Natural Language Processing

Lecture 16: Semantic Parsing II -
Abstract Meaning Representation (AMR)

11/20/2018

COMS W4705
Daniel Bauer

Logical Forms

- Logical form satisfies many goals for meaning representations (unambiguous, canonical form, supports inference, expressiveness)

- But difficult to annotate on a large scale.

Event Semantics

- Typically events and relations are expressed as predicates in first-order logic.

  $\exists x \; \exists y \; Computer(x) \wedge School(y) \wedge donate(Apple,x,y)$

- Problem: predicate arguments are not semantic roles.
  Model-theoretic semantics is problematic:

  donate(Apple,x,y) should imply *donate(Apple,x)*

- One approach: Event semantics (neo-Davisonian semantics).
  Events are treated like entities.

  $$\exists \mathbf{e} \; \exists x \; \exists y \; \boldsymbol{Donate(e)} \wedge Computer(x) \wedge School(y) \wedge$$
  $$Donor(\mathbf{e},Apple) \wedge Theme(\mathbf{e},x) \wedge Receipient(\mathbf{e},y)$$

- How is this related to frames and semantic roles?

Abstract Meaning Representation (AMR)

(Banarescu et al., 2013)

- Uses a single, simple data structure (feature structures / directed graphs) to represent many aspects of meaning.
- Focus on "who does what to whom" but leave out details (tense, quantifiers, etc.)
- This level of abstraction facilitates **consistent, large-scale human annotation.**
  Goal: build a giant "semantics bank" (comparable to treebanks for syntax).

(amr.isi.edu)

AMR Example

The dog is eating a bone.

```
(e / eat-01
    :ARG0 (d / dog)
    :ARG1 (b / bone))
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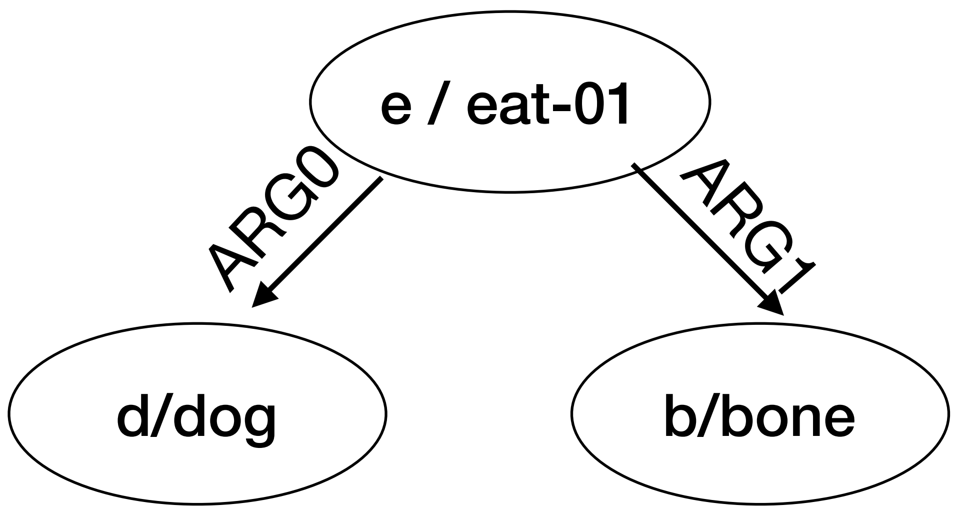

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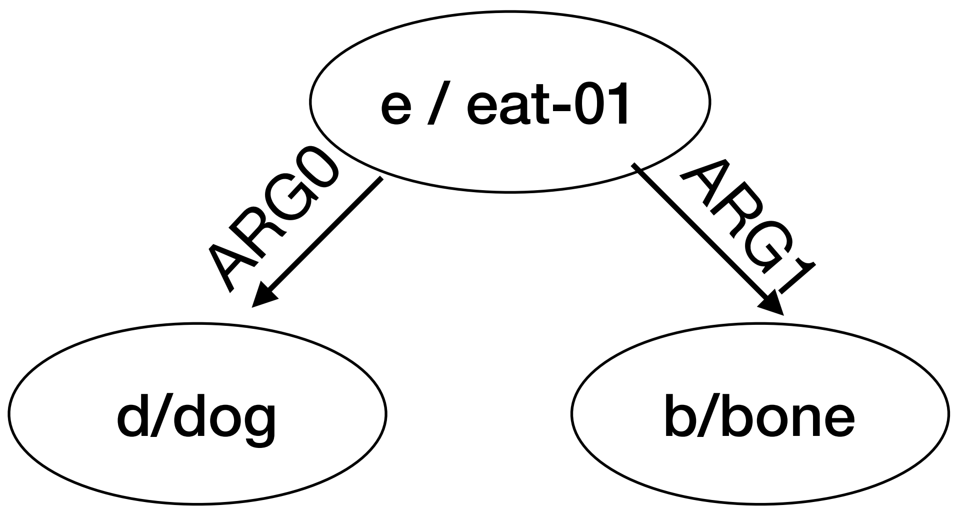

- Edges are labeled with **relations (including semantic roles)**
- Each node has a **variable.**
- Nodes are labeled with **concepts.**

- PropBank framesets used wherever possible.

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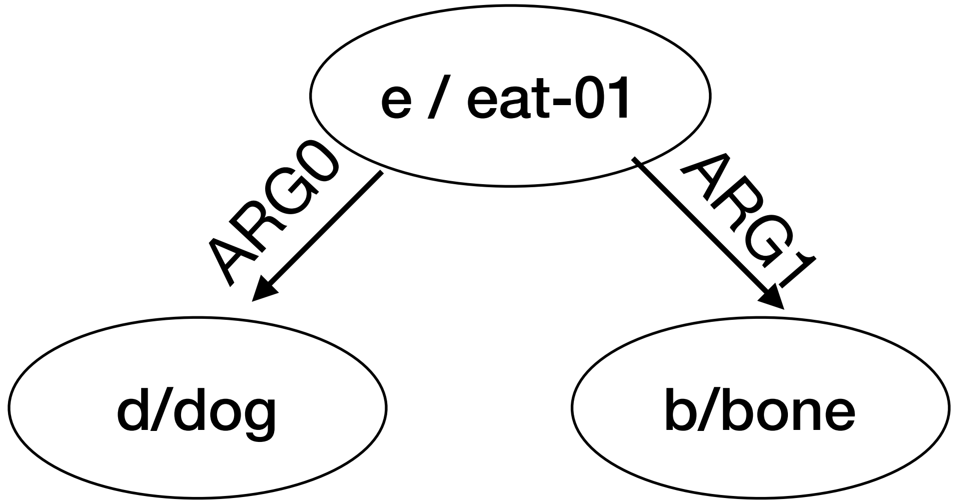

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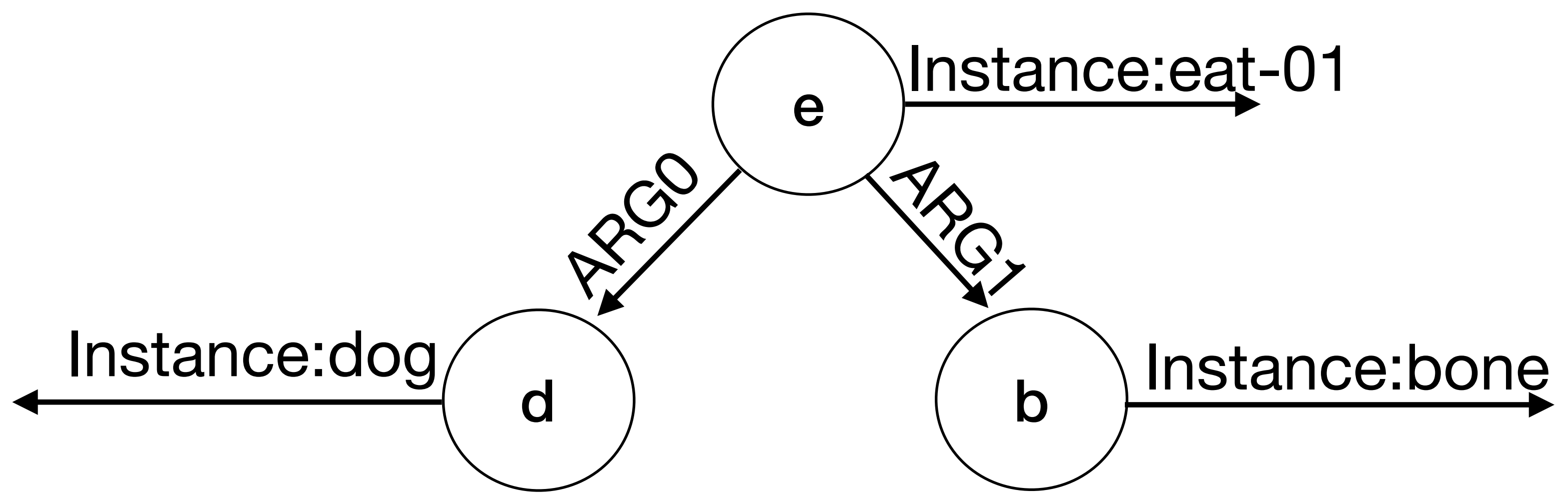


- Edges are labeled with **relations (including semantic roles)**
- Each node has a **variable.**
- Nodes are labeled with **concepts.**
    - Concepts can also be represented as edges.
- PropBank framesets used wherever possible.

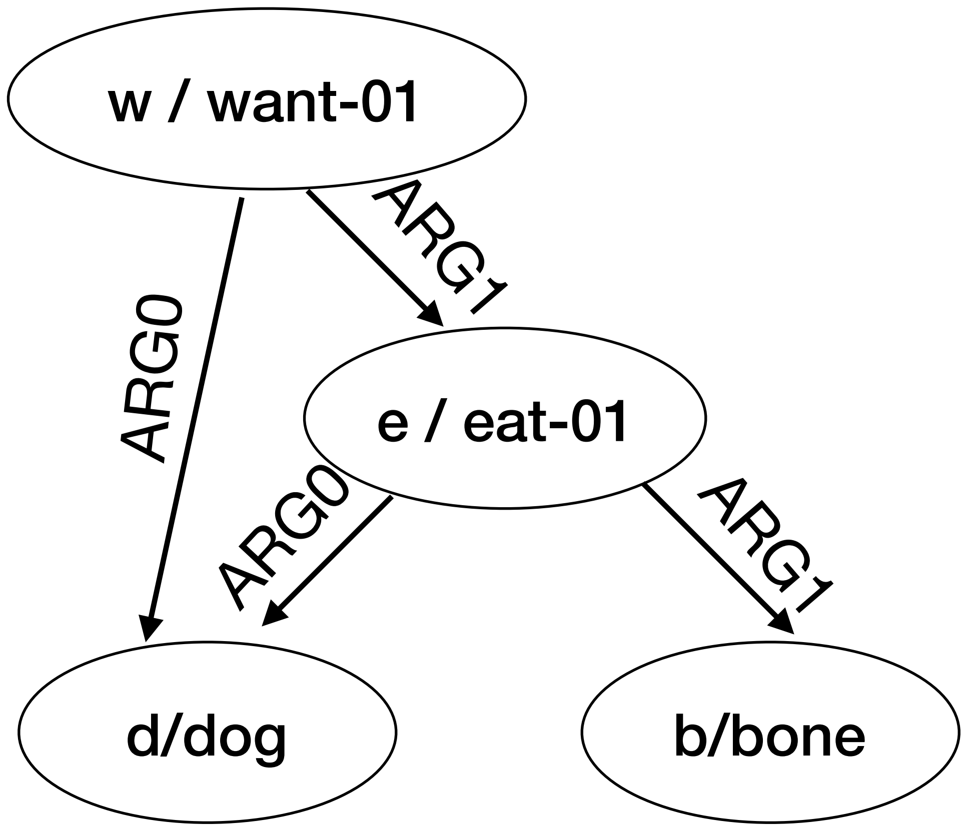
Reentrancy

The dog wants to eat a bone.

Reentrancy

The dog wants to eat a bone.

```
(w / want-01
    :ARG0 (d / dog)
    :ARG1 (e / eat-01
        :ARG0 d
        :ARG1 (b / bone))
```

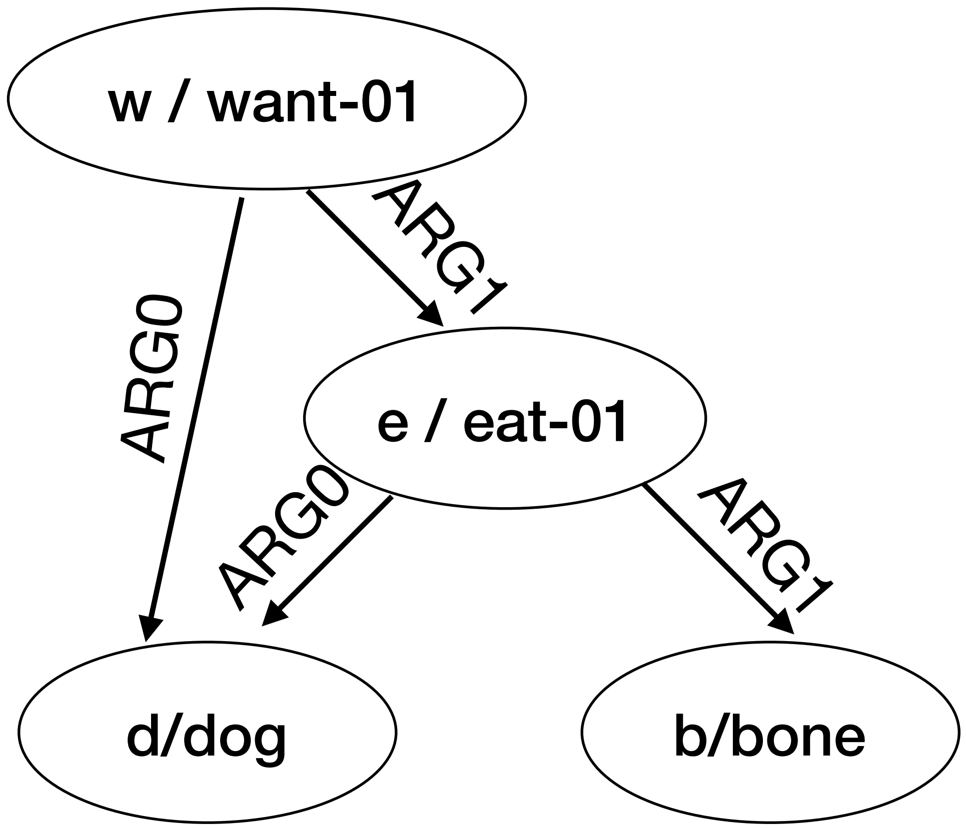


- Why the graph representation? Entities can play multiple roles.
- Two incoming edges in the graph, re-used variable in string notation.

AMR and Event Logic

The dog wants to eat a bone.

```
(w / want-01
    :ARG0 (d / dog)
    :ARG1 (e / eat-01
        :ARG0 d
        :ARG1 (b / bone)))
```



- AMR is related to event logic:
  - All concepts are existentially quantified.
  - Relations and concept labels are predicates.

AMR and Event Logic

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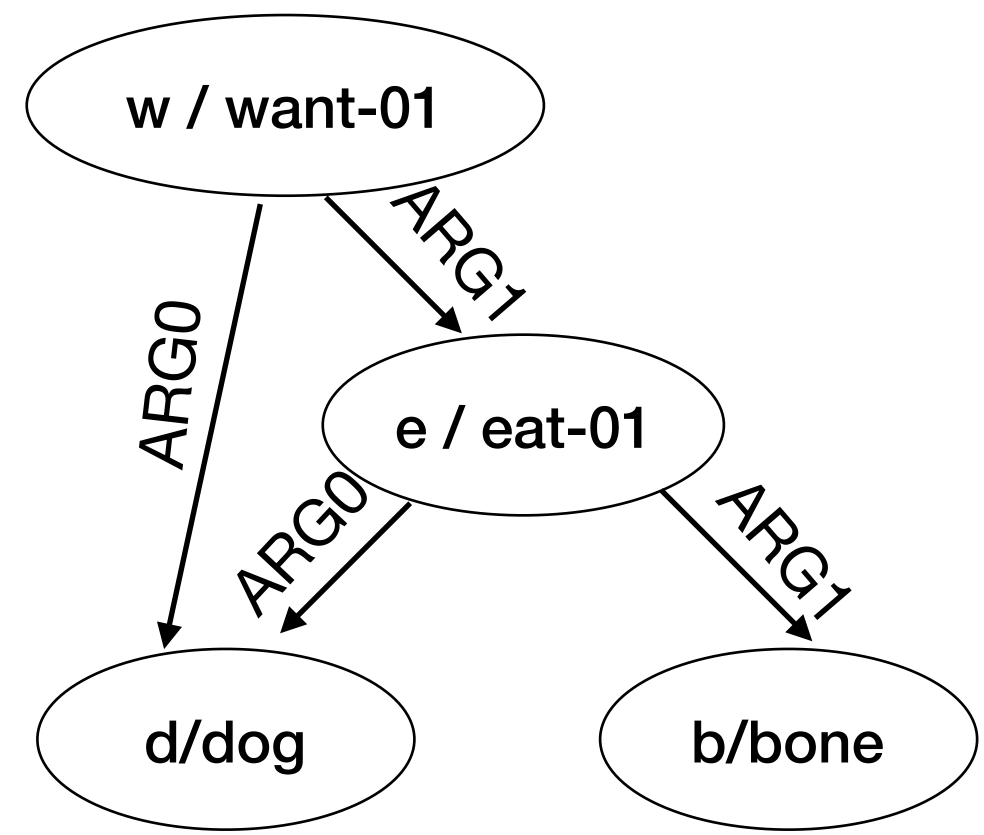


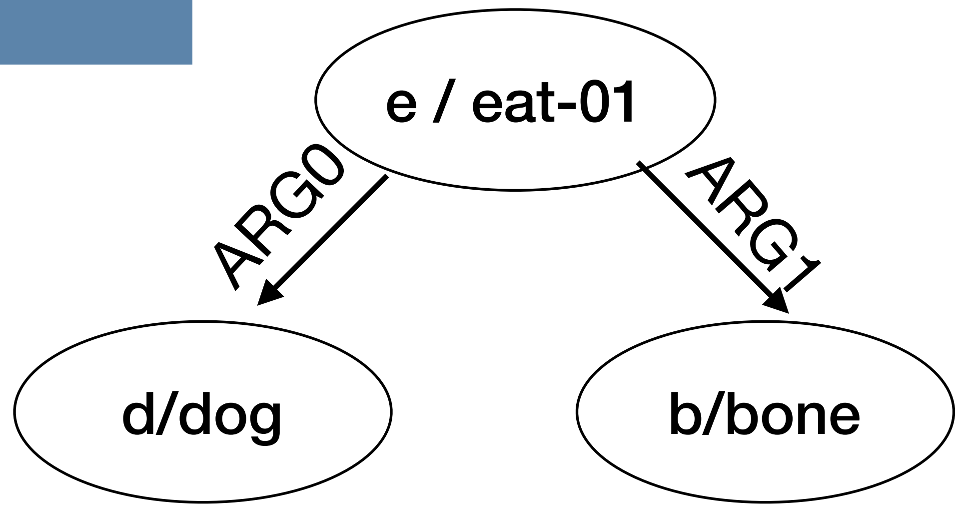
- AMR is related to event logic:
  - All concepts are existentially quantified.
  - Relations and concept labels are predicates.

$$\exists w\ \exists d\ \exists e\ \exists b\ \mathit{Want}(w) \wedge \mathit{Dog}(e) \wedge \mathit{Eat}(e) \wedge \mathit{Bone}(b) \wedge \mathit{ARG0}(w,d) \wedge \mathit{ARG1}(w,e) \wedge \mathit{ARG0}(e,d) \wedge \mathit{ARG1}(e,b)$$

Canonical Representaiton

The dog is eating a bone.
The bone was eaten by the dog.
The dog's eating of the bone.
...

```
(e / eat-01
    :ARG0 (d / dog)
    :ARG1 (b / bone))
```



- Many different sentences can have the same AMR representation.
- Nouns can describe events too.

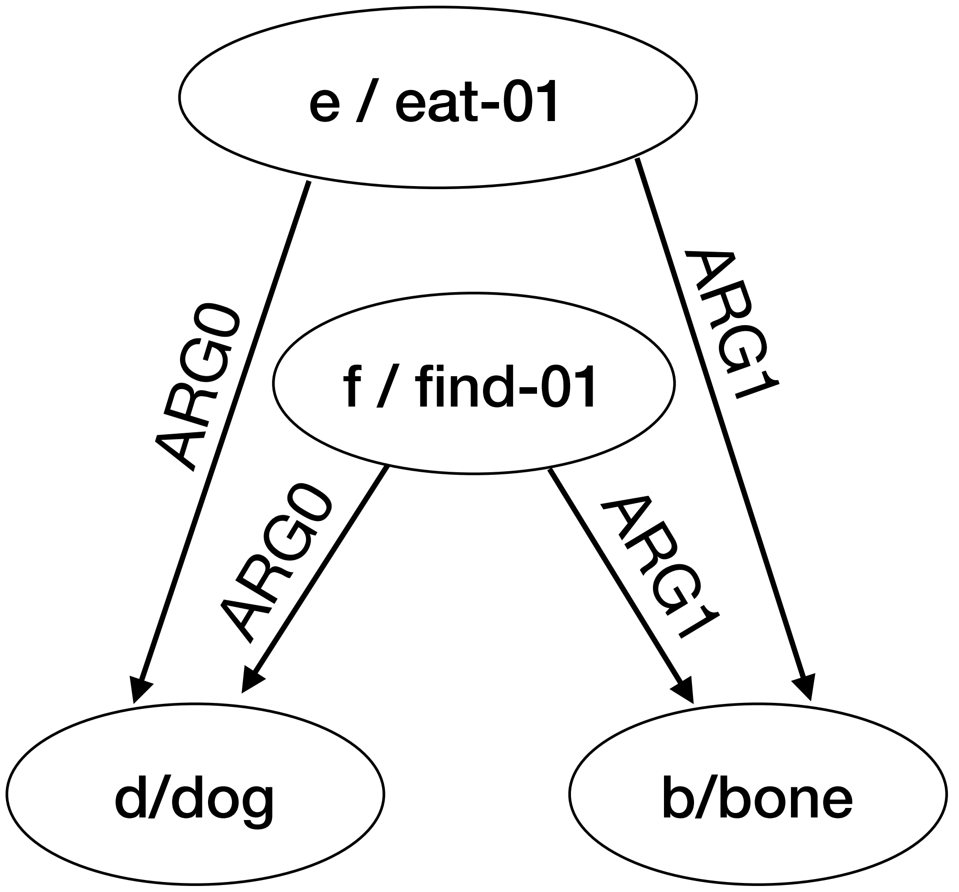
Inverse relations

The dog ate a bone that he found.

Inverse relations

The dog ate a bone that he found.

```
(e/ eat-01
    :ARG0 (d / dog)
    :ARG1 (b / bone))
(f/ find-01
    :ARG0 d
    :ARG1 b)
```

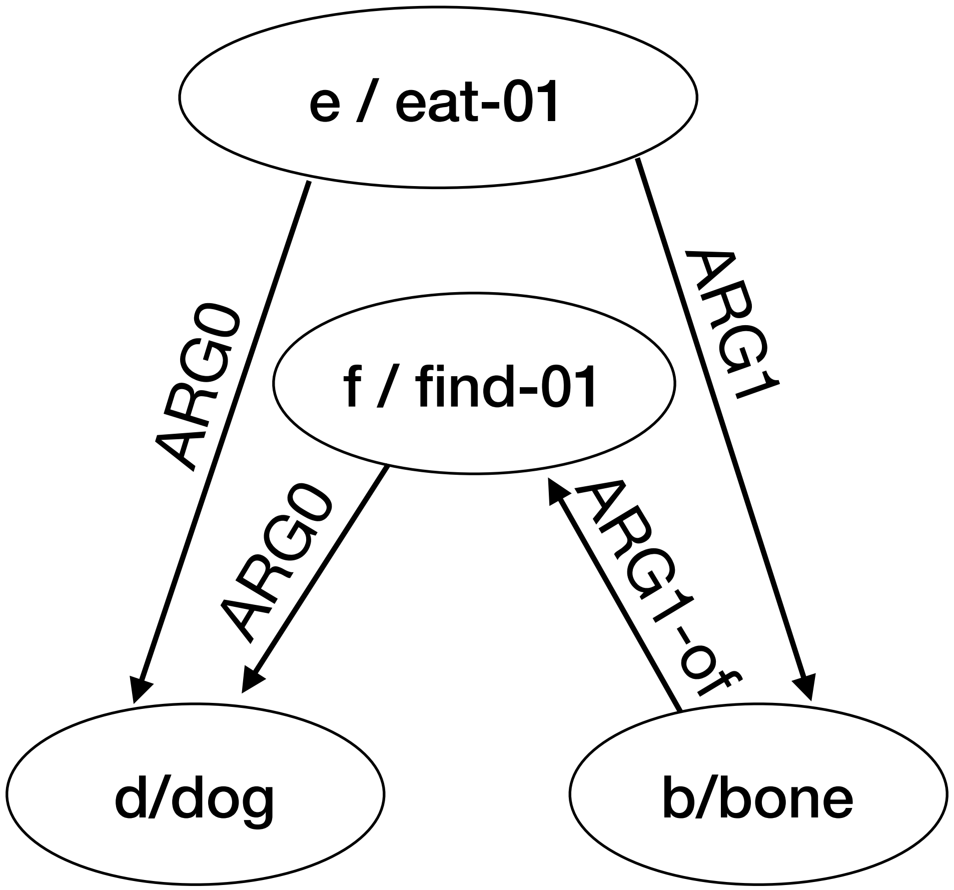


- AMR annotations are typically single-rooted (tree plus reentrancy)
- The single root is the "focus" of the sentence.

Inverse relations

The dog ate a bone that he found.

```
(e/ eat-01
    :ARG0 (d / dog)
    :ARG1 (b / bone
            :ARG1-of (f / find
                        :ARG0 d))
```



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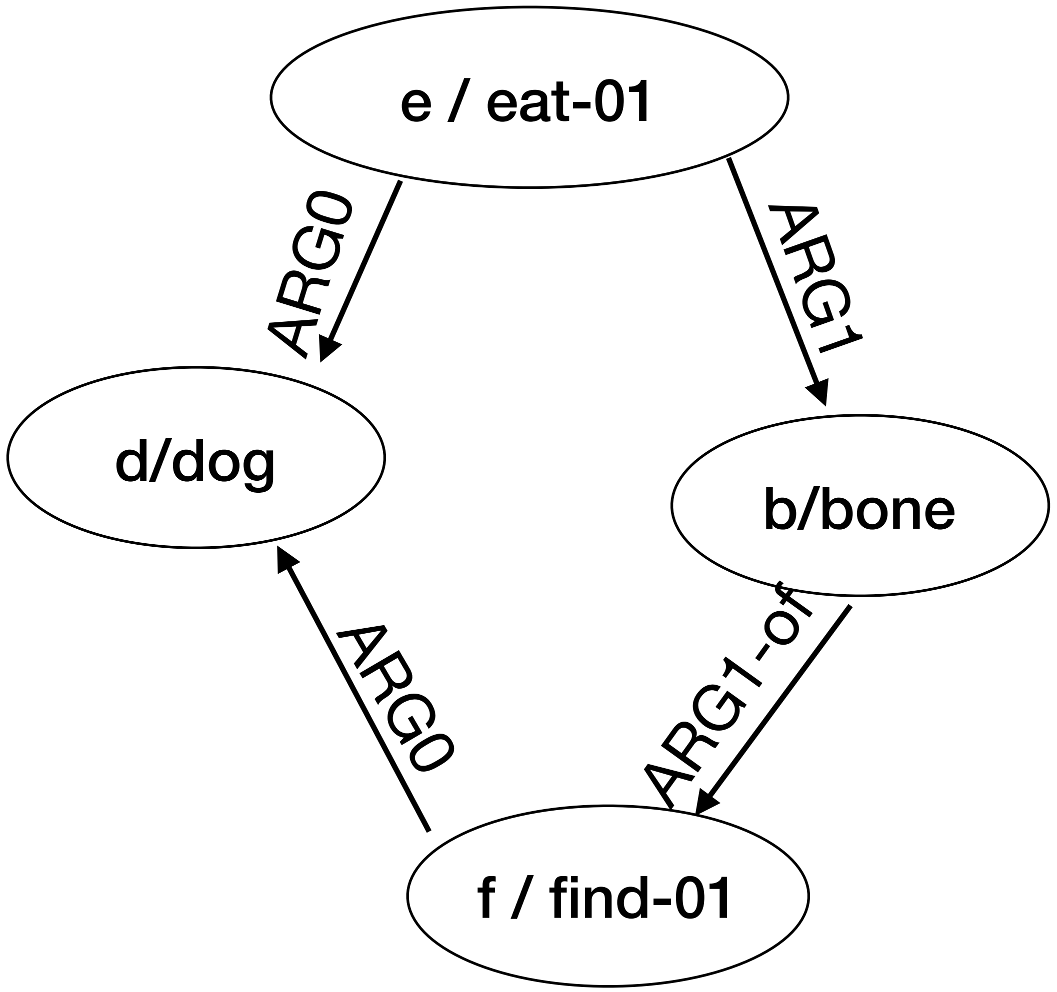
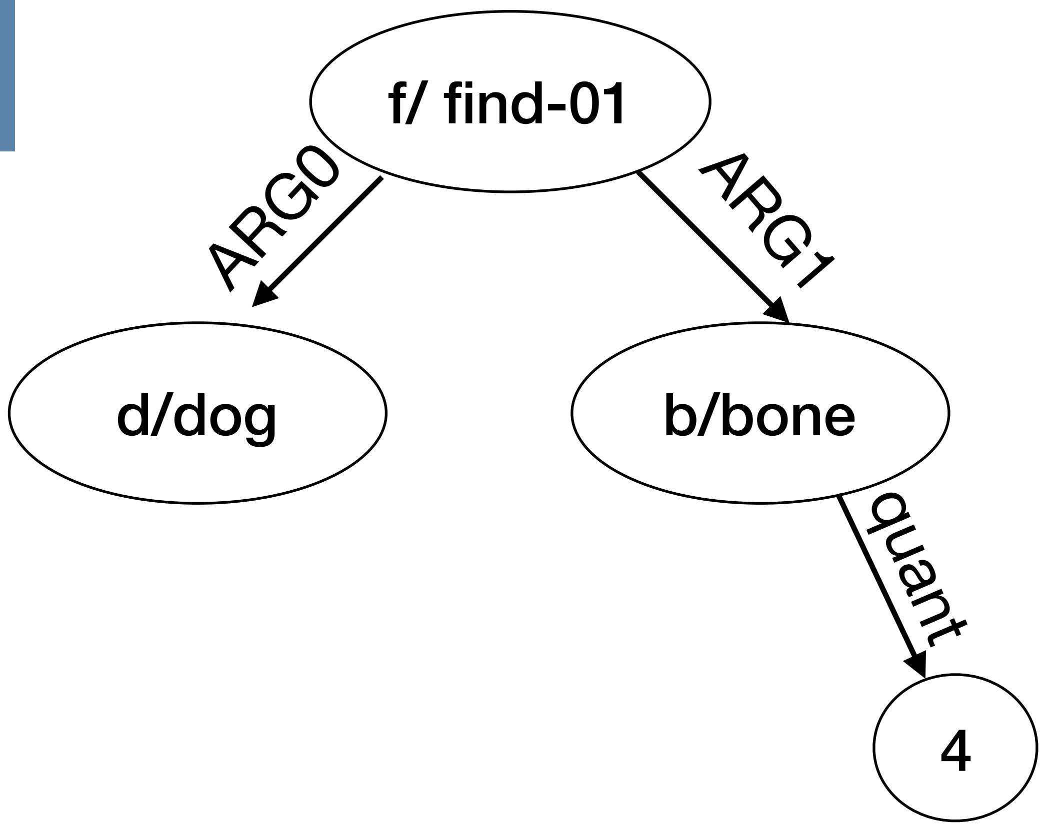


- AMR annotations are typically single-rooted (tree plus reentrancy)
- The single root is the "focus" of the sentence.

Constants

*The dog found **four** bones.*

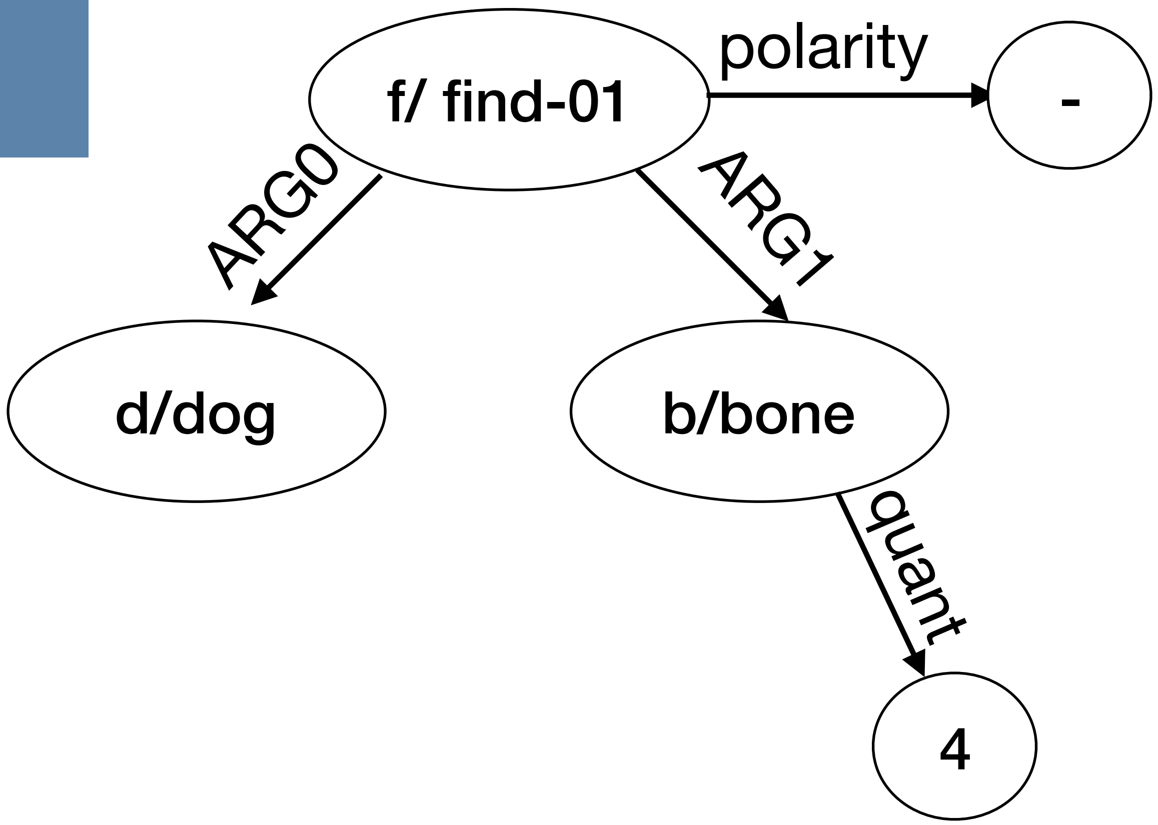
```
(f/ find-01
    :ARG0 (d / dog)
    :ARG1 (b / bone
            :quant 4))
```



- Constants are used to represent quantities (node gets no variable).
- Also used for negation.

Constants

*The dog did not find **four** bones.*




```
(f/ find-01
    :ARG0 (d / dog)
    :ARG1 (b / bone
           :quant 4)
    :polarity -)
```

- Constants are used to represent quantities (node gets no variable).
- Also used for negation.

Non-Core Roles

- AMR annotations use some built-in relations (not in PropBank)
  :time, :location, :manner, :part, :frequency
- :mod and :domain for attributes
- :op1, op2, ...for lists of arguments (for example in conjunctions).

```
(t/ truck
    :mod (m / monster))
```

a monster truck.

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a monster truck.

```
(s/see-01
  (y / yummy
     :domain(f / food))
```

seeing that the food is yummy.

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seeing that the food is yummy.

```
 (a / and
    :op1 (a / apple)
    :op2 (o / orange))
```

apples and oranges.

Names and Dates

```
(j / join-01
      :ARG0 (p / person :wiki -
            :name (p2 / name :op1 "Pierre" :op2 "Vinken")
            :age (t / temporal-quantity :quant 61
                  :unit (y / year)))
      :ARG1 (b / board
            :ARG1-of (h / have-org-role-91
                  :ARG0 p
                  :ARG2 (d2 / director
                        :mod (e / executive :polarity -))))
      :time (d / date-entity :month 11 :day 29))
```

AMR to English

```
(r / read-01
      :arg0 (j / judge)
      :arg1 (t / thing
             :arg1-of (p /propose-01))
```

AMR to English

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      :arg0 (j / judge)
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(p / picture-01
  :ARG0 (i / it)
  :ARG1 (b2 / boa
           :mod (c / constrictor)
           :ARG0-of (d / digest-01
                        :ARG1 (e / elephant))))
```

English to AMR

- "*The girl wants the boy to like her*"
- "*The girl wants the boy to believe that she likes him*"

AMR Data

- The Little Prince
  (publicly available, http://amr.isi.edu/download.html):
  - English and Chinese
  - Biomedical Data
- "AMRBank", 14k sentence, PTB and other corpora
  (including online discussion forums)

Another AMR Example

Back downtown, the execs squeezed in a few meetings at the hotel before boarding the buses again.

Another AMR Example

```
(s / squeeze-02
   :ARG0 (p / person
            :ARG0-of (h2 / have-org-role-91
                         :ARG2 (e / executive)))

   :ARG1 (m / meet-03
           :location (h / hotel)
           :quant (f / few))


   :location (d / downtown
                :mod (b4 / back))
   :time (b / before
           :op1 (b2 / board-01
                    :ARG0 p
                    :ARG1 (b3 / bus)
                    :mod (a / again))))
```

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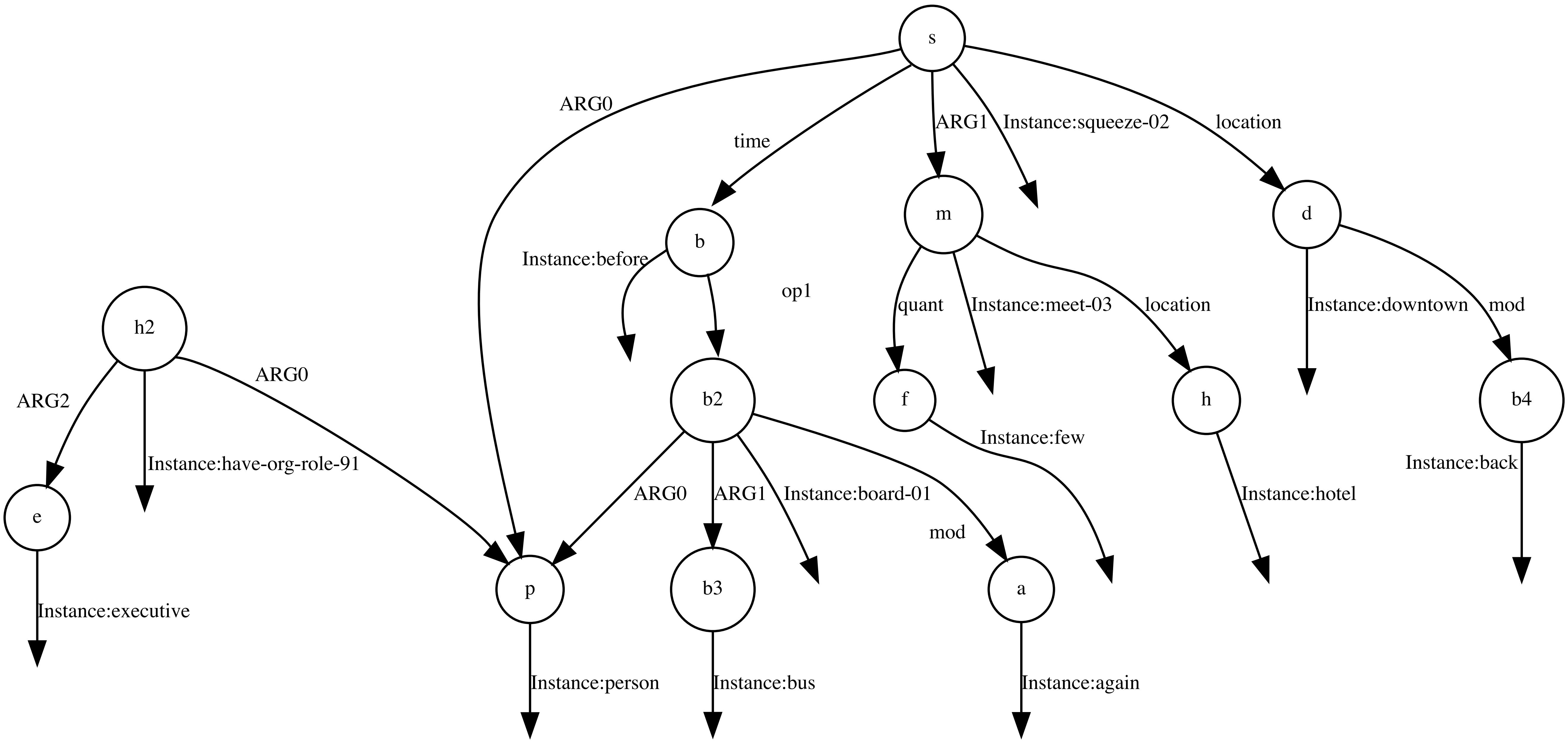

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Applications of AMR

- Semantics-Based Machine Translation
  (Jones, Andreas, Bauer, Hermann & Knight, 2012)
- Summarization:
  - Abstractive Summarization
    (Liu, Flanigan, Thomson, Sadeh & Smith, 2015)
  - Text Compression (text-to-text generation)
    (Thadani, 2015)
- Predicting stock price movement from financial news
  (Xie, 2015)

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  - CCG into logical form + coreference resolution (Artzi 2015)
  - Syntax-based Machine Translation (Pust et al. 2015)
  - Hyperedge Replacement Grammars (Peng 2015, Bauer 2017)

JAMR

(Flanigan et al. 2014)

- Automatically align string spans and graph concepts to obtain a **concept dictionary.**
- For an unseen input sentence:
    - Identify the concepts in the sentence.
    - Identify the relations (edges) between the concepts using a graph-based aproach ("spanning graph").
        - Similar to graph-based dependency parsing.

JAMR - Alignments

(Flanigan et al. 2014)

- Uses a set of hand-crafter rules (patterns for named entities, dates, ...)
- Goal: Compute a concept dictionary.

(Schneider & Flanigan, AMR tutorial @ NAACL 2015)

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IAEA accepted North Korea 's proposal in November.

```
(a / accept-01
    :ARG0 (o / organization
        :ARG0 (n / name
            :op1 “IAEA”))
    :ARG1 (t2 / thing
        :ARG1-of (p / propose-01
            :ARG0 (c / country
                :name (n2 / name
                    :op1 “North”
                    :op2 “Korea”))))
    :time (d / date-entity
        :month 11))
```

(Schneider & Flanigan, AMR tutorial @ NAACL 2015)

JAMR - Concept ID

The boy wants to visit New York City

Figure 2: A concept labeling for the sentence "The boy wants to visit New York City."

JAMR - Concept ID

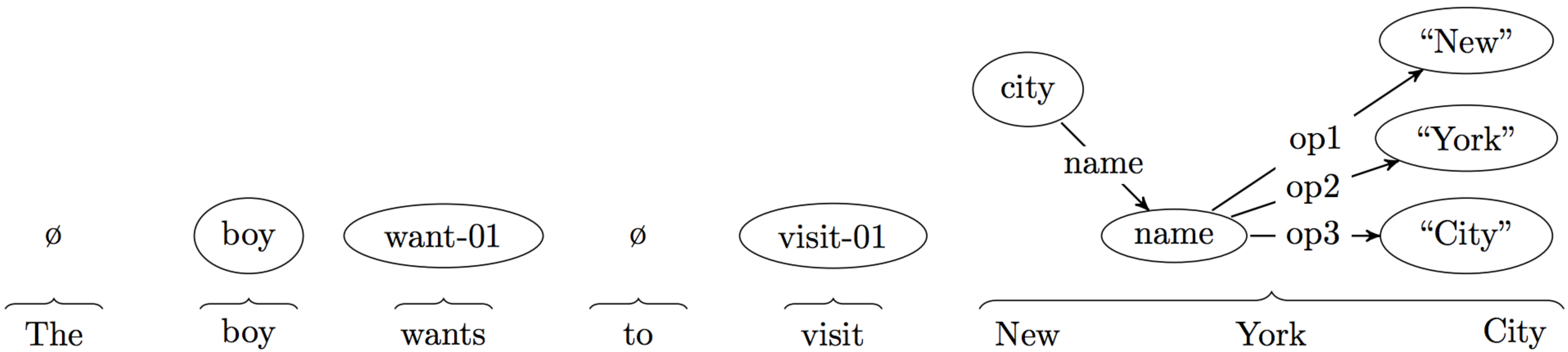
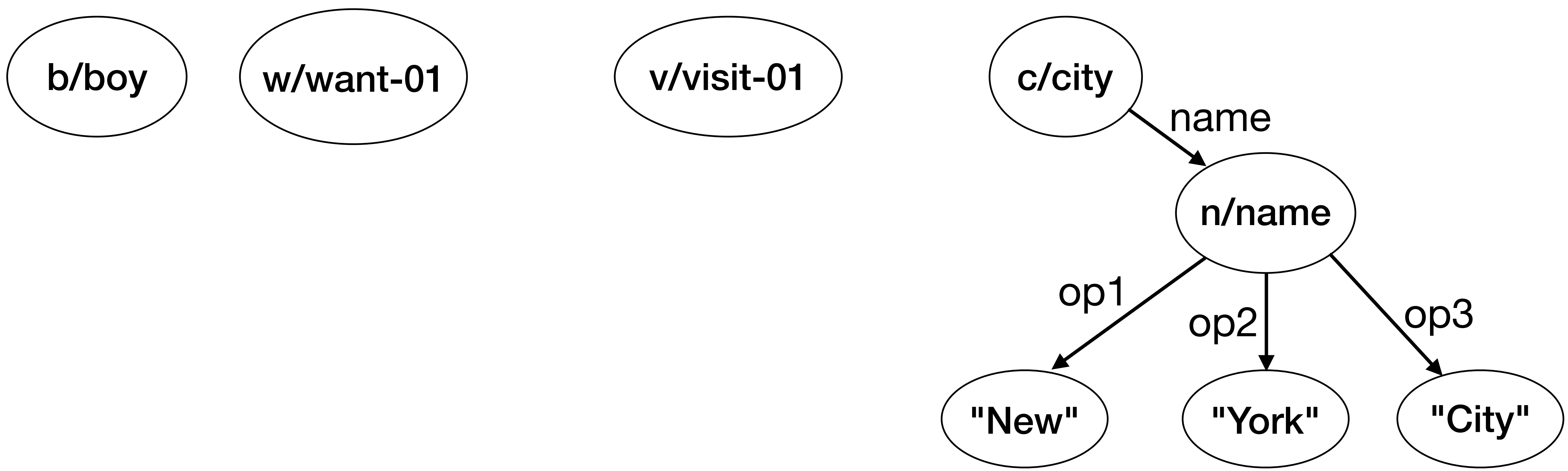


Figure 2: A concept labeling for the sentence "The boy wants to visit New York City."

- Need to compute best span-to-concept assignment.
- But need to consider all different spans.
- Dynamic programing algorithm to solve this.

JAMR - Relation ID



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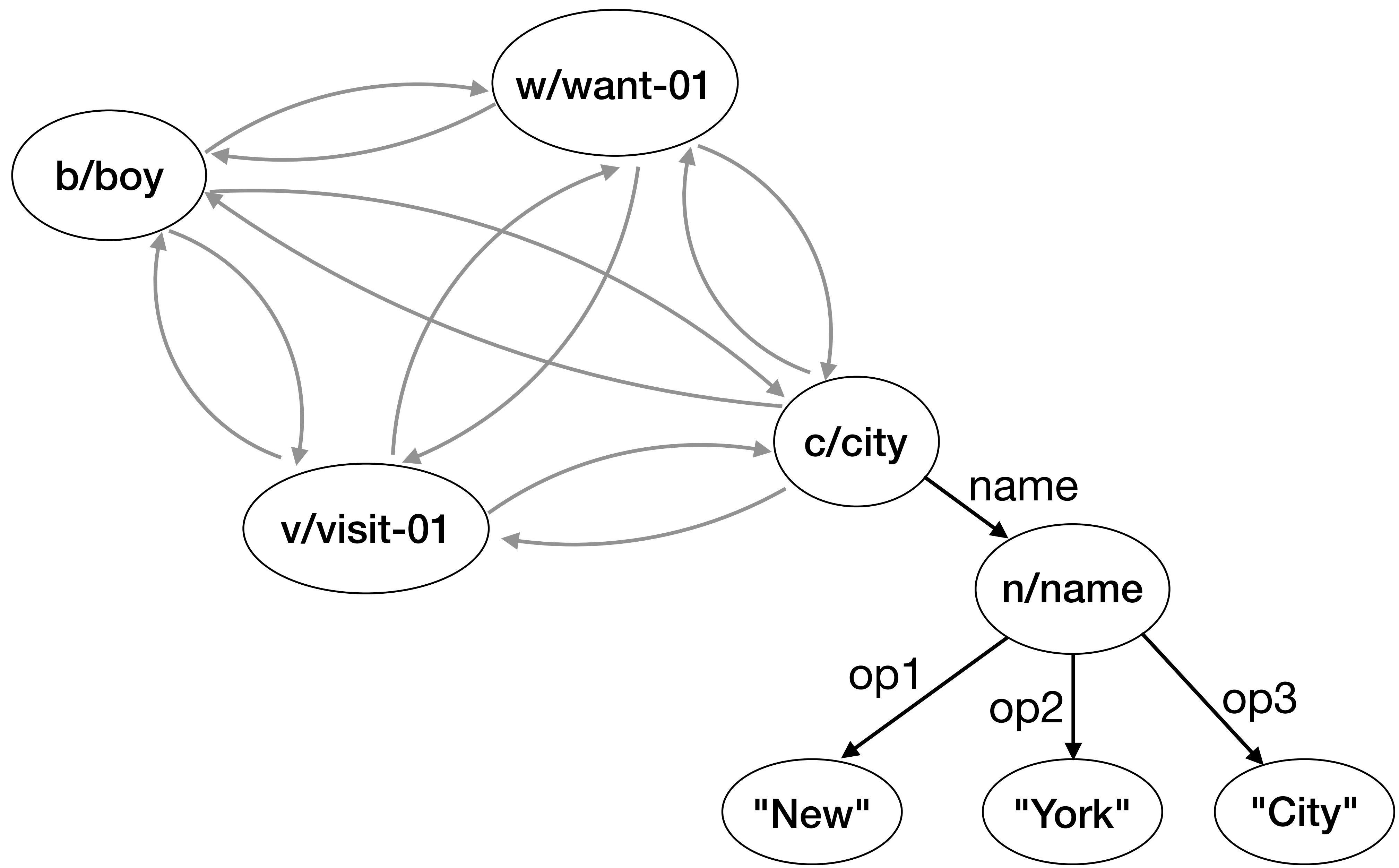
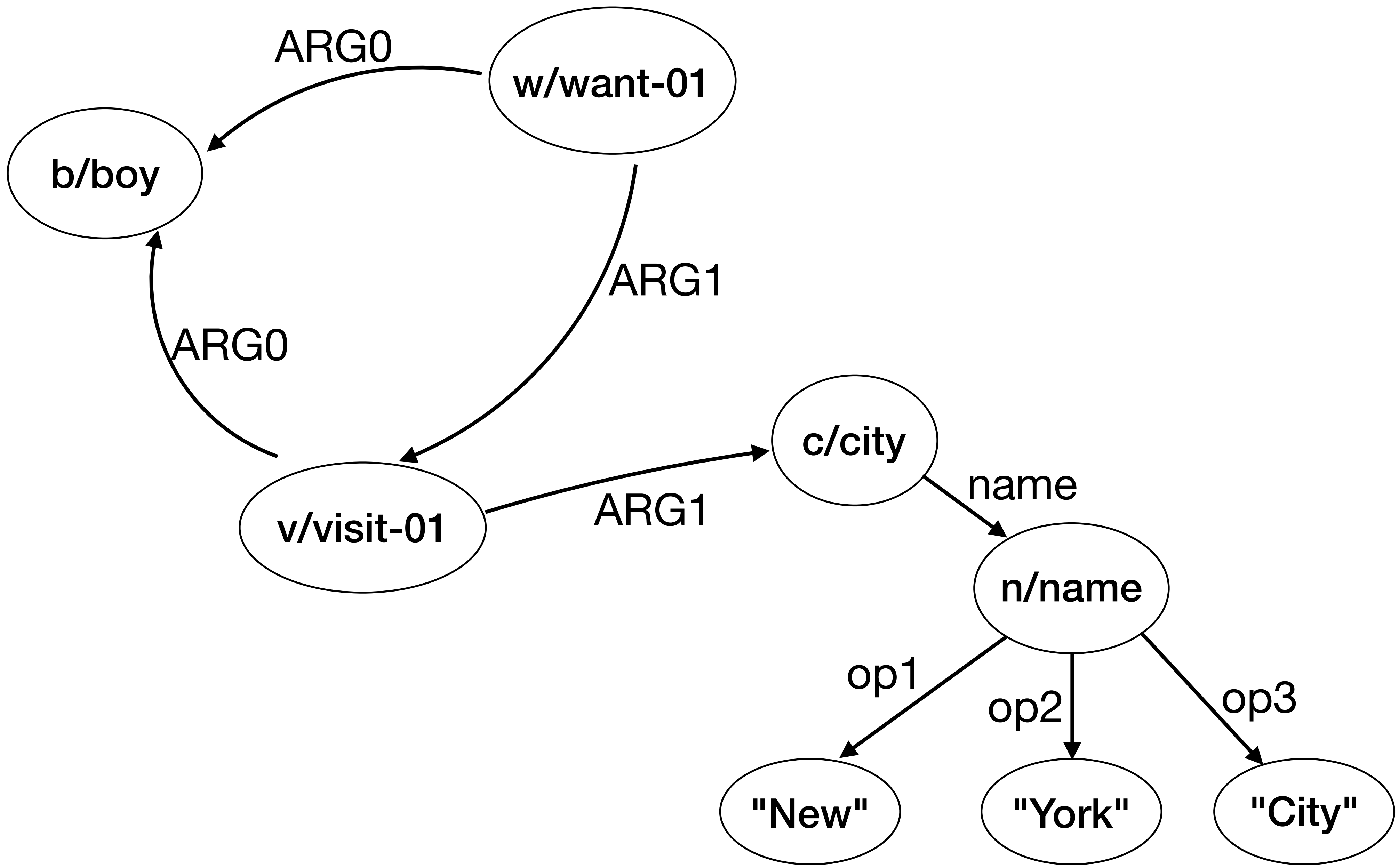


Start with completely connected graph (one edge for each relation).

JAMR - Relation ID



Then compute the "Maximum Spanning Connected Subgraph" (MSCC)

AMR Parsing with Synchronous Hyperedge Replacement Grammar

(Bauer 2017)

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  - Parse the string, then follow the derivation and assemble a graph.

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- Use grammar rules with two matching right-hand sides (string, graph).

    - Parse the string, then follow the derivation and assemble a graph.

- The actual formalism is closer to TAG (lexicalized, allows an adjunction-like operation).

- Rules obtained automatically using alignments.

Recall: String CFG

R1: S → NP VP

R2: NP → *I*

R3: NP → *an elephant*

R4: NP → *my pajamas*

R5: VP → *shot* NP

R6: NP → NP PP

R7: VP → *shot* NP PP

R8: PP → *in* NP

Derivation Tree

Derived String

S

Recall: String CFG

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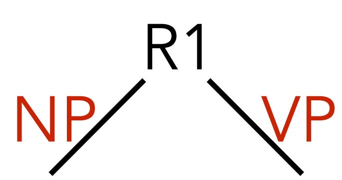
Derivation Tree



Derived String

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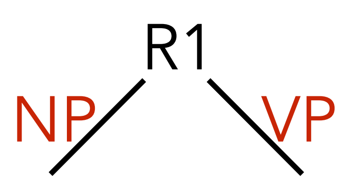

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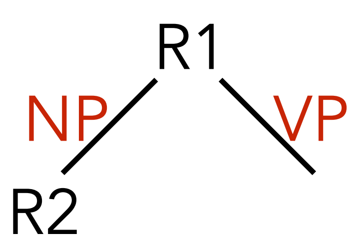

Derived String

I VP

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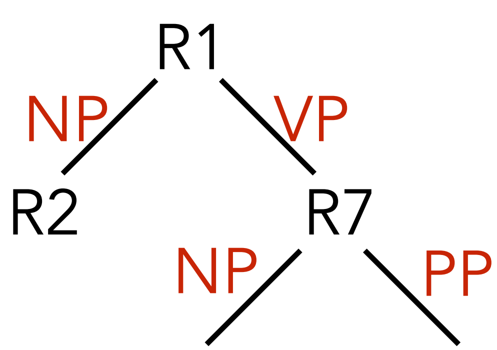

Derived String

I shot NP PP

Recall: String CFG

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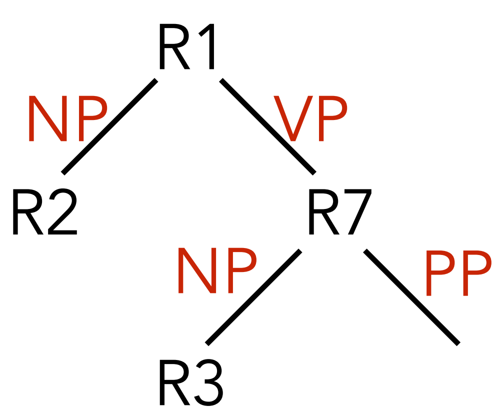

Derived String

I shot an elephant PP

Recall: String CFG

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R3: NP → *an elephant*

R4: NP → *my pajamas*

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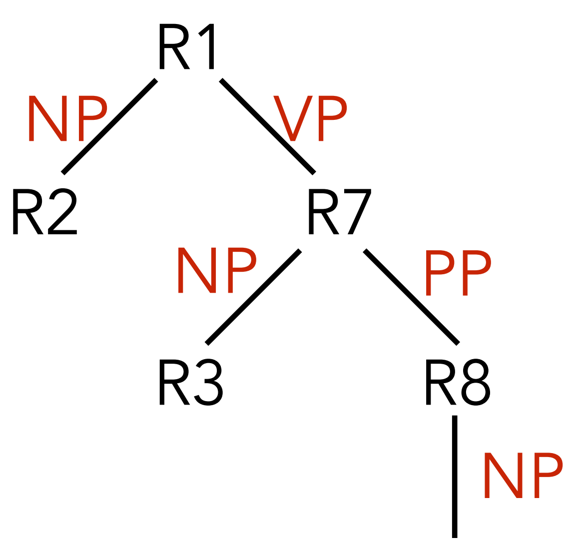
Derivation Tree



Derived String

I shot an elephant in NP

Recall: String CFG

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R3: NP → *an elephant*

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R5: VP → *shot* NP

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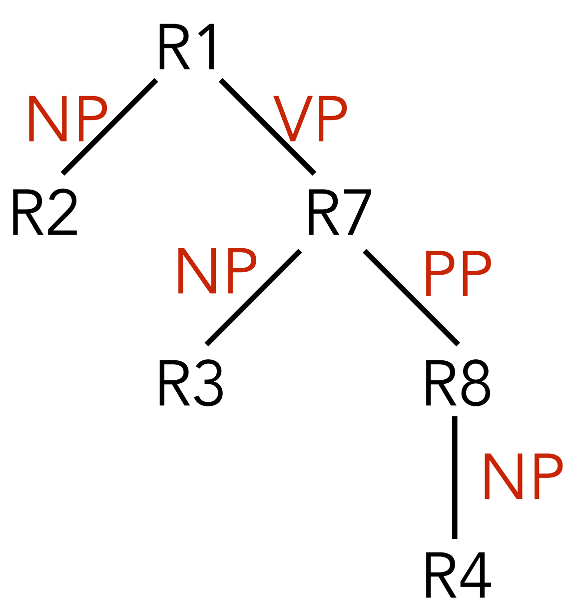
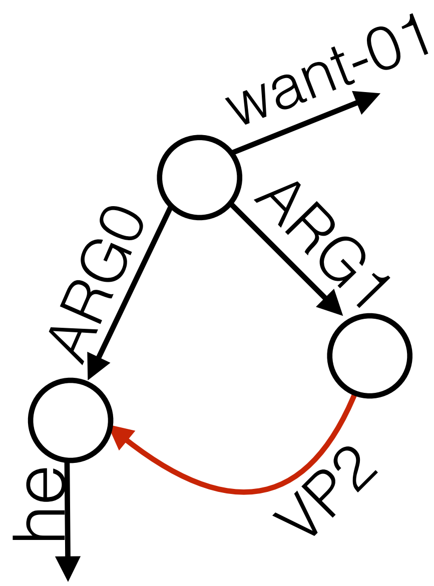
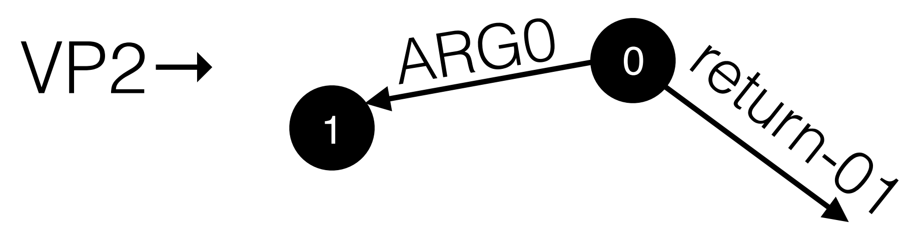


Derived String

I shot an elephant in my pajamas

Hyperedge Replacement Grammar (HRG)





(Drewes et al. 1997)

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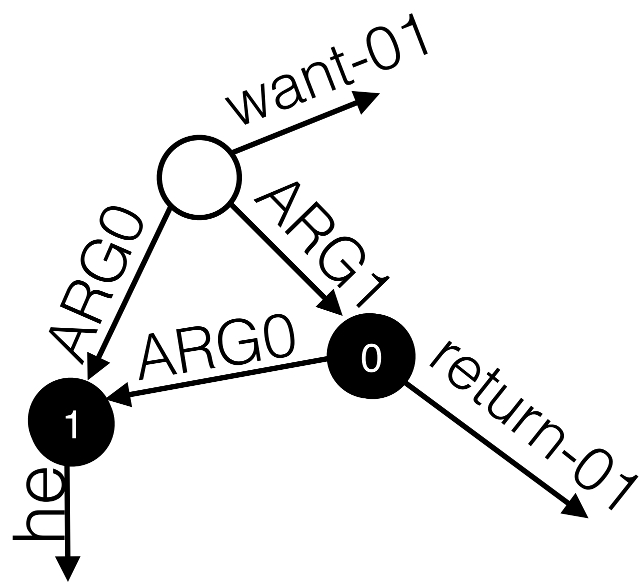
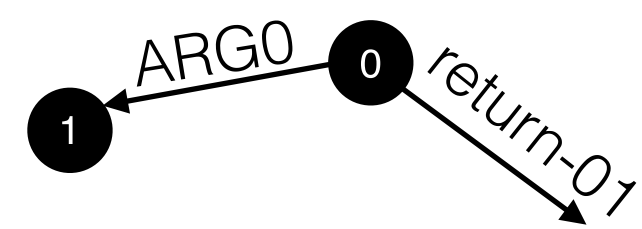


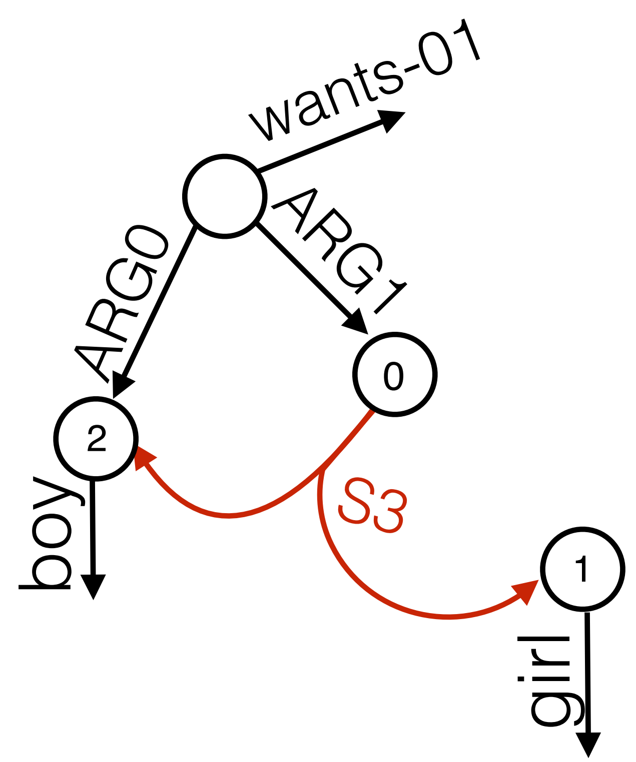
VP2→

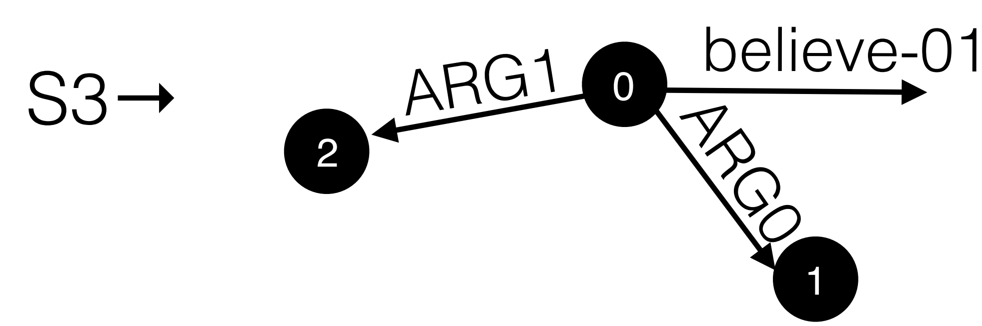


(Drewes et al. 1997)

Hyperedge Replacement Grammar (HRG)

- Hyperedges can have arbitrarily many tentacles. Their endpoints are ordered.





- Number of tentacles: **type** of the hyperedge.
- Terminal / Nonterminal alphabet is also typed.

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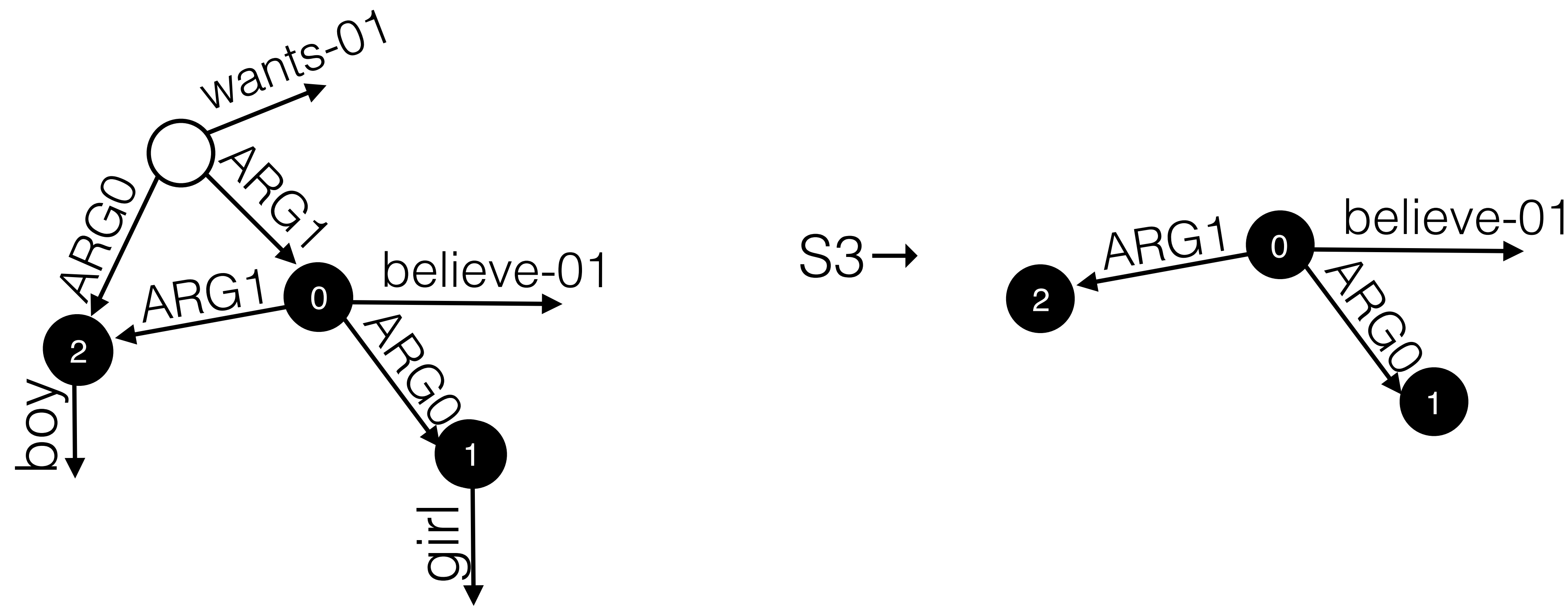

- Number of tentacles: **type** of the hyperedge.
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Hyperedge Replacement Grammar (HRG)

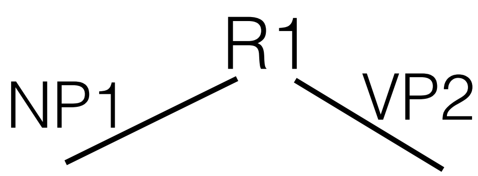
Derivation Tree

Derived Graph

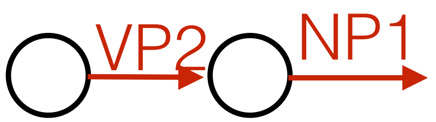
S0

Hyperedge Replacement Grammar (HRG)

Derivation Tree



Derived Graph



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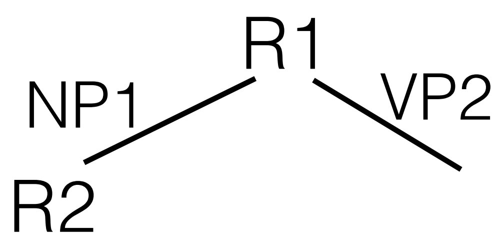

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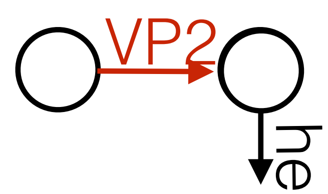

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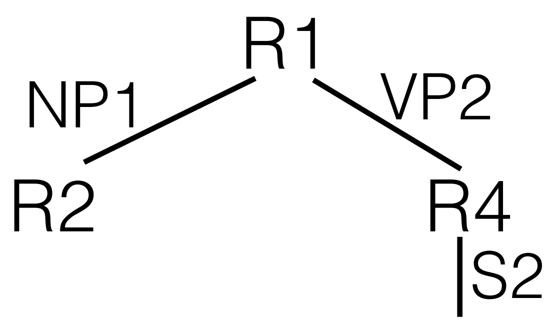

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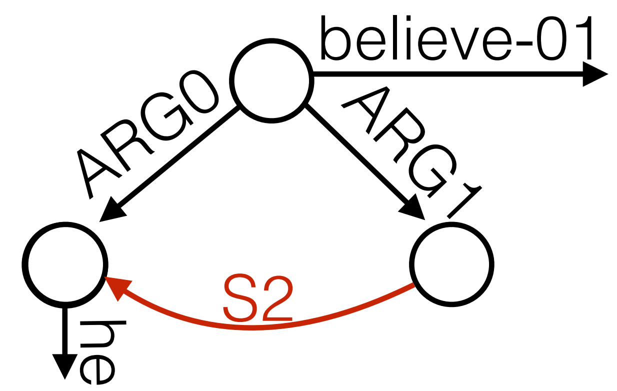

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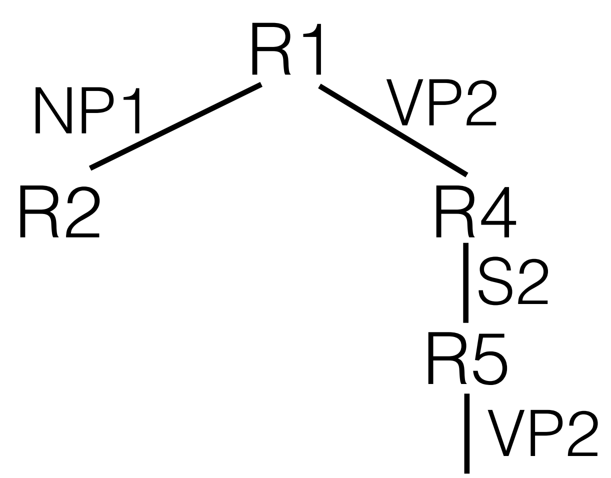

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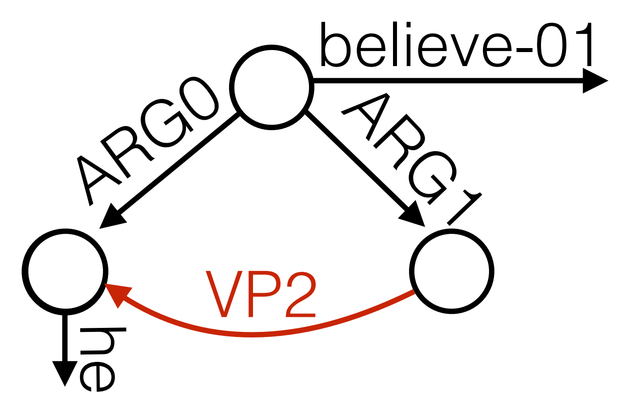

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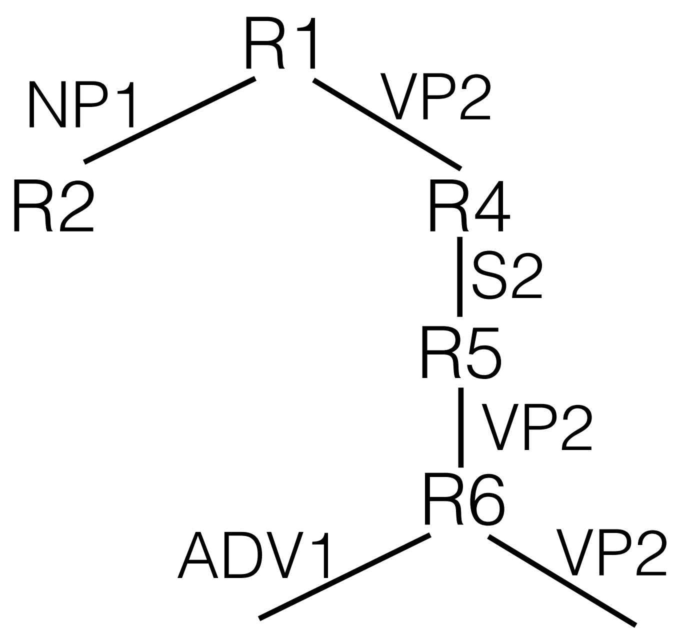

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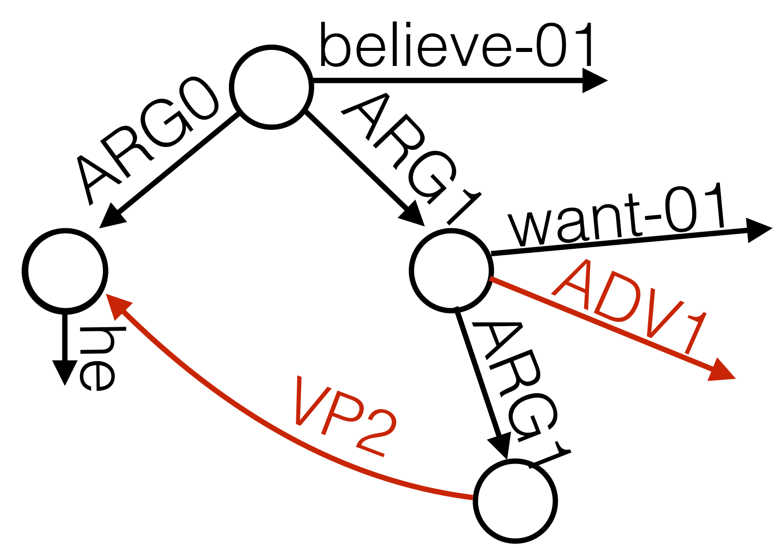

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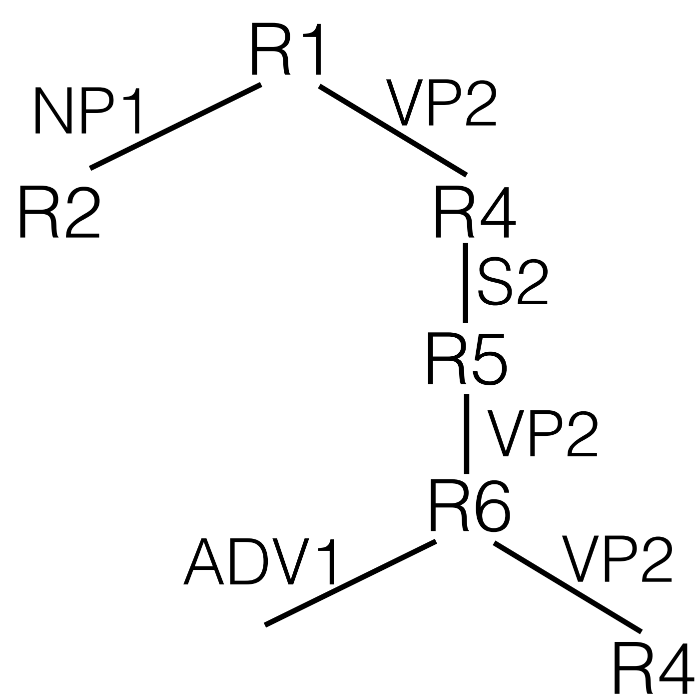

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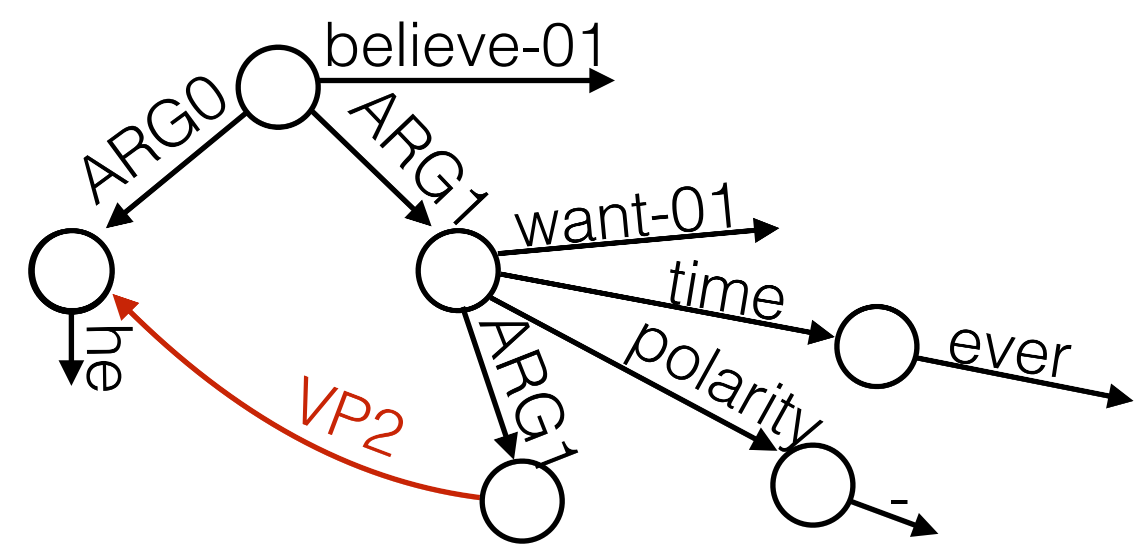

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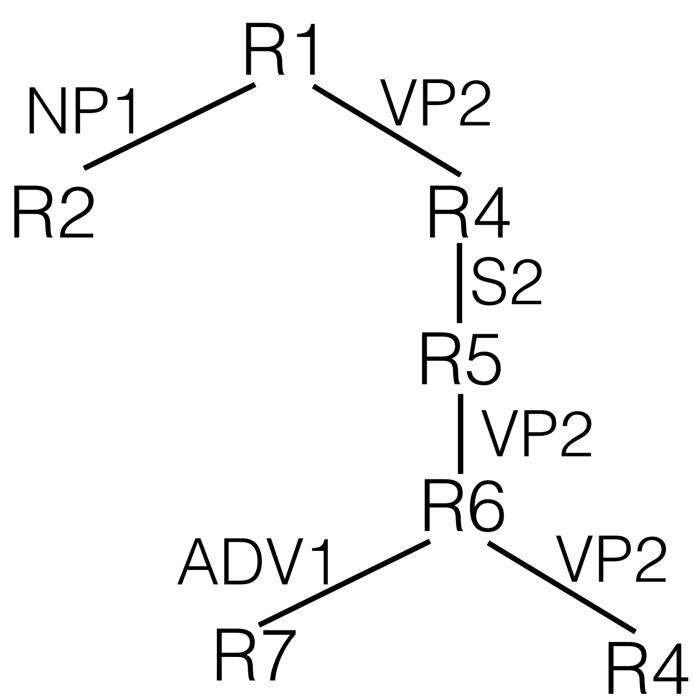

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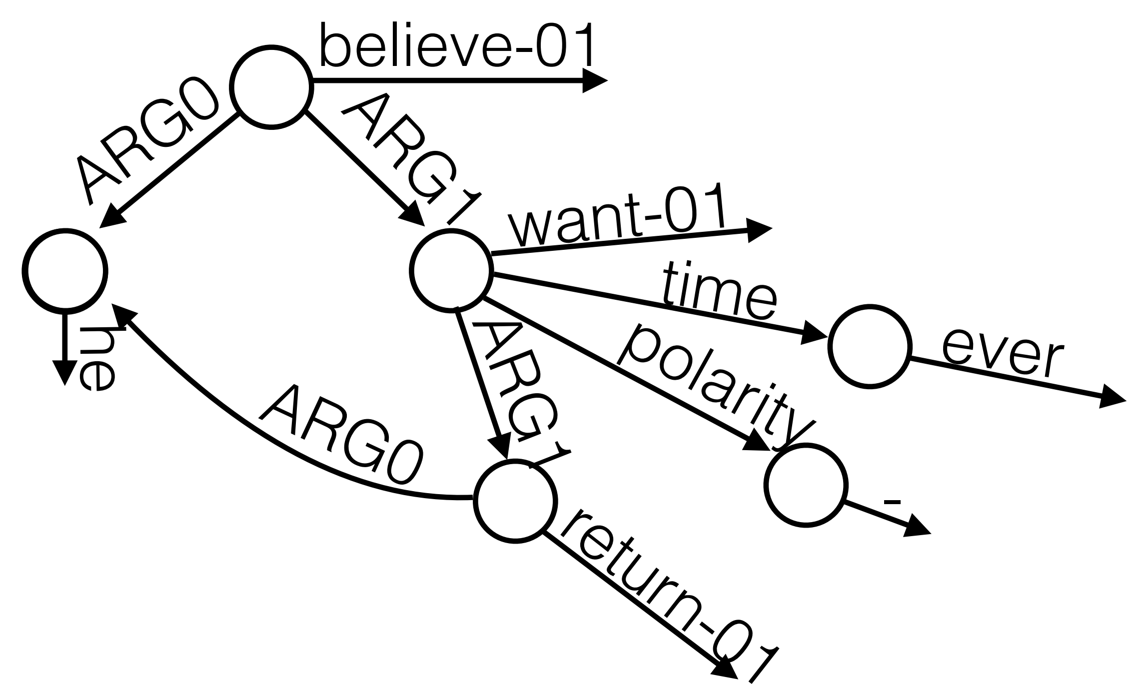

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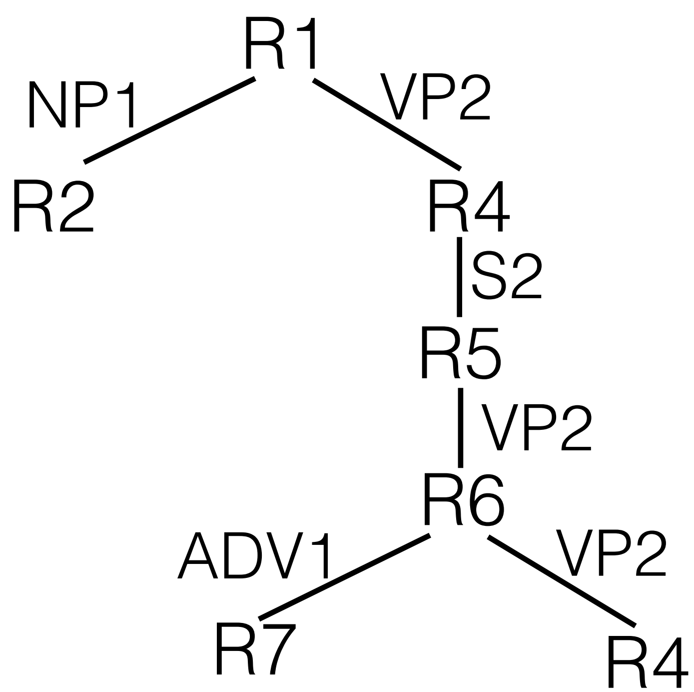

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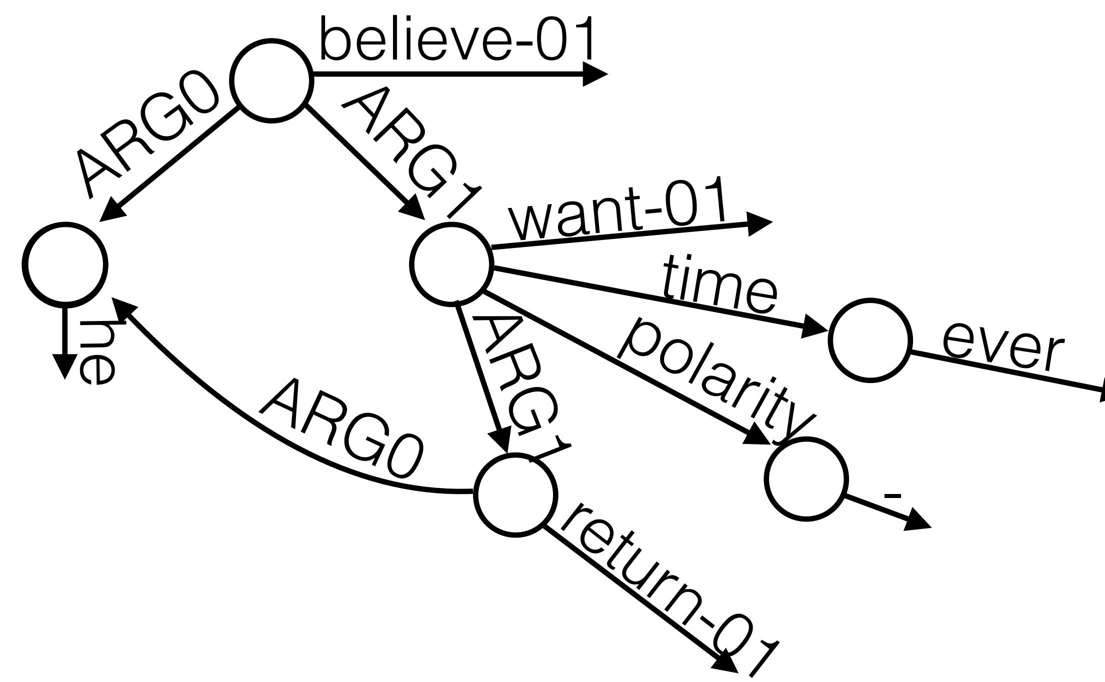
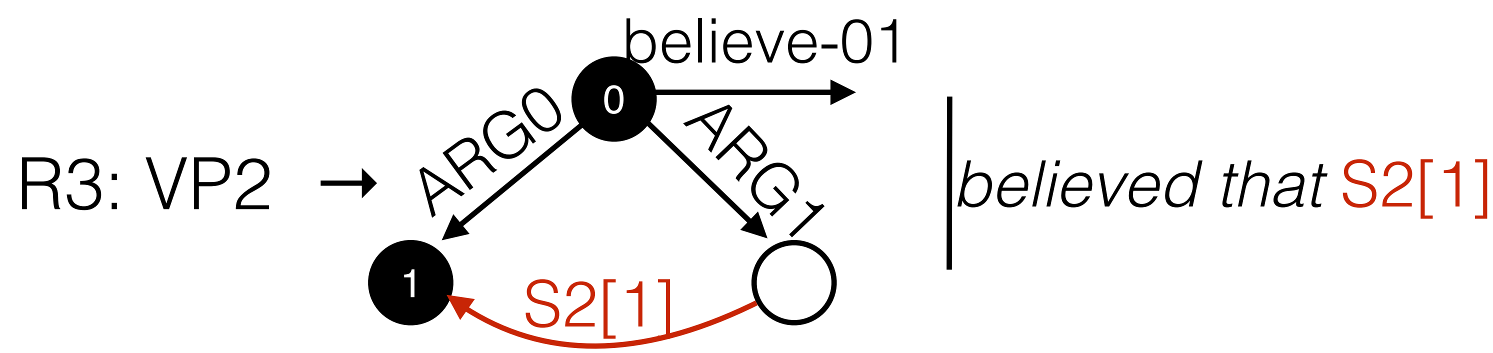


- Polynomial time graph parsing algorithms exist.
  (Chiang, Andreas, Bauer, Hermann, Jones & Knight, 2013)

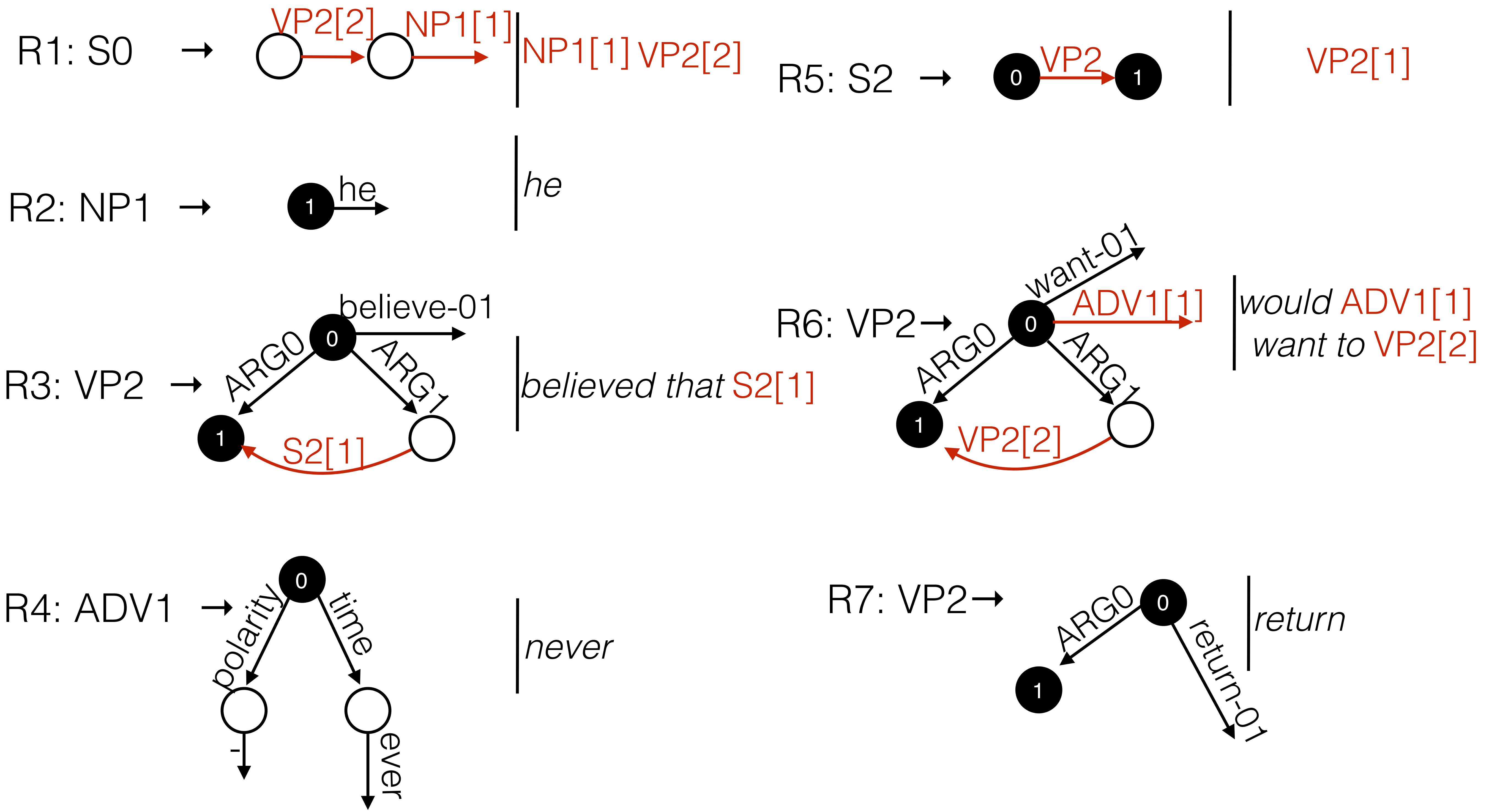
Synchronous Hyperedge Replacement Grammar (SHRG)



- string/graph sides share the same, typed nonterminal alphabet.
- Explicit synchronization (co-indexing).
- Every string derivation is also a valid graph derivation.
- SHRG derive string/graph **pairs.**

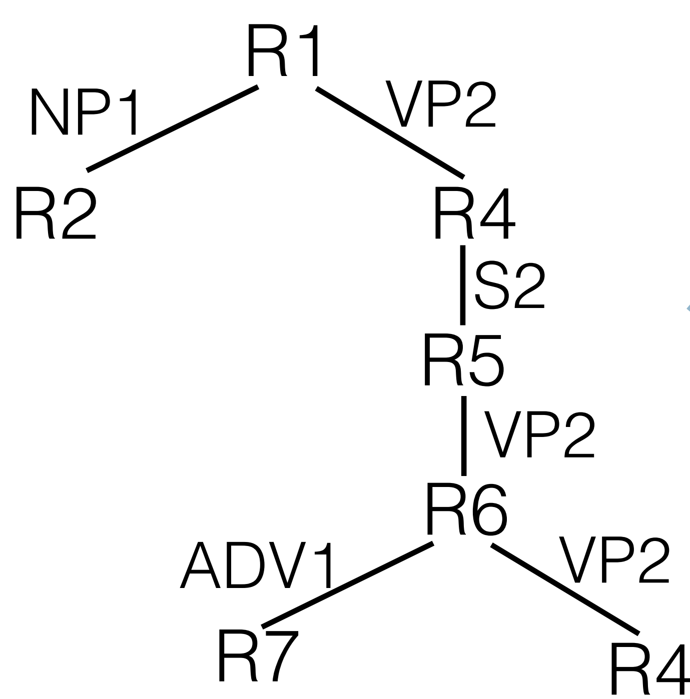
(Jones, Andreas, Bauer, Hermann & Knight, 2012)

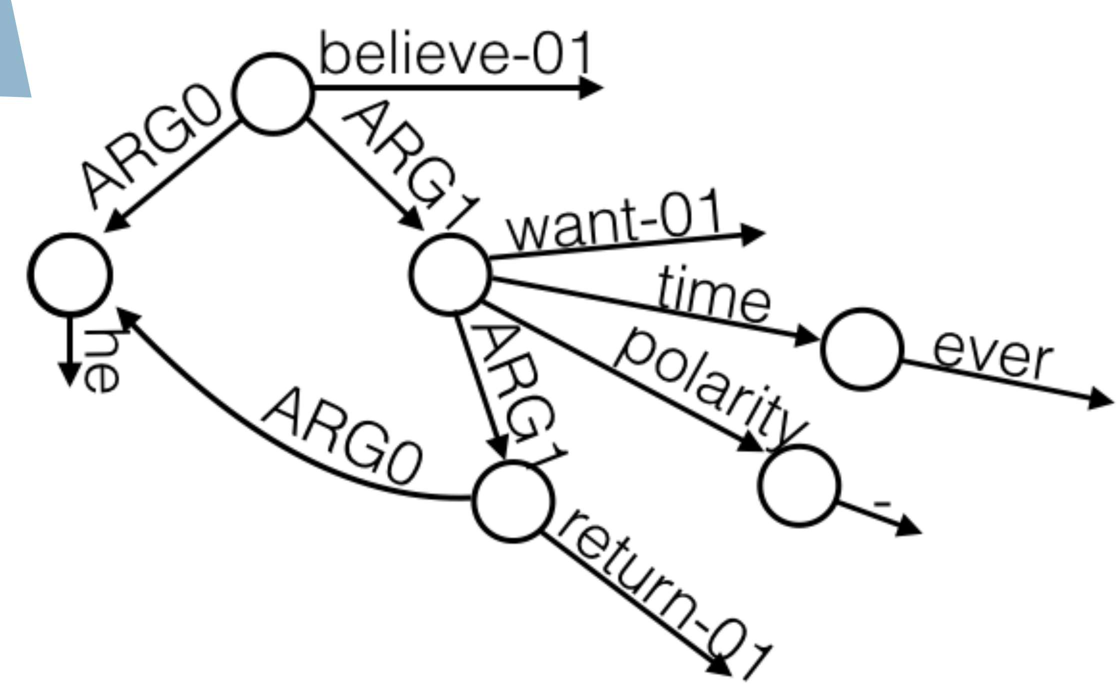
Synchronous Hyperedge Replacement Grammar (SHRG)



Synchronous Hyperedge Replacement Grammar (SHRG)

he believed that he would never want to return





SHRG for Semantic Construction

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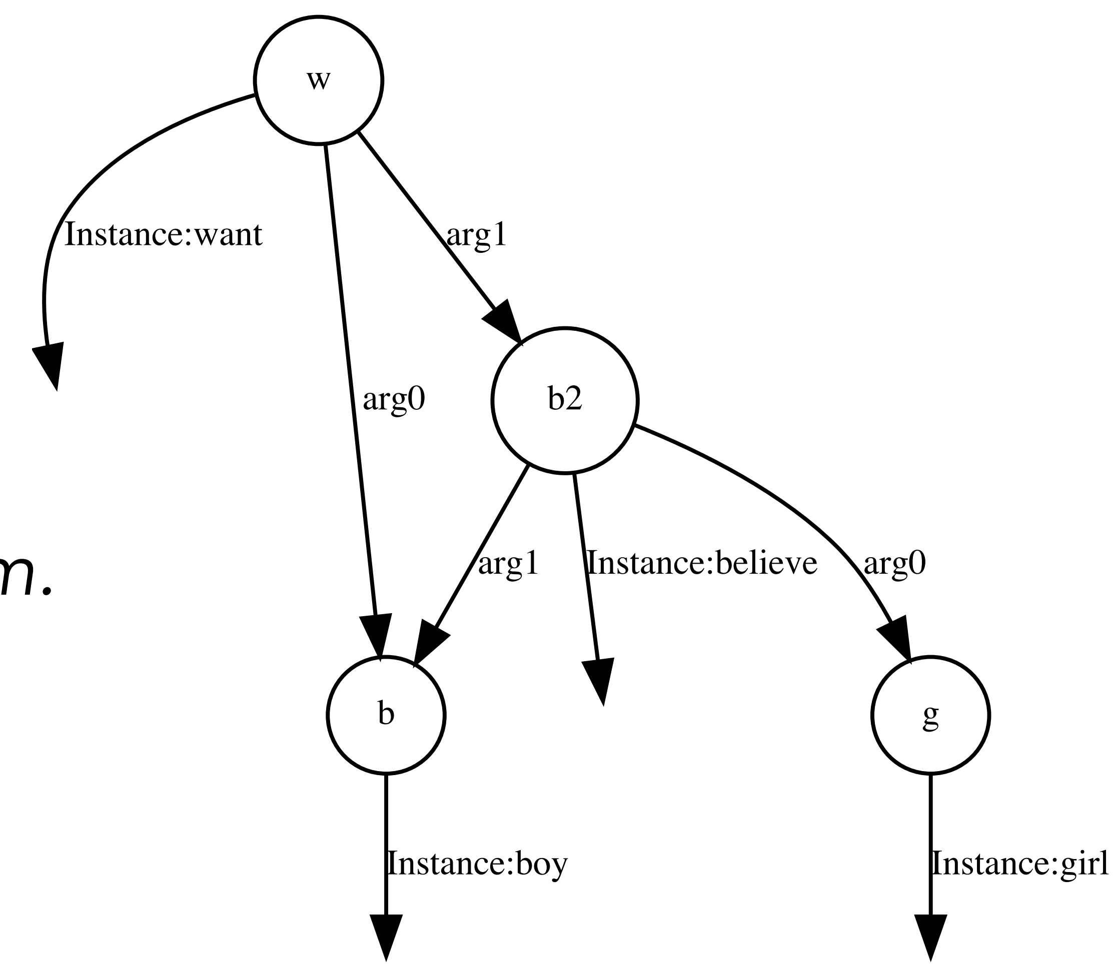
  - Yes, restriction to CFG limits graph structures that can be constructed. For example, no cross-serial dependencies.
  - Yes, maximum hyperedge type in a grammar implies a hierarchy of grammars. Cannot build up arbitrary complexity.

Extracting Synchronous Grammars

Task: Given a corpus of string/graph pairs, learn a SHRG that

- can derive all string/graph pairs in the corpus.
- is compact (small number of rules).
- generalizes well to unseen data.

The boy wants the girl to believe him.

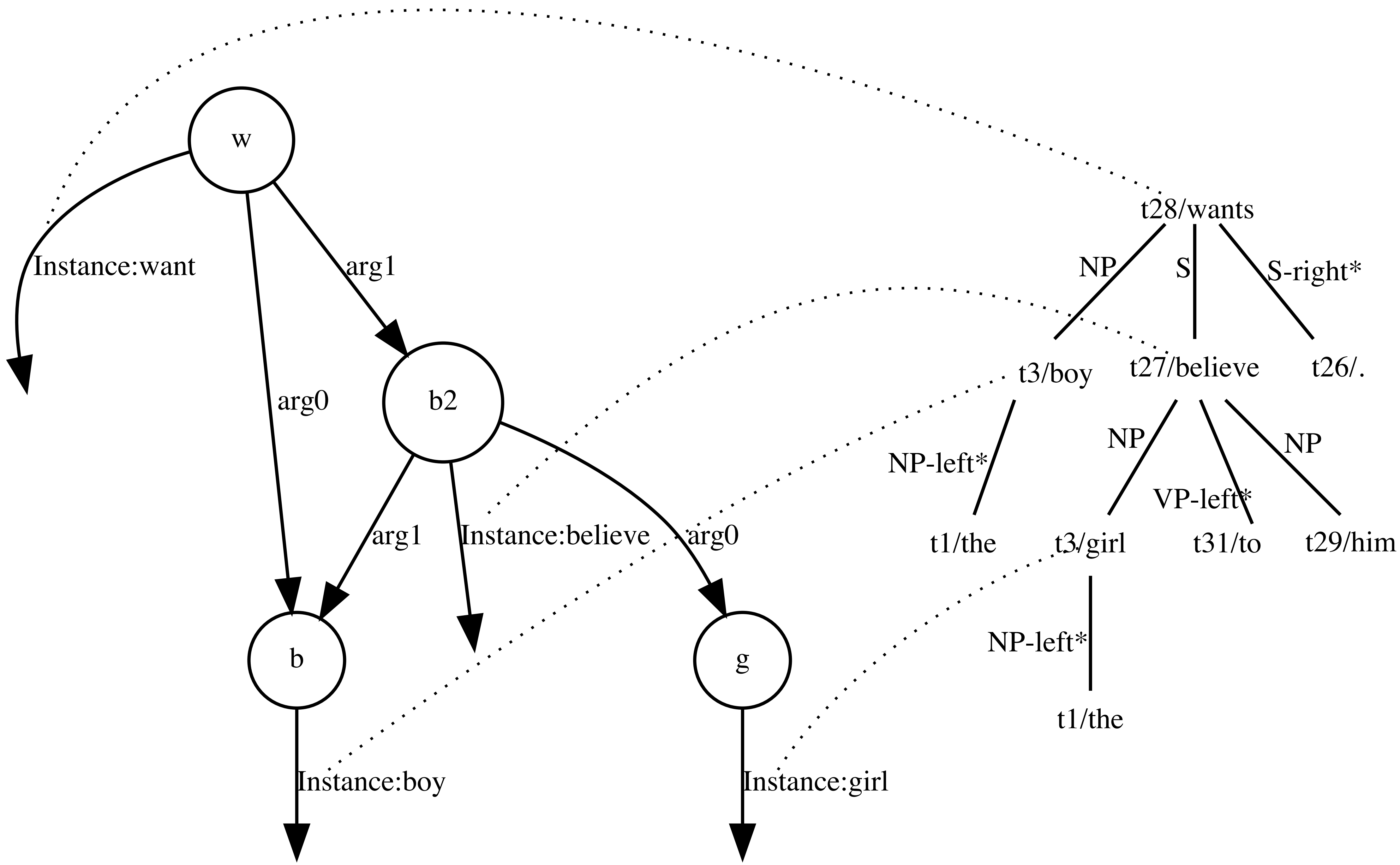


Extracting SHRG/LSHRG Grammar Rules

My approach uses syntactic derivations to guide rule extraction.

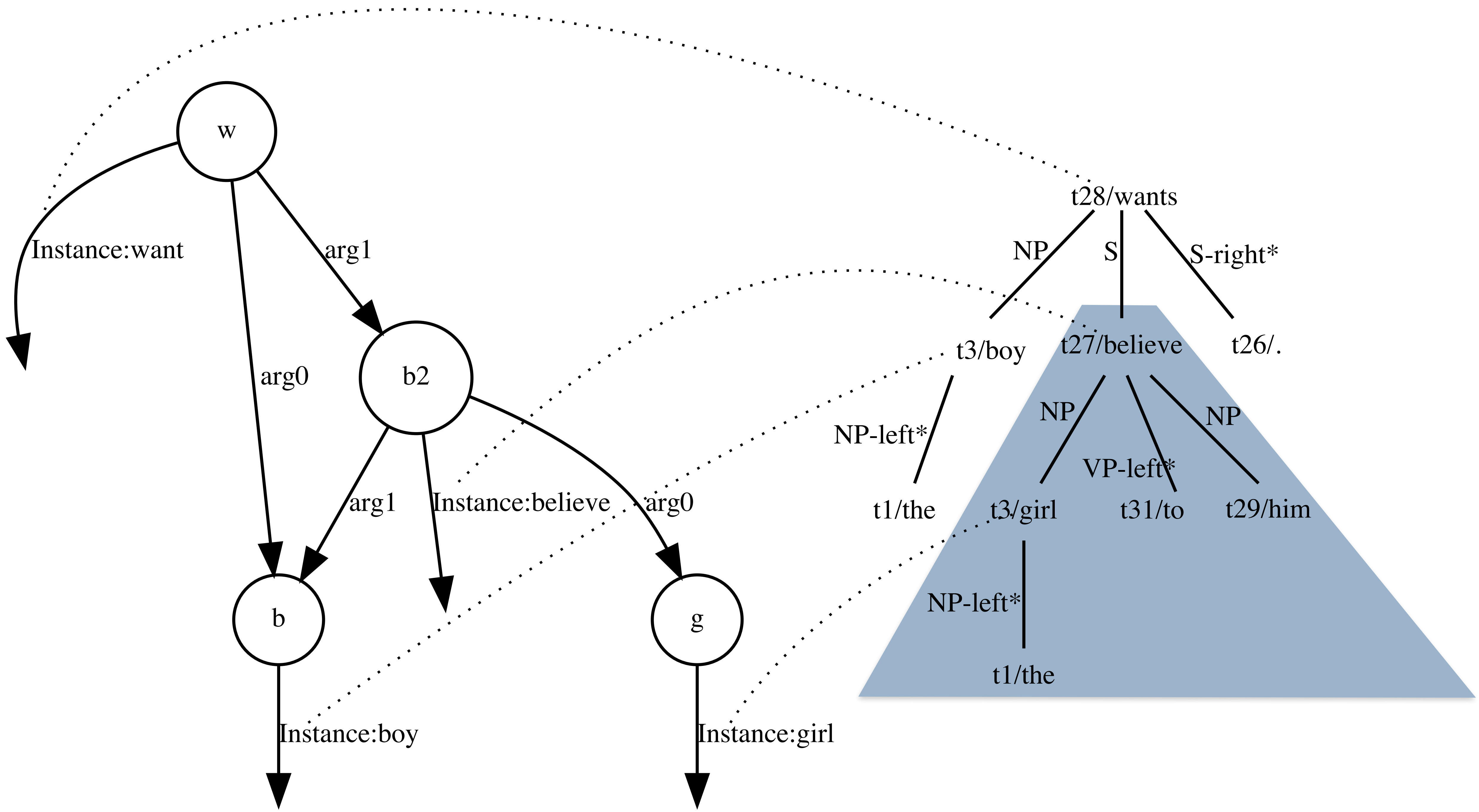
1. Syntactic parser creates string derivations (MICA parser).
2. Aligner computes string-to-graph alignments.
3. Partitioning algorithm creates a rule forest.
4. EM-based rule selection extracts a compact set of rules.

Alignments And Derivation Trees



- Project alignments to nodes in the derivation tree.
- Every subtree is aligned to a subset of graph edges.

Alignments And Derivation Trees



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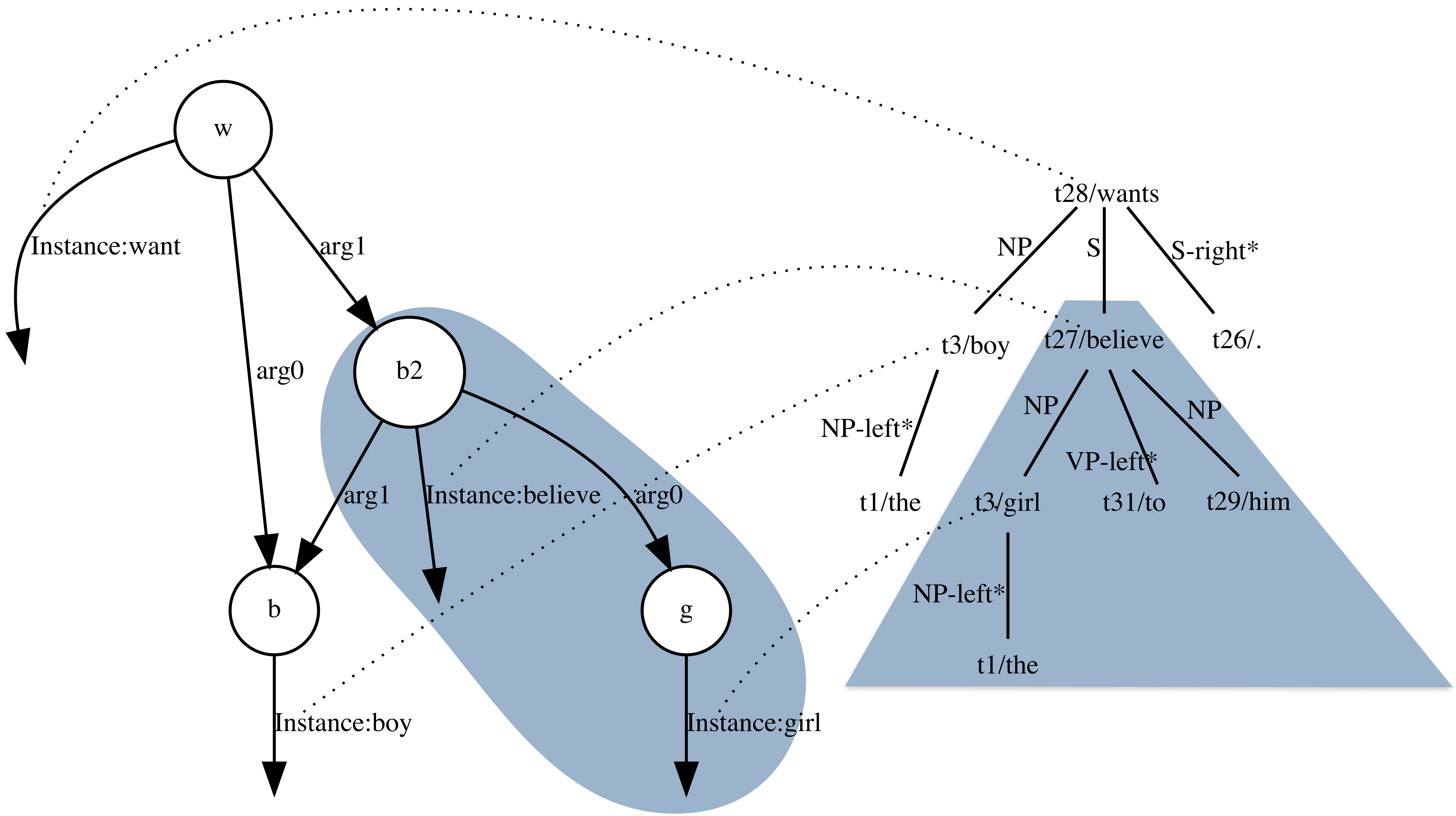

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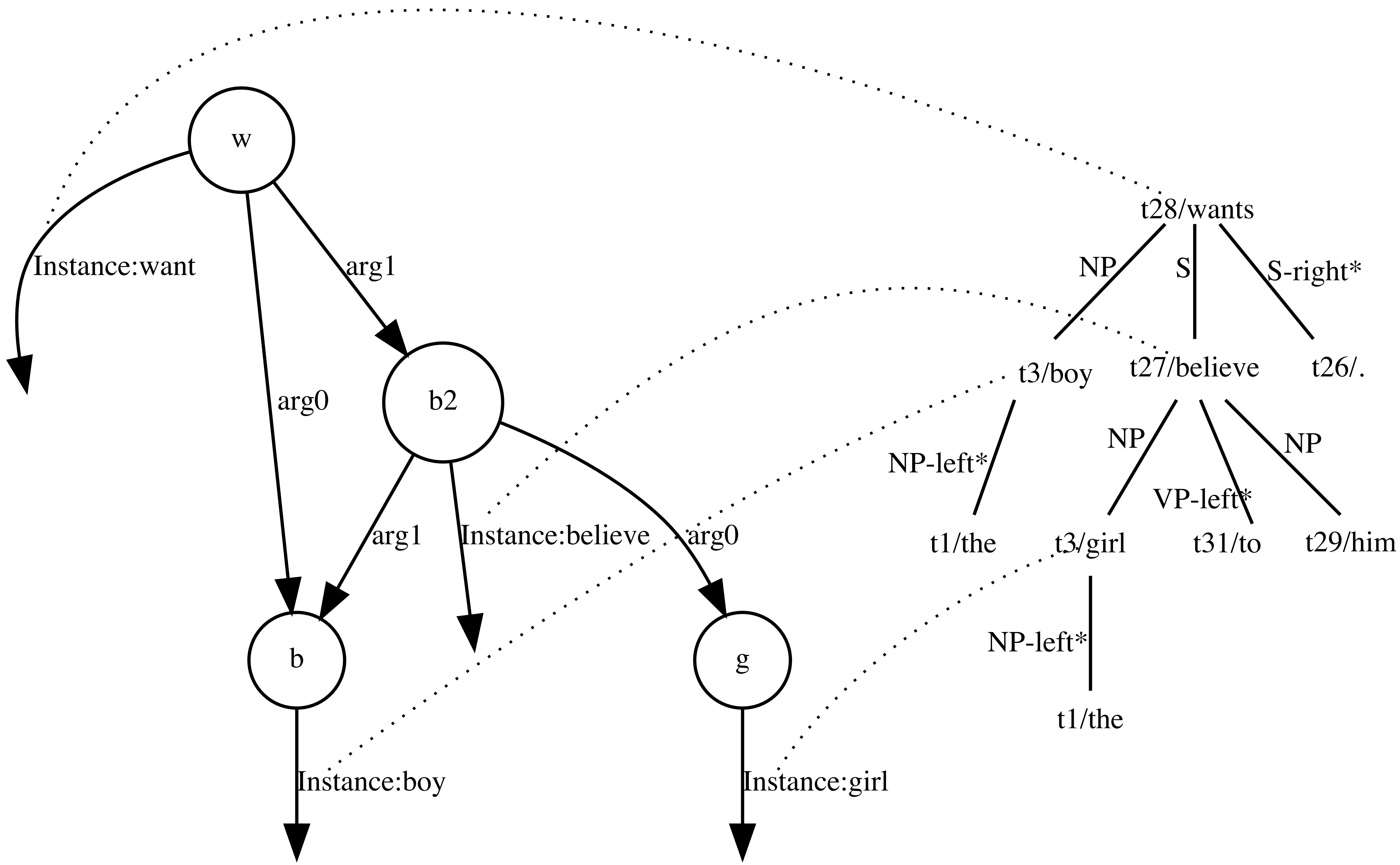
Partitioning Algorithm



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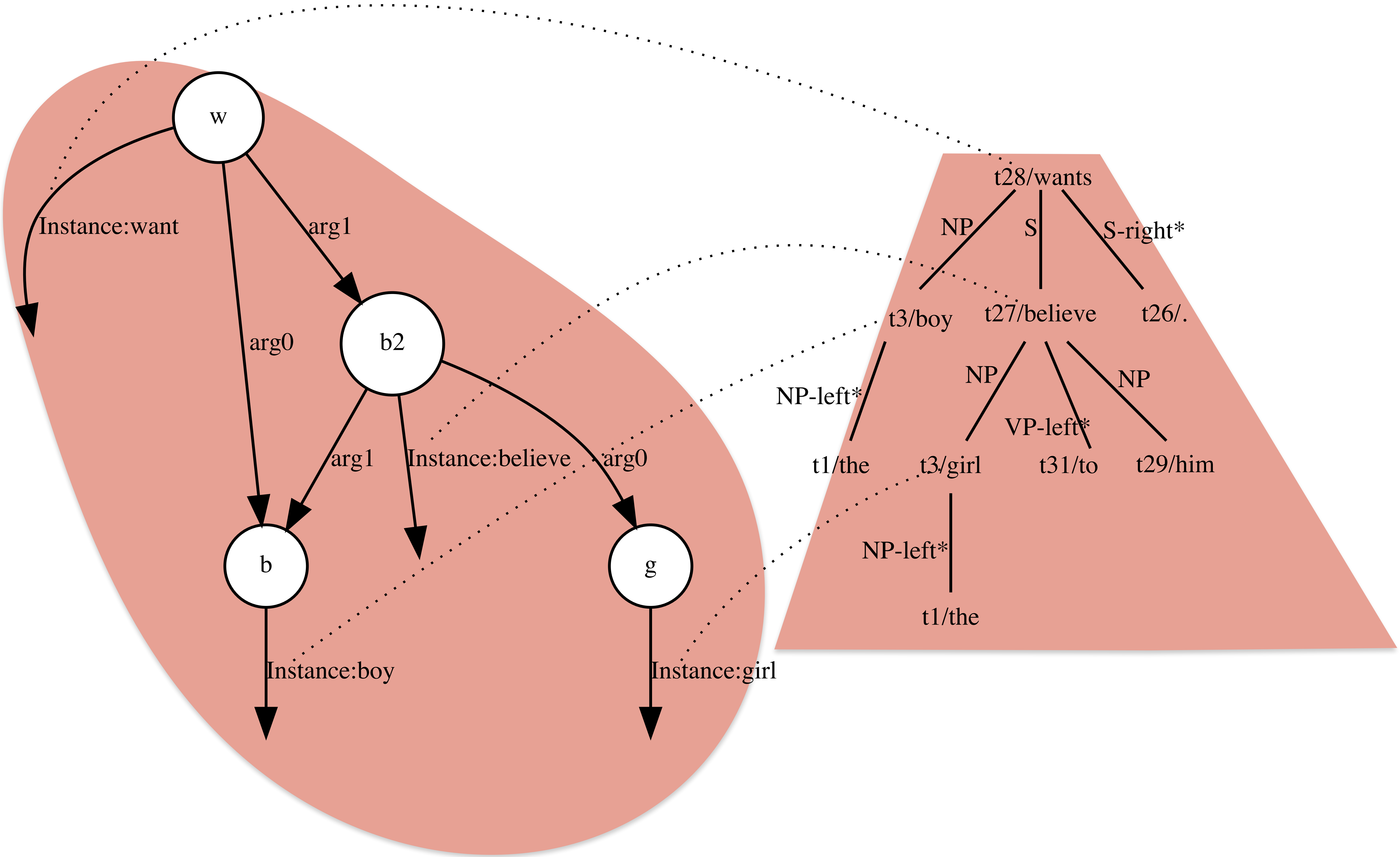

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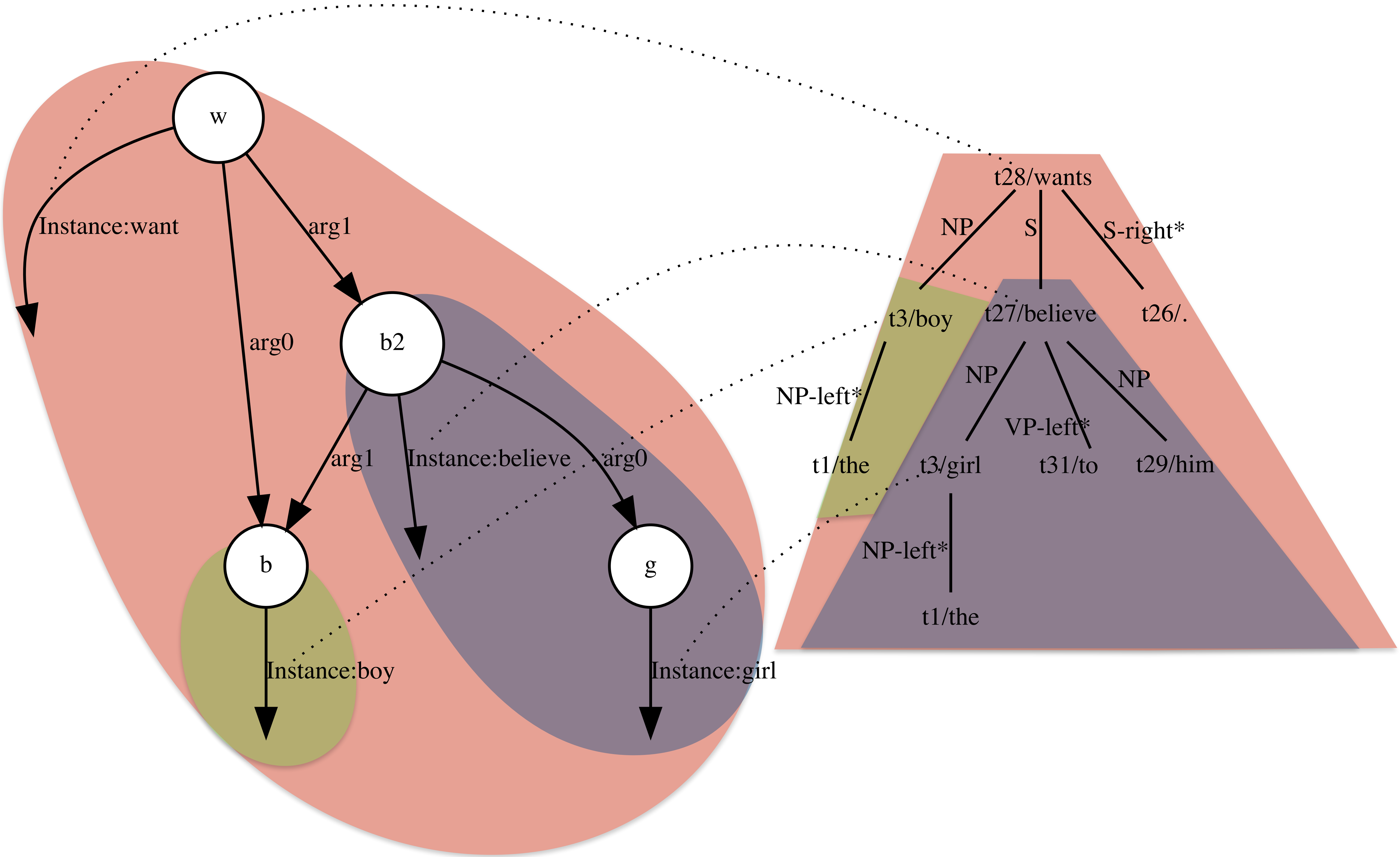

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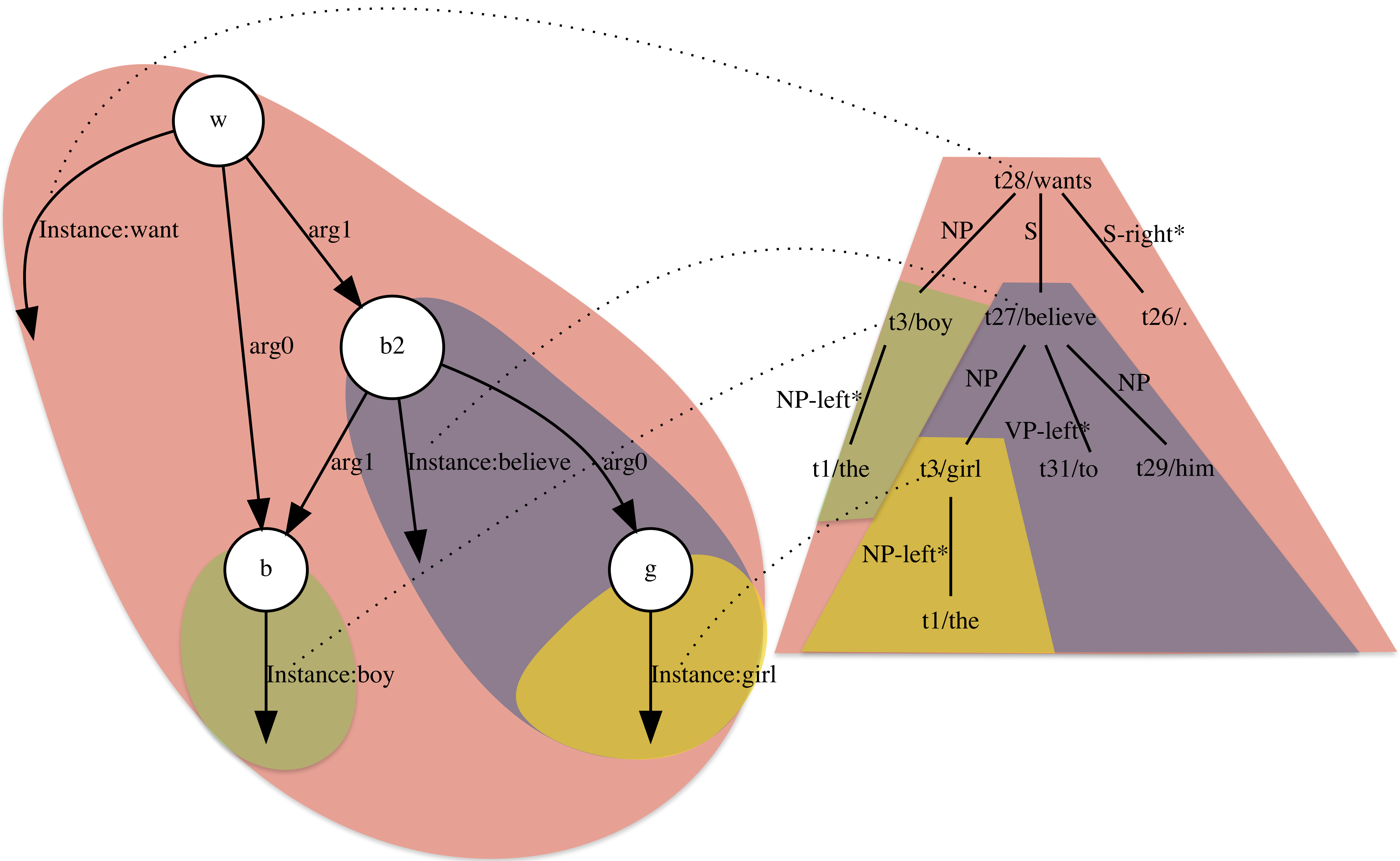

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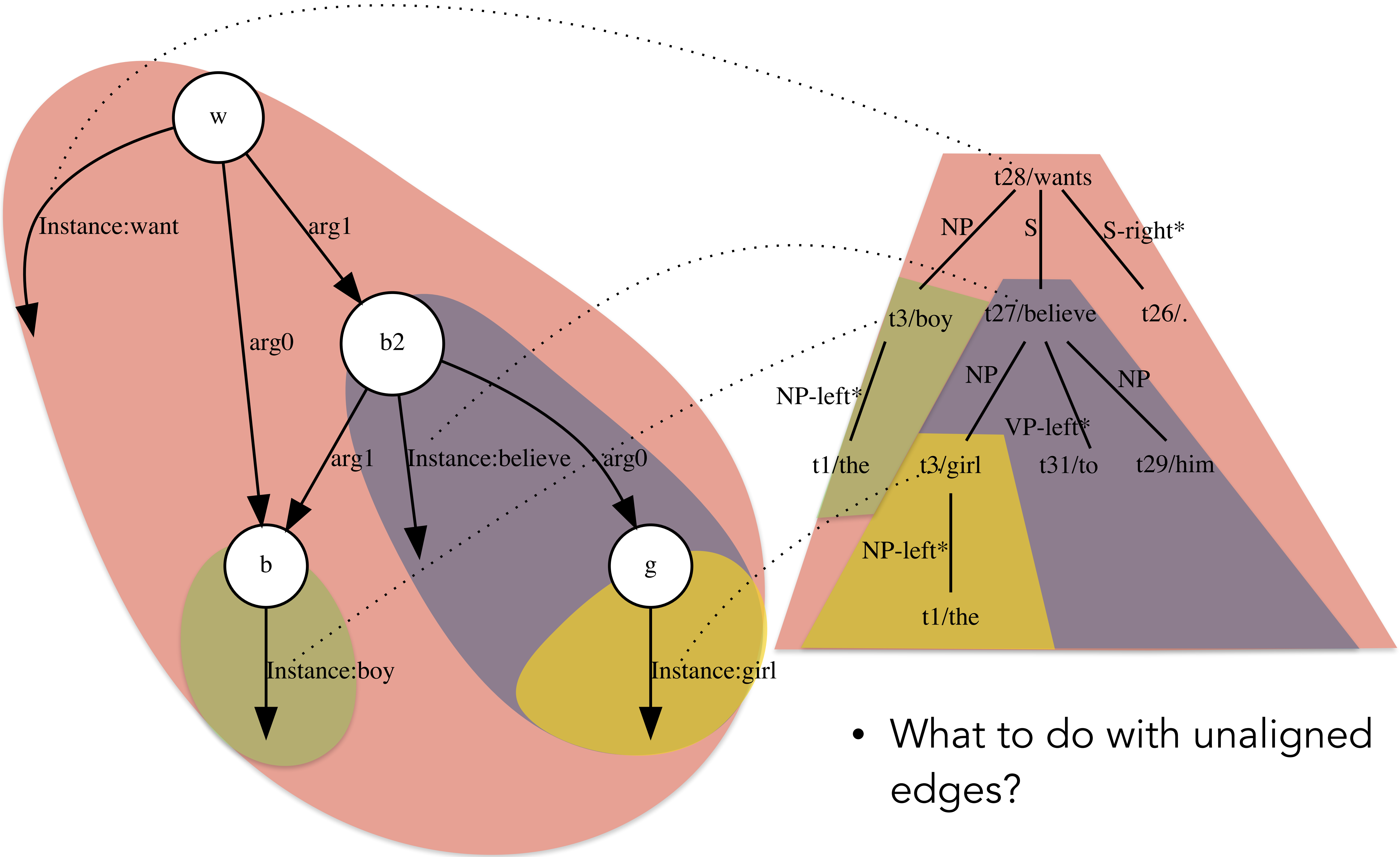
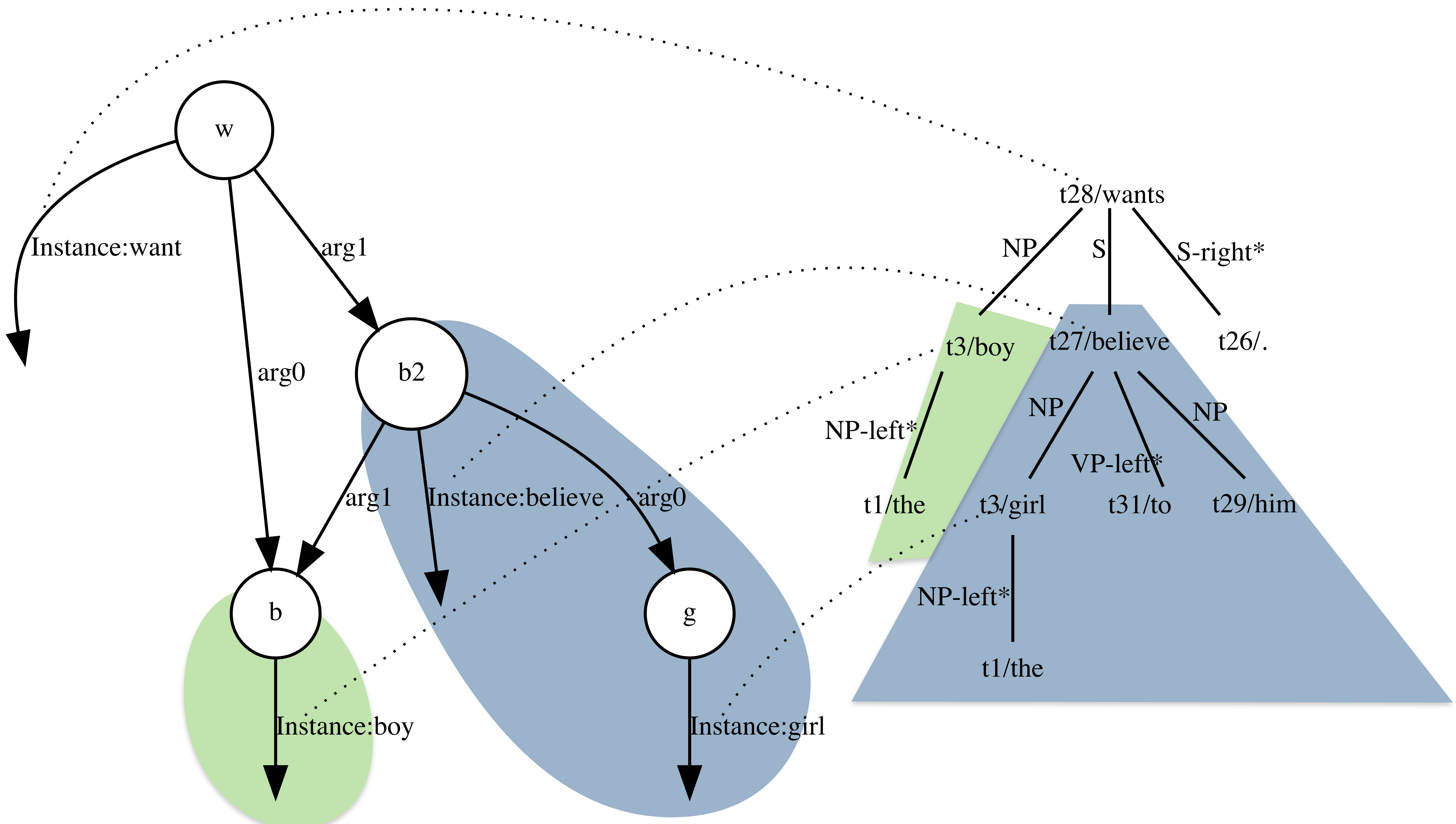


- What to do with unaligned edges?

Binary Partitioning



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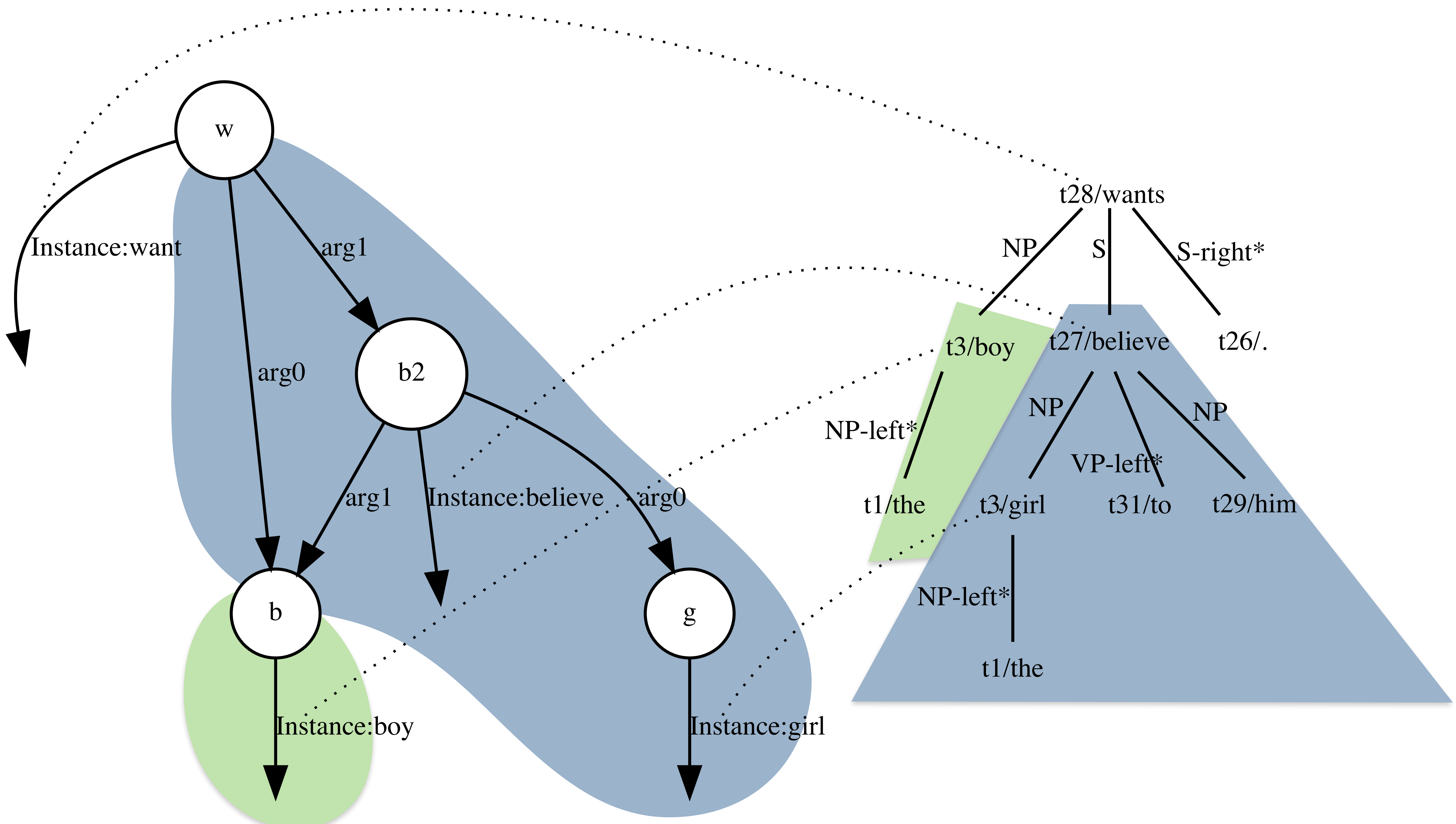

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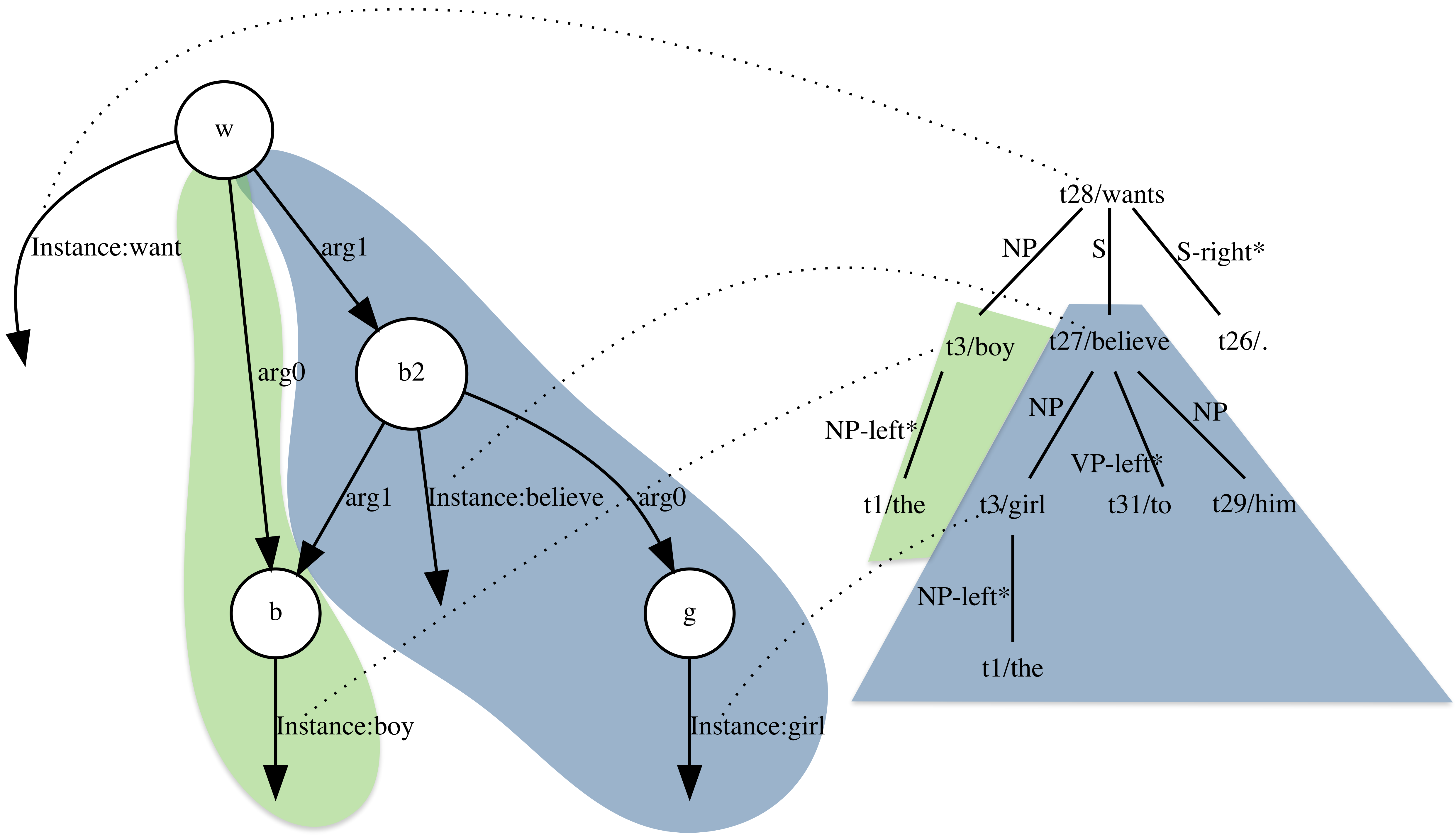

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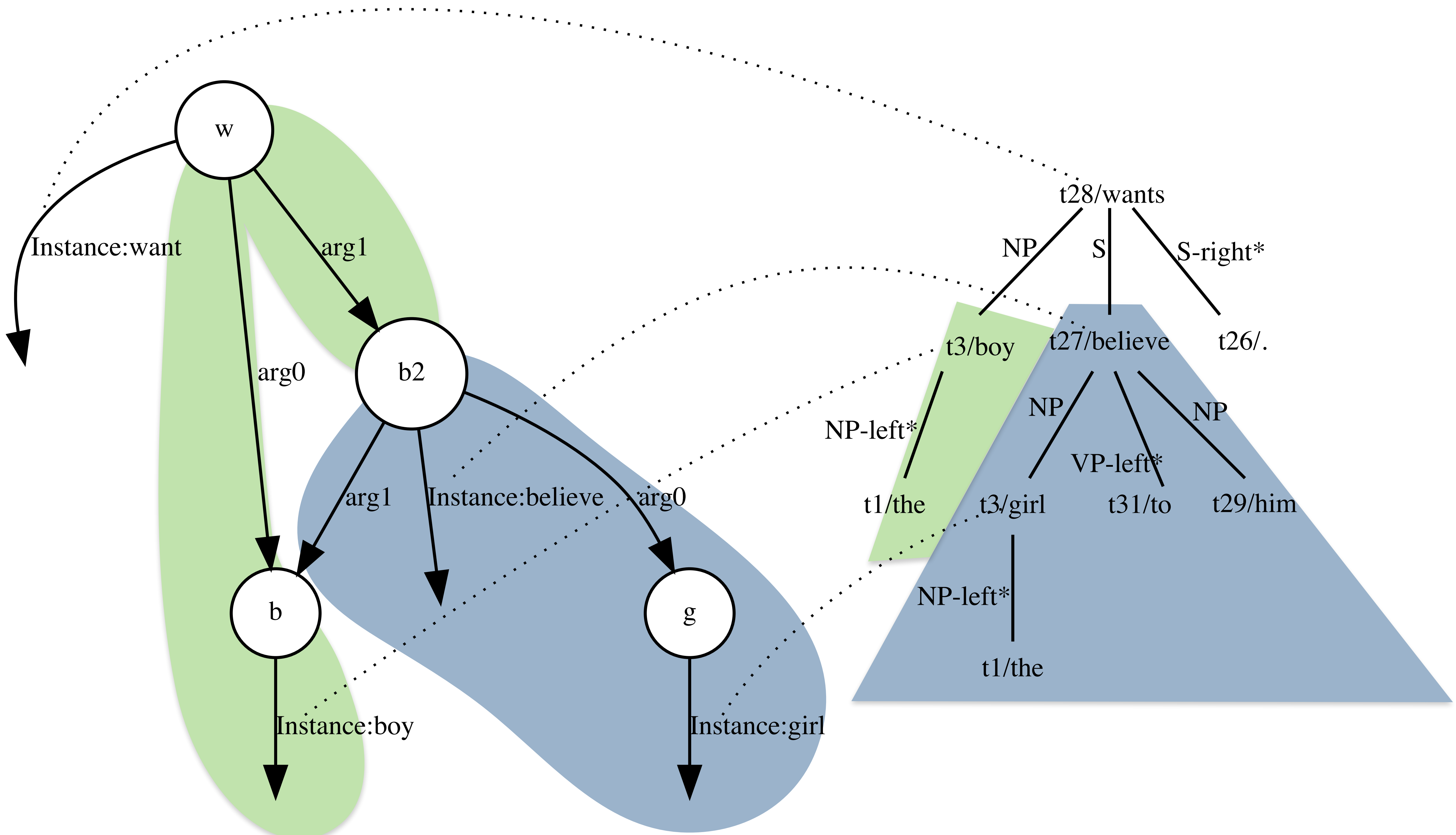
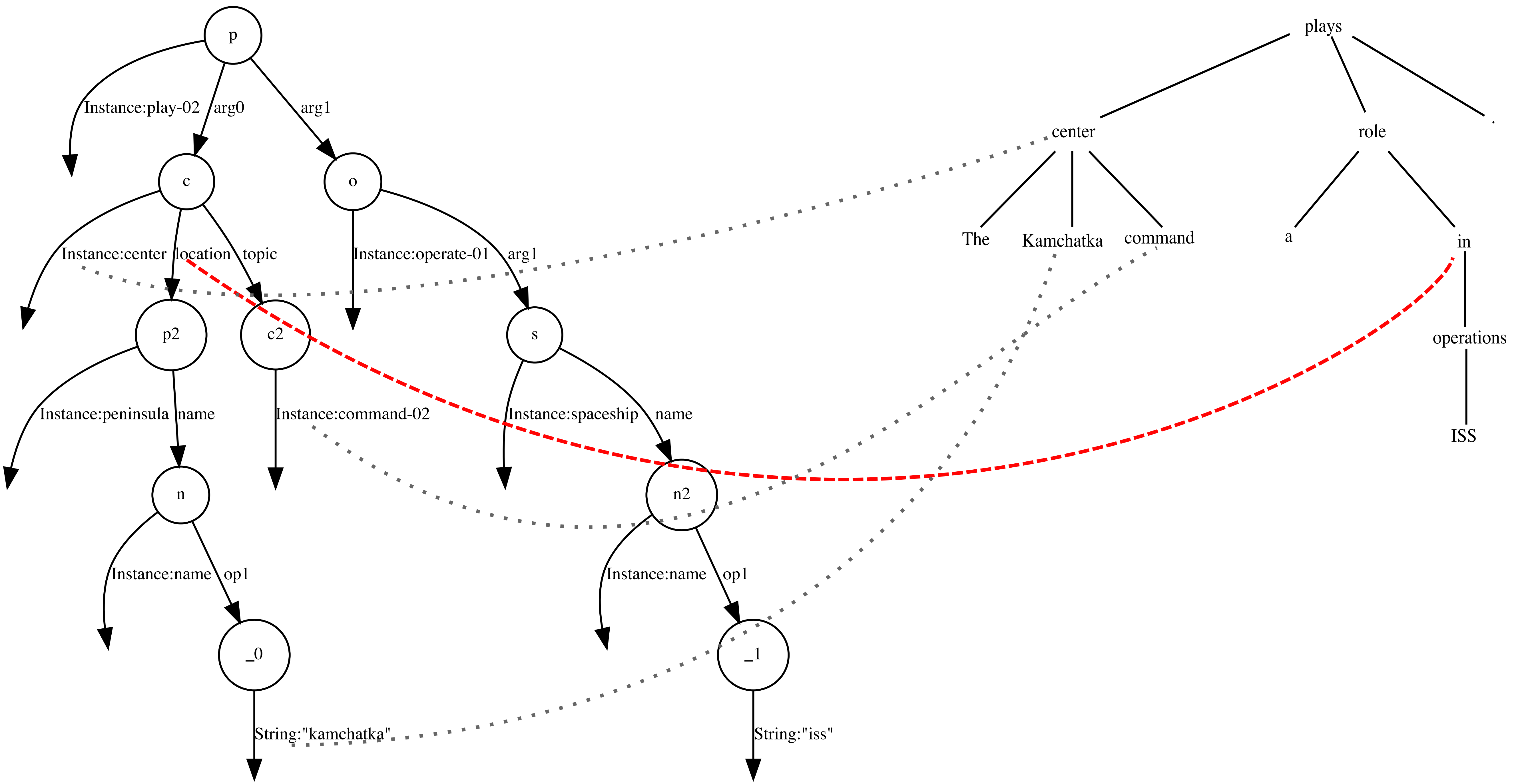


Problematic Alignments



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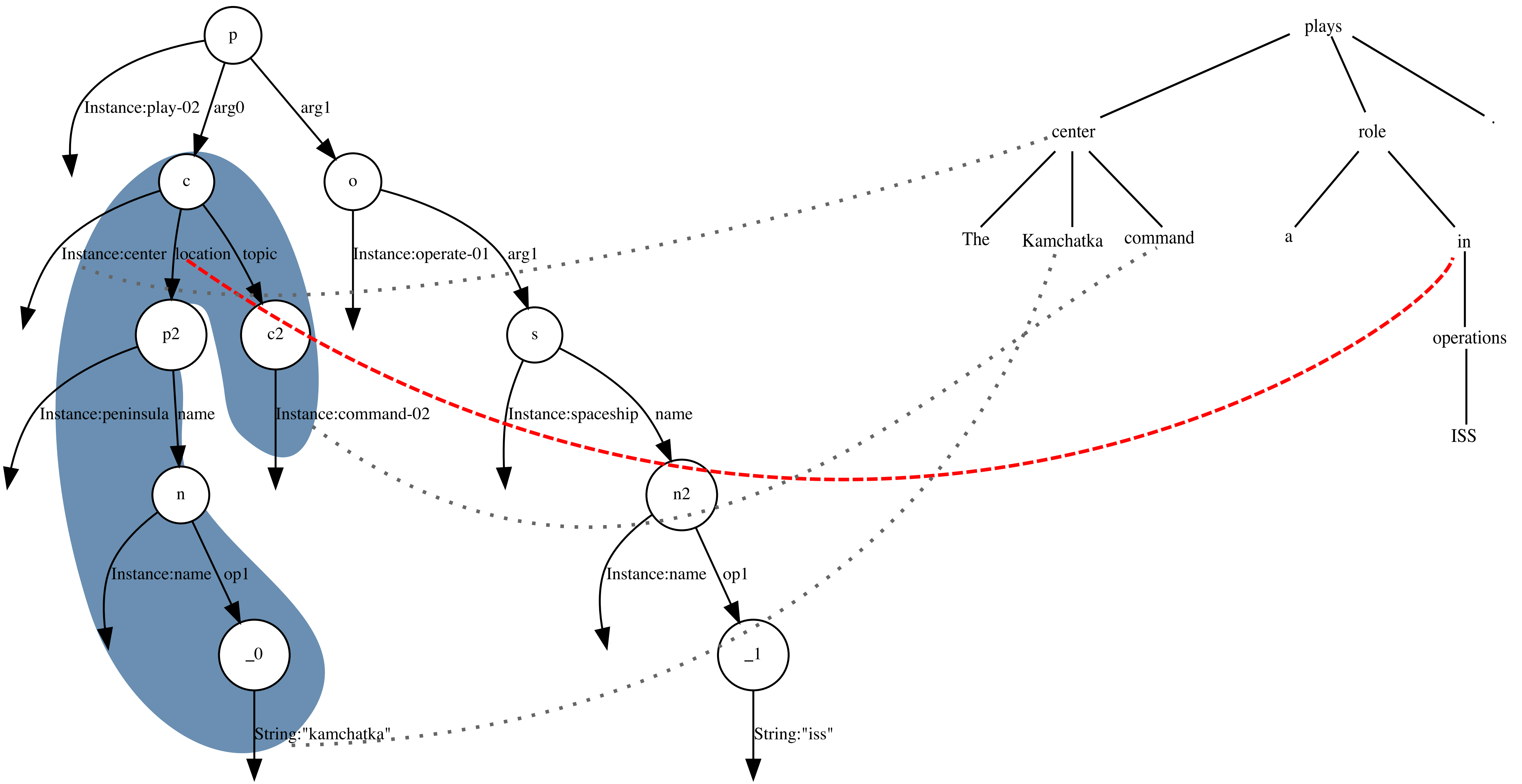

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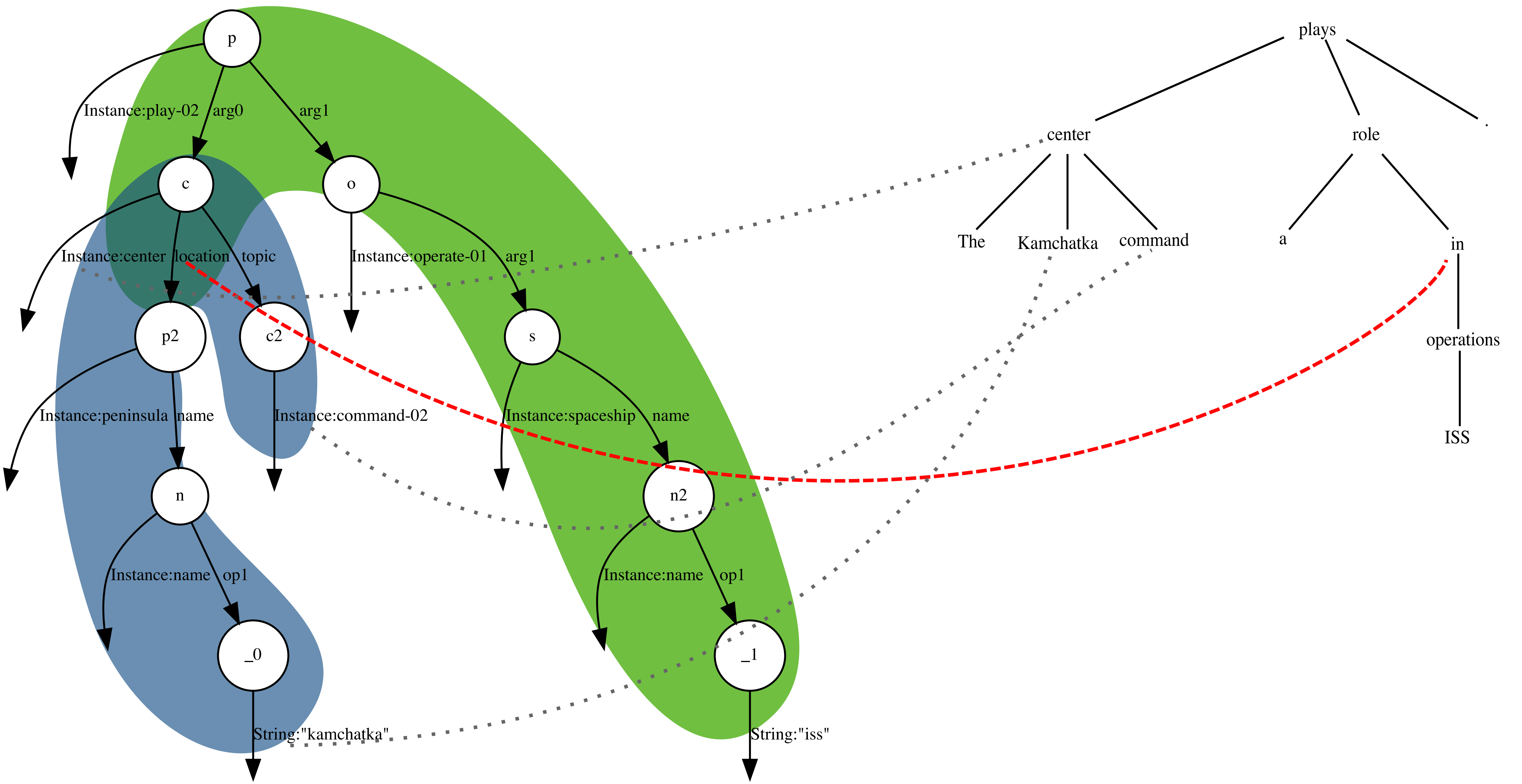

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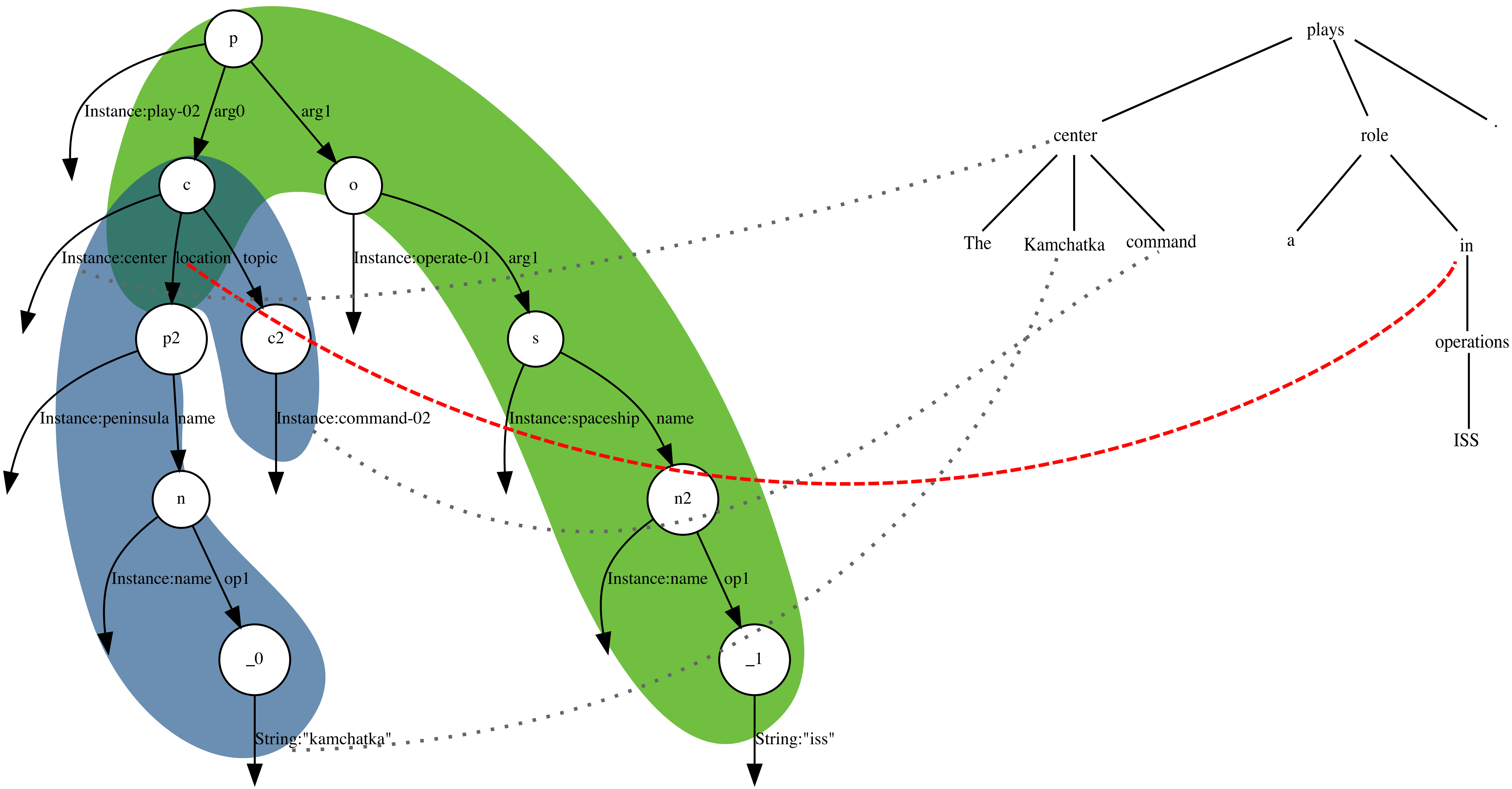
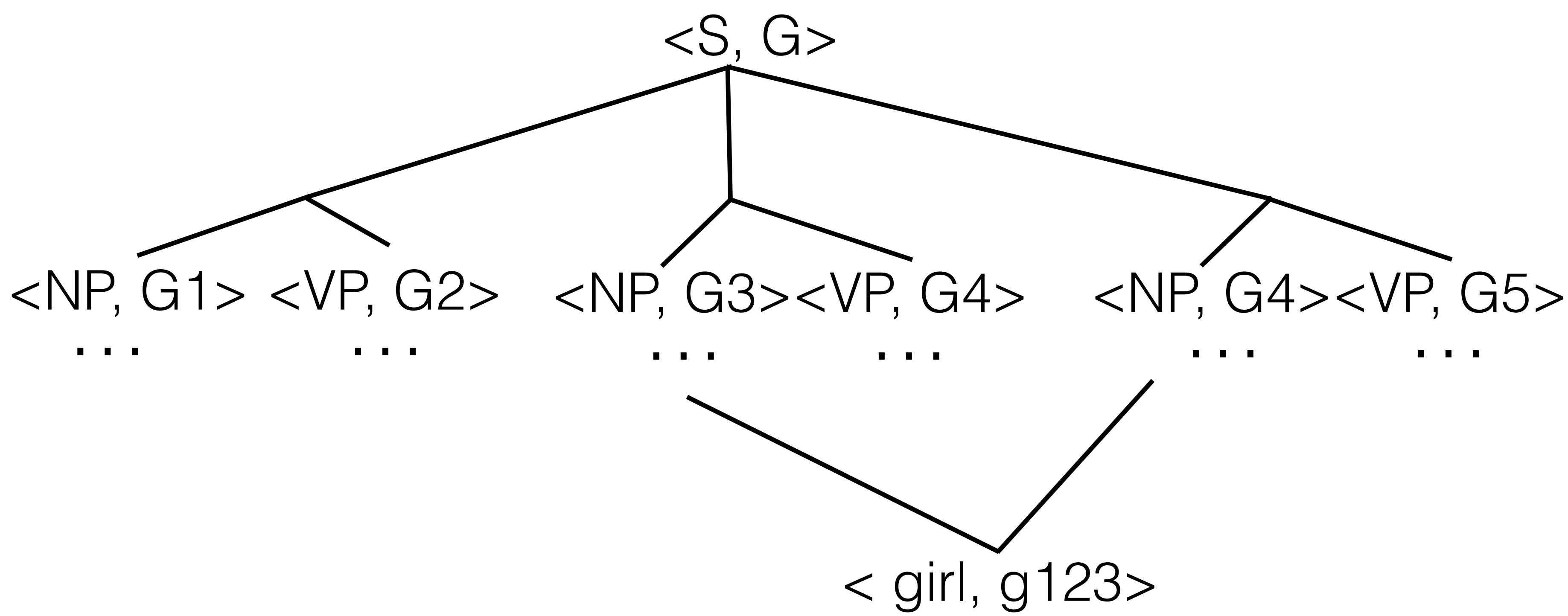


Solution: Compute spanning trees for each phrase.
Remove edge alignments in the intersection.

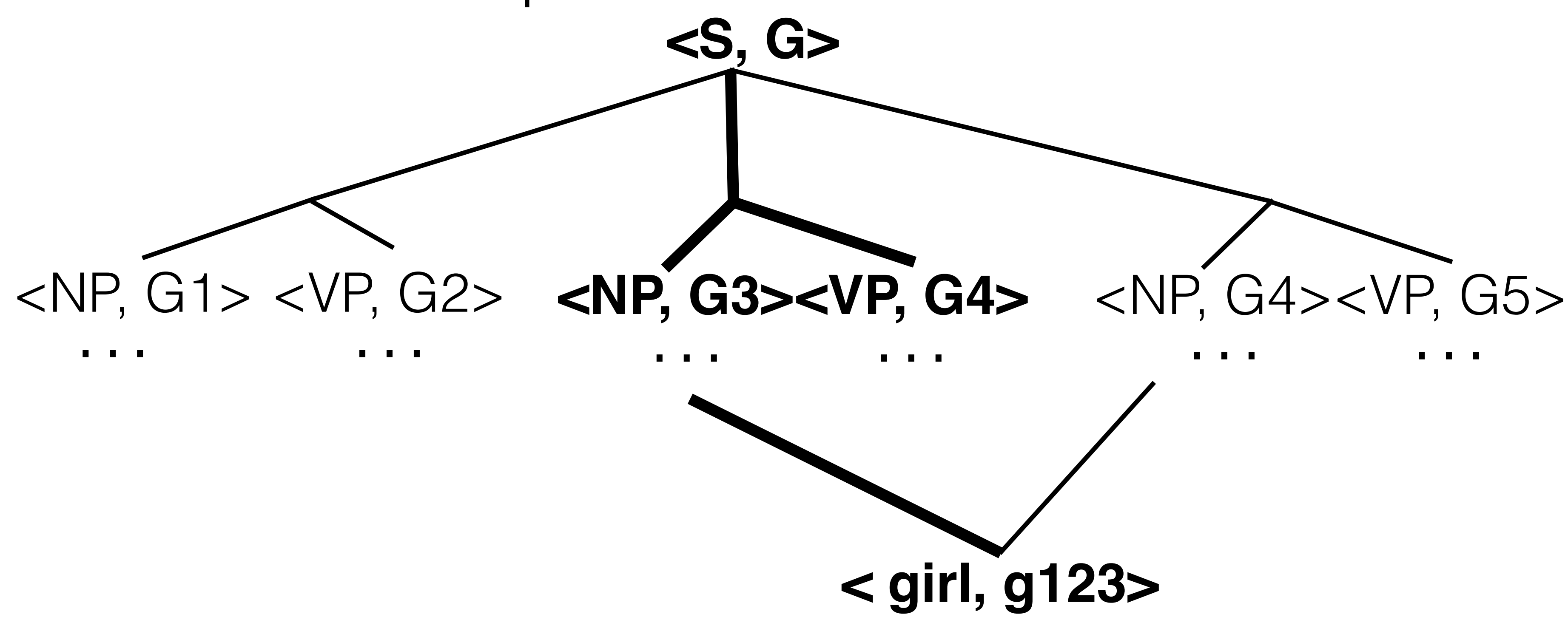
Constructing A Decomposition Forest

- For each way of partitioning the graph, recursively run partitioning on the subtrees and subgraphs.
- This is expensive! Need memoization.
- The result is a packed forest.



Selecting a Grammar

- Extract forests for all string/graph pairs in the training data
- Run EM with inside/outside algorithm on the collection of forests.
- Select 1st best Viterbi tree from each forest. Extract rules from these forests and keep trees as “bronze derivations”



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417k rules

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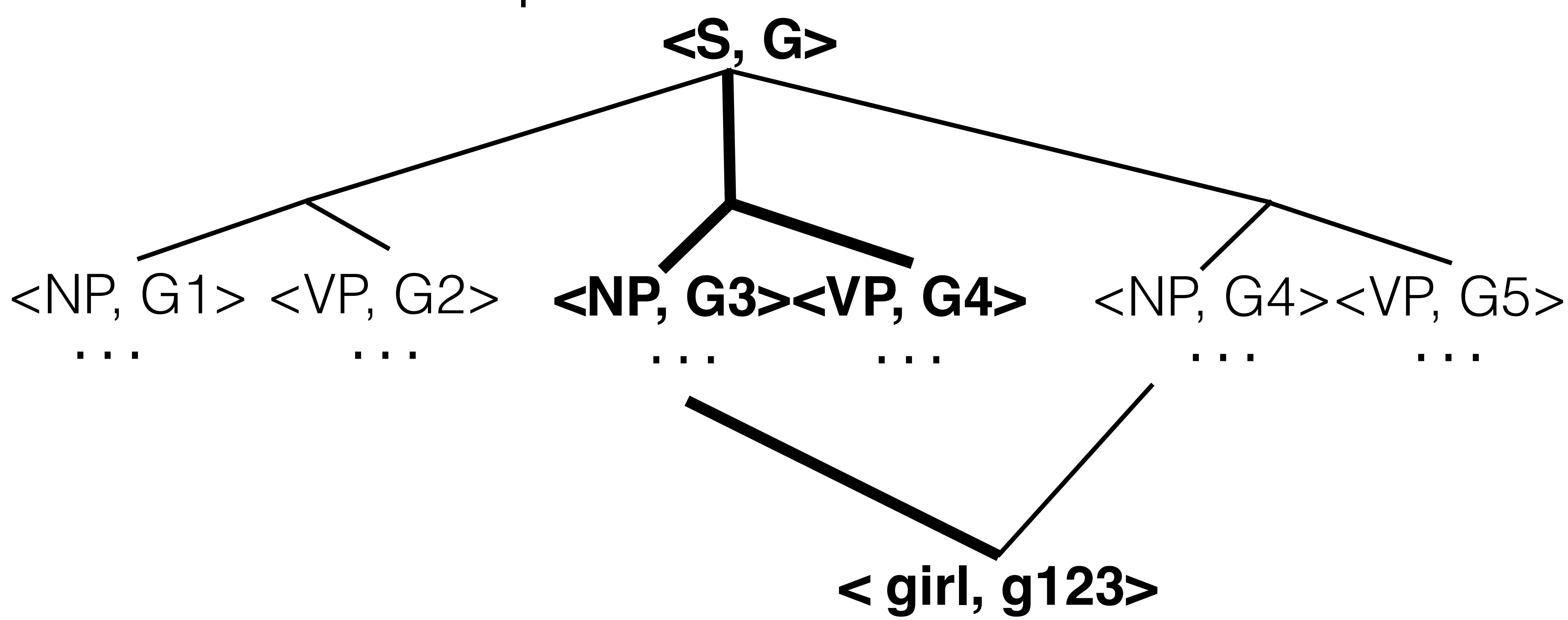
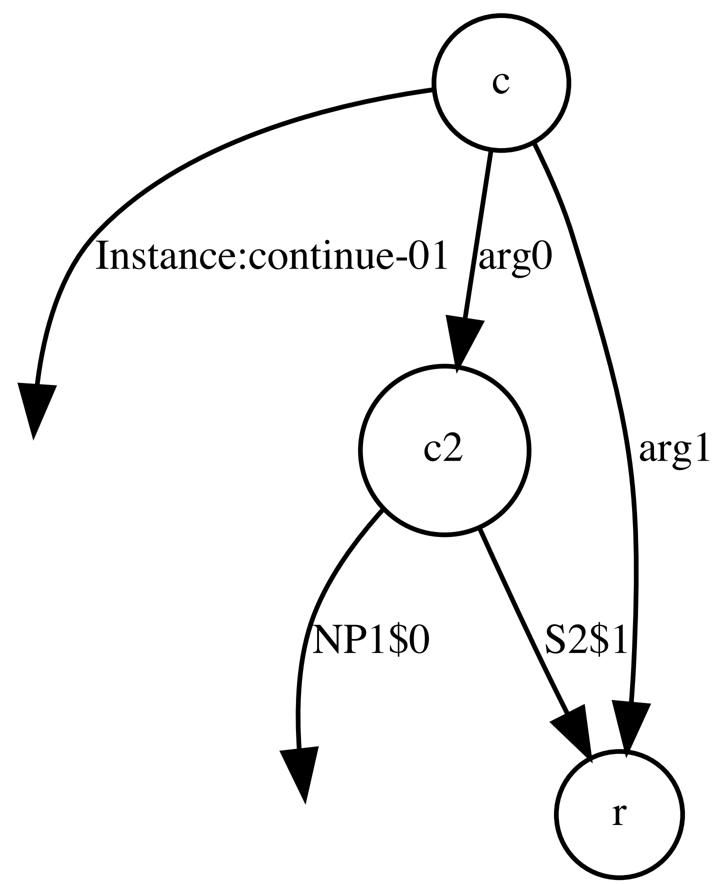
31k rules



Extracted LSHRG Grammar Rule

S0 → NP1$_{[0]}$ VP-left* continue/t28 S2$_{[1]}$ S-right*



HRG Demo

- "Bolinas" package for Hyperedge Replacement Grammars.
  https://github.com/isi-nlp/bolinas

Acknowledgments

- Some slides from Nathan Schneider & Jeff Flanigan's AMR tutorial at NAACL 2015.