*.

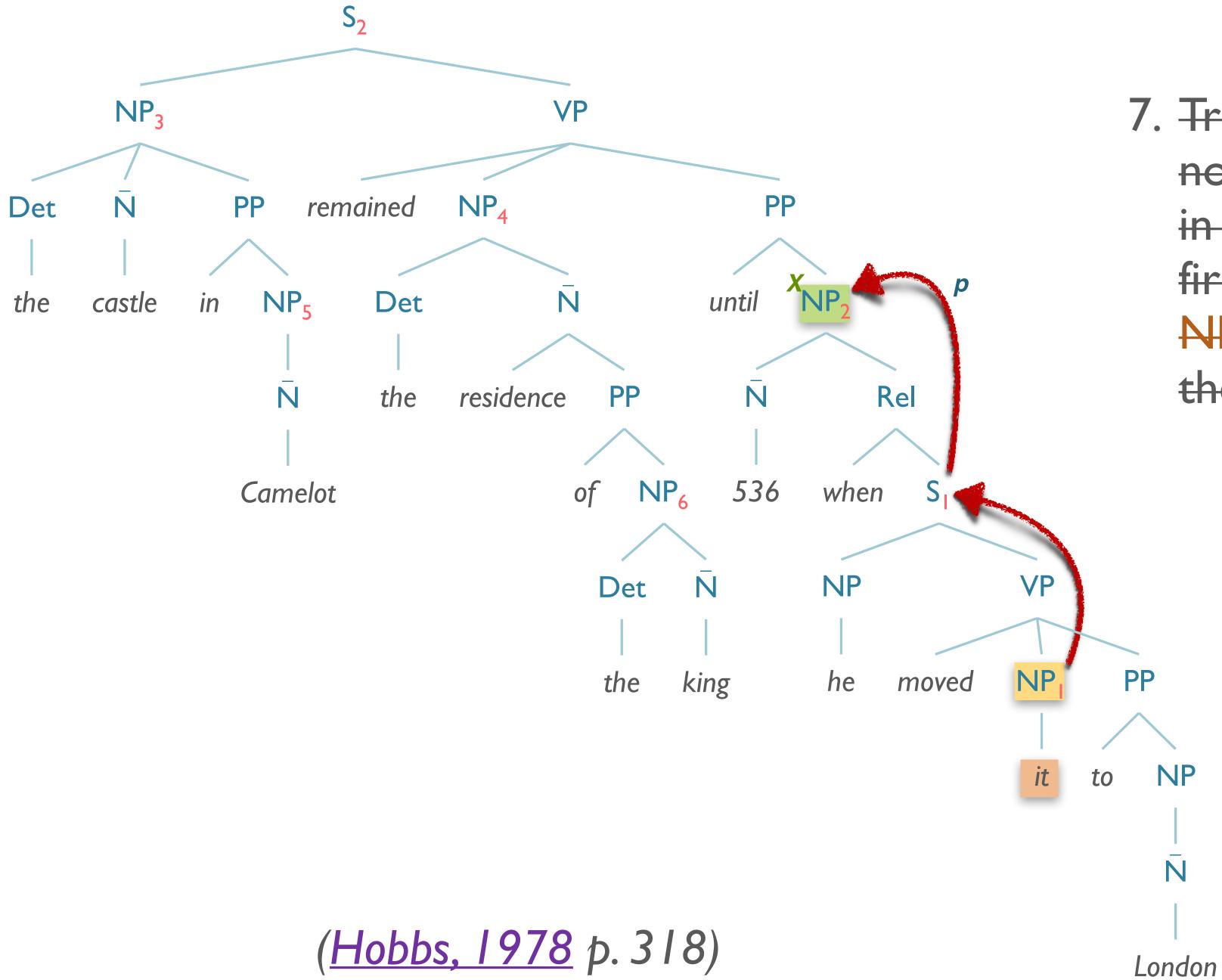


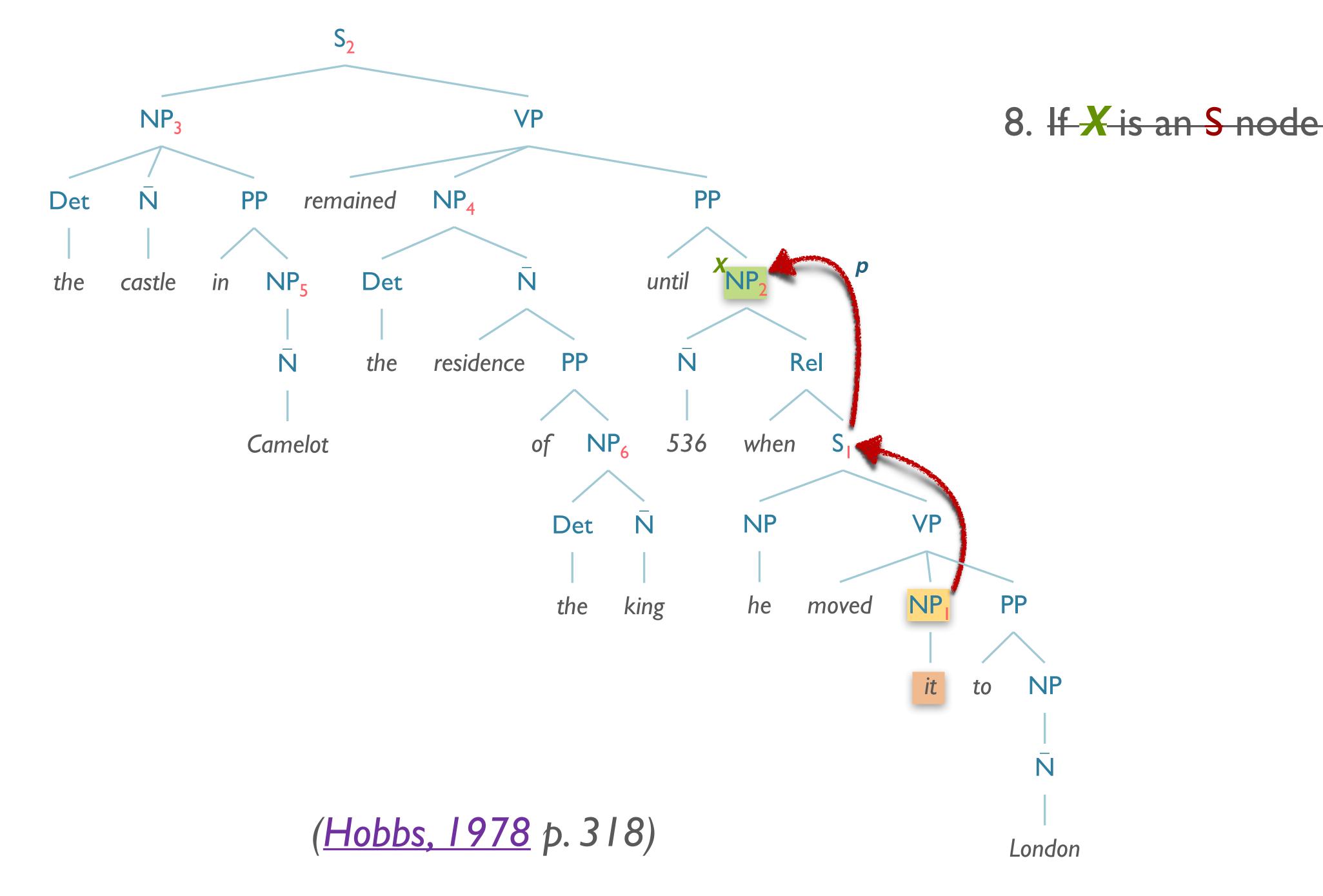
6. If X is an NP node and if the path p to X did not pass through the Nominal node that X immediately dominates, propose X as the antecedent.

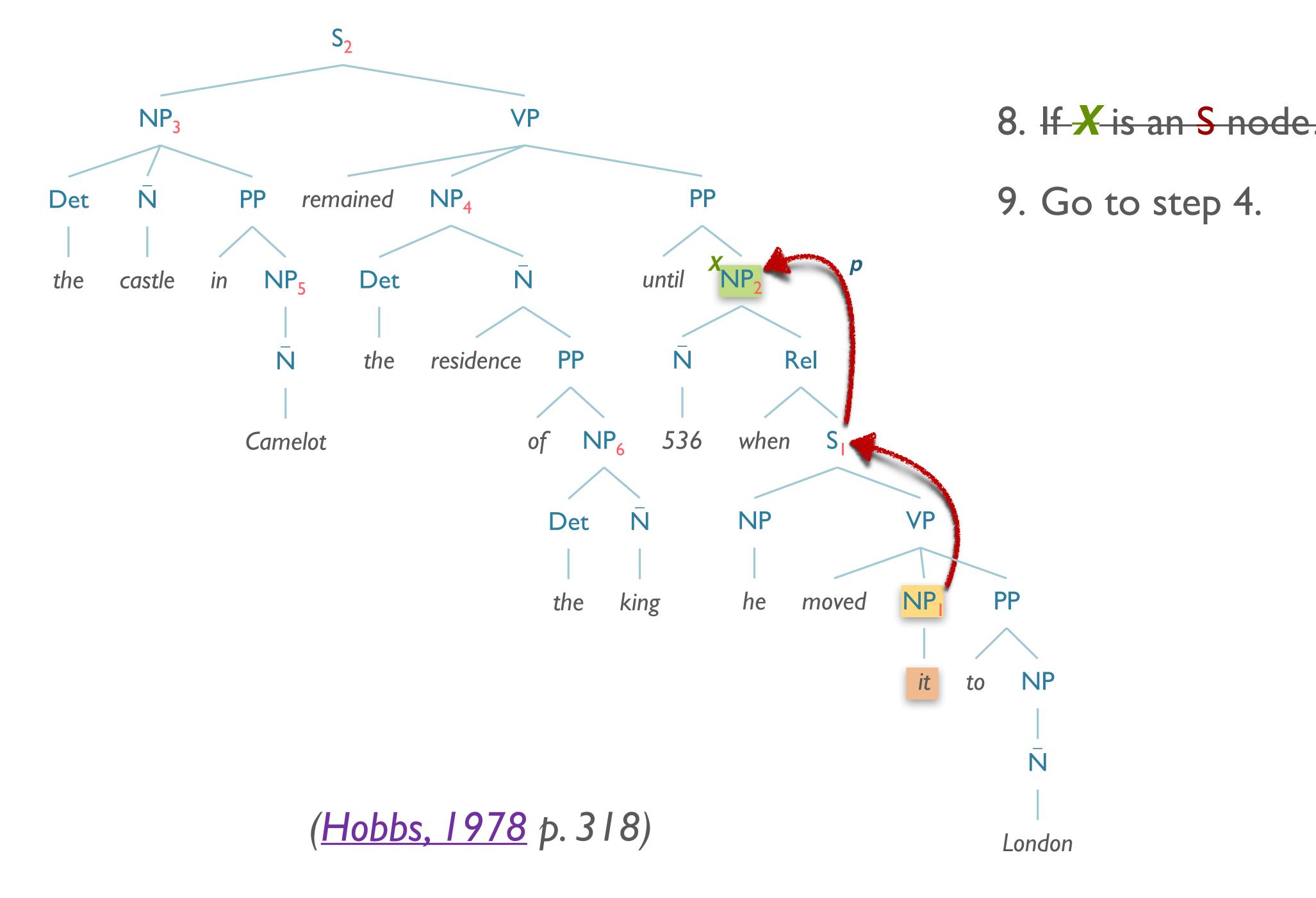


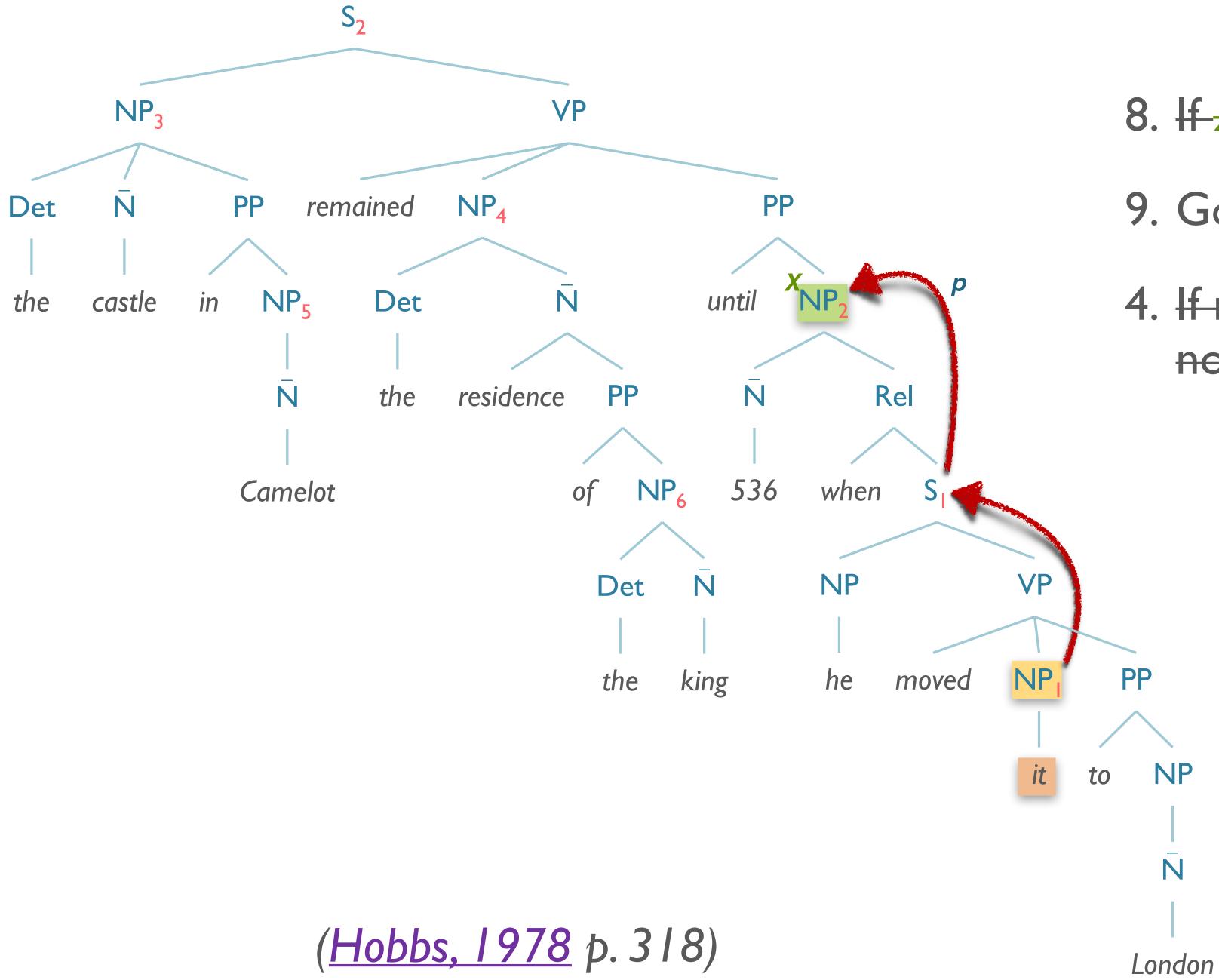
6. If X is an NP node and if the path p to X did not pass through the Nominal node that X immediately dominates, propose X as the antecedent.

"536" can't be "moved"!





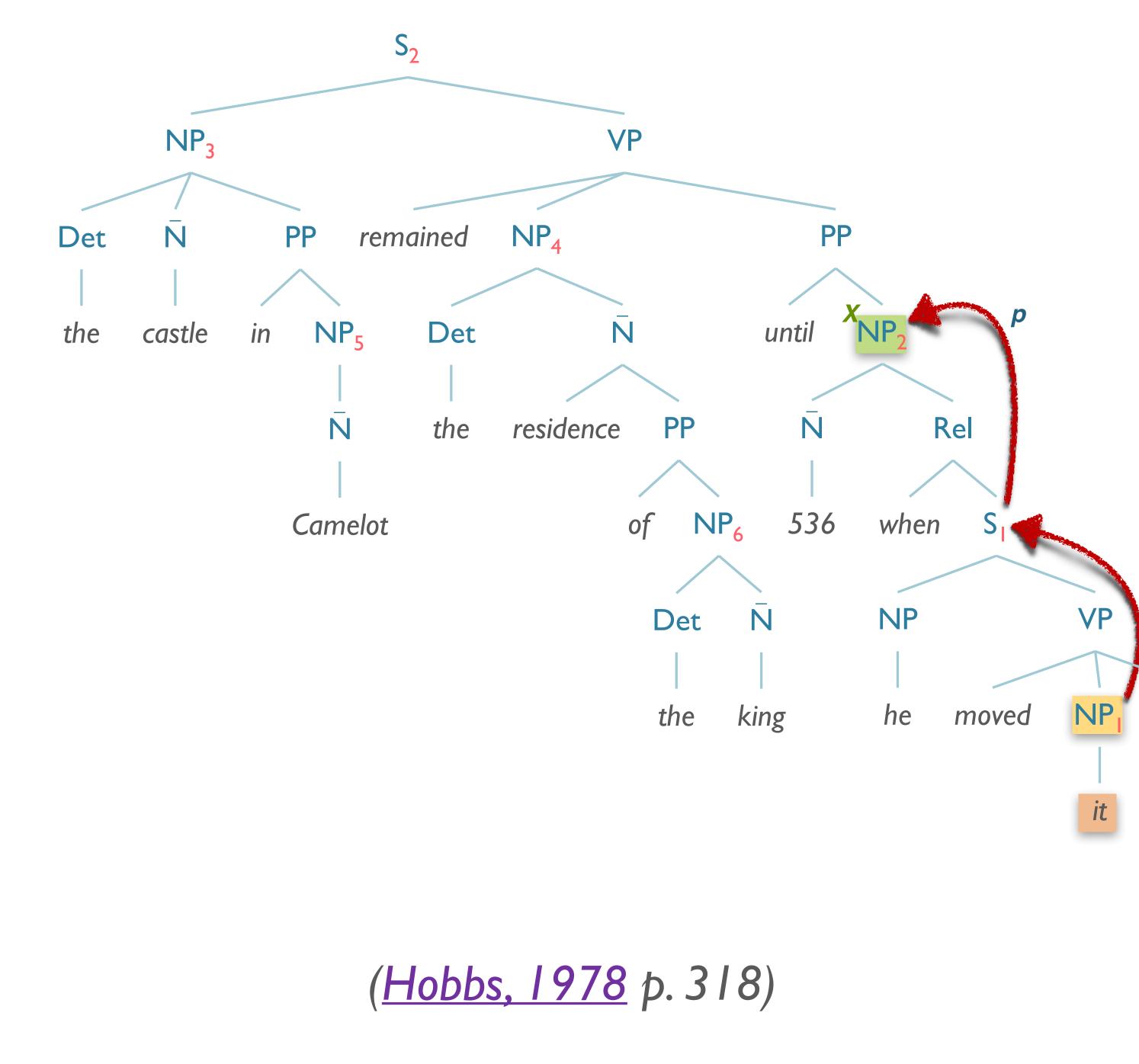




8. If X is an S node...

9. Go to step 4.

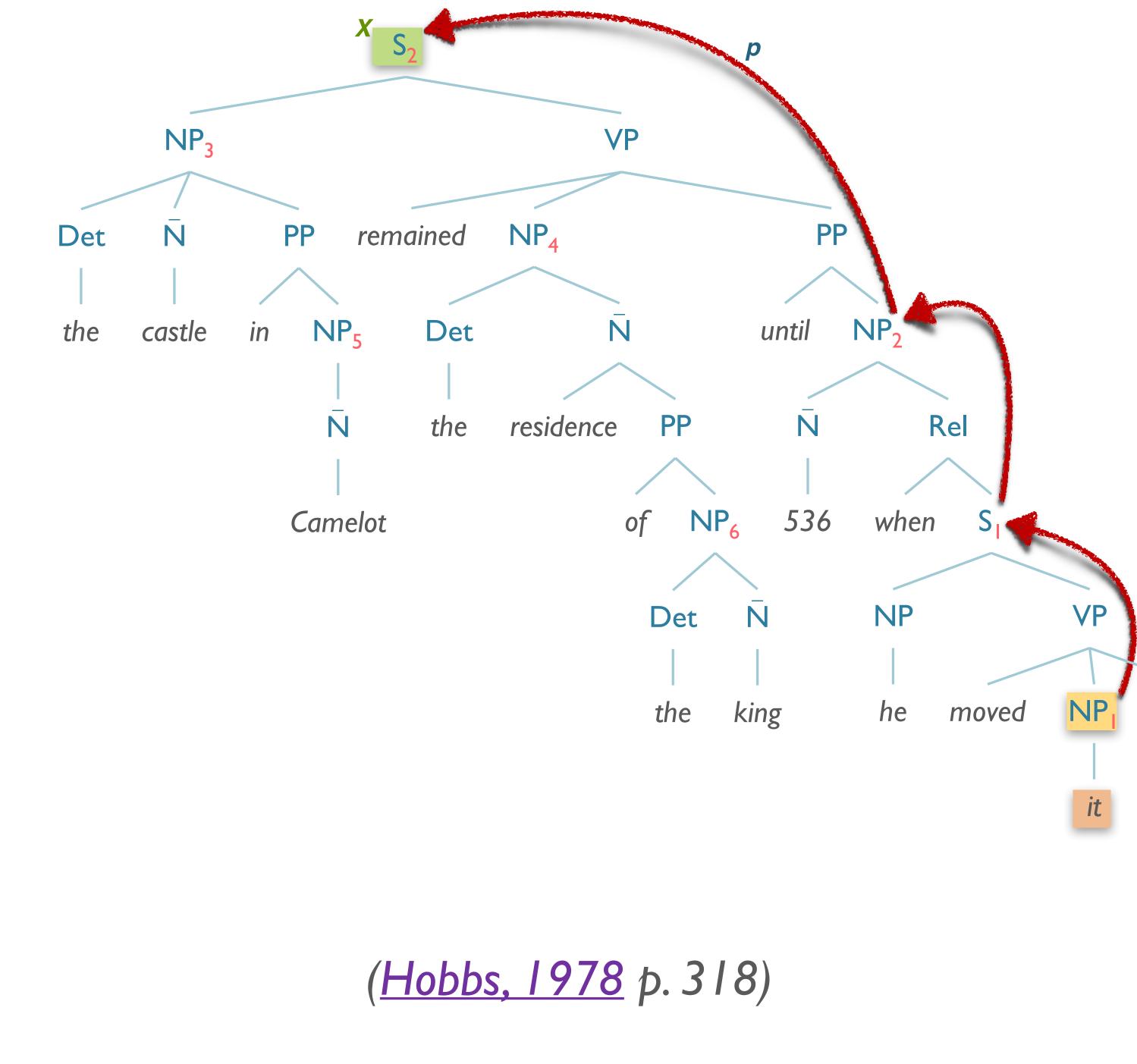
4. If node X is the highest S



- 8. If X is an S node...
- 9. Go to step 4.
- 4. If node X is the highest S node in the sentence...
- 5. From node X, go up the tree to the first NP or S node encountered. Call this new node X, and call the path traversed to reach it p.

NP

to

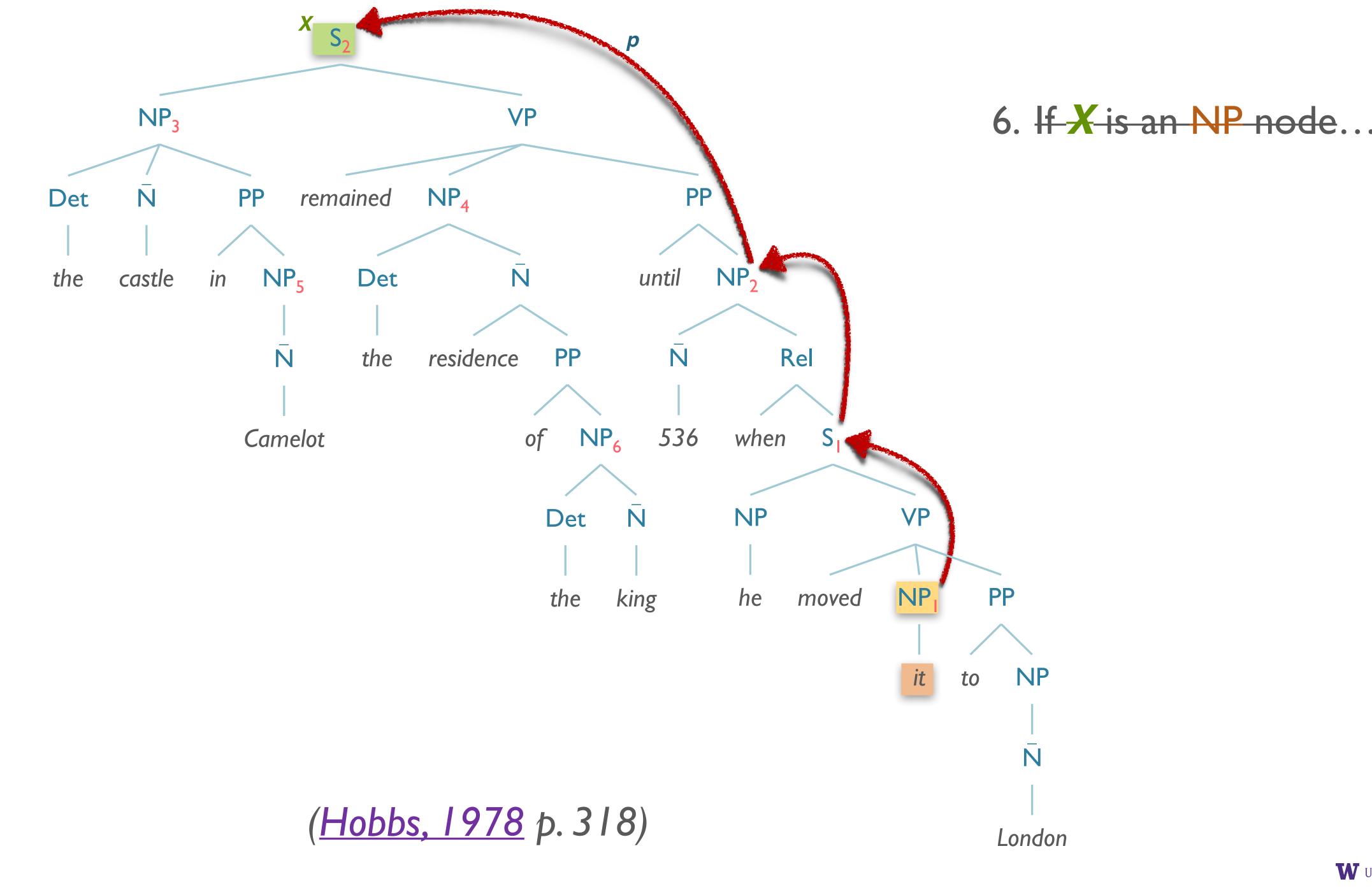


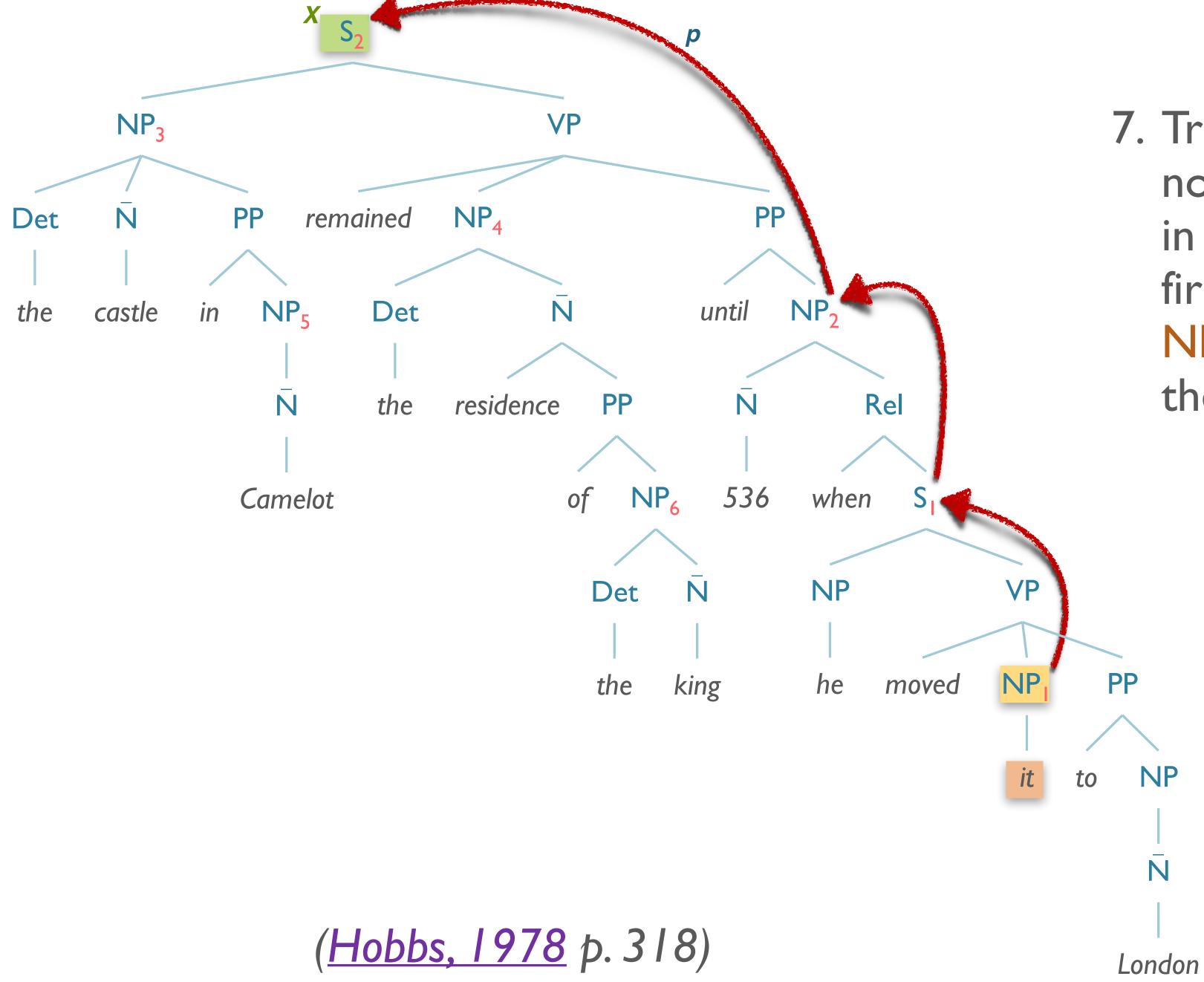
- 8. If X is an S node...
- 9. Go to step 4.

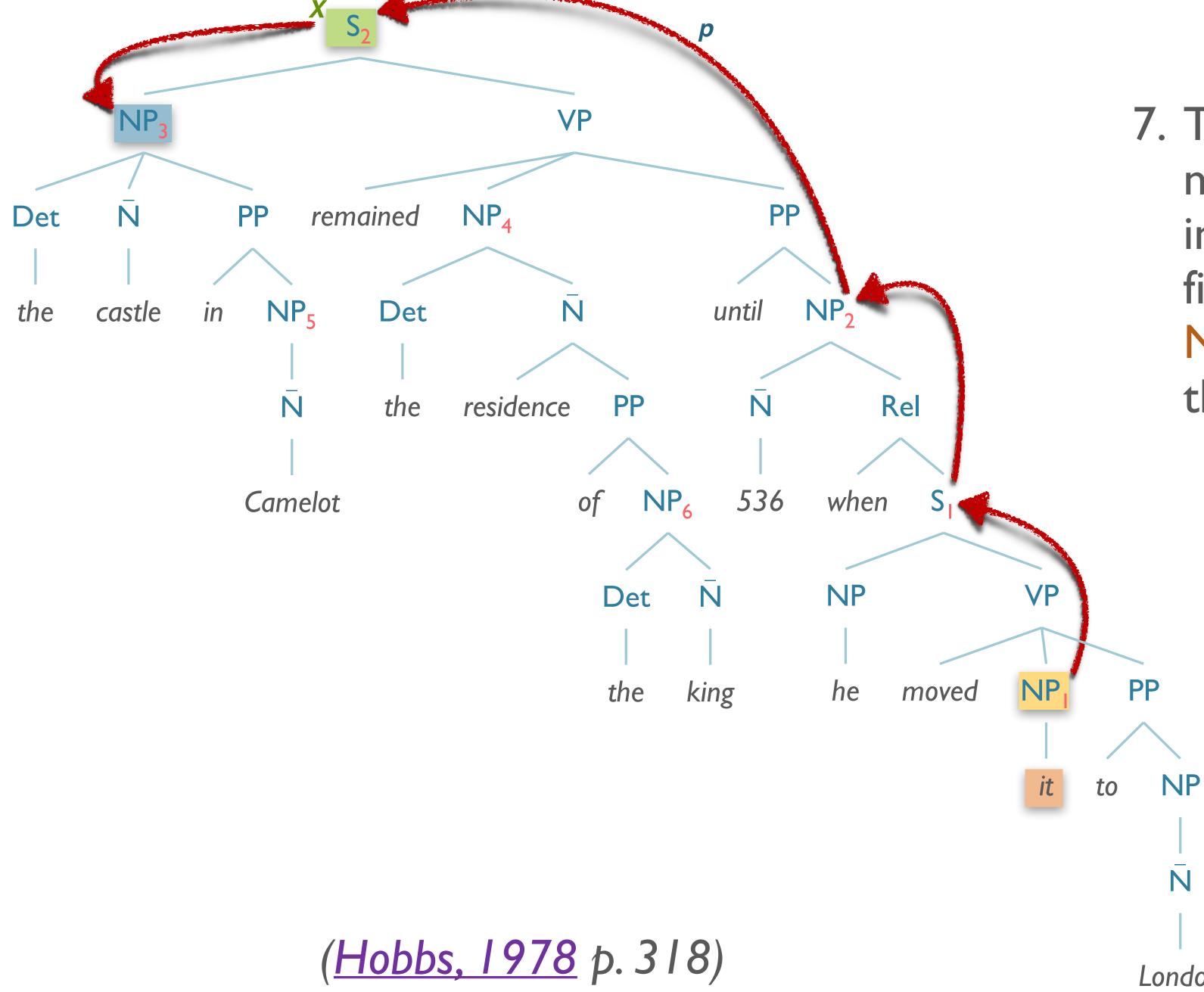
to

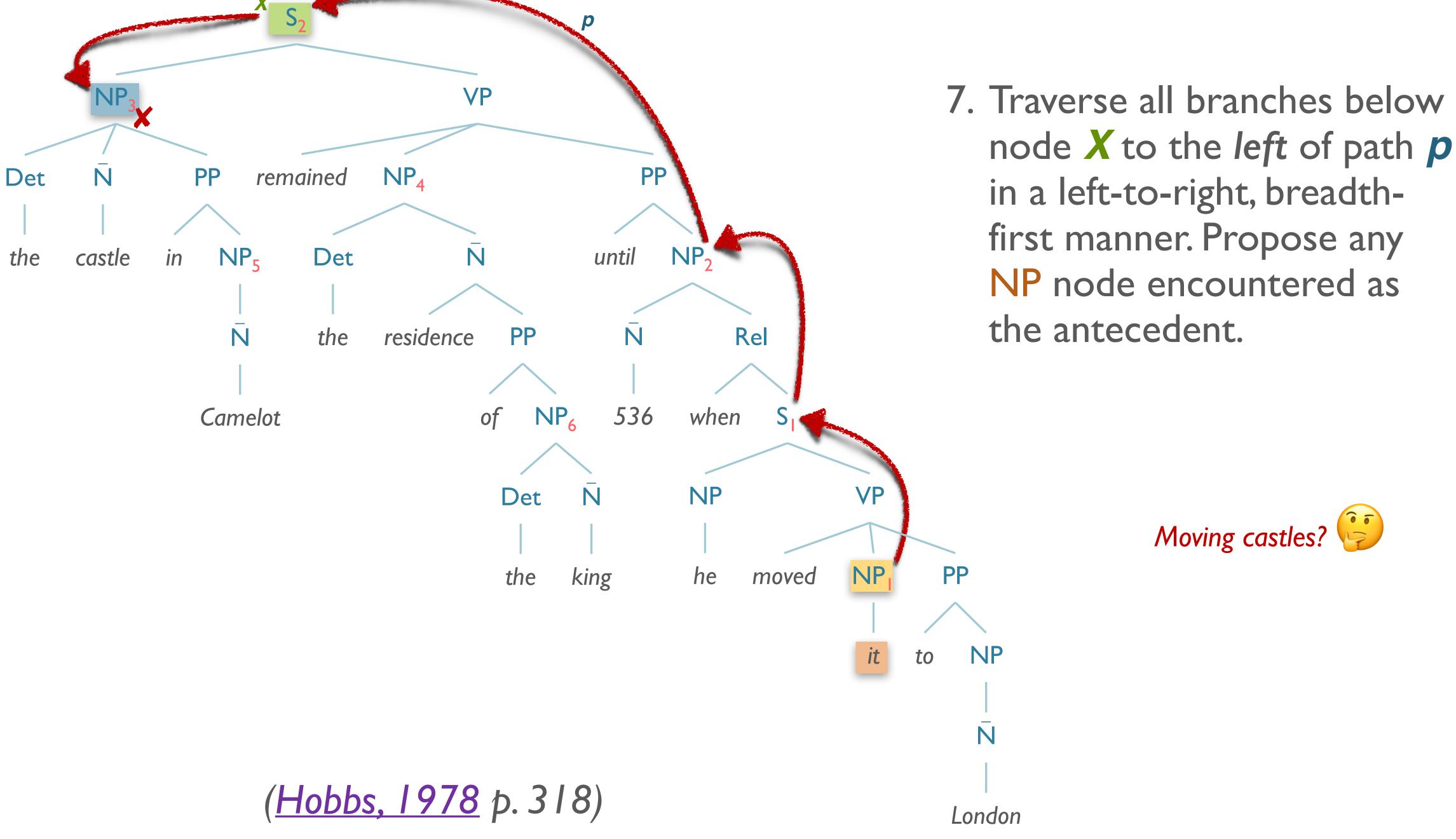
London

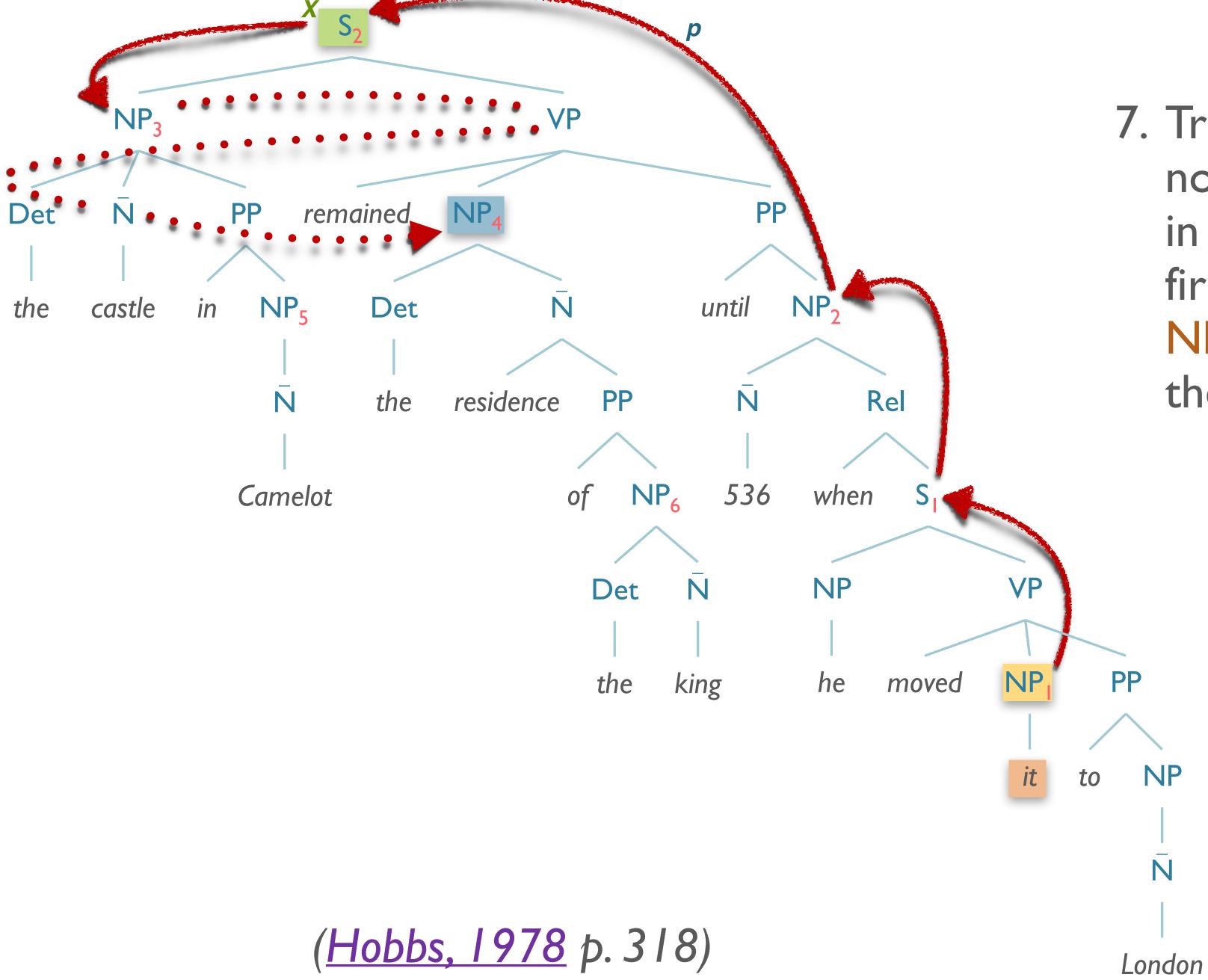
- 4. If node X is the highest S node in the sentence...
- 5. From node X, go up the tree to the first NP or S node encountered. Call this new node X, and call the path traversed to reach it p.

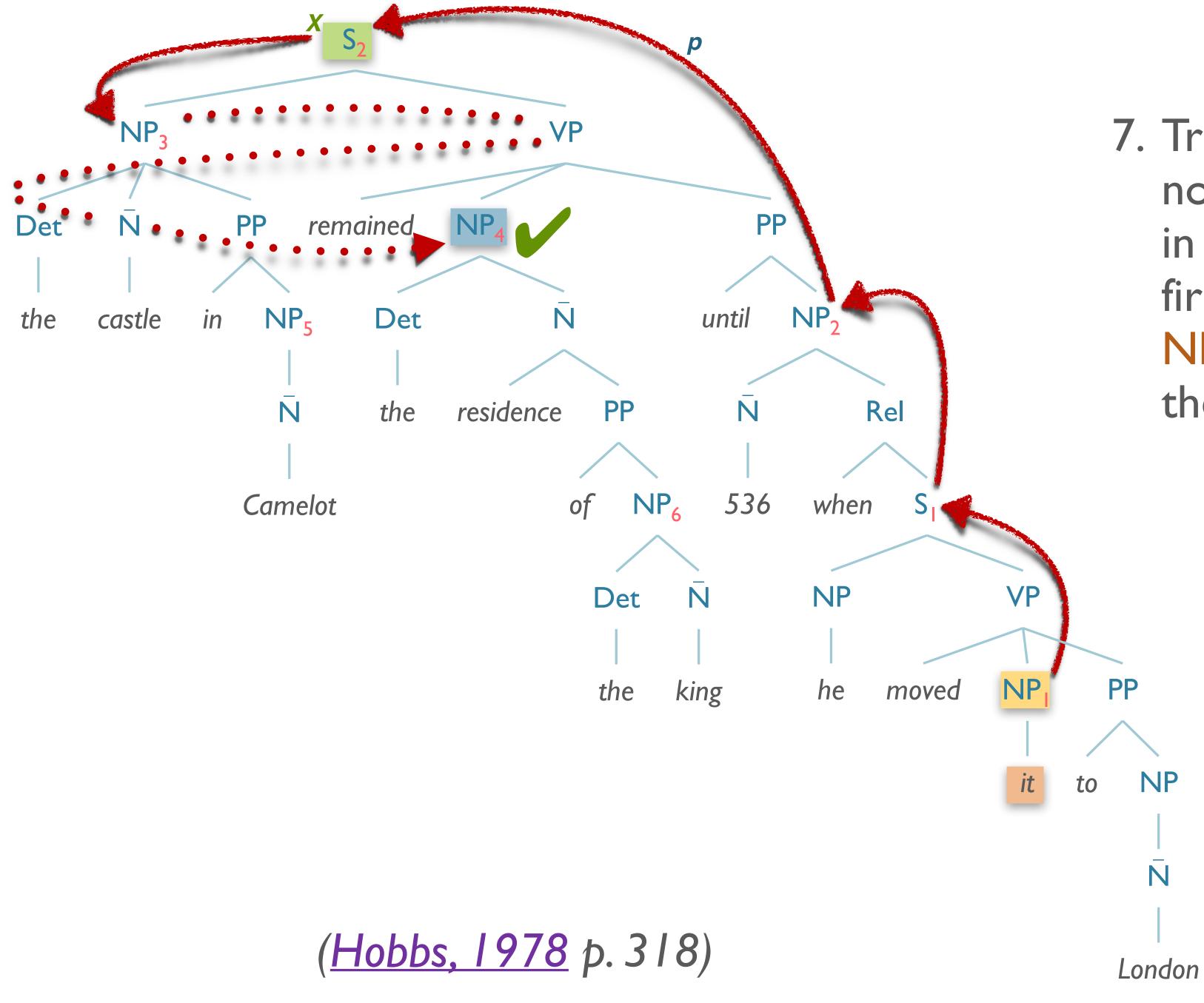












"the residence of the king"

Hobbs Algorithm Detail (Hobbs, 1978)

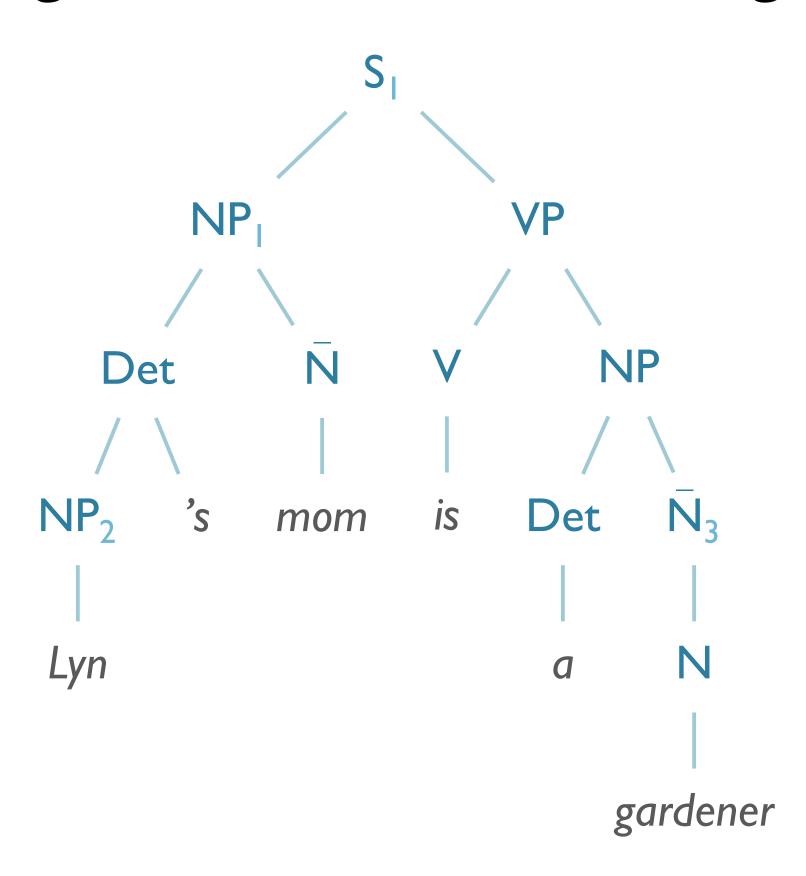
- 1. Begin at the noun phrase (NP) node immediately dominating the pronoun
- 2. Go up the tree to the first NP or sentence (S) node encountered. Call this node X, and call the path used to reach it p.
- 3. Traverse all branches below node X to the left of path p in a left-to-right, breadth-first fashion. Propose as the antecedent any encountered NP node that has an NP or S node between it and X.
- 4. If node X is the highest S node in the sentence, traverse the surface parse trees of previous sentences in the text in order of recency, the most recent first; each tree is traversed in a left-to-right, breadth-first manner, and when an NP node is encountered, it is proposed as antecedent. If X is not the highest S node in the sentence, continue to step 5.

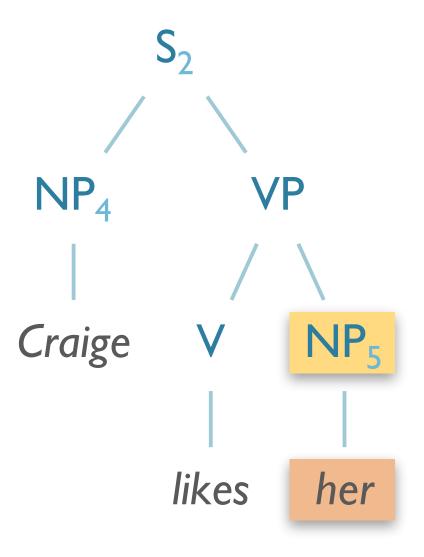
Hobbs Algorithm Detail (Hobbs, 1978)

- 5. From node X, go up the tree to the first NP or S node encountered. Call this new node X, and call the path traversed to reach it p.
- 6. If X is an NP node and if the path p to X did not pass through the Nominal node that X immediately dominates, propose X as the antecedent.
- 7. Traverse all branches below node X to the *left* of path p in a left-to-right, breadth-first manner. Propose any NP node encountered as the antecedent.
- 8. If X is an S node, traverse all branches of node X to the right of path p in a left-to-right, breadth-first manner, but do not go below any NP or S node encountered. Propose any NP node encountered as the antecedent.
- 9. Go to step 4.

Lyn's mom is a gardener.

Craige likes her.

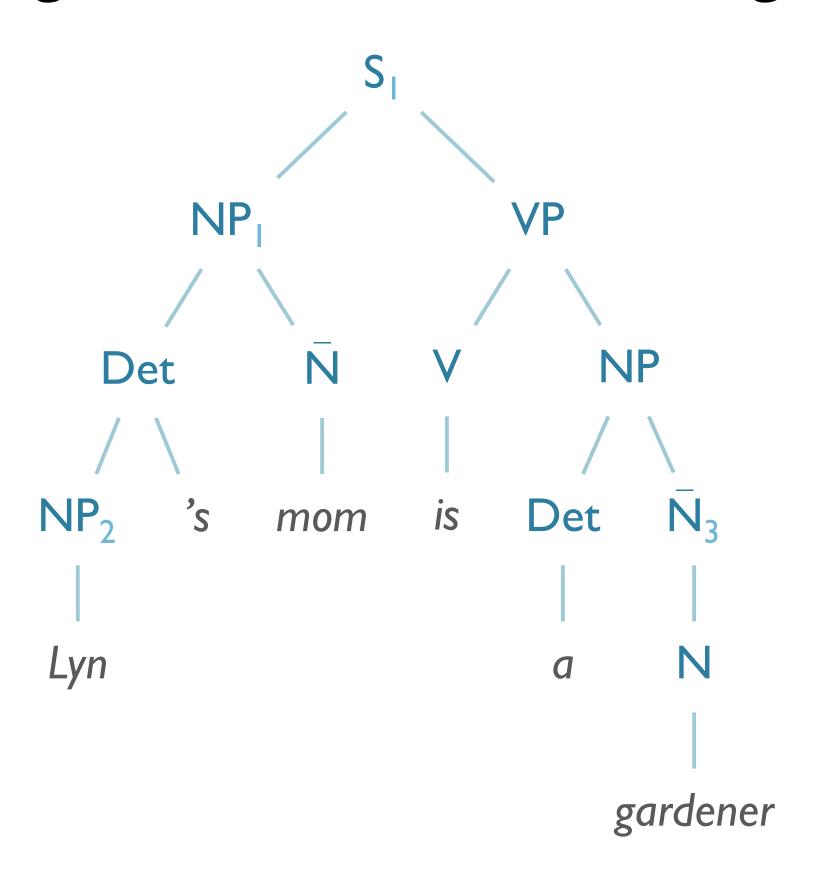


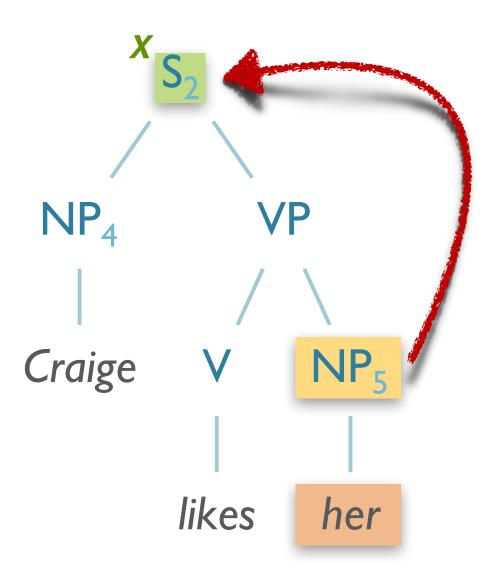


I. Begin at the noun phrase (NP) node immediately dominating the pronoun

Lyn's mom is a gardener.

Craige likes her.

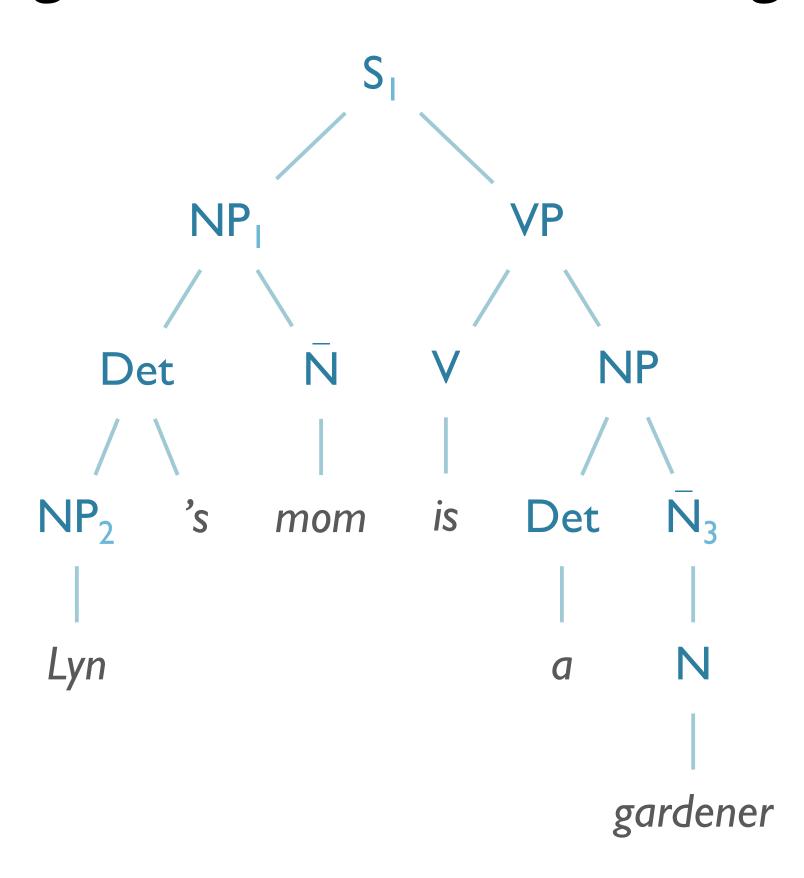


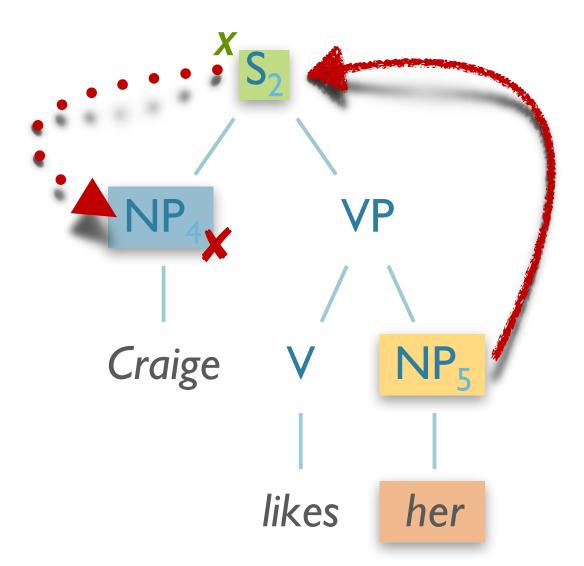


Go up the tree to the first NP or sentence (S) node encountered. Call this node X, and call the path used to reach it **p**.

Lyn's mom is a gardener.

Craige likes her.

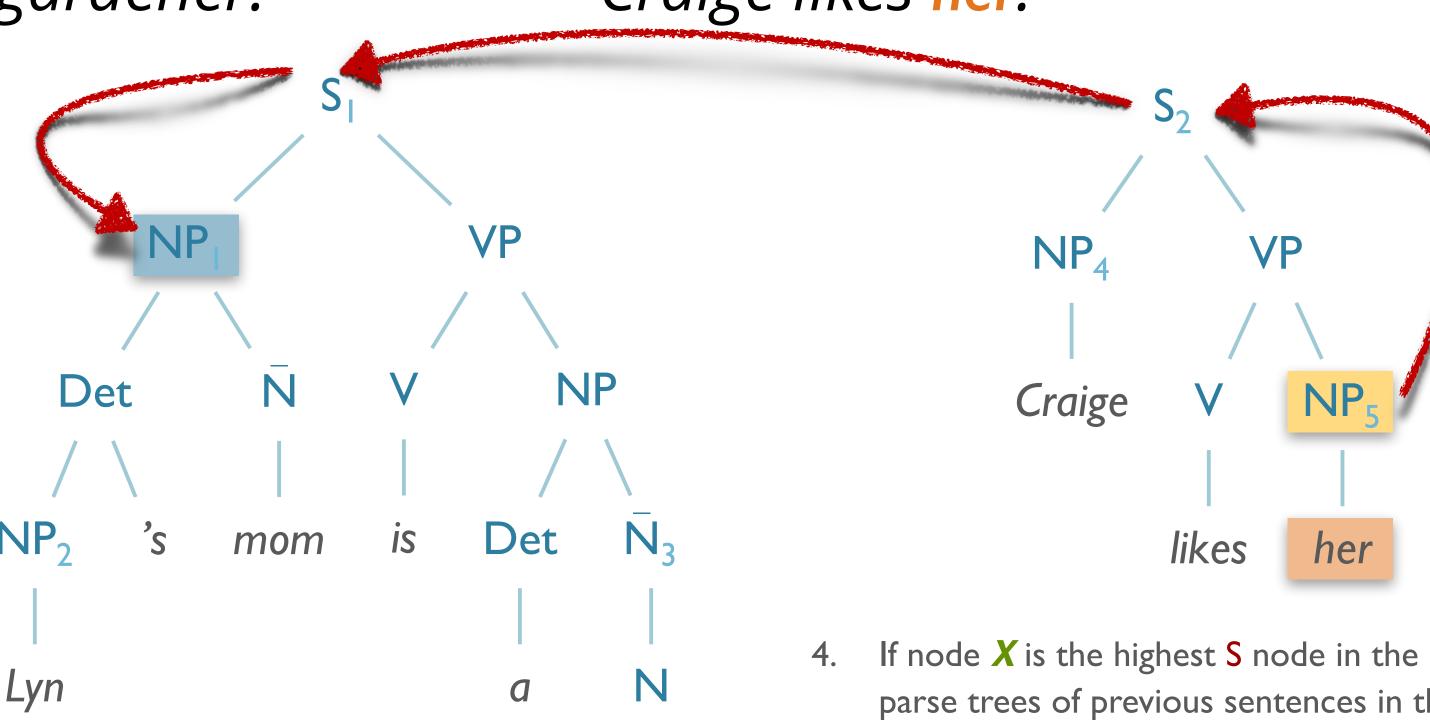




3. Traverse all branches below node *X* to the left of path *p* in a left-to-right, breadth-first fashion. Propose as the antecedent any encountered NP node that has an NP or S node between it and *X*.

Lyn's mom is a gardener.

Craige likes her.



gardener

If node X is the highest S node in the sentence, traverse the surface parse trees of previous sentences in the text in order of recency, the most recent first; each tree is traversed in a left-to-right, breadth-first manner, and when an NP node is encountered, it is proposed as antecedent.

- What about...?
 - Lyn's mom is hired a gardener.
 - Craige likes her.