Discourse Structure

LING 571 — Deep Processing Methods in NLP
December 2, 2020
Shane Steinert-Threlkeld

Ambiguity of the Week

The kids were playing Rock Paper Scissors.

: Scissors

: Everything!

: What?

: Nothing beats everything.

: Ok play again, Rock Paper Scissors shoot!

: Everything!

: Nothing!

Breaking Language Technology

https://twitter.com/xkcd/status/1333529967079120896

Roadmap

- Coreference
  - Recap
  - Hobbs Walkthrough
  - Other approaches
  - Evaluation
- Discourse Structure
  - Cohesion [Segmentation]
  - Coherence

Discourse & Coref Recap

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)*

- Understanding depends on **context**
  - Word sense — *plant*
  - Intention — *Do you have the time?*
  - Referring expressions — *it*, *that*, *the screen*

Reference: Terminology

Queen Elizabeth set about transforming her husband, King George VI, into a viable monarch. Logue, a renowned speech therapist, was summoned to help the King overcome his speech impediment.

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    - *Queen Elizabeth*, *her*, *the Queen*
    - *Logue*, *a renowned speech therapist*
  - Entities in **purple** do not corefer to anything.

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- ***Antecedent:***
  - An expression that introduces an item to the discourse for other items to refer back to
  - Queen Elizabeth… her

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- ***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.*"

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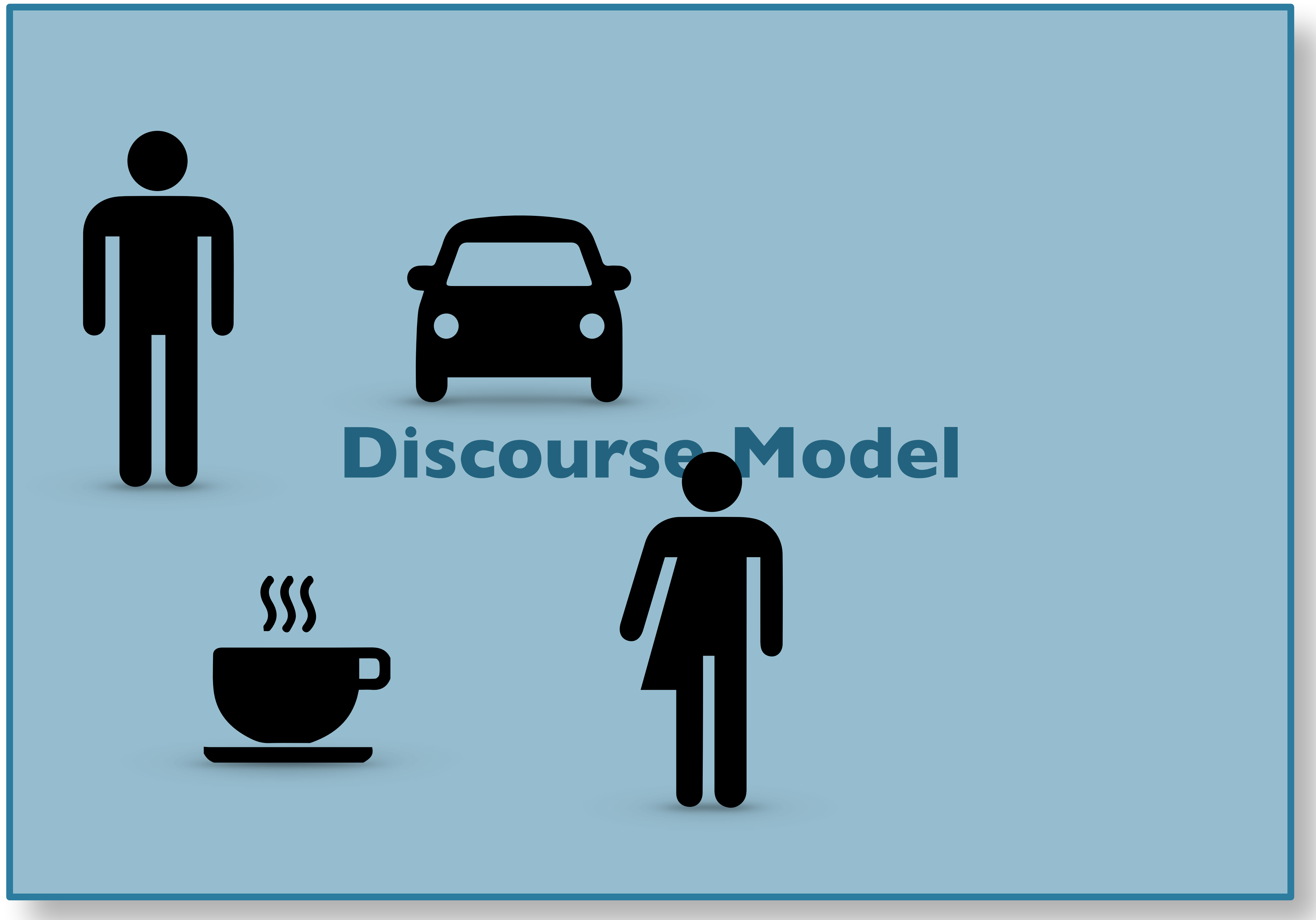
Referring Expressions

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

Reference and Model



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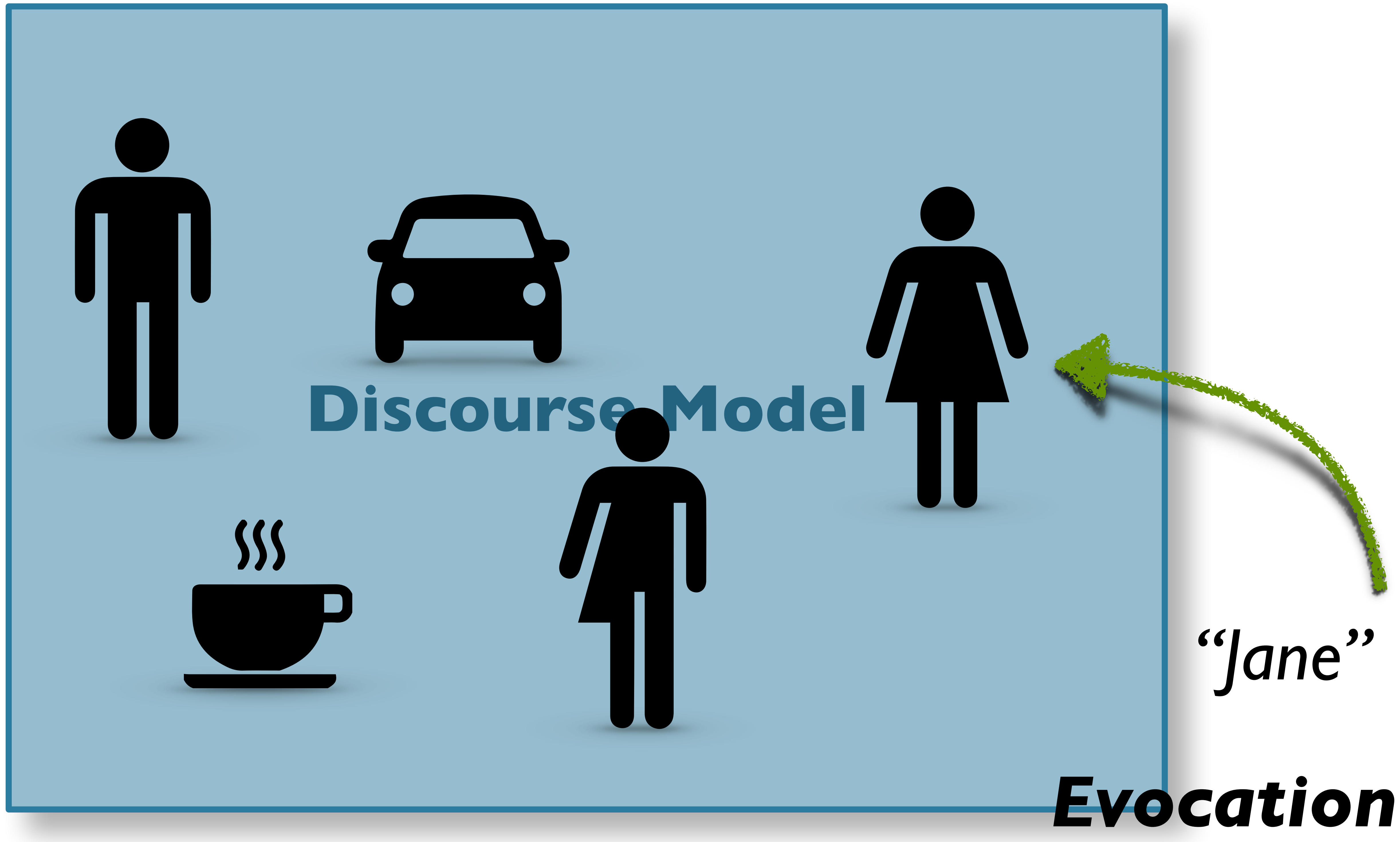

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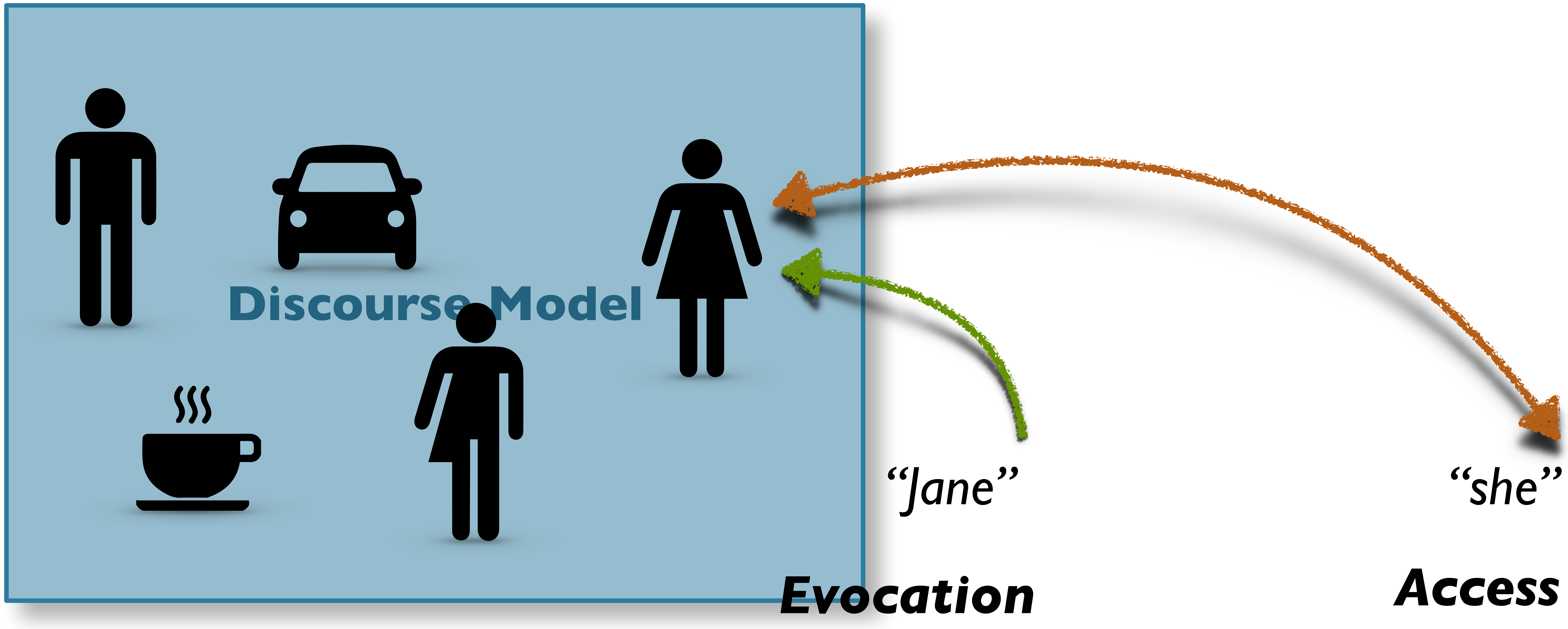

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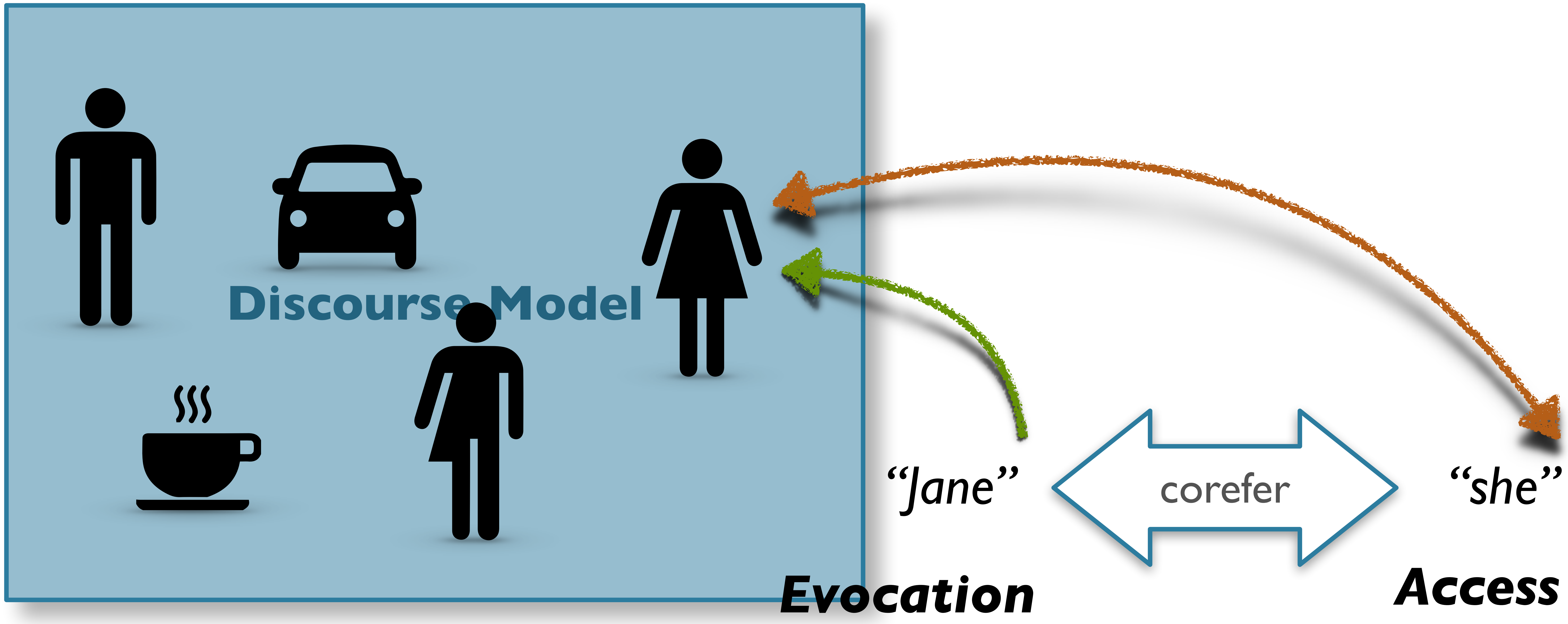

Reference Tasks

- **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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  - Find all expressions referring to the same entity in a text.
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- **Pronomial anaphora resolution:**
  - Find antecedent for a single pronoun.
  - Subtask of coreference resolution

Hobbs Algorithm Walkthrough

(h/t Ryan Georgi)

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.

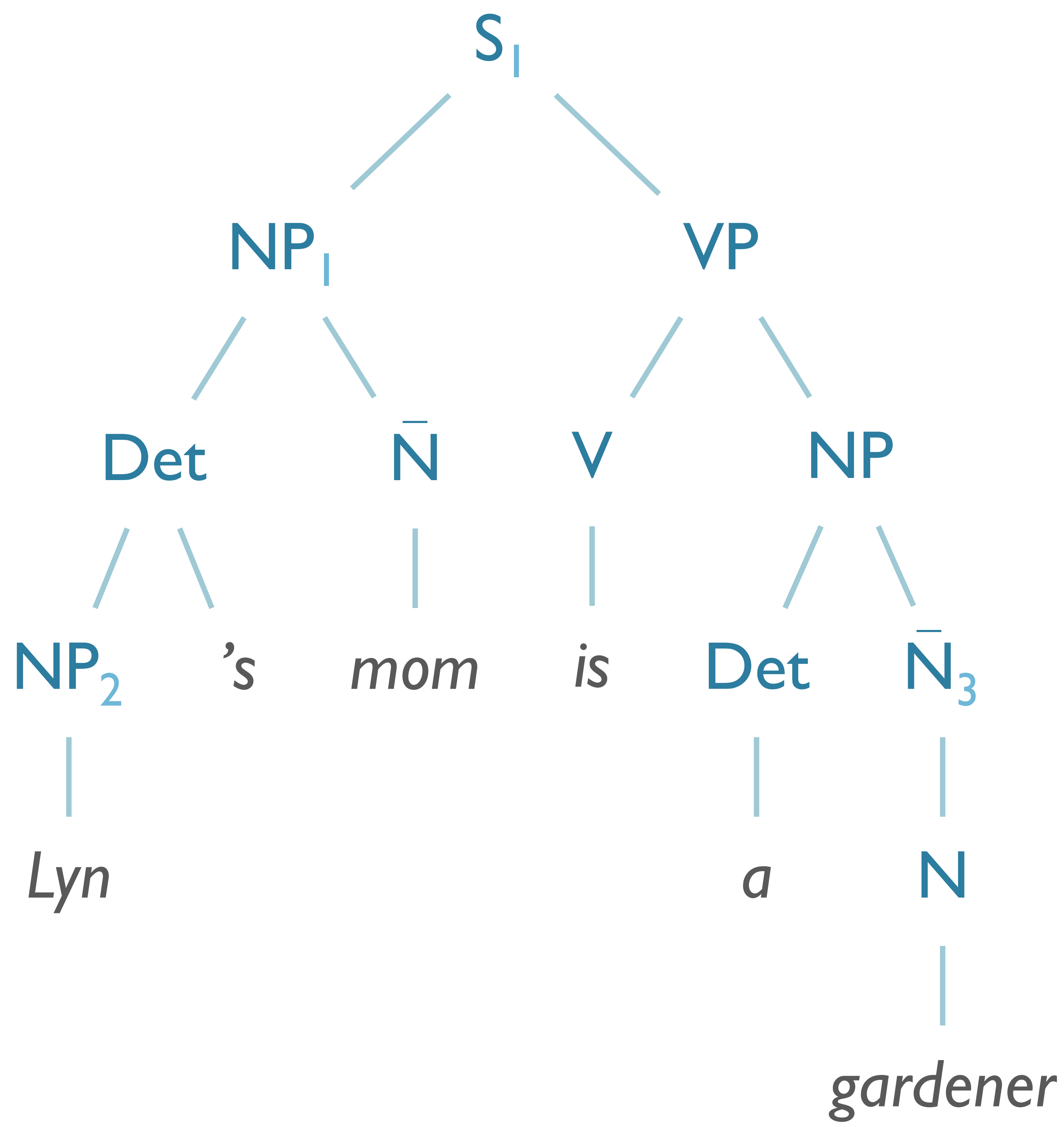
7. Traverse all branches below node X to the ***left*** of path p in a left-to-right, breadth-first manner. Propose any NP node encountered as the antecedent.

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.

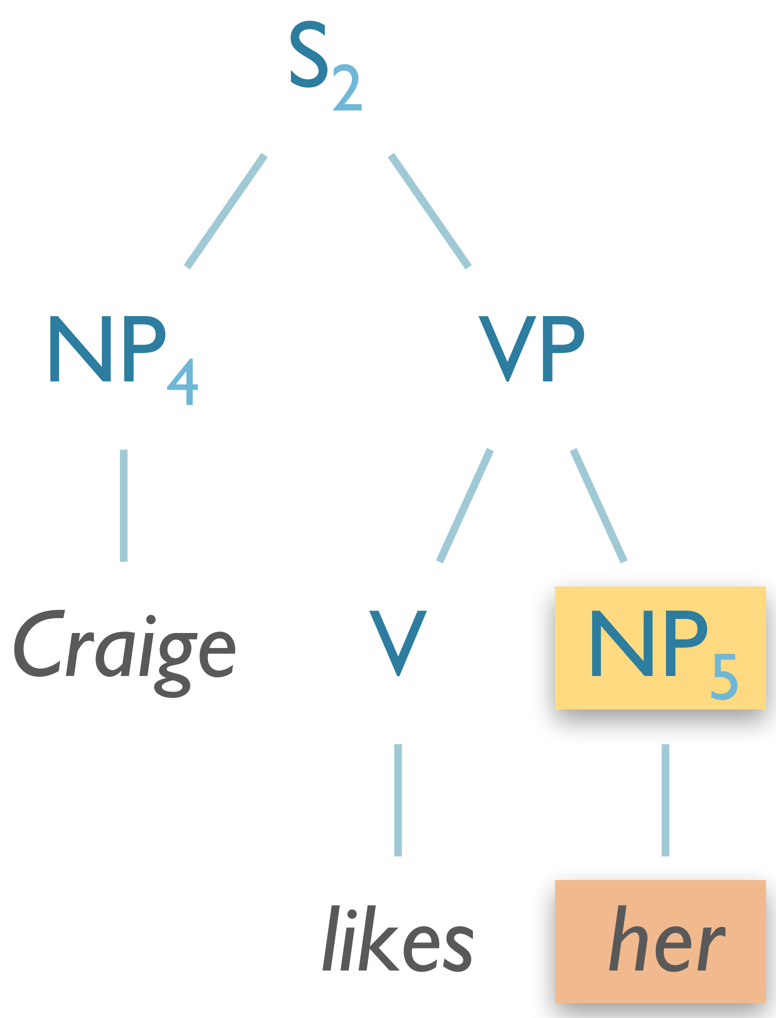
9. Go to step 4.

Hobbs Example

Lyn's mom is a gardener.



Craige likes ***her****.*



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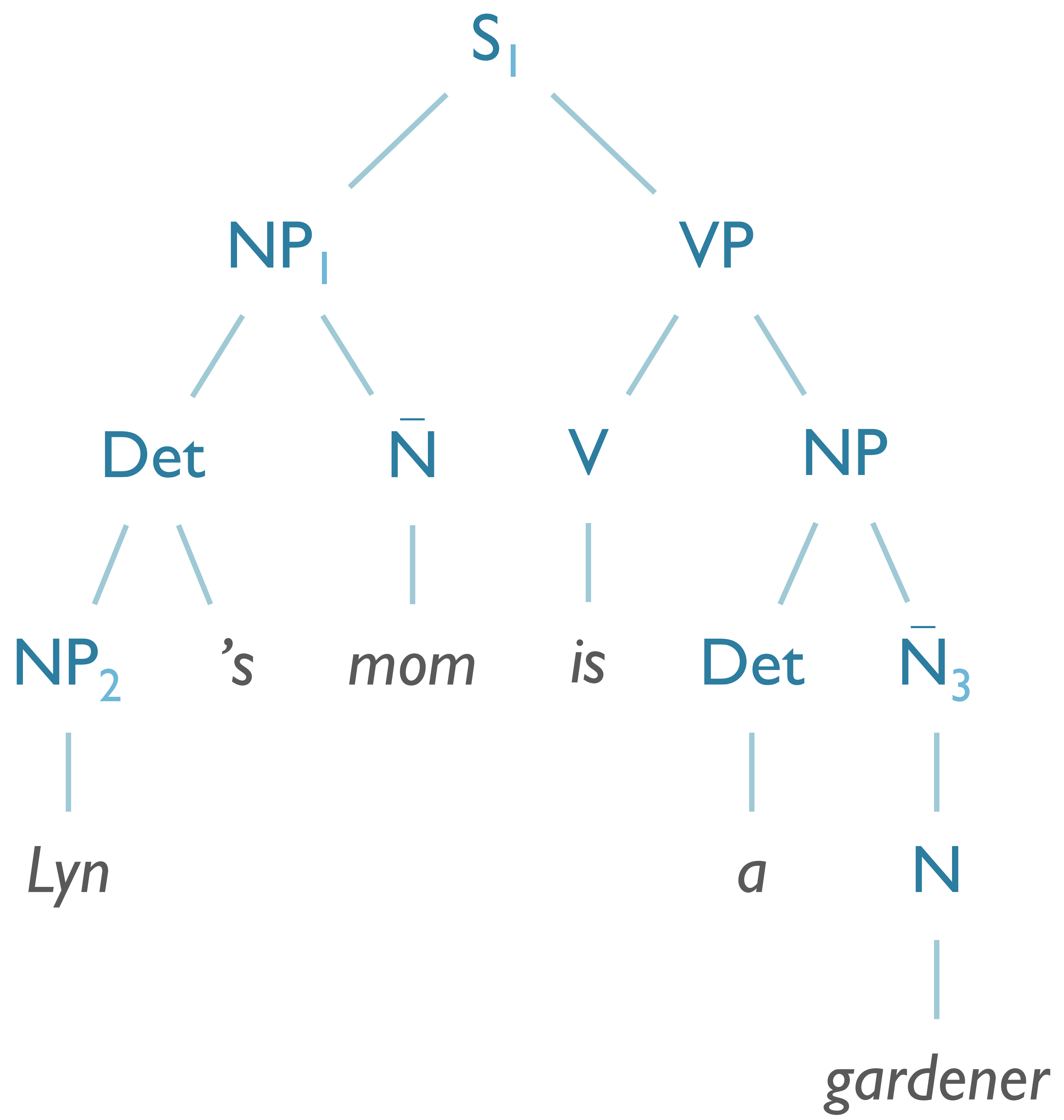

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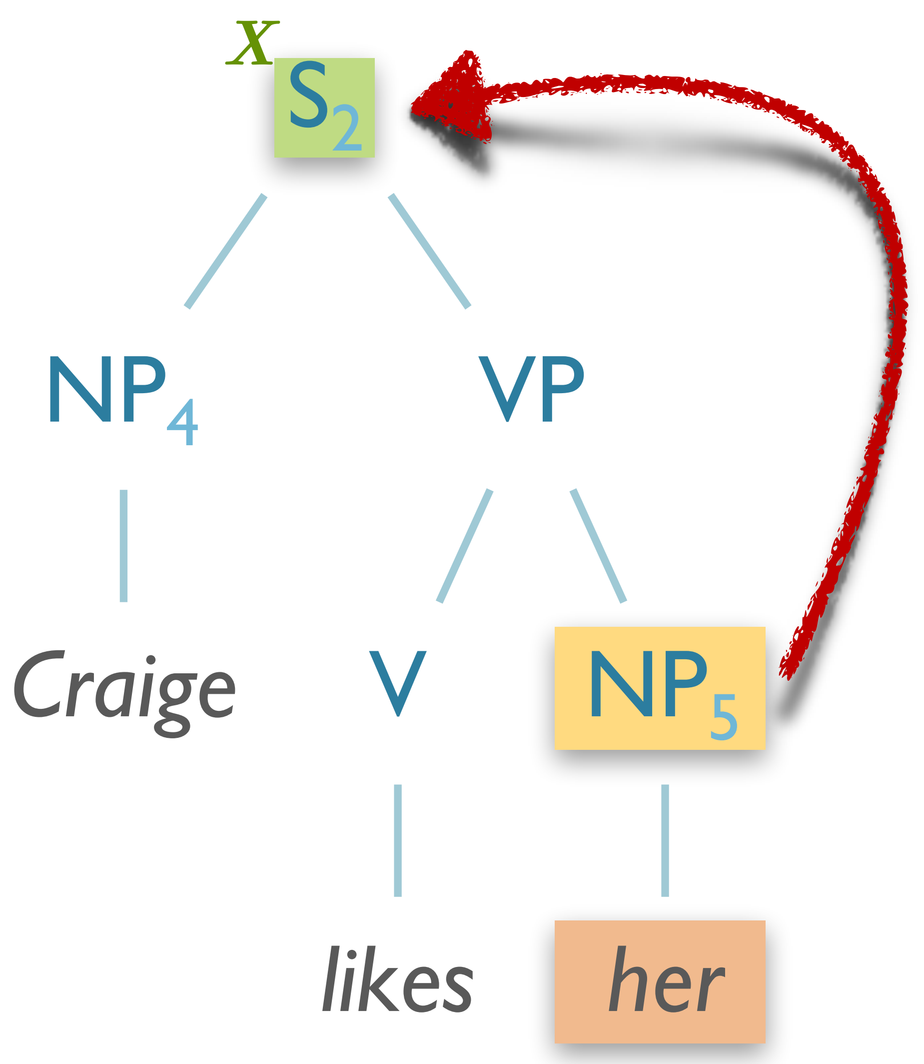

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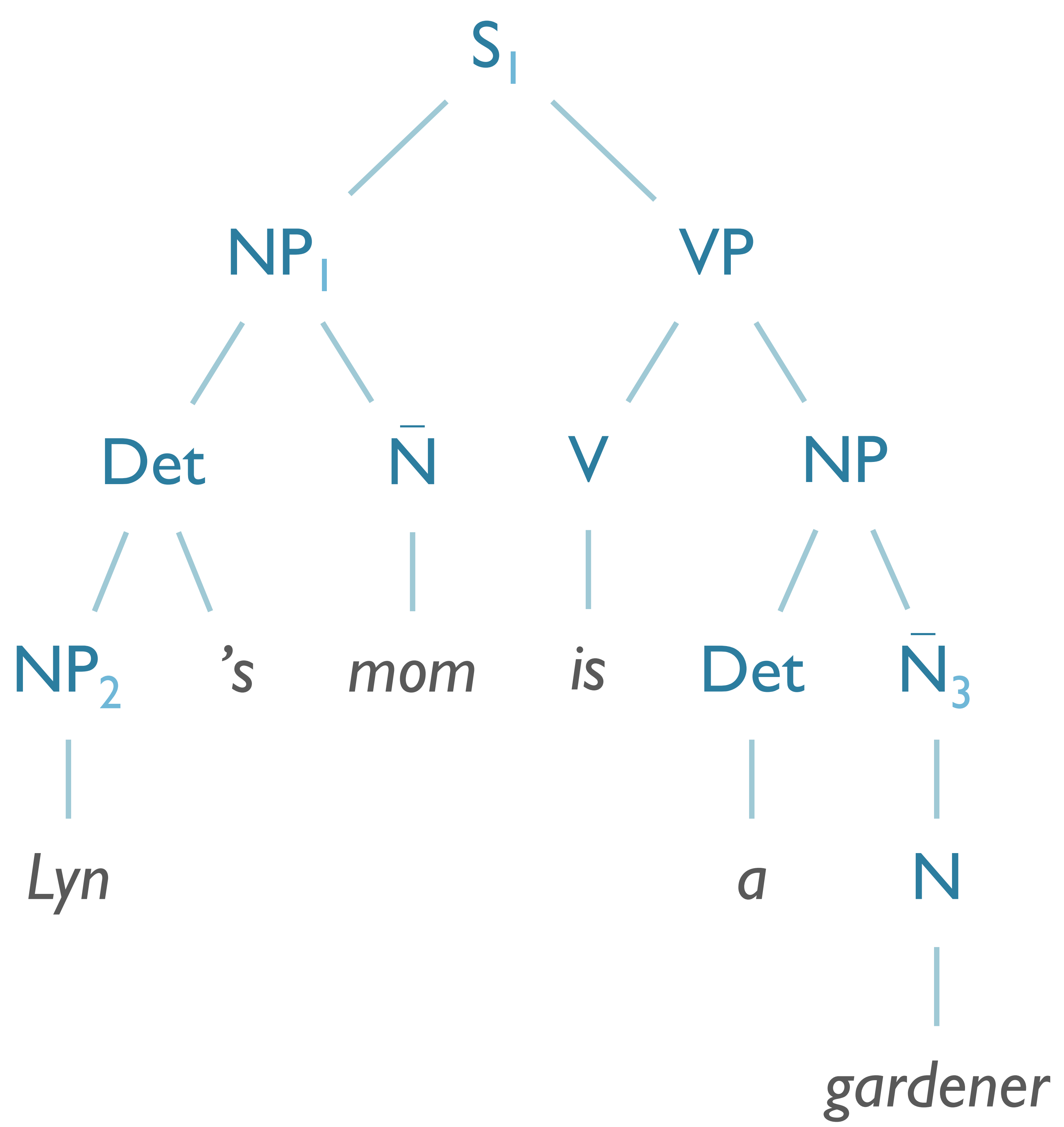
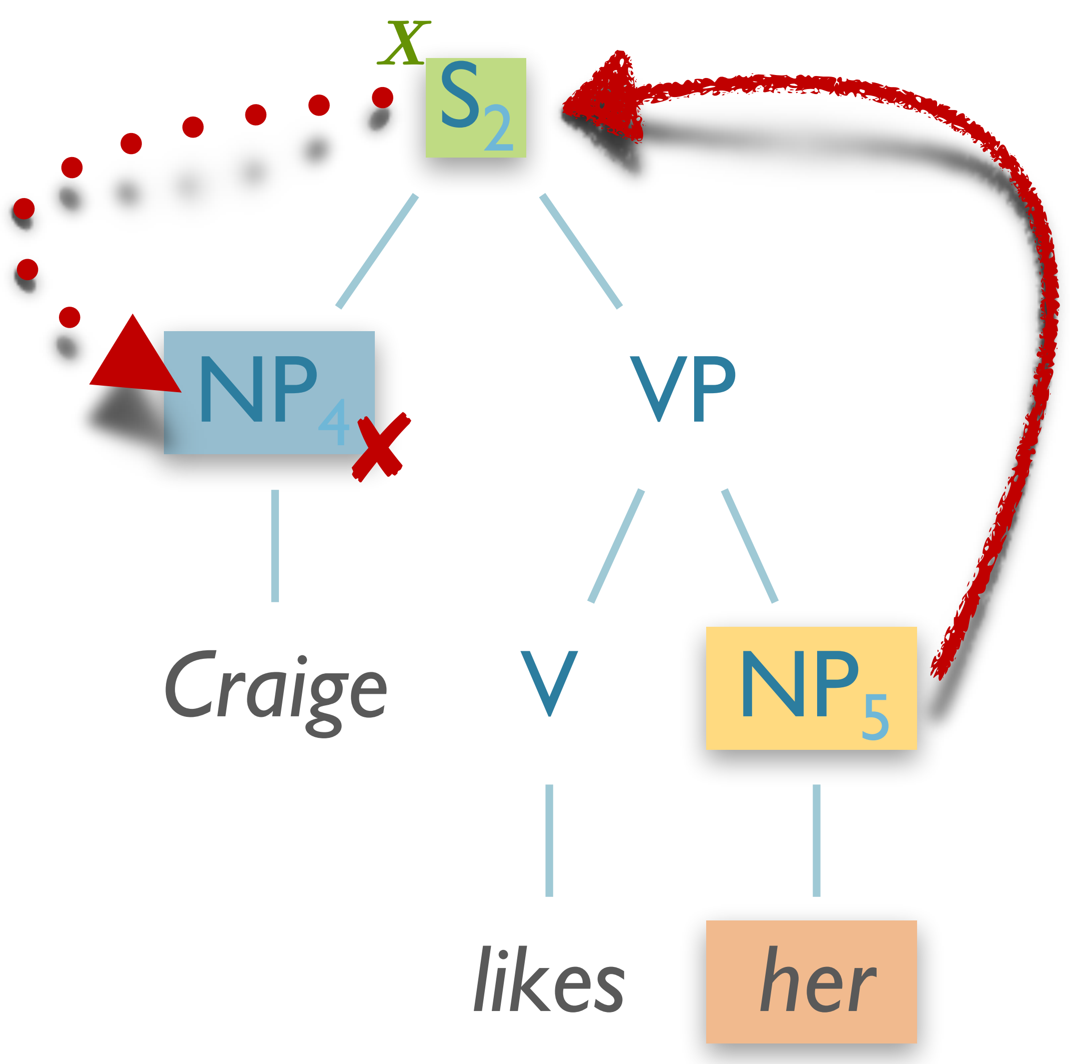


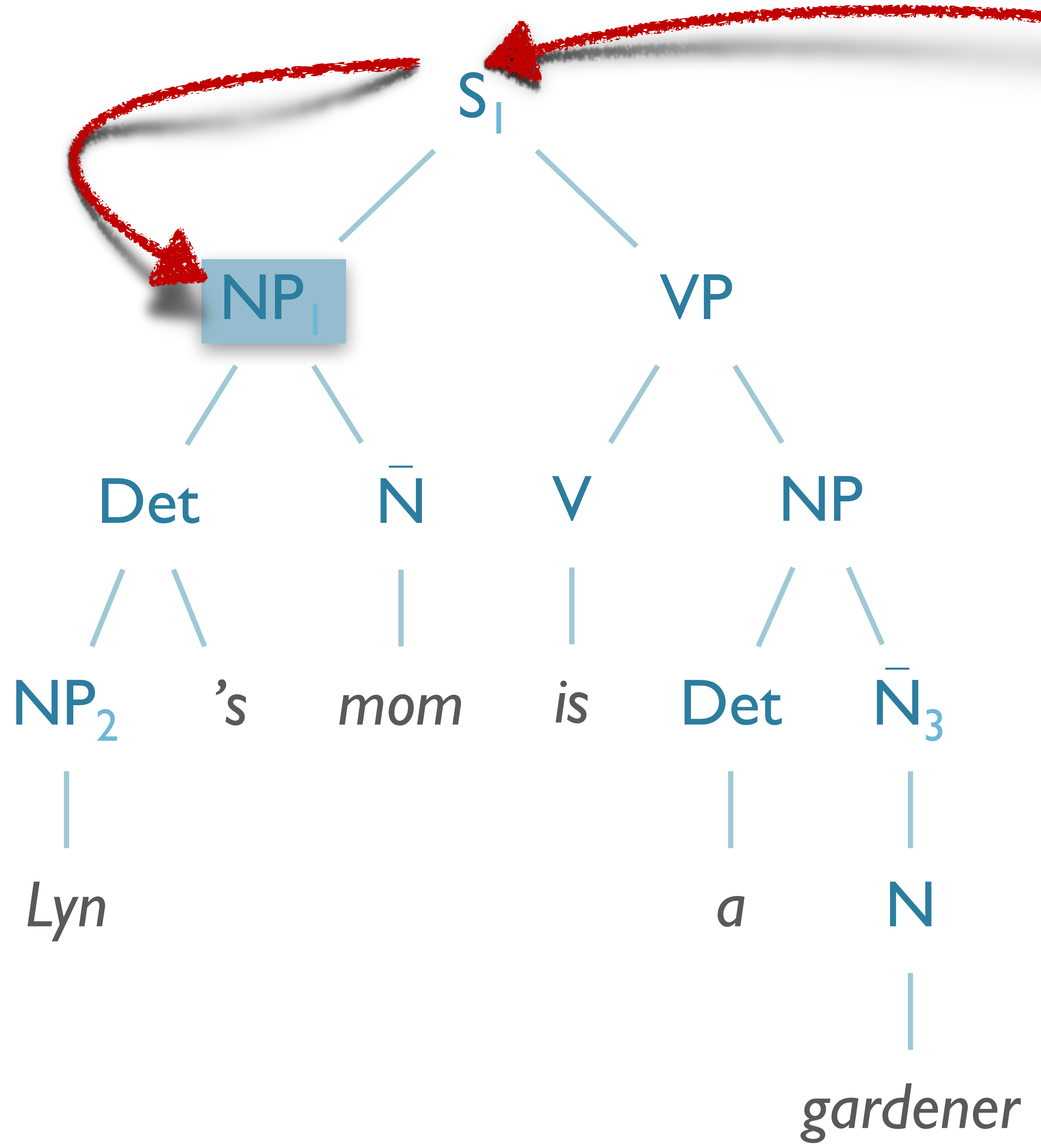
*Craige likes **her**.*

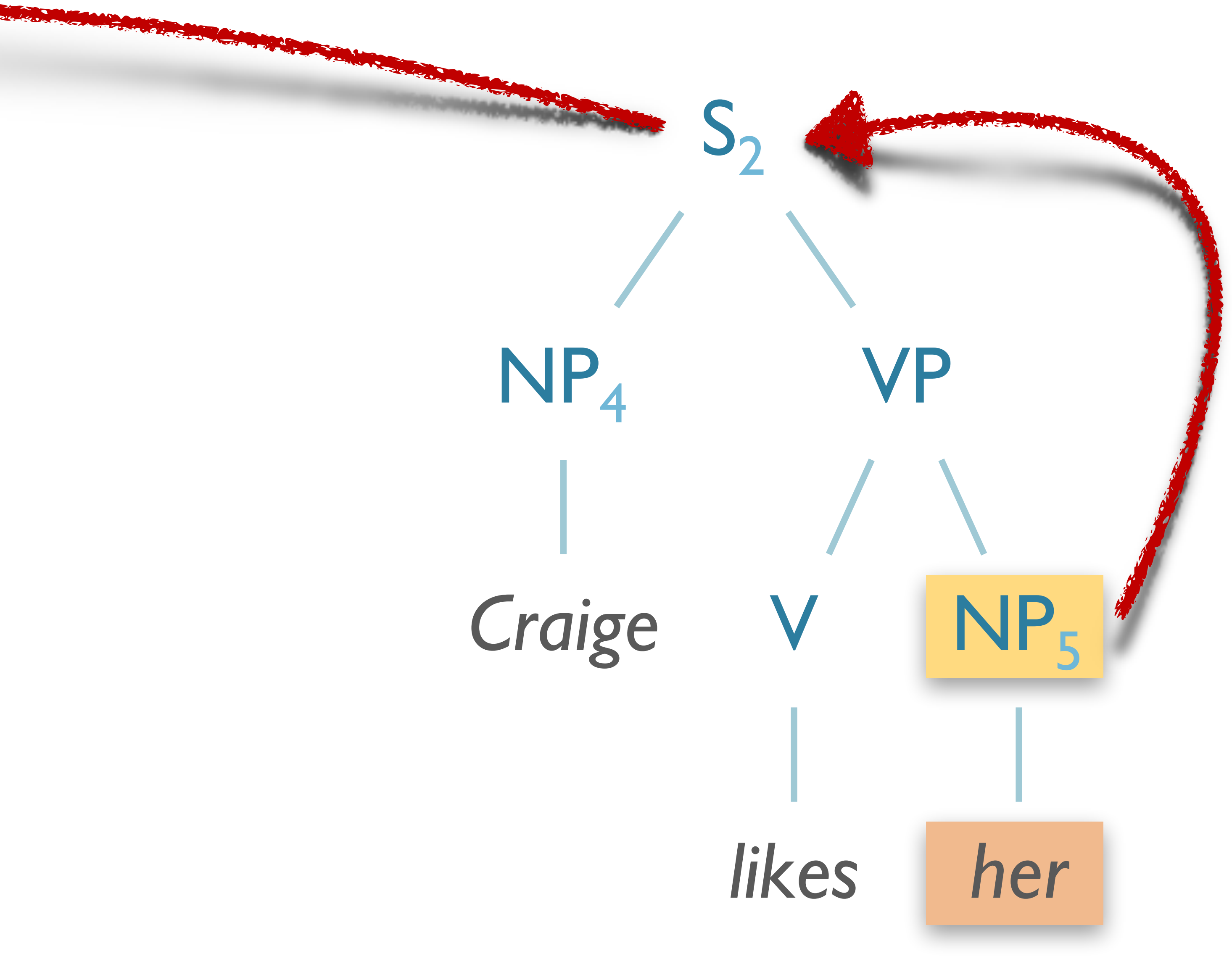


3. Traverse all branches below node X to the left of path p in a left-to-right, breadth-first fashion. Propose as the antecedent any encountered NP node that has an NP or S node between it and X.

Hobbs Example

Lyn's mom is a gardener. *Craige likes **her**.*





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.

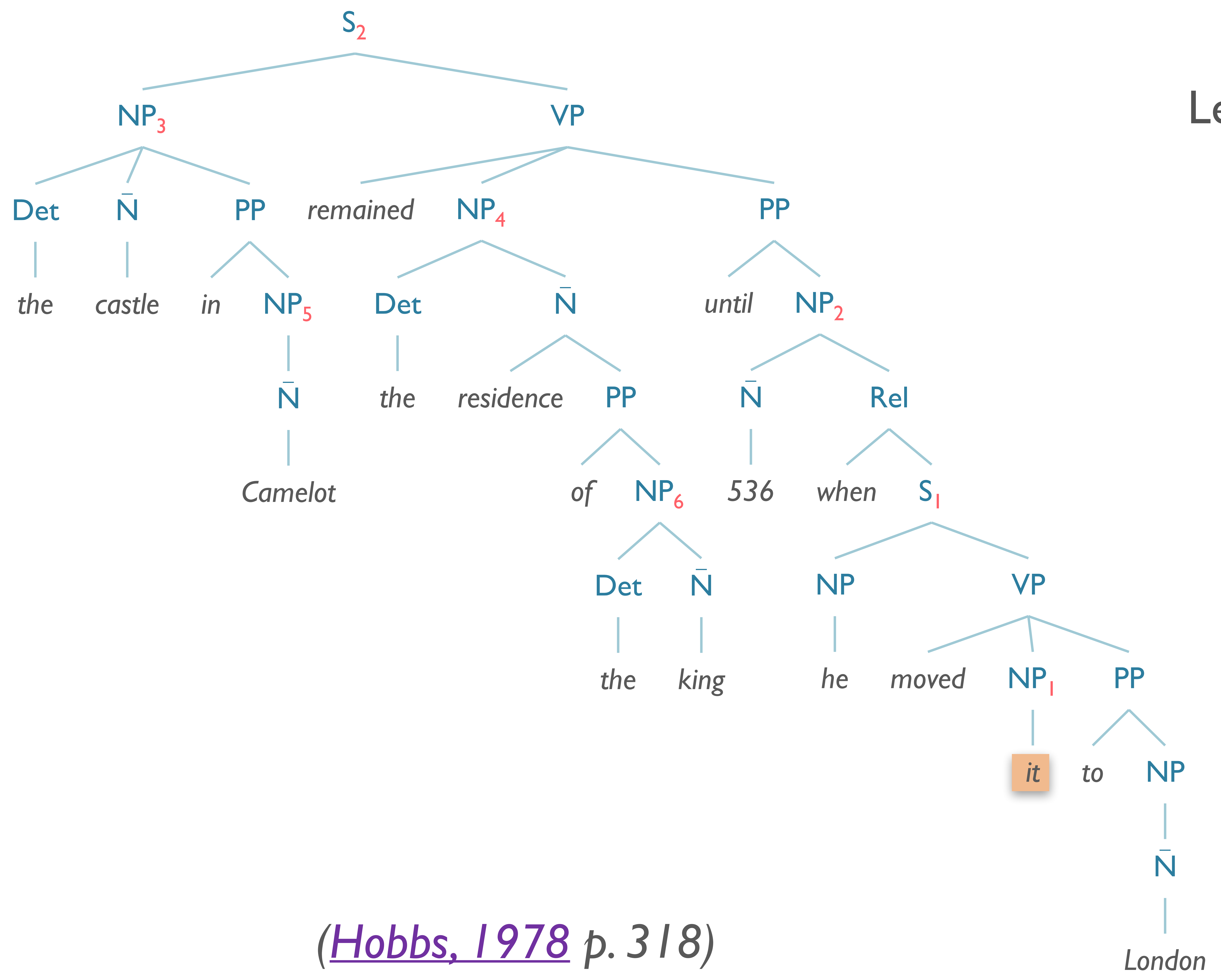
Hobbs Example

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

More Complex Example

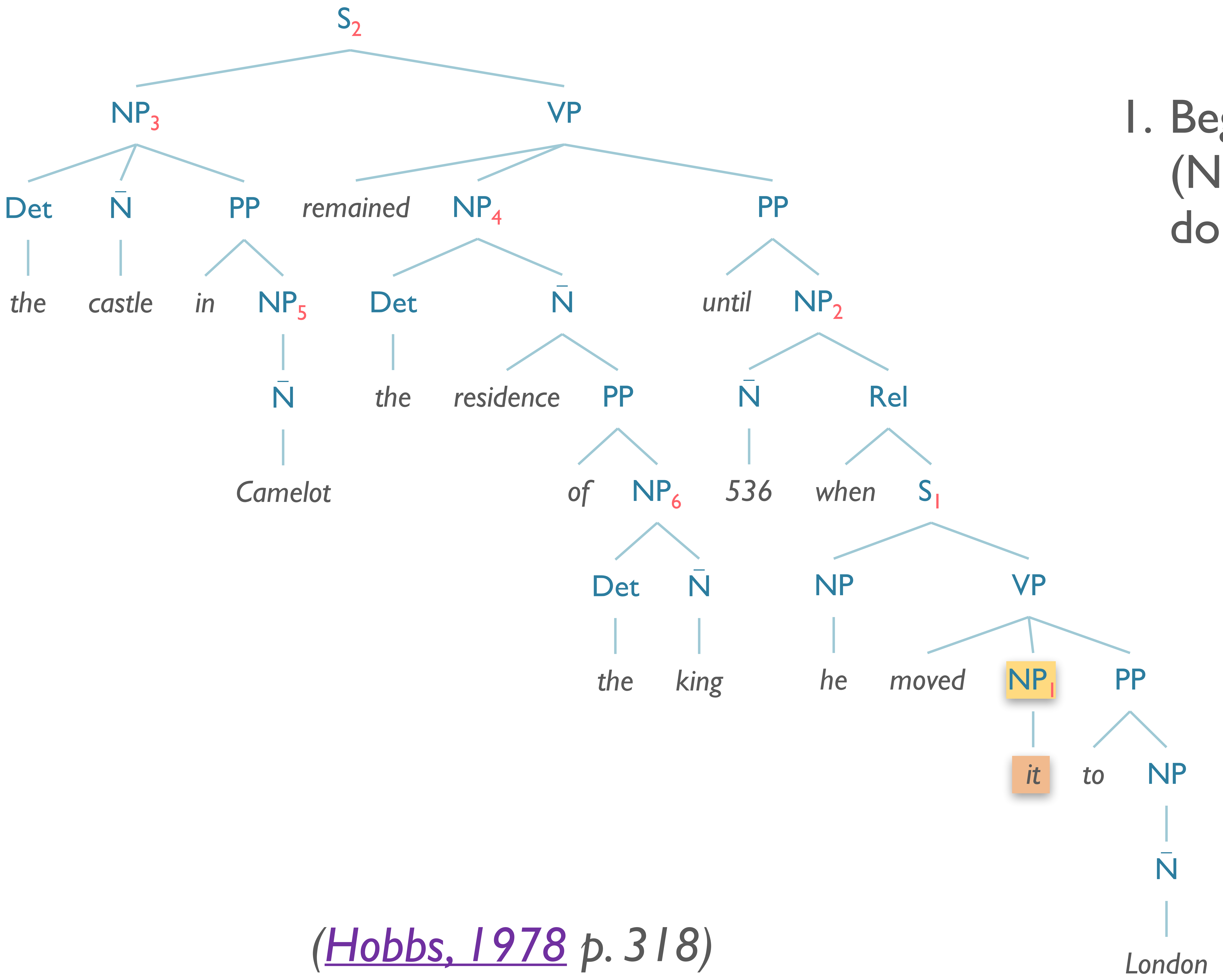
- …the castle in Camelot remained the residence of the King until 536 when he moved ***it*** to London

Poll!



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

(Hobbs, 1978 *p. 318*)



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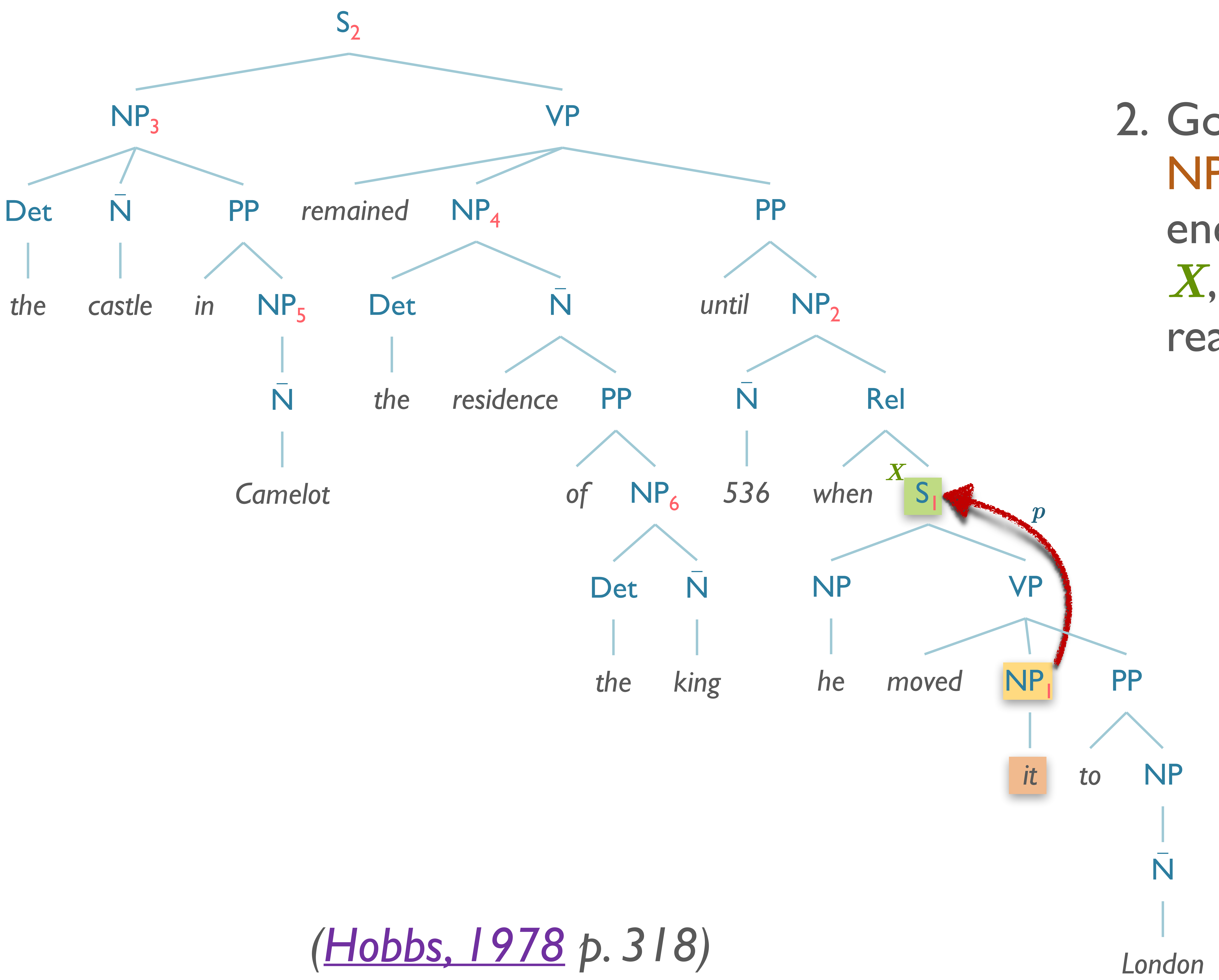

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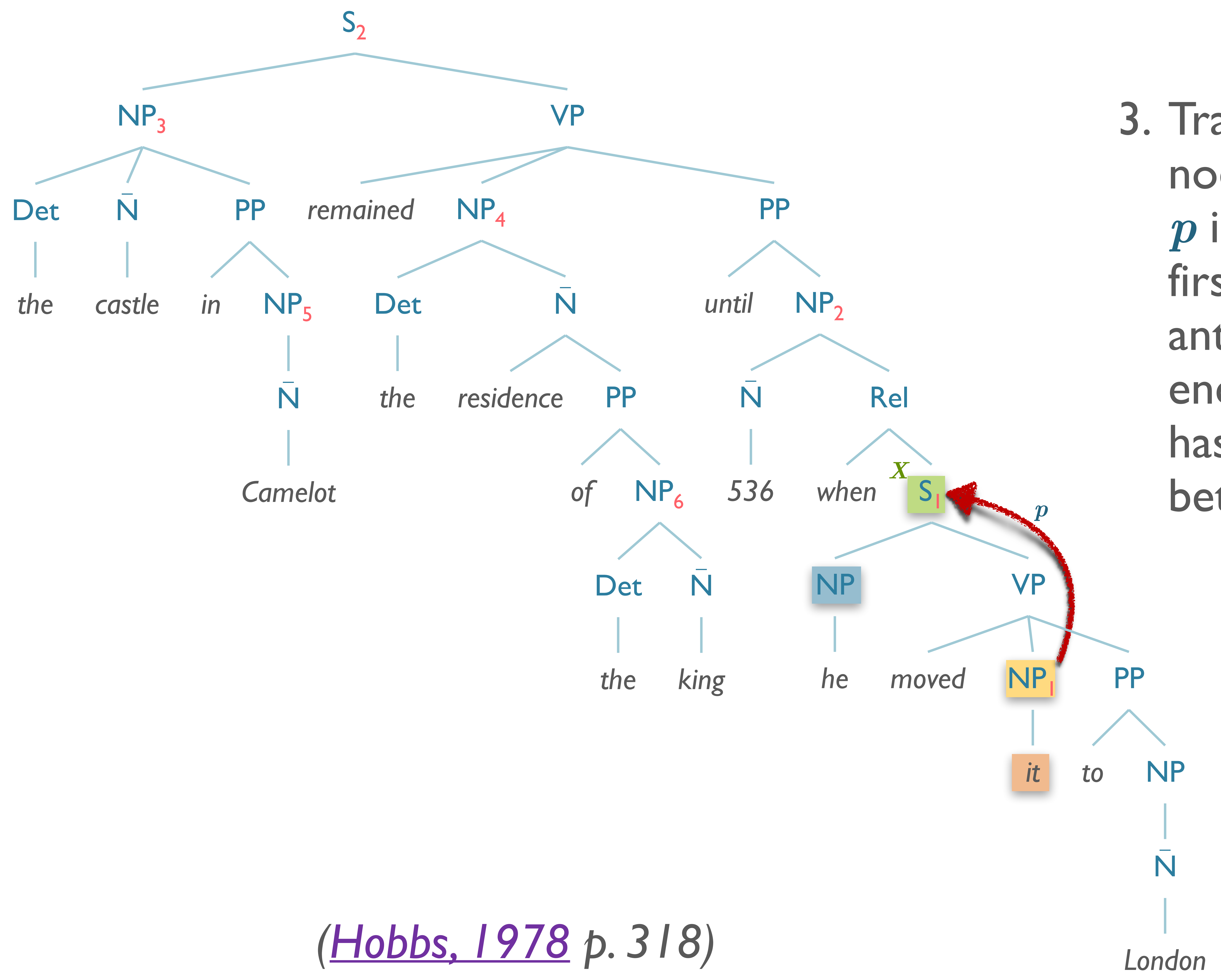
(Hobbs, 1978 p. 318)



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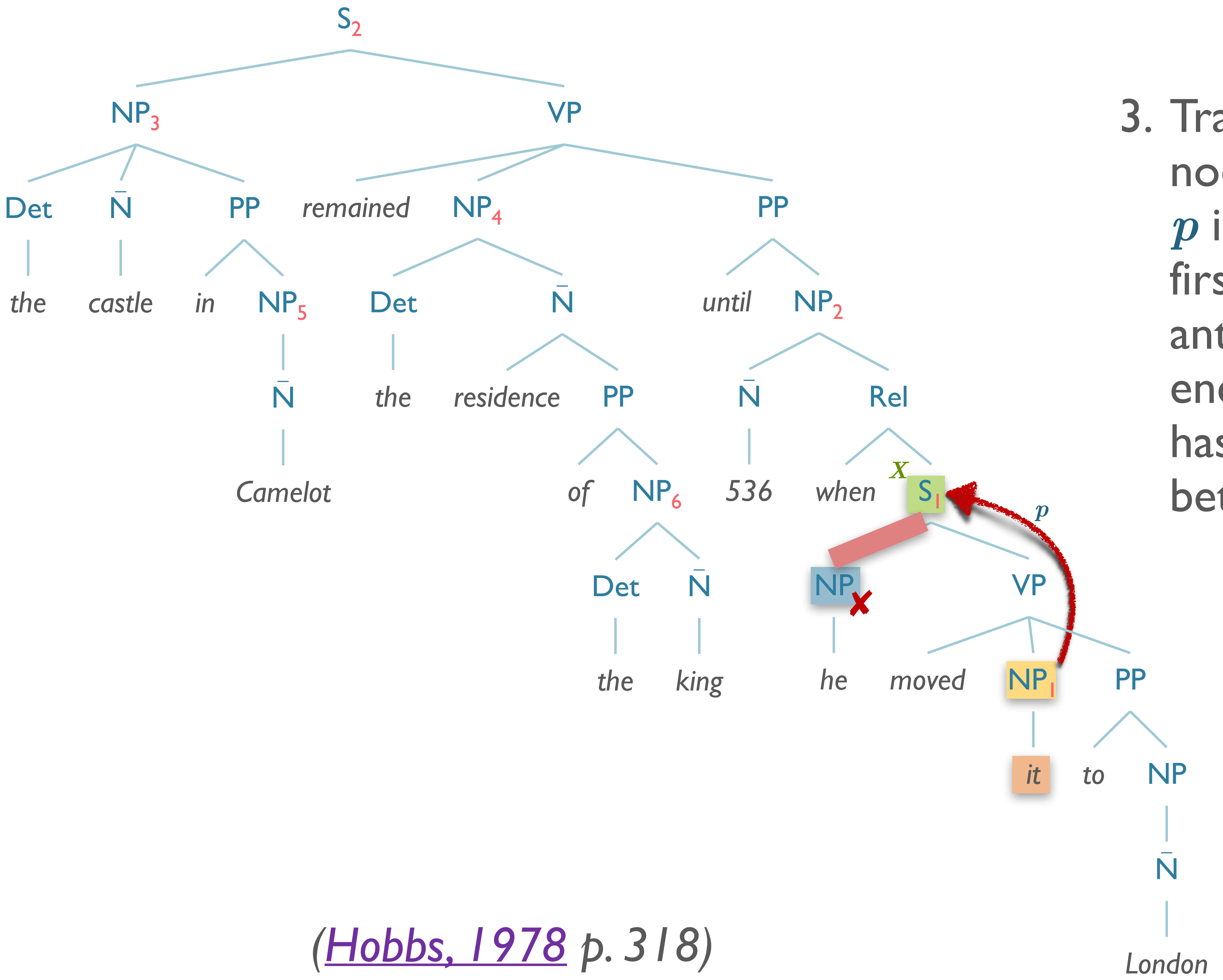

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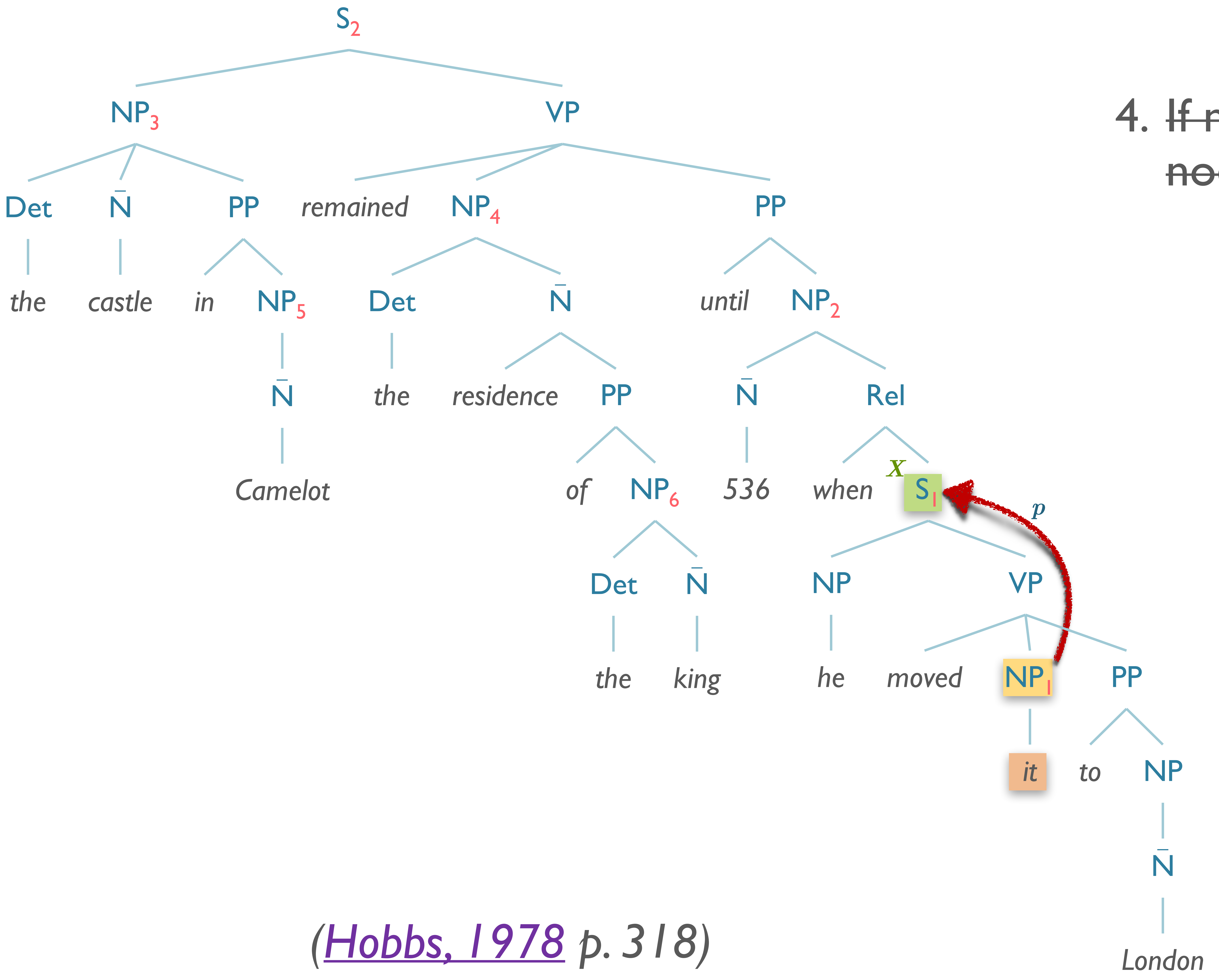
No NP or S between "he" NP and X

([Hobbs, 1978](#) *p. 318*)



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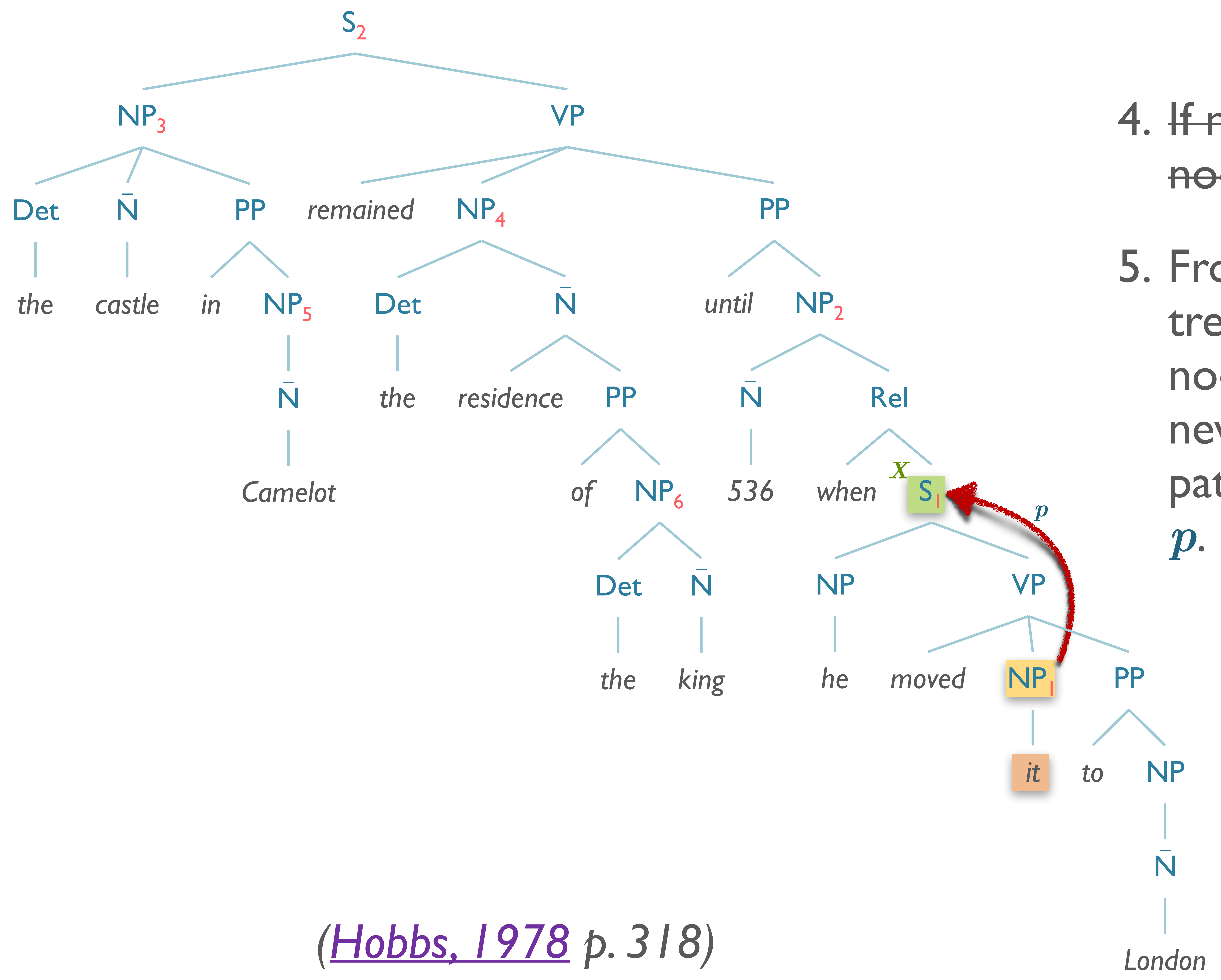

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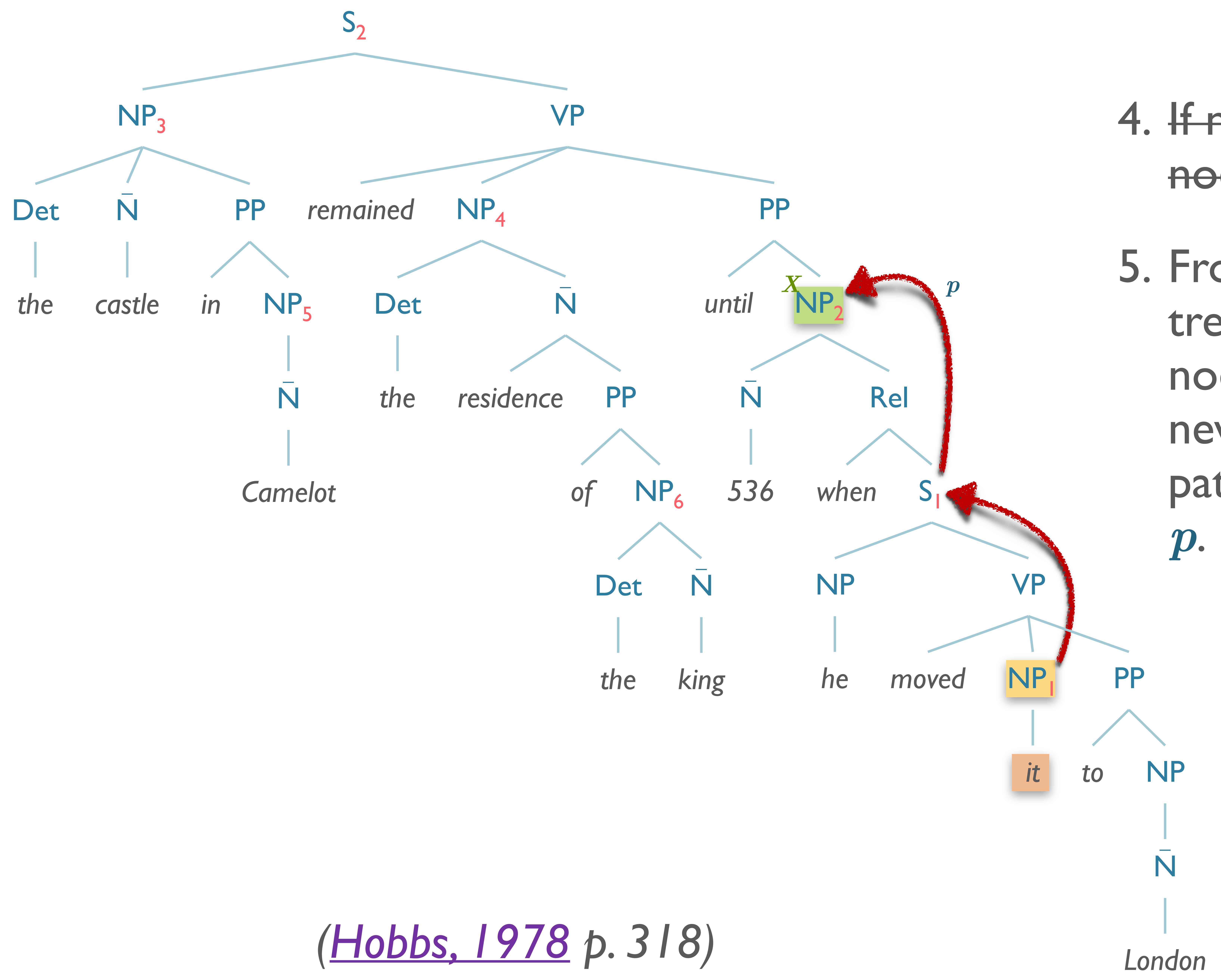

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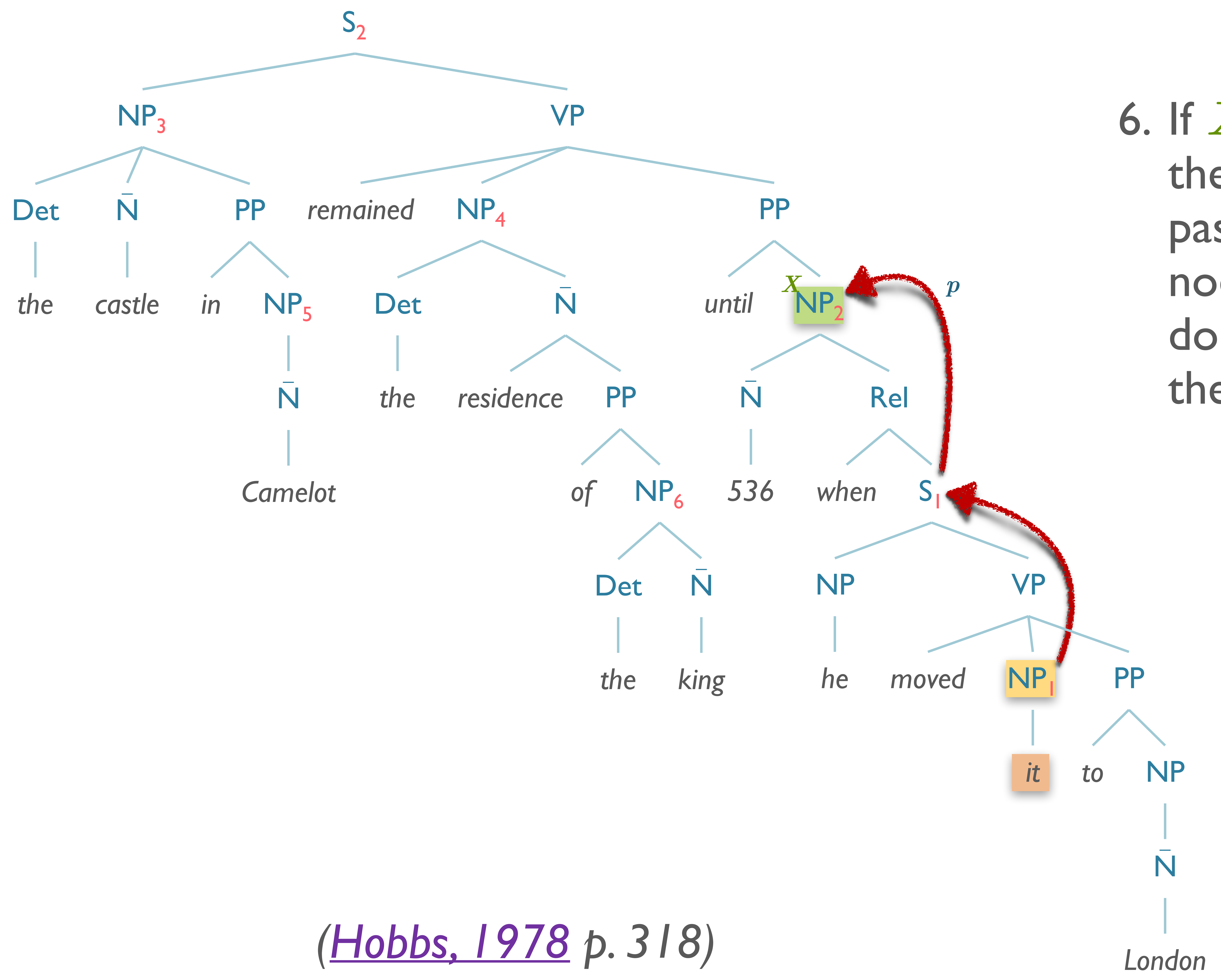

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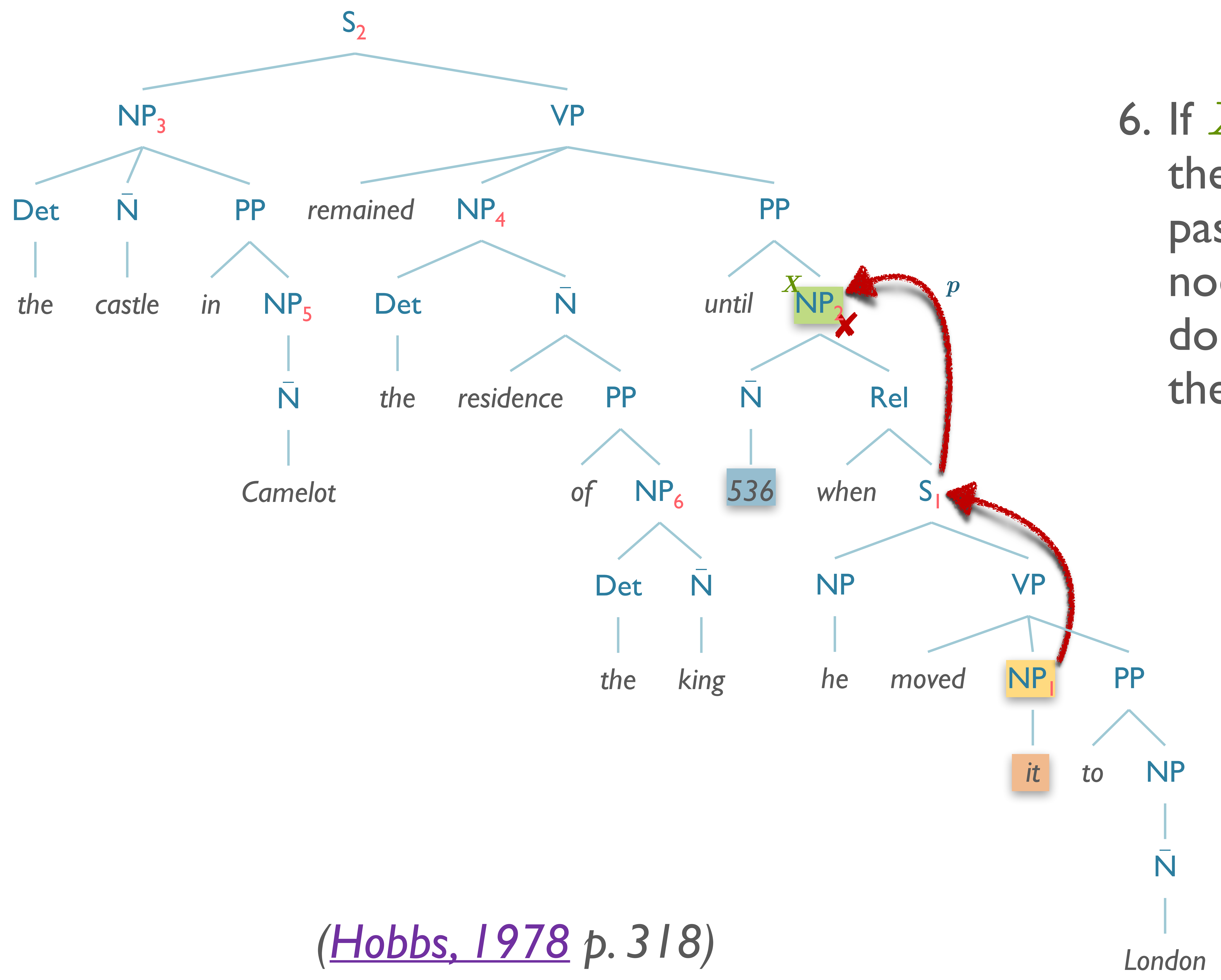

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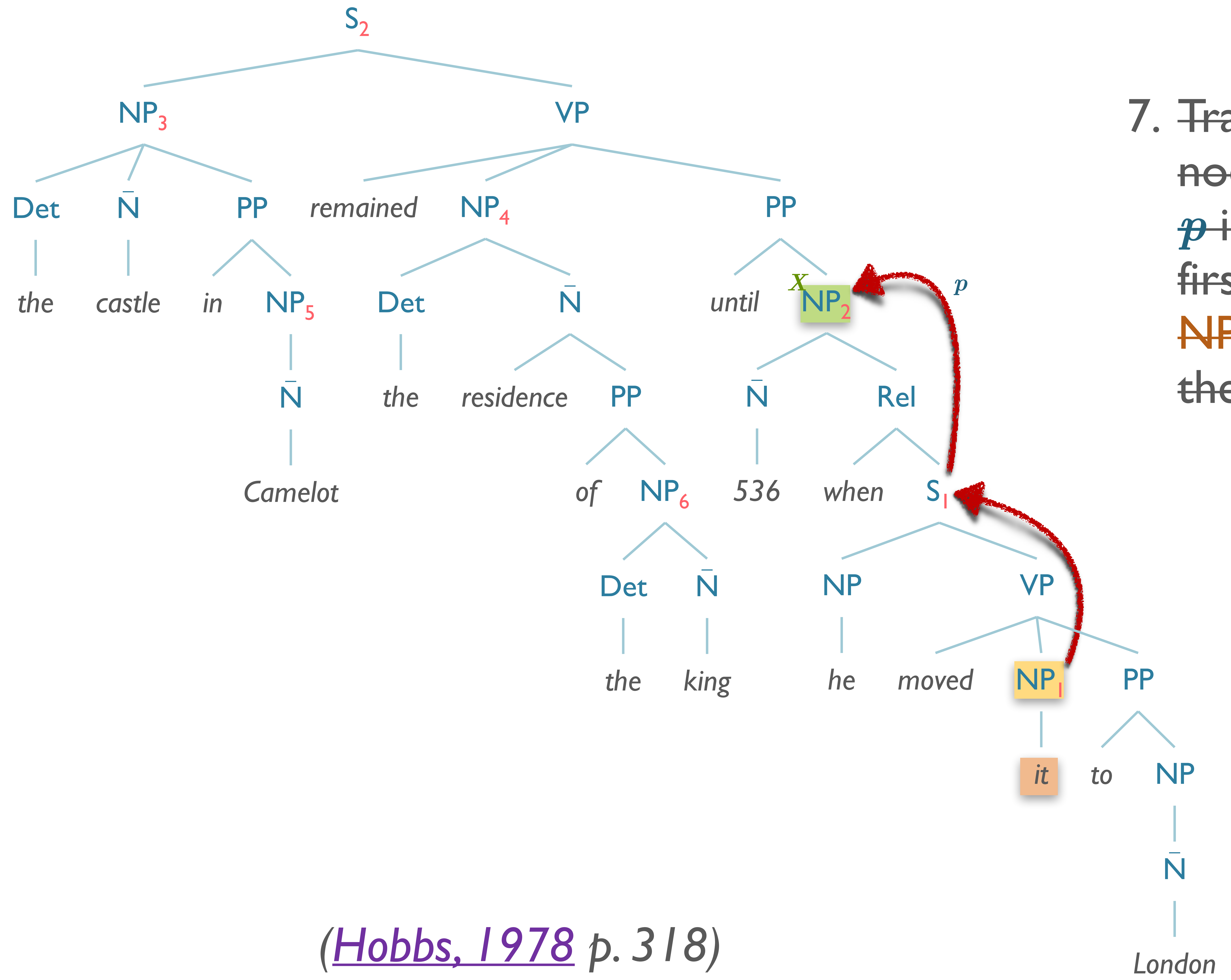
"536" can't be "moved"!

(Hobbs, 1978 p. 318)



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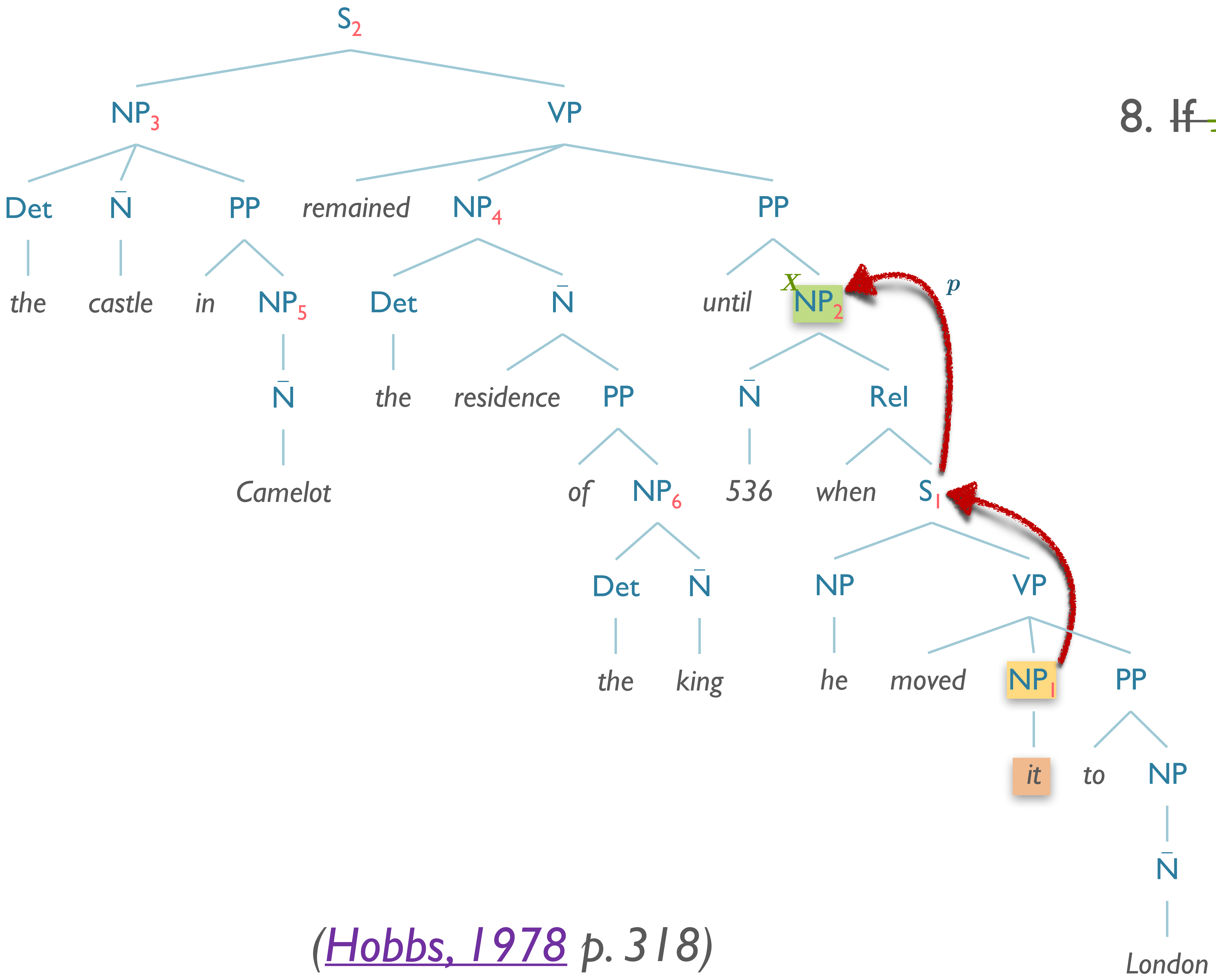

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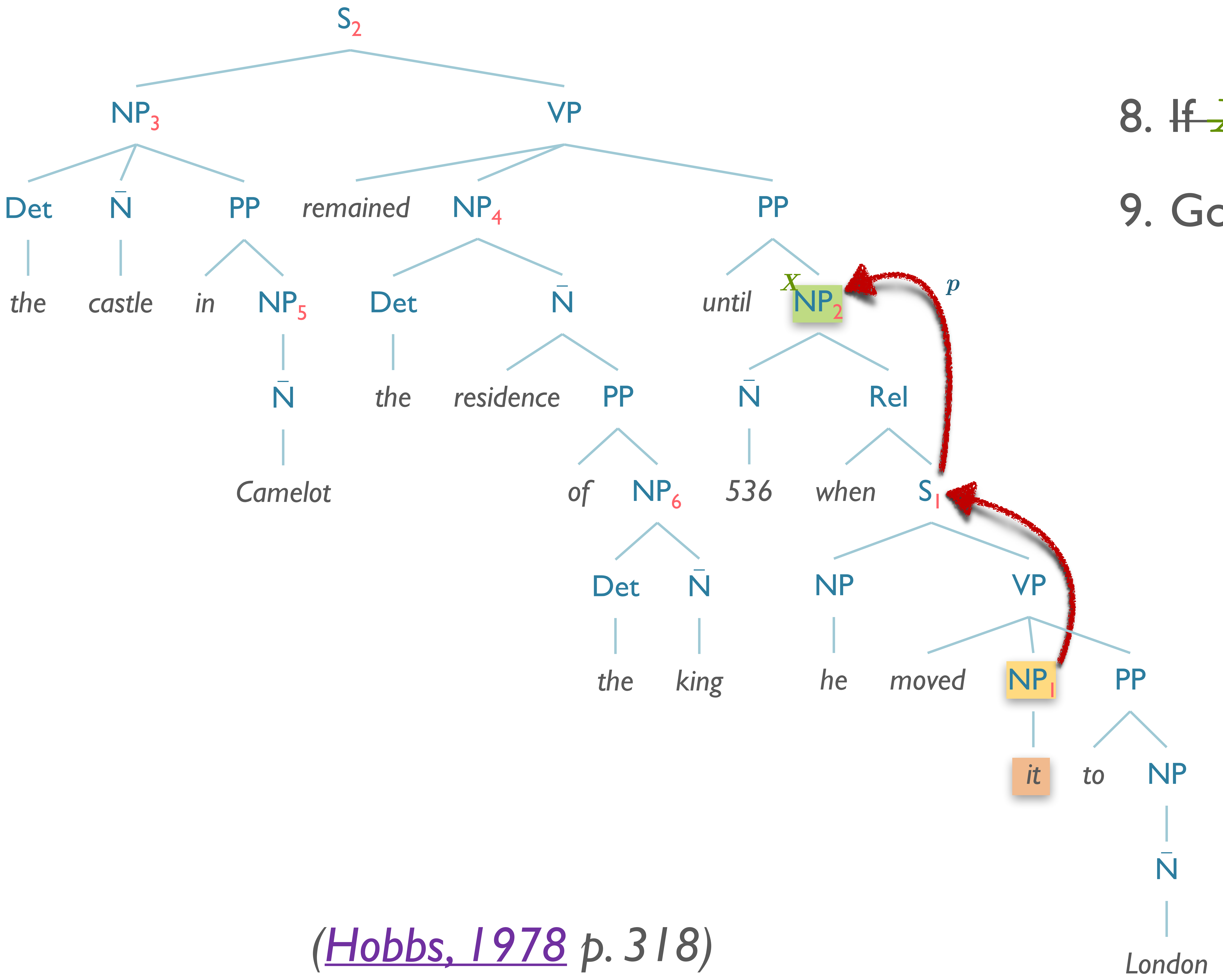

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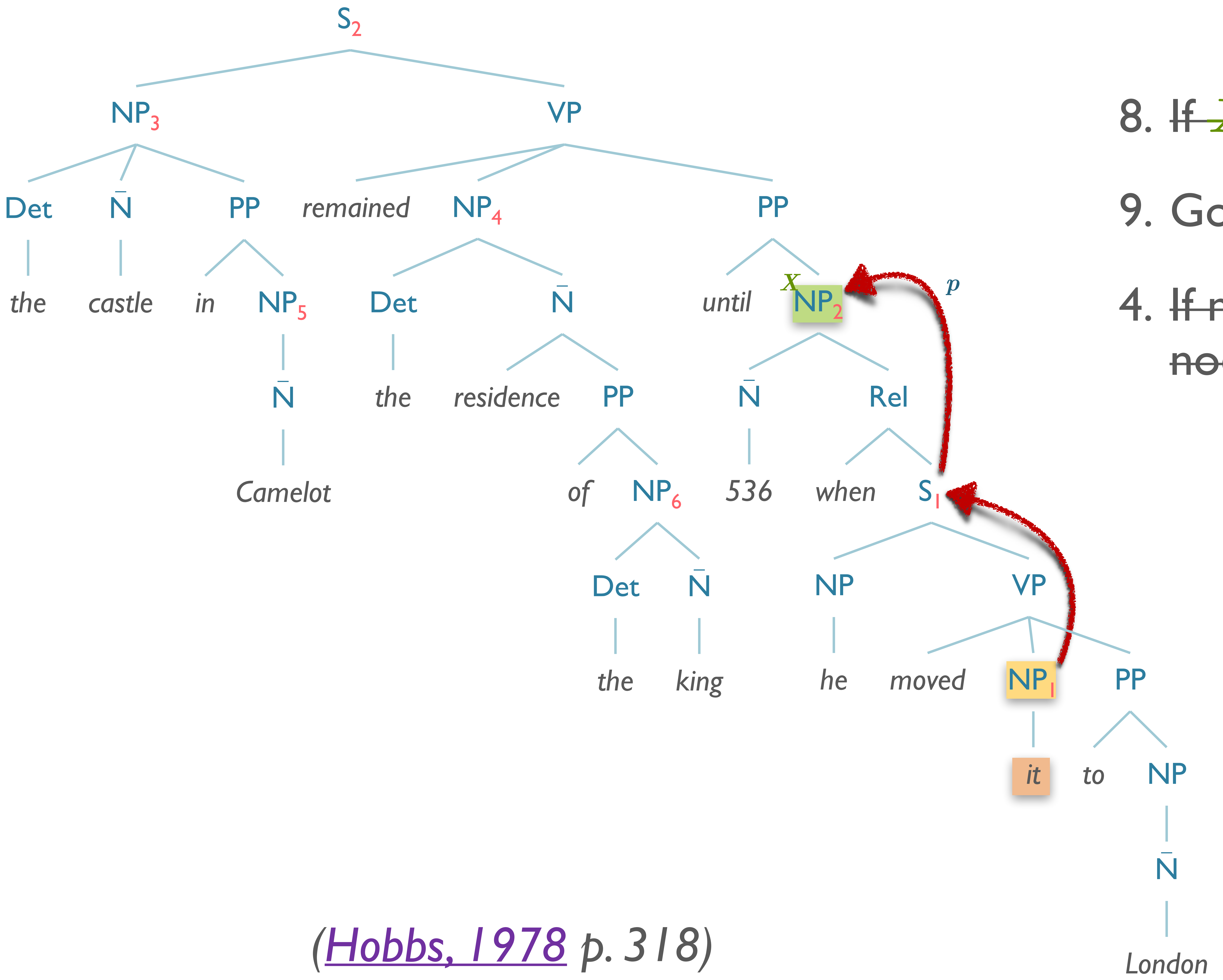

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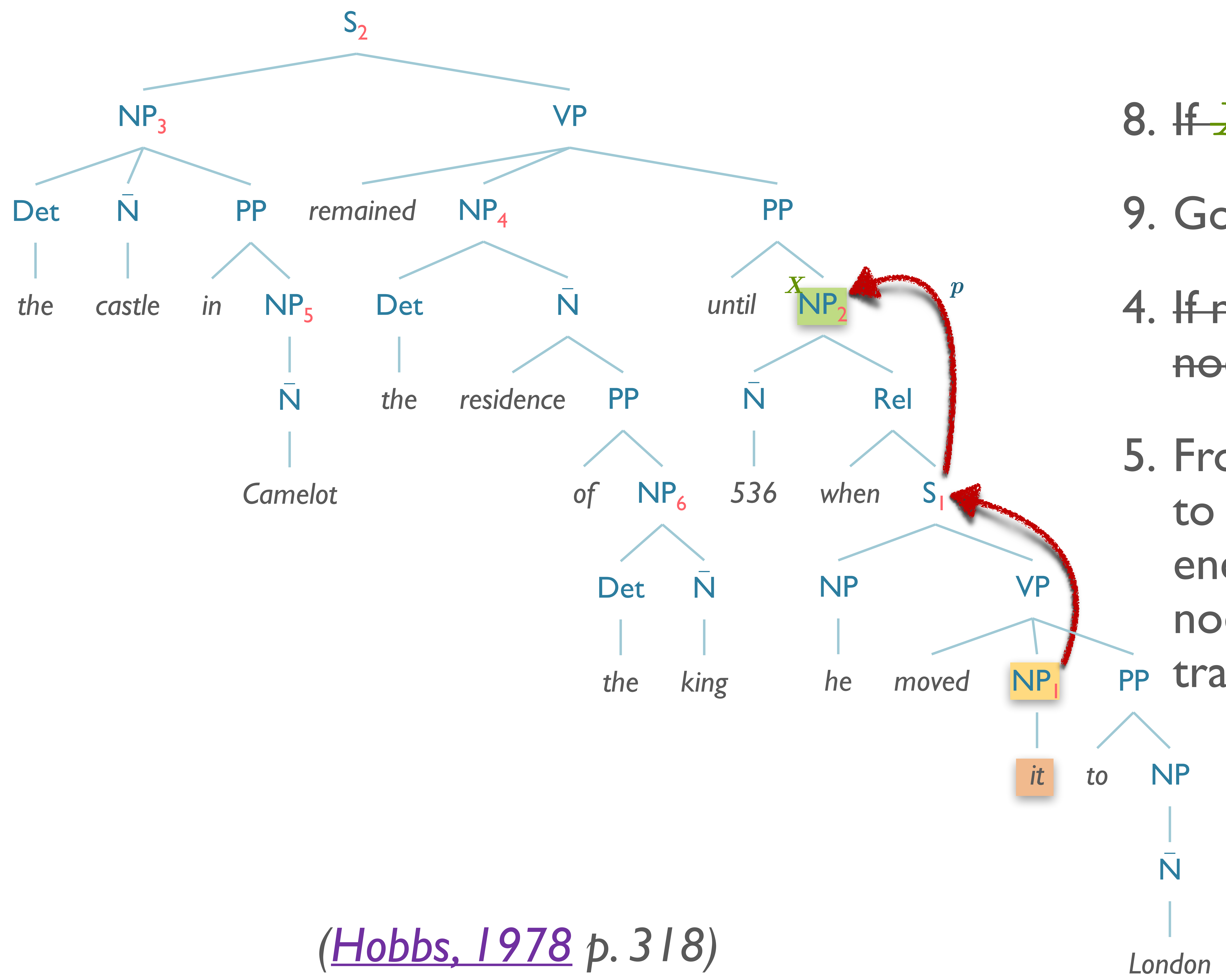
(Hobbs, 1978 *p. 318*)



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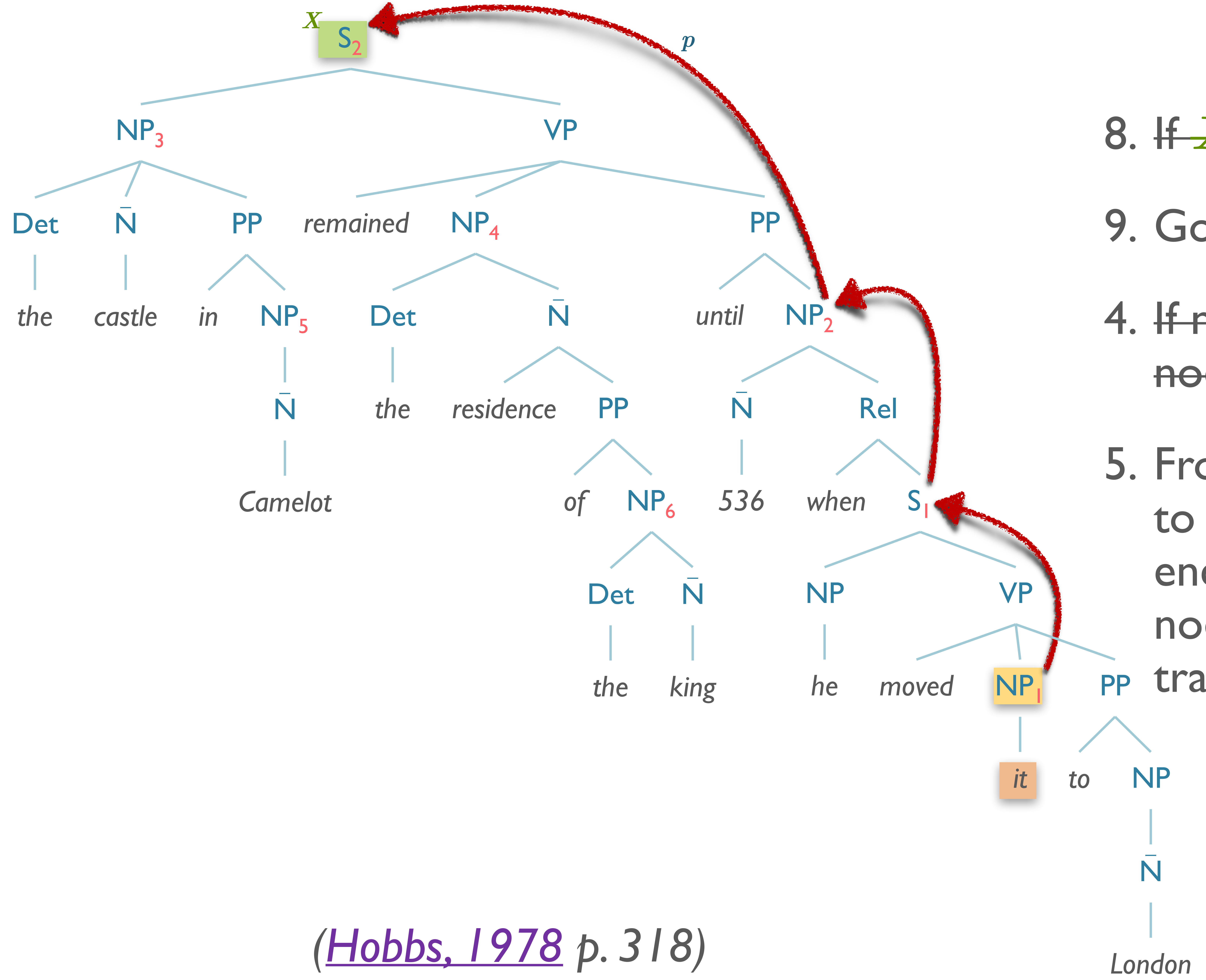

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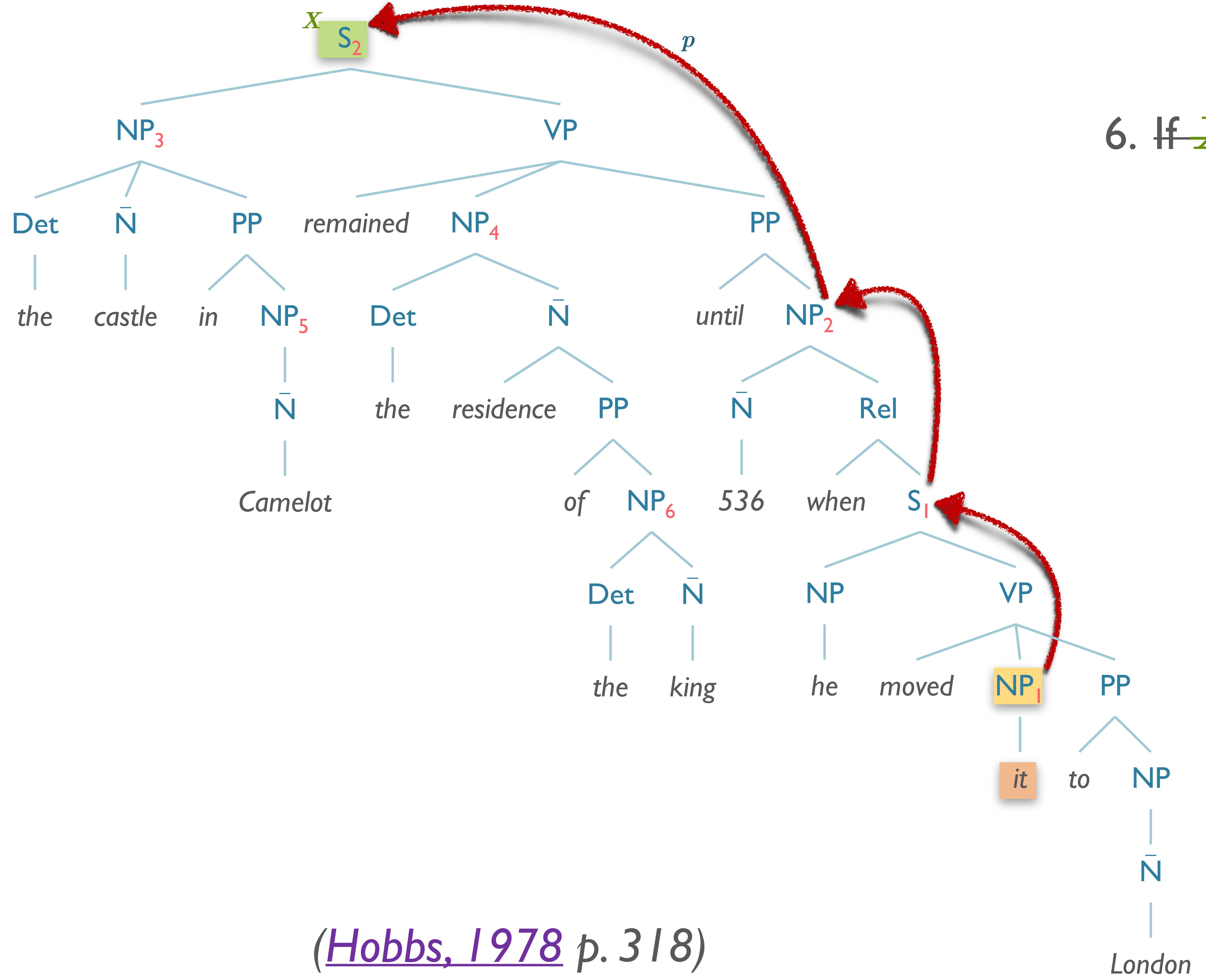

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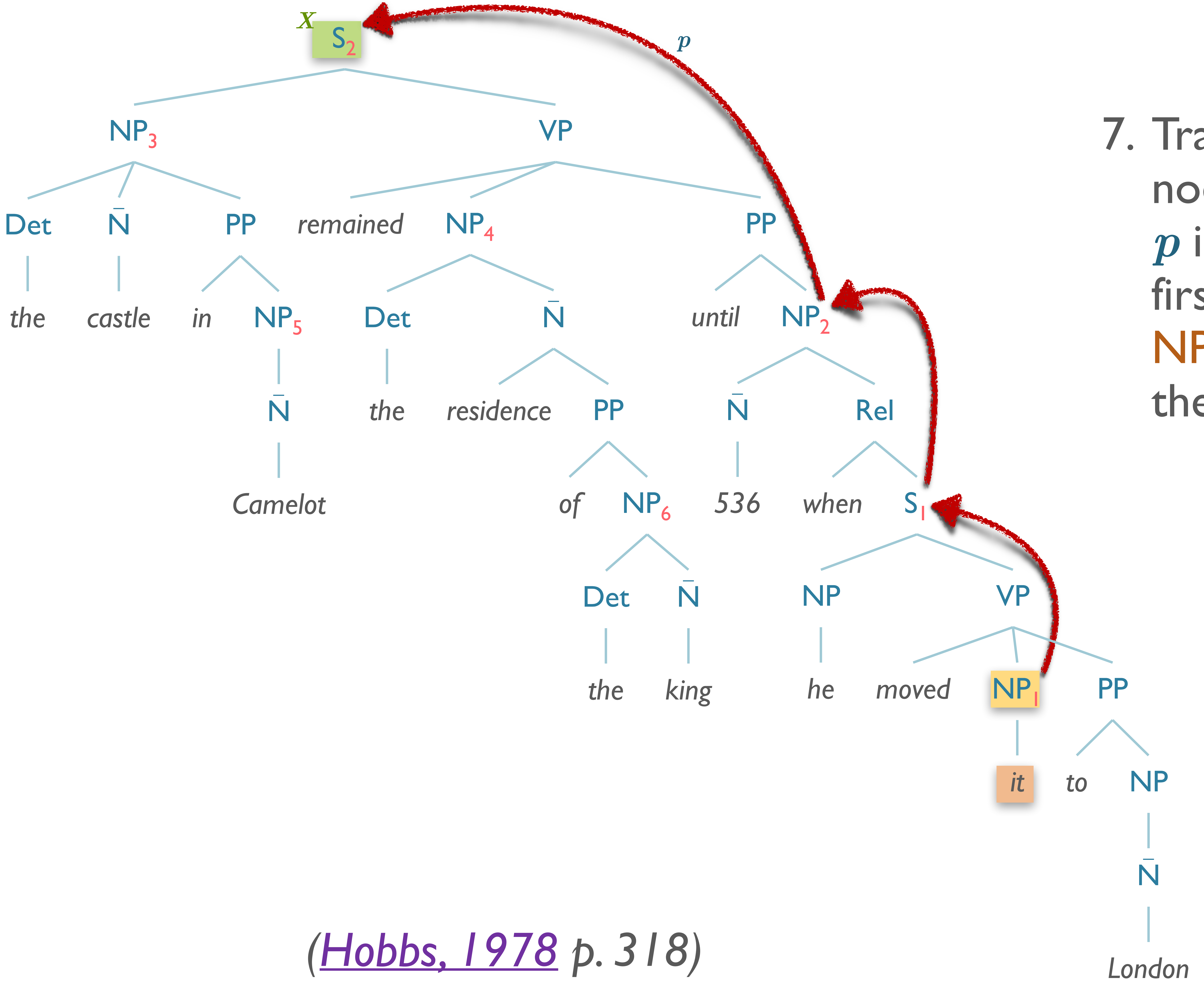

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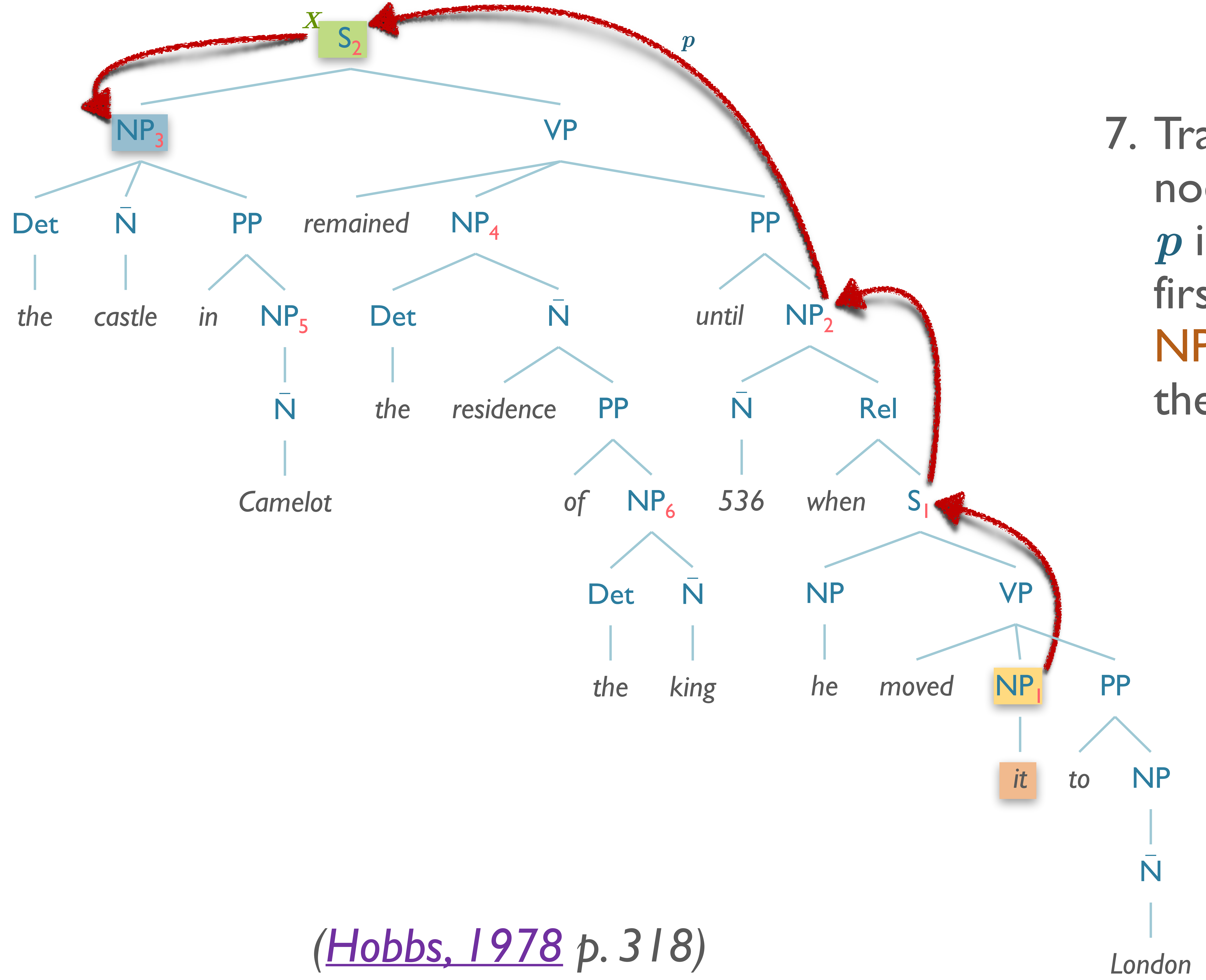

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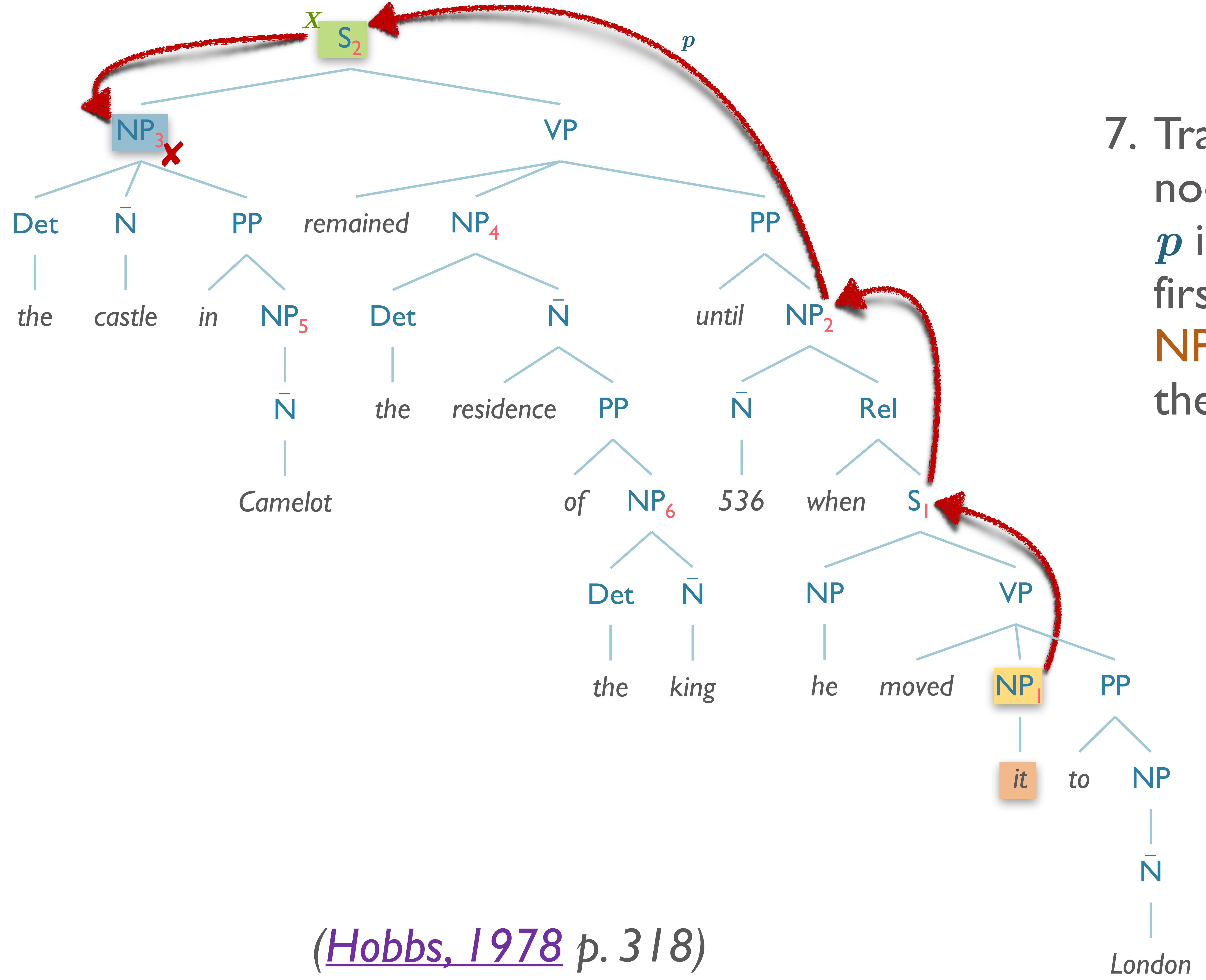

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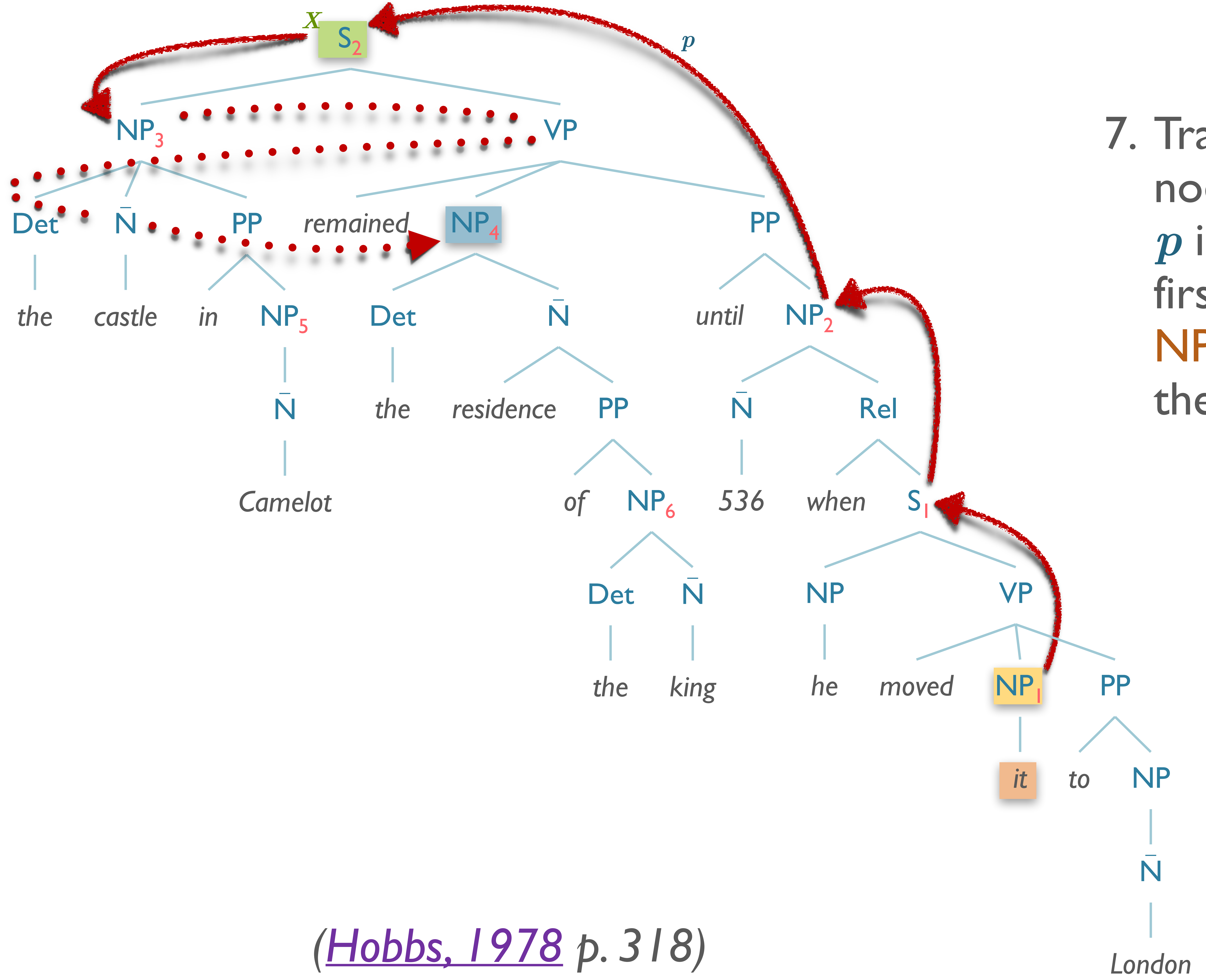
Moving castles? 🤔

(Hobbs, 1978 p. 318)



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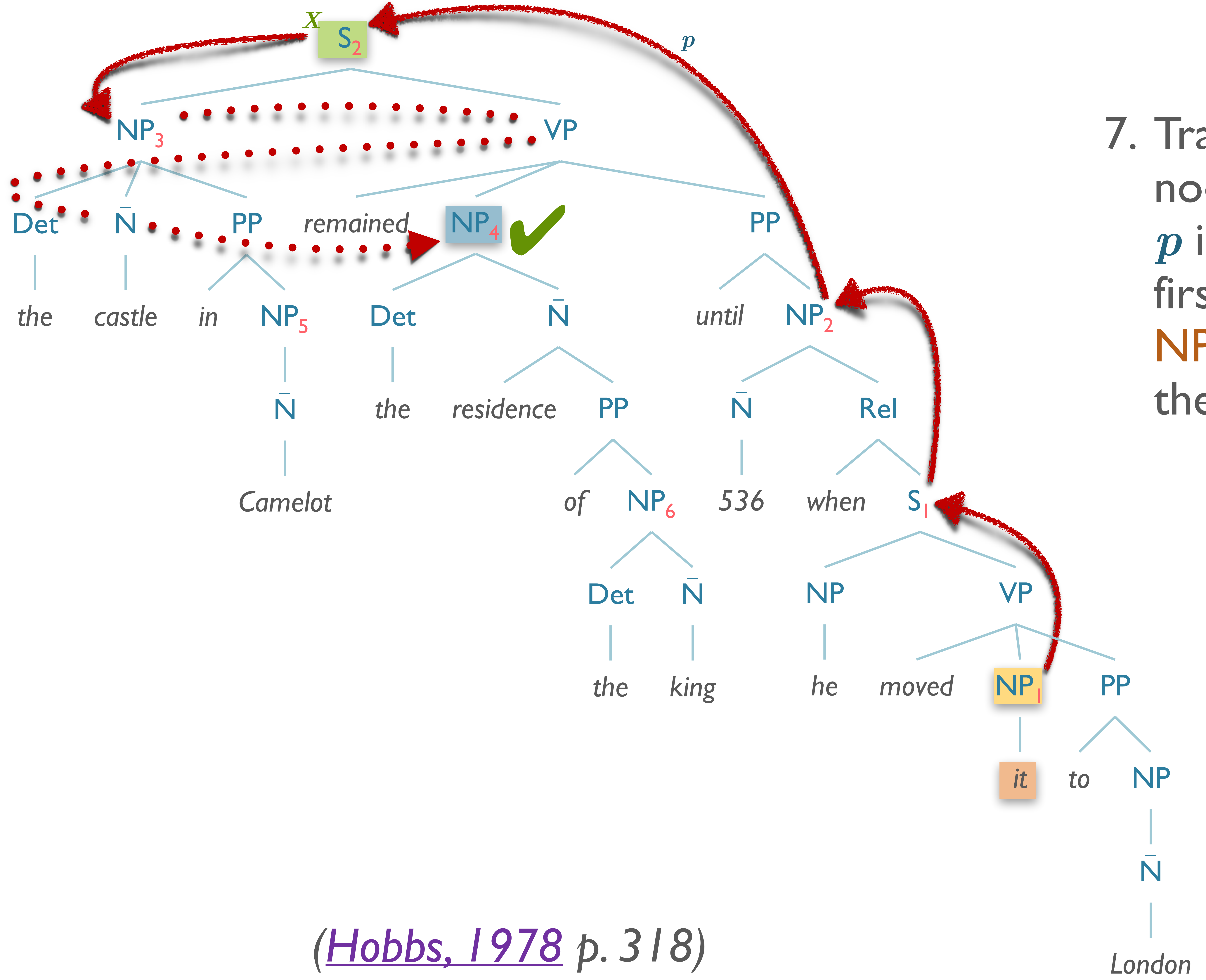

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"the residence of the king"

([Hobbs, 1978](#) *p. 318*)

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

Other Coreference Approaches

Data-driven Reference Resolution

- Prior approaches:
  - Knowledge-based, hand-crafted (e.g. Hobbs' Algorithm)
- Surely, there must be ML methods to approach the problem?

Other kinds of Coreference Models

- **Mention-Pair Models**
  - Treat coreference chain as pairwise decisions (classification task)
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  - Join together by transitivity

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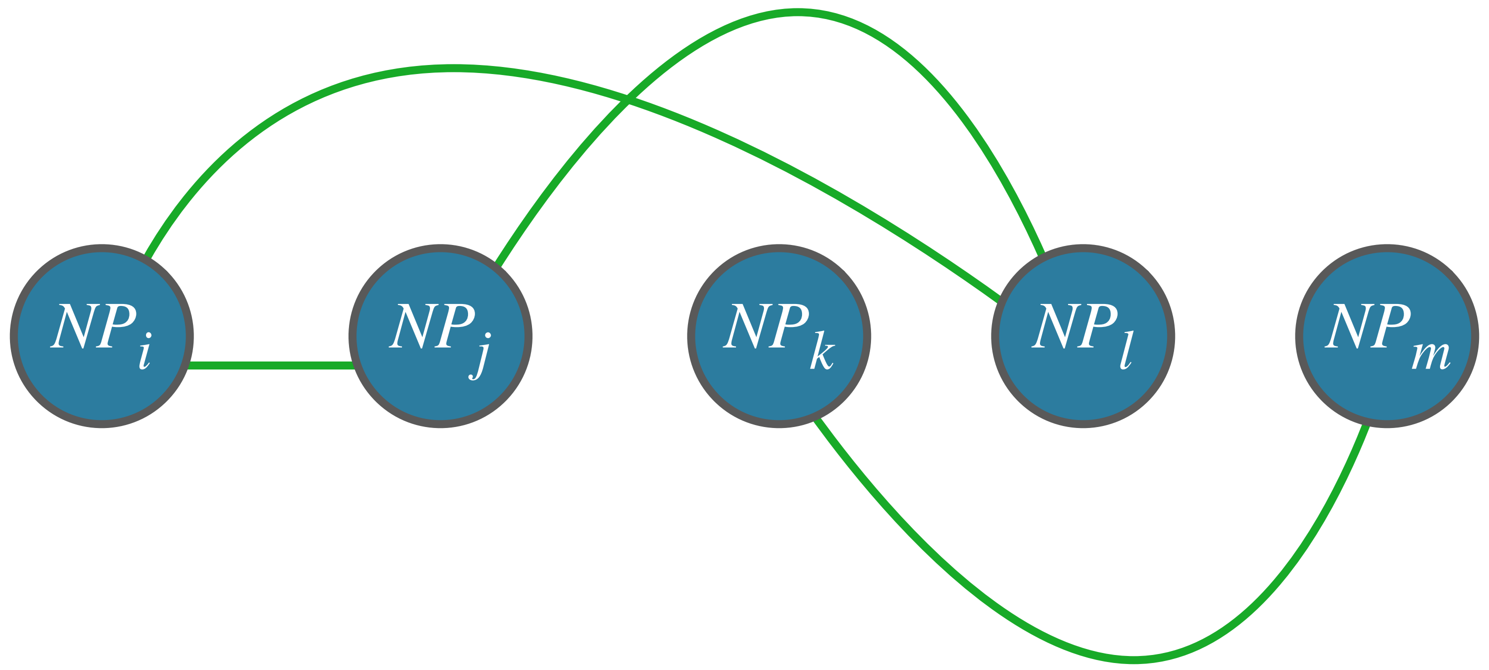

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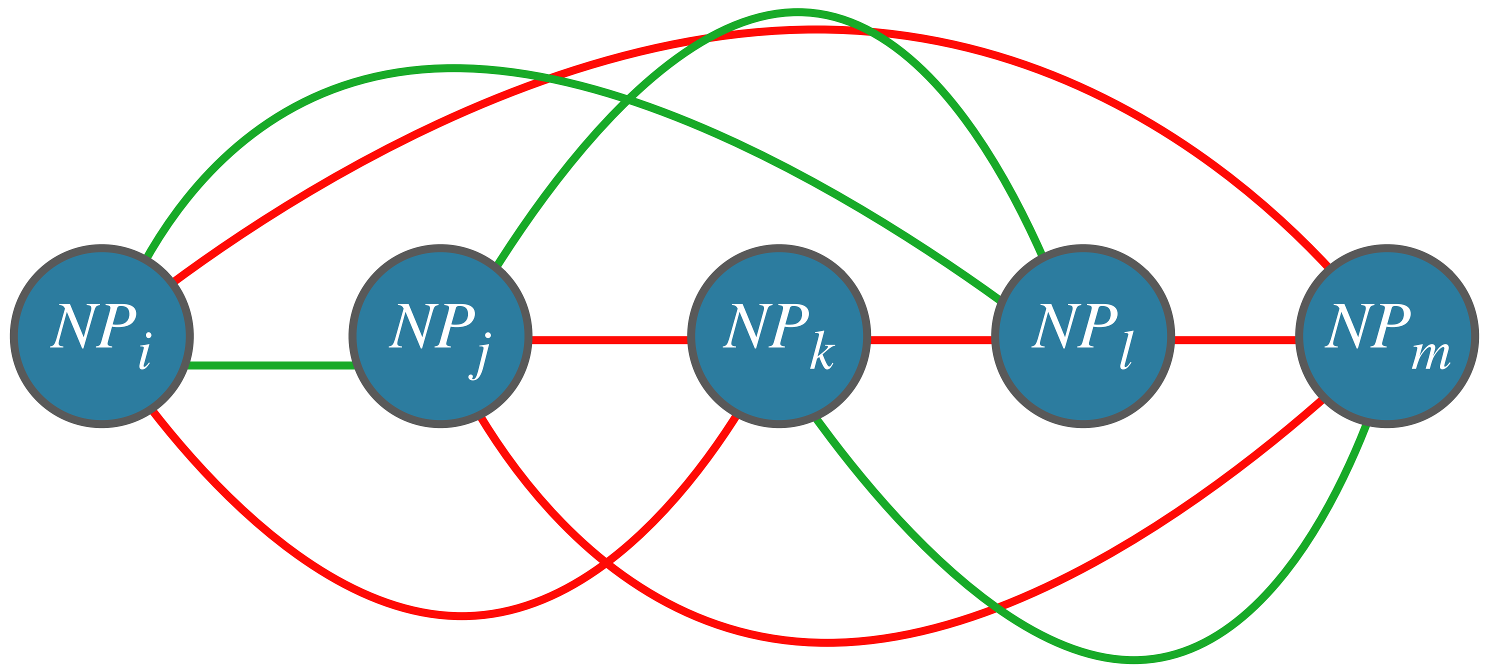

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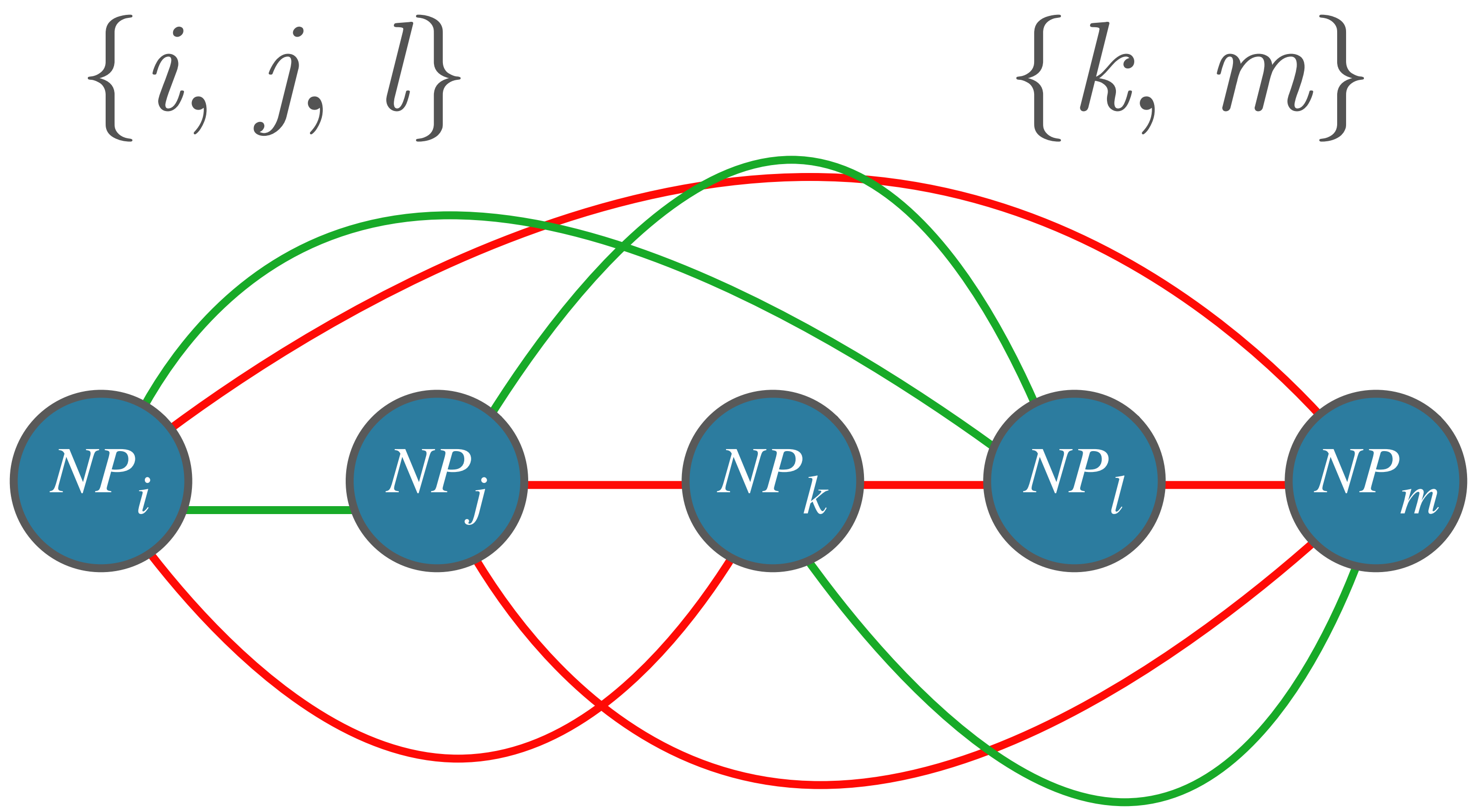
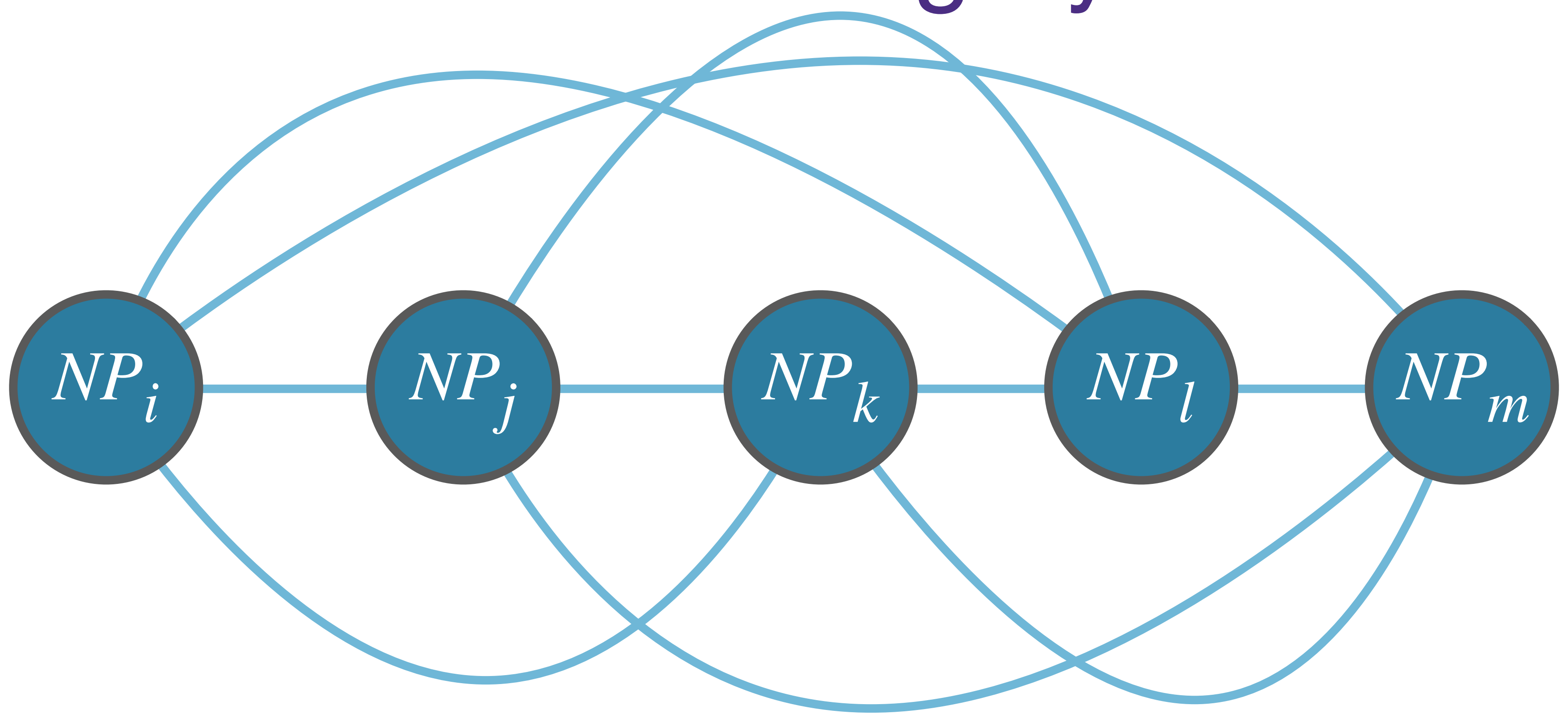
  - For each NP_i, NP_j, do they corefer? YES/NO
  - Join together by transitivity



Other kinds of Coreference Models

- **Mention Ranking Models**
  - For each NP_k and all candidate antecedents, which one is the best suggestion?
  - Can be thought of as clustering method
    - Each entity a different cluster
  - Ranking problems, also well-studied category



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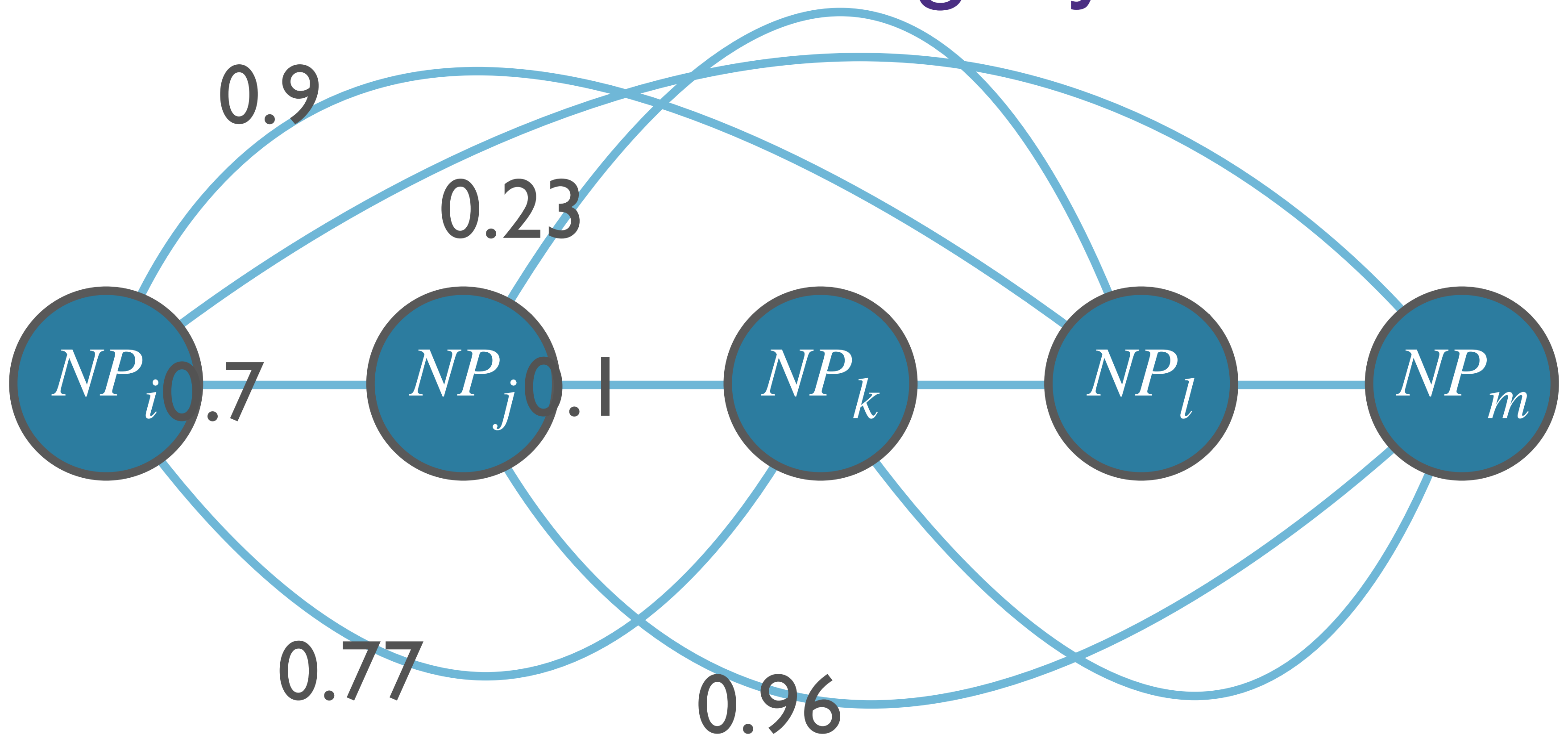
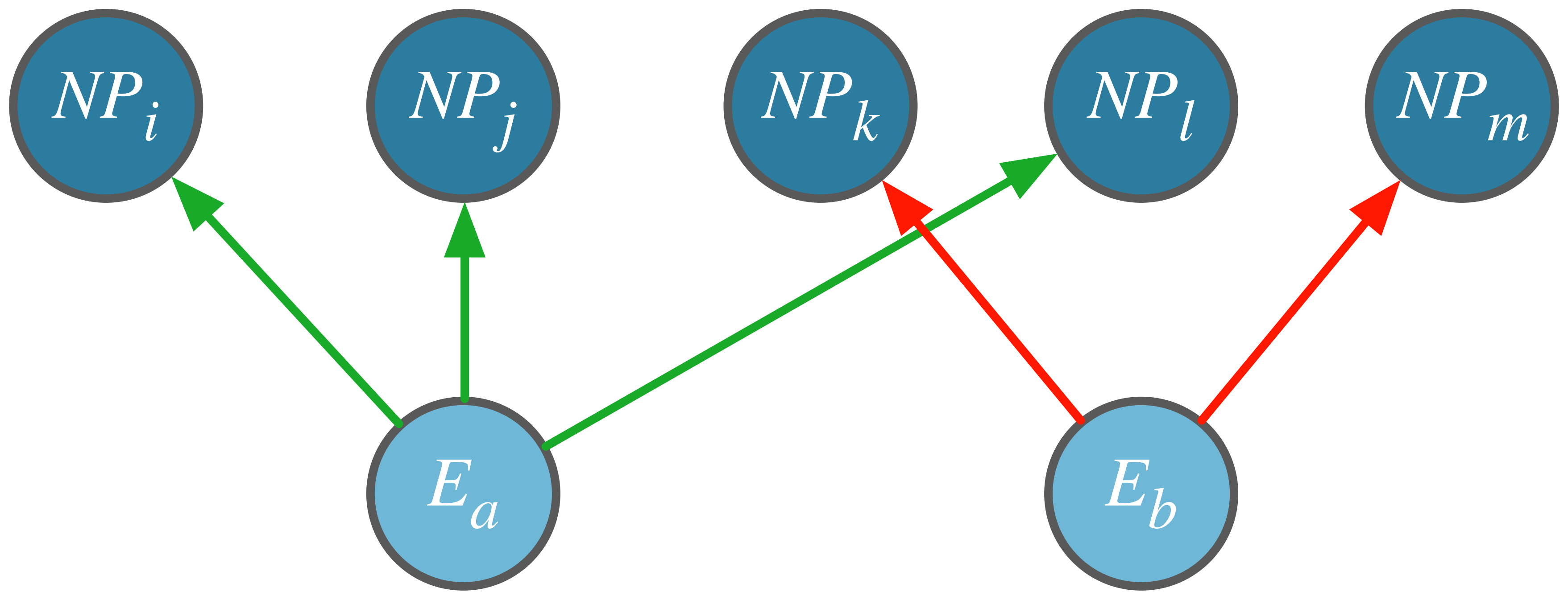


Other kinds of Coreference Models

- **Entity-Mention Model:**
  - Posit underlying entities in discourse model
  - Each “mention” is linked to a discourse entity
  - More theoretically satisfying, but less successful work done on this approach



ML Methods for Coreference Resolution

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  - You know the drill, what are our features?
    - Word embeddings plus…

Typical Feature Set (Soon et. al, 2001)

- **lexical**
  - String Matching (e.g. *Mrs. Clinton* ⇔ *Clinton*)

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- **lexical**
  - String Matching (e.g. *Mrs. Clinton* ⇔ *Clinton*)
- **grammatical/syntactic**
  - i-Pronoun, j-Pronoun — Are the NPs pronouns
  - Demonstrative, Definite… — Are the NPs a demonstrative, or definite noun phrase
  - Agreement — number, gender, animacy
  - appositive (*The prime minister of Germany, Angela Merkel…*)
  - binding constraints
  - span, maximal-np, …

Typical Feature Set (Soon et. al, 2001)

- **semantic**
  - Same semantic class (e.g. Person, Organization, Location, etc)
  - Alias (e.g. *1-08-2018, Jan 8*)
- **positional**
  - distance between the NPs in terms of # of words/sentences
- **knowledge-based**
  - Naïve pronoun resolution algorithm (Hobbs)

Reference Resolution Algorithms

- Coreference Models with NNs:
  - (Clark and Manning, 2016)
    - Assign a score to each candidate antecedent
    - Each possible candidate also has possible “new referent” symbol
    - Also utilize word embeddings + avg embeddings
      - Plus ‘manual’ features as well
    - Non-RNN, essentially just local classification w/some distributional semantics

Coreference Evaluation

Coreference Annotated Corpora

- **Available Shared Task Corpora**
  - MUC-6, MUC-7 (Message Understanding Conference)
    - 60 documents each, newswire, English
  - ACE (Automatic Content Extraction)
    - English, Chinese, Arabic
    - blogs, newswire, Usenet, broadcast
- **Treebanks**
  - OntoNotes — English, Chinese (Trad/Simp), Arabic
    - Used in CoNLL 2012 shared task
  - German, Czech, Japanese, Spanish, Catalalan, Medline

Coreference Evaluation

- **Which NPs are evaluated?**
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Coreference Evaluation

- **Which NPs are evaluated?**
  - Gold standard tagged?
  - Automatically extracted?
- **How good are the coreference chains?**
  - Any cluster-based evaluation could be used
  - MUC scorer (Vilain et al, 1995)
    - F1 for hypothesized vs gold co-reference links
    - Problem: Link-based — ignores singletons; penalizes large clusters

How do the muppets corefer?

D.5 Pairwise Relations (ELMo and OpenAI Transformer)

Pretrained Representation	Syntactic Dep. Arc Prediction		Syntactic Dep. Arc Classification		Semantic Dep. Arc Prediction	Semantic Dep. Arc Classification	Coreference Arc Prediction
	PTB	EWT	PTB	EWT			
ELMo (original), Layer 0	78.27	77.73	82.05	78.52	70.65	77.48	72.89
ELMo (original), Layer 1	89.04	86.46	96.13	93.01	87.71	93.31	71.33
ELMo (original), Layer 2	88.33	85.34	94.72	91.32	86.44	90.22	68.46
ELMo (original), Scalar Mix	89.30	86.56	95.81	91.69	87.79	93.13	73.24
ELMo (4-layer), Layer 0	78.09	77.57	82.13	77.99	69.96	77.22	73.57
ELMo (4-layer), Layer 1	88.79	86.31	96.20	93.20	87.15	93.27	72.93
ELMo (4-layer), Layer 2	87.33	84.75	95.38	91.87	85.29	90.57	71.78
ELMo (4-layer), Layer 3	86.74	84.17	95.06	91.55	84.44	90.04	70.11
ELMo (4-layer), Layer 4	87.61	85.09	94.14	90.68	85.81	89.45	68.36
ELMo (4-layer), Scalar Mix	88.98	85.94	95.82	91.77	87.39	93.25	73.88
ELMo (transformer), Layer 0	78.10	78.04	81.09	77.67	70.11	77.11	72.50
ELMo (transformer), Layer 1	88.24	85.48	93.62	89.18	85.16	90.66	72.47
ELMo (transformer), Layer 2	88.87	84.72	94.14	89.40	85.97	91.29	73.03
ELMo (transformer), Layer 3	89.01	84.62	94.07	89.17	86.83	90.35	72.62
ELMo (transformer), Layer 4	88.55	85.62	94.14	89.00	86.00	89.04	71.80
ELMo (transformer), Layer 5	88.09	83.23	92.70	88.84	85.79	89.66	71.62
ELMo (transformer), Layer 6	87.22	83.28	92.55	87.13	84.71	87.21	66.35
ELMo (transformer), Scalar Mix	90.74	86.39	96.40	91.06	89.18	94.35	75.52
OpenAI transformer, Layer 0	80.80	79.10	83.35	80.32	76.39	80.50	72.58
OpenAI transformer, Layer 1	81.91	79.99	88.22	84.51	77.70	83.88	75.23
OpenAI transformer, Layer 2	82.56	80.22	89.34	85.99	78.47	85.85	75.77
OpenAI transformer, Layer 3	82.87	81.21	90.89	87.67	78.91	87.76	75.81
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OpenAI transformer, Layer 5	84.53	82.77	93.12	90.34	81.95	90.25	76.05
OpenAI transformer, Layer 6	85.47	83.89	93.71	90.63	83.88	90.99	74.43
OpenAI transformer, Layer 7	86.32	84.15	93.95	90.82	85.15	91.18	74.05
OpenAI transformer, Layer 8	86.84	84.06	94.16	91.02	85.23	90.86	74.20
OpenAI transformer, Layer 9	87.00	84.47	93.95	90.77	85.95	90.85	74.57
OpenAI transformer, Layer 10	86.76	84.28	93.40	90.26	85.17	89.94	73.86
OpenAI transformer, Layer 11	85.84	83.42	92.82	89.07	83.39	88.46	72.03
OpenAI transformer, Layer 12	85.06	83.02	92.37	89.08	81.88	87.47	70.44
OpenAI transformer, Scalar Mix	87.18	85.30	94.51	91.55	86.13	91.55	76.47
GloVe (840B.300d)	74.14	73.94	77.54	72.74	68.94	71.84	72.96

Table 9: Pairwise relation task performance of a linear probing model trained on top of the ELMo and OpenAI contextualizers, compared against a GloVe-based probing baseline.

No significant improvement over global embedding baseline [BERT slightly better]

Liu et al 2019

Coreference and World Knowledge

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- 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
  - WinoGrande

SuperGLUE GLUE Paper </> Code Tasks Leaderboard FAQ Diagnostics Submit

Leaderboard Version: **2.0**

Rank	Name	Model	URL	Score	BoolQ	CB	COPA	MultiRC	ReCoRD	RTE	WiC	WSC	AX-g	AX-b
1	SuperGLUE Human Baselines	SuperGLUE Human Baselines		89.8	89.0	95.8/98.9	100.0	81.8/51.9	91.7/91.3	93.6	80.0	100.0	99.3/99.7	76.6
2	T5 Team - Google	T5		88.9	91.0	93.0/96.4	94.8	88.2/62.3	93.3/92.5	92.5	76.1	93.8	92.7/91.9	65.6
3	Facebook AI	RoBERTa		84.6	87.1	90.5/95.2	90.6	84.4/52.5	90.6/90.0	88.2	69.9	89.0	91.0/78.1	57.9
4	IBM Research AI	BERT-mtl		73.5	84.8	89.6/94.0	73.8	73.2/30.5	74.6/74.0	84.1	66.2	61.0	97.8/57.3	29.6
5	SuperGLUE Baselines	BERT++		71.5	79.0	84.8/90.4	73.8	70.0/24.1	72.0/71.3	79.0	69.6	64.4	99.4/51.4	38.0
		BERT		69.0	77.4	75.7/83.6	70.6	70.0/24.1	72.0/71.3	71.7	69.6	64.4	97.8/51.7	23.0
		Most Frequent Class		47.1	62.3	21.7/48.4	50.0	61.1/0.3	33.4/32.5	50.3	50.0	65.1	100.0/50.0	0.0
		CBoW		44.5	62.2	49.0/71.2	51.6	0.0/0.5	14.0/13.6	49.7	53.1	65.1	100.0/50.0	-0.4
		Outside Best		-	80.4	-	84.4	70.4/24.5	74.8/73.0	82.7	-	-	-	-
-	Stanford Hazy Research	Snorkel [SuperGLUE v1.9]		-	-	88.6/93.2	76.2	76.4/36.3	-	78.9	72.1	72.6	-	47.6

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Heavily supervised

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2	T5 Team - Google	T5		88.9	91.0	93.0/96.4	94.8	88.2/62.3	93.3/92.5	92.5	76.1	93.8	92.7/91.9	65.6
3	Facebook AI	RoBERTa		84.6	87.1	90.5/95.2	90.6	84.4/52.5	90.6/90.0	88.2	69.9	89.0	91.0/78.1	57.9
4	IBM Research AI	BERT-mtl		73.5	84.8	89.6/94.0	73.8	73.2/30.5	74.6/74.0	84.1	66.2	61.0	97.8/57.3	29.6
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		BERT		69.0	77.4	75.7/83.6	70.6	70.0/24.1	72.0/71.3	71.7	69.6	64.4	97.8/51.7	23.0
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Questions

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- Conversational speech?
  - Fragments, disfluencies, etc…
- Dialogue?
  - Multiple speakers introduce referents
- Multimodal communication?
  - How can entities be evoked in other ways?
  - Are all equally salient?

Questions

- **Other languages?**
  - Are salience hierarchies the same?
  - Syntactic constraints?
    - Reflexives in Chinese, Korean…?
- **Zero anaphora?**
  - How do you resolve a pronoun if you can't find it?
  - e.g. "*There are two roads to eternity, a straight and narrow, and a broad and crooked.*"
    - Each indefinite here implies a gap [road], that would be anaphoric, but leaves a gap

Conclusions

- Coreference establishes ***coherence***
- Reference resolution depends on coherence
- Variety of approaches:
  - Syntactic constraints, recency, frequency, role
- Similar effectiveness - different requirements
- Coreference can enable summarization within and across documents (and potentially languages!)

Discourse Structure

Why Model Discourse Structure?

Theoretical Concerns

- Discourse: not just constituent utterances
- Creation of joint meaning
- Context guides interpretation of constituents

Why Model Discourse Structure?

Theoretical Concerns

- Understanding how discourse is structured:
  - What are the units of discourse?
  - How do they combine to establish meaning?
  - How can we derive structure from surface forms?
  - What makes discourse coherent vs. incoherent?
  - How do the units of discourse influence reference resolution?

Why Model Discourse Structure?

Applied Concerns

- Design better summarization, understanding systems
- Improve speech synthesis (discourse-contextual intonation, emphasis)
- Develop approach for generation of discourse
- Design dialogue agents for task interaction
- Guide reference resolution

Discourse (Topic) Segmentation

- BBC Global News Podcast 11/26/2018:
- “I’m Valerie Saunderson, and in the early hours of Monday, the 26th of November, these are our main stories. || After forty-five years, both parties call it a day as Britain’s Brexit agreement is signed off by EU leaders. So, what happens next? We hear from our correspondents in Brussels and London. || There’s been a sharp escalation in a Naval dispute near Crimea, with Ukraine accusing Russian special forces of seizing three of its vessels || An investigation discovers many medical implants haven’t been properly tested before they’re put in patients. || Also in this podcast, NASA prepares for “seven minutes of terror,” the latest landing on the Red planet [Voice #2:] Although we’ve done it before, landing on Mars is hard, and this mission is no different. || [Voice #1:] A year and a half after the start of Brexit Negotiations…”

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Discourse Segmentation

- Basic form of discourse structure
  - Divide document into linear sequence of subtopics
- Many genres have conventional structures
  - **Academic**: Intro, Hypothesis, Previous Work, Methods, Results, Conclusion
  - **Newspapers**: Headline, Byline, Lede, Elaboration
  - **Patient Reports**: Subjective, Objective, Assessment, Plan
- Can guide summarization, retrieval

Cohesion

- Use of linguistic devices to link text units
  - Lexical cohesion: Link with relations between words
    - Synonymy, Hypernymy
    - *Peel, core, and slice the **pears** and **apples**. Add **the fruit** to the skillet.*
  - Nonlexical Cohesion
    - e.g. anaphora
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- Cohesion chain establish link through sequence of words
- Segment boundary = dip in cohesion.

Coherence Relations & Discourse Structure

Coherence Relations

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

?? *John hid Bill's car keys. He likes spinach.*

Coherence Relations

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- Why is this odd?
  - No obvious relation between sentences
    - Readers often try to construct relations
- How are the first two related?
  - Explanation/cause
- Utterances should have meaningful connection
  - Establish through ***coherence relations***

Coherence Relations

- **Result**: Infer that the state or event asserted by S_0 causes, or could cause the state asserted by S_1.
  - *The Tin Woodman was caught in the rain. His joints rusted.*

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- **Explanation:** Infer that the state or event asserted by S_1 causes or could cause the state or event asserted by S_0.
  - *John hid Bill's car keys. He was drunk.*
- **Parallel:** Infer $p(a_1, a_2, \ldots)$ from the assertion of S_0 and $p(b_1, b_2, \ldots)$ from the assertion of S_1, where a_i and b_i are similar, for all i.
  - *The Scarecrow wanted some brains. The Tin Woodman wanted a heart.*

Coherence Relations

- **Elaboration**: Infer the same proposition P from the assertions of S_0 and S_1.
  - *Dorothy was from Kansas. She lived in the midst of the great Kansas prairies.*

Coherence Relations

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  - *Dorothy was from Kansas. She lived in the midst of the great Kansas prairies.*
- **Occasion:** A change of state can be inferred from the assertion of S_0 whose final state can be inferred from S_1, or a change of state can be inferred from the assertion of S_1.
  - *Dorothy picked up the oil-can. She oiled the Tin Woodman's joints.*

Coherence Relation Hierarchy

S1 – Armin went to the bank to deposit his paycheck

S2 – He then took a train to Kim's car dealership.

S3 – He needed to buy a car.

S4 – The company he works for now isn't near any public transportation.

S5 – He also wanted to talk to Kim about their softball league.

Adapted from J&M 2nd ed p. 690

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- This discourse ***isn't linear***
- Primarily about S1, S2
  - S3-S5 relate to different parts of S1, S2

Adapted from J&M 2nd ed p. 690

Coherence Relation Hierarchy

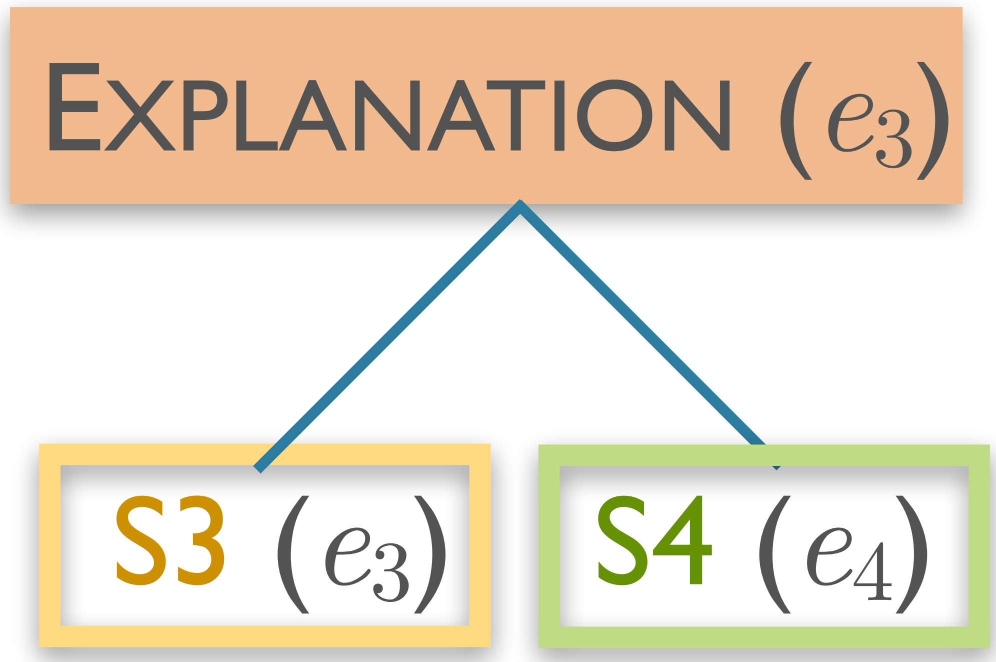
S1 – Armin went to the bank to deposit his paycheck

S2 – He then took a train to Kim's car dealership.

S3 – He needed to buy a car.

S4 – The company he works for now isn't near any public transportation.

S5 – He also wanted to talk to Kim about their softball league.



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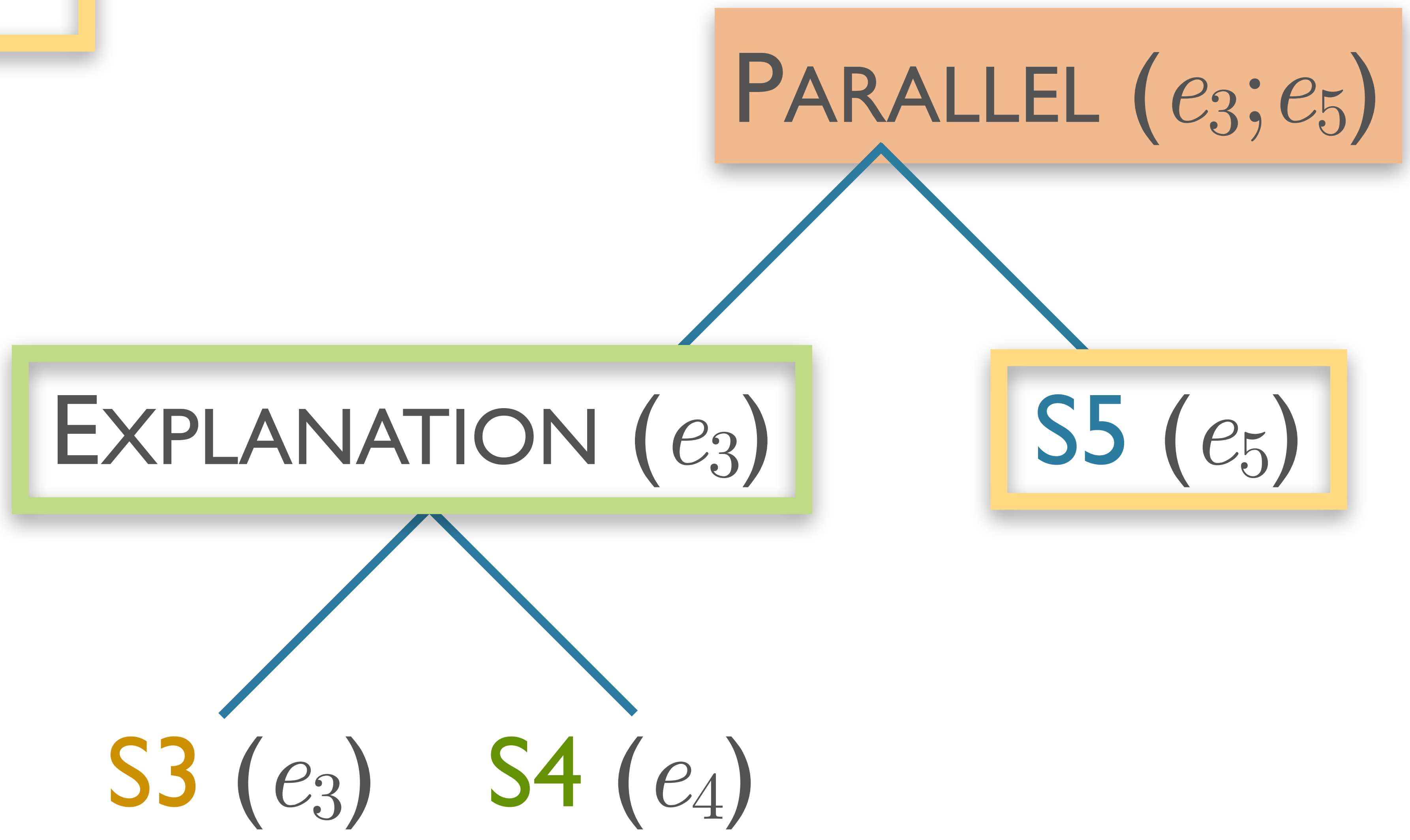

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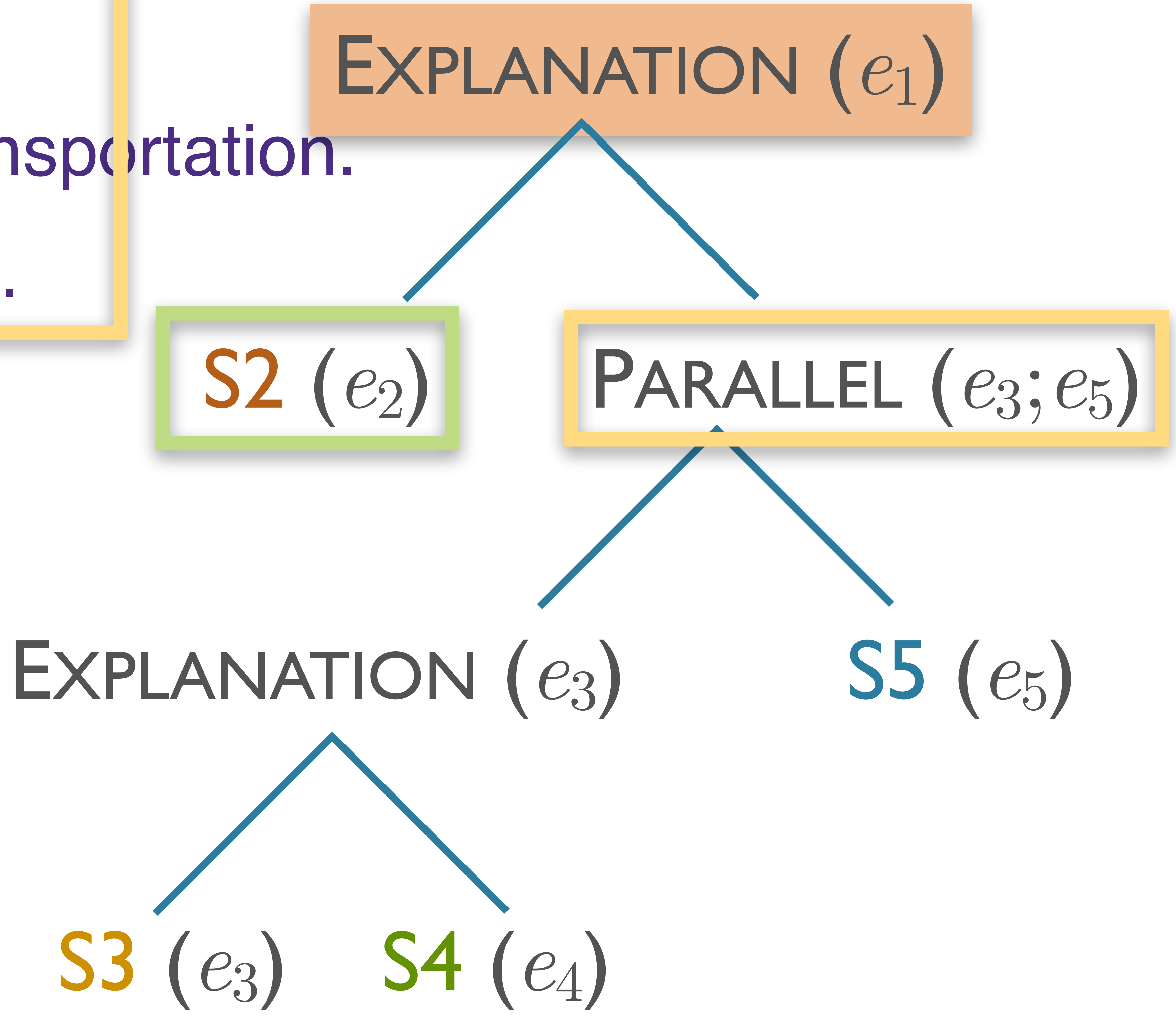

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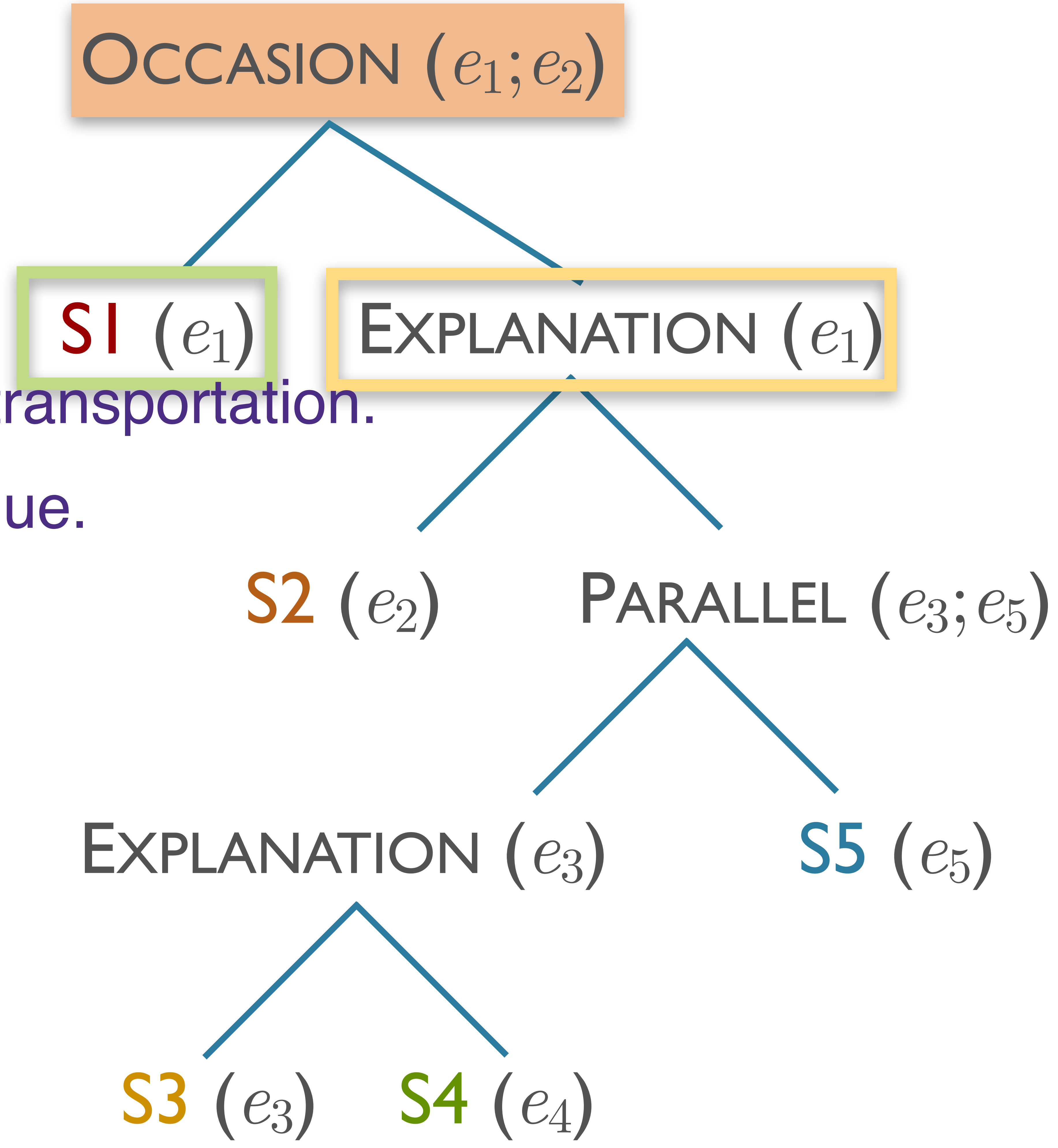

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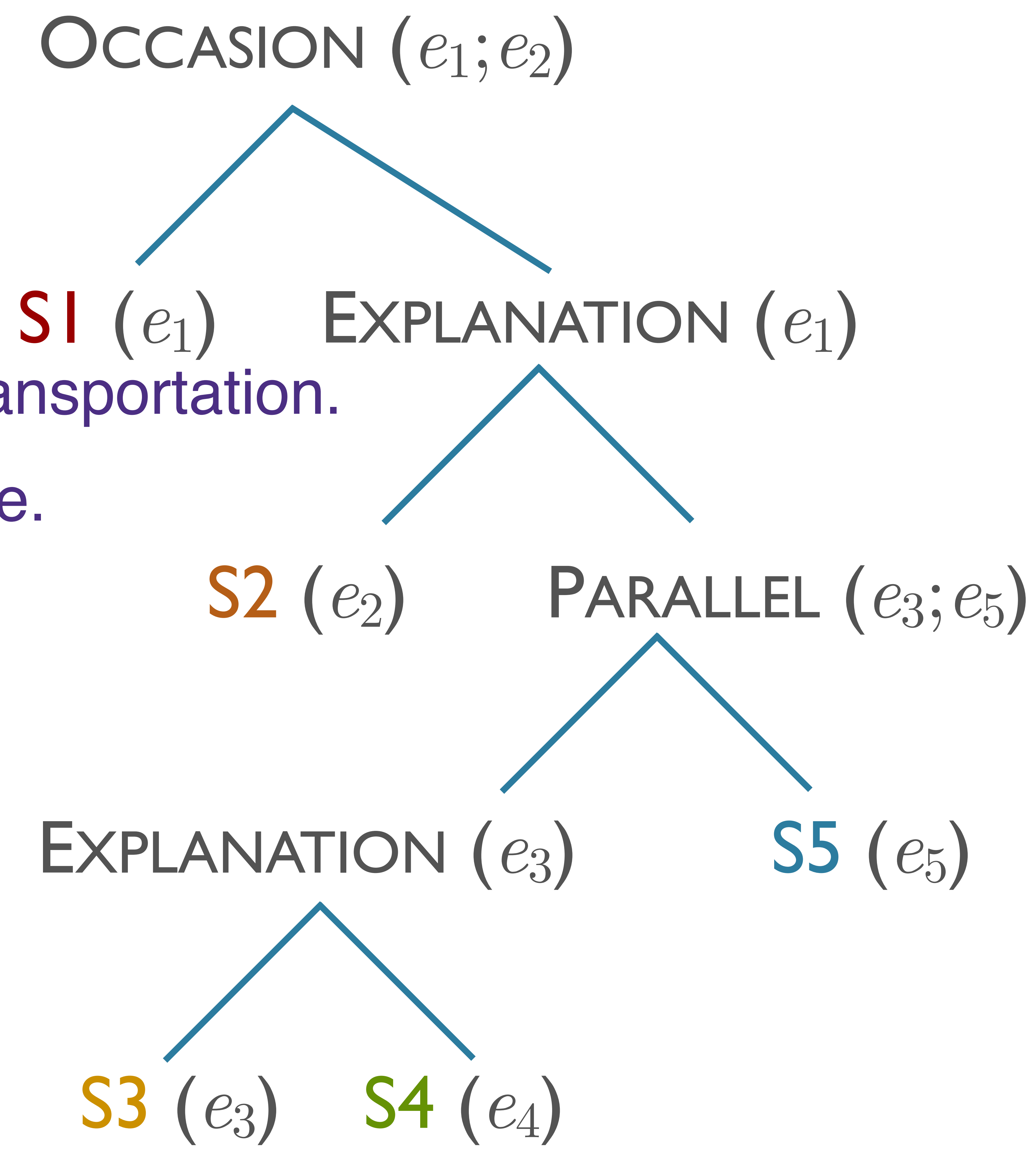

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The Penn Discourse Treebank (PDTB) ([Prasad et al, 2008](#))

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- *U.S. Trust, a 136-year-old institution that is one of the earliest high-net worth banks in the U.S., has faced intensifying competition from other firms that have established, and heavily promoted, private-banking businesses of their own.* ***As a result***, *U.S. Trust's earnings have been hurt.*

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- PDTB annotation links $\mathbf{S_1}$ to $\mathbf{S_2}$ by way of connective
  - Provides sense label

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  - triggered by lexical markers ('*but*', '*as a result*') between spans
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- **Implicit Relations**:
  - Adjacent sentences assumed related
  - Arg_1: first sentence (can be anywhere in discourse)
  - Arg2: second sentence, in linear sequence
  - Annotators provide implicit discourse unit, label

Shallow Discourse Parsing

- For extended discourse
- …for each clause/sentence pair in sequence
- …identify discourse relation, Arg_1, Arg_2
- CoNLL15 Shared task Results:
  - **61**% overall (**55**% blind)
    - Explicit discourse connectives: **91**% (**76**% blind)
    - Non-explicit discourse connectives: **34**% (**36**% blind)

Identifying Relations: Issues

- Ambiguity: discourse vs. sentential use
  - ***With*** *its distant orbit, Mars exhibits frigid weather.*
  - *We can see Mars* ***with*** *a telescope.*

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  - ***Because***: CAUSE, or EVIDENCE
  - ***But***: CONTRAST, or CONCESSION
- Sparsity:
  - Only **15-25**% of relations marked by cues

Entity-Based Coherence and Centering Theory

Entity-Based Coherence

John went to his favorite music store to buy a piano.
He had frequented the store for many years.
He was excited that he could finally buy a piano.

- Versus:

John went to his favorite music store to buy a piano.
It was a store John had frequented for many years.
He was excited that he could finally buy a piano.
It was closing just as John arrived.

- Which is better? Why?

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- Which is better? Why?
  - First focuses on a single entity
  - Second interleaves entities *John* and the *music store*

Centering Theory

- Entity-based coherence is inspiration for ***Centering theory*** (Grosz et al, 1995)
  - Explicitly encodes a discourse model
  - Different entities are uniquely "***centered***" at different points in discourse

Centering Theory Details

- Two adjacent utterances:
  - U_n
  - U_{n+1}
- Two ideas of "centers"
  - **backward-looking** center — $C_b(U_n)$
  - **forward-looking** centers — $C_f(U_n)$

Centering Theory Details

- **backward-looking** center — $C_b(U_n)$
  - The entity that is currently being focused ("centered") after U_n is interpreted

- **forward-looking** centers — $C_f(U_n)$
  - A list of all entities mentioned in U_n which could be focused in subsequent utterances
  - Order with precedence list:
    - subject > existential predicate nominal > object > indirect object or oblique > demarcated adverbial PP

- C_p — shorthand for highest-ranked forward-looking candidate

Centering Theory Hand-wavy Algorithm

- John saw a beautiful 1961 Ford Falcon at the used car dealership. (U_1)
- He showed it to Bob. (U_2)
- He bought it. (U_3)

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After U1

$C_f(U_1)$: {*John, Ford, dealership*}

$C_p(U_1)$: *John*

$C_b(U_1)$: undefined

Centering Theory Hand-wavy Algorithm

- John saw a beautiful 1961 Ford Falcon at the used car dealership. (U_1)
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- He bought it. (U_3)

Processing U₂

$C_f(U_1)$: {*John, Ford, dealership*}

$C_p(U_1)$: *John*

$C_b(U_1)$: undefined

he=John, it=Ford

Centering Theory Hand-wavy Algorithm

- John saw a beautiful 1961 Ford Falcon at the used car dealership. (U_1)
- He showed it to Bob. (U_2)
- He bought it. (U_3)

After U_2

$C_f(U_2)$: {John, Ford, Bob}

$C_p(U_2)$: John

$C_b(U_2)$: John

Computational Discourse:
Summary

- **Cohesion**
  - Modeled with linking lexical terms and thematic overlap
- **Coherence**
  - Determine relevance of discourse units to one another
  - Can add structure to discourse to model relations and their importance

Computational Discourse:
Key Tasks

- **Reference resolution**
  - Constraints and preferences
  - Heuristic, learning and sieve models
- **Discourse structure modeling**
  - Linear topic segmentation
  - Shallow discourse parsing
  - Also see: Rhetorical Structure Theory (RST)

HW #9

Goals

- Explore the task of pronomial anaphora resolution
- Gain familiarity with syntax-based resolution techniques
- Analyze the effectiveness of the Hobbs algorithm by applying it to pairs of parsed sentences.

Task

- Given pairs of sentences (S_0, S_1) as context
  - Resolve the pronoun(s) in S_1 using the Hobbs algorithm.
    - J&M p. 704-705
- **Subtasks**:
  - **Parsing Sentences** — Automatic (CKY, Earley, etc)
  - **Hobbs Algorithm** — May be done either:
    - **Manually** — manually mark up the output parse tree
    - **Coded** — implement Hobbs algorithm — will require feature grammar or similar for finding agreement, etc.

Notes

- For implementation
  - May use any NLTK tools for parse tree manipulation
    - …*as long as it doesn't directly implement the Hobbs algorithm!*
  - May create lookup table/dictionary for agreement
- Two results files:
  - One for all parsed output
  - One for remaining manual steps
    - (Based on a copy of the first)

NLTK Tools

- "Climbing" parse trees:
  - NLTK ParentedTree
    - nltk.org/howto/tree.html
  - Conversion from standard tree `t`
    - `parented_tree = nltk.tree.ParentedTree.convert(t)`

- Accessing feature structures

```
fs = nltk.grammar.FeatStructNonterminal(parented_tree.label())
pronoun_agr = fs['agr']
antecedent_agr.subsumes(pronoun_agr)
```