Feature-based Parsing
+
Computational Semantics

LING 571 — Deep Processing for NLP

Shane Steinert-Threlkeld

Announcements

- HW3 et al:
  - Readme: TXT or PDF file extension please
  - Graceful degradation / no parses

Announcements

- No improvements (e.g. upper/lower-case) in first 3 parts of assignment
  - Parser will miss some sentences :)
- In shell script for part 5: hard code **full** paths to `evalb` and `parses.gold`
- Example grammars: `toy.pcfg` (UPDATED!) is gold induced from `toy_output.txt`; `example_induced.pcfg` is **NOT** a gold reference
- Parent annotation and evaluation:
  - Splitting non-terminals = introducing new ones, may not be in gold/eval data
  - For this assignment, need to “de-parent” your parses at the end
- Note on underflow: $$\log \prod_i P_i = \sum_i \log P_i$$

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@adam_macqueen

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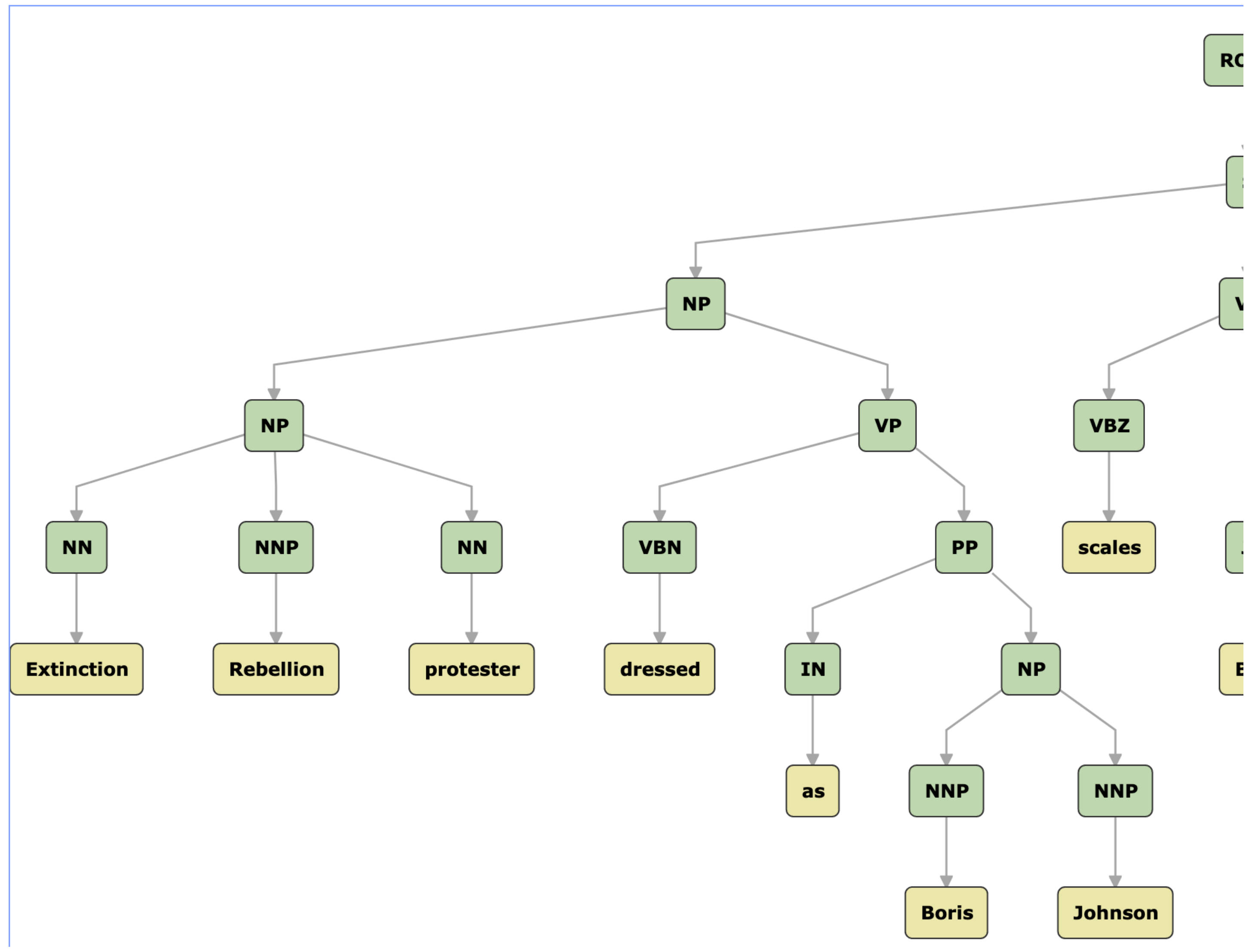

http://corenlp.run/

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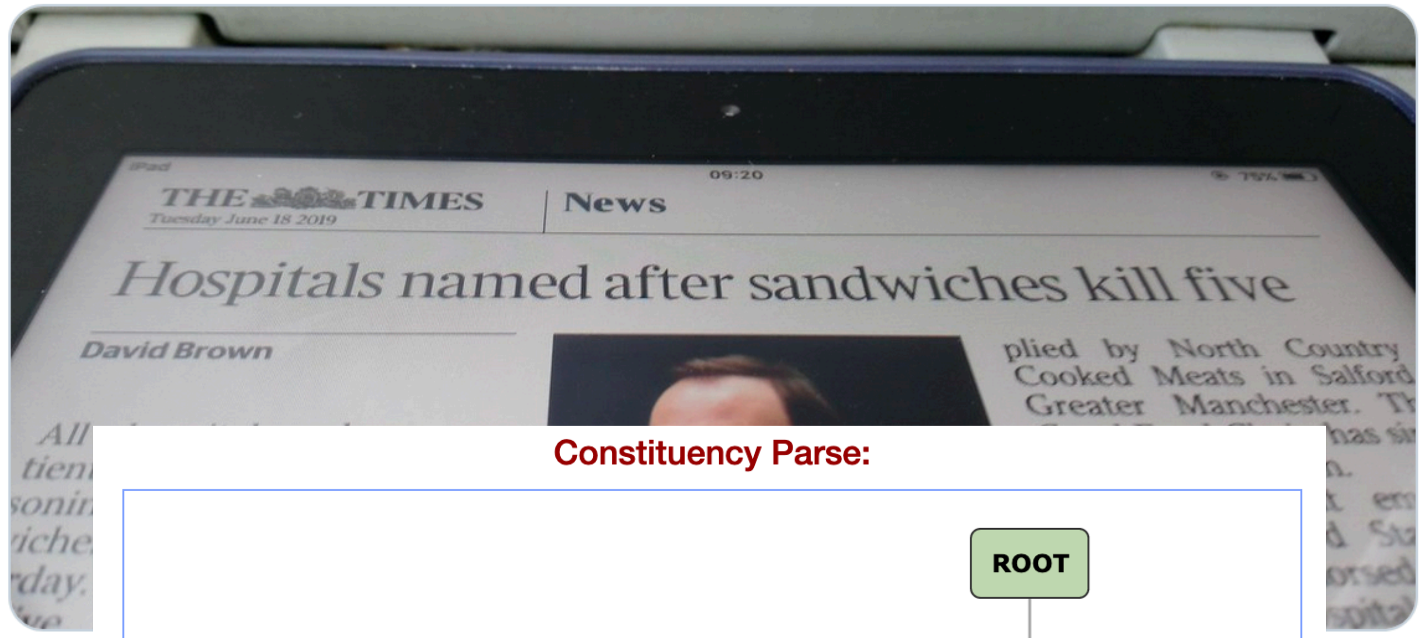

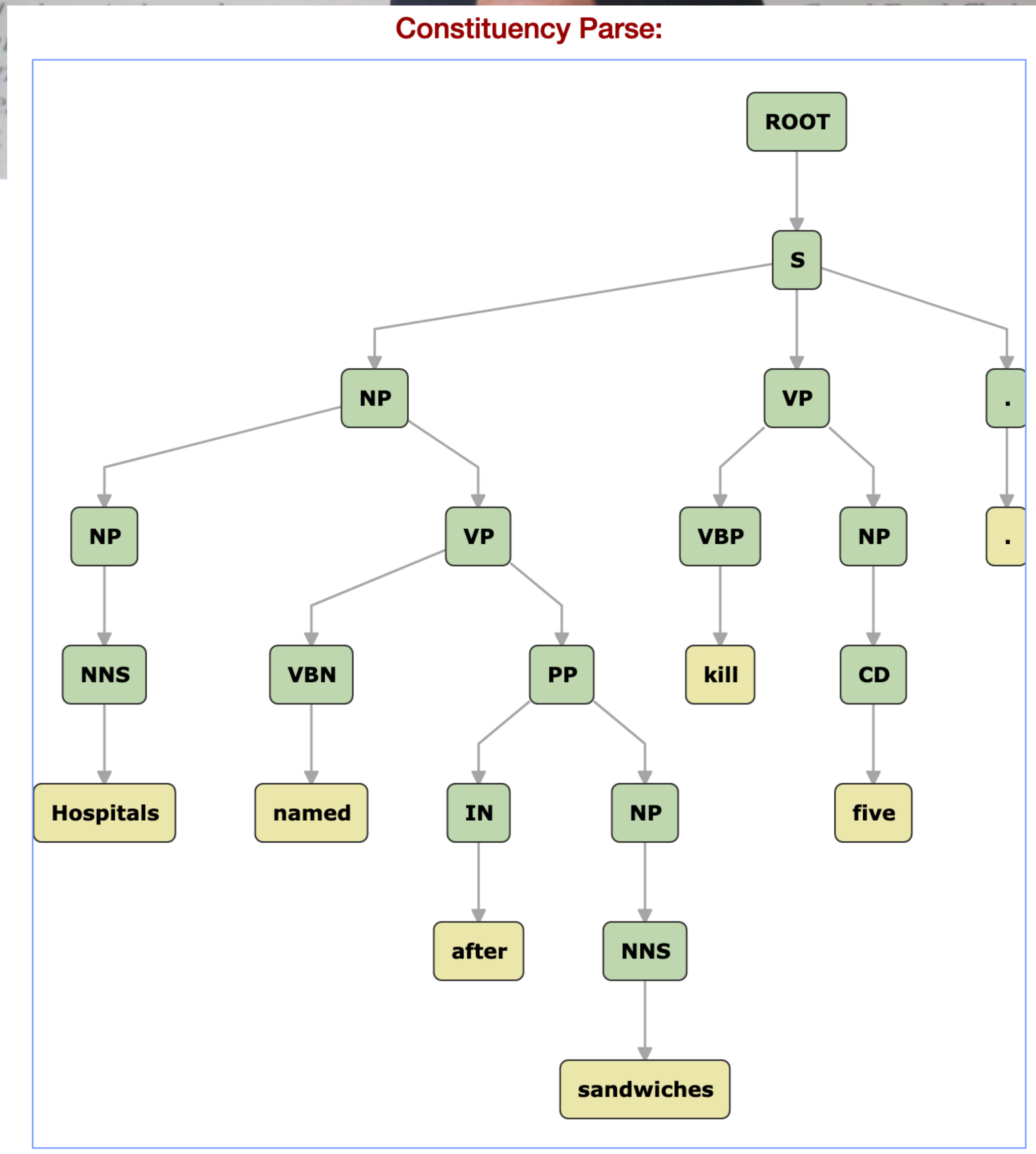

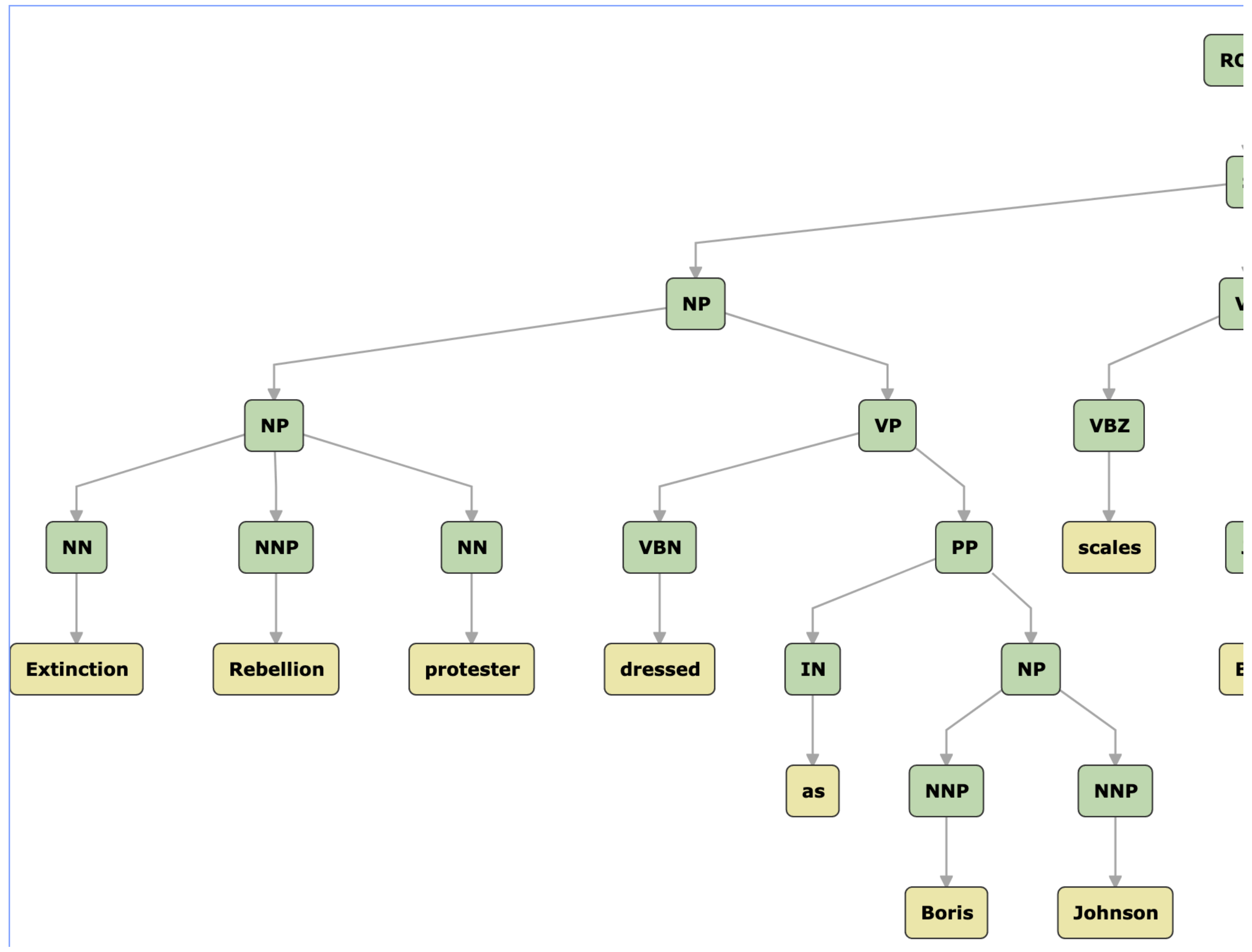

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Roadmap

- Feature-based parsing
- Computational Semantics
  - Introduction
  - Semantics
  - Representing Meaning
    - First-Order Logic
    - Events

Computational Semantics

Dialogue System

- User: *What do I have on Thursday?*

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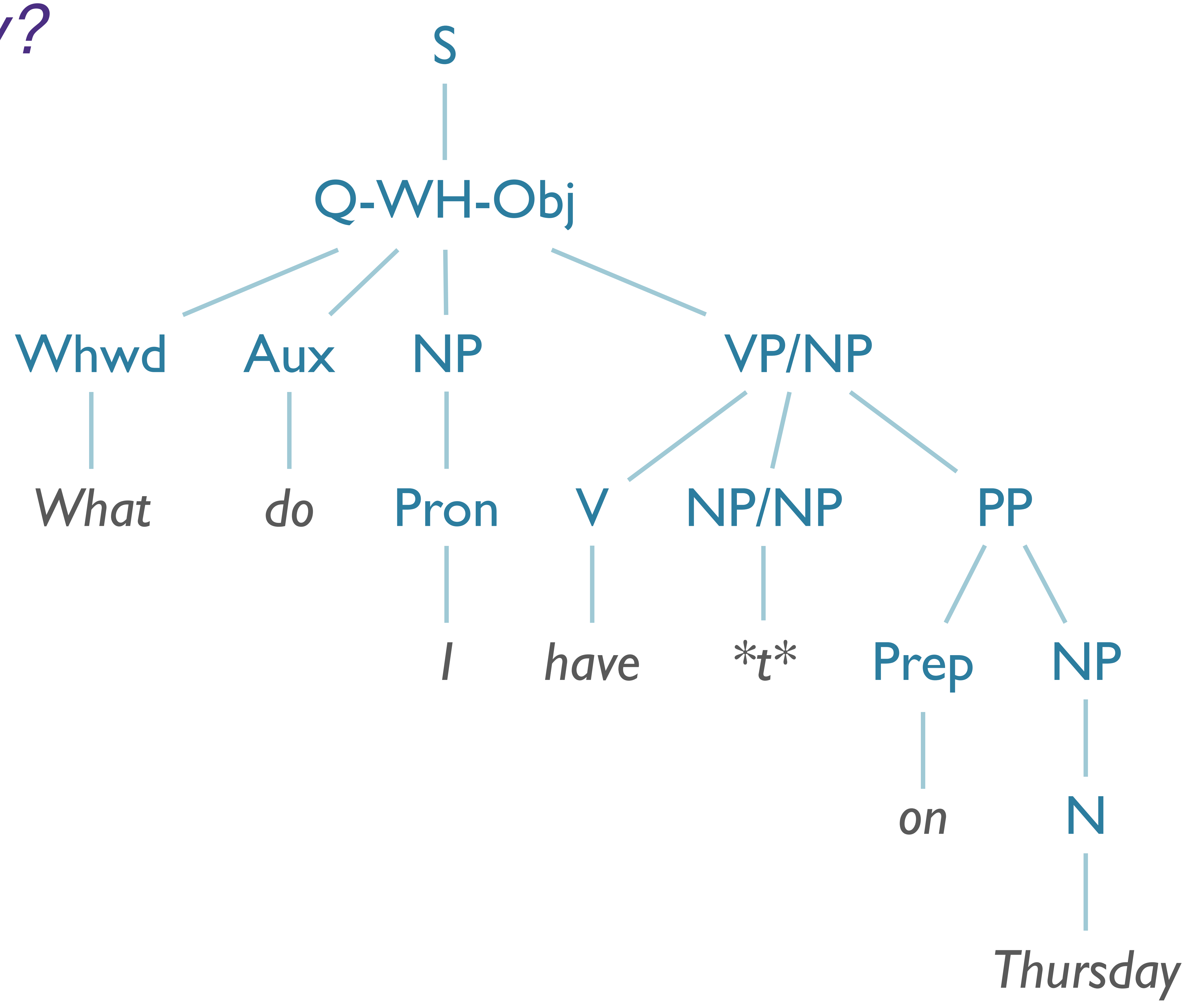

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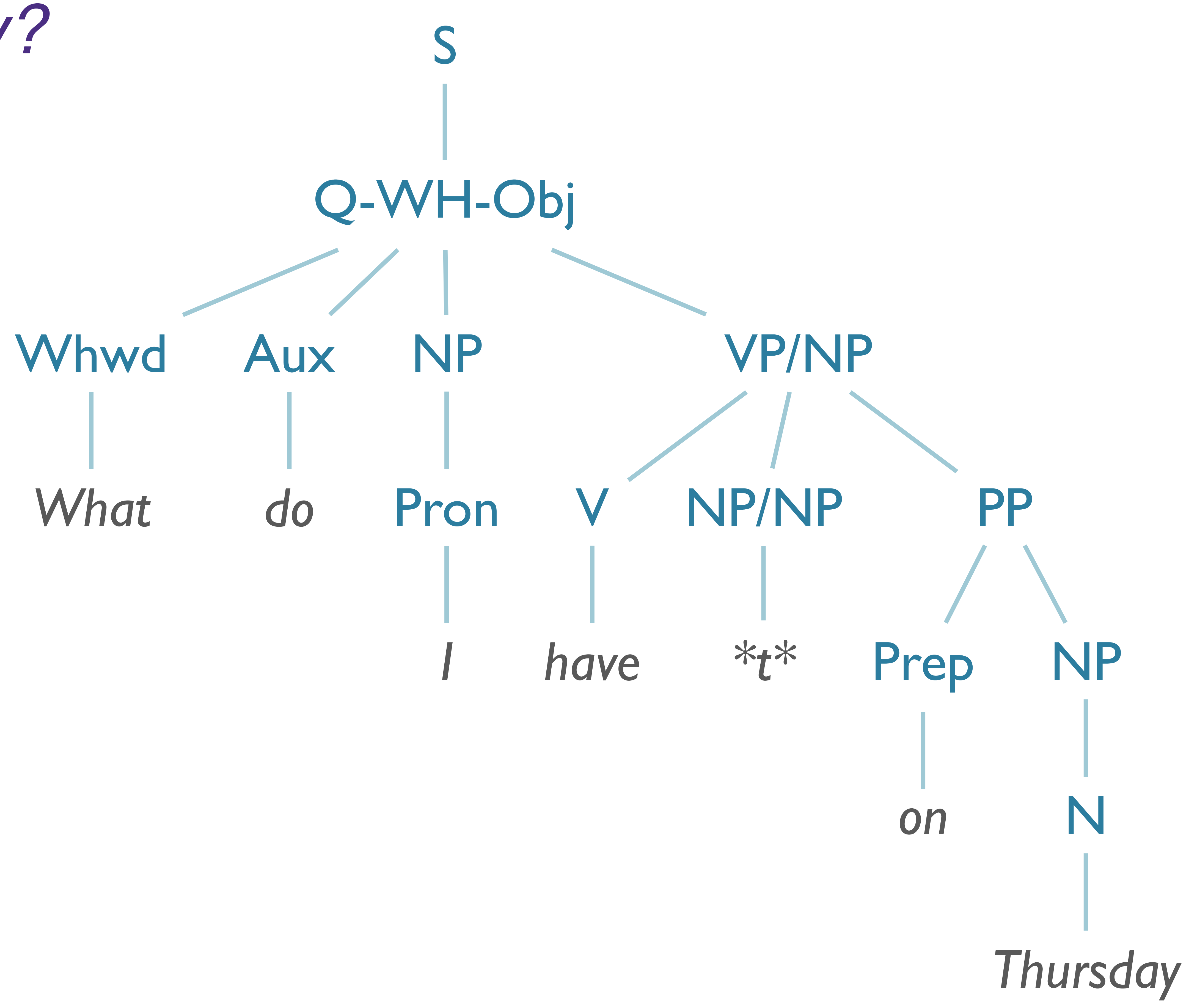

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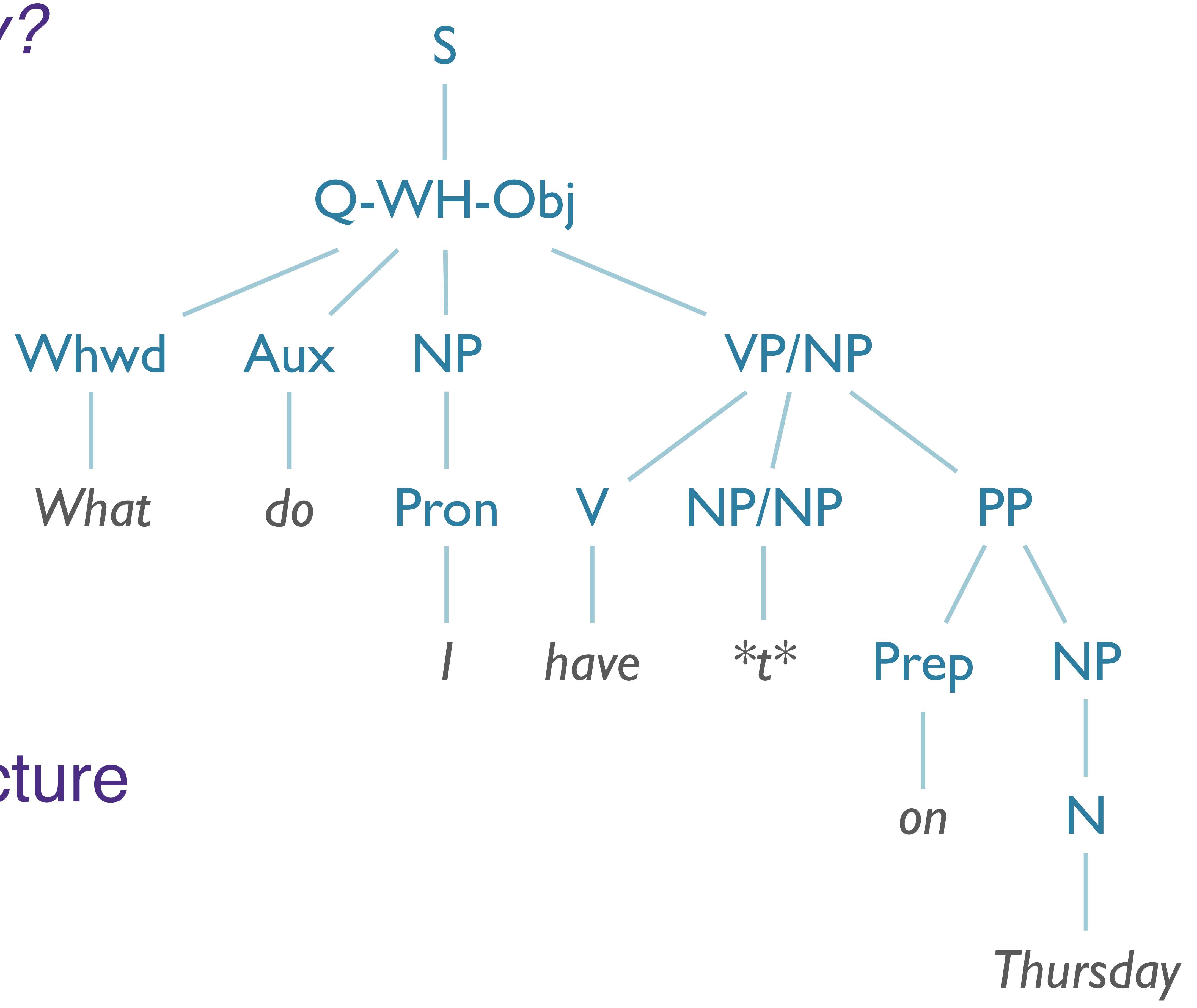
- System:
  - Great, but what do I *DO* now?
- Need to associate meaning w/structure



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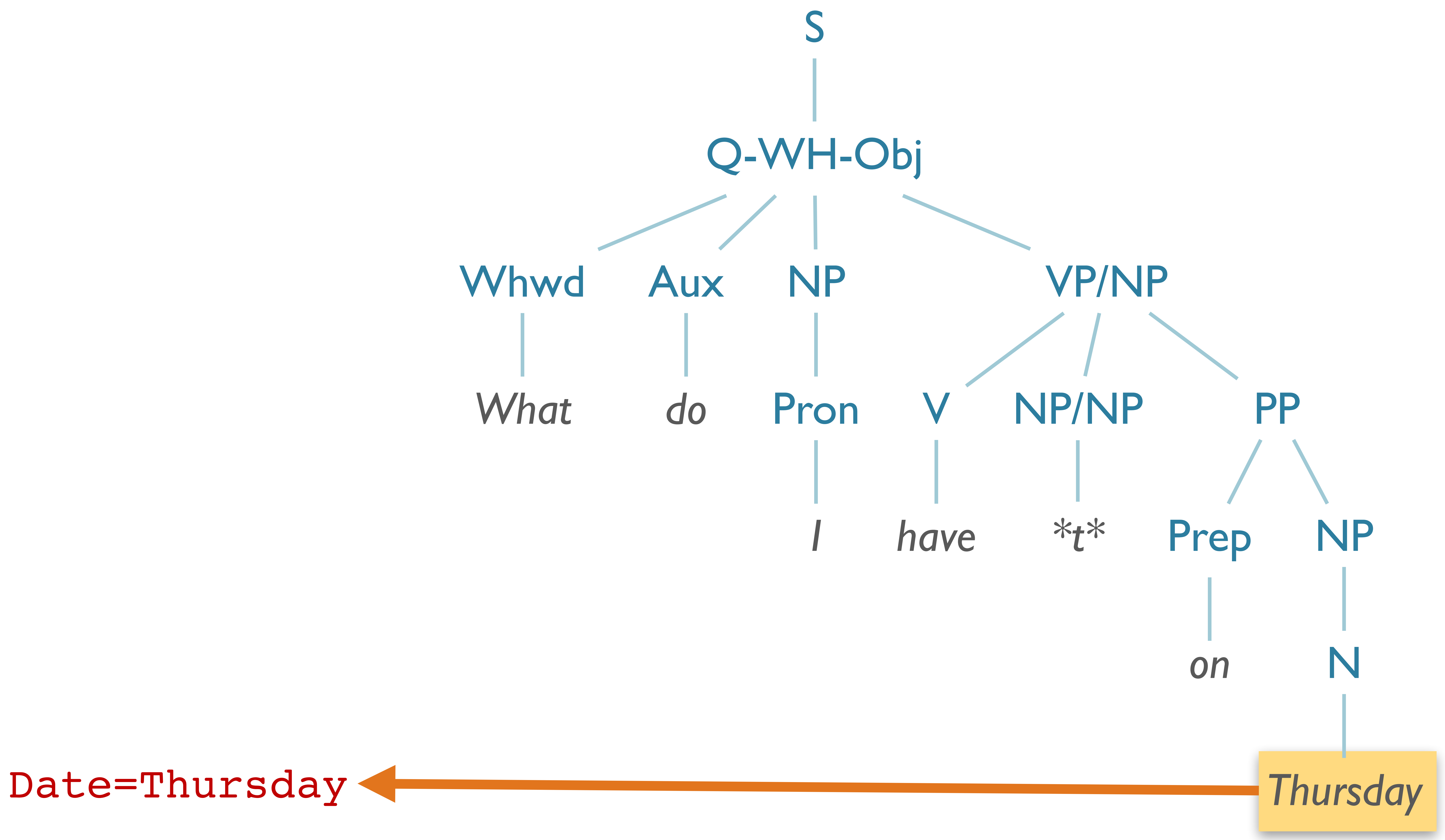

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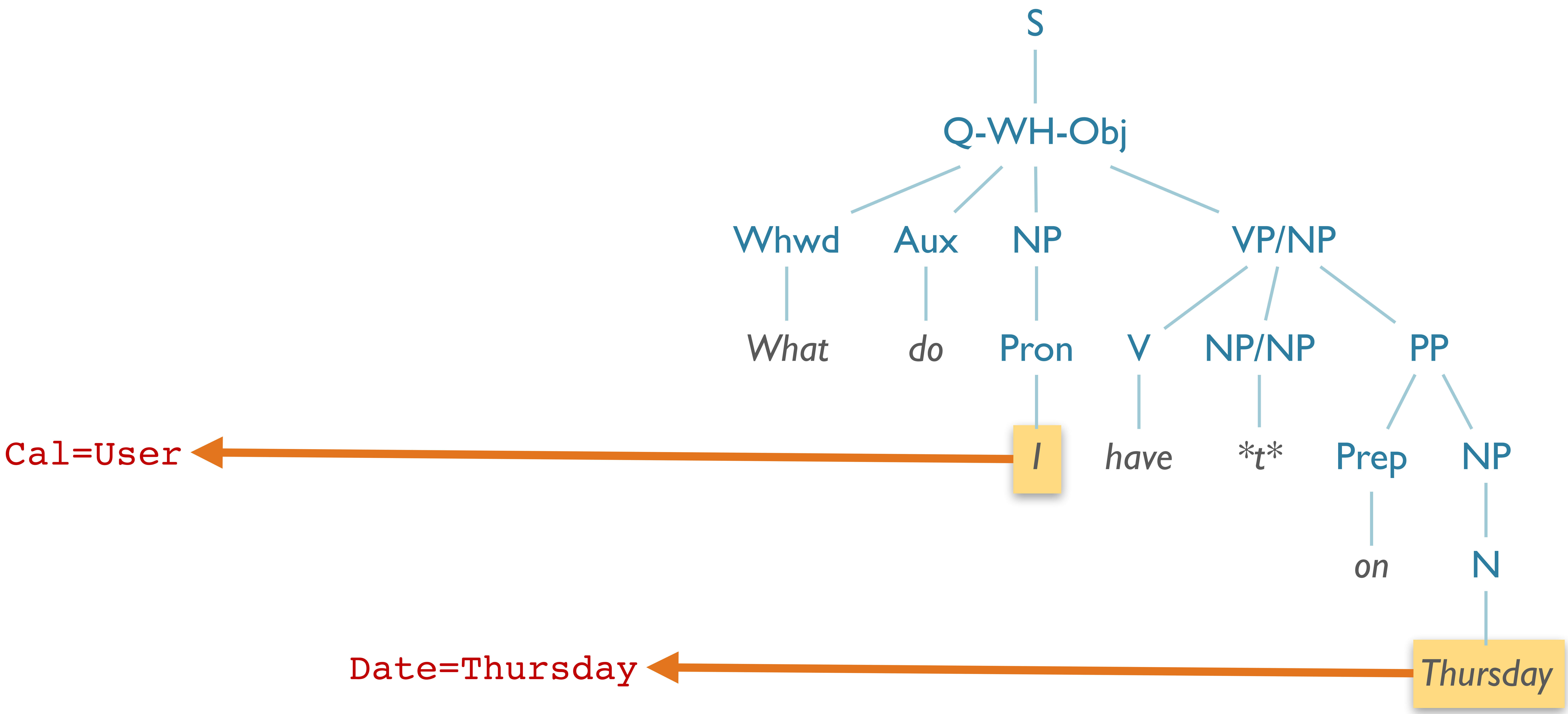

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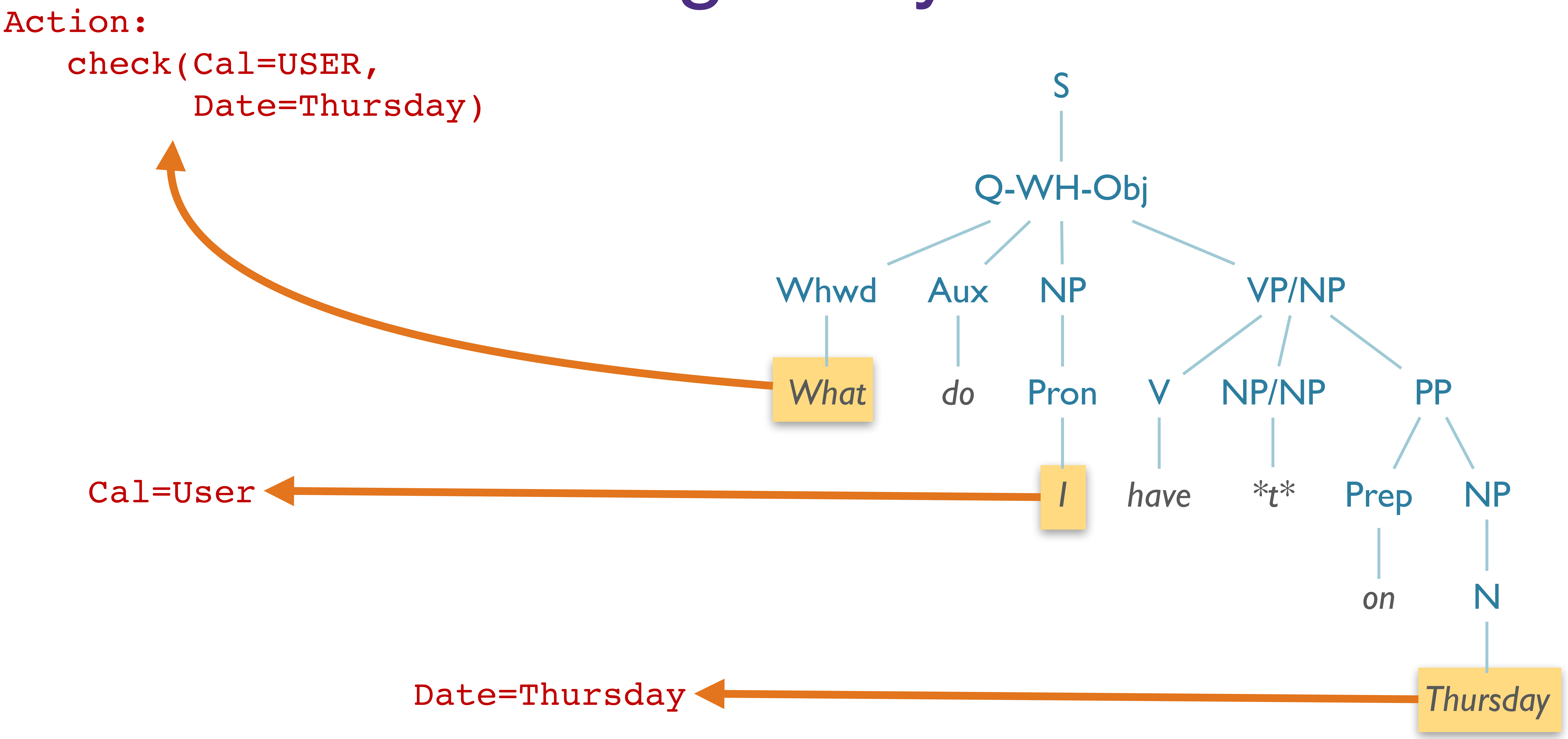

Syntax vs. Semantics

- Syntax:
  - Determine the ***structure*** of natural language input

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- Semantics:
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High-Level Overview

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  - …but what does “meaning” mean?

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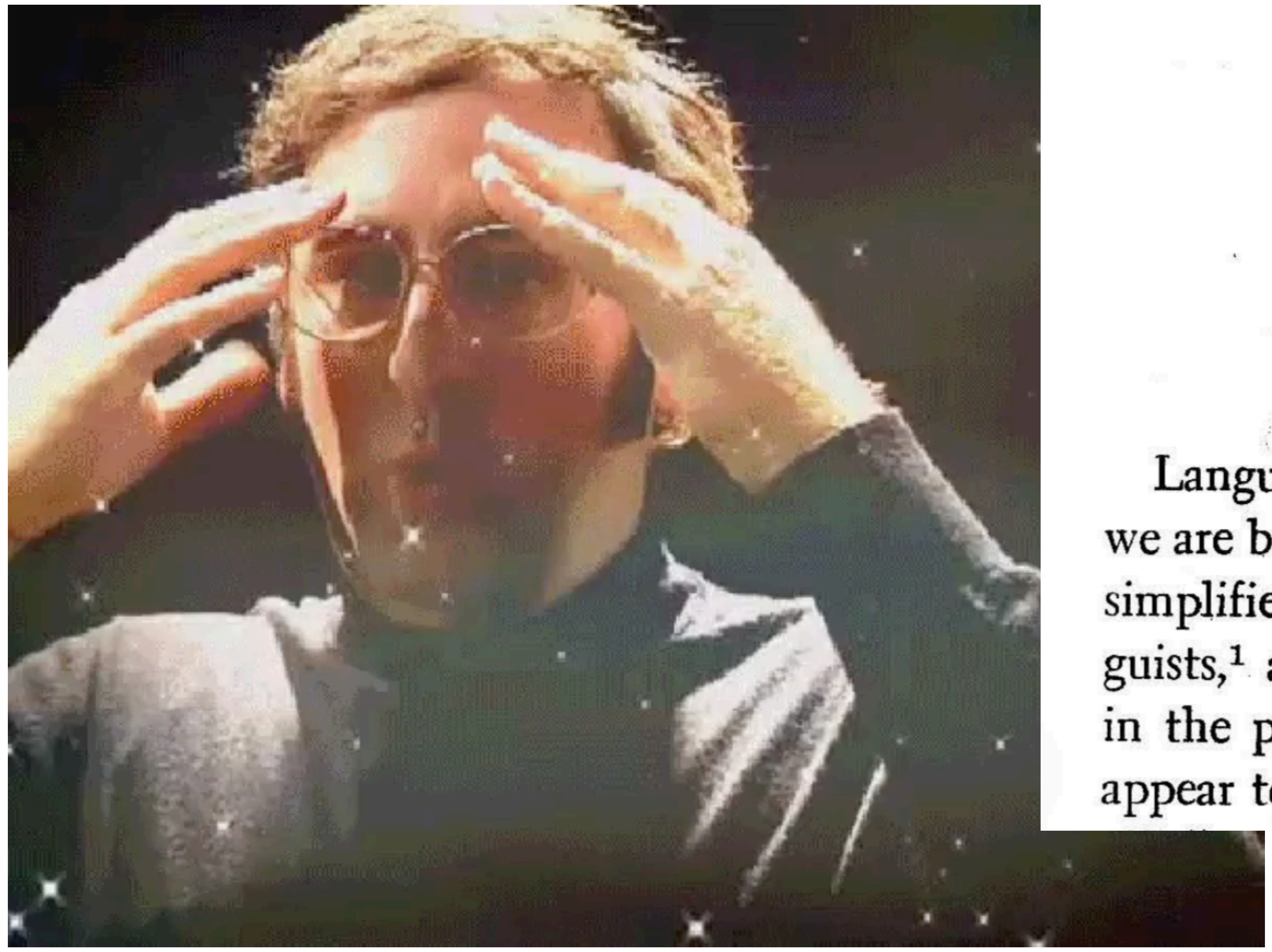
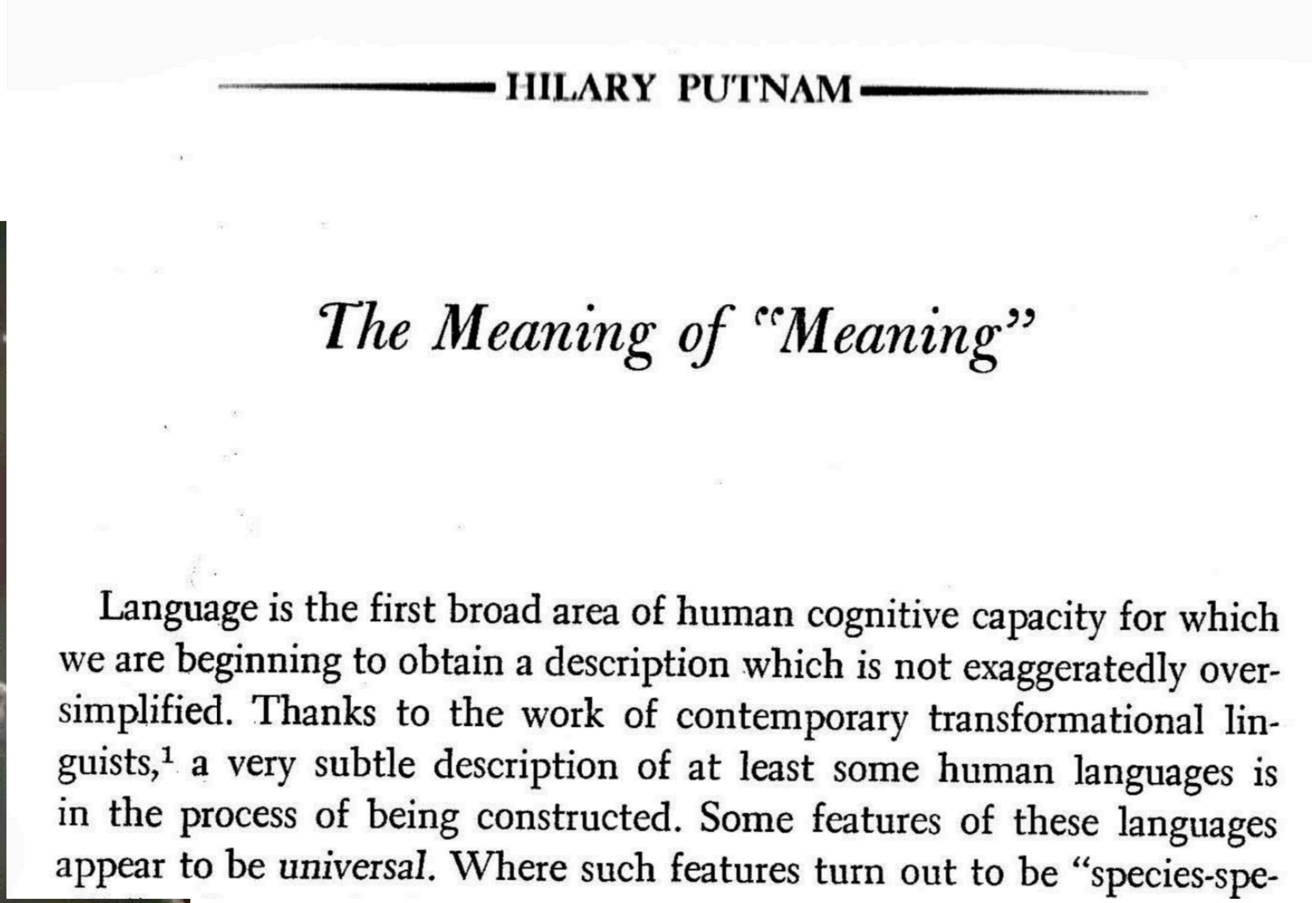




HILARY PUTNAM

The Meaning of “Meaning”

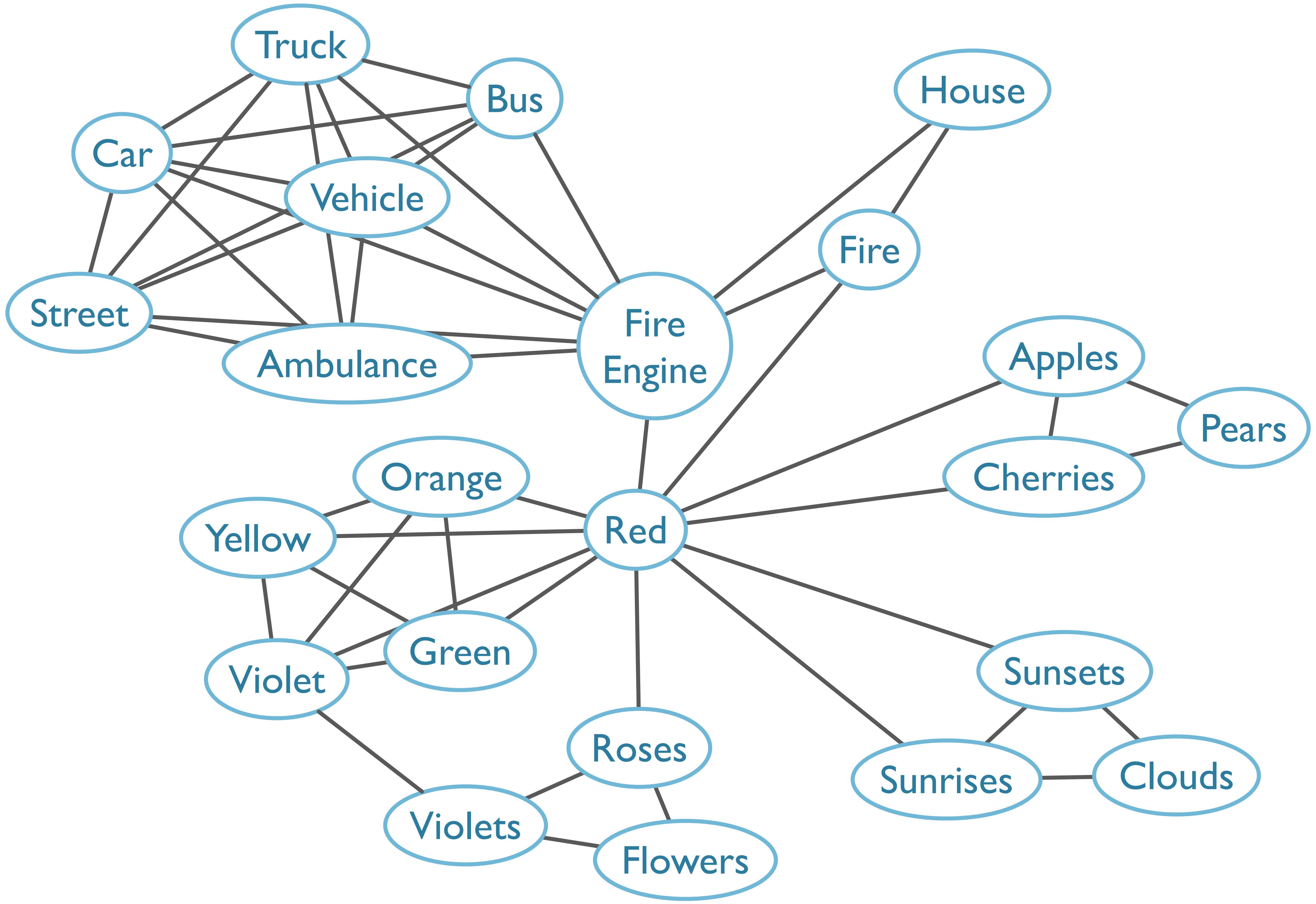
Language is the first broad area of human cognitive capacity for which we are beginning to obtain a description which is not exaggeratedly over-simplified. Thanks to the work of contemporary transformational linguists,[1] a very subtle description of at least some human languages is in the process of being constructed. Some features of these languages appear to be *universal*. Where such features turn out to be “species-spe-

We Will Focus On:

- Concepts and representations that have *truth-conditions*: they can be true or false in the world (or, more generally, “executable”).
- How to connect strings and those concepts.

We ***Won't*** Focus On:

1. Building knowledge bases / semantic networks



Roadmap

- Computational Semantics
  - Overview
  - **Semantics**
  - Representing Meaning
    - First-Order Logic
    - Events
- HW#5
  - Feature grammars in NLTK
  - Practice with animacy

Semantics: an Introduction

Uses for Semantics

- Semantic interpretation required for many tasks
  - Answering questions
  - Following instructions in a software manual
  - Following a recipe
- Requires more than phonology, morphology, syntax
- Must link linguistic elements to world knowledge

Semantics is Complex

- Sentences have many entailments, presuppositions, implicatures
- *Instead, the protests turned bloody, as anti-government crowds were confronted by what appeared to be a coordinated group of Mubarak supporters.*

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  - …etc.

Challenges in Semantics

- **Semantic Representation**:
  - What is the appropriate formal language to express propositions in linguistic input?
  - e.g.: predicate calculus: $\exists x\left(dog\left(x\right) \wedge disappear\left(x\right)\right)$

Challenges in Semantics

- **Semantic Representation**:
  - What is the appropriate formal language to express propositions in linguistic input?
  - e.g.: predicate calculus: $\exists x\left(dog(x) \wedge disappear(x)\right)$
- **Entailment**:
  - What are all the conclusions that can be validly drawn from a sentence?
    - *Lincoln was assassinated* $\vDash$ *Lincoln is dead*
    - $\vDash$ "semantically entails": if former is true, the latter must be too

Challenges in Semantics

- **Reference**
  - How do linguistic expressions link to objects/concepts in the real world?
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- **Reference**
  - How do linguistic expressions link to objects/concepts in the real world?
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- **Compositionality**
  - How can we derive the meaning of a unit from its parts?
  - How do syntactic structure and semantic composition relate?
  - ‘rubber duck’ vs. ‘rubber chicken’ vs. ‘rubber-neck’
  - *kick the bucket*

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- Develop methods for **reasoning** about these representations
  - …and performing inference

Tasks in Computational Semantics

- Semantic similarity (words, texts)
- Semantic role labeling
- Semantic parsing / Semantic analysis
- Recognizing textual entailment (RTE) / natural language inference (NLI)
- Sentiment analysis
- …

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- **Reasoning**
  - Given a representation and world, what new conclusions (bits of meaning) can we infer?

Complexity of Computational Semantics

- Effectively AI-complete
  - Needs representation, reasoning, world model, etc.

Representing Meaning

Meaning Representations

- All consist of structures from set of symbols
  - Representational vocabulary

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- Here we focus on **literal** meaning (“what is said”)

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- Inference and Variables
  - Way to draw valid conclusions from semantics and KB
- Expressiveness
  - Represent any natural language utterance

Meaning Structure of Language

- Human Languages:
  - Display basic predicate-argument structure
  - Employ variables
  - Employ quantifiers
  - Exhibit a (partially) compositional semantics

Predicate-Argument Structure

- Represent concepts and relationships

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- Some words behave like arguments
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- Subcategorization frames indicate:
  - Number, Syntactic category, order of args, possibly other features of args

First-Order Logic:
Syntax

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  - Provides sound computational basis for verifiability, inference, expressiveness

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- Supports inference
- Supports generalization through variables

First-Order Logic Terms

- **Constants**: specific objects in world;
  - $A,\ B,\ John$
  - Refer to exactly one object
  - Each object can have multiple constants refer to it
    - $WAStateGovernor$ and $JayInslee$

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- **Functions**: concepts relating ***objects*** → ***objects***
  - $GovernerOf(WA)$
  - Refer to objects, avoid using constants
- **Variables**:
  - $\boldsymbol{x},\ \boldsymbol{e}$
  - Refer to any potential object in the world

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- **Predicates**
  - Relate ***objects*** to other ***objects***
  - *'United serves Chicago'*
    - $Serves(United,\ Chicago)$

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- **Predicates**
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- **Logical Connectives**
  - $\{\wedge,\ \vee,\ \Rightarrow\}$ = {and, or, implies}
  - Allow for compositionality of meaning* [* many subtleties]
  - *'Frontier serves Seattle and is cheap.'*
    - $Serves(Frontier,\ Seattle) \wedge Cheap(Frontier)$

Quantifiers

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- **A non-stop flight** that **serves Pittsburgh**:

$$\exists x\ Flight(x) \wedge Serves(x, Pittsburgh) \wedge Non\text{-}stop(x)$$

Quantifiers

- $\forall$: **universal** quantifier: *"for all"*
  - **All flights include beverages.**

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  - **All flights include beverages.**

    $\forall x \; Flight(x) \Rightarrow Includes(x, \; beverages)$

FOL Syntax Summary

$$
\begin{array}{lcl}
\textbf{\textit{Formula}} & \rightarrow & \textit{AtomicFormula} \\
 & | & \textit{Formula Connective Formula} \\
 & | & \textit{Quantifier Variable, … Formula} \\
 & | & \neg\ \textit{Formula} \\
 & | & (\textit{Formula}) \\
\textbf{\textit{AtomicFormula}} & \rightarrow & \textit{Predicate}(\textit{Term},\ldots) \\
\textbf{\textit{Term}} & \rightarrow & \textit{Function}(\textit{Term},\ldots) \\
 & | & \textit{Constant} \\
 & | & \textit{Variable}
\end{array}
$$

$$
\begin{array}{lcl}
\textbf{\textit{Connective}} & \rightarrow & \wedge \mid \vee \mid \Rightarrow \\
\textbf{\textit{Quantifier}} & \rightarrow & \forall \mid \exists \\
\textbf{\textit{Constant}} & \rightarrow & \textit{VegetarianFood} \mid \textit{Maharani} \mid \ldots \\
\textbf{\textit{Variable}} & \rightarrow & x \mid y \mid \ldots \\
\textbf{\textit{Predicate}} & \rightarrow & \textit{Serves} \mid \textit{Near} \mid \ldots \\
\textbf{\textit{Function}} & \rightarrow & \textit{LocationOf} \mid \textit{CuisineOf} \mid \ldots
\end{array}
$$

J&M p. 556 (3rd ed. 19.3)

Compositionality

- The meaning of a complex expression is a function of the meaning of its parts, and the rules for their combination.

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- The meaning of a complex expression is a function of the meaning of its parts, and the rules for their combination.
- Formal languages **are** compositional.
- Natural language meaning is ***largely compositional,*** though arguably not fully.*

Compositionality

- …how can we derive:
  - $loves(John, Mary)$

Compositionality

- …how can we derive:
  - $loves(John,\ Mary)$
- from:
  - $John$
  - $loves(x,\ y)$
  - $Mary$

Compositionality

- …how can we derive:
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  - $Mary$
- Lambda expressions!

Lambda Expressions

- Lambda (λ) notation (Church, 1940)
  - Just like lambda in Python, Scheme, etc
  - Allows abstraction over FOL formulae
  - Supports compositionality

- Form: (λ) + variable + FOL expression
  - $\lambda x.P(x)$ "Function taking x to $P(x)$"
  - $\lambda x.P(x)(A) = P(A)$ [called beta-reduction]

λ-Reduction

- λ-reduction: Apply λ-expression to logical term
  - Binds formal parameter to term

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$$\lambda x.P(x)$$
$$\lambda x.P(x)(A)$$
$$P(A)$$

- Equivalent to function application

Nested λ-Reduction

- Lambda expression as body of another

$$\lambda x.\lambda y.Near(x,\ y)$$

Nested λ-Reduction

- Lambda expression as body of another

$$\lambda x.\lambda y.Near(x,\ y)$$
$$\lambda x.\lambda y.Near(x,\ y)(Midway)$$

Nested λ-Reduction

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$$Near(Midway,\ Chicago)$$

Nested λ-Reduction

- If it helps, think of λs as binding sites:

Chicago

Midway

$$\lambda x.\lambda y.Near(x,\ y)$$

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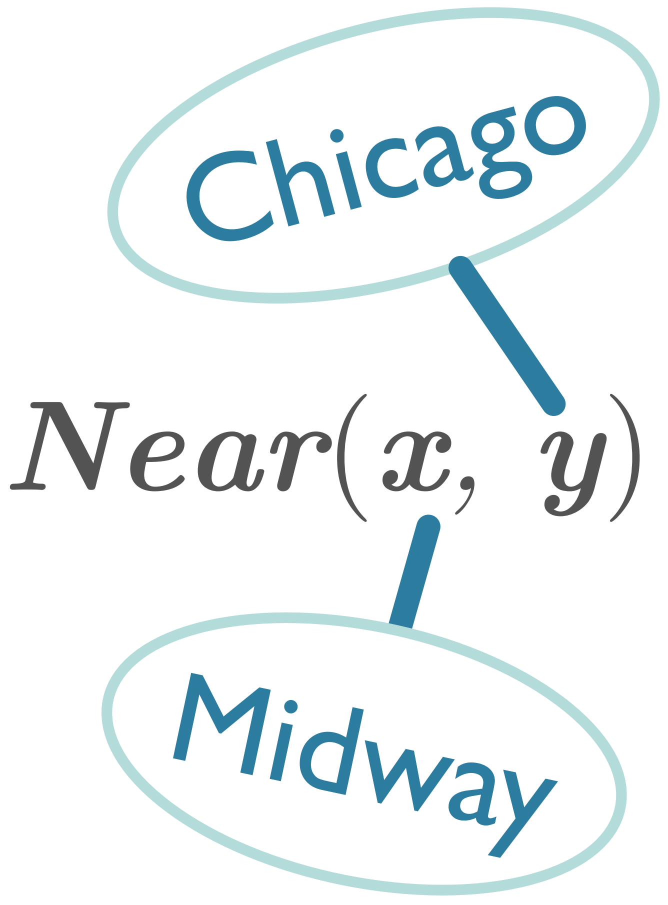

Lambda Expressions

- ***Currying***
  - Converting multi-argument predicates to sequence of single argument predicates
  - Why?
    - Incrementally accumulates multiple arguments spread over different parts of parse tree

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- …or *Schönkfinkelization*

Logical Formulae

- FOL terms (objects): denote elements in a domain
  - Properties: sets of domain elements
  - Relations: sets of tuples of domain elements

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- Formulae based on logical operators:

P	Q	$\neg P$	$P \wedge Q$	$P \vee Q$	$P \Rightarrow Q$
F	F	T	F	F	T
F	T	T	F	T	T
T	F	F	F	T	F
T	T	F	T	T	T

Logical Formulae: Finer Points

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  - *Your choice is pepperoni or sausage*
  - …use $\veebar$ or $\oplus$

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  - …use $\veebar$ or $\oplus$
- $\Rightarrow$ is the logical form
  - Does not mean the same as natural language “if”, just that if LHS=T, then RHS=T

Inference

1. α

1. $\forall x \, \alpha(x)$

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- Standard AI-type logical inference procedures
  - Modus Ponens
  - Forward-chaining, Backward Chaining
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  - Resolution
  - Etc…

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LINC: A Neurosymbolic Approach for Logical Reasoning by Combining Language Models with First-Order Logic Provers

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Abstract

Logical reasoning, i.e., deductively inferring the truth value of a conclusion from a set of premises, is an important task for artificial intelligence with wide potential impacts on science, mathematics, and society. While many prompting-based strategies have been proposed to enable Large Language Models (LLMs) to do such reasoning more effectively, they still appear unsatisfactory, often failing in subtle and unpredictable ways. In this work, we investigate the validity of instead reformulating such tasks as modular neurosymbolic programming, which we call LINC: Logical Inference via Neurosymbolic Computation. In

1 Introduction

Widespread adoption of large language models (LLMs) such as GPT-3 (Brown et al., 2020), GPT-4 (OpenAI, 2023), and PaLM (Chowdhery et al., 2022) have led to a series of remarkable successes in tasks ranging from text summarization to program synthesis. Some of these successes have encouraged the hypothesis that such models are able to flexibly and systematically reason (Huang and Chang, 2022), especially when using prompting strategies that explicitly encourage verbalizing intermediate reasoning steps before generating the final answer (Nye et al., 2021; Wei et al., 2022; Kojima et al., 2022; Wang et al., 2023b). However,

https://arxiv.org/abs/2310.15164

Roadmap

- Computational Semantics
  - Introduction
  - Semantics
  - Representing Meaning
    - First-Order Logic
    - **Events**

Events

Representing Events

- Initially, single predicate with some arguments
  - $Serves(United,\ Houston)$
  - Assume # of args = # of elements in subcategorization frame

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  - *The flight arrived*
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  - *The flight arrived in Seattle on Saturday.*
  - *The flight arrived on Saturday.*
  - *The flight arrived in Seattle from SFO.*
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- Variable number of arguments; many entailment relations here.

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  - Davidsonian (Davidson 1967):
    - $\exists \boldsymbol{e}\ Arrival(\boldsymbol{e}, Flight, Seattle, SFO) \wedge Time(\boldsymbol{e}, Saturday)$
  - Neo-Davidsonian (Parsons 1990):
    - $\exists \boldsymbol{e}\ Arrival(\boldsymbol{e}) \wedge Arrived(\boldsymbol{e}, Flight) \wedge Destination(\boldsymbol{e}, Seattle) \wedge Origin(\boldsymbol{e}, SFO)$
      $\wedge\ Time(\boldsymbol{e}, Saturday)$

Why events?

- “Adverbial modification is thus seen to be logically on a par with adjectival modification: what adverbial clauses modify is not verbs but the events that certain verbs introduce.” —Davidson

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  - Distill event to single argument for main predicate
  - Everything else is additional predication
- Pros
  - No fixed argument structure
  - Dynamically add predicates as necessary
  - No unused roles
  - Logical connections can be derived

Meaning Representation for Computational Semantics

- Requirements
  - Verifiability
  - Unambiguous representation
  - Canonical Form
  - Inference
  - Variables
  - Expressiveness
- Solution:
  - First-Order Logic
    - Structure
    - Semantics
    - Event Representation

Summary

- FOL can be used as a meaning representation language for natural language
- Principle of compositionality:
  - The meaning of a complex expression is a function of the meaning of its parts
- λ-expressions can be used to compute meaning representations from syntactic trees based on the principle of compositionality
- In next classes, we will look at syntax-driven approach to semantic analysis in more detail