Compositional Neural Semantic Graph Parsing

TaCoS 29

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Based on joint work with
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Meaghan Fowlie and Mark Johnson

June 21, 2019

What do we want to do

We want to obtain **symbolic** meaning representations of sentences.

- interpretable for experts (that is: you!)
- useful for NLP applications like dialog system, question answering, etc.

In this talk:

- we focus on meaning representation in form of **semantic graphs**.
- we approach **semantic parsing**: (English) sentence $\rightarrow$ meaning representation
- we do this for several kinds of semantic graphs.

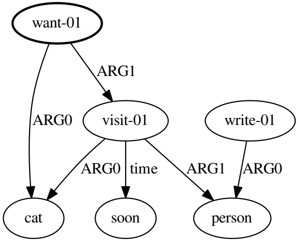
Outline

Semantic graphs

Abstract Meaning Representation (Banarescu et al., 2013)

Abstract Meaning Representation (AMR) is a sentence-level **broad coverage** meaning representation language.
AMRs

- are directed, acyclic and labeled **graphs**
- capture semantic relations, e.g. predicate argument structure
- abstract away from syntactic surface



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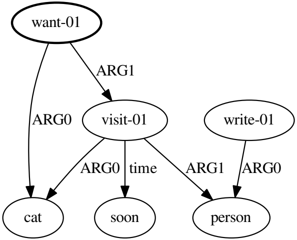

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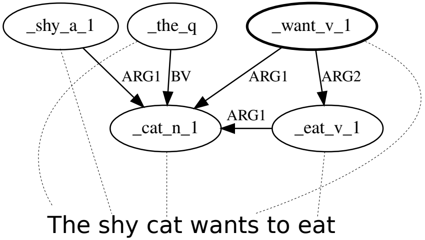
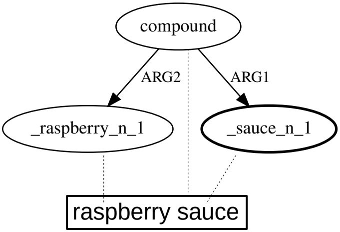
The cats wanted to visit the writer soon

Elementary Dependency Structures (Oepen and Lønning, 2006)

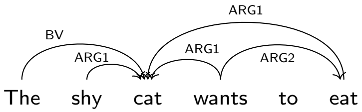




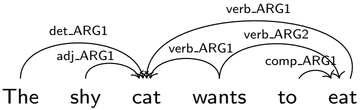
- derived from semantic annotations produced by English Resource Grammar (Flickinger, 2000), a broad-coverage HPSG grammar
- nodes are aligned to words or phrases.

Semantic Dependencies (Oepen et al., 2015)

- DM, derived from EDS



- PAS



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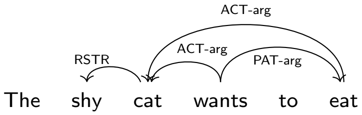

- automatically derived from annotations on WSJ
- nodes are the words from the sentence

Comparison of kinds of semantic graphs

Name	Alignments	Nodes $\approx$ Words	Similarity to surface
AMR	✗	✗	potentially low
EDS	1-many	✗	high
DM	1-1	✓	high
PAS	1-1	✓	high
PSD	1-1	✓	high

- handle certain phenomena differently, e.g. copula and coordination

Deriving semantic graphs

Compositionally deriving graphs

Principle of **Compositionality**

The meaning of a **complex expression** is determined by **meanings of its sub-expressions** and the **rules used to combine** them.

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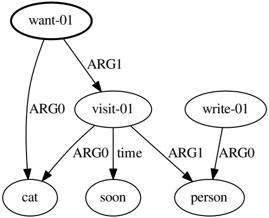

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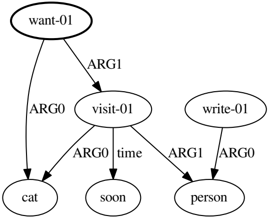

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We know that meaning is constructed compositionally.
. . . but we only see the result of the compositional process.
So, we must come up with such a process!

Formal perspective

What kind of formalism do we need to **compositionally** derive **graphs**?

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Formalism	**Derivation structure**	**Derived structure**
CFG	Tree	String
TSG,TAG	Tree	Tree
?	Tree	Graph

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Algebra	**Domain**
Elementary Algebra	$\mathbb{R}$
Boolean Algebra	$\{0, 1\}$
Graph Algebra	Graphs

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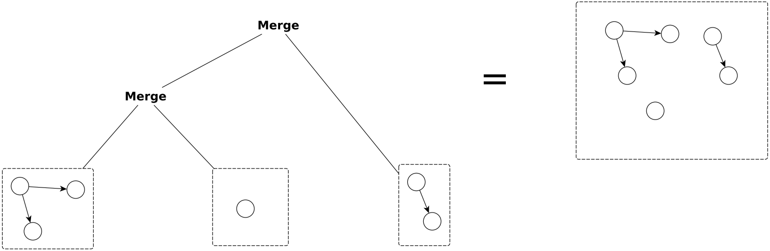
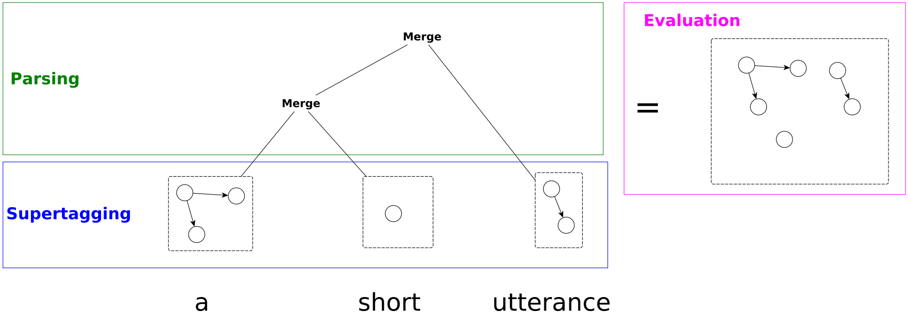


$$[\![\mathrm{F}(t_1, t_2, \ldots, t_n)]\!] = [\![\mathrm{F}]\!]([\![t_1]\!], [\![t_2]\!], \ldots, [\![t_n]\!])$$

Graph Algebra and Graph Parsing



With a Graph Algebra, we can parse a sentence into a graph by:

- Supertagging: finding an appropriate graph constant for every word
- Parsing: finding a term over all constants
- Evaluating the term

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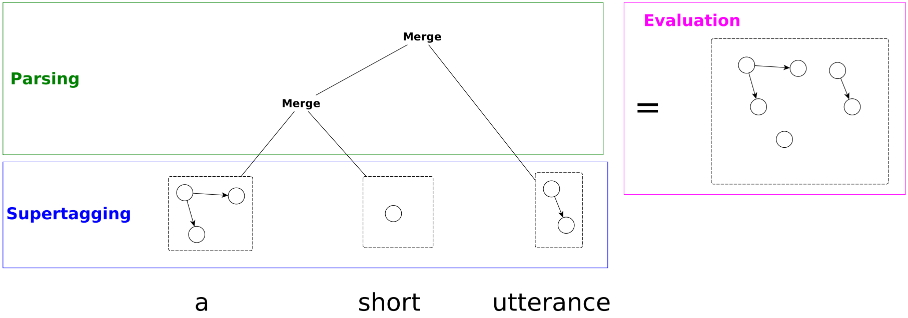

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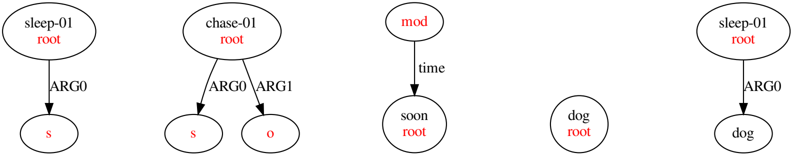
We need a graph algebra that exploits the compositional structure of our graphs.

AM Algebra (Groschwitz et al., 2017; Groschwitz, 2019)

- linguistically inspired and constrained graph algebra
- built for AMR (but works on the other semantic graphs as well!)
- handles phenomena like control, coordination and relative clauses

In the AM Algebra, we generalize graphs to *s-graphs*:



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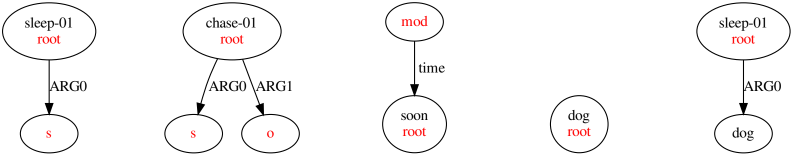

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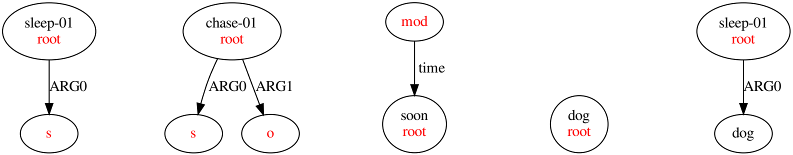

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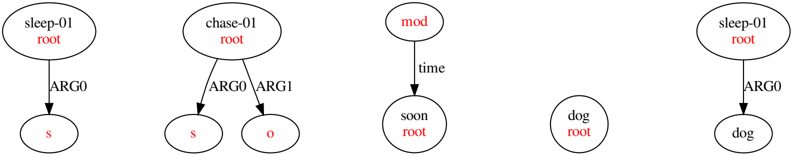
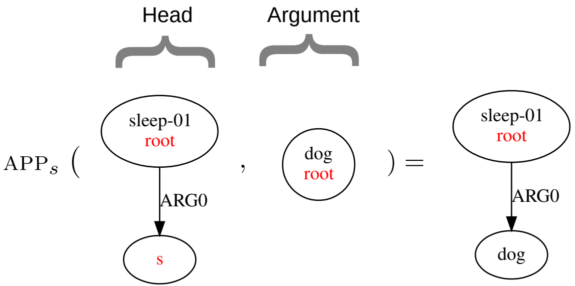


Type [s]　Type [s, o]　Type [mod]　Type []　Type []

- some nodes of an s-graph (called sources) have an additional name (s for subject, o for object,...)
- all s-graphs have a source called root, which marks the "head"
- s-graphs are typed (≈ source names excluding root)

Operations of AM Algebra: Apply

APP_{α} fills argument slot α of the head with root of the argument:



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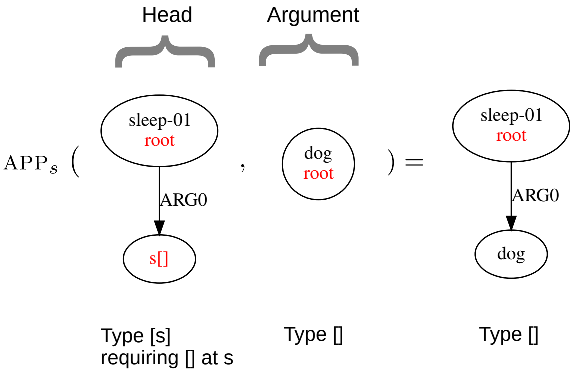

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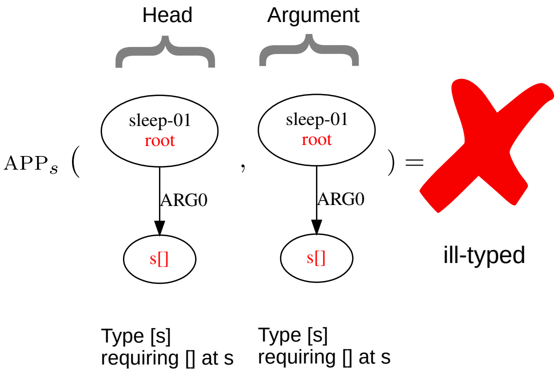
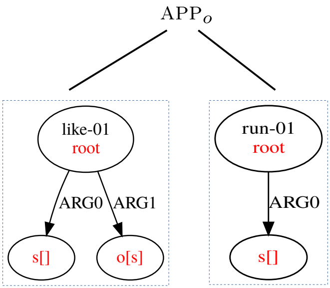


APP can create reentrancy



Type [s,o[s]]
requiring [] at s
requiring [s] at o

Type [s]
requiring [] at s

The fox likes running.

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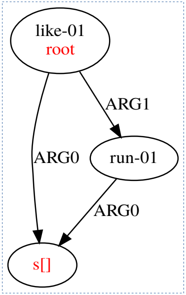

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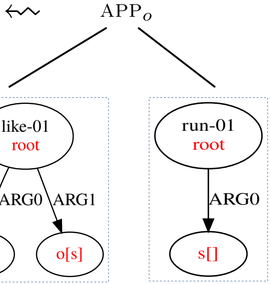

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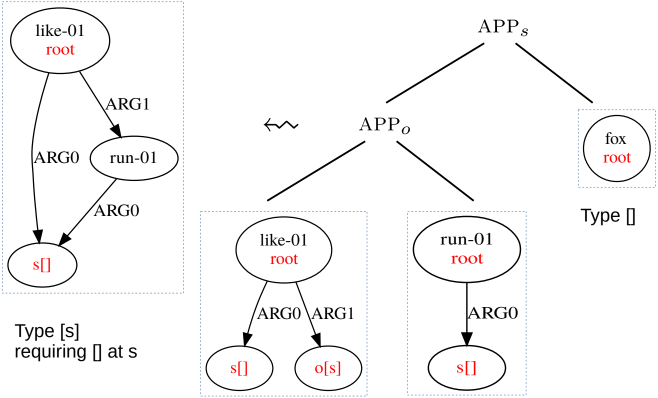

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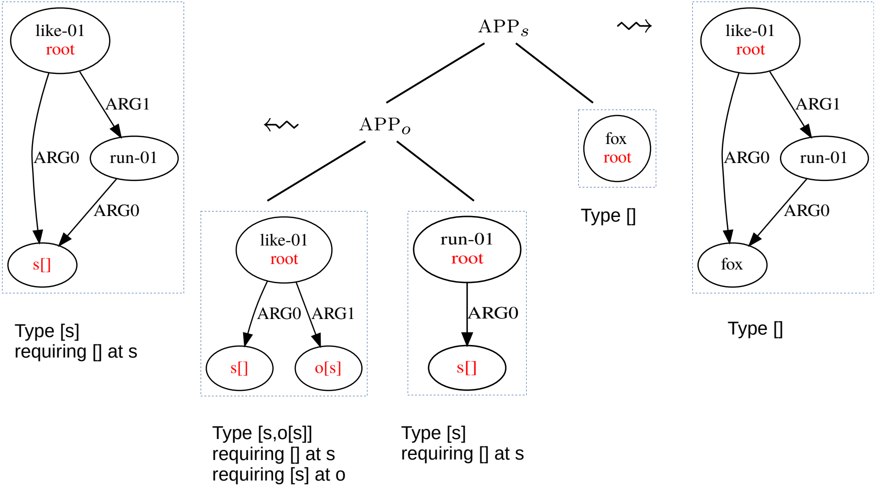

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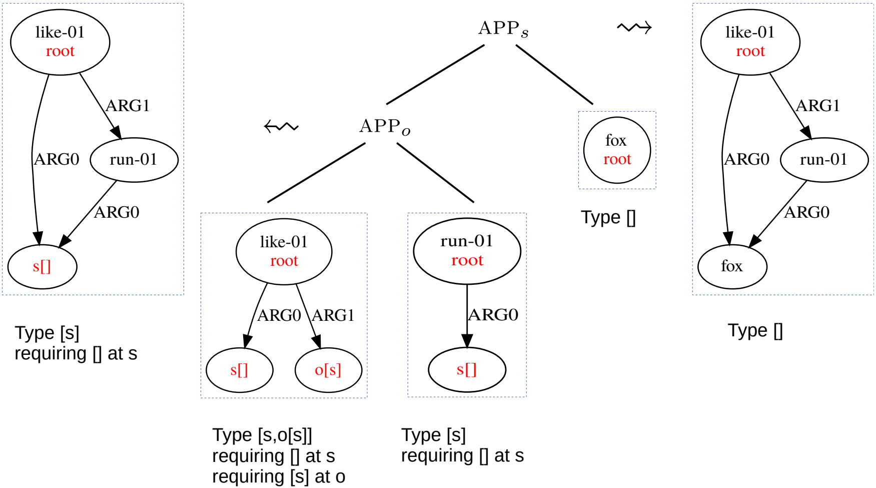

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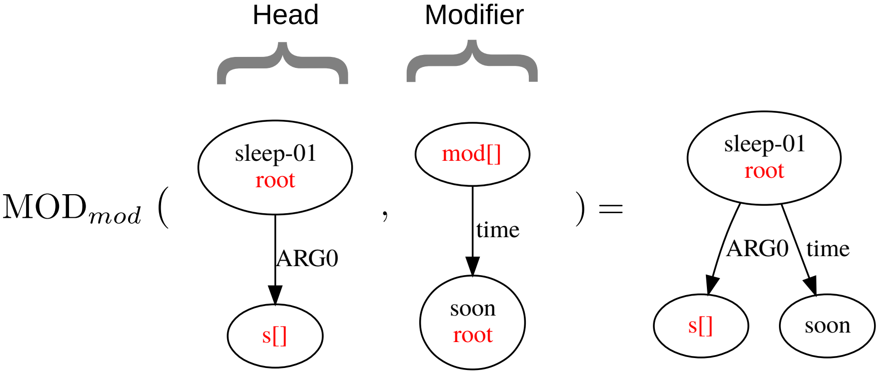
Sources with same names collapse.
This constant for *likes* enforces reentrancy!

Operations of AM Algebra: Modify

MOD_{α} plugs α-source of the modifier into the root of the head:



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Type [mod]
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Type [s]
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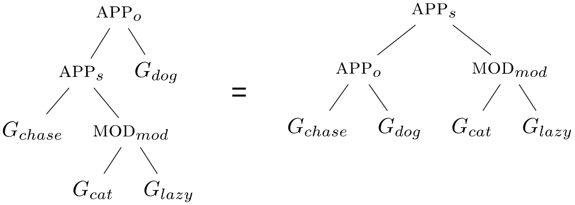
Spurious Ambiguity

Order of operations does not always matter:



The lazy cat chases the dog

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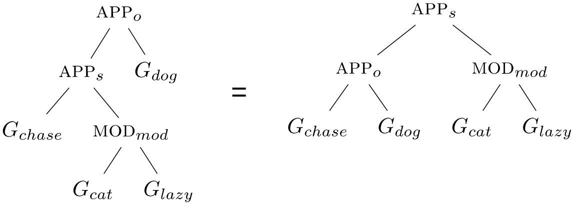
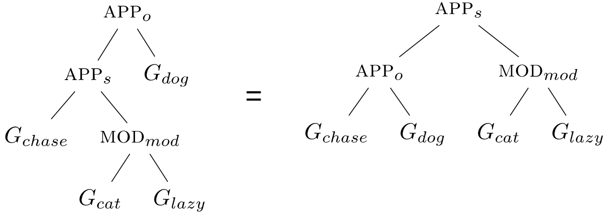


The lazy cat chases the dog

Problem:
We predict terms instead of graphs. Which term shall we pick for training the parser?

AM Dependency Trees

Solution: TRANSFORM terms to dependency trees with *unspecified order*.



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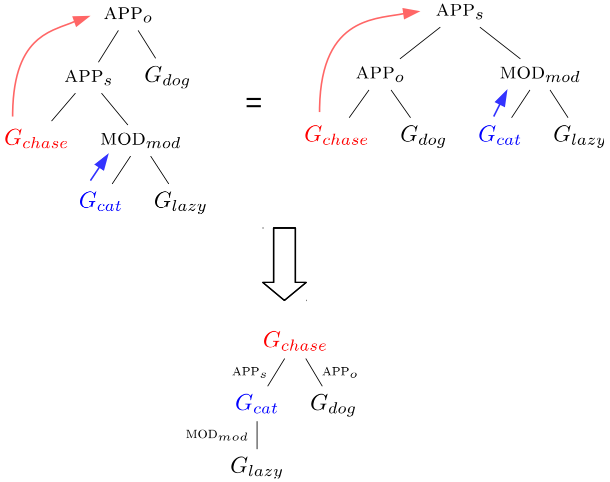

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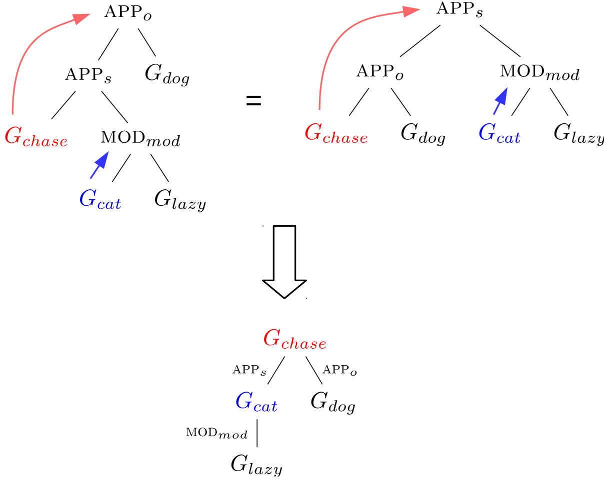

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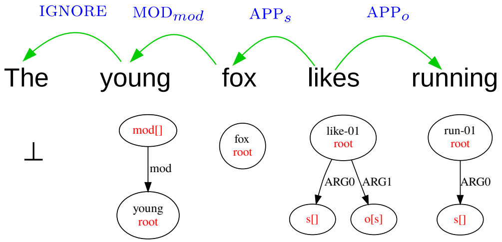
Note: it can be proven that an AM dependency tree *uniquely* denotes a graph (Groschwitz, 2019)

Parsing

Graph Parsing is now AM Dependency Parsing

Graph Parsing = Supertagging + Dependency Parsing:



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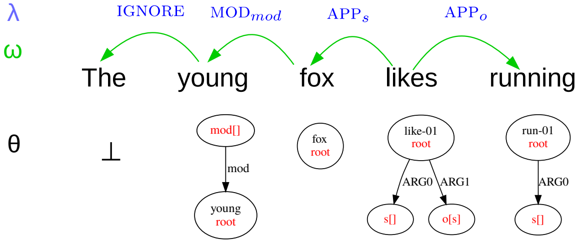

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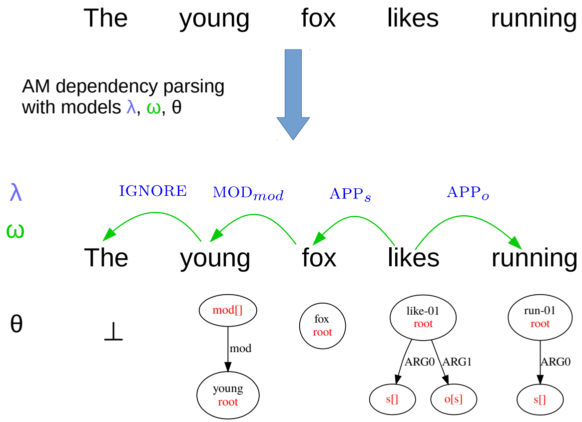

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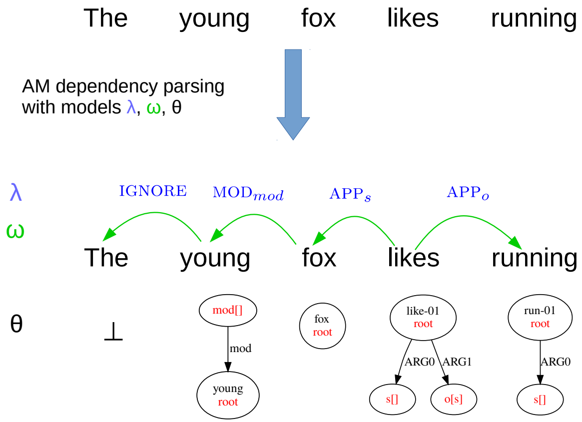

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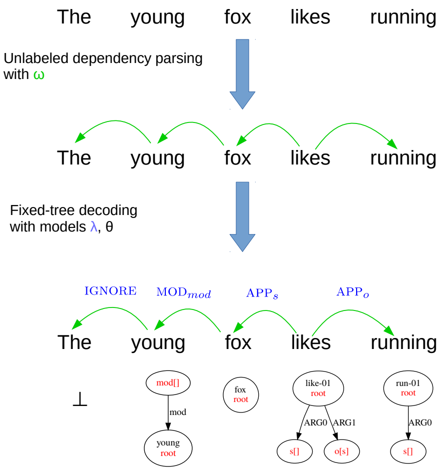
- **NP-complete!**

Make the problem easier



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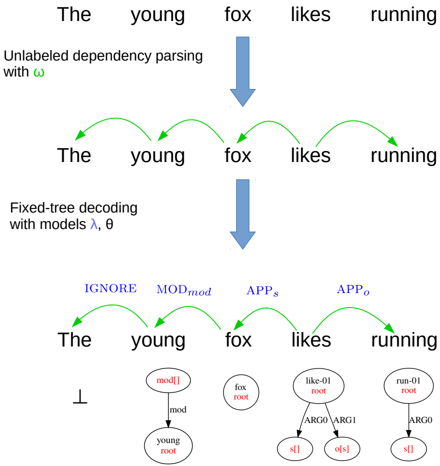
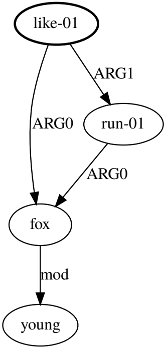


- (relatively) efficient approach
- fixed-tree decoding guarantees well-typedness
- if unlabeled tree is bad, no chance to recover – but works well in practice

Corpus creation

Problem: We only have graphs, but need AM dependency trees and supertags for training



The young fox likes running

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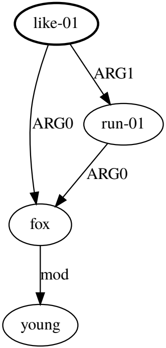

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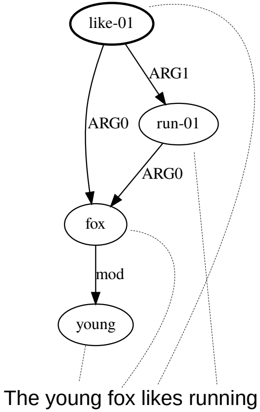

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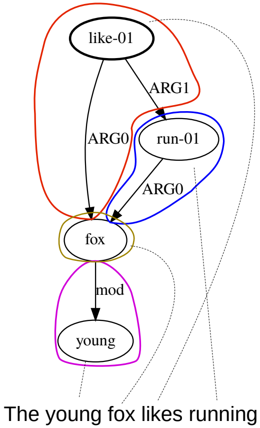

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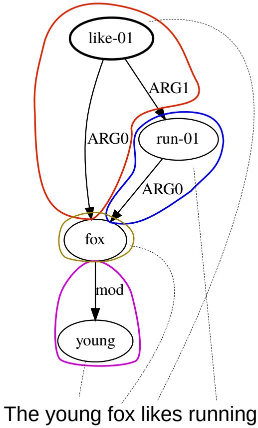
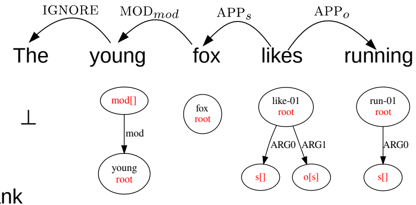


Create treebank



Steps:

- align words to nodes (only required for AMR)
- identify "blobs": decide where edges belong
- assign sources names and type requirements
- find AM dependency tree that evaluates to correct graph

Experiments

Experimental setup

Embeddings:

- Baseline: GloVe (Pennington et al., 2014)
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Evaluation metrics:

- (Smatch) F-score: find best mapping from system output to gold graph, compute overlap
- EDM (only for EDS): also takes alignment into account

Results

	DM		PAS		PSD		EDS		AMR 2015	AMR 2017
	id F	ood F	id F	ood F	id F	ood F	Smatch F	EDM	Smatch F	Smatch F
Lyu and Titov (2018)	-	-	-	-	-	-	-	-	73.7	74.4 ±0.16
Zhang et al. (2019)	-	-	-	-	-	-	-	-	-	**76.3** ±0.1
Peng et al. (2017) Basic	89.4	84.5	92.2	88.3	77.6	75.3	-	-	-	-
Dozat and Manning (2018)[1]	93.7	88.9	94.0	90.8	81.0	79.4	-	-	-	-
Buys and Blunsom (2017)	-	-	-	-	-	-	85.5	85.9	60.1	-
Chen et al. (2018)	-	-	-	-	-	-	**90.9**[2]	**90.4**[3]	-	-
This work (GloVe)	90.4 ±0.2	84.3 ±0.2	91.4 ±0.1	86.6 ±0.1	78.1 ±0.2	74.5 ±0.2	87.6 ±0.1	82.5 ±0.1	69.2 ±0.4	70.7 ±0.2
This work (BERT)	**93.9** ±0.1	**90.3** ±0.1	**94.5** ±0.1	**92.5** ±0.1	**82.0** ±0.1	**81.5** ±0.3	90.1 ±0.1	84.9 ±0.1	**74.3** ±0.2	75.3 ±0.2
Peng et al. (2017) Freda1	90.0	84.9	92.3	88.3	78.1	75.8	-	-	-	-
Peng et al. (2017) Freda3	90.4	85.3	92.7	89.0	78.5	76.4	-	-	-	-
This work, MTL (GloVe)	91.2 ±0.1	85.7 ±0.0	92.2 ±0.2	88.0 ±0.3	78.9 ±0.3	76.2 ±0.4	88.2 ±0.1	83.3 ±0.1	(70.4) ±0.2	71.2 ±0.2
This work, MTL (BERT)	**94.1** ±0.1	**90.5** ±0.1	**94.7** ±0.1	**92.8** ±0.1	**82.1** ±0.2	**81.6** ±0.1	90.4 ±0.1	85.2 ±0.1	(74.5) ±0.1	75.3 ±0.1

[1] Computed macro-averages instead of micro-averages

[2] Uses gold syntax information from the HPSG DeepBank annotations at training time.

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Questions?

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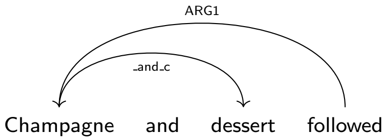
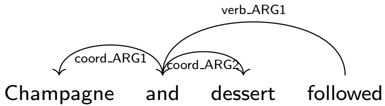
Dan Flickinger. 2000. On building a more effcient grammar by exploiting types. *Natural*

Coordination

- DM



- PAS



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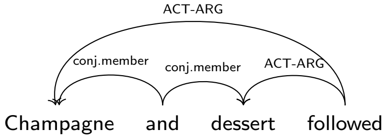
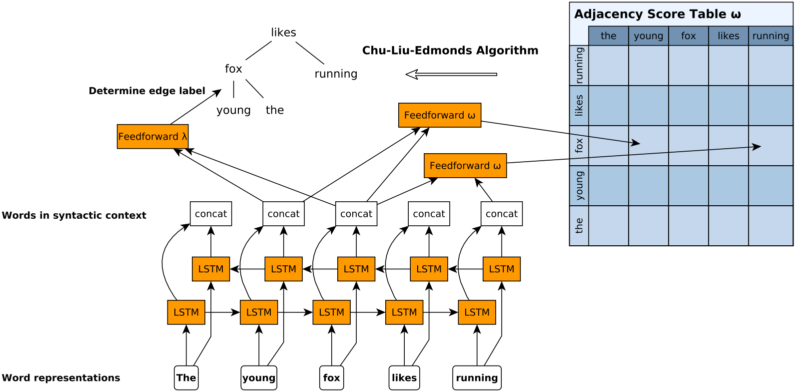


Corpora

Approach evaluated on the following English corpora:

- PTB ($\approx 35,000$ sentences, news text) annotated with DM, PAS, PSD and EDS
- AMR 2015: $\approx 19,000$ sentences
- AMR 2017: $\approx 39,000$ sentences (news text, blog articles, online discussions)
- AMR 2015 $\subseteq$ AMR 2017

A Recent Dependency Parser (Kiperwasser and Goldberg, 2016)



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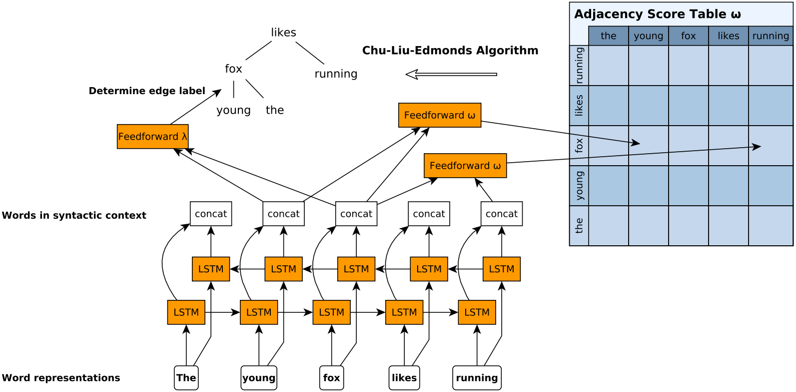
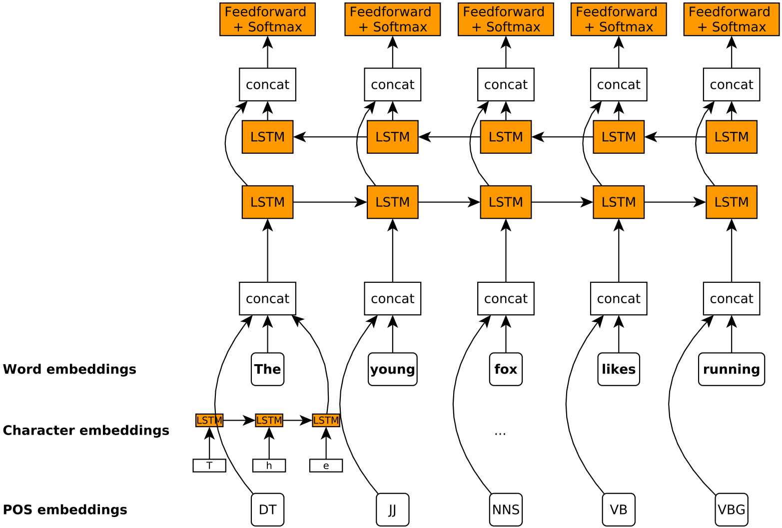


Training objective: Push the score of the correct edges higher than (wrong) alternatives

Supertagging (similar to Lewis et al. (2016))

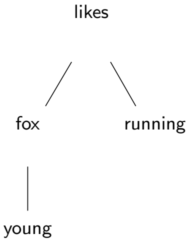


For each token and supertag, the NN gives us a score
$\theta(w_i, s) = \log P(w_i \text{ has supertag } s | w_1, \ldots, w_n)$

Fixed-Tree Decoding Algorithm

- bottom-up dynamic programming algorithm (similar to Viterbi)
- runtime complexity $\mathcal{O}(2^d \cdot n \cdot d)$ where d is maximal number of children in tree, n is size of the tree
- core idea: efficiently go through all AM terms that transform to the fixed tree, check types and manage scores

Fixed-Tree Decoding Algorithm



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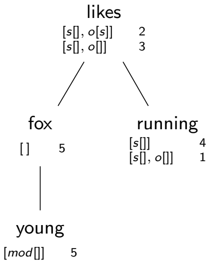

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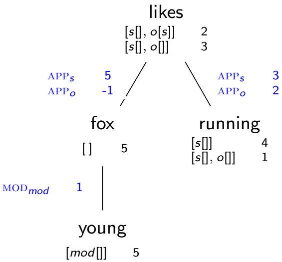

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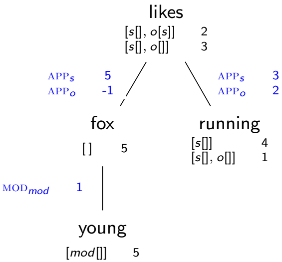

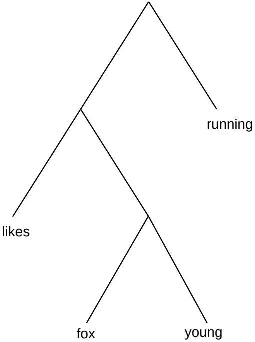

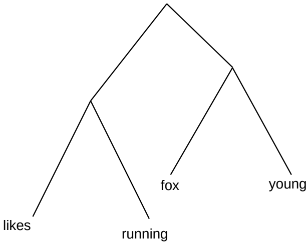

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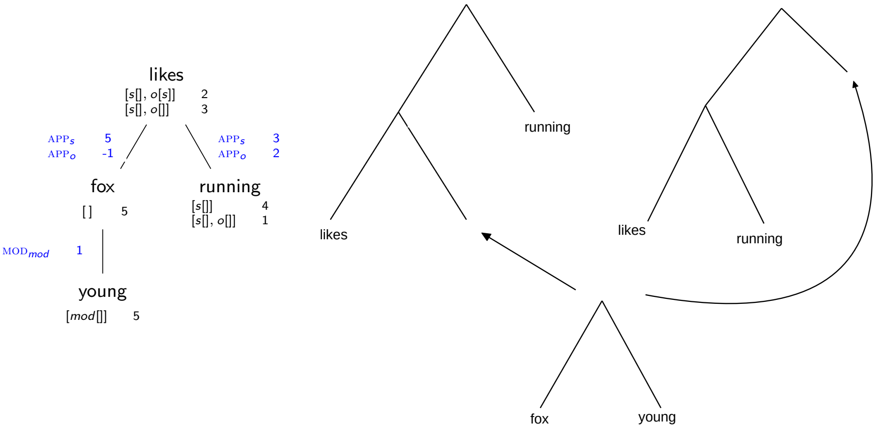

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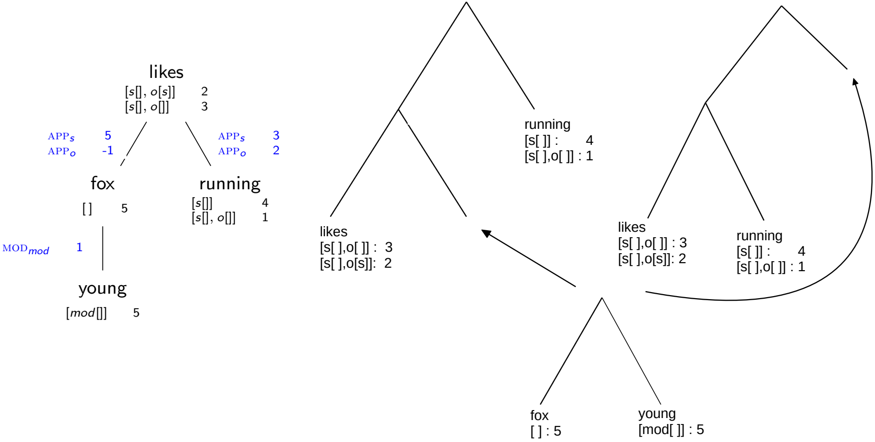

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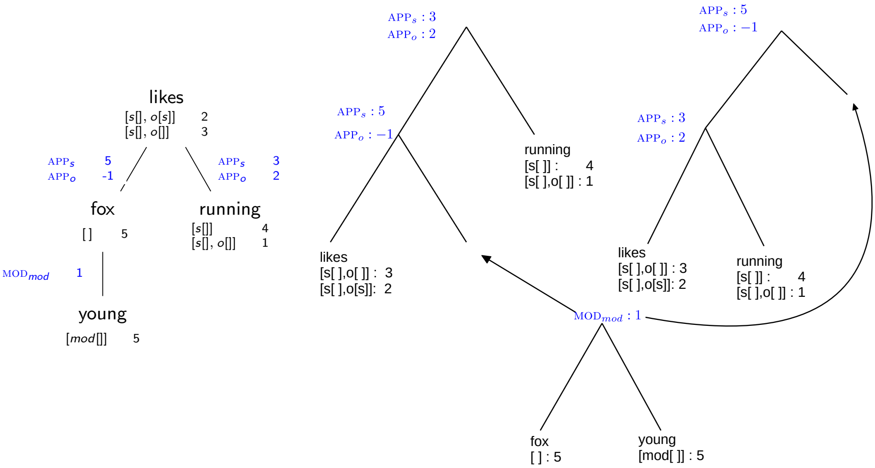

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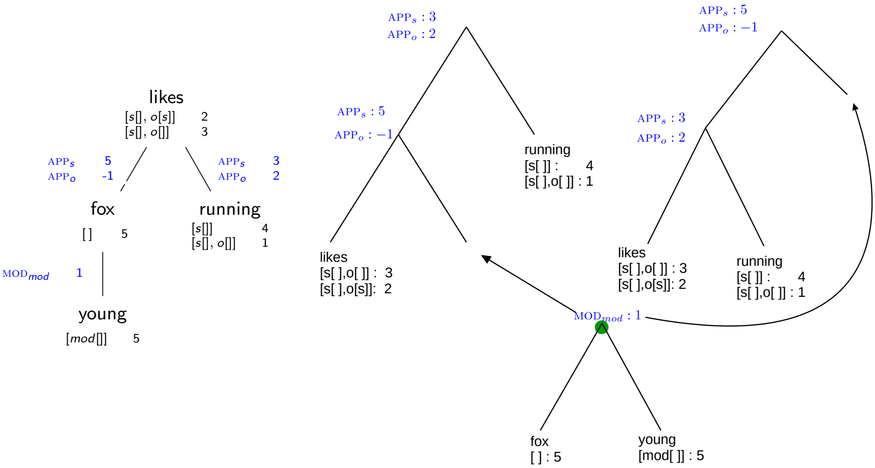

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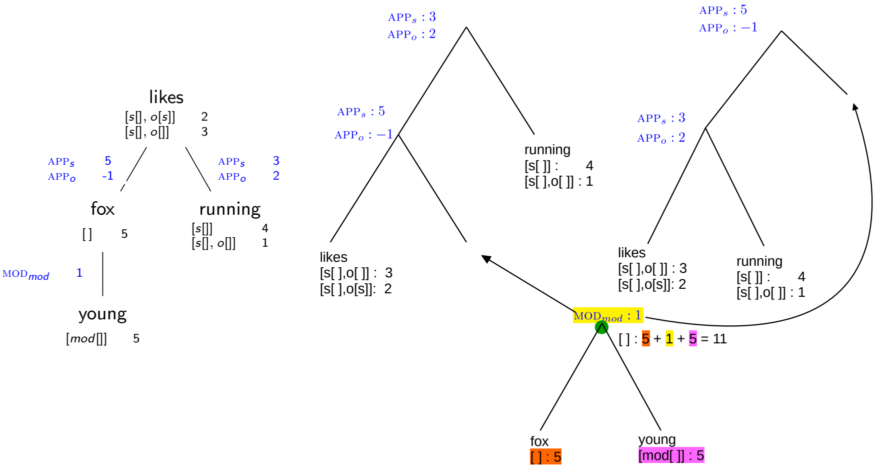

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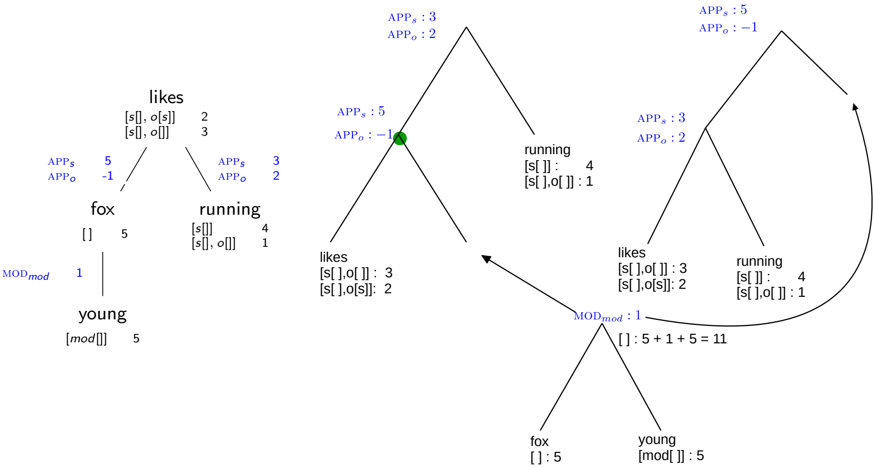

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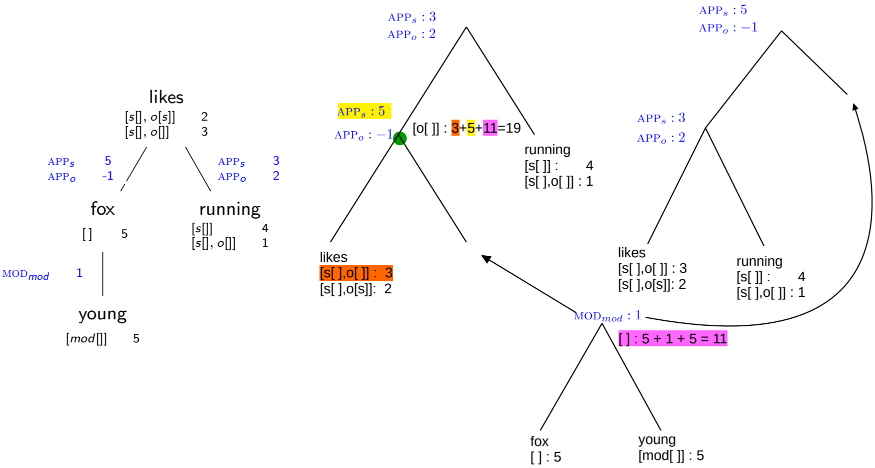

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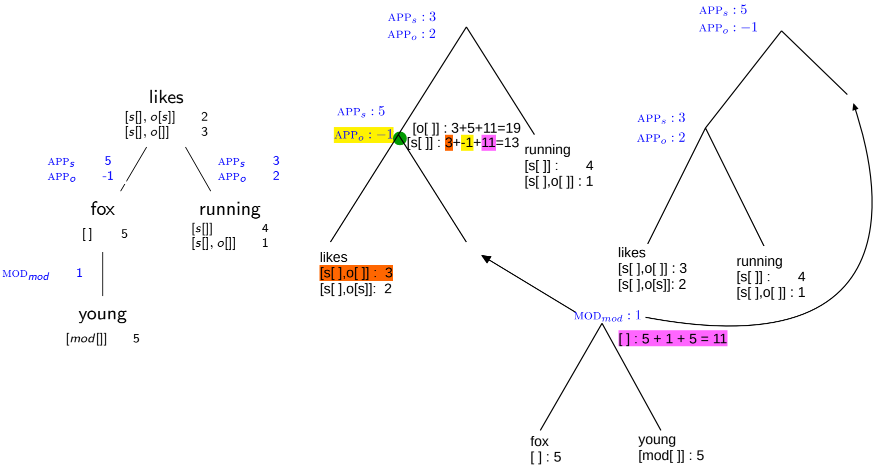

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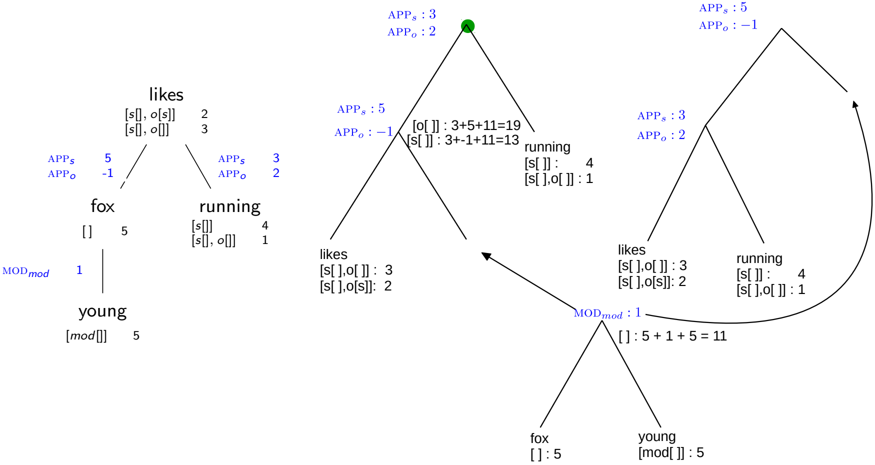

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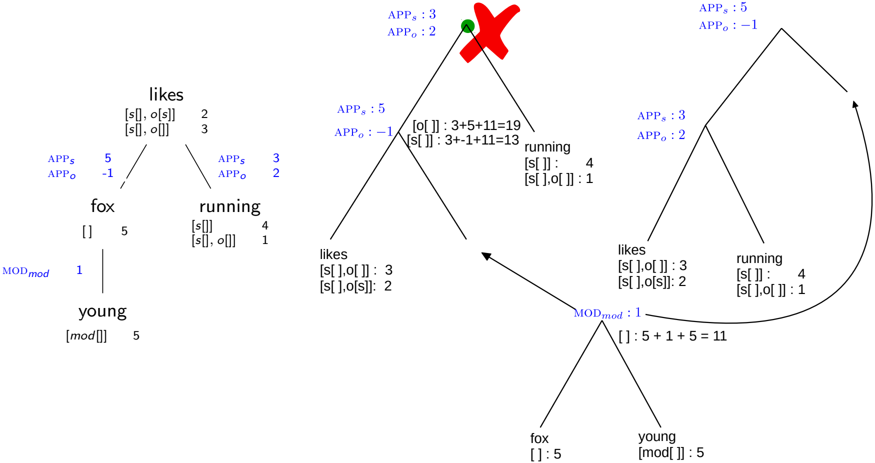

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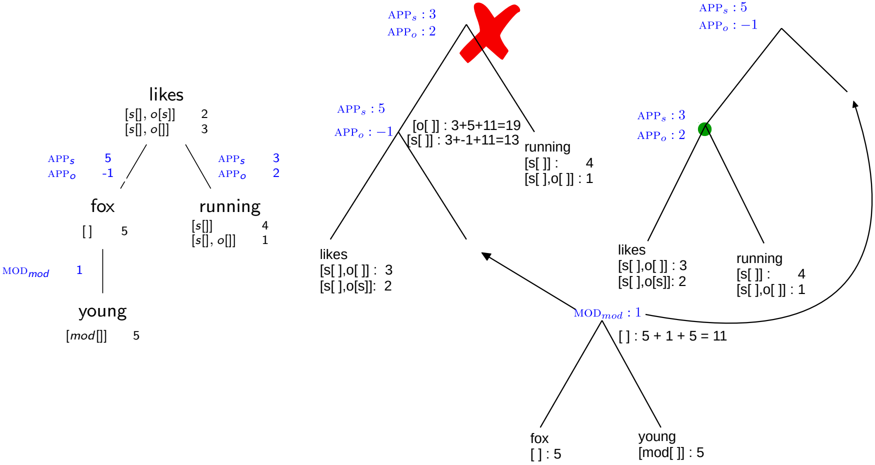

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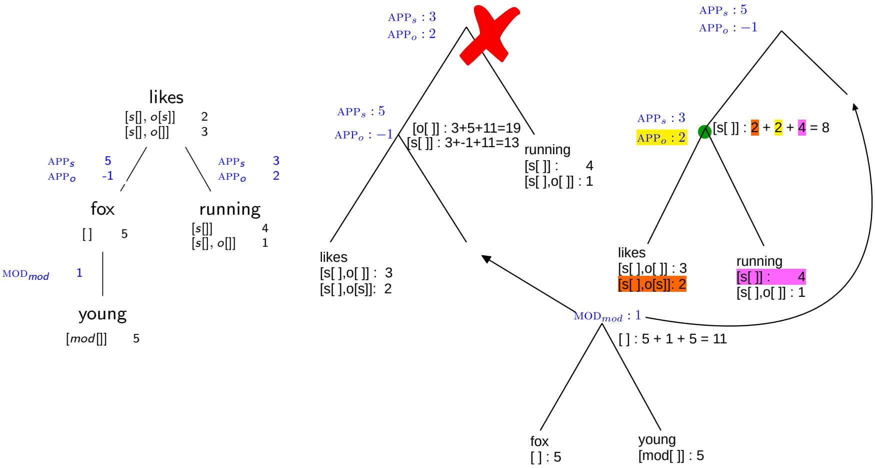

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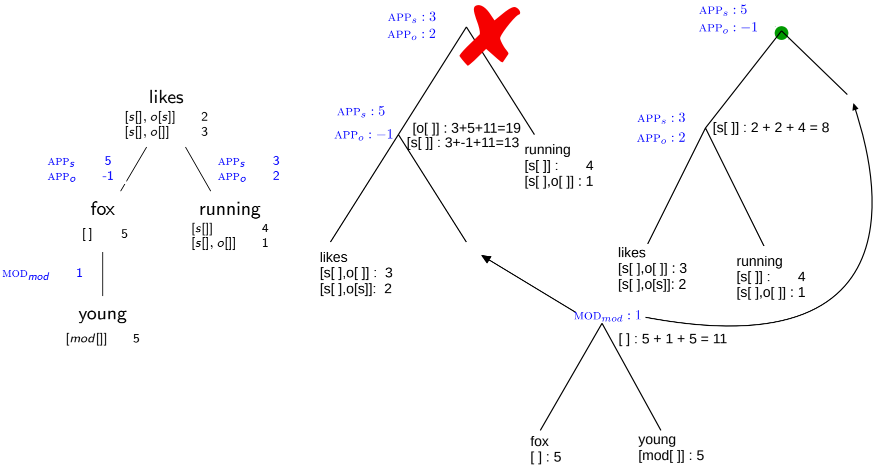

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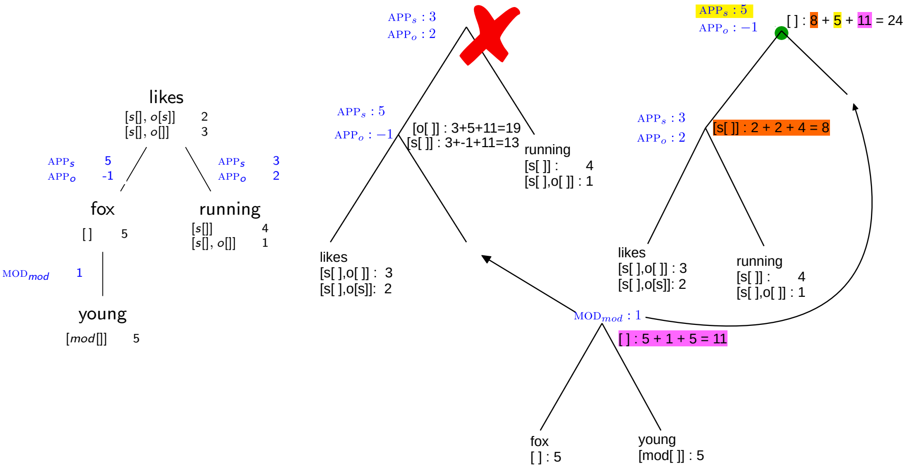

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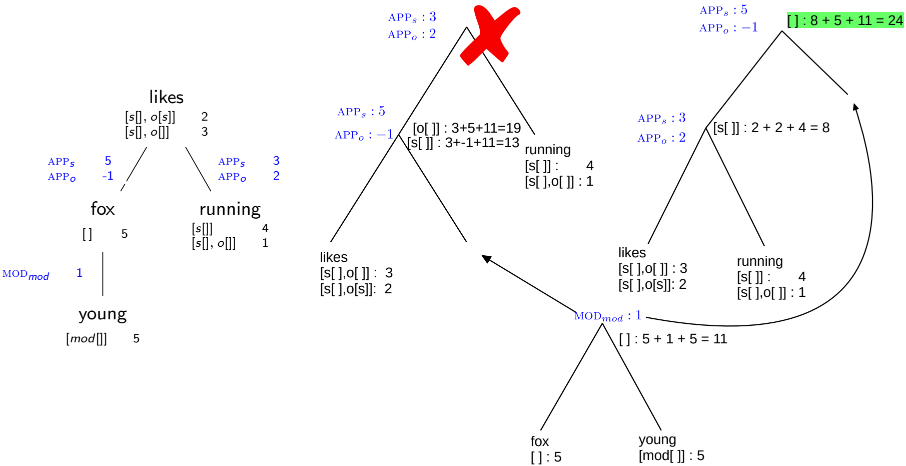

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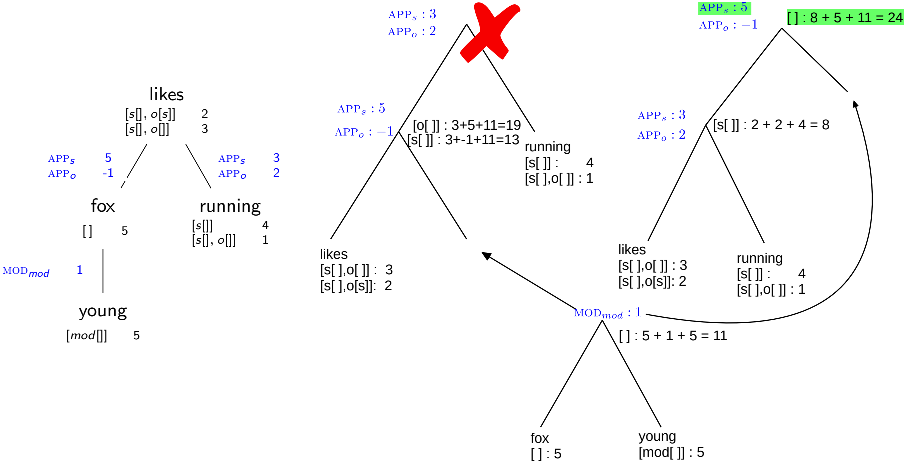

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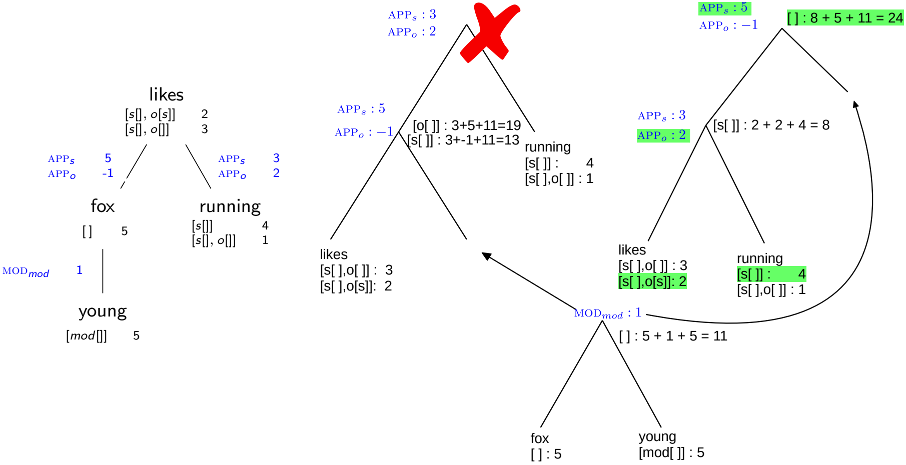

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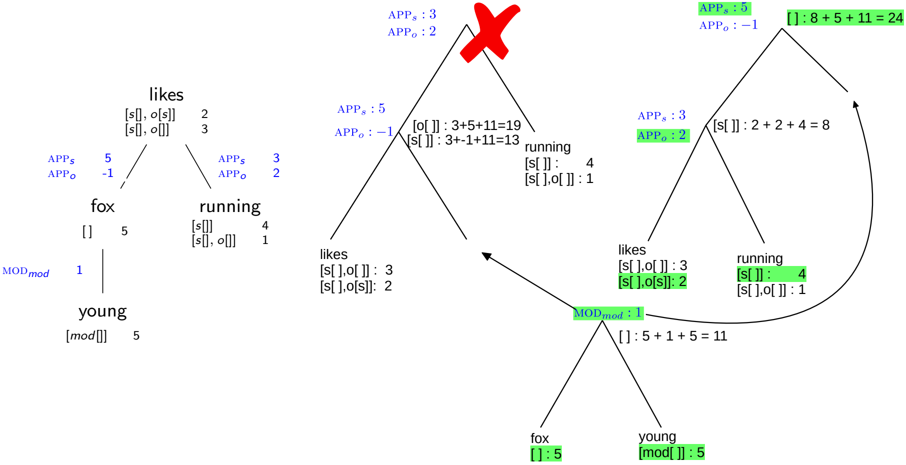

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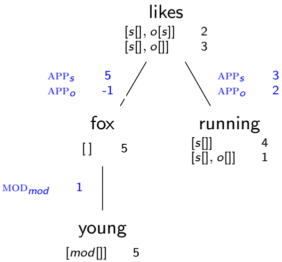

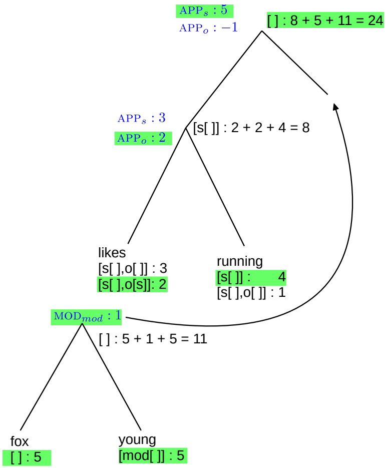

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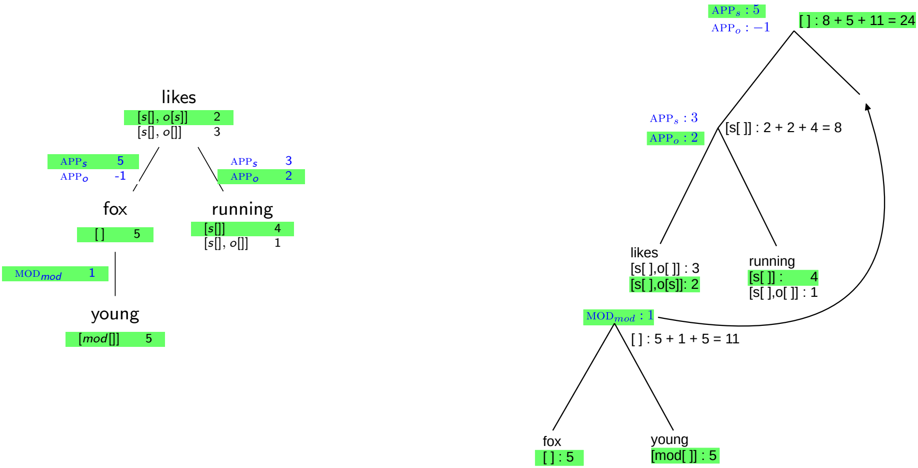

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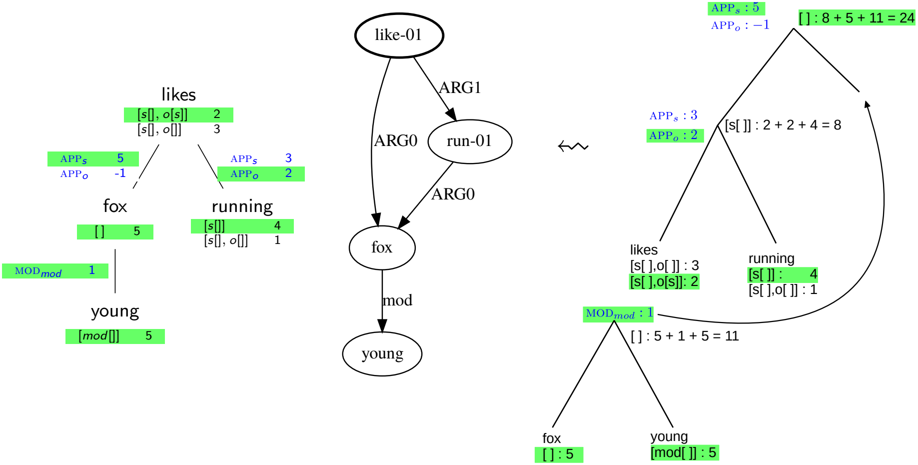
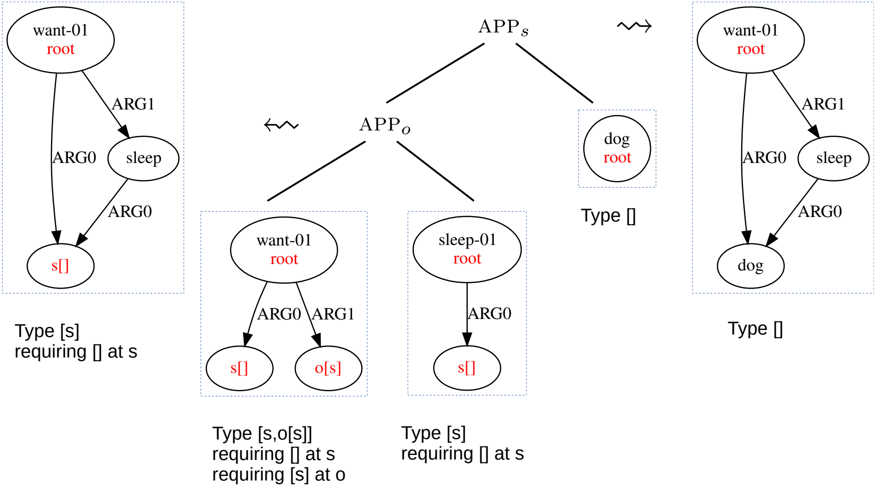


APP and Reentrancy

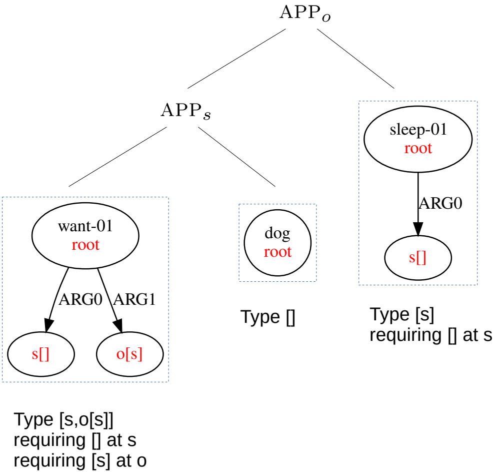


The dog wants to sleep

Constant for *want* enforces reentrancy!

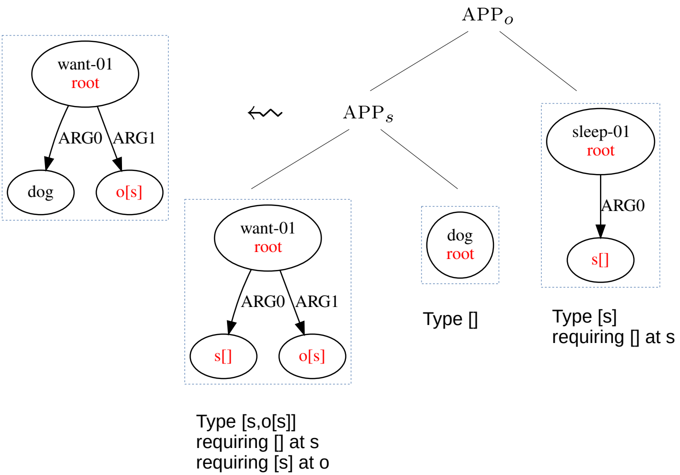
Can we first fill in the subject?

No!



APP$_o$
APP$_s$
want-01
root
ARG0
ARG1
s[]
o[s]
dog
root
sleep-01
root
ARG0
s[]
Type []
Type [s]
requiring [] at s
Type [s,o[s]]
requiring [] at s
requiring [s] at o

No!


want-01
root
ARG0
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o[s]
APP$_o$
APP$_s$
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ARG0
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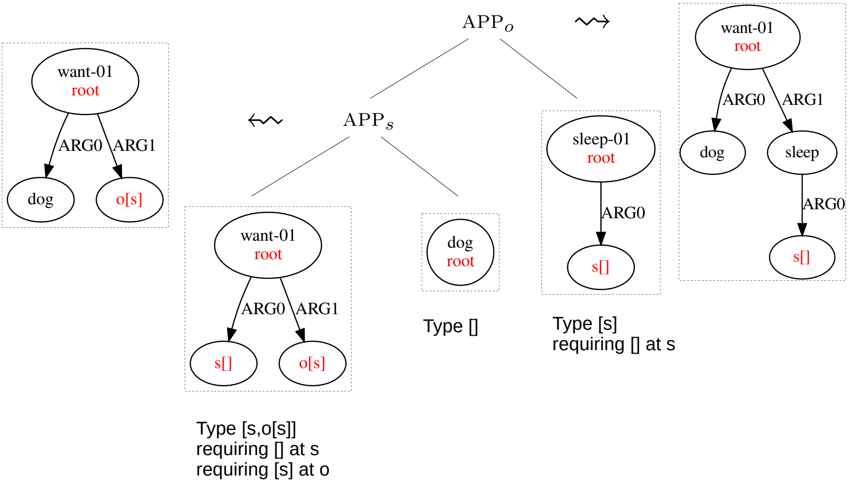
No!



APP$_o$
APP$_s$
want-01
root
ARG0
ARG1
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o[s]
s[]
dog
root
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root
ARG0
s[]
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ARG0
ARG1
dog
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s[]
Type [s,o[s]]
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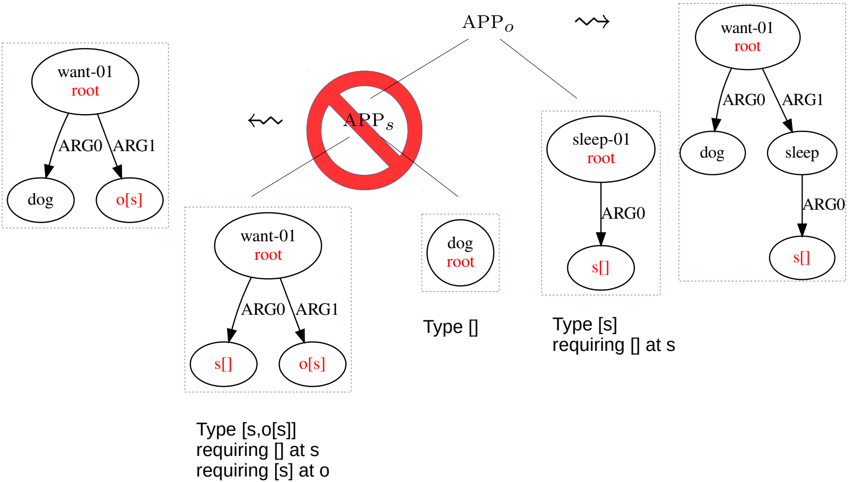
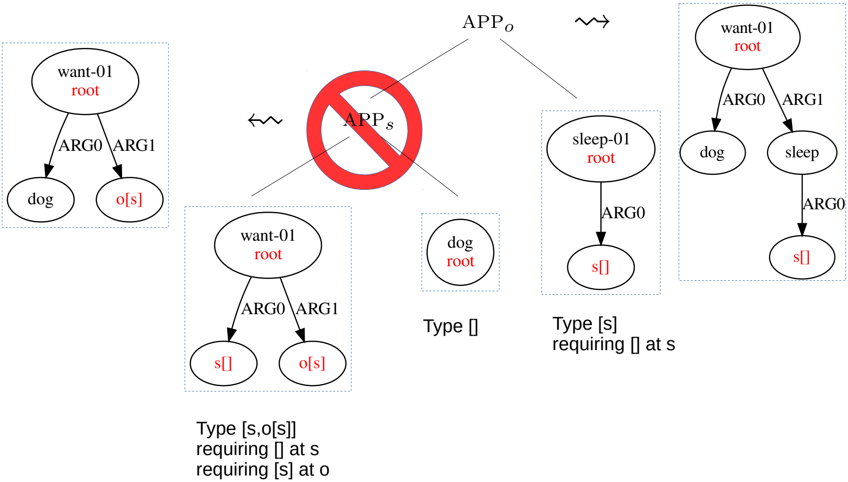
requiring [s] at o
Type []
Type [s]
requiring [] at s

No!



APP_s must not come first because s is in the requirement of o-source!

No!



APP_s must not come first because s is in the requirement of o-source!
Conclusion: Order of application is not arbitrary.