

# AMR dependency parsing with a typed semantic algebra

Jonas Groschwitz<sup>\*^</sup>, Matthias Lindemann<sup>\*</sup>,  
Meaghan Fowlie<sup>\*</sup>, Mark Johnson<sup>^</sup>, Alexander Koller<sup>\*</sup>

<sup>\*</sup>Saarland University

<sup>^</sup>Macquarie University



ACL 2018  
Melbourne, Australia  
July 17





**Matthias Lindemann**  
Saarland University



**Meaghan Fowlie**  
Saarland University



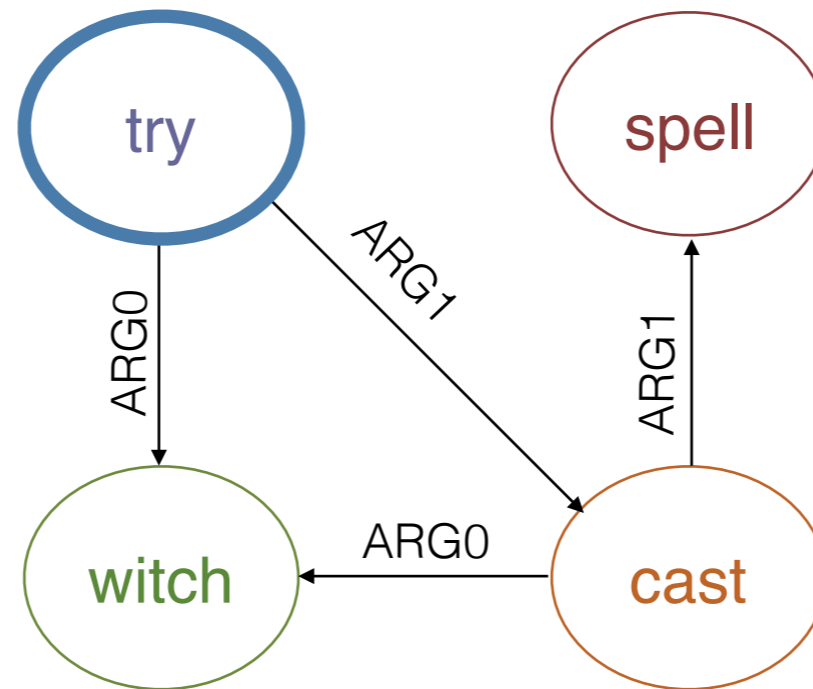
**Mark Johnson**  
Macquarie University



**Alexander Koller**  
Saarland University

# Abstract Meaning Representation (AMR)

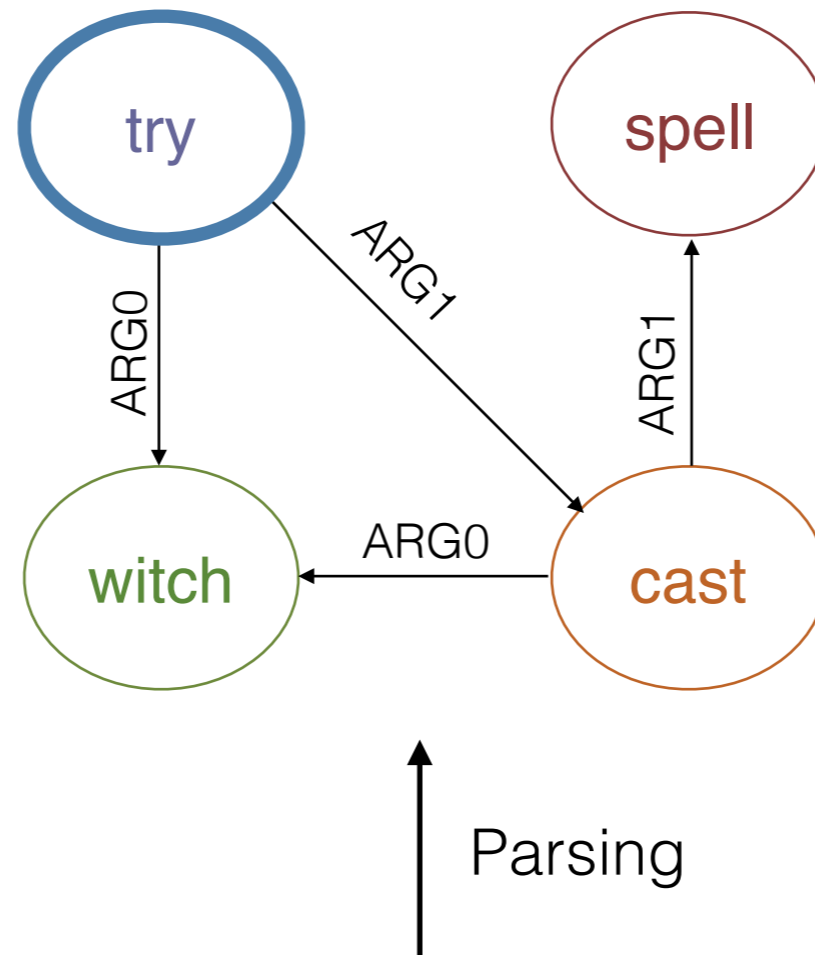
Banarescu et al. 2013



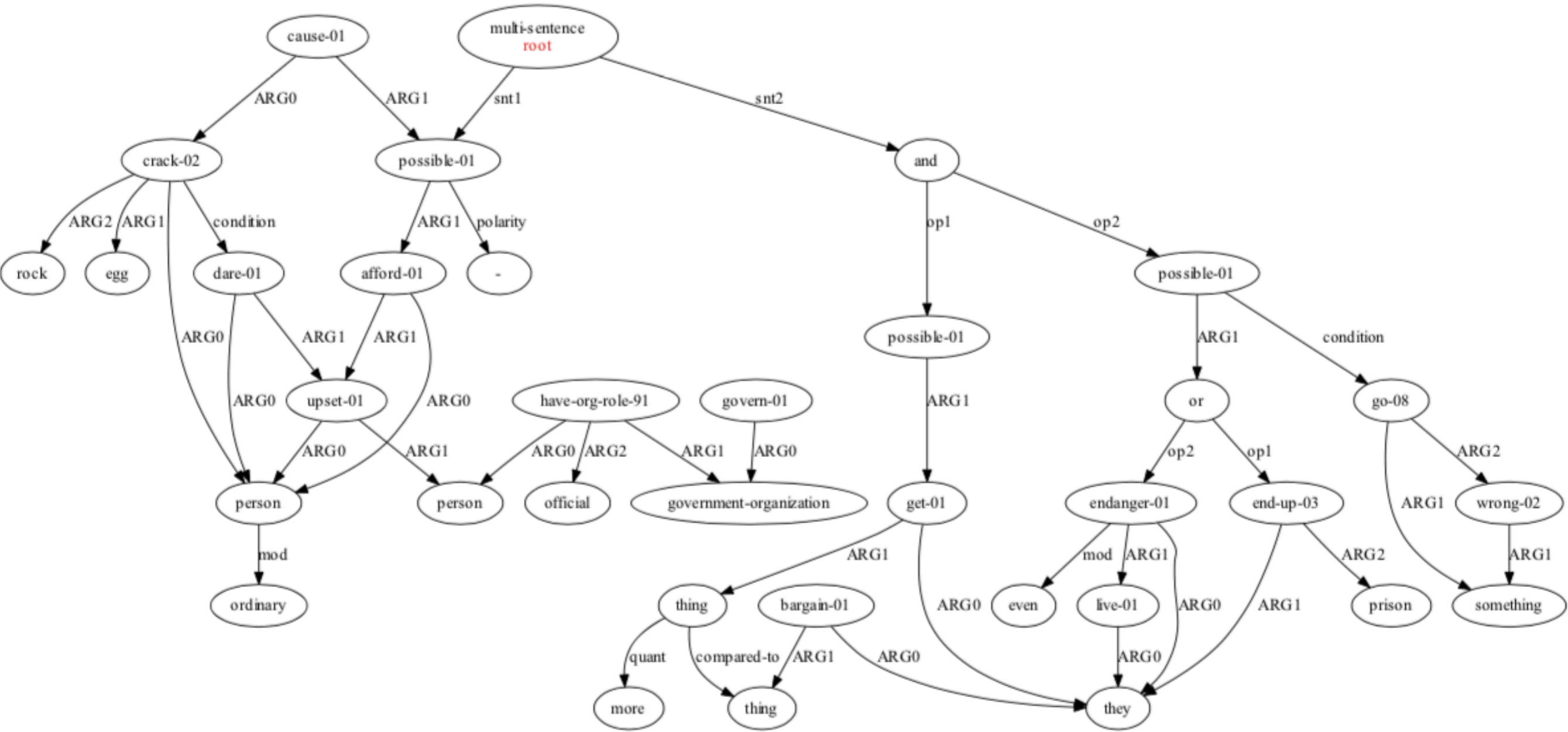
The witch tried to cast a spell

# Abstract Meaning Representation (AMR)

Banarescu et al. 2013



The witch tried to cast a spell

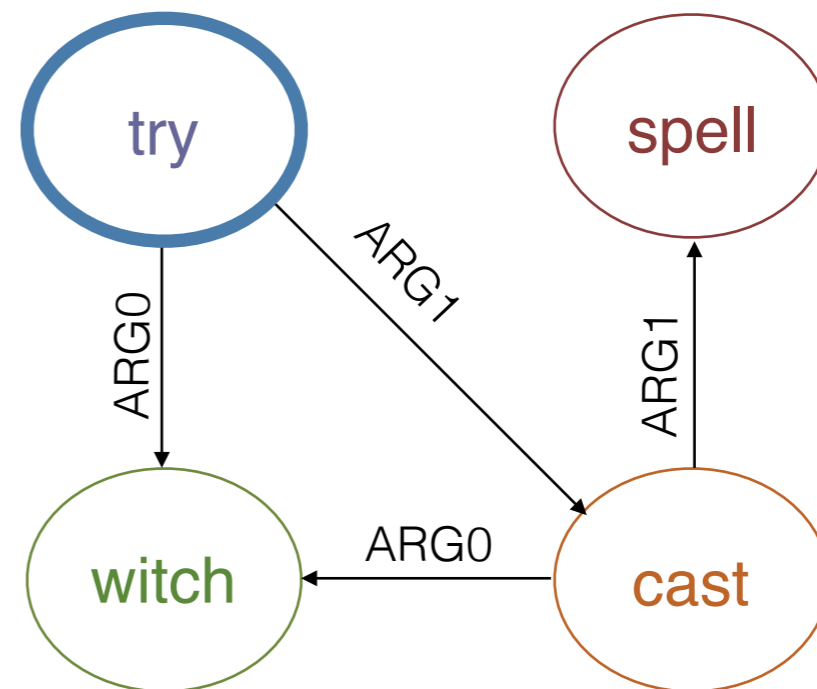


# Classic AMR parser (e.g. JAMR 2014)

Step 1: Predict nodes

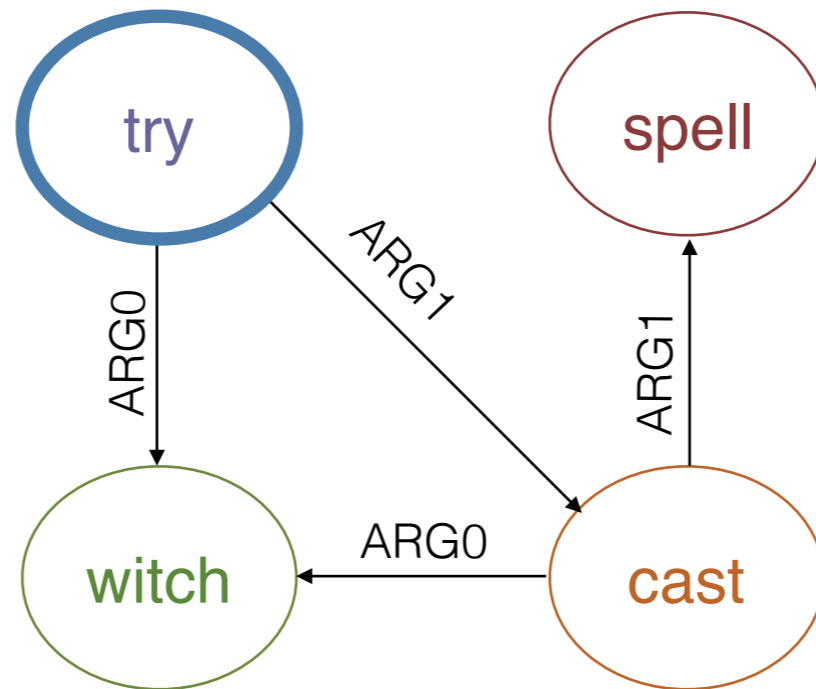


Step 2: Predict edges

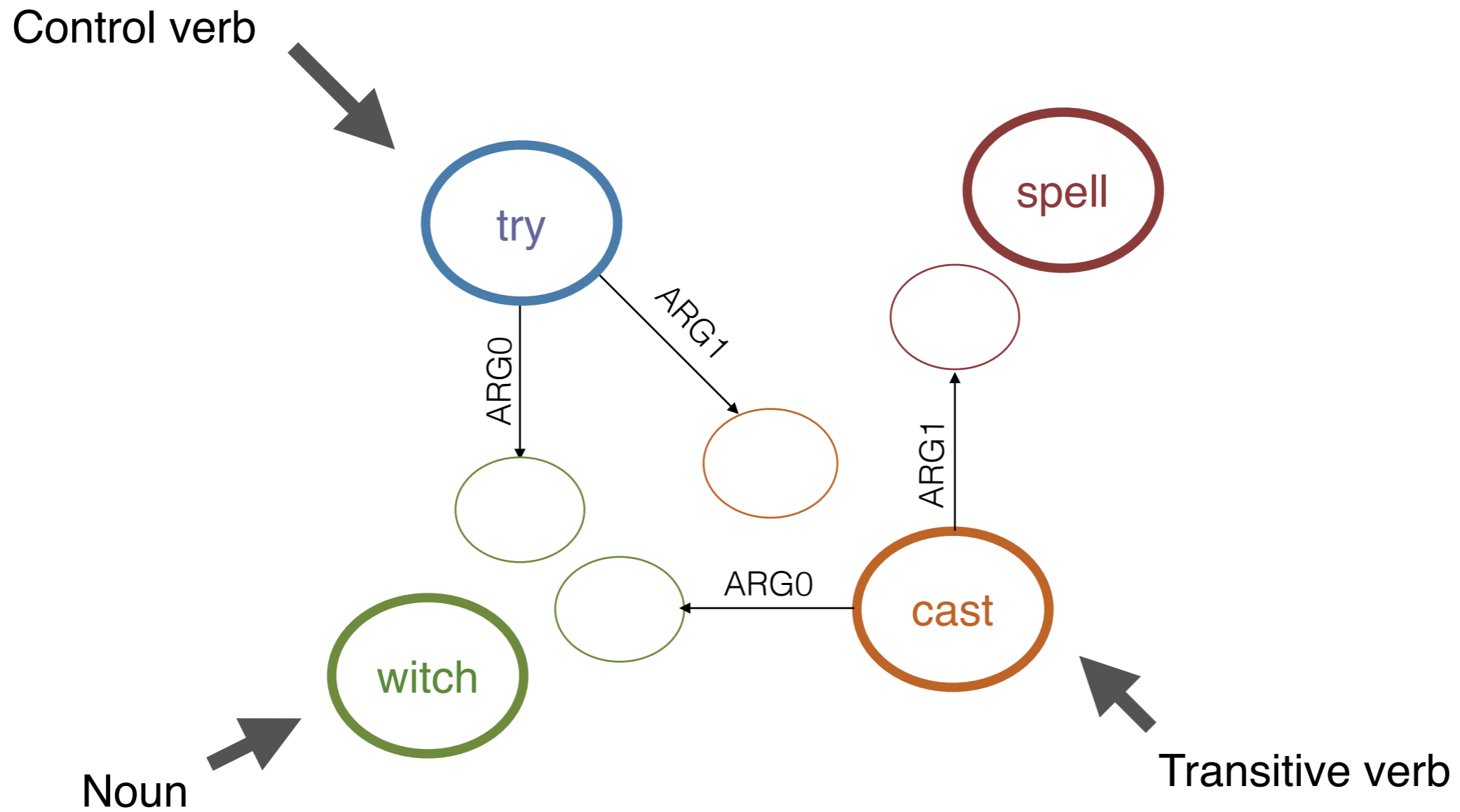


The witch tried to cast a spell

# Not just nodes and edges



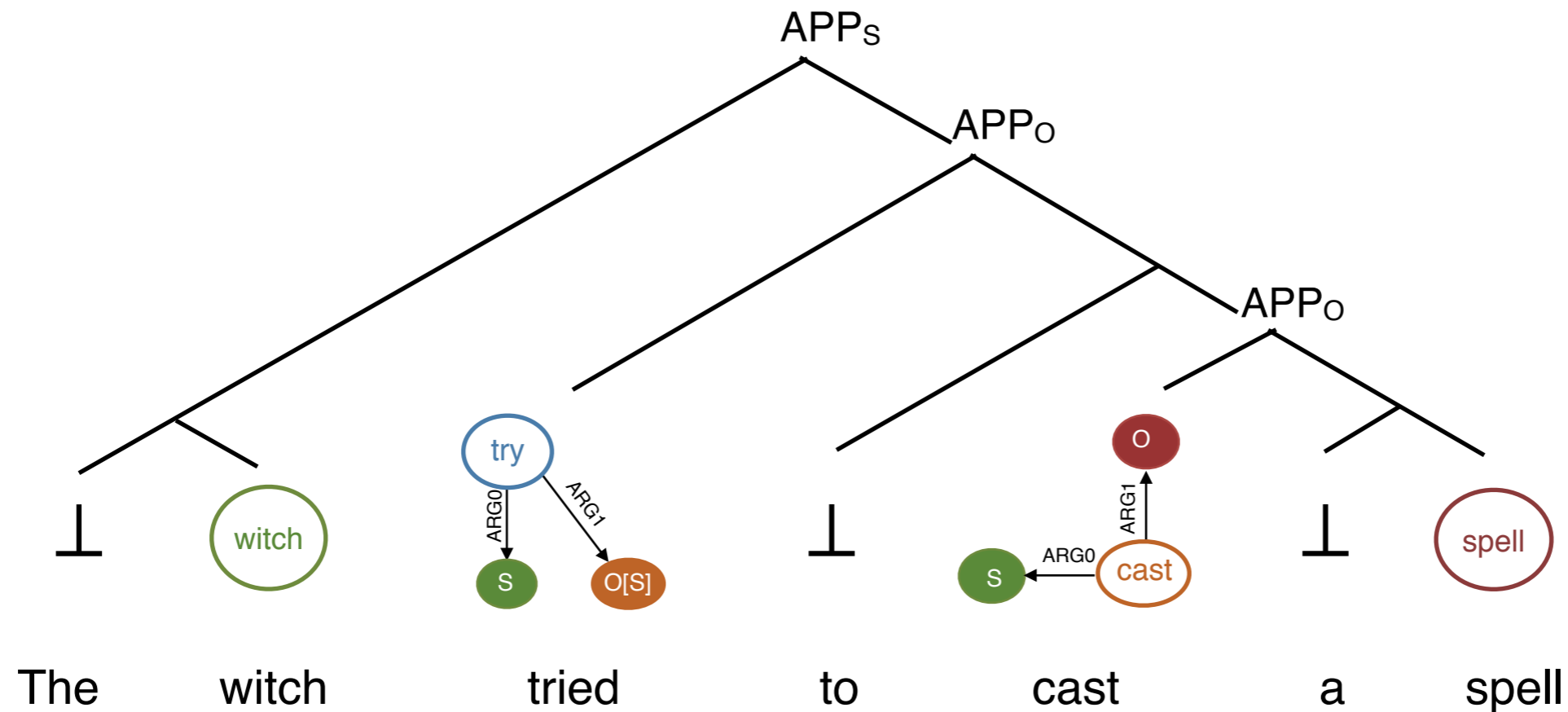
# Not just nodes and edges





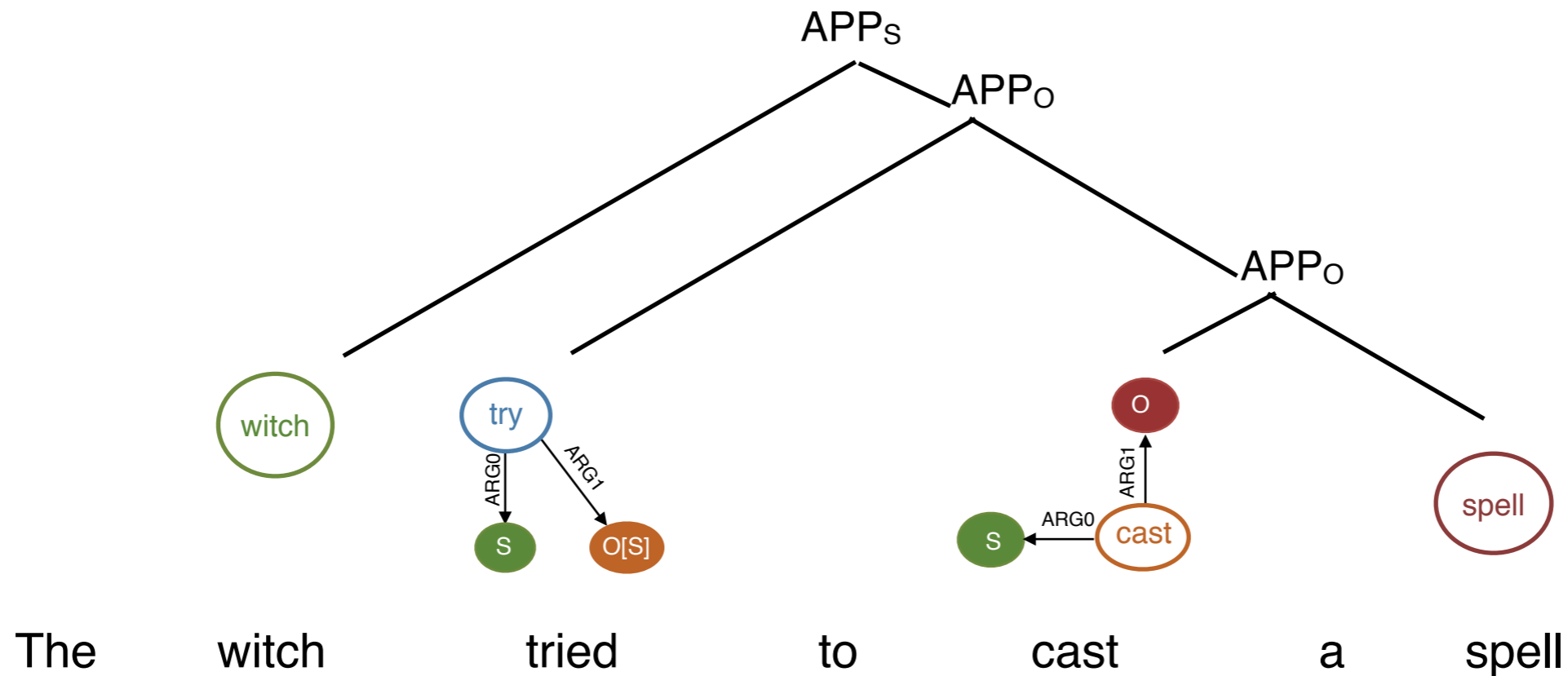
# Hidden compositional structure

Principle of compositionality: the meaning of a complex expression is determined by the meanings of its constituent expressions and the rules used to combine them.



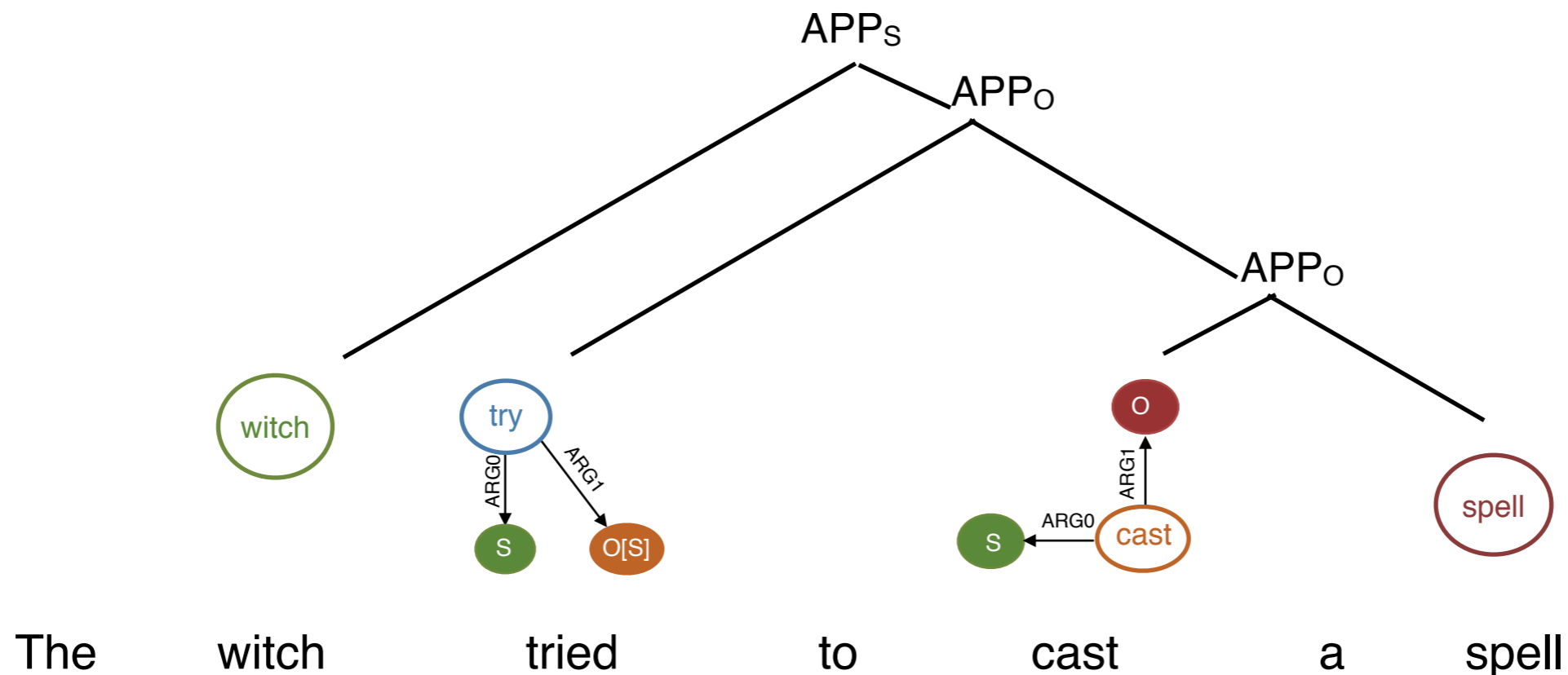
# Hidden compositional structure

Principle of compositionality: the meaning of a complex expression is determined by the meanings of its constituent expressions and the rules used to combine them.

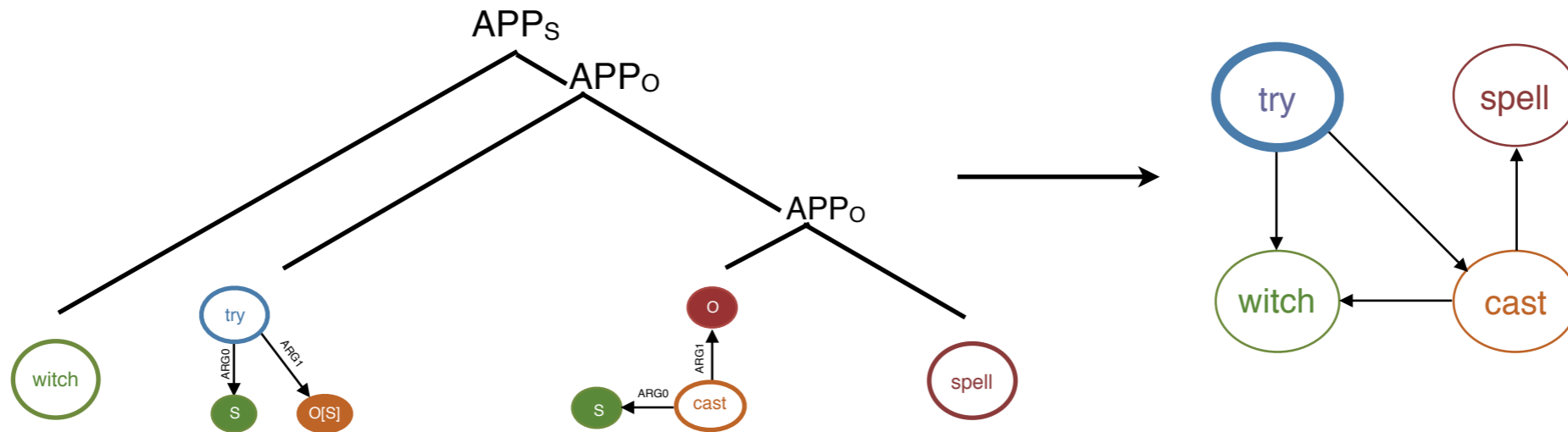


# Hidden compositional structure

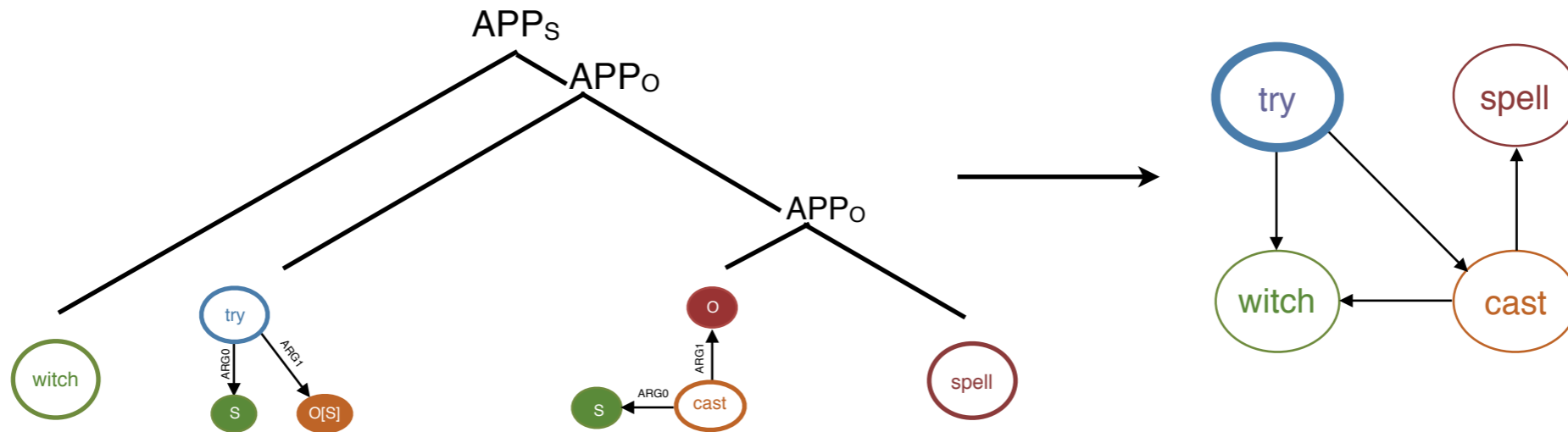
Principle of compositionality: the meaning of a complex expression is determined by the meanings of its constituent expressions and the rules used to combine them.



- Widely accepted in linguistics, long history (Frege 1800s)
- Use this knowledge to guide machine learning!

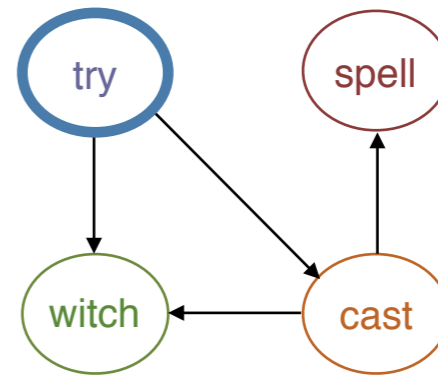
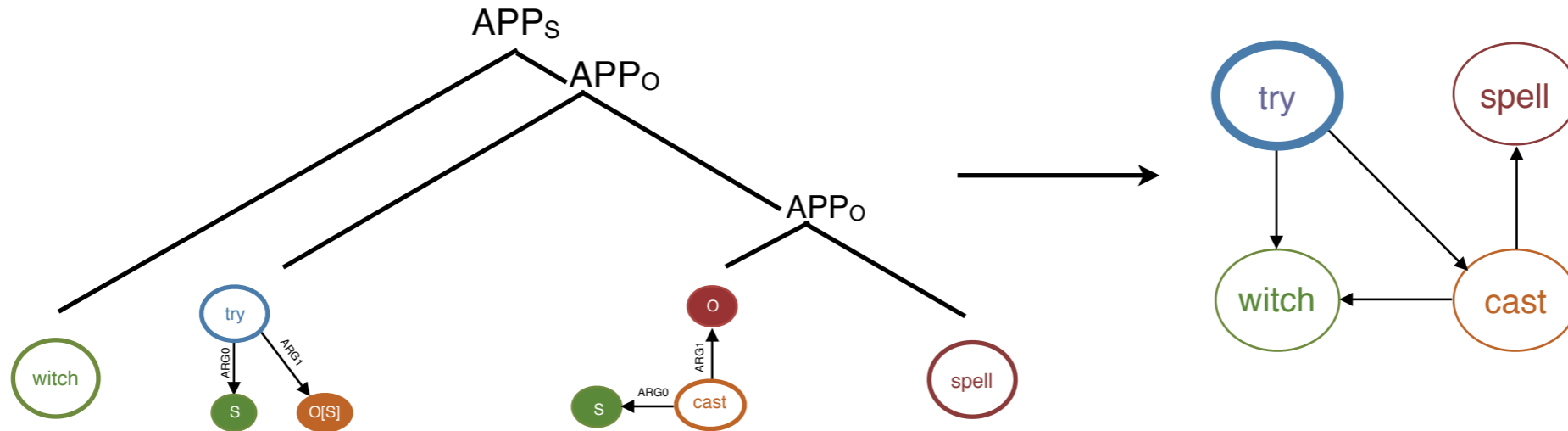


The witch tried to cast a spell

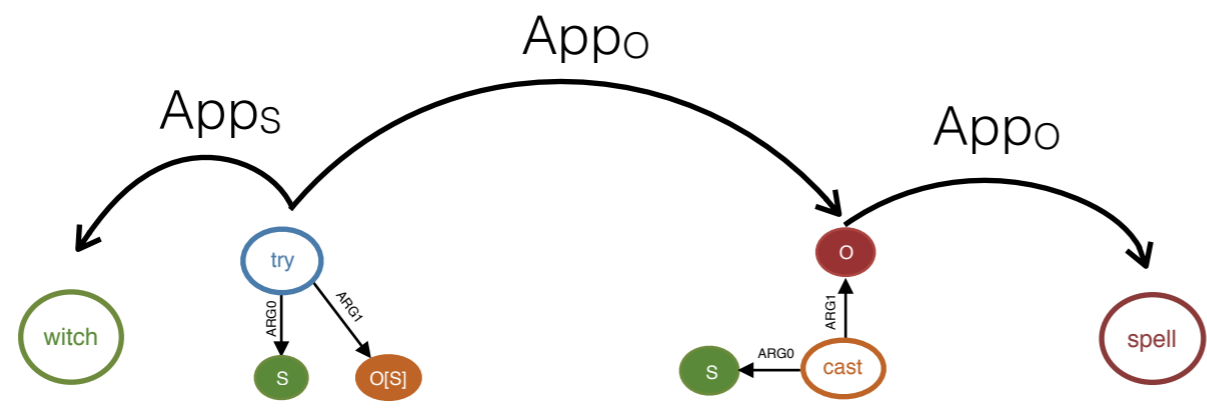


↑  
difficult

The witch tried to cast a spell



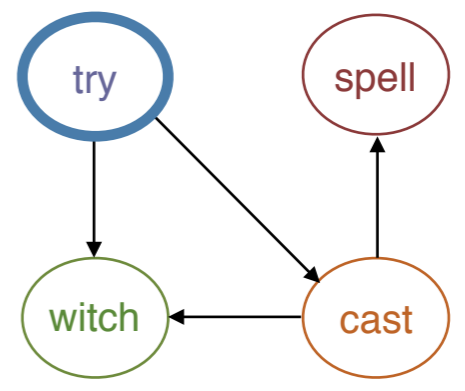
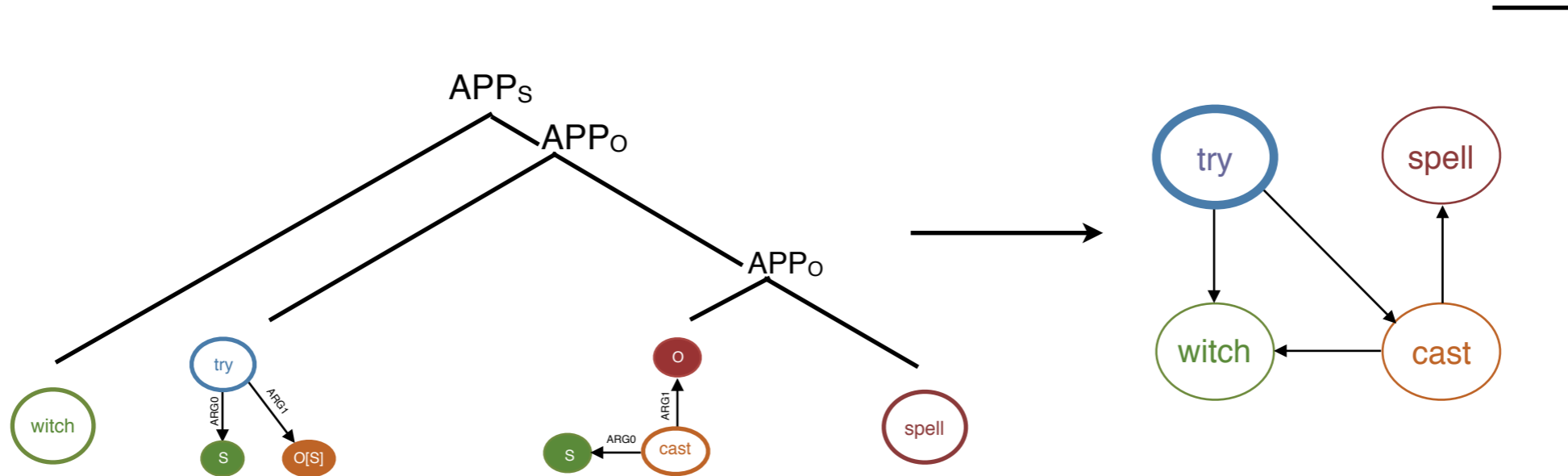
equivalent



dependencies!

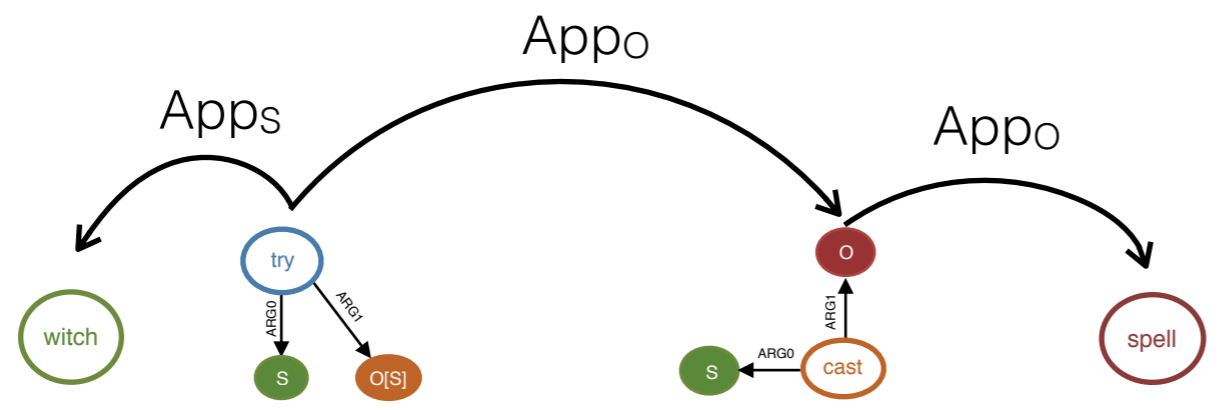
easy (easier)

The witch tried to cast a spell



Part 1

equivalent



dependencies!

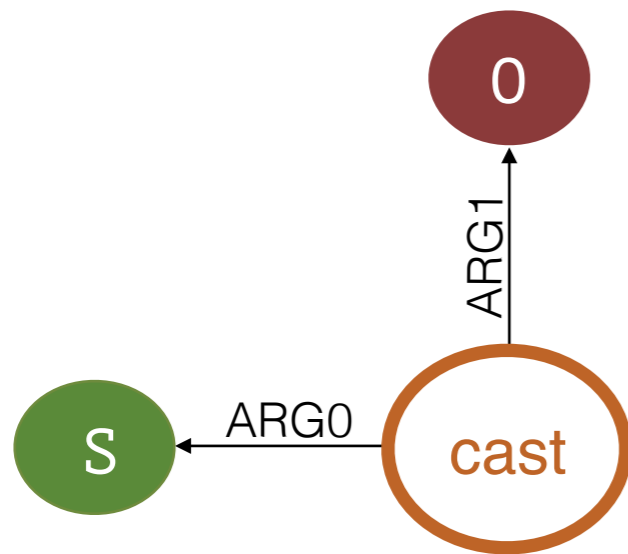
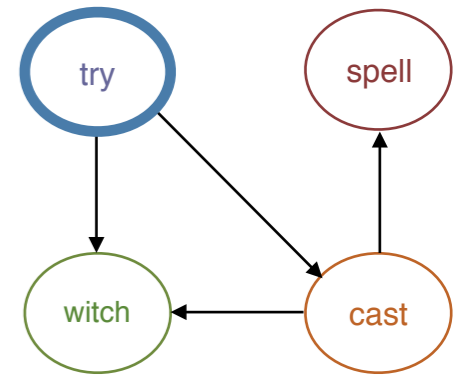
easy (easier)

The witch tried to cast a spell

Part 2

# Apply-Modify (AM) Algebra

G. et al, IWCS 2017

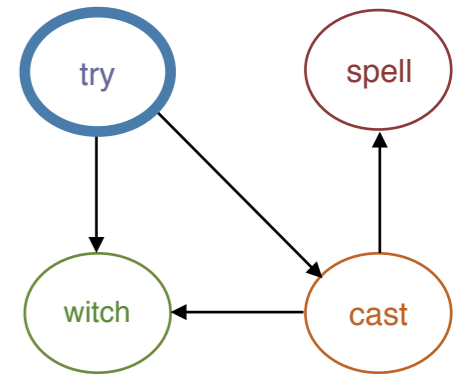


\*HR algebra, Courcelle & Engelfriet 2012

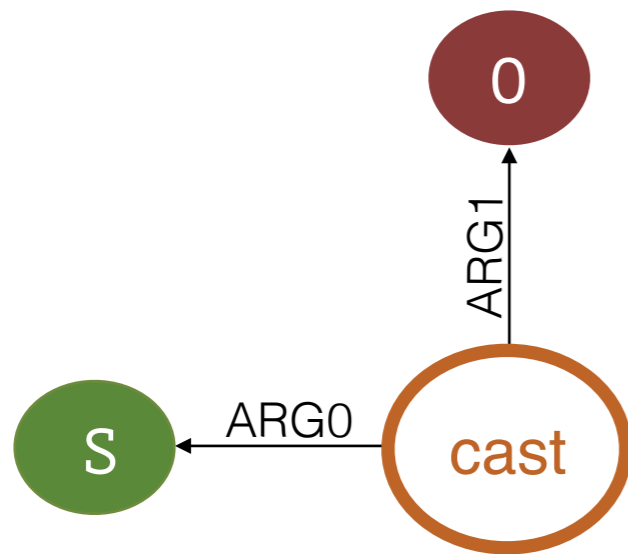


# Apply-Modify (AM) Algebra

G. et al, IWCS 2017



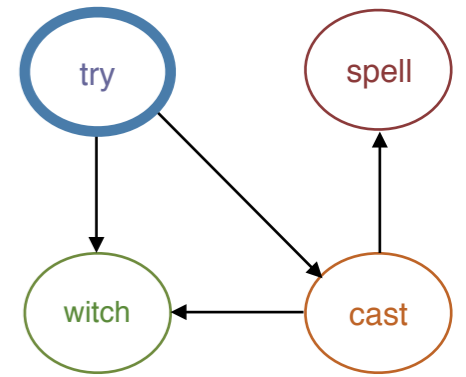
- Empty argument slots are labeled with sources\* S,O,... (subject, object,...)



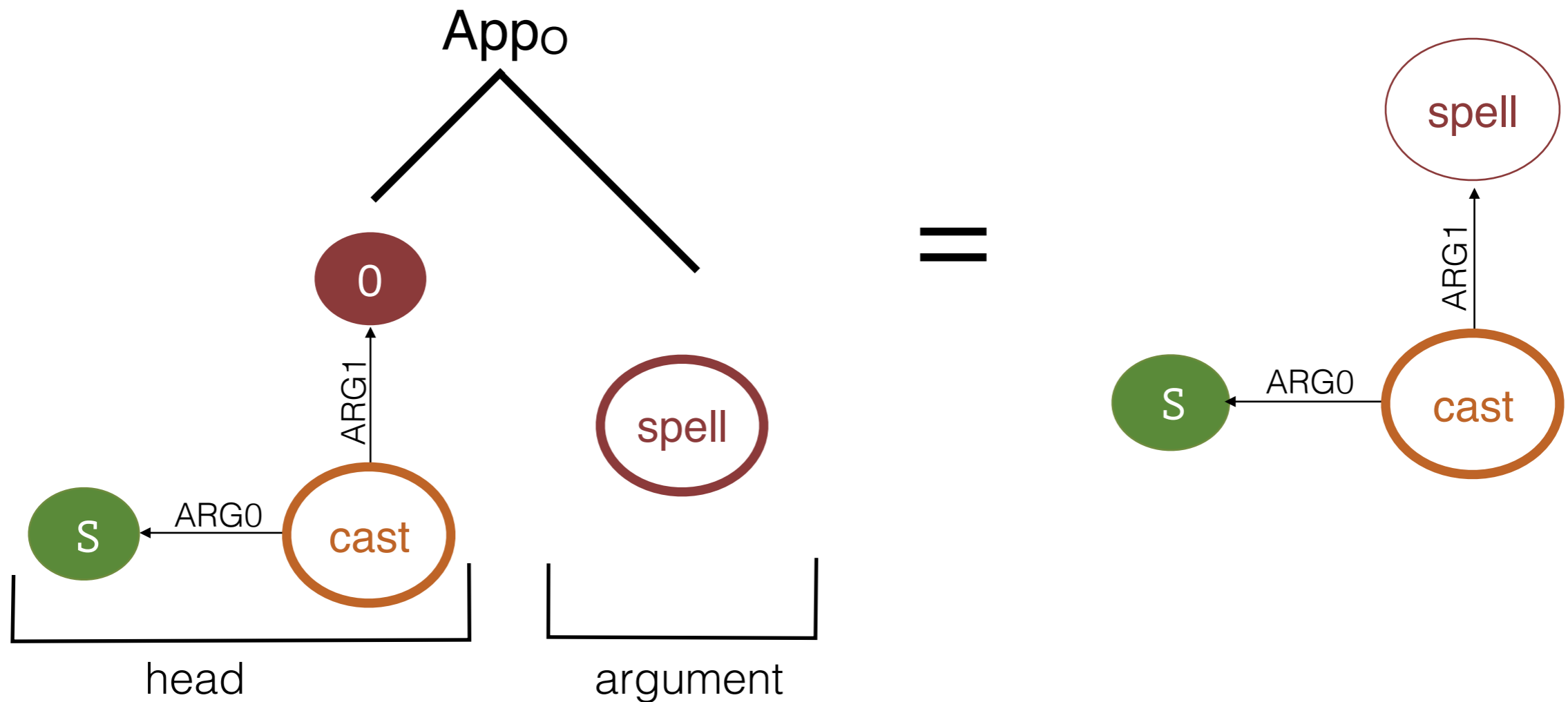
\*HR algebra, Courcelle & Engelfriet 2012

# Apply-Modify (AM) Algebra

G. et al, IWCS 2017

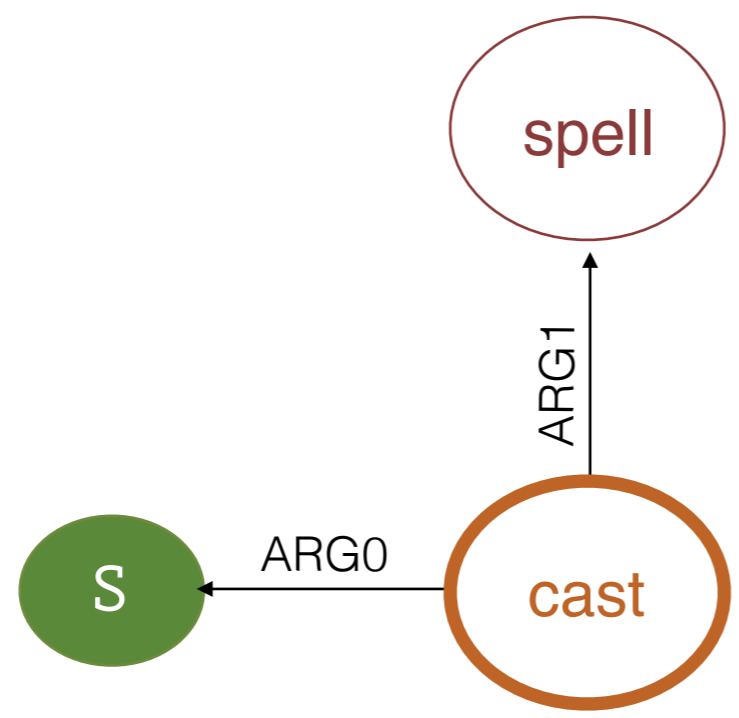
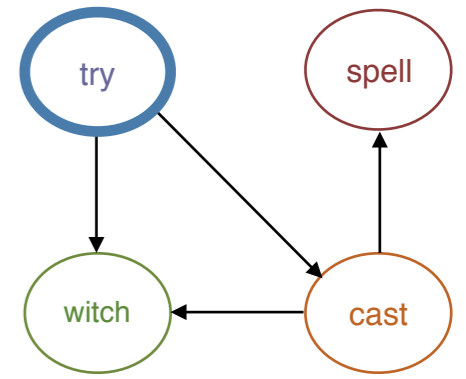


- Empty argument slots are labeled with sources\* S,O,... (subject, object,...)
- Have 'apply' operation for each source, e.g.  $APP_O$



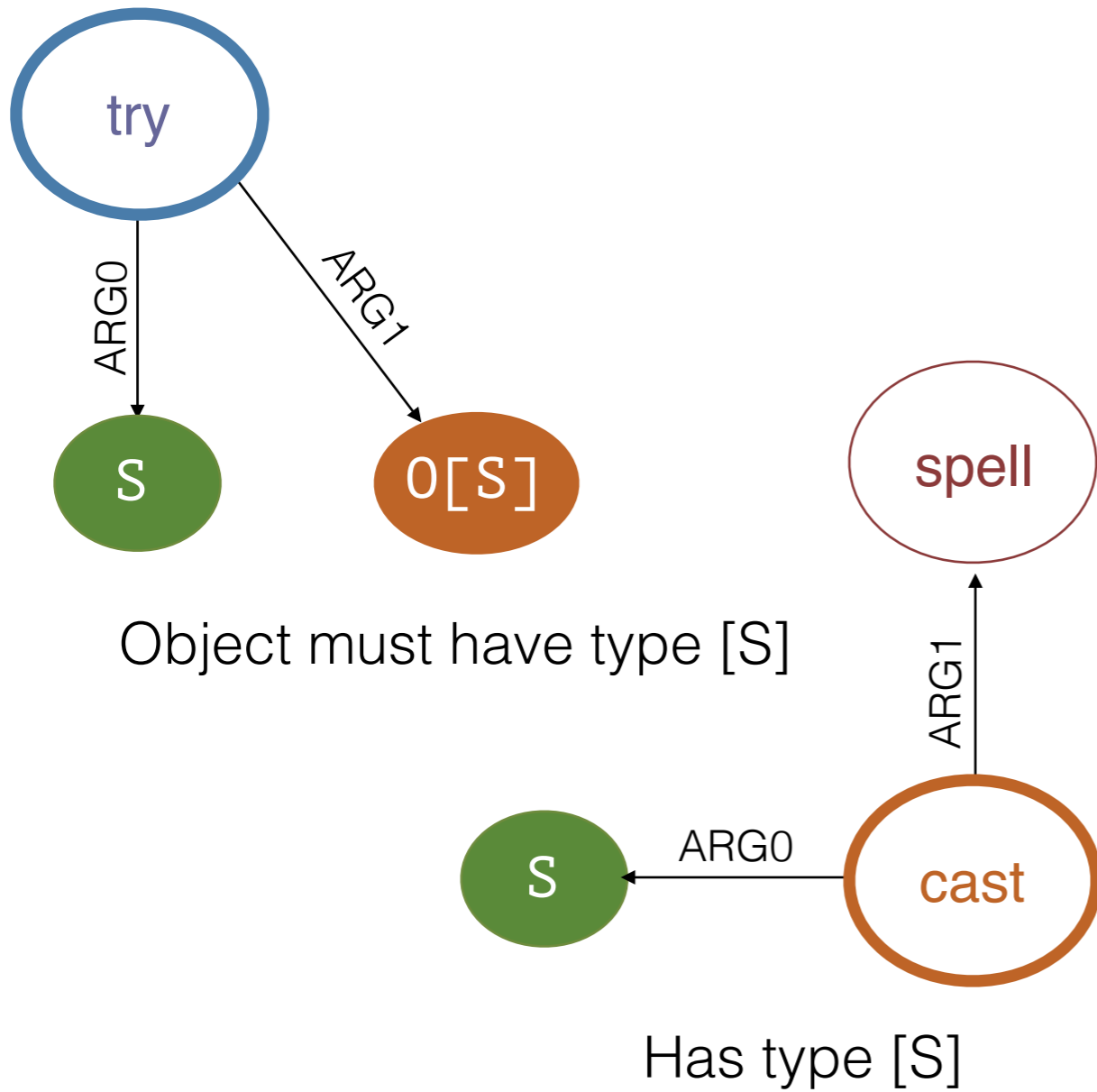
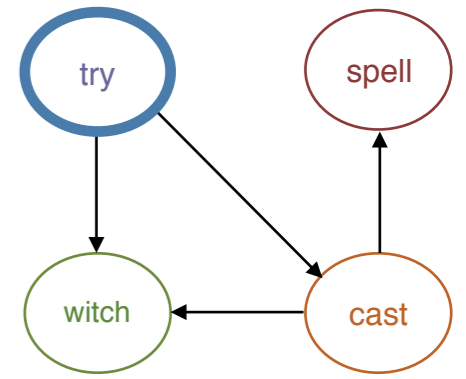
\*HR algebra, Courcelle & Engelfriet 2012

# Typed AM Algebra

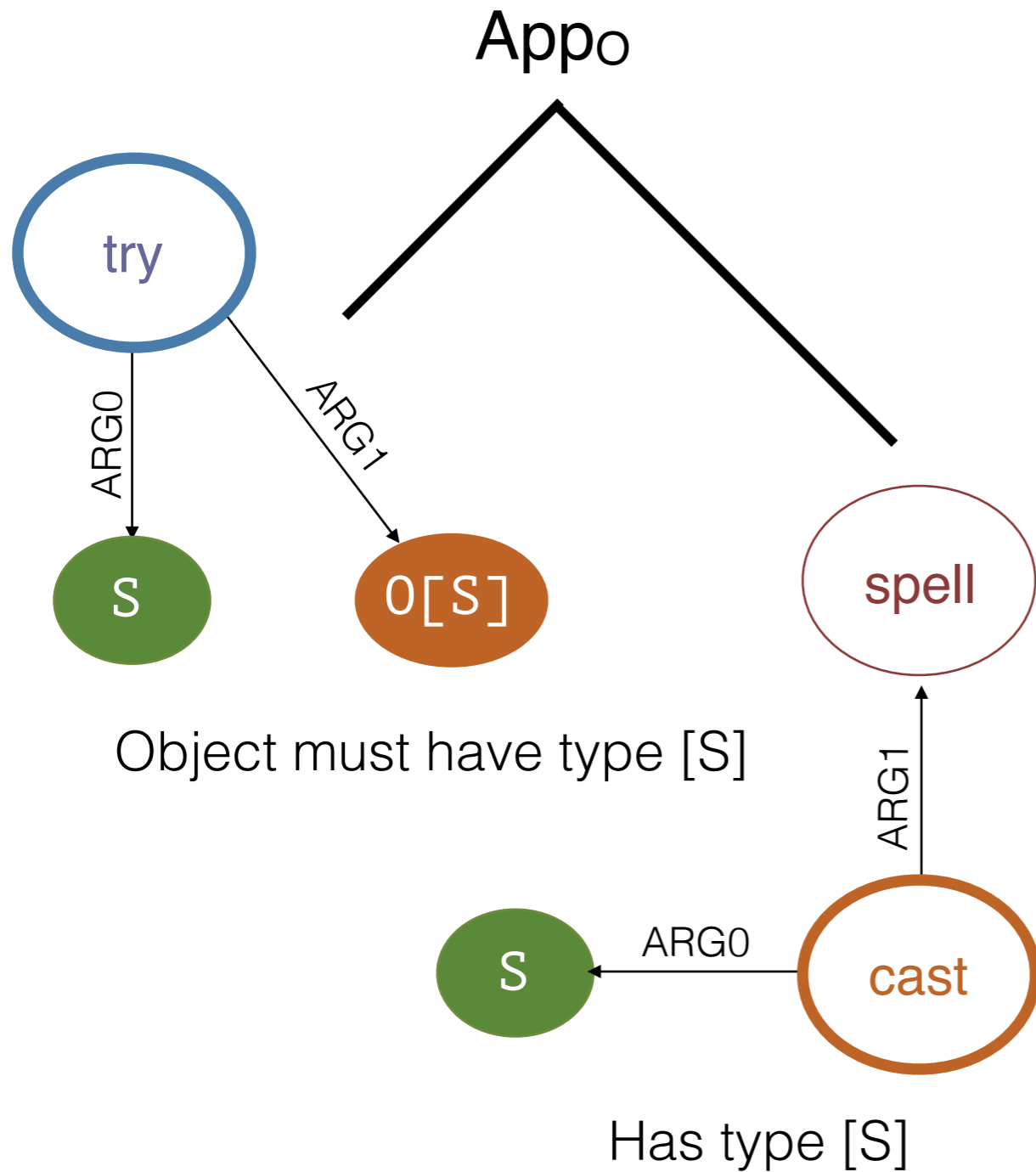
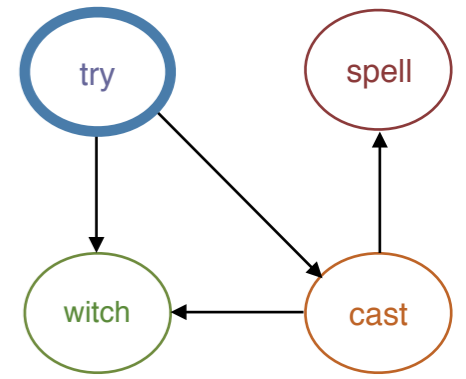


Has type [S]

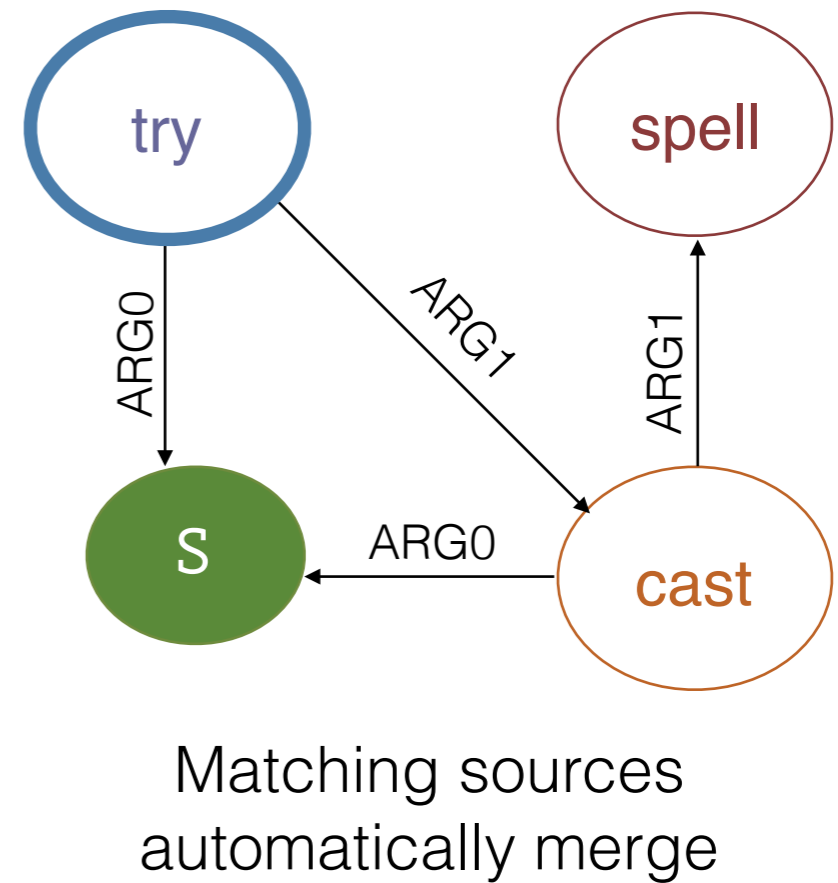
# Typed AM Algebra



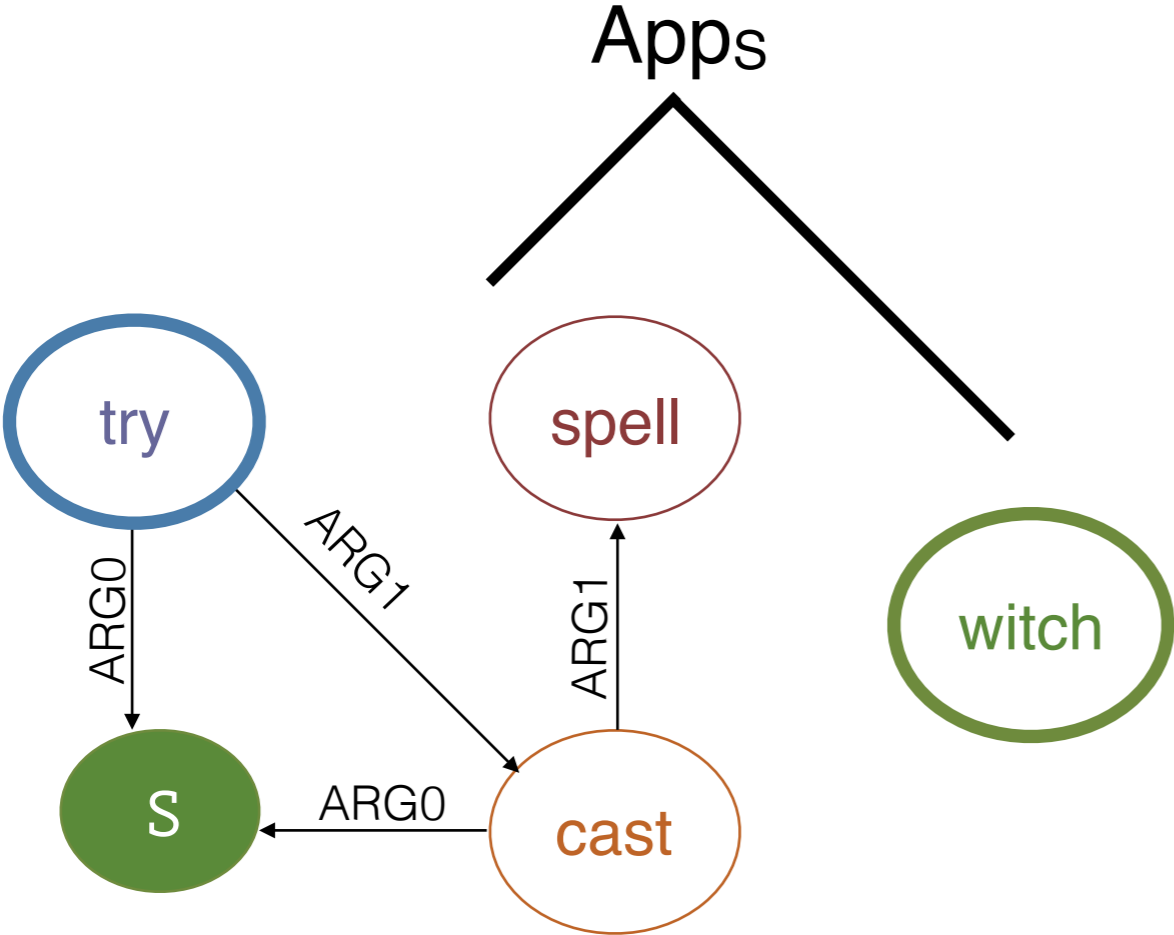
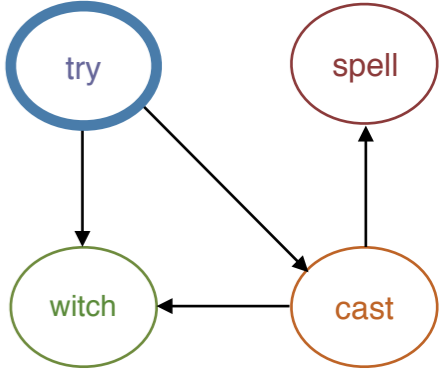
# Typed AM Algebra



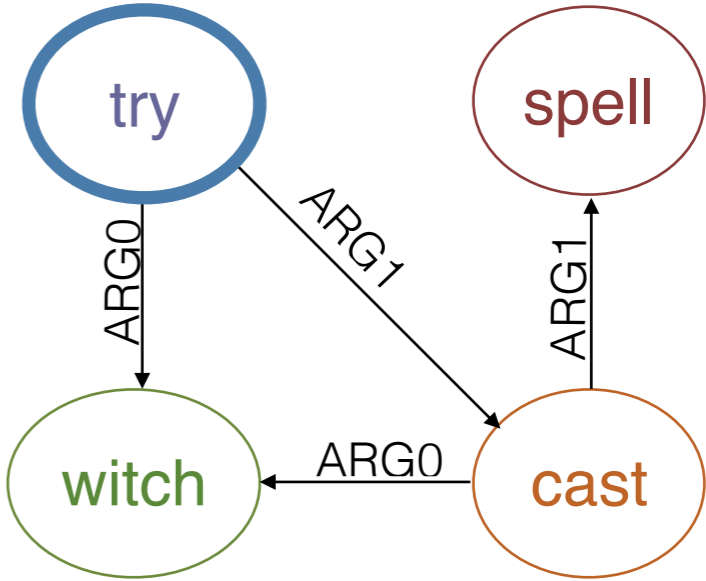
==



# Apply-Modify Algebra

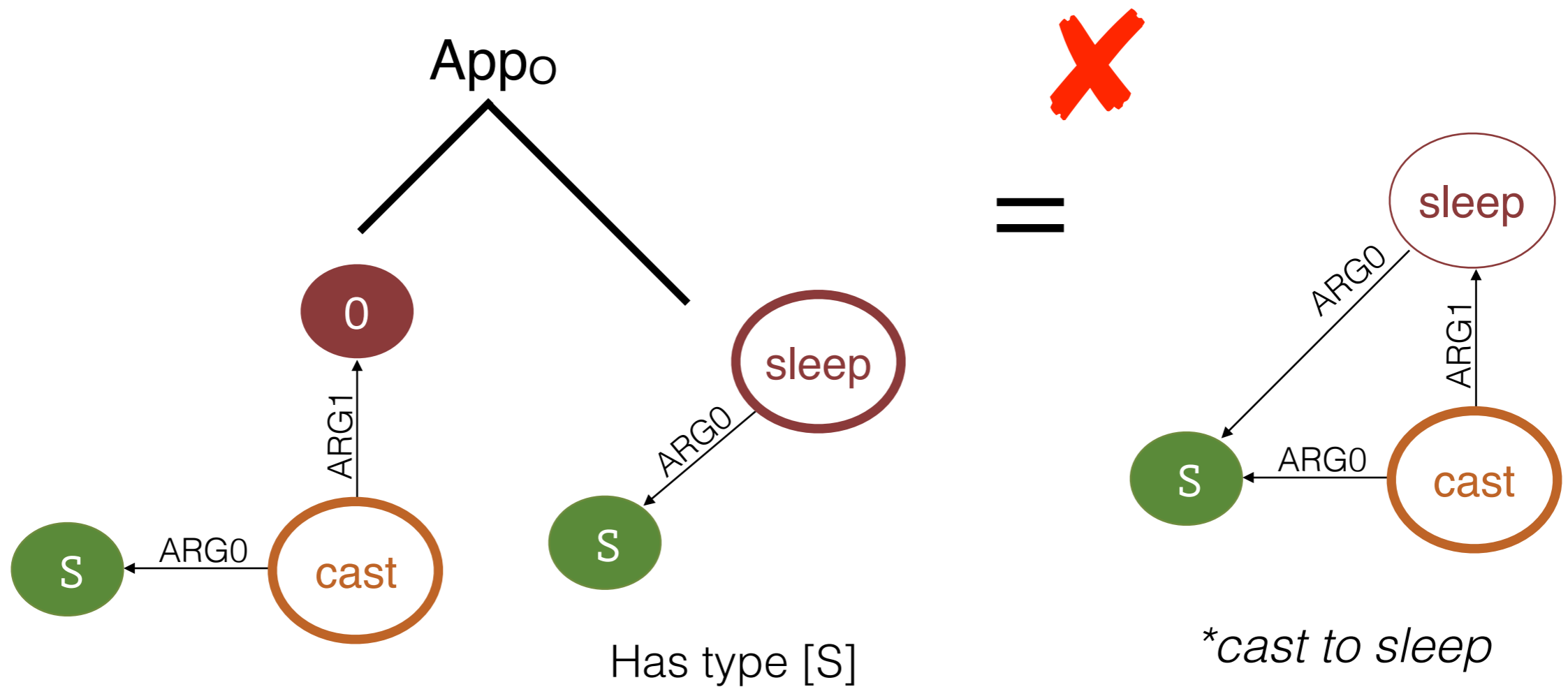


=

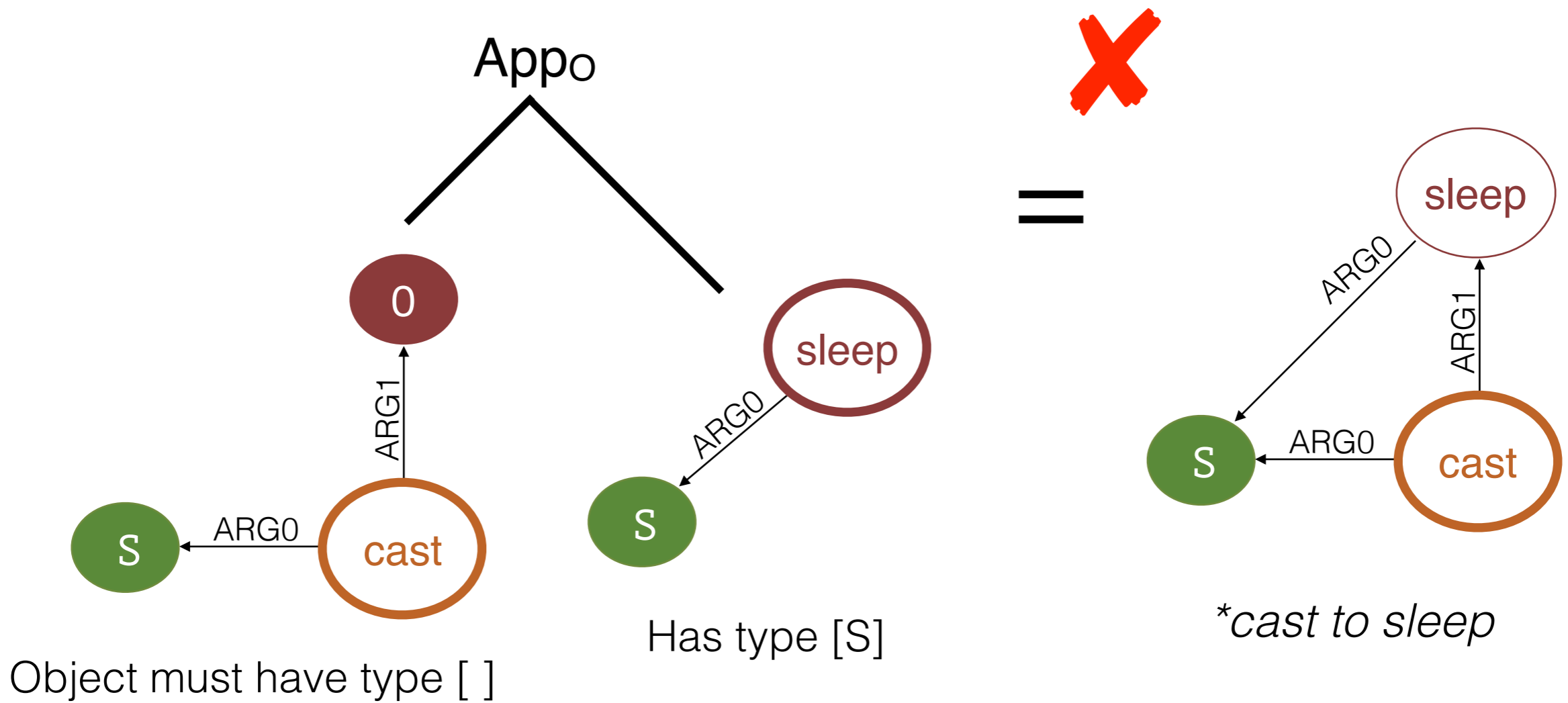


The witch tried to cast a spell

# Types control reentrancies

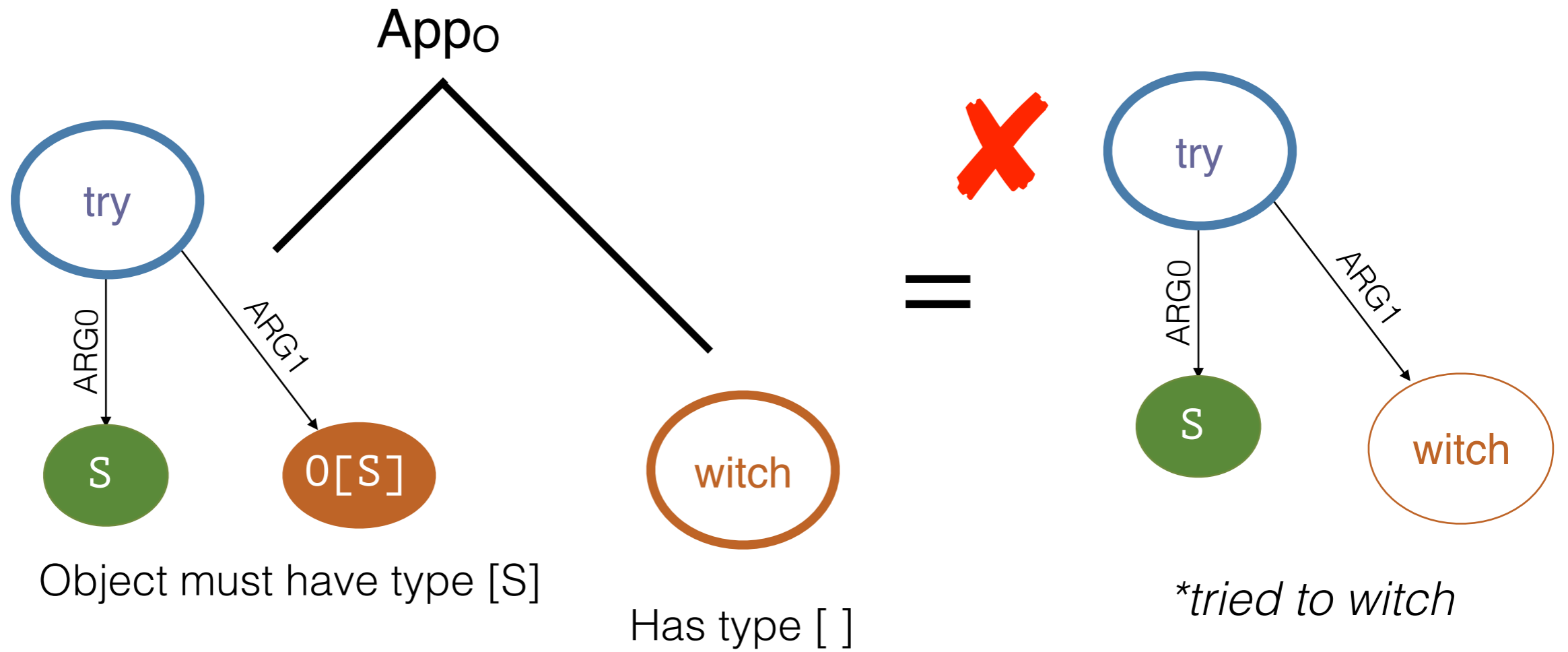
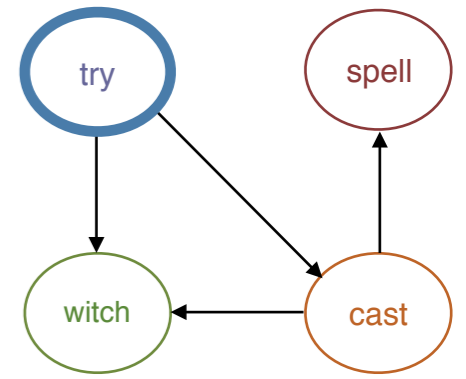


# Types control reentrancies



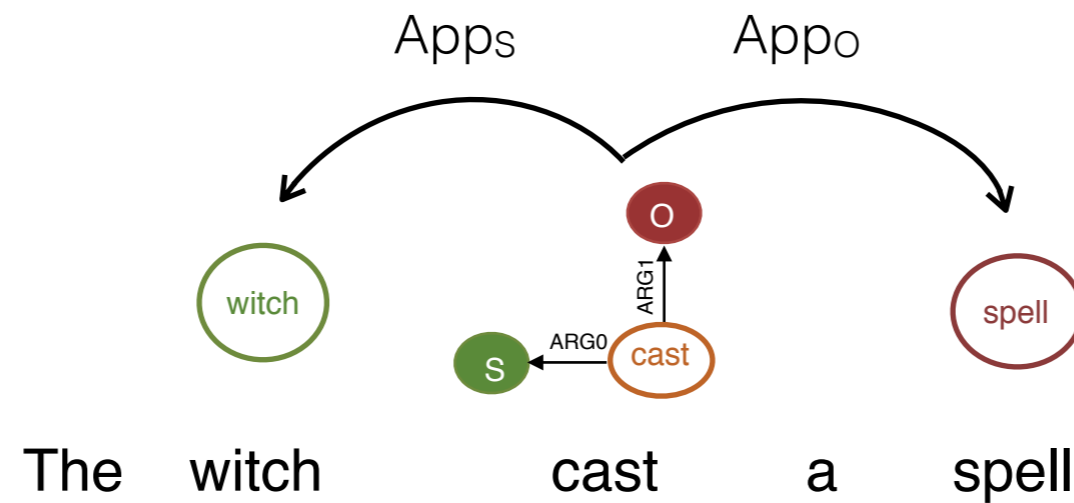


# Types control reentrancies



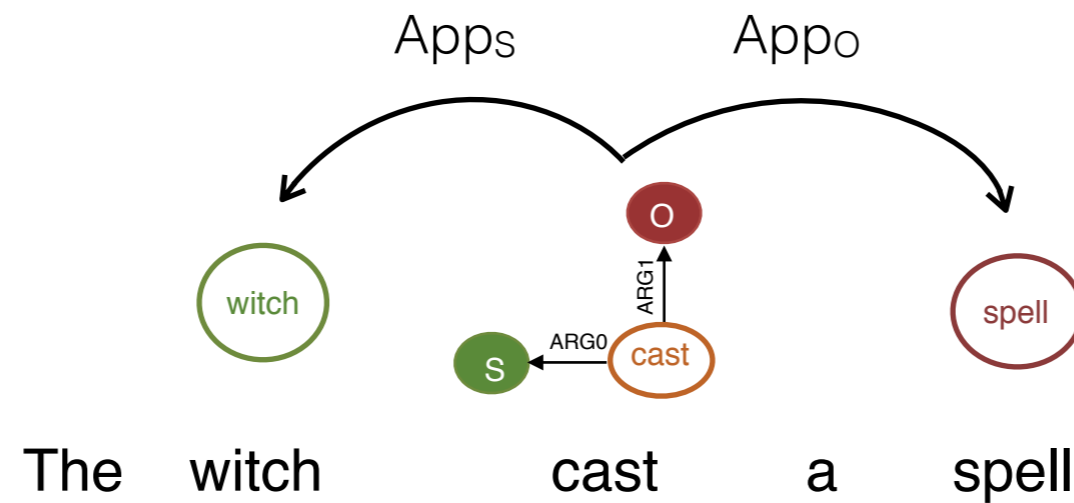
# AM Dependency Trees

dependencies define operations, but not their order



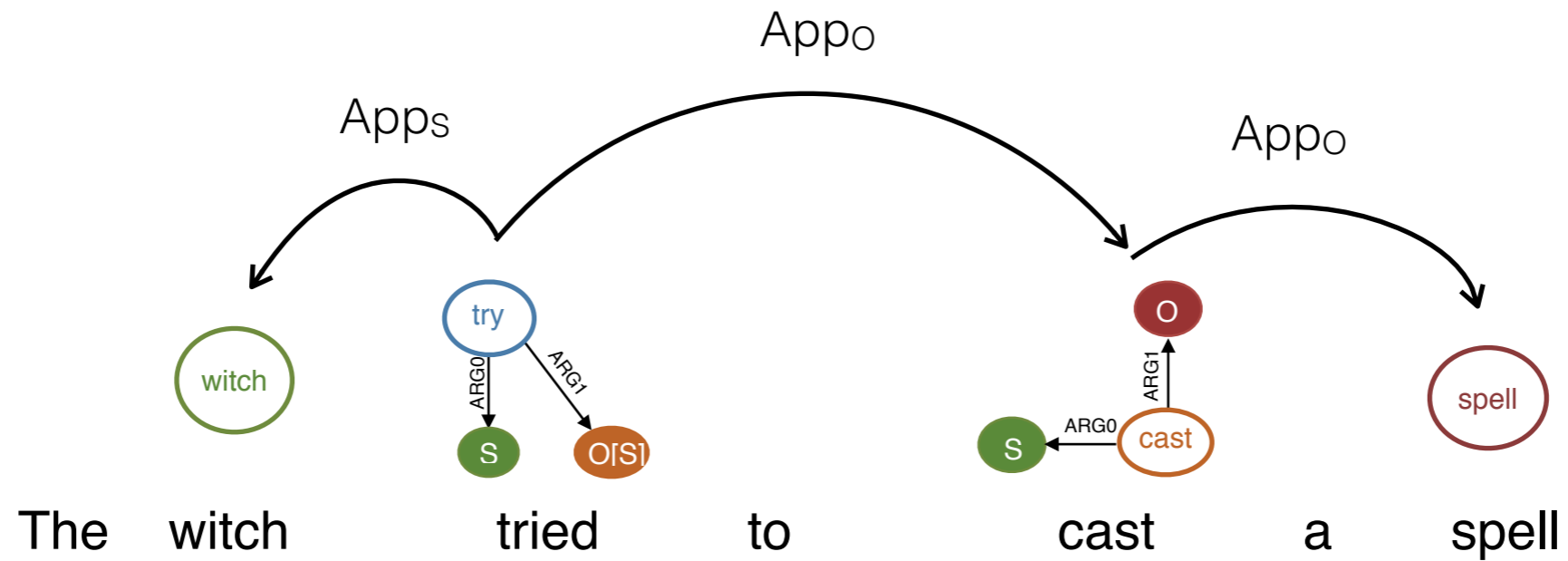
# AM Dependency Trees

dependencies define operations, but not their order



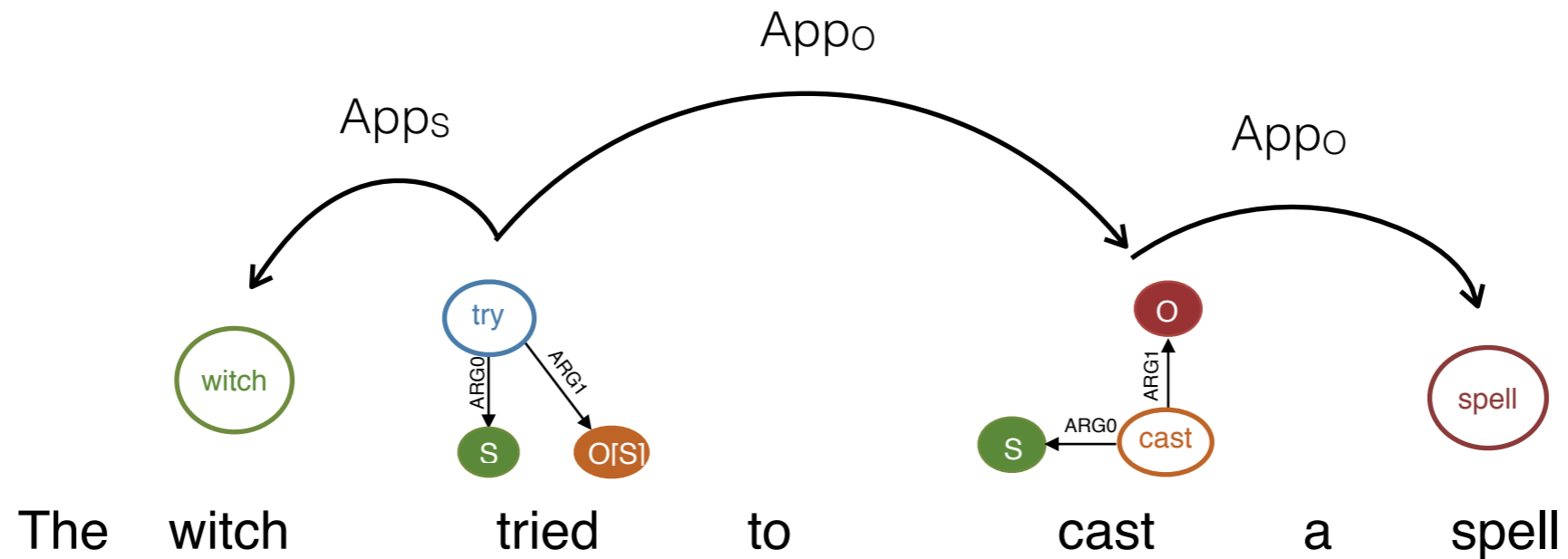
here: order does not matter

# AM Dependency Trees



here: need APP<sub>O</sub> before APP<sub>S</sub> to get reentrancies

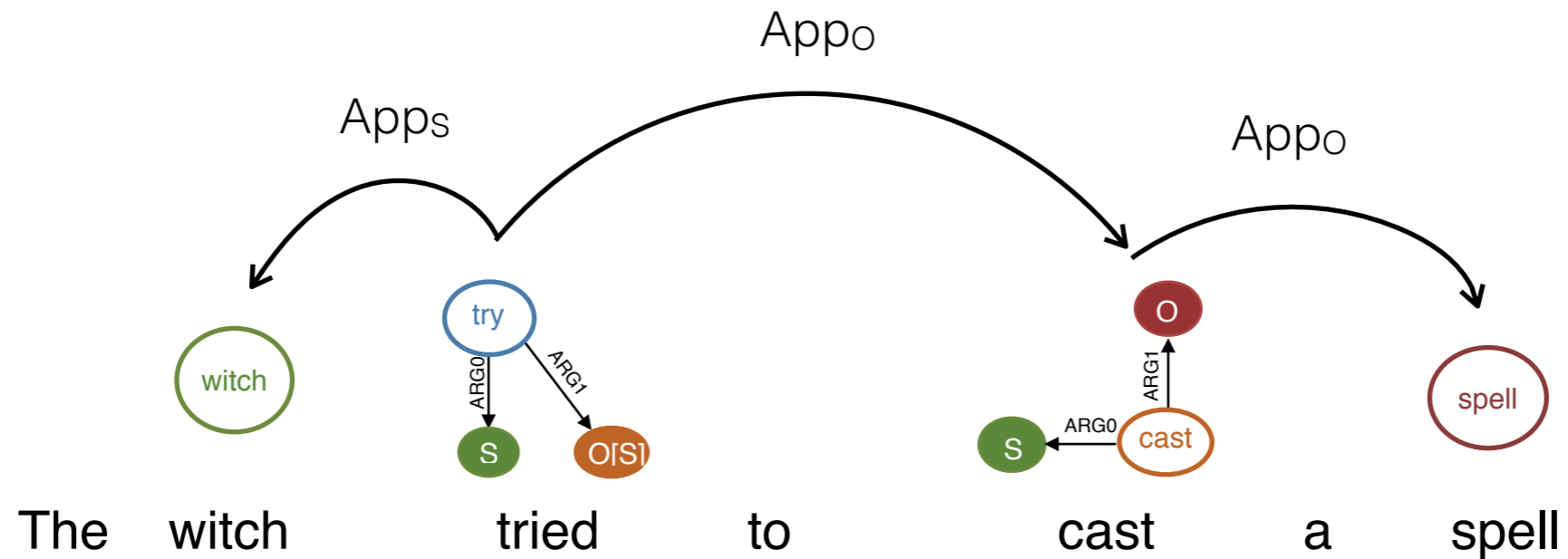
# AM Dependency Trees



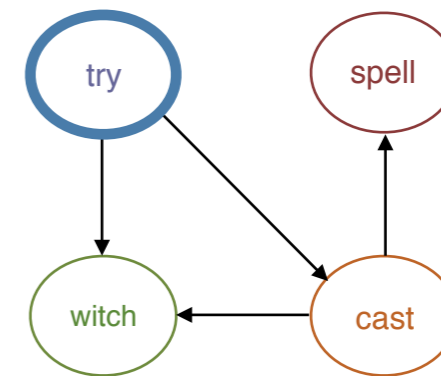
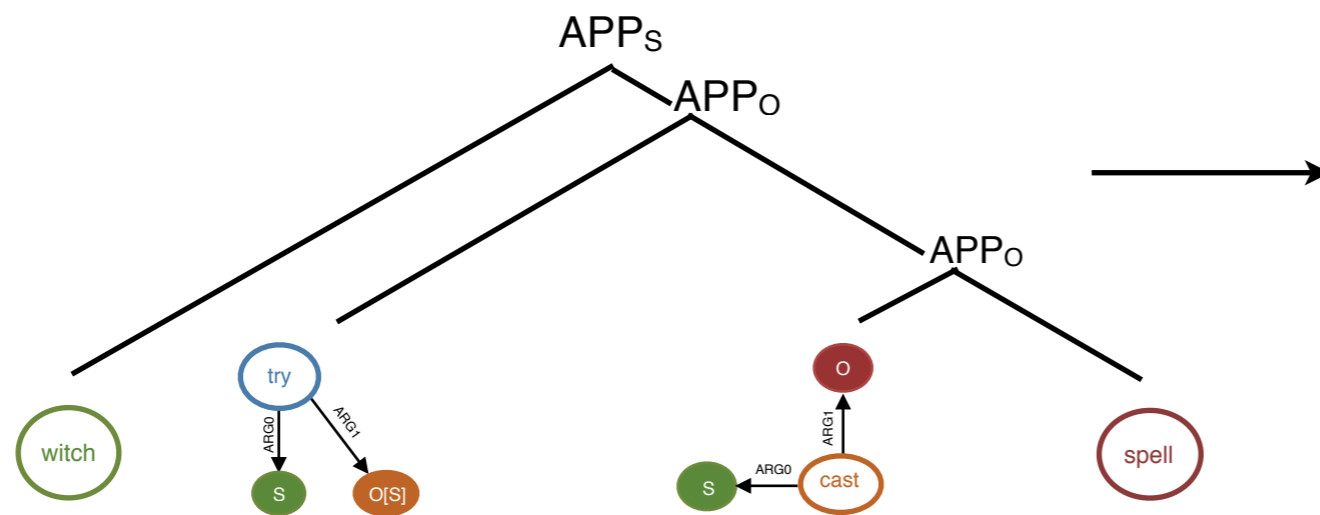
here: need  $APP_O$  before  $APP_S$  to get reentrancies

- Always need to resolve reentrancies first
- Types encode reentrancies
- ➔ use type system to determine operation order

# AM Dependency Trees

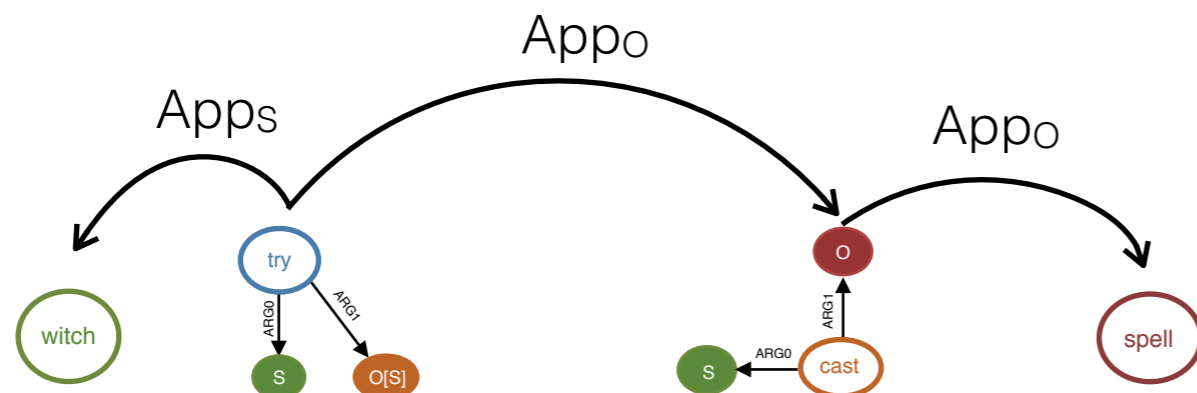


Building instructions for an AMR that we know how to predict



Part 1

equivalent



easy (easier)

Part 2

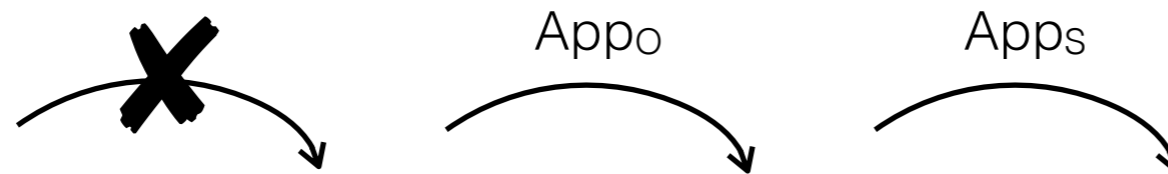
The witch tried to cast a spell

# Model

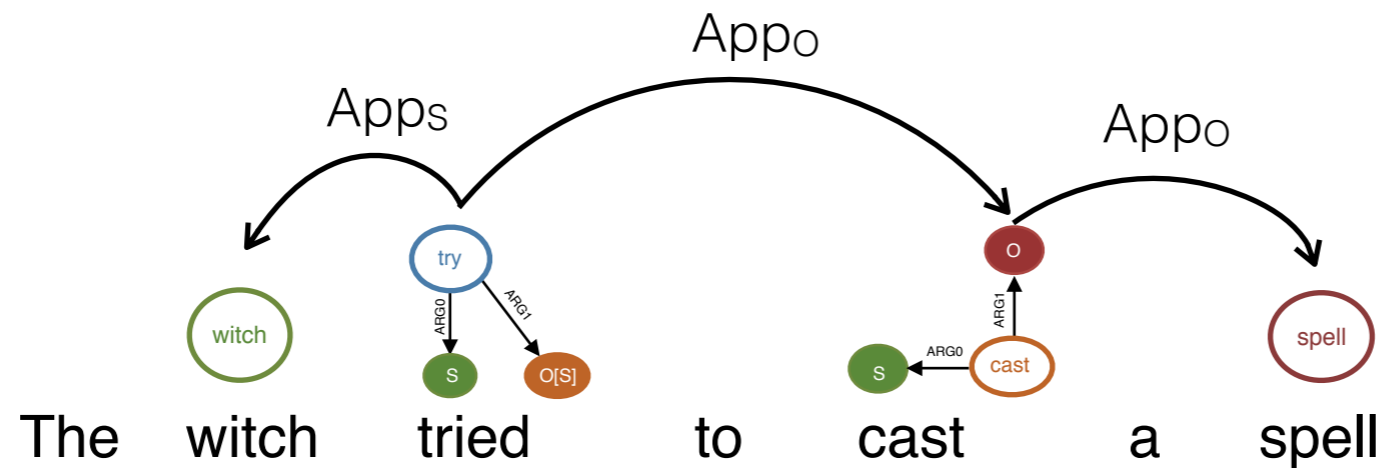
1. Supertagging: score graph fragments for each word



2. Dependency model: score operations



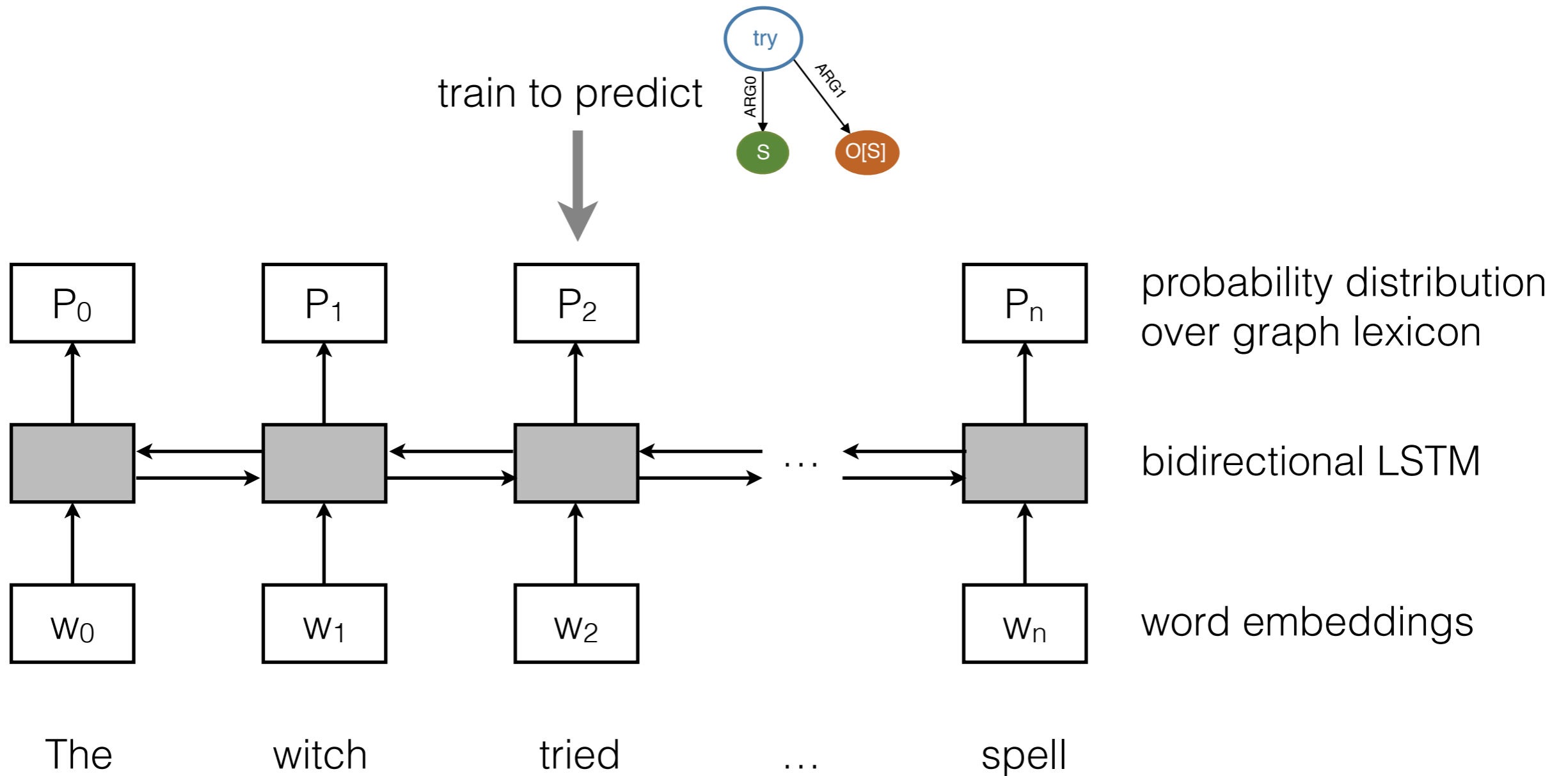
3. Decoding: find highest-scoring well-typed tree





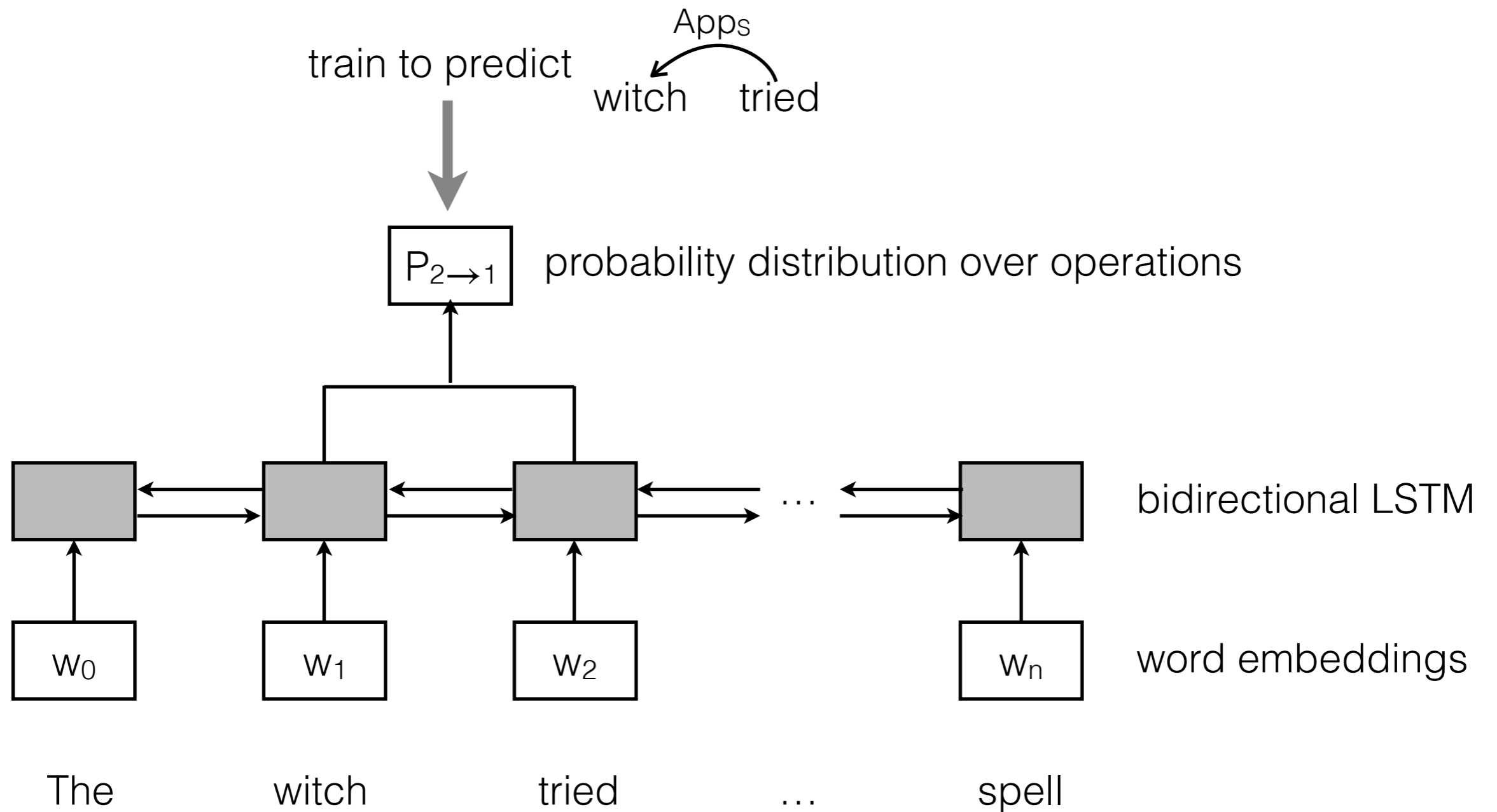
# 1. Supertagging

E.g. Lewis et al. (2014) for CCG

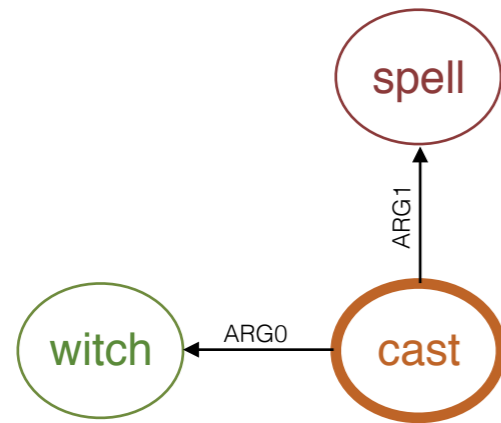


# 2. Dependency Model

Kiperwasser & Goldberg (2016) for syntactic dependencies

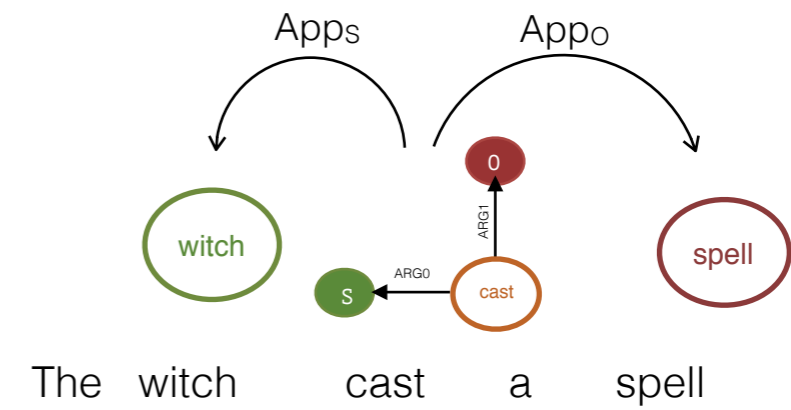


# AMR Corpus

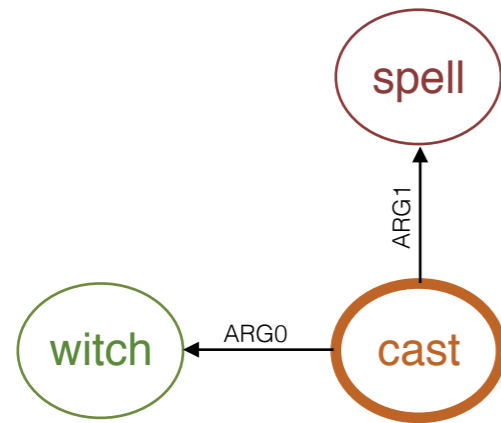


The witch cast a spell

# Required training data

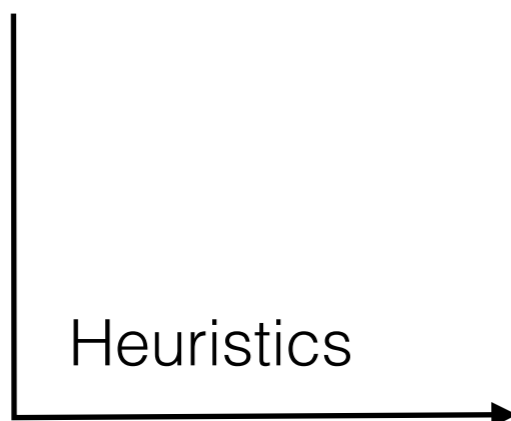
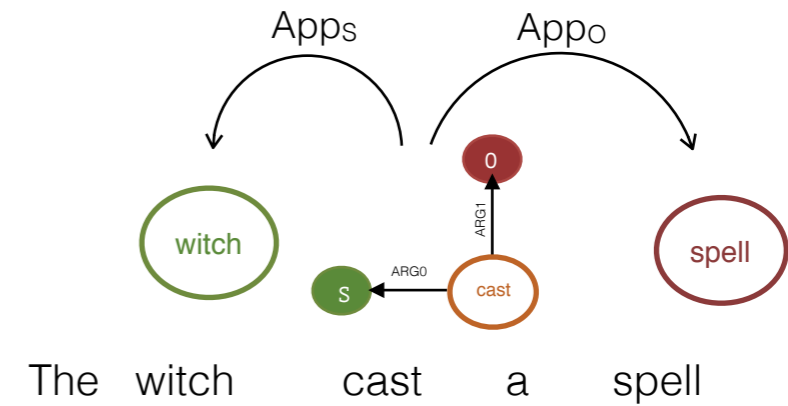


# AMR Corpus

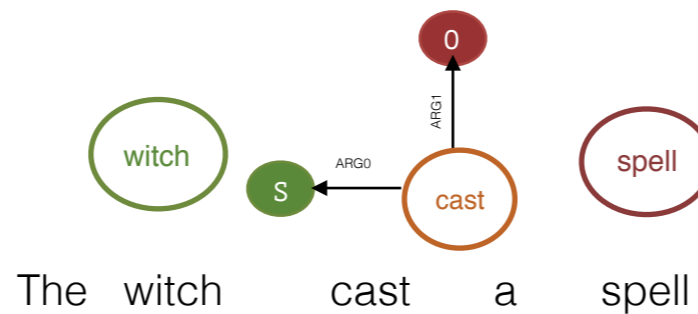


The witch cast a spell

# Required training data

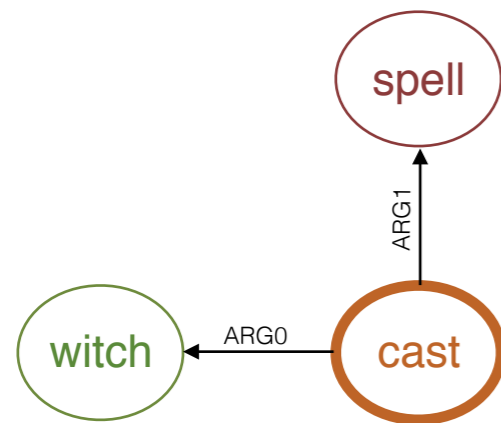


- Alignments
- Attaching edges
- Source names
- Source annotations



# AMR Corpus

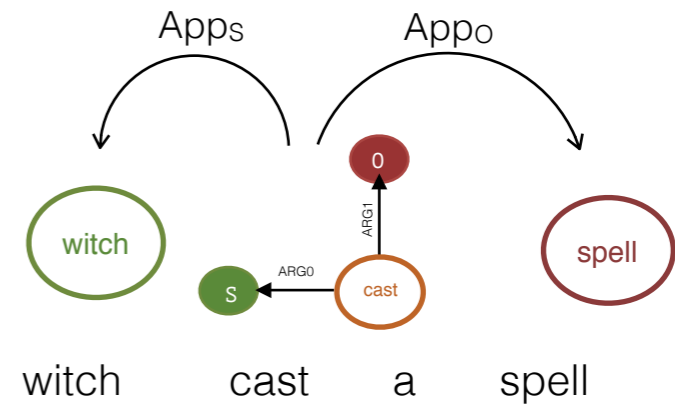
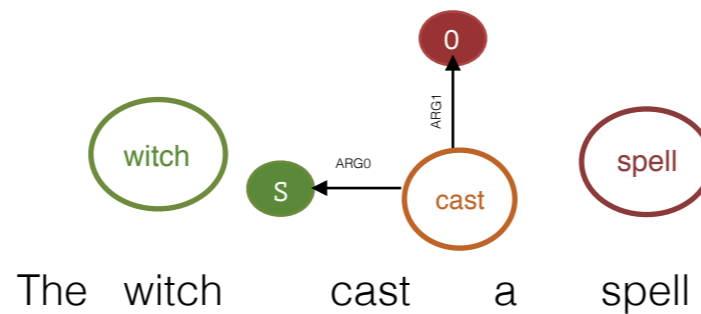
# Required training data



The witch cast a spell

## Heuristics

- Alignments
- Attaching edges
- Source names
- Source annotations



# 3. Decoding

Find the **best well-typed** dependency tree

# 3. Decoding

Find the **best well-typed** dependency tree

- ill-typed trees do not evaluate to AMRs
- ill-typed trees do not match our linguistic intuitions

# 3. Decoding

Find the **best well-typed** dependency tree

- ill-typed trees do not evaluate to AMRs
- ill-typed trees do not match our linguistic intuitions
- Exact typed decoding is NP-hard
- Untyped decoding: 74% of trees are ill-typed



# 3. Decoding

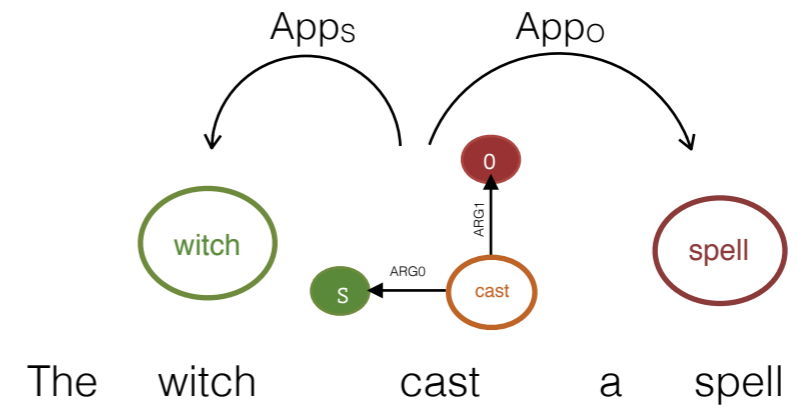
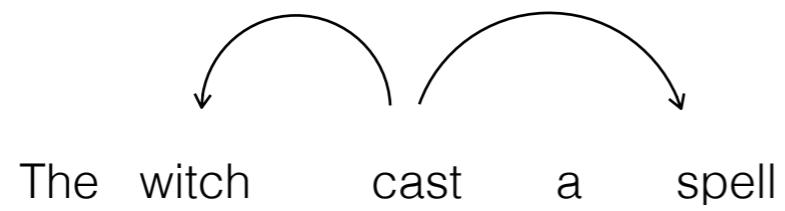
Find the **best well-typed** dependency tree

- ill-typed trees do not evaluate to AMRs
- ill-typed trees do not match our linguistic intuitions
- Exact typed decoding is NP-hard
- Untyped decoding: 74% of trees are ill-typed

➔ **Approximate decoders**

# Approximate decoders

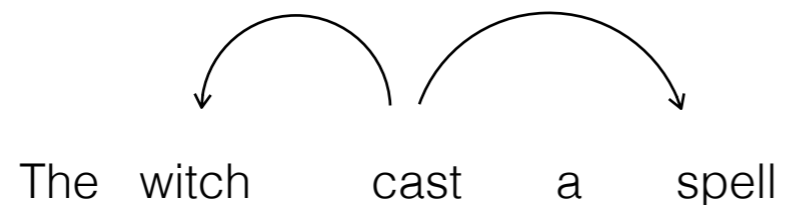
**A:** Fixed tree



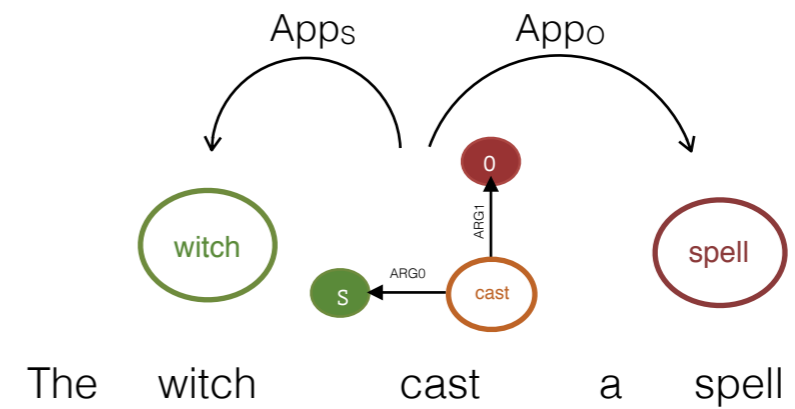
# Approximate decoders

## A: Fixed tree

1. Fix unlabeled tree



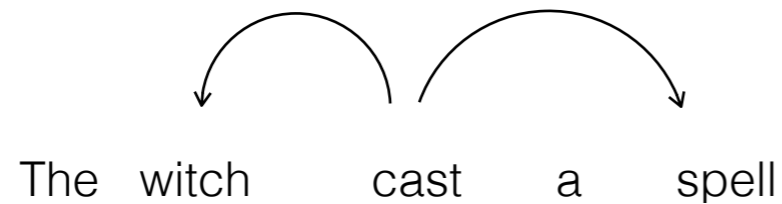
2. Label tree, with type checking



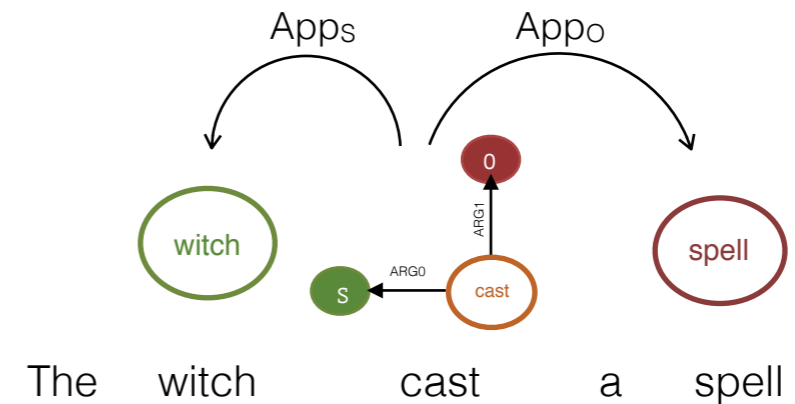
# Approximate decoders

## A: Fixed tree

1. Fix unlabeled tree



2. Label tree, with type checking



**B:** Projective: can only combine adjacent constituents

"CKY parsing with types as nonterminals"

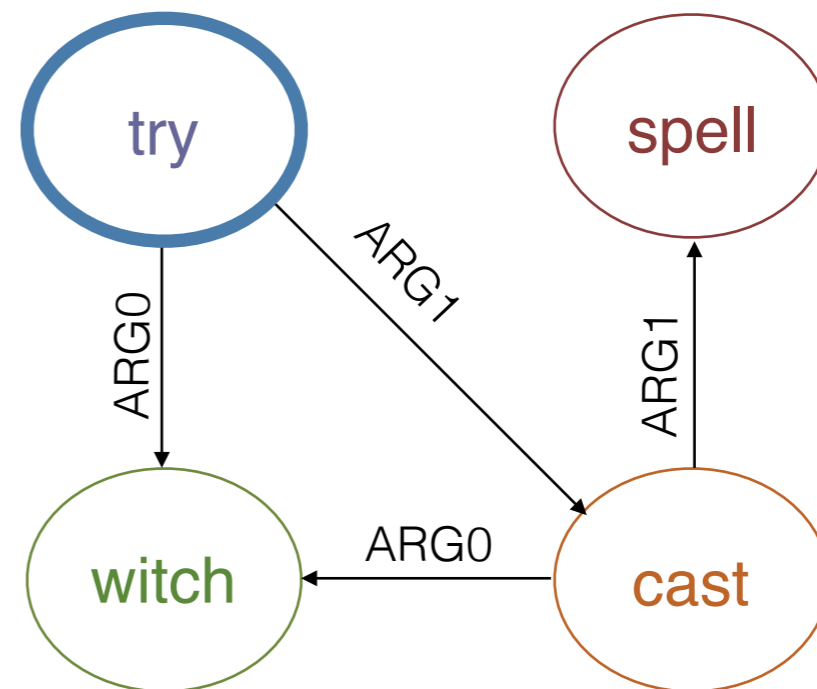
# Results

# Classic AMR parser (*graph decoder*)

Step 1: Predict nodes



Step 2: Predict edges



# Results

Model	Method	Smatch score
JAMR (Flanigan et al. 2016)	graph decoder	67
Foland & Martin 2017	graph decoder	70.7
van Noord & Bos 2017	neural seq2seq	68.5
Lyu & Titov (ACL 2018)	graph decoder	<b>73.7</b>
<b>Our baseline</b>	graph decoder	66.1
<b>Our projective decoder</b>		70.2
<b>Our fixed tree decoder</b>		70.2

Dataset: LDC2015E86

# Conclusion

- We built a competitive compositional AMR parser
- Clear avenues to improvement
  - Update to recent advancements in training regimen (e.g. Lyu & Tivov 2018)
  - Look into specific phenomena, e.g.
    - anaphora
    - ellipsis
- Future work: extend method to other formalisms



# Conclusion

- We built a competitive compositional AMR parser
- Clear avenues to improvement
  - Update to recent advancements in training regimen (e.g. Lyu & Tivov 2018)
  - Look into specific phenomena, e.g.
    - anaphora
    - ellipsis
- Future work: extend method to other formalisms

