Contextual Hyperedge Replacement Grammars for the Generation of Abstract Meaning Representations

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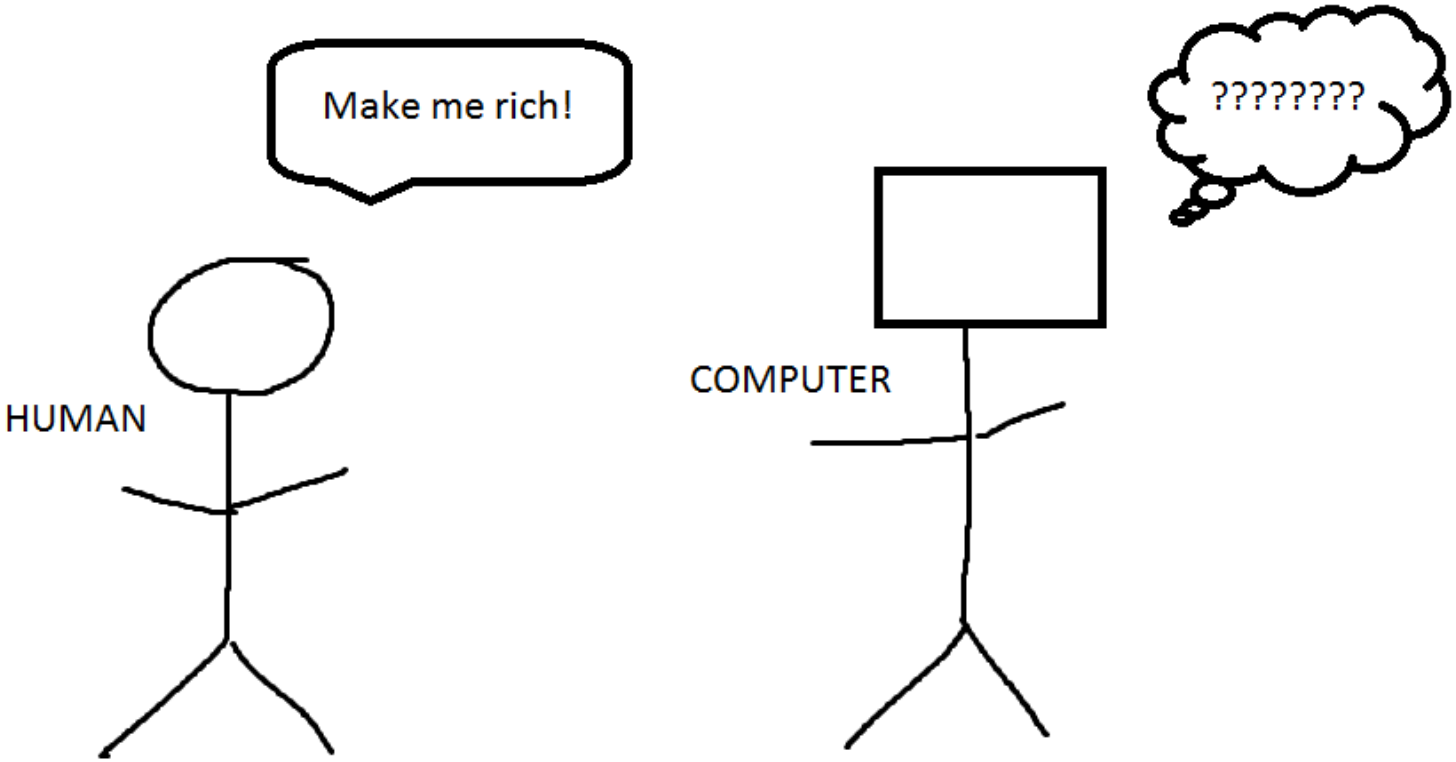
Aim of natural language processing



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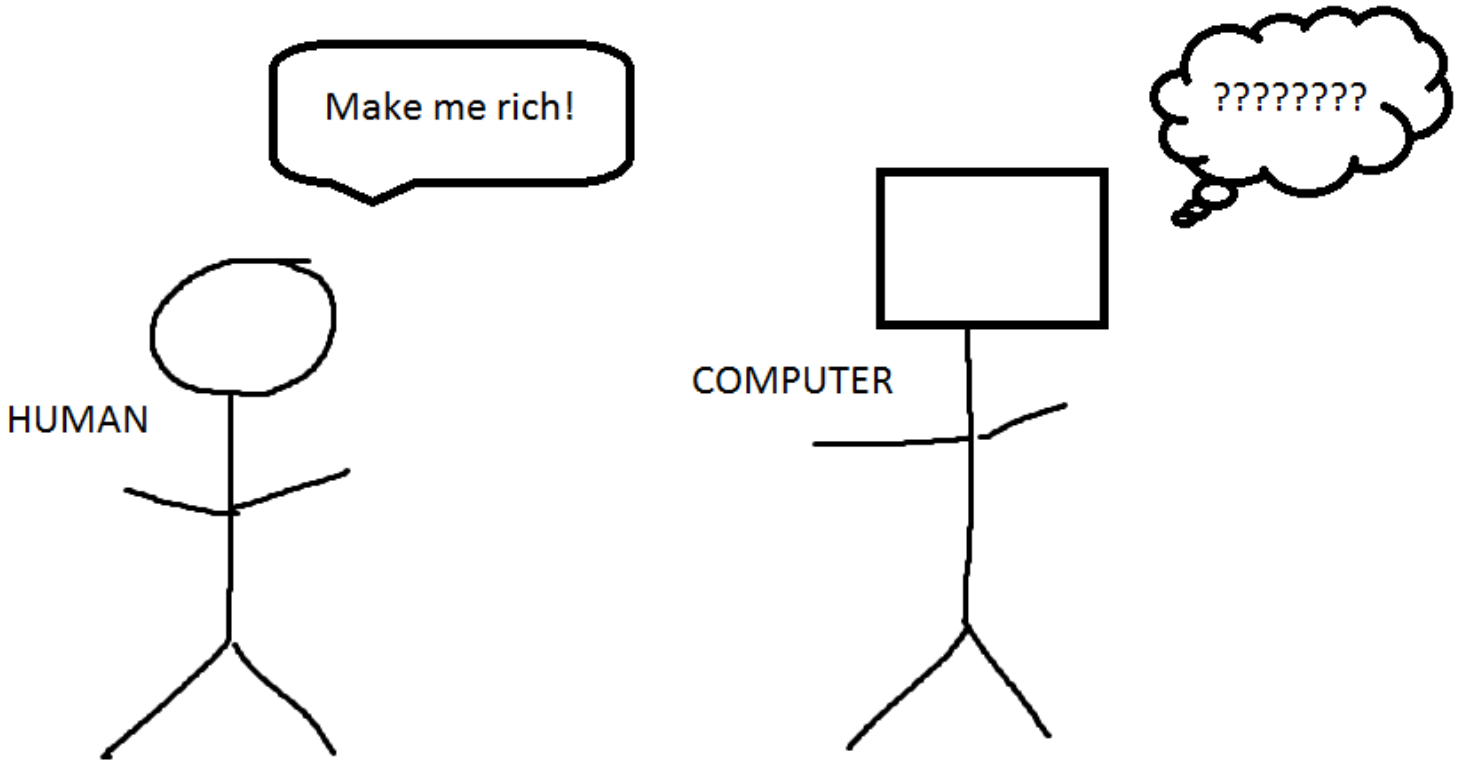

1. Parse
2. Analyse
3. Respond

Natural language in computers

- Natural language is complex – we must use approximations
- A model (e.g. an automaton, a grammar, a neural network) can be used for approximating language
- In, e.g., machine learning and natural language generation

Correct vs. incorrect sentences

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- Semantics – the meaning

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- "Colourless green ideas sleep furiously." [Chomsky, 1956]

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- "Colourless green ideas sleep furiously." [Chomsky, 1956]
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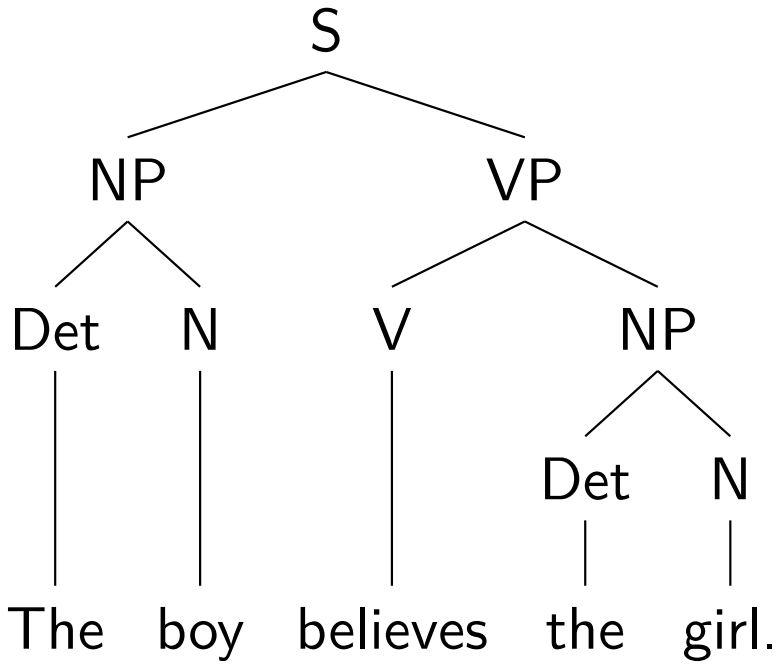
Formal representation of syntax

Parse tree:



Formal representation of semantics

- Semantics is more difficult to represent
- There is no equivalence of parse trees
- Do we really need one?

Motivating example: Robot

Input:

"Feed her cat food."

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Output:

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Output:

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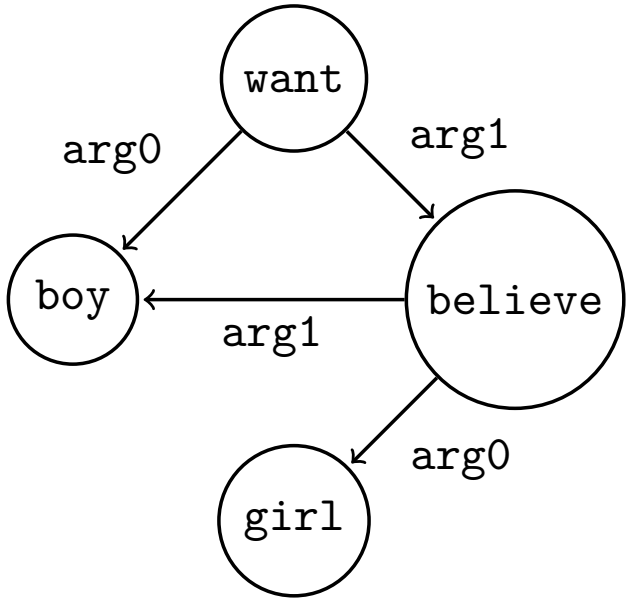
We need an unambiguous semantic representation!

Abstract meaning representation[1]

- Semantic representations of natural language sentences
- Directed graphs
  - Acyclic
  - Rooted
  - Node and edge labelled
- The nodes represent *concepts* ($\approx$ words)
- The edges represent *relations* between the concepts

[1] [Banarescu et al., 2013]

Abstract meaning representation[1]



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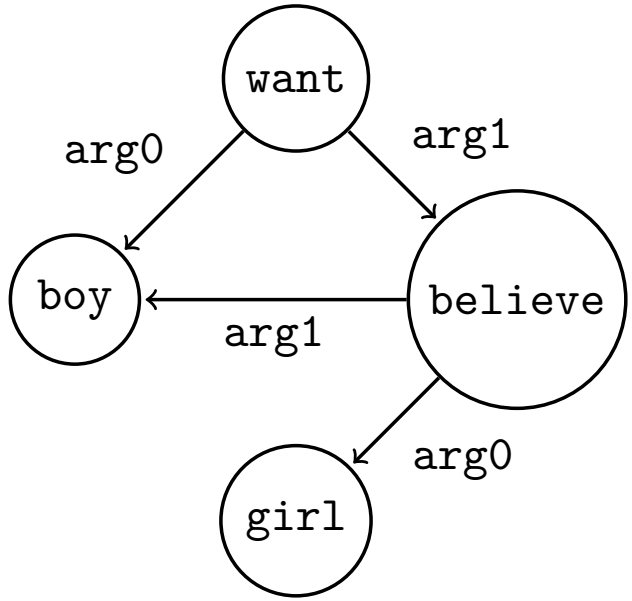

"The boy wants the girl to believe him"

"It is wanted by the boy that the girl has belief in him"

[1] [Banarescu et al., 2013]

Boy-girl AMRs

- From the boy-girl AMR corpus [Braune et al., 2014]
- Domain:
  - Concepts: `boy`, `girl`, `want` and `believe`
  - Relations: `arg0` and `arg1`
- Requirements (for correct meanings):
  - `boy` and `girl` can only occur once each and are leaf nodes
  - There must be at least one occurence of `boy` or `girl`
  - `want` and `believe` can have at most one each of `arg0` and `arg1` as outgoing edges
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- **We limit ourselves to boy-girl AMRs**

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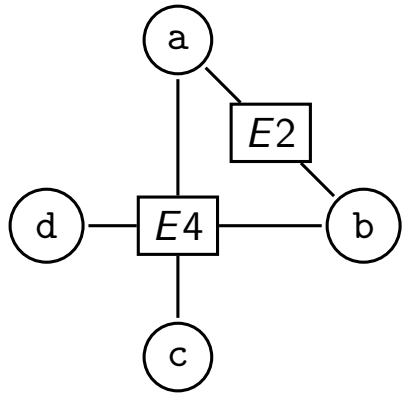
Correctness of AMRs

- Since AMRs are not (yet) formally defined, we use an informal description (the list of requirements)
- Framework in which the correctness can be expressed
- As previously mentioned, possible frameworks are automata, grammars and neural networks
- We want a **graph grammar** that generates the **language of all correct AMRs (over the boy-girl domain)**
- For practical feasibility: Correctness check (parsing) must be done in **polynomial time**

Previous work

- Two graph grammar types were used for building boy-girl grammars [Jonsson, 2016]
  - Predictive top-down parsable grammars [Drewes et al., 2015]
  - Restricted directed acyclic graph grammars [Björklund et al., 2016]
- Both are hyperedge replacement grammars (HRGs) [Drewes et al., 1997] (but with restrictions)
- Both have polynomial-time parsing algorithms (which is not true for all HRGs)

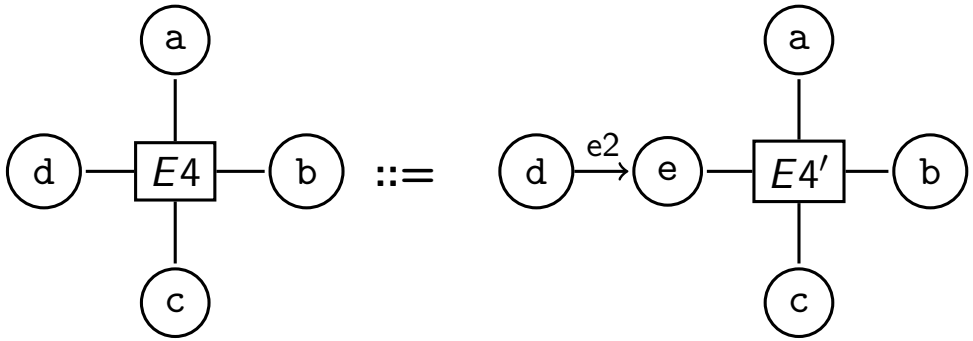
Hyperedges and hypergraphs



- A *hyperedge* is an edge that can be connected to an arbitrary number of nodes; the sequence of connected nodes is called the *attachment* of a hyperedge
- A hyperedge attached to exactly two nodes is equivalent to an ordinary directed edge
- A *hypergraph* is a graph containing hyperedges

Hyperedge replacement[2]

Rule for the *nonterminal* $E4$:



[2] [Drewes et al., 1997]

Hyperedge replacement[2]

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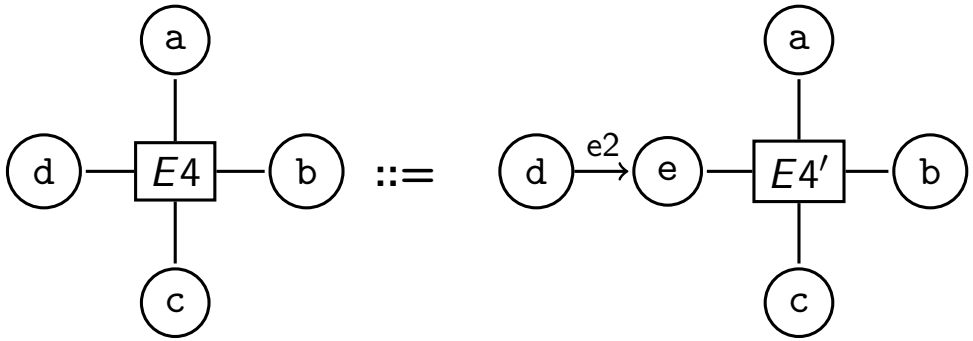
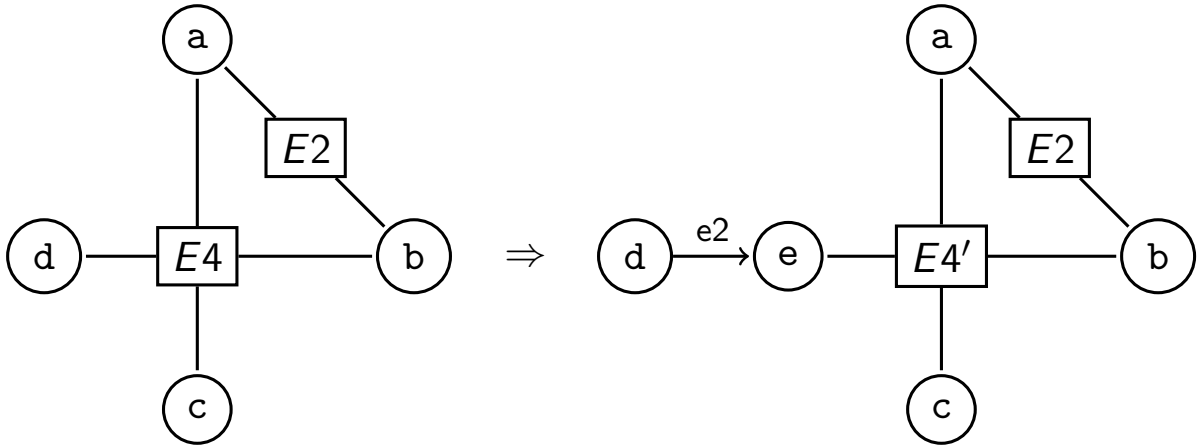


Rule application (derivation step):



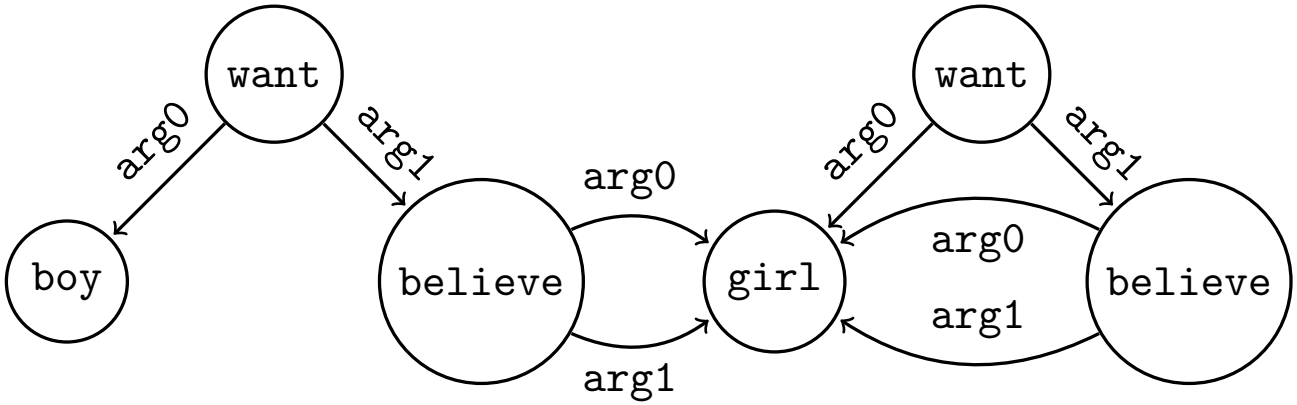
[2] [Drewes et al., 1997]

A boy-girl HRG

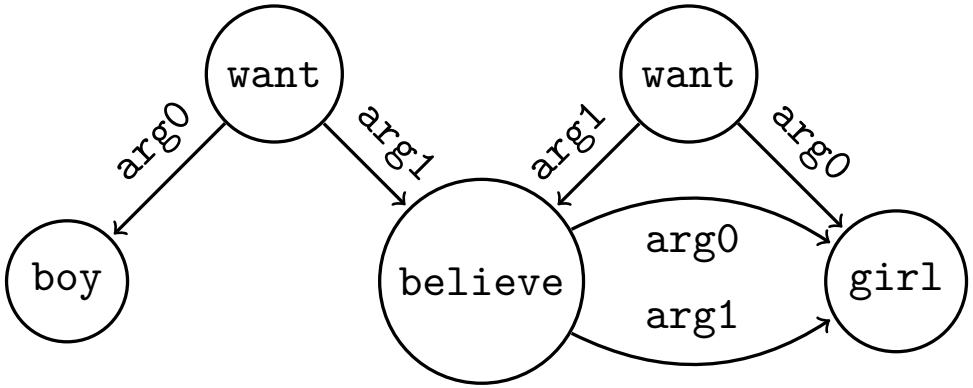
A set of rules specifying hyperedge replacements intended to generate boy-girl AMRs.

Results

Observation (same meaning – two AMRs):



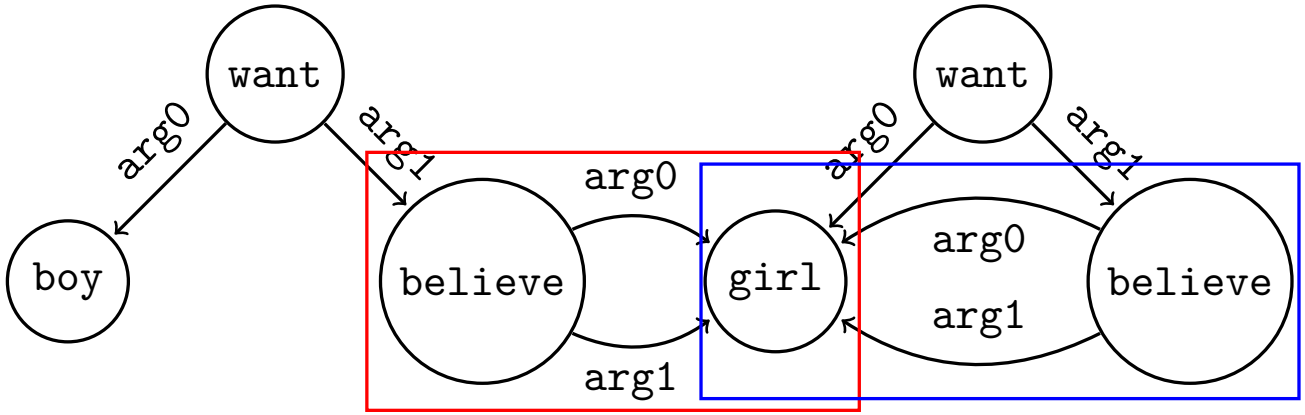
Could be generated



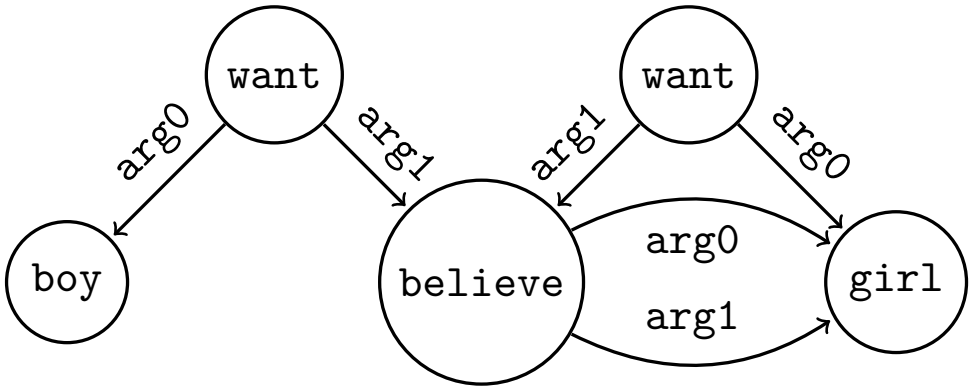
Could not be generated

Minimal AMRs

Here, we say that an AMR that contains no duplicate substructures is minimal



Non-minimal



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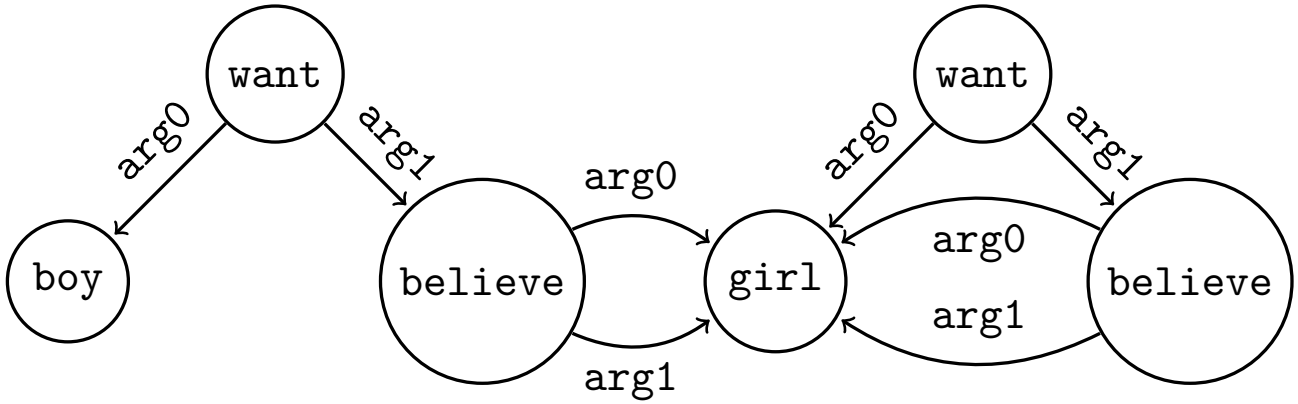

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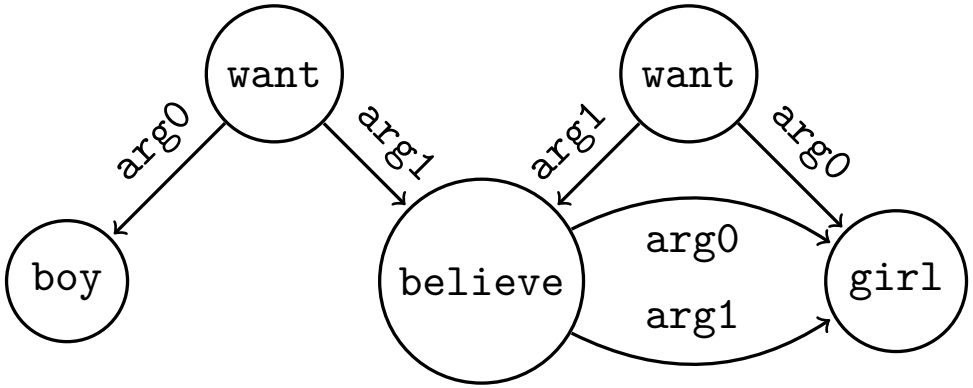

Minimal

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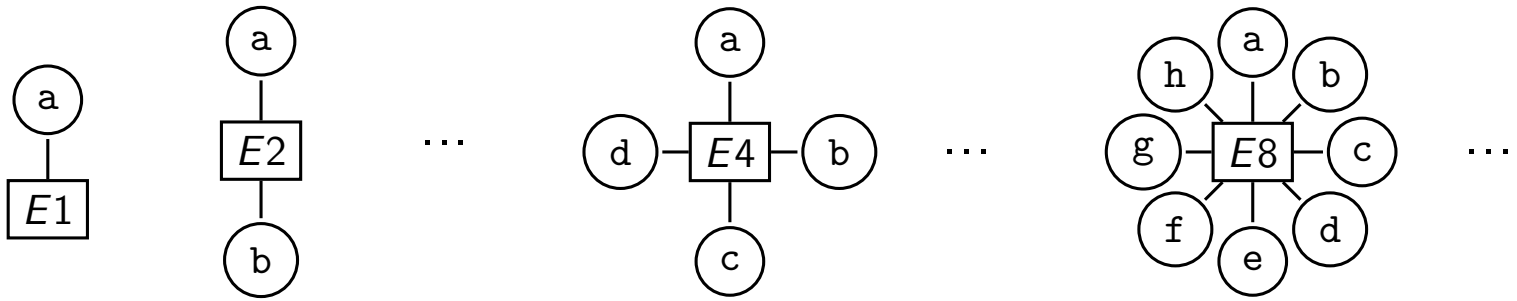
Why does not hyperedge replacement seem to be powerful enough for the generation of minimal AMRs?

Intuitively, infinitely many nonterminals – and thereby rules – would be needed.

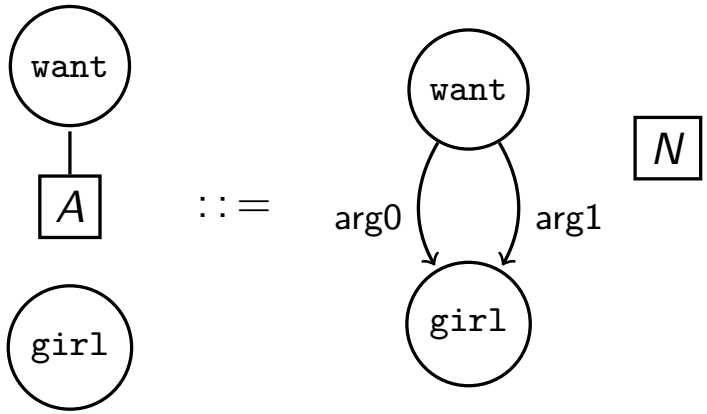


Question 2

Is there another grammar type that can generate minimal AMRs in general?

Contextual hyperedge replacement[3]

Contextual rule:



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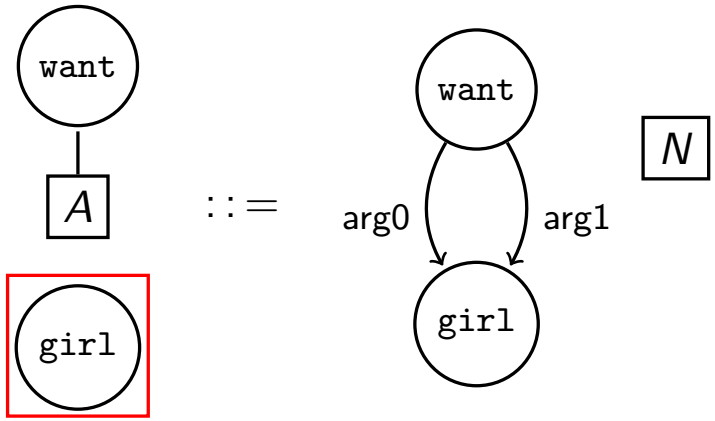

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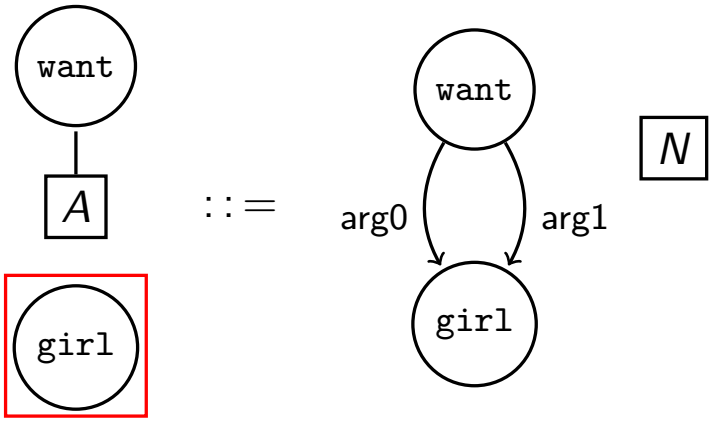
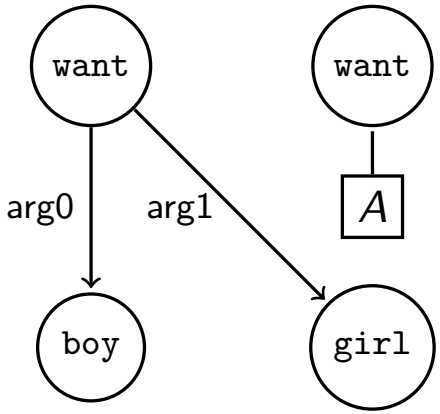


Rule application:



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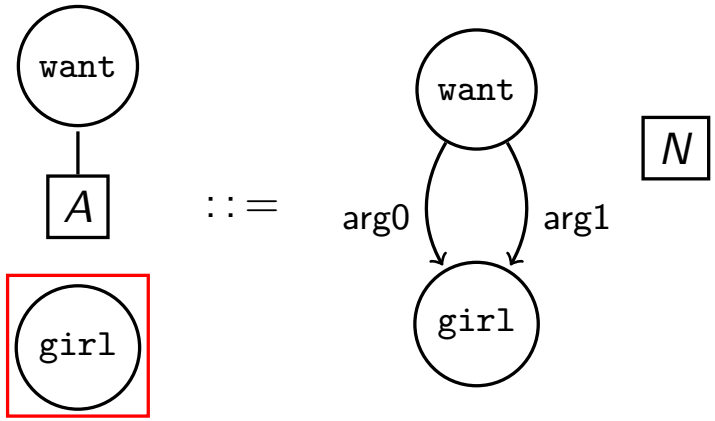

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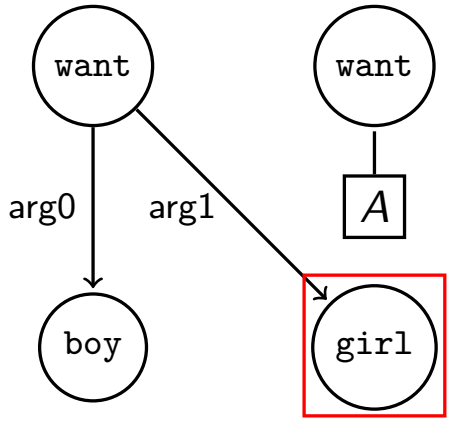

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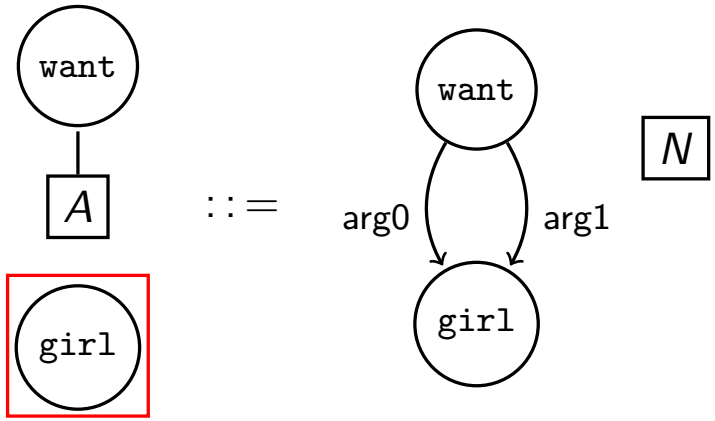

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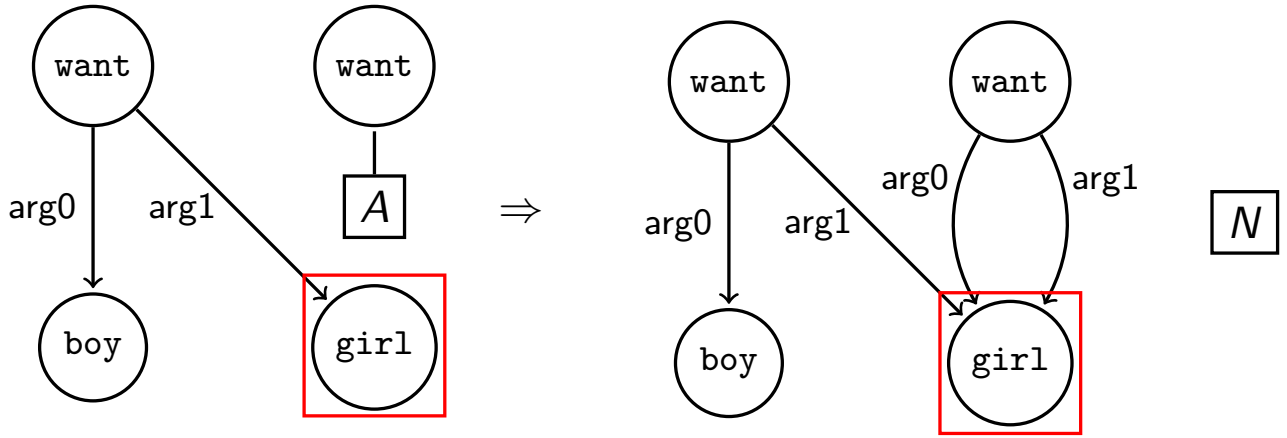

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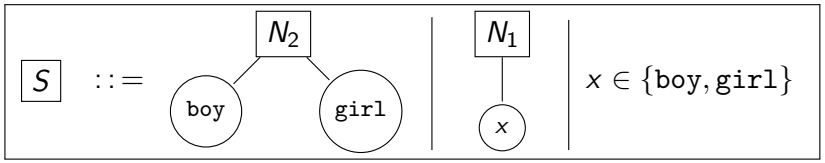
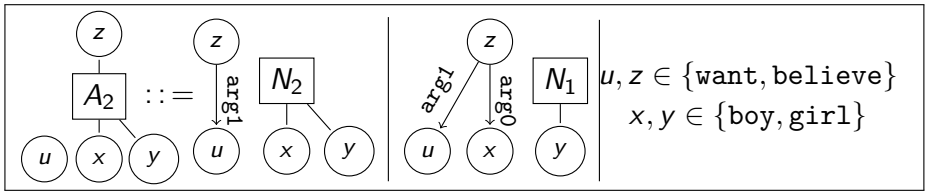
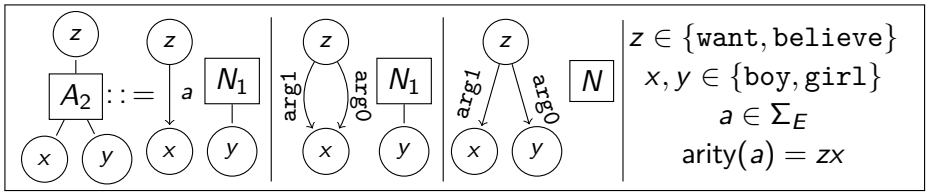
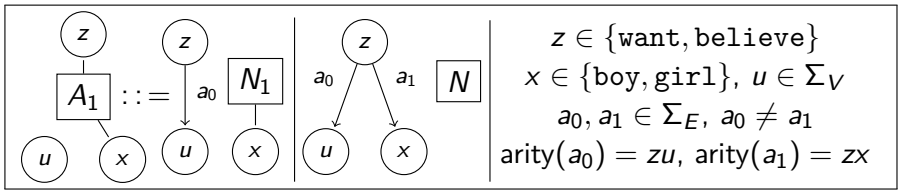
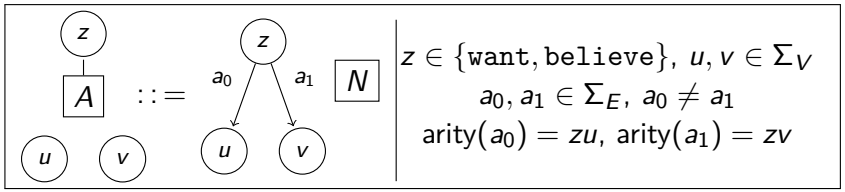
A contextual boy-girl HRG

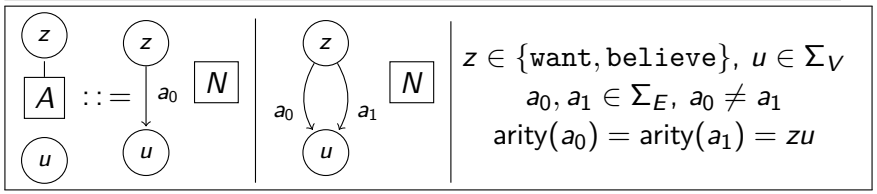


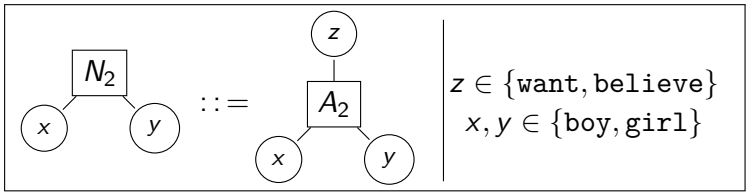


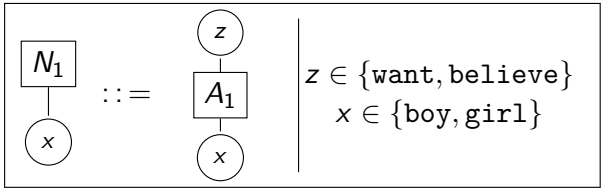


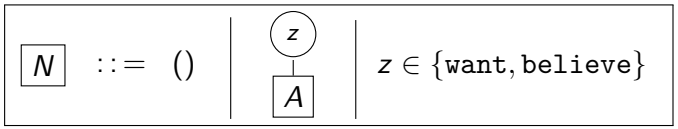


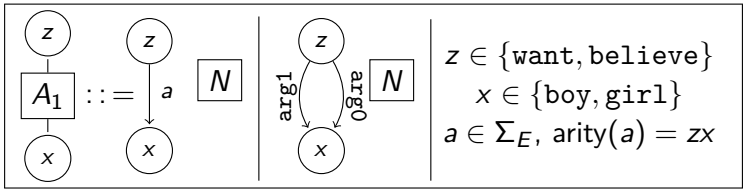


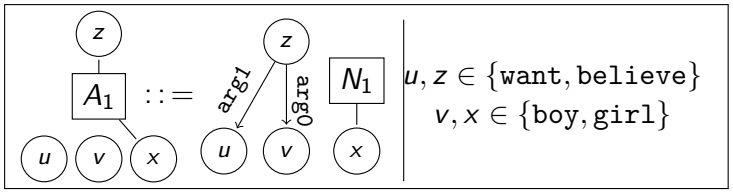




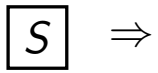








An example derivation



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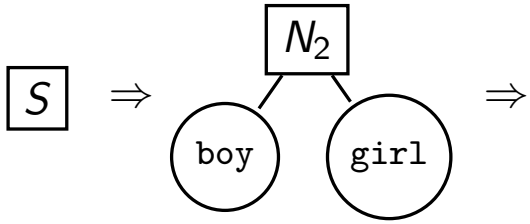

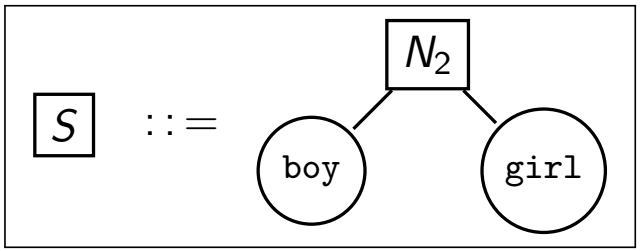

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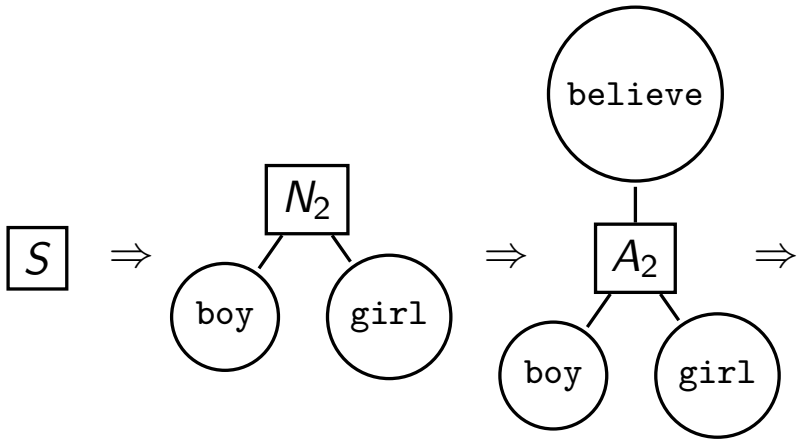

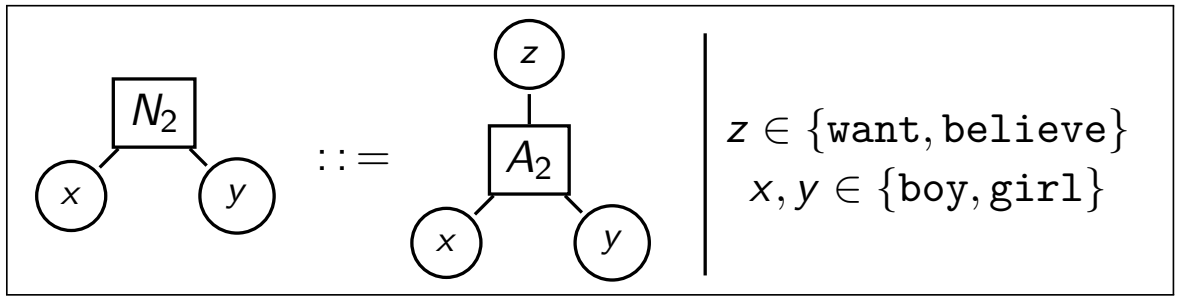

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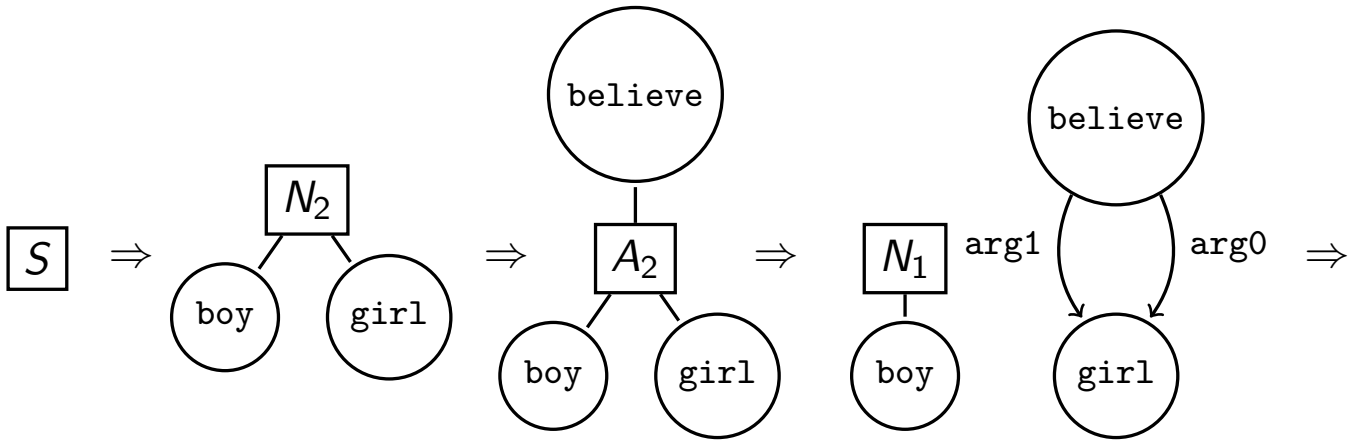

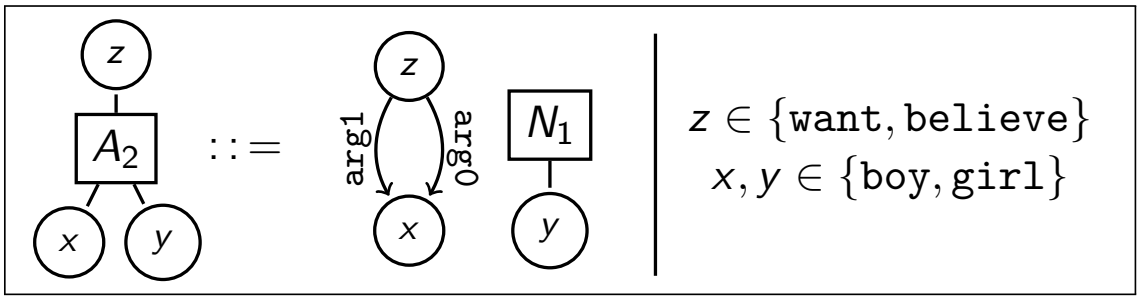

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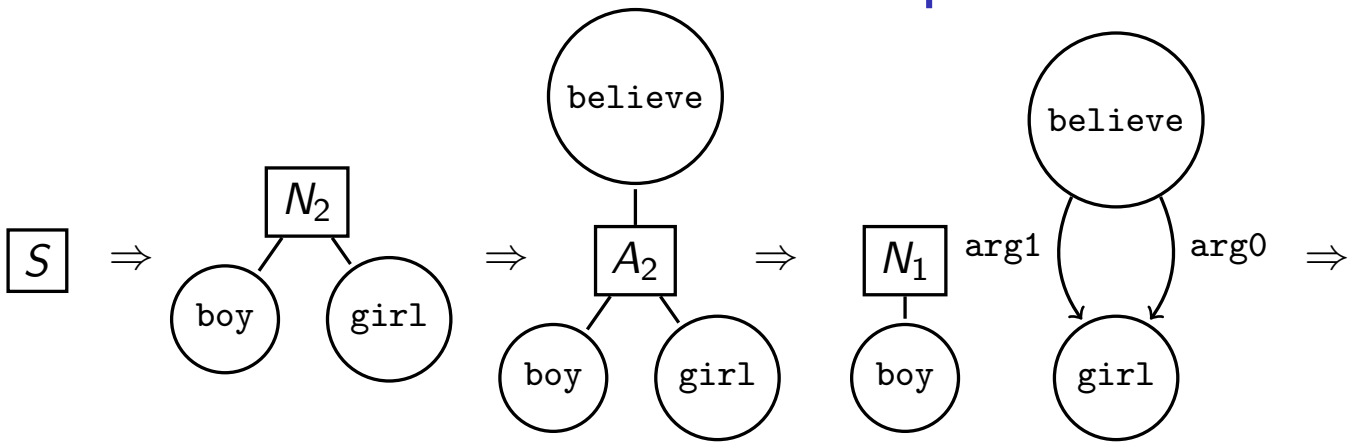
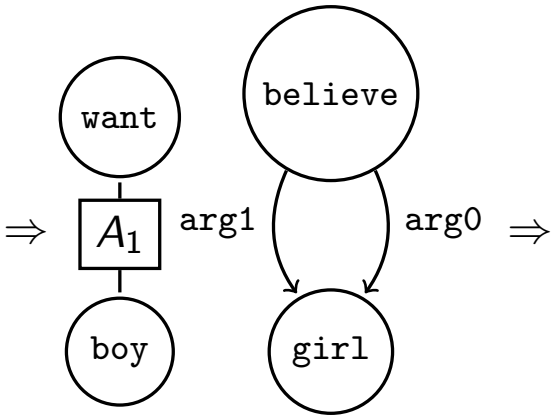
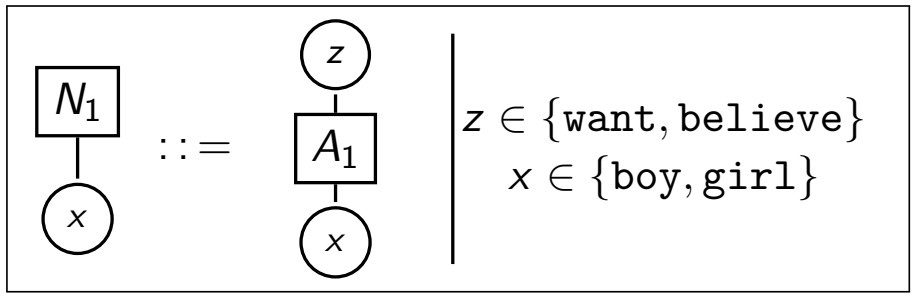
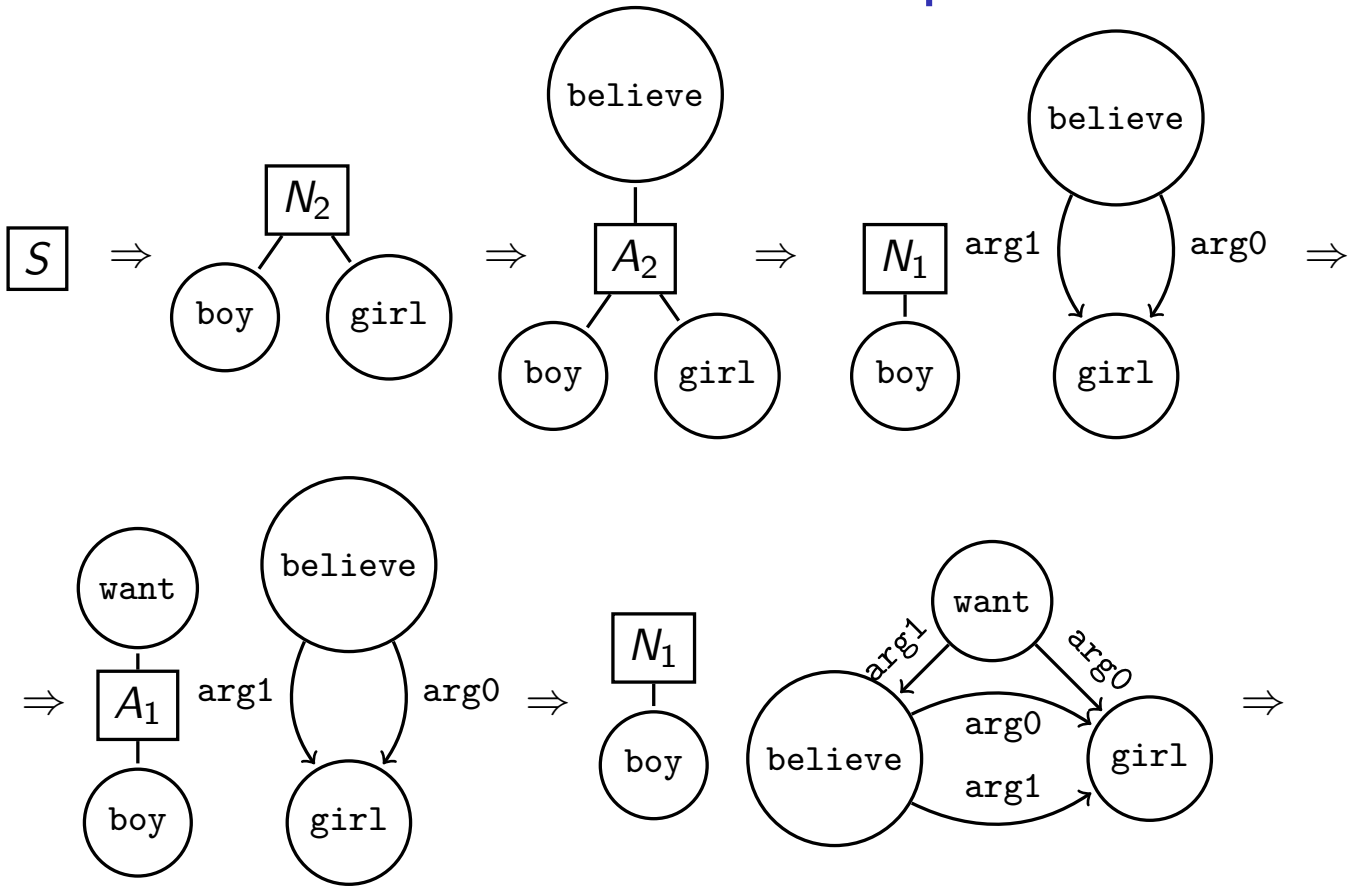
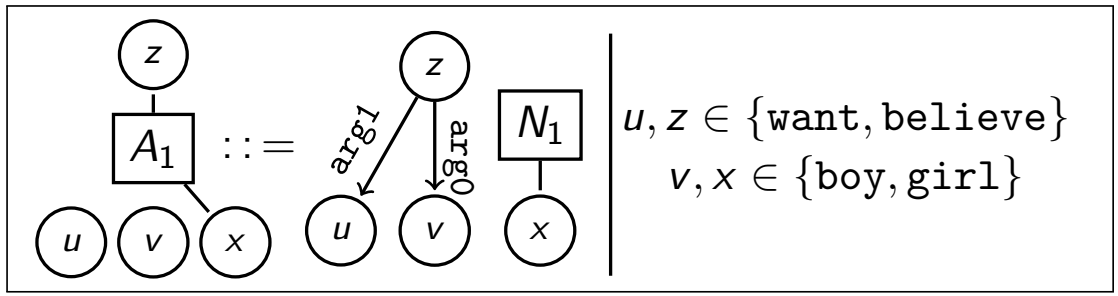




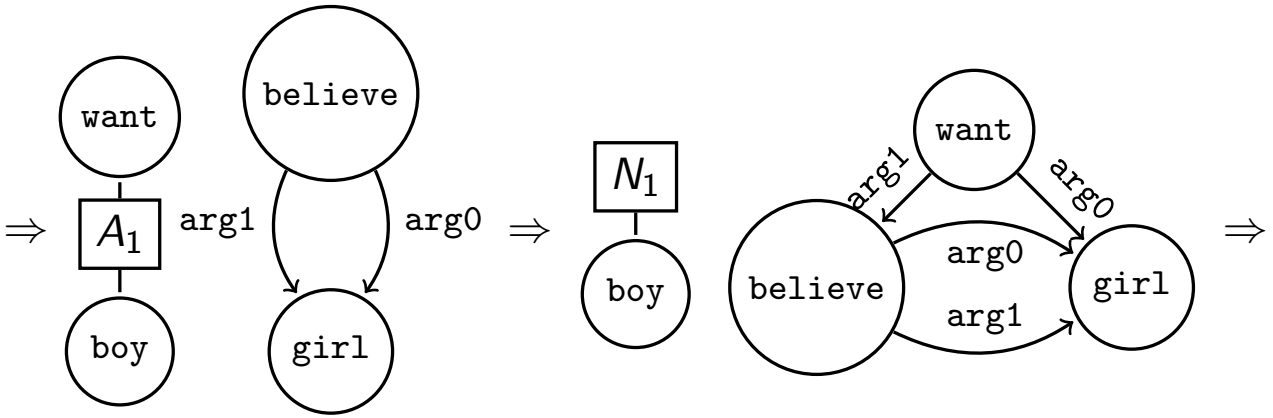


An example derivation

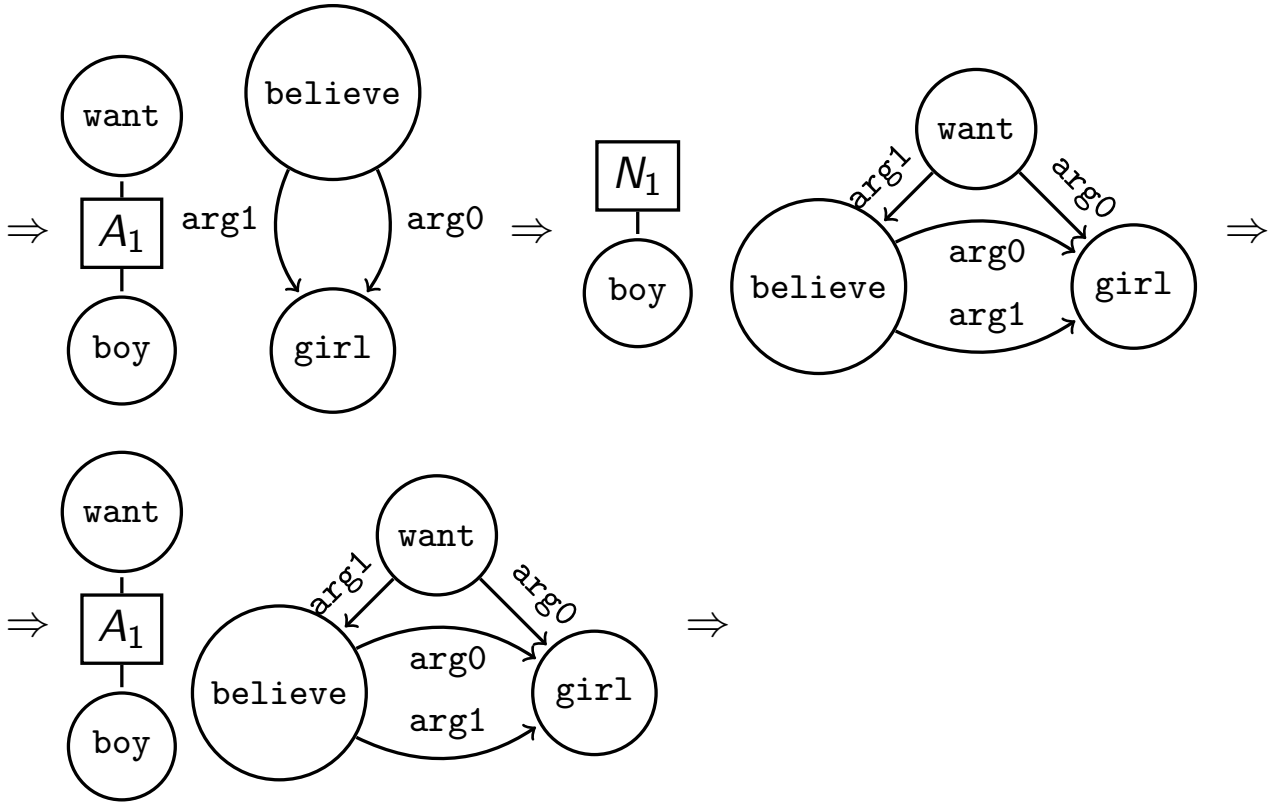




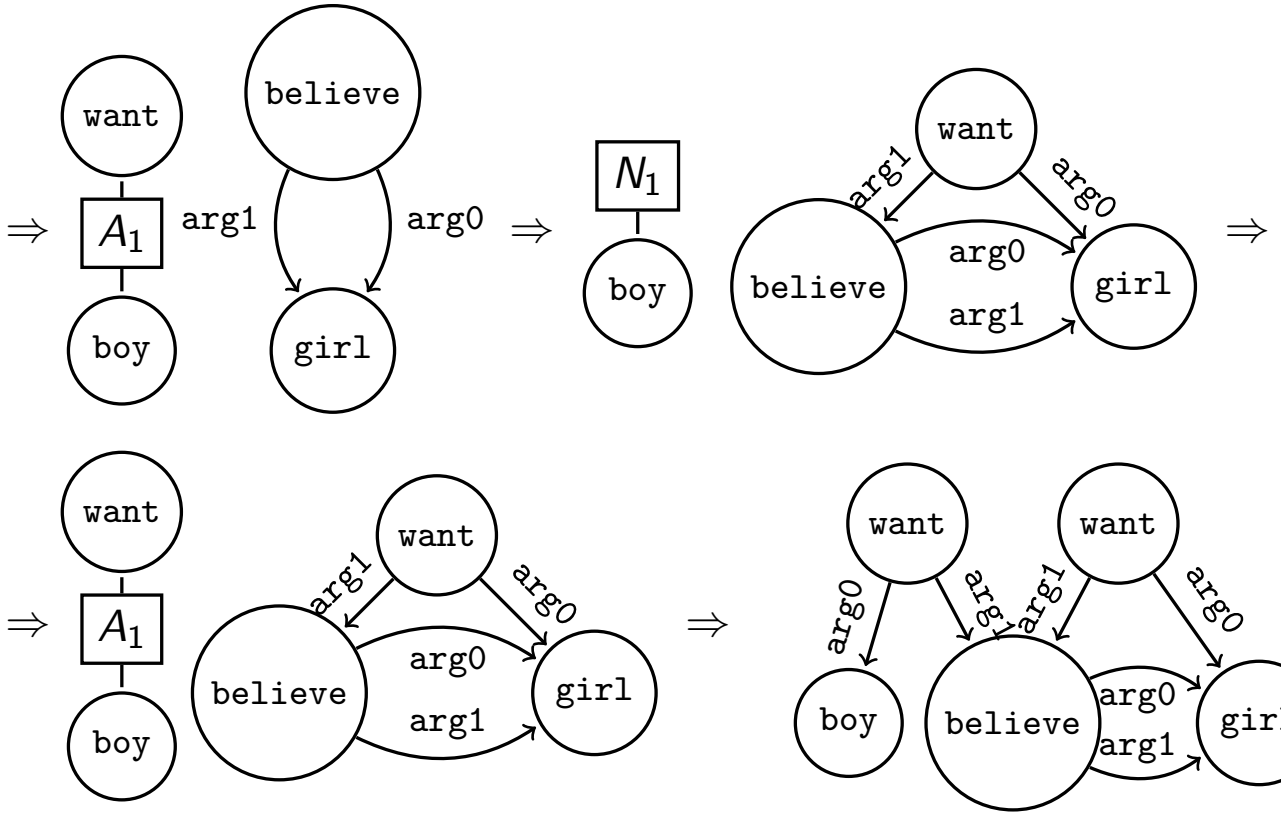
An example derivation

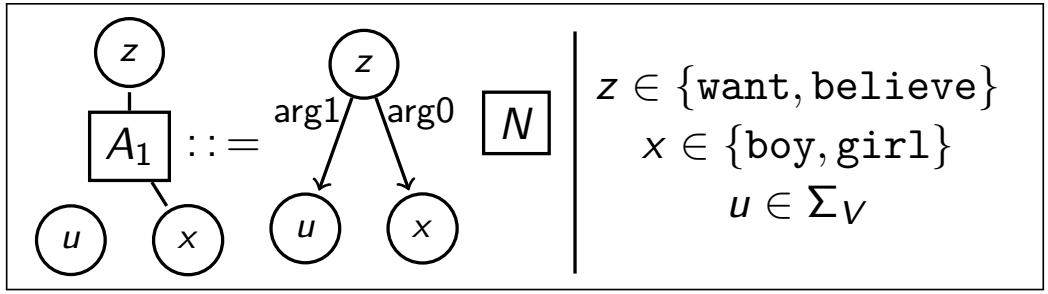


An example derivation



An example derivation





$N ::= ()$

Are CHRGs more suitable than HRGs for AMR generation?

HRGs

Contextual HRGs

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- Cannot generate minimal AMRs in general

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Contextual HRGs

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- No polynomial-time parsing for subclasses (yet)

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Contextual HRGs

- Can generate minimal AMRs
- No polynomial-time parsing for subclasses (yet)
- Likely to be efficiently parsable subclasses (parsing problem at least not harder than for HRGs)

Conclusion:

- Contextual HRGs can generate minimal boy-girl AMRs
- ... and seemingly also minimal AMRs in general

Future work:

- Proof!
- Is there a unique minimal AMR for each meaning?
- Parsing algorithm for subclasses of CHRG
- Other semantic representations and other formalisms

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Thank you for listening!

Summary:

- AMRs are semantic representations of natural language sentences in the form of directed graphs
- Minimal AMRs do not have any repeated substructures
- We want to be able to check the correctness of AMRs
- Previously, hyperedge replacement was used, but minimal AMRs were not fully captured
- Here, contextual hyperedge replacement was used, and even the minimal AMRs could be generated
- Contextual rules cannot be used in practice since there is no efficient parsing algorithm for such grammars, but it is likely that there will be